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Alder pollen in Finland ripens after a short exposure to warm days in early spring, showing biennial variation in the onset of pollen ripening

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Abstract

We developed a temperature sum model to predict the daily pollen release of alder, based on pollen data collected with pollen traps at seven locations in Finland over the years 2000 to 2014. We estimated the model parameters by minimizing the sum of squared errors (SSE) of the model, with weights that put more weight on binary recognition of daily presence or absence of pollen. The model results suggest that alder pollen ripens after a couple of warm days in February, while the whole pollen release period typically takes up to 4 weeks. We tested the model residuals against air humidity, precipitation and wind speed, but adding these meteorological features did not improve the model prediction capacity.

Our model was able to predict the onset of pollen season with similar accuracy as models describing only the start of the pollen release period (average prediction error 8.3, median 5.0 days), while for the end of the pollen release period the accuracy of our predictions was not as good. We split the pollen data into odd and even years, and fitted our model separately to each half. Difference in the parameter values suggests a biennial behavior in the onset of pollen ripening, with almost two weeks of difference in the modeled starting date of the pollen development. Monte Carlo resampling of the observation data confirmed that the difference is not just a random anomaly in the data.

Introduction

In Finland, alder (*Alnus* sp.) is together with the far less common hazel (*Corylus* sp.) the starter of the allergenic pollen season. It belongs to the *Betulaceae* family including also birch (*Betula* sp.), which is the most important genus for pollen allergies in Finland. The major allergen of alder (Aln g 1) resembles the major allergen of birch (Bet v 1) both structurally and immunochemically (Matthiessen et al. 1991, Pehkonen and Rantio-Lehtimäki 1995), and allergic cross reactivity is common. The temporal sequence of alder and birch flowering lengthens the period of allergenic exposure for those sensitive to *Betulaceae* pollen. Moreover, exposure to high alder pollen counts may increase the sensitiveness to pollen later on during the season (Emberlin et al. 1997). In their study concerning alder and birch, Jantunen et al. (2012) found a fair correlation between allergy symptoms and pollen counts, but further concluded that the risk of developing symptoms is influenced by the progression of the *Betulaceae*

pollen season. Therefore, more accurate predictions of the onset of alder pollen release, by means of modeling, would help the allergy sufferers to manage their symptoms.

A number of phenological models have been produced to predict the onset of alder flowering. Some of these are simple temperature sum models, starting the temperature sum accumulation from a fixed day in spring (Linkosalo 2000, Linkosalo et al. 2006). Also more complex models including a chilling submodel have been proposed (Andersen 1991, Jato et al. 2000, Rodríguez-Rajo et al. 2006, 2009, González-Parrado et al. 2006). However, Linkosalo (2000) found that the temperature sum model without the chilling submodel performs better for predicting the start of alder flowering in Finland, and Linkosalo et al. (2008) showed that this applies at least to later-flowering species also when using independent data for model evaluation.

The pollen release period of birch was predicted using temperature sum as the driving environmental variable of pollen release in a previous paper (Linkosalo et al. 2010). With the application to provide input for the long range transport model, another version of the model was produced, using also air humidity and wind speed as controls of the pollen release (Sofiev et al. 2013). The latter model is in use of a prediction system for birch long-range pollen transport events (Siljamo et al. 2013). For this study, we used similar model structures than in the two papers mentioned above.

The aim of this study was to develop and test a pollen release model for alder. Our model uses only temperature sum as control of the pollen release period. Further we tested if additional environmental variables would improve the prediction potential of the model. We split the data to odd and even years and fitted the model separately to each half. Difference in optimal model parameter values revealed a biennial behaviour in the onset of pollen ripening. We utilised Monte Carlo resampling from a large matrix of parameter values combinations to enhance the calculation efficiency of the Monte Carlo resampling.

Materials and methods

There are two common species of alder in Finland, namely Black Alder (*Alnus glutinosa* (L.) Lam.) and Grey Alder (*Alnus incana* (L.) Moench.). Using historical time series of onset of flowering, Linkosalo (2000) found that in Finland Black Alder starts flowering on average 6 days before Grey Alder. However in the pollen trap data, it is not possible to distinguish between the pollen of the two species.

