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NEURAL NETWORK FOR VERY SHORT-TERM HYDROLOGICAL FORECASTING

Cintia Pereira de Freitas

Master's Dissertation of the Graduate Course in Applied Computing, guided by Dr. Leonardo Bacelar Lima Santos, approved in March 28, 2022.

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No dia 28 de março de 2022, as 14h, por teleconferência, o(a) aluno(a) mencionado(a) acima defendeu seu trabalho final (apresentação oral seguida de arguição) perante uma Banca Examinadora, cujos membros estão listados abaixo. O(A) aluno(a) foi APROVADO(A) pela Banca Examinadora, por unanimidade, em cumprimento ao requisito exigido para obtenção do Título de Mestre em Computação Aplicada. O trabalho não precisa de correções.

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"Judge your success by what you had to give up in order to get it".

DALAI LAMA, XIV

My parents ***Fatima*** *and* ***César***

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First, I thank God for life and my parents, who always encourage me to achieve the best and never give up.

To my brother César Junior and my friend Denise, for all their support and encouragement. To my nephew Henry, for all moments of fun necessary along this journey.

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ABSTRACT

Extreme hydrological events have occurred with increasing frequency and severity. Systems for monitoring and forecasting the hydrometeorological conditions of a watershed are of growing importance, as they allow decision-makers to act in time, adopting preventive measures and mitigating the effects caused by these events. Empirical hydrological prediction models, based on Artificial Neural Networks (ANN), are an alternative to these predictions and have shown excellent results. In this context, this dissertation presents two empirical hydrological models for a very short-term forecast of river level for a small basin located in Nova Friburgo, a city in the mountainous region of the State of Rio de Janeiro. The models were created with a Multilayer Perceptron (MLP) neural network. The first model was trained based on rainfall and water level data from five hydrological stations, and the second uses rainfall data estimated by weather radar. The metrics used to evaluate the models were the Root Mean Square Error (RMSE) and the Nash-Sutcliffe Efficiency Coefficient (NSE). Forecasts were evaluated for a horizon of 15 to 120 minutes, and both models performed well. For the model using stations, the NSE value obtained in the 15-minute forecast was 0.994, and in the 120-minute forecast, it was 0.9016. For the model using radar data, the NSE value in the 15-minute forecast was 0.8779, and in the 120-minute forecast, it was 0.8590.

Palavras-chave: Artificial Neural Networks. Empirical Hydrological Forecast. Very short-term Forecast. Hydrometeorological Data.

REDES NEURAIS PARA PREVISÃO HIDROLÓGICA DE CURTÍSSIMO PRAZO

RESUMO

Os eventos hidrológicos extremos têm ocorrido com frequência e severidade cada vez maiores. Sistemas de monitoramento e previsão das condições hidrometeorológicas de uma bacia hidrográfica são cada vez mais importantes, pois permitem que tomadores de decisão possam atuar a tempo, adotando medidas preventivas e mitigadoras dos efeitos causados por estes eventos. Os modelos de previsão hidrológica empírica, baseados em Redes Neurais Artificiais (RNA), são uma alternativa para essas previsões, e têm apresentado excelentes resultados. Neste contexto, esta dissertação apresenta dois modelos hidrológicos empíricos, para uma previsão de curtíssimo prazo de nível de rio para uma pequena bacia localizada na cidade de Nova Friburgo, região serrana do Estado do Rio de Janeiro. Esta é uma região bastante suscetível a eventos como inundações e movimentos de massa. Os modelos foram criados com uma rede neural do tipo Multilayer Perceptron (MLP). O primeiro modelo foi treinado com base em dados de chuva e nível de água de cinco estações hidrológicas e o segundo utilizando dados de chuva estimada por radar meteorológico. As métricas utilizadas para a avaliação dos modelos foi a Raiz do Erro Quadrático Médio (RMSE) e o Coeficiente de Eficiência de Nash-Sutcliffe (NSE). As previsões foram avaliadas para um horizonte de 15 até 120 minutos, sendo que ambos os modelos apresentaram um bom desempenho. Para o modelo utilizando estações, o valor do NSE obtido na previsão de 15 minutos foi de 0.994 e na previsão de 120 minutos foi 0.9016. Já para o modelo utilizando dados de radar, o valor do NSE, na previsão de 15 minutos foi 0.8779 e na previsão de 120 minutos foi 0.8590.

Keywords: Redes Neurais Artificiais. Previsão Hidrológica Empírica. Previsão de curtíssimo prazo. Dados Hidrometeorológicos.

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LIST OF ABBREVIATIONS

AI	–	Artificial Intelligence
ANN	–	Artificial Neural Networks
CAPPI	–	Constant Altitude Plan Position Indicator
DECEA	–	Department of Airspace Control
DEM	–	Digital Elevation Model
DTM	–	Digital Terrain Model
HAND	–	Height Above Nearest Drainage
INEA	–	State Environmental Institute
MAE	–	Mean Absolute Error
ML	–	Machine Learning
MLP	–	Multilayer Perceptron
MSE	–	Mean Square Error
NSE	–	Nash–Sutcliffe model efficiency coefficient
ReLU	–	Rectified Linear Unit
RMSE	–	Root Mean Square Error
SRMT	–	Shuttle Radar Topography Mission
SVM	–	Support Vector Machine
WMO	–	World Meteorological Organization

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1 INTRODUCTION

The World Meteorological Organization (WMO) published a report on the disasters caused by weather, climate, and water extremes that occurred between 1970 and 2019 (WORLD METEOROLOGICAL ORGANIZATION (WMO), 2021). According to this report, the number of disasters that occurred in the world has quintupled during this period. Between 1970 and 1979, 711 disasters occurred, while between 2000 and 2009, there were 3536 disasters. In South America, in a total of 867 disasters registered in this period, 59% were caused by flooding. Brazil is the South American country with the highest number of occurrences, with 193 events, and a loss of US$41,7 billion. Furthermore, the floods in 2011 in the mountains region of Rio de Janeiro were the second most fatal event in South America, when recorded 900 deaths.

This report also indicated that economic losses had increased considerably, as these events have become increasingly frequent and severe. According to the Secretary-General of WMO, this version of the report "shows that implementation of multi-hazard early warning systems (MHEWSs) has led to a significant reduction in mortality." Monitoring and alert systems have been used more as an important tool to identify extreme events that can cause harm to the population, allowing stakeholders and policymakers to work with security measures in time to avoid further damage. However, to reach this objective, the systems need quality inputs with a high spatial and temporal resolution for the monitored area.

Pagano et al. (2014) point out that these systems have been implemented in several countries and allow actions to be taken in time, saving lives. The authors also related four challenges encountered in extreme event forecasting agencies visited by the lead author, in 24 countries, between developed and developing, namely: making the most of available data, making accurate predictions using models, turning hydrometeorological forecasts into effective warnings, and managing an operational service. Besides, the author suggests some research opportunities for each challenge, evidencing that can still do much in this area. Therefore, it is increasingly important to study and create tools that can accurately simulate environmental processes, especially those involving meteorological observations such as rainfall and hydrological observations such as river levels.

Hydrological modeling has been an object of study for over a century. However, according to Fayal (2008), it was from 1930 onwards that great advances occurred when government agencies from developed countries began to develop their research programs in the area. Since then, different models have emerged to meet the most diverse needs. The application and the data available in the study area are the watersheds for choosing a particular model type. For Elsafi (2014), two main approaches are used in hydrological forecasting, physical and empirical. The first considers the physical dynamics between the main interacting components of the hydrological system. And the second approach is based on the statistical relation between the hydrological inputs and outputs, explicitly considering the relation between the process carried out without involvement.

A very short weather forecast between 0 and 6 hours is often referred to as nowcasting (WORLD METEOROLOGICAL ORGANIZATION (WMO), 2016) and is critical in managing extreme events. In several situations, predicting the overflow of rivers in advance is essential. However, some meteorological events that are precursors to flooding, such as heavy convective rain, occur on a short spatial scale and with a fast temporal evolution, making it difficult to predict the event while maintaining adequate accuracy. Recently, artificial neural networks (ANNs) are widely used techniques to make this very short-term prediction (ZOUNEMAT-KERMANI et al., 2020; REN et al., 2020; ZAKARIA et al., 2021).

1.1 Goals

The main goal of this work is to develop empirical hydrological models based on different data sources for very short-term hydrological forecasting. To achieve it was necessary to carry out the following specific goals:

- Develop and assess the performance of an ANN model trained with rainfall data from hydrological stations;
- Develop and assess the performance of an ANN model trained with rainfall data estimated by weather radar;
- Analyze weights of a network trained with radar data to identify correlation with relief and hydrographic data;
- Perform sensitivity analysis on network inputs trained with rainfall data from hydrological stations;
- Assess the performance of an ANN model to different datasets.

In this context, the scientific question to be answered is: is it possible to use models based on ANN for very short-term hydrological forecasting? The hypothesis of this work is that empirical hydrological models built with ANN, based on hydrological station data or weather radar, can show good performance to very short-term hydrological forecasting even when compared with persistence and physical models.

1.2 Document structure

The structure of this research work is described below:

- Chapter 2. Conceptual Context: basic concepts on hydrological modeling, weather and hydrological data, neural network, and a literature overview on empirical hydrological forecasting.
- Chapter 3. Case Study 1: proposes a multilayer perceptron neural network to forecast temporal series of water level at the outlet of a watershed using hydrological monitoring stations.
- Chapter 4. Case Study 2: proposes a multilayer perceptron neural network to forecast temporal series of water level at the outlet of a watershed using weather radar data.
- Chapter 5. Further and comparative analyzes: analysis of the results obtained in both networks developed in this work.
- Chapter 6. Final Remarks.

2 CONCEPTUAL CONTEXT

This chapter introduces the main concepts used in this work, in addition to a literature overview, with a panorama of the use of neural networks for hydrological forecasting.

2.1 Hydrology concepts

Hydrology is the area that involves natural phenomena found in the hydrological circle. According to Tucci (2005), it includes rainfall, infiltration, evaporation, flow in rivers, among others. These phenomena depend on a huge number of factors, which condition both quantitative and qualitative analysis.

In Brazil, Federal law 9.433, from January 8, 1997, established the watershed as a territorial unit to implement a National Water Resources Policy (PNRH). According to Tucci (2012), the watershed is a physical system where the input is the precipitated water volume, and the output is the volume of water drained from the outlet (which corresponds to the lowest point in the watershed), considered as intermediate losses, the volumes that evaporated, transpired, and deeply infiltrated. Thereby, the hydrological paper of a watershed is turning an input of concentrated water in time (rainfall) into an output of water (flow) in a way better distributed in time.

Important greatness of a watershed, related to its response time, is the concentration time. It is the central concept when analyzing and monitoring a watershed, independent of its size. In literature, there are several definitions of the concentration time. One of these is the time for a water particle to travel from the hydraulically most distant point to the watershed outlet (MCCUEN, 2009). Almeida et al. (2016) presents other ways to define concentration time.

Several factors can influence in concentration time of a watershed, such as the slope and shape, the type of vegetal cover, the sinuosity and slope of its main course, among others. As different factors influence it, its calculation is quite complex can be done empirically or semi-empirically (MATA-LIMA et al., 2007). As it involves several variables and different parameters, the value obtained can vary significantly according to each calculation, so it is essential to know the applicability of each methodology.

Another essential greatness of a watershed study is the flow, which corresponds to the volume of water drained for time unit. According to Tucci (2005), the hydrological models arose from the need to obtain longer hydrological series and representative flow.

2.2 Hydrological modeling

Models are abstractions of reality created to simulate and understand the process involved in this reality. Several areas apply this abstraction, such as weather forecast and climate, economics, agriculture, hydrology, and others. According to RENNÓ and SOARES (2003) models are increasingly being used in environmental studies, as they help to understand the impact of changes in land use and cover and to predict future changes in ecosystems. However, no single best model can represent since the same real-world process is different. Tucci (2005) defines hydrological model as a tool used to represent the processes that occurred in a watershed and predict the consequences of different occurrences concerning the observed values.

Different features can classify hydrological models. Some of them were discussed in Chow et al. (1988) and Tucci (2005) and presented here:

- deterministic or stochastic: by the presence or absence of random variables
- discrete or continuous: according to its distribution in space
- stationary or dynamic: according to its temporal variation
- empirical or physically based: according to the hydrological processes involved

In this work, the focus will be on empirical models, also known as "black-box". These models have no explicit representation of physical processes of a watershed (DAWSON; WILBY, 2001), they fit the calculated values to the observed data, using functions that are unrelated to physical processes.

2.3 Weather and hydrological data

There are several meteorological and hydrological data sources with different spatial and temporal resolutions. Can use these data in different areas such as agriculture, aviation, civil construction, among others. The performance of a hydrological model is directly connected to the quantity and quality of these data.

As defined by the WMO (WORLD METEOROLOGICAL ORGANIZATION (WMO), 2016), nowcasting is applied to weather that occurs on the local scales over very short time periods, between 0 and 6 hours. Observational data, such as radar, weather stations, satellite and lightning networks, are essential to predict this period.

2.3.1 Weather stations

Stations can be classified according to the data acquisition mode, can be conventional or automatic. In conventional stations, observers register data that take note at certain times. Already in automatic stations, sensors record the measurement automatically. These stations are composed of a datalogger where measurements are stored. This data can be transmitted manually or automatically using the GSM (Global System for Mobile) technology or satellite. Stations that record and send data automatically are also called telemetry stations.

This work uses telemetry type stations equipped with water level and rainfall sensors. These stations were installed by State Environmental Institute (INEA) in Rio de Janeiro to control floods in the region.

Traditionally, the pluviometers/rain gauges are one of the main equipment used to measure rainfall. Figure 2.1 presents one of the pluviometers from INEA located in Nova Friburgo, RJ. This equipment collect the drops in a small area close to the ground (KAISER, 2006). They have a relatively low cost compared to other equipment, such as radar and satellite, however, they have a spatial limitation.

