

Forecast for Pollen Allergy

A Review from Field Observation to Modeling and Services in Korea



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KEYWORDS

• Pollen • Observation • Calendar • Forecast • Allergy risks • Climate change

KEY POINTS

- Daily pollen monitoring helps understanding regional differences and long-term changes in pollen allergy risks.
- Pollen risks forecasts of 2 to 3 days are possible using daily forecasts and the relationship between daily pollen concentration and weather conditions.
- Increasing temperature and CO₂ concentration during the climate change will elevate the risks by the pollen allergy in the future.

INTRODUCTION

It is well established that the severity of allergic symptoms is related to airborne pollen concentration.^{1–8} Forecast services for pollen-related allergy risk are provided in many countries.^{9–12} The basic data and models of such services are pollen observation and modeling.^{13–29} The Korea Meteorological Administration (KMA) operates a daily pollen-monitoring network, develops forecast models, and provides daily pollen forecast.^{30–32} The major efforts exerted during the last 20+ years for pollen forecast in Korea are summarized in this review to provide the readers with insight on forecast systems and their critical components of observation, modeling, and service.

OBSERVATION

For the prediction of allergy risks by pollen, pollen concentration has long been observed at many places worldwide. The KMA along with the Korean Academy of

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Pediatric Allergy and Respiratory Disease (KAPARD) established the national pollen observational network in Korea in 1997. As of 2020, the network is composed of 12 stations with Burkard traps. Using 7-day recording drums and an optical microscope, daily pollen concentrations of all species are collected, identified, and counted in each site, every week (Fig. 1).³³

- Pros: It constitutes real observational data, on which both model development and validation are based. In other words, all diagnostic and forecasting models are basically developed using these data.
- Cons: The entire process needs much effort and takes a long time from observation to identification resulting in at least 7 days, or more, delay. It is a site-specific observation and cannot fully represent the spatial distribution of pollen species and counts.

POLLEN CALENDAR

Pollen season, a specific time period with many region-specific pollen grains in the air, is a yearly phenomenon. Pollen calendar, which indicates the region, period, and species of abundant pollen, is developed based on this recurrence.

The methods can be simply temporal averaging or statistical derivation from a probability density function.

The first pollen calendar in Korea was developed in 2004 using observational data gathered from 1997 to 2002. It presented national average pollen seasons of 21 species.³⁴ After 10 years of observation, regional pollen characteristics were analyzed. Moreover, revised pollen calendars were developed.^{34,35} The pollen calendar shows major pollen species and region seasons. Although pollen species in Korea are largely similar around the country, there are regional differences both in representative species and their peak concentrations. The 3 data points of each month are selected out of 10-day running averages from 6 observational stations (Seoul, Busan, Daegu, Gwangju, Gangneung, and Jeju). Several key points are identified from the calendar.

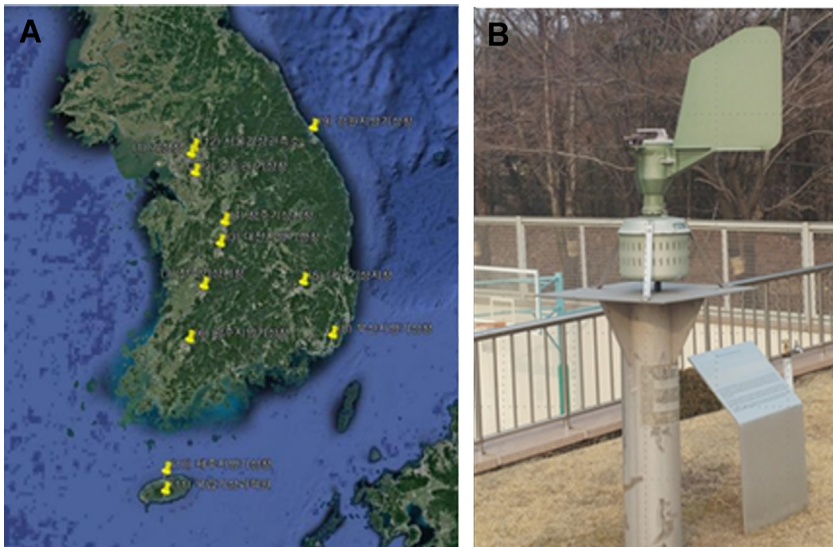


Fig. 1. (A) Pollen observation network in Korea and (B) Burkard pollen trap. (From Google Maps. Available at: <https://www.google.com/maps/> Accessed: 2020; with permission.)

