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Wine grape cultivar influence on the performance of models that predict the lower threshold canopy temperature of a water stress index

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ABSTRACT

The calculation of a thermal based Crop Water Stress Index (CWSI) requires an estimate of canopy temperature under non-water stressed conditions (T_{nws}). The objective of this study was to assess the influence of different wine grape cultivars on the performance of models that predict T_{nws}. Stationary infrared sensors were used to measure the canopy temperature of the wine grape cultivars Malbec, Syrah, Chardonnay and Cabernet franc under well-watered conditions over multiple years and modeled as a function of climatic parameters – solar radiation, air temperature, relative humidity and wind speed using multiple linear regression and neural network modeling. Despite differences among cultivars in T_{nws}, both models provided good prediction results when all cultivars were collectively modeled. For all cultivars, prediction error variance was lower in neural network models developed from cultivar-specific datasets than regression models developed from multi-cultivar datasets. Overall, the cultivar-specific models had less prediction error variance than multi-cultivar models. Multi-cultivar models generally resulted in prediction bias whereas cultivar-specific models eliminated the prediction bias. All predictive models had an uncertainty of ± 0.1 in calculation of the CWSI despite significantly different prediction error variance between models.

1. Introduction

Wine grapes (*Vitis vinifera* L.) are widely grown in arid and semiarid regions where irrigation is used to supplement annual precipitation. The desired amount of water to supply during an irrigation event is usually less than estimated vine water demand (ET_c), with the goal of inducing some vine water stress to manage vegetative growth, induce beneficial changes in berry composition (Sadras and Moran, 2012), and increase water productivity (Shellie, 2014; Chaves et al., 2007; Fereres and Soriano, 2007). Decisions about when to irrigate and how much water to supply during an irrigation event ultimately influence production profitability in terms of input costs, yield and fruit quality. The Penman-Monteith model is commonly used to estimate how much water to supply during an irrigation event (Allen et al., 1998). The model estimates vine water demand (ET_c) from the evapotranspiration of a reference crop (ET_r), a crop specific coefficient (K_{cb}), and a stress coefficient (K_s) to account for a decrease in water demand when transpiration is restricted by unfavorable environmental conditions. The equation for estimating ET_c under transpiration-limiting conditions is:

$$ET_{c-adj} = ET_r(K_{cb}K_s) \tag{1}$$

If the value of K_s represents the amount of transpiration being limited by a water deficit, the value of K_s could serve as a guide for irrigation scheduling. However, determining a reliable value for K_s has been difficult. The methods commonly used to monitor vine water status, such as soil moisture or plant water potential, often have poor spatial and temporal resolution or are too laborious for automation. Also, wine grape cultivars are known to differ in their hydraulic behavior and alter their usual behavior under different environmental conditions (Pou et al., 2012; Chaves et al., 2010; Lovisolo et al., 2010; Vandeleur et al., 2009). This poses an additional level of difficulty in estimating K_s. For example, Hochberg et al. (2017) supplied the same fractional amount of ET_c to different wine grape cultivars under identical environmental conditions and reported differing levels of vine water stress severity among cultivars and higher or lower than intended severities of water stress at different vine phenological stages. This suggests that K_s values may differ according to cultivar and to the phenological stage of vine development.

Thermal remote sensing has been used to estimate drought stress in many crops, including grapevine (Maes and Steppe, 2012). An empirical crop water stress index (CWSI) was developed by Jackson et al. (1981) and Idso et al. (1981) to indirectly estimate K_s. Jackson (1982)

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compared *in situ* measurements of leaf temperature with soil volumetric water content and found leaf temperature to be a more reliable indicator of plant water status. The equation used to calculate the CWSI is:

$$CWSI = \frac{(T_{canopy} - T_{nws})}{(T_{dry} - T_{nws})} \tag{2}$$

where T_{canopy} is the measured temperature of the vine canopy, and T_{dry} and T_{nws} are the upper and lower canopy temperature thresholds when transpiration is completely limited or non-restricted, respectively. The CWSI ranges in value from 0 to 1 where 0 indicates optimum conditions for maximum transpiration (T_{nws}) and 1 represents a non-transpiring condition (T_{dry}). The need for an irrigation event is signaled when the CWSI value exceeds a desired numerical threshold. The CWSI (Colaizzi et al., 2003) and the ratio of T_{canopy} to T_{nws} (Bausch et al., 2011) have been used in cotton and corn, respectively, to guide irrigation scheduling and indirectly estimate K_s for determining ET_c.

The CWSI has been of limited use with wine grapes due to the practical difficulty of determining values for T_{nws} and T_{dry} while simultaneously measuring T_{canopy} (Jones et al., 2002). Approaches that have been used to estimate T_{nws} include energy balance equations (Sepúlveda-Reyes et al., 2016; Möller et al., 2007) natural or artificial reference surfaces (Sepúlveda-Reyes et al., 2016; Pou et al., 2014; Möller et al., 2007), and the difference in temperature between T_{canopy} and air relative to evaporative demand (Bellvert et al., 2015; Idso et al., 1981). A constant has been used to estimate a value for T_{dry} (Möller et al., 2007; King and Shellie, 2016). The influence of cultivar hydraulic behavior on the accuracy of these approaches has not been evaluated.

King and Shellie (2016) predicted lower canopy temperature threshold values for the wine grape cultivars Syrah and Malbec using a neural network (NN) model developed from cultivar-specific datasets. The importance of cultivar specificity in the dataset used to train, test and validate the NN predictive model was not evaluated. The objective of this research was to ascertain the influence of cultivar on model predictive performance. Under well-watered field conditions, we continuously monitored the canopy temperature of grape cultivars Cabernet franc (CF), Chardonnay (CH), Malbec (MB) and Syrah (SY) over consecutive growing seasons and used the measured temperatures to develop neural network (NN) and multiple linear regression models to predict T_{nws}. Cultivar influences were indirectly evaluated by comparing the predictive performance of models developed from a cultivar-specific dataset to that of models developed from a multi-cultivar dataset.

2. Materials and methods

2.1. Trial site and irrigation

This study was conducted over three growing seasons (2014, 2015, and 2016) in three experimental vineyards located at the University of Idaho Parma Research and Extension Center in Parma, ID (lat. 43°37′7.9716″N, long. 116°12′54.1″W, 750 m asl). Two of the vineyards were located adjacent to one another and were planted in 2007 with un-grafted, dormant-rooted cuttings of either MB or SY. The other vineyard was located ~0.5 km southeast of the MB and SY trial sites and was planted in 1997 with un-grafted, dormant-rooted cuttings of CF and CH. Vines in all three vineyards were managed according to local commercial practices (double-trunked, bilateral cordon, spur-pruned annually to 16 buds/m of cordon, vertically positioned on a two-wire trellis with moveable wind wires). The vineyards are described in more detail by Shellie (2007) and King and Shellie (2016).

