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UNIVERSITY OF SOUTHAMPTON

FACULTY OF SOCIAL AND HUMAN SCIENCES

Geography and Environment

Global Environmental Change and Earth Observation Research Group

**Modelling and mapping the birch and grass pollen seasons using
satellite sensor time-series in the United Kingdom**

by

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Thesis for the degree of Doctor of Philosophy

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UNIVERSITY OF SOUTHAMPTON

ABSTRACT

FACULTY OF SOCIAL AND HUMAN SCIENCES

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Doctor of Philosophy

**MODELLING AND MAPPING THE BIRCH AND GRASS POLLEN SEASONS
USING SATELLITE SENSOR TIME-SERIES IN THE UNITED KINGDOM**

Nabaz Rasheed Khwarahm

Grass and birch pollen grains are two the most important aeroallergens that cause hay fever in around 20% of the population in the UK. Currently, prediction of these allergens in the UK is based on (i) measurements of pollen counts at a limited number monitoring stations across the country and (ii) general information about the phenological status of the vegetation. Thus, the prediction methodology provides only coarse spatial resolution representations of the pollen distribution.

Phenological parameters derived from satellite-derived vegetation indices, characterise the stages of vegetation development during the growing season. Thus, potentially they can be related to biological definitions of plant phenology, for example, flowering phenophase related to pollen release. In this research, time-series of the MERIS Terrestrial Chlorophyll Index (MTCI), pollen count, and meteorology data at nine sites were used to derive the date of flowering phenophase for birch and grass at 1 km spatial resolution for the whole UK. Detailed relationships were established between pollen count, meteorological data, and flowering phenophase derived from the MTCI. Thereafter, these data were used to construct regression-based predictive models. The employment of the flowering phenopase as a covariate in the models led to significantly greater explanatory power (Sig. *F* Change < 0.05) across all the sites for both birch and grass. The models promise to be beneficial to the medical field in areas of allergenic pollen planning and treatment, demonstrating that satellite-derived vegetation parameters holds great potential for aerobiology.

This research demonstrated several novel approaches that contribute significantly to the field of aerobiology and plant phenology, including: (i) developing a technique to define the start and end of pollen season from pollen data (ii) developing a technique to define the onset of flowering from MTCI data and (iii) incorporating the flowering phenophase parameter into predictive models for pollen forecasting. The findings of the research are related directly to producing more accurate pollen prediction models in the UK through: (i) investigation of the source-based dimension of aerobiology of birch and grass by applying satellite sensor time-series in deriving important phenological parameters, (ii) investigation of the receptor-based dimension of aerobiology of birch and grass through comprehensive analysis of the spatial and temporal relationships of the pollen with various meteorological parameters.

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DECLARATION OF AUTHORSHIP

I, Nabaz Khwarahm, declare that the thesis entitled “Modelling and mapping the birch and grass pollen seasons using satellite sensor time-series in the United Kingdom” and the work presented in it are my own and have been generated by me as the result of my own original research.

I confirm that:

- This work was done wholly or mainly while in candidature for a research degree at this University;
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Definitions and abbreviations

Aerobiology (studies airborne biological particles)

AVHRR: Advanced Very High Resolution Radiometer

AMSR-E: Advanced Microwave Scanning Radiometer for EOS

APTRA: Approximate trajectory

ART: Aerosols and Reactive Trace Substances

BAF: British Aerobiology Federation

BADC: British Atmospheric Data Centre

BNSC: British National Space Centre

BISE: Best index slope extraction

BC: Black Carbon

CEH: Centre for Ecology & Hydrology

CLC2000: Corine Land Cover 2000

CORINE: Coordination of Information on the Environment

CO₂: Carbon dioxide

CO: Carbon monoxide

CN: Condensation nuclei

CMAQ: Congestion Mitigation and Air Quality Improvement

CMDC: Climate Monitoring and Diagnostics Laboratory

CAPITA: Centre for Air Pollution Impact and Trends Analysis

CMC: CAPITA Monte Carlo

DFT: Discrete Fourier transform

DM: Derivative Method

DEM: Digital Elevation Model

DOY: Day of Year

DREAM: The Dust REgional Atmospheric Model

ESC-DSS: UK Ecological Site Classification Decision Support System

EEA: European Environment Agency

Ean: European Aeroallergen Network Pollen

EPI: European Pollen information

ESA: European Space Agency

EVI: Enhanced vegetation Index

ETM+: Enhanced Thematic Mapper Plus

EODC: Earth Observation Data Centre

ECMWF: European Centre for Medium-Range Weather Forecasts

EMEP: European Monitoring and Evaluation Programme

FORMOSAT-2/ ROCSAT 2: Republic of China Satellite 2

FASIR: Fourier-adjusted, sensor and solar zenith angle corrected, interpolated, reconstructed

FLEXPART: FLEXible PARTicle dispersion model

HYSPLIT: HYbrid Single-Particle Lagrangian Integrated Trajectory

HANTS: Harmonic Analysis of NDVI Time Series

HiProGen: High level Product Generation

IOWT: Isle of Wight

IKONOS (Greek for “image”)

IPCC: Intergovernmental Panel on Climate Change

KOMPSAT-2: Korea Multi-Purpose Satellite-2

LSP: Land Surface Phenology

LAI: Leaf area index

LAGRANTO: Lagrangian trajectory tool

MERIS: MEdium Resolution Imaging Spectrometer

MTCI: MERIS Terrestrial Chlorophyll Index

MGVI: MERIS global vegetation index

MODIS: Moderate Resolution Imaging Spectroradiometer

Met Office: Meteorological Office, UK

MSS: Multispectral Scanner

MSC: The Multi-Spectral Camera

MIDAS: Integrated Data Archive System

METRAS: Mesoscale Transport and Stream

NOAA: National Oceanic and Atmospheric Administration

NASA: National Aeronautics and Space Administration

NERC: Natural Environment Research Council

NCAS: National Centre for Atmospheric Science

NEODC: NERC Earth Observation Data Centre

NDVI: Normalized Difference Vegetation Index

NPARU: National Pollen and Aerobiology Research Unit

NO_x: Mono-nitrogen oxides

NAME: The Met Office's Numerical Atmospheric-dispersion Modelling Environment

NMC: National Meteorological Centre

OSA: Optical Sensor Assembly

Phenology (studies the development stages of plants such as budburst, first flower emergence, first leaf emergence, etc. in relation to the climate)

PhenoCam: Phenological Cameras

PM: Particulate Matter

PM₁₀: Particulate Matter up to 10 micrometres in size

RSI: Remote Sensing Instrument

SPOT: Système Probatoire pour l'observation de la Terre

SOS: Start Of Season

SO₂: Sulfur dioxide

SILAM: Finnish Emergency Dispersion Modelling System

SRTM: Shuttle Radar Topographic Mapping Mission

TM: Thematic Mapper

TFA: Temporal Fourier analysis

Tees-Exe line: An imaginary line dividing the UK into lowland and upland regions

TRAIET: Tri-dimensional Atmospheric Interpolation Evaluation of Trajectory

UGAMP: Universities Global Atmospheric Modelling Programme

UK-DMC2: United Kingdom Disaster Monitoring Constellation

VegDRI: Vegetation drought response index

VI: Vegetation index

VOCs: Volatile Organic Compounds

CHAPTER 1: Introduction

1.1 Background

Seed plants produce tiny to coarse biological grains for reproduction, which eventually produce male gametes or sperm cells of a particular species, known as pollen. These bioparticles (particles of biological origin) are important in the continuation of plant life through enriching genetic diversity. The process of transferring pollen from the male part of the flower to the female part is known as pollination. Pollination acts like an ecological service, for example, for reproduction and diversification of species. Pollen is produced in vast numbers in *Anemophilous* (wind-pollinated) plants, for example, in birch and in most grasses, and is mostly allergic. These plants usually have odourless catkins and flowers, whereas *Entomophilous* (insect pollinated) plants have colourful flowers and tend to have few sticky and heavy pollen grains which are rarely allergic in nature, and they do not come in contact with respiratory mucosa or eyes in sufficient numbers to trigger an immune reaction or to cause allergy (Emberlin Volcheck, 2009).

The typical clinical terms for an allergy to pollen are Seasonal Allergic Rhinitis (hay fever), Seasonal Conjunctivitis (pink eye or red eye) and Asthma which often occur in the same patient simultaneously during the pollen season (Cecchi et al. 2010). Allergy to pollen, most commonly hay fever, costs heavy annual expenditure in medication and consultation in industrialised countries (Sofiev and Bergmann 2013). In the UK and other parts of the EU (e.g., Finland, Denmark) grass and birch are two major causes of hay fever (Varney et al. 1991; Emberlin et al. 1997). In the USA, hay fever accounts for 2 million lost school days, \$6 million in lost work days, and more than \$3 billion in medical expenditure annually (Volcheck 2009). However, it is not the pollen itself which causes a reaction; it is the protein allergens attached to the pollen grains. Hay fever is clinically described as a symptomatic disorder of the nose induced by immunoglobulin E (IgE) (i.e., antibody) mediated inflammation after pollen allergens come into contact with the membranes lining the nose. Symptoms include nasal blockage, sneezing, nasal itching, and rhinorrhea (runny nose) (Bousquet et al. 2001). The allergenicity of pollen is related to the relative amount of allergen on them. The chemical structure of allergenic extracts is generally polypeptide (chain of amino acids) and polysaccharides (polymeric carbohydrate) (Mygind and Scadding 2000).

Pollen release into the atmosphere during the pollination season, generally, is in the beginning of spring and later on during the year depending on the plant species and geographical regions. The behaviour of transport, distribution and suspension of pollen in the atmosphere after release is dependent on both the properties of the atmosphere and the constituent of atmospheric particles (Agashe and Caulton 2009). Pollen is capable of following small flow and turbulent eddies for its transportation and dispersal from its sources. Knowledge of both the pollen producing source and location of pollen emissions together with meteorological factors are necessary to predict pollen transportation along its trajectory (Sofiev et al. 2006; Vogel et al. 2008).

Predicting the main characteristics of the pollen season, for example, the start of the pollen season in the UK, is performed by relating ground pollen count observations with meteorological variables. In other words, the pollen count data from monitoring stations are used together with meteorological data to estimate the behaviour of pollen through the season. Daily pollen count, apart from meteorology, also varies as a function of flowering rhythm at the source (Bringfelt et al. 1982). Other environmental factors also affect, partly, the variation of pollen in the air, for example, topography. Moreover, none of these factors (i.e., meteorology and flowering rhythm) alone is suffice to draw a near-complete picture of pollen behaviour in the air due to the influence of transport pollen. Phenological events such as flowering at the source areas together with meteorological covariates are two major components for building a near-complete picture of the pollen season characteristics. Pollen grains are known to transport over long distances (hundreds of Kilometres) and therefore may influence significantly local pollen season timing (Ranta et al. 2006).

The aim of this chapter, apart from addressing the research objectives and the relevance of the research, is to describe briefly the main components of the research. The first component is a short description of two key aeroallergens causing hay fever in the UK and in most of the industrialised countries; grass and birch pollen (*sections 1.1.2 to 1.1.5*). The second and third components address the use of satellite sensor time-series data in studying plant phenology and provide a brief description of transport models (*sections 1.1.6 and 1.1.7*).

1.1.2 Grass and birch Pollen

The branch of science that studies airborne biological particles (organic particles) is known as aerobiology. Furthermore, it includes plant phenology (studying the development stages of plants such as budburst, first flower, first leaf, leaf unfolding, etc.) in relation to climate factors. The general application of aerobiology in the fields of public health, environmental pollution and genetic diversity is well-known. The bioparticles could be pollen, spores, viruses, bacteria, microalgae, microfungi, lichen fragments, soredia, seeds, protozoan cysts, spiders and insect parts. Moreover, the branch of aerobiology that focuses on the study of airborne pollen is called aeropalynology (Agashe and Caulton 2009). Two major plant families that produce airborne pollen grains in vast numbers to guarantee genetic variation in an evolutionary process over millions of years are grass and birch.

The Poaceae family (previously known as Gramineae), include plants usually called grasses. They are widely distributed in the world, comprising over 10,000 species (Emberlin 2009). This family has both economic and ecological importance, mostly producing wind-blown (*anemophilous*) pollen grains which are known to produce allergic reactions (*section 1.1.3*). According to their responses to photoperiodism, this family is divided into long-day plants (flowers with fewer hours of darkness in each 24 hrs. period, meaning that daylight hours increase through spring to summer) and short-day plants (which initiate flowering when day light hours decrease and dark periods increase through late summer to autumn). The former occurs geographically in cool temperate regions such as North America and Europe. The latter occurs in warm temperate to subtropical regions (Emberlin 2009). Most grass pollen grains share the same appearance; they are spheroid and monoporate (a single pore on the pollen surface (Fig.1-1a)) and, therefore, there has been little effort to describe them at the species level through pollen sampling. Mostly the size of the pollen gains of this family ranges from 30-to-60 μm . Grass pollen generally pollinates in early morning of the summer, and this decreases in the evening when the air cools (Abreu et al. 2008).

The birch tree (*Betula*) is a genus belonging to the Betulaceae family, an *anemophilous* plant which produces large numbers of pollen grains. A single catkin is estimated to produce around 6 million grains in total (Erdtman 1934). Pollen from birch is allergic

and responsible for causing seasonal allergic rhinitis in the United States, Canada and north Europe (*section 1.1.3*). Birch grain size ranges from 19-to-22 μm in diameter and they are triporate (three pores on the pollen surface (Fig.1-1b)) with a smooth to a slightly granular surface texture (Hyde and Williams 1945; Volcheck 2009; Agashe and Caulton 2009). The prevalence of hay fever and other pollen-related allergies (commonly referred to as hay fever), from the above pollen types are described more thoroughly in *section 1.1.3*.

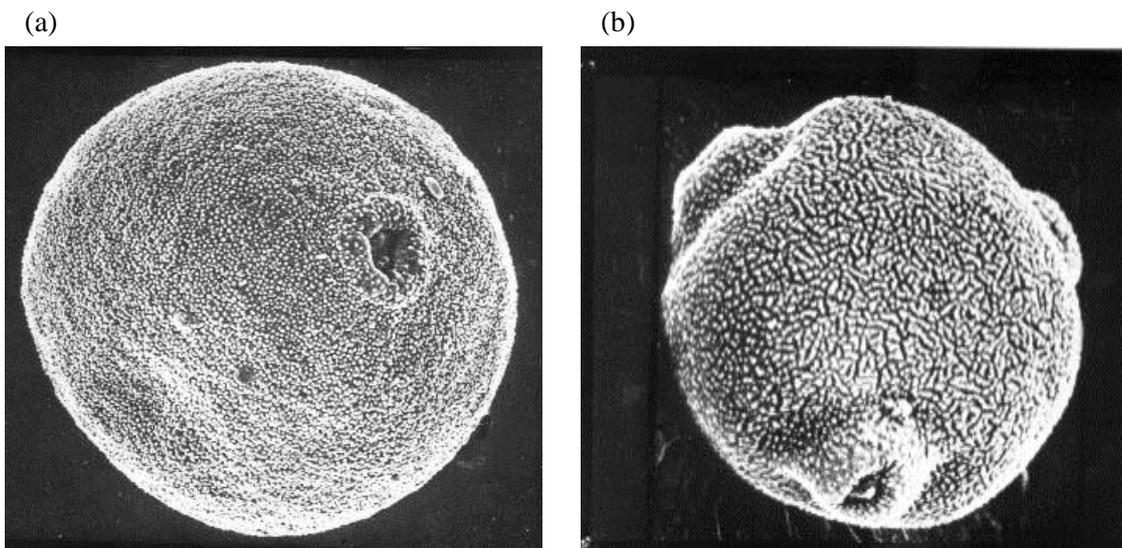


Fig.1-1 (a) Monoporate grass pollen and (b) triporate birch pollen. Images are courtesy of Beverley Adams-Groom at the National Pollen and Aerobiology Research Unit (NPARU), University of Worcester, UK.

1.1.3 Occurrence of hay fever from birch and grass pollen

The prevalence of sensitisation to grass and birch allergens varies substantially geographically (i.e., from region-to-region depending on their source abundance and the amount of allergen extract on the pollen). High sensitisation to grass pollen has been reported for parts of UK, France, New Zealand, Switzerland and the USA. Similarly, high prevalence of sensitisation to birch was reported for parts of northern and mid-Europe, New Zealand and parts of the USA (Bousquet et al. 2007). Several Studies have reported local, annual, regional, temporal and geographical variation in both birch and grass pollen counts, and birch allergen extracts for different biogeographical areas (Emberlin et al. 1993a; Emberlin et al. 1993b; Emberlin et al. 1999; Emberlin et al. 2000; Buters et al. 2008).

According to Mygind and Scadding (2000) grass pollen is known to be the most common cause of hay fever in the world, and influences more than 95% of seasonal allergic rhinitis patients in the UK. In the northern hemisphere about 20% of the population is affected at some time during their lives. Hay fever usually starts in childhood or the teenage years. The symptoms usually decrease with ageing. Severity of symptoms in the eyes and nose is correlated with pollen count in the air. During a hot day the pollen may rise to 500 m high in the atmosphere and can travel several kilometres at that altitude. Thus, people in urban areas can be affected. In the USA, seasonal allergic rhinitis is estimated to affect up to 25% of the adult population and 40% of children (Volcheck 2009).

According to the National Pollen and Aerobiology Research Unit (NPARU) based at the University of Worcester the UK, most sufferers develop an allergenic manifestation when grass pollen reaches the moderate category 30-49 grains m^{-3} of air. The NPARU usually gives its grass pollen forecast based on the Low ($30 < \text{grains m}^{-3}$), Moderate (25-50 grains m^{-3}) High (50-149 grains m^{-3}) and Very high ($150 \geq \text{grains m}^{-3}$) categories. These categories may vary for tree pollen due to pollen size and allergenicity. Most sufferers will start to experience symptoms when the concentration of pollen reaches the moderate category, although concentrations vary in space and time (*section 1.1.4*).

1.1.4 Pattern of occurrence of pollen in the air

The concentration of pollen (grains m^{-3}) in the air depends on the pollen producing species (genetic make-up, physiology), environmental factors (i.e., meteorology, topography, and land use) and distance from the source, as well as the sampling method used to record the data. The existence of pollen in the air, considering the climate conditions, is the outcome of numerous development processes which may occur interdependently or independently. These processes phenotypically start from the first phenological stages such as first-bud and first-leaf. Genotypically, the genetic make-up (genotype) of the aeroallergen producing plant determines the flower morphology and grain sizes. The photoperiod (light/dark) suppresses or expresses this process depending on the plant species (Richardson et al. 2009).

Variation in the concentration (pollen grains m^{-3}) of pollen in the air close to the source of release is influenced by the diurnal dispersal of the pollen from flowers. In contrast, it is influenced by the weather conditions distant from the source of release (Minero et al. 1998). Knowledge of both the source of pollen producing plants and its distance from the sampler is crucial. This information together with daily weather, mostly wind direction, is important to determine the pollen catch with respect to the source. As some pollen may travel long distances in large numbers, it is important to have information about the occurrence of pollen over regions beyond the local area (Tyldesley 1973). The seasonal occurrence of pollen can be determined in the atmosphere through air sampling, such as pollen count stations, to determine the quantity and quality of the pollen during the pollen season. Understanding the pattern of pollen concentration in the atmosphere requires understanding the influence of the environmental factors (*section 1.1.5*).

1.1.5 Influence of weather conditions on pollen

Climatic conditions are generally known to influence the quantity of pollen before release and the availability of pollen in the air after release. The phenological developments of plants such as shortening and lengthening of the flowering period or shifting this period to earlier or later in the year is believed to be controlled by temperature in the northern hemisphere. According to studies conducted by Emberlin et al. (1997, 2002), cumulative temperature (over 5.5°C) determines the start of the birch pollen season in the UK. Similarly, a few other studies elsewhere in the world supported this conclusion, for example, in Denmark (Rasmussen 2002), Switzerland (Frei and Gassner 2008) and the northern hemisphere (Schwartz et al. 2006). The length of the pollen season is controlled by temperature, humidity, wind speed and rainfall. Moreover, the release, dispersal, distribution, floatation, refloatation and deposition are known to be influenced by environmental conditions (i.e., meteorology, topography) (Minero et al. 1998; Agashe and Caulton 2009). Hyde (1952) claimed that the quantity of annual catches of individual pollen types varies significantly and attributed this to variation in pollen productivity and, in turn, attributed variation in pollen productivity, especially for herbaceous species, to rainfall during vegetative growth, weather during the preceding year and during the current year, and the cyclic variation of flowering.

It is believed that pollen grains are to some extent hygroscopic which behave like nuclei for water vapour and make up raindrops (Montoyuroy et al., 1992). In contrast, Norris-Hill (1995), in a four-year study period in north-central London, observed several occasions where pollen counts were high during rainfall. This raises the question of the mechanism of pollen dispersal. Agashe and Caulton (2009) argued the possibility of involvement of other meteorological drivers, independently, influencing pollen dispersal, such as wind speed; stormy and showery weather is usually accompanied by strong wind. High velocity wind may disperse more pollen in the air despite rainfall. However, the size of the pollen grains in this respect should also be considered as larger grains wash out of the air during rainfall faster than smaller grains.

1.1.6 Pollen dispersion

The dispersion of pollen grains in the atmosphere depends on atmospheric flow and turbulence fields. Furthermore, they are capable of following even small turbulent eddies. This justifies application of existing transport or dispersion models to their transportation and distribution from their sources (Vogel et al., 2008, Sofiev et al., 2006). Recent studies have employed these models to estimate pollen transport (Efstathiou et al. 2011; Hernández-Ceballos et al. 2011). Atmospheric dispersion models, depending on their designs, have several applications, especially in the field of air-pollutants emerging from various sources. Details are given in the literature review chapter (*section 2.2.1*).

1.1.7 Plant phenology

Phenology can be defined as “the study of the timing of recurring biological phases, the causes of their timing with regard to biotic and abiotic forces, and the interrelation among phases of the same or different species” (Linderholm 2006). With availability of satellite data at a high temporal frequency help us to track the growth stages of vegetation at regional to global scales.

Phenological variables or events within temporal profiles of vegetation indices characterise objectively the stages of vegetation development during the growing season

(White et al. 2009; de Beurs and Henebry 2010; Roerink et al. 2011). The events are important tools to detect and measure the impact of climate variability on vegetation. Furthermore, they can be related to biological definitions of plant phenology, for example, the flowering phenophase related to pollen release. Linkosalo (1999, 2000) found in southern Finland that the difference in time from birch (*Betula pendula*) male flowering to the first date of budburst was only 1.1 days, with male flowering occurring first. Thus, the timings of male flowering and leaf budburst of birch are well correlated ($r = 0.97$). Moreover, the timing of male flowering, leaf budburst and pollen release appear to be quite closely synchronised (Newnham et al. 2013). This indicates that birch phenophases, observed as leaf budburst or, for example, greenness of birch trees, could be used to determine the timing of local birch pollen release. This suggests that measurements of the flowering phenophase of aeroallergens like grass and birch from remote sensing could be used to map local pollen release nationwide (Karlsen et al. 2008). Satellite sensor images have been used widely to detect variables related to vegetation phenology, for example, the start of season and end of season (Dash et al. 2010; Fisher and Mustard 2007; Lloyd 1990; Reed et al. 1994; Roerink et al. 2011), but to a lesser extent for the flowering phenophases which for some species are during or before budburst (e.g. for birch) and for others are at a different growth stage (e.g. for grass).

The flowering phenophase can be derived indirectly from satellite image-predicted vegetation indices, for example, the Normalised Difference Vegetation Index (NDVI), the MERIS Terrestrial Chlorophyll Index (MTCI). However, the phenological stages derived from satellite data are referred as Land surface phenology (LSP) rather than vegetation phenology as the satellite pixel generally also include signal from non-vegetated targets. Moreover, satellite remote sensing provides a spatially complete coverage that can be used to interpolate traditional ground-based phenological observations. Measurements of the flowering phenophase of aeroallergens like grass and birch from remote sensing could be used to predict the timing of local pollen release. Details of which is provided in the literature review chapter (*section 2.3*).

1.2 Research problem and objectives

Prediction of pollen concentration in the air in the United Kingdom and elsewhere in the world is often based on a few local measurements in combination with weather conditions and is undertaken to help pollen allergic sufferers mitigate exposure. These predictions are generally established using empirical models (Isabelle and Jordina 2004; García-Mozo et al. 2009; Laaidi 2001; Smith et al. 2009). These models are well-known for their limitations as they are very specific to the area where they are produced (Stach et al. 2008b). Most importantly, these models do not consider explicitly the distribution of pollen sources and their phenological development. Phenological studies can be very useful in interpreting aerobiological monitoring data because pollen release is linked with the flowering phenophase, together with other environmental variables (Jato et al. 2002). A few studies have demonstrated the use of medium spatial resolution (250 m) time-series satellite-driven vegetation indices in Norway and Fennoscandia, to characterise the onset of the birch pollen season (i.e., flowering phenophase related to pollen release) and accomplished moderately large positive correlation with ground observations (Karlsen et al. 2008b; Karlsen et al. 2008a). Therefore, there is a clear need to explore a new approach for combining important phenological phase information related to pollen release determined from time-series satellite sensor data, ground measurements, and meteorological parameters together to provide a detailed spatial distribution of pollen. This is the focus of the thesis. Methods and outputs of this research may contribute significantly to the aerobiology and phenology disciplines, and may benefit allergy sufferers by producing more accurate and comprehensive pollen forecasting models for the UK.

The overall objective of this study was to estimate the flowering phenophase parameters (timing of pollen release) of birch and grass for the entire United Kingdom at 1 km spatial resolution from times-series MERIS Terrestrial Chlorophyll Index (MTCI), and use these variables together with relevant meteorological parameters to construct predictive models for birch and grass pollen distribution. Specifically, there were three main objectives to this study.

- (i) To investigate the spatio-temporal relationship between birch and grass pollen and meteorological variables from historic data. (research paper one)

- (ii) To identify the spatial distribution (i.e., source area) of birch (silver birch (*Betula pendula*) downy birch (*Betula pubescens*), and grass (grassland, excluding lawns)), and then estimate their flowering phenophase (timing of pollen release) from 1 km spatial resolution time-series of the MTCI. (research paper two)
- (iii) To construct daily predictive models for birch and grass pollen counts by incorporating the estimated flowering phenophase and relevant meteorological variables. (research paper three)

To address the above-mentioned objectives a methodology was established (Fig.1-1) and all the required datasets were collected. The datasets are composed of:

- 1- 11 year (2000-2010) historic pollen count data (pollen grains m⁻³) for both grass and birch at nine stations across the UK. These data were kindly provided by the National Pollen and Aerobiology Research Unit (NPARU) of the University of Worcester.
- 2- 11 year (2000-2010) meteorological station data from locations closest in distance to the pollen count stations. The source of these data is the UK Met Office through the BADC (British Atmospheric Data Centre). The variables include daily: rainfall, maximum, minimum, average air temperatures, cumulative sum Sun duration, wind speed, wind direction, and relative humidity.
- 3- Time-series MTCI Level 3 product satellite sensor data (2003-2010), with 1 km ground resolution and 8-day temporal resolution. These data were downloaded from (<http://neodc.nerc.ac.uk>).
- 4- The CORINE land cover map from 2007 with 100 m ground resolution and 90 m ground resolution DEM derived from the Shuttle Radar Topographic Mapping Mission (SRTM).

1.3 Relevance, importance and application of the research

Analysing the source (spatial distribution of allergic pollen source) and biological development related to pollen release (i.e., flowering phenophase) of the two key aeroallergens and investigating their interactions with meteorological factors as proposed in this research would be of great value in producing more accurate and finer spatial resolution grass and birch pollen predictive models. This in turn, offers benefits

to millions of hay fever sufferers, public health organisations, and other scientific disciplines. The production of finer spatial resolution predictive models of pollen concentrations in the air would increase the awareness of hay fever sufferers and, in turn, may reduce annual expenditure in medication and consultation. For example, such information will also be useful for pharmaceutical companies and the health care industry who market and stock hay fever treatments, for example, supporting the just-in-time (JIT) method of stock control often used in industry (Emberlin et al. 1999). Furthermore, it is useful for the medical profession, including allergists planning treatment and physicians scheduling clinical trials.

Investigating atmospheric pollen concentrations of grass and birch in space and time and understanding their relationships with meteorology and phenology characteristics at their sources, is relevant to some other scientific disciplines such as aerobiology and phenology. For example, phenological phases can be used as climate indicators and are feasible to be considered in climate monitoring nationally and internationally, air pollution (pollen is considered as natural air pollutant), biodiversity (genetic diversity from transport pollen, especially, genetically modified crops that may contaminate other crops), ecology (relationships and energy flow), quaternary palynology (insight on pollen catch in respect to source area), plant pathology (organisms that cause infectious disease, for example, fungi and oomycetes), and agrology (crop production in relation to climate variables). Moreover, elements of the approach could be adapted in other fields such as geospatial health (wind-blown or wind dispersed diseases, caused by bacteria, parasite, or virus) and in chemical, biological or nuclear agents which have significant health, safety, security, economic, and ecological implications such as for pollutant particles in the atmosphere, in terms of estimating their transport and distribution behaviour using dispersion models.

1.4 Research plan and organisation

The research was divided into six main chapters and a conclusion; the first chapter is the introduction which includes the background and the objectives of the study. The second chapter highlights the past and the recent literature relevant to this research in the United Kingdom and worldwide. Chapter three (research paper one) investigates birch

and grass pollen count data, such as determining the start of the pollen season, their spatio-temporal variation over time, and their relationship to meteorological variables. Chapter four (research paper two) focuses on estimating birch and grass flowering phenophase from the MTCI and their relationship with the corresponding ground pollen counts at the monitoring stations. In chapter five (research paper three) the knowledge and deliverables produced from papers two and three were used to build short term (daily) predictive models for birch and grass pollen counts for nine sites in the UK. Chapter six provides general and specific discussions for the papers produced in this research together with their appraisal and suggestions for future investigation. Finally, Chapter seven highlights the most important conclusions drawn from the papers. The structure of the research organisation and the approaches to address the main objectives and analysis are briefly sketched in Fig.1-1.

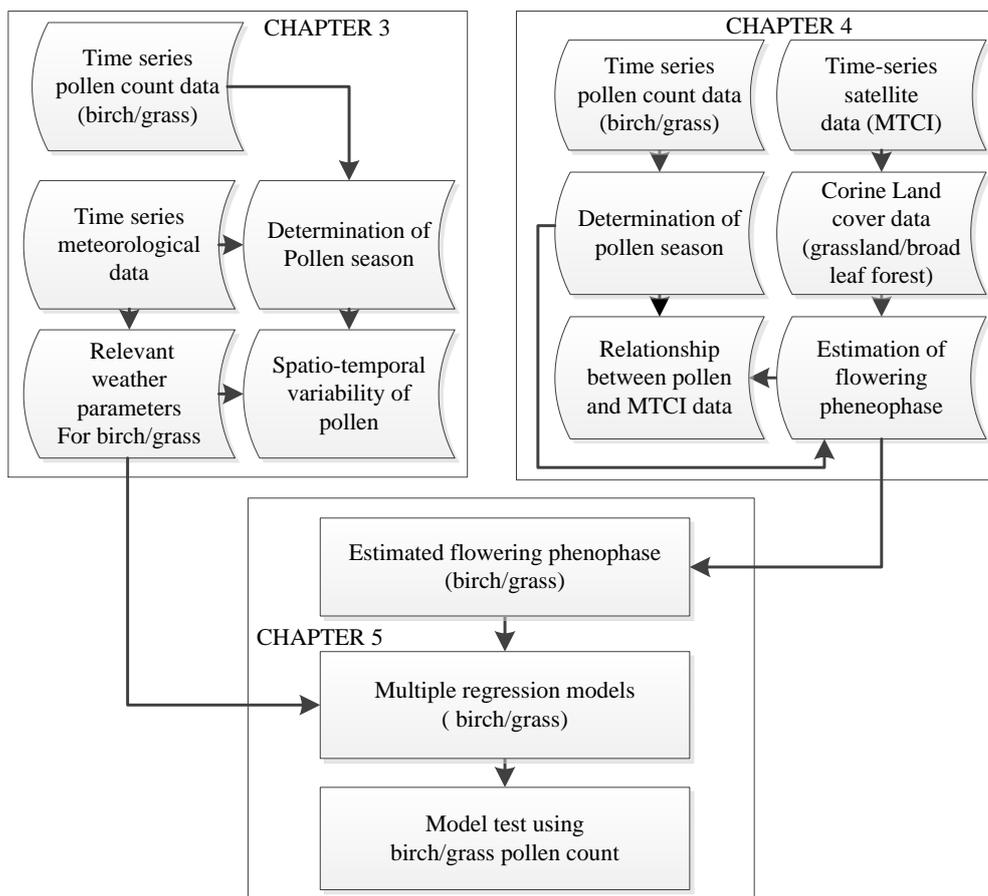


Fig.1-2 Main research workflow

CHAPTER 2: Literature review

2.1 Introduction

The function of pollen and its importance was well known to the old Assyrians and Babylonians around 3000-4000 B.C.: lithographs illustrate an eagle-headed human holding a bucket full of pollen and dusting female flowers with male inflorescence (Agashe and Caulton 2009). After the discovery of the microscope by Robert Hook in 1665 knowledge on pollen grains increased enormously. The establishment of a methodology to scientifically record the occurrence of pollen both quantitatively and qualitatively was first published in 1916 by Professor Lennart Von Post, a Swedish botanist (Von Post 1916). Another prominent palynologist of the 20th century who started work in pollen analysis after Professor von Post was Gunnar Erdtman (Erdtman 1934), known as the inventor of the method of using pollen from peat bogs to reconstruct past vegetation environments, in his case in Sweden.

Hyde and Williams (1945) in the United Kingdom, for the first time coined the word Palynology as a science that explores pollen grains and spores. The exploration of pollen grains or bioparticles (from animals, plants and other sources) which become airborne, was later defined as aerobiology by Meier (1930). However, in 1993 Ariatti and Comtois published a paper in *Aerobiologia*, titled 'Louis Pasteur: the first experimental aerobiologist' (Ariatti and Comtois 1993) and claimed Pasteur had discovered most of the principles of aerobiology in 1869, about 70 years before Meier coined the term 'aerobiology', such as: the necessity of volumetric sampling (Fig. 2-1), the heterogeneity of airborne particles, and the aerobiological pathway (take-off, dispersal, deposition). To separate pollen from other biological particles borne in the air such as viruses, bacteria, microalgae, microfungi, lichen fragments, soredia, seeds, protozoan cysts, spiders and insect parts, some aerobiologists prefer to use 'aeropalynology' to describe the science of airborne pollen (Agashe and Caulton 2009). According to Gregory (1961) the field of aerobiology is broad and includes the study of phenology, pollination, pollution, dispersion, transport, concentration, viability, physiology, sampling, morphology, identification, pollinosis (hay fever), and diurnal and seasonal patterns. The main objective of aerobiology is to monitor, detect and determine the occurrence of pollen, other bioparticles, and their relative representation

in the atmosphere. In applied aerobiology only the bioparticles which cause allergy are of interest (Agashe and Caulton 2009).



Fig.2-1 A volumetric spore trap (Burkard trap) sits on the roof of the Kentucky University Health Services Building, for collecting pollen and other particles (source: Cheryl Truman, 2012).

One of the first scientists from the UK to sample airborne particles, mainly pollen grains and fungal spores, to find the cause of fever incidents in two jails in Calcutta-India, was David Douglas Cunningham in 1870. Other scientists later tried to correlate airborne particles to fever and disease incidents through experiments such as Charles H. Blackley's (1873) famous experiments on pollen reviewed in detail in Agashe and Caulton (2009). Blackley was the first to provide evidence that hay fever was caused by pollen and he called it a 'disease'. Blackley (1873) stated that "the disease does not usually appear till the grass comes in flower: and as long as any flower remaining on the grass, the disease continues". Moreover, in the 1940s and 1950s, using volumetric traps (Hirst 1952), monitoring and studying airborne pollen began in Wales and London. The studying of aerobiology in the frame of establishing a collaborative network across the UK started in 1990 with the establishment of the British Aerobiology Federation (BAF) under the leadership of Professor Jean Emberlin. The network started to operate at the North East London University where Professor Emberlin was working. A few years

later the headquarters of BAF moved to the University of Worcester, where Emberlin established the NPARU (National Pollen and Aerobiology Research Unit) which has around 40 monitoring sites scattered across the UK (Agashe and Caulton 2009). In June 2011, the Met Office took over the management of the pollen monitoring network in the UK (personal communication with Met Office).

The above paragraphs briefly touched upon the historical development of investigating and exploring airspora, mainly pollen grains and spores in the air, in the UK and elsewhere in the world, and the establishment of terminologies to define the study of airborne particles. Most of the work discussed above was accomplished based upon understanding, or at least awareness of the pathway of aerobiology, which is: liberation from the source, dispersion into the atmosphere, behaviour of transportation and eventually deposition (wet or dry deposition). Since, the potential application of this study is on the occurrence of hay fever or seasonal allergic rhinitis, understanding how the pollen disperses into the atmosphere (which is coincidental with emerging allergy symptoms) is important.

2.2 Pollen dispersion

Blackley (1873) and Meier (1930) were the very first pioneers to explore and sample the vertical profile of the atmosphere for pollen and spores. This indicates the awareness of these scientists of the atmospheric transportation of the airborne particles at higher altitudes. For example; Blackley used kite carrying sticky slides to capture airborne particles at different altitudes. Similarly, Meier sampled the vertical profile of air for fungal spores using an adhesive microscope slide called a 'Sky-Hook' mounted on an aircraft at the altitudes of 150m to 11,000 m. It was a common assumption among scientists like Erdtman (1934) and Rempe (1937) that most pollen after liberation is carried by upward or convection currents to high altitude, transported long distances and then deposited on the ground and in lakes in a more or less vertical pattern as 'pollen rain' due to rain washout and gravity. Rempe (1937) in his experiment sampled the tree pollen vertical profile at various altitudes during a series of aeroplane flights. He concluded that, under certain weather conditions during the daytime a large amount of pollen is borne by upward currents to 2000 m elevation and during the night time some deposition occurs. He also concluded under moderate wind velocities (over 17 km hour⁻¹

¹) more than one-third of the whole amount of pollen in the atmosphere may be transported over a distance of 300 km. However, Tauber (1967) argued against the concept of ‘pollen rain’ used by Erdtman (1934) and Rempe (1937). Tauber claimed that the idea of ‘pollen rain’ was too simple as it did not take into consideration factors like; variation in wind direction, temporal variation of atmospheric turbulence, variation in the aerodynamic properties of pollen grains of different species, and variation in the structure of vegetation that influences the dispersion process. Tauber also claimed the extent of dispersion (transport) of most of the pollen in closed canopy woodland did not take place above the canopy, but within the trunk space. However, the idea of trunk space as a component of pollen transport was rejected by Andersen (1967). Anderson concluded that, in his study at a forest with varying composition in Denmark, there was a large correlation between pollen deposited on the forest floor and that of the canopy immediately overhead.

Recent studies on pollen dispersion, in *anemophilous* plants, in complex terrain (Water et al. 2007) and flat terrain (Luna et al. 2001; Jarosz et al. 2003) reported that pollen dispersion tends to follow the wind direction; most pollen is deposited within and immediately around its source; the amount of deposited pollen tends to dilute rapidly away from the source with a tail that extends many kilometres. However, in the case of complex terrain or topography, for instance mountains and valleys, the extended tail was broken up, due to the fact that complex terrain creates local meteorological patterns and eventually influences the transport of pollen to longer distances. Furthermore, there are examples from different parts of the world of allergenic pollen travelling long distances, for instance, pollen travelled from North Africa to Southwest Europe (Cabezudo et al. 1997). Birch pollen before the onset of local flowering has been documented to transport from Germany and Poland to Denmark (Skjøth et al. 2007). Other studies have also reported long-distance pollen transport (Ranta et al. 2006; Lorenzo et al. 2006). Bassett and Terasmae (1962) recovered Ambrosia (ragweed) pollen about 600 km away from its source in Canada. Pollen can travel further distances if carried to the upper strata of the atmosphere. Faegri and Iversen (1975) expressed a natural limit of pollen dispersal in the range of 50 to 100 km. Information on long-distance transport of pollen is useful when regional variation of pollen in a specific area is concerned, as long-distance transport of pollen may greatly affect the timing of the local pollen season (Ranta et al. 2006). However, applying these transport models to

characterise the behavior of pollen transport is still under development. Therefore, atmospheric dispersion or transport models are necessary to characterise the episodes of transport pollen of the pollen season.

2.2.1 Atmospheric dispersion models

The long-distance transport of pollen which comes from other regions, mentioned in *section 2.2*, overestimates the local sampling of pollen counts, thus influences the local timing of the pollen season. Therefore, it is intuitively important to model pollen transport and trace back to the source from observational results (i.e., pollen monitoring sites). Several studies reported the long-distance transport of allergic pollen in different parts of the world (Lorenzo et al. 2006; Water et al. 2007). The transport of pollen grains in the atmosphere depends on atmospheric flow and turbulence fields.

Furthermore, pollen is capable of following even small turbulent eddies. This justifies application of existing dispersion models to their transportation and distribution from their sources (Vogel et al., 2008, Sofiev et al., 2006). Dispersion models use mathematical formulations to characterise the atmospheric processes that disperse an airborne particle emitted by a source, thus, apart from source area characteristics these models require meteorology information as inputs to predict concentrations in space and time. Recent studies have employed these models to estimate pollen transport (Veriankaitė et al. 2010; Efstathiou et al. 2011; Hernández-Ceballos et al. 2011).

Atmospheric dispersion models or transport models, depending on their design, have several applications, especially in the field of air-pollutants emerging from various sources. Atmospheric dispersion models are generally categorised into two types based on the source of release and deposition at the receptors (pollen traps). The most widely used model is inverse-modelling also known as backwards trajectory modelling which is based on the analysis of the pollen catch and determination of the source areas, considering weather conditions. The second category is known as forward-dispersion modelling which is based on the simulation of the pollen pathways (i.e., production, release into the air, dispersion or transport and impact on deposition) from the source of release together with weather conditions (Sofiev and Bergmann 2013).

