A MULTI-OBJECTIVE APPROACH TO URBAN FLOOD FORECASTING: CASE STUDY OF CAVEIRAS RIVER, LAGES, SANTA CATARINA

1Renata Bulling Magro, 2Silvio Luis Rafaeli Neto, 3Olavo Pedrollo, 4Alexandre C. Botazzo Delbem
1Universidade de São Paulo (USP), e-mail: renatamagro@usp.br; 2Universidade do Estado de Santa Catarina (UDESC), e-mail: silvio.rafaeli@udesc.br; 3Universidade Federal do Rio Grande do Sul, e-mail: pedrollo.olavo@gmail.com, 4Universidade de São Paulo (USP), e-mail: acbd@usp.br

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Abstract

In recent decades, floods have emerged as a growing global threat. The increase in urbanization of floodplain regions coupled with the impacts of climate change, has significant effects on the hydrological processes on Earth's surface (MILLER; HUTCHINS, 2017). To address this challenge, developing robust and accurate flood forecasting models is imperative. However, the complex interactions among hydrological and hydrodynamic factors within urban environments present a significant obstacle to developing such models (PARQUIER; BAZIN, 2014).

While physically-based models offer accurate representations of water flow and dynamics, their complexity and computational requirements often make them impractical for real-time flood forecasting. As an alternative, machine learning models can provide cost-effective solutions (MOSAVI, et al., 2018). Artificial Neural Networks (ANNs), for instance, offer advantages in flood disaster contexts due to their ability to learn from data and capture intricate relationships with less computational time, making them a valuable tool for flood forecasting. However, traditional ANN-based models often rely on upstream data to forecast downstream river levels, potentially introducing uncertainties when converting these forecasts into actual water depths across the urban floodplain (ALFIERI, et al. 2012). Additionally, predicting water depths at various locations in floodplains is highly valuable for disaster response agencies. This flood forecasting strategy, which considers spatialized multiple control points in space, can be translated into a multi-objective optimization problem. The multi-objective approach treats the accuracy of various control points as simultaneous goals, optimizing multiple objectives at once. This is different from single-objective algorithms that focus on a single criteria (or objective) (GASPAR-CUNHA; VIEIRA, 2005). In the context of this work, a multi-objective approach means predicting water depth at many points while exploring the trade-offs between their accuracy. This study aimed to investigate a multi-objective approach for multi-site water depth forecasting using ANNs.

The study area corresponds to Lages, Santa Catarina, Brazil, focusing on a section of the Caveiras River. Flood events from May 2005, August 2011, and June 2017 were selected for developing the ANN-based forecasting models. These events were chosen due to the significant negative impacts they caused on the urban floodplain residents. Two water depth control points (CAV3 and CAV4) were employed to assess the single and multi-objective approaches for flood forecasting water depth (Figure 1). The ANN 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 from HEC-HMS 4.2 (FIELDMAN, 2000) and water depth from HEC-RAS 2D (BRUNNER, 2016) were used as input data. The output is the predicted water depth at each control point for the lead times of 3, 6, 8, 12, 14, 18, and 20 hours, respectively. These lead times were chosen to test the forecasting capability of the models. Data were partitioned into training, validation, and verification datasets. The final model performance was assessed with the verification dataset.

Figure 1: Schematic representation of the location of control points.

One of the great benefits of ANNs is their ability to generate multiple outputs for a given set of inputs. In this study, we investigated the use of single-objective and multi-objective ANNs. Initially, single-objective models were developed to forecast water depth at one individual control point. Subsequently, a multi-objective approach was utilized to simultaneously forecast water depth at multiple control points (Table 1). To evaluate the model's performance, we used the mean absolute error (MAE), the Nash-Sutcliffe coefficient (NS) (MORIASI, et al. 2015), and the 90th percentile (E90), which indicates the error values not exceeded in 90% of the predictions.

Spatial input information	Model	Objective
CAV3	ANN_{CAV3}	Accuracy of CAV3 forecasting (single-objective)
CAV4	ANN_{CAV4}	Accuracy of CAV4 forecasting (single-objective)
CAV3 and CAV4	$ANN_{CAV3,4}$	Accuracy of CAV3 and CAV4 (multi-objective)

Table 1: Summary of single and multi-objective models used to forecast water depth at each control point. The objective corresponds to the model's accuracy at each control point (single-objective) or both control points (multi-objective).

