Graph Transformer Network for Flood Forecasting with Heterogeneous Covariates

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Abstract—Floods can be very destructive causing heavy damage to life, property, and livelihoods. Global climate change and the consequent sea-level rise have increased the occurrence of extreme weather events, resulting in elevated and frequent flood risk. Therefore, accurate and timely flood forecasting in coastal river systems is critical to facilitate good flood management. However, the computational tools currently used are either slow or inaccurate. In this paper, we propose a <u>Flood</u> prediction tool using <u>G</u>raph <u>T</u>ransformer <u>N</u>etwork (FloodGTN) for river systems. More specifically, FloodGTN learns the spatio-temporal dependencies of water levels at different monitoring stations using Graph Neural Networks (GNNs) and an LSTM. It is currently implemented to consider external covariates such as rainfall, tide, and the settings of hydraulic structures (e.g., outflows of dams, gates, pumps, etc.) along the river. We use a Transformer to learn the attention given to external covariates in computing water levels. We apply the FloodGTN tool to data from the South Florida Water Management District, which manages a coastal area that is prone to frequent storms and hurricanes. Experimental results show that FloodGTN outperforms the physics-based model (HEC-RAS) by achieving higher accuracy with 50% improvement while speeding up run times by at least 500x.

Index Terms—deep learning, graph transformer network, flood prediction

I. Introduction

Floods can result in catastrophic consequences with considerable loss of life, huge socio-economic impact [32], property damage [2], and environmental devastation [33]. Floods are a threat to food and water security and to sustainable development [13]. What is more alarming is that studies suggest that global climate change may lead to drastically increased flood risks, in both frequency and scale [10], [31]. Therefore, accurately predicting flood events is of utmost importance.

Flood forecasting is traditionally achieved by building detailed physics-based computational models [28] that take into consideration high-resolution terrain data, groundwater data, reservoirs, man-made structures, canals, and river networks [24], [35]. Hydrological dynamics of the entire watershed are simulated on detailed grid-based terrain elevation maps [22], [30] by solving complex partial differential equations (PDEs)

[21], [34]. Consequently, good simulations are accurate but computationally prohibitive, especially on large watersheds [12], [14].

Machine learning (ML) and deep learning (DL) have emerged as powerful approaches for cutting-edge research in this domain [4], [19], [37]. Many of the previous efforts on this problem have used ML/DL tools as black boxes with little or no domain knowledge incorporated in architecting a model [7], [9], [20], [23], [25], [27], and often with little or no fine-tuning. Some of them also usually ignore the heterogeneity of the input variables and/or the geospatial relationships between the measurement sites [11], [15]. Finally, almost all of them ignore useful and reliable predictions of some external covariates, such as precipitation and tide [5], [36].

In this work, we propose a machine learning tool called <u>Flood</u> prediction tool using <u>G</u>raph <u>T</u>ransformer <u>N</u>etwork (FloodGTN). We present two possible architectures for FloodGTN, one that connects the components in *parallel* and one that connects it in *series*, as shown in Figs. 1 and 2. Details are given in Section II. An important feature of our work is that the graph underlying the GNN component has edge connections that mirror the geospatial layout of the river system, a distinct advantage resulting from the use of GNNs, not afforded by other machine learning models. A second important feature of our work is the use of forecast-informed covariates [5] in our model, thus recognizing the fact that modern weather and tide predictions are reliable enough to be extremely useful in flood prediction. Finally, the attention component of the transformers in the architecture allows us to incorporate *explainability* into our models.

II. Problem Formulation & Methodology

A. Problem Description

Flood forecasting will be achieved by predicting water levels, Y, at multiple control points in a river system for $k > 0$ time steps in the future, taking inputs, X, from the past $w \geq 0$ time steps, while making use of additional information on external covariates that can be reliably predicted for k time

steps in the future. We train machine learning models to learn a mapping function f with parameters θ from input matrix X to output matrix Y:

$$f_\theta : (X_{t-w+1:t}, X^{cov}_{t+1:t+k}) \rightarrow Y_{t+1:t+k}, \qquad (1)$$

where the subscripts of the time-series variables X and Y represent the time ranges under consideration, and the superscript cov refers to the input covariates that are known to be reliably predicted and available for computations. In particular, we use DL models that combine multiple approaches such as graph neural networks (GNNs), attention-based transformer networks, long short-term memory networks (LSTMs), and convolutional neural networks (CNNs) to achieve our objectives.