Pine is the most abundant species at most stations; although, it presents low allergenicity. Japanese cedar is the most abundant species in Jeju. Warmer southern stations have earlier pollen seasons than northern ones. The pollen species with high allergenicity and large extent are oak and Japanese hop. In the pollen calendar, warning levels of pollen allergenicity are standardized for trees, grasses, and weeds. Its impacts on Korean patients could have been inconsistent, because the levels were adapted from the US standard³⁶ without a rigorous statistical analysis.

As the observation continues after the development of the pollen calendar based on the first 10 years of observation, there are accumulated changes in vegetation distribution and land use as well as regional climate. The pollen calendar must reflect these changes using the newly observed data. In addition to the original 6 stations, 2 more were added (Jeonju and Daejeon) to fully use all data gathered from 2007 to 2017. The daily mean of observed data during the 11 years were smoothed using probability density functions, which were fitted using Julian day as X (independent variable) and pollen concentration as Y (dependent variable) for individual species and stations. The risk benchmarks according to pollen concentration were also determined using the fitted probability distribution for each pollen species. Consistent benchmarks are needed due to the necessity of magnitude comparison regarding the concentrations across the nation despite its high spatial variability. The highest magnitudes among the studied stations in South Korea were considered the benchmark concentrations for each pollen species. The 4 levels in the benchmarks are defined as low (0%–50%), moderate (51%–75%), high (76%–87.5%), and very high (87.6%–100%) in **Table 1**. The actual risk level values were determined from the cumulative distribution curves of the fitted distribution. The periods of yearly cumulative pollen, less than 2.5% or more than 97.5%, were removed from the calendar to prevent unnecessary lengthening of the pollen season. In this way, the pollen risk information for each city was consistently developed and delivered. The revised calendar shows regional risks more clearly with continuous pollen periods in contrast to the older version.³⁷ It only has one benchmark for a pollen species so that one can compare pollen risks

Table 1**Benchmarks of pollen concentration levels used in the pollen calendar of Korean cities**

Allergenic Pollens	Concentration Levels			
	Low	Moderate	High	Very High
Alder	0–6	7–27	28–60	≥61
Japanese cedar	0–12	13–54	55–127	≥128
Birch	0–6	7–15	16–27	≥28
Hazelnut	0–3	4–9	10–15	≥16
Oak	0–14	15–56	57–133	≥134
Elm	0–5	6–15	16–30	≥31
Pine	0–6	7–33	34–86	≥87
Ginkgo	0–16	17–67	68–152	≥153
Chestnut	0–5	6–17	18–33	≥34
Grass	0–2	3–4	5–6	≥7
Ragweed	0–3	4–9	10–16	≥17
Mug wort	0–6	7–15	16–27	≥28
Japanese hop	0–9	10–29	30–62	≥63

Unit is grain/m³.

among the cities as well as reversely find his/her hazardous cities and periods based on the personal symptom history (Fig. 2).

- Pros: It can be used as a preliminary predictor for pollen risks.
- Cons: It is an average over certain past dates (up to 2 decades) so daily changing weather is not of concern. A calendar developed for a region represents the specific region where the data were collected, having the spatial distribution not readily presented.

FORECAST MODEL

Daily pollen concentration is highly dependent on weather conditions such as air temperature, relative humidity, solar radiation, and precipitation. Diagnostic models, developed from the observed data, can predict daily pollen concentration using the daily weather forecast (Box 1).

