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Models for Estimating the Cold Hardiness of Sweet Cherry (*Prunus avium* cv. Sweetheart and Lapins) in Cold Climate Regions

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***Abstract.* Plant cold hardiness is a dynamic process, and seasonal changes occur through cold acclimation and deacclimation to help prevent lethal injury from the cold. Cold weather injury resulting from inadequate plant cold hardiness can result in significant economic losses to growers of perennial crops in temperate climates. The objective of the current study was to develop models that estimate the lethal temperature that causes 10%, 50%, and 90% mortality (LT10, LT50, LT90) to two cultivars of sweet cherry (*Prunus avium*) flower buds from the early fall through to spring. We parameterized regression models using lethal temperature data collected in the Okanagan Valley, British Columbia, Canada, over six seasons (2013–17, 2019–20, 2021–22) for 'Sweetheart' sweet cherry and three seasons (2013–15, 2016–17) for 'Lapins' sweet cherry. These models incorporate parameters that are based on equations that describe chill and heat accumulation that rely on measures of hourly air temperature. Model evaluation and validation using several seasons of lethal temperature data not included in model development were completed. Models for estimating the cold hardiness of sweet cherry showed good agreement between model lethal temperature predictions and observed values for both sweet cherry cultivars. In addition, an open-access, interactive, web-based application was developed to access the outputs of these models in real time for use by growers, researchers, and extension workers. These current models of sweet cherry cold hardiness have potential application for use as a decision support tool for cold damage management as well as crop site suitability modeling.**

Sweet cherry (*Prunus avium*) trees are adapted to temperate climates that experience winters with sufficiently cold temperatures to satisfy plant chilling requirements and sufficiently warm summers to support fruit development (Fadón et al. 2020). As such, these perennial plants must experience cool enough winter temperatures to produce fruit in the following year (Wenden et al. 2017). To survive these cold temperatures, sweet cherry trees undergo seasonal changes in cold hardiness through cold acclimation and deacclimation processes that help protect vulnerable plant tissues from irreversible cold damage (Wisniewski et al. 2003). Although cold temperatures are necessary during winter, cherry trees are still susceptible to cold damage and become increasingly susceptible in spring. Cold damage resulting from inadequate plant cold hardiness can greatly reduce fruit yield and quality in temperate climates and result in agricultural economic losses (Rugienius et al. 2016). Cold damage is a common problem for commercial cherry growers in the Pacific Northwest, including growers in the Okanagan Valley of the southern interior of British Columbia (BC), Canada, a region that accounts for ~84% of Canada's sweet cherry production (Agriculture and Agri-Food Canada 2021; BC Ministry of Agriculture, Food, and Fisheries 2020).

Processes related to cold acclimation and deacclimation are largely driven by temperature and photoperiod (Kalberer et al. 2006). The reliance of these processes on ambient temperatures makes them susceptible to climate change. Rising temperatures in temperate regions may advance the onset of spring and alter the timing of processes like budburst and flowering, promoting cold hardiness deacclimation, and delay autumn senescence and cold acclimation (Gill et al. 2015; Richardson et al. 2013). Furthermore, increases in the frequency and magnitude of extreme temperature events, such as late spring frosts or winter cold snaps (Semenov 2012), may also increase the risk of cold damage of sweet cherry (Vitasse et al. 2014).

Because of potential impacts of cold damage on crop yield and quality, it is important that growers can anticipate the susceptibility of cherry crops to freezing temperatures so that informed decisions about costly cold damage mitigation measures, such as the use of wind machines (fans) or helicopters, can be efficiently implemented (Blanke et al. 2017; Kappel 2010). To this end, differential thermal analysis (DTA) is a method commonly used to measure the cold hardiness of dormant flower buds in *Prunus* species that supercool, including sweet cherry (Liu et al. 2019; Quamme 1978; Salazar-Gutiérrez et al. 2014). This method involves placing flower buds on thermoelectric modules (TEM) and exposing the buds to freezing temperatures. DTA determines when freezing occurs within, and around, the buds by determining the latent heat of fusion (Kaya et al. 2020). DTA can distinguish low temperature exotherms (LTE), which are assumed to correspond to the temperature at which the supercooled water in the bud crystallizes and the buds become critically injured through freezing. These LTE measures can provide estimates of the temperatures that would cause lethal cold damage in the field. Conducting cold hardiness measurements via DTA is both time-consuming and costly. Furthermore, cherry growers typically do not have access to the equipment required to determine bud hardiness, making DTA a nonviable tool in practice.

Although practical considerations limit the viability of DTA, model simulations of cold hardiness can be used to estimate plant cold susceptibility for long-term analysis. However, it is often difficult to obtain sufficiently frequent, long-term, cold hardiness datasets to develop such models (Kimura et al. 2021). Cold hardiness monitoring is typically done by those working in extension; however, there are limitations to the frequency of measurements and the geographic ranges that can be sampled by these workers. Cold hardiness has been modeled in several plants including grapevine buds (*Vitis vinifera* and *Vitis labruscana*) (Ferguson et al. 2011, 2014; Kovaleski et al. 2023), tea buds (*Camellia sinensis*) (Kimura et al. 2021), Scots pine (*Pinus sylvestris*) (Leinonen 1996), wheat (*Triticum aestivum*), and rye (*Secale cereale*) (Bergjord et al. 2008; Fowler et al. 1996), and a wide range of cereal species and genotypes (Byrns et al. 2020). Recently, simplified cold hardiness models were developed for the sweet cherry cultivars Bing, Chelan, and Sweetheart in Washington, USA (Salazar-Gutiérrez and Chaves-Cordoba 2020). To the authors' knowledge, no models or associated cold hardiness decision support tools for sweet cherry have been published for Canada, to date.

The present study's objective is to build models that can be used to estimate the cold hardiness of sweet cherry flower buds for the cultivars Sweetheart and Lapins in cold climate regions, focusing on the Okanagan Valley located in the southern interior of BC, Canada. Within the Okanagan Valley, Sweetheart and Lapins are among the top three cherry cultivars grown, in order of acres covered, making them varieties of interest for local growers (BC Ministry of Agriculture, Food, and Fisheries 2020). These models will help cherry growers better understand the susceptibility of their crops to cold damage throughout the fall to spring season and can be used to assist with cold damage management decision-making. Furthermore, developing these models may improve our ability to model changes in regional suitability for crop establishment under future scenarios of climate change (Neilsen et al. 2017).

Materials and Methods

Data acquisition

To develop and validate these models, flower bud lethal temperature (LT) was measured over seven seasons for the cultivar Sweetheart (2013–17, 2019–22) and four seasons for the cultivar Lapins (2013–17) grown at midelevation sites in Summerland, BC (located in the Okanagan Valley). 'Sweetheart' LT was also measured for one season at a high elevation site near Summerland, BC (2020–21) and one season at a low elevation site in Summerland, BC (2021–22). In addition, the LT of the cultivars Staccato, Sonata, and Skeena (2015–16) grown at midelevation in Summerland, BC, was measured for cultivar comparisons. Staccato is the most grown cultivar in the Okanagan Valley, and Skeena is the fifth most common cultivar, by acre (BC Ministry of Agriculture, Food, and Fisheries 2020). 'Staccato' and 'Sonata' have similar midseason bloom times to 'Sweetheart', and 'Skeena' has similar early season bloom times to 'Lapins' (Quero-García et al. 2017).

Plant material. To collect plant material for cold hardiness measurements, flower bud spurs were randomly selected from trees at Agriculture and Agri-Food Canada's Summerland Research and Development Center (AAFC SuRDC, 49°34′ N/119°39′ W, 420 m a.s.l.) in years ranging from 2013 to 2017 and from commercial orchards (high elevation: 49°42′ N/119°48′ W, 755 m a.s.l., midelevation: 49°37′ N/119°42′ W, 510 m a.s.l., low elevation: 49°38′ N/119°40′ W, 415 m a.s.l.) in or near Summerland, BC from 2020 to 2022. Buds were collected during the dormant season until about budbreak in the spring of most years and to bud bloom in 2015–17 and 2020–21. Bud spurs were placed in a sealed plastic bag with a moist paper towel and immediately transported to AAFC SuRDC on ice in a cooler to conduct cold hardiness measurements.

Flower bud LT: DTA. Flower bud cold hardiness was measured using DTA in the fall and winter months following modified methods by Mills et al. (2006). The LT of 48 to 54 individual flower buds excised from the bud spur was measured by placing them on TEM plates in a Tenney Freezer Unit programmable freezer (Thermal Product Solutions, New Columbia, PA, USA) held at an initial temperature of 3 °C. Buds were subjected to cooling temperatures at a rate of −4 °C/h for 9 h until −36 °C was reached. The peak identification software Bud Processor (v.1.8.0, Brock University, St. Catherines, ON, CA) was then used to identify the temperature at which the LTEs occurred, which were assumed to be the buds' LT.

Flower bud LT: Controlled freezing test. It has been observed that DTA is unreliable during flower bud deacclimation in the spring (Andrews et al. 1983; Kaya et al. 2018, 2020; Quamme et al. 1995). Therefore, controlled freezing tests were used instead of DTA for LT measurements in the spring following modified methods from Salazar-Gutiérrez et al. (2014). Subsamples of 10 excised flower buds in sealed plastic bags were placed in a Tenney Unit programmable freezer initially cooled to 1 °C, and the temperature was lowered by 1 °C every 15 min (−4 °C/h). To provide an internal bud reference temperature, a thermocouple was inserted into one reference bud and placed in the freezer. One bag of 10 buds was removed once the reference bud had reached each target temperature. Target temperatures were selected based on the most recent LT measurement, with the aim of selecting a range of temperatures that would result in buds experiencing 0% to 100% mortality. Flower buds were refrigerated overnight and then held at room temperature for at least 2 h the following day before they were cut open to visually assess cold damage, as indicated by browning tissue.

