EVALUATION OF THE SENSOR SUITE FOR DETECTION OF PLANT WATER STRESS IN ORCHARD AND VINEYARD CROPS

Rajveer Dhillon, Vasu Udompetaikul, Francisco Rojo, Shrini Upadhyaya, and David Slaughter

Biological and Agricultural Engineering Department
University of California, Davis
Davis, California

Bruce Lampinen, and Ken Shackel

Department of Plant Sciences
University of California, Davis
Davis, California

ABSTRACT

A mobile sensor suite was developed and evaluated to predict plant water status by measuring the leaf temperature of nut trees and grapevines. It consists of an infrared thermometer to measure leaf temperature along with relevant ambient condition sensors to measure microclimatic variables in the vicinity of the leaf. Sensor suite was successfully evaluated in three crops (almonds, walnuts and grapevines) for both sunlit and shaded leaves. Stepwise linear regression models developed for shaded leaf temperature yielded coefficient of multiple determination values of 0.89, 0.86, and 0.85 for almonds, walnuts, and grapevines, respectively. Stem water potential (SWP) and air temperature (T_a) were found to be significant variables in all models. Regression models were used to classify trees into stressed and unstressed categories with critical misclassification error for sunlit and shaded leaf models of 8.8 and 5.2% for almonds, 5.4 and 6.9% for walnuts, and 12.9 and 8.1% for grapevines, respectively. Canonical discrimination analyses were also conducted using sensor suite data to classify stressed and unstressed trees with critical misclassification error for sunlit and shaded leaves of 9.3 and 7.8% for almonds, 2 and 4.1% for walnuts, and 9.6and 1.6% for grapevines, respectively. These results show the feasibility that the sensor suite can be used to determine plant water status for irrigation and quality management of nut and vineyard crops.

Key words: Infra-red thermometer, leaf temperature, Stem water potential, plant water status.

INTRODUCTION

California is nation's primary producer of fruit and nut crops and accounted for 52% of total national production of fruit and nut crops worth $13.3 billion in the year 2010 (CDFA, 2011). On the other hand, California is also leading in withdrawing irrigation water, consuming more than one-fourth of total irrigation water withdrawn in the nation (USGS, 2005). Because of limited water resources and continuous increase in urban demand for water, optimizing the use of irrigation water for these tree crops is a prime concern for many researchers.

Irrigation scheduling techniques have been developed based on soil moisture monitoring and plant's response to water stress over the years (Jones, 2004). Primary requirement to various irrigation scheduling techniques is frequent monitoring of plant water status. Pressure chamber measurements are considered as the standard method to measure plant water status as it measures leaf water potential (Boyer, 1967, Lampinen et al., 2001). However, measurements of plant water status using pressure chamber are very time consuming and labor demanding which makes it impossible to obtain large number of samples necessary to develop efficient irrigation scheduling techniques. When a plant is under no water stress, it tends to open the stomata. When the stomata are open the water vapor diffuses out of the leaf and tends to cool the leaf. On the other hand, if the plant is experiencing water stress, the stomata tend to close and the leaf temperature may increase depending on the ambient conditions (solar radiation, wind speed, relative humidity, and surrounding air temperature). Therefore leaf temperature can be a good water stress indicator for plants (Jackson et al., 1981, Carlson et al., 1994). In recent studies, aerial thermal imaging has been used to measure canopy temperature to predict plant water status (Moller et al., 2007, Cohen et al., 2012). Inexpensive proximal leaf temperature measurements can also be used to predict plant water status. These measurements can be obtained conveniently and rapidly by use of non-contact infra-red sensors. As leaf temperature is not only function of plant water status, but also influenced by environment factors around the leaf (Jones, 1994). Therefore, we expect that simultaneous measurement of canopy temperature and other influential environmental parameters can be useful to predict plant water stress.

The objectives of this research were:

(I) to evaluate a sensor suite to measure plant water status based on simultaneous measurements of leaf temperature, photosynthetically active radiation (PAR), air temperature and humidity, and wind speed, and

(II) to validate its ability to measure plant-water status in almond, walnut and grape crops.

