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

3

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13

## 14 Abstract

15 Over the last 40 years, perceptible advances in dates of flowering stages have been observed  
16 in apple and pear trees growing in three cropping areas in France and one in Switzerland. The  
17 time-course variation of dates of flowering stages was established for eight chronological  
18 sequences. Our aim was to propose a statistical modelling framework for such sequences with  
19 the objective of characterizing the relationship between flowering advances in fruit trees and  
20 global warming. After an exploratory analysis, change-point models were applied to  
21 multivariate and univariate sequences. The results clearly support the occurrence of a  
22 significant abrupt change in the time-course variation of flowering dates at the end of the  
23 1980s toward more frequent early dates, the most probable change instant being between  
24 1988 and 1989. The coincidence between this abrupt change in phenological variations and  
25 marked increases in temperature recorded particularly in France at the end of the 1980s led us

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

38

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

41

## 42 Introduction

43 Global warming of the climate system is unequivocal, as is now evident from observations  
44 of increases in average air temperatures in many parts of the world. Eleven of the last twelve  
45 years (1995-2006) rank among the twelve warmest years since 1850. Mean temperature will  
46 probably rise between 1.8°C and 4.0°C for the end of the 21<sup>st</sup> century, according to climatic  
47 scenario (IPCC, 2007). As plant phenology is mainly influenced by temperature, climate  
48 warming has caused renewed interest in phenological methods and observations. Long-term  
49 phenological records at specific sites provide useful measures of species-level biological  
50 responses to climate changes according to Schwartz (1999). A lot of phenological studies

51 focused on changes in natural systems (Parmesan and Yohe, 2003), while few studies dealt  
52 with phenological changes in perennial horticultural crops (Schultz, 2000). Changes in tree  
53 phenology have been observed in European countries where earlier onsets of leafing dates  
54 were associated with global warming (Chmielewski and Rötzer, 2001). In fruit tree orchards,  
55 changes in the timing of flowering phenology could have important impacts on production,  
56 because of the indirect influences of phenology on spring frost damage, pollination and fruit  
57 set efficiency (Cannell and Smith, 1986; Zavalloni et al., 2006).

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

## 76 Materials and methods

### 77 *Plant material and temperature conditions*

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

89 Thus, the date when about 10% of flower buds are opened (F1 stage) was chosen for apple  
90 tree cultivar 'Golden Delicious', while the date when nearly 100% are opened (F2 stage) was  
91 chosen for the three pear tree cultivars. F1 dates for 'Golden Delicious' were recorded during  
92 different periods at three locations representative of the main cropping areas of France: from  
93 1963 to 2006 at INRA research station near Angers (47° 28 N, 0° 33 W) in Pays de Loire,  
94 from 1976 to 2002 at Domaine de Castang (grower farm) near Bergerac (44° 51 N, 0° 29 E)  
95 in Aquitaine and from 1974 to 2006 at Ctifl professional station near Nîmes (43° 50 N, 4° 21  
96 E) in Languedoc. Regarding F2 dates for pear trees, data were recorded mainly at Angers  
97 from 1959 to 2006 for 'Williams' and 'Passe Crassane' and from 1972 to 2006 for 'Doyenné  
98 du Comice'. Data were also recorded at Bergerac from 1972 to 2003 for 'Williams'. In  
99 addition to French data, F2 dates collected for 'Williams' from 1971 to 2003 at the Agroscope  
100 Changins-Wädenswil research station near Nyon in Switzerland (46° 24 N, 6° 14 E) were

101 used. This was achieved with the collaboration of Doctor Danilo Christen, in order to  
102 compare French phenological sequences with one sequence representative of those collected  
103 in another European country.

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

122

### 123 *Statistical models*

124 Multiple change-point models are used to delimit segments for which the data  
125 characteristics are homogeneous within each segment while differing markedly from one

126 segment to another. In a probabilistic framework, the observed sequence of length  $T$ ,  
 127  $x_0, \dots, x_{T-1}$  is modelled by  $T$  random variables  $X_0, \dots, X_{T-1}$  which are assumed to be  
 128 independent. In the following  $x_0^{T-1}$  is a shorthand for  $x_0, \dots, x_{T-1}$ .

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

$$136 \quad \text{if } \tau_j \leq t < \tau_{j+1}, \quad \begin{cases} E(X_t) = \mu_j, \\ V(X_t) = \sigma^2. \end{cases}$$

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

$$139 \quad \text{if } \tau_j \leq t < \tau_{j+1}, \quad \begin{cases} E(X_t) = \mu_j, \\ V(X_t) = \sigma_j^2. \end{cases}$$

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

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

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

$$153 \quad \hat{\mu}_j = \frac{\sum_{t=\tau_j}^{\tau_{j+1}-1} x_t}{\tau_{j+1} - \tau_j} \quad \text{and} \quad \hat{\sigma}_j^2 = \frac{\sum_{t=\tau_j}^{\tau_{j+1}-1} (x_t - \hat{\mu}_j)^2}{\tau_{j+1} - \tau_j}. \quad (1)$$

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

$$155 \quad \hat{\sigma}^2 = \frac{\sum_{j=0}^{J-1} \sum_{t=\tau_j}^{\tau_{j+1}-1} (x_t - \hat{\mu}_j)^2}{T}. \quad (2)$$

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

$$159 \quad \hat{\tau}_1, \dots, \hat{\tau}_{J-1} = \arg \max_{0 < \tau_1 < \dots < \tau_{J-1} < T} \log L_J(x_0^{T-1}; \hat{\theta}),$$

160 with

$$161 \quad \begin{aligned} \log L_J(x_0^{T-1}; \hat{\theta}) &= -\frac{T}{2} (\log \hat{\sigma}^2 + \log 2\pi + 1) && \text{for model } M_m, \\ \log L_J(x_0^{T-1}; \hat{\theta}) &= -\frac{1}{2} \sum_{j=0}^{J-1} (\tau_{j+1} - \tau_j) (\log \hat{\sigma}_j^2 + \log 2\pi + 1) && \text{for model } M_{mv}. \end{aligned}$$

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

166 The Gaussian multiple change-point models can be directly generalized to multivariate  
167 sequences. In our context, the  $N$  variables correspond to different locations or to different

168 cultivars and the elementary random variables at a given time  $t$  are assumed to be  
 169 independent. In the multivariate case, the log-likelihood of the  $J$ -segment model is given by:

$$170 \quad \log L_J(x_0^{T-1}; \hat{\theta}) = -\frac{NT}{2} (\log \hat{\sigma}^2 + \log 2\pi + 1) \quad \text{with} \quad \hat{\sigma}^2 = \frac{\sum_{j=0}^{J-1} \sum_{a=1}^N \sum_{t=\tau_j}^{\tau_{j+1}-1} (x_{a,t} - \hat{\mu}_{j,a})^2}{NT},$$