In-field bud damage. To support model validation, in-field flower bud damage was evaluated for all sample locations measured from 2020 to 2022 following days when recorded daily temperatures approached or fell below the measured LT value for the cultivar Sweetheart. To determine damage, a subsample of 40 to 120 flower buds was assessed by cutting them open and recording the number of individual primordia that were damaged per bud, as indicated by browning tissue. The proportion of bud damage was determined by dividing the number of browned primordia by the total number of primordia in the measured sample of buds.

Weather data. Weather data used in this study for plant material collected from AAFC SuRDC were obtained from the Government of Canada's online historical weather and climate database (Government of Canada 2023) (https://climate.weather.gc.ca). Hourly records of air temperature from the nearest weather station to the collected flower buds, located at AAFC SuRDC (Summerland CS, 49°33′ 45.2″ N/119°38′ 55.3″ W, 454 m a.s.l) were used. For plant material collected from the high, mid-, and low elevation commercial orchards in Summerland, BC, an HOBO® data logger (Onset®, Bourne, MA, USA), installed in each orchard at a height of ∼1.3 m above the ground, was used to record hourly air temperatures.

Statistical procedure

All statistical analyses were performed using RStudio (v1.3.1093; R Core Team 2020) and the following packages: nlme (v3.1–149; Pinheiro et al. 2020), MuMIn (v1.43.17; Bartoń 2020), and hydroGOF (v0.4–0; Zambrano-Bigiarini 2020).

When cold hardiness was measured using DTA, the 90th percentile, median, and 10th percentile of the identified LTEs were calculated and assumed to correspond to the LT that damaged 10%, 50%, and 90% of the buds (LT10, LT50, LT90), respectively. Sampling dates that had fewer than 10 identified LTEs were omitted. Usually, about one LTE per bud was observed when conducting DTA. However, during periods when buds were acclimating in the fall, or as they started to deacclimate in the spring, it was not uncommon for less than one LTE per bud to be detected. When LT was measured using controlled freezing tests, logistic regression was completed; the proportion of new bud damage was assumed to be binomially distributed and was modeled using a logit link (Eq. [1]; Zuur et al. 2009) with a generalized linear model (GLM) as recommended in Zuur et al. (2009). The parameter estimates from these models were used to calculate the LT10, LT50, and LT90 values for each sampling date (assumed to be at a probability of 0.1, 0.5, and 0.9, respectively).

$$\text{Bud Damage} \sim \text{Binomial}\ (1,\ \pi_i)$$

$$\text{with } \pi_i = \frac{e^{\beta_0+\beta_1\times\text{Temperature}}}{1+\ e^{\beta_0+\beta_1\times\text{Temperature}}} \quad [1]$$

The correlation between the measured LT values and daily mean temperature, up to

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1 week prior, was calculated to determine which temperature lags were most strongly correlated with the measured LT values. Daily mean temperatures were used to help make these models more robust to potential temperature measurement errors.

Chill and heat requirements must be met to release buds from endodormancy and ecodormancy, respectively, and to initiate flowering in the spring (Fadón et al. 2020; Lang et al. 1987). Endodormancy refers to a period where the signal inducing the dormant state comes from within the affected structure. In contrast, ecodormancy refers to a period when growth is limited by environmental conditions, such as temperature or water deficits (Lang 1987). The developmental and physiological changes that occur during the transition from endodormancy, ecodormancy, and through to growth resumption can help explain changes in flower bud LT (Hillmann et al. 2021) and as such, equations for chill and heat accumulation were included as potential parameters for these LT models. Chill unit (CU) and heat accumulation, here referred to as forcing unit (FU), were calculated using the 'Sweetheart'-specific chilling and forcing equations developed by Neilsen et al. (2015) for the Okanagan Valley, BC, Canada, from hourly air temperatures (Eqs. [2] and [3]). CU accumulation began in the fall when the accumulated CU reached a minimum value, indicating chill inception. CU requirements were considered to be met when they reached the value of 1119, as determined for 'Sweetheart' by Neilsen et al. (2015), and subsequent values of CU were assigned to a value of 1119 for model fitting. FU accumulation began after these CU requirements were met. The coefficients for budbreak presented in Neilsen et al. (2015) were used to calculate FU (Eq. [3]) and FU calculated at temperatures below 5 °C were nullified. Furthermore, any FUs that were accumulated before CU accumulation reached a value of 2000 were nullified (although all CU values above 1119 were assigned a value of 1119 for model development). This was done because weaknesses in the models' ability to predict LT were identified in preliminary modeling; we found that LT predictions made on seasons with periods of winter warm spells that resulted in early FU accumulation tended to deacclimate at a rate faster than measured LTs. Nullifying FU accumulated below a value of 2000 CU was chosen to improve model predictions; in the LT data used to develop the 'Sweetheart' and 'Lapins' models, it was observed that rapid deacclimation typically occurred after 2000 CU had accumulated.

$$\text{If } -2 \geq x < 16 \ \ CU = 1 - \frac{46.80e^{\left(-e^{\left(-\frac{x-9.83}{2.14}\right)}\right)}}{42.81} \quad [2]$$

$$\text{If } x < -2,\ CU = 0;\ \text{if } 16 < x < 18,$$
$$CU = -0.5;\ \text{if } x > 18,\ CU = -1$$

$$FU = \frac{1.5}{1 + e^{\left(-\frac{x-22.8}{5.7}\right)}} \quad [3]$$

Where x is the hourly air temperature (°C).

Because hourly ambient temperature data were used to calculate CU and FU, the value accumulated by 12:00 PM on each date was assigned as the accumulated CU and FU, to bring these calculations to a daily resolution.

Model selection and calibration

The observed LTs (LT10, LT50, LT90) were consolidated from September 15 to April 30 of each season and were used to build a model for each LT and cultivar. Six seasons of LT data were used to develop separate LT10, LT50, and LT90 models for 'Sweetheart' [four seasons of data collected from AAFC SuRDC (2013–17) and two seasons collected from the midelevation orchard in Summerland, BC (2019–20, 2021–22)]. Three seasons of LT data were used to develop separate LT10, LT50, and LT90 models for 'Lapins' [all data collected from AAFC SuRDC (2013–15, 2016–17)].

Model development was separated into two stages for each cultivar and LT (10%, 50%, 90%). Unique models were developed to estimate cold hardiness when the accumulated FUs were less than 30 (t1) or greater than or equal to 30 (t2) for 'Sweetheart' and when accumulated FUs were less than 25 (t1) or greater than or equal to 25 (t2) for 'Lapins'. These values were chosen based on when rapid deacclimation was generally observed to begin in the LT datasets used for model development. A lower value for FU accumulation was used to split the models into t1 and t2 for 'Lapins', as this cultivar was observed to begin deacclimating earlier than 'Sweetheart', likely as a result of the fact 'Lapins' has an earlier bloom time than 'Sweetheart' (Quero-García et al. 2017).

The predictor variables used for the LTs during t1 included daily mean air temperature from 1 (lag1), 2 (lag2), and 3 (lag3) days prior, accumulated CU and log transformed accumulated FU. The inclusion of photoperiod as a model parameter was explored, as it is a factor that can influence cold tolerance (Maibam et al. 2013). However, we aimed to develop models independent of parameters tied to dates and therefore decided to omit photoperiod as a potential model parameter.

The predictor variables for t2 LTs included accumulated FU and bud stage, as described by the BBCH scale (Fadón et al. 2015). Bud stages were assigned as follows: side green (BBCH 52), green tip (BBCH 53), tight cluster (BBCH 55), open cluster (BBCH 56), first white (BBCH 57), first bloom (BBCH 60), and full bloom (BBCH 65). For the t2 period for 'Sweetheart' and 'Lapins', only 14 and 8 measurements of cold hardiness were taken, respectively, across years on bud that ranged in stages from side green to first white.

The initial full models including all predictor variables were fitted using generalized least squares technique and maximum likelihood. The information theoretic approach (Burnham et al. 2011), using Akaike's information criterion corrected for small sample sizes (AICc), was then used to identify the parameters that improved model fit and best explained the observed LT values. Model parameters for the top models were then estimated using restricted maximum likelihood.

Model evaluation

The best fit models for t1 and t2 for each LT and cultivar were evaluated by the root mean square error (RMSE) (Janssen and Heuberger 1995) and the index of agreement (d) (Willmott 1981; Yang et al. 2014) using the 'd' function in the hydroGOF package (Zambrano-Bigiarini 2020). In addition, one-to-one regressions of the models' predicted values and the observed values were completed on the combined t1 and t2 predictions and the predicted and observed values were compared for each season of data used in

Table 1. R^2 values of linear regression between the measured lethal temperature (LT) values and daily mean ambient air temperature up to 1 week prior for 'Sweetheart' and 'Lapins' during the t1 and t2 period. LT10, LT50, LT90 = lethal temperature that causes 10%, 50%, and 90% mortality.

