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Spatial interpolation of current airborne pollen concentrations where no monitoring exists

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A B S T R A C T

Background: Pollen is naturally emitted and is relevant for health, crop sciences and monitoring climate change, among others. Despite their relevance, pollen is often insufficiently monitored resulting in a lack of data. Thus, spatial modelling of pollen concentrations for unmonitored areas is necessary. The aim of this study was to develop an automatic system for calculating daily pollen concentrations at sites without regular pollen monitoring.

Method: We used data from 14 pollen taxa collected during 2015 at 26 stations distributed across Bavaria, Germany. The proposed system was based on the Kriging interpolation method to spatially model pollen concentrations for unmonitored areas, in combination with regression of environmental parameters. The method also took into account weather effects on daily pollen concentrations.

Results: An automatic system was developed for calculating current pollen concentrations at any location of the county. The results were displayed as daily pollen concentrations per m^3 in maps of 1 km^2 resolution. The models are trained automatically for every day by using the pollen and weather inputs. Automatic inputs will increase the usability of the model. In 50% of the cases, Gaussian Kriging was selected as the optimal model. An R^2 of 0.5 is reached in external validation without considering the effect of the weather. An R^2 of 0.7 is reached after considering the effect of daily weather parameters.

Conclusions: A fully automatic pollen network (ePIN) was built in Bavaria during 2018 that delivers data on-line

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without delay. The proposed method allows for a comparably small number of automatic devices per study area, but still providing information on pollen on any location in the study area.

1. Introduction

Many environmental parameters are routinely monitored worldwide (Casazza et al., 2018; Li et al., 2017). Pollen monitoring is especially important for society due to the critical impact on public health but also in other sectors such as agronomy, forestry or ecology. Climate change has potential effects on vegetation and this is also increasing the impacts of pollen on human societies (Bisbis et al., 2018). Although pollen is a natural pollutant, it can also be considered as anthropogenic due to human influence on pollen emission (Crenna et al., 2017). Furthermore, anthropogenic sources of pollen, such ornamental plants or crop fields, impact the biological content of the air (Cariñanos et al., 2017). A recent discovery point out to pollen as the main vector for airborne endotoxins (Oteros et al., 2018).

Modelling of pollen data is necessary because global comprehensive spatio-temporal monitoring is not possible. Scientific modelling tries to explain most of the variability by using the simplest mathematical complexity. For modelling, the dependent variable is related to a mathematical function often including other parameters easier to measure (independent variables). The variability of some phenomena shows well defined patterns through time or space, in those cases time or spatial position are valuable independent variables too. Modelling let us understand the dependent variables and enables the estimation of pollen concentrations at unmonitored locations or time intervals.

Spatially, a high resolution monitoring of regionalized parameters has only recently been possible by using remote instrumentation (e.g. satellites or unmanned drones). However, just a few environmental parameters can be accurately monitored by using this technology (Fishman et al., 2003; Running et al., 2004; Yang et al., 2017). Additionally, the resolution of monitoring can still be improved. Thus, most of regionalized variables are being monitored at local stations by using ground-based technologies. The interpolation of values between measuring stations is a historical issue in environmental monitoring (Bargaoui and Chebbi, 2009; Hengl et al., 2009).

Although some environmental parameters such as temperature have been historically spatially interpolated with high precision, this is not the case for most other parameters. The main reasons are the lack of monitoring stations or the complexity of the modelling process. In the case of airborne pollen, stations are few due to the laborious, manual and, hence, highly resources demanding methods: https://www.zaum-online.de/pollen/pollen-monitoring-map-of-the-world.html (Buters et al., 2018). For pollen monitoring, a special scientific device is needed to collect airborne pollen grains, followed by manual and microscopic analysis. (CEN/TS-16868, 2015). The process is laborious and time consuming, and requires experienced personnel (Galán et al., 2014). Because of this, global monitoring of pollen is unlikely and geostatistical models are necessary for determining pollen concentrations at unmonitored areas. Up to date, different versions of spatial interpolation and regressions were used for flowering or pollen spatial analyses (Aguilera et al., 2015; Garcia-Mozo et al., 2006; Rojo et al., 2016; Rojo and Perez-Badia, 2015). Very often, the density of actual pollen monitoring stations is not enough to perform accurate interpolations. In Europe, automation in airborne pollen monitoring has recently been established (Crouzy et al., 2016; Oteros et al., 2015). Automation increases the amount of available information with minimal cost and effort, allowing for application of more complex interpolation.

It is often necessary to obtain the data with a time resolution bigger than that monitored. Downscaling of independent variables is necessary in areas like field phenology (Oteros et al., 2013), meteorology (Young et al., 1998) or even for pollen data (Orlandi et al., 2014). Modelling is also necessary when we need to perform projections of conditions during unmonitored periods in the both directions: past and future (Graumlich, 1987; Radic et al., 2014). In the case of airborne pollen, long term modelling has been previously conducted (Laaidi et al., 2003; Orlandi et al., 2006; Ribeiro et al., 2006; Rojo et al., 2017; Sikoparija et al., 2017). Pollen long term modelling is used for agronomy or

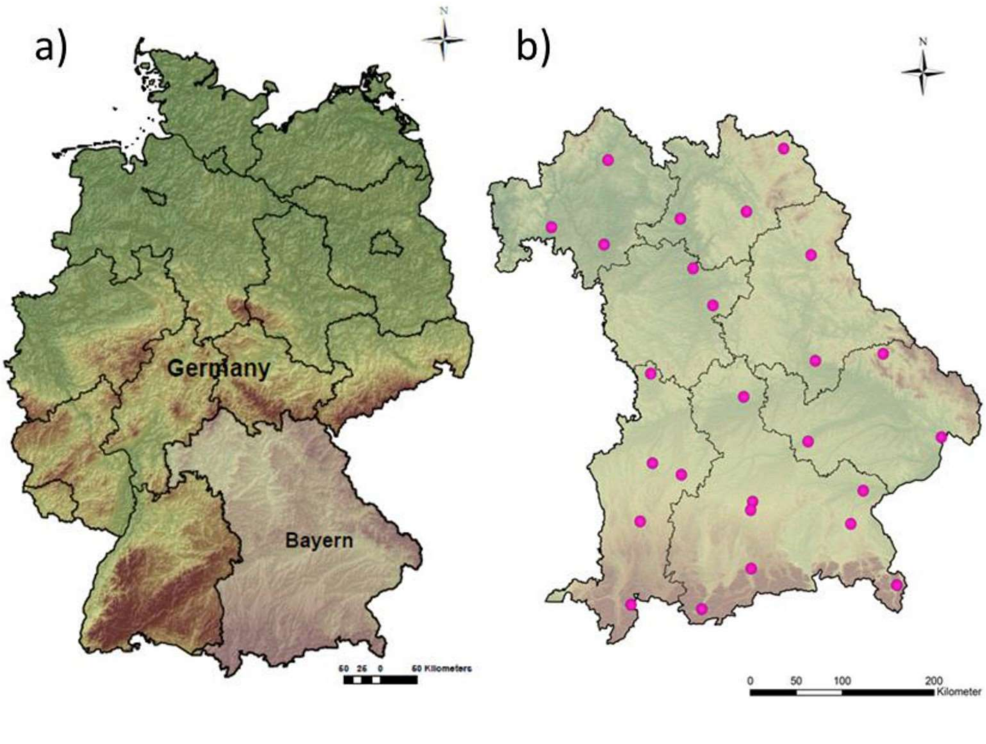

Fig. 1. Bavaria (Germany). Pollen monitoring locations in Bavaria only.