The vineyards were irrigated to field capacity each year prior to bud break to encourage uniform bud break and at the end of the growing season to reduce the risk of freeze injury. Vines were also drip-irrigated 3–5 times a week with an amount of water estimated to meet or exceed

Table 1
Climate data from 1 Apr through 31 Oct collected at the PMAI weather station located 3 km from the research vineyards in Parma, ID [(www.usbr.gov/pn/agrimet/), latitude 43°48′00″, longitude 116°56′00″, elevation 702 m] and amount of irrigation water supplied during berry development.

	2014	2015	2016	1994–2012 average
Precipitation (mm)	88	113	120	99.6 ± 35
Daily average total direct solar radiation ($MJ\,m^{-2}$)	22.3	21.9	22.6	22.1 ± 0.9
Days daily maximum temperature exceeded 35 °C	27	25	26	28 ± 12
[z]Accumulated growing degree days (°C)	1759	1865	1688	1708 ± 115
Alfalfa-based reference evapotranspiration (ET_r) (mm)	1314	1265	1329	1212 ± 55
Irrigation amount (mm)				
Syrah	726	514	1322	
Malbec	521	514	973	
Cabernet franc	NE	599	1369	
Chardonnay	NE	599	1369	

[z] Accumulated growing degree days were calculated from daily maximum and minimum temperature with no upper limit and a base temperature of 10 °C.

Table 2
Least square mean values for midday leaf water potential (Ψ_{md}) of vines drip-irrigated to supply estimated vine water demand (ET_c) from fruit set until harvest. Vines were grown in field plots in a research vineyard in Parma, ID and measured weekly on a day preceding an irrigation event.

		Preveraison (MPa)	Postveraison[a] (MPa)
		−0.84	
Year	2014[b]		−0.75b
	2015		−0.88c
	2016		−0.55a
Cultivar	Syrah		−0.73b
	Malbec		−0.73b
	Cabernet franc		−0.86a
	Chardonnay		−0.81ab
	p values[c]		
	Preveraison	Postveraison	
Year	ns	**	
CV	ns	*	
Year * CV	ns	ns	

[a] Same lowercase letter within a treatment level column indicates no significant difference at $p \le .05$ by Tukey-Kramer adjusted *t* test.
[b] Analysis excludes cultivars Cabernet franc and Chardonnay.
[c] *, **, and ns indicate $p \le .05$, 0.01, and not significant, respectively.

Table 3
Minimum and maximum values for vineyard environmental conditions and well-watered canopy temperatures measured between 13:00 and 15:00 MDT in Parma, ID in 2014 (26 June through 6 Oct), 2015 (25 June 25 through 23 Sept), and 2016 (23 June through 27 Sept) and used to linearly scale Neural Network input parameters.

	Minimum	Maximum	Mean[a]
Air temperature (°C)	10.8	38.6	27.3 ± 4.9
Relative humidity (%)	10.0	89	27.0 ± 11.6
Wind speed ($m\,sec^{-1}$)	0.2	5.7	1.5 ± 0.7
Solar radiation ($W\,m^{-2}$)	18	1107	760 ± 190
Canopy temperature			
Malbec (°C)	9.6	33.3	24.9 ± 3.7
Syrah (°C)	9.6	34.2	25.1 ± 3.8
CF (°C)	9.7	36.1	26.4 ± 3.9
CH (°C)	9.8	34.8	26.2 ± 4.3

[a] ± Standard deviation.

ET_c beginning when berries were ~7 mm in diameter at growth stage 31 of the modified E-L grapevine growth stage system (Coombe, 1995) and continuing until harvest at fruit maturity. The Penman-Monteith model (Allen et al., 1998) was used to estimate ET_c with K_{cb} increasing during canopy development from 0.3 to 0.7 and $K_s = 1$. Alfalfa reference crop (ET_r) values were obtained from a weather station located 3 km from the study location (http://www.usbr.gov/pn/agrimet/wxdata.html). Midday leaf water potential (Ψ_{md}) was checked weekly to ensure a value less negative than −1.0 MPa, a threshold below which was previously observed to restrict shoot growth (Shellie, 2006). Irrigation delivery amount was recorded using flow meters.

2.2. Plant water status measurements

Vine water status was monitored weekly throughout berry development by measuring leaf water potential at midday (Ψ_{md}) using a pressure chamber[1] (model 610; PMS Instruments, Corvallis, OR) following the method of Turner (1988) as described by Shellie (2006). Two, fully expanded, sunlit leaves were measured per vine in two vines per cultivar. Weekly Ψ_{md} pre- and postveraison measurements collected were analyzed by phenological stage using a repeated measure analysis of variance (ANOVA) with cultivar as a fixed effect and years as a repeated measure (ver. 9; SAS Institute, Cary NC). The probability of a significant difference among treatment levels ($p \leq .05$) was determined using the Tukey-Kramer adjusted t test. Seasonal cumulative growing degree days were calculated from daily minimum (base threshold of 10 °C) and maximum (no upper limit) temperatures recorded at the nearby weather station (http://www.usbr.gov/pn/agrimet/wxdata.html) from 1 Apr to 31 Oct.

2.3. Measurement of canopy temperature and vineyard environmental conditions

Stationary infrared temperature sensors (SI-121 Infrared radiometer; Apogee Instruments, Logan, UT) were positioned approximately 15 to 30 cm over the top of the vine canopy (viewing 2–5 leaves) and used to measure canopy temperature as described by King and Shellie (2016). Two infrared temperature sensors were installed for each cultivar, with each sensor located on a different vine. The leaf temperature sensing area was approximately 15–30 cm in diameter and the center of field of view was aimed at the center of leaves receiving full sunlight exposure during midday.

The environmental conditions monitored in the vineyard were: wind speed (WS) (05305 anemometer, R.M. Young, Traverse City, MI), air temperature (T_{air}), relative humidity (RH) (HMP50 temperature and humidity probe, Campbell Scientific, Logan, UT), and solar radiation (SR) (LI-200SZ pyranometer, LI-COR Biosciences, Lincoln, NE). Environmental sensors were located in the vine row, above the grapevine canopy with T_{air}, RH and SR measured at 2.2 m and WS measured at 2.5 m above ground level, as described by King and Shellie (2016). Wind speed was adjusted to a standard height of 2 m (Allen et al., 1998).

