Analyzing the time-course variation of apple and pear tree dates of flowering stages in the global warming context

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Abstract

Over the last 40 years, perceptible advances in dates of flowering stages have been observed in apple and pear trees growing in three cropping areas in France and one in Switzerland. The time-course variation of dates of flowering stages was established for eight chronological sequences. Our aim was to propose a statistical modelling framework for such sequences with the objective of characterizing the relationship between flowering advances in fruit trees and global warming. After an exploratory analysis, change-point models were applied to multivariate and univariate sequences. The results clearly support the occurrence of a significant abrupt change in the time-course variation of flowering dates at the end of the 1980s toward more frequent early dates, the most probable change instant being between 1988 and 1989. The coincidence between this abrupt change in phenological variations and marked increases in temperature recorded particularly in France at the end of the 1980s led us

to consider the flowering advances in apple and pear trees as impacts of global warming. The suddenness in the response to global warming could be explained by changes in rates for completion of chilling and heat requirements, successively essential to the development of floral primordia within buds. In all cropping areas, annual mean temperatures had suddenly increased since 1988 (1.1-1.3°C), but including noticeable monthly differences. Particularly, warming was clearly more pronounced in February and March (mean temperature increases of 1.6°C) corresponding to the main period of heat requirements, than in November and December (0.8°C) corresponding to the main period of chilling requirements. So marked temperature increases during the heat phase would have suddenly resulted in more frequent years with relatively short duration for completion of the heat requirements and consequently more frequent early flowering years, despite some years with relatively long duration of chilling requirements.

Key words: Change-point detection, Chilling requirement, Climate change, Fruit tree, Heat requirement, Phenology.

Introduction

Global warming of the climate system is unequivocal, as is now evident from observations of increases in average air temperatures in many parts of the world. Eleven of the last twelve years (1995-2006) rank among the twelve warmest years since 1850. Mean temperature will probably rise between 1.8°C and 4.0°C for the end of the 21st century, according to climatic scenario (IPCC, 2007). As plant phenology is mainly influenced by temperature, climate warming has caused renewed interest in phenological methods and observations. Long-term phenological records at specific sites provide useful measures of species-level biological responses to climate changes according to Schwartz (1999). A lot of phenological studies focused on changes in natural systems (Parmesan and Yohe, 2003), while few studies dealt with phenological changes in perennial horticultural crops (Schultz, 2000). Changes in tree phenology have been observed in European countries where earlier onsets of leafing dates were associated with global warming (Chmielewski and Rötzer, 2001). In fruit tree orchards, changes in the timing of flowering phenology could have important impacts on production, because of the indirect influences of phenology on spring frost damage, pollination and fruit set efficiency (Cannell and Smith, 1986; Zavalloni et al., 2006).

Over the last forty years, similar evolutions toward an advance in dates of flowering stages have been observed for several fruit species in distant countries in the northern hemisphere and related to global warming (Omoto and Aono, 1990; Kai et al., 1993; Chmielewski et al., 2004; Legave and Clauzel, 2006; Miller-Rhushing et al., 2007; Legave et al. 2008). Nevertheless, it is less clear how these evolutions might be described to rightly characterize the response to global warming and how they might be explained by changes in temperature conditions during the flowering process. Thus, this study aimed to analyze the time-course variation of dates of flowering stages through a statistical modelling approach over ranges of years including the end of the 1980s when a marked increase in air temperature has been recorded worldwide (IPCC, 2007). For this aim, we collected and analyzed long-term chronological sequences of dates of flowering stages for apple and pear trees in three cropping areas in France and one in Switzerland. After an exploratory analysis of these data, we chose to estimate change-point models on the basis of these phenological sequences. It was thus assumed that there were two periods within which the flowering dates follow the same or nearly the same distribution and between which the flowering dates have different distributions. This statistical modelling of phenological sequences was completed by an analysis of temperature changes during the successive chilling and heat phases up to flowering dates in the case of apple trees.

Materials and methods

Plant material and temperature conditions

The flowering data are issued from a French database (called ‘PhénoClim’) devoted to fruit trees and vine. Flowering dates of one apple tree cultivar (‘Golden Delicious’) and three pear tree cultivars (‘Williams’, ‘Passe Crassane’, ‘Doyenné du Comice’) were selected owing to their economic importance. Dates of flowering stages are recorded since a long time and in various locations in France for such main cultivars for various agronomic purposes like parasitism control, breeding and modelling. Such dates are commonly assessed from observations on several adult trees growing in long-term orchards managed by commercial practices. The assessments of floral dates by experienced observers are made with an inaccuracy of 2-3 days. Among the different phenological stages considered in past observations, we selected stages that were subjected to reliable recording dates over the longest ranges of years.

Thus, the date when about 10% of flower buds are opened (F1 stage) was chosen for apple tree cultivar ‘Golden Delicious’, while the date when nearly 100% are opened (F2 stage) was chosen for the three pear tree cultivars. F1 dates for ‘Golden Delicious’ were recorded during different periods at three locations representative of the main cropping areas of France: from 1963 to 2006 at INRA research station near Angers (47° 28 N, 0° 33 W) in Pays de Loire, from 1976 to 2002 at Domaine de Castang (grower farm) near Bergerac (44° 51 N, 0° 29 E) in Aquitaine and from 1974 to 2006 at Ctifl professional station near Nîmes (43° 50 N, 4° 21 E) in Languedoc. Regarding F2 dates for pear trees, data were recorded mainly at Angers from 1959 to 2006 for ‘Williams’ and ‘Passe Crassane’ and from 1972 to 2006 for ‘Doyenné du Comice’. Data were also recorded at Bergerac from 1972 to 2003 for ‘Williams’. In addition to French data, F2 dates collected for ‘Williams’ from 1971 to 2003 at the Agroscope Changins-Wädenswil research station near Nyon in Switzerland (46° 24 N, 6° 14 E) were used. This was achieved with the collaboration of Doctor Danilo Christen, in order to compare French phenological sequences with one sequence representative of those collected in another European country.

The temperature conditions of the four locations involved were studied on the basis of mean daily temperature of 30 years (1973-2002) covering an appropriate period to highlight temperature increases. The data were issued from databases managed by INRA in France and Météo Suisse in Switzerland. Moreover, in order to analyse the change in flowering stage date in relation to temperature changes, mean temperatures were assessed respectively during the phase of chilling effects required to break bud endodormancy (Lang et al., 1987) and the successive phase of heat effects required to active growth resulting in flower bud opening. To do this, we determined the corresponding periods of these two phases for each annual flowering process (chilling onset in the autumn of year n - 1 to heat completion in the spring of year n). In practical terms, this analysis was applied to F1 stage of ‘Golden Delicious’ for which previous work provided parameters to estimate a date of completion of the chilling requirement for each year at each location (Legave et al, 2008). Moreover the 1st of October of year n - 1 was found in France as an appropriate date to situate the onset of chilling effects for each flowering year (n) and location (Bidabé, 1967). Thus, the mean temperature of the chilling phase was calculated from this fixed date to the estimated date of chilling completion for the flowering years 1976-2002 for which F1 dates were recorded at all three locations. The mean temperature of the heat phase was calculated from the estimated date of chilling completion to the observed F1 date for the same situations (year x location).

Statistical models

Multiple change-point models are used to delimit segments for which the data characteristics are homogeneous within each segment while differing markedly from one segment to another. In a probabilistic framework, the observed sequence of length *T*, $x_0,\ldots,x_{T-1}$ is modelled by *T* random variables $X_0,\ldots,X_{T-1}$ which are assumed to be independent. In the following x_0^{T-1} is a shorthand for $x_0,\ldots,x_{T-1}$.

