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REVIEW ARTICLE

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Floating in the air: forecasting allergenic pollen concentration for managing urban public health

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ABSTRACT

The presence of airborne allergenic pollen causes a variety of immune reactions and respiratory diseases, threatening human life in severe cases. Climate change is exacerbating the allergenic pollen-induced health risks and adding a significant economic burden to societies. Despite the pressing threats, vital health-related information is not available to the public to date, and the reshaping of future geographic allergenic pollen patterns remains unknown. To help establish a critical allergenic pollen forecasting capacity, a systematic review was conducted and three promising future directions were identified: (1) resolving heterogeneous urban plant species distribution and phenology using fine-resolution satellite constellations; (2) acquiring ancillary information about allergenic pollen and patient symptoms from emerging geospatial big data, such as social media; (3) deciphering the coupled effect of climate change and urbanization on future geographic patterns and phenology of allergenic species. On this basis, we recommend an optimized workflow that combines real-time pollen monitoring networks with high-resolution vegetation information and weather forecast systems, comprehensively considering the production and diffusion process of pollen to establish advanced prediction models. By focusing on critical knowledge gaps, this review provides much needed insight to propel the allergenic pollen forecasting research and eventually benefit the management of urban public health.

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1. Background

Sexually reproducing plants, especially those that rely on wind-pollination, release substantial amounts of pollen into the air during their reproductive season. Certain pollen grains contain allergenic substances that can trigger hypersensitivity reactions in human bodies, often termed as pollen allergy, which are associated with two typical symptoms: allergic rhinitis and allergic asthma (Erbas et al. 2012). In certain severe cases, such as when triggering asthma, pollen allergies can be life-threatening.

Seasonal allergies and asthma impose significant health burdens, with an estimated 10%–30% of the global population afflicted by allergic rhinitis (or hay fever) and 300 million people worldwide affected by asthma (Pawankar et al. 2011). Pollen allergy has become increasingly prevalent globally, with Austria, the United States, and Italy reporting incidence rates of 16.4%, 14.5%, and 15.1% of their total populations. In China, pollen allergy is a significant factor in approximately 30% of allergic rhinitis patients, affecting tens of millions. Prevalence of this allergy is showing an upward trend and billions of dollars are spent annually on the treatment of pollen allergy in many countries (Bicakci et al. 2017; Rodinkova et al. 2018).

Urban green spaces play an important role in urban residents' well-being and offer valuable ecological services, such as mitigating air pollution, sequestering carbon and regulating temperature (Reyes-Riveros et al. 2021; Sodoudi et al. 2018). However, the inappropriate selection of plant species for planting can produce large amounts of allergenic pollen, posing a considerable threat to human health (Cariñanos and Casares-Porcel 2011; Werchan et al. 2017). Moreover, with rapid urbanization and global warming, factors such as rising temperatures, hard surfaces and air pollution have accelerated the spread of pollen with enhanced allergenicity (Carlsten and Rider 2017; D'Amato et al. 2016; Ziska et al. 2011).

Given the above, accurate prediction of airborne allergenic pollen concentration is urgently needed to alert the relevant population to take necessary precautions, hence reducing the incidence of hay fever and alleviate the burden on public medical resources. Fortunately, countries with high allergy prevalence and committed public health efforts, such as Australia, United States, United Kingdom and Germany, were among the first to establish real-world pollen forecasting systems, contributing to improved allergy and public health management. For example, the German Meteorological Office (Deutscher Wetterdienst – DWD) provides daily pollen forecasts, including grass, tree and weed pollen; Japan and Australia mainly provide pollen forecasts for urban areas; The Met Office's comprehensive pollen forecast system provides pollen concentrations for various regions in the UK for the next five days; Spain, the United States, China and other countries also have their own pollen forecast services and can distinguish different allergenic pollen categories. While a single country is universally recognized as the best, these examples illustrate global efforts to improve the accuracy of pollen forecasting systems, with ongoing progress being made to benefit individuals with respiratory conditions.

Nonetheless, a timely review of the progress related to airborne allergenic pollen concentration forecasting is still lacking, preventing us from identifying key knowledge gaps and prioritizing future research directions that can lead to improved forecasting results. As such, here we performed a comprehensive review to summarize the recent advances in forecasting airborne allergic pollen concentration (Figure 1). The hope is to shed light on the importance of advancing pollen prediction capabilities, which can significantly contribute to public health and enhance our ability to mitigate the impact of pollen allergies on society, eventually leading to sustainable urban green space planning.

2. What data can be utilized for predicting pollen concentration?

Pollen concentration forecasting commonly relies on several essential datasets, including aerobiology data (pollen concentration and classification), meteorological data (air temperature, precipitation and wind speed), vegetation distribution and phenology data (flowering date), as well as emerging geospatial big data.

