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Pollen Monitoring and Modelling (POMMEL)

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Rialtas na hÉireann
Government of Ireland

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EPA RESEARCH PROGRAMME 2021–2030

Pollen Monitoring and Modelling (POMMEL)

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EPA Research Report

Prepared for the Environmental Protection Agency

by

Technological University Dublin

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The EPA Research Programme addresses the need for research in Ireland to inform policymakers and other stakeholders on a range of questions in relation to environmental protection. These reports are intended as contributions to the necessary debate on the protection of the environment.

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Executive Summary

Primary biological aerosol particles consist of particles such as bacteria, fungal spores and pollen. The deleterious impacts of such particles on both human and plant health have grown in importance as our understanding of their concentration and composition has developed. Pollen, in particular, has a significant effect on the public during much of the year, with up to 30% of the current European population having some form of pollen allergy (Lake *et al*., 2017). Indeed, allergy prevalence has significantly increased in the last few decades, mainly due to changes in climate. As a result, the number of allergy sufferers is expected to more than double by the year 2060 (Beggs *et al*., 2017; Lake *et al*., 2017).

While many of those who suffer from a pollen allergy (hay fever) see it as an inconvenience and a quality-of-life issue, the same cannot be said for those with underlying respiratory diseases. Ireland has the fourth highest rate of asthma in the world, and thus pollen represents a serious risk to the Irish public, as it can trigger and exacerbate asthma attacks. However, there is currently no established aeroallergen network in Ireland to provide detailed and accurate forecasts for those at risk. Thus, mitigation of exposure to pollen is non-existent.

This report describes the establishment of Ireland's first pollen monitoring network, which has been used to determine both the concentrations and the species of airborne pollen. This was followed by the creation of pollen forecasts from the data collected. Furthermore, several recommendations on the size, scale and cost of a potential Irish pollen monitoring network were formulated.

Ambient sampling in both urban (Dublin) and rural (Carlow) settings was undertaken using traditional microscopy methodologies (Hirst-type sampler). Significant differences between the concentrations of pollen and pollen species distribution at each site were seen during the sampling phase of the project. Grass pollen (Poaceae) dominated at both the Carlow (70% of total pollen) and Dublin (32% of total pollen) sites. However, the diversity of pollen species was greater at the Dublin site than at the Carlow site. These recently collected data were combined with previously unanalysed historical data from the 1970s. This allowed the construction of the first Irish pollen calendar, highlighting the concentrations of significant pollen species present in the Irish atmosphere at different times of the year.

In addition to using traditional pollen analysis methodologies, real-time instruments measuring both light scattering and fluorescence was co-located at the Dublin site to evaluate their capabilities versus traditional methods and gauge the potential for their use in an automated network. A wideband integrated bioaerosol sensor – new electronics option (WIBS-NEO) and a Japanese pollen counter were compared with the impaction methodologies. Correlations between the instruments were observed, with Pearson coefficients (r) of approximately 0.5 noted for both devices and the analysis taking a fraction of the time needed when using traditional methods. However, in general, the instruments were unable to differentiate between species of pollen, instead acting more as a bulk pollen detector. The same WIBS-NEO data were also compared with ambient fungal spore concentration data, with total fungal spores and *Alternaria* spores returning correlations of $r = 0.7$–0.8.

Using the ambient pollen data collected in conjunction with concurrently collected meteorological parameters and phenological observations, several predictive pollen models were created, and these are now capable of forecasting pollen concentrations for a variety of species. Both numerical and classification models were used and, in the case of the numerical forecasts, an ensemble approach using the mean and median of the models yielded the most accurate results (predicted vs observed). The Spearman's rank correlation coefficient for these models varied between approximately 0.7 and 0.8 for the species modelled (birch, alder, grass).

Finally, recommendations related to the size, geographical placement, establishment and cost of a potential Irish pollen monitoring network were considered and outlined. This last chapter of this report outlines the potential for Ireland to skip a generation of sampling equipment and join the select group of countries with novel, real-time pollen monitoring networks.

1 Introduction

1.1 Background

1.1.1 Importance of pollen monitoring

The atmosphere is a diverse environment containing a vast range of gaseous and particulate matter (PM) components, with bioaerosols representing approximately 16.5% of $PM_{2.5}$ (PM $\leq 2.5\,\mu m$ in diameter) and 16.3% of PM_{10} (PM $\leq 10\,\mu m$ in diameter) atmospheric concentrations, respectively (Hyde and Mahalov, 2019). Pollen grains are the male reproductive cells of flowering plants and trees and represent the coarser fraction of the bioaerosol class, generally in the range of 10–100 µm (Sofiev and Bergmann, 2013). Recently it has been determined that atmospheric concentrations of pollen may influence the hydrological cycle and climate in the form of cloud condensation/ice nuclei, which affect cloud formation and radiative forcing of the planet (Després *et al*., 2012; Diehl *et al*., 2001; Pummer *et al*., 2012; Sun and Ariya, 2006). However, pollen has more notoriously been associated with triggering undesirable health effects in humans, such as allergic rhinitis (hay fever) (Jantunen *et al*., 2012), and exacerbating other existing medical conditions such as chronic obstructive pulmonary disease (COPD), eczema and asthma. More worryingly, the prevalence of pollen allergies has increased considerably in recent years (D'Amato *et al*., 2007). Approximately 30% of the European population currently have a pollen allergy. This figure is predicted to more than double by 2060 (Lake *et al*., 2017), as this increasing trend is expected to continue (Beggs *et al*., 2017; Lake *et al*., 2017). Therefore, a reliable pollen forecasting system represents a valuable tool that can not only warn allergy sufferers of periods of high pollen exposure but also aid in optimising the medical treatment of patients. Monitoring the ambient concentrations of pollen and other bioaerosols can also provide important information for agricultural purposes, for example in plant pathology, predicting crop yields and assessing plant distribution (Bastl *et al*., 2016). As a result, monitoring efforts can help in determining the presence of invasive species such as ragweed and plant diseases and preventing their spread.

Despite these significant health, agricultural and climate implications, the monitoring of anthropogenic pollutants has historically taken precedence over that of bioaerosols. However, increasing public awareness of the risks posed by allergies and other respiratory diseases has led to increased interest in the development of accurate, rapid and predictive approaches to monitoring pollen, fungal spores and other bioaerosols in our atmosphere. This increased interest in advancing and expanding bioaerosol monitoring networks has come about as a result of climatic concerns, which will affect global bioaerosol distributions and therefore have effects not only on human health, but also on the ecology of the planet. Global warming has had serious effects on the planet, including harmful effects on human health. It is estimated that over 1 million people have lost their lives as a result of the effects of global warming since 2000, with a further 800,000 deaths caused annually by air pollution (Farmer and Cook, 2013). The increasing global temperatures also affect the phenology and diversity of ecosystems. This has been observed in the commencement and duration of the seasons: spring starts earlier than it used to and summer ends later, resulting in extended growing periods for plants and higher concentrations of ambient pollen released (Farmer and Cook, 2013).

1.1.2 Pollen monitoring in Ireland

Other European countries have been routinely monitoring pollen for decades, since the establishment of the European Aeroallergen Network (EAN) in 1986 (Nilsson, 1988). Although Ireland was one of the original countries to join the EAN, its own initial monitoring efforts were prematurely adjourned in the early 1980s. A recent study documented and mapped all the active pollen and fungal spore monitoring sites around the globe; thus, the original Irish monitoring site established in 1988 was not included (Buters *et al*., 2018; Nilsson, 1988). By the end of 2016, over 525 sampling sites existed across Europe with an additional 182 and 151 sampling sites in Asia and the USA, respectively (Buters *et al*., 2018). However, since the 1980s Ireland has largely refrained from carrying out any extensive monitoring campaigns.

The few relevant pollen monitoring publications for Ireland are decades old and provide little detail on the various pollen types recorded and their long-term trends (McDonald, 1980; McDonald and O'Driscoll, 1980). Interestingly, relevant and extensive pollen data do exist for Ireland, mainly for Dublin city, but have yet to be fully explored in the scientific literature. However, a recent publication covering the spatial and temporal variations in the distribution of birch trees and airborne *Betula* pollen in Ireland highlighted the potential of using such historical data (Maya-Manzano *et al*., 2021).

In addition, other recent Irish aerobiological research has focused on assessing the suitability of real-time methods such as the wideband integrated bioaerosol sensor (WIBS) in monitoring primary biological aerosol particles (PBAPs) such as fungal spores and pollen (Healy *et al*., 2012a,b, 2014; O'Connor *et al*., 2013, 2014). Several field monitoring campaigns were conducted around Ireland using the WIBS, but the durations of the campaigns were relatively short, offering little information on the seasonal concentrations of and trends in PBAPs. Likewise, because of the inability of the WIBS to discriminate between pollen from a large range of species, the campaigns provided little detail on the prevalent pollen types. Overall, the understanding of allergenic bioaerosols in the historical Irish context is severely limited, with little known about the pollen species and their seasonality.

Given the lack of monitoring data, Irish pollen forecasts are provided by the University of Worcester and the Meteorological (Met) Office using pollen collections made in the UK. However, these might not be fully representative of the pollen concentrations experienced by the Irish public: according to one report, the pollen found in a specific location is representative only of an area of 30 km^2 (Katelaris *et al*., 2004). This is not an acceptable long-term approach, as respiratory diseases and allergies present a significant health risk to the Irish public. In fact, Ireland has one of the highest hospital discharge and death rates associated with asthma in western Europe, with 60–80% of Irish asthmatics also suffering from allergic rhinitis (Asthma Society of Ireland, 2020). With allergy prevalence and pollen release expected to increase with climate change, establishing a fully operational pollen monitoring network will be crucial in tackling these concerns. The Pollen Monitoring and Modelling (POMMEL) project aims, in part, to address these limitations through the development of appropriate predictive models.

1.2 Pollen Monitoring Methods

1.2.1 Traditional volumetric methods

Considering that pollen monitoring has seen an appreciable rise in interest over recent decades, it is somewhat surprising that the vast majority (80%) of all documented sampling sites still use Hirst or Rotorod collection methods, which were originally developed as far back as the 1950s (Buters *et al*., 2018; Sodeau and O'Connor, 2016). Long-term datasets are available across much of Europe (although not Ireland) and represent a necessary starting point for pollen monitoring networks. After all, there are reasons why such equipment has been in operation for so long; the instruments are relatively inexpensive to purchase and operate and their robustness allows them to perform well in outdoor settings (Beggs *et al*., 2017).

The Hirst volumetric trap (Hirst, 1952) is the most commonly used sampler for pollen monitoring and is recommended as a sampling method by the EAN and the European Aerobiology Society (EAS) (Oteros *et al*., 2015). It operates on a continuous basis to determine airborne pollen (and fungal spore) concentrations by employing a pump to capture the aerosols on a suitable substrate, generally a tape. The substrate moves sequentially, producing hourly results. The substrate is then mounted using an appropriate colourant and quantitatively and qualitatively analysed manually using optical microscopy. However, this method is far from perfect. Several studies have highlighted problems such as notable differences being observed between Hirst samplers located in close proximity (Tormo Molina *et al*., 2013) and differences between the flow rates determined by different machines (Oteros *et al*., 2017). In addition, this off-line technique is notoriously time-consuming and requires highly skilled operators to visually identify pollen types correctly. The precision of results therefore relies heavily on the skill of the operator. As well as being labour intensive, this method is incredibly impracticable for near real-time monitoring, and it can take up to a week to circulate the results. Furthermore, because the identification process is slow, only a sample of the slides are analysed and the overall count determined by extrapolation (Maya-Manzano *et al*., 2020). Therefore, the biggest problem that pollen monitoring networks face is the time delays between sampling, analysis and the dissemination of the results to the public and relevant bodies. As a result, new methods for the atmospheric sampling of bioaerosols have been the focus of recent aerobiological research.

1.2.2 Real-time methods

Real-time methods may offer a suitable alternative to the impracticable traditional Hirst-type methods. The initial development of real-time methods for PBAP monitoring was largely motivated by the need to warn the public and national defence of the threats of airborne aerosols, including forecasting aeroallergens and acts of bioterrorism (Huffman *et al*., 2019). As a result, there is a range of techniques available for real-time monitoring. Most real-time bioaerosol methods currently in use exploit physical and/or chemical properties to detect and differentiate between bioaerosols and have been reviewed in depth in recent years (Fennelly *et al*., 2017; Huffman *et al*., 2019).

Although the incorporation of real-time instruments into bioaerosol monitoring networks offers the potential for rapid retrieval and subsequent dissemination of data, only two real-time monitoring networks are currently in operation in Europe: in Bavaria, Germany, currently using the BAA500 instrument that operates on the principle of image recognition (Oteros *et al*., 2015), and in Switzerland, which employs the Swisens Poleno air-flow cytometry system that uses optical discrimination based on fluorescence and light scattering (Crouzy *et al*., 2016; Sauvageat *et al*., 2020). In total, only four European countries (France, Germany, Luxembourg and Switzerland) use real-time monitoring instruments regularly, but not at all their sampling locations (Buters *et al*., 2018). This is mainly because of the high costs associated with real-time instruments. As European legislation on air quality does not yet cover bioaerosols, most monitoring stations/networks are not run by national governments, with only a handful of countries including Switzerland (MeteoSwiss) and France (Réseau National de Surveillance Aérobiologique; RNSA) possessing state-owned networks (Buters *et al*., 2018). The real-time devices, such as the BAA500 and Swisens Poleno, therefore often exceed the budgets available to most monitoring networks, especially at this early stage in their development. Outside Europe, there are two sampling sites in the USA and 120 in Japan that exclusively employ real-time instruments for pollen monitoring (Buters *et al*., 2018). However, these sites tend to examine only a select few pollen taxa of specific interest (Kawashima *et al*., 2007), using variants of the Japanese counter. Hence, other alternative and cost-effective real-time techniques based on spectroscopic methodologies have been trialled and deployed during the POMMEL project, including the KH-3000-01 and WIBS instruments.

The KH-3000-01 Japanese Pollen Sensor, developed by Yamatronics, operates based on light scattering. An air sample is collected and irradiated with a laser that measures the forward and side scatter of particles, producing immediate results (Kawashima *et al*., 2007). Real-time monitoring is possible through the instantaneous processing of data. This approach has been used across Japan since 2002 for pollen monitoring and forecasting. It has been used extensively for monitoring cedar pollen, the main cause of pollinosis, as part of the Japanese cedar pollen network (Kawashima *et al*., 2017). However, Japan has few other dominant allergenic species, and cedar pollen is easily separated from other pollen types because of its distinct large size and shape and characteristic winter-pollinating season (Huffman *et al*., 2019). Since the original development and use of the device in 2002, it has been applied to a range of pollen types including Urticaceae, Poaceae, *Ambrosia* (Kawashima *et al*., 2007), Cupressaceae, *Fraxinus, Betula* and *Quercus*. Discrimination between pollen taxa is made possible by comparing scattered light intensity and the degree of polarisation. Deploying this device in Ireland for pollen monitoring would represent one of few preliminary European studies. Although the discriminatory power of the KH-3000-01 for the in situ analysis of numerous pollen types remains uncertain, its low cost makes it an attractive option to test in a pilot real-time pollen monitoring network.

Instrumentation based on the use of fluorescence spectroscopy for biological particle detection has also been developed for the real-time analysis of bioaerosols. The WIBS is another example of one such method: it is a three-channel single aerosol particle fluorescence monitor that operates using light-induced fluorescence to detect the fluorescent signature of atmospheric particles. The WIBS provides high-resolution information on the size, shape and fluorescence intensity of a particle using a dual wavelength optical detection chamber. Particles of interest are pumped into the instrument and irradiated with a 635-nm laser (Huffman *et al*., 2019). The subsequent light scatter is then used to estimate the size and shape of the particles of interest (Sodeau and O'Connor, 2016). The fluorescent properties of the particles are then investigated by setting the two xenon flash lamps to the excitation wavelengths of two common bio-fluorophores: tryptophan (280 nm) and NAD(P)H (370 nm). The resulting emission bands are then detected by two photomultiplier detectors, one at 310–400 nm and the other at 420–650 nm. This provides three separate measurements of detection: excitation at 280 nm with emission detected at (1) 310–400 nm and (2) 420–650 nm and (3) excitation at 370 nm with emission detected at 420–650 nm (Fennelly *et al*., 2017; Healy *et al*., 2012a; Huffman *et al*., 2019; Sodeau and O'Connor, 2016). Sampled particles can then be categorised according to their fluorescent properties. A series of laboratory and field investigations have been conducted to assess the performance of the WIBS for the real-time monitoring of PBAPs, including in Ireland (Healy *et al*. 2012a,b, 2014; O'Connor *et al*., 2013, 2014). Field studies have highlighted the proficiency of the WIBS in identifying ambient bioaerosols when compared with traditional volumetric sampling methods ($R^2 > 0.9$) (O'Connor *et al*., 2014). However, only a select few have specifically attempted to use the WIBS to monitor and differentiate between pollen types (Healy *et al*., 2012a; O'Connor *et al*., 2014). Laboratory studies using the WIBS-4 [now surpassed by the WIBS-NEO (WIBS – new electronics option)] illustrated the potential for the WIBS to discriminate pollen grains from other bioaerosols, such as fungal spores, and from other aerosols of non-biological origin (Healy *et al*., 2012a).

1.3 Pollen Modelling and Forecasting Methods

There are three broad classes of modelling that have routinely been applied to predicting and forecasting ambient pollen concentrations, namely observation-based, process-based and source-orientated models. A detailed review of these has been published (Maya-Manzano *et al*., 2020).

1.3.1 Observation-based models

Observational models refer to mathematical/statistical constructs that aim to describe and predict the behaviour of and trends in dependent variables using independent variables. In this case, the dependent variables are ambient pollen concentrations that can be predicted using independent variables, which could include meteorological and phenological parameters. However, since the independent variables (model inputs) are quite site specific, so too will be the predicted outcomes. As a result, these types of models are often location limited and can be difficult to extrapolate to other locations. To date, a wide range of observational model techniques have been applied to forecasting the day-to-day variations in airborne pollen concentrations, including traditional regression and time series approaches as well as more modern, machine learning approaches.

Regression analysis remains a popular approach in aerobiological studies, including in developing prediction models. The simplest is linear regression, which involves establishing a relationship between two variables (one dependent and one independent) using a straight line and remains a popular pollen forecasting method (Frenguelli *et al*., 2016; García-Mozo *et al*., 2014; Piotrowska-Weryszko, 2013a). However, most dependent variables are rarely fully explained by modelling only one variable, and the complex release of pollen grains is no different. As a result, multiple and polynomial regression analyses have also received much attention (Jarlan *et al*., 2014; Novara *et al*., 2016; Sabariego *et al*., 2012; Tseng *et al*., 2018), including backwards elimination and stepwise multiple regression (Howard and Levetin, 2014; Janati *et al*., 2017; Sicard *et al*., 2012), logistic regression (Katz and Batterman, 2019; Myszkowska, 2014a; Myszkowska and Majewska, 2014) and partial least squares regression (Brighetti *et al*., 2014; Lara *et al*., 2019). Regression models have been used to model a variety of different pollen season parameters, including daily pollen concentrations (Janati *et al*., 2017; Smith and Emberlin, 2005), season start/peak (García-Mozo *et al*., 2009; Myszkowska, 2014a,b; Zhang *et al*., 2015), season duration (Zhang *et al*., 2015) and season intensity (Bonini *et al*., 2015), for many different pollen types. Regression models have mainly been constructed for pollen taxa of known allergenic/invasive importance including *Alnus* (Myszkowska, 2014a; Novara *et al*., 2016), *Betula* (Robichaud and Comtois, 2017; Zhang *et al*., 2015), *Corylus* (Myszkowska, 2014a; Novara *et al*., 2016), Poaceae (de Weger *et al*., 2014; Janati *et al*., 2017; Piotrowska, 2012), *Quercus* (Myszkowska *et al*., 2011; Picornell *et al*., 2019), Cupressaceae (Picornell *et al*., 2019; Sabariego *et al*., 2012), *Artemisia* (Piotrowska-Weryszko, 2013b; Zhang *et al*., 2015), *Ambrosia* (Howard and Levetin, 2014; Zhang *et al*., 2015) and Urticaceae (Picornell *et al*., 2019).

