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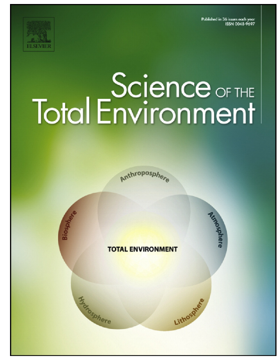

Predictive models of minimum temperatures for the south of Buenos Aires province

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Predictive models of minimum temperatures for the south of Buenos Aires province

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Abstract

Depending on the time of development of a crop temperature below 0 ° C can cause damage to the plant, altering its development and subsequent yield. Since frosts are identified from the minimum air temperature, the objective of this research paper is to generate forecast -(predictive) models at 1, 3 and 5 days of the minimum daily temperature (T_{min}) for Bahía Blanca city. Non-linear numerical models are generated using artificial neural networks and geometric models of finite elements. Six independent variables are used: temperature and dew point temperature at meteorological shelter level, relative humidity, cloudiness observed above the station, wind speed and direction measured at 10 m altitude. Data have been obtained between May and September from 1956 to 2015. Once the available data had been

analysed, this period was reduced to 2007-2015. For the selection of the most suitable model, the correlation coefficient of Pearson (R), the determination coefficient (R^2) and the Mean Absolute Error (MAE) are evaluated. The results of the study determine that the geometric model of finite elements with 4 variables, over 9 years (2007-2015) and separated by the season of the year is the one that presents better adjustment in the forecast of T_{min} with up to 5 days of anticipation.

1. Introduction

The southeastern region of South America, comprising part of central-eastern Argentina, Uruguay and southern Brazil, frequently suffers from cold air incursions. These appear as cold fronts coming from the southwest of the continent, which associated to polar sea air mass, can give rise to extreme events and frosts in the period from autumn to spring. Several studies in the field have addressed extreme cold events (e.g. Rusticucci and Barrucand, 2004; Fernández Long and Müller, 2006; Cavalcanti et al. 2013; Müller et al., 2017) and frost in the east center of Argentina, productive region par excellence (Müller, et al., 2003; Müller, et al., 2005; Müller, 2007, 2010; Müller and Berri, 2012). These incursions generate great damage to local crops (Repetto, Vergara & Casagrande, 2014).This is why, in order to avoid damage, it is necessary to foresee it. In this case, mathematical models are one of the tools available to farmers for decision-making (Fernández Long, et 2015)

The importance of minimum temperature forecast lies in the fact that through this variable frost can be predicted. It should be noted that frost damage can have a drastic effect on the crop, either for the entire plant or for a small part of the plant tissue. In addition, it implies a reduction on the yield or depreciation of the quality of the product (Food and Agriculture Organization of the United Nations, FAO, 2010). This depends on the time of frost occurrence, its intensity, its duration and the phenological state of the plants. Considering the time of occurrence, frosts are classified into autumn, winter, spring and summer. Frosts are frequent in winter, but they also occur in autumn and spring. Autumn frosts are known as early frosts and spring frosts as late frosts. That is why the time when frost occurs, that is the date of first frost (FPH) and date of last frost (FUH), are of fundamental importance in the programming of the agricultural calendar (Fernández Long and Barnatán, 2013). This is because, small differences in the time of occurrence of a frost surprises the plants at different times of their development and may cause damage of different magnitude or not cause any damage. The FPH series is conformed as the first Julian day in which a frost is registered, as long as the same occurs before the Julian day 196 (July 15), otherwise, in that particular year the event will not have occurred. Similarly, the FUH series is defined as the last Julian day in which a frost is recorded, as long as it occurs after day 196; and, as in the previous series, the non-occurrence of the event is possible (Fernández Long and Barnatán, 2013).

Therefore, the short and medium term forecasts of the risk of frost are of paramount importance because the accuracy of the results and the timing of the frost forecast will depend on the time margin that the farmer will have to avoid frost of their products. Some of the options horticulturists have to mitigate frost damage of their crops are active protection methods: stoves, fans, helicopters, sprinklers, surface irrigation, foam insulation and combinations of methods. All methods and combinations are implemented during the night of frost occurrence to mitigate the effects of sub-zero temperatures (FAO, 2010). For this reason, having a frost forecast several days in advance makes it possible to take decisions about the application of frost control methods. In this way it is possible to minimize possible economic losses in crops and improve productivity.

In the scientific literature, there are several methods that analyse frost forecast, starting from the minimum temperature. Among them, Blennow and Persson (1998) use linear models. The authors analyzed the spatial variations of the air temperature in an area of southern Sweden in summer nights and from the independent variables: sky vision factor, altitude, relative relief and presence of peat soils. In this case, the objective was to generate a map with areas prone to low temperatures within a total area of 7.2 km^2. Subsequently, numerous studies have been carried out to predict the minimum temperature from neural networks, for example, Abdel-Aal (2004), Ramyaa (2004), Poonnoy, et al. (2007), Jain, et al. (2006), Sallis, et al. (2009), Smith, et al. (2009). In this type of models, meteorological variables such as air temperature, relative humidity, wind speed, precipitation, rain and solar radiation are used as input variables. Ustaoglu, et al., (2008) compare three neural network models and a multiple linear regression model to predict mean, maximum and minimum daily temperatures in the Marmara region (Turkey), using 15 years of data (1989-2003). The same authors compare the predictions obtained with a multiple linear regression model with those of the neural network methods. The three neural network models and the multiple linear regression model used by the authors provide satisfactory predictions. Kaur and Singh (2011) evaluate the application of neural networks to study the minimum temperature in the city of Chandigarh, India. The results show that the minimum temperature can be predicted with reasonable accuracy using the artificial neural network. Robinson and Mort (1997) conclude that the ability of a neural network to predict the minimum temperature varies with the structure used. Ghielmi and Eccel (2006) compare traditional models of minimum temperature estimation with neural networks, obtaining better results with the latter. They conclude that the temperature at sunset is the most important predictor, followed by extreme temperatures and relative humidity. Ovando, et al., (2005) develop models based on backpropagation neural networks to predict the occurrence of frost at Rio Cuarto station, Córdoba, Argentina. They demonstrated the good performance and general efficacy of this methodology in the estimation of frosts.

In this work, predictive models of the minimum temperature that are applicable to a region of high horti-floriculture production located in the south of Buenos Aires province are generated . For this purpose, non-linear numerical models based on neural networks have been used applying computational software developed in Matlab program environment and using some Toolbox libraries (Neural Network Toolbox). In geometric models of finite elements, the methodologies developed by Navarro-González and Villacampa (2012, 2013, 2016) were used. Generated models help the elaboration of a minimum temperature forecast through its correlation with other observed meteorological variables. The tool obtained will provide a new methodology for the prediction of frost in the area studied. It is expected to provide a method of short-term minimum temperature forecasting resulting from the use of a limited number of variables. This would demand less computational requirement. In future instances the methodology would be evaluated in other regions adapting the model to local characteristics.

2. Methodology

2.1. Study region

The study region is located in the southwest of Buenos Aires province (Argentina), in the city of Bahía Blanca (figure 1) with coordinates 38ºS; 62ºW. The region is characterized by its great agricultural production being one of the main in the world. Its climate is temperate with average annual temperature between 14º C and 20º C. The rains provide a sub-humid or transitional character with an average of 584.6 mm annually. According to the Horti-floriculture Census of Buenos Aires province (2005) the horticultural belt of the city of Bahía Blanca has a productive sector composed by around 46 horti-floriculture exploitations that occupy 663,400 ha, of which 177,145 ha are dedicated exclusively to horti-floriculture production. These farms produce 2448 tons per harvest, of which 174,675 ha are produced in the field, that is to say, without a cover to protect them from weather inclemency. Vegetables are classified according to whether they are winter or summer vegetables, according to the thermal requirements for their development. In general, species grown in summer are usually damaged by frost, although the degree of damage will be different according to the sensitivity of each crop.

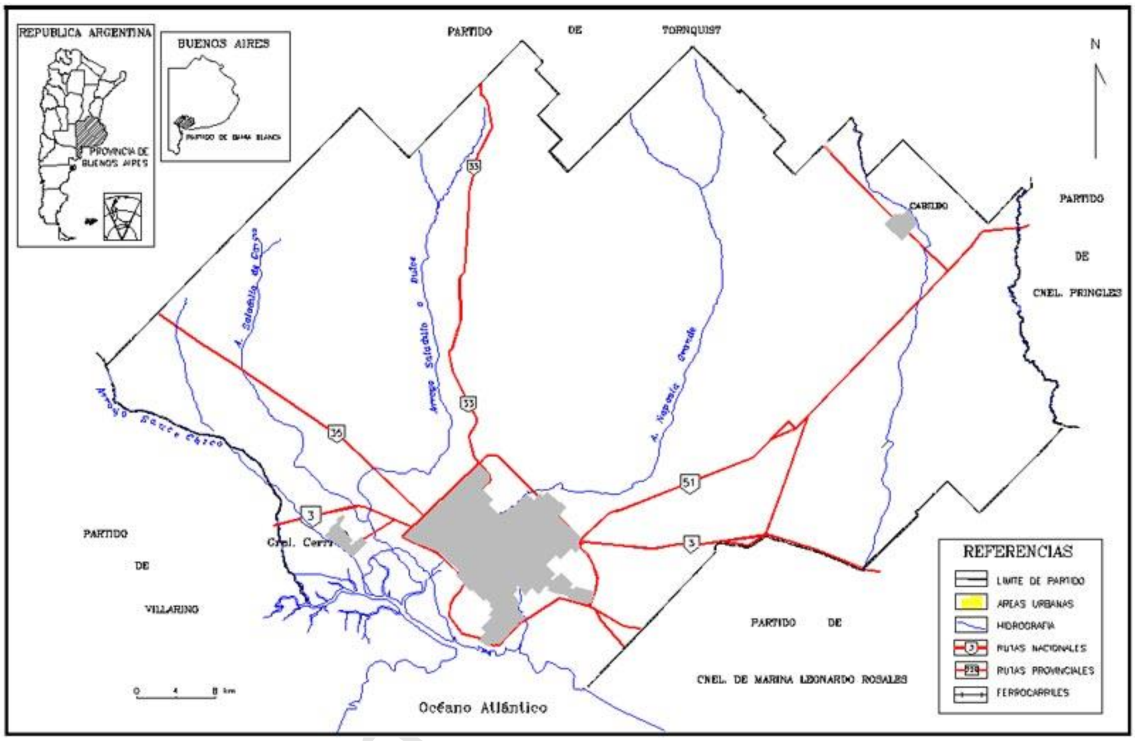

Figure 1: Buenos Aires Province (Source: preparation and digitization Formiga and Gárriz, 2008)

