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Forecasting Daily Urticaceae Pollen Count By Artificial Neural Networks

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Abstract:
Pollen and spore forecasting has become an important aim in aerobiology and is one of the most studied topics. Air pollen forecasting is directly related to a regional agriculture, environment, health and other aspects of people's lives. The most used tools for this problem are regression models. The advanced mathematical methods can be applied to the problems that cannot be solved in any other effective way, and are suited to predicting the concentration of Urticacea airborne pollen in relation to weather conditions. A few works have used more sophisticated methods such as Artificial Neural Networks (ANNs). In this paper, we developed some of ANNs models to forecast Urticaceae pollen concentrations for pre-peak, post-peak and whole periods in the atmosphere of Tirana, Albania.
This method gave good results for Pearson's correlation and R-square: the correlation was 0.98, R-square was 0.82 for the pre - peak period and the correlation 0.97, R-squared 0.85 for whole correlation, respectively. We used different MPL with three layers and a various number of neurons in the hidden layer. Experimental results show an advantage of the ANNs against statistical methods, although there is still room for improvement. Used models gave more satisfactory predictive results, where it was best for the pre-peak, then for the whole period and weak for the post-peak period.

Key words: *Neural Networks, Multilayer perceptron, Urticaceae pollen, prediction.*

1.Introduction

All over Europe, the most allergenic weeds are plants belonging to Asteraceae and Urticaceae (Jäger and D'Amato, 2001). Airborne pollen of Urticaceae is very common everywhere (Charpin et al., 1977), but only Parietaria, the most pollenosis-inducing plant in the Mediterranean regions (D'Amato and Sieksma, 1990; D'Amato et al., 1991), is significant in inducing allergic diseases (Bousquet et al., 1986; Jäger and D'Amato, 2001).

Pollinosis, a pollen related disease, is caused by airborne allergenic pollens from certain plants. The prevalence of paleness has happened in recent decades. Modern epidemiological studies from various countries indicate that currently 10–25% of the average population suffers from allergic diseases (Jianan et al., 2007; Dykewicz et al., 2010). This percentage is higher in the child population compared with the adult population (Burge, 2002; Beggs, 2004). In order to prevent pollinosis, it is a great importance to do the research on airborne pollen. The presence and amount of airborne pollen depends on a wide range of factors including meteorological (temperature, rain, humidity, wind, etc.), biological (phenological and physiological state of plants, plants distribution, etc.) and geological (topography) issues (Qian et al., 2005; Jianan et al., 2007). Actually, this is a highly chaotic and thus a hard to model problem.

Early forecasting of airborne pollen concentrations is undeniably of a high importance because of its medical, environmental and biological effects. Several statistical techniques have been used to forecast pollen concentration in the air and has yielded results not entirely satisfactory (Diaz de la Guardia et al., 2003; Galan et al., 2001). Some forecasting techniques are based on the analysis of airborne pollen time series, due to the autocorrelation of daily pollen count and, in addition, of meteorological variables involved in the phenomena (Moseholm et al., 1987; Katyal, 1997). A time series is a set of measurements of a variable taken over time at equally spaced time intervals. The most frequently used time series models include the autoregressive integrated moving average (ARIMA) models (Box and Jenkins, 1976). Recently, some works have applied Neural Networks to pollen forecasting, reporting encouraging results (Castellano-Mendez et al., 2005; Ranzi et al., 2003; Sanchez-Mesa et al., 2002), due to their good performances with complex and non-linear phenomena.

2.Material And Method

The aerobiological behaviour of Urticaceae in Tirana and the correlations with the meteorological parameters were examined. Airborne pollen was collected from 1995 – 2004 using a volumetric suction sampler based on the impact principle, that is, a Hirst-type spore trap (Hirst, 1952). The main pollen season of Urticaceae goes from April to November. The daily pollen count does not reach high values but pollen remains in the air for a long period due to the contribution of many species from the Urticaceae family. This species is one of the allergenic in Tirana. The general term "Urticaceae" is often used which includes the genera of Urtica and Parietaria.

It has recently been reported that people living in urban areas are more prone to suffer from pollen-induced respiratory allergies than those living in rural areas. For that reason, samplers tend to be located in urban areas (D'Amato and Cecchi, 2008).

The pollen trap was placed on the flat roof 15 m above the ground level at the University Hospital Center in Tirana (41º 19' 39 lat N, 19 º 49' 8 lon E) for the study years, 1995, 1996, 1998, 2002, 2003, 2004) in the east side of the city. The space where the trap was placed is an open area with no nearby buildings, which could interrupt the movement of the air. The daily weather data for (maximum, minimum) temperature and rainfall for the study period has been obtained from the Meteorological Institute in Tirana. Due to technical problems running the trap, unfortunately there are some years with missing data. The missing data are from the years of 1997, 1999, 2000 and 2001.

