Original citation: Maya-Manzano, J.M., Smith, Matt, Markey, E., Hourihane Clancy, J., Sodeau, J. and O´Connor, D.J. (2020) *Recent developments in monitoring and modelling airborne pollen, a review.* Grana. ISSN 1651-2049

Permanent WRaP URL: https://eprints.worc.ac.uk/id/eprint/9573

Copyright and reuse:

Publisher's statement:

This is an Accepted Manuscript of an article published by Taylor & Francis in Grana on 7 July 2020, available online: https://www.tandfonline.com/doi/full/10.1080/00173134.2020.1769176

A note on versions:

For more information, please contact wrapteam@worc.ac.uk

Recent developments in monitoring and modelling airborne pollen, a review

JOSE MARÍA MAYA-MANZANO[1*], MATT SMITH[2], EMMA MARKEY[1],

JERRY HOURIHANE CLANCY[1], JOHN SODEAU[3], & DAVID J. O´CONNOR[1]

[1]School of Chemical and Pharmaceutical Sciences, Technological University Dublin, Dublin, Republic of Ireland

[2]School of Science and the Environment, University of Worcester, Worcester, United Kingdom

[3]University College Cork, Cork, Republic of Ireland

** Corresponding author. Jose María Maya-Manzano. E-mail address: jomanz.jmm@gmail.com*

Kevin Street, D08 X622, Dublin, Republic of Ireland

Abstract

Public awareness of the rising importance of allergies and other respiratory diseases has led to increased scientific effort to accurately and rapidly monitor and predict pollen, fungal spores and other bioaerosols in our atmosphere. An important driving force for the increased social and scientific concern is the realization that climate change will increasingly have an impact on worldwide bioaerosol distributions and subsequent human health. In this review we examine new developments in monitoring of atmospheric pollen as well as observation and source-orientated modelling techniques. The results of a Scopus® search for scientific publications conducted with the terms "Pollen allergy" and "Pollen forecast" included in the title, abstract or keywords show that the number of such articles published has increased year on year. The 12 most important allergenic pollen taxa in Europe as defined by COST Action ES0603 were ranked in terms of the most 'popular' for model-based forecasting and for forecasting method used. *Betula*, Poaceae and *Ambrosia* are the most forecast taxa. Traditional regression and phenological models (including temperature sum and chilling models) are the most used modelling methods, but it is notable that there are a large number of new modelling techniques being explored. In particular, it appears that Machine Learning techniques have become more popular and led to better results than more traditional observation-orientated models such as regression and time series analyses.

Keywords: Aerobiology, Phenology, Aeroallergen, Pollen forecasting, Real-time pollen monitoring networks, Machine Learning

Public awareness of the rising importance of allergies and other respiratory diseases has led to increased scientific effort to accurately and rapidly monitor and predict pollen, fungal spores and other bioaerosols in our atmosphere. An important driving force for the increased social and scientific concern is the realization that climate change will increasingly have an impact on worldwide bioaerosol distributions and subsequent human health (Beggs et al. 2017).

This is symbolised by the results of a Scopus® (Elsevier B.V.) search for scientific publications we conducted with the terms "Pollen allergy" and "Pollen forecast" included in the title, abstract or keywords (Source: Scopus, December 2019). The results obtained show that the number of such articles published has increased year on year (Figure 1). In the 1970s, there were less than 150 papers on pollen allergy and only the occasional paper on pollen forecasting published each year. By the end of the 2010s, this increased to about 600 pollen allergy papers (maximum 618 in 2017) and 12 pollen forecasting papers (maximum 16 in 2014) published annually.

This increased interest in pollen allergy contributed to the creation of several European Cooperation in Science and Technology Actions (COST), these were for the "*Assessment of production, release, distribution and health impact of allergenic pollen in Europe (ES0603 - EUPOL)*", the *"Sustainable Management of Ambrosia artemisiifolia in Europe (FA1203 - SMARTER)*", and the current network for examining "*New approaches in detection of pathogens and aeroallergens (CA18226)".* One of the main outputs from COST Action ES0603 was the influential book entitled "*Allergenic Pollen*", edited by Mikhail Sofiev, Karl-Christian Bergmann, which has more than 10,000 downloads since it was published in 2013. The book examined pollen sources (Skjøth et al. 2013), the onset, course and intensity of the pollen season (Dahl et al. 2013), monitoring, modelling and forecasting of the pollen season (Scheifinger et al. 2013), airborne pollen transport (Sofiev et al. 2013a), the impact of pollen (de Weger et al. 2013) and the presentation and dissemination of pollen information (Karatzas et al. 2013). However, since then there have been a number of notable advancements in the field of aerobiology, particularly the development of devices capable of automated real-time monitoring (e.g. Oteros et al. (2015) and Crouzy et al. (2016)) and the continued development of numerical forecast models (Sofiev et al. 2015).

This review paper came from the Pollen Monitoring and ModELling (POMMEL) project that aims to produce a reliable and fully operational pollen forecast system for Ireland (https://www.pommel.ie). The focus of this review is to examine the current state-of-the-art in pollen monitoring and forecasting for the 12 most allergenic taxa as defined by COST Action ES0603 (i.e. *Alnus, Ambrosia, Artemisia, Betula,* Chenopodiaceae (Amaranthaceae), *Corylus,* Cupressaceae, *Olea, Platanus,* Poaceae, *Quercus,* Urticaceae (*Urtica, Parietaria*) (Skjøth et al. 2013)), with particular emphasis on developments since the publication of the pivotal work "*Allergenic Pollen*".

Advances in bioaerosol monitoring

Before we can talk about recent developments in modelling and forecasting airborne pollen concentrations, we need to discuss recent advances in bioaerosol monitoring as one is intimately linked to the other. Today, the vast majority of monitoring networks still use technology that dates back to the middle of the last century (Buters et al. 2018). For instance, many aerobiological networks are based on volumetric spore traps of the Hirst (1952) design, which were developed some 70 years ago. This technology is not without its problems and workers have reported differences between Hirst type traps located only a few meters apart (Tormo Molina et al. 2013) and errors in determining the flow rate (Oteros et al. 2017a). The Hirst type trap is by no means the only sampler used in networks and another widely used volumetric/impaction technique is the Rotorod (Grinnell et al., 1961); a rotating mechanism that is said to have a sampling efficiency of ~85% (Noll 1970).

Hirst-type sampling protocols require at least one full day before the drum can be changed and the sample processed. Although this period is quite often extended to 7-days for logistical and financial reasons. Subsequent analysis of the pollen-covered tapes by light microscopy requires high levels of skill to accurately count and properly identify the particles collected. This is a slow process and, as a result, only a small sub-sample of individual microscope slides are examined and the overall count is an extrapolation (Comtois et al. 1999; Šikoparija et al. 2011). The data also relies on the skill of the operator and so there have been concerted efforts of late to evaluate data quality (Galán et al. 2014; Sikoparija et al. 2017a; Smith et al. 2019) and standardise methods (Galán et al. 2014; Galán et al. 2017). Having said this, however, there are reasons why such equipment has been in operation for so long. Hirst type traps are relatively inexpensive to purchase and operate. The technique is also robust and performs well outdoors (Beggs et al. 2017). Furthermore, long-term datasets are now available with wide geographical distributions that can be used for examining changes in plant phenology and distribution (Ziska et al. 2011; Ziello et al. 2012; Smith et al. 2014; Sikoparija et al. 2017b).

One of the main problems (or greatest weaknesses) that pollen monitoring networks face is the time delay between sampling, analysis and eventual communication of the findings to the general public and health care professionals. As a consequence it is now recognised that aerobiological studies should focus on creating reliable, real-time monitoring networks. A comprehensive review of the real-time sensing of bioaerosols has been published by Huffman et al. (2020) and several of these methods are discussed below.

The KH-3000-01 samples a portion of air containing particles by use of a laser beam to irradiate the air flow (Kawashima et al. 2007). It makes real-time pollen monitoring possible because the light-scattering particle data are processed by a computer instantaneously. The device has been developed by Yamatronics Corporation (Japan) and employs one light source and two light receptors, which are able to discriminate Japanese cedar or cypress pollen from other particles. It is able to do so by comparing scattered light intensity and degree of polarization. Its low-cost makes it an attractive proposition for piloting a real-time pollen monitoring network.

Instrumentation based on the fluorescence spectroscopy of biological particles has recently been developed to provide rapid, on-line, real-time counting (if not yet identification) of bioaerosols. For instance, the Waveband Integrated Bioaerosol Sensor (WIBS-4 - now superseded by the WIBS-NEO) has been described in a number of publications (O'Connor et al. 2014; O'Connor et al. 2015; Fennelly et al. 2018) and it has been successfully deployed in the field resulting in strong correlations with traditional volumetric techniques (e.g. R^2 >0.9) (O'Connor et al. 2014; Calvo et al. 2018).

The PA-300, and its successor the Rapid E, is also available (Crouzy et al. 2016; Huffman et al. 2020). The instrument uses the measurement of fluorescence signals as a simple diagnostic to distinguish between airborne particles that emit light and those that do not. The technique offers great potential for the rapid determination of the fluorescence properties of target samples, in addition to being non-destructive and reagent free.

Auto-fluorescence is a known property of biological particles because their structural components (e.g. tryptophan, flavonoids, chitin, lignin, ''sporopollenin'' and secondary metabolites such as phenols and terpenoids) have been shown to absorb and emit light over a range of visible and UV wavelengths (Roshchina 2008; Pöhlker et al. 2012). Hence the WIBS and the Plair instruments, in particular, have been applied to the detection of many types of bioaerosols in both the laboratory and field settings (Healy et al. 2014; Crouzy et al. 2016; Feeney et al. 2018).

In Europe, two automatic real-time pollen networks are now being established. The first is in Bavaria, Germany, and uses BAA500 automatic image recognition technology (Oteros et al. 2015). Whilst in Switzerland, MeteoSwiss is establishing a real-time pollen monitoring network upon the Swisens Poleno air-flow cytometry system (Sauvageat et al. 2020). Currently real-time devices such as the BAA500 and Swisens Poleno surpass the budgets available to most national pollen service providers. They are also relatively untested. In fact, only four European countries (France, Germany, Luxemburg and Switzerland) are monitoring with automatic samplers and not in all their locations (Buters et al. 2018). There are also two locations in the USA, and a further 120 in Japan where only a few taxa are of allergenic interest to the population (Kawashima et al. 2007).

Alternative molecular biology methods have been developed for examining aeroallergens. For example, pollen and fungal spore allergens sampled from the atmosphere can be quantified using enzyme-linked immunosorbent assays (ELISA) and reagents are available in kit form. Studies using such techniques have shown that the presence of pollen allergens in the atmosphere do not always correlate with the occurrence of airborne pollen grains (Buters et al. 2012; Buters et al. 2013; Galan et al. 2013), which could impact on the information provided to allergy sufferers and strategies for managing their symptoms. The use of DNA metabarcoding can also provide information on the ecology of the atmosphere (Brennan et al. 2019). Nonetheless, molecular techniques are still a long way from being able to monitor the atmosphere on a routine basis.

Modelling and forecasting the pollen season

It is hoped that the cost of automatic real-time monitoring devices will decrease in the near future due to increasing commercial production and expertise. This would allow much faster sampling and analytical processing to occur, thereby lengthening forecast horizons and improving forecasts. Furthermore, measurements with high temporal resolution will also increase our knowledge of atmospheric processes (Šikoparija et al. 2018b; Chappuis et al. 2020). Here we discuss the two main approaches for modelling and forecasting airborne pollen as described in Scheifinger (2013); observation-orientated and source based models.

Observation-orientated models

Observation-orientated models are based on our environmental knowledge of a certain location. For instance, average pollen concentrations from the same day in previous years can turn pollen calendars into forecasting tools (Šikoparija et al. 2018a). In observation-orientated mathematical and statistical models the dependent variables are phenological observations or airborne pollen concentrations that can be predicted using one or more independent variable (e.g. meteorological data). The main disadvantage of this approach is that it is site-specific, which can lead to difficulties in extrapolating to other locations if the model is not adjusted appropriately. With this in mind, it should be noted that Oteros et al. (2019a) successfully used a combination of linear regressions and Kriging interpolation to spatially model pollen concentrations for unmonitored areas in Bavaria, Germany.

Traditional methods include regression and time series analyses and process-based phenological models. On the other hand, so-called Machine Learning (or Deep Learning) is a new technique that has been successfully integrated into many aspects of data mining over the last few years. Indeed, it is seen as an analytical solution in many different disciplines and applications such as self-drive vehicles or image recognition (Zhang et al. 2018).