We used alder pollen data counts measured at seven pollen measurement sites (table 1, Fig. 1). The sampling followed the Burkard-spore trap procedure described by Hirst (1952). In Turku, where the flowering starts first of all observations sites, the pollen data is collected throughout the year. On the other sites the collection is started once pollen is observed in the Turku site, and carried on until the pollen season has clearly ended.

The traps were located on open rooftops. The alder pollen grains were identified and counted on bi-hourly basis, taking 2 randomized samples per each strip representing a 2 hour time period (Mäkinen 1981). The resulting variable was average pollen grain concentration /m^3. We studied the pollen counts on a daily basis, and daily data were summed up from the bi-hourly samples for each day.

The meteorological data were obtained from the Finnish Meteorological Institute (https://en.ilmatieteenlaitos.fi/open-data). The weather stations were located on average 8 kilometers from the corresponding pollen trap. Tri-hourly data from meteorological stations closest to the pollen traps were used and daily averages (or in the case of precipitation, daily sum) were calculated for the analyses.

Boreal wind-pollinated trees typically show quite large inter-annual variation in the amount of pollen release, and alder is no exception. There are some attempts to model the pollen amounts based on weather conditions and pollen intensity of previous years (Masaka and Magushi 2001, Ranta et al. 2008), but these models lack prediction power on independent data (Ranta et al. 2008). Therefore we decided to normalize the pollen amounts for each year, and focus our modeling on the timing of the pollen release only. For this purpose, the total accumulated pollen amount for each year and site was calculated, and daily pollen observations were divided with this annual total. Similarly, the pollen model predicts the daily pollen amounts as fractions of annual total. As the pollen count captures with Burkard traps is normalized, we used it as proxy for the released pollen, which was then predicted with the model.

The pollen model predicts the ripening of the pollen to depend on a temperature sum, *TS*, accumulated from a fixed starting date, t_0, in spring. Temperature sum is accumulated from the fraction of daily temperature, *T*, above a critical temperature threshold, T_{Crit}. The cumulative amount of ripened pollen, *P*, is modeled to increase as a linear function between two temperature sum thresholds TS_{min} and TS_{max}, as was modeled for birch by Linkosalo et al. (2010).

$$TS(t) = \sum_{x=t_0}^{t} \max(T(x) - T_{Crit}, 0) \quad (1)$$

$$P(t) = \begin{cases} 0, & TS < TS_{min} \\ \frac{TS(t) - TS_{min}}{TS_{max} - TS_{min}}, & TS_{\min} \leq TS(t) < TS_{max}, \\ 1, & TS \geq TS_{max} \end{cases} \quad (2)$$

Our model assumes that the pollen is released as it ripens. The model has 4 parameters, the starting date t_0, critical temperature threshold T_{Crit}, and the two temperature sum thresholds TS_{min} and TS_{max}.

We estimated the model parameters by minimizing the sum of squared errors (SSE) between the model predictions and measured data. To emphasize the model accuracy in predicting the start and end of the pollen season, we modified the calculation of SSE with a weight function *W*, that was 1 in the case both observed *(O)* and predicted *(P)* pollen counts were positive, but had a value of 10 if either predicted or observed pollen count was zero:

$$W(t) = \begin{cases} 1, & P(t) > 0 \; and \; O(t) > 0 \\ 10, & P(t) = 0 \; or \; O(t) = 0 \end{cases} \quad (3)$$

$$Q(t) = P(t) - O(t) \quad (4)$$

$$SSE = \sum (Q(t)^2 * W) \quad (5)$$

Parameter estimation of phenological models tends to be a challenge to optimization algorithms, and take a multitude of model evaluations. To reduce the calculation time, to be able to find the parameter set that minimizes the model prediction error, and to be sure that we have reached a global minimum of the SSE, we calculated the model in a large matrix of parameter values, covering the potential range of parameters, and at the same time fine enough to correspond to sufficient accuracy of parameter values. In phenological models, both observations and temperature data come with a time-step of one day, so this was obvious value for the starting day parameter, t_0. On a typical spring day, the temperature is several degrees above the temperature threshold used in the model, so we concluded that a step of one degree-day will be sufficient for the two temperature-sum thresholds, TS_{min} and TS_{max}. Finally we chose a step of 0.1 °C for the temperature threshold T_{Crit}. After calculating the model predictions in the matrix, finding the optimal parameter combination was simply finding the minimum SSE value in the matrix.

