Rainfall-runoff modeling for flood forecasting: application of global methodologies to a medium-size basin in Brazil

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Abstract: The scarcity of hydrologic information related to the reality of the Brazilian hydropluviometric networks, leads one to study the behavior of the basins by means of simpler global empirical models, with few parameters to calibrate. In DPFT method (First Differences of the Transfer Function) one uses a multi-events rainfall-runoff set and an iterative algorithm for the simultaneous identification of the average Unit Hydrograph (Transfer Function) of the basin and of a series of effective precipitations associated to each event. This last particularity allows to the calibration and comparison, a posteriori, of different Loss Function models, relating observed precipitations to calculated effective precipitations identified by the methodology. Results of the application of the method are presented here, concerning the Velhas river basin, in the Honório Bicalho station. To the selected basin, two simple Loss Function models were calibrated: GR3 model and a reservoir model. Otherwise, a non-linear Artificial Neural Network (ANN) model approach was used to compare with the DPFT methodology. The results were analyzed and discussed.

Key words: rainfall-runoff modeling, DPFT methodology, GR3 model, Artificial Neural Network model

INTRODUCTION

This paper deals with the modeling of hydrologic rainfall-runoff, employing an approach using the unit hydrograph method applied to a medium scale basin.

In general the Brazilian hydrologic gauging stations network display only data for precipitation and runoff and, in the majority of cases, only daily data is available. Due to the difficulty in the calibration of the large number of parameters that conceptual models generally require, global empirical methods are currently used in studies and technological applications. The use of the DPFT (First Differences of the Transfer Function) methodology to identify the Unit Hydrograph and effective precipitation, by means of sets of total precipitation and observed runoff, makes it possible for us to obtain the loss function model which best fits the characteristics of the hydrographic basin under study. The DPFT method was applied to Honório Bicalho, a cross section of the hydrographic basin of the Rio das Velhas, with a drainage area of 1655 km^2 . Two simple models of loss function were studied and calibrated: the reservoir model (with three parameters) and the GR3 model (with one parameter). The results were analyzed and compared with regards to their efficiency.

Artificial Neural Networks are currently being presented as an alternative approach to traditional methods in the solution of problems in predicting temporal runoff series. In the case in question, the use of this technique is attractive as, in order to use it, it is not necessary to have a prior knowledge of the mathematical relationships that describe the nonlinear complex relationships between the input variables (precipitations) and the output variables (run-off). Here this type of black box model is compared to the Unit Hydrograph method (DPFT methodology,) regarding it as a semi-conceptual model.

RAINFALL-RUNOFF MODELING

The Unit Hydrograph and the DPFT methodology

The Unit Hydrograph method was proposed by Sherman (1932). Basically, this classical Unit Hydrograph method (UH) proposes that, for a given hydrographic basin, runoff is the result of a loss function (LF) and of a linear Transfer Function (H). The LF is strongly non-linear, and transforms the total measured precipitation, either weighted or arithmetic mean (P), into effective precipitation (Pe), which produces the surface runoff. This transformation depends on the type and use of the soil and its conditions of humidity prior to the rainfall event. The linear Transfer Function (H) increases over time the effective rainfall Pe, so as to obtain the surface runoff, as in Figure 1.

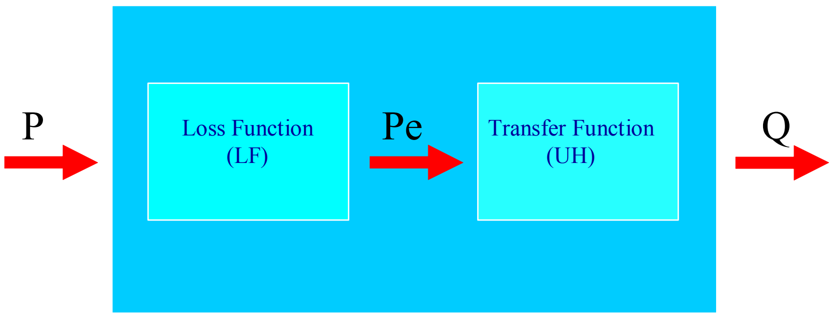

Figure 1 – Diagram of the transformation of rainfall into surface runoff

Classically, a LF model (assumed to be the most appropriate for the basin) is required *a priori* to obtain the effective rainfall for each event (Khan and Ormsbee, 1989; Liang, 1988). In this form the Unit Hydrograph can be identified resolving the convolution equation 1, which combines *Pe* (effective rainfall), H_i (k discretized order UH) and Q_j (runoff in time j):

$$Q_j = \sum_{i=1}^{k} H_i . Pe_{j-i+1} \tag{1}$$

As opposed to this classic approach, the DPFT method, proceeding iteratively from an array of episodes of total rainfall – runoff, establishes the Transfer Function (H) and the effective rainfall (Pe) for each event, and the relation P-Pe (Duband et al.,1993; Nalbantis et al. 1995; Maia et al., 2006). This distinctiveness permits a comparison and choice of the best Loss Function for a given hydrographic basin (Versiani, 1983; Sempere-Torres et al., 1992).