	'Sweetheart' R^2			'Lapins' R^2		
Variable	LT10	LT50	LT90	LT10	LT50	LT90
t1 Mean ambient air temperature						
No lag	0.58	0.61	0.61	0.65	0.72	0.71
Lag 1	0.65	0.68	0.69	0.68	0.76	0.77
Lag 2	0.61	0.66	0.65	0.68	0.77	0.76
Lag 3	0.65	0.69	0.68	0.58	0.66	0.68
Lag 4	0.61	0.64	0.64	0.55	0.62	0.63
Lag 5	0.56	0.58	0.61	0.51	0.57	0.58
Lag 6	0.57	0.57	0.58	0.54	0.56	0.56
Lag 7	0.49	0.50	0.51	0.51	0.54	0.54
t2 Mean ambient air temperature						
No lag	0.00	0.02	0.03	0.07	0.01	0.08
Lag 1	0.02	0.00	0.02	0.02	0.04	0.13
Lag 2	0.04	0.14	0.13	0.29	0.04	0.00
Lag 3	0.01	0.12	0.14	0.07	0.01	0.00
Lag 4	0.00	0.01	0.02	0.20	0.02	0.01
Lag 5	0.07	0.00	0.01	0.01	0.02	0.07
Lag 6	0.01	0.01	0.02	0.08[i]	0.03[i]	0.00[i]
Lag 7	0.23	0.08	0.01	0.07	0.16	0.17

Note: All regression P values for t1 were <0.001 and t2 were <0.05 with the exception of values denoted with [i] indicating P values were above 0.05.

Table 2. Akaike's information criterion corrected for small sample sizes (AICc)-based model selection of generalized least squares models fitted using maximum likelihood for 'Sweetheart' and 'Lapins' lethal temperature that causes 10%, 50%, and 90% mortality (LT10, LT50, and LT90) during t1 and t2. The top two models or all models within ΔAICc of two are shown. The initial, full models for t1 were fitted with the fixed effects of daily mean air temperature from 1 (Temp.lag1), 2 (Temp.lag2), and 3 d prior (Temp.lag3), accumulated chill units (CU) and log transformed accumulated forcing units (logFU). The initial, full models for t2 were fitted with the spring flower bud developmental stage (Bud stage) and accumulated forcing units (FU).

Response	Top models' fixed effects	AICc	ΔAICc
'Sweetheart' t1			
LT10	1. Intercept + Temp.lag1 + Temp.lag3 + CU + logFU	471.9	0.00
	2. Intercept + Temp.lag1 + Temp.lag2 + Temp.lag3 + CU + logFU	472.6	0.68
LT50	1. Intercept + Temp.lag1 + Temp.lag3 + CU + logFU	430.5	0.00
	2. Intercept + Temp.lag1 + Temp.lag2 + Temp.lag3 + CU + logFU	432.7	2.24
LT90	1. Intercept + Temp.lag1 + Temp.lag3 + CU + logFU	438.9	0.00
	2. Intercept + Temp.lag1 + Temp.lag2 + Temp.lag3 + CU + logFU	440.4	1.47
'Sweetheart' t2			
LT10	1. Intercept	41.28	0.00
	2. Intercept + Bud stage	44.37	3.09
LT50	1. Intercept	42.20	0.00
	2. Intercept + FU	44.46	2.26
LT90	1. Intercept	54.51	0.00
	2. Intercept + FU	56.27	1.76
'Lapins' t1			
LT10	1. Intercept + Temp.lag1 + CU + logFU	308.6	0.00
	2. Intercept + Temp.lag1 + Temp.lag2 + CU + logFU	310.6	2.01
LT50	1. Intercept + Temp.lag1 + CU + logFU	287.8	0.00
	2. Intercept + Temp.lag1 + Temp.lag2 + CU + logFU	288.2	0.36
	3. Intercept + Temp.lag1 + Temp.lag2 + Temp.lag3 + CU + logFU	289.6	1.71
LT90	1. Intercept + Temp.lag1 + CU + logFU	294.9	0.00
	2. Intercept + Temp.lag1 + Temp.lag2 + CU + logFU	296.1	1.26
	3. Intercept + Temp.lag1 + Temp.lag3 + CU + logFU	296.7	1.87
'Lapins' t2			
LT10	1. Intercept	25.4	0.00
	2. Intercept + FU	30.6	5.28
LT50	1. Intercept	26.9	0.00
	2. Intercept + Bud stage	32.1	5.17
LT90	1. Intercept	32.4	0.00
	2. Intercept + FU	36.6	4.25

model development. These further evaluation methods were required as AICc does not provide information on model validity but rather a relative ranking for a pool of candidate models (Burnham and Anderson 2004).

Model validation

To validate the final models, LT predictions were made and compared with measured LT from additional data not included in model development. The RMSE and d were calculated. In addition, one-to-one regression of the models' predicted values against the observed values was conducted and the predicted and observed values were compared for each season of validation data. Validation data included 'Sweetheart' LT data collected from a low elevation site (2021–22), midelevation site (2020–21), and high elevation site (2020–21) and 'Lapins' LT data collected from an orchard at AAFC SuRDC (2014–15). The 'Sweetheart' models were also validated by comparing estimated damage (assumed to occur when the minimum daily temperature fell below LT estimates) to in-field measures of bud damage. In addition, model predictions were compared with LT data collected for the cultivars Staccato (2015–16), Sonata (2015–16), and Skeena (2015–16).

Results

Model description. A significant, strong correlation between LT10, LT50, and LT90 and mean daily ambient temperatures from 1 to 7 d prior was observed during the t1 period (Table 1). The highest R^2 values were observed 1 to 3 d prior (lag 1, lag 2, and lag 3) during the t1 period. Because of this strong correlation, parameters for the mean daily air temperature with lag 1, lag 2, and lag 3 were included in the initial full models for t1 model selection. The correlation between LT10, LT50, and LT90 and mean daily ambient temperature was weak during the t2 period

Table 3. Estimated parameters coefficients, 95% confidence limits in brackets, and P values for final, top 'Sweetheart' and 'Lapins' lethal temperature that causes 10%, 50%, and 90% mortality (LT10, LT50, and LT90) models fitted using restricted maximum likelihood for t1 and t2.

Coefficient	LT10 Estimate	P value	LT50 Estimate	P value	LT90 Estimate	P value
'Sweetheart' t1						
$\hat{\beta}_{S0}$	−18.2 [−20.6, −15.8]	<0.0001	−17.7 [−19.7, −15.6]	<0.0001	−18.1 [−20.2, −16.0]	<0.0001
$\hat{\beta}_{S1}$	0.18 [0.083, 0.27]	0.0003	0.15 [0.077, 0.24]	0.0002	0.16 [0.078, 0.25]	0.0002
$\hat{\beta}_{S2}$	0.11 [0.025, 0.20]	0.0127	0.11 [0.035, 0.18]	0.0047	0.099 [0.023, 0.18]	0.0121
$\hat{\beta}_{S3}$	−0.006 [−0.007, −0.005]	<0.0001	−0.006 [−0.007, −0.005]	<0.0001	−0.006 [−0.007, −0.005]	<0.0001
$\hat{\beta}_{S4}$	4.5 [3.5, 5.5]	<0.0001	3.3 [2.5, 4.2]	<0.0001	2.5 [1.6, 3.4]	<0.0001
'Sweetheart' t2						
$\hat{\beta}_{S0.2}$	−4.3 [−4.8, −3.8]	<0.0001	−5.8 [−6.3, −5.3]	<0.0001	−7.4 [−8.1, −6.6]	<0.0001
'Lapins' t1						
$\hat{\beta}_{L0}$	−15.9 [−20.7, −11.1]	<0.0001	−19.9 [−24.0, −15.7]	<0.0001	−21.2 [−25.5, −16.8]	<0.0001
$\hat{\beta}_{L1}$	0.28 [0.15, 0.42]	<0.0001	0.34 [0.23, 0.45]	<0.0001	0.38 [0.26, 0.50]	<0.0001
$\hat{\beta}_{L2}$	−0.006 [−0.008, −0.004]	<0.0001	−0.006 [−0.008, −0.005]	<0.0001	−0.006 [−0.008, −0.004]	<0.0001
$\hat{\beta}_{L3}$	3.3 [1.1, 5.5]	0.0045	3.9 [2.0, 5.8]	0.0001	3.2 [1.2, 5.2]	0.0028
'Lapins' t2						
$\hat{\beta}_{L0.2}$	−4.1 [−4.7, −3.5]	<0.0001	−5.2 [−5.8, −4.5]	<0.0001	−6.3 [−7.2, −5.4]	<0.0001

Table 4. Root mean square error (RMSE) and index of agreement (d) for final t1 and combined results from t1 and t2 models for 'Sweetheart' and 'Lapins' lethal temperature that causes 10%, 50%, and 90% mortality (LT10, LT50, and LT90) predictions. Data used for 'Sweetheart' model prediction evaluations were i) six seasons of LT data used for model development and ii) three seasons of LT data collected from a high elevation, midelevation, and low elevation orchard in Summerland, BC, used for model validation. Data used for 'Lapins' model prediction evaluations were i) three seasons of LT data used for model development and ii) one season of LT data used for model validation. RMSE and d were not calculated for t2 independently, as these models were intercept-only models.

			t1			t1 & t2		
Cultivar	Data used for model evaluation	Parameter	LT10	LT50	LT90	LT10	LT50	LT90
Sweetheart	Model development	RMSE	1.48	1.25	1.30	1.43	1.22	1.31
		d	0.96	0.97	0.97	0.97	0.98	0.98
	Model validation	RMSE	1.47	1.78	2.19	1.42	1.63	1.99
		d	0.93	0.89	0.84	0.97	0.97	0.96
Lapins	Model development	RMSE	1.97	1.70	1.79	1.88	1.64	1.74
		d	0.93	0.96	0.96	0.95	0.97	0.97
	Model validation	RMSE	1.35	1.44	1.61	1.29	1.51	1.95
		d	0.96	0.97	0.96	0.98	0.97	0.96

(Table 1) and as such, mean temperature was omitted from the initial full models for t2.