It is desirable to have other meteorological data such as humidity and wind speed. The wind data were obtained from the airport of Tirana, which is 40 km away from the location of the pollen trap. The wind data were used as possible variables for forecast models. The humidity is auto correlated with temperature and rainfall and is not forecast regularly in Tirana, so it cannot be used for pollen forecasting. We note also that in Tirana weather forecast of the wind is often given as direction rather than its speed.

Choosing just one type of pollen produces a less noisy dataset, because the phenological behaviour is consistent.

To better model the time series some preprocessing data is necessary. Besides of rescaling the dataset into the interval (0, 1), some special characteristics of the dataset suggests that further transformation could be used (Moseholm et al., 1987; Toro et al., 1998). The square root transformation is usually used when the data to be transformed obtained by counting. There is generally a Poisson's distribution and, when it is transformed, the variances become generally independent of the means. One of the advantages of this type of transformation is that after application the variances are not significantly different, so that the transformed counts can be square again (Toro et al., 1998).

To study the features of the pollen season, the pollen count days are often referred to as the number of days starting from the 1st of January. To better study the influence of these meteorological parameters on pollen concentrations, the daily forecast model for Urticaceae pollen in Tirana was constructed for three different periods of the Urticaceae pollen season, pre-peak, peak and post-peak. The pre-peak period was considered to be the period from the start of Urticaceae pollen season with method 5% till the first day of the start of peak period, peak period was considered the period from the start of the peak period observed from Pathirane, 1975), method until 80% of accumulated values were recorded and post-peak period was considered to be the period from 80% of accumulated values till the end when 95% of accumulated values were recorded, as do many authors (Recio et al., 1997; Aboulaich et al., 2013).

Spearman's correlation was used to establish the relationship between the daily pollen counts and the daily meteorological data both considering their quantitative values and transformed values according to their day by day changes. Daily pollen concentration present usually positive correlation with temperature, negative with rainfall and wind speed and no correlation with humidity (Rizzi-Longo et al., 2004). Better results were obtained with transformed values.

Three regression models were constructed as follows:

- Multiple regression model in order to forecast the daily variations of Urticaceae pollen counts during the pre-peak period
- Multiple regression model in order to forecast the daily variations of the Urticaceae pollen counts during the peak period
- Multiple regression model in order to forecast the daily variations of the Urticaceae pollen counts during the post-peak period

All the environmental variables (maximum temperature, minimum temperature, rainfall, 5-days, 4-days, 3-days and 2-days moving average of pollen counts) were subject to correlation analysis in order to choose the variables with the higher correlation coefficient for entering into the multiple regression.

Some attempts were made to use the wind direction and wind data in the model. Before doing this, the Kruskal Wallis test was performed to check if these variables did make any contributions to the variations daily Urticaceae pollen counts. The wind variables did not have any significant relationships with the daily Urticaceae pollen counts so they were discarded from the data set.

The multiple regressions were calculated using the relationships between the daily Urticaceae pollen and the meteorological data with the highest correlation coefficient for each period in order to construct models for daily Urticaceae pollen. Predicted values were squared and tested with the actual daily Urticaceae pollen counts from the 2003 and 2004 season.

Predicted Urticaceae pollen counts obtained by correlation analysis were compared with the real (observed) data in order to check if the models were strong enough to predict the patterns of the Urticaceae pollen counts. The correlation analysis showed that the forecast daily model for Urticaceae in the pre-peak period was sufficiently robust to explain the pattern of daily Urticaceae pollen counts.

3.Artificial Neural Networks (ANN)

A considerable number of correlated variables, which often non-linearly influence pollen and/or concentration in air, suggest the application of one of the most advanced methods of data analysis: artificial neural networks. An artificial neural network is a mathematical model that is inspired by the structure and/or functional aspects of biological neural networks (Haykin, 1999). The

