

The use of a neural network to forecast daily grass pollen concentration in a Mediterranean region: the southern part of the Iberian Peninsula

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Summary

Background Pollen allergy is a common disease causing hayfever in 15% of the population in Europe. Medical studies report that a prior knowledge of pollen content in the air can be useful in the management of pollen-related diseases.

Objectives The aim of this work was to forecast daily Poaceae pollen concentrations in the air by using meteorological data and pollen counts from previous days as independent variables.

Methods Linear regression models and co-evolutionary neural network models were used for this study. Pollen was monitored by a Hirst-type spore trap using standard techniques. The data were obtained from the Spanish Aerobiology Network database, University of Cordoba Monitoring Unit. The set of data includes a series of 20 years, from 1982 to 2001. A classification of the years according to their allergenic potential was made using a K-mean cluster analysis with pollen and meteorological parameters. Statistical analysis was applied to all the years of each class with the exception of the most recent year, which was used for model validation.

Results It was observed that cumulative variables and pollen values from previous days are the most important factors in the models. In general, neural network equations produce better results than linear regression equations.

Conclusion Co-evolutionary neural network models, which obtain the best forecasts (an almost 90% “good” classification), make it possible to predict daily airborne Poaceae pollen concentrations. This new system based on neural network models is a step toward the automation of the pollen forecast process.

Keywords aerobiology, allergy, forecast model, grass pollen, hayfever, linear regression, neural network

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Introduction

Anemophilous plants disperse their pollen grains through the air. The pollinating vector is the wind, which lacks direction; as a result plants of this type must produce a large quantity of pollen grains to achieve their ultimate objective of cross-fertilization. Pollen grains have a series of proteins in their wall with the function of recognizing pollen-stigma. However, these proteins can cause allergy problems to a large part of the population. In fact, 15% of the current population of Europe suffers some type of pollen allergy. Of all airborne pollen grains, those of the Poaceae family are considered one of the main causes of pollen allergy in Europe [1–4]. In Córdoba, 82.5% of pollen-allergic patients are sensitive to this pollen type [5].

Once the pollen grains are produced in the anthers, they undergo an aerobiological process involving their emission, dispersion and deposition. All these mechanisms are greatly influenced by meteorological variables. The relation between

concentrations of grass pollen in the air and environmental factors has been studied by several authors [6, 7].

One of the main objectives of Aerobiology is to obtain predictive models that allow allergists to plan their treatments and allergy sufferers to plan their activities. Only a few works have tackled this subject, producing models to predict the mean concentration of pollen grains/m³/day, 24 h in advance, by using linear regressions [8–10], polynomials [9, 11] or time series [12].

A neural network consists of a mathematical model that performs a computational simulation of the behaviour of neurones in the human brain by replicating on a small scale the brain's patterns, in order to form results from the events perceived, i.e. it is a model based on learning a set of training data. It is about being able to analyse and reproduce the learning mechanisms and recognition of events possessed by the more highly evolved animal species. In recent years, neural network use has spread to practically all sciences, particularly in pattern classification and non-linear models of prediction.

For the present study a historical database of 20 years of pollen and meteorological data was used. Prior to the study, the years were classified into groups. This classification has a high applicability in the area of prevention, as the allergenic

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potential of a year can be determined with a high degree of reliability, based on a series of meteorological variables accumulated prior to the pollen season.

The present work aims to produce a comparative study between the use of different methods to predict the daily mean value of pollen grains by means of step-wise linear regression, and by models of recurring neural networks, with the purpose of checking whether these networks improve the prediction system, as this is a first step towards the automation and hardware implementation of the models.

Materials and methods

The study was carried out in the city of Córdoba (4°45'-W, 37°50'-N), in the southwestern part of the Iberian Peninsula. The climate is influenced by the Mediterranean Sea, the annual average temperature being 18 °C and total annual rainfall 650 mm (according to the records for the last 40 years from the National Institute of Meteorology).

For this study a historical database was used of 20 years of pollen counts and meteorological data, from 1982 to 2001 inclusive. The concentration of pollen in the air was measured using a Hirst-type volumetric sampler, located at a height of 15 m above ground level. In order to read daily samples obtained from the Hirst-type sampler, we have used the method recommended by the Spanish Aerobiology Network [13]. The result obtained is a daily average, expressed as pollen grains/m³. This is the dependent variable, i.e. the value to predict [Pollen(t)].

