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## Urban flood forecasting with multi-output neural networks: a physically-based and data-driven approach

*Previsão de inundações urbanas com redes neurais de saídas múltiplas: uma abordagem baseada em física e em dados*

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### ABSTRACT

Physically based models for spatial flood prediction are time and computationally expensive. Data-driven models, while faster, require large amounts of data for adjustment. This study presents an original methodology combining these two approaches, using a physically-based model (HEC-RAS 2D), adjusted with known events, to generate water depth data at control points and multi-output artificial neural networks (ANNs) for flood forecasting at these points. The performance of the ANN in this research, with application to the urban area of Lages-SC, southern Brazil, resulted in average mean absolute errors of 3.9, 9.8, and 46 cm, with corresponding Nash-Sutcliffe coefficients of 0.99, 0.98, and 0.75 at lead times of 3 h, 8 h, and 20 h, respectively. Multi-output ANNs exhibited greater robustness compared to single-output ANNs for spatial flood prediction. The methodology is suitable for developing models for spatial predictions of urban flooding, with sufficient agility to take necessary measures.

**Keywords:** Urban flooding; Hydrodynamic modeling; Computational intelligence; Forecasting model.

### RESUMO

Modelos baseados em física para previsão espacial de inundações são caros em termos de tempo e processamento computacional. Modelos baseados em dados, embora mais rápidos, requerem grandes quantidades de dados para ajuste. Este estudo apresenta uma metodologia original que combina essas duas abordagens, utilizando um modelo baseado em física (HEC-RAS 2D), ajustado com eventos conhecidos, para gerar dados de profundidade de água em pontos de controle, e redes neurais artificiais (ANNs) de múltiplas saídas para previsão de inundação nesses pontos. O desempenho das ANNs nesta pesquisa, com aplicação na área urbana de Lages-SC, resultou em erros médios absolutos de 3,9, 9,8 e 46 cm, com coeficientes de Nash-Sutcliffe correspondentes de 0,99, 0,98 e 0,75, para horizontes de previsão de 3 h, 8 h e 20 h, respectivamente. As ANNs de múltiplas saídas demonstraram maior robustez em comparação com ANNs de saída única para a previsão espacializada de inundações. A metodologia é adequada para o desenvolvimento de modelos de previsão de inundações urbanas, com agilidade suficiente para que as medidas necessárias sejam tomadas.

**Palavras-chave:** Inundações urbanas; Modelagem hidrodinâmica; Inteligência computacional; Modelo de previsão.

## INTRODUCTION

Flooding has posed an increasing threat worldwide in recent decades. Urbanization and the chaotic occupation of floodplain areas, associated with climate change impacts, severely affect the hydrological processes occurring on the Earth's surface (Miller & Hutchins, 2017). Flood monitoring and forecasting models have been improved over time to create appropriate technologies for forecasting and warning within sufficient lead time. However, flood forecasting in urban areas remains challenging due to the complex hydrological interactions, the quantitative and qualitative scarcity of available data, and the lack of qualified technical teams with specific domain knowledge (Pereira et al., 2020; Brunner et al., 2021).

Physically-based models are widely used for analyzing hydrological processes, as they accurately represent water flow in river channels and floodplains (Alfieri et al., 2013; Teng et al., 2017). On the other hand, these models are extremely complex, involve numerous physical parameters, and demand high computational time (Teng et al., 2015). This led researchers to redirect their efforts towards developing simpler and more efficient models, capable of providing useful information for early forecasts with less computational time.

Artificial neural networks (ANNs) are an alternative since they can learn from examples and capture subtle functional relationships among the data, even if the underlying relationships are unknown or hard to describe (Mosavi et al., 2018). ANNs have been successfully used in forecasting streamflow (Badrzadeh et al., 2015; Debastiani et al., 2019) and flood levels (Bermúdez et al., 2019; Pedrollo, 2017; Pedrollo & Pedrollo, 2013). These models have also shown promising results in other hydrodynamic contexts, such as tidal rivers, where they have been applied to predict water surface elevations with high accuracy (Adib, 2008; Adib et al., 2017).

Recently, ANNs have proved capable of emulating the results of two-dimensional physically-based models (Bermúdez et al., 2018; Chu et al., 2020). Data generated from hydrodynamic models can be further applied to training the ANNs, which are then used in the operational activities of flood forecasting systems (Bhola et al., 2018). Thus, it is possible to develop flood forecasting models and warning systems for data-sparse regions with little or no hydrological data availability (Dikshit et al., 2020).

Due to the lack of observed data to perform flood forecasting in a region of Taiwan, Jhong et al. (2017) used data generated by the FLO-2D hydrodynamic model to develop an SVM (Support Vector Machine) based model capable of forecasting the spatial distribution from 1 h to 6 h ahead. Berkhahn et al. (2019) used a database simulated by the HYSTEM-EXTRAN 2D (HE 2D) model to develop an ANN for flood inundation mapping. The results provided small computational time and sufficient accuracy for flood forecasting in an urban area. Chu et al. (2020) used a Generalized Regression ANN (GRNN) to map flooded areas based on hourly water depth data generated by the TUFLOW 2D hydrodynamic model. The GRNN model was applied to an Australian central area. The results indicated that even with simulated data, ANN-based models can be a fast and efficient alternative for flood forecasting in a complex environmental system such as urban regions.

Traditionally, ANN flood forecasting has been performed based on fluvial level data from upstream river sections located far from the flooded area (problem domain), which is the most common approach to disaster management (Hapuarachchi et al.,

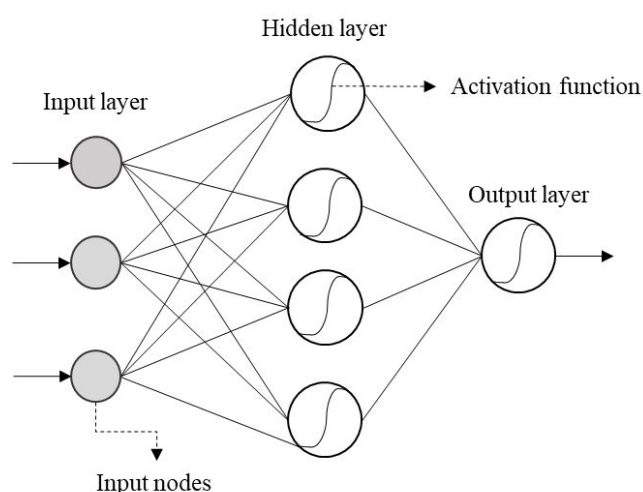
2011). However, carrying out forecasts at several points distributed spatially throughout the flooded area may be more useful, providing comprehensible and robust decision guidelines. Modeling water depth at spatialized locations based only on their correlations with upstream river levels may present inaccuracies due to the nonlinearity of hydrodynamic processes (Alfieri et al., 2012). Thus, it may be useful to have flood forecasting over several points spatially distributed along the flooded area, since they are usually used as references for the flood event evolution by agencies and institutions involved with preparedness and response activities (Pan et al., 2011).

Some studies have used ANN-based models for simultaneously forecasting water depths at several locations, configuring a multi-output model (Kabir et al., 2020; Rjeily et al., 2017). Although the multi-output modeling approach presents operational advantages, the potential gain or loss in model accuracy compared to single-output models has not been evaluated, remaining an important gap to be filled. To this end, this study aimed to assess the applicability of Multilayer Perceptron (MLP) ANNs for water depth forecasting at multiple spatially distributed control points within an urban floodplain during flood events. The dataset for training and verifying the forecasting models based on single and multi-output ANNs resulted from simulation with the HEC-RAS 2D hydrodynamic model due to the scarcity of inundation observed data. This study focused on the urban area of Lages City in Santa Catarina State, Brazil, and hydrologic and hydrodynamic models were used to generate the necessary data. Eight control points along the Carahá, Ponte Grande, and Caveiras rivers were selected to provide comprehensive spatial coverage for model training and validation.