neural network is a group of interconnected neurons, which usually consists at least three layers. The first is called the input, and the final output. All layers located between them are called hidden layers. The data is placed on the input neurons of the first layer and then, by the existing connections, the output values of the previous layer are transmitted to the inputs of the next layer. The results of calculations are the results obtained at the output of the last layer.
A neural network consists of an interconnected group of artificial neurons and it processes information using a connectionist approach to computation (Tadeusiewicz, 1993).
The determination of valid parameter values for a specific network architecture (weights of connections between artificial neurons) is called neural network learning. This is a necessary stage in the construction of the neural model. The neural network learning is carried out using appropriate algorithms based on data collected by the user, describing the course of the studied phenomenon.
In most cases, an ANN is an adaptive system that changes its structure based on external or internal information that flows through the network during the learning phase. ANNs are non-linear statistical data modelling tools. ANNs are able to learn from examples and to capture the functional relationships among time series values, even if the underlying relationship are unknown or hard to describe by the analytical approach (Zhang, 1998; Patterson, 1996). They are usually used to model Complex relationships between inputs and outputs or to find patterns in data.
Knowledge and experience gained during statistical data analyses and the development of models can be further used to elaborate the methodology of advanced, predictive model construction.
The MLP, trained by the standard backpropagation algorithm is the most widely used neural network approach for complex mappings between input and output. Its mathematical properties for non-linear function approximation are well-documented (Rumelhart et al., 1986).

4.Results And Discussion

The meteorological variables used to forecast the daily Urticaceae pollen count during the pre-peak period were 3-days moving average of normalized pollen (0.654**) and maximum temperature (0.376*) with a correlation signification at the 0.01 level (2-tailed). These two meteorological variables were obtained through using the Pearson correlation (Table 1). These two variables were used to construct a model for daily Urticaceae pollen season during the pre-peak period.

		pre-peak period (142)	**during peak period (329)**	**post-peak period (175)**
Maximum temperature	Pearson correlation	.376**	–.219**	.282**
	Sig. (2-tailed)	.000	.000	.000
Minimum temperature	Pearson correlation	.188*	–.288**	.298**
	Sig. (2-tailed)	.025	.000	.000
rainfall	Pearson correlation	-.177*	–.098	-.153**
	Sig. (2-tailed)	.035	.094	.044
5-days moving average	Pearson correlation	.629**	.625**	.501**
	Sig. (2-tailed)	.000	.000	.000
4-days moving average	Pearson correlation	.650**	.642**	.524**
	Sig. (2-tailed)	.000	.000	.000
3-days moving average	Pearson correlation	.654**	.648**	.558**
	Sig. (2-tailed)	.000	.000	.000
2-days moving average	Pearson correlation	.646**	.655**	.544**
	Sig. (2-tailed)	.000	.000	.000

Table 1: Urticaceae Pollen Count In A) Pre-Peak B) During Peak And C) Post-Peak Period
*** Correlation Is Significant At The 0.01 Level (2-Tailed).*
** Correlation Is Significant At The 0.05 Level (2-Tailed).*

Before constructing the model a checking system for assumptions was performed. The relationship between the independent variables (Tmax and 3-days moving average/ Tmin and 2-days moving average/Tmin and 3-days moving average) and the dependent variable (normalized Urticaceae pollen) show a clear relationship. In this case the independent variables correlate with Urticaceae pollen counts with a correlation coefficient 0.654 and 0.376, 0.655 and □0.288, 0.558 and 0.298, respectively for each model. The correlation between two independent variables was checked to see if it was high. The correlation coefficient between two independent variables is 0.382 that means less than 0.7, therefore two independent variables will be retain in the model.
The column headed "Tolerance" was checked also in case a value very low is detected as this presumes the possibility of multicollinearity. In this case the value was 0.854, that means not a value near value 0 (Table 2). Therefore this value did not appear to have violated the assumption.

		Unstandardized coefficients		Standardized coefficients			Collinarity statistics	
Model		B	Std. Error	Beta	t	Sig.	Tolerance	VIF
1[a]	(Constant)	.303	.652		.464	.643		
	3-days moving average	0.115	.013	. 598	8.750	.000	.854	1.171
	Max. temp	.056	.026	.148	2.164	.032	.854	1.171
2[b]	(Constant)	3.580	2.561		1.398	.165		
	4-days moving average	.060	.006	.713	9.664	.000	.889	1.168
	Min. temp	-.059	.092	-.047	-.643	.522	.889	1.168
3[c]	(Constant)	.407	.377		1.078	.282		
	3-days moving average	.117	.015	.515	7.814	.000	.901	1.110
	Min. temp	.058	.028	.136	2.061	.041	.901	1.110

Table 2: Coefficients

[a] Dependent Variable: Normalised Urticaceae Pollen Count In Pre-Peak Period
[b]Dependent Variable: Normalised Urticaceae Pollen Count During Peak Period
[c] Dependent Variable: Normalised Urticaceae Pollen Count In Post-Peak Period

Model	R	R Squared	Adjusted R Squared	Std. Error of the Estimate
1[b]	.668[a]	.446	.438	1.32686
2[d]	.678[c]	.459	.456	1.26343
3[f]	.572[e]	.328	.320	1.12147

