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Special Edition

Neural network for seasonal climate precipitation prediction Brazil

Rede neural para previsão climática sazonal de precipitação no Brasil

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RESUMO

Precipitação é o campo meteorológico mais difícil de ser predito. Uma abordagem ba rede neural ótima é aplicada para previsão de precipitação para o Brasil. Uma re perceptron de múltiplas camadas (RN-PMC) auto-configurada é usada como ferrament A topologia da MLP-NN é encontrada resolvendo um problema de otimização pelo al colisão de múltiplas partículas (MPCA). Previsões para estações de inverno e mostradas. A previsão neural é avaliada usando dados de reanálise do NCEP/NCAR e satélite GPCP (*Global Precipitation Climatology Project -- monthly precipitation dataset*).

Palavras-chave: Precipitação; Previsão climática sazonal; Rede neural auto-configurad

ABSTRACT

Precipitation is the hardest meteorological field to be predicted. An approach based on a neural network is applied for climate precipitation prediction for the Brazil. A self-configu layer perceptron neural network (MLP-NN) is used as a predictor tool. The MLP-NN found by solving an optimization problem by the Multi-Particle Collision Algorith Prediction for Summer and Winter seasons are shown. The neural forecasting is ev using the reanalysis data from the NCEP/NCAR and data from satellite GPCP (Global P Climatology Project -- monthly precipitation dataset).

Keywords: Precipitation; Seasonal climate prediction; Self-configured neural network.

1 INTRODUCTION

The climate forecast is a key factor for many social and economic sectors, su defense for disasters, energy production, agricultural, transportion systems, insurance p is a country with a great territorial extension, with different precipitation and temperatur The CPTEC-INPE (CPTEC: Center for Weather Prediction and Climate Studies, INPE Institute for Space Research) has global and regional models to perform the weather a predictions based on numerical integration of partial differential equations. These are cc sophisticated computer models executed by a supercomputer.

Models for carrying out prediction and climate monitoring using artificial intelli already employed in research related to climate precipitation (ANOCHI and CAMPO 2014), hydrology (SOUZA *et al*., 2010), severe weather (RUIVO *et al*., 2015), (BAB 2010), among others.

Brazil presents a strong climate variability, having equatorial, tropical, and s climate regions. In the North, there is a rainy equatorial climate, practically without dry the Northeast, the rainy season, with low rainfall rates, is restricted to a few months, cha a semi-arid climate and presents higher climatic predictability. The Southeast and C regions are influenced by both tropical and mid-latitude systems, with a well defined dry winter and a rainy season in summer with convective rain-fall. Both regions have low pr due to less dependence on ocean conditions and the wide variety of meteorological sy affect them. Finally, the Southern region of Brazil, as well as the North region, do not ha or dry seasons well defined. In the South of Brazil, there is approximately an unifo distribution during all year. But this region is characterised by medium predictability, and latitudinal location, it is more influenced by medium latitude systems, where frontal syste main cause of rainfall during the year.

Several climatic regimes motivated (ANOCHI and SILVA, 2009) to develop prediction model for the precipitation field by Neural Networks (NN). The neural model wa to the precipitation field for monthly and seasonal forecasting.

Different from our previous studies, where the NN were designed for climate associated at each Brazilian regions, here the NN forecaster is applied for the entire cour

2 MATERIAL AND METHODS

The proposal is focused on the application of neural networks in meteoro methodological novelty consists in the definition of an optimal neural network. The optim identification is formulated as an optimization problem, solved by the meta-heuristic M methodology is called the self-configuring network.

The methodology can be applied without the support from an expert on neural ne applying the methodology, the user provides a data set, and the system defines the b network type multilayer perceptron type for the application.

2.1 Neural Networks

Artificial neural networks are computational methods in which the operating p
conducted by a mathematical model inspired by the functioning of the basic elements th
neural structure of intelligent organisms, that acquire knowledge through experie
behavior results from the interactions between the processing units, from their en
through a learning process.

Neural networks are distributed parallel systems, composed of neurons or proces
which compute certain mathematical functions, usually non-linear. Processing neuro
distributed in one or more layers and interconnected by a large number of connection
weights), which store the knowledge represented in the model.

