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Bayesian analysis of climate change effects on observed and projected airborne levels of birch pollen

Yong Zhang [a,b], Sastry S. Isukapalli [a], Leonard Bielory [c], Panos G. Georgopoulos [a,*]

[a] Environmental and Occupational Health Sciences Institute (EOHSI), A Joint Institute of UMDNJ-RW Johnson Medical School & Rutgers University, 170 Frelinghuysen Road, Piscataway, NJ 08854, USA
[b] Department of Chemical and Biochemical Engineering, Rutgers University, 98 Brett Road, Piscataway, NJ 08854, USA
[c] Center for Environmental Prediction, Rutgers University, New Brunswick, NJ 08901, USA

HIGHLIGHTS

► A Bayesian framework is presented to model climate change effect on birch pollen.
► Airborne pollen levels are estimated based on observed and projected climate factors.
► Pollen emission fluxes are generated using the output from Bayesian model.
► Pollen season tends to start earlier with rising airborne pollen levels in the future.

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ABSTRACT

A Bayesian framework is presented for modeling effects of climate change on pollen indices such as annual birch pollen count, maximum daily birch pollen count, start date of birch pollen season and the date of maximum daily birch pollen count. Annual mean CO_2 concentration, mean spring temperature and the corresponding pollen index of prior year were found to be statistically significant accounting for effects of climate change on four pollen indices. Results suggest that annual productions and peak values from 2020 to 2100 under different scenarios will be 1.3–8.0 and 1.1–7.3 times higher respectively than the mean values for 2000, and start and peak dates will occur around two to four weeks earlier. These results have been partly confirmed by the available historical data. As a demonstration, the emission profiles in future years were generated by incorporating the predicted pollen indices into an existing emission model.

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1. Introduction

Climate change exerts important effects on annual cumulative airborne pollen count, maximum daily pollen count, start date of pollen season and the date of maximum daily pollen count (Fitter and Fitter, 2002; Damialis et al., 2007; Alizoti et al., 2010). These pollen indices hereafter referred to as *annual production*, *peak value*, *start date* and *peak date*, are closely associated with allergic airway diseases (AAD) (Blando et al., 2012) and genetic manipulation of plants (Martin et al., 2010). These four pollen indices are further classified as pollen quantity indices (annual production and peak value) and pollen timing indices (start and peak dates). An increasing number of individuals suffering from seasonal AAD caused by pollen (Singh et al., 2010a), and the corresponding increased healthcare and financial costs have been reported in many industrialized countries (Lamb et al., 2006).

Modeling efforts have been made to understand the exacerbation of AAD and genetic contamination caused by increased pollen levels (Sofiev et al., 2006). These models are either based on simple regression of phenological and aerobiological observations (Jato et al., 2007), or utilize physical principles of transport and meteorology (Siljamo et al., 2008; Martin et al., 2009). Pollen concentration estimations generated by most of these models are qualitative or semi-quantitative (Schueler and Schlünzen, 2006; Sofiev et al., 2006) due to the scarcity of emissions information.

A major challenge for the physics-based models to construct exact pollen spatial and temporal distribution is establishing an accurate emissions module that incorporates the influence of multiple climatic factors. Different methods have been utilized to

* Corresponding author. Tel.: +1 848 445 0159; fax: +1 848 445 0915.
E-mail addresses: panosg@ccl.rutgers.edu, panosg@comcast.net (P.G. Georgopoulos).

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try to tackle this issue. Kawashima and Takahashi (1999) and Schueler and Schlünzen (2006) adopted regression equations of phenological observations as emission modules to simulate pollen transport and distribution from cedar and oak, respectively. Starting from the measured pollen count, Lagrangian algorithms were used by Aylor (2005) and Pasken and Pietrowicz (2005) to simulate pollen transport and distribution from maize and oak, respectively. Mechanistic models based on the formulation of Helbig et al. (2004) were developed by Efstathiou et al. (2011) and linked to the Community Multiscale Air Quality model in order to simulate the transport and distribution of birch and ragweed pollen. The above mentioned methods do not account for the long term influence of multiple climatic factors in the emission module.

In this work, Bayesian models are employed to describe climatic change effects on annual production, peak value, start date and peak date of birch (Betula) pollen. The modeling process consists of four steps: variable selection, parameterization, evaluation and prediction. Probabilities of each sub-model, and probabilities of inclusion of each variable in the full model were calculated and analyzed. Then Bayesian parameterizations of these selected models were conducted with published data (Rasmussen, 2002). The parameterized models were evaluated using data from Yli-Panula et al. (2009), Frei and Gassner (2008) and two pollen stations in the US, and used to predict plausible global mean trends of pollen indices of future years based on the climatic data reported in the Intergovernmental Panel on Climate Change (IPCC) assessment report (IPCC, 2007a,c). The intrinsic inter-annual variations of pollen indices were also examined and used to simulate the fluctuations around the mean trends. Finally, a case study demonstrates using the results of Bayesian modeling for generating the future spatiotemporal emission profiles of birch pollen in the Northeastern US. The statistical calculation and simulation were carried out in R and visualizations were implemented in Matlab and ArcGis.