Environmental conditions and vine canopy temperatures were concurrently measured continuously between grapevine growth stage 31 (berries 7 mm diameter) and stage 38 (berries harvest-ripe) (Coombe, 1995). Data were measured at 1-min intervals and recorded as 15-min average values on a datalogger, as described by Shellie and King (2016). Canopy temperature and environmental data were collected in 2014 from 26 June through 6 Oct; in 2015, from 2 July through 23 Sept; and in 2016, from 7 July through 27 Sept. The canopy temperatures of Syrah and Malbec were measured in all three study years and that of CH and CF were measured in 2015 and 2016.

2.4. Datasets and T_{nws} predictive models

The entire, multiyear dataset was filtered to include only data recorded between 13:00 and 15:00 MDT (±90 min around solar noon), as described by King and Shellie (2016). Time of solar noon at the study site ranged from 13:53 to 13:35 MDT over the measurement dates in each year. The filtered dataset was subdivided to create two unique datasets for each cultivar. One dataset contained only the measured temperatures for a specific cultivar (cultivar-specific) and the other dataset contained all the measured temperatures in the filtered dataset for the three remaining cultivars (multi-cultivar). Each dataset contained the measured canopy temperatures and the corresponding vineyard environmental conditions (SR, T_{air}, RH, WS) recorded at the time of canopy temperature measurement. The cultivar-specific and multi-cultivar dataset for each cultivar was used to develop a neural network (NN) model and a multiple linear regression model to predict T_{nws}. The same environmental data and measured canopy temperatures were used as input parameters for both model types. MATLAB Neural Network Toolbox software (MathWorks, Natick, MA) was used to develop the NN models and Microsoft Excel was used to develop the multiple linear regression models. Each NN model was trained, tested and validated by subdividing the dataset into three parts, each of which contained 70, 15, and 15% of the total dataset, respectively. Neural network model input parameters were linearly scaled to a range of −1 to 1 based upon the maximum and minimum values for the measured parameter. The Levenberg-Marquardt back propagation method (Haykin, 2009) was used to train the network with the training dataset. A multilayer perceptron feed forward NN architecture was used. Hidden layer neurons and the single output neuron used a hyperbolic tangent activation function. The NN models had one hidden layer with five neurons.

2.5. Model predictive performance

For each cultivar, the predictive performance of models developed from cultivar-specific datasets was compared to models developed from multi-cultivar datasets. Model predictive performance was compared by goodness of fit parameters mean square error (MSE), model efficiency (ME) and percent bias (PBIAS). The MSE is a measure of the amount of error between predicted and observed values. The MSE was calculated as:

$$MSE = \left[\frac{\sum (O_i - P_i)^2}{n}\right] \tag{3}$$

where O_i was the observed ith data value, P_i was the predicted ith data value, and n was the number of data values. Values for MSE range from 0.0 to ∞, with an optimal value of zero. A model with a lower MSE is more accurate than a model with a higher MSE. Model efficiency (ME) is analogous to the common correlation coefficient for linear regression. Model efficiency was calculated as:

$$ME = 1 - \left[\frac{\sum (O_i - P_i)^2}{\sum (O_i - O_{avg})^2}\right] \tag{4}$$

where O_{avg} is the average value of all measured O_i data values (Nash and Sutcliffe, 1970). Values of ME range from −∞ to an optimal value of 1.0. A value of zero indicates that the values predicted by the model are no more accurate than the mean value of the observed data. The ME is not based upon the proportion of variation explained by a regression's independent variable, so its value can be < 0 if the data set contains extreme values, a non-linear function is fit to observed data, or model predicted values are less accurate than the mean of the observed values. The PBIAS is a measure of how much the fitted model over or under predicted the observed values. The PBIAS was calculated as

[1] The mention of trade names of commercial products in this article is solely for the purpose of providing specific information and does not imply recommendation or endorsement by the U.S. Department of Agriculture.

Table 4
Prediction error variances for neural network (NN) and multiple linear regression (REG) models developed to predict the well-watered canopy temperature of grapevine cultivars Malbec, Syrah, Cabernet franc (CF) and Chardonnay (CH) using multi-cultivar and cultivar-specific datasets.

Model	Dataset	Malbec[a]	Syrah	CF	CH	All cultivars
NN	Multi-cultivar	1.40ab	1.08bc	1.14a	0.89c	1.25a
NN	Cultivar-specific	1.23b	0.88c	0.75b	0.77c	NE
REG	Multi-cultivar	1.64a	1.33a	1.21a	1.13a	1.46a
REG	Cultivar-specific	1.56ab	1.20b	0.97a	1.05b	NE

[a] Variances with the same letter within a cultivar column are not significantly different using the Bonferroni correction for multiple pair-wise comparisons ($p \leq .01$).

(Yapo et al., 1996):

$$PBIAS = \left[\frac{\sum (P_i - O_i)}{\sum (O_i)}\right](100) \tag{5}$$

Values for PBIAS range from $-\infty$ to ∞ with an optimal value of zero; however, values close to zero can occur if the fitted model over predicts as much as it under predicts (Moriasi et al., 2007).

Model performance was also evaluated by statistical analysis of the variance of model prediction errors. Model prediction performance is inversely related to the magnitude of the variance of model prediction errors. Normal Q-Q plots, histograms, and Shapiro-Wilk's test ($p \leq .05$) and Kolmogorov-Smirnov test ($p \leq .05$) were used to ascertain whether prediction errors were approximately normally distributed. Equality of variances for normally distributed data were evaluated using a Levine test and, for data not normally distributed, using a non-parametric Levine test (Nordstokke and Zumbo, 2010; Nordstokke et al., 2011). Multiple comparisons of variance were tested using the Bonferroni correction to minimize the likelihood of incorrectly rejecting a null hypothesis (Type I error).

The influence of model prediction error on error distribution of the CWSI was estimated for the cultivar SY using Monte Carlo simulation in an Excel spreadsheet to calculate the CWSI as:

$$CWSI\ \ error = \frac{(T_{mnws} - T_{pnws})}{(T_{dry} - T_{pnws})} \tag{6}$$

where T_{pnws} is the model predicted canopy temperature when measured (assumed known) canopy temperature (T_{mnws}) was 26 °C and T_{dry} was 44 °C (29 °C air temperature +15 °C) (King and Shellie, 2016). Values for T_{pnws} were obtained from the linear regression model developed from the multi-cultivar dataset and the NN model developed from the cultivar-specific dataset. Model prediction error variances were assumed to be approximately normally distributed for simulation purposes. Graphs in figures were generated using Sigmaplot 11.2 (Systat Software, San Jose, CA).