Mathematically, we can describe a neuron *k* by writing the following pair of
(HAYKIN, 2001):

$$\boldsymbol{input}: v_k \sum_{j=1}^{n} w_{kj} x_j$$

$$\boldsymbol{output}: y_k = \varphi(v_k + b_k)$$

where x_n are the inputs; w_{kj} are the connection weights; b_k is the bias; φ is the
function; and y_k is the output.

The different architectures of neural networks can be formed by the combination
neurons and are defined by the type of connection between networks. Each neuron tı
signal to the neurons that are in one of the subsequent layers.

In this work, the Multiple Layer Perceptron (MLP) network was used. The MLP ha
as an alternative solution for non-linearly separable problems and has been successfully
solve complex problems through its supervised training using the error backpropagation
based on the learning rule for correction of error (HAYKIN, 2001).

The architecture of the MLP network consists of the topological arrangem
processing units of the neurons with the respective values of weights associated
connections. The synaptic weights are adjusted by delta rule. The MLP network has an
at least one intermediate layer, and an output layer.

Although a NN model has great potential, its performance depends on the defir
parameters, since the definition of the topology can significantly influence the phase of t
process.

2.2 MPCA to identify the best topology NN

In practice, the NN topology is usually selected by using empirical or statistical me
are used to find the best parameters. Here, we use the Multiple Particle Collision Algorith
metaheuristic for configuration the topology of the MLP network. The strategy applied b

and CAMPOS VELHO, 2014, can be considered as an optimization problem, where ea the search space represents a NN with different topologies.

The MPCA metaheuristic was introduced by (LUZ et al., 2008), and it is an exten canonical Particle Collision Algorithm (PCA) (SACCO, 2005). The proposed structure for algorithm uses a set of *n* particles, independently exploring but collaboratively, the sa space. The introduction of *n* particles leads to the need to implement an indirect com mechanism between particles.

The MPCA starts with a selection of an initial solution, it is modified by a perturbation conducing to the construction of a new solution. The new solution is com this solution can or cannot be accepted. If the new solution is not accepted, the parti send to a different location of the search space. If a new solution is better than the new absorbed. The figure 1 shows the pseudo-code of the MPCA metaheuristics (LUZ, 2008)

Figure 1 – Pseudo-code for MPCA. Adaptada de (LUZ, 2008)

```
Generate an initial solution: Old-Config
Best-Fitness = Fitness{Old-Config}
Update Blackboard
For n = 0 to # of particles
    For n = 0 to # iterations
    Update Blackboard
    Perturbation{.}
        If Fitness{New-Config} > Fitness{Old-Config}
            If Fitness{New-Config} > Best-Fitness
                Best-Fitness = Fitness{New-Config}
            End If
            Old-Config = New-Config
            Exploration{.}
        Else
            Scattering{.}
        End If
    End For
End For
```

The MPCA has been used successfully in several optimization problems, such as of failures (ECHEVARRÍA *et al*., 2014), identification of atmospheric temperatu (SAMBATTI *et al*., 2012), climate prediction (ANOCHI and CAMPOS VELHO, 2014), sc radiative inverse problem (TORRES *et al*., 2015), and the other applications.

2.3 Meteorological data

For the climatic forecasting of precipitation using neural networks, different data collected, from reanalysis data from the National Centers for Environmental (NCEP/NCAR) to Global Precipitation Climatology Project monthly precipitation dataset (

The NCEP/NCAR provides historical series of meteorological data obtained tl assimilation and analysis of data observed for the entire planet from 1948 up to the pres data come from radiosondes, land surface meteorological stations, oceanic buoys, ship, satellites, GNSS (General Navigation Satellite Systems) stations, and data from mod and analysis (assimilation process). For the constitution of these data, global atmos surface flow fields derived from numerical forecasting and data assimilation systems (KALNEY, 1996).