171 for model  $M_m$  and

$$172 \quad \log L_J(x_0^{T-1}; \hat{\theta}) = -\frac{1}{2} \sum_{j=0}^{J-1} (\tau_{j+1} - \tau_j) \sum_{a=1}^N (\log \hat{\sigma}_{j,a}^2 + \log 2\pi + 1) \quad \text{where } \hat{\sigma}_{j,a}^2 \text{ is given by (1),}$$

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

$$177 \quad \log L_J(x_0^{T-1}; \hat{\theta}) = -\frac{N}{2} \sum_{j=0}^{J-1} (\tau_{j+1} - \tau_j) (\log \hat{\sigma}_j^2 + \log 2\pi + 1) \quad \text{with} \quad \hat{\sigma}_j^2 = \frac{\sum_{a=1}^N \sum_{t=\tau_j}^{\tau_{j+1}-1} (x_{a,t} - \hat{\mu}_{j,a})^2}{N(\tau_{j+1} - \tau_j)}.$$

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

$$182 \quad \hat{J} = \arg \max_{J \geq 1} \{ \log L_J(x_0^{T-1}; \hat{\tau}_1, \dots, \hat{\tau}_{J-1}, \hat{\theta}) - \text{Penalty}(J) \}$$

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

190 (2007) used in Guédon et al. (2007). Zhang and Siegmund proposed a modified BIC criterion  
 191 in the case of the univariate model  $M_m$ . This criterion is given by

$$192 \quad \text{mBIC}_J = 2 \log L_J(x_0^{T-1}; \hat{\tau}_1, \dots, \hat{\tau}_{J-1}, \hat{\theta}) - 2J \log T - \sum_{j=0}^{J-1} \log(\hat{\tau}_{j+1} - \hat{\tau}_j), \quad (3)$$

193 where

$$194 \quad \begin{aligned} \min_{0 < \tau_1 < \dots < \tau_{J-1} < T} \sum_{j=0}^{J-1} \log(\hat{\tau}_{j+1} - \hat{\tau}_j) &= \log(T - J + 1) \\ &\approx J \log T - (J - 1) \log T \quad \text{if } J \ll T, \\ \max_{0 < \tau_1 < \dots < \tau_{J-1} < T} \sum_{j=0}^{J-1} \log(\hat{\tau}_{j+1} - \hat{\tau}_j) &= J \log \frac{T}{J} \\ &= J \log T - J \log J. \end{aligned}$$

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

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

$$201 \quad P(M_J | x_0^{T-1}) = \frac{\exp\left(\frac{1}{2} \Delta \text{mBIC}_J\right)}{\sum_{k=1}^{J_{\max}} \exp\left(\frac{1}{2} \Delta \text{mBIC}_k\right)},$$

202 with

$$203 \quad \Delta \text{mBIC}_J = \text{mBIC}_J - \max_K \text{mBIC}_K,$$

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

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

208 
$$\log L_j(x_0^{T-1}; \hat{\tau}_1, \dots, \hat{\tau}_{j-1}, \hat{\theta}) = \max_{0 < \tau_1 < \dots < \tau_{j-1} < T} \sum_{j=0}^{j-1} \log f(x_{\tau_j}, \dots, x_{\tau_{j+1}-1}; \hat{\theta}_j)$$

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

213 
$$f(x_0, \dots, x_{\tau_1-1}; \hat{\theta}_0) f(x_{\tau_1}, \dots, x_{T-1}; \hat{\theta}_1) / \sum_t f(x_0, \dots, x_{t-1}; \hat{\theta}_0) f(x_t, \dots, x_{T-1}; \hat{\theta}_1),$$

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

217

## 218 Results

### 219 *Exploratory analysis of temperature conditions*

220 In France, similar patterns were observed between the three locations regarding the annual  
 221 evolution for monthly mean temperatures. However, for each monthly temperature, gradual  
 222 ranges according to the latitude degree of location were obvious (data not shown). Thus,  
 223 Angers is characterised by the coldest monthly temperatures with a mean annual temperature  
 224 of 11.9°C and Nîmes the warmest (mean annual temperature of 14.5°C), while intermediate  
 225 monthly temperatures are observed at Bergerac (mean annual temperature of 12.8°C).  
 226 Changins is characterised by a relatively cold climate with a mean annual temperature of  
 227 9.7°C.

228 Temperature increases have been clearly marked from the year 1988 in the three French  
 229 growing locations as expressed by the comparison of means of annual temperatures between  
 230 the two successive periods 1973-1987 and 1988-2002. The mean increases of annual

231 temperatures in the second period were +1.1°C at Angers, +1.2°C at Bergerac and +1.3°C at  
232 Nîmes. A similar change has been obvious at Changins (+1.2°C during the period 1988-  
233 2002). Nevertheless, these increases include noticeable monthly differences for the months  
234 involved in the annual flowering process. Particularly, in France warming was clearly more  
235 pronounced in the period February - March (mean temperature increases of 1.4-1.8°C  
236 according to location), than in the period November - December (0.6-0.8°C).

237

### 238 *Exploratory analysis of the variability within the flowering dates*

239 The time-course variation of flowering dates was established for each of the eight  
240 selected sequences (Figures 1, 2 and 3). This highlighted differences in flowering date  
241 according to location and cultivar. For apple tree cultivar 'Golden Delicious', marked  
242 differences are observed between the three regional sequences during the period 1976-2002  
243 (Figure 1). The F1 date is consistently earlier at Nîmes than at Angers, while most of the time  
244 an intermediate date is observed at Bergerac. The mean F1 dates for this period are April 22 at  
245 Angers, April 14 at Bergerac and April 7 at Nîmes (8 days earlier at Bergerac than at Angers  
246 and 7 days earlier at Nîmes than at Bergerac). The same range of variability in mean dates is  
247 observed between the three locations when means are considered separately for the 1976-  
248 1988 sub-period (April 25, April 19, April 11 respectively) and the 1989-2002 sub-period  
249 (April 18, April 11, April 4 respectively). Such data clearly underline a constant influence of  
250 location on the date of stage F1 for 'Golden Delicious' apple trees. The lower the latitude of  
251 location, the earlier the flowering date in the apple tree growing area extending from North-  
252 West to South-East of France.

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

256 F2 dates for the period 1972-2003 are April 7 at Bergerac, April 9 at Angers and April 20 at  
257 Changins. The differences in mean dates are unchanged when means are considered  
258 separately for the 1972-1988 sub-period (April 11, April 13 and April 25 respectively) and the  
259 1989-2003 sub-period (April 2, April 4 and April 15 respectively).

260 Differences in flowering date according to cultivar are highlighted by the comparison of  
261 sequences of three pear tree cultivars growing at Angers during the period 1972-2006 (Figure  
262 3). The F2 date is consistently earlier for 'Passe Crassane' than for 'Doyenné du Comice',  
263 while 'Williams' shows an intermediate date most of the time. The mean F2 dates for the  
264 period 1972-2006 are April 8 for 'Passe Crassane' and April 14 for 'Doyenné du Comice'.  
265 This difference of 6 days is unchanged when means are considered separately for the 1972-  
266 1988 sub-period (April 12 and April 18 respectively) and the 1989-2006 sub-period (April 3  
267 and April 9 respectively).