The inverse or backward-modelling approach as it has been reported by Sofiev and Bergmann (2013) meets two main goals: first; understanding the behaviour of pollen concentration in the air. This is performed with a few trajectories directed backwards in time for few hours or few days from known pollen trap sites). The resulting trajectories are estimates of the historical trajectories of air masses reaching the site over the specified period (i.e., a few hours or a few days back in time. Second; understanding the source areas that have most influence on certain regions, this requires time-series data for statistical analysis. One of the most common models for back-tracing from pollen being observed to the source areas is known as the Lagrangian trajectory model. Recently, in a few studies the output of this model, which is qualitative, was enhanced by clustering the trajectories starting from different points (Stach et al. 2007) and from different heights (Sofiev and Bergmann 2013). The goal of the majority of studies which used backward trajectory modelling was to trace back to the origin of the observed pollen (Gassmann and Pérez 2006; Kuparinen et al. 2007; Mahura et al. 2007; Stach et al. 2007; Hernández-Ceballos et al. 2011). Furthermore, backward trajectories were used in studying pollen transport over long distances, for example, understanding the origin of exotic pollen (Smith et al. 2005; Ranta et al. 2006; Water et al. 2007; Siljamo et al. 2008; Veriankaitè et al. 2010; Efstathiou et al. 2011). The complexity of the Lagrangian backward-modelling approach is directly proportional to the number of Lagrangian particles. Each particle is dispersed by the wind, therefore, drawing a trajectory and is randomly relocated at each model time step. Thus, the particle reflects the influence of the atmospheric diffusion. The large number of particles allows replicating the actual shape of the clouds and makes the process of linear transformation possible such as dry and wet deposition. Seibert and Frank (2004) reported that statistical analysis of numerous backward trajectories from the receptor sites is an efficient tool in identification of source and sink of airborne particles, and in reconstructing their spatial distribution. Several studies have reported the capability of using trajectory statistical methods in the source areas of various species of pollen, for example, beech pollen in Catalonia (Belmonte et al. 2008) and other pollen types in Tenerife (Izquierdo et al. 2011).

Forward-dispersion modelling aims to estimate the pollen emission from a source, for example plants, dispersion in the atmosphere and the concentration of the dispersed grains or particles as they move away from the source of release at any distance from

the source (Sofiev and Bergmann 2013). The forward-dispersion approach is similar to the backward-modelling approach as both rely on Lagrangian and Eulerian models. The applications of these models have been reported by several authors to address the local scale dispersion and transport of pollen, specifically genetically modified pollen grains (Kuparinen 2006; Arritt et al. 2007; Jarosz et al. 2004; Aylor et al. 2006; Fraile et al. 2006), and later on its applications extended to meso-scale dispersion (Kuparinen et al. 2007). It is worth mentioning, that long before this more recent work, the importance of atmospheric conditions in trajectory modelling to estimate the direction of transport of pollen at a regional scale was considered by Davis and Main (1984).

Various atmospheric models have been used to characterise the state and flow of particulate matter in the atmosphere. The most common atmospheric models applied in various disciplines are: Gaussian models, statistical models, numerical models (Chamecki et al. 2009), trajectory and puff models. See Table 2-1 for more details about the applications of some of the models used for investigating both organic and inorganic particles in the atmosphere.

This section covered the available dispersion models and their applications. Irrespective of the fact that the focus of the research is not on the dispersion models, but in the frame of the research the context of dispersion models was seen interrelated and worth mentioning. The section briefly reviewed (i) forward-dispersion models that estimate particle emission from a source, for example plants, (ii) phenological phases of plants that are related to the pollination or pollen release. *Section 2.3* will cover the concept of phenology of terrestrial plants and the capability of satellite remote sensing imagery in investigating phenological events.

Table 2-1 Most commonly used dispersion or transport models referred to in the literature to investigate the trajectories (i.e., both backward and forward) of both organic and inorganic particles in the atmosphere.

Model	Species	Location/Country	Reference
TRADOS	CO ₂ , O ₃ , SO ₂	Pallas, Finland	(Aalto et al. 2002)
HYSPLIT	O ₃ , NO _x , PM	Birmingham, UK	(Baker 2010)
UGAMP	O ₃ , NO _x , CO	Mace Head, Ireland	(Evans et al. 2000)
NMC	O ₃ , CO, VOCs	Pacific (aircraft)	(Gregory et al. 1997)
FLEXPART	O ₃ , BC	Zeppelin, Alert, Barrow	(Hirdman et al. 2010)
CMC	PM, aerosols	Barrow, Arctic	(Sharma et al. 2006)
HYSPLIT	PM ₁₀	Belfast, UK	(Abdalmogith and Harrison 2005)
HYSPLIT	PM	Philadelphia, US	(Begum et al. 2005)
HYSPLIT	PM	Athens, Greece	(Borge et al. 2007)
NAME	PM	UK and European sites	(Malcolm et al. 2000)
ECMWF	PM	Manchester, UK	(Martin et al. 2011)
CAPITA	PM	Big Bend, Texas	(Schichtel et al. 2006)
HYSPLIT	O ₃	White mountains, USA	(Burley and Bytnerowicz 2011)
UGAMP	O ₃	Mace Head, Ireland	(Cape et al. 2000)
LAGRANTO	O ₃	Jungfrauoch, Switzerland	(Cui et al. 2011)
FLEXPART	O ₃	Mexico City	(de Foy et al. 2009)
APTRA	O ₃	Uccle, Belgium	(Delcloo and De Backer 2008)
FLEXPART	O ₃	Pic du Midi, France	(Gheusi et al. 2011)
EMEP	O ₃	Norway	(Solberg et al. 1997)
LAGRANTO	O ₃	Yellowstone NP	(Lefohn et al. 2011)
HYSPLIT	O ₃	Jinan, China	(Shan et al. 2009)
FLEXTRA	O ₃ , aerosols	Mace Head and Europe	(Forster et al. 2001)
ECMWF	Aerosols	Antalya, Turkey	(Doğan et al. 2008)
FLEXPART	Aerosols	Arctic Ocean	(Chang et al. 2011)
ECMWF	Aerosols	Antalya, Turkey	(Güllü et al. 2005)
NAME	Mercury	Mace Head, Ireland	(Ebinghaus et al. 2011)
LAGRANTO	Aerosols	Greenland (aircraft)	(Schmale et al. 2011)
CMDC	CN, aerosols	Barrow, Alaska	(Polissar et al. 1999)
TRAIET	CO ₂	Plateau Rosa, Switzerland	(Apadula et al. 2003)
FLEXPART	Organic Pollutants	86 European stations	(Halse et al. 2011)
HYSPLIT	Organic Pollutants	Kosetice, Czech Republic	(Dvorská et al. 2009)
CMAQ	Birch pollen	USA	(Efstathiou et al. 2011)
Gaussian	Cidar pollen	Japan	(Kawashima and Takahashi 1999)
DREAM	Junipers Pollen	USA	(Luvall et al. 2011)
HYSPLIT	Ragweed Pollen	Thessaloniki, Szeged	(Makra et al. 2010)
HYSPLIT	Oak pollen	USA	(Pasken and Pietrowicz 2005)
SILAM	Birch pollen	Finland	(Sofiev et al. 2006)
METRAS	Oak pollen	Germany	(Schueler and Schlünzen 2006)
ART	Birch pollen	Switzerland	(Vogel et al. 2008)

2.3 Plant phenology and pollen release

The timing of the biological life cycle events or phenophases of plants, animals, and microbes and their connection to climate, is generally known as phenology. Such events include the first leaf-burst, flowering, timing of bird migration, moulting, mating, hibernation, first-leaf coloration and leaf senescence.

Phenology has a long history; the famous Belgian Botanist Charles Moien in 1853 introduced the term phenology. It has recently gained, especially vegetation phenology, a lot of interest due to the fact that phenological events can be quite sensitive to environmental conditions that have been reported to be changing, for instance, increases in global temperature. Moreover, long before Moien, ‘amateur’ scientists in Europe and Asia recorded the timing of leaf-burst, flowering and arrival of birds; nowadays this is called ‘citizen science’. The records of the timing of cherry blooming in Japan in the 8th century, the timing of wine harvest in France in 1300 (Chuine et al. 2004), and the famous Marsham family tradition of recording, of around 211 years spring events in Britain (1736-1958) are some of the early records of phenology events (Sparks and Carey 1995). Furthermore, in 1952 the Aarne Juhonsalo family in Finland, and the family sequence of Henry David Thoreau 1851–1858, Alfred Hosmer 1888–1902, and Primack and Miller-Rushing 2003–2007 in the United States, practiced phenological recordings as a family tradition (Tooke and Battey 2010).

Phenology, similar to other environmental disciplines, relies on techniques to measure and describe quantitatively the occurrence of events and patterns in the natural world. This can be accomplished on various scales ranging from long-distance observations to field observations. The phenological events recorded by these individuals contributed significantly to establishing historic datasets that have been used recently by researchers in the field of phenology (Tooke and Battey 2010).

Investigating methods for establishing a link between long-distance observations to field observations provide a unique opportunity to better understand biological response to the climate. There have been reports of the link between the date of the birch budburst and the availability of pollen in the air, suggesting a connection between the timing of pollen release and flowering phenophase (Linkosalo 1999, 2000; Newnham et

al. 2013). Local phenological observations of the flowering plants provide useful hints for knowing the arrival of the local pollen season. In general, allergic plant species in the UK have various timings for pollen release, thus, various timings of flowering phenophase, for example, birch and grass pollen seasons (Fig.2-2).

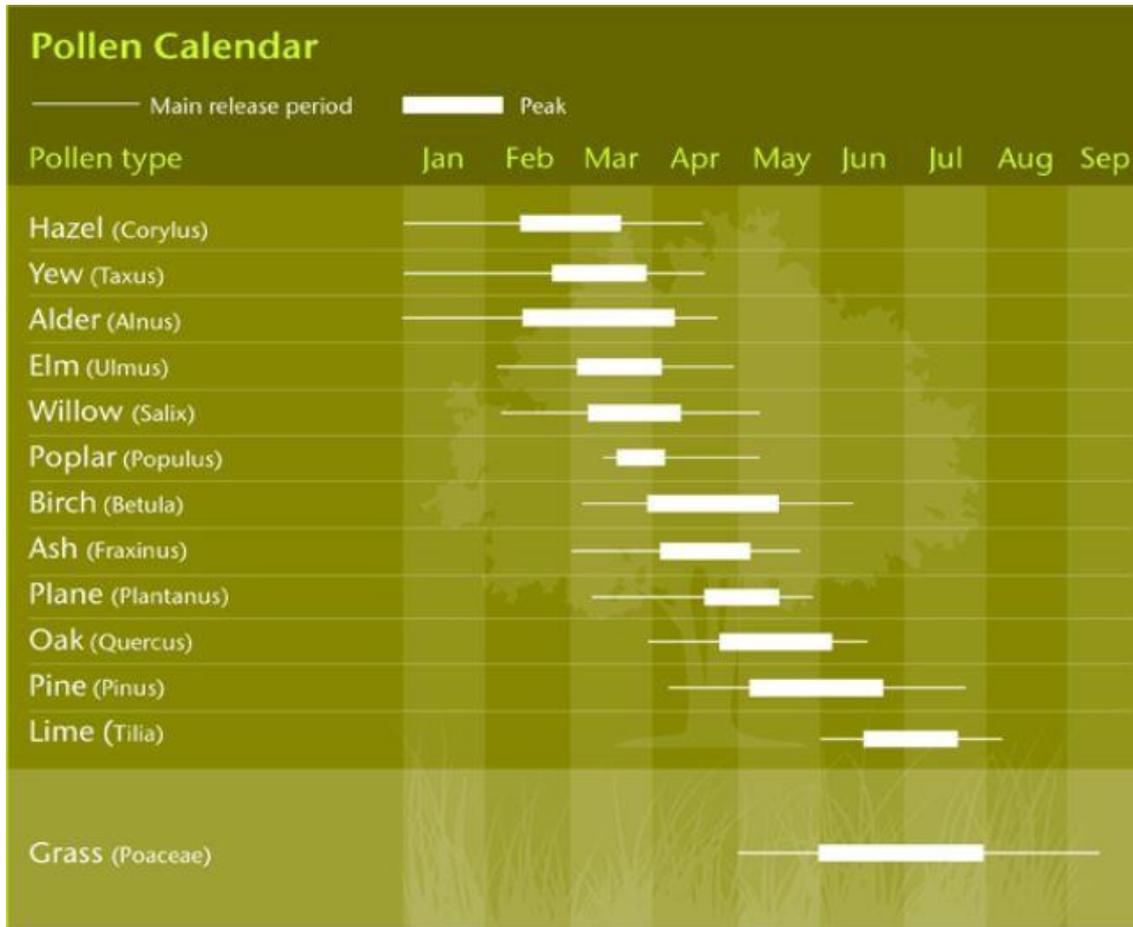


Fig.2-2 Pollen calendar for tree and grass pollen seasons in the UK (source: Met Office).

In the UK and elsewhere in the EU, there has been a focus on the use of pollen count data as phenological phenomena in investigation of biological responses to recent climate change (Newnham et al. 2013; Thackeray et al. 2010). Shift in the timing of plant phenology, especially flowering phenophase, influences directly the timing of pollination and hence pollen release. In the UK, the start of the birch pollen season has become earlier in recent decades consistent with warmer spring temperatures (Emberlin et al. 2002). In the EU, the increase in temperature observed in recent decades has influenced the phenology of plants, for example; (i) an earlier start of plant flowering in spring and summer (Menzel and Estrella 2001; Parmesan and Yohe 2003; Root et al.

2003; Menzel et al. 2006), (ii) an earlier start of the pollen season in the Northern Hemisphere (Frei and Leuschner 2000; Beggs 2004; Estrella et al. 2006) and a lengthening of the pollen season duration (Ziska et al. 2011).

In addition to the records provided by individuals, networks of recorders were established in the UK in 1875 by the Royal Meteorological Society and in Germany in 1951 by the German Meteorological Service. Annual reports from these networks were compiled by reporters and archived (Tooke and Battey 2010). In the United Kingdom the Centre for Ecology and Hydrology (CEH) has been publicizing phenology and encouraging public participation. With the cooperation of the Woodland Trust, nearly 50,000 people across the UK are currently involved with the Nature's Calendar survey (www.naturescalendar.org.uk).

Recently the European Pollen information (EPI) network was established to gather information from more than 600 pollen monitoring stations across Europe through the European Aeroallergen Network Pollen (Ean) Database (<https://ean.polleninfo.eu/Ean/>). Similarly, the National Phenology Network (NPN) in the USA has been actively involved, with the cooperation of various groups, in gathering and sharing phenology data (<http://www.usanpn.org>).

2.4 Variability of atmospheric pollen

Pollen concentration (grains m^{-3}) varies from year to year, day to day, even hour to hour in the air with space and time. Variation in pollen concentration close to pollen producing sources is influenced by diurnal dispersion of the pollen. However, the concentrations distant from the sources are influenced more by weather factors. Peak times noted at sampling stations are altered by the distance from the pollen sources, for example, if the pollen sampler is far from the source, the peak time will be hours later, because time is needed for pollen to travel. In general, it is accepted that variation in atmospheric pollen in space and time is dependent on environmental factors such as meteorology and topography. Two main groups of meteorological variables influence the pollen count; first, those that influence the production and release of pollen through the season such as temperature, precipitation, wind and humidity. Second, those that

influence the dispersion and the transportation of pollen such as turbulence, precipitation and wind (Di-Giovanni et al. 1989). Topography, including natural and non-natural areas such as low-lying flat areas, mountainous areas, and urban development affect the pattern and extent of pollen dispersal. However, the behaviour of suspension and distribution of pollen in the atmosphere is dependent on both the properties of the atmosphere and the suspended particles (size, aerodynamic).

Various studies in different parts of the world have been conducted on the influence of meteorological factors such as temperature, precipitation, wind and humidity, sunshine hours on pollen release and dispersion in *anemophilous* plants (Galán et al. 1995; Laaidi 2001; Sánchez Mesa et al. 2003; Green et al. 2004; Jato et al. 2009; Sabariego et al. 2011; Puc 2011). More detail on the relationships between the pollen counts of birch and grass in the air and meteorological variables are covered in chapter 3.

2.4.1 Regional variation

The history of studying regional variation of pollen in the United Kingdom dates back to 1946 in Cardiff in South Wales, where Hyde and Williams (1944) recorded a day-to-day survey of pollen deposition, employing depositional samplers. Later on, the pollen deposition survey extended to further locations, spatially stretching from Wales to London and then to Aberdeen in the north (Hyde 1952). The objective of Hyde's study was to estimate the variability in the composition of pollen from day-to-day and from place to place in relation to local weather and source areas. Hyde concluded that there was considerable spatial variation in the pollen season from south to north, with Scottish sites lagging up to a fortnight behind compared to southern sites. He also concluded that weather variables have an influence on the pollen catch across the stations. Employing a different methodology to collect pollen (Hirst trap) Davies et al. (1963) investigated the pollen catch variation at two sites; London and Liverpool. They concluded that the grass pollen season at London reaches its peak 9 days earlier than at Liverpool. The reason for the spatial variation was later explained in another study in 1969 by Davies. Davies (1969) explained the variation as being associated with the cumulative temperature at different sites. In addition to climatic variables Davies included topography by making comparison with studies in Switzerland and the Alps.

Collaboration between researchers from Brussels, London, Munich, and Strasbourg in 1973 contributed more literature on comparative atmospheric grass pollen concentrations at the regional level. The European collaboration advanced atmospheric pollen studies as it defined the start of the season as the day that the pollen count is greater than or equal to 50 grains per cubic metre of air, assuming this amount of pollen induces the full first day of hay fever symptoms (cited in Jones 1995, Unpublished). Furthermore, in the United Kingdom, Brown and Jackson (1978, 1980) produced several papers on grass and nettle pollen concentrations in the air in Derby using a volumetric sampling method. From the late 1980s Emberlin and co-workers produced papers on allergic pollen throughout Europe and other parts of the world (Emberlin et al. 1990; Emberlin and Norris-Hill 1991; Emberlin et al. 1993a; Emberlin et al. 1993b; Emberlin et al. 1997; Emberlin et al. 1999; Emberlin et al. 2000; Emberlin et al. 2002). Most of early work of Emberlin and co-workers took place in the London area and then extended to other parts of the UK and EU. In 1990 she produced a pollen calendar for tree pollen in London. Later, in 1991, 1993a, 1993b the spatial variation of pollen deposition in north London, the annual variation in grass pollen seasons in London, and the annual variation in the concentrations of birch pollen in London were investigated, respectively. Making use of up to 42 years of time-series pollen data for three sites in the UK, probably the longest in the world, Emberlin in 1997 looked at the influence of weather conditions, especially cumulative temperatures, on the start of the birch pollen season and the results showed a trend for the pollen seasons to begin earlier. Similarly, in 1999 employing the same dataset at three sites for grass, Emberlin and co-workers explored the regional variation of grass pollen and forecasted the severity of the pollen season using empirical methods such as multiple regression. They concluded that the predictive models achieved a high degree of explanation in predicting pollen season severity and emphasized the need for more extensive regional data. From 1995 onwards Emberlin as a co-worker in collaborations with other workers from other parts of Europe, especially Poland and Europe, contributed in publishing several papers on forecasting of pollen and continental pollen variation in relation to meteorological parameters (Galán et al. 1995; Corden et al. 2000; Adams-Groom et al. 2002; Sánchez Mesa et al. 2003; Smith et al. 2005; Smith and Emberlin 2006; Stach et al. 2008a; Stach et al. 2008b). The main objective of these studies was to understand the variation of the pollen season in contrasting bio-geographical areas and the possibility of building short-term and long-term forecasting models.

The spatial variation of pollen from other EU countries at either the regional and continental levels or comparing European sites is reported in the literature. For example; Lejoly-Gabriel and Leuschner (1983) compared two sites in Belgium and Switzerland for the period of 1979-1980. The concept of Lejoly-Gabriel was not new in respect of looking at the different bio-geographical areas in understanding the variation of pollen, but the work was significant as they introduced 'principal period of pollination' which meant to define the pollen season (start to end) as "it begins on the day when the sum of the annual pollen percentage reaches 5%, provided that this day corresponds to a release of greater than or equal to 1% of the total catch. The period ends on the last day when the daily percentage is greater than or equal to 1%, and the sum of the pollen percentage for this day and the preceding days is greater than or equal to 3%".

In Sweden, Larsson et al (1984) investigated the variation of pollen incidence at three sites for a 7-year period (1976-1982), in Kuwait, Halwagy (1988) compared airborne pollen between three sites for a 6-year period, in France, Meiffren (1988) compared three sites for a 3-year period, in the Netherlands, Spieksma et al. (1989) compared sites in the Netherlands to sites in Italy for a 4-year period and in Spain, Sánchez Mesa et al. (2003) looked at variation in grass pollen in relation to the influence of weather parameters at 6 sites in southern Spain and the UK.

2.5 Pollen and phenological predictive models

Much has been published about spatio-temporal variation of pollen concentration in the air especially regional pollen variation, and how pollen behaves temporally in response to climate factors, including work on pollen modelling and forecasting. Building predictive models to estimate the main characteristics of pollen season such as start date, magnitude of the season or length of the season, peak days, and end of the season has been the focus of several previous studies. Generally, two kinds of datasets are employed for building such models: (i) pollen counts (ii) phenological date events (e.g. date of first leaf-emergence, date of first leaf). The predictive models are in general empirical models such as complex or simple regression models. However, recently there have been attempts to model the behaviour of the allergic pollen in the air temporally using other approaches such neural network analysis, process-based models, and

source-oriented models. These studies are reviewed and they are mentioned in the following paragraphs.

In 1970, Raynor in the United States used predictive models to estimate the daily ragweed pollen concentration using prior year climatology information and predicted weather conditions or weather forecasts. This research reached an important conclusion that the accuracy of pollen prediction is completely dependent on weather forecast accuracy. Later, Davies and Smith (1973) in the United Kingdom were the first to establish predictive models to forecast the start of the grass pollen season. They used 10-year time-series pollen count records together with weather variables for four stations in London, and concluded that mean air temperature in April and May influences the start of the pollen season during the period of flowering. Similarly, Spieksma (1980) constructed a predictive model to forecast daily hay fever in the Netherlands. Bringfelt et al. (1982) in Sweden used statistical models to predict birch and grass pollen concentration in the air of Stockholm from several years' data with meteorological conditions. They concluded that the timing of the start of the pollen season and the day-to-day variation is strongly influenced by daily temperature. Frenguelli et al (1989) and Fornaciari et al (1998) modelled the start of olive and grass pollen seasons at two sites in Italy and concluded that the pre-season air temperature determines the start of the season. Ong et al (1997) in Australia built a linear regression model based on an inverse relationship between the date of the onset of the grass pollen season and the sum of rainfall for July. Laaidi et al. (2003) proposed two statistical methods to forecast the start and duration of the ragweed pollen season in Lyon in France. They employed a multiple regression model with relevant meteorological variables and a cumulative temperature sum model drawing thresholds from the start of the season. They concluded that the regression model was more accurate than the cumulative temperature sum model in both predicting the start and the duration of the ragweed season. Moreover, in 2002 Sánchez Mesa et al. (2003) compared a co-evolutive neural network and linear regression models in forecasting daily grass pollen concentration in Spain. Their results showed that the neural network performed more accurately than regression. Furthermore, recently, some workers extended modelling of the main characteristics of the allergic pollen season employing neural network analysis (Rodríguez-Rajo et al. 2010), data-driven analysis or computational intelligence (CI) methods (Voukantsis et al. 2010) and a process-based model (García-Mozo et al. 2009).

García-Mozo conceptualised a model to predict the start and peak date of the grass pollen season in Spain, using three main parameters; rainfall, photoperiod and flowering. The model assumes that flowering or pollination occurs when flower development reaches a critical point as a result of a forcing function at a specific time. The forcing functions in this case were a critical amount of rainfall and critical level of photoperiod. In general, few studies have been conducted on pollen using physiology-based or process-based models other than receptor-based models due to their complexity.

Most of the studies mentioned above employed the receptor-based approach for forecasting the main characteristics of the allergic pollen season. In other words, the pollen count data from monitoring stations were used together with meteorological data to estimate the behaviour of pollen through the season. However, daily pollen count, apart from meteorology, also varies as a function of the flowering rhythm at the source (Bringfelt et al. 1982). Yet, Ranta et al. (2006) reported that phenological events, such as flowering, alone are insufficient to determine the timing of the season due to the influence of pollen transport. To overcome this, recently there have been attempts to model the main characteristics of allergic pollen in the air employing both the source-receptor-oriented approach using satellite sensor data in determining the source and phenology events (Karlsen et al. 2008a) and atmospheric dispersion models to track pollen distribution (Luvall et al. 2011). Tables 2-2 and 2-3 show the most commonly used receptor-based and process-based models (i.e., phenological models) in characterising pollen season and phenological studies worldwide.

Table 2-2 Empirical models that have been used in allergic pollen studies worldwide.

Observation-based models	Species	Location/Country	Reference
<i>A- regression models</i>			
Simple linear regression	Grass	Poznań, Poland	(Stach et al. 2008b)
Multiple regression	Grass	Malaga, Spain	(Toro et al. 1998)
Multiple regression	Grass	North London, UK	(Smith and Emberlin 2005)
Step-wise multiple regression	Birch	Stockholm, Sweden	(Bringfelt et al. 1982)
Step-wise multiple regression	Grass	Córdoba, Spain	(Galán et al. 1995)
Step-wise multiple regression	Birch, Ulmus	Copenhagen, Denmark	(Goldberg et al. 1988)
Standard multiple regression	Ragweed	Southern Hungary	(Makra et al. 2004)
Standard multiple regression	Grass	North London, UK	(Smith and Emberlin 2005)
Standard multiple regression	Grass	Poznań, Poland	(Stach et al. 2008b)
Polynomic regression	Grass	Malaga, Spain	(Toro et al. 1998)
Semi-parametric Poisson	Ragweed	Kalamazoo, USA	(Stark et al. 1997)
<i>B- Time series models</i>			
Box-Jenkins method	Grass	Copenhagen, Denmark	(Moseholm L et al. 1987)
Box-Jenkins method	Cypress	Granada, Spain	(Ocana-Peinado et al. 2008)
Neural networks	Cupressus	Mar del Plata, Argentina	(Arizmendi et al. 1993)
Neuro-fuzzy approach	Olive	Granada, Spain	(Aznarte M et al. 2007)
Functional regression	Cypress	Granada, Spain	(Ocana-Peinado et al. 2008)
<i>C- Computational Intelligence</i>			
Artificial neural networks	Grass	Iberian Peninsula	(Sánchez Mesa et al. 2002)
Artificial neural networks	Grass	Emilia-Romagna, Italy	(Ranzi et al. 2003)
Artificial neural networks	Birch	Spain	(Castellano-Méndez et al. 2005)
Artificial neural networks	Olive	Granada, Spain	(Aznarte M et al. 2007)
classification and regression trees	Spruce	North America	(Lindbladh et al. 2002)

Table 2-3 Process-based models that have been used in allergic pollen and phenological studies worldwide.

Process-based phenological models	Species	Location/Country	Reference
<i>A- Tree physiology based models</i>			
Thermal only forcing model	Oak	Cordoba, Spain	(García-Mozo et al. 2000)
Thermal only forcing model	Birch, Alder	Helsinki, Finland	(Linkosalo et al. 2006)
Thermal only forcing model	Cherry tree	Kyoto, Japan	(Aono and Kazui 2008)
Chilling only forcing model	Birch, Alder	Spain and Italy	(Jato et al. 2000)
Chilling only forcing model	Olive	Umbria, Italy	(Orlandi et al. 2004)
Thermal and chilling only model	Olive, Field Elm	Montpellier, France	(Chuine et al. 2003)
Thermal and chilling only model	Birch, Alder	Helsinki, Finland	(Linkosalo et al. 2006)
Thermal, chilling, and photoperiod model	Birch	Helsinki, Finland	(Linkosalo 2000)
<i>B- Herbaceous physiology based models</i>			
Temperature, photoperiod, and soil water model	Grass, shrub	Cabrils, Spain	(Clary et al. 2004)
Temperature, photoperiod, and soil water model	Birch	Poland and UK	(Stach et al. 2008a)
Temperature, photoperiod, and soil water model	Grass	Spain	(García-Mozo et al. 2009)
<i>C- Generalized models</i>	Deciduous trees	Montpellier, France	(Chuine 2000)
Generalized models	Forest trees	Germany	(Schaber and Badeck 2003)

2.6 Role of satellite remote sensing

The study of vegetation phenology, or more strictly land surface phenology (LSP), employing remote sensing techniques in the past two decades, has made remarkable progress. This progress has been accomplished not just through generating and processing satellite datasets from various sensors, but also through developing methodologies to derive various metrics to define the timing of phenological events (Reed et al. 2009). Since one of the most conspicuous characteristics of vegetation is its

seasonal variability, de Beurs and Henebry (2004) described LSP as the seasonal pattern of variation in the vegetation on the land surface observed from satellite sensors.

The applications of LSP in various studies have been reported, due to the growing volume of terrestrial remote sensing products, such as in:

- (i) Ecosystem studies (carbon, water, energy budgets, and biodiversity indicators) using Moderate Resolution Imaging Spectroradiometer (MODIS) biophysical products like EVI and NDVI (Ahl et al. 2006; Balzter et al. 2007; Bradley et al. 2011; Clerici et al. 2012) and Landsat products (Fisher et al. 2006).
- (ii) Environmental disasters. Westerling et al. (2006) related early spring to increased forest wild fire. Similarly, using start of season anomalies derived from AVHRR (Advanced Very High Resolution Radiometer) as an input to a vegetation drought response index (VegDRI) Brown et al. (2008) identified drought conditions in near-real time.
- (iii) Indicator of land use change. Change in LSP in several studies was used as an indicator of land use change (White et al. 2002; Zhang et al. 2004; de Beurs and Henebry 2004; Reed 2006).
- (iv) The response of phenology to climate change. Phenology was used extensively to indicate changes in climate. Recent studies concentrating on temporal shifts in biogeophysical cycles have detected significant signs of local and regional changes in observations of phenology both at the ground (Menzel et al. 2006; Schwartz et al. 2006; Richardson et al. 2009; Dufour and Morin 2010) and from space (Reed 2006; Zhang et al. 2007; Delbart et al. 2008; Zhang et al. 2009; Ganguly et al. 2010).
- (v) Short-term forecasting and real-time monitoring and modelling. LSP employing satellite remote sensing schemes contribute significantly in fire forecasting (Roads et al. 2005), ecosystem forecasting (White and Nemani 2004), insect pest phenology (Mussey and Potter 1997), organism dispersal (Gage et al. 1999), human health (Traidl-Hoffmann et al. 2003), and pollen forecasting (Karlsen et al. 2008a; Luvall et al. 2011).

Most of the studies mentioned above employed fine temporal (near-daily) and moderate spatial resolution satellite sensors (from 250 m to 8 km ground or spatial resolution)

which provide adequate precision in studying phenology regardless of challenges that arise from specific plant types or communities and validation (White and Nemani 2006).

Land surface phenology (LSP) has been predicted using various satellite sensors ranging from optical sensors like Landsat (Morisette et al. 2008), AVHRR (Hogda et al. 2002; de Beurs and Henebry 2004; Delbart et al. 2006; Scharlemann et al. 2008; Sehgal et al. 2011), SPOT (Système Probatoire pour l'observation de la Terre) (Delbart et al. 2006; Upadhyay et al. 2008), MODIS (Ahl et al. 2006; Ganguly et al. 2010; Luvall et al. 2011; Shen et al. 2011; Roerink et al. 2011), and MERIS (Zurita-Milla et al. 2009; Dash et al. 2010; Boyd et al. 2011; O'Connor et al. 2012) to microwave sensors like AMSR-E (Advanced Microwave Scanning Radiometer for EOS) (Doubkova and Henebry 2006; Shi et al. 2008).

According to Reed et al. (2009) the current generation of sensors such as MODIS and MERIS, due to their spatial and temporal resolutions, are better suited for phenology studies. Similarly, Verstraete et al. (2008) suggested that MERIS which has a global coverage capability of every 3 days at 15 spectral bands and 300 m spatial resolution is well suited for phenology studies. Table 2-4 shows the sensors and their specifications which have the potential to be used in LSP studies.

2.6.1 Phenological variables

There are several quantitative methods to extract variables related to vegetation phenology from satellite-derived vegetation indices, for example, start of the season (SOS). These methods are listed as: inflection point methods, trend derivative methods, and threshold-based methods (Reed et al. 1994; White et al. 2009). The inflection point phenology method is based on detecting points where the maximum curvature occurs in a plotted time-series of vegetation indices, whereas, the trend or curve derivative phenology method attempts to identify points of departure between the original vegetation temporal signal data and a derivative curve. The threshold-based methods use either a pre-defined or relative reference value to define phenology transition dates (Fisher and Mustard 2007; Lloyd 1990). Roerink et al. (2011) used a derivative method to define the SOS of the deciduous forest in the Netherlands.

Phenological variables that characterise the stages of vegetation development during the growing season (Reed et al. 2009; de Beurs and Henebry 2010; Roerink et al. 2011), can be related to biological definitions of plant phenology, for example, the flowering phenophase related to pollen release. Linkosalo (1999, 2000) found in southern Finland that the difference in time from birch (*Betula pendula*) male flowering to the first date of budburst was only 1.1 days, with male flowering occurring first. Thus, the timings of male flowering and leaf budburst of birch are well correlated. Moreover, the timing of male flowering, leaf budburst and pollen release appear to be quite closely synchronised (Newnham et al. 2013). This indicates that birch phenophases, observed as leaf budburst or, for example, greenness of birch trees, could be used to determine the timing of local birch pollen release. This suggests that measurements of the flowering phenophase of aeroallergens like grass and birch from remote sensing could be used to map local pollen release nationwide (Karlsen et al. 2008b). Karlsen et al. (2008a) determined the onset of birch season, in Norway from mean values of MODIS-NDVI time-series, as when the NDVI value each year exceeded 0.85% of the July 12th until August 28th. Such studies are very limited, and further investigation of methods to generate links between flowering phenophase and pollen was necessary.

Table 2-4 Satellite sensors and datasets that have been used, and have the potential to be used, in diagnostic/prognostic land surface phenology studies.

Satellite	Sensor	Service	Spatial resolution	Temporal resolution
Landsat 1-3	MSS	1973–1985	79 m	18 days
Landsat 4	TM	1982–	30 m	16 days
Landsat 5	TM	1984–	30 m	16 days
Landsat 7	ETM+	1999–present	15 m	16 days
Landsat 8	ETM+	2003–present	15 m	16 days
SPOT	Vegetation	1999–present	1 km	1–2 days
NOAA	AVHRR	1982–present	8 km	biweekly
NOAA	AVHRR	1989–present	1 km	biweekly
Terra	MODIS	2000–present	250 m, 500 m, 1 km	1–2 days
Aqua	MODIS	2002–present	250 m, 500 m, 1 km	1–2 days
Envisat	MERIS	2002–present	300 m	1–3 days
IKONOS	OSA	1999–present	0.8 m, 3.2 m	3-5 days
KOMPSAT-2	MSC	2006–present	1- 4 m	3 days
FORMOSAT-2	RSI	2004–present	2-8 m	daily

2.7 Summary

In order to have a good grasp of the scientific content of the research presented in the thesis, it was needed to review four interconnected scientific components or fields. These components were: aerobiology (specific related discipline is aeropalynology), vegetation phenology (specific related discipline is LSP), pollen count pattern modelling in the air (i.e., process-based and observation-based modelling), and atmospheric boundary transport models (i.e., Lagrangian models, Eulerian models). The review has promptly highlighted the current and historical methods most relevant to the research. The comprehensive and thorough literature review established here provides useful information on the interconnected components mentioned above.

The investigation of atmospheric allergic pollen variation in the world, EU and UK from past to present is as follows:

- (i) Studies were mostly on local pollen variation and then extended to regional variation.
- (ii) Studies extended further to the continental level, for example, comparing sites from different bio-geographical areas.
- (iii) Predictive models were developed, mostly empirical receptor-based models and eventually process-based models (very limited).
- (iv) Transport models were used mostly for particulate matter simulation in both backward and forward directions. The notion of pollen transport necessitated the adoption of transport models or atmospheric dispersion models to trace back the pollen to its source or to track pollen movement away from the source.
- (v) Satellite-driven greenness products or indices (i.e., NDVI, MTCI, etc.) were used to estimate phenological variables (i.e., start of season, end of season), but their link to flowering phenophases is still under development.

Therefore, investigating the combination of points (iii) and (v) together to build a more realistic picture of the pattern of pollen in the air by including the source of release (predicted from satellite sensor data) and pollen data and meteorology is a clear gap in the allergic pollen episode and aerobiology fields in the UK and worldwide (Fig.2-3).

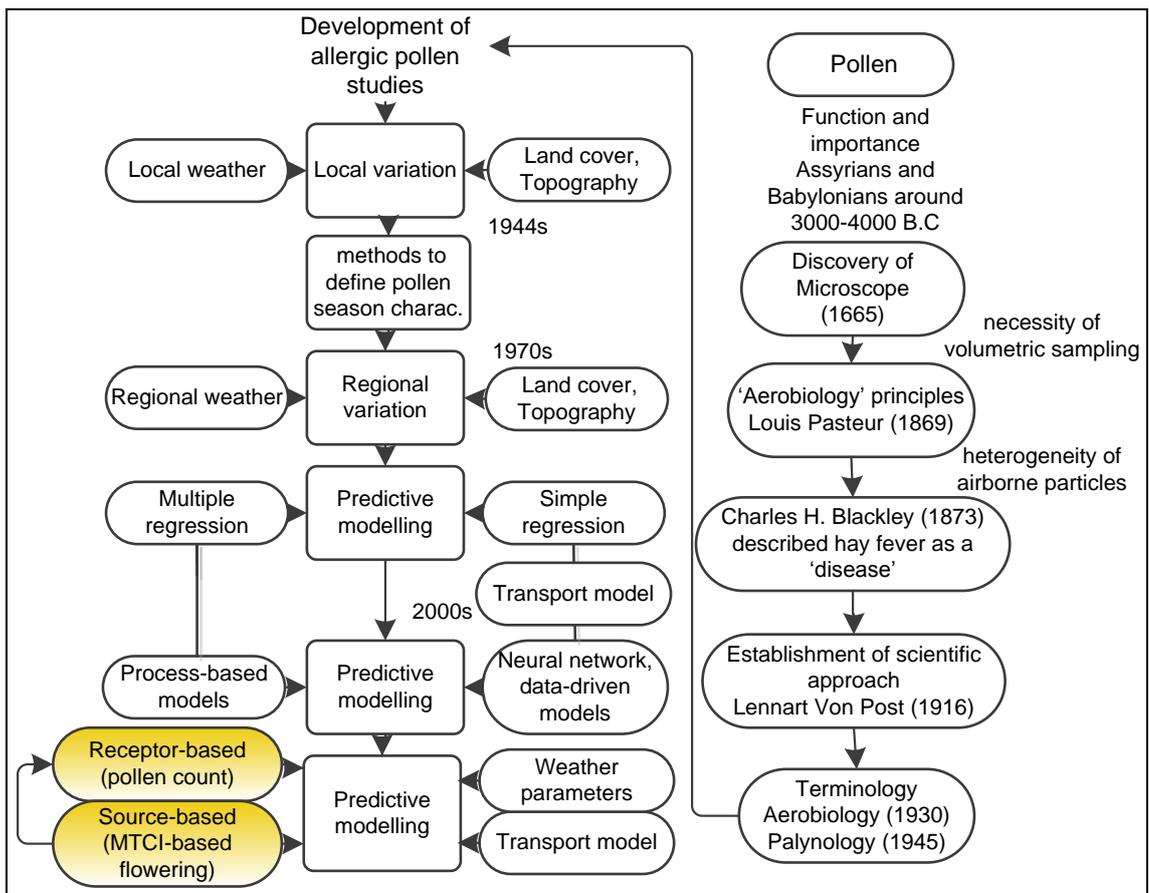


Fig.2-3 Historical development of the study of pollen, highlighting the relationship with the two amber coloured boxes which were the main elements that focused on, and which added to the field of aerobiology and allergic pollen studies, in this research.

CHAPTER 3: Exploring the spatio-temporal relationship between two key aeroallergens and meteorological variables in the United Kingdom¹

3.1 Introduction

Hay fever is a common allergic reaction that can cause extensive suffering in individuals and great losses in terms of productivity and medical expense. For example, in the USA alone, hay fever is estimated to affect up to 25% of the adult population and 40% of children. It accounts for 2 million lost school days, \$6 million from lost working days, and more than \$3 billion in medical expenditure annually (Volcheck 2009). Grass and birch pollen are two major causes of seasonal allergic rhinitis (hay fever) in the United Kingdom and parts of Europe (Varney et al. 1991; Emberlin et al. 1997).

The prevalence of sensitisation to grass and birch allergens varies geographically (i.e., from region to region) depending on the source abundance and the amount of allergen extract on the pollen. High sensitisation to grass pollen was reported for parts of the UK, France, New Zealand, Switzerland and the USA. Similarly, high prevalence of sensitisation to birch pollen was reported for parts of northern and mid-Europe, New Zealand and parts of the USA (Bousquet et al. 2007).

Several studies have reported local and regional variation in both time and space in both birch and grass pollen counts, and birch allergen extracts (Emberlin et al. 1993a; Emberlin et al. 1993b; Emberlin et al. 1999; Emberlin et al. 2000; Buters et al. 2008). Furthermore, previous studies have shown that the increase in temperature observed in recent decades is linked with an earlier start of plant flowering in spring and summer (Menzel and Estrella 2001; Parmesan and Yohe 2003; Root et al. 2003; Menzel et al. 2006), an earlier start of the pollen season in the Northern Hemisphere (Frei and Leuschner 2000; Beggs 2004; Estrella et al. 2006) and a lengthening of the pollen season duration (Ziska et al. 2011). In the UK, the start of the birch pollen season has become earlier in recent decades consistent with warmer spring temperatures (Emberlin et al. 2002).