Data base

The historical data observed at the National Weather Service (SMN) meteorological station of the Bahía Blanca AERO station were used to conduct the research. The series of temperature, dew point temperature, relative humidity, cloudiness and wind speed and direction of this station satisfy the quality control requirements established in Chapter 9 of the World Meteorological Organization's Guide to Hydrological Practices (WMO, 2009). The period in which experimental data were obtained is 1956-2015 (60 years), considering the months in which frost occurs mostly, that is, from May to September. However, since the climatic changes produced within this time period are large (Fernandez Long and Barnatan, 2013), it has been considered that the last 9 years (2007-2015) of information are more suitable for temperature prediction today. When analyzing the temporal evolution of the period with frosts from 1997 to 2015, it is observed that in Bahía Blanca there have been 4 years with late frosts after October 1. In other words, in a period of 19 years there is a probability of occurrence equal to or greater than 21%. With respect to the early frosts, it is observed that they have occurred in 5 occasions, which supposes a probability of occurrence of 26% or more (CIAg, Agroclimatic Information Center, 2015). According to this, the analysis is developed for the autumn (March, April, May), winter (June, July, August) and spring (September, October, November) seasons. In this way it is expected to verify the functionality of the model and evaluate its ability to identify early and late frosts.

The daily time series of the variables analyzed were created by organizing the information supplied. The robustness and reliability of the database is fundamental when applying statistical analyses. In order to make a database reliable, it is necessary to: (i) have a sufficient number of data, (ii) have good accuracy in the data, and to clean up dubious or erroneous data. The percentage of periods without sufficient data was considered irrelevant. In the period 1956-2015 it was only 5%, the series being complete between 1997 and 2015. In accordance with the objective of generating short-term predictions, three time horizons were studied (1, 3 and 5 days), so that the modelling methodologies considered in this research are applied to each one, which is described in the next section.

2.2. Method

The methodology applied for the forecast of the T_{min} in Bahía Blanca has been the generation of numerical models through the use of artificial neural networks and geometric models of finite elements. Linear models were previously generated and rejected because of their poor results, with indexes of explanation of the experimental data smaller than 30 %. However, the existence of multicollinearity between the predicting variables has been analyzed using the SPSS program, through the study of the variance inflation factor and condition number. If, in addition, the variables are typified, there is clearly a multicollinearity problem for the 5-day forecast. Also, an analysis of the bivariate correlations has been carried out, resulting in: a) relative humidity presents a strong significant correlation with the variables: temperature, dew temperature and wind direction; b) the same occurs with wind direction. Therefore, these two variables, humidity and wind direction, are eliminated. The analysis of multicollinearity is carried out again and it is deduced from the results that there is no problem of multicollinearity for any of the forecast cases with the four variables. That is, with the variables- temperature, dew temperature, wind speed and cloudiness- the existence of multicollinearity is not possible in the three cases analyzed: 1 day, 3 days and 5 days.

The numerical models have been generated with 4 and 6 predictive variables to analyze if the best numerical models are those that use variables without multicollinearity problems.

The predicted or independent variable is the daily minimum temperature. The predictor variables are 6 in a first analysis: temperature and dew point temperature at meteorological shelter level, relative humidity, cloudiness observed in the season and wind speed and direction measured at 10 m altitude. The measurement of the variables is made based on the indications of the WMO 2009. The selected period is May to September 1956 to 2015 with the 6 variables mentioned. The analysis is repeated using 4 predictor variables (temperature, dew point temperature, wind intensity and cloudiness), considering not only the May-September period, but also the different seasons of the year separately: autumn (March-May), winter (June-August) and spring (September-November) based on information from a reduced period of 9 years (2007-2015). The aim is to evaluate the performance of the models using a smaller amount of information, and at the same time extending the analysis to those months of greater susceptibility for the crops. The selection of these variables is due to the fact that they are easy to obtain and are measured at surface weather stations. The dependent variable is a daily value while the predictors or independent variables correspond to each of the four main hours of the day (03, 09, 15 and 21 local time).

2.3. Nonlinear Numerical Models

For the generation of non-linear numerical models in the period indicated, 9899 data corresponding to the period 2007 - 2015 have been used. A percentage of this information is used to validate the model, which varies according to whether it is generated to the neural network models, or the geometric models of finite elements.

a) Artificial Neural Nets, ANN

Initially, models of artificial neural networks (ANN) were generated to predict the minimum temperature with 1, 3 and 5 days of anticipation and with 6 predictor variables. Experimental data are randomly divided into three groups: i) data for training (75%), ii) data for validation (10%) and iii) data for testing (15%). The neural network is a one hidden layer in which the number of neurons is selected to avoid over-parameterization of the model. For this purpose, various information parameters are used and 50 models have been generated: the average of the R values of the 50 models, the average of the R^2 values of the 50 models and the error.
Neural network models are analyzed for both 4 and 6 predictive variables.

To select the best neural network studies for different architectures with a number of neurons in the hidden layer given by powers of, 2n, from 1 to 128 have been realized.

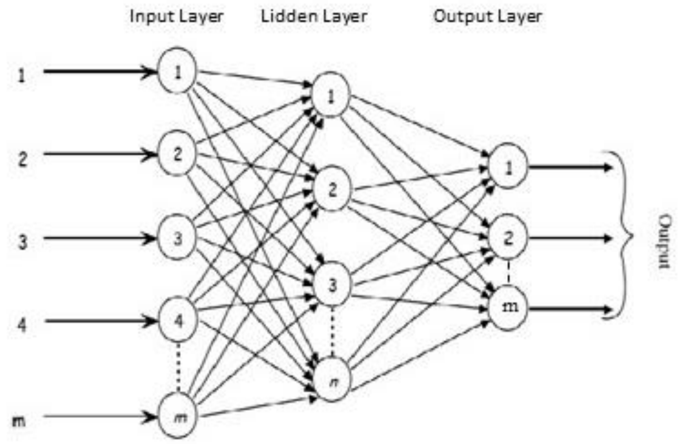

Figure 2: Neural network architecture with 1 hidden layer

For any architecture with 1 hidden layer, 50 models are generated, subsequently calculating the average of R y R^2. The best neural network architectures are architectures that have between 1 and 20 neurons in the hidden layer. Models are also generated with 4 independent/predictor variables and 9 years (2007 - 2015), avoiding multicollinearity, but the models obtained are not good for forecasting the minimum temperature 1, 3 and 5 days in advance. Models are also generated with 4 independent/predictor variables, avoiding multicollinearity and in the same period of time, but the results are not good for the minimum temperature prediction with 1, 3 and 5 days in advance. Only the results for 5 days in advance are included to compare with the results obtained when applying geometric models of finite elements (Navarro-González and Villacampa, 2012, 2013, 2016), analyzing the periods of May-September, autumn, winter and spring. Since the test and validation results do not present significant differences, only the training results are presented for each of the forecasts made.

Once the sample is randomly divided into three parts, the Multilayer Percepton method is applied to determine the minimum temperature forecasts T_{min} at 1, 3 and 5 days. In the ANNs developed in this work, three layers are defined: i) an input layer whose neurons are the predictor variables used (6 and 4) ii) a hidden layer, whose number of neurons in the hidden layer (HN) is determined through a coarse binary search with HN= 2, 4, 8, 16, 32, 64, 128. (Later, performing a finer search to find the optimal number of neurons will be necessary), and iii) finally, an output layer corresponding to the dependent variable, i.e. the minimum temperature, T_{min}.

A Matlab code program has been generated using some libraries of the Toolbox (Neural Network Toolbox) that allows to automatically obtain families of models for each one of the analyzed architectures. With the information obtained from the generated models, the network architecture is selected, based on the best results of the following averages R, R^2 and the lowest values for the maximum and minimum errors; defined as the difference between the average of R and its maximum and minimum values respectively.

b) Geometric model of Finite Elements

In order to obtain numerical models, the methodologies based on the generation of geometric models of finite elements developed in Navarro-Gonzalez F. J. and Villacampa, Y. 2012, 2013, and 2016, have been applied.