THEORETICAL CONCEPT

As mentioned earlier, a plant under water stress tends to close leaf stomata to reduce transpiration which in turn rises temperature of the leaf surface. Cooling of leaf surface due to evaporation of water through leaf stomata during the transpiration process is an indicator of percentage opening or closing of the leaf stomata. Therefore, difference of leaf temperature from ambient temperature has been studied to determine water stress level of plants. Involvement of other weather parameters effecting leaf temperature can be obtained by studying the energy balance equation for the leaf surface as follows:

$$\Phi n - H - \lambda E = S \qquad [eq. 1]$$

where, Φ_n (W/m^2) is net heat gain from radiation, and H (W/m^2) is 'sensible' heat loss given by:

$$H = \frac{\rho\, c_p\, (T_L - T_a)}{r_h} \qquad [eq. 2]$$

where, ρ = density of air in kg/m^3, cp is specific heat capacity of air (1012 J/kg/K), T_L and Ta are temperature of leaf and air respectively, r_h is resistance to heat transfer, λE (W/m^2) is heat loss due to evaporation from leaf surface derived from the difference between water vapor concentration in leaf and air. This evaporative cooling can be represented as:

$$\lambda E = \frac{\rho\, c_p\, (e_s[T_L] - e[T_a])}{\gamma\, (r_L + r_w)} \qquad [eq. 3]$$

where, r_L is stomatal resistance, r_w is boundary layer resistance to water vapors in s/m, γ is psychrometric constant in Pa/K, e is water vapor pressure in Pa, e_s is saturation vapor pressure in Pa, and S [eq.1] is physical heat storage in leaf which is relatively small compared to other terms in eq. 1, especially when changes in ambient temperature occur slowly.

By substitution of eq.2 and 3, into eq. 1, it can be modified to calculate leaf temperature as follows:

$$T_L = T_a + \frac{r_h \left(\gamma\, \Phi n\, [r_L + r_w]\, \rho\, c_p\, \delta e \right)}{\rho\, c_p\, (\gamma\, [r_L + r_w] + s\, r_h)} \qquad [eq. 4]$$

where, $\delta_e = (e_s\,[T_a] - e[T_a])$, is vapor pressure deficit of air in kg/m^3, $s = (e_s[T_L] - e_s[T_a])/(T_L - T_a)$ is slope of curve relating saturation vapor pressure to temperature in units of Pa/K.

From equation 4, we can see that T_L is a function of Ta, Φ_n, r_L, r_W, r_h and δ_e. In this study, all these variables were measured simultaneously except $r_{L.}$ For a plant, r_L depends on the percentage opening of stomata which in turn depends upon current water status of the tree. Other major factor that comes into play is the exposure of leaf to the sun, because stomatal sensitivity to the light is not the same under different exposure conditions. Therefore for each tree sunlit and shaded leaves were studied separately.

Infra-red radiation ($\Phi_{ir)}$ emitted by leaf surface was measured as it was related to leaf temperature by Stefan-boltzman law, $\Phi_{ir} = \varepsilon\sigma T_L^4$, where, ε is the emissivity of leaf surface and was assumed to be 0.98 and σ is Stefan-Boltzmann constant. Since, net long-wave radiation depends on the temperature difference between leaf and its environment (e.g., soil, sky, and other leaves). However, this part is expected to be relatively small and could be neglected (Jones and Rotenberg, 2011). The incident solar radiation, Φ_n is related to photosynthetically active radiation (PAR) falling on leaf surface and r_w depends on wind speed, i.e., $r_w = 151\ (d/u)^{0.5}$ (Jones, 1994), where, d is characteristic dimension of leaf and u is wind speed in m/s. Wind speed was measured to calculate r_w. The parameter, δ_e is a function of relative humidity and temperature of air around the leaf.

MATERIALS AND METHODS

Sensor suite development

A mobile sensor suite developed by Udompetaikul et al. (2011) was used to measure leaf temperature using an infrared sensor (6000L, Everest Interscience, Tucson, AZ). The sensor suite consisted of three other sensors to measure environmental parameters such as photosynthetically active radiation (PAR) using a PAR sensor (LI-190, LICOR inc., Lincoln, NE), air temperature and humidity using an air temperature and humidity probe (HMP35C, Visalia Inc., Woburn, MA) and wind speed around tree canopy using an anemometer (WindSonic, Gill Instruments Ltd., Hampshire, UK). Sensor suite with all its components is shown in figure 1. Standard pressure chamber (figure 1) measurements were taken for validation of sensor suite measurements. Data logger (CR3000 micrologger, Campbell scientific Inc., Logan, UT) was used to acquire and store data for all the sensors.