Table 3: Model Summary

[a] Predictors (Constant) Maximum Temperature, 3-Days Moving Average Urticaceae Pollen Count
[b] Dependent Variable: Normalised Urticaceae Pollen Count In Pre-Peak Period
[c] Predictors (Constant) Minimum Temperature, 2-Days Moving Average Urticaceae Pollen Count
[d] Dependent Variable: Normalised Urticaceae Pollen Count During Peak Period
[e] Predictors (Constant) Minimum Temperature, 3-Days Moving Average Urticaceae Pollen Count
[f] Dependent variable: normalised Urticaceae pollen count in post-peak period

5.Evaluating The Models

The R-square under the Model summary box (Table 3) has a value of 0.45 therefore the model for the daily Urticaceae pollen count during the peak period achieved approximately 45 % of explanation. Adjusted R Square has a value of 0.43. Under the table coefficients the Beta value are larger for 3-day moving average than the maximum temperature presuming that this variable do contribute more into the model.

The sample size for the pre-peak period has 142 cases, so it fulfills the requirement from Tabanich et al., 2006).

5.1.Predicted Daily Urticaceae Pollen In The Pre-Peak Period = 0.303+ (0.115 x 3-days MA + 0.056x Tmax)

The predicted and actual daily Urticaceae pollen counts were converted into numerical scores. Percent accuracy obtained was 90% in 2003 and 89%in year 2004. Then the predicted and actual Urticaceae pollen count were subjected to correlation analysis to check if the constructed model was able to predict the pattern of daily Urticaceae pollen counts during the pre-peak period. The constructed model was able to predict the pattern of daily Urticaceae pollen counts during the pre-peak period

Through using the Excel program the actual and predicted Urticaceae pollen count were compared (Fig. 31, 32).

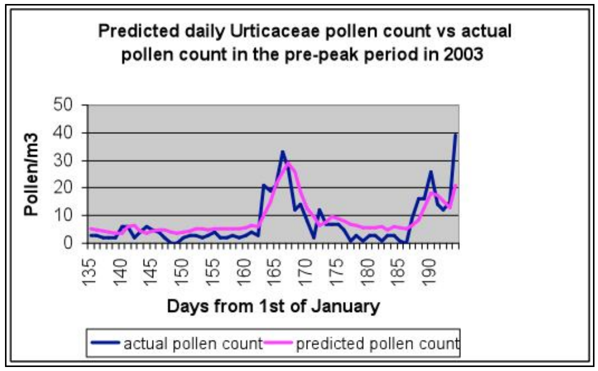

Figure 1: The Prediction Model For Urticaceae Pollen Counts During The Pre-Peak Period With The Regression Method For 2003

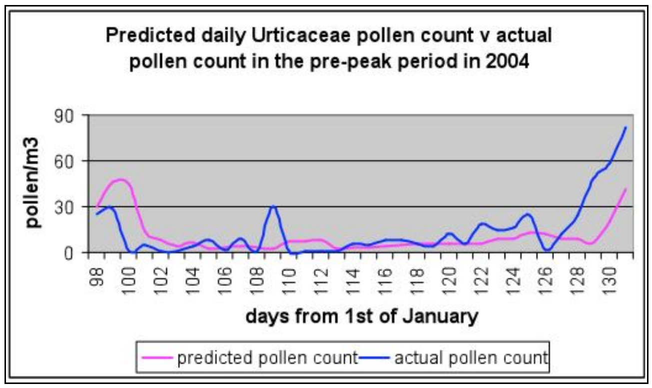

Figure 2: The Prediction Model For Urticaceae Pollen Counts During The Pre-Peak Period With The Regression Method For 2004

The R square under the Model summary box (Table 3) has a value of 0.459 therefore the model for the daily Urticaceae pollen count during the peak period achieved approximately 46 % of explanation. Adjusted R Square has a value of 0.456. Under the table coefficients the Beta value are larger for 2-day moving average than the temperature minimum presuming that the variable 2-days moving average do contribute more into the model than the variable temperature minimum.
The sample size for the peak period does fulfill the requirement from Tabanich et al., 2006).

5.2.Predicted Daily Urticaceae Pollen In The Peak Period = 2.965+ (0.126 X 2-Days MA – 0.105 X Tmin)
The predicted and actual daily Urticaceae pollen counts were converted into numerical scores. Percent accuracy obtained was 90% in year 2003 and 79 %in year 2004. Then the predicted and actual Urticaceae pollen count were subjected to correlation analysis to check if the constructed model was able to predict the pattern of daily Urticaceae pollen counts during the peak period.
Through using the Excel program the actual and predicted Urticaceae pollen count were compared (Fig. 3, 4).

