Case Study

Artificial Neural Networks–Based Model Parameter Transfer in Streamflow Simulation of Brazilian Atlantic Rainforest Watersheds

Regiane Souza Vilanova[1]; Sidney Sara Zanetti, D.Sc.[2]; and Roberto Avelino Cecílio, D.Sc.[3]

Abstract: This paper presents an assessment of the calibration and transfer of artificial neural networks (ANNs) to simulate streamflow at Brazilian Atlantic Rainforest basins. Primary data consisted of rainfall and a streamflow daily series (32 years in extent) of 12 subbasins of the Itapemirim River basin (IRB). First, data from three subbasins were used to adjust three ANNs to estimate daily specific streamflow from input parameters related to rainfall. After, the ANNs were applied to simulate the flows in all other IRB subbasins. The ANNs were able to reproduce the subbasin discharges for which they were adjusted. They also reached satisfactory performance when applied in most of the other subbasins. The obtained results demonstrate that the ANN technique is a viable alternative for simulating flows in regions lacking primary data for hydrological modeling. Besides, calibrating ANNs with subbasin data of an intermediate size or position tends to present a better overall performance than calibrating for the smaller (upstream) or the larger subbasins (downstream). **DOI: 10.1061/(ASCE)HE.1943-5584.0001947.** *© 2020 American Society of Civil Engineers.*

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Introduction

Hydrological models are widely used computational tools to simulate the hydrological responses of watersheds. The hydrologic modeling of basins streamflows is a crucial factor for evaluating the impacts of climate change on water resources, especially concerning extreme events, such as droughts and floods (Alfieri et al. 2015; de Oliveira et al. 2017; Trenberth et al. 2014). The assessment of variations in water resource quality and quantity is one of the most relevant applications of hydrological models (Pereira et al. 2014) and converts computational models into essential tools for watershed planning and management. Several hydrological models have been developed and applied to simulate the rainfall-runoff relationship at the basin scale. These models are classified as empirical, conceptual, or physically based models (Devi et al. 2015).

Physically-based approaches aim to estimate streamflow by utilizing a conceptual understanding of the physics describing the hydrological cycle by approximating physical processes (Booker and Woods 2014). Although physically-based and conceptual models can explore the hydrological mechanism underlying the dynamic runoff process at the catchment scale (Kar et al. 2015), they are not applicable (or present a worse performance) to catchments in which detailed primary data and input parameters for hydrological modeling are not available (Lin et al. 2018; Yaseen et al. 2019). This is the case of most of the Brazilian Atlantic Rainforest watersheds where there is a significant lack of primary data (climatic, soil properties, geological, and environmental).

In case of the impossibility of the application or reduced performance of the physically-based and conceptual models, an alternative is the application of empirical models (Chau 2017; Maier et al. 2014). These models involves mathematical equations derived from concurrent input and output hydrological time series and not from the physical processes of the catchment (Jain and Kumar 2007; Nourani et al. 2011; Vertessy et al. 1993). Examples of empirical models are the unit hydrograph method, regression and correlation methods (Bitew et al. 2019), and machine learning techniques, such as artificial neural networks (ANN) (Devi et al. 2015).

The primary advantage of ANNs is their ability to extract the nonlinear relationship between inputs and outputs of a complex process without prior and explicit knowledge of the physical characteristics of that process (Shiau and Hsu 2016). ANNs have been conceived to mimic the functioning of the human brain by acquiring knowledge through a learning process (Persson et al. 2002). An ANN consists of a set of computing elements called artificial neurons, disposed in different layers, and connected by transfer functions. They require only limited knowledge of the internal functions of a system in order to recognize relationships between input and output (Rezaeian-Zadeh et al. 2013a). The development of an ANN consists in determining its architecture, that is, the number of layers and neurons in each layer, as well as fitting their free parameters (connections) in a phase known as training (Hagan and Menhaj 1994; Moreira et al. 2016). The accuracy of the forecasts from these models depend on how much training data the model is using.

The application of ANNs to forecast problems in hydrology has been one of the major goals for hydrologists (Zemzami and Benaabidate 2016). Recently, the application of ANNs has demonstrated excellent results as a method for analyzing complex temporal variables, such as rainfall and streamflow (Aichouri et al. 2015;

[1]Forestry Engineer, Programa de Pós-graduação em Ciências Florestais, Universidade Federal do Espírito Santo, Av. Gov. Lindemberg, 316, Jerônimo Monteiro, ES, CEP 295000-000, Brasil. Email: regiane-mell@hotmail.com

[2]Professor, Departamento de Ciências Florestais e da Madeira, Universidade Federal do Espírito Santo, Av. Gov. Lindemberg, 316, Jerônimo Monteiro, ES, CEP 295000-000, Brasil. Email: sidney.zanetti@ufes.br

[3]Professor, Departamento de Ciências Florestais e da Madeira, Universidade Federal do Espírito Santo, Av. Gov. Lindemberg, 316, Jerônimo Monteiro, ES, CEP 295000-000, Brasil (corresponding author). ORCID: https://orcid.org/0000-0003-2894-2481. Email: roberto.cecilio@ufes.br

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Danandeh Mehr et al. 2015; Dariane and Azimi 2018; Huo et al. 2012; Jain and Kumar 2007; Kişi 2007; Lin et al. 2018; Noori and Kalin 2016; Rezaeian-Zadeh et al. 2013a; Veintimilla-Reyes et al. 2016; Yaseen et al. 2015, 2019). Considering the existence of sufficient data for training ANN's, a major concern is the selection of the combination of the input parameters (Ray and Sarma 2016; Shiau and Hsu 2016), such as rainfall amounts of an specific day or rainfall amounts accumulated in an specific time period. Previous studies at Atlantic Rainforest basins (Vilanova 2017; Vilanova et al. 2019) showed significant gains in the ANN performance when taking as input variables the daily precipitated depths occurring on the same days of the measured flows and on each one of the five antecedent days. According to these studies, the inclusion of these daily rainfall amounts provides a better simulation of the overland flow that reaches the streams. The same studies (Vilanova 2017; Vilanova et al. 2019) also demonstrated that the inclusion of the rainfall depth accumulated in the 30 days prior to the day of the measured streamflow also provided gains in the streamflow estimation, due a better baseflow prediction.