To evaluate the data dependency of our model parameters, we did a Monte Carlo –resampling of pollen observations, in which each combination of year and sampling site acted as one data point. We picked 49 random data points from each subset of observations with resampling, and repeated this 900 times. We then picked the model prediction deviations for the random data points for the whole parameter matrix, summed up the SSE values for all parameters combinations, and found the parameter values that minimized the SSE value for that specific subset on observations. Thus the model parameter estimation for each Monte Carlo sample was done by tallying the model predictions errors for all observations drawn into that sample, over the whole parameter value matrix, and then selecting the parameter combination that resulted in the smallest sum of squared prediction errors. The models and scripts managing the parameter-related data were written in R, and the calculations were done on a Unix mainframe calculation server, using at most 25 parallel cores.

We classified the days into 4 classes depending on if the observed and model predicted pollen release were positive or zero. We further classified the days where observations were positive but predictions were zero, or the other way round, to three classes, before, during and after the predicted pollen release period.

Preliminary results indicated that the model parameters would have different values for the odd and even years, so we split the pollen data to two subsets and fitted the model to both subsets independently.

Results

We first fitted the model to all the observed data. Adding the weights as in eq. 3 to 5 improved the prediction accuracy of the starting date of pollen release considerably. Minimizing the SSE without the weights would sum the squared difference of the modeled and observed pollen count for each day. Adding the weights emphasize the binary recognition of presence of pollen, and improved the model considerably. The resulting model gave rather good estimates for the start of the pollen release period, average deviation was -8.3 days (table 2), which is of the same magnitude as with temperature sum models predicting observed onset of flowering (Linkosalo 2000). Negative values indicate that the observed date precedes the predicted. The median prediction error is -5.0 days, indicating that the

distribution of the errors is skewed. The mean error for Turku is considerably large and negative, which is probably due to long range transported pollen present in the Turku observations. In Turku the pollen data is collected continuously throughout the year, while on the other sites the collection is only started when the presence of pollen is observed in the Turku site.

Similar analysis for the end of the pollen season show much larger deviation of the predicted end of the season from the observed one (table 3). Typically the prediction error of the model is positive, so there are pollen observations after the last predicted pollen release date. The penalty coefficient in the SSE calculation (eq. 3 to 5) tends to set the end of the predicted pollen release period for the first occurrence of consecutive multiple days without observed pollen. We therefore conclude that the observed airborne pollen during the days after the model has predicted the pollen release period to end are likely to be cases of long-range transported pollen from more Northerly locations. The model-predicted pollen season is on average 24.2 days, and the length is consistent throughout the sites on the same year (table 4).

On counting the binary pollen event days, the model caught correctly 1860 “event” days, but missed 724 days and falsely predicted the pollen release to take place on 1472 days (Table 5a). However, of the 1472 “false alarms”, a majority, 872 cases occurred during the modeled pollen release period, that is between the predicted starting and ending dates of the pollen season (Table 5b). Therefore it is likely that these dates are such that the air was washed from pollen due to local precipitation or some similar event. In a similar fashion, majority of the “misses” were after the modeled pollen season had ended, so these are likely to be cases of long-range transport events (Table 5b).