The starting point is an experimental dataset $\left\{\left(x_{[k]}^1, x_{[k]}^2, x_{[k]}^3, \ldots\ldots, x_{[k]}^d, y_{[k]}\right)\right\}_{k=1,2,\ldots,p}$ corresponding to some standardized variables $(\vec{x}, y) = \left(x^1, \ldots, x^d, y\right) \in \Omega \times \mathbb{R} = [0,1]^{d+1} \subset \mathbb{R}^{d+1}$ where there exists a functional relationship of the type $y = f\left(x^1, \ldots, x^d\right)$. The geometric model of finite elements is defined dividing Ω in elements, and defining in each element some points named nodes where the model is obtained. The complexity of the geometric model, c, is defined as the number of subintervals in which each segment $[0,1]$ is divided. So, the initial domain $[0,1]^n$ is divided into a set of c^n hypercubics elements. Once the geometric model in a hypercube has been defined, the model is obtained by solving an optimization problem.

By applying these, geometric models of finite elements have been generated with complexities of 30, 50, 70 and 90 to forecast the T_{min} 1, 3 and 5 forecast days. Initially, using the 6 predictive variables and in the period from May to September for years 1956 to 2015. Since the results with complexity 50 do not show significant differences with respect to those obtained with 30, only the results obtained with 30, 70 and 90 are presented. In addition, for the model to better represent the current evolution of the minimum temperature, a shorter period of time comprising the last 9 years of the series (2007 - 2015), is considered. In this case it is the models for 5 days forecast and using the 6 variables described above that obtain a good prediction. The same types of models are generated with the 4 selected predictor variables, where the 9-year series is then divided into the autumn, winter and spring periods generating models for 1, 3 and 5 days forecast with 6 variables. Since the best results are for 5 days forecast, the models are generated again reducing the number of variables to 4. For each analysis, the data have been randomly divided into 80% for model training and 20% for model validation. The results for each model are analyzed using overlapping scatter plots, consisting of overlapping pairs of x-y variables, each pair being distinguished by different colours or shapes, and scatter plots in analyses with 9 years of data. In all cases the results obtained with the validation data reflect similar trends to those developed with the model, so they are not shown.

On the other hand, the percentage of model successes is analyzed when the T_{min} is less than 0 °C (frost). It is carried out for 5-day forecasts with 9 years of data with 4 and 6 variables in the period from May to September and with 4 variables in the periods autumn, winter and spring.

3. Results and discussion

In this section we present the results obtained for the 1, 3 and 5 day T_{min} forecast obtained with neural networks and geometric models of finite elements. As it was previously commented linear models were generated but the results are not presented because the models are not good, which indicates that there is no linear relationship between the variables.

3.1. Neural networks

Table 1 shows the comparison of the average of R and R^2 of the 50 models generated for any neural network architecture in training and for 1 forecast day with 6 variables. The best result is with 16 neurons, since of all, it is the architecture with the highest R and smaller difference between the extreme values and the average.

Table 1. Training. 1 forecast day. 6 variables. 1956-2015

R	Training Neurons							
	1	2	4	8	16	32	64	128
Average	*0,579*	*0,636*	*0,674*	*0,684*	*0,688*	*0,689*	*0,693*	*0,697*
Maximum	*0,587*	*0,676*	*0,683*	*0,689*	*0,693*	*0,696*	*0,700*	*0,703*
Minimum	*0,573*	*0,586*	*0,591*	*0,670*	*0,683*	*0,623*	*0,688*	*0,689*
Max error	*0,007*	*0,040*	*0,009*	*0,005*	*0,005*	*0,007*	*0,007*	*0,007*
Min error	*0,006*	*0,050*	*0,083*	*0,014*	*0,005*	*0,066*	*0,005*	*0,007*
Average R^2	*0,335*	*0,405*	*0,454*	*0,467*	*0,473*	*0,475*	*0,481*	*0,485*

Figure 3 shows the averages of 50 R and R^2 after 50 iterations of training for architectures from 1 to 20 neurons, used to model the data corresponding to 1-day forecasting and 6 variables.

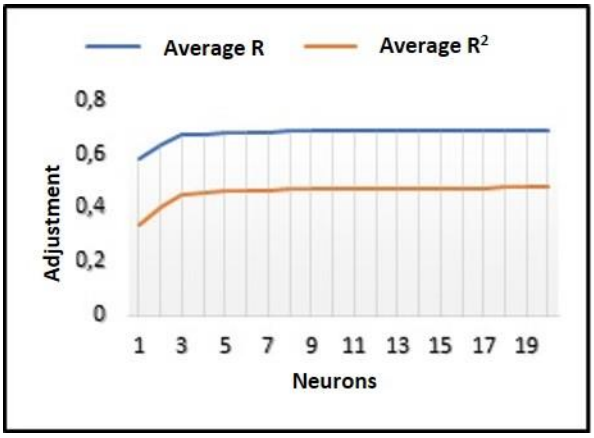

Figure 3 Training Neural from 1 to 20. 6 variables. 1956-2015

Table 2 shows the average R and maximum and minimum errors of the 50 runs of the training model for any architecture. It is evident that from 7 or 8 neurons the results are similar. The average and the maximum and minimum errors show that architecture of 11 neurons in a hidden layer would be sufficient.

Table 2. Average, maximum, minimum and dispersion of R. Neural Training from 1 to 20; 6 variables. 956 - 2015

R	Training Neurons																			
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
Average	0,579	0,636	0,668	0,674	0,678	0,681	0,682	0,684	0,683	0,685	0,686	0,686	0,686	0,687	0,688	0,688	0,688	0,688	0,689	0,688
Maximum	0,587	0,676	0,681	0,683	0,684	0,687	0,688	0,689	0,691	0,69	0,691	0,691	0,692	0,692	0,693	0,693	0,693	0,694	0,693	0,692
Minimum	0,573	0,586	0,586	0,591	0,665	0,667	0,669	0,67	0,668	0,67	0,681	0,681	0,68	0,681	0,682	0,683	0,684	0,68	0,677	0,679
Max error	0,007	0,04	0,013	0,009	0,006	0,006	0,006	0,005	0,008	0,005	0,005	0,004	0,005	0,005	0,006	0,005	0,005	0,005	0,005	0,004
Min error	0,006	0,05	0,081	0,083	0,014	0,015	0,013	0,014	0,015	0,015	0,005	0,005	0,007	0,006	0,006	0,005	0,005	0,008	0,012	0,009
Dispersion	0,013	0,09	0,095	0,092	0,019	0,02	0,019	0,019	0,023	0,02	0,01	0,009	0,012	0,011	0,011	0,01	0,01	0,014	0,017	0,013

On the other hand, the results obtained for the test and the validation cases are similar to those of training considering the architecture of 11 neurons. In the case of Test R =0,683 and R^2 =0,46649 . The results of the validation are R =0,6833 and R^2 =0,4669.

According to this, to model the minimum temperature forecast 1 day in advance, the best architecture of neural network corresponds to 11 neurons in the hidden layer. However, since the results of the determination coefficient are very low, the use of this model is discarded.

Tables 3 and 4 present the averages of R for the 50 models generated for any architecture of the type 2^n, in the case of training and for the 3 and 5-day forecast respectively. The maximum and minimum values of R and their differences with respect to the average (maximum and minimum error) are determined. For the 3-day forecast/prediction it is observed that between 16 and 32 neurons there is a significant difference in R, from 0,29 to 0,68. Further from 32, the increase in neurons does not represent a substantial change in the R outcome. The results for 32 neurons are similar in test (R =0,6827 y R^2 =0,469) and validation (R =0,679 y R^2 =0,461)

The 5-day forecast shows a variation between 16 and 32 neurons, i.e., to find an R close to 0,7 it is necessary to use 32 neurons in the hidden layer. Results for test and validation are similar to training. In the test case R =0,6797 and R^2 =0,462; whereas in the validation R =0,688 and R^2 =0,473 As these results are insufficient to use the model in forecasting, a more in-depth analysis is not continued.

Table 3 Training using powers of 2 for 3 days and 6 variables. 1956 - 2015

R	Training Neurons							
	1	2	4	8	16	32	64	128
Average	*0,258*	*0,270*	*0,286*	*0,292*	*0,297*	*0,689*	*0,693*	*0,697*
Maximum	*0,264*	*0,291*	*0,297*	*0,299*	*0,307*	*0,696*	*0,700*	*0,703*
Minimum	*0,251*	*0,253*	*0,257*	*0,270*	*0,286*	*0,623*	*0,688*	*0,689*

Max error	*0,007*	*0,021*	*0,011*	*0,008*	*0,010*	*0,007*	*0,007*	*0,007*
Min error	*0,007*	*0,017*	*0,029*	*0,022*	*0,011*	*0,066*	*0,005*	*0,007*

Table 4 Training using powers of 2 for 5 days and 6. 1956 - 2015

R	**Training Neurons**							
	1	**2**	**4**	**8**	**16**	**32**	**64**	**128**
Average	*0,171*	*0,175*	*0,184*	*0,193*	*0,201*	*0,689*	*0,693*	*0,697*
Maximum	*0,177*	*0,188*	*0,200*	*0,206*	*0,213*	*0,696*	*0,700*	*0,703*
Minimum	*0,165*	*0,164*	*0,170*	*0,172*	*0,179*	*0,623*	*0,688*	*0,689*
Max error	*0,006*	*0,013*	*0,015*	*0,012*	*0,013*	*0,007*	*0,007*	*0,007*
Min error	*0,006*	*0,011*	*0,015*	*0,022*	*0,022*	*0,066*	*0,005*	*0,007*

Table 5 below shows the results of the models obtained for the 5-day forecast with 4 variables; temperature, dew point temperature, wind speed and cloudiness in the 9 years between 2007 and 2015. Specifically, the results of the R average and its maximum and minimum values of 50 models for each 2^n architecture are shown for the forecast made using data from May to September for training., The values of R and R2 do not exceed 0,5 of 0,25 respectively, being similar in training, test and validation. In addition, more than 16 neurons are needed in a hidden layer to reach this value. The analysis carried out for one or 3 days and those obtained separating data in seasons (autumn, winter and spring) show similar results to those presented here, in no case exceeding an R of 0,47.

