

Artificial neural network models of relationships between *Alternaria* spores and meteorological factors in Szczecin (Poland)

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Abstract *Alternaria* is an airborne fungal spore type known to trigger respiratory allergy symptoms in sensitive patients. Aiming to reduce the risk for allergic individuals, we constructed predictive models for the fungal spore circulation in Szczecin, Poland. Monthly forecasting models were developed for the airborne spore concentrations of *Alternaria*, which is one of the most abundant fungal taxa in the area. Aerobiological sampling was conducted over 2004–2007, using a Lanzoni trap. Simultaneously, the following meteorological parameters were recorded: daily level of precipitation; maximum and average wind speed; relative humidity; and maximum, minimum, average, and dew point temperature. The original factors as well as with lags (up to 3 days) were used as the explaining variables. Due to non-linearity and non-normality of the data set, the modelling technique applied was the artificial neural network (ANN) method. The final model was a split model with classification (spore presence or absence) followed by regression for spore seasons and $\log(x+1)$ transformed *Alternaria* spore concentration. All variables except maximum wind speed and precipitation were important factors in the overall classification model. In the regression model for spore seasons, close relationships were noted between

Alternaria spore concentration and average and maximum temperature (on the same day and 3 days previously), humidity (with lag 1) and maximum wind speed 2 days previously. The most important variable was humidity recorded on the same day. Our study illustrates a novel approach to modelling of time series with short spore seasons, and indicates that the ANN method provides the possibility of forecasting *Alternaria* spore concentration with high accuracy.

Keywords *Alternaria* · Artificial neural networks · Meteorological parameters · Szczecin (Poland)

Introduction

The air is seldom free of fungal spores (Lacey 1981). Spore concentrations measured in the atmosphere are the result of a wide range of complex interrelated environmental and biological factors such as the growth and differentiation of spores. The concentration of fungal spores in the atmosphere at any particular moment is influenced by the processes involved in their production, release, and deposition. The eventual rate of spore deposition and resuspension depends mainly on meteorological factors and on the size and shape of the spores (Lyon et al. 1984).

A better understanding of the relative importance of these factors and their interrelationships would help determine the role of spore dispersal in allergies to airborne fungal spores. However, there are comparatively few advanced forecasting models of airborne fungal spore circulation (Katial et al. 1997), and most of these usually display low predictability (Angulo-Romero et al. 1999; Mitakakis et al. 2001; Troutt and Levetin 2001; Stennett and Beggs 2004). Problems in the modelling of airborne

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fungal spore circulation result partly from the limitations of statistical methods. Many widely used methods of data analysis, such as linear or multiple regressions, are based on assumptions of linearity and normality. Such requirements often cannot be fulfilled even after variable transformations, and the performance models thus obtained can be insufficient. This situation is particularly typical for time series with short spore seasons, where no airborne fungal spores are present during most of the year. Therefore, there is a need to verify other statistical techniques for application in the field of biometeorology to try to overcome the above mentioned problems.

One methods that has recently turned out to be useful in ecological modelling is the artificial neural network (ANN) technique. Neural networks function as a universal approximating system with the ability to learn, adapt and generalise the knowledge acquired. The ANN method is especially applicable to multivariate data sets with non-linear dependencies, and it does not require variables to fit any theoretical distribution (Carling 1992; Fausett 1994; Tadeusiewicz 2001; Osowski 1996; Lek and Guegan 1999). Therefore, ANNs might be useful as advanced forecasting models of airborne fungal spore circulation.

Alternaria has been considered one of the most prevalent mould allergens (Budd 1986). It has been described as one of the major fungi responsible for inhalation allergies in humans (Caretta 1992), thus explaining why *Alternaria* spores are counted in many aerobiological stations along with airborne pollen. Climatic information is of great importance in the management and/or prevention of respiratory allergic diseases (Hasnain 1993).

The aim of this study was to examine the relationship between the atmospheric *Alternaria* spore content and the prevailing meteorological parameters in the area of Szczecin, Poland using a novel data analysis technique—ANNs. No predictive modelling of the aeroallergen circulation season has been developed in Poland before. Our ultimate goal was to create forecasting models of high predictability that might be applicable also to other regions.

Materials and methods

Aerobiological monitoring was performed in Szczecin from 1 January 2004 to 31 December 2007. Szczecin is situated in the Odra river valley in north-west Poland, approximately 60 m above sea level, 53°26'26" N, 14°32'50" E. The volumetric method using a Lanzoni 7 Day Recording Trap was employed in this study. The trap was installed on a rooftop in the Szczecin city district of Śródmieście, at a height of 21 m above ground level. Meteorological data covering the 4 years of the study were provided by an Automatic Weather Station (Vaisala, Finland). The meteo-

rological parameters taken into account for the assessment of the effect of meteorological conditions on airborne fungal spores were: daily level of precipitation; maximum wind speed; average wind speed; relative humidity; maximum, minimum and average air temperature; and dew point temperature. The daily values of particular parameters were taken as totals, arithmetic means or maxima and minima. Additionally meteorological variables with 1-, 2- and 3-day lags were introduced into the data set.