We split the data to two halves, odd and even years, and used Monte Carlo resampling to produce 900 different subsamples of each half of the date. We fitted the model separately to each subsample of the data by finding a set of parameter values that minimize the SSE. We then calculated distributions of the model parameters for each half and over the Monte Carlo samples. The model parameter values for either half of the data were remarkably stable, there were very few Monte Carlo samples where any of the parameter values differed from those values for the majority (fig 2). The optimal parameter values for each half of the data were, however, different (table 6). Especially the starting day parameter value differed considerably for the two data sets, by 11 days (day-of-year 44 vs. 55, for odd and even years). When splitting the data to early and late years, the parameter values for the two subsets were similar (Table 6).

The result suggests that alder shows a biennial behavior of the timing of onset of pollen development in spring. When comparing the model parameters, they mostly deviated in the value of the starting date of temperature sum accumulation. There was also a slight difference in the temperature sum threshold for the start of the pollen season, but taking into account the low value of critical temperature, the difference should not make much difference in the timing of the onset of flowering. The other two model parameters had practically similar values for both halves of the data (Table 6).

The model was able to reproduce the pollen release days with rather good accuracy, but did not do so well in reproducing the day-to-day variation of the pollen release. Fig. 3 shows an XY plot of the

observed vs. predicted pollen release. The figure indicates a rather poor correlation between the two, and also shows how the magnitude of the observed pollen release is threefold to that of modeled. When we compare only the points where both observed and modeled pollen release are positive, there is very little correlation between the two. The model seems to perform better in binary prediction of timing the pollen release than predicting the intensity of the pollen release.

The residuals of the model did not show correlation with environmental features such as temperature, air humidity, precipitation or wind speed (results not shown). However, a previous model for birch pollen release used air humidity and wind speed as controls of the release of ripe pollen from the catkins (Soviev et al. 2013). Therefore we also fitted another model version to the observed data, with humidity, expressed as water vapour pressure deficit (VPD), controlling the pollen release. Adding the VPD to the model did not increase the variance explained (results not shown).

Model parameter values for the model are given in table 6. It should be noted that the temperature sum threshold for the start of the pollen season is quite low, only 2 to 10 degree days. Combined with the low threshold of effective temperature, -1.5 °C this means that our model predicts the Alder flowering to start after just a few warm days in the spring, following the onset of temperature sum accumulation on 10th of February.

Discussion

In this paper we developed a pollen release period model for alder. The model follows the structure that Linkosalo et al. (2010) suggested for birch, where only the accumulating temperature sum controls the pollen release. Additional meteorological features such as air humidity have been used as control of the release of ripe pollen in other models, such as the current version of the birch pollen release model used in the SILAM atmospheric transport model (Sofiev et al. 2013), which proposes that the ripened pollen is stored in the catkins and then released when conditions are favorable. The model structure is also quite similar to the approach is described in Zink et al. (2013) for COSMO-ART model. The birch model in SILAM uses both humidity and wind speed as drivers of the pollen release. When we related the residuals of our temperature sum based model against meteorological features, we found that the correlations were minimal. However for a comparison with the birch pollen model used in SILAM, we still developed a model where air humidity impacts pollen release. This model did not fit observed data any better (as indicated by the model SSE values). We conclude that temperature sum is the main driver of Alder pollen release.

The model proved quite accurate on predicting the onset of the pollen release period, the results were of similar precision as models aiming only to predict the start of the pollen season (e.g. Linkosalo 2000, Linkosalo et al. 2006). However, the predictions of the end of the pollen release period seemed less accurate, with typical prediction error of 30 days or even more. We assume that the error in the latter is actually caused by outlying observations of long-range transported pollen in the data, as the model-predicted results for the end of the pollen release and the length of pollen release period are consistent and in good agreement between years and observation sites. We do not know of any consistent and

objective means of recognizing the outliers in the pollen trap data, and therefore did not use any outlier-cleaning.

