

Toward optimized temperature sum parameterizations for forecasting the start of the pollen season

Andreas Pauling · Regula Gehrig · Bernard Clot

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Abstract The start date of flowering of allergenic species is of great interest in the context of allergy. Such forecasts can help to plan the therapy and design the medical treatment. For this purpose, temperature sum models are usually employed. Designing temperature sum models requires the selection of different parameters such as the base temperature and the start date for the temperature sum. However, the optimal parameterization is often unknown and varies depending on location and species. The purpose of this study was to systematically test parameterizations of temperature sum models based on 12 Swiss pollen stations. The examined taxa include *Corylus*, *Alnus*, *Fraxinus*, *Betula*, and Poaceae. We tested the simple thermal model type (forcing-only model hereafter) which relies solely on forcing temperatures and the sequential model type that includes also chilling temperatures. The mean absolute error was used to

assess the performance of the models. Our study shows that the sequential model could not achieve a discernible reduction of the (statistical) error compared to the forcing-only model for all taxa. The mean absolute error lies roughly between 2 and 4 days with the lowest values for *Betula*. The optimized parameterizations in combination with temperature forecast and the climatological mean were used during the 2012 pollen season to provide daily updated forecasts of the start of flowering for all five taxa. Improvements of the models could possibly be achieved by testing additional temperature parameters as well as other meteorological factors such as precipitation or irradiation. Identification of a process-oriented model with high statistical performance for all stations would facilitate the implementation in numerical pollen dispersion models.

Keywords Temperature sum models · Chilling · Parameterization · Start of flowering · Pollen season · Optimization

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A. Pauling (✉) · R. Gehrig
Federal Office of Meteorology and Climatology
MeteoSwiss, Kraehbuehlstrasse 58, 8044 Zurich,
Switzerland
e-mail: andreas.pauling@meteoswiss.ch

B. Clot
Federal Office of Meteorology and Climatology
MeteoSwiss, Chemin de l'Aérologie, 1530 Payerne,
Switzerland

1 Introduction

In Europe, about 15 % of the population suffer from pollinosis. Pollen forecasts are a helpful tool for allergy sufferers to plan pollen avoidance strategies and the medicine intake which reduces the symptoms. Starting the medication two weeks before the pollen season improves the efficacy (Scadding et al. 2008).

Hence, forecasts of the start of the pollen season can be very helpful to doctors and allergy sufferers.

The most widely used approach to forecast the species-specific start of the pollination period is temperature sum models. Réaumur (1735) introduced the idea that the development of plants depends on temperature sums. During the most recent decades, the approach of temperature sums to forecast the state of the vegetation has been used in a number of aerobiological, phenological, and agricultural studies (e.g., Sarvas 1974; Andersen 1991; Cannell and Smith 1983; Chuine et al. 1998; García-Mozo et al. 2009; Kramer 1994; Clot 1998, 2001; Rodríguez-Rajo et al. 2003; Cesaraccio et al. 2004).

Generally, temperature sum models can be divided into two main categories. Models that take into account only the influence of forcing temperatures (thermal time model; Cannell and Smith 1983) and models that consider chilling as well. The latter can be further divided into parallel models (Landsberg 1974), sequential models (Sarvas 1974), and alternating models (Cannell and Smith 1983). The parallel model suggests that chilling and forcing temperature can be accumulated during the same period of time. On the other hand, the sequential model requires chilling to be completed prior to forcing temperatures can be active. Finally, the alternating model uses a certain temperature threshold to determine whether chilling or forcing is accumulated. Hence, this model allows alternate accumulation of chilling and forcing, respectively. Kramer (1994) and Chuine et al. (1998) provide a detailed description of all these various model types. Linkosalo et al. (2006) introduced both the nullifying and the reversing model type. They assume that low air temperature can offset accumulated forcing units by nullifying or even reversing them. Obviously, this can lead to delayed starting dates of flowering. García-Mozo et al. (2009) suggest that apart from temperature also precipitation and photoperiod play a certain role when determining the start of the Poaceae pollen season in Spain. Galán et al. (1998) even identified minimum temperature of October and December rainfall to be the main factors determining the onset of Cupressaceae pollen season in Spain using regression analysis.

There are still large gaps in the knowledge regarding the effects of weather parameters on physiological processes of the plants because most of them are not visible (Linkosalo et al. 2006). For example, there is

no clear consensus about when high temperatures are physiologically effective. Häkkinen et al. (1998) found that until midwinter there is no physiologically effective forcing of high temperatures for *Betula*, while experiments on seedlings suggest that high temperatures after late autumn can start ontogenetic development (Sarvas 1974). Moreover, the physiologically correct way how to accumulate the chilling or forcing units is largely unknown and varies not only among species but also probably from region to region. Therefore, a large number of models have been proposed, trying to simulate the physiological processes (e.g., Sarvas 1974; Andersen 1991; Cannell and Smith 1983; Kramer 1994; Chuine 2000; García-Mozo et al. 2009; Linkosalo et al. 2006).

Despite the numerous applications of temperature sum models for modeling phenological phases such as the start of flowering, only few attempts have been made so far to optimize this approach. Cross and Zuber (1972) tested 22 methods to estimate the thermal units to predict the flowering dates of maize. Chuine et al. (1998) used simulated annealing to find the best model, and Chuine et al. (1999) used eight different models for temperate trees described in the literature to identify the best model. They found that for most models taking chilling into account outperformed thermal time models. Kramer (1994) tested various models predicting the onset of growth of *Fagus sylvatica* using optimized parameter sets. He found that only an improved version of the sequential model performed better than the null model (i.e., the mean).