Spore data were analysed to determine the start, end and duration of the season using the 90% method. The start of the season was defined as the date on which 5% of the seasonal cumulative spore count was trapped, and the end of the season as the date on which 95% of the seasonal cumulative spore count was reached.

Data analysis

The spore seasons were relatively short, and zero values prevailed in the *Alternaria* time series (Fig. 1). As shown in Fig. 2, the *Alternaria* spore data approximated an exponential distribution. Meteorological parameters mostly approximated a normal distribution; however, the Shapiro-Wilk test confirmed significant deviations from normality (results not shown). Scatter plots for variables without lags indicated non-linear dependencies between *Alternaria* spore concentration and meteorological parameters.

Due to non-linearity and non-normality, neither the Pearson's correlation coefficient nor multiple regression could be used. Therefore, Spearman's rank correlation and ANN models were applied in order to examine the studied relationships. Meteorological parameters (original and with lags) were used as input variables while the *Alternaria*

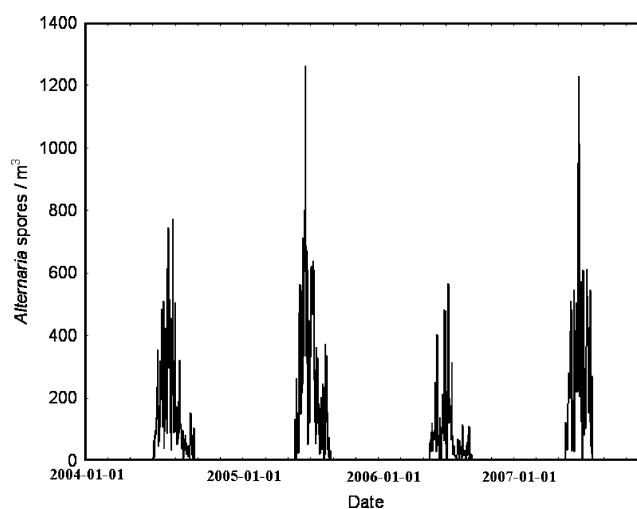
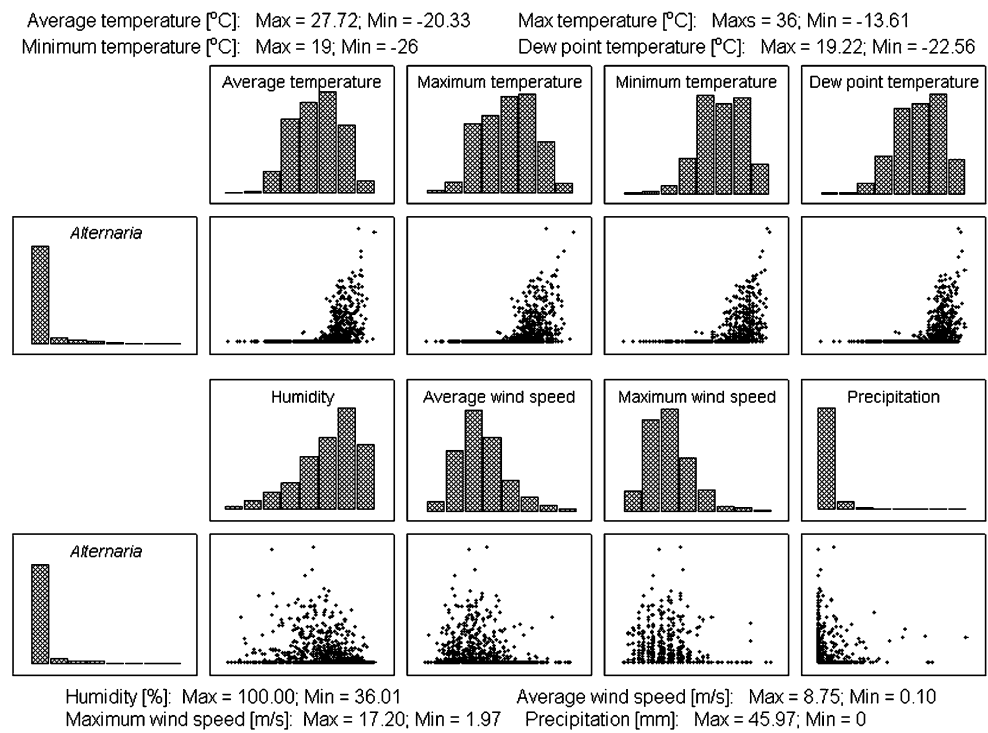


