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DEEP LEARNING-BASED FLOOD INUNDATION PREDICTION IN THE PATTANI RIVER BASIN

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ABSTRACT: Accurate flood prediction is critical for effective disaster management and mitigation. This study employs deep learning models, including Gated Recurrent Unit (GRU), Long Short-Term Memory (LSTM) networks, and Convolutional Neural Networks (CNNs), to enhance flood forecasting for both water level and flood inundation predictions. By integrating upstream river flow, river water level, and tidal level data, the models aim to improve prediction accuracy. Water level forecasting involved evaluating GRU and LSTM models across four scenarios over lead times up to 24 hours, using Root Mean Squared Error (RMSE) and Nash-Sutcliffe Efficiency (NSE) as performance metrics. The results showed that GRU models consistently outperformed LSTM models when using all three parameters, while LSTM exhibited the worst performance, with higher RMSE and lower NSE values. For flood inundation prediction, CNNs were employed using Sentinel-1 GRD images as target data. Scenarios incorporating all three parameters achieved the highest average True Positive Rate (TPR) for both non-flooded and flooded areas, underscoring the value of integrating diverse data sources for accurate flood predictions. This research presents a sustainable, real-time flood prediction solution that reduces computational time while maintaining high accuracy. The findings support smarter water management strategies, aiding authorities in minimizing flood impacts on communities and infrastructure.

Keywords: Convolutional neural network, Deep learning, Flood inundation, River hydraulics

1. INTRODUCTION

Flooding is a severe natural disaster that causes environmental damage, economic losses, and human casualties. Predicting water levels accurately is essential for early flood warning and mitigating flood disasters. Identifying areas susceptible to flooding beforehand is particularly useful for flood warnings. Typically, the main approaches to forecast the water level and flood inundation with high accuracy rely extensively on the rainfall-runoff, hydraulic, or hydrodynamic model. These models require comprehensive datasets, including topographic, meteorological, and hydrological data [1,2,3]. Furthermore, the flood simulation needs a lot of computation time based on a complexity of scheme. These models are not suitable for real-time predictions.

Another method to predict water levels and flood inundation areas involves data-driven models. These models analyze the relation between input and output parameters, overcoming the limitations of physically based models by reducing the need for extensive datasets and lengthy simulations. In recent years, Deep Learning (DL) techniques have been widely integrated into water resource engineering, particularly in the time series parameter, including river water level rainfall and discharge, which are the main parameters in flood warning systems [4]. LSTM and GRU are high-performing models for forecasting water levels. The lead time of 1 hour to 12 hours was predicted using LSTM and GRU by evaluating the input parameters, including water level and rainfall [5]. The results indicated that water level had a greater effect on predictions than rainfall. In Hongze Lake, researchers applied SSA with LSTM to predict water levels [6]. Different feature selection methods have been used to predict stream discharge with 1-hour to 12-hour lead times using RNN, LSTM, and GRU in Thailand [7]. Euang [8] used LSTM combined with ANN to predict discharge in a river by using various recurrent times and different epochs. They found that LSTM predicts high flow better than low flow, as shown by comparing the flow duration curve.

Flood inundation prediction is particularly challenging due to the scarcity of observational data. Typically, flood inundation areas are mapped using aerial photos, optical satellite images, and SAR images [9]. Sentinel-1 SAR have been applied in UK by using VH and VV polarization for delineating water surface during winter flood of 2015-2016 [10]. The RAPID system has been used for automated flood mapping in the contiguous United States from 2016 to the present. This system integrates radar statistics and machine-learning techniques to process Sentinel-1 SAR imagery, providing high-resolution flood inundation data. The dataset includes inundation events with temporal scales ranging from several days to months, demonstrating high accuracy and robustness. This archive is anticipated to facilitate applications in flood loss and risk assessment, and inundation model calibration and validation [11-13]. However, these methods are limited by the temporal scale of the image data. The primary objective of this research is to introduce an innovative approach that leverages deep learning to enhance flood forecasting, including both water level and flood inundation predictions.