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

273

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

275 A multivariate sequence was built taking each location (three for apple tree cultivar  
276 'Golden Delicious' and for pear tree cultivar 'Williams') or cultivar (three pear tree cultivars  
277 growing at Angers) as a variable. Applying multiple change-point detection method to one of  
278 these multivariate sequences consists then in detecting change points common to the  
279 individual sequence (while the means are estimated for each segment and each variable, and  
280 the global variance is estimated for model  $M_m$ , the variances are estimated for each segment

281 for model  $M_{msv}$  and for each segment and each variable for model  $M_{mv}$ ); see Figures 1, 2 and  
 282 3. Since the variances estimated for each segment and each variable are close, the modified  
 283 BIC of Zhang and Siegmund (2007) always ranks the models from the more to the less  
 284 parsimonious for a fixed number of segments i.e.  $M_m$  followed by  $M_{msv}$  and  $M_{mv}$  (results not  
 285 shown); see the corresponding standard deviations estimated for the different 2-segment  
 286 models in Table 1. We thus chose to focus on models  $M_m$  for the selection of the number of  
 287 segments. The modified BIC favoured the 2-segment model for apple tree, cultivar ‘Golden  
 288 Delicious’ and for pear tree, cultivar ‘Williams and the 3-segment model for pear tree at  
 289 Angers (Table 2). In this last case, both the 2-segment and the 3-segment models are possible  
 290 models according to their posterior probabilities. It should be noted that the penalty used in  
 291 (3) is likely to slightly underpenalized the log-likelihood (and thus to select a too large  
 292 number of segments) since this penalty was derived in the case where the global variance  $\sigma$   
 293 is known (instead of being estimated); see Zhang and Siegmund (2007).

294 In the case of the 2-segment models, we obtained the same instant for the change point  
 295 (1988  $\rightarrow$  1989) in the three cases with a low uncertainty (posterior probability between 0.67  
 296 and 0.87 for the change point 1988  $\rightarrow$  1989 computed using  $M_{msv}$  models; see Figure 4). The  
 297 change-point magnitudes as given by the mean difference between the two segments  
 298  $\hat{\mu}_{1,a} - \hat{\mu}_{0,a}$  are very similar (between -7.5 and -10; see Table 1). The sample autocorrelation  
 299 function computed from the residual sequences obtained by subtracting the two successive  
 300 segment means from the original sequences (Lavielle, 1998) showed that the residual  
 301 sequences were stationary and close to white noise sequences (results not shown).

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

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

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

322 Finally, despite usual yearly fluctuations, we may conclude that a change in the time-  
323 course variation of flowering dates occurred abruptly at the end of the 1980s (1988 → 1989)  
324 toward more frequent early dates. This evolution was similar for the eight sequences  
325 analysed, regardless of the respective influences of location and cultivar (Figures 1, 2 and 3).  
326 When the period 1976-2002 common to all sequences is considered to compare the advances  
327 in flowering date (Table 5), this clearly highlights earlier mean dates of F1 and F2 stages  
328 during the sub-period 1989-2002 in comparison with the sub-period 1976-1988, although

329 higher mean advances in pear tree (10-11 days for F2 stage) than in apple tree (by 7-8 days  
330 for F1 stage) can be noted.

331

### 332 *Temperature changes related to flowering date changes*

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

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

356 Since a single change point was detected at one year apart in both the flowering date  
 357 sequence for apple tree cultivar 'Golden Delicious' and the corresponding chilling and heat  
 358 temperature sequences (and the ratios between the average absolute mean difference between  
 359 the two segments and the global standard deviation  $\sum_{a=1}^N |\hat{\mu}_{1,a} - \hat{\mu}_{0,a}| / N\hat{\sigma}$  are relatively close  
 360 in the three cases; see Tables 1 and 6), the flowering date can be directly related to the  
 361 corresponding chilling (respectively heat) temperature by a simple linear correlation  
 362 coefficient. In the two cases, the correlation coefficients are largely below the threshold of -  
 363 0.22 corresponding to the hypothesis of no correlation and clearly indicate negative  
 364 correlation between the temperature and the flowering date. It should be noted that the heat  
 365 temperature is far more correlated with the flowering date (correlation coefficient of -0.79)  
 366 than the chilling temperature (-0.3).

367

## 368 Discussion

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

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

383 Despite some statistical uncertainties, our analysis of phenological sequences and their  
384 relationship with temperature changes provide elements for a right description and  
385 explanation of the impact of global warming on apple and pear tree phenology in France. In  
386 the case of apple tree ‘Golden Delicious’, the advances in flowering date have been similar  
387 from North-West to South-East of France, i.e. without interaction with the location.  
388 Moreover, the mean range in flowering advance (7-8 days) was similar to the mean difference  
389 in flowering date between adjacent locations (6-8 days). Thus, as a result of the abrupt change  
390 in flowering date, ‘Golden Delicious’ is now flowering at the northern location of Angers  
391 within the same date range it was previously flowering further south at Bergerac. The same  
392 relative change was observed between Bergerac and Nîmes (Table 5). For pear tree cultivars  
393 growing at Angers, similar mean flowering advances were observed, i.e. without interaction  
394 with cultivar. In comparison with apple tree ‘Golden Delicious’ in the same French locations,  
395 pear tree cultivars showed higher mean flowering advances (10-11 days), exceeding the mean  
396 difference between adjacent locations (2-3 days between Angers and Bergerac for  
397 ‘Williams’). A similar higher advance (10 days) was also found for ‘Williams’ at Changins in  
398 Switzerland. For each of the eight phenological sequences, there was a clear time coincidence  
399 between the beginning of marked increases of annual temperatures and the most probable  
400 instant (1988 → 1989, according to the statistical models) of abrupt change of flowering

401 dates. Thus, our results confirm a general impact of global warming in Europe toward earlier  
402 flowering dates at the end of the 1980s (Chmielewski et al., 2004) and contribute to an  
403 accurate characterisation of this impact (abrupt change, most probable change instant). In  
404 addition, they suggest genetic differences in phenological response between apple and pear  
405 trees, as already reported for cherry tree (Miller-Rhushing et al., 2007).

