Use of Cordon Wire Tension for Static and Dynamic Prediction of Grapevine Yield

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Abstract: An automated system was used during three growing seasons to monitor the change in tension (ΔT) in the load-bearing wire of a trellis to estimate yield in vineyards. Actual yield varied nearly four-fold among the three study years, but in each year the fruit was uniformly distributed along the length of the wire. The automated sensor detected sequential harvests up to ~12 m to either side of the sensor, or 24 m total wire length, in a nonlinear fashion. Yield was predicted statically from ΔT at the lag phase (L) of berry growth (ΔT_L) and dynamically from continuous output of ΔT. Relationships between ΔT_L and yield were linear. Estimated yield was not sensitive to the date of ΔT_L, within 10 days. In using the ratio between the current year ΔT and that of a specific previous year, the differences between estimated and observed yields depended upon the choice of predictor year(s), where years with similar ΔT were the most accurate. Across an estimation interval of L to harvest, the precision of dynamic estimates was determined by the similarity in the day-to-day shapes of the double-logistic curves of ΔT over time. Due to a catastrophic frost in the second year of the study, an extremely small crop and an uncharacteristic growth curve made it difficult to predict yield either statically or dynamically. In practice, the method requires a grower to collect multiple years of growth curves from which to build a robust linear relationship between ΔT_L and yield (static estimates), or to apply an average of multiple years' ΔT values dynamically.

Key words: crop level, sensitivity, lag phase, sensor, remote estimation, automated system

Limitations associated with traditional or heuristic approaches to yield estimation in vineyards prompted development of an automated system to provide a remote, dynamic indicator of fruit growth during each growing season (Tarara et al. 2004, 2005). Despite proposals for using remote imaging in vineyards and orchards (e.g., Ye et al. 2008, Nuske et al. 2011, Férnandez et al. 2013), the standard means of estimating yield at the vineyard level relies on periodic (once to several times per season) manual sampling that involves counting and/or weighing fruit clusters and/or berries. The critical estimate is made at the lag phase (L) in berry growth, a period of variable duration (Coombe 1976) in which there is little increase in mass or volume of the fruit. Lag phase can be difficult to determine accurately by visual scouting.

Approaches for computing yield estimates at L are described in the scientific and grey literature (e.g., Antcliff et al. 1972, Wolpert and Vilas 1992, Clingeleffer et al. 2001, Dunn 2010). Generally, a company-specific and/or cultivar-specific value is used to scale numbers of fruit clusters per vine and/or an average cluster mass to estimate values at harvest (Price and Lombard 1988, Wolfe 2006). Some producers do not disclose computational details for proprietary reasons. Unquantified subjective inputs may be used to modify unexpectedly large or small predictions. In those cases, adjusted estimates often are biased toward the long-term average. Efficient schemes have been developed to adequately sample and estimate the number of clusters per vine (Jones 1990, Wolpert and Vilas 1992, Wulfsohn et al. 2012), but mass at harvest is more difficult to predict. Self-reporting in the United States suggests an industry-wide bulk accuracy of ±10%, although this may range up to 20% or more in some years (N. Dokoozlian, author's unpublished data, 2013). The difficulty of obtaining accurate yield estimates is not unique to grapes (e.g., macadamia [*Macadamia integrifolia*], Mayer et al. 2006; satsuma mandarin [*Citrus unshiu* Marc.], Ye et al. 2008).

Yield estimates by site are subject to larger variation (e.g., ~20 to 100% errors; Blom and Tarara 2009, Clingeleffer et al. 2001) than are collective or regional values. Temporal trends in yields for various crops have been investigated with weather-based models (Lobell and Field 2011), but these models emphasize aggregate outcomes: for example, by county. Accurate estimation by vineyard is critical economically, as it is essential for crop price negotiation, harvest logistics, batch processing, and marketing decisions related to specific cultivars and quality tier of the finished juice or wine.

The trellis tension monitor (TTM) could be a replacement for, or adjunct to, traditional yield estimation techniques (Tarara et al. 2004, Blom and Tarara 2009). Briefly, the TTM

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continuously detects tension (T) in a load-bearing trellis wire using a temperature-compensated load cell. Over a single growing season, the resulting output is a double sigmoid curve that represents the annual growth of shoots and fruit, expressed as the change in T (ΔT) from initial conditions at bud break (T_0). Before fruit set, the increase in mass reflects shoot growth; thereafter, fruit mass is a progressively higher proportion of fresh mass. For example, within three weeks of estimated fruit set, fruit mass represented up to 57% of the total fresh mass from the current season's growth (Tarara et al. 2013). Under deficit irrigation, shoot growth is deliberately controlled after fruit set.

In a common case in winegrapes (i.e., multi-wire trellis, deficit irrigation), the following objectives were investigated: 1) determine the apparent spatial sensitivity, or detection bounds, of the TTM sensor; 2) use ΔT at L to predict ΔT immediately before harvest (ΔT_H) and consequently, predict yield with a regression approach (static estimation); 3) use one or two previous years' ratios of ΔT-to-yield to estimate yield in the current year (ratio method); and 4) estimate yield on a daily basis from L onward, also using previous years' ratios of ΔT-to-yield (dynamic estimation).

Materials and Methods

Site description. Data were collected over three years (2007 to 2009) in two commercial vineyards near Waterford, CA (37.66° N; 120.83° W; 41 m asl). Climate descriptors and soil classifications at the site were described previously (Tarara et al. 2013). Both vineyards were planted in 1994 with 3.05 m between rows and 2.44 m between vines for an average plant density of 1345 vines/ha. Experimental rows were on average 420 m long (vineyard 1) and 250 m long (vineyard 2). Vineyard 1 was planted to *Vitis vinifera* L. cv. Merlot (22.32 ha) and vineyard 2 to *V. vinifera* cv. Chardonnay (30.68 ha). In both cultivars, vines were trained to a unilateral cordon at ~1.1 m aboveground. Vines were dormant-pruned annually to two-bud spurs spaced 15 to 20 cm apart. The trellis included a single cordon wire (galvanized, commercial Class 3; 2.30 mm diam; 11 AWG [American Wire Gauge]), hereafter referred to either as the cordon wire or the load-bearing trellis wire. At every vine trunk, there was one steel stake (t-post) to which the cordon wire was fixed by a wire loop the same diameter as the trellis wire. End posts were circular steel pipe (10 cm diam). Shoots were trained in a loose vertical arrangement with a central catch wire 25 cm above the cordon wire and two foliage wires at 56 cm above the cordon wire, spaced 43 cm apart by a horizontal steel cross member with guide notches but no other restrictions on the wire.

