



# Performance analysis of physically-based (HEC-RAS, CADDIES) and AI-based (LSTM) flood models for two case studies

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**Abstract.** Megacities in developing countries are commonly affected by flooding events. The use of flood models can contribute to an evidence-based decision-making process. For a good representation, these models require physical data for catchment parameterization, and observed data for calibration and validation, which is often scarce. In this study, we analysed the performance results of physically-based (HEC-RAS, CADDIES) and AI-based (LSTM) flood models for two case studies: the Narmada basin in India and the Aricanduva catchment in Brazil. The models were evaluated for accuracy, interpretability, running time, and complexity.

## 1 Introduction

Flood models are good tools to guide public policies for mitigation and adaptation to extreme rainfall events since they allow simulation of different strategies scenarios. It is possible to separate the models into two main categories, those based on physical processes and characteristics of the area (here called physically-based) and those based on artificial intelligence (AI), which are mainly based on time series analysis of the data (here called AI-based).

Batalini de Macedo et al. (2022) performed a bibliometric review of flood models and observed a significant increase in their use since 2016, both for physically-based and AI-based. Furthermore, the main keywords identified in the literature were “HEC-RAS” for studies with physical models,

and “machine learning” for studies with AI models, between them, “LSTM”.

The different purposes when using flood modelling requires different results generated by the model (such as spatial-temporal resolution) and different processing time (e.g. early warning systems requires results in enough time to take response actions). Additionally, the monitoring conditions of the basin (e.g. ungauged or poorly gauged) may affect the applicability of a model and the quality of the results.

Thus, studies resembling these models for different scales and purposes of use can provide important information to help decision-makers choose which model to adopt.

Therefore, in this study, we analysed the performance of two physically-based flood models, with different levels of complexity and of a AI-based model. The comparison was

made for two case studies in partially-gauged basins with different scales in India and Brazil.

## 2 Methodology

The models chosen for evaluation and the metrics used to analyse their performance (in terms of accuracy, interpretability, running time, and complexity) are briefly presented. The analysis was made for two case studies are presented, with different scales of application, located in India and Brazil.

### 2.1 Physically-based (PB) flood models

The physical models chosen for evaluation were the HEC-RAS and the CADDIES, both open-access. The HEC-RAS is a physical model developed by the US Army Corps of Engineers (HEC, 2018) that allows simulations of one-dimensional steady and unsteady flow and two-dimensional unsteady flow calculations (here called as HEC-RAS 2D). HEC-RAS uses the four-point implicit finite difference scheme. Its main input parameters for the development of flood maps are bathymetry data or Digital Elevation Models (DEM), roughness coefficients for each type of land use, and the series of stage and flow hydrographs as boundary conditions. In the absence of observed data downstream, the model also allows defining normal depth as a boundary condition.

CADDIES is a cellular automata model that allows discretely simulating shallow water equations (SWEs) in grids. Instead of using transition rules, this model is based on the previous state of the cell and neighbouring cells, with rules that control the evolution of the state of each cell (Guidolin et al., 2016). The model uses rainfall series, the DEM, and an average roughness coefficient for the catchment as input data, therefore, with a high simplicity for the user. Its professional version (CADDIES PRO) allows different roughness coefficients for each land use; however, it is not open access.

### 2.2 Artificial intelligence (AI) flood model

The AI model chosen was the LSTM. This model is a variation of the recurrent neural network (RNN), incorporating the ability to learn long-term dependencies, especially in sequence prediction problems (Shen, 2018). Compared to simple RNN, instead of having one state variable, the information in LSTM units is controlled by cell states and input, forget, and output gates. There are many variants of LSTM based on the interconnection of these gates, which control what information should be added, forgotten, and obtained as output from the LSTM cell. In this study, we evaluate the simple LSTM network for predicting flow in the river.

