

## A hybrid deep learning framework for regional-scale forecasting of hurricane-driven flood evolution

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### Summary

Notwithstanding substantial advancements in high-fidelity hydrodynamic simulations for evaluating flooding evolution in coastal communities under hurricane hazards, their considerable computational demands can hinder widespread applications in engineering practices, particularly in the context of uncertainty propagation. To overcome this challenge, this paper develops a hybrid deep learning framework for efficiently predicting community-scale spatio-temporal flooding evolution by integrating convolutional and recurrent neural networks. To deal with the high-dimensionality associated with large geographic domains, convolutional autoencoders are first employed to reduce community-scale water levels to lower-dimensional latent representations while preserving essential spatial characteristics. Subsequently, a hybrid deep learning-based emulator is trained to capture both spatial and temporal features within the latent space using convolutional and recurrent neural networks. Through the illustration on Marco Island, Florida, the proposed framework has been demonstrated to be capable of accurately predicting large-scale flooding evolution over long periods.

**Keywords:** *Hurricane-driven floods, Spatio-temporal prediction, Coastal Communities, Convolutional neural networks, Recurrent neural networks*

## 1 INTRODUCTION

Coastal regions are highly susceptible to flooding hazards caused by extreme hurricanes, potentially resulting in substantial economic losses, infrastructure damage, and threats to human safety. To enhance coastal resilience, it is essential to model storm surge and flooding at high spatial and temporal resolution. A common approach involves the utilization of high-fidelity numerical simulations capable of providing detailed representations of the underlying hydrodynamic processes. However, these models generally require considerable computational cost, thereby limiting their applicability for flood forecasting under uncertainty, especially over large geographic domains or extended time horizons. To address this issue, data-driven techniques that establish mappings between hurricane parameters and community-scale flood water levels have emerged as promising alternatives. These approaches enable the development of emulators that can predict flood evolution with a high level of accuracy while achieving significant computational speedups. However, most existing studies have primarily focused on predicting peak water levels, with relatively few addressing predictions of the entire flood evolution (Adeli et al., 2023, Saviz et al. 2025). Emulating dynamic flood processes over coastal regions remains challenging due to: (a) the high dimensionality associated with large geographic domains; and (b) the complex and nonlinear dynamics that evolve across both spatial and temporal scales. To tackle these challenges, this work develops a hybrid deep learning framework for predicting spatio-temporal flood dynamics by combining convolutional autoencoders (CAE) with convolutional recurrent neural networks. The accuracy and practicality of the proposed scheme are demonstrated through an application involving the prediction of the time history of water levels in a coastal community.

## 2 PROBLEM SETTING

Consider a dynamical system subject to hurricane hazards, characterized by uncertain time-varying parameters  $\boldsymbol{\theta}(t) = [x_{\text{lat}}(t), x_{\text{lon}}(t), v_{\text{tr}}(t), \alpha(t)]^T$ , where  $x_{\text{lat}}(t)$  and  $x_{\text{lon}}(t)$  denote the latitude and longitude of the hurricane eye,  $v_{\text{tr}}(t)$  represents the translational wind speed, and  $\alpha(t)$  is the hurricane heading direction, at time step  $t$ . The evolution of system-level flood water levels,  $\mathbf{h}(t) \in \mathbb{R}^{n_1 \times n_2}$ , where  $n_1$  and  $n_2$  represent the dimensions of the system, can be expressed as a function of  $\boldsymbol{\theta}(t)$  as follows:

$$\mathbf{h}(t) = f(\boldsymbol{\theta}(t), t) \quad (1)$$

High-fidelity hydrodynamic simulations are generally employed to provide accurate solutions to Eq. (1). However, these models are computationally impractical for accommodating a considerable number of hurricane realizations in the context of uncertainty propagation. To tackle this limitation, this paper develops an emulation framework that efficiently establishes a sequence-to-sequence mapping between  $\boldsymbol{\theta}(t)$  (i.e., inputs) and  $\mathbf{h}(t)$  (i.e., outputs).

