Smart City Clima, an approach for reducing vulnerability to climate change and increasing resilience in cities – a case study for Buenos Aires city.

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Abstract

Climate change and the growing rate of urbanization are increasing the levels of vulnerability for larger amounts of citizens worldwide. That is the case of Buenos Aires city, a megalopolis in South America, the capital city of Argentina. With a population close to fourteen million people the city has been showing increasing levels of impacts of the climate on the functioning of the city resulting in extreme flooding events with several deaths a year and also more heat waves with their correlation in the amount of people affected. Historical records show that yearly rainfall has been increasing to close to twenty percent last century and occurs in fewer major events. This coupled with the unplanned and significant growth of the city during the same period of time which was over tenfold has resulted in a city with higher probabilities for flooding, more vulnerable people and growing needs for infrastructure investment, financial assistance to the affected people and enterprises, and emergency procedures to assist after the extreme events. This paper has developed an approach named Smart City Clima to dealing with climate events in cities and it is being implemented in Buenos Aires as an initial case study. The project and its approach is relevant because it is a general framework for dealing with extreme and uncertain climate events in cities and that is, as we know, a common issues for many of the larger and growing cities worldwide.

Keywords: Cities, resilience, vulnerability, Big Data, Data Science, Artificial Intelligence, Machine Learning, Smart Cities.

Introduction

A potential increase in world population living in cities by 2050 is expected (6 billion people will be living in them). Furthermore, they will be exposed to climate change, particularly, the increase in intensity and frequency of the consequential effects of intensive urbanization (McCarthy, Best, & Betts, 2010), such as the urban heat island and

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flooding. Since these regions account for a large part of the population, the potential impact of the given phenomena is important, as it carries an increased risk for people and their productive activities. In order to diminish the risk by reducing the vulnerability of the population, it is important to assess the frequency and intensity of the occurrence of extreme events.

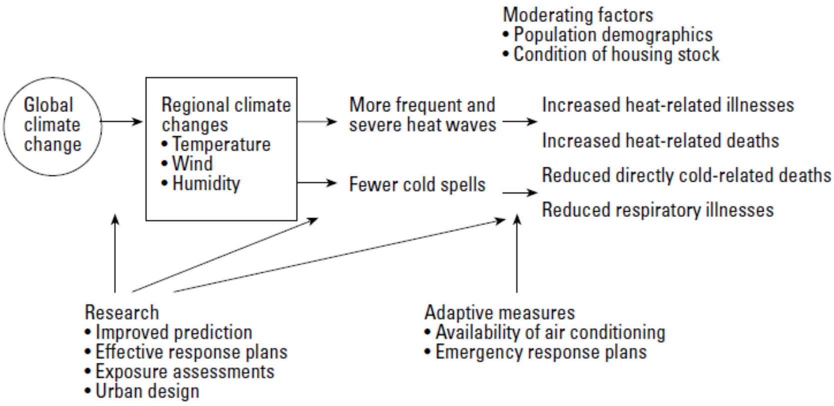


Figure 1 Influence of climate change on temperature-related diseases (McGeehin & Mirabelli , 2001).

On the other side, under the new paradigm of Big Data, immediate access as well as a simple and direct disposition of abundant data is becoming increasingly common. Thus, systems that are capable of handling large amounts of data and convert them into useful information for decision-making purposes turn out to be ideal for solving complex problems. Consequently, with the consolidation of this technological trend, it is possible to address the adversity that climate change presents.

Moreover, the project called *Smart City Clima* is an innovative way of dealing with extreme weather events in cities, so as to generate a network among the inhabitants of the city (in this case study, Buenos Aires and its metropolitan area - AMBA), in order to increase their *resilience* to these events, reducing the uncertainty associated with prognosis and providing geo-referenced and personalised information. This approach is framed in a variety of global initiatives currently in progress, which aim to change the paradigm of how to improve the operation and management of cities (Massachusetts Institute of Technology (MIT), 2015), (Institute of Governmental Studies, 2015).