The LSTM model was trained for both study areas using daily meteorological forcing (rainfall, temperature, solar radiation, relative humidity, wind speed) and static watershed attributes (mean elevation and slope, land use land cover

characteristics and soil characteristics). The RMSE between the observed and simulated streamflow was chosen as the loss parameter to be minimized across training sequences. As a pre-processing of the dataset, the daily streamflow and rainfall distributions were transformed to get the distribution close to normal since rainfall and streamflow typically have the Gamma distribution (Mangukiya et al., 2023). The hyperparameter of the LSTM model was manually optimized, and finally, 365 d of training instances, a hidden-state size of 256, and a dropout rate of 0.5 were used. As final result, the ensemble results from five simulations with different random seeds were obtained to reduce the uncertainty of the LSTM model output due to its stochastic nature. More details of the LSTM model strategy adopted can be read from Mangukiya et al. (2023).

### 2.3 Metrics for evaluation

To evaluate the applicability of the flood models for different study areas, their performance was compared in terms of accuracy, running time, complexity, and interpretability. For accuracy, the NSE (Eq. 1) and NRMSE (Eq. 2) of the water level were calculated.

$$\text{NSE} = 1 - \frac{\sum_{t=1}^T (Q_o^t - Q_m^t)^2}{\sum_{t=1}^T (Q_o^t - \bar{Q}_o)^2} \quad (1)$$

$$\text{NRMSE} = \frac{1}{\bar{Q}_o} \sqrt{\frac{\sum_{t=1}^T (Q_m^t - Q_o^t)^2}{T}} \quad (2)$$

Where:  $Q_o$  is the observed discharges,  $Q_m$  is the modelled discharge, at times  $t$ . For HEC-RAS,  $Q_o$  and  $Q_m$  were obtained for a intermediate gauge station in the catchment, as for LSTM they were obtained for the exutory gauge station.

The accuracy was assessed just for HEC-RAS and LSTM simulations, as the CADDIES model generates only maximum flood depth instead of a time series; in the second case, a qualitative analysis was performed, comparing with pictures taken from citizens during the event modelled, for point known.

For the running time, it was presented the time taken for each model to provide the final flood map and a description of the CPU features used for each case. The complexity was evaluated from each model's input parameter and configurations. Finally, interpretability is a more subjective metric, including discussing the results provided by each model and the ease of understanding its results and applying them in the decision-making process.

### 2.4 Study areas

Two study areas were selected for this study, representing different contexts for floods.

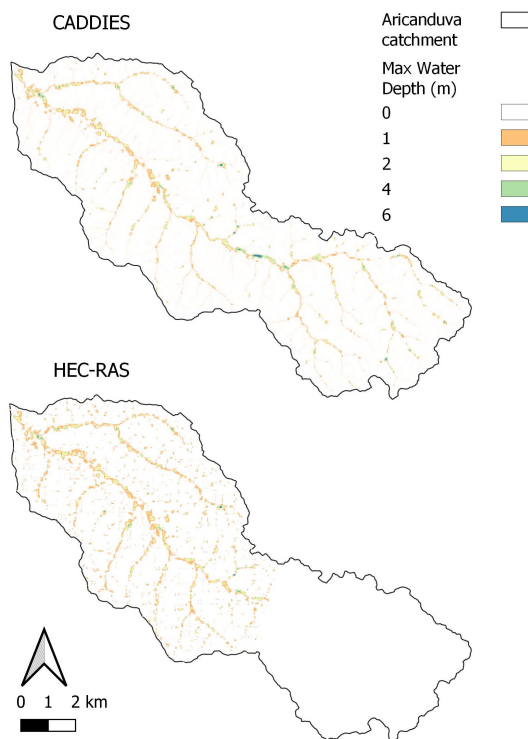
The first case study is the Aricanduva catchment, located in São Paulo – SP, Brazil (Fig. 1), covering an area of



**Table 1.** Model performance metrics.

Model	Type of result	Case study	NSE/NRMSE	Running time
HEC-RAS	Spatial and temporal	Aricanduva	0.72/0.19	25 s <sup>a</sup>
		Narmada	0.85/0.15	31 min 15 s <sup>a</sup>
CADDIES	Spatial	Aricanduva	–	1 min 43 s <sup>a</sup>
		Narmada	–	10 h 1 min 33 s <sup>a</sup>
LSTM	Temporal	Aricanduva	0.79/0.88	57 min 21 s <sup>b</sup>
		Narmada	0.80/0.94	55 min 45 s <sup>b</sup>