Fig.1. Mobile sensor suite and pressure chamber during data collection in an almond orchard.

Sensor suite was evaluated on three different crops i.e. almonds, walnuts and grapevines during 2010 and 2011 growing seasons. More information regarding study areas is presented in table 1.

Trees/grapevines of all three crops were subjected to different stress levels to cover the whole practical range of water stress level encountered by each crop. These orchards/vineyard were visited multiple times throughout the season to collect data. During each visit, mid-day stem water potential of each tree was measured using the pressure chamber (figure 1) and simultaneously leaf temperature, air temperature, relative humidity, wind speed, and PAR data were recorded using the sensor suite for 10-20 leaves/tree within a time span of 5-10 minutes. In case of almond and walnut crops, data was recorded for ten leaves per tree. But, for grapevines twenty leaves were studied per vine. However, in all cases half of the leaves studied were sunlit and half were shaded leaves.

Table 1: Study areas and crops used for sensor suite evaluation

	Almonds	**Walnuts**	**Grapevines**
Growing season	2011	2010	2011
Site name	Nickel’s/Madera	Nickel’s	MAST Ranch
county	Colusa/Madera	Colusa	Yolo
Crop variety	Nonpareil(5 yrs)/Nonpareil(4 yrs)	Howard(8 yrs) & Chandler(4 yrs)	Cabernet sauvignon

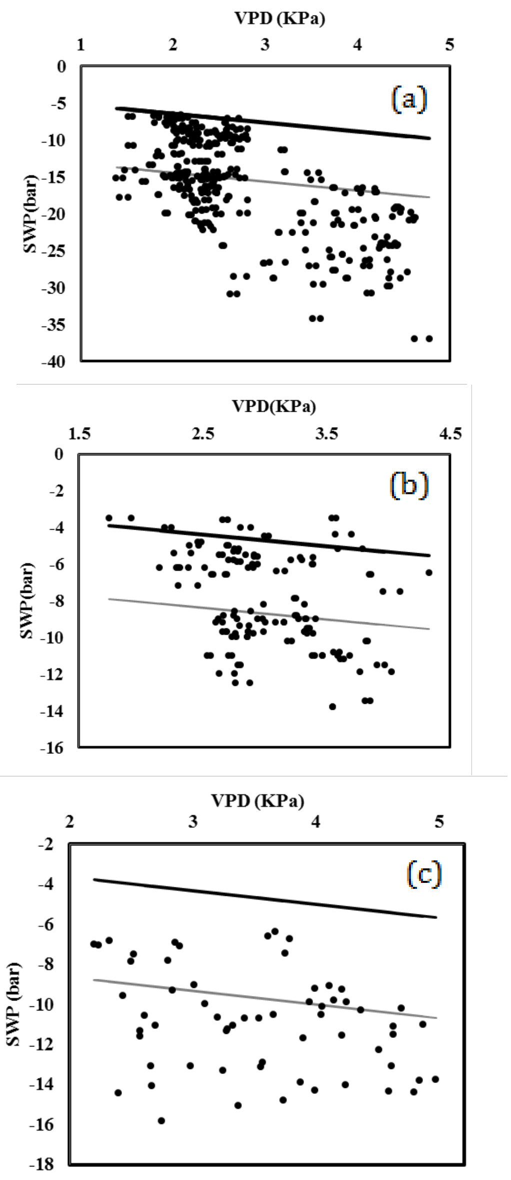
Statistical analysis

Ultimate goal of developing sensor suite was to predict real-time plant water status by measuring leaf temperature and microclimatic information and then classify the trees into stressed or unstressed categories so that this information can be used to implement variable rate irrigation management. In this study, data obtained from the sensor suite and pressure chamber were analyzed using SAS software package (SAS Institute, Inc. v.9.2. Cary, NC) to develop regression models for leaf temperature as the dependent variable. By utilizing stepwise model selection approach with k-fold cross validation (Hastie et al., 2009; SAS, 2010), empirical models for leaf temperature as functions of SWP, PAR, air temperature, RH, and wind speed were developed for each crop and light exposure conditions. Second order polynomial model was used to account for quadratic effects, if any.

Moreover, we proposed a technique to classify the plant water status as stressed or unstressed based on the critical values of stem water potential. The prediction models were used to determine critical values of the leaf temperature (T_L^c) corresponding to critical values of stem water potential (SWPc). Plants were classified as stressed if its leaf temperature T_L was higher than T_L^c. Classification accuracy was verified by comparing predicted stress to the measured stress level.

