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Evaluation of neural network modeling to predict non-water-stressed leaf temperature in wine grape for calculation of crop water stress index

B.A. King[a,*], K.C. Shellie[b]

[a] USDA-ARS, Northwest Irrigation and Soils Research Laboratory, 3793 N 3600 E, Kimberly, 83341-5076 ID, USA
[b] USDA-ARS, Horticultural Crops Research Unit-worksite, 29603 University of Idaho Lane, Parma, 83660 ID, USA

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ABSTRACT

Precision irrigation management of wine grape requires a reliable method to easily quantify and monitor vine water status to allow effective manipulation of plant water stress in response to water demand, cultivar management and producer objective. Mild to moderate water stress is desirable in wine grape in determined phenological periods for controlling vine vigor and optimizing fruit yield and quality according to producer preferences and objectives. The traditional leaf temperature based crop water stress index (CWSI) for monitoring plant water status has not been widely used for irrigated crops in general partly because of the need to know well-watered and non-transpiring leaf temperatures under identical environmental conditions. In this study, leaf temperature of vines irrigated at rates of 35, 70 or 100% of estimated evapotranspiration demand (ET_c) under warm, semiarid field conditions in southwestern Idaho USA was monitored from berry development through fruit harvest in 2013 and 2014. Neural network (NN) models were developed based on meteorological measurements to predict well-watered leaf temperature of wine grape cultivars 'Syrah' and 'Malbec' (*Vitis vinifera* L.). Input variables for the cultivar specific NN models with lowest mean squared error were 15-min average values for air temperature, relative humidity, solar radiation and wind speed collected within ±90 min of solar noon (13:00 and 15:00 MDT). Correlation coefficients between NN predicted and measured well-watered leaf temperature were 0.93 and 0.89 for 'Syrah' and 'Malbec', respectively. Mean squared error and mean average error for the NN models were 1.07 and 0.82 °C for 'Syrah' and 1.30, and 0.98 °C for 'Malbec', respectively. The NN models predicted well-watered leaf temperature with significantly less variability than traditional multiple linear regression using the same input variables. Non-transpiring leaf temperature was estimated as air temperature plus 15 °C based on maximum temperatures measured for vines irrigated at 35% (ET_c). Daily mean CWSI calculated using NN estimated well-watered leaf temperatures between 13:00 and 15:00 MDT and air temperature plus 15 °C for non-transpiring leaf temperature consistently differentiated between deficit irrigation amounts, irrigation events, and rainfall. The methodology used to calculate a daily CWSI for wine grape in this study provided a daily indicator of vine water status that could be automated for use as a decision-support tool in a precision irrigation system.

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1. Introduction

In many arid wine grape production areas irrigation is widely used to manage vine vigor and yield to induce desirable changes in berry composition for wine production (Chaves et al., 2010; Lovisolo et al., 2010). In red-skinned wine grape cultivars, a mild to moderate water stress in determined phenological periods has been found to increase water productivity and to improve fruit quality (Romero et al., 2010; Shellie, 2014). The optimum severity and phenological timing of imposed water deficit is influenced by cultivar, climatic and edaphic growing conditions, and wine grape cultural practices. Application of precision irrigation techniques requires accurate, reliable methods for determining vine water demand and for monitoring vine water status coupled with an irrigation system capable of applying water on-demand, in precise amounts (Jones, 2004). The lack of a rapid, reliable method for monitoring vine water status with high spatial and temporal resolution has hindered the adoption of precision irrigation practices in wine grape production.

* Corresponding author.
E-mail addresses: brad.king@ars.usda.gov (B.A. King), Krista.shellie@ars.usda.gov (K.C. Shellie).

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Many of the methods currently available for determining water demand and monitoring vine water status are either too laborious for automation or have poor spatial and temporal resolution. The Penman–Monteith equation is commonly used to estimate evapotranspiration demand (ET_c) and calculate an irrigation amount (Allen et al., 1998); however, periodic measurements of plant or soil water status are required to verify that the supplied amount actually induced the desired severity of water stress. Soil volumetric water content is not a suitable indicator of vine water status because it has low spatial resolution and is influenced by spatially heterogeneous soil attributes, such as texture and depth. Williams and Trout (2005) found that measurement of soil water content to a depth of 3m at nine locations within one-quarter of an individual vine root zone was necessary to accurately determine the amount of water within the soil profile available to drip-irrigated vines. Also, a given soil volumetric water content may induce differing severities of water stress in different grapevine cultivars due to intrinsic differences among cultivars in their hydraulic behavior ranging from isohydric to anisohydric (Schultz, 2003; Shellie and Bowen 2014; Williams et al., 2012; Bellvert et al., 2015a). Thus, bulk changes in soil water content or soil water potential may not correspond with changes in vine water status (Jones, 2004; Williams and Trout, 2005; Ortega-Farias et al., 2012). Measurements of leaf or stem water potential offer the advantage of integrating soil, plant and environmental factors; however, their poor temporal and spatial resolution and high labor requirement limit their potential for automation into a precision irrigation system. Plant water potential has poor temporal resolution due to its high sensitivity to environmental conditions (Rodrigues et al., 2012; Williams and Baeza, 2007; Jones, 2004). There also is no general agreement as to which measurement of plant water potential (pre-dawn leaf or midday stem or leaf) most reliably indicates vine water status (Williams and Araujo, 2002; Williams and Trout, 2005; Ortega-Farias et al., 2012). Williams and Trout (2005) found that pre-dawn leaf water potential was unsatisfactory for accurately determining vine water status while midday leaf and stem water potential were linearly correlated and equally suitable for determining vine water status. Midday leaf water potential is the most common method used in California to indicate vine water status (Williams et al., 2012) perhaps because it is less time consuming than either pre-dawn leaf water potential or midday stem water potential allowing more acreage to be covered during midday climatic conditions (Williams and Araujo, 2002). Midday stem and leaf water potential of grape vines are highly correlated with vapor pressure deficit (VPD) under semi-arid conditions but the correlations differ for leaf water potentials less than or greater than 1.2 MPa (Williams and Baeza, 2007; Williams et al., 2012) In general, a midday value of leaf water potential less negative than −1.0 MPa under high evaporative demand has generally been accepted as indicative of well-watered vines (Shellie, 2006; Williams and Trout, 2005; Williams et al., 2012; Shellie and Bowen, 2014; Bellvert et al., 2014).

Thermal remote sensing has recently been used to estimate evapotranspiration and drought stress in many crops, including grapevine (Maes and Steppe, 2012). Water stress promotes stomatal closure, reducing transpiration and evaporative cooling while increasing leaf temperature. Infrared radiometers have been used under field conditions to measure the increase in wine grape leaf surface temperature under differing severities of deficit irrigation (Cohen et al., 2005; Glenn et al., 2010; Shellie and King 2013; Bellvert et al., 2014, 2015a). Changes in leaf temperature have been correlated with rates of stomatal conductance and leaf or stem water potential in grapevine and responsiveness has been shown to vary by cultivar (Cohen et al., 2005; Glenn et al., 2010; Pou et al., 2014; Bellvert et al., 2015a,b). The difference in leaf temperature between stressed and non-water stressed plants relative to ambient air temperature has been used to develop a normalized crop water stress index (CWSI) (Idso et al., 1981; Jackson et al., 1981) for quantifying plant water status. The CWSI is defined as:

$$\mathrm{CWSI} = \frac{\left(T_{\mathrm{canopy}} - T_{\mathrm{nws}}\right)}{\left(T_{\mathrm{dry}} - T_{\mathrm{nws}}\right)} \tag{1}$$

where T_{canopy} is the temperature of fully sunlit canopy leaves (°C), T_{nws} is the temperature of fully sunlit canopy leaves (°C) when the crop is non-water-stressed (well-watered) and T_{dry} is the temperature of fully sunlit canopy leaves (°C) when the crop is severely water stressed due to low soil water availability. Temperatures T_{nws} and T_{dry} are the lower and upper baselines used to normalize CWSI for the effects of environmental conditions (air temperature, relative humidity, radiation, wind speed, etc.) on T_{canopy}. Ideally, CWSI ranges from 0 to 1 where 0 represents a well-watered condition and 1 represents a non-transpiring, water-stressed condition. Practical application of the CWSI has been limited by the difficulty of estimating without actually measuring T_{nws} and T_{dry} (Maes and Steppe, 2012). Experimental determination of a crop specific constant for T_{nws} and T_{dry} relative to ambient air temperature has not been fruitful due to the poorly understood and complex influences of environmental conditions on the soil–plant–air continuum (Idso et al., 1981; Jones, 1999, 2004; Payero and Irmak, 2006). In the original development and application of the CWSI, T_{nws} and T_{dry} were experimentally determined with T_{nws} correlated with VPD to account for climatic effects on T_{canopy} measurements. Canopy temperature measurements and application of the CWSI were restricted to times near solar noon on cloudless days to account for the effect of solar radiation on stomatal conductance. Artificial wet and dry reference surfaces have been used successfully to estimate T_{nws} and T_{dry} under the same environmental conditions as T_{canopy}. (Jones, 1999; O'shaughnessy et al., 2011; Jones et al., 2002; Leinonen and Jones, 2004; Cohen et al., 2005; Grant et al., 2007; Möller et al., 2007; Alchanatis et al., 2010; Pou et al., 2014); however, the required maintenance of the artificial references limits potential use for automation in a precision irrigation system.

