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

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Abstract

Moulds are common aeroallergens and *Cladosporium* is considered to be one of the more prevalent examples of these. 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 *Cladosporium*, 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, 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, *Cladosporium* spore concentrations were predicted using artificial neural networks (ANN). The final model included classification (spore presence or absence) and regression for spore seasons with $\log(x+1)$ transformed *Cladosporium* spore concentration. All variables, except average wind speed 3 days previously and precipitation (on the same day and with lags) were factors important in classification. In the regression model for spore seasons, close relationships were noted between *Cladosporium* spore concentration and dew point temperature the previous day, humidity, and minimum and maximum temperatures. Additionally, time series prediction was performed. Our study shows that ANN models are applicable to forecasting *Cladosporium* spore concentration with high accuracy.

Keywords: *Cladosporium*, artificial neural networks, meteorological parameters, Szczecin

Fungal spores are consistently present in the airborne environment, although levels vary according to climate, season, diurnal influences, vegetation and location, e.g., indoor versus outdoor (Hjelmroos, 1993; Li & Kendrick, 1995; Mitakakis et al., 1997). The most prevalent airborne fungal spores in the temperate zones year round, in both indoor and outdoor environments, are those belonging to *Cladosporium* (Davies, 1969; Sneller & Roby, 1979; Ebner et al., 1989, 1992; Ballero et al., 1992; Hjelmroos, 1993; Li & Kendrick, 1994).

Sensitisation to airborne fungal spores varies and is dependent upon the allergenic potency of the fungal proteins, human genetic predisposition to disease (atopy) and levels of exposure to allergens (Rapiejko et al., 2004).

The *Cladosporium* threshold concentrations for evoking allergic symptoms are estimated to be 80 spores $\times$ m⁻³ air (Rapiejko et al., 2004). *Cladosporium* seems to be responsible for clinical symptoms of oculorhinitis and/or bronchial asthma (D'Amato & Spieksma, 1995).

Forecasting of aeroallergens (pollen grains and fungal spores) has been a popular scientific goal for many researchers. However, the majority of these efforts have more frequently aimed at the prediction of airborne fungal spore circulation. There are relatively few such models, and most of them usually display low predictability (Katial et al., 1997). One of the reasons for such a situation lies in non-normality and non-linearity of variables involved in modelling, when typically used statistical methods (linear or multiple regression) reveal insufficient

performance. This is particularly typical for time series with short spore seasons, where no airborne fungal spores are present most of the year. Therefore, applicability of other modelling techniques should be verified. One of the methods that has lately turned out to be useful in ecological modeling is the artificial neural network technique (ANN). Neural networks function as a universal approximating system with ability to learn, adapt and generalise the acquired knowledge. This 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, 1993, 2001; Osowski, 1996; Lek & Guegan, 1999).

The aim of this work was to study the influence of meteorological factors upon the concentration of *Cladosporium* spores in the atmosphere of the Szczecin area using a novel data analysis technique – artificial neural networks. No predictive modeling of the aeroallergen circulation season has been developed in Poland before. Our ultimate goal is to create forecasting models of high predictability which might be applicable to other regions as well.

Material and methods

The results of this investigation are based on aerobiological monitoring performed in Szczecin in 2004–2007. Szczecin is situated in the Odra river estuary in North-West Poland, 60 m a. s. l., 53°26'26"N, 14°32'50"E. The city is surrounded by forests, farmlands and abandoned farmland areas which provide suitable media for spore production. The present, "baltic" climate of Szczecin is created by the impact of an Atlantic component which is characterised by mild winters and cool summers (Table I).

Daily summed counts of airborne fungal spores were performed using a 7-day recording Lanzoni volumetric trap. The trap was installed on a roof top in Śródmieście, a Szczecin city district, at the height of 21 m above ground level (52 m above sea level). The urban structure is not dense with many green squares and parks. The measuring site was 0.5 km

NW of Jan Kasprowicz Park, the largest green complex in Szczecin on the east side of the Odra river.

The methodology followed was that described by the British Aerobiology Federation (1995): each weekly tape was cut into seven pieces – each corresponding to one day of the weekly sampling. Afterwards these were stained (with a solution of saffron, gelatine, glycerol and phenol) and mounted on the microscope slides with cover slips and stored in special cases. Daily records of the airborne fungal spores were obtained by means of counting all spores in one longitudinal traverse per microscope slide at $\times 400$. After the spore counting in each sampling area, a specific – for the microscope used – correction factor was applied. The factor (F) was calculated using specific formula:

$$F = a / [(b)^* c]$$

- (a) total area of glass
- (b) analysed area = width $\times$ length of transect $\times$ 2
- (c) volume of analysed air = 10 l/min = 14.4 m³/24 h

Value of b is related to the number of counted belts on a slide (1, 2 or 4).

Thus, the final counts of fungal spores were expressed as average daily number of spores per cubic meter of air.

The meteorological data covering four years of studies were provided by the Automatic Weather Station (Vaisala MAWS101 and MAWS201, Finland). The meteorological station was located in the immediate neighbourhood of the Lanzoni trap. The meteorological parameters considered were: daily level of precipitation, maximum wind speed, average wind speed, relative humidity, maximum, minimum and average air temperature, temperature of the dew point. The daily values of these parameters were taken as arithmetic means. Additionally, meteorological variables with 1, 2 and 3-day lags were introduced into the data set.