However, despite their convenience and easy construction, regression models are generally based on assumptions of linearity and normality and often fail to account for the seasonality of aerobiological data, which can result in low model predictability (Astray *et al*., 2010; Damialis and Gioulekas, 2006). These time-dependent limitations can be accounted for using time series analysis. Time series forecasting involves predicting future values based on past values by considering a number of components such as general and seasonal trends, unknown cycles and random components (Maya-Manzano *et al*., 2020). Time series try to separate (decompose) different patterns with the goal of isolating all the disturbances in the time series dataset caused by ordinary seasonal behaviour such as weather parameters. Different time series approaches have been applied to pollen data, including ARIMA (autoregressive integrated moving average) models (García-Mozo *et al*., 2014) and locally weighted smoothing (LOESS)-based decompositions (Rojo *et al*., 2017). Again, this modelling approach has been used for years to predict concentrations of a variety of pollen types including *Alnus* (Nowosad, 2016; Siniscalco *et al*., 2015), *Ambrosia* (Puc and Wolski, 2013), *Artemisia* (Puc and Wolski, 2013), *Betula* (Nowosad *et al*., 2016), *Corylus* (Nowosad *et al*., 2016), Poaceae (Fernández-Rodríguez *et al*., 2018; Rojo *et al*., 2017; Tassan-Mazzocco *et al*., 2015), *Quercus* (Fernández-Rodríguez *et al*., 2016) and Urticaceae (Tassan-Mazzocco *et al*., 2015; Valencia *et al*., 2019).

Although these traditional models remain popular, they often fail to truly depict the complex relationship between pollen concentrations and influencing parameters. This represents a major obstacle in modelling biological systems. As a result, more sophisticated machine learning techniques have become increasingly popular in atmospheric and aerobiological studies. Often they are designed to mimic biological information processing systems (Recknagel, 2001) and are used to try and simulate intricate systems in which the relationships between variables are difficult to explain (Scheifinger *et al*., 2013). A number of machine learning techniques have been applied to pollen forecasting in recent years, including artificial neural networks (ANNs) (Astray *et al*., 2016; Burki *et al*., 2019; Liu *et al*., 2017; Puc, 2012), support vector machines (SVMs) (Bogawski *et al*., 2019; Du *et al*., 2017; Liu *et al*., 2017) and ensemble techniques such as random forest (RF) (Navares and Aznarte, 2019; Zewdie *et al*., 2019a,b). ANNs have become particularly popular for pollen forecasting, owing to the ease with which they can analyse non-linear relationships and high-order interactions and their tolerance of discontinuous data (Jedryczka *et al*., 2015). However, these algorithms require a lot of training data to develop suitably accurate and robust models. ANNs have recently been applied to predicting *Ambrosia* (Csépe *et al*., 2014, 2019), *Betula* (Puc, 2012), *Quercus* (González-Naharro *et al*., 2019) and *Olea* (Iglesias-Otero *et al*., 2015) pollen concentrations. SVMs have also been used to forecast daily concentrations and flowering periods (Bogawski *et al*., 2019; Zewdie *et al*., 2019c; Zhao *et al*., 2018) but are often outperformed by ANN and RF. The latter is another popular machine learning method for pollen prediction but, unlike the others, involves the construction of a series of decision trees. RF models have been developed for a range of different pollen types, such as *Alnus, Betula, Corylus* (Nowosad *et al.*, 2016) and Poaceae (Navares and Aznarte, 2019). Although these sophisticated approaches have not been covered to the same extent as more traditional deterministic models in the literature, their high accuracy and robustness make them a promising solution.

1.3.2 Process-based models

Phenology refers to the study of recurring seasonal events that are influenced by meteorological factors. Phenological data have been shown to complement aerobiological studies and have been used regularly to develop efficient models for predicting key phases in plant development, notably flowering periods for pollen forecasting (Grundström *et al*., 2019;

Tormo *et al*., 2011). These process-based models determine the dates of phenological phases in relation to environmental factors and are often used in atmospheric transport models (Maya-Manzano *et al*., 2020). To date, phenological models have been developed for *Alnus* (Pauling *et al*., 2014; Siniscalco *et al*., 2015), *Betula* (Pauling *et al*., 2014), *Corylus* (Novara *et al*., 2016; Pauling *et al*., 2014), *Olea* (Achmakh *et al*., 2015) and Poaceae (Pauling *et al*., 2014) pollen.

Along with more complex numerical models, other, simpler, tools can also be developed for pollen forecasting. Despite the advantages of previously discussed modelling techniques, they require a great deal of site-specific data, including large datasets for model calibration, and access to additional data, such as meteorological data, and also need to meet any essential computational requirements. These requirements cannot be met at every sampling site. In such cases, a pollen calendar may offer a suitable alternative method. A pollen calendar is the most rudimentary form of pollen forecasting tool and graphically represents the average annual/seasonal trends in major pollen types, typically those of allergenic concern, for a particular location (Pecero-Casimiro *et al*., 2020). Since pollen emission is directly dependent on plant phenology and seasonality (Dahl *et al*., 2013), a pollen calendar essentially represents the simplest process-based/observation-orientated prediction tool for any given area (Sofiev and Bergmann, 2013). Pollen calendars have been used for decades and have been shown to be very helpful for understanding the distribution and concentration of various pollen taxa at different locations (Elvira-Rendueles *et al*., 2019; Emberlin *et al*., 1990; Katotomichelakis *et al*., 2015; Lo *et al*., 2019; Martínez-Bracero *et al*., 2015; O'Rourke, 1990; Pecero-Casimiro *et al*., 2020; Šikoparija *et al*., 2018; Werchan *et al*., 2018). The temporal resolution of these models tends to be in the order of several days, which does limit their use with regard to daily forecasts (Šikoparija *et al*., 2018). In the case of accurate daily forecasts, statistically based model approaches are more accurate (if resources are available).

1.3.3 Source-orientated models

Source-orientated and transport models can be used to predict the spatiotemporal distribution of pollen concentrations (Verstraeten *et al*., 2019). Transport models can overcome the heavy data requirements of previously discussed observational techniques but do require an understanding of certain aerosol characteristics such as diffusion. Another important criterion to consider is pollen emission sources, the inclusion of which has been shown to improve model performance. These models are based on chemistry transport models that have later been adapted to account for the dispersal of bioaerosols, firstly with pollen. Several transport models that are capable of simulating pollen dispersion include SILAM (Siljamo *et al*., 2013; Verstraeten *et al*., 2019), COSMO-ART (Vogel *et al*., 2009; Zink *et al*., 2012, 2017), ENVIRO-HIRLAM (Mahura *et al*., 2009), CMAQ-pollen (Efstathiou *et al*., 2011) and the WRF-CHEM model (Skjøth *et al*., 2015). Recent studies have investigated the dispersion of several different pollen types, including *Alnus* (Prank *et al*., 2016), *Ambrosia* (Prank *et al*., 2013; Zink *et al*., 2012), *Artemisia* (Prank *et al*., 2016), *Betula* (Sofiev *et al*., 2015; Zhang *et al*., 2014), Poaceae (Sofiev *et al*., 2017) and *Quercus* (Zhang *et al*., 2014).

1.4 POMMEL Objectives and Outputs

1.4.1 Objectives

- To develop a comprehensive systematic review of the potential model/forecast options used by European countries, extracting the data required to implement such models. This review will also focus on the state-of-the-art methods for pollen identification and quantification.
- To analyse historical unpublished pollen data from the 1970s.
- To establish and maintain the only pollen monitoring network in Ireland (via traditional methods) for the duration of the study, thus recording seasonal ambient concentrations of pollen for each sampling site.
- To enhance the traditional network via the use of novel spectroscopic instrumentation, including the WIBS-4+ (as described in the OLBAS project; Sodeau *et al*., 2029) and the Japanese pollen monitor, to ascertain their potential as real-time monitors.
- To develop an Irish pollen forecasting tool that will combine Ireland-specific pollen data directly with

meteorological and phenological data, and thus predict future ambient pollen concentrations.
- To provide recommendations pertaining to the efficiency and future spatial and temporal direction of the model developed.

These objectives, as set in the original research proposal, were achieved as described in Chapters 2–6.

1.4.2 Outputs

Peer reviewed manuscripts:

1. Maya-Manzano, J.M., Skjøth, C.A., Smith, M., Dowding, P., Sarda-Estève, R., Baisnée, D., McGillicuddy, E., Sewell, G. and O'Connor, D.J., 2021. Spatial and temporal variations in the distribution of birch trees and airborne *Betula* pollen in Ireland. *Agricultural and Forest Meteorology* 298: 108298.
2. Maya-Manzano, J.M., Smith, M., Markey, E., Hourihane Clancy, J., Sodeau, J. and O'Connor, D.J., 2021. Recent developments in monitoring and modelling airborne pollen, a review. *Grana* 60(1): 1–19.

Presentations:

1. Oral presentation at the 37th AAAR Annual Conference, 14–18 October 2019 at the Oregon Convention Center in Portland, Oregon.
2. Oral presentation at the 11th International Congress on Aerobiology, 3–7 September 2018 in Parma, Italy.
3. Poster presentation at the 7th European Aerobiology Society Symposium, 17–20 November 2020 in Cordoba, Spain.

2 Traditional Pollen Monitoring

The ambient pollen concentrations at several locations over Ireland were monitored using traditional volumetric microscopy methods during the entirety of the POMMEL project. Traditional monitoring was carried out to identify the prevalent ambient pollen types and seasonal pollen trends present in Ireland. Pollen data from the Dublin and Carlow sites (Figure 2.1) were monitored continuously from 2018.

2.1 Overview of Prevalent Pollen Types and Trends

Over the course of the 2018–2019 seasons, over 60 different pollen types were identified: 31 of those identified were herbaceous/grass in nature with another 30 originating from trees. The prevalent pollen types were slightly different in the two locations as shown in Figure 2.2.

The dominant pollen types identified in Dublin were Poaceae (grass), Urticaceae (nettle), Cupressaceae and Taxaceae (cypresses and yews), *Betula* (birch), *Quercus* (oak), *Pinus* (pine), *Fraxinus* (ash), *Alnus* (alder) and *Platanus* (plane), which accounted for 93% of the total pollen sampled. The most abundant pollen types identified in Carlow were Poaceae, Urticaceae, *Betula, Quercus, Fraxinus* and *Pinus*, which accounted for 91% of the total pollen sampled.

Overall, the pollen season in Ireland was found to be bimodal, as illustrated in Figures 2.3 and 2.4. The first peak period, from April to May, was mainly attributed to high concentrations of tree pollen, most notably *Betula* pollen, and the second peak period, seen in the summer months (June–July), resulted from higher concentrations of Poaceae pollen. This peak in summertime Poaceae pollen concentrations was also seen in early studies carried out in Galway city (McDonald, 1980; McDonald and O'Driscoll, 1980). These characteristic pollen types are of particular concern, as they are two of the most allergenic pollen types present in Ireland. As a result, the determination

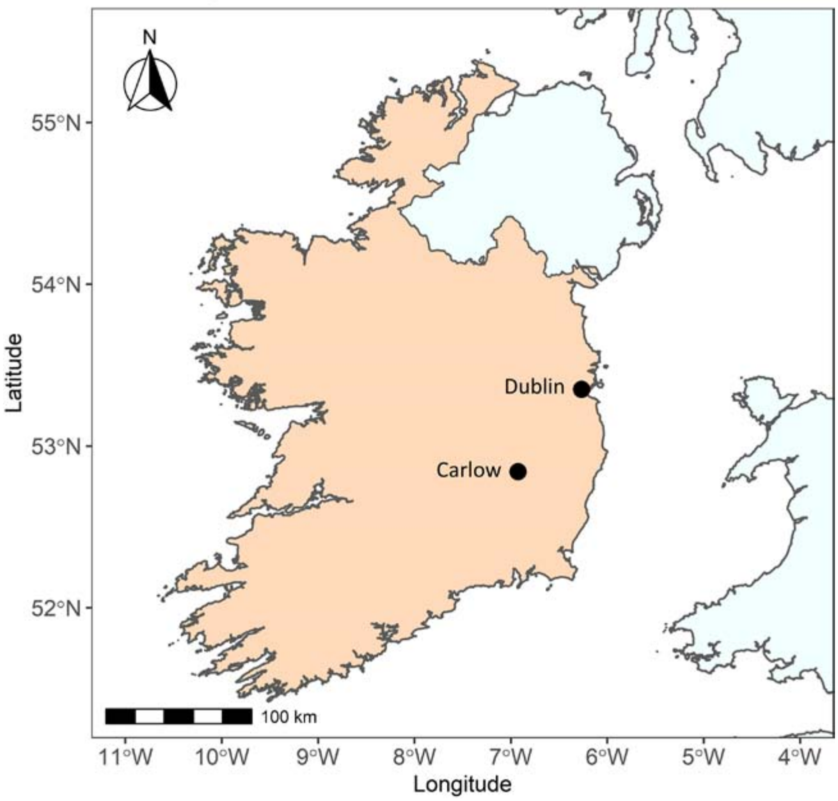

Figure 2.1. Pollen sampling locations at Dublin and Carlow.

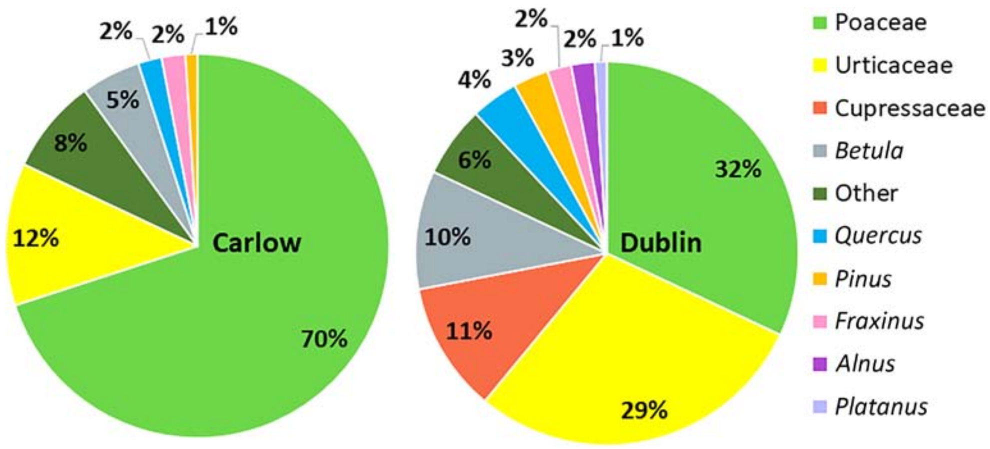

Figure 2.2. Prevalent pollen types in Dublin and Carlow.

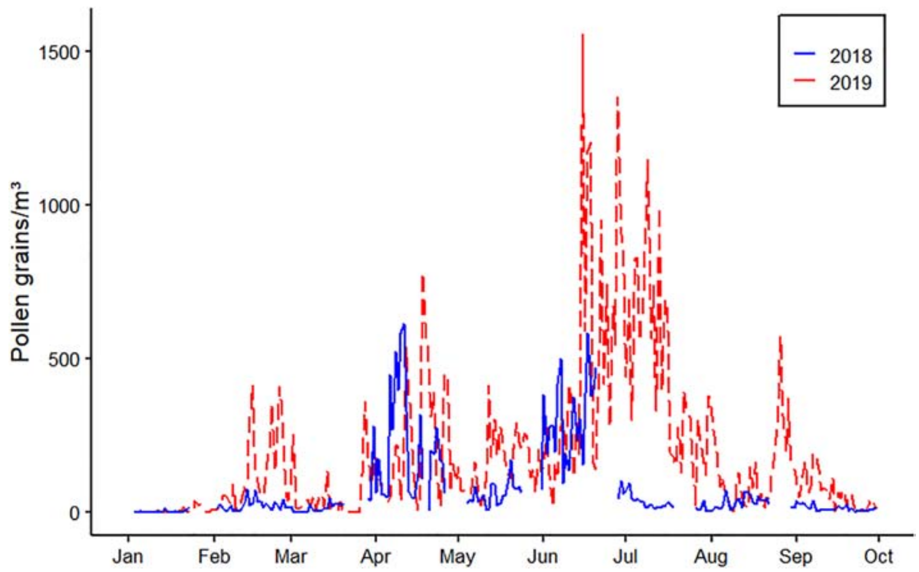

Figure 2.3. Daily total pollen concentrations – Dublin.

of seasonal trends in *Betula* and Poaceae pollen types and their relationship with meteorological parameters would be vital in establishing a functional allergenic pollen forecasting system.

Notable differences can be seen in the main pollen seasons (MPSs) of different allergenic pollen types between the two years and locations, as shown in Tables 2.1 and 2.2. The MPS is considered to start when the pollen concentration reaches 5% of the total annual concentration and to end when it reaches 95% of the total annual concentration (Cristofori *et al*., 2010; Nilsson and Persson, 1981). The major pollen types were defined as the pollen types with an annual pollen integral (APIn) ≥ 100 pollen × day/m^3 (Galán *et al*., 2017), expressed as the average daily pollen concentration per m^3 of air.

To summarise, annual pollen concentrations were higher in 2019 than 2018. In addition, MPS start dates and durations also changed between the two years. A range of factors can influence the concentration of pollen release in one MPS (Galán *et al*., 1995). The main reason for the differences in pollen concentration and season duration between the two years is the difference in meteorological conditions. During 2018, the east of Ireland experienced unseasonably cold weather during February and March, which led to a reduction in ambient tree pollen concentrations during March of 2018 and delayed the onset of pollen release from grass. Similar decreases in soil temperature in early spring have been shown in other studies to result in an increase in grass pollen concentrations during the following summer (Emberlin *et al*., 1999).

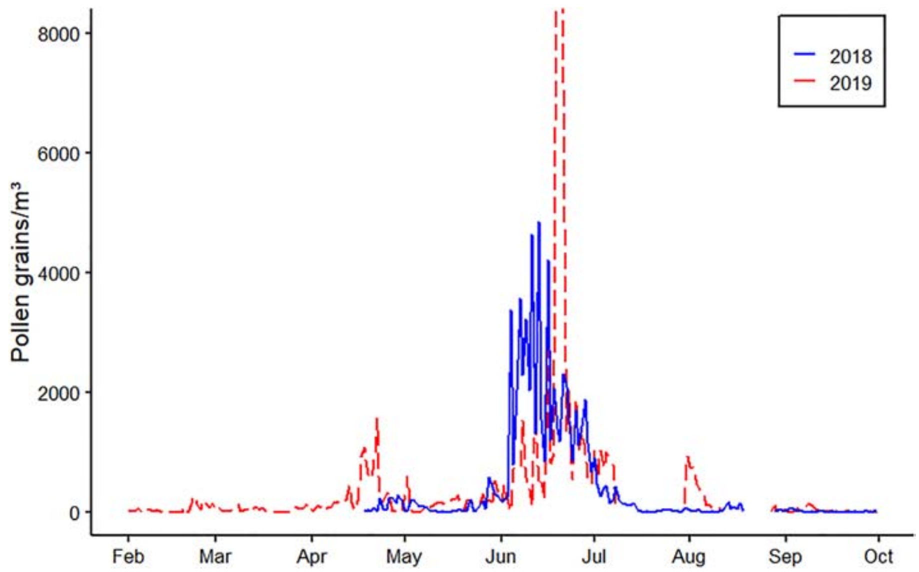

Figure 2.4. Daily total pollen concentrations – Carlow.

