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RESEARCH

Nowcast flood predictions in the Amazon watershed based on the remotely sensed rainfall product PDIRnow and artificial neural networks

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Abstract The aim of this study was to develop artificial neural network (ANN) models to predict floods in the Branco River, Amazon basin. The input data for the models included the river levels and the average rainfall within the drainage area of the basin, which was estimated from the remotely sensed rainfall product PDIRnow. The hourly water level data used in the study were recorded by fluviometric telemetric stations belonging to the National Agency of Water. The multilayer perceptron was used as the neural framework of the ANNs, and the number of neurons in each layer of the model was determined via optimization with the SCE-UA algorithm. Most of the fitted ANN models showed Nash–Sutcliffe efficiency index values greater than 0.9. It is possible to conclude that the ANNs are effective for predicting the flood levels of the Branco River, with horizons of 6, 12 and 24 h; thus, constituting a viable option for use in river-flood warning systems in the Amazon basin. For the forecast with a 24-h horizon, it is essential to include the average rainfall of the basin that accumulated over the last 48 h as input data into the ANNs, along with the levels measured by the streamflow stations. The indirect rainfall estimates provided by PDIRnow are

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an excellent alternative as input data for ANN models used to predict floods and constitute a viable solution for regions where the density of rain gauge stations is low, as is the case in the Amazon basin.

Keywords Artificial intelligence · Warning system · Floods · Hydrological model · Civil defense

Introduction

Floods are among the most recurrent natural disasters in the world, and pose risks to human life and can cause damage to urban and agricultural infrastructure. These extreme events alter the routine of affected populations and cause high socioeconomic losses (Saeed et al., 2021; Chebii et al., 2022; Conticello, 2020; Mosavi et al., 2018). According to Sausen and Narvaes (2015), flooding events are responsible for 55.0% of all recorded disasters and for approximately 72.5% of economic losses around the world.

Although it cannot be avoided, flooding can be controlled or its damage mitigated through structural and nonstructural measures. Among the nonstructural measures, short-term flood prediction models can be used to issue alerts and conduct risk assessments by civil defense agencies; furthermore, these models can be used to help with relocation of people in risk areas, determine road closures and determine other measures needed to save lives. (Gude et al., 2020; Mistry & Parekh, 2022; Saeed et al., 2021; Zhang et al., 2021). Chebii et al. (2022) emphasize that developing strategies for the prevention, protection and mitigation of the impacts of floods should be a government priority.

In Brazil, flooding events are the third leading cause of disasters, second only to droughts and flash floods, according to the Brazilian Atlas of Natural Disasters (CEPED, 2013; MDR, 2023). Additionally, according to information from the Atlas, in the northern region of the country, which is almost entirely located in the Amazon basin, inundation is the extreme event that causes more damage and changes in the routine of the population. In this region of the country, cities and agricultural communities have been established near water courses, as in some places, waterway transport is the main means of access. In this context, predicting extreme events related to river flow and river levels is essential for mitigating impacts and increasing the resilience of the population, thus helping these groups deal with these natural events, as highlighted by Kabir et al. (2020).

Hydrological models for flood prediction can be classified as conceptual, physically based and empirical, and the latter are also called black-box or data-driven models. The conceptual and physical models are based on simulations of hydrological processes and usually require, in addition to the rainfall and watershed data, information related to the soil, vegetation and hydraulic characteristics of the runoff channel for model parameterization (Le et al., 2019; Mosavi et al., 2018). In addition to being difficult to quantify and calibrate, obtaining some of these characteristics requires a series of field campaigns, which are costly and usually irreconcilable with the financial reality of developing countries.

Authors such as Guo et al. (2021) and Le et al. (2019) and Sahoo et al. (2021) emphasize another obstacle in utilizing physical models for real-time flood prediction, which is the high computational processing time required to solve the equations. In many cases, this processing time is incompatible with the time of rate that extreme events occur.

In turn, data-driven models try to find the relationship between the input and output data without considering the physical processes involved (Le et al., 2019; Miau & Hung, 2020; Tabbussum & Dar, 2020), and due to this characteristic, they are promising tools for use in watersheds where monitoring and knowledge regarding the physical characteristics are limited (Chebii et al., 2022). Furthermore, Berkhahn et al. (2019) state that hydrological simulations within data-driven models have processing times on the order of seconds, which is much faster when compared to physical-based models. This makes them the best option for short-term prediction, also known as nowcasting. In this study, a nowcast is defined as a forecast with a horizon of up to 24 h.

Among the empirical models applied in hydrology, artificial neural networks have stood out due to their ability to simulate the complex and nonlinear relationship between the variables associated with the expected behavior of a river as its flow and level are changed by rainfall (Ali & Shahbaz, 2020; Miau & Hung, 2020). Authors such as Berkhahn et al. (2019), Chebiiet al. (2022), Kabir et al. (2020), Kim and Han (2020), Windheuser et al. (2023), Guo et al. (2021), Le et al. (2019), Chen et al. (2022), Miau and Hung

(2020), Ali and Shahbaz (2020), and Saeed et al. (2021), among others, successfully used ANNs for flood prediction or mapping of risk areas.

Hydrological forecasting in Brazil presents challenges due to the country's large territory, diverse climates and biomes, and flood occurrences on different temporal scales (Fan et al., 2016). This scenario applies equally to the Amazon Basin, given its extension, hydraulic complexity, and climate variations. Research performed by Collischonn et al. (2008), Paiva et al. (2011, 2013a, b), and Petry et al. (2023) used the MGB-IPH large basin model (Collischonn et al., 2007) or its continental version for South America (MGB-SAS), to predict flows in the rivers of the Amazon Basin, achieving satisfactory results in their simulations.

In general, in Brazil, several models are used to predict extreme hydrological events in the short and long term, ranging from data-driven models to distributed conceptual models. Fan et al. (2016) provide an overview of hydrological forecasting practices in the country and highlight the MGB-IPH as the main model used. This model incorporates surface data, rainfall information obtained through remote sensing and quantitative rainfall forecasts from numerical models such as ETA-15 from CPTEC-INPE or projections from NOAA's GEFS. Furthermore, models such as HEC-HMS/RAS are applied to predict floods in the Itajaí River, located in southern Brazil, while linear statistical models are used for 12-h forecasts in the Rio Doce Basin and artificial neural networks are employed in the basin of the São Francisco River.

Conceptual hydrological modeling has already been explored in the Amazon basin; however, ANNs, despite having been applied in basins in different parts of the world to predict floods, few researches explored its potential in Amazon rivers, and this case study aims to show the potential that they have for flood prediction and operational use in warning systems in cities in the Amazon region. According to Kim and Han (2020), although many studies have been conducted to predict hydrological data with ANNs, studies that test new input data, architectures and optimizations of these models are still necessary and should consider the characteristics of each study region.

In addition to the lack of information related to the physical characteristics of the basin and the drainage channel, which are needed to simulate hydrodynamic processes, rainfall monitoring with pluviometers in the Amazon region also remains a challenge. Compared to other Brazilian basins, the Amazon basin has the lowest density of rainfall and flow measurement stations. This is due to the high percentage of the area covered with native forest and the difficulty in accessing certain locations by land. Due to this problem, indirect rainfall estimation by remote sensing is a promising alternative for monitoring the spatial and temporal distribution of rainfall in the region.

In 2020, the Center for Hydrometeorology and Remote Sensing of UCIrvine (CHRS-UCIrvine) released a new remote sensing rainfall product entitled PDIRnow (dynamic infrared rainfall rate). This dataset will replace the PERSIANN-CCS and has an hourly temporal resolution and latency time of 15 to 60 min, which is compatible with flood prediction (Nguyen et al., 2020). Considering these characteristics, it is believed that the PDIRnow product may be a potential input for artificial intelligence models used to develop short-term river-level predictions in the Amazon basin.

According to Maggioni and Massari (2018), it is essential to analyze the regional limitations of rain products through remote sensing. Furthermore, effective integration of these products with flood warning systems can significantly improve forecasting and response capabilities in flood situations, which is crucial to evaluate their performance in real and operational flood scenarios.

In this context, the objective of this study was to develop artificial neural network models to predict floods in the Branco River in the city of Boa Vista. The model utilized input data such as the river level and the average rainfall of the basin within the estimated drainage area obtained from the remote sensing product PDIRnow.

Materials and methods

Study area and database

The water level prediction model was established for a monitoring section of the Branco River (code: 14,620,000), located in the city of Boa Vista, as shown in Fig. 1. The city of Boa Vista (capital of the state of Roraima) has a population of 436,591,

