Forecasting Functionality States of Road Networks During Extreme Rainfall using ConvLSTM-based Data-Driven Surrogate Model

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ABSTRACT: A quick foresight or a short-term forecast of the likely functionality states of road networks during extreme rainfall events can provide excellent reference for proactive risk mitigation interventions. However, traditional physics-based flood simulation and road network analysis at community scales can be time-consuming, making it difficult to support real-time decision making. This study presents a novel solution: a data-driven surrogate model using deep learning techniques to forecast the dynamic functionality states of a road network during an extreme rainfall-induced flooding evolution. The complex spatiotemporal correlations among the functionality states of road network components during an extreme rainfall event, introduced by the road topology and the community's meteorological, geographical and hydrological conditions, are captured by a Convolutional Long Short-Term Memory (ConvLSTM) network with an Encoder-Decoder framework. This method allows for stable multi-step-ahead predictions of road network functionality states. To demonstrate the potential application of the surrogate model, a case study is conducted with a flood-prone community of Lin-An in Zhejiang Province, China, during a heavy rainfall event. The results highlight the effectiveness of the model in forecasting the functionality states of road networks during extreme rainfall events.

1. INTRODUCTION

Extreme rainfall caused by tropical cyclones can result in severe flooding and pose a significant threat to transportation systems in coastal regions. Accurate prediction of the likely functionality states of road networks during heavy rainfall can provide excellent support for real-time risk mitigation decision-making, including evacuation planning, rescue operations and emergency supplies scheduling.

There are two major technical frameworks for addressing this problem: simulation-based prediction and data-based prediction. Simulation-based prediction methods, such as those presented by Suarez et al. (2005), Chen et al. (2015) and Yang et al. (2020), establish and solve mathematical equations that describe the evolution of disasters, including rainfall-runoff, overflow and road network analysis. While these approaches have the potential to provide highly accurate solutions, they can be computationally demanding and may not be suitable for real-time disaster mitigation decisions at a regional scale.

On the other hand, data-driven prediction methods, such as those proposed by Stamos et al. (2015) and Wang et al. (2020), rely on advanced data algorithms (such as machine learning and neural network methods), trained on historical data to make rapid predictions. These methods are more computationally efficient than physics-based simulation models, but their accuracy can be limited by the quality and availability of historical data.

In recent years, various studies have employed machine learning techniques to construct data-driven surrogate models for flood prediction, as demonstrated in works of Mekanik et al. (2013), Gude et al. (2020), Kao et al. (2020), Guo et al. (2021), and Yin et al. (2021).

Additionally, some studies have developed surrogate models for transportation network analysis, such as Mastio et al. (2018) and Shang et al. (2020). Despite these advancements, there remains a gap in availability of an end-to-end surrogate model that can establish a direct correlation between rainfall inputs and road network functionality states, to support community's emergency response planning.

To fill this gap, we employ data-driven techniques to develop an end-to-end surrogate model that can predict the functionality states of road networks directly from the precipitation forecast. To accomplish this, we first introduce a topological rasterization method that preserves crucial topological features of road networks. Next, we use the Convolutional Long and Short-Term Memory (ConvLSTM) network to capture the spatiotemporal dynamics of road network functionality evolution during extreme rainfall events. Furthermore, we create an encoder-decoder framework within the ConvLSTM network that can effectively integrate multiple variables into a multimodal input to predict the future functionality status of the road network.

2. METHODOLOGY

2.1. Topological rasterization method

Many studies have presented valuable models for capturing the spatial characteristics of transportation networks. These include utilizing spatial-temporal matrices (Wang et al., 2016), rasterization models (Zhang et al., 2017), and graph neural network models (Jindal et al., 2017; Pan et al., 2019).

Rasterization models transform a road network into a raster image by dividing the road network area into grid cells through geospatial gridding. The resulting image reflects the functionality state of each node (an intersection) of road network through the pixel value of the corresponding grid. While this simplistic approach preserves intact topological information of a road network, the raster image tends to be sparse and retains a large amount of redundant information, i.e., empty grids without road. In disastrous situations where decision-makers are more concerned with topology-based functionality metrics such as connectivity (or accessibility) of roadways, the sparse raster data can make it difficult for a surrogate model to learn the critical spatial relationships among the roadway nodes that are key to the metrics of concern.

