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From Monitoring to Modelling: Harnessing Pollen Data for Adapting to Exposure Risks in a Changing Climate

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From Monitoring to Modelling: Harnessing Pollen Data for Adapting to Exposure Risks in a Changing Climate

Sofia Tagliaferro

PhD thesis

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Dedico questa tesi a mio babbo,
il mio primo e più grande sostenitore.
Grazie per aver sempre creduto in me:
il tuo ricordo vive ogni giorno nel mio cuore.

Table of Contents

Sommario

L’aumento delle malattie respiratorie allergiche può essere relazionato ai cambiamenti climatici, che sembrano influire sulla quantità e stagionalità dei pollini. I dati sul polline misurati dalle stazioni di monitoraggio sono spesso incompleti e poche ricerche hanno valutato l'accuratezza dei metodi di imputazione nei dataset aerobiologici. Inoltre, le reti di monitoraggio hanno una copertura spaziale limitata. Aumentare la risoluzione temporale e spaziale delle informazioni sui livelli di polline potrà essere utile per la salute pubblica. In particolare, l’implementazione di modelli accurati di previsione del polline potrà aiutare il paziente affetto da allergie respiratorie a gestirle meglio. L'obiettivo della tesi è colmare queste lacune di conoscenza: (i) testando un nuovo metodo basato sui dati per imputare i dati mancanti nei dataset aerobiologici, (ii) stimando le variazioni temporali degli indicatori di esposizione al polline nella regione del Veneto (Italia settentrionale) negli ultimi due decenni, e (iii) implementando un nuovo sistema di modellazione del polline che possa essere utilizzato per fornire previsioni ad alta risoluzione delle concentrazioni di polline nella regione del Veneto.

I dati pollinici per la regione Veneto (e le aree circostanti) sono stati scaricati gratuitamente dal database POLLnet o forniti direttamente da ARPAV. È stato utilizzato il pacchetto R "AeRobiology" per la gestione dei dati pollinici e il calcolo della stagione pollinica, così come per ricavare gli indici stagionali. Per raggiungere gli obbiettivi della tesi, sono state applicate differenti metodologie. Per (i), è stato condotto uno studio di simulazione per confrontare un nuovo metodo di imputazione basato sui dati (Gappy Singular Value Decomposition, GSVD) con uno statistico (media mobile). I dati mancanti sono stati generati casualmente in un dataset aerobiologico di durata annuale per 2 tipi di polline e 2 stazioni di monitoraggio, poi sono stati imputati con i due metodi e, infine, è stata valutata l'accuratezza dell'imputazione. Per (ii), è stata condotta un'analisi per stimare le variazioni temporali, dal 2001 al 2022, negli indici stagionali dei principali pollini allergenici (9 tipi di polline, 20 stazioni di monitoraggio) su tutta la regione e per aree climatiche, applicando il metodo non parametrico dello stimatore Theil-Sen. Per (iii), è stato validato un nuovo sistema modellistico per simulare i processi di dispersione, diffusione e deposizione di cinque tipi di polline nella regione Veneto,

investigando l'impatto della risoluzione delle mappe di copertura vegetale sulle concentrazioni predette.

I risultati di questa tesi hanno mostrato che: (i) il nuovo metodo GSVD ha un'accuratezza di imputazione dei dati pollinici simile al metodo della media mobile, e che l'accuratezza dell'imputazione è fortemente influenzata dalla variabilità temporale del polline, (ii) per diversi taxa pollinici, le concentrazioni e la durata delle stagioni polliniche sono notevolmente aumentati nella regione Veneto negli ultimi vent'anni, specialmente nelle aree con clima subcontinentale, e (iii) l'utilizzo di mappe di vegetazione dettagliate come input dei sistemi di modellizzazione dei pollini può migliorare la stima delle concentrazioni dei pollini arborei, specialmente su superfici complesse (quali le zone alpine), aumentando potenzialmente la qualità delle previsioni giornaliere e stagionali.

In conclusione, i nostri risultati contribuiscono alle conoscenze in termini di monitoraggio, analisi e previsione dei dati aerobiologici. Evidenziano inoltre la necessità di ulteriori studi per migliorare le tecniche di imputazione dei dati pollinici e per comprendere e prevedere meglio le variazioni temporali e spaziali del polline. Le nostre analisi hanno confermato variazioni nelle concentrazioni dei pollini in atmosfera negli ultimi vent'anni suggestive di un impatto molto rilevante dei cambiamenti climatici. La ricerca in questo settore contribuirà a sviluppare nuove misure preventive e di adattamento per affrontare le future variazioni nell'esposizione al polline causate dai cambiamenti climatici.

Abstract

Increasing trends in allergic respiratory diseases may be linked to climate change affecting pollen levels and seasonality. Pollen data from monitoring stations are usually incomplete, and limited research has assessed the accuracy of imputation methods in aerobiological data. Moreover, monitoring networks have limited spatial coverage. Increasing the temporal and spatial resolution of the information on pollen levels will be useful from a public health perspective. In particular, implementing accurate pollen forecasting models can help patients with respiratory allergies manage their symptoms more effectively. The aim of the thesis would cover these gaps of knowledge, (i) testing a new data-driven method to impute missing data in aerobiological datasets, (ii) assessing temporal trends of pollen exposure indicators in the Veneto Region (northern Italy) in the last two decades, and (iii) implementing a novel pollen modelling system that can be used to provide high-resolution forecasts of pollen concentrations in the Veneto Region.

Pollen data for the Veneto Region (and the surrounding areas) were downloaded freely from the POLLnet database or directly provided by ARPAV. The "AeRobiology" R package was used to manage pollen data and calculate pollen seasons and seasonal indexes. Different methodologies were applied to achieve the three objectives. For (i), a simulation study was conducted to compare a new data-driven method (Gappy Singular Value Decomposition, GSVD) to a statistical one (moving mean). The gaps were randomly generated in an annual pollen dataset for 2 pollen types and 2 monitoring stations, imputed with the two methods, and lastly, the imputation accuracy was assessed. For (ii), a trend analysis was conducted to estimate temporal changes in seasonal pollen indexes between 2001 and 2022 (9 pollen types, 20 monitoring stations). The non-parametric Theil-Sen median slope method was used to examine the trends in the whole region and by climatic areas. For (iii), a novel pollen modelling system was validated to simulate the dispersion, diffusion, and deposition processes of five pollen types over the Veneto Region, investigating the impact of vegetation cover maps resolution on predicted concentrations.

The results of this thesis showed: (i) the GSVD method and the moving mean

approach showed a similar effectiveness in imputing pollen data, and that the imputation accuracy was affected by temporal variability of pollen, (ii) for several pollen taxa, concentrations and the duration of pollen seasons have increased in the Veneto Region over the last twenty years, particularly in subcontinental areas, and (iii) the use of detailed vegetation maps as input to pollen modelling systems can improve the estimation of arboreal pollen concentrations, especially on complex surfaces (such as alpine zones), potentially increasing the quality of daily and seasonal forecasts.

In conclusion, our findings contribute to knowledge in terms of monitoring, analysis and prediction of aerobiological data. They also highlight the need for further studies aimed at improving pollen data imputation techniques and to better understand and predict temporal and spatial variations in pollen. Our analyses have confirmed variations in pollen concentrations in the atmosphere over the past two decades, suggesting a substantial impact of climate change. Research in this field can lead to the development of new measures of prevention and adaptation to address future variations in pollen exposure due to climate change.

Abbreviations

APIn: Annual Pollen Integral

ARPAV: Environmental Protection Agency of the Veneto Region

CAMS: Copernicus Atmospheric Monitoring Service

CO_2: Carbon dioxide

CI: Confidence Interval

CLC: Corine Land Cover

CV: Coefficient of Variation

EFI: European Forest Institute

ENEA: Italian National Agency for New Technologies, Energy and Sustainable Economic Development

FAR: False Alarm Ratio

FARM: Flexible Air quality Regional Model

FMI: Finnish Meteorological Institute

GSVD: Gappy Singular Value Decomposition

MA: Model Accuracy

MEETOUT: Mitigation of the Effects of Environmental Triggers on the OUTcomes of chronic respiratory diseases

MINNI: Italian National Integrated Model to support the International Negotiation on atmospheric pollution

NAs: Missing data

O_3: Ozone

POD: Probability Of Detection

Q1: First quartile

Q3: Third quartile

QC: Quality Control function

RMSE: Root Mean Square Error

SD: Standard Deviation

SDV: Singular Value Decomposition

SILAM: System for Integrated modeLling of Atmospheric composition

SIAMA: Italian Society of Aerobiology Medicine and Environment

SNPA: National System for Environmental Protection

SPIn: Seasonal Pollen Integral

SubE: Subcontinental Eastern

SubW: Subcontinental Western

SURFPro: SURface-atmosphere interFace PROcessor

TSS: Theil-Sen slope

VC: Vegetation Cover

VIn: Variation Index

WHO: World Health Organization

WRF: Weather Forecast and Research

1. Introduction

1.1. Allergic diseases and trends over time

Allergic diseases are chronic conditions that affect various organs and systems, often causing severe symptoms throughout the lifespan of affected subjects (Pawankar et al., 2013). Among these diseases, allergic rhinitis and asthma are highly prevalent globally, representing significant public health concerns. The World Health Organization (WHO) has estimated that allergic rhinitis affects 400 million people worldwide, while asthma affects 300 million, with a particularly high prevalence in the pediatric population (Pawankar et al., 2013).

Allergic rhinitis arises from inflammation of the nasal mucosa mediated by IgE, manifesting symptoms primarily in the upper respiratory tract, such as nasal congestion, rhinorrhoea, sneezing, and nasal itching. This condition significantly impacts the quality of life of patients, often resulting in sleep disorders, fatigue, anxiety, impaired learning and attention (Baldacci et al., 2015; Pawankar et al., 2013; Suanno et al., 2021; Wise et al., 2023). Currently, allergic rhinitis affects between 5% and 50% of the global population and about 25% of the European population (Wise et al., 2023).

Asthma is a chronic inflammatory disorder of the airways persisting throughout life, with associated symptoms like wheezing, breathlessness, chest tightness, and cough. It affects individuals of all ages, inducing airway hyperresponsiveness and airflow obstruction. Uncontrolled asthma seriously diminishes the quality of life of individuals, interfering with daily activities. Allergic rhinitis is a recognized risk factor for asthma, coexisting in over 40% of patients; on the other hand, more than 80% of patients with asthma also experience rhinitis (Baldacci et al., 2015; De Marco et al., 2012; Pawankar et al., 2013; Wise et al., 2023). The inflammation of the lower airways is aggravated in subjects with allergic asthma, occasionally leading to fatal outcomes (Pawankar et al., 2013; Suanno et al., 2021). The prevalence of asthma varies between 1% and 13% in America and Asia, and between 1% and 21% in Europe (Dierick et al., 2020).

Allergic respiratory diseases pose a substantial economic burden, comprising both direct healthcare costs and indirect costs that impact patients and society at large

(Baldacci et al., 2015; Dierick et al., 2020; Lake et al., 2017; Pawankar et al., 2013). Therefore, the WHO recommends conducting more epidemiological studies to gather new evidence on the risk factors associated with allergic diseases, enabling the implementation of effective environmental control measures (Pawankar et al., 2013).

The current knowledge highlights that several risk factors contribute to the onset and exacerbation of allergic diseases, including genetics, pollen, dust, and molds. Sensitization to aeroallergens, resulting from exposure to foreign proteins in the environment, is widely acknowledged as a major global risk factor. Among these, pollen could be an important contributor to the rising prevalence of allergic diseases worldwide, particularly in industrialised countries (Baldacci et al., 2015; Wise et al., 2023), whilst evidence is still inconclusive to date (Marchetti et al., 2017). Although hereditary factors play a key role in the development of these diseases, changes in these factors are unlikely to fully account for this rapid upward trend (Baldacci et al., 2015; Wise et al., 2023). In recent years, a growing body of evidence suggests climate change as a potential contributing factor; one of the mechanisms through which climate change may impact respiratory health is by influencing pollen production, which can, in turn, initiate and trigger allergic reactions (Choi et al., 2021; D'Amato et al., 2023).

1.2. Global climate change and the Mediterranean hotspot

It is now established that human activities are responsible for the observed global warming, leading to a temperature increase of approximately 1.1 °C between 2011 and 2020 compared to the 1850-1900 baseline. This rise was more pronounced over land (1.6 °C) than over the ocean (0.9 °C) (Calvin et al., 2023). The Earth experiences natural climatic fluctuations driven by millennial solar astronomical cycles (Calvin et al., 2023; Choi et al., 2021), transitioning between glacial and interglacial periods. However, since 1750, the rapid increase in the concentrations of carbon dioxide (CO_2, 47%) and methane (156%) has far exceeded the natural variations observed over the past 800,000 years. Again, current CO_2 levels exceed any levels recorded over the past two million years. Human activities, particularly the emission of greenhouse gases into the atmosphere, are responsible for the increase in global temperatures by 1.0 to 2.0 °C (Calvin et al., 2023; WMO, 2024). Other human forcings, such as aerosols, ozone (O_3), and land-use changes (contributing, for example, to solar reflectance), resulted in a cooling effect of 0.0 °C to 0.8 °C. In contrast, natural forcings (solar and volcanic) and internal climate variability led to changes in global surface temperature of approximately ± 0.1 °C and ± 0.2 °C, respectively (Calvin et al., 2023).

Consequently, the mean land surface temperature is rising rapidly, with the past nine years (2015-2023) ranking as the warmest in the 174-year observational record. Notably, an exceptional warming occurred in 2022-2023, with 2023 being the warmest year on record (1.45 °C above the 1850–1900 average) (WMO, 2024). However, certain regions of the Earth are warming faster than others. Of these, the Mediterranean region is experiencing more pronounced warming than at the global scale, with land surface temperatures exceeding pre-industrial levels by 1.5 °C. This is largely due to the unique features of this region. Indeed, the Mediterranean basin is a semi-enclosed marine basin surrounded by Europe, Asia and Africa continents. The meteorology of the Mediterranean area is heavily influenced by interactions between the ocean and land, as well as its complex topography. Subject to both mid-latitude and subtropical atmospheric circulation regimes, the region experiences various impacts of climate change. With most of its large population residing along its coastlines, the region is highly vulnerable to the effects of climate change, making it one of the world's primary climatic hotspots. Climate change is affecting the region in multiple ways, including more frequent and intense heatwaves and droughts, especially in the Northern part of the Mediterranean basin. Additionally, sea surface temperatures have steadily risen since the 1980s, with a more pronounced increase in the eastern part of the basin. Sea levels have also consistently risen throughout the 20th century, and a moderate increase in sea acidity has been observed. Conversely, precipitation trends show regional variability (Ciardini et al., 2016; Pörtner et al., 2023).

Climate projections suggest that the Mediterranean region will continue to experience a 20% higher warming than the global average, accompanied by increasingly frequent heat waves. Likewise, extreme weather events are expected to increase in frequency, especially in the Alpine region. Conversely, precipitation is expected to decrease, leading to a transition toward strong aridification, particularly in the central Mediterranean area. The diminishing water resources, reduced river flows, and increasingly drier soils will heavily impact the water cycle and ecosystems. As a consequence, a northward shift in climatic zones is projected, exposing current ecoregions to climatic conditions that are no longer suitable for the species and habitats currently present. This may lead to biodiversity loss, species migration, and ecological imbalances, as well as impact human activities like agriculture. Furthermore, future warming will further impact ocean ecosystems and contribute to sea-level rise, threatening coastal areas and historical sites (Ciardini et al., 2016; Pörtner et al., 2023).

1.3. Climate change effects on plant phenology and distribution

The timing of seasonal events in plants, such as leaf unfolding, flowering, and leaf fall, as well as their photosynthetic processes and pollen production, are strongly influenced by climate factors (Beggs et al., 2023; Choi et al., 2021; Gordo & Sanz, 2010). Consequently, plants act as valuable bioindicators of climate change (Gordo & Sanz, 2010). The impact of climate change on plants manifests in multiple ways, varying locally and according to plant type (Beggs et al., 2023; Choi et al., 2021; Gordo & Sanz, 2010). Nevertheless, there is consensus that phenological changes are linked to variations in weather patterns and greenhouse gas concentrations (Choi et al., 2021).

Increasing global evidence suggests that changes in weather patterns are primary drivers of variations in pollen load and seasonality, i.e. the occurrence of start and end dates of the season, as well as its duration (Beggs et al., 2023; Choi et al., 2021; D'Amato et al., 2020; Gordo & Sanz, 2010; Schramm et al., 2021). Weather conditions greatly influence plant responses during and prior to the phenological phases. Spring phenological events demonstrate greater sensitivity to weather fluctuations compared to those in autumn, resulting in more pronounced effects earlier during the year (Gordo & Sanz, 2010). In the Mediterranean area, the alternation of seasons, characterised by peaks of rainfall typically concentrated in spring and autumn, amplifies the influence of climate on ecosystems during these periods (Gordo & Sanz, 2010).

Overall, temperature exerts the most significant effects, likely linked to the globally widespread warming phenomenon (Gordo & Sanz, 2010; Schramm et al., 2021). Warmer temperatures lead to earlier and prolonged pollination periods, along with increased pollen production (Beggs et al., 2023; Choi et al., 2021; D'Amato et al., 2020; Gordo & Sanz, 2010; Pörtner et al., 2023; Schramm et al., 2021). Notably, changes in mean and maximum temperatures are more pronounced than those in minimum temperatures (Gordo & Sanz, 2010). Furthermore, the impact of higher temperatures is more pronounced on woody plants than herbaceous ones, owing to their seasonal characteristics. As trees flower in early spring, they are more sensitive to warmer and shorter winters, which can result in an anticipated and prolonged pollen season. Instead, herbaceous plants, which typically bloom in late spring or summer, are less affected (D'Amato et al., 2020; Schramm et al., 2021). Moreover, it is believed that climate change could elevate the amount of allergenic protein present within individual pollen grains (Choi et al., 2021). Experimental evidence suggests that, for ragweed, rising temperatures are related to enhanced pollen allergenicity (Gentili et al., 2019).

Even precipitation plays a key role in plant phenological variability. Undoubtedly, water availability and soil moisture are vital factors for the plants' functioning (Gordo & Sanz, 2010). Water scarcity distresses plants, resulting in reduced pollen production, but simultaneously leads to more suspended pollen in the atmosphere. Conversely, higher precipitation promotes plant well-being, increasing pollen production, but pollen is removed from the atmosphere more quickly by the so-called 'washout' effect (Schramm et al., 2021). However, precipitation events are localized, making it challenging to derive consistent results across continents. Consequently, the relationship between precipitation and plant phenology, alongside pollen production, is complex to establish (Gordo & Sanz, 2010; Schramm et al., 2021). A systematic review indicates that higher precipitation is generally correlated with lower daily pollen concentrations for each plant type, and with higher pollen load and prolonged season only for grasses (Schramm et al., 2021). Indeed, herbaceous plants are believed to be more sensitive to changes in rainfall than to temperature variations, due to their delayed seasonality.

The combined effect of temperature and precipitation also affects another aspect: the geographical distribution of plant species. Indeed, water scarcity and drought expansion can lead to the migration of plant species towards higher latitudes (Case & Stinson, 2018; D'Amato et al., 2023; Pörtner et al., 2023). This phenomenon has already been observed in Australia, with a progression of warm-season grasses relative to cool-season grasses. This shift was attributed to variations in seasonal rainfall rather than temperature variations (Xie et al., 2022). In addition, the accelerated warming in higher latitude regions, driven by climate change, has repercussions on plant phenology. For instance, the duration of ragweed pollen season has increased by 13-27 days with latitudes above 44°N since 1995 (Ziska et al., 2011). However, conflicting findings exist, as another study indicates no latitudinal trend in variations of pollen loads and pollen season duration over time, proposing a global temperature effect instead (Ziska et al., 2019).

Other meteorological parameters, such as solar radiation and humidity, can affect plant phenology and pollen production. However, their impact is generally considered less important and correlated to temperature and precipitation (Gordo & Sanz, 2010). Instead, atmospheric circulation patterns play a crucial role in the long-distance distribution of pollen. Airborne particles are typically carried by wind and turbulence in the lowest atmospheric layer. The stronger the convection, the more particles can be carried into the upper atmosphere, enabling long-distance transport and allowing them to be deposited far from their source (D'Amato et al., 2007). Variations in atmospheric circulation patterns due to climate change can alter the spatial distribution of pollen, leading to the geographical expansion of some plant species into new areas that become climatically suitable for them (D'Amato et al., 2007). Moreover, warming has been shown to contribute to wind-driven movements that favour pollen dispersal and spread (Kuparinen et al., 2009).

Greenhouse gases promote plant growth, proliferation, and production of airborne allergens. In particular, elevated CO_2 levels impact plant metabolism, stimulating net photosynthetic carbon fixation by leaves by about 40% and reducing overall plant water use by 5-20% (Ainsworth & Rogers, 2007; Beggs et al., 2023; D'Amato et al., 2023; Leakey et al., 2009; Taub, 2010; Wayne et al., 2002). Consequently, plants experience accelerated growth rates and decreased tissue concentrations of nitrogen and proteins. Experimental studies on various plants, including trees, ragweed, and grasses, have demonstrated reproductive effects resulting in substantially increased pollen production and higher allergen content in pollen (Albertine et al., 2014; El Kelish et al., 2014; Kim et al., 2018; Rauer et al., 2021; Rogers et al., 2006; Taub, 2010; Wayne et al., 2002). Among the other gases related to climate change, O_3 also plays a significant role. O_3 is taken up by leaf stomata and causes oxidative stress (Pöschl & Shiraiwa, 2015). Nonetheless, its adverse effects are largely mitigated by increased levels of CO_2, which significantly enhance plant growth, even in conditions where O_3 stress is present.

Lastly, in urban environments characterised by elevated CO_2 levels and warmer temperatures, plants tend to flower earlier and exhibit higher allergenicity than those in rural areas, as observed for ragweed (Ghiani et al., 2012; Ziska et al., 2003).

1.4. Implications for respiratory health

Alterations in plant phenology and distribution are expected to affect respiratory health (Beggs et al., 2023; Choi et al., 2021; D'Amato et al., 2023; Wise et al., 2023). Indeed, the population experiences progressively higher exposure to pollen, increasing the risk of experiencing more severe allergic symptoms. The severity of symptoms depends on the amount of allergenic pollen encountered by allergic individuals (D'Amato et al., 2020). Additionally, longer pollen seasons extend symptomatic periods for individuals with allergic diseases and may increase sensitization among the population through prolonged exposure to allergens. Furthermore, shifts in plant distribution and wind-dispersal of pollen at different latitudes raise the likelihood of population exposure to new allergens. Changes in land use practices also contribute to increased exposure to allergenic plants such as grasses (Beggs & Bambrick, 2005; Choi et al., 2021; D'Amato et al., 2023; Pörtner et al., 2023).

The increasing trend in allergic diseases observed in recent decades may reflect the growing population exposure, with the burden of disease associated with aeroallergens expected to escalate due to climate change (Beggs & Bambrick, 2005; Choi et al., 2021; D'Amato et al., 2023; Pörtner et al., 2023). Studies analysing historical data and projecting future trends have reported the relation between climate-driven variations in pollen patterns and the rise in allergic conditions.

In western Liguria, Italy, a 27-year study investigated the relationship between pollen exposure, meteorological data, and clinical records of skin prick tests. The findings showed an increase in direct radiation, temperature, high-temperature days, pollen levels, and sensitization rates, suggesting a potential role of climate in influencing pollen allergies (Ariano et al., 2010). Similarly, other studies have shown a relationship between the observed shifts in pollen season timing, driven by climate change, and a higher risk for springtime asthma hospitalization and hay fever in different population subgroups in the United States (Sapkota et al., 2019, 2020). A two-decade study on children found links between increased pollen-sensitization rates and longer pollen seasons, as well as with increasing temperatures (Lee et al., 2021).

Nonetheless, the impact of long-distance pollen transport on the risk of allergic sensitization remains uncertain. In a study conducted in the German Alps, researchers investigated whether sensitized individuals experienced symptoms in environments typically considered low-risk for pollen due to sparse vegetation. Findings revealed that, with rising temperatures, higher atmospheric pressure, and low precipitation, long-distance transport phenomena elevated pollen concentrations, accounting for 87% of the presence of allergic symptoms (Bayr et al., 2023). An Italian study conducted in central Italy showed that individuals not residing in ragweed-infested areas may still be sensitized to the pollen due to frequent transport events from Eastern Europe with concentrations above clinical thresholds (Cecchi et al., 2006). However, a subsequent and a more in-depth clinical analysis questioned these findings (Cecchi et al., 2010).

Future projections assess the potential public health implications of changing pollen patterns driven by climate change. By 2090, it is forecasted that the extension of the grass pollen season will exacerbate emergency room visits for asthma in the US (Neumann et al., 2019). Other future climate projections indicate a likely increase in ragweed sensitization and symptom severity in Europe due to the expansion of ragweed to new regions, alongside an increase in pollen load and an extension of the season duration (Lake et al., 2017). This aligns with findings from another European modelling study, indicating that airborne ragweed pollen concentrations could be four times higher by 2050 compared to the current levels. One-third of this increase is attributed to seed wind dispersal without considering the contribution of climate change, while the remaining two-thirds are driven by climate and land-use changes (Hamaoui-Laguel et al., 2015). Another projection study warns that delaying action on ragweed control will make its spread more difficult to manage, leading to increased allergy-related costs if no intervention measures are implemented (Richter et al., 2013). Specifically, they estimate that, in Austria and southern Germany, mean annual allergy-related costs could range from €290 million to €365 million by 2050, depending on current or extreme climate change scenarios, if no management measures (e.g. eradication) are implemented. Effective ragweed management could save up to €12 billion over 40 years (Richter et al., 2013). Another US study projected future climate scenarios for 13 pollen taxa, suggesting that, by the end of the century, pollen seasons will start earlier, last longer, and be characterised by increased annual pollen emissions. Besides climate-driven changes associated with temperature and precipitation, the amplified impact of CO_2 on pollen production could lead to substantial emission increases. This could potentially double pollen production alongside climate-related changes, leading to an increase in emissions of more than 200% by the end of the century. These alterations could increase population exposure and exacerbate symptoms for individuals with allergic rhinitis and asthma triggered by pollen (Zhang & Steiner, 2022).

In this context, implementing effective prevention measures is imperative to reducing population exposure to pollen and its associated health risks. Strengthening aerobiological knowledge, expanding monitoring, and refining pollen prediction models are critical steps for mitigating future health impacts, particularly in light of climate change.

1.5. Aerobiology: monitoring, modelling, and prevention

Aerobiology investigates the dispersion, behaviour, and effects of airborne biological particles, including pollen (Vélez-Pereira et al., 2021). Aerobiological monitoring is essential to assess pollen exposure in the population. Moreover, it is useful to establish long-term data series to track changes in pollen concentrations driven by climate change and human activities, serving as a tool for assessing changes in pollen exposure in the population (Sofiev et al., 2020; Suanno et al., 2021).

Nevertheless, several limitations in the monitoring process impact population exposure assessment. Pollen samplers are often positioned at the top of buildings, a location that does not accurately represent personal exposure (Sofiev et al., 2020). Pollen monitoring is primarily conducted manually, leading to the publication of weekly pollen bulletins that limit the frequency of updates for individuals with allergies (Sofiev et al., 2020; Suanno et al., 2021). Furthermore, these bulletins categorize pollen levels rather than providing specific concentrations, yielding qualitative information about pollen-related air pollution. To date, automated systems for real-time monitoring are still emerging and seldom employed, largely due to the high costs associated with the advanced technology required (Beggs et al., 2023; Picornell et al., 2019; Sofiev et al., 2020). The significant expenses related to both manual and automated monitoring hinder the establishment of dense pollen monitoring networks, leading to limited spatial coverage (Beggs et al., 2023; Sofiev et al., 2020; Suanno et al., 2021). To overcome this problem and ensure spatial coverage, statistical interpolation techniques (e.g. kriging methodologies, Convolutional Neural Networks) can be applied to estimate pollen concentrations at unmonitored locations with high spatial resolution (Navares & Aznarte, 2019; Oteros et al., 2019; Suanno et al., 2021; Zhu et al., 2024). However, the accuracy of these methods relies heavily on the density of monitoring stations and the topographic characteristics of the region (Zhu et al., 2024).

A further challenge with monitoring networks is the interruption of monitoring due to malfunctions or intentional discontinuation during periods considered non-essential for measurement, which leads to significant data gaps in aerobiological records (Navares & Aznarte, 2019; Suanno et al., 2021). A variety of imputation methodologies have been employed to address this issue. These include univariate methods (e.g. statistical techniques), which rely solely on the data series itself, and multivariate methods (e.g. machine learning techniques), which leverage information from other time series (Bleidorn et al., 2022; Damialis et al., 2007; Makra et al., 2011, 2023; Marchetti et al., 2017; Navares & Aznarte, 2019; Picornell et al., 2021; Šikoparija et al., 2018). Machine learning techniques hold promise for repairing corrupted or incomplete datasets by extracting relevant spatio-temporal information directly from the data, although their application in imputing missing pollen data is still emerging. However, the complexity of spatio-temporal pollen dynamics poses challenges for imputation methods, primarily due to the dominant non-linear structures that evolve over time, including seasonality and climate variations. As a result, fully understanding and predicting these patterns can be difficult. Given the limitations outlined above, which significantly impact exposure assessment and hinder allergen avoidance strategies, there is a clear need to transition to more accurate pollen modelling tools (Beggs et al., 2023; Sofiev et al., 2020; Suanno et al., 2021).