## ARTIFICIAL NEURAL NETWORKS

ANNs are characterized as parallel and distributed systems that relate a set of input vectors to a set of output vectors (Braga et al., 2007). The functional relationship among inputs and outputs is defined implicitly through the connection of nodes across layers and activation functions. Hence, the primary objective is minimizing the error between predicted and actual outputs, achieving the highest possible accuracy. This process, often conducted using backpropagation with optimization algorithms such as gradient descent, enables ANNs to approximate highly complex, nonlinear relationships that are difficult to represent with explicit equations (Maier et al., 2023). The MLP ANN originated from the pioneering work of MacCulloch & Pitts (1943) with modeling biological neurons. ANNs work through weighing connections and activation functions among the processing units (nodes) and are arranged into successive layers: the first one is the input layer - where external information is received; the intermediate ones, also called hidden layers, as well as the last one, called the output layer (which provides the solution to the problem) have activation functions, usually non-linear, to process the information. The ANN with one hidden layer is based on the work of Hornik et al. (1989), which stated that a neural network with a single hidden layer can represent any measurable relationship (Figure 1).

The backpropagation algorithm, a generalization of the Delta Rule (Widrow & Hoff, 1960), for training MLPs, was first introduced by Rumelhart et al. (1986). To speed up the ANN training, Vogl et al. (1988) proposed improvements to the backpropagation algorithm by adding a heuristic learning rate to the ANN training



**Figure 1.** The architecture of a three layer Artificial Neural Network.

and combining it with a momentum factor. The heuristic learning rate method consists of increasing the rate for the next cycle when the error of the previous training cycle is reduced. Conversely, the learning rate is reduced when the errors increase. Given an initial rate of  $C = 0.00001$ , a reduction and increase factor of 0.5 and 1.1, respectively, is recommended.

Because of their great approximation capabilities, ANNs may be overly adjusted to the data, resulting in overfitting which may make the model unsuitable for other applications. A cross-validation procedure may overcome the overfitting problem (Hecht-Nielsen, 1990). Data are divided into three datasets: training; validation; and verification. The first dataset is used for training with a backpropagation algorithm in successive epochs. To avoid overfitting, the results are assessed with the validation dataset at the end of each epoch to identify the stopping point at which errors increase. The third dataset is used to verify the model performance and prediction accuracy with data not applied in the previous steps (Hecht-Nielsen, 1990).

Some extreme input and output values should be included in the training dataset, as ANNs are not suitable for extrapolations outside the numerical training domain (Pedrollo, 2017). Moreover, some extreme values are also included in the verification dataset to verify if the training has ensured a good generalization (Eckhardt, 2008).

The training algorithm depends on the initial set of weights because an eventual poor initialization of its parameters may result in non-convergence or local minima, compromising the ANN performance. This problem can be avoided by using repetitions in the training and choosing the model that best performs with the validation sample. This grants greater robustness to the model (Dornelles, 2007; Oliveira et al., 2014).

## MATERIAL AND METHODS

### Study area

The urban basins of Lages City, located in the Santa Catarina State in southern Brazil were adopted as the study area due to

the high frequency of flood events impacting the population that lives on the floodplain. With a population of 164,981 inhabitants (Instituto Brasileiro de Geografia e Estatística, 2022) and elevation ranging from 800 to 1000 meters, Lages is intersected by three main urban rivers: the Carahá, Passo Fundo, and Ponte Grande. These rivers significantly influence the region's landscape and contribute to the city's vulnerability to flooding. Between 1970 and 2017, this city experienced over 40 flooding events (Liz, 2018). The study area encompasses the Ponte Velha System watershed sub-basins, which are necessary for modeling hydrologic data relevant to urban flooding (Figure 2).

Lages City has a humid temperate climate type (Cfb) with an average annual precipitation of 1,540.3 mm (Padilha, 2017). Municipality records indicate that the flooding events in May 2005, August 2011, and June 2017 were particularly severe, causing significant impacts on the urban floodplain population. Thus, these three flood events were selected to develop the ANN forecasting models.

To develop the proposed methodology, eight water depth control points were identified within the study area: three along the Carahá River (CH-1, CH-2, and CH-3); three along the Ponte Grande River (PG-1, PG-2, and PG-3); and two along the Caveiras River (CAV-3 and CAV-4) (Figure 3). The control points were numbered in increasing order from downstream to upstream. The selection criteria for these locations included the distance from residences to the riverbank, the area's topography, and ease of access. These control points were used for water depth data collection and the development of the forecasting models.