To address this issue, a novel topological rasterization process is proposed. This approach focuses particularly on preserving connectivity relationships of the roadway nodes while disregards other information (e.g., distances or directions) which is redundant to the prediction of roadway accessibility.

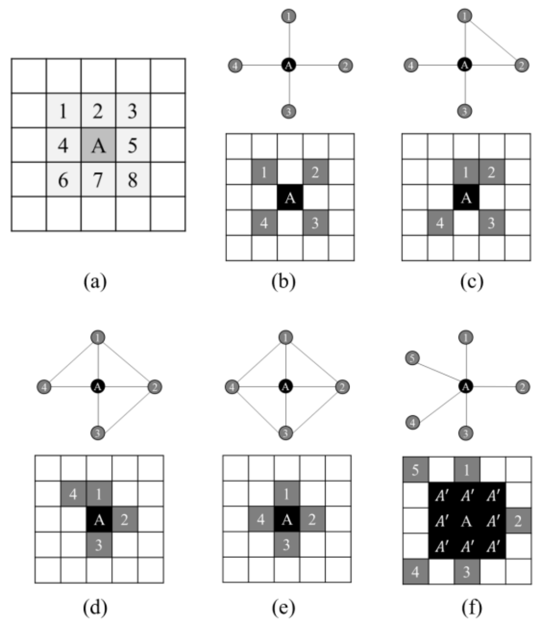

Figure 1: Topological rasterization method

In the proposed approach, each grid of a raster image represents a node of the road network. All adjacent grids represent nodes that are connected by roads (e.g., as shown in Figure 1(a), the node represented by grid A has 8 adjacent nodes). For examples, Figure 1(b)-(e) show representations of road intersections with three or four roads. Particularly, for intersections (or nodes) directly connected to other 5 or even more independent nodes (which are not interconnected), we create augmented nodes, such as A' in Figure 1(f), to increase the number of connection ports for these nodes. These intersections typically have more significant impact on the accessibility of the road network and thus occupy larger areas in the raster image. The accessibility of node A is thereby calculated as the average of the pixel values of all its augmented nodes.

As this rasterization approach disregards other spatial features of roadways, such as relative location and distance of adjacent nodes, it is not suitable for prediction of functionality metrics that require an understanding of traffic flow or travel trajectories. On the other hand, this method is efficient for emergency response situations where roadway accessibility is of particularly concern.

2.2. Convolution Long and Short-Term memory networks (ConvLSTM)

The Long Short-Term Memory (LSTM) network is a type of Recurrent Neural Network (RNN) introduced by Hochreiter et al. (1997). It excels in processing time-series data and has been successful in overcoming the gradient explosion or vanishing problem that occurs in traditional RNNs. However, LSTMs struggle with complex spatial relationships (Pascanu et al., 2013). To address this limitation, Shi et al. (2015) proposed the hybrid Convolutional LSTM (ConvLSTM), in which spatial information at each time is encoded and captured through convolutional operations while learning temporal relationships. The ConvLSTM has since become the mainstream method in the field of spatio-temporal prediction, and is used in this study as the building block for the data-driven surrogate model.

2.3. Network structure of data-driven surrogate model

Forecasting the road network accessibility during an extreme rainfall event requires the consideration of meteorological variables. Sutskever et al. (2014) proposed to use an LSTM-based Sequence to Sequence deep learning model for natural language processing tasks, which offers greater flexibility in input and output states. This model consists of independent RNN models, known as encoder and decoder, that allow for input and output sequences to be processed separately. Building on this work, researchers have used multiple encoders or decoders to process multimodal inputs or outputs (Kao et al., 2020; Yin et al., 2021).

