

# Prediction of Seasonal Temperature Using Soft Computing Techniques: Application in Benevento (Southern Italy) Area

Salvatore Rampone · Alessio Valente

Received: date / Accepted: date

**Abstract** In this work two soft computing methods, Artificial Neural Networks and Genetic Programming, are proposed in order to forecast the mean air temperature that will occur in future seasons. The area in which the soft computing techniques were applied is that of the surroundings of the town of Benevento, in the south of Italy, having the geographic coordinates (lat.  $41^{\circ}07'50''$ N; long.  $14^{\circ}47'13''$ E). This area is not affected by maritime influences as well as by winds coming from the west. The methods are fed by data recorded in the meteorological stations of Benevento and Castelvenere, located in the hilly area, which characterizes the territory surrounding this city, at 144 m a.s.l. Both the applied methods show low error rates, while the Genetic Programming offers an explicit rule representation (a formula) explaining the prevision.

**Keywords** Seasonal Temperature Forecasting · Soft Computing · Artificial Neural Networks · Genetic Programming; Southern Italy

## 1 Introduction

Air temperature is a measure of how hot or cold the air is. The knowledge of the mean air temperature of the future seasons is very helpful for individuals, but even more for organizations whose workers and machines have to operate outdoors (agriculture, armed force, railways, maintenance of roads, tourism,

---

In collaboration with the Environmental Data Processing Course Group of Università del Sannio: Fabio Caporaso, Antonio Di Mezza, Guido Razzano, Pasquale Clemente, and Alessio Giardiello.

---

Department of Science and Technology (DST)  
Università del Sannio  
Via dei Mulini 59/A, Benevento, Italy, I-82100  
E-mail: {rampone, valente}@unisannio.it

etc.) and for gas and electricity companies. The seasonal temperature values, in fact, have a great economic impact for both organizations and companies, and their prediction would allow a more efficient activity planning.

The accurate prediction of the air temperature is very complex and usually requires a processing of a large amount of data on the weather conditions as well as the scientific understanding of atmospheric processes and their possible spatial and temporal variations (Sarda et al. 1996, Anderson et al. 1999, Stockdale 2000). Moreover, it is not possible to perform the prediction of the seasonal temperature with a minimum error for all the months and places in the world. Generally, the quality of seasonal forecasting has reached a good reliability over the most of the tropical regions, while the extra tropical latitudes have achieved reliable results only in certain regions (for example, in Northern America). More specifically, in Europe the predictability of temperature is quite complicated due to the variability and external influences of the local climate (Rodwell and Doblas-Reyes 2006). However in the recent decades a considerable effort has been made to improve the understanding of physical phenomena responsible for the seasonal variability of climate parameters (Saha et al. 2006, Ineson and Scaife 2009).

In order to forecast the temperature that will occur in future seasons, climatological models are frequently used. Some of them follow an empirical approach based on several series of historical data, useful for building predictive models; others develop a theoretical approach on complex calculations with parameters and functions that are able to understand the behaviour of the atmospheric system.

The first approach considers a set of minimum, maximum and mean temperatures recorded for several decades (at least thirty years) in representative meteorological stations in the area, while the second approach uses numerical analysis techniques which involve data observed by radiosondes, weather satellites and surface weather observations of land and oceans processed by powerful supercomputers, which are necessary because of the huge amount of data. For the latter approach, the horizontal spatial domain is global, if it covers the entire Earth, or regional, if it covers only a small part of the planet. In the first approach, the forecast is in somewhat approximate, although it is indicative of the future trend of the seasonal temperature in a certain area; in the second approach the values of minimum and maximum temperature of the foreseen seasons can be estimated very reliably, because it takes into account the correlations of anomalies in the atmospheric circulation at large scale. However, it is difficult for operators to arrange the numerical approach on a smaller scale for planning purposes.

In order to make the forecasting of foreseen seasonal temperatures less sophisticated, in this work two soft computing methods are applied: Artificial Neural Networks (ANNs) (Bishop 1996, Haykin 2008) and Genetic Programming (GP) (Koza 1992).

