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Evaluation of recent trends in Australian pome fruit spring phenology

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Abstract Temporal and temperature driven analyses were conducted for eight spring phenology datasets from three Australian pome fruit growing regions ranging from 24 to 43 years in length. This, the first such analysis for Australia, indicated significant temporal change in phenophase timing for only one of the datasets. To determine relationships to temperature, a sequential chill and growth method as well as mean springtime temperatures were used to estimate phenophase timing. Expected advancement of phenophase ranged from 4.1 to 7.7 days per degree Celsius increase in temperature. The sequential chill and growth approach proved superior, with coefficients of determination between 0.49 and 0.85, indicating the inclusion of chill conditions are important for spring phenology modelling. Compared to similar phenological research in the Northern Hemisphere, the changes in response variables were often shallower in Australia, although significance of observed hemispheric differences were not found.

Keywords Apple . Pear . Climate change . Growing degree day . Chill . Sequential model . Green tip . Full bloom

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Introduction

Fruit trees cyclically respond to annual changes in environmental conditions. These periodic biological responses represent the phenology of the tree (Schwartz [2003\)](#page-12-0). Assessment of recent historical trends in biological pheonology records demonstrate how systems have responded to recent climate warming (e.g. Doi [2007](#page-11-0); Fujisawa and Kobayashi [2010;](#page-11-0) Gordo and Sanz [2009;](#page-11-0) Webb et al. [2011;](#page-12-0) Wolfe et al. [2005\)](#page-12-0). These types of studies also provide insight into how future climate changes may manifest in biological systems. Rosenzweig et al. [\(2008](#page-12-0)) conducted an extensive global meta-analysis of studies reporting recent phenological trends to assess whether results were in line with changes expected from anthropogenic warming. They considered both physical and biological analyses, including over 28,000 biological studies, incorporating results from marine, terrestrial and freshwater systems. Less than 50 of these studies were recorded for the entire Southern Hemisphere and of these only 22 were in the Australian region with none from agricultural systems. These results highlight that both the Southern Hemisphere and Australia are underrepresented in regard to global biological phenological studies, with agricultural information particularly sparse.

More recently several studies on biological phenology trends in Australia have been published (Chambers and Keatley [2010a,](#page-11-0) [b;](#page-11-0) Gallagher et al. [2009;](#page-11-0) Kearney et al. [2010](#page-11-0)) including those for winegrapes (Petrie and Sadras [2008](#page-11-0); Sadras and Petrie [2011;](#page-12-0) Webb et al. [2011](#page-12-0)). However, analyses of phenology records for pome fruit in Australia have not been reported. Thereby any recent changes are unknown and future predictions of impacts on production cannot be evaluated. Many other countries have conducted historical phenological analysis for pome fruit, including France (Guedon and Legave [2008;](#page-11-0) Legave et al. [2008](#page-11-0)), South Africa (Grab and Craparo [2011](#page-11-0)), North America

(Wolfe et al. [2005](#page-12-0)), Germany (Blanke and Kunz [2009](#page-11-0); Chmielewski et al. [2004](#page-11-0)), Spain (Gordo and Sanz [2009\)](#page-11-0) and Japan (Fujisawa and Kobayashi [2010](#page-11-0)).

The timing of spring phenophases in cultivated fruit trees are dictated by temperature, water availability, nutrients and genetics (Guitton et al. [2012](#page-11-0); Tromp [1976](#page-12-0); Wielgolaski [2001\)](#page-12-0). Temperature is commonly regarded as the primary driver of timing in spring phenology for pome fruit, with many authors implicating temperature as the determinant of phase timing (Doi [2007;](#page-11-0) Fujisawa and Kobayashi [2010](#page-11-0); Grab and Craparo [2011](#page-11-0); Guedon and Legave [2008](#page-11-0); Legave et al. [2008;](#page-11-0) Ruiz et al. [2007;](#page-12-0) Viti et al. [2010](#page-12-0); Wolfe et al. [2005\)](#page-12-0).

The independent sequential effects of winter chilling and springtime growth are often modelled to predict spring phenology (Cesaraccio et al. [2004;](#page-11-0) De Melo-Abreu et al. [2004](#page-11-0); Farajzadeh et al. [2010](#page-11-0); Fuchigami and Nee [1987](#page-11-0); Guedon and Legave [2008;](#page-11-0) Hunter and Lechowicz [1992](#page-11-0); Legave et al. [2008](#page-11-0); Luedeling et al. [2009](#page-11-0); Rea and Eccel [2006](#page-11-0)). Models of these processes are often temperature dependent. The basic structure of the sequential method requires calculating accumulated chill exposure over winter to a predetermined threshold, indicating dormancy has been broken. This marks the initiation of the growth model, which is then run until a growth limit is met, predicting the timing of the phenophase.

