Forecast of Extreme Precipitation Events in São Paulo using Neural Networks

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Introduction

Extreme rainfall events are responsible for severe human and material losses, specially in densely populated urban areas such as the city of São Paulo[1,2]. A skillful and reliable precipitation forecast is vital to mitigate the impacts of these events.

The current global operational Numerical Weather Prediction (NWP) models are unable to resolve convective and microphysical processes directly. This limitation requires the employment of parametrizations. Given the empirical nature and limitations of parametrizations, the precipitation forecasts of global NWP are often poor, specially for extreme events.

The goal of this study is to provide an operational methodology to improve and downscale the short-range (24-hour) precipitation forecast in the city of São Paulo employing state-of-the-art deep learning techniques.

Deep Neural Networks

An Artificial Neural Network (ANN) is a supervised machine learning algorithm very efficient in approximating non-linear functions. The multi-layer perceptron is a class of ANN consisting of a set of nodes organized in fully-connected layers. Each node has an associated vector of parameters (weights **w** and bias **b**) . The dot product of the parameter vector with the input vector **x** is activated by a function **g**. The output of a single node of the network is given by:

$$y = g(\sum_{i=1}^{n} x_i w_i + b)$$

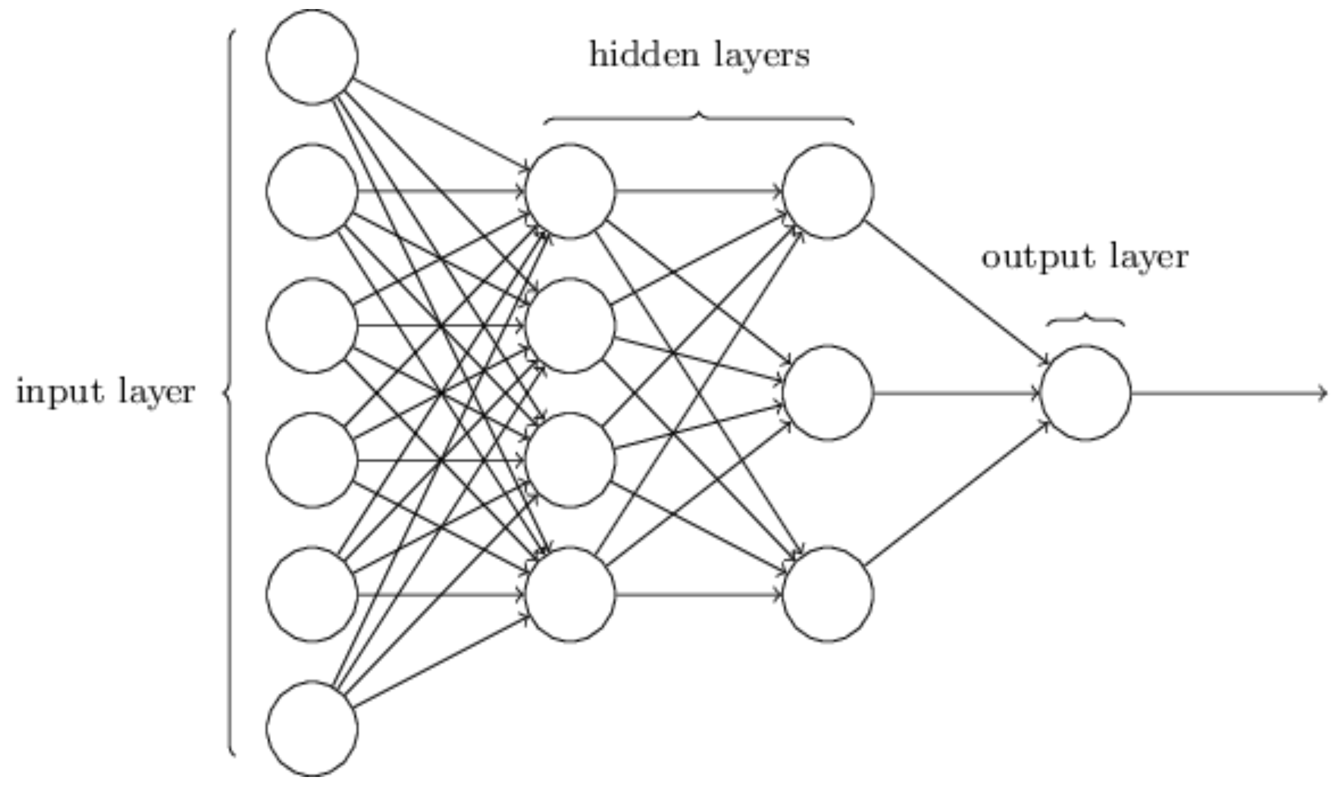

Figure 1 - Multi-layer perceptron scheme.

The backpropagation algorithm is used to tune the network parameters to minimize the Root Mean Squared error function. This process is referred as "training".