Regardless of the type of ANN, streamflow prediction in ungauged watersheds is still a challenging task (Isik et al. 2013). Direct application of ANN is not possible to ungauged watersheds because ANNs require observed streamflow data to train the model (Noori and Kalin 2016). This is a factor limiting a wider dissemination of the ANN's application for streamflow estimation.

The present paper proposes an alternative to minimize this limitation of an ANN's application. The alternative is based in a multisite calibration associated with an ANN's transfer from one to another subbasin. Literature shows that one ANN calibrated to one specific basin (single-site) cannot always be satisfactorily applied (transferred) to its subbasins (Vilanova et al. 2019). On the other hand, several authors have demonstrated the effectiveness of a multisite calibration of physically-based and conceptual models over a single-site calibration (Bai et al. 2017; Brighenti et al. 2016; Molina-Navarro et al. 2017; Shrestha et al. 2016; Wang et al. 2012). In this way, we consider plausible the establishment of ANN not only to the entire basin but also to its subbasins in a procedure similar to multisite calibration of the conceptual models. Then, the calibrated ANNs can be transferred to other not-calibrated subbasins. The novelty of this paper also consists of investigating the feasibility of transferring the ANNs among catchments (subbasins).

However, the magnitude of the streamflow differs considerably among subbasins. In order to permit the ANNs transfer, we consider the training of ANNs that estimates not only the streamflow (volume per time) but the specific streamflow (volume per time per basin area). Finally, it can be relied upon that an ANN calibrated for a specific subbasin can be transferred to other watersheds of the same basin, depending on the characteristics of each, especially the dimensions.

Therefore, the present paper proposes a novel assessment of the calibration and the transfer of ANNs among subbasins for rainfall-streamflow modeling. The proposal was tested with data of a specific Brazilian Atlantic Forest basin previously assessed in other studies (Vilanova 2017; Vilanova et al. 2019). Therefore, the specific objectives were as follows: (1) to calibrate ANNs to estimate daily flows in three cascade subbasins of different sizes (from the smallest to the largest one); and (2) to assess the feasibility of transferring these ANNs to other cascade subbasins.

Materials and Methods

The research was divided into two stages and is illustrated in the flowchart of Fig. 1 and described subsequently in this paper.

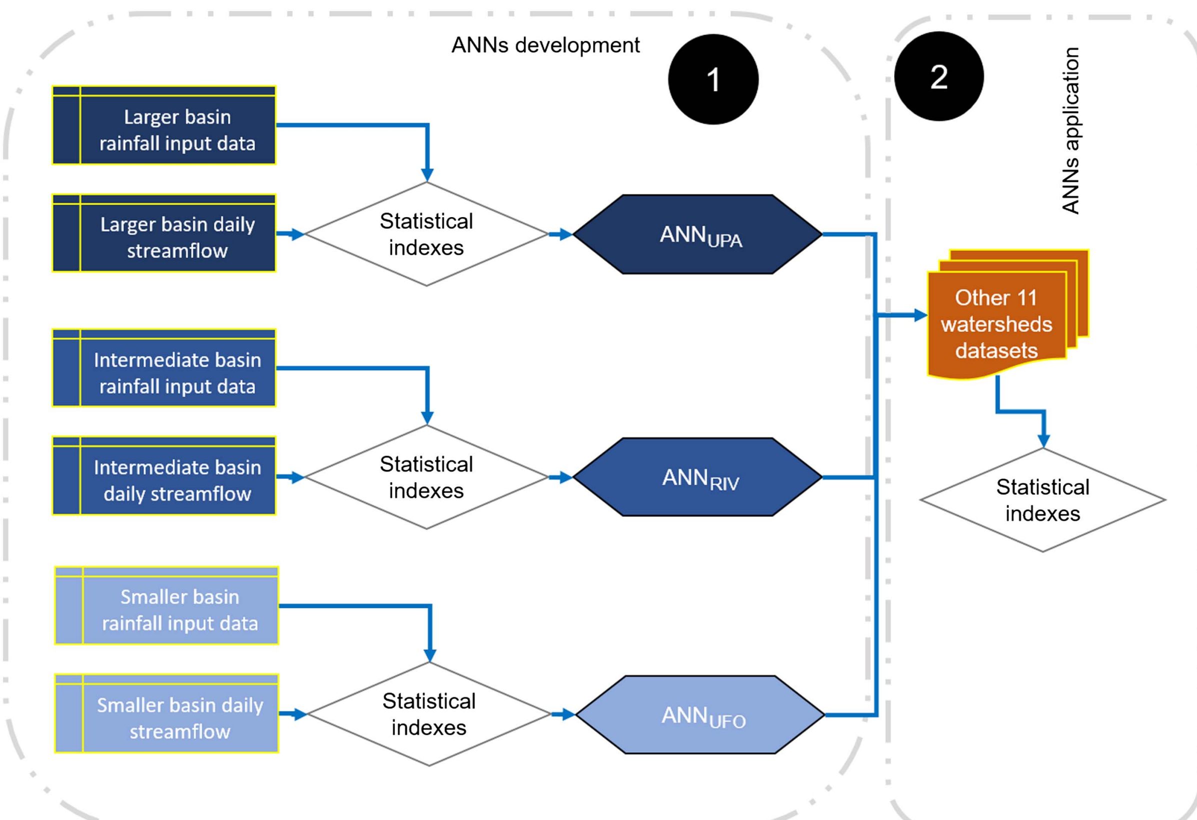

Fig. 1. Flowchart of the methodological stages.