Regression analysis

Linear regression (two quantitative variables, one of them dependent Y, and other independent, X, explained by a straight line) or multiple regression analyses (one quantitative variable, dependent Y and more than two quantitative independent variables $X_1 \ldots X_k$ being related in a linear or non-linear way) work by predicting future values for one dependent parameter, such as pollen, by means of one or more parameters including their historical observations (Kinnear & Gray 1999). Paul Comtois (1998) entertainingly stated that "*because of its predictive values, the establishment of a regression is often pompously called model building, even in reality it concerns only the establishment (and testing) of a slope (b) and of a correlation coefficient (r)*".

Nevertheless, due to the relative ease of construction regression models remain popular in aerobiological studies and a number of papers have been published in recent years that include simple linear regression analysis (Piotrowska-Weryszko 2013b; Bonini et al. 2015; García-Mozo et al. 2015; Frenguelli et al. 2016; Picornell et al. 2019b) as well as polynomial and multiple regression analysis (Sabariego et al. 2012; Ocaña-Peinado et al. 2013; Oteros et al. 2013a; de Weger et al. 2014; Donders et al. 2014; Novara et al. 2016; Ritenberga et al. 2016; Tseng et al. 2018). Approaches include the more traditional stepwise or backwards elimination multiple regressions (Sicard et al. 2012; Aboulaich et al. 2013; Myszkowska 2013; Howard & Levetin 2014; Malkiewicz et al. 2014; Zhang et al. 2015; Murray & Galan 2016; Janati et al. 2017; Robichaud & Comtois 2017; Galera et al. 2018; Volkova & Severova 2019), which are by far the most frequently used, as well as logistic or 'logic' regressions (Escabias et al. 2013; Myszkowska

2014b; Myszkowska & Majewska 2014; Katz & Batterman 2019) , Partial Least Squares (Brighetti et al. 2014; Oteros et al. 2014; Aguilera et al. 2015a; Bogawski et al. 2019b; Lara et al. 2019) and Generalized Linear Model (Charalampopoulos et al. 2018).

Regression analysis continues to be used to model daily average airborne pollen concentrations (Janati et al. 2017) in addition to different characteristics of the pollen season including start date (Myszkowska 2014a; Zhang et al. 2015; Novara et al. 2016), peak day (Myszkowska 2013), duration (Zhang & Huang 2015) and intensity (Oteros et al. 2013a; Bonini et al. 2015). Regression models have been constructed for different pollen types including *Alnus* (Piotrowska-Weryszko 2013b; Myszkowska 2014b; Novara et al. 2016), *Ambrosia* (Howard & Levetin 2014; Zhang et al. 2015), *Artemisia* (Piotrowska-Weryszko 2013a; Zhang et al. 2015), *Betula* (Myszkowska 2013; Inatsu et al. 2014; Zhang et al. 2015; Robichaud & Comtois 2017; Tseng et al. 2018; Bogawski et al. 2019b), *Corylus* (Myszkowska 2014b; Frenguelli et al. 2016; Novara et al. 2016), Cupressaceae (Sabariego et al. 2012; Ocaña-Peinado et al. 2013; Charalampopoulos et al. 2018; Picornell et al. 2019b), *Olea* (Sicard et al. 2012; Oteros et al. 2013a; García-Mozo et al. 2014; Frenguelli et al. 2016; Charalampopoulos et al. 2018; Picornell et al. 2019b), *Platanus* (Frenguelli et al. 2016; Charalampopoulos et al. 2018; Picornell et al. 2019b), Poaceae (Piotrowska 2012; Aboulaich et al. 2013; de Weger et al. 2014; Zhang et al. 2015; Janati et al. 2017; Picornell et al. 2019b), *Quercus* (Fernández-Llamazares et al. 2014; Jato et al. 2014; Frenguelli et al. 2016; Picornell et al. 2019b) and Urticaceae (Picornell et al. 2019b).

Despite their convenience, regression techniques do not take into account seasonal variations in daily temperatures during the year or the associated increases in pollen concentrations in Spring and Summer. Time-dependence is also an important factor when considering the potential impact of external influences, like environmental change, on long-term datasets of plant phenology. Such factors can be included in models using time series analysis. These are a sequence of observations for which a variable Y is sorted by sampling date (with a certain level of correlation amongst them) as a function of time (t).

Time-series analysis

Time series analysis is a technique used in aerobiology for obtaining insight from the underlying relationships observed in the data, by studying longer datasets with an aim to forecast the possible future behaviour of the parameter Y (usually, but not always, sometimes it can be used to reconstruct past time series). The time series are associated with various controlling components of variability, the two most important are defined below (Aznarte M et al. 2007; Scheifinger et al. 2013; García-Mozo et al. 2014; Rojo et al. 2017):

General trend (G). — The predominant behaviour that Y shows from the start to the end of the series. It is expected to be unidirectional and smooth, clearly showing future expectations, be it an increase, a stationary trend or a decrease.

Seasonality (S). — Small fluctuations along the timeline associated with natural cycles of less than one year in length. They are ordinarily repeated every year in a recognised way.

However, in spite of having two well identified components, sometimes the behaviours of some natural parameters are much more complex.

unknown cycles (C). — They may also contribute. Often, these are cycles observed in more than one-year period and could provide explanations for variability, especially in changing climatic conditions (e.g. North Atlantic Oscillation or El Niño–Southern Oscillation). These variables are obviously very complex and so sometimes they are simply included as part of the general trend.

Nonetheless, the complete time series approach clearly requires one further component of variability before an accurate, overall model can be constructed:

Random components (R). — Possible fluctuations without a known seasonality or pattern, which make it impossible to accurately predict future behaviour.

Therefore the full general time series predictive model can be summarised as:

$$Y(t) = G(t) + S(t) + C(t) + R(t)$$

Time series analyses are intended to separate (decompose) different patterns with the goal of isolating all the disturbances provoked in the time series datasets by ordinary seasonal behaviour (S) such as weather parameters. However, in addition to ill-defined random components, residual noise (R) can be present as a consequence of inter-annual variability or unknown factors.

As a result of this decomposition, the general trend (G) is shown in a more accessible way to be interpreted, and we can avoid that other parameters mask the true pattern. In this sense, seasonal-trend decomposition procedure based on LOcally wEighted Scatterplot Smoothing (LOESS smoothing) has been applied with more interest in aerobiological studies lately (Rojo et al. 2017). For example, Rojo et al. (2017) found the decomposition of time series to be suitable for analysing the phenological and meteorological factors influencing airborne Poaceae pollen concentrations, including seasonal effects of species with different pollination periods. García-Mozo et al. (2014) also used the decomposition procedure based on Loess (STL), and an ARIMA (Auto Regressive Integrated Moving Average) model to examine changes in the flowering pattern of *Olea* in Córdoba (Spain) in relation to global climate change. Although

Aguilera et al. (2015b) were not able to verify these findings even though they used a similar method for decomposing seasonal time series.

Time series analyses have been performed for many years for different pollen types (e.g. see Scheifinger et al.(2013) and references therein). Recently, time series analyses have been used to model airborne concentrations of *Alnus* (Siniscalco et al. 2015; Nowosad et al. 2016), *Ambrosia* (Puc & Wolski 2013; Siniscalco et al. 2015), *Artemisia* (Puc & Wolski 2013; Siniscalco et al. 2015), *Betula* (Nowosad et al. 2016), *Corylus* (Nowosad et al. 2016), Cupressaceae (Silva-Palacios et al. 2016), *Olea* (García-Mozo et al. 2014; Aguilera et al. 2015b; Fernández-Rodríguez et al. 2016c), *Platanus* (Siniscalco et al. 2015), Poaceae (Puc & Wolski 2013; Brighetti et al. 2014; Tassan-Mazzocco et al. 2015; Fernández-Rodríguez et al. 2016a; Rojo et al. 2017; Fernández-Rodríguez et al. 2018), *Quercus* (Fernández-Rodríguez et al. 2016b), and Urticaceae (Tassan-Mazzocco et al. 2015; Valencia et al. 2019).

Process-based phenological models

Phenology is the timing of naturally recurring seasonal events in animals and plants, such as migration and flowering. Phenological phases are influenced by meteorological parameters, particularly temperature, and as such can be used as a proxy for climate change (e.g. Thackeray et al. (2010), Ziello et al. (2012) and Dahl et al., (2013) and references therein). Phenological observations of plants can be separated into different stages of the flowering process, such as anthers closed, anthers open and full flowering (Lukasiewicz 1984). On the other hand, characteristics of the airborne pollen season like start date, peak day and duration, which are also phenological phenomena, can be defined using different techniques (Jato et al. 2006). Phenological records can complement aerobiological data (Tormo et al. 2011) but temporal mismatches have been identified between flowering phenophases and the appearance of pollen in the air (Estrella et al. 2006). With long-distance transport of pollen being an important source of uncertainty (Linkosalo et al. 2010; Sofiev et al. 2013b).

Phenological models determine the recorded dates of phenological phases as a function of environmental factors (e.g. chilling temperature, forcing temperature, photoperiod, and water availability) and are important components of numerical atmospheric transport models. For example, Sofiev et al. (2013b) described the emission module for the SILAM numerical model of birch pollen emission and dispersion (System for Integrated modeLling of Atmospheric coMposition, http://silam.fmi.fi). The output of this pollen emissions module is described as a 'release flux' of pollen grains (Sofiev et al. 2006; Sofiev et al. 2013b). The pollen emission module proposed by the authors follows the principle of a double-threshold thermal time phenological model described by Linkosalo et al. (2010) that can describe the whole period of flowering from beginning to end (Linkosalo et al. 2010; Sofiev et al. 2013b). It has been noted that the simplest thermal time models perform better than more complicated approaches (Linkosalo et al. 2008; Sofiev et al. 2013b). Indeed, Pauling et al. (2014) tested parameterizations of temperature sum models for 12 pollen stations in Switzerland. The authors examined a simple thermal model that relies solely on forcing temperatures and a sequential model that also used chilling temperatures, and concluded that the addition of chilling did not substantially improve the statistical skill of the models (Pauling et al. 2014).

Several studies have been published in recent years that have included forcing temperatures (Pauling et al. 2014; Achmakh et al. 2015; Linkosalo et al. 2017; Picornell et al. 2019a) and chilling (Siniscalco et al. 2015; Novara et al. 2016). Most phenological models were constructed for spring flowering trees of the Betulaceae family namely *Alnus* (Pauling et al. 2014; Siniscalco et al. 2015; Novara et al. 2016; Linkosalo et al. 2017), *Betula* (Pauling et al.

2014) and *Corylus* (Pauling et al. 2014; Novara et al. 2016), but also for *Olea* (Achmakh et al. 2015) and Poaceae (Pauling et al. 2014).

Machine Learning

Since more traditional models often poorly depict the intricate relationships between various factors influencing airborne pollen concentrations (Nowosad 2016), more complex methods such as machine learning are often employed to overcome these limitations. Machine learning (ML) is the application of computational techniques that mimic characteristics of biological information processing systems for data modelling (Recknagel 2001). As previously discussed by Scheifinger et al., (2013), the use of these advanced techniques is on the rise due to their ability to out-perform deterministic models. In recent years this trend has continued with more and more studies utilizing ML methods to forecast pollen concentrations.

A number of ML techniques are available with Artificial Neural Networks (ANNs), Support Vector Machines (SVMs) and Random Forests (RFs) being some of the most widely discussed for pollen forecasting. However, other ML techniques have been studied with less popularity, such as Least Absolute Shrinkage and Selection Operator (LASSO) (Liu et al. 2017), plus Cubist algorithms and Multivariate Adaptive Regression Splines (MARS) (Nowosad et al. 2018).

In recent years, Artificial Neural Networks have become particularly popular in modelling the non-linear behaviour of pollen (Astray et al. 2016). ANNs are composed of individual neurons in multiple layers, mimicking the biological neural system and is able to learn from complex, noisy, incomplete data to model non-linear relationships (Valencia et al. 2019). Deep learning occurs when there is an intrinsic learning in the neural network and the number of hidden layers is greater than two. Deep learning ANNs contain a number of epochs (iterations), which improve the learning capability of the ANN and thus the performance (Zewdie et al. 2019b). The application of ANNs have assessed a variety of aspects relating to the modelling and forecasting of pollen. For example, Multilayer Perceptron ANNs (MLPs) have been used to predict the daily *Ambrosia* concentration over different cities up to 7 days ahead (Csépe et al. 2014) and in the construction of a *Ambrosia* pollen alarm system in the Pannonian biogeographical region (Csépe et al. 2020). The use of ANNs to model aerobiological data is not new (Sánchez-Mesa et al. 2002; Arca et al. 2004; Sánchez Mesa et al. 2005; Aznarte M et al. 2007; Rodríguez-Rajo et al. 2010) and more recent studies have been employed to model the relationship between pollen taxa such as *Ambrosia* (Csépe et al. 2014; Csépe et al. 2019; Zewdie et al. 2019a), *Betula* (Puc 2012), *Quercus* (González-Naharro et al. 2019), *Olea* (Oteros et al. 2013b; Iglesias-Otero et al. 2015) with various meteorological, phenological and remote sensing parameters. Current applications of ANNs have included the adaption of existing models to improve performance in emission models, e.g. Burki et al. (2019) improved the efficiency of the COSMO-ART dispersion prediction model by combining ANN functionality.