As ANN we use a feedforward Multi Layer Perceptron (MLP) Neural Network, a computational structure made by many processing elements (units), the neurons, operating in parallel, aiming to approximate an unknown func-

tion of its inputs (Beale and Jackson1990). To configure the MLP we use the training procedure called “back propagation” (Beale and Jackson1990). It uses a subset of the data set feature vectors, each one labeled with the correct output, as examples of the correct input/output relationship. Artificial Neural Networks have already been successfully applied in different contexts (Rampone 2013, Rampone et al. 2013, Rampone and Valente 2012), including the atmospheric researches, such as the prediction of maximum daily precipitation (Nastos et al. 2014), the monthly precipitation and evapotranspiration index (Deo and Sahin 2015) and air temperature (Sahin 2012, Venkadesh et al. 2013). Generally, in these works, in addition to the change of the reference framework, which can be on a local or regional scale, a wide range of parameters is used. The use of parameters depends on the availability of data. It is not always possible to have them at the local level as well as the reduction in a local scale of the information available at the regional scale cannot be free from errors and approximations.

We also employ GP in order to improve the understanding of the neural method performance. GP is an evolutionary computational technique proposed by Koza (Koza 1992, Koza 1994) in order to extract automatically intelligible relationships in a system without being explicitly programmed. It has been used in many applications such as symbolic regressions (Davidson et al. 2003), and classifications (De Stefano et al. 2002, Zhang and Bhattacharyya 2004). It works by using genetic algorithms (Goldberg 1989) to generate and evolve automatically composite functions, traditionally represented as tree structures (Cramer 1985). GP is then able to show the relation between input data and output data by means of an explicit formula. Also this soft computing method has been successfully applied to many problems of practical order (Makkeasorn et al. 2008, Shiri et al. 2012, Stanislawski et al. 2012, Sivapragasam et al. 2007).

This paper is organized in the following way: in the next Section we describe the application area and in Section 3 the environmental data used for tuning the methods. The results are reported in the Experiments Section.

## 2 Application Area

The area in which soft computing techniques are applied is that of the surroundings of the town of Benevento having the geographic coordinates (lat.  $41^{\circ} 07' 50''$  N; long.  $14^{\circ} 47' 13''$  E). It is located equidistant from the seas and protected by the hills located in the west that is an inner area of the Italian peninsula. Therefore, the area of this application is not affected by maritime influences, nor by winds coming from the west. Nevertheless, its geographic location falls in the context of a Mediterranean climate with a tendency to continental features. More specifically, along the Italian peninsula it is observed, in winter, the interaction between the area flows from the northwest and west and those who move from the east, which causes heavy rains, while in summer the presence of subtropical anticyclone determines a prolonged drought inter-

rupted by sporadic thunder phenomena. The north-western winter air streams can bring down the minimum temperature to a few degrees above zero, and the maximum in summer exceeds 30°C.

This synoptic situation is made evident by the data recorded in the meteorological station of Benevento (Centro Agrometeorologico Regionale 2016). It is located in the hilly area, which characterizes the territory surrounding this town, at 144 m a.s.l. Although it has recorded rainfall and temperature data since 1882, the official ones published on the Hydrological Annals are available only from 1925 until 1998 with occasional missing data. The decommissioning of the Benevento station forced us to examine the data of another site, at a distance of less than twenty kilometers north-west from Benevento. So the data corresponding to the last 13 years come from the Castelvenere station (lat. 41°14'15"N; long. 14°33'16"E), that is located in a similar geographical position (140 m a.s.l.) and it presents a minimal difference with the data of temperature and precipitation recorded in Benevento. However, in order to avoid mistakes, these data have been scaled according with this difference. In both stations, for each year the available data are the daily minimum temperature, the daily maximum temperature, the daily mean temperature, the daily amount of rainfall and the number of rainy days that occurred during each month.

