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Comparing Apple and Pear Phenology and Model Performance: What 7 Decades of Observations Reveal

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Abstract: Based on observations for the beginning of the flowering stage of *Malus domestica* (apple) and *Pyrus communis* (pear) for the 1950-2018 period, phenological trends in north-eastern Belgium were investigated in function of temperatures during dormancy. Moreover two different phenological models were adapted and evaluated. Average flowering dates of apple and pear were 9.5 resp. 11.5 days earlier following warm dormancy periods but the relationship between bloom date and temperature was found to be not linear, suggesting delayed fulfilment of dormancy requirements due to increased temperatures during the chilling period. After warm chilling periods, an average delay of 15 days in the occurrence date of dormancy break was detected by means of Partial Least Squares Regression, and an average delay of 1–9 days by the phenological models. Our results suggest overlapping chilling and forcing processes in a transition phase. Regarding the beginning of flowering, a dynamic chill model coupled to a growing degree days estimation yielded on average significantly lower prediction errors (5.0 days) than a sequential chill-forcing model (6.0 days), at 99% confidence level. Model performance was sensitive to the applied parametrisation method and limitations for the application of both models outside the past temperature ranges became apparent.

Keywords: climate change; pome fruit; apple; pear; sequential modelling; dynamic modelling dormancy break; chilling requirements; partial least square regression

1. Introduction

In 2018, pome fruit orchards represented 2.4% of the agricultural land in the Northern Belgian region Flanders (~15000 hectares), of which 74% were attributed to the one apple cultivar 'Jonagold' (*Malus domestica)* and one pear cultivar 'Conférence' (*Pyrus communis,*)[1]. Belgium's production of 'Conférence' is about 35% of the total European production in its favourable Atlantic climate. However, climate change might alter these conditions, and during recent years the Belgian fruit sector has more frequently experienced weather conditions that have heavily compromised the quantity and quality of fruits. A severe frost night in 2017 (19-20 April), that coincided with the end of pear bloom and beginning of bloom of most commercially exploited apple cultivars, had in Belgium the Europe-wide highest losses : 68% yield loss on average for apple and 7% loss for pear as compared to the mean of the nine preceding years [2]. The difference between apple and pear losses suggests that the impact of extreme events or adverse weather conditions relates to the timing of phenological stages and the differences therein.

Other weather related hazards were several light frost nights, frequent local hail storms and three heatwaves in 2019, an extensive drought period for more than two months in combination with a heat wave in 2018, water excess and storms in 2016, and a devastating summer storm in 2011. The combination of extreme weather with the Russian Embargo for importation of fruit since 2014 led the entire Belgian fruit sector into an officially recognized crisis, to the extent that federal and regional governments are preparing policies to increase resilience in the face of more frequent extreme weather events and in the

context of a changing climate in general. Therefore a better understanding is needed of the impacts of warming on phenology.

Following [3], the part of the growth cycle between late summer and budburst is conceptualized as dormancy period, and can be decomposed in a sequence of paradormancy, endodormancy and ecodormancy phases. Endodormancy, i.e. 'chilling period', is induced by lower temperatures in late fall. The moment that a species' specific exposure to cold temperatures has been fulfilled, ecodormancy is induced and the accumulation of growing degree hours becomes the determining process for further phenological development [4], i.e. 'forcing period'. From then onwards, warmer temperatures favor earlier and no longer later bloom. Insolation and temperature commonly explain substantial shares of the inter-annual variability of bloom dates, but currently no model based on chilling and temperature forcing has been published that yields satisfying accuracy to predict bloom dates [5]. Furthermore, these phenology models have been developed for certain growing areas (like Israel [6], Finland [7], Germany [8]) but their temporal and geographical transferability is very limited [9], making the parameterisation of a phenological model to local bloom observations necessary. In general, limitations of phenological models are related to the difficulty to observe the transition between dormancy phases and to the low number of available observations as compared to the number of variables involved. Statistical methods like Partial Least Square Regression (PLSR, of air temperatures and phenology), have been used to overcome the challenge of the limited number of observations (bloom dates) with regard to the number of variables (temperature of individual days) [10,11].

The evolution of the timing of the bloom is decisive for selecting adequate and 'climate proof' cultivars with regard to frost risk. As suggested by an Austrian study [12], there is a tendency towards an earlier timing of the last spring frost, but late occurrences are not excluded since inter-annual variability is substantial and regionally blocked atmospheric conditions more frequent [13]. For mountainous areas it might be reasonable to assume chilling requirements not to be compromised [12], but for orchards in temperate lowlands the trajectory is less certain. Studies of phenological changes across Europe reveal a large spatial variability with a consistent tendency towards earlier bloom in higher latitudes and a mixed signal in northern Mediterranean settings. Observations in Nîmes, France (lat. 43.8°N) hint at a trend reversal where the years between 2003 and 2013 show again a later bloom than in the 1990s [14]. Projections for future years show similar contrasts: for Styria (Austria, lat. 47.3°N), mountainous terrain, consistently earlier bloom is projected [12], whereas others projected a consistent delay of bloom for northern Spain (lat. 42.4°N) [11]. Observations in the Southern Mediterranean region, Tunisia in particular, showed important delays and even frequent failures of flowering for the case of pistachios [15]. These delays observed in the South are explained by a delayed completion of chilling requirements due to warmer temperatures during the endodormancy phase, whereas the trend towards earlier flowering in the North is mainly explained by a more rapid accumulation of forcing or degree hours as a direct consequence of the increased temperature during the forcing phase [16,17].

Recent experimental studies on cherry trees in Germany [18] suggest that faster accumulation of forcing can substitute up to 50% of lower accumulated chilling but with a minimum amount of chilling to be fulfilled before forcing can be effective. This motivates the choice of a sequential modelling approach, that explicitly accounts for a cultivar specific relationship between chilling and forcing requirements. Such a model set-up emerged as the most adequate for climate change impact studies from an extensive evaluation of mechanistic models for the beginning of apple blossom in Germany [8] and has been applied in several studies [12,19,20]. The inherent advantage of fast and transparent computations allows for easy adaptation to different fruits and local conditions, but results in less reliable estimations of chilling requirements [21]. Hence, the sequential model only leads to reasonable results within a narrow range of temperatures, where chilling is fulfilled before an accumulation of Growing Degree Hours is possible.

The chilling and subsequent forcing expressed in a sequential model are thought to hold for the past in Belgium, but seem inadequate in a warming world. Reviews of chill and phenology models [5,9,22] suggest a more complex dynamic process [6,23], that accounts more realistically for chilling and forcing processes. We hypothesised that dynamic phenological modelling captures the chilling and forcing requirements in a better manner, and can be used to simulate phenological development of apples and pears in a warming climate.

The major objectives of this paper are 1) to analyse phenologic responses to increasing temperatures during chilling and forcing periods, with the hypothesis that bloom dates are not linearly advancing; 2) to detect shifts of dormancy break using Partial Least Square Regression and compare them to modelled dates and finally, 3) to quantify chilling and forcing requirements for a range of cultivars of apples and pears at a study site in Belgium, while comparing the sequential and dynamic phenological models and their sensitivity to parameter optimisation.

2. Materials and Methods

2.1. Study Area

In Flanders, the northern administrative region of Belgium, the fruit growing area is mostly concentrated on a plateau with low rolling hills and elevations between 30 and 200m ASL, divided over the natural regions Hageland and Haspengouw. A more recent cluster is found in the north (west of Antwerp) in the Waasland natural region (**Figure 1**). The study site is located in the first zone, where the annual average temperature during the period 1950-2018 was 10.1°C.