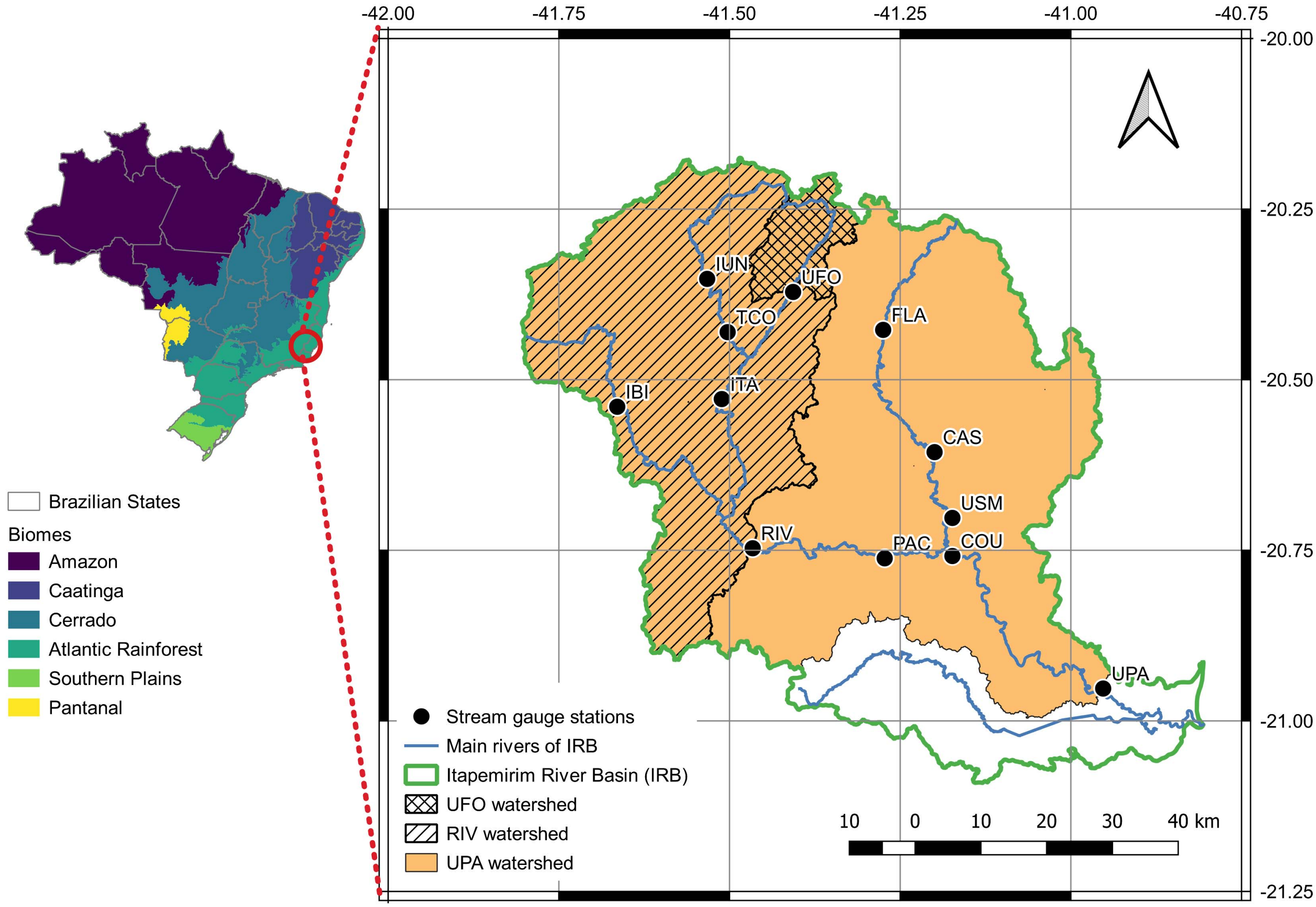

Fig. 2. Spatial address of the Itapemirim River basin, IRB's subbasins, and stream gauge stations. For comparative purposes, the grids in this map match those used in the precipitation gridded database (Xavier et al. 2016).

The first stage consisted in the training of the three ANNs: one representing the largest drainage area—Usina Paineiras (UPA), one representing the intermediate drainage area—Rive (RIV), and another representing the smallest drainage area—Usina Fortaleza (UFO). These three ANNs were called ANN_{UPA}, ANN_{RIV}, and ANN_{UFO}, respectively. The ANNs were established to estimate daily specific streamflow using a daily precipitation database as the input variables and a daily streamflow as the output. The data used in this stage and the training procedures are described subsequently in this paper.

The second stage of the research consisted of transferring, applying, and evaluating the performance of each of the three ANNs to estimate the specific daily flows in the other 11 catchments (subbasins) of the basin under evaluation.

Description of the Study Site

The Itapemirim River basin (IRB) (Fig. 2) is situated in Southeastern Brazil and has an area of approximately 5,920 km^2. According to the Köppen classification, the predominant climates are of the Cwa at higher altitudes and Aw in the lower basin. The average annual rainfall varies between 1,000 and 1,300 mm, while the annual average temperature is 24°C in the lower areas and 21°C in the mountainous section of the basin (Alvares et al. 2013). The vegetation is within the domains of the Atlantic Forest biome, presenting two of the main forest variations: a dense ombrophilous forest and a semideciduous seasonal forest (Instituto Brasileiro de Geografia e Estatística 2012).

Databases

Intending to train and test the ANNs, daily specific streamflow data (Q_{daily}) (streamflow per unit area) between 1980 and 2013 were taken for 12 IRB stream gauge stations (Fig. 2 and Table 1).

