Artificial neural networks applied to time series for flood prediction

Laleska A. F. Mesquita[1], Caetano M Ranieri[1], Jó Ueyama[1]

[1]ICMC - Instituto De Ciências Matemáticas e de Computação - Universidade de São Paulo (USP)
Av. Trab. São Carlense, 400 - Centro, São Carlos - SP, 13566-590, Brazil

laleska.m@usp.br, cmranieri@usp.br, joueyama@icmc.usp.br

Abstract. *Extreme hydrological events and lack of urban planning can generate climate-related disasters. Several fields of study, including artificial intelligence, contribute to mitigate this problem and develop preventive solutions. This study focuses on flood forecasting the Xingu River using time series data. The main approach is to standardize the pure data from different stations using quantiles, and thus generate recurrence plots for the time series and then transform them into two-dimensional representations to be applied in the convolutional neural network model. The combination of recurrence plot with CNN provided data metrics in the prediction test with superior performance compared to the algorithms models implemented as LSTM, RNN.*

1. Introduction

Brazil has a significant number of records related to natural disasters, ranking 79th on the scale of countries with the most natural catastrophes [Brasil 2018]. According to the Confederação Nacional de Municípios (CNM), there have been over 9,000 incidents recorded between 2008 and 2018 [Brasil 2018]. The Amazon Basin comprises the largest hydrological system on Earth and, over the past few decades, has experienced an increased occurrence of floods. In 2021, river levels surpassed historical records, and such disasters have caused significant economic and social damages [Espinoza et al. 2022].

With the advent of artificial intelligence, a range of opportunities has emerged to address issues that previously had limited scope [Aurelien 2019, 'L'heureux et al. 2017]. Significant efforts have been made to enhance the prediction methods of natural phenomena. Research efforts are focusing in this direction, applying different prediction models to achieve increasingly accurate and effective results. Recurrent neural networks (RNNs) are frequently employed due to their capacity to retain memory and learn patterns that evolve over time. Some memory-augmented algorithms, such as LSTM and GRU, are also used in an attempt to overcome the obstacles of long-term dependencies [Guha et al. 2022, Hochreiter and Schmidhuber 1997]. More recently, CNN models have also been applied, due to their complex feature extraction capability [Chen et al. 2021]. Another approach used as an alternative to optimizing the performance of Artificial Neural Networks (ANNs) is algorithm combination, the so-called hybrid models [Kai Feng and Jing Niu 2021, Fathian et al. 2019].

The work by [Kai Feng and Jing Niu 2021] proposed an algorithm combination method composed of a Cooperation Search Algorithm (CSA) integrated into the learning process of an Artificial Neural Network (ANN), resulting in a hybrid method called Artificial Evolutionary Neural Network. The RNA-CSA method outperformed five tested configurations, demonstrating approximately 11% higher efficiency compared to standard ANN without CSA. However, the model prediction was only superior to ANN when applied with no hybrid combination, but was comparable to support vector machine (SVM) and extreme learning machine (ELM) results, with prediction errors of about 15%. [Hu et al. 2018] proposed an LSTM approach to predict the Fen River basin flood events, and the result showed LSTM can outperform ANN models for better prediction. However, the authors pointed out that a large dataset was needed to achieve prediction values higher than 90%.

ANN and DNN models require abundant data for accuracy, but obtaining such data through field measurements is challenging due to resource and cost constraints and also the limited number of recorded flood events per year. To overcome such obstacles, [Kimura et al. 2019] proposed the use of a CNN model due to its capability of capturing spatial patterns and features within data by leveraging convolutional layers to extract localized patterns and acquire hierarchical representations. Additionally, the authors proposed a transfer learning to pre-train the model and reapply it in the target dataset. The conversion from time series data to image data was done through binary classification of upward/downward trends of water levels. This approach was able to reduce training time by 1/5 and decreased the average error by 15% compared to CNN with no transfer learning. Nevertheless, the CNN prediction model was not as effective as the traditionally used models.

Enhancing the prediction accuracy of the CNN model when applied to time series data is a crucial task that can be accomplished by exploring various techniques for converting the dataset into image data. In recent studies [Kirichenko et al. 2021], recurrence plot (RP) has emerged as a valuable tool for improving the classification of electroencephalogram (EEG) images. RP analysis offers a sophisticated method for studying nonlinear data, where a square matrix represents the occurrence times of specific states in dynamic systems. The visual representation captures recurrent patterns in the system's phase space, providing valuable insights into its behavior and dynamics [Marwan et al. 2007] [Maddala and Lahiri 2009]. Recurrence constitutes an inherent attribute of a multitude of dynamic systems, offering potential for delineating a system's conduct within phase space. A recurrence plot (RP) emerges as the visual mechanism employed to display this characteristic. RPs are particularly useful for analyzing nonlinear and complex time series data [Fragkou et al. 2022]. They provide a visual representation of recurrent patterns that might not be easily identifiable through traditional linear techniques, revealing hidden patterns, periodicities, and trends in time series data. They can uncover intricate relationships and interactions within the data that might not be evident in the original time series [Packard et al. 1980].