Table 2.1. Main pollen season characteristics – Dublin

Year	Pollen type	Start date	End date	Duration of season (days)	Maximum daily concentration (grains/m³)	Day of maximum concentration
2018	*Alnus*	03/02/2018	31/03/2018	56	16.9	12/02/2018
	Betula	06/04/2018	25/04/2018	19	345.8	11/04/2018
	Corylus	14/01/2018	02/04/2018	78	16.9	16/02/2018
	Poaceae	20/05/2018	05/07/2018	46	410.15	17/06/2018
2019	*Alnus*	27/01/2019	02/03/2019	34	167.7	15/02/2018
	Betula	28/03/2019	11/05/2019	44	553.15	18/04/2018
	Corylus	21/01/2019	02/03/2019	20	11.7	15/02/2019 22/02/2019
	Poaceae	07/06/2019	01/08/2019	55	1056.9	15/06/2019

Table 2.2. Main pollen season characteristics – Carlow

Year	Pollen type	Start date	End date	Duration of season (days)	Maximum daily concentration (grains/m³)	Day of maximum concentration
2018	*Betula*	23/04/2018	05/06/2018	43	124.8	04/05/2018
	Poaceae	04/06/2018	04/07/2018	30	4658.55	13/06/2018
2019	*Alnus*	07/02/2019	16/03/2019	51	222.3	22/02/2019
	Betula	08/04/2019	01/05/2019	27	1384.5	22/04/2019
	Poaceae	08/06/2019	03/07/2019	25	19,203.6	20/06/2019

Other factors, such as mast years (i.e. the fluctuating and harmonised production of seeds and/or pollen by a cohort of plants), should also be considered. In addition, several tree species, such as *Fraxinus*, have been known to exhibit naturally occurring periods of significantly reduced pollen production every couple of years (Gassner *et al*., 2019).

Although the prevalent pollen types/season varied slightly by location and year, the Irish pollen season generally begins with the release of tree pollen in

January/February and ends with the release of grass/herb pollen in October.

2.2 Differences between Urban and Rural Sampling Locations

Although the progression of the pollen seasons in Dublin and Carlow is similar, several differences between the urban and rural sites were also noted. During the sampling period in both years, Carlow experienced substantially higher ambient pollen concentrations than Dublin: the mean APIn for Dublin was 34,217 pollen × day/m^3, whereas the mean APIn for Carlow was 78,389 pollen × day/m^3. This difference in pollen concentration between the two sites is mainly the result of significant Poaceae concentrations released over Carlow during the month of June. Comparable concentrations are not seen in Dublin. This was not unexpected, as the Carlow sampling equipment was sited on a platform 2 metres above the ground in an area of rural grassland, whereas in Dublin the sampling equipment was located on the rooftop of a five-storey building (20 metres high). For the remainder of the year, pollen concentrations did not differ as significantly between the two sites.

Although Dublin experienced relatively lower pollen concentrations than Carlow, there were 36 additional pollen types identified in Dublin that were not present in Carlow, many of which are classified as "ornamental". This is not uncommon, as many other studies have highlighted the increased presence of ornamental plant and tree species in urban environments that would not be present in more rural settings (Velasco-Jiménez *et al.*, 2020). The Carlow site offers an interesting indication of source strength from agricultural grassland, and determining this source strength will be of interest should dispersion modelling be used in the future. While such a site may overestimate the concentration of grass pollen at peak season it still offers phenological and pollen emission information.

3 WIBS Real-time Monitoring Campaign

3.1 Campaign Overview

Pollen (and fungal spore) monitoring was conducted at the sampling site at the Technological University Dublin, Kevin Street. During this campaign, traditional methods of PBAP monitoring (Hirst volumetric traps) were compared with newer spectrometric methods such as the WIBS-NEO to assess their real-time monitoring potential. The monitoring campaign took place over the course of 41 days from 7 August to 16 September 2019. The spectrometric instrument (WIBS-NEO) was positioned on the roof of TU Dublin, Kevin Street, in appropriate proximity to the Hirst–Lanzoni volumetric trap, to permit parallel monitoring.

3.2 Pollen Monitoring Data

During the investigation, more than 13 different pollen taxa were identified by microscopic analysis of the PBAPs sampled by the Hirst–Lanzoni trap. The total number of pollen grains measured over the entire campaign was 4859 grains/m^3, with an hourly average of 5 grains/m^3 sampled.

The most dominant pollen types and their percentage contribution are illustrated in Figure 3.1.

Of the pollen types identified, Poaceae (grass pollen) and Urticaceae (nettle pollen) pollen were by far the most abundant, representing a combined 89% of the total pollen count for the sampling period. Urticaceae alone represented 78% of the total pollen count, with a total count of 3783 grains/m^3. In comparison, Poaceae contributed a much lower 19% of the total count, with a total of 537 grains/m^3; this low value seen for Poaceae pollen is because it was the end of the Poaceae pollen season. The highest daily pollen concentration was recorded on 26 August and was due to the presence of high ambient Urticaceae concentrations (Figure 3.2). Thereafter, there was a general downwards trend in pollen concentration, coinciding with the ending of the pollen season.

3.3 WIBS Monitoring Data

For particle size/shape determination, the WIBS-NEO uses an approach based on the construction of a calibration curve. This curve was produced by nebulising particles of known size and shape into the WIBS instrument. In this case, a number of polystyrene latex (PSL) spheres with a range of sizes were aerosolised into the WIBS. These data act as the basis for all subsequent sample data. Particles are struck by a 635-nm diode laser beam and their elastic scattering intensities are sampled in the forward and side (90 degree) directions. The software then uses the Mie theory, which assumes that the particles are spherical and of a specific refractive index, to designate a size and shape parameter to each particle. The particles are subsequently evaluated for their

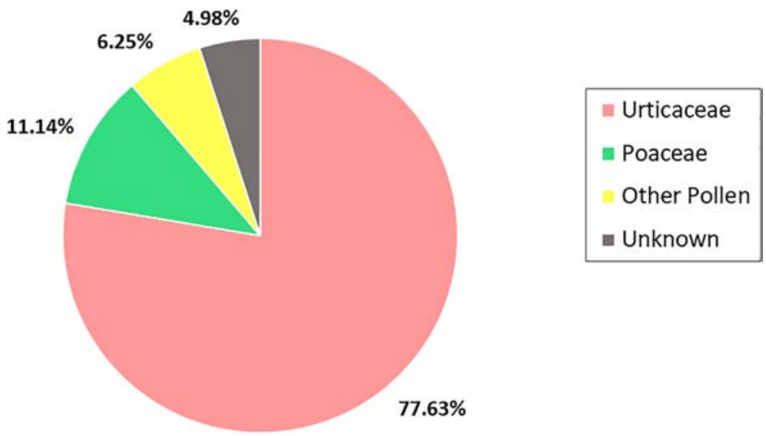

Figure 3.1. Distribution of pollen types during the campaign.

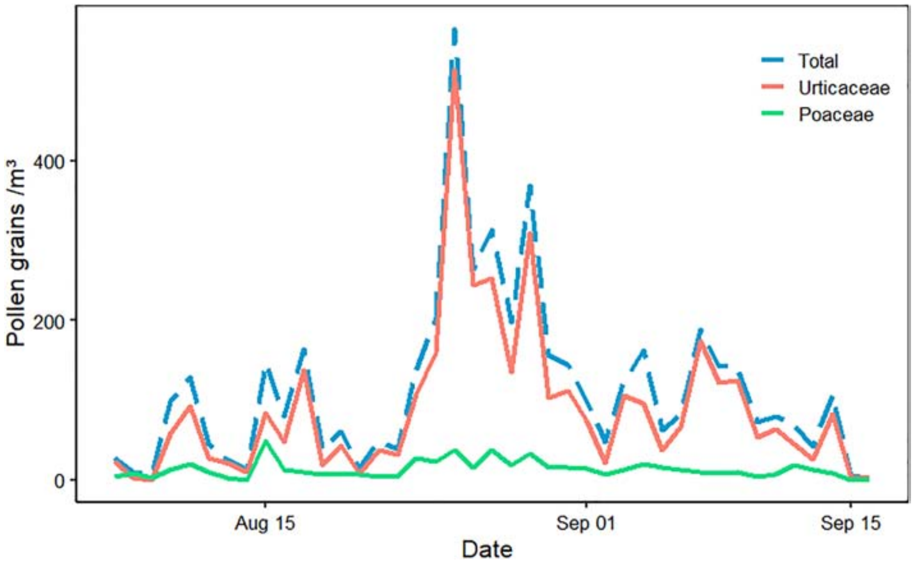

Figure 3.2. Time series of pollen counts over the campaign.

fluorescent characteristics. A full explanation of the WIBS instrument can be found in Healy *et al.* (2012b).

Fluorescent particle monitoring was carried out using the WIBS-NEO. Over the course of the campaign (from 12:00 on 7 August 2019 to 12:00 on 16 September 2019) a total of 56,818,969 particles were recorded. Fluorescent aerosol particles (FAPs) were determined by applying a force trigger threshold (baseline). The baseline was set as three standard deviations greater than the mean fluorescence intensity in each channel (3δ) during the absence of particles, which is a measured forced trigger threshold. Of all the particles sampled, only 11.2% possessed fluorescent intensities exceeding the forced trigger threshold. The filtered FAPs were then subdivided into seven classes based on their fluorescent characteristics in the three detector channels (FL1, FL2 and FL3), as shown in Table 3.1.

The percentage contribution of WIBS particle types to total FAPs is shown in Figure 3.3.

B-type particles accounted for over 43% of the FAPs recorded. Interestingly, no previous studies have associated B-type particles with biogenic activity, and they are likely to have resulted from anthropogenic sources. This is not unexpected considering the urban location of the sampling site in Dublin city centre. The WIBS particle types with the next highest contributions were BC (15%) and ABC (14%), both of which have been associated with the presence of airborne PBAPs.

Figure 3.4 shows the daily variation in FAP classes during the monitoring campaign.

Table 3.1. WIBS particle types

Channel	Excitation (nm)	Emission (nm)
A	280	310–400
B	280	420–650
C	370	420–650
AB	280	310–400 420–650
AC	280 370	310–400 420–650
BC	280 370	420–650
ABC	280 370	310–400 420–650 420–650

In addition to fluorescence intensity, the WIBS-NEO also provides information on the size and shape of the particles sampled. An asymmetry factor (AF) is used to describe the relative shape of particles, providing a numerical value between 0 and 100. The closer the value is to zero, the more spherical the particle is, with particles closer to 100 exhibiting a rod-like shape. The size and AF distribution of the fluorescent WIBS

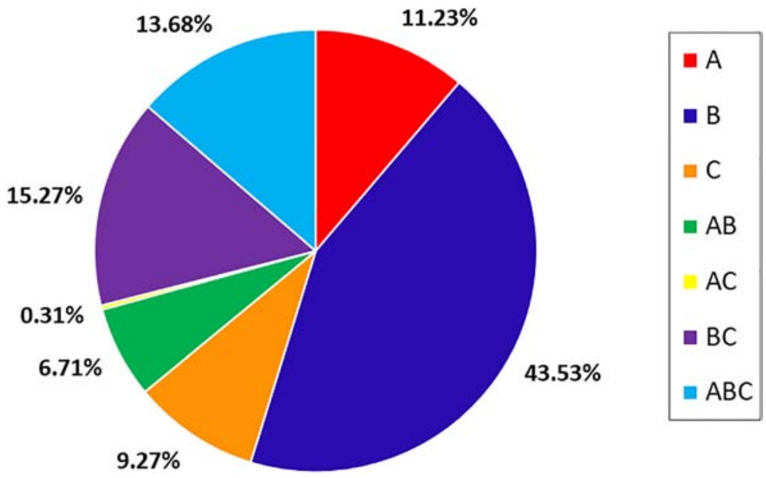

Figure 3.3. WIBS particle distribution during the campaign (δ = 3).

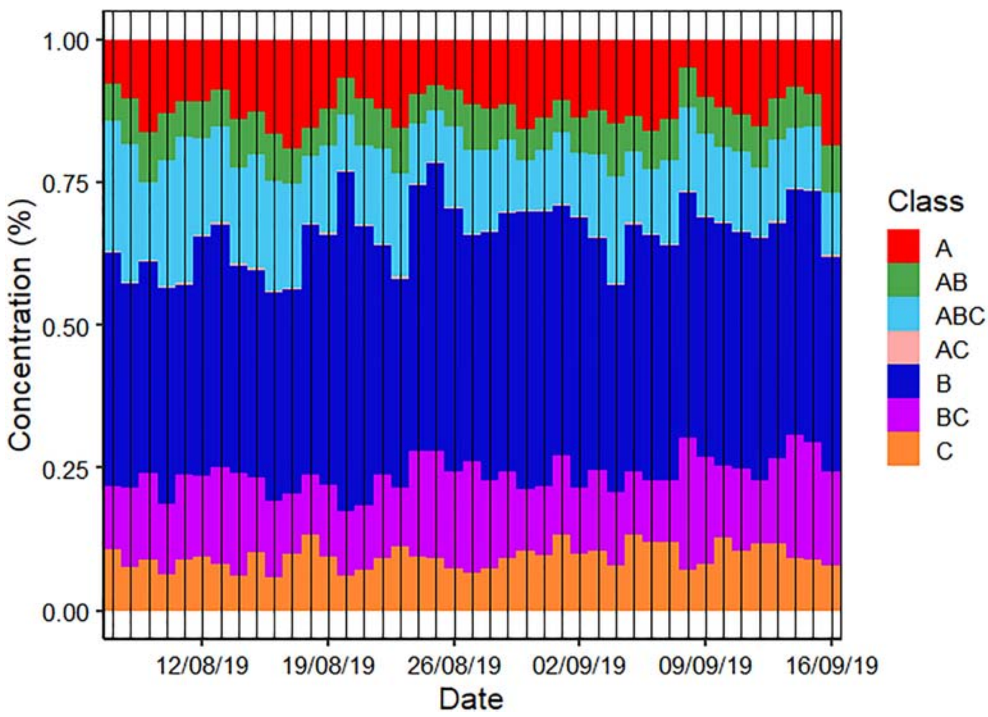

Figure 3.4. Daily relative concentrations of WIBS particle fractions.

particles can aid in the possible identification of the contributing PBAPs (Figure 3.5).

Most particle types were dominated by particles of less than 10–15 µm, except for ABC particles, which were seen to peak at larger size ranges and lower AF values. These values indicate the presence of larger spherical particles that could be accounted for as pollen grains, especially considering the high fluorescence intensity. However, this expected relationship was not seen when the WIBS particle counts were compared with the pollen counts recorded by the Hirst microscope method.

3.4 Comparison of Hirst–Lanzoni Trap and WIBS Data

The real-time monitoring potential of the WIBS was evaluated by comparing its ability to distinguish between the PBAPs of pollen and fungal spores and other interfering particles (anthropogenic particles, etc.). Pollen and fungal spore counts were determined by microscopic analysis of Hirst sample slides. Total daily pollen counts were shown to correlate most strongly with BC particles greater than 10 µm in size at a higher threshold of 6δ yielding a Pearson

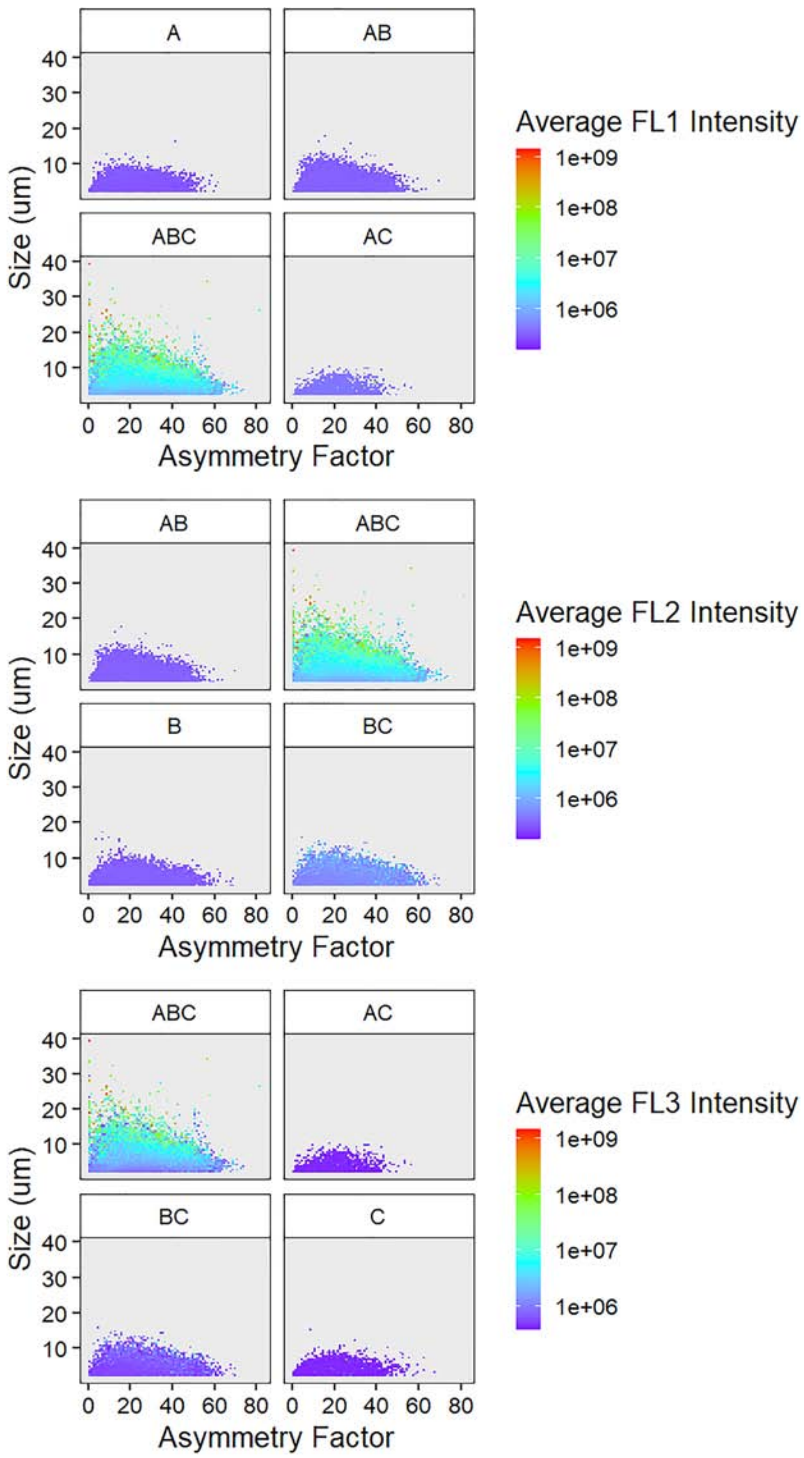

Figure 3.5. Size vs AF distribution for the different WIBS fluorescent categories.

correlation coefficient (r) of 0.78 and R^2 of 0.6, shown in Figure 3.6. The same relationship with BC-type particles was also witnessed for Urticaceae pollen, with a slightly higher Pearson correlation coefficient ($R^2 = 0.64$).