As independent variables, a series of meteorological data was used from time t-1 (the day before to the day to be predicted), as well as other meteorological data accumulated from 1 January of the corresponding year up to time t-1, pollen data of times t-1 and t-2, and pollen accumulated from 1 January of the corresponding year up to time t-1.

Definitions were as follows: Rain (t-1), previous day rainfall; Trank (t-1), difference between maximum and minimum temperature of the previous day; MaxT (t-1), previous day maximum temperature; MinT (t-1), previous day minimum temperature; Hum (t-1), previous day humidity; SunH (t-1), previous day sunshine hours; CumRain (t-1), accumulated rainfall from 1 January to the previous day; CumAveT (t-1), accumulated temperature from 1 January to the previous day; CumHum (t-1), accumulated humidity from 1 January to the previous day; CumSunH (t-1), accumulated sunshine hours from 1 January to the previous day; CumPollen (t-1), accumulated Pollen from 1 January to the previous day; Pollen (t-1), previous day pollen; Pollen (t-2), two previous days pollen.

Meteorological data were supplied by the National Institute of Meteorology, 4 km from the sampling point.

The beginning of the pollen season was considered when a mean value of at least 1 pollen grain/m³/day was detected, and at least 1 grain/m³ on the following days, with no more than one consecutive day of 0 grains/m³. The end of the season was considered at the middle of summer, when the flowering period for spring grass species finishes and pollen concentration in the air decreases to 1 or 2 grains/m³/day. This technique eliminates the long tails at the beginning and the end of the season that lead to serious errors in the statistical analyses.

Classification

The Mediterranean climate is characterized by enormous variability. Normally wet periods alternate with dry spells, which are more frequent than rainy weather. Significant differences can even exist within a year, resulting in, for example, a very rainy winter and a very dry spring, or vice versa. Grasses, which include gramineous species, are plants with a development (and consequently the amount of pollen emitted into the atmosphere) that depends directly on rainfall. The second meteorological variable that most influences herbaceous plants is temperature.

Our objective was to classify the 20 study years according to their potential allergic load by analysing conglomerates of mean values. Pre-season meteorological variables were used, as well as a series of characteristics that form part of the season. When considering pre-season meteorological variables, winter variables were separated from early spring variables due to the nature of the Mediterranean climate, as explained above.

Below are the pre-season variables that were used:

DaysrainDJ = December and January rainy days

MintDJF = December, January and February accumulated minimum temperature (°C)

DaysrainFMA = 1 February to 15 April rainy days

Spring = spring factor obtained from the following equation:

$$\text{Spring} = \text{RainFMA} * \text{DaysrainFMA} * \text{MintMA} / 100\,000$$

where

RainFMA = 1 February to 15 April accumulated rainfall

MintMA = 1 March to 15 April accumulated minimum temperature.

This factor has been used to quantify the degree to which early spring conditions were favourable for grass development; a directly proportional relation was considered between rainfall and gramineous development. Minimum temperature was considered to be directly proportional, as grasses require heat during this part of the year for vegetative development to occur normally. The total result was divided by 100 000 to correct the scale.

The season variables are as follows:

TotPollen = the whole season total pollen

Maximum = pollen concentration of the maximum concentration day (grains/m³/day)

Daysbefpeak = number of days from the start of the season to the peak day.

The ANOVA test reveals that there are significant differences between the mean values of each class for all the variables, with a significance level of 0.05.

As a result of classification, the 20 study years were divided into three classes. For each class, one linear regression and one neural network model were built. To build the models, all the years belonging to each class were used with the exception of the most recent year, which was used for validation.

The models were validated first by comparing observed and expected data from a quantitative point of view, comparing R² and MSE (mean square error), and were then compared from a qualitative point of view. The percentage of good classification for the prediction year was estimated by replacing quantitative values for qualitative values based on the following classification:

0 Nulls

1–25 Low

26–50 Moderate

> 50 High

in order to calculate the percentage of accuracy between predicted and observed values. The intervals were considered according to how pollen concentrations affect the allergic population. It was observed that when the mean value of pollen grains/m³/day is ≥ 50 , almost all patients in the area clinically sensitive to gramineous pollen experience symptoms [14, 15].