By converting the time series into graphical representations, RP effectively reduces the dimensionality of the data while preserves essential temporal information. This simplification can aid in visual analysis and potentially enhance computational efficiency. RPs are also sensitive to changes in the underlying dynamics of a system. Slight alterations in the data can lead to noticeable changes in the recurrence plot, making it a potentially powerful tool for detecting anomalies or shifts in patterns. RPs are particularly well-suited for capturing the behavior of chaotic systems, where traditional linear methods might struggle to make sense of the dynamics [Dimitriev D 2020].

However, interpreting recurrence plots can be subjective, as there isn't a fixed criterion to define what constitutes a meaningful pattern or recurrence threshold. This can lead to variations in analysis results among different researchers. The effectiveness of RPs can be influenced by the choice of parameters such as the embedding dimension and time delay [Fragkou et al. 2022]. Determining optimal parameter values can be challenging and might require trial and error. Recurrence plots are useful for visual representations of data, but require additional techniques to provide quantification information [Marwan et al. 2007]. Extracting quantitative measures directly from the plots can be difficult though. Quantifying the characteristics of patterns and using them in modeling or analysis might require additional steps. RPs are most effective for capturing recurrent patterns in time series data. If the underlying data doesn't exhibit significant recurrence or has high levels of noise, RPs might not provide meaningful insights [Marwan et al. 2007, Kirichenko et al. 2021, Dimitriev D 2020].

Back to the study of Kirichenko et al. (2021), by converting time series data into graphical representations of RP, researchers achieved higher accuracy in distinguishing exams with epileptic behavior traces. This innovative approach, coupled with Convolutional Neural Networks (CNN), enabled the successful classification of these graphs, reaching impressive accuracy and learning quality indicators of 98% and 95%, respectively [Babichev et al. 2020]. These promising results encourage further research in leveraging the power of CNNs to analyze and classify/predict time series data associated with various phenomena [Tan and Le 2019]. However, to the best of our knowledge, no previous studies have applied the combination of recurrence plots and CNNs for flood prediction.

This research focuses on assessing the effectiveness of using convolutional neural networks (CNNs) for flood forecasting through two-dimensional graphical representations, specifically recurrence plots (RP). The primary objective is to enhance prediction accuracy by adopting this novel approach of employing 2D images.The main goal of this study is to introduce an innovative data-driven flood modeling approach that integrates Recurrence Plot (RP) analysis with Convolutional Neural Networks (CNNs) to contribute to the well-being of communities residing near the Amazon basin, an area prone to recurrent flooding. The research is centered around the monthly rainfall data from the Altamira region's Xingu River. Additionally, the study incorporates transfer learning to demonstrate potential accuracy improvements. To enable a comprehensive comparison, the paper also includes comparative analysis with other approaches in the literature, as the traditional recurrent neural networks - Gated Recurrent Units (GRU) and Long Short-Term Memory (LSTM) models - using the same Xingu River dataset. By effectively tackling the challenges of flood prediction through this hybrid RP+CNN methodology, the research aims to provide valuable insights to the flood prediction community and offer practical support to flood-prone populations.

2. Methods

The hypothesis proposed in this study consisted of using CNNs in the flood prediction process through the evaluation of time series. The evaluated data, corresponding to the maximum river level, was converted into images in order to obtain conversion points for the implementation of the prediction. This approach allows assessing the feasibility of using convolutional neural networks for applications in the field of prediction and regression, not only classification, as conventionally applied. To make this resource possible, the recurrence plot technique was evaluated. To enable and corroborate the raised hypothesis, experiments were conducted applying the same dataset from the Xingu River to traditional neural networks used in regression problems, which in this work were RNN, LSTM, and GRU. Additionally, the pre-training method was also applied in order to analyze the performance of the CNN model previously trained with data from other river basins. The results were compared using metrics to assess the effectiveness of the algorithms used.

2.1. Dataset

The hydrological data used in this study are freely available in the Hydrometeorological Database of the National Water Agency (ANA), accessible through the HIDROWEB portal. This platform is a complementary tool to the National Water Resources Information System (SNIRH), providing access to an extensive set of information, including river levels, flows, precipitation, and water quality, among other observation points. These data are collected by hydrological technicians and engineers in daily field measurements, details about the data are accessible on the HIDROWEB portal. In the scope of this work, datasets from the ANA were used, with 13 river bases selected for analysis. The central dataset, the focus of the implementation of this study, concerns the maximum levels of the Xingu River, extracted from the fluviometric station of the Amazon River Basin in the state of Pará. Each entry in the dataset represents the river's maximum value of a single month. The Xingu River dataset encompasses a total of 444 months of measurements, covering a collection period extending from 1974 to 2019. In addition to the main Xingu River set, 12 other databases were employed, such as Kokraimoro, Joari, São João Felix do Xingu, Neris1883 base, Neris1886 base, port, Santo Antonio 1 base, Santo Antonio 2 base, Belo Horizonte, Santo José, and Jusante. These datasets were designated for training the neural network, with the Xingu River serving as the final target for flood prediction. In Table 1 below it is possible to see the quota capitation period and the corresponding database used in this work.