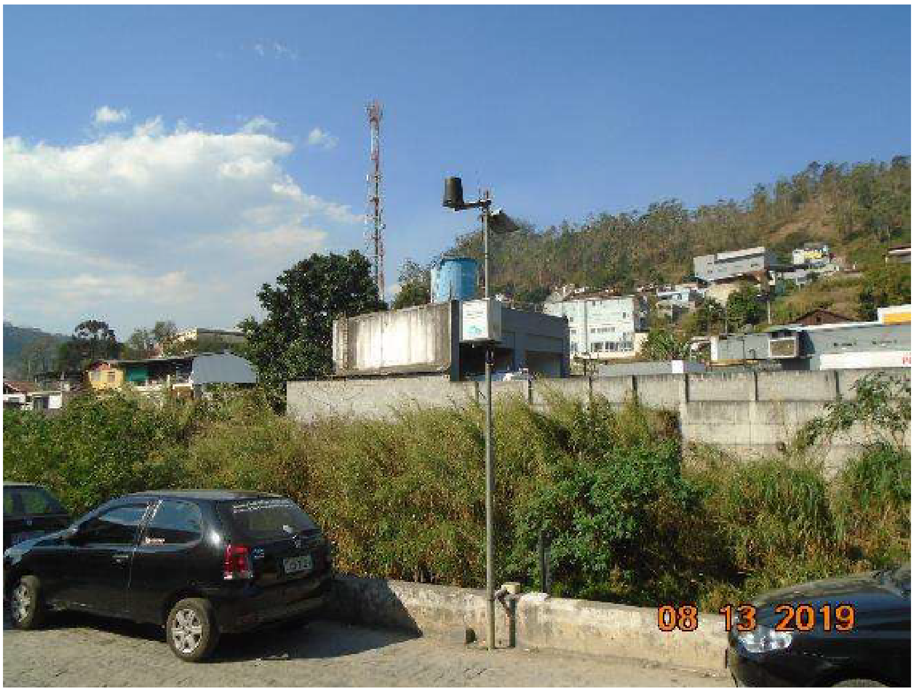
2.3.2 Water level sensors

The comprehension of the hydrological processes is fundamental for the management and monitoring water resources. However, it is necessary to acquire data, including for historical periods. According to Vanelli et al. (2020), the most common source of hydrological data is monitoring stations, which provide historical series of measured data.

Water level sensors used to be installed on bridges and capture the water level for different timestamps in these places using, for example, electromagnetic waves with a pre-set frequency: the water level is determined based on this frequency and the interval of time between consecutive pulses (VANELLI et al., 2020).

Traditionally, one of the inputs of the physical hydrological model is the flow data. However, few watersheds have the measurement of this variable, being more common the water level measurement. Thereby, one of the ways to obtain this data is using a rating curve, which is an instrument used to transform level data into the flow. An equation with parameters calibrated for each point of interest does this transformation (BACELAR, 2017).

Figure 2.1 - Pluviometer from INEA.



SOURCE: INSTITUTO ESTADUAL DO AMBIENTE (INEA) (2019).

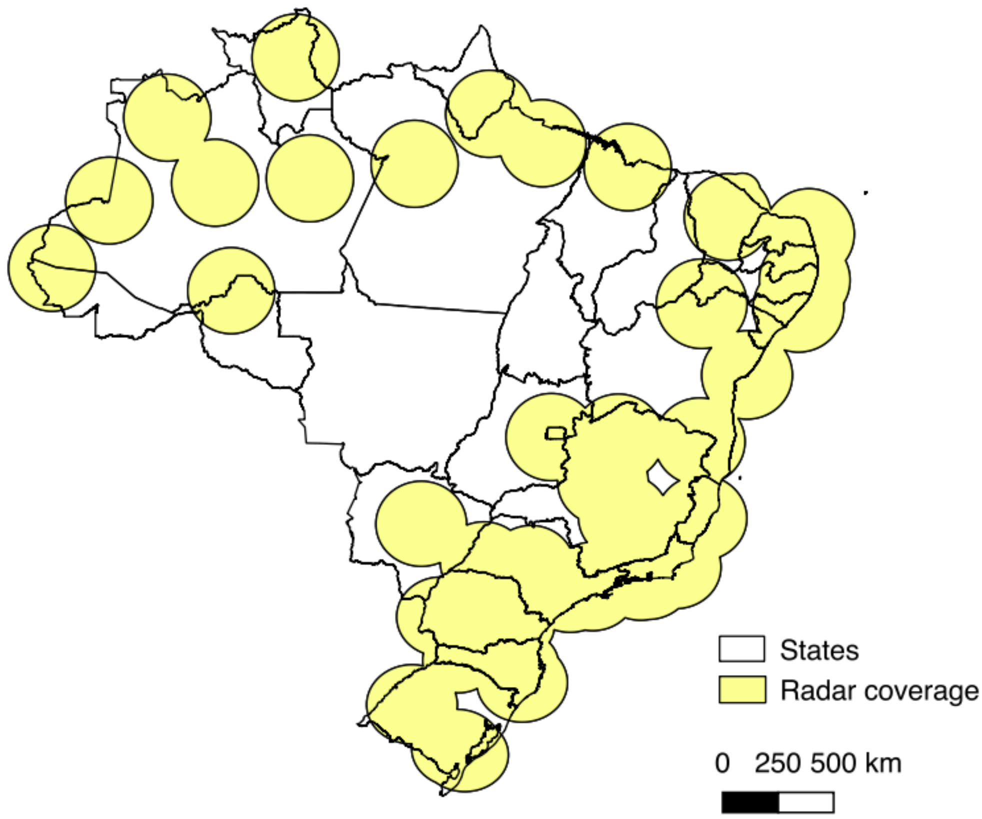
2.3.3 Weather radar

Radar is an acronym for Radio Detection and Ranging. According to Queiroz (2009), radar is an electromagnetic system for detecting and locating targets by means of radio echoes. They can be applied in different areas, for example, in control of flights and ships, in traffic, to control the speed of vehicles, in scientific applications, in meteorology, among other applications.

World War II used radars widely, and it was at the end of the war, in the 1940s, that radars began to be used as an aid in meteorology. Weather radar has been increasingly important in predicting possible storms and can prevent many tragedies. As presented in Angelis and Bacelar (2018) and Thorndahl et al. (2013), short-term weather forecasting (Nowcasting) uses weather radar, which corresponds to forecasts for up to 6 hours.

There are more than 40 radars currently in operation in Brazil, belonging to various public and private institutions (FERREIRA, 2021). Figure 2.2 presents a coverage map of these radars. This coverage embraces approximately 71% of the municipalities, with the South and Southeast regions having the greatest coverage and the North and Midwest regions having the lowest coverage. The quantity of radars installed in the northeast region has increased significantly in the last few years compared to 2006 (ANGELIS et al., 2006). This increase was due to the need for data for the operation of monitoring and alert centers.

Figure 2.2 - Cover of weather radars in Brazil.



SOURCE: Author production.

As explained Volpato et al. (2008), the meteorological works as follows: radar transmits electromagnetic waves, then when passing by a cloud, cause each drop to resonate at the frequency of the incident wave. Each drop produces electromagnetic waves radiated in all directions, and part of this energy is generated by the total volume of drops. Since the moment when the radar emitted the wave beam and the signal returned is known, it is possible to calculate the distance between the target and the radar.

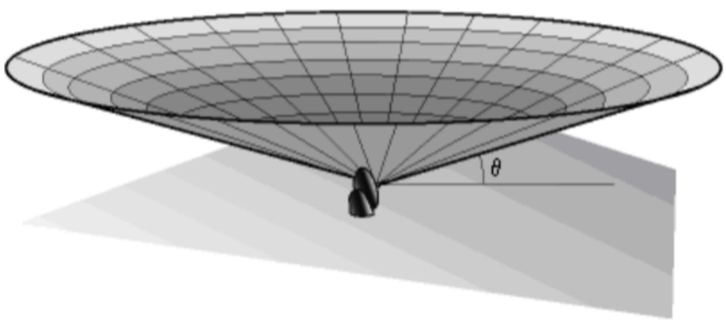
The radar does not measure rainfall directly, and it receives a certain power density reflected by the rainfall targets, called reflectivity (QUEIROZ, 2009). The unit of reflectivity is dBZ (reflectivity decibel). Through Equation 2.1, called the Z-R relation, it is possible to find the relation between the rain rate and reflectivity:

$$Z = aR^b \tag{2.1}$$

being R the rain rate measure in mm/h, a and b, empirical constants, related to drops size and distribution spectrum. In literature, several Z-R relations were proposed (BLANCHARD, 1953; JOSS et al., 1970; CALHEIROS; ZAWADZKI, 1987; MORAES, 2003), being the Marshall and Palmer (1948) the best known, where a and b, are equal to 200 and 1,6 respectively.

According to Costa (2007), extracting reflective radar values collected at each azimuth and elevation obtain radar data. The end of each electronic radar scan obtains a three-dimensional volume of data. Figure 2.3 represents this scan. The radar system samples the reflectivity values in 360º for each elevation, thus forming a three-dimensional volume of data.

Figure 2.3 - Scanning process for radar data acquisition.



SOURCE: Costa (2007).

From this volumetric data, several radar products can be generated according to the purpose. The Constant Altitude Plan Position Indicator (CAPPI) is a widely used product. A volumetric scan at a certain height obtains this product. This scan, which is in polar coordinates, is then converted to cartesian coordinates and corrected for the curvature of the Earth. In this work, we use the product CAPPI at the height of 3 km. According to Rodrigues (2018), this is one of the main radar products used for monitoring rainfall.

2.4 Neural network

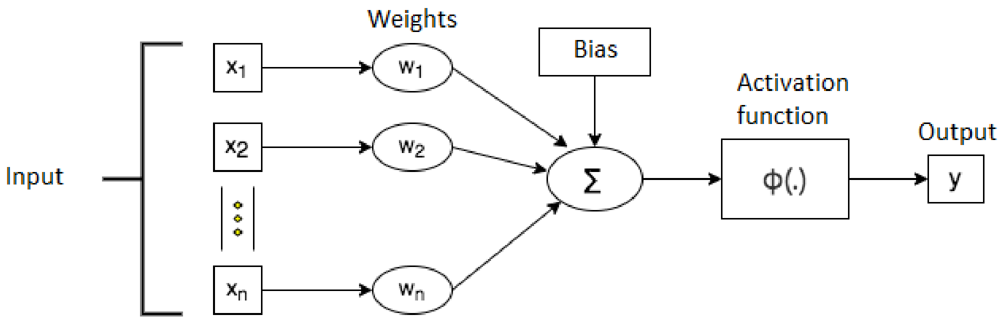
For centuries humanity has been concerned with creating devices that imitate human behavior. Although, understanding this behavior to reproduce it is not an easy task. For this, since the 50's when Alan Turing created the Turing test, countless studies and tests have been done. However, it is so complex that several areas, such as computing, biology, philosophy, psychology, and engineering, are carrying out studies, and much remains to be discovered.

According to McCarthy et al. (2006) Artificial Intelligence (AI) is the ability of machines to reason, learn, recognize patterns and deduce. One of the techniques used in AI is Machine Learning (ML). Samuel (1967) defined ML as a field of study that gives computers the ability to learn without being explicitly programmed. A widely used ML technique in different areas is ANNs.

Haykin (2007) defines ANN as a machine that is designed to model how the brain performs a particular task or function of interest. Therefore, an ANN can be understood as a computational model whose structure is based on the biological neural network model. The neuron is formed by a set of inputs, weights, a bias, and an activation function, as shown in Figure 2.4. This model corresponds to that presented by Mcculloch and Pitts (1943). In this research, line emerged the single-layer perceptron model (ROSENBLATT, 1958) and the Adaline model (WIDROW; HOFF, 1960). All these models have a limited ability to classify only linearly separable patterns.

For not solving the problem of the 'exclusive OR', the Perceptron model was criticized in Minsky and Papert (1969), discouraging research in the ANN area for some years. Some solutions have been proposed over the years. However, with the publication of Rumelhart et al. (1986), from the error backpropagation algorithm, the solution was widespread. This algorithm made it possible to insert one more layer in the network, allowing the solution of non-linearly separable problems. Since then, several other models have emerged, making progress in this area.

Figure 2.4 - Artificial Neuron.



SOURCE: Adapted from Haykin (2007).

In this work, we use the Multilayer Perceptron (MLP) type network composed of at least one hidden layer. The network uses learning called supervised. It shows the expected output for each input to the network. The network's weights are adjusted to minimize the error using the backpropagation algorithm. We carried out the process in two steps. First, random weights are assigned to the network inputs, and we obtain the output layer passing through the other layers. In the second step, we compared the output obtained with the desired output, and the error was calculated. And then, the backpropagation process is performed, where the error propagates from the output layer to the input layer. The weight of each connection is updated to approximate the network output to the observed value.

The MLP network is feedforward type, so the data flow is always in a single direction. Then, there is no feedback. So, the output of neurons from one layer is connected to the inputs of neurons from the next layer, with propagation in a single sense.

Activation functions insert a non-linear component into neural networks, making non-linear transformations on the input data, rendering the network capable of learning to perform more complex processes. Through the activation function, the network knows whether or not a neuron should be activated. The choice of which activation function to use depends on the nature of each problem.

2.5 Empirical hydrological forecast - a literature overview

A bibliographic overview was carried out, considering the use of empirical models in hydrological forecasting. Teschl and Randeu (2006) proposed an ANN to predict flow for a small watershed located in Austria, using weather radar data. In that work, the author mentioned that weather radar data in hydrological applications is quite indicated for presenting a good spatial and temporal resolution.

Physical models are difficult to calibrate and require extensive knowledge of the physical processes that occur inside the watershed. The proposal presented by Kia et al. (2012) is a flood model using ANN techniques, taking as input several causing flooding factors to simulate flood-prone areas in the Johor River watershed in Malaysia. That work also highlighted that there is no strict rule about the number of layers and hidden neurons, being applied in most cases the trial and error.

Early warning centers have been interested in empirical hydrological models as well. Lima et al. (2016) proposed an ANN for estimating the level on the station Conselheiro Paulino in the Mountain Region of Rio de Janeiro, Brazil. On the other hand, Silva et al. (2016) developed an ANN to forecast the discharge in the river "Rio claro" in Caraguatatuba, São Paulo, Brazil.

Sung et al. (2017) also proposed a model to predict water level using ANN. The input data were rainfall and water level from 4 monitoring stations. Tests were made varying the number of monitoring stations considered. The results indicate that including multiple water level data on the main river in the network provides water level forecasts with greater accuracy.

Mosavi et al. (2018) presents an extensive review of flood prediction using machine learning showing multiple methods for short-term and long-term predictions. The review started with thousands of articles but selected almost two hundred original research articles, then analyzed and compared. These methods are mostly based on ANN but also include neuro-fuzzy or adaptive neuro-fuzzy inference systems (ANFIS), and support vector machine (SVM), among other methods. Different classes of neural networks are discussed. Hybrid approaches combining different methods and ensemble prediction systems were also presented. Most articles propose a given method to compare it to another one that appeared before in a literature reference. According to the considered article, different variables can be predicted. There are continuous variables like river water level (stage level), river water flow, rainfall, rainfall-runoff, or categorical variables like flood, urban flood, and flash flood.