406 At present, such a phenological change do not affect fruit tree production, but it is  
407 important to understand the mechanism by which climate warming exerts its influence,  
408 especially because this was poorly investigated since the old works of Cannell and Smith  
409 (1986). An interesting feature to explain is why the flowering advance would have been  
410 expressed through an abrupt change and not in a progressive way. One explanation would lie  
411 in different changes in the respective rates of completion of the chilling and heat  
412 requirements. Indeed in the case of ‘Golden Delicious’ in France, previous works (Legave et  
413 al., 2008) showed that a constant regional gradient of annual F1 dates (the latest dates at  
414 Angers to the earliest dates at Nîmes) is determined by differences in length of the heat phase  
415 (the longest at Angers and the shortest at Nîmes) since an inverse gradient of the dates of  
416 chilling completion occurred constantly (the earliest at Angers and the latest at Nîmes).  
417 Similarly, earlier F1 dates since 1989 at all three locations have been explained by a major  
418 effect of warming in reducing the length of the heat phase (more frequent years with relatively  
419 short lengths), in spite of noticeable trends, at the same time, toward some years with longer  
420 lengths of the chilling phase (Legave et al., 2008). In agreement with these previous findings,  
421 the present study clearly shows that the mean temperature during the heat phase has been the  
422 main climatic factor determining the F1 date (the higher temperature, the earlier date), while  
423 the mean temperature during the chilling phase has been a less important factor (poorly linked  
424 to the F1 date). Indeed, the recent warming was non-uniform at all locations but particularly  
425 pronounced in months corresponding to the heat phase (February and March particularly),

426 while warming was limited in months corresponding to the chilling phase (October to early  
427 January). Moreover, the mean temperature during the heat phase clearly increased from 1988  
428 to 1990 at Angers and Nîmes and more progressively at Bergerac (Figure 7). Then, from 1991  
429 to 2002, the mean temperatures during the heat phase remained relatively high at all three  
430 locations (particularly from 1994) in comparison with the mean temperatures prevailing  
431 before 1988 (Figure 7). Such temperature changes led to a marked increase in the rate of  
432 completion of the heat requirements since 1988 and can explain the abrupt change of  
433 flowering dates. Nevertheless, as previously mentioned, climate warming also affected the  
434 rate of completion of the chilling requirements which was clearly decreased in some years  
435 (high temperatures during the chilling phase). In such cases, relatively long dormancy tended  
436 to delay the flowering date despite the short length of the heat phase linked to a high rate of  
437 completion of the heat requirements. This was markedly the case for the annual cycle 1987-  
438 1988 characterized by relatively high temperatures at the end of chilling process (January  
439 1988), particularly at Nîmes. Such a temperature feature at this time (Figures 6 and 7) can  
440 explain that the most probable instant of abrupt change of flowering date is detected only  
441 between 1988 and 1989, i.e. one year after the beginning of the marked warming in France  
442 which started in 1988 as confirmed by our results .

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

448 Finally, it may be emphasized that cultivars of fruit trees have been suitable plants to  
449 highlight climatic change factors during the recent climate warming in France (temperature  
450 increases from autumn to early spring) as probably in other European countries. A first

451 advantage of fruit trees is due to the considerable longevity of cultivars (clone) permitting  
452 analyses of phenological sequences over long terms. Another interesting feature lies in the  
453 fact that their flowering process is highly linked to two temperature requirements, which  
454 allows to highlight significant temperature changes during the different seasons. Therefore, it  
455 is important to continue to collect and analyse flowering data for some main cultivars of fruit  
456 trees, in order to detect new changes in main temperature factors and consequently select  
457 cultivars adapted to possible phenological disorders in the future (Sunley et al., 2006).

458  
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463

## 464 References

- 465 Atkinson, C.J. and Taylor, L., 1994. The influence of autumn temperature on flowering time and  
466 cropping of *Pyrus communis* cv. Conference. *Journal of Horticultural Science*, 69: 1067-  
467 1075.
- 468 Auger, I.E. and Lawrence, C.E., 1989. Algorithms for the optimal identification of segment  
469 neighborhoods. *Bulletin of Mathematical Biology*, 51: 39-54.
- 470 Bidabé, B., 1967. Action de la température sur l'évolution des bourgeons de pommier et  
471 comparaison de méthodes de contrôle de l'époque de floraison. *Annales de Physiologie*  
472 *Végétale*, 9: 65-86.
- 473 Cannell, M.G.R. and Smith, R.I., 1986. Climatic warming, spring budburst and frost damage  
474 on trees. *Journal of Applied Ecology*, 23: 177-191.

- 475 Chmielewski, F.M. and Rötzer, T., 2001. Response of tree phenology to climate across Europe.  
476 *Agricultural and Forest Meteorology*, 108: 101-112.
- 477 Chmielewski, F.M., Müller, A. and Bruns, E., 2004. Climate changes and trends in phenology of  
478 fruit trees and field crops in Germany, 1961-2000. *Agricultural and Forest Meteorology*, 121:  
479 69-78.
- 480 Guédon, Y., Caraglio, Y., Heuret, P., Lebarbier, E. and Meredieu, C., 2007. Analyzing growth  
481 components in trees. *Journal of Theoretical Biology*, 248: 418-447.
- 482 IPCC, 2007. Summary for policymakers. In: *climate change 2007: the physical science basis*.  
483 Contribution of working group I to the fourth assessment report of the intergovernmental  
484 panel on climate change [Solomon, S., D. Qin, M. Manning, Z. Chen, M. Marquis, K.B.  
485 Averyt, M. Tignor and H.L. Miller (eds.)]. Cambridge university press, Cambridge,  
486 United Kingdom and New York, NY, USA.
- 487 Kai, K., Kainurma, M., Murakoshi, N. and Omasa, K., 1993. Potential effects on the  
488 phenological observation of plants by global warming in Japan. *Journal of Agricultural  
489 Meteorology*, 48: 771-774.
- 490 Lang, G.A., Early, J.D., Martin, G.C. and Darnell, R.L., 1987. Endo-, para-, and ecodormancy:  
491 physiological terminology and classification for dormancy research. *HortScience*, 22: 371-  
492 377.
- 493 Lavielle, M., 1998. Optimal segmentation of random processes. *IEEE Transactions on Signal  
494 Processing*, 46: 1365-1373.
- 495 Lavielle, M., 2005. Using penalized contrasts for the change-point problem. *Signal  
496 Processing*, 85: 1501-1510.
- 497 Lebarbier, E., 2005. Detecting multiple change-points in the mean of Gaussian process by  
498 model selection. *Signal Processing*, 85: 717-736.