2. RESEARCH SIGNIFICANCE

This research significantly contributes by introducing an innovative approach to flood prediction using deep learning. By leveraging Gated Recurrent Unit (GRU), Long Short-Term Memory (LSTM) networks, and Convolutional Neural Networks (CNNs), the study enhances the accuracy of flood forecasting by integrating upstream river flow, river water level, sea water level, and satellite data. This approach not only improves the precision of predicting water levels and flood extents but also reduces computational time, making it a sustainable solution for real-time flood prediction. By providing accurate and timely flood warnings, this research supports smarter water management strategies, enabling authorities to mitigate the impacts of floods on communities and infrastructure effectively.

3. METHODOLOGY

We utilize various input parameters, such as the release flow from hydraulic structures, river water levels, and tidal levels, to forecast river water levels and potential flood inundation using deep learning techniques. In our study, we compared the performance of Gated Recurrent Units (GRU) and Long Short-Term Memory (LSTM) networks for river water level prediction across different scenarios, as illustrated in Table 1. Additionally, flood inundation predictions will be made based on these scenarios using a Convolutional Neural Network (CNN) model, which incorporates inundation data collected from Sentinel-1 Ground Range Detected (GRD) images. This section provides detailed information about the study area, flood inundation classification, model development, and performance evaluation.

Table 1. Input parameters for different scenarios

Scenarios	Release flow	River Water Level	Tidal Level
SCN1	✓	✓	-
SCN2	✓	-	✓
SCN3	-	✓	✓
SCN4	✓	✓	✓

3.1 Study Area

This study focused on the Pattani River basin in southern Thailand, between 5°36′ N and 101°00′ E and 6°54′ N and 101°30′ E. The total watershed area is approximately 219.23 km². The Pattani River basin covers 94.43 percent of Yala Province and 5.27 percent of Pattani Province. This river basin can be divided into the upper part and lower part of the Pattani River basin. The main river in the Pattani River Basin is the Pattani River, which is 210 kilometers in length. While the flood mostly occurs in the Pattani province, therefore this study mainly focused on the Pattani province as shown in Fig. 1.

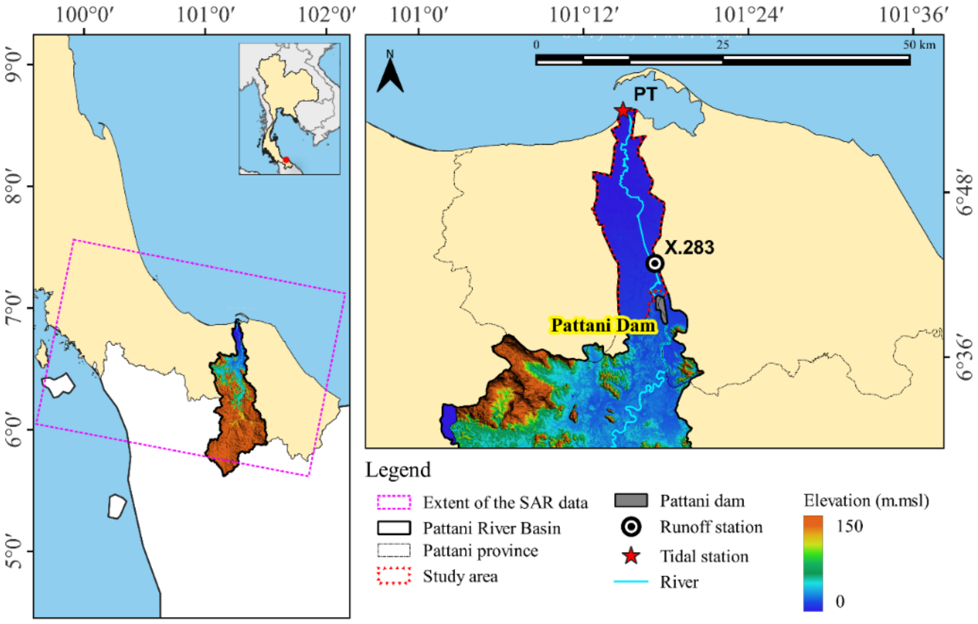

Fig. 1 Study area and topography

3.2 Sentinel-1 Flood Inundation

The Sentinel-1 SAR data includes information about backscatter intensity, which reflects how radar waves are scattered back from the Earth's surface. This information is crucial for distinguishing different land cover types. Plus, the sentinel-1 SAR has a frequent temporal resolution (6-12 days). Hence, the flood inundation can be produced by using the different backscatter between baseline and focused periods [10-13]. The Sentinel-1 SAR data required preprocessing steps: orbit file correction, thermal noise removal, radiometric correction, terrain correction, and convert the backscatter into decibels [14]. These preprocessing steps have already been applied to the Sentinel-1 SAR dataset provided by Google Earth Engine. Furthermore, the speckle filtering was applied to smoother images and the Digital Elevation Model (DEM) provided by SRTM was applied to calculate slope which using to filter out the topography with more than 5 degrees as shown in Fig. 2.