Fig. 1 *Alternaria* spore time series. Szczecin (Poland) 2004–2007

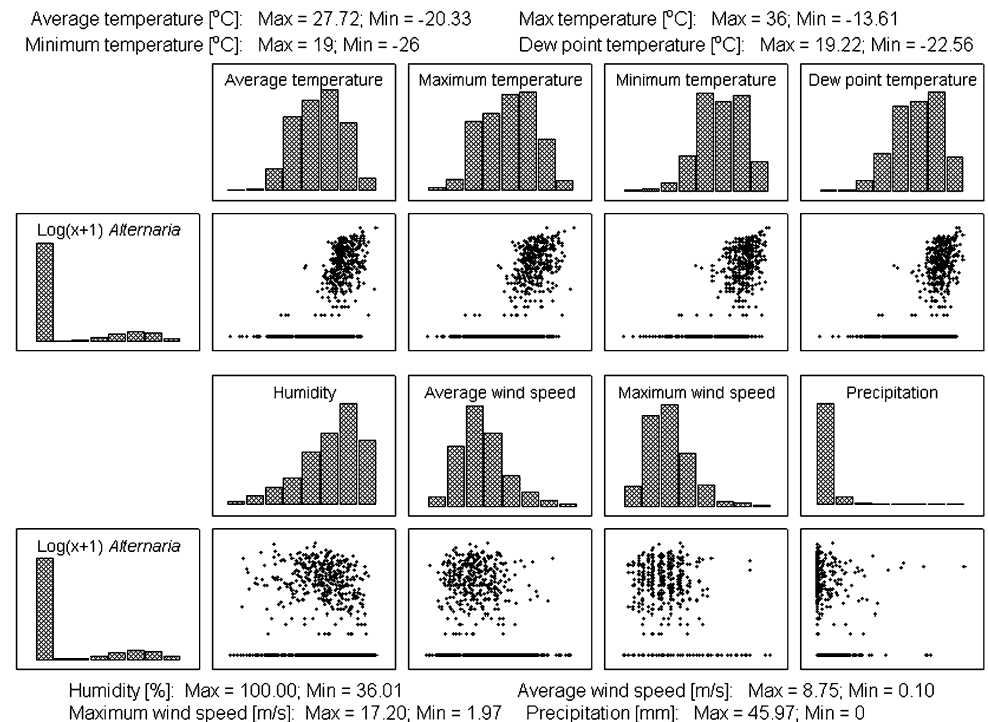
Fig. 2 Frequency distributions and matrix scatter plots between *Alternaria* spore concentration and meteorological factors (raw data)



spore concentration was the output variable. The following models were created:

1. Overall regression model, raw variables.
2. Overall regression model, $\log(x+1)$ transformed *Alternaria* spore concentration. $\log(x+1)$ transformation was applied to the *Alternaria* spore concentration. The aim was to dampen the effect of many zero values and
3. Split models. The transformation used in model 2 did not normalise the *Alternaria* spore concentration; furthermore, a division into two subsets was visible in the scatter plots—zero and higher than zero values of *Alternaria* spore concentrations (Fig. 3). Separate

Fig. 3 Frequency distributions and matrix scatter plots between $\log(x+1)$ transformed *Alternaria* spore concentration and meteorological factors



modelling of those two subsets was assumed to yield satisfactory results, therefore two submodels were used:

3a. Overall classification model. *Alternaria* spore concentration was substituted by a dummy variable, with 0 as the absence and 1 as the presence of *Alternaria* spores.

3b. Regression model for spore seasons, $(x+1)$ transformed *Alternaria* spore concentration. Only cases for spore seasons were used (Fig. 4).

In this study, multi layer perceptrons (MLP) were applied, which perform a mathematically stochastic approximation of multivariate functions (Osowski 1996). Calculations were performed using StatSoft software Statistica 6.1 with an implemented neural network module (Lula 2000; Tadeusiewicz 2001). Due to the considerable number of input parameters, variable selection was made using a combination of probabilistic and generalised regression networks with a backward variable selection algorithm. This algorithm is considered to be more suitable for inter-correlated input variables than forward selection (Osowski 1996). The data set obtained was then used in regression and classification modelling. Consecutive neural networks were designed and trained using back propagation (Haykin 1994; Fausett 1994; Patterson 1996) and conjugate gradient algorithms (Bishop 1995) using Automatic Problem Solver. Using a bootstrap method, cases were divided into three subsets:

- Training (Tr)—used for training a neural network;
- Verification (Ve)—used for verifying performance of a network during training;

- Testing (Te)—used for assessing predictability and accuracy of a neural model on data not presented during training and validation (cases remained after creating a training subset during bootstrap).

The choice criteria of the best neural network were: value of *standard deviation (SD) ratio* (ratio between error SD and SD of experimental data) and *correlation* (Pearson's correlation coefficient between experimental and calculated data).