As technological foundation, the project is based on Artificial Intelligence (AI) algorithms; particularly Genetic Programming (GP) and Artificial Neural Networks (ANN) were used. These methods allow a more accurate forecast of the meteorological variables and have the advantage of being adaptive and versatile to a large number of problems. A forecast with four daily horizons (for the same day and up to three days in advance) was performed. The variables studied were temperature (maximum and minimum), humidity, wind speed and atmospheric pressure.

Methods

Big Data and Data Science

As mentioned previously, an approach based on Big Data (BD) and Data Science (DS) was used. Firstly, BD refers to systems that are based on a collection and massive accumulation of data; then they are transformed into information through procedures related to DS seeking to identify patterns and relationships between variables by incorporating statistical and mathematical techniques, particularly elements of IA, and develop an innovative product that is of interest for the community.

Under these concepts, meteorological information from various sources is gathered, both daily measurements and forecasts. In addition, personal information concerning the individual to whom the service will be provided is incorporated (profile of the person, unsafe, location and value of personal property, etc.). Also, data on the existing infrastructure of the city and its behaviour against extreme events, such as flood maps stains or hazard, insurance and subsidies, is added.

Data of meteorological variables are employed in the algorithms developed with the purpose of obtaining refined forecasts.

Genetic Programming and Artificial Neural Networks

As mentioned previously, AI techniques were used to improve existing weather forecasts and increase its spatial density in order to improve their quality with the aim of geo-referencing them.

To achieve it, RNA and PG were implemented. The first one is a series of interconnected units at different levels, which are called neurons; and has its analogy in the human brain. In other words, it is a system of processing units linked together to collaborate in order to generate a stimulus output, which in this case is the improved prognosis. One of the main virtues of this method is its associative and learning from examples capacity, making it particularly attractive to implement when large data sets are possessed (Guitiérrez, Cano, Cofiño, & Sordo, 2004).

Meanwhile, PG is a methodology based on evolutionary structures, i.e. programs that are modified with different iteration steps to develop a structure that performs a specific task; in this case, generate a weather forecast for a given variable. The process by which programs are subjected is based on biological evolution, in which the fittest organisms are those that survive and therefore pass on their genetic information to the next generation. In PG, the selection of individuals or programs is done by the Adaptability or Adjustment Function, which evaluates the ability of each program to perform the commanded assignment. These are optimization methods; especially valuable when the aim is to find a certain relationship among a large number of variables but the nature of the problem is unknown or extremely complex to be solved (Koza, Bennett, Andre, & Keane, 1999).

Methodology

In order to have a forecast with spatial characteristics, thirteen stations were set within the Metropolitan Area of Buenos Aires, from which forecasts are obtained. They include stations belonging to the National Weather Service (NWS) and private stations under the supervision of Weather Underground (WU).

Both described techniques were used for short-term forecasts with four different anticipations (zero, one, two and three days in advance). The information includes both measurements and forecasts from private and public sources, for example those by the NMS, as mentioned timely stated. These variables constitute the set of terminals of PG and the input neurons in the RNA. Among the meteorological variables that comprise it are: maximum and minimum daily temperature, relative humidity, atmospheric pressure, wind speed and direction and gusts. In addition, for some of the aforementioned, we count with the prognostic of other agencies. Given the fact that they have different horizons of forecast they were subsequently uniformed to match their predecessors.

Following a calibration process, the values of the main parameters of both networks and the PG were fixed. They vary by location and anticipation studied, in order to provide maximum flexibility to the algorithm, since by its means, independent structures for each combination of city – prognosis horizon are developed.