By examining size ranges greater than 10 µm, the effects of smaller PBAPs, such as fungal spores, were filtered out. This enabled the prospective sampling of bigger PBAPs, namely pollen. The Urticaceae produce a relatively small pollen grain, generally between 12 µm and 15 µm. However, owing to the light scattering method used to size the particles sampled by the WIBS, particle size values can vary depending on deviations in light scatter. This could explain the higher correlation observed for Urticaceae and BC

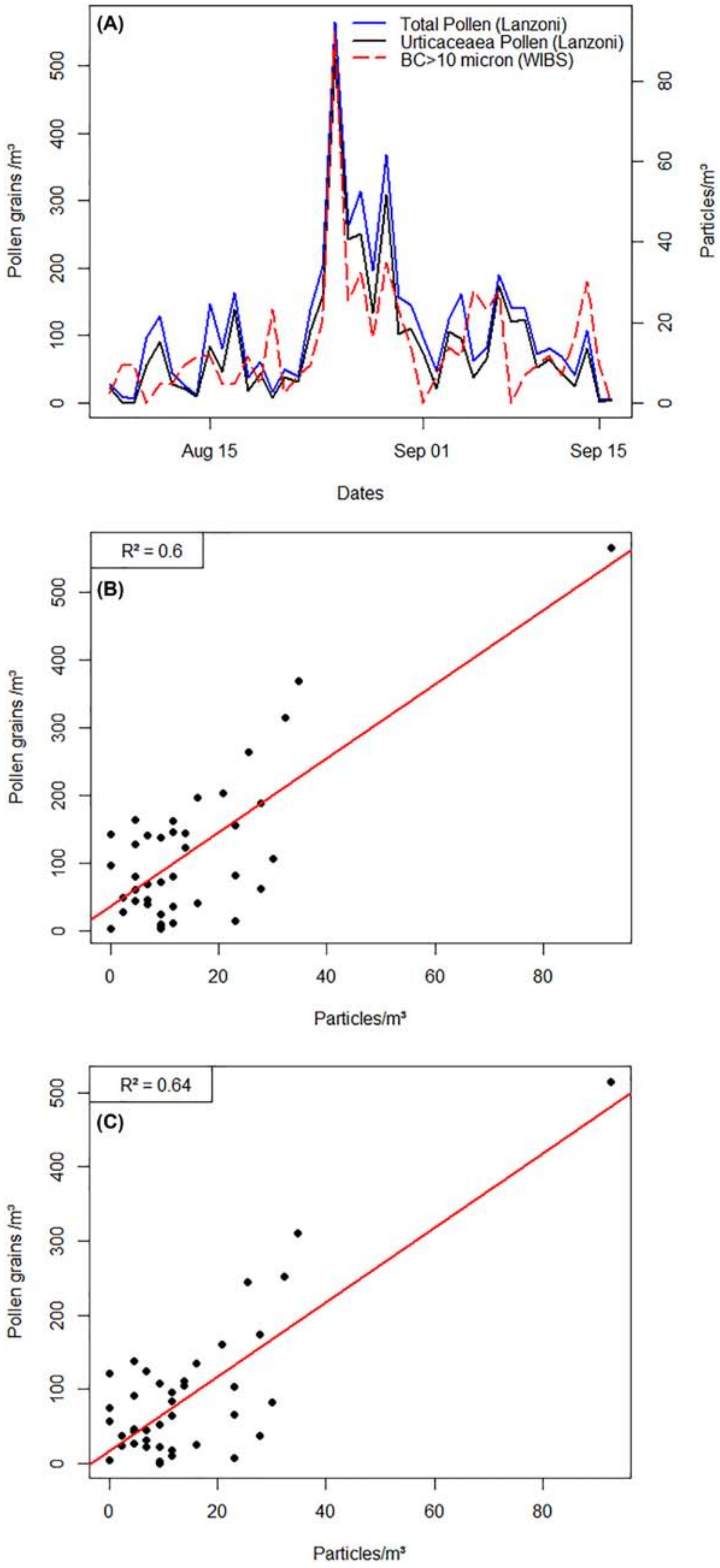

Figure 3.6. (A) Time series of daily pollen (Hirst–Lanzoni trap) and BC particle (WIBS) counts, (B) linear regression for daily BC particle (WIBS) and daily total pollen counts (Hirst–Lanzoni trap) and (C) linear regression for daily BC particle (WIBS) and Urticaceae pollen counts (Hirst–Lanzoni trap) for the 2019 monitoring campaign.

particles between 10 µm and 20 µm; however, this size range could also include potentially interfering concentrations of larger fungal spores. As indicated by the above plot, the isolated BC particles followed the trends recorded for both total and Urticaceae pollen concentrations well for most of the monitoring campaign. This is particularly true for peak pollen concentrations recorded on 25 August. Although a clear relationship exists between the two instruments, there are times when a high Urticaceae pollen concentration was not observed by the WIBS-NEO, for example the unknown BC peak recorded on 20 August. This peak illustrates the potential limitations of using the WIBS for the selective detection of specific pollen taxa. Although the isolated BC particles do closely follow the trend in observed pollen, there are unexplained deviations, which may be other biological particles or highly fluorescent interferents that cannot be successfully accounted for.

Although a good correlation was observed between the WIBS and the Hirst for both total and Urticaceae pollen, the same cannot be said for Poaceae pollen. During the analysis, no substantial relationship was observed for Poaceae pollen at any fluorescent threshold. The best correlation for Poaceae pollen was observed for WIBS BC particles greater than 8 µm at 3σ ($r = 0.53$ and $R^2 = 0.30$).

Examination of the time series compared in Figure 3.7 showed that this isolated fraction of BC particles greater than 8 µm at 3σ failed to account for the predominant peak in Poaceae pollen on 15 August and accounted only for the peaks in Poaceae pollen that occurred on days with a high Urticaceae pollen concentration. As a result, the relationship between BC particle and Poaceae pollen concentrations is more representative of the correlation between Poaceae and Urticaceae pollen than the correlation between the WIBS particles and Poaceae pollen concentrations. The poor representation observed for Poaceae pollen is due to the relatively low concentrations observed during the sampling period and the difficulties encountered by the WIBS when sampling larger particles (O'Connor *et al.*, 2014).

Making comparisons between the Hirst and WIBS-NEO instruments is not faultless, since the systems use vastly different operating principles. The WIBS-NEO operates at a considerably higher resolution than the Hirst and has a much higher capability for sampling smaller particles. The WIBS-NEO can record particles as small as 0.5 µm, making it suitable for monitoring bacteria and other small PBAPs. The Hirst trap is more limited because it uses microscopic analysis and, therefore, is less efficient than the WIBS-NEO at monitoring PBAPs less than 2 µm in size. As a result, for most of the campaign, the number of FAPs sampled by the WIBS-NEO was higher than the number of pollen grains sampled by the Hirst trap. Furthermore, the Hirst operates at a flow rate of 10 L/min, whereas the WIBS-NEO operates at a significantly lower flow rate of 0.3 L/min. This makes the Hirst trap more efficient at sampling

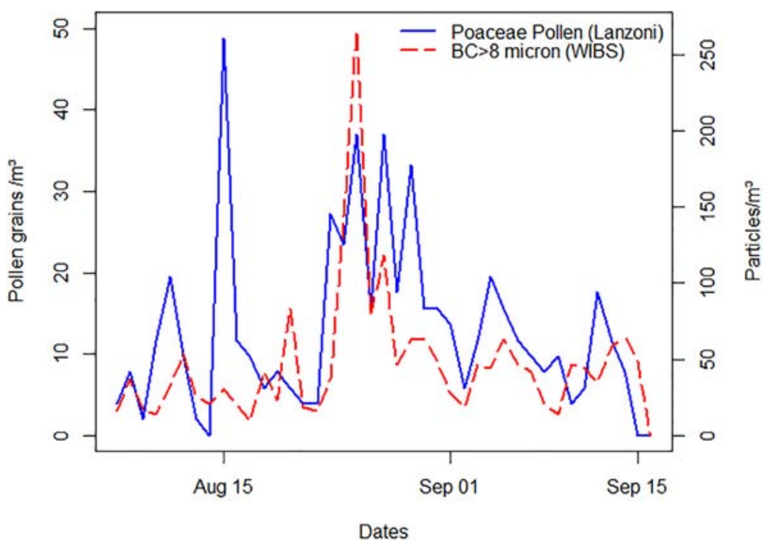

Figure 3.7. Time series of daily Poaceae (Hirst–Lanzoni trap) and BC particle (WIBS) counts at 3σ for the 2019 monitoring campaign.

larger (potentially faster moving) particles that are unaffected by the lower flow rate of the WIBS-NEO. Meteorological conditions, such as high wind speeds, could also inhibit the ability of the WIBS-NEO to successfully sample pollen (O'Connor *et al*., 2014). This could explain why certain pollen peak periods were not recorded by the WIBS-NEO. Therefore, to selectively monitor pollen routinely using the WIBS-NEO, modifications would be necessary to ensure the effective and representative sampling of a range of pollen sizes.

Similar real-time monitoring campaigns have previously been carried out in Ireland using the WIBS instrumentations (WIBS-4), but for a shorter period and not in such a diverse urban environment. Previous proof-of-principle studies have shown the capability of the WIBS to monitor selected pollen species in less diverse Irish environments (O'Connor *et al*., 2014). Studies have concluded, however, that the introduction of other PBAP types, such as additional pollen taxa and fungal spores, could further complicate the selective monitoring ability of the WIBS. This would be especially true for late summer/autumn months when fungal spore concentrations are usually high. The presence of such fungal spores probably affected the correlation of FAPs to pollen count.

Difficulties could have also arisen because of the urban sampling site. PBAPs are not the only fluorescent particles present in the ambient environment. A range of other material/particle types, such as polycyclic aromatic hydrocarbons (PAHs), humic-like substances, mineral dust, secondary organic aerosols and black carbon, may also contribute to the fluorescence (Savage *et al*., 2017; Yu *et al*., 2016). Owing to the urban location of the sampling site, interfering non-biological compounds were anticipated. To reduce the overall degree of interference experienced, the fluorescence threshold was raised from 3δ to 6δ and 9δ; this has been shown to reduce the impact of interfering particles while maintaining the supposed biological fraction of fluorescent particles (Savage *et al*., 2017). Even so, this method is not suitable for sampling PBAPs in the presence of highly fluorescent non-biological particles, as PBAPs would be subsequently categorised as non-fluorescent at higher δ values. One such highly fluorescent particle that is pervasive in urban environments is diesel soot. These particles have also been known to adhere to the surface of PBAPs, such as pollen, which could also have an impact on size, AF and fluorescent characteristics (Visez *et al*., 2020). These particles could also adhere to larger, otherwise non-fluorescent, particles, which could further affect the estimated pollen count (O'Connor *et al*., 2014). A series of other effects could also lead to changes in characteristic pollen shape/size and fluorescence in polluted urban environments, such as fluorescent ageing, adsorption/absorption of anthropogenic pollution and increased concentrations of chemicals that may provide protection against pollen degradation. The further study of these will be essential to improve the interpretation of measurements of fluorescent particles in such environments.

Previous studies have suggested adding extra detection channels between 600 nm and 750 nm to the WIBS in an attempt to visualise chlorophyll. The presence of chlorophyll has been shown to correlate well with certain pollen grains, notably Poaceae and Urticaceae pollen (Sodeau *et al*., 2019). Inclusion of these additional channels could have led to further differentiation by the WIBS of FAPs from pollen concentrations, as Poaceae and Urticaceae together account for the vast majority of pollen encountered during the monitoring period. Similarly, more complex data analysis and clustering analysis could further aid in identifying which FAP fractions correspond to different PBAP types. Although *k*-means clustering of WIBS particles was performed, no further improvement in the correlation with pollen was observed. Other clustering techniques have been shown to improve real-time particle discrimination between PBAP particle types and other anthropogenic particle types (Crawford *et al*., 2015; Robinson *et al*., 2013; Ruske *et al*., 2018; Savage and Huffman, 2018). However, these methods require considerable computational power.

Overall, the WIBS-NEO has been shown to be capable of providing increased sensitivity and time resolution for the monitoring of PBAPs when compared with traditional volumetric methods. The smaller particle size ranges measured by the WIBS-NEO also make it suitable for monitoring smaller PBAPs that cannot be measured with the Hirst trap, such as bacteria. However, improved filtering procedures and accessible data mining techniques are required for the routine use of such data-intensive methods. Traditional methods are both labour intensive and time-consuming, and generally require a trained analyst to successfully and correctly identify PBAP taxa. The real-time data collection of instrumentation such as the WIBS has the potential to drastically reduce the time such monitoring efforts take, enabling the rapid dissemination of results to the public and relevant bodies. However, this is ultimately dependent on suitable statistical clustering techniques and machine learning algorithms to provide accurate and timely identifications from such large quantities of data. This is especially true for complex environments, such as urban and polluted locations, that contain significant concentrations of other interfering compounds.

3.5 Suitability for Monitoring Other PBAPs

The suitability of the WIBS for monitoring other PBAPs of interest was also investigated for fungal spores. The WIBS has previously been shown in the literature to be capable of monitoring fungal spores in real time (O'Connor *et al*., 2011, 2014, 2015). During the monitoring campaign, fungal spores were also counted and identified using Hirst trap data. These data were later compared with analysed WIBS particle data. Promising results were obtained for both total fungal spore count (Pearson correlation coefficient of 0.6) and *Alternaria* spore counts (Pearson correlation coefficient of 0.75), as illustrated in Figures 3.8 and 3.9.

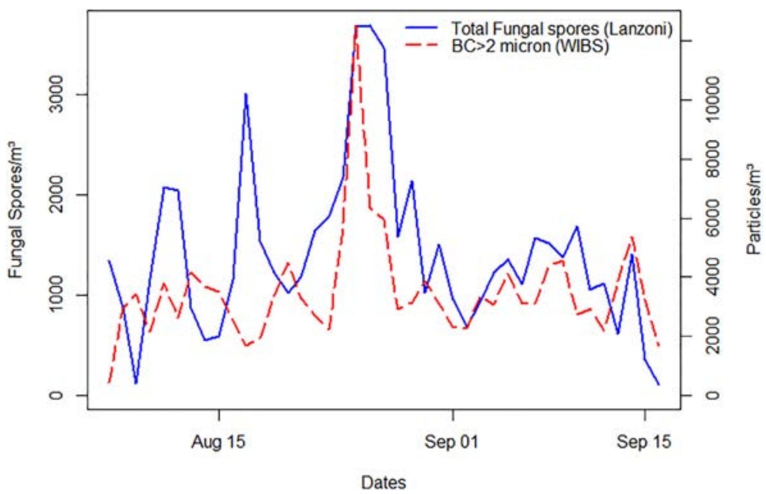

Figure 3.8. Time series of daily fungal spore count (Hirst trap) and daily BC particle count at 9σ (WIBS) for the 2019 monitoring campaign.

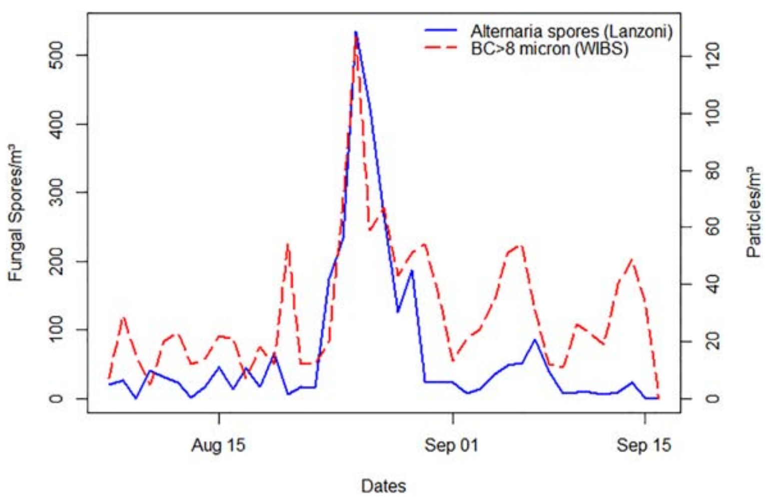

Figure 3.9. Time series of daily *Alternaria* spore count (Hirst trap) and daily BC > 8 μm particle count at 6σ (WIBS) for the 2019 monitoring campaign.

4 Japanese Pollen Counter Monitoring Campaign

4.1 Campaign Overview

The KH-3000-01 pollen counter represents a possible alternative, cost-effective, real-time pollen monitoring technique (at relatively low cost). This monitor measures the forward and side scatter of incident particles using a laser. By analysing known pollen samples, suitable extraction windows can be calculated for individual pollen taxa. An extraction window simply defines the range of values indicative of the forward and side scatter produced for each pollen type. Since different pollen taxa have a range of sizes and surface features, these limits can be used to differentiate between them. Extraction windows for common allergenic ambient pollen types using the same instrumentation are published in the literature. These extraction window parameters were applied to ambient data collected in Dublin city from 1 May 2019 to 10 July 2019. The KH-3000-01 instrument was positioned on the roof of TU Dublin, Kevin Street, close to the Hirst–Lanzoni volumetric trap, to permit parallel monitoring. Following the extraction of pollen-type particles defined by the predetermined extraction windows, a comparison was made with the observed pollen concentrations obtained using the traditional volumetric method.

4.2 Determination of Extraction Window – Literature

Extraction window limits were defined by Kawashima *et al*. (2017) in a similar study. Following collection of ambient data, a scatterplot of forward scattering intensity versus sideward scattering intensity was constructed. Following this, suitable ranges of forward and side scatter were determined for the different pollen taxa investigated. The location and size of the extraction windows were determined by trial and error but were further refined by comparison with observed concentrations obtained from a Hirst sampler. The correlation between the daily values obtained using the two methods measured by the Pearson product–moment correlation coefficient, was used to optimise the exact location and size of extraction window for each pollen type examined (Kawashima *et al*., 2017).

Table 4.1. Extraction windows and collection factors for the major types of allergenic pollen

	Range of extraction window	
Subject pollen	**Sideward (mV)**	**Forward (mV)**
Cupressaceae	250–500	400–750
Fraxinus	570–950	270–480
Betula	1000–1500	900–1300
Quercus	500–760	500–850
Poaceae	670–900	870–2200
Total pollen	300–900	300–2000

Source: Kawashima *et al*. (2017).

Determined extraction windows are summarised in Table 4.1.

4.3 Comparison of KH-3000-01 and Hirst Sampler Data

During the sampling period, Poaceae pollen was the most prevalent pollen type, accounting for almost 50% of the total pollen samples. Owing to the limited ambient concentrations of Cupressaceae, *Fraxinus*, *Betula* and *Quercus* pollen observed during the campaign, only extracted Poaceae and total pollen concentrations were compared with observed concentrations.

Total pollen and Poaceae concentrations detected by the KH-3000-01 counter were characterised as any point within the predefined extraction windows. To account for the differences in collection efficiency between the instruments and convert the pollen monitor count to the standard units of pollen grains per cubic metre (the same units used for Hirst observations), a collection factor was applied to the KH-3000-01 data. We used the collection factors provided by Kawashima *et al*. (2017), which were calculated as the ratio of the sum of daily pollen concentrations obtained from the Hirst sampler to the sum of the daily pollen counts obtained from the KH-3000-01 instrument. The collection factor was calculated as 5.8 for total pollen and 20.4 for Poaceae pollen (see Figures 4.1 and 4.2).