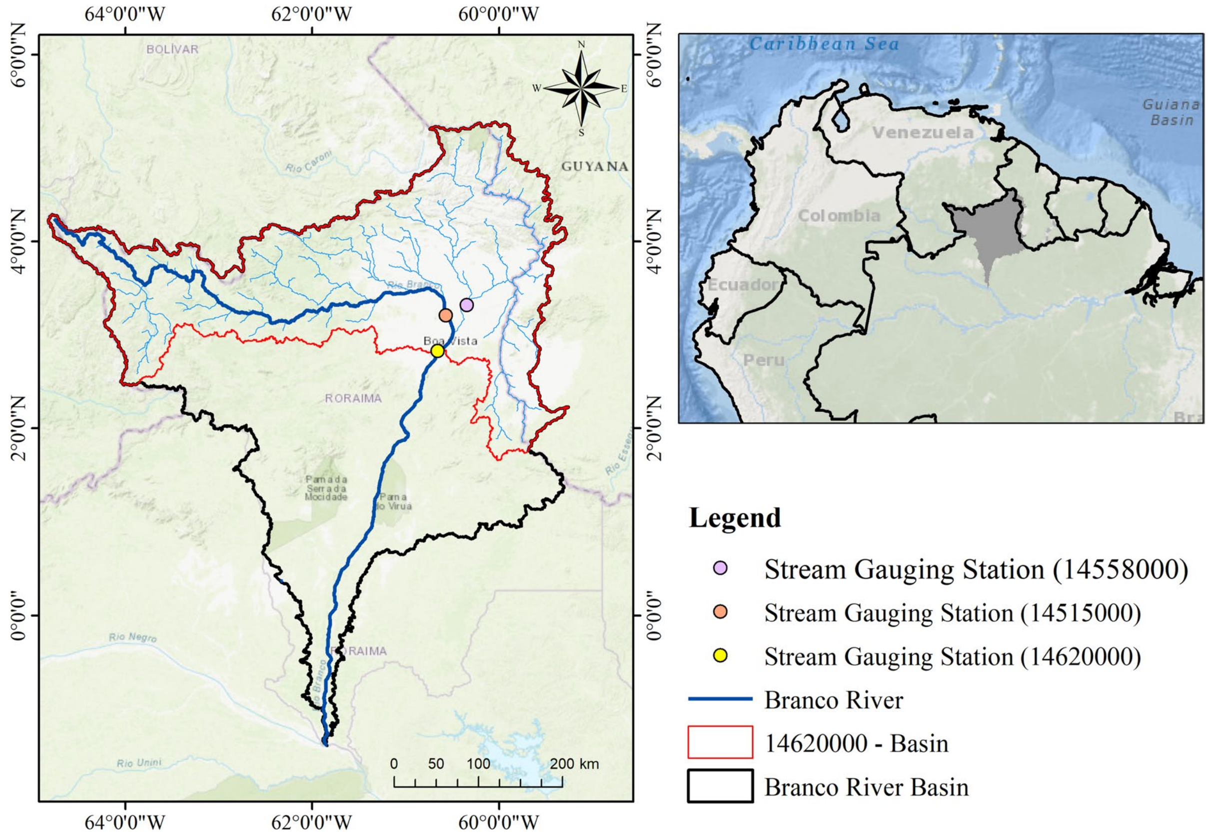

Fig. 1 Map of the Branco River basin with the location of the monitoring stations shown and drainage area considered in this study is highlighted (code: 14,620,000)

according to the IBGE estimate (2021), which represents more than 65% of the state's population.

The Branco River is the main watercourse in the region, and its sources are within the Yanomami Indigenous Land, near the border with Venezuela, where it is called the Uraricoera River. Approximately 30 km upstream of Boa Vista, the Branco River receives one of its main tributaries, the Tacutu River, and after flowing through much of the state (1,250 km), it reaches the river mouth, which is located on the left bank of the Negro River.

The basin being studied has a drainage area of 96,229.4 km^2 and a perimeter of 4,409.1 km. According to the Climatological Standards of the National Institute of Meteorology (INMET, 2023) for the period 1991 to 2020, the average annual precipitation is 1,754.0 mm, the average monthly maximum temperature in Boa Vista ranges between 32.0 and 35.7 °C, and the minimum monthly average temperature ranges between 23.3 and 24.9 °C.

When performing a precipitation analysis in the Rio Branco basin using rain gauge data, Ribeiro et al. (2019) found that the rainy season in the basin occurs between April and September, with an average monthly total ranging between 112.7 and 318.5 mm. The months with the highest rainfall are May, June and July, with average totals of 318.5, 314.9 and 289.9 mm, respectively. The dry season in the basin occurs between the months of October and March, with an average rainfall height varying between 67.8 and 100.4 mm. The average annual rainfall of the basin, according to the same authors, is approximately 1,900.0 mm.

Figure 2 shows the hypsometric map of the basin and the profile of the main river with the slope in mm $^{-1}$. The classification of land use and land cover

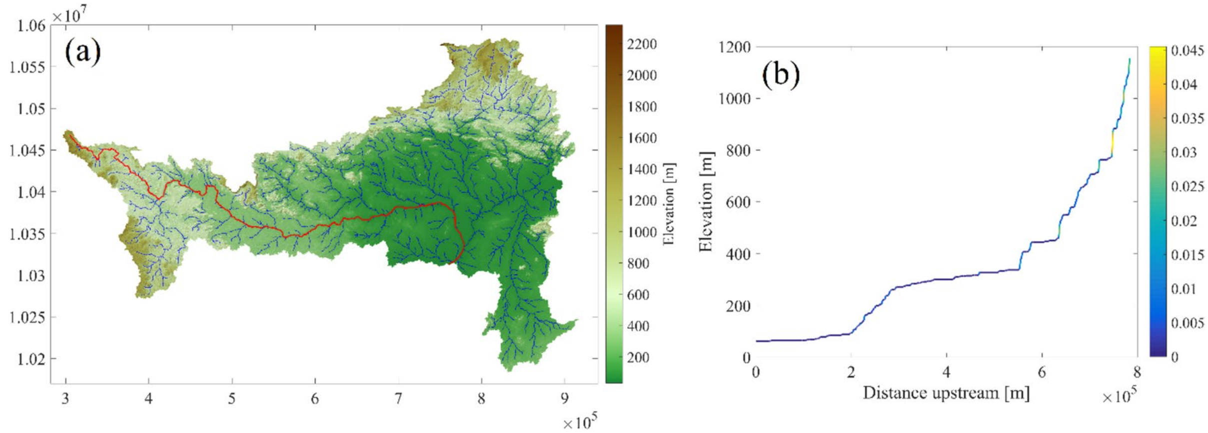

Fig. 2 Hypsometric map of the station code 14,620,000 drainage area (**a**), profile and slope (mm.$^{-1}$) of the main river (**b**)

performed by the MapBiomas project (2023) for 2021, based on Landsat images, estimates that at least 82% of the drainage area under study is composed of forest and non-forested natural formations.

To calibrate the prediction models, hourly water level data recorded at the stations listed in Table 1 were used. These stations belong to the National Water Agency and Sanitation (ANA) and are operated by the Brazilian Geological Service (SGB). The stations are of the telemetric type, in which the river level is measured automatically with a pressure sensor or radar, and data transmission occurs at hourly intervals through the GOES satellite. These data, as well as other station information, can be found in the Hydrotelemetry system at the following address: < https://www.snirh.gov.br/hidrotelemetria >.

In addition to the water level data, the average rainfall that accumulated in the base over the last 48 h was used as input data for the artificial neural network (ANN) models. This rainfall was estimated from the PDIRnow—Dynamic Infrared Rain Rate near real-time rainfall product obtained via remote sensing (Nguyen et al., 2020), which was made available by the Center for Hydrometeorology and Remote Sensing of UCIrvine (CHRS-UCIrvine) at the following address: < https://chrsdata.eng.uci.edu/ >. This rainfall product has an hourly temporal resolution, a spatial resolution of 0.04° (4,443.5 m) and the availability time of the platform varying between 15 and 60 min. According to Nguyen et al. (2020), PDIRnow offers greater precision and accuracy than PERSIANN-CCS and was developed with the objective of nowcasting flood predictions.

Downloading data involved delineating the drainage area that contained the telemetry station (code: 14,620,000), which was exported in the ArcGrid format (.asc). The hourly rainfall data for the period January 2015 to August 2022 were downloaded. After this procedure, with the aid of a routine developed in the MATLAB software package, the average hourly rainfall for the drainage area of the basin was calculated. Next, the average accumulated rainfall over the last 48 h (P_{48}) was determined for each hour of the

Table 1 Information on the water level and flow monitoring telemetry stations used in the study

Code[(1)]	Latitude(°)	Longitude(°)	Name	River	A_d (km^2)	Period
14,515,000	3.208	-60.571	Fazenda Passarão (H_{ps})	Uraricoera	49,391.8	2015–2022
14,558,000	3.318	-60.345	Paraíso Farm (H_p)	Tacutu	41,238.7	2015–2022
14,620,000	2.827	-60.656	Boa Vista (H_{bv})	White	96,229.4	2015–2022

(1) Code of the National Water Agency and Sanitation. Other information related to the stations can be obtained from the Hydro—Telemetry System at the following electronic address: https://www.snirh.gov.br/hidrotelemetria/Mapa.aspx

river elevation historical series. It is noteworthy that different times were evaluated for the accumulation of rainfall, and the values for the last 48 h were the ones that resulted in the best level forecasts. A similar procedure was performed in the study by Ali and Shahbaz (2020).

Figure 3 shows the monthly spatiotemporal distribution of the accumulated PDIRnow precipitation in the basin, as well as the flows, water levels and average monthly rainfall recorded by the monitoring station in Boa Vista (code:14,620,000). The heaviest rainfall in the region occurs between May and August, which is the period when the flooding risk is greatest.

At station code 14,620,000, located in the city of Boa Vista-RR, the alert system considers water levels that range between 750 and 800 cm as “Attention Levels”, between 800 and 850 as “Alert Levels” and greater than 850 as “Flood Levels”. Since the main objective of this study was to predict maximum water levels, water level data from the stations in Table 1 and P_{48} precipitation were used for periods in which the elevation of the Branco River in Boa Vista was greater than or equal to 600 cm. This criterion was justified by a preliminary analysis in which it was found that when considering all the values of the historical series, including those of the drought period, the performance of the models decreased when forecasting maximum water levels. Therefore, the models proposed in this study are valid for prediction when the level of the Branco River in Boa Vista (code: 14,620,000) exceeds 600 cm.

Figure 4 shows the boxplots of the elevation and P_{48} data for the months of May to August, which were used as input data for training, validation and testing of the prediction models.