Mechanism for the identification of the Unit Hydrograph and effective rainfall

The calculations are made by first order difference, that is, the variations of discharge are calculated over a time interval. From this, using Equation 1, we obtain:

$$q_j = \sum_{i=1}^{k} h_i Pe_{j-i+1} \tag{2}$$

where q_j represents a variation of discharge at the instant j:

$$q_j = Q_j - Q_{j-1} \tag{3}$$

and h_i are the DPFT coefficients (Equation 4):

$$h_i = H_i - H_{i-1} \tag{4}$$

Written in matrix form, for N rainfall-runoff events, each one presenting n discharge values, with k being the amplitude of the Transfer Function in intervals of time, Equation 2 becomes (Duband et al., 1993):

$$[q]_{nN,1} = [Pe]_{nN,k} [h]_{k,1} \tag{5}$$

Where:

q is the vector of nN variations of discharge; h is the vector of k DPFT coefficients (unknown); Pe is the matrix (nN lines, k columns) of effective rainfall.

On the other hand, Equation 5 is equivalent (Versiani, 1983) to N matrix products of the form:

$$[q] = [H^*][Pe] \tag{6}$$

Where:

[H*] is the matrix formed by the DPFT coefficients; [Pe] is a vector of the effective rainfall for each event n (n=1, ..., N).

The deconvolution consists in identifying the values of Pe (effective rainfall), resolving Equation 6, which is:

$$[Pe] = \left\{ [H^*]^t [H^*] \right\}^{-1} [H^*]^t [q] \tag{7}$$

In this case, the Pe_i are multiple regression coefficients of the multilinear relationship between the q_i (dependent variables) and h_i (independent variables).

The ARMAX model (Box et al., 1994) is the substitute of equation 5, principally avoiding problems of numeric instability in the estimate of DPFT coefficients. It consists of calculating the sequence of the coefficients H_1, H_2, ... H_k (the Unit Hydrograph) as the result of the division of polynomials in z^{-1}, with z^{-1} being the "delay" operator. Working in variations of discharge, we have;

$$q_t\left(1 + c_1 z^{-1} + c_2 z^{-2} + ... + c_v z^{-v}\right) = Pe_t\left(b_0 + b_1 z^{-1} + b_2 z^{-2} + ... + b_w z^{-w}\right) \tag{8}$$

Where $c_1,...,c_v$ are the autoregressive coefficients of the variable q and $b_0,...,b_w$ are the autoregressive coefficients of the exogenous variable Pe.

Consequently:

$$q_t = \frac{B(z^{-1})}{C(z^{-1})} Pe_t \tag{9}$$

where B (z^{-1}) and C (z^{-1}) are the polynomials in z. Equation 9 realizes the following formulation, of the Unit Hydrograph type:

$$q_t = -\sum_{i=1}^{v} c_i q_{t-i} + b_o Pe_t + \sum_{i=1}^{w} b_i Pe_{t-i} \tag{10}$$

where the coefficients c_i and b_i are the multiple regression coefficients of the multilinear relationship between q_t e Pe_t.

In accord with the DPFT method iterative process, the proposed algorithm makes an estimate of the DPFT coefficients and the effective rainfalls, alternating at each step of the calculation:

Step 1) The estimate of h, using the ARMAX formulation (equation 10);

Step 2) Following this, knowing the h_i, a deconvolution (equation 7) is made, event by event, obtaining the values for Pe_i

The Loss Function Models

After the identification of the Unit Hydrograph, the Loss Function can be calibrated *a posteriori*, relating the series of total rainfall P to the effective rainfall Pe, calculated in the last iteration. This is the principal interest of this work.

The GR3 model is a global empirical model developed by Edijatno and Michel (1989) with 3 parameters with a daily time step. It is the result of a study in which the principal objective was to obtain the simplest possible empirical representation of the rainfall-runoff process which would be capable of allowing a correct simulation of the rainfall-runoff transformation in a hydrographic basin (Nascimento, 1995).

Nonetheless, an adaptation of this model was made, since the Unit Hydrograph to be used is that obtained by use of the DPFT methodology. Thus, this model recreates the condition of a reservoir, where a neutralization between the daily precipitation and the daily evaporation (here taken as being constant throughout the analysis, and equal to 5 mm/day) is predicted, in such a way as there will be only one input in the model.

The parameters to be calibrated are A which characterize the basin and S_1, which simulates the initial condition of average humidity of the basin lands for each event considered, which will supply us with the relation S_1/A. The single reservoir has a maximum capacity A, the first parameter of the model, and a level S_1, second parameter, which changes in conformity to the action of the precipitation or the evaporation.

The second model is the Rerservoir Model, proposed by Lorent (1975). In this model, α and β are two parameters characterizing the basin and should be calibrated with respect to the condition $0 < (\alpha,\beta) < 1$. $D(0)$ is a parameter which characterizes the initial conditions for each event, taking into account the previous hydrologic state (conditions of humidity prior to the beginning of the event). These parameters relate the reservoir deficit behavior with the reservoir retention or loss.