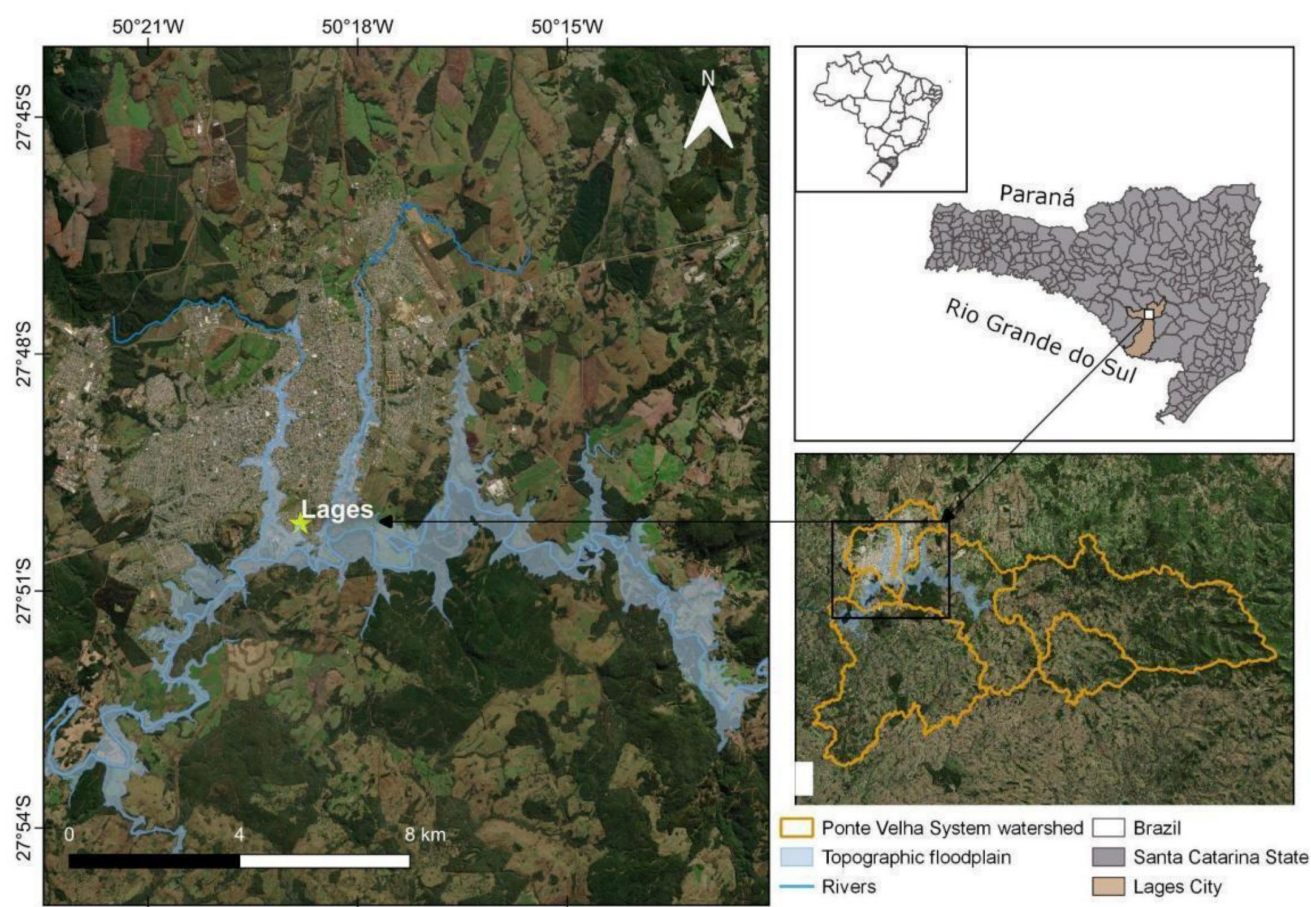
### Overall research strategy

Figure 4 illustrates the five steps in developing and assessing the flood forecasting models. Step (1): generating hydrographs of the flood events that occurred in Lages in 2005, 2011, and 2017 through hydrological simulation in HEC-HMS 4.6; Step (2): Using these hydrographs as the boundary conditions to drive a 2D-hydrodynamic model (HEC-RAS 5.0.6 was adopted in this study) to create time-series of water depth inundation. Steps (3-4): developing the MLP-ANN single-output and multi-output water depth forecasting models for different lead times; and Step (5): assessing the performance of the forecasting models.

The context of this research was an urban environment without observed fluvial level data. The ANN forecasting model approach considered the water depth data generated by the hydrodynamic model as an indicator of the system condition at specific control points in the Lages urban floodplain. Therefore, the results of the hydrodynamic model are considered a representation of reality, and the ANN is expected to be able to emulate it.

### Generating input hydrographs

To obtain the hydrographs representing the rainfall-runoff volumes that flow into the study area, hydrologic modeling was performed using a calibrated model developed by the Hidro-Lages Project in HEC-HMS 4.6 (Rafaeli Neto, 2019a). This model corresponds to the Ponte Velha System watershed, which



**Figure 2.** Map of the study area.

covers the urban basins of Lages and is specifically relevant to the problem domain of this study.

Rainfall and runoff data on a daily frequency were obtained from five rain gauge stations: Bocaina do Sul (Code 02749035), Lages (Code 02750005), Coxilha Rica (Code 02850004), Paineira (Code 02750007), and Vila Canoas (Code 02749031). These data were collected from the HIDROWEB platform, provided by ANA (Brasil, 2024).

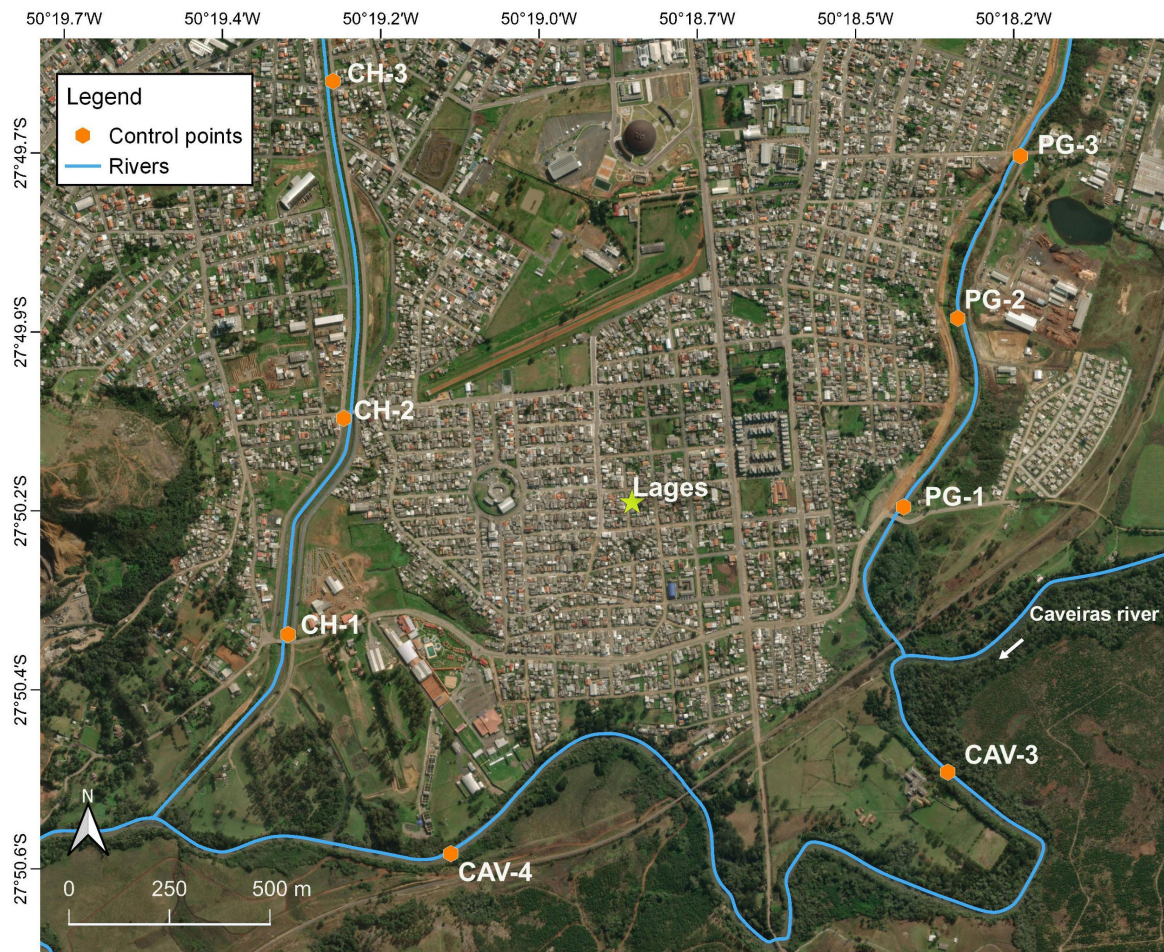
Regarding the HEC-HMS parameters, we applied the CN-SCS (Curve Number - Soil Conservation Service) method to transform rainfall data into surface runoff. The CN values were derived from literature sources (Collischonn & Dornelles, 2013; Sartori et al., 2005; Tucci, 2009). The exponential recession method was applied to calculate the baseflow, while the Muskingum-Cunge method was utilized to simulate flood wave propagation over time. The hydrological model was calibrated using the 2005 flood event by comparing simulated outputs with observed flow data from the Ponte Velha station (Code 71620500/02750026), resulting in a Nash-Sutcliffe Efficiency (NSE) of 0.901 (Rafaeli Neto, 2019a). The hydrographs for the calibrated 2005 event, as well as the validation events of 2011 and 2017, are presented in Figure 5. NSE values of 0.582 and 0.686 were obtained for the 2011 and 2017 events, respectively, indicating satisfactory model performance during these simulations. The hydrographs generated from the hydrologic model were subsequently used as input to the hydrodynamic model.