Table 5 Training using powers of 2 for 5 days and 4 variables. 2007 - 2015

R	Training Neurons							
	1	2	4	8	16	32	64	128
Average	*0,457*	*0,458*	*0,465*	*0,470*	*0,476*	*0,483*	*0,493*	0,505
Maximum	*0,466*	*0,473*	*0,477*	*0,483*	*0,487*	*0,495*	*0,509*	0,523
Minimum	*0,446*	*0,443*	*0,451*	*0,460*	*0,465*	*0,466*	0,471	*0,468*
Max error	0,010	*0,015*	*0,012*	*0,013*	*0,011*	*0,012*	*0,016*	*0,017*
Min error	*0,010*	*0,015*	*0,014*	0,010	*0,012*	*0,016*	*0,022*	*0,038*
Dispersion	0,020	*0,03*	*0,026*	*0,024*	*0,023*	*0,028*	*0,038*	*0,055*

The results obtained in the analysis using neural networks, both with 6 and with 4 predictor variables, show that with this methodology a good prediction is not achieved in more than 50% of the cases.

In other words, this methodology does not yield results good enough to be applied to the prediction of T_{min}, unlike the results obtained by other authors such as Ustaoglu et al. (2008), Kaur and Singh (2011), Robinson and Mort (1997), Ghielmi and Eccel (2006), Ovando, et al. (2005) and Bocco et al. (2007), who obtained good results in the prediction of T_{min} or frost with neural networks. In all the studies analyzed the sample was small and corresponding to short periods of time. The absence of satisfactory results in the present study compared with those obtained by other researchers could have as explanation the higher complexity of working with data comprising periods of time of 60 and 9 years. It should also be noted that, since the study areas are different the independent variables necessary for their study may also be different.

3.2. Geometric Model of Finite Elements

The results obtained applying the methodologies developed in Navarro-Gonzalez F. J. and Villacampa, Y. 2012, 2013, and 2016 to generate numerical models are presented below. The number of independent variables considered and the complexity of the model affect the computational complexity. In addition, by the characteristics of the algorithm, a great value in complexity leads to overfitting. However, the methodology Navarro-Gonzalez F. J. and Villacampa, Y. 2016 presents an improvement in computational complexity with respect to previous researches. Therefore, increased complexity does not necessarily imply an improvement in the model. In order to select the best complexity, other parameters must be taken into account, such as R^2, MAE, MSE and RMSE

Table 6 shows the results of the geometric model of finite elements for the forecast with 1, 3 and 5 days of anticipation and with complexity 30, 70 and 90. With 1 day of anticipation, for a complexity of 30 the adjustment shows an R^2 of 0,52 and an MAE of 2,63. With the complexity of 70 the values are 0, 8 for R^2 and 1,36 for MAE, and for complexity 90 the R2 is 0,90 with a MAE of 0,92. According to these data, the best results are obtained with the complexity of 90, given that the R^2 increases, explaining 90% of the data and decreases the MAE. For the 3-day forecast, complexity model 30 shows an R^2 of 0, 26 and a MAE of 3, 31. With complexity 70 the R^2 is 0, 74 and the MAE decreases to 1, 78. The best results are found with a complexity of 90, with an R^2 of 0, 85 and a MAE of 1, 20. In the analysis of the models for the 5-day forecast we find results similar to the previous ones: the best results are obtained with a complexity of 90, with an R^2 of 0, 84 and a MAE of 1, 22. On the other hand, with complexity 70 the R^2 is 0, 73 with a MAE of 1, 81 and with 30 in R^2 it is 0, 22 with a MAE of 3, 37.

Table 6. R^2 with complexities 30.70 y 90 for 1, 3 y 5 days of prediction. 6 variables 1956 – 2015. May-September

Forecast 1 day	**Complexity 30**	**Complexity 70**	**Complexity 90**
R2	*0,52*	*0,83*	*0,90*
Mean absolute error. MAE	*2,63*	*1,36*	*0,92*
Mean square error.MSE	*10,797*	*3,848*	*2,24*
Root Mean square error, RMSE	*3,286*	*1,962*	*1,496*

Forecast 3 days	Complexity 30	Complexity 70	Complexity 90
R2	*0,26*	*0,74*	*0,83*
Mean absolute error	*3,3*	*1,77*	*1,20*
Mean square error.MSE	*16,646*	*6,25*	*3,58*
Root Mean square error, RMSE	*4,08*	*2,5*	*1,89*
Forecast 5 days	**Complexity 30**	**Complexity 70**	**Complexity 90**
R2	*0,23*	*0,7*	*0,81*
Absolute error variance	*3,36*	*1,81*	*1,22*
Mean square error.MSE	*17,29*	*6,62*	*3,81*
Root Mean square error, RMSE	*4,16*	*2,57*	*1,2*

Figure 4 a, b and c shows the relationship between observed and modeled data and the complexity of the model.

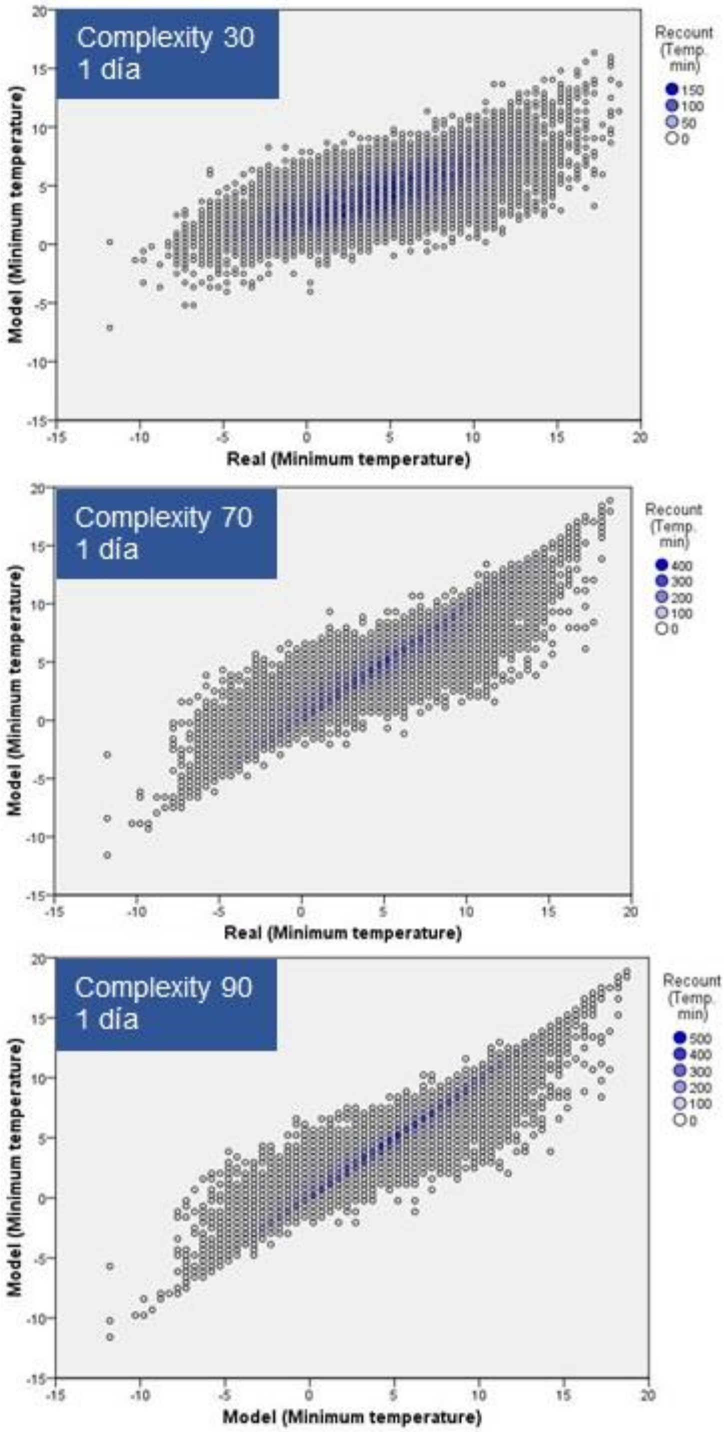

Figure 4a Dispersion diagram of observed T_{min} and the one obtained with the model. Complexity 30, 70 and 90. 1, forecast days, 6 variables. 1956 – 2015.