Physical and empirical models have been developed to estimate T_{nws} and T_{dry} with varying degrees of success. A leaf energy balance (Jones, 1992) approach was used by Jones (1999) to develop the following equations for calculating T_{wet} and T_{dry}:

$$T_{\mathrm{wet}} = T_{\mathrm{air}} - \frac{r_{\mathrm{HR}} r_{\mathrm{aW}} \gamma R_{\mathrm{ni}}}{\rho c_p \left[\gamma r_{\mathrm{aW}} + s r_{\mathrm{HR}}\right]} - \frac{r_{\mathrm{HR}} \delta_e}{\gamma r_{\mathrm{aW}} + s r_{\mathrm{HR}}} \tag{2}$$

$$T_{\mathrm{dry}} = T_{\mathrm{air}} + \frac{r_{\mathrm{HR}} R_{\mathrm{ni}}}{\rho c_p} \tag{3}$$

where T_{wet} is the temperature (°C) of an artificially wet leaf, T_{air} is air temperature (°C), r_{aW} is boundary layer resistance to water vapor (s m^{-1}), R_{ni} is the net isothermal radiation (W m^{-2}), δ_e is water air vapor pressure deficit (Pa), r_{HR} is the parallel resistance to heat and radiative transfer (s m^{-1}), γ is the psychrometric constant (Pa °C^{-1}), ρ is the density of air (kg m^{-3}), c_p is the specific heat capacity of air (J kg^{-1} °C^{-1}) and s is the slope of the curve relating saturation vapor pressure to temperature (Pa °C^{-1}). Sensible heat loss for a dry surface with the same radiative and aerodynamic properties of a leaf was assumed to be equal to net absorbed radiation (Eq (3)). Heat transfer resistance in leaves (r_{HR}) was estimated to be a function of characteristic dimension (d) and wind speed (μ) (Jones, 1992) and, assuming isothermal radiation, can be estimated as (Jones, 1999):

$$r_{\mathrm{HR}} = 100\sqrt{\left(\frac{d}{\mu}\right)} \tag{4}$$

where d and μ are measured in m and m s^{-1}, respectively. Fuentes et al. (2012) found excellent agreement between artificial reference leaf surface temperatures and T_{wet} and T_{dry} calculated using Eqs. (2)–(4) and in-canopy micrometeorological measure-

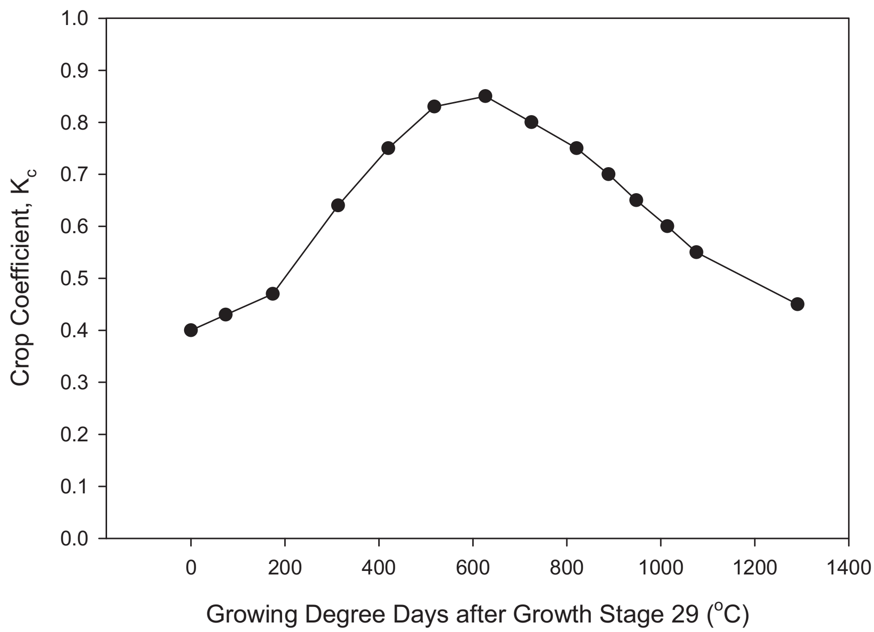

Fig. 1. Generalized growing degree day alfalfa based wine grape crop coefficient used to estimate daily evapotranspiration of all wine grape varieties at Parma, ID. Grapevine growth stage 29 corresponds to berry size of 4 mm (Coombe, 1995).

Table 1
Minimum and maximum 15-min average values measured at 1-min intervals between 13:00 and 15:00 MDT from July 11 through September 22, 2013 and July 3 through September 28, 2014 at Parma, ID used to linearly scale neural network input parameters.

	Minimum	Maximum
Air temperature, (°C)	14.0	38.3
Relative humidity, (%)	8	84
Wind speed, (m s^{-1})	0.4	5.7
Solar radiation, (W m^{-2})	17	1139
Well-watered 'Malbec' leaf temperature, (°C)	13.9	36.6
Well-watered 'Syrah' leaf temperature, (°C)	13.7	38.1

ments under minimal wind conditions. Numerical estimation of T_{nws} and T_{dry} eliminates the need for artificial reference surfaces or well-watered and water stressed reference plots; however Eqs. (2) through (4) require ancillary measurements to reliably estimate equation parameters. Multiple linear regression equations have also been used to estimate T_{nws} and T_{dry} as a function of air temperature, solar radiation, crop height, wind speed, and vapor pressure deficit (or relative humidity), with correlation coefficients of 0.69–0.84 between the predicted and measured leaf temperature of well-watered corn and soybean (Payero and Irmak, 2006). Irmak et al. (2000) determined in corn that T_{dry} was 4.6–5.1 °C above air temperature and, in several subsequent studies with crops other than corn (including grapevines), a value of air temperature plus 5.0 °C has been used for T_{dry} in Eq. (1) (Cohen et al., 2005; Möller et al., 2007; Alchanatis et al., 2010). O'shaughnessy et al. (2011) used maximum daily air temperature plus 5.0 °C for T_{dry} of soybean and cotton. Regression equations have been the most promising, practical approach used to estimate T_{nws} and T_{dry} for the CWSI. However, regression, by necessity, simplifies complex, unknown interactions into a priori or assumed multiple linear or nonlinear relationships (Payero and Irmak, 2006).

Artificial Neural Networks (NN) have been used successfully to model complex, unknown relationships and predict physical conditions, such as evapotranspiration (Kumar et al., 2002; Bhakar et al., 2006; Trajkovic et al., 2003) and many other water resource applications (ASCE, 2000). A common NN architecture consists of multiple layers of simple computing nodes that operate as nonlinear summing devices interconnected between layers by weighted links. Each weight is adjusted when measured data are presented to the network during a training process with an objective function such as minimizing mean square error. Successful training of a NN results in a numerical model that can predict an outcome value for conditions that are similar to the training dataset. To the best of our knowledge, a NN has not ever been used to predict T_{nws} or T_{dry} for calculation of a CWSI. A NN is particularly well-suited for predicting T_{nws} and T_{dry} because the relationships between environmental factors and their interaction with vine response are complex, poorly understood, and difficult to represent mathematically. Also, a training database for NN model development can be rapidly and reliably generated.

The CWSI can potentially be used to continuously monitor water stress severity in wine grape However, the need to measure T_{nws} and T_{dry} under the same environmental conditions as T_{canopy} poses logistical problems in commercial vineyards where neither T_{nws} nor T_{dry} are desirable soil moisture conditions. The objective of this study was to investigate the feasibility of using a NN to estimate leaf temperature of well-watered grapevine and demonstrate applicability in calculating a CWSI for wine grape under deficit irrigation. Performance of the developed NN was evaluated by comparing NN predicted well-watered leaf temperature with measured well-watered leaf temperature and estimated well-watered leaf temperature using traditional multiple linear regression modeling. Applicability of the NN model was demonstrated by calculating a daily CWSI for vines deficit irrigated at fractional amounts of evapotranspiration demand (ET_c).

2. Materials and methods

2.1. Vineyard and experiment description

The study was conducted during the 2013 and 2014 growing seasons in two field trial sites located adjacent to one another at the University of Idaho Parma Research and Extension Center in Parma, ID (lat: 43′78°N; long: 116′94°W; 750 m asl). The soil (sandy loam, available water-holding capacity of 0.14 cm/cm soil), climatic

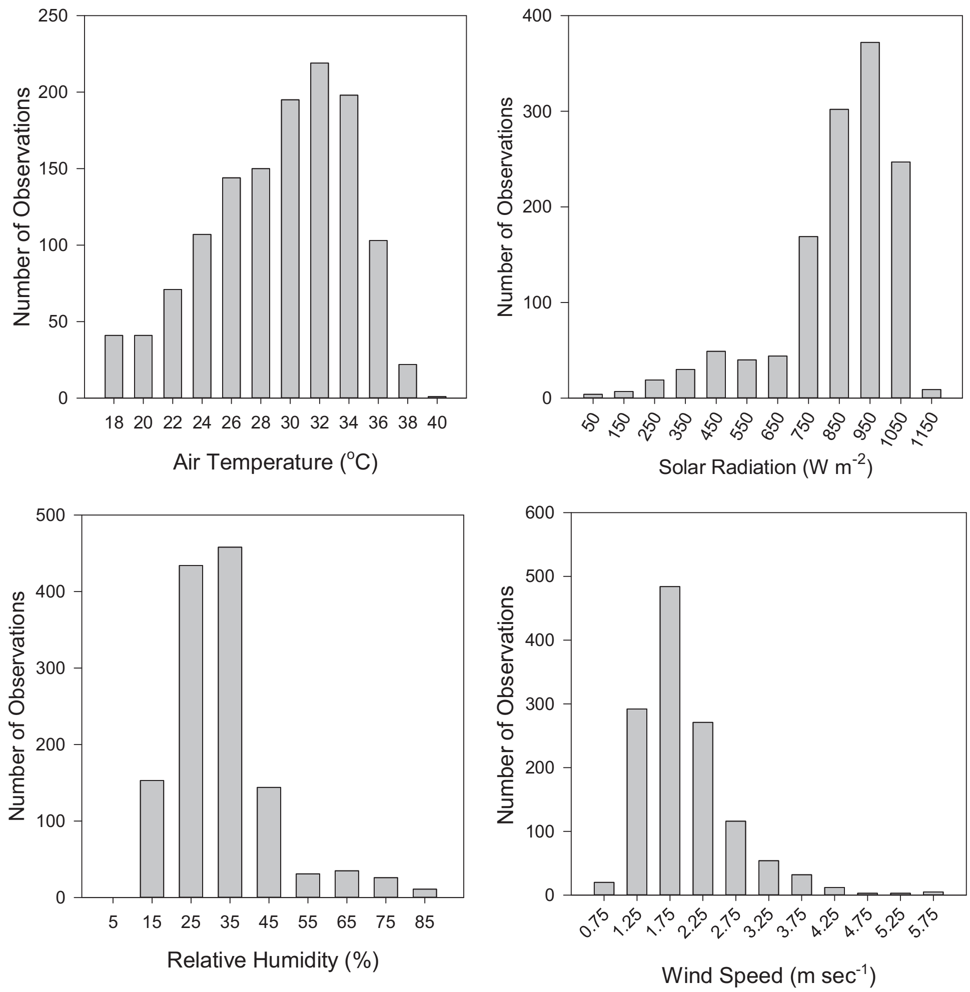

Fig. 2. Histograms showing the frequency of recorded 15-min averaged climatic values measured at 1-min intervals between 13:00 and 15:00 MDT from July 11 through September 22, 2013 and July 3 through September 28, 2014 at Parma, ID.

conditions (semi-arid, dry steppe with warmest monthly average temperature of 32 °C), and irrigation water supply (well water with sand media filter) at this location were well-suited for conducting deficit irrigation field research. Vines were planted as un-grafted, dormant-rooted cuttings in 2007 and were well-watered using above ground drip through the 2010 growing season. One trial was planted with the wine grape cultivar 'Malbec' and the other was planted with the cultivar 'Syrah'. Row by vine spacing (1.8 × 2.4 m), training and trellis system (double-trunked, bilateral cordon, spur-pruned annually to 16 buds/m of cordon, vertical shoot positioned on a two wire trellis with moveable wind wires) followed local commercial practices. Disease and pest control were also managed according to local commercial practices. Alley and vine rows were maintained free of vegetation.

