Evaluation of Neural Network Modeling to Calculate Well-Watered Leaf Temperature of Wine Grape

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Abstract. *Mild to moderate water stress is desirable in wine grape for controlling vine vigor and optimizing fruit yield and quality, but precision irrigation management is hindered by the lack of a reliable method to easily quantify and monitor vine water status. The crop water stress index (CWSI) that effectively monitors plant water status has not been widely adopted in wine grape because of the need to measure well-watered and non-transpiring leaf temperature under identical environmental conditions. In this study, a daily CWSI for the wine grape cultivar Syrah was calculated by estimating well-watered leaf temperature with an artificial neural network (NN) model and non-transpiring leaf temperature based on the cumulative probability of the measured difference between ambient air and deficit-irrigated grapevine leaf temperature. The reliability of this methodology was evaluated by comparing the calculated CWSI with irrigation amounts in replicated plots of vines provided with 30, 70 or 100% of their estimated evapotranspiration demand. The input variables for the NN model were 15-minute average values for air temperature, relative humidity, solar radiation and wind speed collected between 13:00 and 15:00 MDT. Model efficiency of predicted well-watered leaf temperature was 0.91 in 2013 and 0.78 in 2014. Daily CWSI consistently differentiated between deficit irrigation amounts and irrigation events. The methodology used to calculate a daily CWSI for wine grape in this study provided a real-time indicator of vine water status that could potentially be automated for use as a decision-support tool in a precision irrigation system.*

Keywords. Canopy temperature, wine grape, irrigation management, water stress.

Introduction

Irrigation is commonly used in arid region wine grape production to manage growth and induce desirable changes in berry composition for wine production (Chaves et al. 2010, Lovisolo et al. 2010). A mild to moderate water deficit in red-skinned wine grape has been found to increase water productivity and improve fruit quality (Romero et al. 2010, Shellie 2014). However, the ability to uniformly and reliably induce and maintain a desired water stress within a vineyard is hindered by the lack of a rapid method to monitor vine water status with high spatial and temporal resolution. The ability to use precision irrigation techniques in wine grape to manage the severity and duration of water deficit requires a reliable method for monitoring vine water status coupled with an irrigation system capable of applying water on-demand, in precise amounts (Jones, 2004).

Soil- and plant-based methods currently available for monitoring vine water status include measurement of soil water content and plant water potential both of which are either too laborious for automation and/or have poor spatial and temporal resolution. Traditional soil volumetric water content measurement has low spatial resolution and is not necessarily a reliable indicator of vine water status because water availability is influenced by soil attributes, such as texture and depth, which are spatially heterogeneous. Wine grapes are commonly irrigated with drip irrigation which leads to non-uniform spatial wetting of the plant root zone, exacerbating reliable determination of bulk root zone water content. A given soil volumetric water content may induce different severities of water stress in different grapevine cultivars due to differing hydraulic behaviors (Shellie and Bowen 2014) and rooting patterns. Consequently, vine response may not correspond with bulk changes in soil water content or soil water potential (Jones 2004, Ortega-Farias et al. 2012). Plant-based methods of monitoring water status integrate 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. The poor temporal resolution of plant water potential is due to its high sensitivity to environmental conditions (Rodrigues et al. 2012, Jones 2004). Also, there is no general agreement as to which measurement of plant water potential (leaf or stem measured pre-dawn or midday) most reliably indicates vine water status (Williams and Araujo 2002, Ortega-Farias et al. 2012). However, a midday value of leaf water potential greater (less negative) than -1.0 MPa has generally been accepted to be indicative of a well-watered condition (Shellie 2006, Williams et al. 2012, Shellie and Bowen 2014).

Canopy temperature has been used successfully to monitor water status in crops other than grapevine (Raschke 1960, Jackson 1982). The difference in leaf temperature between stressed and non-water stressed plants relative to ambient air temperature has been used to develop an empirical crop water stress index (*CWSI*) (Idso et al. 1981, Jackson et al. 1981) for monitoring plant water status. The *CWSI* is defined as:

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

where T_{canopy} is the temperature of the crop canopy (˚C), T_{nws} is the temperature of the canopy (˚C) when the crop is non-water-stressed and T_{dry} is the temperature of the canopy (˚C) when the crop is severely water stressed under dry conditions. Temperatures T_{nws} and T_{dry} are the lower and upper baselines used to normalize the index for environmental conditions (air temperature, relative humidity, radiation, wind speed, etc.) of T_{canopy}. The *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 T_{nws} and T_{dry}. 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, Jones 2004, Payero and Irmak 2006). 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); however, the required maintenance of the artificial reference conditions 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; eq. 9.6) was used by Jones (1999) to model grape leaf temperature as a function of environmental conditions. Fuentes et al. (2012) found excellent agreement between artificial reference leaf surface temperatures and T_{wet} and T_{dry} calculated using the physical model of Jones (1999). Alves and Pereira 2000 developed a physical approached to estimate T_{nws} based on the Penman-Monteith equation and a saturation pressure curve approximation relating T_{nws} to wet bulb temperature. They obtained a correlation coefficient of 0.92 between calculated T_{nws} and measured canopy temperature of well-watered lettuce when model parameters were independently calibrated. Physically based models require measurement of additional plant characteristics in order to estimate model parameters needed to calculate baseline canopy temperature(s). Empirical models using 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, with correlation coefficients ranging from 0.69 to 0.84 between 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 ˚C to 5.1 ˚C above air temperature and, in several subsequent studies in crops other than corn, a value of air temperature plus 5.0 ˚C has been used to estimate T_{dry} in equation 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 physical relationships and predict responses in water resource applications (ASCE, 2000), such as estimating stream flow, sediment transport and evapotranspiration (Kumar et al. 2002, Bhakar et al. 2006, Trajkovic et al. 2003). A common NN architecture consists of multiple layers of simple parallel 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 training. 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, NN modeling has not been used to predict T_{nws} and 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, plant physical characteristics and plant response are complex, poorly understood, and difficult to represent mathematically. Also, a training database of T_{nws} and T_{dry} for NN model development can be rapidly and reliably generated.