Final model parameters were selected by ranking the initial full models using AICc to identify parameters that improved model fit. All final models were the top models as ranked by AICc values (Table 2). The equation for the final best fit models for 'Sweetheart' and 'Lapins' t1 and t2 LT10, LT50, and LT90 were expressed as follows (Eqs. [4] to [7]):

$$LT_{Sweetheart.t1} = \hat{\beta}_{S0} + \hat{\beta}_{S1}T_{lag1} + \hat{\beta}_{S2}T_{lag3} + \hat{\beta}_{S3}CU + \hat{\beta}_{S4}logFU + \varepsilon_S \quad [4]$$

$$LT_{Sweetheart.t2} = \hat{\beta}_{S0.2} + \varepsilon_{S.2} \quad [5]$$

$$LT_{Lapins.t1} = \hat{\beta}_{L0} + \hat{\beta}_{L1}T_{lag1} + \hat{\beta}_{L2}CU + \hat{\beta}_{L3}logFU + \varepsilon_L \quad [6]$$

$$LT_{Lapins.t2} = \hat{\beta}_{L0.2} + \varepsilon_{L.2} \quad [7]$$

where $LT_{Sweetheart.t1}$ and $LT_{Lapins.t1}$ represent the lethal temperature of maximum injury at LT10, LT50, and LT90 for 'Sweetheart' and 'Lapins' at t1, respectively, and $LT_{Sweetheart.t2}$ and $LT_{Lapins.t2}$ represent the lethal temperature of maximum injury at LT10, LT50, and LT90 for 'Sweetheart' and 'Lapins' at t2, respectively. Subscripts "S" and "L" denote coefficients for 'Sweetheart' and 'Lapins' models, respectively. $\hat{\beta}_{S0}$ and $\hat{\beta}_{L0}$ are the intercepts. $\hat{\beta}_{S1}$ and $\hat{\beta}_{L1}$ are the coefficients for the first order lag mean daily air temperature (T_{lag1}). $\hat{\beta}_{S2}$ is the coefficient for the third order lag mean daily air temperature (T_{lag3}). $\hat{\beta}_{S3}$ and $\hat{\beta}_{L2}$ are the coefficients for the accumulated CUs. $\hat{\beta}_{S4}$ and $\hat{\beta}_{L3}$ are the coefficients for the log transformed accumulated FUs (logFU). ε_S and ε_L are the error terms. $\hat{\beta}_{S0.2}$ and $\hat{\beta}_{L0.2}$ represent the model intercepts at t2 and $\varepsilon_{S.2}$ and $\varepsilon_{L.2}$ represent the error terms at t2.

Model calibration. Unique models for 'Sweetheart' and 'Lapins' were developed for each period (t1 and t2) for every LT (LT10, LT50, LT90). Final 'Sweetheart' models for t1 had negative intercepts ($\hat{\beta}_{S0}$), positive coefficients of the mean daily air temperature 1 d prior ($\hat{\beta}_{S1}$) and 3 d prior ($\hat{\beta}_{S2}$), negative coefficients for the accumulated CUs ($\hat{\beta}_{S3}$), and positive coefficients for the log transformed accumulated FUs ($\hat{\beta}_{S4}$) (Table 3). The intercepts and coefficients were all significant. Final 'Lapins' models for t1 had negative intercepts ($\hat{\beta}_{L0}$), positive coefficients for the mean daily air temperature of 1 d prior ($\hat{\beta}_{L1}$), negative coefficients for the accumulated CUs ($\hat{\beta}_{L2}$), and positive coefficients for the log transformed

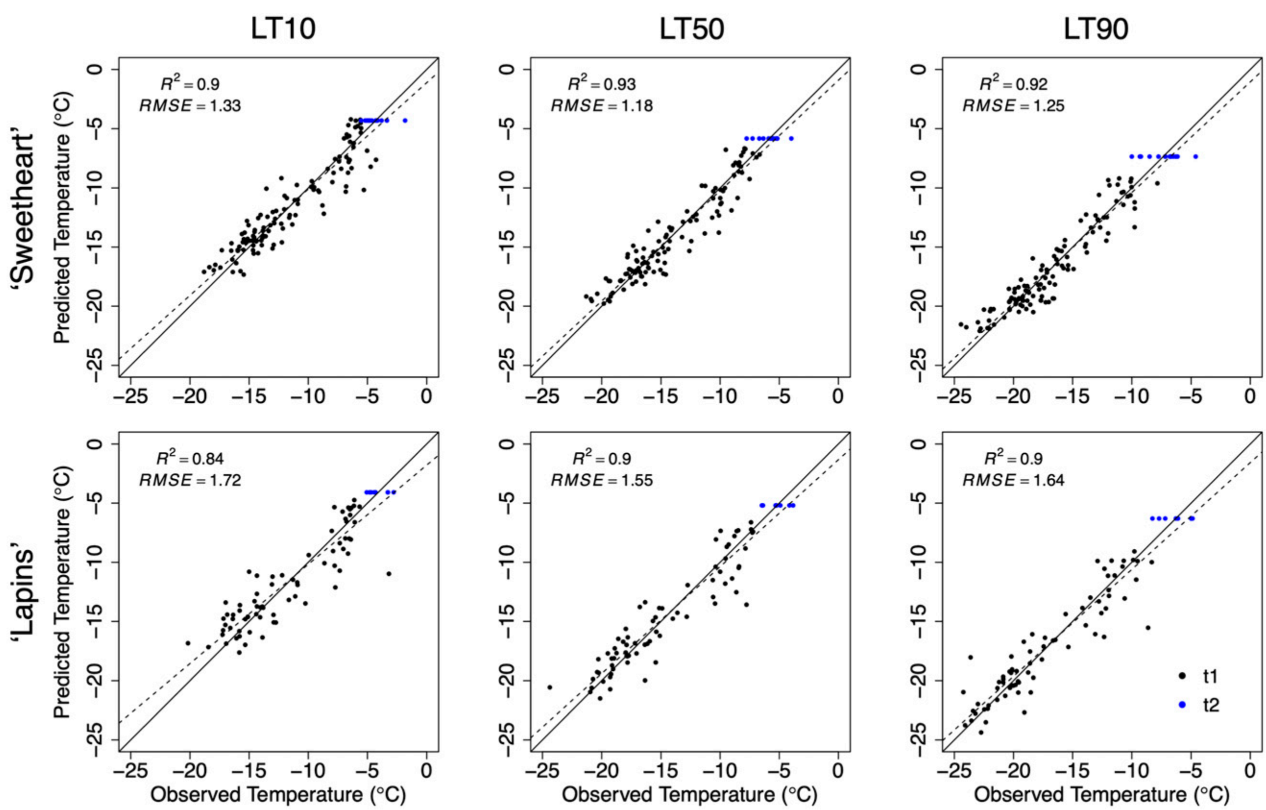

Fig. 1. One-to-one regression of all seasons predicted and observed lethal temperature that causes 10%, 50%, and 90% mortality (LT10, LT50, LT90) for 'Sweetheart' and 'Lapins' data used in model development.

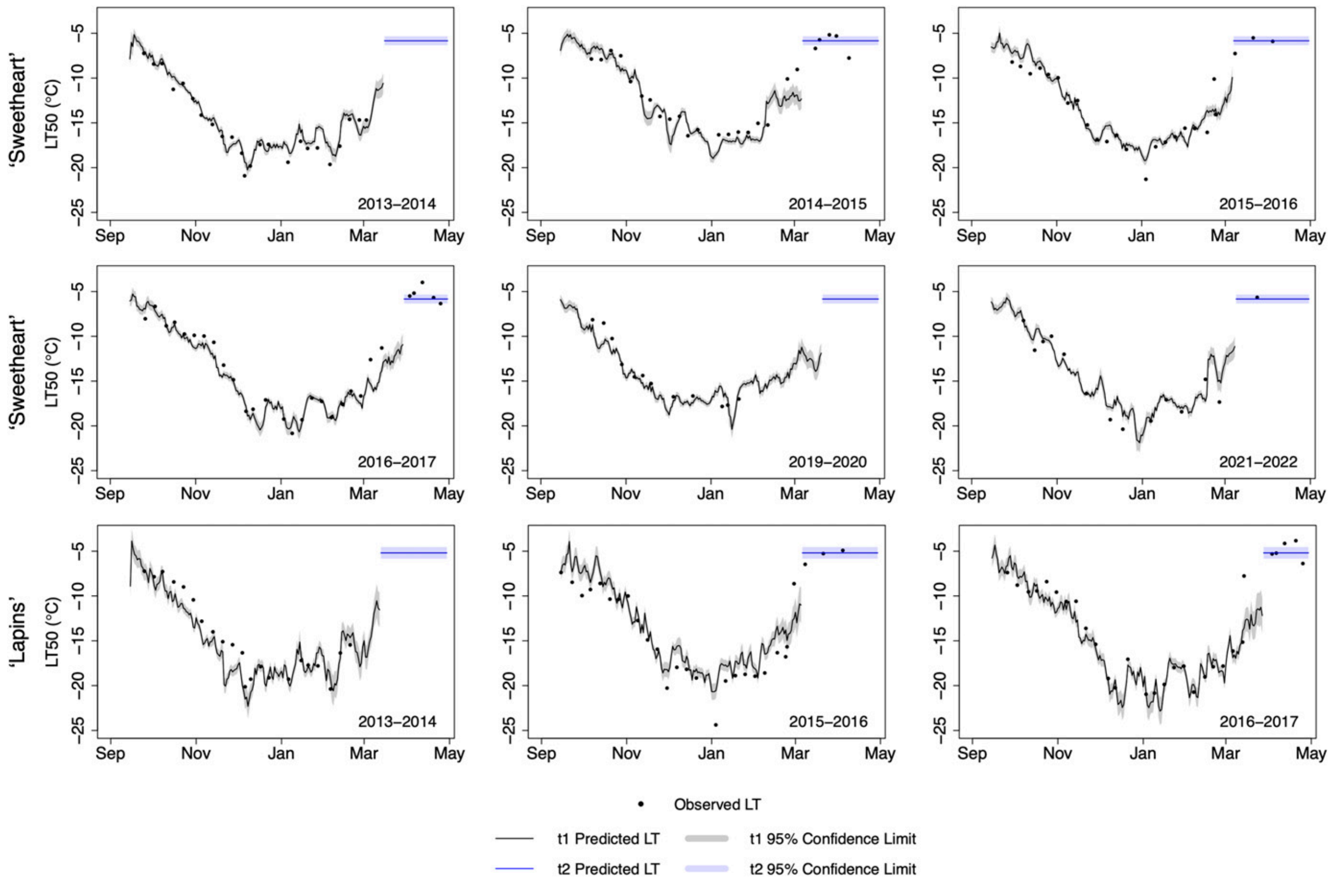

Fig. 2. Predicted lethal temperature that causes 50% mortality (LT50) values plotted against the observed LT50 values for all seasons of data used to develop the 'Sweetheart' (six seasons) and 'Lapins' (three seasons) models.