2. Methods

2.1. Model

We assumed that observed pollen indices are normally distributed variables which fluctuate around mean trends depending on the combination of multiple random climate/meteorology factors, and that pollens of the same genus (Betula) have similar responses to climate/meteorology changes. The ordinary norm linear regression model (Marin and Robert, 2007a) is presented in Equation (1)

$$\left(Y\middle|\beta,\sigma^2,X\right)\sim N_n\left(X\beta,\sigma^2 I_n\right) \tag{1}$$

where $Y = (y_1,\cdots,y_n)^T$ is a vector of pollen indices, the five year overlapping mean of either annual production (pollen m^{-3}) or peak value (pollen m^{-3}) or start date (day) or peak date (day). With day 1 being January 1st, the start date is defined when the cumulative pollen count reached a certain percentage of the annual production (e.g. 2.5%) (Rasmussen, 2002) and peak date is reached when the daily maximum count is registered. X is the $n \times k$ matrix of explanatory variables in which each column vector x_i corresponds to values of a climatic factor in n years and k is the number of variables. I_n is the $n \times n$ identity matrix. β and σ^2 are the unknown vector of coefficient and variance, respectively.

Equation (2) is the likelihood function of the Bayesian model.

$$f\left(Y,X\middle|\beta,\sigma^2\right) = \left(2\Pi\sigma^2\right)^{-\frac{n}{2}}\exp\left[-\frac{1}{2\sigma^2}(Y-X\beta)^T(Y-X\beta)\right] \tag{2}$$

Zellner's informative G-priors (Zellner, 1971) are assumed for β and σ^2 as shown in Equation (3),

$$\begin{cases}\left(\beta|\sigma^2,X\right)\sim N_{k+1}\left(\tilde{\beta},c\sigma^2\left(X^TX\right)^{-1}\right)\\ \Pi\left(\sigma^2|X\right)\propto\sigma^{-2}\end{cases} \tag{3}$$

where $\tilde{\beta}$ and c are further assumed to be $\mathbf{0}_{k+1}$ and 100 respectively so that parameterizations are mainly dependent on the explanatory matrix X. In this study $c = 100$, the prior gets a weight corresponding to 1% of the sample.

2.2. Variable selection

Fig. 1 schematically depicts the Bayesian modeling framework. Multiple climatic factors were first prescreened by regressing each individual pollen index against each individual climatic factor of a given month for historical data of twenty years. Climatic factors in two periods influence the pollen indices (Masaka and Maguchi, 2001): (1) initiation of flower primordial during the burst period in spring and early summer of the current year; and (2) development of flower inflorescences in autumn and winter of the previous year. In this study, monthly climatic factors for CO_2, temperature, precipitation, cloud coverage, and sunshine hours in June to December of previous year and January to May of current year were taken into account in the prescreening stage. First, multiple monthly climatic factors were consecutively screened starting from the smallest P value and the largest R^2; then monthly climatic

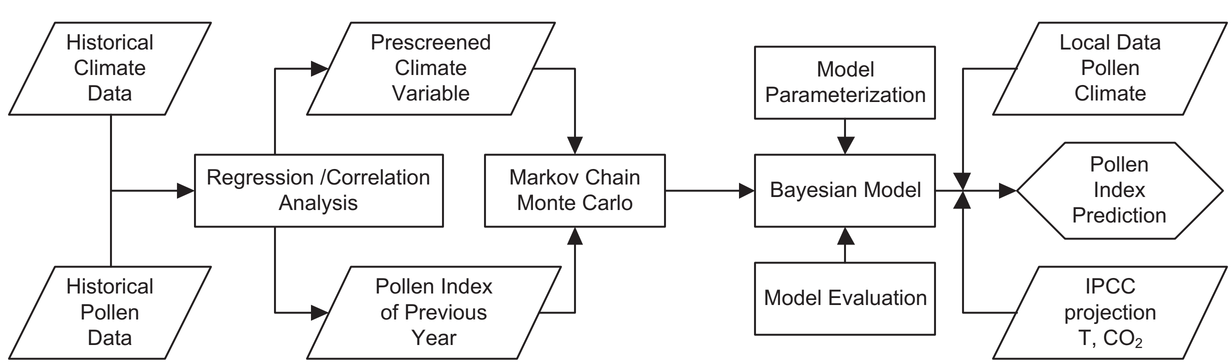

Fig. 1. Overall flow of Bayesian modeling framework. Multiple monthly climatic factors from June of previous year to May of current year were first screened using simple linear regression and correlation analysis. The prescreened climatic factors and pollen indices were then further selected using method of Markov Chain Monte Carlo based on Bayesian statistics. Finally, the selected Bayesian models were parameterized and evaluated using different datasets, and utilized to predict future pollen indices based on IPCC projection.

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