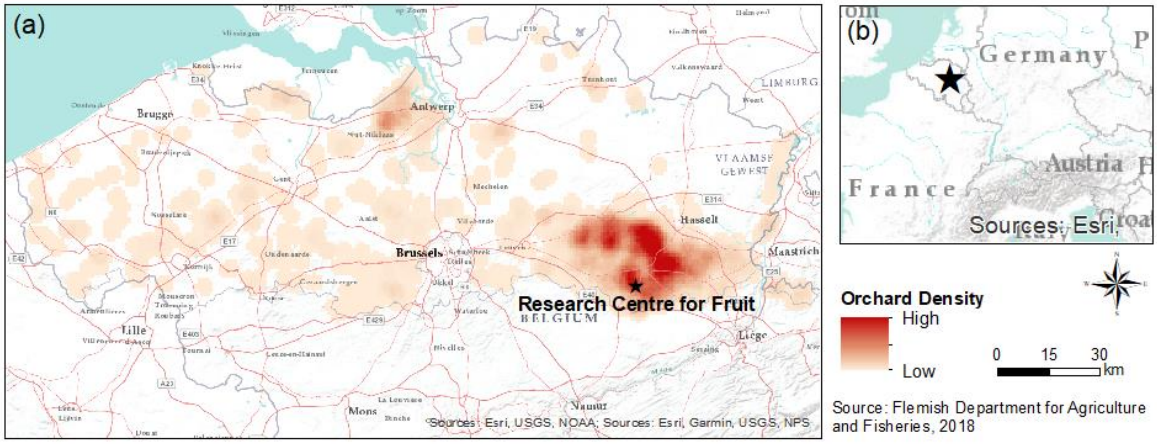


Figure 1 Distribution of apple and pear orchards in the Flemish Region, Belgium. The star marks the study site, the Research Centre for fruit (50°46'N, 5°09'E, 92m ASL).

2.2. Phenology and Meteorology

The timing of the phenological stages following the definitions of the Biologische Bundesanstalt, Bundessortenamt and CHemical industry (BBCH) [24] has been recorded for main apple and pear cultivars by the Research Station for fruit 'pcfruit' since 1950. For 19 cultivars of economic relevance, observations for the beginning of flowering (BBCH61) were transcribed in machine-readable format and inconsistent observations were deleted. Based on the length and completeness of the records, four pear varieties ('Conference', 'Durondeau', 'Doyenné' and 'Triomphe') and four apple varieties ('Jonagold', 'Golden Delicous', 'Boskoop' and 'Cox Orange') were retained.

Time series of daily minimum and maximum temperatures were recorded by a synoptic weather station since 1950 at the research centre with only 3 missing records (0.01 %), which were gap filled using the average of the preceding and following day. Hourly data were computed as an idealized daily temperature curve that uses a sine function for daytime warming (sunrise to sunset) and a logarithmic decay function for night time cooling [25], as implemented in the function *'make_hourly_temps'* from the R package 'chillR' [26]. The decay functions were found to compare well with the observed hourly temperatures for exemplary years 2016 and 2017 from an identical synoptic weather station at 1km from the station of the long term records. The monitored orchards were within 500m distance from this synoptic weather station.

All analyses were done using Python programming language version 3.6, making use of the rpy2 translator [27] to call scripts published in R language [26].

2.3. Ranking Observations to Derive Past Change Signals

Climate change signals were studied based on 68 years of observations (1951-2018) for which temperatures for the full dormancy period were available (bloom observation for 1950 had to be excluded for this reason). Climate change impact on growth and productivity of arable crops in Belgium showed significant differences in temperature before and after a change point in 1988 [28], which allowed to compare weather impacts on the growing season and on sensitive phenological stages from two contrasting periods.

A change point analysis was applied directly to phenology data for West Germany, Switzerland and the Balkans [29–31]. For temperate locations, the comparison between a linear and a 2-segmented pairwise constant model to correlate temperature and phenological stages did not allow to favour one of those models according to the modified Bayesian information criterion [14]. As the focus of this study was to disentangle effects of warming on chilling and forcing, contrasting periods were selected based on rankings of mean temperatures during resp. the full dormancy periods (October to April incl.), chilling periods (October, November and December) and forcing periods (January to April incl.). The inclusion of January to the forcing period in contrast to [14] is motivated based on the results of the PLSR (**Figure 4**).

Since the dormancy state is overlapping two calendar years, observations were attributed to the year of flowering (i.e. October 2017 to April 2018 were associated to 2018). Contrasting periods were selected in two ways: i) by dividing the ranked 68-year period in two halves of 34 years each (referred to as 'cold' and 'mild'); and ii) in three parts (the 25% cold years (n=17); the mild 25% years (n=17) and the remaining average 50% (n= 34). Segments were based on the number of years, not based on the values itself with no special treatment for extremes.

Considering only hourly temperatures in October, November and December (OND), relevant hours were counted using different thresholds for effective chilling temperatures as [0, 10°C] (sequential model), [-2, 14°C] (dynamic model) and [3, 9°C] (the most effective temperatures for chilling). This was done using the contrasting segments of years in terms of average temperature during OND and for comparison, the effective hours were expressed as a percentage of the total number of hours in OND.

2.4. Partial Least Square Regression

Partial Least Square Regression (PLSR) is a method that uses a linear multivariate model to relate two data matrices **X** and **Y** to each other. While it is commonly used in chemometrics [32], its application to plant phenology is novel, but has generated good results in studies on walnuts in California [10,33], cherries in Germany [33] and apples in China [34]. The method goes beyond common multiple linear regression by modelling the structure of the matrices **X** and **Y** and thereby allows to link a comparatively small number of observations for the dependent variables, i.e. date of achieving phenological stages, to a large dataset of highly auto-correlated variables, i.e. meteorological time series. In this application, the observed flowering date per year [Julian Day of Year (DOY)] was related to the antecedent temperatures on a daily basis [°C], thereby reaching back until the approximate beginning of the dormancy period, here defined as 1st of October.

In PLSR a variable compression is performed on the covariance matrix to reduce auto-correlation between predictor variables and to keep only linear combinations of maximum covariance between the explanatory variables **X** (daily temperatures) and the dependent variables **Y** (yearly bloom date) [10]. Temperatures of each day were scaled by their standard deviations, so that all predictors had the same variation. This allowed assessing the influence of variation through time of variables independent of their magnitude. Following [10], a 11-day running mean filter was consequently applied on the daily temperature data for noise reduction.

The function yields two metrics for each day: the Variable Importance in the Projection (VIP) and the regression coefficient. The VIP indicates the weighted sum of squares of the PLS loadings, and represents the relative importance of the given predictor (x- variable) in the PLS model. VIP values above a fixed threshold value of 0.8 are considered as significant [35]. The sign of the regression coefficient indicates the direction of the relationship between an x-variable and the y-variable and the magnitude of the regression coefficient reflects the VIP and is proportional to the contribution of warmer temperatures to the timing of blossom. In other words, positive coefficients suggest a delaying and negative ones an advancing effect

of the 11-days average daily mean temperature on bloom date for the given time period, while higher absolute values indicate the strength of the effect in a given period of the year.

The function 'PLS_pheno' from the 'chillR' R-package [26] was used on the temperature records (68 years) to delimit the chilling and forcing periods per cultivar; as well for two contrasting segments within the time series: the 34 cold resp. 34 mild years. Using the tabular output of the PLS function, the date of the dormancy break, i.e. the transition from chilling to forcing, is inferred as the first occurrence of a sign change from a positive to a negative coefficient, followed by the occurrence of VIP value > 0.8 given negative coefficients. Only dates after 1st of December were retained.

2.5. Phenological Models

Two conceptually different models of the chilling and forcing processes towards flowering were calibrated and validated for each considered cultivar. The calibration years consisted of the even years between 1950 and 2018 while uneven years were used to validate the models, similar to [8]. Thereby both the calibration and validation datasets included cold and mild years.

2.5.1. Sequential Model

The model referred to as 'sequential model' largely draws on the model ('M2') [7,36] as described in the phenological model comparisons for fruits in Germany [8], with a few modifications as given in the equations below.

Per year with bloom observations, antecedent chilling and forcing was estimated on a daily basis, starting from a fixed day, the 1st of August. Chilling units (R_c) were accumulated (Equation 1) until the accumulated chilling (S_c) equalled the chilling requirement C (Equation 4). Only positive temperatures were taken into account as this was considered most appropriate for the German context [8] and by extension also for Belgium. The day t_1 is considered the modelled day of dormancy break.

$$R_c(T_i) = 0 \qquad if\ T_i \le 0.0\ or\ T_i > T_{Up} \tag{1}$$

$$R_c(T_i) = \frac{T_i}{T_{Bc}} \qquad if\ 0.0 < T_i \le T_{Bc} \tag{2}$$

$$R_c(T_i) = \frac{T_i - 10.0}{T_{Bc} - 10.0} \qquad if\ T_{Bc} < T_i \le T_{Up} \tag{3}$$

$$S_c(t) = \sum_{i=t_0}^{t} R_c(T_i),\ \ where\ S_c(t_1) =: C \tag{4}$$

where R_c expresses daily chilling units that accumulate to S_c; T_{Bc} and T_{Up} are variable parameters that determine temperature ranges with defined chilling efficiency and T_i is the average temperature of the day t_i.