- 499 Legave, J.M. and Clauzel, G., 2006. Long-term evolution of flowering time in apricot cultivars  
500 grown in southern France: which future impacts of global warming ? *Acta Horticulturae*, 717:  
501 47-50.
- 502 Legave, J.M., Farrera, I., Alméras, T. and Calleja, M., 2008. Selecting models of apple flowering  
503 time and understanding how global warming has had an impact on this trait. *Journal of*  
504 *Horticultural Science & Biotechnology*, 83: 76-84.
- 505 Miller-Rhushing, A.J., Katsuki, T., Primack, R.B., Ishii, Y., Don Lee, S. and Higuchi, H., 2007.  
506 Impact of global warming on a group of related species and their hybrids: cherry tree  
507 (*Rosaceae*) flowering at Mt Takao, Japan. *American Journal of Botany*, 94: 1470-1478.
- 508 Omoto, Y. and Aono, Y., 1990. Estimation of change in blooming date of cherry flower by urban  
509 warming. *Journal of Agricultural Meteorology*, 46: 123-129.
- 510 Menzel, A., Sparks, T.H., Estrella, N. and Roy, D.B., 2006. Altered geographic and temporal  
511 variability in phenology in response to climate change. *Global Ecology and Biogeography*,  
512 15: 498-504.
- 513 Parmesan, C. and Yohe, G., 2003. A globally coherent fingerprint of climate change impacts  
514 across natural systems. *Nature*, 421: 37-42.
- 515 Picard, F., Robin, S., Lavielle, M., Vaisse, C. and Daudin, J. J., 2005. A statistical approach  
516 for array CGH data analysis. *BMC Bioinformatics*, 6.
- 517 Schultz, H.R., 2000. Climate change and viticulture: a European perspective on climatology,  
518 carbon dioxide and UV-B effects. *Australian Journal of Grape and Wine Research*, 6: 2-12.
- 519 Schwartz, M.D., 1999. Advanced to full bloom: planning phenological research for the 21st  
520 century. *International Journal of Biometeorology*, 42: 113-118.
- 521 Sunley, R.J., Atkinson, C.J. and Jones, H.G., 2006. Chill unit models and recent changes in the  
522 occurrence of winter chill and spring frost in the United Kingdom. *Journal of Horticultural*  
523 *Science & Biotechnology*, 81: 949-958.

524 Zavalloni, C, Andresen, J.A., Winkler, J.A., Flore, J.A., Black, J.R. and Beedy, T.L., 2006. The  
 525 pileus project: climate impacts on sour cherry production in the great lakes region in  
 526 pastand projected future time frames. *Acta Horticulturae*, 707: 101-108.

527 Zhang, N.R. and Siegmund, D.O., 2007. A modified Bayes information criterion with  
 528 applications to the analysis of comparative genomic hybridization data. *Biometrics* 63: 22-  
 529 32.

530

531 Table 1. Apple tree, cultivar ‘Golden Delicious’ at Angers, Bergerac and Nîmes (1976-2002);  
 532 pear tree, cultivar ‘Williams’ at Angers, Bergerac and Changins (1972-2003); pear  
 533 tree cultivars ‘Williams’, ‘Passe Crassane’ and ‘Doyenné du Comice’ at Angers  
 534 (1972-2006): estimated multivariate 2-segment model parameters ( $\hat{\tau}_1 = 1989$  for  
 535 models  $M_m$ ,  $M_{msv}$  and  $M_{mv}$  in the three cases).

536

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

537

538 Table 2. Apple tree, cultivar ‘Golden Delicious’ at Angers, Bergerac and Nîmes (1976-2002);  
 539 pear tree, cultivar ‘Williams’ at Angers, Bergerac and Changins (1972-2003); pear  
 540 tree cultivars ‘Williams’, ‘Passe Crassane’ and ‘Doyenné du Comice’ at Angers  
 541 (1972-2006): choice of the number of segments for multivariate models  $M_m$ .  
 542

Sequence	$J$	$2\log L_J$	Free param.	mBIC $_J$	$P(M_J   x_0^{T-1})$
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

543  
 544 Table 3. Apple tree, cultivar ‘Golden Delicious’ (Angers, Bergerac and Nîmes) and pear tree,  
 545 cultivars ‘Williams’ (Angers, Bergerac and Changins), ‘Passe Crassane’ (Angers)  
 546 and ‘Doyenné du Comice’ (Angers), (1976-2002): choice of the number of segments  
 547 for multivariate model  $M_m$ .  
 548

$J$	$2\log L_J$	Free param.	mBIC $_J$	$P(M_J   x_0^{T-1})$
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

549

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

551

Cultivar	Location	Year range	1988 → 1989 probability	Maximum probability (change point)
Golden Delicious	Angers	1963-2006	0.23	0.21 (2002 → 2003)
	Bergerac	1976-2002	0.27	
	Nîmes	1974-2006	0.15	
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	

552

553 Table 5. Mean dates of F1 stage (apple tree) or F2 stage (pear tree), expressed in calendar day

554 from 1<sup>st</sup> January, according to cultivar and location during the two successive

555 observation periods.

556

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

557

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

562

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

563

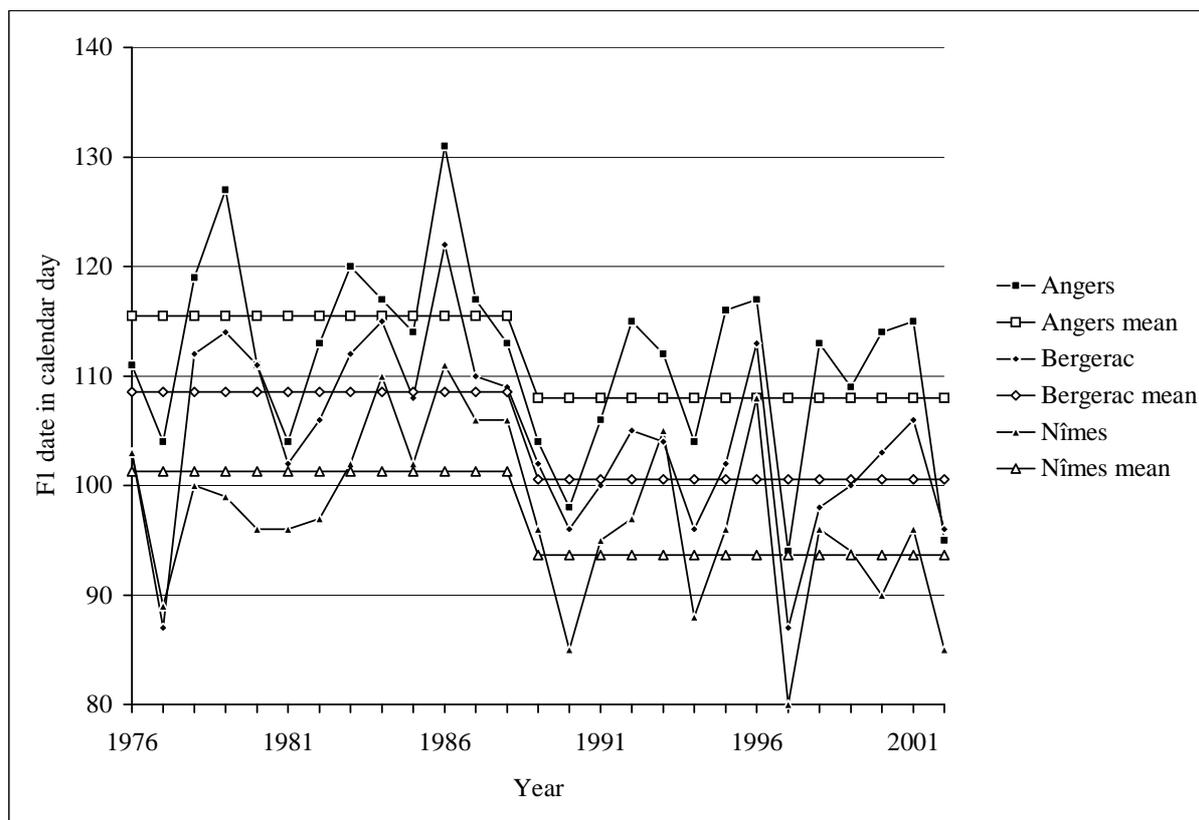
564 Table 7. Mean temperatures during the chilling and heat phases of the flowering process for  
 565 cultivar ‘Golden Delicious’ at Angers, Bergerac and Nîmes (1976-2002): choice of  
 566 the number of segments for multivariate models  $M_m$ .