## Generating water depth data

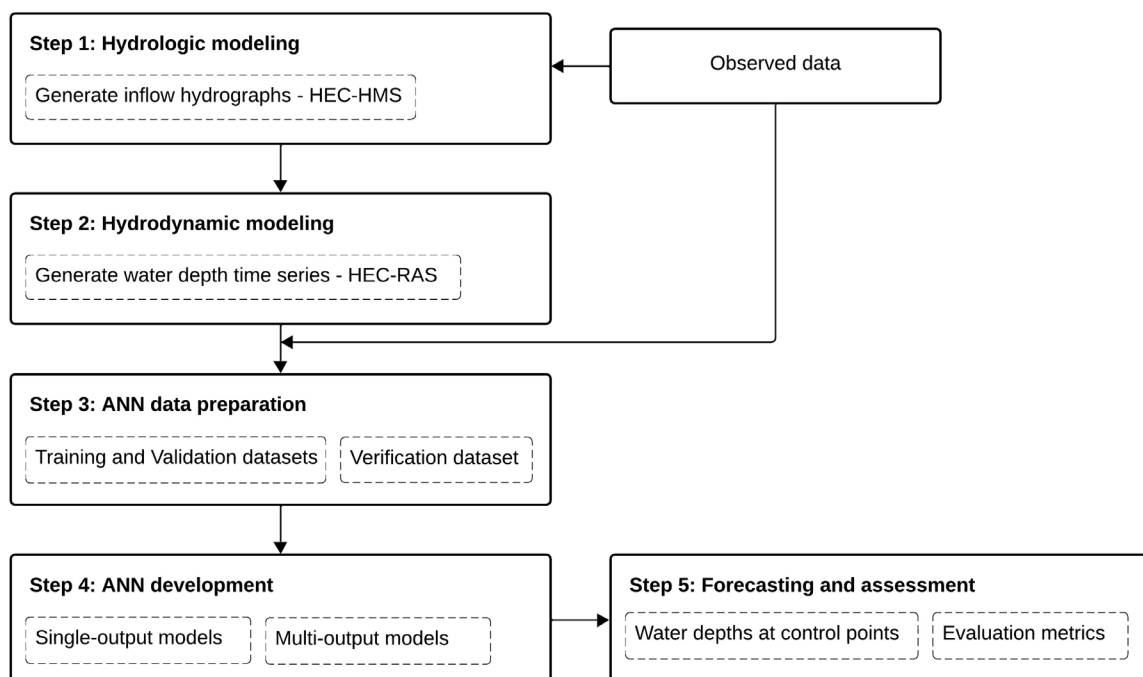
To generate the flood depths, we conducted 2D-hydrodynamic simulations using HEC-RAS 5.0.6. A high-resolution DEM (Digital Elevation Model) with a resolution of 30 cm (Rafaeli Neto, 2019c) was employed which is essential for achieving reliable results. DEMs with this level of resolution provide sufficient detail of the terrain surface for accurately representing flood inundation depths. The modeling geometry was configured with a grid cell size of 5 m x 5 m, resulting in a simulation domain of 107, 327 grid cells. Break lines were added along the river path to create adjusted cells that better fit the river section.

HEC-RAS 2D fluvial flooding requires two main inputs: DEM and river boundary conditions. There are three upstream inflow boundaries (J4, J8, and J13 in Figure 6) and one downstream boundary (outflow) in the model domain (Figure 6). Hydrographs obtained from the hydrological model were used as input boundary conditions to the 2D hydrodynamic model. The normal depth method was adopted for the downstream boundary condition (output boundary) with the default value of 0.001 m/m (Brunner, 2016).

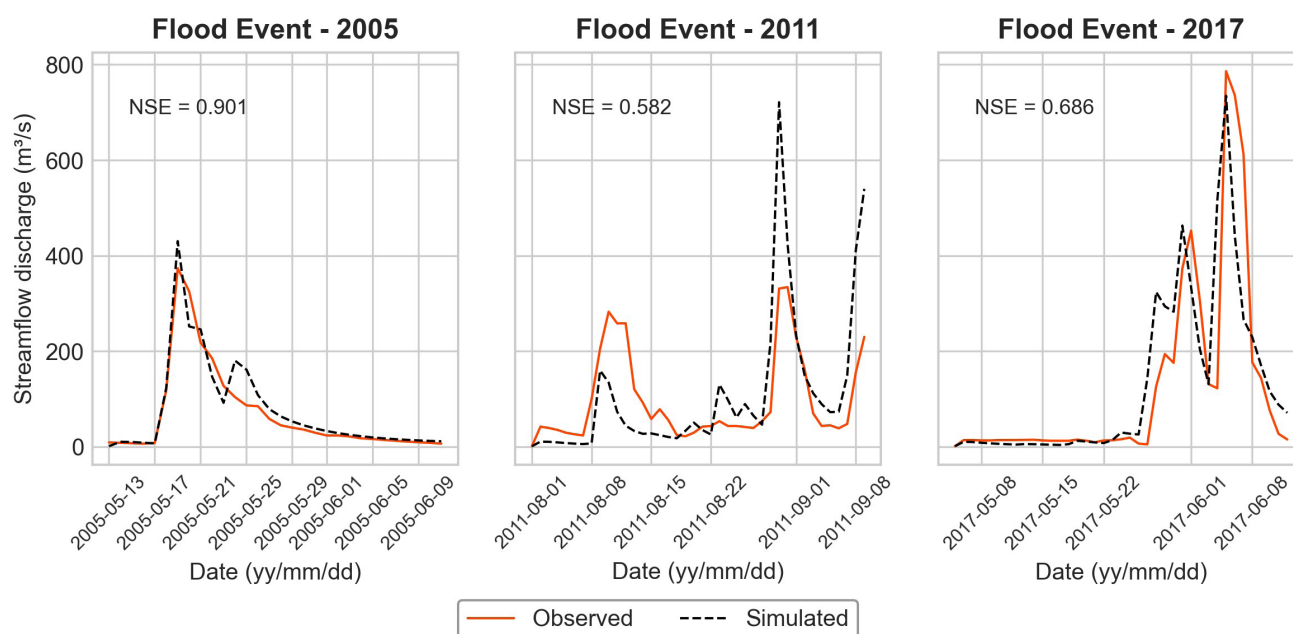
Manning's coefficient was set to a unique value of 0.085 s.m<sup>-1/3</sup> for the entire grid, based on literature considerations and previous hydrodynamic studies conducted in the study domain (Hicks & Peacock, 2005; Liz, 2018; Rafaeli Neto, 2019b); Simulation



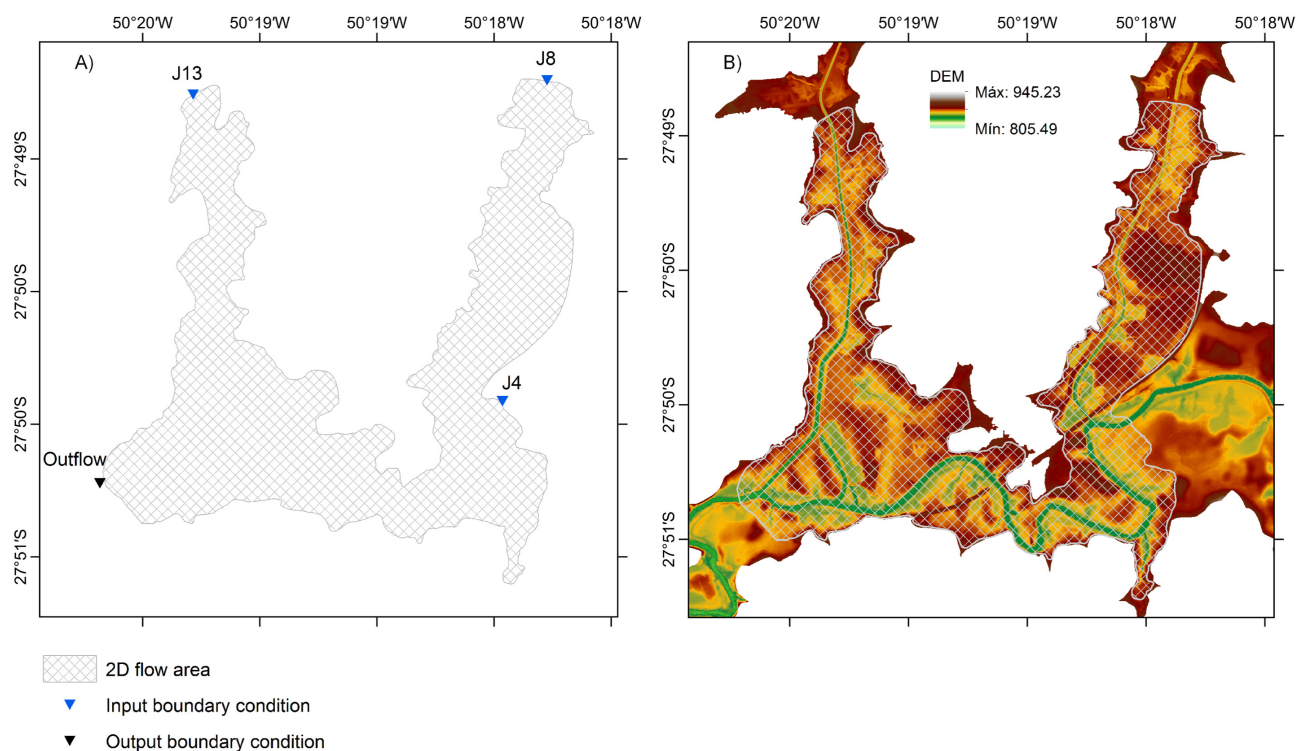
**Figure 3.** Visualization of the eight control points specified for water depth forecasting. Three along the Carahá River (CH-1, CH-2, CH-3), three along the Ponte Grande River (PG-1, PG-2, PG-3), and two along the Caveiras River (CAV-4, CAV-3).