The spore data was analysed to determine the start, the end and the duration of the season using the 90% method. The start of the season was defined as the date when 5% of the seasonal cumulative spore count was trapped and the end of the season as the date when 95% of the seasonal cumulative spore count was reached (BFA, 1995).

Data analysis

Due to non-linearity and non-normality of the analysed variables, particularly visible in matrix histograms and scatter plots, the Spearman's rank

Table I. Some features of the climate of Szczecin (Woś, 1999).

Feature	Value
Mean annual temperature	8.0–8.4°C
Mean annual air pressure	1014 hPa
Mean annual RH	70%
The warmest month	July
The coldest month	January
Vegetation season	220–227 days
Mean annual precipitation	500 mm

correlation and artificial neural network models were applied in order to examine the studied relationships. Meteorological parameters (original and with lags) were used as input variables while the *Cladosporium* spore concentration was an output variable.

In this study multi layer perceptrons (MLP) were applied, which mathematically perform a stochastic approximation of multivariate functions (Osowski, 1996). Calculations were performed using StatSoft software Statistica 6.1 with implemented neural network module (Lula, 2000; Tadeusiewicz, 1993, 2001). Due to the considerable number of input parameters, variable selection was made using a combination of probabilistic and generalised regression networks with backward variable selection algorithm. This algorithm is considered to be more suitable for the inter-correlated input variables than forward selection (Osowski, 1996). The obtained data set was then used in regression and classification modelling. Moreover, time series prediction was performed, using *Cladosporium* spore concentration in the first year as the additional input.

The consecutive neural networks were designed and trained using back propagation (Haykin, 1994; Fausett, 1994; Patterson, 1996) and conjugate gradient algorithms (Bishop, 1995) by Automatic Problem Solver. Cases were divided by the bootstrap method into 3 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 criterion of the best neural network in regression and time series modelling were: (1) value of SD Ratio (ratio between error standard deviation and standard deviation of experimental data), and correlation (Pearson's correlation coefficient between experimental and calculated data). In case of classification, the percentage of correctly classified cases was analysed.

Special emphasis was placed on sensitivity analysis and response plots. Sensitivity analysis creates 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 the one with ignored variables is the basis of ordering variables according to their importance. 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 – one-dimensional section through response surface in N-dimensional space of input variables.

Results

The spore seasons were relatively short and for a large number days the *Cladosporium* count was zero (Figure 1). As shown in Figure 2, the *Cladosporium* spore histogram approximated an exponential distribution. In turn, meteorological parameters seemed to approximate normal distribution, however, the Shapiro-Wilk test confirmed significant deviations from normality (results not shown). The scatter plots for variables without lags indicated non-linear dependencies between *Cladosporium* spore concentration and meteorological parameters.

The analysis of Spearman's rank correlations (Table II) revealed, that average, maximum, minimum and dew point temperatures (both on the same day and 1, 2 and 3 days prior) were most strongly and directly proportional to the concentration of *Cladosporium* spores. Highly significant negative correlations of rather low level were observed in case of humidity, average and maximum wind speed. Association with precipitation turned out to be weak and insignificant.

ANN overall regression model for raw variables displayed very low accuracy (correlation below 0.5). Log(x+1) transformation of *Cladosporium* spore concentration dampened the effect of rapid changes but not the effect of many 0 values and the performance of ANN regression model did not improve. Additionally, after the transformation, division into two subsets was visible in the scatter plots – zero and higher than 0 values of *Cladosporium* spore concentration (Figure 3). Separate modelling of spore seasons brought satisfactory results and two submodels were used: ANN overall classification model and ANN regression model for spore seasons with log(x+1) transformed *Cladosporium* spore concentration.

Overall classification model

In the overall classification model, *Cladosporium* spore concentration was substituted by a dummy variable with 0 as the absence and 1 as the presence of *Cladosporium* spores. The most important factors, indicated by backward variable selection using ANN module were all the variables except for average wind speed 3 days previously and precipitation on the same day and with lags. The obtained network was MLP 27:27-18-18:1, trained with 100 epochs of back propagation and 46 epochs of conjugate gradient algorithm. A good performance was obtained – 95.25% of "0" cases and 78.47% of "1" cases were predicted correctly.

Sensitivity analysis, shown in Table III, indicated dew point temperatures (3 days previously, on the same day and 2 days previously) as the most important variables. All the remaining variables were less important.