¹ Khwarahm, N., Dash, J., Atkinson, P.M., Newnham, R.M., Skjøth, C.A., Adams-Groom, B., Caulton, E., & Head, K. (2014). Exploring the spatio-temporal relationship between two key aeroallergens and meteorological variables in the United Kingdom. *International Journal of Biometeorology*, 1-17

There are over 10,000 species of grasses belonging to the Poaceae family, distributed widely in the world, and their pollen grains range in size from 18 to 120 μm . This family mostly produces wind-blown (anemophilous) pollen grains which are known to produce allergies (Agashe and Caulton 2009). Most grass pollen grains share the same general appearance, being spheroid and monoporate (pollen grains with a single pore on the surface), commonly not distinguishable to species by appearance. Furthermore, it has been well documented that many grass pollen allergens cross-react. Hence, sensitisation to any of these can be diagnosed with a single allergen (Weber 2004). Birch (*Betula*) as a genus belongs to the Betulaceae family and is one of the most important aeroallergens, with pollen grain sizes ranging from 19 to 40 μm . Birch pollen is round and triporate (pollen grains with three pores on the surface) (Emberlin 2009).

The allergenicity of birch and grass is related to the relative amount of allergen and allergenic extracts such as polypeptides (chains of amino acids) and polysaccharides (complex carbohydrates) in the pollen grains. To cause hay fever the aeroallergens must be airborne in large quantities, and able to induce an immune response. These allergens are released when pollen is dispersed on a humid and wet medium in the human body such as the upper respiratory tract or the eyes of allergic patients. In response, the immune system sees the allergen as an intruder and takes action to neutralise it. The body accomplishes this by making antibodies and stimulating other defence mechanisms (Volcheck 2009).

Quantification of the amount of allergen on pollen is challenging due to variability in space and time (Buters et al. 2008; Buters et al. 2012). Therefore, measurement is usually done through pollen grain count sampling in a cubic metre of air. This is done by employing a special motor to suck in the pollen from the atmosphere, such as a volumetric trap, and then counting and identifying allergenic pollen under a microscope.

The onset and the length of the grass and birch pollen seasons vary both spatially and temporally. This is due to the factors that influence the abundance and dispersal of pollen such as local vegetation type, altitude, land use and climate (Galán et al. 1995; Emberlin et al. 1997; Emberlin et al. 1999; Emberlin et al. 2000). Studies have shown that flowering, pollination and dispersion of grass pollen are closely related to variation in meteorological variables, specifically: rainfall and temperature in Spain and Australia (Green et al. 2004; V. Jato et al. 2009; Sabariego et al. 2011); relative humidity, mean

and maximum air temperature, rain and sunshine hours in Poland (Stach et al. 2008b; Puc 2011); and windy conditions, low relative humidity and precipitation for birch pollen dispersion in France (Laaidi 2001). Moreover, maximum temperatures and precipitation are important drivers that control the timing and magnitude of the grass pollen season in the United Kingdom and southern Spain (Newnham et al. 2013; Sánchez Mesa et al. 2003). Furthermore, previous research in the UK has demonstrated that rainfall and temperature are the most important factors controlling the production of pollen in the spring and that their overriding influence continues into the pollen season for the release and dispersal of pollen grains (Davies and Smith 1973; Emberlin and Norris-Hill 1991; Emberlin et al. 1993a; Emberlin et al. 1999). Galán et al. (1995) in their study around London reported that maximum and average temperature, and hours of sunshine are important drivers directly influence the concentration of grass pollen.

Although some of the earlier studies attempted to use multiple sites (Emberlin et al. 1993a; Emberlin et al. 1993b; Emberlin et al. 1999; Emberlin et al. 2000; Emberlin et al. 2002), but in general many of the above earlier studies were limited by poor spatial or temporal representation and, thus, could not account for variation in the environmental and meteorological conditions suitable for pollen dispersion. In particular, in the UK, which has relatively unstable climatic conditions, fine spatial and temporal resolution representations of the pollen count and meteorological variables (time-series) may increase our understanding of the relationships between the daily pollen count (grains m^{-3}) and meteorological variables. Moreover, this will facilitate development of more accurate prediction models and greater understanding of pollen dispersal mechanisms.

This paper presents the findings of an investigation into the correlations between daily birch and grass pollen grain counts in the air and meteorological variables for nine pollen monitoring sites in the UK for an 11-year period from 2000 to 2010. The main aim was to quantify the influence of the relevant meteorological variables on the counts of birch and grass pollen in the atmosphere.

3.2 Materials and methods

3.2.1 Pollen count data

Daily average grass and birch pollen (grains m⁻³) data were collected by volumetric spore traps of the Hirst design (Hirst 1952) at nine monitoring sites across the UK from 2000 to 2010 (Fig.3-1). The data were provided by the National Pollen and Aerobiology Research Unit (NPARU) of the University of Worcester. The monitoring sites cover the entire geographical extent of the country with contrasting local climate, height above sea level and distance from the coast. A standard airborne pollen count sampling method is employed at each of the monitoring stations. The methodology used for collecting pollen data followed the standard method of the UK National Pollen Monitoring Network described in the British Aerobiology Federation (BAF) guide for trapping and counting airborne pollen and spores (BAF 1995). The trap has a built-in vacuum pump that sucks in pollen and other particles through an entrance orifice. Behind the orifice there is a revolving drum covered with an adhesive-coated, transparent plastic tape. Particles in the air impact on the tape to give a time-related sample (Emberlin 2000). After its removal from the trap, the tape is divided into segments corresponding to 24-h periods. The segments are then examined under a light microscope and a counting procedure is applied. In the UK, pollen grains are counted along twelve latitudinal transects (Smith et al. 2009).

The traps were elevated at 10-15 m above ground level usually placed on an open roof with no surrounding obstacles.

3.2.2 Meteorological data

Meteorological data for the period 2000 to 2010 at locations which were closest to the pollen count monitoring stations were obtained from the Met Office through the British Atmospheric Data Centre (BADC) website (www.badc.nerc.ac.uk). The majority of the meteorological stations were within 5 km of the pollen count stations (Table 3-1). This study uses daily (24 hr) records for the following meteorological variables: rainfall; maximum, minimum and average air temperature; cumulative sum sunshine duration; wind speed; wind direction; and relative humidity (Table 3-2). The dataset is stored in a database known as the Met Office Integrated Data Archive System (MIDAS) Land and

Marine Surface Stations Data (1853-current). Land surface and marine surface observations data from the Met Office stations are stored in the Met Office MIDAS database. The dataset comprises daily and hourly weather measurements. The data is available in a simple ASCII format and are subjected to quality control by the UK Met Office.

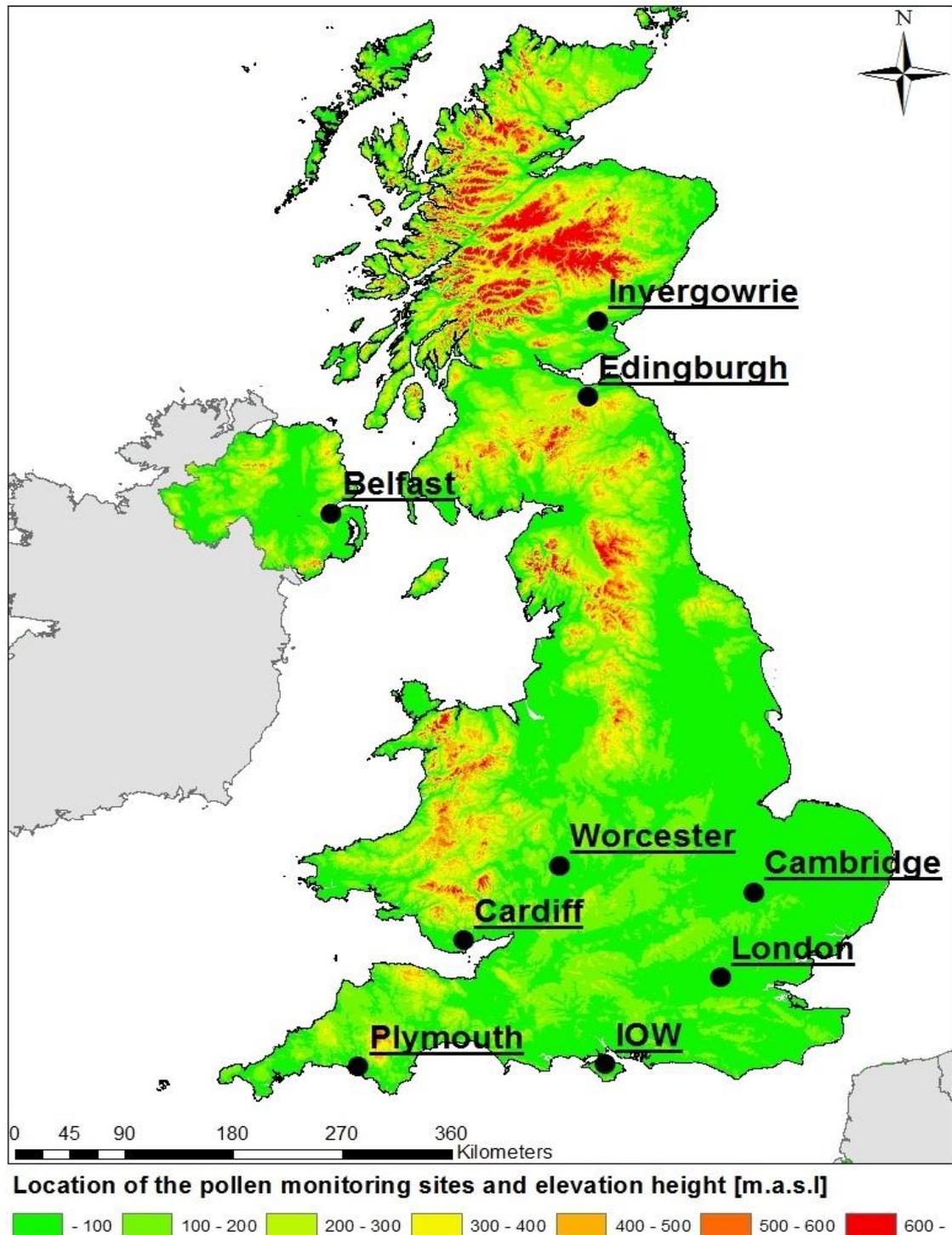


Fig.3-1 Location of the pollen monitoring sites and elevation height.

Table 3-1 Name, location and distance between the pollen traps and meteorological stations used in this study.

Meteorological station name	Site of pollen traps	Area	Latitude	Longitude	Distance to meteorological stations (km)
Cambridge: botanic garden	Cambridge	Cambridgeshire	52.1935	0.13113	1.2
Belfast: Ravenhill road	Belfast	Down	54.5837	-5.90879	3.3
Wight: Shanklin	IOWT(Isle of wight)	Isle of Wight	50.6231	-1.17934	11.8
Pershore	Worcester	Hereford & Worcester	52.148	-2.03979	12
Cardiff: Bute park	Cardiff	South Glamorgan	51.4878	-3.18728	1.9
Edinburgh: royal botanic garden no 2	Edinburgh	Midlothian (in Lothian region)	55.9667	-3.21063	1.8
Mylnefield	Invergowrie	Angus	56.457	-3.07182	1.1
London meteorological centre	London	Greater London	51.521	-0.11088	2
Plymouth: Mountbatten	Plymouth	Devon	50.3544	-4.11986	7.5

3.2.3 Data processing

The pollen count variable measured for each year was the daily average pollen count (grains m⁻³) for each station with most of the data recorded between March and September. Pollen counts for the remainder of the year were minimal; these data need to be excluded to avoid bias in the statistical analysis. Therefore, several techniques were developed in the literature to estimate the start and end of the pollen season from the annual pollen count data. One of the more common technique is, the cumulative sum technique of Driessen et al. (1990), which estimates the start date of the birch and grass pollen seasons as the day when the cumulative daily average pollen count reached 75 or 125, respectively, referred to throughout as cumulative $\Sigma 75$ and cumulative $\Sigma 125$. This technique is useful in forecasting as it does not rely on retrospective data (i.e., depend

on the data of the previous season) which is necessary for other methods such as the total annual catch threshold (e.g., of 1%, 2.5% and 5%) which requires the total pollen catch of the previous year (Emberlin 2009). However, the cumulative daily average methods were species specific and do not provide the end of pollen season information. Therefore, a new technique based on first derivative of the pollen count data was proposed in this study. First, the pollen count data set were smoothed using a seven days moving average and then the first derivative was calculated. The start of the pollen season was defined as the date when the first derivative is greater than five and remained positive for five consecutive days. Similarly, the end of season was defined as the date when the first derivative was less than five and remained negative for five consecutive days after the peak date (day with largest count of pollen).

The justification for using five derivatives for the start of the season is based on the clinically significant amount of pollen (in grains m^{-3}) that induces allergy. In this case, the six day cumulative amount of pollen is at least 30 grains m^{-3} . This amount of pollen has been classified as Moderate (25-50 grains m^{-3}) by NPARU (National Pollen and Aerobiology Research Unit) based at the University of Worcester in the UK. According to NPARU, most sufferers develop an allergenic manifestation when pollen reaches the Moderate category (30-49 grains m^{-3} in the air). A similar argument may be given for the end of the season except that in most cases the end of the pollen season is longer (longer tail) due to re-suspension of pollen or pollen re-floatation. Furthermore, Koivikko et al. (1986) reported that 30 – 80 grains m^{-3} is the range likely to trigger an allergic reaction. Similarly, Mygind and Scadding (2000) reported that most patients develop allergic symptoms when the pollen count (of trees, grasses, weeds) reaches 25-50 grains m^{-3} .

To adhere to one method which can be applied uniformly to both grass and birch pollen, the derivative approach was applied in this research as it is not species-dependent and not liable to bias compared with other techniques such as the cumulative sum. In addition, both as cumulative $\Sigma 75$ and cumulative $\Sigma 125$ were also used to identify start of season for comparison.

The meteorological variables for each year were also smoothed using a 7-day moving average window. The daily pollen count data for both birch and grass, from the start to end of the season (defined by the derivative method) were then correlated (using

bivariate Pearson's product-moment correlation) with meteorological variables for the following temporal supports:

- (i) the same day;
- (ii) 1-day prior,
- (iii) 1-day mean prior (mean of the same day and the day before),
- (iv) 3-day mean prior (mean of the same day and three previous days) and
- (v) 7-day mean prior (mean of the same day and seven previous days).

The correlation coefficients were also estimated for three stages during the pollen season:

- (vi) whole season from the defined start of season to the end of season,
- (vii) pre-peak season from the start of the pollen season to the day of maximum pollen count and
- (viii) post-peak season from the day of maximum pollen count to the end of the season (Fig.3-2).

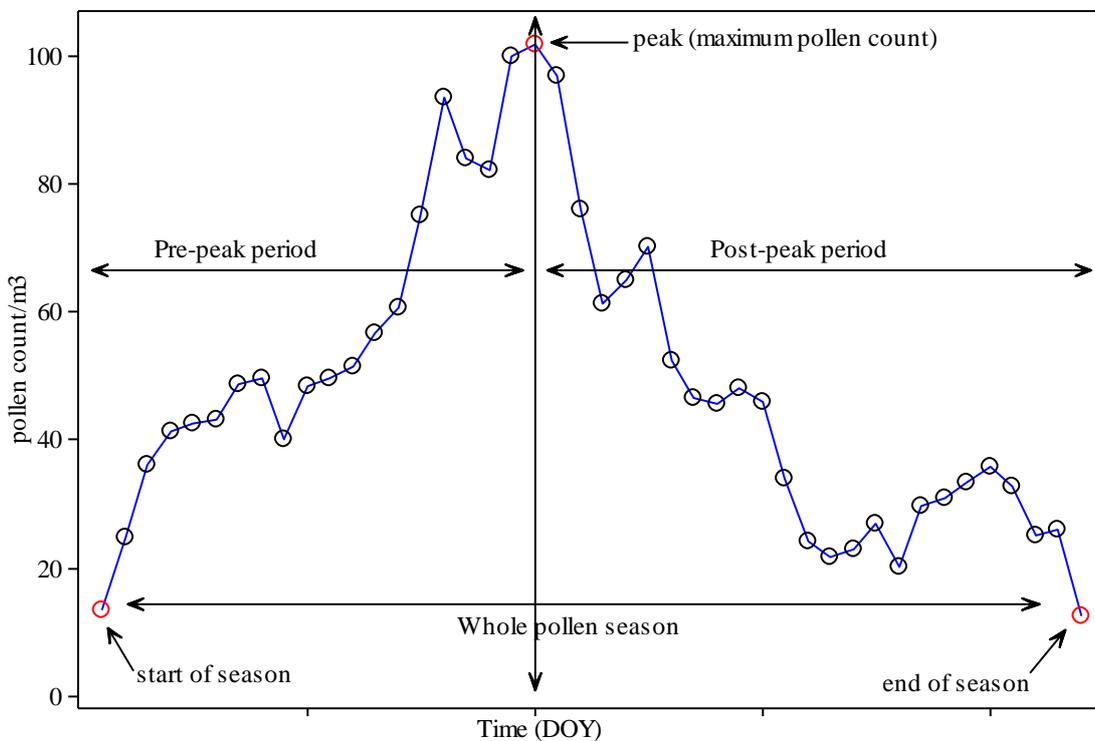


Fig.3-2 Definition of pollen season periods (whole season, pre-peak, post-peak) used in the correlation of both grass and birch pollen counts with meteorological variables.

Table 3-2 Descriptive statistics for Cambridge meteorological station for year 2009 for the period of 2 May- 18 August ($N=109$).

parameters	Minimum	Maximum	Mean	Stdev
prcp_amt (mm)	0.00	8.43	2.10	2.16
max_air_temp (deg °C)	16.43	27.96	21.51	2.79
min_air_temp (deg °C)	4.64	15.06	10.82	2.38
wind_speed (knot)	2.00	15.57	6.93	2.95
air_temperature (deg °C)	11.71	23.21	17.22	2.81
rltv_hum (%)	55.26	82.43	68.03	6.39
sun_dur (hr)	3.00	10.43	6.26	1.82

3.3 Results

3.3.1 Onset and duration of the pollen season

As expected, spatio-temporal variation existed in the start of the grass and birch pollen seasons across all the sites (spatial) and within the sites (temporal) (Tables 3-3 and 3-4). The spatial variation is due to the relationship between the start date and latitudinally-varying regional climates which influence the phenological development of grass and birch over time. The start of pollen season, for both grass and birch, is earlier in the south and tends to be later as one moves northwards. For grass, for example, the pollen season starts at 138 Day-Of-Year (DOY) (17 May) in the Isle of Wight (IOWT) whereas for Edinburgh the average start of season was detected at 157 DOY (5 June) using the $\Sigma 75$ method. For birch, for example, the season starts in the IOWT at 100 DOY (9 April) whereas for Edinburgh the average start date of the season was 107 DOY (16 April) using the $\Sigma 75$ method. For the derivative and $\Sigma 125$ methods a similar south-to-north delay in the start of the season was observed. In Plymouth, the birch season starts 9 days earlier than in Invergowrie using the $\Sigma 75$ method. Similarly, the grass pollen season in Plymouth starts 13 days earlier than in Invergowrie using the $\Sigma 125$ method.

Table 3-3 11-year average start dates for the grass pollen season defined by the derivative method (DM), $\Sigma 75$, and $\Sigma 125$ methods and end of season estimated using the DM at nine pollen stations. Start and end dates are shown as number of days from 1st January.

Grass Stations	Start date			peak day	End date
	DM	$\Sigma 75$	$\Sigma 125$		DM
Worcester	150	139	146	169	216
Belfast	158	150	156	170	213
Cambridge	150	143	148	169	208
Cardiff	154	153	156	170	203
Edinburgh	160	156	161	179	214
Invergowrie	162	158	162	177	209
IOWT	143	138	145	169	215
London	152	144	149	168	210
Plymouth	150	144	149	167	198

Of the three methods used to define the pollen season, the $\Sigma 75$ method estimated the earliest start dates, whereas the $\Sigma 125$ and derivative methods were more similar, especially for the grass season. In contrast, the derivative method estimated the earliest start dates for the birch season compared to the $\Sigma 75$ and $\Sigma 125$ methods. However, all three methods revealed a delayed south-to-north trend in the start of pollen season (Fig.3-3). A similar south-to-north trend in the start of the grass pollen season in New Zealand was reported by Newnham (1999).

At any one pollen monitoring site, the difference in start day over the 11-year sampling period is generally 7-14 days and appears to be dependent upon variation in the local weather conditions prior to and during the pollen season. Across all the stations the birch season starts earlier than the grass season by an average of 54, 45 and 49 days (calculated with the DM, $\Sigma 75$ and $\Sigma 125$ methods, respectively). The length of the birch season across all the stations was on average 21.5 days, whereas for grass it was 56.3 days.

Table 3-4 11-year average start dates for the birch pollen season defined by the derivative method (DM), $\Sigma 75$, and $\Sigma 125$ methods and end of season estimated using the DM at nine pollen stations. Start and end dates are shown as number of days from 1st January.

Birch	Start date			peak day	End date
	DM	$\Sigma 75$	$\Sigma 125$		DM
Stations	DM	$\Sigma 75$	$\Sigma 125$	peak day	DM
Worcester	93	95	96	108	122
Belfast	110	109	113	118	119
Cambridge	93	96	97	107	120
Cardiff	99	99	101	112	121
Edinburgh	97	107	106	114	123
Invergowrie	106	110	110	116	118
IOWT	99	100	102	111	121
London	94	94	95	109	123
Plymouth	100	101	104	112	118

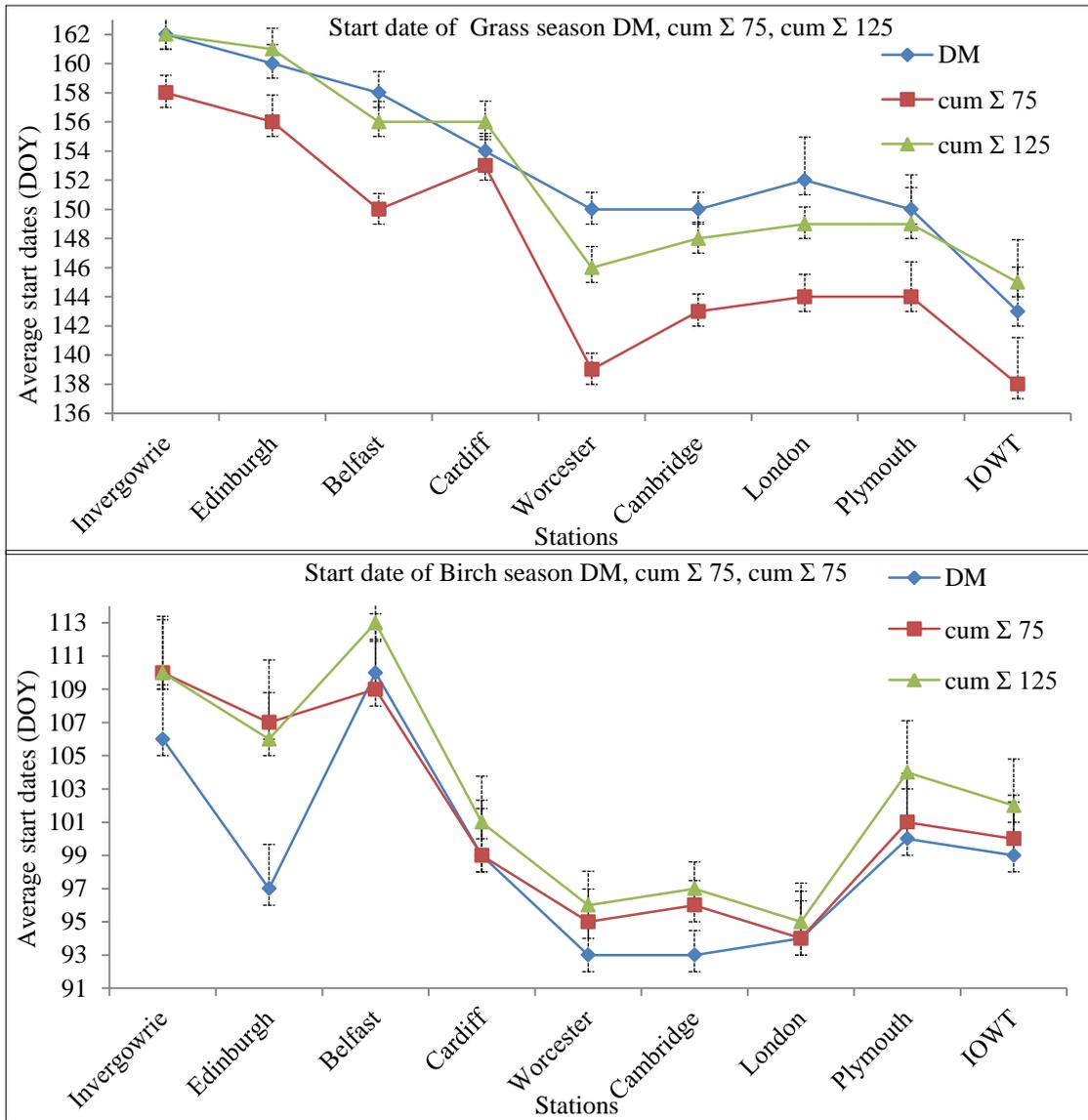


Fig.3-3 South-to-north trend in the start date of grass (top) and birch (bottom) pollen seasons determined by the derivative, Σ 75, and Σ 125 techniques.

3.3.2 Relationship between pollen count and meteorological variables

Relationships between daily birch and grass pollen counts and daily meteorological variables were investigated at each site for the whole season, pre-peak and post-peak periods using correlation analysis (see *section 3.2.3*). For each site, the count of statistically significant (at the 0.01 level; 2-tailed) positive (upwards bar) and negative (downwards bar) correlations were plotted for each meteorological variable for the following temporal supports (i) the same day; (ii) 1-day prior, (iii) 1-day mean prior ,

(iv) 3-day mean prior and (v) 7-day mean prior. Each temporal support is composed of one upwards bar and one downwards bar.

3.3.3 Pollen count and rainfall

When examining the whole season, almost all stations produced a higher count of negative correlations than positive correlations between daily grass pollen count and rainfall (all temporal supports) (Fig.3-4). The largest counts of negative correlations were observed for Edinburgh and Cambridge and the smallest was observed for London. The count of positive correlations observed at some of the stations (e.g., Belfast, Invergowrie) was largest for the 7-day mean prior temporal support. The lowest count of positive correlations was observed for the same-day temporal support. A similar pattern was observed for birch pollen, but the count of negative correlations was generally lower and the count of positive correlations was generally higher than for grass (Fig.3-4). The largest counts of negative correlations were observed for Cambridge and Cardiff and the smallest were for London, Worcester and Plymouth. All nine stations produced at least one count of negative correlations between birch pollen count and rainfall.

For the pre-peak season, seven out of nine stations produced a higher count of negative correlations between daily grass pollen count and rainfall (all temporal supports) (Fig.3-4). The largest counts of negative correlations were observed at Edinburgh and Cardiff stations. Belfast station produced a larger positive correlation for all temporal supports whereas London produced both negative and positive correlations. The count of positive correlations at some of the stations (e.g., Belfast, Invergowrie) tended to increase when shifting from the same-day temporal support towards the prior temporal supports and this is most obvious for the 7-day mean prior temporal support. This implies that during the pre-peak part of the season, rainfall occurs prior to grass pollen release. A similar pattern was observed for birch pollen, but the count of negative and positive significant correlations was lower than for grass (Fig.3-4). The largest correlations were observed for Belfast and Cardiff and the smallest for London.

For the post-peak season, all stations produced a much higher count of negative, than positive, correlations between daily grass pollen count and rainfall (all temporal supports) (Fig.3-4). For the same day temporal support, the largest counts of negative correlations were observed at IOWT and Belfast stations and the smallest was observed for London. The count of positive correlations at some of the stations (e.g., London and Invergowrie) tended to increase when shifting from the 1-day mean prior temporal support to the 3-day and 7-day mean temporal supports. This strong pattern is believed to reflect the washing of grass pollen from the air by rain. A different pattern was observed for birch pollen, with the count of negative correlations being lower than for grass (Fig.3-4). For the same day temporal support, the largest count of correlations for birch pollen was observed for Cardiff and the smallest for London. All nine stations, except for London, produced a greater count of negative, than positive, correlations between birch pollen count and rainfall.

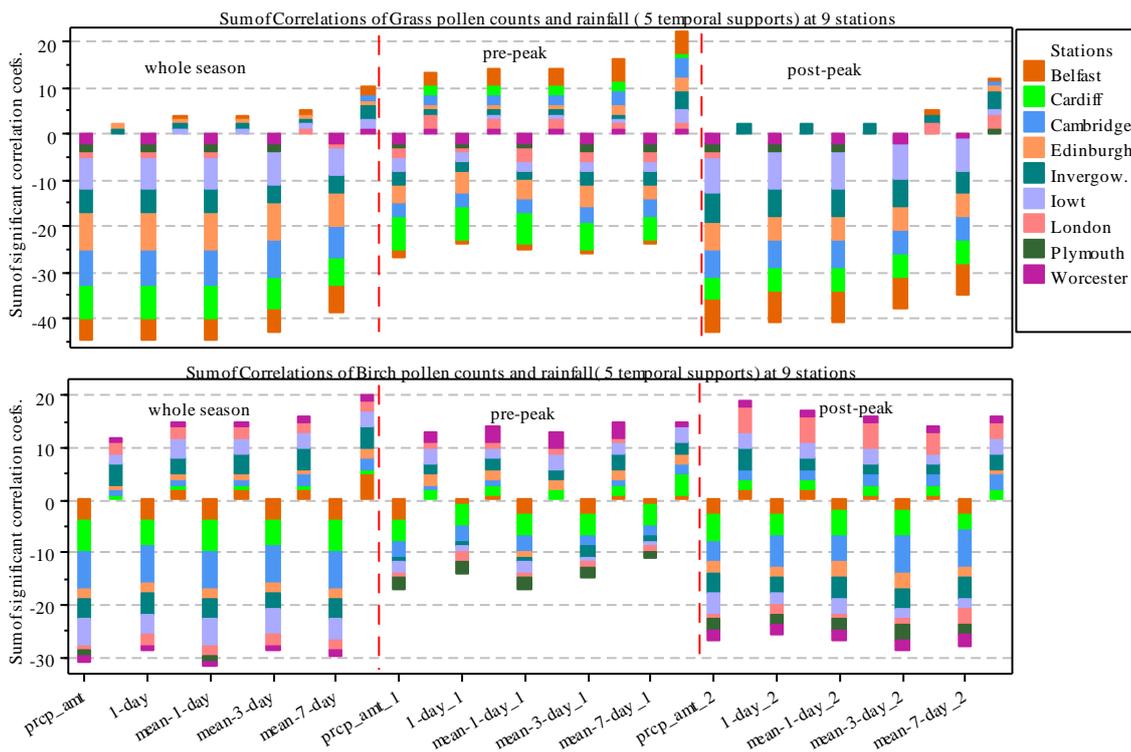


Fig.3-4 Sum of significant positive and negative correlations of daily grass (top) and birch (bottom) pollen counts with rainfall plotted against the five temporal supports (same-day, 1-day prior, 1-day mean prior, 3-day mean prior and 7-day mean prior: each temporal support is composed of two bars; one upwards bar and one downwards bar), for the period of 11-year for the whole season, pre-peak season and post-peak season (separated by vertical broken-line) for nine stations.

3.3.4 Pollen count and relative humidity

All nine stations produced a greater count of negative, compared to positive, correlations between daily grass pollen count and relative humidity (Fig.3-5). The largest counts of negative correlations were observed for Plymouth and Cardiff and the smallest for Edinburgh. The count of positive correlations observed at some stations (e.g., IOWT, Edinburgh and Worcester) tended to increase when shifting from the same-day temporal support towards the prior day supports, with the largest correlation for the 7-day mean prior temporal support. As for rainfall, the smallest number of positive correlations was produced with the same-day temporal support. In contrast, daily birch pollen count produced a greater number of positive, compared to negative, correlations with humidity for most of the stations given the 1-day prior, 1-day mean, 3-day mean, and 7-day mean prior temporal supports (Fig.3-5). For example, for the same-day support Edinburgh and Cardiff produced a greater count of positive correlations and the remaining seven stations produced predominantly negative correlations. For the 1-day prior temporal support Plymouth and IOWT produced negative correlations and the remaining seven stations produced positive correlations. London produced both large negative and large positive correlations with humidity whereas Plymouth produced the largest negative correlations. Overall, no clear pattern emerges for the relation between birch pollen count and relative humidity.

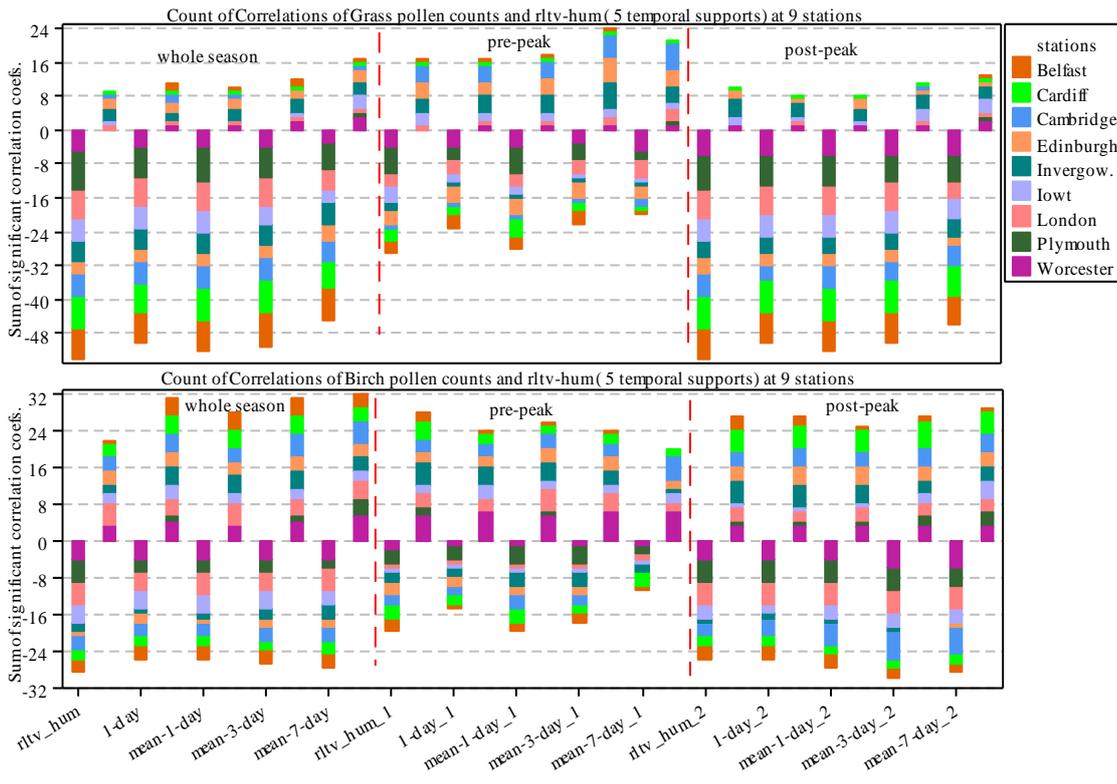


Fig.3-5 Sum of significant positive and negative correlations of daily grass (top) and birch (bottom) pollen counts with relative humidity plotted against the five temporal supports (same-day, 1-day prior, 1-day mean prior, 3-day mean prior and 7-day mean prior: each temporal support is composed of two bars; one upwards bar and one downwards bar), for the period of 11-year for the whole season, pre-peak season and post-peak season (separated by vertical broken-line) for nine stations.

For the pre-peak season, six out of nine stations produced an overall greater count of negative correlations between daily grass pollen count and relative humidity (Fig.3-5). Edinburgh station demonstrated a greater count of positive correlations for the 1-day prior and 1-day mean prior temporal supports only, whereas Cambridge and Invergowrie demonstrated a greater count of positive correlations for all temporal supports. The largest count of negative correlations was observed at Plymouth and the smallest at Edinburgh. The count of positive correlations at some of the stations (e.g., Edinburgh and Cambridge) tended to increase when shifting from the same-day temporal support towards the prior temporal supports. In contrast, six out of nine stations produced an overall larger count of positive correlations between daily birch pollen count and relative humidity for most temporal supports (Fig.3-5). However,

Belfast, Edinburgh and Plymouth produced a larger count of negative correlations. The largest counts of positive correlations were observed at Worcester and Invergowrie.

For the post-peak season, all stations produced a greater count of negative correlations between daily grass pollen count and relative humidity (Fig.3-5). The largest negative correlations were observed at Plymouth and Cardiff and the smallest was at Edinburgh and Invergowrie. This negative relationship is presumed to relate to rainfall and the washing of grass pollen from the air. However, daily birch pollen was observed to demonstrate a mix of positive and negative correlations with relative humidity at most of the stations.

3.3.5 Pollen count and maximum air temperature

Seven of the nine stations produced a greater count of negative, compared to positive, correlations between daily grass pollen count and maximum air temperature for all the temporal supports (Fig.3-6). The smallest count of negative correlations was observed for the same-day temporal support and the count increased when moving towards the prior temporal supports. The largest number of stations with a predominantly negative correlation was observed for the 7-day mean prior temporal support. A similar pattern was observed for daily birch pollen count. However, all stations produced overall negative correlations (Fig.3-6).

For the pre-peak season, in contrast to the whole season period, all stations produced a high count of strong positive correlations between daily grass pollen count and maximum air temperature for all temporal supports (Fig.3-6). The largest count of correlations was generally observed for the same-day temporal support. A similar pattern was observed for daily birch pollen count; however, the influence of maximum temperature on birch pollen count was less uniform across the stations and diminished more for the 7-day temporal support (Fig.3-6).

For the post-peak season, daily grass pollen count produced a slightly larger number of negative, compared to positive, correlations with maximum air temperature for all temporal supports (Fig.3-6). Inverse relations were observed for four out of six stations

for the same-day, 1-day prior and 1-day mean prior temporal supports. This count increased to six out of eight, and nine out of nine, stations for the 3-day and 7-day mean temporal supports, respectively. A similar pattern was observed for daily birch pollen count; however, the count of the negative correlations across the stations was slightly higher than for grass (Fig.3-6).

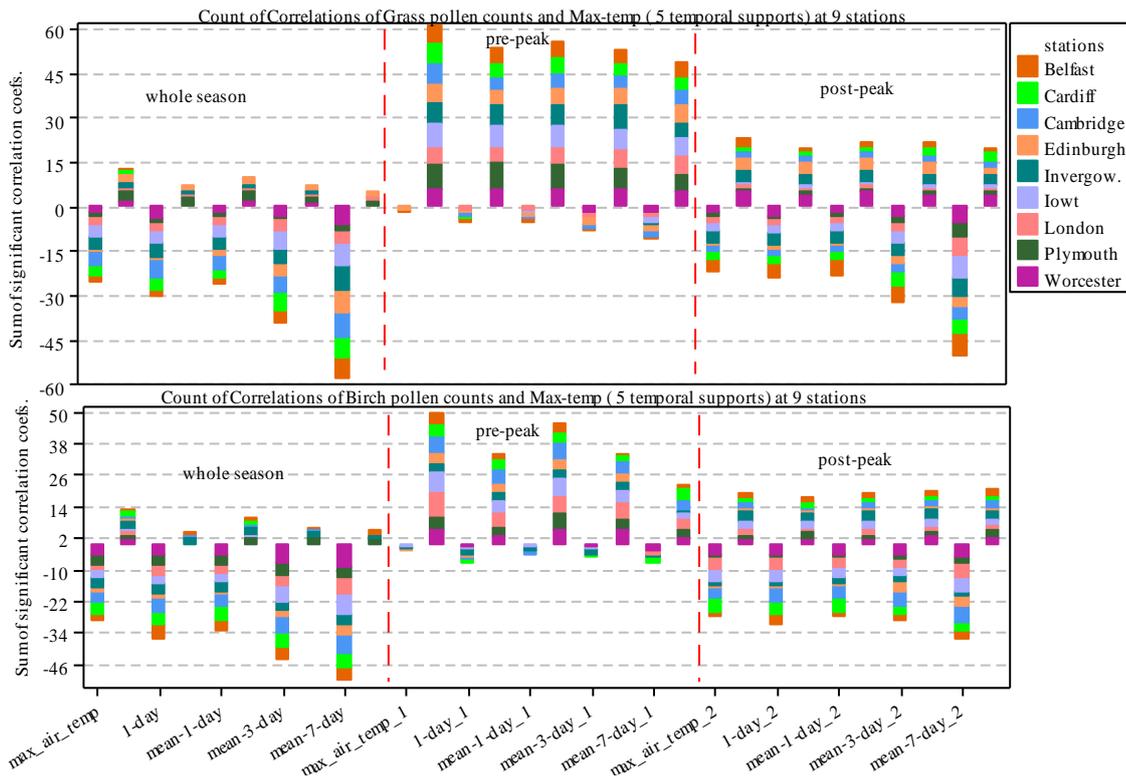


Fig.3-6 Sum of significant positive and negative correlations of daily grass (top) and birch (bottom) pollen counts with maximum temperature plotted against the five temporal supports (same-day, 1-day prior, 1-day mean prior, 3-day mean prior and 7-day mean prior: each temporal support is composed of two bars; one upwards bar and one downwards bar), for the period of 11-year for the whole season, pre-peak season and post-peak season (separated by vertical broken-line) for nine stations.

3.3.6 Pollen count and minimum air temperature

The relations observed between grass and birch pollen counts and minimum air temperature are similar to those observed with maximum air temperature. For the whole season, daily grass pollen count was predominantly negatively correlated with minimum air temperature for all nine stations and for all temporal supports. The count of negative

correlations generally increased with an increase in the size of temporal support towards prior days. Most stations demonstrated the largest count of negative correlations for the 7-day mean prior temporal support. A similar pattern was observed for daily birch pollen except that the count of negative correlations per station was smaller than for grass. The largest negative count was produced for IOWT and Worcester and the smallest for London (Fig.3-7).

Similar to maximum air temperature, for the pre-peak season, all nine stations produced a greater count of strong positive, compared to negative, correlations between daily grass pollen count and minimum air temperature for all temporal supports (Fig.3-7). The largest count of correlations was observed for the same-day and 1-day prior temporal supports. A similar pattern was observed for daily birch pollen count, although with a smaller count of positive correlations generally than for grass pollen (Fig.3-7).

