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Prediction of harvest start date in highbush blueberry using time series regression models with correlated errors

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ABSTRACT

This work proposes a model for predicting the harvest start date sufficiently far ahead to enable the farmer to make a well-informed plan. The heat unit method is widely used in agriculture as the phenological unit of time, which offers the least variation in date predictions, and heat units have been used to estimate the start of harvesting in various crops. The problem is that the farmer needs to know the number of days and not the number of heat units that are needed until the harvest can begin. It is proposed that the daily maximum and minimum temperature time series be modelled through regression models with errors correlated using a sine curve. Using the requirements reported by Carlson and Hancock (1991) for the start of harvest of 13 varieties of blueberry over 15 years, a model has been developed that allows the requirements of heat units to be translated into days remaining until harvest. The models are estimated at intervals of 3 months, 2 months, 1 month, 14 days and 7 days before the date at which the heat unit requirements are reached. Three months ahead, the error was less than 10 days late, and 7 days ahead, it was 2 days late. A blueberry orchard in Temuco, Chile, was used as a case study and had similar results. All the errors are within the variability of the heat unit models. The models can be used by farmers to predict and plan the blueberry harvest with adjustments for location and variety.

1. Introduction

Blueberry cultivation is an important economic activity in Chile, where it is practiced between the Valparaíso and Los Lagos regions and covers more than 7000 ha (ODEPA and CIREN, 2010). In the 2010 season, more than 50,000 tons of blueberries were exported, mainly to the United States and the European Union (Bravo, 2011). Blueberries can be exported either frozen or fresh; however, the latter draw a higher sale price in the final markets. In 2011, for example, frozen blueberries drew only 40% of the value of fresh fruit (ODEPA, 2011). These exports to the northern hemisphere are favoured by the high sale prices achieved in the early and late varieties produced in the off-season. There are two important aspects for fresh blueberry exporters to consider: estimating the yield, which has been addressed (Hancock et al., 2000; Salvo et al., 2012), and the harvest start date. Knowing the harvest start date accurately at least 2–3 weeks in advance allows coordination of the procedures required for marketing large volumes (Mainland, 2000). Moreover, with this coordination, pre-packing delays can be reduced and the cold chain needed to export fresh blueberries at an acceptable quality can be maintained (Jackson et al., 1999). The procedures to be coordinated are obtaining certified clamshells, hiring a sufficient number of qualified pickers, training new personnel, preparing the packing process and obtaining refrigerated transport.

The traditional method of estimating the harvest start date is to count the days from flowering; but this approach is subject to too much variability between seasons (Baptista et al., 2006). The variability in early varieties to reach 50% mature fruit is from 4 to 9 days between seasons (Lyrene and Sherman, 1984), with a variation coefficient between 6.5 and 8% (Gupton et al., 1996). For example, Mainland (2000) determined that the number of days elapsed from flowering to harvest may be between 52 and 62. However, the harvest date is highly correlated with the days needed for the fruits to reach maturity ($r = 0.718$) and is negatively correlated with the weight of the individual fruits ($r = -0.660$) (Suzuki and Kawata, 2001). This correlation is due to the blueberry phenology being highly dependent on climatic conditions and the development stages of the fruit. However, the accumulation of heat units is a more robust phenological indicator, which starts to accumulate from the end of the latency period (Carlson and Hancock, 1991). The heat unit method has been used for numerous crops, including soft fruit (Everaarts, 1999), sweet potato (Villordon et al., 2009), corn (Lass et al., 1993), brassica (Adak and Chakravarty, 2010), sugar cane (de Souza et al., 2011) and opium poppy (Kamkar et al., 2012). Heat

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units are also used for predicting the start of harvests for fruit such as apple (Perry et al., 1987), cucumber (Perry and Wehner, 1990, 1996), banana (Umber et al., 2011), loquat (Hueso et al., 2007), musk melon (Jenni et al., 1998) and yellow pitaya (Nerd and Mizrahi, 1998). In rabbiteye blueberries, using heat units reduces the coefficient of variation associated with the days for fruit development, thus improving the prediction of the harvest start date (Carlson and Hancock, 1991; NeSmith, 2006).