3. Results and discussion

3.1. Vineyard environmental conditions

Growing season precipitation, solar radiation and the number of days that the daily maximum temperature exceeded 35 °C was similar each year to the 19-year site average (Table 1). In 2014 and 2016, accumulated growing degree days (GDD) were similar and reference evapotranspiration (ET_r) was greater than the 19-year site average. In 2015, GDD were greater and ET_r was similar to the 19-year site average. The amount of irrigation water supplied during berry development

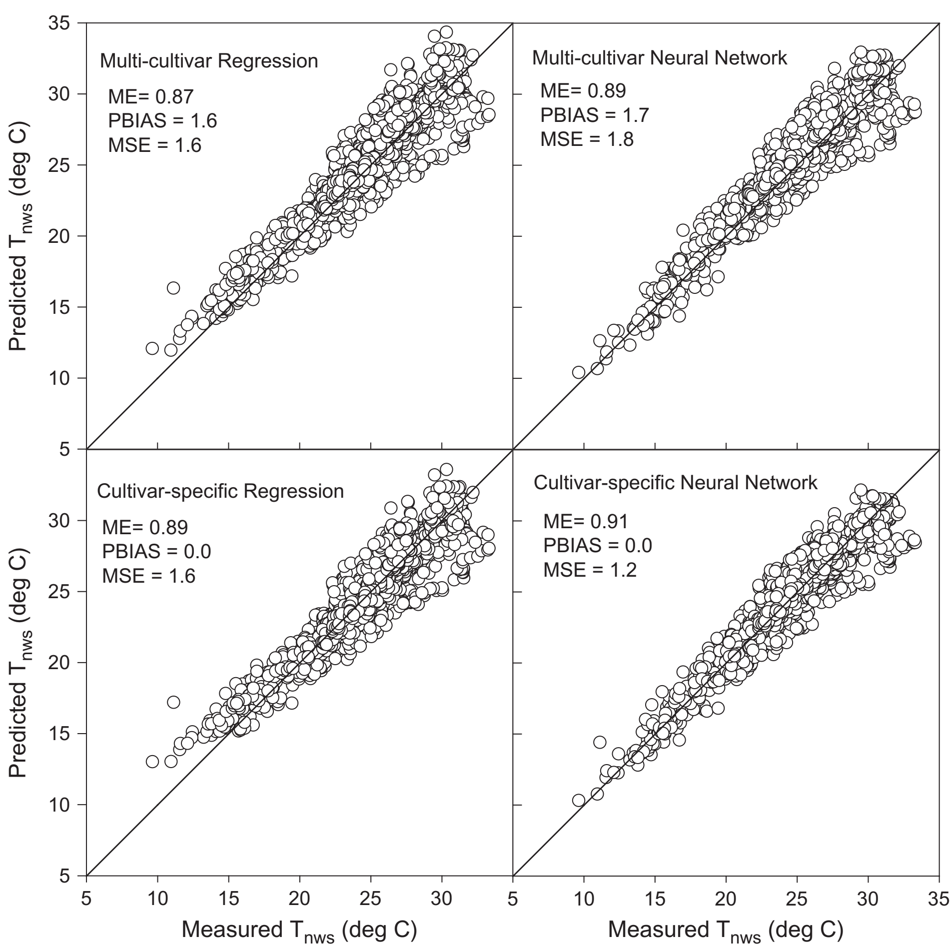

Fig. 1. Neural network and regression model performance values for predicting the non-water-stressed canopy temperature (T_{nws}) of the cultivar Malbec developed from the multi-cultivar dataset or a data subset that contained only the measured T_{nws} for cultivar Malbec.

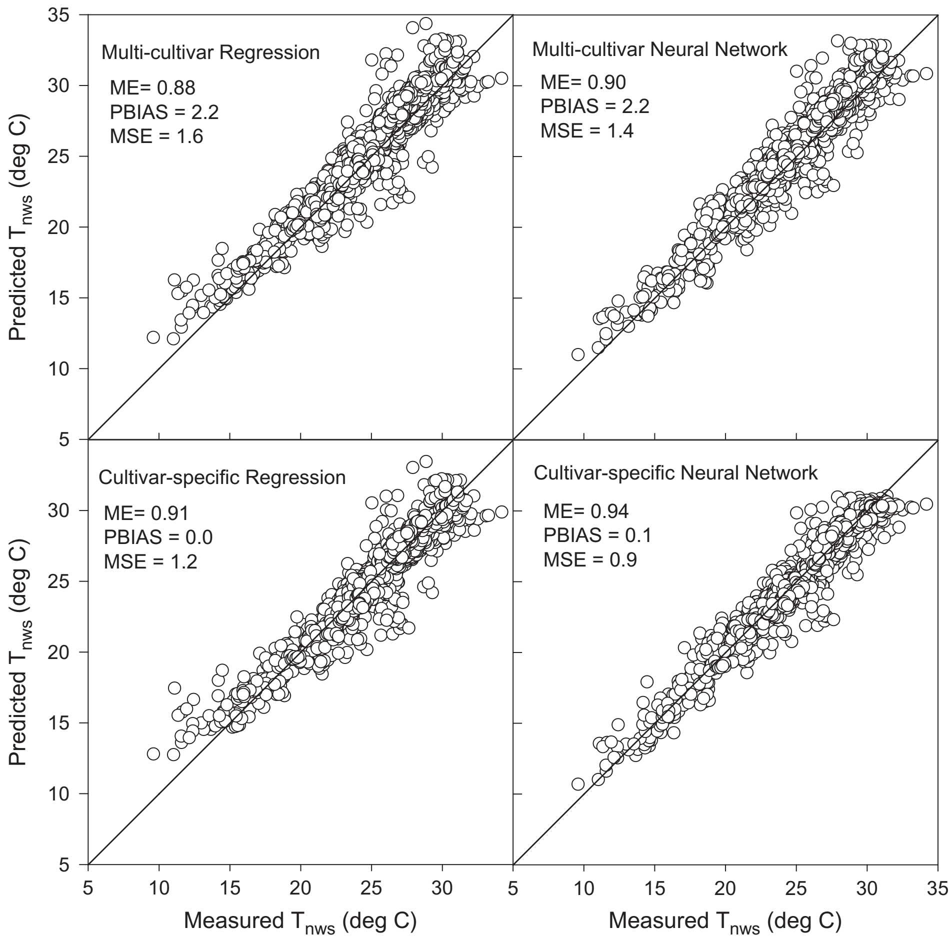

Fig. 2. Neural network and regression model performance values for predicting the non-water-stressed canopy temperature (T_{nws}) of the cultivar Syrah developed from the multi-cultivar dataset or a data subset that contained only the measured T_{nws} for cultivar Syrah.

relative to ET_r was ~53% in 2014 and 2015 and ~94% in 2016 (Table 1).