climate change studies (Damialis et al., 2007; De Linares et al., 2017; Oteros et al., 2014). Pollen short term modelling is used to forecast pollen/spores concentrations (Norris-Hill, 1995; Sadyś and West, 2017; Sánchez-Mesa et al., 2002). Ultimately, pollen data are widely used by physicians and allergy patients for allergy prophylaxis (de Weger et al., 2013; Traidl-Hoffmann et al., 2003).

Many methods have been applied for modelling daily and hourly pollen concentrations, e.g. different kind of regression, artificial neural networks (Kasprzyk, 2006; Rodriguez et al., 2010). For short-term modelling, the autocorrelation function information of the pollen time series has been reported as the most valuable parameter for forecasting (Fernández-Rodríguez et al., 2018; Matyasovszky and Makra, 2011; Rodriguez-Rajo et al., 2006). In addition, other automated systems based on the input of pollen measurements have been developed (Hidalgo et al., 2002; Turner et al., 2006). However, the difficulty for displaying pollen measurements with a short delay make the models difficult to apply. This is an important reason why most of pollen models are not assimilation based systems. Usually, forecasting systems are based on modelling the parameters involved in pollination without assimilation (Sofiev et al., 2006, 2015; Vogel et al., 2008; Zink et al., 2012).

Pollen information can be displayed with three levels of uncertainty:

a. Real pollen concentrations measurement at static locations.

b. Pollen concentrations at locations without real pollen measurements but estimated from known actual concentration from surrounding stations. This second level of uncertainty is only estimating pollen concentration in the space but not predicting in the future.

c. Pollen forecast for future conditions. This forecast contains the highest uncertainty because the displayed information is based on unknown future conditions.

The aim of this study is to develop a system for the estimation of airborne pollen at unmonitored sites (displaying the second level of uncertainty), trained for the state of Bavaria (Germany). The system is based on a model that uses real pollen data and environmental conditions and extrapolates these data to unmonitored sites. The system aimed an automatic, on-line and accurate estimation of daily pollen concentrations in unmonitored areas, by applying a geospatial model based on spatial interpolation and influence of the weather.

2. Material and Methods

2.1. Study area and data

Bavaria is the biggest state of Germany, in the south of the country, near the Alps. The surface of Bavaria comprises 70.553 km^2 and the most distant locations are more than 400 km apart (Fig. 1). Bavaria is heterogeneous in terms of emission sources of pollen, climatic conditions and of topography, and this heterogeneity makes pollen forecasting complex. There is significant rainfall throughout the year, being maximum in the Alpine region (Zugspitze 2656 m a.s.l. with an annual total precipitation of 2071 mm, on average; DWD, reference period 1981–2010) and minimal in the northwest (Würzburg 177 m a.s.l. with an annual total precipitation of 601 mm, on average; DWD, reference period 1981–2010) and minimal in the northwest (Würzburg 177 a.s.l. with an annual mean precipitation of 601 mm; DWD, reference period 1981–2010). Bavaria has a temperature gradient from northwest to south (Würzburg annual mean temperature of 9.6 °C; Munich annual mean temperature of 8.7 °C; Zugspitze in the Alps has one of the most extreme conditions: annual mean temperature of −4.3 °C, DWD, reference period 1981–2010). For a better understanding of climatic conditions see Supplementary Fig. S1 (Hijmans et al., 2005).

We describe a system for performing automatic and on-line pollen forecast based on input data about pollen concentrations at different monitoring stations (using the same time frame, the forecast is not done in time but in space) and rainfall data. The training of the system was performed using data from the year 2015 and altitude. For the training, gridded daily rainfall data from the study period in Bavaria were obtained from E-OBS dataset (Haylock et al., 2008).

Table 1
Pollen monitoring locations included in the study. Monitoring stations were set-up using fixed criteria (homogeneous conditions, see methods).

City	Longitude º	Latitude º	Altitude (m a.s.l.)
Altötting	48.23	12.68	398
Augsburg	48.33	10.9	497
Bamberg	49.9	10.89	238
Bayreuth	49.94	11.53	419
Berchtesgaden	47.64	13.01	573
Munich	48.16	11.59	510
Donaustauf	49.04	12.21	425
Erlangen	49.60	11.01	284
Feucht	49.38	11.2	365
Gaissach	47.75	11.58	717
Garmisch-Partenkirchen	47.49	11.1	821
Hof	50.32	11.9	531
Kitzingen	49.74	10.14	246
Kösching	48.82	11.51	391
Landshut	48.54	12.14	397
Marktheidenfeld	49.85	9.624	216
Mindelheim	48.04	10.49	610
Munich	48.13	11.56	538
Münnerstadt	50.2	10.2	347
Oberjoch	47.52	10.4	870
Oettingen	48.96	10.6	431
Passau	48.56	13.44	318
Trostberg	48.03	12.56	483
Viechtach	49.08	12.87	459
Weiden	49.68	12.17	403
Zusmarshausen	48.4	10.61	483

Airborne pollen was collected at 26 monitoring stations distributed over the area (Fig. 1). These stations ran during 2015 in frame of the building of the electronic Pollen Information Network (ePIN) in Bavaria, Germany (Buters and Oteros, 2015; Oteros et al., Under review). Monitoring stations were located under homogeneous conditions, meaning: 1) on a flat and horizontal surface, 2) at a height of 9–15 m from the ground (on a roof or an elevation tower), 3) with no roofs and other wind walls that are higher than the station within a proximity of 200 m, 4) at least 2 m away from the edge of a building, and 5) pollen monitoring device elevated 150 cm above ground on the rooftop, following the minimum recommendations for Aerobiology (Galán et al., 2014). For detailed information about the monitoring network, see Oteros et al. (Oteros et al., Under review). The exact location of each monitoring site is shown in Table 1.