The *CWSI* could be used for real time monitoring of water stress severity in wine grape. An increase in the surface temperature of deficit irrigated grapevine canopy has been remotely monitored using infrared thermometers (Glenn et al. 2010, Shellie and King 2013). 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 (Glenn et al. 2010). However, measurement of 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 model to estimate leaf temperature of well-watered grapevine and to evaluate the reliability of its use in calculating a *CWSI* for wine grape under deficit irrigation. Feasibility was evaluated by comparing predicted with measured values of well-watered leaf temperatures and relating the calculated *CWSI* to irrigation amounts to wine grape that were deficit-irrigated at fractional amounts of evapotranspiration demand (ET_c).

Materials and Methods

The study was conducted during the 2013 and 2014 growing seasons in a field trial site located 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 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. The wine grape cultivar Syrah was planted as un-grafted, dormant-rooted cuttings in 2007 and was well-watered using above ground drip through the 2010 growing season. Row by vine spacing (1.8 x 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), and disease and pest control were managed according to local commercial practices. Alley and vine rows were maintained free of vegetation.

The irrigation system provided for the application of four, independent irrigation treatment levels in a randomized block design with four (Syrah) replicate blocks and independent irrigation water supply to border vines located in the field 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; however, in 2014 the 70% ET_c three irrigations per week treatment was not included in the study. The 70% ET_c amount was intended to induce a sustained, mild water deficit throughout berry development that was similar to standard local industry practice (Keller et al. 2008). Irrigation amount was calculated weekly using the 1982 Kimberly–Penman equation (Jensen et al. 1990) with alfalfa as a reference crop obtained from a weather station (http://www.usbr.gov/pn/agrimet/wxdata.html) located within 3 km of the study site and a variable crop coefficient (0.3 to 0.7) (Allen et al. 1998; Keller et al., 2008). Midday leaf water potential of border vines was monitored every 14 days in 2013 and weekly in 2014. The irrigation amount was adjusted as needed to ensure that the midday leaf water potential of well-watered vines was less negative than -1.0 MPa. Deficit irrigation treatments were initiated each year just after fruit set and were continued throughout berry development. Deficit irrigation in all plots was first initiated in the 2011 growing season.

Canopy temperature was measured with infrared temperature sensors (SI-121 Infrared Radiometer; Apogee Instruments, Logan, UT) positioned approximately 30 cm above fully expanded 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 sunlight leaves. The measured canopy area received full sunlight exposure during midday. The temperature sensing area was approximately 20 cm in diameter. 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 sunlit leaves on the top of the canopy. Temperature sensors were installed in one well-watered and one deficit-irrigated data vine in a single replicate of each irrigation amount and irrigation frequency. In 2014 two temperature sensors were used in the well-watered border plot. Environmental parameters; wind speed (*WS*), air temperature (T_{air}), relative humidity (*RH*), and solar radiation (*SR*) were measured in the vineyard adjacent to the irrigation treatment plots. Canopy temperature and environmental parameters were sampled at 1-min intervals and 15-min averages recorded on a data logger from July 11 (berries were pea-sized) until September 22 (fruit maturity) in 2013 and from June 26 until September 25 in 2014. Environmental sensors were located in the vine row, above the grapevine canopy. Air temperature (T_{air}), *RH* and *SR* were measured 2.2 m and *WS* was measured 2.5 m above ground level. Wind speed was adjusted to a standard height of 2 m (Allen et al. 1998).

Neural network software NeuroIntellligence (Alyuda Research Inc., Cupertino, CA) was used to develop a NN model for estimating T_{canopy}. The recorded well-watered canopy temperature and environmental dataset for 2013 was filtered to include only values collected between 13:00 and 15:00 MDT based on previous experience with grapevine canopy temperature measurement (Shellie and King 2013). The filtered dataset was randomly subdivided into one of three datasets used to train, validate and test the NN model. Sixty-five 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 complete, filtered dataset 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 with 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 NN architecture (number of hidden layer neurons, input parameters) was selected based on maximizing model efficiency (ME) (Nash and Sutcliffe 1970), while using a minimum number of neurons to reduce risk of over-training the NN to the data. Model efficiency, which is commonly used for hydrologic model evaluation (Moriasi et al. 2007), is defined as:

$$ME = 1 - \frac{\sum \left(y_i - y_{pred}\right)^2}{\sum \left(y_i - y_{ave}\right)^2} \tag{1}$$

where y_i is the ith data value, y_{pred} is model predicted value for y_i and y_{ave} is the mean of the data values. Model efficiency is similar to the correlation coefficient associated with linear regression in that its value ranges from $-\infty$ to 1. A value of 1 means the model is a perfect fit to the data. A negative *ME* value signifies that the data mean is a better prediction of data values than model output.