Table 2
Historical, 2013 and 2014 climate data (± standard deviation) for April 1 through October 31 collected from Bureau of Reclamation AgriMet system [(www.usbr.gov/pn/agrimet/), latitude 43°48′00″, longitude 116°56′00″, elevation 702 m] for Parma, Idaho weather station and seasonal irrigation amounts applied to irrigation treatments. Accumulated growing degree days were calculated from daily maximum and minimum temperature with no upper limit and a base temperature of 10 °C.

	2013	2014	1994–2012 average
Precipitation (mm)	101	88	99.6 ± 35
Daily average total direct solar radiation (MJ m^{-2})	22.3	22.3	22.1 ± 0.9
Days daily maximum temperature exceeded 35 °C	35	27	28 ± 12
Accumulated growing degree days (°C)	1798	1759	1708 ± 115
Alfalfa-based reference evapotranspiration, ET_r (mm)	1307	1314	1212 ± 55
Well-watered Syrah (mm)	603	776	
'Syrah' 70% ET_c with 1 irrigation/week (mm)	432	491	
'Syrah' 70% ET_c with 3 irrigations/week (mm)	423	482	
'Syrah' 30% ET_c with 1 irrigation/week (mm)	214	285	
'Syrah' 30% ET_c with 3 irrigations/week (mm)	215	287	
Well-watered Malbec (mm)	603	554	
'Malbec' 70% ET_c with 1 irrigation/week (mm)	456	399	
'Malbec' 70% ET_c with 3 irrigations/week (mm)	413	397	
'Malbec' 30% ET_c with 1 irrigation/week (mm)	220	219	
'Malbec' 30% ET_c with 3 irrigations/week (mm)	210	226	

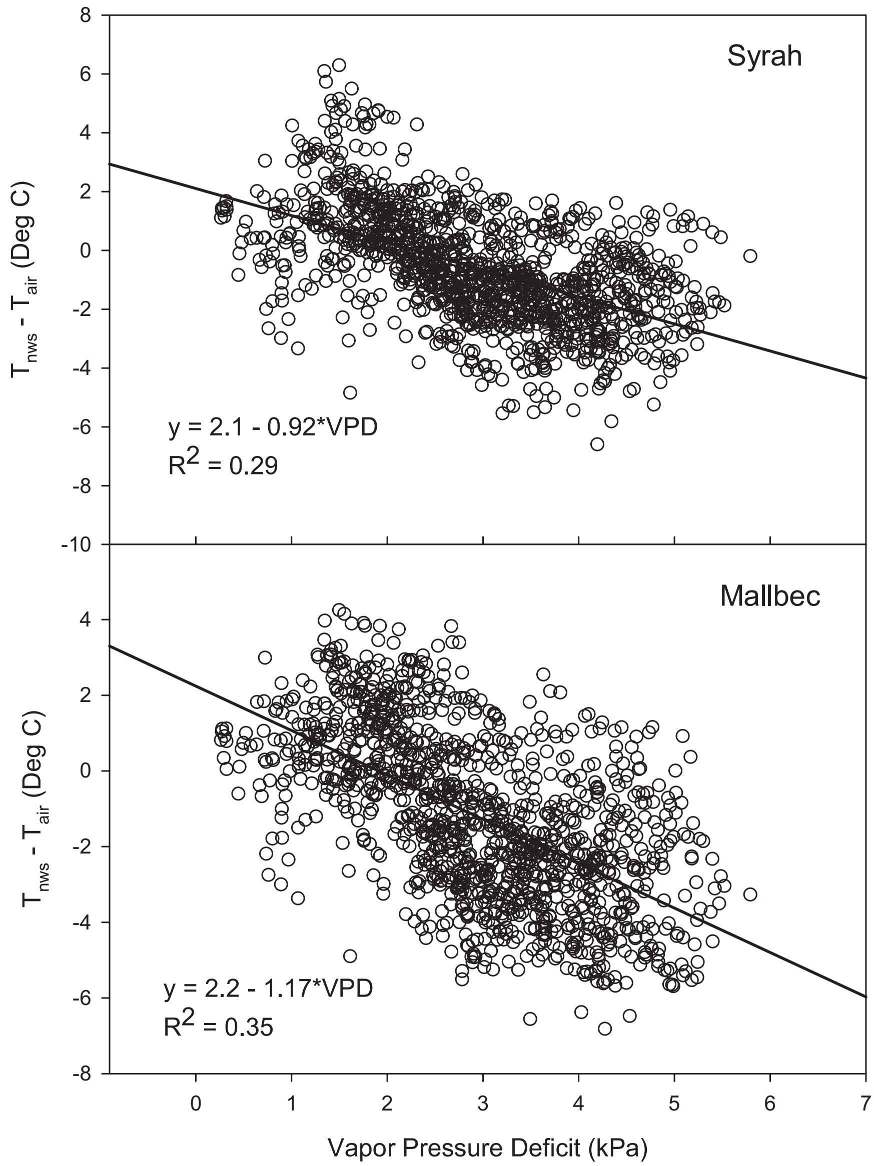

Fig. 3. Influence of vapor pressure deficit on the difference between surface temperature of an sunlit, leaves (T_{nws}) of the well-watered wine grape cultivars 'Syrah' (a) and 'Malbec' (b) and ambient air temperature (T_{air}) measured at 1-min intervals and recorded as 15-min averaged values from July 11 until September 22, 2013 and July 3 through September 28, 2014 at Parma, ID.

Irrigation design in each trial was identical and provided for the application of four, independent irrigation treatment levels in a randomized block design with six ('Malbec') or four ('Syrah') replicate blocks and independent irrigation water supply to border vines in the trial perimeter. Each water supply manifold was equipped with a programmable solenoid, a flow meter (to measure delivered irrigation amount), a pressure regulator and a pressure gauge (to monitor delivery uniformity). Treatment plots consisted of three vine rows with six vines per row (18 vines per plot). The vines in outer plot rows were considered buffers and data were collected on interior vines in the center row of each plot. The trial was bordered by a two-vine deep perimeter. Border vines in the trial perimeter were irrigated frequently with an amount of water that met or exceeded ET_c throughout canopy and berry development. Border vines were used to measure T_{nws}. Treatment plot replicates received one of four irrigation treatments: deficit irrigation amounts supplying either 70 or 35% ET_c at a frequency of one or three times per week. The 70% ET_c amount was intended to induce a sustained, mild water deficit throughout berry development similar to standard local commercial wine grape industry practice (Keller et al., 2008). Daily ET_c was estimated as alfalfa reference crop evapotranspiration (ET_r) (Jensen et al., 1990) multiplied by a general crop coefficient (K_c, Fig. 1) ($ET_c = ET_r \times K_c$) for all cultivars. Reference crop evapotranspiration was obtained from a weather station (http://www.usbr.gov/pn/agrimet/wxdata.html) located within 3 km of the study site. Well-watered vine irrigation amounts were equal to cumulative estimated ET_c since last irrigation and adjusted according to midday leaf water potential

Table 3
Multiple linear regression equations for predicting well-watered sunlit leaf temperature (T_{nws}, °C) as a function of air temperature (T_{air}, °C), solar radiation (SR, W m^{-2}), relative humidity (RH, %) and wind speed (WS, m s^{-1}).

Cultivar	Equation	R^2
Syrah	$T_{nws} = 0.696T_{air} + 0.005RS + 0.265RH + 0.019WS + 2.760$	0.90
Malbec	$T_{nws} = 0.638T_{air} + 0.005RS + 0.387RH + 0.010WS + 4.357$	0.84

