

Prediction of *Alternaria* and *Pleospora* concentrations from the meteorological forecast and artificial neural network in L'Aquila, Abruzzo (Central Italy)

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Abstract In a previous work a 1-year time series of fungal spore concentrations was used to calibrate an artificial neural network for the estimation of *Alternaria* and *Pleospora* concentrations associated with observed meteorological variables in the atmosphere of L'Aquila, Italy. In this article the possibility to use the neural model calibrated with observed meteorological variables to predict the future fungal spore concentration from meteorological forecast is investigated. The results show that the proposed technique appears to be a suitable device to operationally predict the *Alternaria* and *Pleospora* concentrations a few days in advance. Emphasis is given to the actual use of these predictions for establishing a preventive strategy for allergy sufferers and for an appropriate use of fungicide treatments in agricultural

activities, avoiding unsafe and useless pollution of the atmosphere, crops and fields.

Keywords Aerobiological monitoring ·
Alternaria · Artificial neural network ·
Fungal spores · *Pleospora*

1 Introduction

The relationship of spore concentration with meteorological factors has been pointed out by many authors in the last years for many geographical domains. A calendar of fungal spore seasons for Melbourne, Australia, was established by Mitakakis and Guest (2001) for 29 genera and 5 spore groups; they showed that *Cladosporium* and *Alternaria* peak in spring and summer, while *Leptosphaeria* and *Ganoderma* air concentrations mainly increase towards summer and autumn. The annual variation of *Alternaria* spores in a semi-arid region of the southern part of east Spain was discussed by Giner and Carrión García (1995), and a similar analysis was carried out by Hjelmroos (1993) for Stockholm, Sweden.

Nevertheless, the observed concentration of fungal spores is characterized by a strong temporal variability, and therefore these concentrations cannot be considered as a simple function of average seasonal conditions. For example, Stennett and Beggs (2004) used Spearman's rank correlation and multiple

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regression to show a significant correlation of the *Alternaria* concentration with the daily average, minimum and maximum temperature, dew point temperature and air pressure. Burch and Levetin (2002) demonstrated that the increases in temperature, dew point and surface air pressure is strongly correlated with an increase in spore concentration, but no single weather variable predicted the appearance of the spore plume.

Hollins et al. (2004) analyzed two different time series of *Cladosporium* conidia observed in England and Wales over 27 years; the results demonstrated that the number of days in summer when the *Cladosporium* spores are above the allergenic concentration was positively correlated with regional temperature and negatively correlated with precipitation for both sites over the study period. A study was made by Sabariego et al. (2000) of the link between climatic factors and the daily content of certain fungal spores (*Alternaria*, *Ustilago* and *Cladosporium*) in the atmosphere of the city of Granada (southern Spain) in 1994. They analyzed the Spearman correlation coefficients between the spore concentrations and the meteorological parameters showing that *Alternaria* and *Cladosporium* are significantly correlated with temperature and hours of sunlight, while *Ustilago* shows positive correlation indices with relative humidity and negative indices with wind speed. The multiple regression carried out by Herrero et al. (1996) showed a positive correlation between minimum temperature and *Cladosporium* spore concentrations, while for *Alternaria* a positive correlation with maximum temperature and a negative correlation with precipitation was found. *Pleospora* conidia are typical airborne spores (Hirst 1953). Their aerial behavior has been investigated by many authors (Domínguez-Santana and La Serna-Ramos 1998; Ibáñez-Henríquez et al. 2001; Sabariego et al. 2000) because of their allergenic effects on human health. *Pleospora* is the causal agent of brown spot disease on pear (*Pyrus communis* L.); the fungus causes extended necrotic areas on leaves, shoots and fruits, which are unmarketable. Numerous pear orchard areas are affected by disease in Italy, France, Portugal, Spain and Holland (Llorente and Montesinos 2002, 2004; Montesinos et al. 1995).

Besides the possibility to efficiently estimate the spore concentrations from meteorological variables, a possible important application could be the prediction

of these concentrations from meteorological forecasts. Diseases caused by fungi can cause economic losses, and chemical treatments are applied depending on meteorological conditions or plant development stages.