According to that review, there is an increasing trend in the use of neural networks, in comparison to other methods over the years, intended for an antecedence of a few hours, as in this work. However, some works consider an antecedence of a few days in this class. In tropical countries, many of these events start and end in a short time, so hydrological forecast based on observed data is hard to do. In the case of high temporal resolution flood prediction, multilayer perceptron (MLP) neural networks seem to be often employed, despite the difficulty of optimizing its architecture and choosing suitable activation functions.

Sit et al. (2020) presented the comprehensive review of deep learning applications in hydrology and water resources fields, showing that many works use empirical models for hydrological prediction. However, few works in the area can be reproduced, either because it is not open-source or because it is not made available the dataset used. The research community does not build upon previous work in terms of constructing better neural network architectures and moving state-of-the-art to the next iteration.

In recent work, Zakaria et al. (2021) showed that the proposed models are capable of forecasting the river level with a high level of precision by only using previous observed water level as inputs.

Table 2.1 presents the characteristics of the data used by some of the cited works, comparing the different configurations of inputs and outputs adopted by each network. The table also presents the main metrics used by these works, with the RMSE being the most used in a regression model. For this metric, the table presents the best value obtained in each work.

Table 2.1 - Article comparison using different network configuration.

Paper	Network	Input	Output	Domain	Metrics
(TESCHL; RANDEU, 2006)	MLP	Radar Rain gauge	River flow 90 minutes	15 minutes 01-12/2000	R^2 RMSE = 0.0596
(KIA et al., 2012)	MLP	Elevation Slope Flow accumulation Geology Land use Soil Rainfall	River flow	1987 - 2006	R^2 SSE MSE RMSE = 2,4-23
(LIMA et al., 2016)	MLP	7 monitoring stations (Rainfall and water level), 1 (Only Rainfall)	Water level 15 and 120 minutes	15 minutes 2013-2014 Train: 01/2013 - 06/2014 Test: 07-11/2014	ME MAE NSE RMSE = 0.0150
(SUNG et al., 2017)	MLP	4 monitoring stations (Rainfall and water level)	Water level 1, 2 and 3 hours	Hourly 2007–2016	R^2 NSE RMSE = 0.0502
(ZAKARIA et al., 2021)	MLP ANFIS	Water level	Water level 1-hour to 24-hour	2008 to 2018	R^2 MAPE WI RMSE = 0.01299

3 CASE STUDY 1: EMPIRICAL HYDROLOGICAL FORECAST WITH DATA FROM HYDROLOGICAL STATION[1]

This chapter presents our first case study, which proposes a multilayer perceptron neural network to forecast temporal series of water level at the outlet of a watershed using hydrological monitoring stations.

3.1 Introduction

Occurrences of natural disasters are increasing every year, due to climatic changes and man-induced susceptibilities and vulnerabilities. Among these disasters are the floods, which are frequent in many countries, and have an obvious potential of causing injuries, fatalities and damages. However, such effects can be eventually mitigated by forecasts issued with a minimum antecedence. This work proposes the forecast of water level at the outlet of a watershed in the city of Nova Friburgo, located in the mountain region of the state of Rio de Janeiro in Brazil, which has been affected by floods and landslides.

A neural network is proposed to forecast temporal series of water level at the outlet of the watershed with up to a 2-hour antecedence. Input data was collected by a set of hydrological monitoring stations in the Bengalas river, on a subwatershed of Grande river watershed. It is composed of temporal series of water level and rainfall measures acquired with a 15-minute resolution. The programming environment includes the Python language, the Tensorflow library and the Keras API. Three different sets of predictions tests were performed, using only temporal series of water level, rainfall and water level and rainfall. Results show that temporal series of water level at the watershed can be predicted with acceptable accuracy for up to two hours antecedence, using at least temporal series of water level as input for the neural network.

A multitude of forecast schemes for variables related to floods, such as water level or discharge/flow of rivers, have been proposed in the last decades. Mathematical models can be applied, but depend on the knowledge of physical parameters and also accurate initial and boundary conditions. On the other hand, the so-called data-driven models are based on algorithms that can be trained using known post-mortem data in order to "learn" and thus make predictions or classifications from new data.

[1] We based this chapter on the paper "Combining Rainfall and Water Level Data for Multistep High Temporal Resolution Empirical Hydrological Forecasting" published in Annals of the XXIII ENMC - Encontro Nacional de Modelagem Computacional, Palmas, TO (FREITAS et al., 2020).

These are the machine-learning algorithms applied to hydrological forecasting, and are discussed in Section 3.2.

It is difficult to conclude what is the better method/approach since each prediction depends on the implementation of the proposed method, the availability of data, and the particular geographical and physical scenario. Therefore, a good method/approach is possibly the one that achieves a prediction performance that is acceptable for operational use in terms of issuing warnings of disasters for the civil defense.

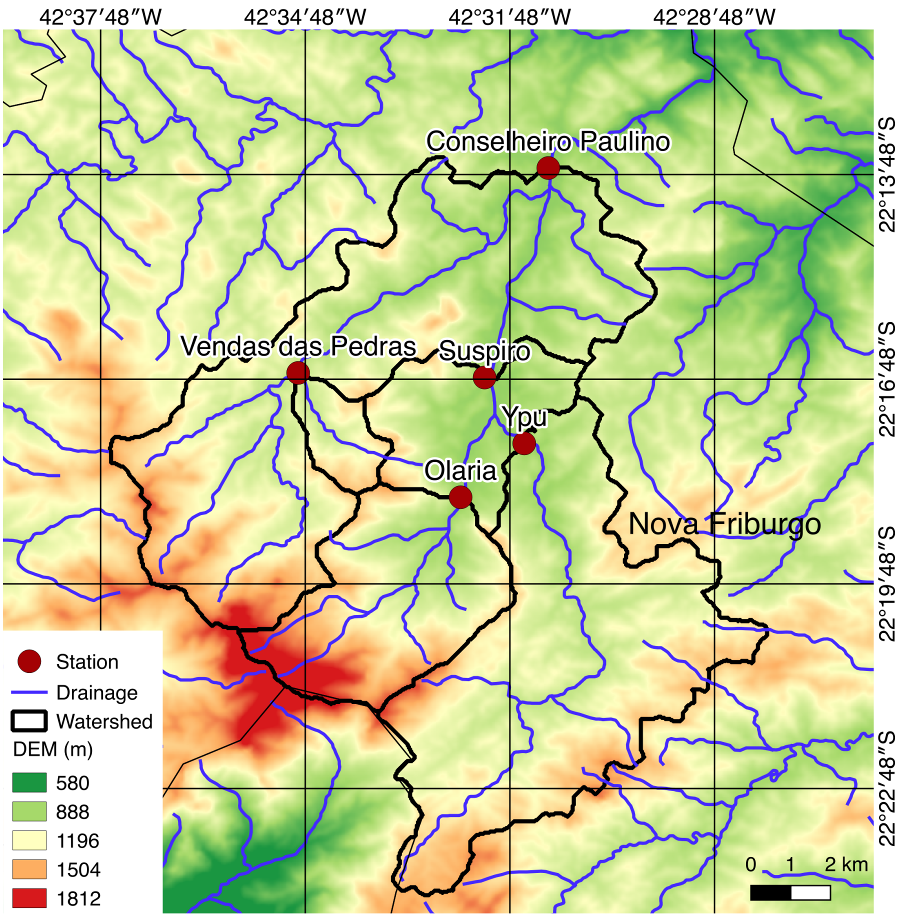
The current work is a development of a former prediction approach for the water level at the outlet of the same watershed (LIMA et al., 2016), using a neural network, but not applied to time series.

3.2 Data and method

The area of study of this work is a small watershed, located in the mountainous region of the state of Rio de Janeiro, in Nova Friburgo city (Figure 3.1). This is an area susceptible to natural disasters like floods or landslides, with a potential of causing serious harm to the local population Lima et al. (2016). The watershed was delineated using the software TerraHidro (ABREU et al., 2012) and a 30-meter resolution Digital Elevation Model (DEM), obtained by an on-board radar of the Shuttle Radar Topography Mission (SRTM). TerraHidro (INSTITUTO NACIONAL DE PESQUISAS ESPACIAIS (INPE), 2007) is a free software for distributed hydrological modeling written in C++ developed by National Institute for Space Research (INPE) and written in the C++ language. TerraHidro employs INPE's and TerraView GIS for manipulating maps, which includes the Terralib library and a spatial database.

The data for this study was collected from five hydrological monitoring stations of the State Environmental Institute (INEA), as listed in Table 3.1. These stations are in located in Nova Friburgo, being the Conselheiro Paulino station located in the pour point (outlet) of the watershed. All the stations provide rainfall and water level data, with a 15-minute temporal resolution. Data was collected between December 1, 2011 and March 24, 2013, amounting to 46,080 samples for each station. There were data failures in eight samples in this time series, one at Olaria station, two at Conselheiro Paulino station, and five at Suspiro station. As there were moments without rainfall, the value observed in the previous moment was repeated.

Figure 3.1 - Area of study - Bengalas river watershed.



SOURCE: Author production.

Table 3.1 - Hydrological monitoring stations used in this study.

Name	Longitude	Latitude
Conselheiro Paulino	42º31'12.49"W	22º13'42.47"S
Olaria	42º32'31.96"W	22º18'31.83"S
Suspiro	42º32'05.36"W	22º16'46.43"S
Venda das Pedras	42º34'53.51"W	22º16'42.47"S
Ypu	42º31'35.41"W	22º17'45.09"S

SOURCE: Author production.

The related data-driven model was implemented in the Python language using Tensorflow, an open library developed by Google using the Keras API (CHOLLET et al., 2015), which is also open, modular and user-friendly. This model is based on a MLP neural network. Such network architecture is composed of multiple layers that allow to solve complex problems related to non-linearly separable datasets in several areas of study as Meteorology, Medicine, Criptography, etc. (RUMELHART et al., 1986). The Keras API is employed in much complex neural networks than the MLP, such as convolutional and recurrent neural networks, typical of Deep Learning implementations, but it was adopted in this work anticipating the use of such neural networks in the ensuing work.

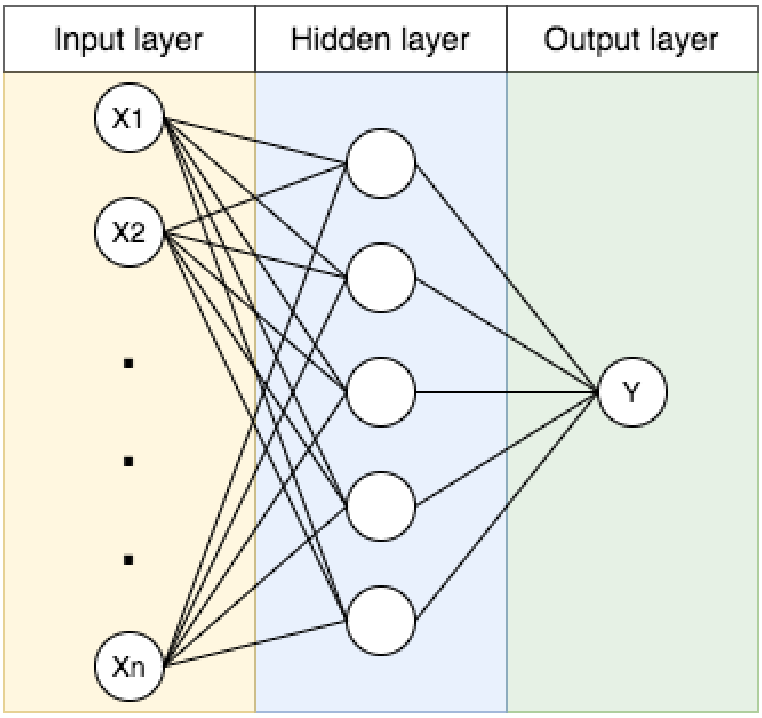
The hyperparameters used in this network are shown in Table 3.2. On the implemented MLP network, the input layer has one neuron for each input parameter, one hidden layer with 5 neurons and the output layer has one neuron, as shown in Figure 3.2. It employs the Rectified Linear Unit (ReLU) activation function for the hidden layer, and the linear function for the output layer. The ReLU function is a non-linear activation function, commonly used in Deep Learning. The advantage of this activation function over the other ones is not to activate all the neurons at the same time since, when an input is negative, its value is converted to 0, not activating the corresponding neuron. This MLP neural network with a single hidden layer using the ReLU activation function achieved a good prediction performance, as shown ahead, and thus a more complex multiple-hidden layer MLP neural network was not required.The adopted loss function for the MLP network was the Mean Absolute Error (MAE) and the optimization algorithm was Adam (Adaptive Moment Estimation), used instead of the classical stochastic gradient descent procedure to update the network weights. The training process was limited by a total of 100 epochs. These parameterization was achieved by trial and error.

Table 3.2 - Neural network hyperparameters using hydrological station data.

Hyperparameter	Value
Batch size	100
Loss	MAE
Optimizer	Adam
Activation function	ReLU, Linear

SOURCE: Author production.

Figure 3.2 - The architecture of the proposed MLP network.



SOURCE: Author production.

This work employs two metrics to evaluate the prediction performance of the proposed neural network. The first one is the Nash–Sutcliffe model efficiency coefficient (NSE), commonly used for hydrological models and defined as:

$$NSE = 1 - \frac{\sum_{t=1}^{T} (O_t - P_t)^2}{\sum_{t=1}^{T} \left(O_t - \overline{O}\right)^2} \quad , \tag{3.1}$$

where $\overline{O}$ is the mean of the observed value in the time interval $[1, T]$ that contains T discrete values, P_t is the predicted value at time t, and O_t is the observed value at time t. The NSE is qualitatively equivalent to the correlation coefficient between predicted and observed data. The better the prediction, the higher is the NSE above the threshold value of 0.5, but it is difficult to reach the top value of 1.0 that corresponds to a perfect prediction. The second metric is the well known root mean square error (RMSE), which is the standard deviation of the prediction errors. It is also calculated here for the discrete times t in the interval $[1, T]$, and its value should be close to zero for a good prediction. RMSE is defined by the following equation:

$$RMSE = \sqrt{\frac{\Sigma_{t=1}^{T}\Big(P_t - O_t\Big)^2}{T}} \quad , \tag{3.2}$$

where P_t and O_t are respectively the predicted and observed values at time t, as in the former equation for NSE.

Input data were split as follows: 70% for the training, 17.5% for the validation, and 12.5% for the neural network test. Data from December 2011 to January 2013 with randomly sorted samples were used for training and validation, while data from February and March 2013 was used for the test.