The choice of the best parameters for each model is made through the minimization of the Root Mean Square Error (RMSE) between the effective rainfall calculated by the DPFT methodology and the effective rainfall generated by the loss function models, as indicated by formula 11.

$$RMSE = \sqrt{\frac{1}{N}\sum_{t=1}^{N}\left[\mathrm{Pe}_{\mathrm{dpft}} - \mathrm{P}_{\mathrm{model}}\right]^2} \tag{11}$$

where, N is the number of observations; Pe_{dpft} is the effective rainfall calculated by DPFT method; Pe_{model} is the effective rainfall of the proposed Loss Function model.

To compare the observed and the calculated floods, the Nash coeficient was used (formula 12).

$$NASH = 1 - \frac{\sum_{t=1}^{N}\left[Q_{obs}(t) - Q_{calc}(t)\right]^2}{\sum_{t=1}^{N}\left[Q_{obs}(t) - \overline{Q_{obs}}\right]^2} \tag{12}$$

where Q_{obs} (t) is the observed discharge. in time t; Q_{calc} (t) is the calculated discharge in time t; $\overline{Q_{obs}}$ is the average observed discharge.

The Artificial Neural Networks approach in Rainfall-Runoff modeling

The simplest artificial neuron model is the MCP model (McCulloch and Pitts, 1943, as per Braga et al, 2006), which is a simplification of what is known about the neurological neuron. It concerns a model with n input terminals, which receive the values $x_1, x_2, ..., x_n$ and only one output terminal y. To represent the behavior of synapses, the input terminals of the neuron have coupled synaptic weights $w_1, w_2, ..., w_n$.. The activation of the neuron is obtained through application of an activation function, which may or may not activate the output, depending on the value of the weighted sum $x_i w_i$, compared to the excitation threshold θ of the neuron. The networks of a unique layer have a limitation in that they can only resolve problems with linear characteristics.

The nonlinearities are incorporated in neural models by means of the activation functions (nonlinear) for each neuron of the network and for its structural composition in successive layers. The neural network of multiple layers composed of neurons with sigmoidal activation functions in the intermediary levels is given the name Multilayer Perceptron (MLPs).

In training the multi-layer network, the problem consists of estimating the weight adjustment for the intermediary layers, which do not have the desired outputs, contrary to the single layer networks, where there is a difference between the desired output and the output flow of the networks. The solution to this problem was discovered in the 1980´s, with the description of the *backpropagation* algorithm, which consists of a retropropagation of errors (Braga et al, 2006). Figure 2 illustrates a typical MLP network, with an intermediary layer ('hidden layer').

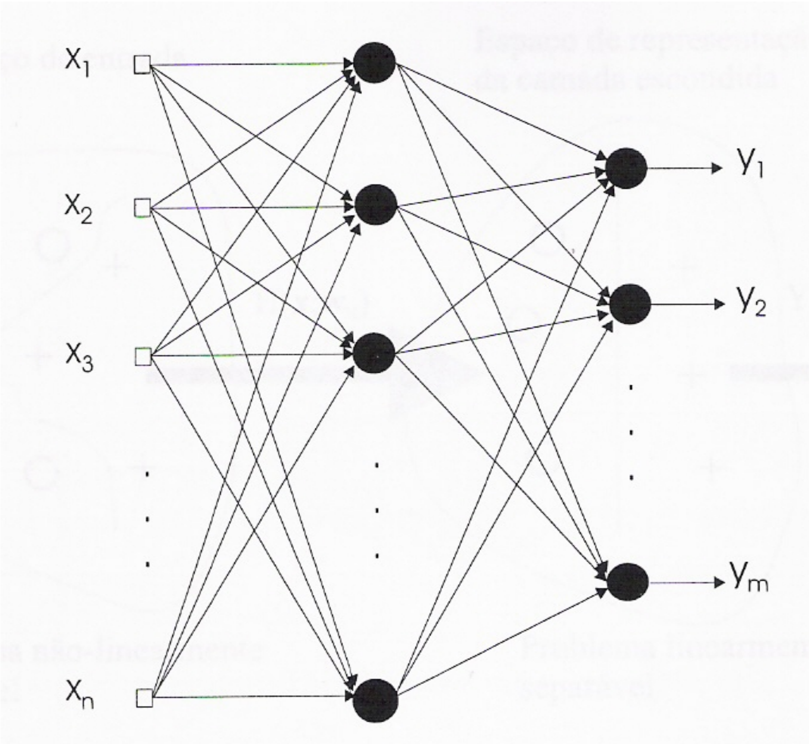

Figure 2 – A single hidden layer MLP network

The structure of the network shown in Figure 2 shows a similarity to the rainfall-runoff transformation diagram shown in Figure 1. In Figure 2, the inputs x_i and outputs y_i of the nonlinear system correspond respectively to the total rainfall P_i and the observed runoff Q_i in the hydrographic basin. Instead of first identifying the Unit Hydrograph (linear) of the basin and the effective rainfall, and after verifying which is the best nonlinear model of the Loss Function, the modeling of the rainfall-runoff process for the Neural Networks considers the direct transformation (nonlinear) between the total rainfall and the observed runoff.