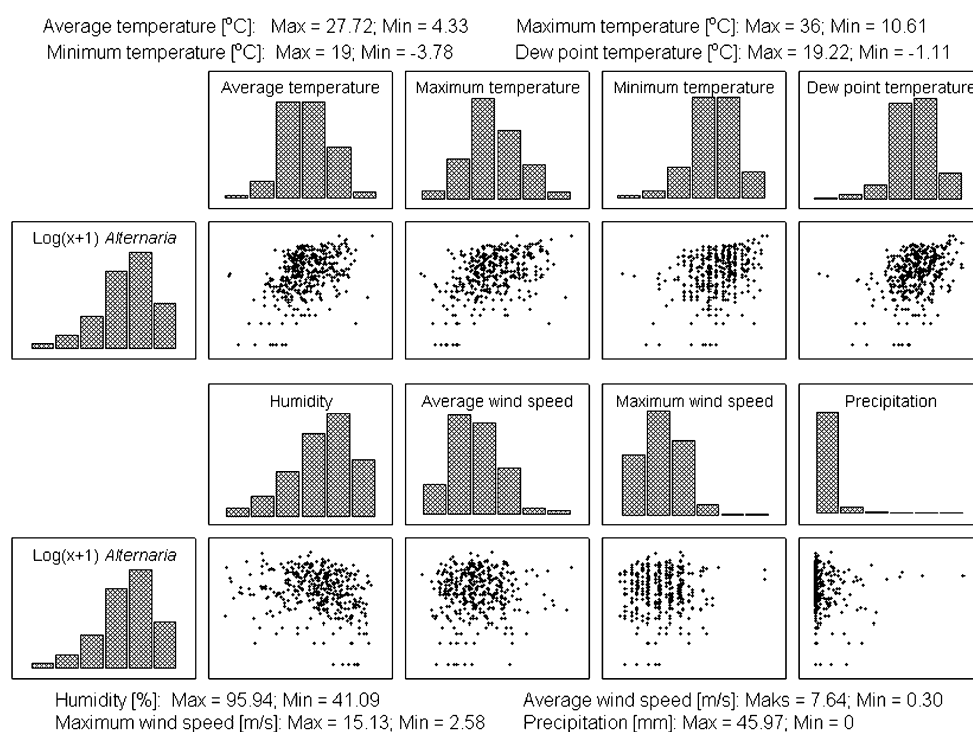
Special emphasis was placed on sensitivity analysis and response plots. Sensitivity analysis creates a ranking of input variables and is based on calculations of the error when a given input variable is removed from the model. The ratio of the error for the complete model to that with the ignored variable forms the basis for ordering variables according to their importance. The response plot is the model response (output) as the function of one selected input variable, assuming constant values of other variables or, in other words, a one-dimensional section through the response surface in the N-dimensional space of input variables.

Results

Overall regression model, raw variables

Analysis of Spearman's rank correlations revealed that average, maximum, minimum and dew point temperatures (both on the same day and 1, 2 and 3 days previously) were most strongly and directly proportional to the concentration of

Fig. 4 Frequency distributions and matrix scatter plots between $\log(x+1)$ transformed *Alternaria* spore concentrations and meteorological factors for spore seasons



Alternaria spores (Table 1). Highly significant negative correlations of a rather low level were observed in the case of humidity, and average and maximum wind speed, with the exception of relative humidity with a 2-day lag. Association with precipitation turned out to be weak and insignificant.

Backward variable selection using the ANN module indicated the following parameters as the optimal set of input factors: average temperature, average temperature 2 days previously, maximum temperature, maximum temperature 1 day previously, maximum temperature 2 days previously, and dew point temperature 2 days previously. This result is consistent with the Spearman's correlation analysis.

The ANN model obtained was an MLP network with six input neurons, ten hidden and one output neuron (MLP 6:6-10-1:1), trained with 100 epochs of back propagation and 46 epochs of conjugate gradient algorithm. Performance of the overall regression model reached a medium level. The SD ratio was over 0.7, the correlation slightly above 0.6, and a scatter plot for the observed and calculated values indicated quite high dispersion (Fig. 5). The model can partly reproduce seasonality and only small variations in *Alternaria* spore concentration, probably because it is biased by zero values.