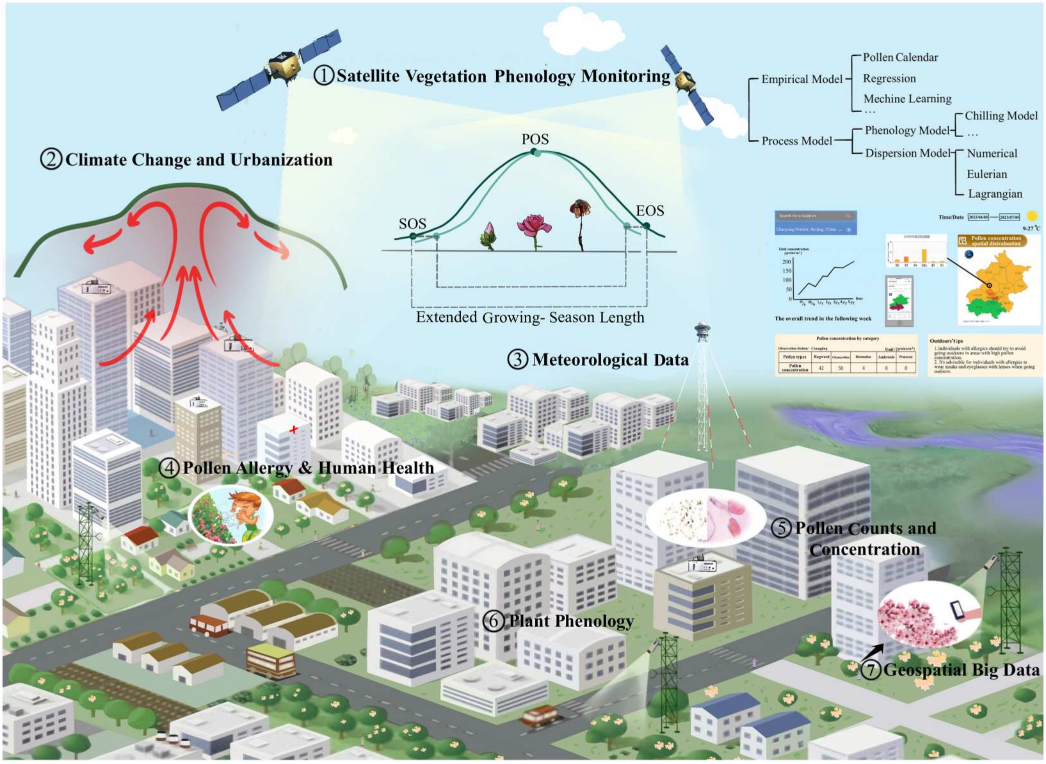

Figure 1. Conceptual diagram of the major factors related to pollen concentration forecasting.

2.1. Aerobiology data

Aerobiological data collected either manually or by automatic monitors encompass the records of biological aerosols present in the atmosphere, such as pollen, spores, bacteria and viruses (Fennelly et al. 2017; Núñez et al. 2016). These records hold important information about the airborne distribution and temporal variation of biological particles and are thus critical to the development and validation of pollen concentration forecasting models (García-Mozo et al. 2014).

Numerous regions and countries have established pollen monitoring networks, such as European Pollen Monitoring Program, National Allergy Bureau in the USA and Australian Pollen Allergen Partnership (AusPollen) (Beggs et al. 2018; Buters et al. 2018). Despite the growing emphasis, current pollen networks remain limited to a few major cities, leading to a serious lack of sufficient geographic coverage and spatial continuity (Oteros et al. 2019). To partially relieve this issue, attempts have been made to interpolate pollen data in unmonitored areas using Kriging or Convolutional Neural Networks (CNNs) techniques (Lops et al. 2020; Navares and Luis Aznarte 2019). These methods help bridge data gaps, although their accuracy is still highly dependent on the density of the available sampling points and the topographic heterogeneity.

2.2. Biometeorological data

Meteorological conditions play a critical role in modulating the timing of pollen production and release, as well as the direction and speed of dispersal in the air. Numerous studies have demonstrated a strong correlation between meteorological conditions and airborne pollen concentrations (Dorota 2013; Oduber et al. 2019). Factors such as temperature, dew point, wind speed, wind direction, humidity, and precipitation have been shown to exhibit both short-term and long-term effects on the seasonal patterns of airborne pollen, making them valuable predictors for explaining the spatio-temporal pollen dynamics (Cristofori et al. 2020; Howard and Levetin 2014).

While previous studies have mostly relied on direct correlations to develop prediction models, the intricate nature of the pollen release process and plants' sensitivity to multiple meteorological factors have highlighted the need for a more sophisticated and systematic approach. As such, Biometeorological Indices (BI) that incorporate various meteorological parameters have been proposed to better predict pollen outbreak dates (Navares and Luis Aznarte 2017). Examples of BI include heat indices (e.g. annual average temperature and accumulated temperature) and moisture indices (e.g. annual precipitation, precipitation variation coefficient, etc.). A study showed that a multiple regression model using BI as input tended to outperform a model using solely meteorological variables in predicting the release of pollen from olive trees (Oteros et al. 2013). By considering multiple meteorological variables and biometeorological indices, researchers were able to improve the accuracy of pollen concentration predictions and gain a deeper understanding of the complex interactions between meteorological conditions and pollen release (Rojo et al. 2021).

2.3. Vegetation distribution and phenology data

Plant flowering phenology is generally divided into early flowering, peak flowering, and late flowering stages, with different species having distinct flowering phenology. Therefore, it is crucial to understand the spatial distribution of urban plant species and their phenologies (seasonal growth and development changes) to improve the spatiotemporal representativeness of pollen concentration forecasting (Devadas et al. 2018; Yang, Zhu, and Zhao 2022). Traditional ground-based phenology monitoring is limited in space and is labour-intensive. In contrast, satellite remote sensing can effectively provide high-resolution and large-scale synchronous observations, facilitating the study of the spatiotemporal distribution of plant species and phenology across the heterogeneous urban landscape (Devadas et al. 2018; Li et al. 2017; Li et al. 2019; Li et al. 2022).

In addition to spaceborne sensors, tower-mounted high-resolution timelapse digital cameras (also known as PhenoCams) can acquire very detailed plant growth and phenology information (Brown et al. 2016; Cui et al. 2019; Klosterman et al. 2014; Richardson et al. 2018). These cameras are installed close to the Earth surface, enabling them to provide high-frequency imagery and remain relatively unaffected by clouds and aerosols (Tran et al. 2022; Zhang et al. 2018). PhenoCams capture plant growth and continuously record key phenological events, including leaf unfolding, flower blooming, and fruit ripening, thereby revealing plants' responses to seasonal and inter-annual environmental changes (Liu 2021) (Figure 2). Furthermore, by utilizing advanced imaging sensors, PhenoCams offer a remarkable opportunity for analyzing spatial heterogeneity, producing digital images of land cover scenes with sufficient temporal and spatial details (Baumann et al. 2017; Ma et al. 2022). Therefore, in highly heterogeneous urban spaces, PhenoCams serve as an innovative and valuable tool for investigating phenological disparities among various plant species, which are associated with different pollen types, and further revealing the spatial distribution of potential pollen sources in the urban landscape (Zhang et al. 2018).