Table 1. Stream gauge stations of Itapemirim River basin

Code	Station name	River	Subbasin area (km^2)
UPA	Usina Paineiras	Itapemirim River	5,170
COU	Coutinho	Itapemirim River	4,510
PAC	Pacotuba	Itapemirim River	2,720
RIV	Rive	Itapemirim River	2,180
USM	Usina São Miguel	Castelo River	1,420
ITA	Itaici	Braço Norte Esquerdo River	1,010
CAS	Castelo	Castelo River	972
TCO	Terra Corrida	Pardo River	566
IUN	Iúna	Pardo River	412
FLA	Fazenda Laginha	Castelo River	410
IBI	Ibitirama	Braço Norte Direito River	337
UFO	Usina Fortaleza	Braço Norte Esquerdo River	205

Table 2. Statistical indices of the trained ANNs

Statistics	ANN		
	ANN_{UPA}	ANN_{RIV}	ANN_{UFO}
RMSE ($m^3\ s^{-1}\ km^{-2}$)	0.007	0.010	0.014
MBE ($m^3\ s^{-1}\ km^{-2}$)	0.00003	0.0001	0.0011
NSE	0.86	0.80	0.75
r^2	0.86	0.80	0.75

For the same time period, and for the subbasins of each station of Table 2, daily rainfall depths were obtained from a gridded-maps database available from the interpolation of data from the Brazilian stations (Xavier et al. 2016), using the shapes of each catchment delineation as a mask. Data from the UPA, RIV, and UFO stations (Table 2) were used to train three different ANNs. Data from the other nine stations were used to test the application of the trained ANNs. Thus, these nine stations were taken to simulate ungauged stations where ANNs couldn't be adjusted. All these database were the same used in previous IRB's rainfall-streamflow studies (Vilanova 2017; Vilanova et al. 2019).

ANN Training

All the procedures of training and testing the ANNs were conducted using MATLAB software (version R2016a). Three ANNs were trained: one with data from the stream gauge station with the largest drainage area (ANN_{UPA}); another with data from the one with the lowest drainage area (ANN_{UFO}); and the last with data of the intermediate size station (ANN_{RIV}). All ANNs had Q_{daily} as the output variable.

ANN architecture was taken from studies that assessed many different ANN's architectures for the IRB, using the same database of the present paper (Vilanova 2017; Vilanova et al. 2019). The type of ANN used was the *multiLayer perceptron*, with three layers: one input layer with 7 neurons (as described in the next paragraph), one intermediate layer with 30 neurons, and one output layer with only one neuron (Fig. 3). Only one intermediate layer was used due to its proven satisfactory performance (Maier and Dandy 2000). The activation function and the number of neurons in the intermediate layer were the hyperbolic tangent sigmoid function and 30 neurons, as taken from previous papers that proved its better performance (Hasanpour Kashani et al. 2014; Rezaeian-Zadeh et al. 2013b, a). The size of the training sample ($N = 10{,}200$ daily records) is much larger than the number of ANN parameters ($W = 271$ due 7 inputs, 30 neurons in the intermediate layer, and one output). When $N > 30\,W$ (in this case, N is equal to 38 W), the ANN tendency to overfit is asymptotic (Haykin 1999), which means that the improvement in the generalization performance produced by the use of the early stopping method of training over exhaustive training is small (Haykin 1999). However, for precaution, the early stopping method was still applied in the ANN training.

The parameters of the ANNs input layer were also chosen based on previous studies conducted for IRB using the same rainfall and streamflow database (Vilanova 2017; Vilanova et al. 2019), which analyzed the correlation between rainfall and streamflow data. These studies showed significant gains in the ANN performance when taking as input variables the daily precipitated depths occurring on the same day of the measured/simulated streamflow (P_0) and on each one of the five antecedent days (P_{-1}, P_{-2}, P_{-3}, P_{-4}, and P_{-5}). According to these studies, the inclusion of these daily rainfall amounts (P_0, P_{-1}, P_{-2}, P_{-3}, P_{-4}, and P_{-5}) provides a better simulation of the overland flow that reaches the streams of the IRB. The same studies have also demonstrated that the inclusion of the rainfall depth that accumulated in the 30 days prior to the day of the measured/simulated streamflow (Pac_{30}) also provided gains in the streamflow estimation, due a better baseflow prediction. Therefore, the variables that best simulated IRB streamflow in the study by Vilanova (2017) were the daily precipitated amount for the same day of the measured streamflow (P_0); the daily rainfall depth of each of the 1st (P_{-1}), 2nd (P_{-2}), 3rd (P_{-3}), 4th (P_{-4}), and 5th prior day (P_{-5}); and the accumulated rainfall depths along the antecedent 30 days (Pac_{30}). Thus, the ANNs had seven input variables, as shown in Fig. 3.