Table 1. General Datasets

Dataset	Start Date	End Date	Number of Stations	Nº Date
Kokraimoro	01/02/1978	01/12/1985	31	3705
Joari	01/10/1981	01/11/1998	31	19914
São João Feliz do Xingu	01/06/1975	01/02/1998	31	15582
Neris1883	01/11/2000	01/12/2001	31	1221
Neris1886	01/12/2000	01/12/2001	31	1183
Porto	01/10/1981	01/12/1986	31	4854
Santo Antonio1	01/11/2000	01/12/2001	31	1221
Santo Antonio2	01/12/2000	01/12/2001	31	1183
Belo Horizonte	01/05/1976	01/03/1998	31	22353
São José	01/05/1976	01/03/1998	31	22353
Jusante	01/05/2001	01/12/2001	31	670
Xingu	01/01/1979	01/12/2019	31	444

2.2. Data Processing

The treatment of the Xingu River dataset started with the selection process of the data columns refering to the elevations that represent the maximum values of the river level. This data selection is necessary since the raw data set from the ANA system has several variables such as flow. Thus, the selection process was made of the columns of quotas that corresponded to the maximum river level data that for this work corresponds to the significant data for the execution of the forecast hypothesis proposed in this project. From this, a new dataframe was generated referring to the monthly measurement data of the river level with only the values of interest for the forecast. In order to refine the dataframe, the aggregated data process was also carried out by means of the statistical measure of quantile of the data and the selection of the maximum and minimum values. Extracting the quantile values aimed above all to standardize the data structure between different measuring stations. Since if one station measured quotas at 10 points and the other measured at 12, it would not be possible to use all quotas directly in the model, as the data scheme would be different (one station will have 10 variables and the other 12). Thus, using some summarizing measures and generating a standardized data structure, it became possible to train and perform inferences in the model using data from different stations. In addition, with the quantiles it was possible to identify trends in the data set. For the Xingu River data set the quantile split applied corresponded to the 25%, 50% and 75% quartiles of the data and the maximum and minimum values.

After obtaining the quantile dataframe and the corresponding maximum and minimum values for the initially applied water level data, the Xingu River time series were generated for the 5 columns of the dataframe.Once the Xingu River time series were defined, preprocessing was performed using the recurrence plot technique. After the recurrence plot was produced for each segment, the next phase was treated as a regression problem, utilizing deep CNN (Convolutional Neural Network). Thus, the final dataset for the experiment consisted of recurrence plot images configured as a 20x20 matrix with 5 channels corresponding to the time series. These images were then fed as input to the convolutional neural network. The implementation utilized the TensorFlow library, setting the input shape as (20x20x5). The convolutional layers and the first two fully connected layers of this model used the Rectified Linear Unit (ReLU) activation function. The same dataset was also used in the RNN (Recurrent Neural Network), LSTM (Long Short-Term Memory), and GRU (Gated Recurrent Unit) models, but without utilizing the recurrence plot technique. For training the models a proportion of 75% of the data was used for training and 25% for testing. The data was separated in such a way that the most recent months were used for the testing step. Similarly, transfer learning technique was applied to the CNN model. The flow presented in Figure 1 outlines the rationale adopted for the study's development.

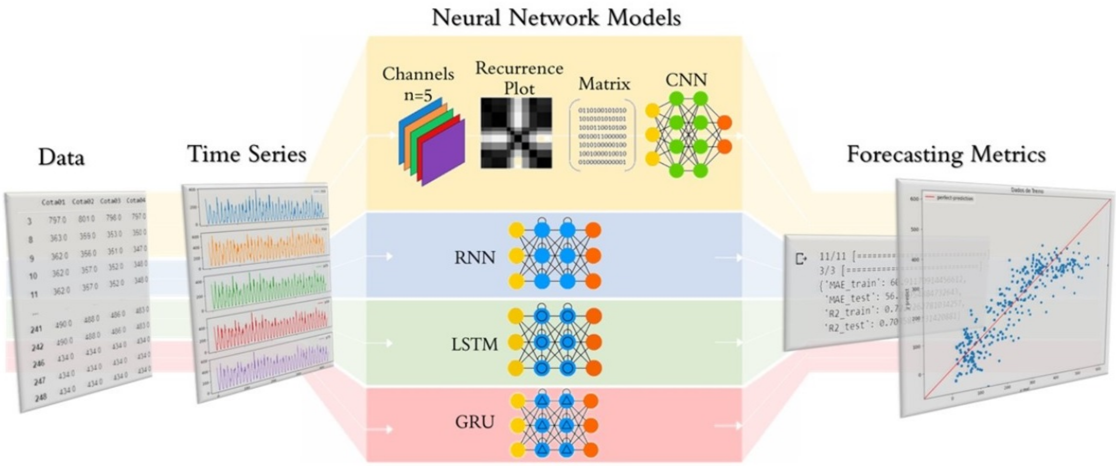


Figure 1. Approach developed for evaluating the application of the combined use of recurrence plot + CNN for flood forecasting compared to RNN, LSTM and GRU.