For each location and pollen type, pollen data were expressed as daily concentrations: pollen grains/m^3 of air during a 24 h period (from 0:00 h to 23:59 h). Samples of airborne pollen (microscope slides) were all prepared at a central laboratory thus evading heterogeneity. The whole process followed the minimum recommendations for Aerobiology (Galán et al., 2014). Pollen analysis was decentral and performed following CEN norms (CEN/TS-16868, 2015). Pollen data collection was subjected to an external independent quality control process (Smith et al., Under review).

In the proposed model we estimate daily pollen concentrations at unmonitored sites by cokriging. The daily effect of weather was taken into account for forecasting pollen concentrations over the whole surface by the development of a three-steps method: 1. Subtracting the effect of weather to each delivered data, trying to produce an interposable database with homogeneous conditions (the expected pollen without rainfall). 2. Applying a cokriging method to the homogenized database. And 3. Subtracting the rainfall effect, from the interpolated values.

2.2. Cokriging model

Geographical interpolation was based on cokriging method, using elevation above sea level (alt) over the whole study area as co-predictor. Kriging is a probabilistic method for modelling a variable in space, in which the values for a variable at sites with unknown values are estimated from a model constructed using data from sites with known values and their relationship related with space.

An automatic fixing method for daily Kriging of each pollen type was applied, in order to create an automatic system able to perform outputs from automatic continuous inputs. Elevation was taken into account as the only covariable.

The parameters automatically fixed in the cokriging were: model method, sill, range, kappa and nugget effect. Tested model methods are: Exponential, Gaussian, Linear, Mathematical and Spherical. The automatic fixing method is based on finding the best fitting function in the experimental variogram being the one with the smallest residual sum of squares (RSS). The model fixing and grid processing in the system is performed by using a combination of different R packages: “gstat” “sp”, “raster”, and “geoR” (Hijmans and van Etten, 2014; Pebesma, 2004; Pebesma and Bivand, 2005; Ribeiro Jr and Diggle, 2015).

2.3. Rainfall effect

After performing cokriging, the cross validation error was calculated. The residual in full cross validation is the observed minus the expected value at that position, in full cross validation that position is excluded for training the model.

The rainfall effect was calculated by linear regression between the cokriging full cross validation residuals and daily precipitation. Most of the negative residuals were related with rainy days (rainfall was related with lower pollen). A model for each pollen type was developed for calculating the rainfall effect. The residuals of the cokriging (r) can be decomposed in two components: observed pollen (*P*) and expected pollen from cokriging cross validation (*EC*), equation (1).

$$r_i = P_i - EC_i \tag{1}$$

To explain r, we introduced in the model the effect of the daily rainfall. The linear model explaining observed pollen from expected pollen and amount of rainfall (*Rf*) follows equation (2).

$$P_{k,l,n} = EC_{k,l,n} - \beta_k * Rf_{l,n} * EC_{k,l,n} \tag{2}$$

Where “B” is the rainfall effect which is a constant for each pollen type found with the solution of the linear equation (2) by least squares method between P and EC, “*k*” is the pollen type, “*l*” is the location, “*n*” is the day. is the daily rainfall (mm) of the location “*l*” and during the day “*n*”.

In order to include the effect of rainfall on our predictions, we designed a three-steps method. This three-steps method is based on the penalization of predicted values based on the rainfall effect and the amount of rainfall:

a. Artificial increasing pollen loads in situations of precipitation by adding the rainfall effect (summation of observed pollen value plus the result of multiplying the amount of rainfall and the rainfall effect and observed pollen value). With this step we emulate pollen concentrations under homogeneous weather conditions in all locations (no rainfall conditions). This emulated variable is termed homogenized pollen concentrations (H). This step is performed by applying equation (3) to observed pollen (P).

$$H_{k,l,n} = P_{k,l,n} + \beta_k * Rf_{l,n} * P_{k,l,n} \tag{3}$$

where “B” is a constant calculated at equation (2). Note that, under conditions of no rainfall ($Rf_{l,m} = 0$), homogenized pollen ($H_{k,l,n}$) is equal to observed pollen ($P_{k,l,n}$).

b. then we perform the cokriging of homogenized concentrations, with the aim of obtaining a prediction of pollen in the whole surface of studied area. At this step, we get expected pollen (EH) for all sites from the whole Bavaria under homogeneous non-rainy days.

c. Finally, we include the effect of rainfall by applying equation (4). At this step we are calculating expected real pollen concentrations (E) by applying a penalization to the expected pollen (EH) depending on precipitation.

$$E_{k,l,n} = \frac{EH_{k,l,n}}{1 + (\beta_k * Rf_{l,n})} \tag{4}$$

where E is expected pollen concentration and EH is the predicted by cokriging of homogenized concentration. Note that, under conditions of no rainfall ($Rf_{l,m} = 0$), homogenized expected pollen ($EH_{k,l,n}$) is equal to expected pollen ($E_{k,l,n}$).

2.4. Validation

The validation of the geostatistical model were performed in three ways: 1) Internal validation of the cokriging before the application of rainfall effect, calculating R^2 and RMSE of the model. 2) A full cross validation of residuals before the application of rainfall effect, calculating Q^2. 3) A full cross validation of residuals after applying rainfall effect (Rfe) corrections, calculating Q^2 Rfe and RMSE Rfe. The Root Mean Square Error (RMSE) is calculated by following equation (5). The method for full cross validation is the leave-one-out cross-validation (LOOCV) method.

$$RMSE = \sqrt{\frac{\sum (Observed - Expected)^2}{n}} \tag{5}$$

All the analyses were performed by using R statistical software (R-Team, 2013).

3. Results

The kriging of daily pollen concentrations in combination with a regression of environmental parameters (rainfall and altitude) was applied for performing an interpolation of pollen concentrations across Bavaria. In order to produce automatic outputs from automatically measured pollen data, an algorithm was applied for automatically fixing the parameters of the model by weighted least-squares. Table 2 shows the kind of interpolation model selected by the system. Of all models, the Gaussian model showed the best correlations. Exponential and Mathematical models interpolated pollen with a lower correlation.In Table 3 we show the summary statistics of the co-kriging (including altitude as co-variable) for each pollen type. First, the training of the co-kriging models was performed, including altitude as predictor.

Table 2
Frequencies of interpolation models (covariance functions) used for universal Kriging. Number of days during 2015 pollen season included in the analysis (N). From 20 to 26 pollen stations are used for each day, depending on missing data.