In fact, an accurate forecast of spore concentrations over a wide geographical area could drive local authorities to limit the use of fungicide treatments in agricultural activities, avoiding unsafe and useless pollution of the atmosphere, crops and fields (Frenguelli 1998). These treatments are usually applied at fixed times of the year, although, as stated above, the critical correlation between spore concentrations and meteorological conditions has long been recognized by many authors, so the major peaks of such concentrations can reasonably be expected to occur in different periods in different years depending on the specific meteorological conditions, especially during spring and summer.

Understanding the fluctuations of spore concentrations may be of value in the clinical management of allergies. It is possible to establish a preventive and appropriate strategy for allergy sufferers, encouraging, for example, the patients affected by oculorhinitis and bronchial asthma to spend the critical periods in locations where the spore concentration peaks are expected to be lower.

To this aim, a very simple model for the prediction of fungal spores was calibrated by Stephen et al. (1990). They combined an estimated diurnal rhythm with a simple, one-parameter time series model, providing a short-term forecast. A more sophisticated technique was adopted by Angelosante Bruno et al. (2007) to estimate the spore concentration from meteorological conditions using a neural network-based approach; they showed that the *Alternaria* and *Pleospora* concentrations can be obtained with high accuracy through a recurrent network using the daily average, minimum and maximum temperature, relative humidity, daily average wind speed, daily total precipitation and average surface wind speed as input variables. In the cited paper, it was seen that in the atmosphere of L'Aquila, the concentration of *Alternaria* spores increased from early April, with the maximum peaks (around 80 m^{-3}) occurring during the summer months, while the maximum concentration of *Pleospora* spores (about 40 m^{-3}) occurred during April, with only a few spikes observed during the summer months. The reproductive life cycles and

dispersal mechanisms of fungi through the atmosphere are related to meteorological factors, but the influence of the different factors varies depending on the fungal type.

In this work we used the complex neural device described by Angelosante Bruno et al. (2007) to predict *Alternaria* and *Pleospora* concentration from the MM5 meteorological forecast.

The paper is organized as follows: in the next section a quick description of the MM5 meteorological model is reported together with a discussion on the ability of the meteorological model to reproduce in a realistic way the meteorological variables recognized as critical for fungal spore growth and depletion. In Sect. 3, the main characteristics of the artificial neural network (ANN hereafter) based application for *Alternaria* and *Pleospora* concentration estimation are briefly given, and a short synthesis of the results of the previous work is also reported. In Sect. 4, the results obtained for the fungal spore prediction from meteorological variables are discussed. The future developments and applications of the proposed neural approach are also briefly discussed in the same section.

2 MM5 meteorological model forecast

The meteorological model used in this work is the non-hydrostatic version of the NCAR/Pennsylvania State University Mesoscale Model MM5. MM5 is a primitive equation, σ vertical coordinate model used by a broad research community for a variety of applications. It also includes a number of different options for physical parameterizations. MM5 has been operational for Central Italy since 1998; for the daily simulations the Kain–Fritsch cumulus cloud scheme (Kain and Fritsch 1990), along with an explicit cloud water/ice scheme (Grell et al. 1994), is used. Radiative transfer is represented by the simplified scheme described in Grell et al. (1994), and boundary layer physics is described by the MRF scheme (Troen and Mahrt 1986). For land surface processes the standard MM5 scheme is used in which the surface temperature is calculated via a force-restore method, and evaporation is computed using a fixed moisture availability parameter (the ratio of actual to potential evaporation) dependent on the surface vegetation type. A complete description of the model is beyond the scope of this paper; a

complete reference is given in Dudhia (1993) and Grell et al. (1994). The configuration used for the operational activities in Central Italy uses 24 unevenly spaced σ levels. All the simulations are driven by the ECMWF (European Center for Medium-range Weather Forecast) global analyses; forecast and boundary conditions are upgraded every 6 h, and no data assimilation is done during the operational runs. Figure 1 shows the model triple-nested domain used in the experiments. The outer domain covers Italy and the surrounding regions at a grid interval of 27 km; the intermediate domain covers central Italy at a 9-km grid interval, while the innermost domain encompasses the Abruzzo region at a 3-km grid interval.