accumulated FUs ($\hat{\beta}_{L3}$) (Table 3). The intercepts and coefficients were all significant. The positive coefficient values for mean temperatures indicated acclimation occurred with negative temperatures and deacclimation occurred with positive temperatures. The negative coefficient for CU indicated that CU contributed to acclimation. CU accumulation ranged from 0 to 1119 to represent how many CUs were required to satisfy chill requirements (Neilsen et al. 2015) and CU in the days following satisfying these requirements were assigned a value of 1119. This means that once CUs were satisfied, the CU contributions to this model remained constant and the other parameters drove the changes in the models' LT predictions. Furthermore, positive coefficients for the log transformed FUs indicated their accumulation contributed to an increase in deacclimation. The top final 'Sweetheart' and 'Lapins' models for t2 included only significant negative intercepts ($\hat{\beta}_{S0.2}$ and $\hat{\beta}_{L0.2}$), which represented the average LT for these periods.

Model evaluation. For the 'Sweetheart' and 'Lapins' t1 LT10, LT50, and LT90 models, the RMSE ranged from 1.25 to 1.48 and 1.70 to 1.97, respectively, and d ranged from 0.96 to 0.97 and 0.93 to 0.96, respectively, when calculated on data included in model development. Similarly, for the combined t1 and t2 LT10, LT50, and LT90 models for 'Sweetheart' and 'Lapins', the RMSE ranged from 1.22 to 1.43 and 1.64 to 1.88, respectively, and d ranged from 0.97 to 0.98 and 0.95 to 0.97, respectively (Table 4). The average difference between the t2 intercept and the observed LT10, LT50, and LT90 values across all seasons of data used in model development were −0.0007 °C, 0.0021 °C, and 0.0029 °C for 'Sweetheart' and 0.0038 °C, 0.0013 °C, and 0.0000 °C for 'Lapins'. One-to-one regression of the combined predicted LT and the observed LT for all seasons of data used to develop these cultivar-specific models revealed very good agreement, as indicated by the high R^2 values, ranging from 0.84 to 0.93, and low RMSE values, ranging from 1.18 to 1.72 (Fig. 1). These combined statistics indicate a strong agreement between the predicted and observed values for all 'Sweetheart' and 'Lapins' LTs. This agreement is evident when the observed LT values were plotted against the predicted LT values, as displayed for LT50 (Fig. 2). The estimates for LT10 and LT90 showed similarly good results when plotted against the observed values (Supplemental Figs. 1 and 2).

Model validation. Model LT estimates were compared with three seasons of LT data not used in model development. For the t1 and t1 and t2 periods combined for the LT10, LT50, and LT90 models, the 'Sweetheart' and 'Lapins' calculated RMSE values ranged from 1.42 to 2.19 and 1.29 to 1.95, respectively; the 'Sweetheart' and 'Lapins' calculated d values ranged from 0.84 to 0.97 and 0.96 to 0.98, respectively (Table 4). One-to-one regression of the combined predicted LT and the observed LT data for the data not used in model development revealed high R^2 values, ranging from 0.88 to 0.90, and low RMSE values, ranging from 1.31 to 1.68 (Fig. 3). The 'Sweetheart' models showed good agreement between the predicted and observed LT values in the t1 and t2 periods (Fig. 4A–I). On 26 and 27 Dec 2021, at the low elevation site (2021–22), minimum daily temperatures fell below the estimated LT10 (−16 and −18 °C) by 1 to 3 °C for 9 h and 1 to 3 °C for 19 h, respectively. Temperatures also dropped below the LT50 (−18 °C) by 1 °C for 1 h on 26 Dec 2021 and the LT50 (−20 °C) by 1 °C for 4 h on 27 Dec 2021 (Fig. 4A and B). These estimates suggest that 10% to 50% in-field cold damage would be expected after this event; however, 0% damage was measured on 4 and 17 Jan 2022. On 23 Feb 2022, temperatures also fell below the LT10 (−10 °C) by 1 to 2 °C for 6 h, with 0% in-field cold damage measured on 1 Mar 2022 after this event (Fig. 4A).

At the midelevation site (2020–21) on 9 Feb 2021, minimum daily air temperatures fell below the estimated LT10 (−13 °C) by 1 to 3 °C for 5 h (Fig. 4D). On 11 Feb 2021, air temperatures dropped below the estimated LT50 (−17 °C) by 1 to 2 °C for 4 h (Fig. 4E). This suggests 10% to 50% in-field damage would occur; however, 0% damage was recorded on 10 and 22 Feb, and on 9 Mar 2021.

At the high elevation site (2020–21), a cold event occurred on 25 Oct 2020, with

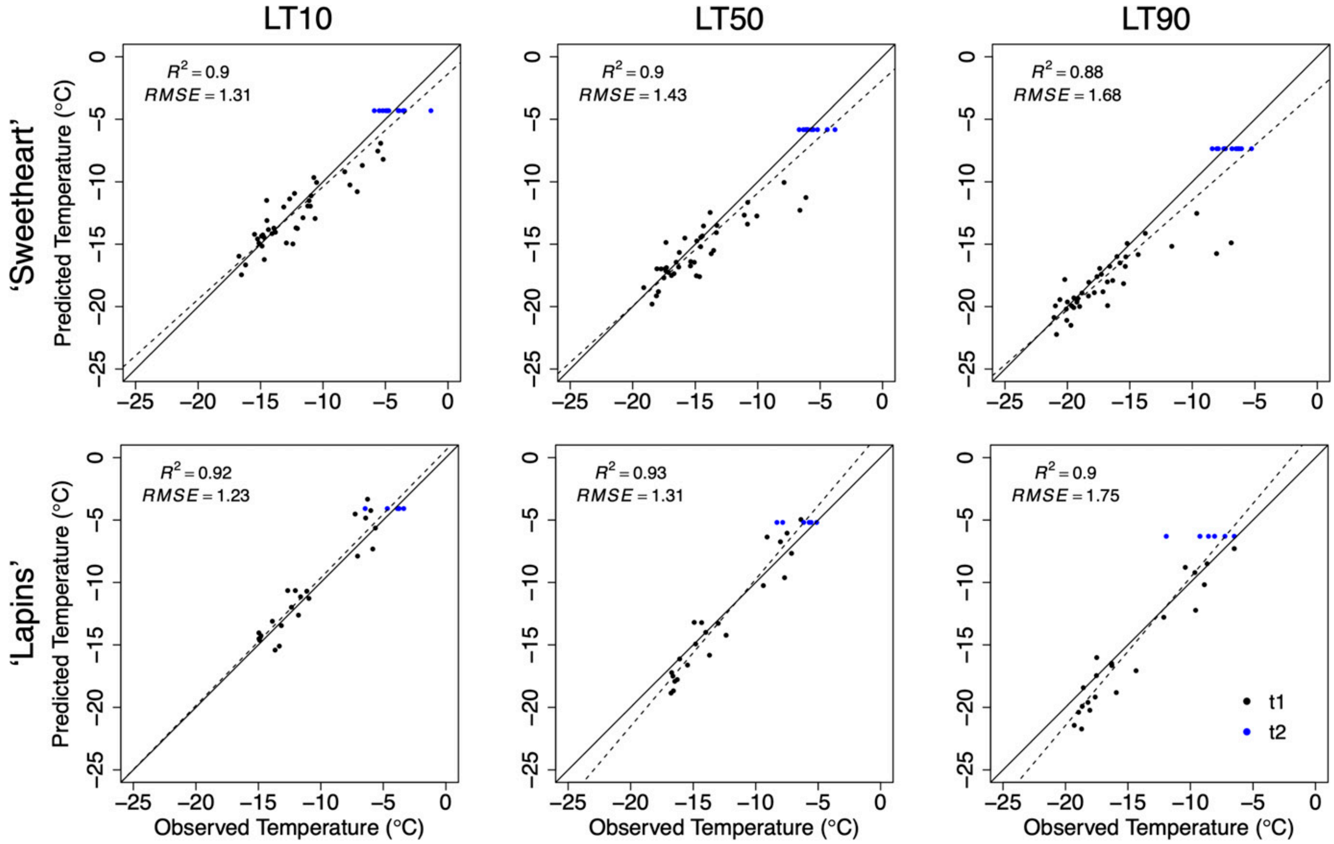

Fig. 3. One-to-one regression of all seasons predicted and observed lethal temperature that causes 10%, 50%, and 90% mortality (LT10, LT50, LT90) for 'Sweetheart' and 'Lapins' data not used in model development.

minimum daily air temperatures dropping below the estimated LT10 (−11 °C) by 1 to 3 °C for 4 h and the estimated LT50 (−13 °C) by 1 °C for 3 h (Fig. 4G and H). No in-field flower bud damage was observed when measured 2 d after this event. In addition, on 9 and 10 Feb 2021, temperatures dropped below the estimated LT10 (−16 and −17 °C) by 1 to 2 °C for 7 h and 1 to 3 °C for 4 h, respectively (Fig. 4G); on 11 Feb 2021, recorded temperatures fell below the estimated LT90 (−23 °C) by 1 °C for 3 h (Fig. 4I). After this February cold event, 6% damage was observed on 22 Feb 2022 and 18% damage was observed on 9 Mar 2022 at this site.