In order to better show the weather characteristics of the area, we provide some information obtained from the considered series. The mean maximum temperature recorded during the summer season varies from 25.6°C to 32.1°C. The mean minimum and maximum value has been reached respectively in 1976 and 1928. The mean minimum temperature in the winter season ranges from a low of -0.8°C in 1982 to a maximum of 7.8°C in 1979. Also in 1982, the highest annual temperature range of 31.1°C was reached, although the yearly mean temperature remains below 17°C. The daily mean temperature is slightly below 15°C.

Just to complete the data relating to the maximum temperatures recorded in the last decades, Castelvenere station shows a tendency to increase with peaks that have exceeded abundantly 40° during summer months, whereas in the same station the minimum temperature has gone down to 7° below zero during the winter months. The mean maximum temperature of the summer months is within the same range defined before, but basically the values are higher. Even the mean minimum temperature of the winter months falls between the extremes defined at a general level, however, it should be noticed that it is not unusual to have periods of more than one week with temperatures below zero (2009 and 2012). As for precipitations, it can be seen clearly in the annual distribution of the data that they are highest in autumn and winter seasons and at a minimum in the summer. In particular, the range of the annual precipitation varies from a minimum of 256 mm in 2003 to a maximum of 1127 mm in 1955, with an average value which is near to 800 mm. The largest quantities were mainly recorded in the autumn months (nearly 600 mm in 2010 and over 500 mm in 1966), while the lowest ones were recorded in the summer months (20 mm in 2000 and 21 mm in 1987). This effect is confirmed by the

frequency of rainfall, which sees a concentration of rainy days in the autumn months (56 rainy days in 2002), in contrast to summer months in which it is reduced dramatically, as in the months of the beginning of this century with one day in 2000.

### 3 Data

In the proposed application we want to predict the mean seasonal temperature of the subsequent years. Therefore, a number of parameters (features) to assess the seasonal conditions of this area are calculated from the available data from 1925 to 2012. Such parameters are then used for the prediction. According to the data availability in the series of the meteorological stations in Benevento area, we consider 9 features:

**Table 1** Parameters calculated from the available data from 1925 to 2012.

Feature	Range
Year ( $Y$ )	From 1925 to 2012
Season ( $S$ )	Winter, Spring, Summer, Autumn
Mean Seasonal Temperature ( $MST$ )	C degrees
Mean Seasonal of Daily Maximum Temperatures ( $MSDMT$ )	C degrees
Mean Seasonal of Daily minimum Temperatures ( $MSDmT$ )	C degrees
Mean Yearly Temperature ( $MYT$ )	C degrees
Mean Seasonal Rainfall ( $MSR$ )	mm
Number of Seasonal Raining Days ( $NSRD$ )	Positive Integer
Mean Seasonal Temperature in the Next Year ( $MSTNY$ )	C degrees

With the exception of the Season ( $S$ ) all the features are expressed as numeric variables. They should contribute to the prediction of seasonal mean temperature of the year following the year in progress. In addition to temperature values, which express the most features used, two sets of data concerning the precipitation are considered. They have been inserted in the input data, since the temperature is to be put in relation to the general circulation and disturbances that could be incurred. In some cases the occurrence of rainfall can be enforced by local situations, such as mountain range and vegetation, which determine the amount of moisture in the air. Such amount is to be put in relation with the temperature that is observed. Furthermore, rainfall is also related to the number of rainy days, useful to detect the frequency with which this phenomenon occurs.

Missing data are restricted to the period of the Second World War (1942-1948) and the failure of the stations for certain periods; however, this has not compromised the quality of information used for the application. To obviate these data, it has not been made any interpolation, while for the data of the second station an appropriate correction has been introduced taking into

account the local influences on the recorded data (different exposure to the Solar Radiation, moisture conditions, etc.).