Efficiency's evaluation

In order to evaluate the best combination of parameters during the calibration, we proceeded to evaluate each model through two indexes: the Index of Agreement (IoA) and the Root Mean Square Error (RMSE). The expressions for the previous indicators are listed below .

$$RMSE = \left(\frac{1}{n}\sum_{i=1}^{n}(P_i - O_i)^2\right)^{\frac{1}{2}}$$

Equation 1 Root Mean Square Error.

$$IoA = 1 - \frac{\sum_{i=1}^{n}(P_i - O_i)^2}{\sum_{i=1}^{n}(|P_i - O_{ave}| + |O_i - O_{ave}|)^2}$$

Equation 2 Index of Agreement.

The Root Mean Square Error is often used in predictive models to illustrate the differences between predicted values and actual or observed ones. It provides information on the capacity of the short-term resolution of the model, with RMSE = 0 the ideal result. This parameter can take values in the range [0; ∞). Moreover, the Index of Agreement is a dimensionless parameter that reflects the correlation between the predicted values (Pi) and observed (Oi), being IoA = 1 a perfect relation and IoA = 0 an unrelated correlation. Therefore its application range is IoA = [0; 1] .

Bellow, in Figure 2 the results obtained for the calibration of the maximum temperature in the four horizons is detailed, as this variable is appropriate to analyze and study the phenomenon of urban heat islands.

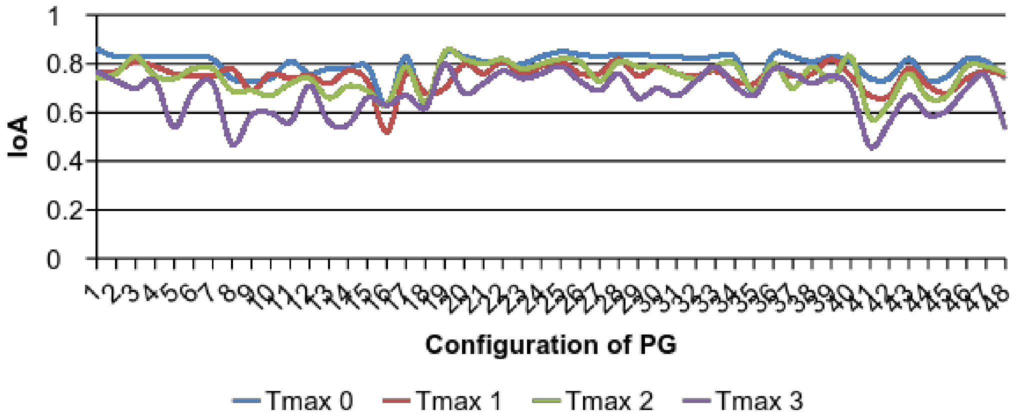


Figure 2 Calibration process of the PG model for maximum daily temperatures, for the Agronomía station.

As noted, there is a range of configurations for which higher and stable values of IoA are achieved for all anticipations referred; that is where the ideal parameters are.

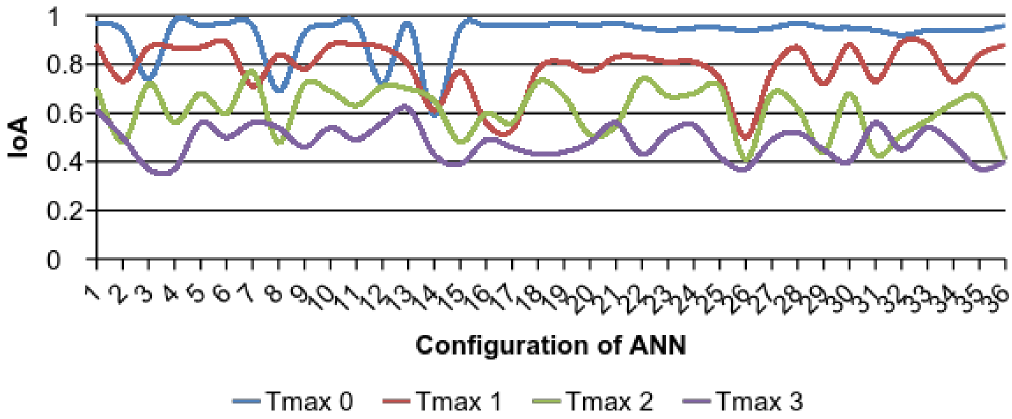


Figure 3 Calibration process of RNA model for maximum daily temperatures, for the Agronomía station.