Linear regression model

The forward step-wise method was used, based on the selection of variables in a multiple regression model. In the forward selection method, the first variable considered to enter into the equation is the one which shows the greatest correlation coefficient (positive or negative) with the endogenous variable.

Co-evolutionary neural network model

Neural networks are computational models, the main characteristic of which is their capacity for learning by example. This means that by using a neural network there is no need to programme how the outputs are obtained, given certain inputs; but rather examples are shown of the relations between inputs and outputs, and the neural network will learn the existing relation between the two by means of a learning algorithm. This learning will materialize in the network's topology and in the value of its connections. Once the neural network has 'learnt' to carry out the desired function, it can be used, i.e. input values for which the output is unknown can be entered, and the neural network will calculate the output.

In this work we describe a co-evolutionary architecture for evolving a population of artificial neural networks. The co-evolution of separate populations [16, 17] presents successful approaches

to incorporate the aspects of mutual interaction of different adaptive landscapes into evolutionary algorithms. There are two types of coevolution: competitive, such as in predator–prey interactions, implies that the adaptive landscape of individuals of one species changes as members of the other species make their adaptive move [18, 19]. Co-operative, used in problems that are very difficult to be resolved by a single population, implies that the adaptive landscape of one species' individuals depends on how well it collaborates with individuals in other species to obtain a global solution [20]. In this case, the co-operative model was used, as several populations of neurones had to co-operate to make up the networks belonging to the neural network population.

Two kinds of population were used: several populations of neurones and a population of networks. Figure 1 shows a graphical representation of the proposed model.

There were several populations of neurones (the same as the number of neurones in the network). If there were just one population of neurones, as in SANE [21], the neurones would form species slowly, with each one specialized in some task. By having a population for each kind of neurone, these species do not need to organize themselves [22], so the evolution process is accelerated. Moreover, the behaviour of a neurone in a recurrent or a non-recurrent multilayer network depends to a large extent on the rest of the neurones. With just one population it would be very difficult to find the suitable neurones to make up a network that performs the desired task. In this way, a connection c_i will always be associated with a neurone from population P_i . So, as the population specializes, neurones will evolve knowing the kind of neurones that they will be connected to. For this reason it does not make sense to use the migration operator.

There is only one network population. The alleles of each individual of this population are references to the neurones of the different neurone populations.