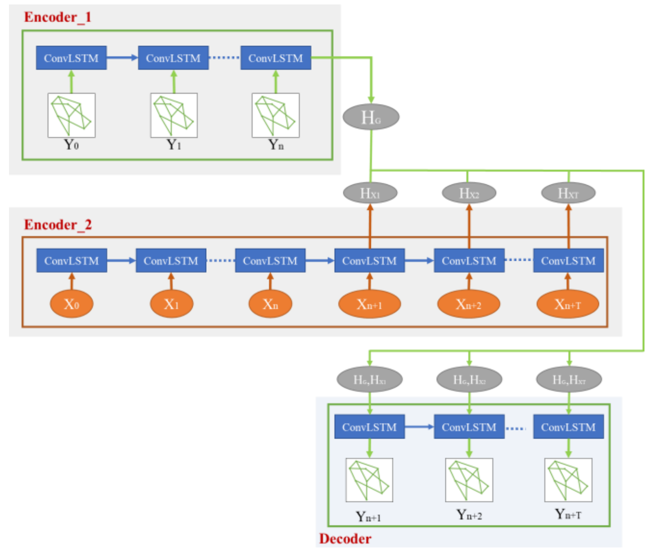

Figure 2: The network structure of the data-driven surrogate model

This study develops a deep learning network that forecast future accessibility of road network by incorporating roadway accessibility states and precipitation data in the past hours as well as the precipitation forecast of the future hours. The neural network, as shown in Figure 2, consists of three independent RNNs, i.e., two encoders and one decoder, which are composed of with ConvLSTM units. For the T-steps ahead prediction task, the first RNN (Encoder_1) extracts spatiotemporal features from past roadway accessibility states (from Y_0 to Y_n) and outputs a hidden state representation, H_G. The second RNN (Encoder_2) learns the spatiotemporal features of rainfall sequence data, including actual precipitation records (from X_0 to X_n) and precipitation forecasts (from X_{n+1} to X_{n+T}). This encoder outputs T hidden states, H_{Xi} $(i = 1,2,\cdots,T)$, each containing information about the precipitation sequence from X_{n+1} to X_{n+i}. The hidden states H_G and H_{Xi} are then combined to form a new hidden state vector,

H_{G_Xi} , which servs as the input to the third RNN (Decoder). The Decoder with its ConvLSTM units, is capable of predicting the future nodal accessibilities of the road network.

3. CASE STUDY

3.1. Introduction of the study area

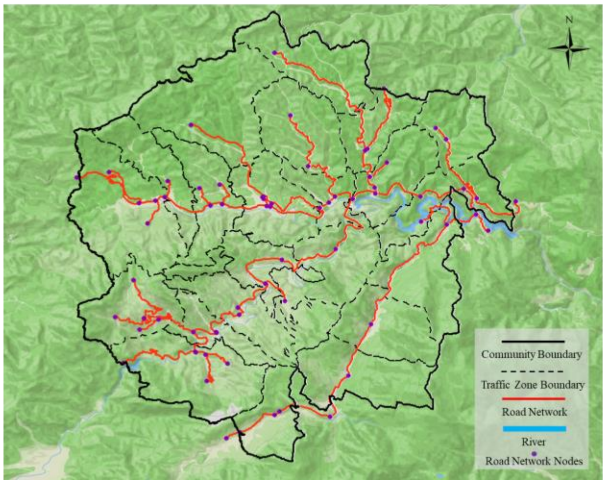

Figure 3 : Road network in the community of Lin-An

This section highlights the creation and implementation of a surrogate model utilizing the methodology discussed in Section 2, using a flood-prone community of Lin-An Town in Zhejiang Province, China as a case study.

Lin-An Town covers an area of 139.1 square kilometers and is situated in a mountainous basin landscape with a dense network of rivers and abundant groundwater and precipitation (average annual precipitation is 1590mm), making it susceptible to severe flood. The road network of Lin-An Town consists of 69 road nodes and 70 road segments, totaling approximately 115 km, as depicted in Figure 3. The community is further divided into 22 traffic analysis zones.

3.2. Surrogate modeling process

The development of the surrogate model involves the following 4 steps:

1. Simulation of inundation scenarios using physics-based simulation techniques;
2. Connectivity analysis of the road network to understand the impact of inundation;
3. Preprocessing the above training data for model development;
4. Training a neural network for accurate predictions of roadway accessibility for future hours.

The latter two steps are part of the construction phase of the data-driven model, as outlined in Section 2. The first two steps, which include disaster simulation and roadway accessibility analysis, are the data generation phase of the modeling process. The following section describes the data generation methods and the physics-based models employed in this particular case study.