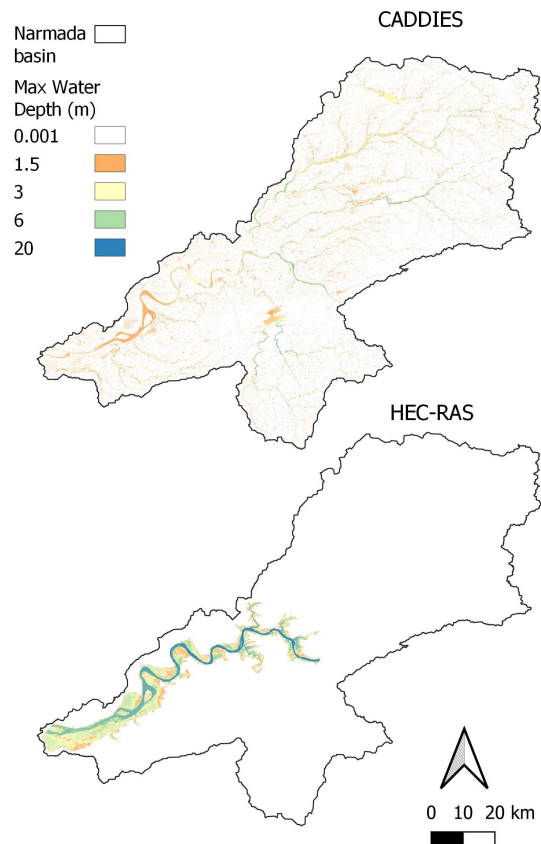
<sup>a</sup> i7-8565U CPU@ 1.80 GHz 1.99 GHz, RAM 8 GB. <sup>b</sup> Intel Xeon CPU E5-1650 v3@3.50 GHz 3.50 GHz, RAM 8 GB, training time and test time considered.



**Figure 3.** Flood maps results for Aricanduva catchment when using CADDIES and HEC-RAS models.

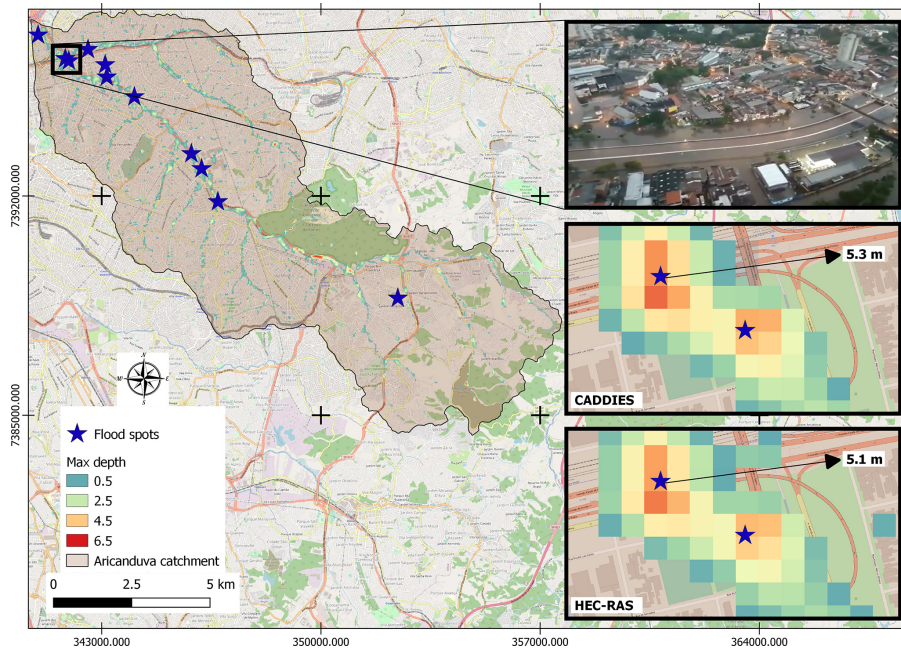
Another aspect to consider about the HEC-RAS is the higher level of knowledge of hydrological variables required from the user and their influence on the results. Thus, small changes in the variables used can be very significant in the final values, so uncertainty needs to be considered. On the other hand, there is also greater flexibility in adjusting and calibrating the model until obtaining satisfactory results.