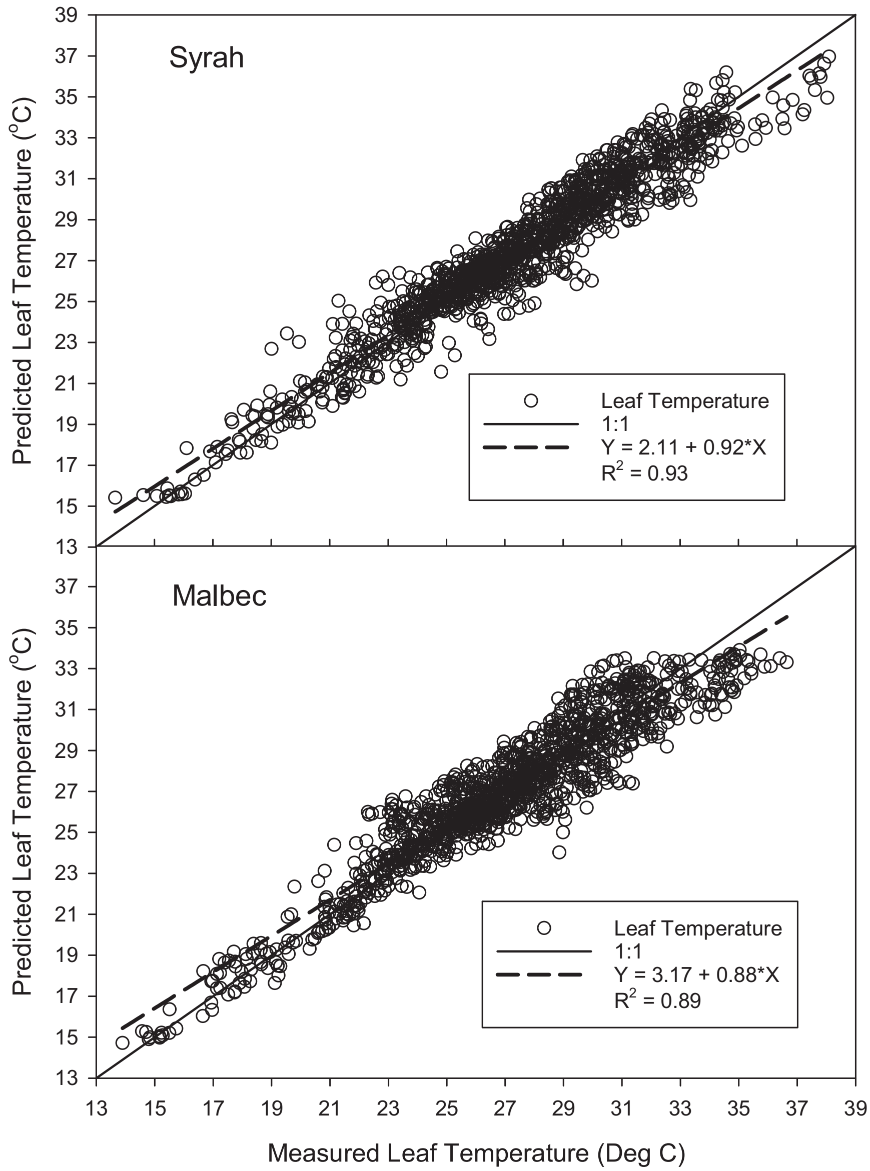

Fig. 4. Performance of neural network models for predicting sunlit leaf temperature relative to the measured sunlit leaf temperature of well-watered 'Syrah' and 'Malbec' grapevines recorded between 13:00 and 15:00 MDT as 15-min averaged values measured at 1-min intervals from July 22 until September 22, 2013 and July 3 through September 28, 2014 at Parma, ID.

measured the day prior to scheduled irrigation to maintain a consistent range in vine water stress. The irrigation amount to deficit irrigated treatments was delivered weekly in a single event or divided into three portions delivered three times per week, depending upon treatment. Deficit irrigation in all plots was first initiated in the 2011 growing season.

2.2. Plant water status measurements

Vine water status was monitored weekly throughout berry development on the day preceding an irrigation event by measuring the midday leaf water potential of two, fully expanded, sunlit leaves per treatment plot using a pressure chamber (model 610[1]; PMS Instruments, Corvallis, OR) as described by Shellie (2006). Midday leaf water potential of border vines the day prior to irrigation was monitored every 14 days in 2013 and weekly in 2014. The irrigation amount, equal to cumulative preceding week ET_c was increased if leaf water potential was more negative than −1.0 MPa or less than the previous measurement.

2.3. Yield measurements

Harvest was determined each year to occur when a composite sample of clusters randomly collected from all plot replicates had a target soluble solids concentration (SS) of ~24% and juice titratable acidity (TA) of 4 to 6 g/L. All plots were harvested on the same day to ascertain treatment effects on fruit maturity. On the day of harvest, clusters were counted as they were removed from the vine and their total weight was used to determine yield per vine.

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

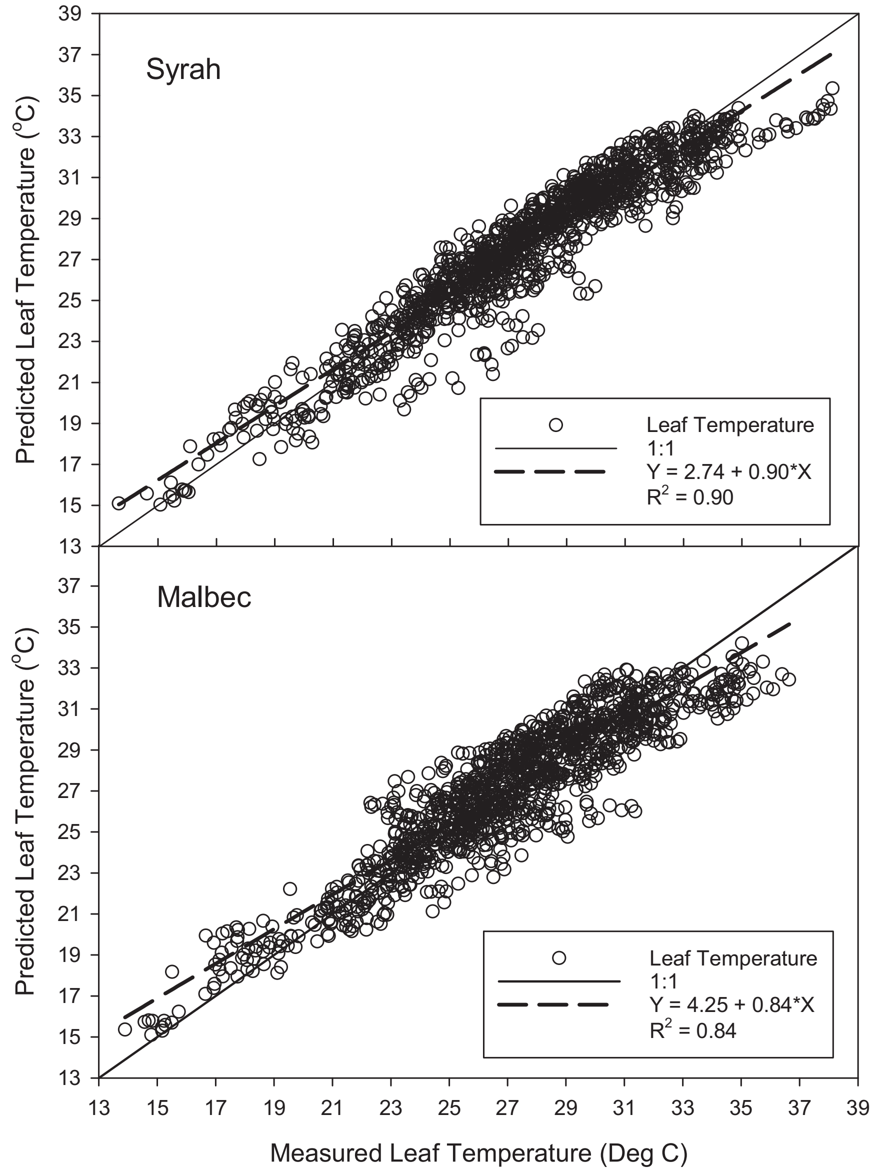

Fig. 5. Performance of multiple linear regression models for predicting sunlit leaf temperature relative to the measured sunlit leaf temperature of well-watered 'Syrah' and 'Malbec' grapevines recorded between 13:00 and 15:00 MDT as 15-min averaged values measured at 1-min intervals from July 22 until September 22, 2013 2013 and July 3 through September 28, 2014 at Parma, ID.

2.4. Leaf temperature and climatic monitoring

Canopy temperature was measured with infrared temperature sensors (SI-121 Infrared radiometer; Apogee Instruments, Logan, UT) positioned approximately 15–30 cm above recent fully expanded sunlit leaves located at the top of the vine canopy and pointed northerly at approximately 45° from nadir with the center of field of view aimed at the center of sunlit leaves. The temperature sensors were factory calibrated within 18 months of installation. The measured canopy area received full sunlight exposure during midday. The temperature sensing area was approximately 15–30 cm in diameter to ensure only sunlit leaves were in view of the infrared temperature sensor. The possibility of bare soil visibility in the background was limited by leaf layers within the canopy below the measured location. Temperature sensor view was periodically checked and adjusted as necessary to ensure the field of view concentrated on recently fully expanded sunlit leaves on the top of the canopy. Infrared temperature sensors were installed in the 'Malbec' and 'Syrah' trials on one well-watered and one deficit-irrigated data vine in a single replicate of each irrigation amount and irrigation frequency. Environmental parameters; 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) were measured in the vineyard adjacent to the irrigation treatment plots. Canopy temperature and environmental parameters were sampled at 1-min intervals from July 11 through September 23, 2013 and July 3 through September 28, 2014 (grapevine growth stage 31 through 38 [Coombe, 1995]) and the 15-min average value was recorded on a Campbell data logger (CR1000 or CR10X, Campbell Scientific, Logan, UT) as described by Shellie and King (2013). 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. Wind speed was adjusted to a standard height of 2 m (Allen et al., 1998).