Support Vector Machines also express complex non-linear relationships by learning but do so by using Vapnik-Chervonenkis dimensional theories (Du et al. 2017). Unlike, ANNs and RFs, very few studies have exclusively employed SVMs for pollen forecasting and are generally compared alongside other modelling methods. SVMs in the past have been used in developing models for the prediction of flowering periods (Bogawski et al. 2019b) as well as forecasting daily pollen concentrations (Zhao et al. 2018; Zewdie et al. 2019a). In these studies, SVMs tend to perform better than deterministic regression models but are often out performed by ANNs and RFs, perhaps equating to the lack of independent SVM studies.

Random Forests differ slightly from the other methods in that it is an ensemble technique and involves constructing a series of decision trees. This method generates a number of regression trees relating to the sample data and then combines them by averaging (Navares & Aznarte 2020). This method has the added capability of determining the most important variables contributing to a model (Zewdie et al. 2019a) and as such have been used in several studies to identify the most important variables for improving ML models (Navares & Aznarte 2017; Navares & Aznarte 2020). Aside from this, RFs have been used to develop prediction models for high concentrations of different pollen types, such as *Alnus*, *Betula* and *Corylus* (Nowosad 2016; Nowosad et al. 2016) and Poaceae (Navares & Aznarte 2017). However, the performance of RFs and the other ML methods can produce poor predictions if the range of training data is insufficient (Bogawski et al. 2019b). As such, comparisons between different ML methods are often conducted to determine the best performing model.

Model performance is strongly dependent on the data provided, particularly when it comes to model training. Overfitting is often observed if the model corresponds too strictly to training data to the extent that it learns the noise and fluctuations, which in turn impacts negatively on the model's ability to adapt to other data (Zanotti et al. 2019). The extent of overfitting depends on the model type, the predictor variables as well as the correlation between those variables and the output (Nowosad et al. 2018). Every model can overfit but ANNs are notorious for illustrating this behaviour (Zanotti et al. 2019). Cross-validation is commonly used to prevent overfitting and involves producing a series of miniature training sets from the original training data to essentially tune the model. A variety of cross validation techniques are available including leave-one-out cross-validation, Monte Carlo cross-validation, and k-fold cross-validation (Nowosad et al. 2018). Pruning is another well documented algorithm used to limit the effect of model overfitting and is commonly applied to RFs (Singh et al. 2013; Csépe et al. 2014). Alternative methods to correct overfitting include bootstrap aggregation/bagging (Navares & Aznarte 2020; Soundiran et al. 2019), gradient boosting (Dai et al. 2019) and Bayesian Regularization (Balram et al. 2019; Zanotti et al. 2019).

To determine the best machine learning method for the task, many studies have opted to compare various ML techniques. In fact, the majority of ML studies for predicting pollen concentrations cover a selection of modelling methods. For instance, Csépe et al. (2014) compared a series of MLP and tree based algorithms for the prediction of *Ambrosia* pollen concentrations and Nowosad et al. (2018) compared nine different modelling techniques including both linear and non-linear models for *Alnus*, *Betula* and *Corylus* pollen concentrations. Additionally, Bogawski et al. (2019b) predicted the onset of the *Betula* flowering period by comparing five types of model, including: SVMs, RFs, partial least squares, ordinary least squares and linear regression. Similarly, Zewdie et al. (2019b) employed RF, extreme gradient boosting, deep neural networks and linear Bayes ridge models to forecast the airborne *Ambrosia* concentration over Tulsa. These studies illustrate the superior performance of ML methods over less sophisticated models. RFs (Liu et al. 2017; Nowosad et al. 2018; Bogawski et al. 2019b) and ANNs (Zewdie et al. 2019b), especially MLPs (Csépe et al. 2014) have performed particularly well in past studies and their applications will likely be further explored in the future.

Pollen production, release and dispersal are affected by a plethora of factors and, in order to improve the development of future ML models, authors have suggested the incorporation of additional parameters to improve model performance such as spatial location, the distribution of potential sources, phenological data, past pollen concentrations, chemical air pollutants and land use (Csépe et al. 2014; Nowosad 2016; Nowosad et al. 2018). One leading concern is the tendency of ML models to underestimate pollen concentrations during days of unusually high concentration. These errors can arise for several reasons, one being as a result of mass transport from distant sources. Therefore, focus should be placed on the incorporation of forward and back trajectories into ML models (Zewdie et al. 2019b). Since one ML method cannot accurately predict all pollen types in various locations efficiently, future work is likely to include additional comparisons and combinations of various advanced modelling techniques (Voukantsis et al. 2010). There has also been a notable progression from point source meteorological data to weather radar. Recent studies have illustrated the benefits of utilizing gridded meteorological data opposed to station data, which is confined to its point scale and may not fully represent the study area (Nowosad 2016; Zewdie et al. 2019c). Moreover, weather radar allows for the prediction of pollen concentrations over larger spatial scales and is increasing in popularity (Zewdie et al. 2019b; Zewdie et al. 2019c).

Overall, Machine Learning models represent some of the most promising pollen modelling methods and are likely to see large developments in the coming years with the increasing prevalence of aeroallergens and availability of remote sensing databases, including those coming from the Sentinel 2 project (Ottosen et al. 2020).

Source-orientated models

Source-orientated pollen emission and transport models quantify and forecast temporal and spatial distributions of near surface airborne pollen levels (Verstraeten et al. 2019). These models are based on Chemistry Transport Models (CTM's) that have been extended to deal with the atmospheric dispersal of pollen and, unlike observation-orientated models, require knowledge of source conditions and calculations of diffusion (Scheifinger et al. (2013), Sofiev et al. (2013a) and references therein). Sofiev et al. (2015) provides an overview of the seven models in the European MACC modelling consortium: CHIMERE, EMEP, EURAD-IM, LOTOS-EUROS, MATCH, MOCAGE, and SILAM. In addition, other source-orientated numerical forecast models able to simulate the dispersion of pollen include COSMO-ART (Vogel et al. 2008; Vogel et al. 2009; Zink et al. 2012; Zink et al. 2017) and ENVIRO-HIRLAM (Mahura et al. 2009) in Europe, and CMAQ-pollen (Efstathiou et al. 2011) in the USA. Furthermore, the WRF-CHEM model (Weather Research and Forecasting model coupled to Chemistry), developed by the American National Oceanic and Atmospheric Administration, has been used in the UK (Skjøth et al. 2015c). Recent studies examining the use of source-orientated models include the following pollen types: A*lnus* (Prank et al. 2016), *Ambrosia* (Zink et al. 2012; Prank et al. 2013; Liu et al. 2016; Prank et al. 2016), *Artemisia* (Prank et al. 2016), *Betula* (Siljamo et al. 2013; Zhang et al. 2014; Sofiev et al. 2015; Prank et al. 2016; Sofiev 2017; Pauling et al. 2020), *Olea* (Hernandez-Ceballos et al. 2014; Zhang et al. 2014; Prank et al. 2016; Sofiev et al. 2017), *Platanus* (Zhang et al. 2014), Poaceae (Prank et al. 2016; Sofiev 2017), and *Quercus* (Zhang et al. 2014; Jeon et al. 2018).

A major cause of uncertainty in source-orientated models is data of pollen emission sources (Sofiev et al. 2006; Verstraeten et al. 2019). For instance, Verstraeten et al. (2019) increased correlations between SILAM modelled and observed time series of daily average *Betula* pollen concentrations using a combination of an updated source inventory of *Betula* trees derived from forest inventory data, MODIS vegetation photosynthesis data (GPP), and updated start and end dates of airborne *Betula* pollen seasons. This so called 'bottom-up' approach of preparing source inventories using forest inventories was advocated by Skjøth et al. (2008a) and Pauling et al. (2012). Conversely, a 'top-down' approach combining land use data, annual pollen indices and local knowledge of species distribution has been successfully used for mapping the invasive and highly allergenic *Ambrosia artemisiifolia* (Sikoparija et al. 2009; Skjøth et al. 2010; Thibaudon et al. 2014; Karrer et al. 2015; Bonini et al. 2018). Zink et al. (2017) showed that the *Ambrosia* pollen inventory for France published by Thibaudon et al.

(2014), produced using this top-down approach, resulted in the best agreement between COSMO-ART simulated and observed airborne *Ambrosia* pollen concentrations.

The identification of potential source regions of airborne pollen has been a productive area of research in aerobiology in recent years, and examples include the Concentric Ring Method for *Olea* (Rojo et al. 2016) and *Quercus* (Oteros et al. 2017b). Air mass trajectory analysis has traditionally been used to identify potential sources of pollen such as *Ambrosia* (Stach et al. 2007; Sikoparija et al. 2009; Skjøth et al. 2009; Kasprzyk et al. 2011) and *Betula* (Hjelmroos 1991; Hjelmroos 1992; Skjøth et al. 2008b; Skjøth et al. 2009). The analysis of air masses continues to be an accepted method for investigating the paths taken by airborne pollen. *Ambrosia* (Sommer et al. 2015; Grewling et al. 2016; Bilińska et al. 2017) and *Betula* (Skjøth et al. 2015a; Skjøth et al. 2015b; Izquierdo et al. 2017; Bogawski et al. 2019a) remain popular subjects, but target species have been expanded to include *Alnus* (Skjøth et al. 2015a; Skjøth et al. 2015b; Bilińska et al. 2019), *Artemisia* (Qin et al. 2019), Olea (Fernández-Rodríguez et al. 2014; Hernandez-Ceballos et al. 2014), and *Quercus* (Skjøth et al. 2015a; Maya-Manzano et al. 2016). The use of remote sensing techniques such as LiDAR (Katz & Batterman 2019; Pecero-Casimiro et al. 2019) and interpolation techniques like Kriging (Oteros et al. 2019a; Pecero-Casimiro et al. 2019) represent the present state-of-the-art.

Discussion and Conclusions

The 12 most important allergenic pollen taxa in Europe as defined by COST Action ES0603 were ranked by Karatzas et al. (2013) in terms of the most ‘popular’ for model-based forecasting and for forecasting method used. An update of these results (2012-2019) shows that *Betula* and Poaceae are still the most forecast taxa. Although *Betula* has overtaken Poaceae for first place and the invasive *Ambrosia* has replaced *Olea* in third (Table I). A broad range of pollen forecasting methods are now available for researchers. Regression and phenological models (including temperature sum and chilling models) remain the most used methods (Table II), but there has been a sea change and it is notable that there are a number of new modelling techniques being explored (16% of the total) (Table III). This includes Bayesian statistics (Zhang et al. 2013; Jochner-Oette et al. 2019), which are difficult to pigeonhole along with other methods discussed. The fact that the most popular forecasting goal is now numerical modelling reflects this change (Table I). In particular, it appears that Machine Learning techniques are becoming more accepted and have led to better results than more traditional observation-orientated models such as regression and time series analyses.

Forecasting atmospheric concentrations of pollen is not generally considered to be excessively expensive, because the computational resources required are not exceptionally demanding and the necessary data for processing are not difficult to obtain. Improvements in monitoring are likely to drive further innovations in forecasting as real-time information becomes available for data hungry models. Although it is essential we continue to monitor environmental change by extending long-term datasets, e.g. by maintaining some sites that use traditional Hirst type traps, as seen in the Bavarian model (Oteros et al. 2019b). Finally, it is important that fungal spores are also studied and modelled. This is because of their allergic impact and because they can penetrate deep into our respiratory system due to their small size ($PM_{2.5}$ range for some of the most important). There is presently less literature concerned with modelling airborne fungal spores, compared to pollen, but this will also change in the future as real-time methods become more prevalent.

Acknowledgements

This work is part of the Pollen Monitoring and ModELling (POMMEL, Ref. 2017-CCRP-FS.35) project. It has been fully funded by the Irish Environmental Protection Agency (EPA) under the EPA´s Research programme 2014-2020 (Climate 2017) as well as Met Éireann. Particularly, EPA funds to J.H.C from Technological University Dublin (Dublin, Ireland) to develop an MPhil programme entitled "The Development of Fungal Monitoring and Modelling System". EPA and Irish Research Council funds to E.M from Technological University Dublin (Dublin, Ireland) under the project GOIPG/2019/4195 in the 2019 Postgraduate Scholarship programme. The Authors would like to thank to all bodies for their support.