Figure 5 shows SAISP reported flood locations in the Aricanduva catchment and the detailing of a flooding area in Aricanduva avenue near the bridge Eng. Alberto Badra during the flood event simulated by the models. The extent and



**Figure 4.** Flood maps results for Narmada basin when using CADDIES and HEC-RAS models.

values of the flooded spot are very similar for both models, including the numerical values for the pixel, 5.3 and 5.1 m using the CADDIES and HEC-RAS model, respectively. Thus, although we do not have enough data to validate the generated flood maps, we can consider the results satisfactory since most of the points reported as flood sites had the highest depths reported in the maps generated by the models, in addition to the consistency between both results.



**Figure 5.** Flood spots reported by SAISP and the max depth results for the area using CADDIES and HEC-RAS. Picture source: Paulino (2020).

LSTM and HEC-RAS models can generate discretized results in time. However, LSTM does not perform hydrodynamic simulations. The LSTM made reasonable estimates for both case studies (Table 1), proving to be quite flexible for different applications. It also had lower execution time than CADDIES, but still above HEC-RAS. The running time for LSTM have considered both training time and test time since we were comparing the entire applicability of the models. However, for practical application of the LSTM, after the training, only the test time must be considered, which was 19 s for both cases.

#### 4 Conclusions

This study evaluated the performance of physically-based and AI-based models in predicting floods at (i) an urban catchment and relatively small area in Brazil and (ii) a rural and huge catchment in India.

From the results, the only unsuitable outcome from the models was the one for the Narmada basin using the CADDIES model. From this, we can conclude that the model is most adequate for urban areas, especially for pluvial floods, without a considerable amount of flow insertion in the system from some other river or upstream structure.

CADDIES and HEC-RAS had very similar results for the Aricanduva catchment. The advantage of CADDIES is that it is much simpler to configure, does not require the insertion of boundary conditions, and uses only rainfall as an input variable. However, the CADDIES model takes much longer to run. HEC-RAS has the advantage of allowing us to evaluate

results over time. Further, it allows the simulation of several processes, simpler to complex settings depending on the data availability, and structured processes for model calibration and validation.

When considering execution time, accuracy, and temporal results, the LSTM model and the HEC-RAS appear ahead. Depending on the application of the results, the LSTM model may be more suitable, for example, for flow prediction for the operation of reservoirs and drainage control structures, since the flood extent visualization is not required for these cases and has the advantage of being more easily applied in different case studies.

We strongly suggest performing uncertainty analysis for future studies, as data limitation leads to significant uncertainty beyond the complexities in all the models used. Moreover, several other model configurations, metrics, and statistics should be analyzed in-depth when evaluating models' performance.

**Code availability.** The HEC-RAS software is freely available from US Army Corps of Engineers Hydrologic Engineering Section (HEC, 2018, <https://www.hec.usace.army.mil/software/hec-ras/>). The CADDIES software is freely available from University of Exeter (Guidolin et al., 2016, <https://www.exeter.ac.uk/research/centres/cws/resources/caddies/>). The python code for developing the LSTM model can be accessed from <https://github.com/mhpi/hydroDL> (Feng et al., 2023), this code was developed from a third part.

**Data availability.** The digital elevation map is available from the Shuttle Radar Topography Mission dataset from USGS Earth-explorer (<https://earthexplorer.usgs.gov/>, USGS, 2023). The rainfall and streamflow datasets for the Narmada basin are available from India Meteorological Department (IMD) (2023, <https://dsp.imdpune.gov.in/>) and India Water Resource Information System (India-WRIS) (2023, <https://indiawris.gov.in/wris/>), respectively. The rainfall and streamflow datasets for the Aricanduva catchment are available from the São Paulo Alert System of Inundation (SAISP) (SAISP, 2023, <https://www.saisp.br/estaticos/sitenovo/home.html>, <https://portal.inmet.gov.br/>).

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