For the post-peak season, daily grass pollen count at all nine stations, with all the temporal supports, showed a larger count of negative, than positive, correlations with minimum temperature (Fig.3-7). Edinburgh produced the smallest negative count and IOWT and Plymouth produced the largest across all the temporal supports. A similar pattern was observed for daily birch pollen except that the largest count of negative correlations was observed for Worcester and Cambridge and the smallest for London.

3.3.7 Pollen count and mean air temperature

The relations observed between pollen count and mean air temperature are similar to those for maximum and minimum air temperature (Fig.3-8). For the whole season, all stations produced a larger count of negative correlations between daily grass pollen count and average daily air temperature. The count of the negative correlations across the stations increased when moving towards the prior temporal supports. At 7-day mean prior temporal support the majority of the stations demonstrated high count negative correlations. The largest negative counts were observed for Worcester, Plymouth and Cambridge for all temporal supports, whereas the smallest was observed for Cardiff. Similar behaviour was observed for birch pollen except that the count of negative correlations per station was larger than for grass (Fig.3-8). The smallest negative count

was observed for London whereas the largest were produced by Plymouth and Worcester.

For the pre-peak season, all nine stations produced a large positive correlation between daily grass pollen count and daily average temperature for all temporal supports (Fig.3-8). The largest count of correlations was observed for the same-day, 1-day prior and 1-day mean prior temporal supports. A similar pattern was observed for daily birch pollen count (Fig.3-8).

For the post-peak season, all the stations demonstrated a generally larger count of negative correlations between daily grass pollen count and average daily air temperature (Fig.3-8). However, Edinburgh and Invergowrie were observed to show overall positive correlations throughout most of the temporal supports. The largest number of stations (eight out of nine stations) produced a larger count of negative correlations for the 7-day mean prior temporal support. The largest negative counts were observed for Worcester, Plymouth and London throughout the temporal supports whereas the smallest was observed for Cambridge. A similar pattern was observed for birch pollen except that the count of negative correlation per stations was larger than for grass (Fig.3-8).

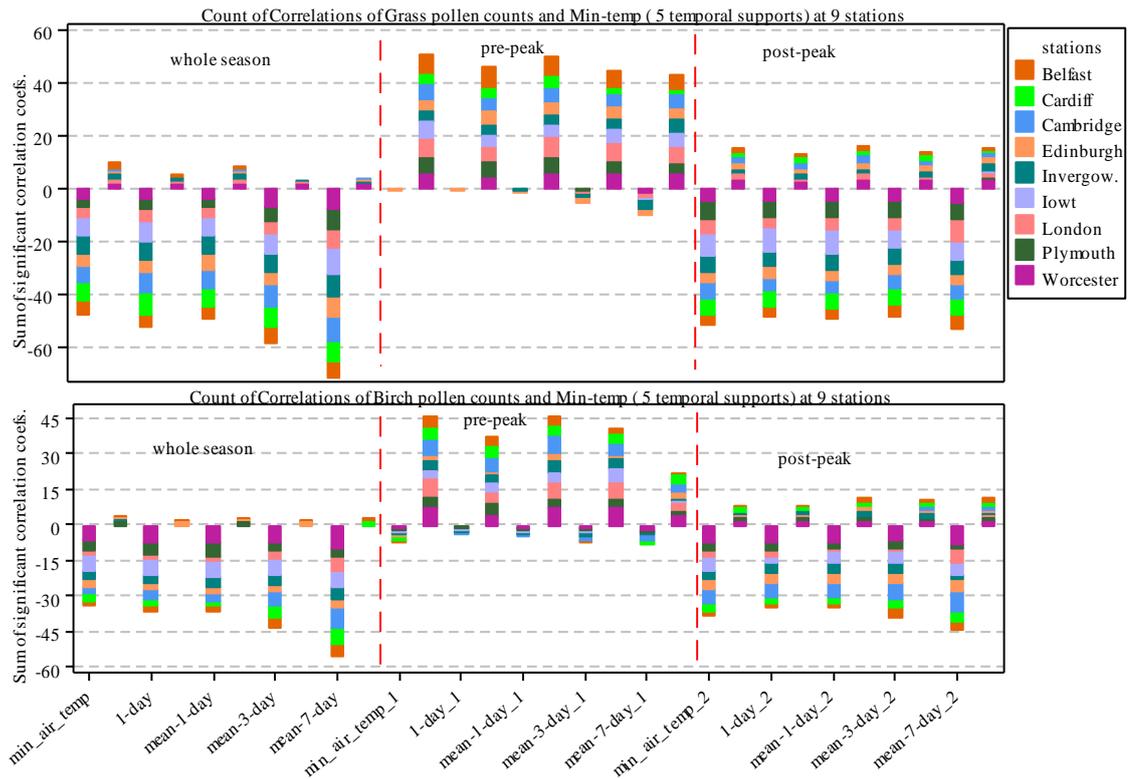


Fig.3-7 Sum of significant positive and negative correlations of daily grass (top) and birch (bottom) pollen counts with minimum temperature plotted against the five temporal supports (same-day, 1-day prior, 1-day mean prior, 3-day mean prior and 7-day mean day mean prior: each temporal support is composed of two bars; one upwards bar and one downwards bar), for the period of 11-year for the whole season, pre-peak season and post-peak season (separated by vertical broken-line) for nine stations.

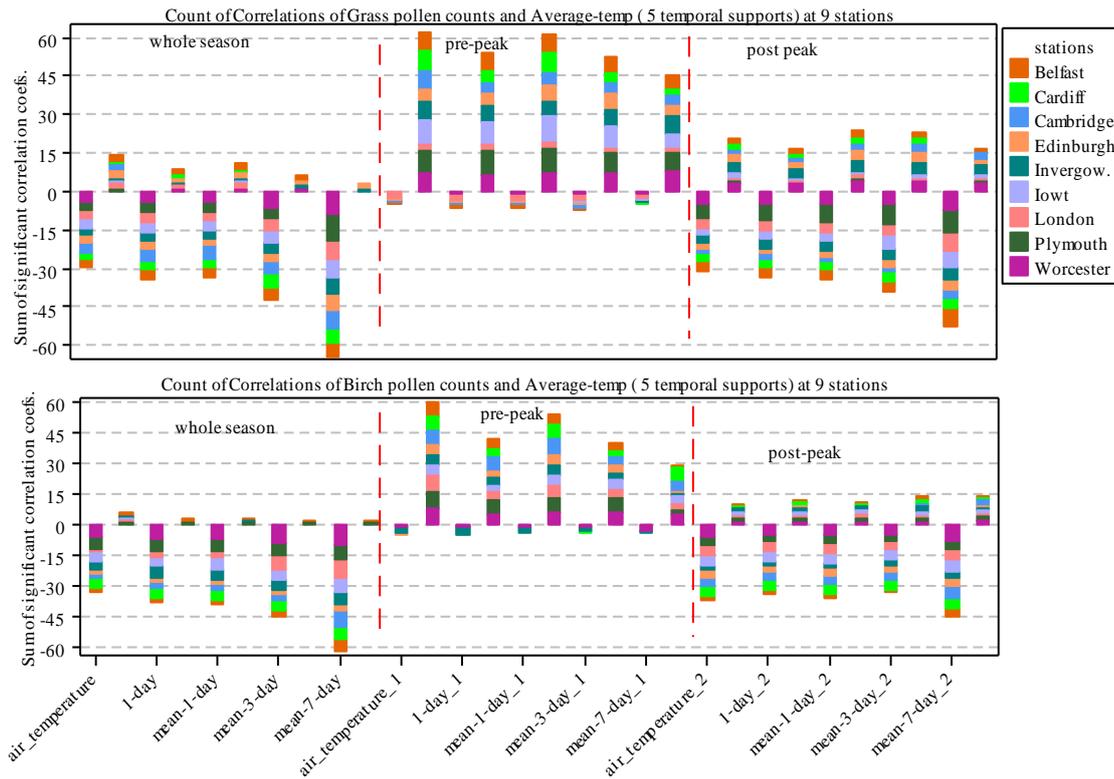


Fig.3-8 Sum of significant positive and negative correlations of daily grass (top) and birch (bottom) pollen counts with average temperature plotted against the five temporal supports (same-day, 1-day prior, 1-day mean prior, 3-day mean prior and 7-day mean prior: each temporal support is composed of two bars; one upwards bar and one downwards bar), for the period of 11-year for the whole season, pre-peak season and post-peak season (separated by vertical broken-line) for nine stations.

3.3.8 Pollen count and wind speed

For the whole season, five of the nine stations produced a greater count of negative correlations between daily grass pollen count and wind speed at all the temporal supports, except for the 7-day mean temporal support where only four stations produced the greatest count (Fig.3-9). The largest negative count of correlations was observed for Plymouth, IOWT and Worcester whereas the smallest was observed for London. However, a greater count of positive correlations with wind speed was observed for Cambridge, Edinburgh, Invergowrie and London. Thus, the relationship between pollen count and wind speed for the whole season appears rather mixed. However, for birch pollen the pattern is clearer, with most stations producing a larger count of negative correlations across all temporal supports (Fig.3-9). For the pre-peak season, five out of

seven stations (the remaining two of the total of nine stations showed no correlation) produced predominantly negative correlations between daily grass pollen count and wind speed for all temporal supports, except for the 3-day mean and 7-day mean temporal supports where only three out of six stations produced a predominantly negative count) (Fig.3-9). For the 1-day mean and larger temporal supports, grass pollen was observed to produce both negative and positive and/or no correlation with wind speed across all stations. The largest count of positive correlations was observed for London and Edinburgh, whereas the largest count of negative correlations was observed at Worcester and Invergowrie. However, birch pollen across seven of the nine stations produced a high count of negative correlations with wind speed for all temporal supports. The pattern of overall negative influence is, thus, more obvious for birch than grass (Fig.3-9), but again, is rather counter-intuitive.

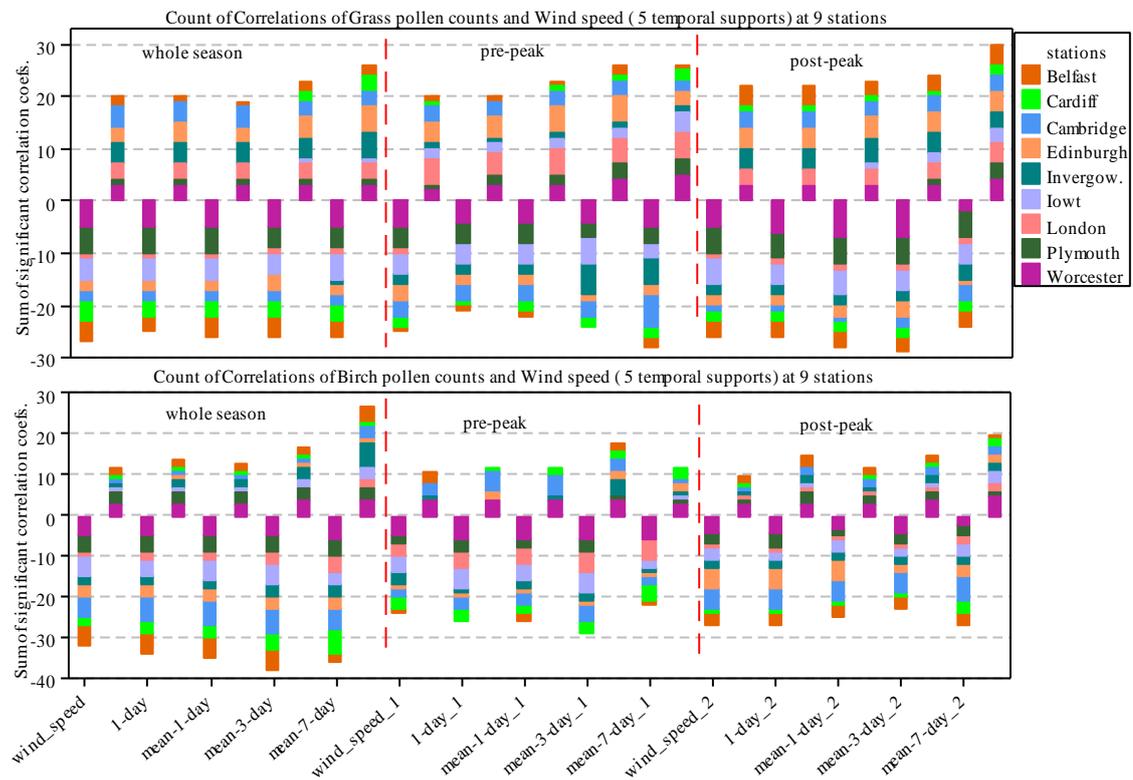


Fig.3-9 Sum of significant positive and negative correlations of daily grass (top) and birch (bottom) pollen counts with wind speed plotted against the five temporal supports (same-day, 1-day prior, 1-day mean prior, 3-day mean prior and 7-day mean prior: each temporal support is composed of two bars; one upwards bar and one downwards bar), for the period of 11-year for the whole season, pre-peak season and post-peak season (separated by vertical broken-line) for nine stations.

For the post-peak season, five out of nine stations produced a greater count of positive correlations between daily grass pollen count and wind speed, for the same-day and 1-day prior supports (Fig.3-9). For the 1-day mean and 3-day mean prior temporal supports, from a total of nine stations four stations produced a greater count of positive correlations and four produced a greater count of negative correlations. The largest counts of positive correlations were observed at Invergowrie, Edinburgh and Belfast, whereas the smallest was observed at Cardiff. Thus, the picture is mixed. In contrast, birch pollen across all nine stations and for all the temporal supports produced a larger count of negative correlations (Fig.3-9). The smallest count of negative correlations was recorded for London and Cardiff stations and the largest for Edinburgh and Cambridge.

3.3.9 Pollen count and Sunshine duration

For the whole season, four stations out of four (data available only for four stations) produced a large count of positive correlations between daily grass pollen count and cumulative daily Sun duration for all the temporal supports (Fig.3-10). The pattern for the same-day, 1-day prior and 1-day mean prior was similar, but the count decreased gradually for the 3-day and 7-day mean prior supports. The largest count was observed for Edinburgh, whereas the smallest was observed for London. In contrast, for birch pollen, three out of four stations produced a strong, but small count of negative correlations with cumulative sunshine duration. For the 7-day mean prior temporal support four out of four stations produced predominantly negative correlations (Fig.3-10).

For the pre-peak season, four out of four stations produced a large count of positive correlations between daily grass pollen count and cumulative daily sunshine duration for all temporal supports (Fig.3-10). The largest count of positive correlations was observed for London whereas the smallest was observed for Edinburgh. However, for birch, three out of four stations produced a strong, but small count, of positive correlations for the same-day temporal support. For the 1-day prior temporal support three out of four stations produced a greater count of negative correlations and for the 1-

day mean and 3-day mean prior supports two out of three stations produced a greater count of negative correlations.

For the post-peak season, four out of four stations produced a greater count of positive correlations between daily grass pollen counts and cumulative daily sunshine duration for all temporal supports. The patterns for the same-day, 1-day prior and 1-day mean prior temporal supports were similar, but the count decreased gradually for the 3-day and 7-day mean prior temporal supports. The largest count was observed for Edinburgh whereas the smallest was observed for London. In contrast, for birch, the pattern was mixed. The largest count of negative correlations was observed for London and IOWT whereas the smallest was observed for Edinburgh and Invergowrie (Fig.3-10).

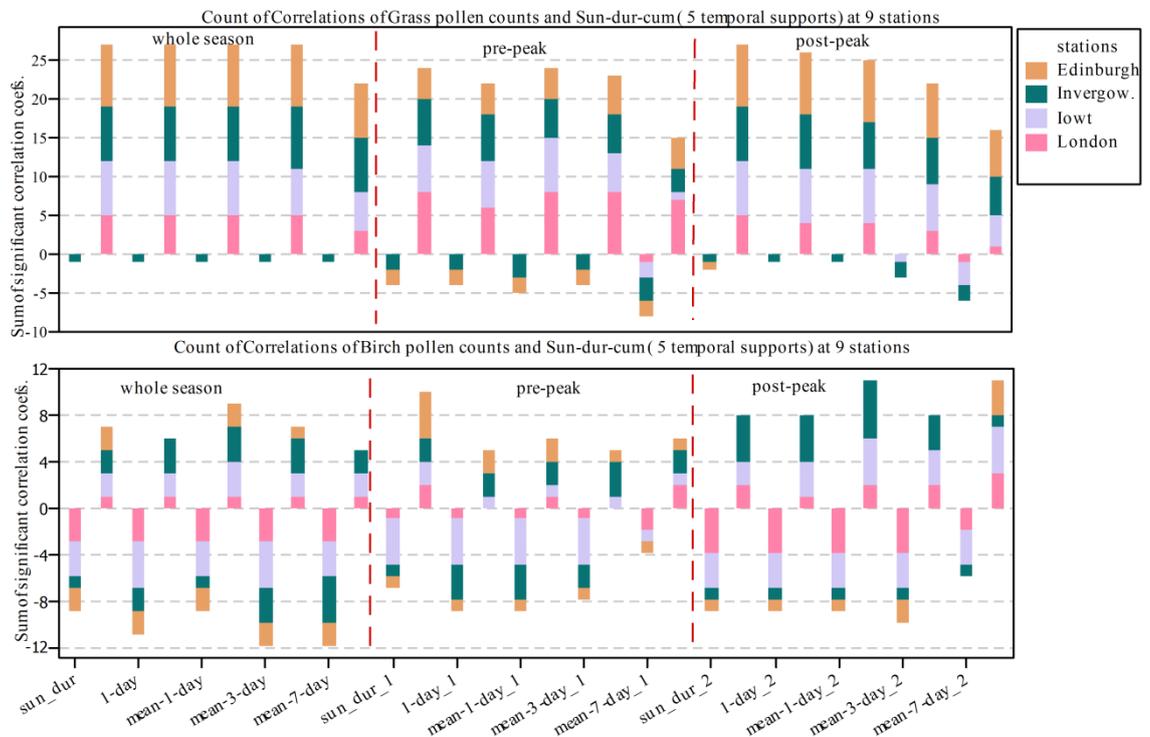


Fig.3-10 Sum of significant positive and negative correlations of daily grass (top) and birch (bottom) pollen counts with Sun duration plotted against the five temporal supports (same-day, 1-day prior, 1-day mean prior, 3-day mean prior and 7-day mean prior: each temporal support is composed of two bars; one upwards bar and one downwards bar), for the period of 11-year for the whole season, pre-peak season and post-peak season (separated by vertical broken-line) for four stations.

3.4 Discussion

Using different methods to determine the start of the pollen season for grass and birch in the United Kingdom, this research has revealed spatial and temporal variation in the start of season across stations and over time. Generally, as expected, the pollen seasons start earlier in the south of the United Kingdom than they do in the north. The average of the 11-year time-series shows that the birch pollen season in Plymouth starts ($\Sigma 75$) 9 days earlier than at Invergowrie and 6 days earlier than at Edinburgh (Table 4).

Similarly, the grass pollen season in Plymouth starts ($\Sigma 125$) 13 days earlier than at Invergowrie and 12 days earlier than at Edinburgh (Table 3). These results concur with previous studies focused on regional variation in pollen counts (Emberlin et al. 2000; Corden et al. 2000; Sánchez Mesa et al. 2003). Climate variation across the UK causes spatial variation in the timing of the onset of the pollen seasons. Increases in temperature in the spring influence phenological development, including the timing of flowering or anthesis prior to the main pollen season (Emberlin et al. 1999). The earlier the start of flowering, the earlier the end of the annual life cycle of grass and birch, but not necessarily the end of the pollen season due to the possibility of pollen being transported in the air as well as re-suspension.

The length of the birch season across all stations was on average 21.5 days, whereas for grass it was 56.3 days. The start and length of pollen seasons are generally dependent on the factors that influence the abundance and dispersal of pollen such as local vegetation type, altitude, land use and climate (Emberlin et al. 2000; Green et al. 2004; Jato et al. 2009; Sabariego et al. 2011). In addition, factors such as local topography and urban climate (including the urban heat island effect) that affect re-suspension and early flowering of local plants are also important, and are also plausible causes of the early start of the birch pollen season in London.

Overall, in the UK daily birch and grass pollen count in the air was negatively correlated with rainfall. Pollen grains, after their release, become suspended in the atmosphere and follow the turbulence of the air. It is believed that pollen is to some extent hygroscopic (i.e., behaves like nuclei for water vapour and lead to raindrops) (Agashe and Caulton 2009) which means that pollen is washed from the atmosphere by rainfall. However, the size of the pollen grains should be considered, as larger grains

wash out faster than smaller grains during rainfall. This can be noticed in the analysis as grass pollen grains, which are larger in size, demonstrate a larger count of negative correlations with rainfall than birch grains. The negative correlation between pollen grains and rainfall continues throughout the whole season, pre-peak season and post-peak season, particularly for grass pollen. The United Kingdom with a temperate climate has fairly well distributed rainfall throughout the year, especially from February to August. However, during the pre-peak period, the count of positive correlations tends to increase towards prior days especially for grass. Grass species have fairly regular daily flowering patterns. Thus, rainy prior days may trigger flower blooming and pollen release in the following days during the pre-peak period at the source. Furthermore, London and Belfast show a rather weak positive correlation with rain for the same-day temporal support. This result supports the study conducted by Emberlin and Norris-Hill (1991) for a four-year period in north-central London, which observed several occasions when pollen counts were high during rainfall.

Daily birch and grass pollen counts are highly correlated with temperature in the UK. However, the direction of the relationship varies with the stage of pollen season: specifically whole season, pre-peak season, and post-peak season. The pre-peak season reveals a large count of significant positive correlations with maximum, minimum and average temperature for both birch and grass. In contrast, a large count of significant negative correlations was observed when the whole season, and post-peak season pollen counts were correlated with temperature. Temperatures in the spring influence phenological development including timing of flowering, as noted above. Therefore, birch and grass pollen counts from the beginning of the season until the maximum count, when generally the maximum floret population sheds pollen, are predominantly controlled by temperature. However, the influence of temperature beyond the peak-day should continue through promoting re-suspension and shedding of pollen, especially for grass. The result implies that maximum air temperature, on the day of measurement, exerts a strong control on pollen count through pollen release and re-suspension mechanisms. Interestingly, the patterns observed in the post-peak season for minimum air temperature are more striking than for maximum air temperature. This negative relation is interesting as it implies that warmer days lead to less pollen in the post-peak

part of the season. In the UK, most grass species flower throughout May, June and July, with the greatest number blooming in June (Hubbard 1992).

The results reveal that the temperate maritime climate of Britain, with temperatures not much lower than 0°C in winter and not much higher than 32°C in summer, influences pollen count positively during the pre-peak season, but produces a non-causal negative relationship after the peak. From January and February onwards the temperature gradually increases until it reaches a maximum in July and August. The birch pollen season starts at the beginning of April and ends in May. The grass pollen season starts in late May and ends in August, but with the maximum in June. Thus, as Fig. 3-11 illustrates, the post-peak season generally involves a negative correlation between the gradually falling pollen count and gradually increasing temperature. The birch and grass post-peak seasons are usually longer compared to the pre-peak seasons. This means that statistically the negative influence of the post-peak relation dominates the pre-peak relation when the whole season is considered (Fig.3-11). Again, this underlines the importance of analysing the different parts of the pollen season separately.

Overall, all the stations produced an inverse correlation between grass pollen count and relative humidity for the whole season and post-peak periods, with the same, but weaker pattern for the pre-peak period. Most grass species flower in the early morning, typically from 4 to 9 am. For most plants, low relative humidity is crucial for pollen detachment by wind from the anther, as the grains must be dry on the anther (Emberlin 2009). Relative humidity is high early in the morning and it decreases towards midday due to increase in air temperature. Birch pollen produced a slightly greater count of positive, than negative, correlations with humidity for most of the stations.

The analysis reveals clearly that the birch pollen count is smaller on windy days than for grass pollen. This is surprising as the physical structure of birch catkins where the pollen grains are situated is composed of overlapping plates which must be shaken by the wind to release the pollen. However, wind speed is also an important factor in diluting particles floating in the air. High wind speed dilutes the particles quicker and moves them away from the source depending on the height of release and size. Conversely, pollen accumulates in slowly moving air and this gives rise to a high count locally. Local eddying, shearing of wind directions and turbulent flows make pollen,

like any other particles, follow a heterogeneous pattern. Therefore, the count of pollen might change remarkably within short distances both vertically and horizontally depending on the topography and position of the source (Emberlin 2009).

Pollen count measured at the pollen sites may be related to both local and remote sources (Stach et al. 2007). Previous studies from different parts of the world have reported of allergenic birch and grass pollen travelling long distances (Smith et al. 2005; Ranta et al. 2006; Water et al. 2007; Skjøth et al. 2013b). Birch pollen before the onset of local flowering has been documented to transport from Germany and Poland to Denmark (Skjøth et al. 2007). The long-distance transport of pollen which come from other regions over-estimates the local sampling of pollen counts, thus influences the local timing of the pollen season. Therefore, it is intuitively important to model pollen transport and trace back to the source from observational results. Backward trajectory modelling or inverse-modelling is one of the widely used models in studying pollen transport over long distances, for example, understanding the origin of exotic pollen (Siljamo et al. 2008; Veriankaitė et al. 2010; Efstathiou et al. 2011).

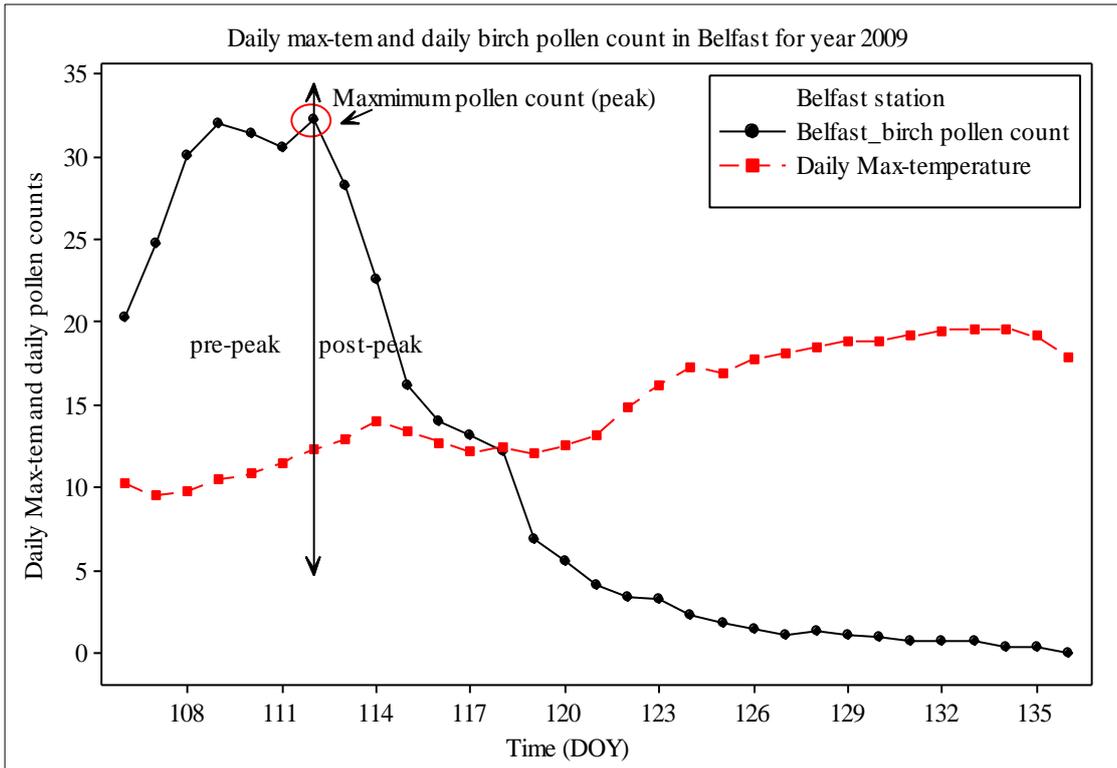


Fig.3-11 Birch pollen count and temperature plotted against DOY of season. The pre-peak and post-peak periods are separated by the vertical line. The direction of the correlation is positive at the pre-peak and negative at the post-peak

3.5 Conclusion

To understand the influence of meteorological variables on atmospheric pollen counts it is important to consider possible effects during the pre-peak period as most flower blooming occurs within a short duration before the maximum pollen count is recorded. During the post-peak period, apart from a reduction in flowering in the majority of the grass and birch population, the process of re-suspension is more relevant, ultimately making this period longer than the pre-peak period. The fact that the post-peak period is longer than the pre-peak period means that, for both grass and birch, the true magnitude and direction of meteorological effects on pollen counts may be masked when the whole season is considered.

Spatio-temporal variation in the start of the grass and birch pollen seasons and their counts in the air in the United Kingdom are controlled primarily by maritime meteorological variables. The influence of meteorological variables on dispersion,

release and re-suspension persist throughout the pollen seasons. The pre-peak period generally produces a larger correlation with meteorological variables for both birch and grass pollen counts in the air. Furthermore, the influence of meteorological variables on birch pollen count in the atmosphere is subtly different from that for grass pollen count due to differences in the heights of release, the pattern of transportation, dispersion within the layers of the atmosphere, and the size and aerodynamic properties of the grains.

Correlation analysis of 11-year time-series daily average pollen counts and the corresponding meteorological variables revealed that the maximum temperature, sunshine duration and rainfall were the most important variables influencing grass pollen count in the atmosphere as recorded at pollen monitoring stations. Both maximum temperature (pre-peak) and sunshine produced a large count of positive correlations, and rainfall produced a large count of negative correlations with grass pollen count in the air. Similarly, average temperature, wind speed and rainfall were the most important variables influencing birch pollen count in the air. Both wind speed and rainfall produced large numbers of negative correlations and average temperature produced large numbers of positive correlations with birch pollen count in the air.

CHAPTER 4: Mapping the birch and grass pollen seasons in the UK using satellite sensor time-series²

4.1 Introduction

Grass and birch pollen are two major causes of seasonal allergic rhinitis (hay fever) in the UK and parts of Europe affecting around 15-20% of the population (Emberlin et al. 1997; Varney et al. 1991). The prevalence of sensitisation to grass and birch allergens varies geographically depending on the source abundance and the amount of allergen extract on the pollen. High prevalence of sensitisation to grass pollen has been reported for parts of the UK, France, New Zealand, Switzerland and the USA (Bousquet et al. 2007). Similarly, high prevalence of sensitisation to birch pollen has been reported for parts of northern and mid-Europe, New Zealand and parts of the USA (Bousquet et al. 2007).

The most common species of birch in the UK are Downy birch (*Betula pubescens*) and Silver birch (*Betula pendula*). The former is the most abundant birch in Scotland and North West England (Emberlin 2009). Birch is a catkin-bearing deciduous tree, native to northern temperate regions, and belongs to the Betulaceae family. Birch is an anemophilous tree and its pollen, which ranges in size from 21 to 27 µm, can under favourable conditions be transported hundreds of kilometres from its source (Izquierdo et al. 2011). In Europe, birch pollen is the second most widely distributed aeroallergen and its overall abundance is exceeded only by *Parietaria* (including *Parietaria* and the non-allergenic *Urtica*) (Skjøth et al. 2013a; Skjøth et al. 2013b).

In the UK, there are about 150 species of grass, although only around 12 species contribute significant amounts of pollen to the atmosphere (Emberlin 2009). However, the high degree of cross-reactivity between different grass pollen species broadens the susceptibility of an allergic individual to many pollen types (Emberlin et al. 1999). The length of the grass and birch pollen seasons varies both spatially and temporally. This is due to variation in the factors that influence the abundance and dispersal of pollen such

² Khwarahm, N.R., Dash, J., Skjøth, C.A., Newnham, R.M., Adams-Groom, B., Head, K., Caulton, E., & Atkinson, P.M (2014), corrections resubmitted to the Remote Sensing of Environment Journal

as local vegetation type, altitude, land use and climate (Emberlin et al. 1999; Emberlin et al. 2000; Emberlin et al. 1997; Galán et al. 1995). Europe-wide, grass pollen is the most widely spread aeroallergen (Skjøth et al. 2013a) with the highest concentrations in the Western Iberian Peninsula, central Europe and the UK (Skjøth et al. 2013a).

Atmospheric concentrations of the birch and grass aeroallergens are usually predicted based on meteorological data together with pollen count data collected at a specific pollen station, to help pollen allergic sufferers avoid exposure. The predictions are generally established using empirical models (García-Mozo et al. 2009; Isabelle and Jordina 2004; Laaidi 2001; Smith et al. 2009). These models are well-known for their limitations as they are specific to the area where they are produced (Stach et al. 2008), such as large urban areas like London (Smith and Emberlin 2005) and Copenhagen (Skjøth et al. 2008a), that are known to have a warmer climate compared to their surroundings. Moreover, the spatial representation of these prediction models is low as pollen grains are generally collected from a limited number of pollen sites. Within the urban environment, gardens and small woodlands are considered to be an important source of birch pollen in the atmosphere of cities (Skjøth et al. 2008b) and urban environments often have advanced flowering compared to the surrounding rural landscape due to the urban heat island effect (Estrella et al. 2006). Similarly, grass areas are commonly found in or near urban areas (Pauleit and Duhme 2000) and it has been shown that these urban sources can cause considerable variation in the grass pollen load throughout the urban landscape (Skjøth et al. 2013b). Any characterisation of flowering and overall pollen concentration load obtained using a fixed and small number of pollen counting stations will, therefore, be limited. Additional information about grass phenology at finer spatial resolution would, therefore, be highly useful. For the UK, this is particularly relevant due to its unique composition; a patchy landscape which includes some of the largest urban areas in Europe.

Phenological variables derived from temporal profiles of satellite-derived vegetation indices can be used to characterise the stages of vegetation development during the growing season (Olsson et al. 2005; Heumann et al. 2007; Seaquist et al. 2009; Reed et al. 2009; White et al. 2009; de Beurs and Henebry 2010; Roerink et al. 2011). Thus, they can be related to biological definitions of plant phenology, for example, the flowering phenophase related to pollen release. Satellite sensor imagery has the

advantage that it provides spatially complete coverage that can be used to interpolate traditional ground-based phenological observations. Linkosalo (1999, 2000) found in southern Finland that the difference in time from birch (*Betula pendula*) male flowering to the first date of budburst was only 1.1 days, with male flowering occurring first. Thus, the timings of male flowering and leaf budburst of birch are well correlated ($r = 0.97$). Moreover, the timing of male flowering, leaf budburst and pollen release appear to be quite closely synchronised (Newnham et al. 2013). This indicates that birch phenophases, observed as leaf budburst or, for example, greenness of birch trees, could be used to determine the timing of local birch pollen release. This suggests that measurements of the flowering phenophase of aeroallergens like grass and birch from remote sensing could be used to map local pollen release nationwide (Karlsen et al. 2008).

Satellite sensor images have been used widely to detect variables related to vegetation phenology, for example, the start of season and end of season (Dash et al. 2010; Fisher and Mustard 2007; Lloyd 1990; Reed et al. 1994; Roerink et al. 2011), but to a lesser extent for the flowering phenophases which for some species are during or before budburst (e.g. for birch) and for others are at a different growth stage (e.g. for grass). One reason may be related to the fact that phenological phases at the species level are most easily observed with remote sensing in areas where the observational target (e.g. birch) is the dominant species. This is the case for birch in Scandinavia (Skjøth et al. 2008b), while oak and beech outnumber birch in most other European countries including England (Skjøth et al, 2008). Similar results have, therefore, not been produced in other European countries, although mapping of birch flowering could be very useful. It is therefore important to explore if flowering phenophases can be estimated indirectly with remote sensing. One approach could be to investigate if the overall increase in leaf area index and chlorophyll concentration in woodland areas with a mixed composition of trees correlates well with birch flowering during spring. A similar argument can be used for grass considering that foliage development for most grasses precedes flower blooming.

Several studies have used time-series satellite-driven vegetation indices to characterise important phenological variables related to pollen release. Hogda et al. (2002) used coarse spatial resolution satellite sensor data, specifically the Global Inventory

Monitoring and Modeling System (GIMMS) Normalized Difference Vegetation Index (NDVI), to characterise the start of birch pollen season in Fennoscandia. They related the NDVI time-series with birch pollen count data from five stations, and reported significant positive correlation coefficients (r) in the range 0.55 to 0.85. Similarly, Karlsen et al. (2008) used finer spatial resolution satellite sensor data, specifically MODIS (Moderate Resolution Imaging Spectroradiometer) NDVI with 250 m spatial resolution and 16-days compositing to determine the start of birch flowering in Norway. They reported large significant positive correlations in the range 0.78 to 0.92 between station pollen count data and the start of birch flowering. Furthermore, Luvall et al. (2011) used the MODIS Enhanced Vegetation Index (EVI) to characterise the start of Juniper plant species flowering, which is also categorised as an aeroallergen. They reported that EVI has the capability to detect inter-annual variation in the Juniper pollen season and showed close agreement with ground-based pollen observations.

Vegetation phenological changes during the growing season were studied by examining changes in the remote sensing-based Medium Resolution Imaging Spectrometer (MERIS) Terrestrial Chlorophyll Index (MTCI) value (Dash and Curran 2004; Dash et al. 2010).

The use of spectral reflectance bands in the red edge wavelengths and sensitivity to changes in chlorophyll content related to different phenological events make MTCI a useful product for monitoring overall greenness and phenological changes at regional to global scale (Dash and Curran 2004). The MTCI is defined as the ratio of the difference in reflectance (R) between band 10 and band 9 and the difference in reflectance between band 9 and band 8 of the MERIS standard band setting.

$$\text{MTCI} = \frac{R_{753.75} - R_{708.75}}{R_{708.75} - R_{681.25}}$$

Where, $R_{753.75}$, $R_{708.75}$, $R_{681.25}$ are the reflectances in the centre wavelengths (nm) of the MERIS standard band setting in bands 10, 9 and 8. The MTCI is a standard L2 MERIS product and is produced from the L2 normalised surface reflectance in bands 8, 9, 10 of the MERIS sensor (Dash 2010).

The main objective of this paper was to predict the onset of flowering phenophase related to the timing of pollen release for birch and grass for the whole UK from time-series MTCI data and investigate its relationship with pollen counts at nine pollen monitoring sites across the country. First, we developed a technique to define the onset of flowering for both birch and grass using the MTCI data at a spatial resolution of 0.0089° (~1 km by ~1 km) from the MERIS sensor. Second, we employed three methods of defining the onset of the birch and grass pollen seasons from pollen count data for nine pollen sites distributed across the UK. Third, we explored the relationship between the onset of flowering and the onset of the grass and birch pollen seasons. Fourth, we generated several maps for the UK at 1 km spatial resolution, which show the spatial variability of the onset of flowering for birch and grass for the period 2003-to-2010. Finally, we validated these maps with ground pollen count data. We suggest that this method, used together with the pollen forecast from the UK Met Office, can provide useful and reliable information to pollen allergy sufferers in the UK.

4.2 Materials and methods

4.2.1 Pollen count data

Time-series grass and birch pollen count data (daily average grains m^{-3}) for the 2003-to-2010 period were taken from nine pollen monitoring sites in the UK (Fig. 4-1). The data were provided by the National Pollen and Aerobiology Research Unit (NPARU) at the University of Worcester. These monitoring sites sample across much of the UK's regional diversity in climate, land cover and distance from the coast (Table 3-1). Active pollen count sampling using the Hirst design (Hirst 1952) was used to trap the pollen and the counting was done based on the standard method of the UK National Pollen Monitoring Network described in the British Aerobiology Federation (BAF) guide for trapping and counting airborne pollen and spores (BAF 1995). The trap has a built-in vacuum pump that sucks in pollen and other particles through an entrance orifice (i.e., active sampling). Behind the orifice there is a revolving drum covered with an adhesive-coated, transparent plastic tape. Particles in the air impact on the tape to produce a time-varying sample (Emberlin 2000). After its removal from the trap, the tape is divided into segments corresponding to 24-h periods. The segments are then examined under a

light microscope and a counting procedure is applied. In the UK, pollen grains are counted along twelve latitudinal transects (Smith et al. 2009). In contrast, Passive sampling is more dependent on gravity settling or removing pollen from the air by a normal Petri-dish. This method is simpler but suffers from bias as only the larger grains settle.

These traps are usually placed on the roof of a tall building mostly 10 m above the ground, with no obstacles around the building. The pollen count data for each year were the daily average pollen count (grains m⁻³) for each station with most of the data available during the pollen season. The remainder of the year had either no data or a very low pollen count; these data need to be excluded to avoid bias in the statistical analysis (Corden et al. 2002; Emberlin et al. 1997; Nilsson and Persson 1981; Sánchez Mesa et al. 2003; Smith et al. 2009; Stach et al. 2007). Several techniques were developed to estimate the start and end dates of the pollen season from the annual pollen count data. Three techniques were applied to estimate the start and end dates of the pollen season after the data were smoothed using a seven day moving average. The cumulative sum technique of Driessen et al. (1990) was used to determine the pollen starting seasons. The start dates of the birch and grass pollen seasons were defined as the day when the cumulative daily average pollen count (grains m⁻³) reaches a threshold of 75 (and 125) and is referred to as cumulative $\Sigma 75$ (and cumulative $\Sigma 125$). This technique is useful in forecasting as it does not rely on retrospective data (i.e., depend on data of the previous year) compared to other methods such as the total annual catch threshold (e.g., of 1%, 2.5% and 5%) which requires the total pollen catch of the previous season (Emberlin 2009).

In addition, a derivative method (DM) (Khwarahm et al. 2014) was used to define the start and end of both the grass and birch seasons. The derivative method is based on the inflection point which is the point on a curve where the curvature changes sign from positive to negative or *vice versa*. Additionally, the peak days where the highest counts of pollen were recorded are also indicated. First, the pollen count datasets were smoothed using a seven-day moving average and then the first derivative was calculated. The start of the pollen season was defined as the date when the first derivative was greater than five and remained positive for five consecutive days. Similarly, the end of season was defined as the date when the first derivative was less than five and remained

negative for five consecutive days after the peak date (day with largest count of pollen). The justification for a derivative threshold is based on the clinically significant amount of pollen that induces allergy: the definition used is that the six-day cumulative amount of pollen is at least 30 grains m⁻³. This amount of pollen has been classified as Moderate (25-50 grains m⁻³) by NPARU (National Pollen and Aerobiology Research Unit) based at the University of Worcester in the UK. According to NPARU, most sufferers develop an allergenic manifestation when pollen reaches the Moderate category (25-50 grains m⁻³ in the air). A similar argument may be given for the end of the season except that in most cases the end of the pollen season is longer (longer tail) due to re-suspension of pollen or pollen re-floatation. Furthermore, Koivikko et al. (1986) and Antepara et al. (1995) reported that 30-80 grains m⁻³ is the range likely to trigger an allergic reaction. Similarly, Mygind and Scadding (2000) reported that most patients develop allergic symptoms when the pollen count (of trees, grasses, weeds) reaches 25-50 grains m⁻³. Most importantly, this technique is not species-specific and also provides information on the end of the pollen season.