For the RNN, the first layer is a SimpleRNN layer with 300 neurons and uses the ”RELU” activation function. The second layer is a Dense layer with 1 neuron. The total number of adjustable parameters in the model is 92,101. LSTM (Long Short-Term Memory) models are a specialized type of recurrent neural network (RNN) capable of learning and storing long-term information within their structure. The model used in this work consisted of two layers. The first layer is an LSTM layer with 300 neurons, and the second layer is a Dense layer with 1 neuron. The total number of adjustable parameters in the model is 367,501. GRU (Gated Recurrent Unit) models are dedicated to handling long-term dependencies in sequences and are less susceptible to overfitting than LSTM models. The implemented model configuration consists of a GRU layer with 300 neurons and a Dense layer with 1 neuron. The total number of adjustable parameters in the model is 367,501.

Considering the primary focus of this study, which is the time series data from the Xingu River, one of the challenges to overcome in the prediction process was the data scarcity. Since the Xingu dataset does not have a large enough volume of data to train a model from scratch, the transfer learning process was attempted to enhance the robustness of the CNN with RP model and generate potentially more accurate prediction results. For this purpose, 13 river datasets were selected, with the criterion of also containing maximum river level data. The same data treatment procedure associated with the recurrence plot technique was applied for this implementation. The goal of transfer learning was to apply the Xingu dataset to the pretrained model, which would lead to improved efficiency in the network’s generalization capability to a new dataset.

The pretraining process involved using the same CNN configuration to train the model with the 13 river datasets, comprising a total of 1,200 data points. For the testing phase with the Xingu dataset, the first nine layers (deepest layers) were frozen, and the last layers, which interpret the learned information and generate the river level prediction values, were fine-tuned.

To evaluate and monitor the prediction results regarding the configuration of the defined neural network model, the following metrics were used: Mean Absolute Error

(MAE) loss function and coefficient of determination (R2). In environmental monitoring problems, predicting values with large errors can have negative environmental consequences. For example, inaccurate river level predictions can result in catastrophic floods with large losses. Therefore, using metrics such as MAE, which measures the mean of the absolute differences between model predictions and actual values, one of the advantages of MAE being that it treats all errors equally, is useful in situations where large errors can be problematic. The use of R2 is justified from the point where this metric is useful to understand the overall fit of the model to the data. Since it varies between 0 and 1, a value closer to 1 indicates that the model is able to explain a large part of the variability in the data.

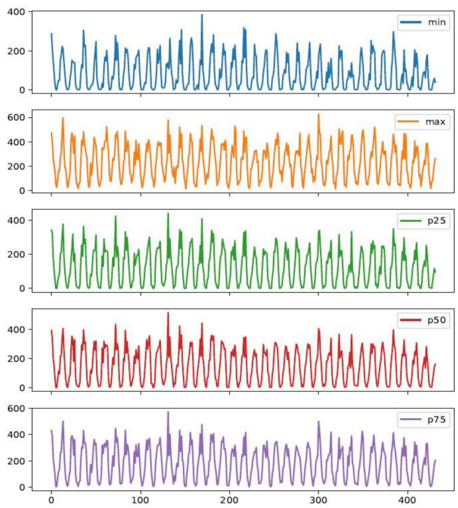
3. Results

3.1. Data processing

Figure 2 (a) and (b) represent, respectively, the resulting dataframe from the quantile, maximum, and minimum division process, containing 431 rows and 5 columns of data, and the time series of the Xingu River for the 5 columns. The architecture of the model, along with the information about the matrices that were fed into the CNN's input, is summarized in Table 2. Figure 3 presents the recurrence of time series patterns of the Xingu River. Where each pixel in the recurrence matrix represents a point in the time series.

	min	max	p25	p50	p75
0	286.9	471.6	342.7	392.9	430.1
1	205.8	404.4	322.9	338.0	379.5
2	142.9	264.8	177.0	197.5	216.9
3	75.2	207.5	105.3	150.4	158.7
4	24.0	152.4	46.5	56.2	85.5
...	...	...	...	...	...
426	0.2	16.9	1.6	3.2	4.3
427	0.1	69.0	0.7	2.9	16.6
428	26.6	80.5	39.3	46.0	59.5
430	59.4	219.9	117.5	142.0	170.4
431	38.1	263.8	96.2	161.6	203.5

a)



b)

Figure 2. (a) The dataframe corresponding to the quartiles, maximum, and minimum values, and (b) the time series related to the Xingu River dataset.