As the accumulation of heat units depends on the maximum and minimum daily temperatures occurring during the year, the relation between the days elapsed and the heat accumulated does not remain constant from 1 year to another. The problem is that the farmer needs to know the number of days and not the number of heat units that are needed until the harvest can begin.

Hean and Cacho (2003) approximated the annual temperature fluctuation with a sine function, an approach that allows the accumulated heat to be converted to the days remaining to the start of the harvest. The objective of this work is, therefore, to predict the date on which the heat unit requirements are met and harvesting can begin. We also seek to determine the error, in days, when the prediction is made 3 months, 2 months, 1 month, 14 days and 7 days ahead to generate a degree of confidence that will enable the farmer to plan harvest logistics well in advance.

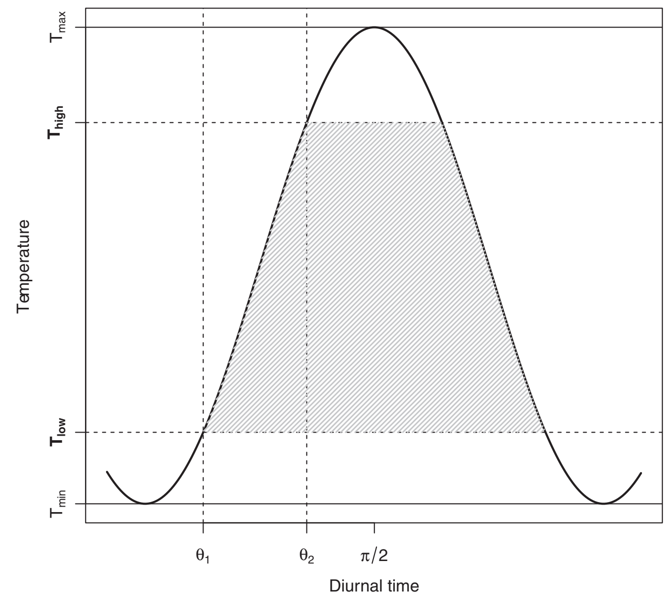

Fig. 1. Calculation of heat units per day as the area under the curve between the low and high thresholds of the daily temperature using a sine function.

2. Materials and methods

2.1. Heat model

In this study, the heat unit requirements for the start of blueberry harvesting reported by Carlson and Hancock (1991) are used. In that study, the authors investigated variability in the start of harvesting by comparing the heat unit model (heat units for the start of harvest) with the calendar day model (average date of the start of harvest) and concluded that there is less variability in the heat unit model. The study was carried out for 13 varieties of blueberry over 15 consecutive years in Bloomingdale, MI. For the heat unit model, the heat units were calculated using the Baskerville–Emin method, which uses high and low temperature thresholds (Baskerville and Emin, 1969). This method uses a sine curve approach to daily temperature based on the maximum (T_{max}) and minimum (T_{min}) daily temperatures. The daily quantity of heat is calculated as the area under the curve of this sine function between a low (T_{low}) and high (T_{high}) threshold (see Fig. 1).

The date for the start of heat unit accumulation and the low and high temperature thresholds for accumulation were determined using values that would reduce the variability in days to the start of harvesting. Table 1 shows the parameters determined for the heat unit and calendar day models. The parameters in the heat unit model were the start date of heat accumulation (SDATE), the low temperature threshold (T_{low}), and the high temperature threshold (T_{high}). These parameters were used to calculate the heat units to the start of harvesting (HU_m) and the variation in days to the start of harvesting once the heat accumulation was complete (σ_{hu}). For the calendar day model, the parameter used for the start of harvesting (HDATE) was the average of the last 15 years, which allowed the variation in days of HDATE (σ_{cal}) and the relation between the variations in days in the two models (σ_{hu}/σ_{cal}) to be obtained.