Vines were managed under regulated deficit irrigation delivered by drip from fruit set to near harvest. All cultural practices, including pest and disease interventions, were performed according to commercial standards in the area. Specific practices that caused minor consequences for the mass borne by the trellis wire were described previously (Tarara et al. 2013). Of critical note is that in 2008, a late spring freeze defoliated the vines overnight on days of year (DOY) 111 to 112 (20 to 21 Apr) with two primary consequences: (1) annual growth was reset by 4 to 6 weeks, causing a compressed growing period and atypical growth curve and (2) substantially less fruit was produced from the secondary buds. The onset of L was defined by our cooperator as the date at which one half of sampled berries were soft to the touch, with the remainder hard and green. The onset of ripening was defined as the date at which at least one half of a sample of berries from sentinel vines exhibited softening to the touch and color change.

Instrumentation and data processing. In each vineyard in 2007, one TTM system was installed per row in three consecutive rows. The arrangement was replicated in another section of each vineyard for a total of 12 TTMs in the experiment. The load cells were installed in-line with the trellis wire in the central portion of the rows, so that sensing was bidirectional. Equipment details and the method of initial post-processing of the data have been described elsewhere (Blom and Tarara 2009, Tarara et al. 2004, Tarara et al. 2013). Data were recorded continuously from installation in 2007 through dormant pruning in 2010. Initial conditions (T_0) were set each year for each TTM as the day before T began to increase after bud break. The ΔT was plotted in daily time intervals (ΔT_d). Use of ΔT rather than T normalized the data among years and adjusted for the variation in T_0 among rows. Double logistic functions were fitted to the observed ΔT_d (Hau et al. 1993) with the parameters adjusted as described by Tarara et al. (2013) (Figure 1).

Immediately before the vineyard was harvested by machine, experimental vines (five vines in the same row as, and to either side of the instruments: n = 10 vines per TTM) were harvested by hand, the fruit was weighed, and clusters were counted. During hand harvest, signals from the TTM were scanned every 1 sec and averaged every 1 min to ensure identification of the drop in ΔT that resulted from stepwise removal of fruit mass from the trellis wire. Vines were harvested sequentially in pairs opposite the sensor beginning with the vine position nearest the sensor. The load removed for each length of trellis wire that was encompassed by the vine pair was expressed as kg fruit. Measured, or actual yield (Y_a; kg), for each TTM was defined as the total mass of fruit harvested from 10 vines.

The sensitivity (s) of the TTM to the removal of a distributed mass, or load on the wire, was estimated from the difference between ΔT immediately prior to fruit picking (ΔT_H) and the subsequent remainder (ΔT_R). Each remainder ($\Delta T_{R,1}$, $\Delta T_{R,2}$, and so on) also was expressed as a percent of the total difference (ΔT_H - ΔT_R) due to the harvest of the five pairs of vines. The trend of (ΔT_H - ΔT_R) is nonlinear and is represented by an exponential function

$$s = (\Delta\hat{T}_H) * e^{[-(\Delta T_H - \Delta T_R)*w]} \qquad \text{Eq. 1}$$

where ($\Delta\hat{T}_H$) is the estimation of ΔT_H, (ΔT_H - ΔT_R) is the average decrement after harvest, and w is the total length of trellis wire represented by the specified vine pair on either side of the TTM sensor. Wire lengths were reported as vine spacing maxima; in other words, 4.88 m represents the total length of wire encompassing the first vine pair harvested, 9.76 m represents the total length encompassing the second vine pair harvested, and so on, up to 24.4 m for the total length of wire represented by 10 vines.

From the logistic curves, a ΔT_L was used that had been resolved analytically (Tarara et al. 2013) to make static predictions of ΔT_H, and thus Y_e through a simple linear relationship:

$$\Delta T_H = a_1 + b_1 \Delta T_L \qquad \text{Eq. 2a}$$

or:

$$Y_e = a_2 + b_2 \Delta T_L \qquad \text{Eq. 2b}$$

where a_x is the intercept and b_x the slope of the relationship. The sensitivity of the yield prediction to the analytically determined date of L was determined in time intervals of one day, from L to L + 10 d. The fitted double logistic curves of ΔT_d were used as independent variables to estimate yield in daily time steps ($_d$), computed with the function

$$Y_{d,c} = \left(\frac{\Delta T_{d,c}}{\Delta T_{d,i}}\right) \cdot Y_{a,i} \qquad \text{Eq. 3}$$

where the subscript $_c$ refers to the current year and the subscript $_i$ refers to other year(s) with known yield. For making a point estimate at L, Equation 3 is referred to as the ratio method. Moving or dynamic estimates at daily intervals from fruit set to harvest and L to harvest also were computed using Equation 3. Yield for the current year was predicted both from a single comparison year and from the mean of the other two years in the dataset.

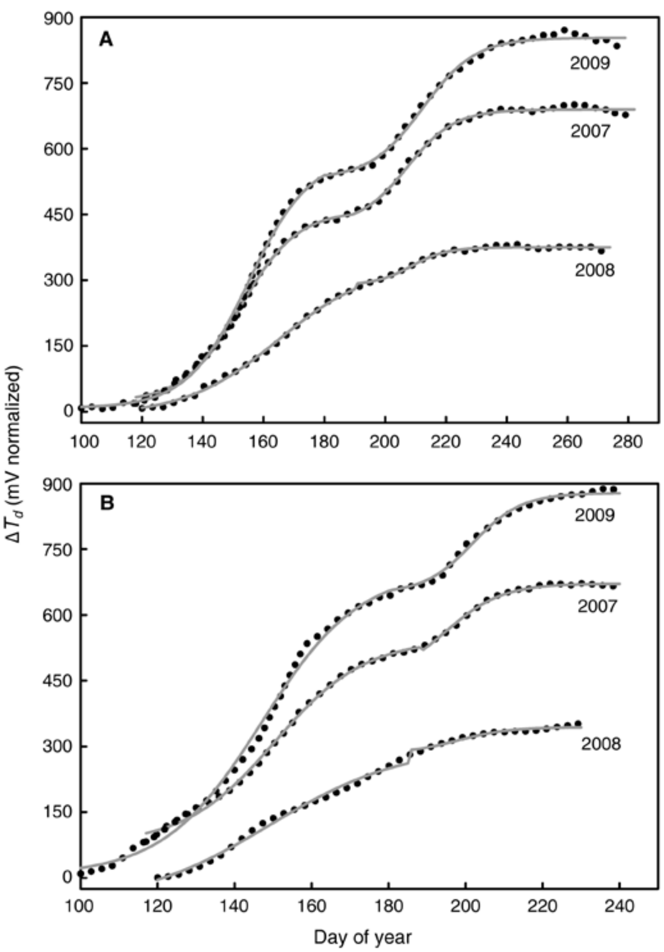

Figure 1 Double logistic curves fitted to the average change in tension in daily time steps (ΔT_d) in the main load-bearing trellis wire. (**A**) vineyard 1 and (**B**) vineyard 2. Vineyard 1 (cv. Merlot) was harvested 30 to 50 days after vineyard 2 (cv. Chardonnay). The estimated dates of fruit set were days of year 142 (2007) and 156 (2008; vineyard 1), and days of year 135 (2007), 156 (2008), and 144 (2009; vineyard 2). The date of fruit set was not estimated for vineyard 1 in 2009 (from Tarara et al. 2013).