Architecture and training of ANNs

In this study, artificial neural network models were developed that considered only the water levels from the telemetry stations (H_{ps};H_p;H_{bv}). Another

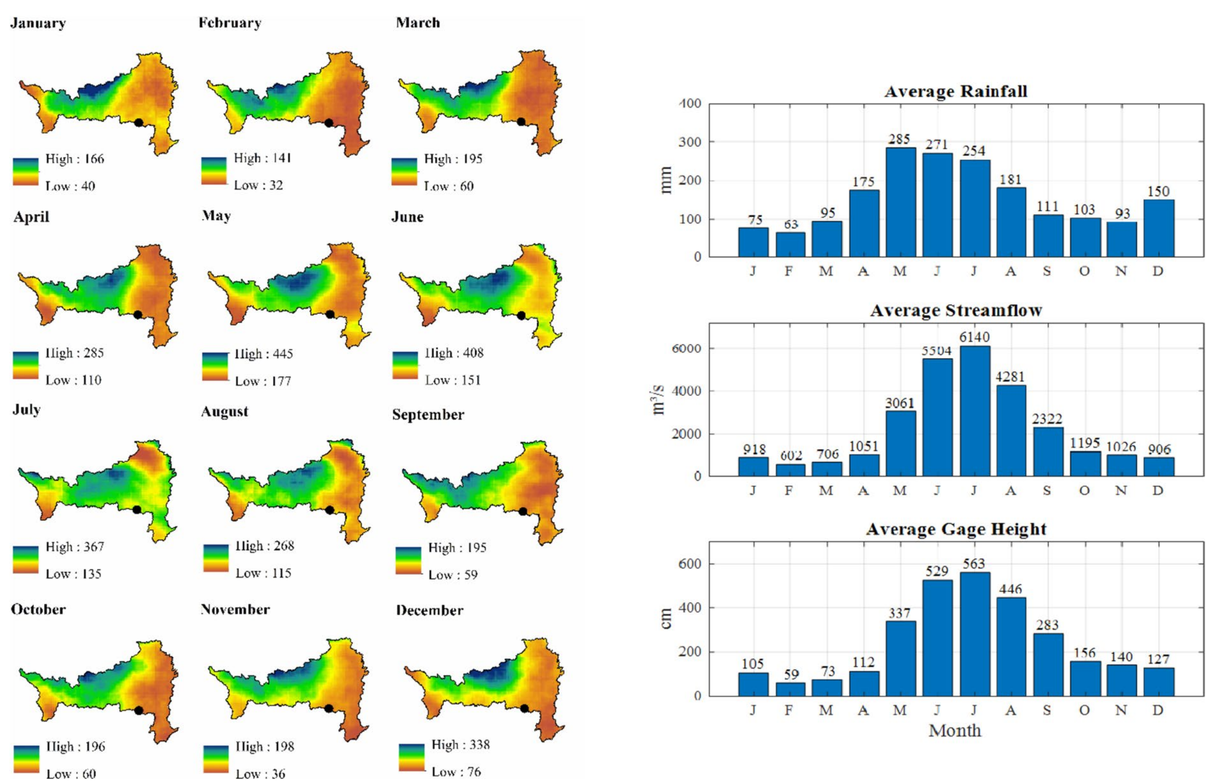

Fig. 3 Spatiotemporal distribution of precipitation (PDIRnow) in the basin, average monthly flow and water level form the monitoring station in Boa Vista (code: 14,620,000)

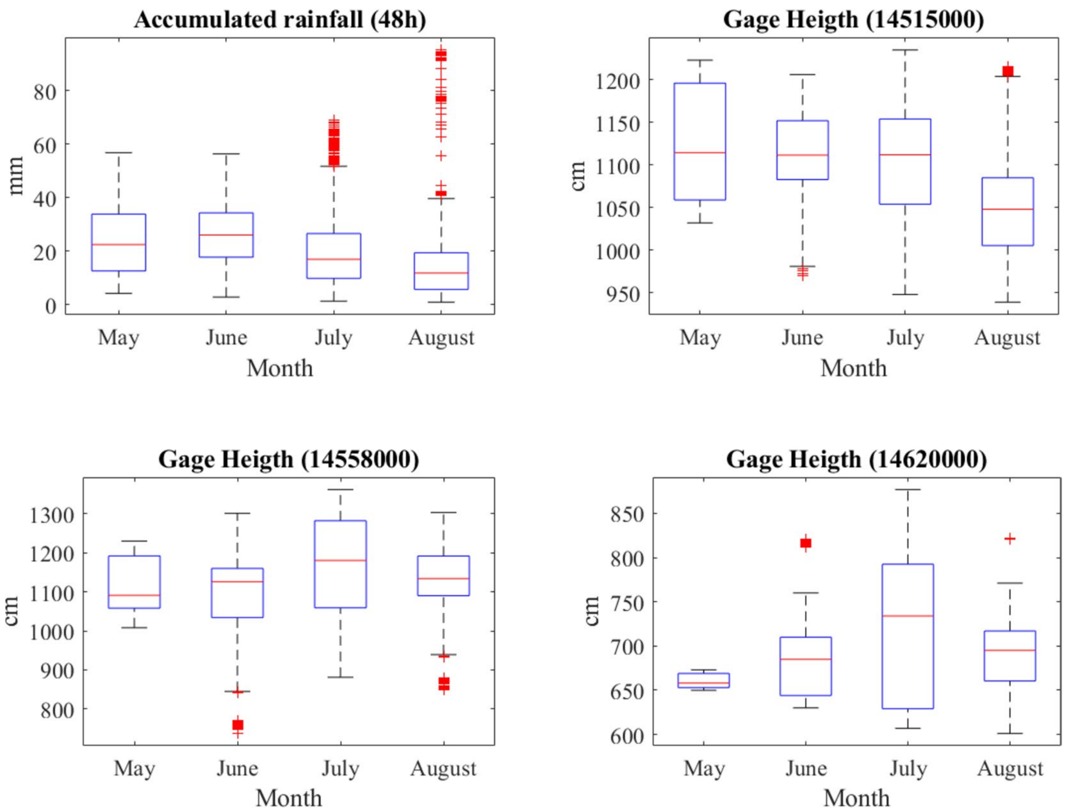

Fig. 4 Boxplot of the average rainfall of the basin accumulated over 48 h (PDIRnow) and hourly levels of the telemetry stations for the months of May to August. This information was used as input data for the ANN models

set of models considered the average cumulative precipitation over 48 h as well as the water levels (P_{48h};H_{ps}; H_p;H_{bv}). The outputs of the ANNs were the levels of the Branco River during the time periods of 6 ($H_{t+6\ h}$), 12 ($H_{t+12\ h}$) and 24 h ($H_{t+24\ h}$) hours, individually (Table 2). In addition to the water levels from the upstream stations "Fazenda Passarão" (H_{ps}) and "Fazenda Paraíso" (H_p), the levels of the Boa Vista control section (H_{bv}) were also used as inputs into the models. According to Berkhahn et al. (2019), it is valid to use an initial current state of water levels as input to calculate a future water level state. Through preliminary tests, it was found that this consideration allowed us to improve the performance of the ANNs for the water level forecasts.

The data in Table 2 were separated into three categories: training, validation and test data. For training and validating the ANNs, hourly flood event data from January 2015 to December 2021 were used, with 85% of the values used for training and 15% for validation. Hourly data of flood events recorded from June 2022 to August 2022 were used to test the models.

Table 2 Input and output data of the artificial neural network models

ANN entry	ANN output
H_{ps};H_p;H_{bv}	$H_{t+6\ h}$
H_{ps};H_p;H_{bv}	$H_{t+12\ h}$
H_{ps};H_p;H_{bv}	$H_{t+24\ h}$
P_{48h};H_{ps};H_p;H_{bv}	$H_{t+6\ h}$
P_{48h};H_{ps};H_p;H_{bv}	$H_{t+12\ h}$
P_{48h};H_{ps};H_p;H_{bv}	$H_{t+24\ h}$

$H_{ps;}$ $H_{p;}$ H_{bv} are the hourly elevations (cm) recorded at the stations Fazenda Passarão (code: 14,515,000), Fazenda Paraíso (code: 14,558,000) and Boa Vista (code: 14,620,000), respectively.P_{48h} is the accumulated precipitation over 48 h, obtained from the product PDIRnow. $H_{t+6\ h,}$ $H_{t+12\ h,}$ $H_{t+24\ h}$ are the levels of the next 6, 12 and 24 h in the Boa Vista monitoring section (code: 16,420,000), respectively, which correspond to the forecast horizons adopted in the study

The input and output data of the ANNs used for the training and validation stages were randomly organized and normalized using Eq. 1. Wang and Deng (2018) emphasize that data normalization avoids the discrepancy that arises when water level values measured at different stations are used, this is due to the different reference levels. In addition, this procedure is also important when the units of measurement of the input data are different, such as rainfall in mm and water level in cm.

$$pn = \frac{2(p - minp)}{(maxp - minp)} - 1 \tag{1}$$

where pn is the normalized value (ranging from -1 to 1), p is the value of the variable, and minp and maxp are, respectively, the lowest and highest values of the variable in the series under study.

The multilayer perceptron was used as the neural framework (Fig. 2), which, according to Araújo et al. (2015), Uysal et al. (2016), and Zemzami and Benaabidate (2016), is widely used for modeling hydrological phenomena. The ANNs were of the feedback type, having an input layer, two hidden layers and an output layer (Fig. 5).

As transfer functions (f), the sigmoid tangent in the hidden layers and the linear tangent in the output layer of the ANNs were adopted. The hyperbolic tangent sigmoid function (tansig) was prioritized in this study because of its superior performance compared to other functions, as reported by Sezen and Partal (2019), particularly in flow forecast applications.

The number of neurons in each layer of the ANN was defined with the SCE-UA optimization algorithm. (Duan et al., 1992) During the network training process to obtain the lowest estimation error of the hourly levels, the optimization algorithm was coupled to the ANN training algorithm, and the root mean square error (RMSE) was used as the objective function. The maximum number of artificial neurons in each intermediate layer was limited to 15 to avoid ANN overfitting.

The *backpropagation algorithm,* also known as the error backpropagation algorithm, was incorporated into the Levenberg–Marquardt optimization algorithm, as proposed by Asadi et al. (2013), to minimize the computational effort and the problem of very slow convergence resulting from the isolated use of the *backpropagation* algorithm.