567

Sequence	$J$	$2\log L_j$	Free param.	mBIC $_j$	$P(M_j   x_0^{T-1})$
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

568

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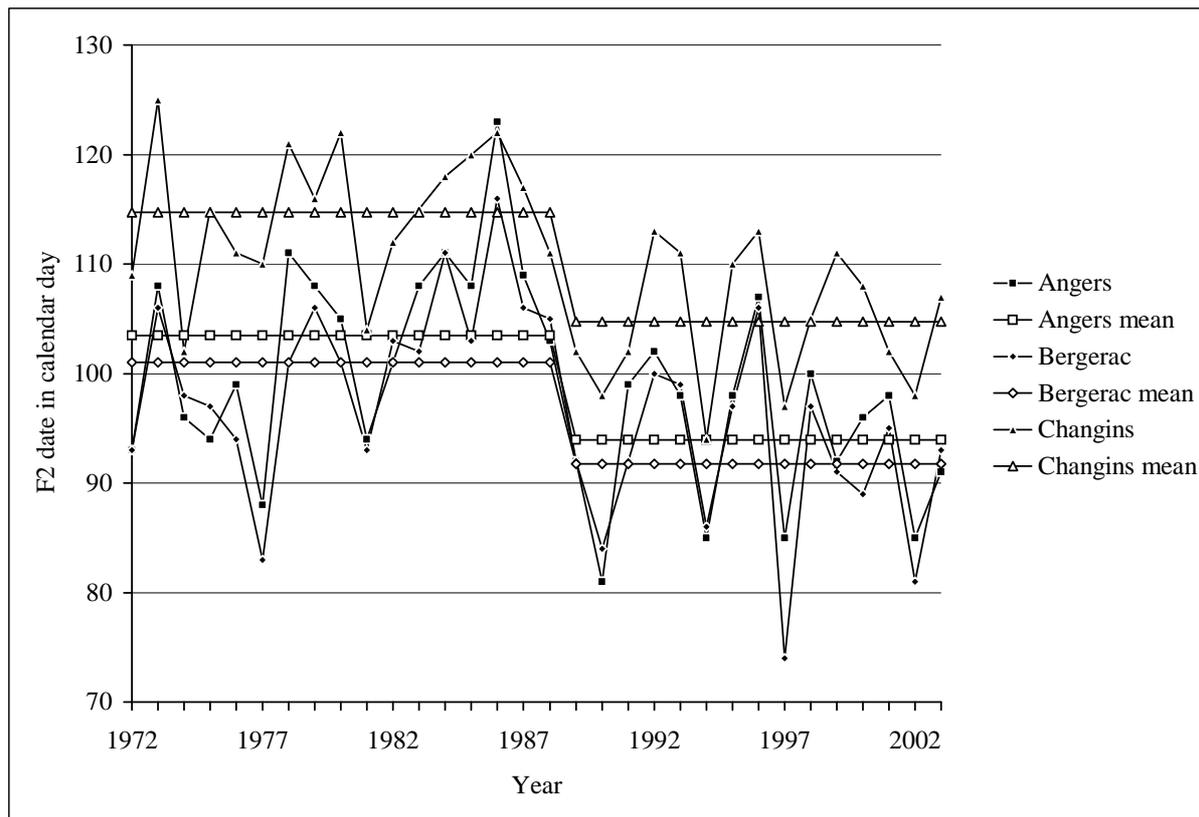


570

571 Figure 1. Segmentation of three chronological sequences of F1date for apple tree, cultivar

572 'Golden Delicious' at three locations.

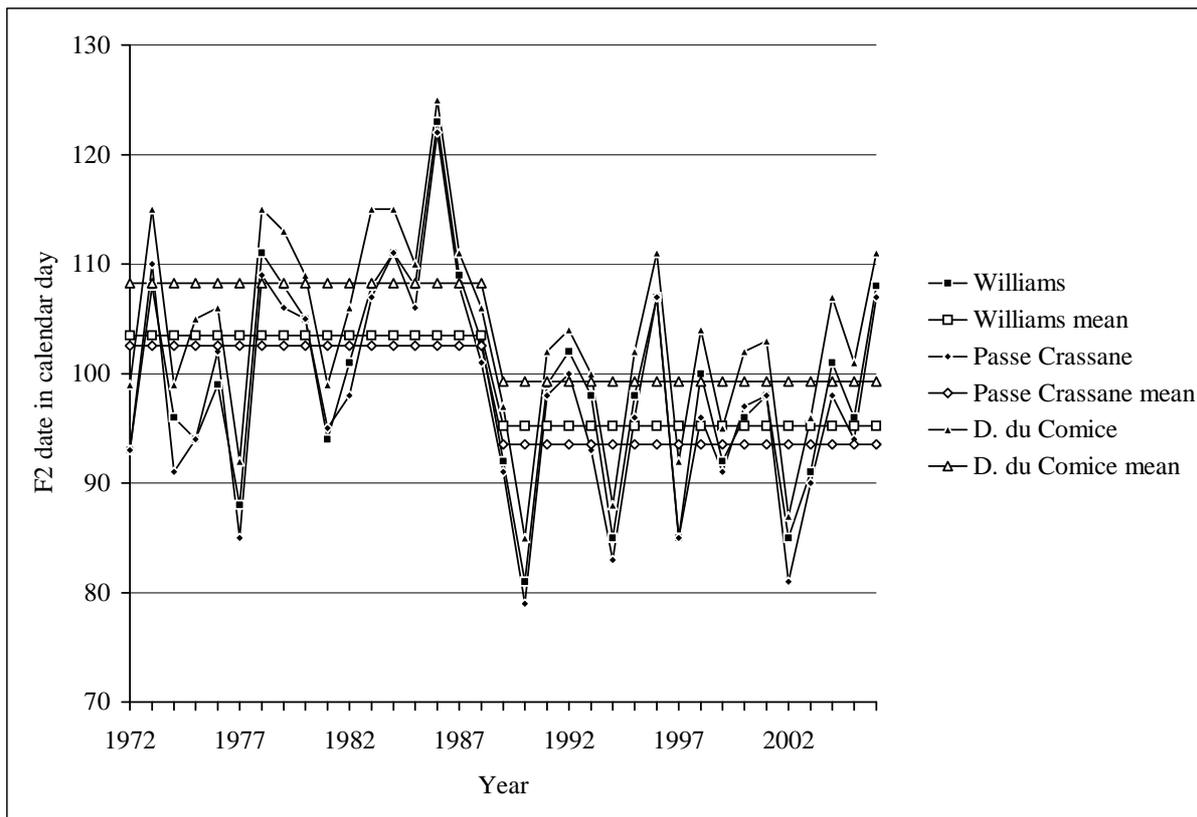
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574

575 Figure 2. Segmentation of three chronological sequences of F2 date for pear tree, cultivar  
 576 'Williams' at three locations.

