Methods paper

Reducing the uncertainty on chilling requirements for endodormancy breaking of temperate fruits by data-based parameter estimation of the dynamic model: a test case in apricot

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The Dynamic model has been described as one of the most accurate models to quantify chill accumulation based on hourly temperatures in nuts and temperate fruits. This model considers that a dynamic process occurs at a biochemical level that determines the endodormancy breaking through the accumulation of the so-called portions. The kinetic parameters present in the model should reflect how the fruit trees integrate chilling exposure and thus they should be characteristic for each species. However, the original parameter values, reported in the late 1980s, are still being used. Even if the use of such parameter values is useful to compare among chilling requirements (CRs) for different species or cultivars, it is not the optimal choice when one intends to explain the CR variations in different years for a given cultivar. In this work we propose a data-based model calibration that makes use of phenological data for different apricot cultivars within different years to obtain model parameters, which minimize the variations among years and that have, at the same time, physical meaning to characterize the incumbent species. Results reveal that the estimation not only reduces the accumulated portion dispersion within the considered time periods but also allows to improve the CR predictions for subsequent years. We propose a set of model parameter values to predict endodormancy breaking dates in the apricot cultivars studied here.

Keywords: Dynamic model, endodormancy, parameter estimation, temperate fruits.

Introduction

The production of deciduous fruits is threatened by climate change (Luedeling 2012). Sufficient winter chill is crucial to break dormancy in each variety, and the increase of the average temperatures forecasted for the next decades may have a profound impact on this process (Campoy et al. 2011b). The situation is especially critical in the Mediterranean basin, where the climate change effects will be more intense (Giorgi and Lionello 2008, Cramer et al. 2018). Countries in the Mediterranean basin are important producers of temperate fruits; thus strategies for mitigation and possible alternatives to address climate change must be devised in that area, where chilling negation (i.e. loss of accumulated chill due to high temperatures) can occur. Recent studies in the Mediterranean area reveal the impact on temperate fruit tree phenology caused by climate change (El Yaacoubi et al. 2014, Ghrab et al. 2014, Funes et al. 2016, Benmoussa et al. 2017, 2018, Rodriguez et al. 2019). Other studies in different geographical areas have also pointed out the problem of climate change related to future fruit production (Luedeling et al. 2009, Darbyshire et al. 2011, Atkinson et al. 2013, Guo et al. 2015, 2019, Chmielewski and Götz 2016, Chuine et al. 2016, Martinez-Lüscher et al. 2017, Parkes et al. 2020).

This scenario of climate change with higher average temperatures enhances the need to have quantitative modeling tools regarding dormancy that are available to accurately predict, e.g., dates for (endo)dormancy release, bud burst, blossom and
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It is widely used in the literature dealing with CR. We have formulated different objective functions based on the CV that produce solutions with different characteristics (see Optimization problem Section).

**Materials and methods**

**The Dynamic model**

The Dynamic model for chill accumulation was proposed by Fishman, Erez and Couvillon in 1987 (Fishman et al. 1987a, 1987b). It considers that the endodormancy completion is achieved when a certain amount of a given substance is accumulated in the plant. This ideal substance is called ‘dormancy breaking factor’ (DBF), and its formation is represented by the set of reactions in Eq. (1)

\[
\begin{align*}
    k_0 & \quad \text{PDBF} \rightarrow \text{DBF} \\
    k_1 &
\end{align*}
\]

where \(k_0\) and \(k_1\) are the rate constants for the formation and destruction of the DBF precursor (PDBF), respectively, by means of a reversible reaction. These rate constants were defined as an Arrhenius type by the original authors, according to Eq. (2):

\[
k_i = A_i e^{-\frac{E_i}{T}}
\]

The model parameters \(A_i\) and \(E_i\) with \(i = 0, 1\) are, respectively, the pre-exponential factor and the activation energy of the Arrhenius kinetics. The subindex indicates the direction of the corresponding reaction. \(T\) represents the temperature in Kelvin.

The Dynamic model assumes that when a certain amount of PDBF is accumulated, it undergoes an irreversible transition to the state DBF (Fishman et al. 1987a). The amounts of PDBF and DBF are represented as \(x\) and \(y\), respectively, and the critical amount that takes place to the transition is arbitrarily chosen as \(x = 1\). This means that when the amount of PDBF equals one, it automatically creates one unit of DBF (or a ‘portion’), and PDBF disappears completely to start the process again. According to the reaction set from Eq. (1), the changes of \(x\) with time are quantified by the following differential equation:

\[
\frac{dx}{dt} = k_0 - k_1 x
\]
These variables and the range of values defined in Fishman et al. (1987) during the experimental stage. Keeping the original notation for model parameters were related to some observed variables (e.g. the optimal chill accumulation temperature \( \theta^* \)) and the diminishing of chilling negation of the chilling depending on the time interval to application of dual effect of warm temperatures (enhancement and negation of the bell shape of the thermal dependence of the rest break, the developers performed a thorough mathematical analysis of the variables in Table 1 and fixing \( \theta_1 \), \( \theta_2 \) and \( \eta \) as stated above, values for the kinetic model parameters can be retrieved. The model was completed in Fishman et al. (1987b) introducing a term to correct a systematic discrepancy between the model predictions and the observations in temperatures < 4 °C. It is considered that the transition from PDBF to DBF is temperature dependent following a sigmoidal dependence, which defines the probability of transition as

\[
P = \frac{e^{\frac{\Delta H}{T} - \frac{\Delta H}{T'}}}{1 + e^{\frac{\Delta H}{T} - \frac{\Delta H}{T'}}}
\]

The transition temperature, \( \theta_t \), was set at 277 K, and the slope of the curve, which equals \( \frac{\Delta H}{40^2} \), was fixed to 0.4 in order to fit the observations.