The different domains are nested in a two-way mode, as described, for example, by Zhang et al. (1986). The MM5 model in the configuration described above is used for operational forecasts. Its performance in reproducing synoptic and mesoscale circulation over the region of interest here is discussed in Paolucci et al. (1999; see also <http://cete.mps.aquila.infn.it/mm52web>), and MM5 performance in reproducing thermally driven circulation in a region of complex topography with different planetary boundary layer (PBL) parameterizations has been investigated by Bianco et al. (2006), while Tomassetti et al. (2003) demonstrated the ability of the model to efficiently simulate the effects of land

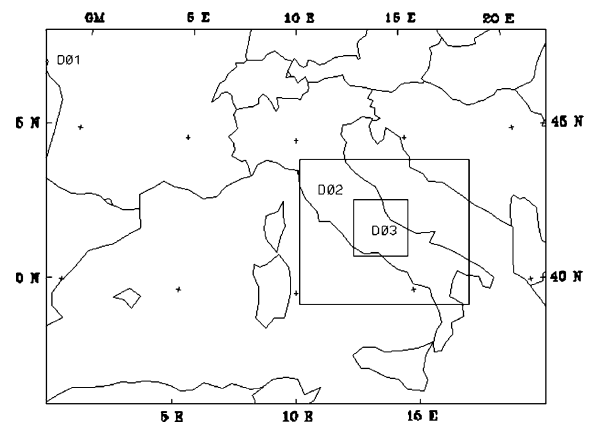


Fig. 1 Schematic view of three nested domains used for operational meteorological forecast in the Abruzzo region with a MM5 mesoscale model. The outer domain covers Italy and the surrounding regions at a grid interval of 27 km; the intermediate domain covers central Italy at a 9-km grid interval, while the innermost domain encompasses the Abruzzo region at 3-km horizontal resolution

use change on the hydro-meteorological cycle on the same Abruzzo region whose simulation is used in the present paper. Every day the first 24 h of a 72-h operational simulation are archived at hourly time steps for what concerns the main meteorological fields at the ground level, and this archive will be used for the discussion of the simulations that follows.

A first preliminary step consists of the validation of MM5 data. The time series of observed and predicted meteorological variables are then compared in the Figs. 2 and 3.

MM5 meteorological fields are defined on a 67×64 (latitude $\times$ longitude) grid of 3 km of horizontal resolution. From these fields the value in L'Aquila is established with a simple geometrical

interpolation weighting the four closest grid points with the inverse of the distance. In the three panels of Fig. 2, the daily maximum, minimum and average temperatures are compared, respectively. Daily minimum temperatures (Fig. 2a) range from -10°C in February to 15°C in summer, while the maximum (Fig. 2b) values are observed in the range of $5\text{--}30^{\circ}\text{C}$. The sequence of minimum temperature is quite well reproduced by the model, while the daily maximums are lightly underestimated with respect to the observed values. In fact, the bias is negligible (bias and other statistical indexes are defined in Sect. 4) for the minimum temperature. It is found to be -2.5°C , and the RMSE error is around 3°C for both time series. The correlation coefficient is over 90%. The average temperature variability (Fig. 2c) is well

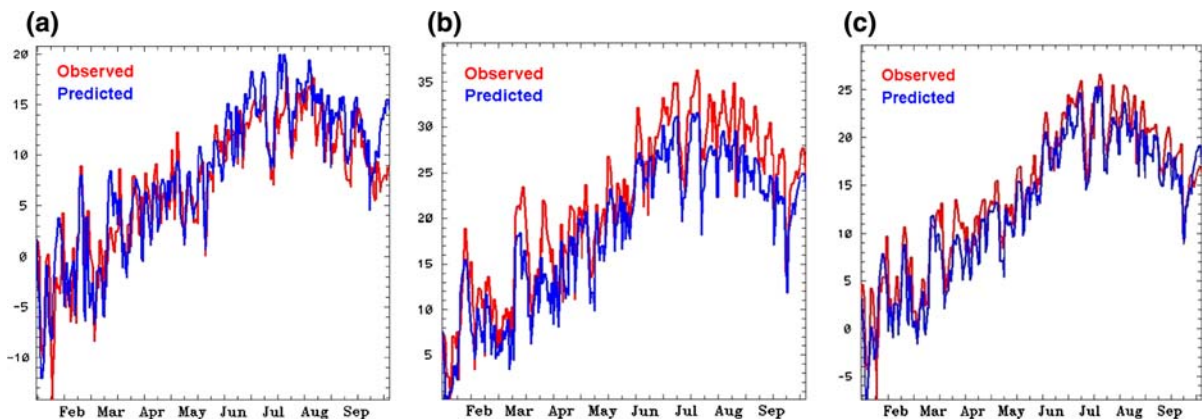


Fig. 2 Comparison of daily minimum (a), maximum (b) and average (c) temperatures in L'Aquila as observed (red line) and predicted (blue line) from the MM5 meteorological model from February to September 2004