Using a sequential model approach is appealing as chill exposure and subsequent warming is in line with growth cycle theory of pome fruit (summarised in Atkins and Morgan [1990;](#page-11-0) Horvath [2009](#page-11-0)). This modelling approach requires substantial knowledge of the chilling mechanism, chill requirements, the growth mechanism and the threshold amount of warming required to reach the phenophase.

Specific understanding of the underlying physiological chilling process for pome fruit remains unknown with many temperature-based models available to approximate the chilling process (Cesaraccio et al. [2004](#page-11-0); Erez et al. [1990](#page-11-0); Fishman et al. [1987](#page-11-0); Gilreath and Buchanan [1981;](#page-11-0) Linsley-Noakes and Allen [1994](#page-11-0); Richardson et al. [1974](#page-12-0); Shaltout and Unrath [1983](#page-12-0); Weinberger [1950\)](#page-12-0). Consensus on chill model choice has not been achieved, with authors often using different models (Erez et al. [1990](#page-11-0); Linsley-Noakes and Allen [1994](#page-11-0); Luedeling et al. [2009;](#page-11-0) Rea and Eccel [2006](#page-11-0); Schwartz and Hanes [2010\)](#page-12-0).

A widely used chill model, the Utah model (Richardson et al. [1974](#page-12-0)) has been smoothed by Linvill [\(1990](#page-11-0)) to create the Modified Utah model. Another chill model, the Dynamic model (Erez et al. [1990](#page-11-0); Fishman et al. [1987](#page-11-0)) has performed well in many different assessments of chilling models (Alburquerque et al. [2008](#page-11-0); Erez et al. [1990](#page-11-0); Luedeling et al. [2009;](#page-11-0) Perez et al. [2008](#page-11-0); Ruiz et al. [2007](#page-12-0); Viti et al. [2010](#page-12-0)). A recent review of the state of knowledge on dormancy also indicated that the Dynamic model is the current milestone chilling model due to its structure as well as its positive field performance (Campoy et al. [2011a](#page-11-0)).

Further to chill model selection, varietal chill thresholds are needed for a sequential model approach. To date, no studies of field experimentation into pome fruit chill requirements under Australian conditions have been found. The use of chill requirements that have been reported internationally is not advisable as a chill threshold for a variety in one climate is unlikely to be transferrable to a different climate (Luedeling and Brown [2010\)](#page-11-0).

Similarly to winter chill, comprehension of the underlying relationship between bloom phenology and growth promoting temperatures is not fully understood, although the connection between springtime temperatures and spring phenology has been observed for some time (Reaumur [1735](#page-12-0)). The summation of growing degree days (GDD) is frequently utilised as a method to evaluate growth requirements (Hunter and Lechowicz [1992](#page-11-0); Luedeling et al. [2009;](#page-11-0) Rea and Eccel [2006;](#page-11-0) Roltsch et al. [1999](#page-12-0); Stanley et al. [2000;](#page-12-0) Valentini et al. [2001](#page-12-0); Yuri et al. [2011](#page-12-0)). An alternate growth model, the Growing Degree Hour (GDH) model (Anderson et al. [1986](#page-11-0)), is also widely used for phenological assessments (Azarenko et al. [2008;](#page-11-0) Lopez and Dejong [2007;](#page-11-0) Luedeling et al. [2009;](#page-11-0) Okie and Blackburn [2011;](#page-11-0) Ruiz et al. [2007](#page-12-0)). Uncertainty in appropriate chill and growth model selection as well as parameterisation of the models, necessitate testing of different models and parameters (e.g. Hunter and Lechowicz [1992;](#page-11-0) Legave et al. [2008](#page-11-0); Stanley et al. [2000](#page-12-0); Valentini et al. [2001](#page-12-0)).

The objective of this study was to assess relationships between climate and spring phenology of pome fruit in Australia and highlight potential differing responses between Northern and Southern Hemisphere localities. A sequential chill and growth model approach was used, with many different permutations of parameters for two chilling and two growth models used to optimise combinations for each individual phenological series. Data were additionally modelled to springtime temperatures and compared to the sequential modelling approach as well as other pome fruit phenology studies.

Materials and methods

Data

Spring phenology datasets for several varieties in southeast Australia were sourced from three pome fruit growing regions in Australia (Table [1](#page-2-0) and Fig. [1\)](#page-2-0). The data include one green tip series (Jonathan apple) and seven full bloom datasets (Granny Smith apple [2], Red Delicious apple, Golden Delicious apple, Josephine pear, Packham's Triumph pear and Williams' Bon Chretien pear).