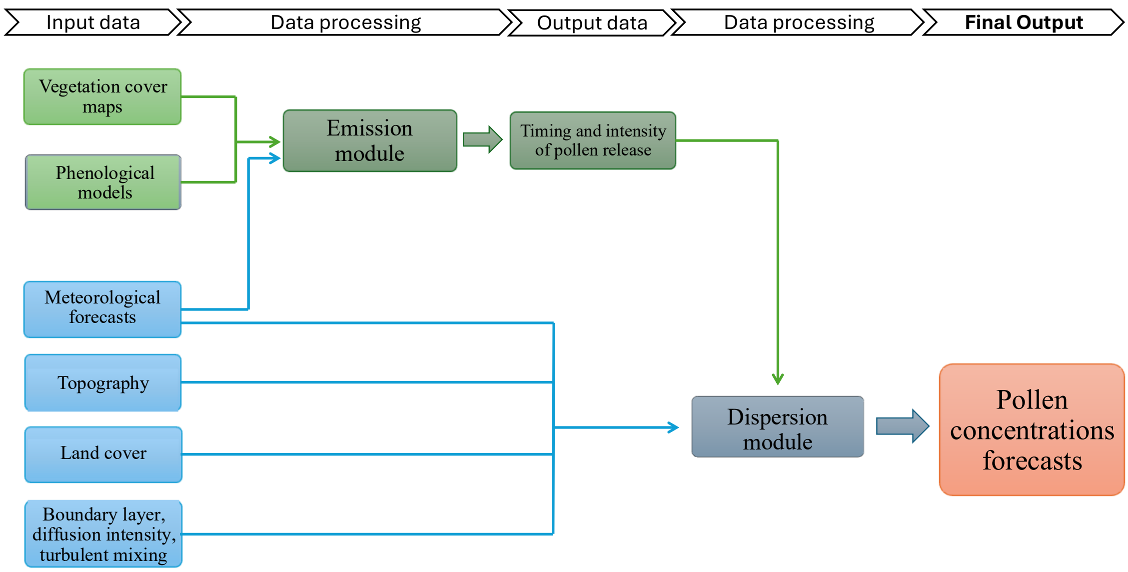
In recent decades, interest has grown in developing pollen forecasting tools (Vélez-Pereira et al., 2021; Picornell et al., 2019; Stafoggia et al., 2019). Various techniques have been employed to forecast pollen concentrations, from simple statistical to highly complex process-based models (Picornell et al., 2019; Suanno et al., 2021).

Statistical or empirical models are observation-based approaches that correlate pollen concentrations with one or more independent variables, such as meteorological factors. These models identify key predictors significantly influencing pollen levels and utilize established correlations to forecast pollen concentrations (Suanno et al., 2021; Vélez-Pereira et al., 2021; Zhu et al., 2024). They encompass a variety of methodologies, including general statistical analyses such as pollen calendar models and regression analysis, as well as time series analysis techniques like time series decomposition. Additionally, they include machine learning methods, such as neural networks and random forests, along with stochastic approaches like Hidden Markov Models. The latter techniques are better suited to capturing the complex and non-linear nature of pollen dynamics compared to traditional statistical methods (Beggs et al., 2023; Suanno et al., 2021; Zhu et al., 2024). Common input data are past pollen concentrations, phenological observations (providing the timing of pollen season), and meteorological factors.

Records of meteorological factors—such as temperature, wind speed and direction, relative humidity, and precipitation—or weather forecasts from meteorological models are valuable predictors of spatio-temporal pollen dynamics. However, statistical models do not make assumptions about pollen sources and atmospheric dynamics, and they lack adaptability to changes in climate, vegetation, and land use (Suanno et al., 2021; Zhu et al., 2024). Additionally, being limited to local scales and daily pollen averages, they are unable to provide detailed information on the variations of the allergenic risk throughout the day or be generalized across larger geographic areas (Suanno et al., 2021).

Simulation or process-based models are advanced models based on *a priori* assumptions on the two processes underlying the spatiotemporal concentrations of pollen: pollen emission and pollen dispersion (Suanno et al., 2021; Zhu et al., 2024). In a pollen modelling system, these two processes are integrated to simulate all aspects of pollen behaviour, from production (emission module) to dispersion (dispersion module), ultimately producing pollen concentration forecasts (Figure 1.1).

Figure 1.1. Scheme of the functioning of a pollen modelling system.



Pollen emission depends on the plant distribution and phenological responses to environmental factors. Plant distribution, represented by vegetation cover maps, provides critical information about the density and spatial distribution of pollen-producing species, identifying sources of pollen production (Suanno et al., 2021; Vélez-Pereira et al., 2022). However, obtaining high-quality vegetation maps remains a challenge. While arboreal species have well-documented forest and agricultural spatial data at national or subnational levels, comprehensive inventories for herbaceous plants remain limited, resulting in less accurate simulations (Vélez-Pereira et al., 2022). The timing and intensity of pollen release (phenological responses) are modelled using phenological models, which assume that the pollen season aligns with flowering times. These models require data on temperature, photoperiod, precipitation, plant phenology, and pollen season characteristics. Developing such models is particularly challenging, as it involves identifying seasonal features like the start and end of the pollen season (Suanno et al., 2021; Vélez-Pereira et al., 2021, 2022; Zhu et al., 2024). Pollen dispersion is simulated using air dispersion models, where pollen is treated as an atmospheric pollutant. These models simulate the dispersion, long-range transport, and dry (gravity) and wet (rain) deposition of pollen. Input data includes outputs from the emission module (Figure 1.1), along with topography, meteorological forecasts, boundary layer dynamics, diffusion intensity, and turbulent mixing. Dispersion mechanisms can be modelled using two main approaches: the Eulerian approach, which considers airborne particles as a continuum and represents them as a concentration field on a fixed grid in both space and time; and the Lagrangian approach, which treats particles as discrete entities and models their individual trajectories in continuous space by deforming the grid coordinates (Suanno et al., 2021; Vélez-Pereira et al., 2022; Zhu et al., 2024).

An example of an advanced atmospheric modelling system is SILAM (*System for Integrated modeLling of Atmospheric coMposition*), developed by the Finnish Meteorological Institute (FMI), which simulates and predicts the emission, dispersion, transport, and deposition of atmospheric pollutants, including pollen, at different scales in Europe (https://silam.fmi.fi/). The phenological emission model (pollen emission module) developed by the FMI is one of the most sophisticated and widely used. It uses thermal time phenological algorithms, also known as the double-threshold air temperature-sum method, to parameterize the flowering of trees like birch and olive. This approach assumes that the timing of flowering is mainly driven by the accumulation of ambient temperature at the start and end of the pollen season, which is regarded as stable from year to year (Siljamo et al., 2013; Sofiev et al., 2006, 2013, 2017; Suanno et al., 2021; Vélez-Pereira et al., 2022). In contrast, the phenological models for herbs such as grass, ragweed, and mugwort are primarily based on fixed calendar days (Prank et al., 2013; Verstraeten et al., 2021). Additionally, these models account for other environmental factors that influence pollen emission, with ambient humidity and precipitation acting as suppressants, while wind speed and atmospheric turbulence facilitate the release and dispersion of pollen (Sofiev et al., 2006, 2013, 2017; Suanno et al., 2021; Vélez-Pereira et al., 2022). The FMI pollen emission modules have been integrated into the Copernicus Atmospheric Monitoring Service (CAMS), a European air quality operational service providing detailed four-day forecasts of air quality pollutants, aerosol tracers, and several highly allergenic pollen types, including alder, birch, grass, mugwort, olive, and ragweed, on a continental scale (https://atmosphere.copernicus.eu/charts/packages/cams_air_quality/products/europe-air-quality-forecast-pollens). CAMS integrates eleven individual state-of-the-art systems developed by different European countries (included SILAM), which are used in the operational ensemble. This approach has demonstrated the ability to deliver more robust predictions than individual systems (Sofiev et al., 2020). For Italy, the operational system MINNI (*Italian National Integrated Model to support the international negotiation on atmospheric pollution*) joined the CAMS European air quality ensemble in June 2022 (https://atmosphere.copernicus.eu/cams-european-air-quality-ensemble-forecasts-welcomes-two-new-state-art-models), developed and operated by the Italian National Agency for New Technologies, Energy and Sustainable Economic Development (ENEA). MINNI is based on the Flexible Air quality Regional Model (FARM) (Bessagnet et al., 2016; Gariazzo et al., 2007; Silibello et al., 2008), a Eulerian Chemical Transport Model that accounts for the transport (advection and turbulent diffusion), chemistry (gas-phase, with flexible mechanism configuration, and aerosol module) and dry/wet removal of atmospheric pollutants. MINNI also incorporates modelling of the pollen species mentioned above, utilizing the FMI phenological emission algorithms.

CAMS and other pollen forecasting models mentioned above support smartphone apps that help users manage and reduce exposure to airborne allergens, for example, by planning outdoor activities (Beggs et al., 2023; Bousquet et al., 2019; Matricardi et al., 2020; Sofiev et al., 2020; Suanno et al., 2021). These apps provide pollen forecasts and real-time concentration data, often integrating educational resources and tools for tracking symptoms and medication, with the goal of enabling users to manage their allergies better. By linking symptom severity with pollen concentrations, these apps can also improve diagnostic accuracy and assist doctors in tailoring treatment plans, especially for poly-sensitized patients (Matricardi et al., 2020; Tripodi et al., 2020). Smartphone apps offering these services alongside pollen forecasts are most frequently utilized during pollen seasons, highlighting the need for this tool. However, a study on the 9 mobile apps providing pollen information and forecasts highlighted the need for improvement in the quality of pollen forecasts (Bastl et al., 2017). Inaccuracies in pollen forecasting can result in both under- and overestimations of allergenic risk, misleading individuals with allergies and adversely affecting their health (Suanno et al., 2021).

2. Aims of the Thesis

The present thesis was conducted in the frame of the MEETOUT project (*Mitigation of the Effects of Environmental Triggers on the OUTcomes of chronic respiratory diseases*), aimed at investigating the spatial distribution, temporal variations, and health impact of environmental triggers, including pollen, with the goal of reducing the burden of chronic respiratory diseases in the population. This project involved collaborations between the University of Verona, the ARIANET-SUEZ air pollution modelling company (Milan, Italy), ENEA (Bologna, Italy), the Environmental Protection Agency of the Veneto Region (ARPAV), and the Polytechnic University of Madrid.

Within this framework, the thesis aimed to advance the project's objectives by introducing and evaluating novel methodologies for both monitoring and modelling pollen data. It addressed challenges related to imputing missing data in aerobiological databases, a topic that has been underexplored in previous literature. Additionally, it examined pollen variations over time in the Veneto Region, Northern Italy, which is particularly vulnerable to climate change due to its location in the Mediterranean climate hotspot and its heterogeneous/diversified climatic conditions. For future prevention of allergic symptoms and promoting public health, the thesis aimed to improve a pollen modelling system to predict pollen levels over the region.

In particular, the following aims were pursued:

i. Implementing and testing for the first time a method based on physical patterns to impute missing data in aerobiological datasets.
ii. Assessing temporal trends of pollen exposure indicators in the Veneto Region over a 21-year period.
iii. Implementing and validating a novel pollen modelling system to provide high-resolution pollen predictions over the Veneto Region.

Within the thesis aims three publications in open access were achieved:

i. Paper 1: Tagliaferro, S., Corrochano, A., Marchetti, P., Marcon, A., & Le Clainche, S. (2024). A new method based on physical patterns to impute aerobiological datasets. *PLoS ONE*, *19*(11): e0314005. https://doi.org/10.1371/journal.pone.0314005.

ii. Paper 2: Tagliaferro, S., Marchetti, P., Dall'Ara, B., Domenichini, F., Lazzarin, S., Nicolis, M., Selle, D., Silibello, C., & Marcon, A. (2024). Temporal trends of seasonal pollen indexes in a region of Northern Italy (2001-2022). *Atmospheric Environment*, 120826. https://doi.org/10.1016/j.atmosenv.2024.120826.

iii. Paper 3: Tagliaferro, S., Adani, M., Pepe, N., Briganti, G., D'Isidoro, M., Bonini, M., Piersanti, A., Finardi, S, Marchetti, P., Domenichini, F., Mircea, M., Villani, M. G., Marcon, A., & Silibello, C. (2024). The impact of the spatial resolution of vegetation cover on the prediction of airborne pollen concentrations over northern Italy. *Agricultural and Forest Meteorology*, *355*, 110153. https://doi.org/10.1016/j.agrformet.2024.110153.

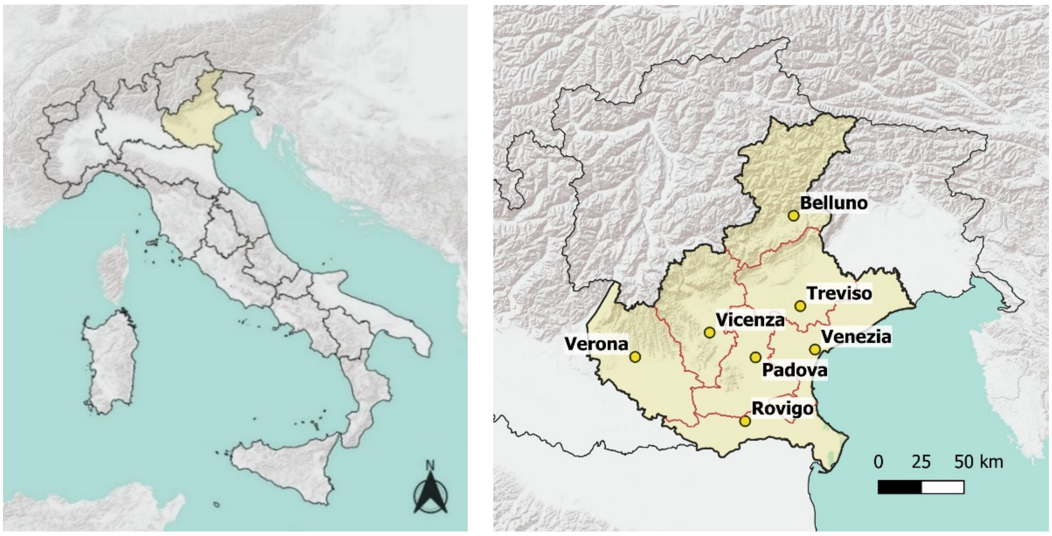
With the first publication (i), a brief overview of the paper and a video explanation of the methodology were made available on the ModelFLOWs-app website (https://modelflows.github.io/modelflowsapp/airpollution/), along with all the materials underlying the results presented in the study.

3. Study area

3.1. Veneto Region and surrounding areas

The Veneto Region, an administrative area located in the Northeast of Italy, has a population of 5 million inhabitants and covers approximately 18,400 km^2, making it one of the most densely populated regions in Italy. It shares borders with the Emilia-Romagna Region to the south, Lombardia to the west, Trentino-Alto Adige to the northwest, and Friuli-Venezia Giulia to the northeast (Figure 3.1). Geographically, the region consists of about 15% mountainous terrain (in the northern part, including Dolomites), 30% pre-alpine and hilly areas, and 55% plains, where the majority of the population is concentrated, particularly in the cities of Venezia (Venice), Verona, and Padova (Padua) (ARPAV, 2005). Regarding land use, agriculture prevails, covering 57.7% of the territory, with cereal crops accounting for 60% of this portion. Forests cover 29.1% of the land, while urbanized soils and wet lagoon areas encompass 7.6% and 5.6%, respectively (ARPAV, 2005).

Figure 3.1. Location of the Veneto Region (left panel) and a detailed view of the study area (right panel) showing major cities with higher population density and provinces' boundaries.



The map was produced using the QuickMapServices plugin (NextGIS, 2019) in QGIS software version 3.34.9 (QGIS Development Team. QGIS Geographic Information System. Open-Source Geospatial Foundation Project. http://qgis.org). The basemap used is ESRI Terrain (ESRI, Redlands, CA, USA).

The areas surrounding Veneto share similar geographical features, with mountainous areas to the north and plains to the south. In contrast, Emilia-Romagna presents a different topography, with the Apennine mountains dominating the southern region. Consequently, the plains are enclosed by these two mountain chains, with a main opening to the east on the Adriatic Sea, thereby forming the Po Valley-Veneto basin.

3.2. Climatological and vegetational aspects

The Veneto Region presents a variety of climatological and vegetational characteristics due to its geographical diversity and its transitional position between two climatic zones: the Mediterranean, characterized by a temperate climate with a dry summer and temperature of the hottest month > 22° C (Koeppen classification Csa), and central European, characterised by a temperate climate without a dry season and temperature of the hottest month < 22° C, but at least 4 months with T > 10°C (Cfb) (ARPAV, 2022). Its regional climate is influenced (ARPAV, 2022; Peel et al., 2007):

- at the macroscale by:
  - The Mediterranean Sea, source of humid and mild air masses in all seasons.
  - The Atlantic Ocean, which facilitates the influx of large western air currents into the Mediterranean basin, bringing humid and relatively mild air masses, as well as marine polar air from the North Atlantic. The Atlantic Ocean air masses, being colder than those originating from the Mediterranean, play a significant role in generating atmospheric perturbations that lead to the main precipitation in Italy.
  - The Euro Asiatic area, source of continental polar air masses originating from Siberia.
  - The Artic Circle, source of both continental and marine cold polar air masses.

    - The intertropical area, source of torrid subtropical air masses, both continental and marine, which tend to humidify as they pass over the Mediterranean.
- At the meso- and microscale by:
    - The Adriatic Sea and the Garda Lake, which exert a mitigating effect on the air masses, releasing humidity into the atmosphere and generating breeze winds.
    - The Alpine and pre-alpine mountain chains, which act as a barrier to the atmospheric circulation, altering the trajectories of air masses.
    - The Po Valley-Veneto basin, which traps air masses, keeping them stationary.

As a consequence of all these factors, various climatic conditions and vegetation are present in the region (ARPAV, 2022). The lowland area features a temperate sub-continental climate, with annual temperatures averaging 13°C in inland regions and 14°C near the coast (climatological period 1993-2021). Coastal breezes help moderate temperatures during the spring and summer months. Evenly distributed throughout the year, rainfall gradually increases from the southern to the northern part of the plain, ranging between 700 and 1000 mm annually. Vegetation in the plains mainly consists of pine, holm oak, hopbeam, and hornbeam forests, alternating with crops and meadows. Towards the Adriatic Sea (southeastern part), wet lagoon environments prevail, characterized by hygrophilous and halophilic plants, interspersed with crops (ARPAV, 2005, 2023). In the orographic area of the Veneto Region, characterized by northern foothills, pre-alpine and alpine regions, the climate is primarily cool temperate at lower altitudes and transitioning to cold temperate or cold at higher altitudes. Average annual temperatures are influenced by altitude, location, and exposure, resulting in greater continentality. They range from an average of 12°C in the pre-alpine region to 0°C at higher altitudes in the Alps. Precipitations are abundant, averaging about 1200-1500 mm annually, with maximum values reaching 2000 mm. This climatic pattern fosters the growth of hornbeam, hopbeam, chestnut, ash, oak, birch and beech forests in the pre-alpine area, while in the alpine area, coniferous, pine, larch, and beech forests are common, along with shrubs (ARPAV, 2022).

3.3. Allergic plants in Veneto

Europe hosts a rich botanical diversity, but only certain plants produce pollen that triggers allergies. Throughout the continent, distinct vegetational zones shaped by different climates can be identified, each characterized by the predominant prevalence of the following allergenic plants: i) the arctic area with birch trees; ii) central Europe with birch, deciduous forests, and grasses; iii) eastern Europe with grasses, mugwort, and ragweed; iv) mountains with grasses; v) the Mediterranean with pellitory, olive trees, grasses, and cypress (D'Amato et al., 2007). As mentioned in Section 3.2, the multi-climate features of the Veneto Region allow for the presence of all these plants, thus posing a significant health risk. Approximately 20% of the region's territory is covered by forest vegetation associations, including allergenic taxa (ARPAV, 2011), along with herbaceous plants whose exact distribution is challenging to quantify.

Poaceae (commonly known as Graminaceae, "grass" in English) are the most allergenic family among herbaceous plants (D'Amato et al., 2007). According to data provided by the Allergology Service of the Department of Environmental Medicine and Public Health in Padua, the Poaceae family is the leading source of sensitization among patients with pollen allergies, exhibiting an upward trend from 69% to 80% between 1996 and 2004 (ARPAV, 2011). The allergenic potency of Poaceae family arises from its broad diversity of grasses, which includes over 600 genera and 10,000 species. Italy alone hosts more than 120 genera and 400 species (D'Amato et al., 2007). This wide diversity results in an extended pollen season, typically spanning from March to late July, with occasional peaks in May and September, thereby exposing individuals to allergens for prolonged periods. Given these characteristics and widespread distribution, the Poaceae family holds significant allergological importance (ARPAV, 2011; D'Amato et al., 2007; ISPRA, 2021).

Even Urticaceae and Compositae (or Asteraceae) are prominent among herbaceous plant families with notable allergenic potential. Within the Urticaceae family, the genera *Parietaria* (pellitory) and *Urtica* (nettle) produce highly allergenic pollen (ARPAV, 2011; D'Amato et al., 2007). In the Veneto Region, sensitization to

Parietaria affects a notable portion of the sensitized population (32% in 1996 and 24% in 2004), although its prevalence is not as widespread as in coastal Mediterranean areas (ARPAV, 2011). However, Urticaceae pollen has a long persistence in the atmosphere due to its prolonged pollen season, spanning from April to November with two peaks (April-May and August-September). This leads to symptoms persisting across multiple seasons and, in some cases, enduring throughout the entire year (ARPAV, 2011; D'Amato et al., 2007; ISPRA, 2021).

The Compositae family includes around 20,000 species, with *Ambrosia* (ragweed) and *Artemisia* (mugwort) being the most significant contributors to pollinosis (D'Amato et al., 2007). In Veneto, the proportion of the sensitized population with sensitization shifted from 10% to 7% for *Ambrosia* and from 33% to 28% for *Artemisia* between 1996 and 2004 (ARPAV, 2011). *Ambrosia artemisiifolia* is an alien species in Italy. Its expansion started in the Milan area, Lombardia Region, and gradually spread across northern Italy, although not reaching the infestation levels observed in the Balkans and Pannonian Plain. The allergological interest for *Ambrosia* stems not only from its large production of highly allergenic pollen but also from its invasive nature, which facilitates its widespread dissemination. *Artemisia vulgaris* is another invasive plant of allergological interest commonly growing in urban and suburban environments. This species is known for producing vast quantities of pollen, with a single plant capable of generating millions of pollen grains. *Ambrosia* and *Artemisia* bloom during nearly identical periods, typically from the end of July to October, with peaks occurring between August and September, often resulting in concurrent allergies to both (ARPAV, 2011; D'Amato et al., 2007; ISPRA, 2021).

Allergenic trees include Betulaceae, Corylaceae, Cupressaceae, and Oleaceae families. The pollen of these plants is considered emerging for the Veneto territory because they are typical of other areas. For instance, Betulaceae is mainly widespread in the Scandinavian countries and central Europe, while Cupressaceae and Oleaceae are common in central-southern Italy, Spain, and Greece. Their increasing diffusion in the Veneto territory is attributed to their incorporation into public and private green spaces for ornamental purposes, as well as their use in agriculture, such as for olive trees (ARPAV, 2011; D'Amato et al., 2007).

The *Alnus sp.* (alder) and *Betula sp.* (birch) genera, within the Betulaceae family, produce highly allergenic pollen. In the Veneto population, the prevalence of sensitization to these genera in the sensitized population doubled from 1996 to 2004 (from 19% to 39%) (ARPAV, 2011). *Alnus* is commonly found along riverbanks and in periodically submerged or swampy areas, and flowers from February to April (ARPAV, 2011; D'Amato et al., 2007; ISPRA, 2021). In contrast, *Betula*, recognised as the tree with the highest allergenic potential, flowers from April to June (ARPAV, 2011; D'Amato et al., 2007; ISPRA, 2021). *Betula* is commonly used as an ornamental plant in urban settings. The Corylaceae family, including *Carpinus* (hornbeam), *Corylus* (hazel), and *Ostrya* (hopbeam), has been recently incorporated into the Betulaceae family (D'Amato et al., 2007). Between 1996 and 2004, in the Veneto Region, the proportion of the sensitized population with sensitization to *Carpinus* and *Corylus* changed from 24% to 35% and from 24% to 45%, respectively (ARPAV, 2011). In northern Italy, *Carpinus* is prevalent throughout the Alps, *Ostrya* in the northeastern and Adriatic regions, while *Corylus* is widespread from the plains to the mountains. *Carpinus* and *Ostrya* bloom from April to May, whereas *Corylus* blooms from January to March (ARPAV, 2011; D'Amato et al., 2007; ISPRA, 2021).

Among the Cupressaceae family, the genus *Cupressus* (cypress) is notably considered the most allergenic, as it releases large quantities of highly allergenic pollen (ARPAV, 2011; D'Amato et al., 2007). The spread of *Cupressus* in the Veneto Region has led to a significant rise in skin prick test positivity among the sensitized population, increasing from 4% to 28% between 1996 and 2004 – a 7-fold increase. However, this strong increase is partially attributed to an improvement in the sensitivity of the diagnostic extract (ARPAV, 2011). *Cupressus* pollinates during months when no other allergenic plants are flowering, typically between December and March (D'Amato et al., 2007).

Regarding the Oleaceae family, the genus *Olea* (olive) is the most allergenic, although other genera, such as *Fraxinus* (ash) and *Ligustrum* (privet), also contribute to allergic disorders (ARPAV, 2011; D'Amato et al., 2007). In Veneto, the proportion of the sensitized population with sensitization to *Olea* ranged from 14% to 32% between 1996 and 2004 (ARPAV, 2011). *Olea* typically blooms between April and June (ARPAV, 2011; ISPRA, 2021). In Veneto, *Olea* trees are commonly found around Garda Lake, as well as in certain areas of the Verona and Vicenza provinces (ARPAV, 2011; D'Amato et al., 2007).

3.4. Aerobiological monitoring

The Italian aerobiological monitoring network, POLLnet, is part of the National System for Environmental Protection (SNPA), consisting of 57 monitoring stations spread across 15 regions. Its primary function is to monitor the biological component of airborne particulate matter in the atmosphere by measuring daily pollen and fungal spore concentrations (expressed in pollen per cubic meter of air, p/m^3, and spores per cubic meter of air, s/m^3). This data is collected and stored in a national, publicly accessible database (https://pollnet.isprambiente.it/).

Monitoring follows the European Standard (EN 16868, 2019): the monitoring stations consist of Hirst-type volumetric samplers (Hirst, 1952), with a pump calibrated to aspirate 10 L/min of air (14.4 m^3 in 24 h). Following the air flux aspiration, the airborne particles are captured by their impact on a plastic adhesive tape of silicone oil placed on a metallic drum, which rotates at the speed of 2 mm/h (ARPAV, 2004). Every seven days, the sampling drum is extracted from the device, and the strip with adherent atmospheric particles is cut into fragments corresponding to the monitoring days; then, it is placed on a slide and covered with glycerine jelly mixed with basic fuchsine (Ogden et al., 1974). Daily pollen grains are examined under a microscope at 400× magnification and counted by a specialized technician based on their morphological characteristics (ARPAV, 2004). Then, the number of pollen grains collected from the sampler is multiplied by a conversion factor that accounts for the following characteristics: diameter of the view field under the microscope (expressed in mm); number of horizontal reading lines (=4); number of grains, per type of pollen, identified over the entire examined area; method of reading and sampling area; volume of air sampled (14.4 m^3 per day). In this way, pollen counts are converted to concentrations, expressed as the number of pollen grains per unit volume of air (p/m^3) (Bastl et al., 2018).

In the Veneto Region, the Environmental Protection Agency of the Veneto Region (ARPAV) is responsible for conducting daily aerobiological monitoring of pollen and spores. The number of monitoring stations operated by ARPAV has varied over time, with a total of 24 established, though not all were active simultaneously. Currently, 8 stations remain active, 7 of which are located in provincial capitals of the region (Belluno, Padova, Rovigo, Treviso, Venezia, Verona, and Vicenza), while one is located in Feltre. ARPAV joins the POLLnet monitoring network, contributing to the database construction.

For this thesis, daily pollen concentrations for the Veneto region were provided by ARPAV. Data from monitoring stations outside the region were retrieved from the POLLnet dataset (https://pollnet.isprambiente.it/).

4. Pollen data management

4.1. Pollen dataset preparation

To conduct the analyses, daily pollen concentrations were organized in datasets consisting of a first column in the date format (dd-mm-yyyy) and additional columns representing individual pollen time series. Each pollen time series corresponds to a specific pollen type obtained from a specific monitoring station.

The general approach to preparing a pollen dataset for analysis typically involves two main steps: firstly, exploration of the dataset to check for data quality; secondly, missing data imputation. To manage pollen data, there are several R packages that allow general operations for data cleaning and analysis processes, such as "pollen", "forecast", and "openair" packages. However, none of these are complete for managing aerobiological data (Rojo et al., 2019). For this thesis, the "AeRobiology" R package was used as it offers algorithms for checking aerobiological data quality, filling in the missing data, visualising the data, and calculating the pollen season and seasonal indexes using several methods (Rojo et al., 2019).

The pollen datasets used in this thesis were constructed using the statistical software STATA version 18 and/or RStudio version 4.2.2.

4.2. Data quality check and missing data imputation

Missing data (NAs) could compromise the robustness of results derived from the analysis. The presence of NAs is a significant concern in pollen datasets, as these datasets consist of continuous time series data with daily temporal resolution. Ideally, to be considered valid for analysis, the pollen time series should contain no more than 20% NAs during the pollen season and in the adjacent periods immediately before and after it. Therefore, it is crucial to examine the dataset to identify the number, length, and position of NAs (Picornell et al., 2021; Rojo et al., 2019). For this thesis, the quality check process was performed by using the "quality_control" (QC) function, available in the "AeRobiology" R package. The QC function allows for the exploration of NAs in the entire dataset, providing information on the quality of pollen data for each pollen type and season. This function returns a risk index, with values from 0 to 5, calculated according to 5 criteria that consider how missing data are distributed: (i) within the year; (ii) within the pollen season; (iii) nearby the start date; (iv) nearby the end date; (v) nearby the peak date. A higher value of the risk index indicates lower data quality (Rojo et al., 2019).

Once missing data are identified, it may be necessary to apply imputation methodologies to fill these gaps and enable effective statistical analysis. Various methods have been employed in aerobiological studies, spanning from statistical to machine learning approaches. Common statistical techniques include linear interpolation (Damialis et al., 2007; González-Fernández et al., 2022; Makra et al., 2011; Šikoparija et al., 2018), cubic spline interpolation (Šikoparija et al., 2018), the Gaussian method (Makra et al., 2023), and averaging values from corresponding days in different years (Damialis et al., 2007). In contrast, machine learning methods used for imputing missing data in aerobiological datasets include Convolutional Neural Networks (Navares & Aznarte, 2019), Denoising Convolutional Auto-encoder (Makra et al., 2023), k-Nearest Neighbours algorithm (Marchetti et al., 2017). Within the "AeRobiology" R package, the "interpollen" function integrates various methodologies for gap filling: the moving average of daily concentrations; linear or spline regressions models; use of the seasonality from the historical database; use of data obtained from nearby stations (Picornell et al., 2021; Rojo et al., 2019). For this thesis, missing data imputation was performed using the “movingmean” method of the “interpollen” function. This is a statistical univariate approach that fills missing values by averaging nearby data within a symmetrical interval twice the length of the gap (Rojo et al., 2019). The moving mean method was selected for its better performance within the package, given its reduced sensitivity to factors like data availability, time series length, and fluctuations in pollen concentrations across consecutive days (Picornell et al., 2021).