2.2. Databases

The daily temperature series (maximum, minimum and mean) recorded from 1974 to 1988, which was the period of Carlson and Hancock's study (1991), were obtained by the Bloomingdale, MI, meteorological station (42.38N, 85.96W, elevation 220.98 m). During these 15 years, the minimum temperature ranged from −30 °C to 24 °C, and the maximum ranged from −15 °C to 38 °C.

2.3. Time series model

The proposed models correspond to two linear regression models with errors correlated in discrete time, one for minimum temperature ($i = T_{min}$) and the other for maximum temperature ($i = T_{max}$).

$$T_i(k) = \beta_{i,0} + \beta_{i,1}\cos(\omega k) + \beta_{i,2}\sin(\omega k) + e_i(k), \quad i = T_{min}, \quad T_{max} \tag{1}$$

where $\beta_{i,j}$ are the parameters of the two models, k is a correlate that corresponds to the number of calendar days since 1 January 1988 and $e_i(k)$ is the error after elimination of the series trend in each of the models. The structure of both models includes a sine curve approximation, with a period of $\omega = 2\pi/365.2422$, to eliminate the annual trend of the series. The $\beta_{i,j}$ parameters are calculated by minimising the squared error between the maximum and minimum temperatures measured and those determined by these models.

The $e_i(k)$ errors were analysed to look for an autocorrelation greater than zero with the Durbin–Watson test. In the resulting ARMA(p,q) (Auto Regressive Moving Average) model, p is the order of the autoregressive model and q is the order of the moving average, given by Eq. (2).

$$\begin{aligned} e_i(k) = {} & \varphi_{i,1}e_i(k-1) + \varphi_{i,2}e_i(k-2) + \cdots + \varphi_{i,p}e_i(k-p) \\ & + \theta_{i,1}\varepsilon_i(k-1) + \theta_{i,2}\varepsilon_i(k-2) + \cdots + \theta_{i,q}\varepsilon_i(k-q) \\ & + \varepsilon_i(k) \quad i = T_{min}, T_{max} \end{aligned} \tag{2}$$

where $\varphi_{i,j}$ are the parameters of the autoregressive model, $\theta_{i,j}$ are the parameters of the moving average model and $\varepsilon_i(k)$ is the normal distribution error with an average of zero and a variance σ_i^2. The order of parameters p and q is obtained from the model with the smallest Akaike Information Criterion (AIC) (Akaike, 1974). The models were validated using tests on the residuals to verify the normality, independence and homogeneity of the variance.

For the 1988 season, the date when the heat unit requirements were met for the start of harvesting is called HUDATE. This date

Table 1
Heat unit requirements and estimated harvest start dates.[a]

Variety	Heat-unit model					Calendar-day model		σ_{hu}/σ_{cal}
	SDATE	T_{low} (°C)	T_{high} (°C)	HU_m	σ_{hu} (days)	HDATE	σ_{cal} (days)	
Berkeley	1 March	−7	32	2960	5.43	1 August	6.95	0.78
Bluecrop	1 February	7	27	1047	5.08	28 July	9.48	0.54
Bluejay	1 February	2	21	1495	4.69	23 July	8.75	0.54
Blueray	1 February	−7	27	2943	5.38	28 July	7.00	0.77
Bluetta	1 February	4	21	970	4.10	9 July	7.43	0.55
Collins	1 February	−7	21	2478	5.28	14 July	7.37	0.72
Coville	1 February	−7	No	3224	4.49	7 August	8.03	0.56
Earliblue	1 March	4	21	958	3.29	8 July	6.89	0.48
Elliott	1 February	2	21	2068	4.30	26 August	8.59	0.50
Jersey	1 February	−7	32	3336	6.97	11 August	9.40	0.74
Patriot	1 March	7	21	859	2.46	21 July	7.95	0.31
Rubel	1 February	−7	27	3100	6.23	3 August	8.08	0.77
Spartan	1 February	−7	21	2487	3.79	15 July	5.96	0.64
Average					4.73		7.84	0.60

[a] Carlson and Hancock (1991).

was validated with the calendar day model of Carlson and Hancock (1991) (Table 1).