Pollen	Kriging model (%)					N
	Exponential	Gaussian	Linear	Mathematical	Spherical	
Alnus	2.4	68.3	7.3	7.3	14.6	41
Ambrosia	8.7	73.9	8.7	4.3	4.3	23
Artemisia	6.5	58.1	12.9	9.7	12.9	31
Betula	14.1	64.1	6.4	3.8	11.5	78
Carpinus	9.7	54.8	16.1	6.5	12.9	31
Cupressaceae	9.7	47.2	16.7	9.7	16.7	72
Fraxinus	4.4	48.9	20.0	6.7	20.0	45
Picea	10.6	46.8	10.6	10.6	21.3	94
Pinus	13.2	62.0	8.3	8.3	8.3	121
Plantago	2.8	33.9	43.1	1.8	18.3	109
Poacea	16.1	46.6	8.5	17.8	11.0	118
Populus	5.4	48.6	18.9	13.5	13.5	37
Tilia	3.9	9.8	66.7	2.0	17.6	51
Urticaceae	16.5	37.6	11.0	10.1	24.8	109

Table 3
Summary statistics of interpolation model for each pollen type: Universal Kriging using altitude as co-variable. Determination coefficient (R^2); Root Mean Squared Error of internal validation (RMSE); Determination coefficient of external full cross validation (Q^2); Rainfall effect by lineal correction of errors (in equation (2)); Q^2 after rainfall effect (Rfe) correction (Q^2 Rfe) and RMSE after rainfall effect correction (RMSE Rfe).

Pollen	Models without Rainfall			Models with Rainfall effect		
	R^2	RMSE	Q^2	Rainfall effect	Q^2 Rfe	RMSE Rfe
Alnus	1.00	3	0.38	0.06	0.50	44
Ambrosia	0.66	1	0.03	0.07	0.53	2
Artemisia	0.90	1	0.23	0.10	0.48	2
Betula	0.98	36	0.47	0.03	0.60	197
Carpinus	0.53	18	0.39	0.06	0.52	20
Cupressaceae	0.56	93	0.10	0.12	0.59	101
Fraxinus	0.91	36	0.49	0.36	0.66	82
Picea	0.97	8	0.52	0.03	0.66	31
Pinus	0.99	23	0.37	0.05	0.58	169
Plantago	0.53	3	0.18	0.06	0.55	4
Poacea	0.93	11	0.53	0.05	0.69	29
Populus	0.93	10	0.10	0.12	0.38	36
Tilia	0.07	16	0.00	0.18	0.33	15
Urticaceae	0.95	10	0.38	0.05	0.62	37

The frequency of each fitting function is shown in Table 2 and the result of internal validation, where most of the pollen types showed high R^2, is presentedin Table 3. *Tilia* pollen shows a low determination coefficient, which means that it cannot be interpolated by this method. Then, in Table 3, Q^2 is the determination coefficient of external full cross validation (training the system with all monitoring locations excluding the one to be validated, and with the same process being repeated for each pollen type). To increase the precision and robustness of the system, the effect of rainfall was taken into account. The rainfall effect in Table 3 (Rainfall effect) stands for the capacity of rainfall to reduce airborne pollen concentrations, and it was calculated by the regression between the co-kriging residuals and daily rainfall (as explained in Material and Methods). We observed a negative effect for all pollen types, with increased rainfall always associated with a reduction of daily pollen concentration. The highest effect was observed for arboreal taxa (*Fraxinus*, *Tilia*, *Cupressaceae* and *Populus*). Finally, in Table 3, columns "Q^2 Rfe" and "RMSE Rfe" show the performance of the external validation of the combined model of co-kriging with altitude as predictor and the rainfall effect. The highest RMSE values were observed for the most abundant pollen taxa, *Betula* and *Pinus*.

As can be seen in Fig. 2, the sampled conditions of the network are balanced. The variability of environmental parameters over the interpolated surface is similar to the conditions at the sampling sites, i.e. the Gaussian distribution of the parameters altitude, rainfall and temperature of the pollen sampling sites was similar to the Gaussian distribution for the whole of Bavaria. This means that the monitoring stations are properly distributed over the area and all the climatic situations are properly covered, allowing the extension of the model to unmonitored areas.

Our calculations resulted in the interpolation of daily pollen concentrations over the whole surface of Bavaria. Fig. 3 shows an example of a time series of the outputs of the system during nine continuous days within the grass pollen season. For a dynamic visualization please visit:

https://oteros.shinyapps.io/Pollen_season_Bayern/

4. Discussion

There are numerous methods for spatial interpolation of environmental parameters (Li and Heap, 2008). They can be classified in three categories: Non-geostatistical methods, geostatistical methods and combined methods. Non-geostatistical methods are based on numerical interpolation of values or in the relationship between variables, but they are not based on the spatial autocorrelation of the interpolated variable. Statistical methods are based on the autocorrelation over the space of the modelled variable, these methods come from the work of Krige (1951), and they termed "Kriging" methods. We can find numerous versions of both, univariate Kriging and multivariate Kriging (when other variables are used as predictors). The combined methods are a combination of statistical and non-statistical methods. In the current work, we have developed a new version of the combined method by joining a multivariate Kriging (Cokriging of pollen concentrations, using altitude as co-variable) by adding the effect of rainfall calculated by least squares method.

We selected Cokriging as interpolation method due to the need to combine spatial autocorrelation of pollen with another covariable identifying areas with similar emission states. Altitude has been selected as an environmental covariable in view of its considerable influence on flowering phenology of the modelled area; being highly correlated with the temperature, the main driver of phenology (Ziello et al., 2009) and as the best predictor of species distributions for

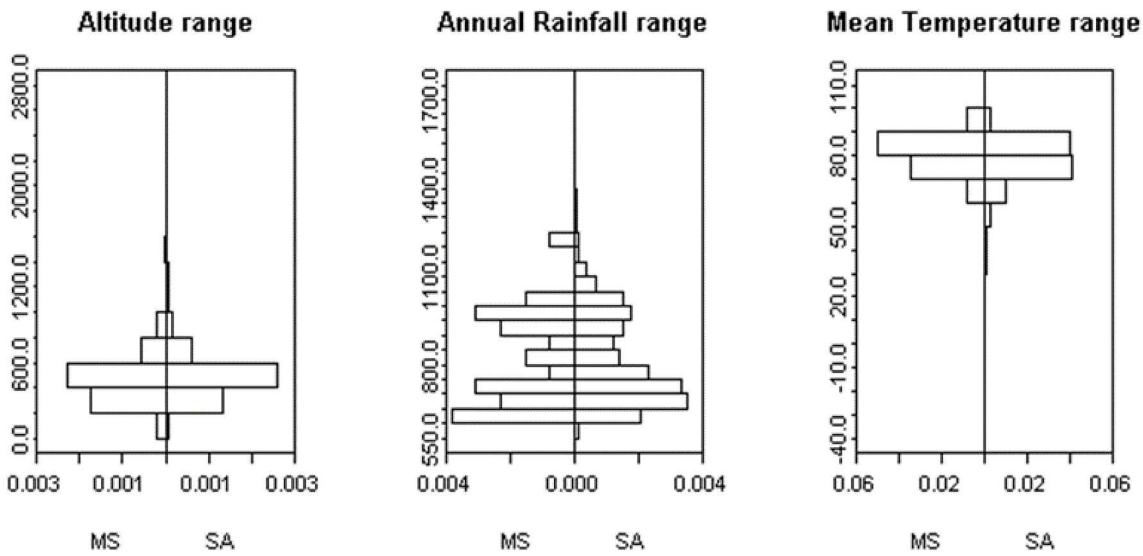

Fig. 2. Studied range of environmental conditions over the 26 monitoring stations (MS) and over the study area (SA), Bavaria (Germany). Variables: Altitude (m.a.s.l.), Annual rainfall (mm) and Annual Mean Temperature (ºC*10).