Statistical analyses. An analysis of variance for the sensitivity of ΔT_H to removal of the distributed load was computed with a general linear model procedure (SAS ver. 9.3; SAS Institute, Cary, NC). Input data for ΔT_H were derived from the double-sigmoid curves derived from the original TTM signals. Dependent variables were the harvest-induced drop in ΔT (ΔT_H-ΔT_R), ΔT_R, and fruit mass removed. Year, vineyard, and length of trellis wire were the sources of variation analyzed as single factors and for interactions among factors. Residuals were evaluated for the normality assumption with the Shapiro–Wilk test. The Bonferroni test was used to detect significant differences among single factors. The ΔT_H-ΔT_R and ΔT_R by wire length were modeled with exponential curves that were adjusted using a nonlinear regression procedure with Gauss Newton optimization (SAS ver. 9.3). Simple linear regressions were fitted to estimate functional relationships between ΔT_L and ΔT_H, and ΔT_L and Y.

Total harvested mass from the ten experimental vines per row (Y_a) was compared with Y_e. The bias, variance (var), and root mean square error (RMSE) for the mean yield estimate in a period between fruit set and harvest, or between L and harvest were calculated, where

$$\text{RMSE} = [(\text{average } bias(Y_e))^2 + \text{var}(Y_e)]^{1/2} \qquad \text{Eq. 4}$$

For the dynamic estimates, $Y_{d,c}$ was analyzed by year and vineyard.

Results

The ΔT_H-ΔT_R differed by year ($p < 0.001$) and length of wire ($p < 0.001$), but not by vineyard. Among years, the difference in the relationship between ΔT_H-ΔT_R and wire length was a consequence of the sensitivity of the TTM to pre-harvest initial conditions (e.g., 262 [2008] vs. 480 mV [2009] in vineyard 1) and the magnitude of the fruit mass removed. There were no significant interaction terms between vineyard and either year or length of wire. Thus, for further analysis of the apparent spatial sensitivity of the TTM, data from the two vineyards were pooled.

There was no interaction between fruit mass per vine and length of trellis wire, indicating an exceptionally uniform load distribution for a biological system: approximately the same mass was removed from each vine pair (Table 1). Beyond 19.52 m total length of wire, or the fourth vine pair, removing fruit mass did not significantly increase ΔT_H-ΔT_R, implying that the TTM in a trellis system such as this may detect significant changes in mass up to ~10 m on either side of the sensor. At our plant density, one could suggest using four vines to either side of the sensor to estimate yield. However, to provide a maximum sample size for Y_a, the total fruit mass for all 10 experimental vines per row was used (24.4 m total wire length).

Yield varied considerably by year in the order 2009 > 2007 >> 2008. Over three years, vineyard 2 produced less total fruit mass ($p = 0.002$) than vineyard 1. This outcome was driven by an inter vineyard difference in 2008, when vineyard 2 produced only 60% of the fruit mass of vineyard 1. In contrast, in 2007 and 2009, total fruit mass in vineyard 2 was 96 to 97% that of vineyard 1 (data not shown). The response of ΔT to sequential load removal was nonlinear and dependent upon year (Figure 2), with the greatest sensitivity to the vine pair or load nearest the sensor (Table 1).

The relationship between ΔT_L and ΔT_H was linear for the pooled data ($p < 0.001$; Figure 3A). Vineyard-specific models also were linear and were significantly different from zero (Figure 3B,C; $p < 0.001$). There was low relative variability in the models (CV = 7.8%, vineyard 1; CV = 5.8%, vineyard 2). This initial step demonstrated that in any given year, it is possible to predict preharvest ΔT, both collectively and, more importantly, at the vineyard level, from a small number of years with substantially different input values. As with ΔT_H, the 10-vine yield over three years was also a linear function of ΔT_L (Figure 4). This held for both pooled and vineyard-specific inputs, indicating the possibility of developing the vineyard-specific yield estimates that are important for harvest logistics. In effect, ΔT_L was used as a surrogate for average mass per cluster or number of clusters per vine as growers would use at L. Equations without intercepts (Figure 5) were also fitted because growers seek a single scalar when estimating yield. In these cases, the slopes of the relationships had a smaller range between pooled and vineyard-specific data, suggesting the possibility of a unified model to be applied initially in subsequent years until an adequate database could be developed for specific cultivars and sites. Note that the calculation of the sums of squares differs from that of a model that includes an intercept, resulting in higher coefficients of determination (R^2) in the zero-intercept model. However, model fits (RMSE) were not as good as those that included intercepts. Although the no-intercept equations may be more practical, ΔT_L is never zero. The regression approach using ΔT_L may be the most straightforward application of TTM data and require the fewest years to determine a relationship with outcomes that are acceptable to the industry. Using vineyard-specific relationships that included intercepts, yield was underestimated in 2007 (7.9%, vineyard 1; 11.4%, vineyard 2). Yield was overestimated in 2008 (11.4%, vineyard 1; 27.8%, vineyard 2). In 2009, yield was slightly overestimated (1.5%, vineyard 1; 2.4%, vineyard 2).

Considered by vine pair, or distance from the sensor, the relationships between ΔT_L and yield were linear. Relative errors in the estimated yield were similar to one another by distance (Table 2). The slopes of the relationships were highest for the 10-vine set, supporting the notion that it is desirable to use the largest practical sample size within the detection bounds of the sensor.

An analytical solution for the onset of L was determined from the second derivative of the first logistic equation (Figure 1; Tarara et al. 2013). The sensitivity of Y_e to the date of ΔT_L was low; in other words, an identifiable L occurred where there was very little change in ΔT_d. Consequently, Y_e was consistent over the 10-day window. For each 1-day increment from L to L+10, the change in Y_e was 0.26 kg/vine (data not shown).

Table 1 Sensitivity of trellis tension monitor (TTM) to stepwise removal of uniformly distributed load from the horizontal supporting wire (cordon wire) of a vineyard trellis. Fruit was harvested sequentially from five sets of vines paired on either side of the sensor; n = 12 TTMs.