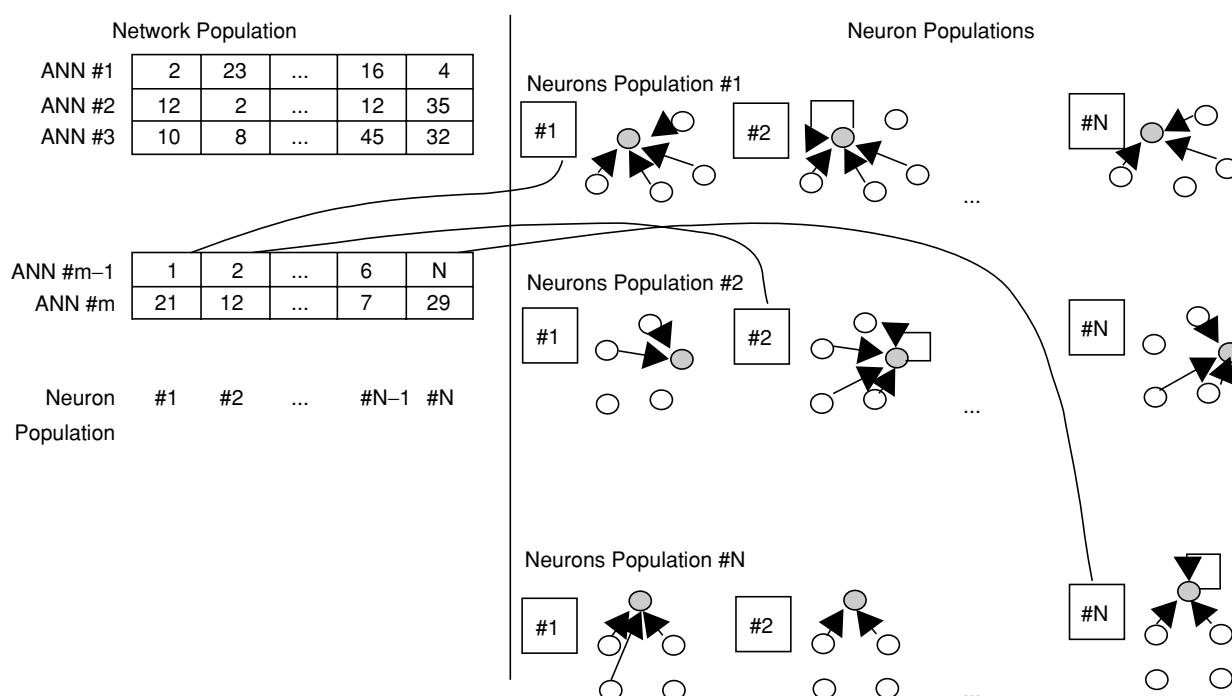


Fig. 1. Co-evolutionary neural network model.

Results

Classification

As a result of the classification, the 20 study years were divided into three classes:

Class 1 contains 8 years: 1982, 1983, 1987, 1992, 1993, 1994, 1995 and 1999. The analyses (linear regression and neural networks) were applied to the first 7 years and the year 1999 was used for validation. The class 1 years were characterized by reaching very low concentrations of grass pollen in the air. People sensitive to this type of pollen had very few problems during the class 1 years, which had the characteristics shown in Table 1. The meteorological conditions prior to the pollen season of the years in this class were highly unfavourable for the development of annual grasses. The winter was scarcely rainy, with a mean of 12 rainy days in the months of December and January. The winter was characterized by being cold, with a mean accumulated minimum temperature for the months of December, January and February of 310.7 °C. Early spring was also quite dry, with a mean of 12 rainy days on which it rained from 1 February to 15 April. Late frosts, which irretrievably damage the plant, often occur in spring.

Class 2 contains 9 years: 1984, 1985, 1988, 1989, 1990, 1991, 1997, 1998 and 2000. The analyses were applied to the first 8 years, and the year 2000 was used to validate the models. For people sensitive to gramineous pollen, these were moderate years with several days of high concentrations. This class

includes years that were typically Mediterranean from the climatic point of view, i.e. years with a very rainy winter and a dry early spring, or years with a dry winter and a very rainy early spring. During the winter it rained a mean number of 20 days during the months of December and January. The mean for accumulated minimum temperatures for the months of December, January and February was 471.6 °C. From 1 February to 15 April it rained a mean number of 16 days.

Class 3 contains 3 years: 1986, 1996 and 2001. The analyses were applied to the first 2 years, and 2001 was used to validate the models. The years in class 3 were those that produced the greatest number of allergy episodes among the population. The meteorology of the years in this class was characterized by the abundance of rainfall episodes in both winter and early spring. In winter it rained a mean number of 30 days during the months of December and January. The mean accumulated minimum temperature in December, January and February was 576.8 °C. Such a high value is justified because these were rainy years, making for a milder winter. Early spring was also rainy, with a mean number of 24 days with rainfall from 1 February to 15 April.

Statistical analysis

The complexity of the formulas obtained according to the model of neural networks is greater than that of the formulas obtained from linear regressions (Table 2). The diagrams shown in Fig. 2 simplify the complexity of the models based on neural networks, showing which are the input variables, the transfer functions involved in the model and the output. The numbers by the arrows indicate the weight of each relation established between each of the network's components.

Model validation (comparing real data observed during 1999, 2000 and 2001, and the data expected according to the proposed models) is shown in Fig. 3. The R^2 and mean quadratic error resulting from the quantitative validation, and the percentage of good classification for each predicted year, are shown in Table 3.