Location State		Variety	Phenology phase	Years	Sample size (years)	
Lenswood	SА	Jonathan apple	Green tip	1963-1965,1968-2009	43	
Tatura	Vic	Granny Smith apple	Full bloom	1982-1985,1987-2000,2002-2009	24	
Tatura	Vic	Josephine pear	Full bloom	1983-2007	24	
Tatura	Vic	Packham's Triumph pear	Full bloom	1982-2009	26	
Tatura	Vic	Williams' Bon Chretien pear	Full bloom	1982-2009	26	
Yarra Valley	Vic	Golden Delicious apple	Full bloom	1977-2002,2003-2005	27	
Yarra Valley	Vic	Red Delicious apple	Full bloom	1977-2001	24	
Yarra Valley	Vic	Granny Smith apple	Full bloom	1976-2002,2004-2005	28	

Table 1 Summary of phenology data and locations

Australian authorities have not, and still do not, commission the systematic monitoring and collection of phenological data from pome fruit and thus the only available historical data is from non-national sources. Extensive Australian-wide searches were conducted to acquire data for this study with many sources deemed inadequate due to length (i.e. data less than 20 years following Sparks and Menzel [2002\)](#page-12-0), missing data or recording inconsistencies.

Data at Lenswood were sourced from the Lenswood Research Centre, a South Australian state body. The data were collected by growers and paid observers through comparison of samples in the orchard to several standard photographs of green tip (i.e. buds are broken showing a small amount of green). Green tip was defined to occur when at least 50 % of trees had reached the green tip phase. The Yarra Valley full bloom dates were recorded by a single grower, defined to occur after king bloom and prior to any petal fall for at least 70 % of the block. Similarly, the Tatura data were collected by the long-term orchard managers using a consistent methodology, being when the majority of flowers (>80 %) in the orchard were open and had not yet begun petal drop. All three locations observed the phenophases through at least daily inspections.

In situ meteorological data at the sites in this study were not available. As a result, daily temperature data were sourced from $0.05^{\circ} \times 0.05^{\circ}$ grids created by Jones

Fig. 1 Locations of the study sites

et al. [\(2009\)](#page-11-0). These were produced through a combination of empirical interpolation and function fitting applied to the Australian Bureau of Meteorology's network of quality controlled weather stations. This dataset was designed, in particular, for use in historical climate variability and climate change analyses. Extensive cross-validation processes and quality control procedures were performed by Jones et al. ([2009](#page-11-0)) to assess the quality of the gridded data. This primarily involved randomly excluding 5 % of the observer network and using the remaining 95 % of data to estimate the excluded stations. Total daily temperature root mean square error (RMSE) for 1910–2000 was less than 2 °C and negligible bias was reported. RMSE declined over time with greater improvements in values from the 1970s onwards. Almost all the data in this study is post 1970 (Table [1](#page-2-0)). Finally, RSME decreased with increased proximity to density of stations. All three locations in this study are in relatively populous areas by Australian standards, with one or more weather stations within a 20 km radius of each site. These surfaces have been previously used for Australian phenological investigation by Webb et al. [\(2011](#page-12-0)) in winegrapes and by Darbyshire et al. [\(2011\)](#page-11-0) for analyses in chilling trends.

Modelling

Sequential chill and growth models were used to approximate green tip and full bloom. The modelling process initially involved defining an initiation date for the chill model. Chill units were then accumulated over time until a prescribed chill threshold was reached. This marked the initiation of the growth model, in turn summing growth units over time until a defined growth threshold was reached. The day of year that the growth model ended was recorded and these values were then compared to the observed green tip or full bloom day to evaluate predictive ability of the models.

Two chilling models, the Modified Utah and Dynamic models, and two growth models, the Growing Degree Day (GDD) and the Growing Degree Hour (GDH) models, were tested using the sequential model approach.

The mathematical structures of both the chill models (Modified Utah and Dynamic) are contained in Darbyshire et al. ([2011\)](#page-11-0). The two growth models GDD and GDH are respectively described in Eqs. 1 and 2. Hourly temperatures for both of the chilling models and the GDH model were interpolated from daily maximum/ minimum values following Linvill ([1990\)](#page-11-0) and Darbyshire et al. ([2011\)](#page-11-0).

$$
GDD = \begin{cases} 0; T_i \le T_b \\ (T_i - T_b); T_i > T_b \end{cases} \tag{1}
$$

Where T_i is the mean daily temperature for day i and T_b the base temperature

$$
GDH = \begin{cases} F\left(\frac{T_u - T_b}{2}\right) \left(1 + \cos\left(\pi + \pi \frac{T_i - T_b}{T_u - T_b}\right)\right), T_u \ge T_i \ge T_b\\ F(T_u - T_b) \left(1 + \cos\left(\frac{\pi}{2} + \frac{\pi}{2} \frac{(T_i - T_u)}{(T_c - T_u)}\right)\right), T_c \ge T_i > T_u\\ 0, T_b T_i \ge T_u \end{cases}
$$
(2)

Where F is the stress factor, T_i is the hourly temperature for hour *i*, T_b the base temperature, T_u is the optimum temperature and T_c is the critical temperature. F was set to 1 as commonly practiced as no known stress was placed on the trees and T_c and T_u were respectively set to 25 and 36 °C as defined by the original authors (Anderson et al. [1986](#page-11-0)).