Fishman et al. (1987b) presented different sets of parameter values based on some combinations of values for variables in Table 1. The latter were observed during their experiments with peach, but they may not necessarily be optimal for other deciduous fruits (e.g. the optimal chill accumulation temperature \( \theta^* \) could be slightly different among species and even among cultivars within the same species). However, the proposed original parameter values have been used since the late 1980s every time the Dynamic model has been used for phenological studies. Since loads of experiments would be necessary to confirm that such parameter values are also representative for other species or cultivars, we propose here an optimization procedure to estimate them from a range of values with biological sense in order to minimize the dispersion of the calculated CR for a cultivar or a group of cultivars in different years. In the following section, we formulate this optimization problem and show different objective functions based on the coefficient of variation that could be considered.

### Optimization problem

The aim of the proposed optimization procedure is to minimize the dispersion of the calculated CR for a group of cultivars through the Dynamic model. To do this, phenological data (i.e. start dates for chill accumulation, dates for endor-mancy release and time-interval temperatures) must be available. Based on these data, values for the parameters of the

| Variable | Range     | Description                                      |
|----------|-----------|--------------------------------------------------|
| \( \theta^* \) | 279–281 K | Optimal constant temperature for chill accumulation |
| \( \theta_c \) | 286–287 K | Critical temperature above which no portions can be accumulated |
| \( \tau^* \) | 16–48 h   | Time interval for accumulating one portion at the optimal temperature |
| \( \pi_c \) | 24–28 h   | Critical period in a combined temperature cycle leading to chilling negation |

### Equation (3) only has an analytical solution in the case of constant temperature. In practice, controlled or field temperatures are provided within a time interval where they can be considered as constant. In such cases, the evolution of \( x \) with time is given by

\[
x(t) = x_s - (x_s - x_0) e^{-k_1 t}
\]

where \( x_0 \) is the initial value of \( x \) within this time interval, \( x_s = \frac{k_0}{k_1} \) is the so-called steady-state value and \( t \) is the elapsed time within the time interval considered (usually 1 h). The model developers performed a thorough mathematical analysis of the model to prove that it could explain three observed phenomena: the bell shape of the thermal dependence of the rest break, the dual effect of warm temperatures (enhancement and negation of the chilling depending on the time interval to application of the high temperature) and the diminishing of chilling negation when the cycle length increases (Fishman et al. 1987a). The model parameters were related to some observed variables during the experimental stage. Keeping the original notation for these variables and the range of values defined in Fishman et al. (1987b), they are presented in Table 1.

From the variables in Table 1, \( \pi_c \) depends on other arbitrarily chosen variables like the two temperatures applied in the cycle (\( \theta_1, \theta_2 \)) and the proportion of the cycle that \( \theta_1 \) is applied (denoted as \( \eta \) in Fishman et al. (1987a)). Since the number of combinations of all the possible values for (\( \theta_1, \theta_2 \) and \( \eta \)) is infinite, we have used the same values proposed by the original authors (i.e. \( \theta_1 = 297 \) K, \( \theta_2 = 279 \) K, \( \eta = \frac{1}{3} \)), assuming that the range of \( \pi_c \) is more or less the same for different species of deciduous fruit trees.

The variables in Table 1 are related to the model parameters (i.e. \( E_0, E_1, A_0, A_1 \)) through the system of nonlinear equations resulting from the mathematical analysis in Fishman et al. (1987a) and shown in Eqs (5–8):

\[
E_1 = E_0 \frac{E_0 - E_1}{e^{(E_1 - E_0)q} - 1} \frac{1}{\ln(1 - e^{(E_0 - E_1)q})}
\]

\[
A_1 = \frac{e^{(E_0 - E_1)q}}{\tau^*} \ln\left(\frac{1 - e^{(E_0 - E_1)q}}{\tau^*}\right)
\]

\[
A_0 = A_1 e^{(E_0 - E_1)q}
\]

\[
e^{\left(\frac{E_1 - E_0}{\tau^*}\right)} - e^{\left(\frac{E_1 - E_0}{\tau_1}\right)} - e^{\left(\frac{E_2 - E_0}{\tau_2}\right)} - e^{\left(\frac{E_2 - E_0}{\tau_1}\right)} = \frac{1}{1 - \frac{e^{-((k_1 (t_1) - k_1 (t_2) (1- \eta)) \pi_c)}}{e^{-((k_1 (t_1) - k_1 (t_2) (1- \eta)) \pi_c)}}}
\]

where \( q = \frac{1}{\theta^*} + \frac{1}{\theta_c} \)

Solving the system of Eqs (5–8) with selected values for the variables in Table 1 and fixing \( \theta_1, \theta_2 \) and \( \eta \) as stated above, values for the kinetic model parameters can be retrieved. The model was completed in Fishman et al. (1987b) introducing a term to correct a systematic discrepancy between the model predictions and the observations in temperatures < 4 °C. It is considered that the transition from PDBF to DBF is temperature dependent following a sigmoidal dependence, which defines the probability of transition as
Dynamic model can be found to minimize the dispersion of CR for a cultivar or a group of cultivars among years. These parameter values would then be useful to predict endodormancy release dates for other years more efficiently than currently. In this work we will use as calibration data those published in Ruiz et al. (2007) for eight apricot cultivars in the periods 2002–03, 2003–04 and 2004–05. Note that this is an illustrative example of the application of the proposed methodology. Similar steps would be followed in the case of other species or with different time series of phenological data.