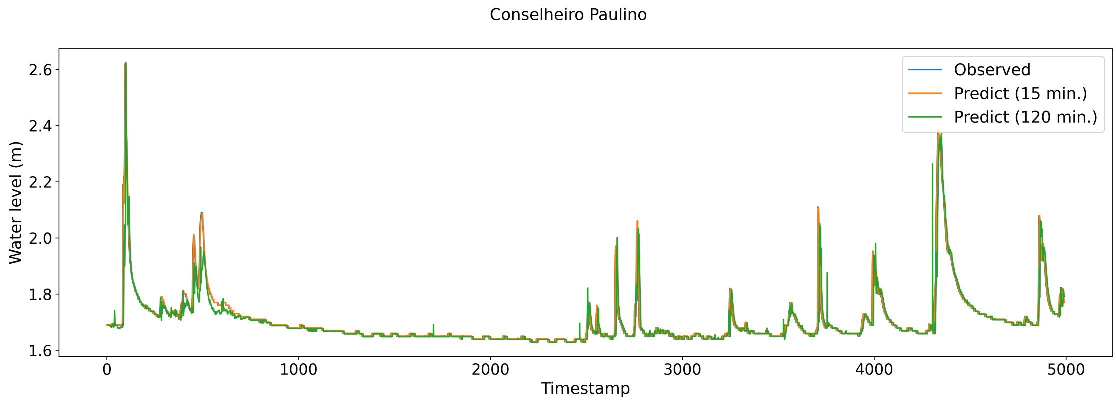
3.3 Results and discussion

In this work, we proposed a neural network to predict a water level temporal series at the outlet of the watershed using as input temporal series of water level and/or rainfall at different hydrological monitoring stations. The prediction is done for antecedences ranging from 15 to 120 minutes.

Three set of tests were performed, based on different combinations of the available input datasets. The first test employs only water level data, the second one uses only rainfall data, while the third one inputs both water level and rainfall data. All tests were devised for the prediction of the water level at the Conselheiro Paulino station for up to 2 hours antecedence using as input the datasets from the five hydrological monitoring stations described above.

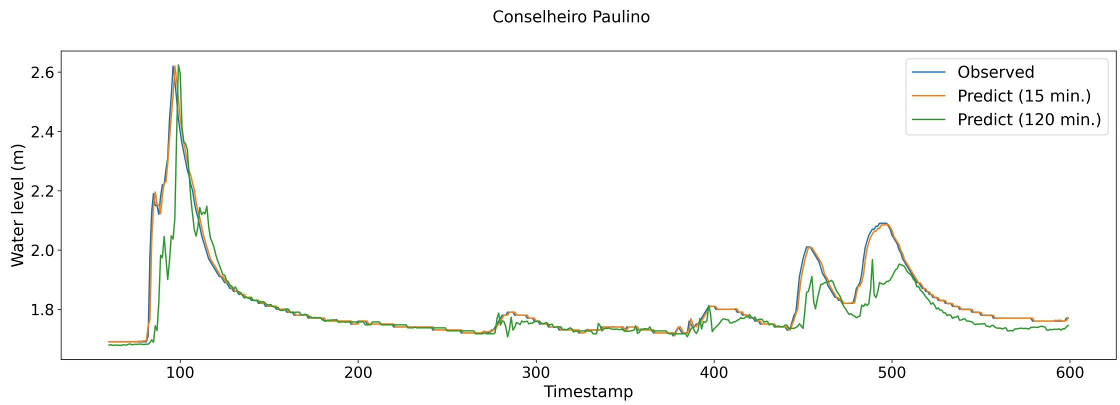
Predicted and actual/observed temporal series of the water level at the Conselheiro Paulino station with an antecedence of 15 and 120 minutes is shown in Figure 3.3 for a period of nearly 5,000 time intervals, corresponding to about 52 days of the months of February and March 2013. More detailed curves of the same predicted and actual/observed temporal series are shown in Figure 3.4 for time intervals 60 to 600 and in Figure 3.5 for time intervals 2500 to 2800, but in this case, for all five antecedences from 15 to 120 minutes. Input data included water level and rainfall temporal series. These figures show a good agreement between predicted and actual values.

Figure 3.3 - Observed and predicted values of water level at the outlet for 15 and 120 minutes of antecedence considering all the 5,000 time intervals.



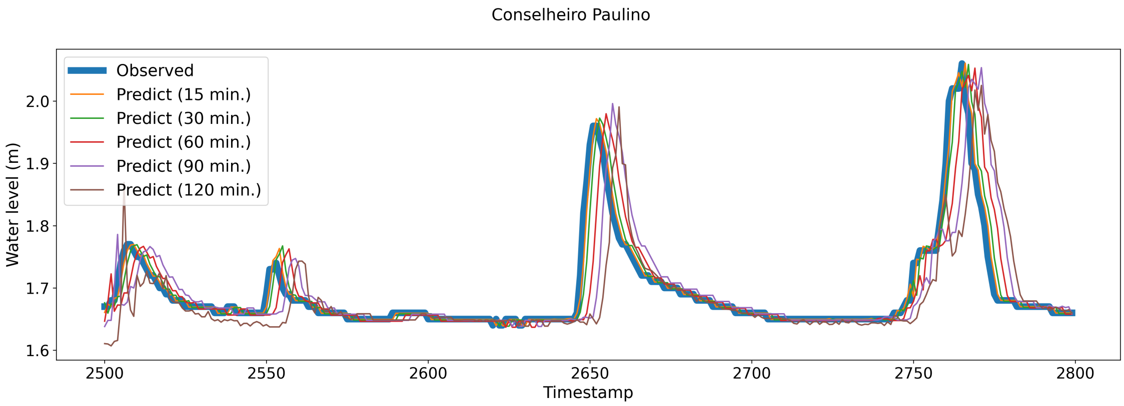
SOURCE: Author production.

Figure 3.4 - Observed and predicted values of water level at the outlet for 15 and 120 minutes of antecedence considering time intervals 60 to 600.



SOURCE: Author production.

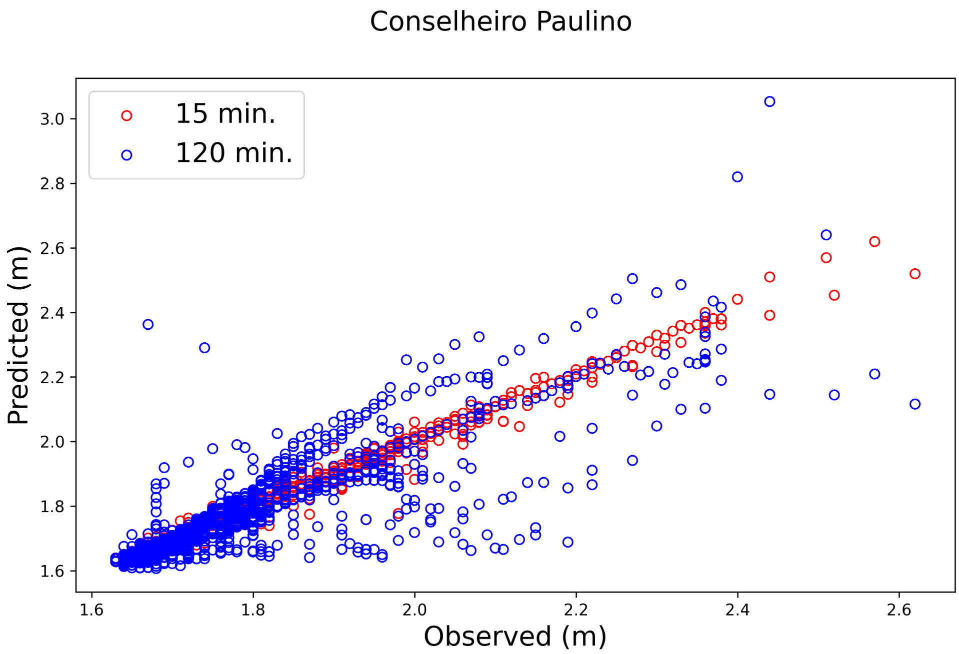
Figure 3.5 - Observed and predicted values of water level at the outlet for 15, 30, 60, 90 and 120 minutes of antecedence considering time intervals 2500 to 2800.



SOURCE: Author production.

The scatter plot between the predicted and observed values of the water level (in meters) at the outlet of the watershed, for 15 and 120 minutes of antecedence, is shown in Figure 3.6.

Figure 3.6 - Scatter plot between predicted and observed values of water level at the outlet of the watershed for 15 and 120 minutes of prediction antecedence.



SOURCE: Author production.

The performance of the three sets of predictions can be evaluated in Table 3.3 for the NSE and Table 3.4 for the RMSE. Both tables show the values of these two metrics for antecedences from 15 to 120 minutes and for the three different sets of input time series: only water level, only rainfall and water level and rainfall. According to Table 3.3 and 3.4, the test with only rainfall inputs did not succeed, showing very low values of NSE and higher values of RMSE in comparison to other other two sets of predictions. When only water level inputs were considered, the performance was good, the RMSE did not exceed 0.0066 and the NSE was at least 0.8858. Adding rainfall inputs besides the water level ones, the performance sligthly improves for all regarded antecedences, raising these values to 0.0063 (RMSE) and 0.9016 (NSE). As expected, on these two sets of tests, the quality of the prediction decreases as the antecedence increases.

Figure 3.3 shows that the agreement between observed and predicted values is substantially better for 15 than for 120 minutes antecedence. The mismatch is more accentuated when the variation of the water level is high, especially when the water level is increasing. As seen in Figure 3.5, the prediction curve is delayed in relation to the observed one, with the delay increasing as the antecedence of prediction increases. However, the delay is rather small, being all the observed water level peaks at the outlet reproduced by the predictions.

Table 3.3 - Values of NSE for the different predictions.

Antecedence	Water level	Rainfall	Water level + Rainfall
15 min.	0.9941	0.0692	0.9944
30 min.	0.9827	0.082	0.9842
45 min.	0.9682	0.1007	0.9715
60 min.	0.9537	0.1135	0.9589
75 min.	0.9381	0.1202	0.947
90 min.	0.9182	0.1343	0.9301
105 min.	0.902	0.1377	0.9159
120 min.	0.8858	0.1406	0.9016

SOURCE: Author production.

Table 3.4 - Values of RMSE (in meters) for the different predictions.

Antecedence	Water level	Rainfall	Water level + Rainfall
15 min.	0.0013	0.0353	0.0013
30 min.	0.0022	0.0352	0.0022
45 min.	0.0031	0.0351	0.0031
60 min.	0.0039	0.0351	0.0038
75 min.	0.0047	0.0349	0.0046
90 min.	0.0054	0.0348	0.0052
105 min.	0.006	0.0347	0.0057
120 min.	0.0066	0.0346	0.0063

SOURCE: Author production.

The scatter plot of Figure 3.6 indicates that, in general, the models for 15 and 120 minutes of antecedence have no bias to overestimate or underestimate the prediction. The mean errors (mean difference between observed and predicted values) of both models were close to zero, 0.0002 and 0.0044 respectively, which confirms this fact.

3.4 Conclusions

We proposed in this work the use of a neural network to predict temporal series of water level at the outlet of a watershed with antecedences ranging from 15 to 120 minutes using as input data temporal series of (i) water level or (ii) rainfall or (iii) both, collected by five hydrological monitoring stations in the watershed.

We trained and validated the neural network using temporal series of water level and rainfall data comprising 14 months of data with a temporal resolution of 15 minutes and tested using two months of data. We found a good agreement between the predicted and actual time series for an antecedence of 15 minutes using the neural network trained with water level and rainfall data. The quality of the predictions was assessed with the NSE and RMSE metrics. Naturally, higher antecedences resulted in prediction with lower accuracy, but NSE was above 0.94 for up to a 75-minute antecedence using water level and rainfall data or up to 60-minute antecedence using only water level data. In both cases, RMSE was very low. On the other hand, predictions using only rainfall data did not succeed.

The proposed approach was tested for a case of study, showing the possibility of its use in an operational scenario. As future work, we propose to compare these results to the results obtained by other hydrological prediction models and to perform further prediction tests for other Brazilian watersheds. In addition, it is intended to perform an operational test of this forecasting tool using data from the network of hydrological monitoring stations of the Brazilian Centre for Monitoring and Early Warnings of Natural Disasters (CEMADEN).

4 CASE STUDY 2: EMPIRICAL HYDROLOGICAL FORECAST WITH DATA FROM WEATHER RADAR

This chapter presents the second case study, which proposes a multilayer perceptron neural network to forecast temporal series of water level at the outlet of a watershed using meteorological radar data. The content of this chapter will be submitted to a journal to be defined.

4.1 Introduction

On the one hand, precipitation is one of the most difficult atmospheric variables to measure due to its high variability in a small spatial and temporal scale. On the other hand, it is the most critical input in a hydrometeorological model (ZHU et al., 2016). According to Bacelar (2017), sudden floods require the nowcasting of the precipitation estimative to be predicted in real-time and timely to send and receive alerts. However, it points out that many uncertainties follow this estimate, depending on the meteorological process involved. Although, as presented in Silva (2021), a model based on neural networks for level prediction, taking rainfall data as input, can represent the hydrological system of the basin, even with a disturbance in the input data.

Reliable predictions of the occurrence of extreme events with high spatial and temporal resolution and for a very short time horizon (up to 6 hours) are fundamental since many of these events develop quickly and are usually localized in nature (SPYROU et al., 2020). Monitoring, with short-term forecasting, becomes even more important in small watersheds, which are usually where these events occur (VIVONI et al., 2006). Moreover, several works point to weather radar and monitoring and warning systems for this type of watershed, especially urban ones, which have a shorter concentration time, due to urbanization and where significant losses occur (SHARIF et al., 2006; HORITA et al., 2018).

