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TRANSPIRATION AND CROP COEFFICIENTS FOR IRRIGATED OLIVES WITH PREDICTIVE EQUATIONS DERIVED FROM MODIS REMOTELY SENSED VEGETATION INDICES AND GROUND-BASED TEMPERATURE DATA

Francisco L. Santos, Alice F. Ramos

Instituto de Ciências Agrárias e Ambientais Mediterrânicas, ICAAM, Universidade de Évora, Apartado 94, 7002-554 Évora Codex, Évora, Portugal

Abstract

Olive transpiration T can be predicted by combining MODIS remotely sensed vegetation indices (EVI* and NDVI*), tree ground-based transpiration derived from sap flow measurements and maximum daily air temperature t_a. The feasibility of developing a single predictive equation of olive orchard transpiration through the relationship between sap flow based transpiration (T) and remotely sensed Enhanced and Normalized Difference Vegetation Indexes (EVI and NDVI) of an irrigated orchard in southern Portugal was tested. A correlation matrix relating T as the dependent variable to VIs and micrometeorological data as independent variables was constructed. Regression equations were then developed from the micrometeorological variable that most closely correlated with ground transpiration T data, and finally predictive multivariate equations were derived from EVI^*- t_a and $NDVI^*$- t_a, being the maximum air temperature t_a the ground-measured micrometeorological variable found most closely correlated with field T. Such predictive responses were validated with olive sap flow ground based transpiration data, being the measured and predicted T based on EVI^*-T_a within 11% of the 1:1 line. The robustness of the method is attributed to spectral vegetation indices being able to describe well vegetation amount and condition and strongly correlate with micrometeorological variables that drive olive transpiration. The predictive responses were used here to calculate and propose crop coefficients that can be made routinely operational and available to guide irrigation. The modeling study also shows that the method can offer a reliable way for verification and scaling up of sap flow measurements to wider olive growing areas, and for providing data for other applications.

Keywords: Transpiration, crop coefficient, MODIS, EVI, NDVI, vegetation indices, *Olea europaea,* olive trees

Introduction

Olive trees in southern Portugal undergo two main growth stages: an intense stage during spring and early summer, and a less vigorous stage in early autumn. Olives also undergo a reduced vegetative growth from July to mid September, of yield formation, stone hardening and coloring, a period known to be less critical to soil water deficit (Moriana et *al.*, 2007; Ramos and Santos, 2009). To accurately quantify this crop water needs is not a straightforward matter. According to Ninemets (2007), over a long time period of water-stress or other unfavorable conditions, crops tend to reduce their foliage density and leaf area, and adjust their leaves chlorophyll content and dependent physiological processes to use resources efficiently. This time evolution of foliage density and condition can be evaluated by time-series spectral vegetation indices (VIs), radiometric measures of vegetation amount and state that use the spectral contrast in vegetation canopy-reflected energy in the red and near infrared (NIR) portions of the electromagnetic spectrum (Huete, 2004). Combined with ground data or appropriately calibrated models those data produced valuable estimates of crop transpiration and related processes at the canopy or ecosystem scale (Glenn et *al*., 2008). As for olive trees, during the reduced vegetative growth period they shed leaves and use their inbuilt mechanisms to temporarily shut down their stomata and lower their photosynthesis and growth activity until the cooler temperatures of late summer or early autumn arrive (Tognetti et *al*., 2005; Sofo et *al*., 2008). From centuries of self preservation and adaptation to atmospheric and water stresses such behavior seems ever present even when trees are well-irrigated, as Diaz-Espejo et *al*. (2007), and Ramos and Santos (2009) document.

Combining Enhanced Vegetation Index (EVI) values from the MODIS sensor on the NASA Terra satellite, air temperature, and surface net radiation Wang et *al*. (2007) successfully used a direct semi-empirical method to predict ET in the Southern Great Plains of the U.S. Also, combining remote sensing and in-situ measurements to estimate evapotranspiration (ET) from riparian vegetation over large reaches of western U.S. Rivers, Nagler et *al*. (2005a,b) demonstrated the existence of a strong correlation between ground-measured crop ET and Enhanced Vegetation Index (EVI) values from the MODIS sensor. They showed that time-integrated EVI data over 16 day intervals could be pooled with ground-measured maximum daily air temperatures t_a to further improve this relationship and map regional riparian transpiration fluxes. We followed that general approach in the present research.

Our goal was to use the capacity of VIs in estimating transpiration to develop and calibrate a site-specific predictive model of olive orchard transpiration (T) that combining readily available remotely sensed vegetation indices from MODIS and ground-based micrometeorological data could be made operational and used for farmers and irrigation managers. With the established algorithms, and to guide irrigation scheduling and planning, olive crop coefficients were derived.