The input variables to the neural network were selected from the NCEP Rean from the NOAA/OAR/ESRL PSD, Boulder (CO), USA, by the wel https://www.esrl.noaa.gov/psd/}. The input variables are: zonal and meridional winds at t (300hPa, 500hPa, 850hPa), air temperature at 850hPA, and specific humidity at 850hPa

The GPCP Monthly product provides a consistent analysis of global precipitatic integration of various satellite data sets over land and ocean, and a analysis calibration Data from rain gauge stations, satellites, and sounding observations have been merged monthly rainfall on a 2.5º global grid from 1979 to the present (ADLER, 2003).

The variable used as output to the NN was selected from the monthly precipitatio GPCP provided by the NOAA/OAR/ESRL PSD, Colorado, USA.

3 EXPERIMENTAL SETTINGS

The strategy for optimizing the NN architecture is considered as a mon optimization problem. Four search space parameters will be optimized: two continuous (the learning rate parameter (η), and the momentum constant (α), and two discrete var number of neurons in the hidden layer, and the type of activation function).

For the neural network learning phase, a well known procedure is the delta rul correction $\Delta w_{ji}(n)$ is applied to the synaptic weight, for minimizing the square differenc the network output and the target values δ. Following the rule delta, the synaptic weigh by (HAYKIN, 2001):

$$\Delta w_{ji}(n) = \alpha \Delta w_{ji}(n-1) - \eta \frac{\delta \varepsilon(n)}{\delta w_{ji}}$$

where $\Delta w_{ji}(n) \equiv w_{ji}(n)$ -$w_{ji}(n-1)$.

In this experiment, several realizations are executed to find representative solu configuration of the NN topology for the climatic prediction experiment is described belo is applied for each grid point:

- Nine inputs (meteorological variables).

- One output node for the results: the precipitation at the grid point. In t algorithm, the MLP computes the output y_k and does a comparison with data y_k (observed precipitation).
- One hidden layer with 12 neurons.
- The hyperbolic tangent is the activation function.
- Learning rate η and momentum value α produce the best fitness (MLP-MP following numerical values: $\eta = 0.57$ and $\alpha = 0.65$.
- The iteration the training phase stops when the error reaches the value 10^{-}
- For determining the NN configuration by the MPCA, 25 experiments are pe find the best fitness to NN.

4 RESULTS AND DISCUSSION

The results presented in this section show the behavior of the neural network as model of the precipitation variable.

The numerical experiments carried out in this study show a good performance o MPCA tool. The procedure identifies the best parameters for the NN application, topology by minimizing the a cost functional. The mentioned approach does not require a to the task for NN configuration. The neural model can be implemented for both applic operational use or/and in research activities.

Figure 2(a) is the observed precipitation by GPCP in the summer at 2015 in Bra 2(b) is the forecast of precipitation obtained by the Artificial Neural Network (ANN) at sa (summer 2015). The NN presented a good performance for describing the precipitation p the Brazilian regions: North, Northeast, Midwest, and Southeast. In the states of São Mato Grosso do Sul, the NN underestimated the precipitation. For the Santa Catarina sta model overestimated the precipitation. However, in general, the results obtained with model showed a good behavior when compared with the observed data (GPCP).