Due to uncertainties in parameterisation of both the chilling and growth models, various values were tested for predictive ability (Tables 2 and [3](#page-4-0)). For the chilling models, several different initiation dates and threshold chilling requirements were investigated (Table 2). For the growth models, various base temperatures and threshold growth requirements were trialled (Table [3\)](#page-4-0). Note different growth thresholds were used for the green tip data as opposed to the full bloom data reflecting the earlier timing of this phase.

In total 30,780 different parameter combinations were tested for the green tip data and 34,020 combinations for each of the full bloom datasets. Some parameter combinations were unable to be evaluated due to certain permutations being unrealistic. For instance, consider a combination with a high chill threshold (e.g. 100 CP), a high base temperature (e.g. 12 °C) and a high GDD threshold (e.g. 300 GDD). The chill threshold will occur relatively late in the season, meaning the GDD model will be started late. Compounding this, a high GDD threshold requires a large number of GDD to accumulate. Accentuating this, a high base temperature slows the accumulation of GDD. As a result the combination may not yield a result even by the end of the growing season, for all or some of the years under consideration. These few combinations were excluded from further analysis (less than 5 % of all combinations).

Table 2 Parameters tested for the chill component of the sequential model

Chilling initiation day of year	Chill model	Chill threshold
1-Mar; 15-Mar; 1-Apr; 15-Apr; $1-May$; $15-May$	Dynamic	$30-100$ CP in 5 CP intervals
	Modified Utah	600-1300 CU in 50 CU intervals

CU chill units, CP chill portions

Table 3 Parameters tested for the growth component of the sequential mode

Base temperature (T _b)	Growth model	Green tip growth threshold	Full bloom growth threshold
$4-12$ °C in $1^{\circ}C$ intervals	GDD	$20 - 180$ GDD in 20 GDD intervals	50-300 GDD in 20 GDD intervals
	GDH	2000–6500 GDH in 500 GDH intervals	5000-8500 GDH in 500GDH intervals

GDD growing degree days, GDH growing degree hours

The predictive ability of each of combination was tested through linear regression using ordinary least squares. For every phenology data series, each set of predicted values determined by the specified parameters were modelled to the observations. That is, the observations were kept independent of model development in order to test model suitability. Individual model performance was evaluated through considering significance with p-values (p <0.05), proportion of variability explained using the coefficient of determination (R^2) and precision via root mean square error (RMSE). Akaike Information Criterion (AIC) (Akaike [1974\)](#page-11-0) was also used to assist in determining relative model performance. AIC is a statistical method that maximises goodness-of-fit and applies penalties based on the number of variables used to fit the model. Generally, the model with the minimum AIC of a suite of models is considered more favourable, although models within two units of this minimum may also be considered.

The top four models were selected for each phenological data series based on two models with the highest $R²$ and two models with the lowest RMSE. For each data series, the best model out of the four was then identified based on maximising R^2 and minimising RMSE. Minimising AIC was used to assist in ranking model performance when selecting between two similarly performing models.

In addition to sequential modelling, each of the phenological data series were modelled to springtime temperature conditions. This was performed to consider whether simple climate variables had similar predictive capacity to a sequential modelling approach. Twelve different springtime temperature models were individually fitted to green tip data: mean daily maximum (Tmax), mean daily minimum (Tmin) and mean temperature (Tmean) for 1–31 August (Aug), 1–30 September (Sep), 1 August–30 September (AugSep) and 15 August–15 September (15Aug15Sep). The same temperature variables with different time slices were used for the full bloom data reflecting the difference in timing between the phenophases. These were 1–31 August (Aug), 1–30 September (Sep), 1–31 October (Oct), 1

August–30 September (AugSep) and 1 September–31 October (SepOct), resulting in 15 springtime temperature based models for the full bloom data. Evaluation of the performance of springtime temperature models used p-values, R^2 and AIC.

Results

Temperature trends

Environmental conditions at the three locations in this study are summarised in Table [4](#page-5-0). Of the locations, Tatura is the most mild while Lenswood and Yarra Valley have similar characteristics. Mean temperatures were calculated according to years coincident with the available phenological data.