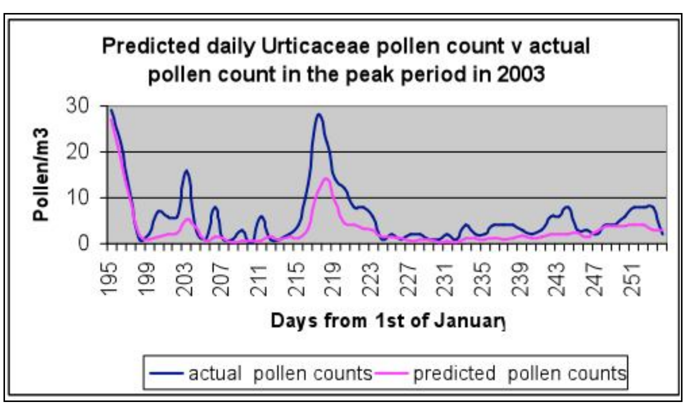

Figure 3: The Prediction Model For Daily Urticaceae Pollen Counts During The Peak Period With The Regression Method For 2003

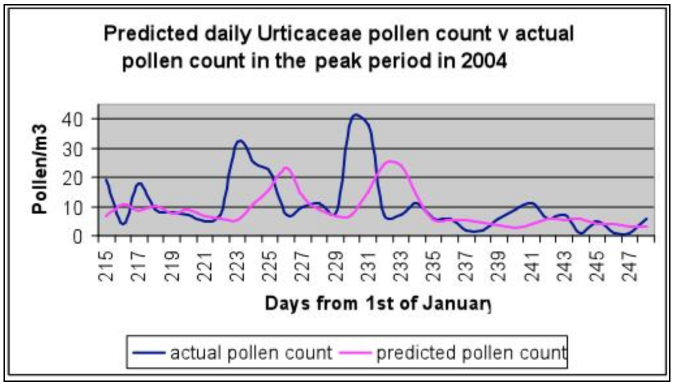

Figure 4: The Prediction Model For Urticaceae Pollen Counts During The Post-Peak Period With The Regression Method For 2004

The R square under the Model summary box (Table 3) has a value of 0.328 therefore the model for the daily Urticaceae pollen count during the post-peak period achieved app 32.8 % of explanation. Adjusted R Square has a value of 0.328. Under the table coefficients the Beta value are larger for 3-day moving average than the temperature minimum.
The sample size for the post- peak period fulfills the requirement from Tabanich et al., 2006).

5.3.Predicted Daily Urticaceae Pollen In The Post-Peak Period = 0.407+ (0.117 X 3-Day) - (0.058x Tmin)

The predicted and actual daily Urticaceae pollen counts were converted into numerical scores. Percent accuracy obtained was 65% in year 2003 and 67% in year 2004. Then the predicted and actual Urticaceae pollen count were subjected to correlation analysis to check if the constructed model was able to predict the pattern of daily Urticaceae pollen counts during the post-peak period. The correlation analysis has shown that the predicted Urticaceae pollen during the post-peak period did not predict any trend in the Urticaceae pollen. Through using the Excel program the actual and predicted Urticaceae pollen count were compared (Fig. 5, 6).

5.4.Predicted Daily Urticaceae Pollen In The Peak Period = 2.965+ (0.126x Two-Days Run - 0.105x Tmin)

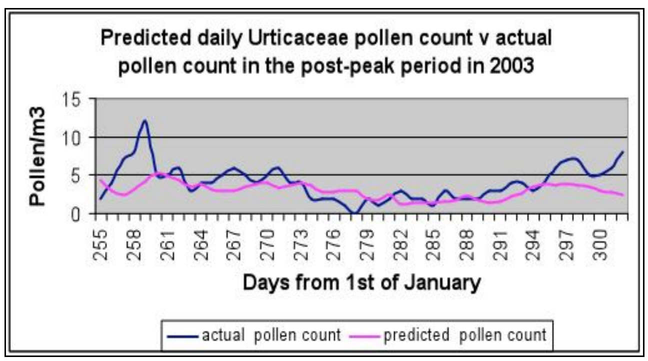

Figure 5: The Prediction Model For Daily Urticaceae Pollen Counts In The Post-Peak Period With The Regression Method For 2003

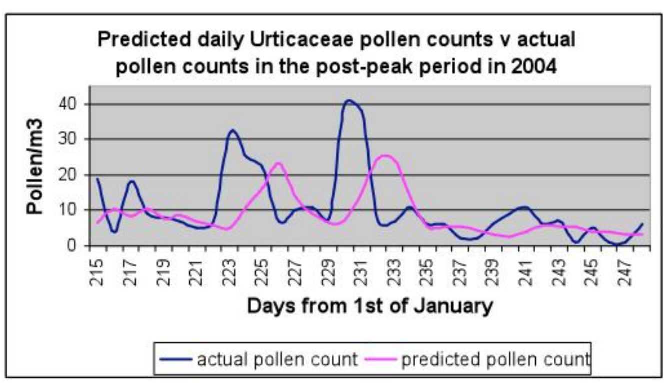

Figure 6: The Prediction Model For Daily Urticaceae Pollen Counts In The Post-Peak Period With The Regression Method For 2004