Even if the usual parameter estimation procedure uses the model parameters as decision variables (for the Dynamic model, they would be \( E_0, E_1, A_0, A_1 \)), in this case they do not have a biological meaning nor do we have an idea about their feasible range. For that reason, the optimization is carried out in the domain of the variables in Table 1. The advantage of using \( \theta^*, \theta_c, \tau^* \) and \( \pi_e \) as decision variables is that they have both biological meaning and defined ranges (see Table 1). The disadvantage is that each iteration of the optimization procedure involves solving the system of nonlinear Eqs (5–8), which can present numerical problems. Another disadvantage is that, although the decision variables \( \theta^*, \theta_c, \tau^* \) and \( \pi_e \) take values with biological meaning individually, their combination could lead to values of \( E_0, E_1, A_0 \) and \( A_1 \) that cannot be assimilated to any biological system. For that reason, our optimization problem has an additional constraint to account for the \( Q_{10} \) temperature coefficients. \( Q_{10} \) represents the rate of change of system as a consequence of increasing the temperature by 10 °C (Eq. (10)):

\[
Q_{10} = \left( \frac{R_2}{R_1} \right) \frac{T_2^{10}}{T_1^{10}} 
\]

Using the Arrhenius kinetics defined in the Dynamic model, \( Q_{10} \) results in Eq. (11)

\[
Q_{10i} = \left( e^{\frac{E_i}{R T_1}} \right)^{10 \cdot 10} 
\]

where \( E_i, i = 0, 1 \) stands for the energies of activation of the involved reactions and \( T_1, T_2 \) are selected as 297 and 279 K, respectively, as indicated above. Biological reactions usually exhibit \( Q_{10} \) values ranging from 2 to 3 (Reyes et al. 2008). Fishman et al. (1987a) obtained \( Q_{10} \) values of 1.4 and 3.7, and they considered them as ‘realistic ones’. Following this idea, we have formulated the \( Q_{10} \) constraint so that the feasible parameter values produce \( Q_{10} \) values between 1.5 and 3.5. The mathematical formulation of the optimization problem is as follows:

\[
\min_J(z, p, d, T) \quad (12)
\]

Subject to

\[
F(z) = 0 \quad (13)
\]

where \( J(z, p, d, T) \) is the objective function to be optimized, which depends on the decision variables \( z = (\theta^*, \theta_c, \tau^*, \pi_e) \), on a set of time-invariant parameters \( p = (\theta_1 = 297 K, \theta_2 = 279 K, \eta = \frac{1}{3}) \), on an input vector of phenological data \( d \) (i.e. dates of beginning of chill accumulation and endodormancy break) and hourly temperatures, \( T \), for the periods defined in \( d \). Equation (13) represents the system of nonlinear Eqs (5)–(8) to be solved to obtain the model parameters \( (E_0, E_1, A_0, A_1) \) from the decision variables. Equation (14) is the \( Q_{10} \) constraint mentioned above, and, finally, \( z_l \) and \( z_u \) are, respectively, the lower and upper bounds for the decision variables. In our work, and following the guidelines from Fishman et al. (1987b), those values are \( z_l = (278 K, 285 K, 16 h, 22 h) \) and \( z_u = (282 K, 288 K, 48 h, 32 h) \). Figure 1 summarizes the proposed algorithmic procedure as a flowchart.

**Objective functions considered** The objective function from Eq. (12) can have different forms. If the species PDBF and DBF could be identified and measured (as \( x \) and \( y \)), the objective function should be based on minimizing the differences between their experimental measurement during the endodormancy process and the predicted values provided by the model. Since...
these species are ideal substances and have not yet been identified with any biochemical compound, we must follow a different approach. As commented before, taking advantage of the plethora of phenological data available in breeding groups worldwide, an objective function based on minimizing the differences of CR for a cultivar or a group of cultivars among years could be considered. Different statistical parameters can be chosen as the basis for the objective functions. In this work we have chosen the coefficient of variation of the number of accumulated portions needed to break endodormancy for each among different years. The coefficient of variation is defined as

$$ CV = \frac{\sum_{i=1}^{n} (y_i - \frac{\sum_{i=1}^{n} y_i}{n})^2}{\sum_{i=1}^{n} y_i} $$(16)

If we now consider a set of $m$ cultivars studied during those $n$ years, we can calculate each $CV_j$ with $j = 1, 2, \ldots, m$. We have considered the following objective functions based on $CV_j$ to be minimized.

**Objective function #1**: sum of the $CV_j$. Minimizing this objective function ensures that the sum of all the coefficients of variation is minimum, but does not ensure that all individual coefficients will be low (e.g. the optimal solution could consider a perfect fit for several cultivars but a high dispersion for others).

**Objective function #2**: maximum $CV_j$. Minimizing this objective function ensures that the maximum coefficient of variation is minimum. The optimization procedure will focus on minimizing the highest coefficients of variation at the possible expense of increasing others that were initially low.