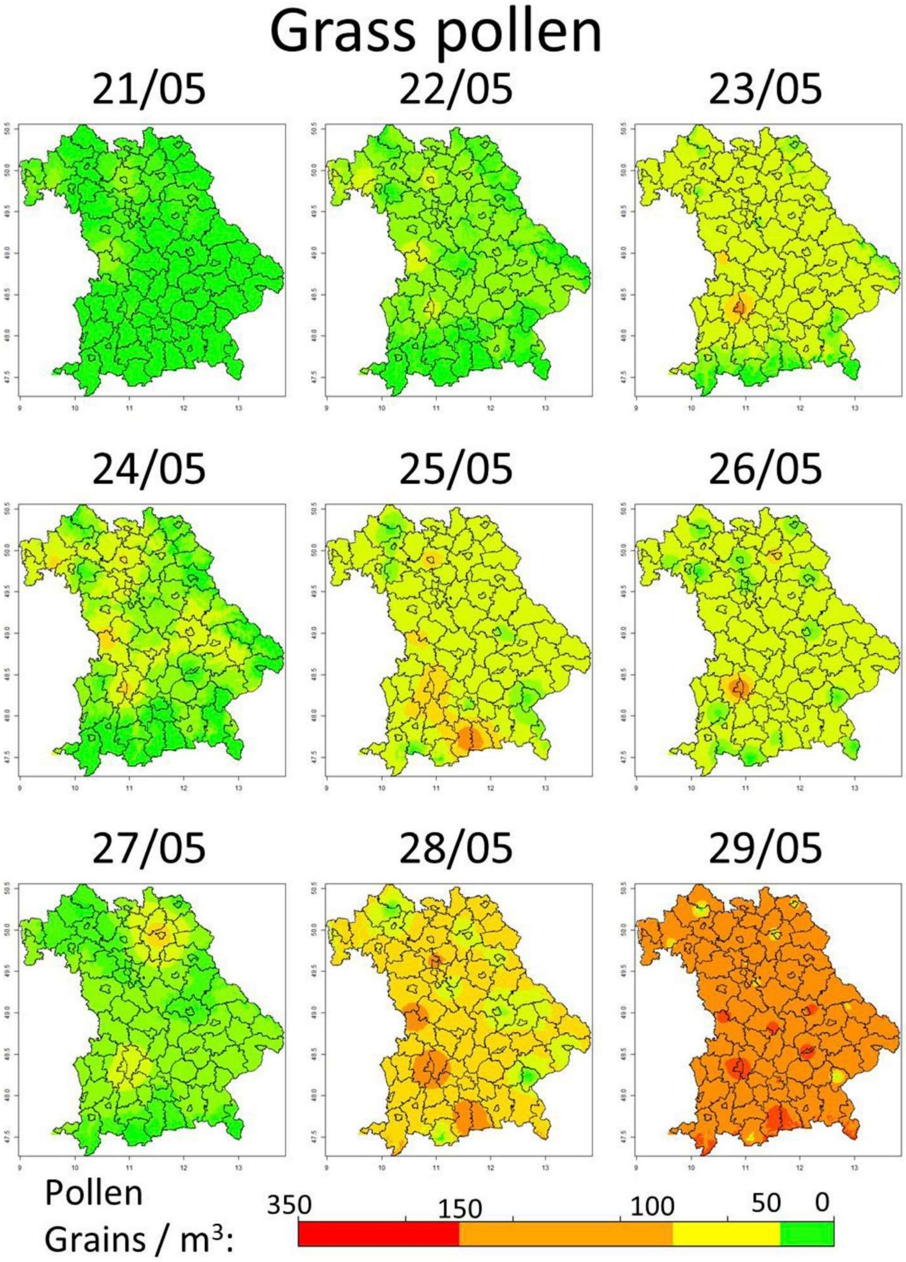

Fig. 3. Sequence of Poaceae pollen concentrations at Bavaria during 9 consecutive days of the beginning of the 2015 pollen season (21/5–29/5). The sequence has been calculated by applying the automatic system.

homogeneous longitudinal distributed areas (Austin, 2002), in this sense also influencing pollen emission sources.

We have further improved the quality of Cokriging by including the effect of rain. Rainfall is the main weather factor affecting daily variations in airborne pollen during the flowering season (Makra et al., 2014; Sadys et al., 2016). Bavaria is a region with significant rainfall, even during the driest season. Here we developed a new way to include the effect of rainfall by applying a penalty to the amount of pollen depending on the amount of rainfall and the effect of rainfall per pollen type (i.e. each pollen type reacts differently to rainfall).

Other weather parameters such as wind or temperature were not taken into account. Temperature is a very important parameter for the emission process and it is closely related with pollen concentrations (Fernández-Rodríguez et al., 2016). In the long term, temperature determines the timing of the year of flowering season and in the short time, temperature determines the moment of the day when pollen is emitted. However, we are using actual measured pollen concentrations from the surroundings as the main predictor in our model with a time resolution of one day. Actual pollen concentrations are already replacing the information that temperature gives about phenological state. In the case of wind, this is an essential parameter for understanding pollen concentrations (Maya-Manzano et al., 2017; Rios et al., 2016). We are working with daily pollen concentrations; this parameter should be interpreted as the averaged concentration of airborne pollen at a site during 24 h. A pollen plume can move hundreds of kilometers during one day and it could pass the whole Bavaria just in hours (Sofiev et al., 2013). In this sense, wind is essential for understanding airborne pollen at hourly resolution but less relevant at daily resolution, once we know pollen concentrations at the surrounding measuring stations. Furthermore, the effect of wind on transport and emission is also supplied from the knowledge of actual pollen from surroundings locations.

Our results show that the Gaussian model interpolates the measured values bests. This means that the daily pollen concentrations do not have abrupt variations over the whole region between close locations.

On the other hand, Exponential and Mathematical models were the less suited, meaning the same: seldom abrupt changes in daily concentrations between close sites. By analyzing the determination coefficient, *Tilia* pollen had the lowest coefficient and cannot be properly interpolated by our model. *Tilia* pollen belongs to ornamental trees, whose concentrations depend on isolated local sources and probably with high human intervention when in urban green areas. Hence, a spatial interpolation of such a pollen type is somewhat expected to be highly varying and unpredictable.