The resulting dataset is composed of 248 labeled examples, where each example has the following structure

$$Xp; tp = (Y; S; MST; MSDMT; MSDmT; MYT; MSR; NSRD); MSTNY \quad (1)$$

## 4 Experiments

### 4.1 MLP

According to the 10-fold cross-validation methodology (Devijver and Kittler 1982), the whole data set has been partitioned into 10 non overlapping subsets. Of these 10 subsets, one can be chosen to evaluate the neural network performance (validation set), and the remaining 9 can be used to instruct it (training sets), i.e. setting the network weights. This procedure has been repeated 10 times, corresponding to all possible choices of the validation set and the corresponding average performance has been gauged in terms of an average %-misclassification error. Cross-validation is important in testing hypotheses suggested by the data, especially where further samples are costly or impossible to collect.

For our experiments we adopted an Excel-based system which simulates a neural network developed by Angshuman Saha, that is freely available all over the web<sup>1</sup>. By using this tool, we can define feed-forward back-propagation networks with 1 or 2 hidden layers, enter training data, set various learning parameters, start a learning phase and see the results (e.g. error rate) presented in various ways, for example graphically (see Fig. 1). Categorical values are automatically converted into numerical ones. The weights  $W_{kn}$  are initially randomly chosen in a fixed range. The error back propagation algorithm has several parameters, and the most important ones are called, respectively, “learning rate” and “momentum term”. The first term is a measure of the influence degree, in the formula for updating weights, of the error term, whereas the latter one determines the influence of the past history of weight changes in the same formula.

One of the most important characteristics of a MLP is the number of neurons in the hidden layer(s). If an inadequate number of neurons are used, the network will be unable to model complex data, and the resulting fit will be poor. If too many neurons are used, the network generalizes poorly to new, unseen data. So the hidden layers have been configured by a random initial choice and

- pruning, i.e. eliminating nodes, when the network learns easily the training set but shows bad performances on the validation set; and

<sup>1</sup> <http://xoomer.virgilio.it/srampone/NNpred01.zip>.

**Network Architecture Options**

Number of Inputs (between 2 and 50)	<input type="text" value="8"/>	Number of Outputs (between 1 and 10)	<input type="text" value="1"/>
Number of Hidden Layers (1 or 2)	<input type="text" value="1"/>	Hidden Layer sizes (Maximum 20)	Hidden 1: <input type="text" value="2"/> Hidden 2: <input type="text" value="2"/>
Learning parameter (between 0 and 1)	<input type="text" value="0,5"/>	Initial Wt Range (0 +/- w) =	<input type="text" value="0,5"/>
Momentum (between 0 and 1)	<input type="text" value="0,9"/>		

**Training Options**

Total #rows in your data (Minimum 10)	<input type="text" value="248"/>	No. of Training cycles (Maximum 500)	<input type="text" value="500"/>
Present Inputs in Random order while Training ?	<input type="text" value="NO"/>	Training Mode (Batch or Sequential)	<input type="text" value="Sequential"/>

**Save Network weights**

**Training / Validation Set**

If you want to partition, how do you want to select the Validation set ?

Please choose one option

Please fill up the input necessary for the selected option

Option 1 : Randomly select	<input type="text" value="10% of data as Validation set"/>
Option 2 : Use last	<input type="text" value="24 rows of the data as validation set"/>

**Save model in a separate workbook?**

**Fig. 1** Parameter set by using the Excel-based system which simulates the MLP neural network.

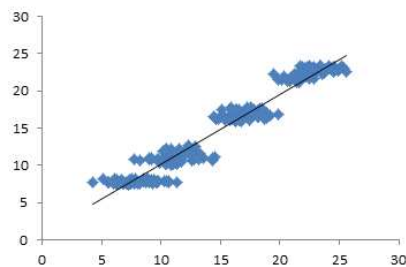
- growing, i.e. adding nodes when the network shows bad performances on the training set.

In our case the resulting architecture is made up of 8 inputs, a single hidden layer of 2 neurons, and one output.

The number of training cycles (epochs) has been fixed to 500.

To value the performances, we use the error percentage resulting from the 10-fold cross-validation methodology and the coefficient of determination, denoted  $R^2$ , that indicates the proportion of the variance in the dependent variable that is predictable from the independent variable.