Following [37], a cultivar specific exponential relationship between the chilling and the forcing requirement is assumed following Equation 5.

$$F = a * \exp\left(bS_c(t_1)\right) \tag{5}$$

where the factors a and b determine the dependent forcing requirement F in function of the calibrated chilling requirement C. The forcing temperature (R_f) was accumulated according to Equations 6 and 7.

$$R_f(T_i) = 0, if\ T_i \le T_{Bf} \tag{6}$$

$$R_f(T_i) = \frac{28.4}{(1 + \exp\left(-0.185(T_i - T_{Bf} - 18.4\right)}, if\ T_i > T_{Bf} \tag{7}$$

where T_{Bf} is a similar parameter to T_{Bc} to adjust forcing efficiency ranges, starting from day t_1, until day t_2, when the accumulated forcing (S_f) equals the forcing requirement F, as expressed by Equation 8:

$$S_f(t) = \sum_{i=t_i}^{t} R_f(T_i),\ where\ S_f(t_2) \coloneqq F \quad (8)$$

In summary, six parameters (**Table 1**) needed to be adjusted for each cultivar within ranges based on values for different fruit growing regions in Germany [8,20] where annual mean temperature between 1961-2005, ranged from 8.7°C to 10.1°C. To adapt the model to our particular study site, T_{Bf} and T_{Bc} were subjected to calibration.

Table 1. Parameter space – in squared brackets: lower and upper bound and step; in round brackets: Initial guess (best fit parameters and boundaries based on parametrisations for German fruit growing regions [20]).

	Equation	Apple	Pear
T_{Bf} [°C]	Equation 6	[4 , 6 , 0.1] (4.5)	[2 , 5 , 0.1] (3.8)
T_{Bc} [°C]	Equations 1,3	[2 , 10 , 0.1] (3.5)	[2 , 10 , 0.1] (5.2)
C [chill units]	Equation 4	[40 , 70 , 1] (50)	[30 , 80 , 1] (50)
a	Equation 5	[140 , 200 , 1] (172)	[200 , 220 , 1] (206)
b	Equation 5	[-0.05 , -0.001 , 0.001] (-0.001)	[-0.05 , -0.01 , 0.001] (-0.002)
T_{Up} [°C]	Equation 1,3	[8 , 14 , 0.1] (10.4)	[8 , 14 , 0.1] (10)

2.5.2. Dynamic Model

The selected dynamic model was originally developed to study dormancy break of peach trees in Israel [6,23] and is to date widely accepted as the most robust phenological model for this purpose [5,9,21]. As it does not predict phenological stages beyond dormancy break, it has been combined with a Growing Degree Hour (GDH) accumulation estimation following [4], using the function 'Bloom_prediction3' in the R package 'chillR' [26]. In this study the term 'dynamic model' always refers to this combined setup.

The function takes only two parameters: a cultivar specific chilling requirement (CR) in the unit 'Chill Portions' of the base model and a heat requirement (HR) in GDH. The day of dormancy break is reached when the accumulated daily chill portions equal the given CR. The day of flowering was determined as the day of year when the GDH equalled the HR, not considering accumulation prior to dormancy break since the inherent assumption is that GDH accumulation only starts when rest completion is reached. Unlike the sequential model, chilling and forcing requirements were given independent from each other and substitution, as documented for other tree species is not considered in the coupling of chilling and forcing modules [38].

Chilling accumulation efficiency followed a bell shaped curve with a maximum efficiency at 6°C and zero effect below -2°C and above 14°C. Higher temperatures can undo chill portions in a dynamic way. For the detailed equations we refer to the original documentation of the model [23,26]. The start of accumulation was defined in the function as 1st of November. Daily GDH were derived using Equations 9 and 10.

$$GDH = \frac{T_U - T_B}{2} * \left(1 + \cos\left(\pi + \pi * \frac{(T_i - T_B)}{(T_u - T_B)}\right)\right), if\ T_B < T_i < T_U \quad (9)$$

$$GDH = (T_U - T_B) * \left(1 + \cos\left(\frac{\pi}{2} + \frac{\pi}{2} * \frac{(T_i - T_U)}{(T_C - T_U)}\right)\right), if\ T_U < T_i < T_C \quad (10)$$

where the base temperature T_B is 4°C, the optimum temperature T_U is 25°C and the critical temperature T_C is 36°C, following predefined thresholds for fruit trees [4] .

To calibrate the model parameters for Belgian conditions, the parameters were optimized using a range of possible parameters adapted from [26], as shown in Table 2.

Table 2. Parameter space in squared brackets: lower and upper bound and step; in round brackets: Initial guess (values approximated based on [26]).

	Apple	Pear
CR	**[50.0, 80.0,1] (60)**	**[30, 70,1] (45)**

HR	**[3000,5000,10](4000)**	**[3000,4500,10](3500)**

2.5.3. Parameter Optimisation

Both the sequential and dynamic model were calibrated to match the observations by cultivar using the SPOTPY package in python [39] and a selection of optimisation algorithms: Monte Carlo (MC), Markov Chain Monte Carlo, (MCMC), Differential Evolution Markov Chain (z= with matrix extension [45], DE-MCz), Maximum Likelihood Estimation (MLE), Simulated Annealing (SA), Latin Hypercube Sampling (LHS). The root mean square error (RMSE) was minimized as objective function in all cases except for the MCMC) and DE-MCz algorithms, which come with their own likelihood function (logarithmic probability density).

The parameter distribution was assumed to be uniform for the 6 resp. 2 parameters, resulting in spaces as described in **Table 1** and **Table 2.** The 'best guess' gives the starting point for the optimisation procedure. The step size was adapted to be one order of magnitude below the chosen values. Only the algorithm MCMC is sensitive to the step size of the parameter function. The number of repetitions needed to find a reliable result was calculated with Equation 11 [40] except for the LHS algorithm for which Equation 12[39] is applicable

$$N = \left(1 + 4\,M^2(1 + (k - d)d)\right)k \quad (11)$$

$$N_{max} = (p!)k - 1 \quad (2)$$

where N = needed parameter iterations, k = the number of parameters of the model, M= inference factor (SPOTPY default M=4) and d= frequency step (the minimum being 0.01), p = the divisions per parameter.

The minimum necessary number of iterations was 390 for the sequential model and 160 for the dynamic model. Finally, 500 resp. 200 iterations were called. Both models were evaluated based on the Root Means Square Error (RMSE), the mean absolute error (MAE) and the Ratio of Performance to InterQuartile distance (RPIQ) [40], which is defined as the ratio of the interquartile range of the observations and the RMSE of the prediction, thereby not making assumptions about the distribution of the observed values (in contrast to the commonly used Ratio of Performance to Deviation (RPD).

3. Results

3.1. Past Change Signals

All distinct temporal segments within a panel in **Figure 2** are significantly different from each other at the 99% confidence level. The majority of mild dormancy periods occurred in the second half of the time series (after 1984), which is four years prior to the before mentioned change point of 1988. This way of dividing the years allowed for disentangling physiological differences between mild and cold winters. Considering the full dormancy period (**Figure 2** (d)), the 25% mild years even occurred only in the last 3 decades, with the exception of 1961. Considering only the cold years in terms of the forcing period (**Figure 2** (f)), cold springs still occurred due to interannual variability despite the general warming of the air temperature, suggesting that the risk for late spring frost remains considerable.