6.Neural Networks Models

Artificial neural networks are widely used to calibrate the non-linear relationships between two or more parameters, and have been adapted to predict airborne pollen concentration. A network is established as a series of coefficients or nodes that are adjusted during calibration to provide the closest possible fit, and then pollen may be estimated from any meteorological variables assemblage.

The parameterization of ANN for the Urticaceae during pre-peak period was chosen with 103 neurons. The architecture of the model was chosen as 3-103-1, 3-99-1, 3-103-1 (as shown in the Table 4). (The input layer has 3 neurons for maximum/minimum temperature, rainfall and daily Urticaceae pollen counts, the output layer has 1 neuron that represents the predicted Urticaceae pollen count.) The parameterization of ANN for the Urticaceae pollen during pre-peak, post-peak and whole period was chosen to be one with 103, 99 and 117 neurons, respectively. The architectures, iterations, Pearson's correlations and R-squared of these models was shown in Table 4. The value of the learning rate was 0.05 (network complexity).

The tested models in 2004 with the ANN are shown in the Fig. 7 - 9.

	pre-peak period	post-peak period	whole period
Network error	0.014139	0,013139	0,014657
Error improvement	9.47*10^(-7)	8.08*10^(-7)	0,00002
Iteration	1221	2655	429
Training speed	40,16442	12,02458	39,72224
Architecture	3-103-1	3-99-1	3-103-1
Training algorithm	Quick propagation	Quick propagation	Quick propagation
Training stop reason	Desired error achieved	Desired error achieved	Desired error achieved
Correlation	0.98	0.95	0.97
R-squared	0.82	0.76	0.85

Table 4: The Structural And Functional Characteristic Of The MPL ANN For Urticaceae Polen

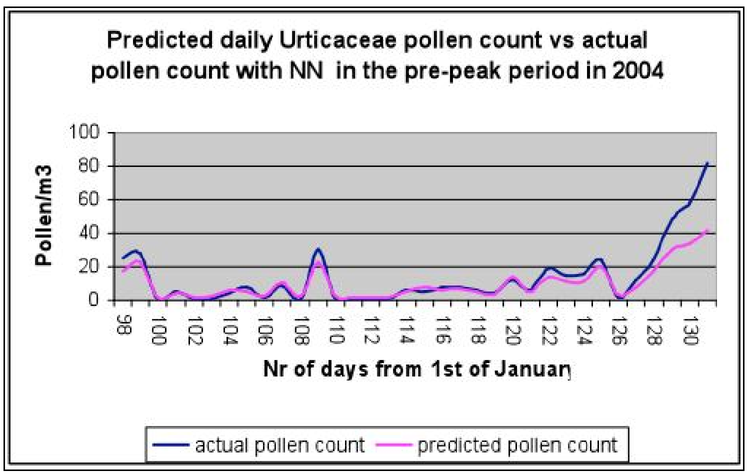

Figure 7: The Prediction Model For Daily Urticaceae Pollen Counts During The Pre-Peak Period With The ANN Method

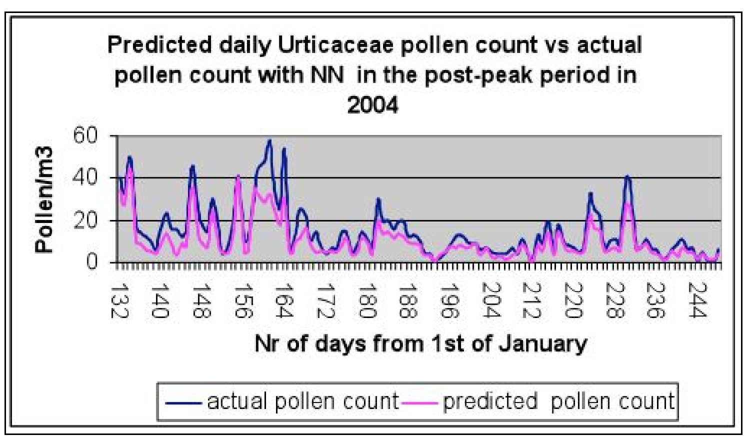

Figure 8: The Prediction Model For Daily Urticaceae Pollen Counts During The Pre-Peak Period With The ANN Method