Year/ no. of vines	Maximum wire length[a] (m)	Cumulative ΔT_H-$\Delta T_{R,x}$[b] (mV)	Fraction of total ΔT_H-ΔT_R (%)	Avg fruit mass removed (kg /vine pair)[c]	Cumulative mass removed (kg)
2007					
2	4.88	142	40.2	47.9 ± 4.45	47.9
4	9.76	214	20.4	49.4 ± 12.06	97.3
6	14.64	282	19.5	51.2 ± 3.42	148.5
8	19.52	330	13.5	50.2 ± 8.31	198.7
10	24.40	353	6.4	49.9 ± 10.10	248.6
2008					
2	4.88	46	36.2	17.0 ± 4.97	17.0
4	9.76	82	27.9	16.4 ± 6.47	33.4
6	14.64	106	19.1	17.2 ± 6.68	50.6
8	19.52	118	9.3	15.4 ± 6.46	66.0
10	24.40	127	7.4	16.0 ± 5.48	82.0
2009					
2	4.88	257	50.6	65.8 ± 7.63	65.8
4	9.76	373	22.9	63.0 ± 10.33	128.8
6	14.64	452	15.6	64.1 ± 9.77	192.9
8	19.52	484	6.5	61.0 ± 14.21	253.9
10	24.40	507	4.4	61.1 ± 12.92	315.0

[a]Length of trellis wire is expressed as the maximum distance as a function of vine spacing (2.44 m between vines).
[b]ΔT_H-$\Delta T_{R,x}$ is the normalized difference in wire tension (ΔT) between immediately before harvest (ΔT_H) and that remaining after removal of fruit ($\Delta T_{R,x}$) incrementally from pairs of vines to either side of the sensor, where x = 1 to 5.
[c]Mean ± standard deviation.

There was variability across TTMs, or vineyard rows, resulting in both under- and overestimates of Y_a. However, an analysis of the number of TTMs deployed within a vineyard is outside the scope of this study. Using specific predictor year(s) under Equation 3, but fixing the ratios at $d = L$, the difference between estimated (Y_e) and observed Y_a depended primarily on the choice of predictor year(s) (Table 3). For vineyard 1, the yield for 2007 was best estimated from the mean ΔT_L of 2008 and 2009. This is important for selection of comparison years (ΔT_d) once one has collected a larger database of ΔT curves. For 2008, 2007 was a better estimator of Y_a than was 2009. Despite the exceptionally small yield, errors in estimating yield in 2008 were <26%. In 2009, the mean of 2008 and 2007 was slightly more accurate than 2007 alone. The best estimators in vineyard 2 differed little from those of vineyard 1: Y_a of 2007 was best estimated by the ΔT_L of 2009 alone. Yield in 2009 was best estimated from the ΔT_L of 2007, the other large-crop year. However, Y_a in 2008 was very poorly estimated because of the exceptionally low crop load (average 6.1 kg/vine) but similar ΔT_c:ΔT_i to vineyard 1. The reason for similar ΔT_L between vineyards is unclear, but it may indicate a substantial contribution to ΔT of vegetation relative to the very low crop load of vineyard 2.

Between fruit set and L, the precision, bias, and accuracy of dynamic predictions were highly variable in time and were excluded from further analysis (data not shown). The earliest reliable daily estimates from the dynamic approach may be L, because of interannual differences in the period during which there is measurable canopy growth coincident with early fruit growth. From L to harvest, there was temporal variation in the bias of daily estimates under specific predictor years (Figure 6). This is due to the timing of the divergence, or non-parallel behavior of the ΔT_d curves between years (Figure 1). An abrupt drop or rise in bias marks the time of greatest difference in the change in slopes between the curves. The effect of the atypical logistic growth curve of 2008 is more evident in vineyard 1 (Figure 6A, C) than in vineyard 2 (Figure 6D, F). Between L and veraison, there were larger changes in the differences between slopes of the curves (2008 vs. 2007 or 2009) in vineyard 1 than in vineyard 2. More consistent over time were the daily Y_e of 2007 using 2009 as the estimator (Figure 6A, C) and Y_e of 2009 estimated from 2007 data (Figure D, F), the years with "normal" growth functions. In vineyard 1, the 2007 and 2009 ΔT_d curves were nearly identical beyond fruit set with the

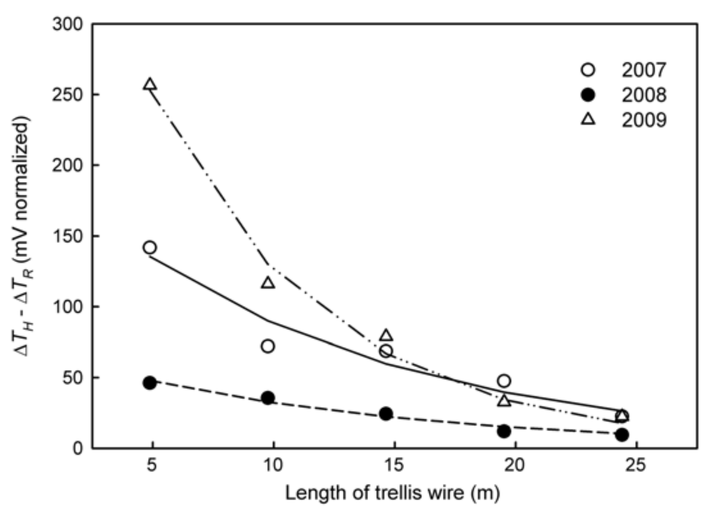

Figure 2 The drop in trellis wire tension at harvest (ΔT_H-ΔT_R) as a function of equivalent length of wire encompassing the trellis tension monitor. The uniformly distributed load was sequentially removed from the wire by harvesting equidistant vine pairs on opposite sides of the sensor.