**Figure 4.** Overview of the workflow for the development and testing of the ANN forecasting approach.



**Figure 5.** Flood hydrographs of the 2005, 2011, and 2017 flood events simulated using the HEC-HMS hydrological model. The orange solid line represents the observed streamflow at Ponte Velha station, while the black dashed line indicates the simulated streamflow. Nash-Sutcliffe Efficiency (NSE) values of 0.901, 0.582, and 0.686 were achieved for the respective events.



**Figure 6.** HEC-RAS two-dimensional hydrodynamic modeling, with detail on input and output boundary conditions. (A) J4, J8, and J13 correspond to the time series of inflow input; Outflow corresponds to the downstream boundary condition; (B) HEC-RAS two-dimensional terrain and geometry.

time step was modified to satisfy the Courant-Friedrichs-Lewy (CFL) condition (Brunner, 2016), thus a time step of 5 seconds was adopted for the simulations.

Water depth time series at each of the eight control points were obtained based on their respective locations within the hydrodynamic model grid domain. The control points were placed

to coincide with the grid cells as closely as possible, ensuring an accurate water depth time series acquisition.

## Development of the forecasting models

ANN forecasting models were fully implemented by the authors on MATLAB 2019a. Three-layer ANNs were used, consisting of an input layer, a hidden one, and an output one.

Hydrographs, obtained with HEC-HMS, and water depths in each control point, obtained with HEC-RAS 2D, are relevant factors for forecasting future inundation depths. These variables were used as input data for the ANN models. Additionally, the models incorporate daily precipitation data from two rainfall stations, Lages (Code 02750005) and Painei (Code 02750007). The model's output is the forecasted water depth at each control point for lead times of 3, 6, 8, 12, 14, 18, and 20 hours.

The first step in developing the ANN models was pre-processing the data with temporal lags. This was done by synchronizing all data by undergoing temporal translation according to time lags and lead times, to compose ordered input-output datasets. For instance, rainfall data were organized to include both the current state of the basin (*dayt*) and previous states (*rainfall data from dayt - 1, t - 2, t - 3, and t - 4*).

We used the sigmoid unipolar activation function - with outputs in the interval  $[0, 1]$ , whose derivative function can be calculated only as a function of the output (Equations 1 and 2) in which “*f*” is the unipolar sigmoid function; “*a*” is its image and “*f*’” is its derivative. The input and output variables were scaled to values within the sensitivity range of the activation function.

$$a = f(x) = \frac{1}{(1 + \exp(-x))} \quad (1)$$

$$f'(x) = a(1 - a) \quad (2)$$

We used the backpropagation algorithm for training the three-layer ANN models, combined with cross-validation (Rumelhart et al., 1986; Hecht-Nielsen, 1990) and well-established training acceleration techniques (Vogl et al., 1988). The learning

rate ( $\tau$ ) was initialized at  $\tau = 0.00001$  for all models and adjusted dynamically during training. Following Vogl et al. (1988), if the square error increases,  $\tau = 0.5\tau$ ; if it decreases,  $\tau = 1.1\tau$ .

For training using the cross-validation method, data were partitioned into training, validation, and verification datasets. The 2017 event was used as a training dataset because it has extreme values of flow and water depth, which must be present in the training dataset. The 2005 event was used as the validation dataset and the 2011 event was used as the verification dataset. The training procedure was performed with five repetitions, considering 500,000 epochs. ANN models were developed for each control point. Final performances were assessed with the verification dataset.

The internal complexity of each ANN model (number of neurons in the hidden layer) was defined based on a theoretical paradigm stated by Lucchese et al. (2020). It consists of adopting the minimum complexity that, trained without overfitting, still results in a validation performance equivalent to that of a purposefully oversized neural network trained under the same conditions. The procedure is performed by a graphical analysis of the relationship between the validation step squared error and the number of internal neurons, which starts from an oversized neural network (20 internal neurons) to the smallest possible number of neurons (one internal neuron). The total internal neurons inspected in this study were 1, 2, 4, 6, 8, 10, 12, 14, 16, 18, and 20, respectively. Table 1 presents a summary of the input-hidden-output architecture of each final model.

One of the great benefits of ANNs is that they can generate multiple outputs for the same set of inputs. Thus, a single neural network can provide water depth values for several control points at the same time. In this study, we investigated the use of single-output and multi-output ANNs. Firstly, single-output ANNs were developed to provide water depth forecasts at one control point at a time. Secondly, we evaluated multi-output ANN to forecast simultaneously the water depth at more than one control point (Table 1).

## Evaluation metrics

Three relevant recommendations should be included for evaluating the performance of forecasting models: (1) at least one absolute error metric (presented in the same unit as the output variable); (2) a dimensionless index (or relative error indicator) to quantify the model performance; and (3) a graphical representation

**Table 1.** Summary of the single-output and multi-output models for water depth forecasting at each control point. The architecture details of each model, specifying the number of input nodes, hidden nodes, and output nodes are also included.

| ANN model | Corresponding control point | Model architecture (I:H:O) | Model description   |
|-----------|-----------------------------|----------------------------|---------------------|
| ANN_CAV4  | CAV-4                       | 14:6:1                     | Single-output model |
| ANN_CAV3  | CAV-3                       | 14:5:1                     | Single-output model |
| ANN_CH1   | CH-1                        | 14:6:1                     | Single-output model |
| ANN_CH2   | CH-2                        | 14:4:1                     | Single-output model |
| ANN_CH3   | CH-3                        | 14:10:1                    | Single-output model |
| ANN_PG1   | PG-1                        | 14:8:1                     | Single-output model |
| ANN_PG2   | PG-2                        | 14:5:1                     | Single-output model |
| ANN_PG3   | PG-3                        | 14:10:1                    | Single-output model |
| ANN_CAV   | CAV-4, CAV-3                | 16:6:2                     | Multi-output model  |
| ANN_CH    | CH-1, CH-2, CH-3            | 16:6:2                     | Multi-output model  |
| ANN_PG    | PG-1, PG-2, PG-3            | 16:8:2                     | Multi-output model  |

of the relationship between model estimates and observations (Ritter & Muñoz-Carpena, 2013), which provides an overview of model performance (American Society of Civil Engineers, 1993; Moriasi et al., 2015).