Regional Regression Model

Regional pollen risk forecast using regression models is performed in 3 steps as in Box 1.³⁰ KMA developed monthly pollen concentration models and provided trees/weeds pollen risks in spring (April and May)/autumn (September and October) (Fig. 3A). Selected weather variables are daily air temperature, temperature range, relative humidity, wind speed, precipitation hours, total precipitation, and 7-day accumulated sunshine hours. Using the pollen concentration, estimated from the regression models, risk grade was determined and daily risk levels were provided. Evaluation during the 2010 to 2011 period over the 6 regions showed an accuracy range from 31% to 100% (mean: 57.4%).

- Pros: The pollen risk forecast reflects daily weather conditions by assimilating output from the operational numerical weather forecasts.
- Cons: Models are developed for individual observational sites so that regional distribution and differences are not considered.

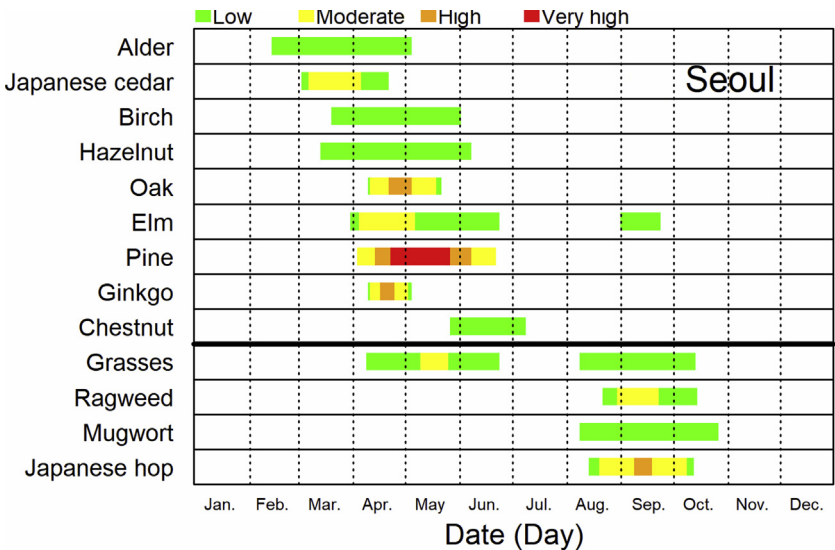


Fig. 2. Pollen calendar for Seoul, Korea, based on the updated observations in 2020.

Box 1**Procedures of the development of the pollen risk forecast model using regression analysis**

- ① Find weather variables that affect pollen variability.
- ② Develop regression models for pollen concentration using the weather variables.
- ③ Estimate pollen concentration from the model and determine the pollen risk based on the concentration.

Probability-Regression Model

This is a unified model based on the analysis of probability distribution.³¹ Simple regression models were developed from the data of individual sites and were able to predict specific sites. For the development of a nationwide service for pollen risks, it is needed to develop a unified model for pollen prediction that explains the weather conditions, which is commonly observed during the pollen outbreak. The find weather variables step ①-1 of **Box 2** is followed by 2 additional sub-steps: ①-2 fitting the histogram of pollen concentration by weather conditions to Weibull probability density function (PDF) and ①-3 calculating the daily probability of pollen appearance. The daily probability is then assimilated into the ② regression modeling and ③ risk estimation (see **Box 2**).

The PDF-regression model was developed using the daily weather variables (air temperature, degree-days, daily temperature range, relative humidity, wind speed, 7-day accumulated sunshine hours) and daily pollen concentration of oak and Japanese hop from 1997 to 2009 (**Fig. 3B**). Daily pollen concentration is represented as a histogram according to each weather variable. The histogram is the sum of probability of pollen appearance at a specific weather event and it is fitted to Weibull PDF. In other words, the PDF represents the probability of pollen observation by each weather variable. Then, regression models were developed using the PDFs of individual