Furthermore, in the case of models developed by means of ANN (Figure 3), the amplitude between different anticipations is significantly greater than in the case of PG (Figure 2); however, more accurate results for the smaller anticipations are obtained.

Having set the parameters' values, they remain fixed to each respective model. Nevertheless, for the daily forecast, both of these models are run, efficiency is evaluated based on the data available so far and the one with the best result is chosen to perform the forecast. In this way, the best optimized prognosis for each location is acquired.

Following the calibration, validation approaches; through which the true correlation between predictions and measurements is studied. As shown in Figure 4, to greater anticipations entails greater errors. Also as mentioned, it is seen that depending on the day when the forecast was made, the optimum method is also modified, i.e. it is not static.

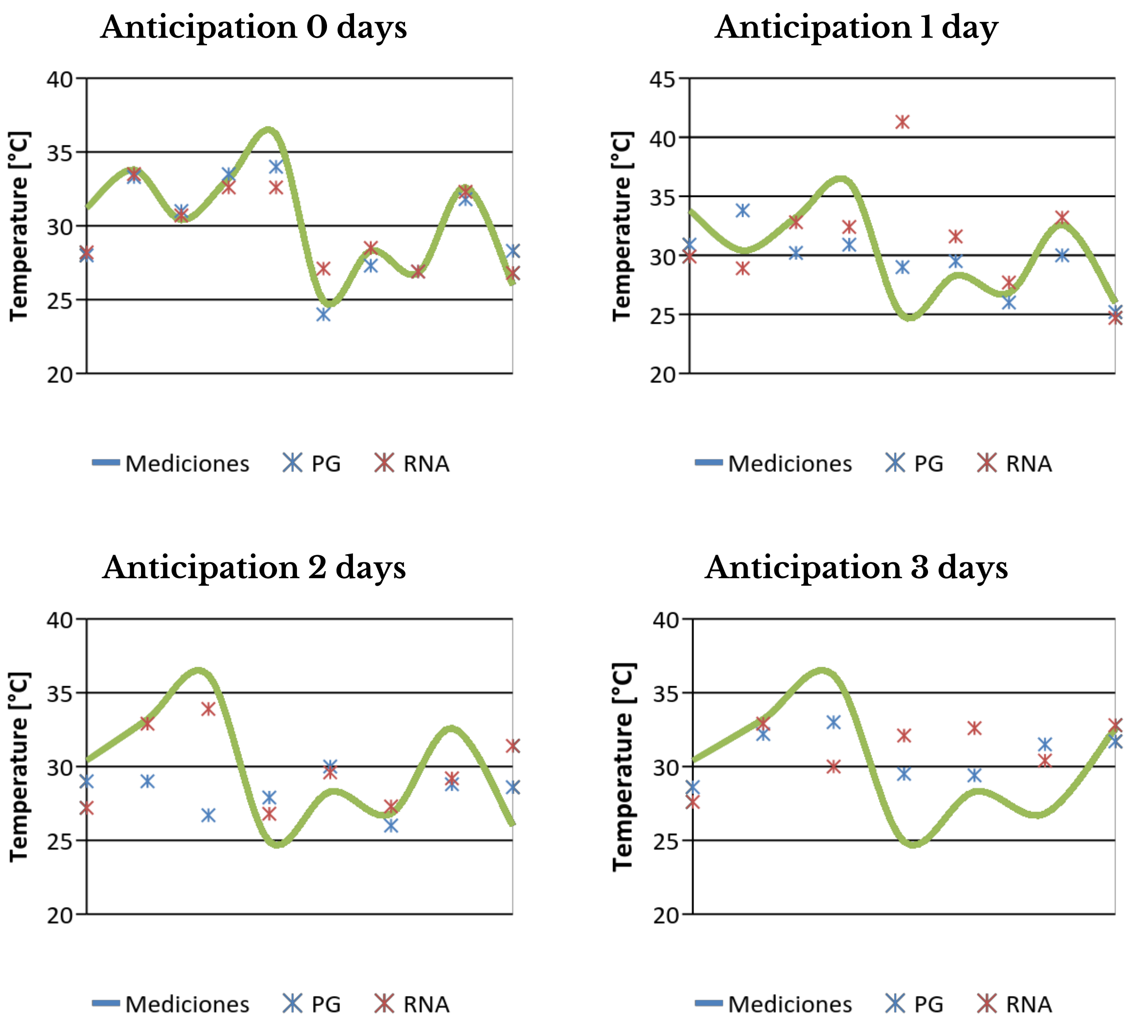


Figure 4 Validation process of the models according to the different anticipations studied, for Agronomía station.

Results

The product isotherms' maps are presented in Figure 6. In them, the best predictor measurements are appreciated with a spatial distribution. Accordingly it can be viewed as temperature variations occur between different locations.

By analyzing the generated images, it can be seen that the error between prediction and prognosis is between 1°C and 3°C depending on the station studied. Furthermore, the isotherms corresponding to the measurements and the prognosis correlated in the majority of the cases, and when this does not happen, the intersecting lines indicate the coincidence between predicted and measured values.