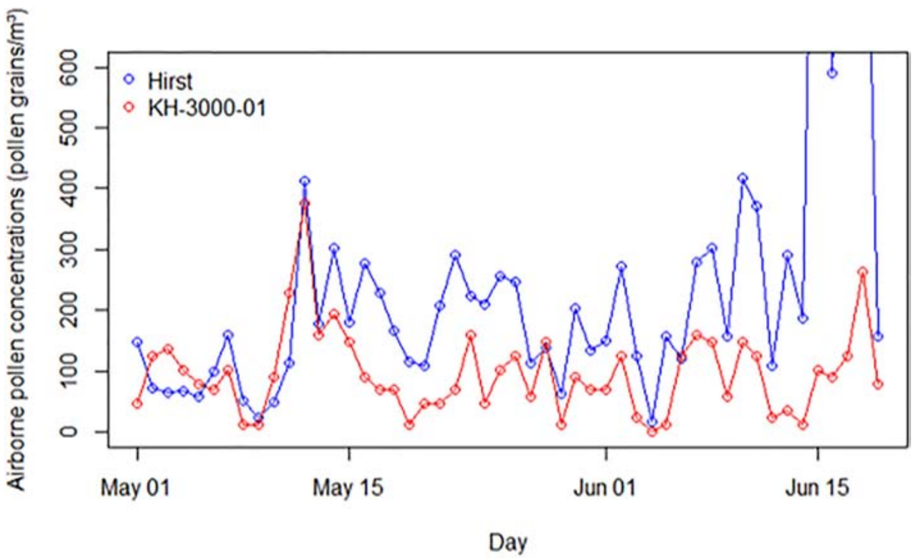

Figure 4.1. Comparison of total pollen concentrations detected by the Hirst and KH-3000-01 instruments during the 2019 monitoring campaign.

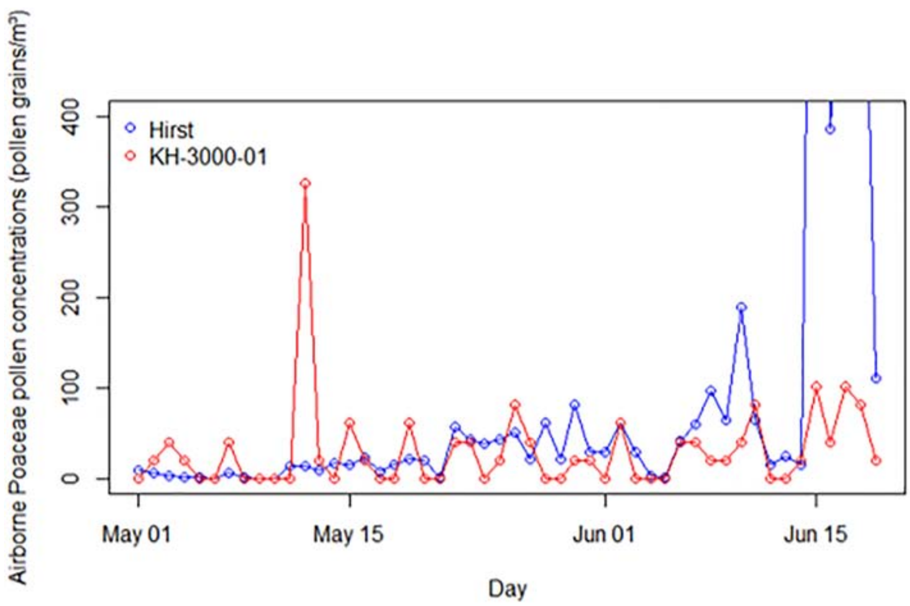

Figure 4.2. Comparison of Poaceae pollen concentrations detected by the Hirst and KH-3000-01 instruments during the 2019 monitoring campaign.

Pearson correlation coefficients were determined to compare the performance of the instruments in monitoring both total ($r=0.47$) and Poaceae ($r=0.54$) pollen concentrations. The correlation was better for the specific extraction of allergenic pollen types (Poaceae) than for total pollen. Similar trends were also observed in the original study performed by Kawashima *et al*. (2017).

Discrepancies between the two methods are most notable for several days at the end of the monitoring periods, when high pollen concentrations were recorded by the Hirst instrument but not by the KH-3000-01. A high peak of Poaceae pollen was also recorded by the KH-3000-01 instrument on 12 May 2019 but not by the Hirst method. Differences between the pollen monitoring efficiency of the instruments are likely because:

- The principles on which the instruments operate are very different, as was the case with the WIBS and the Hirst instrument. As a result, a degree

of uncertainty is introduced by comparing two dissimilar methods.
- Differences in instrument flow rate, sample inlet orientation and the fluctuations in sampling efficiency associated with wind speed and direction were probably not fully compensated for using the collection factors obtained from the literature.
- Interfering particles of similar size and other similar-sized pollen grains, incorrectly grouped by the extraction windows, could have accounted for the high pollen signal seen on 12 May 2019.

Although the KH-3000-01 instrument has been shown to perform exceptionally well for very large and smooth pollen grains, such as Japanese cedar pollen, the device does not appear to perform as well for other pollen types of varying shape and sizes (Kawashima *et al*., 2007, 2017; Matsuda and Kawashima, 2018). The extraction window limits and the collection factors used for this investigation, determined by Kawashima *et al*. (2017), differed significantly from those used in later studies (Matsuda and Kawashima, 2018). This further highlights the need for location-specific suitable extraction windows and collection factors for pollen species, which could improve results. However, the determination of such parameters could be very time-consuming if the original “trial and error” method is to be followed. Nevertheless, efforts are currently ongoing to develop suitable data analysis procedures to enable improved differentiation between pollen taxa using the KH-3000-01 instrument (Miki and Kawashima, 2021).

Although the KH-3000-01 device provides a robust and cost-effective approach for developing a real-time pollen monitoring network, several factors need to be addressed before it can be truly considered fit for the purpose of real-time pollen monitoring. These include improving data analysis, storage and calibration techniques and developing an official external instrument housing. Combining these considerations with the current lag time in data dissemination, because of the time-consuming data analysis steps, the KH-3000-01 does not currently meet the requirements for real-time pollen monitoring in Ireland.

5 Pollen Forecasting and Modelling

5.1 Pollen Calendar – Dublin

A number of pollen types have been considered of particular importance owing to their allergenic effects and atmospheric abundance (Sofiev and Bergmann, 2013). Several of these are prevalent in the Irish environment, with the main allergenic Irish pollen types being *Alnus* (alder), *Corylus* (hazel) and *Betula* (birch) pollen from the Betulaceae family and Poaceae (grass) pollen. As a result of the adverse health effects caused by these allergenic pollen types, predicting periods of high pollen concentrations would be beneficial for allergy sufferers so that suitable precautions and treatments could be taken. Forecasting the daily pollen concentration for a particular location is often done using observational or source-orientated mathematical models, which are covered in the sections below. However, these methods require high concentrations of pollen, meteorological, phenological and transport data, etc., as well as suitable computational support. These resources are not always available, particularly in regions with underdeveloped pollen monitoring networks. More simplistic observational methods, such as pollen calendars, can help early-stage monitoring campaigns by overcoming such limitations. Pollen calendars are the most rudimentary method of pollen forecasting and are largely based on the seasonality of flowering phenophases (Dahl *et al*., 2013) and require fewer data.

A pollen calendar is a graphical representation of the average annual/seasonal trends of major pollen types for a particular location. In this case, the first pollen calendar for Dublin was developed. Although an approximation of the seasonal trends can be observed annually, variations can exist depending on the year; for example, the MPS could differ substantially from one year to the next, typically influenced by changes in meteorology. Therefore, it is recommended that at least 5–7 years of data are incorporated into the construction of a pollen calendar to account for such variations (Galán *et al*., 2017). For this reason, the data obtained solely from the POMMEL monitoring campaign are insufficient for the construction of a reliable pollen calendar for Dublin. Unpublished pollen data from 1978–1980 and 2010–2011 were used in creating the first pollen calendar for Dublin (see Figure 5.1). However, at least 2–3 more years of monitoring will be required before a preliminary pollen calendar can be constructed for the other pollen monitoring sites at Carlow and Cork with any degree of certainty.

5.1.1 Pollen calendar construction

Data from unpublished Dublin pollen monitoring campaigns from 1978–1980 and 2010–2011 and from the POMMEL monitoring campaign (2017–2019) were combined to construct the first pollen calendar for Dublin. The mean daily pollen values for all years were calculated for 21 prevalent pollen taxa present in the Irish environment. Several different methods have been suggested for developing pollen calendars over the years (D’amato and Spieksma, 1992; Lo *et al*., 2019; O’Rourke, 1990; Rojo *et al*., 2019; Werchan *et al*., 2018). Most studies tend to use methods based on the Spieksma model, originally developed in 1992 (Rojo *et al*., 2019). Daily values for each month are further divided into five sections per month, containing 6 days each. The mean value for each section is then calculated. This is repeated in each pollen type. The main flowering period for a particular pollen type is then calculated (from 10% to 90%), beginning once 10% of the mean annual pollen concentration is reached and ending once 90% is reached. Early and late flowering periods outside the main flowering periods are determined in a similar manner. The early flowering period is defined as occurring when the annual mean pollen concentration ranges from $>5\%$ to $<10\%$, and the late flowering period corresponds to an annual mean pollen concentration $>90\%$ and $<99.5\%$. Finally, the possible occurrence time is determined as any time outside the 0.5–99.5% range when pollen is observed. The pollen calendar is then constructed and coloured according to the level of allergenicity posed by each pollen type and shaded according to possible, early/late and main flowering periods.

The calendar (Figure 5.1) represents a useful resource for allergy sufferers in managing their allergies and respiratory health.

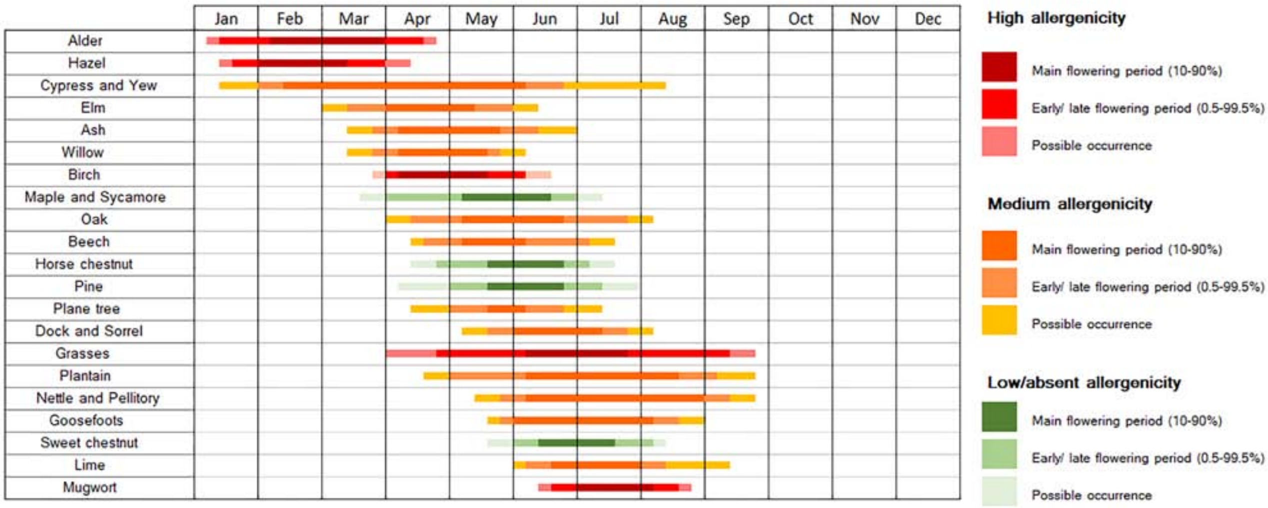

Figure 5.1. First pollen calendar for Dublin (incorporating data from 1978–1980, 2010–2011 and 2017–2019).

5.2 Observation-based Models – Dublin

Although pollen calendars offer an approximate prediction of the commencement and duration of the MPS for a variety of prevalent pollen types, they cannot predict days of imminent concern. Airborne pollen concentrations are largely related to both meteorological and phenological parameters. By understanding the complex relationships that exist between pollen concentrations (dependent variable) and one or more independent variables, predictions of future values can be made. With the increasing trends in allergy prevalence, the ability to predict pollen concentrations, especially those of allergenic significance, is of great benefit to allergy sufferers. This provides sensitised members of the public with ample warning to take any necessary precautions/ treatments. The best form of allergy prevention is often avoidance. Therefore, knowing in advance the exact days when pollen exposure will be high can be more practical and beneficial than knowing the seasonal trends depicted by pollen calendars alone. A vast range of observational modelling approaches exist, and these have been applied to aerobiological data (Maya-Manzano *et al*., 2020). However, observation-based modelling approaches do require sufficient recorded data to train models appropriately so that they can accurately relate variations in pollen concentration to significant meteorological parameters (Scheifinger *et al*., 2013). Therefore, a series of classification and regression models have been developed for Dublin city, as sufficient, unpublished historical data also exist for the sampling area, providing more accurate modelling potential than the other sampling locations in the POMMEL network.

Typically, prediction models are developed for pollens of allergenic concern, since total pollen concentrations may not necessarily indicate high allergen exposure. As a result, we focused on developing prediction models for the most allergenic pollen types present in the Irish environment. These are *Alnus*, *Betula* and Poaceae. In fact, most pollen sensitisations in Europe are caused by exposure to Poaceae and *Betula* pollen (Bousquet *et al*., 2007). This is an important point, as many of those who suffer from hay fever do not realise it, as their symptoms occur outside the summer months and are due to tree pollen. The bimodal pollen trend observed for Dublin was also dominated by *Betula* and Poaceae. Two peak pollen periods appear annually for Dublin: the first spring peak period is dominated by *Betula* pollen and a second summer peak results from higher concentrations of Poaceae pollen. These periods therefore represent the periods of notable allergenic importance. In addition, *Alnus* dominates early pollen release, generally commencing in January. *Alnus* pollen, released to a lesser extent than *Betula* and Poaceae pollen, still plays a vital role in pollen sensitisation. Studies have identified the relationship between *Alnus* and *Betula* pollen allergenicity, particularly in already sensitising urban environments such as Dublin. The successive flowering of both Betulaceae genera results in a "priming effect" (Fernández-González *et al*., 2020): individuals sensitised to *Betula* pollen could suffer allergic symptoms during January and then later experience heightened symptoms in spring from lower levels of *Betula* pollen because the "priming effect" reduces the concentration threshold for symptom presentation (Fernández-González *et al*., 2020).

The remainder of this chapter will discuss the predictive models developed for *Alnus, Betula* and Poaceae ambient pollen concentrations for Dublin. However, the work here could also be applied to highly allergenic ornamental pollen species in the future. Input variables varied slightly depending on pollen type and model algorithm. This is not unexpected, since pollen release and transport are largely dependent on various meteorological and phenological conditions. Because flowering and pollen-producing periods differ, the significance of these parameters can vary with plant type. The importance of predictor variables has been shown to vary between plants of the same family that have relatively complementary pollinating periods, such as trees of the Betulaceae family (*Alnus, Betula, Corylus*) (Nowosad *et al*., 2018). As a result, the models developed below are selective for both pollen type and sampling location.

5.2.1 **Alnus** ***models***

Alnus data for 1978–1980 (unpublished), sampled at Trinity College Dublin, for 2011 (unpublished), sampled at Baldonnel aerodrome, and for 2018–2019, sampled at TU Dublin, Kevin Street, were used to develop several regression models for *Alnus* pollen prediction. Meteorological data from the weather station located in Phoenix Park in Dublin were obtained from the Met Éireann website (http://www.met.ie/climate/available-data/historical-data). Input variables represent daily mean values unless otherwise stated. Regression models refer to predicting the approximate numerical value output of ambient daily pollen concentration, whereas classification models refer to predicting a result of character or label class.

The models developed for *Alnus* pollen prediction included stepwise multiple regression (MR) and SVM regression (SVMR) models. In each case, the models were trained with the first 80% of the data collected and validated with the remaining 20%, an approach known as supervised learning. The initial input variables used included both past daily *Alnus* concentrations (dependent variables) and the various meteorological and phenological parameters shown in Table 5.1. Each model type assesses the input–output relationship slightly differently using the training data. The model can then mathematically mimic this behaviour and predict output results from input independent variables. Model inputs were selected based on significance and likely connection to the overall biological process. Although a list of initial parameters is provided in Table 5.1, models were optimised using this method for input selection to further simplify the model, and this was repeated for all of the models. The omitted 20% validation subset was predicted using the trained model. Predicted results can then be compared with known pollen concentrations. In addition, combining the two sets of predicted results from both models enables the mean, median and weighted mean values to be determined. The weighted mean was calculated using the weighted Spearman's rank correlation coefficient, which compared model performance with the true, observed values.

Predicted results can then be evaluated by comparing them with the observed concentrations (Figures 5.2 and 5.3). As well as examining the normality of predicted results (using the Lilliefors test), several metrics can be used to evaluate the overall model performance and compare different models, including Spearman's rank correlation coefficient, symmetric mean absolute percentage error (SMAPE), root mean square error (RMSE), mean absolute error (MAE) and standard deviation (SD). These metrics were used to evaluate the predicted results (Table 5.2). Correlation coefficients provide information on the strength of the relationship between the predicted and recorded values, whereas SMAPE, RMSE and MAE provide information on the error in the forecast. Lower values of SMAPE, RMSE and MAE indicate fewer errors.

5.2.2 **Betula** ***models***

Betula pollen data for 1978–1980 (unpublished), sampled at Trinity College Dublin, for 2010–2011 (unpublished), sampled at Baldonnel aerodrome, and for 2018–2019, sampled at TU Dublin, Kevin Street, were used to develop several regression and classification models for *Betula* pollen prediction. Meteorological data from the weather station located in Phoenix Park in Dublin were obtained from the Met

Table 5.1. *Alnus* model input variables

Variable class	Input variables
Pollen inputs	Pollen concentration of previous day Average pollen concentration of previous 5 days Average pollen concentration of previous 10 days Slope of pollen concentrations during previous week Normalised slope of pollen concentrations during previous week
Phenological inputs	Growing degree-days (Base temperature = 2–10°C)
Meteorological inputs	Slope for atmospheric pressure during the last week Wind direction Wind speed Rainfall Average rainfall of previous 10 days Cloud cover Maximum temperature Minimum temperature Mean temperature Average mean temperature of previous 10 days Sunshine duration Grass minimum temperature Global radiation

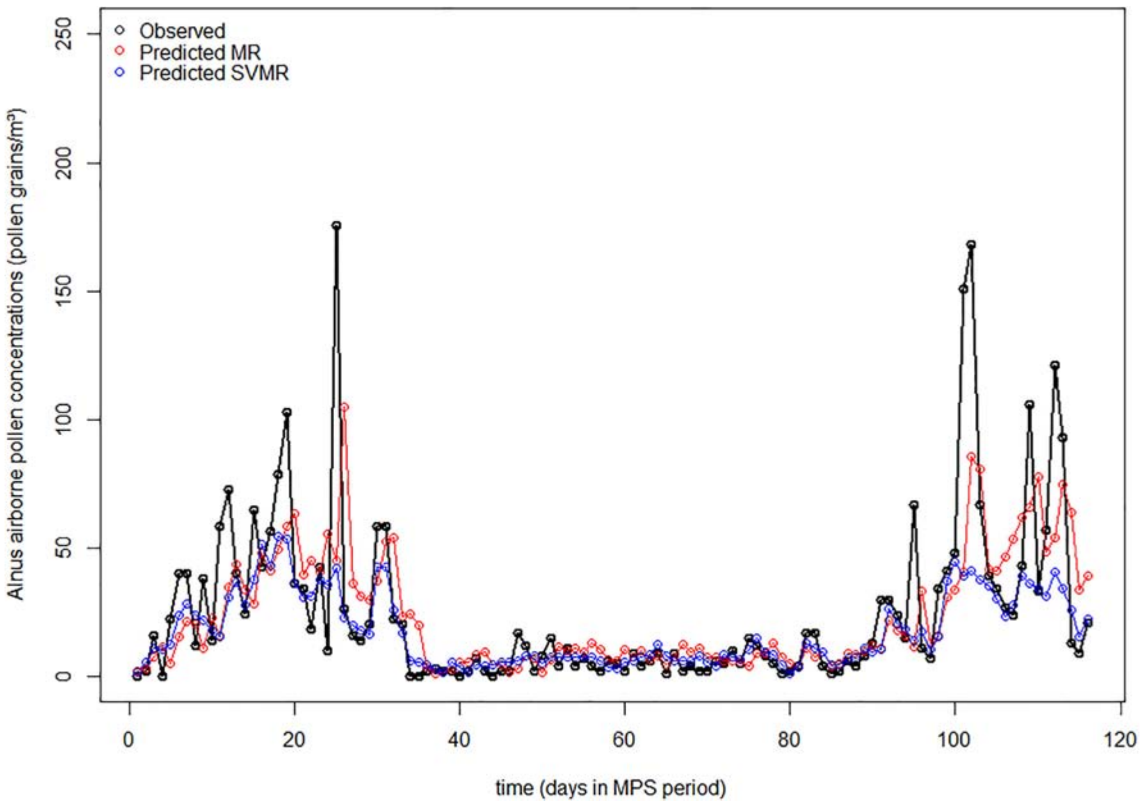

Figure 5.2. Comparison of *Alnus* airborne pollen concentration regression models.