We observed the biggest rainfall effect in arboreal species (*Cupressaceae*, *Fraxinus*, *Populus*). Rainfall reduced the concentrations in all pollen kinds, in agreement with other authors (Dahl et al., 2013).

From the 27 stations distributed over Bavaria we worked with only 26. The one station excluded was special because of its extreme conditions as it is the highest scientific observatory of Europe (UFS, http://www.schneefernerhaus.de/startseite.html) located at the top of the mountain Zugspitze in the Alps at 2656 m a.s.l. (Jochner et al., 2012). Being an ecological cutting site, this station was not included in the study. We observed that the environmental conditions at the used 26 monitoring sites were similar to the general conditions of Bavaria (see Fig. 2).

The current work provided an accurate system for the interpolation of daily pollen concentrations at unmonitored sites. Daily pollen concentrations were calculated by the average of a wide range of conditions during 24 h. Daily concentrations have a high spatial autocorrelation allowing the application of geostatistical methods like Kriging. When we would increase the time resolution, environmental conditions are more heterogeneous and this reduces the autocorrelation over the space. During a common day, hourly pollen concentrations can range from dramatic levels to nothing (Grewling et al., 2016). However, the time restraint of the classical pollen monitoring method would not allow us to disseminate current pollen information with less than one day of delay (Galán et al., 2014). Due to this, under the current monitoring framework, to display information with a more detailed time resolution than 24 h makes no sense. Nevertheless, we are now able to perform automatic and high resolution pollen monitoring (Crouzy et al., 2016; Oteros et al., 2015). The interpolation of pollen data is probably not the optimal approach for a smaller time resolution. In the case of predicting hourly concentrations at unmonitored areas, further parameters should be added to the model like species distribution, phenological information and wind dispersion simulations, preferably by models assimilating real pollen data.

Automation of pollen measurements opens new opportunities for knowing and predicting local pollen concentrations. With this method we hope to provide allergy sufferers with accurate pollen information about extensive areas and at a minimum of cost i.e. few stations.

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References

Aguilera, F., Ben Dhiab, A., Msallem, M., Orlandi, F., Bonofiglio, T., Ruiz-Valenzuela, L., Galan, C., Diaz-de la Guardia, C., Giannelli, A., Trigo, M.D., Garcia-Mozo, H., Perez-Badia, R., Fornaciari, M., 2015. Airborne-pollen maps for olive-growing areas throughout the Mediterranean region: spatio-temporal interpretation. Aerobiologia 31 (3), 421–434.

Austin, M.P., 2002. Spatial prediction of species distribution: an interface between ecological theory and statistical modelling. Ecol. Model. 157 (2–3), 101–118.

Bargaoui, Z.K., Chebbi, A., 2009. Comparison of two kriging interpolation methods applied to spatiotemporal rainfall. J. Hydrol. 365 (1–2), 56–73.

Bisbis, M.B., Gruda, N., Blanke, M., 2018. Potential impacts of climate change on vegetable production and product quality – a review. J. Clean. Prod. 170, 1602–1620.

Buters, J., Oteros, J., 2015. Electronic pollen information network for Bavaria, Germany (ePIN). Int. Aerobiol. Newslett. 78, 8–9.

Buters, J.T.M., Antunes, C., Galveias, A., Bergmann, K.C., Thibaudon, M., Galan, C., Schmidt-Weber, C., Oteros, J., 2018. Pollen and spore monitoring in the world. Clin. Transl. Allergy 8 (1), 9.

Cariñanos, P., Casares-Porcel, M., de la Guardia, C.D., Aira, M.J., Belmonte, J., Boi, M., Elvira-Rendueles, B., De Linares, C., Fernández-Rodriguez, S., Maya-Manzano, J.M., 2017. Assessing allergenicity in urban parks: a nature-based solution to reduce the impact on public health. Environ. Res. 155, 219–227.

Casazza, M., Lega, M., Liu, G., Ulgiati, S., Endreny, T.A., 2018. Aerosol pollution, including eroded soils, intensifies cloud growth, precipitation, and soil erosion: a review. J. Clean. Prod. 189, 135–144.

CEN/TS-16868, 2015. Ambient air. Sampling and analysis of airborne pollen grains and fungal spores for allergy networks. Volumetric Hirst method. In: CEN.

Crenna, E., Sala, S., Polce, C., Collina, E., 2017. Pollinators in life cycle assessment: towards a framework for impact assessment. J. Clean. Prod. 140, 525–536.

Crouzy, B., Stella, M., Konzelmann, T., Calpini, B., Clot, B., 2016. All-optical automatic pollen identification: towards an operational system. Atmos. Environ. 140, 202–212.

Dahl, Å., Galán, C., Hajkova, L., Pauling, A., Sikoparija, B., Smith, M., Vokou, D., 2013. The Onset, Course and Intensity of the Pollen Season, Allergenic Pollen. Springer, pp. 29–70.

Damialis, A., Halley, J.M., Gioulekas, D., Vokou, D., 2007. Long-term trends in atmospheric pollen levels in the city of Thessaloniki, Greece. Atmos. Environ. 41 (33), 7011–7021.

De Linares, C., Delgado, R., Aira, M.J., Alcázar, P., Alonso-Pérez, S., Boi, M., Cariñanos, P., Cuevas, E., de la Guardia, C.D., Elvira-Rendueles, B., 2017. Changes in the Mediterranean pine forest: pollination patterns and annual trends of airborne pollen. Aerobiologia 1–17.

de Weger, L.A., Bergmann, K.C., Rantio-Lehtimäki, A., Dahl, Å., Buters, J., Déchamp, C., Belmonte, J., Thibaudon, M., Cecchi, L., Besancenot, J.-P., Galán, C., Waisel, Y., 2013. Impact of pollen. In: Sofiev, M., Bergmann, K.-C. (Eds.), Allergenic Pollen. Springer Netherlands, Dordrecht, pp. 161–215.

Fernández-Rodríguez, S., Duran-Barroso, P., Silva-Palacios, I., Tormo-Molina, R., Maya-Manzano, J.M., Gonzalo-Garijo, A., 2016. Regional forecast model for the Olea pollen season in Extremadura (SW Spain). Int. J. Biometeorol. 60 (10), 1509–1517.

Fernández-Rodríguez, S., Durán-Barroso, P., Silva-Palacios, I., Tormo-Molina, R., Maya-Manzano, J.M., Gonzalo-Garijo, Á., Monroy-Colin, A., 2018. Environmental assessment of allergenic risk provoked by airborne grass pollen through forecast model in a Mediterranean region. J. Clean. Prod. 176 (1), 1304–1315.

Fishman, J., Wozniak, A.E., Creilson, J.K., 2003. Global distribution of tropospheric ozone from satellite measurements using the empirically corrected tropospheric ozone residual technique: identification of the regional aspects of air pollution. Atmos. Chem. Phys. 3 (4), 893–907.