The ARMAX models represented by equation 10 are able to represent very well the behavior of a system whose characteristics of input and output are approximately linear. They can be seen as a simplified version of an artificial neural network with a linear activation function and no hidden layer. In the case in question, it is to be expected, however, that a MLP network with a hidden layer and nonlinear activation function effectively represents the nonlinearities of the rainfall-runoff stochastic process.

The program used here in the application of the Artificial Neural Networks was the NeuroHidro Software (Valença, 2005). The architecture used is that of a network composed of Nonlinear Sigmoidal Regression Blocks Networks (NSRBN). A NSRBN network is a combinatorial network composed of the sum of p blocks (p=1,…,d) with a structure similar to a MLP, in which the hidden units of these blocks make a linear sigmoidal regression in the inputs (such as a MLP), and the output units make a nonlinear sigmoidal regression of the hidden units (such as a nonlinear logistic regression), (Valença, 2005).

The minimized Objective Function for obtaining the synaptic weights is the MSE, given by equation 13, as follows:

$$\text{MSE}=\frac{1}{N}\sum_{t=1}^{N}\left[\text{Q}_{\text{obs}}-\text{Q}_{\text{calc}}\right]^2 \tag{13}$$

where Q_{obs} is the observed discharge and Q_{calc} is the discharge calculated by the neural network.

In summary, the retropropagation algorithm adjusts the weights between the layers of the neural network, both between the input layer and the hidden layer, as well as between the hidden layer and the output layer. By the descending gradient method (calculation of the mean quadratic error for all examples n and all the output neurons), the weight adjustment must be proportional to the opposite direction of the gradient of the error function, in relation to the weights.

RESULTS AND DISCUSSION

The Figure 3 shows the Rio das Velhas basin, located in the State of Minas Gerais, Brazil. Data of average daily discharge as well as of intense daily precipitation were used for calibration of the Unit Hydrograph and of the effective rainfall, spatially averaged by Thiessen method, using 4 rain-gauge stations, relative to the surface basin of 1655 km^2 , concerning of Honorio Bicalho stream-flow station.

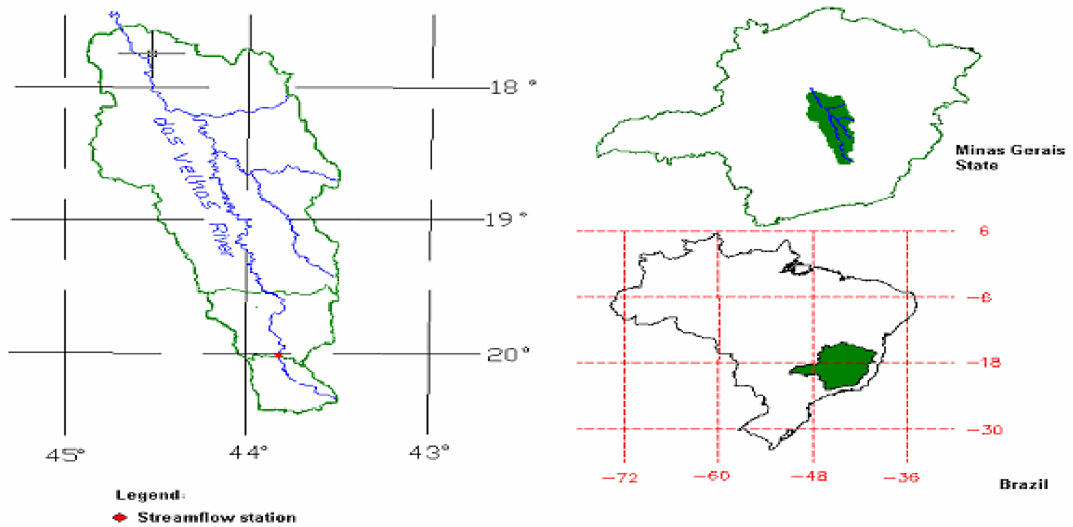

Figure 3 – Location of the basin and streamflow station analyzed

Two samples of rainfall-runoff events were selected for this study case: the first sample, using 8 events for calibration and the second, with 7 events, for validation. Figure 4 shows the two adimensional Transfer Functions (Unit Hydrographs) obtained by the DPFT methodology for these two samples, using v=3 and w=5 (equation 10).

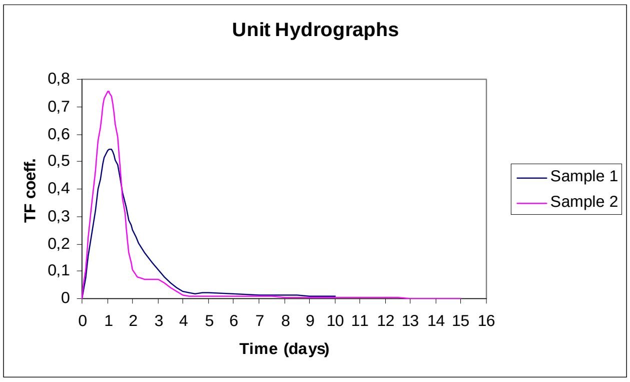

Figure 4 – Transfer functions – DPFT method

The Nash coefficients corresponding to the observed and calculated discharges (given by equation 1), by means of effective rainfall using the DPFT method, are presented in Table 1.