When the same segments of years were plotted against the corresponding flowering dates two important observations can be made. Firstly, relating to the upper row of **Figure 3**: although all segments were significantly different in terms of daily average temperatures, the corresponding bloom dates were only significantly different (99% confidence level) when the full dormancy period (**Figure 3** (a)) or the forcing period (**Figure 3** (c)) was considered. For apple resp. pear, resulting advances of the median flowering date were 9.5 resp. 11.25 days (12.5 days for 'Conférence', **Figure 3** (a)), and 10.3 resp. 13.38 days (14.5 days for 'Conférence', **Figure 3** (c)). In contrast, with 0.5 days delay resp. 1.6 days advance (median), no significant change was detected when temperatures during October, November and December determined the segmentation, **Figure 3** (b). This could imply that rising temperatures during these months were affecting the bloom date less than the rising temperatures from January to April or that there were antagonistic processes involved. The difference between the cold and mild segments was slightly higher during forcing (2.35°C, January to April) as compared to during chilling (1.71°C, October, November and December).

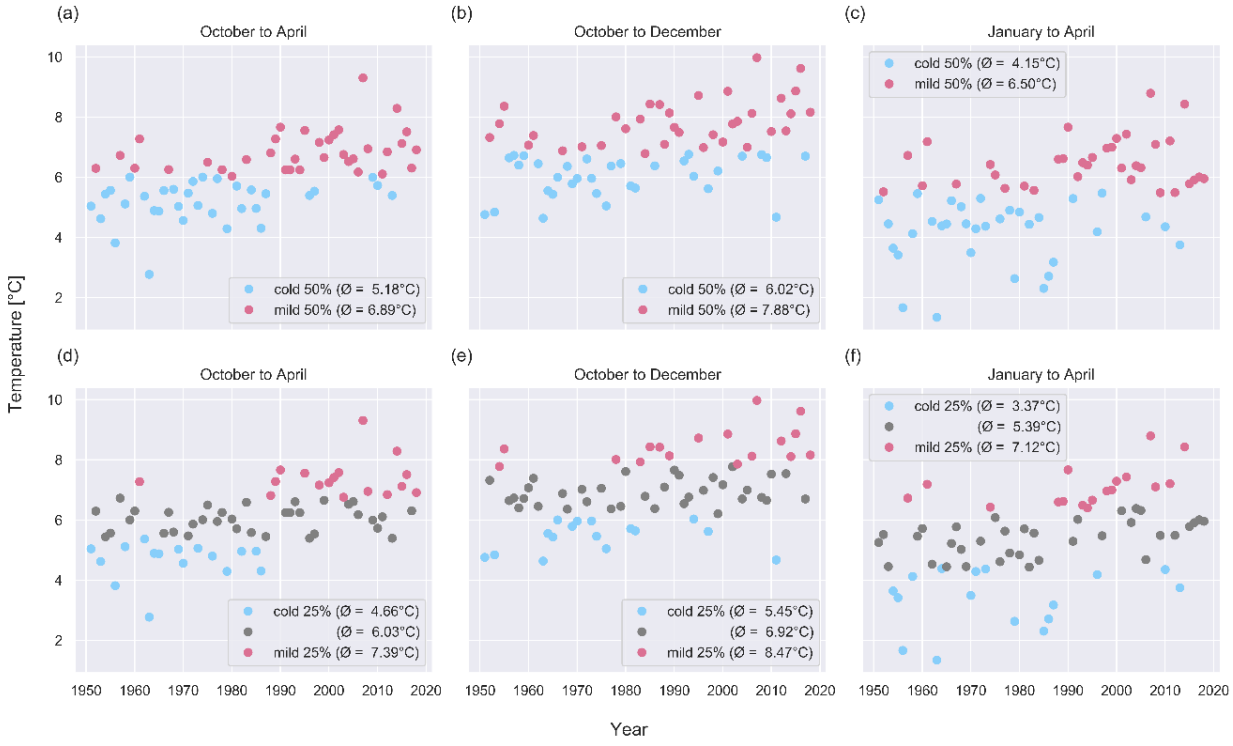


Figure 2. Average daily temperatures during the 'full dormancy' period (panels (a) and (d)), the approximate chilling period (panels (b) and (e)) and forcing periods (panels (c) and (f)) studied either after segmentation in halves (34 years each, upper row) or in 3 parts (17-34-17 years each, lower row). Average temperature refers to daily average 2m-temperature during the indicated months at the study site.

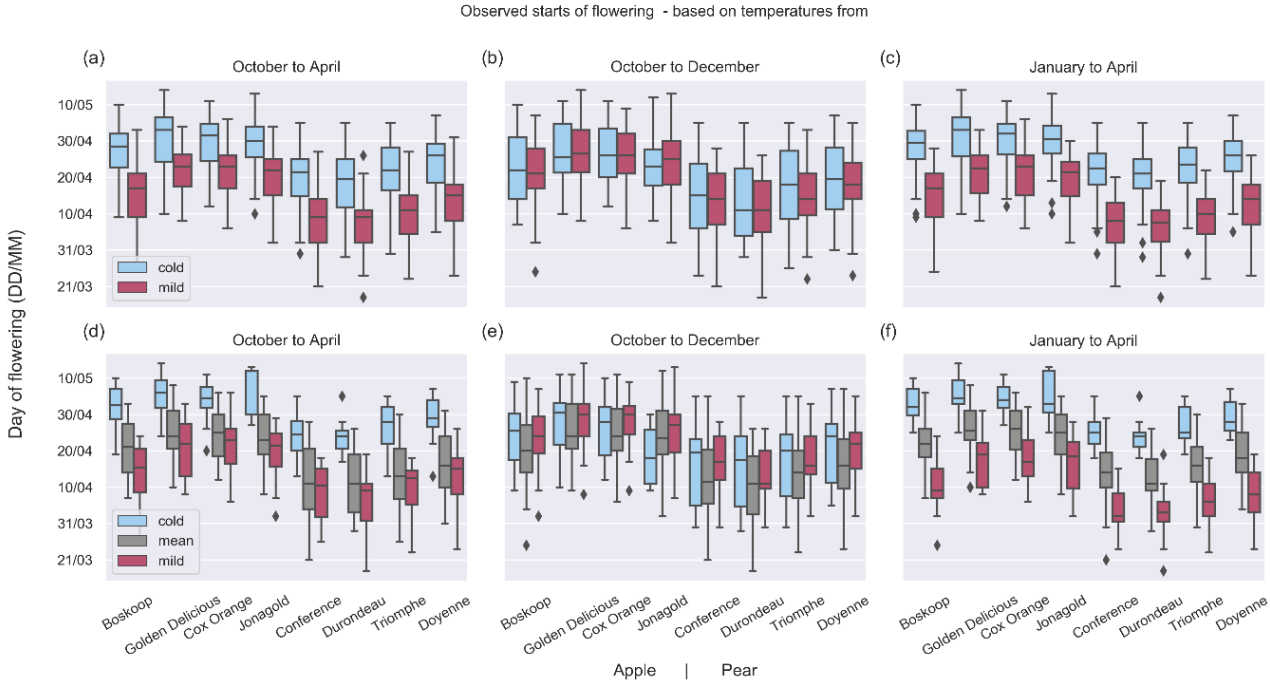


Figure 3. Bloom date (DD/MM) of 8 cultivars during the 'full dormancy' period (panels a and d), the approximate chilling (panels b and e) and forcing periods (panels c and f) presented after segmentation in two halves (34 years each, upper row) or three parts (17-34-17 years each, lower row). Diamonds depict outliers, defined as outside 1.5 times the interquartile range.

A nonlinear relationship between the bloom date and the temperature during the full dormancy period was observed for the cold 25% of all bloom dates, **Figure 3** (d), which occurred significantly later than during the mean years (at 99% conf. level): 13.0 resp. 13.6 days on average (apple resp. pear), while the difference between the mild 25% years and the middle segment was 3.75 resp. 1.0 days and statistically not significant. However, the difference in mean temperature between the first and second resp. second and third segment is nearly identical (1.36 and 1.37°C). In most cases, the trends were stronger for pear than for apple.

The decomposition of the analysis into temperatures during chilling resp. forcing revealed also disparate patterns: The relationship of rising temperatures during January to April and bloom date was consistently and strongly negative (17.5 resp. 20.75 days advance from the cold to the warm segment), whereas the increasing temperature in October, November and December, **Figure 3** (e), revealed a negative relationship considering the first two segments, and a positive relationship considering the last two segments. In the case of 'Jonagold' there is even an overall positive relation discernible, which is probably caused by a smaller number of available observations.