References

Aboulaich N, Achmakh L, Bouziane H, Trigo MM, Recio M, Kadiri M, Cabezudo B, Riadi H, Kazzaz M. 2013. Effect of meteorological parameters on Poaceae pollen in the atmosphere of Tetouan (NW Morocco). International Journal of Biometeorology 57; 197-205. 10.1007/s00484-012-0566-2

Achmakh L, Bouziane H, Aboulaich N, Trigo MM, Janati A, Kadiri M. 2015. Airborne pollen of Olea europaea L. in Tetouan (NW Morocco): heat requirements and forecasts. Aerobiologia 31; 191-199. 10.1007/s10453-014-9356-0

Aguilera F, Fornaciari M, Ruiz-Valenzuela L, Galán C, Msallem M, Dhiab A, la Guardia C-d, del Mar Trigo M, Bonofiglio T, Orlandi F. 2015a. Phenological models to predict the main flowering phases of olive (Olea europaea L.) along a latitudinal and longitudinal gradient across the Mediterranean region. International Journal of Biometeorology 59; 629-641. 10.1007/s00484-014-0876-7

Aguilera F, Orlandi F, Ruiz-Valenzuela L, Msallem M, Fornaciari M. 2015b. Analysis and interpretation of long temporal trends in cumulative temperatures and olive reproductive features using a seasonal trend decomposition procedure. Agricultural and Forest Meteorology 203; 208-216. 10.1016/j.agrformet.2014.11.019

Arca B, Pellizzaro G, Canu A, Vargiu A. 2004. Use of neural networks to short-term forecast of airborne pollen data. 16th Biometeorology and Aerobiology (16BIOAERO), Vancouver, Canada, American Meteorological Society

Astray G, Fernández-González M, Rodríguez-Rajo FJ, López D, Mejuto JC. 2016. Airborne castanea pollen forecasting model for ecological and allergological implementation. Science of The Total Environment 548–549; 110-121. 10.1016/j.scitotenv.2016.01.035

Aznarte M JL, Benítez Sánchez JM, Lugilde DN, de Linares Fernández C, de la Guardia CD, Sánchez FA. 2007. Forecasting airborne pollen concentration time series with neural and neuro-fuzzy models. Expert Systems with Applications 32; 1218-1225. 10.1016/j.eswa.2006.02.011

Balram D, Lian K-Y, Sebastian N. 2019. Air quality warning system based on a localized PM2.5 soft sensor using a novel approach of Bayesian regularized neural network via forward feature selection. Ecotoxicology and Environmental Safety 182; 109386. 10.1016/j.ecoenv.2019.109386

Beggs PJ, Šikoparija B, Smith M. 2017. Aerobiology in the International Journal of Biometeorology, 1957–2017. International Journal of Biometeorology 61; 51-58. 10.1007/s00484-017-1374-5

Bilińska D, Kryza M, Werner M, Malkiewicz M. 2019. The variability of pollen concentrations at two stations in the city of Wrocław in Poland. Aerobiologia 35; 421-439. 10.1007/s10453-019-09567-1

Bilińska D, Skjøth CA, Werner M, Kryza M, Malkiewicz M, Krynicka J, Drzeniecka-Osiadacz A. 2017. Source regions of ragweed pollen arriving in south-western Poland and the influence of meteorological data on the HYSPLIT model results. Aerobiologia 33; 315-326. 10.1007/s10453-017-9471-9

Bogawski P, Borycka K, Grewling Ł, Kasprzyk I. 2019a. Detecting distant sources of airborne pollen for Poland: Integrating back-trajectory and dispersion modelling with a satellite-based phenology. Science of The Total Environment 689; 109-125. 10.1016/j.scitotenv.2019.06.348

Bogawski P, Grewling Ł, Jackowiak B. 2019b. Predicting the onset of Betula pendula flowering in Poznań (Poland) using remote sensing thermal data. Science of The Total Environment 658; 1485-1499. 10.1016/j.scitotenv.2018.12.295

Bonini M, Šikoparija B, Prentović M, Cislaghi G, Colombo P, Testoni C, Grewling L, Lommen STE, Müller-Schärer H, Smith M. 2015. Is the recent decrease in airborne Ambrosia pollen in the Milan area due to the accidental introduction of the ragweed leaf beetle Ophraella communa? Aerobiologia 31; 499-513. 10.1007/s10453-015-9380-8

Bonini M, Šikoparija B, Skjøth CA, Cislaghi G, Colombo P, Testoni C, Smith M. 2018. Ambrosia pollen source inventory for Italy: a multi-purpose tool to assess the impact of the ragweed leaf beetle (Ophraella communa LeSage) on populations of its host plant. International Journal of Biometeorology 62; 597-608. 10.1007/s00484-017-1469-z

Brennan GL, Potter C, De Vere N, Griffith GW, Skjøth CA, Osborne NJ, Wheeler BW, McInnes RN, Clewlow Y, Barber A. 2019. Temperate airborne grass pollen defined by spatio-temporal shifts in community composition. Nature Ecology & Evolution 3; 750-754. 10.1038/s41559-019-0849-7

Brighetti MA, Costa C, Menesatti P, Antonucci F, Tripodi S, Travaglini A. 2014. Multivariate statistical forecasting modeling to predict Poaceae pollen critical concentrations by meteoclimatic data. Aerobiologia 30; 25-33. 10.1007/s10453-013-9305-3

Burki C, Šikoparija B, Thibaudon M, Oliver G, Magyar D, Udvardy O, Leelőssy Á, Charpilloz C, Pauling A. 2019. Artificial neural networks can be used for Ambrosia pollen emission parameterization in COSMO-ART. Atmospheric Environment 218; 116969. 10.1016/j.atmosenv.2019.116969

Buters JT, Albertini R, Annesi-Maesano I, Antunes C, Berger U, Brandao R, Cecchi L, Celenk S, Galan C, Grewling L, Kennedy R, Prank M, Rantio-Lehtimaki A, Reese G, Sauliene I, Smith M, Sofiev M, Thibaudon M, Weber B, Group HW. 2013. Grass pollen count and grass group 5-allergen release across eight European countries: results from HIALINE. Allergy 68; 102.

Buters JTM, Antunes CM, Galveias A, Bergmann KC, Thibaudon M, Galán C, Schmidt-Weber C, Oteros J. 2018. Pollen and Spore Monitoring in the world. Clinical and Translational Allergy 8; 89. 10.1186/s13601-018-0197-8

Buters JTM, Thibaudon M, Smith M, Kennedy R, Rantio-Lehtimaki A, Albertini R, Reese G, Weber B, Galan C, Brandao R, Antunes CM, Jaeger S, Berger U, Celenk S, Grewling L, Jackowiak B, Sauliene I, Weichenmeier I, Pusch G, Sarioglu H, Ueffing M, Behrendt H, Prank M, Sofiev M, Cecchi L, HIALINE-Working-Group. 2012. Release of Bet v 1 from birch pollen from 5 European countries. Results from the HIALINE study. Atmospheric Environment 55; 496-505. 10.1016/j.atmosenv.2012.01.054

Calvo A, Baumgardner D, Castro A, Fernández-González D, Vega-Maray A, Valencia-Barrera R, Oduber F, Blanco-Alegre C, Fraile R. 2018. Daily behavior of urban fluorescing aerosol particles in northwest Spain Daily behavior of urban fluorescing aerosol particles in northwest Spain. Atmospheric Environment 184; 262-277. 10.1016/j.atmosenv.2018.04.027

Chappuis C, Tummon F, Clot B, Konzelmann T, Calpini B, Crouzy B. 2020. Automatic pollen monitoring: first insights from hourly data. Aerobiologia 36; 159-170. 10.1007/s10453-019-09619-6

Charalampopoulos A, Lazarina M, Tsiripidis I, Vokou D. 2018. Quantifying the relationship between airborne pollen and vegetation in the urban environment. Aerobiologia 34; 285-300. 10.1007/s10453-018-9513-y

Comtois P. 1998. Statistical Analysis of Aerobiological Data. In: P. Mandrioli, P. Comtois and V. Levizzani eds. Methods in Aerobiology. 262 pp. Bologna Pitagora Editrice. ISBN 88-371-1043-X

Comtois P, Alcazar P, Neron D. 1999. Pollen counts statistics and its relevance to precision. Aerobiologia 15; 19-28. 10.1023/A:1007501017470

Crouzy B, Stella M, Konzelmann T, Calpini B, Clot B. 2016. All-optical automatic pollen identification: Towards an operational system. Atmospheric Environment 140; 202-212. 10.1016/j.atmosenv.2016.05.062

Csépe Z, Leelőssy Á, Mányoki G, Kajtor-Apatini D, Udvardy O, Péter B, Páldy A, Gelybó G, Szigeti T, Pándics T, Kofol-Seliger A, Simčič A, Leru PM, Eftimie AM, Šikoparija B, Radišić P, Stjepanović B, Hrga I, Večenaj A, Vucić A, Peroš-Pucar D, Škorić T, Ščevková J, Bastl M, Berger U, Magyar D. 2020. The application of a neural network-based ragweed pollen forecast by the Ragweed Pollen Alarm System in the Pannonian biogeographical region. Aerobiologia 36; 131-140. 10.1007/s10453-019-09615-w

Csépe Z, Makra L, Voukantsis D, Matyasovszky I, Tusnády G, Karatzas K, Thibaudon M. 2014. Predicting daily ragweed pollen concentrations using Computational Intelligence techniques over two heavily polluted areas in Europe. Science of The Total Environment 476–477; 542-552. /10.1016/j.scitotenv.2014.01.056

Dahl A, Galán C, Hajkova L, Pauling A, Sikoparija B, Smith M, Vokou D. 2013. The onset, course and intensity of the pollen season. pp 29–70. In: Sofiev M, Bergmann K-C eds. Allergenic pollen. A review of the production, release, distribution and health impacts. Springer Science+Business Media, Dordrecht, Netherlands.

Dai W, Jin H, Zhang Y, Liu T, Zhou Z. 2019. Detecting temporal changes in the temperature sensitivity of spring phenology with global warming: Application of machine learning in phenological model. Agricultural and Forest Meteorology 279; 107702. 10.1016/j.agrformet.2019.107702

de Weger LA, Beerthuizen T, Hiemstra PS, Sont JK. 2014. Development and validation of a 5-day-ahead hay fever forecast for patients with grass-pollen-induced allergic rhinitis. International Journal of Biometeorology 58; 1047-1055. 10.1007/s00484-013-0692-5

de Weger LA, Bergmann K-C, Rantio-Lehtimäki A, Dahl Å, Buters J, Déchamp C, Belmonte J, Thibaudon M, Cecchi L, Besancenot JP, Galán C, Waisel Y. 2013. Impact of Pollen. pp 161-216. In: Sofiev M and Bergmann K.C eds. Allergenic Pollen. Springer Science+Business Media, Dordrecht, Netherlands.