Results and Discussion

In 2013, April 1 through October 31 precipitation and average total direct solar radiation were nearly equal to the 19-yr site average (Table 1). The number of days that daily maximum temperature exceeded 35˚C was greater than the 19-yr site average, but was within one standard deviation of average. Cumulative growing degree days (GDD) in 2013 were 5% greater, but within one standard deviation of the 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 cultivar Syrah. Reference evapotranspiration (ET_r) for the study site in 2013 was more than one standard deviation greater than the 19-yr site average. April 1 through September 30 climatic conditions in 2014 were very similar to 2013 (Table 1) with the exception that GDD and days with maximum daily temperature greater than 35˚C were less. Growing season amount of water provided to well-watered vines was ~50% of ET_r. Since the crop coefficient used to calculate irrigation amount varied from 0.3 to 0.7 during the growing season, the irrigation amount supplied to well-watered vines provided 100% of ET_c. The irrigation amounts supplied to vines deficit-irrigated with 35 or 70% ET_c were ~35 and 70% of the irrigated amount of well-watered vines in both years.

The study site had a high evaporative demand with vapor pressure deficits (*VPD*) up to 6 kPa in 2013 (Fig. 1). Linear correlation between the temperature difference of well-watered leaves and ambient air (T_{nws}-T_{air}) and *VPD* were significant (p<0.0001) with a correlation coefficient of 0.32 (Fig. 1). The high variability of T_{nws}-T_{air} at any given value of *VPD* illustrates a strong influence of additional factors on leaf temperature that is unrelated to water deficit which makes determining plant water status difficult with only measurement of T_{nws}-T_{air} and *VPD*.

The NN model developed to predict leaf temperature provided excellent estimation of well-watered leaf temperature for the 2013 test dataset (Fig 2). Model efficiency of predicted versus measured well-watered leaf temperature was 0.89 and root mean square error of the NN model was 1.06 ˚C. The feed-forward NN model architecture selected to estimate well-watered grapevine leaf temperature (T_{nws}, Eqn. 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 or increase in ME. 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 performance of the NN model using the entire filtered dataset (training, validation and test datasets combined) was similar to the performance of the test dataset (Fig. 2) indicating that the randomly selected test dataset was representative of the entire dataset. Root mean square error of the NN model for the composite dataset was 0.98 ˚C and ME was 0.91. The NN model has a slight bias to over-estimate canopy temperature < 23 ˚C and under estimate canopy temperature > 31˚C. This bias may be a result of the limited number of training dataset values for low and high canopy temperatures (Fig. 2). A larger dataset over multiple years with a greater proportion of high and low leaf temperature

Table 1. Historical, 2013, and 2014 climate data (± standard deviation) 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. Accumulated growing degree days were calculated from daily maximum and minimum temperature with no upper limit and a base temperature of 10˚C.

April 1 through October 31	2013	1994 – 2012 Average
Precipitation (mm)	101	99.6 ± 115
Daily average total direct solar radiation (MJ m^{-2})	22.3	22.1 ± 0.9
Days daily maximum temperature exceeded 35˚C	35	28 ± 12
Accumulated growing degree days (˚C)	1798	1708 ± 115
Alfalfa-based reference evapotranspiration, ET_r (mm)	1307	1212 ± 55
April 1 through September 30	2013	2014
Precipitation (mm)	81	80
Daily average total direct solar radiation (MJ m^{-2})	23.8	24.0
Days daily maximum temperature exceeded 35˚C	35	27
Accumulated growing degree days (˚C)	1752	1667
Alfalfa-based reference evapotranspiration, ET_r (mm)	1226	1230
Well-watered vines (mm)	603	614
70% ET_c with 1 irrigation/week (mm)	407	448
70% ET_c with 3 irrigations/week (mm)	413	---
30% ET_c with 1 irrigation/week (mm)	214	240
30% ET_c with 3 irrigations/week (mm)	215	244