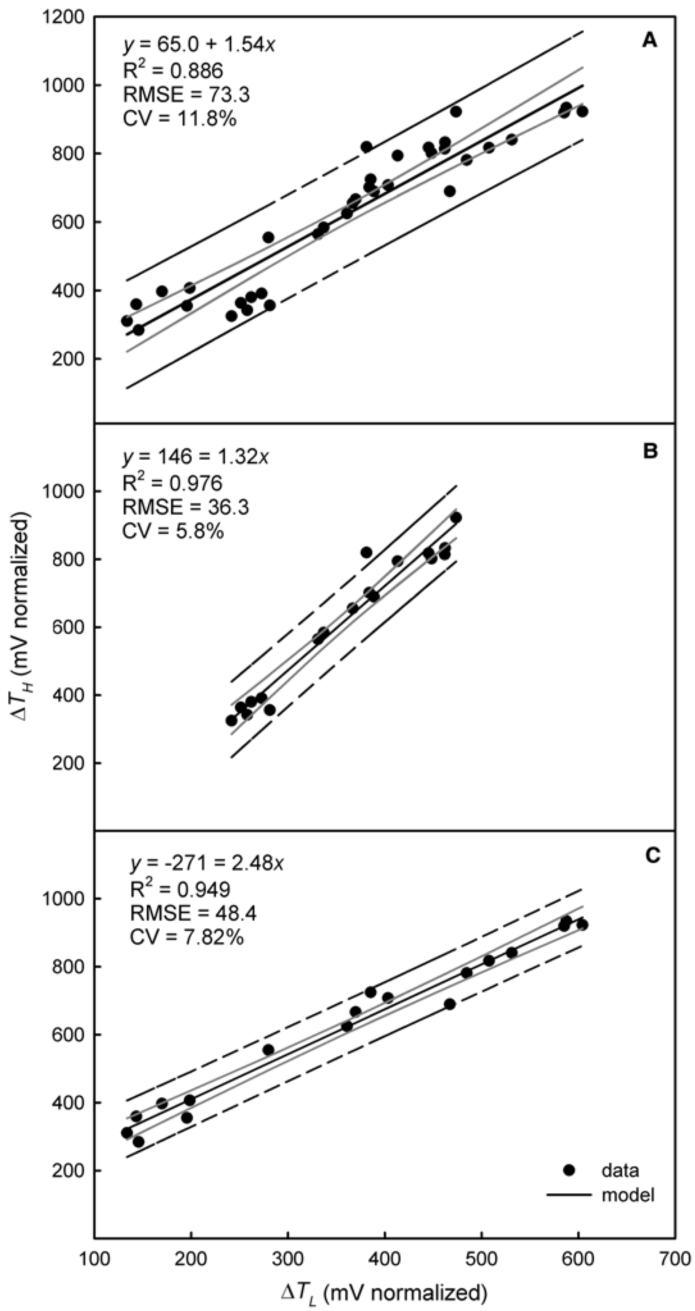

Figure 3 The change in tension (ΔT) in the trellis wire immediately preceding harvest (ΔT_H), or the initial condition immediately before manual removal of load from the trellis wire, as estimated from ΔT at the lag phase of berry growth (ΔT_L) over three years. (**A**) pooled data; (**B**) vineyard 1; (**C**) vineyard 2. Grey lines are 95% prediction intervals and the outer black lines are 95% confidence intervals. All models were significantly different from zero ($p < 0.0001$).

slopes diverging before L, thus providing early rather than late changes in both bias and accuracy. By 50 to 60 days before harvest, the bias and error in the estimates that did not include 2008 were fairly constant (Figure 6). In vineyard 2, the slopes of ΔT_d between 2007 and 2009 diverged around or soon after fruit set, after which the two curves were approximately parallel. Thus, by ~100 days before harvest, the bias and errors in the estimates that did not include 2008 were fairly constant, meaning that $\Delta T_{d,c,}:\Delta T_{d,i}$ (Equation 3), and thus Y_e, were consistent over time.

Mean values of the precision, bias, and accuracy of the dynamic estimates were calculated across an estimation period of L to harvest (Equation 4; Table 4). Estimated yield reflected patterns that were observed in the point prediction at ΔT_L (Equation 3)–in other words, driven by the choice of predictor years. There was much higher variability among rows in vineyard 1 than in vineyard 2, although there was more consistency among rows in 2007 and 2009 than in 2008. The most precise predictions were for the 2007 crop when 2009 data were used as the predictor and 2007 as predictor of 2009. As with the point estimates, because the mean yields of 2008 and 2009 bracketed those of 2007, the predictions

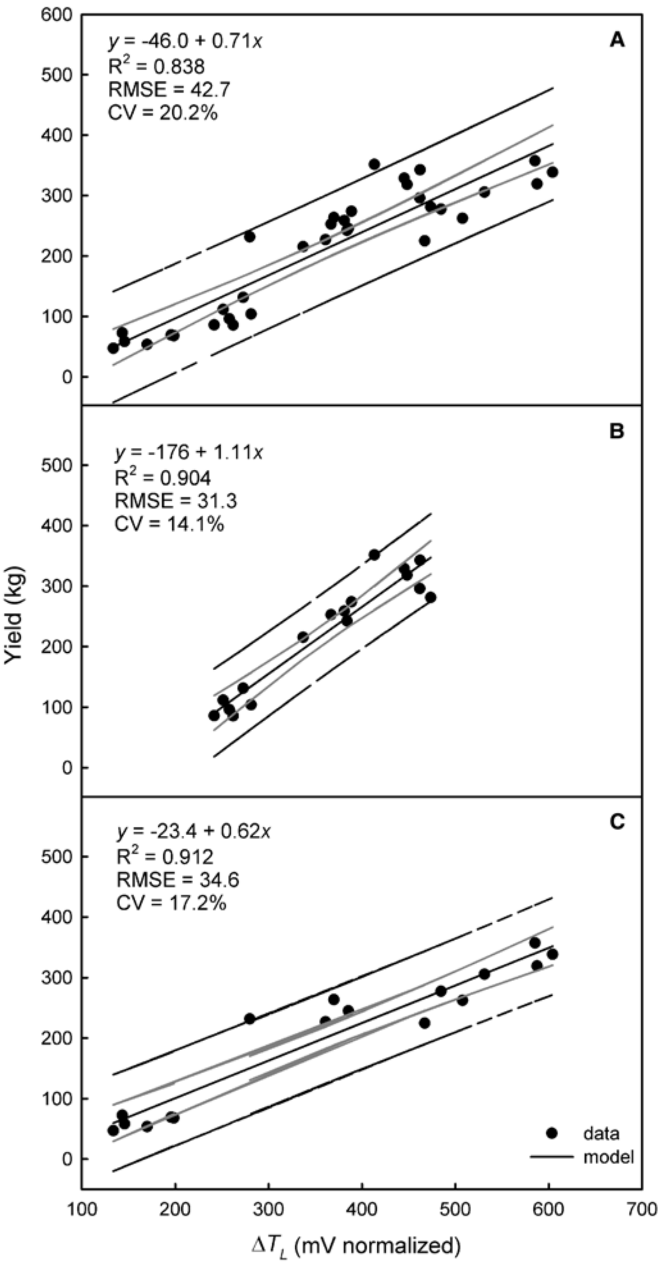

Figure 4 Total yield for 10 vines estimated (Y_e) from the change in trellis wire tension at berry lag phase (ΔT_L). (**A**) pooled data; (**B**) vineyard 1; (**C**) vineyard 2. Grey lines are 95% prediction intervals and the outer black lines are 95% confidence intervals. All models were significantly different from zero ($p < 0.0001$).