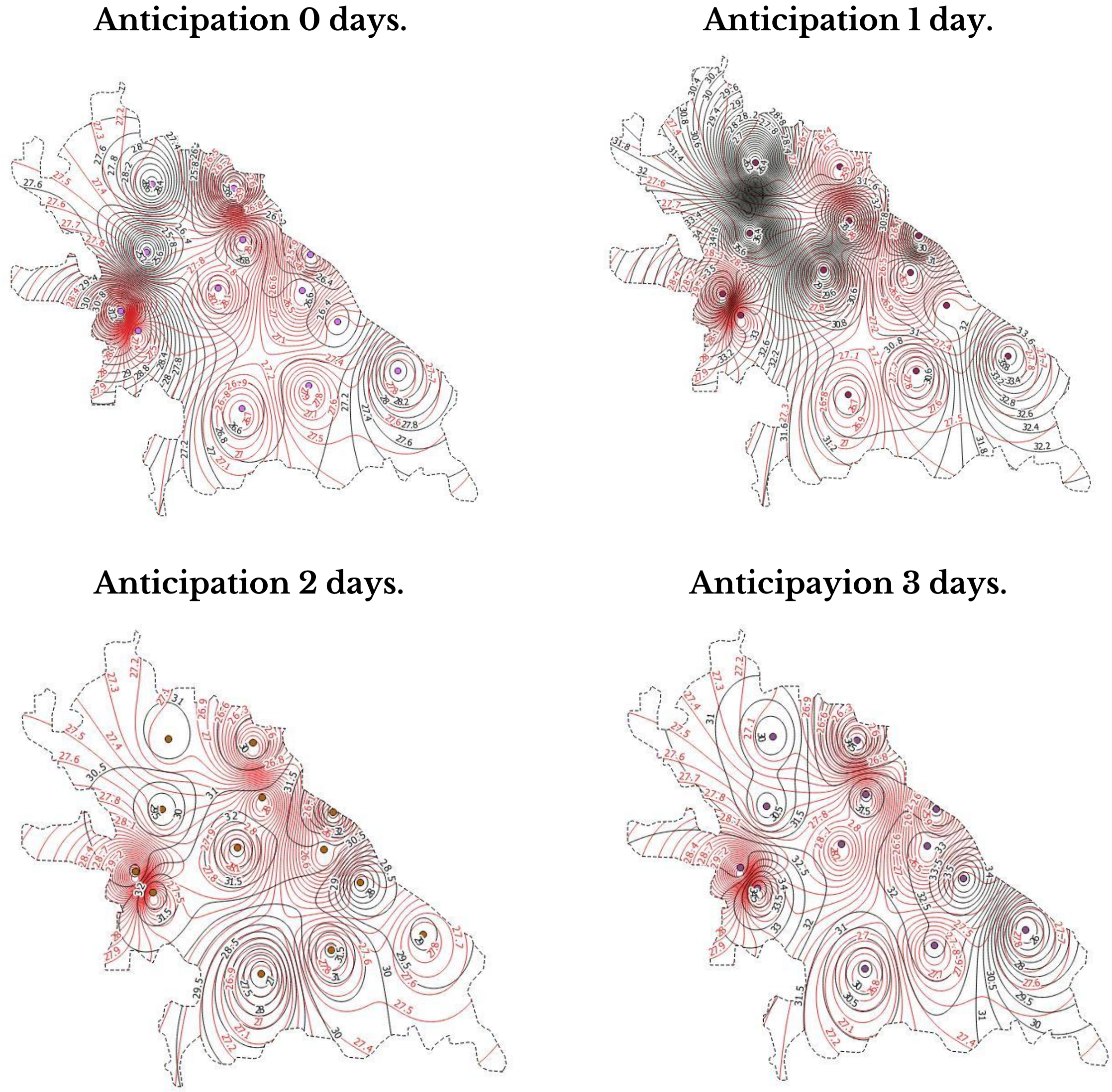


Figure 5 Isotherms of forecasts (black lines) and measurements (red lines) for all the anticipations.

Additionally, in Table 1 a ranking of the forecasters of maximum temperature for the thirteen cities within the locality of AMBA is detailed.

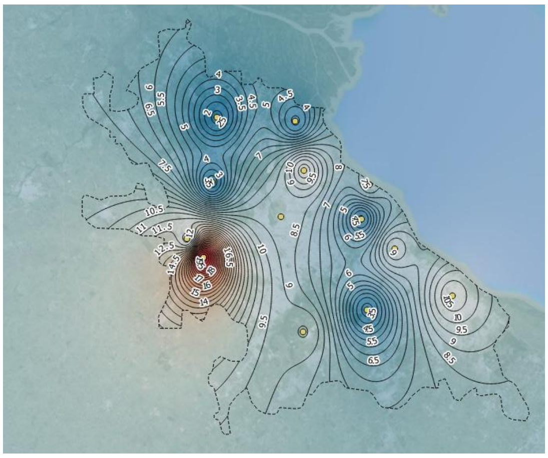
It is important to outstand how the method presented, which combines different AI techniques, it is the best predictor (indicated as MN -AI) in 56% of the cases analyzed (combinations of town - anticipation). What is more, these values are of the order of 70 % if the slightest advance, 54% for one and two days in advance, and finally 46% for three days in advance.