Fitting a model to a single data set always poses a risk that the model reflects some specific features of the data set, and cannot therefore be generalized. Thus the use of independent data is proposed. Lacking sufficient amounts of data to use part of it as independent test data, we did a Monte Carlo resampling of the observations to induce variation in the observation data, and studied how this variation impacts the optimal model parameter values. We also split the data to odd and even years to compare if we observe different model behavior on these halves. This test with splitting the data revealed an interesting observation that the Alder shows a biennial pattern in the onset of pollen development, presented in the model as the accumulation of temperature sum, as the value of the starting day parameter is one and half weeks earlier on odd years compared to even years. Our dataset is too short to give conclusive results on the phenomenon or to speculate what environmental features could be driving the difference. Yet when we repeated the calculation splitting the data to two consecutive sections, the feature of model parameters depending on data was totally dissipated, suggesting that indeed there is a difference in the timing of development of Alder pollen between odd and even years. We did not find similar results in earlier publications. Emberlin et al. (2007) found the Alder pollen release *intensity* to have a slight biennial pattern in the UK, but not the timing. Skjoth et al. (2015) claim the biennial variation in the pollen release timing only occurs in Birch, not in Alder. Biennial variation in pollen release intensity and hence acorn production has been observed e.g. in oak (Díaz-Fernández et al. 2004, Otárola et al. 2013) on more Northerly growing sites where annual seed production would be hard for the limited growth resources, but this does not explain why onset of pollen development should show a biennial pattern.

Our pollen release model resulted with considerably smaller day-to-day variation of released pollen amounts than was observed in the data, the maximum daily values in observed pollen amounts were four times larger than the model predicted (fig 3). It remains unclear what is the cause for this larger variation in the data, whether it is some environmental feature that could not be captured in a model, or if it is some imminent random feature produced in a trap-collected pollen data. In some stations the main pollen source areas are not evenly located around the trap. In Turku and Vaasa for instance, there is only a short distance to the sea in the southern or western direction, whereas in other directions the forest cover is wider. In these conditions the wind direction may have a major impact on the trapped pollen counts even if the actual pollen release intensity does not change. Also, wind speed is known to affect trapping efficiency. A study on clubmoss spores (which are about the same size as alder pollen grains) showed that a change in wind speed from 1.5 to 9 m/s resulted in approximately 30 % increase in trapping efficiency (Lacey and Venette 1995).

Even though our model was not able to promptly capture the variation in pollen amounts, it did a good work on capturing the timing of pollen release period. The model fitting emphasized the amount of daily pollen catch, and yet the prediction accuracy of the start of the pollen season was comparable to the results from models aiming only to predict the very start of the season. We conclude that the presented temperature-sum based model works well in predicting the onset of the pollen release period of Alder

for Finland. Added features of the air humidity provide no improvement in the accuracy of pollen release. The end of the pollen period is most likely also predicted with similar accuracy, but outliers in the pollen data indicate larger deviation of the model prediction from measured data. The modeled figures of the day-to-day variation in the daily pollen counts are not very predictive, but for the aerobiological forecasting the binary data for presence or absence of airborne pollen is more important anyway. Thus the model can be used to predict the Alder flowering to give in advance a warning of the becoming pollen season. If the model is to be used to provide input for long range transport models, then the parameters probably need to be estimated against a dataset covering a larger geographical (more southerly) area. The biennial behavior of Alder flowering also needs to be further addressed.

A number of previous studies of phenological modeling have shown that estimating the model parameters with SSE (or RMSE) minimization, using optimization algorithms, is computer time-consuming. Even worse, the results may vary depending on the data and starting point of the optimization. Our method of calculating the model SSE in a large matrix of parameter values, and using Monte Carlo sampling to produce distributions of the model parameters should provide more robust and reliable results for model parameters. For one thing, calculating the model in parameter matrix ensures that the whole parameter space is covered when looking for the optimum. Further, the parameter distributions give information on how sensitive the model parameters are. And finally calculating the model deviations for each observation into a matrix, and then doing the Monte Carlo simulations by sampling these model prediction deviations, turned out to be more computer-time efficient than the traditional method of using an optimization algorithm repeatedly for each Monte Carlo sample.

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Literature cited

Andersen, T.B., 1991. A model to predict the beginning of the pollen season. Grana 30: 269–275.