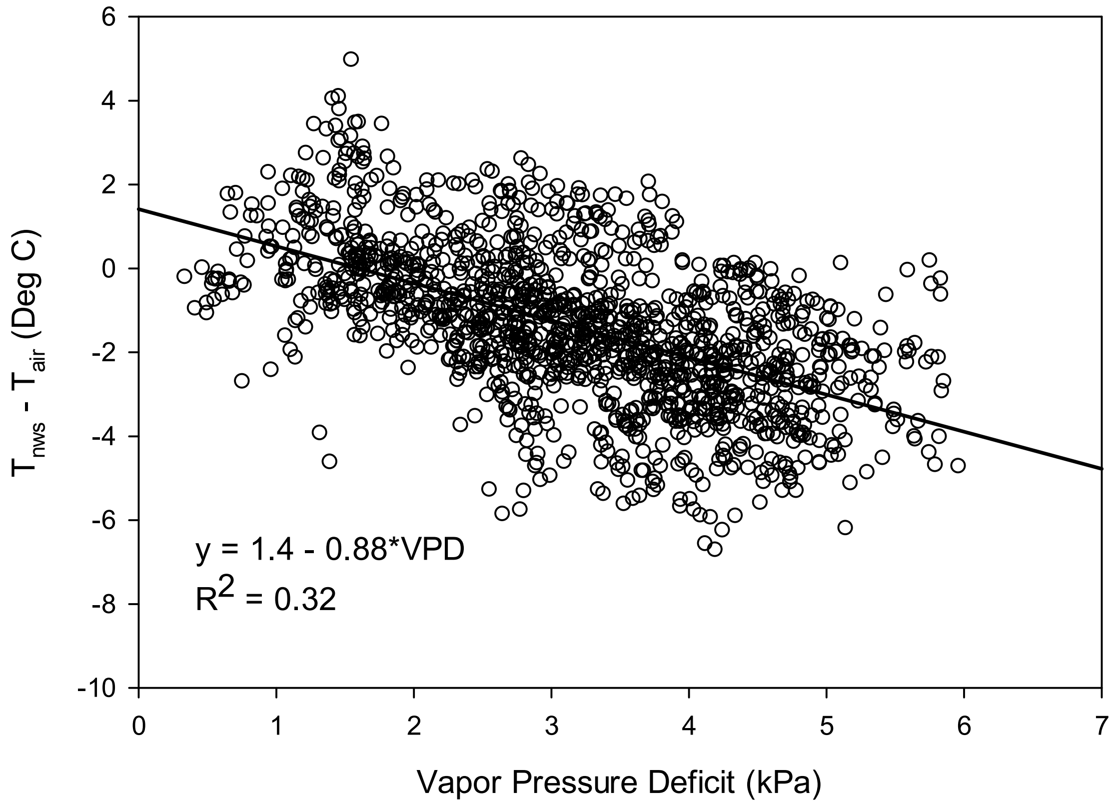

Figure 1. Influence of vapor pressure deficit on the difference in surface temperature of an exposed, well-watered leaf (T_{nws}) of the wine grape cultivar Syrah and the temperature of ambient air (T_{air}) measured between 12:00 and 16:00 MDT at 1-min intervals and recorded as 15-min average values from July 11 until September 22, 2013 at Parma, ID.

measurements would likely improve NN model performance at the upper and lower temperatures. A dataset larger than the one used in this study that is filtered to include an even occurrence of data values over a range of measured leaf temperatures during NN model development could also further minimize bias.

Prediction performance of the NN model for well-watered leaf temperature measured in 2014 was less than for 2013 but still provided a good estimate of leaf temperature (Fig. 3). Model efficiency for prediction of well-watered leaf temperature in 2014 was 0.78 with a root mean square error of 1.8 ˚C. The NN model tended to over predict leaf temperature for measured leaf temperatures < 23 ˚C in 2014. Leaf temperatures < 20 ˚C was rarely measured in 2013, which was the data set used to develop and train the NN model. Model bias can likely be reduced by using data from both years to retrain the NN model.

Cumulative probability distributions of measured temperature differences between the canopy and air of deficit-irrigated vines supplied with 35% ET_c were used to determine an appropriate value for T_{dry} (Fig. 4) needed to calculate CWSI (eqn. 1). Irrigation frequency influenced the maximum measured temperature difference between the canopy of deficit-irrigated vines and