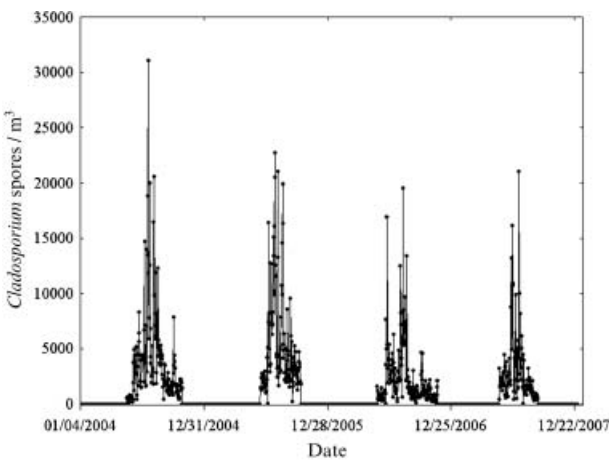
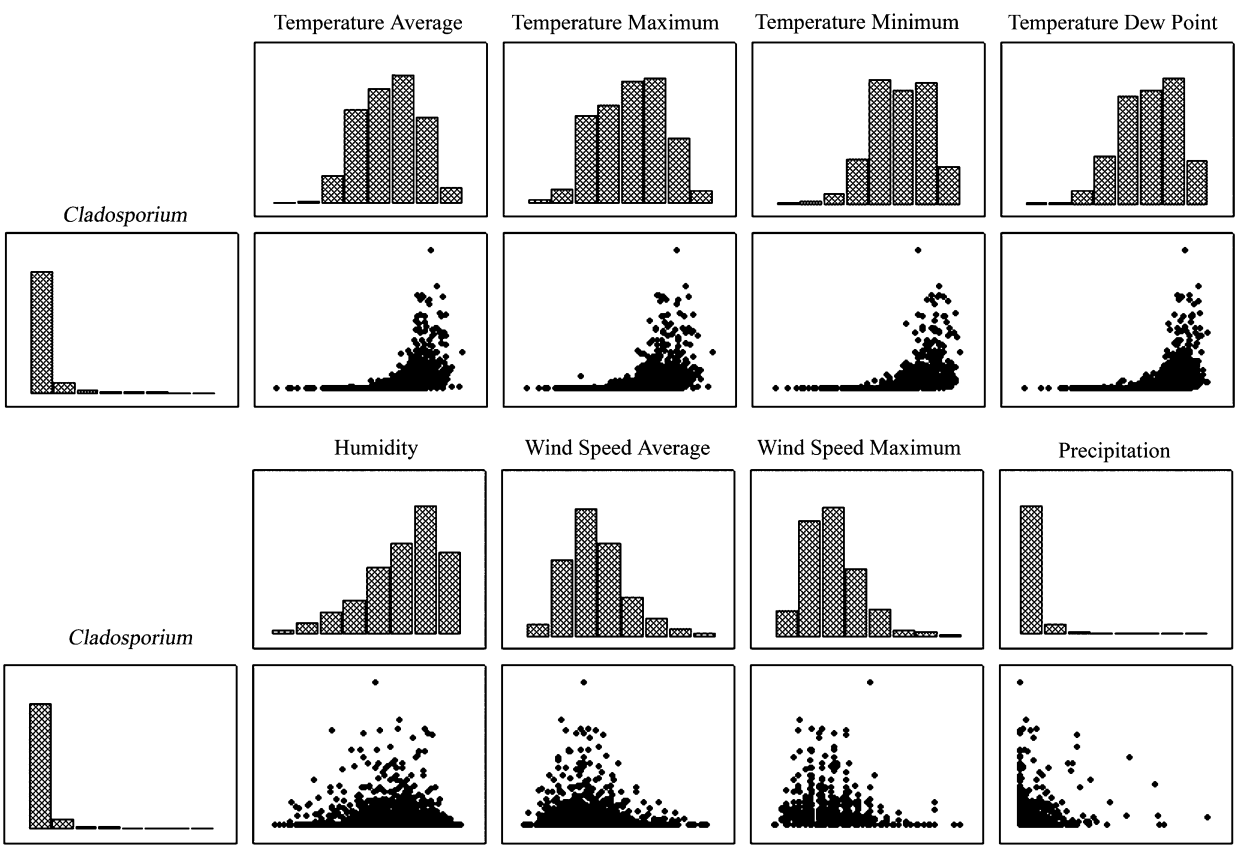


Figure 1. *Cladosporium* spore time series. Szczecin (Poland) 2004–2007.

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

For the spore season data set the elimination of zero counts improved (Figure 4) and again Spearman's rank correlations were calculated (Table IV). As for the original data set, directly proportional and highly significant dependencies between the *Cladosporium* spore concentration and meteorological factors were observed in case of average, maximum, dew point and minimum temperatures. However, those correlations were weaker the longer the lags. Relatively high negative correlations were found for humidity recorded on the same day, average and maximum wind speed 1 and 2 days prior. No significant correlation was observed between precipitation and the *Cladosporium* spore presence.



Temperature average [°C]: Max = 27.72; Min = -20.33	Temperature Maximum [°C]: Max = 36.0; Min = -13.61
Temperature minimum [°C]: Max = 19.0; Min = -26.0	Temperature Dew Point [°C]: Max = 19.22; Min = -22.56
Humidity [%]: Max = 100.00; Min = 36.01	Wind Speed Average [m/s]: Max = 8.75; Min = 0.10
Wind Speed Maximum [m/s]: Max = 17.20; Min = 1.97	Precipitation [mm]: Max = 45.97; Min = 0.00

Figure 2. Matrix scatter plots between *Cladosporium* spore concentration and meteorological factors (whole data set, raw data).