577

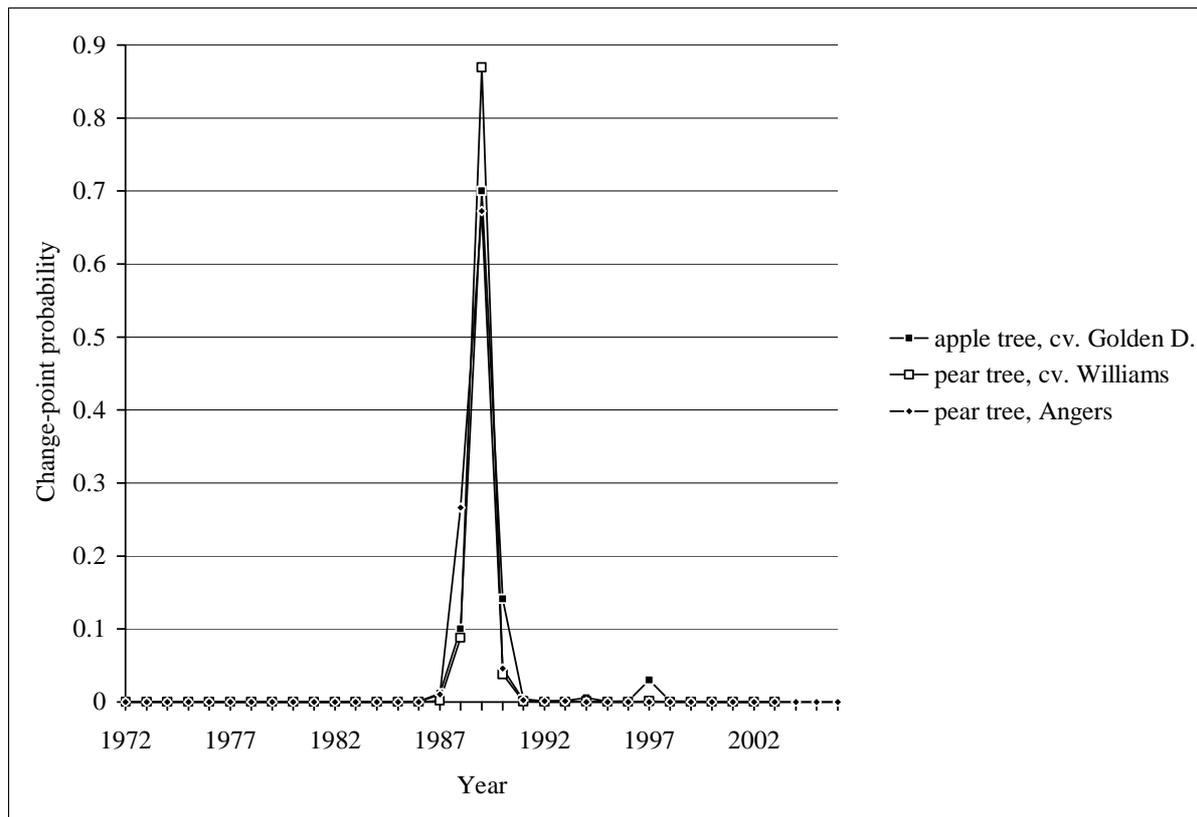


578

579 Figure 3. Segmentation of three chronological sequences of F2 date for three pear tree

580 cultivars at Angers.

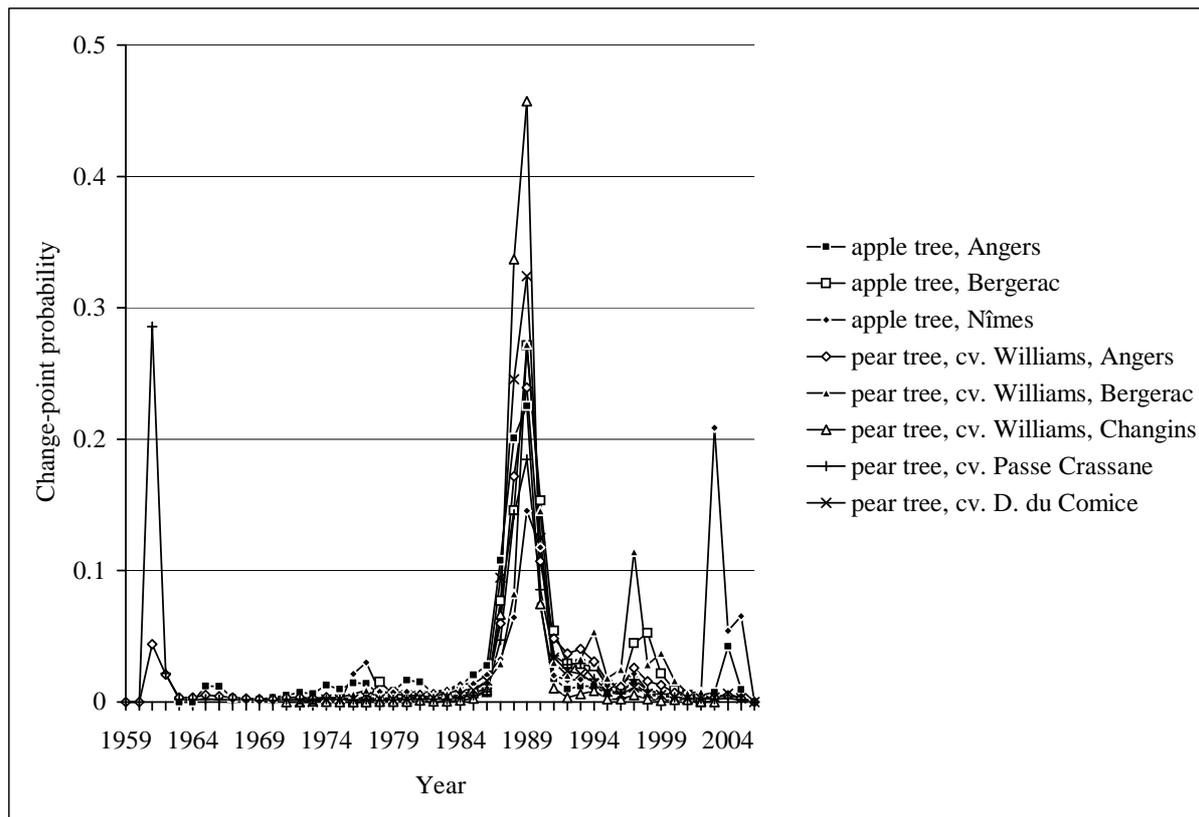
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582