2.4. Geospatial big data

Geospatial big data encompasses two main categories based on the types of sensors used and the objects recorded: big Earth observation data and big human behavior data (Pei et al. 2020). Here 'big' highlights the large volume compared to traditional statistical or survey data, and 'geospatial' means that all data are geospatially registered with accurate geographic coordinates and time/date information. This characteristic makes them ready for further integrated analysis with other geospatial data in a GIS system (Chen et al. 2016; Yang et al. 2017). In this section, we focus solely on the latter. Human behavior data are records of various human activities, such as movement patterns, social interactions, and consumption behaviors, primarily obtained through smart devices, social

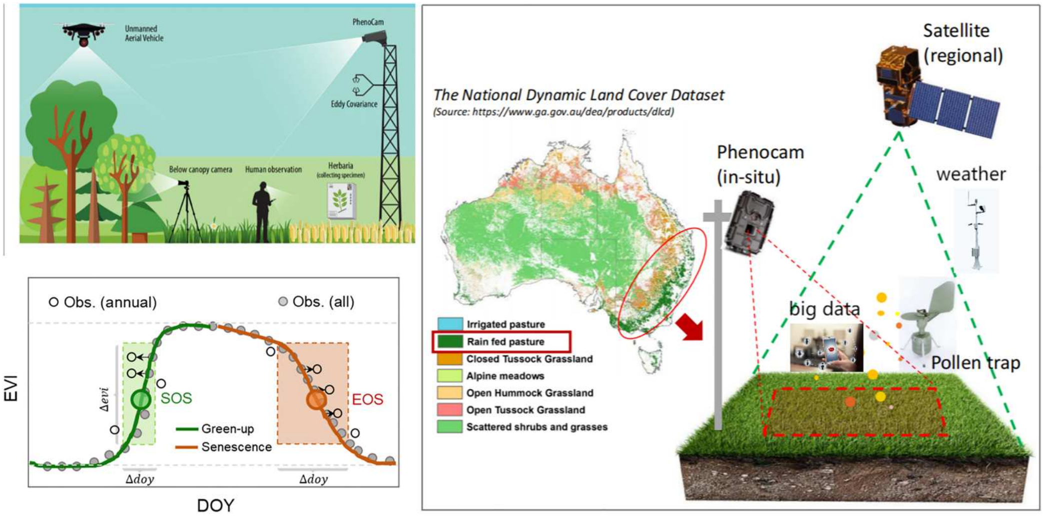

Figure 2. Multi-scale remote sensing monitoring of plant species distribution and phenology. A(upper left): Near-surface, UAV, and satellite-based remote sensing, source: Katal et al. (2022); B(lower left): EVI (Enhanced Vegetation Index, a remote sensing measure of vegetation greenness) time series depicting vegetation growth and phenology, source: Li et al. (2019); C(right): integrated use of a pollen trap, PhenoCam, meteorological station, and satellite to achieve multi-scale and multi-metrics monitoring of grass pollen dynamics in southeast Australia.

media platforms, and navigation systems. The applications of human behavior data are wide-ranging, ranging from disease epidemiology research, health services, environmental exposure assessment, and studies on human mental health (Gruebner et al. 2017; Pei et al. 2020; Wang et al. 2022).

In recent years, search engines like Google, Bing, and Baidu, as well as social media platforms such as Twitter, Facebook, Instagram, and Weibo, have become significant sources of public medical information (Andreu-Perez et al. 2015; Jing et al. 2023). In the context of pollen allergies, studies have found that a considerable number of affected individuals turn to the Internet to search for symptoms and medical advice (Bousquet et al. 2019; Straumann et al. 2010). As traditional pollen monitoring stations are limited to certain locations within specific cities (Huete et al. 2019), scientists are exploring the potential of supplementing pollen data for regions without in situ pollen monitoring by using Google Trends or the Baidu Index, which are services that can analyze the popularity of top search queries (Andreu-Perez et al. 2015; Hall et al. 2020; Navares and Luis Aznarte 2019).

Geospatial big data, such as those from Google Trends, offer valuable insights into the dynamics of the pollen season of targeted areas, aiding in pollen concentration forecasting and supporting public health initiatives related to pollen allergies (Bastl et al. 2014; Karatzas et al. 2014). Studies have found a positive association between the frequency of Google searches for terms like 'hay fever', 'allergies', and 'runny nose' and local pollen concentrations. However, different countries have different understandings and search methods for allergy terms, which may have an impact on the statistical results (Bousquet et al. 2017; Kang et al. 2015) (Figure 3). Therefore, when incorporating geospatial big data, such as Google Trends, to assist in predicting pollen concentrations, it is critical to take factors like geographical location, cultural diversity, and the seasonal characteristics of pollen into consideration (Bousquet et al. 2019; Kaidashev et al. 2019).