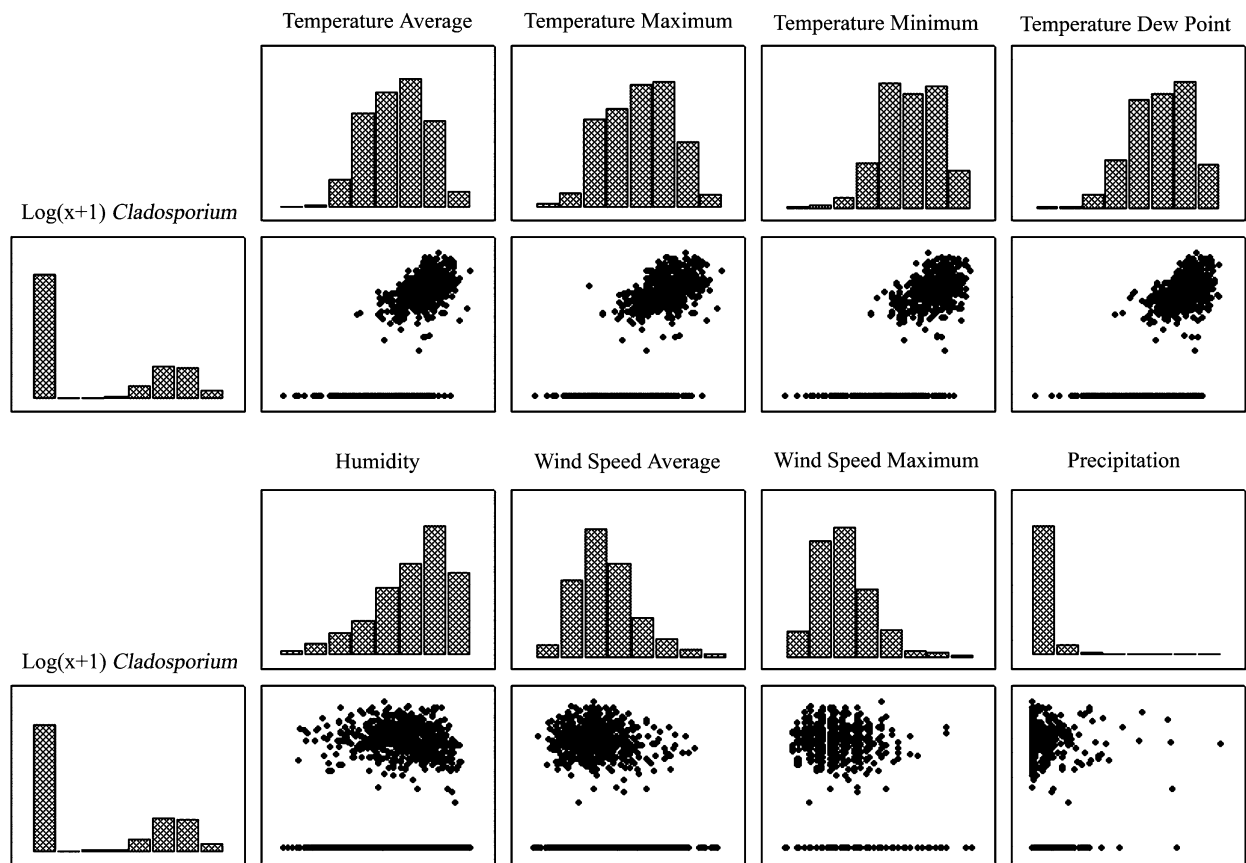
Table II. Spearman's rank correlation coefficients between average daily *Cladosporium* spore concentration and meteorological variables for all the years taken. P-value: ***p < 0.001.

Variable	Same day	Lag 1	Lag 2	Lag 3
Average temperature	0.754 ***	0.754 ***	0.752 ***	0.753 ***
Maximum temperature	0.725 ***	0.723 ***	0.721 ***	0.723 ***
Minimum temperature	0.725 ***	0.725 ***	0.723 ***	0.724 ***
Dew point temperature	0.761 ***	0.763 ***	0.759 ***	0.757 ***
Humidity	-0.327 ***	-0.317 ***	-0.322 ***	-0.330 ***
Average wind speed	-0.150 ***	-0.161 ***	-0.157 ***	-0.145 ***
Maximum wind speed	-0.134 ***	-0.144 ***	-0.142 ***	-0.128 ***
Precipitation	0.016	0.035	0.040	0.031

Backward variable selection using ANN module excluded from the model the following variables: humidity 1 and 2 days prior, maximum wind speed on the same day and 1 day prior, precipitation with lag 3. The obtained ANN model was MLP 27:27-18-11-1:1, trained with 100 epochs of back propagation and 196 epochs of conjugate gradient algorithm. The regression model for spore seasons reached

satisfactory statistics (SD Ratio between 0.728 and 0.818, correlation between 0.580 and 0.687). Direct comparison of the observed and calculated values (Figure 5) confirmed good predictability of the obtained model and ability to recreate most of the variations.