4.3. Pollen season definition and seasonal pollen indexes

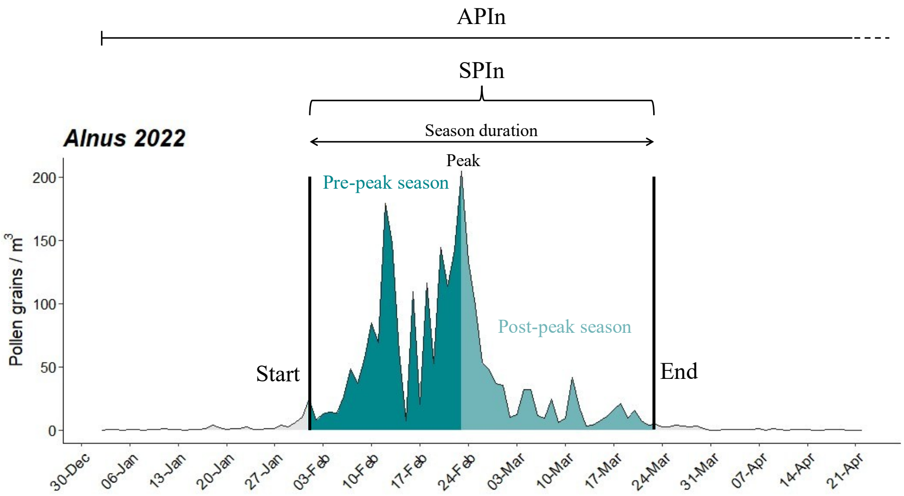
The definition of pollen season is fundamental for research in aerobiology, as well as in clinical practice, allergen immunotherapy, and the assessment of climate change's impact on plants. Various methodologies are employed to determine the start and end of pollen season. Among these, the percentage methods are the most used approaches in aerobiological studies (Tasioulis et al., 2022). They consist of retrospectively attributing the start and end of the season to specific percentages of the annual integrals of daily pollen concentrations. These percentages can vary, and the most used to define the start and end dates of pollen season, respectively, are: 2.5% and 97.5%, 5% and 95%, 1% and 99%, or 1% and 95% (Tasioulis et al., 2022). In particular, the 95-percentage method (start: 2.5%; end: 97.5%) is considered accurate and less sensitive to external advection phenomena, ensuring precise pollen detection during and in the days surrounding the actual pollen season (Andersen, 1991; Fuhrmann et al., 2016; Tasioulis et al., 2022; Ugolotti et al., 2015). However, as pollen concentrations and within-season patterns vary by year, this approach may lead to an inaccurate contraction or expansion of the season's duration independently of climate change. Indeed, the threshold for starting the pollen season varies with the cumulative pollen concentration throughout the year; a higher annual concentration requires a greater cumulative concentration of pollen for the season to begin. Consequently, using this method to determine the start and end of the pollen season may obscure any climate-related changes affecting the duration of the pollen season (Gehrig & Clot, 2021; Glick et al., 2021). Despite this, the percentage method is considered effective in capturing the pollen season, even when pollen concentrations are low. This capability is especially important for studying temporal variations in phenological indexes (Tasioulis et al., 2022). For clinical purposes, the EAACI method (Pfaar et al., 2017) is gaining popularity due to its focus on clinical thresholds and its consideration of allergy symptom manifestation in defining the pollen season. EAACI recommends to define the pollen season based on specific thresholds of daily concentrations over consecutive days; for example, the start of the grass pollen season is identified as the first day in a 7-day window during which at least 5 days record concentrations ≥ 3 p/m^3, with a cumulative total of at least 30 p/m^3 (Pfaar et al., 2017). This approach has recently been applied in climate change studies due to its independence from the annual pollen concentration (Gehrig & Clot, 2021; Glick et al., 2021; Tasioulis et al., 2022). However, since it considers pollen concentrations relevant for the health of allergic individuals, the EAACI thresholds can be unsuitable to accurately describe low pollen concentrations; the method may also fail to identify the pollen season.

Furthermore, EAACI thresholds are available only for certain pollen taxa, such as birch, cypress, grass, olive, and ragweed (Gehrig & Clot, 2021; Glick et al., 2021; Tasioulis et al., 2022). Therefore, the choice of the pollen season definition depends on the specific focus of the study and the characteristics of pollen data (Bastl et al., 2018; Tasioulis et al., 2022).

Once the pollen season is identified, various indexes are typically calculated in aerobiological studies to describe its characteristics and fluctuations over time. By examining these indexes, researchers can assess trends in pollen seasonality and pollen load over the years, evaluate the impact of climate change, and analyse the relationship between pollen exposure and allergic reactions in vulnerable populations. The main seasonal pollen indexes are (Figure 4.1):

i. Start and end of the pollen season, expressed as date (1 Jan to 31 Dec) or Julian day (0-365): the beginning and conclusion of the pollen season, as defined by the method applied.
ii. Peak day, expressed as date or Julian day: the day of the year when the maximum concentration of pollen occurs.
iii. Peak concentration, expressed as p/m^3: the maximum concentration of pollen observed during the year.
iv. Pollen season duration, expressed as the number of days of the defined pollen season.
v. Seasonal Pollen Integral (SPIn), expressed as p/m^3: the cumulative concentration of pollen during the defined pollen season.
vi. Annual Pollen Integral (APIn), expressed as p/m^3: the cumulative concentration of pollen in the year.

Figure 4.1. Example of pollen daily distribution for *Alnus* in 2022 and illustration of the seasonal pollen indexes. The figure was produced with the "AeRobiology" R package.



APIn: Annual Pollen Integral; SPIn: Seasonal Pollen Integral (SPIn).

The pollen season and the respective indexes can be easily calculated using the "AeRobiology" R package. This tool integrates various methodologies, offering optimal solutions for different study applications. By utilizing one of these methods, users can create datasets that include all seasonal parameters and pollen intensity measurements for each pollen type, monitoring station, and year (Rojo et al., 2019). For this thesis, pollen seasons were identified using the 95-percentage method (Andersen, 1991).

5. Development and application of methods for missing data imputation (Paper 1)

5.1. Knowledge gaps and research aims

Missing data are common in aerobiological datasets. Potential causes include instrument malfunctions, maintenance interruptions, adverse weather conditions, and intentional pauses during out-of-season periods (Picornell et al., 2021).

The Gappy Singular Value Decomposition (GSVD) is a data-driven approach capable of recognizing data patterns linked to physical processes, enabling its application across multiple fields (Díaz-Morales et al., 2024; Hetherington et al., 2023, 2024). It has been successfully employed to reconstruct fluid flow (Hetherington et al., 2023; Venturi & Karniadakis, 2004) and oceanographic datasets (Beckers & Rixen, 2003), but it had not been tested on aerobiological data before this thesis. Furthermore, the imputation challenges specific to aerobiological datasets are less explored, with few simulation studies conducted to assess the accuracy of imputation methods in this field (Makra et al., 2023; Navares & Aznarte, 2019; Picornell et al., 2021).

To address these gaps, this thesis introduced a novel implementation of the GSVD method. The algorithm was specifically tailored for application to aerobiological datasets. To assess its effectiveness, the imputation accuracy of the GSVD method was compared to the widely recognized statistical method, the moving mean algorithm. To achieve this, a simulation study was conducted to address the knowledge gap concerning the evaluation of imputation methods for aerobiological data.

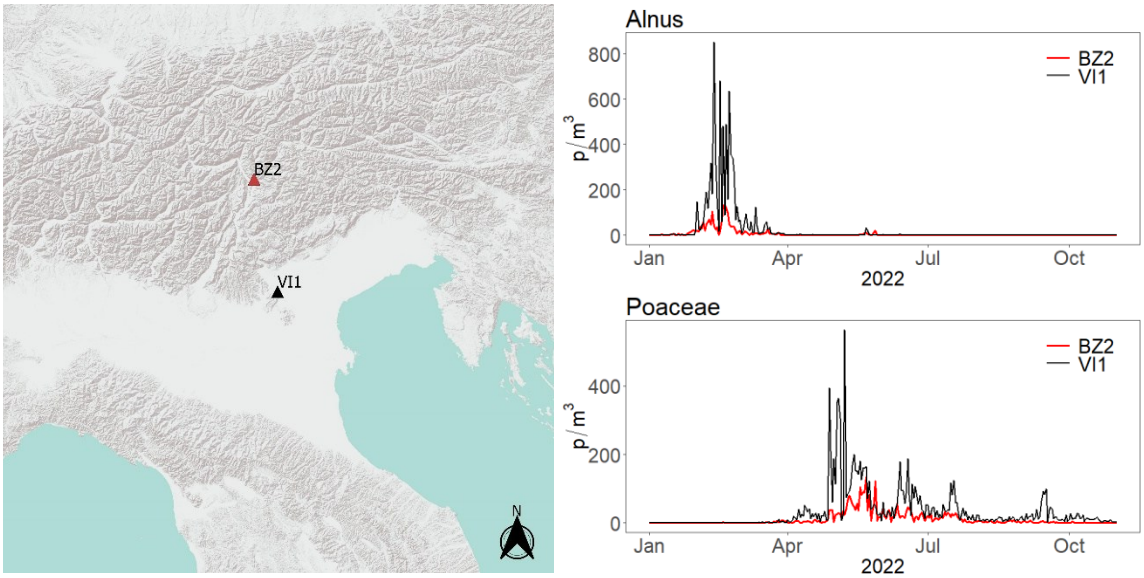
5.2. Materials and methods

5.2.1. Pollen dataset

For the study purposes, we selected two monitoring stations representing different environments in the northeast of Italy (Figure 5.1): VI1 in Vicenza, located in the lowlands with a continental climate, and BZ2 in Bolzano, situated in the mountains with an alpine climate. For these stations, we downloaded daily pollen concentrations for the period 2018-2022 from the POLLnet database. The dataset is available at https://modelflows.github.io/modelflowsapp/airpollution/. *Alnus* and

Poaceae pollens were specifically chosen for the analysis due to their different seasonality, temporal distribution, and load characteristics, as evident from the 2022 time series depicted in Figure 5.1.

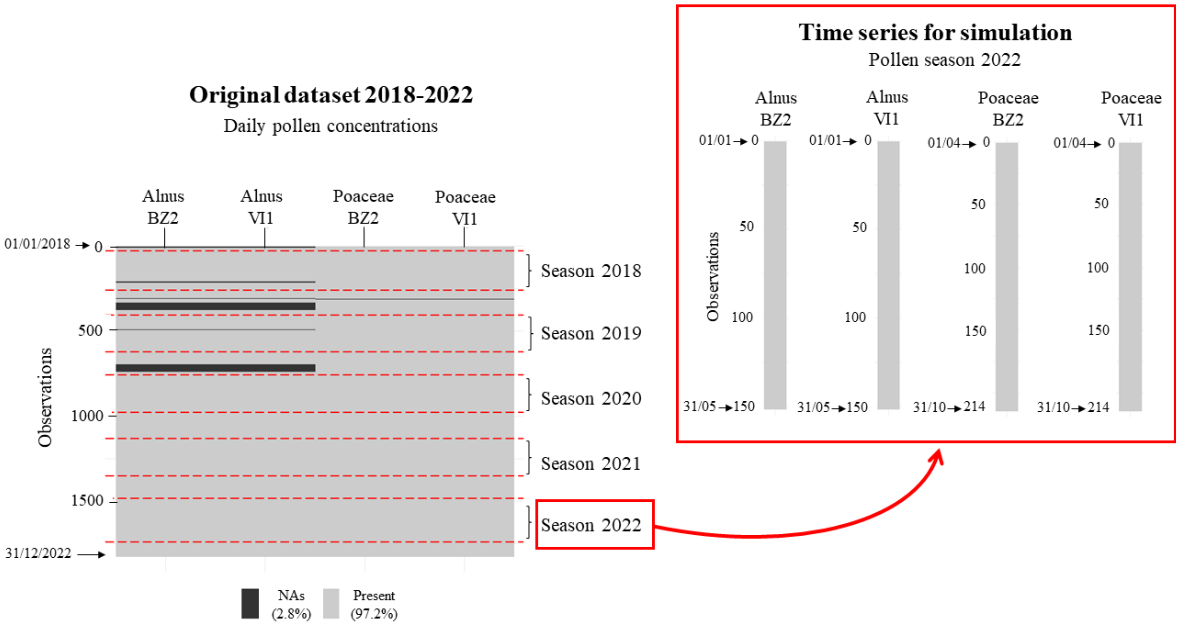
Figure 5.1. Location of the selected monitoring stations in the northeast Italy and the respective pollen time series for the year 2022.



The map was produced using the QuickMapServices plugin (NextGIS, 2019) in QGIS software version 3.34.9 (QGIS Development Team. QGIS Geographic Information System. Open-Source Geospatial Foundation Project. http://qgis.org). The basemap used is ESRI Terrain (ESRI, Redlands, CA, USA). BZ2: Bolzano; VI1: Vicenza; p/m^3: pollen/cubic meter

In simulation studies, complete datasets are necessary to create scenarios with missing data and to compare the imputed values to the observed ones. For this reason, in our study, we defined the pollen season to establish appropriate periods for the random generation of missing data. Then, we examined missing data to identify the year with the most complete data coverage during the seasonal pollen period. The years from 2020 to 2022 showed no missing data at station VI1, whereas station BZ2 had complete data throughout the period (2018-2022). We chose to simulate the pollen season of the year 2022 to ensure a complete data series for the preceding years, thus guaranteeing the applicability of the data-driven method. The structure of the original dataset and the time series extracted for the simulation study are shown in Figure 5.2.

Figure 5.2. Scheme depicting the original dataset of daily pollen concentrations for the period 2018-2022 and time series extracted for the simulation study.



BZ2: Bolzano; VI1: Vicenza; NAs: missing data. Each season was obtained from the earlier start and later end day of the observed pollen seasons across the two monitoring stations: Season 2018 (start: 31/01/2018, *Alnus* BZ2; end: 17/09/2018, Poaceae VI1); Season 2019 (start: 11/02/2019, *Alnus* VI1; end: 17/09/2019, Poaceae VI1); Season 2020 (start: 30/01/2020, *Alnus* BZ2; end: 05/09/2020, Poaceae VI1); Season 2021 (start: 08/02/2021, *Alnus* VI1; end: 14/09/2021, Poaceae VI1); Season 2022 (start: 26/01/2022, *Alnus* BZ2; end: 08/10/2022, Poaceae VI1).

Descriptive statistics of pollen concentrations at each station in the pollen season 2022 were calculated: mean ± Standard Deviation (SD), quartiles, coefficient of variation (CV = (SD/mean) × 100) (%), and duration of the pollen season.

As the start and end dates varied depending on the monitoring station, for each pollen, we considered a common seasonal period in the year 2022. This was done by extending the season to the first day of the month on which the minimum start date occurred and to the last day of the month on which the maximum end date occurred. As a result, the period considered for imputation was 01/01/2022 to 31/05/2022 for *Alnus* and 01/04/2022 to 31/10/2022 for Poaceae.

5.2.2. Methods of imputation investigated

We utilized the moving mean method from the "AeRobiology" R package as specifically designed for aerobiological datasets. The GSVD was used as data-driven method because it is designed to handle missing data by extending the properties of Singular Value Decomposition (SVD), a powerful tool for post-processing and data management. Grounded in linear algebra, SVD is the primary technique behind various dimensionality reduction methods, such as Principal Component Analysis. It effectively identifies and extracts relevant spatio-temporal information, removes noise, and filters out spatial redundancies, thereby reducing data dimensionality (Hetherington et al., 2023; Venturi & Karniadakis, 2004). By leveraging SVD's capabilities, GSVD iteratively repairs and reconstructs datasets, enhancing its effectiveness in managing incomplete information. The GSVD algorithm employed in this study was originated from the ModelFLOWs-app (code available at https://modelflows.github.io/modelflowsapp/airpollution/), an innovative software that implements modal decomposition methods and hybrid machine learning tools. This software is designed to address problems in complex nonlinear dynamical systems, with applications in pattern identification, data reconstruction, and data forecasting (Hetherington et al., 2023).

We initialised the GSVD algorithm by assigning an initial value to the missing data. The mean value of the time series (hereafter GSVD mean) and the linear interpolation between values of the time series (hereafter GSVD interp) were used for the initialisation. SVD was then applied to the initial dataset, as $X = U\Sigma V^T$. The matrices U and V contain the modes (i.e. the spatio-temporal data decomposed using the Proper Orthogonal Decomposition approach) and the temporal coefficients, $()^T$ denotes the matrix transpose, and Σ is the diagonal matrix containing the singular values of the matrix X. The first modes contain the physical modes related to the problem, while the rest are related to noise, spatial redundancies or to fit this initial guess. Retaining the first number N of modes, which can be tuned, one can approximate the dataset as $X^* = U^*\Sigma^*V^{T^*}$. The gaps in the original dataset were updated using the values of this approximation. Afterwards, SVD was iteratively applied again until the Mean Square Error (calculated as the ratio between the difference of the original and the reconstructed dataset and the total number of samples) of the gaps between two iterations is lower than a tolerance level set at 10^{-6}. Further details on the algorithm and the implementation can be found in Díaz-Morales et al. (2024) and Hetherington et al. (2023, 2024).

5.2.3. Simulation study

For each pollen type and station, we generated 12 simulation scenarios by combining 3 proportions of missing data (5%, 10%, 25%) and 4 gap lengths (number of consecutive missing days: 3, 5, 7, 10 days). For each simulation scenario, we obtained 100 simulated datasets. We randomly removed daily observed data from the complete pollen seasonal time series following the subsequent procedure (see Table 5.1):

i. Calculation of the number of days within the pollen season corresponding to the total proportions of NAs of 5%, 10%, and 25%.
ii. Calculation of the number of gaps for each gap length pattern (3, 5, 7, and 10 days) to approximate the total number of days with NAs from step i.
iii. Implementation of the algorithm to randomly remove data iteratively 100 times in RStudio, setting the number of consecutive days and the number of gaps from steps i and ii without overlapping gaps.

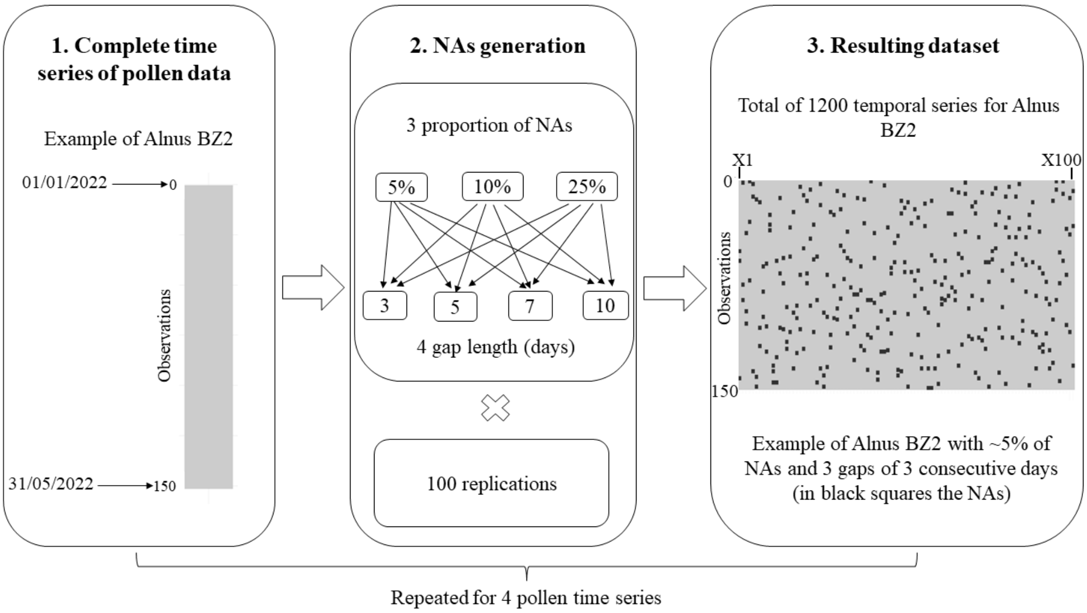
Table 5.1. Settings of simulation scenarios and the resulting percentages of NAs obtained from simulations.

Pollen	***Season duration (days)***	***NAs simulation settings***				***Resulting NAs***	
		%	Total days	Gap length (consequent days)	Number of gaps	Total days	%
Alnus	151 (01 Jan - 31 May)	5	7.6	3	3	9	6
				5	2	10	6.6
				7	1	7	4.6
				10	1	10	6.6
		10	15.1	3	5	15	9.9
				5	3	15	9.9
				7	2	14	9.3
				10	2	20	13.2
		25	37.8	3	13	39	25.8
				5	8	40	26.5
				7	5	35	23.2
				10	4	40	26.5
Poaceae	214 (01 Apr - 31 Oct)	5	10.7	3	4	12	5.6
				5	2	10	4.7
				7	2	14	6.5
				10	1	10	4.7
		10	21.4	3	7	21	9.8
				5	4	20	9.3
				7	3	21	9.8
				10	2	20	9.3
		25	53.5	3	18	54	25.2
				5	11	55	25.7
				7	8	56	26.2
				10	5	50	23.4

NAs: Missing data. The simulations are in total 12 for each pollen and station.

As a result, we obtained a total of 48 simulations (12 scenarios x 2 stations x 2 pollens), each with 100 time series for imputation. An example of the NAs generation process and resulting dataset is reported in Figure 5.3.

Figure 5.3. Example of generation of missing values (NAs) and resulting dataset for *Alnus* BZ2.



BZ2: Bolzano

The R code for missing data generation and examples of gappy datasets are available at https://modelflows.github.io/modelflowsapp/airpollution/.

5.2.4. Missing data imputation and accuracy evaluation

As part of the "AeRobiology" R package, we executed the moving mean method using RStudio. We developed an algorithm to iteratively apply the "interpollen" function with "movingmean" method to each column of individual datasets (pollen/station). After that, we merged the imputed dataset with the original corresponding pollen time series, and we implemented a function to iteratively calculate the Root Mean Square Error (RMSE) between real data and the 100 replications of the simulated data. This statistic was used to evaluate imputation accuracy by comparing the reconstructed datasets with the observed time series. The RMSE consists of the sum of the squared differences between the predicted and observed values divided by the total number of observations.

We implemented the GSVD algorithm in Python and ran it with Visual Studio Code version 1.86. As data-driven methods rely on extensive datasets to effectively capture data variability (Kasam et al., 2014), we incorporated the 100 incomplete time series from each pollen, station, and simulation scenario into the original dataset including monitoring data spanning from 2018 to 2022. We studied different settings, changing the first initialisation of the values of the gaps and the number of modes, and evaluated the performance reconstruction of the gaps. Two imputation cases are shown in this study for the sake of clarity, although other combinations showed similar results: the GSVD mean 5modes and the GSVD interp 10modes. After each imputation, the algorithm calculated the RMSE for each repetition and for each pollen time series and extracted the results as a dataset.

Finally, we merged the RMSE from the different imputations, and then we calculated the median RMSE for each imputation method and each combination of NAs.

Besides this, we checked if the temporal short-term variability of pollen may affect imputation quality (Picornell et al., 2021). Indeed, pollen distribution, load, and seasonality differ according to the environment, climate, and phenology of the plant. All these factors may impact the accuracy of the imputation. So, for each pollen time series, we calculated the Variation index (VIn), an indicator of variability in pollen concentrations between consecutive days, based on Picornell et al (2021):

i. The 2-day moving mean and 2-day moving SD within the pollen season were calculated.
ii. The moving coefficients of variation (CV) were calculated as the ratio between the moving SD and the moving mean.
iii. The VIn was derived as the average moving CV over the pollen season.

Then, we related the median RMSE and the VIn using boxplots in order to explore the relation between imputation accuracy and pollen variability. Moreover, we employed multiple linear regression models stratified by pollen and monitoring station (M1: *Alnus* and BZ2 station; M2: *Alnus* and VI1 station; M3: Poaceae and BZ2 station; M4: Poaceae and VI1 station) to explore this relationship further. The dependent variable was the RMSE from the 100 replications by all the simulations (total of 4800 time series), which we log-transformed to satisfy the normality assumption in linear regression. Additionally, we applied a robust estimator of standard errors to relax the homoskedasticity assumption. Model covariates included the imputation method, proportion of NAs, and gap length. We exponentiated the regression coefficient β (Exp(β)) to provide an estimate of the relative change in RMSE.

5.3. Results

5.3.1. Pollen data description

Table 5.2 reports descriptive statistics of pollen observations in the pollen season 2022.

Table 5.2. Descriptive statistics of pollen data in the pollen season 2022.

	Station	***Mean ± SD*** *(p/m^3)*	***CV*** *(%)*	***VIn*** *(%)*	***Q1*** *(p/m^3)*	***Median*** *(p/m^3)*	***Q3*** *(p/m^3)*	***Max*** *(p/m^3)*	***Season duration*** *(days)*
Alnus	BZ2	12.1±24.1	198.8	12.1	0.5	2.0	10.4	132.4	122
	VI1	50.1±129.5	258.7	50.1	0.0	1.5	23.6	852.6	47
Poaceae	BZ2	14.5±22.1	152.9	14.5	1.0	4.7	20.2	135.4	150
	VI1	47.2±71.3	150.9	47.2	10.3	21.4	51.8	564.4	180

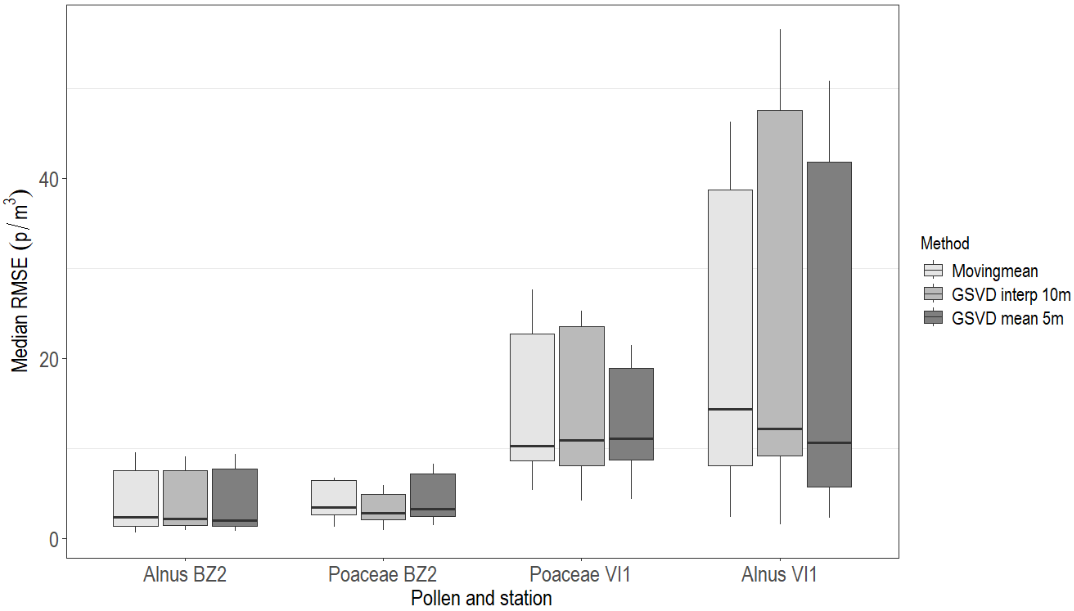
SD: Standard Deviation; CV: Coefficient of Variation; VIn: Variation Index; Q1: 1st quartile; Q3: 3rd quartile; Max: maximum; BZ2: Bolzano; VI1: Vicenza; p/m^3: pollen/cubic meter.

For both pollen types, the mean and SD were higher at the VI1 monitoring station compared to BZ2. For *Alnus*, the duration of the pollen season was shorter in VI1 compared to BZ2, but pollen variability was higher. In contrast, Poaceae showed a shorter pollen season in BZ2 than in VI1, but a higher variability in VI1 in terms of VIn.

5.3.2. Performance analysis

No specific pattern resulted in the distribution of median RMSE values for pollen and station by imputation methods (Figure 5.4). The variability in the distribution of median RMSE was lower at the BZ2 monitoring station (*Alnus*: from 0.6 to 9.5 p/m^3; Poaceae: from 0.9 to 8.2 p/m^3) and higher at the VI1 monitoring station (*Alnus*: from 1.5 to 56.5 p/m^3; Poaceae: from 4.1 to 27.6 p/m^3).

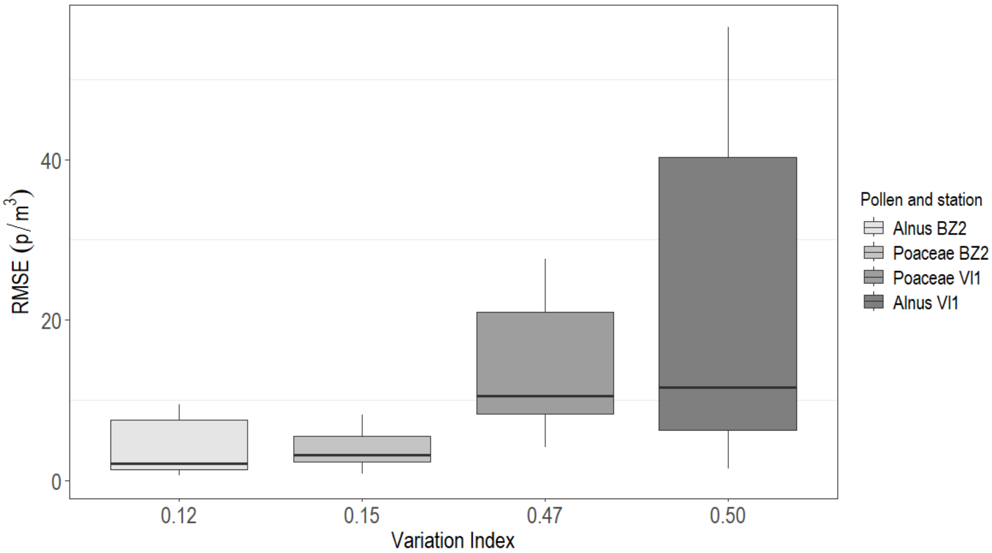
Figure 5.4. Distribution of the median Root Mean Square Error (RMSE) values for pollen/station by imputation method.