Overall regression model, $\log(x+1)$ transformed *Alternaria* spore concentration

In the overall model with the $\log(x+1)$ transformed *Alternaria* variable, the most important factors, indicated

Table 1 Spearman's rank correlation coefficients between *Alternaria* spore concentration and meteorological variables

Variable	Same day	1-day lag (Lag 1)	2-day lag (Lag 2)	3-day lag (Lag 3)
Average temperature	0.642 ***	0.645 ***	0.644 ***	0.647 ***
Maximum temperature	0.618 ***	0.620 ***	0.620 ***	0.620 ***
Minimum temperature	0.623 ***	0.626 ***	0.625 ***	0.630 ***
Dew point temperature	0.645 ***	0.647 ***	0.648 ***	0.649 ***
Humidity	-0.279 ***	-0.277 ***	-0.271 ***	-0.274 ***
Average wind speed	-0.127 ***	-0.145 ***	-0.147 ***	-0.134 ***
Maximum wind speed	-0.115 ***	-0.133 ***	-0.133 ***	-0.121 ***
Precipitation	-0.001	0.015	0.020	0.020

* $P < 0.05$, ** $P < 0.01$, *** $P < 0.001$

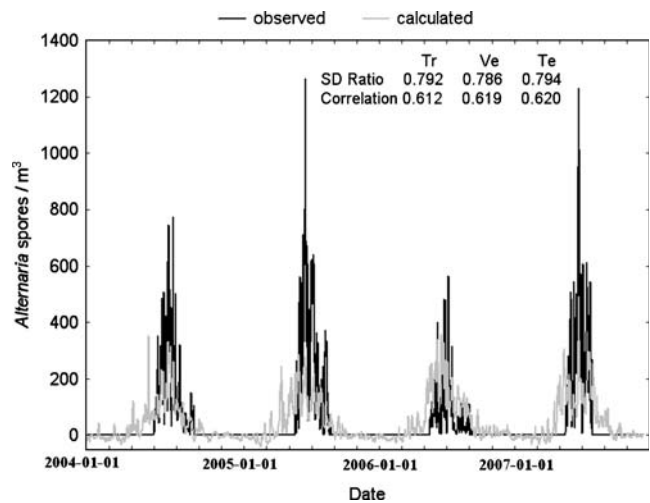


Fig. 5 Comparison of observed *Alternaria* spore time series and those calculated from a multi layer perceptron (MLP) 6:6-10-1:1 neural network. The overall model with raw variables

by backward variable selection using the ANN module, were all the variables except for precipitation on the same day and 1, 2 and 3 days previously.

The obtained ANN model was an MLP 28:28-11-80-1:1 neural network, trained with 100 epochs of back propagation and 46 epochs of conjugate gradient algorithm. The SD ratio was below 0.7 and the correlation for subsets was between 0.736 and 0.802, which indicates quite good performance. Direct comparison of the observed and calculated time series (Fig. 6) revealed that the model underestimated high spore concentrations and extended spore seasons, probably due to prevailing 0 values.

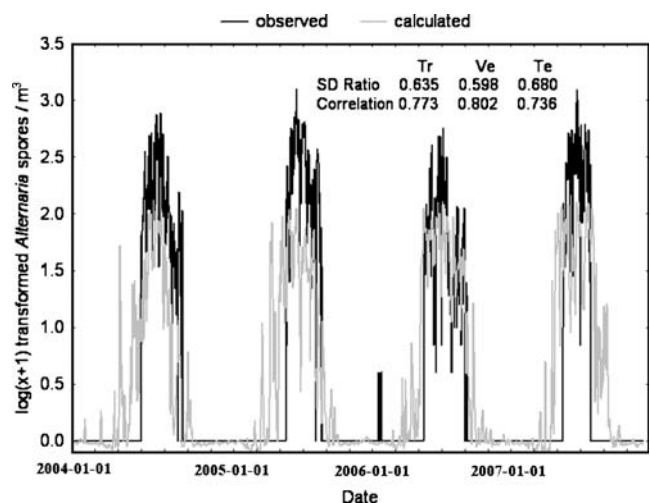


Fig. 6 Comparison of observed *Alternaria* spore time series and those calculated from an MLP 28:28-11-80-1:1 neural network. The overall model with $\log(x+1)$ transformed *Alternaria* spore concentration

Split models

Overall classification model

In the overall classification model, the most important factors, indicated by backward variable selection using the ANN module, were all the variables except for maximum wind speed and precipitation on the same day and 1, 2 and 3 days previously. The obtained network was an MLP 27:27-11-80-1:1 neural network, trained with 100 epochs of back propagation and 46 epochs of conjugate gradient algorithm. Good performance was obtained—92.97% of “0” cases and 71.88% of “1” cases were predicted correctly.

Sensitivity analysis indicated dew point temperatures (1 day previously, on the same day and 3 days previously) as the most important variables (Table 2). All the remaining variables were less important although some also contrib-

uted to improvement of model performance (ratio slightly above 1).

Regression model for spore seasons, $\log(x+1)$ transformed *Alternaria* spore concentration

Spearman's rank correlations were calculated for the spore season data set (Table 3). As for the original data set, directly proportional and highly significant dependencies between the *Alternaria* spore concentration and meteorological factors were observed in the case of average, maximum, minimum and dew point temperatures. However, those correlations became weaker as the lag increased. Quite high positive correlation was also observed for humidity recorded on the same or the previous day. Average and maximum wind speed revealed moderate inversely proportional correlations, but these were significant only for 1 or 2 days of lag and 1 day of lag, respectively. No significant correlation was observed between precipitation and *Alternaria* spore concentrations.