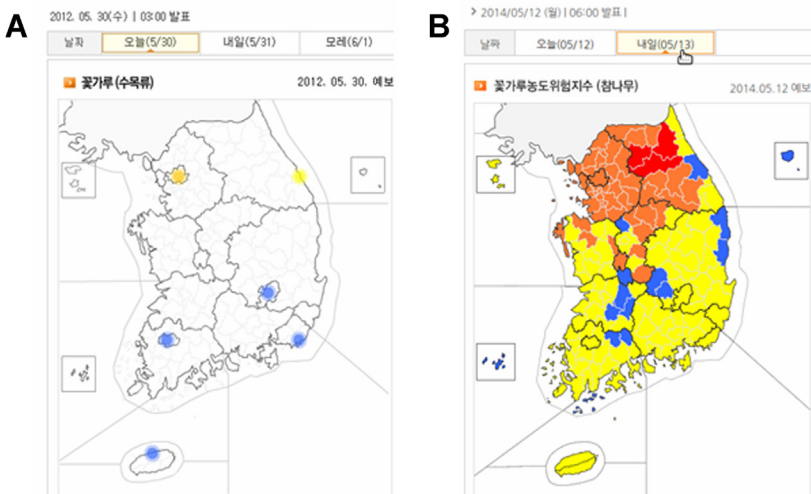


Fig. 3. (a) Regional pollen risk forecast based on the regional regression models in 2012 (b) National web service of pollen risk distribution by KMA using the PDF-regression model in 2014. From Korea Meteorological Administration. Available at: www.kma.go.kr Accessed 2012 and 2014. With permission.

Box 2**Procedures for the development of the pollen risk forecast model using probability density function and regression analysis**

- ① -1 Find weather variables → ①-2 Fit the daily pollen probability into the Weibull probability density function → ①-3 Calculate daily pollen probability.
- ② Perform regression analysis.
- ③ Calculate pollen concentration and determine the risk grade from the concentration.

weather variables as independent ones and pollen concentration at all observational sites as the dependent one. Daily risk level was determined according to the risk grade standard. The model was validated using the observed data from 2010 to 2012. During the major pollen seasons of April and May for oak trees and September and October for Japanese hop, the index of agreement (IOA) between the model and observation was 70.8% and 90.3%, respectively—a large improvement from 60.4% and 78.1% of the original regional regression models.

- Pros: The regional regression models were simplified in the PDF-regression model, which is also able to predict the nationwide distribution of pollen risks using the operational numerical weather forecast because of its sole dependence on weather conditions.
- Cons: Other than weather conditions such as vegetation distribution and the physiologic difference is not reflected. Therefore the regional and yearly differences are excluded from the analysis and forecast. Also, despite the high IOA in pollen allergy risks, the pollen concentration was underestimated in general. The simulated length of pollen season and the dynamic fluctuation of pollen concentration such as daily maximum pollen concentration were suboptimal.

Probability-Machine Learning Model

The probability-regression model of the previous section failed to simulate peaks in the daily forecast and underestimated overall daily pollen concentration (**Box 3**). It was mainly caused by the characteristics of the dataset utilized in the model development of a high number of low concentration days. Additionally, the relationship between weather conditions and pollen concentration is not linear. To solve these problems, the probability of pollen appearance is estimated from weather data before machine learning models are programmed to predict pollen concentration (see **Box 3**). Additionally, to prevent over-fitting of the Deep Neural Network (DNN) model to the training data and underestimate the concentration, the bootstrap aggregating-type ensemble model was developed.³² Nine stations with sufficient data during 2007 to

Box 3**Procedures of the development of pollen risk forecast model using probability density function and machine learning technique**

- ① Find the probability of pollen appearance based on weather variables
- ② Train up machine learning models (eg, deep neural network, Random Forest) by the probability
- ③ Estimate pollen concentration and determine its risk level

2014 were selected for the training data. Because there are too many dates with a mild grade, the training set was re-composed as mild—the lowest grade—and non-mild grades equally by changing sampling frequency: mild 7%, moderate 80%, severe 90%, and extreme 100%. Several weather input variables were transformed into the daily probability of pollen appearance. The structure of the DNN model was determined through many kinds of experiments. The developed model was evaluated using the 9 station data during 2015 to 2016. Mean absolute percentage error (MAPE) of the pollen concentration was 5.6% to 4.5% and mean accuracy for the extreme grade was 45.5%, which was a great improvement from 28.4% of the regional regression models. Periods of pollen season, when taking action against pollen allergy is needed, are compared by the dates of start and end of the season. During the evaluation period, the DNN model outperformed the regression models: deviations from the observed start/end of the season were 4 to 8/7 to 11 days and 13 to 26/29 to 36 days by the DNN and regression models, respectively. The DNN models have been implemented as an operational service in KMA since 2017.