Actual tree stress level was defined by considering the plant water potential below the baseline, which is maximum SWP achieved when plant gets fully irrigated. This baseline depends on crop type and vapor pressure deficit. Baseline functions (BSWP) for almonds, walnuts and grapevines[1] given by (McCutchan and Shackel, 1992;Shackel et al., 1997) are shown in figure 2 with their respective critical SWP and measured pressure chamber SWP data.

The plant stress threshold was defined as a straight line parallel to the baseline (figure 2). In our study, the plant stress threshold was placed under the baseline by 8 bars, 4 bars and 6 bars for almonds, walnuts, and grapevines, respectively.



BSWP = -1.20 VPD – 4.10
Critical SWP = BSWP – 8

BSWP = -0.64 VPD – 2.78
Critical SWP = BSWP – 4

BSWP = -0.68 VPD – 2.29
Critical SWP = BSWP – 6

Fig. 2. Baseline and critical SWP for (a) almonds, (b) walnuts and (c) grapevines used for classification analysis.

1 Grapevine baseline equation was provided by Dr. Ken Shackle in personal communication

SWP value on the threshold line is the critical SWP (SWPc). A tree was considered as stressed if the measured SWP is lower than the SWPc at that ambient condition (i.e., VPD value). This criterion was used to define the true stress level of trees and vines in discriminant analysis also.

In the discriminant analyses trees and vines were classified into two groups, stressed and unstressed, from leaf temperature, air temperature, RH, PAR, and wind speed data. Canonical discriminant analysis was used to find canonical variables which are linear combinations of the quantitative variables that provide maximal separation between classes (SAS, 2010). Since only two classes were involved in this study, one canonical variable was necessary. Separate analyses were conducted for each crop and light exposure condition. Classification accuracies of discriminant models were determined by performing leave-one-out cross-validation technique (Khattree and Naik, 2000). Both classification techniques were compared to propose suitable models to discriminate between stressed and unstressed trees.

RESULTS AND DISCUSSION

Regression analysis

Table 2 shows basic descriptive statistics of data collected for all the variables by sensor suite in field experiments for 193, 74, and 62 observations on almonds, walnuts and grapevines, respectively. Stepwise regression linear models developed for leaf temperature yielded high correlations between stem water potential and other microclimatic variables. Multiple linear regression models obtained and their respective R^2 values for sunlit and shaded leaves are given in table 3. Quadratic models did not improve the model performance significantly as compared to simple linear models. Shaded leaf prediction models had higher R^2 values as compared to sunlit leaf models in all cases, in spite of more variables turning up as significant in sunlit leaf models in almonds and walnuts. This outcome can be due to factors like sun angle and leaf orientation in case of sunlit leaves as PAR was found to be significant in all sunlit models.

As expected from theoretical considerations, SWP was found to be significant variable in all the models. Air temperature was also significant in all cases expect in model for sunlit grapevine leaf. This explains the lower R^2 value for sunlit grapevine leaf model. But other important reason for low R^2 value was high variability of temperature over the sunlit grapevine leaf. Due to the bigger size and cone-like shape of grapevine leaves, different parts of the leaf surface received different amount of solar radiation at different angle as seen in infra-red thermal camera picture (figure 3). Therefore it was hard to get one representative value of leaf temperature. To verify this effect, multi spectral images of shaded and sunlit leaves were taken using a multispectral camera (Tetracam inc., Chatsworth, CA) with NIR, red and green bands.

Table 2: Descriptive statistics for sunlit and shaded leaf data for almonds, walnuts and grapevines