Figure 2 – Climate precipitation prediction in Brazil for summer 2015

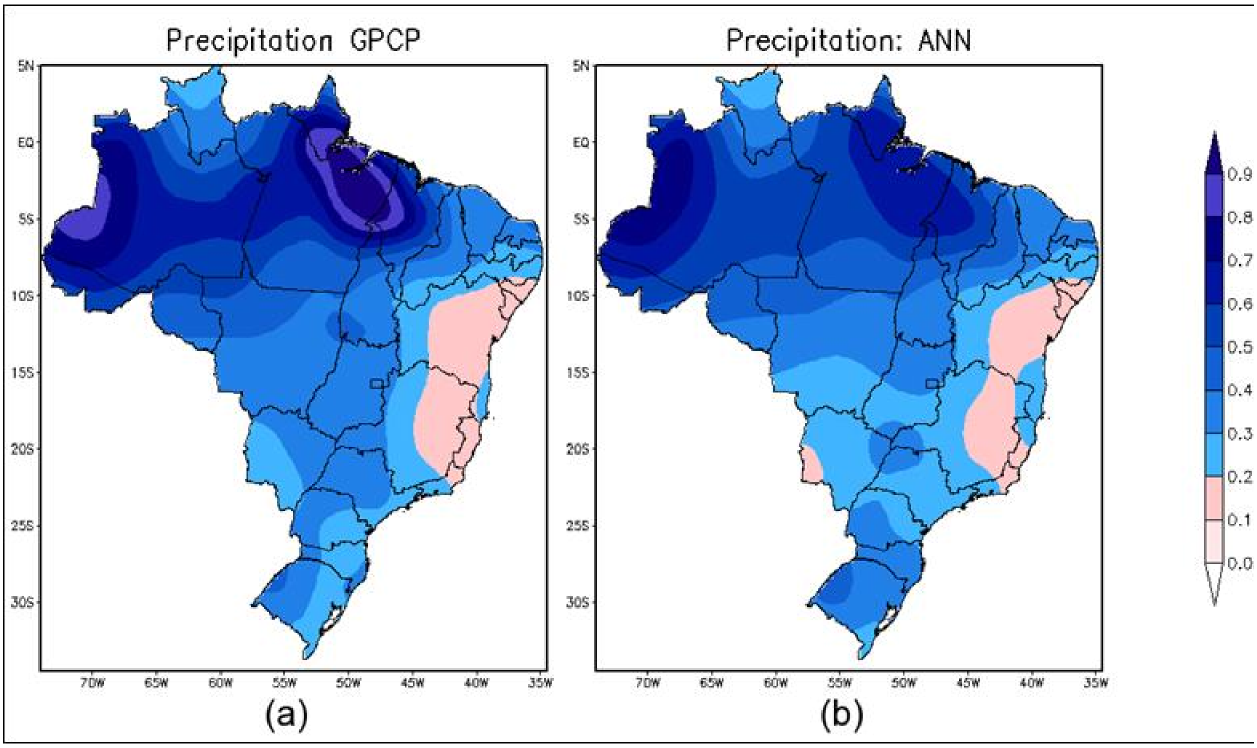


Figure 3(a) is the precipitation observed by GPCP in the autumn at 2015 in Bra 3(b) is the prediction of precipitation predicted by ANN in the autumn 2015. For the cite the neural network did a good prediction for the rainfall behavior for the regions: in the northeast (period of the rainy season); the extreme north of Brazil, and in the South Brazil, composed by the states of Paraná, Santa Catarina, and Rio Grande do Sul - t states form the South (Brazilian) region, presenting a subtropical climate regime precipitation is well distributed throughout the year in this region.