Overall, a reasonable agreement between estimated damage based on model predictions of cold hardiness when compared with daily minimum ambient temperature and measures of in-field bud damage was observed. In general, model predictions were conservative, predicting higher levels of damage than was observed on some dates.

One-to-one regression of the combined predicted LT and the observed LT data for 'Lapins' models with data not used in model development resulted in high R^2 values, ranging from 0.90 to 0.93, and low RMSE values, ranging from 1.23 to 1.75 (Fig. 3). The 'Lapins' LT estimates also showed excellent fit to observed LT values not used in model development in the t1 period. However, model estimates in the t2 period were not as good in the higher percentage LT50 and LT90 estimates (Fig. 5). Flower bud damage in the field was not measured for the seasons in which 'Lapins' LT was measured.

These models were also validated against three different sweet cherry cultivars including Staccato, Sonata, and Skeena (Fig. 6) to determine their applicability to other cultivars. The LTs of these additional cultivars were only measured during the t1 period. Both 'Lapins' and 'Sweetheart' LT estimates did a reasonably good job at estimating the LT of these additional cultivars during the t1 period.

Discussion

Interactive web application. Using the package shiny (v1.6.0; Chang et al. 2021) in RStudio (v1.3.1093; R Core Team 2020), an interactive web application was developed to allow for simplified and open access to the outputs of these models, with the option for model application in real time. It was important that this interface was developed to access these models, as it is likely that much of the target audience that would benefit most from these models does not have the coding skills, nor the time required to fit these models and run analyses independently. Without this interface, these models would likely be less useful, in practice, to growers, extension workers, and even researchers.

The interactive web application developed to access these models provides users with the background information required to understand and apply the developed 'Sweetheart' and 'Lapins' LT models ("Background" tab), a detailed description of the models and their performance ("About the Models" tab), instructions on how to use the models ("How to Use" tab) as well as access to model outputs ("Estimates" tab). Both graphical (Fig. 7) and downloadable numeric outputs from the models' LT10, LT50, and LT90 predictions are available on this web application. This web application allows users to either input their own hourly temperature data or access the Government of Canada's Historic Climate database (Government of Canada 2023) to automatically input weather data for select locations in the Okanagan Valley, BC. By including an option to use weather data from the Government of Canada's Historical Climate database, this allows users to access hourly air temperature data from as recent as 1 d before the current date to make real-time predictions if they do not have access to their own, more site-specific, weather data. If the option to access weather data from the Government of Canada's Historical Climate database is selected, it will also provide 3 d of future LT estimates based on weather forecasts accessed from OpenWeather (OpenWeather 2022) (https://openweathermap.org). This online web application is free to use and does not require users to sign up. The code for this interactive web application can be found at https://github.com/ElizabethHoughton/cherrycoldhardiness, and the openly accessible, online version of this application can be found at https://sweetcherry.shinyapps.io/cherrycoldhardiness/.

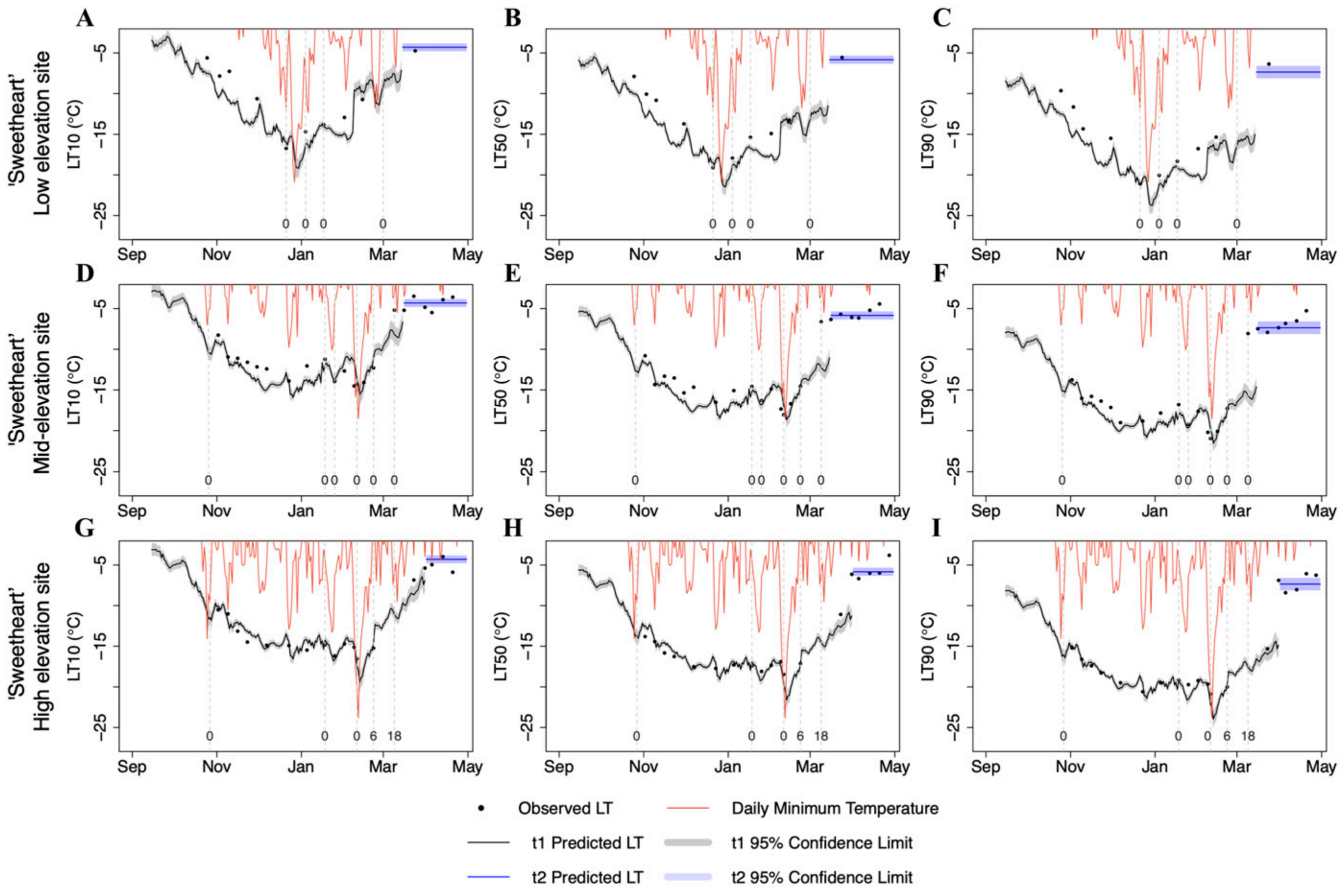

Fig. 4. Predicted lethal temperature that causes 10%, 50%, and 90% mortality (LT10, LT50, and LT90) values plotted against the observed LT values for three seasons of 'Sweetheart' data that were not used in model development at three different elevation orchards in Summerland, BC (low elevation 2021–22: **A**, **B**, and **C**; midelevation 2020–21: **D**, **E**, and **F**; high elevation 2020–21: **G**, **H**, and **I**). Daily minimum temperature (red lines) and measures of in-field percent bud damage collected throughout the season (vertical dashed gray lines and numeric values at the bottom of each plot) are also displayed. Measures of bud damage throughout the season help validate models by comparing percent damage estimated by models (10%, 50%, and 90% damage are assumed to occur when the daily minimum temperatures fall below the LT10, LT50, and LT90 estimates, respectively) with damage measured in-field.

Models for estimating the cold hardiness of sweet cherry. In this work we developed, evaluated, and validated models that successfully estimated the LT (LT10, LT50, LT90) of the sweet cherry cultivars Sweetheart and Lapins in a cold climate region (Okanagan Valley, BC, Canada) and developed an online interactive web application for easy access and use of these models. These models focused on incorporating parameters that accounted for the temperature-driven processes of cold acclimation and deacclimation, including their relationship to accumulated chilling and forcing temperatures and the mean daily air temperatures experienced 1 to 3 d prior. Predictor variables associated with dates (e.g., photoperiod, accumulative Julian date) were omitted from this modeling approach; this approach separates our models from the sweet cherry cold hardiness models developed by Salazar-Gutiérrez and Chaves-Cordoba (2020), developed out of Washington, USA, which included a model parameter of the accumulative day for the study period and which may not be applicable to growers in BC.

Overall, model performance was very good during the t1 period, as indicated by the RMSE, d, one-to-one regression of the predicted and observed LT values, and by model validation through comparisons of estimated LT to observed LT data that were not included in model development. In addition, measures of in-field bud damage for 'Sweetheart' showed a reasonable agreement between potential predicted damage, indicated by minimum daily air temperatures that fell below the predicted LTs, which helped validate model estimates. In general, when the models were incorrect, their estimates were conservative meaning greater estimates of damage were predicted than what was observed. Factors such as HOBO® data logger placement within the orchard, flower bud cold damage measurements, and the accuracy of the model estimates all may have contributed to the discrepancies between the expected cold damage based on LT estimates and the observed cold damage. In addition, these differences in estimated flower bud damage determined from LT predictions and the observed in-field bud damage may be attributed to factors such as cold spell duration, rate of cooling, and how extreme these events were, given that temperatures only ever fell 1 to 3 °C below the estimated LT. The short duration of many of these cold events may have resulted in lags between the ambient air temperatures and the internal flower bud temperatures.