Table 2. Convolutional Neural Network Architecture

Layer	Input	Output	kernel size	padding
$Conv1$	$20 \times 20 \times 5$	$20 \times 20 \times 5$	3	$same$
$Conv2$	$20 \times 20 \times 5$	$20 \times 20 \times 100$	3	$same$
$Conv3$	$20 \times 20 \times 100$	$20 \times 20 \times 100$	3	$same$
$Maxpooling$	$20 \times 20 \times 5$	$20 \times 20 \times 100$	2	$same$
$Conv4$	$20 \times 20 \times 100$	$20 \times 20 \times 10$	3	$same$
$Conv5$	$20 \times 20 \times 10$	$20 \times 20 \times 10$	3	$same$
$Maxpooling$	$20 \times 20 \times 10$	$20 \times 20 \times 10$	2	$same$
$Conv6$	$20 \times 20 \times 10$	$20 \times 20 \times 40$	3	$same$
$Conv7$	$20 \times 20 \times 40$	$20 \times 20 \times 40$	3	$same$
$Maxpooling$	$20 \times 20 \times 40$	$20 \times 20 \times 40$	2	$same$
$Dropout1$	$20 \times 20 \times 40$	$20 \times 20 \times 40$	$-$	$-$
$Flatten$	$20 \times 20 \times 40$	16000	$-$	$-$
$Dropout2$	16000	16000	$-$	$-$
$Dense1$	16000	512	$-$	$-$
$Dropout3$	512	512	$-$	$-$
$Dense2$	512	32	$-$	$-$
$Dropout4$	32	32	$-$	$-$
$Dense3$	32	1	$-$	$-$

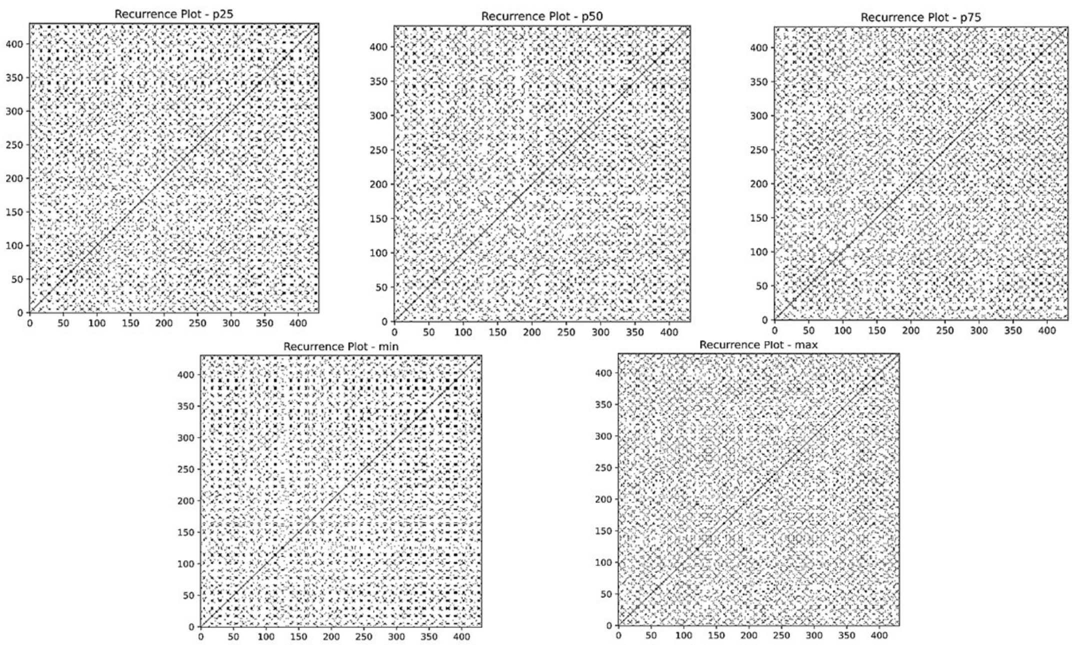


Figure 3. Recurrence Plots from data series of Xingu river

Recurrence plots are uncomplicated to visualize black and white representations. The black states represent the occurrence of patterns or similarities in the time series, this is possible if two points in the time series are similar or close, the remaining white states represent dissimilarities or differences between the points in the time series, i.e. when there is no similarity between two points in the time series, a white point appears in the recurrence plot [Marwan et al. 2007]. The image b) of Figure 2 shows the time series graph referring to the data of the dataset columns of the image a) of Figure 2, thus corresponding to the trend of behavior of the river maximum variable over time. For each column of the dataset seen in image a) there is a corresponding time series seen in image b) and therefore there is the representation in recurrence graph of this time series seen in Figure 3. The analysis of recurrence plots represents an effective way to examine the correlation structure of a system. Therefore, these graphs enable the prediction of the maximum river level when applied as input data to a convolutional neural network.