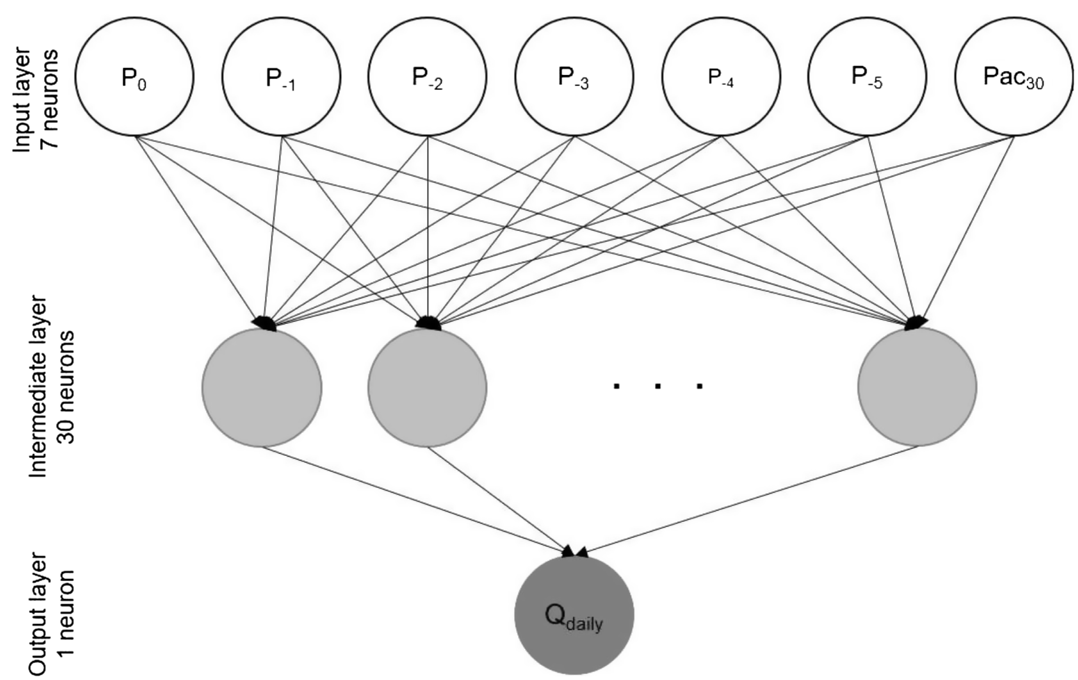

Fig. 3. Architecture of the developed ANNs to estimate daily specific streamflow at Itapemirim River basin.

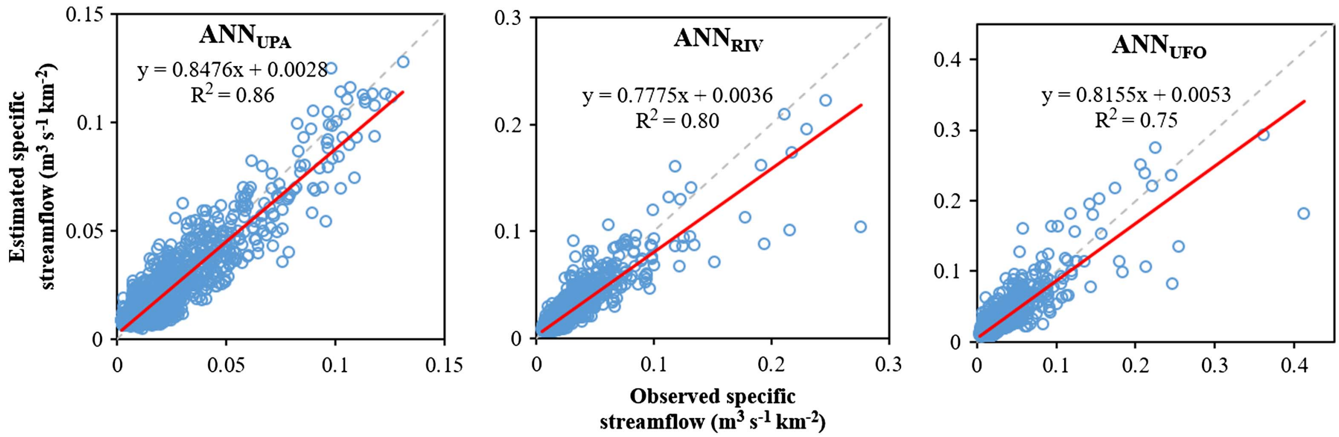

Fig. 4. Graphical dispersion between the streamflows estimated by the ANNs and the observed streamflows in UPA, RIV, and UFO subbasins.

The ANNs were trained using the Levenberg-Marquardt algorithm because it is one of the most efficient algorithms and is used for similar purposes (Behzad et al. 2009; Chang et al. 2014; Hasanpour Kashani et al. 2014; Rezaeian-Zadeh et al. 2013b). Although the Levenberg-Marquardt algorithm demands a longer processing time than the standard backpropagation for each training iteration, its fast convergence sensibly reduces the total number of iterations that are necessary to the training, therefore reducing the processing time too (Zanetti et al. 2007). All the input data were standardized between −1 and 1 [Eq. (1)]

$$X_{\mathrm{norm}} = 2\frac{X_i - X_{\mathrm{min}}}{X_{\mathrm{max}} - X_{\mathrm{min}}} - 1 \quad (1)$$

where X_{norm} = standardized values of the input variable (rainfall); X_i = original value of the input variable (rainfall); and X_{max} and X_{min} = maximum and minimum values of the input variable (rainfall).

For each subbasin, the daily databases were divided into training (70% of the database), cross-validation (15% of the database), and testing samples (15% of the database). Each ANN was trained ten times, adopting the one with the lowest root mean square error (as described in the next section of this paper), calculated using the cross-validation sample. The test sample was used to calculate statistical performance indexes of the ANNs, as is also described in the next section.

Application and Performance Analysis of the ANNs

After training the three ANNs, they were applied to forecast Q_{daily} in all the 12 IRB subbasins. In order to evaluate the performance, four of the most used statistical indicators (Rauf and Ghumman 2018; Yaseen et al. 2015) were calculated: the root mean square error (RMSE), the mean bias of the estimate (MBE), the Nash and Sutcliffe efficiency (NSE), and the coefficient of determination (r^2)

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(E_i - O_i)^2}{n}} \quad (2)$$

$$\mathrm{MBE} = \frac{1}{n}\sum_{i=1}^{n}(E_i - O_i) \quad (3)$$

$$\mathrm{NSE} = 1 - \frac{\sum_{i=1}^{n}(E_i - O_i)^2}{\sum_{i=1}^{n}(O_i - \bar{O})^2} \quad (4)$$

where E_i = estimated specific streamflow, m^3 s^{-1} km^{-2}; O_i = observed specific streamflow, m^3 s^{-1} km^{-2}; n = number of observations; and $\bar{O}$ = average observed specific streamflow, m^3 s^{-1} km^{-2}.