To evaluate the performance of the forecast models, we used the mean absolute error (MAE) (Equation 3), the Nash-Sutcliffe coefficient (NS) (Equation 4), and the quantile 90% (E90), which corresponds to the values that were not exceeded in 90% of the forecasts.

$$MAE = \frac{1}{N} \sum_{t=1}^N |y_t - \hat{y}_t| \quad (3)$$

$$NS = 1 - \frac{\sum_t (y_t - \hat{y}_t)^2}{\sum_t (y_t - \bar{y})^2} \quad (4)$$

where  $y_t$  is the observed values in time  $t$ ,  $\hat{y}_t$  is the calculated values in time  $t$ , and  $\bar{y}$  is the average observed values.

## RESULTS AND DISCUSSION

### Spatio-temporal analysis of flood wave and flood depths

After running the hydrodynamic simulations, we observed a time delay of approximately 24 hours between the initial elevation of water levels at the main channel and the occurrence of maximum flood depths within the floodplain for all three events. This time lag reflects the time required for floodwaters to propagate through the basin and spread across the floodplain. This pattern can be attributed to the gradual onset of floods in the study area. Typically, floods in this region result from accumulated precipitation causing the river to overflow (Liz, 2018; Rafaeli Neto, 2019a).

The flood wave recession also occurred slowly for all three test cases, with several days passing by before the flow of urban rivers returned to normal conditions. This could mean that residents evacuated from affected buildings had to stay in shelters for a relatively extended time.

We observed differences in water level elevation over time among the urban rivers (Figure 7). At first, it occurred in the Caveiras River and subsequently in the Ponte Grande River. The Ponte Grande River overflows above its natural channel around 14-16 hours after the event begins. Approximately, 8 to 12 hours separate the overflow starting point in the Ponte Grande River from the Carahá River overflow. Thus, it is possible to infer that the control points in the Caveiras River (CAV-4 and CAV-3) and in the Ponte Grande River (PG-1, PG-2, PG-3) may be used for monitoring the depths reached in the Carahá River floodplain. By analyzing water evolution over the urban floodplain, a relationship among all control points may be established to optimize flood inundation depth forecasting. Therefore, it may also be possible to guide actions of preparedness and response to the events in a strategic way.

Water depth is represented in HEC-RAS 2D in terms of water elevation, considering the channel bathymetric level as a

reference. Data were obtained from the hydrodynamic model for each control point at hourly intervals throughout the simulation (Figure 7). Then, the water depth data were organized in MS Excel and used for the development of ANN models.

### Single-output ANN forecasting

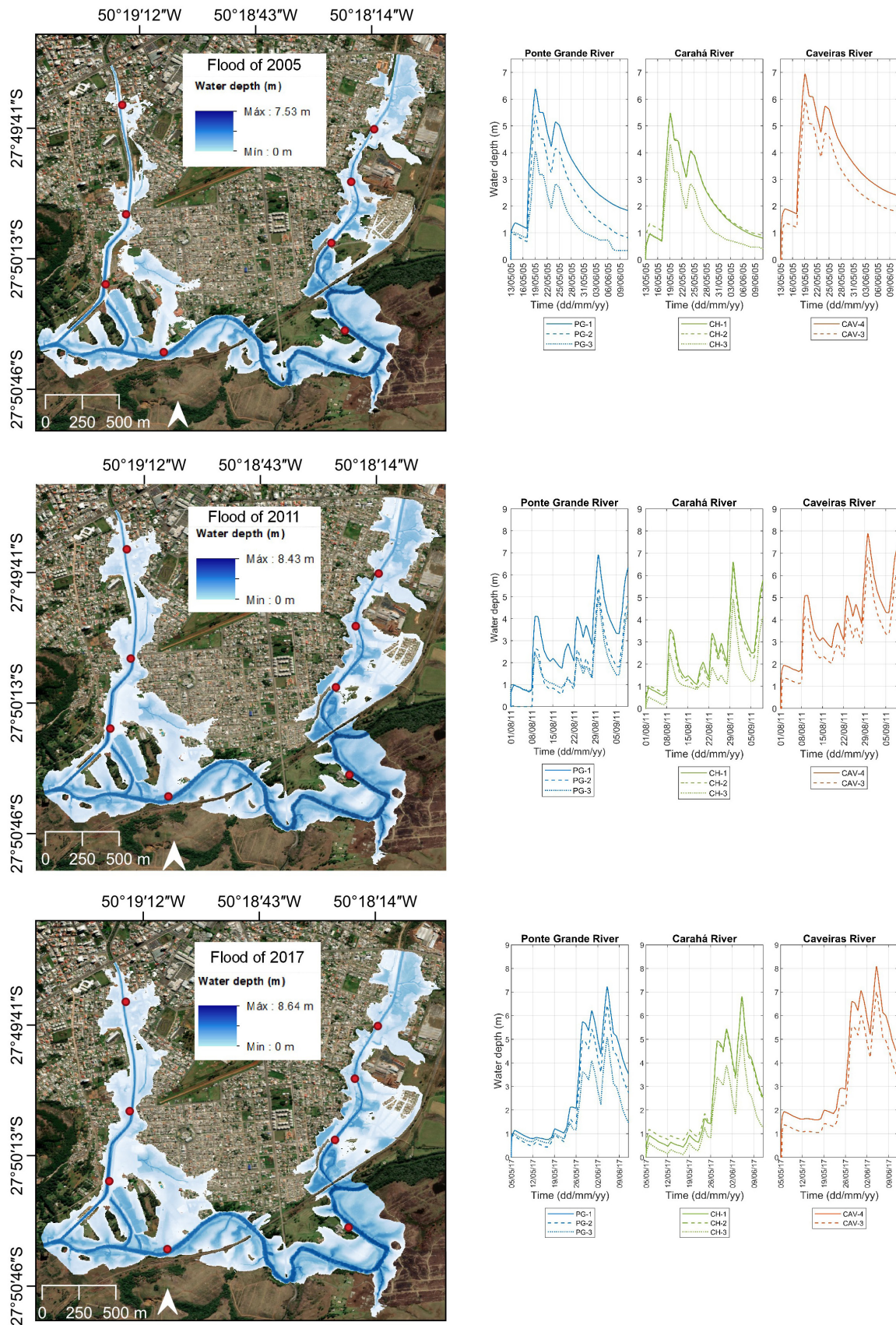
In this section, all eight single-output ANN models designed for each control point were analyzed. The ANN models have a single output variable corresponding to the water depth at the respective control point. The forecast considered 3, 6, 8, 12, 14, 18, and 20-hour lead times.

The results of the performance indicators, with varying lead times, are shown in Figure 8. As expected, we observed a deterioration in forecast accuracy as the lead time increased. This suggests that the model's ability to understand and represent the relationships among variables is reduced for more far-reaching predictions. Therefore, data used for forecasting at extended ranges (14 h - 20 h) may include irrelevant information that does not improve model performances (Jhong et al., 2017). The data may also lack representation of what occurs between the forecast time and the corresponding lead time. This behavior is expected and can be improved for rainfall-runoff models by using upstream flow data as an additional input (Badrzadeh et al., 2015). Overall, the models were able to forecast up to 20 hours ahead with an MAE of 52 cm and NS greater than 0.67.