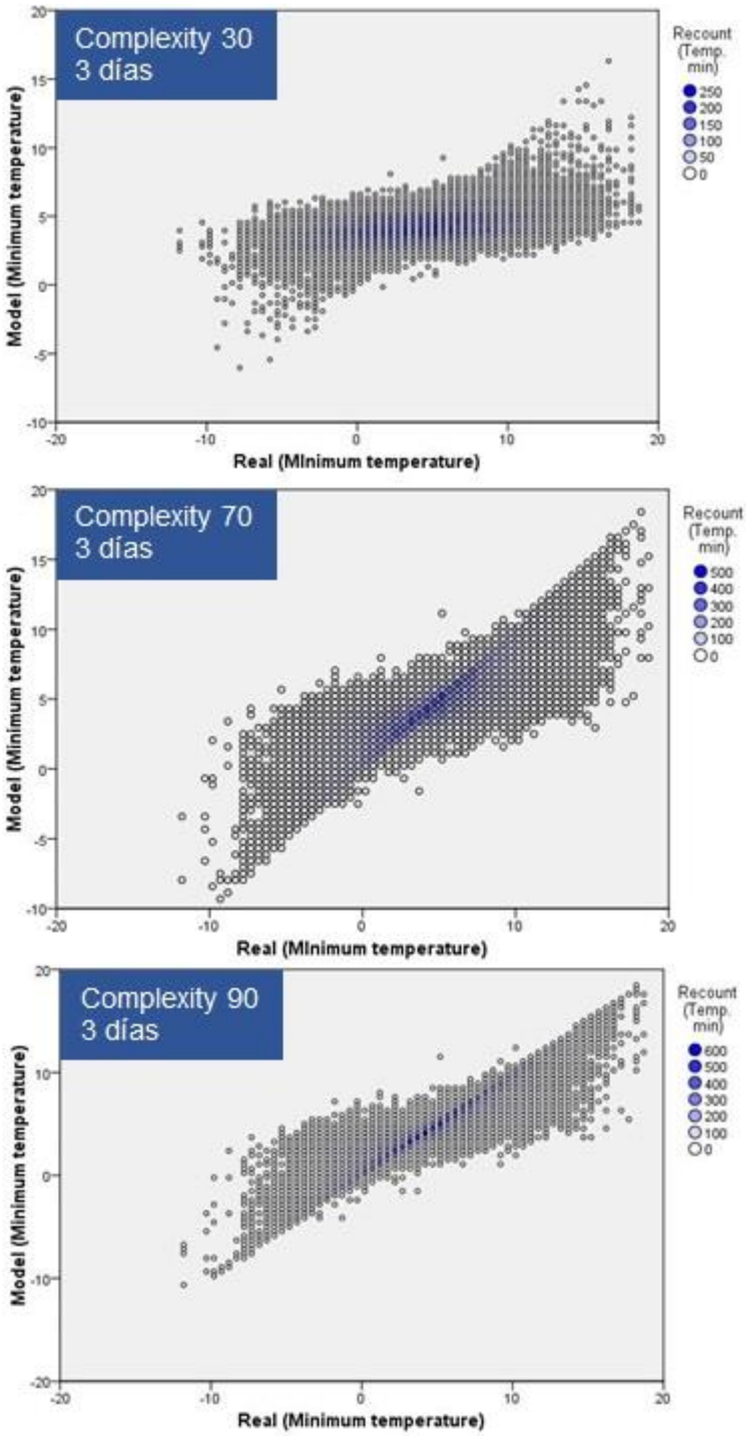

Figure 4b Dispersion diagram of observed T_{min} and the one obtained with the model. Complexity 30, 70 and 90. 3, forecast days, 6 variables. 1956 – 2015.

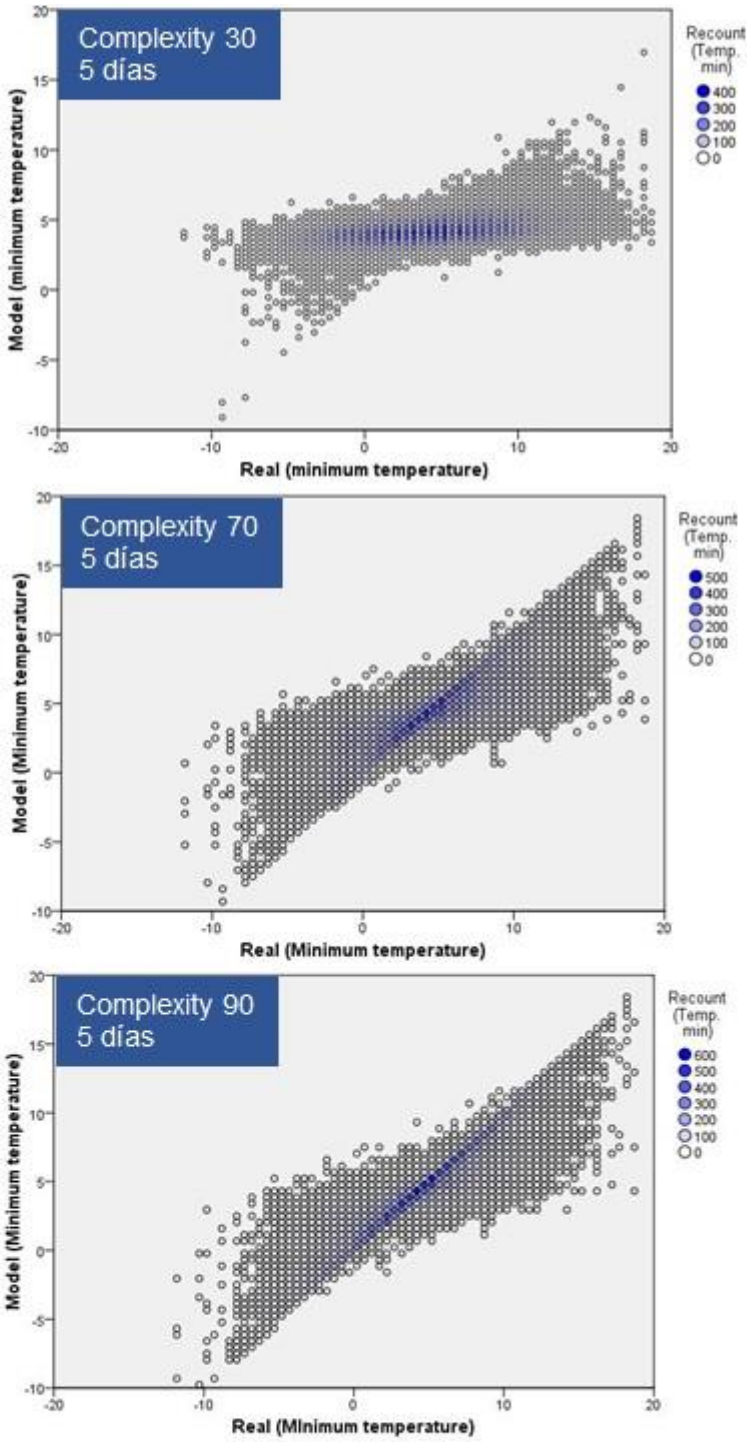

Figure 4c Dispersion diagram of observed T_{min} and the one obtained with the model. Complexity 30, 70 and 90. 5, forecast days, 6 variables. 1956 – 2015.

For all the analyses carried out, it is observed that the models that use less complexity (30) tend to forecast the average value of the minimum temperature, especially when the forecast is made earlier (3 and 5 days). This is illustrated by the horizontally elongated "point cloud" as a constant straight line equal to a value close to the average of the minimum temperature of Bahía Blanca. Models tend to always predict these values close to the mean, except for a few extreme values. As the complexity of the model increases (90), the forecast improves. Figure 4 (scatter plot) shows the data observed as opposed to those predicted, with the best models being those whose data coincide with the straight line.

3.3. T_{min} prediction with 9 year series (2007 - 2015)

Since when all the data of the series are included, the execution time of the model is greater than 1 day, the aim is to decrease this time obtaining similar results in R^2 and MAE. Table 7 shows the 5-day forecast made in the months of May to September, with 6 predictor or independent variables with a series of 9 years of data. Initially, one begins with a complexity of 70 and obtains an R^2 of 0, 78 and a MAE of 1, 96; with 90 0, 86 of R^2 and 1, 52 of MAE and with complexity of 110 one reaches the best result with a R^2 of 0, 9 and a MAE of 1, 16. In models with 4 predictor variables, the results obtained show the need to increase complexity to 120 in order to obtain results similar to the previous analyses. With complexity of 70 the R^2 is 0, 61 and the MAE 2, 78; with 100 nodes 0. 8 of R^2 and 1, 87 of MAE and with 120 the best result is reached with an R^2 of 0, 87 and a MAE of 1, 41.

Table 7. R^2 for 5 prediction days, 2007 – 2015.With 6 and 4 variables, May - September

	Forecast 5 days		
6 variables	**Complexity 30**	**Complexity 70**	**Complexity 90**
R2	*0,78*	*0,86*	*0,90*
Mean absolute error	*1,96*	*1,52*	*1,16*
Mean square error.MSE	*6,86*	*4,57*	*3,06*
Root Mean square error, RMSE	*2,61*	*2,13*	*1,75*
4 variables	**Complexity 30**	**Complexity 70**	**Complexity 90**
R2	*0,61*	*0,80*	*0,87*
Absolute error variance	*2,78*	*1,87*	*1,41*
Mean square error.MSE	*13,2*	*6,95*	*4,43*
Root Mean square error, RMSE	*3,64*	*2,63*	*2,1*

Figure 5 shows that with 6 variables the dispersion is greater with complexities of 70 and 90 that is to say that the greatest correlation between the observed and the predicted data is obtained with a complexity of 110. With 4 variables, the dispersion found is greater with less complexity and the best correlation between the observed and the estimated data is obtained with the greatest complexity analyzed, 120.