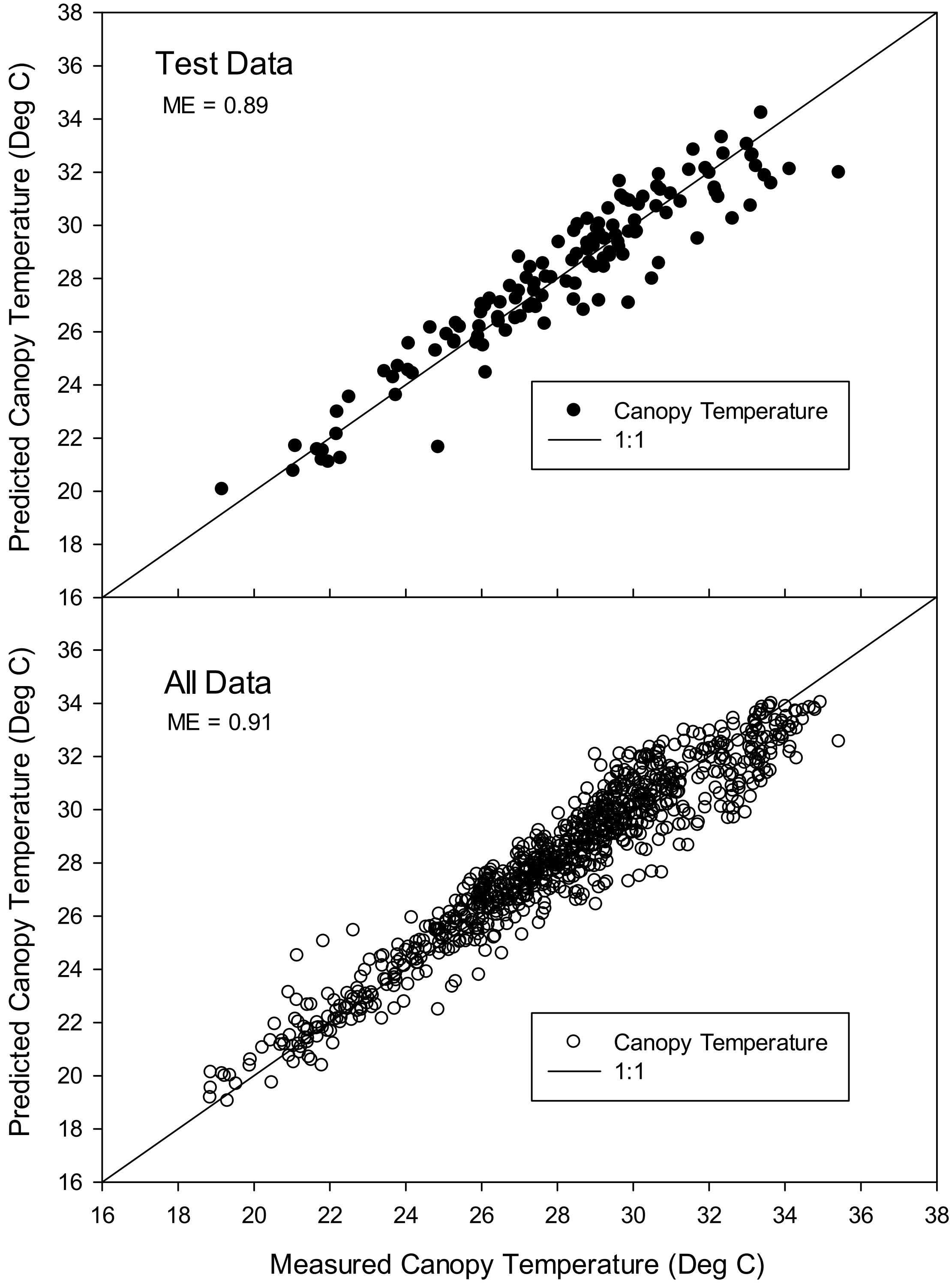

Figure 2. Performance of neural network model for predicting non-water stressed canopy temperature relative to the measured leaf temperature of well-watered Syrah grapevines recorded between 13:00 and 15:00 MDT as 15-min average values measured at 1-min intervals from July 22 until September 22, 2013 in Parma, ID.

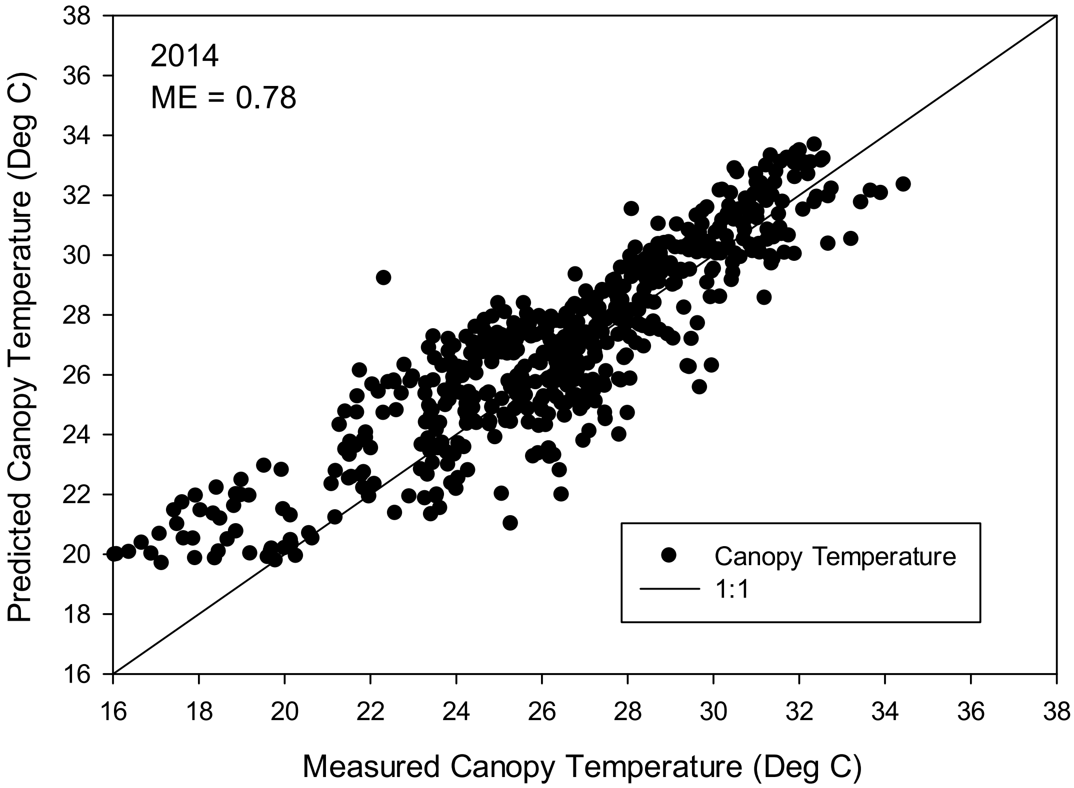

Figure 3. Performance of neural network model for predicting non-water stressed canopy temperature relative to the measured leaf temperature of well-watered Syrah grapevines recorded between 13:00 and 15:00 MDT as 15-min average values measured at 1-min intervals from July 17 until October 6, 2014 in Parma, ID.