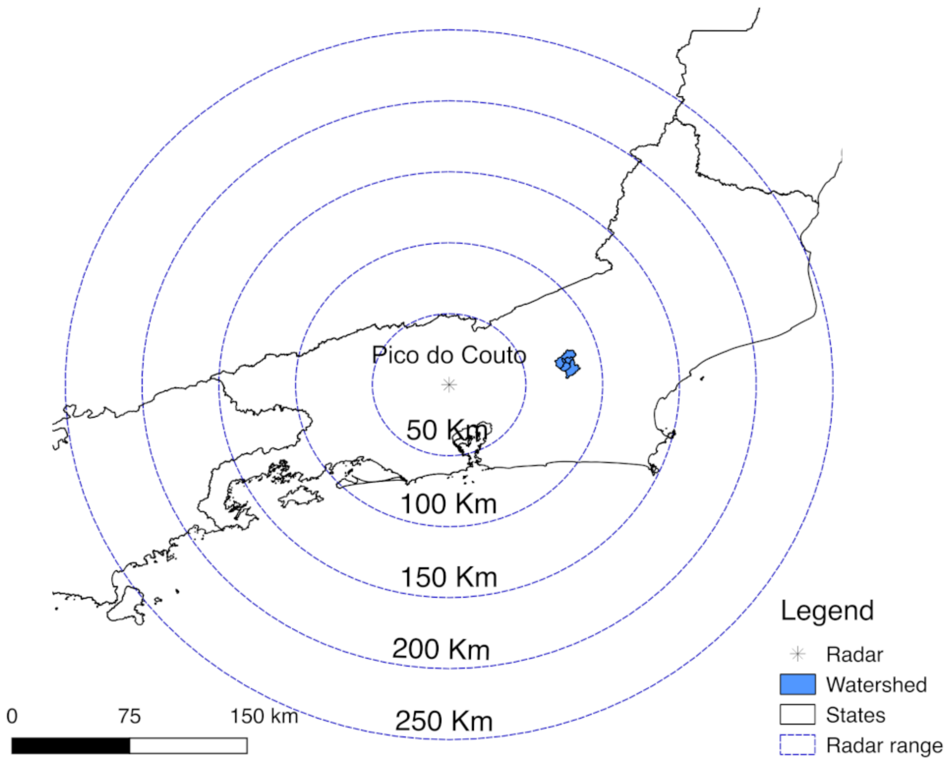
In this context, this work uses weather radar data to predict the water level for a small watershed located in the mountain region of Rio de Janeiro through neural networks. We trained the model and evaluated its performance for two short-term predictions: 15 and 120 minutes.

4.2 Data and method

The upper reaches of the Rio Grande watershed locate the study area of this work, in the sub-watershed of the Bengalas river locates the study area of this work. It is a small watershed located in the mountain region of Rio de Janeiro, in the city of Nova Friburgo. Due to the inadequate occupation of slopes and river channels, the city is subject to risks of landslides and floods (FUNDAÇÃO COPPETEC, 2007). According to (WORLD METEOROLOGICAL ORGANIZATION (WMO), 2021), in this region, the second most tragic event in South America happened between 1970 and 2019, where more than 900 people died. It is a mountainous region with a steep slope and densely urbanized. With a drainage area of approximately 190 km^2, the watershed concentration time is around 2 hours.

For training the neural network, data from the weather radar Pico do Couto, installed in the 1990s, in the city of Petrópolis, Rio de Janeiro, and operated by the Department of Airspace Control (DECEA) were used. In this work, the watershed studied is located within a radius between 50 and 100 km from the radar installation, as can be seen in Figure 4.1.

Figure 4.1 - Cover area of Pico do Couto radar.

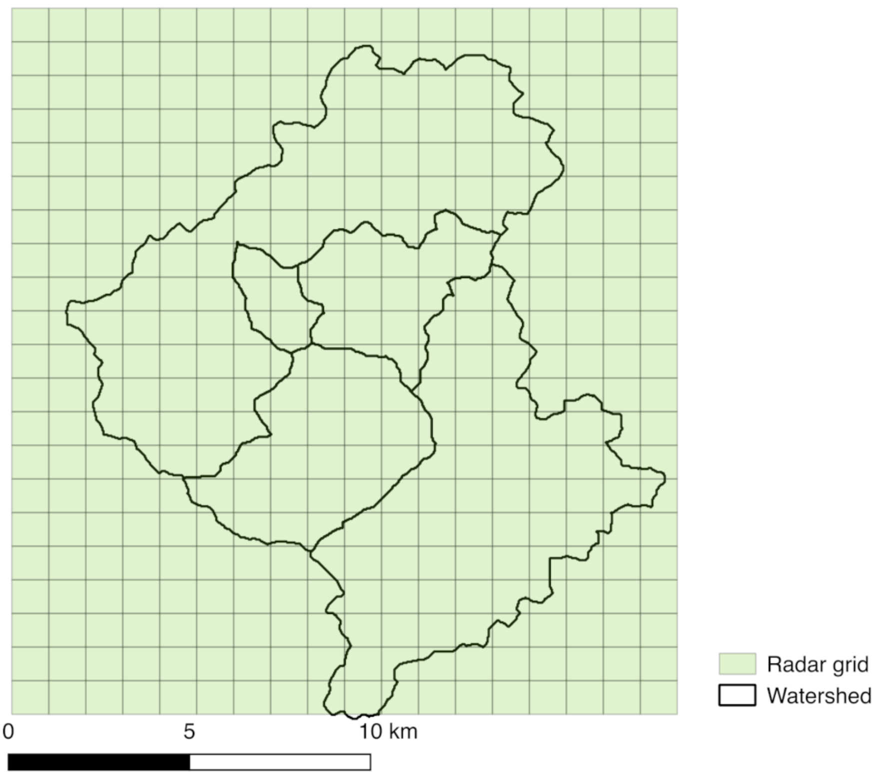


Cover area of Pico do Couto radar with the watershed under study in this work.
SOURCE: Author production.

Data from December 1, 2011, to March 31, 2013, was used, with the same period plus seven days of the period used in the network trained with the station data. During this period, the temporal resolution of the radar was 15 minutes, being that currently, the resolution is 10 minutes. Approximately 69% of the data were available for the analyzed period, totaling 32271 instants. This lack of data can occur due to several factors, such as internet signal failure at the station located next to the radar, the inoperability of the radar for maintenance, or some technical failure. In addition, it can occur for a few moments or even for months.

The spatial resolution of the radar product used (CAPPI - 3 km) is approximately 1 km, represented by a matrix of 500 by 500 points. A clipping was made, considering all the points in the surrounding watershed's quadrant, totaling 378 points. Figure 4.2 represents this clipping on grid way, where each square represents a radar grid point.

Figure 4.2 - Radar grid points around the watershed.

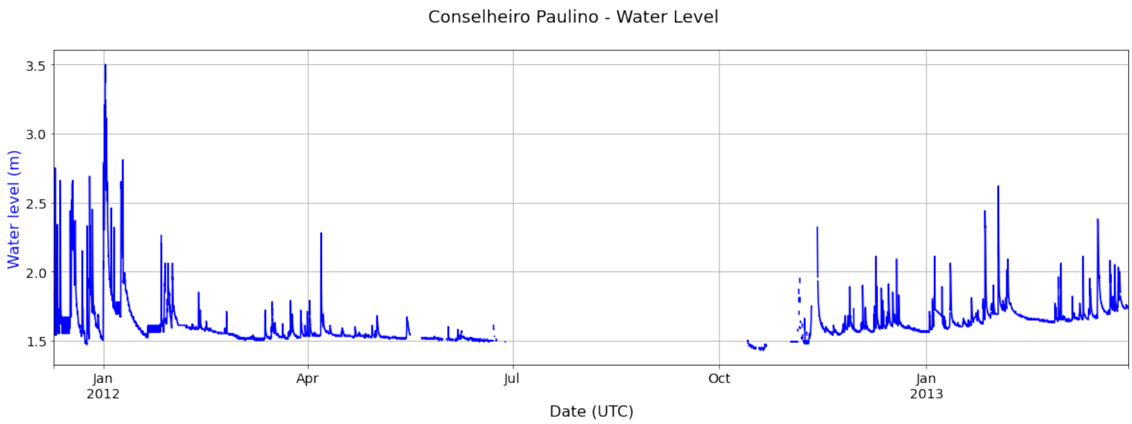


SOURCE: Author production.

This study used the current radar data in reflectivity and calculated the accumulated, considering up to 48 hours. As the reflectivity has a logarithmic scale, it was necessary to convert the reflectivity data (dBZ) to the rain rate (mm/h) to calculate the accumulated data. For this, was used the Marshal Palmer relation (MARSHALL; PALMER, 1948). Values under 20 dBZ, which corresponds to approximately 1 mm/h, were disregarded. This was done to avoid possible noise in the data.

In addition to the radar data, used water level data from a hydrological monitoring station of the State Environmental Institute (INEA) as network output. Located in Nova Friburgo (RJ), the station used is Conselheiro Paulino, which is at the lowest point of the watershed. The same period of the radar data was used, and the temporal resolution is also the same, 15 minutes. This time series is complete, so the periods in which there is no radar data were discarded. Figure 4.3 presents the time series of these data, where it is possible to observe the absence of data between the end of June and the beginning of October 2012.

Figure 4.3 - Water level time series for Conselheiro Paulino station.



SOURCE: Author production.

The network architecture we use is the MLP, implemented in the Python language, using the Keras library. Three hidden layers were used, with 120, 50, and 10 neurons, respectively, and one neuron in the output layer. In the literature, so far, there is no consensus on the best way to define the number of hidden layers and neurons for a neural network. Several methods have already been suggested (LI et al., 1995; TAMURA; TATEISHI, 1997; XU; CHEN, 2008; SHIBATA; IKEDA, 2009; HUNTER et al., 2012; SHEELA; DEEPA, 2013). However, Vujicic et al. (2016) evaluated these methods and concluded that the methods have different results for each dataset. So they can be used to initialize a network topology, but to reach a good configuration is necessary to carry out the training and testing process until finding the ideal result. The best configuration is related to the dataset and the problem to be solved, hence the difficulty in generalizing a method.

Table 4.1 presents the hyperparameters used in the network configuration. It was the best configuration found. However, to reach these values, several tests were performed. The input data were normalized to values between 0 and 1, thus making the network learning process faster. One of the ways to avoid overfitting the network is to define a time to stop training. Thus, the network training is finished when the learning process stops evolving, considering the validation dataset. In the Keras library, this process is called EarlyStopping, and we use it to train this network, so the number of epochs varies for each test run.

Table 4.1 - Neural network hyperparameters using radar data.

Hyperparameter	Value
Batch size	1024
Loss	MSE
Optimizer	Adam
Learning rate	1e-3
Activation function	ReLU, ReLU, ReLU, Linear

SOURCE: Author production.

Input data were randomly sorted and were split as follows: 80% for training, 10% for validation, and 10% for the neural network test. The same distribution was considered for all tests.

4.3 Results and discussion

We proposed a neural network trained to predict the water level for the Conselheiro Paulino station, 15 and 120 minutes in advance. Thus, in both networks, the radar data up to the current instant was passed in the input layer (t) and the target, for the 15 minutes forecast, was the level for the instant t+1, and in the 120 minutes forecast, the network target was the level for the instant t+8. Performed tests, considering as input the current value (value observed at instant t) in reflectivity and the value converted into rain rate. In addition, we test performed considering the accumulated values for 1, 2, 6, 12, 24, and 48 hours of the radar. Performed the training, validation, and testing process for all tests, and the network's hyperparameters were maintained, varying only the network's input data.

Tables 4.2 and 4.3 presents the tests performed and the metrics evaluated were the NSE and RMSE. These were the metrics obtained from the test dataset.

Table 4.2 - Network performance for a 15 minutes forecast.

Input	Epochs	RMSE	NSE
Current (dBZ)	119	0.1053	-0.2567
Current (mm/h)	266	0.0983	0.0882
Acc. 1 hour (mm)	270	0.0743	0.5486
Acc. 2 hours (mm)	351	0.0572	0.6996
Acc. 6 hours (mm)	152	0.0601	0.7099
Acc. 12 hours (mm)	241	0.0380	0.8779
Acc. 24 hours (mm)	186	0.0329	0.8769
Acc. 48 hours (mm)	179	0.0391	0.8495

SOURCE: Author production.

Table 4.3 - Network performance for a 120 minutes forecast.

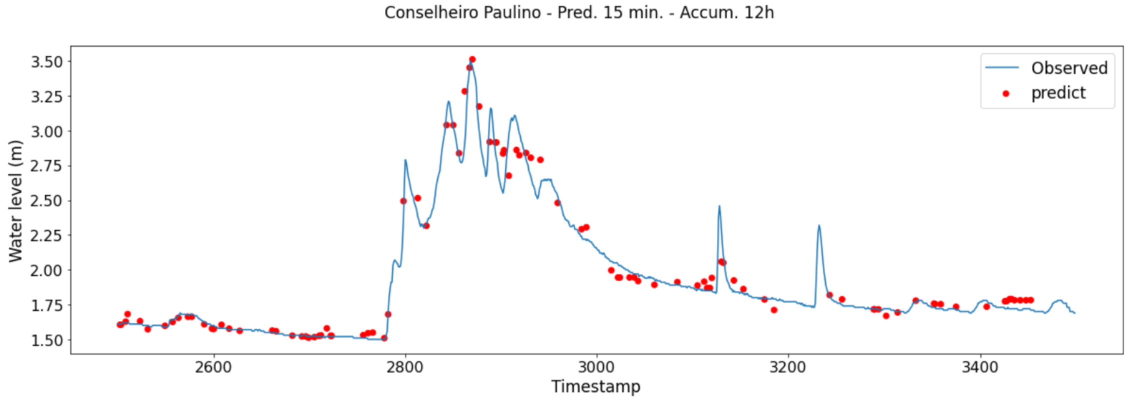
Input	Epochs	RMSE	NSE
Current (dBZ)	113	0.1033	-0.1978
Current (mm/h)	249	0.0972	0.2122
Acc. 1 hour (mm)	331	0.0754	0.4929
Acc. 2 hours (mm)	258	0.0650	0.6621
Acc. 6 hours (mm)	266	0.0434	0.7960
Acc. 12 hours (mm)	183	0.0416	0.8590
Acc. 24 hours (mm)	186	0.0366	0.8588
Acc. 48 hours (mm)	123	0.0508	0.7792

SOURCE: Author production.

The results show a good performance of the network, mainly from the accumulated of 6 hours, both for the forecast of 15 and 120 minutes, being that the best result was obtained considering a cumulative 12 hours. As the time of concentration of the watershed is less than 2 hours, it is expected that the accumulation of rainfall up to 2 hours would be enough for the learning of the network, however, this need for a greater accumulation may be related to soil moisture.