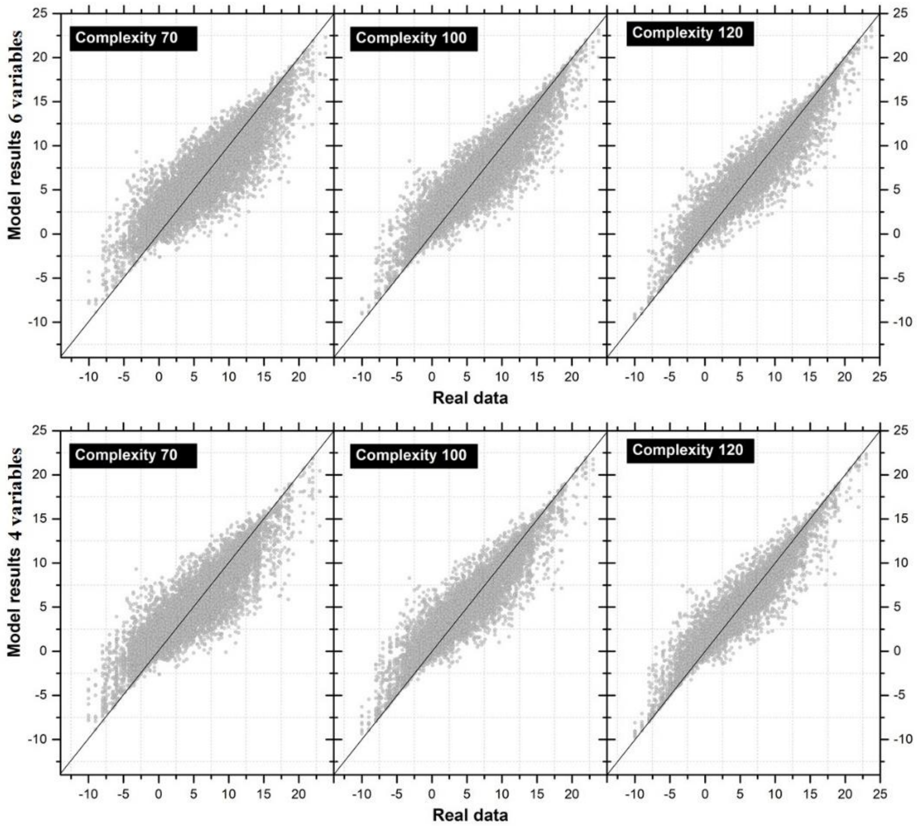

Figure 5. Scatter plot of Tmin. 5 days. 6 and 4 variables

Table 8 presents the analysis performed by dividing the data from the 9-year series into three periods: autumn, winter and spring with 6 variables for 1 forecast day. With both 70 and 90 complexity, R^2 is reached at 0,99 in autumn. In winter a R^2 of 0,97 with 70 and 0,98 with 90 is obtained and in spring 0,98 with 70 and 0,99 with 90. For 3 and 5 days of anticipation, the results are similar to those obtained for the forecast with 1 day of anticipation. There is a good adjustment with R^2 ranging from 0,96 to 0,99 with 70 and 90 for the three seasons. The higher values of R2 in winter may be due to the nature of the data, given that the dispersion of minimum temperatures is lower in the winter season.

Table 8. R^2 for 1, 3 y 5 prediction days, 2007 – 2015.With 6 variables and autumn, winter and spring.

Forecast 1 day	Comp. 70	Comp. 90	Forecast 3 days	Comp. 70	Comp. 90	Forecast 5 days	Comp. 70	Comp. 90
Autumn			**Autumn**			**Autumn**		
R2	*0,990*	*0,99*	**R2**	*0,985*	*0,992*	**R2**	*0,983*	*0,991*
Mean absolute error. MAE	*0,19*	*0,10*	**Mean absolute error. MAE**	*0,25*	*0,13*	**Mean absolute error. MAE**	*0,26*	*0,14*
Mean square error.MSE	*0,27*	*0,143*	**Mean square error.MSE**	*0,4*	*0,2*	**Mean square error.MSE**	*0,47*	*0,25*
Root Mean square error, RMSE	*0,52*	*0,38*	**Root Mean square error, RMSE**	*0,64*	*0,45*	**Root Mean square error, RMSE**	*0,69*	*0,5*
Winter			**Winter**			**Winter**		
R2	*0,978*	*0,989*	**R2**	*0,97*	*0,983*	**R2**	*0,972*	*0,986*
Mean absolute error. MAE	*0,26*	*0,14*	**Mean absolute error. MAE**	*0,33*	*0,18*	**Mean absolute error. MAE**	*0,32*	*0,17*
Mean square error.MSE	*0,42*	*0,21*	**Mean square error.MSE**	*0,65*	*0,33*	**Mean square error.MSE**	*0,58*	*0,27*
Root Mean square error, RMSE	*0,65*	*0,46*	**Root Mean square error, RMSE**	*0,81*	*0,58*	**Root Mean square error, RMSE**	*0,76*	*0,52*
Spring			**Spring**			**Spring**		
R2	*0,985*	*0,995*	**R2**	*0,983*	*0,993*	**R2**	*0,980*	*0,992*
Mean absolute error. MAE	*0,24*	*0,11*	**Mean absolute error. MAE**	*0,30*	*0,13*	**Mean absolute error. MAE**	*0,31*	*0,13*
Mean square error.MSE	*0,32*	*0,11*	**Mean square error.MSE**	*0,42*	*0,145*	**Mean square error.MSE**	*0,48*	*0,17*
Root Mean square error, RMSE	*0,57*	*0,33*	**Root Mean square error, RMSE**	*0,65*	*0,38*	**Root Mean square error, RMSE**	*0,69*	*0,41*

Figures 6,7 and 8 show the scatter diagrams, therefore, the good correlation between the real and predictive data, for the three stations with both complexities.

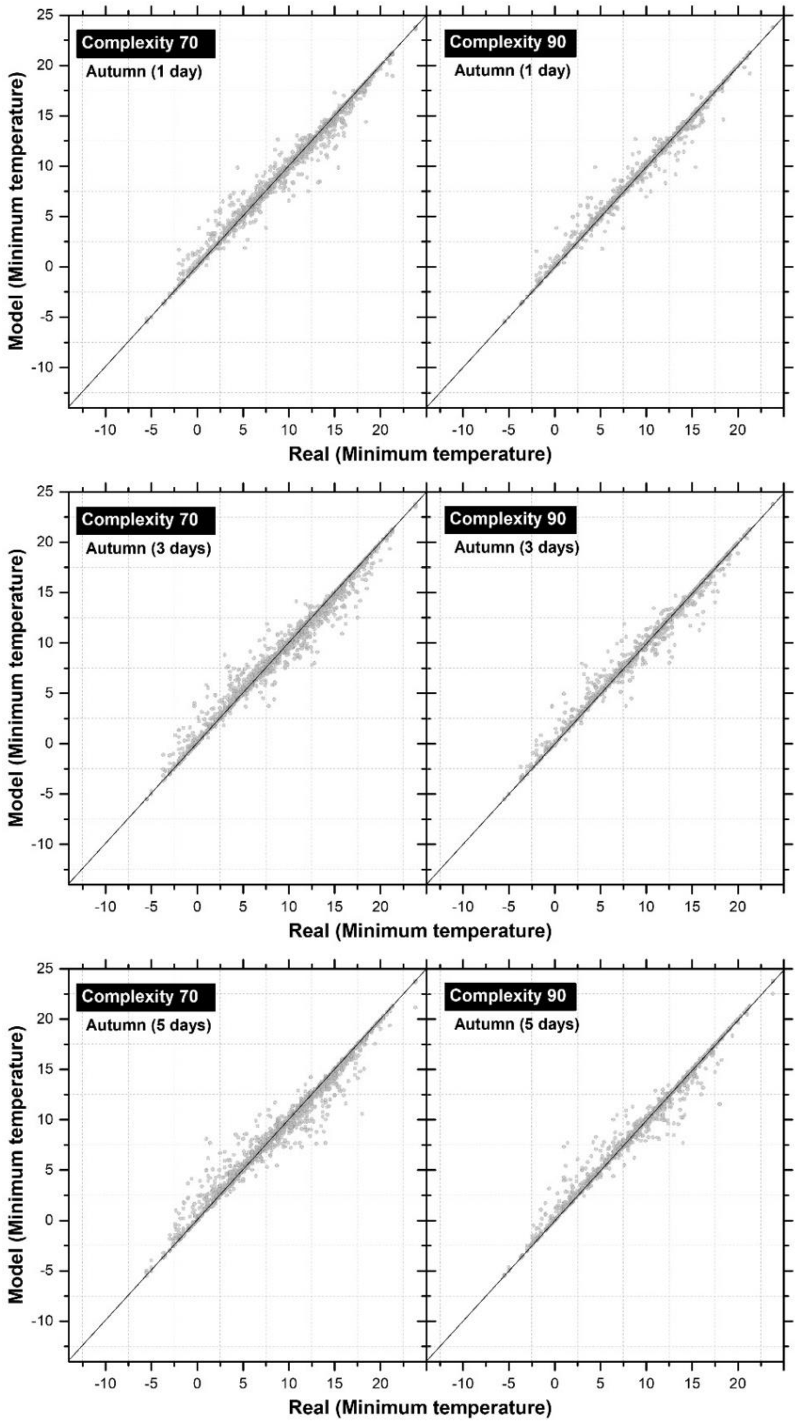

Figure 6. Dispersion diagram of observed Tmin and the one obtained with the model. 70 and 90 complexity. 1, 3 and 5 prediction days. 6 variables. Autumn.