Donders TH, Hagemans K, Dekker SC, de Weger LA, De Klerk P, Wagner-Cremer F. 2014. Region-specific sensitivity of anemophilous pollen deposition to temperature and precipitation. PLoS ONE 9; e104774. 10.1371/journal.pone.0104774

Du J, Liu Y, Yu Y, Yan W. 2017. A prediction of precipitation data based on support vector machine and particle swarm optimization (PSO-SVM) algorithms. Algorithms; 10, 57. 10.3390/a10020057

Efstathiou C, Isukapalli S, Georgopoulos P. 2011. A mechanistic modeling system for estimating large-scale emissions and transport of pollen and co-allergens. Atmospheric Environment 45; 2260-2276. 10.1016/j.atmosenv.2010.12.008

Escabias M, Valderrama MJ, Aguilera AM, Santofimia ME, Aguilera-Morillo MC. 2013. Stepwise selection of functional covariates in forecasting peak levels of olive pollen. Stochastic Environmental Research and Risk Assessment 27; 367-376. 10.1007/s00477-012-0655-0

Estrella N, Menzel A, Krämer U, Behrendt H. 2006. Integration of flowering dates in phenology and pollen counts in aerobiology: Analysis of their spatial and temporal coherence in Germany (1992-1999). International Journal of Biometeorology 51; 49-59. 10.1007/s00484-006-0038-7

Feeney P, Rodríguez SF, Molina R, McGillicuddy E, Hellebust S, Quirke M, Daly S, O'Connor D, Sodeau J. 2018. A comparison of on-line and off-line bioaerosol measurements at a biowaste site. Waste management 76; 323-338. 10.1016/j.wasman.2018.02.035

Fennelly MJ, Sewell G, Prentice MB, O’Connor DJ, Sodeau JR. 2018. The use of real-time fluorescence instrumentation to monitor ambient primary biological aerosol particles (PBAP). Atmosphere 9; 1. 10.3390/atmos9010001

Fernández-Llamazares Á, Belmonte J, Delgado R, De Linares C. 2014. A statistical approach to bioclimatic trend detection in the airborne pollen records of Catalonia (NE Spain). International Journal of Biometeorology 58; 371-382. 10.1007/s00484-013-0632-4

Fernández-Rodríguez S, Durán-Barroso P, Silva-Palacios I, Tormo-Molina R, Maya-Manzano JM, Gonzalo-Garijo Á. 2016a. Forecast model of allergenic hazard using trends of Poaceae airborne pollen over an urban area in SW Iberian Peninsula (Europe). Natural Hazards 84; 121-137. 10.1007/s11069-016-2411-0

Fernández-Rodríguez S, Durán-Barroso P, Silva-Palacios I, Tormo-Molina R, Maya-Manzano JM, Gonzalo-Garijo Á. 2016b. Quercus long-term pollen season trends in the southwest of the Iberian Peninsula. Process Safety and Environmental Protection 101; 152-159. 10.1016/j.psep.2015.11.008

Fernández-Rodríguez S, Durán-Barroso P, Silva-Palacios I, Tormo-Molina R, Maya-Manzano JM, Gonzalo-Garijo Á. 2016c. Regional forecast model for the Olea pollen season in Extremadura (SW Spain). International Journal of Biometeorology 60; 1509-1517. 10.1007/s00484-016-1141-z

Fernández-Rodríguez S, Durán-Barroso P, Silva-Palacios I, Tormo-Molina. R, Maya-Manzano JM, Gonzalo-Garijo A, Monroy-Colín A. 2018. Environmental assessment of allergenic risk provoked by airborne grass pollen through forecast model in a Mediterranean region. Journal of Cleaner Production 176; 1304-1315.

Fernández-Rodríguez S, Skjøth CA, Tormo-Molina R, Brandao R, Caeiro E, Silva-Palacios I, Gonzalo-Garijo Á, Smith M. 2014. Identification of potential sources of airborne Olea pollen in the Southwest Iberian Peninsula. International Journal of Biometeorology 58; 337-348. 10.1007/s00484-012-0629-4

Frenguelli G, Ghitarrini S, Tedeschini E. 2016. Time linkages between pollination onsets of different taxa in Perugia, central Italy - An update. Annals of Agricultural and Environmental Medicine 23; 92-96. 10.5604/12321966.1196860

Galan C, Antunes C, Brandao R, Torres C, Garcia-Mozo H, Caeiro E, Ferro R, Prank M, Sofiev M, Albertini R, Berger U, Cecchi L, Celenk S, Grewling L, Jackowiak B, Jäger S, Kennedy R, Rantio-Lehtimäki A, Reese G, Sauliene I, Smith M, Thibaudon M, Weber B, Weichenmeier I, Pusch G, Buters JTM. 2013. Airborne olive pollen counts are not representative of exposure to the major olive allergen Ole e 1. Allergy: European Journal of Allergy and Clinical Immunology 68; 809-812. 10.1111/all.12144

Galán C, Ariatti A, Bonini M, Clot B, Crouzy B, Dahl A, Fernandez-González D, Frenguelli G, Gehrig R, Isard S, Levetin E, Li DW, Mandrioli P, Rogers CA, Thibaudon M, Sauliene I, Skjoth C, Smith M, Sofiev M. 2017. Recommended terminology for aerobiological studies. Aerobiologia 33; 293-295. 10.1007/s10453-017-9496-0

Galán C, Smith M, Thibaudon M, Frenguelli G, Oteros J, Gehrig R, Berger U, Clot B, Brandao R. 2014. Pollen monitoring: minimum requirements and reproducibility of analysis. Aerobiologia 30; 385-395. 10.1007/s10453-014-9335-5

Galera MD, Elvira - Rendueles B, Moreno JM, Negral L, Ruiz-Abellón MC, García-Sánchez A, Moreno-Grau S. 2018. Analysis of airborne Olea pollen in Cartagena (Spain). Science of The Total Environment 622-623; 436-445. 10.1016/j.scitotenv.2017.11.349

García-Mozo H, Oteros J, Galán C. 2015. Phenological changes in olive (ola europaea l.) reproductive cycle in southern Spain due to climate change. Annals of Agricultural and Environmental Medicine 22; 421-428. 10.5604/12321966.1167706

García-Mozo H, Yaezel L, Oteros J, Galán C. 2014. Statistical approach to the analysis of olive long-term pollen season trends in southern Spain. Science of The Total Environment 473-474; 103-109. 10.1016/j.scitotenv.2013.11.142

González-Naharro R, Quirós E, Fernández-Rodríguez S, Silva-Palacios I, Maya-Manzano JM, Tormo-Molina R, Pecero-Casimiro R, Monroy-Colin A, Gonzalo-Garijo Á. 2019. Relationship of NDVI and oak (Quercus) pollen including a predictive model in the SW Mediterranean region. Science of The Total Environment 676; 407-419. 10.1016/j.scitotenv.2019.04.213

Grewling Ł, Bogawski P, Jenerowicz D, Czarnecka-Operacz M, Šikoparija B, Skjøth CA, Smith M. 2016. Mesoscale atmospheric transport of ragweed pollen allergens from infected to uninfected areas. International Journal of Biometeorology 60; 1493-1500. 10.1007/s00484-016-1139-6

Healy D, Huffman J, O'Connor DJ, Pöhlker C, Pöschl U, Sodeau J. 2014. Ambient measurements of biological aerosol particles near Killarney, Ireland: a comparison between real-time fluorescence and microscopy techniques. Atmospheric Chemistry and Physics 14; 8055-8069. 10.5194/acp-14-8055-2014

Hernandez-Ceballos MA, Soares J, García-Mozo H, Sofiev M, Bolivar JP, Galán C. 2014. Analysis of atmospheric dispersion of olive pollen in southern Spain using SILAM and HYSPLIT models. Aerobiologia 30; 239-255. 10.1007/s10453-013-9324-0

Hirst JM. 1952. An automatic volumetric spore trap. The Annals of Applied Biology 39; 257-265. 10.1111/j.1744-7348.1952.tb00904.x

Hjelmroos M. 1991. Evidence of long distance transport of *Betula* pollen. Grana 30; 215-228. 10.1080/00173139109427802

Hjelmroos M. 1992. Long-distance transport of *Betula* pollen grains and allergic symptoms. Aerobiologia 8; 231-236. 10.1007/BF02071631

Howard LE, Levetin E. 2014. Ambrosia pollen in Tulsa, Oklahoma: aerobiology, trends and forecasting model development. Annals of Allergy, Asthma and Immunology 113; 641-646. 10.1016/j.anai.2014.08.019

Huffman JA, Perring AE, Savage NJ, Clot B, Crouzy B, Tummon F, Shoshanim O, Damit B, Schneider J, Sivaprakasam V, Zawadowicz MA, Crawford I, Gallagher M, Topping D, Doughty DC, Hill SC, Pan Y. 2020. Real-time sensing of bioaerosols: Review and current perspectives. Aerosol Science and Technology 54; 465-495. 10.1080/02786826.2019.1664724

Iglesias-Otero MA, Astray G, Vara A, Galvez JF, Mejuto JC, Rodriguez-Rajo FJ. 2015. Forecasting Olea airborne pollen concentration by means of Artificial Intelligence. Fresenius Environmental Bulletin 24; 4574-4580.

Inatsu M, Kobayashi S, Tekeuchi S, Ohmori A. 2014. Statistical analysis on Daily variations of Birch pollen amount with Climatic Variables in Sapporo. SOLA 10; 172-175. 10.2151/sola.2014-036

Izquierdo R, Alarcón M, Mazón J, Pino D, De Linares C, Aguinagalde X, Belmonte J. 2017. Are the Pyrenees a barrier for the transport of birch (Betula) pollen from Central Europe to the Iberian Peninsula? Science of The Total Environment 575; 1183-1196. 10.1016/j.scitotenv.2016.09.192

Janati A, Bouziane H, del Mar Trigo M, Kadiri M, Kazzaz M. 2017. Poaceae pollen in the atmosphere of Tetouan (NW Morocco): effect of meteorological parameters and forecast of daily pollen concentration. Aerobiologia 33; 517-528. 10.1007/s10453-017-9487-1

Jato V, Rodríguez-Rajo FJ, Alcázar P, De Nuntiis P, Galán C, Mandrioli P. 2006. May the definition of Pollen Season influence aerobiological results. Aerobiologia 22; 13-25. 10.1007/s10453-005-9011-x

Jato V, Rodríguez-Rajo FJ, Fernández-González M, Aira MJ. 2014. Assessment of Quercus flowering trends in NW Spain. International Journal of Biometeorology 59; 517-531. 10.1007/s00484-014-0865-x

Jeon W, Choi Y, Roy A, Pan S, Price D, Hwang M-K, Kim KR, Oh I. 2018. Investigation of Primary Factors Affecting the Variation of Modeled Oak Pollen Concentrations: A Case Study for

Southeast Texas in 2010. Asia-Pacific Journal of Atmospheric Sciences 54; 33-41. 10.1007/s13143-017-0057-9

Jochner-Oette S, Menzel A, Gehrig R, Clot B. 2019. Decrease or increase? Temporal changes in pollen concentrations assessed by Bayesian statistics. Aerobiologia 35; 153-163. 10.1007/s10453-018-9547-1

Karatzas KD, Riga M, Smith M. 2013. Presentation and Dissemination of Pollen Information. pp 217-247. In: Sofiev M, Bergmann K-C eds. Allergenic Pollen. Springer Science+Business Media, Dordrecht, Netherlands.

Karrer G, Skjøth CA, Šikoparija B, Smith M, Berger U, Essl F. 2015. Ragweed (*Ambrosia*) pollen source inventory for Austria. Science of The Total Environment 523; 120-128. 10.1016/j.scitotenv.2015.03.108

Kasprzyk I, Myszkowska D, Grewling Ł, Stach A, Šikoparija B, Skjøth CA, Smith M. 2011. The occurrence of Ambrosia pollen in Rzeszów, Kraków and Poznań, Poland: investigation of trends and possible transport of *Ambrosia* pollen from Ukraine. International Journal of Biometeorology 55; 633-644. 10.1007/s00484-010-0376-3

Katz DSW, Batterman SA. 2019. Allergenic pollen production across a large city for common ragweed (Ambrosia artemisiifolia). Landscape and Urban Planning 190; 103615. 10.1016/j.landurbplan.2019.103615

Kawashima S, Clot B, Fujita T, Takahashi Y, Nakamura K. 2007. An algorithm and a device for counting airborne pollen automatically using laser optics. Atmospheric Environment 41; 7987-7993. 10.1016/j.atmosenv.2007.09.019

Kinnear PR, Gray CD. 1999. SPSS for Windows made simple. 400 pp. Taylor & Francis. ISBN-13: 978-0863776113

Lara B, Rojo J, Fernández-González F, Pérez-Badia R. 2019. Prediction of airborne pollen concentrations for the plane tree as a tool for evaluating allergy risk in urban green areas. Landscape and Urban Planning 189; 285-295. 10.1016/j.landurbplan.2019.05.002

Linkosalo T, Lappalainen HK, Hari P. 2008. A comparison of phenological models of leaf bud burst and flowering of boreal trees using independent observations. Tree Physiology 28; 1873–1882. 10.1093/treephys/28.12.1873

Linkosalo T, Le Tortorec E, Prank M, Pessi A-M, Saarto A. 2017. Alder pollen in Finland ripens after a short exposure to warm days in early spring, showing biennial variation in the onset of pollen ripening. Agricultural and Forest Meteorology 247; 408-413. 10.1016/j.agrformet.2017.08.030

Linkosalo T, Ranta H, Oksanen A, Siljamo P, Luomajoki A, Kukkonen J, Sofiev M. 2010. A double-threshold temperature sum model for predicting the flowering duration and relative intensity of Betula pendula and B. pubescens. Agricultural and Forest Meteorology 150; 1579-1584. 10.1016/j.agrformet.2010.08.007

Liu L, Solmon F, Vautard R, Hamaoui-Laguel L, Torma CZ, Giorgi F. 2016. Ragweed pollen production and dispersion modelling within a regional climate system, calibration and application over Europe. Biogeosciences 13; 2769-2786. 10.5194/bg-13-2769-2016

Liu X, Wu D, Zewdie GK, Wijerante L, Timms CI, Riley A, Levetin E, Lary DJ. 2017. Using machine learning to estimate atmospheric Ambrosia pollen concentrations in Tulsa, OK. Environmental Health Insights 11; 1178630217699399. 10.1177/1178630217699399

Lukasiewicz A. 1984. Need to standardize phenological methodology in Polish botanic gardens and arboretums. Botanic News 28; 153–8.