Pre- and post-veraison Ψ_{md} was less negative than −1.0 MPa in all cultivars each year (Table 2). Preveraison Ψ_{md} was similar each year among cultivars and among years. Postveraison Ψ_{md} was least negative in 2016 and most negative in 2014. The postveraison Ψ_{md} of CF was more negative than that of SY and MB and similar to that of CH.

The maximum and minimum values recorded between 13:00 and 15:00 MDT in 2014 used to linearly scale input parameters for the NN model are presented in Table 3. Minimum and maximum canopy temperatures were always cooler than ambient air temperatures and the magnitude of the difference varied among cultivars. The difference between vine canopy temperature and ambient air was greatest (~4.0 °C) when air temperature was warmest. When ambient air temperature was coolest, vine canopy temperature was an average of 1.1 °C cooler. Malbec had the coolest and CF had the warmest maximum canopy temperature. The range among cultivars in minimum and maximum canopy temperature was 0.2 and ~3 °C, respectively.

3.2. Model predictive performance for T_{nws} for different cultivars

For each of the four cultivars, the models developed from a multi-cultivar dataset tended to have higher prediction error variance than the models developed from a cultivar-specific dataset (Table 4). For models developed using the multi-cultivar dataset, the prediction error variance of the NN model was lower than that of the regression model for each of the four cultivars; however, the difference was of statistical significance only for SY and CH. When a cultivar-specific dataset was used for model development, the NN model had lower prediction error variance than the regression model; however, the difference was of statistical significance only for CF.

The relative performance of model parameters among the four models that were developed for each cultivar differed by cultivar. For the cultivar MB, the ME was similar among the four models; however, models developed from the cultivar-specific dataset had the lowest PBIAS (Fig. 1). The positive bias of the multi-cultivar datasets suggests that MB had a lower T_{nws} than other cultivars in the multi-cultivar dataset. The cultivar-specific regression model shows a visual positive bias when $T_{nws} < 20$ °C and a negative bias when $T_{nws} > 25$ °C, which tend to balance resulting in a zero bias. This bias was not visually apparent in the cultivar-specific NN model. The cultivar-specific NN model had the lowest MSE and had significantly less prediction error variance relative to the multi-cultivar regression model (Table 4).

There was a wider range in ME among the models developed for SY than among the models developed for MB (Fig. 2). The NN model had a higher ME than the regression model developed from the same dataset. The cultivar-specific NN model had the highest ME. The PBIAS was highest in models developed from the multi-cultivar dataset. The positive bias of both multi-cultivar datasets suggests that SY, like MB, had a lower T_{nws} than other cultivars in the multi-cultivar dataset. Syrah and MB also had similar and less negative postveraison Ψ_{md} than CH and CF (Table 2). The cultivar-specific NN model had the lowest MSE. The multi-cultivar regression model had the highest MSE and highest prediction error variance (Table 4). The cultivar-specific NN model had lower prediction error variance than either of the regression models.

For CF, the multi-cultivar developed models had lower ME, greater PBIAS and higher MSE than the cultivar specific models and there was little performance difference between the NN and regression model developed from each dataset (Fig. 3). The PBIAS of the multi-cultivar models was negative suggesting that CF has a higher T_{nws} than other

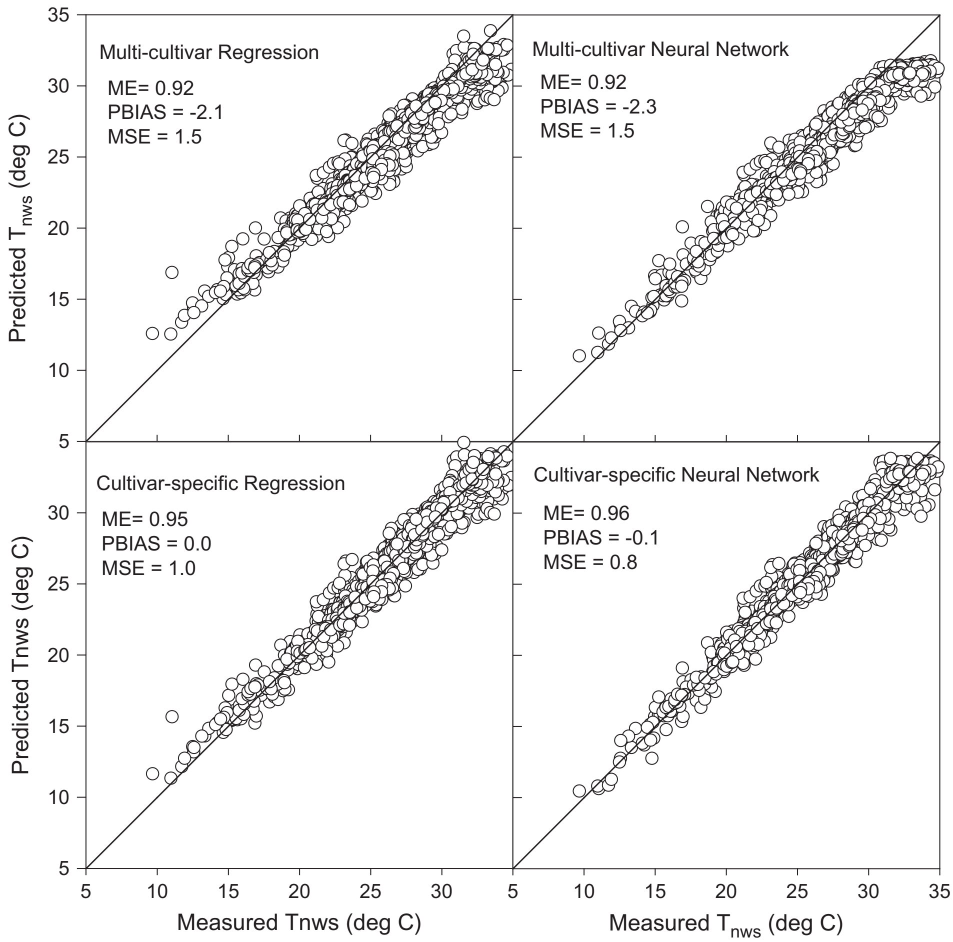

Fig. 3. Neural network and regression model performance values for predicting the non-water-stressed canopy temperature (T_{nws}) of the cultivar Cabernet franc (CF) developed from the multi-cultivar dataset or a data subset that contained only the measured T_{nws} for cultivar CF.

cultivars in the multi-cultivar dataset. The cultivar-specific NN model had lower prediction error variance than any of the other models (Table 4).