4.2.2 Landcover data

The Corine Land Cover 2000 (CLC2000) 100 m, version 9/2007 in TIFF raster format (European Commission, 2005) was used as a reference for grass and birch source areas (European Environment Agency (EEA) (<http://www.eea.europa.eu>)). The product provides coverage for most of Western Europe with 100 m spatial resolution. The data were resampled to the MTCI pixel size using a majority function and reclassified to five important classes which are seen as significant in their contribution to atmospheric pollen and can be considered as pollen sources for Birch and Grass. The classes were Broadleaf Forest, Mixed Forest, Green urban area, Grassland and Pasture. The first three classes were considered as main sources of Birch pollen and the last two as Grass sources. After the data were processed it was decided to aggregate the Grassland and Pasture classes together as the main source of grass pollen. Despite the fact that the Grassland and Pasture classes have differences in structure and management approach, they have quite similar spectral signals. Moreover, Timothy grass (*Phleum pratense*), a

very common species found in pasture throughout the UK, is known to produce allergic pollen.

Table 4-1 Corine land cover 2000 (CLC2000) standardized nomenclature (44 classes). The 5 classes highlighted in black are selected as sources of birch and grass in this study.

Class	Label 1	Label 2	Label 3
1	Artificial surfaces	Urban fabric	Continuous urban fabric
2	Artificial surfaces	Urban fabric	Discontinuous urban fabric
3	Artificial surfaces	Industrial, commercial and transport units	Industrial or commercial units
4	Artificial surfaces	Industrial, commercial and transport units	Road and rail networks
5	Artificial surfaces	Industrial, commercial and transport units	Port areas
6	Artificial surfaces	Industrial, commercial and transport units	Airports
7	Artificial surfaces	Mine, dump and construction sites	Mineral extraction sites
8	Artificial surfaces	Mine, dump and construction sites	Dump sites
9	Artificial surfaces	Mine, dump and construction sites	Construction sites
10	Artificial surfaces	Artificial, non-agricultural vegetated areas	Green urban areas
11	Artificial surfaces	Artificial, non-agricultural vegetated areas	Sport and leisure facilities
12	Agricultural areas	Arable land	Non-irrigated arable land
13	Agricultural areas	Arable land	Permanently irrigated land
14	Agricultural areas	Arable land	Rice fields
15	Agricultural areas	Permanent crops	Vineyards
16	Agricultural areas	Permanent crops	Fruit trees and berry plantations
17	Agricultural areas	Permanent crops	Olive groves
18	Agricultural areas	Pastures	Pastures
19	Agricultural areas	Heterogeneous agricultural areas	Annual crops, with permanent crops
20	Agricultural areas	Heterogeneous agricultural areas	Complex cultivation patterns principally occupied by agriculture
21	Agricultural areas	Heterogeneous agricultural areas	Agro-forestry areas
22	Agricultural areas	Heterogeneous agricultural areas	Agro-forestry areas
23	Forest and semi natural areas	Forests	Broad-leaved forest
24	Forest and semi natural areas	Forests	Coniferous forest
25	Forest and semi natural areas	Forests	Mixed forest
26	Forest and semi natural areas	Scrub and/or herbaceous vegetation	Natural grasslands
27	Forest and semi natural areas	Scrub and/or herbaceous vegetation	Moors and heathland
28	Forest and semi natural areas	Scrub and/or herbaceous vegetation	Sclerophyllous vegetation
29	Forest and semi natural areas	Scrub and/or herbaceous vegetation	Transitional woodland-shrub
30	Forest and semi natural areas	Open spaces with little or no vegetation	Beaches, dunes, sands
31	Forest and semi natural areas	Open spaces with little or no vegetation	Bare rocks

32	Forest and semi natural areas	Open spaces with little or no vegetation	Sparsely vegetated areas
33	Forest and semi natural areas	Open spaces with little or no vegetation	Burnt areas
34	Forest and semi natural areas	Open spaces with little or no vegetation	Glaciers and perpetual snow
35	Wetlands	Inland wetlands	Inland marshes
36	Wetlands	Inland wetlands	Peat bogs
37	Wetlands	Maritime wetlands	Salt marshes
38	Wetlands	Maritime wetlands	Salines
39	Wetlands	Maritime wetlands	Intertidal flats
40	Water bodies	Inland waters	Water courses
41	Water bodies	Inland waters	Water bodies
42	Water bodies	Marine waters	Coastal lagoons
43	Water bodies	Marine waters	Estuaries
44	Water bodies	Marine waters	Sea and ocean

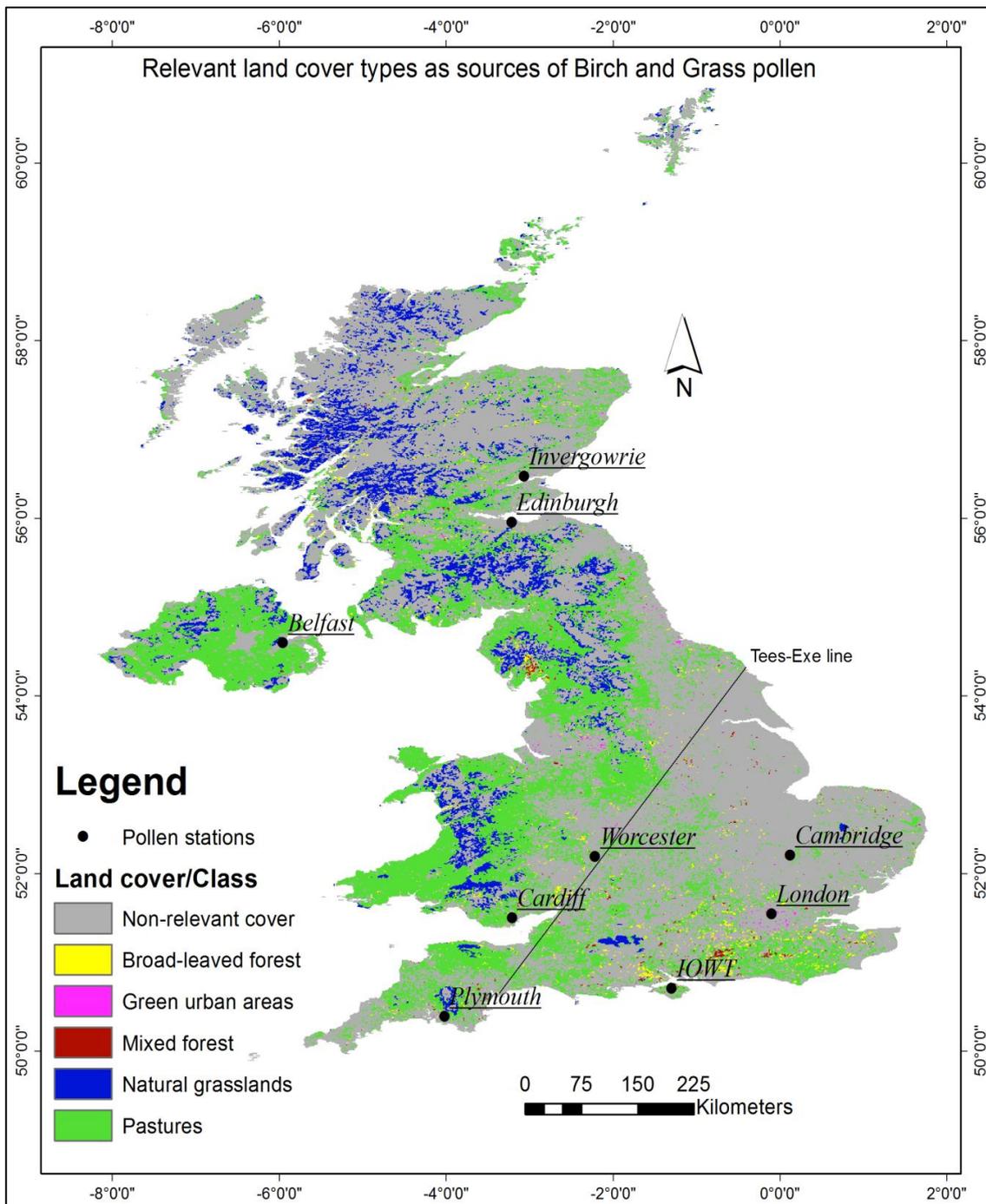


Fig.4-1 Source land cover types relevant to Grass and Birch and the location of the pollen stations. The Tees-Exe line (an imaginary line dividing the UK into lowland and upland regions) is shown.

4.2.3 MTCI data

A time-series of MTCI data (level 3 arithmetic mean composite) was obtained from the Natural Environment Research Council (NERC) Earth Observation Data Centre

(EODC) for the period 2003-to-2010 (<http://neodc.nerc.ac.uk>). The data are supplied by the European Space Agency (ESA) and processed by Geo-Intelligence division of Airbus Defence and Space. The composites were produced from standard MERIS L2 MTCI products using an arithmetic mean compositing and resampled into 1 km grid using a fast flux conversion algorithm. The algorithm uses the fast Sutherland-Hodgeman area clipping method to resample the orbital pixels into the desired grid (Sutherland and Hodgman 1974).

The MTCI data were composed of two sets: the 2003-to-2007 period was represented by an 8 days composite with 46 images and the 2008-to-2010 period was represented by a dekadal composite with 36 images for each year. The data were available in GEOTIFF format with latitude–longitude geocoded grids, accompanied by an XML metadata file and a JPEG browse image. The ground resolution for the MTCI composites (i.e., 8-day and 10-day composite) was 0.0089°.

Before, the data pre-processing the MTCI composites were stacked chronologically to produce a time-series layer stack for each year. The MTCI time-series data were processed by applying techniques described and discussed by Dash et al. (2010). The methods are briefly: (i) identifying and removing low-quality pixels caused by noise, (ii) filling data gaps with linear interpolation, (iii) smoothing images with the discrete Fourier transform (DFT), and (iv) estimating the phenological parameters.

Data smoothing was used to remove any residual cloud contamination and noise coming from the compositing and re-sampling procedures without compromising the phenological signal information in the time-series data. Careful consideration needs to be given to the choice of smoothing method (Boyd et al. 2011). There are several smoothing approaches for interpolation of removed erroneous or missing data in a time-series satellite product. An example is Gaussian model fitting in the Timesat software programme (Jönsson and Eklundh 2004). This approach has been used to remove noise in the composite data whilst preserving phenological event information (Jonsson and Eklundh 2002). Hird and McDermid (2009) compared various smoothing approaches statistically and reported that the double logistic and asymmetric Gaussian fitting methods performed comparatively more accurately. Some further approaches are: best index slope extraction (BISE) (Viovy et al. 1992), median filters (Vandijk 1987),

splines and weighted least-squares (White et al. 2005), discrete Fourier transformation (DFT) (Geerken et al. 2005; Jakubauskas et al. 2001), locally adjusted cubic-splines (Chen et al. 2006), and the double logistic function (Zhang et al. 2004). More recently, Roerink et al. (2011) used HANTS (Harmonic Analysis of NDVI Time Series) to process and analyse time-series satellite sensor data. The HANTS algorithm is based on the least-squares curve fitting of cosine-functions (Atkinson et al. 2012).

Here, the MTCI stacks were smoothed using the DFT with four harmonics (Jakubauskas et al. 2001). According to this approach a complete reconstruction of the phenological signals from the Fourier transform needs to consider the appropriate number of harmonics needed to capture a naturally varying phenological cycle. This study focuses on determining the onset of greenness and the end of season and it has been demonstrated that the first four harmonics can adequately capture these variables for natural vegetation (Dash et al. 2010). The Fourier transform approach has the advantage of minimal user input (Dash et al. 2010) and has been applied to many regional-to-global AVHRR time-series datasets (e.g., the Fourier-adjusted, sensor and solar zenith angle corrected, interpolated, reconstructed (FASIR) dataset (Los et al. 2000), and the temporal Fourier analysis (TFA) dataset (Hay et al. 2006)).

4.2.3.1 Estimating phenological variables from MTCI data

From the smoothed MTCI data stacks phenological parameters were estimated for the entire UK for each pixel across each of the eight years under investigation. The phenological parameters included onset of season (or onset of greenness), onset of flowering and peak of season for the most relevant land cover types (i.e., Broadleaf forest, Grassland).

Several quantitative methods exist to extract variables related to vegetation phenology, for example: inflection point methods, trend derivative methods and threshold-based methods (Reed et al. 1994; White et al. 2009; de Beurs and Henebry 2010). The inflection point phenology method is based on detecting points where maximum curvature occurs in a plotted time-series of vegetation indices, the trend or curve derivative phenology method attempts to identify points of departure between the original vegetation temporal signal and a derivative curve, and threshold-based methods

use either a pre-defined or relative reference value to define phenology transition dates (Fisher and Mustard 2007; Lloyd 1990). In this study, the inflection point approach of Dash et al. (2010) was used to derive key phenological parameters for two reasons: (i) it has the advantage of being easy to implement and also permits discrimination of multiple growing seasons for land cover types with multiple growth seasons such as crops (Reed et al. 1994) and (ii) one of the methods of defining the start of pollen season from pollen count data was the derivative method (DM) (see *pollen count data*), which is also based on the inflection point method. As a single phenology cycle following a smooth sinusoidal pattern, onset of season was defined as a valley point at the beginning of the growing cycle, peak of a season was defined as the maximum value of MTCI, and end of senescence was defined as a valley point occurring at the decaying end of the phenology cycle (Fig. 4-2).

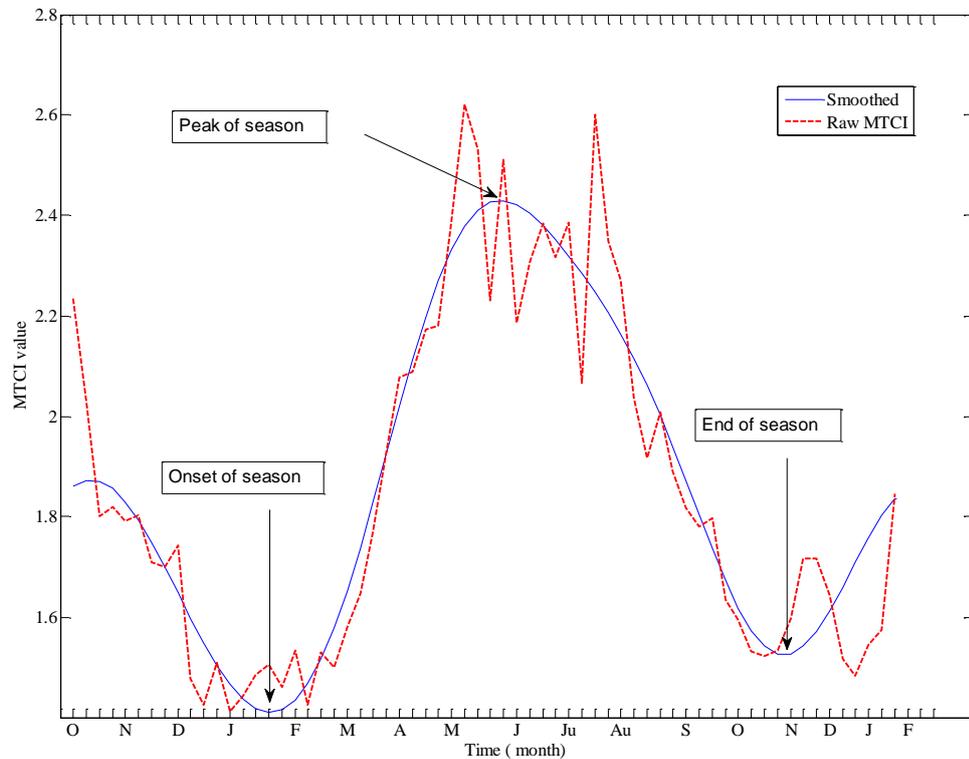


Fig.4-2 Raw and smoothed MTCI time-series for one pixel for one year and the position of the estimated phenological parameters (i.e., Onset of season, Peak of season and End of season).

4.2.3.2 Onset of flowering

Detection of flowering phenophases which occur at the same time or after the start of the season is challenging from time-series of vegetation indices. Several studies have documented a strong link between male flowering and the first date of budburst (Linkosalo 1999, 2000; Jato et al. 2002; Newnham et al. 2013). Thus, the correlation between male flowering and leaf budburst indicates that the phenophase observed as leaf budburst or start of season could be used to determine the timing of local birch pollen release. This was the rationale behind the study by Karlsen et al (2008) that provided a satellite-based observation of greenness of woodlands in Norway which was converted into a map that showed local flowering of birch. A similar argument can be used for grass considering the biological fact that the foliage development for most grasses precedes flower blooming. In other words, most grasses start flowering when the foliage development has almost reached a peak (i.e., peak in greenness from the MTCI profile). At the same time, the difference in time between flowering at the source and atmospheric pollen count should be acknowledged.

After estimating the onset of season and end of season (*section 4.2.3.1*), based on the birch and grass flower and foliage development process, a technique was developed to predict the timing of flowering by using (i) the mean temporal profile of the MTCI within a 50 km buffer of the pollen monitoring station and (ii) onset of pollen season derived from the pollen count data for the stations. The total pollen count dataset, for eight years and from nine pollen stations ($n=72$), was divided randomly into a calibration ($n=54$) and validation dataset ($n=18$). For the validation dataset, the randomly selected points were re-selected if there were more than three points per station or zero points per station.

For each station, the timing when the value of MTCI from the start of the season reaches 10% the MTCI maximum was determined and this was varied in 5% increments to define the start of flowering phenophases. The timing of the resulting start of season was correlated (Pearson's correlation) with the start of the pollen season. The MTCI onset of flowering for birch which is based on the Broad leaf forest land cover type demonstrated large significant correlations with the start of pollen season using the three methods (i.e., DM, $\Sigma 75$, $\Sigma 125$). Five out of the eight years produced significant correlations using the DM method with an average r -value for the eight years and for the nine sites of $r = 0.89$ (significant at the 0.01 level; St. Error= 3-4 days). The $\Sigma 75$

and $\Sigma 125$ both demonstrated significant correlations for seven out of eight years for the nine sites with an average r -value of $r = 0.96$ (significant at the 0.01 level; St. Error= 2 days) and $r = 0.93$ (significant at the 0.01 level; St. Error= 2.6 days), respectively (Tables 4-1 and 4-2).

Table 4-2 8-year average correlation between onset of the birch season defined from the pollen count (Derivative Method (DM), and Cumulative Sum 75 and 125 ($\Sigma 75$, $\Sigma 125$) methods), and defined from the MTCI (25% Maximum value of MTCI from SOS) for the nine stations across the UK.

Station	Year ave.8y	MTCI Day	DM		$\Sigma 75$		$\Sigma 125$	
			r	Day	r	Day	r	Day
Belfast		97	0.891**	107	0.962**	107	0.937**	110
Cambridge		85		94		96		97
Cardiff		92		98		99		101
Edinburgh		99		100		105		107
Invergowrie		101		107		109		111
IOWT		87		98		99		102
London		79		92		92		94
Plymouth		88		98		100		102
Worcester		86		93		95		96

** . Correlation is significant at the 0.01 level * . Correlation is significant at the 0.05 level

Table 4-3 Relationship between onset of birch season defined from the pollen count (Derivative Method (DM), and Cumulative Sum 75 and 125 ($\Sigma 75$, $\Sigma 125$) methods), and defined from the MTCI (25% Maximum value of MTCI from SOS) for nine stations across the UK.

Year	DM		$\Sigma 75$		$\Sigma 125$	
	r	St error	r	St error	r	St error
2003	0.590	7.4	0.880**	4.8	0.913**	3.7
2004	0.800**	6.6	0.764*	7.1	0.784*	6.9
2005	0.725*	5.5	0.737*	5.4	0.782*	4.9
2006	0.603	5.2	0.606	5.1	0.600	5.2
2007	0.391	8.7	0.770*	6.0	0.720*	6.5
2008	0.803**	6.6	0.870**	5.4	0.862**	5.6
2009	0.698*	5.4	0.755*	4.9	0.761*	4.9
2010	0.902**	3.4	0.730*	5.4	0.779*	4.9
Aver.	0.891**	3.4	0.962**	2.0	0.937**	2.6

** . Correlation is significant at the 0.01 level * . Correlation is significant at the 0.05 level

For grass, the three methods produced significant correlations for five out of eight years for the DM method and seven out of eight years for the $\Sigma 75$ method and eight out of eight years for the $\Sigma 125$ method for the nine sites across the UK. For the average of

eight years the r -value for the methods were: for DM the $r=0.83$ (significant at the 0.01 level; St. Error=4 days), for $\Sigma 75$ the $r=0.93$ (significant at the 0.01 level; St. Error=2.7 days), and for $\Sigma 125$ the $r=0.94$ (significant at the 0.01 level; St. Error=2.5 days) (Tables 4-3 and 4-4). The $\Sigma 75$ method for defining the birch pollen season seemed to produce closer agreement with the 25% maximum MTCI onset of flowering date than the other methods. The $\Sigma 125$ method for defining the grass pollen season produced closer agreement with the 75% maximum MTCI onset of flowering date than the DM and $\Sigma 75$ methods.

Table 4-4 8-year average correlation between onset of the grass season defined from the pollen count (Derivative Method (DM), and Cumulative Sum 75 and 125 ($\Sigma 75$, $\Sigma 125$) methods), and defined from the MTCI (75% Maximum value of MTCI from SOS) for the nine stations across the UK.

Station	Year ave.8y	MTCI Day	DM		$\Sigma 75$		$\Sigma 125$	
			r	Day	r	Day	r	Day
Belfast		152	0.839**	158	0.932**	150	0.944**	156
Cambridge		138		150		143		148
Cardiff		151		154		153		156
Edinburgh		152		160		156		161
Invergowrie		156		162		158		162
IOWT		139		143		138		145
London		140		152		144		149
Plymouth		146		150		144		149
Worcester		138		150		139		146

** . Correlation is significant at the 0.01 level * . Correlation is significant at the 0.05 level

Table 4-5 Relationship between onset of grass season defined from the pollen count (Derivative Method (DM), and Cumulative Sum 75 and 125 ($\Sigma 75$, $\Sigma 125$) methods), and defined from the MTCI (75% Maximum value of MTCI from SOS) for nine stations across the UK.

Year	DM		$\Sigma 75$		$\Sigma 125$	
	r	St error	r	St error	r	St error
2003	0.883**	3.3	0.682*	5.2	0.877**	3.4
2004	0.685*	3.8	0.793*	3.2	0.798**	3.2
2005	0.611	8.9	0.816**	6.5	0.773*	7.1
2006	0.704*	6.0	0.604	6.8	0.755*	5.6
2007	0.904**	2.4	0.831**	3.1	0.896**	2.5
2008	0.325	5.8	0.815**	3.5	0.823**	3.5
2009	0.678*	11.6	0.789*	9.7	0.755*	10.4
2010	0.562	7.7	0.781*	5.8	0.804**	5.6
Aver.	0.839**	4.1	0.932**	2.7	0.944**	2.5

** . Correlation is significant at the 0.01 level * . Correlation is significant at the 0.05 level

For birch, the timing of flowering was defined as the time after the onset of the growing season when the MTCI value reaches 25% of the maximum. Similarly for grass this was defined as the time when MTCI reached 75% of the maximum (Fig. 4-4). The 75% and 25% thresholds were selected as they demonstrated smaller standard errors compared to the other thresholds (e.g., 85% or 35% of the maximum value of MTCI) (Fig. 4-3).

The above technique was applied to each pixel (i.e., $0.0089^\circ \sim 1$ km) for the UK to produce detailed onset of flowering pollen maps of birch and grass across the UK. The maps (i.e., 8-year average for 2003-to-2010) for grass and birch depict the spatial variation in the onset of flowering and were validated with pollen count data from the nine pollen monitoring stations.

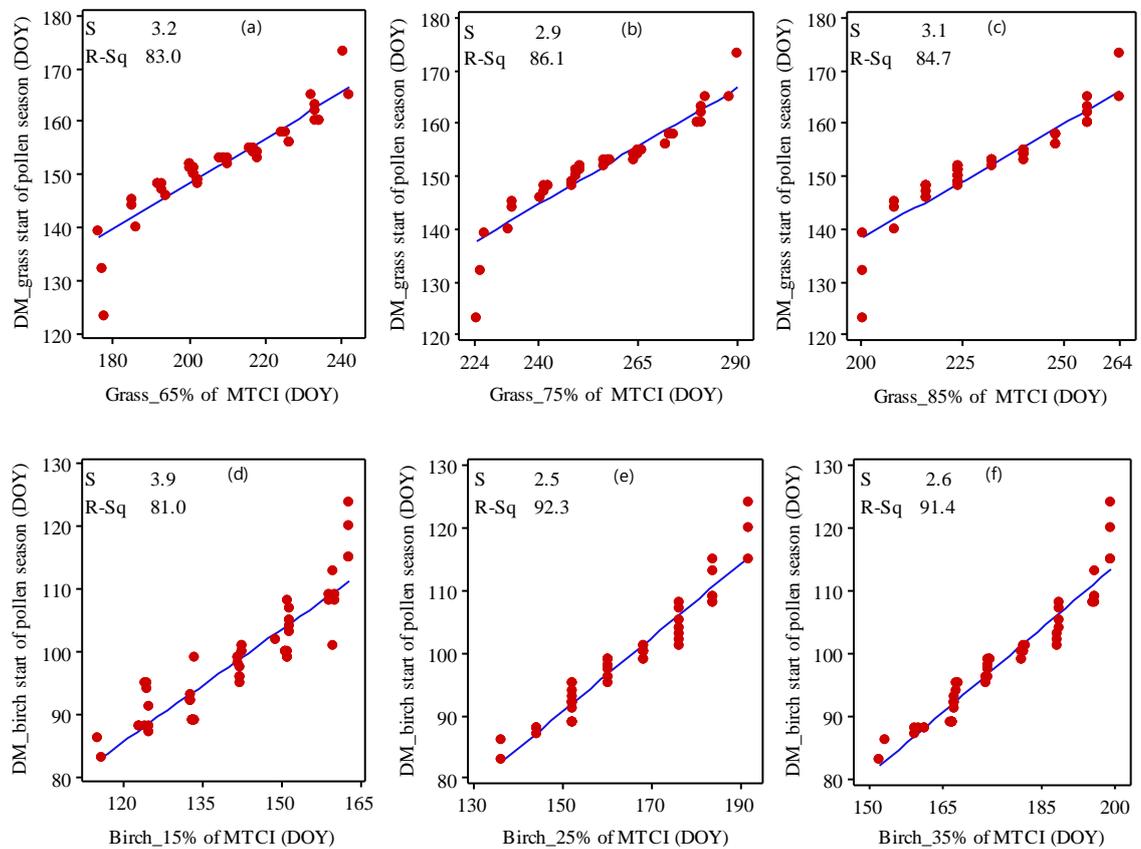


Fig.4-3 Estimated standard error (S) and coefficient of determination ($R-Sq$) derived from the regression line for ($N=54$) points of the observed start dates of grass (top (a,b,c)) and birch (bottom (d,e,f)) seasons from pollen count (y -axis) and the estimated start dates from grassland MTCI and broad leaf forest MTCI within a 50 km buffer around the nine pollen sites for the period of 8 years.

Apart from natural annual variation in the start of the pollen season, the transport of pollen and unpredictable weather conditions (e.g. strong gust and storm) also play an important role in affecting the magnitude of the local pollen season. The transport of pollen could unpredictably advance the local pollen season at a certain site (e.g. IOWT, London and Belfast). In general, the pollen season estimated from the MTCI data starts 7-13 days earlier than the start dates defined from the pollen count data. These discrepancies in the start of the pollen season together with the spatial extent of the points (i.e., the nine sites) led to some points appearing as outliers regardless of the fact that there was a spatial trend (Fig. 4-3).

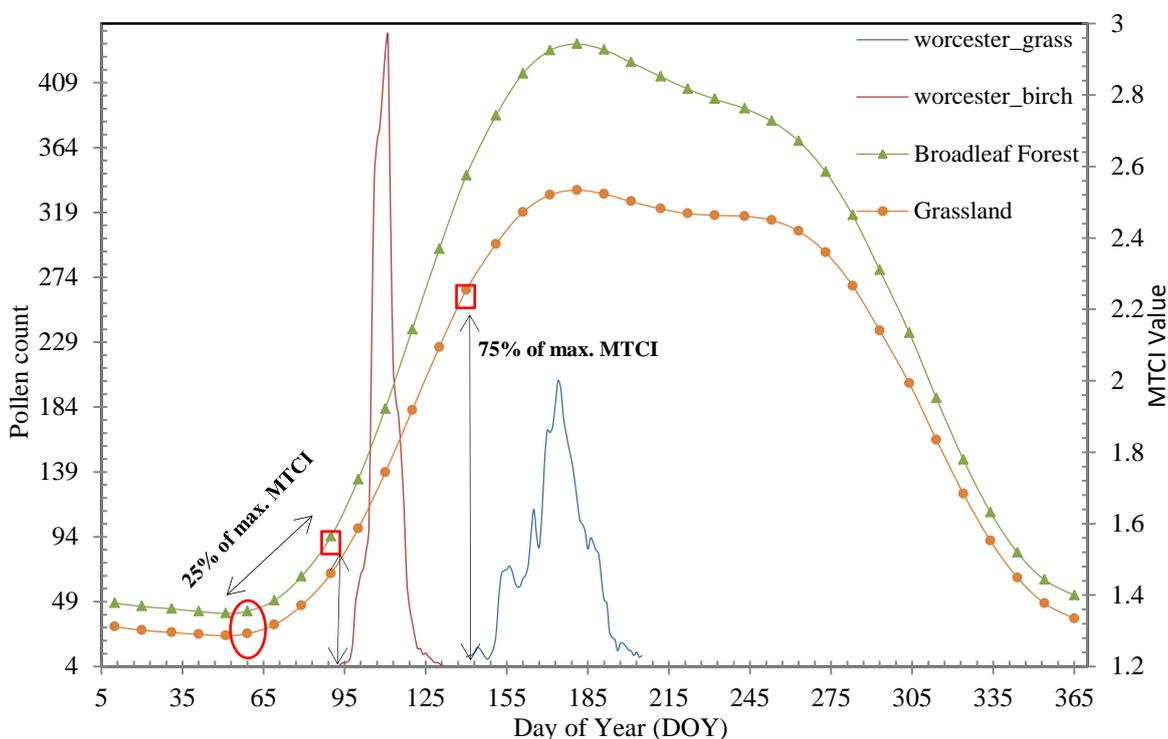


Fig.4-4 Determination of flowering season of birch and grass as 25% (square shape on the broadleaf forest profile) and 75% (square shape on the grassland profile) of the maximum value of MTCI, respectively, from the onset of the season (SOS) (circular shape). The birch and grass pollen profiles (seasons) at Worcester are shown.

4.2.3.3 Relationship between onset of flowering and pollen count data

After the onset of flowering for birch and grass was defined from the MTCI time series data within a 50 km buffer around the stations (*section 4.2.3.2*), a correlation analysis (bivariate Pearson’s product-moment correlation) with the start of pollen season

(estimated using the three methods defined in *section 4.2.1*) was undertaken for the nine stations across the UK. The 50 km buffer around the stations was used to define the average start dates of flowering season for both birch and grass by averaging only those pixels within the buffer and only those pixels of the land cover classes of relevance (*section 4.2.2*). The start dates of onset of flowering (in Day of Year (DOY)) were correlated with the start dates of grass and birch pollen season (DOY) for the period 2003-to-2010.

4.2.3.4 Validation of the onset of flowering maps

The onset of flowering for each pixel for each year for the whole of UK for the MTCI data under investigation (i.e., 2003-to-2010) was estimated (*section 4.2.3.2*). From this we produced two maps: (i) an 8-year average (2003-to-2010) start of season for Broadleaf forest (ii) an 8-year average start of season for Grassland. These maps show the timing of flowering that is coincidental with the start of the pollen season for the entire UK.

The Validation was undertaken based on a correlation analysis between the corresponding pollen start dates from the validation data ($n=18$) and onset of flowering maps (i.e., within the 50 km buffer).

4.3 Results

4.3.1 Onset of pollen season from pollen count data

Spatio-temporal variation exists in the start of the grass and birch pollen seasons across all the sites. This spatial variation is due to the relationships between the start dates, defined by the methods, and the latitudes with different regional climates which influence the phenological development of grass and birch over time. As expected, the start of season, for both grass and birch, is earlier in the south and tends to be later as one moves northwards. For grass, for example, the season starts at 138 DOY (17 May) in the Isle of Wight (IOWT) whereas for Edinburgh the average start of season was detected at 156 DOY (4 June) using the $\Sigma 75$ method. For birch, for example, the season starts in IOWT at 99 DOY (8 April) whereas for Edinburgh the average start date of the season was 105 DOY (14 April) using the $\Sigma 75$ method. For the derivative and $\Sigma 125$

methods a similar south-to-north delay in the start of the season was observed. In Plymouth, the birch season started 9 days earlier than in Invergowrie using the $\Sigma 75$ method. Similarly, the grass pollen season in Plymouth started 13 days earlier than in Invergowrie using the $\Sigma 125$ method. From the three methods used to define the pollen season, the $\Sigma 75$ method estimated the earliest start dates, whereas the $\Sigma 125$ and derivative methods are more similar, especially for the grass season. In contrast, the derivative method estimated the earliest start dates for the birch season compared to the $\Sigma 75$ and $\Sigma 125$ methods. Yet, the three methods equally revealed the south-to-north trend in the start of season (Fig.3-3).

The difference in days within a pollen monitoring site over time was generally 7-14 days depending on variation in the local weather conditions prior to and during the pollen season. Across all the stations the birch season started earlier than the grass season by an average of 54, 45, 49 days (for the DM, $\Sigma 75$ and $\Sigma 125$ methods, respectively). The length of the birch season across all the stations was on average 21.5 days, whereas for grass it was 56.3 days.

4.3.2 Validation of onset of flowering

As expected, there was statistically significant agreement between the ground pollen start date observations of both the grass and birch seasons defined by the three methods (*section 4.2.1*) and the MTCI onset of flowering of grass and birch individual year maps (Fig. 4-6) (*sections 4.2.3.2 to 4.2.3.4*). MTCI onset of flowering for grassland and the start dates of the grass pollen season from the DM method produced the largest statistically significant positive correlation ($r = 0.71$; significant at the 0.01 level; St. Error(S) = 3.7 days). The $\Sigma 75$ method demonstrated a relatively smaller statistically significant positive correlation ($r = 0.49$; significant at the 0.05 level; St. Error(S) = 8.4 days). Similarly for birch (Fig. 4-6), statistically significant correlations were produced between pollen start dates defined by the three methods and the onset of flowering of Broad leaf forest. The correlation was stronger than for grass but produced larger standard errors (for DM $r = 0.74$; significant at the 0.01 level; St. Error(S) = 7.2 days: for $\Sigma 125$ $r = 0.72$; significant at the 0.01 level; St. Error(S) = 7.1 days: for $\Sigma 75$ $r = 0.74$; significant at the 0.01 level; St. Error(S) = 7 days).

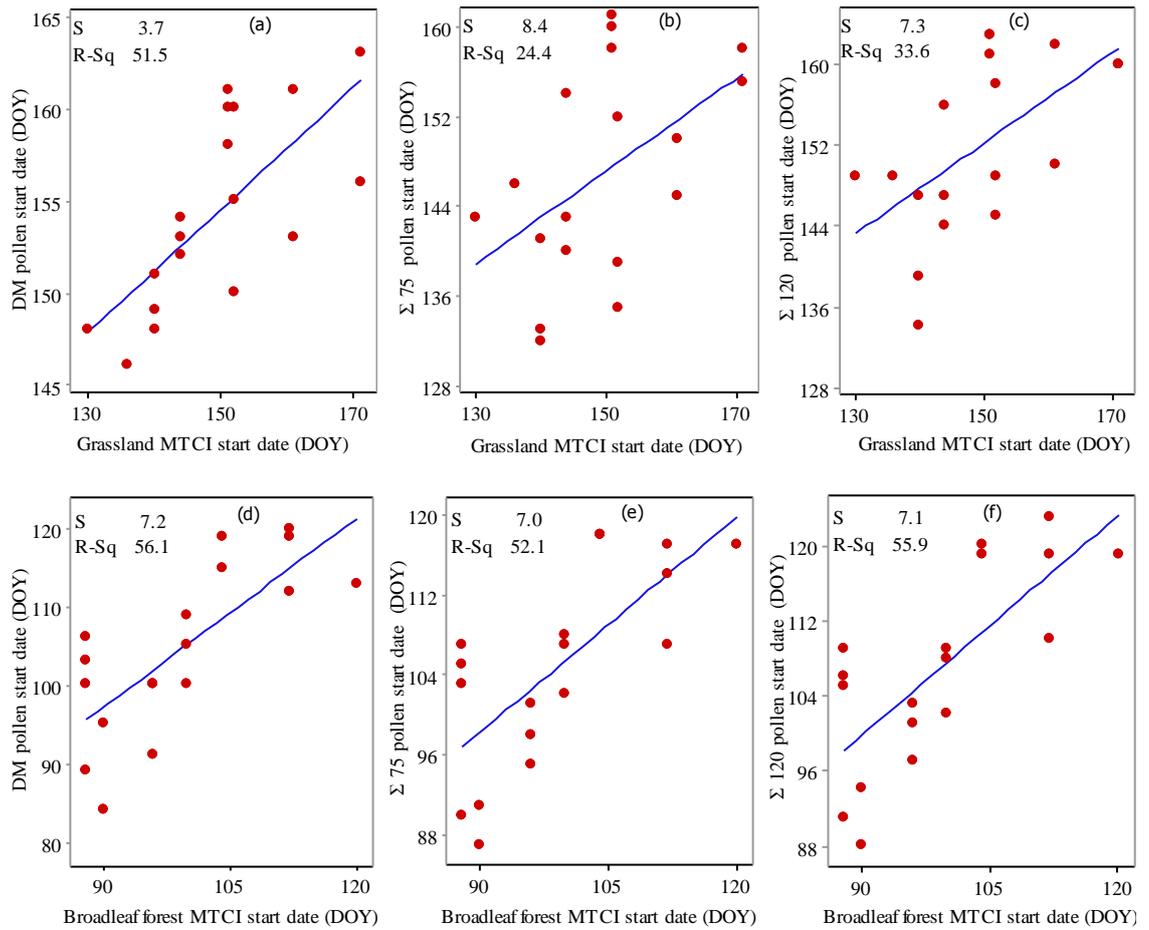


Fig.4-5 Regression of pollen start date estimated using the (a, d) DM, (b, e) $\Sigma 75$ and (c, f) $\Sigma 120$ methods for (a, b, c) grass pollen and (d, e, f) birch pollen against MTCI start date for (a, b, c) grassland and (d, e, f) broadleaf forest within a 50 km buffer around the nine pollen sites, for a random selection of 18 of the possible points. Estimated standard error (S) and coefficient of determination (R-Sq) are shown.

4.3.3 Start of flowering across UK

The start of flowering pattern for the UK demonstrated variation from year-to-year for the period of 8-years (2003-to-2010). A clear spatial gradient in the start of flowering for both birch and grass can be observed (Tables 4-1 and 4-3). For example, the flowering dates for birch for northern sites (i.e., Belfast, Edinburgh, and Invergowrie) are 97, 92, and 101, respectively, whereas for the southern sites (i.e., IOWT, Plymouth, London, Worcester, and Cambridge) are 87, 88, 79, 86, 85 DOY, respectively. The London area demonstrated earlier flowering dates in comparison to other sites due to the

urban heat island effect. A similar south-to-north trend was also demonstrated by the grass flowering dates (Table 4-3 and Fig. 4-8).

The patterns observed reflect the unique composition of a patchy landscape, the unique climate and the varied topography of the UK. The flowering patterns of both birch and grass reveal more than just a south-to-north trend, and are influenced also by proximity to the coast. The distribution of broad-leaved forest is mostly in southern England spreading in a patchy pattern towards the north. The average start of flowering for birch in the southwest, for example, in Plymouth was 88 DOY, yet there were some areas that demonstrated flowering before and after that date depending on the proximity of these pixels to urban areas and the coast. A similar pattern was observed for other sites, for example, for Cardiff and Worcester. In the remote highlands of Scotland (Grampian Mountain areas) early flowering dates of birch can be observed far from residential areas (Fig. 4-7). The early flowering is due to the fact that Downy birch is the most abundant birch type which prefers cooler and wetter environments (UK Forestry Commission).