Flood inundation was assessed by applying various thresholds to image collections taken before and during the flood period. Specifically, images from March to April of each year, which are typically the driest months, were used as baseline (pre-flood) images. The ratio of backscatter between these baseline images and those captured during the flood was utilized to identify inundated areas. To establish the optimal threshold for identifying flood inundation, the ratio of pre-flood to post-flood images was calibrated against flood inundation data provided by the Geo-Informatics and Space Technology Development Agency (GISTDA), which offers annual flood extent maps. The calibrated ratio was found to be 1.15. This threshold was used to classify flood inundation areas from 2017 to 2024, covering a total of 93 events, resulting in a binary layer that distinguishes between flooded and non-flooded areas. Additionally, data on permanent water bodies from the Land Development Department (LDD) was utilized to mask these areas in the binary flood extent layer.

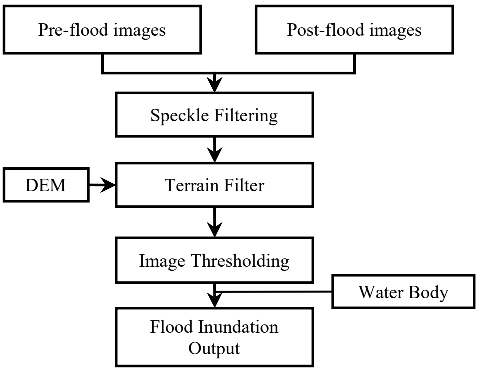

Fig 2. Method for produce flood inundation

3.3 Model Development

In this research, deep learning model is developed in Python programming using Keras module with in the Tensorflow 2.11 package.

The data scaling which is the method used to ensure that the features contribute equally to the learning process and that the optimization algorithms converge faster and more reliably. In this research, the standardization technique was used to transforms the data to have a mean of zero and a standard deviation of 1. It is calculated using the formula below.

$$x' = \frac{x - \bar{x}}{s.d.} \tag{1}$$

in which x' is the standardized values of the original value of the data point that is being standardized (x), $\bar{x}$ is the mean of dataset and $s.d.$ is the standard deviation of dataset.

3.3.1 Water level prediction model

The water level which is time series data will be predicted using deep learning. Recurrent Neural Networks (RNNs) are widely recognized for their ability to handle time series data. However, they are prone to the vanishing and exploding gradient problem. To address this issue, Long Short-Term Memory (LSTM) model incorporates memory cells with two types of gates, 'input' and 'output', which function multiplicatively to regulate the importance of input to the next state [15]. Similarly, the Gated Recurrent Unit (GRU) is a form of recurrent neural network (RNN) developed to handle sequence data and address the vanishing gradient problem [16]. The GRU has a simpler structure than the LSTM by replacing the forget gate and input gate with an update gate, resulting in fewer parameters and lower training time. Given that we cannot definitively say whether GRU or LSTM performs better, this paper conducts an experiment comparing the performance of both models.

The water level prediction involves training separate models using GRU and LSTM units, both utilizing the past 24 hours of input data. The dataset is split into training (70%) and testing (30%) datasets by using data from 2019 to 2021. The feature of this prediction model including daily discharge from dam, river water level from observed station, and tidal level. Then feed in to hidden layer which have the recommend of units in memory cell is 256 units [4]. Hence, this research will setup a single layer with 256 GRU or LSTM units to capture temporal dependencies. After the GRU or LSTM layer, the output is passed through a dense layer with 128 nodes using the ReLU activation function. The final layer has 24 output nodes, corresponding to the forecasted hours as shown in Fig. 3. Both models are trained using the RMSE as a loss function, The learning rate and batch size are 0.0005 and 256, respectively, and the models are trained for 200 epochs using the ADAM optimizer.