Rising temperatures during October, November and December have consequences on the availability of effective chilling, which was confined between boundaries that depended on the applied model. The share of effective hours is reduced by 0.95 – 2.58 % if the years are split in two halves, with the more pronounced reduction in the most efficient interval (3-9°C); and by 2.39 to 4.31% when the cold resp. mild 25% of the years are considered **(Table 3**). The strongest signals were found between the mild 25% and the average years when the interval around the most efficient temperature for chilling was considered.

Table 3. Percentage of the total number of hours of effective chill hours during the chilling phases (October, November and December) of sets of cold or mild years as defined by the average temperature during the same months; efficient temperature interval boundaries are given in °C.

Interval	50 % cold chilling phases	50 % mild chilling phases	25% cold chilling phases	50% average chilling phases	25% mild chilling phases
[0,12]	**73.76**	**70.31**	**73.47**	**72.67**	**69.46**
[-2,14]	**85.21**	**83.19**	**85.85**	**85.43**	**83.47**
[3,9]	**49.69**	**46.29**	**42.05**	**40.91**	**37.76**

3.1.1. Phenological Response to Warming : Partial Least Square Regression

The absolute value of the model coefficients resulting from the PLSR indicate the relative importance of daily temperature on the onset of the bloom period (BBCH61) whereas positive values indicate that an increase in temperature at a given day increased the day of bloom expressed as Julian Day of Year (DOY), where a higher DOY means a later bloom period. The persistent change from a positive to a negative coefficient is interpreted as a change in dormancy phases, from endodormancy to ecodormancy, further referred to as dormancy break.

The PLSR model coefficients for all studied cultivars over all 68 years are shown in **Figure 4**. For all cultivars the months October and November featured mostly positive coefficients, while February, March and April show only negative coefficients. In all cases the latter two months have higher relative importance on the bloom date with the highest (absolute) coefficients. The months December and January show both positive and negative relationships between rising temperatures and bloom date, which can imply that the timings of chilling and forcing overlap.

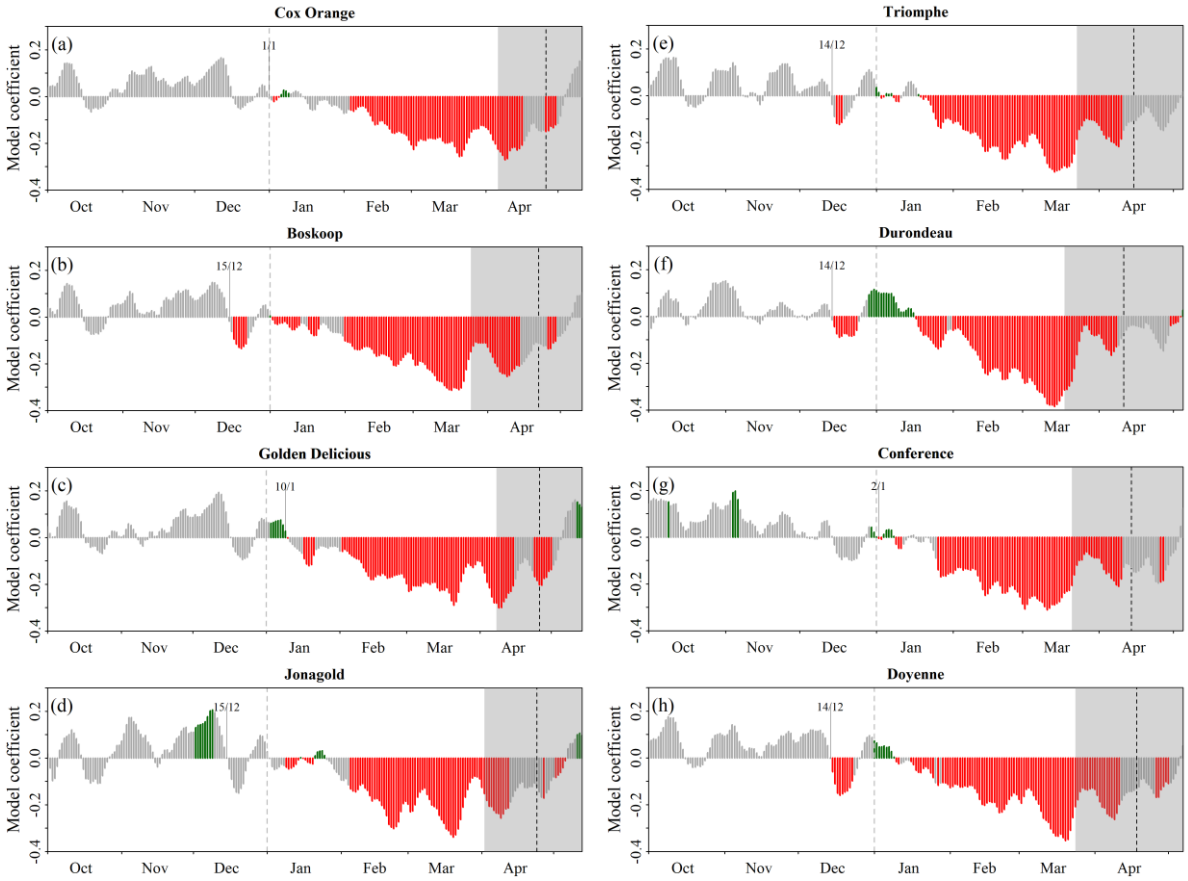


Figure 4. Results of the PLSR for selected cultivars of apple and pear during 68 years between the start date of flowering (BBCH61) and daily average temperatures during the dormancy. Green (positive) and red (negative) areas depict daily coefficients of the model (11-days running average daily mean temperature values) where the Variable Importance of the Projection (VIP) value exceeds the threshold of 0.8, indicating that the corresponding variable was important for the model. In this figure, all years for which bloom date observations were available have been considered. The shaded area represents the range of observed bloom dates, the black dashed line within the shaded area the median value of the bloom date and the grey dashed line the 1st of January as reference. Called out dates indicate the derived date of dormancy break.

Focusing on the commercially most relevant pear cultivar in Belgium, 'Conference', a side by side comparison of the results of the PLSR for cold and mild years is given in **Figure 5**, showing that different warming effects can be noted, either by the average temperature during the full dormancy period (ONDJFMA), chilling (OND) or forcing (JFMA). A common element is that on the right side of the figure (mild years), the delaying effect during October, November and December is notably higher. Also, on the left side (colder years) the advancing effect during February, March and April is less sensitive to the way the observations have been separated in colder and warmer periods.

Figure 5 (a) and (d) resemble each other much more than **Figure 5** (c) and (f), implying that the warming trend during January to April dominated the ranking, similar to **Figure 3**. When years were segmented based on *chilling* periods (**Figure 5** (e) vs (b)), the coefficients are more homogenous in the mild segment, where the characteristic transition from positive to negative coefficients was more pronounced. In these years, mid-December days have delaying properties (**Figure 5** (e)), while the same days were strongly advancing in cold years, **Figure 5** (b)). This suggests a shift of the dormancy completion towards a later day, as expected from less chilling temperatures.

When years were segmented such that the *forcing* periods were mild (**Figure 5** (f) vs (c)), a strongly alternating pattern in December and January becomes more pronounced and warming effects are less

clearly associated to either delaying or advancing bloom. Daily coefficients are more accentuated in the segment of mild years than in the one of cold years.