Table 1 Best forecaster for maximum daily temperature by station in AMBA.

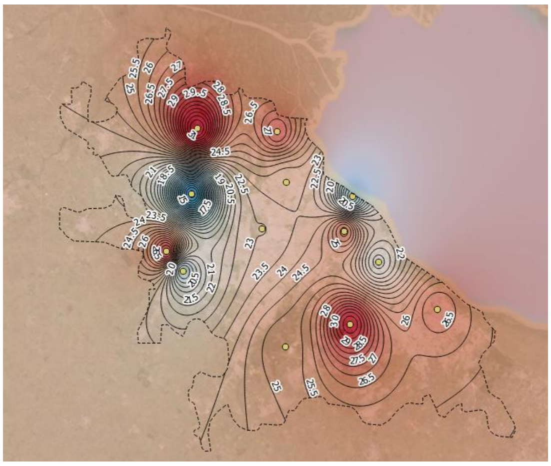
Station	Anticipation [days]			
	0	1	2	3
Aeroparque Bs. As.	MN-AI	MN-AI	MN-AI	MN-AI
Agronomía	INTELL	INTELL	MN-AI	INTELL
El Palomar	INTELL	MN-AI	MN-AI	INTELL
Ezeiza	MN-AI	MN-AI	MN-AI	MN-AI
IBUENOSA133	MN-AI	MN-AI	INTELL	MN-AI
IBUENOSA194	INTELL	INTELL	MN-IA	INTELL
IBUENOSA197	MN-AI	INTELL	WUNDER	INTELL
IBUENOSA47	MN-AI	YRNO	YRNO	MN-AI
IBUENOSA49	MN-AI	WUNDER	WUNDER	WUNDER
IBUENOSA85	MN-AI	MN-AI	INTELL	MN-AI
San Miguel	MN-AI	MN-AI	MN-AI	MN-AI
Merlo	INTELL	MN-AI	MN-AI	INTELL
San Fernando	MN-IA	INTELL	SMN	WUNDER