Besides Kramer (1994), there are very few studies that attempted to find systematically the best parameterization for the prediction of flowering dates using a parameter discretization scheme fine enough to make sure the optimal parameter configuration is not missed. Hence, the overall goal of our study was to identify optimized parameterizations to calculate the temperature sum based on systematical tests to ensure that the best solution is found. By testing all possible parameter combinations, we implicitly addressed this lack of knowledge about physiological processes regarding chilling accumulation and ontogenetic development. These optimized parameterizations shall be operationally employed to provide the best possible forecast for the start of the pollen season. Moreover, optimized temperature sum parameterizations can help improve numerical dispersion models such as COSMO-ART

(Vogel et al. 2008, 2009) as the correct calculation of start of the pollen season is mandatory for the correct calculation of the pollen dispersion during the first days of the pollen season.

We focused on the sequential model and the forcing-only model (thermal time model) to investigate the effect of chilling parameters. Three major goals were set:

1. optimization of the forcing-only and the sequential model parameterization
2. comparison and evaluation of these two model types by quantifying the additional skill of the sequential models due to chilling
3. implementation of the optimized parameterizations and operational use

2 Data and methods

We used daily pollen data from 12 stations of the Swiss pollen monitoring network which are mostly situated in major Swiss cities. The stations are Basel, Bern, Buchs, Geneva, Lausanne, Locarno, Lugano, Lucerne, Münsterlingen, Neuchâtel, Visp, and Zurich. All stations are equipped with Hirst-type pollen traps. The longest time series used in this study goes back to 1982, some start in the early 1990s, and the shortest time series begins in 1997. The last year is 2011 in all cases. We focused our analyses on *Corylus*, *Alnus*, *Fraxinus*, *Betula*, and Poaceae because of their allergological relevance and the great variability of the start of pollination which highlights the need for precise long-term forecasts.

Air temperature data come from meteorological stations located nearby. We restricted the analysis to temperature data measured at 12 h UTC which served as a proxy for daily maximum temperature data. This decision was made to facilitate later operational application of the models when employing gridded weather model data which have hourly resolution. Plus, given the generally very high correlation between temperature time series such as daily maximum and 12 h UTC temperature (not shown), the results of this study are not expected to be highly affected by this decision. Moreover (computational), resources can be placed on more critical issues.

When computing the temperature sums, some decisions have to be taken regarding the following parameters:

1. definition of the start of the pollen season (cf. Table 1)
2. start date of temperature sum
3. base temperature
4. temporal weighting
5. start date of the chilling temperature sum (only sequential model)
6. base temperature for chilling (only sequential model)
7. critical temperature sum for chilling (only sequential model)

We restricted our analyses to temperature and excluded potentially meaningful factors such as irradiation or precipitation. This was done to limit the effort and to stick to straightforward implementation-friendly methods. For the same reasons, the weights used for temperature are only dependent on the Julian day (spring temperatures receive different weights than winter temperatures) and not on the actual value (high temperatures receive different weights than low temperatures) which would represent an additional parameter.

Figure 1 illustrates the principle of the sequential model using a hypothetical temperature curve and base temperatures. Only temperatures above (below) the base temperature contribute to the temperature sum for forcing (chilling). The critical temperature sum for chilling and forcing is represented by the integrals (shaded areas). We calculate the forcing temperature sum as follows (adapted from Chuine et al. 1999)

$$T_{\text{sum}_{\text{forc}}}(t) = \sum_{t_{0,\text{forc}}}^t w_{\text{forc}} \times R_{\text{forc}}(x_t)$$

$$R_{\text{forc}}(x_t) = \begin{cases} 0 & \text{if } x_t < T_{b,\text{forc}} \\ x_t - T_b & \text{if } x_t \geq T_{b,\text{forc}} \end{cases}$$

where $R_{\text{forc}}(x_t)$ = forcing rate function, w_{forc} = sequence of weights, x_t = temperature at 12 h UTC, $t_{0,\text{forc}}$ = start date of temperature sum for forcing, $T_{b,\text{forc}}$ = base temperature for forcing.

The chilling temperature calculation was done in an analog way. Mathematical descriptions of how to calculate the temperature sums for a number of

Table 1 Discretization scheme of the temperature sum parameters

Taxon	Parameters for the forcing-only and the sequential model				Additional parameters for the sequential model		
	$T_{b,forc}$	$t_{0,forc}$	$thres_{flow}$	w_{forc}	$T_{b,chill}$	$t_{0,chill}$	$T_{sum_{crit,chill}}$
<i>Corylus</i>	0, 12, 1	1, 124, 10	10, 50, 10	None, Linear, Quadratic, Root	−6, 8, 2	1, 124, 10	−300, 0, 20
<i>Alnus</i>	0, 12, 1	1, 124, 10	10, 50, 10		−6, 8, 2	1, 124, 10	−300, 0, 20
<i>Fraxinus</i>	1, 16, 1	1, 152, 10	10, 50, 10		−6, 8, 2	1, 124, 10	−300, 0, 20
<i>Betula</i>	1, 16, 1	1, 152, 10	10, 50, 10		−6, 8, 2	1, 124, 10	−300, 0, 20
Poaceae	1, 16, 1	1, 183, 10	10, 50, 10		−6, 8, 2	1, 124, 10	−300, 0, 20

The parameter ranges are given in the format start, end, increment. For the sequential models, $t_{0,forc}$ is not relevant as the start date of the forcing temperature sum is determined by $T_{sum_{crit,chill}}$. Temperature values always refer to 12 h UTC

$T_{b,forc}$ = base temperatures for forcing (°C)

$t_{0,forc}$ = start dates of temperature sum for forcing, given as dates since October 1

$thres_{flow}$ = thresholds of mean daily pollen concentrations (m^{-3}). The first day of the year with pollen concentrations larger than the threshold is defined as the start of flowering

w_{forc} = sequence of weights used for the daily temperature values. None: no weights. Linear: $w_1 = 1$; $w_n = w_{n-1} + 1$. Quadratic: $w_1 = 1$; $w_n = (w_{n-1} + 1)^2$. Root: $w_1 = 1$; $w_n = (w_{n-1} + 1)^{1/2}$