Despite the promising potential of utilizing new geospatial big data for pollen concentration forecasting, there are important cautions associated with these data sources. Firstly, obtaining the precise geolocation of allergic individuals is often challenging due to technical constraints and privacy considerations (Leyens et al. 2017). Secondly, internet and social media usage may not be evenly distributed among countries, regions, and age groups, leading to potential biases

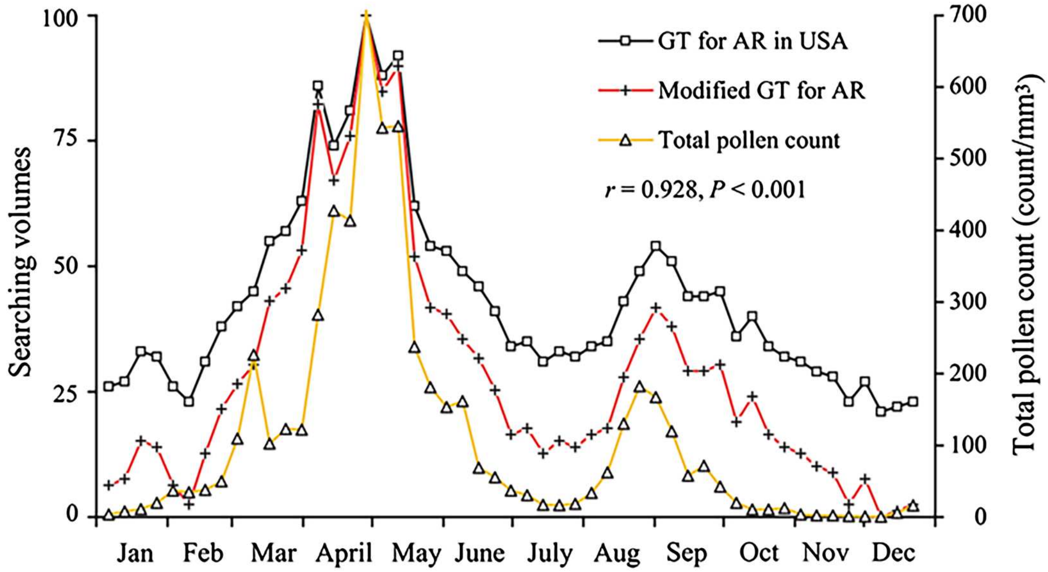

Figure 3. Correlation between Google Trends (GT) outcomes for Allergic Rhinitis (AR) and real-world epidemiological data ($r = 0.928$, $P < 0.001$). Source: Kang et al. (2015).

Table 1. Summary of data sources used in forecasting pollen concentrations and their limitations.

Data	Usage	Limitations	References
Aerobiological data	Calibration and validation of pollen forecasting models	Long-range transmission events, where the collected pollen data are not representative of the actual concentration at the site;	Scheifinger et al. (2013), Oteros et al. (2019)
Biometeorological data	Model input data; investigate relationship between climate change and pollen season	the same meteorological factor has different effects on the spread of pollen release;	Tseng et al. (2018), Bogawski, Grewling, and Jackowiak (2019)
Phenology index	Flowering-related phenological information as model input	Highly accurate weather information is difficult to obtain; especially in heterogenous urban heat/light environment.	Huete et al. (2019), Li et al. (2019)
Geospatial big data	Supplement pollen count data; Provide direct human physical and mental reactions to pollen allergy.	Correlated with the frequency of Internet use and search terms; There is no uniform data clearance and standardization protocols;	Kaidashev et al. (2019), Hall et al. (2020)

in incidence reports. Lastly, the choice of keywords used to identify relevant social media feeds and searches can significantly impact the accuracy of data analysis (Gesualdo et al. 2015). Given these limitations, further research is necessary to fully explore the potential of geospatial big data in forecasting airborne pollen concentrations while explicitly considering the aforementioned constraints (Table 1).

3. What models can we use to predict pollen concentration?

3.1. Empirical models

Empirical models correlate pollen concentration with one or more independent variables (e.g. meteorological and phenological factors). These models identify the predictors that have a significant impact on pollen concentration and use established correlations to make predictions. Commonly employed methods for constructing empirical models encompass general statistical

Table 2. Summary of empirical pollen forecasting models, their applicability and limitations. Explanations of the abbreviations are provided below the table.

	Methods	Input	Output	Applicability	Limitations	References
General statistical analysis	Calendar model	Past pollen concentrations; Past phenology observations	Trend and duration of future pollen season	Routine seasonal forecasting	Over-reliance on authentic pollen records; Not sensitive to climate change	Jae-Won et al. (2012), Calderón-Ezquerro et al. (2016)
	Regression analysis; GAM	Past pollen concentrations; Past phenology observations; Meteorological parameters	Shape and duration of future pollen season	Seasonal forecasting when there is strong interannual meteorological variability	Multiple regression relationship is complex	Novara et al. (2016), Charalampopoulos et al. (2018)
Time- series analysis	ARMA (S/ARIMA) STL	Past pollen concentrations; Seasonal characteristics	Future airborne concentrations of pollen	Pollen forecasting for specific studies where the timescale is important	Pollen concentration is a non-stationary sequence	García-Mozo et al. (2014), Scheifinger et al. (2013)
Machine Learning	ANN; RF; SVM;	Past pollen concentration; Past phenology observations; Meteorological parameters and thresholds		Complex modeling among factors associated with pollen concentration	A large amount of sample data is required; feature selection has a great impact on the model	Zewdie et al. (2019a), Huete et al. (2019)
Stochastic approach	HMM	Past pollen concentration; Vegetation phenology; Meteorological parameters;	Future SPIn	Seasonal forecasting when pollen concentrations are influenced by stochastic variations	Current state relies only on the previous; Interruption of the cycle is not considered;	Tseng et al. (2020)

Abbreviations: GAM (Generalized Additive Model), ARMA (Autoregressive Moving Average), ARIMA (Autoregressive Integrated Moving Average), SARIMA (seasonal Autoregressive Integrated Moving Average), STL (Seasonal-Trend decomposition using LOESS), ANN (Artificial Neural Network), RF (Random Forest), SVM (Support Vector Machine), HMM (Hidden Markov Model), SPIn (Seasonal Pollen Index).

analysis, time series analysis, machine learning, and stochastic approaches (Astray et al. 2016; Bonini et al. 2015; Suanno et al. 2021). Table 2 summarizes the various empirical models. The basic concept and latest progress related to each model type is discussed in the following section.