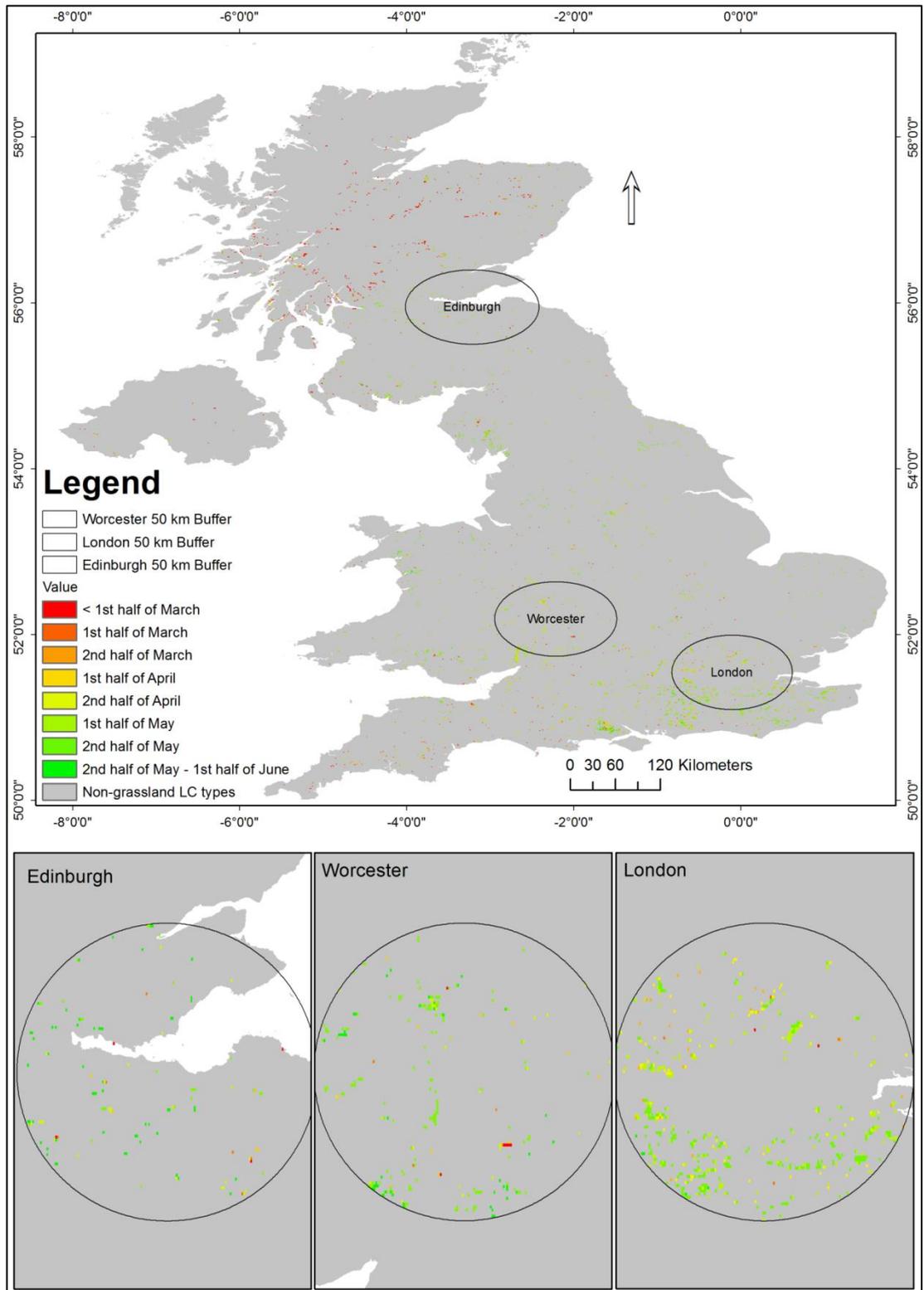


Fig.4-6 8-year average MTCI-based onset flowering map of broadleaf forest as a source of birch pollen. The map depicts the spatial variation in the onset of flowering coincidental with the start of the pollen season.

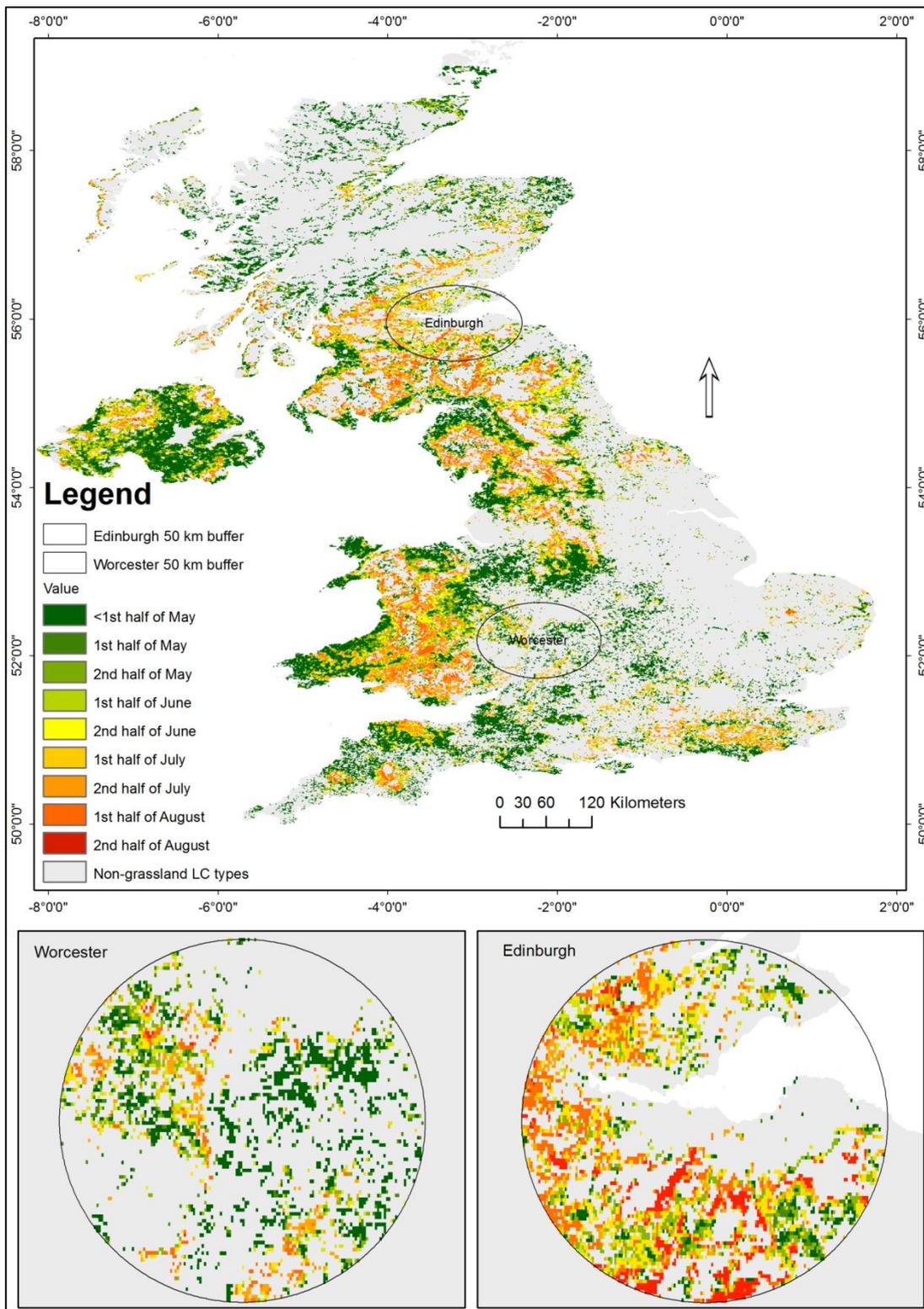


Fig.4-7 8-year average MTCI-based onset flowering map of grassland as a source of grass pollen. The map depicts the spatial variation in the onset of flowering coincidental with the start of pollen season.

4.4 Discussion

4.4.1 Onset of pollen season from pollen count data

Employing various methods, this research quantified the spatial and temporal variation in the start of the grass and birch pollen seasons in the UK. Generally, as expected the pollen seasons start earlier in the southern of the UK than they do in the north. More importantly, the research quantified the expected local values in the absolute sense and their relative variation across space and time. The average of the 8-year time-series shows that the birch pollen season in Plymouth starts ($\Sigma 75$) 9 days earlier than at Invergowrie and 6 days earlier than at Edinburgh. Similarly, the grass pollen season in Plymouth starts ($\Sigma 125$) 13 days earlier than at Invergowrie and 12 days earlier than at Edinburgh. These results concur with previous studies focused on regional variation in pollen counts (Corden et al. 2000; Emberlin et al. 2000; Sánchez Mesa et al. 2003). Climate variation across the UK causes spatial variation in the timing of the onset of the pollen seasons. Increases in temperature in the spring influence phenological development, including the timing of flowering or anthesis prior to the main pollen season (Emberlin et al. 1999). The earlier the start of flowering, the earlier the end of the annual life cycle of grass and birch, but not necessarily the end of the pollen season due to the possibility of pollen being transported in the air as well as re-suspension.

Using the pollen data we were able to estimate the average length of the pollen season across all stations as 21.5 days for birch, and 56.3 days for grass in the UK. The length of pollen seasons is generally dependent on factors that influence the phenological development of vegetation, and the abundance and dispersal of pollen such as local vegetation type, altitude, land use and climate (Emberlin et al. 2000; Green et al. 2004; Jato et al. 2009; Sabariego et al. 2011). In addition, factors such as local topography and urban climate (including the urban heat island effect) that affect early flowering of local plants and re-suspension of pollen are also important, and are also likely causes of the early start of the birch pollen season in London.

4.4.2 Relationship between MTCI-based onset of flowering and pollen count data

The simple mathematical technique used to define the onset of flowering of birch and grass was based on phenological development, especially the leaf emergence phenophase temporal profile, measured indirectly using a satellite sensor chlorophyll index (i.e., MTCI). The temporal profile provides information on the timing of flowering which is coincidental with pollen release and hence the pollen season and the emergence of hay fever symptoms. Moreover, the MTCI-based prediction of flowering phenophase is effectively a spatial representation of birch and grass pollen sources tagged with the timing of a biological event (i.e., flowering phenophase) which varies from year-to-year depending on environmental conditions, especially temperature, in the UK. The spatial representation of birch and grass sources is at the 1 km pixel ground resolution for the whole UK; this information is extensive in comparison to the limited number of pollen monitoring sites across the country. Importantly, the combination of the MTCI-predicted timing of flowering at the ‘source’ areas together with the (ground measured) pollen profile at the ‘sink’ or receptor has the potential to increase our understanding of local variation in pollen, local start date and length of pollen season.

This research found statistically significant positive correlations between the pollen count-derived starting dates of the pollen seasons of both birch and grass, and the MTCI-based start dates, indicating the suitability of using the MTCI to predict the start of pollen season indirectly, potentially in combination with relevant weather parameters, for example, temperature and precipitation. This result supports the study by Karlsen et al. (2008a) which used a threshold of MODIS NDVI to define the start of the birch pollen season and related it with pollen season start date. The slightly smaller correlation coefficients for grass are likely related to the larger number of grass species in the UK and, thus, the various physiological differences in leaf development. In the UK, there are about 150 species of grass, although only around 12 species significantly contribute pollen to the atmosphere (Emberlin et al. 1999). Conversely, the most commonly found species of birch in the UK are Downy birch (*Betula pubescens*) and Silver birch (*Betula pendula*).

4.4.3 Spatial variation in the birch and grass flowering across the UK

The MTCI-based flowering phenophases of birch and grass estimated in this research vary spatially and temporally (2003-to-2010). The spatio-temporal variation is determined by weather conditions during and preceding a growing season (Sánchez Mesa et al. 2003). Apart from spatio-temporal variation, local variation (i.e., pixel-based) was also noticed near residential areas, most likely due to the influence of the urban heat island on phenological development.

Both birch and grass MTCI-based flowering maps showed a south-to-north spatial pattern and, hence, produced large positive correlations with the corresponding dates of the pollen sites. Yet, a smooth gradient from south-centre-north is not obvious due to the uneven distribution of grass and birch land cover types across the UK and influence of microclimate. For example, with regard to the birch distribution on the IOWT, the upper southern region has only a few pixels whereas many pixels exist near London. Furthermore, the 50 km buffer average of the dates of flowering is more realistic in terms of spatial representation of the dates of flowering where the buffer fully intersects with the cover types, for example, in Worcester and London.

4.4.4 Use of MTCI-based map of onset of birch and grass flowering

Currently, the Met Office pollen forecast in the UK (<http://www.metoffice.gov.uk>) is based mainly on the pollen counts being collected at various stations for various regions across the country linked to weather conditions. The pollen stations are distributed based on regional climate variation. The pollen forecast for each region is based on pollen counts from the pollen stations and subjective evaluation of weather forecasts and pollen counts from previous years. The produced link between the pollen data and relevant weather variable or predictors is mostly a statistical one. The MTCI-based onset of flowering maps of birch and grass (which present the average 8-year variation for the UK) together with the pollen forecast from the Met Office provide more accurate information to allergy sufferers and such maps could be used as (i) a reference for new pollen stations to be established in terms of spatial representation (Karlsen et al. 2008a), and (ii) they could provide up-to-date geographically complete coverage of the source

distribution. Thus, averaging the results over many years for onset of flowering is necessary to develop a reference map of the mean timing of onset of birch flowering, given the large variation in the timing of the flowering from year-to-year (Karlsen et al. 2008a).

Long distance transport of pollen, especially birch pollen that may advance the local pollen season, is well documented (Mahura et al. 2007; Oikonen et al. 2005; Ranta et al. 2006; Skjøth et al. 2008a; Skjøth et al. 2008b). The MTCI-based prediction of birch flowering does not necessarily reflect the experienced local timing of the pollen season. The transport of pollen in the UK may vary from region-to-region, for example, as a function of topography. England consists mostly of lowland terrain, with upland or mountainous terrain only found north-west of the Tees-Exe line (an imaginary line dividing the UK into lowland and upland regions, Fig. 4-1), whereas the rest of the country (i.e., Scotland, Wales, and Northern Ireland) has more mountainous topography. Thus, England is more likely to be affected by regional transport of pollen than the rest of the country. Smith et al. (2005) reported grass pollen in the UK (i.e., in Worcester city: Midland of England) that originated from continental Europe. Considering the size of the buffer (i.e., 50 km buffer around the pollen sites) used in this research, the recorded large correlation between MTCI-based date of onset of flowering of birch and grass and the start dates of their corresponding pollen seasons defined using three threshold methods (Tables 4-1 and 4-3) raises the question of how significant is the role of pollen transport in influencing the local start of pollen season in the UK.

Although high positive correlations were observed in this research suggesting the applicability of satellite sensor data to predict pollen release, theoretically it would be desirable to account for the known physical pollen transport mechanisms when mapping local pollen count, particularly for allergy sufferers who, in general, experience pollen at sink (i.e., pollen sites which, in most cases, are located in urban areas), not at source (i.e., cover classes identified as sources of pollen emission). The use of phenological models together with weather parameters could help address this issue and, thus, increase the correlations reported here.

4.5 Conclusion

The use of satellite sensor data to characterise vegetation phenology is well documented (White and Nemani 2006; Seaquist et al. 2009; Reed et al. 2009; de Beurs and Henebry 2010; Roerink et al. 2011; Jeganathan et al., 2014). In this study, MERIS MTCI data were used to estimate the timing of onset of pollen release (or flowering) at source locations for two important aeroallergens in the UK. Specifically, the onset of flowering determined from MTCI produced a high positive correlation with the timing of start of pollen season determined from ground pollen station data using the cumulative and derivative methods. Thus, it was demonstrated that MTCI-based estimation of the flowering phenophase of birch and grass can be used to predict the start of the birch and grass pollen seasons in the UK. This information provides an important potential input to atmospheric dispersion models for pollen forecasting.

As far as this study is aware of, this is the first time that remote sensing has been used to estimate the phenological phases related to pollen release in the UK, and worldwide such investigations are rare (Karlsen et al. 2008a; Luvall et al. 2011). The methodology of determining the flowering phenophase of birch and grass from a vegetation profile demonstrated here is novel and it has great potential for use in pollen forecasting and the flexibility to be applied elsewhere in the world.

CHAPTER 5: Satellite-based predictive models for birch and grass pollen in the United Kingdom³

5.1 Introduction

Early prediction of allergenic pollen counts in the air can be valuable for medical professionals, allergy sufferers and pharmaceutical companies. The increasing prevalence of allergic diseases, mainly hay fever, triggered by aeroallergens affects hundreds of millions of people worldwide (Bousquet et al. 2008). In the United Kingdom, the most common types of allergic pollen are birch and grass, which, respectively affecting approximately 25% and 95% of the population of the hay fever sufferers (Emberlin et al. 1999). In Europe, the overall prevalence of hay fever is approximately 15–20% (Aas 1997). The highest prevalence occurs in late adolescence/early adulthood, with between 8 and 35% of young adults in the European Union having IgE (Immunoglobulin E) serum antibodies to grass pollen (Burr 1999; D'Amato 2000).

Aerobiologists often monitor and record the amount of daily airborne pollen (daily average grains m^{-3}) from pollen monitoring sites. These data can be used in construction of models to predict various characteristics of the pollen season, for example, start of the season, severity of the season (Dahl and Strandhede 1996; Stach et al. 2008a), peak of the season, end of the season (Stach et al. 2008b), magnitude of the season (Smith et al. 2005) and daily pollen concentration (Angosto et al. 2005; Voukantsis et al. 2010; Makra and Matyasovszky 2011). The abundance and concentration of pollen in the air depends on various environmental factors including meteorology at various scales, biological status of plants, geology (topography), land use, and atmospheric condition for dispersion (Rousi and Pusenius 2005; Emberlin 2009; Sabariego et al. 2011).

Various empirical or statistical techniques have been used to predict the amount and distribution of the allergic pollen season. The techniques are generally either complex or simple regression models using meteorological factors as covariates. In the United Kingdom, some early work has produced predictive models for a limited number of

³ Nabaz Khwarahm, Jadunandan Dash, Peter M. Atkinson, C. A. Skjøth, R. M. Newnham, B. Adams-Groom, K. Head, Eric Caulton. Under preparation for submission to journal of Environmental Research

sites (Davies and Smith 1973; Norris-Hill 1995; Adams-Groom et al. 2002; Smith and Emberlin 2005; Smith and Emberlin 2006). In the Netherlands Spieksma (1980) and Sweden Bringfelt et al. (1982) statistical models have been developed to predict birch and grass pollen concentrations. Frenguelli et al. (1989) and Fornaciari et al. (1998) modelled the start of olive and grass pollen seasons at two sites in Italy. In Australia Ong et al. (1997) built a linear regression model based on an inverse relationship between the date of the onset of the grass pollen season and the sum of rainfall for July. Laaidi et al. (2003) proposed two statistical methods to forecast the start and duration of the ragweed pollen season in Lyon in France. They employed a multiple regression model and a cumulative temperature sum model drawing thresholds from the start of the season. In Spain Sánchez Mesa et al. (2003) used a co-evolutive neural network and linear regression models in forecasting daily grass pollen concentration. Furthermore, recently, some studies have extended modelling of the main characteristics of the allergic pollen season, employing neural network analysis (Rodríguez-Rajo et al. 2010), data-driven analysis or computational Intelligence (CI) methods (Voukantsis et al. 2010) and a process-based model (García-Mozo et al. 2009).

In general, few studies have been conducted on pollen using physiology-based or process-based models other than receptor-based models due to their complexity. Most of the studies mentioned above employed the receptor-based approach for forecasting the main characteristics of the allergic pollen season. In other words, the pollen count data from monitoring stations were used together with meteorological data to estimate the behaviour of pollen through the season without the knowledge of source conditions (Norris-Hill 1995). However, pollen count, apart from meteorological parameters, also varies as a function of the flowering rhythm at the source (Bringfelt et al., 1982).

Satellite sensor data provide a unique opportunity to determine source and phenology events or variables (Karlsen et al., 2008a). Phenological events such as leaf budburst and flowering phenophase characterise the stages of vegetation development during the growing season and can be derived indirectly from satellite sensor image analysis. Thus, they can be related to biological definitions of plant phenology, for example, the flowering phenophase can be related to pollen release. Satellite remote sensing provides a spatially complete coverage that can be used to interpolate traditional ground-based phenological observations. This indicates that remote sensing measurement of the

flowering phenophase of aeroallergens like birch and grass from remote sensing could be used to predict the timing of local pollen release (Karlsen et al., 2008). Satellite sensor images have been used widely to detect variables related to vegetation phenology, for example, the start of season (start of growing season) and end of season (Lloyd 1990; Reed et al. 1994; Fisher and Mustard 2007; Dash et al. 2010; Roerink et al. 2011).

A relatively small number of studies have used time-series of satellite-derived vegetation indices to characterise important phenological variables related to pollen release. Hogda et al. (2002) used coarse spatial resolution satellite sensor data, specifically Global Inventory Monitoring and Modeling System (GIMMS) Normalized Difference Vegetation Index (NDVI), to characterise the start of birch pollen season in Fennoscandia. They related the NDVI time-series with birch pollen count data from five stations, and reported correlation coefficients (r) in the range 0.55 to 0.85. Similarly, Karlsen et al. (2008a) used finer spatial resolution satellite sensor data, specifically Moderate Resolution Imaging Spectroradiometer (MODIS) NDVI with 250 m spatial resolution and 16-days compositing to determine the start of birch flowering in Norway. They reported larger positive correlations between station pollen count data and start of birch flowering. Furthermore, Luvall et al. (2011) used MODIS Enhanced Vegetation Index (EVI) to characterise the start of Juniper flowering, which is also categorised as an aeroallergen.

Vegetation phenological changes during the growing season can be studied by examining changes in the remote sensing-based Medium Resolution Imaging Spectrometer (MERIS) Terrestrial Chlorophyll Index (MTCI) value (Dash and Curran 2004). The MTCI related-chlorophyll index from the MERIS sensor, onboard the Envisat satellite, provides global coverage every three days and acquires data in 15 spectral bands at 300 m and 1.2 km spatial resolutions, and is well suited for plant phenology studies (Reed et al. 2009). MTCI is related directly to canopy chlorophyll content and is, thus, a function of chlorophyll concentration and leaf area index (LAI) (Dash and Curran 2007).

The main goal of this paper was to construct short-term (daily) predictive models for nine sites in the United Kingdom using time-series of pollen count data as the predicted

variable, and meteorological and satellite sensor-driven flowering phenophase as the covariates, for both birch and grass aeroallergens. First, a technique was developed to define the onset of flowering for both birch and grass using the MTCI data at a spatial resolution of 0.0089° (~1 km by ~1 km) from the MERIS sensor. Second, a technique was developed to define the start of the birch and grass pollen seasons from pollen count data for the nine pollen monitoring sites. Third, detailed correlation analysis was performed between the birch and grass pollen seasons and the meteorological and flowering phenophase covariates at five temporal supports including: the same day, 1-day prior, 1-day mean prior, 3-day mean prior, and 7-day mean prior. Fourth, eighteen multiple linear regression models were constructed for the nine sites (nine each for birch and grass) and the accuracy of each was tested with two years of independent pollen count data.

5.2 Materials and methods

5.2.1 Birch and grass pollen data

The British Aerobiology Federation (BAF) describes a standard for trapping and counting pollen and spores in the air. This standard, adopted by the UK National Pollen Monitoring Network was the method used to acquire data on birch and grass pollen as daily average grains m^{-3} (BAF 1995). The dataset for the period of (2003-2010) was obtained for nine UK sites within the National Pollen and Aerobiology Research Unit (NPARU) from the University of Worcester (Fig.4-1). Details provided in (*section 4.2.1 Pollen count data*).

5.2.1.1 Birch and grass pollen season limits

The pollen data comprises daily average pollen count (grains m^{-3}) at each site with most of the data covering the duration of birch and grass pollen seasons (March-July). The remainder of the year had either no data or a very low pollen count; these data were excluded to avoid bias in the statistical analysis (Sánchez Mesa et al. 2003). Therefore, a derivative technique (DM) (Khwarahm et al. 2014) was used to define the start and end of both the birch and grass seasons (see *section 4.2.1*). Additionally, the peak days where the highest counts of pollen were recorded are also indicated (Table 5-1).

5.2.2 Meteorological data

Time-series meteorological data for the period (2003 - 2010) were obtained from the Met Office through the British Atmospheric Data Centre (BADC) (details in *section 3.2.2*). The data were acquired from the nearest meteorological stations to the pollen count sites, in most cases within 5 km (Table 3-1).

5.2.3 Land cover data

The Corine Land Cover 2000 (CLC2000) 100 m, version 9/2007 in TIFF raster format (European Commission, 2005) was used as a reference for birch and grass source areas. The source area classes were Broad leaf forest, Mixed forest, Green urban area, Grassland and Pasture (Fig.4-1). The first three classes were considered as the main sources of Birch pollen and the last two as Grass sources (details in *section 4.2.2*).

5.2.4 MTCI data

Time-series of MTCI was obtained from the NERC Earth Observation Data Centre (EODC) for the period 2003 - 2010. The data are provided by the European Space Agency and processed by Airbus Defence and Space (www.airbus-geo.com). Details on the data and stages of processing are provided in *section 4.2.3*.

5.2.4.1 Estimating phenological parameters from MTCI data

Given a single phenology cycle following a smooth sinusoidal pattern, onset of season was defined as a valley point at the beginning of the growing cycle, peak of season was defined as the maximum value of MTCI, and end of senescence was defined as a valley point occurring at the decaying end of the phenology cycle; all in terms of day of year (Fig.4-2). Details provided in *section 4.2.3.1*.

5.2.4.2 Onset of flowering

Previous studies have documented a strong link between male flowering and the first date of bud burst (Linkosalo 1999, 2000; Jato et al. 2002; Newnham et al. 2013). Thus, the correlation between male flowering and leaf-bud burst indicates that the phenophase

observed as leaf-bud burst or start of season could be used to determine the timing of local birch pollen release (see *section 4.2.3.2*). For birch, the timing of flowering was defined as the time after the onset of the growing season when the MTCI value reaches 25% of the maximum. Similarly for grass this was defined as the time when MTCI reached 75% of the maximum (Fig.4-4). The estimated MTCI flowering phenophase of birch and grass was then interpolated to daily values using linear interpolation. This was necessary before correlation analysis as the meteorological data and pollen count data were also daily.

5.2.5 Relationship between onset of flowering and pollen season limits

The estimated onset of flowering for birch and grass from MTCI (*section 5.2.4.2*) was correlated with the defined pollen season limits from pollen count data (*section 5.2.1.1*). The correlation was undertaken for the nine stations (Fig.4-1) across the UK within a 50 km buffer around the stations. Details are provided in *section 4.2.3.3*.

5.2.6 Validation of the onset of flowering maps

From the estimated onset of flowering for each pixel for each year (2003-2010) (*section 5.2.4.2*), (i) an 8-year average (2003 to 2010) map of start of the birch season corresponding to the distribution of Broadleaf forest (ii) an 8-year average start of the grass season based on the distribution of Grassland, were produced. Validation was then undertaken as it is detailed in *section 4.2.3.4*.

5.2.6.1 Relationship between pollen count and covariates

The daily pollen count data for both birch and grass, from the pre-peak season (i.e., from the start of the pollen season to the day of maximum pollen count) were correlated (using bivariate Pearson's product-moment correlation) with daily meteorological variables and daily MTCI flowering phenophase of birch and grass (*section 5.2.1.1 – 5.2.4.2*) for the following temporal supports:

- (ix) the same day;
- (x) 1-day prior,
- (xi) 1-day mean prior (mean of the same day and the day before),

- (xii) 3-day mean prior (mean of the same day and three previous days) and
- (xiii) 7-day mean prior (mean of the same day and seven previous days).

Relationships between daily birch and grass pollen counts and the covariates were investigated at each site for the pre-peak period using correlation analysis. The aim of the investigation was to select the most significant variables affecting the daily variation in birch and grass pollen.

5.2.6.2 Predictive model

To predict the daily birch and grass pollen count during the pre-peak season, this study used the method of stepwise multiple regression analysis, an empirical method, which aerobiologists commonly adopt due to its simplicity and straightforwardness (Smith and Emberlin, 2005; Smith and Emberlin, 2006; Angosto et al. 2005; Stach et al. 2008b). Regression analysis makes several assumptions (e.g. normality of residuals, linearity of relation, and in relation to outliers) about the data that should not be violated (Pallant 2010; Gray and Kinnear 2012). The birch and grass pollen data used for this study are normally distributed and data were also checked to see whether outliers and collinearity had a significant effect on the results of the modelling.

Eighteen regression models were fitted for birch and grass for the nine sites, and each model was tested against two years hold-back data (*section 5.2.6.4*). The regression models predict daily pollen count variation for birch and grass during the pre-peak period.

5.2.6.3 Covariates entered into the regression models

Based on the correlation between the daily birch and grass pollen count and covariates (*section 5.2.6.1*), only statistically significant and the most relevant variables reported in the literature were entered in the regression models. Meteorological variables included in the multiple linear regression models were either maximum or average temperatures for birch and grass, rainfall or relative humidity, and wind speed (see chapter 3, section 3.3.2). These variables are the most important known to affect birch and grass pollen concentration in the air (Galán et al. 1995; Emberlin 2009; Sánchez Mesa et al. 2003;

Puc 2011; Newnham et al. 2013; Khwarahm et al. 2014). These variables were combined carefully due to potential multi-collinearity issues, as there exists a large correlation between daily maximum and minimum temperature values and relative humidity and rainfall values. Other covariates entered into the models include MTCI flowering phenophase for birch and grass (*section 5.2.4.2*).

To test whether the flowering phenophase adds significant predictive power to the regression models the sequential significance test (Change Statistics or Sig. F Change) was used. For this, it was necessary to construct the regression model in stages or blocks (i.e., sequential models). This is accomplished by entering the covariates in different blocks. For example, block one contained the meteorological covariates and the MTCI and in block two the MTCI was removed. This resulted in two models; one with MTCI and one without MTCI, accounting for changes between the models. Thus, the role of the MTCI covariate could be determined by evaluating the performance differences between these models.

5.2.6.4 Model test

To evaluate the accuracy of the generated models, a hold-back dataset was created comprising 18 site years of observation points (i.e., two years of observation points per site ($n=18$)). The points were selected randomly from the eight years and nine pollen stations ($n=72$). The randomly selected points were re-selected if there were two consecutive years selected per site. The evaluation was undertaken based on the coefficient of determination (R^2 adjusted) and estimated standard error (S) derived from regression between the actual pollen values (y -axis) and predicted values (x -axis).

5.3 Results

5.3.1 Birch and grass pollen season limits

The start of the birch and grass pollen season is earlier in the south and tends to be later as one moves northwards. The grass season starts at 141 DOY (20 May) at Isle of Wight (IOWT) whereas for Edinburgh the average start of season was detected at 160 DOY (8 June) using the DM method. The birch season starts at IOWT at 98 DOY (7 April)

whereas for Edinburgh the average start date of the season was 100 DOY (9 April) (Table 5-1).

Year-to-year variation in start date at any one site was generally 7-14 days, modulated by variation in the local weather conditions prior to and during the pollen season.

Across all the sites the birch season started earlier than the grass season by an average of 54 days.

Table 5-1 8-year average start and end dates for the birch and grass pollen seasons defined by the derivative method (DM) at the nine pollen stations. Start and end dates are shown as number of days from 1st January (DOY).

Stations	Birch season			Grass season		
	start date	peak day	end date	start date	peak day	end date
Worcester	93	108	121	149	169	215
Belfast	107	118	119	156	170	213
Cambridge	94	107	119	151	169	205
Cardiff	98	112	122	152	170	203
Edinburgh	100	114	120	160	179	214
Invergowrie	107	116	120	161	177	208
IOWT	98	111	120	141	169	215
London	92	109	122	149	168	210
Plymouth	98	112	117	152	167	192

5.3.2 Onset of flowering across the UK

The patterns of flowering onset across the UK estimated from MTCI data also demonstrated variation from year-to-year. A clear spatial difference in the start of flowering for both birch and grass can be noticed. For example, the flowering dates for birch for northern sites (i.e., Belfast, Edinburgh, and Invergowrie) were 97, 92, and 101 DOY, respectively, whereas for the southern sites (i.e., IOWT, Plymouth, London, Worcester, and Cambridge) were 87, 88, 79, 86, 85 DOY, respectively. The London

area demonstrated earlier flowering dates in comparison to other sites. A similar spatial pattern was also demonstrated for grass flowering dates (Table 5-2).

The onset of flowering (in DOY) was correlated with the observed start dates of birch and grass pollen season (DOY) for the period 2003-2010. The correlation was undertaken for the nine stations across the UK within a 50 km buffer around the stations. The 50 km buffer around the stations contains the average start dates of flowering season for both birch and grass. For both birch and grass statistically positive correlations of ($r = 0.89$ $r = 0.83$ at the 0.01 level) were recorded, respectively (Table 5-2).

Table 5-2 8-year average start dates for the birch and grass pollen seasons defined by the derivative method (DM) and estimated flowering phenophase from the MTCI at the nine pollen stations. Start and end dates are shown as number of days from 1st January (DOY).

Station	birch start date			grass start date		
	MTCI	<i>r</i>	DM	MTCI	<i>r</i>	DM
Belfast	97	.891**	107	152	.839**	158
Cambridge	85		94	138		150
Cardiff	92		98	151		154
Edinburgh	92		100	152		160
Invergowrie	101		107	156		162
IOWT	87		98	139		143
London	79		92	140		152
Plymouth	88		98	146		150
Worcester	86		93	138		150

**Correlation is significant at the 0.01 level

5.3.3 Validation of onset of flowering

As expected, there was statistically significant positive correlation ($r = 0.71$; significant at the 0.01 level; St. Error(S) =3.7 days) between the MTCI onset of flowering for grass and the start dates of the grass pollen season. Similarly for birch, statistically significant correlations were produced between pollen start dates and onset of flowering of Broad

leaf forest. The correlation was larger than for grass, but produced larger standard errors ($r = 0.74$; significant at the 0.01 level; St. Error(S) =7.2 days) (Fig.5-1).

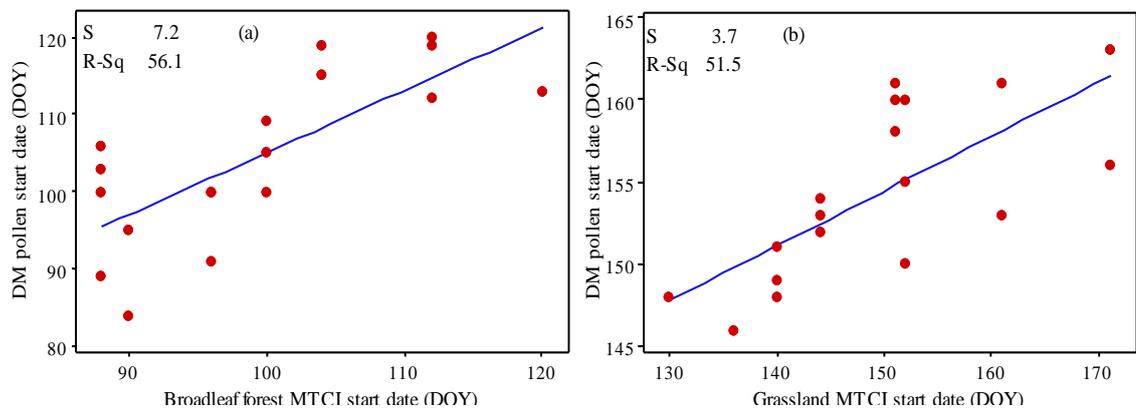


Fig.5-1 Regression of pollen start date estimated for (a) birch pollen and (b) grass pollen against MTCI start date for (a) broadleaf forest and (b) grassland within a 50 km buffer around the nine pollen sites, for a random selection of 18 of the possible points. Estimated standard error (S) and coefficient of determination (R^2 -adjusted) are shown.

5.3.4 Relationship between pollen count and covariates

The correlation analysis for the pre-peak period of birch and grass pollen season and the covariates are shown in (Tables 5-3 and 5-4). As expected, there was statistically significant correlation between pollen count and the covariates. Daily MTCI flowering phenophase demonstrated large positive correlation with daily birch and grass pollen. For grass, the MTCI flowering phenophase across eight sites was statistically significant at the 0.01 level and at one site at the level of 0.05. For birch, only eight out of the nine sites demonstrated significant correlation. The correlations for birch in general were slightly smaller in comparison to grass.

Table 5-3 Significant correlations between the daily birch pollen counts and covariates for pre-peak season across the pollen sites.

Independent variable	Significance (<i>r</i>)
Belfast :	
<i>mtci7dmp</i> (MTCI 7-day mean prior)	.314*
<i>max_air_temp_7dmp</i> (maximum air temperature 7-day mean prior)	.560**
Cambridge :	
<i>mtci7dmp</i> (MTCI 7-day mean prior)	.591**
<i>prcp_amt_1dmp</i> (precipitation amount 1-day mean prior)	-.255*
<i>max_air_temp_3dmp</i> (maximum air temperature 3-day mean prior)	.476**
Cardiff :	
<i>mtci7dmp</i> (MTCI 7-day mean prior)	.231*
<i>prcp_amt_3dmp</i> (precipitation amount 3-day mean prior)	-.272*
<i>air_temperature_7dmp</i> (air temperature 7-day mean prior)	.769**
Edinburgh :	
<i>mtci1dp</i> (MTCI 1-day prior)	.675**
<i>prcp_amt_7dmp</i> (precipitation amount 7-day mean prior)	-.362*
<i>air_temperature_7dmp</i> (air temperature 7-day mean prior)	.800**
Invergowrie :	
<i>mtci1dp</i> (MTCI 1-day prior)	.649**
<i>prcp_amt_1dp</i> (precipitation amount 1-day prior)	-.299*
<i>air_temperature_7dmp</i> (air temperature 7-day mean prior)	.513**
IOWT :	
<i>mtci7dmp</i> (MTCI 7-day mean prior)	.193
<i>prcp_amt_7dmp</i> (precipitation amount 7-day mean prior)	.366**
<i>air_temperature_3dmp</i> (air temperature 3-day mean prior)	.504**
<i>wind_speed</i> (same-day)	-.377**
London :	
<i>mtci7dmp</i> (MTCI 7-day mean prior)	.491**
<i>max_air_temp_1dp</i> (maximum air temperature 1-day prior)	.421**
<i>rltv_hum</i> (relative humidity samed-day)	.359**
Plymouth :	
<i>mtci7dmp</i> (MTCI 7-day mean prior)	.256*
<i>air_temperature_3dmp</i> (air temperature 3-day mean prior)	.816**
Worcester :	
<i>mtci7dmp</i> (MTCI 7-day mean prior)	.696**
<i>air_temperature_3dmp</i> (air temperature 3-day mean prior)	.793**
<i>rltv_hum_1dp</i> (relative humidity 1-day prior)	-.253*

**Correlation is significant at the 0.01 level *Correlation is significant at the 0.05 level

Table 5-4 Significant correlations between the daily grass pollen counts and covariates for pre-peak season across the pollen sites.

Independent variable	Significance (r)
Belfast:	
<i>mtci1dmp (MTCI 1-day mean prior)</i>	.778**
<i>prcp_amt_1dmp (precipitation amount 1-day mean prior)</i>	-.338**
<i>max_air_temp_1dp (maximum air temperature 1-day prior)</i>	.509**
Cambridge :	
<i>mtci1dp (MTCI 1-day prior)</i>	.187*
<i>prcp_amt_7dmp (precipitation amount 7-day mean prior)</i>	-.479**
<i>max_air_temp_7dmp (maximum air temperature 7-day mean prior)</i>	.739**
Cardiff :	
<i>mtci1dp (MTCI 1-day prior)</i>	.392**
<i>max_air_temp_7dmp (maximum air temperature 7-day mean prior)</i>	.513**
Edinburgh :	
<i>mtci1dp (MTCI 1-day prior)</i>	.583**
<i>wind_speed (same-day)</i>	.248*
<i>air_temperature_7dmp (air temperature 7-day mean prior)</i>	.372**
Invergowrie :	
<i>mtcisd (MTCI same-day)</i>	.521**
<i>air_temperature_3dmp (air temperature 3-day mean prior)</i>	.711**
IOWT :	
<i>mtci1dp (MTCI 1-day prior)</i>	.492**
<i>max_air_temp_7dmp (maximum air temperature 7-day mean prior)</i>	.742**
<i>rltv_hum_1dp (relative humidity 1-day prior)</i>	-.221*
London :	
<i>mtci1dp (MTCI 1-day prior)</i>	.308**
<i>air_temperature_3dmp (air temperature 3-day mean prior)</i>	.695**
<i>prcp_amt_7dmp (precipitation amount 7-day mean prior)</i>	-.286*
Plymouth :	
<i>mtci7dmp (MTCI 7-day mean prior)</i>	.343**
<i>max_air_temp_3dmp (maximum air temperature 3-day mean prior)</i>	.669**
<i>rltv_hum_3dmp (relative humidity 3-day mean prior)</i>	-.490**
Worcester :	
<i>mtci1dp (MTCI 1-day prior)</i>	.391**
<i>max_air_temp_3dmp (maximum air temperature 3-day mean prior)</i>	.617**
<i>rltv_hum_7dmp (relative humidity 7-day mean prior)</i>	-.433**

**Correlation is significant at the 0.01 level *Correlation is significant at the 0.05 level

5.3.5 Multiple regression models predicting daily birch and grass pollen counts

Eighteen multiple regression models were fitted to predict the daily birch and grass pollen counts across the nine sites for the pre-peak period (Tables 5-5 and 5-6). In general, the nine models for grass have a smaller estimated standard error (S) in comparison to the models of birch. In all the models for birch except for IOWT the MTCI covariate significantly enhanced the level of explanation (coefficient of determination (R^2 -adjusted)). For grass, across the majority of the station the mtc1dp (MTCI 1-day prior) temporal support with the combination of 3-7 day prior temperature and either precipitation or relative humidity produced an R^2 -adjusted in the range of 52%-71% with $S=13-50$ grains m^{-3} . In contrast, for birch the mtc7dmp (MTCI 7-day mean prior) temporal support with the combination of 3-7 day prior temperature and either precipitation or relative humidity produced an R^2 -adjusted in the range of 47% - 77% with $S=11-115$ grains m^{-3} .

5.3.6 Predictive power of the flowering phenophase

The flowering phenophase across the nine sites for both birch and grass added statistically significant (Sig. F Change < 0.05 (p -value)) predictive power to the regression models. For birch, the increase in power for Edinburgh (Sig. F Change = 0.01) and Plymouth (Sig. F Change = 0.01) was slightly less in comparison to other sites. For grass, overall the increase in power was very high except for Cambridge (Sig. F Change = 0.02). Overall, the increase in predictive power for the grass regression models was greater than for birch (Tables 5-7 and 5-8).

Table 5-5 Multiple regression models for predicting daily birch pollen counts (grains m⁻³) for the pre-peak period across the nine sites, using the meteorological and the phenological parameters. The equations are accompanied by the *R*²-adjusted and the estimated standard error.