We made the assumption of Gaussian multiple change-point models. Gaussian multiple change-point models differ in the parameters assumed to be constant within segments (i.e. between change points). This can be the mean or the mean and the variance. The two associated models are denoted by M_m (for mean), and M_{mv} (for mean/variance). For model M_m, we suppose that there exist some $J-1$ instants $\tau_1 < \cdots < \tau_{J-1}$ (with the convention $\tau_0 = 0$ and $\tau_J = T$) such that the mean is constant between two successive change points and the variance is assumed to be constant:

$$\text{if } \tau_j \le t < \tau_{j+1}, \quad \begin{cases} E(X_t) = \mu_j, \\ V(X_t) = \sigma^2. \end{cases}$$

For model M_{mv}, the modelling of the variance is different since it is also affected by the $J-1$ change points:

$$\text{if } \tau_j \le t < \tau_{j+1}, \quad \begin{cases} E(X_t) = \mu_j, \\ V(X_t) = \sigma_j^2. \end{cases}$$

The problem now is to estimate the parameters of these Gaussian multiple change-point models: the number of segments *J*, the instants of the $J-1$ change points $\tau_1,\ldots,\tau_{J-1}$, the *J* within-segment means μ_j and, the global variance σ^2 (for model M_m) or the *J* within-segment variances σ_j^2 (for model M_{mv}). We shall adopt here a retrospective or off-line approach where change points are detected simultaneously. Let us denote by θ the set of mean and variance parameters. For model M_m, $\theta = \{\mu_0,\ldots,\mu_{J-1},\sigma^2\}$ while for model M_{mv}, $\theta = \{\mu_0,\ldots,\mu_{J-1},\sigma_0^2,\ldots,\sigma_{J-1}^2\}$. In a first step, we suppose that the number of segments *J* is known and the purpose is to obtain the optimal segmentation of the sequence into *J* segments.

We discuss in a second step the choice of J which can be put into a model selection framework.

Once the change points have been fixed, the mean and variance parameters are estimated by maximum likelihood. For model M_{mv}, we obtain the empirical mean and variance for each segment:

$$\hat{\mu}_j = \frac{\sum_{t=\tau_j}^{\tau_{j+1}-1} x_t}{\tau_{j+1}-\tau_j} \quad \text{and} \quad \hat{\sigma}_j^2 = \frac{\sum_{t=\tau_j}^{\tau_{j+1}-1} \left(x_t - \hat{\mu}_j\right)^2}{\tau_{j+1}-\tau_j}. \qquad (1)$$

For model M_m, the estimated global variance is given by:

$$\hat{\sigma}^2 = \frac{\sum_{j=0}^{J-1} \sum_{t=\tau_j}^{\tau_{j+1}-1} \left(x_t - \hat{\mu}_j\right)^2}{T}. \qquad (2)$$

Then, if we denote by L_J the likelihood of a J-segment model, the estimation of the $J-1$ change points $\tau_1, \ldots, \tau_{J-1}$, which corresponds to the optimal segmentation into J segments, is obtained as follows:

$$\hat{\tau}_1, \ldots, \hat{\tau}_{J-1} = \underset{0<\tau_1<\cdots<\tau_{J-1}<T}{\arg\max} \log L_J\left(x_0^{T-1}; \hat{\theta}\right),$$

with

$$\begin{aligned} \log L_J\left(x_0^{T-1}; \hat{\theta}\right) &= -\frac{T}{2}\left(\log \hat{\sigma}^2 + \log 2\pi + 1\right) && \text{for model } M_m, \\ \log L_J\left(x_0^{T-1}; \hat{\theta}\right) &= -\frac{1}{2}\sum_{j=0}^{J-1}\left(\tau_{j+1}-\tau_j\right)\left(\log \hat{\sigma}_j^2 + \log 2\pi + 1\right) && \text{for model } M_{mv}. \end{aligned}$$

For this optimisation task, the additivity in j of the sum of squared deviations from the means (see (2)) for model M_m, or the additivity in j of the log-likelihood for model M_{mv} (see above) allows us to use a dynamic programming algorithm (Auger and Lawrence, 1989) which reduces the computational complexity from $O\left(T^J\right)$ to $O\left(JT^2\right)$ in time.

The Gaussian multiple change-point models can be directly generalized to multivariate sequences. In our context, the N variables correspond to different locations or to different cultivars and the elementary random variables at a given time *t* are assumed to be independent. In the multivariate case, the log-likelihood of the *J*-segment model is given by:

$$\log L_J\left(x_0^{T-1};\hat{\theta}\right)=-\frac{NT}{2}\left(\log\hat{\sigma}^2+\log 2\pi+1\right)\quad\text{with}\quad \hat{\sigma}^2=\frac{\sum_{j=0}^{J-1}\sum_{a=1}^{N}\sum_{t=\tau_j}^{\tau_{j+1}-1}\left(x_{a,t}-\hat{\mu}_{j,a}\right)^2}{NT},$$

for model M_m and

$$\log L_J\left(x_0^{T-1};\hat{\theta}\right)=-\frac{1}{2}\sum_{j=0}^{J-1}\left(\tau_{j+1}-\tau_j\right)\sum_{a=1}^{N}\left(\log\hat{\sigma}_{j,a}^2+\log 2\pi+1\right)\quad\text{where } \hat{\sigma}_{j,a}^2 \text{ is given by (1),}$$

for model M_{mv}. In the multivariate case, we introduce a supplementary model which is intermediate between models M_m and M_{mv}. In this new model denoted by M_{msv} (for mean/segment variance), the variance is common to the *N* variables within a segment. The log-likelihood of the *J*-segment model M_{msv} is given by:

$$\log L_J\left(x_0^{T-1};\hat{\theta}\right)=-\frac{N}{2}\sum_{j=0}^{J-1}\left(\tau_{j+1}-\tau_j\right)\left(\log\hat{\sigma}_j^2+\log 2\pi+1\right)\quad\text{with}\quad \hat{\sigma}_j^2=\frac{\sum_{a=1}^{N}\sum_{t=\tau_j}^{\tau_{j+1}-1}\left(x_{a,t}-\hat{\mu}_{j,a}\right)^2}{N\left(\tau_{j+1}-\tau_j\right)}.$$

Once a multiple change-point model has been estimated for a fixed number of segments *J*, the question is then to choose this number. Indeed, in real situations this number is unknown and should be estimated. In a model selection context, the purpose is to estimate *J* by maximizing a penalized version of the log-likelihood defined as follows:

$$\hat{J}=\arg\max_{J\geq 1}\left\{\log L_J\left(x_0^{T-1};\hat{\tau}_1,\ldots,\hat{\tau}_{J-1},\hat{\theta}\right)-\text{Penalty}(J)\right\}$$

The principle of this kind of penalized likelihood criterion consists in making a trade-off between an adequate fitting of the model to the data (given by the first term) and a reasonable number of parameters to be estimated (control by the second term: the penalty term). The most popular information criteria such as AIC and BIC are not adapted in this particular context since they tend to underpenalize the log-likelihood and thus select a too large number of segments *J*. New penalties have therefore been proposed in this context; see for example Lavielle (2005) used in Picard et al. (2005), and Lebarbier (2005) and Zhang and Siegmund

(2007) used in Guédon et al. (2007). Zhang and Siegmund proposed a modified BIC criterion in the case of the univariate model M_m. This criterion is given by

$$\mathrm{mBIC}_J = 2\log L_J\left(x_0^{T-1};\hat{\tau}_1,\ldots,\hat{\tau}_{J-1},\hat{\theta}\right) - 2J\log T - \sum_{j=0}^{J-1}\log\left(\hat{\tau}_{j+1}-\hat{\tau}_j\right), \qquad (3)$$

where

$$\begin{aligned}\min_{0<\tau_1<\cdots<\tau_{J-1}<T}\sum_{j=0}^{J-1}\log\left(\hat{\tau}_{j+1}-\hat{\tau}_j\right) &= \log(T-J+1)\\ &\approx J\log T-(J-1)\log T \quad \text{if } J<<T,\\ \max_{0<\tau_1<\cdots<\tau_{J-1}<T}\sum_{j=0}^{J-1}\log\left(\hat{\tau}_{j+1}-\hat{\tau}_j\right) &= J\log\frac{T}{J}\\ &= J\log T - J\log J.\end{aligned}$$

Hence each change point contributes between 1 and 2 dimensions to the penalty term (instead of systematically 1 dimension for each mean or variance parameter) and this penalty term is maximized when the change points are evenly spaced.