Table 1 – Events of samples 1 and 2 and Nash coefficients (between observed and calculated floods, DPFT methodology)

Sample 1		Sample 2	
Event	*NASH*	Event	*NASH*
1	**0.9710**	12	**0.9682**
2	**0.9804**	13	**0.7632**
4	**0.8861**	14	**0.9613**
6	**0.9471**	16	**0.9979**
7	**0.7401**	17	**0.9969**
9	**0.9954**	18	**0.9600**
10	**0.8821**	19	**0.7748**
11	**0.9328**		

Using the Nash coefficient (*NASH*) as validation criteria, the model was considered satisfactory when the values were greater than 0.7. All the selected events satisfied this condition and provided a good reconstitution of the observed runoff.

Loss Functions

The parameters of the two proposed Loss Functions used in this work were calibrated for the rainfall-runoff events selected. In this calibration were used programs for the minimization of the *RMSE* between effective precipitation calculated by the DPFT method and effective precipitation calculated, respectively, for the GR3 model and the reservoir model, using FORTRAN and MATLAB computer programs (Cruz et al, 2006). The results of the parameter calibration for Sample 1 are shown in Table 2.

Table 2 – Calibrated paremeters for GR3 and Reservoir model (Sample 1)

Sample 1				
	GR3	Reservoir		
Event	S_1/A	alfa (α)	beta (β)	$D(0)$ (mm)
1	0.33	0.92	0.99	333
2	0.29	0.8	0.99	246
4	0.24	0.92	0.99	132
6	0.38	0.92	0.99	40
7	0.41	0.8	0.99	121
9	0.19	0.92	0.99	236
10	0.40	0.8	0.99	215
11	0.17	0.92	0.99	419

The obtained average values for GR3 model were: S_1 = 298 mm and A = 946 mm (S_1/A = 0.32). The obtained average values for Reservoir model were: α = 0.88, β = 0.99 and $D(0)$ = 218 mm. Figure 5 shows the graphs generated by the loss functions corresponding to the event 1.

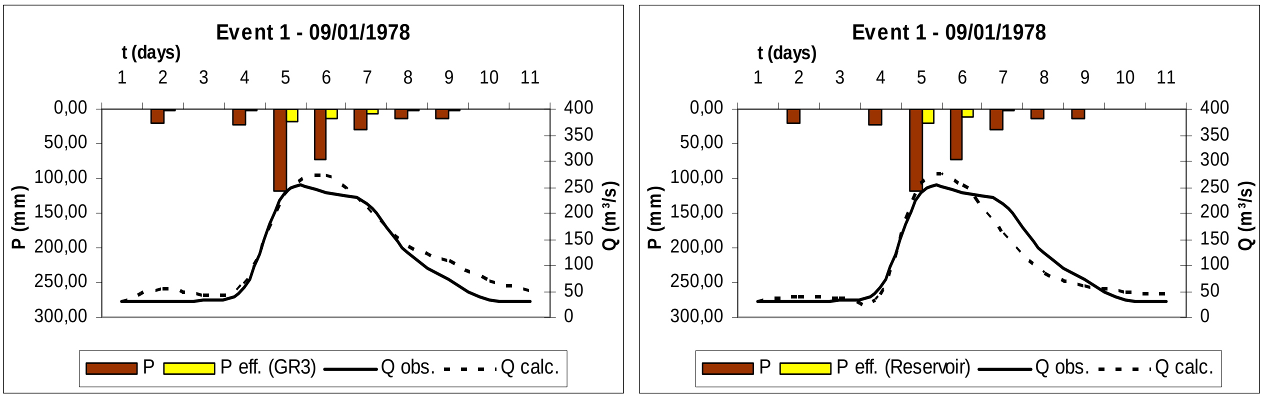

Figure 5 – Total and effective rainfall obtained by GR3 and Reservoir models; observed and calculated floods.

The Nash coefficients corresponding to the events of sample 1, with respect to the comparison between the observed and calculated discharges by means of equation 1 for the rainfall generated by GR3 and Reservoir LF models, are presented in Table 3.

Table 3 –Nash coefficients corresponding to the events of sample 1 (GR3 and Reservoir)

GR3		Reservoir	
Event	NASH	Event	NASH
1	**0.9303**	1	**0.9136**
2	**0.2860**	2	**0.3942**
4	**0.8952**	4	**0.8325**
6	**0.6140**	6	**0.6911**
7	**0.4164**	7	**0.0207**
9	**0.8781**	9	**0.7534**
10	**0.8174**	10	**0.8744**
11	**0.6722**	11	**0.4646**

By means of a visual analysis and using the Nash coefficients of observed and calculated discharges, it can be concluded that the GR3 and Reservoir models present similar behavior for the sample of selected events.