T_{air} (Fig. 4). Vines irrigated one time per week had a slightly greater maximum temperature difference than vines irrigated three times per week. The maximum canopy to air temperature difference was 14˚C. Using the physical grape leaf model of Jones (1999), the cumulative probability distribution calculated for a non-transpiring leaf (zero transpiration) had a maximum temperature difference between canopy and ambient air of 20˚C (Fig. 4). This value appeared to be an extreme estimate of the maximum value of T_{dry} for the study conditions. We therefore estimated T_{dry} for calculation of the *CWSI* (Eqn. 1) as T_{air} + 15˚C, which will rarely be exceeded (Fig. 4). It is possible that leaf transpiration may not be zero at T_{air} + 15˚C, but the rate of transpiration is likely less than required for desirable yield and berry composition. Reference temperatures do not necessarily need to be an absolute canopy temperature limit, but serve rather as indicator temperatures to scale measured canopy temperature to the environment for calculating relative water stress (Grant et al. 2007).

A daily *CWSI* was calculated for vines deficit-irrigated at 70% or 35% ET_c using the NN estimated values for T_{nws} and T_{air} + 15˚C for T_{dry} by averaging 15-min *CWSI* values for each 15-min average value of T_{air} and T_{canopy} recorded daily between 13:00 to 15:00 MDT. The daily *CWSI* of deficit-irrigated vines in 2013 irrigated three times per week at a rate equal to 70% ET_c (Fig. 5) was consistently lower than the daily *CWSI* of vines deficit-irrigated with 35% ET_c and the daily *CWSI* consistently corresponded to irrigation events. The *CWSI* decreased following

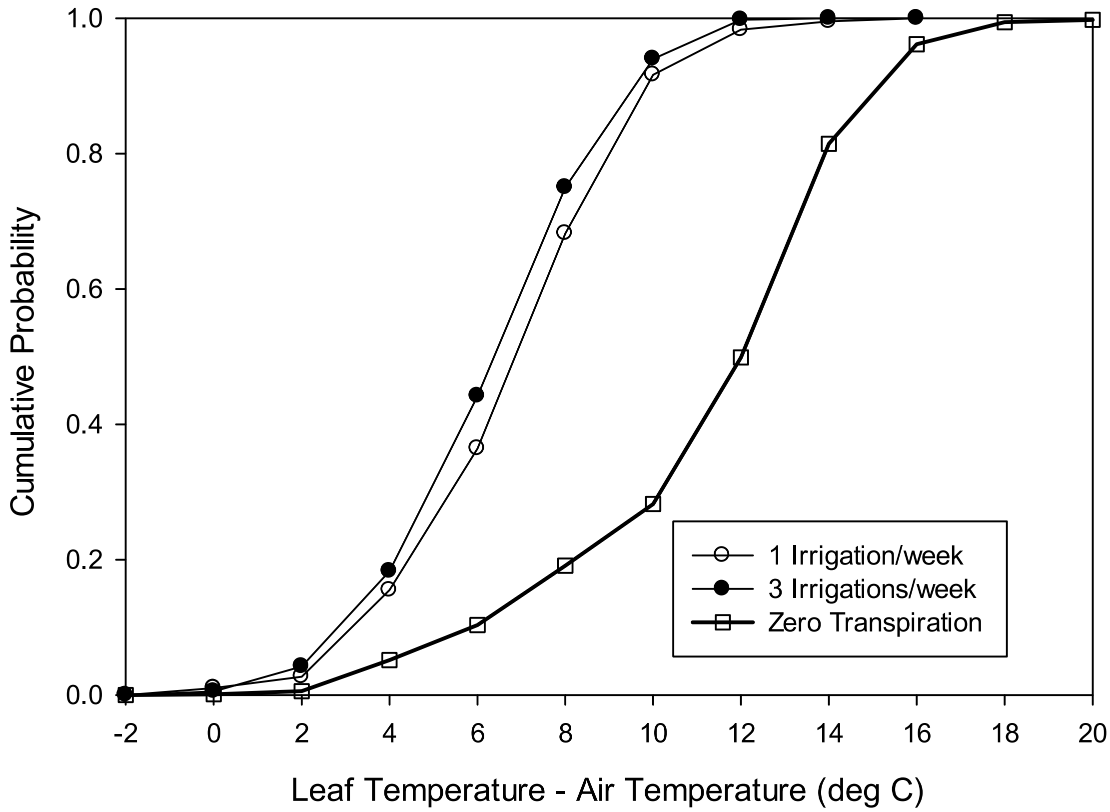

Figure 4. Cumulative probability for difference between canopy and ambient air temperature in Syrah grapevines deficit-irrigated at 35% of well-watered evapotranspiration rate (ET_c) irrigated with a frequency of once or three times per week. Temperatures were 15-min average values measured at 1-min intervals between 13:00 and 15:00 MDT from July 11 until September 22, 2013 in Parma, ID. Zero transpiration represents the estimated difference between a non-transpiring leaf and air temperature for the environmental conditions assuming isothermal radiation.

an irrigation event and gradually increased between irrigation events as soil water was withdrawn for ET_c. The same trend in daily *CWSI* between irrigations was present for vines irrigated once per week (Fig. 5). The response of CWSI to weekly irrigations was more pronounced due greater variation in soil moisture content resulting from larger irrigation amounts and greater time interval between irrigations. The response of CWSI to weekly irrigations of deficit irrigated vines in 2014 (Fig. 6) was nearly identical to 2013 indicating that application of the NN model developed using 2013 data provided an effective estimate of well-watered canopy temperature in 2014. The CWSI for vines irrigated with 70% ET_c was consistently lower than for vines irrigated with 35% ET_c. The response of CWSI of vines irrigated three times per week at the rate of 35% ET_c (Fig. 8) was very similar to 2013 (70% ET_c was not present in the study trial in 2014).