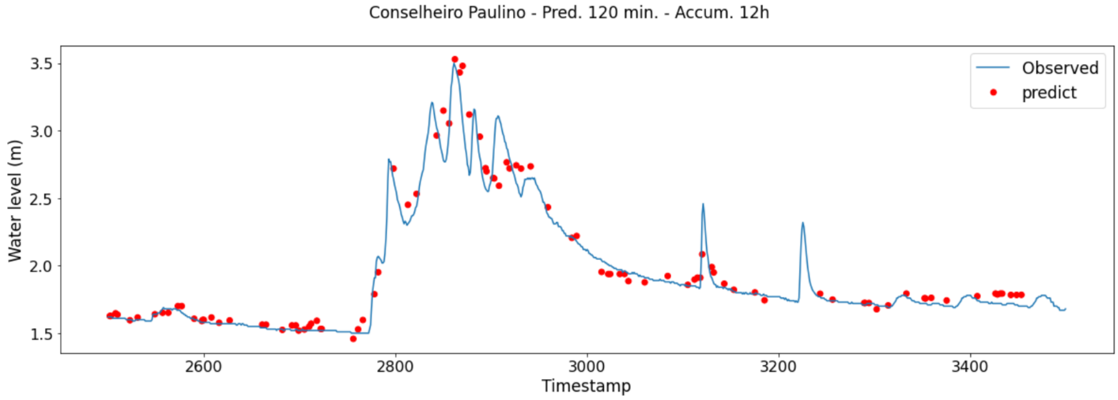
Figures 4.4 and 4.5 present the observed and predicted values for 15 and 120 minutes using the accumulated 12 hours for a part of the test dataset, between December 29, 2011 and January 8, 2012 considering the period where the highest value was observed in the time series. In both time series, the predicted value was plotted as a point to represent that only these instants were used for the network test.

Figure 4.4 - Observed and predicted time series for 15 minutes, between December 29, 2011 to January 8, 2012.



SOURCE: Author production.

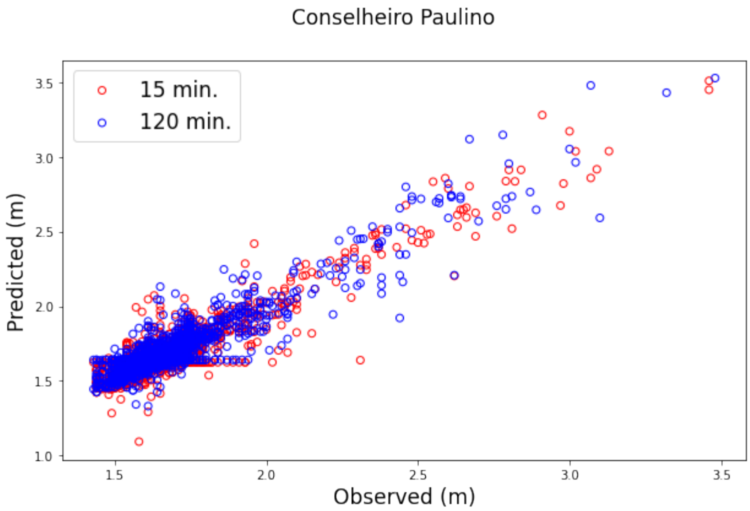
Figure 4.5 - Observed and predicted time series for 120 minutes, between December 29, 2011 to January 8, 2012.



SOURCE: Author production.

The scatter plot between the predicted and observed values of the water level (in meters) at the watershed outlet for 15 and 120 minutes of antecedence is shown in Figure 4.6. For both forecasts, it is possible to observe a great correlation between the predicted and the observed, even for the highest water level values.

Figure 4.6 - Scatter plot between predicted and observed values of water level at the outlet of the watershed for 15 and 120 minutes of prediction antecedence using weather radar.



SOURCE: Author production.

As well as the best number choice of layers and neurons for the network, the selection of the best input features also does not have a rule for its definition, requiring tests to be performed. In this work, performed tests, considering as input only the radar cell corresponding to the watershed outlet and its eight neighbors, using nine inputs. However, as can be seen in Tables 4.4 and 4.5, the network performance was not good, even considering the accumulated ones. In this case, the best result obtained was considering the accumulated 48 hours as input to the network.

Table 4.4 - Network performance for a 15 minutes forecast considering only the target cell and its 8 neighbors.

Input	RMSE	NSE
Current (dBZ)	0.0907	0.0679
Current (mm/h)	0.0929	0.0863
Acc. 1 hour (mm)	0.0919	0.1290
Acc. 2 hours (mm)	0.0935	0.1351
Acc. 6 hours (mm)	0.0924	0.2272
Acc. 12 hours (mm)	0.0801	0.3656
Acc. 24 hours (mm)	0.0750	0.4971
Acc. 48 hours (mm)	0.0675	0.5958

SOURCE: Author production.

Table 4.5 - Network performance for a 120 minutes forecast considering only the target cell and its 8 neighbors.

Input	RMSE	NSE
Current (dBZ)	0.0901	0.0559
Current (mm/h)	0.0924	0.0912
Acc. 1 hour (mm)	0.0908	0.1496
Acc. 2 hours (mm)	0.0883	0.1645
Acc. 6 hours (mm)	0.0865	0.2398
Acc. 12 hours (mm)	0.0799	0.3885
Acc. 24 hours (mm)	0.0700	0.4997
Acc. 48 hours (mm)	0.0708	0.5782

SOURCE: Author production.

4.4 Conclusions

We proposed in this work the use of radar data to predict water level for a point that corresponds to the outflow of the watershed using neural networks, presenting a good correlation between the predicted and the observed results.

Even with a concentration time of less than 2 hours, the results show that, even so, having the accumulated rainfall data for a period longer than the concentration time, greatly improves the network's performance. which may have some relation with soil moisture, the network needs a memory of the physical systems, even with no direct relation to physical processes of watershed.

In addition, the poor performance of the network considering only radar data close to the target as input, shows the importance of data distributed in space, such as radar data. However, one of the limitations found in this work is the need for continuous data since, in the analyzed period, more than 30% of the data were not available. Then, as future work, we propose increasing the historical series of the data so that the network can learn more patterns and thus present a better performance.

5 FURTHER AND COMPARATIVE ANALYZES

This chapter presents the results obtained from analyzing the networks developed in the research. The Sensitivity analysis, detailed in this chapter, was presented at the XL Congresso Nacional de Matemática Aplicada e Computacional, CNMAC, 2021(FREITAS et al., 2021). With the network already trained using station data, tests were done with other periods to test the network performance. For this same network, an analysis was performed to predict the flow. Moreover, an analysis was made for the network trained using radar data considering the network's weights.

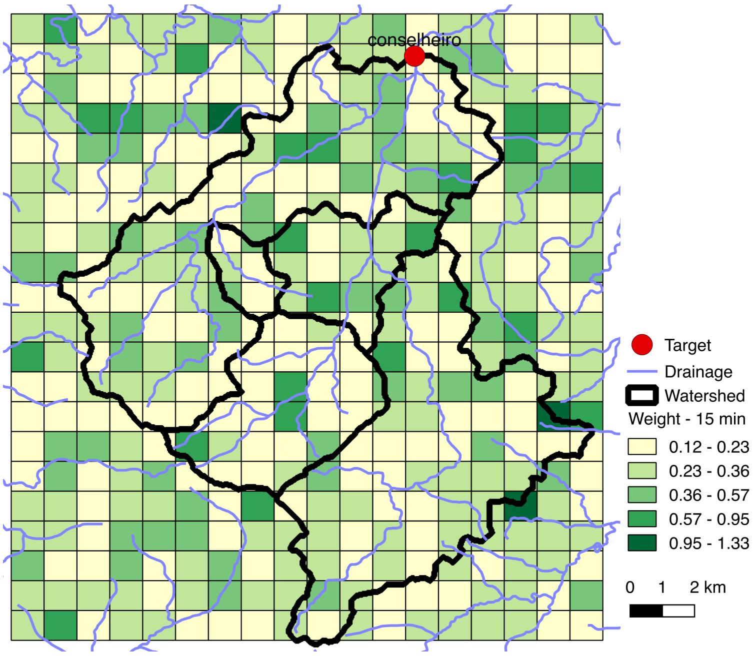
5.1 Weight analysis

For the network trained using radar data and the accumulated 12 hours as input, we performed an analysis considering the input layer's weights. Each entry corresponds to a cell of the radar data and is associated with a geographic coordinate. This analysis's objective was to verify if there is any correlation between the network's weights and the relief and hydrology data of the watershed. One of the limitations related to the use of ANN is related to the fact that it is a 'black box', without many concepts and physical relationships involved in its development process (ASCE TASK COMMITTEE, 2000). Because of it, this attempt to seek a relationship with hydrology variables.

From the network's weights, for the input layer, the minimum, maximum, average, and sum values for each of the inputs were extracted. Figures 5.1 and 5.2 present a spatialization of the maximum values of the weights, considering the forecast for 15 and 120 minutes. For each radar grid point used as a network input, the maximum weight for that input was assigned. With this spatialization, it was possible to analyze the relationship of the weights with the altimetry, with the drainage network, with the fact that the point is inside or outside the watershed, and the relationship of the weights with the proximity of the network target. However, between these analyses, no relationship was observed.

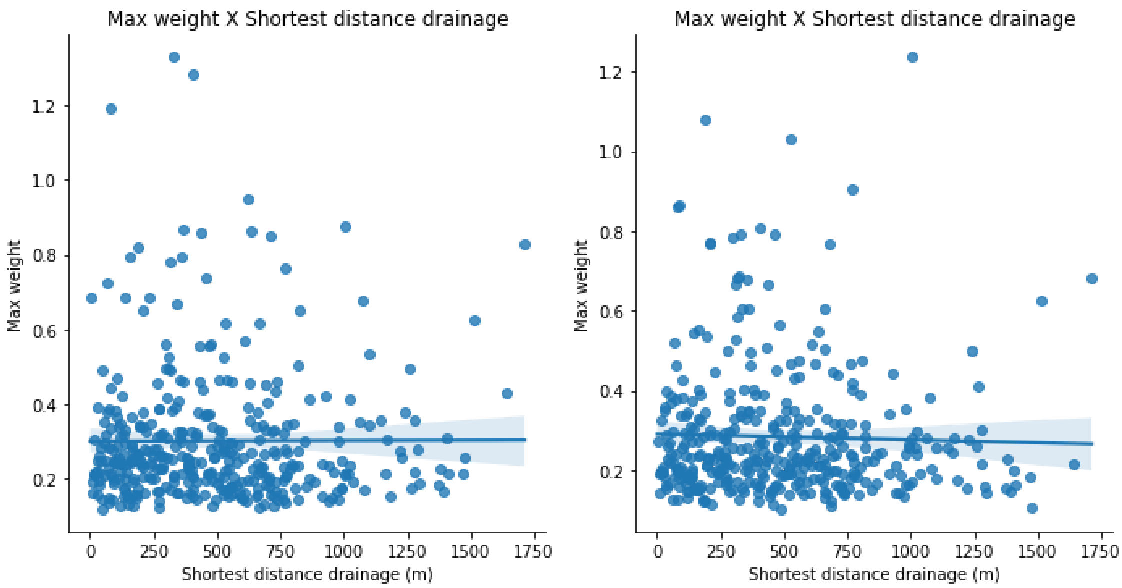
Another analysis was performed considering the maximum weight and the smallest distance between the center point of the radar cell and the drainage network. Figure 5.3 presents this correlation. The objective of this analysis was to verify if the weights have any correlation with the drainage network. However, it was possible to conclude that there is no correlation.

Figure 5.1 - Analysis of the maximum weights of the radar network for 15 minutes forecast.



SOURCE: Author production.

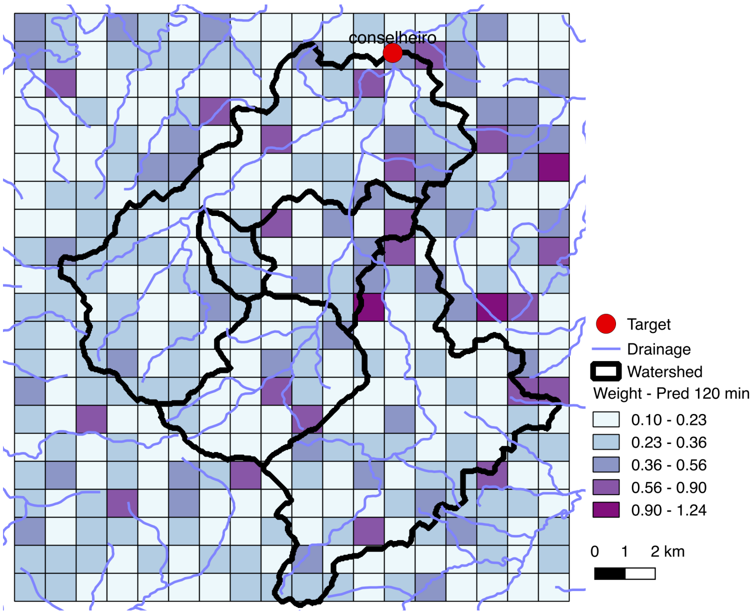
Figure 5.3 - Maximum weights in relation to drainage.



Obtained weights with the trained network using as input the accumulated 12 hours for 15 and 120 minutes forecasts.

SOURCE: Author production.

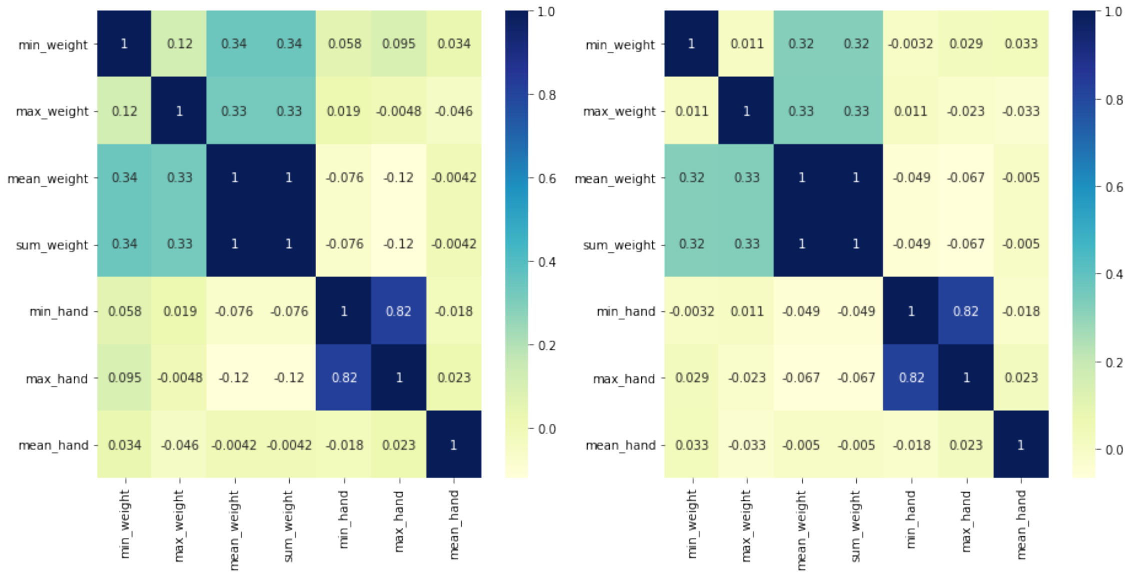
Figure 5.2 - Analysis of the maximum weights of the radar network for 120 minutes forecast.