Both models were used to predict the trends and errors in the maximum and minimum temperatures for the 1988 season. With these predictions, and using the Baskerville–Emin method (Baskerville and Emin, 1969), the heat units for the season and the date when they were reached (FDATE) are predicted. The estimates of the parameters and the predictions are made 3 months, 2 months, 1 month, 14 days and 7 days ahead of HUDATE. The difference between HUDATE and FDATE was compared in each prediction.

2.4. Case study

The blueberry was introduced into Chile in 1979 by the Institute of Agriculture and Livestock Research (Instituto de Investigaciones Agropecuarias – INIA). The Araucanía Region was one of the first areas where the behaviour of the blueberry was evaluated, at the Carillanca Experimental Station (Muñoz et al., 1987). The methods applied for blueberry cultivation in the region are those proposed for organic cultivation of the variety Bluecrop in the immediate area of Temuco (38°46′S, 72°38′W, elevation 114 m). Temuco is located in southern Chile, 670 km south of the capital, Santiago. The prevailing climate is wet temperate, with a Mediterranean influence. Precipitation may occur throughout the year and is mainly concentrated in the winter, with dry months in January and February. The thermal regime is subject to no greater changes than those due to its distance from the sea, with an average annual temperature of 12 °C, 80% relative humidity and an average precipitation of 1324 mm (Romero-Mieres et al., 2009).

The method of Carlson and Hancock (1991) was used to find the optimum combination of start dates for heat unit accumulation and low and high temperature thresholds. Three start dates were chosen at the beginning of winter: 1 June, 1 July and 1 August. In accordance with the work of Carlson and Hancock, six values were selected for low temperature thresholds (−6.7, −3.9, −1.1, 1.7, 4.4 and 7.2 °C) and four values were selected for high temperature thresholds (21.1, 26.7, 33.2 and no threshold). These parameters were the basis for defining 72 combinations, from which the combination with the best Coefficient of Determination and the lowest variability in days was selected. The harvest start dates of the 2001–2005 seasons were used to estimate the heat unit requirements. These requirements were validated with the 2006–2010 seasons. Finally, the regression model with correlated errors was used to predict the 2011 season.

3. Results

3.1. Temperature model

The models estimated for the maximum and minimum temperature series are shown in Table 2. The trend model parameters do not vary as the "Ahead" period is reduced. For both models, the autocorrelation of the errors is greater than zero according to the Durbin–Watson test and all the coefficients are significant ($p < 0.001$).

Because the errors for the two series was auto correlated, the ARMA(p,q) models were fitted. The order of the models was chosen by the AIC criterion shown in Table 3. For both models, the lowest AIC found was with the ARMA(2,2) model.

The coefficients of the ARMA(2,2) model are shown in Table 4. All the parameters are similar, with similar standard errors between coefficients.

The difference between HUDATE and FDATE for the 1988 season is shown in Table 5. Three months ahead, the error is between 10 days late and 2 days early. Seven days ahead, the error is between 2 days late and 1 day early.

Fig. 2 shows the course of maximum and minimum temperatures and the accumulation of heat units. The band shown in the graph corresponds to the temperature interval between 2 and 21 °C for the variety 'Elliott'. When the temperatures are completely outside the band, no heat units are accumulated, causing an interruption in the accumulation of heat units. When such events occur, the harvest start date must be predicted again.

3.2. Case study

Using the data available to date, the method proposed by Carlson and Hancock (1991) was used to determine the heat unit requirements to the start of harvesting (see Table 6). Heat accumulation began on 1 August, with a low temperature threshold of −6.7 °C and a high threshold of 21.1 °C. With these parameters, 2490 heat units must be accumulated before the start of harvesting. The heat unit model explains 86% of the harvest start dates and has low variability in days. The calendar day model predicts the start of harvest for 14 December, with higher variability than the heat unit model. The heat unit model reduces the variability of the calendar day model by 37%.

The heat unit requirements were validated by the 2008 and 2010 seasons. In the 2008 season, the 2490 heat units were obtained on 12 December, and the start of harvesting occurred on 15 December; for the 2010 season, this number of units was accumulated on 20

Table 2
Models for maximum and minimum temperature series.