Overall, none of the locations demonstrated a significant warming trend, with the exception of maximum temperature at Tatura ($P < 0.05$) (Table [5\)](#page-5-0). Tatura was also the only location that showed a non-significant cooling trend in minimum temperature.

Phenology trends

Temporal trends for spring phenology at Lenswood, Tatura and Yarra Valley are respectively shown in Figs. [2,](#page-5-0) [3](#page-6-0) and [4.](#page-7-0) Green tip data at Lenswood was the only series to indicate significant $(p<0.05)$ advancement in timing, with a trend of 2.5 days/decade, or an average of 11.3 day advancement over the entire time period (Fig. [2](#page-5-0)). Data from the Yarra Valley (Fig. [4](#page-7-0)) showed that full bloom advanced for Red Delicious apple by 3.5 days/decade (p value=0.06). All the datasets exhibited poor correlation to time (all $R^2 \le 0.18$) and high season-to-season variability (Figs. [2,](#page-5-0) [3](#page-6-0) and [4\)](#page-7-0).

Sequential modelling

The four top ranking models based on the two models with the highest R^2 and the two models with the lowest RMSE are shown in Table [5.](#page-5-0) Selection of the best model based on maximising R^2 and minimising RMSE (see Table [6](#page-8-0)) was not applied to the green tip data as the top performing models according to R^2 had very poor RMSE (14.6 and 14.8 days), and equally the models with the best RMSE had poor R^2 values (0.31 and 0.27). When expanded to consider the top ten performing models this pattern continued (data not shown).

The green tip series (Lenswood) produced much lower coefficient of determination and higher RMSE than the full bloom datasets. The R^2 values for the full bloom datasets of the selected models (see Table [6\)](#page-8-0) were all greater than 0.75 while the best green tip model according to \mathbb{R}^2 was only 0.49. Similarly, the range of RMSE of the selected models

Location	Latitude (o,	Longitude	Elevation (m)	Mean winter temperature $(^{\circ}C)$			Mean spring temperature $({}^{\circ}C)$				
				Mean	Jun	Jul	Aug	Mean	Sep	Oct	Nov
Lenswood ^a	-34.94	138.80	457	8.9	9.1	8.5	9.1	13.0	10.7	12.8	15.4
Yarra Valley ^b	-37.84	145.68	182	8.4	8.5	7.7	9.0	12.9	10.8	12.8	15.0
Tatura ^c	-36.39	145.31	112	8.8	9.0	8.1	9.4	14.6	11.6	14.4	17.9

Table 4 Study location details. Winter was calculated as June, July and August and spring as September, October and November

 a 1963–2009

 b 1976–2005

 c 1982–2009

was 2.3–4.2 days while the best green tip model was much higher at 7.0 days.

Model parameterisation of the growth period for the tabulated models frequently used the GDH model (24 out of 32). Likewise the Dynamic model was selected more frequently (24 out of 32) than the Modified Utah model. Across all the tabulated models for both green tip and full bloom data series, chill thresholds tended to be reached by late July to early August (Table [6\)](#page-8-0). The length of the growth period varied between and within data series. However, the length of the growth period tended to be longer for the full bloom datasets than the green tip series, reflective of later emergence of this phase.

The combined influence of parameter selections from the chill and growth models can be seen in these results. For instance, the Red Delicious apple Yarra Valley model (15- Mar; 900 CU; 6 °C; 8,000 GDH) had a relatively low chill threshold, which was met early in the season (mean date 1- Jul). However, this was compensated for in the growth model which had a high GDH threshold requirement. Thus, the growth period was extended (mean 107 days) and the model adequately predicted the observations using this combination. Likewise, another model for this variety with a

Table 5 Temperature trends at each location for specified months and time periods

Location	Tmax $(^{\circ}C/$ decade)	Tmin $(^{\circ}C/$ decade)	Tmean $(^{\circ}C/$ decade)
Lenswood $(SA)^a$	0.2	0.0	0.1
Yarra Valley (VIC) ^b	0.1	0.0	0.0
Tatura $(VIC)^c$	0.5^d	-0.3	0.1

Tmax is mean daily maximum temperature, Tmin is mean daily minimum temperature and Tmean is mean temperature. Different months were used for the green tip data due to the earlier emergence of this phase

 a 1 August–30 September (1963–2009)

 b 1 August–31 October (1976–2005)

 c 1 August–31 October (1982–2009)

higher chill requirement and the same base temperature (15- Apr; 75 CP; 6 °C; 6,000 GDH) indicated chill was satisfied much later (mean date 6-Aug) but fewer GDH were needed, compressing the growth period (67 days) thereby also performing well in terms of model predictive capacity.