BZ2: Bolzano; VI1: Vicenza; GSVD: Gappy Singular Value Decomposition. Each box represents the distribution of the median RMSE from the 12 simulations.

When examining the relationship between the median RMSE values and VIn (Figure 5.5), a trend emerged: RMSE tended to increase with higher VIn values. Additionally, higher variability in the distribution of median RMSE values increased with higher VIn values.

Figure 5.5. Distribution of median Root Mean Square Error (RMSE) for the Variation Index by pollen/station.



BZ2: Bolzano; VI1: Vicenza. Each box represents the distribution of the median RMSE from the 12 simulations imputed with the 3 methods.

Multiple linear regression models showed large variability in imputation accuracy across the methods examined, with none of them outperforming the others when adjusting for the simulation scenario (Table 5.3). Moreover, no consistency was found within the GSVD imputation method, even showing contrasting results as in model M3. There was, instead, a consistent association between the simulation settings and imputation accuracy. In fact, the RMSE increased with an increasing proportion of NAs across all models. Notably, the RMSE was 4 to 10 times higher when NAs were set to 25%, compared to the reference of 5%. On the contrary, the RMSE decreased with gap length, with minimum values observed at 7 days for models M1 and M2, and at 10 days for models M3 and M4.

Table 5.3. Association estimates (Exp(β) representing ratios of geometric means) with 95%CI between the Root Mean Square Error (RMSE) and covariates (imputation method, % of NAs, and gap length).

	M1 (Alnus, BZ2)	***M2 (Alnus, VI1)***	***M3 (Poaceae, BZ2)***	***M4 (Poaceae, VI1)***
	Exp(β) (95%CI)	Exp(β) (95%CI)	Exp(β) (95%CI)	Exp(β) (95%CI)
Imputation method:				
Moving mean	Ref.	Ref.	Ref.	Ref.
GSVD interp 10m	1.20 (1.05-1.38)	1.00 (0.81-1.24)	0.88 (0.80-0.97)	0.94 (0.85-1.04)
GSVD mean 5m	1.03 (0.89-1.18)	1.13 (0.93-1.38)	1.10 (1.00-1.21)	0.92 (0.83-1.00)
% of NAs:				
5	Ref.	Ref.	Ref.	Ref.
10	2.12 (1.80-2.49)	3.76 (2.93-4.84)	1.94 (1.72-2.19)	1.80 (1.60-2.01)
25	5.85 (5.11-6.69)	9.86 (8.03-12.10)	3.84 (3.49-4.22)	3.74 (3.39-4.13)
Gap length:				
3 days	Ref.	Ref.	Ref.	Ref.
5 days	0.92 (0.79-1.08)	1.14 (0.88-1.46)	0.84 (0.75-0.94)	0.90 (0.80-1.02)
7 days	0.65 (0.56-0.76)	0.49 (0.39-0.63)	0.94 (0.85-1.03)	0.91 (0.82-1.01)
10 days	0.76 (0.66-0.88)	0.74 (0.60-0.92)	0.77 (0.69-0.85)	0.78 (0.71-0.87)

BZ2: Bolzano; VI1: Vicenza; CI: Confidence Interval; GSVD: Gappy Singular Value Decomposition; NAs: missing values; Ref.: reference category.

5.4. Discussion and conclusions

A simulation study was conducted to compare the imputation accuracy of two methodologies, applying and evaluating for the first time the GSVD method to an aerobiological dataset. Promising results emerged, demonstrating a similar performance of GSVD in comparison to the well-established moving mean method of the "AeRobiology" R package. However, it was found that both the inherent variability in observed pollen concentrations and the pattern of missing data had a more substantial impact on imputation accuracy within aerobiological datasets than the interpolation method applied. These findings contribute to filling the gap of knowledge in this field, considering the limited number of simulation studies conducted on pollen time series (Makra et al., 2023; Navares & Aznarte, 2019; Picornell et al., 2021).

We compared univariate and multivariate methods of interpolation specifically focusing on aerobiological datasets. Previous simulation studies on other types of environmental data (e.g. hydrological, meteorological, air quality) have favoured multivariate methods, leveraging information from other temporal series, over univariate methods, which rely solely on the data series itself (Bleidorn et al., 2022; Junger & Ponce De Leon, 2015; Nelsen et al., 2018). On one hand, we used the moving mean algorithm from the "AeRobiology" R package as an univariate method, which was specifically tailored for aerobiological datasets (Picornell et al., 2021). Its simplicity and growing application in aerobiological studies underscores its relevance and efficacy in reconstructing time series. On the other hand, we used the GSVD algorithm as a multivariate method, first evaluating its performance on aerobiological datasets. The potential of this method lies in its ability to reduce data dimensionality through data-driven decomposition, identifying the main data patterns related to physics without requiring any assumptions (Díaz-Morales et al., 2024; Hetherington et al., 2023, 2024). This characteristic makes it a promising tool for dataset reconstruction, as evidenced by its strong generalization capabilities across different data types. However, additional applications of the GSVD method on aerobiological data are needed to evaluate its effectiveness across various pollen types and environmental conditions. Indeed, the GSVD performance resulted similar to that of the statistical approach, with both methods exhibiting similarly unsatisfactory imputation accuracy in some settings. Moreover, the comparison of these two methods in our study revealed insights into the various factors influencing imputation performance. It suggested that the specific characteristics and requirements of the dataset may play a significant role in determining the most suitable interpolation approach.

The complexity of plant phenology, pollen diffusion, and advection mechanisms compounds the challenge of imputing missing data in aerobiological datasets. Beyond their non-normal statistical distribution, each pollen type is influenced by local environmental and climatic conditions, resulting in differences in quantity, seasonality, and daily concentration patterns (Picornell et al., 2021). Meteorological factors, particularly temperature and precipitation, are widely acknowledged to have the greatest influence on pollen variability, affecting both phenological phases and pollen behaviour in the atmosphere (Blanco-Alegre et al., 2021; Schramm et al., 2021). Hence, the same pollen type may exhibit different distribution curves depending on the location characteristics (Picornell et al., 2021). Such variability has been related to decreased accuracy in imputation, as wider concentration ranges between consecutive days heighten the likelihood of errors during the imputation process (Picornell et al., 2021). This association has been observed in other environmental data as well (Yozgatligil et al., 2013). Our findings align with Picornell et al. (2021), indicating that higher variability in concentration (VIn) resulted in less accurate imputation results, both in terms of values and range of variability of the imputation error. Notably, measurements from the Vicenza station showed greater variability than those from the Bolzano station, likely attributable to the effect of continental climate characteristics of the lowlands on pollen, subjected to significant thermal fluctuations compared to alpine regions. Additionally, *Alnus* pollen generally displayed higher VIn values compared to Poaceae pollen, likely due to significant variability over a shorter season duration.

Besides the pollen type and location of the monitoring station, the pattern of missing data had the most substantial impact on imputation accuracy in our study. We simulated missing data by randomly introducing fixed-length gaps of consecutive days at various percentages in aerobiological datasets. This strategy reflects typical real-world conditions in aerobiological monitoring, where daily missing data do not occur at random along the time series but are rather clustered during periods of variable duration, related to equipment malfunctions or weather-related disruptions requiring maintenance interventions. The results showed a trend of increasing imputation error with higher percentages of NAs, regardless of the pollen/location. Our results align with the findings of Junger et al. (2015) concerning air pollution data, indicating that 5% of missing data yields satisfactory results, but accuracy decreases with more than 10% of missing data (Junger & Ponce De Leon, 2015). In contrast, one study found opposing trends with increasing percentages of missing data for different meteorological variables (Yozgatligil et al., 2013), while another study observed no specific trend between missing data percentage and imputation error in aerobiological databases (Navares & Aznarte, 2019).

Regarding the gap length, our findings differ from those of Picornell et al. (2021). We found that interpolation error decreases as gap lengths increase, depending on the pollen type. Specifically, the imputation error was minimum in datasets with gaps of 7 consecutive days for *Alnus*, and with gaps of 10 days for Poaceae, compared to gaps of 3 days. Despite the higher possibility of abrupt variations in longer gaps (Picornell et al., 2021), the observed decrease in error with longer gaps can be attributed to the smoothing effect of interpolation. This effect leads to a reduction in the likelihood of generating peaks through interpolation, thereby minimizing errors. Notably, this effect appears to be more pronounced for pollens with wider season duration and less variability, as seen for Poaceae. The abundance of pollen-producing taxa within this family leads to high atmospheric pollen levels persisting over extended periods, thereby reducing day-to-day variability and smoothing peaks in pollen concentrations.

In conclusion, real-world aerobiological datasets often experience missingness that is not entirely random, primarily due to interruptions in challenging manual measurements. While missing data in out-of-season periods typically does not introduce significant bias—since the pollen season is the primary focus for analysis—other non-random missingness, such as equipment failures during extreme heat or disruptions for extraordinary events, can bias imputation results by affecting specific phases of the pollen season. Thus, the random missingness simulated in this study simplifies real-world scenarios, and further research could explore how non-random missing patterns influence imputation performance.

Nevertheless, imputation is essential for handling incomplete datasets and improving aerobiological analyses (Gehrig & Clot, 2021; Junger & Ponce De Leon, 2015; Navares & Aznarte, 2019; Picornell et al., 2021). In fact, even small gaps can introduce distortions in estimates in environmental epidemiology or climatological studies (Makra et al., 2023). Omitting to handle missing data can result in significant errors in analysing pollen time series, which in turn can affect the definition of pollen seasonality (Picornell et al., 2021; Smith et al., 2014; Valipour Shokouhi et al., 2024). We introduced and tested a novel method for missing data imputation in aerobiological research, demonstrating comparable performance to the moving mean method in data reconstruction. Both methods yielded favourable results, with the moving mean method being the simpler option. However, the imputation error remained unacceptable for certain pollen types and missing data scenarios. To draw a definitive conclusion, additional research is required to investigate the application of the GSVD method across diverse pollen types and environmental conditions. Furthermore, incorporating meteorological data into pollen datasets should be considered to improve imputation accuracy.

6. Assessment of temporal trends of pollen exposure indicators in the Veneto Region (Paper 2)

6.1. Knowledge gaps and research aims

While research on pollen behaviour has grown in various regions, specific analyses for the Veneto Region remain limited. Moreover, the impact of climate change on plant phenology is expected to vary by climatic area, as pollen patterns may not be consistent across different biogeographic areas (Fernández-Llamazares et al., 2014). Although some studies have analysed temporal pollen trends considering different climatic areas or plant characteristics, these have mainly been conducted at the level of individual monitoring stations (Fernández-Llamazares et al., 2014; Galán et al., 2016; Glick et al., 2021).

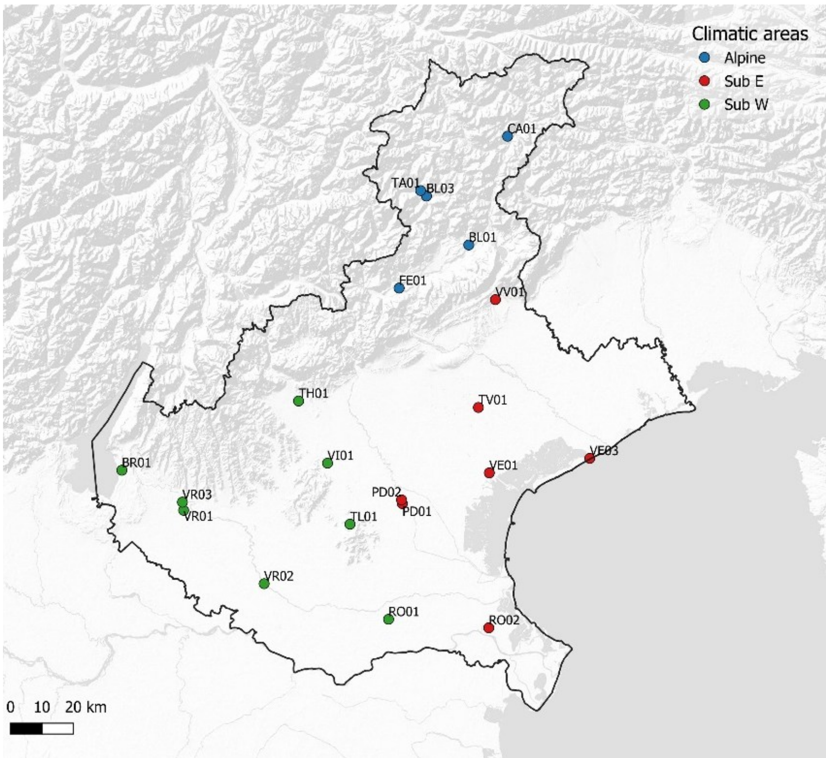
To address these knowledge gaps, this chapter describes recent temporal trends in seasonal pollen indexes for some allergenic species in the Veneto Region, specifically considering variations across climatic areas.

6.2. Materials and methods

6.2.1. Study area and climatic subregions

For the purpose of the analysis, we identified three subregions in the Veneto Region on the basis of climatic and topographic considerations (Figure 6.1): i) the alpine mountain area; ii) the western subcontinental and iii) the eastern subcontinental areas, which correspond to the lowlands (ARPAV, 2005). The subcontinental area was arbitrarily split into two subregions based on the median longitude of the monitoring stations (11.81731E WGS84). This division was conducted to account for the more continental character of the western subregion and the climate mitigation effect of the sea in the eastern subregion, which could impact pollen distribution and behaviours.

Figure 6.1. Spatial distribution of pollen monitoring stations by climatic area.



Sub E: subcontinental eastern area; Sub W: subcontinental western area

6.2.2. Pollen and meteorological data

The study analysis considered nine families/genera of arboreal pollen (Corylaceae, Cupressaceae/Taxaceae (hereinafter Cupressaceae), Oleaceae, *Alnus sp.*, *Betula sp.*) and herbaceous pollen (Poaceae, Urticaceae, *Ambrosia sp.*, *Artemisia sp.*), known for their high allergic potential in the European region (D'Amato et al., 2007; Marchetti et al., 2017). *Alnus, Betula, Ambrosia,* and *Artemisia* were investigated as genera because their families (Betulaceae and Compositae) are composed of the sum of these genera. In the other cases, pollen families were analysed instead of pollen genera because of better time coverage for the former. In fact, measurement quality for pollen genera improved over time in the Veneto Region due to enhanced training of specialized personnel.

Data on daily concentrations from 24 monitoring stations were provided by ARPAV for the period 1995–2022. Of these, 20 monitoring stations with temporal series covering 3 or more consecutive years were identified (Table 6.1).

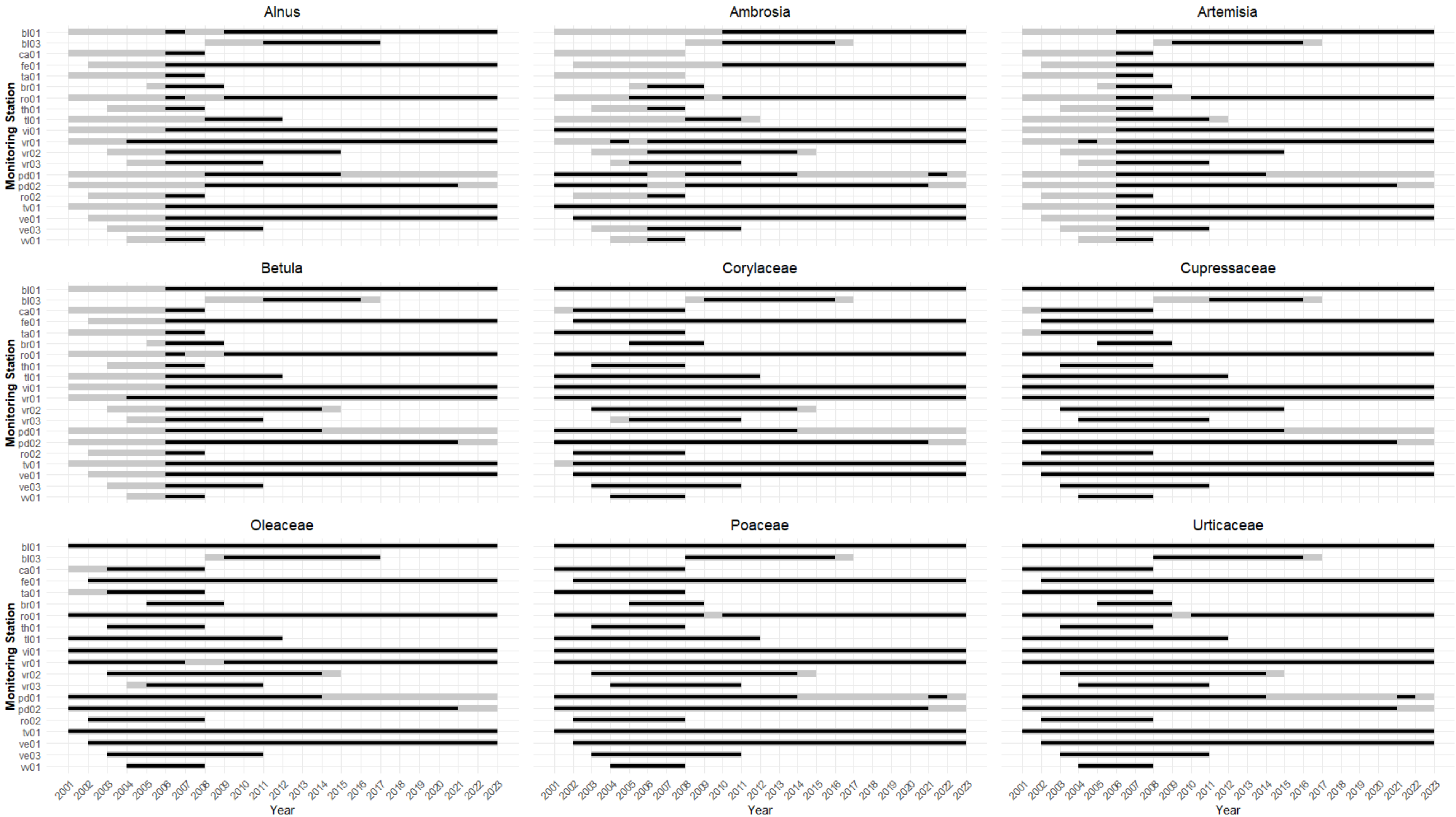
Table 6.1. Characteristics of the pollen monitoring stations considered in the study (Veneto Region).

Station name	*Code*	*Monitoring period*	*Lat (WGS84)*	*Long (WGS84)*
Alpine area:				
Belluno	BL01	2001 – present	46.284494 N	12.023669 E
*Vodo Cadore**	BL02	2008 – 2009	46.418985 N	12.245773 E
Agordo	BL03	2008 – 2016	46.283893 N	12.034501 E
Calalzo di Cadore	CA01	2001 – 2007	46.446177 N	12.380606 E
Feltre	FE01	2002 – present	46.017379 N	11.900829 E
Taibon Agordino	TA01	2001 – 2007	46.300484 N	12.010953 E
Subcontinental western area:				
Bardolino Calmasino	BR01	2005 – 2008	45.522061 N	10.748069 E
*Rovigo***	RO01	2000 – present	45.073155 N	11.817308 E
Thiene	TH01	2003 – 2007	45.707797 N	11.478606 E
*Teolo***	TL01	2000 – 2011	45.348922 N	11.672460 E
*Vicenza***	VI01	2000 – present	45.526849 N	11.588787 E
*Marano Vicentino**	VI02	2008 – 2009	45.692906 N	11.433729 E
*Verona***	VR01	2000 – present	45.403068 N	10.993938 E
Legnago	VR02	2003 – 2014	45.185565 N	11.315855 E
Verona Centro	VR03	2004 – 2010	45.426196 N	10.992196 E
Subcontinental eastern area:				
*Padova***	PD01	1995 – 2022	45.402873 N	11.888499 E
*Padova***	PD02	1995 – present	45.404538 N	11.890034 E
Portoviro	RO02	2002 – 2007	45.036628 N	12.220294 E
Treviso	TV01	2001 – present	4.5670800 N	12.213598 E
*Conegliano**	TV02	2008 – 2009	45.887824 N	12.300265 E
Venezia Mestre	VE01	2002 – present	45.478277 N	12.252883 E
*Venezia Laguna**	VE02	2002 – 2003	45.445031 N	12.271768 E
Jesolo	VE03	2003 – 2010	45.532837 N	12.643471 E
Vittorio Veneto	VV01	2004 - 2007	45.978601 N	12.301797 E

* monitoring stations that were excluded from the analysis due to temporal series covering less than 3 consecutive years. ** the years before 2001 were excluded from the analysis because they were not available for the other monitoring stations.

The pollen dataset was checked using the QC function with the following settings: the maximum percentage of interpolated days within the pollen season was set to the default value of 20%; the maximum number of consecutive days with missing data to interpolate was set to the default value of 30. The years for which the QC function failed to identify the pollen season (NAs >20%) were excluded from the analysis. After the quality check process, the following periods were included in the analysis because they represented most of the stations: 2001-2022 for families (Corylaceae, Cupressaceae, Poaceae, Oleaceae, and Urticaceae), and 2006-2022 for genera (*Alnus*, *Betula*, *Ambrosia*, and *Artemisia*). The distribution of the years retained after quality check for each pollen and station is shown in Figure 6.2.

Figure 6.2. Monitoring period (grey bar) and period retained after quality check (black bar) for each pollen and station.



Daily meteorological data covering the period 2001-2022 were provided by ARPAV. The monitoring stations located within a 10 km buffer of one (or more) pollen monitoring stations that best represented local weather conditions were identified. The distribution of the meteorological stations across climatic areas is as follows: 3 in the alpine region, 5 in the subcontinental eastern region, and 6 in the subcontinental western region. Annual mean temperature and cumulative precipitation were selected as the primary parameters for the analysis. Consistently with standard practices in meteorological data analysis, years with 25% or more missing data were excluded from the analysis.

6.2.3. Statistical analysis

The following seasonal pollen indexes were considered in the analysis: SPIn, start day, and duration of the pollen season. Descriptive statistics were reported as the median, first (Q1) and third (Q3) quartiles. Temporal trends in seasonal pollen indexes were depicted using boxplots showing the distributions at the monitoring stations and cubic smoothing splines ("geom_spline" function in R with 4 degrees of freedom).

The non-parametric Theil-Sen slope (TSS) method was used to assess the slope of the temporal trend in seasonal pollen indexes, specifically quantifying the magnitude of change in the seasonal index (dependent variable) over years (independent variable). The Theil-Sen slope is an estimator of the regression coefficient β based on Kendall's rank correlation tau (Sen, 1968; Theil, 1950). For each pollen index, the median slope was calculated by determining the median value from a collection of slopes computed between all possible pairs of data points corresponding to annual values of the index. Each pollen monitoring station was treated as a distinct stratum to maintain separate trends, ensuring slopes were only calculated within individual stations and not between different stations. This approach preserved the integrity of individual trends observed at each station, accurately representing specific variations and patterns in the overall analysis. The results were reported as median TSS per 10 years with 95% CI.

As some researchers argue that seasonal indexes calculated using the 95-percentage method may be influenced by annual pollen levels (Gehrig & Clot, 2021; Glick et al., 2021; Ziska et al., 2019), two additional season-independent indexes were considered for a sensitivity analysis: the number of days with low-to-high pollen concentrations and the number of days with medium-to-high pollen concentrations. These indicators reflect the count of days exceeding the thresholds for "low" and "medium" pollen concentrations set by the SIAMA (Italian Society of Aerobiology Medicine and Environment). The low and medium thresholds are as follows, respectively:

- 0.5 p/m³ and 16 p/m³ for *Alnus*, *Betula*, and Corylaceae.
- 0.1 p/m³ and 5 p/m³ for *Ambrosia* and *Artemisia*.
- 4 p/m³ and 30 p/m³ for Cupressaceae.
- 0.5 p/m³ and 5 p/m³ for Oleaceae.
- 0.5 p/m³ and 10 p/m³ for Poaceae.
- 2 p/m³ and 20 p/m³ for Urticaceae.

Moreover, a sensitivity analysis was performed on monitoring stations with at least 5 years of data to assess the robustness of the method for estimating temporal trends.

To investigate heterogeneity across climatic areas, the temporal trend analysis for pollen was repeated for each of the three climatic areas (Figure 6.1). The analysis of temporal trends was also conducted for annual temperature and precipitation by climatic areas.

The statistical analyses were carried out using the statistical software STATA and RStudio.

6.2.4. Literature review

A non-systematic review of European studies on temporal trends in seasonal pollen indexes was conducted for discussion purposes. The findings from these studies were summarized, emphasising the trend direction (positive or negative).

6.3. Results

6.3.1. Regional distribution of pollen indexes

Table 6.2 reports descriptive statistics detailing the extension of the pollen seasons in the Veneto Region. The arboreal taxa (*Alnus, Betula*, Corylaceae, Cupressaceae, Oleaceae) typically bloom early (February to June), while the herbaceous taxa (*Ambrosia, Artemisia*, Poaceae, Urticaceae) have a later season (April to October).

Table 6.2. Descriptive statistics of start/end date and duration of pollen seasons over the period 2006-2022 (for genera) and 2001-2022 (for families).

Pollen	***Start date*** *Median (Q1-Q3)*	***End date*** *Median (Q1-Q3)*	***Duration, days*** *Median (Q1-Q3)*
2006-2022			
Alnus	10 Feb (04 – 15 Feb)	31 Mar (18 Mar – 02 Jun)	50 (38 – 111)
Ambrosia	07 Aug (16 Jul – 13 Aug)	27 Sep (20 Sep – 03 Oct)	54 (43 – 80)
Artemisia	09 Aug (03 – 13 Aug)	11 Oct (27 Sep – 19 Oct)	65 (50 – 74)
Betula	21 Mar (03 – 31 Mar)	07 May (30 Apr – 14 May)	49 (38 – 64)
2001-2022			
Corylaceae	10 Feb (01 – 20 Feb)	08 May (01 – 14 May)	90 (75 – 99)
Cupressaceae	15 Feb (04 – 27 Feb)	08 May (22 Apr – 07 Jun)	81 (67 – 110)
Poaceae	16 Apr (09 – 24 Apr)	09 Sep (17 Aug – 18 Sep)	143 (118 – 157)
Oleaceae	21 Mar (02 Mar – 03 Apr)	13 Jun (01 – 21 Jun)	83 (62 – 103)
Urticaceae	27 Apr (19 Apr – 03 May)	26 Sep (19 Sep – 03 Oct)	154 (137 – 166)

Q1, 1st quartile; Q3, 3rd quartile

Alnus, Ambrosia, and *Betula* showed the shortest pollen season, with a median of approximately 50 days. Poaceae and Urticaceae had the longest seasons (medians 143 and 154 days, respectively), as well as the highest SPIn (2529 and 4099 p/m^3, respectively) (Table 6.3). The lowest SPIn was observed for *Ambrosia* (144 p/m^3) and *Artemisia* (111 p/m^3).

Table 6.3. Descriptive statistics of the SPIn (Seasonal Pollen Integral, p/m^3) over the period 2006-2022 (for genera) and 2001-2022 (for families).

Pollen	***Veneto Region*** *Median (Q1-Q3)*	***Alpine*** *Median (Q1-Q3)*	***SubE*** *Median (Q1-Q3)*	***SubW*** *Median (Q1-Q3)*
2006-2022				
Alnus	581 (256 – 1037)	203 (138 – 269)	739 (440 – 1170)	765 (488 – 1293)
Ambrosia	144 (71 – 244)	31 (13 – 71)	178 (108 – 289)	185 (101 – 269)
Artemisia	111 (54 – 198)	36 (24 – 66)	96 (66 – 148)	234 (131 – 618)
Betula	547 (283 – 946)	351 (235 – 628)	411 (272 – 768)	719 (413 – 1407)
2001-2022				
Corylaceae	2101 (1056 – 4492)	4429 (2922 – 7204)	1626 (976 – 3008)	1866 (912 – 4100)
Cupressaceae	1968 (1009 – 4129)	835 (474 – 1222)	2384 (1499 – 3834)	3014 (1409 – 6155)
Poaceae	2529 (1513 – 4046)	1373 (956 – 1962)	2314 (1498 – 3351)	3944 (2762 – 5644)
Oleaceae	1065 (539 – 1966)	1031 (503 – 2052)	1130 (433 – 1929)	1003 (717 – 1961)
Urticaceae	4099 (1908 – 6548)	1294 (719 – 1917)	4298 (2635 – 5904)	6232 (4131 – 11032)

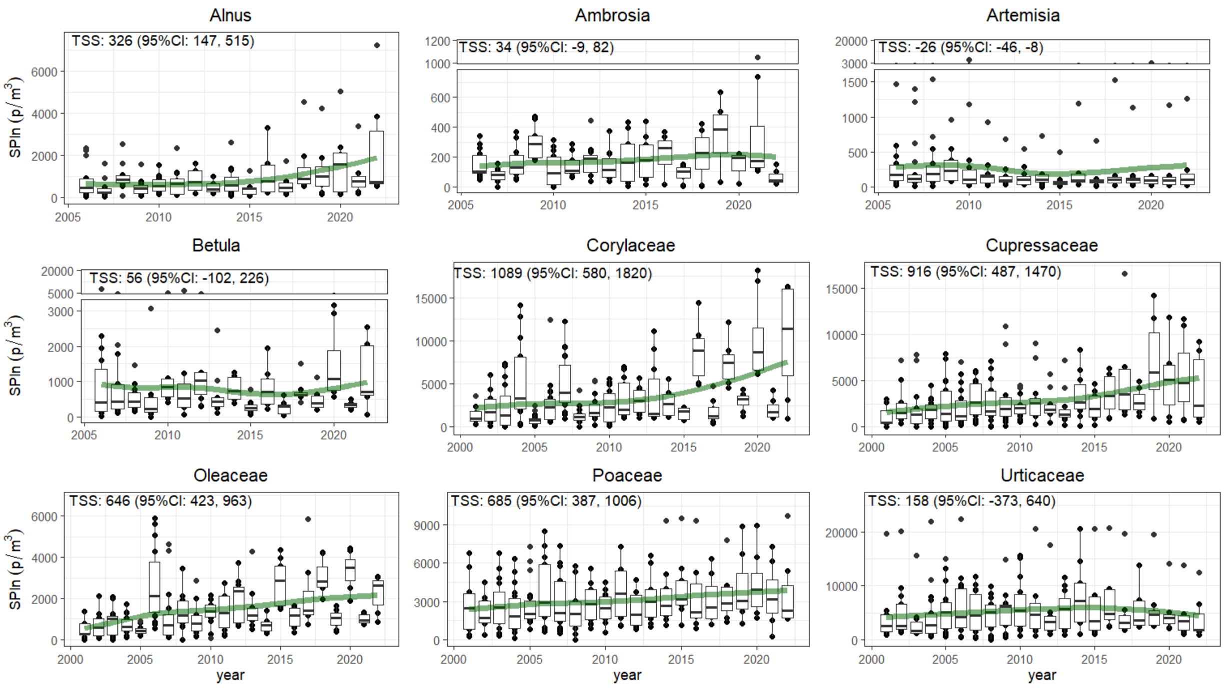
SubE: Subcontinental eastern; SubW: Subcontinental western; Q1, 1st quartile; Q3, 3rd quartile.