A model selection procedure leads generally to a unique solution. However, it could be of interest to rank the models allowing full consideration of other possible models. The posterior probability of the *J*-segment model M_J, given by

$$P\left(M_J \mid x_0^{T-1}\right) = \frac{\exp\left(\frac{1}{2}\Delta\mathrm{mBIC}_J\right)}{\sum_{k=1}^{J_{\max}}\exp\left(\frac{1}{2}\Delta\mathrm{mBIC}_K\right)},$$

with

$$\Delta\mathrm{mBIC}_J = \mathrm{mBIC}_J - \max_K \mathrm{mBIC}_K,$$

can be interpreted as the weight of evidence in favour of the *J*-segment model (among the $J_{\max}$ models).

For models M_{mv} and M_{msv}, the maximum log-likelihood of the *J*-segment model can be written as:

$$\log L_J\left(x_0^{T-1};\hat{\tau}_1,\ldots,\hat{\tau}_{J-1},\hat{\theta}\right)=\max_{0<\tau_1<\cdots<\tau_{J-1}<T}\sum_{j=0}^{J-1}\log f\left(x_{\tau_j},\ldots,x_{\tau_{j+1}-1};\hat{\theta}_j\right),$$

where $\log f\left(x_{\tau_j},\ldots,x_{\tau_{j+1}-1};\hat{\theta}_j\right)$ is the maximum log-likelihood of parameter $\hat{\theta}_j$ attached to segment $x_{\tau_j},\ldots,x_{\tau_{j+1}-1}$. It is often of interest to quantify the uncertainty concerning the instant of change points. In the case of a single change point, the posterior probability of entering the second segment at time τ_1 for $\tau_1 > 0$ is given by:

$$f\left(x_0,\ldots,x_{\tau_1-1};\hat{\theta}_0\right)f\left(x_{\tau_1},\ldots,x_{T-1};\hat{\theta}_1\right)/\sum_t f\left(x_0,\ldots,x_{t-1};\hat{\theta}_0\right)f\left(x_t,\ldots,x_{T-1};\hat{\theta}_1\right),$$

This computation can only be performed for models for which the log-likelihood is additive in j (hence models M_{mv} and M_{msv} but not model M_m). This is the main justification of the introduction of the parsimonious model M_{msv} for multivariate sequences.

Results

Exploratory analysis of temperature conditions

In France, similar patterns were observed between the three locations regarding the annual evolution for monthly mean temperatures. However, for each monthly temperature, gradual ranges according to the latitude degree of location were obvious (data not shown). Thus, Angers is characterised by the coldest monthly temperatures with a mean annual temperature of 11.9°C and Nîmes the warmest (mean annual temperature of 14.5°C), while intermediate monthly temperatures are observed at Bergerac (mean annual temperature of 12.8°C). Changins is characterised by a relatively cold climate with a mean annual temperature of 9.7°C.

Temperature increases have been clearly marked from the year 1988 in the three French growing locations as expressed by the comparison of means of annual temperatures between the two successive periods 1973-1987 and 1988-2002. The mean increases of annual temperatures in the second period were +1.1°C at Angers, +1.2°C at Bergerac and +1.3°C at Nîmes. A similar change has been obvious at Changins (+1.2°C during the period 1988-2002). Nevertheless, these increases include noticeable monthly differences for the months involved in the annual flowering process. Particularly, in France warming was clearly more pronounced in the period February - March (mean temperature increases of 1.4-1.8°C according to location), than in the period November - December (0.6-0.8°C).

Exploratory analysis of the variability within the flowering dates

The time-course variation of flowering dates was established for each of the eight selected sequences (Figures 1, 2 and 3). This highlighted differences in flowering date according to location and cultivar. For apple tree cultivar ‘Golden Delicious’, marked differences are observed between the three regional sequences during the period 1976-2002 (Figure 1). The F1 date is consistently earlier at Nîmes than at Angers, while most of the time an intermediate date is observed at Bergerac. The mean F1 dates for this period are April 22 at Angers, April 14 at Bergerac and April 7 at Nîmes (8 days earlier at Bergerac than at Angers and 7 days earlier at Nîmes than at Bergerac). The same range of variability in mean dates is observed between the three locations when means are considered separately for the 1976-1988 sub-period (April 25, April 19, April 11 respectively) and the 1989-2002 sub-period (April 18, April 11, April 4 respectively). Such data clearly underline a constant influence of location on the date of stage F1 for ‘Golden Delicious’ apple trees. The lower the latitude of location, the earlier the flowering date in the apple tree growing area extending from North-West to South-East of France.

For pear tree cultivar ‘Williams’, slight differences in the date of stage F2 are observed between the two French locations of Bergerac and Angers during the period 1972-2003, while later dates are clearly observed most of time at Changins in Switzerland (Figure 2). The mean

F2 dates for the period 1972-2003 are April 7 at Bergerac, April 9 at Angers and April 20 at Changins. The differences in mean dates are unchanged when means are considered separately for the 1972-1988 sub-period (April 11, April 13 and April 25 respectively) and the 1989-2003 sub-period (April 2, April 4 and April 15 respectively).

Differences in flowering date according to cultivar are highlighted by the comparison of sequences of three pear tree cultivars growing at Angers during the period 1972-2006 (Figure 3). The F2 date is consistently earlier for 'Passe Crassane' than for 'Doyenné du Comice', while 'Williams' shows an intermediate date most of the time. The mean F2 dates for the period 1972-2006 are April 8 for 'Passe Crassane' and April 14 for 'Doyenné du Comice'. This difference of 6 days is unchanged when means are considered separately for the 1972-1988 sub-period (April 12 and April 18 respectively) and the 1989-2006 sub-period (April 3 and April 9 respectively).

The exploratory analysis clearly shows constant influences of location and cultivar on the date of flowering stage. Nevertheless, as it is obviously apparent in the data (Figures 1, 2 and 3), it was not possible to extract regularly decreasing trends (i.e. long-term changes in the mean level) using various symmetric smoothing filters with different filter widths (results not shown) Hence, we chose to apply multiple change-point models.

Analysis of the changes in the flowering dates using multiple change-point models

A multivariate sequence was built taking each location (three for apple tree cultivar 'Golden Delicious' and for pear tree cultivar 'Williams') or cultivar (three pear tree cultivars growing at Angers) as a variable. Applying multiple change-point detection method to one of these multivariate sequences consists then in detecting change points common to the individual sequence (while the means are estimated for each segment and each variable, and the global variance is estimated for model M_m, the variances are estimated for each segment for model M_{msv} and for each segment and each variable for model M_{mv}); see Figures 1, 2 and 3. Since the variances estimated for each segment and each variable are close, the modified BIC of Zhang and Siegmund (2007) always ranks the models from the more to the less parsimonious for a fixed number of segments i.e. M_m followed by M_{msv} and M_{mv} (results not shown); see the corresponding standard deviations estimated for the different 2-segment models in Table 1. We thus chose to focus on models M_m for the selection of the number of segments. The modified BIC favoured the 2-segment model for apple tree, cultivar ‘Golden Delicious’ and for pear tree, cultivar ‘Williams and the 3-segment model for pear tree at Angers (Table 2). In this last case, both the 2-segment and the 3-segment models are possible models according to their posterior probabilities. It should be noted that the penalty used in (3) is likely to slightly underpenalized the log-likelihood (and thus to select a too large number of segments) since this penalty was derived in the case where the global variance σ is known (instead of being estimated); see Zhang and Siegmund (2007).

In the case of the 2-segment models, we obtained the same instant for the change point (1988 → 1989) in the three cases with a low uncertainty (posterior probability between 0.67 and 0.87 for the change point 1988 → 1989 computed using M_{msv} models; see Figure 4). The change-point magnitudes as given by the mean difference between the two segments $\hat{\mu}_{1,a} - \hat{\mu}_{0,a}$ are very similar (between -7.5 and -10; see Table 1). The sample autocorrelation function computed from the residual sequences obtained by subtracting the two successive segment means from the original sequences (Lavielle, 1998) showed that the residual sequences were stationary and close to white noise sequences (results not shown).