$T_{b,chill}$ = base temperatures for chilling (°C)

$t_{0,chill}$ = start dates of temperature sum for chilling, given as days since October 1

$T_{sum_{crit,chill}}$ = critical temperature sum for chilling (°C)

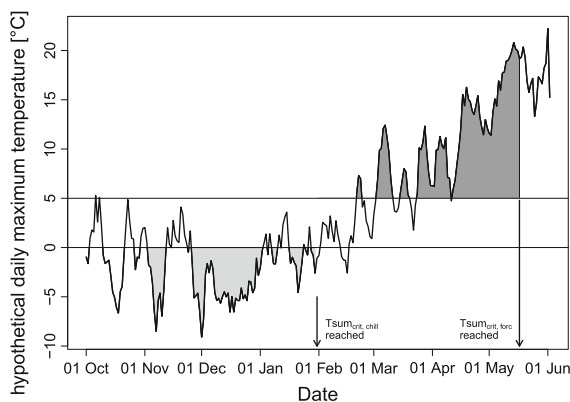


Fig. 1 Illustration of the sequential model using a hypothetical temperature course and base temperatures. In this example, the start date for chilling is November 1. Base temperatures for chilling and forcing are 0 and 5 °C, respectively. The shaded areas represent the temperature sum. The start date for forcing is defined by the critical temperature sum for chilling ($T_{sum_{crit,chill}}$). $T_{sum_{crit,forc}}$ indicates the modeled start of flowering. The forcing-only model uses just the forcing temperature sum

temperature sum models can be found in Kramer (1994) and Chuine et al. (1999) and references therein. Some studies used also a lower threshold for the accumulation of the chilling units, i.e., temperatures below a certain threshold do not contribute to the accumulation of the chilling units (e.g., Kramer 1994;

Linkosalo et al. 2006). However, given the large uncertainties, we renounced to define such a lower threshold.

Definitions for the start date were also kept variable during the optimization process. The start of the pollen season was defined as the date, when the daily concentrations reach a specific threshold. Compared to the definition of a given percentage of the Seasonal Pollen Index (SPI), a threshold value has some advantages. The start date is not dependent on the very variable SPI and it signifies a concentrations class and can therefore be connected to patient symptoms.

The basic idea was to test all possible ways to calculate the temperature sum using the discretized parameters. This approach ensures that the (statistically) best model is found for each station based on a performance criterion. However, some constraints have to be considered. The computational resources limit the number of parameterizations that can be tested. This has implications on the discretization of the parameters. On the one hand, the experimental setup has to ensure that all relevant parameterizations are tested. On the other hand, the discretization steps have to be large enough to account for the computational limitations. Considering these constraints, the discretization of the parameters was done as shown in Table 1.

The number of possible parameter combinations per station follows from Table 1 and ranges between 3'380 (*Corylus*, *Alnus*) and 6'460 (Poaceae) for the forcing-only model, whereas the sequential model required between 432'640 (*Corylus*, *Alnus*) and 565'760 (*Fraxinus*, *Betula*, Poaceae) combinations is to be tested. The relatively low number of combinations of the forcing-only model would allow smaller discretization steps. However, we decided to use the same discretization scheme of the forcing parameters for both the forcing-only model and the sequential model. This setup allowed to quantify the additional skill due to the chilling parameters.

The algorithm used to identify the best model was written in the statistical computing language R version 2.15.0 (R Development Core Team 2010). The analyses were performed on a 12-core Linux cluster. The algorithm sequentially assessed the skill of all possible configurations as defined in Table 1. The following procedure was employed. Using the pollen measurements and the thresholds of mean daily pollen concentrations, the start date of flowering was determined (cf. Table 1). Then, the temperature sum at that date was calculated using the parameter combination to be tested. Averaging over all available years yielded $T_{\text{sum}_{\text{crit,forc}}}$. This was done for each station separately. Ideally, the interannual variability of the yearly critical temperature sum is zero. Using $T_{\text{sum}_{\text{crit,forc}}}$ as a threshold, the start date of flowering was determined based on the year-specific temperature sum. The difference between the calculated and the observed date of flowering was used to assess the skill of the models by calculating the mean absolute error (MAE). This score is defined as

$$\text{MAE} = \frac{1}{n} \sum_{j=1}^n |\text{obs}_j - \text{mod}_j|$$

where obs_j = observed flowering date in year j , mod_j = modeled flowering date in year j , n = sample size (number of years).

MAE is the empirical mean error in days and is a suitable measure for the skill of the parameterizations which is easy to interpret. It also provides a robust estimate of the expected error of the predictions. The parameterization with the lowest MAE value was regarded as the best model. The whole procedure was repeated for each station and taxon.

As both temperature and pollen data of neighboring years are approximately independent, a leave-one-out

cross-validation procedure was employed to test the best model on independent (external) data (e.g., Efron and Tibshirani 1994). $T_{\text{sum}_{\text{crit,forc}}}$ was calculated leaving out the first year. The MAE value was calculated for the omitted year based on the $T_{\text{sum}_{\text{crit,forc}}}$ determined without this year. This step was repeated for each year, yielding a more realistic sequence of MAE than the one calculated during calibration.

3 Results and discussion

A major objective of this study was to quantify the additional skill of the sequential model due to chilling compared to the forcing-only model. Figure 2 shows boxplots of MAE values (from calibration) of these two models using the optimized parameterization for each taxon. This result is based on 12 stations except for *Alnus* where the station Buchs was excluded for the following reason. During the observation period, many early-flowering *Alnus* $\times$ *spaethii* were planted in the vicinity of the pollen trap (Gassner et al. 2012). Hence, the start of flowering dates for *Alnus* at Buchs cannot be assumed to be taken from the same population and was thus excluded. The models for *Betula* and Poaceae display the highest skill, while MAE values for *Fraxinus* and *Alnus* are highest. The latter is also characterized by the highest station-to-station variability as can be seen from the large boxplot.