Except for Oleaceae pollen, which showed an equal distribution in alpine and subcontinental climates (SPIn ~1000-1100 p/m^3), pollen load varied widely across the climatic areas (Table 6.3). The highest median SPIn for Corylaceae was observed in the alpine area (4429 p/m^3). Higher median SPIn values were observed in the subcontinental climate for all remaining taxa, with similar SPIn values for *Alnus* (~750 p/m^3) and *Ambrosia* (~180 p/m^3). The subcontinental western area recorded the highest SPIn values for *Artemisia* (234 p/m^3), *Betula* (719 p/m^3), Cupressaceae (3014 p/m^3), Poaceae (3944 p/m^3), and Urticaceae (6232 p/m^3).

6.3.2. Temporal trends in pollen indexes

Figures 6.3-6.5 show the temporal trends of seasonal pollen indexes in the Veneto Region. A clear increasing trend of SPIn emerged for several pollen types (Figure 6.3): between 2001 and 2022, for Corylaceae (1089 p/m^3 per 10yrs, 95% CI: 580, 1820), Cupressaceae (916 p/m^3 per 10yrs, 95% CI: 487, 1470), Oleaceae (646 p/m^3 per 10yrs, 95% CI: 423, 963), and Poaceae (685 p/m^3 per 10yrs, 95% CI: 387, 1006); and between 2006 and 2022, for *Alnus* (326 p/m^3 per 10yrs, 95% CI: 147, 515).

Figure 6.3. Annual distributions of the SPIn (Seasonal Pollen Integral, p/m^3) at the monitoring stations in the Veneto Region, with temporal trends marked using cubic smoothing splines (green).

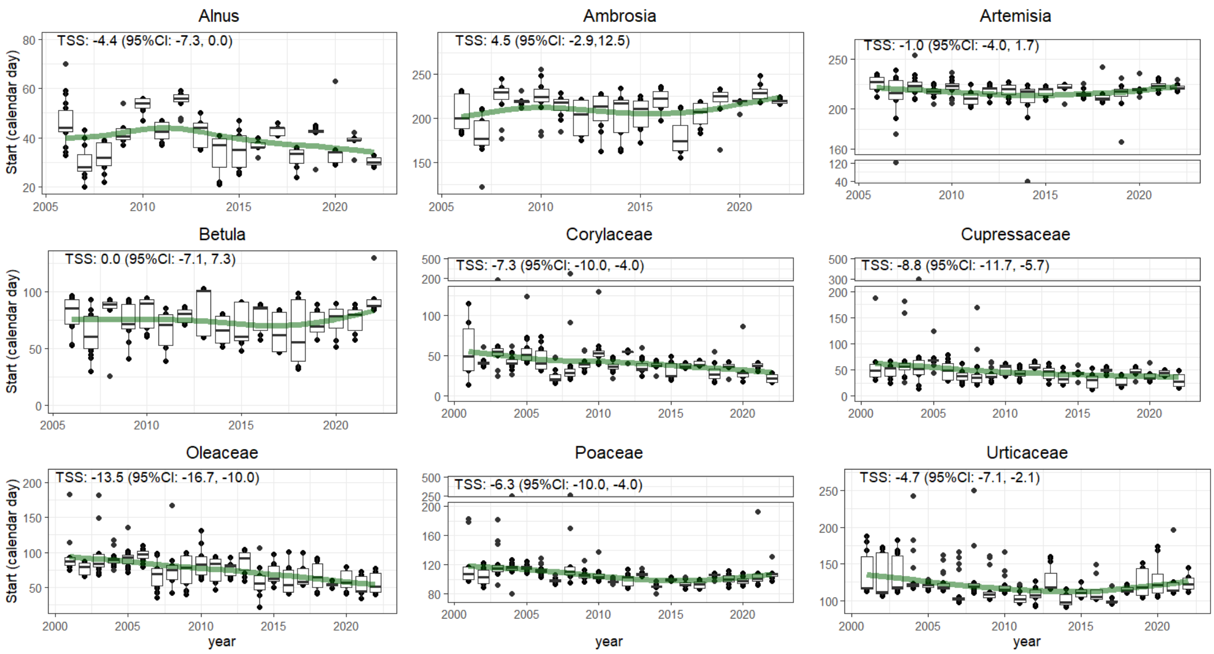


TSS, Theil-Sen median slope in p/m^3 per 10 years

The SPIn for *Alnus*, Corylaceae, and Cupressaceae showed a sharp increase both in the median value and in variability after 2015, while Oleaceae and Poaceae showed a more gradual increase in SPIn over the study period. Conversely, the SPIn of *Artemisia* decreased over time of 26 p/m^3 per 10yrs (95% CI: -46, -8). The SPIn for *Ambrosia*, *Betula*, and Urticaceae did not change over the studied periods.

The start of the pollen season shifted earlier over time for several taxa (Figure 6.4).

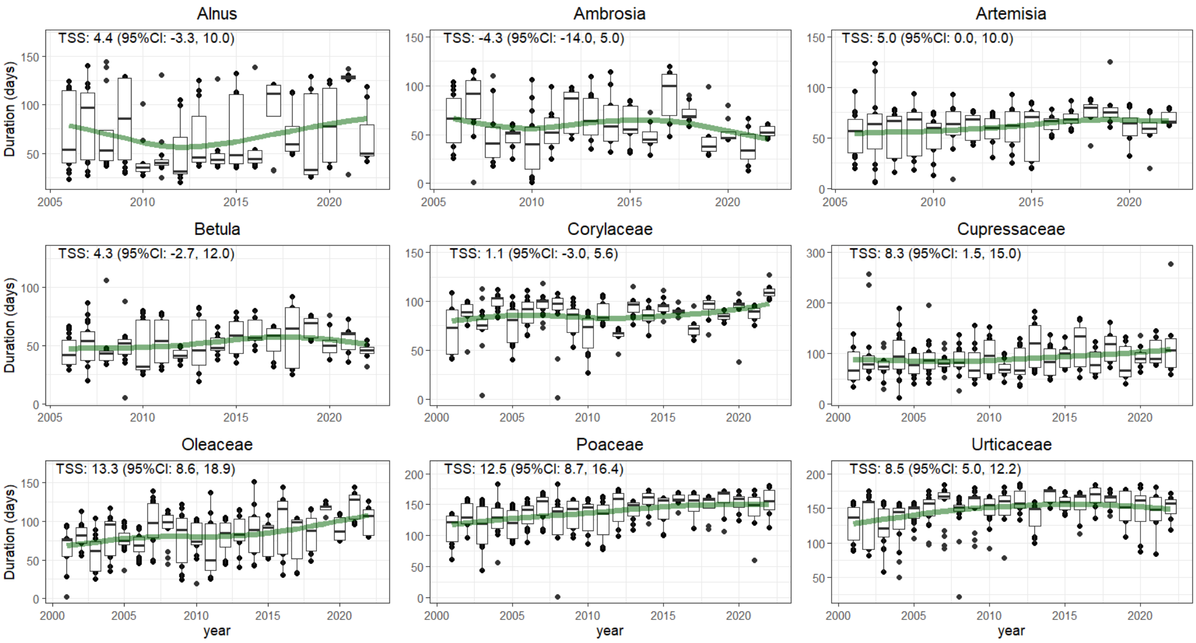
Figure 6.4. Annual distributions of the start of pollen seasons (calendar day) at the monitoring stations in the Veneto Region, with temporal trends marked using cubic smoothing splines (green).



TSS: Theil-Sen median slope in days per 10 years

Earlier pollen seasons were observed for *Alnus* (-4.4 days/10yrs, 95% CI: -7.3, 0.0), Corylaceae (-7.3 days/10yrs, 95% CI: -10.0, -4.0), Cupressaceae (-8.8 days/10yrs, 95% CI: -11.7, -5.7), Oleaceae (-13.5 days/10yrs, 95% CI: -16.7, -10.0), Poaceae (-6.3 days/10yrs, 95% CI: -10.0, -4.0), and Urticaceae (-4.7 days/10yrs, 95% CI: -7.1, -2.1). For all these taxa, with the exception of *Alnus* and Corylaceae, the anticipation resulted in an extension in the duration of the pollen season, ranging between 8 days per 10 yrs (Cupressaceae and Urticaceae) to 13 days per 10 yrs (Oleaceae and Poaceae) (Figure 6.5). Finally, *Artemisia* showed an extended duration of the pollen season (5.0 days/10yrs, 95% CI: 0.0, 10.0), although the start day of the season did not show any trend.

Figure 6.5. Annual distributions of the duration of the pollen seasons (days) at the monitoring stations in the Veneto Region, with temporal trends marked using cubic smoothing splines (green).



TSS: Theil-Sen median slope in days per 10 years

The sensitivity analysis retaining only the stations with time series of 5 years or more showed results that were consistent with the main analysis (Table 6.4).

Table 6.4. Theil-Sen median slopes (TSS), with 95% confidence intervals, estimating the temporal trend for the Seasonal Pollen Integral (SPIn), start and duration of the pollen season in the Veneto Region. Sensitivity analysis restricted to the monitoring stations with time series covering 5 years or more.

	SPIn TSS (95%CI) p/m^3 per 10 years	***Start*** TSS (95%CI) days per 10 years	***Duration*** TSS (95%CI) days per 10 years
2006-2022			
Alnus	326 (147; 515)	-4.4 (-7.1; 0.0)	4.5 (-3.3; 10.0)
Ambrosia	33 (-10; 81)	5.0 (-2.7; 12.5)	-4.3 (-14.0; 5.0)
Artemisia	-26 (-46; -8)	-1.0 (-4.0; 1.8)	5.0 (0.0; 10.0)
Betula	59 (-93, 227)	0.0 (-6.9; 7.5)	4.2 (-2.9; 12.0)
2001-2022			
Corylaceae	1076 (573; 1816)	-7.1 (-10.0; -3.7)	0.8 (-3.1; 5.5)
Cupressaceae	905 (464; 1447)	-8.7 (-11.5; -5.7)	8.2 (1.4; 15.0)
Oleaceae	646 (423; 963)	-13.3 (-16.7; -10.0)	13.3 (8.5; 18.8)
Poaceae	676 (385; 992)	-6.2 (-10.0; -4.0)	12.5 (8.6; 16.2)
Urticaceae	152 (-376; 630)	-4.5 (-7.1; -2.0)	8.2 (5.0; 12.2)

The analysis on season-independent indexes also confirmed the trends observed in the main analysis (Table 6.5).

Table 6.5. Theil-Sen median slopes (TSS), with 95% confidence intervals, estimating the temporal trend for the number of days with low-to-high and medium-to-high pollen concentrations in the Veneto Region. Sensitivity analysis of season-independent indexes.

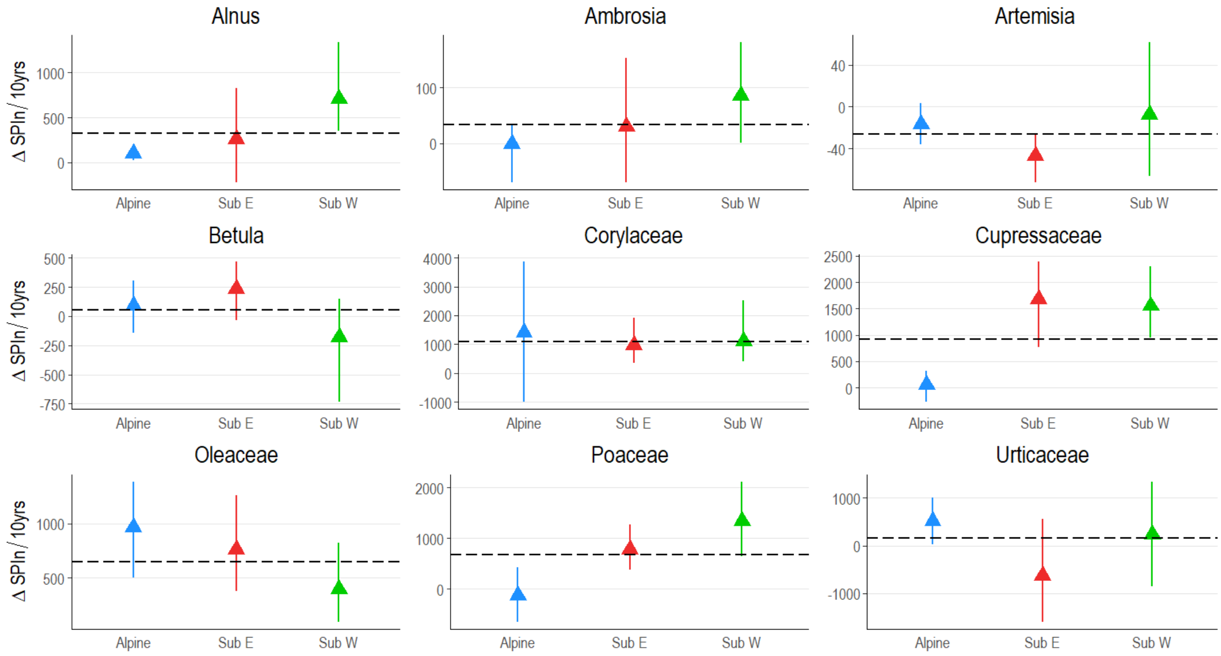
	low threshold*	***n days with low-to-high pollen concentrations***	***medium threshold****	***n days with medium-to-high pollen concentrations***
	p/m^3	TSS (95%CI) per 10 years	p/m^3	TSS (95%CI) per 10 years
2006-2022				
Alnus	>0.5	9.0 (2.0;14.4)	>16	4.8 (2.0;6.7)
Ambrosia	>0.1	1.7 (-6.7;12.9)	>5	0.0 (-0;2.3)
Artemisia	>0.1	3.0 (-2.7;7.8)	>5	-1.4 (-3.3;0.0)
Betula	>0.5	5.0 (-2.5,12.5)	>16	0.0 (-2.3,4.0)
2001-2022				
Corylaceae	>0.5	11.1 (5.5;18.3)	>16	12.9 (7.3;20.0)
Cupressaceae	>4	17.2 (11.8;22.5)	>30	6.7 (4.2;10.0)
Oleaceae	>0.5	26.0 (20.0;31.3)	>5	20.0 (13.3;25.8)
Poaceae	>0.5	21.2 (16.2;27.3)	>10	17.5 (12.5;23.3)
Urticaceae	>2	15.7 (8.8;23.3)	>20	2.2 (-5.6;10.0)

* threshold values by the SIAMA.

6.3.3. Geographical heterogeneity of temporal trends

We observed a marked heterogeneity across the climatic areas of the temporal trends for the SPIn (Figure 6.6).

Figure 6.6. Theil-Sen median slopes, with 95% confidence intervals, estimating the temporal trend for the SPIn (2001-2022 for families, 2006-2022 for genera) by climatic area.

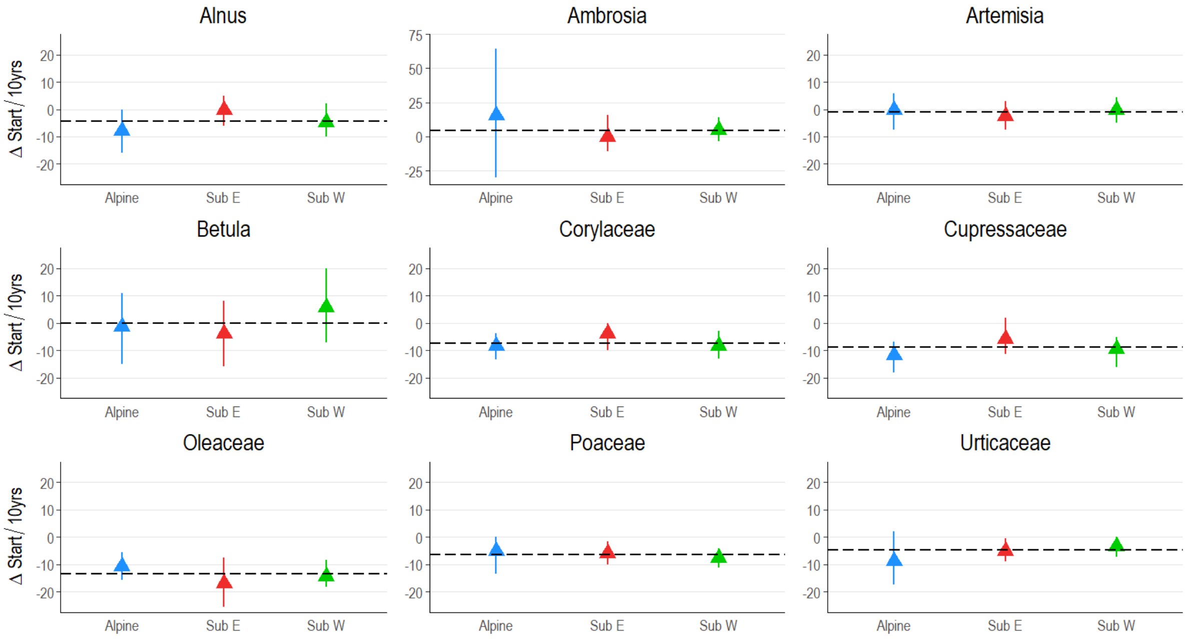


Sub E: Subcontinental eastern area; Sub W: Subcontinental western area; the black line represents the overall trend for the Veneto Region as a whole. Positive and negative median slopes represent increased and decreased SPIn (p/m^3) over time, respectively.

In the alpine area (blue symbols), the increase in SPIn was lower compared to the Veneto Region (black dashed line) for *Alnus* (101 p/m^3 per 10yrs, 95% CI: 29, 206) and Cupressaceae (66 p/m^3 per 10yrs, 95% CI: -276, 311). Unlike the Veneto Region, *Ambrosia* (-1 p/m^3 per 10yrs, 95% CI: -70, 33) and Poaceae (-120 p/m^3 per 10yrs, 95% CI: -646, 422) showed no increase over time. Conversely, Oleaceae showed a higher increase in the SPIn over time (966 p/m^3 per 10yrs, 95% CI: 501, 1385) compared to the Veneto Region, while Urticaceae (525 p/m^3 per 10yrs, 95% CI: 24, 1001) showed an increasing trend in the SPIn not observed for the region as a whole. In the subcontinental eastern area (red symbols), Cupressaceae showed a higher increase in the SPIn (1679 p/m^3 per 10yrs, 95% CI: 775, 2388), while *Artemisia* exhibited a higher decrease (-47 p/m^3 per 10yrs, 95% CI: -73, -27) compared to the Veneto Region. Additionally, Urticaceae tended to decrease (-625 p/m^3 per 10yrs, 95% CI: -1598, 561), unlike the entire region. In the subcontinental western area (green symbols), *Alnus* (710 p/m^3 per 10yrs, 95% CI: 349, 1340), *Ambrosia* (86 p/m^3 per 10yrs, 95% CI: 1, 182), Cupressaceae (1557 p/m^3 per 10yrs, 95% CI: 949, 2304), and Poaceae (1349 p/m^3 per 10yrs, 95% CI: 653, 2123) showed higher increases in the SPIn compared to the Veneto Region. Oleaceae also saw an increase in the SPIn, though the rate of increase was less pronounced over time (399 p/m^3 per 10yrs, 95% CI: 96, 820). Conversely, *Betula* tended to decrease (-176 p/m^3 per 10yrs, 95% CI: -736, 148), contrasting with the stable SPIn observed for the region as a whole. No heterogeneity across climatic areas was observed for the SPIn of Corylaceae.

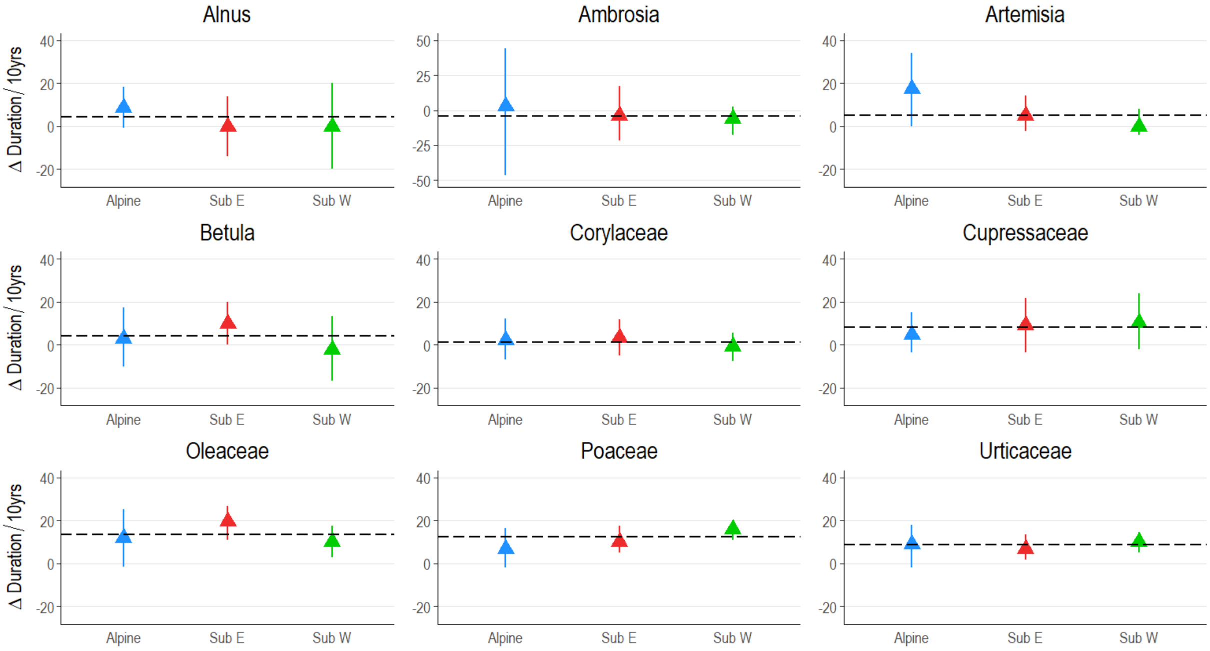
Temporal trends in the start (Figure 6.7) or duration (Figure 6.8) of the pollen season did not show heterogeneity across the climatic areas, except for a greater increase in duration of the pollen season for *Artemisia* in the alpine area (17.5 days/10 yrs, 95% CI: 0.0, 34.0) compared to the Veneto Region.

Figure 6.7. Theil-Sen median slopes, with 95% confidence intervals, estimating the temporal trend for the start of the pollen season (2001-2022 for families, 2006-2022 for genera) by climatic area.



Sub E: Subcontinental eastern area; Sub W: Subcontinental western area; the black line represents the overall trend for the Veneto Region as a whole. Positive and negative median slopes represent a posticipation and anticipation of the start date (days) of the pollen season, respectively.

Figure 6.8. Theil-Sen median slopes, with 95% confidence intervals, estimating the temporal trend for the duration of the pollen season (2001-2022 for families, 2006-2022 for genera) by climatic area.

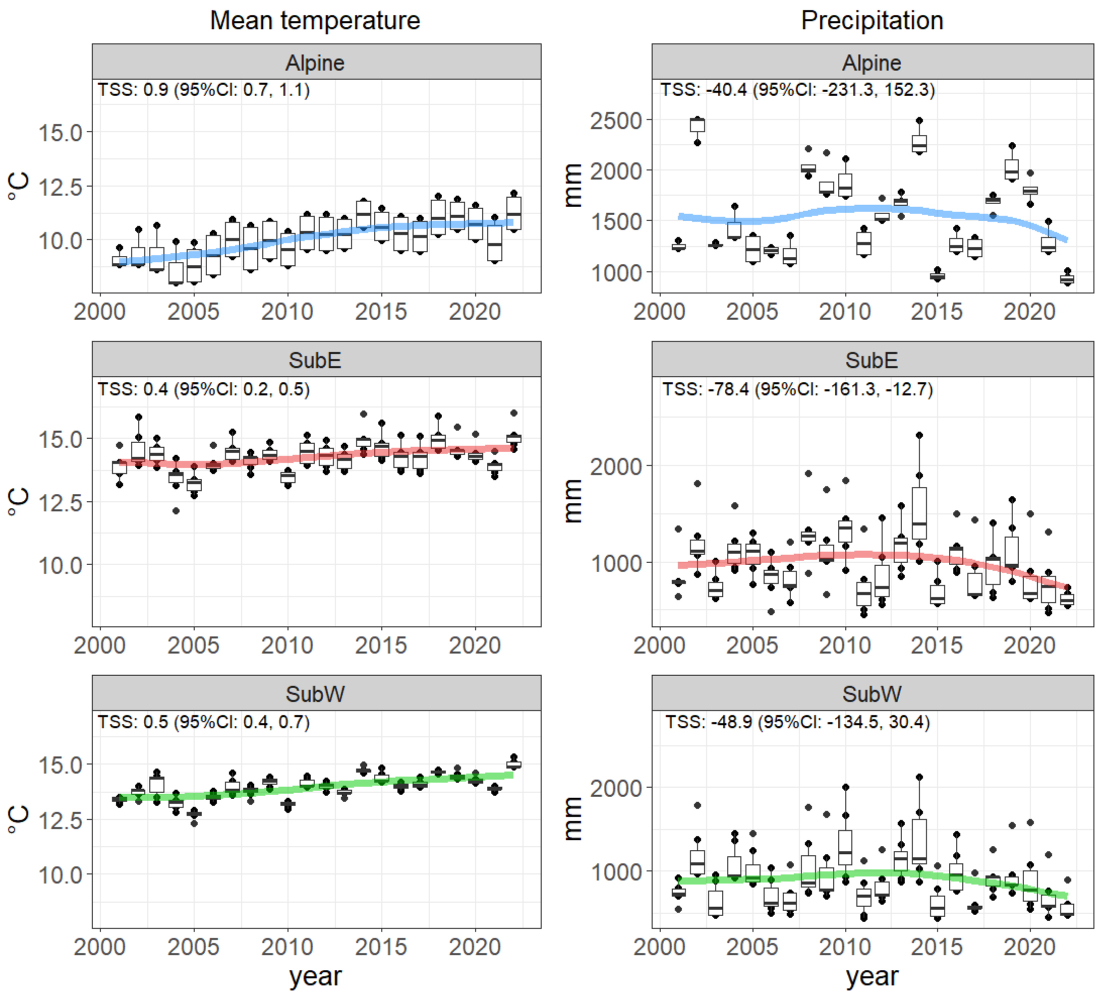


Sub E: Subcontinental eastern area; Sub W: Subcontinental western area; the black line represents the overall trend for the Veneto Region as a whole. Positive and negative median slopes represent an extension or reduction of the duration (days) of the pollen season, respectively.

6.3.4. Temporal trends in meteorological factors

Figure 6.9 depicts the temporal trends of meteorological factors in these climatic areas. Between 2001 and 2022, a clear increasing trend in annual mean temperature was observed across all climatic areas, with the steepest rate of increase estimated in the alpine area (0.9°C per 10 yrs, 95% CI: 0.7, 1.1). Conversely, cumulative precipitation showed wide year-to-year variability and a tendency for decline across all areas, which was particularly marked in the subcontinental eastern area (-78.4 mm per 10 yrs, 95% CI: -161.3, -12.7).

Figure 6.9. Annual distributions of the mean temperature (°C) and cumulative precipitation (millimeter, mm) at the monitoring stations in the Veneto Region by climatic area, with temporal trends marked using cubic smoothing splines (blue: alpine; red: subcontinental eastern area, SubE; green: subcontinental western area, SubW).



TSS: Theil-Sen median slope in °C (mean temperature) and mm (cumulative precipitation) per 10 years; SubE: Subcontinental eastern area; SubW: Subcontinental western area.

6.4. Discussion and conclusions

In the Veneto Region, there has been a notable increase in pollen load for several allergological taxa over the past two decades. Steeper increases were observed for some taxa after 2015, coinciding with a sudden surge in interannual variability. Additionally, changes were observed in the duration of pollen seasons, which commenced earlier and lasted longer for several taxa. An evident heterogeneity across the climatic areas was seen in both pollen load and estimated temporal trends, with the subcontinental western area exhibiting the highest load and more prominent increases over time.

We used the Theil-Sen estimator to identify long-term variations of pollen levels over time. This method is robust against common violations of linear regression assumptions, effectively handling non-linear relationships. In fact, the strength of the Theil-Sen estimator lies in its ability to provide accurate and reliable trend analysis, particularly in the presence of non-normal distributions and heteroskedasticity (Bruffaerts et al., 2018; Fernández-Llamazares et al., 2014; García-Mozo et al., 2014; Gehrig & Clot, 2021; Hoebeke et al., 2018; Sen, 1968; Theil, 1950). Moreover, having data from several monitoring stations over a relatively large geographical area enabled us to investigate the heterogeneity of seasonal pollen indexes across climatic areas. This approach differs from most published studies, which analysed pollen trends at the monitoring station level (Camacho et al., 2017; Cristofolini et al., 2020; Fernández-Llamazares et al., 2014; Galán et al., 2016; Glick et al., 2021).