The results on the whole data set have been reported in Table 2. The mean error is of 8,71% while the coefficient of determination is 0,97, a very high value. Fig. 2 reports comparatively the predicted and expected temperature values.



**Fig. 2** Plot of Expected (X-axis) vs Predicted (Y-axis) temperatures on the whole data set by using MLP.

Then, since the data originated from two different stations, we partitioned the dataset, according to its origin, in two subsets, i.e. from 1925 al 1998

**Table 2** Ten fold cross validation by using the selected architecture on the whole data set

Trial	Validation error	$R^2$
1	3,68%	0,97
2	8,31%	0,97
3	7,70%	0,97
4	9,28%	0,97
5	7,32%	0,97
6	6,15%	0,97
7	16,41%	0,97
8	10,35%	0,97
9	10,41%	0,97
10	7,51%	0,97
<b>Mean</b>	8,71%	0,97

and from 2000 to 2012, and the ten fold cross validation procedure has been repeated for each one. The results on the two subsets have been reported respectively in Table 3 and Table 4.

**Table 3** Ten fold cross validation by using the selected architecture on the subset 1925-1988.

Trial	Validation error	$R^2$
1	10,76%	0,97
2	7,73%	0,97
3	8,85%	0,97
4	6,79%	0,97
5	8,21%	0,97
6	8,63%	0,96
7	7,10%	0,97
8	12,52%	0,97
9	11,87%	0,97
10	13,82%	0,97
<b>Mean</b>	9,63 %	0,97

## 4.2 GP

Given the data set characteristics, we are looking for a formula  $f()$  that satisfies

$$MSTNY = f(Y; S; MST; MSDMT; MSDmT; MYT; MSR; NSRD) \quad (2)$$

We limit the set of component functions to the arithmetic operators (+, -, \*, /) plus some trigonometric functions (sine, cosine and tangent), the exponential and the natural logarithm, the logistic function, the hyperbolic tangent and the minimum function.

As fitness measure we use the mean square error ( $MSE$ ).



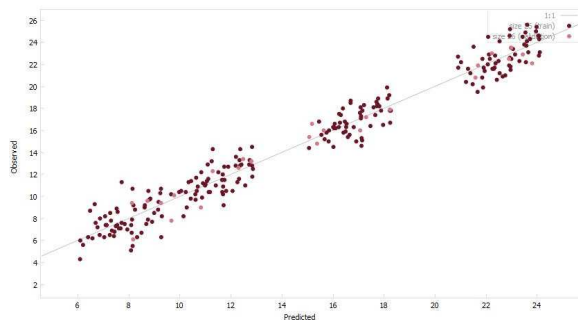
**Table 4** Ten fold cross validation by using the selected architecture on the subset 2000-2012.

Trial	Validation error	$R^2$
1	4,19%	0,97
2	5,89%	0,97
3	8,78%	0,97
4	7,22%	0,97
5	7,48%	0,97
6	3,29%	0,97
7	3,21%	0,97
8	5,03%	0,97
9	1,04%	0,97
10	3,79%	0,97
<b>Mean</b>	<b>4,99%</b>	<b>0,97</b>

The exemplars are split in two groups for training (90%) and validation (10%). The training set is created by randomly selecting samples from the whole dataset.

We use a genetic programming software tool called Eureqa, for detecting equations and hidden mathematical relationships in a given data set. Eureqa works in order to reduce the error function given by the discrepancy between the data and the generated model (Schmidt and Lipson 2009). Eureqa is a proprietary A.I.-powered modeling engine originally created by Cornell's Artificial Intelligence Lab and later commercialized by Nutonian, Inc. The software uses evolutionary search to determine mathematical equations that describe sets of data in their simplest form. It also allows to evidence the behaviour of each solution with respect to its size.

After about 700000 generations we found a set of solution, as reported in Table 5. The performance of each solution are reported in Table 6. A plot of Expected vs Predicted temperatures on the whole data set by using solution 10 is reported in Fig. 3.