3.1.1. General statistical analysis

The **Calendar model** identifies the potential timing of pollen outbreaks in a given year by analyzing pollen season characteristics and aerobiological data. It typically presents the concentration and duration of various airborne allergenic pollens through visual graphics (e.g. Figure 4). The pollen calendar holds clinical utility in managing allergies by allowing patients to adjust their travel plans and aiding hospitals to proactively allocate medical resources. However, the limitation of the calendar model is that it primarily relies on historical observations of pollen concentration and does not fully account for the potential impacts of year-to-year climate variability, land use changes, and other factors that can affect the pollen season. To address this limitation and accommodate changes in flowering time caused by climate change, the pollen calendar requires regular evaluation and updates.

The standard calendar model is typically based on historical records to estimate pollen levels for a specific area. This approach involves averaging or taking the median of past pollen concentrations for the same dates in previous years (Šikoparija et al. 2018). While this approach smooths out short-term seasonal variations in pollen concentration, it conceals daily fluctuations in pollen concentration, limiting its usefulness for allergy sufferers to manage their symptoms effectively.

Recently, improved calendar models have been developed to employ pre-processed signals obtained through moving averages or moving medians. By utilizing sliding window smoothing techniques, the improved calendar model predicts the pollen concentration for a specific day by averaging or taking the median of the pollen concentrations from surrounding days (Martínez-Bracero et al. 2015; Picornell et al. 2019; Shin et al. 2020). Moving averages can attenuate the impact of large fluctuations in pollen concentration and hence have the potential to capture the daily

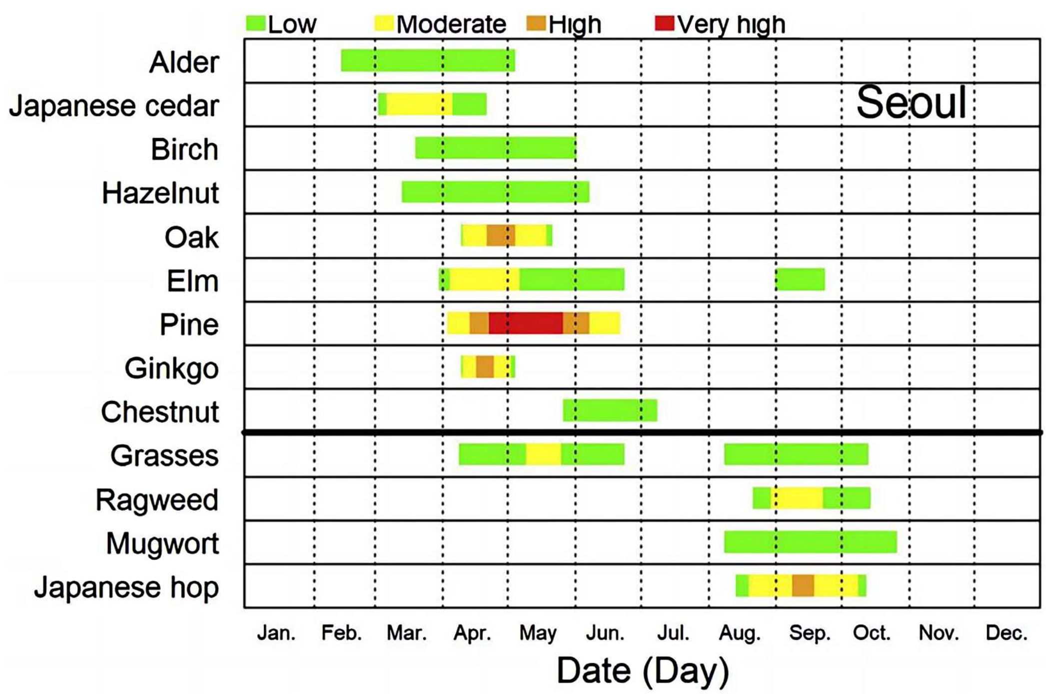

Figure 4. Pollen calendar for Seoul, South Korea. Source: Kim, Han, and Oh (2021).

variations in pollen concentration more accurately than traditional models, providing better flexibility to allergy sufferers or hospitals.

A regression analysis establishes the relationship between past pollen concentrations and one or more meteorological factors and predicts future pollen concentrations based on meteorological forecast. Several methods are commonly used in regression analysis, such as stepwise or backward elimination in multiple regression, which systematically eliminates less influential factors from the model and retains the most significant ones (Murray and Galán 2016; Myszkowska and Majewska 2014). Logistic regression is another valuable technique that assesses the impact of each feature on pollen concentrations, offering strong interpretability and straightforward calculations (Katz and Batterman 2019; Myszkowska and Majewska 2014). Partial least squares regression proves beneficial for limited pollen concentration data and multicollinearity among predictive variables, particularly in small sample sizes (Bogawski, Grewling, and Jackowiak 2019; Oteros et al. 2014). Furthermore, generalized linear models, an extension of the regression family, provide a conceptual modeling framework that allows for the incorporation of nonlinear functions of explanatory variables (Devadas et al. 2018; Ravindra et al. 2019).

3.1.2. Time-series analysis

The **Auto-Regressive Moving Average** model is a technique utilized by aerobiologists to identify patterns in time series data and predict the future behavior of the dependent variable, such as pollen concentration (Sánchez et al. 2007). The widely used ARMA method, known as Box–Jenkins, accounts for long-term trends, seasonality, uncertainty, and random disturbances in time series data. The underlying principle involves treating the pollen concentration time series as a random process and employing a mathematical model to describe or simulate it. Once the model is determined, past or present pollen concentration time series can be leveraged to predict future pollen concentrations (RodrÍguez-Rajo et al. 2006; Sánchez et al. 2007).