Backward variable selection using the ANN module excluded the following variables from the model: average wind speed, maximum wind speed, maximum wind speed 3 days previously, precipitation, precipitation 2 days previously and precipitation 3 days previously. This result is consistent with the Spearman's rank correlations.

The ANN model obtained was MLP 26:26-13-11-1:1, trained with 100 epochs of back propagation and 196 epochs of conjugate gradient algorithm. Of all the created models and low dispersion, the regression model for spore seasons yielded the best statistics (SD ratio below 0.7, correlation above 0.7). Direct comparison of the observed and calculated values (Fig. 7) confirmed the good predict-

Table 2 Sensitivity analysis for a multi layer perceptron (MLP) 27:27-11-80-1:1 neural network. The overall classification model

	Average temperature	Average temperature Lag 1	Average temperature Lag 2	Average temperature Lag 3
Ratio	1.002	1.005	0.101	1.002
Rank	13	6	24	16
	Maximum temperature	Maximum temperature Lag 1	Maximum temperature Lag 2	Maximum temperature Lag 3
Ratio	1.001	1.002	0.100	1.006
Rank	17	15	27	5
	Minimum temperature	Minimum temperature Lag 1	Minimum temperature Lag 2	Minimum temperature Lag 3
Ratio	1.003	1.004	0.101	1.006
Rank	9	7	21	4
	Dew point temperature	Dew point temperature Lag 1	Dew point temperature Lag 2	Dew point temperature Lag 3
Ratio	1.011	1.025	0.100	1.007
Rank	2	1	25	3
	Humidity	Humidity Lag 1	Humidity Lag 2	Humidity Lag 3
Ratio	1.003	1.004	1.000	1.000
Rank	10	8	19	18
	Average wind speed	Average wind speed Lag 1	Average wind speed Lag 2	Average wind speed Lag 3
Ratio	1.002	0.100	1.002	1.000
Rank	11	23	14	20
	Maximum wind speed	Maximum wind speed Lag 1	Maximum wind speed Lag 2	Maximum wind speed Lag 3
Ratio	0.100	1.002	0.100	
Rank	26	12	22	

Table 3 Spearman's rank correlation coefficients between *Alternaria* spore concentration and meteorological variables during spore seasons

Variable	Same day	Lag 1	Lag 2	Lag 3
Average temperature	0.417 ***	0.345 ***	0.254 ***	0.211 ***
Maximum temperature	0.383 ***	0.301 ***	0.211 ***	0.136 **
Minimum temperature	0.322 ***	0.259 ***	0.223 ***	0.236 ***
Dew point temperature	0.342 ***	0.310 ***	0.251 ***	0.213 ***
Humidity	-0.258 ***	-0.181 ***	-0.105 *	-0.053
Average wind speed	-0.019	-0.156 **	-0.135 **	-0.063
Maximum wind speed	0.019	-0.106 *	-0.092	-0.030
Precipitation	-0.066	-0.017	0.070	0.073

* $P < 0.05$, ** $P < 0.01$, *** $P < 0.001$

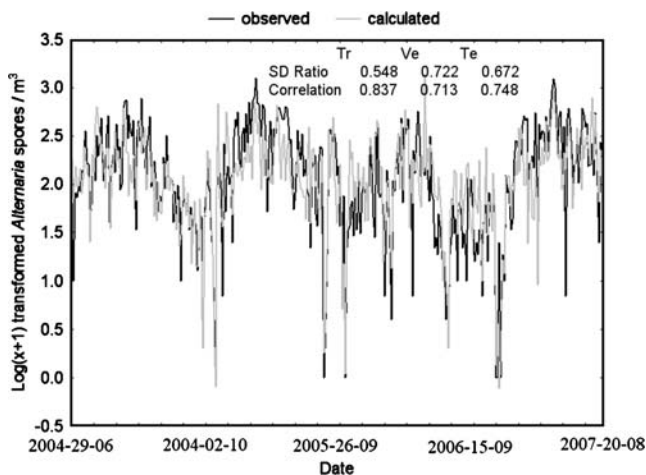


Fig. 7 Comparison of observed *Alternaria* spore time series and those calculated from the MLP 26:26-13-11-1:1 neural network. Regression model for spore seasons

ability of the obtained model as well as the ability to recreate most of the variations.

Sensitivity analysis (Table 4) indicated humidity to be the most important variable in the model, followed by maximum temperature and maximum temperature 2 days previously. Average temperature, humidity 1 day previously, maximum wind speed 2 days previously, maximum temperature 1 day previously and average wind speed 1 day previously were characterised by ratios higher than 1.2, which indicates their significant influence on *Alternaria* spore concentration. The remaining variables also contrib-

uted to the high network performance (ratio above 1) but their impact was less distinct.