The relative difference in performance among models developed for CH was similar to that of CF (Fig. 4). The multi-cultivar developed models had lower ME, greater PBIAS and higher MSE than the cultivar specific models and there was little performance difference between the NN and regression model developed from each dataset. The negative PBIAS of the multi-cultivar models suggests that the T_{nws} of CH, like CF, was higher than that of other cultivars in the multi-cultivar dataset. The postveraison Ψ_{md} of CH and CF also was similar and was more negative than SY and MB (Table 2). The cultivar-specific regression model for CH had a visual positive bias for $T_{nws} < 20\,^{\circ}C$ and negative bias for $T_{nws} > 20\,^{\circ}C$, which tend to balance resulting in a zero bias and greater MSE than the cultivar specific NN model. Both of the NN models had lower prediction error variances than either of the regression models (Table 4).

Prediction error for T_{nws} introduces uncertainty in the calculation of the CWSI since T_{nws} is used in both the numerator and denominator of Eq. (2). To estimate the practical importance of prediction error variance on the calculation of the CWSI, the propagation of T_{nws} prediction error uncertainty was investigated for the cultivar SY using Monte Carlo simulation (Eq. (3)). The importance of error variance on calculation of the CWSI was evaluated by comparing the distribution of a CWSI value about zero when T_{nws} was predicted using the multi-cultivar regression model (prediction error variance of 1.33) to when T_{nws} was predicted using the cultivar-specific NN model (prediction error variance of 0.88) (Table 4). When the multi-cultivar regression model was used to predict T_{nws}, the calculated CWSI was ± 0.05 and ± 0.1 from the true value of zero 55 and 86 percent of the time (Fig. 5). When the cultivar-specific NN model was used to predict T_{nws}, the calculated CWSI was ± 0.05 and ± 0.1 from zero 63 and 93 percent of the time. The lower prediction error variance of the NN model reduced uncertainty by less than 10%. For both models, T_{nws} prediction error resulted in an uncertainty of ± 0.1 in calculation of CWSI, even for the model with the lowest ME. When the filtered dataset that included all cultivars and years was used for model development, the NN and regression models had statistically similar prediction error variance, even though the error variance of the NN model was lower by ~14% (Table 4). Both of the models developed from the filtered dataset had similar ME and a low PBIAS; however, the NN model had a lower MSE (Fig. 6).

The higher prediction error variance of models developed from the filtered and multi-cultivar datasets is likely a reflection of inherent differences in T_{nws} among cultivars. Other indicators that T_{nws} differed by cultivar were the higher PBIAS of multi-cultivar relative to cultivar-specific models, differences in postveraison Ψ_{md} (Table 2) and differences in maximum and minimum canopy temperatures (Table 3). The cultivar differences in T_{nws} across climatic conditions introduced a substantial amount of variance in predicted T_{nws}. The hydraulic behavior of SY, CH and CF has been described as near-anisohydric whereas MB has been described as isohydrodynamic (Lovisolo et al., 2010; Shellie and Bowen, 2014). The influence of vapor pressure deficit on stomatal conductance under high and low soil moisture conditions has been reported to differ between isohydric and anisohydric cultivars (Domec and Johnson, 2012; Hochberg et al., 2017). From a practical point of view, a regression model developed from a large multi-cultivar database is likely to provide as accurate an estimate of T_{nws} with less computational requirements as a NN model.

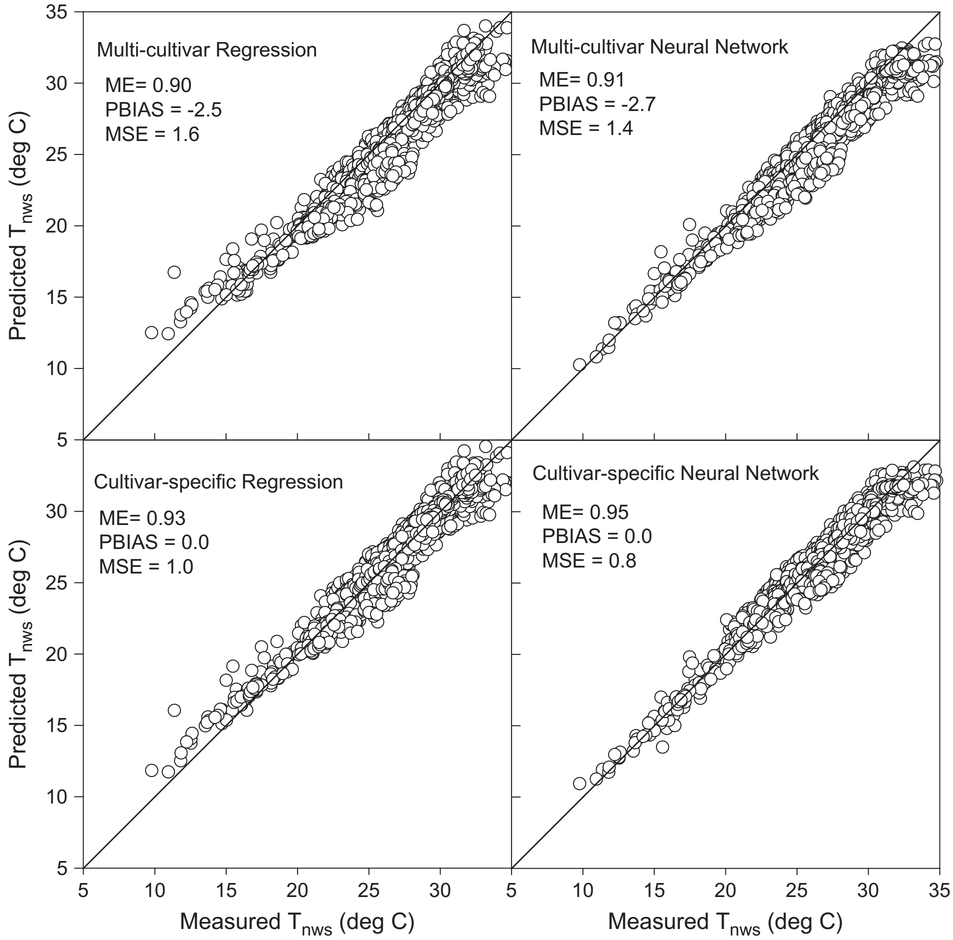

Fig. 4. Neural network and regression model performance values for predicting the non-water stressed canopy temperature (T_{nws}) of the cultivar Chardonnay (CH) developed from the multi-cultivar dataset or a data subset that contained only the measured T_{nws} for cultivar CH.