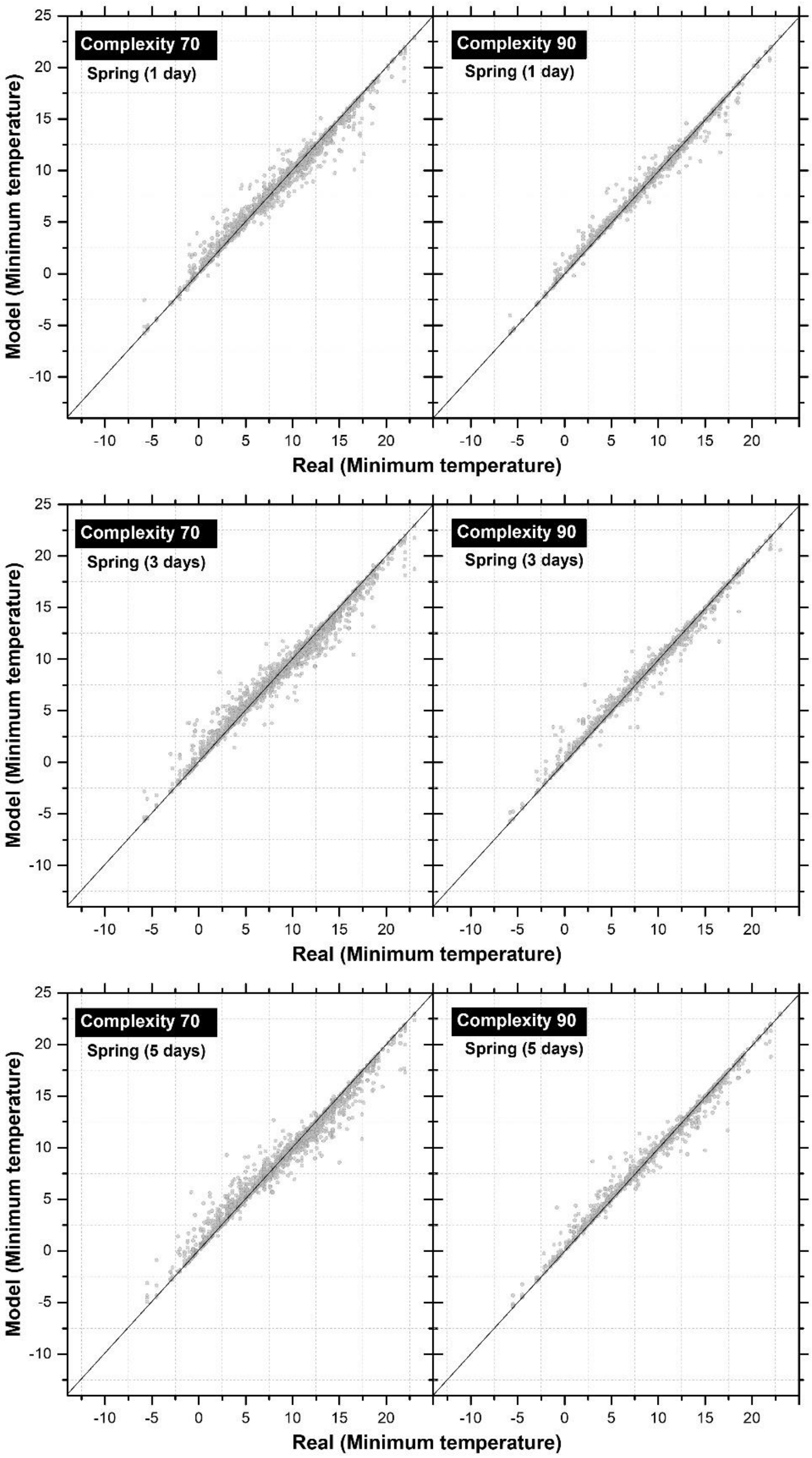

Figure 7. Dispersion diagram of observed Tmin and the one obtained with the model. 70 and 90 complexity. 1, 3 and 5 prediction days. 6 variables. Spring

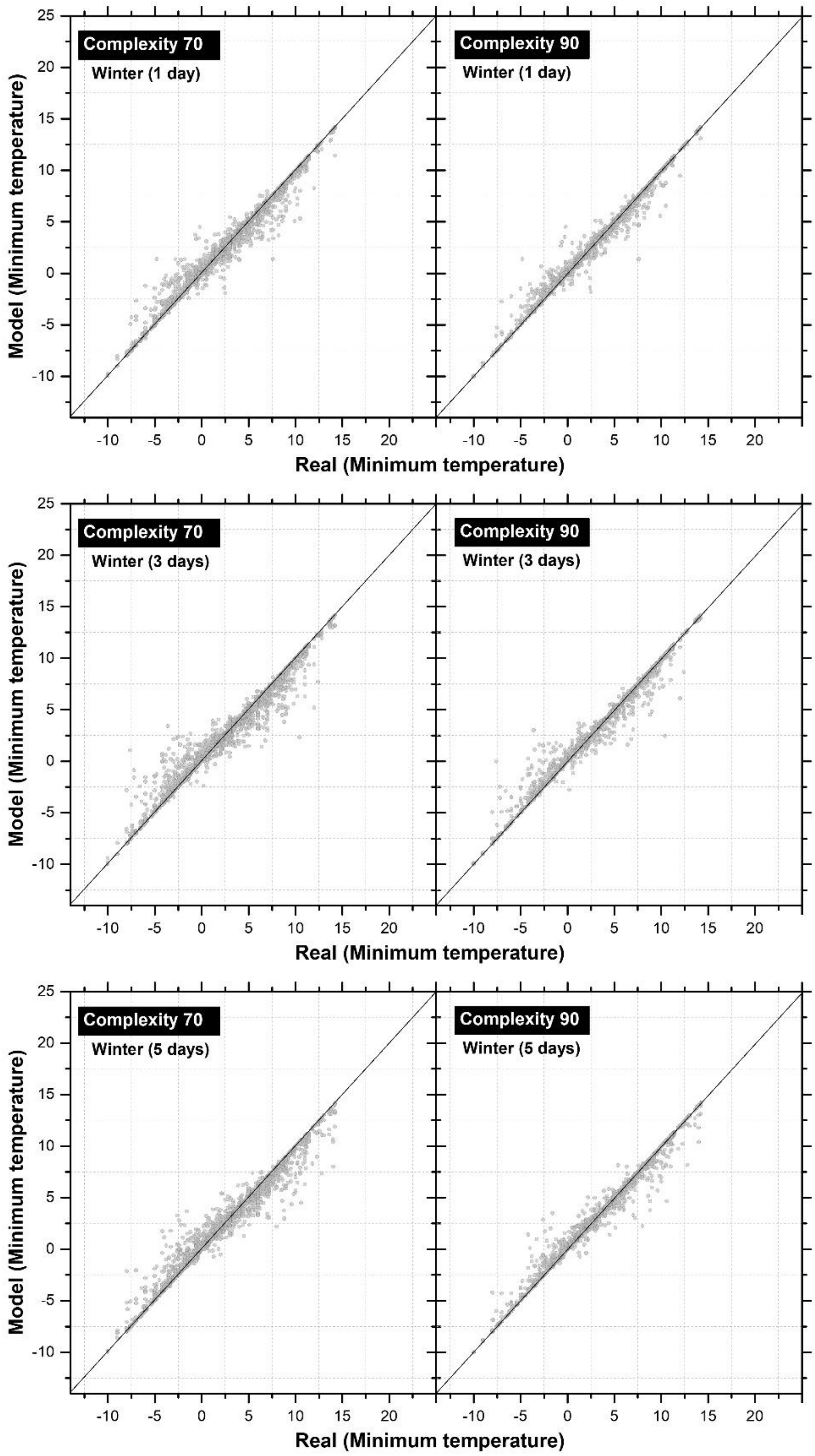

Figure 8. Dispersion diagram of observed Tmin and the one obtained with the model. 70 and 90 complexity. 1, 3 and 5 prediction days. 6 variables. Winter.

When generating models with 4 variables, for 5 forecast days it is necessary to increase the complexity (table 9) to obtain R^2 values similar to those obtained with 6 variables. Although with complexity 70 in the three seasons the value obtained for R^2 is around 0,8 ; it is with 120 when it reaches 0,96 in autumn and spring and 0,93 in winter, decreasing in the same way the MAE.