**Objective function #3**: constrained sum of the $CV_j$. In this approach we try to minimize again the sum of all the coefficients of variation, but we force that the individual coefficients of variation for some (or all) of the considered cultivars must be reduced to a certain amount. This strategy is useful when we want to focus on reducing the coefficient of variation of a given cultivar without increasing the rest. This strategy involves adding new constraints to the optimization problem in Eqs (12)–(15). Note that imposing such constraints may result in infeasible optimization problems (e.g. when it is not possible to reduce some coefficients below the value defined in the constraint). In this work, we have forced that every coefficient of variation must be reduced with respect to those obtained by Ruiz et al. (2007), as we have used the same phenological data to estimate the model parameters.

Minimizing these (or other) objective functions is not enough to ensure that optimal parameters of the Dynamic model for a given species are obtained. The results should be validated because having similar portions for breaking endodormancy does not mean that the process has been well described, as illustrated in Figure 2, where the evolution of accumulated portions from the beginning of November 2001 until the end of February 2002 in Cieza (Región de Murcia, SE Spain) according to the Dynamic model using two different sets of the parameters $E_0, E_1, A_0$ and $A_1$ (one set taken from Erez et al. (1988) and other set using simulated parameters) is shown. Both sets of parameters lead to the same number of portions after during the considered period even if the dynamics during the whole period are different. With this situation we would not be able to distinguish between the right and wrong set of parameters since we only record dates at the end of the process (i.e. endodormancy breaking dates). Thus, the estimation of the parameters must be validated with other sets of phenological data, as it will be shown below.

**Computational information** The Dynamic model as well as the optimization procedure was implemented in R (R Development Core Team 2015). The optimization algorithm was the enhanced scatter search metaheuristic included in the package MEIGO (Egea et al. 2014). A set of 30 independent optimization runs were performed using each objective function. Each run took around 120 s in our computational platform, which means between 2800 and 3000 evaluations of the Dynamic model, including the associated nonlinear problem. The nonlinear system in Eqs (5–8) was solved using the package nleqslv (Hasselman 2017). All the experiments were performed on an Intel Core i7 3.60 GHz workstation, under Windows 10 64-bit.

**Validation** Although the calibration procedure via optimization illustrated here allows selection of a set of parameters for the Dynamic model that reduce the dispersion of results among years while ensuring values with biological meaning for the characteristic variables, the real interest of mathematical models is related to their prediction capabilities. Thus, the estimated parameters must be validated with different input data to check whether they are general enough to be applied in different situations or years. The validation step consists of selecting a new set of data not used for calibration and comparing them with the predictions obtained using the calibrated parameters. If the model predictions fit the real data, then the modeling loop can be considered satisfactory. Otherwise, more data for the calibration step, new designs of experiments or even different prediction models must be used in the next modeling iteration. For validation purposes, we have selected the work from Campoy et al. (2012), which provides phenological data for the same apricot cultivars studied.
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Figure 2. Accumulation of chill portions in Cieza (SE Spain) from November 2001 until February 2002 according to the Dynamic model using different sets of parameters.

here and the same location (Cieza, from Región de Murcia, SE Spain) within different years. We have used the parameters obtained with the constrained formulation (i.e. using $J_3(z)$) in the calibration step (i.e. periods 2002–03, 2003–04 and 2004–05) because they provided a consistent reduction of the CVs for all the cultivars considered. The validation periods are 2007–08 and 2008–09, and the results using the calibrated parameters are compared with those obtained using the set of parameters presented in the computer code of the appendix in Fishman et al. (1987b). The comparison between real and predicted data is done based on dormancy release dates.

**Biological and meteorological data**

As explained above, the basis of the calculations performed in this study are the dates for endodormancy release and the corresponding number of portions provided by Ruiz et al. (2007), where bud weight and phenology stage were used to determine the date of the breaking of endodormancy according to the methodology introduced by Faust et al. (1991) and Guerriero et al. (2002). From the beginning of the chilling accumulation in the orchard (normally late October or beginning of November in the climate conditions of SE Spain), for each cultivar, three branches were picked every 3–4 days from trees in the field and placed in a growth chamber, in controlled conditions under 25 °C. Branches had a length ca 40 cm and base diameters of 8–10 mm and contained two to four fruiting shoots per branch. After 10 days in the growth chamber, the developmental stage of the flower buds was tested. The date of the breaking of endodormancy was established to be when, after 10 days in the growth chamber, at least 30% of the flower buds were in Baggiolini’s stages B–C (Baggiolini 1952) and there was at least a 30% weight increase in the flower buds compared with the relatively constant previous weights. The CR (number of portions in our case) coincided with the chill accumulated until the date of endodormancy release.

Regarding meteorological data, hourly temperatures were collected with the automatic data loggers Escort Junior (Escort Data Logging Systems), and they were used to feed the Dynamic model during the calibration and validation procedures. Identical procedures were carried out for data in Campoy et al. (2012) used in this study to validate the calibrated model.

**Results**

**Assessing the probability of transition**

As explained above, the transition process is considered temperature dependent, defining the probability of Eq. (9). In order to assess the actual shape of the sigmoidal curve for this probability, we have carried out a preliminary optimization test in which the slope of the curve at 277 K is fitted. In particular, we define the optimization problem using the objective function #2 and defining bounds for the slope from 0.3 to 0.5 (the original value reported by Fishman et al. (1987b) was 0.4). Ten optimization runs of 45 s were performed for each tested slope, and the results are presented in Figure 3, where boxplots of 10 solutions are represented for each slope tested. From Figure 3, no significant differences in the solutions are observed. Those runs with the minimum median values correspond to slopes between 0.4 and 0.475. The minimum one corresponds to a slope of 0.425, very similar to the value fitted by Fishman et al. (1987b). For this slope, we also find the best solution, shown as an outlier in its corresponding boxplot. Thus, in subsequent optimization runs, this value of slope (0.425) is used.
Table 2. Model parameters and characteristic values for the optimization of the objective functions.