If the variations of the absolute errors between predictions and measurements are studied, as shown in Figure 5, it will be recognized that there are certain localities for which the error tends to be grater. This is particularly true for those localities whose measurements are provided by Weather Underground's stations. These have the characteristic of being managed and controlled by particulars; therefore we can determine that the observed variations are due to errors in the input data supplied to the model. The flaws in the quality of the data collected can be due to various events, such as the location of the weather station at the site. The last one should present certain standardized characteristics in order to present measurements that prove to be correct and therefore applicable to build a forecast.

Anticipation 0 days.



Anticipation 1 day.



Anticipation 2 days.

Anticipation 3 days.

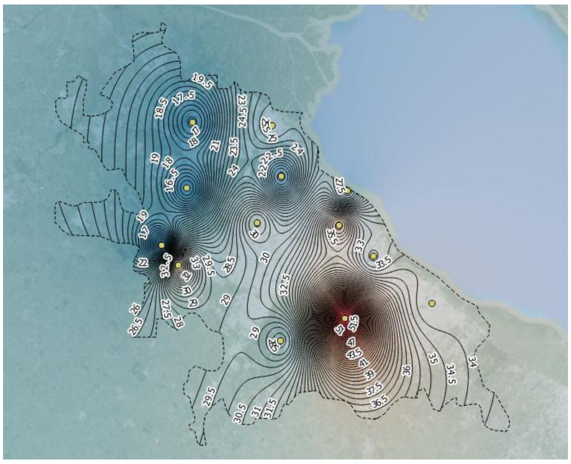


Figure 6 Variation of the absolute error of the forecasts for AMBA.

Developpement of a mobile application (app).

To implement the project a mobile application called ClimaLab that integrates information from the weather, the city and the user profile is being developed, in order to generate individual alerts and establish a platform for the growth of information that allows algorithms to keep on learning (for more information please visit www.smartcityclima.com and www.b3r3c.com). The vision of this development for Buenos Aires could also be applied in other cities.

Figure 7 Screenshots of the app ClimaLab.

Conclusions

In this paper the results of an ongoing work were presented in order to reduce the vulnerability of the population of large cities such as Buenos Aires, increasing its resilience to address climate change and the uncertainties that it presents.

From the analysis of the results, satisfactory results for the prediction of maximum temperatures were obtained. As stated, the model developed is the best prognosis in most cases studied, far outpacing other entities for localities covered by the analysis of AMBA. Consequently, the reduction in the uncertainty of the forecast generation will reduce the vulnerability of the population of the given city.

Furthermore, from the study an issue related to the quality of the data that conform the time series, used in the training and subsequent generation of information, needs to be addressed. While both the PG and the RNA are able to overcome the noise in a series, particularly in the training and calibration stages, once the structures are fixed, in order to construct the forecast, it is important that values employed to feed them are correct.

The approach has a significant potential to be applied in other problems that affect cities, such as the factors that condition urban mobility and energy production and distribution, in order to enable its transformation of the metropolis into an intelligent and resilient territory.

To learn more about the project you can visit the following web pages www.smartcityclima.com and www.berecolabs.com.

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