Modeling spring phenology and chilling requirements using the chill overlap framework

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Abstract

The timing of bloom and leaf-out has important implications for orchard systems. As temperatures continue to shift under climate change, it is important to be able to accurately model the impact of these changes on the timing of spring phenological events. Changing temperatures may impact cultivars differently, and interfere with pollinizer variety bloom overlap. Bloom windows may shift later or earlier, potentially increasing the risk of exposure to frost or to warm conditions that can interfere with ovule fertilization. Recent work modeling the bloom timing of multiple cultivars of *Prunus dulcis* (almond) in California predicted bloom reasonably well based on a chill overlap or 'optimal' framework. This approach uses non-linear regression to integrate the well-documented compensatory relationship between chill and heat accumulation, by which greater chill accumulation requires less heat accumulation for bloom and vice versa. However, this approach used chilling requirements estimated from work in other climates or with other chill accumulation models. The present work extends the chill overlap framework to estimate chilling requirements and the relationship between chill and heat accumulation that results in bloom based on historic records of bloom timing. This approach has the potential to estimate bloom prediction curves for numerous cultivars and crops in silico without the effort and expense of forcing experiments, which have proven difficult for many crops.

Keywords: chilling requirement, heat requirement, bloom, bud break, *Prunus dulcis*

INTRODUCTION

The flower buds of temperate perennial tree crops require a minimum amount of winter chill accumulation and spring heat accumulation to exit dormancy and bloom in the spring (Westwood, 1993). These chilling requirements and heat requirements vary by crop and cultivar. The modeling of phenological timing (e.g. bloom, leaf-out) and chilling requirements in temperate perennial crops has important applications in present day management and planning, and in projecting the impacts of climate change on orchard systems (Richardson et al., 2013). However, building models for chilling requirements and bloom to transfer across space (outside of the geographic region of the parameterizing dataset) or across time (under climate change scenarios) requires model stability outside parameterizing dataset.

Perhaps the most common approach to modeling bloom timing, the sequential model approach, requires accumulation of a specific amount of winter chill, followed by a specific amount of spring heat to break dormancy and achieve bloom (Ashcroft et al., 1977). This was a reasonable approach when first developed, in a time of minimal computing power and stable climate conditions. However, there is a well-documented compensatory relationship between winter chill and spring heat, by which some winter chill above and beyond the minimum chilling requirement can reduce the subsequent amount of spring heat necessary for bloom (Cannell and Smith, 1983).

The sequential model approach does not take this compensatory relationship into account. The structure of the model relegates extreme values to the error portion of the model instead of building those values into the model structure. Thus, it can do well predicting phenological timing in years with average winter and spring conditions, but not necessarily in years with very warm or very cold winters. This is problematic when applying sequential models to estimate chilling requirements or predict bloom timing in climates that differ from the climate used to parameterize the sequential model, or to predict phenological timing under climate change.

In attempting to better model the compensatory relationship between chill and heat accumulation and spring phenology, many have used non-linear exponential decline curves. However, with increased model complexity, the risk of over-fitting also increases, particularly with the small datasets common among historic phenology records. This can result in biologically unrealistic temperature thresholds (e.g. chilling and heat requirements) (Richardson et al., 2013).

In an attempt to avoid this over-fitting, Pope et al. (2014) developed a chill overlap framework to model bloom timing using biologically-based parameters and starting values. This approach used chilling requirement estimates based on values found in the literature for the three cultivars of *Prunus dulcis* (almond). The present work attempts to estimate the chilling requirement of three almond cultivars by iterative model fitting. Two datasets were used to compare the robustness of a model built with a dataset of long duration from one location versus a model built with a dataset from many locations but of a shorter duration. Results show that the chill overlap approach can generate reasonable chilling requirement estimates and model the timing of bloom well, provided a dataset that encompasses a wide variety of winter conditions.

MATERIALS AND METHODS

Two datasets were fit with the chill overlap model, one from a single location with a long duration and one from three locations, but of shorter duration. From each dataset, first bloom or 10% bloom was used to fit models for three cultivars – 'Ne Plus', 'Nonpareil' and 'Mission'.

The longer dataset, the Fruit Frost dataset, gave bloom timing for Chico, California, in the northern part of California's Central Valley. From 1933 to 1992, the Fruit Frost Service division of the United States Weather Bureau, recorded bloom timing for multiple crops in numerous locations throughout the country. Cultivar-specific records were kept by the Northern Sacramento Valley office for Chico and reported annually. These records were paired with weather data from the National Climate Data Center (NCDC) and California Irrigation and Management Information System (CIMIS), as detailed in Pope et al. (2015). Records were used from 1940, the first year that first flowering was recorded, until 1992. Some years were omitted because of weather data quality problems, resulting in 41 years of bloom used in the model fitting.