|       | $J_1(z)$ | $J_2(z)$ | $J_3(z)$ |
|-------|----------|----------|----------|
| $\theta^*$ | 278.1 K  | 281.8 K  | 278.1 K  |
| $\theta_c$ | 285.1 K  | 285.1 K  | 285.1 K  |
| $\tau^*$  | 46.5 h   | 42.8 h   | 47.7 h   |
| $\pi_c$   | 31.5 h   | 32.0 h   | 30.6 h   |
| $E_0$     | 3.757 $\cdot 10^3$ | 7.202 $\cdot 10^3$ | 3.792 $\cdot 10^3$ |
| $Q_{10}(k_0)$ | 1.57    | 2.38     | 1.58     |
| $Q_{10}(k_1)$ | 2.25    | 3.11     | 2.17     |
| $f_{\text{best}}$ | 0.39 | 0.08     | 0.44     |
| $A_0$     | 3.024 $\cdot 10^4$ | 7.825 $\cdot 10^9$ | 3.631 $\cdot 10^8$ |
| $A_1$     | 9.760 $\cdot 10^8$ | 1.827 $\cdot 10^{13}$ |         |

Optimization results

Table 2 presents the model parameters and characteristic values corresponding to the best solution among the 30 runs using each objective function. The best objective function values and the $Q_{10}$ coefficients are also reported.

The best solutions for each objective function provide an idea of the possible characteristic variables for apricot (or at least for the cultivars considered). Results with objective functions #1 and #3 are quite similar, since they optimize the same function with or without constraints. Actually, they provide exactly the same values for $\theta^*$ and $\theta_c$. The optimal constant temperature for chill accumulation would be 5.1 °C, and the constant temperature at which no portions are accumulated would be 12.1 °C, which is lower than the one usually reported in the literature. The estimated values of $\tau^*$ mean that a long period of time (>$40$ h) is needed to accumulate one portion at the optimal temperature. The value of $\pi_c$ is conditioned by the arbitrary election of $\theta_1 = 297 \ K$, $\theta_2 = 279 \ K$, $\eta = \frac{3}{4}$, and it also takes high values within the range suggested by Fishman et al. (1987b). To complement the information obtained in the optimization procedure, Table 3 presents, for each cultivar, the predicted number of portions to break endodormancy according to the three sets of calibrated parameters (one per each objective function) as well as some statistics (i.e. mean, standard deviation and coefficient of variation), and they are compared with the values presented by Ruiz et al. (2007), which used the original model parameters. It is of note that the results obtained via optimization provide lower numbers or portions needed to break endodormancy for all cultivars if we compare them with the results reported by Ruiz et al. (2007). It means that each portion needs longer time to be accumulated with our results than with the original model parameters, as commented above with respect to the values of $\tau^*$. In any case, the order of cultivars ranging from low to high CR is maintained regardless of the set of parameters used.

When using $J_1(z)$ (i.e. minimizing the sum of all the coefficients of variation), the CVs of cultivars with low CR is significantly reduced at the expense of a slight increase for
Table 3. Number of accumulated portions to break dormancy and statistics reported by Ruiz et al. (2007) and those calculated by optimization.