Afterwards, analysis of S_1/A, $D(0)$ and the sum of the rain of the 5 days prior to each event (P_{5days}) were carried out. Figure 6 shows these relationships.

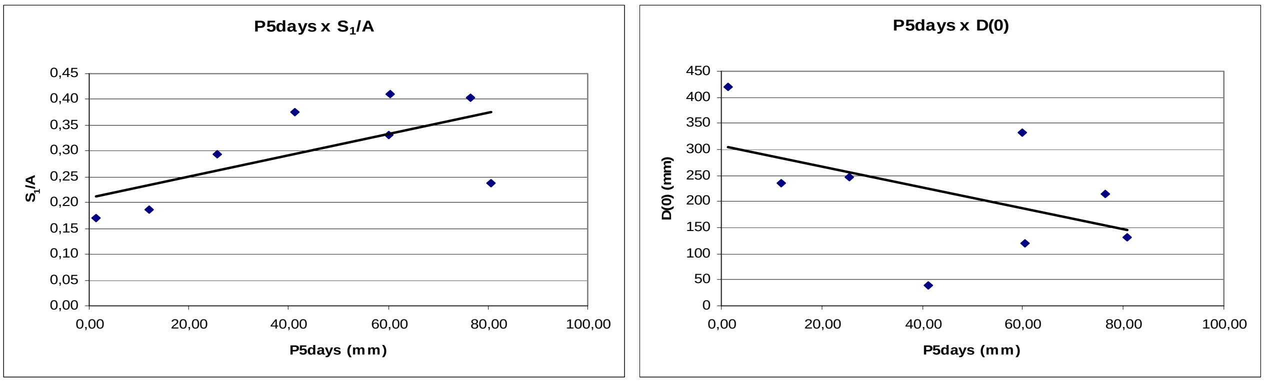

Figure 6 – Relationship between S_1/A and the reservoir deficit *D(0)* and the sum of the rain of the 5 days before each event

When analyzing Figure 6, it may be seen that there is a tendency for the higher values of S_1/A (characteristic of soils with a greater capacity for runoff production) to correspond to the higher values of antecedent rainfall, confirming the hypothesis that humid soils can produce higher surface discharges.

As shown in Figure 6, it may be noted that there is a tendency for a decrease in the reservoir deficit (*D(0)*) with the increase of P_{5days} (sum of the rainfall of the previous 5 days). In other words, the higher values of the humidity deficit correspond to the case when the soil displays a lower contribution of the antecedent rainfall. Otherwise, when the previous 5 days rainfall is higher, the reservoir deficit is lower, as it was expected.

Validation Phase – DPFT methodology

The validation for sample 2 was carried out using the calibrated average values of the parameters of the respective LF models of sample 1. Figure 7 shows the hydrographs corresponding to the observed and calculated discharges, generated by the respective LF models, for event 13 (chosen at random), in the validation phase for sample 2.

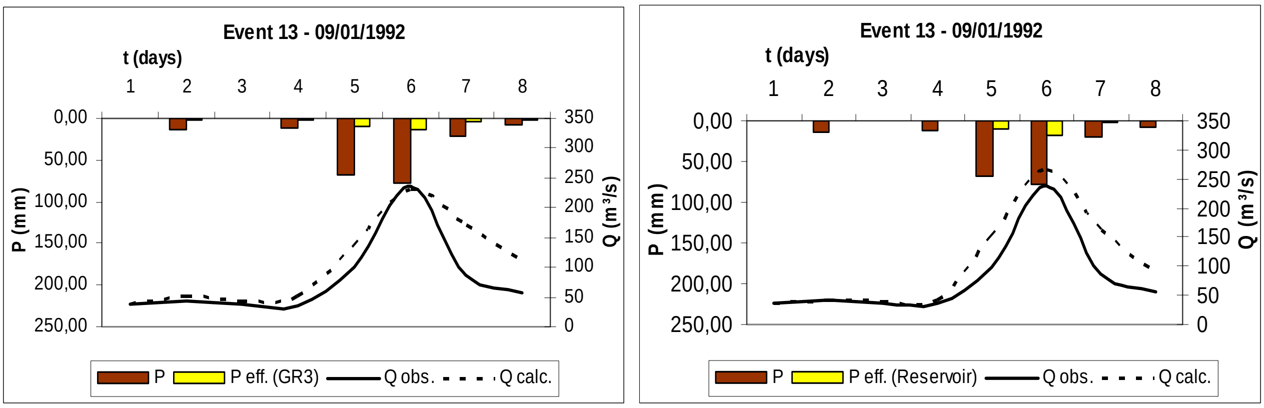

Figure 7 – Total and calculated effective rainfall, using GR3 and Reservoir models; observed and calculated discharges - (Validation for sample 2)

The Nash coefficients corresponding to the validation of Sample 2, for the two models are shown in Table 4.