During training, a maximum limit of epochs (*epochs*) was established as an additional criterion for stopping the algorithm when the specified precision became unattainable. The number of epochs

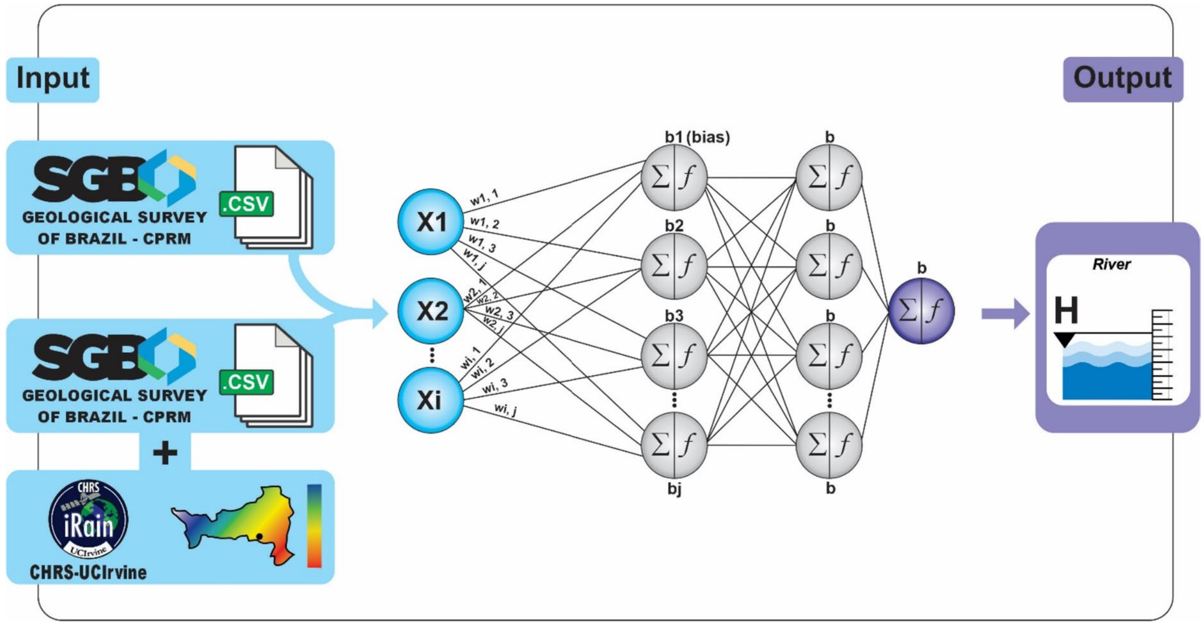

Fig. 5 Architectural representation of a multilayer perceptron ANN. Source: Adapted from Govindaraju (2000) and Silva et al. (2010)

is defined as the number of attempts to adjust the weights (w_{ij}) and biases (b_j) of the ANN to ensure that the estimates of the output variable remain accurate (Govindaraju, 2000).

The aforementioned training, validating and testing procedures applied to the ANN models were performed with the aid of routines developed in MATLAB.

Evaluation of the performance of models

To evaluate the ability of the ANNs to forecast hourly water levels in the Branco River, the following statistical measures were used: mean absolute error (Eq. 2); root mean square error (Eq. 3); bias (Eq. 4); Nash–Sutcliffe efficiency index (Eq. 5) and Kling-Gupta efficiency index (Eq. 6).

$$\mathrm{MAE} = \frac{1}{N}\sum_{i=1}^{N}\left|O_i - P_i\right| \tag{2}$$

$$\mathrm{RMSE} = \left[\frac{1}{N}\sum_{i=1}^{N}\left(O_i - P_i\right)^2\right]^{0.5} \tag{3}$$

$$\mathrm{bias} = \frac{1}{N}\sum_{i=1}^{N}\left(O_i - P_i\right) \tag{4}$$

$$\mathrm{ENS} = 1 - \frac{\sum_{i=1}^{n}\left(O_i - P_i\right)^2}{\sum_{i=1}^{n}\left(O_i - O\right)^2} \tag{5}$$

$$E_{kg} = 1 - \sqrt{(r-1)^2 + \left(\frac{\sigma_e}{\sigma_o} - 1\right)^2 + (\mathrm{bias} - 1)^2} \tag{6}$$

where P_i is the estimated elevation (cm);O_i, the observed elevation (cm);O, the mean of the observed elevations (cm); n, the number of values in the sample; r is the correlation coefficient between the observed and estimated data;σ_e is the standard deviation of the data estimated with the model; and σ_o is the standard deviation of the observed data.

To evaluate the performance of the models in relation to the Nash–Sutcliffe efficiency index (E_{NS}), the classification suggested by Van Liew et al. (2007) was used. According to the classification: $E_{NS} = 1$ means that the data predicted by the model has a perfect fit; $E_{NS} > 0.75$ indicates that the model is adequate and good; $0.36 < E_{NS} < 0.75$ indicates that the model is considered satisfactory; $E_{NS} \le 0.36$ indicates that the model is not satisfactory. In this study, the classification presented was also adopted to evaluate the performance of the models with respect to the Kling-Gupta efficiency index (E_{kg}).

Determination of the forecast confidence interval

After analyzing the error of the models, the 95% confidence interval of the prediction was calculated based on the mean absolute error (MAE) of the model. For this, the following equation was used:

$$95\% - \mathrm{CI} = \left(H_{t+xh}\right) \pm [\mathrm{MAE} + 1.96(\mathrm{Sd})] \tag{7}$$

where 95%-CI is the confidence interval for the 95% level; H_{t+xh} is the elevation predicted by the ANN model for the forecast horizon x (cm); MAE is the mean absolute error in cm; and Sd is the sample standard deviation of the error obtained for the historical series.

The predicted data were also compared with the SGB model used to create flood alerts in several regions of Brazil, which is also used in the Branco River basin, with a horizon of 17 h. Both the SGB model and our model used observed water level data to evaluate the deviation between predated and observed values.

We also performed a persistence analysis to compare our results with a benchmark model. The persistence forecast for the different time horizons simply consisted of the last known observation, that is, the current elevation in the river at the time of the forecast. Thus, the forecast for the next period $(t+x)$ using persistence was expressed by:

$$\widehat{H}_{t+x} = H_t \tag{8}$$

where x represented 6, 12, and 24 h. In Appendix A is possible to verify a complete analysis of the observed values and the predicted values of the models used.

Results

Based on the proposed methodology, it was possible to develop six artificial neural network architectures for forecasting the water levels of the Branco River in the city of Boa Vista with time horizons of 6 h, 12 h and 24 h. A set of three ANNs, one for each horizon mentioned, considered as input data only the current hourly water levels recorded at the upstream stations (H_{ps};H_p) and in the monitoring section of Boa Vista itself (H_{bv}). The other set of ANNs had this same input information; however, they also took into account the average rainfall in the drainage area of the basin that had accumulated over the last 48 h. As detailed in the methodology, the average rainfall was estimated with the rainfall product by remote sensing PDIRnow, made available on the CHRS Data Portal platform in a timely manner to perform the forecasts. It is noteworthy that the models are valid only when the level of the Branco River in Boa Vista is greater than or equal to 600 cm.

Table 3 shows the architectures of the optimized ANNs resulting from the SCE-UA algorithm, where the RMSE was used as the objective function. The most accurate results for elevation prediction were obtained with the number of artificial neurons in the hidden layers varying between 9 and 10. These values are lower than the maximum established during optimization, thus preventing the models from overfitting or underfitting due to the use of excessive or deficient numbers of neurons and training times (epochs). With the SCE-UA, the optimal number of neurons and epochs was found in an efficient and automated way compared to the manual trial and error approach.

The absence of overfitting and underfitting in the developed models was confirmed by analyzing the error metrics presented in Table 4. When comparing the mean absolute error (MAE), root mean square error (RMSE), Nash–Sutcliffe (E_{NS}) and Kling-Gupta efficiency index (E_{KG}) values obtained during the training and validation stages, it was found that the models maintain precision and accuracy in both stages, thus having generalization ability.

Values of E_{NS} and E_{KG} greater than 0.75 indicated, according to the classification by Van Liew et al. (2007), that the models are "adequate and good" and capable of predicting the nowcast water levels for the monitoring section of the Rio Branco in Boa Vista. When comparing the values of the MAE, RMSE and bias metrics for the different input data of the ANNs, it is noticed that they were lower for the ANNs that considered the average rainfall in the drainage area of the basin accumulated over the last 48 h ($P_{48\,h}$), especially for the 24-h forecast horizon. This behavior is related to the longer time needed for surface runoff to travel over the soil surface and its propagation through the channel to the section of interest. For the 6 h and 12 h horizons, considering only the levels from the three fluviometric stations resulted in error values very close to those obtained by the models that also took into account the average rainfall of the basin.

The developed ANN models presented bias values close to zero, indicating that they represent reality well and that the estimates did not show a significant trend. This means that the weights ($W_{i,j}$) and biases of the ANNs were properly adjusted and did not produce estimates of river levels with significant bias. In Table 4, the negative sign of the bias indicates an overestimation of the model, and positive values indicate an underestimate of the inundation levels.

Table 4 also shows the values of the confidence interval at the 95% level for the ANN estimates. For the 6-h forecast horizon, the ANN model that

Table 3 Architecture of Artificial Neural Networks (ANN) optimized using the SCE-UA algorithm, having the root mean square error (RMSE) as the objective function

Model	Input	Horizon	Epochs	N1	N2	N3
ANN	H_{ps};H_p;H_{bv}	6	304	10	9	1
		12	343	10	10	1
		24	191	10	10	1
ANN	P_{48h};H_{ps}; H_p;H_{bv}	6	336	10	10	1
		12	191	10	10	1
		24	185	10	9	1

H_{ps}, H_p e H_{bv} are the hourly elevations (cm) recorded at the stations Fazenda Passarão (code: 14,515,000), Fazenda Paraíso (code: 14,558,000) and Boa Vista (14,620,000), respectively.P_{48h} is the accumulated precipitation in 48 h, obtained from the product PDIRnow

Table 4 Statistical error measure of the artificial neural network (ANN) models for the training and validation stages applied to the nowcasts of the Rio Branco elevations