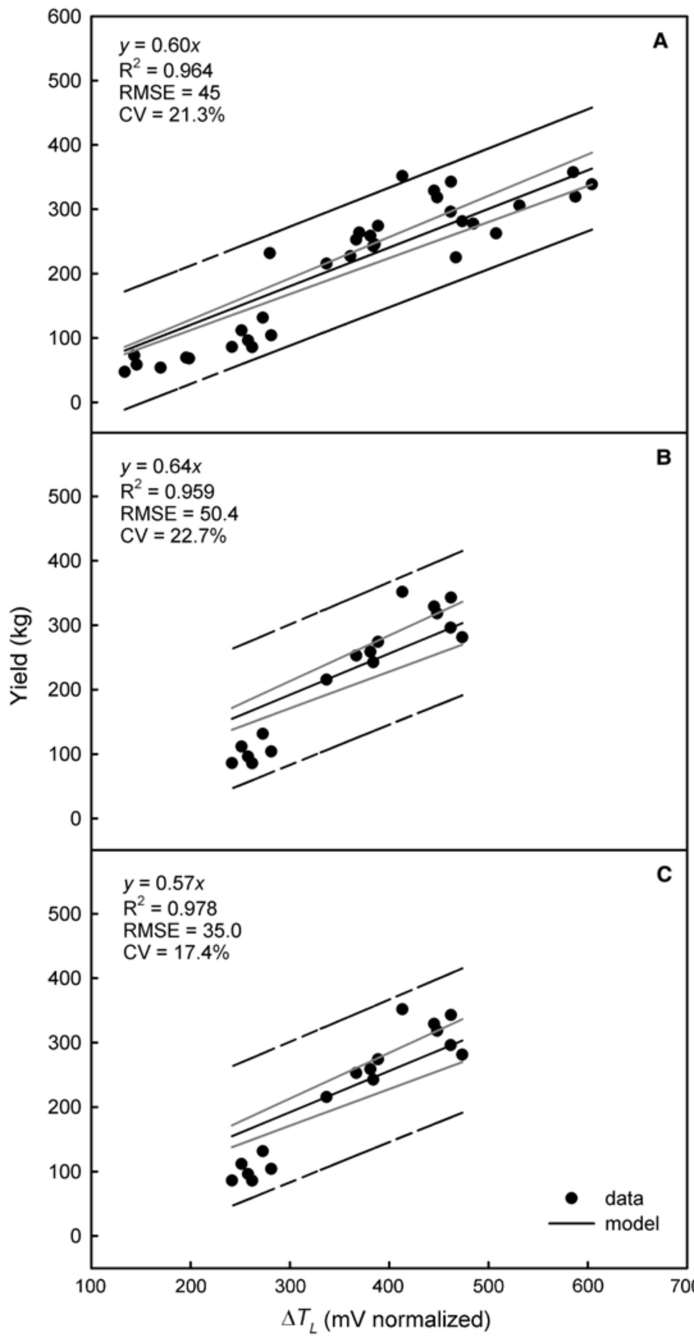

Figure 5 Total yield for 10 vines estimated (Y_e) by the change in wire tension at lag phase (ΔT_L) with intercepts of the linear equations set to zero. (**A**) pooled data; (**B**) vineyard 1; (**C**) vineyard 2. Grey lines are 95% prediction intervals and the outer black lines are 95% confidence intervals. All models were significantly different from zero ($p < 0.001$).

for vineyard 1 had relatively low error. However, 2009 alone was the best predictor of Y_a in 2007 in vineyard 2. Both the largest errors (underestimates) and the largest bias resulted when 2008 was used as the sole predictor of the large-crop years. Conversely, high-crop years (2007, 2009) consistently overestimated Y_a in the extremely low-crop year (2008).

Discussion

Sensor sensitivity to wire length could be estimated because of the uniformity of the distributed fruit load, which allowed us to remove mass consecutively from vine pairs equidistant from the sensor. Under a uniformly distributed load, the strain is equal on either side of the sensor (Megson 2005). The primary driver of the variability in ΔT_H-ΔT_R among years was ΔT_H, the initial condition at harvest. In other words, higher ΔT_H, meaning higher fruit mass at harvest, produced a larger change in ΔT per unit mass removed. Thus, sensitivity with distance from the sensor decreased most rapidly in 2009. In that year, the grape crop across California was the second largest on record (NASS 2011, 2013). By contrast, the crop was exceptionally small in 2008 because of the widespread very late frost, including at our study site. Yield was among the five lowest in the past 30 years (NASS 2011, 2013). In all years, yields in the experimental vineyards mirrored industry-wide trends.

Elastic materials, including steel trellis wire, deform linearly under load (Megson 2005). One might have expected a linear response to the sequential removal of the distributed load, but an ideal elastic response did not occur, as indicated by the curvilinear response of ΔT_H-ΔT_R. However, the elastic modulus of the wire (minimum tensile strength 1380 MPa; nominal permanent elongation 2.5% [ASTM International 2008]) was not the sole determinant of ΔT_H-ΔT_R in the field; it is implicit that the trellis is far from an ideal free-wire system. One consideration in a trellis is that restrictions on the wire in the horizontal plane are non-uniform via variables like vine-to-vine variability in cordons and post-to-post variability in wire attachments. By comparison, in a simpler single-wire trellis (Tarara et al. 2004), load removal also was an exponential function of distance from the sensor when mass was removed sequentially, regardless of the order of removal being nearest-to-farthest from the sensor, or vice versa. The ΔT_R can be used to confirm that the physical system (i.e., trellis, trellis wire) did not store energy, and as a post-hoc indicator of the approximate time at which increases in shoot mass became negligible and fruit mass begins to dominate the system. In practice, particularly under deficit irrigation, a database of several years of measurements from the TTM system would result in a family of curves from which one could estimate the time at which fruit mass begins to dominate wire tension. This would signal the time at which one could begin dynamic predictions. Those predictions would be adjusted as the current season's ΔT_d, or growth curve, diverged from the mean curve derived from the database. The low sensitivity of Y_e to the analytically determined date of L means that in most years, there would be a margin of error for the timing of growers' field sampling.

Table 2 Linear relationships (y = a +bx) between the change in tension at lag phase and yield, segregated by the number of vines in the input data set, which represent the distance from the trellis tension monitor. The vines were in pairs equidistant from the sensor.