Díaz-Fernández, P.M., Climent, J., Gil, L. 2004. Biennial acorn maturation and its relationship with flowering phenology in Iberian populations of Quercus suber. Trees 18(6): 615-621.

Emberlin J, Mullins J, Cordon J, Millington W, Brooke M, Savage M, Jones S (1997). The trend to earlier birch pollen seasons in the UK: a biotic response to changes in weather conditions? Grana 36:29–33

Emberlin, J., Smith, M., Close, R., Adams-Groom, B. 2007. Changes in the pollen seasons of the early flowering trees Alnus spp. and Corylus spp. in Worcester, United Kingdom, 1996–2005. Int J Biometeorol (2007) 51:181–191.

González-Parrado, Z., Fuertes-Rodríguez, C.R., Vega-Maray, A.M., Valencia-Barrera, R.M., Rodríguez-Rajo, F.J., Fernández-González, D. 2006. Chilling and heat requirements for the prediction of the beginning of the pollen season of Alnus glutinosa (L.) Gaertner in Ponferrada (León, Spain). Aerobiologia 22:47

Hirst, J.M. (1952). An automatic volumetric spore trap. Ann Appl Biol. 39(2):257–265

Jantunen, J., Saarinen, K., Rantio-Lehtimäki, A. 2012. Allergy symptoms in relation to alder and birch pollen concentrations in Finland. Aerobiologia 28:2, 169

Jato V, Frenguelli G, Aira MJ (2000) Temperature requirements of Alnus pollen in Spain and Italy (1994–1998). Grana 39:240–245

Lacey, J., Venette, J. 1995. Outdoor air sampling techniques. In: Cox, S.C. and Wathes, C.M. (editors), Bioaerosols handbook. CRC Press, Inc. USA.

Linkosalo, T. 2000. Mutual regularity of spring phenology of some boreal tree species: predicting with other species and phenological models. Canadian Journal of Forest Research 30, 667-673.

Linkosalo, T., Carter, T.R., Häkkinen, R. and Hari, P. 2000. Predicting spring phenology and frost damage risk of Betula sp. under climatic warming: a comparison of two models. Tree Physiology 20, 1175-1182.

Linkosalo, T., Häkkinen, R. and Hänninen, H. 2006. Models of the spring phenology of boreal and temperate trees: Is there something missing? Tree Physiology 26: 1165-1172

Linkosalo, T., Lappalainen, H. K., Hari, P. 2008. A comparison of phenological models of leaf bud burst and flowering of boreal trees using independent observations. Tree Physiology 28:1873–1882.

Linkosalo, T., Ranta, H., Oksanen, A., Siljamo, P., Luomajoki, A., Kukkonen,, J. & Sofiev, M. 2010. A double-threshold temperature sum model for predicting the flowering duration and relative intensity of Betula pendula and B. pubescens. Agricultural and Forest Meteorology 150(12): 1579-1584.

Mäkinen, Y., 1981. Random sampling in the study of microscopic slides. Reports from the Aerobiological Laboratory, University of Turku 5: 27-43.

Masaka, K. and Maguchi, S., 2001. Modelling the masting behaviour of *Betula platyphylla* var *japonica* using the resource budget model. Ann. Bot. 88: 1049-1055.

Matthiesen F, Ipsen H, Løwenstein H (1991) Pollen allergies. In: D'Amato G, Spieksma FTM, Bonini S (eds) Allergenic pollen and pollinosis in Europe. Blackwell,Oxford

Otárola, M.F., Sazima, M., Solferini, V.N. 2013. Tree size and its relationship with flowering phenology and reproductive output in Wild Nutmeg trees. Ecology and Evolution 3(10): 3536–3544.

Pehkonen, E. and Rantio-Lehtimäki, A., 1995. Sensitivity of Ig-GELISA for detecting airborne pollen antigens of Betulaceae. Grana 34: 350-356. Ranta, H., Hokkanen, T., Linkosalo, T., Laukkanen, L., Bondestam, K. and Oksanen, A. 2008. Male flowering of birch; spatial syncronization, year to year variation and relation of catkin numbers and airborne pollen counts. For. Ecol. Manag. 255: 643-650.