Station	Regression equation	R-Sq (adj)	St error
Belfast	= -161.584 + 23.5182 mtci7dmp + 9.49463 max_air_temp_7dmp	76.00%	10.9
Cambridge	= -801.392 + 422.087 mtci7dmp - 116.638 prcp_amt_1dmp + 13.5043 max_air_temp_3dmp	65.03%	64.7
Cardiff	= -968.915 + 261.895 mtci7dmp - 26.7529 prcp_amt_3dmp + 58.6293 air_temperature_7dmp	63.53%	43.25
Edinburgh	= -295.058 + 48.5266 mtci1dp - 10.2692 prcp_amt_7dmp + 24.8315 air_temperature_7dmp	74.28%	18.15
Invergowrie	= -154.855 + 36.6098 mtci1dp - 3.25026 prcp_amt_1dp + 38.5944 air_temperature_7dmp	50.94%	16.03
IOWT	= -253.041 + 38.3261 prcp_amt_7dmp + 36.5241 air_temperature_3dmp - 10.3541 wind_speed	46.68%	75.06
London	= -2531.32 + 930.178 mtci7dmp + 16.1665 max_air_temp_1dp + 12.6725 rltv_hum	47.94%	115.84
Plymouth	= -158.127 + 30.2932 mtci7dmp + 13.2661 air_temperature_3dmp	69.32%	14.91
Worcester	= -940.217 + 264.166 mtci7dmp + 20.7734 air_temperature_3dmp + 4.49283 rltv_hum_1dp	77.38%	34.16

Table 5-6 Multiple regression models for predicting daily grass pollen counts (grains m⁻³) for the pre-peak period across the nine sites, using the meteorological and the phenological parameters. The equations are accompanied by the R²-adjusted and the estimated standard error.

Site	Regression equation	R-Sq (adj)	St error
Belfast	= -3401.11 + 1419.37 mtc1dmp - 5.50666 prcp_amt_1dmp + 5.62965 max_air_temp_1dp	73.54%	25.51
Cambridge	= -393.901 + 61.1205 mtc1dmp - 11.5375 prcp_amt_7dmp + 15.2924 max_air_temp_7dmp	61.12%	36.14
Cardiff	= -526.202 + 149.846 mtc1dmp + 11.6475 max_air_temp_7dmp	52.58%	21.03
Edinburgh	= -771.372 + 257.072 mtc1dmp + 14.6218 wind_speed + 10.1664 air_temperature_7dmp	66.00%	13.86
Invergowrie	= -320.077 + 89.9793 mtcisd + 9.62609 air_temperature_3dmp	64.55%	11.51
IOWT	= -729.628 + 164.344 mtc1dmp + 26.1165 max_air_temp_7dmp - 1.05411 rltv_hum_1dp	63.30%	37.44
London	= -906.244 + 221.131 mtc1dmp + 24.2794 air_temperature_3dmp -14.5283 prcp_amt_7dmp	71.55%	36.62
Plymouth	= -138.633 + 86.3307 mtc17dmp + 10.1932 max_air_temp_3dmp - 2.33112 rltv_hum_3dmp	59.76%	26.47
Worcester	= -637.648 + 362.436 mtc1dmp + 12.0086 max_air_temp_3dmp - 5.83339 rltv_hum_7dmp	58.22%	50.03

Table 5-7 Change statistics for evaluating the predictive power of the estimated birch flowering phenophase for the nine sites. 1= model one that includes: the meteorological and the estimated flowering phenophase from MTCI parameters. 2= model two that only includes the meteorological parameters (Sig. *F* Change < 0.05).

Model Summary		Change statistics		
Model No./site	<i>R</i> ² -adjusted	<i>R</i> ² -adjusted change	<i>F</i> Change	Sig. <i>F</i> Change
Belfast :				
1 (with MTCI)	0.76	0.77	59.59	0.00
2 (without MTCI)	0.29	-0.46	70.88	0.00
Cambridge :				
1 (with MTCI)	0.65	0.67	45.00	0.00
2 (without MTCI)	0.20	-0.44	89.01	0.00
Cardiff :				
1 (with MTCI)	0.63	0.66	31.19	0.00
2 (without MTCI)	0.57	-0.06	9.19	0.00
Edinburgh :				
1 (with MTCI)	0.74	0.76	36.63	0.00
2 (without MTCI)	0.68	-0.06	8.86	0.01
Invergowrie :				
1 (with MTCI)	0.50	0.54	16.92	0.00
2 (without MTCI)	0.37	-0.14	13.33	0.00
London :				
1 (with MTCI)	0.47	0.50	22.79	0.00
2 (without MTCI)	0.22	-0.25	34.43	0.00
Plymouth :				
1 (with MTCI)	0.69	0.70	67.65	0.00
2 (without MTCI)	0.66	-0.04	7.17	0.01
Worcester :				
1 (with MTCI)	0.77	0.78	73.99	0.00
2 (without MTCI)	0.64	-0.13	36.48	0.00

Table 5- 8 Change statistics for evaluating the predictive power of the estimated grass flowering phenophase for the nine sites. 1= model one that includes: the meteorological and the estimated flowering phenophase from MTCI parameters. 2= model two that only includes the meteorological parameters (Sig. *F* Change < 0.05).

Model Summary		Change statistics		
Model No./site	<i>R</i> ² -adjusted	<i>R</i> ² -adjusted change	<i>F</i> Change	Sig. <i>F</i> Change
Belfast :				
1 (with MTCI)	0.73	0.75	63.99	0.00
2 (without MTCI)	0.24	-0.48	122.33	0.00
Cambridge :				
1 (with MTCI)	0.61	0.62	59.69	0.00
2 (without MTCI)	0.59	-0.02	5.03	0.02
Cardiff :				
1 (with MTCI)	0.52	0.54	38.15	0.00
2 (without MTCI)	0.25	-0.28	39.14	0.00
Edinburgh :				
1 (with MTCI)	0.66	0.67	57.29	0.00
2 (without MTCI)	0.25	-0.40	101.48	0.00
Invergowrie :				
1 (with MTCI)	0.64	0.65	86.60	0.00
2 (without MTCI)	0.50	-0.15	38.96	0.00
IOWT :				
1 (with MTCI)	0.63	0.64	82.07	0.00
2 (without MTCI)	0.54	-0.09	34.03	0.00
London :				
1 (with MTCI)	0.71	0.73	74.76	0.00
2 (without MTCI)	0.57	-0.14	43.60	0.00
Plymouth :				
1 (with MTCI)	0.59	0.61	37.13	0.00
2 (without MTCI)	0.49	-0.11	19.71	0.00
Worcester :				
1 (with MTCI)	0.58	0.59	59.99	0.00
2 (without MTCI)	0.44	-0.14	42.70	0.00

5.3.7 Multiple regression models test

Overall, all the models performed with a high level of accuracy when tested with the hold-back dataset. For birch, eighteen out of the eighteen observations demonstrated levels of accuracy from minimum of 38.40% (R^2 -adjusted St. error 51 grains m^{-3}) to maximum 99.70% (R^2 -adjusted St. error 1.6 grains m^{-3}). Similarly, for grass, eighteen out of the eighteen models demonstrated levels of accuracy from minimum of 41.60% (R^2 -adjusted St. error 14.6 grains m^{-3}) to 96.20% (R^2 -adjusted St. error 6 grains m^{-3}). Overall, the grass models showed higher levels of accuracy in picking up the trend and predicting the daily variation in pollen counts in comparison to the birch models (Tables 5-9 and 5-10).

Table 5-9 Accuracy test for the regression models for birch pollen counts (grains m^{-3}) across the nine sites using the two-year dataset.

Site/year	Accuracy (%) R^2 -adjusted	St error (grains m^{-3})
Belfast :		
2003	90.40%	9.128
2008	93.20%	1.612
Cambridge :		
2003	99.70%	1.611
2009	38.40%	51.009
Cardiff :		
2003	91.60%	20.481
2005	47.50%	13.769
Edinburgh :		
2006	77.00%	14.523
2008	79.70%	3.002
Invergowrie :		
2004	39.10%	28.578
2006	70.90%	36.329
IOWT :		
2007	95.90%	7.531
2010	40.50%	37.618
London :		
2004	47.30%	98.997
2010	65.50%	70.804
Plymouth :		
2005	55.30%	8.217
2009	47.90%	3.557
Worcester :		
2005	86.70%	15.477
2010	94.20%	39.254

Table 5-10 Accuracy test for the regression models for grass pollen counts (grains m⁻³) across the nine sites using the two-year dataset.

Site/year	Accuracy (%) R^2 -adjusted	St error (grains m ⁻³)
Belfast :		
2003	83.20%	27.194
2005	95.30%	7.858
Cambridge :		
2004	77.20%	31.298
2007	41.60%	14.609
Cardiff :		
2005	53.80%	25.675
2008	70.50%	30.469
Edinburgh :		
2007	51.00%	17.991
2009	79.50%	22.350
Invergowrie :		
2006	96.20%	7.006
2010	81.30%	25.499
IOWT :		
2005	61.40%	53.783
2009	74.50%	13.663
London :		
2004	73.10%	41.820
2008	60.20%	37.560
Plymouth :		
2005	91.80%	18.381
2008	47.50%	47.547
Worcester :		
2003	83.80%	25.918
2009	44.70%	20.509

5.4 Discussion

5.4.1 Relationship between pollen count and covariates

The technique used to define the onset of flowering of birch and grass was based on phenological developments, especially the leaf emergence phenophase temporal profile, measured indirectly using a satellite sensor chlorophyll index (i.e., MTCI). The temporal profile provides information on the timing of flowering which is coincidental

with pollen release and hence the pollen season and the emergence of hay fever symptoms. Moreover, the MTCI-based prediction of flowering phenophase is effectively a spatial representation of birch and grass pollen sources tagged with the timing of a biological event (i.e., flowering phenophase) which varies from year-to-year depending on environmental conditions, especially temperature, in the UK. The spatial representation of birch and grass sources is at the 1 km pixel ground resolution for the whole UK; this information is extensive in comparison to the limited number of pollen monitoring sites across the country. Importantly, the combination of the MTCI-predicted timing of flowering at the source areas together with the (ground measured) pollen profile at the 'sink' or receptor has the potential to increase our understanding of local variation in pollen, local start date and length of pollen season.

This research found statistically significant positive correlations between the pollen count-derived starting dates of the pollen seasons of both birch and grass, and the MTCI-based start dates, indicating the suitability of using the MTCI to predict the start of pollen season indirectly, potentially in combination with relevant weather parameters, for example, temperature and precipitation. This result supports the study of Karlsen et al. (2008), which used a threshold of MODIS NDVI to define the start of the birch pollen season and related it with pollen season start date. The slightly smaller correlation coefficients for grass are likely related to the larger number of grass species in the UK and, thus, the various physiological differences in leaf development. In the UK there are about 150 species of grass, although only around 12 species significantly contribute pollen to the atmosphere (Emberlin et al. 1999). Conversely, the most commonly found species of birch in the UK are Downy birch (*Betula pubescens*) and Silver birch (*Betula pendula*).

Similar to the correlation between the start dates of birch and grass and the MTCI-based start dates (previous paragraph), there was also statistically significant correlation between daily birch and grass pollen count and the corresponding covariates (i.e., meteorological and phenological) during the *pre-peak period*. Daily MTCI flowering phenophase demonstrated large positive correlations with daily birch and grass pollen. The correlations for birch in general were slightly smaller than for grass. The sparse and diffuse nature of birch distribution across the country and lack of a discrete boundary, together with microclimatic influence on the phenology of the birch contribute to small

or insignificant correlations. For example, at IOWT the correlation between daily MTCI flowering phenophase and the birch pollen counts was insignificant. IOWT is greatly influenced by the maritime climate and the density of birch distribution is very scarce. These in turn make the diurnal pattern of pollen counts in the atmosphere vary within short distances regardless of pollen transport which also should be considered as it may alter the start and the magnitude of the pollen season.

Long distance transport of pollen, especially birch pollen that may advance the local pollen season, is reported (Mahura et al. 2007; Oikonen et al. 2005; Ranta et al. 2006; Skjøth et al. 2008b). The MTCI-based prediction of birch flowering does not necessarily reflect the observed local timing of the pollen season. The transport of pollen in the UK may vary from region-to-region, for example, as a function of topography. England consists mostly of lowland terrain, with upland or mountainous terrain only found north-west of the Tees-Exe line, whereas the rest of the country (i.e., Scotland, Wales, and Northern Ireland) has more mountainous topography. Thus, England is more likely to be affected by regional transport of pollen than the rest of the country. Smith et al. (2005) reported grass pollen in the UK (i.e., in Worcester city: Midlands of England) that originated from continental Europe. Considering the size of the buffer (i.e., 50 km buffer around the pollen sites) used in this research, the large correlations we found between MTCI-based date of onset of flowering of birch and grass and the start dates of their corresponding pollen seasons defined using the DM threshold method raises the question of how significant is the role of pollen transport in influencing the local start of pollen season in the UK.

5.4.2 Predictive power of the flowering phenophase

Apart from meteorology, daily birch and grass pollen counts also vary as a function of flowering rhythm at the source (Bringfelt et al. 1982). Any of them alone is insufficient to determine the dynamic of the pollen season over space and time (Ranta et al. 2006). Yet, this does not infer underestimating other environmental variables such as topography, aerodynamic properties of the pollen grain, distance of the sampler from the source and the significance of pollen transport.

Knowledge of the flowering phenophase of the important wind pollinated species such as birch and grass provides useful information for understanding the relationship between reproductive phenology and the airborne pollen curves. In other words, it provides insights into the relationship between the release of pollen from the anthers and its presence in the atmosphere (Latorre and Bianchi 1998; Jato et al. 2002). The flowering phenophase across the sites for both birch and grass added statistically significant predictive power when entered into the regression models. Overall, the increased predictive power gained by adding the flowering phenophase into the grass regression models was greater than for birch. This is partly because the magnitude of the grass pollen season in the UK is longer than for birch and the spectrum of grass species and hence their distribution are dominant in comparison to birch. For grass, across the majority of the sites, the *mtci1dp* (MTCI 1-day prior) temporal support with the combination of 3-7 day mean prior temperature and either precipitation or relative humidity produced high levels of explanation (R^2 -adjusted). This is a clear indication of the prolonging influence of temperature and rain and/or humidity on the physiology of plants, specifically on the reproductive phase and flower blooming prior to pollen release. This argument is also valid for birch as across the majority of the sites the *mtci7dmp* (MTCI 7-day mean prior) temporal support with the combination of 3-7 day prior temperature and either precipitation or relative humidity also produced high levels of explanation (R^2 -adjusted).

The recorded increase in predictive power gained by adding the MTCI-based flowering phenophase to the regression models for birch and grass clearly indicate a link between the atmospheric pollen count and local plant flowering rhythm. In addition to model improvement, this finding also enhances our understanding of the contribution and importance of pollen transport in influencing the local start and magnitude of pollen season in the UK.

The justification of the inclusion of the pre-peak period into correlation and regression analysis was based on a previous study (Khwarahm et al. 2014), which highlighted the importance of the pre-peak period in understanding the influence of meteorological variables on atmospheric pollen counts as most flower blooming occurs within a short duration before the maximum pollen count is recorded (i.e., during the pre-peak period). During the post-peak period, when flowering is reduced in the majority of the birch and

grass population, the process of re-suspension is more relevant, ultimately making this period longer than the pre-peak period, but less predictable.

5.5 Conclusion

The main aim of this research was to develop improved short-term models to predict daily birch and grass pollen for the pre-peak season for nine sites across the UK using a novel approach that combines meteorological and phenological covariates. Apart from known meteorological variables that influence pollen counts in the atmosphere, a phenological parameter (i.e., flowering phenophase) representing the phenology of the source producing the pollen was also used in building the models. These empirical models are intuitively more realistic and statistically more robust in comparison to other models in which only meteorology was used to predict atmospheric pollen variation. The phenological parameter significantly enhances the power of the predictive models. This indicates that airborne pollen variability is not solely a function of meteorology and topography, but also of flowering phenophase at the source areas.

The application of relevant phenological parameters estimated from satellite sensors in combination with accurate weather forecasts in allergic pollen study has the potential to make a notable contribution to the field of aerobiology. This, in turn, will be of potential assistance to the medical profession and a range of fields related to allergenic pollen.

CHAPTER 6: Discussion

This chapter aims to provide a comprehensive discussion of the analysis chapters (i.e., chapter 3, 4 & 5). The research conducted in these individual chapters enabled the objectives established in the introduction (*section 1.2*) to be met. These individual chapters already included discussion of the chapter-specific outputs and results, evaluated the methods and techniques used, and briefly touched upon some likely sources of uncertainties and limitations. However, the objective here is to consider the bigger picture, discussing the findings of the thesis as a whole and placing them into context. Furthermore, based on evaluation of the research findings and the inherent drawbacks, suggestions are made for future research in this field.

6.1 Daily variation of birch and grass pollen in the United Kingdom

Chapter 3 investigated the variation in daily birch and grass pollen counts, as collected at nine monitoring stations in the UK for the period of 2000-2010, in relation to daily meteorological variables taken from nearby weather stations. From the analysis it can be seen that the daily pollen count for birch and grass at the nine pollen monitoring sites responded differently to the meteorological variables. The responses reflect the spatial and temporal variation of these variables for the 11-year time period. The response of the daily birch pollen counts to the meteorological variables differed slightly from its grass counterpart mainly due to their differences in aerodynamic properties of the pollen and height of release.

6.1.1 Spatial variation of pollen

The start of the pollen season and the total pollen catch at the monitoring sites vary both spatially and inter-annually (from year to year) (Fig. 6-1). This highlights variation in the meteorological and other variables (e.g., topography and local vegetation) between the sites, and within a site over time. Spatio-temporal variation in the start of the grass and birch pollen seasons and their counts in the air in the United Kingdom are primarily controlled by maritime meteorological variables. In general, the climatic conditions of

the British Isles are influenced by low pressure zones which move in from the Atlantic, and are generally classified as maritime temperate. Its characteristics include evenly distributed rainfall which tends towards a maximum during the winter season, a small annual range of temperatures, high humidity and a rapidly fluctuating weather, attributed to passing fronts and anticyclones (Goudie 1996).

The general pattern of the spatial variation has a south-north gradient (i.e., the pollen seasons start earlier in the south than they do in the north). However, apart from the south-north gradient the unique climatic condition of the UK creates a coastal-inland gradient as well. For example, this is most obvious when one looks at the $\Sigma 75$ method to estimate the start of the pollen season for birch: London, Cambridge and Worcester can be considered as inland stations compared to IOW, Plymouth and Cardiff. The pollen seasons at the inland stations (94 DOY, 96 DOY, 95 DOY, respectively) start slightly earlier in comparison to those for the coastal stations (100 DOY, 101 DOY, 99 DOY, respectively). This indicates that plants flower slightly earlier in the inland areas than the coastal areas due to the effect of the urban heat island (Estrella et al. 2006). The pattern of inland-coastal variation was less obvious for the grass pollen season in the UK (Fig.4-7).

The above regional variation necessitates construction of different forecasting models for the individual sites. The start of the birch pollen season in London was the earliest due to the urban heat island effect, which causes the early flowering of birch trees in green urban areas. This, in turn, causes variation in air weight between the immediate city and surrounding areas and, therefore, a consequent vertical rising of air, creating a local air circulation mechanism, much like that which obtains in coastal regions around the warmer months (Goudie 1996). In context of the cities similar to London, the air circulation mechanism influences the pattern of pollen pathway, in particular, its distribution and re-suspension, in turn, is likely to increase heterogeneous variation of pollen load in the air (i.e. local-scale variation within short distances). In other words, urbanisation influences the climatic conditions, for example, in big cities, tall buildings, featuring complex surface patterns, cause increases in air turbulence. In turn, this influence air flow patterns, causing variation in pollen counts locally at both horizontal and vertical levels (Emberlin and Norris-Hill 1991; Goudie 1996).

The UK has around 150 species of grass, although only around 12 species contribute significant amounts of pollen to the atmosphere (Emberlin 2009). Thus, they have a different phenology and have varied responses to environmental factors (Chapman 1990). For example, in rye grass (*Lolium species*) spikelet emergence is dependent on photoperiod whereas the rates of fertile shoot elongation and inflorescence development are controlled primarily by temperature from March onwards (Beddows 1968). Therefore, as a result of the various number of species at a source area and their various responses to environmental factors it is difficult to determine which factors have the greater influence on the start of the season (Emberlin et al. 1993b). The most common birch species in the UK are silver birch and downy birch; the former is abundant mostly in the southern and middle parts of the UK and the latter in the north. In comparison to grass, understanding the relationship between birch phenology and environmental factors is, thus, more straightforward.

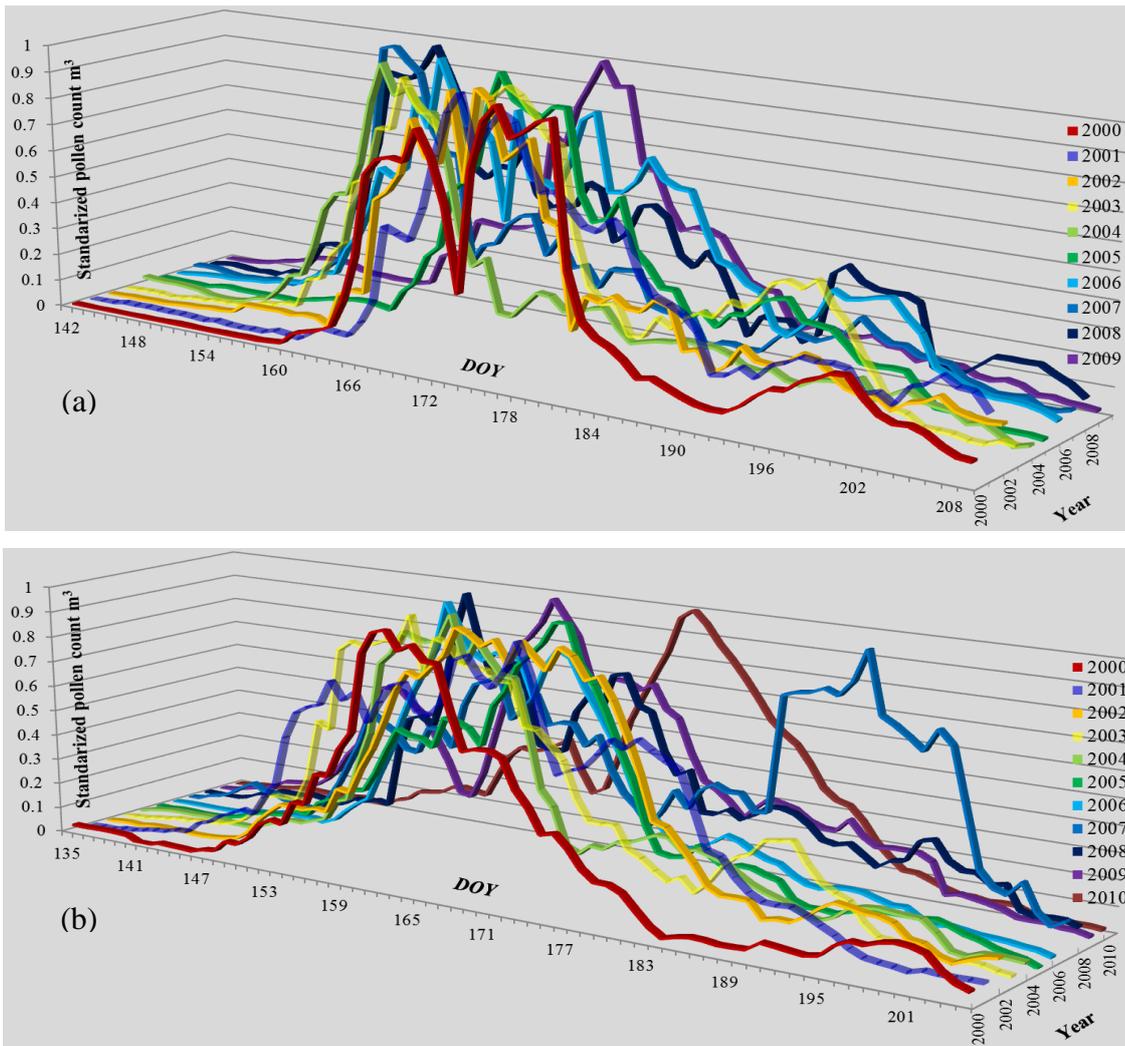


Fig.6-1 Year-to-year grass pollen season variation in (a) Belfast (b) Cambridge, DOY (Day of Year), the pollen data is standardised.

6.1.2 The derivative technique

In general, the birch and grass pollen seasons start with low and sporadic pollen counts until the main seasons start which are represented by a sudden and continuous increase in the number of pollen grains until the peak. Low pollen counts may not fully represent the local variation; for example, the grains may come from other areas (i.e., transport pollen). Furthermore, low counts are known to introduce bias during statistical analysis and, therefore, need to be “cut off” using several available threshold methods. The use of thresholds in defining the main characteristics of the pollen season, for example, start and end of season, has the advantage of making comparison between the seasons of

various years more viable. There are various approaches for defining the start of pollen season; for example, the cumulative sum 75 & 120 methods (Driessen et al. 1990), 1 %, 2.5 % and 5 % methods (Galán et al. 1995; Andersen 1991) and the “Threshold 30 method” used by Smith and Emberlin (2005). The threshold value was set as 30 grains m^{-3} as an adequate amount to trigger allergic symptoms. In addition, to predict the end date of the pollen season, several methods were proposed which mostly define these dates by referring to past data patterns. For example, percentage methods for defining the end of the season include 90% (Nilsson and Persson 1981; Larsson 1993), 95% (Goldberg et al. 1988; Toro et al. 1998) and 98% (Emberlin et al. 1993a; Emberlin et al. 1994). Each of these methods has advantages and disadvantages depending on the objective of their usage. For example, if the intention is to produce pollen predictive models the cumulative method is convenient as there is no need for the previous seasons’ data. However, the cumulative method has limitations for different species of plants with various pollen loads. The derivative technique (DM) (Khwarahm et al. 2014) was developed in this study to overcome the species-dependence limitation and the retrospective data limitation of the percentages methods. Furthermore, the technique will fit with future pollen monitoring technology, for example, there are efforts for automating pollen sampling. To date, pollen counting takes place manually, counting and identification of a wide spectrum pollen species under a light microscope is labour-intensive and tedious to practice. Automating pollen counting together with applying the technique would provide timely characterisation and prediction of pollen season for an array of species.

6.1.3 Uncertainties in pollen count

In addition to natural variation in the start of birch and grass seasons across the UK due to the local climatic conditions, other factors may introduce further variation (which may be treated as uncertainty). For example, uncertainties may occur when one compares the seasons between the sites due to variation in the local vegetation, height of traps (usually placed on the roof of a tall building), and local climate. Thus, ideally all the sites need to be placed at standard altitudes and in a similar kind of habitat or vicinity. Yet, this may be not possible to implement on the ground for practical reasons.

Another factor that intuitively adds to the uncertainty in the actual start of the pollen season is the role of pollen transport and variation in the approaches for defining the start of pollen season (i.e., the lack of an internationally standard method). Moreover, another possible source of uncertainty is in the technique of pollen sampling from the monitoring stations. The question is how representative is the quantity of pollen or pollen concentration obtained from a single monitoring station by sampling a small quantity of air through a volumetric trap? Consider the fact that particles flow in turbulent air and are not mixed homogeneously; and they may vary over very short distances at a specific time both vertically and horizontally in the air (Emberlin and Norris-Hill 1991). Furthermore, trapping of pollen by the volumetric trap of Hirst (1952) varies in efficiency depending on wind speed. Thus, at a wind speed of 1 m sec^{-1} , the efficiency is 100% and as wind speed increases the efficiency decreases (Hirst 1952). This, in turn, results in lower records of pollen from the air and, thus, the pollen count will be underestimated. The above-mentioned factors (i.e., sampling efficiency and atmospheric variation of particles) together with other sources of pollen variation (e.g. pollen transport and local scale early flowering and phenology development) suggest that the uncertainty in the pollen count records is non-negligible and needs to be taken into account. Furthermore, the defined season is based solely on the intact pollen grains identified at the pollen sites, without any regard to whether the pollen grain is loaded with the allergenic particle or not. Finally, the released pollen grain in the atmosphere until its deposition or impact may undergo some physical alteration, which may hinder its correct identification.

6.1.4 Forecasting pollen count

The comprehensive and generic correlation analysis undertaken here highlighted extensively how the pollen concentrations of birch and grass are associated with a wide range of meteorological variables from nearby weather stations that, in turn, enhances our understanding of pollen concentration pattern, in the atmosphere. Moreover, the analysis produced several fascinating and comprehensive results that enhance our understanding of the processes of pollen release and dispersal. This, in turn, aids in building more accurate short-range and medium-range statistical models.

Statistical or empirical models can be used to forecast the start, severity (magnitude) and daily variation of pollen seasons at a relatively early stage of the year. The development of such models is simple and quick with potential use for hay fever sufferers. Yet, these models usually do not include phenological changes and variation in the source areas. It is difficult to quantify the relationship between phenology and environmental factors for a mixture of species and, therefore, difficult to develop theoretical models on this basis (Jones 1995). Previously, most of the statistical models that were built to predict the severity of the birch season achieved a poor level of explanation (Jones 1995; Smith 2003; Emberlin et al. 1999); the reason is likely related to the biennial flowering pattern of birch trees which causes great variation from year-to-year in terms of annual pollen sum or annual catch (Emberlin et al. 1999). These models are usually built based on pollen count, and weather parameters are divided into two categories; for medium range (5-7 days) forecasting models and for long range (1 month) forecasting models. These models are better known as receptor-based models, which are constructed without prior knowledge of source conditions or calculations of diffusion, and relate records of pollen concentrations to one or more variables that can be measured or predicted (Norris-Hill 1995). Although, these models have an empirical basis, some theoretical background is required in understanding the strength and the direction of the relationships between independent and dependent parameters in order to estimate the most important parameters that should be included in the model (DeLurgio 1998).

The daily predictive models constructed here in chapter five by including the estimated MTCI-based flowering phenophase performed better than the models reported by other studies in the UK. For example, for predicting daily grass pollen count for London, Norris-Hill (1995), using polynomial regression reported model accuracy of 52%, Smith and Emberlin (2006), using linear regression reported model accuracy of 0.49%. The accuracy achieved in this research for predicting daily grass pollen count for London was 60% - 70% (Table 5-10).

6.2 Satellite remote sensing of vegetation phenology and estimation of birch and grass flowering phenophase

Understanding large area seasonal phenomena through phenological studies has been the interest of various scientific communities for various applications, for example, climate change, species distribution, and public health. Satellite sensor data with repeated measurement and an abundant inventory of archive time-series data with relatively fine temporal and spatial resolutions (i.e., near-daily and 1 km, respectively) have made them highly suited for studying phenology. The majority of the remote sensing phenology studies have used data gathered from the red and near infrared regions of the electromagnetic spectrum which are transformed into a ‘greenness’ or vegetation index (e.g. NDVI, MTCI). These indices, especially NDVI due to its historical longevity and, hence, popularity have been used extensively for various purposes. The basis for the development of vegetation indices is the exploitation of the physical properties of plants (i.e., spectral reflection and absorption) to describe the biological development of the leaf pigment, chlorophyll, which absorbs only the red part of the spectrum, leading to indices of the ‘greenness’ of a ‘pixel’. More generally, plants are known to absorb red light and reflect energy in the near infrared region of the electromagnetic spectrum. Nevertheless, satellite observations of a ‘pixel’ of vegetation may raise questions on what exactly has been measured on the ground. Importantly, the ‘pixel’ may contain a blend of vegetation types and hence the measurements are not the actual values of a targeted vegetation type but rather a generalized value of mixed vegetation types.

Satellite sensor images with various spatial and temporal resolutions have been used widely in phenological studies to extract key phenological variables, for example, start and end of the growth season (Lloyd 1990; Reed et al. 1994; Fisher and Mustard 2007; Dash et al. 2010; Roerink et al. 2011; Jeganathan et al. 2014). The start and end of the growth season variables are general terms rather than more specific phenological events (e.g., start of first leaf which has a more efficient biological meaning). This is again due to the fact that vegetation indices from satellite sensors are homogenised ‘greenness’ values of a mixed ‘pixel’ rather than of values of a specific population or even a community.

There are various approaches for extracting the key phenological variables; the most common ones are based on the inflection point methods, trend derivative methods, and threshold-based methods (Reed et al. 1994). For example, Lloyd (1990) estimated the start of growing season using AHHRR NDVI as when the NDVI value reaches 0.099 as a threshold, and Jonsson and Eklundh (2002) estimated it as the 10% distance between the minimum and maximum NDVI as a threshold. The variability of the approaches raises the question of which approach performs better and this, in turn, requires further evaluation and investigation. However, an ideal or a universal method to estimate key phenological variables may be challenging partly due to the purpose of the application and also variability in seasonality over space and time, and most importantly due to abundance of different vegetation indices and their relative differences (White et al. 2009). In addition, there are some other confounding issues related to the estimation of phenology from satellite sensor data, specifically for vegetation types with no clear seasonality pattern (e.g. desert shrubland), with little or false seasonality pattern (e.g. evergreen needleleaf forest), and those with multiple seasonality (Reed et al. 2003). The vegetation indices are indicative measures of “greenness”, and a high value of greenness does not necessarily mean more pollen from biological productivity, apart from abiotic factors (weather conditions, topography, soil conditions) and biotic factors (biological processes, e.g. plant hormone, age, genetic make-up). Irrespective of the fact that satellite remote sensing-derived products, including vegetation indices, have limitations, they have demonstrated to be a useful means to monitor, manage, understand, and quantify various aspects of the environment consistently, at various spatial and temporal scales, and in a timely manner.

In Europe and North America, forecasts of atmospheric concentrations of birch and grass aeroallergens are broadcast to help pollen allergic sufferers avoid exposure or manage their symptoms with medication. Moreover, advanced pollen forecasts will lead to better preparedness for other respiratory-related diseases (e.g., asthma), hospital admissions personnel, workforce managers, and pharmaceutical marketing (Aono and Kazui 2008). These forecasts are usually based on meteorological data together with pollen count data collected at a specific pollen station. In most cases the predictions are established using empirical models derived from archived data from pollen stations

(Isabelle and Jordina 2004; García-Mozo et al. 2009; Laaidi 2001; Smith et al. 2009). These models have well-known limitations, however, as they are very specific to the area where they are produced (Stach et al. 2008) and yet are typically applied across much broader regions that encompass wide variation in pollen sources across urban, agricultural and natural environments (Pauleit and Duhme 2000; Skjøth et al. 2008a). These limitations could be reduced through the deployment of more pollen monitoring sites, but to date that has been prohibitively expensive. Satellite remote sensing of vegetation phenology patterns provides a more effective solution. The results outlined in chapter four of this thesis demonstrate that there is a statistically significant positive correlation between the pollen count-derived starting dates of the pollen seasons of both birch and grass, and the MTCI-derived start dates of flowering, indicating the suitability of using the MTCI to predict the start of pollen season indirectly. These results support previous claims made regarding the possibility of a link between the leaf-bud burst (flowering) and pollen release (Linkosalo 1999, 2000; Jato et al. 2002; Newnham et al. 2013) and further support the study of Karlsen et al. (2008) which found relatively large positive correlations between NDVI-derived start dates and pollen count-derived starting dates. The methodology used here is very different from that of Karlsen et al. (2008) in terms of the techniques for extracting phenological variables. Karlsen took the closest pixel (i.e., 250 m MODIS NDVI spatial resolution to represent the source area of birch) around the pollen sites without creating any buffer conditions, which is inadequate considering the fact that pollen may transport over remarkable distances (hundreds of kilometres in dry weather). This research used a 50 km buffer radius accounting for the fact that in most usual situations pollen would be deposited within about a 50 km radius of its source (Emberlin 2009). Since a pollen monitoring site is a point 'sink' for pollen counts, depending on the direction and local turbulence of the wind, the pollen may come from various directions (i.e., north, south, east, west, south-east, south-west, etc.). Therefore, generating a buffer around the site integrates the potential pollen catch from the various directions. Furthermore, this study used MTCI data with a 1 km spatial resolution. Boyd et al. (2011) compared various vegetation indices; MERIS global vegetation index (MGVI), MODIS normalised difference vegetation index (NDVI) and MODIS enhanced vegetation index (EVI) and MTCI in studying vegetation phenology in the UK and they reported support for the use of MTCI mainly due to its sensitivity to canopy chlorophyll content (i.e., limited sensitivity to

high values of chlorophyll). Thus, MTCI is directly related to canopy chlorophyll content, a function of chlorophyll concentration and leaf area index (LAI) and, therefore, is a useful proxy for the canopy physical and chemical alterations associated with phenological change. Moreover, MTCI has limited sensitivity to atmospheric effects, view angle, soil background (Dash et al. 2008).

The flowering phenophase derived from the MTCI represents the average temporal profile of certain land cover types (e.g., broad leaf forest), one of the major sources of birch pollen, within the 50 km radius buffer. Therefore, the temporal profile, apart from being the spatial representation of birch, also represents the timing of a phenological event (i.e., flowering). Moreover, the 50 km buffer encompasses or intersects patches of different land cover types in the countryside where phenological development starts slightly later in comparison to within cities (i.e., all the pollen sites are in cities). Thus, in general, the MTCI-derived flowering phenophase dates arrived slightly earlier in comparison to the pollen count-derived start dates. In addition, the role of pollen transport on the early local pollen season (start dates) of grass and birch should also be considered. However, how significant is the role of the regional pollen transport on the local timing of the pollen season requires further investigation as some of the transported pollen is already eliminated when defining the start of the pollen season (i.e., by the DM and cumulative sum methods).

The positive strong link between the pollen count-derived starting dates of the pollen seasons of both birch and grass, and the MTCI-based start dates of flowering found in both the spatial and the temporal dimensions indicates a synchronised relationship between the flowering phenophases of birch and grass at the “source” and the pollen count at the “sink” taking into account the time lag of pollen travel and the influence of the local or urban pollen catch.

In the UK, there are approximately 150 different species of grasses available and, thus, their response to weather parameters vary and, in turn, have different flowering times or phenological development. This makes developing forecasting models for grasses rather complicated. Furthermore, mixed pixels in satellite sensor data reflect the start dates of a heterogeneous range of grass types and hence do not represent a particular species.

This highlights the need for detailed fine spatial resolution birch and grass source inventories or maps for the UK.

6.2.1 Climate change, plant phenology, and timing of pollen release

Changing patterns of plant and animal behaviour are considered to be one of the most important observed impacts of recent climate trends (Root et al. 2003; Hegerl et al. 2007). Biological impacts are known to be imperative indicators to provide evidence of climate change and the warming of the Earth regardless of independent temperature measurements (Root et al. 2005; Parmesan et al. 2011). There has been a focus on the process of ‘climate change attribution’, assessing the extent to which the observed changes are being driven by human-induced climate change or natural climate variability (Rosenzweig et al. 2008; Zwiers and Hegerl 2008). In addition to the complexity of the inter-relation between the environmental factors (e.g. land use change, exploitation and pollution), the issue of the scale of the impact arises, for example human forcing of the climate is recognisable at wide spatial scales, but organisms experience local weather. Thus, species are likely to respond to climate without differentiation between the sources of change. Plant phenological changes provide a unique opportunity to overcome the scale issue by covering a wide range of species and large spatial scales.

Recently, there has been a focus on the use of pollen release data as phenological phenomena in investigation of biological responses to recent climate change (Newnham et al. 2013; Thackeray et al. 2010). Any shift in the timing of plant phenology, especially flowering, is likely to influence directly the timing of pollination and hence pollen release. Previous studies have shown that the change (i.e., increase) in temperature observed in recent decades has influenced the phenology of plants, for example, an earlier start of plant flowering in spring and summer (Menzel and Estrella 2001; Parmesan and Yohe 2003; Root et al. 2003; Menzel et al. 2006), an earlier start of the pollen season in the Northern Hemisphere (Frei and Leuschner 2000; Beggs 2004; Estrella et al. 2006) and a lengthening of the pollen season duration (Ziska et al. 2011).

In the UK, the start of the birch pollen season has become earlier in recent decades consistent with warmer spring temperatures (Emberlin et al. 2002). In the Netherlands, the start of grass pollen season has advanced by 6 days from the 1970s to the 1990s (van Vliet et al. 2002). In Italy, the start of grass pollen season has advanced by 0.8 days per year between 1982 and 2001 (Frenguelli 2002). The temperature has lengthened the active growing season by an average of 10 days since the early 1960s (Menzel and Fabian 1999; IPCC 2001b). The lengthening was the result of the increased photosynthetic activity which prolonged the growth of plants, in particular between 45 N and 75 N (Myneni et al. 1997). Furthermore, on average the onset of blooming for the temperate zone species has advanced (started earlier) by 5.1 ± 0.1 day per decade and has advanced 2.3 days globally per decade (Root et al. 2003; Parmesan and Yohe 2003). Fitter and Fitter (2002) reported that the average first flowering dates of nearly 385 plant species in south-central England had advanced by 4.5 days during the last decade in comparison with four previous decades. This investigation was determined using temperature as the main indicator. However, there is no clear evidence for how different plant species or groups respond to temperature warming, for example, annual plants, perennial plants, *entomophilous* plants (insect-pollinated), and *anemophilous* plants (wind-pollinated). Ahas et al. (2002) reported that early flowering species, for example, birch and hazel are most affected by the warming.

According to Frenguelli (2002) the projected temperature alterations as a result of global warming are likely to have an enormous impact on the timing of pollination of many plants and, therefore, pollen forecasts must account for these alterations when constructing allergic pollen predictive models. The start of grass pollen season will advance by 11 days from the 2000s to 2090s, according to van Vliet et al. (2002). However, due to the fact that allergenic grass is composed of various species, its response to environmental variables (e.g., temperature and CO₂) varies. For example, in many plants the timing of flowering is controlled by the photoperiod (day length). Thus, the response of such plants to temperature rise and climate change is limited (Emberlin 2000). Furthermore, the response of different grass species to temperature varies; for example, a rise in temperature by 1°C in an experiment by Fitter et al. (1995) showed flowering time advancement by 13-23 days in *Holcus Lanatus* (Yorkshire fog or

meadow soft grass) species and showed late flowering by 10-32 days in *Poa Trivialis* (rough-stalked meadow-grass) species.