Ahead	β_0	β_1	β_2	R^2_a
$T_{\min}(t)$				
3 months	2.64 ± 0.07	−11.29 ± 0.1	−4.37 ± 0.1	0.73
2 months	2.62 ± 0.07	−11.27 ± 0.1	−4.39 ± 0.1	0.73
1 month	2.62 ± 0.07	−11.26 ± 0.1	−4.40 ± 0.1	0.73
14 days	2.62 ± 0.07	−11.26 ± 0.1	−4.40 ± 0.1	0.73
7 days	2.61 ± 0.07	−11.25 ± 0.1	−4.40 ± 0.1	0.73
$T_{\min}(t)$				
3 months	14.13 ± 0.07	−14.10 ± 0.1	−4.46 ± 0.1	0.80
2 months	14.13 ± 0.07	−14.10 ± 0.1	−4.46 ± 0.1	0.79
1 months	14.14 ± 0.07	−14.11 ± 0.1	−4.46 ± 0.1	0.79
14 days	14.15 ± 0.07	−14.13 ± 0.1	−4.45 ± 0.1	0.80
7 days	14.15 ± 0.07	−14.13 ± 0.1	−4.45 ± 0.1	0.89

[a] All the coefficients are significant ($p < 0.001$).

Table 3
Akaike Information Criterion (AIC) values for ARMA(p,q) models fitted for the maximum and minimum temperature series.

Ahead	Akaike Information Criterion						
	ARMA(1,0)	ARMA(0,1)	ARMA(1,1)	ARMA(2,0)	ARMA(2,1)	ARMA(1,2)	ARMA(2,2)
$e_{\min}(t)$							
3 months	28,661	29,325	28,498	28,529	28,496	28,493	28,478
2 months	28,821	29,484	28,655	28,688	28,653	28,650	28,636
1 month	28,993	29,655	28,825	28,857	28,823	28,820	28,804
14 days	29,079	29,739	28,909	28,942	28,908	28,904	28,889
7 days	29,114	29,779	28,945	28,977	28,943	28,940	28,925
$e_{\max}(t)$							
3 months	29,474	30,071	29,453	29,457	29,446	29,435	29,425
2 months	29,665	30,255	29,643	29,647	29,636	29,624	29,615
1 month	29,848	30,436	29,825	29,830	29,818	29,807	29,797
14 days	29,936	30,526	29,914	29,919	29,907	29,895	29,886
7 days	29,971	30,562	29,949	29,953	29,942	29,930	29,921

Table 4
Coefficients of the ARMA(2,2) models fitted for the maximum and minimum temperature series.

Ahead	AR coefficients		MA coefficients		σ^2
	φ_1	φ_2	θ_1	θ_2	
$e_{\min}(t)$					
3 months	0.455 ± 0.057	0.074 ± 0.043	−0.635 ± 0.055	−0.362 ± 0.055	13.8
2 months	0.552 ± 0.060	0.006 ± 0.043	−0.728 ± 0.059	−0.270 ± 0.059	13.7
1 month	0.458 ± 0.056	0.072 ± 0.042	−0.636 ± 0.054	−0.361 ± 0.054	13.7
14 days	0.463 ± 0.056	0.068 ± 0.042	−0.641 ± 0.054	−0.356 ± 0.054	13.7
7 days	0.453 ± 0.056	0.076 ± 0.042	−0.631 ± 0.053	−0.366 ± 0.053	13.7
$e_{\max}(t)$					
3 months	1.309 ± 0.130	−0.372 ± 0.089	−0.630 ± 0.130	−0.16 ± 0.022	16.5
2 months	1.259 ± 0.131	−0.338 ± 0.088	−0.581 ± 0.130	−0.163 ± 0.021	16.5
1 month	1.262 ± 0.131	−0.340 ± 0.088	−0.585 ± 0.130	−0.162 ± 0.021	16.5
14 days	0.295 ± 0.122	0.172 ± 0.080	−0.609 ± 0.121	−0.389 ± 0.121	16.6
7 days	0.296 ± 0.119	0.172 ± 0.078	−0.609 ± 0.118	−0.388 ± 0.118	16.6

Table 5
Prediction errors in days for heat unit requirements to start of harvest. 1988 season.