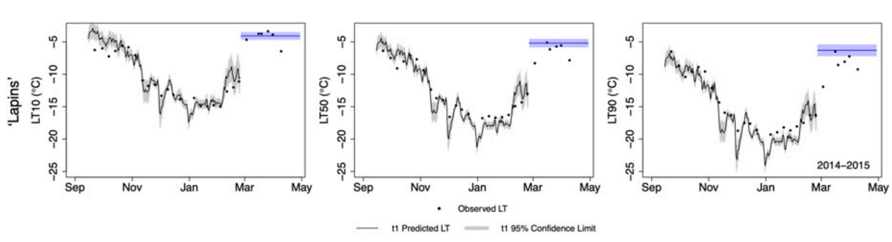

Fig. 5. Predicted lethal temperature that causes 10%, 50%, and 90% mortality (LT10, LT50, and LT90) values plotted against the observed LT values for one season of 'Lapins' data (2014–15) that were not used in model development.

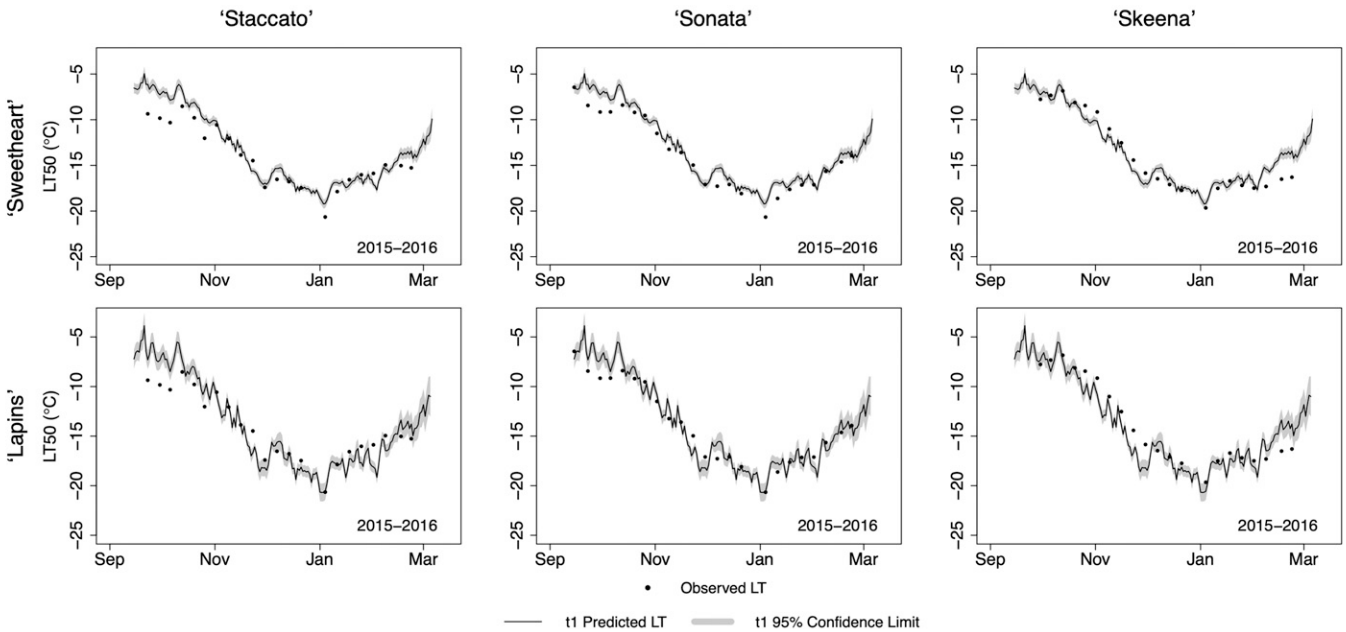

Fig. 6. Predicted 'Sweetheart' and 'Lapins' lethal temperature that causes 50% mortality (LT50) values in the t1 period plotted against observed Staccato, Sonata, and Skeena cultivar LT50 values.

This may have resulted in measures of ambient air temperatures that were below the predicted LT temperatures, but internal bud temperatures that had yet to surpass the predicted LT temperature, helping explain the lack of damage later observed.

Overall, the authors acknowledge that the ability of these models to predict changes in cold hardiness after 30 and 25 accumulated

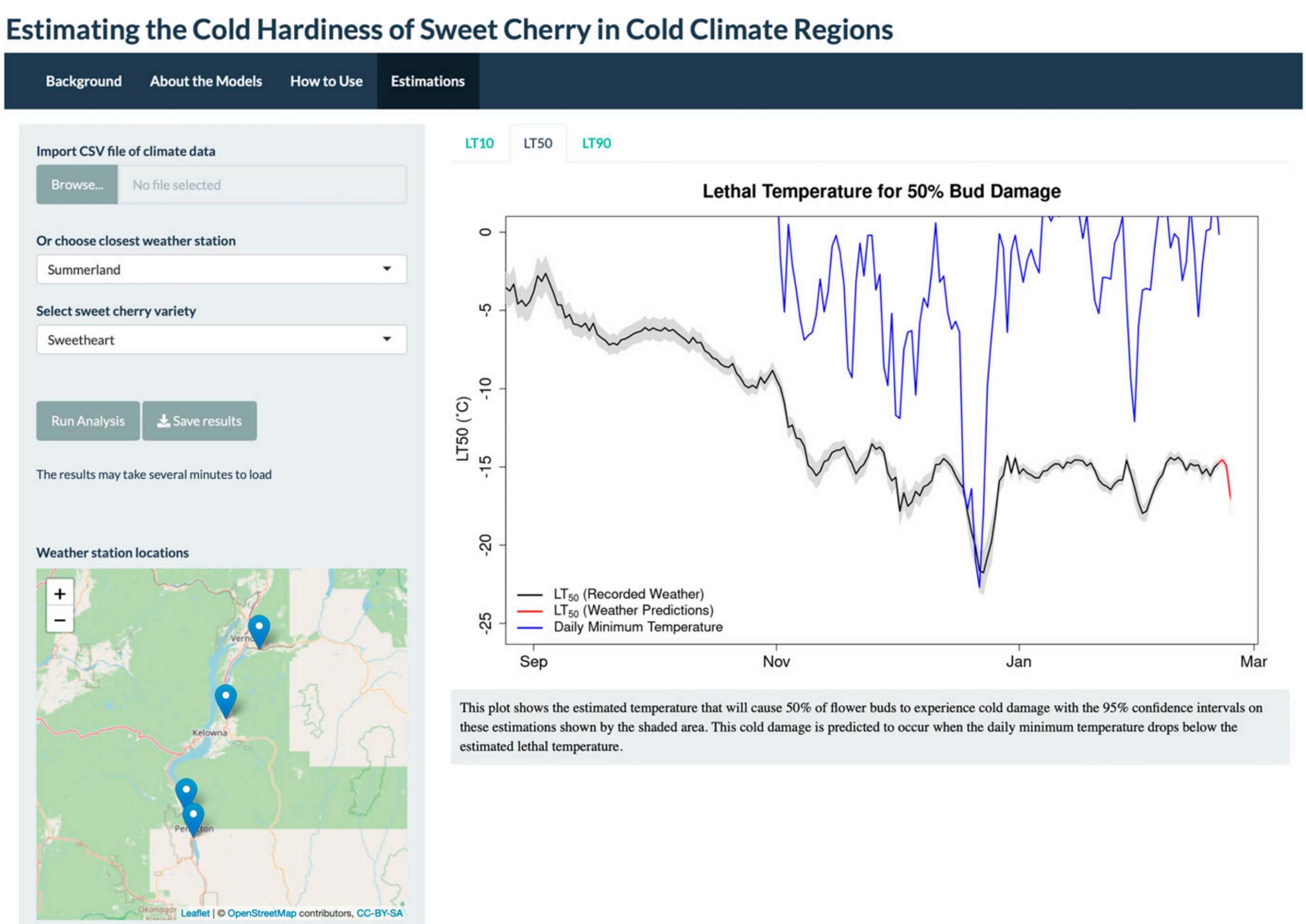

Fig. 7. "Estimations" page of interactive web application designed for simplified and open-access to cold hardiness model estimations made from either user uploaded weather data or the current season's data accessed from the Government of Canada's Historic Climate database (https://climate.weather.gc.ca) and 3 d of weather forecasts from OpenWeather (https://openweathermap.org).

FU (t2) in both ‘Sweetheart’ and ‘Lapins’ is relatively poor because the top selected models were intercept-only models, likely as a result of the limited data available during this period. Additional LT data collected in the late winter and early spring would be required to produce more capable models for estimating cold hardiness during these periods. This is an important period to understand plant susceptibility to frost because as growth resumes in the spring, sweet cherry trees begin to rapidly deacclimate and their ability to tolerate cold temperatures is greatly reduced, making them vulnerable to frost events (Longstroth and Perry 1996; Rodrigo 2000).

Notably, the models during t1 that we have developed here show potential applications to cultivars other than Sweetheart and Lapins. However, we were unable to evaluate t2 model performance of the ‘Sweetheart’ and ‘Lapins’ LT models to additional cultivars (Staccato, Sonata, and Skeena) because of data limitations. It is likely that varietal differences in timing of deacclimation would result in asynchronous estimations of bud deacclimation made by these models and therefore caution should be taken when expanding application to sweet cherry cultivars other than Sweetheart and Lapins. Nonetheless, given the current absence of any models for these other cultivars, our models can provide growers with reasonably accurate predictions that could help inform their cold damage mitigation efforts.