Results and Discussion

Table 2 and Fig. 4 show the performance of ANNs developed with data from Usina Paineiras (ANN$_{UPA}$), Rive (ANN$_{RIV}$), and Usina Fortaleza (ANN$_{UFO}$) stream gauge stations. The NSE of the ANNs (to the test samples) ranged from 0.75 to 0.86 (Table 2). These values lead to an excellent performance (NSE ≥ 0.7) according to the criterion proposed by Noori and Kalin (2016) to evaluate daily streamflows prediction. The best NSE occurred for the largest subbasin (UPA), and the lowest for the smallest one (UFO). All the statistical indices (Table 2) are similar to those of other ANNs calibrated in basins with similar sizes (Aichouri et al. 2015; Dariane and Azimi 2018; Kagoda et al. 2010; Lin et al. 2018).

Fig. 4 shows that there is good agreement between the observed and estimated values of Q_{daily}. Although the general trend of ANNs is to slightly overestimate the streamflows, according to the MBEs values (Table 2), the forecast of the maximum flows presented the most substantial deviations, with a general tendency of underestimation (Fig. 4). These more substantial deviations in the prediction of peakflows are due to the physical processes and natural variability associated with river flow systems, such as time scale (Yaseen et al. 2019) and time lagging (de Vos and Rientjes 2005; Zemzami and Benaabidate 2016). Concerning to the ANN's input variables taken in this paper, we can attribute the deviations to the time scale of rainfall characteristics that exerts influence in rainfall-runoff transformations, mainly rainfall intensity (Yan et al. 2018). A rapid increase of maximum stream discharge is often the result of precipitations with high intensities (Wu et al. 2018; Zumr et al. 2015). In this paper, precipitation intensity is not accomplished in the ANNs due to the daily time scale of the database (Xavier et al. 2016) that only accomplishes daily rainfall depth. Thus, some of the maximum streamflows could not be correctly estimated by the ANNs. This was especially noted in the subbasins with minor areas (RIV and UFO), due to the more significant influence of rainfall intensity variations.

Comparing the performance of the ANNs with physical-mathematical hydrological models is essential in order to know their potential for application in streamflow forecasting. The performance of ANN$_{RIV}$ to simulate RIV flow was better than that found for the SWAT model (NSE = 0.75) in the paper by Fukunaga et al. (2015). The same occurred with ANN$_{UPA}$ and ANN$_{RIV}$ compared to the distributed hydrology soil vegetation model (DHSVM)

Table 3. Performance statistics for each of the three developed ANNs applied to all subbasins of the Itapemirim River basin

ANN	Statistic	Subbasin											
		UPA	COU	PAC	RIV	USM	ITA	CAS	TCO	IUN	FLA	IBI	UFO
ANN_{UPA}	RMSE ($m^3\ s^{-1}\ km^{-2}$)	0.006	0.010	0.011	0.013	0.011	0.013	0.012	0.013	0.015	0.016	0.045	0.021
	MBE ($m^3\ s^{-1}\ km^{-2}$)	0.000	0.000	−0.001	−0.003	0.001	−0.002	0.001	−0.002	−0.001	−0.004	−0.020	−0.008
	NSE	0.86	0.65	0.68	0.63	0.54	0.59	0.55	0.51	0.49	0.31	0.23	0.40
	r^2	0.86	0.65	0.68	0.65	0.57	0.60	0.56	0.55	0.49	0.42	0.53	0.51
ANN_{RIV}	RMSE ($m^3\ s^{-1}\ km^{-2}$)	0.011	0.011	0.008	0.009	0.011	0.009	0.009	0.010	0.011	0.014	0.039	0.017
	MBE ($m^3\ s^{-1}\ km^{-2}$)	0.003	0.003	0.002	0.000	0.003	0.001	0.003	0.001	0.001	−0.001	−0.017	−0.005
	NSE	0.55	0.59	0.82	0.84	0.54	0.78	0.76	0.70	0.73	0.42	0.42	0.61
	r^2	0.67	0.68	0.83	0.84	0.66	0.80	0.79	0.77	0.74	0.57	0.69	0.67
ANN_{UFO}	RMSE ($m^3\ s^{-1}\ km^{-2}$)	0.016	0.016	0.013	0.012	0.015	0.014	0.013	0.014	0.013	0.018	0.034	0.015
	MBE ($m^3\ s^{-1}\ km^{-2}$)	0.007	0.008	0.007	0.004	0.008	0.006	0.008	0.005	0.006	0.003	−0.012	−0.001
	NSE	0.07	0.19	0.54	0.69	0.09	0.51	0.49	0.36	0.62	0.08	0.55	0.71
	r^2	0.62	0.64	0.77	0.79	0.64	0.76	0.76	0.75	0.73	0.56	0.68	0.71

(Wigmosta et al. 1994), which presented the NSE equal to 0.61 and 0.56, respectively, for the UPA and RIV stations in the paper by Mendes (2016). The application of SWAT and DHSVM requires surveying a large number of environmental (meteorological, edaphic, and vegetative) information, which are not needed for the ANNs' application. The presented ANNs only requires daily rainfall amounts as the input parameter to simulate the streamflows. Thus, this demonstrates their potential of the ANN to simulate the streamflows of the entire IRB. Finally, we believe that the establishment of sets of ANNs to each Brazilian Atlantic Forest major basin (with a lack on environmental data), as demonstrated with the IRB, had the potential to satisfactory forecast its hydrologic behavior in response to rainfall.