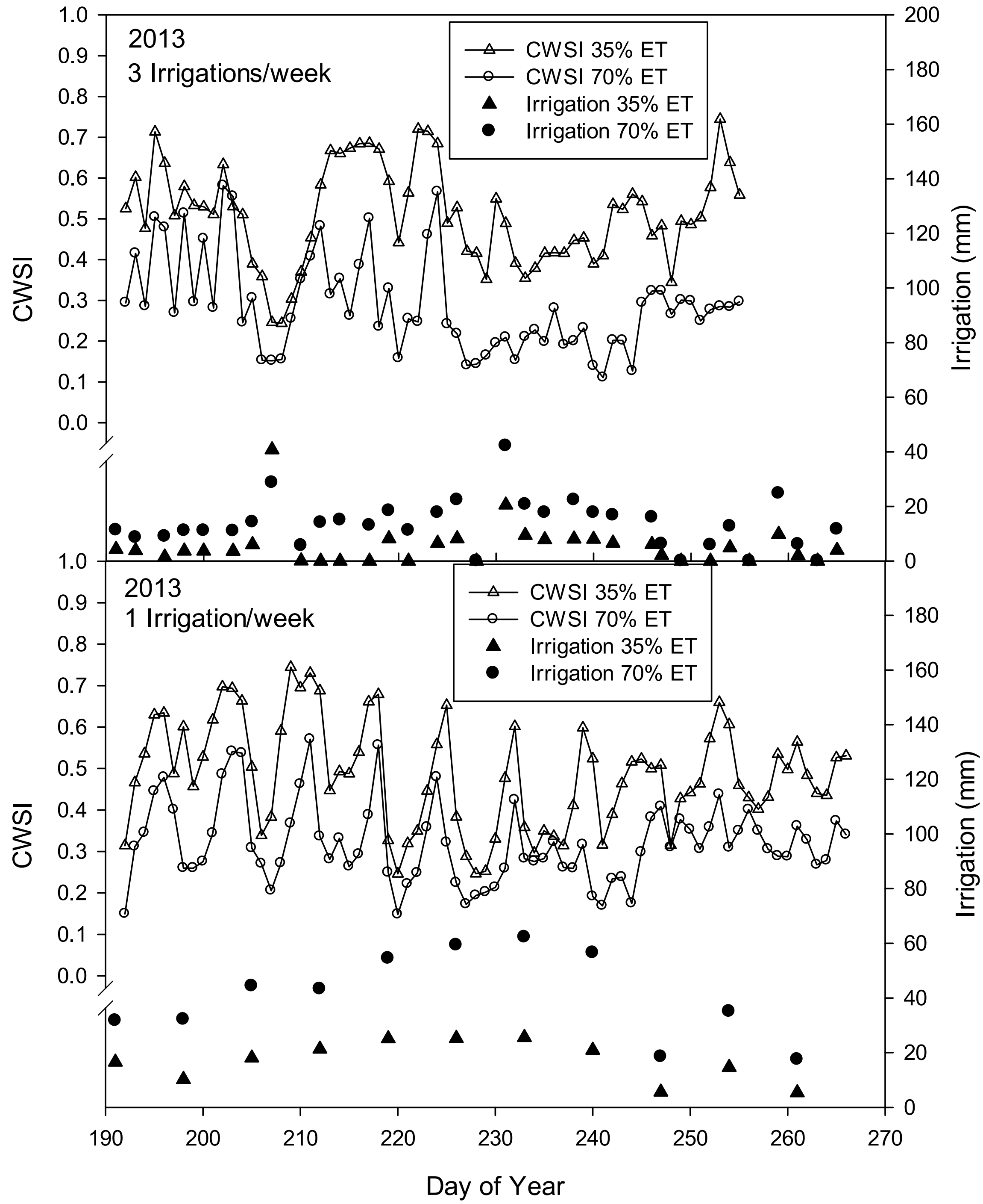

Figure 5. Irrigation amounts and calculated *CWSI* values for Syrah grapevines in treatment plots deficit-irrigated at 35 or 70% of well-watered evapotranspiration rate (ET_c) irrigated three times per week and once per week. Well-watered canopy temperature was estimated using the neural network model. Ambient air and deficit-irrigated leaf temperature were recorded as 15-min average values measured at 1-min intervals between 13:00 and 15:00 MDT from July 11 until September 15, 2013 in Parma, ID.