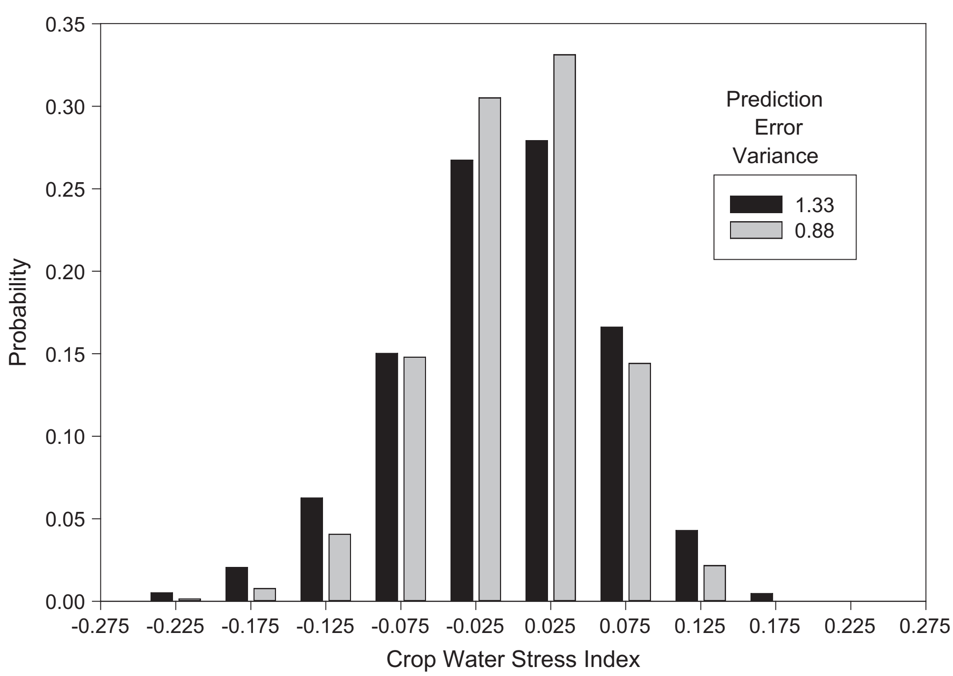

Fig. 5. Influence of Syrah T_{nws} model prediction error on the distribution of calculated crop water stress index (CWSI) values for a known T_{nws} value of 26 °C, air temperature of 29 °C and non-transpiring canopy temperature (T_{dry}) of 44 °C.

4. Conclusions

The canopy temperature of the wine grape cultivars MB, SY, CH, and CF were measured under well-watered conditions over multiple years and modeled as a function of climatic parameters - solar radiation, air temperature, relative humidity and wind speed using multiple linear regression and neural network modeling. Both models provided good prediction results when all cultivars are collectively modeled with

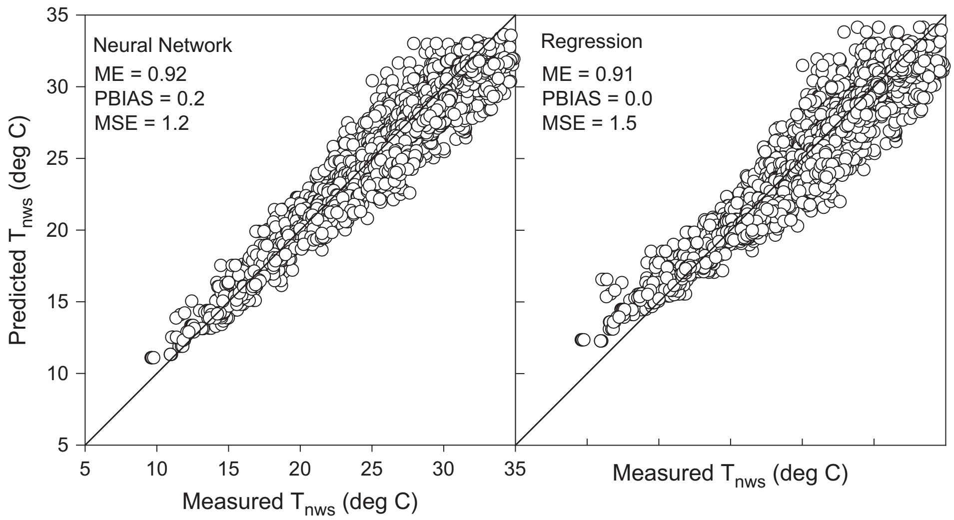

Fig. 6. Performance values for regression and neural network models to predict non-water-stressed canopy temperature (T_{nws}) developed using all measured temperature values for the wine grape cultivars Malbec, Syrah, Chardonnay and Cabernet franc collected during three growing seasons in Parma, ID.

minimal predictive difference between the models. The performance of models developed from cultivar-specific or multi-cultivar datasets were compared to investigate the influence of cultivar differences on model predictive performance. For all cultivars, prediction error variance was lower in NN models developed from cultivar-specific datasets than regression models developed from multi-cultivar datasets. Overall, the cultivar-specific models had less prediction error variance than multi-cultivar models. Multi-cultivar models generally resulted in prediction bias whereas cultivar-specific models eliminated the prediction bias. The effect of model prediction error on uncertainty in calculation of the CWSI was evaluated using Monte Carlo simulation. In general, all models result in an uncertainty of ± 0.1 in calculation of CWSI despite having significantly difference prediction error variance between models and a good estimate of well-watered canopy temperature (ME > 0.85).