Mahura A, Baklanov A, Korsholm U. 2009. Parameterization of the birch pollen diurnal cycle. Aerobiologia 25; 203-208. 10.1007/s10453-009-9125-7

Malkiewicz M, Klaczak K, Drzeniecka-Osiadacz A, Krynicka J, Migała K. 2014. Types of Artemisia pollen season depending on the weather conditions in Wrocław (Poland), 2002–2011. Aerobiologia 30; 13-23. 10.1007/s10453-013-9304-4

Maya-Manzano JM, Fernández-Rodríguez S, Smith M, Tormo-Molina R, Reynolds A, Silva-Palacios I, Gonzalo-Garijo Á, Sadyś M. 2016. Airborne Quercus pollen in SW Spain: Identifying favourable conditions for atmospheric transport and potential source areas. Science of The Total Environment 571; 1037-1047. 10.1016/j.scitotenv.2016.07.094

Murray MG, Galan C. 2016. Effect of the meteorological parameters on the Olea europaea L. pollen season in Bahía Blanca (Argentina). Aerobiologia 32; 541-553. 10.1007/s10453-016-9431-9

Myszkowska D. 2013. Prediction of the birch pollen season characteristics in Cracow, Poland using an 18-year data series. Aerobiologia 29; 31-44. 10.1007/s10453-012-9260-4

Myszkowska D. 2014a. Poaceae pollen in the air depending on the thermal conditions. International Journal of Biometeorology 58; 975-986. 10.1007/s00484-013-0682-7

Myszkowska D. 2014b. Predicting tree pollen season start dates using thermal conditions. Aerobiologia 30; 307-321. 10.1007/s10453-014-9329-3

Myszkowska D, Majewska R. 2014. Pollen grains as allergenic environmental factors – New approach to the forecasting of the pollen concentration during the season. Annals of Agricultural and Environmental Medicine 21; 681-688. 10.5604/12321966.1129914

Navares R, Aznarte JL. 2017. Predicting the Poaceae pollen season: six month-ahead forecasting and identification of relevant features. International Journal of Biometeorology 61; 647-656. 10.1007/s00484-016-1242-8

Navares R, Aznarte JL. 2020. Forecasting Plantago pollen: improving feature selection through random forests, clustering, and Friedman tests. Theoretical and Applied Climatology 139; 163-174. 10.1007/s00704-019-02954-1

Noll KE. 1970. A rotary inertial impactor for sampling giant particles in the atmosphere. Atmospheric Environment 4; 9-19. 10.1016/0004-6981(70)90050-8

Novara C, Falzoi S, La Morgia V, Spanna F, Siniscalco C. 2016. Modelling the pollen season start in Corylus avellana and Alnus glutinosa. Aerobiologia 32; 555-569. 10.1007/s10453-016-9432-8

Nowosad J. 2016. Spatiotemporal models for predicting high pollen concentration level of Corylus, Alnus, and Betula. International Journal of Biometeorology 60; 843-855. 10.1007/s00484-015-1077-8

Nowosad J, Stach A, Kasprzyk I, Chłopek K, Dąbrowska-Zapart K, Grewling Ł, Latałowa M, Pędziszewska A, Majkowska-Wojciechowska B, Myszkowska D. 2018. Statistical techniques for modeling of Corylus, Alnus, and Betula pollen concentration in the air. Aerobiologia 34; 301-313. 10.1007/s10453-018-9514-x

Nowosad J, Stach A, Kasprzyk I, Weryszko-Chmielewska E, Piotrowska-Weryszko K, Puc M, Grewling Ł, Pędziszewska A, Uruska A, Myszkowska D. 2016. Forecasting model of Corylus, Alnus, and Betula pollen concentration levels using spatiotemporal correlation properties of pollen count. Aerobiologia 32; 453-468. 10.1007/s10453-015-9418-y

O’Connor DJ, Daly SM, Sodeau JR. 2015. On-line monitoring of airborne bioaerosols released from a composting/green waste site. Waste management 42; 23-30. 10.1016/j.wasman.2015.04.015

O'Connor DJ, Healy DA, Hellebust S, Buters JT, Sodeau JR. 2014. Using the WIBS-4 (Waveband Integrated Bioaerosol Sensor) technique for the on-line detection of pollen grains. Aerosol Science and Technology 48; 341-349. 10.1080/02786826.2013.872768

Ocaña-Peinado FM, Valderrama MJ, Bouzas PR. 2013. A principal component regression model to forecast airborne concentration of Cupressaceae pollen in the city of Granada (SE Spain), during 1995-2006. International Journal of Biometeorology 57; 483-486. 10.1007/s00484-012-0527-9

Oteros J, Bergmann K-C, Menzel A, Damialis A, Traidl-Hoffmann C, Schmidt-Weber CB, Buters J. 2019a. Spatial interpolation of current airborne pollen concentrations where no monitoring exists. Atmospheric Environment 199; 435-442. 10.1016/j.atmosenv.2018.11.045

Oteros J, Buters J, Laven G, Röseler S, Wachter R, Schmidt-Weber C, Hofmann F. 2017a. Errors in determining the flow rate of Hirst-type pollen traps. Aerobiologia 33; 201-210. 10.1007/s10453-016-9467-x

Oteros J, García-Mozo H, Hervás C, Galán C. 2013a. Biometeorological and autoregressive indices for predicting olive pollen intensity. International Journal of Biometeorology 57; 307-316. 10.1007/s00484-012-0555-5

Oteros J, García-Mozo H, Hervás-Martínez C, Galán C. 2013b. Year clustering analysis for modelling olive flowering phenology. International Journal of Biometeorology 57; 545-555. 10.1007/s00484-012-0581-3

Oteros J, Orlandi F, García-Mozo H, Aguilera F, Dhiab AB, Bonofiglio T, Abichou M, Ruiz-Valenzuela L, Del Trigo MM, Díaz De La Guardia C, Domínguez-Vilches E, Msallem M, Fornaciari M, Galán C. 2014. Better prediction of Mediterranean olive production using pollen-based models. Agronomy for Sustainable Development 34; 685-694. 10.1007/s13593-013-0198-x

Oteros J, Pusch G, Weichenmeier I, Heimann U, Möller R, Röseler S, Traidl-Hoffmann C, Schmidt-Weber C, Buters JTM. 2015. Automatic and Online Pollen Monitoring. International Archives of Allergy and Immunology 167; 158-166. 10.1159/000436968

Oteros J, Sofiev M, Smith M, Clot B, Damialis A, Prank M, Werchan M, Wachter R, Weber A, Kutzora S, Heinze S, Herr CEW, Menzel A, Bergmann K-C, Traidl-Hoffmann C, Schmidt-Weber CB, Buters JTM. 2019b. Building an automatic pollen monitoring network (ePIN): Selection of optimal sites by clustering pollen stations. Science of The Total Environment 688; 1263-1274. 10.1016/j.scitotenv.2019.06.131

Oteros J, Valencia RM, del Río S, Vega AM, García-Mozo H, Galán C, Gutiérrez P, Mandrioli P, Fernández-González D. 2017b. Concentric Ring Method for generating pollen maps. Quercus as case study. Science of The Total Environment 576; 637-645. 10.1016/j.scitotenv.2016.10.121

Ottosen T-B, Petch G, Hanson M, Skjøth CA. 2020. Tree cover mapping based on Sentinel-2 images demonstrate high thematic accuracy in Europe. International Journal of Applied Earth Observation and Geoinformation 84; 101947. 10.1016/j.jag.2019.101947

Pauling A, Clot B, Menzel A, Jung S. 2020. Pollen forecasts in complex topography: two case studies from the Alps using the numerical pollen forecast model COSMO-ART. Aerobiologia 36; 25-30. 10.1007/s10453-019-09590-2

Pauling A, Gehrig R, Clot B. 2014. Toward optimized temperature sum parameterizations for forecasting the start of the pollen season. Aerobiologia 30; 45-57. 10.1007/s10453-013-9308-0

Pauling A, Rotach MW, Gehrig R, Clot B, EAN. 2012. A method to derive vegetation distribution maps for pollen dispersion models using birch as an example. International Journal of Biometeorology 56; 949-958. 10.1007/s00484-011-0505-7

Pecero-Casimiro R, Fernández-Rodríguez S, Tormo-Molina R, Monroy-Colín A, Silva-Palacios I, Cortés-Pérez JP, Gonzalo-Garijo Á, Maya-Manzano JM. 2019. Urban aerobiological risk mapping of ornamental trees using a new index based on LiDAR and Kriging: A case study of plane trees. Science of The Total Environment 693; 133576. 10.1016/j.scitotenv.2019.07.382

Picornell A, Buters J, Rojo J, Traidl-Hoffmann C, Menzel A, Bergmann K, Werchan M, Schmidt-Weber C, Oteros J. 2019a. Predicting the start, peak and end of the Betula pollen season in Bavaria, Germany. Science of The Total Environment 690; 1299-1309. 10.1016/j.scitotenv.2019.06.485

Picornell A, Oteros J, Trigo M, Gharbi D, Fernández SD, Caballero MM, Toro F, García-Sánchez J, Ruiz-Mata R, Cabezudo B. 2019b. Increasing resolution of airborne pollen forecasting at a discrete sampled area in the southwest Mediterranean Basin. Chemosphere 234; 668-681. 10.1016/j.chemosphere.2019.06.019

Piotrowska K. 2012. Forecasting the Poaceae pollen season in eastern Poland. Grana 51; 263-269. 10.1080/00173134.2012.659204

Piotrowska-Weryszko K. 2013a. Artemisia pollen in the air of Lublin, Poland (2001-2012). Acta Scientiarum Polonorum-Hortorum Cultus 12; 155-168.

Piotrowska-Weryszko K. 2013b. The effect of the meteorological factors on the Alnus pollen season in Lublin (Poland). Grana 52; 221-228. 10.1080/00173134.2013.772653

Pöhlker C, Huffman J, Pöschl U. 2012. Autofluorescence of atmospheric bioaerosols–fluorescent biomolecules and potential interferences. Atmospheric Measurement Techniques 5; 37-71. 10.5194/amt-5-37-2012

Prank M, Chapman DS, Bullock JM, Belmonte J, Berger U, Dahl A, Jäger S, Kovtunenko I, Magyar D, Niemelä S, Rantio-Lehtimäki A, Rodinkova V, Sauliene I, Severova E, Sikoparija B, Sofiev M. 2013. An operational model for forecasting ragweed pollen release and dispersion in Europe. Agricultural and Forest Meteorology 182–183; 43-53. 10.1016/j.agrformet.2013.08.003

Prank M, Sofiev M, Siljamo P, Kauhaniemi M. 2016. Increasing the Number of Allergenic Pollen Species in SILAM Forecasts pp 313-317. In: Steyn D and Chaumerliac N eds. Air Pollution Modeling and its Application XXIV. Springer Proceedings in Complexity

Puc M. 2012. Artificial neural network model of the relationship between Betula pollen and meteorological factors in Szczecin (Poland). International Journal of Biometeorology 56; 395-401. 10.1007/s00484-011-0446-1

Puc M, Wolski T. 2013. Forecasting of the selected features of Poaceae (R. Br.) Barnh., Artemisia L. and Ambrosia L. pollen season in Szczecin, North-Western Poland, using Gumbel's distribution. Annals of Agricultural and Environmental Medicine 20; 36-47.

