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Downscaling transpiration rate from field to tree scale

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ABSTRACT

Estimation of field spatial variability of tree actual evapotranspiration (ET_a) in orchards is key when quantifying water and associated nutrient leaching at the field scale. Though ET_a is often measured at the field scale, spatial variations between individual trees are likely due to local differences in soil water availability and canopy cover. It is therefore that we propose seeking a statistical relation between field ET_a, tree midday stem water potential (MSWP), soil water storage (WS), and tree potential evapotranspiration (ET_c) with relative tree canopy cover (C_{rel}). Four years of soil and almond trees water status data were used to optimize an artificial neural network (ANN), to predict field scale ET_a first, followed by downscaling to the individual tree scale. ANN's using two hidden neurons (11 parameters) proved to be the most accurate (RMSE = 0.0246 mm/h, R^2 = 0.944), seemingly because adding more neurons generated overfitting of noise in the training dataset. C_{rel} was the main source of variability of ET_a, while MSWP was the controlling factor for the tree-scale relative ET. At a given soil WS, almond trees of the drip-irrigated block were less affected by root zone water stress than the fanjet micro-sprinklers block, likely because of soil textural differences between the two main experimental blocks. In wet conditions, the predicted tree ET_a followed a normal distribution (with relative standard deviation of about 5%), which was close to the C_{rel} distribution. However, standard deviation values increased (7.6% for the whole orchard) during periods of water stress.

1. Introduction

Both the occurrence and magnitude of droughts is projected to increase in many regions of the world (Parry et al., 2007; IPCC, 2012), thereby affecting irrigation water availability for the very regions that depend largely on irrigated agriculture (Fischer et al., 2000). Therefore, research improving irrigation efficiency has become key (Stanhill, 1986), for example by fine-tuning of irrigation water application (Kandelous et al., 2012; Couto et al., 2013) and irrigation control systems (Shackel, 2011; Dabach et al., 2013, 2015; Shi et al., 2015) based on crop water needs. Central to the effectiveness of improved irrigation management systems is the control of leaching rates. However, the latter has proven difficult to quantify due to difficulties in monitoring leaching confounded by large field-scale variations due to irrigation water applications and soil heterogeneities. Leaching is typically computed from the field water balance method (Tanji and Kielen, 2002) or by inverse modeling (Eching et al., 1994; Hopmans and Schoups, 2005). However, both methods rely on accurate estimations of the crop's actual evapotranspiration rate (ET_a), which typically varies widely across a farmer's field.

For orchards, a common method to estimate tree scale transpiration rate involve sap flow measurements using heat pulse probes. Such sap flow measurements provide a qualitative proxy of tree transpiration rate and will need to be corrected (Shackel et al., 1992), to account for (i) contributing wood cross-sectional area and (ii) sap flux density heterogeneity (Sperling et al., 2012; Guyot et al., 2015). Other methods use prediction of ET_a spatial variability from related state variables, such as canopy temperature by remote sensing (Nagler et al., 2003), tree stem water potential (Duursma et al., 2008), changes in soil water storage (Sinclair et al., 2005), or from incoming solar radiation and vapor pressure deficit (Gharun et al., 2015). If both ET_a and related variables are available, statistical models such as artificial neural networks (ANN's) can be applied to determine quantitative functions that relate ET_a to a variable number of input variables. ANN's (Gurney, 1997) are being used in

Abbreviations: WS, water storage; MSWP, midday stem water potential; ET_c, potential evapotranspiration rate; C_{rel}, tree relative canopy cover; ET_a, actual evapotranspiration rate; ET_{rel}, relative evapotranspiration; RMSE, root mean square error; SD, standard deviation; DOY, day of year.

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many contexts, ranging from the prediction of soil hydraulic properties using textural information (Tamari et al., 1996; Minasny et al., 2004) to the recognition of handwritten characters (Pal and Singh, 2010).

In this study, we propose to use ANN's in a novel context toward characterization of a field-average relation between potential evapotranspiration rate (ET_c), soil water storage (WS), midday stem water potential (MSWP) and actual evapotranspiration rate (ET_a) in an almond orchard. Subsequently, this relationship is downscaled to the individual tree scale level allowing estimation of spatially-distributed tree-scale ET_a. Finally, the quantitative information is used to analyze local variations in ET_a related to soil and tree water status variability across the orchard.

2. Materials and methods

2.1. Field measurements

Forty trees were monitored in an almond orchard (*Prunus dulcis*) near Lost Hills in Kern County, California, U.S.A. (N35°51′, W119°67′), over a period of 4 years (2009–2012). The almond trees were planted in 1999 on a Milham sandy loam, 6.4 m apart in the direction of the rows, and distant of 7.3 m in the perpendicular direction. The 44 ha orchard (550 m by 800 m) was divided into two blocks respectively watered with drip and fanjet micro-irrigation systems. Each of the two irrigation treatments included 20 monitored trees. The top one meter of soil profile in both blocks was coarse, from sandy clay loam in the fanjet block to sandy loam in the drip block, allowing quick infiltration of irrigation water. Some spatial variations in soil layering and textural properties were reported, though two 20 cm thick fine-textured soil layers were repeatedly observed throughout the blocks, at approximate depths of respectively 130 and 200 cm in the fanjet block, and 130 and 180 cm in the drip block (see Kandelous et al. (2014) and Muhammad et al. (2015) for more details). In order to estimate the root-zone soil water retention curves with the program NeuroMultiStep (Minasny et al., 2004), soil texture and bulk density were measured from undisturbed soil samples collected at 30 cm intervals down to 150 cm for each tree.