The skill of the sequential model is almost the same as the skill of the forcing-only model for all tested taxa. Hence, the best of the roughly 500'000 tested parameterizations of the sequential model is only marginally better than the best of the few thousand forcing-only parameterizations. This result suggests that chilling does not substantially contribute to the (statistical) skill of the models at least using the described data and experimental setup. It must be stressed that this conclusion is only based on statistical grounds and does not mean at all that there is no physiological process of chilling. However, Häkkinen et al. (1998), Häkkinen (1999) concluded also based on statistical analyses that predictive models perform better when the start of ontogenetic bud development is based on fixed date (as prescribed by the forcing-only model) compared to those models in which the start and rate of development depended on the stage of

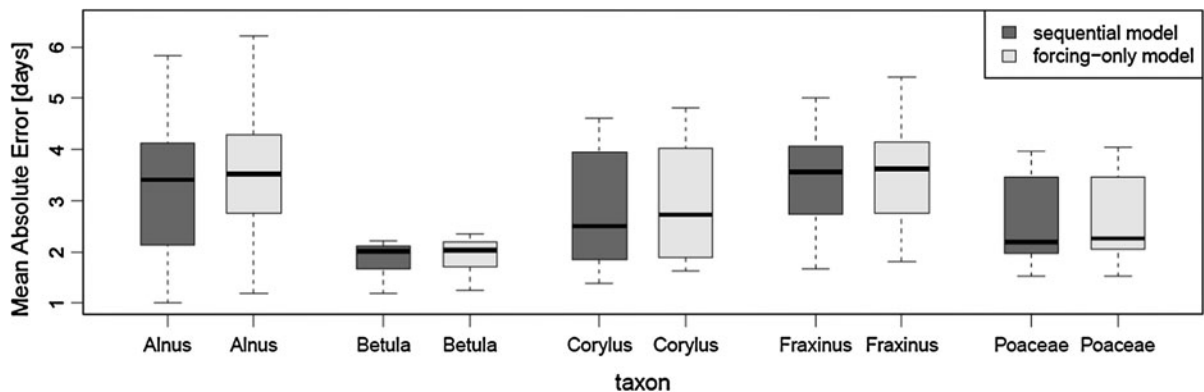


Fig. 2 Boxplots of the mean absolute error (MAE) using the optimal parameterizations for both the forcing-only and the sequential model. The boxplots are calculated for all five taxa, each based on 12 stations (*Alnus* 11 stations)

dormancy (as prescribed in the sequential model). On the other hand, Kramer (1994) found that an improved version of the sequential model performed better than the thermal time model (forcing-only model) to predict the onset of growth of *Fagus sylvatica*. Linkosalo et al. (2006) tested the sequential and the forcing-only model against two new models (nullifying and reversing model) and found the forcing-only model to outperform all the other models. In our study, it is not possible that the forcing-only model performs better than the sequential model due to the experimental design. All parameterizations tested by the forcing-only model are also tested by the sequential model. The chilling part in the sequential model is just additional to the forcing part, giving the sequential model the opportunity to exploit possible benefits from simulating chilling units. As shown by Fig. 2, these benefits are negligible. Therefore, we focused on the forcing-only model for the subsequent analyses.

Figure 3 shows the observed versus modeled start dates of flowering based on all stations and grouped by taxa. The optimized parameterizations given in Table 2 and Appendix 1 in supplementary material were used to produce the modeled start dates. All p values are $\ll 0.001$ independent of the length of the time series. Short time series are more prone to overfitting as they have fewer degrees of freedom. As seen from Appendix 1, short time series tend to result in low MAE values. However, the length of the time series appears to have a rather small impact.

However, especially for *Corylus*, *Alnus*, and *Fraxinus*, there are some years with a large bias. Pollen can be registered many days before local flowering since they can be transported over large distances in some

years (Sofiev et al. 2006). This affects the temperature sum models in two ways. First, the models forecast the start of flowering too late which may be the reason for some biased modeled start dates in Fig. 3. Second, due to transport events, the critical temperature sum is lower than it should be for local flowering, causing some forecasts to be too early. The target of the temperature sum models is local flowering because transport events can never be predicted by temperature sum models. However, in most cases, it is not possible to distinguish between local and transported pollen. In Switzerland, long-range transport is less important for *Betula* as there are very few *Betula* stands south of Switzerland (Pauling et al. 2012). However, for *Fraxinus*, it may play a certain role.

Another source of error is the measurements. Especially, for low pollen concentrations around the threshold for the start of the season, the sampling error of the measurement may be 50 % or more (Comtois et al. 1999; Cotos-Yáñez et al. 2012). Hence, the date when the concentration threshold for flowering is exceeded is also subject to chance. This may play an especially important role with early-flowering *Corylus* and *Alnus* as long cold spells in January and February may separate possible start dates by weeks. In some cases, this may have caused the large observed error in some years. Additionally, there are large differences regarding the flowering date of the individual plants. This may be due to the exposition which determines how much warmth and radiation the plants receive in winter. Precipitation before the observed flowering together with rather mild temperatures may be another source of error. The pollen may be inhibited to fly by precipitation although they are ready and $T_{\text{sum}_{\text{crit,forc}}}$ is

Fig. 3 Observed versus modeled start dates of flowering based on 12 stations for all five taxa (*Alnus* 11 stations). All p values are $\ll 0.001$. Each data point represents one year at one station