Springtime modelling

The phenological data were additionally modelled to springtime temperatures (Table [7](#page-9-0)), with the top two models according to $R²$ tabulated. Similarly to the sequential modelling results, the Jonathan apple green tip data performed poorly compared to the full bloom series.

None of the top models included minimum temperature as a driver. All models were a combination of August and/or September temperature conditions. Further, one of the two top models, with the exception of Williams' Bon Chretien pear, were for mean maximum temperature conditions over August and September.

 d p-value<0.05 **Fig. 2** Green tip dates at Lenswood (SA)

Fig. 3 Full bloom dates at Tatura (VIC)

The $R²$ and AIC values calculated with springtime temperatures were directly compared with those obtained through the sequential modelling process (Table [6](#page-8-0)). The sequential method outperformed the springtime method for all data series. The sequential method, for the selected full bloom models and the best R^2 green tip model had improved coefficient of determination ranging from 0.07 to 0.21. The greatest improvements tended to be for the Tatura datasets, with up to 0.17 improvement recorded. Differences in AIC also supported the improved performance of the sequential models, with the selected sequential models reporting AICs between 21 and 37 units lower than the equivalent springtime models.

Discussion

Phenology trends

The only other study of historical temporal trends in pome fruit phenology found for the Southern Hemisphere (Grab and Craparo [2011\)](#page-11-0) reported similar magnitude responses in South Africa as those found for Australia, although they found greater statistical significance. Golden Delicious is a good example of the similarity with both South Africa and the Yarra Valley indicating an advancement of 1.9 days/ decade. Granny Smith showed a relatively smaller trend of advanced flowering in both South Africa, at 1.1 days/decade, and in the Yarra Valley, at 1.4 days/decade. However, for Granny Smith at Tatura the trend was minimal and tended towards delayed flowering (0.6 days/decade). Similarly, Williams' Bon Chretien pear at Tatura indicated a trend of delayed flowering (1.4 days/decade), while the South African data recorded a significant advancement (1.8 days/decade). This comparison shows that Yarra Valley and the south-western Cape in South Africa may be similar in regard to recent pome fruit phenological response. Coastal influences may have played a role in the similarities between the Yarra Valley and South African results. The study site in South Africa is close to the coast (approximately 20–40 km), while the Yarra Valley is slightly further at approximately 60 km. However, Tatura is much more continental and was less similar to both the Yarra Valley and South Africa. This highlights the impacts that regional climate conditions can have on phenological trend analyses.

In comparison to Northern Hemisphere temporal trends, Australian and South African responses tend to be less. For instance, studies have found advancement in: the beginning of apple blossom (2.2 days/decade) in Germany (Chmielewski et al. [2004\)](#page-11-0); early flowering of

apple (2.6–3.0 days/decade) in France (Legave et al. [2008\)](#page-11-0); early flowering of pear in Switzerland and France (3.3 days/decade) (Guedon and Legave [2008](#page-11-0)); first flower of apple (2.1–3.5 days/decade) in Japan (Fujisawa and Kobayashi [2010](#page-11-0)); and mid-bloom of apple (2.0 days/decade) in the United States (Wolfe et al. [2005\)](#page-12-0). Comparatively, all South African trends showed advancement of less than 2.0 days/decade (Grab and Craparo [2011\)](#page-11-0) and only two of the series in this study indicated (non-significant) trends greater than 2.0 days/decade (Jonathan 2.5 days/decade and Red Delicious 3.5 days/decade). A possible explanation for differences in signal strength lies in the relative warming experienced between the two hemispheres, with the Southern Hemisphere warming slower than the Northern Hemisphere. Observed land-based changes in the Northern Hemisphere temperatures are between 0.29 and 0.34 °C/decade while changes in the Southern Hemisphere are between 0.09 and 0.22 °C/decade for 1979–2005 (IPCC [2007\)](#page-11-0). These observational differences in phenological studies should not be overstretched given differences in study structures including varietal choice, phenophase and data series length. Indeed there is some crossover between signal strengths between the hemispheres and moreover inconsistencies between the datasets make it difficult to investigate statistical significance of these differences.

This study and the above-mentioned studies use temperature singularly as a driver of phenophase timing. A recent study (Webb et al. [2012\)](#page-12-0) indicated that temperature as well as soil moisture and management equally contributed to observed changes in maturity in winegrapes. Additional investigation into other potential influences on phenological timing is required along with more studies from the Southern Hemisphere to add support to potential hemispheric differences.