B. FloodGTN Framework

We tried the graph transformer networks in two manners. In the parallel version, the `Transformer` learns feature representations from covariates while `GCN-LSTM` extracts spatiotemporal dynamics of water levels. `Attention` is used to figure out the water level dependencies on each covariate. The serial version is a geo-spatially aware architecture (see Fig. 2). Here the `Transformer` learns feature representations of each measurement station along the river while `GCN-LSTM` extracts information on the spatiotemporal dynamics of fused feature representations from each station.
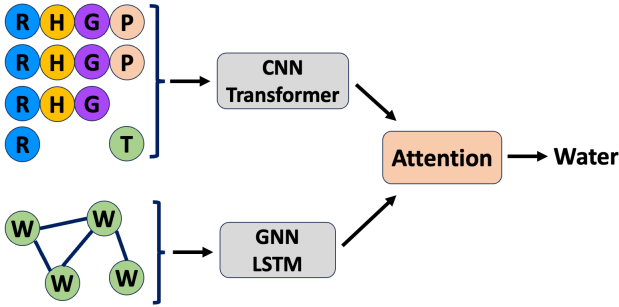

Fig. 1. FloodGTN-Parallel. R, H, G, P, T, W represent the rainfall, head water level, gate schedules, pump schedules, tidal information, and tail water levels, respectively, as shown in Fig. 3.
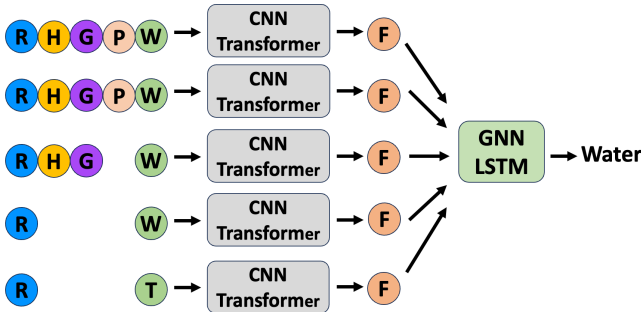

Fig. 2. FloodGTN-Series. Each row represents the information at one station. F refers to $fused$ data.

III. EXPERIMENTS

A. Dataset

We obtained data on the last (coastal) part of the South Florida watershed from the South Florida Water Management District's (SFWMD) DBHydro database. The data set we used in the work recorded the hourly observations for water levels and external covariates from 2010 to 2020. As shown in Fig. 3, the river system has three branches/tributaries and includes several hydraulic structures (gates, pumps) located along rivers to control water flows. Water levels are also impacted by tidal information since the river system empties itself into the ocean. The tool, FloodGTN, was used on this data set to predict water levels at four specific locations marked by green circles in the figure below. It is useful to note that this portion of the river system flows through the large metropolis of Miami, which has a sizable population, commercial enterprises, and an international airport in its close vicinity.
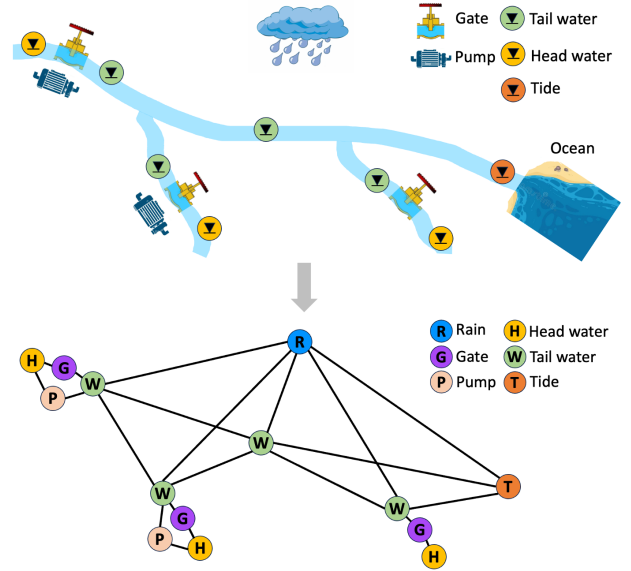

Fig. 3. Coastal river system in the South Florida watershed. Top: schematic diagram of river systems. Bottom: schematic diagram with symbols for better modeling representation.

B. Experimental Design

We set $w = 72$ hours and $k = 24$ hours. The sliding window [6], [18] (also known as looking window, rolling window [26]) was used to process the entire dataset. For deep learning models, the first 80% and the last 20% of the data set were used as the training and test sets, respectively.

C. Baselines

The physics-based model (HEC-RAS) and deep learning (DL) models (other than FloodGTN) compared in this work include the following:

- HEC-RAS [3]: a physics-based model. We use a coupled 1D and 2D hydraulic model.
- RNN [8]: a recurrent neural network designed to iteratively process sequential data.