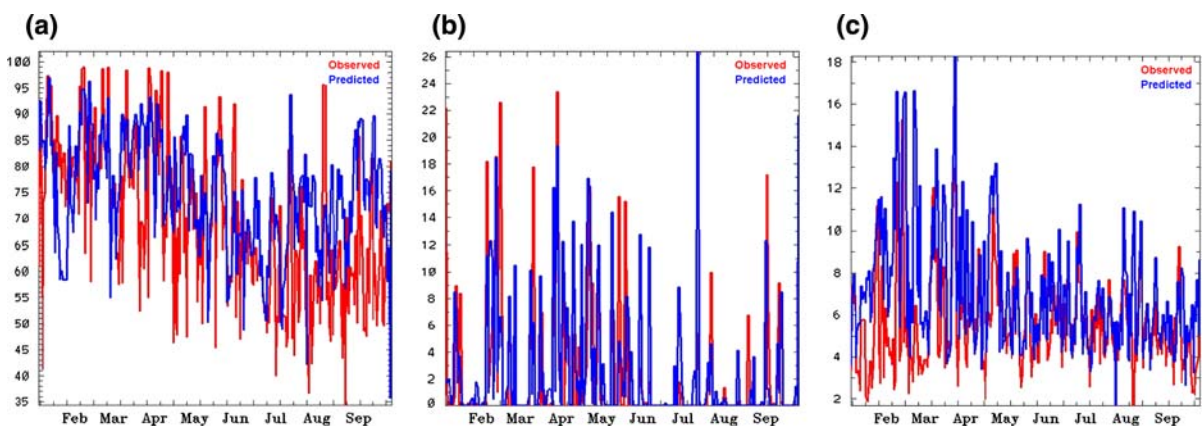


Fig. 3 Comparison of observed (red line) and predicted by MM5 (blue line) time series for daily average relative humidity (a), daily accumulated precipitation (b) and daily average ground wind speed (c)

reproduced with a small underestimation (bias is 1.5°C). The root mean square error is around 2°C, and the correlation is above 97%.

The same comparison is reported in Fig. 3, and the relative humidity in Fig. 3a, daily accumulated precipitation in Fig. 3b and daily average ground wind speed in Fig. 3c. The meteorological prediction of relative humidity is affected by a systematic error of about 5%, while the correlation is around 50%, and the root mean square error is 13.2%. Nevertheless, from Fig. 3 it can be seen that, also for this field, the seasonal variability is reasonably well reproduced, and the occurrence of the major peaks is also well captured.

The bias for the rainfall time series is negligible (less than 1 mm day⁻¹), while the root mean square error is 4.3 mm day⁻¹. For ground wind speed, the bias is about 1.5 km h⁻¹, and the RMSE is 3.0 km h⁻¹. These values are presented in Table 1.

The good performance of the MM5 meteorological model, shown in Figs. 2 and 3, makes it reasonable to use the predicted meteorological fields to estimate the spore concentrations for future time steps. It has to be observed that, in spite of the intrinsic uncertainty of any meteorological forecast, the neural approach is attractive for reducing the effect of such uncertainties. In fact, it has long been recognized that the neural networks are devices allowing the minimization of the propagation of errors (noise) affecting a single input parameter. In other words, because the spore concentration is estimated from the whole input pattern shown in Fig. 2, the presence of an error for a single input parameter will lightly affect the output of the network. This concept is linked to the feature that ANN represents a distributed device. For a more rigorous definition and discussion of this property, see Hecht-Nielsen (1991).

Table 1 Statistical errors for the prediction of daily meteorological parameters by the MM5 meteorological model

	RMSE	Bias	Correlation
Average temperature	2.4	1.5	97.0
Minimum temperature	3.1	-0.8	91.4
Maximum temperature	3.7	2.8	96.1
Relative humidity	14.9	-5.6	46.7
Accumulated precipitation	4.3	-0.4	51.1
Average wind speed	3.0	-1.5	41.7

3 Spore concentration estimation from observed meteorological parameters with a neural network approach

In a previous work (Angelosante Bruno et al. 2007), it was shown that a recurrent ANN architecture can be trained to map the complex relationship between meteorological conditions and spore concentration. The neural architecture used for this purpose is usually referred to as the Elman recurrent network (Elman 1990) and is schematically shown in Fig. 4.