3.2. Forecasting Models Discussion

Based on the MAE_{test} and $R2_{test}$ metrics, the *CNN with RP* model demonstrated the best performance for the Xingu dataset, as depicted in the MAE and R2 performance graphs, as well as the scatter plots (shown in Figure 4).

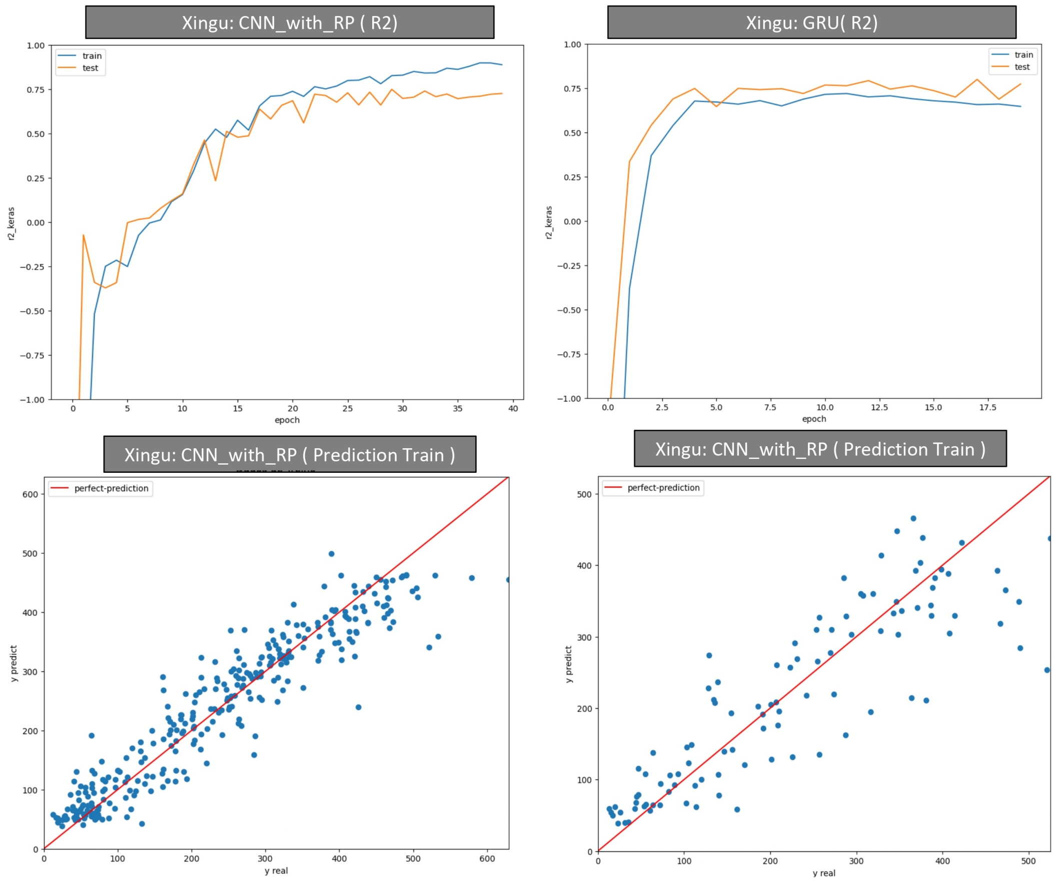


Figure 4. Performance graphs for CNN when combined with recurrence plot

When analyzing the MAE_{test} metric values in the table, the model with the lowest MAE stands out as it indicates better performance in terms of average absolute error in the predictions. Among the listed models, the *Xingu: CNN + RP* model achieved the lowest MAE_{test} value of 50.74, indicating the smallest absolute prediction error. The second-best performance was observed in the *Xingu: LSTM* model with an MAE_{test} value of 53.81. Hence, based on this metric, the *Xingu: CNN + RP* model demonstrated superior performance compared to the other models listed in the table. Figure 5 presents scatter plots of the discussed models, enabling visualization and comparison of the model predictions with the actual values. This visualization aids in evaluating prediction quality and identifying potential patterns or discrepancies between the predicted and actual data.

The dispersion around the trend line in the test graphs of the *Xingu: CNN with RP* model is observed to be closer to the central tendency, indicating a lower dispersion. In contrast, the *Xingu: LSTM* model exhibits a larger dispersion with more scattered points. When the points are closer to the trend line, forming a more compact cloud, it indicates a stronger association between the variables, resulting in better prediction outcomes.