Figure 2 compares single and multi-objective models' performance using the verification dataset. The NS is dimensionless, ranging from -1 to +1, with +1 as optimal; MAE values are measured in meters, where lower values indicate superior performance. The NS results for an 8 h lead time were 0.96 or higher for all models (Figure 2). The MAE confirmed the good results, with less than 0.10 m for lead times from 3 h to 8 h. The multi-objective approach demonstrated superior performance in terms of E90, which was reduced for the lead times from 3 h to 18 h. The lower E90 values suggest the multi-objective model captured extreme values, such as peak values, with a small error.

Additionally, the multi-objective model demonstrated superior consistency compared to single-objective ones. When examining a lead time of 14 h, single-objective models had lower NS and higher MAE. In contrast, the multi-objective model was more stable for all lead times. It had less drastic variations. This stability may come from the joint optimization of both objectives in the multi-objective approach, unlike the individual optimization approach followed by the simpler alternative.

In this work we evaluated single- and multi-objective approaches to forecast distributed (spatialized) water depths at the urban floodplain. The multi-objective model was better at minimizing extreme errors and had more stable results. These findings translate to more robustness and reliability. The model's errors, which are inherent to any model, were less pronounced in the multi-objective approach. Furthermore, the multi-objective model was advantageous in delivering water depth forecasts at many control points across the floodplain. Future research will focus on automating multi-objective optimization of flood modeling techniques, ultimately contributing to more robust flood modeling outcomes.

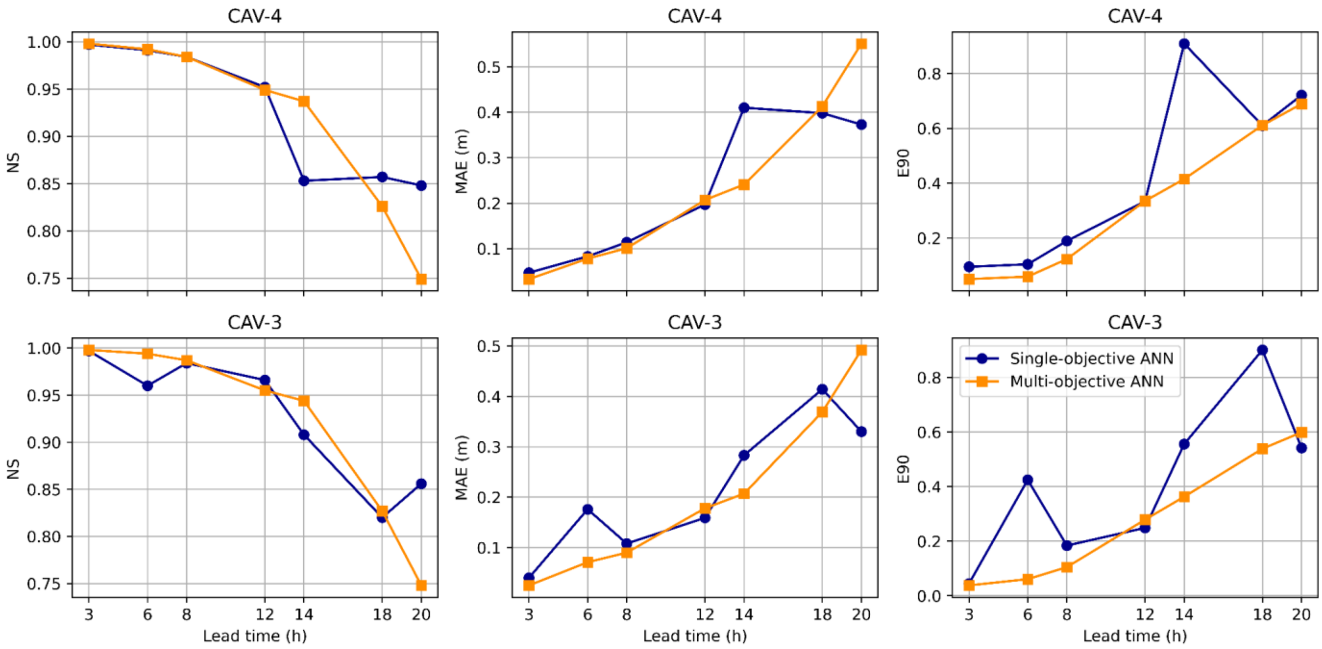

Figure 2: Performance comparison of the single-objective and multi-objective ANNs at each control point (row) and for each evaluation metric (column) for the verification dataset.

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