Galán, C., Smith, M., Thibaudon, M., Frenguelli, G., Oteros, J., Gehrig, R., Berger, U., Clot, B., Brandao, R., Grp, E.Q.W., 2014. Pollen monitoring: minimum requirements and reproducibility of analysis. Aerobiologia 30 (4), 385–395.

Garcia-Mozo, H., Galan, C., Vazquez, L., 2006. The reliability of geostatistic interpolation in olive field floral phenology. Aerobiologia 22 (2), 97–108.

Graumlich, L.J., 1987. Precipitation variation in the Pacific Northwest (1675–1975) as reconstructed from tree rings. Ann. Assoc. Am. Geogr. 77 (1), 19–29.

Grewling, L., Bogawski, P., Smith, M., 2016. Pollen nightmare: elevated airborne pollen levels at night. Aerobiologia 32 (4), 725–728.

Haylock, M., Hofstra, N., Klein Tank, A., Klok, E., Jones, P., New, M., 2008. A European daily high-resolution gridded data set of surface temperature and precipitation for 1950–2006. J. Geophys. Res.: Atmosphere 113 (D20).

Hengl, T., Sierdsema, H., Radovic, A., Dilo, A., 2009. Spatial prediction of species' distributions from occurrence-only records: combining point pattern analysis, ENFA and regression-kriging. Ecol. Model. 220 (24), 3499–3511.

Hidalgo, P.J., Mangin, A., Galán, C., Hembise, O., Vázquez, L.M., Sanchez, O., 2002. An automated system for surveying and forecasting Olea pollen dispersion. Aerobiologia 18 (1), 23–31.

Hijmans, R.J., van Etten, J., 2014. raster: geographic data analysis and modeling. R package version 2, 15.

Hijmans, R.J., Cameron, S.E., Parra, J.L., Jones, P.G., Jarvis, A., 2005. Very high resolution interpolated climate surfaces for global land areas. Int. J. Climatol. 25 (15), 1965–1978.

Jochner, S., Ziello, C., Bock, A., Estrella, N., Buters, J., Weichenmeier, I., Behrendt, H., Menzel, A., 2012. Spatio-temporal investigation of flowering dates and pollen counts in the topographically complex Zugspitze area on the German-Austrian border. Aerobiologia 28 (4), 541–556.

Kasprzyk, I., 2006. Comparative study of seasonal and intradiurnal variation of airborne herbaceous pollen in urban and rural areas. Aerobiologia 22 (3), 185–195.

Krige, D.G., 1951. A statistical approach to some basic mine valuation problems on the Witwatersrand. J. S. Afr. Inst. Min. Metall 52 (6), 119–139.

Laaidi, M., Thibaudon, M., Besancenot, J.-P., 2003. Two statistical approaches to forecasting the start and duration of the pollen season of Ambrosia in the area of Lyon