Figure 3 – Climate precipitation prediction in Brazil for autumn 2015

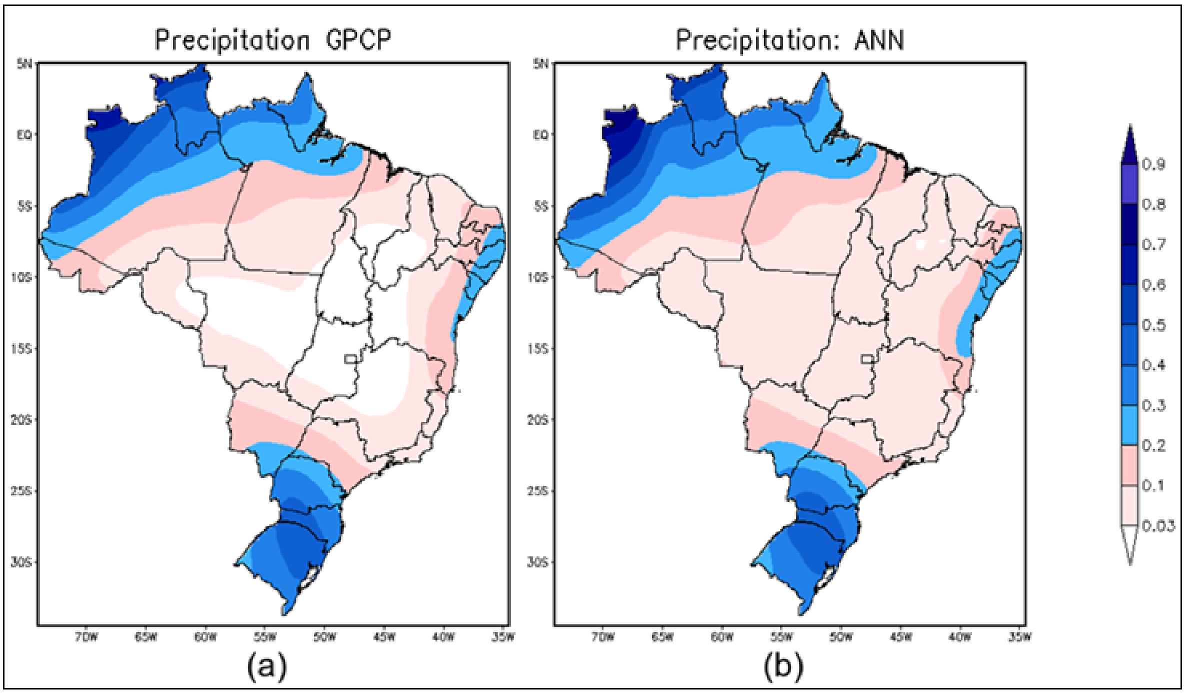


Figure 4(a) is the precipitation observed by GPCP in the winter at 2015 in Brazil. is the prediction obtained with the neural model. The forecast of the neural model (ANN- winter presented a pattern very similar to the observation of the GPCP. The exception northern Maranhão, in eastern Piauí, in the states of Ceará, Rio Grande do Norte, P Pernambuco, where the neural model overestimated precipitation.