A Deep Neural Network (DNN) has several hidden layers with a large set of trainable parameters. Problems such as the vanishing gradient and overfitting must be considered in order to train a DNN. To avoid this problems we have employed the following:

- ReLU activation function[3] instead of logistic;
- Dropout[4] to avoid overfitting and co-adaptation;
- Stochastic gradient-descent with adaptative learning rate[5] to improve convergence.

Data

A 25-year (1985-2010) dataset was used to train the DNNs and a 5-year (2011-2015) dataset to evaluate the results. The precipitation data were extracted from CHIRPS (Climate Hazard Infrared Precipitation with Station data) in a 0.15° grid. The explanatory variables are output variables from the 1° GFS 0 UTC model run (Table 1). The model variables were extracted in the 9 closest grid points to the city of São Paulo. Additionally, 3 climatic indices were used as explanatory variables (AMO, SOI and PDO).

Table 1 - Explanatory variables from GFS 0 UTC model run

Variable name	Height (m)	Forecast time (UTC)
Zonal wind	10	12
Meridional wind	10	12
Precip. water	Integrated	12
Temperature	2	12 and 21
CAPE	Integrated	12
CINE	Integrated	12
Pressure	Mean sea-level	12

Results and discussion

Eleven DNNs were trained to downscale the 1° input variables into a 0.15° grid covering São Paulo. Figure 2 shows the total precipitation of 2015 as forecasted by the DNNs and GFS (sum of the 24-hour forecasts) and CHIRPS observational data as reference. The DNNs provided a significative improvement on the quantification of the annual precipitation and the spatial distribution of the rain within the city.