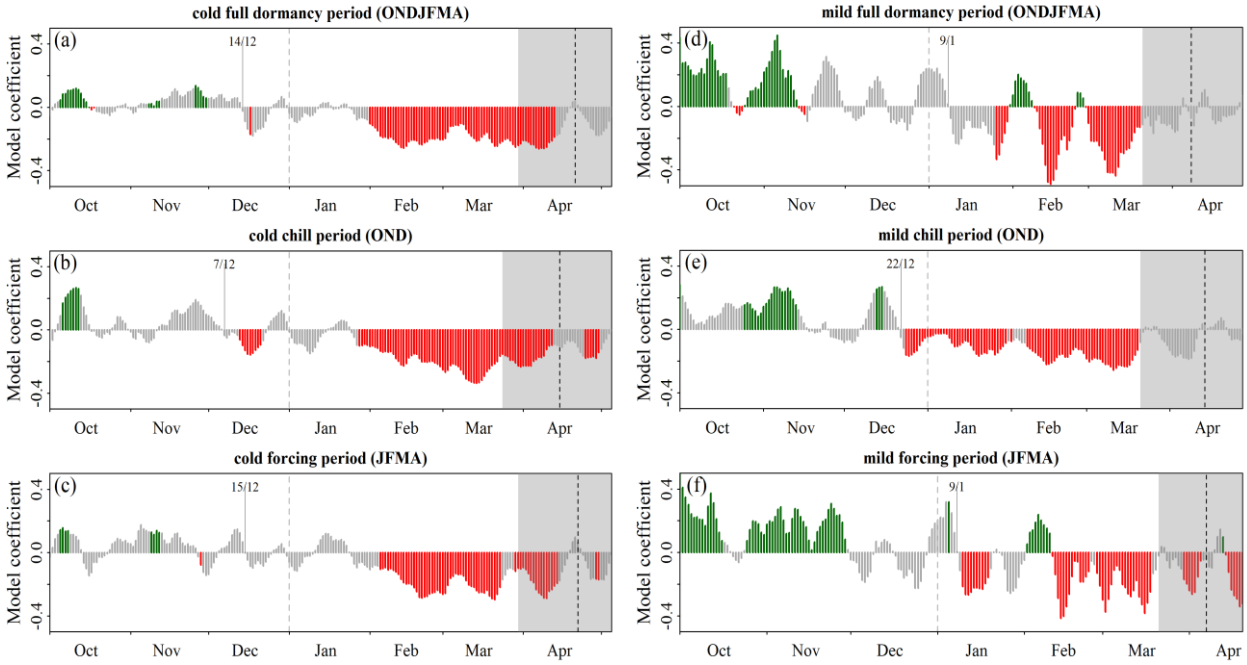


Figure 5. Results of the PLSR analysis for 'Conference' pear for the start date of flowering (BBCH61). Green and red areas depict coefficients of predictors (11-day running mean average daily temperature values) where the Variable Importance of the Projection (VIP) value exceeds the threshold of 0.8, indicating that the corresponding variable is important for the model. Years have been separated in cold (left) and mild (right) halves based on average temperature during either the full dormancy phase (October to April (a) and (d)); the chilling phase (October to December, (b) and (e)); or the forcing phase (January to April, (c) and (f)). The shaded area represents the range of observed bloom dates and the black dashed line within the shaded area its median value. The grey dashed line represents the first of January as reference. Called out dates indicate the derived date of dormancy break.

3.2. Shifts in Dormancy Break

From the PLSR, results of the dormancy break can be identified from the sign change of the daily coefficients predictors. The earliest occurrence of significant negative coefficients has been shifted towards later dates by at least 15 days in all three rows in **Figure 5**. Using the average temperatures during the chilling period (OND) as criterion to separate cold and mild years, the days of dormancy break resulting from the sequential and the dynamic model were plotted against the respective days identified by PLSR in **Figure 6**. Different patterns emerge for both models: The tendency towards later timing (DOY) under mild temperatures is found in the sequential model (9 days on average) and not in the dynamic model (1 day on average). In both cases the modelled dates were consistently much higher (30-52 days) than the dates corresponding to the PLSR sign change. Deviation from the PLSR results are higher for the sequential model than the dynamic model. The latter also has a narrower spread but overall it can be concluded that both modelled dormancy breaks do not reflect the dormancy breaks retrieved from the PLSR.

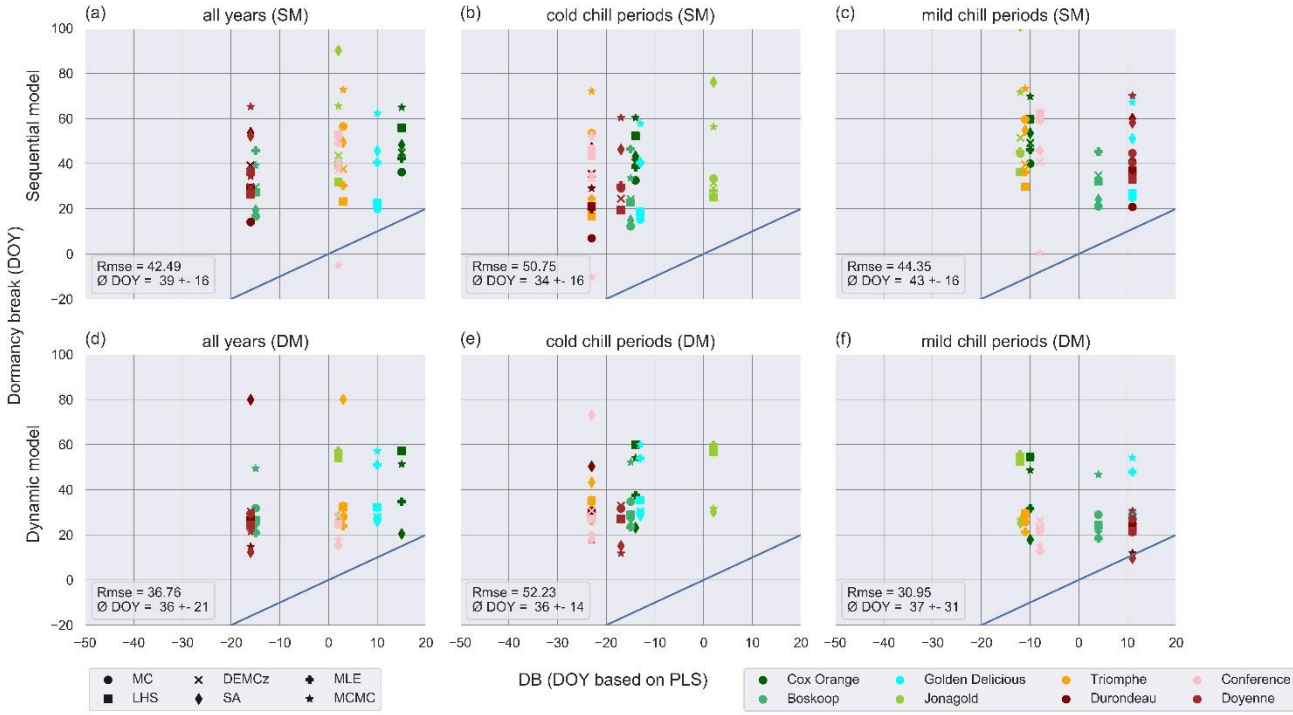


Figure 6. Day of the year (DOY) of the cultivar specific dormancy break (DB) simulated by the sequential model (SM) and the dynamic model (DM), against the DOY of DB estimated using the PLSR method, for all years ((a) and (d)), the 50% cold ((b) and (e)) and 50% mild years ((c) and (f)), as defined by the average temperature during October, November and December. Symbols distinguish between used algorithms, representing the spread of results. The line represents perfect fit between X and Y values and the RMSE value corresponds to the average RMSE between the model output and the PLS results. Ø DOY gives the average DOY by the model for the given years with one standard deviation.

3.3. Phenological models: Sensitivity of predictions to the model and to the parameter calibration algorithm

Models were fitted using six different optimisation algorithms, of which the best has been retained for every cultivar, based on the lowest prediction error. The resulting values are given in **Table A1** and **Table A2** of the Annex. In the case of 'Conférence' for instance the DEMC-z performed best. Over all cultivars, the Root Mean Square Error (RMSE) of the predicted bloom date for the best fit parametrisation varies between 5.36 days and 6.26 days for the sequential model and between 4.15 and 6.36 days for the dynamic model. At 99% confidence level the RMSE for all tested parametrisations and cultivars is significantly lower for the dynamic model. For the latter, the difference between the errors of the calibration and validation subsets (1.68 days) was higher than ~~the~~ for the sequential model (0.30 days).

How the sequential model and the dynamic model predict flowering per year for 'Conférence' is exemplarily illustrated in **Figure 7.** The colouring allows to identify the relative temperature during the full dormancy period (ONDJFMA), where dark dots represent cold and bright mild years.