In comparison to general statistical models, the ARMA model can provide more accurate predictions by considering nonlinear temporal changes in pollen concentrations and incorporating time-varying information (García-Mozo et al. 2014). However, the ARMA model assumes that the time series of independent variables remains stationary and that the structure or development pattern of the time series remains constant over time, both in the past and future. As a result, it is recommended to continually recalibrate the original fitted model with new observations should the model be applied for future use cases.

Seasonal-Trend decomposition by Loess (STL) is a method for decomposing a time series into three components: trend, seasonality, and remainder (residuals). Specifically, STL effectively extracts seasonal and trend features from the original pollen concentration time series data (Rojo et al. 2017). The technique boasts several advantages, including its simplicity and computational efficiency, robustness in yielding reliable results, and the flexibility to handle varying seasonal components. While widely used in the natural sciences, STL has recently gained popularity in aerobiological research (Aguilera et al. 2015; García-Mozo 2017; García-Mozo et al. 2014). STL methods offer distinct advantages when it comes to detecting and understanding long-term trends in pollen seasons. However, it assumes that the trend is linear, which may ignore the impact of nonlinear factors (e.g. urbanization and population increase) on the trend decomposition (Lara et al. 2019).

3.1.3. Machine learning

Artificial Neural Network (ANN) is a powerful tool capable of learning and capturing nonlinear relationships from complex, noisy, and incomplete data. By iteratively processing input variables, such as weather and environmental factors, along with output data on pollen concentrations, ANN significantly enhances the predictability of the trained network (Astray et al. 2016; Zewdie et al. 2019b). Additionally, ANN can be integrated with the fuzzy rule-based systems to form a neuro-fuzzy model, which exhibits higher prediction accuracy, particularly when the pollen concentration exceeds 50 grains/m^3 (Sánchez et al. 2007). In addition, the Multilayer Perceptron

(MLP) stands out as an advanced approach for forecasting pollen concentration. When there is a long sequence of pollen concentration dataset and the data variability is small, the prediction results of the MLP model tend to be more accurate (Csépe et al. 2020).

Other machine learning methods, such as random forest and support vector machines, have also been applied in forecasting pollen concentrations (Bogawski, Grewling, and Jackowiak 2019; Navares and Luis Aznarte 2017; Nowosad et al. 2018; Zewdie et al. 2019a; Zewdie et al. 2019b). Although machine learning performs better at predicting multivariate and nonlinear data, model performance depends heavily on the quality of the training data. Overfitting occurs when training becomes more rigorous and this issue is often addressed through cross-validation (Am Seo et al. 2020). In addition, there is a need to develop models that take into account long-term vegetation changes and regional and annual variations in pollen production (Daood, Ribeiro, and Bush 2016). Therefore, different machine learning methods should be compared to identify the best-performing model for specific uses.

3.1.4. Stochastic methods

The **Hidden Markov Model (HMM)** offers a valuable approach for unraveling the intricacies of plant flowering. A Markov process, also known as a Markov chain, is a probabilistic model that describes a sequence of events. In this model, the likelihood of transitioning from one state to another relies solely on the current state. In the context of plant flowering, these states could represent various growth stages or the essential environmental conditions required for flowering.

By employing HMM to model flowering dates, we can predict the probabilities of transitioning between different flowering states. HMM incorporates observable variables (e.g. flowering stages) and hidden variables (e.g. environmental factors influencing flowering). By incorporating relevant environmental factors such as temperature, humidity, soil moisture, and day length within the HMM, a more comprehensive model for predicting the flowering date outcome can be established. For example, Tseng et al. (2020) applied stochastic models to pollen forecasting using 22 years of data from Hokkaido, Japan. The proposed model achieved accuracies of 83.3% in the training period and 75.0% in the validation period. The model was specified by a transition matrix where the observed sequence was linked to the meteorological conditions of the previous summer, governed by an implicit state with an emission distribution (Tseng et al. 2020).

The primary advantage of using an HMM is to predict how likely it is for a plant to move from one flowering stage to another. For instance, given certain conditions, how likely is it for a plant in the 'budding' state to move to the 'early flowering' state? However, HMM is based on the Markov assumption, which implies that the next state is only dependent on the previous state and independent of earlier or future states. In pollen concentration prediction, however, future pollen concentration levels may be influenced by multiple past states, not just the immediate previous state. Additionally, challenges arise from the two-year periodic interruption of the Markov property (Tseng et al. 2018).

3.2. Process models

Process models for forecasting airborne pollen concentration can be broadly categorized into Phenology Model (PHM) and Dispersion Model (DPM). These models rely on plausible biological and physical mechanisms to understand the relationship between airborne pollen concentration and biotic and abiotic factors. Table 3 summarizes the various process models, which will be reviewed in more detail in the following section.

3.2.1. Phenology model

The **Phenology Model (PHM)** is based on the assumption that the pollen season aligns with the flowering period and is used to predict the onset, peak, and end of the pollen season (Linkosalo et al. 2010; Scheifinger et al. 2013). The fundamental factors controlling the seasonal development

Table 3. Summary of the major features of the process-based pollen prediction models.

	Types	Methods	Assumption	Applicability	Limitation	References
Phenology Model (PHM)	Forcing and chilling temperature	Sequential, Parallel, Alternating, Deepening Rest	Pollen season start is defined by a combination of chilling and forcing units;	Prediction of flowering season characteristics; More targeted pollen forecasts	Long-distance transport of pollen introduces errors; Complexity of Biological Responses	Rodríguez-Rajo et al. (2009), Scheifinger et al. (2013), Linkosalo et al. (2010), Picornell et al. (2019)
	Photoperiod and water availability	–	Photoperiod defines the start date of temperature accumulation; Flowering season is determined by the weather.			
	Generalised phenological model	Unified model	Plant responses to combinations of environmental factors can be simulated by models			
	Numerical model	Statistic	Pollen dispersion is modelled from the relation between pollen concentrations and meteorology	More useful as a sub-model of a complex model	High-resolution simulations can be computationally intensive	Helbig et al. (2004), Scheifinger et al. (2013)
Dispersion Model (DPM)	Mechanistic model	Eulerian (COSMO-ART; KAMM/DRAIS/ MADEsoot; SILAM Eulerian)	Analysis method: Pollen is modeled as a continuum and its future concentration at a point in a fixed grid is calculated based on the advection diffusion equation	Assessment of pollen dispersion	Inaccurate representation of turbulence dispersion in complex terrain	Schueler & Schlünzen, (2006), Sofiev et al. (2015)
		Lagrangian (CALMET/ CALPU; SILAM SMOP-2D)	Simulation method: pollen diffusion by simulating the trajectory of a single particle	Handle the intricacies of complex terrains and atmospheric conditions	Difficulty in simplifying biological information, and high computational costs	Hidalgo et al. (2002). Sofiev et al. (2013, 2006), Müller-Germann et al. (2017)