3.3.2 Flood inundation prediction model

Additionally, this research focuses on flood inundation prediction models, which are represented in raster. Many studies have proven the effectiveness of processing images and videos using CNNs [17]. A deep 1D CNN model, structured as illustrated in Fig. 4, is employed in this study to predict flood inundation. The input features, detailed in Table 1, are processed through a single convolutional layer followed by two fully connected dense layers. The target output comprises flood inundation maps derived from Sentinel-1 SAR images, each containing 30,160 pixels with a spatial resolution of 100 meters. The dataset includes 65 images for training and 28 images for testing. Prior to model training, the input features were pre-processed to ensure consistency and compatibility with the CNN architecture.

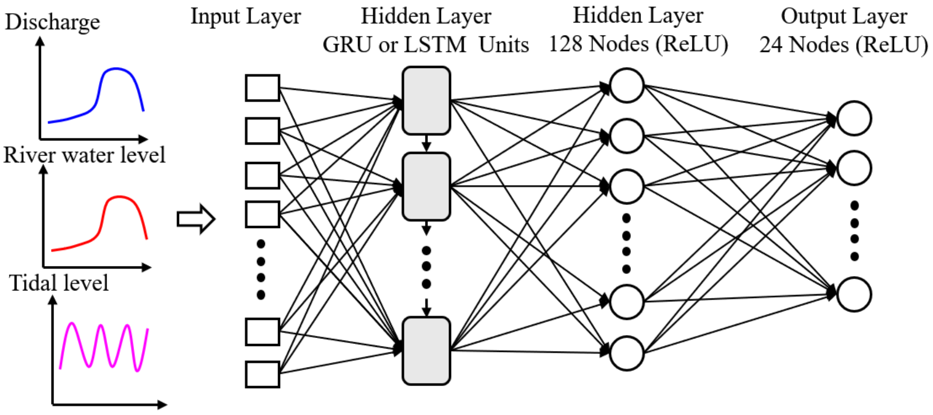

Fig. 3 Structure of water level prediction model

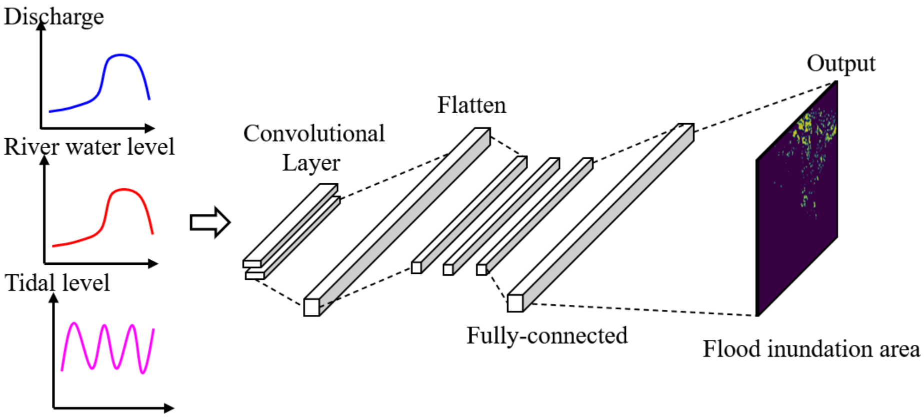

Fig. 4 Structure of flood inundation prediction model

3.4 Model Evaluation

In this study, we utilized the Nash-Sutcliffe Efficiency (NSE) coefficient [18] to assess the performance of the hydrological model. Additionally, the Root Mean Square Error (RMSE) was employed to evaluate the model's predictive accuracy. The NSE and RMSE were computed using Equations (2) and (3), respectively.

$$NSE = 1 - \frac{\sum_{i=1}^{n}(O_i - S_i)^2}{\sum_{i=1}^{n}(O_i - \bar{O})^2} \tag{2}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(O_i - S_i)^2} \tag{3}$$

in which $\bar{O}$ is the mean values of the observed values

(O_i), $\bar{S}$ is the mean values of the simulated values (S_i). The NSE metric ranges from $-\infty$ to 1, with a value of 1 indicating a perfect model representation. RMSE values close to zero signify minimal error and higher accuracy in predictions.