| Cultivar   | Year | Portions (Ruiz et al. 2007) | Portions \(J_1(z)\) | Portions \(J_2(z)\) | Portions \(J_3(z)\) |
|------------|------|-----------------------------|----------------------|----------------------|----------------------|
|            |      | Value | Mean | SD | CV | Value | Mean | SD | CV | Value | Mean | SD | CV |
| Currot     | 2003 | 29.1  | 34.3 | 6.1 | 17.9 | 15.4  | 17.9 | 2.1 | **11.8** | 20.4  | 21.9 | 1.8 | **8.3** |
|            | 2004 | 32.8  | 36.9 | 2.8 | 7.3  | 19.2  | 19.0 | 0.0 | **2.3** | 35.4  | 32.8 | 2.7 | **8.2** |
|            |      | 41.1  | 40.0 | 1.9 | 4.7  | 26.9  | 26.9 | 0.0 | **2.2** | 35.4  | 34.4 | 1.4 | **3.9** |
|            | 2005 | 45.9  | 49.0 | 3.1 | 6.3  | 27.7  | 27.7 | 0.0 | **2.1** | 35.4  | 34.4 | 1.4 | **3.9** |
| Rojo Pasión| 2003 | 52.8  | 51.2 | 4.7 | 9.3  | 28.2  | 25.6 | 0.6 | **2.3** | 35.4  | 32.8 | 2.7 | **8.2** |
|            | 2004 | 51.5  | 51.3 | 0.2 | 0.4  | 28.9  | 28.9 | 0.0 | **2.2** | 35.4  | 34.4 | 1.4 | **3.9** |
|            | 2005 | 55.0  | 53.8 | 3.9 | 7.5  | 27.7  | 27.7 | 0.0 | **2.1** | 35.4  | 34.4 | 1.4 | **3.9** |
| Búlida     | 2003 | 52.8  | 53.8 | 2.9 | 5.3  | 28.2  | 28.9 | 0.6 | **2.2** | 35.4  | 34.4 | 1.4 | **3.9** |
|            | 2004 | 51.5  | 51.3 | 0.2 | 0.4  | 28.9  | 28.9 | 0.0 | **2.2** | 35.4  | 34.4 | 1.4 | **3.9** |
|            | 2005 | 57.0  | 53.8 | 3.9 | 7.5  | 27.7  | 27.7 | 0.0 | **2.1** | 35.4  | 34.4 | 1.4 | **3.9** |
| Murciana   | 2003 | 58.0  | 55.9 | 2.8 | 5.0  | 31.1  | 30.2 | 0.8 | **2.8** | 38.9  | 35.7 | 2.9 | 8.1  |
|            | 2004 | 52.7  | 50.1 | 4.0 | 7.7  | 30.1  | 29.5 | 0.0 | **2.3** | 38.9  | 35.7 | 2.9 | 8.1  |
|            | 2005 | 57.0  | 53.8 | 3.9 | 7.5  | 28.9  | 28.9 | 0.0 | **2.2** | 38.9  | 35.7 | 2.9 | 8.1  |
| Dorada     | 2003 | 55.8  | 56.2 | 3.7 | 6.6  | 30.2  | 30.3 | 0.2 | **0.8** | 37.4  | 35.8 | 2.2 | **6.2** |
|            | 2004 | 52.7  | 50.1 | 4.0 | 7.7  | 30.1  | 29.5 | 0.0 | **2.3** | 38.9  | 35.7 | 2.9 | 8.1  |
|            | 2005 | 60.1  | 58.1 | 2.0 | 3.4  | 28.9  | 28.9 | 0.0 | **2.2** | 38.9  | 35.7 | 2.9 | 8.1  |
| Selene     | 2003 | 55.8  | 57.4 | 1.8 | 3.2  | 30.2  | 30.8 | 1.8 | 5.7  | 37.4  | 36.5 | 1.2 | 3.6  |
|            | 2004 | 59.4  | 59.1 | 0.3 | 0.5  | 30.2  | 30.8 | 1.8 | 5.7  | 37.4  | 36.5 | 1.2 | 3.6  |
|            | 2005 | 57.0  | 56.2 | 0.8 | 1.4  | 30.2  | 30.8 | 1.8 | 5.7  | 37.4  | 36.5 | 1.2 | 3.6  |
| Bergeron   | 2003 | 64.6  | 64.8 | 2.7 | 4.1  | 35.0  | 34.9 | 2.3 | 6.4  | 42.8  | 41.0 | 2.9 | 7.0  |
|            | 2004 | 67.5  | 67.1 | 0.4 | 0.6  | 37.1  | 37.1 | 0.0 | **2.1** | 42.6  | 37.7 | 0.0 | **2.1** |
|            | 2005 | 62.2  | 60.5 | 1.7 | 2.8  | 32.6  | 32.6 | 0.0 | **2.1** | 42.6  | 37.7 | 0.0 | **2.1** |
| Orange Red | 2003 | 71.8  | 69.1 | 3.0 | 4.3  | 39.2  | 37.3 | 2.5 | 6.8  | 47.7  | 44.0 | 3.5 | 8.1  |
|            | 2004 | 69.5  | 66.8 | 2.7 | 4.0  | 38.2  | 38.2 | 0.0 | **2.1** | 43.6  | 40.1 | 0.0 | **2.1** |
|            | 2005 | 65.9  | 63.6 | 2.3 | 3.7  | 34.4  | 34.4 | 0.0 | **2.1** | 43.6  | 40.1 | 0.0 | **2.1** |

Numbers in bold represent improved CV’s using the optimized parameters.
those from cultivars with high CR. This pattern is also observed when using $J_2(z)$ (i.e. minimizing the maximum coefficient of variation). In this case, the algorithm focuses on minimizing the highest coefficient of variation (Currot), and the result is that, again, those CVs for low CR are reduced while those for high CR are increased. These results could suggest that different parameterization should be used for the groups of low and high CR to improve the prediction capabilities. Finally, with $J_3(z)$, which is the same as $J_1(z)$ but forcing all CVs to be below certain values, we obtain better CVs than those reported by Ruiz et al. (2007) simultaneously, although the sum of all CVs is higher than with $J_1(z)$. Note that the selection of the constraints for the formulation of $J_3(z)$ must be done carefully. Here we have forced all the CVs to be lower than those previously reported in Ruiz et al. (2007). If more demanding bounds were set for the constraint (i.e. forcing all the CVs to be below very low values), we would not probably have found any feasible solution.

Figure 4 presents the typical bell-shaped chill accumulation against temperature plot when applied in constant regimes. It simulates 1200 h of constant temperature for different parameterizations of the model, comparing the results using the model parameters proposed by the original authors in the late 1980s with those using the set of parameters obtained by optimization in this work. Figure 4 shows that the qualitative shape is similar in every case. The original parameters predict a higher chill accumulation than those obtained in this work, which is in accordance with the high obtained $r^*$ values and the differences in accumulated portions observed in Table 3. The curves for results from objective functions #1 and #3 are almost identical, as are the values for their characteristic variables shown in Table 2.

**Validation results**

Tables 4 (period 2007–08) and 5 (period 2008–09) show the expected dates to break endodormancy using the model parameters from Fishman et al. and those estimated with data, as well as their comparison with the actual date of endodormancy release reported in Campoy et al. (2012). In both periods the chill accumulation starts at the end of October/beginning of November and ends in February.