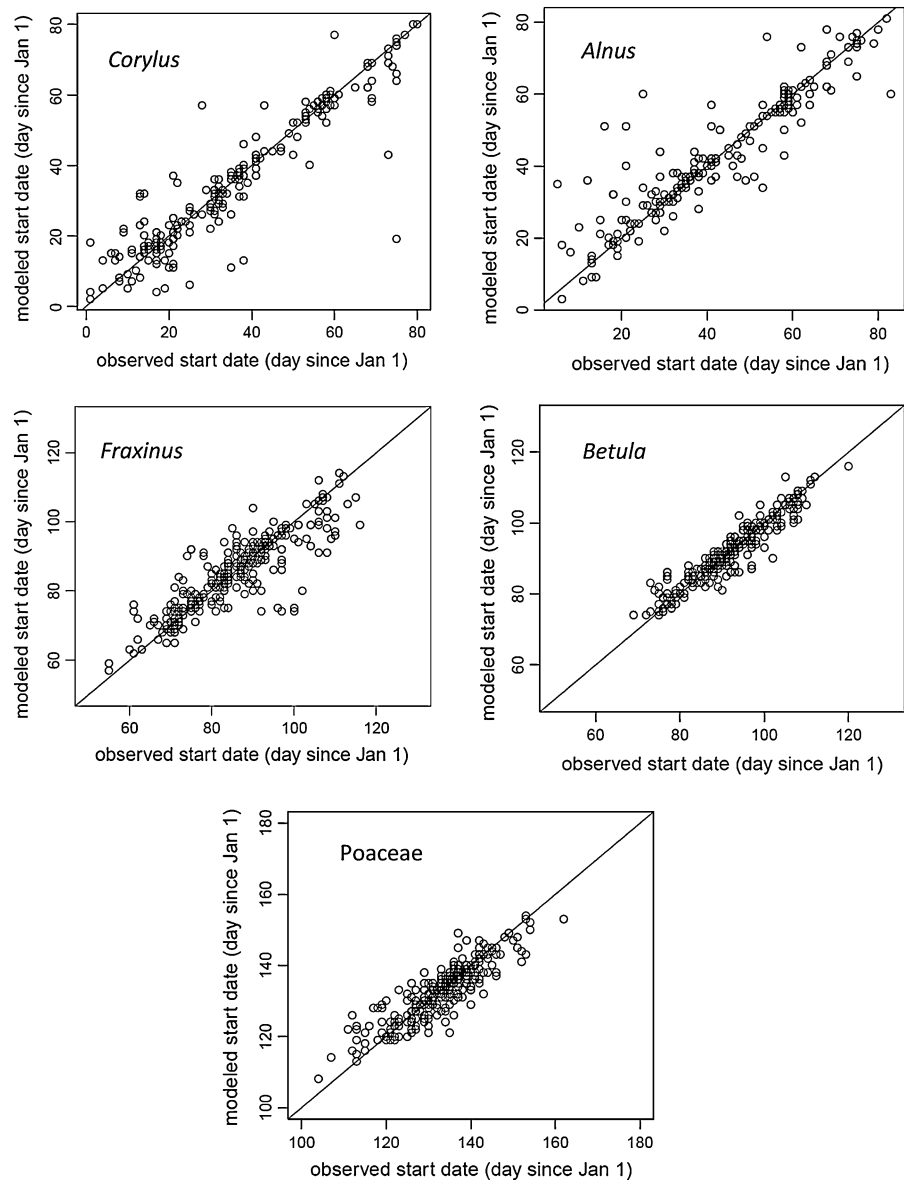


Table 2 Optimized parameterization and performance (MAE from cross-validation) of the forcing-only model for the station of Basel which is based on data from 1982 to 2011. The mean

difference between the observed date and the climatological mean date (null model, NULL) is given for comparison

Taxon	$T_{b,forc}$ (°C)	$t_{0,forc}$	$thres_{flow}$ (m ⁻³)	w_{forc}	MAE (days)	NULL (days)	n (years)
<i>Corylus</i>	7	30 Dec	20	None	4.5	15.9	28
<i>Alnus</i>	8	9 Jan	30	Linear	6.2	13.9	28
<i>Fraxinus</i>	9	29 Jan	20	Root	4.3	10.5	29
<i>Betula</i>	10	9 Jan	40	Quadr	2.1	7.1	30
Poaceae	0	30 Nov	40	Linear	3.5	5.7	30

exceeded. Such situations lead to biased estimates of $T_{\text{sum}_{\text{crit,forc}}}$. However, excluding years with more than 2 mm precipitation during each of the two days preceding the observed start of flowering did not improve the skill which suggests this effect to be small.

Different from the other taxa, the modeled start dates for Poaceae never show a very large error (Fig. 3). The primary reason for this is the low overall variability of Poaceae start dates which may be due to their dependence on the length of the day (Niqueux and Arnaud 1967; Laaidi 2001; García-Mozo et al. 2009). Thus, very large errors can already be avoided by the climatological mean date. On the other hand, in most cases, there are small errors of a few days and precise forecasts (error of zero days) are rare. This could indicate that other (meteorological) factors play a certain role. In addition, the gradual increase in the Poaceae pollen concentrations at the beginning of the season together with the sampling error introduces some uncertainties. As there is a gradual increase of measured pollen concentrations at the start of the season, the sampling error is more important for Poaceae than for *Betula* and *Fraxinus* with their rather sharp increase at the start of the pollen season.

Table 2 shows the best parameterization of the forcing-only model for the station of Basel. This was chosen as an example because of the length of the time series. Similar tables for the other stations can be found in Appendix 1. Some time series are much shorter than the one of Basel partly because the observations started later and partly because there are more missing values. Especially for *Alnus* and *Corylus*, there are many missing years as previously the pollen measurements started later than the onset of the pollen season. These years were omitted to ensure no start of flowering is missed.

In Table 2, the base temperatures for forcing are between 7 and 10 °C except for Poaceae with 0 °C. The optimal start date for the temperature sum is close to the beginning of the year. Only for Poaceae, a substantially earlier date performed best. The easiest-to-predict pollen thresholds for the start of flowering lie between 20 and 40 Pollen/m⁻³ and weighting schemes vary between taxa.

