Improved Extreme Rainfall Events Forecasting Using Neural Networks and Water Vapor Measures

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Abstract. In the last few years, many studies claimed that machine learning tools would soon overperform the classical conceptual models in extreme rainfall events forecasting. In order to better investigate this statement, we implement advanced deep learning predictors, such as the deep neural nets, for the forecasting of the occurrence of extreme rainfalls. These predictors are proved to overperform more simple models such as the logistic regression, which are traditionally used as a benchmark for these tasks. Also, we evaluate the value of the information provided by the Zenith Tropospheric Delay. We show that adding this variable to the traditional meteorological data leads to an improvement of the model accuracy in the order of 3-4 %. We consider an area composed by the catchments of four rivers (Lambro, Seveso, Groane, and Olona) in the Lombardy region, northern Italy, just upstream from the metropolitan area of Milan, as a case study. Data of convective extreme rainfall events from 2010 up to 2017 (more than 600 extreme events) have been used to identify and test the predictors.

Keywords: Nowcasting, Extreme Rain Events, Deep Neural Networks, Global Navigation Satellite System, Zenith Tropospheric Delay.

1 Introduction

Many researchers in the field of meteorology claim that machine learning techniques will soon overperform the traditional physically based models in weather forecasting.

Also, black box models seem to be well suited for real-time application, since they are faster due to the lower computational effort required with respect to the traditional meteorological nowcasting methodologies, which are based on physically based models.

In particular, extreme events are very difficult to predict with classical Numerical Weather Prediction (NWP) models because they usually affect very small and localized areas and the convection is triggered by peculiar and local conditions, requiring both high-resolution NWP and high temporal and spatial resolution observations.

In this work, we deal with the problem of forecasting the occurrence of extreme local rainfall events 30 minutes ahead.

The considered area, located in Lombardy region, Northern Italy, is composed by the hydrological basin of four torrential rivers (Lambro, Seveso, Groane, and Olona). This is a high-risk territory due to the high frequency of severe and short thunderstorms, which usually trigger flash floods. The situation is even more critical due to the presence of the metropolitan area of Milan, where the flows coming from the four considered rivers are drained, causing severe damage. In 2014, for instance, floods produced damages evaluated in several million euros in the Milan municipality.

In this work, we adopted advanced machine learning tools, the Deep Neural Networks (DNNs hereafter), which receive as input some meteorological variables sampled inside and around the study area and return as output the prediction about the occurrence of an extreme event.

In addition to the classical meteorological variables (temperature, pressure, humidity, wind speed), we also included the Zenith Tropospheric Delay (ZTD), which seems to be promising since it is a proxy of water vapor in the atmosphere, a fundamental variable in rain events genesis [1] [2] [3] [4].

This represents a novel element of this research since it is one of the first attempts to use the ZTD in a black box model for prediction of severe storms [5] [6]. We quantify the impact of ZTD repeating the task twice: the first time without considering ZTD, the second including it within the model inputs.

Developing a black box model for this environmental problem could become an innovative nowcasting product exploitable also by Civil Protection Agencies to face emergencies.

This work is part of the Lombardy based Advanced Meteorological Predictions and Observations (LAMPO) project (http://www.geolab.polimi.it/projects/lampo-project/).

2 Methods

2.1 Extreme Event Definition

The objective of this work is to identify machine learning models able to forecast the occurrence of extreme rainfall events 30 minutes ahead.

We consider a rainfall event as extreme if it persists for more than 25 minutes within the study area and if the radar reflectivity factor is greater than 50 dBZ.

2.2 Machine Learning Models

Since the model's output is a Boolean variable (occurrence of the extreme event), the task we are dealing with is a binary classification task.

As it is well-known, while developing machine learning tools, it is important to start with some simple models which will be considered as a benchmark for more complex (and hopefully more performing) ones. In this case, we adopted a logistic regression (see Fig. 1) as a baseline model, using its Python implementation provided by Scikit-learn library [7].

The logistic regression is a linear classifier which splits the feature space (which in this case is a high-dimensional one) with a linear manifold and classifies each sample according to its position relative to a linear decision boundary.