Material and Methods

The *in-situ* research to obtain estimates of irrigated olive orchard transpiration rates was conducted during 2006 at the Herdade dos Lameirões located near Safara (lat. 38º 04' 57″ N; long. 07º 16' 27″ W; alt. 75 m), in the region of Moura, southern Alentejo, Portugal, using an orchard stand of mature olive trees (*Olea europaea* L. cv. Cordovil). The over 80 year-old mature olive orchard was planted on a 12 by 12 m spacing layout and trees were irrigated from mid March to the end of October under the sustained deficit irrigation (SDI) to provide for approximately 450 mm of irrigation. Reference evapotranspiration (ET0) was calculated using the FAO-Penman-Monteith method.To evaluate sap flow rates and estimate crop transpiration, the compensation heat pulse technique (CHP) described in Green *et al*. (2003) was used. Stomatal conductance g_s were also estimated from measured sap flow, tree canopy and local meteorological variables, as in Yunusa *et al*. (2008a) and Ramos and Santos (2009).

Soil moisture status required for the root zone soil water balance budgeting was continuously monitored throughout the irrigation season. The average apparent bulk soil density was 1.58 Mg m^{-3}. Volumetric soil water content at field capacity was 0.36 m^3 m^{-3} in the top layer and 0.34 m^3 m^{-3} in the root zone, whereas it was 0.27 m^3 m^{-3} in the top layer and 0.24 m^3 m^{-3} in the root zone at standard wilting point.

MODIS data include radiometrically corrected, reflectance values at 250 m resolution for blue, red and near infrared (NIR) bands, the input for generation of EVI, one of the two VIs available products from the MODIS sensors. For this study MODIS (250 m) subsetted land products from 16 pixels of estimated 1 km^2 area centered on the orchard location site were obtained for as atmospherically corrected reflectance values through the Oak Ridge National Laboratory Distributed Active Archive Center (ORNL DAAC, 2009). The olive grove location was supplied by its geographic coordinates and visually confirmed by reference to geo-referenced images registered to the MODIS site. Micrometeorological data, solar and net radiation (kW m^{-2}), maximum and minimum air temperature (ºC), partial pressure of water vapor in the air (kPa), wind speed (m s^{-1}) and precipitation (mm), were collected by an automatic meteorological station placed within a few hundred meters from the olive grove. The 16-day mean values of olive orchard transpiration T were calculated from daily sap flow values for Day 81 to Day 289. Similarly, 16-day mean values of micrometeorological variables were prepared for the referred period. For the 16-day data sets and looking for significant association between crop transpiration T and combined VIs, correlation analysis were conducted, with the closeness of the relationships reported as correlation coefficients (r). To model the T response to VIs, EVI and NDVI were converted to scaled values (EVI^* and $NDVI^*$), as recommended by Nagler et *al*., (2005b), and the following model was used:

$$T = a\,(1 + e^{-bVI^*}) \tag{1}$$

Similarly, search was conducted on the meteorological variable described above that most closely correlate with field T. Maximum daily temperature t_a was the variable most significantly associated with T. Again, to model the T response to temperature we normalized T data so to have minimum T as zero and the maximum as 1.0, and fitted a dose response sigmoid curve to the T vs. t_a for combined data sets. The sigmoid curve allows the encompassing of a minimum temperature due to the physiological status of the crop below which T approaches zero; a middle, exponential portion of the curve which fits the vapor pressure deficit as a function of t_a and an upper limit, above which physiological limitations to T also apply. Hence, air temperature accounts for both atmospheric water demand and the physiological limitations on T, at the low and high ends of the temperature scale.

With T dependent on VI and the T vs. temperature established through the sigmoid relationship, the final transpiration predictive regression model was obtained by assuming that for well irrigated olives trees transpiration rates is dependent on canopy conductance via the proxy light intercepted by the canopy (Nagler et al., 2005 a,b) times a scaling factor to account for the effect of t_a. Hence, the two equations were multiplied together and subjected to linear regression to produce the predictive equation:

$$T = a\,(1 + e^{-bVI^*})\,(c\,/\,(1 + e^{-(t_a - d)/e}) + f \tag{2}$$

where the coefficients a, b, c, d, e, and f are constants generated by the regression analysis to produce a curve of best fit between T and the independent variables. All correlation and regression analysis were calculated with the NLREG Nonlinear Regression Analysis Program (Sherrod, 2008).