Response plots (Fig. 8) indicated nonlinear dependencies. Assuming constant values for the remaining factors, the *Alternaria* spore concentration turned out to increase up to 70–80% humidity and then decrease slightly. A monotonic increase was observed in the case of average temperature and maximum wind speed 2 days previously, while a decrease was seen for humidity 1 day previously and maximum temperature 3 days previously. The response plot indicated an interesting dependence of *Alternaria* spore concentration on maximum temperature: a decrease up to 20°C and then an increase.

Discussion

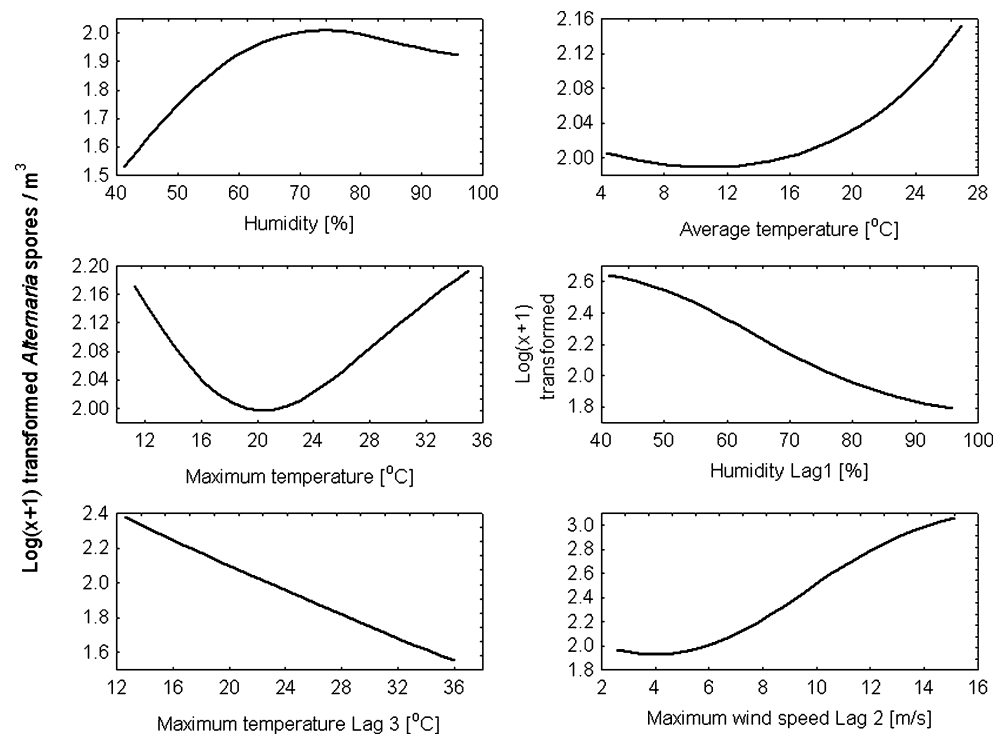
Alternaria airborne spores have been documented as a highly allergenic agent in Poland (Rapiejko et al. 2004), and in many other locations worldwide (Targonski et al. 1995; D'Amato et al. 1997; Halonen et al. 1997; Corsico et al. 1998; Resano et al. 1998; Verini et al. 2001; Mari et al. 2003; Gioulekas et al. 2004). Some researchers have related the occurrence of respiratory allergy symptoms to the presence of *Alternaria* spores in the ambient air (Kauffman et al. 1995; Downs et al. 2001; Rapiejko et al. 2004).

As the existing predictive models are sometimes poor forecasters (Hjelmroos 1993; Angulo-Romero et al. 1999; Mitakakis et al. 2001; Troutt and Levetin 2001; Stennett and Beggs 2004; Damialis and Gioulekas 2006), there is

Table 4 Sensitivity analysis for the MLP 26:26-13-11-1:1 neural network. Regression model for spore seasons

	Average temperature	Average temperature Lag 1	Average temperature Lag 2	Average temperature Lag 3
Ratio	1.286	1.094	1.112	1.060
Rank	4	18	15	21
	Maximum temperature	Maximum temperature Lag 1	Maximum temperature Lag 2	Maximum temperature Lag 3
Ratio	1.338	1.218	1.131	1.322
Rank	2	7	11	3
	Minimum temperature	Minimum temperature Lag 1	Minimum temperature Lag 2	Minimum temperature Lag 3
Ratio	1.124	1.199	1.107	1.079
Rank	13	9	16	20
	Dew point temperature	Dew point temperature Lag 1	Dew point temperature Lag 2	Dew point temperature Lag 3
Ratio	1.056	1.115	1.176	1.107
Rank	22	14	10	17
	Humidity	Humidity Lag 1	Humidity Lag 2	Humidity Lag 3
Ratio	1.477	1.254	1.126	1.048
Rank	1	5	12	23
	Average wind speed Lag 1	Average wind speed Lag 2	Average wind speed Lag 3	Maximum wind speed Lag 1
Ratio	1.212	1.094	1.020	1.031
Rank	8	19	26	24
	Maximum wind speed Lag 2	Precipitation Lag 1		
Ratio	1.230	1.031		
Rank	6	25		

Fig. 8 Response plots for the most important input variables in the MLP 26:26-13-11-1:1 neural network. Regression model for spore seasons



increasing interest in the development of statistical models of high predictive power for atmospheric levels of airborne fungal spores that will allow allergic individuals to take preventative action. For the above reasons, here, for the first time, we develop a model to forecast *Alternaria* spore levels in Poland.