SOURCE: Author production.

Still, about the weights, a final analysis was made considering the ground model HAND (Height Above Nearest Drainage). Developed by Brazilian researchers, the HAND corresponds to a topographical normalization of the landscape that uses the Digital Terrain Model (DTM) as input and provides as output, a new normalized DTM, which can be classified according to vertical distances relative to watercourses closer (NOBRE et al., 2011). TerraHidro software (INSTITUTO NACIONAL DE PESQUISAS ESPACIAIS (INPE), 2007) was used to generate the model for this analysis. Figure 5.4 shows the results of this last analysis, where it is also possible to observe that these data are not related to the network's weights.

Figure 5.4 - Maximum weight in relation to HAND.



Obtained weights with the trained network using as input the accumulated 12 hours for 15 and 120 minutes forecasts.

SOURCE: Author production.

5.2 Sensitivity analysis

Sensitivity analyses are valuable tools for identifying important model parameters, testing the model conceptualization, and improving the model structure (SIEBER; UHLENBROOK, 2005). This analysis can also be applied to models based on neural networks, as seen in Liong et al. (2000), Kia et al. (2012), Wu et al. (2021).

We performed a sensitivity analysis for the network with data from hydrological stations as input to assess each input variable's sensitivity. We carried out the analyses with the forecast for 15 and 120 minutes using the water level and rainfall data as the network input. Initially, the network was trained with ten inputs, being five stations, with rainfall and water level data. The entire training, validation, and testing process performed to this analysis, considers removing one of the inputs in each test, leaving the network with nine inputs. Through the RMSE and NSE metrics, evaluated the impact of each input on the network performance.

The results obtained are in Tables 5.1 and 5.2, in order of worst to best result. The results show that the network target (Water level for Conselheiro Paulino station) at the previous instant is the most important input for both 15 minutes and 120 minutes forecasts. In the 15 minutes forecast, the rainfall variable of the target station indicates that it is important. However, in the 120 minutes forecast, it is not essential.

Table 5.1 - Sensibility model for a 15 minutes forecast.

Suppressed input	*RMSE*	*NSE*
Water level - Conselheiro Paulino	0.02067	0.65103
Rainfall - Conselheiro Paulino	0.00135	0.99379
Water level - Ypu	0.00133	0.99412
Rainfall - Olaria	0.00132	0.99437
Water level - Venda das Pedras	0.00131	0.99440
Rainfall - Venda das Pedras	0.00129	0.99441
Water level - Suspiro	0.00129	0.99446
Rainfall - Ypu	0.00134	0.99448
Rainfall - Suspiro	0.00130	0.99449
Water level - Olaria	0.00132	0.99451

SOURCE: Author production.

Table 5.2 - Sensibility model for a 120 minutes forecast.

Suppressed input	*RMSE*	*NSE*
Water level - Conselheiro Paulino	0.02000	0.67000
Water level - Olaria	0.00612	0.90589
Rainfall - Suspiro	0.00618	0.90608
Water level - Ypu	0.00609	0.90695
Rainfall - Ypu	0.00613	0.90709
Rainfall - Venda das Pedras	0.00614	0.90710
Water level - Suspiro	0.00610	0.90723
Water level - Venda das Pedras	0.00609	0.90778
Rainfall - Olaria	0.00607	0.90905
Rainfall - Conselheiro Paulino	0.00607	0.90922

SOURCE: Author production.

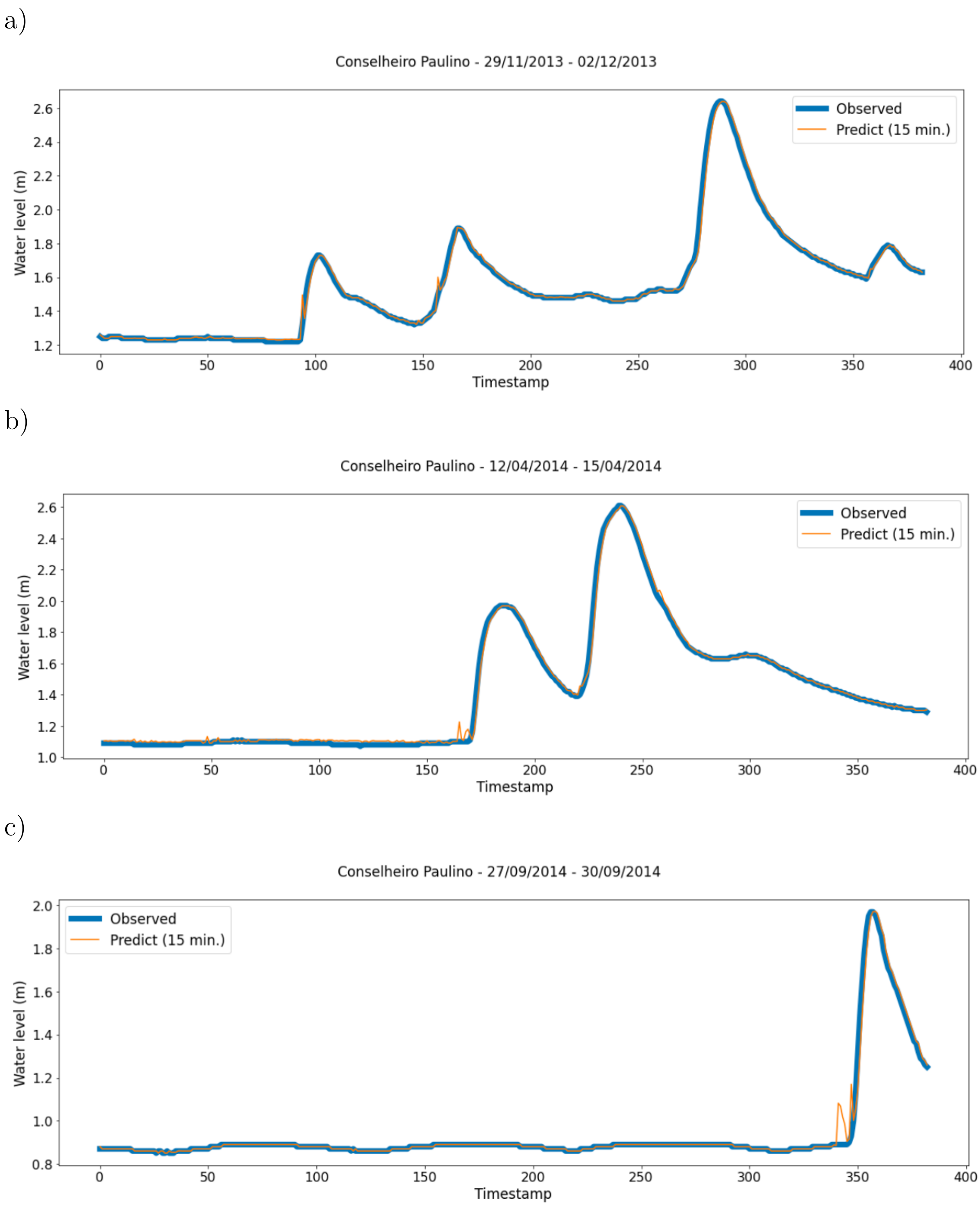
5.3 Analyses with other datasets

Using the network already trained with station data, for the period from December 2011 to March 2013, we carried out a test to verify the network's performance with other periods, being the same used in Bacelar (2017). The periods were: November 29, 2013, to December 02, 2013, April 12, 2014, to April 15, 2014, and September 27, 2014, to September 30, 2014. There were sudden floods in the region under study in these three periods.

Figures 5.5 and 5.6 show the results for the 15 and 120 minutes forecast, respectively. Even after a few years of the period used for training, the network could predict the values for both predictions well. For the 120 minutes forecast, it was possible to obtain an NSE of 0.8805, which can be considered a good result.

Another test was done to verify the network's performance with more recent periods. The period analyzed here was between January 01, 2018, to March 31, 2018. Figures 5.7 and 5.8 present the results obtained for the 15 and 120 minutes forecast, respectively, and confirm the good performance of the network even in more recent periods. In time series, the discontinuity of the lines is due to the absence of one or more network inputs.

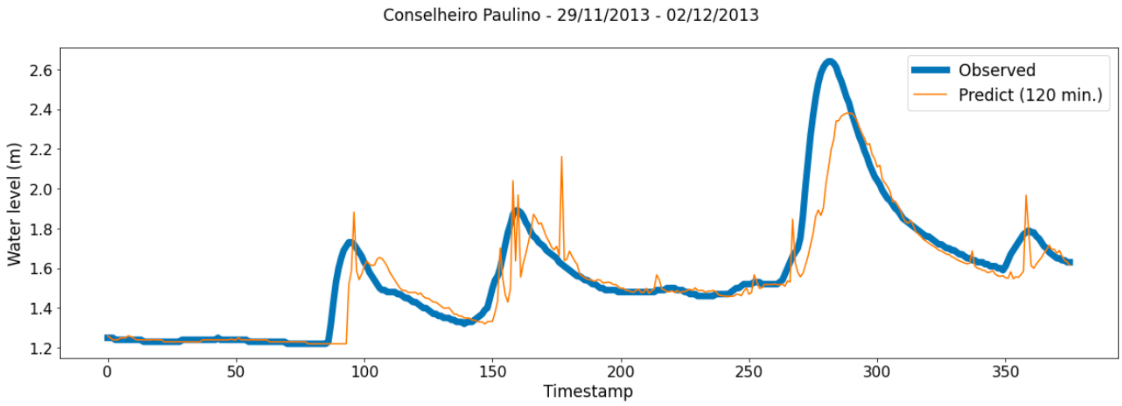
Figure 5.5 - Results with a network already trained for 15 minutes forecast.



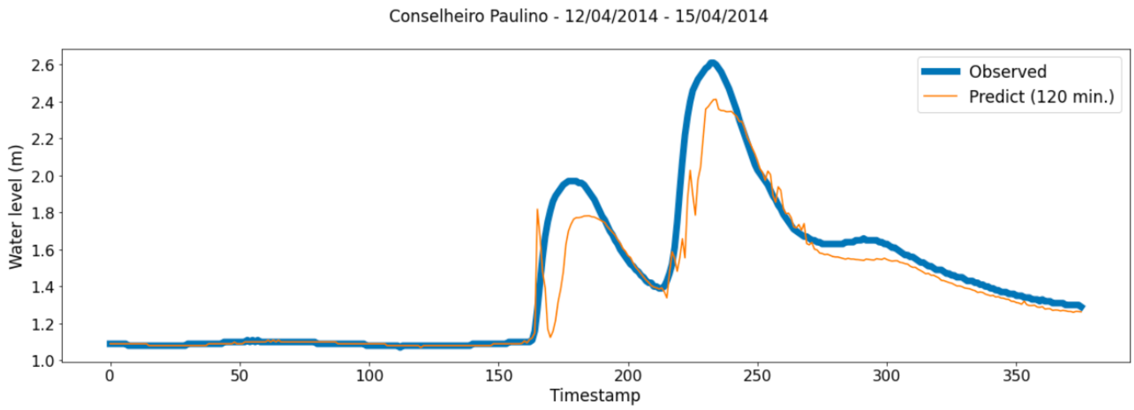
The NSE value obtained for each period was: a) 0.9937; b) 0.9949; c) 0.9831.
SOURCE: Author production.

Figure 5.6 - Results with a network already trained for 120 minutes forecast.

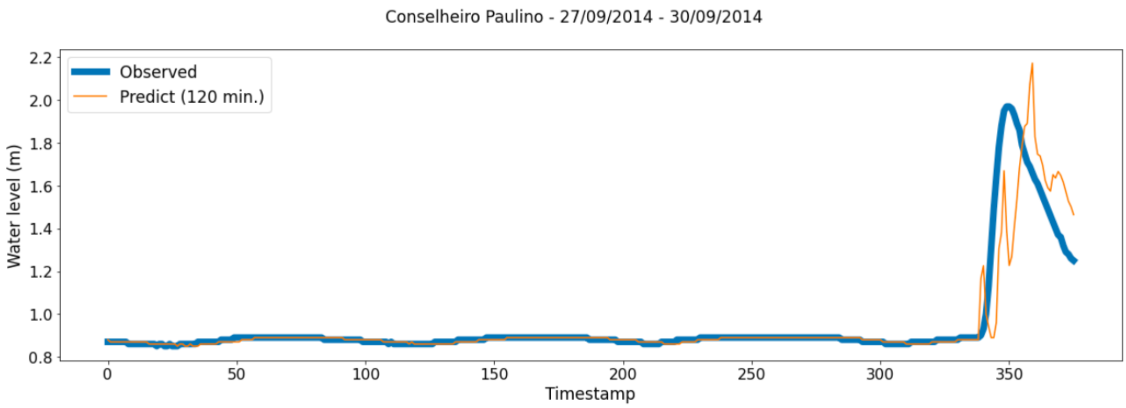
a)



b)

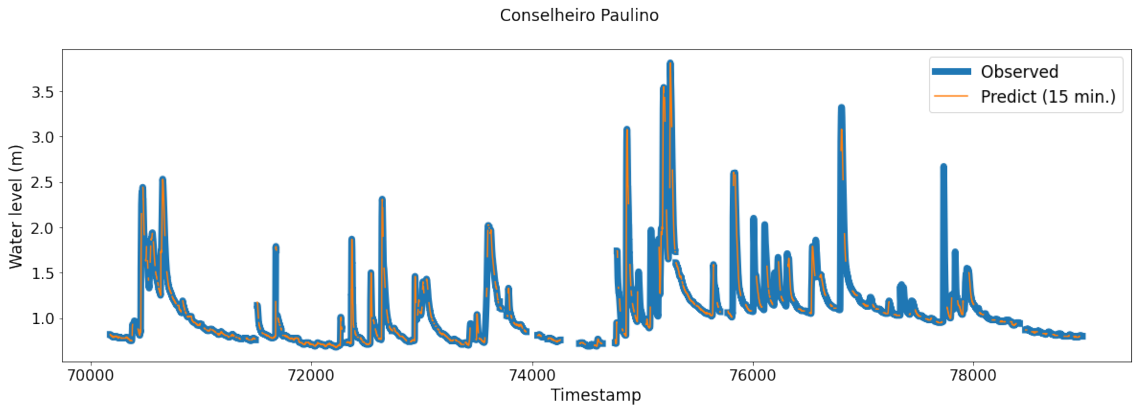


c)



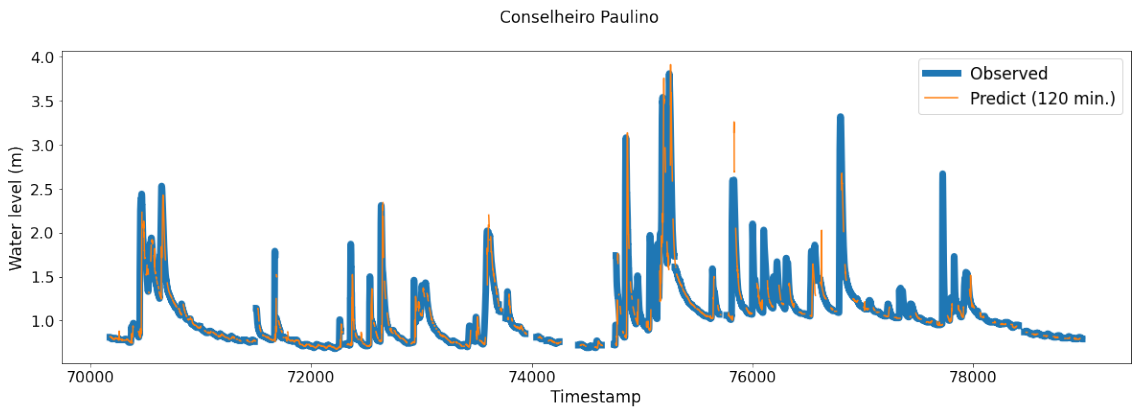
The NSE value obtained for each period was: a) 0.8042; b) 0.8805; c) 0.7335.
SOURCE: Author production.