To date, few studies on pollen temporal series have been conducted in Italy, especially in the Veneto Region. Our findings are consistent with most studies conducted across European regions, indicating increases in pollen load and shifts in the timing (anticipation) and duration (elongation) of the pollen seasons for several taxa. However, these trends across Europe resulted clearer for arboreal pollens compared to herbaceous ones (Tables A.1-A.3 in the Appendix). Our findings also revealed that arboreal pollen exhibited more pronounced trends of increasing SPIn and earlier season start (except for *Betula*), while herbaceous pollen showed clearer increases in the season duration (except for *Ambrosia*). These results indicate that changing weather patterns affect plant flowering differently: arboreal plants tend to bloom earlier due to warmer and shorter winters, while herbaceous plants exhibit less predictable behaviours since they are mainly influenced by water availability (Bruffaerts et al., 2018; Dąbrowska-Zapart & Niedźwiedź, 2022; D'Amato et al., 2020; Fernández-Llamazares et al., 2014; Galán et al., 2016; Makra et al., 2011). Although analysing the relationship between climate variables and pollen is beyond the scope of this study, we speculate that the observed rises in annual mean temperatures, and the tendential decrease and higher interannual variability of precipitation in the Veneto Region over the last two decades, may have affected the observed trends in pollen indexes.

Factors besides climate change may have contributed to the observed variations in pollen trends (Bogawski et al., 2014; Cristofolini et al., 2020; De Weger et al., 2021; Galán et al., 2016; Gehrig & Clot, 2021; Hoebeke et al., 2018; Makra et al., 2011; Marchesi, 2020; Ugolotti et al., 2015). The decreasing trends in herbaceous pollen levels (such as *Artemisia* and Poaceae) observed across Europe have been linked to increasing urbanization, which replaces natural habitats with built environments, thereby reducing areas available for wild plant growth and consequently impacting pollen production. Additionally, targeted interventions aimed at mitigating allergenic sources can play a role in pollen trends (Bogawski et al., 2014; De Weger et al., 2021; Gehrig & Clot, 2021; Hoebeke et al., 2018; Ziello et al., 2012). These factors could explain the decreasing trends of pollen load observed in some areas of our study for *Artemisia* and Urticaceae, but not the increasing trends for Poaceae and *Ambrosia*. We were not able to further elaborate on this due to a lack of detailed maps of changes in plant distributions and information on weed control measures implemented over time. The variability of Poaceae temporal trends could be linked to further factors such as regional environmental differences (e.g. land use, climate, elevation) and the diverse endogenous processes of plants' adaptation to climate change reflecting the wide variety of plants within the family (Galán et al., 2016; Smith et al., 2014). Additionally, it is important to note the potential influence of agricultural land use in the Veneto Region. Approximately 58% of the region's land is dedicated to agriculture (ARPAV, 2005), and the extensive cultivation of crops could represent a substantial source of Poaceae pollen, contributing to the observed increase in Poaceae pollen. However, previous research has shown that natural areas contribute more significantly to Poaceae pollen production than agricultural ones (Rojo et al., 2022; Tagliaferro et al., 2024). Concerning *Ambrosia*, the gradual spread of this plant from Milan (Bonini et al., 2018; D'Amato et al., 2007) likely contributed to the increasing pollen levels observed in the subcontinental western area of Veneto. This expansion suggests that *Ambrosia* is establishing itself in new areas, likely due to factors such as climate suitability and human-mediated dispersal. The similarity in pollen level trends observed in the western part of the Emilia-Romagna Region, which borders Veneto to the South, further supports the idea of *Ambrosia's* regional spread (Ugolotti et al., 2015). A further factor potentially impacting pollen trends is the use of ornamental plants (e.g., Betulaceae, Cupressaceae, Oleaceae) (Bruffaerts et al., 2018; Ziello et al., 2012). However, the impact of climate change appears to be more significant compared to afforestation, which may not occur rapidly enough to explain the observed rise in pollen load (Bruffaerts et al., 2018; Ziello et al., 2012). In the subcontinental western area of the Veneto Region, a marked decrease in *Betula* pollen load has been noted, contrasting with overall trends observed across Europe. This divergence prompts consideration of potential contributing factors. One plausible explanation could be improper pruning practices, where the way trees are pruned might inadvertently affect pollen production. Another significant consideration is the influence of climate change, as previously mentioned. Moreover, specific tree-cutting policies aimed at disease control, targeting pathogens carried by parasites or fungi, might also play a role in reducing pollen levels. However, no official documentation is present to support these hypotheses.

Additionally, methodological factors could contribute to varying results across European regions, with the pollen season calculation being particularly significant (Gehrig & Clot, 2021; Glick et al., 2021; Tasioulis et al., 2022). Some researchers argue that the EAACI method (Pfaar et al., 2017) more effectively captures variations in pollen seasons related to climate change (Gehrig & Clot, 2021; Glick et al., 2021). However, no "gold standard" method is currently defined, and individual sensitivity complicates the choice of pollen thresholds (Steckling-Muschack et al., 2021; Tasioulis et al., 2022). Furthermore, threshold-based methods can be problematic with low pollen concentrations and may fail in seasonality calculation (Gehrig & Clot, 2021; Glick et al., 2021; Tasioulis et al., 2022). We chose the 95-percentage method (Andersen, 1991; Tasioulis et al., 2022) for its wide use and its accuracy in pollen detection (Fuhrmann et al., 2016; Tasioulis et al., 2022; Ugolotti et al., 2015). Although it depends on the APIn, the sensitivity analysis on the trends in the number of days exceeding predefined pollen concentrations, which does not rely on the derivation of pollen seasons, confirmed the main analysis results. Another factor that may contribute to the challenge of detecting long-term variations in pollen indexes is the length of the time series available. There is consensus that time series of at least 30 years are ideal for detecting long-term changes attributable to climate, as in pollen trend analyses shorter time series may not capture the full extent of natural variability and long-term trends, leading to potential misinterpretations of the data (Adams-Groom et al., 2022; De Weger et al., 2021; Fernández-Llamazares et al., 2014; Galán et al., 2016; Hoebeke et al., 2018). A limitation of our study was the availability of shorter time series, ranging from 15 to 21 years, depending on the pollen taxa. While we could have chosen to base the analysis solely on the most recent years of each series, this would have led to time series too short to support robust trend analyses, ultimately compromising our scientific objective. Instead, we opted to remove only those years for which we had well-founded concerns about data quality. In the Veneto Region, the quality of pollen monitoring has improved over time, thanks to increased technical training sessions and enhanced collaboration among monitoring organisations within the Italian network. This effort has led to a more refined and focused approach to pollen analysis.

In summary, over the past two decades, the Veneto Region has experienced an overall increase in pollen load and an extension of pollen seasons, especially in the subcontinental areas. The important increase in Poaceae levels observed in Veneto, unlike the European trends, prompted a need for heightened control measures due to its strong allergenic nature. Conversely, the decrease in pollen levels from *Artemisia*, *Betula*, and *Urticaceae* in specific areas of the region suggests progress toward reducing allergen exposure, potentially bringing relief to allergy sufferers. However, the extended season of *Artemisia* pollen remains a concern. In light of ongoing and anticipated changes, targeted strategies to mitigate exposure are essential.

7. Implementation and validation of a novel pollen modelling system for the Veneto Region (Paper 3)

7.1. Knowledge gaps and research aims

Data on the distribution of pollen sources is essential for effective aerobiological modelling and forecasting using atmospheric dispersion models. This information acts as a critical input for simulating or predicting pollen emission, its transport, and deposition (Kurganskiy et al., 2020; Vélez-Pereira et al., 2022). However, pollen dispersion models typically rely on coarse-resolution datasets, limiting their accuracy and relevance for localized predictions. Despite the increased recognition of the importance of high-resolution data, many regions lack models that can effectively capture the complexity of pollen dispersion at a finer spatial scale.

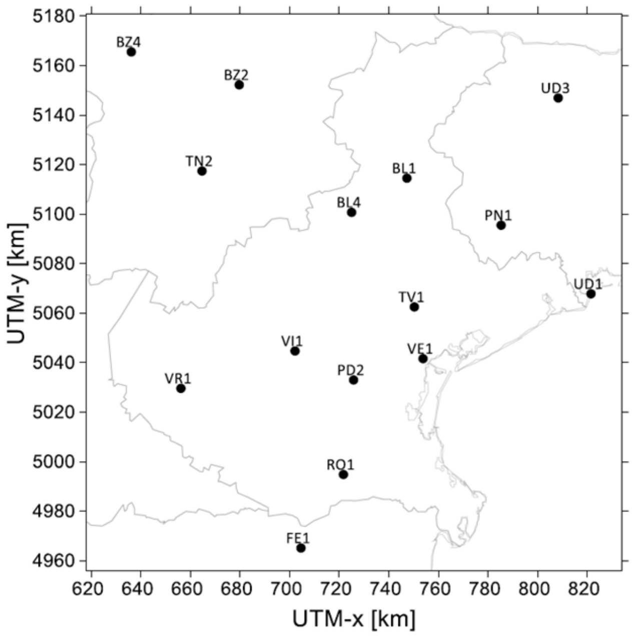
This chapter describes the implementation and validation of a modelling system providing high-resolution pollen predictions over the Veneto Region. To evaluate the ability of the proposed modelling system to provide accurate pollen forecasts, we implemented an application for the year 2019. This application incorporates two Vegetation Cover (VC) datasets: the coarse maps used by MINNI, joining CAMS air quality service (see subchapter 1.5 of the Introduction), at the European scale (available at 0.15° x 0.1° regular grid in latitude and longitude) and interpolated on the target grid, and high-resolution VC maps derived from various datasets.

7.2. Materials and methods

7.2.1. Pollen monitoring data and study domain

Figure 7.1 depicts the study domain covering the Veneto Region and parts of the surrounding regions, along with the available POLLnet monitoring stations. The study domain is 216 x 225 km^2 wide and has a horizontal spatial resolution of 3 km. Within this domain, there are 15 monitoring stations distributed in two main topographic territories: mountain (BL1, BL4, BZ2, BZ4, TN2, UD3) and lowland (FE1, PD2, PN1, RO1, TV1, UD1, VE1, VI1, VR1).

Figure 7.1. The study domain including the available POLLnet monitoring stations.



7.2.2. Pollen modelling system

The pollen modelling system was based on FARM (Bessagnet et al., 2016; Gariazzo et al., 2007; Silibello et al., 2008) (Figure 7.2), which computes hourly pollen concentration fields by simulating the processes of emission, advection, turbulent diffusion, and dry/wet removal (as pollens were considered passive scalars).

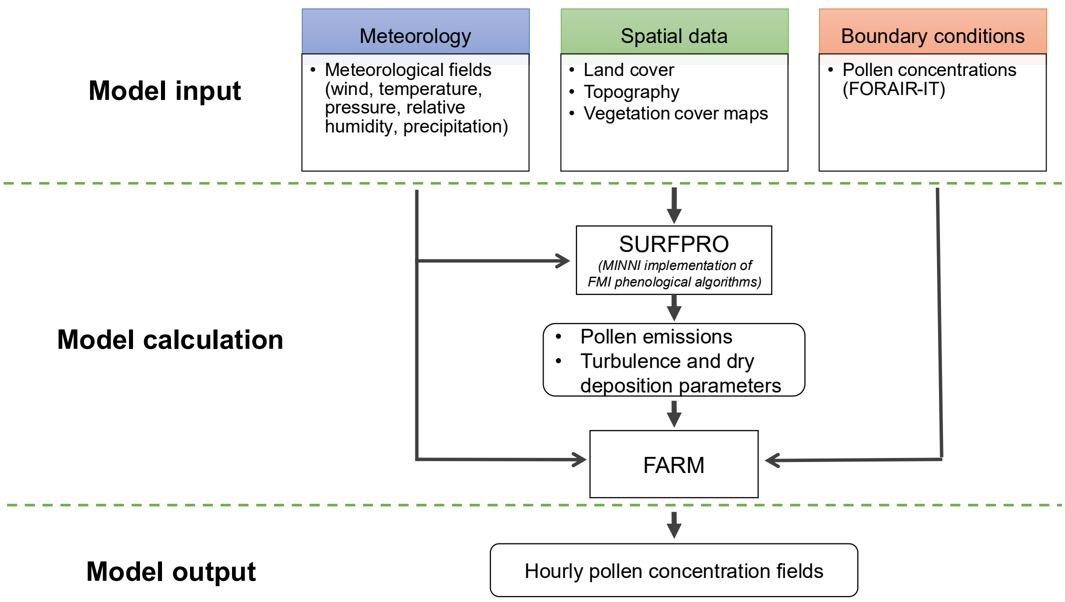
Inputs to the pollen modelling system were provided by three modules aimed at:

i. Producing meteorological fields and related turbulence parameters (meteorology module).
ii. Providing spatial data on pollen emission sources (spatial data module).
iii. Including pollen contributions from the surrounding areas (boundary conditions module).

The meteorological module was based on the Weather Forecast and Research (WRF) model (Skamarock et al., 2008), which is a prognostic non-hydrostatic model. This model is driven by ERA5 reanalyses (Hersbach et al., 2020), produced by ECMWF and distributed by the Copernicus Climate Change Service (https://cds.climate.copernicus.eu/). The configuration of WRF was based on three computational nested domains covering continental Europe, northern Italy, and the

Veneto Region, which were characterized by horizontal resolution meshes of 45, 9, and 3 km, respectively. Thirty-five vertical levels were used, with grid spacing increasing with height, from the surface up to the altitude corresponding to an atmospheric pressure of 50 hPa, with the lowest level located around 25 m over the ground. The calculations were performed in two-way-nesting mode. The WRF meteorological fields together with land cover, topography, and VC maps (spatial data module), were provided to the interface module SURFPro (SURface-atmosphere interFace PROcessor) (Finardi et al., 2008), which computed deposition velocities, horizontal and vertical diffusivities, and implemented the phenological algorithms adopted by the MINNI modelling system to estimate pollen emissions. The VC maps (details in the next paragraph) were computed as the fraction of vegetation cover for each grid cell of the modelling domain.

Figure 7.2. Scheme of the pollen modelling system.



FARM: Flexible Air quality Regional Model; FORAIR-IT: operational air quality forecasting model for Italy; MINNI: Italian National Integrated Model to support the international negotiation on atmospheric pollution; FMI: Finnish Meteorological Institute; SURFPRO: SURface-atmosphere interFace PROcessor.

Time-varying pollen boundary conditions to the Veneto Region simulations were provided by the operational forecast system FORAIR-IT (boundary conditions module), developed by ENEA in 2017, that routinely performs air quality predictions over the Italian peninsula, with a spatial horizontal resolution of 4 km (Adani et al., 2020, 2022). Thanks to the experience gained in CAMS activities, a preliminary version of FORAIR-IT including pollens was applied to the full 2019 year to provide 3-D concentration fields, from which we derived hourly boundary conditions.

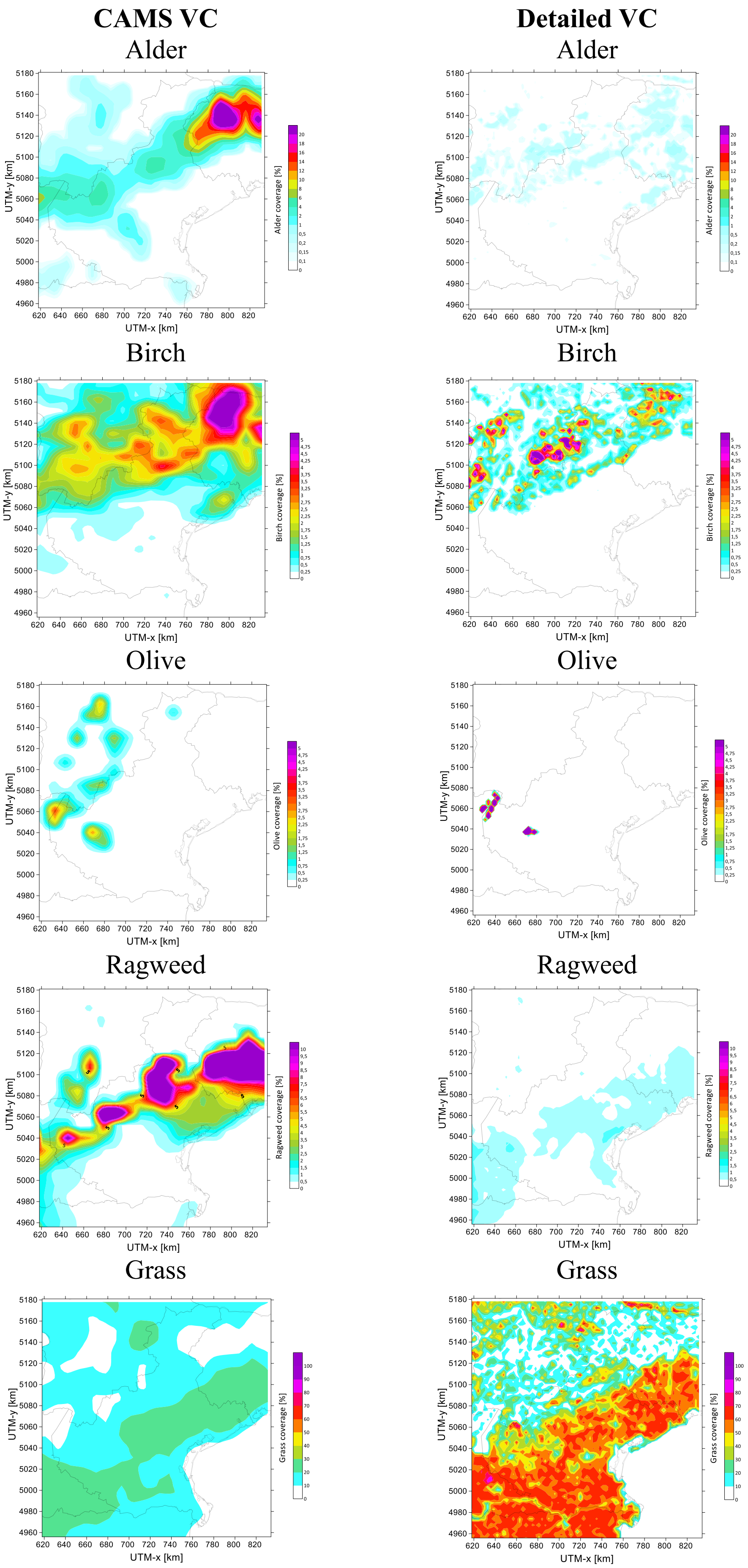
7.2.3. Vegetation cover maps

VC maps were the fundamental input data on pollen emissions. We have considered two vegetation fraction cover datasets:

1. The CAMS VC dataset, available at a horizontal resolution of 0.15° x 0.10° (ca. 10 km).
2. A high-resolution VC dataset (hereafter detailed VC) derived from different sources:
   a. For olive and grass, data from the pan-European CORINE Land Cover (CLC) inventory for the 2012 reference year was used. This inventory includes 44 thematic classes and was available at a 250 m spatial resolution (https://land.copernicus.eu/en/products/corine-land-cover).
   b. For alder and birch, the dataset on tree species from the European Forest Institute (EFI) was used. This dataset provides information on the distribution of 20 tree species over Europe at 1 km spatial resolution (https://efi.int/knowledge/maps/treespecies) (Brus et al., 2012).
   c. For ragweed, a pollen source inventory specific to Italy at 1 km spatial resolution was used (Bonini et al., 2018).

We spatially interpolated both datasets on the target Veneto domain (3 km spatial resolution) (Figure 7.3).

Figure 7.3. CAMS (left) and detailed (right) vegetation cover maps.



While the CLC inventory provides a single class for olive trees, several classes were identified for grasses. Based on a literature review, the following CLC classes were considered as sources of grass pollen for the detailed VC: “Pastures”, “Natural grassland”, and “Sclerophyllous vegetation” (Hjort et al., 2016; Khwarahm et al., 2017; McInnes et al., 2017; Rojo et al., 2015). In this study, for the detailed VC dataset, we assumed that 66% of grass-covered areas emit pollen. This assumption was based on preliminary sensitivity tests conducted with the pollen modelling system (other proportions tested were 33% and 100%, which resulted in significant under- and overestimation, respectively). Due to the unavailability of detailed maps specifically for mugwort and the primary focus of the study on assessing the influence of different VC datasets on pollen prediction, we did not consider this taxon in the analysis.

7.2.4. Model performance evaluation

Daily pollen concentrations for 2019 from the 15 POLLnet monitoring stations within the modelling domain (Figure 7.1) were used for the model validation. For each pollen and monitoring station, daily average concentrations predicted from the model fed by CAMS and detailed VC maps were plotted along with observed daily concentrations; differences between predicted and observed daily concentrations averaged over the 15 monitoring stations were plotted to provide a summary view. Predicted and observed daily pollen concentrations were then compared using Spearman’s correlation coefficient and RMSE, as suggested by Suanno et al. (2021). To evaluate model capability in predicting days likely when pollen concentrations may lead to outbreaks of allergy symptoms, predicted and observed daily pollen concentrations were dichotomised based on the low-concentration class thresholds defined by SIAMA: 0.5 p/m^3 for alder, birch, grass, and olive; 0.1 p/m^3 for ragweed (http://www.pollnet.it/valori_di_riferimento_it.asp). The pollen data distributions did not allow the use of higher thresholds. We calculated model performance indicators as follows: model accuracy (MA), as the number of correct predictions over the total number of predictions; probability of detection (POD), as the fraction of correct predictions of “events” of threshold exceedance (events/(events + missed events)); false alarm ratio (FAR), as the fraction of wrong “event” predictions (false alarms/(events + false alarms)) (Mimić et al., 2021;

Siljamo et al., 2013; Suanno et al., 2021). For all these indicators, the median values and the 5th and 95th percentiles over the 15 monitoring stations, for each pollen type, are reported.

To further assess model performance, seasonal indexes (start/end days, SPIn) were calculated for both observed and predicted pollen time series. The absolute differences between seasonal indexes obtained from predicted and observed daily concentrations were calculated for the 15 monitoring stations and compared graphically using boxplots. For the SPIn, percent relative differences were also calculated as follows: 100 × (predicted – observed) / observed (%).

To compare model performance between the mountain and lowland areas, all the previously described analyses were repeated separately for monitoring stations located in these two environments (Figure 7.1).

The statistical analyses were conducted using RStudio.

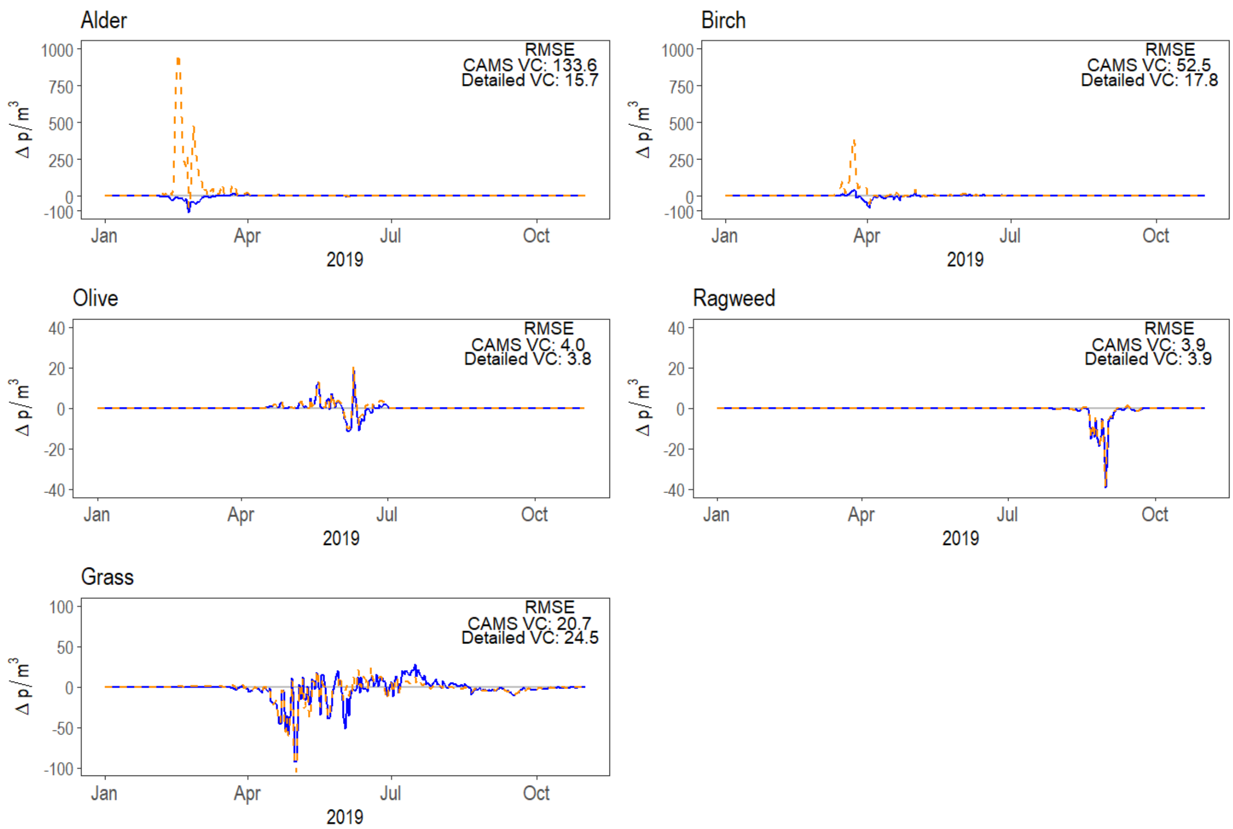
7.3. Results

7.3.1. Daily pollen concentrations

The comparison of predicted and observed temporal series for each pollen and monitoring station is shown in the Appendix (Figures A.1-A.5). The difference between predicted and observed daily pollen concentrations ($\Delta p/m^3$) averaged over the 15 monitoring stations is shown in Figure 7.4.

The use of detailed VC resulted in a substantial improvement in estimations of alder and birch daily pollen concentrations compared with CAMS VC, which overestimated daily concentrations up to 1000 (alder) and 400 (birch) p/m^3. For both detailed and CAMS VC predictions, olive and grass daily concentrations resulted in over- and underestimations, with a slightly better performance for grass when using CAMS VC. Ragweed mean daily predictions were generally underestimated, without difference between the use of different VC maps. The mean RMSEs over the 15 monitoring stations were consistent with this pattern of the results, indicating that the use of detailed VC resulted in notable enhancements in estimating daily pollen concentrations for alder and birch compared to CAMS VC (Figure 7.4). An important reduction in the mean RMSE was obtained for alder and birch pollens when using detailed VC (detailed VC vs. CAMS VC: 15.7 vs. 133.6; 17.8 vs. 52.5 p/m^3, respectively). For grass, the mean RMSE resulted higher when using detailed VC (24.5 vs. 20.7 p/m^3). Similar mean RMSEs were obtained for olive (3.8 vs. 4.0 p/m^3) and ragweed pollen (3.9 vs. 3.9 p/m^3) regardless of the VC used.

Figure 7.4. Difference between predicted (CAMS VC: dashed-orange line; detailed VC: solid blue line) and observed daily pollen concentrations averaged over the 15 monitoring stations. The horizontal grey line at 0 p/m^3 represents the equality between predicted and observed daily concentrations.



The Spearman's correlation coefficients and the threshold-based statistics were similar between models using CAMS and detailed VC, with slightly better values using CAMS (Table 7.1).

Table 7.1. Median (5th and 95th percentiles) validation metrics for the model fed by CAMS and detailed Vegetation Cover maps.

Pollen	***Simulation***	***Corr*** *Median (5p-95p)*	***MA*** *Median (5p-95p)*	***POD*** *Median (5p-95p)*	***FAR*** *Median (5p-95p)*
Alder	CAMS VC	0.65 (0.50-0.69)	0.83 (0.67-0.86)	0.90 (0.62-1.00)	0.45 (0.31-0.73)
	Detailed VC	0.61 (0.45-0.68)	0.84 (0.70-0.88)	0.83 (0.54-0.99)	0.42 (0.28-0.63)
Birch	CAMS VC	0.56 (0.40-0.66)	0.84 (0.76-0.89)	0.79 (0.67-0.98)	0.45 (0.25-0.57)
	Detailed VC	0.55 (0.40-0.62)	0.84 (0.77-0.88)	0.75 (0.64-0.94)	0.44 (0.25-0.57)
Olive	CAMS VC	0.45 (0.23-0.62)	0.88 (0.81-0.93)	0.86 (0.46-1.00)	0.61 (0.41-0.94)
	Detailed VC	0.45 (0.23-0.56)	0.88 (0.81-0.93)	0.82 (0.38-0.96)	0.61 (0.36-0.94)
Ragweed	CAMS VC	0.56 (0.30-0.62)	0.93 (0.87-0.95)	0.77 (0.64-0.87)	0.19 (0.06-0.74)
	Detailed VC	0.56 (0.30-0.62)	0.92 (0.89-0.95)	0.83 (0.57-0.87)	0.22 (0.04-0.74)
Grass	CAMS VC	0.84 (0.79-0.89)	0.84 (0.82-0.91)	0.90 (0.80-0.99)	0.12 (0.03-0.23)
	Detailed VC	0.82 (0.77-0.87)	0.70 (0.56-0.89)	0.53 (0.38-0.90)	0.03 (0.00-0.13)

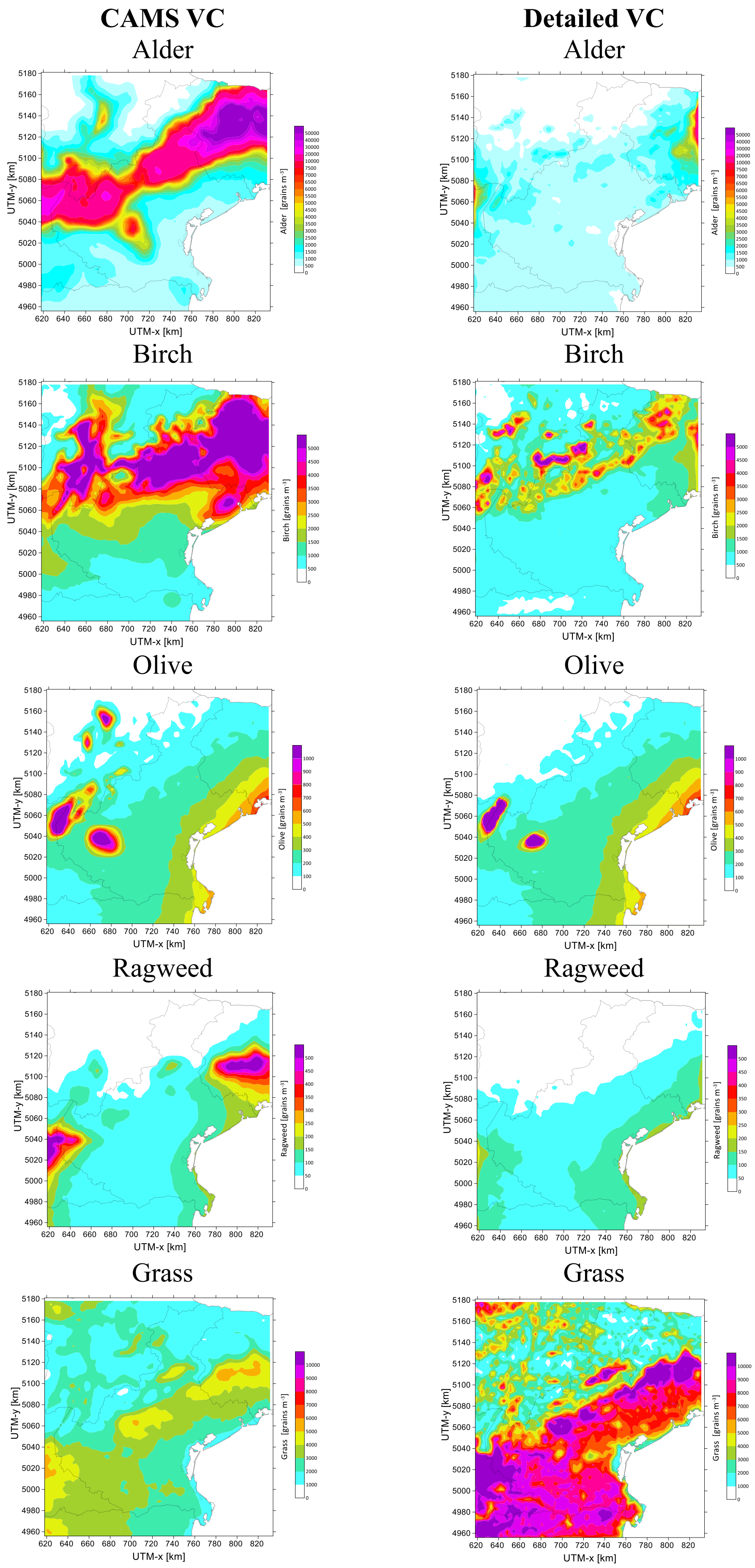
Corr: Spearman’s Correlation coefficient; MA: Model Accuracy; POD: Probability of Detection; FAR: False Alarm Ratio

The median correlation coefficients ranged from 0.45 for olive to 0.82-0.84 for grass. Model accuracy was high (between 0.70 and 0.93), as was the probability of detection (between 0.75 and 0.90, except for grass, detailed VC: 0.53), while the false alarm ratio ranged from very low values (from 0.03 to 0.12 for grass), indicating few false alerts, to high values (0.61 for olive), suggesting a higher occurrence of false alarms.