Sensitivity analysis (Table V) indicated dew point temperature recorded 1 day prior to be the most



Temperature Average [°C]: Max = 27.72; Min = -20.33 Temperature Maximum [°C]: Max = 36.0; Min = -13.61
 Temperature Minimum [°C]: Max = 19.0; Min = -26.0 Temperature Dew Point [°C]: Max = 19.22; Min = -22.56

Humidity [%]: Max = 100.00; Min = 36.01

Wind Speed Average [m/s]: Max = 8.75; Min = 0.10

Wind Speed Maximum [m/s]: Max = 17.20; Min = 1.97

Precipitation [mm]: Max = 45.97; Min = 0.00

Figure 3. Matrix scatter plots between log(x+1) transformed *Cladosporium* spore concentration and meteorological factors (whole data set).

Table III. Sensitivity analysis for MLP 27:27-18-18-1:1 neural network. The overall classification model.

	Average temperature	Average temperature Lag 1	Average temperature Lag 2	Average temperature Lag 3
Ratio	0.990	0.976	0.999	0.992
Rank	19	23	10	16
	Maximum temperature	Maximum temperature Lag 1	Maximum temperature Lag 2	Maximum temperature Lag 3
Ratio	1.001	0.973	1.001	0.999
Rank	6	26	4	8
	Minimum temperature	Minimum temperature Lag 1	Minimum temperature Lag 2	Minimum temperature Lag 3
Ratio	0.984	0.991	0.994	0.998
Rank	21	17	15	12
	Dew point temperature	Dew point temperature Lag 1	Dew point temperature Lag 2	Dew point temperature Lag 3
Ratio	1.007	0.966	1.002	1.017
Rank	2	27	3	1
	Humidity	Humidity Lag 1	Humidity Lag 2	Humidity Lag 3
Ratio	0.985	0.979	0.973	0.976
Rank	20	22	25	24
	Average wind speed	Average wind speed Lag 1	Average wind speed Lag 2	Maximum wind speed
Ratio	0.995	0.995	1.001	0.999
Rank	13	14	5	9
	Maximum wind speed Lag 1	Maximum wind speed Lag 2	Maximum wind speed Lag 3	
Ratio	1.000	0.999	0.991	
Rank	7	11	18	

important variable in the model, then humidity, maximum temperature on the same day and with lag 1. The remaining variables also contributed to the high network performance (ratio above 1) but their impact was less distinct.

Response plots (Figure 6) indicated nonlinear dependencies. Assuming constant values of the remaining factors, the *Cladosporium* spore concentration turned out to increase up to 60–70% of humidity and then decrease. Monotonic increase was observed in case of dew point temperature 1 day previously and minimum temperature, while decrease for maximum temperature with lag 1 was observed.

Overall time series model for raw variables

Since meteorological variables did not explain the high part of the *Cladosporium* spores variance, a time-series approach was used. Apart from meteorological variables recorded on the same day, *Cladosporium* spore concentration in the first year was used as an input in order to substitute information contained in other, not recorded variables. Backward variable selection using ANN module excluded precipitation from the model. The obtained ANN network was MLP s365 7:2555-10-6-1:1, trained with 100 epochs of back propagation and 23 epochs of conjugate gradient algorithm. Time series prediction was of high accuracy (SD ratio below 0.3, correlation above 0.9). Direct comparison of the observed and calculated values (Figure 7) confirmed good

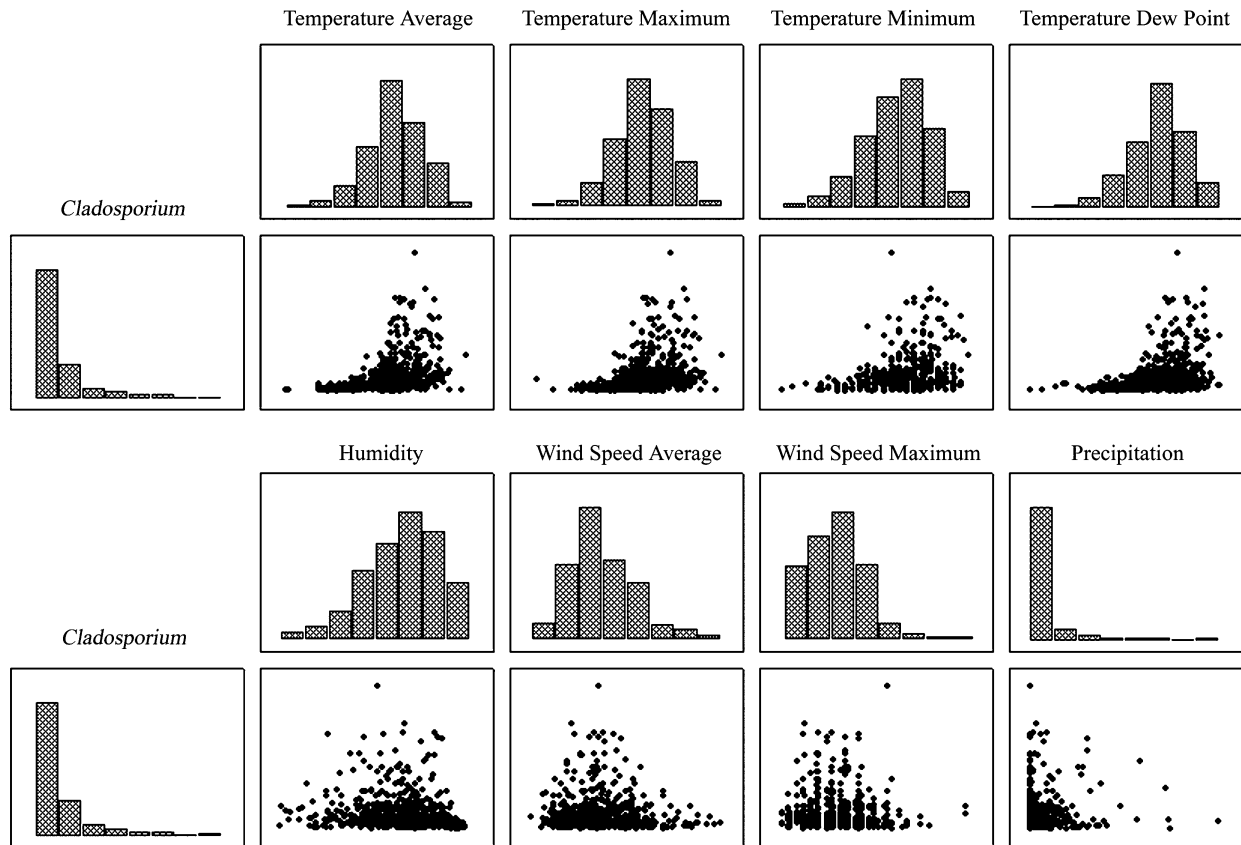
performance of the obtained model and ability to recreate most of the variations.