The input layer is set with the normalized values of the daily minimum ($T_{\min}$), maximum ($T_{\max}$) and average temperature (T_{av}), the total accumulated precipitation (Prec.), the daily average for relative humidity (R. Hum) and wind speed (W. Speed). It is also assumed that the spore concentration depends on other heterogeneous seasonal factors, and, in order to take those factors into account, a sinusoidal function of the Julian day is also considered (Daylight in Fig. 4). Because of the different scales and value ranges, all the input/output variables are normalized according to:

$$x \rightarrow \frac{x_{\max} - x}{x_{\max} - x_{\min}}$$

where $x_{\min}$ and $x_{\max}$ are the minimum and the maximum value for each variable. The number of

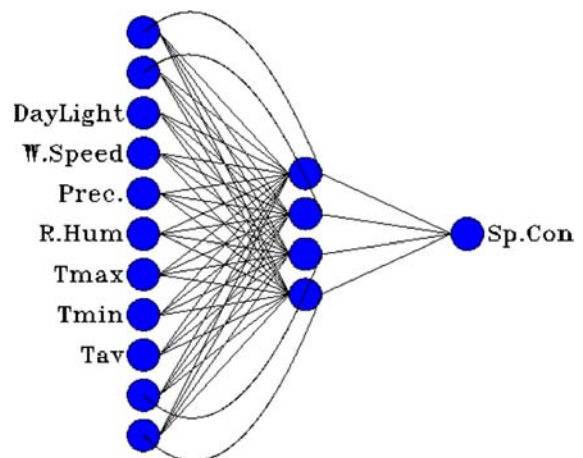


Fig. 4 Schematic view of recurrent neural network used for fungal spore prediction and estimation. Input variables are daylight, daily minimum ($T_{\min}$), maximum ($T_{\max}$) and average temperature (T_{av}), the total accumulated precipitation (Prec.) and the daily average for relative humidity (R. Hum) and wind speed (W. Speed)

neurons in the hidden layer is established with the constraint that the total number of weights of the network must be one order of magnitude lower with respect to the number of training patterns used to calibrate the network. For the architecture shown in Fig. 4, the total number of weights is given by:

$$11 \times 4 + 4 \times 1 = 48$$

The first 11×4 weights connect the first with the second layer; the other 4 weights connect the hidden and the output layers. The number of training patterns corresponds to the input/data set available for the network calibration, namely the number of daily observations of spore concentration and meteorological parameters. In our case about 280 training patterns are available corresponding to the daily observation from January to October 2004 (Angelosante Bruno et al. 2007). This condition is usually adopted (Lombladd et al. 1992) to avoid the problem of overtraining with respect to the simple multi-layer perceptron (for a general reference, see Hecht-Nielsen 1991). The recurrent architecture allows to implement a sort of dynamic memory, and then, in our application, the concentration of fungal spore is not simply determined by the single input pattern, but by a temporal sequence of meteorological patterns. To train the neural device a modified version of the Jetnet package (Lombladd et al. 1992) has been used; with respect to the original version of the package discussed by Lombladd et al. (1992), the possibility to use the recurrent neural architectures has been implemented. Angelosante Bruno et al. (2007) showed that such architecture is able to estimate the concentrations of *Alternaria* and *Pleospora* from the meteorological variables with high accuracy. Spore concentrations and meteorological variable measurements were collected in L'Aquila (Italy) from January to October 2004. L'Aquila is located in central Italy at latitude 42.355°N and longitude 13.395°E , at about 700 m above sea level. The concentration of *Alternaria* spores increased from early April, with the maximum peaks (around 80 m^{-3}) occurring during the summer months, while the maximum concentration of *Pleospora* spores (about 40 m^{-3}) occurred during April. The average concentration considering the whole observed time series is respectively 7.4 m^{-3} for *Alternaria* and 2.1 m^{-3} for *Pleospora* spores. As has been reported by Angelosante Bruno et al. (2007), the daily average spore concentrations have been

collected using a Hirst volumetric spore sampling (Lanzoni VPPS 2000) located ~ 20 m above ground level on the roof of the Faculty of Sciences at the University of L'Aquila. Daily data obtained from the sampler were read following the method recommended by the Italian Association of Aerobiology (I.A.A.) (Mandrioli 1994). The results obtained were a daily average, expressed as spore m^{-3} .