For the flood inundation prediction, we have proposed True Positive Rate (TPR) to evaluate the performance of the flood inundation prediction.

$$TPR = \frac{T_p}{T_p + F_n} \tag{4}$$

Here, T_P represents the number of pixels in the flooded, as identified by Sentinel-1 SAR data, that are correctly predicted as flooded by the prediction model. F_n denotes the number of pixels that is detected as the opposite class by the prediction model. TPR evaluates the proportion of correctly identified instances in both flooded and non-flooded conditions. For flooded areas, a high TPR for flooded areas reflects the model's strength in detecting the spatial extent of flooding, which is essential for emergency response and mitigation planning. Conversely, for non-flooded areas, TPR represents the accuracy with which the model identifies pixels that remain dry. This is essential for ensuring that resources are not misallocated to areas incorrectly predicted as flooded.

4. RESULT AND DISCUSSION

In this research, we trained deep learning models using various input parameters from different scenarios to predict water levels and flood inundation.

4.1 Water Level Prediction

The water levels were predicted using both LSTM and GRU models across four different scenarios. The performance of these models was evaluated over different lead times using RMSE and NSE as the metrics for accuracy.

Fig. 5 and Fig. 6 illustrate the model performance covering the training and testing periods. During the training period, LSTM models exhibited the best performance, as indicated by the lower RMSE and higher NSE values. However, during the testing period, GRU models demonstrated superior performance across all scenarios. The results showed that GRU models generally outperformed LSTM models across all scenarios and lead times. For instance, SCN1-GRU achieved an RMSE of 0.17 meters at T+1, increasing to 0.61 meters at T+24, while SCN1-LSTM had a higher RMSE of 0.19 meters at T+1 and 0.63 meters at T+24. Among the GRU models, SCN2-GRU and SCN4-GRU demonstrated particularly strong performance, with SCN2-GRU achieving the best RMSE values of 0.09 meters at T+1 and 0.53 meters at T+24, and SCN4-GRU achieving 0.08 meters at T+1 and 0.54 meters at T+24.

In the same way, Fig 6 shows that NSE values align with RMSE values, further validating the superior performance of GRU models. The NSE values for GRU models were consistently higher than those for LSTM models. These findings underscore the effectiveness of GRU models, particularly SCN2-GRU and SCN4-GRU, in both RMSE and NSE metrics.

The results highlight the superior performance of GRU models compared to LSTM models when utilizing all available input parameters (tidal, water level, and release flow). GRU models demonstrated consistently better accuracy across all lead times (T+1 to T+24) when all parameters were included, with significantly lower RMSE and higher NSE values compared to scenarios where individual parameters were excluded. This indicates that GRU models effectively leverage the full dataset to improve predictive performance. On the other hand, the LSTM models showed the poorest performance when all parameters were used, exhibiting higher RMSE and lower NSE values.

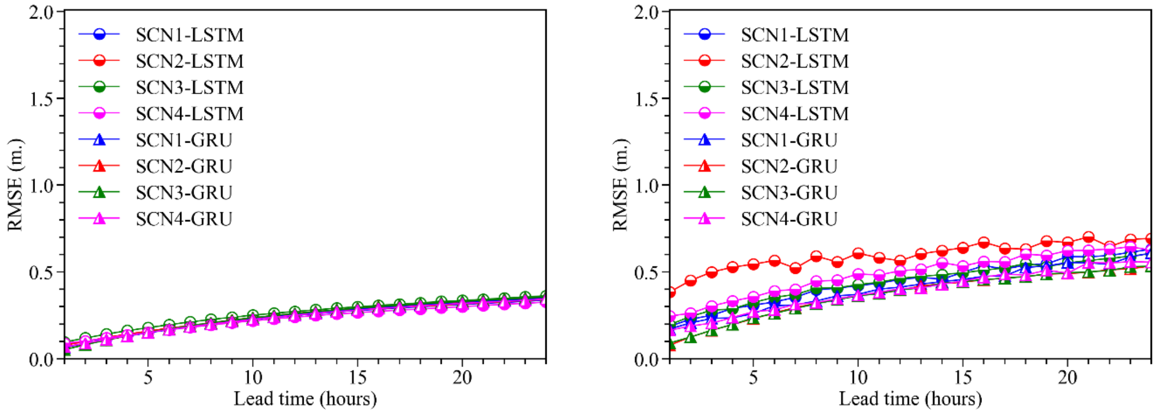

Fig. 5 Root Mean Square Error (RMSE) during training (left) and testing (right) periods