As a result of the analyses, it was observed that the accumulated variables and the pollen values for the previous day and

Table 1. Main features of each class considered in this study

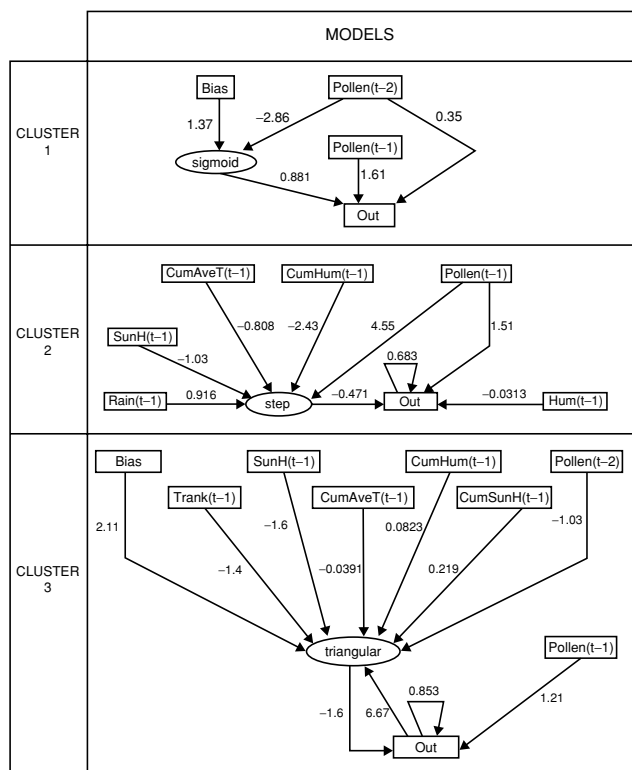
	Cluster 1	Cluster 2	Cluster 3
DaysrainDJ	12	20	30
MintDJF	310.7	471.6	576.8
DaysrainFMA	12	16	24
spring	4.36	7.93	18.85
TotPollen	1871	4033	7760
Maximum	159	347	813
Daysbefpeak	39	63	84

Table 2. Equations obtained for each class according to the linear regression and neural network models

Linear regression equations	
Cluster 1	$\text{Pollen}(t) = 0.82 \text{ Pollen}(t-1) - 0.0078 \text{ CumPollen}(t-1) + 0.0074 \text{ CumHum}(t-1) - 0.035 \text{ CumAveT} + 0.053 \text{ CumSunH}(t-1) - 43.75$
Cluster 2	$\text{Pollen}(t) = 0.6 \text{ Pollen}(t-1) + 0.21 \text{ Pollen}(t-2) - 0.0067 \text{ CumPollen}(t-1) + 0.0043 \text{ CumHum}(t-1) - 21.55$
Cluster 3	$\text{Pollen}(t) = 0.57 \text{ Pollen}(t-1) + 0.27 \text{ Pollen}(t-2) + 3.78 \text{ SunH}(t-1) - 0.0032 \text{ CumPollen}(t-1) - 14.9$
Neural network equations	
Cluster 1	$\text{Pollen}(t) = 1.61 \text{ Pollen}(t-2) + 0.35 \text{ Pollen}(t-1) + 0.881 \frac{1}{1 + \exp(-5(1.37 - 2.86 \text{ Pollen}(t-1)))}$
Cluster 2	$\text{Pollen}(t) = 0.683 \text{ etPollen}(t-1) + 1.51 \text{ Pollen}(t-1) - 0.0313 \text{ Hum}(t-1) - 0.471 \text{ step}(h(t))$ $h(t) = 0.916 \text{ Rain}(t-1) - 1.03 \text{ SunH}(t-1) - 0.808 \text{ CumAveT}(t-1) - 2.43 \text{ CumRain}(t-1) + 4.55 \text{ Pollen}(t-1)$ $\text{step}(x) = 1 \text{ if } x \geq 0 \text{ and } 0 \text{ if } x < 0$ $\text{etPollen}(t-1) = \text{estimate Pollen}(t-1)$
Cluster 3	$\text{Pollen}(t) = 0.853 \text{ etPollen}(t-1) + 1.21 \text{ Pollen}(t-2) + 1.6 i(t)$ $i(t) = \text{triangular}(2.11 - 1.4 \text{ RankT}(t-1) - 1.6 \text{ SunH}(t-1) - 0.0391 \text{ CumAveT}(t-1) + 0.0823 \text{ CumHum}(t-1) + 0.219 \text{ CumSunH}(t-1) - 1.03 \text{ Pollen}(t-1) + 6.67 \text{ etPollen}(t-1))$ $\text{Triangular}(x) = 0 \text{ if } x < -1; x + 1 \text{ if } -1 \leq x < 0; -x + 1 \text{ if } 0 \leq x < 1; 0 \text{ if } x \geq 1$