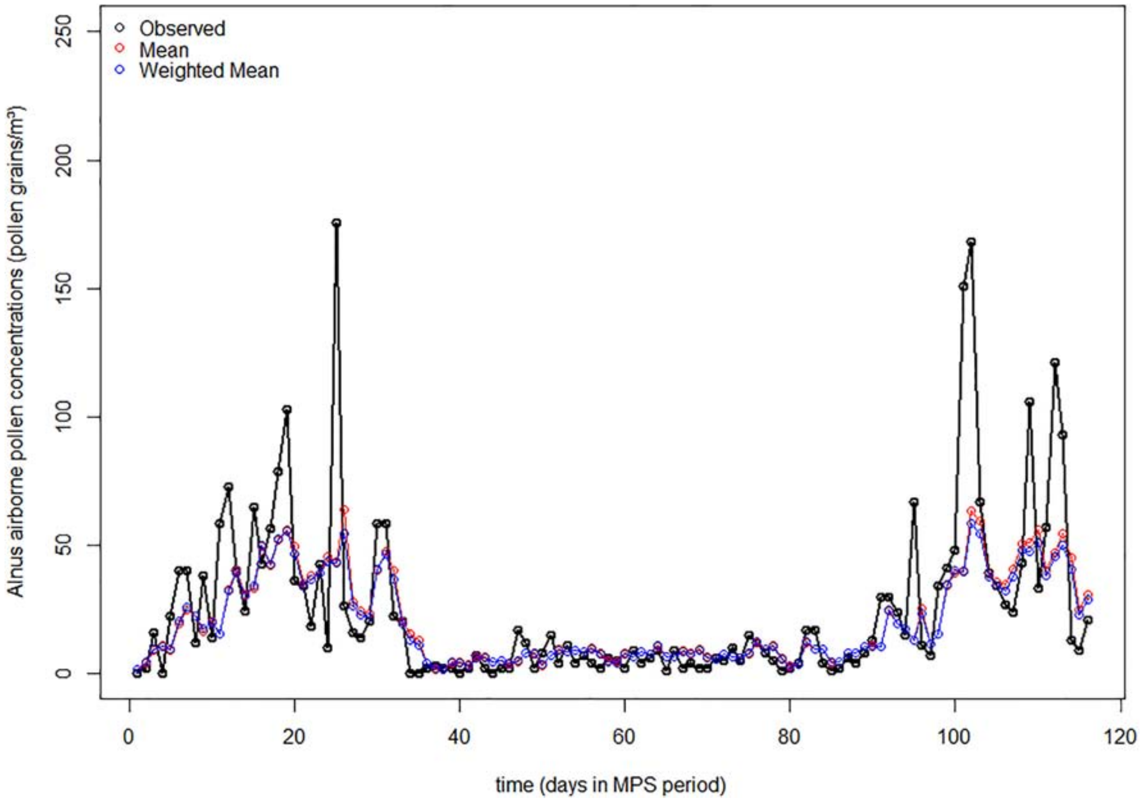

Figure 5.3. Comparison of combined *Alnus* airborne pollen concentration model results.

Table 5.2. Evaluation of predicted *Alnus* pollen concentration

Method	Spearman's *r*	SMAPE	RMSE	MAE	SD
Median	0.81	0.64	24.99	13.20	17.20
Mean	0.81	0.64	24.99	13.20	17.20
Weighted mean	0.82	0.63	25.01	12.85	16.28

Éireann website (http://www.met.ie/climate/available-data/historical-data). Input variables represent daily mean values unless otherwise stated. In this case, classification refers to predicting whether daily pollen concentrations will be low (<30 grains/m^3) or high (>30 grains/m^3).

The models developed for *Betula* pollen prediction included stepwise MR, SVMR, ANN regression, *k*-nearest neighbour (KNN), RF classification and SVM classification models. In each case, the models were again trained with the first 80% (training dataset) of the collected data and validated with the remaining 20% (test dataset). The data used consisted of both past daily *Betula* pollen concentrations (dependent variables) and various parameters shown in Table 5.3. Each model type assesses the input–output relationship slightly differently using the training data. Predicted model results for the test data were compared with the observed concentrations (Figures 5.4 and 5.5). Furthermore, combined mean, median and weighted mean predicted model results were evaluated by examining their normality (Lilliefors test) and comparing Spearman's rank correlation coefficient, SMAPE, RMSE, MAE and SD results (Table 5.4).

In addition to the regression analysis of model performance for predicting ambient *Betula* pollen concentrations discussed above, several classification models, including RF and SVM, were developed. These classification models were again trained and validated using the sample data split as specified above and their performance was assessed by comparing the overall classification accuracy. The correct *Betula* pollen levels were predicted accurately 77% of the time and 64% of the time by the RF and SVM classification models, respectively.

5.2.3 Poaceae *models*

Poaceae pollen data for 1978–1980 (unpublished), sampled at Trinity College Dublin, and for 2017–2019

Table 5.3. *Betula* model input variables

Variable class	Input variables
Pollen inputs	Pollen concentration of previous day
	Average pollen concentration of previous 5 days
	Average pollen concentration of previous 10 days
	Slope of pollen concentrations during previous week
	Normalised slope of pollen concentrations during previous week
Phenological inputs	Growing degree-days
	(Base temperature = 2–10°C)
Meteorological inputs	Slope for atmospheric pressure during the last week
	Wind direction
	Wind speed
	Rainfall
	Average rainfall of previous 10 days
	Cloud cover
	Maximum temperature
	Minimum temperature
	Mean temperature
	Average mean temperature of previous 10 days
	Sunshine duration
	Grass minimum temperature
	Global radiation

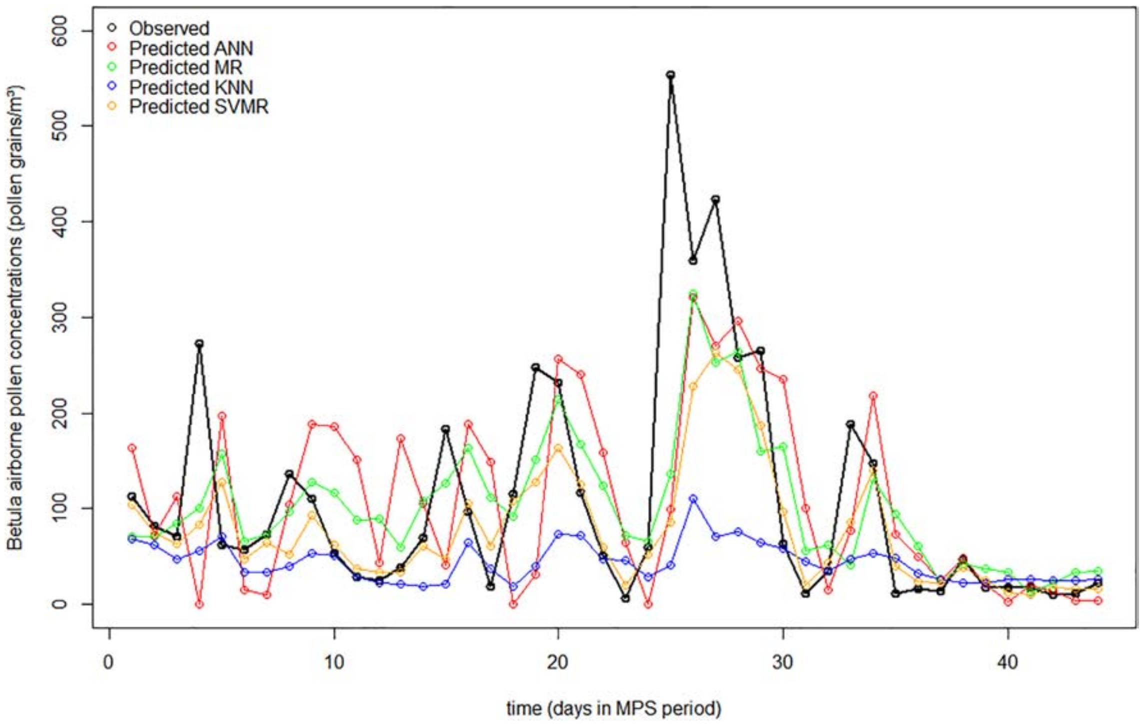

Figure 5.4. Comparison of *Betula* airborne pollen concentration regression models.

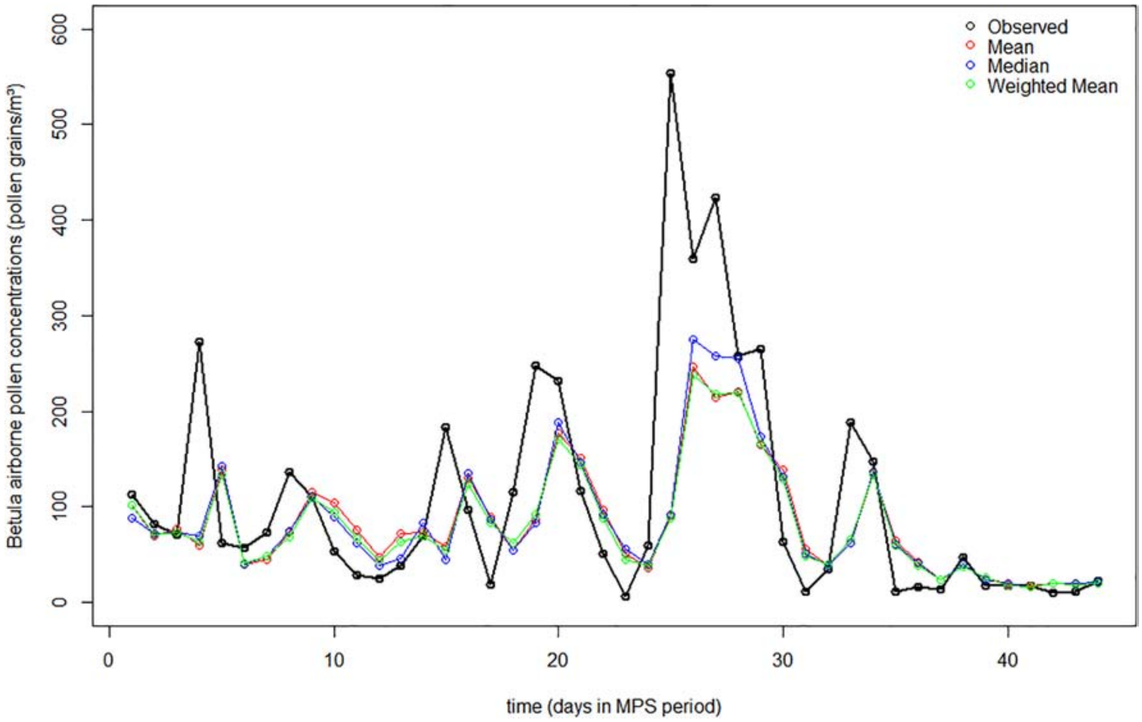

Figure 5.5. Comparison of combined *Betula* airborne pollen concentration model results.

Table 5.4. Predicted *Betula* pollen concentration evaluation

Method	Spearman's *r*	SMAPE	RMSE	MAE	SD
Median	0.72	0.54	95.53	53.60	64.52
Mean	0.68	0.57	99.27	58.10	57.22
Weighted mean	0.73	0.54	98.32	55.59	56.21

sampled at TU Dublin, Kevin Street, were used to develop several regression and classification models for *Betula* pollen prediction. Meteorological data from the weather station located in Phoenix Park in Dublin were obtained from the Met Éireann website (http://www.met.ie/climate/available-data/historical-data). Input variables represent daily mean values unless otherwise stated.

The models developed for Poaceae pollen prediction included stepwise MR, SVMR, ANN regression, KNN, RF regression, and RF and SVM classification models. In each case, the models were trained with 80% (training dataset) of the collected data and validated with the remaining 20% (test dataset). The data used consisted of both past daily Poaceae pollen concentrations (dependent variables) and various meteorological parameters, as shown in Table 5.5. Each model type assesses the input–output relationship slightly differently using the training data. Predicted model results for the test data were compared with the observed concentrations (Figures 5.6 and 5.7). Furthermore, combined mean, median and weighted mean predicted model results were evaluated by examining their normality (Lilliefors test) and comparing Spearman's rank correlation coefficient, SMAPE, RMSE, MAE and SD results (Table 5.6).

In addition to the regression analysis of model performance for predicting ambient Poaceae pollen concentrations discussed above, several classification models, including RF and SVM, were developed. These models were again trained and validated using the sample data split as specified above and their performance was assessed by comparing the overall classification accuracy. Both the RF and SVM classification models accurately predicted the Poaceae pollen level 94% of the time.

Compared with many other European networks that have decades of pollen monitoring data that can be used for forecasting studies and model training and enhancement, the Irish network is very much in its infancy. For the most part, the performance of the regression models developed for the three pollen taxa examined does tend to follow the general trend

Table 5.5. Poaceae model input variables

Variable class	Input variables
Pollen inputs	Pollen concentration of previous day
	Average pollen concentration of previous 5 days
	Average pollen concentration of previous 10 days
	Slope of pollen concentrations during previous week
	Normalised slope of pollen concentrations during previous week
Phenological inputs	Growing degree-days
	(Base temperature = 2–10°C)
Meteorological inputs	Slope for atmospheric pressure during the last week
	Wind direction
	Wind speed
	Rainfall
	Average rainfall of previous 10 days
	Cloud cover
	Maximum temperature
	Minimum temperature
	Mean temperature
	Average mean temperature of previous 10 days
	Sunshine duration
	Grass minimum temperature
	Global radiation
	North Atlantic Oscillation (NAO) index
	Relative humidity
	Mean soil temperature
	Evapotranspiration
	Potential evapotranspiration

of the observed pollen season. However, notable deviations are observed, particularly for periods of observed high ambient pollen concentrations. This is not unexpected at this early stage of forecasting and is related to the fact that the developed models are not fully capable of predicting such high deviations using only a few years of training data. The expansion and continuation of monitoring efforts and incorporation of subsequent seasonal data will improve future model performance. This reasoning can also explain the acceptable performance of the classification models, since they can predict broad classes more accurately than specific numerical values. At the current time, it is suggested that classification models are used for pollen prediction rather than regression models.

5.3 Public Forecasts

During the POMMEL project, several public forecasts were predicted for Dublin using the previously mentioned models and readily disseminated to the public through the @IrishPollen social media account on Twitter (Figure 5.8). The latest forecasting run took place during late April 2020 to warn the public of high *Betula* pollen concentrations.

Future work is required to further develop these initial models and expand the forecasts to the other pollen sampling locations. This will be achieved by continuing monitoring efforts in the coming years to further expand model training data and improve model robustness.

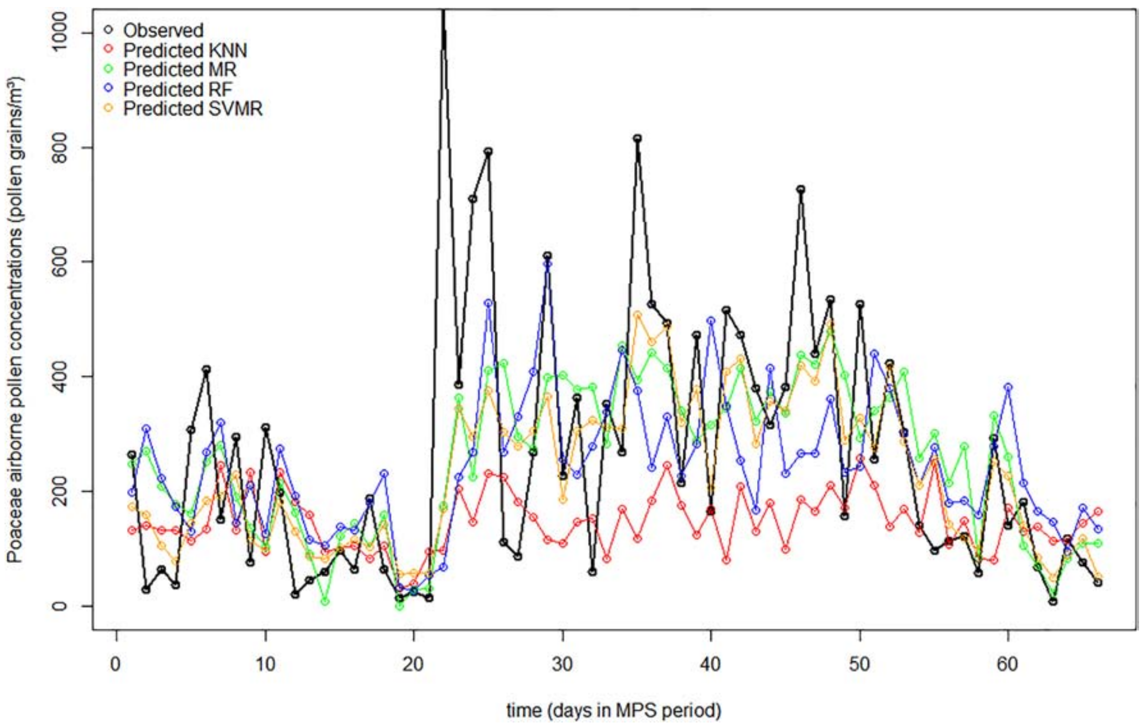

Figure 5.6. Comparison of Poaceae airborne pollen concentration regression models.

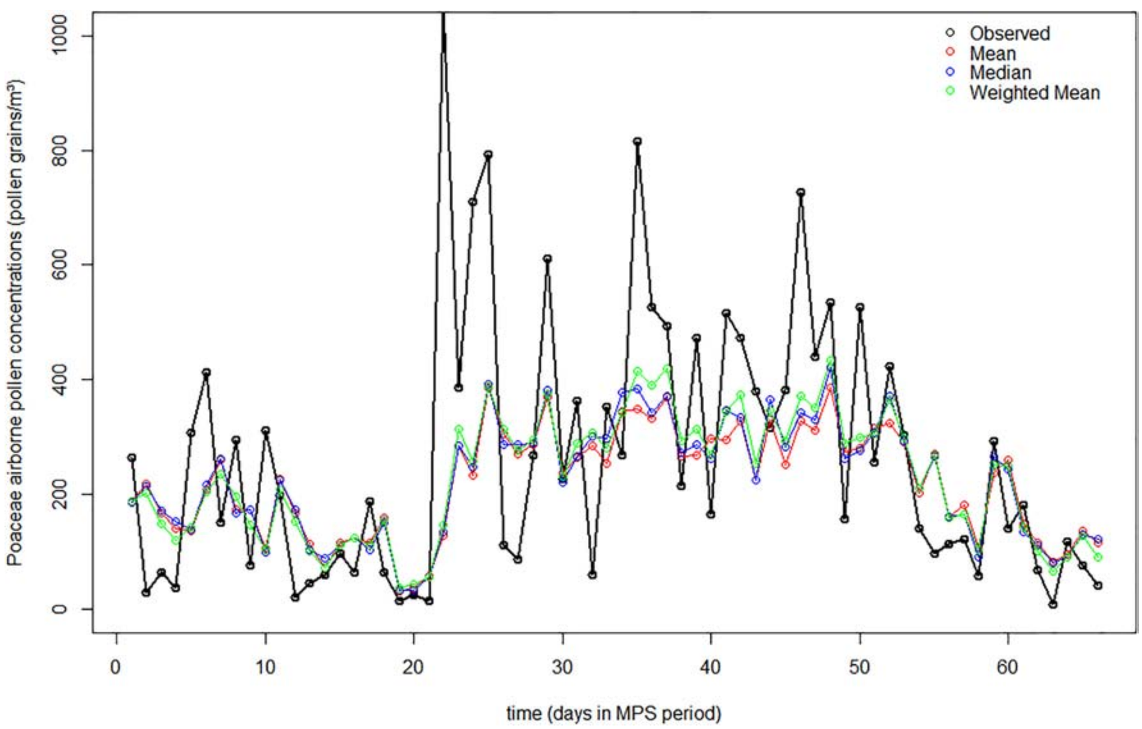

Figure 5.7. Comparison of combined Poaceae airborne pollen concentration model results.