7.3.2. Seasonal pollen indexes

Figure 7.5 depicts the maps representing the predicted spatial distributions of SPIn over the modelling domain.

Figure 7.5. Seasonal Pollen Integral (SPIn, grains m^3) estimated across the study domain using model fed by CAMS (left) and detailed (right) Vegetation Cover datasets.

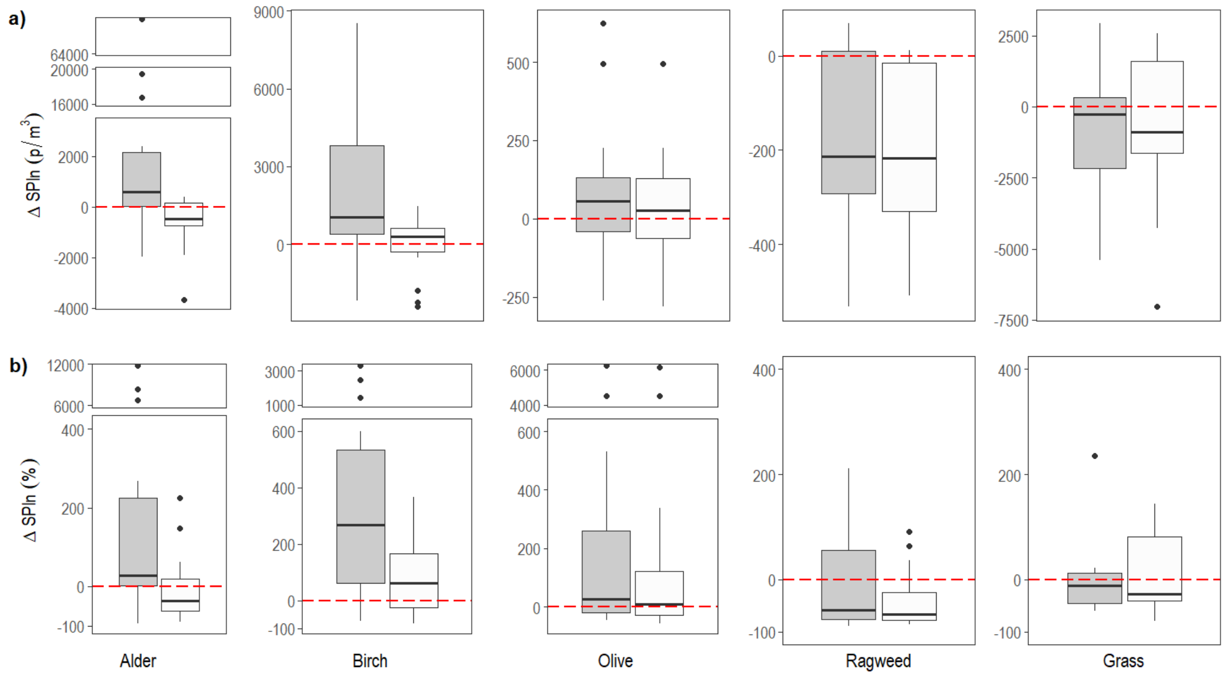


Each map is obtained for the period calculated from the earlier start to the later end of the observed pollen season across the 15 monitoring stations: Alder (26/01/2019 – 08/07/2019), Birch (27/02/2019 – 04/06/2019), Olive (03/05/2019 – 02/07/2019), Ragweed (13/06/2019 – 30/09/2019), Grass (30/03/2019 – 05/10/2019).

The SPIn predicted using CAMS VC was higher compared to the detailed VC for all pollens, except for grass. In line with the vegetation distribution depicted in Figure 7.3, the SPIn for alder and birch was higher in the mountains compared to the lowlands. This difference was more pronounced in the map obtained from CAMS VC. For olive, the hotspots of SPIn aligned with the plant distribution depicted in Figure 7.3, with an additional contribution from the Eastern margin of the modelled domain. For grass, the SPIn appeared more produced in the lowland environment, and it was generally higher when using detailed VC. For ragweed, the SPIn showed higher values at the margins of the modelled domain, especially when using the CAMS VC.

Figure 7.6 shows the distribution of absolute (panel a) and relative (panel b) differences between SPIn from predictions (CAMS and detailed VC) and observations at the 15 monitoring stations.

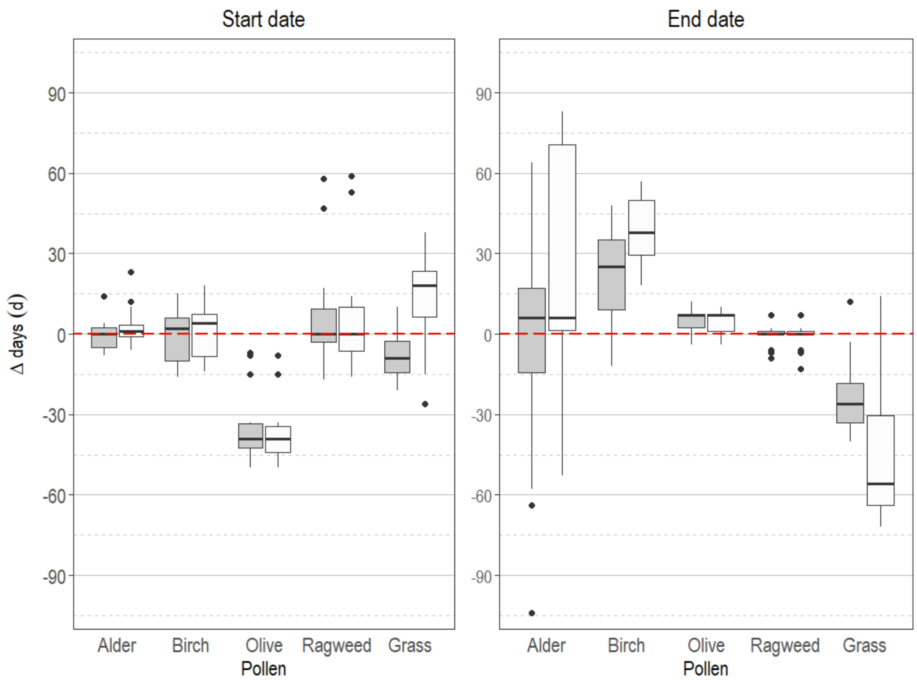
Figure 7.6. Distribution of absolute (a) and relative (b) differences between Seasonal Pollen Integrals (ΔSPIn) predicted (CAMS VC: grey box; detailed VC: white box) and observed at the 15 monitoring stations.



The boxplots reflect the spatial distribution of the seasonal pollen load in Figure 7.5. For arboreal pollen (alder, birch, olive), the median SPIn value was closer to the observed SPIn when using detailed VC, and the boxes were narrower, suggesting higher prediction accuracy. Using CAMS VC significantly overestimated the SPIn for alder, with values up to 12,000% higher compared to observed SPIn. The SPIn was similarly underestimated for ragweed with both CAMS and detailed VC (almost 100 % lower compared to observed SPIn), although the relative error was lower when using detailed VC. For grass, the SPIn was better estimated using CAMS VC.

Performance in the prediction of the season start date was similar between models using CAMS and detailed VC, except for grass, whose season was markedly shifted toward earlier and later dates using CAMS VC and detailed VC, respectively (left panel of Figure 7.7). The start date of the olive pollen season was strongly anticipated by approximately a median of 40 days in both predictions. The estimation of the season-end dates was less accurate compared to the estimation of the season-start dates. However, great results were obtained for olive and ragweed using both VC maps (Figure 7.7, right panel).

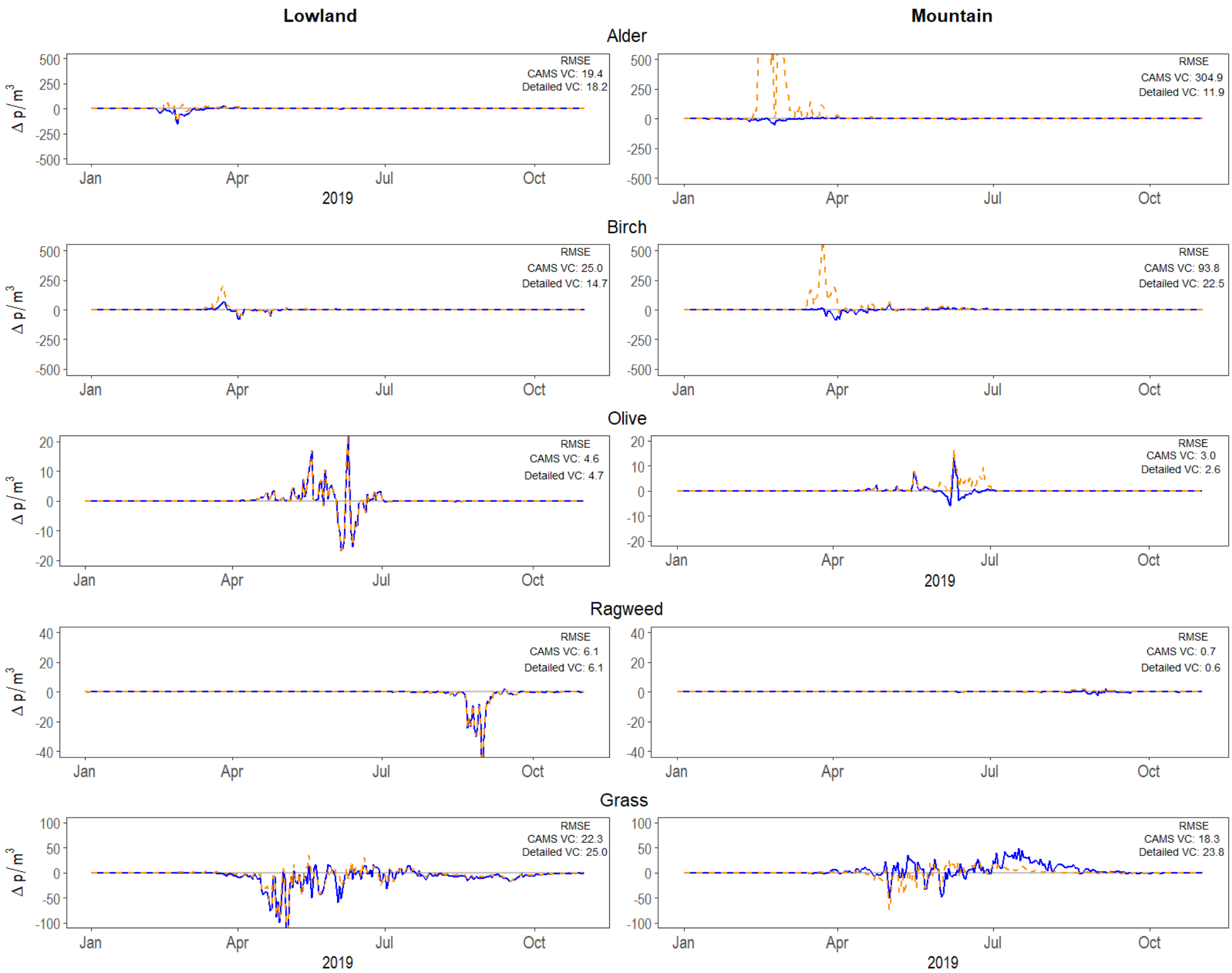
Figure 7.7. Distribution of differences (in days) between start and end dates obtained from predictions (CAMS VC: grey box; detailed VC: white box) and observations at the 15 monitoring stations.



7.3.3. Analysis stratified by geographical areas

The difference in model performance appeared magnified according to the geographical area (Figure 7.8).

Figure 7.8. Difference between predicted (CAMS VC: dashed-orange line; detailed VC: solid blue line) and observed daily pollen concentrations at the monitoring station according to the geographical environment. The horizontal grey line at 0 p/m^3 represents the equality between predicted and observed daily concentrations.

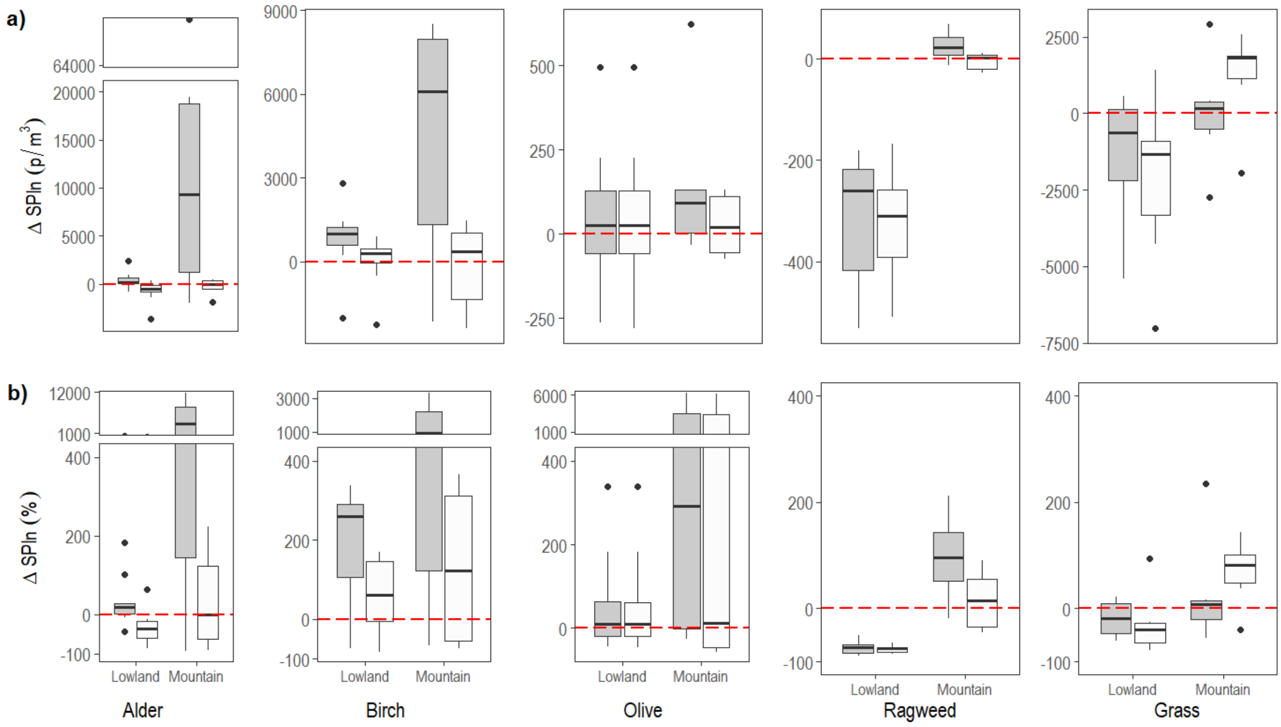


Regarding alder and birch pollen, the improved prediction of daily concentrations using detailed VC was particularly evident in the mountain environment compared to the lowlands, consistently with the mean RMSE values (CAMS VC vs. detailed VC in the mountains: 304.9 vs. 11.9 p/m^3, for alder; 93.8 vs. 22.5 p/m^3, for birch).

The predictions of olive and ragweed daily concentrations were similar using different VC maps in both environments. The higher performance of daily grass pollen predictions using CAMS VC compared to detailed VC did not depend on the environment.

The distribution of absolute and relative differences between observed and predicted SPIn at the monitoring stations divided by geographical area was shown in Figure 7.9. The results are consistent with those from Figure 7.8, pointing out the higher accuracy in the SPIn estimations in lowland environment compared to the mountains (except for ragweed), and better performance for the mountain environment when using the detailed VC (except for grass).

Figure 7.9. Distribution of absolute (a) and relative (b) differences between Seasonal Pollen Integrals (ΔSPIn) from predictions (CAMS VC: grey box; detailed VC: white box) and from observations at the 15 monitoring stations, stratified by geographical environment.



7.4. Discussion and conclusions

A modelling system implementing phenological emission algorithms was used to simulate dispersion, diffusion, and deposition of allergenic pollens over a domain including the Veneto Region. The use of high-resolution VC data turned out in improved predictions of arboreal pollen (alder, birch, olive), especially in the mountain environment. More accurate predictions have been obtained in areas where the density of the plants and pollen emissions were higher, usually corresponding to the lowland environment.

Some authors have outlined that the performance of pollen prediction models depends on the study area and the vegetation inventories used (Suanno et al., 2021; Vélez-Pereira et al., 2022). With this respect, we have assessed the sensitivity of pollen predictions to the spatial resolution of VC maps (high versus low resolution). Similar approaches have been used in the literature: integration of pollen data among source maps for pollen dispersion models, alone or in combination with land-use information; use of ecological models combining plant inventories along with habitat suitability; update of source maps with more detailed ones (Kurganskiy et al., 2020; Mimić et al., 2021; Prank et al., 2013; Verstraeten et al., 2019, 2021; Zink et al., 2017).

The detailed VC maps exhibited significant differences compared to the coarser CAMS VC maps, even up to orders of magnitude for alder and ragweed. Since there are no available detailed descriptions of the study area in biogeographic terms, it has not been possible to determine which of the VC maps offered the most accurate representation of the actual distribution of plants. Nevertheless, it is documented in the literature that ragweed is not widely spread in the Veneto Region (Bonini et al., 2018), suggesting that the CAMS distribution map is likely inaccurate. In Italy, ragweed originated in the Province of Milan (a western area outside the study domain) and spread to the Po Valley (including the lowlands in our study domain) (Bonini et al., 2018). Ragweed is uncommon in the mountain environment and is not locally transported due to the barrier effect of the Alpine Mountain chain.

Various metrics were considered for the validation of prediction models, in accordance with the literature (Mimić et al., 2021; Prank et al., 2013; Siljamo et al., 2013; Suanno et al., 2021). A good agreement between the metrics employed (graphical methods (boxplots), RMSE, seasonal indexes) was found, except for threshold-based statistics, which showed apparently contradictory results. Threshold-based statistics were probably not appropriate for our data, due to the low density of plants and low pollen concentrations. In fact, we used the phenological algorithms developed for the SILAM model by the Finnish Meteorological Institute, focusing on pollens that are uncommon in our study domain (alder, birch, ragweed, and olive). For this reason, unlike other studies (Mimić et al., 2021; Siljamo et al., 2013), in our analysis there were few days when pollen concentrations exceeded the medium or high concentration thresholds set by the SIAMA. Consequently, it was impossible to evaluate the models' ability to predict medium to high concentrations.

7.4.1. Arboreal pollen

Using detailed VC, a greater improvement in predictions of daily pollen concentrations and SPIn was obtained for alder and birch, particularly emerging in the complex and heterogeneous territory of the mountains. About olive, the differences between the two predictions were few and only seemed to be expressed in the BZ2 station (Figure A.3 in the Appendix).

Our findings highlight that the performance of the model using CAMS VC maps was significantly reduced in the orographic areas, probably attributed to the inadequate description of the spatial distribution of species in these areas. Indeed, the olive hot spots in the northwestern part of the domain by the CAMS map might be responsible for the slightly decreased performance of the prediction for this pollen.

The CAMS ensemble models, including MINNI, were originally implemented for large-scale predictions, covering the European domain with a 10 km grid cell size (Sofiev et al., 2017). This resolution is not designed to capture the local pollen distribution, especially in complex topography, such as valleys and mountains, where the airflow is constrained and the land cover changes over short distances due to elevation variations (Sofiev et al., 2013, 2017). Our study confirms the potential of the model running at high-spatial resolutions to capture the pollen distribution also in the mountain environment, where the spatial distribution of the emitting species is correctly mapped. Our findings align with Pauling et al. (2020), who demonstrated realistic predictions for birch pollen in the context of the European Alps when incorporating high-resolution datasets in the COSMO-ART model (Pauling et al., 2020).

The start and end dates of alder and birch pollen seasons were better estimated using CAMS VC maps. The worst model performance emerged in the prediction of end dates. Nonetheless, for individuals suffering from allergies, the correct prediction of the start date of the pollen season is more important than the end (Suanno et al., 2021). From our results, only the start season of olive was not predicted well using both vegetation maps. This error may be due to the phenological emission algorithms, likely not be properly adequate for our region. As reported by Sofiev et al. (2017), the heat-sum formulations, threshold values, and temperature predictions by weather forecasting models result in predicting the start of the olive pollen season too early. In fact, heat-accumulation algorithms for olive are still not well developed and not easily fixable (Aguilera et al., 2014; Sofiev et al., 2017).

7.4.2. Herbaceous pollen

Our results showed no difference in ragweed pollen predictions between models using CAMS and detailed VC, but important differences in grass pollen predictions. Ragweed daily concentrations and SPIn predictions were generally underestimated, in accordance with Mimic et al. (2021). However, this underestimation primarily impacted lowland areas, potentially due to the inability of the model to predict occasional transport events coming from eastern Europe (Pannonian Plain). These phenomena are well-known and are responsible for high concentrations peaks detected by monitoring stations in the Veneto territory (https://www.arpa.veneto.it/temi-ambientali/pollini/articoli-1) (D'Amato et al., 2007; Prank et al., 2013). As depicted in our maps, the spatial distributions of the SPIn for ragweed suggest a likely contribution of pollen transported from the margins of the domain, but the model failed to predict these peaks (Figure A.4 in the Appendix). As these transport events do not affect the mountain environment, the SPIn predictions obtained with detailed VC resulted more accurate in this environment, although differences in RMSE were minimal. This discrepancy could be attributed to the incompleteness of the CAMS VC map (unrealistically low and patchy distribution of the plant) and the method of model calibration, which may have introduced a systematic error in the emission model (Prank et al., 2013). Nonetheless, the model was able to predict the main features of the ragweed season in Europe, as reported by Mimić et al. (2021) and Prank et al. (2013). From our results, the end of ragweed season was reproduced better than the start, consistently with Prank et al. (2013).

Using detailed VC maps, the predictive performance of grass pollen was consistently lower across all the validation statistics considered (although the difference was small in terms of RMSE): this was amplified in the mountain environment. These findings could be related to the arbitrary selection of the CLC classes, a task further complicated by conflicting opinions on emitting species found in the literature. We selected the "Natural grasslands," "Sclerophyllous vegetations," and "Pastures" as potential emitting classes, aligning with studies suggesting higher pollen production in natural areas than in agricultural ones (Hjort et al., 2016; Khwarahm et al., 2017; McInnes et al., 2017; Prieto-Baena et al., 2003; Rojo et al., 2015, 2022; Verstraeten et al., 2021). Predicting grass pollen is inherently challenging due to the variety and quantity of characterising species that shape the larger extension of the pollen season (Verstraeten et al., 2021). This complexity holds significant importance when considering the pollen load. The lack of specific maps for grass pollen emission (Vélez-Pereira et al., 2022) increases prediction errors. It should be highlighted that not all grass taxa emit pollen, and pollen production varies widely across species; currently, no maps differentiate between emitting and non-emitting species (Verstraeten et al., 2021).

7.4.3. Strengths and limitations

A strength of this study, compared to existing literature, was the availability of a high number of monitoring stations (15) belonging to a standardised network within a relatively small territory. This enabled the evaluation of model performance even in a complex topography, such as the Alpine Mountain chain. For the pollen dispersion model validation in Belgium and Serbian (region of Vojvodina, Pannonian Plain) studies, only five monitoring stations were used (Mimić et al., 2021; Verstraeten et al., 2019, 2021). Kurganskiy et al. (2020) compared predictions with measurements from 12 stations located in Finland, Denmark, and Russia. Sofiev et al. (2017) did not validate the European olive model in our study area, although they considered the Italian territory; we provided the first validation for olive pollen in this region.

Although a future evaluation of model performance by urban and non-urban areas would be of interest, such an analysis was not feasible here, as all monitoring stations in our dataset are located in urban environments. This represents a limitation in evaluating the model's applicability to more rural or natural areas.

As our study aimed to assess the impact of using more detailed vegetation cover data on estimated pollen concentrations, we restricted the analysis to a single year. We selected the year 2019 due to the potentially smaller impact of the exceptionally high temperatures recorded in 2021 and 2022, and, more importantly, the absence of monitoring data for olive pollen before 2019. As a consequence, we could not assess interannual variability, which is important as evidenced by previous research that has shown considerable changes in the SPIn over time, particularly for some plants like birch (Dąbrowska-Zapart & Niedźwiedź, 2022; Fernández-Llamazares et al., 2014; Spieksma et al., 2003). However, it is essential to note that the phenological algorithms were previously validated over multiannual periods within the context of CAMS (Prank et al., 2013; Sofiev et al., 2006, 2013, 2017). Given that vegetation maps remain static over time, the main parameter affecting variations in pollen seasonality was weather, which was not the focus of the present study. Another limitation is the lack of pollen emission maps to be used for model input, necessitating the use of VC maps as proxy indicators for emission sources. Moreover, the available VC maps were not homogeneously coded and managed, requiring processing to obtain the reference landcover (Vélez-Pereira et al., 2022).

7.4.4. Conclusions

Our research shows that using detailed maps in pollen dispersion models improves prediction accuracy, especially in complex terrains where high-resolution data is essential. However, this improvement relies on having detailed maps of species distribution, which are currently lacking. Future research will explore the ability of the pollen modelling system to simulate year-to-year variability and develop new models for pollen taxa specific to Italy, like Cupressaceae, Corylaceae and Urticaceae. Given the impact of climate change on pollen patterns, new emission algorithms beyond fixed seasonal periods are needed. These advancements can improve short-term pollen forecasts and improve the quality of life of individuals affected by allergies.

8. General conclusions

This thesis focused on the analysis of aerobiological data obtained through both monitoring and modelling approaches, with a particular emphasis on the Veneto Region, a geographically diverse area that is highly susceptible to the effects of climate change. The research highlighted the importance and potential of aerobiological data in developing effective public health strategies, particularly in addressing the challenges posed by climate change and enhancing our understanding of airborne allergens.

Detailed information on the spatio-temporal distribution of pollen contributes to expanding territorial knowledge and helps identify populations at higher risk from exposure to allergenic pollen. Such data supports the development of targeted interventions to reduce respiratory issues, allowing for efficient resource allocation in high-allergen areas. Key strategies to mitigate health risks for susceptible/allergic individuals include urban landscaping and vegetation management, such as reducing allergenic plants in populated areas. Proactive weed control helps to reduce ambient pollen levels, particularly for highly allergenic species like ragweed. Replacing allergenic ornamental plants with less allergenic alternatives in urban areas can significantly reduce pollen exposure, improving respiratory health for city residents. Implementing these strategies is crucial for reducing pollen-induced health risks and improving the quality of life for sensitive populations amidst evolving environmental conditions.

Accurate pollen forecasting emerges as another essential component of community health initiatives, enabling proactive measures of adaptation to exposure risks. For instance, public health authorities can advise individuals with respiratory conditions to avoid outdoor activities during peak pollen periods, while municipal authorities can schedule landscaping activities, such as lawn mowing, before grass pollen is released to reduce the spread of allergenic particles into the air. Additionally, pollen forecasts can help schedule outdoor public events to minimize exposure during periods of high allergenic pollen release (Geller-Bernstein & Portnoy, 2019). These forecasting tools empower individuals and communities to take preventive actions, reducing allergy symptoms and asthma exacerbations, and alleviating the public health burden associated with environmental allergens.

At the same time, this thesis raises new questions about pollen data. Undoubtedly, much effort is still required to fully understand the complexity of plant phenology and pollen transport mechanisms. Both are influenced by a multitude of factors, including temperature, humidity, wind, and environmental features, all of which vary with climate change. Phenological changes may alter pollen emission periods, affecting individuals sensitive to specific allergens. Advanced models and continuous data collection are needed to deepen understanding of pollen dynamics, accurately predict pollen release and dispersion, and improve methods to impute missing data in aerobiological datasets.