	HUDATE	HUDATE–FDATE				
		3 months	2 months	1 month	14 days	7 days
Berkeley	29 July	0	1	1	1	1
Bluecrop	25 July	2	4	4	2	2
Bluejay	26 July	4	3	3	1	1
Blueray	27 July	2	1	2	1	1
Bluetta	6 July	4	2	2	1	1
Collins	14 July	5	3	1	1	0
Coville	3 August	−1	1	−1	0	−1
Earliblue	6 July	5	3	2	2	1
Elliott	6 September	11	9	4	1	0
Jersey	7 August	−1	0	0	−1	−1
Patriot	19 July	5	3	1	0	0
Rubel	1 August	1	2	1	1	−1
Spartan	14 July	5	2	1	1	0

Table 6
Heat unit and calendar day models for Temuco.

Variety	Heat-unit model						Calendar-day model		
	SDATE	T_{low} (°C)	T_{high} (°C)	HU_m	σ_{hu} (days)	R^2	HDATE	σ_{cal} (days)	σ_{hu}/σ_{cal}
Bluecrop	1 August	−6.7	21.1	2490	0.5	0.86	14 December	1.3	0.37

Table 7
Temperature regression models for Temuco.

Ahead	β_0	β_1	β_2	R_a^2
$T_{min}(t)$				
3 months	5.95 ± 0.06	2.29 ± 0.09	0.93 ± 0.09	0.17
2 months	5.95 ± 0.06	2.29 ± 0.09	0.93 ± 0.09	0.17
1 month	5.95 ± 0.06	2.29 ± 0.09	0.93 ± 0.09	0.17
14 days	5.95 ± 0.06	2.29 ± 0.09	0.93 ± 0.09	0.17
7 days	5.95 ± 0.06	2.29 ± 0.09	0.93 ± 0.09	0.17
$T_{max}(t)$				
3 months	18.79 ± 0.05	6.19 ± 0.07	2.41 ± 0.07	0.68
2 months	18.79 ± 0.05	6.19 ± 0.07	2.41 ± 0.07	0.68
1 month	18.79 ± 0.05	6.19 ± 0.07	2.41 ± 0.07	0.68
14 days	18.79 ± 0.05	6.19 ± 0.07	2.41 ± 0.07	0.68
7 days	18.79 ± 0.05	6.19 ± 0.07	2.41 ± 0.07	0.68

[a] All the coefficients are significant ($p < 0.001$).

Table 8
ARMA(p,q) models fitted to the residuals of the regression model for Temuco.

Ahead	AR coefficients			MA coefficients		σ^2
	φ_1	φ_2	φ_3	θ_1	θ_2	
$e_{min}(t)$						
3 months	0.52 ± 0.08			−0.03 ± 0.08	−0.07 ± 0.04	11.8
2 months	0.52 ± 0.08			−0.03 ± 0.08	−0.07 ± 0.04	11.8
1 month	0.52 ± 0.08			−0.03 ± 0.08	−0.07 ± 0.04	11.8
14 days	0.52 ± 0.08			−0.03 ± 0.08	−0.07 ± 0.04	11.8
7 days	0.52 ± 0.08			−0.03 ± 0.08	−0.07 ± 0.04	11.8
$e_{max}(t)$						
3 months	1.62 ± 0.02	−0.81 ± 0.03	0.17 ± 0.02	−0.89 ± 0.02		5.2
2 months	1.62 ± 0.02	−0.81 ± 0.03	0.17 ± 0.02	−0.89 ± 0.02		5.2
1 month	1.62 ± 0.02	−0.81 ± 0.03	0.17 ± 0.02	−0.89 ± 0.02		5.2
14 days	1.62 ± 0.02	−0.81 ± 0.03	0.17 ± 0.02	−0.89 ± 0.02		5.2
7 days	1.62 ± 0.02	−0.81 ± 0.03	0.17 ± 0.02	−0.89 ± 0.02		5.2