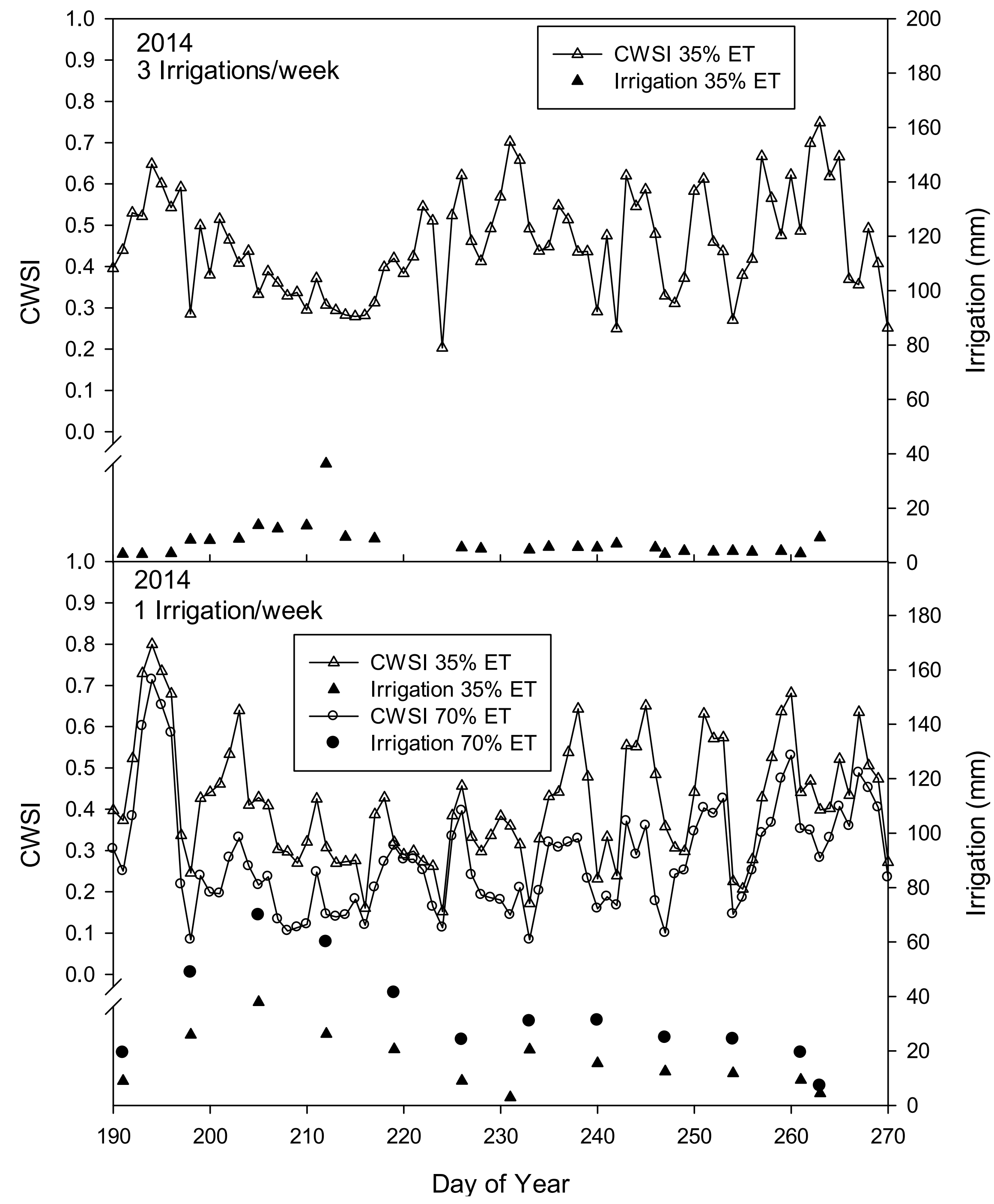

Figure 6. Irrigation amounts and calculated *CWSI* values for Syrah grapevines in treatment plots deficit-irrigated at 35 or 70% of well-watered evapotranspiration rate (ET_c) irrigated three times per week or once per week. Well-watered canopy temperature was estimated using the neural network model. Ambient air and deficit-irrigated leaf temperature were recorded as 15-min average values measured at 1-min intervals between 13:00 and 15:00 MDT from July 9 until September 27, 2014 in Parma, ID.

Averaging 15-min *CWSI* values between 13:00 to 15:00 MDT to calculate a daily *CWSI* reduced the potential influence of transient environmental conditions. Daily *CWSI* consistently corresponded with irrigation events and differentiated irrigation amounts throughout the growing seasons of 2013 and 2014. The 15-min averaging approach in this study deviates from the calculation method 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 and results in a more representative value of *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); however estimating the constant value from the cumulative probability of measured leaf temperatures under water deficit generated an effective estimate of T_{dry} for the study conditions.

Conclusions

The feasibility of using neural network (NN) modeling to estimate the lower threshold temperature (T_{nws}) needed to calculate the traditional *CWSI* was demonstrated for wine grape. The neural network model developed for estimating T_{nws} based on 2013 measured canopy temperature of Sarah wine grape performed exceptionally well for calculating CWSI of deficit irrigated vines in 2013 and 2014. Use of NN model estimated T_{nws} for calculating *CWSI* over a 70-day period in 2013 and 2014 successfully differentiated between two levels of water stress. The maximum difference in temperature between the vine canopy and ambient air for the 35% ET_c irrigation treatments was found to be about 14˚C, much greater than 5˚C used in other studies as an estimate for non-transpiring leaf temperature (T_{dry}). Air temperature plus 15˚C used to estimate T_{dry} in calculation of *CWSI* provided an effective upper reference temperature. A 2-hour averaged *CWSI* value based on 15-minute averaged canopy temperature, T_{air}, solar radiation, relative humidity and wind speed values provided a consistent daily *CWSI* value under variable climatic conditions. Additional research should focus on evaluation of the NN modeling approach to estimate T_{nws} for other grape cultivars over multiple years and across locations to determine the range of applicability of a large database for calculation of a daily *CWSI* that could be automated to provide decision support in a precision irrigation system for wine grape.

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