Spearman's rank correlation analysis for the whole data set revealed that average, maximum, minimum and dew point temperatures were the most strongly and directly proportional to the concentration of analysed fungal spores. Highly significant negative correlations were observed in the case of humidity, and average and maximum wind speed. There was no significant association with precipitation. Similar correlations were observed for meteorological variables on the same day as well as with lags. In Spearman's rank correlations for spore seasons, all the variables except precipitation were significant. The correlation level decreased with lag time, i.e. opposite to the analysis for the whole data set, and was lower. The presence of many 0 values in the *Alternaria* variable probably overstated Spearman's correlation coefficients for the whole data set. A similar significant correlation between *Alternaria* spore counts and maximum temperature was noted by Munuera Giner and Carrión García (1995), where relationships between fungal spores and weather variables were explored using the Spearman rank correlation coefficient method. The same methods plus multiple regression were used by Stennett and Beggs (2004) in Sydney, Australia. The daily mean, minimum and maximum temperatures and dew point temperature were most

strongly and consistently associated with the concentration of *Alternaria* spores. The same authors found positive, but markedly lower and less consistent, relationships between *Alternaria* spore concentration and rainfall 2 and 3 days previously and relative humidity in the previous 1, 2 and 3 days. During a 3-year study (2004–2006) in Poland (Szczecin), a positive significant correlation was noted between *Alternaria* spore count and minimum temperature; *Alternaria* was the only taxon that had a negative significant correlation with relative humidity (Grinn-Gofroń and Mika 2008).

All variables except maximum wind speed and precipitation were significant factors in the overall classification model. Sensitivity analysis for the MLP 27:27-11-80-1:1 neural network showed dew point temperature as the variable most influencing the presence or absence of *Alternaria*. Contrasting results for dew point temperature were obtained by Troutt and Levetin (2001) in Tulsa, Oklahoma in the United States. The results of a multiple regression analysis performed in forward stepwise mode showed a significant negative correlation between *Alternaria* spore count and dew point temperature, but a positive correlation for temperature. They conclude that temperature and dew point are probably the best predictors for *Alternaria*, appearing with a positive and negative relationships, respectively, in all regressions.

In the regression model for spore seasons, close relationships were noted between *Alternaria* spore concentration and average maximum temperature (on the same day and 3 days previously), average humidity 1 day previously and

average maximum wind speed 2 days previously. The most important variable was humidity recorded on the same day. We found no dependence between precipitation and the presence of *Alternaria* spores. The ANN model revealed actual non-linear relationships.

A similar importance of maximum temperature and wind speed was observed by Herrero et al. (1996) in Palencia (Spain). They also noted a positive significant correlation for precipitation using two statistical analyses: multiple regression and Duncan's multiple range test. Lyon et al. (1984; in Manhattan, KA), using multiple regression analysis, also noted that the maximum and minimum temperatures are significantly correlated with concentrations of *Alternaria*. Using autoregressive predictive models, Damialis and Gioulekas (2006) observed that *Alternaria* spores were strongly related to air temperature in Thessaloniki (Greece). The interaction effects of rainfall and wind were also considered necessary for long-term (annual) predictions of airborne fungal concentrations.

In contrast to the results presented above, Hjelmroos (1993; in Stockholm, Sweden) and Katial et al. (1997; in Denver, CO) noted no statistically significant correlation between *Alternaria* spore count and weather variables, and considered that no statistical model can be proposed for *Alternaria* spore concentrations in relation to climate.

Our study shows that the ANN method provides the possibility of satisfactory forecasting of *Alternaria* spore concentrations. Time series with many 0 values of *Alternaria* spore concentration turned out to be quite hard to predict, since they actually consist of two subsets (equal to 0 and higher than 0). In this case, the most suitable tool is the split model with classification (spore presence or absence), followed by regression for spore seasons and $\log(x+1)$ transformed output variables, in order to dampen the effect of rapid changes in spore concentrations. Our results indicate that precise ANN modelling of *Alternaria* spore concentration with non-normality and non-linearity requires a basic set of meteorological variables widened by variables with lags. We believe that our forecasting models could be still further improved, and could be focussed more profoundly on seasonal variations in spore–meteorological variable time series.

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