If all the data are gathered in a single multivariate sequence [apple tree, cultivar ‘Golden Delicious’ (Angers, Bergerac and Nîmes) and pear tree, cultivar ‘Williams’ (Angers, Bergerac and Changins), ‘Passe Crassane’ (Angers) and ‘Doyenné du Comice’ (Angers)], the 2-

segment model M_m is by far the best model with very few uncertainty (posterior probability of 0.99 for this model; see Table 3) and there also remains almost no uncertainty for the instant of the change point 1988 → 1989 with a posterior probability of 0.99.

At the opposite, on the basis of 2-segment models M_m estimated from univariate sequences, the change point 1988 → 1989 was detected for all the apple and pear tree sequences. On the basis of 2-segment models M_{mv}, the change point 1988 → 1989 was detected for apple tree cultivar 'Golden Delicious' at Angers and Bergerac, pear tree cultivar 'Williams' at Angers, Bergerac and Changins and pear tree cultivar 'Doyenné du Comice' at Angers, but not for apple tree cultivar 'Golden Delicious' at Nîmes and pear tree cultivar 'Passe-Crassane' at Angers (Table 4). Nevertheless, there is a strong consensus among the univariate 2-segment models M_{mv} for the change point 1988 → 1989 since 1988 → 1989 is a possible change point even for apple tree cultivar 'Golden Delicious' at Nîmes and pear tree cultivar 'Passe-Crassane' at Angers (Table 4 and Figure 5). It should be noted that some of the univariate sequences are longer than the multivariate sequences since only the common range of years can be used to build multivariate sequences. However, this increase in length of the univariate sequence does not compensate for the combination with another sequence in terms of sample size for estimating change points.

Finally, despite usual yearly fluctuations, we may conclude that a change in the time-course variation of flowering dates occurred abruptly at the end of the 1980s (1988 → 1989) toward more frequent early dates. This evolution was similar for the eight sequences analysed, regardless of the respective influences of location and cultivar (Figures 1, 2 and 3). When the period 1976-2002 common to all sequences is considered to compare the advances in flowering date (Table 5), this clearly highlights earlier mean dates of F1 and F2 stages during the sub-period 1989-2002 in comparison with the sub-period 1976-1988, although higher mean advances in pear tree (10-11 days for F2 stage) than in apple tree (by 7-8 days for F1 stage) can be noted.

Temperature changes related to flowering date changes

Firstly, the changes in temperature during the chilling and heat phases for the three locations regarding apple tree cultivar 'Golden Delicious' (Figures 6 and 7) were analysed with the same approach used for the flowering dates. Multivariate sequences were built taking each location as a variable for the 'chilling temperatures' and the 'heat temperatures'. Since the variances estimated for each segment and each variable are close, the modified BIC of Zhang and Siegmund (2007) always ranks the models from the more to the less parsimonious for a fixed number of segments i.e. M_m followed by M_{msv} and M_{mv} (results not shown); see the corresponding standard deviations estimated for the different 2-segment models in Table 6. We thus chose to focus on models M_m for the selection of the number of segments. The modified BIC favoured the 2-segment model for the chilling temperatures and the heat temperatures (Table 7). We obtained the same instant for the change point (1987 → 1988) in the two cases with a very low uncertainty (posterior probability of 0.94 in the chilling temperature case, and of 0.93 in the heat temperature case for the change point 1987 → 1988 computed using M_{msv} models). The change-point magnitudes as given by the mean difference between the two segments $\hat{\mu}_{1,a} - \hat{\mu}_{0,a}$ are very close for the three locations in the chilling temperature case while they are more variable in the heat temperature case (Table 6 and Figures 6 and 7). The sample autocorrelation function computed from the residual sequences obtained by subtracting the two successive segment means from the original sequences (Lavielle, 1998) showed that the residual sequences were stationary and close to white noise sequences (results not shown).

On the basis of 2-segment models M_m estimated from univariate sequences, the change point 1987 → 1988 was detected for all the chilling temperature sequences and for the heat temperature sequences at Angers and Nîmes.

Since a single change point was detected at one year apart in both the flowering date sequence for apple tree cultivar ‘Golden Delicious’ and the corresponding chilling and heat temperature sequences (and the ratios between the average absolute mean difference between the two segments and the global standard deviation $\sum_{a=1}^{N} \left| \hat{\mu}_{1,a} - \hat{\mu}_{0,a} \right| / N\hat{\sigma}$ are relatively close in the three cases; see Tables 1 and 6), the flowering date can be directly related to the corresponding chilling (respectively heat) temperature by a simple linear correlation coefficient. In the two cases, the correlation coefficients are largely below the threshold of -0.22 corresponding to the hypothesis of no correlation and clearly indicate negative correlation between the temperature and the flowering date. It should be noted that the heat temperature is far more correlated with the flowering date (correlation coefficient of -0.79) than the chilling temperature (-0.3).

Discussion

One difficulty with these data sets is the similar orders of magnitude of the mean difference between the two segments and the standard-deviation attached to each segment (see Table 1). Hence, the two underlying Gaussian distributions estimated for the two segments exhibit a large recovering. For instance in the case of two Gaussian random variables $X_0 \sim \mathrm{N}(\mu_0, \sigma^2)$ and $X_1 \sim \mathrm{N}(\mu_1, \sigma^2)$ with common variance σ^2 such that $\mu_0 - \mu_1 = \sigma$, we have $P(\mu_1 \leq X_0 \leq \mu_0) = P(\mu_1 \leq X_1 \leq \mu_0) = 0.34$ and $P(X_0 \leq \mu_1) = P(X_1 \geq \mu_0) = 0.16$.

Another source of difficulty lies in the relatively short length of segments (between 13 and 18; see Figures 1, 2 and 3). Assuming a segment length of 16, the confidence interval for μ_j is roughly $\hat{\mu}_j \pm \hat{\sigma}/2$. Hence, our statistical analysis clearly supports the idea of abrupt change of the dates of flowering stages at the end of the 1980s, but the statistical model (a single change point between two stationary segments) is not fully validated because of the quite short length of the segments in conjunction with the recovering of the two Gaussian distributions estimated for the two segments.

Despite some statistical uncertainties, our analysis of phenological sequences and their relationship with temperature changes provide elements for a right description and explanation of the impact of global warming on apple and pear tree phenology in France. In the case of apple tree ‘Golden Delicious’, the advances in flowering date have been similar from North-West to South-East of France, i.e. without interaction with the location. Moreover, the mean range in flowering advance (7-8 days) was similar to the mean difference in flowering date between adjacent locations (6-8 days). Thus, as a result of the abrupt change in flowering date, ‘Golden Delicious’ is now flowering at the northern location of Angers within the same date range it was previously flowering further south at Bergerac. The same relative change was observed between Bergerac and Nîmes (Table 5). For pear tree cultivars growing at Angers, similar mean flowering advances were observed, i.e. without interaction with cultivar. In comparison with apple tree ‘Golden Delicious’ in the same French locations, pear tree cultivars showed higher mean flowering advances (10-11 days), exceeding the mean difference between adjacent locations (2-3 days between Angers and Bergerac for ‘Williams’). A similar higher advance (10 days) was also found for ‘Williams’ at Changins in Switzerland. For each of the eight phenological sequences, there was a clear time coincidence between the beginning of marked increases of annual temperatures and the most probable instant (1988 → 1989, according to the statistical models) of abrupt change of flowering dates. Thus, our results confirm a general impact of global warming in Europe toward earlier flowering dates at the end of the 1980s (Chmielewski et al., 2004) and contribute to an accurate characterisation of this impact (abrupt change, most probable change instant). In addition, they suggest genetic differences in phenological response between apple and pear trees, as already reported for cherry tree (Miller-Rhushing et al., 2007).