Springtime versus sequential modelling

A notable difference in R^2 and RMSE between the full bloom datasets and the green tip series was observed for both sequential and springtime modelling methods (Tables [6](#page-8-0) and [7](#page-9-0)). The lower capability to model green tip may be due to the earlier timing of the phenophase, meaning that it was likely to be more sensitive to small changes in environmental conditions. Sparks and Menzel ([2002\)](#page-12-0) comment on early event variability suggesting it may be reflective of higher variability in temperatures experienced for springtime events. They discuss additional factors such as soil and grass temperature, carbon dioxide concentrations and pollutants that may influence the magnitude of phenological responses. Additionally, the assumption of a linear response of green tip to temperature may have been inadequate, causing the

RMSE root mean square error, AIC Akaike Information Criterion

^a Selected models

 b The top performing models were the same according to $R²$ and RMSE</sup>

The model structure is defined by the parameters with the first entry indicating the initiation date of the chill model, chill threshold (CU = chill units, CP = chill portions), base temperature as well as growing degree days (GDD) and growing degree hours (GDH) threshold. Chill date is the mean date the defined chill threshold was met and growth days is the mean number of days between the chill satisfaction date and the date the GDD/GDH threshold was met. For each dataset, the upper two rows refer to the top performing models according to $R²$ and the lower two rows are the top models according to RMSE. Both the chill date and growth days are mean values. All tabulated models were statistically significant $(p<0.05)$

Table 7 Springtime temperature model performance and associated parameterisations

Variety	Parameters	R^2	AIC	Coefficient (days/ ${}^{\circ}$ C)
Jonathan apple (Lenswood)	Tmax; AugSep	0.39	302	-4.1
	Tmax; Aug	0.36	305	-2.8
Granny Smith apple (Tatura)	Tmean; AugSep	0.67	150	-6.5
	Tmax; AugSep	0.63	153	-4.4
Josephine Pear (Tatura)	Tmax; AugSep	0.61	144	-4.3
	Tmax; Aug	0.59	145	-4.0
Packham's Triumph pear (Tatura)	Tmean; AugSep	0.72	155	-6.4
	Tmax; AugSep	0.63	161	-4.4
Williams' Bon Chretien pear (Tatura)	Tmean; Sep	0.63	167	-6.1
	Tmean; AugSep	0.58	171	-6.4
Golden Delicious apple (Yarra Valley)	Tmax; AugSep	0.68	162	-5.5
	Tmean; AugSep	0.64	165	-6.7
Red Delicious apple (Yarra Valley)	Tmean; AugSep	0.69	149	-7.5
	Tmax; AugSep	0.67	151	-5.9
Granny Smith apple (Yarra Valley)	Tmean; AugSep	0.74	164	-7.7
	Tmax; AugSep	0.73	166	-6.1

Tmax, Tmin and Tmean, respectively, represent mean daily maximum, minimum and mean temperature. Aug, AugSep and Sep represent the time spans August, August and September, and September. The units for the coefficient of the models are in days per °C according to the described parameters (e.g. days per °C change in AugSep maximum temperature). All tabulated models were statistically significant (p <0.05)

lack of observed effect. This was explored by Sparks et al. [\(2000](#page-12-0)) for flowering timing in various plant species. They suggested a horizontal asymptotic response to temperature, with species at the upper or lower extreme of the temperature curve having a non-linear influence on flowering. If climate conditions at Lenswood fall within the extremes of phenological response for Jonathan apple this may explain the lack of significance found in this study. Further experimentation is needed to determine if external factors and/or a non-linear approach are more appropriate for this data series.

A large number of parameters were tested for the sequential models. For some of the top performing models (Table [6\)](#page-8-0), differences in parameterisations were apparent. For instance, the top models for Packham's pear contained three different chill initiation dates, two different base thresholds, three different threshold growth requirements and three different threshold chill values. Yet all models illustrated good predictive capacity. The implication of these differences is difficult to delineate. For instance, using either the GDD or GDH model, a high base temperature and low threshold requirement may also correlate well to a growth model with a lower base threshold but higher threshold growth requirement. A similar effect can occur for the chilling parameters, whereby an early initiation time and high chill threshold may be equivalent to a later initiation time and lower chill requirement. However, clear evidence of these aspects were not found in the results.

The sequential modelling approach allowed for analysis of the individual chilling and growth components of the models. By testing a large number of parameters for both the chilling and growth components of the models it is clear that the two halves of the model can compensate for each other. Red Delicious apple is a good example with a top rating model parameterised by a low chill threshold (900 CU) and a high growth requirement (8,000 GDH). Another top model for this variety had higher chill requirement (75 CP) but lower growth requirement (6,000 GDH). Field testing is required in order to separate models that perform similarly but have different parameter requirements.