Another key focus is identifying pollen taxa linked to severe health outcomes, such as emergency room visits and hospital admissions for allergy and asthma symptoms. By identifying these specific taxa, researchers can establish pollen concentration thresholds that indicate when respiratory symptoms are most likely to occur. These thresholds would be valuable indicators in public health systems, allowing for more accurate public health interventions.

Furthermore, multi-exposure studies are essential for understanding how pollen interacts with other air pollutants, as highlighted in the 2021 WHO Air Quality guidelines (World Health Organization, 2021). Chemical pollutants like ozone, nitrogen dioxide, and particulate matter can exacerbate allergic reactions and respiratory diseases, particularly when combined with high pollen concentrations. Research indicates that air pollution may even increase pollen allergenicity by altering its protein composition. Multi-exposure studies could clarify how specific pollutants amplify the health effects of pollen exposure, potentially leading to more nuanced health guidelines that account for these synergistic effects. A deeper understanding of these interactions could improve population-level exposure assessments, allowing for more accurate estimates of the health burden associated with combined exposures to airborne allergens and pollutants.

Lastly, although risk assessments, pollen forecasts, and pollen bulletins typically rely on pollen counts or levels, greater attention should also be given to pollen allergenicity. Pollen counts alone may not fully reflect the risk for allergic and asthmatic patients, as it is the allergenic proteins—not the pollen grains themselves—that trigger IgE-mediated immune responses. Furthermore, the relationship between pollen counts and airborne allergen levels is not linear, and it is affected by environmental conditions and air pollution, as previously discussed, which are further influenced by climate change (Fuertes et al., 2024).

Achieving these goals requires ongoing scientific progress and collaboration among scientists, healthcare providers, and policymakers to translate findings into targeted public health strategies. Adapting these strategies to changing environmental conditions is essential to building resilience against the rising health impacts of allergens due to climate change.

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Appendix

Table A.1. Non-systematic review of the evidence on the presence and direction of temporal trends in annual/seasonal pollen load in Europe.

Reference	***Location***	***Period***	***Alnus***	***Ambrosia***	***Artemisia***	***Betula***	***Corylaceae***	***Cupressaceae***	***Oleaceae***	***Poaceae***	***Urticaceae***
Ziello et al., 2012	13 European countries	1977-2009	+	+	-	+	+ (*Corylus*)	+	+/- (*Olea*)	Null	Null
Smith et al., 2014	13 European cities	1990-2009	+ (Betulaceae)	- (Asteraceae)	- (Asteraceae)	+ (Betulaceae)	+ (Betulaceae)		+/-	+/-	
Dąbrowska-Zapart & Niedzwiedz, 2022	Sosnowiec (Southern Poland)	1997-2020				Null					
Bogawski et al., 2014	Poznań (Western Poland)	1996–2011			-					-	+
De Weger et al., 2021	Benelux	1981-2020	+		-	+	+ (*Corylus*)		+ (*Fraxinus*)	-	
Adams-Groom et al., 2022	UK	1995-2020				+				Null	
Hoebeke et al., 2018	Brussels (Belgium)	1982-2015	+		-	+	+ (*Corylus*)		+ (*Fraxinus*)	-	
Makra et al., 2011	Szeged (Hungary)	1999-2009	-	+	-	-				+	+ (*Urtica*)
Gehrig and Clot, 2021	Switzerland	1969-2018	+	-	-	+	+ (*Corylus, Carpinus*)	+	+ (*Fraxinus*)	-	+
Galan et al., 2016	Iberian Peninsula	1994-2013			+/-	+		+	+	+/-	-

									(*Olea*, *Fraxinus*)		
García-Mozo et al., 2014	Cordoba (Spain)	1982-2011							**+** (*Olea*)		
Fernández-Llamazares et al., 2014	Catalonia (Spain)	1994–2011			-	Null	**+** (*Corylus*)			Null	
Camacho et al., 2017	Portugal	2003-2012	+/- (Betulaceae)	+/- (Asteraceae)	+/- (Asteraceae)	+/- (Betulaceae)		+/-	+/- (*Olea*)	+/-	+/-
Damialis et al., 2007	Thessaloniki (Greece)	1987-2005	**+**	-	+		**+** (*Carpinus, Corylus*)	**+**	**+**	**+**	**+**
Marchesi, 2020	Emilia-Romagna (Italy)	1991-2017	**-** (Betulaceae)	**-** (Compositae)	**-** (Compositae)	**-** (Betulaceae)	+/-	+/-	**+**	**-**	**-**
Ugolotti et al., 2015.	Parma (Italy)	1994-2011	-	**+**	**-**	**-**	- (*Corylus*)	-		**-**	**-**
This work	Veneto (Italy)	2001-2022					+	+	+	+	Null
		2006-2022	+	Null	-	Null					

+ : positive trend representing increasing SPIn over time; - : negative trend representing decreasing SPIn over time; +/-: heterogeneous trends across the monitoring stations; Null: no trend observed; **bold** text denotes the stronger temporal trends; in brackets the pollen family or genera analysed if different from the taxa indicated in the column heading.

Table A.2. Non-systematic review of the evidence on the presence and direction of temporal trends in the start of the season in Europe.

Reference	***Location***	***Period***	***Alnus***	***Ambrosia***	***Artemisia***	***Betula***	***Corylaceae***	***Cupressaceae***	***Oleaceae***	***Poaceae***	***Urticaceae***
Smith et al., 2014	13 European cities	1990-2009	**-** (Betulaceae)	**-** (Asteraceae)	**-** (Asteraceae)	**-** (Betulaceae)	**-** (Betulaceae)		+/-	**-**	
Bogawski et al., 2014	Poznań (Western Poland)	1996–2011			**-**					**-**	-
De Weger et al., 2021	Benelux	1981-2020	**-**		**-**	**-**	**-** (*Corylus*)		**-** (*Fraxinus*)	**-**	
Adams-Groom et al., 2022	UK	1995-2020				Null				Null	
Hoebeke et al., 2018	Brussels (Belgium)	1982-2015	Null		-	-	- (*Corylus*)		- (*Fraxinus*)	**-**	
Makra et al., 2011	Szeged (Hungary)	1999-2009	+	**+**	-	Null				Null	**-** (*Urtica*)
Gehrig and Clot, 2021	Switzerland	1969-2018	-			**-**	**-** (*Corylus, Carpinus*)	**-**	**-** (*Fraxinus*)	-	**-**
García-Mozo et al., 2014	Cordoba (Spain)	1982-2011							- (*Olea*)		
Damialis et al., 2007	Thessaloniki (Greece)	1987-2005	Null	Null	Null		**+** (*Carpinus*)	-	+/-	**-**	**-**
Cristofolini et al., 2020	Italy	2000-2016	Null	+/-	**+**	+/-	**-** (*Corylus*)	-	+/- (*Olea, Fraxinus*)	-	-
Marchesi, 2020	Emilia-Romagna (Italy)	1991-2017	+/- (Betulaceae)	**+** (Compositeae)	**+** (Compositeae)	+/- (Betulaceae)	Null	-	-	**-**	**-**

Ugolotti et al., 2015.	Parma (Italy)	1994-2011	Null	-	+	+	- (*Corylus*)	-		+	+
This work	Veneto (Italy)	2001-2022					-	-	-	-	-
		2006-2022	-	Null	Null	Null					

+ : positive trend representing the posticipation of the start date of the pollen season over time; - : negative trend representing the anticipation of the start date of the pollen season over time; +/-: heterogeneous trend across the monitoring stations; Null: no trend observed; **bold** text denotes the stronger temporal trends; in brackets the pollen family or genera analysed if different from the taxa indicated in the column heading.

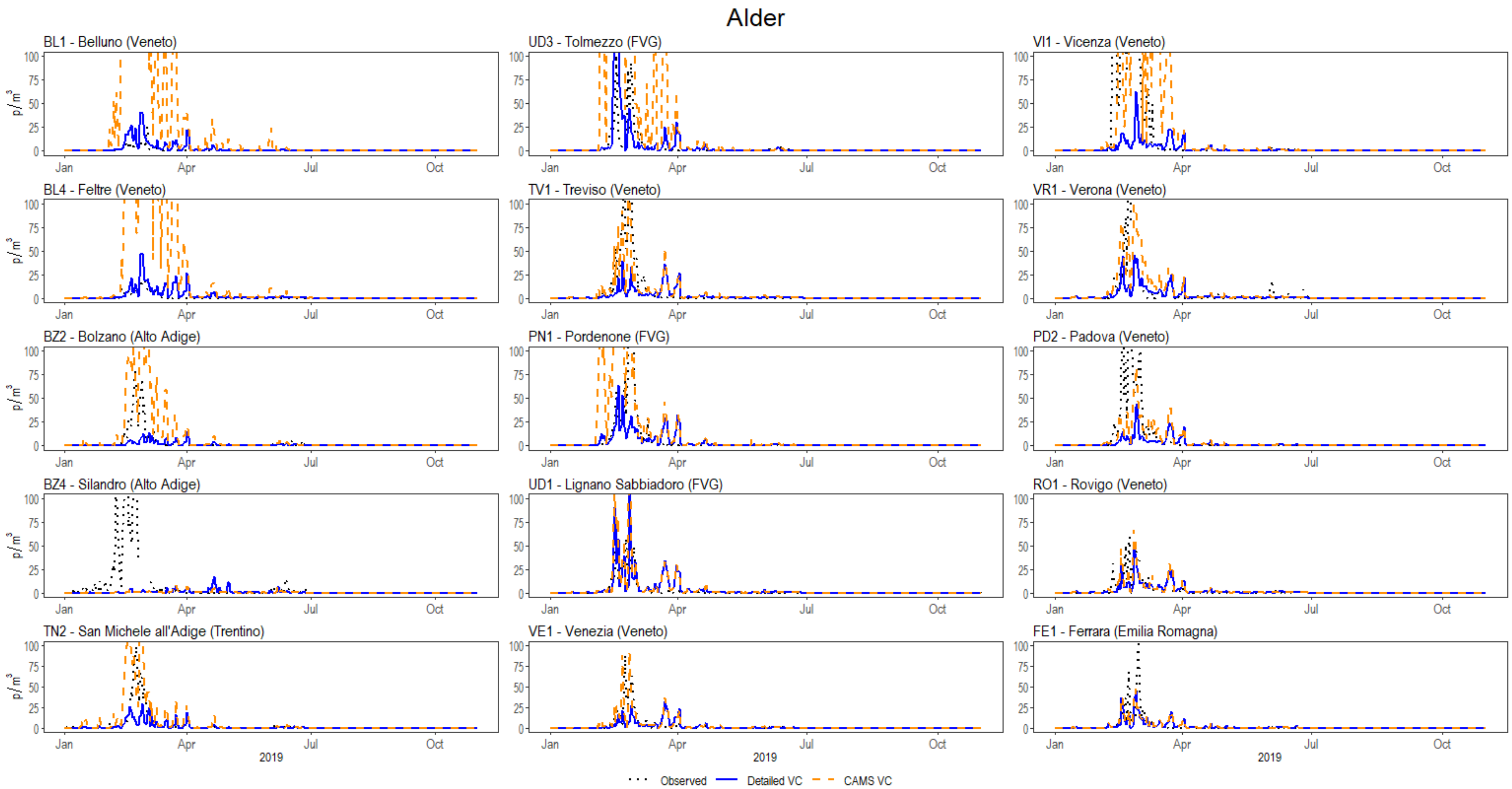
Table A.3. Non-systematic review of the evidence on the presence and direction of temporal trends in the duration of the season in Europe.

Reference	***Location***	***Period***	***Alnus***	***Ambrosia***	***Artemisia***	***Betula***	***Corylaceae***	***Cupressaceae***	***Oleaceae***	***Poaceae***	***Urticaceae***
Smith et al., 2014	13 European cities	1990-2009	**+** (Betulaceae)	+ (Asteraceae)	+ (Asteraceae)	**+** (Betulaceae)	**+** (Betulaceae)		**-**	+/-	
Dąbrowska-Zapart & Niedzwiedz, 2022	Sosnowiec (Southern Poland)	1997-2020				-					
Bogawski et al., 2014	Poznań (Western Poland)	1996–2011			**+**					**+**	**+**
De Weger et al., 2021	Benelux	1981-2020	**+**		**+**	**-**	**+** (*Corylus*)		+/- (*Fraxinus*)	**+**	
Adams-Groom et al., 2022	UK	1995-2020				Null				Null	
Hoebeke et al., 2018	Brussels (Belgium)	1982-2015	Null		+	Null	+ (*Corylus*)		Null (*Fraxinus*)	Null	
Makra et al., 2011	Szeged (Hungary)	1999-2009	Null	-	+	Null				**+**	**+** (*Urtica*)
Gehrig and Clot, 2021	Switzerland	1969-2018	Null			Null	**+** (*Corylus*)	**+**	**-** (*Fraxinus*)	**-**	**+**
García-Mozo et al., 2014	Cordoba (Spain)	1982-2011							**+** (*Olea*)		
Damialis et al., 2007	Thessaloniki (Greece)	1987-2005	Null	Null	Null		**-** (*Carpinus*)	Null	Null	Null	Null
Cristofolini et al., 2020	Italy	2000-2016	+/-	+/-	Null	**-**	**+** (*Corylus*)	+	+/- (*Olea*)	+	+
Marchesi, 2020	Emilia-Romagna (Italy)	1991-2017	**-** (Betulaceae)	- (Compositeae)	- (Compositeae)	**-** (Betulaceae)	-	+/-	+/-	**+**	**+**

Ugolotti et al., 2015.	Parma (Italy)	1994-2011	+	Null	Null	-	+ (*Corylus*)	+		+	-
This work	Veneto (Italy)	2001-2022					Null	+	+	+	+
		2006-2022	Null	Null	+	Null					

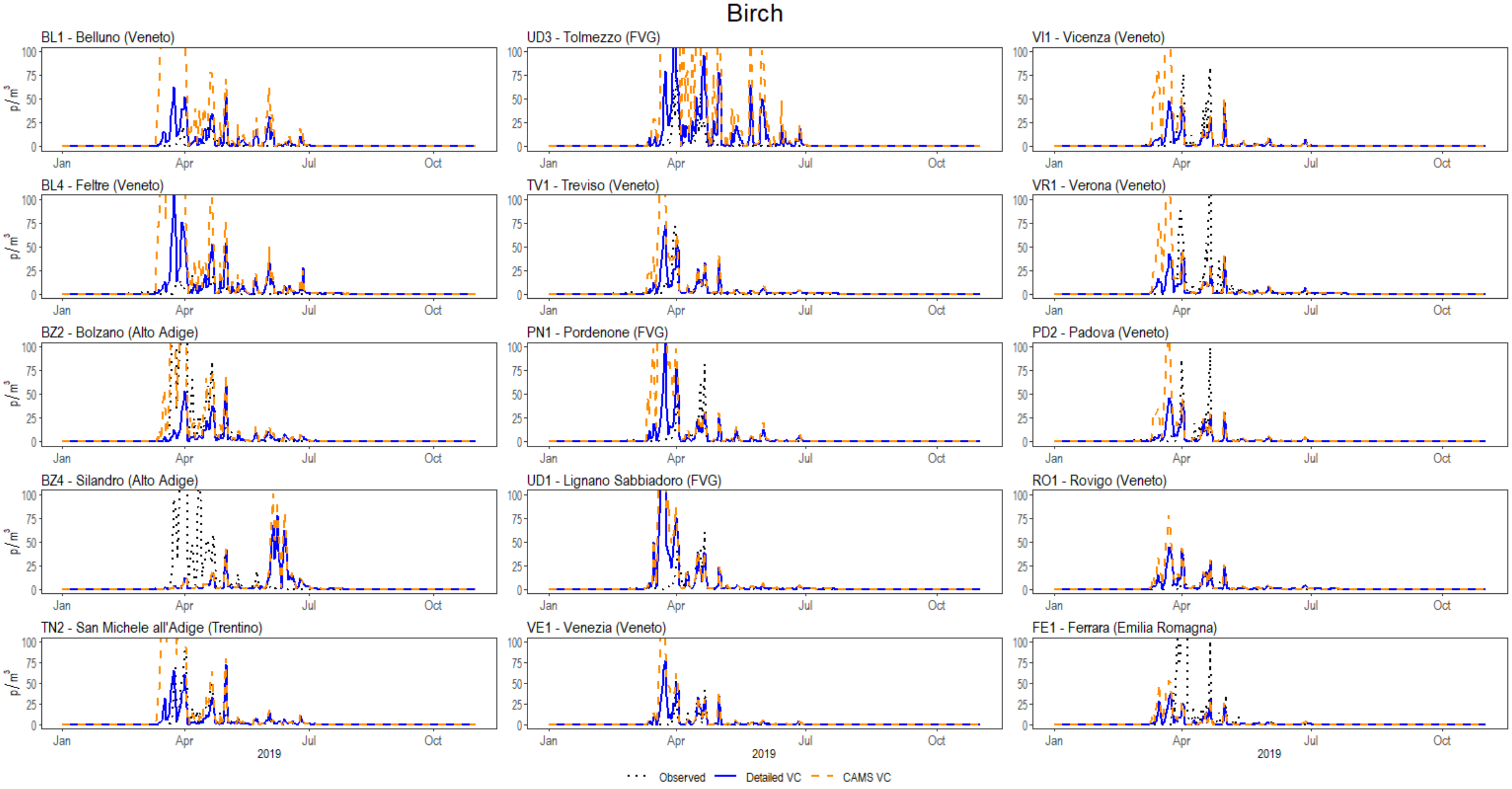
+ : positive trend representing the extension of the pollen season over time; - : negative trend representing the reduction of the pollen season over time; +/-: heterogeneous trend across the monitoring stations; Null: no trend observed; **bold** text denotes the stronger temporal trends; in brackets the pollen family or genera analysed if different from the taxa indicated in the column heading.

Figure A.1. Observed (black dotted line) and predicted (detailed VC: solid blue line; CAMS VC: dashed-orange line) daily alder pollen concentrations at each monitoring station.



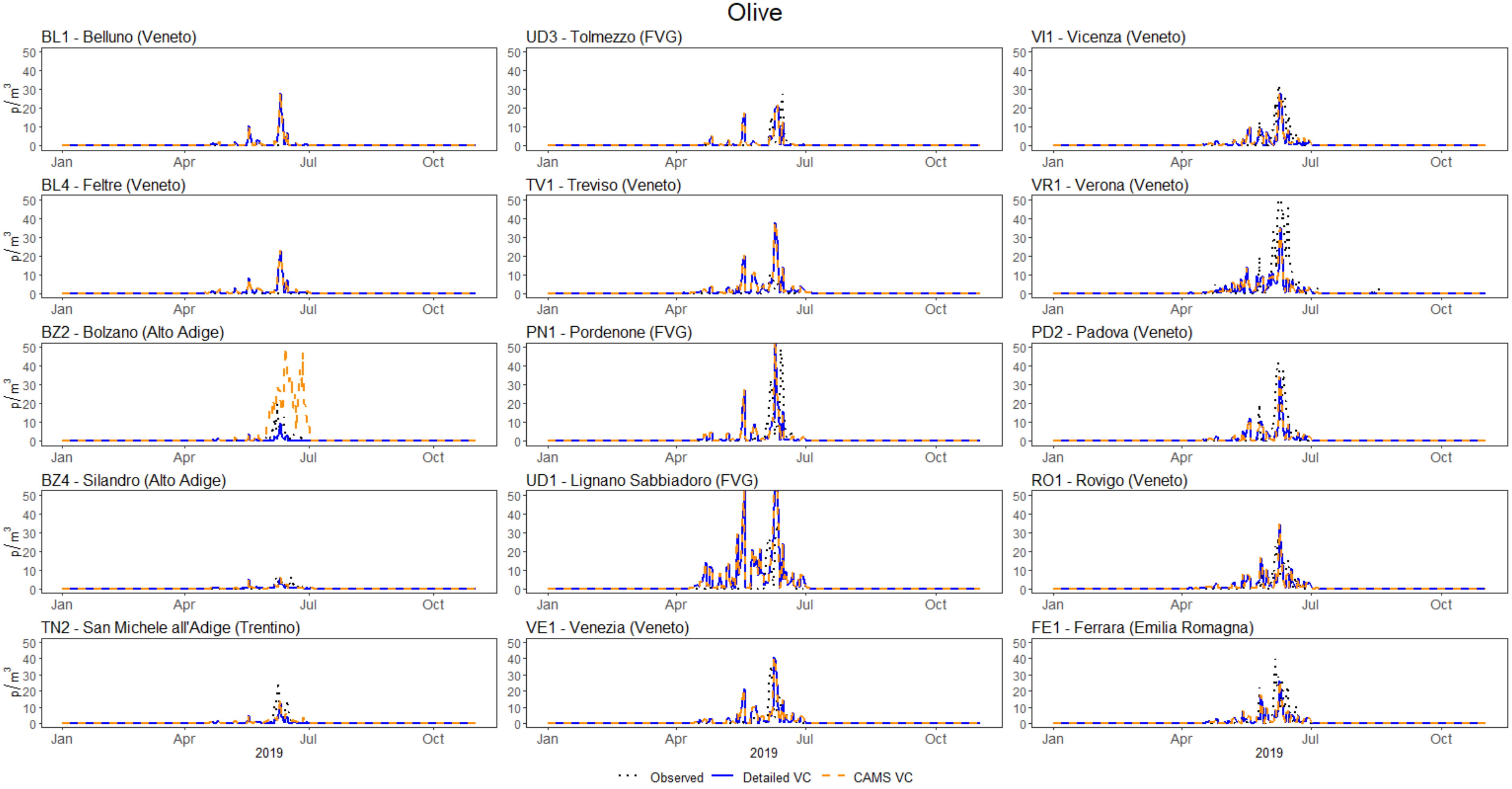
FVG: Friuli-Venezia Giulia

Figure A.2. Observed (black dotted line) and predicted (detailed VC: solid blue line; CAMS VC: dashed-orange line) daily birch pollen concentrations at each monitoring station.



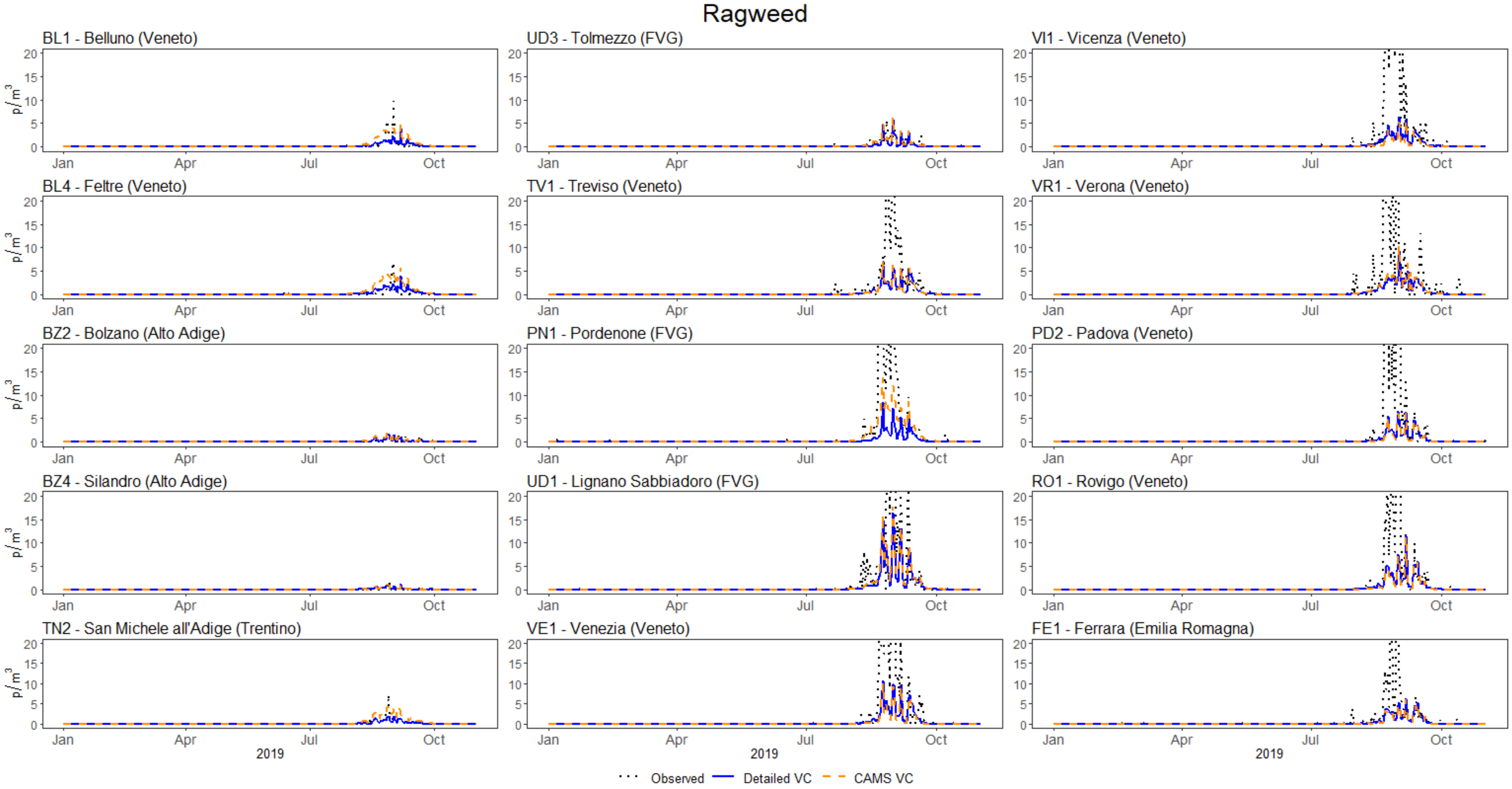
FVG: Friuli-Venezia Giulia

Figure A.3. Observed (black dotted line) and predicted (detailed VC: solid blue line; CAMS VC: dashed-orange line) daily olive pollen concentrations at each monitoring station.



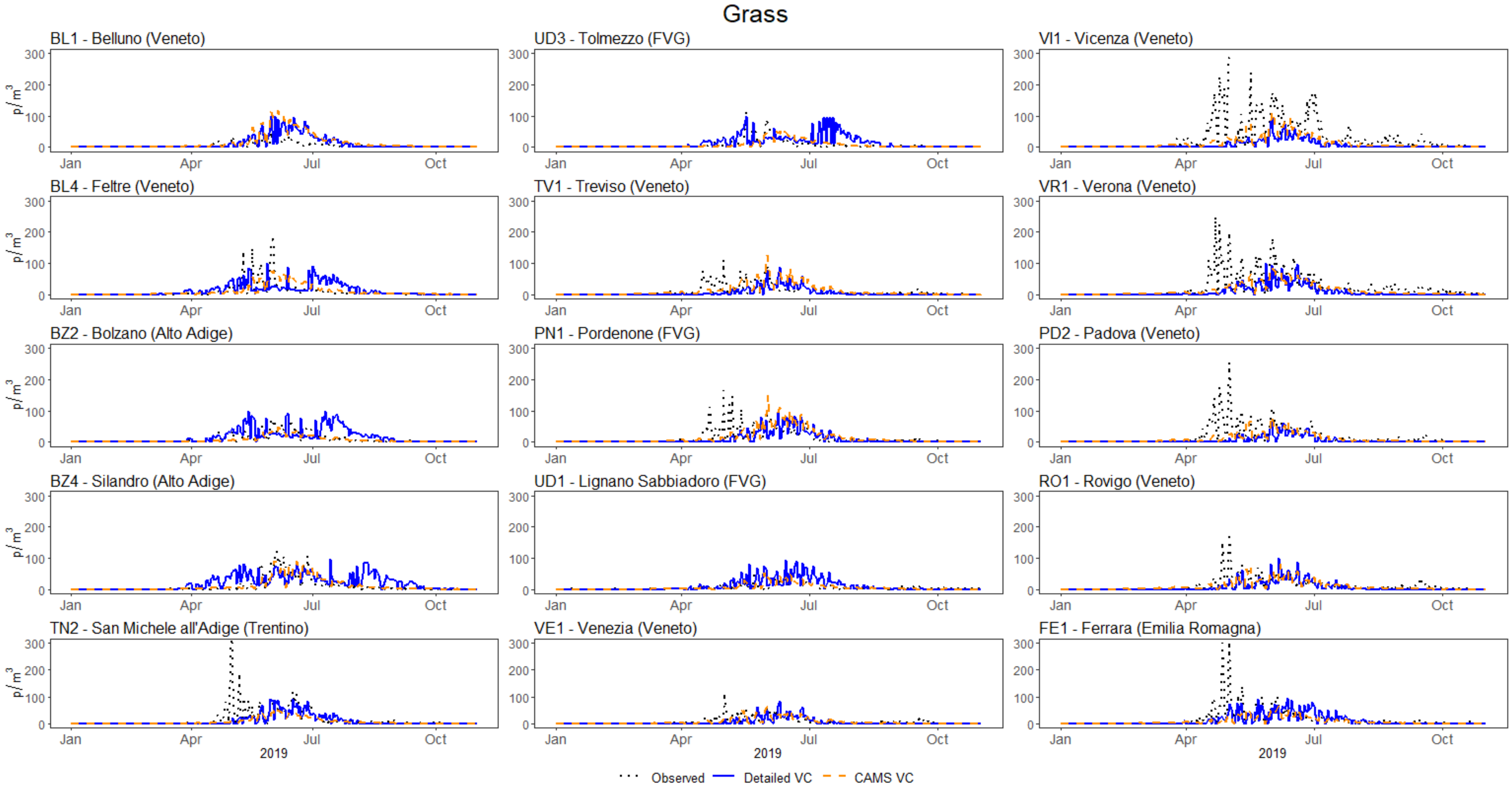
FVG: Friuli-Venezia Giulia

Figure A.4. Observed (black dotted line) and predicted (detailed VC: solid blue line; CAMS VC: dashed-orange line) daily ragweed pollen concentrations at each monitoring station.



FVG: Friuli-Venezia Giulia

Figure A.5. Observed (black dotted line) and predicted (detailed VC: solid blue line; CAMS VC: dashed-orange line) daily grass pollen concentrations at each monitoring station.



FVG: Friuli-Venezia Giulia

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