At present, such a phenological change do not affect fruit tree production, but it is important to understand the mechanism by which climate warming exerts its influence, especially because this was poorly investigated since the old works of Cannell and Smith (1986). An interesting feature to explain is why the flowering advance would have been expressed through an abrupt change and not in a progressive way. One explanation would lie in different changes in the respective rates of completion of the chilling and heat requirements. Indeed in the case of 'Golden Delicious' in France, previous works (Legave et al., 2008) showed that a constant regional gradient of annual F1 dates (the latest dates at Angers to the earliest dates at Nîmes) is determined by differences in length of the heat phase (the longest at Angers and the shortest at Nîmes) since an inverse gradient of the dates of chilling completion occurred constantly (the earliest at Angers and the latest at Nîmes). Similarly, earlier F1 dates since 1989 at all three locations have been explained by a major effect of warming in reducing the length of the heat phase (more frequent years with relatively short lengths), in spite of noticeable trends, at the same time, toward some years with longer lengths of the chilling phase (Legave et al., 2008). In agreement with these previous findings, the present study clearly shows that the mean temperature during the heat phase has been the main climatic factor determining the F1 date (the higher temperature, the earlier date), while the mean temperature during the chilling phase has been a less important factor (poorly linked to the F1 date). Indeed, the recent warming was non-uniform at all locations but particularly pronounced in months corresponding to the heat phase (February and March particularly), while warming was limited in months corresponding to the chilling phase (October to early January). Moreover, the mean temperature during the heat phase clearly increased from 1988 to 1990 at Angers and Nîmes and more progressively at Bergerac (Figure 7). Then, from 1991 to 2002, the mean temperatures during the heat phase remained relatively high at all three locations (particularly from 1994) in comparison with the mean temperatures prevailing before 1988 (Figure 7). Such temperature changes led to a marked increase in the rate of completion of the heat requirements since 1988 and can explain the abrupt change of flowering dates. Nevertheless, as previously mentioned, climate warming also affected the rate of completion of the chilling requirements which was clearly decreased in some years (high temperatures during the chilling phase). In such cases, relatively long dormancy tended to delay the flowering date despite the short length of the heat phase linked to a high rate of completion of the heat requirements. This was markedly the case for the annual cycle 1987-1988 characterized by relatively high temperatures at the end of chilling process (January 1988), particularly at Nîmes. Such a temperature feature a this time (Figures 6 and 7) can explain that the most probable instant of abrupt change of flowering date is detected only between 1988 and 1989, i.e. one year after the beginning of the marked warming in France which started in 1988 as confirmed by our results .

For pear tree cultivars, we may suppose that abrupt change of flowering dates is explainable in the same way as for apple tree ‘Golden Delicious’. However, higher mean advances in flowering dates for pear tree cultivars in same locations and periods suggest that climate warming exerted a lower effect on the lengthening of dormancy in the case of pear trees, due to their lower chilling requirements (Atkinson and Taylor, 1994).

Finally, it may be emphasized that cultivars of fruit trees have been suitable plants to highlight climatic change factors during the recent climate warming in France (temperature increases from autumn to early spring) as probably in other European countries. A first advantage of fruit trees is due to the considerable longevity of cultivars (clone) permitting analyses of phenological sequences over long terms. Another interesting feature lies in the fact that their flowering process is highly linked to two temperature requirements, which allows to highlight significant temperature changes during the different seasons. Therefore, it is important to continue to collect and analyse flowering data for some main cultivars of fruit trees, in order to detect new changes in main temperature factors and consequently select cultivars adapted to possible phenological disorders in the future (Sunley et al., 2006).

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Table 1. Apple tree, cultivar ‘Golden Delicious’ at Angers, Bergerac and Nîmes (1976-2002); pear tree, cultivar ‘Williams’ at Angers, Bergerac and Changins (1972-2003); pear tree cultivars ‘Williams’, ‘Passe Crassane’ and ‘Doyenné du Comice’ at Angers (1972-2006): estimated multivariate 2-segment model parameters ($\hat{\tau}_1 = 1989$ for models M_m, M_{msv} and M_{mv} in the three cases).

Sequence		$\hat{\mu}_{1,a} - \hat{\mu}_{0,a}$	$\hat{\sigma}_{0,a}$	$\hat{\sigma}_{1,a}$
apple tree, cv. ‘Golden Delicious’, 1976-2002	Angers	-7.46	7.49	7.66
	Bergerac	-7.97	7.99	5.85
	Nîmes	-7.67	5.89	7.33
	$\hat{\sigma}_j$		7.18	6.99
	$\hat{\sigma}$		7.08	
pear tree, cv. ‘Williams’, 1972-2003	Angers	-9.54	8.47	7.19
	Bergerac	-9.33	7.48	7.84
	Changins	-9.97	6.25	6.04
	$\hat{\sigma}_j$		7.46	7.06
	$\hat{\sigma}$		7.27	
pear tree, Angers, 1972-2006	Williams	-8.25	8.47	7.44
	Passe Crassane	-8.97	8.79	7.7
	Doyenné du Comice	-8.96	7.83	7.41
	$\hat{\sigma}_j$		8.37	7.52
	$\hat{\sigma}$		7.94	

Table 2. Apple tree, cultivar ‘Golden Delicious’ at Angers, Bergerac and Nîmes (1976-2002); pear tree, cultivar ‘Williams’ at Angers, Bergerac and Changins (1972-2003); pear tree cultivars ‘Williams’, ‘Passe Crassane’ and ‘Doyenné du Comice’ at Angers (1972-2006): choice of the number of segments for multivariate models M_m.

Sequence	J	$2\log L_J$	Free param.	mBIC$_J$	$P\left(M_J \mid x_0^{T-1}\right)$
apple tree, cv. ‘Golden Delicious’, 1976-2002	1	-567.93	4	-588.81	0.3
	2	-546.98	8	-587.34	0.62
	3	-532.86	12	-591.33	0.08
	4	-525.8	16	-601.77	0
pear tree, cv. ‘Williams’, 1972-2003	1	-688.11	4	-709.83	0
	2	-653.42	8	-695.48	0.71
	3	-635.57	12	-697.24	0.29
	4	-629.26	16	-710.19	0
pear tree, Angers, 1972-2006	1	-760.89	4	-783.06	0.01
	2	-733.19	8	-776.15	0.4
	3	-712.58	12	-775.38	0.58
	4	-702.38	16	-783.86	0.01

Table 3. Apple tree, cultivar ‘Golden Delicious’ (Angers, Bergerac and Nîmes) and pear tree, cultivars ‘Williams’ (Angers, Bergerac and Changins), ‘Passe Crassane’ (Angers) and ‘Doyenné du Comice’ (Angers), (1976-2002): choice of the number of segments for multivariate model M_m.

J	$2\log L_J$	Free param.	mBIC$_J$	$P\left(M_J \mid x_0^{T-1}\right)$
1	-1555.99	9	-1607.67	0
2	-1475.15	18	-1577.11	0.99
3	-1435.14	27	-1586	0.01
4	-1416.19	36	-1615.35	0

Table 4. Univariate 2-segment models M_{mv} : posterior change-point probabilities.

Cultivar	Location	Year range	1988 → 1989 probability	Maximum probability (change point)
Golden Delicious	Angers	1963-2006	0.23	
	Bergerac	1976-2002	0.27	
	Nîmes	1974-2006	0.15	0.21 (2002 → 2003)
Williams	Angers	1959-2006	0.24	
	Bergerac	1972-2003	0.27	
	Changins	1971-2003	0.46	
Passe Crassane	Angers	1959-2006	0.18	0.29 (1960 → 1961)
Doyenné du Comice	Angers	1972-2006	0.32	

Table 5. Mean dates of F1 stage (apple tree) or F2 stage (pear tree), expressed in calendar day from 1st January, according to cultivar and location during the two successive observation periods.

Cultivar	Location	Stage	Observation period 1976-1988	1989-2002
Golden Delicious	Angers	F1	115	108
	Bergerac	F1	109	101
	Nîmes	F1	101	94
Williams	Angers	F2	105	94
	Bergerac	F2	102	92
	Changins	F2	115	105
Passe Crassane	Angers	F2	104	93
Doyenné du Comice	Angers	F2	109	98

Table 6. Mean temperatures during the chilling and heat phases of the flowering process for cultivar ‘Golden Delicious’ at Angers, Bergerac and Nîmes (1976-2002): estimated multivariate 2-segment model parameters ($\hat{\tau}_1 = 1988$ for models M_m, M_{msv} and M_{mv} in the two cases).