	No. of vines	Parameter a	Parameter b	Statistic[a] R^2 (%)	Statistic[a] RMSE	Statistic[a] CV (%)
Pooled	2	-15.8	0.16	80.6	9.93	23.7
	4	-27.7	0.31	81.1	19.01	22.5
	6	-39.9	0.46	82.2	27.37	21.4
	8	-51.3	0.60	80.7	37.91	22.3
	10	-63.1	0.75	82.2	44.77	21.2
Vineyard 1	2	-49.6	0.26	92.8	6.31	14.2
	4	-82.0	0.48	93.5	11.96	12.2
	6	-113.2	0.69	92.2	17.52	12.9
	8	-141.6	0.89	88.7	27.73	15.4
	10	-176.9	1.11	90.4	31.30	14.1
Vineyard 2	2	-9.3	0.13	91.6	6.59	16.7
	4	-19.0	0.26	88.3	15.95	20.1
	6	-28.8	0.40	89.4	22.83	19.0
	8	-38.0	0.53	87.6	33.13	20.7
	10	-44.2	0.66	88.2	39.91	19.8

[a]RMSE: root mean square error; CV: coefficient of variation.

Table 3 Observed yield (Y_a; kg/10 vines) in 2007, 2008, and 2009, and estimated yield (Y_e) in 2007, 2008, and 2009 from the change in trellis wire tension set at berry lag phase (ΔT_L), using the ratio between ΔT_L in the current year to ΔT_L in the predictor year(s) (n = 6).

		Y_a and Y_e[a] by year											
		2007				2008				2009			
			Y_e				Y_e				Y_e		
Vineyard	Statistic	Y_a	ΔT_{L08}	ΔT_{L09}	ΔT_{L0809}	Y_a	ΔT_{L07}	ΔT_{L09}	ΔT_{L0709}	Y_a	ΔT_{L07}	ΔT_{L08}	ΔT_{L0708}
1	Mean	248.6	233.7	275.3	262.5	102	104	127.8	116	320	284.2	276.7	285.5
	SD	21.9	54.0	44.0	40.8	17.5	24.52	43.12	36.1	27.1	21.63	59.02	28.93
	Error (%)		-6.0	10.7	5.6		1.96	25.3	13.7		-11.2	-13.5	-10.8
2	Mean	238.3	145.2	234	194.1	61.5	139.9	137.1	137.8	310	315.4	161	262.2
	SD	15.76	46.75	28.95	42.9	10.1	19.3	12.1	15.2	36.1	47.9	22.83	35.93
	Error (%)		-39.1	-1.8	-18.5		127.5	123.0	124		1.74	-49.8	-15.4

[a]Y_e = yield estimated from trellis tension monitor output of the change in wire tension (ΔT) at berry lag phase (ΔT_L) from 2007 (ΔT_{L07}), from 2008 (ΔT_{L08}), from 2009 (ΔT_{L09}), from the mean of 2007 and 2008 (ΔT_{L0708}), from the mean of 2008 and 2009 (ΔT_{L0809}), or from the mean of 2007 and 2009 (ΔT_{L0709}).

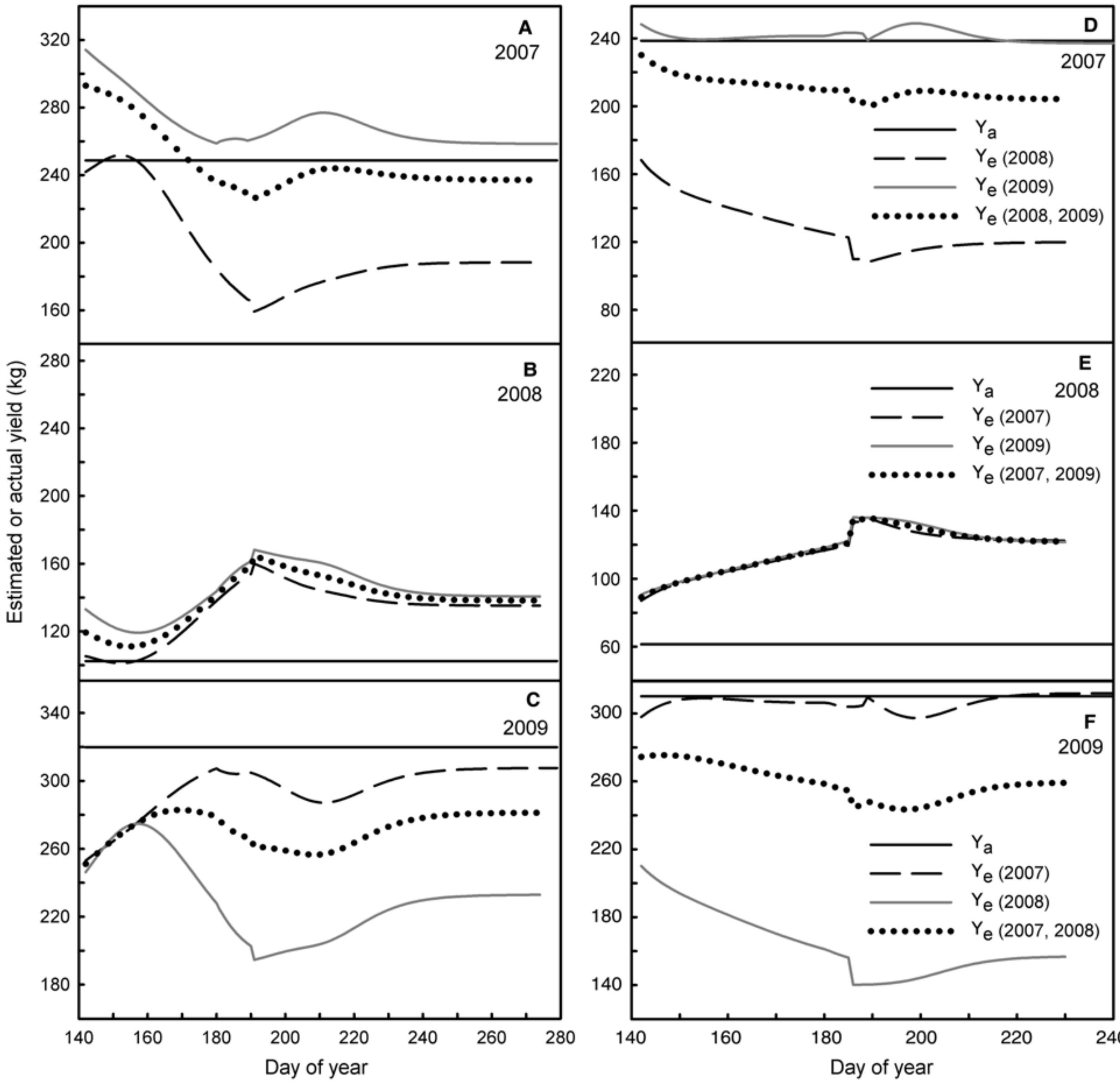

Figure 6 Dynamic estimation of yield (Y_e) for 10 vines computed from the change in trellis wire tension (ΔT) in daily time steps (ΔT_d). (**A**–**C**) vineyard 1; (**D**–**F**), vineyard 2. Numbers in parentheses are the predictor years. Because of year-to-year differences in yield, all vertical axes are scaled to a range of 200 kg. Vineyard 1 (cv. Merlot) was harvested 30 to 50 days after vineyard 2 (cv. Chardonnay). The horizontal line is Y_a.