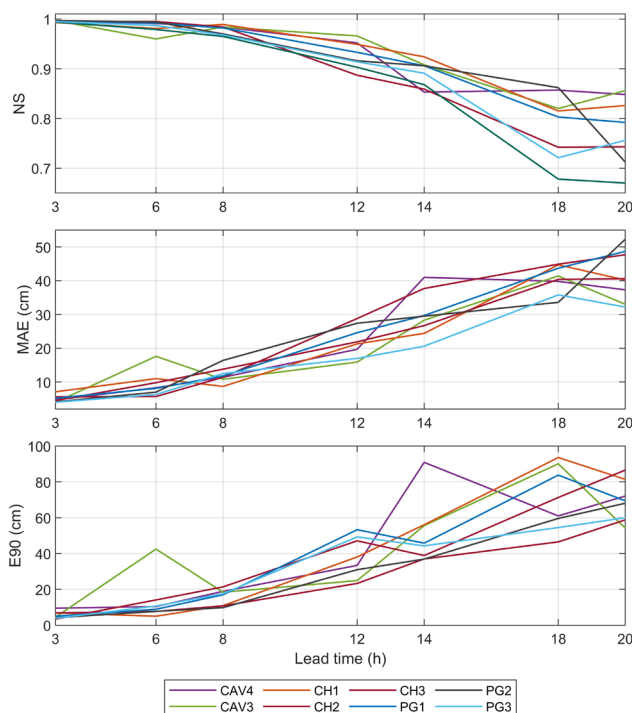
Discrepancies in the results can be seen at CAV-4, CH-3, and PG-3 (Figure 8). This is explained by their location in the floodplain; CH-3 and PG-3 are located upstream of the flooded areas and do not have some data as input that may be more relevant for earlier forecasting. The CAV-4 is situated in a zone of high volumes and significant changes in water flow direction - due to a pronounced curve in the Caveiras River. In this case, the frequency of water depth data used for model training (1-hour intervals) may not capture the flood behavior in detail. Similar results were found by Chu et al. (2020), who reported that at control points with rapid changes in the water flow pattern, insufficient data were generated for training the forecast models. Using data with a smaller time interval could be a feasible strategy to overcome this issue.

Understanding relationships between variables by the ANN models is linked to the quality and spatial resolution of the DEM used in hydrodynamic simulations (Bermúdez et al., 2018). Studies suggest that a coarser grid resolution of the DEM results in larger inundation areas and larger depths by the effect of terrain smoothing and the decrease in differences among surface points (Muthusamy et al., 2021; Saksena & Merwade, 2015). A refined representation of the terrain surface for hydrodynamic simulations, such as the one used in this study, can allow the ANN to consider the dynamic interactions of the flood system (Chu et al., 2020). Thus, the forecasting models may assimilate the dynamics of flood events with high accuracy.

For a lead time of 8 h, the NS of the verification dataset was equal to or higher than 0.96 for all ANN models; the good performance of the models was confirmed by the results obtained for the MAE, which were lower than 18 cm for lead times from 3 h to 8 h. These results are comparable to a study conducted in Itajaí-Açu River, Santa Catarina, Brazil that reported an NS



**Figure 7.** Maximum water depth maps from the HEC-RAS 2D model simulations for the 2005, 2011, and 2017 flood events. Each map shows the extent and depth of inundation in the study area, with depth values ranging from 0 meters (min) to the maximum depth recorded during each event (7.53 m, 8.43 m, and 8.64 m, respectively). Adjacent to each map, the line plots illustrate the inundation depths at each control point within the area.



**Figure 8.** Nash-Sutcliffe (NS), mean absolute error (MAE), and E90 values for the verification dataset across all lead times for the single-output ANN.

value of 0.98 and MAE values of 11 cm for a 6-hour river level forecasting (Alberton et al., 2021). Pedrollo (2017) proved that it is possible with MLP-ANN to accurately predict river levels with time horizons between 5 and 11 h, horizons similar to those of the present study. Being able to forecast flood events for lead times of 3, 6, or 8 hours can provide sufficient time for preparedness and response measures to be implemented, such as warning the population and conducting evacuation activities within the area.

Overall, the models demonstrated satisfactory predictive capabilities for water depths at spatially distributed control points. They provided valuable insights into water dynamics across the urban floodplain and may be employed in a flood forecasting system. Furthermore, the results indicate that it is feasible to accurately estimate water depths during floods at specific control points within urban areas. This information is of primary interest to the government and stakeholders so that effective preparedness and response measures can be taken.

Additionally, observations from upstream river sections can be combined with forecasted water depth at specific urban control points. Therefore, the knowledge of these floodplain water depths and, in consequence, about the hydrodynamic behavior of urban rivers and their effect on a flood disaster occurrence can contribute to developing specific strategies for improving decision-making at different stages of disaster risk reduction (Rana et al., 2021; van Wesemael et al., 2019).

To enhance model accuracy, expanding the training dataset is essential. The main limitation of this research was the lack of flood depth data from field observations, mainly due to resource constraints and inadequate operational river gauges. Despite this, the simulated datasets may contribute to developing a flood

forecasting and warning system strategy, which could help mitigate the adverse impacts of flood events in urban areas.

## Multi-output ANN forecasting

Multi-output ANNs were implemented to evaluate their performance in forecasting water depths simultaneously at multiple control points, compared to the conventional single-output approach.

The ANN\_CAV model was trained to forecast inundation water depths concurrently at the CAV-4 and CAV-3 control points. Notably, the multi-output ANN demonstrated improved evaluation metrics (Figure 9). The E90 metric - the error threshold not exceeded in 90% of predictions - was reduced across all lead times, indicating the model's enhanced ability to minimize extreme errors.

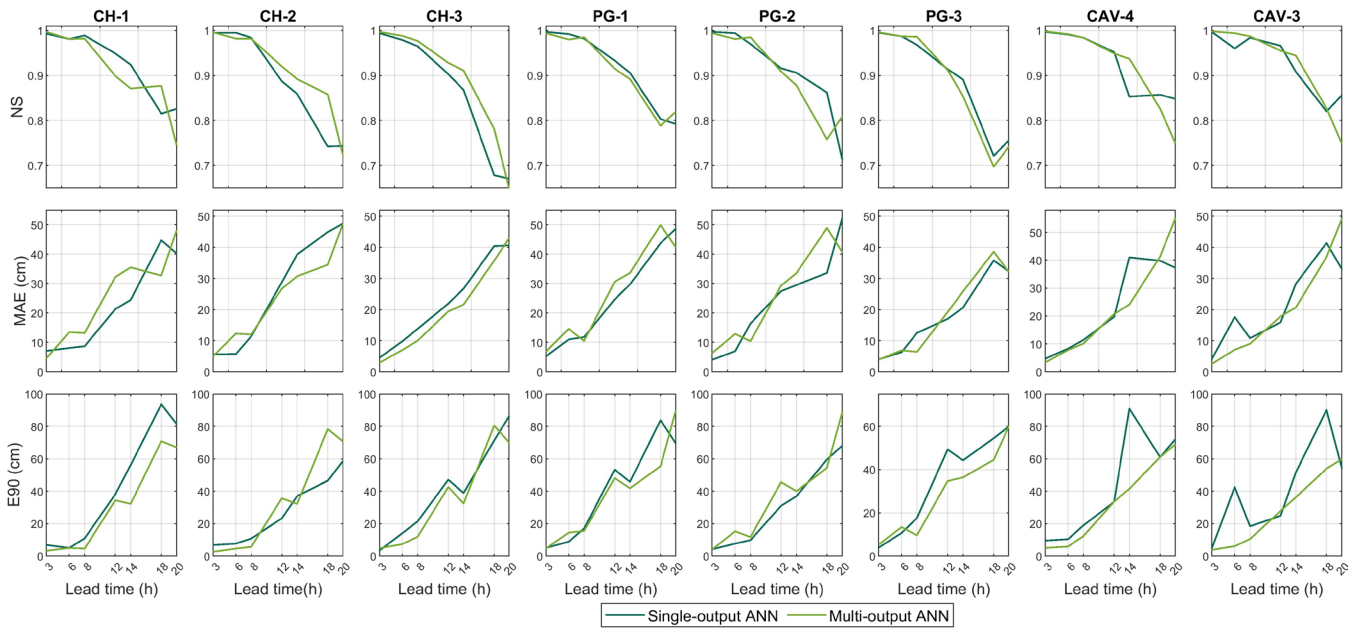
Similarly, the ANN\_CH model exhibited a significant advantage in accuracy when forecasting water depths at control points CH-2 and CH-3, compared to single-output ANNs (Figure 9). At control point CH-2, the NS metric was greater than 0.78, reflecting improved accuracy for lead times between 12 and 18 hours. For shorter lead times (3 to 8 hours), the MAE was consistently below 15 cm across all control points in the Carahá River when using the multi-output model. However, evaluation metrics for forecasts 20 hours ahead were comparable to those of single-output models, indicating a decline in performance at longer lead times when the models can no longer effectively perform well.