Table 9. R^2 for 5 prediction days 2007 – 2015. 4 variables. Autumn, winter and spring

Forecast 5 days			
Autumn	**Complexity 70**	**Complexity 100**	**Complexity 120**
R2	*0,860*	*0,94*	*0,96*
Mean absolute error. MAE	*1,4*	*1,10*	*1,10*
Mean square error.MSE	*4,27*	*2,26*	*2,26*
Root Mean square error, RMSE	*2,1*	*1,5*	*1,5*
Winter	**Complexity 70**	**Complexity 100**	**Complexity 120**
R2	*0,77*	*0,9*	*0,93*
Mean absolute error. MAE	*1,43*	*0,81*	*0,59*
Mean square error.MSE	*4,4*	*1,96*	*1,29*
Root Mean square error, RMSE	*2,1*	*1,4*	*1,14*
Spring	**Complexity 70**	**Complexity 100**	**Complexity 120**
R2	*0,8*	*0,92*	*0,96*
Mean absolute error. MAE	*1,55*	*0,79*	*0,58*
Mean square error.MSE	*4,84*	*1,60*	*0,90*
Root Mean square error, RMSE	*2,2*	*1,26*	*0,95*

As in previous models, figure 9 indicates how the correlation between real and estimated values increases when complexity increases. At the end of the analysis carried out with geometric models of finite elements it is observed that, for the best results, the model overestimates the T_{min} for its lowest values and underestimates them for the highest values in the different periods analyzed. According to this, if the model forecasts frost ($T_{min} \leq 0$) there is a high probability of success; however when the model does not forecast frost, this can occur in many cases.

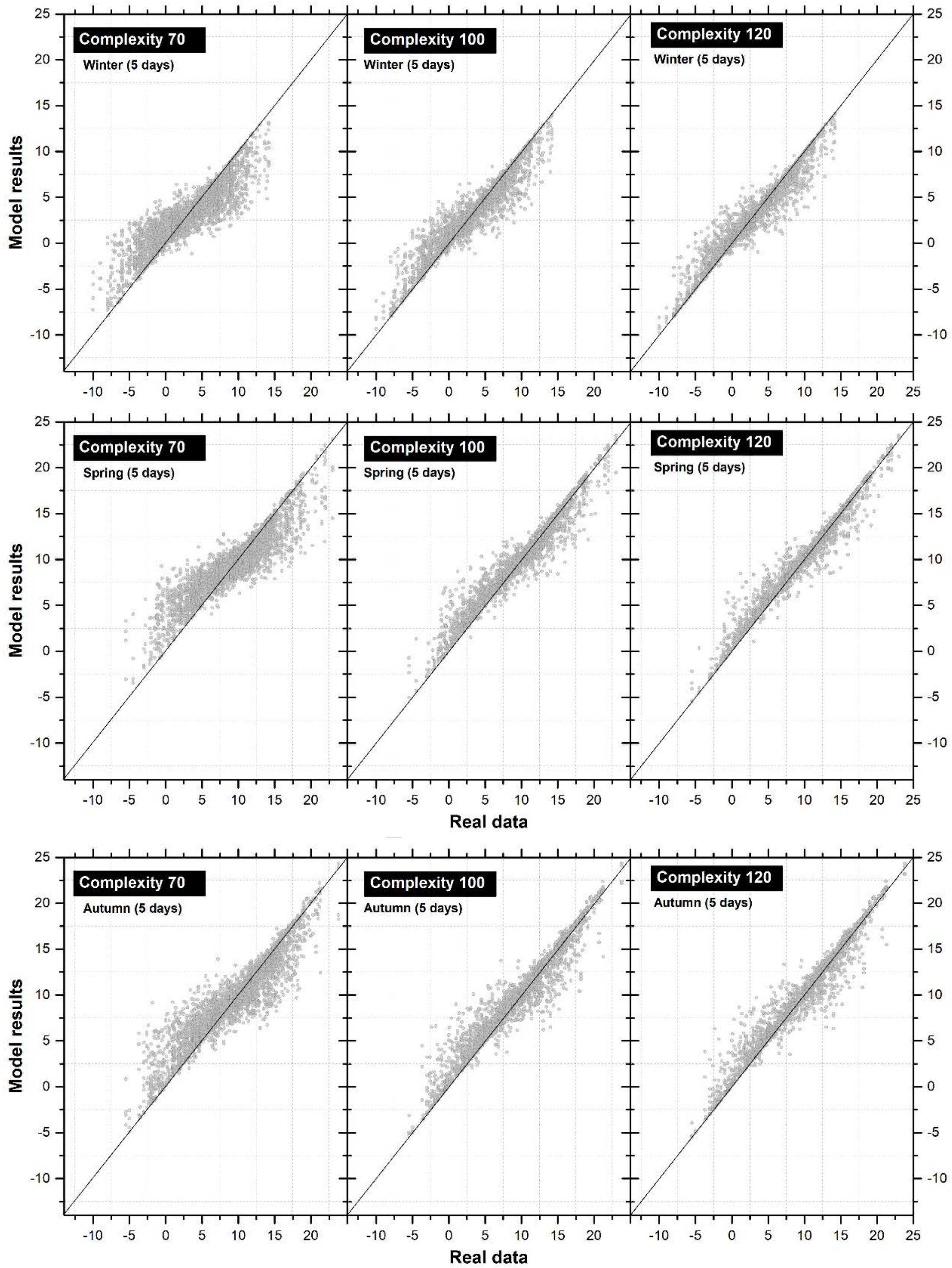

Figure 9. Dispersion diagram of observed T $_{min}$ and the one obtained with the model, complexity 70 100 and 120. 5 precision days. 4 variables. Autumn, winter and spring.

Table 10 presents a summary of the results in frost prediction, considering also the number of cases when at least agrometeorological frost (Tmin ≤ 3°C) is predicted, for the model with 6 variables and the 4-variable model with grouped data and by season.

Table 10. 6 variables model. 4 variables model (May to September, Autumn, Winter, Spring)

		Predicted meteorological frost Tmin<=0ºC	Tmin abs average error	Tmin max. error	Predicted agrometeorological frost Tmin<=3ºC
Frost	**Observed cases: 1123 6 variables (May - September)**	*Cases: 712 (63.4 %)*	*0.9 ºC*	*6.7 ºC*	*Cases: 1056 (94 %)*
	Observed cases: 1123 4 variables (May - September)	*Cases: 493 (44 %)*	*1.4 ºC*	*7.3 ºC*	*Cases: 954 (85 %)*
	Observed cases: 172 4 variables (Autumn)	*Cases: 130 (75.6 %)*	*0.4 ºC*	*2.7 ºC*	*Cases: 165 (96 %)*
	Observed cases: 880 4 variables (Winter)	*Cases: 750 (85.5 %)*	*2.13 ºC*	*6.02 ºC*	*Cases: 35 (93 %)*
	Observed cases: 96 4 variables (Spring)	*Cases: 60 (62.5 %)*	*0.5 ºC*	*3.3 ºC*	*Cases: 92 (96 %)*

According to these results and the analyses presented so far, the best models are those performed with 4 variables per station because it reaches R^2 values of about 0,95 and there is a high percentage of success of the model to predict frost.

4. Conclusions

The research developed focuses on the T_{min} of the city of Bahía Blanca, Buenos Aires province, with the objective of forecasting through this variable the occurrence of frost in the short term. The purpose of the study is based on the fact that Bahía Blanca is surrounded by a horticultural belt where species susceptible to frost are cultivated. For that reason, with the implementation of a simple method that allows alerting the occurrence of the above mentioned events with some days of anticipation, a tool that helps in the decision making is offered. In this way, producers would benefit from having valuable information that would allow them to improve their profits by making a more effective and timely protection of their crops.

From the exhaustive analysis carried out, we can affirm the existence of methodologies that applied according to the particularities of each region, can be of valuable help for the short term forecast of the T_{min} and therefore of frosts, based on observations of meteorological variables of surface mainly. The particular advantage of the proposed methods is that they require a limited number of observed local meteorological variables, which can be used without too much computational time. For the selected station, Bahía Blanca, the optimal methodology is the one developed in Navarro-Gonzalez and Villacampa (2012, 2013, 2016), applying geometric models of finite elements.

From the studies carried out for the prediction of T_{min} it is concluded that:

Numerical models of finite elements improve the prediction of neural networks. When analyzing the whole time series (1956-2015) with the 6 variables and complexities of 90, for the 1 day forecast success is achieved in 90% of the cases, and for 3 and 5 days the success is in 84% of the cases. When the analysis is performed with the time series of 9 years and 6 variables for the 3 forecast periods for each of the three seasons of the year (autumn, winter and spring) a R^2 of 0,98 is reached with 90 complexity. For 4 variables, in the forecast obtained for 5 days in advance, it is necessary to increase the complexity of the model to 120, to obtain R^2 greater than 0,9 in the three seasons. Therefore, it is the 120 complexity model that provides the best results because it serves for the forecast in the 3 seasons of the year. In all the cases analyzed, the data obtained with the validation confirms the trend found with the model. This trend shows an increase in R^2 when complexity increases and the EAM decreases. Of the independent variables necessary for its prediction, temperature, dew point temperature, wind speed and cloudiness are necessary. In order to obtain experimental data, it is considered that a period of 9 years is sufficient for the proposed objective.

In future research it is proposed to analyze the methodology of geometric models of finite elements with 4 variables, in a period of time of 10 years and in other cities. In this way it will be possible to conclude if the numerical models carried out in this research are the best to study this phenomenon in other regions.

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Graphical abstract

Highlights

Predictive model for crop temperature by modeling of surface meteorological variables.

Minimize possible economic losses in crops and improve productivity.

Tool for predicting of frost useful for horticultural producers.