- Pros: Accuracy is higher than in conventional models. Machine learning models make the most use of the observed data.
- Cons: It is a black-box model. Developed models have not considered the long-term vegetation changes nor regional and yearly variations in pollen production so that they need a periodic update with continued observation. As with the pollen types with a lower concentration, machine learning models are equally disadvantageous as other conventional models. Only the pollen types observed commonly and frequently are applicable for practical modeling.

Pollen Dispersal Model

Detailed mid- and long-range pollen forecast can be achieved by simulating dissemination-transportation-deposition with dispersal models like the Asian dust forecast. Pollen dispersal and risk models can be developed over a large area based on vegetation distribution and phenological flowering models even though the insufficient observational data for probability-regression or machine learning models. The birch and the Japanese cedar forecast of Finland and Japan, respectively, incorporated dispersal forecast models.^{26,38–42}

CMAQ, developed by the US Environmental Protection Agency, was used as the basic modeling system. The UK Met office's Unified Model Local Data Assimilation and Prediction System, one of KMA's operational numerical weather prediction systems, was assimilated as the input. The behavior of pollen grains was simulated as an aerosol with the property of chemically inactive coarse particles. Moreover, a module for pollen emission and data processing was newly developed.

The Forestry Geographic Information System (FGIS) tree stand data (1:5000) was provided by the Korea Forest Service. Gridded pollen emission was estimated from the oak tree distribution, which is converted from the FGIS coverage map of oak trees according to the grid resolution of the numerical weather forecast. The key components of the emission model were flowering period and yearly total pollen production. In the emission model, daily pollen release was determined from the Weibull PDF model, which was tuned to produce yearly total pollen concentration of 85,000 grains m^{-3} , which was observed in 2-year intensive observation at the Gwangneung oak forest. For the evaluation of the model, temporal changes in the spatial distribution of the pollen emission were investigated. Because the daily pollen concentration model is driven by degree-days, the shift of emission place from southern plain to northern mountain areas was simulated as expected (Fig. 4). However, the temporal patterns