It was clear that the Dynamic chilling model and GDH growth model dominated the best performing models across all the data series. The Dynamic model has been found to perform equally or better in many chill assessments (Alburquerque et al. [2008;](#page-11-0) Campoy et al. [2011b](#page-11-0); Erez et al. [1990](#page-11-0); Luedeling et al. [2009;](#page-11-0) Perez et al. [2008;](#page-11-0) Ruiz et al. [2007](#page-12-0); Viti et al. [2010](#page-12-0)). Previous studies are less clear on appropriate growth model choice with some authors using different forcing algorithms or parameterisations (Legave et al. [2008](#page-11-0); Stanley et al. [2000;](#page-12-0) Valentini et al. [2001\)](#page-12-0). Indeed, the sequential modelling method itself may need improvement.

Parallel chilling and growth, a less explored mechanism, has also been proposed as a method to evaluate phenological events, although it has been shown to perform poorly compared to the sequential model (Hunter and Lechowicz [1992\)](#page-11-0). In order to better understand chilling and growth responses, their interaction and optimise parameter selection, field and laboratory work is required to validate both chilling and growth conditions. This is particularly pertinent for Australia as no published studies regarding chill or growth requirements for bloom phenology in pome fruit have been found.

In addition to sequential chill and growth modelling, the data were modelled to various springtime warming variables. Mean minimum temperatures were not found to be amongst the top models (Table [7\)](#page-9-0), in agreement with the Grab and Craparo [\(2011\)](#page-11-0) findings for South Africa. The results here indicate August and September to be the important period for determining phenophase timing, however this was later in South Africa (September and October). This difference is likely due to the earlier phenophase timing recorded in this study. The results found here differ from those for Germany which indicated a longer period of warming is important for phenophase timing with February–April correlated to emergence (Chmielewski et al. [2004](#page-11-0)).

Climate change implications

If the assumptions behind the springtime temperature method hold, these results can be used to help illustrate how future warming may impact phenology timing. It is likely that there will be regionally different rates of response, expected due to regionally different climate change signals (CSIRO [2007](#page-11-0)). Further, differences between varieties will also be expected, for instance, using the variables Tmean AugSept at Yarra Valley, Granny Smith will advance by 7.7 days/°C increase while Golden Delicious is likely to advance by 6.7 days/°C. An investigation for New Zealand considering climate impacts on apple flowering timing (Austin and Hall [2001](#page-11-0)), using a springtime warming approach, suggests that warming will only advance flowering by approximately 1 week by 2100, which correlates to over a 2 °C increase (Ministry for the Environment [2008](#page-11-0)). This provides further reflection on regional differences, with New Zealand likely to experience a lower change to flowering timing than Australia in response to anthropogenic warming.

What is unclear using the springtime method is the likely impact of the lengthening of the chilling period. Other authors (Guedon and Legave [2008](#page-11-0); Legave et al. [2008](#page-11-0)) indicate that the rate of advancement of flowering may be buffered by a prolonged chilling period. However, no significant change to the length of chill period for the selected models in Table [6](#page-8-0) was found (data not shown). Nonetheless, impact assessments of future climate conditions on bloom phenology should

include chilling effects as well as springtime warming to incorporate this characteristic. The sequential approach allows for this interaction to be considered. Indeed, models identified here could be used to inform such impact assessments.

Under future climate conditions, coincidence of changes to bloom phenology and other factors may become important. For instance, full bloom could advance at a faster rate than spring frosts retreat. Hence, crops would be at greater frost risk as a result of climate change. Species mismatch may also begin to occur, whereby natural insect pollinators may not alter their phenology in line with the tree, interrupting pollination processes and potentially reducing fruit loads (e.g. Gordo and Sanz [2005\)](#page-11-0). Further, cross-pollination between varieties will be affected if trees respond at different rates, as was found in this study. In deciding methodology for such projections the sequential approach appears to provide more precision. In addition, the sequential model accounts for a lengthening in the chilling period, which was not included in the springtime models. However, appropriate parameterisation of the sequential models is unclear. Under warming conditions, parameter choice may have a significant impact on results. Again, field and laboratory research is required to provide clarification on parameterisation.

Conclusions

Historical trends for eight phenology series for pome fruit in south-eastern Australia were presented, the first description of such information for Australia and only the second for the Southern Hemisphere. Some similarities were found between these two studies, although regional differences were also apparent. The two Southern Hemisphere studies show that changes in pome fruit bloom phenology may be occurring slower than in the Northern Hemisphere, although notable methodological differences and some cross-over in signal strengths between the two hemispheres makes the significance of these observed differences unclear. Sequential chill and growth models were found to outperform simple springtime models for all datasets. However, clear appropriate parameterisations were not always found with field and laboratory work required for clarification. Future impact assessments of climate change on pome fruit may be informed by historical relationships and models established in this study.

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