Discussion

Cladosporium spores are the main components of the airborne mycoflora over the city. The average of the four years for 2004–2007 represents 45% of the spore total. Similar values were observed by other authors (Goodman et al., 1966; Kotimaa, 1977; Nogales et al., 1985; Infante & Domínguez, 1988; Hjelmroos, 1993; Herrero et al., 1996; Stępańska et al., 1999). As mentioned previously, *Cladosporium* is one of the most important aeroallergens in Poland (Rapiejko et al., 2004).

The sporulation and dispersion of the *Cladosporium* spores are closely related to the variations in the atmospheric conditions. Therefore, there is an 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 these mentioned reasons, it is the first time that *Cladosporium* spore level was forecasted in Poland.

Spearman's rank correlations for the whole data set showed a direct correlation with dew point temperature, three temperature parameters (maximum, minimum and average) and inverse correlation with relative humidity, average and maximum wind speed. Similar results were observed for spore seasons, although correlation level decreased with lags and was lower. The presence of many 0 values



Temperature Average [°C]: Max = 27.72; Min = -1.0
 Temperature Minimum [°C]: Max = 19.0; Min = -5.0
 Humidity [%]: Max = 96.69; Min = 41.09
 Wind Speed Maximum [m/s]: Max = 15.13; Min = 2.58

Temperature Maximum [°C]: Max = 36.0; Min = 1.0
 Temperature Dew Point [°C]: Max = 19.22; Min = -4.39
 Wind Speed Average [m/s]: Max = 7.64; Min = 0.30
 Precipitation [mm]: Max = 45.97; Min = 0.00

Figure 4. Matrix scatter plots between $\log(x+1)$ transformed *Cladosporium* spore concentration and meteorological factors for spore seasons.

in the *Cladosporium* variable probably overstated Spearman's correlation coefficients for the whole data set. ANN models confirmed the importance of the above listed parameters. The classification model indicated dew point temperatures (3 days prior, the same day and 2 days prior) as the most important variables, while the regression model for spore seasons- dew point temperature recorded the previous day, then humidity, maximum temperature on the same day and with lag 1.

The study by Hjelmroos (1993) modeling *Cladosporium* counts in Sweden showed a positive correlation with daily temperature and precipitation. Sabariego et al. (2000) noted a positive relationship between *Cladosporium* spore count and maximum, minimum and average temperatures. Similar results were also reported by other authors (Li & Kendrick, 1995; Herrero et al., 1996; Kurkela, 1997; Méndez et al., 1997; Troutt & Levetin, 2001), who observed that maximum *Cladosporium* levels coincided with

high temperatures. Hasnain (1993) also found a strong correlation between maximum temperature and *Cladosporium* concentrations. Dew point might play a secondary role in *Cladosporium* release but, as the atmosphere warmed, more *Cladosporium* seemed to be found in the air. The significant, negative correlation between *Cladosporium* spore count and dew point was noted in multiple regression analysis employed by Troutt & Levetin (2001). They noted that the temperature and dew point seemed to be the most important meteorological factors associated with *Cladosporium*.

The number of *Cladosporium* spores decreased with relative humidity in Szczecin. The same results were noted by Kurkela (1997) in Finland in a three year study. The highest spore counts were obtained when relative humidity was between 40 and 70%. In our study, the levels of spores increase when the values of relative humidity achieved 60–70% and then decreased. The positive, significant correlation

Table IV. Spearman's rank correlation coefficients between average daily *Cladosporium* spore concentration and meteorological variables during spore seasons. P-value: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Variable	Same day	Lag 1	Lag 2	Lag 3
Average temperature	0.461 ***	0.418 ***	0.382 ***	0.392 ***
Maximum temperature	0.430 ***	0.376 ***	0.341 ***	0.344 ***
Minimum temperature	0.420 ***	0.390 ***	0.361 ***	0.383 ***
Dew point temperature	0.459 ***	0.454 ***	0.408 ***	0.384 ***
Humidity	-0.181 ***	-0.079	-0.081	-0.107 *
Average wind speed	-0.078	-0.177 ***	-0.183 ***	-0.117 **
Maximum wind speed	-0.045	-0.147 ***	-0.157 ***	-0.084
Precipitation	-0.023	0.064	0.078	0.018

between relative humidity and *Cladosporium* spore count was observed in Denver, Colorado by Katial et al. (1997).