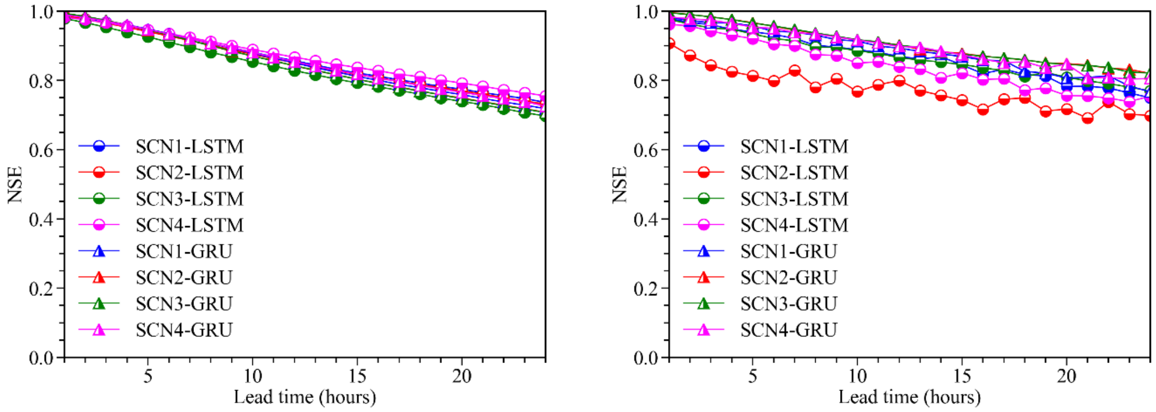

Fig. 6 Nash-Sutcliffe model efficiently (NSE) coefficient during training (left) and testing (right) periods

4.2 Flood Inundation Prediction

To predict flood inundation, we utilized flood inundation data generated by Sentinel-1 from 93 images and tested four different input scenarios. Fig. 7 showed the example result of comparing between flood inundation by Sentinel-1 and CNN model on 16 July 2020.

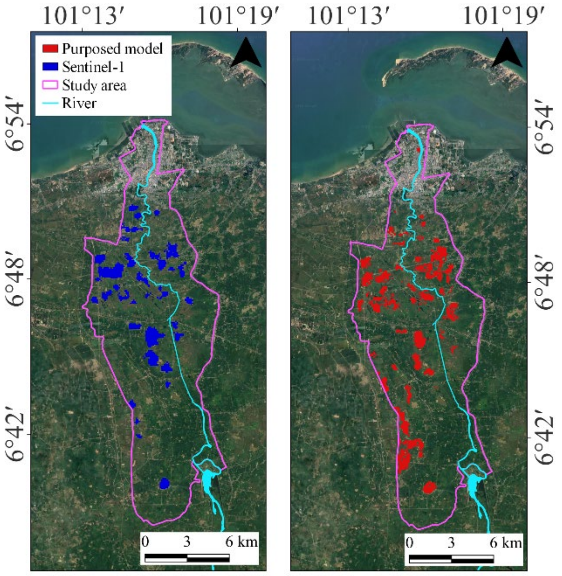

Fig. 7 Comparison of flood inundation between Sentinel-1 SAR and CNN model on 16th July 2020

The performance of each scenario was evaluated using the average TPR for both non-flooded and flooded conditions. As shown in Table 2, SCN1 achieved an average TPR of 98.92% for non-flooded areas and 70.56% for flooded areas. SCN2 demonstrated a slightly higher average TPR of 99.24% for non-flooded areas but a lower TPR of 67.35% for flooded areas, indicating its stronger performance in identifying non-flooded regions while sacrificing accuracy in flooded areas. SCN3 achieved similar results to SCN1, with a TPR of 98.95% for non-flooded areas and 70.13% for flooded areas. SCN4, which incorporated all input parameters (release flow, river water level, and tidal level), yielded the best overall performance, achieving the highest TPR of 99.25% for non-flooded areas and 76.47% for flooded areas. Fig 8. and Fig. 9 illustrate the pixel-level accuracy and the TPR distribution for flooded and non-flooded areas in SCN4.

Table 2 The performance to predicted flood inundation in different scenarios

No	Input Parameter	Average TPR (%)	
		Non flooded	flooded
1	SCN1	98.92	70.56
2	SCN2	99.24	67.35
3	SCN3	98.95	70.13
4	SCN4	**99.25**	**76.47**

Note: Bold is the best performance.