Not all years and cultivars were equally well predicted and the modelled bloom dates in cold years were generally better correlated with the observations. The ratio of the RMSE and the Mean Absolute Error (MAE) of the mild 25% years over cold 25% years (values in brackets) indicates in most cases higher errors in the mild years. From a year by year comparison over all cultivars and algorithms emerged that the early 2000- years are largely underestimated by both models and that only few years (2004, 2005 and 1975) have consistently failed for both models (mean absolute error >= 7 days).

In **Figure 8**, the Ratio of Performance to InterQuartile distance (RPIQ) is given, where higher values are desirable [40] since it implies the RMSE is smaller compared to the interannual variability of the bloom date. In this representation it can be seen, that the more complex optimization algorithm (SA and MCMC) perform less well and the sequential model led to more underperforming parametrizations (strong outliers) than the dynamic model. While the differences in terms of the RMSE between apple and pear are

of less than half a day for both models, in terms of RPIQ they are performing better for pear than for apples This is due to higher inter quartile range (14-17 days for pears; 12 days for apples except for Boskoop (16 days)).

Based on the RMSE and MAE **(Error! Not a valid bookmark self-reference.)** as well as the RPIQ (**Figure 8**) the dynamic model is better performing, confirming the initial hypothesis. It also has a lower spread of errors and higher agreement between the optimisation functions than the sequential model.

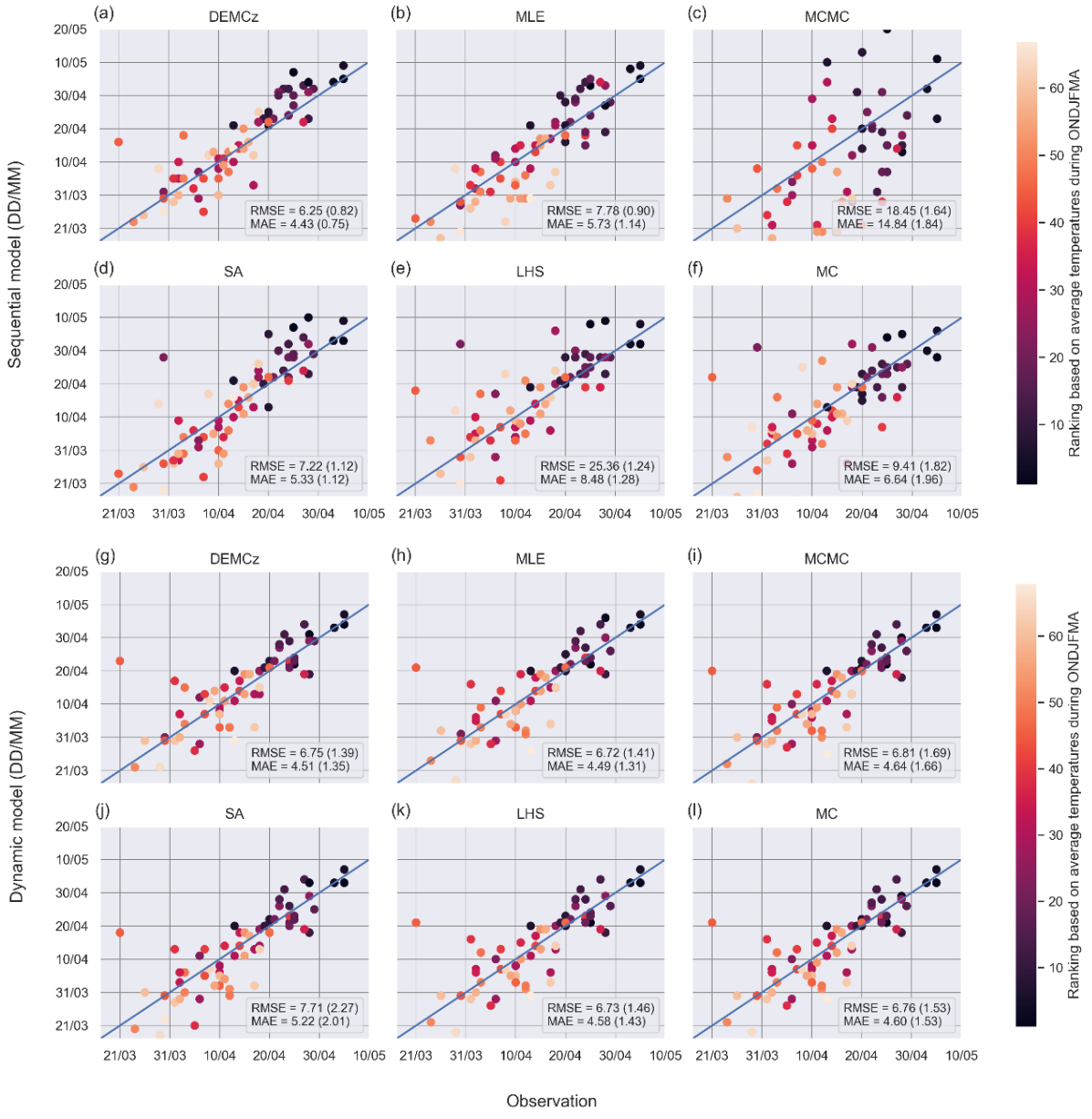


Figure 7. Performance of the sequential model ((a) to (f))and the dynamic model ((g) to (i)) for 'Conference' to predict bloom date. Colours represent the position in the ranking based on average temperature during the full dormancy phase (October to April), dark tones representing the cold years. RMSE and MAE values refer to the entire period, the values in brackets give the ratio of the respective error for the warm 25% of the years over the cold 25% of the years. For improved visibility some points are omitted.

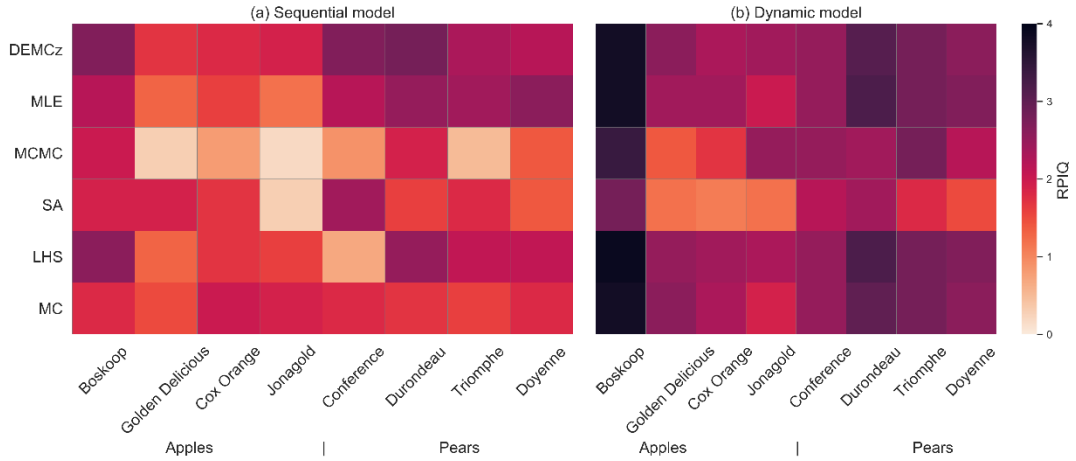


Figure 8. Ratio of Performance to InterQuartile distance (RPIQ) for all cultivars and algorithms for the sequential model (a) and the dynamic model (b). Mean indexes for apple resp. pear are 1.6 resp. 1.9 (sequential model) and 2.4 resp. 2.6 dynamic model.

4. Discussion

4.1. Past Change Signals

Segmenting 68 years of phenological observations into contrasting segments allowed to compare flowering under relatively cold and mild dormancy periods for apple and pear. The determining phase for changed bloom timing was the forcing phase (January to April), with a significant negative relationship between temperature and the DOY of flowering which has also been reported for other temperate regions [14,41]. Effects of a warm and a cold year compared to a typical year have been studied for mountainous forest trees [42] with similar results regarding the magnitude of the effect of warming during the winter and spring months. This present study allows for more robust conclusions due to the higher number of analysed years.