Figure 4 – Climate precipitation prediction in Brazil for winter 2015

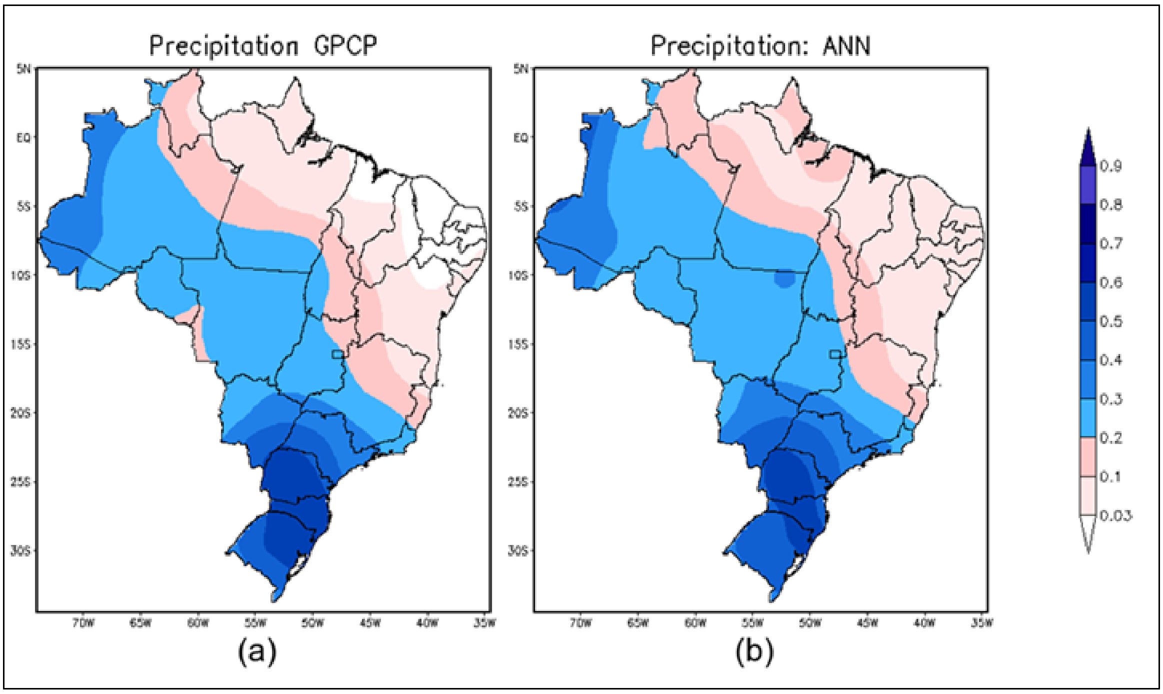
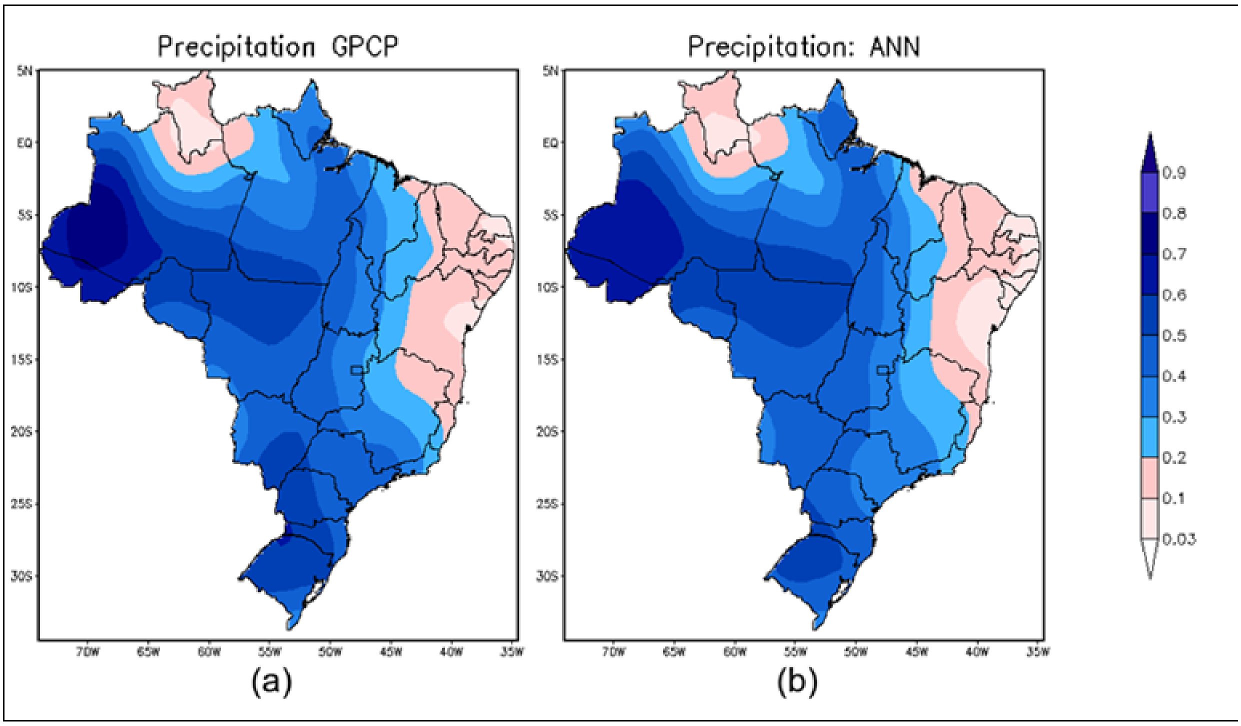


Figure 5(a) is the precipitation observed by GPCP in the Spring at 2015 in Brazil. is the prediction obtained with the neural model. During this period of spring, the ne shows a good forecast in almost the entire Brazilian territory, mainly in the north, nor central west regions.

Figure 5 – Climate precipitation prediction in Brazil for Spring 2015



5 CONCLUSION

Brazil is a country with different climatic conditions: equatorial, tropical, and climatic zones. The variable precipitation has a high variability implying in difficul predicted. Precipitation has a strong impact for the society (natural disasters) and economical sectors.

It is a hard task to develop models to predict the precipitation. There are many r such difficulties: local and synoptic patterns has different influences, and different variat conditions are associated with the rain-fall depending on the season of the year. In ac precipitation has high variability in space and time. All these factors has strongly influe behavior of the precipitation.

Neural network is a prestigious area of Artificial Intelligence and has shown their e various application areas, being meteorology one of them. Predictive models based o easy to use, and do not require very powerful computers.

The results present in this paper are consistent with observation data (GPCP), b good tool to support seasonal climate prediction.

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