These results underscore the significant impact of input parameters on the model's ability to predict flood inundation. The consistently high TPR values for non-flooded areas across all scenarios indicate that the model effectively identifies dry regions. However, the variation in TPR for flooded areas reveals that incorporating more comprehensive input parameters improves the model's performance in identifying inundated regions. SCN4's superior performance highlights the importance of combining multiple data sources, such as release flow, water levels, and tidal information, to capture the complex dynamics of flood inundation. This integration allows the model to more accurately distinguish between flooded and non-flooded areas, especially in scenarios where flooding is more challenging to predict.

Interestingly, the higher TPR values for non-flooded areas compared to flooded areas across all scenarios can be attributed to the larger proportion of non-flooded pixels in the dataset. Non-flooded areas typically dominate the study region, resulting in a greater number of non-flooded examples for the model to learn from during training. This imbalance enables the model to generalize more effectively for non-flooded conditions, leading to higher classification accuracy. In contrast, the smaller number of flooded pixels limits the model's ability to fully capture the complexities of flood events, resulting in slightly lower TPR values for flooded areas.

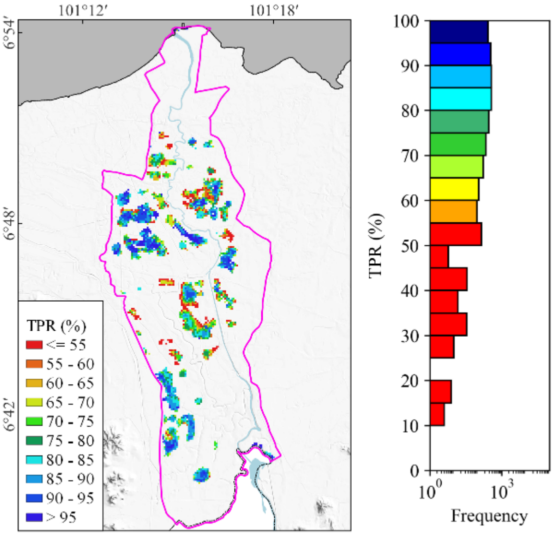

Fig. 8 TPR in each pixel for the flooded area

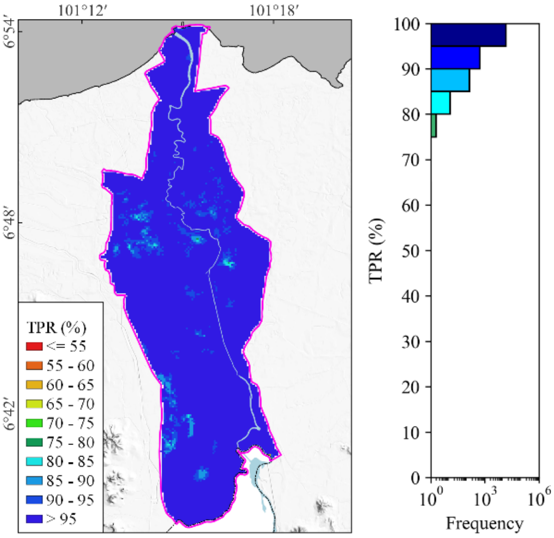

Fig. 9 TPR in each pixel for the non-flooded area

5. CONCLUSION

This study demonstrates the effectiveness of deep learning models, specifically Gated Recurrent Unit (GRU) networks, Long Short-Term Memory (LSTM) networks, and Convolutional Neural Networks (CNNs), in enhancing flood prediction accuracy. The GRU network showed superior performance in predicting water levels, particularly when using all three input parameters: release flow, water level station data, and tidal level data. Additionally, the CNN model exhibited robust performance in predicting flood extents. The integration of all three input parameters in the CNN model resulted in the highest average TPR for both non-flooded and flooded conditions, as demonstrated by the comparison between actual flood extents captured by Sentinel-1 and predicted flood extents. This high accuracy in classifying flooded and non-flooded areas underscores the model's reliability in predicting flood inundation.

This research can be applied to enhance flood warning systems and improve flood risk planning by providing more accurate and timely forecasts. Future research could focus on extending the prediction for long-term forecasting. Additionally, there is potential to further improve prediction accuracy, especially for flood inundation predictions, by integrating additional data sources and refining model architectures to capture more complex patterns.

6. ACKNOWLEDGMENTS

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