of plants encompass chilling temperature, forced temperature, photoperiod, and water availability (Migliavacca et al. 2012; Siniscalco et al. 2015). In temperate trees, low temperature (breaking bud dormancy) and forced temperature (stimulating bud development) are believed to drive flowering, while the pollen seasons of herbaceous taxa and tropical and Mediterranean trees are often associated with precipitation and photoperiod.

Andersen (1991) was among the pioneers who applied PHM to aerobiological studies, using 'cooling units' and 'hours of growth length' to predict the onset of pollen seasons for Danish alder, elm, and birch. Siniscalco et al. (2015) evaluated the performance of several temperature-based phenology models in predicting the pollen season onset in a densely populated urban area (Turin, Italy) using airborne pollen records collected between 1983 and 2009. However, uncontrollable and quantifiable uncertainties associated with phenology models arise from model drivers, primarily caused by unpredictable changes in future climate (Suanno et al. 2021). In addition, PHM lacks consideration of long-distance pollen transport, which may lead to time discrepancies between phenological events in source areas and pollen outbreaks in sink areas (Scheifinger et al. 2013).

Numerical models employs regression equations to simulate pollen dispersal by establishing correlations between weather conditions and the amount of pollen released into the atmosphere. These models provide future predictions of airborne pollen concentration for specific locations (Helbig et al. 2004; Scheifinger et al. 2013). The approach was initially introduced by Kawashima and Takahashi (1999), who calculated potential pollen release based on correlations with hourly air temperature, wind speed, and estimated male flower counts derived from summer temperature changes (Kawashima and Takahashi 1999). Subsequently, the model was enhanced by incorporating the biological characteristics of pollen-producing plants.

3.2.2. Dispersion models

Pollen dispersal is facilitated by air mass motion and turbulence, hindered by gravity (dry deposition) and precipitation (wet deposition), and influenced by the chemo-physical changes that occur in the pollen during its journey. Although about 90% of wind-borne pollen grains fall within a relatively short distance range of 100 to 2700 m from their source, the remaining 10% may become entrained into the atmospheric turbulence layer, spreading hundreds to thousands of kilometres (Green et al. 2018; Sofiev et al. 2006).

Dispersion models employ mathematical formulations of atmospheric transport and dispersion to calculate concentrations at various distances from known sources (Cai et al. 2019; Skjøth et al. 2009). By considering environmental factors and pollen characteristics such as shape, density, and size, dispersion models describe the dynamics of atmospheric pollen distribution and can effectively map distant pollen sources (Sofiev et al. 2006; Zink et al. 2012).

A **mechanistic model** requires very comprehensive inputs, including source plant distribution maps, pollen emission sub-models, past pollen season characteristics, detailed topographic information, and weather forecasts (Sofiev and Bergmann 2012). These models are derived from the principles of atmospheric physics that describe the motion of particles in the air, and they consider factors such as gravity, wind speed, and turbulence to simulate pollen dynamics based on concurrent environmental conditions. Mechanistic models are based on the advection–diffusion equation, which can accurately describe the non-inertial motion of pollen (Sofiev et al. 2006).

There are two main approaches used in mechanistic models: the Eulerian method and the Lagrangian method. In the Eulerian method, particles in the air are considered as a continuum and modeled as a concentration field on a fixed grid in space and time (Jia et al. 2021; Nguyen et al. 1997). In contrast, the Lagrangian method treats particles in the air as discrete phases and models their independent paths in continuous space by deforming the grid coordinates.

The Eulerian model, often adapted from existing mesoscale models of air pollution dispersion and combined with meteorological models, forecasts pollen concentrations in specific regions (Sofiev et al. 2015). The Lagrangian Stochastic (LS) turbulence model, such as the SMOP-2D model, simulates the paths of individual pollen grains from release to deposition. The LS model is particularly useful for long-distance pollen dispersion and can provide more accurate estimates of observed pollen concentrations compared to some classical Eulerian models (Müller-Germann et al. 2017)(Müller-Germann et al. 2017). However, terrain complexity in the study area can pose challenges for modeling particle trajectories (Sofiev et al. 2015; Sofiev and Bergmann 2012).

4. What are the existing challenges and future perspectives?

Over the years, the forecast of urban allergenic pollen has seen significant progress in monitoring methods, data sources, and model complexities. However, several prominent challenges still persist.

First, the availability of pollen monitoring stations remains critically insufficient, and the data from different stations often lack standardization in terms of data structure and recorded information. As a result, researchers and users often face the burdensome task of data pre-processing and clearance.

Second, obtaining high-precision plant species distribution and phenological period information is challenging due to the limited spatio-temporal resolution of satellite remote sensing data and a lack of georeferenced plant distribution information. In many cases, researchers resort to using coarse land cover or vegetation-type maps, which may lead to artificial boundaries among vegetation classes and unrealistic homogeneity within classes.