Given the complexity of almost all the real-world applications, it is unlikely that the decision boundary is actually a linear one. For this reason, we introduced a more advanced machine learning model which can efficiently deal with problems where classes are not linearly separable: a DNN [8] (see Fig. 1).

The deep neural network here considered has a traditional fully connected structure [9] and has been implemented in Keras [10] with TensorFlow backend.

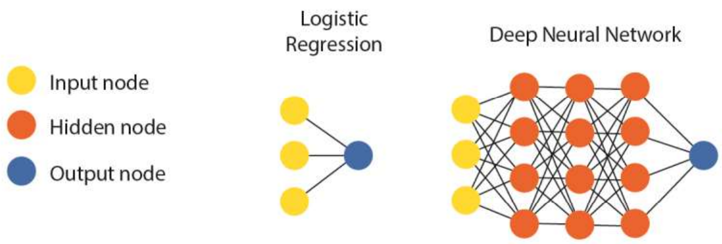

Fig. 1. Representation of the considered model's architectures.

To find the best combination of hyper-parameter (learning rate, batch size, regularization rate, activation functions shape, number of hidden layers, number of neurons for each layer, class weights) values, we implemented a traditional grid search approach.

The dataset used to identify the classifiers has been split into training (70 % of the samples), validation (15 %) and test (15 %) sets, as it is common practice in the neural network's identification procedure.

Since we are dealing with a classification task, we considered the binary cross-entropy as loss function and the overall classification accuracy as validation metrics.

Early stopping and L2 norm weight regularization have been used to avoid overfitting on training data. The performances, in terms of overall accuracy and confusion matrix, are then evaluated on the test set.

2.3 Meteorological Variables

Several classical meteorological variables are measured every 10 minutes: temperature, air pressure, wind speed, and relative humidity. In addition, another variable has been considered: the Global Navigation Satellite System (GNSS) derived ZTD estimated from the observations of the permanent geodetic station of Como. ZTD represents the zenithal delay in the transmission of the GNSS signal from the satellite to the ground receiver caused by the troposphere [11]. It is the sum of a delay caused by the troposphere gases in hydrostatic equilibrium, called Zenith Hydrostatic Delay

(ZHD) and a delay caused by the presence of water vapor called Zenith Wet Delay (ZWD). Since the temporal variations of the first term are very small, the ZTD could be considered a proxy of the presence of water vapor in the atmosphere [12], which is a fundamental variable in rain events genesis.

Each sample in the dataset is thus formed by an input vector, whose elements are the meteorological variables, and by an output value, a boolean variable which represents the occurrence (or not) of the rainfall extreme event.

The dataset considered in this work covers the period from 2010 to 2017 and contains 656 extreme events (together with thousands of cases where the extreme events did not occur).

3 Results

The baseline situation (i.e., using logistic regression with traditional meteorological variables only) guarantees an overall classification accuracy of 72.5 % corresponding confusion matrix is reported in Fig. 2.

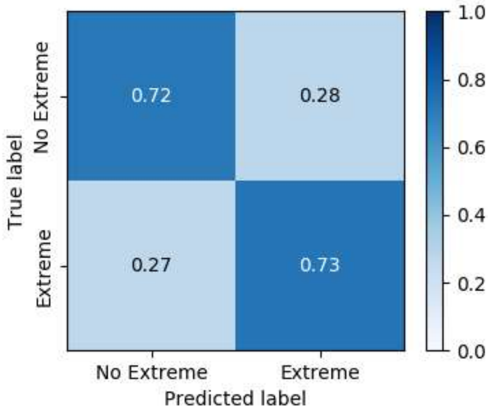

Fig. 2. Confusion matrix obtained with the logistic regression considering traditional meteorological variables only.

As already stated in the previous section, given the complexity and the nonlinear nature of the processes which occur in the atmosphere, it is very unlikely that a simple model such as the logistic regression would turn out to be the best approach to deal with the considered problem.

This idea is confirmed by the performances obtained with a more complex model: a DNN with three hidden layers, each one composed by ten neurons: the overall accuracy grows up to 79.0 % (see Fig. 3 for the confusion matrix).