**Fig. 3** Plot of Expected (X-axis) vs Predicted (Y-axis) temperatures on the whole data set by using GP.

**Table 5** Ten fold cross validation by using the selected architecture on the subset 2000-2012.

Solution num.	Size	Fit	Solution
1	1	1,000	$MSTNY = MST$
2	3	0,985	$MSTNY = 0,99 * MST$
3	6	0,806	$MSTNY = MST - \cos(MSDMT)$
4	5	0,982	$MSTNY = 0,51 + 0,96 * MST$
5	10	0,762	$MSTNY = 0,55 + 0,95 * MST - \cos(MSDMT)$
6	14	0,445	$MSTNY = MYT - 6,67 - 5,28 * S * \cos(0,55 + S)$
7	38	0,309	$MSTNY = MYT - 7,00 - \cos(4884, 11 * Y) * \min(\cos(0,48 * Y), \cos(0,28 * Y)) - 5,41 * S * \cos(0,54 + S)$
8	32	0,340	$MSTNY = 0,84 * MYT - 4,34 - \cos(4884, 11 * Y) * \cos(2,584 + 0,84 * MYT) - 5,32 * S * \cos(0,54 + S)$
9	28	0,350	$MSTNY = MYT - 6,66 - \cos(4884, 10 * Y) * \cos(0,58 * MYT) - 5,32 * S * \cos(0,54 + S)$
10	26	0,436	$MSTNY = 7,77 + 0,64 * \cos(4951,06 * Y) - \cos(MYT) - 5,33 * S * \cos(0,54 + S)$

**Table 6** Performance of the solution set in terms of  $R^2$  and  $MSE$ .

Solution	1	2	3	4	5	6	7	8	9	10
$R^2$	0,92	0,92	0,92	0,94	0,94	0,96	0,97	0,97	0,97	0,98
$MSE$	$2 \times 10^4$	$2 \times 10^7$	$2 \times 10^7$	$2 \times 10^7$	$2 \times 10^6$	1,00	0,98	0,78	0,76	0,69

As it was evidenced by the solution expressions, just 3 parameters determine the solution. We value the relevance of each variable in terms of

**Sensitivity:** The relative impact within this model that a variable has on the target variable.

**% Positive:** The likelihood that increasing this variable will increase the target variable.

**Positive Magnitude:** When increases in this variable lead to increases in the target variable, this is generally how big the positive impact is.

**% Negative:** The likelihood that increasing this variable will decrease the target variable

**Negative Magnitude:** When increases in this variable lead to decreases in the target variable, this is generally how big the negative impact is.

The results, for the best solution found are reported in Table 7.

**Table 7** Variable Sensitivity in the solution 10.

Variable	Sensitivity	% Positive	Positive Mag.	% Negative	Negative Mag.
$Y$	3,0141	46%	3,3674	54%	2,7143
$S$	1,3642	67%	1,1636	33%	1,7654
$MYT$	0,1883	100%	0,1883	0%	0

Then the experiment has been repeated by adding the Gaussian function to the set of functions. In this case the best solution considers more and different variables, as reported in Table 8.

**Table 8** Variable Sensitivity in the solution  $MSTNY = 0,6354 * MYT - 0,183 - 0,07226 * \tan(MYT) - 0,0005114 * MYT * MSDMT S2 - 0,901 * MST * \sin(2,203 + 0,9123 * S)$ ,

Variable	Sensitivity	% Positive	Positive Mag.	% Negative	Negative Mag.
<i>S</i>	1,1779	67%	1,1357	33%	1,2622
<i>MST</i>	0,55971	100%	0,55971	0%	0
<i>MSDMT</i>	0,41929	0%	0	100%	0,41929
<i>MYT</i>	0,16345	80%	0,12137	20%	0,33176

## 5 Discussion

In this study, two soft computing methods, as Artificial Neural Networks, in the Multi-Layer Perceptron (*MLP*) approach, and Genetic Programming (*GP*), were applied to predict next year's seasonal temperatures. In both methods we considered the same weather variables extracted from the records of two meteorological stations of Benevento and Castelvenere. While the traditional statistical methods need several a priori assumptions, *MLP* and *GP* are non-parametric tools and suitable for any situations and data sets.