In our study, the maximum and minimum wind speed correlated negatively with the number of *Cladosporium* spores. Lyon et al. (1984) found negative correlation between the wind speed and spore concentrations (multiple regression analysis) and Kurkela (1997), using Pearson correlation, noted positive, significant relationship. The long distance dispersal of spores depends on the wind conditions, but wind also plays an important role in the detachment of spores being dispersed in dry conditions

(Mallaiah & Rao, 1982). According to Dutzmann (1985), *Cladosporium* spore release by wind occurs in connection with the decrease of relative humidity during the morning hours. When the spore bearing structures are sufficiently dry, mature spores will be almost instantly released by wind.

Our model for *Cladosporium* found no correlation with precipitation. This parameter has bearing on other weather parameters, such as relative humidity, and therefore may indirectly affect spore counts. The precipitation used for data analysis was a daily average of multiple observations. We did not take into consideration more precise values which have an effect on spore sampling and this may explain the lack of correlation between spore counts and precipitation. The positive, significant correlation with this parameter was noted by Kurkela (1997). Maximum concentrations occurred at the onset of rain but the influence of weather was found to be different in different years. Higher concentrations of fungal spores were noted in seasons with higher precipitations and temperatures, and abundant dead plant material for the fungi to grow on. Low concentrations were associated with a period of dry weather.

Our study shows that the ANN method gives the possibility of satisfactory forecasting *Cladosporium* spore concentration. It turned out that time series with many 0 values are quite difficult to predict, since they actually contain 2 subsets (equal to 0 and higher than 0). Two ways of forecasting *Cladosporium* spore concentration are proposed in this study. The first model includes classification of spore presence or absence with good accuracy, and the focus on the prediction of $\log(x+1)$ transformed spore concentration during spore seasons. The second modelling possibility is to use time series prediction, based on meteorological parameters and other unknown factors, "hidden" in spore concentration values recorded in one sample year. Both of those forecasting methods gave a satisfactory performance and we believe that they can be successfully applied in other regions.

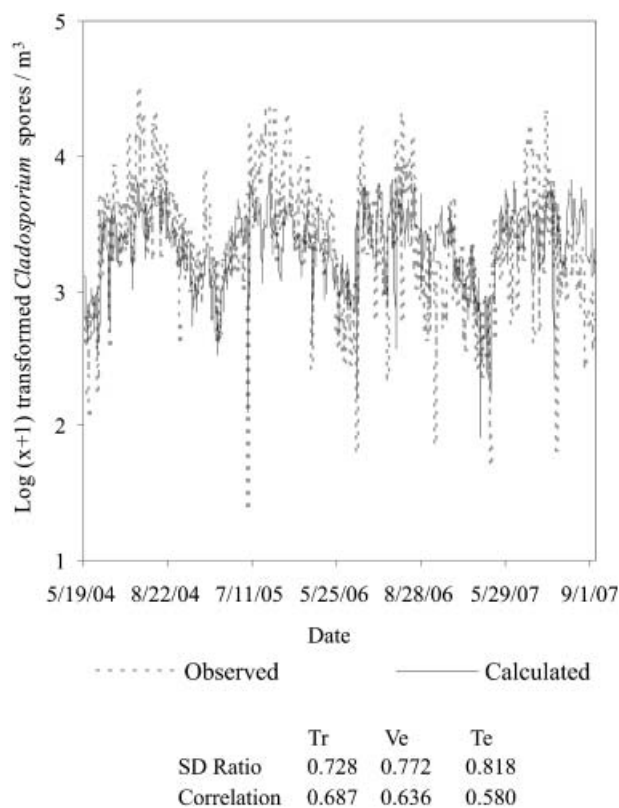


Figure 5. Comparison of observed *Cladosporium* spore time series and those calculated from MLP 27:27-18-11:1 neural network. Regression model for spore seasons.

Table V. Sensitivity analysis for MLP 27:27-18-11-1:1 neural network. Regression model for spore seasons.