Sequence		$\hat{\mu}_{1,a} - \hat{\mu}_{0,a}$	$\hat{\sigma}_{0,a}$	$\hat{\sigma}_{1,a}$
Chilling temperature	Angers	1	0.57	0.85
	Bergerac	1.08	0.67	0.91
	Nîmes	1.12	0.65	0.63
	$\hat{\sigma}_j$		0.63	0.81
	$\hat{\sigma}$		0.73	
Heat temperature	Angers	1.28	0.62	0.95
	Bergerac	0.98	0.76	1
	Nîmes	1.77	0.9	0.91
	$\hat{\sigma}_j$		0.77	0.96
	$\hat{\sigma}$		0.88	

Table 7. Mean temperatures during the chilling and heat phases of the flowering process for cultivar ‘Golden Delicious’ at Angers, Bergerac and Nîmes (1976-2002): choice of the number of segments for multivariate models M_m.

Sequence	J	$2\log L_J$	Free param.	mBIC_J	$P\left(M_J \mid x_0^{T-1}\right)$
Chilling temperature	1	-213.78	4	-234.65	0
	2	-179.58	8	-219.92	1
	3	-174.02	12	-232.46	0
	4	-163.49	16	-240.5	0
Heat temperature	1	-247.44	4	-268.31	0
	2	-208.85	8	-249.2	0.53
	3	-199.11	12	-258.11	0.01
	4	-172.27	16	-249.46	0.46

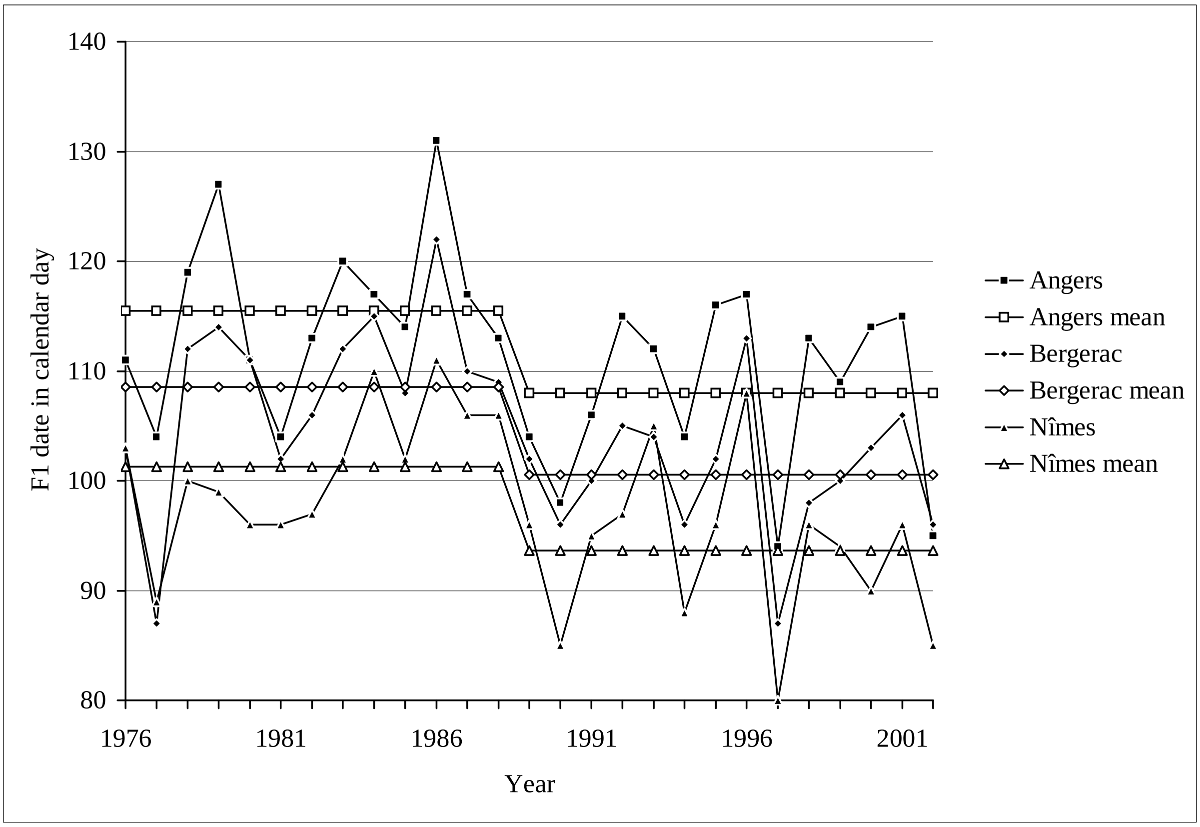
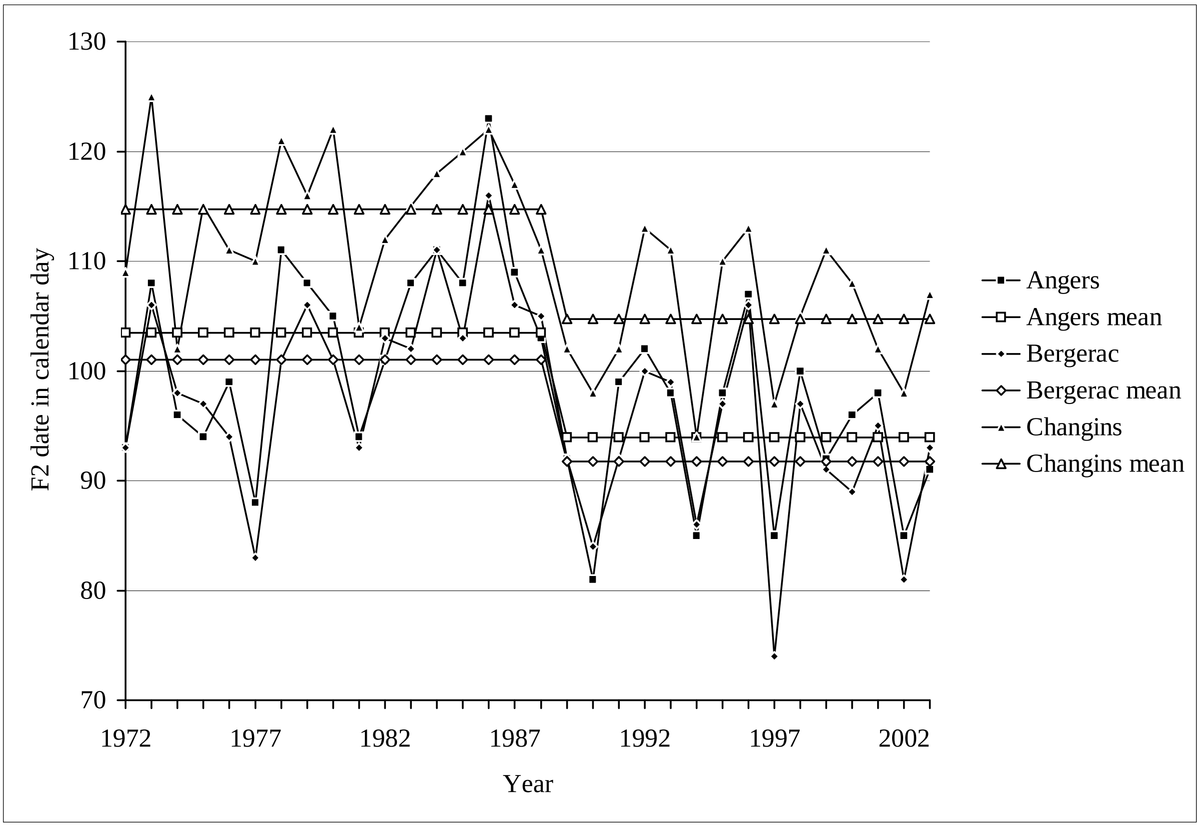


Figure 1. Segmentation of three chronological sequences of F1date for apple tree, cultivar 'Golden Delicious' at three locations.



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575 Figure 2. Segmentation of three chronological sequences of F2 date for pear tree, cultivar

576 'Williams' at three locations.