Qin X, Li Y, Sun X, Meng L, Wang X. 2019. Transport pathway and source area for Artemisia pollen in Beijing, China. International Journal of Biometeorology 63; 687-699. 10.1007/s00484-017-1467-1

Recknagel F. 2001. Applications of machine learning to ecological modelling. Ecological Modelling 146; 303-310. 10.1016/S0304-3800(01)00316-7

Ritenberga O, Sofiev M, Kirillova V, Kalnina L, Genikhovich E. 2016. Statistical modelling of non-stationary processes of atmospheric pollution from natural sources: example of birch pollen. Agricultural and Forest Meteorology 226; 96-107. 10.1016/j.agrformet.2016.05.016

Robichaud A, Comtois P. 2017. Statistical modeling, forecasting and time series analysis of birch phenology in Montreal, Canada. Aerobiologia 33; 529-554. 10.1007/s10453-017-9488-0

Rodríguez-Rajo FJ, Astray G, Ferreiro-Lage JA, Aira MJ, Jato-Rodriguez MV, Mejuto JC. 2010. Evaluation of atmospheric Poaceae pollen concentration using a neural network applied to a coastal Atlantic climate region. Neural Networks 23; 419-425. 10.1016/j.neunet.2009.06.006

Rojo J, Orlandi F, Pérez-Badia R, Aguilera F, Ben Dhiab A, Bouziane H, Díaz de la Guardia C, Galán C, Gutiérrez-Bustillo AM, Moreno-Grau S, Msallem M, Trigo MM, Fornaciari M. 2016. Modeling olive pollen intensity in the Mediterranean region through analysis of emission sources. Science of The Total Environment 551-552; 73-82. 10.1016/j.scitotenv.2016.01.193

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. International Journal of Biometeorology 61; 335-348. 10.1007/s00484-016-1215-y

Roshchina VaV. 2008. Fluorescing world of plant secreting cells, 356 pp. CRC Press. ISBN 9781578085156.

Sabariego S, Cuesta P, Fernández-González F, Pérez-Badia R. 2012. Models for forecasting airborne Cupressaceae pollen levels in central Spain. International Journal of Biometeorology 56; 253-258. 10.1007/s00484-011-0423-8

Sánchez Mesa JA, Galán C, Hervás C. 2005. The use of discriminant analysis and neural networks to forecast the severity of the Poaceae pollen season in a region with a typical Mediterranean climate. International Journal of Biometeorology 49; 355-362. 10.1007/s00484-005-0260-8

Sánchez-Mesa JA, Galan C, Martínez-Heras JA, 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. Clinical & Experimental Allergy 32; 1606-1612. 10.1046/j.1365-2222.2002.01510.x

Sauvageat E, Zeder Y, Auderset K, Calpini B, Clot B, Crouzy B, Konzelmann T, Lieberherr G, Tummon F, Vasilatou K. 2020. Real-time pollen monitoring using digital holography. Atmospheric Measuring Techiques Discussions 13; 1539-1550. 10.5194/amt-2019-427

Scheifinger H, Belmonte J, Buters J, Celenk S, Damialis A, Dechamp C, García-Mozo H, Gehrig R, Grewling L, Halley JM, Hogda K-A, Jäger S, Karatzas K, Karlsen S-R, Koch E, Pauling A, Peel R, Sikoparija B, Smith M, Galán-Soldevilla C, Thibaudon M, Vokou D, Weger LA. 2013. Monitoring, Modelling and Forecasting of the Pollen Season. pp 71-126. In: Sofiev M and Bergmann K.C eds. Allergenic Pollen. Springer Science+Business Media, Dordrecht, Netherlands.

Sicard P, Thibaudon M, Besancenot J-P, Mangin A. 2012. Forecast models and trends for the main characteristics of the Olea pollen season in Nice (south-eastern France) over the 1990–2009 period. Grana 51; 52-62. 10.1080/00173134.2011.637577

Sikoparija B, Galán C, Smith M, EAS_QC_Working_Group. 2017a. Pollen-monitoring: between analyst proficiency testing. Aerobiologia 33; 191-199. 10.1007/s10453-016-9461-3

Šikoparija B, Marko O, Panić M, Jakovetić D, Radišić P. 2018a. How to prepare a pollen calendar for forecasting daily pollen concentrations of Ambrosia, Betula and Poaceae? Aerobiologia 34; 203-217. 10.1007/s10453-018-9507-9

Šikoparija B, Mimić G, Panić M, Marko O, Radišić P, Pejak-Šikoparija T, Pauling A. 2018b. High temporal resolution of airborne Ambrosia pollen measurements above the source reveals emission characteristics. Atmospheric Environment 192; 13-23. 10.1016/j.atmosenv.2018.08.040

Šikoparija B, Pejak-Šikoparija T, Radišić P, Smith M, Galan-Soldevilla C. 2011. The effect of changes to the method of estimating the pollen count from aerobiological samples. Journal of Environmental Monitoring 13; 384-390. 10.1039/c0em00335b

Sikoparija B, Skjøth CA, 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 LA, Gehrig R, Hendrickx M, Hoebeke L, Ianovici N, Kofol Seliger A, Magyar D, Mányoki G, Milkovska S, Myszkowska D, Páldy A, Pashley CH, 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. 2017b. Spatial and temporal variations in airborne Ambrosia pollen in Europe. Aerobiologia 33; 181-189. 10.1007/s10453-016-9463-1

Sikoparija B, Smith M, Skjoth CA, Radisic P, Milkovska S, Simic S, Brandt J. 2009. The Pannonian Plain as a source of Ambrosia pollen in the Balkans. International Journal of Biometeorology 53; 263-272. 10.1007/s00484-009-0212-9

Siljamo P, Sofiev M, Filatova E, Grewling Ł, Jäger S, Khoreva E, Linkosalo T, Ortega Jimenez S, Ranta H, Rantio-Lehtimäki A, Svetlov A, Veriankaite L, Yakovleva E, Kukkonen J. 2013. A numerical model of birch pollen emission and dispersion in the atmosphere. Model evaluation and sensitivity analysis. International Journal of Biometeorology 57; 125-136. 10.1007/s00484-012-0539-5

Silva-Palacios I, Fernández-Rodríguez S, Durán-Barroso P, Tormo-Molina R, Maya-Manzano JM, Gonzalo-Garijo Á. 2016. Temporal modelling and forecasting of the airborne pollen of Cupressaceae on the southwestern Iberian Peninsula. International Journal of Biometeorology 60; 297-306. 10.1007/s00484-015-1026-6

Singh KP, Gupta S, Rai P. 2013. Identifying pollution sources and predicting urban air quality using ensemble learning methods. Atmospheric Environment 80; 426-437. 10.1016/j.atmosenv.2013.08.023

Siniscalco C, Caramiello R, Migliavacca M, Busetto L, Mercalli L, Colombo R, Richardson AD. 2015. Models to predict the start of the airborne pollen season. International Journal of Biometeorology 59; 837-848. 10.1007/s00484-014-0901-x

Skjøth CA, Baker P, Sadyś M, Adams-Groom B. 2015a. Pollen from alder (Alnus sp.), birch (Betula sp.) and oak (Quercus sp.) in the UK originate from small woodlands. Urban Climate 14; 414-428. 10.1016/j.uclim.2014.09.007

Skjøth CA, Bilińska D, Werner M, Malkiewicz M, Adams-Groom B, Kryza M, Drzeniecka-Osiadacz A. 2015b. Footprint areas of pollen from alder (Alnus) and birch (Betula) in the UK (Worcester) and Poland (Wroclaw) during 2005-2014. Acta Agrobotanica 68; 315-324. 10.5586/aa.2015.044

Skjøth CA, Geels C, Hvidberg M, Hertel O, Brandt J, Frohn LM, Hansen KM, Hedegård GB, Christensen J, Moseholm L. 2008a. An inventory of tree species in Europe - an essential data input for air pollution modelling. Ecological Modelling 217; 292-304. 10.1016/j.ecolmodel.2008.06.023

Skjøth CA, Šikoparija B, Jäger S, EAN. 2013. Pollen Sources. pp 9-27. In: Sofiev M and Bergmann K.C eds. Allergenic Pollen. Springer Science+Business Media, Dordrecht, Netherlands.

Skjøth CA, Smith M, Brandt J, Emberlin J. 2009. Are the birch trees in Southern England a source of Betula pollen for North London? International Journal of Biometeorology 53; 75-86. 10.1007/s00484-008-0192-1

Skjøth CA, Smith M, Šikoparija B, Stach A, Myszkowska D, Kasprzyk I, Radišić P, Stjepanović B, Hrga I, Apatini D, Magyar D, Páldy A, Ianovici N. 2010. A method for producing airborne pollen source inventories: An example of Ambrosia (ragweed) on the Pannonian Plain. Agricultural and Forest Meteorology 150; 1203-1210. 10.1016/j.agrformet.2010.05.002

Skjøth CA, Sommer J, Brandt J, Hvidberg M, Geels C, Hansen KM, Hertel O, Frohn LM, Christensen JH. 2008b. Copenhagen - significant source to birch (Betula) pollen? International Journal of Biometeorology 52; 453-462. 10.1007/s00484-007-0139-y.

Skjøth CA, Werner M, Kryza M, Adams-Groom B, Wakeham A, Lewis M, Kennedy R. 2015c. Quality of the Governing Temperature Variables in WRF in relation to Simulation of Primary Biological Aerosols. Advances in Meteorology 2015. 10.1155/2015/412658

Smith M, Jäger S, Berger U, Šikoparija B, Hallsdottir M, Sauliene I, Bergmann KC, Pashley CH, De Weger L, Majkowska-Wojciechowska B, Rybníček O, Thibaudon M, Gehrig R, Bonini M, Yankova R, Damialis A, Vokou D, Gutiérrez Bustillo AM, Hoffmann-Sommergruber K, Van Ree R. 2014. Geographic and temporal variations in pollen exposure across Europe. Allergy: European Journal of Allergy and Clinical Immunology 69; 913-923. 10.1111/all.12419

Smith M, Oteros J, Schmidt-Weber C, Buters JT. 2019. An abbreviated method for the quality control of pollen counters. Grana 58; 185-190. 10.1080/00173134.2019.1570327

Sofiev M. 2017. On impact of transport conditions on variability of the seasonal pollen index. Aerobiologia 33; 167-179. 10.1007/s10453-016-9459-x

Sofiev M, Belmonte J, Gehrig R, Izquierdo R, Smith M, Dahl A, Siljamo P. 2013a. Airborne Pollen Transport. pp 127-160. In: Sofiev M and Bergmann K.C eds. Allergenic Pollen. Springer Science+Business Media, Dordrecht, Netherlands.

Sofiev M, Berger U, Prank M, Vira J, Arteta J, Belmonte J, Bergmann KC, Chéroux F, Elbern H, Friese E, Galan C, Gehrig R, Khvorostyanov D, Kranenburg R, Kumar U, Marécal V, Meleux F, Menut L, Pessi AM, Robertson L, Ritenberga O, Rodinkova V, Saarto A, Segers A, Severova E, Sauliene I, Siljamo P, Steensen BM, Teinemaa E, Thibaudon M, Peuch VH. 2015. MACC regional multi-model ensemble simulations of birch pollen dispersion in Europe. Atmos. Chem. Phys. 15; 8115-8130. 10.5194/acp-15-8115-2015

Sofiev M, Ritenberga O, Albertini R, Arteta J, Belmonte J, Bernstein CG, Bonini M, Celenk S, Damialis A, Douros J. 2017. Multi-model ensemble simulations of olive pollen distribution in Europe in 2014: current status and outlook. Atmospheric Chemistry and Physics 17; 12341-12360. 10.5194/acp-2016-1189

Sofiev M, Siljamo P, Ranta H, Linkosalo T, Jaeger S, Rasmussen A, Rantio-Lehtimaki A, Severova E, Kukkonen J. 2013b. A numerical model of birch pollen emission and dispersion in the atmosphere. Description of the emission module. International Journal of Biometeorology 57; 45-58. 10.1007/s00484-012-0532-z

Sofiev M, Siljamo P, Ranta H, Rantio-Lehtimäki A. 2006. Towards numerical forecasting of long-range air transport of birch pollen: theoretical considerations and a feasibility study. International Journal of Biometeorology 50; 392-402. 10.1007/s00484-006-0027-x

Sommer J, Smith M, Šikoparija B, Kasprzyk I, Myszkowska D, Grewling Ł, Skjøth CA. 2015. The risk of exposure to airborne Ambrosia pollen from local and distant sources in Europe –

An example from Denmark. Annals of Agricultural and Environmental Medicine 22; 625-31. doi: 10.5604/12321966.1185764

Soundiran R, Radhakrishnan T, Natarajan S. 2019. Modeling of greenhouse agro-ecosystem using optimally designed bootstrapping artificial neural network. Neural Computing and Applications 31; 7821-7836. 10.1007/s00521-018-3598-7

Stach A, Smith M, Skjoth CA, Brandt J. 2007. Examining Ambrosia pollen episodes at Poznan (Poland) using back-trajectory analysis. International Journal of Biometeorology 51; 275-286. 10.1007/s00484-006-0068-1

Tassan-Mazzocco F, Felluga A, Verardo P. 2015. Prediction of wind-carried Gramineae and Urticaceae pollen occurrence in the Friuli Venezia Giulia region (Italy). Aerobiologia 31; 559-574. 10.1007/s10453-015-9386-2