Table 5.6. Predicted Poaceae pollen concentration evaluation

Method	Spearman's *r*	SMAPE	RMSE	MAE	SD
Median	0.70	0.57	190.47	130.12	100.94
Mean	0.68	0.59	196.09	135.50	93.22
Weighted mean	0.74	0.54	183.16	121.56	107.46

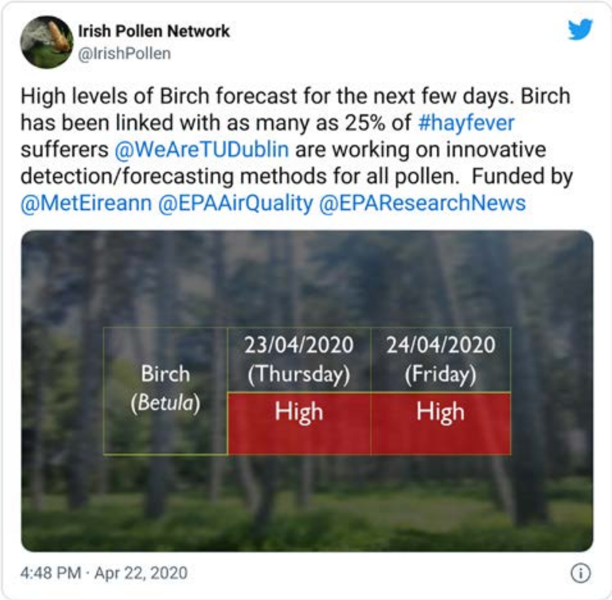

Figure 5.8. Example Twitter forecast.

6 Recommendations

Given the extensive work undertaken by the POMMEL project in constructing a network and prototype forecast system, it is imperative that such work should act as the building blocks for a sustainable system in future, rather than a single output. Thus, this section of the report outlines a number of recommendations and three possible directions or networks that could incorporate these recommendations and enable the establishment of an operational network for Ireland. These three potential networks (termed small, medium and large in scale) differ by cost, and the output (i.e. the data required for a potential prototype forecast for Ireland) is also considered. They will come to fruition only if the recommended funding is in place; this could be obtained via the National Development Fund (2018–2026), as this project spans the four pillars of the fund (urban regeneration and development, rural development, disruptive technologies and climate action). In tandem with support from the EPA and Met Éireann, this would allow an operational network to be established.

Initially, a 5-year tenure will act as the time frame for this breakdown of costs. However, how such networks can continue into the future, and the costs they will incur, are also considered. The recommended monitoring stations also take into account the data required for the constructed models shown in Chapter 4. Thus, real-time instrumentation for identifying pollen would be necessary.

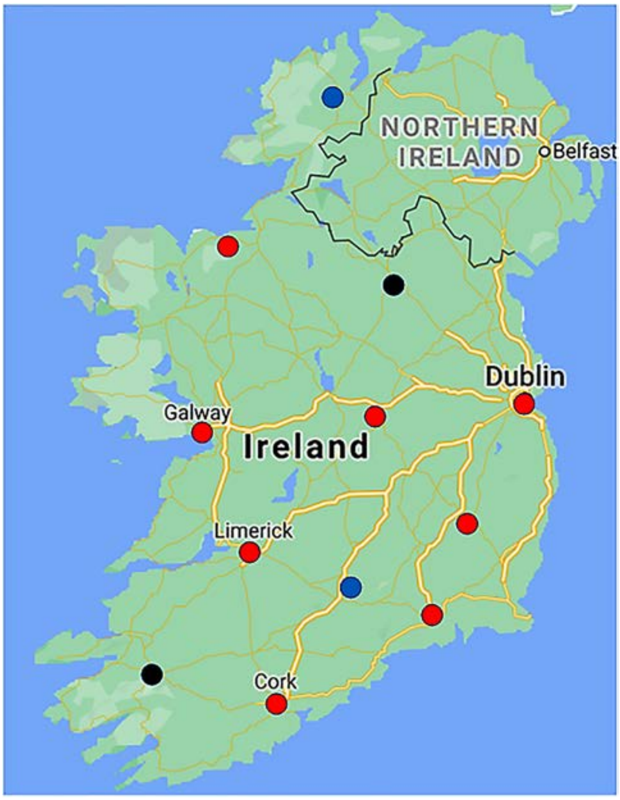

Figure 6.1. Sampling sites for the Irish pollen network. Red symbols indicate the sites for the small-scale network (eight sites). Red and black symbols combined indicate 10 sites for the medium-scale network, and red, black and blue symbols combined indicate the 12 potential locations for the large-scale network.

Figure 6.1 exhibits an outline of the potential geographical spread of the aforementioned stations/sites for the three options proposed by this work. The red symbols indicate the sites for the small-scale network (eight in total), the red and black symbols combined constitute the medium-scale network (10 sites) and the combination of red, black and blue symbols illustrates the large-scale network with a total of 12 locations.

The locations were selected for several reasons.

- To permit a good geographical spread of stations, which in turn could enable the transport and dispersion of pollen over the island of Ireland to be determined. This will become more important should dispersion modelling be used in the future.
- To allow the greatest number of people to benefit from site-specific data on pollen/fungal spores and help them reduce their exposure to pollen during the pollen season, it is recommended that most stations should be placed in the most populous conurbations in the country (Dublin, Cork, Limerick, etc.). The costs and benefits of such an approach are discussed later in this report.
- To allow additional work on determining the influence of agriculture on the production of both pollen and fungal spores, some stations

are located in regions where crop production is prominent.
- To understand the climatic influences on pollen (fungal spore) release, the stations are positioned the length and breadth of the country.

The options presented here aim to bring Ireland into line with the rest of Europe. All other countries have operational networks/forecasts, and several have either created and/or are developing real-time variants (e.g. Germany, Belgium, Switzerland). Switzerland, for instance, is currently using and developing an automated pollen monitoring network (similar to the one recommended here), using 14 stations (Figure 6.2) distributed around the country. Switzerland is approximately 60% the size of Ireland and the network has a good geographical coverage, with only mountainous areas having fewer stations. The average distance between stations is less than that envisaged for the Irish network. Other countries, such as France and Spain, with 65 and approximately 40 sampling sites, respectively, have more networks with more stations, as they have greater areas to cover.

During the POMMEL project, sampling was undertaken at Dublin and Carlow throughout the work and partially in Cork and Sligo. Thus, it is recommended that these sites are retained, as they offer extended datasets for those regions. This will allow new data to be collated with data already collected and aid the further refinement of the models created for these regions in this study. Moreover, the continued presence of the project team for the roll-out and implementation of the selected network (be it small, medium or large in scale) is recommended, given the expertise the team has developed during the process.

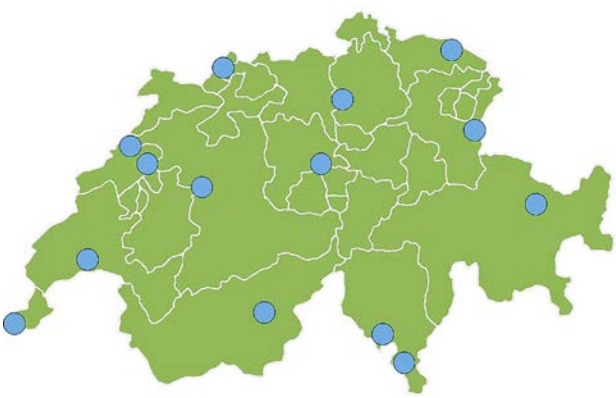

Figure 6.2. MeteoSwiss pollen monitoring network (https://www.meteoswiss.admin.ch/home/measurement-values.html?param=messnetz-pollen).

Although the results from the project highlight the potential for real-time instrumentation to deliver results in a fraction of the time required by traditional methods, the instruments were non-specific, supplying total pollen counts rather than species data. However, in the time taken to implement this project, newer real-time pollen monitoring instrumentation, such as the Rapid-E by Plair (Šauliene *et al*., 2019), the Poleno by Swisens (Sauvageat *et al*., 2020) and the BAA500 by Hund Wetzlar (Oteros *et al*., 2015), have displayed greater precision and accuracy in quantifying and characterising pollen species than demonstrated in this study. Indeed, comparisons between the devices used in this work and the Plair, Poleno and Hund Wetzlar instruments have been undertaken (Lieberherr *et al*., 2021; Tummon *et al*., 2021) and have highlighted the accuracy and selectivity of this new generation of instruments. Thus, the recommendation would be to use these instruments, or at the very least test these devices in an Irish context in a pilot study to understand their capabilities. These instruments should be considered for a potential Irish network, however, given their use in other networks (Swiss, Belgian and German). It may be possible for Ireland to skip a generation of instrumentation in creating its pollen network, placing it at the forefront of what is currently available in pollen detection, and this could also be of particular interest for detecting invasive species of plants and fungi.

Many different considerations were needed and lessons learned when setting up this preliminary Irish pollen network, all of which will feed into the proposed sustainable network. From the sites used (rural and urban), vast differences in the pollen spectrum and concentration were noted; for example, the urban Dublin site recorded a far greater variety of pollen species (at lower concentrations) than sites in rural settings. Thus, an automatic sampler with the capacity to differentiate between pollen from different species would be advantageous, particularly since not all pollen is associated with allergy (Figure 5.1). In the light of the proportion of the Irish population living in the Dublin area, allowing those affected by specific allergens to understand when and what was causing their problem would be very beneficial. This study gives us an understanding of both what the prevalent pollen types are and what pollen species a new network would have to be trained to identify. Again, this is vital information for a new network. Equally, the significant amount of work conducted on the model and forecast creation will be retained, as the models developed in this work would be capable of using the real-time data produced from the newer generation of devices. This project represents the bedrock for any future steps in creating a network. Finally, three options for the use of real-time instrumentation in the main urban areas of Ireland are described below. In addition, consideration is given to the use of larger-scale networks to monitor pollen in rural locations.

6.1 Option A: Small-scale Network

In this option, the network would continue to use the sites established in this work (Cork, Dublin and Carlow and a site in Sligo) alongside additional sites in Limerick, Galway, Waterford and Athlone (red markers in Figure 6.1). These sites provide a good geographical spread, encompass the areas of highest population density and will permit a partial understanding of the climatic influences on the distribution of pollen species and concentrations in Ireland.

These sites would all include novel real-time pollen detection instrumentation (WIBS, Rapid-E, BAA500, Poleno, etc.), which have overtaken the traditional gold standard in pollen collection and analysis (Hirst-type trap) because they enable rapid discrimination between pollen species. Such instruments would focus on the collection of pollen only if the requisite detection features for such an undertaking were costed (see Table 6.1). The results of using such instrumentation are now reported in the literature on this subject (Crouzy *et al*., 2016; O'Connor *et al*., 2014; Šauliene *et al*., 2019; Tummon *et al*., 2021).

Table 6.1 presents the small-scale option. A research assistant and postdoctoral researcher have been costed and would enable the collection, processing and production of the data required to produce the pollen forecast for Ireland. This cost increases year on year, in line with the university research salary scales/guidelines. While the initial capital expenditure (based on manufacturer's prices) may seem high, such instrumentation is now believed to remain operational for a minimum of 10 years and probably longer. Over such a period, costs would average out to €50,000 per year. Purchase of such instrumentation would also permit the supplier's holistic monitoring system to be used, which includes a service arrangement, maintenance of the instruments and data tools for the analysis, storage and streamlined output of pollen concentrations. Additional funding would be required for small amounts of consumables and weather stations to facilitate the operation of the instrumentation and allow weather data to be collected for further refinement of the forecast models produced in this work.

While several countries continue to employ traditional techniques owing to the low initial set-up costs, the robust nature of the instrumentation and the ease with which data can be compared with historical data, such sampling also has several drawbacks. Although the initial instrumental set-up costs may be low, personnel and consumable costs related to instrument maintenance, filter preparation and analysis result in rapidly increasing costs, particularly with several sites (as outlined here). Thus, over the lifetimes of real-time

Table 6.1. Costings associated with the small-scale network

Cost	Year					Total
	1	2	3	4	5	
Personnel (postdoctoral researcher and research assistant)	85,498	87,227	90,151	92,742	95,408	**451,026**
Instrumentation	400,000	–	–	–	–	**400,000**
Service, maintenance, data handling costs	70,000	70,000	70,000	70,000	70,000	**350,000**
Training	4000	–	–	–	4000	**8000**
Consumables, weather station, etc.	32,000	3000	3000	3000	3000	**44,000**
Data visualisation/API and model development	10,000	10,000	10,000	10,000	10,000	**50,000**
Total	**601,498**	**170,227**	**173,151**	**175,742**	**182,408**	**1,303,026**

API, application programming interface.

and traditional instruments, the traditional networks are more costly. In addition, the traditional sampler is associated with an analysis lag time of a minimum of 7–10 days, resulting in its output data being far less valuable for use in the models developed in the POMMEL project.

This point is highlighted in Figure 6.3. Initially, calculated costs for the traditional network are lower than those of the automated network, but personnel costs soon outstrip the upfront expenditure needed to run such a labour-intensive process. By year 5, the costs of a traditional network are higher than those of the automated network and this difference will only increase as the years progress. Thus, the recommendation would be to implement an automated network.

6.2 Option B: Medium-scale Network

The medium-scale network is similar in many of the costings to the small-scale network, with the greatest differences seen in the instrumentation section (Table 6.2). This is because an additional two sites, in Kerry and Cavan, have been incorporated into the network (Figure 6.1; black symbols). In addition, *half of the sites* would use the real-time instrumentation with supplemented detection features (e.g. the ability to count fungal spores). While such an upgrade increases the cost significantly, it also enables the potential determination of other ambient particles that are linked to human and plant health (fungal spores, particulate matter, etc.). Thus, the potential for the creation of a partial bioaerosol network for Ireland would be realised under this proposal.

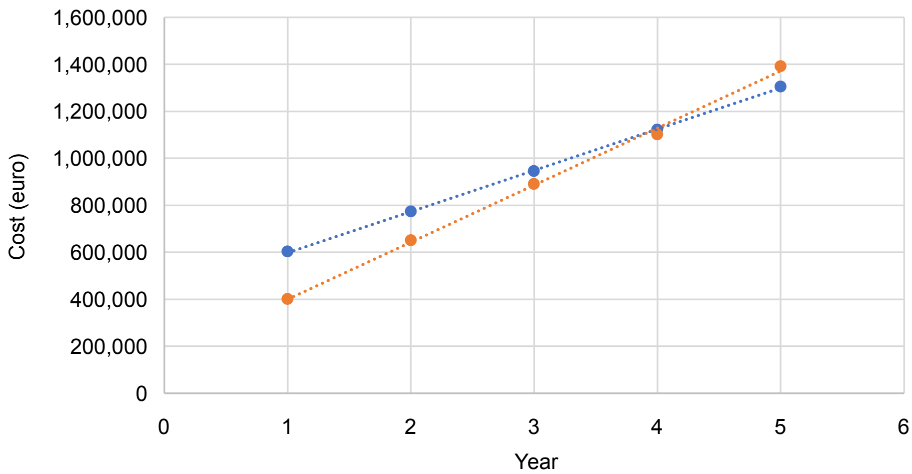

Figure 6.3. Costs of traditional (orange) vs automated (blue) instrumentation for the small-scale pollen network.

Table 6.2. Costings associated with the medium-scale network

Cost	Year 1	2	3	4	5	Total
Personnel (postdoctoral researcher and research assistant)	85,498	87,227	90,151	92,742	95,408	**451,027**
Instrumentation	1,000,000	–	–	–	–	**1,000,000**
Service, maintenance, data handling costs	90,000	90,000	90,000	90,000	90,000	**450,000**
Training	4000	–	–	–	4,000	**8000**
Consumables, weather station, etc.	32,000	3000	3000	3000	3000	**44,000**
Data visualisation/API and model development	10,000	10,000	10,000	10,000	10,000	**50,000**
Total	**1,221,498**	**190,227**	**193,151**	**195,742**	**202,408**	**2,003,027**

API, application programming interface.

The costs and rationale remain the same for the personnel costs, training and consumables. However, further funds would be needed to cover the service, maintenance and data handling costs of such a network. Again, for a traditional network to deliver data comparable to those generated by this option, additional staff would have to be hired and trained to deliver fungal analysis (an even more laborious task than pollen counting). Thus, the automated network is again more cost-effective in the long run.

6.3 Option C: Large-scale Network

The large-scale network again shows resemblances to the previously discussed small- and medium-scale networks, with the greatest differences seen in the instrumentation section (Table 6.3). This is because an additional two sites, in Tipperary and Donegal, have been incorporated into the network in comparison with the medium-scale network (Figure 6.1; blue symbols). In addition, *all of the sites* would use the real-time instrumentation with all potential detection features (e.g. the ability to determine fungal spores). Like the medium-scale network, such an advancement in technology increases the cost substantially, but it also enables the potential determination of other ambient particles that are linked to human and plant health, as mentioned above. Thus, under this proposal, the creation of a full bioaerosol network for Ireland, rather than a partial bioaerosol network (option B) or a pollen network (option A), could become a reality. Indeed, with the additional sites and with *all sites* fitted with instrumentation capable of detecting both pollen and fungal spores, a greater understanding of plant pathogens would be possible than with options A and B. This would be a novel development and, given the EU-mandated need to reduce the farming community's fungicide use by 50% in the coming years, a more targeted approach to fungicide spraying will be needed. Collecting bioaerosol information in real time and incorporating it with meteorological parameters may greatly enhance the forecasting of fungal spores related to crop disease. Thus, such a network outlined here may be able to reduce the need to spray crops on a regular basis. This would have a large benefit in terms of the environment and crop output.

The costs and rationale remain the same for the personnel costs, training and consumables, while further funds would be needed to cover the service, maintenance and data handling costs of such a network. Like the rationale for the other two options, for a traditional network to deliver data comparable with those generated by this option, additional staff would have to be hired and trained. Thus, the automated network is again the more cost-effective option in the long run.

6.4 Pollen Modelling and Forecasting

Should one of the aforementioned networks with real-time instrumentation be instituted, this would allow the models produced in this work to be used. This is a recommendation. As data are collected from a network, the models can be further refined in the future as time goes on. This is recommended, as Ireland lacks information on pollen species and concentrations in the ambient environment.