- CNN [16]: a 1D convolutional neural network for sequence modeling.
- TCN [38]: a temporal dilated convolutional network for sequence modeling.
- GCN [17]: a graph convolutional neural network for time series forecasting.
- Transformer [29]: an attention-based network for sequence modeling.

D. Prediction Errors

The mean average errors (MAEs) and root mean square errors (RMSEs) [1] were the two measures that were used to evaluate these models. The mathematical equations are described below.

$$MAE = \frac{\sum_{i=1}^{N} |\hat{y}_i - y_i|}{N}, \tag{2}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N} (\hat{y}_i - y_i)^2}{N}}, \tag{3}$$

where N is the number of samples in the test set; y_i and $\hat{y}_i$ are the observed and predicted values.

IV. RESULTS & DISCUSSION

A. Prediction Performance

Table I shows MAE and RMSE scores on the test set for all models that are used in this work. Each experiment was performed with and without the future covariates, mirroring the situation when reliable predictions are or are not available for the computation. The results indicate that the use of reliably predicted future information can improve the accuracy of predictions. In addition, our parallel version of `FloodGTN` outperformed other baseline models in this paper while the series version of `FloodGTNs` had a performance level comparable to the best baseline.

B. Visualization

Fig. 4 shows the visualization of observed and predicted water levels of some selected models during the tropical storm *Isalas* that happened on August 1st, 2020. The curve of our parallel version of `FloodGTN` (blue line) is the closest to the ground-truth observed data (red dashed line).
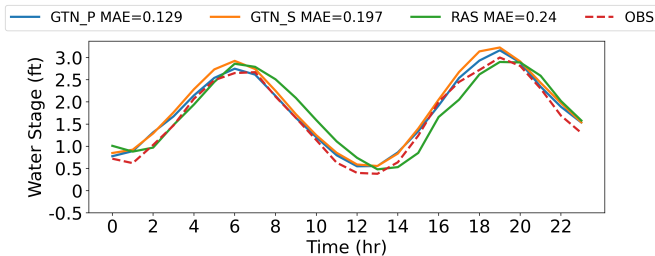

Fig. 4. Visualization of observed & predicted water levels with future predicted covariates. GTN_P, GTN_S, and RAS represent FloodGTN-Parallel, FloodGTN-Series, and HEC-RAS models, respectively. OBS denotes the observed data.

TABLE I
AVERAGE 24-HOUR PREDICTION ERRORS ON TEST SET WITH/WITHOUT
FUTURE PREDICTED COVARIATES (F.P.C.).

Model	With F.P.C.		Without F.P.C.	
	MAE (ft)	RMSE (ft)	MAE (ft)	RMSE (ft)
HEC-RAS	0.185	0.238	0.185	0.238
RNN	0.087	0.112	0.167	0.213
CNN	0.105	0.135	0.203	0.265
TCN	0.085	0.114	0.162	0.207
GCN	0.075	0.102	0.138	0.183
Transformer	0.068	0.091	0.132	0.175
FloodGTN-Series	0.069	0.094	0.135	0.179
FloodGTN-Parallel	**0.055**	**0.079**	**0.127**	**0.169**

C. Computational Time

To compare the efficiency of the physics-based models and DL-based models, we show the simulation time of HEC-RAS and the prediction time of DL models on the test set. Note that we do not concern the training time of DL models, since they are one-time cost. They are only applied during the test phase only if they are well pre-trained beforehand.

TABLE II
SIMULATION TIME OF PHYSICS-BASED HEC-RAS AND THE PREDICTION
TIME OF DL MODELS.

Model	Training time	Test time
HEC-RAS	-	45.92 min
RNN	427 min	4.81 s
CNN	29 min	1.81 s
TCN	366 min	4.95 s
GCN	60 min	4.04 s
Transformer	47 min	4.46 s
FloodGTN-Series	686 min	5.51 s
FloodGTN-Parallel	148 min	5.02 s

V. CONCLUSIONS

We proposed a Graph Transformer Network for Flood prediction called `FloodGTN`. From the accuracy perspective, both FloodGTN-Series and FloodGTN-Parallel models outperform the physics-based `HEC-RAS` model, and FloodGTN-Parallel is better than all other DL-based methods. More importantly, once trained, the prediction speed of the DL models is much faster than the simulation speed of physics-based `HEC-RAS`. This opens the door to the possibility of a high-quality real-time prediction tool, the first step toward building a sophisticated flood management system. We also demonstrate that using future exogenous covariates (such as rainfall and tide) is critical for DL models to produce more accurate predictions.

VI. FUTURE WORK

After we trained an accurate and rapid DL-based model for flood prediction, we are going to use it as the flood evaluator in flood mitigation task, where it can iteratively evaluate the control schedules of gates and pumps until they meet the requirement to mitigate or even avoid flooding.

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