3.2.1. Data generation: physics-based simulation and road network function analysis

Initially, we generate 8500 precipitation sequences with 1-hour resolution and 72-hour length based on the design rainfall patterns and the precipitation records during historical tropical cyclones in Lin-An Town. Of all the sequences, the 1-hour peak precipitation ranges from 20 mm to 80 mm, while the 72-hour cumulative precipitation ranges from 165.5mm to 876.2 mm.

Based on the characteristics of the watershed in Lin-An Town, we utilizes the Soil Conservation Service (SCS) model (Ponce et al., 1996) to forecast rainfall-runoff and the LISFLOOD-FP model (Shustikova et al., 2019) to simulate the inundation process. After acquiring the disaster scenarios, we extract the inundation states of roads by imposing inundation on the roadway topology using ArcGIS, and evaluate service level of roads based on a water depth-traffic disruption function proposed by Pregnolato et al. (2017), and calculate the resilience-based metric of WIPW used in Zhang et al. (2016) to reflect accessibility of each node in the road network.

Subsequently, we use these 8500 original data groups, including rainfall sequences and corresponding roadway's nodal accessibilities, to train a surrogate model.

3.2.2. Model training：data processing and neural network parameter settings

The pre-processing of the original data was necessary before training the surrogate model. The study calculates the accessibility, $\xi \in [0,1]$, of each node during heavy rainfall events, with 0 being no accessibility and 1 being full accessibility as under normal operational condition. The results of the road network topological rasterization introduced in 2.1 are used to map the hourly precipitation and nodal accessibility to corresponding pixels, creating 8500 sets of precipitation raster maps and nodal accessibility raster maps.

The surrogate model is designed to predict nodal accessibility for the future 6 hours, using the past 24 hours of precipitation measurements and nodal accessibility states as well as the future 6 hours of rainfall forecast as the input data (i.e., $n = 24$, $T = 6$ in Figure 2). A sliding time window method is applied to divide each 72-hour time series into 40 30-hour groups. The roadway nodal accessibility raster data of the first 24 hours serves as the input for Encoder_1, the total of 30 hours of precipitation raster data serve as the input for Encoder_2, and the roadway nodal accessibility raster data of the future 6 hours serves as the label data.

This study implements the neural network using the GPU version of Pytorch. The parameters of surrogate model are set as follows. Encoder_1, which contains 24 ConvLSTM units, has a convolution kernel size of 3×3 and the hidden state length of 64; Encoder_2, which contains 30 ConvLSTM units, has a convolution kernel size of 3×3 and the hidden state length of 32; The Decoder, which contains 6 ConvLSTM units, has a convolution kernel size of 3×3 and the hidden state length of 64. The dropout rate of 0.2 is set to prevent overfitting. The learning rate utilizes an exponential decay strategy, with the initial learning rate of 0.1 and a minimum learning rate of 10^{-6}. The batch size is set to be 256 and the loss function used is the mean-square error (MSE).

The test error of the surrogate model quickly converges within the first 40 epochs and stabilized at the 100th epoch.

3.3. Result analysis

Figure 4 presents the surrogate model's prediction of the future 6-hour roadway nodal accessibility of a particular rainfall sequence. The accessibility index of a traffic analysis zone is calculated as the average of the nodal accessibility of all nodes in the zone. The experimental result shows that the ConvLSTM model is capable of effectively forecasting the dynamic accessibility state of each roadway node during heavy storms.

To demonstrate the ConvLSTM model's ability to learn spatial information, we constructed a comparative model using the same neural network structure as depicted in Figure 2 but replaced each unit with a traditional fully connected LSTM (FC-LSTM) which only processes raster data as a one-dimensional vector instead of a graph. It is discovered, as in Figure 4, that the ConvLSTM model outperforms the FC-LSTM in predicting the road network accessibility in terms accuracy. Furthermore, as depicted in Figure 5 in the 24-hour accessibility prediction of a selected node, the ConvLSTM model exhibits lower prediction errors and captures the dynamic accessibility states of the roadways more accurately, in comparison with the FC-LSTM.