As shown in Tables 4 and 5, the mean of the absolute value of the differences (in days) between the expected and the real dates for dormancy breaking is lower using the parameters estimated with data (2.75 vs 3.38 in 2007–08 and 5.38 vs 8.00 in 2008–09). This confirms that our proposed approach to estimate parameters for the Dynamic model using historical data is valid. Regardless of the parameter values used, for some cultivars the expected breaking dormancy date is overestimated, while in others it is underestimated. This would also confirm that sets of different parameters for each cultivar (or groups of cultivars according to their CR) could be more effective in terms of prediction although less manageable from the practical point of view, as discussed below.

**Discussion**

Although some authors consider different factors apart from temperatures (e.g. photoperiod) to influence dormancy release (Heide 2008, Andreini et al. 2014), others consider that, especially for the Rosaceae family, chilling is the main environmental factor to take into account (Vegis 1964, Heide and Prestrud 2005, Campoy et al. 2011b). Thus, we propose the use of the Dynamic model and its calibration through historical climatic and phenological data. Parameter values for the Dynamic model
Table 4. Expected dates of dormancy break using Fishman et al. or estimated parameters and their comparison with the actual dates (period 2007–08).

| Cultivar | Dormancy breaking | Parameters from Fishman et al. | Estimated parameters using J₃(z) |
|----------|-------------------|--------------------------------|---------------------------------|
|          | Expected date     | Difference (days)              | Expected date         | Difference (days) |
| Currot   | 24 December       |                                | 22 December            | −2                |
| Rojo Pasión | 14 January       | +6                             | 19 January            | +5                |
| Búlida   | 24 January        | +1                             | 24 January            | 0                 |
| Murciana | 24 January        | +5                             | 26 January            | +2                |
| Dorada   | 28 January        | +1                             | 26 January            | −2                |
| Selene   | 28 January        | +2                             | 28 January            | 0                 |
| Bergeron | 31 January        | +10                            | 10 February           | +10               |
| Orange Red | 15 February      | +1                             | 14 February           | −1                |
| Mean | 3.38              |                                | 2.75                |

Table 5. Expected dates of dormancy break using Fishman et al. or estimated parameters and their comparison with the actual dates (period 2008–09).

| Cultivar | Dormancy breaking | Parameters from Fishman et al. | Estimated parameters using J₃(z) |
|----------|-------------------|--------------------------------|---------------------------------|
|          | Expected date     | Difference (days)              | Expected date         | Difference (days) |
| Currot   | 28 December       | −5                             | 23 December            | −5                |
| Rojo Pasión | 4 January        | +10                            | 11 January            | +7                |
| Búlida   | 25 January        | −6                             | 16 January            | −9                |
| Murciana | 16 January        | +5                             | 16 January            | 0                 |
| Dorada   | 23 January        | −2                             | 16 January            | −7                |
| Selene   | 18 January        | +7                             | 18 January            | 0                 |
| Bergeron | 31 January        | +6                             | 31 January            | 0                 |
| Orange Red | 21 January      | +23                            | 05 February           | +15               |
| Mean | 8.00              | 5.38                           |

can be deduced from the experimental values of physiological variables (i.e. \(\theta^*, \theta_e, \tau^*\) and \(\pi_c\)), which should be a characteristic for each species or cultivars. As it seems reasonable that different species present different values of such physiological variables, the model parameter values, \(E_0, E_1, A_0\) and \(A_1\), should be also species/cultivar characteristic. In other words, every species would accumulate chill in a different way (probably with the same mechanism but different biochemical rates), and the same temperature profile would produce a different effect in the dormancy completion process. However, researchers have usually used the original model parameters provided by the model developers to quantify accumulated chill regardless of the incumbent species. This involves assuming that any temperate fruit accumulates chill in the same way, which may not be correct, and this could be the cause of observing high discrepancies in the accumulated portions to break dormancy within different years.

Trying to estimate the most accurate model parameters for each species would require a huge amount of experimentation not only due to the high number of different temperate fruits but also due to the high number of temperature cycle combinations to obtain the characteristic variables (i.e. \(\theta^*, \theta_e, \tau^*\) and \(\pi_c\)) of each species. An alternative to such a huge experimental work is to perform a data-driven parameter estimation taking advantage of the amounts of phenological data accumulated by breeding groups and other stakeholders for many years. This parameter estimation should be based on the minimization of a dispersion measure (e.g. standard deviation, coefficient of variation or others) of the accumulated portions to complete dormancy. To illustrate the procedure, we have proposed a parameter estimation problem based on the coefficient of variation for the accumulated portions needed to release dormancy in eight apricot varieties grown in Cieza (Región de Murcia, SE Spain) over 3 years. Three different objective functions to be minimized are proposed: sum of all the coefficients of variation, maximum coefficient of variation and a constrained version of the first one to ensure that all the coefficients of variation are simultaneously reduced. While the first two objective functions tend to reduce only the coefficient of variation of the cultivars with lower CR, the third one ensures the reduction of all of them. The selection of the bounds for the constraints must be realistic because aiming to reduce some coefficients of variations too much could result in an infeasible optimization problem. In this work we have used as a reference for formulating the constraints the coefficients of variation published by Ruiz et al. (2007), which used the classical parameter values to quantify CR through the Dynamic model.
Comparing the values of the physiological parameters obtained by optimization, we observe some differences with respect to those published by Fishman et al. (1987b). These differences are especially remarkable in the parameters $\tau^*$ and $\pi_c$, where we obtain values significantly higher than the classical ones. The most interpretable one is $\tau^*$ (i.e. time interval for accumulating one portion at the optimal temperature), which would indicate that, in the apricot cultivars considered, the time needed to accumulate one portion is higher than the one reported in Fishman et al. (1987b). Small differences can be also appreciated in the parameter $\theta^*$ regarding objective functions #1 and #3. The reported value (278.1 K) is between 1 and 3 °C lower than the one reported by Fishman et al. (1987b). This would mean that the optimal temperature for chill accumulation is a bit lower in the apricot cultivars considered here than the one considered by Fishman et al. (1987b).