Results and Discussion

As expected, T was strongly correlated with t_a (r = 0.79) and VPD (r = 0.78), confirming the strong environmental linkage between both. In fact, a high and significant correlation between t_a and VPD was observed (r = 0.99). However, r values for T on the other meteorological data were low to moderate. Concerning VIs, T significantly correlated with both EVI (r = -0.79) and NDVI (r = -0.77). VPD and t_a also significantly correlated with EVI and NDVI, showing that T could be dependent on g_s via VIs times the scaling factor accounting for their effect (t_a and VPD). When cross associated with the scaling factor t_a or VPD, T was not significantly related to either EVI or NDVI but strong and significantly related with EVI^* and $NDVI^*$. Such results provided statistical reason for conducting the multivariate analysis of T dependency on scaled VIs. Using the multivariate regression model in the form in Eq. (2), a predictive equation for T on EVI^*-t_a was developed. Based on the analysis of factors correlated with T, EVI values were scaled to EVI^* and an exponential equation in the form in Eq. (1) was fit to T vs. EVI^*. Also, the effect of temperature on T was established through a sigmoid curve (r^2 = 0.70). Then as in Eq. (2) the two equations were multiplied together and subjected to linear regression to produce a single predictive equation for T, one that combined EVI^* and t_a with r^2 of 0.79 and root mean squared error of 0.331 mm d^{-1}:

$$T = 1.35(1 + e^{-2.76EVI^*})(0.761/(1 + e^{-(t_a - 22.5)/0.55}) + 1.55 \quad (3)$$

Based on the previous analysis of factors correlated with T, the following single predictive equation for T, one that combined $NDVI^*$ and t_a was also established with a final r^2 of 0.73 and root mean squared error of 0.325 mm d^{-1}. Such values were very similar to obtained for T vs. EVI*-t_a, suggesting that T could confidently be predicted with either relationship.

$$T = 1.22(1 + e^{-1.77NDVI^*})(0.761/(1 + e^{-(t_a - 22.5)/0.55}) + 1.62 \quad (4)$$

Fig. 1 shows the strong match between measured and predicted T based on EVI^*-T_a throughout the experiment irrigated period of 2006 at the Herdade dos Lameirões.
(r^2 = 0.79 and RMSE = 0.33 mm d^{-1}).

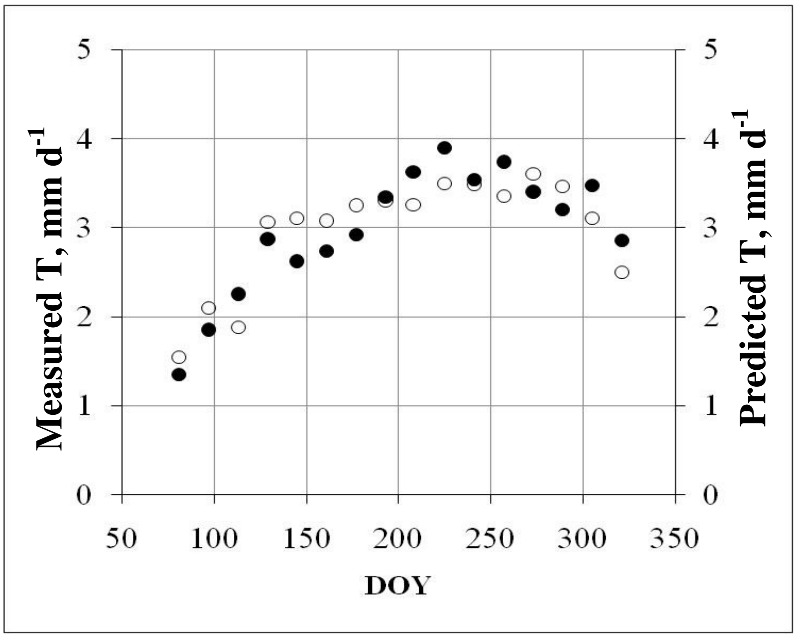

Figure 1 - Seasonal evolution of measured T, (●) compared with predicted T, (○) based on EVI* and t_a (°C) in the period of experiment for the year 2006 at Herdade dos Lameirões.

With one distinct group of data for calibration of the model (2006) and other for validation (2007), generalization of results looks possible. Fig. 2 presents the observed and derived scaled transpiration (T*) for both years.