Model	Input	Stage	Index	Forecast Horizon		
				6 h	**12 h**	**24 h**
ANN	$H_{ps};H_p;H_{bv}$	Training	MAE	1.06	1.41	1.83
			RMSE	1.39	1.88	2.56
			Bias	-1.31E-5	-6.24E-4	-3.82E-4
			AND $_{NS}$	0.999	0.999	0.999
			AND $_{KG}$	0.999	0.999	0.999
		Validation	MAE	1.04	1.35	2.01
			RMSE	1.35	1.75	2.75
			Bias	0.05	0.05	-0.18
			AND $_{NS}$	0.999	0.999	0.998
			AND $_{KG}$	0.999	0.999	0.999
			95% I.C	± 6.0	± 10.0	± 20.0
ANN	$P_{48h};H_{ps}; H_p;H_{bv}$	Training	MAE	0.99	1.21	1.70
			RMSE	1.31	1.63	2.26
			Bias	-5.04E-5	7.66E-7	1.32E-5
			AND $_{NS}$	0.999	0.999	0.999
			AND $_{KG}$	0.999	0.999	0.999
		Validation	MAE	1.01	1.21	1.60
			RMSE	1.27	1.60	2.18
			Bias	0.016	-0.023	-0.130
			AND $_{NS}$	0.999	0.999	0.999
			AND $_{KG}$	0.999	0.999	0.999
			95% I.C	± 8.0	± 10.0	± 14.0

ANN: artificial neural networks;H_{ps}, H_p e H_{bv} are the hourly elevations (cm) recorded at the stations Fazenda Passarão (code: 14,515,000), Fazenda Paraíso (code: 14,558,000) and Boa Vista (code: 14,620,000), respectively.P_{48h} is the accumulated precipitation in 48 h, obtained from the product PDIRnow; MAE: mean absolute error (cm); RMSE: root mean square error (cm); Bias: cm; E $_{NS}$: Nash–Sutcliffe efficiency index; E $_{KG}$: Kling-Gupta efficiency index; and 95% CI is the confidence interval for the 95% level

considers only the current elevations of the fluviometric stations as input has an uncertainty of ± 6.0 cm, and the one that considers the water levels and the average rainfall had a CI of ± 8.0 cm. The higher CI value for this model is due to the higher value of the standard deviation of error since its MAE is comparatively lower. For the 12-h horizon, both ANN models presented CIs equal to ± 10.0 cm. On the other hand, the 24-h forecasts have the largest differences in the CI values, being ± 20.0 cm for the model that considers only the elevations as input and ± 14.0 cm for those considering the accumulated rainfall over the previous 48 h and the water levels from the three stations. This shows that it is essential to use the average rainfall of the basin to reduce the uncertainties of the 24-h forecasts, and the use of the PDIRnow product allowed this to be done quickly and efficiently.

Figures 6 and 7 show the spread of observed and estimated values using the ANN models for the attention (750–800 cm), alert (800–850 cm) and inundation (> 850 cm) ranges in the city of Boa Vista-Roraima.

Performing a more simplified analysis, with only the coefficients E_{NS} and $E_{KG,}$ it is verified by comparing Figs. 6 and 7 that the ANN model that has only the water levels as input data ($H_{ps};H_p;H_{bv}$) produces more precise and accurate forecasts for the 6-h horizon for the attention (AL), alert (ALL) and inundation (FL) ranges. The same occurs for the 12-h horizon in the alert range (ALL). The ANN models that consider the elevations and the average rainfall accumulated in 48 h ($P_{48h};H_{ps};H_p;H_{bv}$) produce the best forecast results with a 12-h horizon for the AL and FL ranges and for both warning ranges during the 24-h horizon.

In addition to the distinct behavior of the models for the proposed ranges established by the flood warning system, the graphs also reveal that, in general, all models have acceptable precision and accuracy for the predictions of water levels in Boa Vista. This was confirmed quantitatively, as shown in Table 5, and the graphs corroborated the results of the error metrics, further allowing a qualitative evaluation of the performance of the models in the predictions.

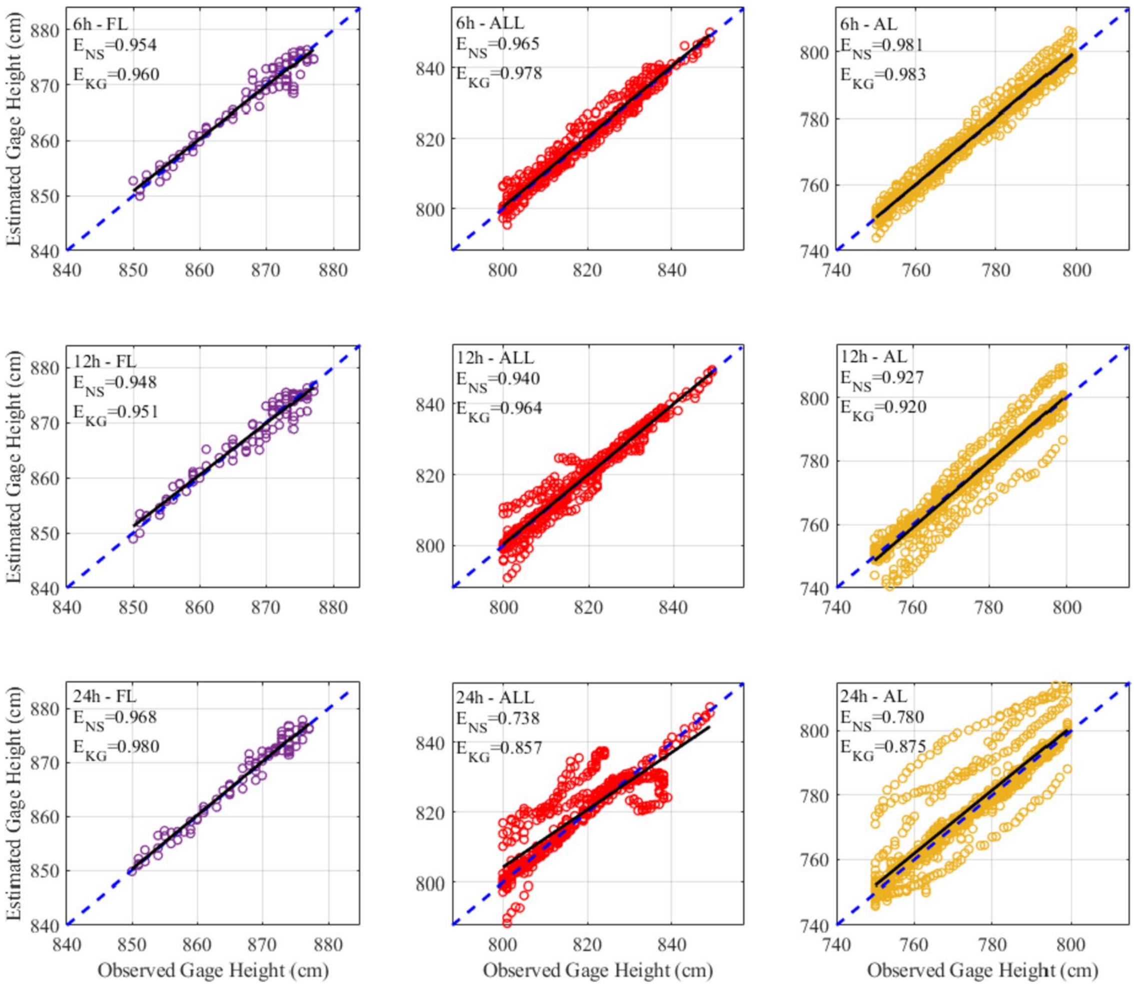

Fig. 6 Relationship between the predicted values with the RNA model (H_{ps};H_p;H_{bv}) and observed values at station 14,620,000 for the inundation (FL), alert (ALL) and attention (AL) ranges for the city of Boa Vista-RR in the period from 2015 to 2022

Data not used in training and validation was used to test the ANN models, this consisted of two flood events that occurred in June/July 2022 and in August 2022. The observed and estimated water levels, as well as the 95% confidence interval (95% CI), are presented in Figs. 8 and 9. A comparative analysis of these figures confirms that the model with the input data H_{ps};H_p;H_{bv} performed better when forecasting levels with a 6-h horizon during the two events that occurred in 2022. The same occurred with the second event (August/2022) for the forecasts with the 12-h horizon. For the other events, the ANN models that also considered the average rainfall of the basin (P_{48h};H_{ps};H_p;H_{bv}) as input data performed better for forecasting flood levels.

The qualitative analysis performed with the aid of the diagrams shown in Figs. 8 and 9 is corroborated with the error metrics from the models used for the 2022 flood events, as shown in Table 4. In general, the metrics from the testing stage continue to indicate that the models are precise and accurate and are suitable for forecasting water levels in Boa Vista, as well as for confirming the generalization ability of the model to data not used in network training and validation. The hypothesis that the ANN models are overfitting or underfitting is also ruled out by using the data obtained and presented in Table 5 and Figs. 8 and 9.

Despite this general condition, it is evident that the use of models that have only the levels of the three fluviometric stations as input data is the best