There is a large improvement of the skill of the optimized parameterization compared to the null model (i.e., the mean difference between the observed

date and the climatological mean date). The optimized parameterizations of the simple forcing-only model outperform substantially the null model as shown by the MAE and NULL values in Table 2. This holds true for the other stations as well, as seen from Appendix 1. This is in line with findings by Andersen (1991), Chuine et al. (1998), and Rodríguez-Rajo et al. (2003) who built temperature sum models for *Alnus* and *Betula*. In all these studies, temperature sum models were found to be useful for the prediction of the start date of flowering.

The optimal parameterization for Poaceae at Basel is somewhat different from the other taxa and other stations regarding $T_{\text{b,forc}}$ and $t_{0,\text{forc}}$ (Table 2; Appendix 1). When interpreting this feature, it should be noted that out of thousands of tested parameterizations, there are many with high skill although they have different configurations. Which one ends up on top of the list is partly random. Hence, also considerations about the underlying biological and physiological processes should be made. The biologically meaningful parameterizations may have slightly lower MAE values but might be better interpreted. Moreover, it may also be easier to identify a common parameterization for various stations which would corroborate that this common parameterization is based on biological processes and not only on statistical optimization which is also subject to random effects of pollen measurements. In addition, such a common parameterization could be used not only for various stations but also as input to Eulerian numerical pollen dispersion models such as COSMO-ART (Vogel et al. 2008, 2009) because at every grid point a temperature sum model is needed.

Concerning the definition of the start date of the pollen season, thresholds of 20–50 pollen/m³ appear to be easier to predict than lower thresholds. From the point of view of the patients, it would be better to predict the start of low or moderate pollen concentrations. However, this would result in a decrease in the accuracy of the predictions.

Figure 4 shows the observed and modeled (cross-validated) time series of the start date using the example of Basel based on the parameterizations described in Table 2. Most of the modeled dates are less than three days off. However, MAE can be wrong up to 10 days or more in some years. García-Mozo et al. (2009) used temperature, photoperiod, and water

availability to predict the start of grass flowering in various Spanish locations. Similar to this study, they found MAE values from 0 to 11 days (mean 3 days) when validating the model during two independent years. García-Mozo et al. (2002) calibrated a growing degree day model (using only temperature) to the start of the *Quercus* pollen season for different Spanish localities and found MAE values of 5.5 days for the year 2000 that was not used for calibration.

The large year-to-year variability of the flowering start date of *Corylus* at Basel is well captured except for the late 1980s (Fig. 4). During these years, the model is biased toward early start dates. Obviously, these springs required higher temperature sums than the following years. The reason for this is not straightforward. Another parameterization may not have led to this feature. Interestingly, this bias coincides with cold or wet periods unfavorable for pollen release during January and February. Additionally, such features may possibly be attributed to uncertainties in the measurements as well (cf. above).

The MAE value for *Alnus* is relatively high (Table 2). As seen from Fig. 4, this is due to the years 1994, 1999, and 2008 when the modeled start date was up to 30 days too late. There are a number of possible reasons for this bias. Due to the relatively high base temperature of 8 °C, the accumulation of thermal units could be stopped for several days around the observed date of flowering. Therefore, the calculated date of flowering could be delayed. Moreover, the extremely early starting date of 1994 (January 5) cannot be captured as the start date for the temperature sum is January 9 in that parameterization (Table 2). The large error of 1999 may also be due to the same reason. This example shows that probably another model with a lower base temperature and an earlier start of the accumulation of forcing temperatures with a similar good MAE could give biologically more meaningful results for *Alnus*.

The start date of flowering for *Fraxinus* and especially *Betula* can be well predicted as shown in Fig. 4. The largest error for *Fraxinus* occurred in 2008 when the observed start date occurred on March 1 while the modeled start date was 15 days later. A cold spell of four days between these two dates may have contributed to this large error. Additionally, the start date in 2008 occurred 20 days earlier than the mean date, which may indicate that this specific parameterization may have some deficiencies with very early

years. Moreover, some transported pollen could have influenced this early start date. In 1994, the predicted start date of *Betula* was 10 days too late. In that year, the pollen data do not show the usual sharp increase in pollen concentrations at the beginning of the season. Rather, moderate concentrations persist for about one week. A possible reasons for this are the temperatures that were rather low during that period (maximum temperatures of 8–12 °C at Basel). Thus, it may be argued that there were only few local pollen emitted if any. The moderate pollen concentrations may also have been caused by transport up the Rhine valley.

The skill of the Poaceae model is rather low compared to the variability of the observed start dates (Table 2; Fig. 4). The reason for this may be warm, but rainy weather which inhibits the start of the grass pollen season. This could be more important for Poaceae than for the other considered taxa as Poaceae is close to the ground and drying the plants after the rain take more time. Additionally, similar to the other taxa, factors other than temperature in determining the start date of flowering such nonlinearities in plant physiology may play a role.

4 Operational use in 2012

The forcing-only model with parameterizations described in Table 2 and Appendix 1 was operational for the first time during the pollen season 2012. Each day the forecasted start date of flowering was updated based on combined time series of temperature measurements, 7-day-Kalman-filtered temperature forecast from the IFS weather model (Integrated Forecasting System) of the European Centre for Medium-range Weather Forecasts (ECMWF) and the climatological mean of the stations afterward. The forecasts were made available to the public via the MeteoSwiss Web site. The purpose of this forecast was to provide the best possible estimates of the start date of flowering of the allergological most relevant species from the beginning of the year. This information is important for the timing of the therapy.