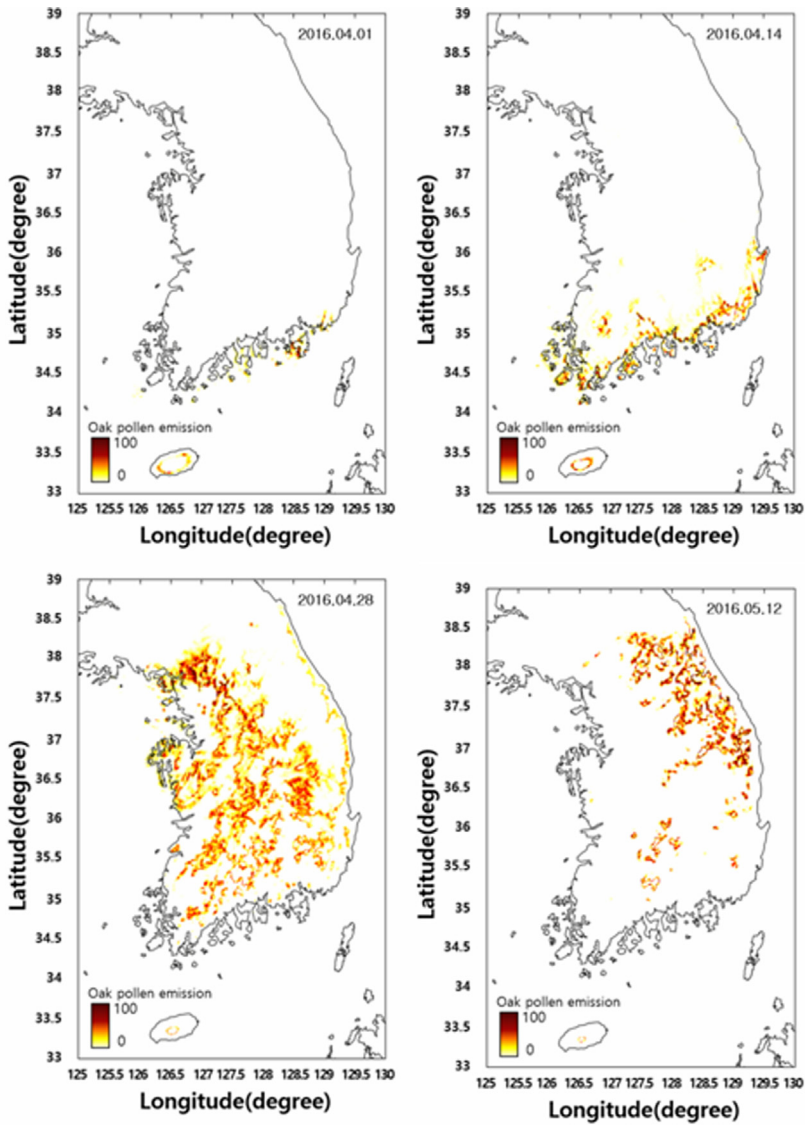


Fig. 4. Temporal changes in national pollen emission estimated by the model according to degree-days. (source: unpublished data).

of simulated daily concentrations in 2016 were earlier or later than the observation depending on the station. The estimated pollen season by the DNN model was also inconsistently matched with the observation. Major shortcomings of the dispersal model existed within the emission model such as the uncertainty of the vegetation distribution and neglected genetic diversity of the oak trees.

- **Pros:** It is possible to integrate a variety of data including meteorology, phenology, and remote sensing. Dispersal models can produce background information against new and novel pollen using the basic knowledge of plant physiology without sufficient direct observation.

- Cons: Pollen production and emission are highly affected by plant phenology (flowering), dispersal meteorology, and hourly emission just like the regional regression model. It is difficult to improve the accuracy of component data/models such as vegetation distribution for source area, plant phenology for the flowering period, and physical behavior of pollen grains for hourly dispersal.

FURTHER RESEARCH

Research items identified to improve operational pollen allergy models and services in KMA are as follows:

Year-Over-Year Variation Model of Pollen Concentration

As described before, the operational KMA pollen allergy forecast models were developed from the relationship between daily weather conditions and pollen concentration using the modeling methods of the probability distribution, statistical regression, and deep neural network. Conventional models for pollen concentration forecasts like these cannot answer to year-over-year variation because they reflect the relationship of daily weather and pollen only. In other words, the same date with the same daily weather conditions will produce the same concentration of pollen. However, the long-term observation shows a great variation of yearly total pollen concentration. Elements that affect the yearly variation of tree pollen can be the conditions for vegetative growth of the previous year, for production of over-wintering dormant buds, and for over-wintering itself.

To predict the regional difference of yearly pollen concentration it is needed to analyze and model the differences using long-term observed data (Box 4).

Analysis of Year-Over-Year Variation of Oak Pollen

Oak pollen, known to exist all around Korea with a high variation over regions and years, was studied to develop a prediction model for yearly pollen concentration using monthly weather data from 1 year before. Daily pollen concentration was observed using Burkard traps at 9 stations in Korea from 1998 to 2019. Yearly total from each station was transformed into a common logarithm (lconc). Selected weather data were daily mean or total at the nearest KMA stations (ASOS or AWS). They were processed as monthly mean air temperature and wind speed and monthly total precipitation and then standardized using their mean and standard deviations. Monthly weather data from January to April were regarded as the previous year's data. Data from 1998 to 2017 were used in the model development and 2018 to 2019 data in the validation.