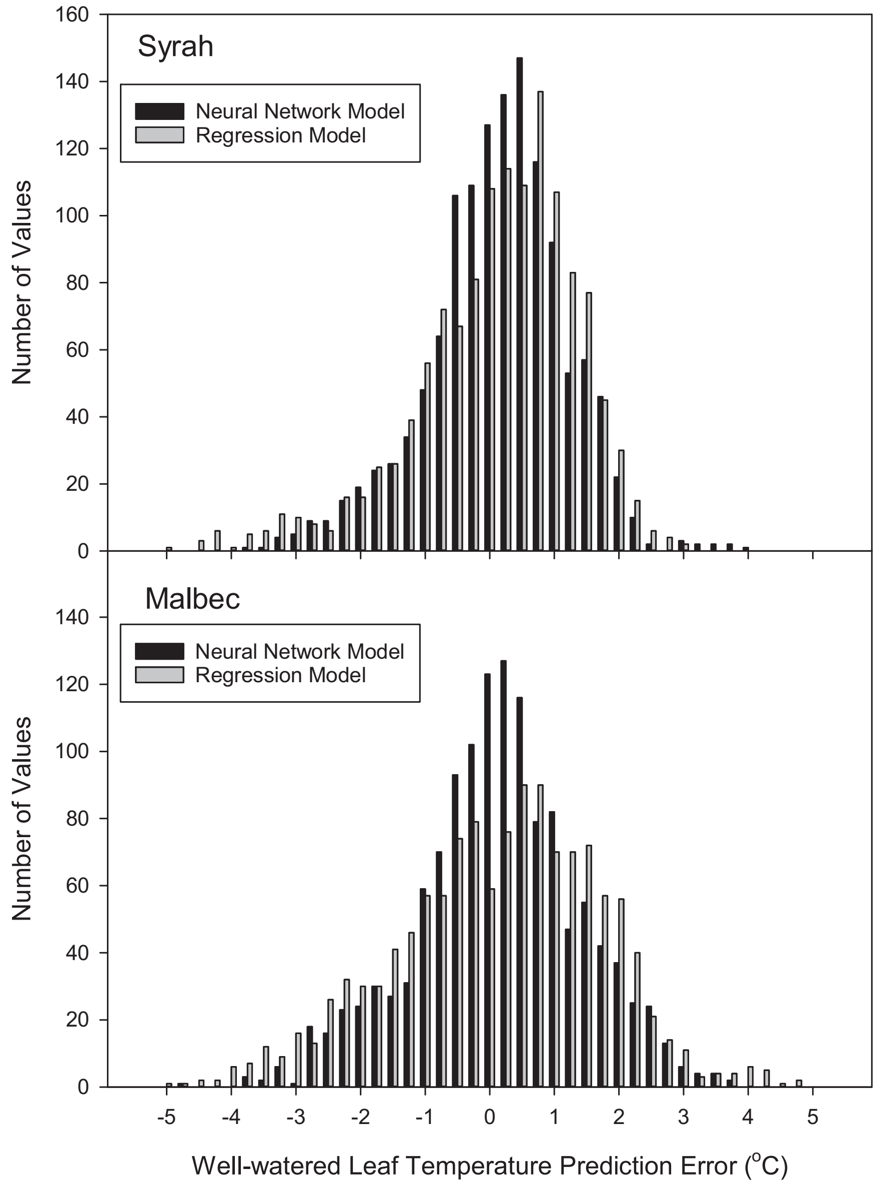

Fig. 6. Histogram of sunlit well-watered leaf temperature prediction error for 'Syrah' and 'Malbec' grapevines recorded between 13:00 and 15:00 MDT as 15-min averaged values measured at 1-min intervals from July 22 until September 22, 2013 2013 and July 3 through September 28, 2014 at Parma, ID.

2.5. *Neural network modeling*

Neural network software (NeuroIntellligence, Alyuda Research Inc., Cupertino, CA) was used to develop and test NN models. The recorded temperature and environmental dataset, 2013 and 2014 combined, was filtered to include only values collected between 13:00 and 15:00 MDT (±90 min of solar noon) based on previous experience with grapevine canopy temperature measurement at the study site (Shellie and King, 2013). The filtered dataset was randomly subdivided into one of three datasets used to train, validate and test the NN models. Sixty-eight percent of the filtered dataset was used for training, 16% for validation, and 16% for testing. Input parameters were linearly scaled to a range of −1 to 1 which is a normal procedure for NN modeling. The maximum and minimum values of measured parameters in the combined, filtered dataset (Table 1) were used for linear scaling. A multilayer perceptron feed forward NN architecture was used to estimate canopy temperature of well-watered grapevines. Hidden layer neurons used a hyperbolic tangent activation function and the single output neuron used a logistic activation function. Neural network architectures were evaluated with one and two hidden layers and up to ten neurons per hidden layer. The Conjugate-Gradient and Quasi–Newton methods (Haykin, 2009) were used to train the network using the training dataset. The best architecture was selected by trial and error based on maximizing correlation (R^2) with the training and test data sets while using a minimum number of neurons to reduce risk of over-training the NN to the data.

2.6. *Statistical analysis*

Graphical, linear and multiple linear regression, and variance analysis were used to quantify and evaluate the performance of NN models. Regression line significance was evaluated using ANOVA ($p \leq 0.05$). Significant differences ($p \leq 0.05$) in regression line intercepts and slopes were evaluated using *t*-test based confidence intervals. Equality of variances were evaluated using a Levine test when data were normally distributed and a non-parametric Levine test (Nordstokke and Zumbo, 2010; Nordstokke et al., 2011) when

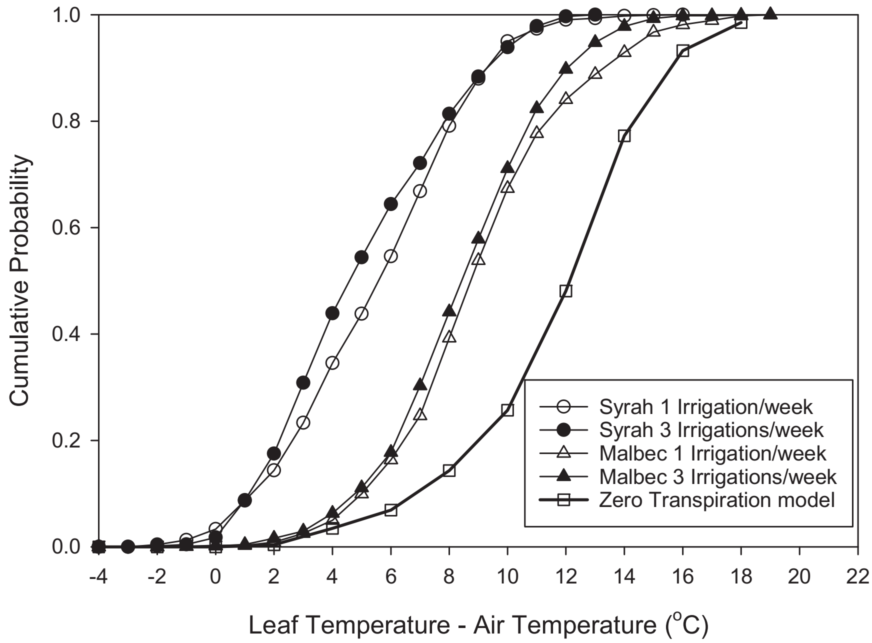

Fig. 7. Cumulative probability for difference between canopy and ambient air temperature in 'Syrah' and 'Malbec' grapevines deficit-irrigated at 35% of ET_c with irrigation events occurring one or three times per week. Temperatures were 15-min averaged values measured at 1-min intervals between 13:00 and 15:00 MDT from July 11 until September 22, 2013 and July 3 through September 28, 2014 at Parma, ID. Zero transpiration represents the leaf energy balance model estimated difference between a non-transpiring leaf and air temperature for the environmental conditions.

data were not normally distributed. Normal Q–Q plots, histograms, and Shapiro–Wilk's test ($p \leq 0.05$) were used to assess if data were approximately normally distributed.

3. Results

3.1. Climatic and canopy temperature characteristics

Growing season precipitation in 2013 was nearly equal to the 19-year average (Table 2) and slightly less in 2014. Average total direct solar radiation in 2013 and 2014 were equal and nearly equal to the 19-year site average, respectively. The number of days that daily maximum temperature exceeded 35 °C was more frequent than the 19-year site average in 2013, but was within one standard deviation of average and nearly equal to the 19-year average in 2014. Accumulated growing degree days (GDD) in 2013 and 2014 were greater, but within one standard deviation of the 19-year site average. The grape production climate classification for the study site, based on cumulative growing degree days in the Winkler system (Winkler et al., 1974), was region III (1666–1944 GDD), which is suitable for production of the wine grape cultivars 'Malbec' and 'Syrah'. Reference evapotranspiration (ET_r) for the study site in both years was more than one standard deviation greater than the 19-year site average. Seasonal amount of water provided to well- watered vines was 46% of ET_r in 2013. In 2014, seasonal amounts of water provided well-watered 'Syrah' and 'Malbec' vines was 60 and 42% of ET_r, respectively. Seasonal irrigation amounts supplied to vines deficit-irrigated with 35 or 70% ET_c in 2013 were ~36 and 70% of the irrigated amount applied to well-watered vines. In 2014, the seasonal irrigation amounts supplied 'Syrah' vines deficit-irrigated at 35 or 70% ET_c were ~37 and 63% of the amount applied to well-watered 'Syrah' vines. 'Malbec' vines deficit irrigated at 35 or 70% ET_c were supplied ~40 and 72% of the amount applied to well-watered 'Malbec' vines, respectively.

Histograms of 15-min averaged values for environmental parameters (T_{air}, SR, RH and WS) measured between 13:00 and 15:00 MDT from July 11 through September 22, 2013 and July 3, through September 28, 2014 combined are presented in Fig. 2. At least 70% or more of measured values for T_{air} and SR were $\geq$26 °C and 750 W m^{-2}, respectively, and RH and WS were $\leq$30% and 2 m s^{-1}, respectively. The frequent incidence of calm, dry, warm, sunny days recorded at this study site is characteristic of a semi-arid steppe climate. Infrequent occurrence of events with high humidity and low solar radiation at the study site limits the applicability of the NN models derived from the dataset obtained in this study to regions with similar warm, arid, sunny conditions. The maximum and minimum values of input parameters used to linearly scale NN dataset values and leaf temperatures of well-watered vines are presented in Table 1. The measured maximum and minimum temperatures of well-watered grape leaves were cooler, respectively, than maximum and minimum ambient air temperatures. Well-watered vines of 'Syrah' had a greater range between maximum and minimum leaf temperatures than well-watered vines of 'Malbec'.

The study site had a high evaporative demand with vapor pressure deficits (VPD) up to 5.9 kPa (Fig. 3). Linear correlations between the temperature difference of well-watered leaves and ambient air ($T_{nws} - T_{air}$) and *VPD* were significant ($p \leq 0.0001$) with correlation coefficients of 0.29 for 'Syrah' and 0.35 for 'Malbec'. The linear relationships were significantly different ($p \leq 0.05$) between cultivars. The difference between cultivars could be a result of unique hydraulic behavior and/or differences in leaf size, shape and orientation that influence leaf energy balance. Bellvert et al. (2015a) found significant differences in the relationships between $T_{nws} - T_{air}$ and VPD of well-watered cultivars. They reported $T_{nws} - T_{air}$ values for well-watered 'Syrah' vines exceeding 4 °C whereas we measured values exceeding 6 °C. The high variability of $T_{nws} - T_{air}$ at any given value of VPD illustrates a strong influence of additional factors on leaf temperature other than soil water availability.