Thackeray SJ, Sparks TH, Frederiksen M, Burthe S, Bacon PJ, Bell JR, Botham MS, Brereton TM, Bright PW, Carvalho L, Clutton-Brock T, Dawson A, Edwards M, Elliott JM, Harrington R, Johns D, Jones ID, Jones JT, Leech DI, Roy DB, Scott WA, Smith M, Smithers RJ, Winfield IJ, Wanless S. 2010. Trophic level asynchrony in rates of phenological change for marine, freshwater and terrestrial environments. Global Change Biology 16; 3304-3313. 10.1111/j.1365-2486.2010.02165.x

Thibaudon M, Šikoparija B, Oliver G, Smith M, Skjøth CA. 2014. Ragweed pollen source inventory for France - The second largest centre of Ambrosia in Europe. Atmospheric Environment 83; 62-71. 10.1016/j.atmosenv.2013.10.057

Tormo Molina R, Maya Manzano JM, Fernández Rodríguez S, Gonzalo Garijo Á, Silva Palacios I. 2013. Influence of environmental factors on measurements with Hirst spore traps. Grana 52; 59-70. 10.1080/00173134.2012.718359

Tormo R, Silva I, Gonzalo Á, Moreno A, Pérez R, Fernández S. 2011. Phenological records as a complement to aerobiological data. International Journal of Biometeorology 55; 51-65. 10.1007/s00484-010-0308-2

Tseng Y-T, Kawashima S, Kobayashi S, Takeuchi S, Nakamura K. 2018. Algorithm for forecasting the total amount of airborne birch pollen from meteorological conditions of previous years. Agricultural and Forest Meteorology 249; 35-43. 10.1016/j.agrformet.2017.11.021

Valencia J, Astray G, Fernández-González M, Aira M, Rodríguez-Rajo F. 2019. Assessment of neural networks and time series analysis to forecast airborne Parietaria pollen presence in the Atlantic coastal regions. International Journal of Biometeorology 63; 735-745. 10.1007/s00484-019-01688-z

Verstraeten WW, Dujardin S, Hoebeke L, Bruffaerts N, Kouznetsov R, Dendoncker N, Hamdi R, Linard C, Hendrickx M, Sofiev M. 2019. Spatio-temporal monitoring and modelling of birch pollen levels in Belgium. Aerobiologia 35; 703-717. 10.1007/s10453-019-09607-w

Vogel B, Vogel H, Bäumer D, Bangert M, Lundgren K, Rinke R, Stanelle T. 2009. The comprehensive model system COSMO-ART–Radiative impact of aerosol on the state of the atmosphere on the regional scale. Atmospheric Chemistry and Physics 9; 8661-8680. 10.5194/acpd-9-14483-2009

Vogel H, Pauling A, Vogel B. 2008. Numerical simulation of birch pollen dispersion with an operational weather forecast system. International Journal of Biometeorology 52; 805-814. 10.1007/s00484-008-0174-3

Volkova O, Severova E. 2019. Poaceae pollen season and associations with meteorological parameters in Moscow, Russia, 1994–2016. Aerobiologia 35; 73-84. 10.1007/s10453-018-9540-8

Voukantsis D, Niska H, Karatzas K, Riga M, Damialis A, Vokou D. 2010. Forecasting daily pollen concentrations using data-driven modeling methods in Thessaloniki, Greece. Atmospheric Environment 44; 5101-5111. 10.1016/j.atmosenv.2010.09.006

Zanotti C, Rotiroti M, Sterlacchini S, Cappellini G, Fumagalli L, Stefania GA, Nannucci MS, Leoni B, Bonomi T. 2019. Choosing between linear and nonlinear models and avoiding overfitting for short and long term groundwater level forecasting in a linear system. Journal of Hydrology 578; 124015. 10.1016/j.jhydrol.2019.124015

Zewdie GK, Lary DJ, Levetin E, Garuma GF. 2019a. Applying Deep Neural Networks and Ensemble Machine Learning Methods to Forecast Airborne Ambrosia Pollen. International Journal of Environmental Research and Public Health 16; 1992. 10.3390/ijerph16111992

Zewdie GK, Lary DJ, Liu X, Wu D, Levetin E. 2019b. Estimating the daily pollen concentration in the atmosphere using machine learning and NEXRAD weather radar data. Environmental Monitoring and Assessment 191; 418. 10.1007/s10661-019-7542-9

Zewdie GK, Liu X, Wu D, Lary DJ, Levetin E. 2019c. Applying machine learning to forecast daily Ambrosia pollen using environmental and NEXRAD parameters. Environmental Monitoring and Assessment 191; 261. 10.1007/s10661-019-7428-x

Zhang Q, Yang LT, Chen Z, Li P. 2018. A survey on Deep Learning for big data. Information Fusion 22; 146-157. 10.1016/j.inffus.2017.10.006

Zhang R, Duhl T, Salam MT, House JM, Flagan RC, Avol EL, Gilliland FD, Guenther A, Chung SH, Lamb BK, VanReken TM. 2014. Development of a regional-scale pollen emission and transport modeling framework for investigating the impact of climate change on allergic airway disease. Biogeosciences 11; 1461-1478. 10.5194/bg-11-1461-2014

Zhang W, Huang B. 2015. Land use optimization for a rapidly urbanizing city with regard to local climate change: Shenzhen as a case study. Journal of Urban Planning and Development 141; 10.1061/(ASCE)UP.1943-5444.0000200

Zhang Y, Bielory L, Cai T, Mi Z, Georgopoulos P. 2015. Predicting onset and duration of airborne allergenic pollen season in the United States. Atmospheric Environment 103; 297-306. 10.1016/j.atmosenv.2014.12.019

Zhang Y, Isukapalli SS, Bielory L, Georgopoulos PG. 2013. Bayesian analysis of climate change effects on observed and projected airborne levels of birch pollen. Atmospheric Environment 68; 64-73. 10.1016/j.atmosenv.2012.11.028

Zhao W, Wang J, Yu D, Zhang G. 2018. Prediction of Daily Pollen Concentration using Support Vector Machine and Particle Swarm Optimization Algorithm. International Journal of Performability Engineering 14; 2808–2819. 10.23940/ijpe.18.11.p27.28082819

Ziello C, Sparks TH, Estrella N, Belmonte J, Bergmann KC, Bucher E, Brighetti MA, Damialis A, Detandt M, Galan C, Gehrig R, Grewling L, Gutierrez Bustillo AM, Hallsdottir M, Kockhans-Bieda M-C, De Linares C, Myszkowska D, Paldy A, Sanchez A, Smith M, Thibaudon M, Travaglini A, Uruska A, Valencia-Barrera RM, Vokou D, Wachter R, de Weger LA, Menzel A. 2012. Changes to Airborne Pollen Counts across Europe. PLoS ONE 7; 10.1371/journal.pone.0034076

Zink K, Kaufmann P, Petitpierre B, Broennimann O, Guisan A, Gentilini E, Rotach MW. 2017. Numerical ragweed pollen forecasts using different source maps: a comparison for France. International Journal of Biometeorology 61; 23-33. 10.1007/s00484-016-1188-x

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. International Journal of Biometeorology 56; 669-680. 10.1007/s00484-011-0468-8

Ziska L, Knowlton K, Rogers C, Dalan D, Tierney N, Elder MA, Filley W, Shropshire J, Ford LB, Hedberg C, Fleetwood P, Hovanky KT, Kavanaugh T, Fulford G, Vrtis RF, Patz JA, Portnoy J, Coates F, Bielory L, Frenz D. 2011. Recent warming by latitude associated with increased length of ragweed pollen season in central North America. proceedings of the National Academy of Sciences of the United States of America 108; 4248-4251. 10.1073/pnas.1014107108

Table I. The forecasting goal for the ranked 12 most allergenic pollen taxa in Europe for model-based forecasting. An update of results from a literature analysis of pollen forecasting models from 2012 to 2019. Data from Karatsas et al. (2013) included for comparison.

Pollen Taxa	Daily Values	Season Start	Peak Day	Season Duration	Season Severity	Phenology	Long Term (1 Month)	**Total 2012-2019**	*Total from Karatsas et al. (2013)*
Alnus	1	6	1	1	2	1	2	**14**	*23*
Ambrosia	7	6	2	2	3	4	1	**25**	*3*
Artemisia	-	3	1	1	-	1	2	**8**	*1*
Betula	4	11	2	5	7	4	2	**35**	*40*
Chenopodiaceae*	-	-	-	-	-	-	-	**0**	*0*
Corylus	1	5	1	1	1	2	2	**13**	*11*
Cupressaceae	3	2	1	2	2	-	1	**11**	*4*
Olea	2	5	4	2	4	5	2	**24**	*24*
Platanus	1	3	1	1	-	-	-	**6**	*9*
Poaceae	9	6	2	3	3	2	5	**30**	*42*
Quercus	3	3	1	2	1	2	2	**14**	*19*
Urticaceae	1	1	1	1	-	-	-	**4**	*3*
Total	**32**	**51**	**17**	**21**	**23**	**21**	**19**	**184**	**179**

The table reports on the forecasting goal for each one of 12 pollen taxa in Europe (note that more than one target may be mentioned per taxa).

NB*Amaranthaceae

Table II. The most 'popular' forecasting methods, models and factors for modelling used for the 12 most allergenic pollen taxa in Europe as listed by Karatsas et al. (2013) and updated in this study (literature analysis of pollen forecasting models from 2012 to 2019). Data from Karatsas et al. (2013) included for comparison.

Methods used in Forecast models	***Alnus***	***Artemisia***	***Ambrosia***	***Betula***	**Chenopodiaceae***	***Corylus***	**Cupressaceae**	***Olea***	***Platanus***	**Poaceae**	***Quercus***	**Urticaceae**	**Total**	*Total from Karatsas et al. (2013)*
Agromet. Coefficient			1							1			**2**	*1*
Artificial Neural Networks	1		5	3		1		4		3	1	2	**20**	*6*
Atmospheric transport model	2	2	3	7				4	2	1	3		**24**	*2*
Chilling	11	1	1	6		4	1	3	2		5		**34**	*29*
Dispersion Model	1	1	5	6				3	2	2	1		**21**	*1*
Linear discriminant analysis								1		1			**2**	*1*
Multiple component analysis				1									**1**	*1*
Non-linear logistic regression model	2		1	1		1			1	1		1	**8**	*4*
Phenological/Climatological methods	5	1	4	10		3	1	8	1	3	4		**40**	*32*
Poisson regression	1									1			**2**	*2*
Polynomic regression										2			**2**	*1*
Regression	13	4	5	30		11	7	19	7	32	13	5	**146**	*69*
Simulated anealing	1	1	1	1				1	1	1	1		**8**	*3*
Temperature SUM	11		1	10		5	2	10	3	2	7		**51**	*45*
Time series analysis	4	1	3	12		4	1	3	1	9	1	2	**41**	*8*
Total	**52**	**11**	**30**	**87**	**0**	**29**	**12**	**56**	**20**	**59**	**36**	**10**	**402**	*205*

The table reports on the forecasting goal for each one of 12 pollen taxa in Europe (note that more than one target may be mentioned per taxa).
NB* Amaranthaceae

Table III. The most popular new modelling techniques organized by the studied pollen taxa and not previously mentioned in Karatsas et al. (2013). An update of results from a literature analysis of pollen forecasting models from 2012 to 2019.

Methods used in Forecast models	***Alnus***	***Artemisia***	***Ambrosia***	***Betula***	**Chenopodiaceae***	***Corylus***	**Cupressaceae**	***Olea***	***Platanus***	**Poaceae**	***Quercus***	**Urticaceae**	**Total**
Bayesian Statistics			1										**1**
Classification and Regression Trees (CART)								3					**3**
Cubist	1			1		1							**3**
Emission Model			2	1				1	1		2		**7**
functional logit regression								1		1			**2**
Gradient boosting			1										**1**
Gumbel's distribution		1											**1**
LASSO	1		1	1		1							**4**
Linear Mixed Models								1					**1**
Multinomial logistic regression analysis	1			1		1				1			**4**
Multivariate Adaptive Regression Splines (MARS)	1			1		1							**3**
Partial Least Squares	1			3		1		4		1			**10**
Random Forests (RF)	3		5	4		3				2			**17**
Support Vector machines	1			3		1							**5**
Total	**9**	**1**	**10**	**15**	**0**	**9**	**0**	**10**	**1**	**5**	**2**	**0**	**62**

The table reports on the forecasting goal for each one of 12 pollen taxa in Europe (note that more than one target may be mentioned per taxa).
NB* Amaranthaceae