Ideally, this forecast is stable over time. Since the actual temperature course is not known in advance, the forecast can fluctuate on a daily basis. Typically, this forecast is thought to have its largest uncertainties at the beginning of the year when it is mostly based on the climatological mean course of temperature. As the

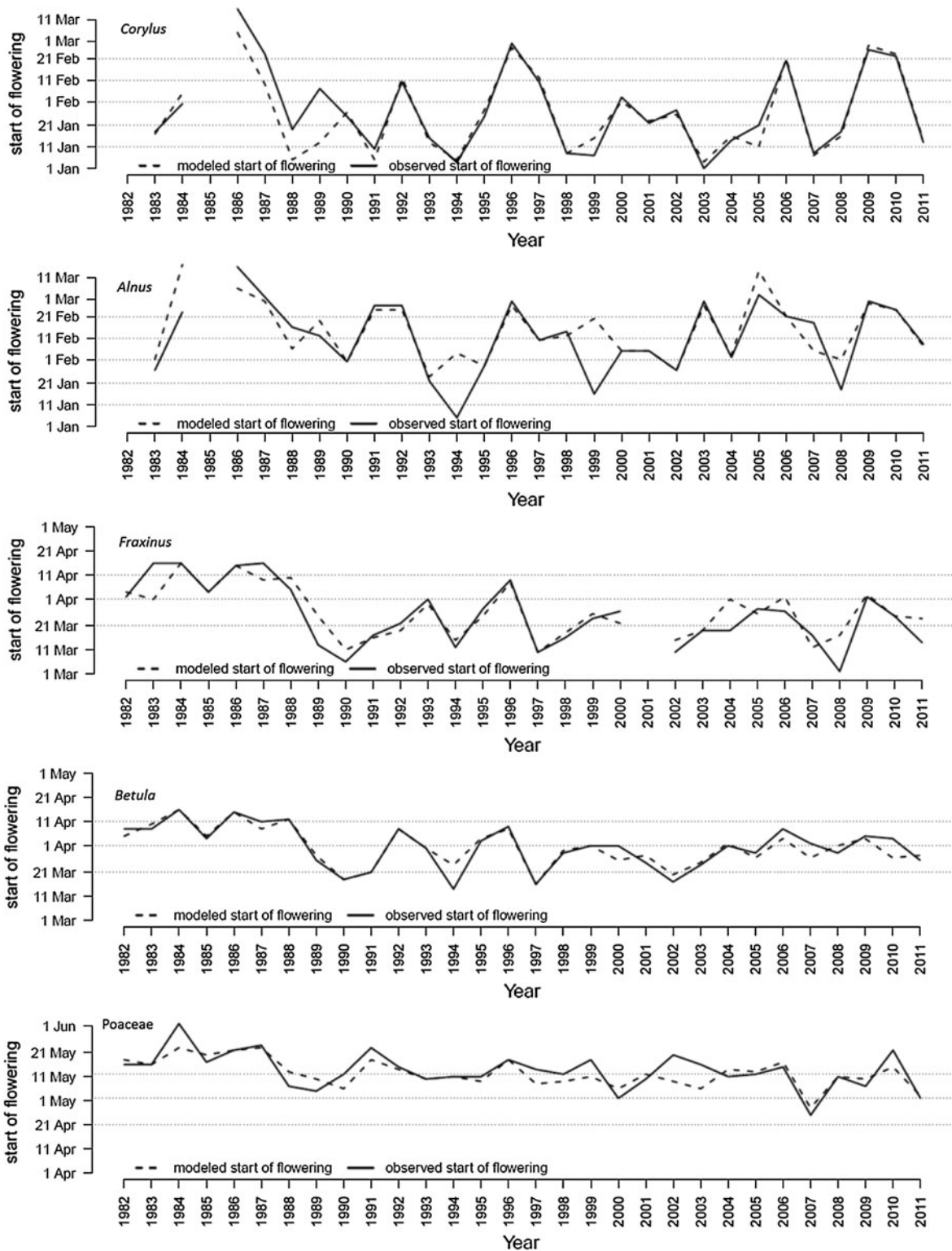


Fig. 4 Observed and modeled (cross-validated) time series of the best forcing-only model based on data from the station of Basel. The model configurations and the performance for these five taxa can be seen from Table 2