Moreover, a reduction in E90 was also observed at control points CH-1, PG-1, and PG-3 with the multi-output ANN. This means that the multi-output approach produced more stable and consistent forecasts by reducing the occurrence of extreme errors.

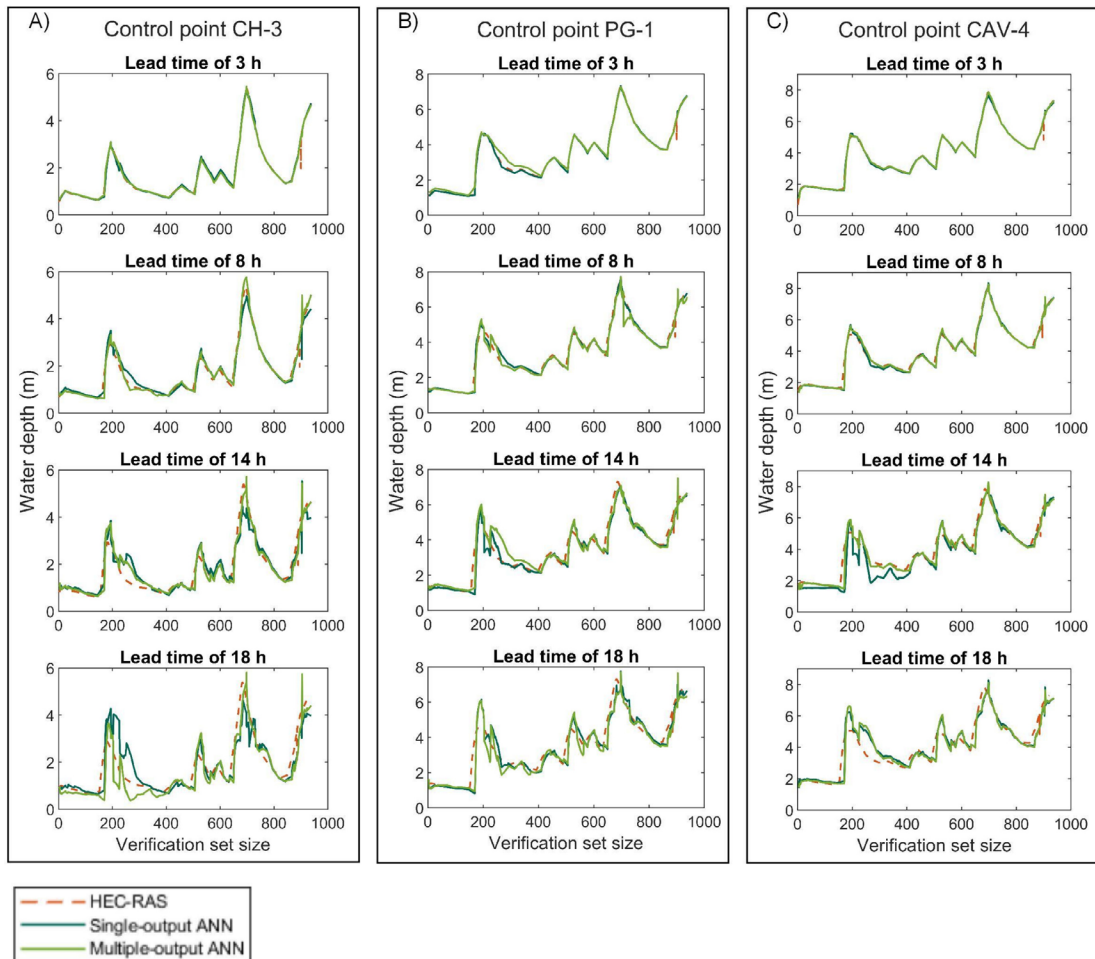
The performance of the verification dataset for lead times of 3 h, 8 h, 14 h, and 18 h at CH-3 (Figure 10A), PG-1 (Figure 10B), and CAV-4 (Figure 10C) illustrate the tendency seen throughout lead times. The multi-output model revealed itself advantageously when considering water depths simulated by the hydrodynamic model and ANNs forecasted values. While single-output ANNs often overestimated or underestimated water depths for 14 h lead-time, the results from the multi-output models showed a difference that was either lower or nearly zero compared to the maximum water depths obtained from HEC-RAS and those forecasted by the ANNs. This suggests that multi-output ANNs provided better predictions of water depths during the flood event, mainly due to their greater stability and lower error rates compared to single-output models.

Multi-output ANN models may exhibit more stable results because, during the training stage, the synaptic weights are jointly adjusted to provide efficient responses for all outputs. This could assist in learning the overall dynamic process and prevent inconsistent results from individual outputs. Although multi-output ANNs do not always yield the most accurate individual results, they may reduce extreme errors and bring greater stability to the overall results. The increase in model stability is directly associated with improvement in reliability, as the errors, which are always present, were less extreme for the multi-output models compared to the ones produced by single-output models.

Our results suggested that multi-output ANN models effectively utilize their internal parameter structure to model the inherent physical relationships of input variables, resulting in more



**Figure 9.** Performance comparison of single-output (blue line) and multi-output (green line) ANNs based on the verification dataset. The metrics evaluated include Nash-Sutcliffe efficiency (NS), mean absolute error (MAE), and the E90 error threshold across all lead times for different control points.



**Figure 10.** Comparison of water depth time-series predictions. Panels (A), (B), and (C) show predictions from single-output ANN and multi-output ANN models against HEC-RAS simulations for control points CH-3, PG-1, and CAV-4, respectively.

reliable forecasting models. Furthermore, this approach allowed inundation water depth forecasting at multiple specified locations along the urban floodplain. In urban settings, complex hydrodynamic interactions occur between hydrological and topographic characteristics. A multi-output ANN may capture these interactions across both temporal and spatial scales. This is particularly advantageous for flood forecasting in highly urbanized regions, where the water flow dynamics can lead to uncertainties in data-driven modeling.

## CONCLUSIONS

In this study, we investigated the applicability of multiple output ANNs developed with data simulated by a hydrodynamic model to forecast flood inundation depths at spatially distributed control points within an urban environment. Water depth data generated by a hydrodynamic model proved useful for training and verifying ANNs for flood forecasting purposes. The single-output ANN approach demonstrated promising results for 3 h to 8 h lead times, showing great potential for practical flood depth forecasting. A key advantage of the approach is its ability to forecast water depth at multiple control points within the urban floodplain, rather than just forecasting water levels at fluvial sections upstream of the affected area. The multi-output ANN approach offered improved stability by reducing drastic variations in forecasting errors. These findings highlight the potential for developing more reliable and efficient flood forecasting models for urban areas.

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Renata Bulling Magro: Conceptualization, methodology, formal analysis, writing - original draft, review & editing.

Olavo Correa Pedrollo: Conceptualization, methodology, writing, review & editing, resources, and supervision.

Silvio Luis Rafaeli Neto: Conceptualization, methodology, review, resources, and supervision.

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