## 3 METHODOLOGY

### 3.1 Dimensionality Reduction

Directly creating a mapping between  $\boldsymbol{\theta}(t)$  and  $\mathbf{h}(t)$  is often challenging, as  $n_1$  and  $n_2$  become very large for extensive geographic domains. To address the high dimensionality, a nonlinear dimensionality reduction technique, e.g., CAE, is employed. Typically, a CAE model consists of two main components: (a) an encoder that projects  $\mathbf{h}(t)$  into lower-dimensional latent representations,  $\mathbf{z}(t) \in \mathbb{R}^{n'_1 \times n'_2}$ , where  $n'_1$  and  $n'_2$  indicate the dimensions of the latent space, using multiple convolutional layers; and (b) a decoder that reconstructs  $\mathbf{h}(t)$  from  $\mathbf{z}(t)$  using transposed convolutional layers, yielding  $\tilde{\mathbf{h}}(t) \in \mathbb{R}^{n_1 \times n_2}$ . The training process aims to minimize the reconstruction error between  $\mathbf{h}(t)$  and  $\tilde{\mathbf{h}}(t)$ , thereby ensuring that  $\mathbf{z}(t)$  captures the essential features of the original flooding data.

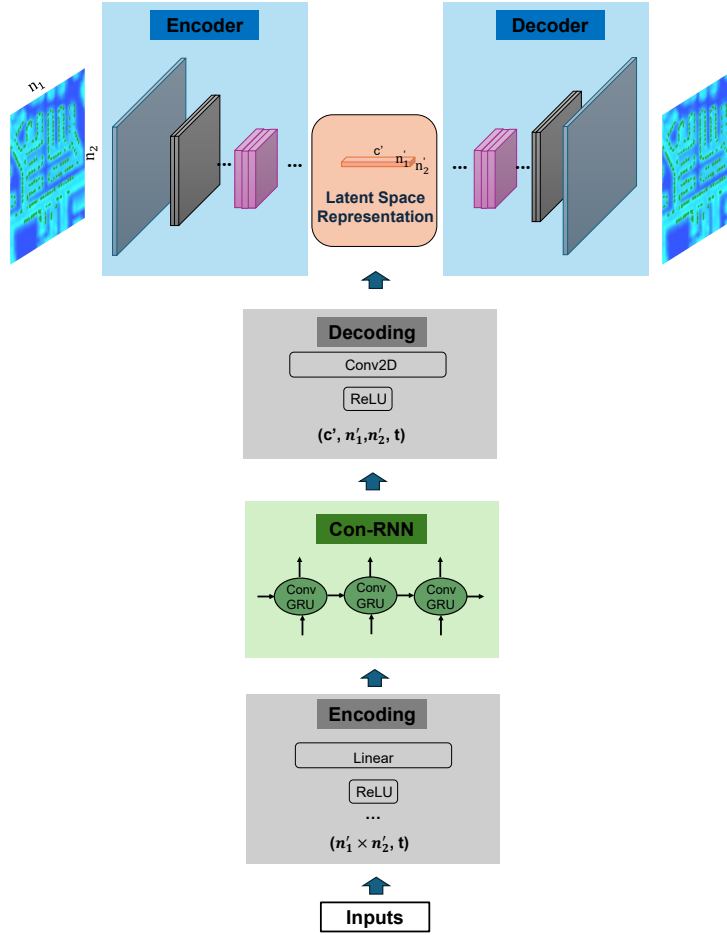
### 3.2 Spatio-temporal Prediction

Once more tractable latent representations are extracted using the CAE encoder, a deep learning-based framework is established to map  $\boldsymbol{\theta}(t)$  to  $\mathbf{z}(t)$ . At each time step  $t_i$ , the input  $\boldsymbol{\theta}(t_i)$  is first encoded into 2-dimensional (2D) maps consistent with the dimensionality of  $\mathbf{z}(t_i)$ . These maps are then processed by convolutional recurrent neural networks (e.g., convolutional Gated Recurrent Units (ConvGRU)) to capture spatio-temporal dependencies. Subsequently, a decoding step reconstructs latent representations at  $t_i$  from the hidden state using convolutional layers. After sequentially processing all time steps, the predicted latent representations are transformed back to the high-dimensional output using the CAE decoder. The overall workflow of the proposed framework is illustrated in Figure 1.