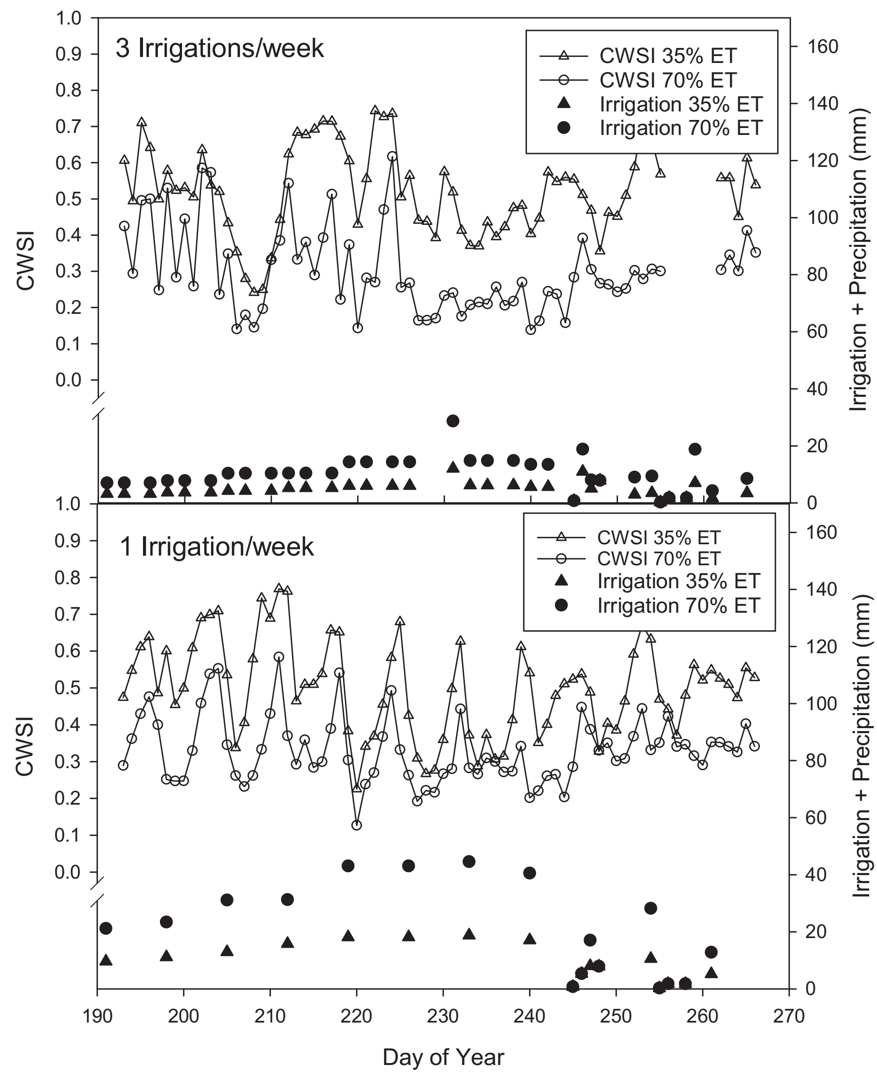

Fig. 8. Actual irrigation and precipitation amounts and calculated CWSI of 'Syrah' grapevines in treatment plots deficit-irrigated at 30 or 70% of ET_c at a frequency of one or three times per week. Non-water stressed and non-transpiring leaf temperatures were estimated, respectively, from the neural network model and air temperature +15 °C. Ambient air and deficit-irrigated leaf temperature were recorded as 15-min averaged values measured at 1-min intervals between 13:00 and 15:00 MDT from July 11 until September 22, 2013 at Parma, ID.

3.2. Neural network model performance

The NN models developed individually for 'syrah' and 'Malbec' vines provided excellent estimation of well-watered leaf temperature for both cultivars (Fig. 4). Linear regression of NN predicted versus measured well-watered leaf temperature resulted in correlation coefficients of 0.93 and 0.89 for 'Syrah' and 'Malbec', respectively. Root mean square errors (RMSE) and mean absolute errors (MAE) of the NN models were 1.07 and 0.82 °C for 'Syrah' and 1.30, and 0.98 °C 'Malbec'. The slope of the regression lines were significantly different ($p < 0.001$) from 1.0 for both cultivars indicating a bias in estimated NN well-watered leaf temperature. The feed-forward NN model architecture selected to estimate well-watered grapevine leaf temperature (T_{nws}, Eq. (1)) used four input parameters, one hidden layer with six nodes, and one output node (4-6-1). The four inputs were the measured environmental parameters T_{air}, SR, RH and WS. Increasing the number of hidden nodes beyond six provided minimal decrease in NN model standard error. Using VPD rather than RH did not affect performance of the NN models, which was expected since RH and VPD are highly correlated for a given air temperature. The slope of the regression line between NN predicted and measured T_{nws} for both cultivars was less than one indicating a negative bias in predicted values when measured leaf temperature was >32 °C and a positive bias when measured leaf temperature was <22 °C. This was more pronounced for the cultivar 'Malbec'. This bias may be the result of the limited number of training dataset values with a leaf temperature >32 and <22 °C. A larger dataset over several years and locations with a greater proportion of high and low leaf temperature measurements may improve NN model performance at the upper and lower temperatures.

Prediction of well-watered leaf temperature using multiple linear regression models ($p \leq 0.001$) with the same input variables (T_{air}, SR, RH and WS) for each cultivar (Table 3) provided results similar to the NN models (Fig. 5). Multiple linear regression of predicted versus measured well-watered leaf temperature resulted in correlation coefficients of 0.90 and 0.84 for 'Syrah' and 'Malbec', respectively, slightly lower than NN model predictions (Fig. 4). The RMSE and MAE of the multiple linear regression models were 1.36 and 1.06 °C for 'Syrah' and 1.6, and 1.29 °C for 'Malbec', respectively, all of which were greater than for the NN models. The multiple linear regression models exhibited the same negative and positive biases as the NN models, but were larger as indicated by smaller regression line slopes (Fig. 5). Prediction error variances for both cultivars were significantly less ($p \leq 0.001$) for the NN

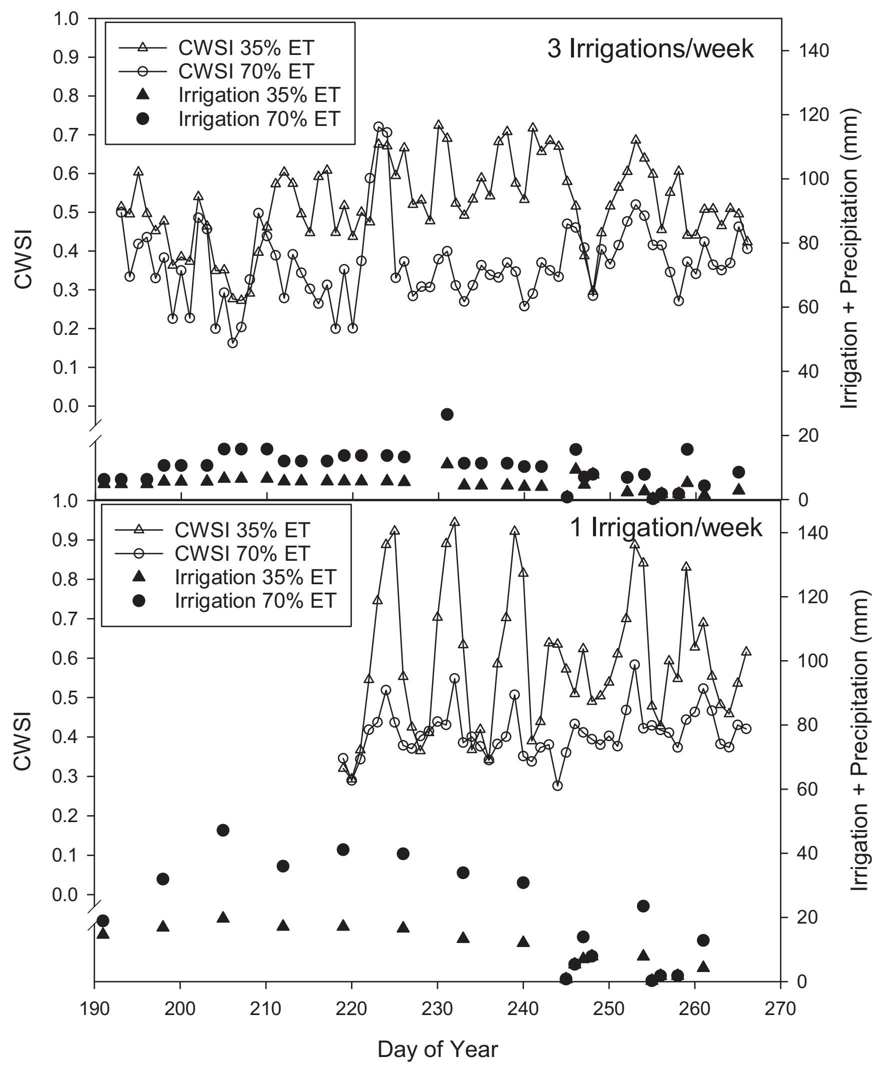

Fig. 9. Actual irrigation and precipitation amounts and calculated CWSI of 'Malbec' grapevines in treatment plots deficit-irrigated at 30 or 70% of ET_c at a frequency of one or three times per week. Non-water stressed and non-transpiring leaf temperatures were estimated, respectively, from the neural network model and air temperature +15 °C. Ambient air and deficit-irrigated leaf temperature were recorded as 15-min averaged values measured at 1-min intervals between 13:00 and 15:00 MDT from July 11 until September 22, 2013 at Parma, ID.

models (Fig. 6), indicating that NN models provided less variability in estimated well-watered leaf temperature than multiple linear regression. The slopes of the regression lines for predicted versus measured well-watered leaf temperature for 'Malbec' were significantly different ($p \leq 0.05$) between the NN model and multiple linear regression model indicating that the NN model provided significantly better estimates of well-watered leaf temperature with less error variance. Slopes of the regression lines for predicted versus measured well-watered leaf temperature for 'Syrah' between NN model and multiple linear regression model were not significantly different even though the NN model provided significantly less error variance in estimated well-watered leaf temperature.