Table 4 – Nash coefficients for sample 2 (validation)

GR3		Reservoir	
Event	NASH	Event	NASH
12	**0.7474**	12	**0.9187**
13	**0.6108**	13	**0.6617**
14	**0.8104**	14	**0.4297**
16	**-1.8113**	16	**-9.6056**
17	**0.7989**	17	**0.4087**
18	**0.4782**	18	**0.2862**
19	**0.2415**	19	**-0.3488**

Taking into account the Nash criteria, it was noted that, in the validation phase, the GR3 model has a better fit than the Reservoir model for the selected events. It is noteworthy that, in this case, average values of D(0) and S_1/A, obtained for Sample 1, were adopted for the validation of sample 2.

Validation Phase – ANN models

The events of sample 1 and 2 (DPFT methodology) are made up of, in general, of rainfall-runoff events that are isolated and of limited duration. To the calibration (training) of artificial neural networks models it is necessary to use greater periods of observations of rainfall and discharge. So, it was necessary to prolong the events of samples 1 and 2, including greater periods at the beginning of each event, in a form that takes into consideration the prior state of the humidity of the basin and taking a greater number of examples for training the network. In other words, the 15 events (samples 1 and 2) were divided in 9 greater events for training of ANN models (named events 1N, 2N,…,9N). For each of the 9 events a model of Neural Network was trained.

Analogously to equation 10 (ARMAX models), the discharge at instant t (Q_t) correspond to the neurons of the output layer (y_t), while the concomitant and previous rainfall and discharges correspond to the neurons of the input layer (x_t, x_{t-1}, x_{t-2}, ...) , as shown in figure 2.

A comparison of 3 types of artificial neural network models, using Nash criteria as a basis, was made in the validation phase (prediction), corresponding to sample 2:

-model 1: 10 neurons

output layer: Q_t

input layer: Q_{t-1}, Q_{t-2}, Q_{t-3} , P_t, P_{t-1}, P_{t-2}, P_{t-3}, P_{t-4}, P_{t-5}

-model 2: 6 neurons

output layer: Q_t

input layer: Q_{t-1}, Q_{t-2}, P_t, P_{t-1}, P_{t-2}

- model 3: 4 neurons

output layer: Q_t

input layer: Q_{t-1}, P_t, P_{t-1}

Table 5 shows the results obtained by the Nash coefficient for the prediction, using the three RNA models for sample 2 (validation). The best results for the calibration phase (events 1N, 2N,…,9N) were used, i.e. the calibrated models for episodes 5N (from 14/11/1987 to 25/03/1988) and 6N (from 08/11/1989 to 18/02/1990), referring respectively to models 1, 2, and 3.

Table 5 – Nash coefficients – Prediction by Neural Networks models

Events	**10 neuron**	**6 neuron**	**4 neuron**
	Model 1	**Model 2**	**Model 3**
	Calibration: event 6N	Calibration: event 5N	Calibration: event 6N
13	-0.0076	0.6747	0.7228
14	0.4526	0.5604	0.7479
16	0.6153	0.6142	0.3425
17	0.7554	0.6779	0.7967
18	-0.6427	0.2084	0.1414
19	0.1273	0.4950	0.4890

In table 5, it can be seen that the best result is that obtained by model 3.

Table 6 shows the comparison in performance, provided by the Nash coefficients, between the DPFT method, (using the loss function given by model GR3) and model 3 (neural networks). It can be seen that the neural network model shows better results that of the DPFT method. It is important to note that the event 12 does nor appear in the list of tables 5 and 6, because it composes the sample 6N, that corresponds to the calibration phase of the neural networks models.

Table 6 – Comparison between Nash coefficients of the ANN model 3
and the DPFTmethod, with GR3 loss function model

Events	ANN	DPFT
13	0.7228	0.6108
14	0.7479	0.8104
16	0.3425	-1.8113
17	0.7967	0.7989
18	0.1414	0.4782
19	0.4890	0.2415

Figure 8 shows the observed and predicted hydrographs, using the DPFT methodology with the GR3 model and the neural networks model (with 4 neurons), for sample 2 (events 13, 14 and 17).