Although some authors assume linear relationships between temperature and phenology [12,43], hints for antagonistic effects could be detected ~~at~~ our study site, revealing non-linear correlations (**Figure 3**), similar to findings for other temperate regions [41,44,45]. It also appeared that the relative influence of temperatures during chilling increases with the average temperature of a location [34].

The fact that despite pronounced warming, two of the last ten years were among the coldest years of the whole time series, underlines the prevailing risk for destructive frosts.

4.1.1. Phenological Response to Warming : Partial Least Square Regression

Based on the analysis of all years, **Figure 4** shows a clear average timing of the transition from chilling to forcing periods per cultivar, other than **Figure 5**, where less years were considered. This study confirmed that the number of years had a major impact on the patterns of the PLSR results, as also concluded by [10], where the detection of the transition point was not possible for observations <20 years. A study based on 15 years [34] also presented unclear and ridged curves that underline that short time with less natural variability, compromise the functioning of PLSR. The 34 years of this study yield in most cases satisfying results, suggesting a limitation of this approach to cultivars which are grown for more than ~30 years .

In nearly all cases, signals in December and January vary strongly and no clear trend is visible, which suggests that either there is an overlap of chilling and forcing in a given year [10], or that interannual variability is too high for clear signals on a long term average. In a global comparison of phenological models for apple fruit overlapping chill-force models outperformed the sequential approach [46].

4.2. Shifts in Dormancy Break

Delays of dormancy breaks have been reported to date for Mediterranean and Japanese settings [11,15,47,48]. For Germany, rather stable dates of dormancy fulfilment for the past years and delayed or no fulfilments for future years were reported, with dormancy break dates between DOY -20 and 20 for apple cultivars with low chilling requirements (700 Chill hours) as well as a high inter annual variability [20]. PLSR on cherry bloom observations in Klein-Altendorf (Germany) revealed phase transitions around end December and similar fluctuations in January.

For our study site in eastern Flanders, Belgium, the chilling phase appeared in all shown cases to end in the first week of January. PLSR analysis in warmer settings report chilling of apples to span until 19 February in China, with 11.5°C annual average temperature, thus 1.4° warmer than this study site [34]. Chilling phases of Walnut in Davis (California) were found to span on average until 15th of January. The findings of the PLSR appear reasonable, however **Figure 6** illustrates important differences between models and PLSR determined timings of dormancy break. While the two models yield surprisingly similar results, they are mostly situated in February while PLSR points to late December or early January. This could be explained by overlapping processes and by the fact that the beginning of forcing (even as dominant process) does not imply that the chilling requirement is fulfilled.

In general, the differences between cold and mild years are small. This is not surprising in light of the small changes in terms of effective chilling hours (**Table 3**). This can be because also a lower boundary for effective chilling is applicable, which is also more often reached with rising temperatures.

4.3. Evaluation of the Sequential and Dynamic Phenological Models

Generally, the development of regional models without field observations of dormancy break has strong limitations [49]. The choice of the model has been shown to be among the biggest factors influencing the model's outcome [9,50] and models cannot be applied across regions without further adaptation. In this study, two contrasting models were therefore calibrated to the Belgian context, where the dynamic model outperformed the sequential model as hypothesised.

The dynamic model has the advantage that accumulated chilling can be partially undone by subsequent high temperatures but on the other hand does not allow to account for overlap of chilling and forcing [46] and interaction terms between respective requirements [38]. Another strong point of it is, that slightly negative temperatures account for chilling, in contrast to the sequential model as adapted to German conditions [8]. Experiments on cherry twigs point to chilling effectiveness below 0°C [18]. The dynamic model used hourly data while the sequential model relied on daily observations alone, but [49] found that using hourly data was not improving the modelling effort by more than 0.24 days of RMSE.

Since none of the tested parameter estimation algorithms led to the best results for all cultivars, we suggest, that a set of algorithms rather than one single algorithm can be used as model ensemble to better cover uncertainties in a similar way as climate model ensembles do. According to [8,19,51–53], Simulated Annealing is preferred. However, in this study SA performed best for 'Golden Delicious' (sequential model) only.

In terms of RMSE the prediction of bloom dates is of similar quality as in the literature [20,46,54], which is commonly judged as acceptable [8]. However, when the values were compared to the variability of the dependent variable (date of bloom), using the RPIQ the performance of both models appears weak.

Prediction errors in studies with long time series for individual cultivars are higher than in studies using shorter time series [12,43,58] or unspecified cultivars [8]. Together with the observation that events in mild years are mostly less well predicted than in cold years, this suggests that the models have a limited temperature interval for which they were developed and in which they performed best. This sheds doubt on their capacity to perform in future warmer regimes.

Models can be improved with dormancy break observations. But to date, only a limited number of controlled experiments on fruit and nut trees allowed for calibrating of models against dormancy phase change observations [6,18,51,59]. New research emerges using experimental indicators to assess the dormancy state such as water content, or metabolites such as abscisic acids or sugars [60–62] but the number of years of observations is still too low for long term analyses, so alternative techniques like the PLSR are preferred. In the absence of local field experiments to determine dormancy break, phenological models can only provide indications of phenological trends.

5. Conclusions

In this study, 68 years of observations of bloom date of eight apple and pear cultivars have been analysed with respect to the average temperature during the periods of full dormancy, chilling and forcing. Advances of bloom dates with warmer dormancy periods have been found to be stronger for pear than for apple. A non-linear relationship between temperatures and bloom timing and antagonistic trends were detected in relation to increasing temperatures during late autumn months (October to December, i.e. the chilling period). For the warmest dormancy periods, which coincide largely with the more recent years, delayed fulfilment of chilling requirements have been noted.

The PLSR method is inherently limited to long time series but was found to be promising to assess timing of phase change between chilling and forcing. The fact that the dates differ from the modelled dormancy breaks, suggesting that chilling and forcing processes occur simultaneously.

In terms of the RMSE, MAE and RPIQ indices over all years, as well as regarding the spread of absolute yearly errors the investigated dynamic model is performing better than its sequential counterpart. Whereas for climate change studies it is important that the model is consistent outside of the calibration ranges, this is not apparent from the studied 68 years.

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Conflicts of Interest: The authors declare no conflict of interest.

Appendix

Table A1: Parameters from optimisations with the lowest RMSE phase, sequential model.

Cultivar	Algorithm	C	TBc	TBf	Tup	a	b	RMSE Calibration	RMSE Validation	RMSE Mean
Boskoop	**DEMCz**	**41.84**	**2.00**	**5.00**	10.87	140.00	-0.001	6.28	5.43	5.85
Cox Orange	**MC**	**54.10**	**2.91**	**5.74**	12.64	162.00	-0.00584	5.90	6.15	6.03
Golden D.	**SA**	**48.44**	**3.61**	**4.77**	10.38	170.00	-0.00392	6.31	6.47	6.39
Jonagold	**DEMCz**	**40.00**	**4.69**	**5.00**	9.17	192.20	-0.00736	7.32	4.80	6.06
Conference	**DEMCz**	**59.44**	**2.00**	**4.61**	13.95	214.50	-0.01	4.15	7.76	5.96
Doyenne	**MLE**	**50.00**	**2.00**	**4.68**	12.14	214.20	-0.01	4.98	5.73	5.36
Durondeau	**DEMCz**	**62.44**	**4.65**	**4.71**	14.00	214.20	-0.01	6.02	6.34	6.18
Triomphe	**MLE**	**42.72**	**3.84**	**4.60**	10.51	203.80	-0.011505	6.55	6.03	6.29

Table A2: Parameters from optimisations with the lowest RMSE, dynamic model.

Cultivar	Algorithm	CR	HR	RMSE Calibration	RMSE Validation	RMSE Mean
Boskoop	LHS	59.16	4430	4.10	4.20	4.15
Cox Orange	LHS	79.6	4268	4.21	5.70	4.95
Golden Delicious	MC	59.84	4980	4.08	5.12	4.60
Jonagold	MCMC	60.66	4644	4.85	4.57	4.71
Conference	DEMCz	60.6	3484	4.48	8.39	6.43
Doyenne	MLE	57.62	4184	3.54	6.35	4.95
Durondeau	MLE	58.66	3464	3.88	6.50	5.19
Triomphe	DEMCz	61.38	3632	4.48	5.98	5.23

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