The presented models were developed using temperature and LT data from one (‘Lapins’) or two (‘Sweetheart’) locations in Summerland, BC. The climate in this region often allows for the sweet cherry chilling requirements to be met early in the dormant season (Guak and Neilsen 2013) resulting in the potential for early forcing accumulation under warmer winter temperatures when using forcing equations defined by Neilsen et al. (2015). In these models, early forcing accumulation was nullified to help account for this and improve model fit under scenarios of winter warm spells. Consequently, it is not recommended that the models described here be applied in regions that experience warmer winters, where chilling requirements may not be met until later in the season, without further validation, because these models may overestimate LT values (more negative) when early warm, forcing temperatures are experienced.

Conclusion

The purpose of the current study was to develop and validate models to estimate the LT that could cause 10%, 50%, and 90% damage (LT10, LT50, LT90) to the sweet cherry cultivars Sweetheart and Lapins. The development of these models contributes to our understanding of sweet cherry cold hardiness throughout the fall and winter months. The limitations of this study are that an improved understanding of spring cold hardiness progression is still needed in this system. Future improvements to these models through modeling with a higher resolution of LT data collected during the spring months would be beneficial. Furthermore, validation of these models using data collected in regions extending beyond the southern Okanagan Valley, BC, Canada is still needed to determine their applicability to a wider range of geographic locations.

These models were made openly accessible through a free, online, interactive web application available for use by growers, researchers, and extension workers. They can be used as a decision support tool in western Canada to aid in decisions regarding the application of strategies to help mitigate cold damage. Through the use of this decision support tool, growers will be able to maximize the opportunity for winter cherry flower bud survival and reduce economic loss to crop cold damage when possible. Furthermore, these models may contribute to improved resource optimization by helping growers avoid implementing frost damage mitigation strategies, such as the use of wind machines or helicopters, when they may not be needed. These models may also help estimate production risk before the establishment of new orchards based on historic records of temperature or to improve our understanding and modeling of changing sweet cherry crop site suitability under present and future predictions of climate change.

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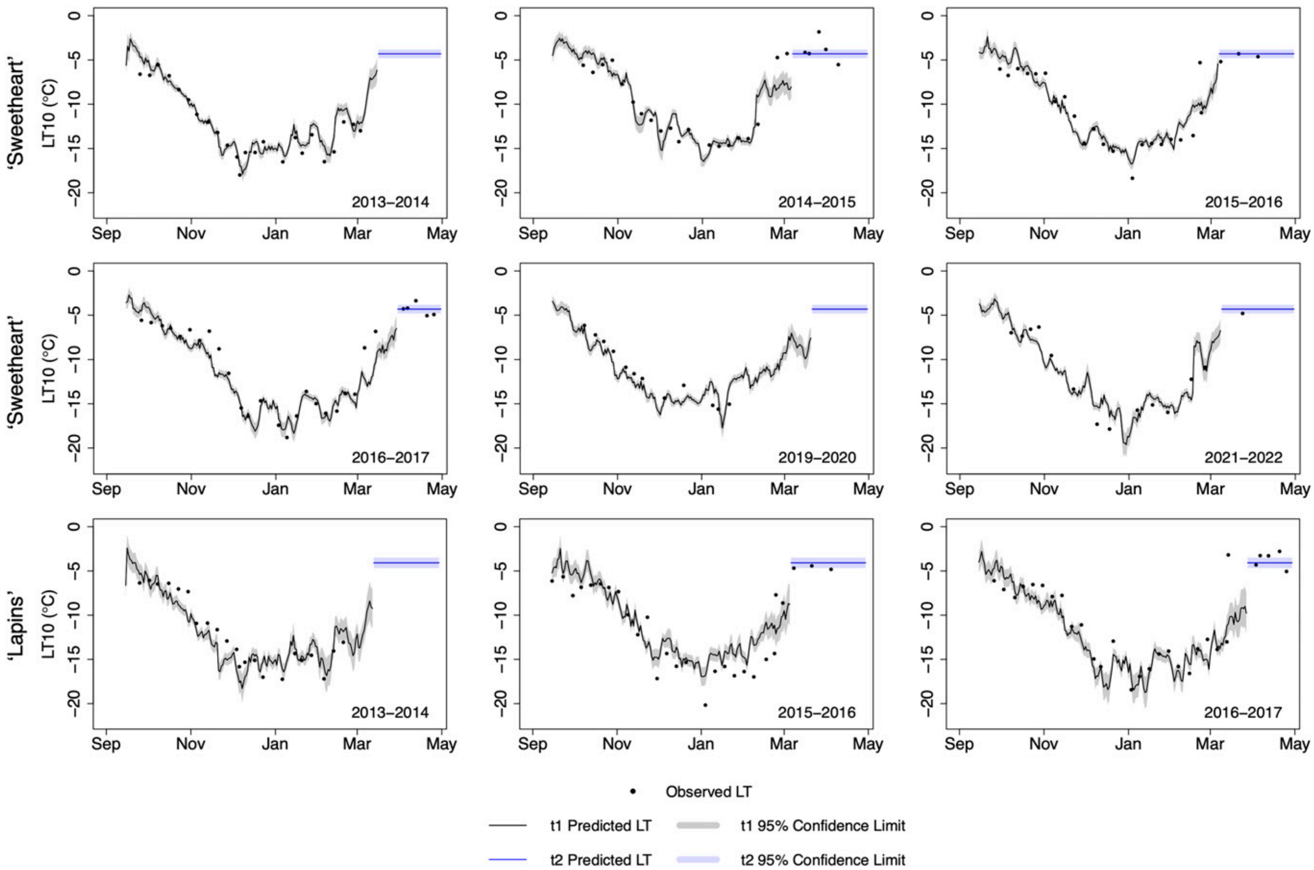
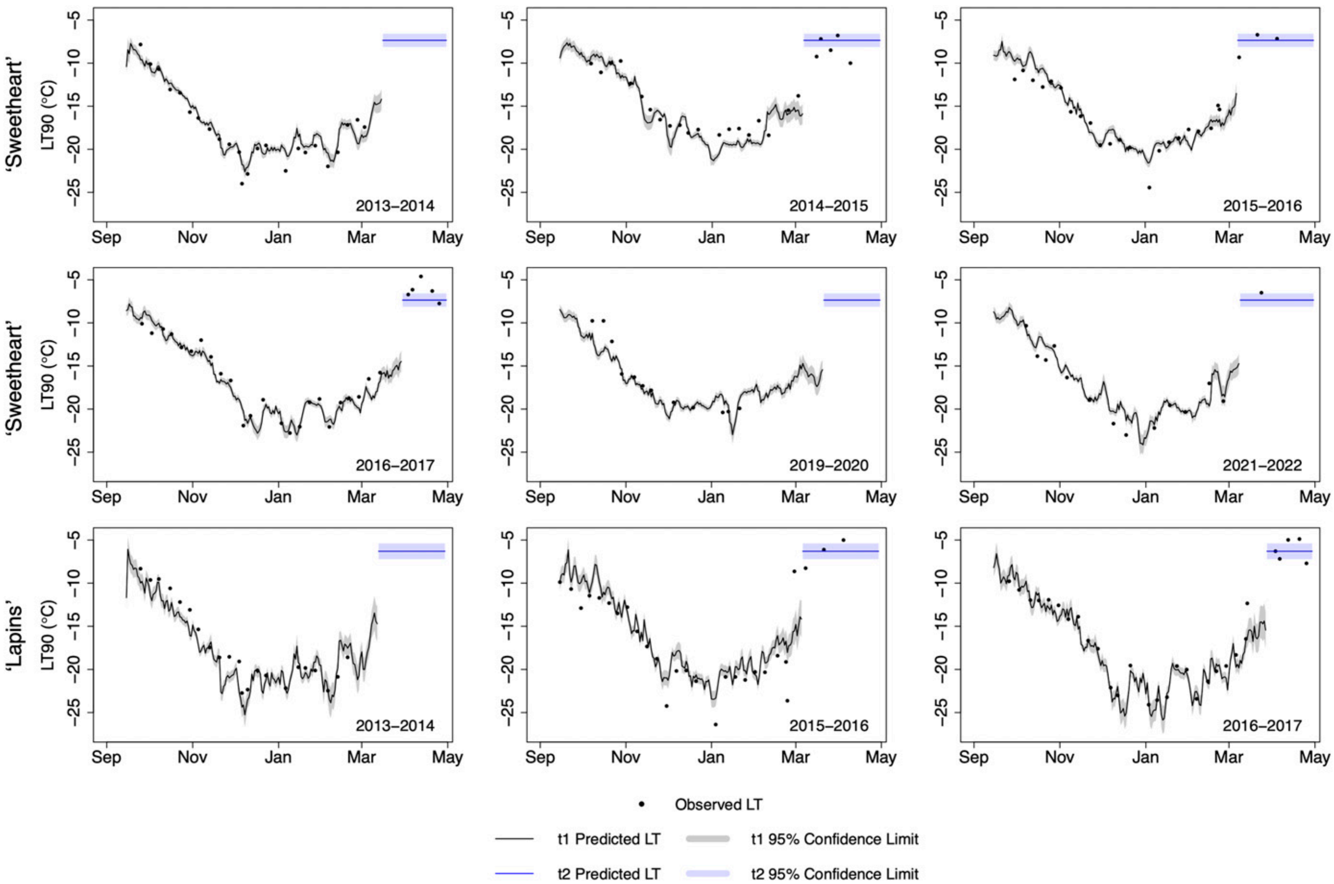


Supplemental Fig. 1. Predicted lethal temperature that causes 10% mortality (LT10) values plotted against the observed LT10 values for all seasons of data used to develop the 'Sweetheart' (six seasons) and 'Lapins' (three seasons) models.



Supplemental Fig. 2. Predicted lethal temperature that causes 90% mortality (LT90) values plotted against the observed LT90 values for all seasons of data used to develop the 'Sweetheart' (six seasons) and 'Lapins' (three seasons) models.