Both the applied methods show low error rates and high correlation values.

As regard the application of *MLP*, the results on the whole data set show a mean error of 8,71% with a very high value of coefficient of determination of 0,97. If we consider only the subset 2000-2012, the ten fold cross validation result is lower than 5% with the same coefficient of determination.

However, from a customer managers point of view, the classification results from the *MLP* are sub-symbolic and are often difficult to comprehend. The proposed *GP* approach offers an explicit rule representation (a formula) while maintaining the low error rates and high correlation values.

As it has been evidenced in the last solution reported in Table 5, a formula which has a relatively low size and a rather good fitness considers just the mean yearly temperature (*MYT*) of the previous year, the actual year (*Y*) and the relative season (*S*). This solution reaches a very good performance in terms of  $R^2$  and *MSE* (the former is 0,98% and the latter is 0,69, as reported in Table 6). The comprehension of the *GP* results has markedly improved in the next serial of tests and it has pointed out that the foreseen of seasonal temperature (*MSTNY*) is related to the tendency of previous mean season temperature (*MST*) and subordinately to the mean yearly temperature (*MYT*) (see Table 8). This result could be linked to the atmosphere circulation acting in the application area, otherwise these variables would have a higher negative sensitivity (Stanislawska et al. 2012). A major impact of the mean seasonal of daily

maximum temperatures (*MSDMT*) and the mean seasonal of daily minimum temperatures (*MSDmT*), as also the mean seasonal rainfall (*MSR*) and number of seasonal raining days (*NSRD*) in the solution test, would be evidence of anomalies in the atmosphere circulation (i.e. higher content in greenhouse gas, frequent cloud burst). In our application, developed in the area of Benevento, the evolutionary trend appears almost linear, so evidencing the dominance of the natural forces. Probably this was to be expected for the natural and mainly agricultural land use, affecting to a lesser degree on the temperature behaviour with respect to industrial areas.

These good results encourage the improving of these methods, by exploring and fine-tuning the various parameters, whose exact determination may be quite complex (e.g. temperature, pressure, moist and so on). In the last decade these estimations have been further complicated by anthropogenic forces that make less comprehensible the behaviour of the temperature (Pasini et al. 2006).

**Acknowledgements** The authors are grateful to L. Rampone for the careful reading of the paper.

## References

- Anderson J, van den Dool H, Barnston A, Chen W, Stern W, Ploshay J (1999) Present-day capabilities of numerical and statistical models for atmospheric extratropical seasonal simulation and predication. *Bull. Am. Meteorol. Soc.* 80:13491361
- Beale R, Jackson T (1990) *Neural Computing: An Introduction*. Hadam Hilger, Bristol
- Bishop CM (1995) *Neural Networks for Pattern Recognition*. Clarendon Press, Oxford
- Centro Agrometeorologico Regionale (2016) Weather data from Campania Region agrometeorological network. <http://www.agricoltura.regione.campania.it/meteo/agrometeo.htm>. Last Accessed 23 August 2016
- Cramer NL (1985) A representation for the Adaptive Generation of Simple Sequential Programs In: Grefenstette JJ (ed) *Proc. International Conference on Genetic Algorithms and their Applications*, Carnegie Mellon University, Pittsburgh, pp 183–187
- Davidson JW, Savic DA, Walters GA (2003) Symbolic and numerical regression: Experiments and applications. *Information Sciences* 150:95117
- Deo RC, ahin M (2015) Application of the Artificial Neural Network model for prediction of monthly Standardized Precipitation and Evapotranspiration Index using hydrometeorological parameters and climate indices in eastern Australia. *Atmospheric Research* 161, 162:6581
- De Stefano C, Della Cioppa A, Marcelli A (2002) Character preclassification based on genetic programming. *Pattern Recognition Letters* 23:14391448