		Almonds		Walnuts		Grapevines	
Parameter	Statistic	Sunlit	Shaded	Sunlit	Shaded	Sunlit	Shaded
PAR	Mean	1818.4	203.3	1763.4	178.8	1415.76	138.15
(mmol s^{-1} m	SD	180.1	28.3	149.8	45.3	203.06	80.8
	Range	1239 to 2131	135 to 284	1320 to 204?	78 to 249	920 to 1978	36 to 284
T_L	Mean	33.8	29	38.4	25.4	35.07	29.74
(°C)	SD	2.9	2.6	5.2	2.7	3.06	3.45
	Range	27.6 to 42.4	22.2 to 34.2	28.9 to 48.1	18.2 to 31.8	29.4 to 41.3	23.3 to 36.2
T_A	Mean	30		30.7		32.8	
(°C)	SD	2.4		1.9		2.6	
	Range	23.3 to 33.8		25.3 to 33.8		28.4 to 37.2	
RH	Mean	40.5		31.8		30.35	
(%)	SD	5.6		5		5.3	
	Range	27.2 to 55.9		17.5 to 45.8		21.8 to 42	
Wind speed	Mean	0.52		0.44		0.54	
(m s^{-1})	SD	0.22		0.24		0.18	
	Range	0.16 to 1.30		0.08 to 1.42		0.23 to 1.08	
SWP	Mean	-15.6		-7.8		-10.87	
(bar)	SD	2.4		2.6		-2.5	
	Range	-22 to -10		-13.8 to -3.5		- 15.85 to - 6.4	
No. of observations		193		74		62	

Table 3: Linear regression models developed for leaf temperature for sunlit and shaded exposure conditions for almonds, walnuts and grape vines

crop	exposure	Linear regression model	R-square
Almonds	Shaded	$TL = 28.68 + 2.49(TA) - 1.45(SWP)$	0.89
	Sunlit	$TL = 31.05 + 2.44(TA) - 2.20\ (SWP) + 2.47(PAR) - 0.36\ (WIND)$	0.86
Walnuts	Shaded	$TL = 25.44 - 1.72(SWP) + 1.46(TA) + 0.29(RH)$	0.86
	Sunlit	$TL = 38.43 - 4.06(SWP) - 0.10(WIND) + 0.66(PAR) + 0.51(TA)$	0.82
Grapevines	Shaded	$TL = 29.73 + 3.69(TA) + 0.96\ (SWP) - 2.36(PAR)$	0.85
	Sunlit	$TL = 35.06 + 2.21(SWP) - 0.76(PAR)$	0.6

NIR and red band reflectance values at different locations over the single leaf surface were measured. Point selection on leaf surface was done in a way to cover low and high values over the leaf surface. Standard deviation of NIR and red reflectance values on shaded and sunlit grapevine leaves (figure 4) shows high variability of leaf temperature over the single leaf surface, especially in sunlit leaves. In the future studies, we plan to incorporate simultaneous NIR and red reflectance measurements along with temperature measurement on multiple locations on a single leaf.

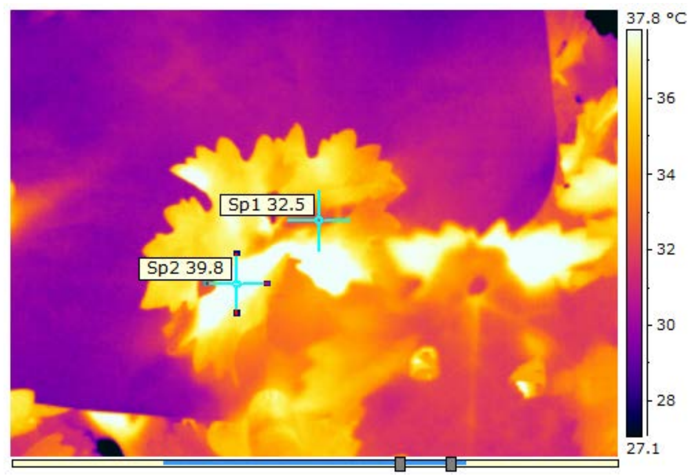


Fig.3. Infra-red thermal camera picture taken for purpose of showing temperature variability on typical sunlit grapevine leaf.