The parameter values obtained by the constrained minimization of the coefficients of variation (i.e. objective function #3) were validated with a set of phenological data from other two later periods. The aim of this second step was to predict the date of the dormancy completion and compare this prediction with that obtained using the classical parameter values. Results presented in Tables 4 and 5 show that the prediction date is more accurate for almost all cultivars using the estimated parameters and the average deviation in days considering all the cultivars is lower. Therefore, we could state that the parameter values calculated by optimization in this work are more reliable to predict dormancy release dates for the considered apricot cultivars and grow areas than the classical ones. Even if the Dynamic model does not provide any information about the physiological state of the trees during the dormancy process (at least while the portions cannot be assimilated with any biochemical species), it is a powerful tool to predict chill accumulation and thus dormancy release dates. Assuming that the model tries to reflect the tree physiology in terms of chill accumulation, adequate parameter values for each species should be used in order to maximize its prediction capabilities. The approach proposed here takes advantage of recorded phenological data to obtain such parameters, and, even if the purpose of this study was to show the methodology rather than proposing a new set of model parameters for apricot, the calibration with only three periods produces better predictions than using the classical parameter values. A similar procedure could be followed with other species in order to obtain parameter values that produce reliable predictions for dormancy breaking dates in current and future climate scenarios. The procedure can be updated as new phenological data are recorded in future periods, which could help to refine the estimated parameters.

The application of the methodology presented here may require a change of mentality when quantifying CR. Indeed, the use of different parameter values for different species makes it difficult to rank them in terms of CR. A clear example is provided here, where the optimal estimated parameters for apricot result in a number of portions needed to break dormancy lower than those obtained with the classical parameters. Portions obtained with different parameter values of the Dynamic model are of different nature and should not be used to do comparisons with different species even if they are the best options to predict dormancy breaking dates for the species with which those parameters were estimated. In other words, the parameters estimated in this work should only be used to predict and rank apricot cultivars (or at least those considered here). What is more, if we opted for estimating different sets of parameters for low and high CR cultivars, the obtained portions should not be used to compare among such cultivars, although they would provide the best predictions of dormancy breaking dates for their corresponding ones. To maintain a tool which provides a general ranking according to CR (in portions) regardless of the species, the classical parameters can still be used. But in order to have a more reliable tool to predict dormancy breaking dates, species-/cultivar-specific parameters should be used.

A possible shortcoming of this methodology (and when using chilling accumulation models in general) is that it does not take into account some factors related to dormancy induction and dynamics (Campoy et al. 2011a, Cooke et al. 2012, Junttila and Hänninen 2012). For instance, the conditions at which dormancy induction is produced may have a significant influence over the CR (Heide 2003, Granhus et al. 2009, Campoy et al. 2012). Discrepancies between temperatures recorded in weather stations and actual temperatures in the trees (Bennett 1949, Erez 1995, Campoy et al. 2010) are not considered in the model either, although corrections using radiation indexes could be incorporated. All the mentioned factors are related to different environmental conditions among years. In this regard, if the set of historical data to calibrate the model is large enough to capture as much heterogeneity as possible, the predictions will be on average more accurate than those obtained using the classical parameter values of the Dynamic model.

**Conclusions**

Quantifying CR in temperate fruit trees is crucial to ensure an optimal orchard management. This is going to be especially critical in the climate change scenario that we are already undergoing. Some discrepancies between predicted and observed required portions to break dormancy are observed in some cases when using the Dynamic model. This can be provoked by the use of the same model parameter values regardless of the species considered, which ignores possible physiological differences among them. Knowing the values of the actual parameters for each species would require a time- and resources-consuming experimentation, which might not be affordable. However, the availability of large sets of phenological data for
temperate fruit trees along many years recorded by different research groups and other stakeholders worldwide allows consideration of the formulation of a parameter estimation problem to minimize the dispersion of the observations among years. The solution of this problem provides not only the values of the kinetic parameter values present in the model but also those of their associated physiological variables, allowing a characterization of the species in terms of such variables.

Here we have illustrated this by estimating the parameter values of the Dynamic model for a group of apricot cultivars, covering different CR, grown in the south east of Spain. The results show that the estimated parameters can be used for predicting dormancy breaking dates in different periods with higher accuracy than the classical parameter values, even if the number of periods for the parameter estimation is low. Considering longer periods for the estimation will probably produce more suitable estimated parameter values in terms of prediction capabilities.

Future work will be devoted to obtaining parameters for single cultivars or at least to small groups of the same species representing low, medium or high CR, as has been suggested by our results. In this study, we have observed that different parameter values provide very similar solutions in terms of optimization. Therefore, we will explore further constraints for the physiological variables and will try to solve practical identifiability problems by using data of more periods for the estimation or solving structural identifiability issues of the Dynamic model.

Authors’ contribution
J.A.E. conceived the study, performed the computational tasks and wrote the main part of the manuscript. D.R. provided the phenological and meteorological data. J.E. provided advice on the bounds of the biological parameters. All the authors participated in the discussion of the results, and read, revised and approved the final text.

Conflict of interest
None declared.

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