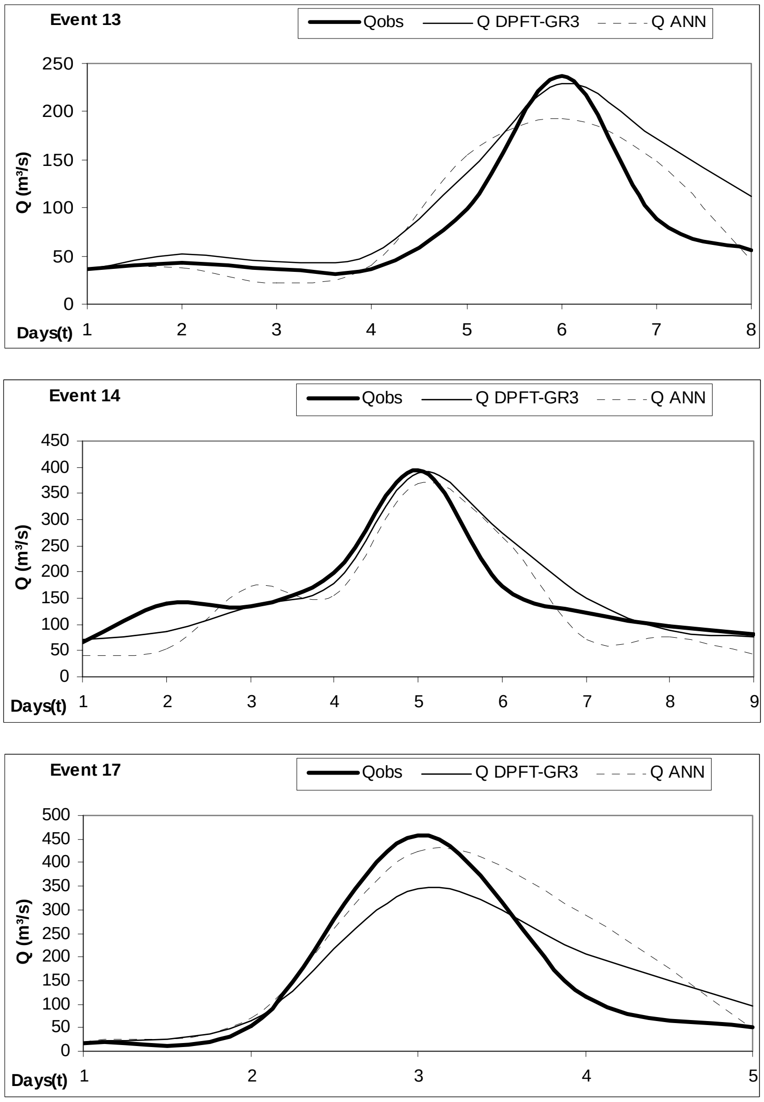

Figure 8 – Observed and predicted hydrographs, using the DPFT method (with GR3 loss function model) and model 3 (Artificial Neural Networks model) – Events 13, 14 and 17.

CONCLUSIONS

In studies and applications of hydrological rainfall–runoff modeling, recent literature always recommends the use of physically based conceptual models. However, many times reality reveals a lack of hydrological information for the hydrolgraphic basin, necessary for the development of these models. This lack of information leads to the use of runoff prediction techniques by means of global models and, if possible, with a smaller number of parameters to calibrate.

In this context, this article shows the utilization and comparison of two global methods for flood prediction, applied to a medium sized hydrographic basin located in the State of Minas Gerais (Brazil), where only daily data for precipitation and intense discharges are available The first technique utilized is based on the Unit Hydrograph method, well known to hydrologists, but here presented by means of a new approach: the DPFT method, proposed in the 1980's. The principal advantage of this method is that it allows the study of Loss Function models, without imposing a priori a nonlinear transformation of total rainfall into effective rainfall. Two simple models of the Loss Function were studied.

The tests made reveal that, initially (calibration phase), the DPFT methodology performs very satisfactorily in the reconstitution of the runoff observed by means of the effective rainfall estimated by the DPFT. It was also verified that the effective rainfalls generated by the method serve as indicators for the investigation and study of simple Loss Function models, with respect to the limitation of the Unit Hydrograph method, concerning basically of the magnitude of the surface basin.

For the two calibrated Loss Function models, the variation of the parameters with respect to the initial state of the humidity of the soil of the hydrographic basin, event by event, given by the sum of the precipitation in the 5 days prior to the event, was shown to be coherent.

When analyzing the performance of the Reservoir and GR3 models in the calibration phase of the data, it was established that the loss function models produced similar results. However, in the validation stage (with the calibrated average parameters), a superior performance of the GR3 model was observed.

The second global method, compared to the DPFT method, is based on a class of black-box models, which used Artificial Neural Networks, applied to hydrological modeling since the 1990's. The architecture of the network employed (NSRBN) proved to be very effective, dealing directly with the nonlinearity inherent in the rainfall-runoff process in the hydrographic basin. In the study of the case shown, where the worked data are only data for rainfall and runoff, this technique is advantageous, in the sense that, as with all black-box models, it is not necessary to know details of the basin studied (basin physiography, state and constitution of the soil, previous humidity) and how they interfere in the extent of the runoff.

As the Neural Network models were trained for each rainfall event, it was not necessary to include neurons for the identification of seasonality.

Among the Neural Networks models analyzed, it was established that a parsimonious model of 4 neurons (3 input and 1 output) demonstrated better performance, with the condition that the events in the calibration phase are prolonged, in such a way as to have a sufficient number of training examples. In accord with the tests made, it was established that the Neural Network models shown here made a more precise prediction for rainy periods that are neither very short, nor excessively long, of a form that does not include periods of drought

Finally, the analysis of figure 8 and table 6 allows us to conclude that, in this case study, both global methods demonstrate very satisfactory results in prediction, taking into consideration the hydrographic information available for each basin, and that the Neural Networks model exhibits a greater efficiency than the DPFT method, even though no physical analysis of the behavior of the basin was possible, using ANN technique.

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