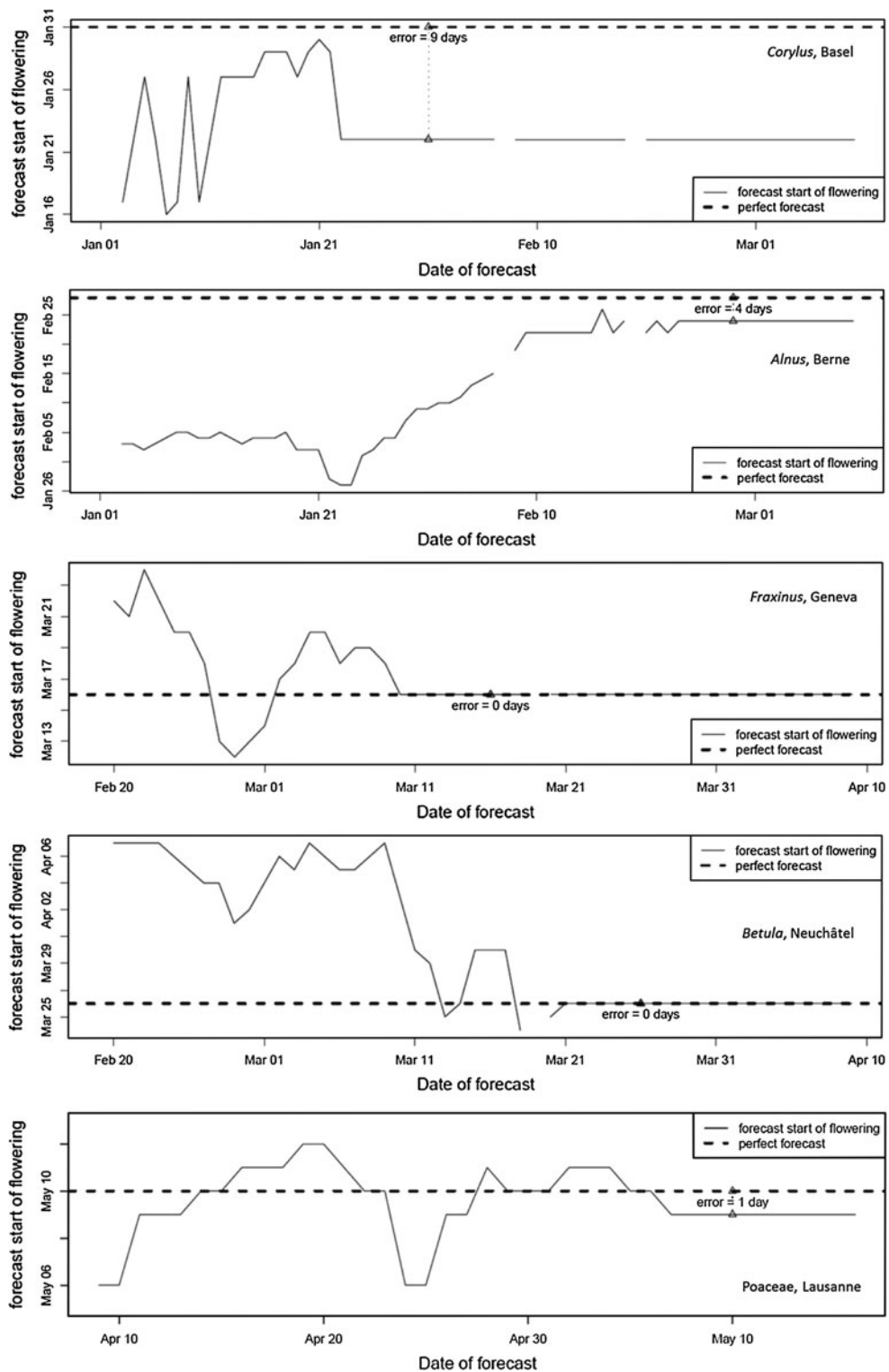


Fig. 5 Temporal evolution of the forecast start date of flowering for the five species at different Swiss stations during the pollen season 2012. The error values refer to the error at the observed start date. *Note* the varying scale on both axes

year goes on, the forecast should gradually approach the actual start date of flowering.

Figure 5 displays examples of the forecast start date of flowering depending on the date of forecast. The dashed line represents the observed forecast date, i.e., perfect forecasts would lie on this line. The errors at the day of the observed start of flowering are also given. In the beginning, the forecasts are mainly based on the climatology. As time goes on, the forecasts are more and more based on measurements. When they are completely based on measurements, the forecast start date obviously cannot change any more. In Fig. 5, this is expressed by the constant forecast start date of flowering. Breaks in the solid line indicate missing forecasts. *Corylus* at Basel was forecasted to flower nine days too early. During the early part of January, the forecasted start dates fluctuated by around 10 days. This is due to the fact that the temperature sum is very sensitive to anomalies at this stage because the accumulation start date is December 30 (Table 2). Forecasts of *Alnus* at Berne during January were about 25 days too early but gradually improved to an error of four days already 20 days before the observed start of flowering. Temperatures lower than normal during late January and early February postponed the forecast date. The forecast for *Fraxinus* at Geneva was forecasted some days too late around February 20. This is due to temperatures lower than normal during the beginning of February. However, higher temperatures caused the forecast flowering date to advance by some days at the end of February. A cold spell delayed it again some days but reached the correct date seven days before the observed start date. The forecast for *Fraxinus* had an accuracy of few days up to four weeks in advance. The course of *Betula* at Neuchâtel is similar to the one of *Fraxinus* at Geneva. Warm anomalies are reflected by the sharp advance of the forecast start dates around March 10 leading to the correct forecast date around 10 days before the observed start of flowering. Forecast dates for Poaceae at Lausanne fluctuated less than for other taxa as the temperature sum is based on a longer time span, and thus, anomalies have smaller impact on the temperature sum.

The results presented in Fig. 5 are based on the year 2012. As temperature is very variable during winter, the course of the forecasts strongly depends on the year. The larger the anomalies during January to March, the larger the errors of early forecasts are. A possible way to make these forecasts more stable is to prescribe for at least

Alnus and *Corylus* that the temperature sum must start already in December or earlier and then search for the optimal parameterizations.

5 Conclusions

Temperature sum models are often used to forecast the start dates of flowering. However, in most cases, it is still unknown how the temperature sum should be calculated depending on location and species. Hence, using the forcing-only (thermal time model) and the sequential model, systematical tests were made by calculating the performance of all possible parameterizations. It could be shown that the mean absolute error of the best parameterization lies roughly between two and four days for the allergy-relevant taxa *Corylus*, *Alnus*, *Fraxinus*, *Betula*, and Poaceae based on 12 Swiss pollen stations. The aim of this study was to optimize the temperature sum approach. Based on this study, it can be argued that temperature is not the only variable responsible for the year-to-year variability of the flowering dates. Precipitation, irradiation, or nonlinearities in plant physiology may be important as well. Additionally, pollen transport and uncertainties in the measurements of pollen concentrations are suggested as factors introducing unexplained variance in temperature sum models.

Comparisons between the forcing-only and the sequential models showed that consideration of chilling processes as done by the sequential model did not lead to discernible reductions of the (statistical) error. However, this result must not be interpreted the way that there is no chilling factors influencing the ontogenetic development leading to flowering. The statistically best model may not be the one with most biological realism. Plus, these results are valid for the 12 Swiss stations. Especially in the Mediterranean, chilling requirements may be important as well. By selecting a process-based parameterization with low error, it may be possible to find a common model for various stations. This could then also be used as input for numerical pollen dispersion models.

During the 2012 pollen season, the optimized parameterizations in combination with temperature forecasts and the climatological mean were used to forecast the start of flowering from the start of the year with daily updates. At the start of the year, the forecasts were rather unstable because they were

mostly based on the climatology. However, the more they were based on measurements in the course of the year, the more stable they became and provided useful forecasts for the public.

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