The consecutive Intergovernmental Panel on Climate Change (IPCC) assessment reports (1990, 1995, 2001, 2007, and 2014) have emphasised with remarkable confidence the contribution of the emissions from human activities to increasing the concentration of greenhouse gases (CO₂, methane, CFCs and nitrous oxide) in the atmosphere, in particular CO₂. These contribute to anthropogenic forcing of climate change. The evidence for this forcing seems to be mounting gradually in the last decades. According to the IPCC (2001a) report, the average surface temperature of the globe due to climate forcing (radiative forcing) has increased by 0.6 ± 0.2 °C in the 20th century and the report also predicted that the figure will increase to 1.4 to 5.8 °C by 2100. Similar arguments for global heating or warming were reported by Ahas et al. (2002). The accumulated excess carbon dioxide (CO₂), methane and greenhouse gases in the atmosphere are usually to blame for the warming. Thus, these gases influence the dynamics of energy by trapping heat in the atmosphere and, in turn, heating-up the Earth's surface (McMichael and Haines 1997). The period of 1990 to 1999 on instrumental records has been reported to be the warmest annually and in the winter in Europe (IPCC 2001b). It is known that the concentration of atmospheric CO₂ influences plant physiology and functioning through the processes of photosynthesis, photorespiration and stomatal functioning (Ziska et al. 2001). Wayne et al. (2002) reported that plants generally grow faster and larger at maturity in an atmosphere enriched with CO₂ concentration. However, the magnitude of these changes varies and depends on environmental conditions and plant species. Therefore, the atmospheric CO₂ concentration and Earth's surface warming have the potential to influence the physiology, the allergenicity, and the phenology of allergenic plants. The influence of the increase in atmospheric CO₂ concentration from the pre-industrial to current day levels on ragweed pollen production (an important aeroallergen) was investigated by Ziska and Caulfield (2000) and Wayne et al. (2002). They reported that CO₂ not only increased the amount of pollen produced by an individual floral spike but rather increased the number of floral spikes. Yet, it is worth mentioning that the CO₂ may have a suppressive effect on plant growth depending on the species. Shaw et al. (2002) reported that increased CO₂ suppresses the net primary productivity in grasslands.

Evaluation of the mixed influence of increasing atmospheric CO₂ and increasing temperature due to climate change on plants is difficult. The IPCC (2001b) report pointed out that climate change affects (i.e., increases) the productivity of grasslands directly through CO₂ and indirectly through temperature and rainfall. However, the effect of climate change varies spatially and this urges construction of more regional allergenic pollen forecasting models. For example, in Europe annual temperature is predicted to warm up at a rate of 0.1 to 0.4 °C per decade, with the greatest increase being in southern and northeast Europe and the smallest increase being along the Atlantic coastline. As far as precipitation is concerned, an increase of +1 to +2 % per decade in northern Europe is predicted and a decrease of -1% in the southern part is predicted (IPCC 2001b).

The physiology of temperate zone trees and their environmental responses has been investigated for many years. Chandler (1925) recognized that during the autumn trees enter a dormant period during which inhibitors accumulate in the bud scales and prevent growth. Kramer and Kozlowski (1979) reported that growth could not be resumed until a period of chilling had taken place. Daily average temperature in the range of 0 - 7.2 °C was the most effective for chilling (Chandler 1925; Brown 1960). Thus, temperatures during the late autumn and winter have an influence on bud growth and pollen production and, in turn, have an overall influence on the potential total birch pollen catch (i.e., annual sum or catch). Moreover, Faust (1989) reported that the exact time of flowering or catkin bloom during the spring was solely dependent on spring temperatures for bud development and growth. Similarly, the flowering of grasses has been studied for over 100 years (Godron 1873), and there has been remarkable controversy over the mechanism of various phases of flower initiation. Gregor (1928), Davidson (1941), and Jones and Brown (1951) all claimed the importance of temperature in flower initiation. Cocks (1958) claimed that humidity hinders flower initiation. In contrast, Gregor (1928) claimed that humidity promotes flower initiation. Recently, there has been clearer understanding of the complex interaction of the external forcing (e.g. meteorological factors) and internal forcing (internal response triggered by external forcing) of plants. Flower initiation among species also varies both spatially and temporally. In any one region, a progression of flowering of different

species occurs throughout the growing season. There is a significant inter-annual variation of the timing of the season depending primarily on cumulated temperatures over 5.5 °C and precipitation in the months preceding the flowering period (Emberlin 2009).

Knowledge of how climate change will affect the growth potential, spatial distribution of grass and birch species is essential for developing climate change adaptation strategies. Recent regional climate models have reported that the distribution of plant species in general will change due to climate change, for example, the UK Ecological Site Classification Decision Support System (ESC-DSS) has produced some future scenarios for various types of plant species. In that context, satellite sensor vegetation products which can be used to derive phenological observations consistently for a wide area have great potential to plan and monitor vegetation dynamics. This, in turn, as far as the source inventories of aeroallergens (i.e., grass and birch) is concerned, can assist in allocating pollen sites and developing more accurate pollen predictive models.

6.2.2 Source areas of birch and grass and annual pollen catch

Annual pollen catch (sum of pollen) collected at the pollen sites varies from year-to-year. This variation, in part, is in correspondence with variation in meteorological conditions during and preceding the growth season. Temperature and precipitation are the key meteorological parameters that affect inter-annual variation of pollen (McLauchlan et al. 2011; Ščevková et al. 2010). Annual pollen count also varies as functions of other factors, for example, source area or spatial area, biological rhythms for productivity (i.e., biennial rhythms or 2-year fluctuating rhythm of high/low biological productivity). There have been studies exploring the relationship between annual pollen catch at pollen sites and meteorological parameters, yet as far as this study is aware, no studies have ever explored how the source areas contribute to the annual pollen catch. Addressing this question fully may be difficult due to the effect of pollen transport, rural and/or urban sources, wind condition and precipitation. During establishing the main analysis chapters of this study, out of curiosity, it was decided to establish a relationship (i.e., bivariate Pearson's product-moment correlation analysis

(Table 6-1)) between the source-areas of birch (i.e., broad leaf forest, green urban, mixed forest land cover types) and grass pollen (i.e., grassland, pasture land cover types) from the MTCI data and their annual pollen catch for the period of 2003-2010. The source areas for birch and grass were identified from the CLC2000 land cover data. Thus, the land cover types of birch and grass are composed of the number of pixels (i.e., 0.0089° (~1 km by ~1 km MTCI spatial resolution)) within the 50 km radius around the nine pollen sites. Intuitively it can be inferred that the areas of the land cover types or number of pixels are constant for the 2003-2010 whereas the annual pollen catch varies from year-to-year. Irrespective of the fact that pollen transport affects the annual catch, especially for birch, the birch pollen demonstrated statistically significant correlations with the areas of the Broadleaf forest and Green urban land cover types for 5 years out of the 8-year period. In contrast, none of the land cover types demonstrated significant correlations with the grass pollen catch. The concentration of pollen after release from the sources tends to dilute as it disperses away from the sources. In other words, the pollen concentration of grass immediately after release at the source tends to be the highest and then dilutes in time due to its height of release which is near the ground. Thus, the pollen catch at the “sink” (at the stations) does adequately represent the source area. However, for birch the source area seemed to be more representative at the ‘sink’. In other words, grass pollen is more likely to be local than birch pollen. Source areas of birch in the UK, for example, broadleaf forest and green urban land cover types contribute significantly in annual pollen catch at the monitoring sites. Skjøth et al. (2008b) reported that urban areas represent an important source of birch pollen concentrations within the city. Such exploration provides some useful information on a suitable spatial extent to evaluate the contribution of land cover type to the annual pollen catch. On the other hand, this kind of exploration may be un-realistic as the biological pollen productivity is not determined by the area of the pixel of a certain land cover type. In other words, a larger the area of a land cover type does not necessarily indicate more pollen, but may indicate more greenness or biomass in the context of this study. This raises a simple but interesting question of how greenness and pollen production are related. Healthy foliage on plants intuitively suggests more flowers and hence more pollen production.

Table 6-1 Relationship between average annual grass and birch pollen catches (sum of pollen for an entire year) and pixel numbers (areas) of several land cover types within a buffer of 50 km around nine stations across the UK for the period of 2003-2010 (r = correlation coefficient).

Station	Number of Pixel per LC types						
	Pollen Catch		Broad leaf forest	Green Urban	Mixed forest	Grassland	Pasture
	Grass	Birch					
Belfast	3574	569	23	8	11	461	6740
Cambridge	3430	2671	74	14	17	19	803
Cardiff	3093	1826	305	14	14	849	4129
Edinburgh	2596	807	127	17	40	1605	3666
Invergowrie	1868	849	93	6	18	747	2383
IOWT	5077	1815	332	11	155	14	1535
London	4055	4828	594	167	17		2848
Plymouth	2446	763	98	11	84	422	2713
Worcester	6643	3588	257	32	31	30	3355
r (Grass)			0.42	0.21	0.24	0.62	0.04
r (Birch)			0.786*	0.799**	0.17	0.59	0.31

6.3 Phenology and pollen predictive models

Certain characteristics of the pollen season, for example, the start of season, are used interchangeably with certain phenological observations on the ground such as flower emergence. Therefore, such events have been used in generating phenological models. The phenological models are in general divided into two types; the purely empirical based models (also known as observation-based models), and process-based models. The process-based models are subdivided into experimental and theoretical-based models (Zhao et al. 2013). In the case of empirical models, the phenological date entries (e.g. first bud burst, or first flower) are related to environmental factors prior to the growing season (e.g. mean temperature in the temperate areas). These models do not include any mechanistic information on the link between the plant physiology and environmental factors. In contrast, process-based models consider several factors that are crucial during the stages of plant development. The importance of these factors is mainly determined through experimental investigations. Plants physiology is governed by various factors (e.g. environmental factors and biological factors) throughout the year and hence there are uncertainties on how these factors interact with each other during the stages of vegetation development. Therefore, quantification of these factors

is challenging and makes developing these models less attractive. In general, process-based phenological models use one or a combination of these well known factors: Chilling temperature, forcing temperature, photoperiod, and water availability. For example, chilling is important to overcome the dormancy of the buds that has been developed during the growth season for the upcoming season but remain dormant. During autumn and early winter dormancy is overcome through chilling. After this, the development of leaf, flower, and shoot buds begins in the following spring (Linkosalo et al., 2006). The theoretical-based models are based on the cost-benefit trade-off, for example carbon-balance-based phenology model of Liideke et al. (1994). The theoretical basis of the carbon-balance-based method is that the carbon balance between the leaf photosynthesis gains (carbon gain) and respiratory costs (carbon loss) determines the leaf onset and offset timings. The most obvious advantage of such models is the broad coverage and an obvious downside is geographical variation in response.

Receptor-based models, better known as observation-based models (i.e., pollen count data with meteorological variables are used for model building), are the most commonly used phenology model to predict the characteristics of the pollen season in comparison to source-based models (i.e., plant based physiology-based models). Receptor-based models are usually constructed using: (i) regression models (e.g. simple linear regression, multiple regression analysis, step-wise multiple regression, standard multiple regression, polynomial regression and semi-parametric Poisson regression), (ii) Time series models (e.g. Box-Jenkins method, Neural networks, Neuro-fuzzy approach, Functional regression), and (iii) computational intelligence (e.g. Artificial neural networks, co-evolutionary neural network, classification and regression trees) (see *section 2.5*). Among these models the simple and the multiple regression models are the most frequently used in aerobiological studies. The question of which of these three above-mentioned models types perform better in aerobiological studies is still to be investigated. There has been very little attempt to address this question, for example, Sánchez Mesa et al. (2003) compared a co-evolutionary neural network and linear regression models in forecasting daily grass pollen concentrations in Spain. They reported that the neural network models performed more accurately than regression models. However, pioneering aerobiologists in the UK have used and are

recommending regression models (Davies and Smith 1973; Emberlin et al. 1993a; Norris-Hill 1995; Emberlin et al. 1999; Adams-Groom et al. 2002; Smith and Emberlin 2005, 2006).

The multiple regression models constructed in this research (chapter 5) in general demonstrated high levels of explanation across most of the sites. The lowest levels of explanation with the highest estimated standard error were recorded for birch at London (R^2 -adjusted= 47% St error = 115 grains m^{-3}) and for grass at Worcester (R^2 -adjusted= 58% St error= 50 grains m^{-3}) (Tables 5-5 and 5-6). Pollen count concentrations in London are highly variable due to sparse distribution of birch trees, urban heat island and meteorology condition. Thus, under unique circumstances the pollen count recorded at the site could be unpredictably or oddly high or low. Regression models have shown sensitivity to such odd events. Moreover, the models are also sensitive to the pollen season with more than one peak which occurs very rarely, especially for grass. The low level of explanation and high estimated standard error for birch at the London site is due to the high pollen count at the peak days in 2005 (Fig. 6-1). At Worcester, the low level of explanation and high estimated standard error for grass is due to the double peak in 2005 (Fig. 6-2). The finding in 2005 is very interesting as it concurs with the weather conditions reported by the Met Office (Fig. 6-3 and 6-4). In 2005, the mean temperatures in England were above average (~ 1.5 °C) and rainfall (~100 mm) and sunshine (80.1 hrs) were generally below average across England. Moreover, in 2005, the November to March rainfall was the driest for England and Wales since 1975/1976 (www.metoffice.gov.uk/climate/uk/2005/march.html).

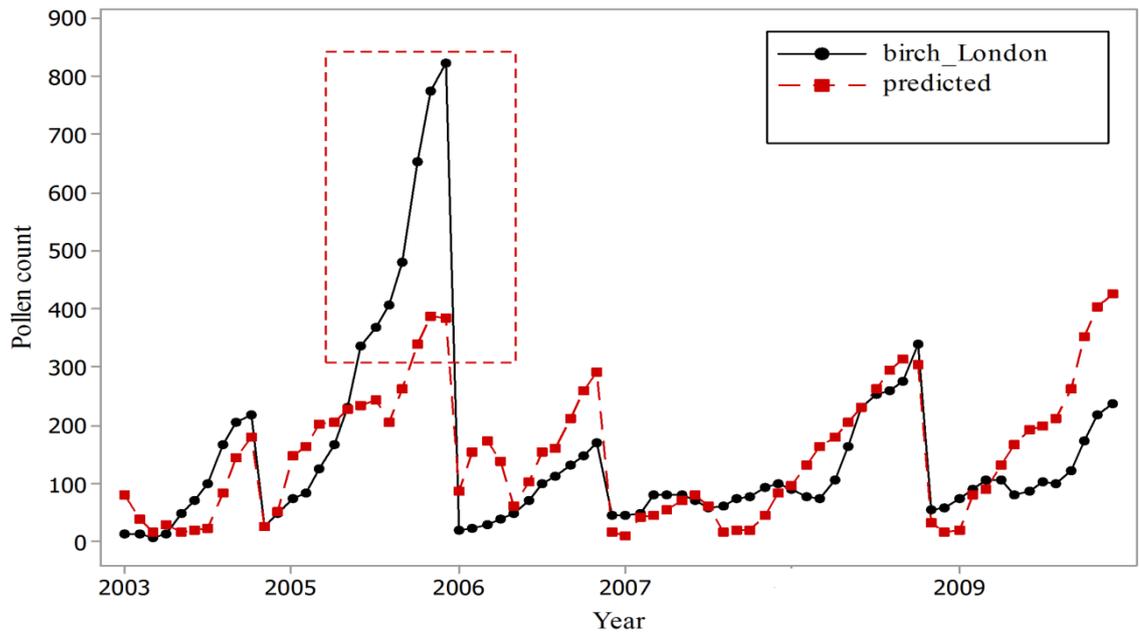


Fig.6-2 Actual daily birch pollen count and predicted daily birch pollen count for London for the period of five years. Year 2005 shows very high pollen count in comparison to the other years.

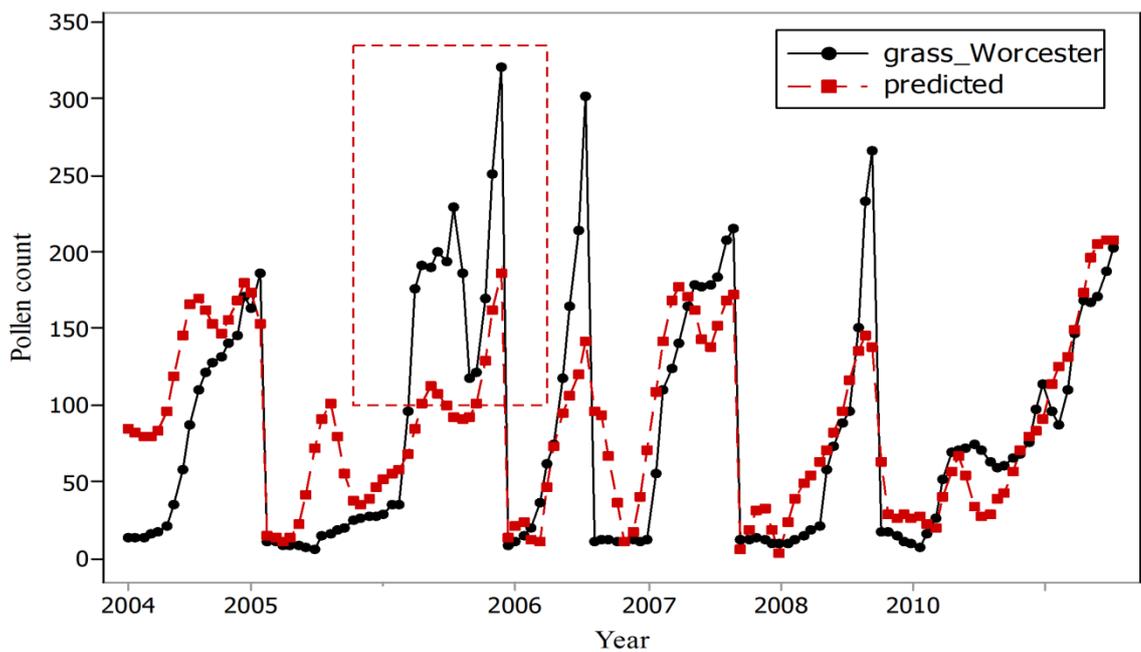


Fig.6-3 Actual daily grass pollen count and predicted daily grass pollen count for Worcester for the period of six years. Year 2005 shows very high pollen count with two peaks in comparison to the other years.

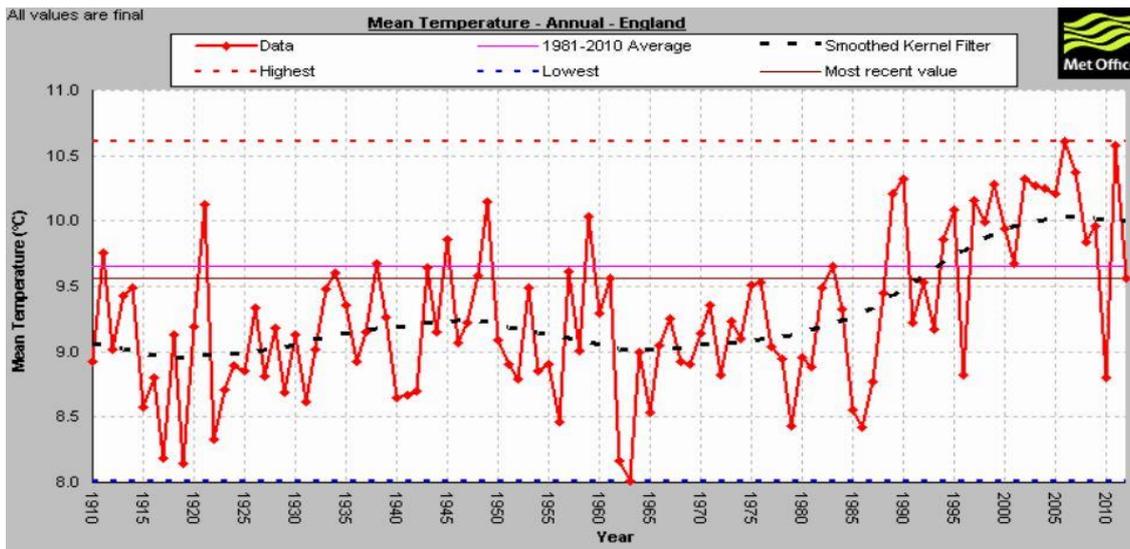


Fig.6-4 Time series average temperature for England (www.metoffice.gov.uk).

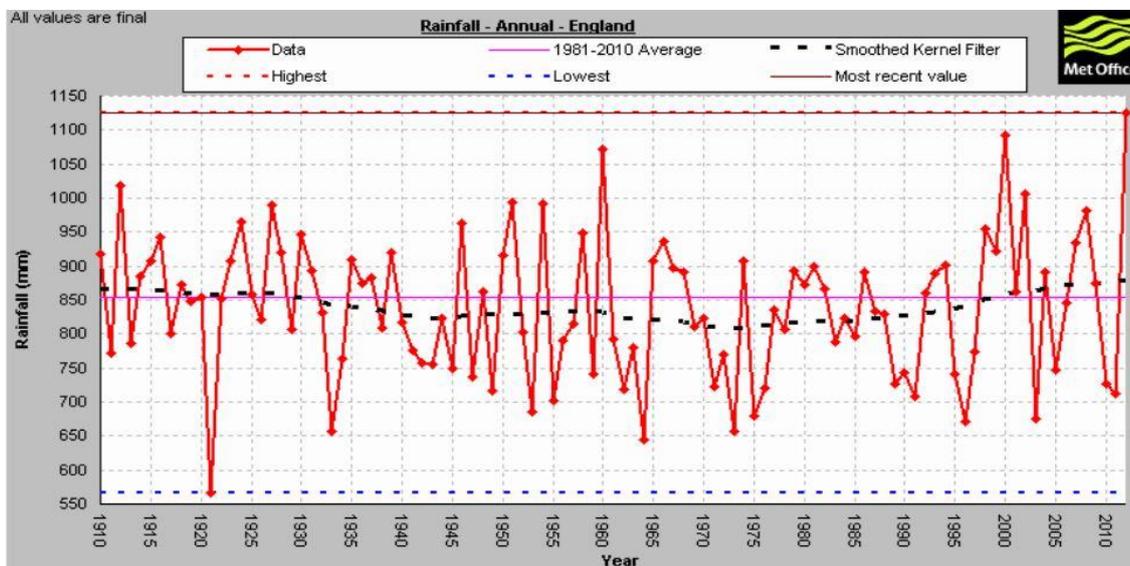


Fig.6-5 Time series average rainfall for England (www.metoffice.gov.uk).

Most of the phenological networks established recently rely on public participation or ‘citizen science’ in reporting local phenological events. These observations by public have inherent noise and inconsistency, which makes describing and modelling them challenging. Moreover, the availability of time-series phenological data has not yet been established over a wide spatial coverage. Furthermore, phenological observations are in fact only reported dates of the event without any information about the quantity of the event. For example, a reported date of flowering event which is a proxy for the date of pollen release, does not provide knowledge on the quantity of pollen. Therefore,

developing predictive models from field phenological observations may be less feasible than for receptor-based models. Nevertheless, the phenological point observations may provide useful ground data for validating satellite data-derived phenological parameters given that some of the challenges have been faced by developing proper techniques for the validation. In other words, ground-based phenological observations often obtained from a small number of individual and species at specific site, and almost never sampled across space within an areas comparable in size to moderate resolution satellite pixels (i.e., sensor-derived phenology measurement) (Schwartz et al. 2013). However, this is still under investigation and has recently gained a lot of attention, in particular, from the satellite remote sensing community. Monitoring vegetation development phases (start of season, end of season, etc.) by analysing satellite vegetation indices has already been investigated in many studies. One of the most obvious limitations of these studies is ground validation of the phases.

The notion of pollen transport over long distances is a limitation of both the phenological models and receptor-based models. In other words, both phenological events, such as flowering, and pollen counts sampled at the sites alone are insufficient to determine the timing of the season due to the influence of pollen transport on the overall seasonal profile. To overcome this, recently there have been attempts to model the main characteristics of allergic pollen in the air employing both the source-receptor-oriented approach using satellite sensor data in determining the source and phenology events (Karlsen et al. 2008a) and atmospheric dispersion models to track the pollen distribution (Luvall et al. 2011). These models employ the mathematical formulae of diffusion to calculate the pollen concentration at different distances from the release site. They are mostly Gaussian, area/box, Plume and gradient transport models that can estimate concentrations of airborne matter within 20-50 km of a point source. These models have various applications under various condition and assumptions, for example assumptions about the dispersal environment that need to be satisfied before application, and known or estimated emission rates (Norris-Hill 1995). However, which phenological model types (i.e., observation-based phenological models, process-based models, theoretical-based models and receptor based models) perform better in characterising pollen season is unknown.

The phenology of plant (in general) development and their interactions with climate vary at various levels of spatial and temporal resolution in correspondence to climatic drivers. The type of climatic driver, depending on the biogeographical area (i.e., Tropical, Subtropical, Temperate and Boreal), are mainly temperature and precipitation. The spatial dimension includes:

- (i) Local (species-specific phenological events in relations to local factors and genetic traits (biotic capability, e.g. nutrient uptake) and characteristics (e.g. age) of the species)
- (ii) Regional (vegetation phenological events and shifts in relation to regional environmental drivers) and
- (iii) Continental (landscape in relation to climate)

The temporal dimensions include intra-seasonal, intra-annual, and inter-annual in respective order with the above-mentioned spatial dimensions. The types of phenological models mentioned above were generated based on these levels of spatial and temporal variation in plant phenology. Yet, these models from the perspective of their spatio-temporal variation, may have some uncertainties related to our understanding of the phenological mechanisms in connection to (i) interactions between plants and their specific climates (ii) the parameterisation processes and, more importantly, (iii) the integration of remotely sensed data and ground data with phenology models across various ecosystem types. Yet, these uncertainties require quantification, and they could be minimized by employing and/or linking between high spatial and temporal resolution satellite observation (e.g., FORMOSAT2- RSI: spatial resolution: 2-8m, temporal resolution: daily), ground phenological observations, and near-surface remote sensing techniques (e.g., Phenological Cameras (PhenoCam)). PhenoCam, high-resolution digital cameras placed on flux towers, would provide a unique opportunity to monitor the dynamic, and better understand the transition stages of plants.

6.4 Future research

The findings, the extensive review, the limitations, and the background readings throughout the research presented in this thesis suggest clear directions for future research and investigation. Such investigations can further enhance our understanding and provide more accurate assessment, and more effective monitoring and analysis of local air quality effects on public health.

This research and most published aerobiology researches are based on the collecting and analysing of physically intact pollen grains from the atmosphere. The complex chemistry and physics of atmospheric composition, in particular in recent decades due to several kinds of pollutants (particulate matter), have led to allergic particles being available in the atmosphere independently of pollen. Thus, for example, the pollen grains may not be loaded with the allergic particle. Thus, the effects of meteorology in the transport of pollen is not only limited to the physical transport processes and conditions for pollen production and release, but also may play a significant alteration in the pollen size distribution. Taylor et al. (2004) reported that birch pollen would rupture in high humidity and moisture. The size of the ruptured pollen grains ranged from 30 nm to 4 microns, much smaller than the range of typical allergenic plant species pollen. Furthermore, the origin of the allergic particles may be from plant material or could result from the cross-reactivity between atmospheric pollutants. These tiny allergic particles contribute to the allergic symptoms in particular during the early and late pollen seasons (Spieksma et al. 1989). Furthermore, Agarwal et al. (1981) reported that pollen counts do not always correlate with the allergen load of the atmosphere. Emberlin et al. (1993b) reported, despite the fact that the grass pollen concentration in London has declined, that allergenicity has increased because of interaction with air pollutants. Therefore, it is important to further investigate and understand in detail the pattern and the significance of the tiny allergic particles (i.e., Micronics) and their relationship with hay fever symptoms.

The use of satellite image-derived products in characterising vegetation phenology is well established and its literature is widely available. Yet, its application and use in estimating parameters related to pollen release is limited. However, there is growing

interest from the aerobiology community in monitoring seasonal vegetation dynamics from satellite-derived products. Satellite remote sensing products provide repetitive and consistent observations of important vegetation phases such that the source and timing of pollen release of a vegetation type can be measured. However, they still have unquantified uncertainties. The most obvious uncertainties are: (i) scale difference between what has been measured from satellite sensors and what has been observed on the ground. The ground level observation of vegetation phenology phases is fundamentally different from the sensor observations (*section 6.3*) (ii) quantification of the density of pollen or ‘pollen stock’ available for dispersion at the measured source. The ‘pollen stock’ varies from year-to-year as a function of the weather pattern and other environmental factors (e.g., pollen transport, urban source pollen). There is room for research exploring and establishing some methodologies, for example, intensive backward trajectory analysis to trace back pollen catch at a certain pollen site (i.e., sink) to a certain source area (i.e., relevant land cover area or pixel). The new generation of fine spatial and temporal resolution satellite sensor products, for example, Sentinel 2 (spatial resolution: 10 – 60 m, temporal resolution: 5 days at equator) are planned to provide field level phenological data that may eventually overcome some of the issues of using 250 m spatial resolution data (moderate resolution satellite pixels).

In respect to the application of the abundant satellite sensor data products in investigating particulate matter and air pollutants (including pollen), apart from its phenology dynamic application, there is also room for making use of specific Aerosol Optical Thickness (AOT) data for pollen studies. AOT, apart from its application in atmospheric correction of satellite sensor imagery, could also be used for monitoring particulate matter. These data products may have resolution issues (generally 1 km spatial resolution) whereas the concentration of the air pollutants may vary in the range of several metres. However, the availability of various fine spatial resolution sensor products (e.g., KOMPSAT-2–MSC with 1-4 m spatial resolution, UK-DMC2 with 22 m spatial resolution and daily temporal resolution) has potential to resolve the issue of scale and resolution.

There are a wide range of approaches for defining the start of the pollen season (i.e., the date that hay fever sufferers manifest allergic symptoms) in the literature. The definition

of pollen season usually varies from country-to-country. For example, one of the most common approaches is the 50 grains m^{-3} threshold approach of Davies and Smith (1973). They observed that when the mean daily concentration of grass pollen grains in the air over central London is 50 grains m^{-3} of air or more, all the patients diagnosed as being sensitive to grass pollen who visited their clinics, manifested symptoms. Driessen et al. (1990) defined the start of the pollen season as the day on which the cumulative total pollen catch was 50, 75, 100, and 125 grains per individual species. An alternative is the total annual catch threshold (e.g., of 1%, 2.5% and 5%) which requires the total pollen catch of the previous year (Emberlin et al. 1999). Therefore, this study urges for a unified international definition of start of pollen season and other characteristics of the pollen season (e.g. length and severity).

Establishing pollen source inventories through fine spatial resolution classification of relevant land cover types can provide useful information considering the challenges (in particular, birch source inventory due to its sparse distribution within the built-up and urban areas). Satellite-driven products in building such inventories provide invaluable information for controlling the number of pollen sites which require budget and manpower to run in addition of the tedious nature of pollen counting and identification.

Pollen counts usually used in aerobiology analysis are averages over 24 hours, thus, masking diurnal variation. In other words, the time of the day at which the pollen count is highest or lowest is not fully clear. Brown (1992) has suggested that symptoms of hay fever are related more tightly to diurnal and nocturnal peak counts than to the average for 24 hours. Therefore, more detailed understanding is required on how pollen concentrations or counts vary over time and space considering the time required for the pollen to travel from the source to the sink.

Phenology is regarded as a valuable tool to detect and measure the impact of climate variability on vegetation (Neil and Wu 2006; Ide and Oguma 2010; Pau et al. 2011). The importance of phenology, therefore, has noticeably increased during the last decade. Leaf unfolding and flowering are the most often observed phenological phases and are examined in many phenology modelling exercises (Kalvāns et al. 2014). There has been less attention on the fruit maturation and senescence phenophases. This is probably due

the fact that the timing of leaf unfolding and flowering can be observed accurately in comparison to fruit maturation and senescence, and more importantly leaf unfolding is very important for primary production (Richardson et al. 2013) and flowering largely determines plant reproductive success (Chuine et al. 2003). Models to predict these phenological phases using observation data have been produced for a variety of applications: (i) inferring the physiological mechanisms or environmental thresholds and drivers that control phenology (Migliavacca et al. 2012); (ii) prediction of the climate change impacts on phenology (Ibáñez et al. 2010); (iii) phenological models in agriculture used to predict pest emergence (Irvine 2011); (iv) improvement of primary productivity models (Kramer and Hänninen 2009), and (v) forecasting of the occurrence of pollen in the air (García-Mozo et al. 2008). This study suggests that there is plenty of room for research in modifying and integrating/coupling process-based models and receptor-based models on one side and dispersion models on the other side. The integration and coupling of a receptor-based model, a process-based model and a dispersion model would give a near-complete picture of the influence of plant phenology on the seasonal pollen profile.

Finally, there is a considerable amount of research that acknowledges that pollen grains can transport over long distances (i.e., hundreds of kilometres). Yet, there are questions to be investigated: for example (i) how significant is the role of pollen transport on local pollen variation?, (ii) how much pollen has been transported?, and (iii) what is the daily pattern of transport in space and time? Some of these questions are likely to be answered by adapting various atmospheric transport models that have been used widely in studying particulate matter and air quality (Table 2-1). For example, the HYbrid Single-Particle Lagrangian Integrated Trajectory (HYSPLIT) transport and dispersion model has been developed by the National Oceanic and Atmospheric Administration (NOAA). The HYSPLIT model is a tool that helps explain how, when, and where particulate matter is atmospherically transported, dispersed, and deposited. The HYSPLIT4 calculation method is a hybrid between the Lagrangian approach, which uses a moving frame of reference for the advection and diffusion calculations as the air parcels move from their initial location, and the Eulerian approach, which uses a fixed three-dimensional grid as a frame of reference to compute the pollutant air concentrations (Fig. 6-6). The main input data for HYSPLIT is composed of (i) source

area information (gridded format), (ii) meteorological parameters (Air Resources Laboratory (ARL) format or gridded format) data, and (iii) the aerodynamic properties of the particles (i.e., size, terminal velocity, and emission rate).

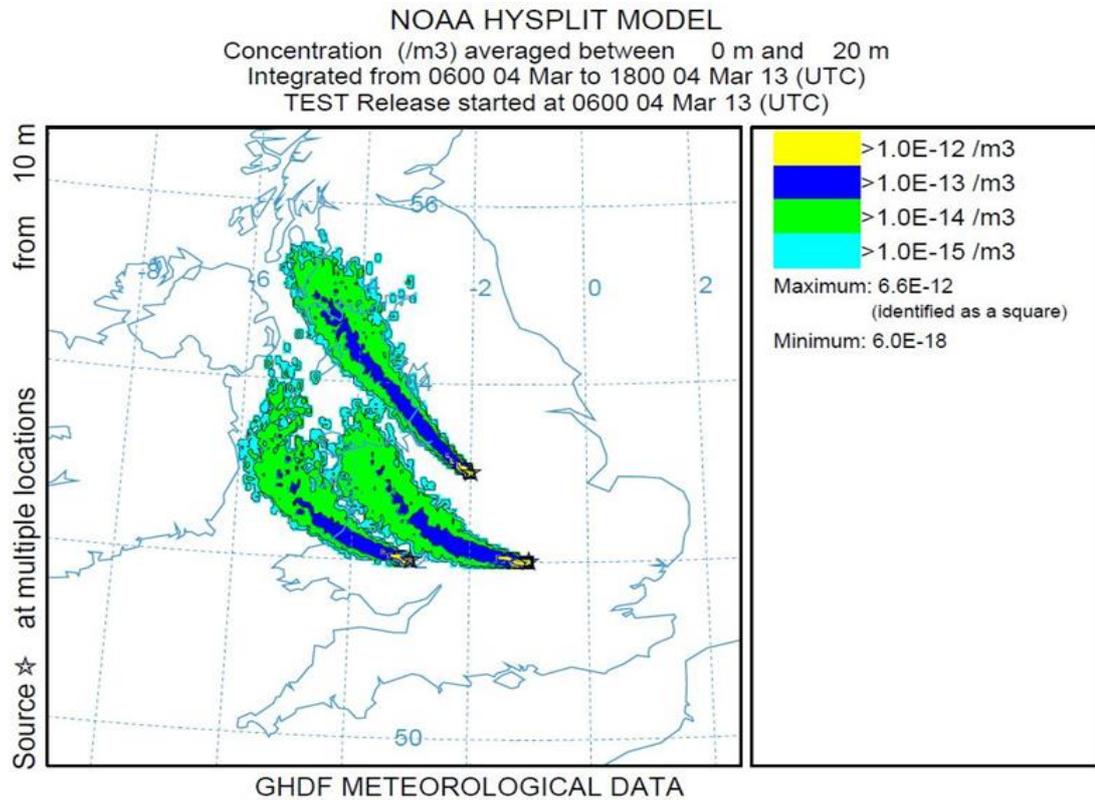


Fig.6-6 HYSPLIT model simulation output for three pixels as sources of emission of a random particle in the UK.

Among all the possible options, mentioned above, for future allergic pollen studies, this research strongly suggests adapting and modifying atmospheric transport models to estimate pollen grain transport from their source inventories. Deliverables from chapter 3 of this research (i.e., two maps depicting the start of pollen birch and grass pollen seasons with a spatial resolution of 1 km for the UK) are important components as input into these models.

CHAPTER 7: Conclusions

The research presented in the thesis has drawn novel findings from the three research papers. The findings will be of interest to: (i) a variety scientific disciplines, for example; climate change and its effect on human health, aerobiology, plant phenology, remote sensing of land surface phenology, agriculture, immunology, biodiversity, and meteorology within the atmospheric boundary and (ii) a variety of end users in building and enhancing pollen predictive models, for example: (a) to assist allergy sufferers directly, (b) to assist those working in the medical profession and (c) to assist pharmaceutical companies to stock medicines. The key findings (detailed further in the previous chapters) include:

- The pre-peak period is the most important period for evaluating the influence of the meteorological parameters on the pattern of grass and birch pollen counts in the atmosphere.
- The influence of meteorological parameters varies for grass and birch pollen counts in the air. Maximum temperature, rainfall and sunshine duration are the most important parameters that influence the availability of the grass pollen counts in the atmosphere. Maximum temperature and sunshine have large positive correlations, whereas rainfall has a large negative correlation, with grass pollen count in the air. Average temperature, rain and wind speed are the most important parameters that influence birch pollen count in the atmosphere. Wind speed and rain have a negative correlation with birch pollen count in the air whereas average temperature has a positive correlation.
- The direction of the influence of wind and rain on the pollen count could be negative or positive depending on their temporal supports. For example, 3-7 days mean prior rainfall enhances flower blooming prior to pollen release whereas rain washes out pollen from the air right after release.
- There was a contrast in the start of the seasons of birch and grass across the UK at the nine monitoring sites (i.e., between the sites). The contrast reflected the south-to-north trend together with a coastal and an inland trend due to their response to the local and regional weather variables during and preceding the

season and the distance to grassland and forest land cover types. A similar contrast was seen within the sites (i.e., within an individual site over time). The pollen season generally starts earlier in the south and tends to be slightly later when ones move towards the north.

- A new technique for defining the start and end of birch and grass pollen seasons was developed and compared with other available methods. The technique is species-independent and easy to apply.
- A new technique was developed to estimate the start of the flowering phenophases of birch and grass from the MTCI profile and was validated with pollen count data. The technique was based on the rationale of the timing of flower development and the investigation and analysis of the MTCI and pollen profile. This technique has the potential to be transformed and applied to the whole EU birch and grass inventories. This, in turn, provides useful insights to the European Aeroallergen Network Pollen Database (www.polleninfo.org) to: (i) assist in planning and establishing pollen monitoring sites, (ii) assist in producing more accurate pollen predictive models, and (iii) the outputs (i.e., maps) generated by applying the technique can be used as an input into atmospheric dispersion models. This, in turn, assists with developing source-based predictive models.
- Both grass and birch start dates estimated from MTCI showed large positive correlations with the start dates defined from pollen counts.
- MERIS MTCI can be used to predict the start dates of grass and birch pollen season in the UK at 1 km spatial resolution.
- The MTCI-based flowering phenophase across the sites for both birch and grass added statistically significant predictive power to the pollen predictive models. This indicates that pollen count variation in the atmosphere is not alone limited to the function of meteorology and hence flowering phenophases at the source areas contribute to local variation in pollen count in the UK.
- The predictive power of the flowering phenophase in the grass predictive models was more significant in comparison to those for birch. The grass pollen season in the UK is longer than for birch and the spectrum of grass species and hence their distributions are dominant in comparison to birch.

- The flowering phenophase with the 1-day prior temporal support (mtci1dp (MTCI 1-day prior)) with the combination of 3-7 day mean prior temperature and precipitation demonstrated the highest levels of explanation (R-Sq (adj)) in the grass model. This is a clear indication of the prolonging influence of temperature and rain on the reproductive phase and flower blooming prior to pollen release.
- The flowering phenophase with the 7-day mean prior temporal support (mtci7dmp (MTCI 7-day mean prior)) with the combination of 3-7 day mean prior temperature and precipitation demonstrated the highest levels of explanation (R-Sq (adj)) in the grass model. Similar to grass, this an indication of the prolonging influence of temperature and rain on the reproductive phase and flower blooming prior to pollen release.
- The increase in predictive power gained by adding the MTCI-based flowering phenophase into the regression models for birch and grass clearly indicates a link between the atmospheric pollen count and local plant flowering rhythm.

The analysis conducted in this research has enabled the objectives established in the introduction to be met. In doing so, this work has provided information that will be of value to those working with allergic pollen and aerobiology and land surface plant phenology, atmospheric science and air quality.

The novel methods used and the deliverables produced from the research are related to producing more accurate pollen prediction models in the UK through: (i) investigation of the source-based dimension of aerobiology of birch and grass by applying satellite remote sensing products in deriving important phenological parameters related to pollen release, (ii) investigation of the receptor-based dimension of aerobiology of birch and grass through comprehensive analysis of the spatial and temporal relationships of the pollen with various meteorological variables, and (iii) combination of the source-based and receptor-based dimensions within the predictive models. The methods used in the research are straightforward and adaptable, and have already contributed to the body of knowledge of aerobiology in general, and have great promise for uptake by organisations interested in predicting aeroallergen concentrations through the pollen season.

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