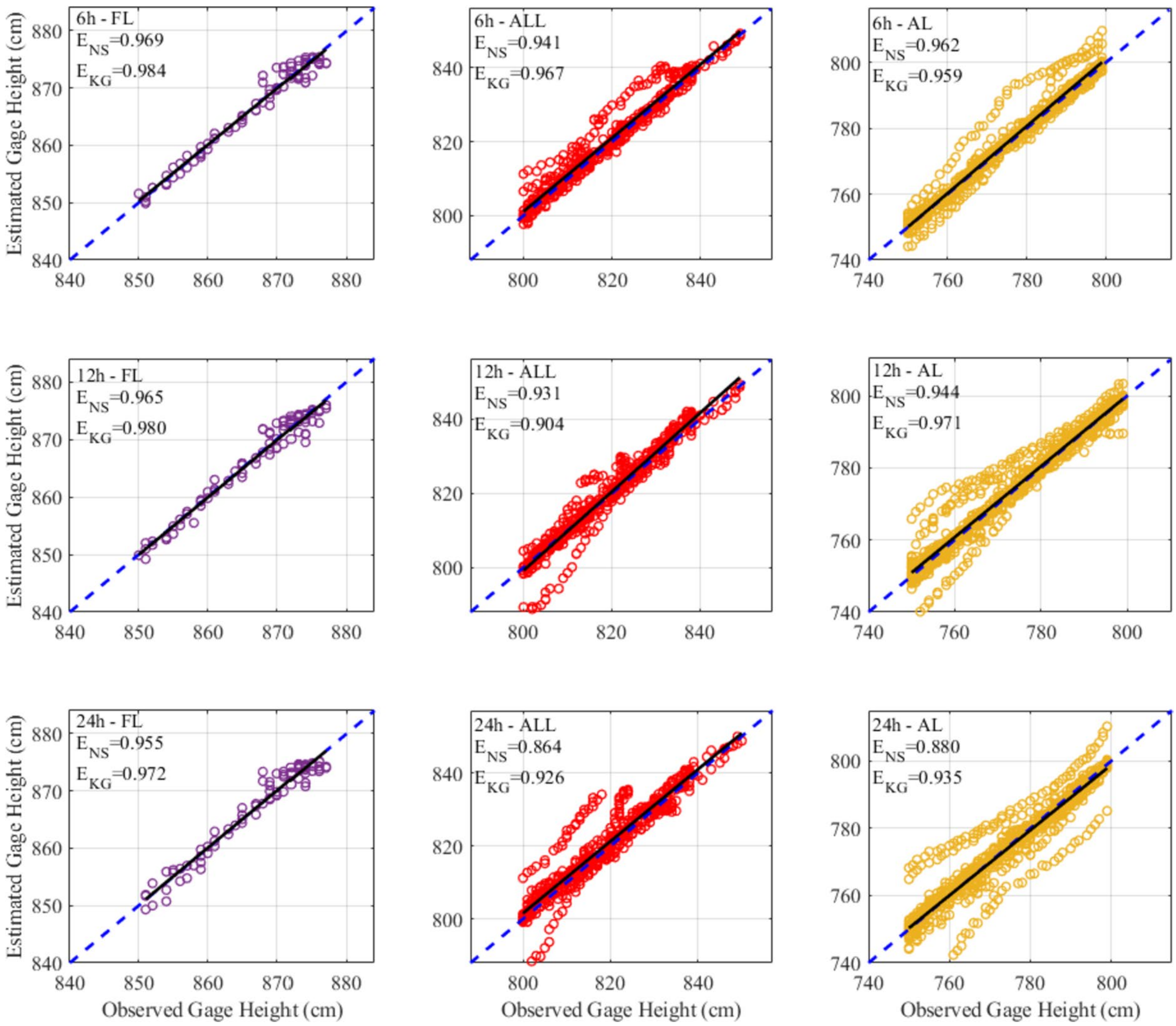

Fig. 7 Relationship between the predicted values with the RNA model (P_{48h};H_{ps}; H_p;H_{bv}) and observed values at station 16,420,000 for the inundation (FL), alert (ALL) and attention (AL) ranges for the city of Boa Vista-RR in the period from 2015 to 2022

option for the 6-h forecast. For 24-h forecasts, it is also essential to use the average rainfall that accumulated in the drainage area of the basin over the last 48 h (P_{48h}) as input data for the models. For the 12-h horizon, it can be considered that there is a lack of definition regarding the best input data. Both models presented very similar results and had the same uncertainty range, which was ± 10.0 cm. The data shown in Table 5 suggest that the best model to use to predict water levels 12 h in advance was the one that considered the variable $P_{48\,h}$, but the test data showed disagreement about this, with the water-level only model being better in some situations. In this case, the hydrologist must evaluate the best option during the forecast process, while also considering the current state of the river level, the rainfall in the basin and the time it takes for the rainfall runoff to reach the section of interest.

ANN model performance in comparison with SBG model and persistence analyzes.

The results of the persistence model were compared with those of the ANNs using the MAE and RMSE metrics, which are presented in Fig. 10.

Figure 10 shows an average reduction of 68% in MAE and 58% in RMSE in comparison with the persistence model with the ANNs that use only the

Table 5 Statistical measure of the error of the artificial neural network (ANN) models applied in the nowcasts of two flood events that occurred in 2022. Event 1 occurred in the period from 06/28/2022–14:00 to 07/06/06. 2022–10 h and event 2 from 08/01/2022–10 h to 08/08/2022–18 h

Model	Input	2022 Event	Error	Forecast Horizon		
				6 h	**12 h**	**24 h**
ANN	H_{ps};H_p;H_{bv}	1	MAE	3.15	5.92	11.14
			RMSE	3.59	8.56	14.0
			Bias	-0.16	2.31	-0.81
			AND $_{NS}$	0.984	0.920	0.846
			AND $_{KG}$	0.937	0.817	0.919
		2	MAE	3.15	5.68	13.59
			RMSE	3.89	6.32	14.01
			Bias	-2.97	-1.18	-13.59
			AND $_{NS}$	0.968	0.936	0.611
			AND $_{KG}$	0.945	0.952	0.956
ANN	P_{48h};H_{ps}; H_p;H_{bv}	1	MAE	3.65	3.21	5.75
			RMSE	4.84	4.17	8.23
			Bias	-2.06	-1.21	1.06
			AND $_{NS}$	0.972	0.981	0.947
			AND $_{KG}$	0.947	0.976	0.941
		2	MAE	4.49	7.04	9.83
			RMSE	6.14	8.21	11.41
			Bias	-4.38	-3.92	-7.68
			AND $_{NS}$	0.931	0.892	0.863
			AND $_{KG}$	0.959	0.876	0.961

ANN: artificial neural networks;H_{ps}, H_p e H_{bv} are the hourly elevations (cm) recorded at the stations Fazenda Passarão (14,515,000), Fazenda Paraíso (14,558,000) and Boa Vista (14,620,000), respectively.P_{48h} is the accumulated precipitation in 48 h, obtained from the product PDIRnow; MAE: mean absolute error (cm); RMSE: root mean square error (cm); Bias: cm; E $_{NS}$: Nash–Sutcliffe efficiency index; and E $_{KG}$: Kling-Gupta efficiency index

water level as an input feature. In the case of the ANN that incorporates PDIR-now and water level as input, this average reduction was 70% in MAE and 56% in RMSE, respectively.

When analyzing the metrics for test events 1 and 2 (Fig. 10), which occurred in 2022, a smaller reduction in MAE and RMSE was identified in relation to the persistence model, approximately 40%. However, even with this more moderate reduction, performance improvements of the proposed ANN models are still evident in comparison to the persistence model. The data provided in the Figure corroborates this finding, emphasizing the advantage of considering PDIR-now data as part of the network input, especially in the 24-h forecast horizon, resulting in better performance compared to models that only use water level as input.

Brazilian Geological Survey (SGB) carries out operational flood forecasts in the Rio Branco basin for a single horizon of 17 h (CPRM 17 h). To compare our predicted values with the SGB data, we run our model for the horizon of 17 h. Figure 11 below presents the histogram of frequencies of the differences between the SGB model and our ANN model compared to the observed water levels.

Figure 11 shows that our values have frequencies of deviation similar to the SGB model, the most advantage of our data is the possibility of precisions for later horizons (24 h), which is essential for urban planning regard to alert the affected population.

Discussion

The results of this study highlighted the potential of artificial neural networks (ANNs) models for the operational prediction of flood events in the Rio

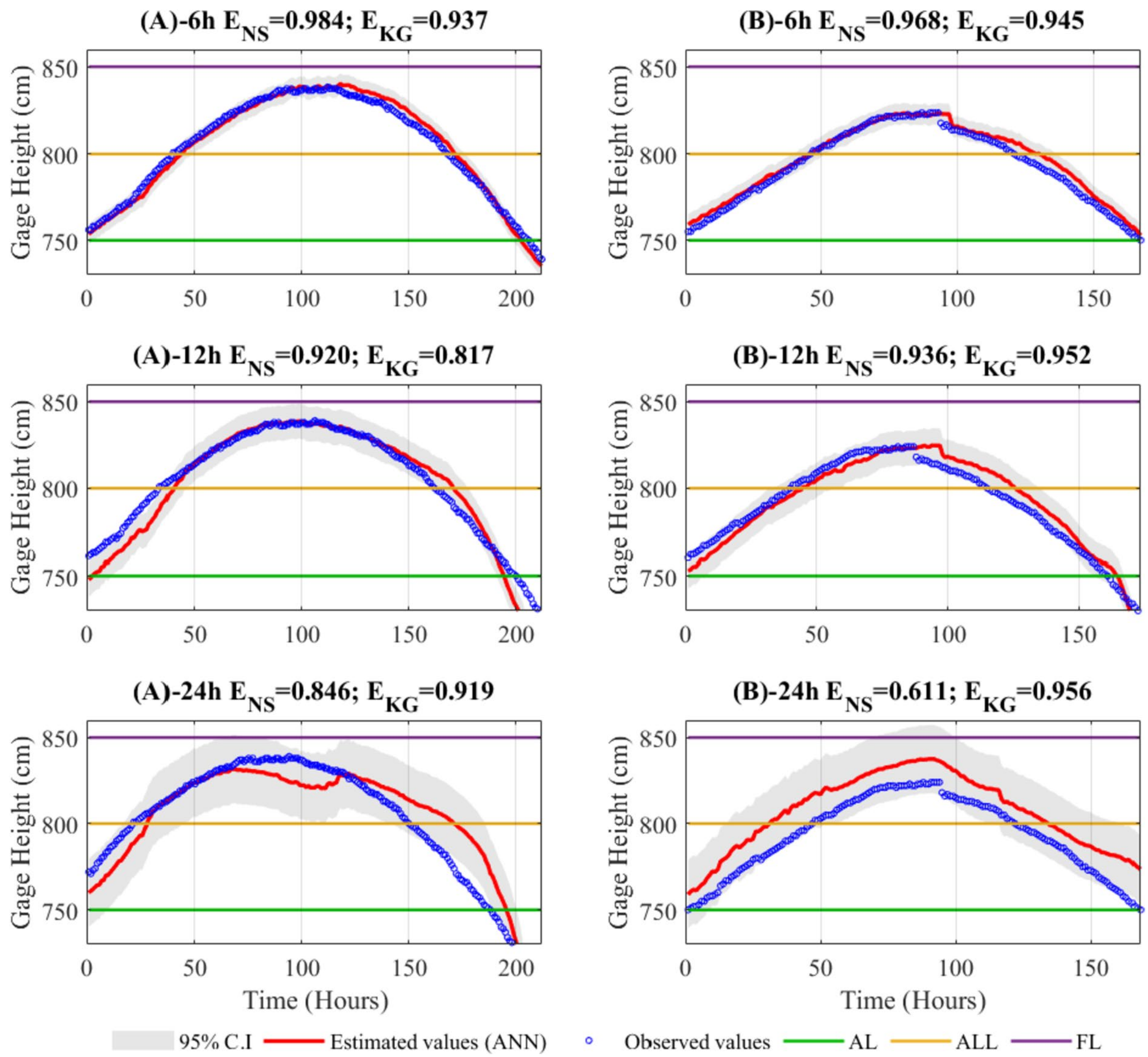

Fig. 8 Diagram of the observed and estimated water levels from the ANN model that used the input data from H_{ps};H_p;H_{bv}. FL represents the "Flood level", ALL the "Alert Level" and AL the "Attention Level". Event A occurred from 06/28/2022–14:00 to 07/06/2022–10:00, and event B occurred from 08/01/2022–10:00 to 08/08/2022–18:00

Branco, in Boa Vista. During the input data selection stage, the focus was on information measured in the basin, readily available online. The water level monitoring system in the basin is robust and transmits data via satellite at intervals compatible with forecasts, which is essential for 24-h forecasts.