Both numerical and classification models were developed in this work; however, it is recommended that the output to the public be in the form of a traffic

Table 6.3. Costings associated with the large-scale network

Cost	Year 1	2	3	4	5	Total
Personnel (postdoctoral researcher and research assistant)	85,498	87,227	90,151	92,742	95,408	**451,027**
Instrumentation	1,300,000	–	–	–	–	**1,300,000**
Service, maintenance, data handling costs	110,000	110,000	110,000	110,000	110,000	**550,000**
Training	4000	–	–	–	4000	**8000**
Consumables, weather station, etc.	32,000	3000	3000	3000	3000	**44,000**
Data visualisation/API and model development	10,000	10,000	10,000	10,000	10,000	**50,000**
Total	**1,541,498**	**210,227**	**213,151**	**215,742**	**222,408**	**2,403,027**

API, application programming interface.

light colour-coding system (red, yellow, green) to indicate the potential for pollen to cause allergic reactions: red indicating high levels of a particular pollen, yellow a medium concentration and green low levels. In a test run of the models, the project team used an example of this in April 2020 (Figure 5.8). This is recommended, as the public (the most important stakeholder) will have little understanding of numerical outputs in a pollen forecast. However, the public will understand such a colour-coded warning system. This would be slightly different from the low, medium, high and very high divisions used by Met Éireann currently.

Initially the provincial output of the pollen forecasts would be retained (Munster, Leinster, Connaught and Ulster); however, as additional data from the network become available over time, additional region-specific forecasts could be developed. Should more advanced instrumentation be used, as noted in network options B and C, there will also be the possibility of fungal spore forecasting.

Work has already begun on the creation of a pollen dispersion model for Ireland using HYSPLIT. Such an approach has been attempted in the past (Hernandez-Ceballos *et al*., 2014; Monroy-Colín, 2020). For this work to be completed, however, a postdoctoral researcher would be required. Thus, approximately €60,000 a year would be necessary for such an endeavour to be undertaken and delivered. This cost has not been factored into the options outlined above.

6.5 Dissemination of Pollen Forecast Information

The forecast created will enable predictions 2–3 days ahead, in line with what is currently produced. The forecast should be displayed in the most public of forums to permit its ready dissemination to those in need. Hence, the forecast could be exhibited on social media (as the Asthma Society of Ireland does) with a dedicated page, and displayed on a web page similar to that used by Met Éireann.

Other European countries have begun to use specifically designed phone apps for the dissemination of pollen data. While not costed here, there is potential for such an information pathway should real-time monitoring be undertaken rather than traditional monitoring networks.

Good information dissemination methods will be necessary to reach those who have health concerns related to exposure to bioaerosols. This is important for both those resident in the country and those visiting Ireland as tourists. Being able to provide relevant information to visitors to the country would help to ensure that they have a satisfactory experience and could encourage repeat visits.

7 Conclusions

In conclusion, the POMMEL project produced the first Irish pollen network, and in doing so sampled and determined the concentrations of ambient pollen species in both rural (Carlow) and urban (Dublin) settings. This was done with both traditional impaction methodologies and with real-time light scattering and light-induced fluorescence (novel) approaches. The traditional methods highlighted the difference between the sites used, with grass pollen more prevalent at the rural site.

These data, along with previously collected pollen data from the 1980s, were collated to create the first pollen calendar for Ireland. This reveals the start and end of the season, and peak release periods, for each pollen type and highlights the most allergenic species present in the Irish environment.

The novel approaches showed decent correlation when compared with the impaction methodologies and had the added benefit of outputting their data at a higher time resolution. These data, in tandem with other air quality data, could be very useful for air quality modelling and risk assessment. However, as these approaches were unable to differentiate between pollen species, they are more useful as bulk pollen monitors than as species-specific detectors.

The pollen data collected, along with meteorological parameters and accumulated phenological observations, were used to develop a pollen forecast model for the main allergenic pollen species in the Irish environment. Several modelling methodologies, including ANNs, regression analysis and SVM learning, were used. We found that the mean and median of the models combined produced the best results (observed vs predicted).

The project makes a number of recommendations based on the work presented, including:

1. An automated pollen network similar to one of the three options presented in the study (small, medium or large scale) should be created, with the network chosen based on the funding available. Such a network should give good spatial and population coverage over Ireland.
2. The use of new iterations of pollen instruments in the network should be considered. At the very least, a pilot study looking at such instrumentation in the Irish context would be useful to determine the instruments' potential for deployment in the recommended network. Such new-generation instrumentation has shown the ability to differentiate between pollen species and deliver the requisite data for the pollen forecasting models developed in this work (Tummon *et al*., 2021).
3. An ensemble approach to predict future pollen concentrations should be used, as such an approach has been shown to deliver the most accurate results.
4. The project team should be involved in the development of the network given the knowledge and expertise developed throughout this work.
5. The regions used in the sampling in this project should be used in the new network, as these areas have been evaluated and will greatly aid in any further development of the models used.
6. A traffic light system should be used to display the pollen forecast to the public.

This research will have an impact on the health and wellbeing of members of the public, as pollen and other PBAPs, even at very low concentrations, can cause congestion and flu-like symptoms. In particular, this work will help those who have compromised respiratory systems, especially asthma sufferers. The cost of allergies to countries in Europe is estimated to be as much as €150 billion a year (Clot *et al*., 2020; Zuberbier *et al*., 2014). The direct and indirect costs to an individual are estimated to be approximately €2400 per year (Zuberbier *et al*., 2014). Ireland is even worse affected given its high prevalence of asthma – the fourth highest in the world (Asthma Society of Ireland, 2022a). It is estimated that 890,000 people in Ireland will experience asthma at some point in their lives, and the health-related cost of asthma to the state is estimated to be €472 million per annum (Asthma Society of Ireland, 2022b). Extending this cost to health concerns related to air pollution increases the cost to the state to approximately €2 billion per year (DCCAE, 2017). Thus, potential solutions that could ease the burden on the health system would effectively pay for themselves in the long run, while also improving the quality of life of people with asthma.

Adults with asthma miss on average 10 days of work a year because of their condition (Asthma Society of Ireland, 2018). Furthermore, 80% of Irish people with asthma also have a pollen allergy (Asthma Society of Ireland, 2020). The impact of seasonal allergies on a person's ability to work and their productivity and quality of life has also been discussed extensively in the literature (Blaiss, 2010; Kessler *et al*., 2001; Vandenplas *et al*., 2008, 2018). Estimates of lost productivity attributable to allergic rhinitis (hay fever) could be as high as 40% (Vandenplas *et al*., 2008). Bioaerosols and anthropogenic pollution are known to heighten and trigger "asthma attacks", and to increase wheezing and other breathing difficulties. Indeed, in Ireland, one person dies every 6 days as a result of asthma, and every 4 minutes a person visits an emergency department because of complications associated with asthma. This research will therefore reduce the prevalence of such events by allowing sensitised individuals to control their interaction with bioaerosols and pollution, allowing them to better manage their condition and increase their wellbeing and economic productivity.

Finally, the work could also be easily adapted to ascertain and mitigate the effect bioaerosols have on agriculture and forestry. Agriculture is one of Ireland's largest economic sectors. The significant benefit to the agricultural sector and the country as a whole will be based on the enhanced understanding of the bioaerosol factors affecting agricultural outputs. Historically, bioaerosols, such as the fungus causing potato blight, have had a devastating effect on Ireland, with the food insecurity caused costing millions their lives and precipitating mass emigration. *Phytophthora infestans* (the fungus causing potato blight) is still responsible for significant loss of crops each year, with €1 billion worth of losses in the EU alone. It is estimated that €5 million is spent annually in Ireland on fungicides to mitigate the impact of the disease, which amounts to between 15 and 20 fungicide applications per season (https://www.teagasc.ie/crops/crops/potatoes/potato-blight-disease-research/). The monitoring and forecasting techniques examined here can be further adapted to include other bioaerosols such as fungal spores. The development and use of accurate forecasting methods for fungal spore concentrations could help limit the use of fungicides in agricultural activities by predicting periods of high risk, thereby avoiding unnecessary pollution of the atmosphere, crops, soil, etc. (Frenguelli, 1998), by providing information so that fewer applications are needed to reduce the risk of complete crop destruction. Such work has been carried out for major agricultural sectors elsewhere in Europe, including extensive work on Mediterranean vineyards (Fernández-González *et al*., 2013; Martínez-Bracero *et al*., 2019; Rodríguez-Rajo *et al*., 2010). Moreover, ash dieback, which is caused by fungal spores, is estimated to have cost cost Ireland €2.6–5.8 million (as of 2018) and caused the death of hundreds of thousands of ash trees (Vasaitis and Enderle, 2017; Viney, 2020). Again, real-time measurements could target the areas of need within Ireland and/or internationally.

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Abbreviations

AF	Asymmetry factor
ANN	Artificial neural network
APIn	Annual pollen integral
EAN	European Aeroallergen Network
FAP	Fluorescent aerosol particle
MAE	Mean absolute error
MPS	Main pollen season
PBAP	Primary biological aerosol particle
RF	Random forest
RMSE	Root mean square error
SMAPE	Symmetric mean absolute percentage error
SVM	Support vector machine
TU	Technological University
WIBS	Wideband integrated bioaerosol sensor
WIBS-NEO	Wideband integrated bioaerosol sensor – new electronics option

AN GHNÍOMHAIREACHT UM CHAOMHNÚ COMHSHAOIL
Tá an Ghníomhaireacht um Chaomhnú Comhshaoil (GCC) freagrach as an gcomhshaol a chaomhnú agus a fheabhsú mar shócmhainn luachmhar do mhuintir na hÉireann. Táimid tiomanta do dhaoine agus don chomhshaol a chosaint ó éifeachtaí díobhálacha na radaíochta agus an truaillithe.

Is féidir obair na Gníomhaireachta a roinnt ina trí phríomhréimse:

Rialú: *Déanaimid córais éifeachtacha rialaithe agus comhlíonta comhshaoil a chur i bhfeidhm chun torthaí maithe comhshaoil a sholáthar agus chun díriú orthu siúd nach gcloíonn leis na córais sin.*

Eolas: *Soláthraímid sonraí, faisnéis agus measúnú comhshaoil atá ar ardchaighdeán, spriocdhírithe agus tráthúil chun bonn eolais a chur faoin gcinnteoireacht ar gach leibhéal.*

Tacaíocht: *Bímid ag saothrú i gcomhar le grúpaí eile chun tacú le comhshaol atá glan, táirgiúil agus cosanta go maith, agus le hiompar a chuirfidh le comhshaol inbhuanaithe.*

Ár bhFreagrachtaí

Ceadúnú
Déanaimid na gníomhaíochtaí seo a leanas a rialú ionas nach ndéanann siad dochar do shláinte an phobail ná don chomhshaol:
- saoráidí dramhaíola *(m.sh. láithreáin líonta talún, loisceoirí, stáisiúin aistrithe dramhaíola)*;
- gníomhaíochtaí tionsclaíocha ar scála mór *(m.sh. déantúsaíocht cógaisíochta, déantúsaíocht stroighne, stáisiúin chumhachta)*;
- an diantalmhaíocht *(m.sh. muca, éanlaith)*;
- úsáid shrianta agus scaoileadh rialaithe Orgánach Géinmhodhnaithe *(OGM)*;
- foinsí radaíochta ianúcháin *(m.sh. trealamh x-gha agus radaiteiripe, foinsí tionsclaíocha)*;
- áiseanna móra stórála peitril;
- scardadh dramhuisce;
- gníomhaíochtaí dumpála ar farraige.

Forfheidhmiú Náisiúnta i leith Cúrsaí Comhshaoil
- Clár náisiúnta iniúchtaí agus cigireachtaí a dhéanamh gach bliain ar shaoráidí a bhfuil ceadúnas ón nGníomhaireacht acu.
- Maoirseacht a dhéanamh ar fhreagrachtaí cosanta comhshaoil na n-údarás áitiúil.
- Caighdeán an uisce óil, arna sholáthar ag soláthraithe uisce phoiblí, a mhaoirsiú.
- Obair le húdaráis áitiúla agus le gníomhaireachtaí eile chun dul i ngleic le coireanna comhshaoil trí chomhordú a dhéanamh ar líonra forfheidhmiúcháin náisiúnta, trí dhíriú ar chiontóirí, agus trí mhaoirsiú a dhéanamh ar leasúchán.
- Cur i bhfeidhm rialachán ar nós na Rialachán um Dhramhthrealamh Leictreach agus Leictreonach (DTLL), um Shrian ar Shubstaintí Guaiseacha agus na Rialachán um rialú ar shubstaintí a ídíonn an ciseal ózóin.
- An dlí a chur orthu siúd a bhriseann dlí an chomhshaoil agus a dhéanann dochar don chomhshaol.

Bainistíocht Uisce
- Monatóireacht agus tuairisciú a dhéanamh ar cháilíocht aibhneacha, lochanna, uiscí idirchriosacha agus cósta na hÉireann, agus screamhuiscí; leibhéil uisce agus sruthanna aibhneacha a thomhas.
- Comhordú náisiúnta agus maoirsiú a dhéanamh ar an gCreat-Treoir Uisce.
- Monatóireacht agus tuairisciú a dhéanamh ar Cháilíocht an Uisce Snámha.

Monatóireacht, Anailís agus Tuairisciú ar an gComhshaol
- Monatóireacht a dhéanamh ar cháilíocht an aeir agus Treoir an AE maidir le hAer Glan don Eoraip (CAFÉ) a chur chun feidhme.
- Tuairisciú neamhspleách le cabhrú le cinnteoireacht an rialtais náisiúnta agus na n-údarás áitiúil *(m.sh. tuairisciú tréimhsiúil ar staid Chomhshaol na hÉireann agus Tuarascálacha ar Tháscairí)*.

Rialú Astaíochtaí na nGás Ceaptha Teasa in Éirinn
- Fardail agus réamh-mheastacháin na hÉireann maidir le gáis cheaptha teasa a ullmhú.
- An Treoir maidir le Trádáil Astaíochtaí a chur chun feidhme i gcomhair breis agus 100 de na táirgeoirí dé-ocsaíde carbóin is mó in Éirinn.

Taighde agus Forbairt Comhshaoil
- Taighde comhshaoil a chistiú chun brúnna a shainaithint, bonn eolais a chur faoi bheartais, agus réitigh a sholáthar i réimsí na haeráide, an uisce agus na hinbhuanaitheachta.

Measúnacht Straitéiseach Timpeallachta
- Measúnacht a dhéanamh ar thionchar pleananna agus clár beartaithe ar an gcomhshaol in Éirinn *(m.sh. mórphleananna forbartha)*.

Cosaint Raideolaíoch
- Monatóireacht a dhéanamh ar leibhéil radaíochta, measúnacht a dhéanamh ar nochtadh mhuintir na hÉireann don radaíocht ianúcháin.
- Cabhrú le pleananna náisiúnta a fhorbairt le haghaidh éigeandálaí ag eascairt as taismí núicléacha.
- Monatóireacht a dhéanamh ar fhorbairtí thar lear a bhaineann le saoráidí núicléacha agus leis an tsábháilteacht raideolaíochta.
- Sainseirbhísí cosanta ar an radaíocht a sholáthar, nó maoirsiú a dhéanamh ar sholáthar na seirbhísí sin.

Treoir, Faisnéis Inrochtana agus Oideachas
- Comhairle agus treoir a chur ar fáil d'earnáil na tionsclaíochta agus don phobal maidir le hábhair a bhaineann le caomhnú an chomhshaoil agus leis an gcosaint raideolaíoch.
- Faisnéis thráthúil ar an gcomhshaol ar a bhfuil fáil éasca a chur ar fáil chun rannpháirtíocht an phobail a spreagadh sa chinnteoireacht i ndáil leis an gcomhshaol *(m.sh. Timpeall an Tí, léarscáileanna radóin)*.
- Comhairle a chur ar fáil don Rialtas maidir le hábhair a bhaineann leis an tsábháilteacht raideolaíoch agus le cúrsaí práinnfhreagartha.
- Plean Náisiúnta Bainistíochta Dramhaíola Guaisí a fhorbairt chun dramhaíl ghuaiseach a chosc agus a bhainistiú.

Múscailt Feasachta agus Athrú Iompraíochta
- Feasacht chomhshaoil níos fearr a ghiniúint agus dul i bhfeidhm ar athrú iompraíochta dearfach trí thacú le gnóthais, le pobail agus le teaghlaigh a bheith níos éifeachtúla ar acmhainní.
- Tástáil le haghaidh radóin a chur chun cinn i dtithe agus in ionaid oibre, agus gníomhartha leasúcháin a spreagadh nuair is gá.

Bainistíocht agus struchtúr na Gníomhaireachta um Chaomhnú Comhshaoil
Tá an ghníomhaíocht á bainistiú ag Bord lánaimseartha, ar a bhfuil Ard-Stiúrthóir agus cúigear Stiúrthóirí. Déantar an obair ar fud cúig cinn d'Oifigí:
- An Oifig um Inmharthanacht Comhshaoil
- An Oifig Forfheidhmithe i leith cúrsaí Comhshaoil
- An Oifig um Fianaise is Measúnú
- Oifig um Chosaint Radaíochta agus Monatóireachta Comhshaoil
- An Oifig Cumarsáide agus Seirbhísí Corparáideacha

Tá Coiste Comhairleach ag an nGníomhaireacht le cabhrú léi. Tá dáréag comhaltaí air agus tagann siad le chéile go rialta le plé a dhéanamh ar ábhair imní agus le comhairle a chur ar an mBord.

EPA Research Report 420

Pollen Monitoring and Modelling (POMMEL)

Authors: David O'Connor, Emma Markey, Jose Maria Maya-Manzano, Paul Dowding, Aoife Donnelly and John Sodeau

Identifying Pressures

A reliable pollen forecast and monitoring system is a valuable tool to help allergy sufferers avoid unnecessary exposure to allergenic pollen and to optimise drug treatments by allergists. As Ireland has no monitoring system in place, forecasts based on Irish data are not available, and the forecast currently used is provided by the University of Worcester (UK).

As a result, the impacts of allergenic pollen on the health of the Irish population and any links to climate forcing remain understudied. The health implications for those who suffer from allergic rhinitis and asthma can be substantial, and this, in turn, places undue pressure on national healthcare services.

This project seeks to address the problem by undertaking the required monitoring and developing a forecast model.

Informing Policy

The direct impact of pollen on society and business can be seen throughout the year, with diminished quality of life and loss of productivity. The consequences can be significant and far-reaching, with financial burdens placed on employees and employers alike.

While most hay fever sufferers experience symptoms more irritating than debilitating, the same cannot be said of those who also have asthma. With Ireland having the fourth highest incidence of asthma in the world, this group constitutes a significant sub-section of the population. Many find that their condition is exacerbated by spores and chemical particulates as well as pollen, resulting in significant strain on public health infrastructure.

In the light of these impacts on the general public, our society must develop "early warning" systems for bioaerosol detection at both national and local levels. POMMEL sets about the task of developing such systems to minimise pollen exposure of those who are negatively affected.

Developing Solutions

POMMEL produced the first Irish pollen network, and in doing so, sampled and determined the concentrations of ambient pollen species in both rural (Carlow) and urban (Dublin) settings. This was done with both traditional impaction methodologies and real-time light-scattering and light-induced fluorescence (novel) approaches. The traditional methods highlighted the difference between the sites, with grass pollen more prevalent at the rural site.

These data, along with pollen data collected in the 1980s, were collated to create the first pollen calendar for Ireland. This reveals the start and end of the season, and peak release periods, for each pollen type and highlights the most allergenic species present in the Irish environment.

The novel approaches showed decent correlation when compared with the impaction methodologies and had the added benefit of outputting their data at a higher time resolution and in a more timely manner. These data, in combination with other air quality data, could be useful for air quality modelling and risk assessment. However, as these approaches could not differentiate between pollen species, they are more useful as bulk pollen monitors than as species-specific detectors.

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