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

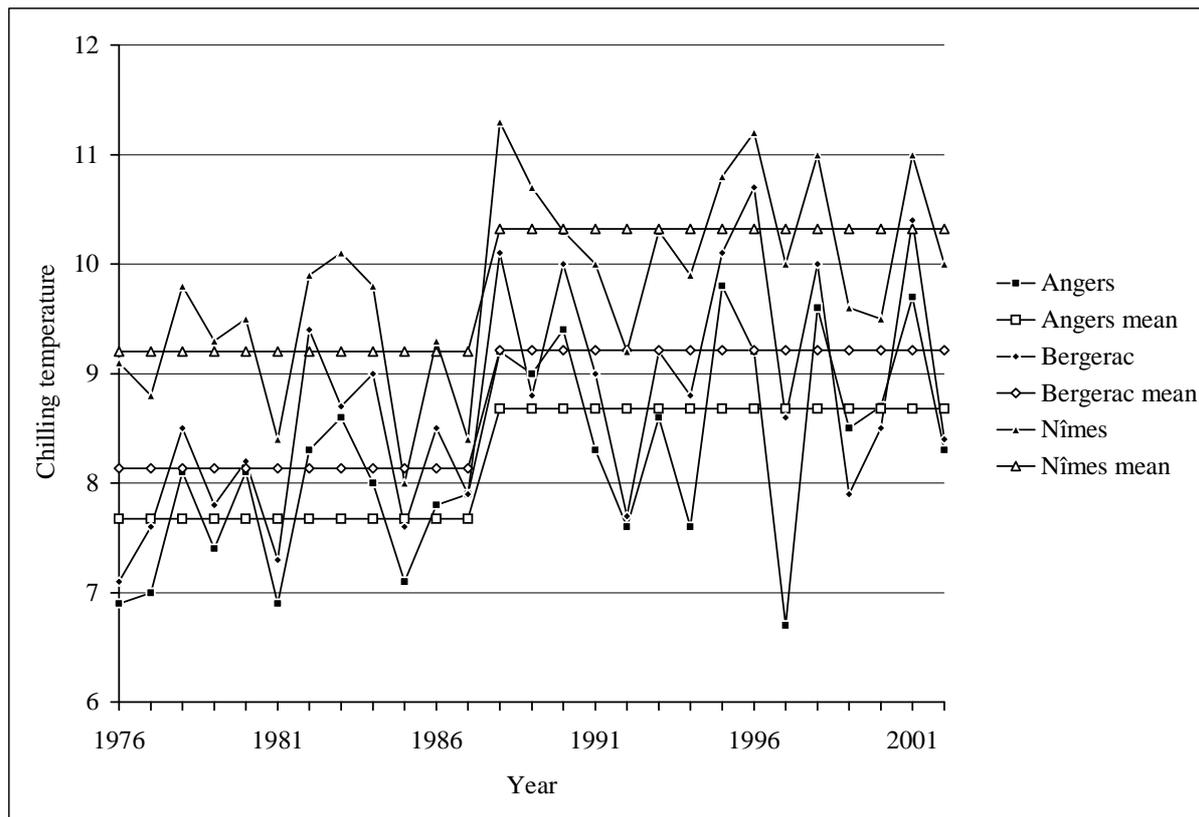
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586 Figure 5. Univariate 2-segment models  $M_{mv}$ : posterior change-point probabilities.

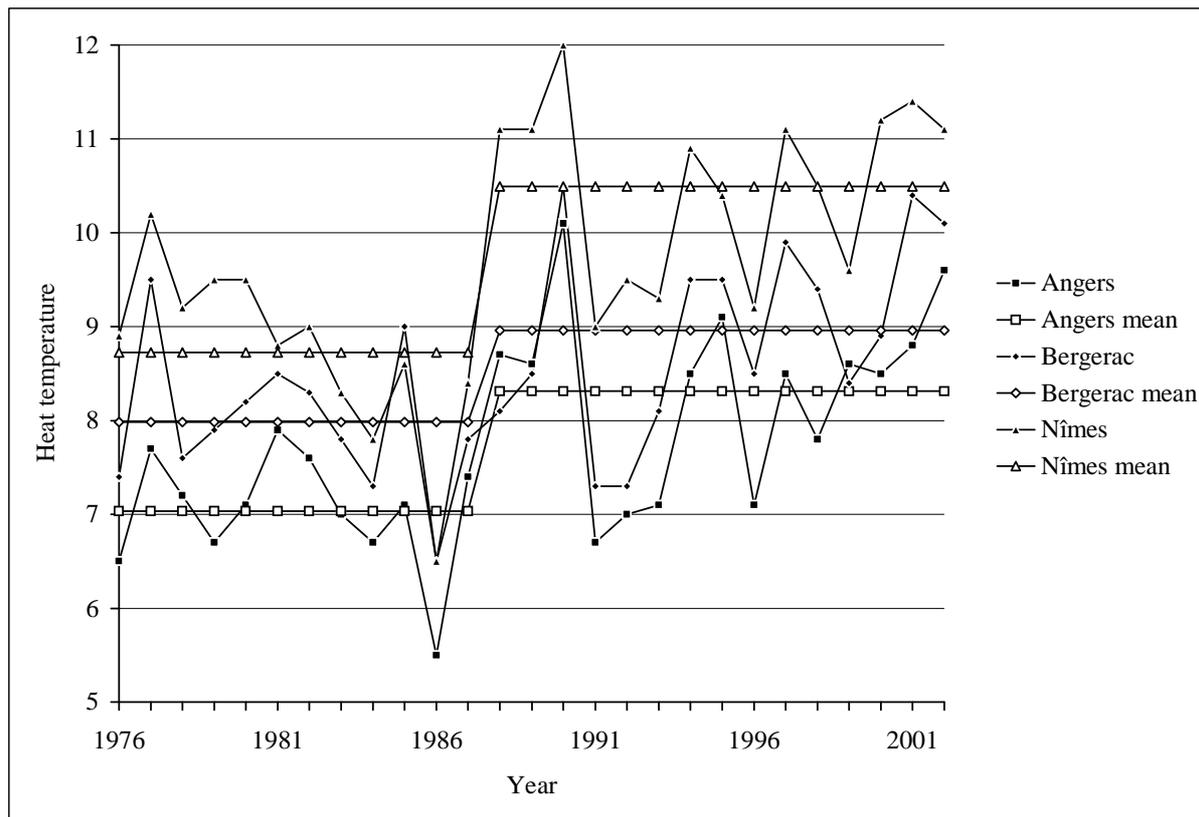
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588

589 Figure 6. Segmentation of three chronological sequences of mean temperature during the  
 590 chilling phase of the flowering process for cultivar 'Golden Delicious' at three  
 591 locations.

592



593

594 Figure 7. Segmentation of three chronological sequences of mean temperature during the heat

595 phase of the flowering process for cultivar 'Golden Delicious' at three locations.

596