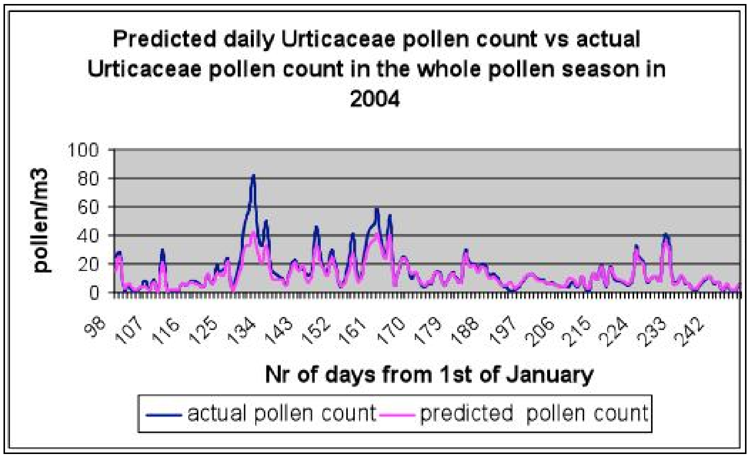

Figure 9: The Prediction Model For 2004 For Daily Urticaceae Pollen Counts During The Whole Pollen Period With The Neural Network Method

7.Conclusion

For three regression models we have that the R-square has a value of 0.446, 0.459, 0.328 for pre-peak, peak and post-peak model for the daily Urticaceae pollen achieved approximately 44.6%, 45.9 and 32.8% explanation for each model respectively. Adjusted R Square has a value of .438, 0.456 and 0.320, respectively. Under the table coefficients the Beta value are larger for 3-day, 2-day moving average of normalized pollen than the maximum/minimum temperature.

The percent accuracy for predicted and actual daily Urticaceae pollen was 90% in year 2003 and 89% in year 2004 for pre-peak model, was 90% in year 2003 and 79% in year 2004 for peak model, and 65% in year 2003 and 67% in year 2004 for post-peak model. A network with 99-103 neurons in hidden layer, 3 neurons in the input layer and one in the output layer were used. A group of variables with Tmax/Tmin, rainfall and normalized pollen were used. The model with ANN for Urticaceae pollen gave higher Pearson's correlation coefficient during the pre- and post-peak period with a correlation coefficient of 98% and 97% respectively while for the whole pollen period was 95%. The R-squared was lower in the model that consider the post-peak period.

As a conclusion the optimal parameterization of MPL for Urticaceae pollen can be summarized as follows:

- An MPL ANN with 99-103 neurons in hidden layer was used while three neurons in the input layer and one in output layer
- 0.05 was the value of learning rate
- A group of variables with Tmax/Tmin, rainfall and normalized pollen was used
- The coefficient of correlation and R-squared were higher at the model in the pre-peak period.
- The iteration was achieved earlier for the whole period with 429 epochs while for pre- and post peak period was achieved with 1221 and 2655 epochs respectively.

8.References

1. Aboulaich, N., Achmakh, L., Bouziane, H., Trigo, M.M., Recio, M., Kadiri, M., Cabezudo, B., Riadi, H., Kazzaz, M. (2013). Effect of meteorological parameters on Poaceae pollen in the atmosphere of Tetouan (NW Morocco), Int J. Biometeorolog., 57 (2), 197-205.
2. Beggs, P. J. (2004). Impacts of climate change on aeroallergens: past and future. Clin. Exp. Allergy, 34, 1507–1513.
3. Bousquet, P., Feldman, J., Atlas D. (1986). An endogenous, non-catecholamine clonidine antagonist increases mean arterial blood pressure. Eur. J. Pharmacol., 124, 167–170.
4. Box, G., Jenkins, G. (1976). Time serie analysis forecasting and control, Holden-Day, San Francisco.
5. Burge, H. A. (2002). An update on pollen and fungal spore aerobiology, J. Allergy Clin. Immunol., 110; 544–552.
6. Castellano-Mendez, M., Aira, M. J., Iglesias, I., Jato, V., Gonzalez-Manteiga, W. (2005). Artificial neural network as a useful tool to predict the risk level of Betula pendula in the air, International Journal of Biometeorology, 49 (5), 310–316.
7. Charpin, H., Davis, R.R., Nolard, N., Spieksma, F.Th., Stix, E. (1977). Concentration urbaine des spores dans les pays de la Communauté Européenne. III. Les Urticacées, Rev. Fr. Allergol., 17, 181–187.
8. D'Amato, G., Cecchi, L. (2008). Effects of climate change on environmental factors in respiratory allergic diseases, Clinical and Experimental Allergy, 38, 1264–1274.
9. D'Amato, G., Spieksma, F.Th.M. (1990). Allergenic pollen in Europe, Grana 30, 67–70.
10. D'Amato, G., Ruffilli, A., Ortolani, C. (1991). Allergenic Significance of Parietaria (Pellitory-of-the-wall) Pollen. In: G. D'Amato, F.Th.M. Spieksma and S. Bonini (eds), Allergenic Pollen and Pollinosis in Europe, Blackwell Scientific Publications, Oxford, pp. 113–118.
11. Diaz de la Guardia, F., Alba, F., Trigo, M. M., Galan, C., Ruiz, L., Sabariego, S. (2003). Aerobiological analysis of Oleaeuropaea L. pollen in different localities of Southern Spain asas., Grana, 42, 234–243.