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References

Allen, R.G., Pereira, L.S., Raes, D., Smith, M., 1998. Crop Evapotranspiration-Guidelines for Computing Crop Water Requirements-FAO Irrigation and Drainage Paper 56. Food Agricultural Organization, Rome.
Bausch, W., Trout, T., Buchleiter, G., 2011. Evapotranspiration adjustments for deficit-irrigated corn using canopy temperature: a concept. Irrig. Drain. 60, 628–693.
Bellvert, J., Marsal, J., Girona, J., Zarco-Tejada, P.J., 2015. Seasonal evolution of crop water stress index in grapevine varieties determined with high-resolution remote sensing thermal imagery. Irrig. Sci. 33, 81–93.
Chaves, M.M., Santos, T.P., Souza, C.R., Ortuño, M.F., Rodrigues, M.L., Lopes, C.M., Maroco, J.P., Pereira, J.S., 2007. Deficit irrigation in grapevine improves water-use efficiency while controlling vigour and production quality. Ann. Appl. Biol. 150, 237–252.
Chaves, M.M., Zarrouk, O., Fransisco, R., Costa, J.M., Santo, T., Regalado, A.P., Rodrigues, M.L., Lopes, C.M., 2010. Grapevine under deficit irrigation: hints from physiological and molecular data. Ann. Bot. 105, 661–676.
Colaizzi, P.D., Barnes, E.M., Clarke, T.R., Choi, C.Y., Waller, P.M., 2003. Estimating soil moisture under low frequency surface irrigation using crop water stress index. J. Irrig. Drain. Eng. ASCE 129, 36–43.
Coombe, B.G., 1995. Growth stages of the grapevine. Austral. J. Grape Wine Res. 1, 100–110.
Domec, J.C., Johnson, D.M., 2012. Does homeostasis or disturbance of homeostasis in minimum leaf water potential explain the isohydric versus anisohydric behavior of *Vitis vinifera* L. cultivars? Tree Physiol. 32, 245–248.
Fereres, E., Soriano, M.A., 2007. Deficit irrigation for reducing agricultural water use. J. Exp. Bot. 58, 147–159.
Haykin, S., 2009. Neural Networks and Learning Machines. Pearson Education, Inc., Upper Saddle River, NJ0-13-147139-2.
Hochberg, U., Herrera, J.C., Degu, A., Castellarin, S.D., Peterlunger, E., Alberti, G., Lazarovitch, N., 2017. Evaporative demand determines the relative transpirational sensitivity of deficit-irrigated grapevines. Irrig. Sci. 35, 1–9.
Idso, S.B., Jackson, R.D., Pinter Jr, P.J., Reginato, R.J., Hatfield, J.L., 1981. Normalizing the stress-degree-day parameter for environmental variability. Agric. Meteorol. 24, 45–55.
Jackson, R., 1982. Canopy temperature and crop water stress. Adv. Irrig. 1, 43–85.
Jackson, R.D., Idso, S.B., Reginato, R.J., Pinter Jr, P.J., 1981. Canopy temperature as a drought stress indicator. Water Resour. Res. 13, 651–656.
Jones, H.G., Stroll, M., Santos, T., de Sousa, C., Chaves, M.M., Grant, O.M., 2002. Use of infrared thermography for monitoring stomatal closure in the field: application to grapevine. J. Exp. Bot. 53, 2249–2260.
King, B.A., Shellie, K.C., 2016. Evaluation of neural network modeling to predict non-water-stressed leaf temperature in wine grape for calculation of crop water stress index. Agric. Water Manag. 167, 38–52.
Lovisolo, C., Perrone, I., Carra, A., Ferrandino, A., Flexas, J., Medrano, H., Shubert, A., 2010. Drought-induced changes in development and function of grapevine (*Vitis* spp.) organs and in their hydraulic and non-hydraulic interactions at the whole-plant level: a physiological and molecular update. Funct. Plant Biol. 30, 607–619.
Maes, W.H., Steppe, K., 2012. Estimating evapotranspiration and drought stress with ground-based thermal remote sensing in agriculture: a review. J. Exp. Bot. 63, 4671–4712.
Möller, M., Alchanatis, V., Cohen, Y., Meron, M., Tsipris, J., Naor, A., Ostrovsky, V., Sprintsin, M., Cohen, S., 2007. Use of thermal and visible imagery for estimating crop water status of irrigated grapevine. J. Exp. Bot. 58, 827–838.
Moriasi, D.N., Arnold, J.G., Van Liew, M.W., Bingner, R.L., Harmel, R.D., Veith, T.L., 2007. Model evaluation guidelines for systematic quantification of accuracy in watershed simulations. Trans. ASABE 50 (3), 885–900.
Nash, J.E., Sutcliffe, J.V., 1970. River flow forecasting through conceptual models of principles. J. Hydrol. 10 (1), 282–290.
Nordstokke, D.W., Zumbo, B.D., 2010. A new nonparametric Levene test for unequal variances. Psicológica 32, 401–430.
Nordstokke, D.W., Zumbo, B.D., Cairns, S.L., Saklofske, D.H., 2011. The operating characteristics of the nonparametric Levene test for unequal variances with assessment and evaluation data. Pract. Assess., Res. Evaluat. 16 (5), 1–8.
Pou, A., Medran, H., Tomás, M., Martorell, S., Ribas-Carbó, M., Flexas, J., 2012. Anisohydric behavior in grapevines results in better performance under moderate water stress and recovery than isohydric behavior. Plant Soil 359, 335–349.
Pou, A., Diago, M.P., Medrano, H., Baluja, J., Tardaguila, J., 2014. Validation of thermal indices for water status identification in grapevine. Agricult. Water Manage. 134, 60–72.
Sadras, V.O., Moran, M.A., 2012. Elevated temperature decouples anthocyanins and sugars in berries of Shiraz and Cabernet Franc. Aust. J. Grape Wine Res. 18, 115–122.
Sepúlveda-Reyes, D., Ingram, B., Bardeen, M., Zúñiga, M., Ortega-Farías, S., Poblete-Echeverría, C., 2016. Selecting canopy zones and thresholding approaches to assess grapevine water status by using aerial and ground-based thermal imaging. Remote Sens. 8, 822. http://dx.doi.org/10.3390/rs8100822.
Shellie, K.C., 2006. Vine and berry response of Merlot (Vitis vinifera L.) to differential water stress. Am. J. Enol. Vitic. 57, 514–518.
Shellie, K.C., 2007. Viticultural performance of red and white wine grape cultivars in southwestern Idaho. HortTechnology 17, 595–603.
Shellie, K.C., 2014. Water productivity, yield, and berry composition in sustained versus regulated deficit irrigation of Merlot grapevines. Am. J. Enol. Vitic. 65, 197–205.
Shellie, K.C., Bowen, P., 2014. Isohydrodynamic behavior in deficit irrigated Cabernet Sauvignon and Malbec and its relationship with yield and berry composition. Irri. Sci. 32, 87–97.
Turner, N.C., 1988. Measurement of plant water status by the pressure chamber technique. Irrig. Sci. 9, 289–308.
Vandeleur, R.K., Mayo, G., Shelden, M.C., Gilliham, M., Kaiser, B.N., Tyerman, S.D., 2009. The role of plasma membrane intrinsic protein aquaporins in water transport through roots: diurnal and drought stress responses reveal different strategies between isohydric and anisohydric cultivars of grapevine. Plant Physiol. 149, 445–460.
Yapo, P.O., Gupta, H.V., Sorooshian, S., 1996. Automatic calibration of conceptual rainfall-runoff models: sensitivity to calibration data. J. Hydrol. 181, 23–48.