The shorter dataset from more locations has been described extensively in Pope et al. (2014). Briefly, the University of California conducted Regional Variety Trials to assess the bloom timing of new cultivars relative to existing cultivars at three locations in California's Central Valley, spanning the warmest winter conditions for commercial production in the southern part of the Central Valley to the coolest winter conditions in the northern part of the Central Valley. Two series of trials were conducted, with data collected from 1983-2008. These records were paired with weather data from NCDC and CIMIS as detailed in Pope et al. (2015). Some bloom records were excluded from analysis due to quality issues with the associated weather records, resulting in 60 bloom records total used from this dataset in model fitting.

The chill overlap framework of Pope et al. (2014) was used to fit the data. The curvilinear bloom prediction model is defined as $H_a = \beta_1 + \frac{\beta_2}{e^{(\beta_3 \times C_a)}}$ where H_a represents heat accumulation from the hour after the chilling requirement, C_r, is met through the day before bloom and C_a represents chill accumulation following the chilling requirement being met. Starting values to fit the models were estimated from the parameterization dataset for each cultivar and chilling requirement. A starting value for parameterizing β_1 was approximated using the lowest heat accumulation between the chilling requirement being met and bloom. A starting value for β_2 was estimated by subtracting the heat requirement, H_r, from the heat optimum, H_o, approximating H_o and H_r using the highest and lowest heat accumulations in the record. For β_3, the starting value of 0.01 was used for all cultivars and chilling requirements. See Pope et al. (2014) for more on the rationale of how these started values are estimated.

Chill accumulation was calculated using the Dynamic Model (Fishman et al., 1987), which has been found to model the timing of spring phenological events as well or better than other horticultural models in Mediterranean climates (Luedeling et al., 2009). The Growing Degree Hours (GDH) ASYMCUR model of Anderson et al. (1986) was used to quantify heat accumulation. Models were fit using nonlinear regression in R v 3.1.2 (R Core Team, 2014) using the nls function. Models were fit using the Gauss-Newton algorithm. The datasets were fit with chill requirements ranging from 10 to 30 chill portions (the Dynamic Model unit of chill measurement) and fit was compared using Root Mean Squared Error (RMSE) of the difference between predicted bloom date and actual bloom date. The chill requirement that resulted in the model with the lowest RMSE for the parameterizing dataset was deemed the estimated chilling requirement for that dataset for that cultivar.

RESULTS

The model failed to converge at many chill portion requirements. There was no agreement between datasets of the chilling requirement for a particular cultivar. As can be seen in Table 1, the Fruit Frost dataset estimated the chilling requirement of 'Nonpareil' as 10 chill portions, whereas the Regional Variety Trial dataset estimated the chilling requirement to be 21 chill portions. The estimates for 'Ne Plus' were more similar, with 16 chill portions estimated using the Fruit Frost data and 19 chill portions using the Regional Variety Trial data. For 'Mission', estimates also varied considerably – 11 chill portions for Fruit Frost and 17 chill portions for Regional Variety Trial.

Table 1. Best fitting chilling requirements and associated parameterizing and validating RMSE values for three cultivars of the Fruit Frost and Regional Variety Trial datasets.

Cultivar	Parameterizing dataset	Chilling requirement	RMSE-parameterizing	RMSE-validating
Nonpareil	Fruit Frost	10	6.1	10.3
	Regional Variety Trial	21	4.2	13.3
Ne Plus	Fruit Frost	16	4.4	8.6
	Regional Variety Trial	19	4	11.2
Mission	Fruit Frost	11	7.8	11.8
	Regional Variety Trial	17	4.3	9.3

When the best models from each dataset for each cultivar were used to predict bloom timing for the other dataset (i.e. parameters from 'Nonpareil' chill requirement = 10 fit with Fruit Frost data, used to predict Regional Variety Trial 'Nonpareil' bloom timing), all had much higher RMSE than with the parameterizing dataset. For all datasets, parameterizing RMSE ranged from 4.0 to 7.8 days from actual bloom. When validated using the other dataset, RMSE values ranged from 8.6 to 13.3 days (Table 1).

Models developed using the Fruit Frost data consistently predicted earlier bloom than actually occurred for the Regional Variety Trial dataset. The opposite was true for models developed using the Regional Variety Trial dataset – these consistently predicted later bloom than actually occurred with the Fruit Frost dataset. This is shown for 'Nonpareil' in Figure 1. A similar pattern was seen with 'Ne Plus' and 'Mission'.