The statistical analysis of ANN performances showed the ability of the proposed technique to provide a good estimation of *Alternaria* spores with an average error of about 4 m^{-3} and also better performances for what concerns the estimation of *Pleospora* concentration. In this work we investigated the possibility of using the trained ANN to predict future spore concentrations from the MM5 meteorological forecast. The values of ANN input variables are obtained from MM5 predicted fields with a simple spatial interpolation from the meteorological model grid. In order to validate this hypothesis, we analyzed the performances of the neural model from January to October 2004, when the observed time series of different fungal spore were available.

4 Spore concentration prediction from meteorological forecast

The neural network shown in Fig. 4 and briefly described in the previous section was used to estimate the spore concentration of *Alternaria* and *Pleospora*. The neural model was calibrated with an observed time series, and the results of calibration and validation of the model were discussed in Angelosante Bruno et al. (2007). The weights characterizing the network used in this paper are the same obtained in the previous work. In this section we compare the results of this prediction with the actual concentration time series.

In order to quantitatively evaluate the performances of the neural model for the prediction of spore concentration, different statistical parameters were used. The bias is defined as

$$\sum_{k=1}^n (x_i - y_i)$$

where the vector x_i and y_i respectively represent the time series of predicted and observed concentration, and the sum is carried out over all the available

observations. The bias value allows us to highlight a systematic underestimation or overestimation of the predicted quantity. The root mean square error defined as:

$$\sqrt{\frac{\sum_{k=1}^n (x_i - y_i)^2}{n}}$$

is a measure of the average error affecting the prediction. Finally, the correlation coefficient of the two time series is calculated as:

$$\frac{\sum_{k=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{(\sigma_x^2 \sigma_y^2)}}$$

where σ_x and σ_y are the SD of two time series. An optimal value of this coefficient is 100 (perfect correlation), and the worst value is -100 (the two series are totally uncorrelated).

The comparison of predicted and observed *Alternaria* concentration time series is reported in the left panel of Fig. 5. The left panel shows the comparison with the prediction with 1 day of time lag. The occurrence of main peaks is well captured by the neural device, and also the high of the peaks is well predicted, especially for the summer season, while the high frequency variability during the spring season seems to be a little bit underestimated by the neural device. It is reasonable to think that this underestimation is probably linked to local meteorological variability that is not well reproduced by the meteorological model. In fact, the limited (3 km) horizontal resolution of the MM5 model has to take into account. The left panel shows the same comparison, but in this case the average concentration for the next 5 days has

been predicted. The peaks and the persistence of *Alternaria* concentration are well predicted as the average level of concentration during May and June. The statistical parameters for the neural predictor are presented in Table 2. In order to make the discussion complete, we also report the statistical errors associated with the estimation of spore concentration discussed in Angelosante Bruno et al. (2007).

The *Alternaria* concentration can be estimated using observed meteorological variables with an RMSE of 4.1 m^{-3} . The same concentration can then be predicted with 1 day of time lag using predicted meteorological variables with RMSE of 10.1 m^{-3} . For all the considered cases the BIAS is almost negligible, and this means that the neural model is not producing a systematic underestimation or overestimation of the concentration. Finally, the correlation coefficient is always very close or above 80% except for the case of 1-day prediction.

Another piece of evidence is that the performances of the neural model seem weaker for *Pleospora* than for *Alternaria*, while the results of the previous work (Angelosante Bruno et al. 2007) showed better performance for *Pleospora* than for *Alternaria*. This observation can be easily argued by comparing the performances of the network for the two spores from Table 2. The different performances of the neural model suggest that *Pleospora* spores are more critically linked to the meteorological condition, and therefore the same error in the meteorological forecast led to a greater error in the concentration prediction. Another technicality dealing with neural network theory could also explain the bad performances of the neural device for *Pleospora*: the

Fig. 5 Left panel shows the comparison of 1-day prediction (blue line) and observed (red line) concentration time series for *Alternaria* spores. Units are spore m^{-3} . The same comparison is shown in the right panel, but for the next 5-day average