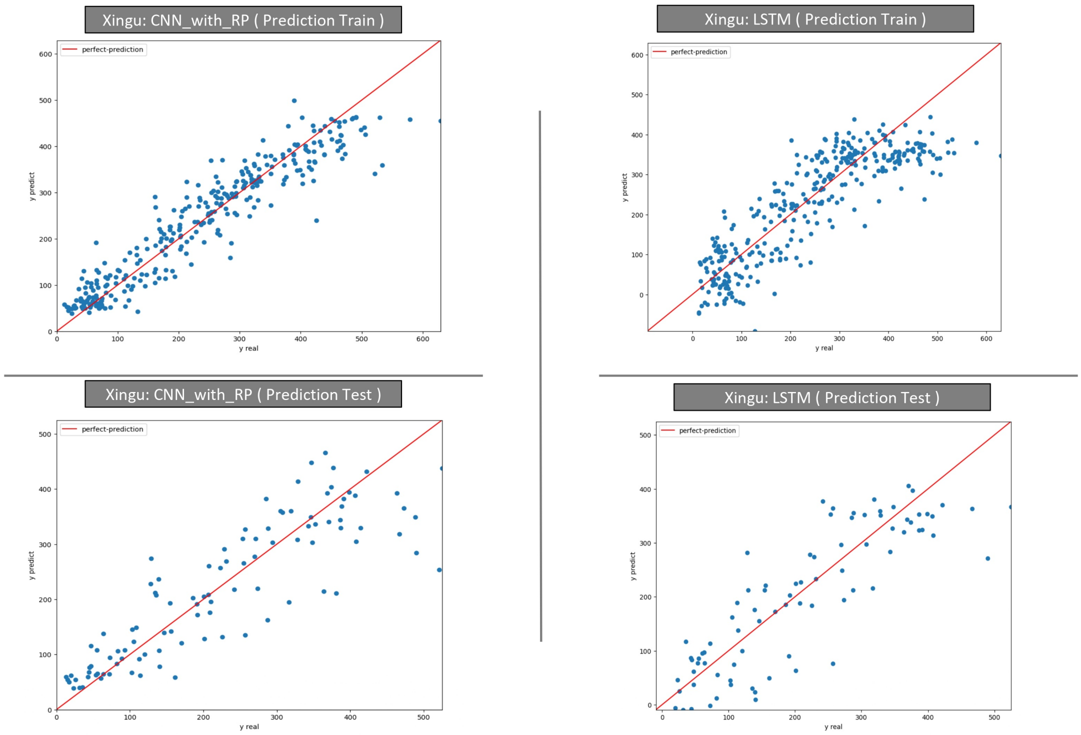


Figure 5. Train and test scatter plots of the proposed models according to CNN associated with RP and LSTM

Considering the R2 metric, a higher value indicates better performance, as it signifies that the model can explain a larger proportion of the variance in the response data. Among the evaluated models, the *Xingu: CNN with RP* configuration achieved the best result with an $R2_{test}$ value of 0.75. The second-best performance, as per this metric, was observed in the *Xingu: GRU* model. This difference from the LSTM model may be attributed to the computational efficiency of GRU models. Due to their simpler structure with fewer computational components, GRU models are generally faster to train and evaluate.

Figure 6 illustrates the R2 curve comparing the *Xingu: CNN with RP* and *Xingu: GRU* models. Overall, the R2 values for the *Xingu: GRU* model remain consistently high and close to 1 over time, both for the training and testing curves, although the training curve shows a more linear behavior. These graphs indicate a good fit of the model to the data, with a high capacity to explain the variation. On the other hand, the R2 values for the *Xingu: CNN with RP* model in the testing curve show more instability, with a value closer to 0.75 and a less close relationship to the training curve.

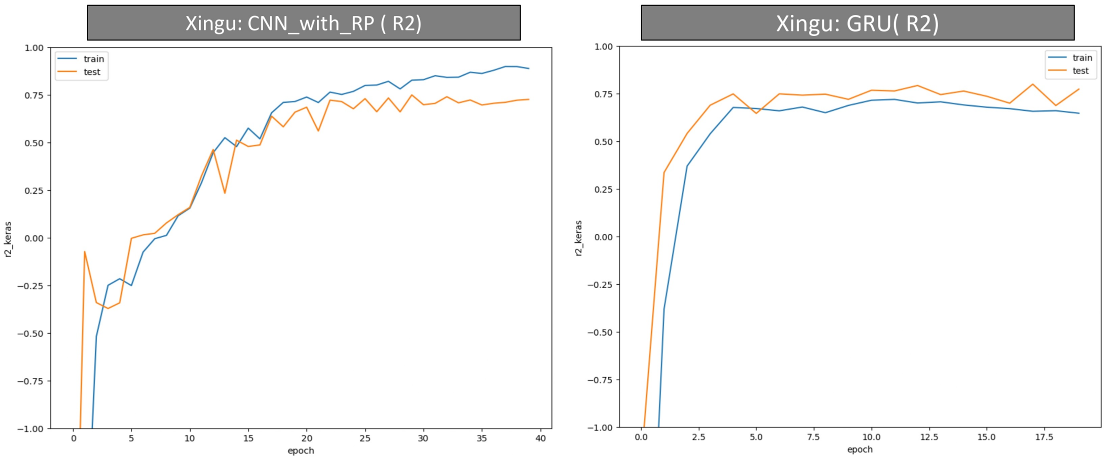


Figure 6. R2 curve from CNN associated with recurrence plot model compared to GRU model over the analyzed period.