577

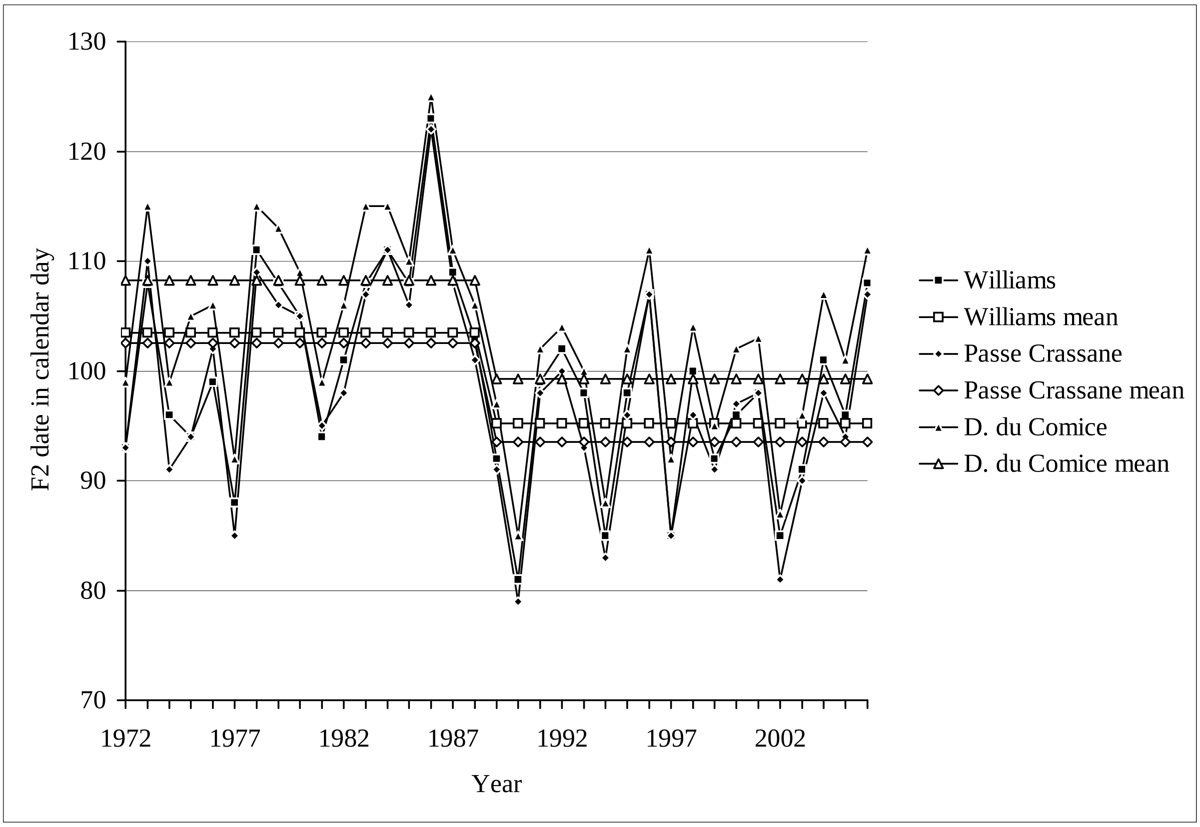

Figure 3. Segmentation of three chronological sequences of F2 date for three pear tree cultivars at Angers.

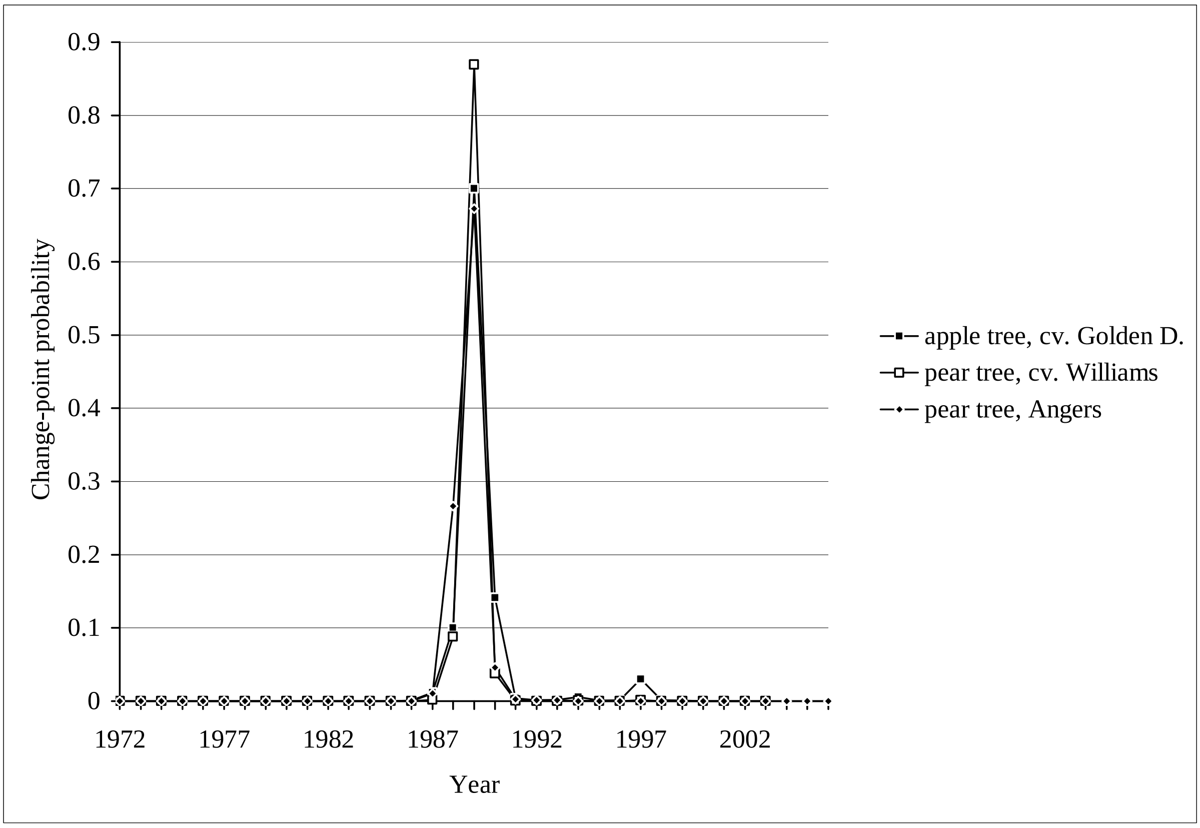

Figure 4. Multivariate 2-segment models M_{msv} : posterior change-point probabilities.