A *t*-test was performed to determine the monthly weather elements on yearly pollen. From each station, years with high and low 20% of yearly total concentration were selected and the differences in monthly (1–12) mean temperature (T), mean wind speed (W), and total precipitation (P) were compared using the *t*-test analysis.

Box 4

Procedures for the development of a prediction model of yearly total pollen

- ① Input data processing for modeling: monthly total pollen concentration and weather conditions of the previous year
- ② Model development: regression analysis
- ③ Predicted variable: yearly total pollen concentration

A forecasting model for yearly total pollen concentration was developed through regression analysis. Seven independent variables were selected based on the t-test analysis: T4 (April temperature) and P8 (August precipitation) had negative and T8, T10, W6, W8, and P12 had positive coefficients. The total pollen concentration of the previous year (lconc1), in addition to the monthly weather variables, were considered as the independent variables to account for regional differences in vegetational distribution. The regression model with these eight selected variables explained 41% of the yearly variation of total pollen ($R^2 = 0.41$). It was evaluated using the data from 2018 to 2019. Its RMSE, MAE, ME, and R^2 were 0.28, 0.22, -0.0073, and 0.24, respectively.

Most of the previous studies regarding long-term changes in pollen concentration emphasized the long-term increase/decrease of the concentration disregarding weather conditions or the future projection based on climate change scenarios. In addition, short-term pollen forecasting models cannot reflect the nature of yearly fluctuation of pollens. A yearly variation model of the current study can be integrated with the daily pollen forecast model to improve the daily forecast's accuracy.

- Pros: Yearly pollen concentration is predicted based on the previous year's plant growth. Information on yearly pollen concentration can be provided prior to the pollen season.
- Cons: It is difficult to analyze the biological meaning of the model's parameters. Regional deviations in phenology observed at the early season of the year need to be reflected in the model for improved accuracy.

Climate Change and Impact Prediction

Climate change due to the increase in atmospheric CO₂ affects plant physiology and ecology.

Weeds: common ragweed

Common ragweed is small and takes a short amount of time from seeding to flowering; therefore, conducting CO₂ enrichment experiments is feasible using climate chambers. Ziska and Caulfield⁴³ reported the changes in ragweed pollen production at current (370 ppm) and future (600 ppm) as 131% and 320% increase, respectively, from pre-industrial CO₂ concentration (280 ppm), based on the climate chamber experiments. Singer and colleagues⁴⁴ analyzed the changes in allergenic protein Amb a1 at the current concentration from the pre-industrial, and at the future from the current as an x1.8 and x1.6 increase, respectively. In Korea, Choi and colleagues⁴⁵ performed CO₂ concentration experiments using climate chambers and on-site difference between urban and suburban sites. The chamber experiments showed a 230% and 272% increase of Amb a1 concentration under two future CO₂ scenarios (600 ppm and 1000 ppm) from the current (380 ppm). At the urban and suburban sites, the mean observed CO₂ concentration was 440 ppm and 320 ppm, respectively. At the urban site, the mean Amb a1 concentration of 20.4 ng/mL was higher than 16.3 ng/mL at the suburban site; although, the difference was statistically insignificant.

Trees: oak

Pollen production experiments of trees by CO₂ concentration are limited by canopy size and long-time exposure. Kim and colleagues⁴⁶ used open-top CO₂ chambers (OTC) to maintain CO₂ concentrations at ambient (~400 ppm), x1.4 (~560 ppm), and x1.8 (~720 ppm) for more than 7 years. The production of pollen grains and allergen Que a1 by sawtooth oak trees under the chambers was quantitatively

assessed. Total pollen counts per tree of the x1.4 and x1.8 treatments showed a significant increase of 353% and 1299%, respectively, from the ambient conditions. Allergenic protein contents at the x1.4 and x1.8 treatments also showed significant increase of 12% and 11%, respectively.