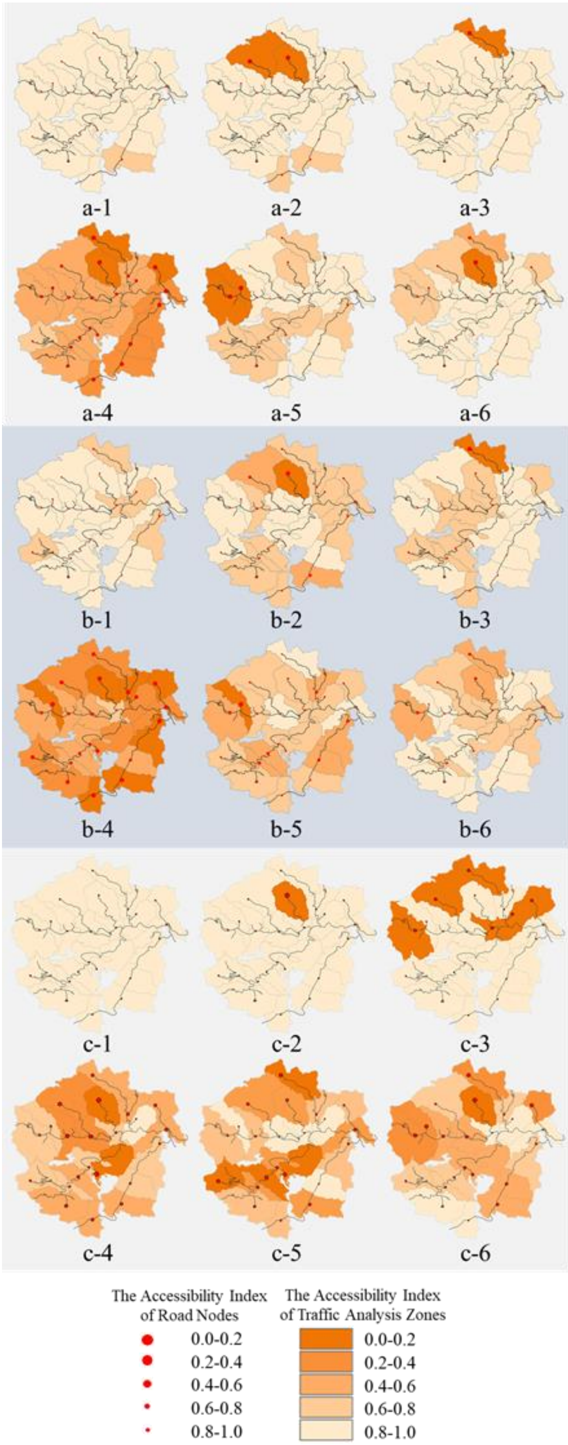

Figure 4: A example for the roadway accessibility forecast, including (a) the groud truth accessibility states, (b) the prediction by ConvLSTM and (c)by FC-LSTM.

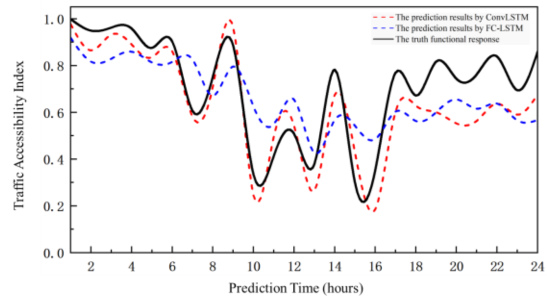

Figure 5: The accessibility forecast for a selected node in the road network

4. CONCLUSIONS

The research establishes an end-to-end data-driven surrogate model that utilizes deep learning methods to improve the computational efficiency of physics-based inundation simulation and road network analysis for real-time decision-making in disaster mitigation. A road network topology rasterization method is proposed to effectively extract relevant spatial information for decision makers, eliminating redundant spatial relationships and improving model learning efficiency. This study develops a ConvLSTM-based neural network with encoder-decoder structure, which enables simultaneous learning of multiple variables, capturing the spatiotemporal correlations and enabling multi-step prediction of future road network accessibility states. To demonstrate the model-building process, an illustration through a flood-prone coastal community is presented. The prediction results demonstrate excellent potential of the surrogate for predicting roadway accessibility during extreme rainfall events.

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