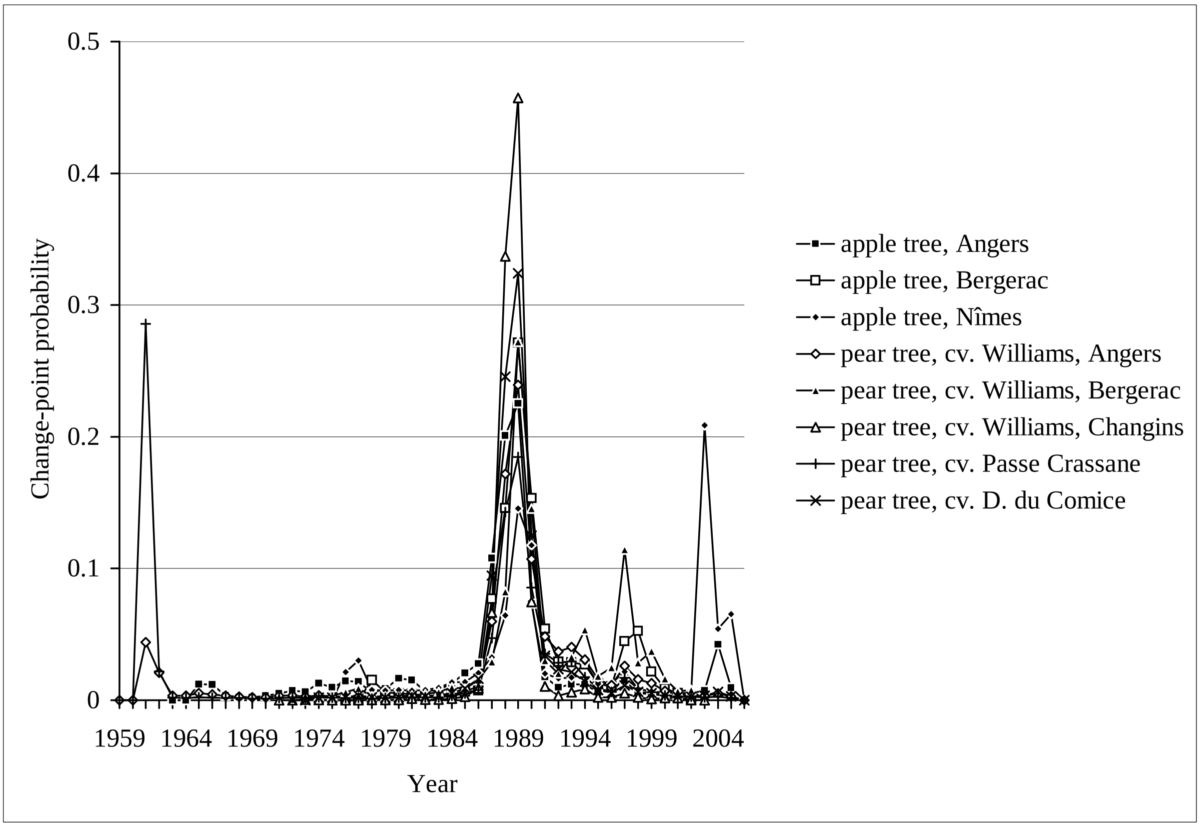

Figure 5. Univariate 2-segment models M_{mv}: posterior change-point probabilities.

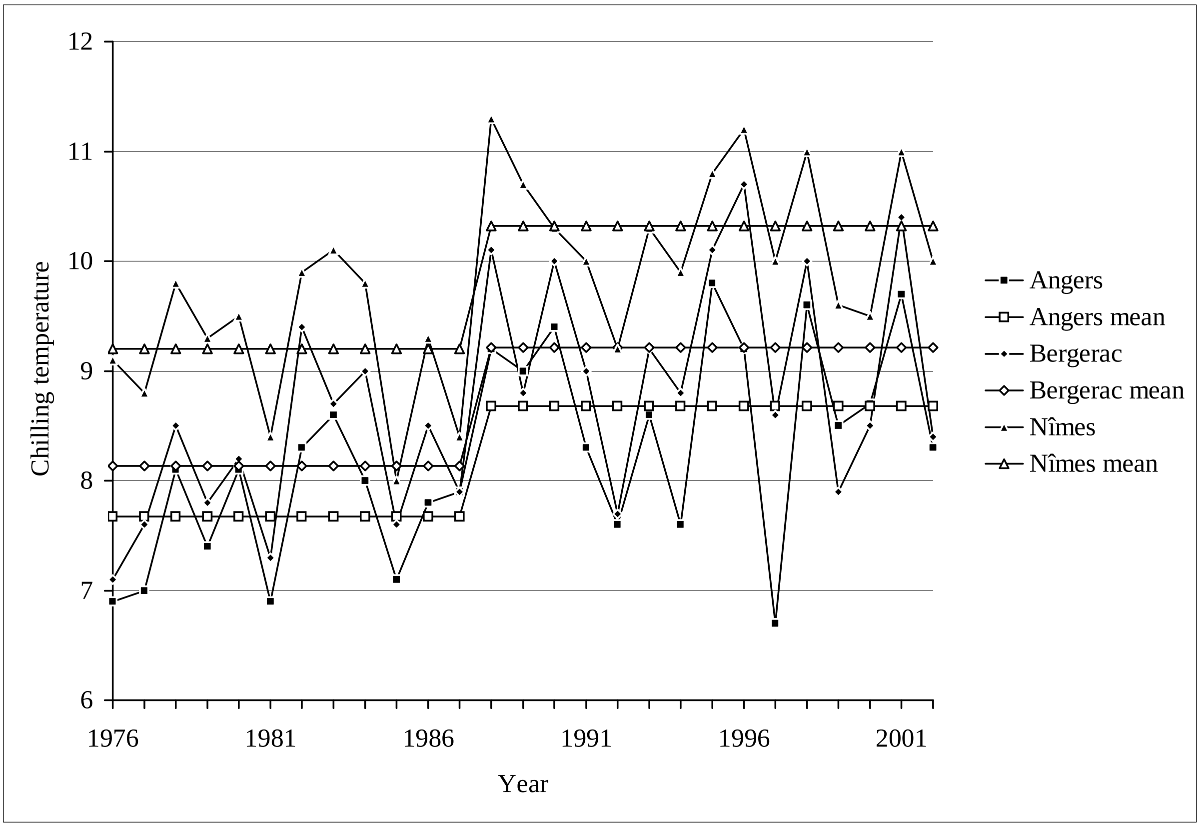

Figure 6. Segmentation of three chronological sequences of mean temperature during the chilling phase of the flowering process for cultivar ‘Golden Delicious ’at three locations.

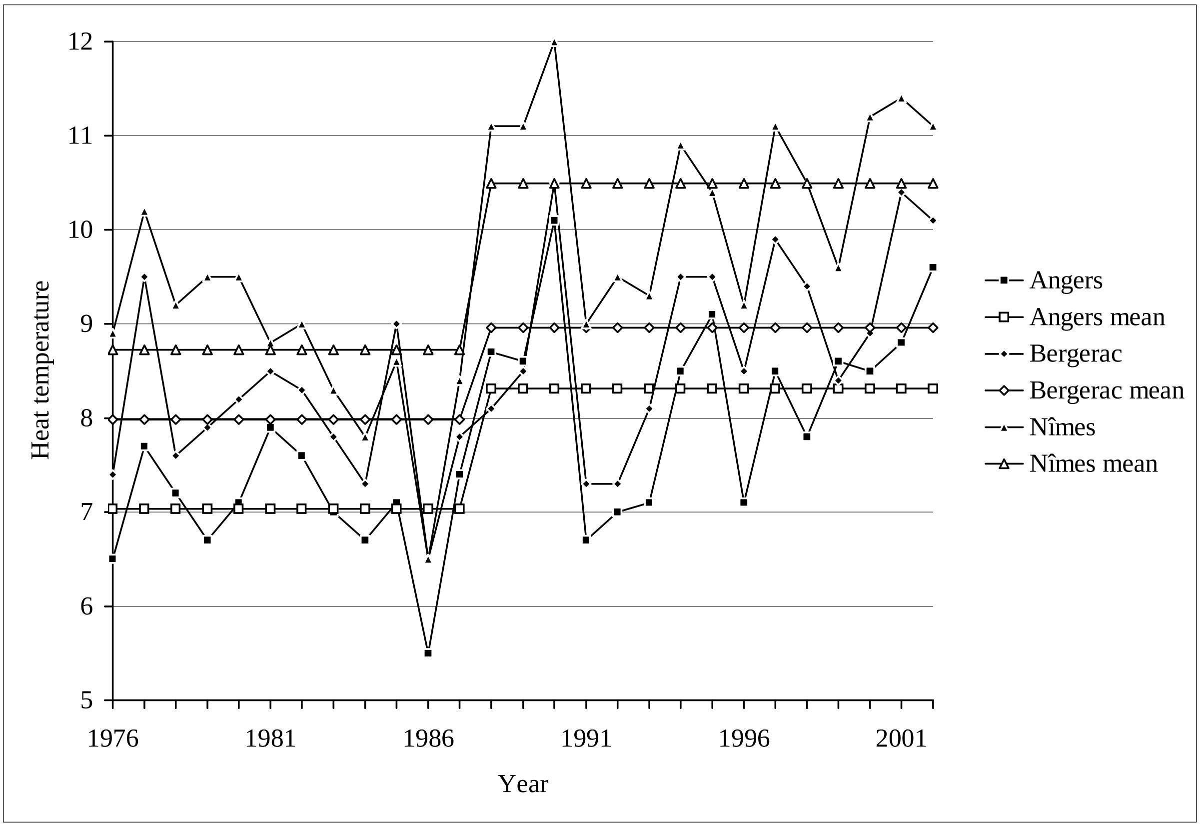

Figure 7. Segmentation of three chronological sequences of mean temperature during the heat phase of the flowering process for cultivar ‘Golden Delicious’ at three locations.