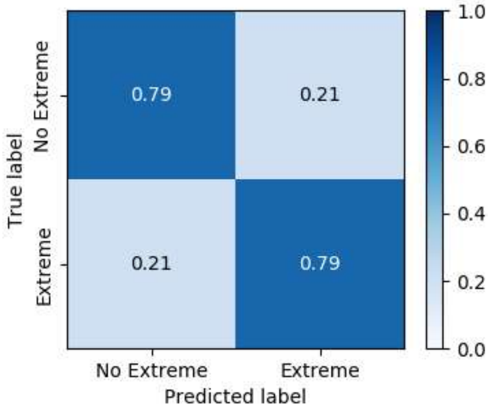

Fig. 3. Confusion matrix obtained with the DNN considering traditional meteorological variables only.

To evaluate the importance of including ZTD estimates, we repeated the identification of the two models with the new set of input variables.

Fig. 4 and 5 show the confusion matrices computed with the logistic regression and the DNN, respectively. Looking at the comparison between the models, the results exhibit almost the same trend when the ZTD is included or not in the inputs: adopting complex models like the DNNs, the overall accuracy in the forecasting of extreme events increases of 6.5 % and 8.5 % for the cases without and with the ZTD, respectively (see Table 1).

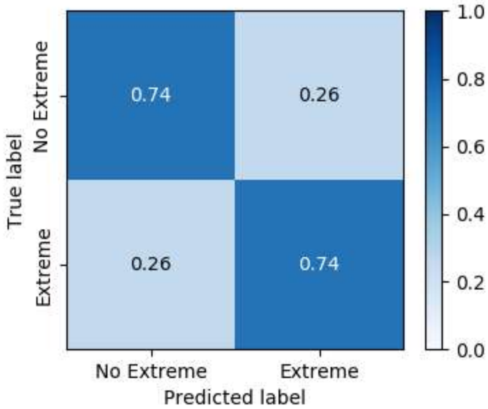

Fig. 4. Confusion matrix obtained with the logistic regression, including the ZTD in the input variable set.

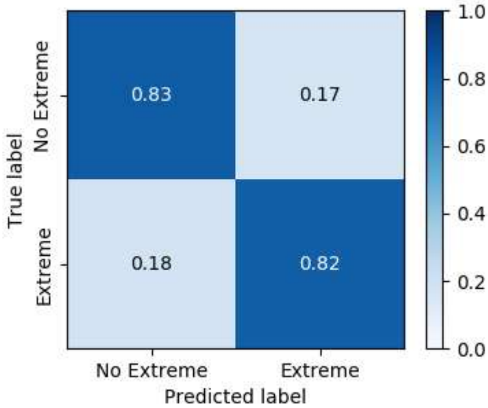

Fig. 5. Confusion matrix obtained with the DNN, including the ZTD in the input variable set.

The performances computed in terms of overall accuracy, which are reported in Table 1, allow quantifying the value of the information provided by the ZTD measured at Como. In fact, considering the logistic regression, including the ZTD within the input set increases the accuracy from 72.5 % to 74.0 % (+1.5 %). The advantage is even more evident when adopting a DNN: the overall accuracy grows from 79.0 % to 82.5 %.

Table 1. Overall accuracy of the models identified in the study.

Model	Overall accuracy
Logistic regression without ZTD	72.5 %
DNN without ZTD	79.0 %
Logistic regression with ZTD	74.0 %
DNN with ZTD	82.5 %

4 Conclusion

In this paper, we showed how machine learning techniques can be effectively used to forecast extreme rainfall events. In particular, the results demonstrate that complex nonlinear models, such as the DNNs, overperform the logistic regression, which has been used as a benchmark. For the considered case study, this advantage can be quantified in the range of 5-10 %.

In addition, we confirm the results recently obtained in [5] and [6]: including the ZTD in the input set leads to an increase of the model accuracy, especially when adopting a DNN, of the order of 3-4 %.

This fact seems interesting because the ZTD station, located in Como, is on the border of our study area. We would expect even better performances in case the station where ZTD is measured was localized closer to the center of the study area or if there were some stations inside and/or outside the considered boundary.

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