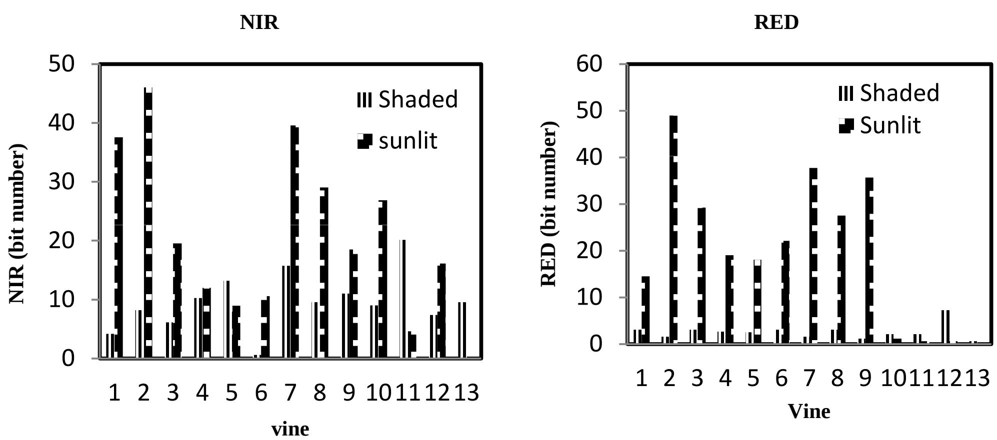


Fig.4. standard deviations of three readings of NIR and red bands obtained from multispectral camera pictures of sunlit and shaded grapevine leaves showing variability of radiations received over the leaf surface.

The regression models obtained were used in classification analysis to classify the observed trees into stressed and unstressed trees. Using critical

SWP values (figure 2) in corresponding regression models (table 3) for each crop, critical leaf temperatures were calculated. If measured leaf temperature is higher than this critical temperature, the tree was classified as stressed. Two types of misclassification errors were possible i.e. predicting an actual stressed tree as unstressed tree, which is designated as "critically wrong decision" as this has implications on plant growth and yield and a less serious error of classifying unstressed tree as stressed tree which is designated as "over irrigation error". The critical errors (table 4) for sunlit and shaded leaf models were 8.8 and 5.2% for almonds, 5.4 and 6.9% for walnuts, and 12.9 and 8.1% for grapevines, respectively. Shaded leaf models yielded overall less error rates, hence better performance in classification analyses also except in walnuts.

Canonical discriminant analysis

Objectives of canonical discriminant classification analyses were also to classify the observed trees into two classes – (i) stressed, and (ii) unstressed trees, and to determine the misclassification error rates. Critical, over irrigation, and total error rates of classification analyses, compared to standard classification according to SWP (figure 2) obtained are listed in table 4. The critical errors rates for canonical discriminant analysis for sunlit and shaded leaves were 9.3 and 7.8% for almonds, 2 and 4.1% for walnuts, and 9.6 and 1.6% for grapevines, respectively. This technique could discriminate stress levels very effectively by keeping the total and critical errors low.

Form the above results, it can be concluded that MLR models show a better relationship between the plant water status and the leaf temperature for shaded leaves than sunlit leaves. According to both classification analyses, classification accuracies for sunlit and shaded leaves were not any different. However, amount of light interception normal to the leaf surface is necessary to make accurate classification based on data obtained from sunlit leaves. This is a very important and interesting outcome as sunlit leaves change leaf orientation depending on the light intensity making it difficult to obtain radiation data normal to the leaf surface. From a practical point of view, it is much more convenient to obtain shaded leaf data using the sensor suite. Results from this study suggest that good regression and discriminant models could be developed using only shaded leaf data. The small number of observations was the reason for differences in results between regression and classification analyses for grapevines, as compared to almonds and walnuts. In addition, some issues with sunlit grapevine leaf explained earlier (figure 3) may also be responsible.

Table 4: Misclassification error rates for almonds, walnuts and grapevines by exposure

Analysis	Error type	Almonds		Walnuts		Grapevines	
		Sunlit	Shaded	Sunlit	Shaded	Sunlit	Shaded
using MLR model	over irrigation	8.8	9.8	5.4	5.5	9.6	14.7
	critical	8.8	5.2	5.4	6.9	12.9	8.1
	total	17.6	15	10.8	12.3	22.5	22.9
Canonical discriminant	over irrigation	6.7	8.3	6.8	5.5	9.6	15
	critical	9.3	7.8	2	4.1	9.6	1.6
	total	16.1	16.1	8.8	9.6	19.3	16.7

CONCLUSIONS

A mobile sensor suite was developed and evaluated to predict plant water status by measuring the leaf temperature of nut trees and vines. It consists of an infrared thermometer to measure leaf temperature along with relevant sensors to measure microclimatic variables. Sensor suite was successfully evaluated in three orchard crops i.e. almonds, walnuts and grapevines on sunlit and shaded leaves. Stepwise linear regression models developed for shaded leaf temperature yielded coefficient of multiple determination values of 0.89, 0.86, and 0.85 for almonds, walnuts, and grapevines, respectively. Stem water potential (SWP) and air temperature (T_a) were found to be significant variables in all models. Regression models were used to classify trees into stressed and unstressed categories. Critical misclassification error (classifying a stressed tree as unstressed) for sunlit and shaded leaf models were 8.8 and 5.2% for almonds, 5.4 and 6.9% for walnuts, and 12.9 and 8.1% for grapevines, respectively. Canonical discrimination analyses were also conducted using sensor suite data to classify stressed and unstressed trees with critical misclassification error for sunlit and shaded leaves of 9.3 and 7.8% for almonds, 2 and 4.1% for walnuts, and 9.6 and 1.6% for grapevines, respectively. These results suggest feasibility that the sensor suite can be used to determine plant water status for irrigation and quality management of nut and vine crops.

