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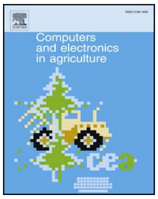

Original papers

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

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

[a] USDA ARS, Northwest Irrigation and Soils Research Unit, 3793 N 3600 E, Kimberly, ID 83341, United States
[b] USDA ARS, HCRU Corvallis, OR-Parma, ID Worksite, 29603 U of I Lane, Parma, ID 83660, United States

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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:

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

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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[*] 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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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.