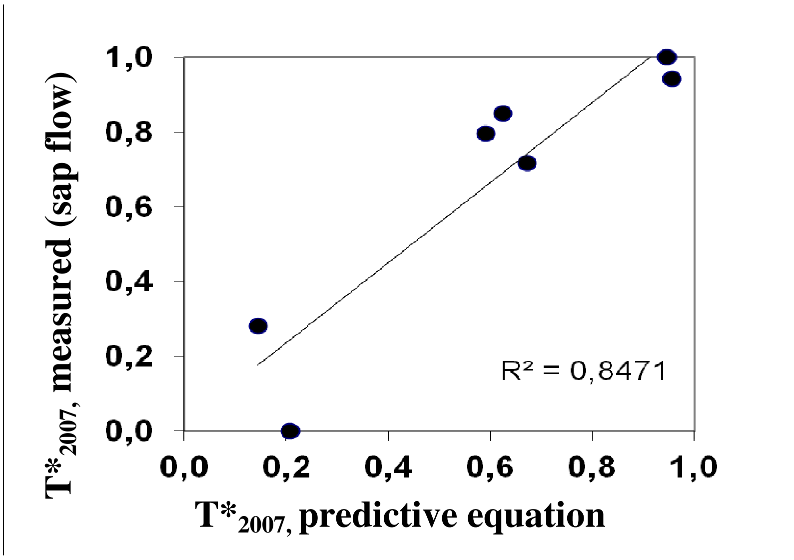

Figure 2 – Measured vs. predicted transpiration T (scaled) for 2007 based on the predictive equation 4. Measured T was obtained from sap flow measurements.

Fig 3 shows the average seasonal evolution curves for predicted Kc (T/ET0) based on T obtained from EVI* and t_a and calculated Kc based on transpiration ground measured rates in the period of experiment at Herdade dos Lameirões. Very similar average crop coefficient values are reported in Ramos and Santos (2009) for southern Portugal and in Fernández (2006) for the well-watered “Manzanilla de Sevilla” trees near Sevilla, southern Spain.

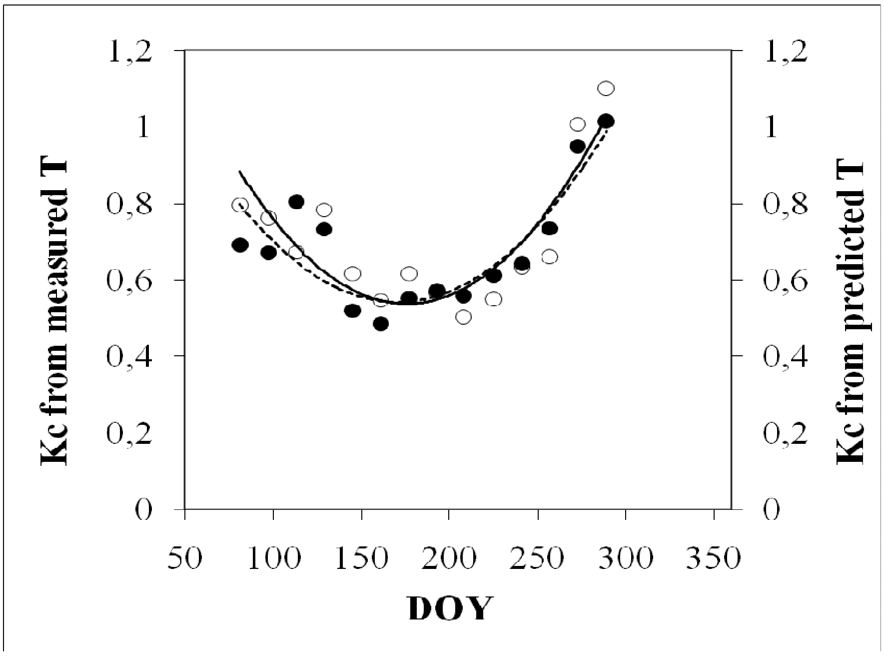

Figure 3 - Seasonal evolution curves for predicted Kc (○) (T/ET0) based on T obtained from EVI* and t_a and calculated Kc based on ground-measured transpiration rates (●) in the period of experiment for the year 2006 at Herdade dos Lameirões.

Conclusion

Readily available MODIS VIs data combined with ground measurements of t_a and T proved to be a non-intrusive method of predicting olive transpiration T, valid for a well irrigated olive grove grown in Alentejo, southern Portugal. With a potential error of about 11% of mean T during the irrigation period, the predictive equations could be made operational and used routinely to monitor T over wide areas and long time spans. Similarly, the Kc predictive equations can be made operational and used to guide irrigation scheduling over large areas and years. Testing the procedure with other olive ground-based T data set across sites and years is advisable before drawing final conclusion.

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