	Average temperature	Average temperature Lag 1	Average temperature Lag 2	Average temperature Lag 3
Ratio	1.009	1.002	1.017	1.008
Rank	15	27	9	17
	Maximum temperature	Maximum temperature Lag 1	Maximum temperature Lag 2	Maximum temperature Lag 3
Ratio	1.018	1.025	1.008	1.007
Rank	7	4	20	22
	Minimum temperature	Minimum temperature Lag 1	Minimum temperature Lag 2	Minimum temperature Lag 3
Ratio	1.036	1.006	1.022	1.015
Rank	3	23	5	11
	Dew point temperature	Dew point temperature Lag 1	Dew point temperature Lag 2	Dew point temperature Lag 3
Ratio	1.014	1.076	1.005	1.008
Rank	13	1	24	19
	Humidity	Humidity Lag 3	Average wind speed	Average wind speed Lag 1
Ratio	1.056	1.021	1.018	1.014
Rank	2	6	8	12
	Average wind speed Lag 2	Average wind speed Lag 3	Maximum wind speed Lag 2	Maximum wind speed Lag 3
Ratio	1.008	1.008	1.007	1.009
Rank	16	18	21	14
	Precipitation	Precipitation Lag 1	Precipitation Lag 2	
Ratio	1.015	1.004	1.003	
Rank	10	25	26	

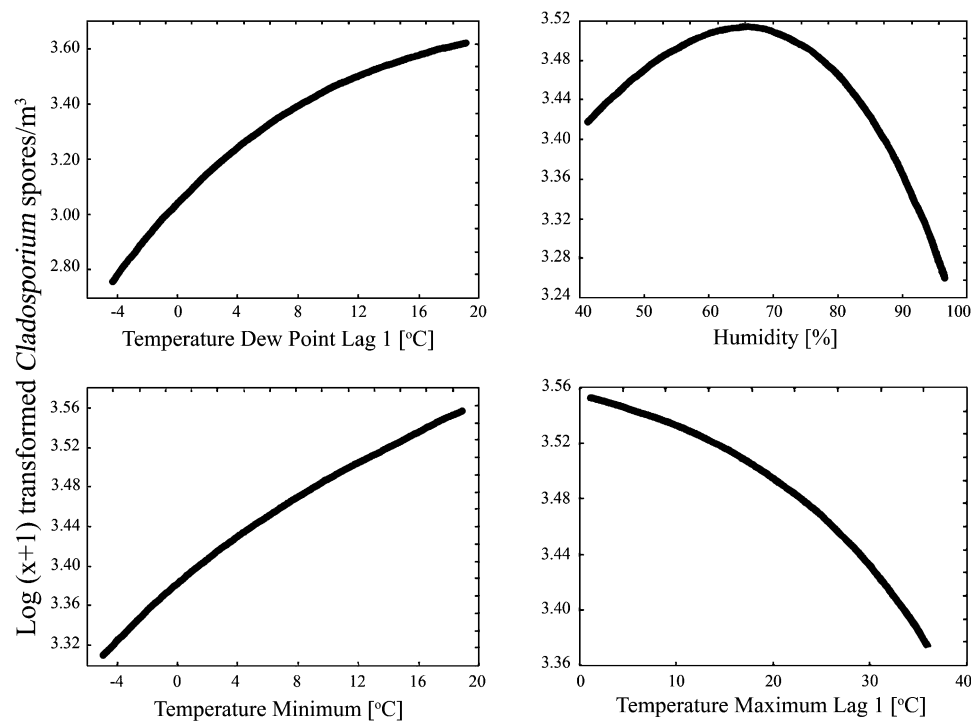


Figure 6. Response plots for the most important input variables in MLP 27:27-18-11-1:1 neural network. Regression model for spore seasons.

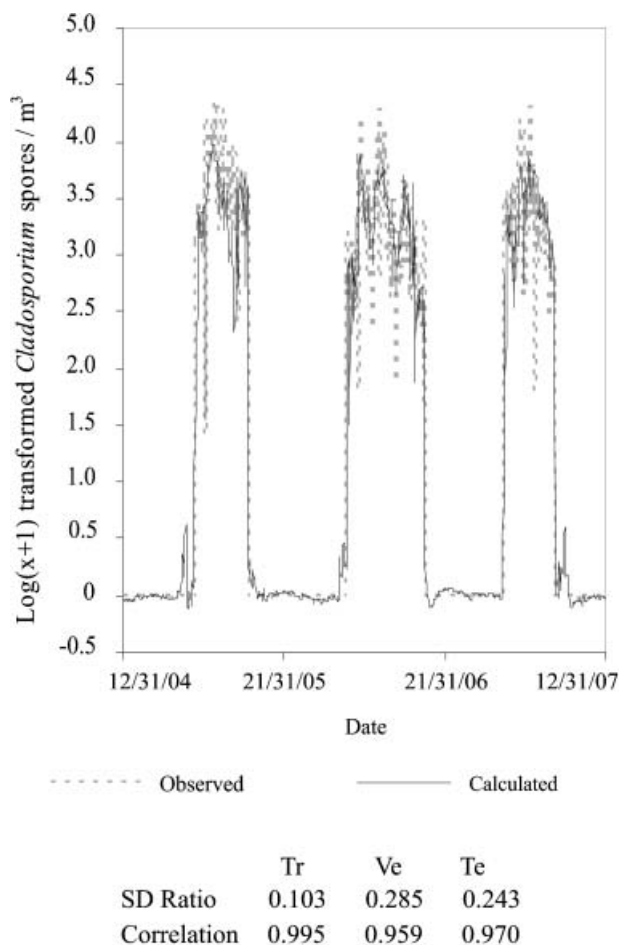


Figure 7. Comparison of observed *Cladosporium* spore time series and those calculated from MLP s365 7:2555-10-6-1:1 neural network. Time series analysis.

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