Table 3 presents the results from the application (transfer) of the ANN_{UPA}, ANN_{RIV}, and ANN_{UFO} in all IRB subbasins. Finally, Fig. 5 shows the hydrographs of the simulated and observed flows in all the 12 subbasins for 1 year and the cumulative specific streamflow for all year. Table 3 and Fig. 5 show that from the 36 transfers of the ANNs in the IRB subbasins (3 ANNs multiplied by 12 subbasins), only five (approximately 14%) presented an unsatisfactory performance ($NSE < 0.3$) according to the adopted criteria (Noori and Kalin 2016). Of these five, one has its place in the ANN_{UPA} [applied in Ibitirama (IBI)] and four in ANN_{UFO} [applied in UPA, Coutinho (COU), Usina São Miguel (USM), and Fazenda Laginha (FLA)]. All ANN_{RIV} applications resulted in $NSE \geq 0.42$, therefore having a satisfactory performance. This demonstrates that the transfer of the ANN trained for the intermediate subbasin presented better results than the transfer of the ANNs of the major or minor subbasins. It occurs due to the fact that the hydrological response of the major subbasin (UPA) tends to be different from the minor ones due to the amortization of the discharges (Neto et al. 2014), the spatial variability of the rainfall, and the lower influence of the intensity variations and landscape. On the other hand, landscape variations among the minor subbasins lead to a different hydrological response (Wu et al. 2018; Yan et al. 2018), reflecting in the worse performance of the transfer of ANN_{UFO} to the other catchments.

Another result that deserves observation is the ANN that best predicted the discharges in each subbasin. ANN_{UPA} (obtained using the data from the largest subbasin) best simulated the flows in the two largest basins (UPA and COU). Analogously, ANN_{UFO} (trained with data of the smallest subbasin) best simulated the flows in the two smaller ones (IBI and UFO). All other eight subbasins had their flows better estimated with ANN_{RIV}. The ANN_{RIV} performances in the smaller subbasins (area less than 2,800 km^2) were better than those of ANN_{UPA}, thereby evidencing that there is indeed a difference in the hydrological behavior of the smaller basins compared to UPA and COU (greater than 4,500 km^2).

The best performance of ANN_{UPA} for the larger subbasins is justified by the tendency of these basins to have a slow hydrological response, which is reflected in the better calibration indices (Neto et al. 2014). The same trend of better performance in larger basins was evidenced in both the application of ANNs (Besaw et al. 2010) and in physically-based hydrological models, such as SWAT (Arnold et al. 2012; Eduardo et al. 2016; Melo Neto et al. 2014; Piniewski and Okruszko 2011). Comparing larger and smaller catchments, responses to rainfall are faster in the smallest subbasins, implying the different dynamics for the streamflow (Neto et al. 2014; Qi and Grunwald 2005). Larger amplitudes between the minimum and maximum Q_{daily} are frequently observed in the smaller basins, as shown in Fig. 5. Therefore, the hydrological response in each subbasin occurs differently. For an input parameter (rainfall) in the system (subbasin), the response (streamflow) will be adjusted to the watersheds inherent physical conditions. ANNs developed for larger subbasins will not be able to represent the streamflow of smaller subbasins with the same efficiency. Thus, it is necessary to develop different ANNs for smaller basins.

As can also be seen in Table 3, ANN_{UFO} presented a better performance for the smaller subbasin. The poor performance for the FLA (which is close to the UFO) shows that these two catchments have different hydrological characteristics due in part to their geological differences (Peixoto-Oliveira et al. 2018). The calibration of ANNs for small subbasins and their subsequent application in other catchments, even with a similar area, may represent a risk. This is because hydrological dynamics can vary considerably between small basins, which is not only due to geological differences, but also to those related to the use and management of soil, and even to rainfall.

Fig. 5 further illustrates the difference in ANN behavior in each subbasin. In the smaller subbasins [Iúna (IUN), FLA, IBI, and UFO], it is observed that Q_{daily} tends to have higher observed values than estimated values (especially of flood flows). The maximum flows observed in UPA and RIV were not higher than 0.16 $m^3\ s^{-1}\ km^{-2}$, while the flood flows observed in the smaller subbasins were frequently higher than this value. ANN_{UFO} tended to present smaller errors in estimating the flood flows for the smaller subbasins because values of up to 0.30 $m^3\ s^{-1}\ km^{-2}$ were known in their training sample and could be estimated, unlike the ANN_{UPA} and ANN_{RIV}, which were unable to estimate values higher than 0.16 $m^3\ s^{-1}\ km^{-2}$.