Figure 5.7 - Results with a network already trained for 15 minutes forecast with recent data.



SOURCE: Author production.

Figure 5.8 - Results with a network already trained for 120 minutes forecast with recent data.

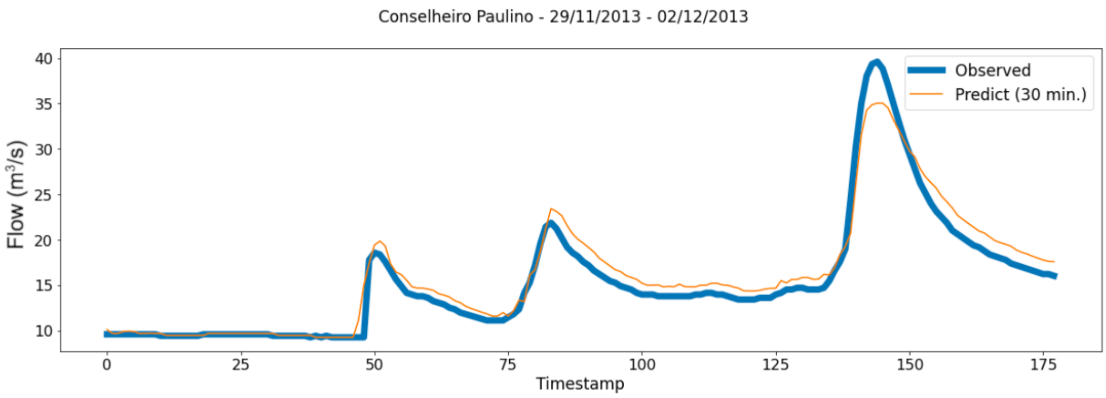


SOURCE: Author production.

5.4 Network analysis for flow forecast

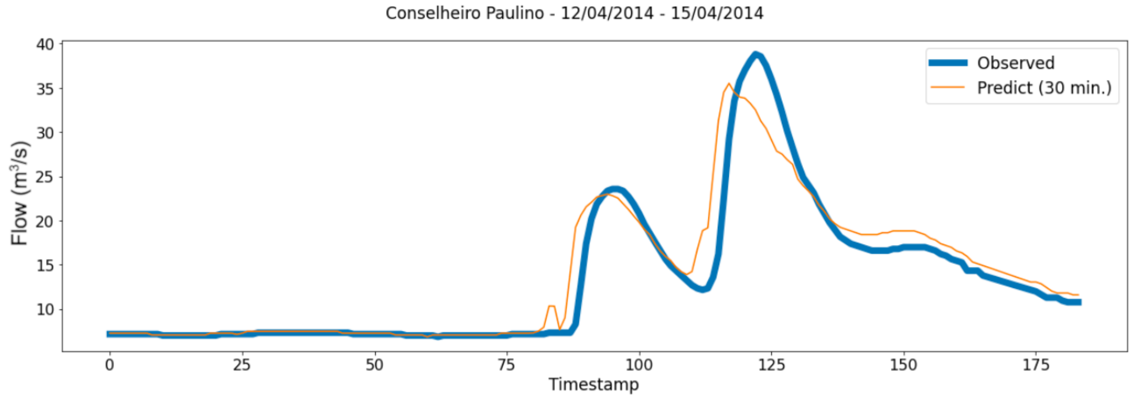
For the same periods analyzed in the previous item, considering the same network already trained were carried out additional tests. However, having as input flow data instead of water level - only for the Conselheiro Paulino station. These flow data are the same used in Bacelar (2017). As the time scale of the flow data is every 30 minutes, the tests were performed with the network trained for 30 minutes forecast. Figures 5.9, 5.10, and 5.11 present the results obtained with the network in each of the analyzed periods, indicating good performance for this prediction. The NSE value obtained for each period was 0.94765, 0.88367, and 0.96158, respectively.

Figure 5.9 - Results with a network already trained for flow forecast - Period 1.



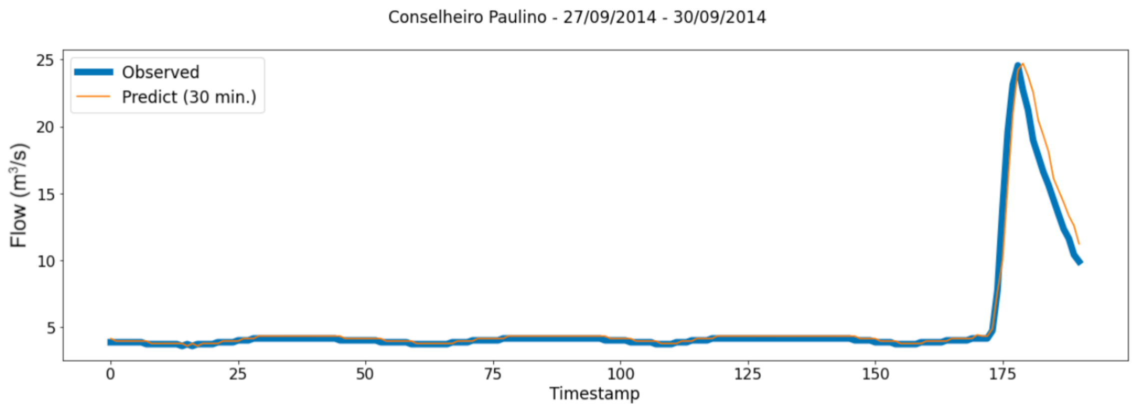
SOURCE: Author production.

Figure 5.10 - Results with a network already trained for flow forecast - Period 2.



SOURCE: Author production.

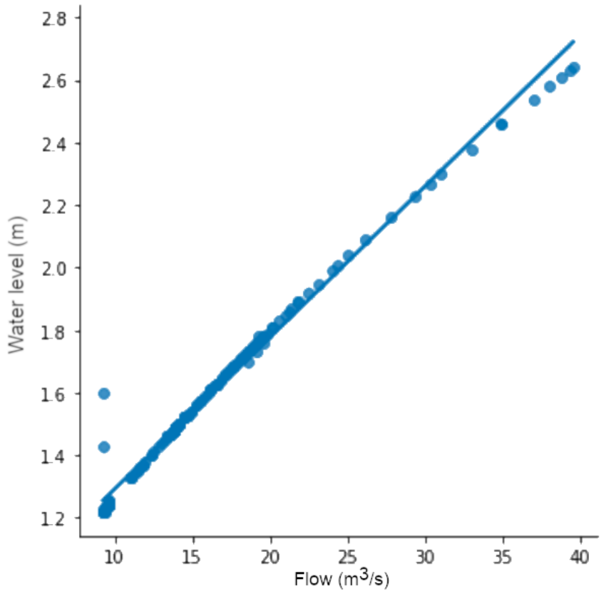
Figure 5.11 - Results with a network already trained for flow forecast - Period 3.



SOURCE: Author production.

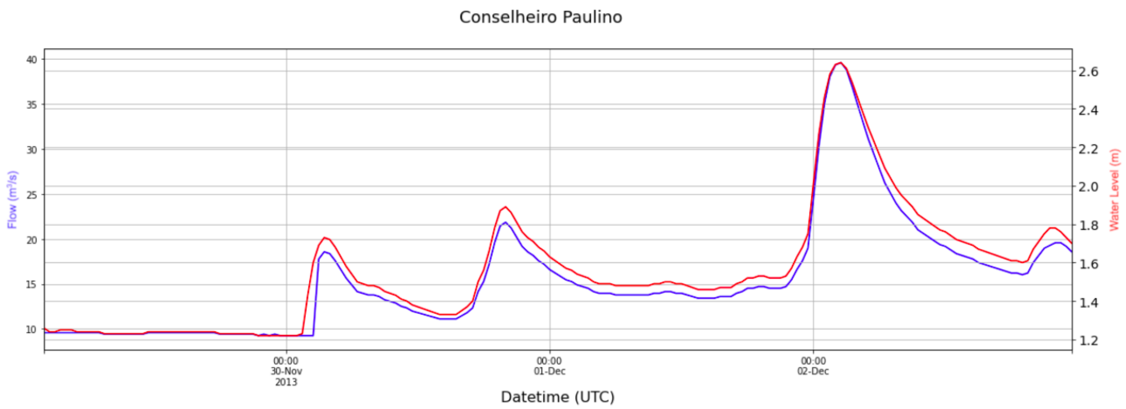
The rating curve can explain this good performance since this point of the watershed can be observed in Figure 5.12. Besides, Figure 5.13 presents the time series of these two variables, which show a strong correlation between them. The graphs show the values observed from November 29, 2013, to December 02, 2013. However, in the other two periods were observed the same behaviors.

Figure 5.12 - Scatter plot between observed values of water level and flow to Conselheiro Paulino station.



SOURCE: Author production.

Figure 5.13 - Observed time series with water level and flow for Conselheiro Paulino station.



SOURCE: Author production.

5.5 Results comparison

Both networks studied here presented a good performance for the short-term water level prediction. Table 5.3 presents the best metrics obtained with each network. The model that uses station data as input showed a better result, even because the level is one of the inputs of this model. The advantage of this fact is that its performance remains good even for a period distant from the one used for training the network. On the other hand, in the model using radar data as input, the advantages are that it was possible to obtain a satisfactory result even using only precipitation data as input, and the performance of this network decreases less as the forecast horizon increases when compared with the model using station data.

Table 5.3 - Better results between the networks.

Input	Antecedence	RMSE	NSE
Station (Water level + rainfall)	15 min.	0.0013	0.9944
Radar (Accum. 12 hours)	15 min.	0.0380	0.8779
Station (Water level + rainfall)	120 min.	0.0063	0.9016
Radar (Accum. 12 hours)	120 min.	0.0416	0.8590

SOURCE: Author production.

With the results obtained in these analyses, it is possible to conclude that a model based on neural networks can present good results, even when we compared to a physical model: in Bacelar (2017), considering the same watershed and period of the radar data-based study, the obtained NSE was 0.56 for the flow forecast - lower than the presented in our study.

6 FINAL REMARKS

Predicting extreme events can avoid significant human and economic losses, especially in densely urbanized regions. The use of ANN for hydrological forecasting can be an excellent tool to mitigate the possible impacts caused by these events. Many works study the performance of networks in large watershed and for a time scale of days. However, as many of these events occur on a very short time scale, a very short-term forecast is essential. Both networks trained in this work showed good water level prediction results, including 2 hours in advance, showing the possibility of using ANN for hydrological prediction in an operational scenario.

The first case study presented a model based on neural networks to forecast temporal series of water level at the outlet of a watershed located in a mountain region in the Brazilian state of Rio de Janeiro with up to a 2 hours antecedence. According to the tests carried out, the network continued to show good results even after five years of the period used for training the network. Even using only the current instant as input data, the network performance was good.

Rainfall data estimated by weather radar was the base of to second case study. Due to their excellent spatial and temporal resolution, these data are quite suitable for very short-term forecasting, showing promising results, as observed in this work. In addition, even in a watershed with a concentration time of less than 2 hours, the network showed a better performance with accumulated rainfall greater than 6 hours. We could not identify any correlation with the physical processes by analyzing the network's weights; however, this need for a history longer than the concentration time may be related. It may indicate that even in an empirical model, where there is no direct relationship with the physical processes of the watershed, the network needs a memory of the physical systems, which may have some relation with soil moisture.

Analyzing both models makes it possible to conclude that hydrological station data and weather radar data can be input to a hydrological model using ANN, thus expanding its use. In many regions, there may be only one data source. In addition, the use of ANN has other advantages, such as the fact that it is relatively easy to operationalize a model after training. They present good results even with data that present some uncertainty and do not require a deep knowledge about the physical processes of the watershed. However, one limitation in its use is the need for a historical and continuous period of data, which was also a limitation found in this work.

For the model using station, the better RMSE value obtained in the 15-minute forecast was 0.0013 and in the 120-minute forecast, it was 0.0063. And using radar data, the value obtained in the 15-minute forecast was 0.0329 and in the 120-minute forecast was 0.0366, which represents a good result compared to the values observed in table 2.1.

As a contribution of this work, the source code and the dataset from the model trained with rainfall data from hydrological stations are available for download on the git repository https://github.com /cpfreitas/networks_neurais/.

The models presented in this work, despite the simple architecture, achieved satisfactory results, showing the potential of an ANN for hydrological prediction, and it allowed the analysis of the weights of the network. Moreover, with the source code and the dataset open, the research community can move state-of-the-art to the next iteration, avoiding a problem pointed out by Sit et al. (2020), in many works related to the use of neural networks in hydrological forecasting.

As perspectives for future work is the use of the networks presented here in other watersheds and implementation with other architectures. As shown in Figure 2.2, in Brazil, there are several areas with radar coverage, in addition to hydrological station data. We suggested using the water level data at the current time as input to the network trained with radar data. And finally, we also suggest analyzing the performance of the networks considering the different seasons of the year and the different meteorological events. If the networks present different seasons performances, separate training for each season may perform better. Regarding meteorological events, it may be necessary to present more patterns of a particular type of event for the network's training and thus obtain better results for that type of event.

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