- Devijver PA, Kittler J (1982) *Pattern Recognition: A Statistical Approach*. Prentice-Hall, London
- Goldberg DE (1989) *Genetic Algorithms in Search, Optimization & Machine Learning*. Addison-Wesley, London
- Haykin S (2008) *Neural Networks and Learning Machines*. Prentice Hall, London
- Ineson S, Scaife AA (2009) The role of the stratosphere in the European climate response to El Niño. *Nature Geoscience* 2:32-36
- Koza JR (1992) *Genetic Programming: On the Programming of Computers by Means of Natural Selection*. MIT Press, Cambridge
- Koza JR (1994) *Genetic Programming II: Automatic Discovery of Reusable Programs*. MIT Press, Cambridge
- Makkeasorn A, Chang NB, Zhou X (2008) Short-term streamflow forecasting with global climate change implications A comparative study between genetic programming and neural network model. *Journal of Hydrology* 352:336354
- Nastos PT, Paliatsos AG, Koukouletsos KV, Larissi IK, Moustris KP (2014) Artificial neural networks modelling for forecasting the maximum daily total precipitation at Athens, Greece. *Atmospheric Research* 144:141150
- Pasini A, Lorè M, Ameli F (2006) Neural network modelling for the analysis of forcings/temperatures relationships at different scales in the climate system. *Ecological Modelling* 191:58-67
- Rampone S, Valente A. (2012) Neural Network Aided Evaluation of Landslide Susceptibility in Southern Italy. *International Journal of Modern Physics C* 23:1250002-1250021
- Rampone S (2013) Three-and-six-month-before forecast of water resources in a karst aquifer in the Terminio massif (Southern Italy). *Applied Soft Computing* 13:40774086
- Rampone S, Pierro V, Troiano L, Pinto IM (2013) Neural Network Aided Glitch-Burst Discrimination and Glitch Classification. *International Journal of Modern Physics C* 24:1350084-1350100
- Rodwell M, Doblas-Reyes FJ (2006) Predictability and prediction of European monthly to seasonal climate anomalies. *J. Climate* 19:6025-6046
- Saha S, Nadiga S, Thiaw C, Wang J, Wang W, Zhang Q, van den Dool HM, Pan H-L, Moorthi S, Behringer D, Stokes D, Pena M, Lord S, White G, Ebisuzaki W, Peng P, Xie P (2006) The NCEP climate forecast system. *J. Climate* 19:34833517
- Sahin M (2012) Modelling of air temperature using remote sensing and artificial neural network in Turkey. *Advances in Space Research* 50:973985
- Sarda J, Plaut G, Pires C, Vautard R (1996) Statistical and dynamical long-range atmospheric forecasts: Experimental comparison and hybridization. *Tellus* 48:518537
- Shiri J, Kii O, Landeras G, Lopez JJ, Nazemi AH, Stuyt LCPM (2012) Daily reference evapotranspiration modeling by using genetic programming approach in the Basque Country (Northern Spain). *Journal of Hydrology* 414 415:302316

- Sivapragasam C, Maheswaran R, Venkatesh V (2007) Genetic programming approach for flood routing in natural channels, *Hydrological Processes* 22:623628
- Schmidt M, Lipson H (2009) Distilling Free-Form Natural Laws from Experimental Data. *Science* 324:81-85
- Stanislawski K, Krawiec K, Kundzewicz ZW (2012) Modelling global temperature changes with genetic programming. *Computers and Mathematics with Applications* 64:37173728
- Stockdale TN (2000) An overview of techniques for seasonal forecasting. *Stochastic Environmental Research and Risk Assessment* 14:305-318
- Venkadesh S, Hoogenboom G, Potter W, McClendon R (2013) A genetic algorithm to refine input data selection for air temperature prediction using artificial neural networks. *Applied Soft Computing* 13:22532260
- Zhang Y, Bhattacharyya S (2004) Genetic programming in classifying large-scale data: an ensemble method, *Information Science* 163:85101