(France). Int. J. Biometeorol. 48 (2), 65–73.
Li, J., Heap, A.D., 2008. A Review of Spatial Interpolation Methods for Environmental Scientists.
Li, S., Feng, K., Li, M., 2017. Identifying the main contributors of air pollution in Beijing. J. Clean. Prod. 163, S359–S365.
Makra, L., Matyasovszky, I., Balint, B., Csepe, Z., 2014. Association of allergic rhinitis or asthma with pollen and chemical pollutants in Szeged, Hungary, 1999-2007. Int. J. Biometeorol. 58 (5), 753–768.
Matyasovszky, I., Makra, L., 2011. Autoregressive modelling of daily ragweed pollen concentrations for Szeged in Hungary. Theor. Appl. Climatol. 104 (1–2), 277–283.
Maya-Manzano, J.M., Sadys, M., Tormo-Molina, R., Fernandez-Rodriguez, S., Oteros, J., Silva-Palacios, I., Gonzalo-Garijo, A., 2017. Relationships between airborne pollen grains, wind direction and land cover using GIS and circular statistics. Sci. Total Environ. 584, 603–613.
Norris-Hill, J., 1995. The modelling of daily Poaceae pollen concentrations. Grana 34 (3), 182–188.
Orlandi, F., Lanari, D., Romano, B., Fornaciari, M., 2006. New model to predict the timing of olive (Olea europaea) flowering: a case study in central Italy. N. Z. J. Crop Hortic. Sci. 34 (1), 93–99.
Orlandi, F., Oteros, J., Aguilera, F., Ben Dhiab, A., Msallem, M., Fornaciari, M., 2014. Design of a downscaling method to estimate continuous data from discrete pollen monitoring in Tunisia. Environ. Sci. Process. Impacts 16 (7), 1716–1725.
Oteros, J., et al., Under Review. Building an Automatic Pollen Monitoring Network (EPIN). Selection of Optimal Stations by Clustering Pollen Zones.
Oteros, J., Garcia-Mozo, H., Vazquez, L., Mestre, A., Dominguez-Vilches, E., Galan, C., 2013. Modelling olive phenological response to weather and topography. Agric. Ecosyst. Environ. 179, 62–68.
Oteros, J., Orlandi, F., Garcia-Mozo, H., Aguilera, F., Ben Dhiab, A., Bonofiglio, T., Abichou, M., Ruiz-Valenzuela, L., del Trigo, M.M., de la Guardia, C.D., Dominguez-Vilches, E., Msallem, M., Fornaciari, M., Galan, C., 2014. Better prediction of Mediterranean olive production using pollen-based models. Agron. Sustain. Dev. 34 (3), 685–694.
Oteros, J., Pusch, G., Weichenmeier, I., Heimann, U., Moller, R., Roseler, S., Traidl-Hoffmann, C., Schmidt-Weber, C., Buters, J.T., 2015. Automatic and online pollen monitoring. Int. Arch. Allergy Immunol. 167 (3), 158–166.
Oteros, J., Bartusel, E., Alessandrini, F., Núñez, A., Moreno, D., Behrendt, H., Schmidt-Weber, C., Traidl-Hoffmann, C., Buters, J., 2018. Artemisia pollen is the main vector for airborne endotoxin. J. Allergy Clin. Immunol. https://doi.org/10.1016/j.jaci.2018.05.040.
Pebesma, E.J., 2004. Multivariable geostatistics in S: the gstat package. Comput. Geosci. 30 (7), 683–691.
Pebesma, E.J., Bivand, R.S., 2005. Classes and methods for spatial data in. R. R news 5 (2), 9–13.
R-Team, C., 2013. R Core Team. 2013. R: a Language and Environment for Statistical Computing. R Foundation for Statistical Computing, Vienna, Austria. http://www.R-project.org.
Radic, V., Bliss, A., Beedlow, A.C., Hock, R., Miles, E., Cogley, J.G., 2014. Regional and global projections of twenty-first century glacier mass changes in response to climate scenarios from global climate models. Clim. Dynam. 42 (1–2), 37–58.
Ribeiro Jr., P.J., Diggle, P.J., 2015. geoR: Analysis of Geostatistical Data. R Package Version 1. 7-5.1.
Ribeiro, H., Santos, L., Abreu, I., Cunha, M., 2006. Influence of meteorological parameters on Olea flowering date and airborne pollen concentration in four regions of Portugal. Grana 45 (2), 115–121.
Rios, B., Torres-Jardon, R., Ramirez-Arriaga, E., Martinez-Bernal, A., Rosas, I., 2016. Diurnal variations of airborne pollen concentration and the effect of ambient temperature in three sites of Mexico City. Int. J. Biometeorol. 60 (5), 771–787.
Rodriguez, A.F.M., Palacios, I.S., Molina, R.T., 2010. Influence of meteorological parameters in hourly patterns of grass (Poaceae) pollen concentrations. Ann. Agric. Environ. Med. 17 (1), 87–100.
Rodriguez-Rajo, F.J., Valencia-Barrera, R.M., Vega-Maray, A.M., Suarez, F.J., Fernandez-Gonzalez, D., Jato, V., 2006. Prediction of airborne Alnus pollen concentration by using Arima models. Ann. Agric. Environ. Med. 13 (1), 25–32.
Rojo, J., Perez-Badia, R., 2015. Spatiotemporal analysis of olive flowering using geostatistical techniques. Sci. Total Environ. 505, 860–869.
Rojo, J., Orlandi, F., Perez-Badia, R., Aguilera, F., Ben Dhiab, A., Bouziane, H., de la Guardia, C.D., Galan, C., Gutierrez-Bustillo, A.M., Moreno-Grau, S., Msallem, M., Trigo, M.M., Fornaciari, M., 2016. Modeling olive pollen intensity in the Mediterranean region through analysis of emission sources. Sci. Total Environ. 551, 73–82.
Rojo, J., Rivero, R., Romero-Morte, J., Fernández-González, F., Pérez-Badia, R., 2017. Modeling pollen time series using seasonal-trend decomposition procedure based on LOESS smoothing. Int. J. Biometeorol. 61 (2), 335–348.
Running, S.W., Nemani, R.R., Heinsch, F.A., Zhao, M.S., Reeves, M., Hashimoto, H., 2004. A continuous satellite-derived measure of global terrestrial primary production. Bioscience 54 (6), 547–560.
Sadyś, M., West, J.S., 2017. Intra-diurnal and daily changes in Didymella ascospore concentrations in the air of an urban site. Fungal Ecol. 27 (Part A), 87–95.
Sánchez-Mesa, J., Galán, C., Martínez-Heras, J., Hervás-Martínez, C., 2002. The use of a neural network to forecast daily grass pollen concentration in a Mediterranean region: the southern part of the Iberian Peninsula. Clin. Exp. Allergy 32 (11), 1606–1612.
Sadys, M., Kennedy, R., West, J.S., 2016. Potential impact of climate change on fungal distributions: analysis of 2 years of contrasting weather in the UK. Aerobiologia 32 (1), 127–137.
Sikoparija, B., Skjøth, C.A., Celenk, S., Testoni, C., Abramidze, T., Alm Kübler, K., Belmonte, J., Berger, U., Bonini, M., Charalampopoulos, A., Damialis, A., Clot, B., Dahl, Å., de Weger, L.A., Gehrig, R., Hendrickx, M., Hoebeke, L., Ianovici, N., Kofol Seliger, A., Magyar, D., Mányoki, G., Milkovska, S., Myszkowska, D., Páldy, A., Pashley, C.H., Rasmussen, K., Ritenberga, O., Rodinkova, V., Rybníček, O., Shalaboda, V., Šaulienė, I., Ščevková, J., Stjepanović, B., Thibaudon, M., Verstraeten, C., Vokou, D., Yankova, R., Smith, M., 2017. Spatial and temporal variations in airborne Ambrosia pollen in Europe. Aerobiologia 33 (2), 181–189.
Smith, M., Oteros, J., Schmidt-Weber, C., Buters, J., Under Review. Electronic Pollen Information Network for Bavaria, Germany (EPIN): a Novel Method for the Quality Control of Pollen Counters.
Sofiev, M., Siljamo, P., Ranta, H., Rantio-Lehtimaki, A., 2006. Towards numerical forecasting of long-range air transport of birch pollen: theoretical considerations and a feasibility study. Int. J. Biometeorol. 50 (6), 392–402.
Sofiev, M., Belmonte, J., Gehrig, R., Izquierdo, R., Smith, M., Dahl, Å., Siljamo, P., 2013. Airborne Pollen Transport, Allergenic Pollen. Springer, pp. 127–159.
Sofiev, M., Vira, J., Kouznetsov, R., Prank, M., Soares, J., Genikhovich, E., 2015. Construction of the SILAM Eulerian atmospheric dispersion model based on the advection algorithm of Michael Galperin. Geosci. Model Dev. (GMD) 8 (11), 3497–3522.
Traidl-Hoffmann, C., Kasche, A., Menzel, A., Jakob, T., Thiel, M., Ring, J., Behrendt, H., 2003. Impact of pollen on human health: more than allergen carriers? Int. Arch. Allergy Immunol. 131 (1), 1–13.
Turner, R., Sripada, S., Reiter, E., Davy, I.P., 2006. Generating spatio-temporal descriptions in pollen forecasts. In: Proceedings of the Eleventh Conference of the European Chapter of the Association for Computational Linguistics: Posters & Demonstrations. Association for Computational Linguistics, pp. 163–166.
Vogel, H., Pauling, A., Vogel, B., 2008. Numerical simulation of birch pollen dispersion with an operational weather forecast system. Int. J. Biometeorol. 52 (8), 805–814.
Yang, Y., Li, Y., Zhang, S., Chen, F., Hou, H., Ma, J., 2017. Monitoring the impact of fugitive CO2 emissions on wheat growth in CCS-EOR areas using satellite and field data. J. Clean. Prod. 151, 34–42.
Young, D.F., Minnis, P., Doelling, D.R., Gibson, G.G., Wong, T., 1998. Temporal interpolation methods for the Clouds and the Earth's Radiant Energy system (CERES) experiment. J. Appl. Meteorol. 37 (6), 572–590.
Ziello, C., Estrella, N., Kostova, M., Koch, E., Menzel, A., 2009. Influence of altitude on phenology of selected plant species in the Alpine region (1971-2000). Clim. Res. 39 (3), 227–234.
Zink, K., Vogel, H., Vogel, B., Magyar, D., Kottmeier, C., 2012. Modeling the dispersion of Ambrosia artemisiifolia L. pollen with the model system COSMO-ART. Int. J. Biometeorol. 56 (4), 669–680.