Rodríguez-Rajo, F.J., Valencia-Barrera, R.M., Vega-Maray, A.M., Suárez, F.J., Fernández-González, D., Jato, V., 2006. Prediction of airborne Alnus pollen concentration by using ARIMA models. Ann Agric Environ Med. 13(1):25-32.

Rodriguez-Rajo, J., Grewling, L., Stach, A., Smith, M. 2009. Factors involved in the phenological mechanism of Alnus flowering in Central Europe. Ann Agric Environ Med. 16(2):277-84.

Siljamo, P., Sofiev, M., Filatova, E., Grewling, L., Jäger, S., Khoreva, E., Linkosalo, T., Ortega Jimenez, S., Ranta,H., Rantio-Lehtimäki, A., Svetlov, A., Veriankaite, L., Yakovleva, E., and Kukkonen, J. 2013. A numerical model of birch pollen emission and dispersion in the atmosphere. Model evaluation and sensitivity analysis. Int J Biometeorol. 57(1): 125–136.

Skjøth, C., Bilińska, D., Werner, M., Malkiewicz, M., Adams-Groom, B., Kryza, M., Drzeniecka-Osiadacz, A. 2015. Footprint areas of pollen from alder (Alnus) and birch (Betula) in the UK (Worcester) and Poland (Wrocław) during 2005–2014. Acta Agrobotanica 68(4). DOI: http://dx.doi.org/10.5586/aa.2015.044.

Sofiev, M., Siljamo, P., Ranta, H., Linkosalo, T., Jäger, S., Rasmussen, A, Rantio-Lehtimaki, A., Severova, E. & Kukkonen, J. 2013. A numerical model of birch pollen emission and dispersion in the atmosphere. Description of the emission module. International Journal of Biometeorology 57:45–58.

Zink, K., Pauling, A., Rotach, M.W., Vogel, H., Kaufmann, P., Clot, B. 2013. EMPOL 1.0: a new parameterization of pollen emission in numerical weather prediction models. Geosci. Model Dev., 6. doi:10.5194/gmd-6-1961-2013.

Table 1: The sites, coordinates and years, where alder pollen was collected with Burkard-type pollen traps.

Site	Years	Latitude	Longitude
Kangasala	2000-2007	61°30´N	24°05´E
Kuopio	2000-2014	62°54´N	27°38´E
Oulu	2000-2012	65°04´N	25°31´E
Rovaniemi	2002-2014	66°33´N	25°44´E
Tampere	2008-2014	61°30´N	23°49´E
Turku	2000-2014	60°32´N	22°28´E
Vaasa	2000-2014	63°06´N	21°37´E

Table 2. Deviations (days) in the start of the alder pollen season between the observation and prediction with the temperature sum model. The observed season is started with the first pollen captured, with long-range transport excluded (see text for details). Negative sign indicates first observation before model predicted season starts

	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	Average
Kangasala	-10.0	-4.0	-35.0	-5.0	-11.0	-2.0	-9.0	-2.0								-9.8
Kuopio	-3.0	-17.0	-9.0	-5.0	-11.0	-1.0	-9.0	5.0	-20.0	-19.0	-9.0	-12.0	-9.0	-5.0	-2.0	-8.4
Oulu	0.0	-3.0	-1.0	0.0	0.0	-1.0	7.0	2.0	-9.0	-2.0	-9.0	10.0	-2.0			-0.6
Rovaniemi			-9.0	7.0	-5.0	-10.0	-5.0	17.0	0.0	17.0	5.0	3.0	-6.0	2.0	-3.0	1.0
Tampere									-7.0	-12.0	-7.0	-13.0	4.0	0.0	4.0	-4.4
Turku	-22.0	-65.0	-44.0	-12.0	-14.0	-1.0	-7.0	-7.0	-26.0	-37.0	-16.0	-24.0	-72.0	-64.0	-23.0	-28.9
Vaasa	-1.0	-5.0	-9.0	0.0	5.0	-1.0	-8.0	0.0	-7.0	-17.0	-9.0	-2.0	5.0	0.0	-1.0	-3.3
Average	-7.2	-18.8	-17.8	-2.5	-6.0	-2.7	-5.2	2.5	-11.5	-11.7	-7.5	-6.3	-13.3	-13.4	-5.0	-8.3

Table 3. Deviations (days) in the end of the alder pollen season between the observation and prediction with the temperature sum model. Observed pollen season may contain long-range transported episodes (see text for details). Negative sign indicates model predictions after the end of observed pollen season.