Table 3. Validation of the models: R^2 , MSE and percentage of good classification

Year	Linear regression			Neural network		
	Quantitative validation		% Good clasification	Quantitative validation		% Good clasification
	R^2	MSE		R^2	MSE	
1999	0.54	114.41	80	0.52	123.74	89.96
2000	0.47	2921.63	82.2	0.56	2396.88	85.5
2001	0.42	9117.24	80	0.60	6152.8	89.96

**Fig. 2.** Neural network models obtained for each class considered in this study.

for two prior days are those with the greatest weighting. Humidity and hours of sunshine are the daily variables that most affect the content of pollen in the air. In particular, humidity has an effect in the driest periods, and sunshine hours in the wettest.

Discussion

The meteorological variables used to classify the 20 study years were rainfall and minimum temperature. With regards to rainfall, it was observed that the number of days with rain was even more important than the amount collected. This is due to the fact that in Mediterranean countries rain tends to be torrential and almost all is lost as run-off. For herbaceous plants it is better if rain falls gradually for better assimilation. As for temperature, a study exists showing that minimum temperature is the most influential factor in the city of Córdoba, whereas in

other cities with a different climate, such as London, the most important factor is maximum temperature [23].

When predicting, the most important meteorological parameters are accumulated parameters. This fact has already been demonstrated by some authors [8]. Among daily values it was observed that the most important variables have been humidity and sunshine hours.

By analysing the results obtained it is observed that the best prediction method was based on neural networks, which improve the linear regression model, with 9% more R^2 in the year 2000, and 18% more in 2001. In 1999, the linear regression model performs better, with a R^2 2% higher than in the case of the neural networks (Table 3). From a clinical point of view, if validation is taken into account according to the good classification percentage, it can be observed that the method based on neural networks (89.96%) improves on the linear model (80%) for 1999.

When modelling and validating, the most complex years are those in class 3, in which airborne pollen concentration is high. However, best results were obtained when validating the neural network model for that year, with 60% of R^2 and almost 90% of good classification. Such a high mean quadratic error indicates that the errors are great, due to the high concentrations reached during the years in this class.

The simplest years when modelling and validating are those in class 1, as pollen peaks are very low. For this reason, mean quadratic errors are less when performing validation than in the other cases.

In the models obtained using linear regressions, the major variables were pollen values for the prior day and for two prior days, as well as the accumulated variables.

Models built using neural networks are more complex than those based on linear regressions, and also include a greater number of variables.

Various works in the UK have dealt with the matter of predicting the grasses pollen season based on meteorological parameters [24, 25]. The aim of the present work was to solve the problem for Mediterranean countries that cannot consider only one type of year from the climatological point of view. According to our study, it would be necessary to consider three classes, due to the major climatic variability that can exist from one year to another in the Mediterranean area. Although for complete classification of a year both the prior variables and the variables of the pollen season itself are needed, it is possible to predict with a high degree of reliability what type of year it will be, by knowing only the prior variables. This fact is enormously applicable in the area of prevention, as it will allow for the severity of the season to be known before it begins.