ACKNOWLEDGEMENTS

The authors would like to acknowledge National Institute of Food and Agriculture grant programs (SCRI-USDA-NIFA No. 2010-01213) for the financial support to conduct these research activities. The authors also acknowledge help of Aaron Whitlatch in data collection.

REFRENCES

Boyer, J.S. 1967. Leaf water potentials measured with a pressure chamber. *Plant Physiology*. 42(1): 133-137

Carlson, T.N., R.R. Gillies and E.M. Perry. 1994. A method to make use of thermal infrared temperature and NDVI measurements to infer surface soil water content and fractional vegetation cover. *Remote sensing reviews.* 9(1-2):161-173.

CDFA. 2011. California Agricultural Resource Directory 2008–2009. California Department of Food and Agriculture. Sacramento, CA.

Cohen, Y., V. Alchanatis, A. Prigojin, A.levi, and Y.cohen. 2012. Use of aerial thermal imaging to estimate water status of plam trees. *Precision Agric.* 13(1):123-140.

Hastie, T., R. Tibshirani, and J. H. Friedman. 2009. *The Elements of Statistical Learning.* 2 ed. Springer.

Jackson, R.D., S.B.Idso, R.J. Reginato,and P.J. Pinter Jr. 1981. Canopy temperature as a crop water stress indicator. *water resources research.* 17(4):1133-1138

Jones, H. G. 1994. *Plants and microclimate : a quantitative approach to environmental plant physiology*. 2nd ed. Cambridge University Press.

Jones, H. G. 2004. Irrigation scheduling: advantages and pitfalls of plant-based methods. *J. Exp. Bot.* 55(407):2427-2436.

Jones, H. G., and E. Rotenberg. 2011. *Energy, Radiation and Temperature regulation in plants.* Published online. John Willey & sons (Hoboken,NJ)

Khattree, R., and D. N. Naik. 2000. *Multivariate data reduction and discrimination with SAS software*. SAS Institute Inc.

Lampinen, B., K. Shackel, S. Southwick, and W. Olson. 2001. Deficit irrigation strategies using midday stem water potential in prune. *Irrigation Science* 20(2):47-54.

McCutchan, H., and K. A. Shackel. 1992. Stem-water Potential as a Sensitive Indicator of Water Stress in Prune Trees (*Prunus domestica* L. cv. French). *J. Amer. Soc. Hort. Sci.* 117(4):607-611.

Moller, M., V. Alchanatis, Y. Cohen, M. Meron, J. Tsipris, A. Naor, V. Ostrovsky, M. Sprintsin, and S. Cohen. 2007. Use of thermal and visible imagery for estimating crop water status of irrigated grapevine. *J. Exp. Bot.* 58(4):827-838.

SAS. 2010. SAS OnlineDoc, Version 9.2. Cary, N.C.: SAS Institute, Inc.

Shackel, K. A., H. Ahmadi, W. Biasi, R. Buchner, D. Goldhamer, S. Gurusinghe, J. Hasey, D. Kester, B. Krueger, B. Lampinen, G. McGourty, W. Micke, E. Mitcham, B. Olson, K. Pelletrau, H. Philips, D. Ramos, L. Schwankl, S. Sibbett, R. Snyder, S. Southwick, M. Stevenson, M. Thorpe, S. Weinbaum, and J. Yeager. 1997. Plant water status as an index of irrigation need in deciduous fruit trees. *HortTechnology* 7(1):23-29.

Udompetaikul, V., S. K. Upadhyaya, D. C. Slaughter, B. D. Lampinen, and Ken Shackel. 2011. Plant water stress detection using leaf temperature and microclimatic information.*An ASABE meeting presentation*, Paper No: 1111555.,St. Joseph, MI. ASABE.

USGS,2005. Total Water Use in the United States.2005. *United States Geological Survey.* Restron, Virginia.