3.3. Estimation of non-transpiring leaf temperature

We used cumulative probability distributions of measured temperature differences between the canopy of deficit-irrigated vines supplied with 35% ET_c and ambient air to estimate a value for T_{dry} (Fig. 7). When we used T_{air} + 5 °C to estimate non-transpiring leaf temperature (T_{dry}), as proposed by Irmak et al. (2000) for corn and used by Möller et al. (2007) for grape, we obtained CWSI values outside the desired range of 0–1. Irrigation frequency influenced the maximum measured temperature difference between the canopy of deficit-irrigated vines and T_{air}, especially for 'Malbec'. Vines irrigated one time per week had a greater maximum temperature difference than vines irrigated three times per week. The cultivars exhibited markedly different leaf temperature response under deficit irrigation. Deficit-irrigated 'Syrah' vines were 2–4 °C cooler than 'Malbec' vines. Bellvert et al. (2015a) also observed differences in leaf surface temperature among grapevine cultivars in response to water stress. Bellvert et al. (2014) reported $T_{nws} - T_{air}$ values exceeding 7.5 °C for water stressed 'Pinot-noir' vines when air temperature was 32.3 °C and VPD was 2.37 kPa (51% relative humidity). We measured maximum $T_{nws} - T_{air}$ values for water stressed vines of 13 °C in 'Syrah' and 17 °C in 'Malbec' under air temperatures as high as 37 °C, VPD's as high as 5.9 kPa (8% relative humidity), wind speeds below anemometer threshold value (<1 m s^{-1}), and solar radiation exceeding 1000 W m^{-2}. The value of $T_{nws} - T_{air}$ for a non-transpiring leaf is determined when radiant and convection energy exchanges for the environmental conditions are balanced. Using the leaf energy balance model (Eqs. (3) and (4)), the cumulative probability distribution calculated for a non-transpiring leaf (zero transpiration) had a maximum temperature

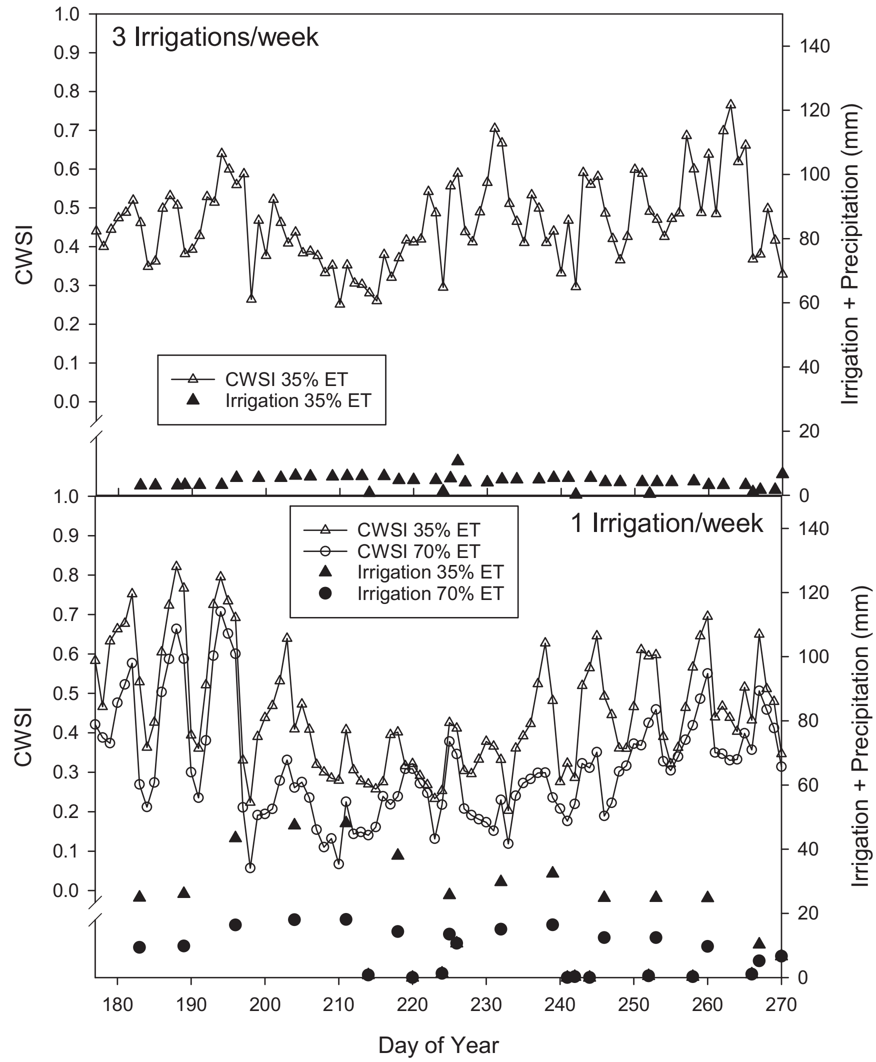

Fig. 10. Actual irrigation and precipitation amounts and calculated CWSI of 'Syrah' grapevines in treatment plots deficit-irrigated at 30 or 70% of ET_c at a frequency of one or three times per week. Non-water stressed and non-transpiring leaf temperatures were estimated, respectively, from the neural network model and air temperature +15 °C. Ambient air and deficit-irrigated leaf temperature were recorded as 15-min averaged values measured at 1-min intervals between 13:00 and 15:00 MDT from July 3 through September 28, 2014 at Parma, ID.

difference between canopy and ambient air of 19 °C (Fig. 7). This value serves as an upper limit for measured values of $T_{nws} - T_{air}$ for deficit-irrigated vines in this study. Based on these results, we elected to estimate T_{dry} for calculation of the CWSI (Eq. (1)) as T_{air} + 15 °C for both cultivars, which is unlikely to be exceeded (Fig. 7) for grapevines irrigated at approximately 70% ET_c, which is a common regional practice. In practical terms, any temperature for T_{dry} greater than that desired for viable berry production could be used for T_{dry} in Eq. (1) to obtain a CWSI value between 0 and 1 for irrigation scheduling purposes. Reference temperatures do not necessarily need to be an absolute canopy temperature limit or even a true T_{dry} value, but serve rather as indicator temperatures to scale measured canopy temperature to the environment for calculating relative water stress (Grant et al., 2007). The overall goal of the CWSI value obtained in this study was a consistent value representing plant water stress to aid irrigation scheduling rather than serve as an absolute measure of plant water stress.

3.4. CWSI characteristics

We calculated seasonal daily CWSI values for vines deficit-irrigated at 70% or 35% ET_c using NN estimated values for T_{nws} and T_{air} + 15 °C for T_{dry} in 2013 (Figs. 8 and 9) and 2014 (Figs. 10 and 11) for both 'Syrah' and 'Malbec', repectively. We calculated a daily CWSI (Eq. (1)) by averaging 15-min CWSI calculated using each 15-min average value of measured T_{air} and NN model estimated T_{nws} between 13:00 to 15:00 MDT(±90 min solar noon). In all cases, daily CWSI of deficit-irrigated vines supplied with 70% ET_c was consistently lower than the daily CWSI of vines deficit-irrigated with 35% ET_c. Daily CWSI decreased following an irrigation or precipitation event and gradually increased between water application events as soil water was withdrawn for ET_c. A similar trend in average daily CWSI was evident when vines were irrigated three times per week (70% ET_c treatment was not monitored in 2014); however, in 2013 for 'Malbec' prior to DOY 215 (Fig. 9) there were instances when daily CWSI values were similar or slightly greater under 70 than 35% ET_c largely due to irrigation timing relative to 13:00 to 15:00 MDT. Averaging 15-min CWSI values between 13:00 to 15:00 MDT to calculate a daily CWSI reduced the potential influence of transient environment conditions such as periodic shadowing due to partly cloudy skies. The daily CWSI consistently corresponded with irrigation or precipitation events and differentiated irrigation treatment amounts throughout the growing season. The 15-min averaging approach used in this study deviates from the calculation method

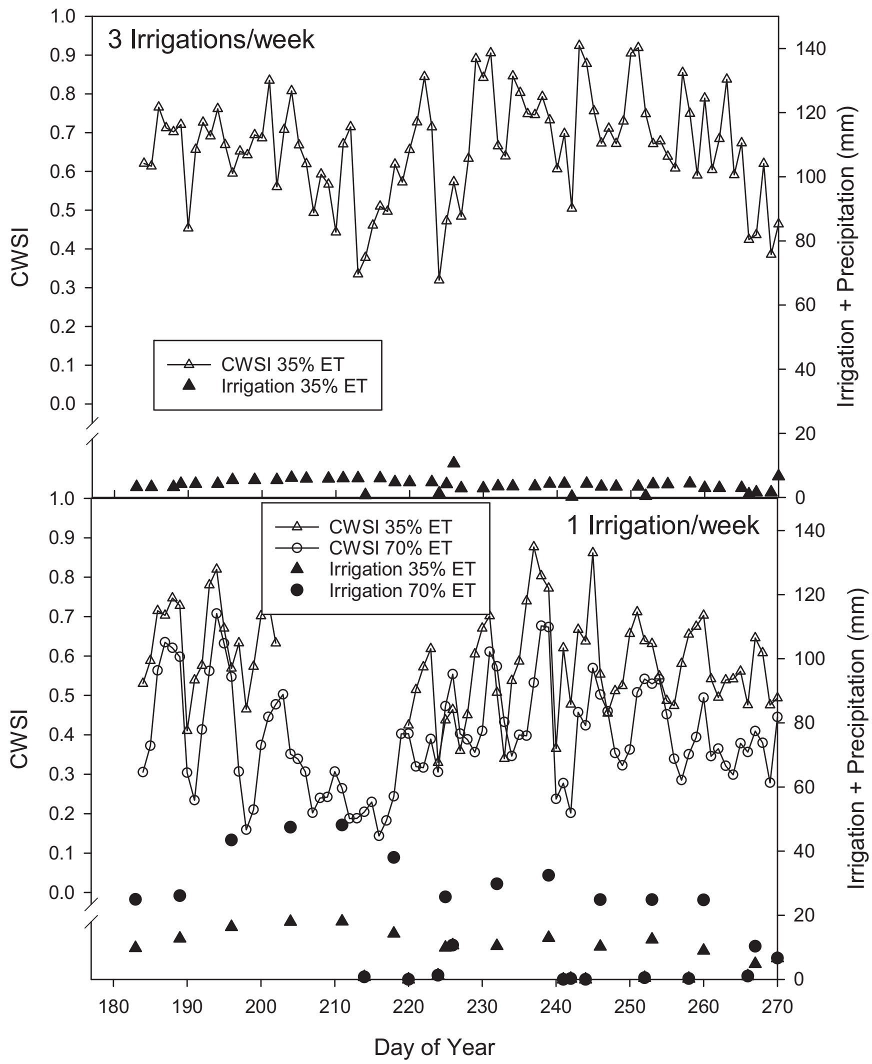

Fig. 11. Actual irrigation and precipitation amounts and calculated CWSI of 'Malbec' grapevines in treatment plots deficit-irrigated at 30 or 70% of ET_c at a frequency of one or three times per week. Non-water stressed and non-transpiring leaf temperatures were estimated, respectively, from the neural network model and air temperature +15 °C. Ambient air and deficit-irrigated leaf temperature were recorded as 15-min averaged values measured at 1-min intervals between 13:00 and 15:00 MDT from July 3 through September 28, 2014 at Parma, ID.