Water status was generally measured a day before each irrigation event. Tree water status was measured on lower canopy bagged leaves using a pressure chamber (Pressure Chamber Instrument Model 600) equipped with a portable tank, assuming the measured leaves to be at hydrostatic equilibrium with the tree stem water potential, measured in units of MPa. Though destructive, the pressure bomb method is considered to be an excellent reference measurement for tree water status (Shackel, 2011). For the 4-year period, MSWP was measured for all 40 trees for a total of 75 times, during the growing season starting at the end of March (full leaf set) to early September (harvest). Results are displayed in Fig. 1b, along with the soil WS data.

Soil water content was measured with a neutron probe (Campbell Pacific Nuclear Hydroprobe 503 DR) at 30 cm intervals from 30 to 150 cm depth near the trunk of each of the 40 trees. The neutron probe is considered to be a preferred method for estimation of field-representative soil water storage as it provides an integrative measure of soil water content with a measurement volume corresponding to a radius of about 30 cm. Hence, water content measurements are not as much affected by local soil heterogeneities as TDR's or Echo sensors (Evett et al., 2006). For the 4-year monitoring period, 3000 soil water storage profile evaluations (over 1.5 m soil depth) were carried out (40 locations and 75 measurement times). Soil water storage (cm) data are presented in Fig. 1b, for each of the 4 years, using the day of year (DOY) as the time scale.

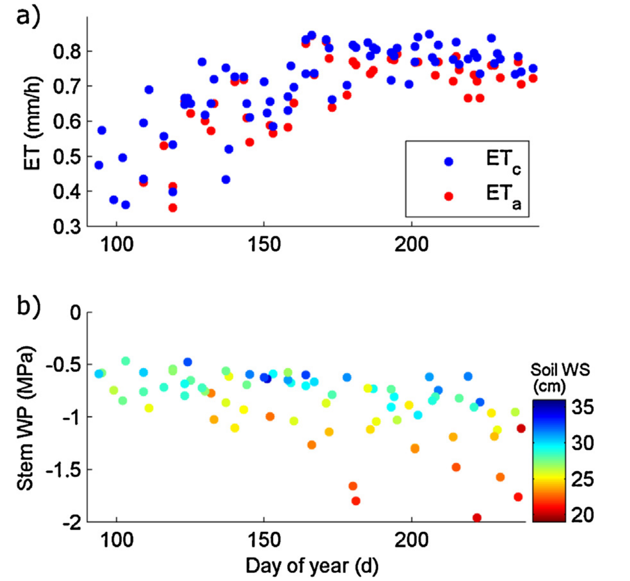

Fig. 1. Field data of (a) weather station ET_c and eddy covariance ET_a, and (b) midday stem water potential (WP) and soil water storage (WS) averaged from 40 tree measurements. The color scale in (a) corresponds to the soil water storage integrated over the root zone (0–1.5 m depth). Data from years 2009 to 2012 are displayed by day of year in this figure.

Field hourly ET_a (mm/h) was measured with a 9 m high triangle type eddy covariance tower located at the center of the orchard (several hundred meters away from the limits of the orchard in all directions). It was equipped at the top with a net radiometer, sonic anemometer, and thermocouples oriented to have no obstructions in the primary upwind direction. For additional details on relevant assumptions and data processing, we refer to Shapland et al. (2013). Midday values were selected in order to correspond to the measurement time of other data. Hourly reference evapotranspiration (ET_0) was obtained from a weather station located approximately 2 km away (Belridge, CIMIS # 146), with tree ET_c (mm/h) computed from multiplication with the almond crop coefficient (K_c). To obtain the K_c values, we assumed that the ET_a/ET_0 ratio corresponds to the ET_c/ET_0 ratio (i.e. K_c) at times the orchard was not water limited (MSWP > −1 MPa). These K_c values displayed a linearly increasing trend over the months covered by the dataset (1.0–1.2 from April to September), which was used to interpolate other K_c values. Nevertheless, ET_a was larger than ET_c for a few days possibly due to the spatial variability of ET_0 or measurement error. In order not to train the ANN to predict ET_a higher than ET_c, we set ET_c equal to ET_a for those few data points, hence at these times the trees are not water stressed.

All data of ET, MSWP and soil WS are presented in Fig. 1, for each of the 4 years, using DOY as the time scale. All presented values are field-average values, simply by computing arithmetic averages from the local scale measurements of the 40 almond trees.

Canopy photo-synthetically active radiation (PAR) interception percentage, or simply referred to as canopy cover was evaluated within one hour of solar noon, once a year during each summer, using a mobile platform lightbar (Lampinen et al., 2012). Unlike yield (Zarate-Valdez et al., 2015; Sanden et al., 2014), canopy cover data can be used to estimate the proportional contribution of individual trees to the field-average ET_c (Goodwin et al., 2005). This information was used when applying local scale ANN to estimate ET_c at the tree scale (see Section 2.3). As trees with higher canopy cover percentage contribute proportionally more to the field-scale ET_c, the latter has to be multiplied by the tree relative canopy cover (C_{rel}, Eq. (1)) to obtain tree ET_c. Thus, in doing so, we assume that tree ET_c is directly proportional to canopy light interception. We