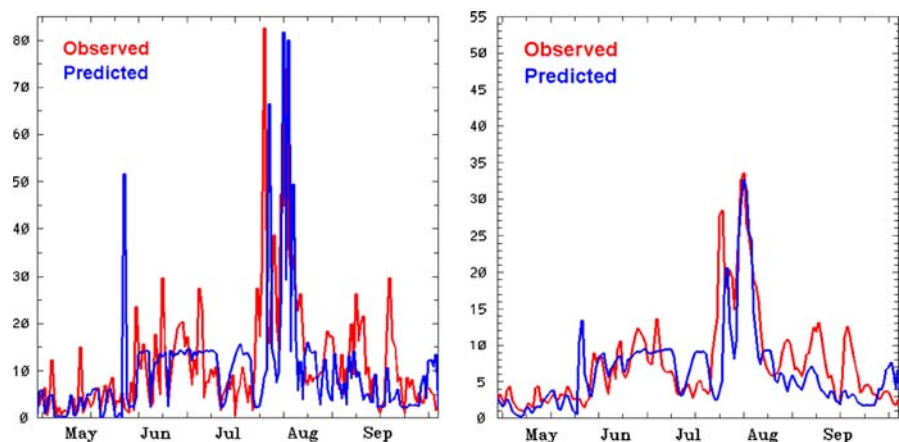


Table 2 Statistical errors for the prediction and estimation of *Alternaria* and *Pleospora* concentration 1 and 5 days in advances

	<i>Alternaria</i>			<i>Pleospora</i>		
	RMSE	Bias	Corr.	RMSE	Bias	Corr.
1-Day estimation	4.1	0.2	92.0	1.9	0.2	93.4
1-Day prediction	10.1	1.4	52.3	4.3	0.6	23.8
5-Day prediction	3.6	0.9	81.3	3.4	0.4	30.9

observed time series of concentration contains only a few spikes, while most of the values are about 10 spore m^{-3} . Therefore, the peak is not adequately represented in the training data set, namely during the training of the network, the ANN “sees” values greater than, say, 50 spore m^{-3} only a few times per more than 280 training patterns. Consequently, the ANN could be more specialized to predict “small” values of concentration in respect to the maximum values. At least two different approaches can be adopted to overcome these difficulties in a further refining phase of the neural device. The simplest approach is to use a longer time series (when available) of *Pleospora* concentration to recalibrate the ANN. A more sophisticated approach consists of the selection of training patterns with selective criteria in order use a flat distribution of concentration. This technique has been proposed and described by Tomassetti et al. (2009).

It is surprising to note from the detailed numerical analysis shown in Table 2 that the performance of the 5-day neural predictor is better than the performance of the 1-day predictor, but we have to remember that in the second case we are predicting the *average*

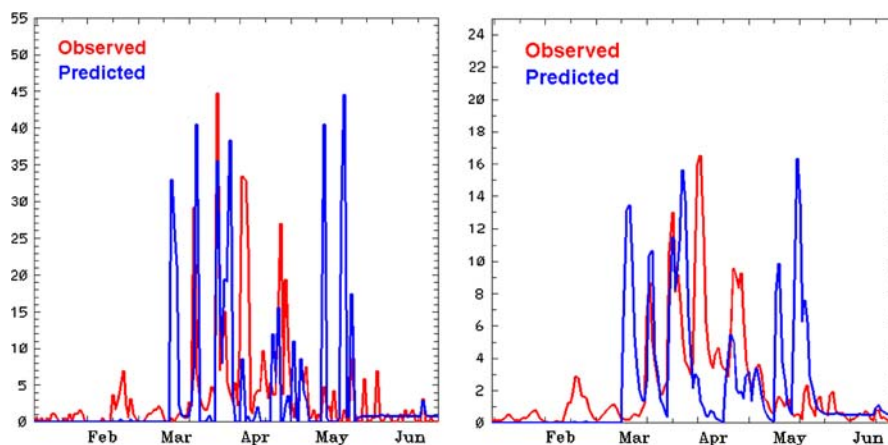
concentration in the next 5 days, and this appears *easier* for the neural device. In fact, from Fig. 6 it is also evident that the neural predictor is often not able to capture the high frequency variability (for example, an intense peak during only 1 day), and this is probably due to other local factors (not meteorological parameters) inducing a sporadic increase of *Alternaria* concentration.