Indirect precipitation estimates from the PDIRnow dataset proved to be an alternative to ANNs used in flood forecasting, especially in regions with few rain gauge stations, such as the Amazon basin. Furthermore, we found that including precipitation data accumulated over the last 48 h as input to ANN models is critical to improving the accuracy of forecasts of Rio Branco levels 24 h in advance, highlighting the importance of considering recent rainfall conditions in flood predictions.

Regarding the robustness of ANN models in predicting floods events, this characteristic had already

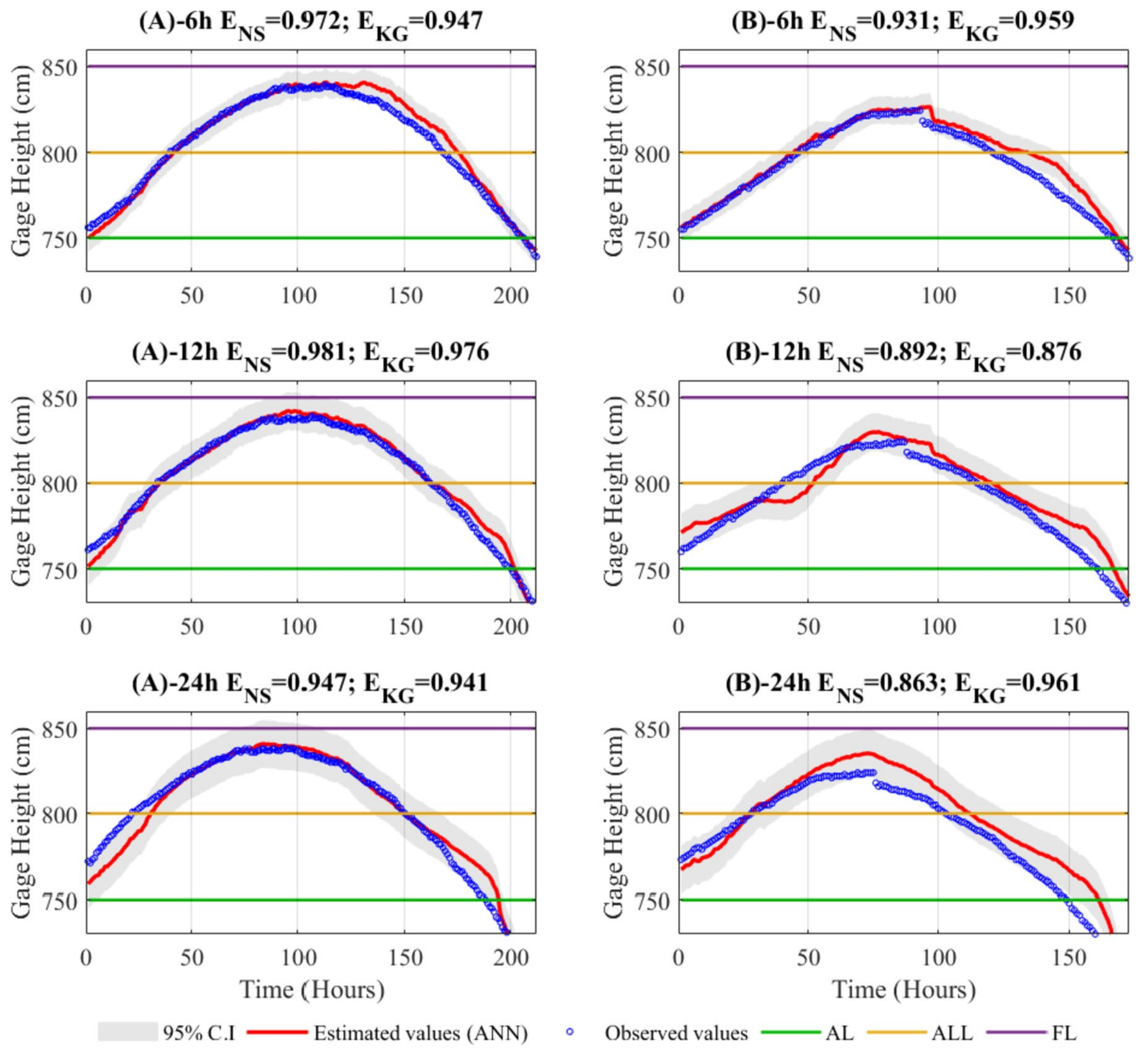

Fig. 9 Diagram of the observed and estimated water levels from the ANN model that used the input data form P_{48h};H_{ps}; H_p;H_{bv}. FL represents the "Flood Level", ALL the "Alert Level" and AL the "Attention Level". Event A occurred from 06/28/2022–14:00 to 07/06/2022–10:00, and event B occurred from 08/01/2022–10:00 to 08/08/2022–18:00

been observed in previous studies, in which ANNs proved to be effective for this purpose (Mosavi et al., 2018), even when they used neural parameters different from those used in this study. However, this research revealed specific particularities of a basin in the Amazon region, related to the input data used in ANNs and the application of the PDIRnow remote sensing rainfall product to predict floods up to 24 h in advance. The results of the forecasts with a horizon of up to 12 h suggest that the propagation of surface runoff in the channel plays a preponderant role, with upstream levels and measurements from the monitoring station in Boa Vista establishing a significant relationship with the ANN output data.

Mosavi et al. (2018) highlighted a pivotal trend in enhancing the precision of flood forecasting models—leveraging optimization algorithms to attain optimal neural network architectures for artificial intelligence (ANNs). Our study employed SCE-UA, a well-regarded optimization algorithm in fine-tuning conceptual hydrological models. Our primary focus was on determining the optimal number of artificial

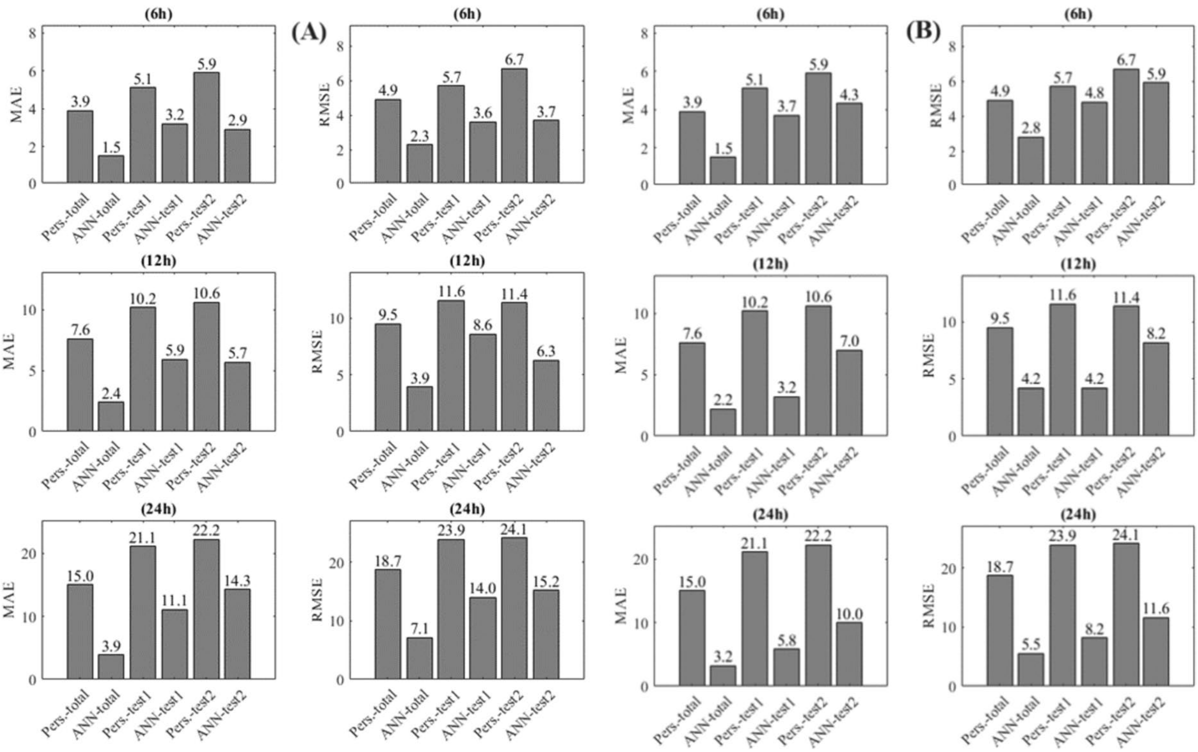

Fig. 10 Mean absolute error (MAE) and root mean square error (RMSE) of the persistence model and artificial neural network models (ANNs) for the predicted total data, for test event 1 (06/28/2022–2:00 p.m. 07/06/2022-10am) and for test event 2 (08/01/2022–10 am to 08/08/2022-6 pm). The first two columns (**A**) are related to the ANN models that had as input only the station elevations and the last two columns (**B**) to the ANN models that had as inputs the PDIRnow precipitation and the monitoring station elevations

neurons within the hidden layers of the ANN model. This approach was crucial in mitigating underfitting and overfitting issues, thereby fortifying the robustness and accuracy of our predictive model.