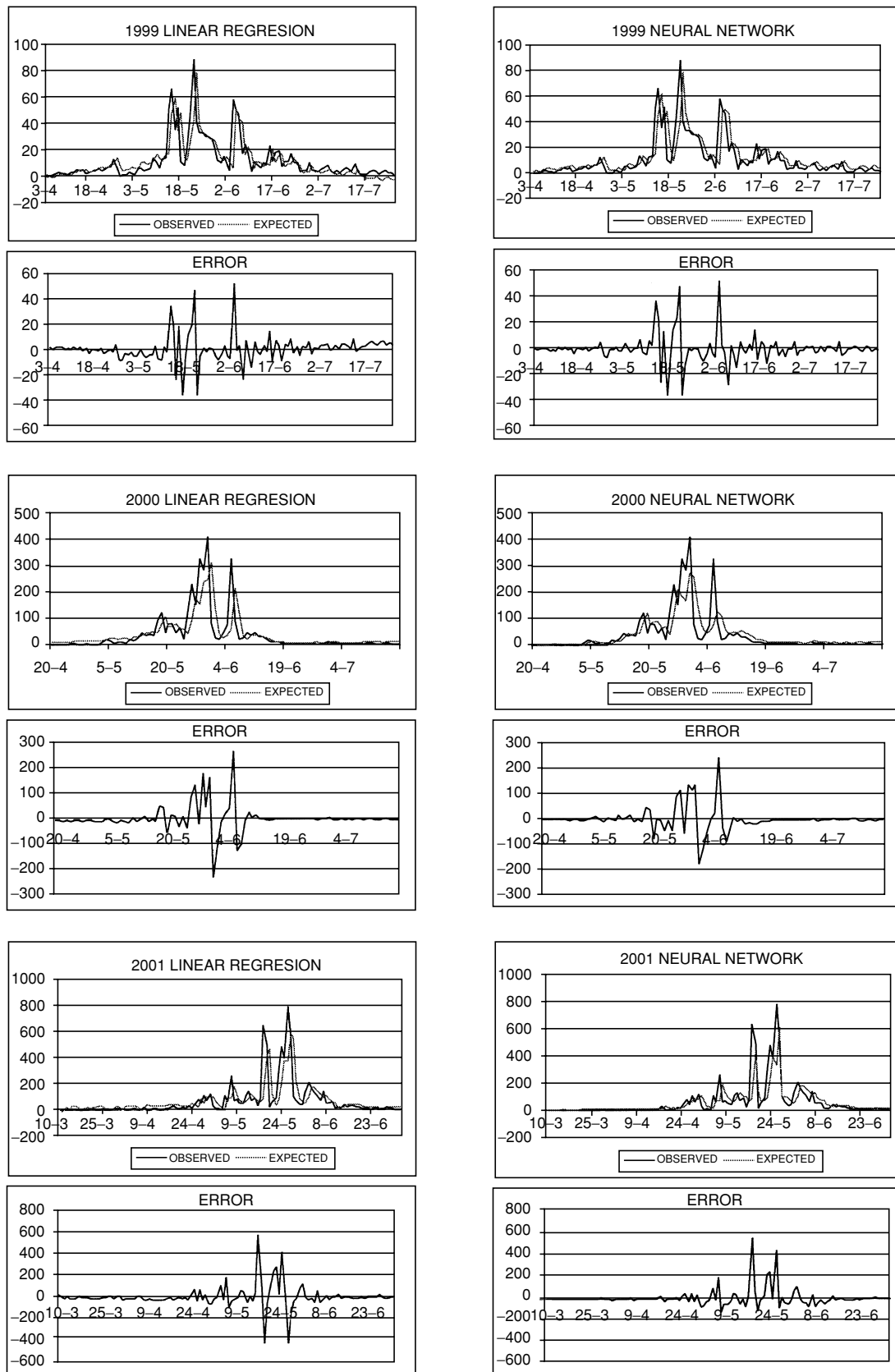


Fig. 3. Real observed data during 1999, 2000 and 2001 and the expected data according to the proposed models.

Conclusion

We report that airborne pollen concentrations can be predicted from one day to the next with a certain degree of accuracy by using previous meteorological and pollen variables. The process is considerably simplified by using the classification, because modelling can be done without the need to train all the years, although the results of the prediction are not greatly improved.

In general, better results are obtained with neural networks than with linear regressions, though their complexity is greater. About an 80% accuracy has been obtained by considering the validation as percentage of good classification in the regression analysis, whereas almost a 90% accuracy was obtained by using neural networks.

The most important variables for the models are the pollen values of previous days, and the accumulated variables.

Pollen concentration predictions are of great interest both for allergy sufferers, who in this way can plan their activities in advance, and for the medical authorities, who can implement suitable prevention measures. The classification of years used in the present work allows us to know the pollen season severity with a minimum percentage of error, before the season begins, based on a series of meteorological parameters. Neural networks are the first step towards automating the prediction process.

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