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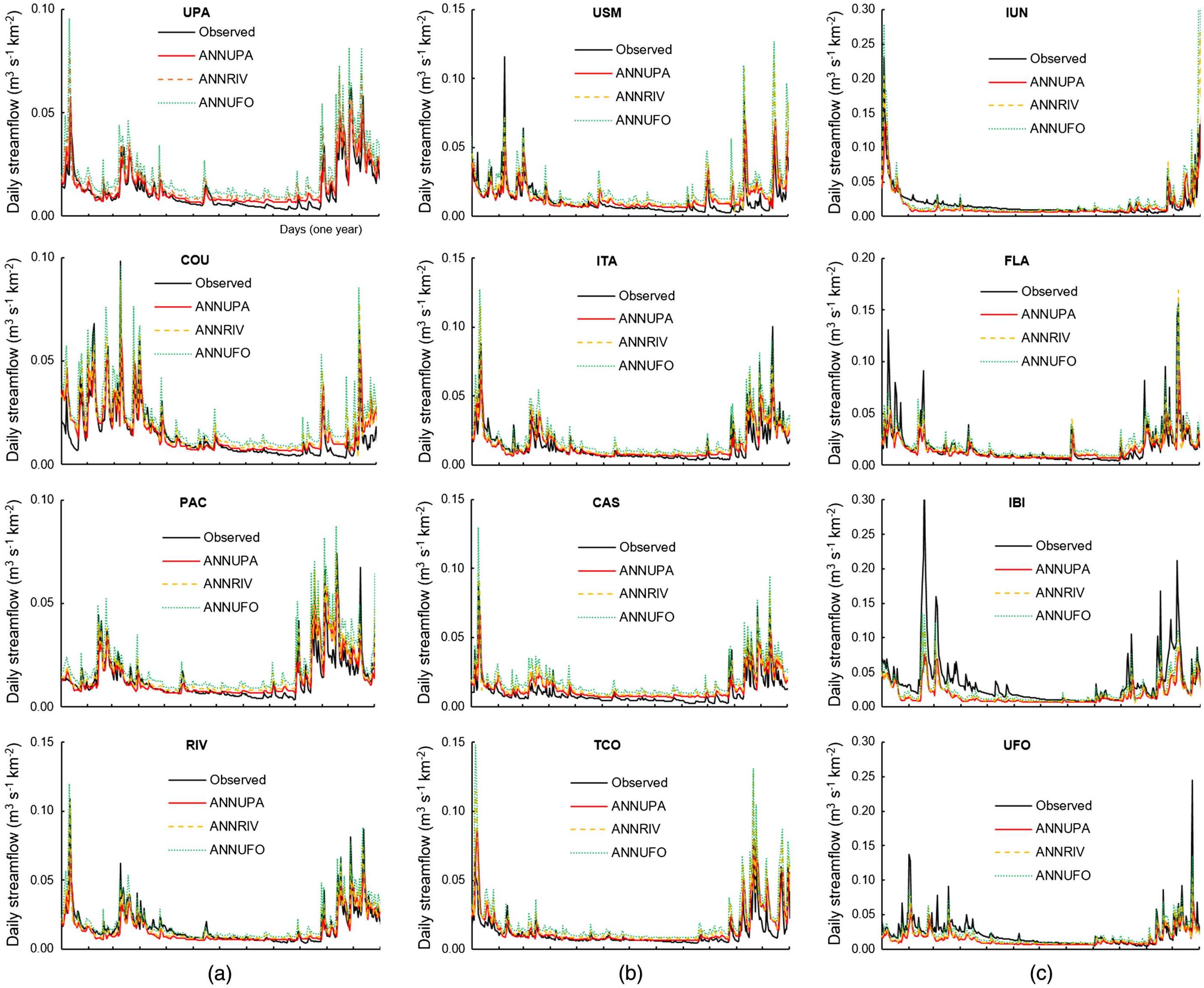

Fig. 5. Hydrographs of observed and simulated (by the three ANNs) specific streamflow for all the IRB subbasins.

In the paper by Mendes (2016), they have also tested the option to calibrate the conceptual hydrological model DHSVM in subbasins of the IRB (UPA and RIV) and performed its application in other subbasins (UPA, RIV, USM, ITA, CAS, TCO, and IUN). The performance of the developed ANNs (Table 3) was better than transferring the DHSVM calibration (Mendes 2016). The NSE of ANN_{UPA} and ANN_{RIV} applied in UPA, RIV, USM, Itaici (ITA), Castelo (CAS), Terra Corrida (TCO), and IUN were superior to those of DHSVM (Mendes 2016) for the same catchments. ANNs presented a worse performance only when applied in FLA. Therefore, the superiority of the ANN performance over the DHSVM hydrological model is evidenced, even when the calibration is transferred.

The results of the present paper demonstrate that the ANN technique is a viable alternative for simulating streamflows in regions with a lack of data for hydrological modeling. They also show that the calibration and transfer of ANNs with subbasin data of intermediate size or position tend to have a better overall performance than the calibration for the upstream (smaller area) or downstream basin (larger area).

In future work, the performance of ANNs can be refined expanding databases that reflects the rainfall intensities in a subdaily basis, rainfall spatial variability in more detail, and catchments' landscape characteristics (Berghuijs et al. 2016), combined with new computational techniques, such as extreme learning machines (Yaseen et al. 2019).

We also consider as an option for future studies forecasting the usage of streamflow and rainfall data from many subbasins together to train a unique ANN for the whole basin. This unique ANN will need to accomplish one or more landscape attributes, such as a drainage area, mean slope, catchment position, average altitude, percent of the main land use, or geology, among others. The drainage area itself could not be sufficient to reflect the hydrological response of the catchments and, consequently, could not provide a reasonable estimative of the discharge. The results presented in this paper illustrates this affirmative: ANN_{UFO} (205 km^2) did not provide a reasonable estimative of FLA (410 km^2) discharges and tended to underestimate IBI (337 km^2) streamflows. We believe that the definition of which landscape attributes would be taken as input variables of ANNs must be preceded by an analysis of its correlation with the streamflow, similarly as the analysis of the correlation of the rainfall parameters with the streamflow (Vilanova 2017).

Conclusions

This paper investigated the training and transferring of artificial neural networks to forecast the daily streamflow in a Brazilian Atlantic Forest basin, concluding the following:

- The ANNs were able to satisfactorily simulate the streamflows of the subbasins for which they were developed.
- The developed ANNs performed satisfactorily when applied to other subbasins of the same basin.
- The ANN developed for the larger subbasin (ANN_{UPA}) presented a better performance when applied to the larger subbasins.
- The ANN developed for the smaller subbasin (ANN_{UFO}) tended to perform better when applied to the smaller subbasins, although this did not occur for all small catchments.
- The ANN developed for the intermediate area subbasin (ANN_{RIV}) presented a better overall performance and had a satisfactory performance for all subbasins.

Data Availability Statement

Some or all data, models, or code generated or used during the study are available from the corresponding author by request.

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