Table 4 Mean precision, accuracy, and error of the dynamic estimation of yield from the change in tension in the trellis wire (ΔT) in daily time steps ($\Delta T_{d,i}$) over the estimation period (berry lag phase to harvest; n = 6).

		Yield estimated by Year and ΔT_d[a]								
		2007			2008			2009		
Vineyard	Statistic	ΔT_{08}	ΔT_{09}	ΔT_{0809}	ΔT_{07}	ΔT_{09}	ΔT_{0709}	ΔT_{07}	ΔT_{08}	ΔT_{0708}
1	Bias	-53.6	21	-2.1	30.2	41.1	36	-24.2	-89.4	-48
	Variance	689.6	185.5	303.6	252.2	190.9	215.5	192.4	515.4	90.8
	RMSE	65.1	28.5	24.7	37.6	45.5	41.6	31.2	95	49.8
	CV (%)	26.2	11.5	9.9	36.7	44.4	40.1	9.8	29.7	15.6
2	Bias	-110.7	2.8	-28.4	54.6	56.3	55.5	-3.5	-171.1	-64.7
	Variance	210.3	10.9	38.66	148.2	162.4	155.4	17.2	355.5	101.7
	RMSE	112.6	5.4	29.7	57.3	59.1	58.3	6.8	148.5	52.9
	CV (%)	47.2	2.3	12.5	93.2	96.1	94.8	2.2	47.88	17.1

[a]Yield estimated from the change in wire tension at day $_d$ (ΔT_d) in year $_i$ from 2007 (ΔT_{07}), from 2008 (ΔT_{08}), from 2009 (ΔT_{09}), from the mean of 2007 and 2008 (ΔT_{0708}), from the mean of 2008 and 2009 (ΔT_{0809}), or from the mean of 2007 and 2009 (ΔT_{0709}).

The growth curve in 2008 was atypical in three respects. First, there was a temporal shift in ΔT_0 such that there was little change in ΔT_d (i.e., growth) between the delayed budbreak and L. Second, sensor output indicated an uncharacteristically short L that could not be resolved analytically (Tarara et al. 2013). Third, the double sigmoid growth curve did not occur, making 2008 an unrealistic predictor year for “normal” years (i.e., 2007, 2009). There was a compressed developmental scale caused by the interrupted or frost-induced 4 to 6 week reset of the growing season. This phenomenon is truly rare in the growing region. A year like 2008 would be excluded from any database meant to allow the computation of average curves that bracket the current season’s curve for either a point estimate at L or for dynamic (i.e., daily) estimates from L to harvest. The regression approach to a point estimate would remain valuable in such an instance.

Traditional approaches to yield estimation in vineyards are based upon a single scalar to convert current cluster number and/or average mass to that anticipated at harvest (e.g., Wolfe 2006). Our attempt to replicate this system by estimating yield from ΔT_L without an intercept for the linear equation did not fit the data as well as the relationships that included an intercept. It is important to note that the zero-intercepts of these models are statistical fits; they do not have physical meaning because ΔT_L is never zero. The advantage of the TTM is that such relationships (Y_e from ΔT_L) can be computed from data collected remotely and automatically, rather than manually, and the relationships can be vineyard-specific. Therefore, a grower is not limited to a single scalar and thus may achieve a yield prediction by vineyard with less error than current practice allows. With the exception of vineyard 2 in 2008, the errors found were within a reasonable range compared to aggregate estimates in the industry, and well below some reported vineyard-specific errors (Blom and Tarara 2009, Clingeleffer et al. 2001). The linear relationships are straightforward and can be computed from a few years of data where yields vary.

It appears that fewer years are required to use the static regression-based approach at L than by fixing ΔT_d to its value at L and computing Y_e from Equation 3, because lower errors were found with the regression models. During the initial years of measuring tension in the trellis wire, a grower would be collecting a series of curves to use for both static and dynamic estimates. Estimates from fixing ΔT_d at L would become more robust (accuracy and bias improved) as the database expanded.

For dynamic estimates, extreme values of ΔT_d or Y_e appear to produce excessive bias by skewing the estimate. From several years’ curves, a mean (i.e., ΔT_d and Y_e values) would be computed to produce an estimator. For daily estimates, there would need to be at least one year of symmetry in the growth curve, in other words, curves that are evaluated periodically for parallel behavior. The time at which reliable yield estimates begin could be adjusted by selecting curves with parallel behavior. This is a limitation in the initial use of the method. As in industry, the more years that are available for comparison, the higher the likelihood of selecting meaningful curves.

Consistent bias and precision across the estimation period indicate symmetry in growth, illustrated throughout the prediction interval in vineyard 2. In practice, precision can be improved by installing the TTMs among the most uniform vines possible. Bias can be reduced and more importantly, accuracy can be improved with the collection of a larger database of ΔT curves from which one could compute a mean of years. Post-hoc analyses showed that from the ratio approach (Equation 3), L may be the earliest useful estimate of yield. Dynamic estimates became consistent over time by a number of weeks before harvest. The mean errors over the estimation period were lower than those of point estimates at L, consistent with previous work (Blom and Tarara 2009). Nonetheless, the power of a dynamic prediction is not for point estimates at L per se, but for a daily estimate between L and harvest, which follows relative changes in crop growth during ripening.

Conclusion

In the trellis system under study, which is widespread across the industry in the United States and elsewhere, the TTM appeared to have a spatial response to removal of uniformly distributed fruit load of up to ~24 m or ~12 m to either side of the sensor. Thus, with an average vine spacing for wine grapes, 8 to 10 vines may constitute a meaningful sample size for the TTM in such a cordon-wire-based trellis. The tension in the main loadbearing wire of this trellis can be used to estimate local yield of grapevines. Vineyard-specific models fit the data better than pooled models, addressing concern about bulk versus vineyard-specific yield estimates, where vineyard specificity is important to harvest logistics. Dynamic and static approaches to yield estimation are feasible. At the developmental stage that traditionally is used by growers to estimate yield from hand sampling, the lag phase, the change in wire tension could be used to estimate fruit mass at harvest with acceptable accuracy. Dynamic estimation of yield after L provides data that are not available by current means, and would provide growers and wineries with updates of yield estimates that are not now practical. Additional work is warranted on the spatial distribution of TTM installations within a single vineyard for the most meaningful sampling design. This is not unique to the TTM, as the same question must be posed for hand sampling.

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