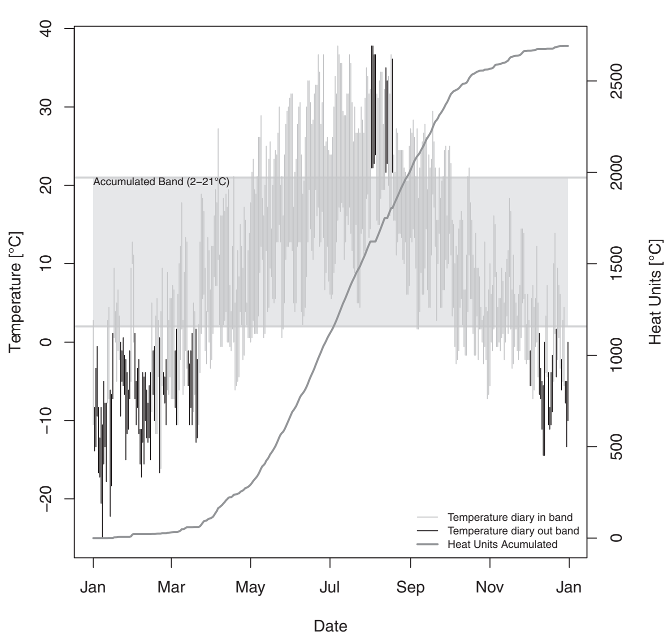

Fig. 2. Heat units and maximum and minimum temperatures for the 1988 season. The band corresponds to the heat accumulation interval between 2 and 21 °C for the variety 'Elliott'. When the daily temperatures are completely outside the band, no heat units are contributed.

Table 9
Dates when the number of heat units is reached for harvesting in Temuco.

Ahead	Error (days)
3 months	−1
2 months	0
1 month	−1
14 days	−1
7 days	−1

December, coinciding exactly with the start of harvesting. Although these results are not based on complete information, they give us a good estimate of the heat units required for the start of the harvest.

The regression model is shown in Table 7. As is indicated in the Table 7, all the coefficients are significant ($p < 0.001$). The average minimum temperature is 5.95 °C, with small oscillations during the year. The average maximum temperature is 18.79 °C, with larger oscillations than the minimum.

The ARMA(p,q) models for the residuals of the regression model are shown in Table 8. The best model for the minimum temperature residual was ARMA(1,2), and that for the maximum temperature was ARMA(3,1). The orders and coefficients of all the models are maintained. The variability of the temperature residuals was 3.4 °C for the minimum temperatures and 2.28 °C for the maximum temperatures.

Table 7 shows the prediction error for when the number of heat units will be reached. In the 2011 season, 15 December was the day when the number of heat units was reached (HUDATE), and the harvest started on 17 December. The errors in the prediction of HUDATE were less than 1 day late in all the predictions (Table 9). This accuracy is an indication of how useful the models are.

4. Discussion and conclusions

All the harvest start dates coincide with the range reported by Carlson and Hancock (1991) for the calendar day model. However, the harvest date for the variety 'Elliott' is outside the range by 2 days.

Three months ahead, the errors are similar to those of the calendar day model and are therefore of little use to the producer. However, the errors diminish as the harvest date approaches and are smaller than in the calendar day model. In particular, the errors at 14 days more or less satisfy the criterion established by Mainland (2000) for harvest planning.

The harvest date depends on the flowering date (Mainland, 2000; Suzuki and Kawata, 2001), and the annual variability of the latter affects the prediction of the harvest start date using calendar methods. With the heat unit model, this effect is isolated and variability is thus reduced. The predictions based on this work consider the whole history of heat units from the winter recess through the flowering and fruit development stages to the harvest.

With the use of weather forecasts from 2 weeks ahead, the prediction of the harvest start date can be further improved. With models calculated by location, the producer can obtain the estimated harvest date sufficiently far in advance and with a small error in the number of days.

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