Analyzing all the scenarios presented in Table 3, for the Xingu dataset, the *CNN with RP* model exhibits the lowest MAE_{test} (50.74) and the highest $R2_{test}$ (0.75), indicating better prediction performance compared to the other models for this dataset. On the other hand, the *CNN with RP and TL* model has a lower MAE_{test} value of 76.73 and an $R2_{test}$ of 0.52, indicating inferior performance compared to the *CNN with RP* model. Upon analysis, it can be proposed that this result reflects a significant difference between the domains of the datasets used in the transfer learning (TL) process. In other words, the training dataset might be very different in terms of distribution from the Xingu dataset, resulting in the transferred knowledge potentially not being useful for the prediction process. Also, some other reasons can explain why transfer learning does not always result in better prediction model efficacy, such as limited target data, incorrect hyperparameters, overfitting, task complexity, mismatched architecture, unrepresentative source task, and inappropriate evaluation metrics [Ebbehoj et al. 2022, Iman et al. 2023]. However, such factors will be further evaluated in future work, since the focus of the paper is on comparing the performance of the recurrence plot with CNN against other conventional RNN models.

Table 3. Metrics of each evaluated model

Dataset	Model	$\text{MAE}_{train}(cm)$	$\text{MAE}_{test}(cm)$	R2_{train}	R2_{test}
13 rivers	CNN with RP	31.65	81.63	0.94	0.67
Xingu	CNN with RP + transfer learning 13 rivers	39.76	76.73	0.82	0.52
Xingu	CNN with RP	34.66	50.74	0.89	0.75
Xingu	LSTM	60.91	53.31	0.72	0.70
Xingu	RNN	59.665	60.83	0.70	0.72
Xingu	GRU	57.66	55.80	0.70	0.74

In addition to the main performance analysis of the CNN model associated with the Recurrence Plot technique, a comparison with other implemented models was also conducted. For the Xingu dataset, the *LSTM* model resulted in an MAE_{test} of 53.31 and an $R2_{test}$ of 0.70, slightly higher than those of the *CNN with RP* model, indicating slightly inferior performance. Furthermore, for the Xingu dataset, the *RNN* and *GRU* models yielded MAE_{test} values of 60.83 and 55.80, respectively, and $R2_{test}$ values of 0.72 and 0.74, respectively. Although these results were similar, they were still inferior to those of the *CNN with RP* model.

Some explanations can support the obtained results. For example, the ability to capture spatial patterns: CNNs are particularly effective in extracting spatial patterns from data. By applying the recurrence plot technique, which represents the relationship between data points in a time series as an image, CNNs can identify complex spatial patterns in these recurrence plots. This ability to capture spatial information helps model relationships between different points in the time series, enabling a better understanding and prediction of the data. Another factor is the utilization of translational invariance: CNNs are designed to be invariant to shifts in input features. This means that CNNs can recognize a pattern regardless of its exact location in the time series. This property is especially useful in time series prediction problems, where patterns may occur at different points in the series. Traditional recurrent neural network models like RNN, LSTM, and GRU may struggle to capture these patterns at different positions, while CNNs are better suited for such tasks.

4. Conclusions

This study investigated for the first time the performance of a convolutional neural network (CNN) combined with the recurrence plot technique for predicting flood using time series data. The performance of this model was compared to traditional models such as RNN, LSTM, and GRU applied to the same dataset. Due to the limited availability of data in the Xingu River dataset, transfer learning with 13 datasets from other rivers was addressed.

Based on the evaluation metrics, the *Xingu: CNN with RP* model, which consisted of an aplication of cnn associated with recurrence plot, demonstrated superior performance. It achieved the lowest mean absolute error (MAE_{test}) value of 50.74 centimeters, indicating the smallest average prediction error among the listed models. Additionally, it obtained the highest coefficient of determination ($R2_{test}$) value of 0.75, signifying its ability to explain a substantial proportion of the variance in the response data. Scatter plots further revealed that the *Xingu: CNN with RP* model exhibited a more compact and closely aligned distribution of data points around the trend line, suggesting a stronger association between variables and better prediction outcomes.

Comparisons with other models confirmed the superiority of the *CNN with RP* model. The *Xingu: LSTM* model demonstrated slightly higher MAE_{test} and $R2_{test}$ values, indicating slightly inferior performance. Similarly, the *RNN* and *GRU* models showed higher MAE_{test} and slightly lower $R2_{test}$ values compared to the *CNN with RP* model. These findings highlight the efficacy of the CNN model in capturing spatial patterns and leveraging translational invariance, which are particularly advantageous for time series prediction tasks.

Overall, this study emphasizes the importance of selecting an appropriate model architecture for time series prediction. The *CNN with RP* model, with its ability to extract spatial patterns and handle shifts in input features, outperformed other models in terms of predictive accuracy for the Xingu River dataset. These results contribute to the understanding and advancement of machine learning techniques in hydrological forecasting and highlight the potential for utilizing CNNs in similar applications.

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