12. Dykewicz, M. S., Hamilos, D. L. (2010). Rhinitis and sinusitis, J. Allergy Clin. Immunol. 125 (2), 103–115.
13. Hirst, J .M. (1952). An automatic volumetric spore trap, The Annals of applied Biology, 39 (2), 257-265.
14. Galan, C., Carinanos, P., Garcia-Mozo, H., Alcazar, P., Dominguez-Vilchez, E. (2001). Model for forecasting Olea europaea L. airborne pollen in South-West Andalusia, Spain. International Journal of Biometeorology, 45, 59–63
15. Jäger, S., D'Amato, G. (2001). Pollenosis in Europe. In: G. D'Amato, S. Bonini, J. Bousquet, S.R. Durham and T.A.E. Platts-Mills (eds), Pollenosis 2000. Global Approach. JGC Editions, Naples, 99–106.
16. Haykin, S. (1994). Neural networks: A comprehensive foundation. Macmillan, New York.
17. Jianan, X., Zhiyun, O., Hua, Z., Xiaoke, W., Hong, M. (2007). Allergenic pollen plants and their influential factors in urban areas, Acta Ecologica Sinica, 27 (9), 3820 – 3827.
18. Katyal, R.K., Zhang, Y., Jones, H. R., Dyer, P. D. (1997). Atmospheric mold spore counts in relation to metrological parameters, Int. J. Biometeorol, 41, 17-22.
19. Moseholm, L., Weeke, E. R., Petersen, B. N. (1987). Forecast of pollen concentrations of Poaceae (grasses) in the air by time series analysis, Pollen et Spores, 19 (2-3): 305-322.
20. Pathirane, L. (1975). Graphical determination of the main pollen season, Pollen et Spores, 17 (4), 609–610
21. Patterson, D. W. (1996). Artificial Neural Networks: theory and applications, Simon and Schuster (Asia) Pte. Ltd., Singapore: Prentice Hall.
22. Qian, L., Ying, J., Zhen-Ling, H., Jia-Xi, H. (2005). Advances in airborne allergenic pollen, Acta Ecologica Sinica, 25 (2): 334-338.
23. Ranzi, A., Lauriola, P., Marletto, V., Zinoni, F. (2003). Forecasting airborne pollen concentrations: Development of local models, Aerobiologia, 19, 39-45.
24. Recio, M., Cabezundo, B., Trigo, M., Javier Toro, F. (1997). Accumulative air temperature as a predicting parameter for daily airborne olive pollen (Olea europaea L.) during the pre-peak period in Malaga (Western Mediterranean area), Grana, 36, 44-48.
25. Rizzi-Longo, L., Pizzulin-Sauli, M., Ganis, P. (2004). Aerobiology of Urticaceae pollen in Trieste (NE Italy), Aerobiologia, 20, 53–61.
26. Rumelhart, D. E., Hinton, G. E., Williams, R. J. (1986). Learning representations by backpropagation errors, Nature, 323, 533–536.
27. Sanchez-Mesa, J. A., Galan, C., Martinez- Heras, J. A., Hervas-Martinez, C. (2002). The use of a neural network to forecast daily grass pollen concentration in a Mediterranean region: the southern part of the Iberian Peninsula, Clinical and Experimental Allergy, 32, 1606-1612.
28. Tabanich, B.C., Fidell, L.S. (2006). Using multivariate statistics, Pearson Education; 5th edition.
29. Tadeusiewicz, R. (1993). Neural Networks, Akademicka Oficyna Wydawnicza, Warszawa, Poland.
30. Toro, F. J., Recio, M., Trigo, M., Cabezudo, B. (1998). Predictive models in aerobiology: data transformation, Aerobiologia, 14, 179-184.
31. Zhang, G., Patuwo B. E., Hu, M. Y. (1998). Forecasting with artificial neural networks: The state of the art, Int. J. of forecasting, 14, 35 – 62.