proposed by Idso et al. (1981) and Jackson et al. (1981), where a near instantaneous measure of canopy temperature was used to calculate the CWSI. A major advantage of the averaging approach used in this study is that it minimizes the influence of rapid fluctuations in leaf temperature due to variability in cloudiness or wind speed resulting in a consistent representative value of the CWSI. Our method of calculating T_{dry} for the CWSI supports the concept used by others of estimating T_{dry} as the sum of measured T_{air} and a constant (Cohen et al., 2005; Möller et al., 2007; Alchanatis et al., 2010; O'shaughnessy et al., 2011); however estimating the constant value from the cumulative probability of measured leaf temperatures under 35% ET_c irrigation treatment generated an estimate of T_{dry} that limited CWSI values to the range of 0–1 for the study conditions.

3.5. Seasonal CWSI and yield

Seasonal mean daily CWSI values between 70 and 35% ET_c irrigation treatments were significantly different ($p \leq 0.001$) regardless of cultivar or irrigation frequency (Table 4). On average there was a 0.14 and 0.22 difference in seasonal mean CWSI value between 70 and 35% ET_c across years and irrigation frequencies for 'Syrah' and 'Malbec', respectively. For 'Syrah', mean vine yields were significantly different ($p \leq 0.05$) between the 35% and 70% ET_c irrigation treatments across irrigation frequency treatments and years (Table 4). For 'Malbec', mean vine yields were significantly different ($p \leq 0.05$) between the 35% and 70% ET_c irrigation treatments in 2013 for only the three irrigations per week treatment and only the one irrigation per week treatment in 2014. Cluster number per vine were significantly different ($p \leq 0.05$) between the 35% and 70% ET_c irrigation treatments for 'Syrah' in 2013 for the one irrigation per week treatment and for 'Malbec' in 2013 for the three irrigation per week treatment (Table 4). There were no significant differences in cluster number per vine between the 35% and 70% ET_c irrigation treatments in 2014 for either cultivar or irrigation frequency.

4. Discussion

Calculation of CWSI for two wine grape cultivars using cultivar specific NN models to estimate T_{nws}, estimating T_{dry} as $T_{air} + 15$ °C, and calculating a daily CWSI from the average of 15-min CWSI values over a two-hour period resulted in consistent differentiation between 35% and 70% ET_c irrigation treatments and irrigation events over multi-month study periods (berries pea sized through

Table 4
Mean comparisons of CWSI, yield per vine, and cluster number per vine by year, cultivar, irrigation treatment and weekly irrigation frequency.

Irrigation treatment	CWSI		Yield/vine (kg)		Cluster number/vine	
	2013	2014	2013	2014	2013	2014
Syrah one irrigation per week						
70% ET	0.33	0.29	7.1	13.0	34.6	53.1
35% ET	0.50	0.44	4.6	7.5	22.3	47.6
	<0.001**	<0.001**	0.0017**	<0.001**	0.008**	0.321
Syrah three irrigations per week						
70% ET	0.30		7.3	12.1	34.2	54.0
35% ET	0.52	0.45	4.6	9.2	27.0	48.3
	<0.001**	–	0.005**	0.040*	0.204	0.381
Malbec one irrigation per week						
70% ET	0.41	0.40	5.2	6.9	42.3	50.1
35% ET	0.59	0.67	4.4	4.7	33.6	47.8
	<0.001**	<0.001**	0.278	0.027*	0.09	0.648
Malbec three irrigations per week						
70% ET	0.37		5.7	5.9	41.7	47.6
35% ET	0.52	0.67	3.2	4.8	30.7	45.3
	<0.001**	–	<0.001**	0.239	0.03*	0.723

* and ** denote statistical significance at $p \leq 0.05$ and $p \leq 0.01$, respectively by paired *t*-test.

fruit maturity) in 2013 and 2014. Separate NN models were used to estimate T_{nws} for each cultivar based on different responses between ($T_{nws} - T_{air}$) and VPD for the cultivars. The use of cultivar specific NN models to estimate T_{nws} may be a disadvantage from an implementation viewpoint but resulted in CWSI values of sufficient accuracy to easily differentiate between irrigation treatments under climatic conditions varying from hot and sunny with low humidity to cool and cloudy between rainfall events. The ability to calculate a reliable and consistent CWSI value under widely varying vineyard conditions is necessary for implementation of cultivar and site-specific irrigation management strategies. The primary disadvantage of using NN models to estimate well-watered leaf temperature for calculation of the CWSI is the need to generate a dataset of well-watered canopy temperatures to train, validate and train the NN model. The NN models developed in this study are region specific at best as they were developed using data from one specific location. A dataset of measured T_{nws} across a range of climatic regions may allow development of NN models capable of estimating T_{nws} for a specific cultivar under a greater range of climatic conditions.

The difference between canopy and air temperature of vines receiving 35% of the irrigation water applied to well-watered vines was found to be as great as 17 °C, much greater than the value of T_{dry} assumed in other research studies and slightly less than the energy balance model based value (Eqs. (3) and (4)) for the study conditions. Using a value of $T_{dry} = T_{air} + 15$ °C to calculate CWSI over two growing seasons provided consistent differentiation between deficit irrigation amounts that supplied ~70 and 35% of the irrigation amount supplied to well-watered vines in both cultivars. A smaller constant (e.g. 13 °C) could potentially have been used to calculate T_{dry} for 'Syrah' based on the maximum measured temperature difference between canopy and T_{air} in vines deficit-irrigated with 35% ET_c (Fig. 7). Reference values T_{nws} and T_{dry} used to calculate CWSI need not be absolute minimum and maximum temperatures (Grant et al., 2007), although doing so restricts the CWSI value to between 0 and 1. Seasonal average mean daily CWSI values for 35% ET and weekly irrigation was about 0.63 and 0.47 for 'Malbec' and 'Syrah' (Table 4), respectively. If $T_{dry} = T_{air} + 13$ °C had been used for 'Syrah', seasonal average mean daily CWSI value would have been nearly the same as 'Malbec' due to a 2 °C decrease in the denominator of Eq. (1). The use of reference temperatures close to cultivar specific absolute minimum and maximum temperatures for the environment may make threshold CWSI values transferable between climatic regions, but needs to be further investigated. Transferability of threshold CWSI would likely require modification of reference temperatures for climatic differences between regions. Eq. (3) could be used to adjust T_{dry} for climatic region differences but would not account for cultivar differences in relationships between water stress and leaf temperature. Modifying T_{nws} for climatic and cultivar differences would need to be accomplished experimentally and the NN model retrained using the new data.

The original application of the CWSI methodology for irrigation scheduling was limited by a requirement to measure T_{nws} on clear cloudless days. In this study, thin cirrus clouds were often present during the two hour time span from 13:00 to 15:00 MDT resulting in rapidly varying levels of solar radiation, which have a large effect on T_{nws} (Eq. (2)). The variable presence of thin, cirrus clouds was the reason why a majority of measured values for solar radiation were less than 900 W m^{-2} (Fig. 2). This variability contributed substantial uncertainty in the linear relationships between $T_{nws} - T_{air}$ and VPD (Fig. 3). This uncertainty leads to substantial uncertainty in the need to irrigate, which is one reason why the CWSI approach has seen limited adoption for irrigation scheduling. From the producer's perspective, uncertainty is minimized by simply irrigating and foregoing use of the CWSI. Use of the NN model to estimate T_{nws} allowed reliable calculation of CWSI in this study despite the limited number of clear cloudless days.

5. Conclusions and future directions

The feasibility of using NN modeling to estimate the lower threshold temperature (T_{nws}) needed to calculate the traditional CWSI was demonstrated for wine grape. Wine grape cultivars 'Syrah' and 'Malbec' were found to have differing canopy temperature response to climatic conditions when well-watered and water stressed. Neural network models developed for estimating T_{nws} of each cultivar performed exceptionally well. Use of NN model estimated T_{nws} for calculating a daily mean CWSI over two growing seasons successfully differentiated between two levels of water stress for each cultivar. The maximum difference in temperature between the leaf and ambient air for the 35% ET_c irrigation treatments was found to be about 13 °C and 17 °C for 'Syrah' and 'Malbec', respectively, much greater than 5 °C used in other studies as an estimate for T_{dry}. Air temperature plus 15 °C used to estimate T_{dry} for both cultivars in calculation of CWSI provided a suitable practical upper reference temperature for both cultivars. A 2-h averaged CWSI value based on 15-min average measured canopy temperature, T_{air}, SR, RH, and WS values provided a consistent daily CWSI value under variable climatic conditions. Additional research should focus on development of NN models to estimate T_{nws} for other grape cultivars over multiple years and across climatic regions to extend applicability of NN models developed in this study to calculate T_{nws}.

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