Considering several aspects of the CO₂ experiments altogether, the elevated CO₂ concentration by the future change of the climate, will surely bring us a higher plant growth and more pollen production. Concentration of allergens from trees and weeds is predicted to increase by higher CO₂ concentration, despite some experimental results, without a statistical significance. In other words, under the future higher CO₂ concentration, people will be exposed to higher allergen levels; therefore, keep-watching and well-preparedness on pollen concentration and patient reaction are needed. However, the actual level of elevated allergy risks is hard to be predicted due to the underlying plant physiology and ecology in the real world resulting from complex impacts of environment change, including air temperature, rainfall, soil nutrition, and changing flowering periods.

DISCUSSION

Pollen allergy risk information and KMA models are summarized in [Table 2](#). The meta data are important in the operation of the observational network. During the network funding sources transition from KAPARD to KMA, several stations missed the observation during that period (2006). In 2018, the observational stations were relocated around the KMA's observational fields around the country. Detailed information along with the meta data are described in the technical note of NIMS/KMA. Meta

Model	Species/ Identification Group	Model Development		Operational Service by KMA	
		Station	Data Period	Interval/ Forecast	Service Year/ Stations (Regions)
Observation	21 (2019–)	12	1997–	Daily (near realtime data only)/NA	2019/2
Pollen Calendar	v2008 17	6	1997–2007	10 days/1 y	2008/6
	v2010 17	6	1997–2009	10 days/1 y	2010/6
	v2019 13	8	2007–2017	Daily/1 y	2019/8
GLM	3	6(7)	2001–2006 (1997–2009)	Daily/2 d	2008 (2011)/6(7)
PDF-GLM	3	7	1997–2009	Daily/2 d	2014/National
PDF-DNN	2	9	2007–2014	Daily/2 d	2017/National
Pollen Dispersal	Oak	1	2015–2016	Daily/2 d	NA/National
Yearly variation	Oak	9	1998–2017	Yearly/1 y	NA/National
CO ₂ impact	Oak		2016	NA/ 30–50 y	NA/NA

Abbreviations: DNN, deep neural network; GLM, general linear model; NA, not applicable; PDF, probability density function.

information, such as site relocation and data loss, should be considered in the data analysis for modeling.³³

By continuing pollen observation, the pollen calendar can be developed and utilized for patient consultation. The accumulated long-term observation data allow the use of probability distribution models to quantitatively estimate daily pollen risks. Individual patients are able to match their own risk levels by comparing their historical symptom diary with the daily risk level obtained by the regional pollen calendar. Integrating information technology (IT) into the pollen calendar would allow the development of a personalized outdoor activity calendar using the symptom diary on their own.

Short-term forecast of pollen allergy using daily weather data was best performed by machine learning methods, in terms of technical advancement and accuracy. In addition, the yearly pollen risk level would be provided if the yearly total pollen concentration model was operated before the pollen season. If long-range transport is challenging, dispersal models can be implemented. However, because most pollens in Korea originate from local flora, the accuracy of the forecast depends on vegetation distribution models, plant phenology, and plant physiology. Conversely, dispersal models have limited functionality. All biometeorological information regarding human health are expected to help increase the people's quality of life. The purpose of these services is to provide adequate pollen allergy information based on field observation. The observational network should be endlessly upgraded, incorporating new technology, such as automatic observation, to maintain its consistency by network expansion. Another important aspect of pollen risk forecast is the relationship between pollen count and the allergic patients' symptom level. Regional difference and temporal changes are essential subjects for the preparedness against climate change.

CLINICS CARE POINTS

- Pollen allergy calendar: If we carefully examine the personal allergic symptom diary with pollen calendar, it will be possible to provide personalized outdoor activity calendar and prescription for the patient.
- Pollen risk forecast: In addition to the pollen calendar, a daily forecast on pollen allergy risks by weather service agencies will provide a more detailed day-to-day risk information.
- Symptom index study: The links between pollen counts and symptom index by allergy patients are highly affected by the characteristics of pollinating plants and regional climate. It should be locally studied considering regional differences.

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DISCLOSURE

The authors have nothing to disclose.

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