	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	Average
Kangasala	79	39	134	75	125	81	85	64								85.3
Kuopio	38	4	79	10	58	108	143	67	58	59	83	49	83	57	118	67.6
Oulu	25	6	131	99	56	43	104	54	79	26	39	30	16			54.5
Rovaniemi			7	-11	51	-4	17	52	4	0	64	43	14	5	12	19.5
Tampere									29	67	72	43	30	117	55	59.0
Turku	22	1	14	15	25	24	39	26	227	66	198	49	43	31	98	58.5
Vaasa	67	53	134	23	98	79	39	26	55	43	93	59	38	119	82	67.2
Average	46.2	20.6	83.2	35.2	68.8	55.2	71.2	48.2	75.3	43.5	91.5	45.5	37.3	65.8	73.0	57.6

Table 4. The length of the alder pollen season (days), modeled with the temperature sum model.

	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	Average
Kangasala	21	21	24	28	21	21	14	27								22.1
Kuopio	23	20	28	35	21	24	15	27	26	11	24	19	20	16	40	23.3
Oulu	21	24	28	40	21	29	16	31	29	15	27	24	24			25.3
Rovaniemi			19	31	21	32	14	35	14	14	30	18	20	21	42	23.9
Tampere									22	20	22	17	33	16	35	23.6
Turku	29	22	24	28	21	15	14	20	41	22	22	20	29	17	30	23.6
Vaasa	25	24	27	31	22	25	14	30	38	22	25	20	38	16	36	26.2
Average	23.8	22.2	25	32.2	21.2	24.3	14.5	28.3	28.3	17.3	25	19.7	27.3	17.2	36.6	24.16

Table 5a. Classification of the binary flowering data. The number of cases where both observation and prediction are zero is not given, as the value is arbitrary, depending on the length of the observation period before and after flowering season.

	Observation > 0	Observation = 0
Model > 0	"hit" 1860	"false alarm" 1472
Model = 0	"miss" 724	"rest of the year"

Table 5b. Classification of the "false alarms" and "misses"

	False alarm	Miss
Total	1472	724
Before predicted flowering	553	59
During predicted flowering	872	100
After predicted flowering	47	565

Table 6. Model parameter values for the model without air humidity coefficient, and number of days of different “events”.

		all	Odd	even	early	Late
Starting date of temperature sum accumulation	Day of the year	46.4	43.93	55.24	46.6	45.5
Critical temperature	°C	-1.30	-1.23	-1.47	-1.39	-1.30
Minimum threshold for pollen ripening	Degree-day	2.32	2.04	10.0	9.7	2.11
Maximum threshold for pollen ripening	Degree-day	187.3	187.8	185.7	185.4	188.2
Model SSE, fitted to all years	(relative)	11.72	17.3	7.01	7.75	15.2

Figure captions

Fig 1. The locations of the pollen measuring sites.

Fig 2. The distribution of the starting day parameter values in the Monte Carlo –resampling, for odd and even years. Average starting date is 43.9 and 55.2 (day-of-year) for odd and even years.

Fig 3. XY-plot of the observed (X-axis) vs. predicted (Y-axis) pollen amounts for the pollen model. Red dots show points where either observed or predicted pollen count is positive, and blue dots require the both to be positive. The number on observations where either one is zero pulls the red regression line to run next to the origin of the graph. For the points where both observed and predicted pollen count is positive, the model poorly reproduces the day-to-day variation in pollen counts.