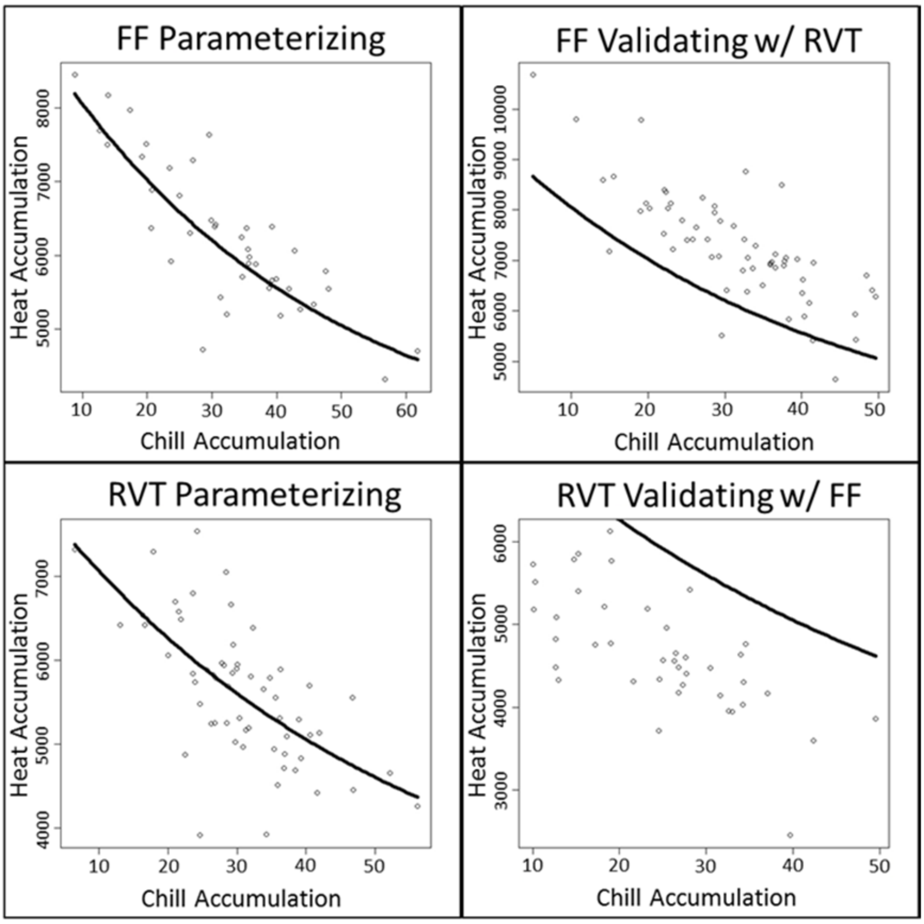

Figure 1. Fit of models with lowest RMSE for Fruit Frost (FF) and Regional Variety Trial (RVT) dataset, for 'Nonpareil'. Fit for both parameterizing and validating datasets.

DISCUSSION

The chill requirements estimates from the Regional Variety Trial were more similar to previous estimates from the literature than the estimates based on the Fruit Frost data. For example, previous work has estimated the chilling requirement of 'Nonpareil' as 23 chill portions (Ramirez et al., 2010; Pope et al., 2014). The only crops documented to have chilling requirements as low as those selected using the Fruit Frost data (10-16 chill portions, depending on cultivar) are super-low chill peach and nectarine varieties bred for the sub-tropical conditions of locations such as Florida (Erez, 2000). This sheds doubt on chilling requirement estimates from the Fruit Frost data.

These dubious chilling requirements, plus the higher RMSE values of the Fruit Frost data and the poor performance of the models when validated shows a weakness of the chill overlap approach. This approach does not create robust models with reasonable chill requirement estimates given a dataset that only captures a small range of weather conditions. This was evident with the Fruit Frost dataset, with which the fitted values of β_1 and β_3 in the range of previous chilling requirements estimates were negative. In essence, the model was trying to be imitate a linear fit. This indicates that there were not enough data points at chill accumulation extremes to make a curve a statistically probable fit.

Though the Fruit Frost dataset covered a large period of time, the climatic variability was not large enough for this dataset to encompass a large variety of conditions. Chill portion accumulation from October 1st to January 1st ranged from 26 to 47 in the Fruit Frost dataset, with 18 out of 41 of those years between 35 and 40 chill portions. Chill accumulation for the same months in the Regional Variety Trial ranged from 16 to 47 chill portions, with only 20 out of 60 between 35 and 40 chill portions. Using data from the more climatically varied Regional Variety Trial, the model fit more appropriate chill requirements and had lower RMSE values (4.0-4.3 days).

The poor performance of the Fruit Frost parameterized models may have been due to a poor estimate of β_2 because winter chill accumulation values in the parameterizing dataset did not sufficiently approach the chilling requirement. The contrast in performance between the two datasets highlights that a large dataset in a variable, mild temperate climate is critical to using the chill overlap framework. Additionally, because the model fit better with some years in the dataset in which little chill was accumulated beyond the minimum chill requirement, better model fit is likely when this chill overlap approach is used with medium-to-high chill requirement crops and marginally warm growing zones.

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