Third, the development and calibration of pollen forecast models are often localized, making it difficult to apply them to different geographical locations. There is a significant lack of critical knowledge about which types of models are most suitable for specific landscapes, population density, climate backgrounds, and biological sources of pollen grains.

Last but not least, a disconnect between scientific research and practical application hinders the timely and accurate dissemination of forecast information on allergenic pollen concentration to the public. Given the considerable financial burden associated with treating pollen allergies, it is surprising to observe a relatively limited amount of Research & Development investment into the building of a reliable allergenic pollen forecasting capability.

In light of the challenges listed above, here we suggest several key perspectives that future studies should focus on.

(1) **Designing consistent pollen data sampling and processing protocols.** It is essential to ensure that data from different locations and times can be utilized in a consistent manner for model calibration and validation. This becomes particularly crucial in rapid urbanizing areas where in situ data from surrounding cities or suburbs may need to be incorporated to achieve reliable forecasting. The lack of comparability in pollen concentration results obtained from different locations can impede large-scale pollen transport modelling research. By implementing standardized approaches for pollen data sampling and processing, the availability of data from existing pollen monitoring stations can be improved (Bastl et al. 2023). In addition, providing accurate and detailed metadata on site characteristics, data continuity, collection procedures, and counting processes is crucial to enable the use of pollen records in concentration prediction studies (Buters et al. 2018). Learning from the ongoing development of regional pollen monitoring networks, such as the AusPollen network, can establish good practices that could be adopted by other regions (Davies et al. 2022).
(2) **Accurate urban spatial species distribution information.** High-resolution species classification plays a vital role in predicting potential pollen allergens and planning healthy urban environments. Cities are known for their high plant species richness compared to rural areas (Knapp et al. 2008), making it essential to have precise distribution patterns of species within urban spaces. This information can be gathered through field surveys or high-resolution airborne or satellite remote sensing imagery (Bohovic, Dobrovolny, and Klein 2016; Davies et al. 2022). Utilizing remote sensing data such as from the PlanetScope constellation

(~3 m) and GF-1/6 (<10 m) can provide daily and seamless multi-spectral observations with high spatial resolution. When combined with field surveys and machine learning algorithms, these satellite data offer an excellent opportunity to generate and update species distribution maps within urban areas and the suburbs.

(3) **Timely plant phenology information.** Having timely and accurate plant phenology information is highly valuable for predicting the onset of flowering seasons, especially considering the altering flowering patterns of various plant species in temperate regions under climate change (García-Mozo 2017; Hájková et al. 2023). It is now possible to integrate satellite remote sensing and in situ PhenoCams to resolve highly heterogeneous urban phenology. Advances in satellite remote sensing, such as the use of micro-nano-satellites constellations allow for improved spatial coverage and temporal–spatial resolution through multi-satellite coordinated observation. A recent study by Miura et al. (2023) demonstrated the effectiveness of utilizing PlanetScope satellites to obtain high temporal and spatial precision data (daily at ~3 m) in a dipterocarp rainforest in Malaysia (Miura et al. 2023). The researchers focused on selected tree species, analyzing their flowering phenology and comparing the results with in situ PhenoCam observations. The multitemporal PlanetScope images captured the transition of tree species' flowering crowns into white or orange, enabling the identification of flowering peaks and species differences. The study found a moderate to very strong correlation (0.52–0.85) between the multitemporal image signatures and in situ phenology observations. By leveraging these emerging new data sources, we can enhance our pollen concentration prediction accuracy and deepen our understanding of pollen sources and dynamics in urban environments.

(4) **Availability of early warning information for allergy sufferers and medical institutions.** In recent years, some countries have established networks catering to individuals with pollen allergies. These networks are dedicated to providing daily pollen counts and forecasts with varying temporal and spatial resolutions (Geller-Bernstein and Portnoy 2019; Jones et al. 2021; Kmenta et al. 2016). For example, in the USA, 'The Weather Channel' offers forecasts of pollen concentrations and respiratory comfort in specific cities up to 7 days in advance. In Australia, the AusPollen project aims to provide accurate, relevant, and localized information on airborne pollen concentration levels to allergy and asthma patients. Similarly, in China, the Beijing Meteorological Bureau and Beijing Tongren Hospital have collaborated to release daily pollen concentration data for allergenic pollens in Beijing since 2010, providing forecasts for the upcoming 7 days. These initiatives are invaluable in equipping individuals with pollen allergies to proactively manage their condition and make informed decisions based on real-time and predictive pollen concentration information. As such, expanding the present forecast services to a broader geographic area would not only reduce economic costs but also truly benefit the public (Medek et al. 2019).

5. Conclusion

Allergenic pollen poses a serious threat to human health and well-being. To enhance the accuracy of airborne allergenic pollen concentration prediction, it is urgent to take comprehensive and immediate actions. This entails integrating diverse remote sensing satellite data, acquiring precise vegetation dynamic parameters, and obtaining accurate species spatial distribution. In addition, advancements in Internet technology and geospatial big data can further complement pollen concentration and human behaviors data. Finally, emerging technologies such as machine learning and artificial intelligence can be used to integrate the complex processes of pollen production and dissemination, effectively improving the accuracy of pollen concentration and seasonal predictions. However, especially in densely populated urban areas, factors such as high spatial heterogeneity, heat island effects, land use, and human activities have a significant impact on pollen release and dispersion. The discontinuity of monitoring sites further limits the accuracy of prediction models, warranting increased future R&D investment. Our review highlights the importance of the commitment to transforming scientific research findings into practical applications to ensure that science and technology effectively contribute to the improvement of human well-being. Accurate predictions of pollen concentrations not only enable allergic individuals to increase prevention awareness and manage their symptoms but also help local governments in better allocating medical resources and conducting public health management. Finally, this provides decision-making support for sustainable urban planning and development, improving the quality of life of urban residents.

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Data availability statement

Data sharing is not applicable to this article as no data sets were generated or analyzed during the current study.

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