## 4 CASE STUDY

### 4.1 Description

To demonstrate the accuracy and efficiency of the proposed framework, a case study was conducted to predict the flooding evolution of Marco Island, Florida, under hurricanes. A high-fidelity model was established in Delft3D to capture the community-scale hydrodynamic features, providing 18-



**Figure 1:** Workflow of the overall framework

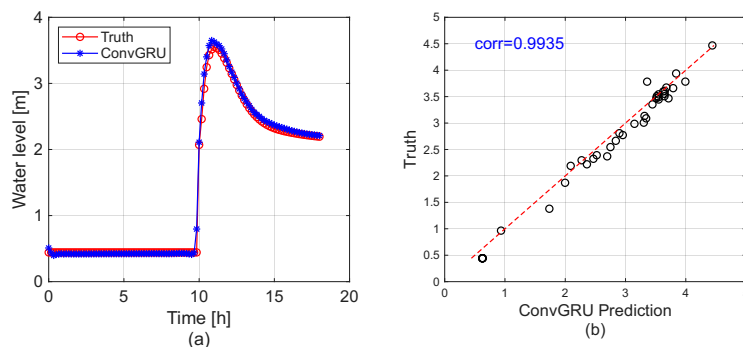
hour water-level time series with a high dimensionality of  $n_1 = n_2 = 256$  and a time step of 10 minutes. A parametric hurricane model, as outlined in Ouyang and Spence (2021), was adopted to model hurricane trajectories. To effectively capture the extreme events, a subset simulation scheme based on the site-specific wind speeds was utilized. In total, 640 samples were generated within the last subset, corresponding to a return period exceeding 500 years.

## 4.2 Training Configuration

To calibrate the proposed framework, a CAE model with 4 convolutional layers in both the encoder and decoder was first trained to extract latent representations  $z(t) \in \mathbb{R}^{32 \times 32}$  capturing key spatial features. Subsequently, the ConvGRU-based model was trained to develop an emulator mapping  $\theta(t)$  to  $z(t)$ . In this model, the 4-dimensional inputs are first encoded to 2D maps of size  $32 \times 32$  using 4 fully connected layers. These 2D maps are then fed with one ConvGRU layer, followed by one 2D convolutional layer for decoding. Finally, the predicted latent representations are mapped back to the high-dimensional space (e.g.,  $256 \times 256$ ) using the CAE decoder. The training process uses 600 samples, with 10% allocated for validation, while the remaining 40 samples are reserved for testing.

### 4.3 Results

To validate the accuracy of the proposed scheme, Figure 2 summarizes the prediction performance using the testing samples. Figure 2(a) compares the water-level time histories at a representative node using one test sample. It can be shown that the ConvGRU-based model effectively captures the time-varying characteristics of flooding evolution over the long observation period of 18 hours. Furthermore, Figure 2(b) compares peak water levels at the same node across 40 testing samples, achieving a high correlation coefficient of 0.9935. Once trained, the emulator predicts the 18-hour flooding time history in 0.58 s, providing significant computational speedups as compared to the high-fidelity simulation model that required approximately 6 hours.



**Figure 2:** Prediction performance of the proposed framework: (a) comparison of water-level time histories at one node using one test sample; and (b) comparison of peak water levels at one node using 40 test samples.

## 5 CONCLUSION

To efficiently predict the spatio-temporal evolution of hurricane-driven flooding in coastal communities, this paper proposes a data-driven emulation framework by harnessing hybrid neural networks. To address the high dimensionality, convolutional autoencoders are employed to extract latent representations while preserving essential spatial features. Within the latent space, convolutional recurrent neural networks are trained to develop an emulator capable of capturing spatio-temporal flooding dynamics. The proposed framework demonstrates both high accuracy and efficiency in predicting time-varying flooding at the community scale, highlighting its potential as a promising alternative for large-scale flood forecasting under uncertainty.

## ACKNOWLEDGEMENTS

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