Comparisons between observed and predicted concentrations for *Pleospora* spores and related statistical indexes are reported in the same Table 2. Both for 1- and 5-day predictions, the two curves are in reasonable agreement, but to a lesser extent. More specifically, it is likely that the predicted and not observed spikes are linked to the few situations for which the meteorological forecast is affected by a strong error. This is more evident if we see the overall performances of the neural device from the statistical indexes summarized in Table 2. For the *Pleospora* spores, the RMSE is around 4 m^{-3} , i.e., it is small if compared with the values of the peaks, while the BIAS is almost negligible.

These results allow us to conclude that the neural model can efficiently be used not only to estimate, but also to predict the future spore concentrations from observed or predicted meteorological variables.

A further interesting analysis is to investigate the relationship between the uncertainties in the prediction of spore concentration versus the error in the prediction of meteorological variables. This kind of comparison has been carried out for all the meteorological variables that are recognized to affect the spore concentration, namely all the input variables of the neural model, and both for *Alternaria* and

Fig. 6 Left panel shows the comparison of 1-day prediction (blue line) and observed (red line) concentration time series for *Pleospora* spores. Units are spore m^{-3} . The same comparison is shown in the right panel, but for next 5-day average



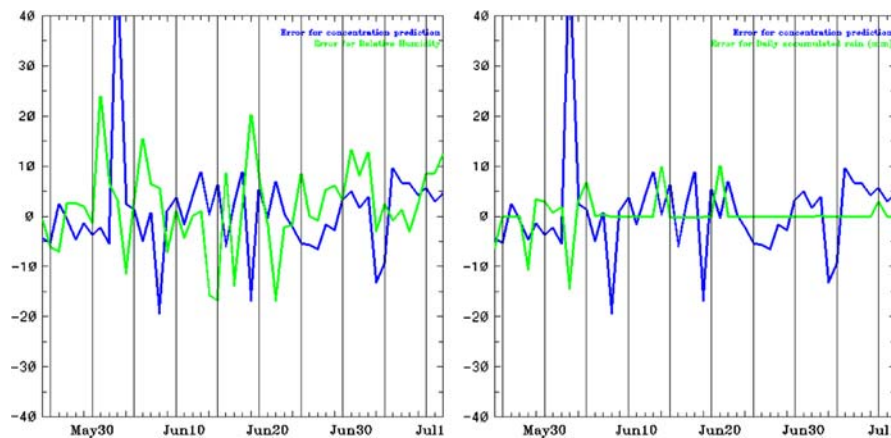


Fig. 7 Comparison between errors in the prediction of meteorological variables by MM5 meteorological model (green lines) and the error in the prediction of *Alternaria* spores from the meteorological variables by the neural model (blue lines). In the left panel the concentration errors are

Pleospora taxa. The most interesting results are shown in Fig. 7 where the sequence of errors for the *Alternaria* concentration prediction is compared with the differences between observed and predicted meteorological variables. The comparison is reported for relative humidity and daily accumulated precipitation. The panels of Fig. 7 seem to suggest mainly the hypothesis that the *Alternaria* spore concentrations are anticorrelated with the precipitation and relative humidity, in the sense that an underestimation (overestimation) of the precipitation or relative humidity leads to an overestimation (underestimation) of *Alternaria* spore concentrations.

5 Conclusion

A complex recurrent artificial neural network has been calibrated to estimate the concentration of two different spore taxa from meteorological parameters. The neural device can then be used to estimate the future spore concentration using as input the meteorological variables predicted by the MM5 meteorological model. The statistical analysis of ANN performances shows the ability of the proposed technique to provide better prediction of *Alternaria* spores with respect to the *Pleospora* spore concentrations. In any case, the results are encouraging for refining the neural methodology and the coupling of the MM5-ANN numerical model to investigate the

compared with uncertainties in the prediction of atmospheric relative humidity; in the right panel the comparison is reported with daily precipitation. The comparison suggest a possible anticorrelation between *Alternaria* spores and these atmospheric variables

possibility of an operational prediction of these two spore taxa using meteorological forecasts. Of course, it cannot be directly supposed that the proposed technique will allow a realistic prediction of spore concentrations for other locations in central Italy where the neural device has been calibrated. Nevertheless, it could be interesting to verify this, and then we strongly encourage other researchers to ask the authors of this paper for the calibrated neural tool to verify the ANN performances using other observed meteorological and spore concentration time series.

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