Maggioni and Massari (2018) conducted a review addressing the performance of satellite precipitation products (SPPs) in river flood modeling. The authors emphasize that the impact of floods is not only determined by their intrinsic characteristics, but also by regional factors, such as climatic, geophysical, demographic and land use conditions. They emphasize the importance of evaluating the performance of SPPs and hydrological models forced by SPPs at the regional level as we carried out in this research.

Conceptual hydrological models, through the calculation of the water balance, are able to offer an instantaneous representation of water storage conditions in the basin, including soil moisture and flow in the channel, as evidenced in previous studies conducted by Collischonn et al. (2008), (Paiva et al. (2011, 2013a, b) and Petry et al. (2023), who employed the MGB-IPH conceptual model in other parts of the Amazon basin. On the other hand, empirical models do not have this ability unless this information is provided as input data. In this research, the inclusion of the current level at the Boa Vista station was crucial to represent the current condition of the river. Without this information as input into the ANNs, the performance of both models fell short of expectations for predicting the elevations of the Rio Branco. These results corroborate previous statements by researchers such as Sousa et al. (2023), Oliveira et al. (2013) and Uliana et al. (2018) for other basins in Brazil.

According to Maggioni and Massari (2018), improving the performance of hydrological models in flood forecasting is feasible by incorporating soil moisture estimates in the basin from remote sensors.

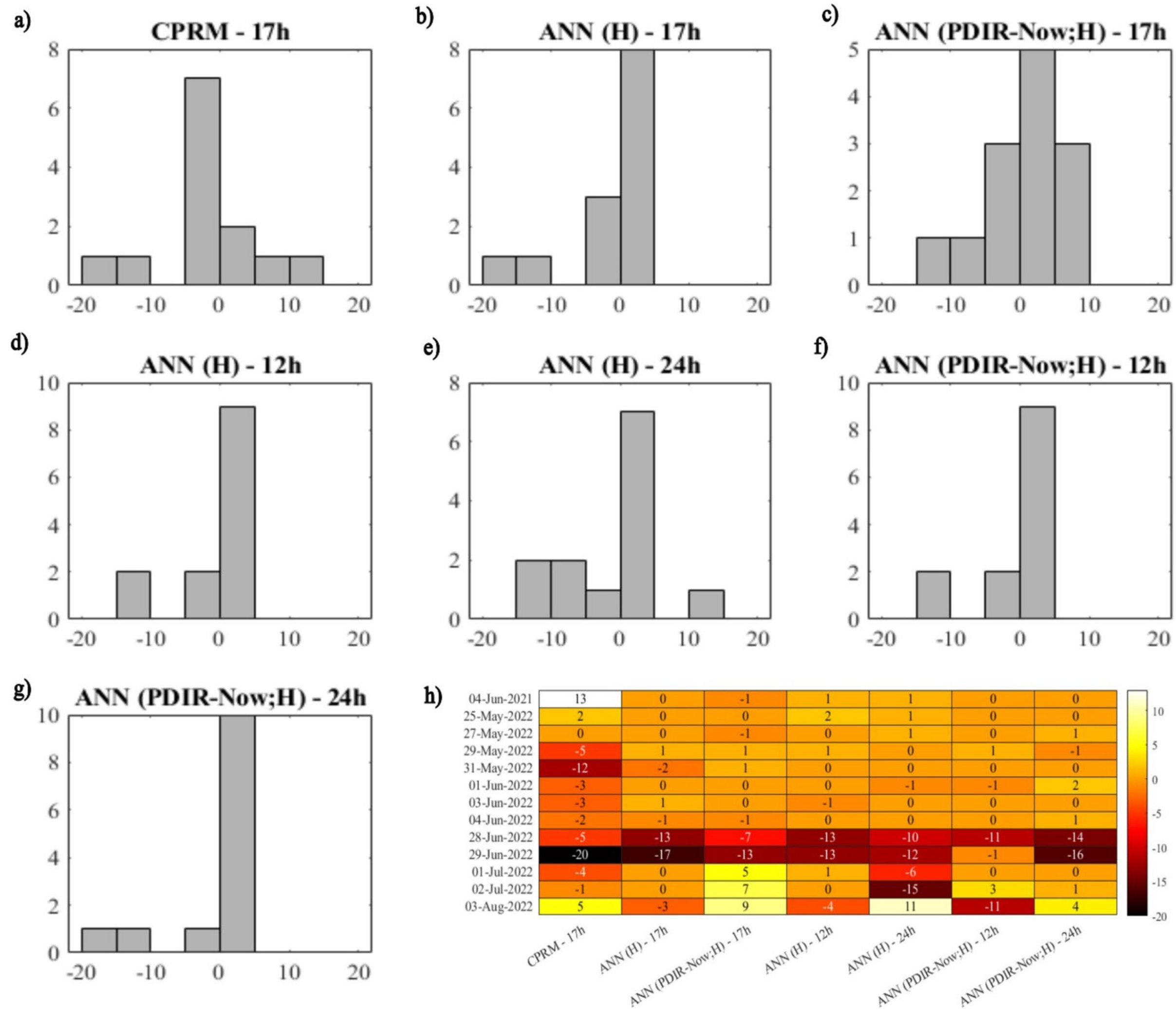

Fig. 11 Histogram of the deviations between the data predicted by the models and the data observed in the Boa Vista monitoring section. Figure (**a**) the acronym CPRM-17 h refers to the prediction of the Brazilian Geological Survey (SGB) model, Figure (**b**) ANN (H) model, and Figure (**c**) ANN (PDIR-now; H) for a single horizon of 17 h. Figures (**d**, **e**) ANN (H) – 12 h and ANN (H) – 24 h are artificial neural network models adjusted for forecast horizons of 12 and 24 h, respectively, taking as input only the elevations of the stations. Figures (**f**, **g**) ANN (PDIR-now; H) – 12 h and ANN (PDIR-now; H) – 24 h are related to the ANN model, where PDIR-now rainfall data and station altitudes are used as input for forecast horizons 12 and 24 h. Figure (**h**) is the deviation of the models for the dates of publication of SGB bulletins. To obtain the deviations, data from bulletins published by SGB in the period from June/2021 and from May to August 2022 were used

Additionally, it is possible to optimize the performance of Satellite Precipitation Products (SPPs) by correcting potential biases and recalibrating them based on data measured at the surface. However, it is important to highlight that the implementation of this last approach requires a dense network of meteorological stations in the basin under study or the use of meteorological radar monitoring.

These can be considerate in future research involving ANNs and other hydrological models in the basin. Additionally, it is advisable to explore the incorporation of quantitative rainfall forecasts, such as those generated by CPTEC-INPE's ETA model or NOAA's GEFS projections, which have already found successful application as input data in conceptual hydrological forecast models in other countries and regions of Brazil, as highlighted by Fan et al. (2016). Considering the low density of automatic rain gauges in the basin, recalibrating SPPs for flood forecasting remains a challenge.

According to Maggioni and Massari (2018) concluded that, in general, there is notable potential in the use of satellite observations in flood forecasting, although they highlight that the performance of Satellite Precipitation Products (SPPs) in hydrological modeling is still lacks suitability for operational applications. However, significant advances are occurring in the development of SPPs, as evidenced by the introduction of the PDIRnow product in 2020. This dataset, with hourly temporal resolution and latency time of 15 to 60 min, proves to be compatible with flood forecasting (Nguyen et al., 2020).

Given these advances, it is undeniable that the PDIRnow product emerges as a promising perspective for integrating artificial intelligence models, aiming to improve short-term forecasting of river levels in the Amazon basin. Our results, as well as the findings of Sousa et al. (2023) for a sub-basin of the Upper Tapajós River, challenge the claim of Maggioni and Massari (2018) about the operational limitations of satellite precipitation products (SPPs), as they corroborate the operational effectiveness of PDIRnow in forecasts in the Amazon region. Although the need for future studies to expand this methodology to other Amazon rivers is indisputable, we are confident that the continuous evolution in the development of SPPs opens a promising horizon for future applications.

Currently, the Brazilian Geological Survey (SGB) carries out operational flood forecasts in the Rio Branco basin, in Roraima. However, the forecasts are not continuous and have a single horizon of 17 h, as can be evaluated in the bulletins available in the flood alert system (SACE, 2023). The results of this study demonstrated the potential for predictions with significantly shorter (6 and 12 h) as well as extended (24 h) lead times compared to those traditionally made by SGB.

The increase in the forecast horizon will have important operational applications in the flood warning in the city of Boa Vista, as it extends the period during which authorities and residents can take precautionary measures, such as evacuating risk areas, blocking roads, and ensuring the safety of urban infrastructure.

Conclusions

From the results obtained, it is possible to conclude the following:

Artificial neural network (ANN) models are effective for predicting flood levels in the Branco River, with horizons of 6, 12 and 24 h, and constitute a viable option for use within river-flood warning systems in the Amazon basin.

The input variables that result in the lowest estimation error for the water level prediction models with 6- and 12-h horizons are the water levels recorded in the telemetric stations in the Branco River basin. For the forecast with a 24-h horizon, it is essential to include, along with the elevations, the average rainfall that accumulated within the basin accumulated over the last 48 h (P_{48}).

Indirect remotely sensed rainfall estimates (PDIRnow) are an excellent alternative as inputs into ANN models used for flood prediction, and are a viable solution for regions where the density of instruments capable of direct rainfall measurements are low, such as in the Amazon basin.

Author contributions **Herval Alves Ramos Filho:** Conceptualization, Methodology, Writing—Original Draft. **Eduardo Morgan Uliana**: Methodology, Writing—Review & Editing. **Uilson Ricardo Venâncio Aires**: Writing—Review & Editing. **Ibraim Fantin da Cruz**: Writing—Review & Editing. **Luana Lisboa**: Review & Editing. **Demetrius David da Silva**: Review & Editing. **Marcelo Ribeiro Viola**: Review & Editing. **Victor Braga Rodrigues Duarte**: Review & Editing.

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Data availability Data and code will be available by contacting the corresponding author.

Declarations

Competing interests The authors declare no competing interests.

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