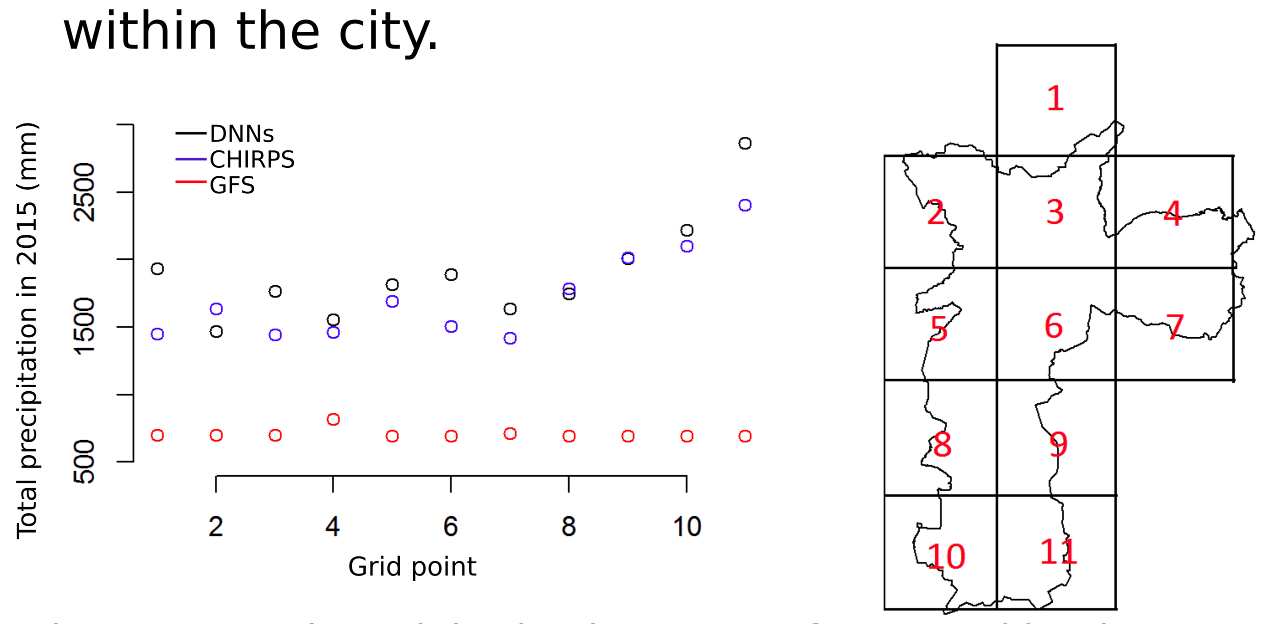

Figure 2 - Total precipitation in 2015 as forecasted by the DNNs, GFS and observed by CHIRPS.

Figure 3 shows the probability of detection (POD) and the false alarm rate (FAR) of rainfall events above a given percentile in São Paulo (2011-2015). The low POD for the most extreme percentiles may be related with GFS errors, insufficient input information or lack of examples of these events. The employment of a regional model as input might improve the DNNs forecast.

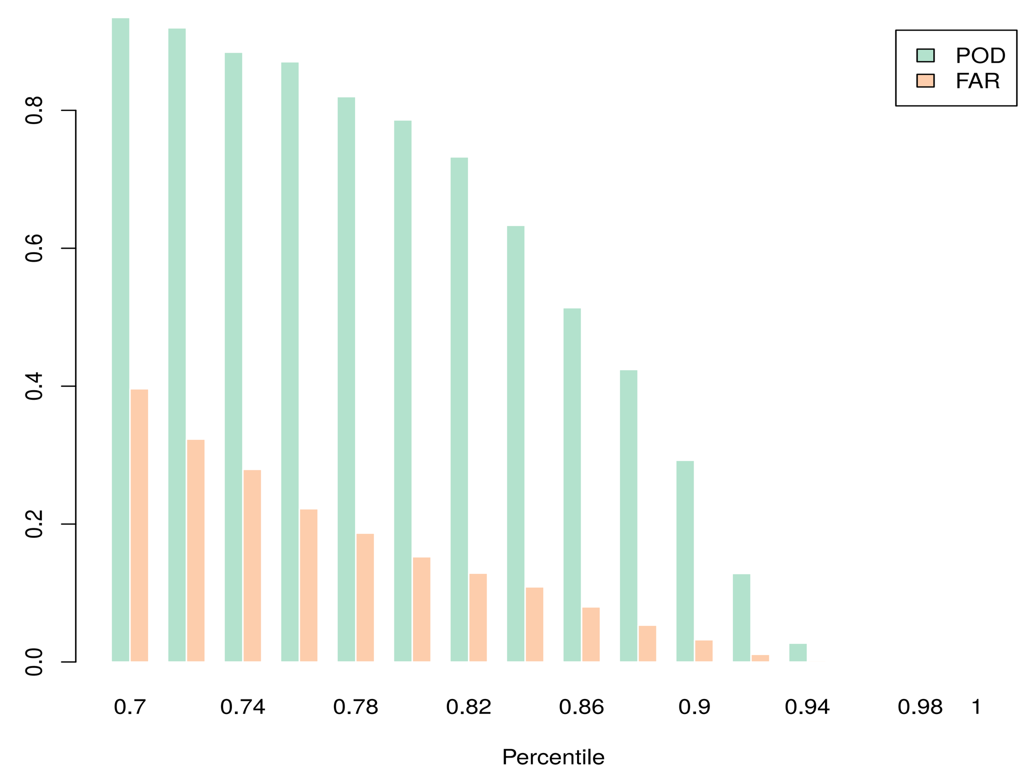

Figure 3 - POD and FAR of DNNs 24-hour precipitation forecast in São Paulo (2011-2015).

References

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