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Dynamic modelling of the baseline temperatures for computation of the crop water stress index (CWSI) of a greenhouse cultivated lettuce crop



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ABSTRACT

The crop water stress index (CWSI) has been shown to be a tool that could be used for non-contact and real-time monitoring of plant water status, which is a key requirement for the precision irrigation management of crops. However, its adoption for irrigation scheduling is limited because of the need to know the baseline temperatures which are required for its calculation. In this study, the canopy temperature of greenhouse cultivated lettuce plants which were maintained as either well-watered or non-transpiring was continuously monitored along with prevailing environmental conditions during a five week period. This data was applied in developing a dynamic model that can be used for predicting the baseline temperatures. Input variables for the dynamic model included air temperature, shortwave irradiance, and air vapour pressure deficit measured at a 10 s interval. During a follow up study, the dynamic model successfully predicted the baseline temperatures producing mean absolute errors (MAE) that varied between 0.17 °C and 0.29 °C, and root mean squared errors (RMSE) that varied between 0.21 °C and 0.35 °C when comparing model predictions with measured values. The model predicted baseline temperatures were applied in calculating an empirical CWSI for lettuce plants receiving one of two irrigation treatments. The empirical CWSI consistently differentiated between the irrigation treatments and was significantly correlated with the theoretical CWSI with correlation coefficient (r) values greater than 0.9. The dynamic model presented in this study requires easily measured input parameters for the prediction of the baseline temperatures. This eliminates the need to maintain artificial reference surfaces required in other empirical approaches for the CWSI calculation and also eliminates the need for computing the complex theoretical CWSI.

1. Introduction

Optimization of crop quality during protected crop cultivation requires finely tuned water management; here, protected crop cultivation refers to crops grown under fixed structures such as greenhouses and polytunnels. The improvement of crop quality is a major aim of protected crop cultivation in humid countries such as the UK (Monaghan et al., 2013). Imposing a certain degree of water stress in determined phenological periods has been found to improve crop quality in a number of crops including lettuce (Monaghan et al., 2017; Oh et al., 2010), strawberries (Weber et al., 2016), tomatoes (Kuscu et al., 2014; Shao et al., 2008). Monitoring tools that provide accurate information regarding plant water status would, therefore, be beneficial for scheduling and management of irrigation in protected crop cultivation (Adeyemi et al., 2017).

Plant canopy temperature (T_c) has long been considered as an

indicator of plant water status (Tanner, 1963) based on the cooling effect of the transpiration process (Jones and Schofield, 2008). Therefore, as a remote monitoring solution, infra-red thermometry offers the potential of acquiring the surface temperature of plant canopies from which plant water status can be inferred (Jones and Leinonen, 2003). T_c is determined not only by the plant water status but also by prevailing environmental conditions including incoming shortwave irradiance, wind speed, air temperature and humidity (Jones et al., 1997).

To use T_c as an indicator of plant water status, it must be normalized to account for the varying environmental conditions (Agam et al., 2013b). One of the most commonly used methods for normalizing T_c as an indicator of plant water status is the crop water stress index (CWSI) originally proposed by Jackson et al. (1981); Idso et al. (1981) in which the measured crop canopy temperature (T_c) is normalized using two baseline temperatures, both assumed to be achieved under the same environmental conditions as T_c ; namely (a) the canopy temperature of a

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well-watered crop (T_{nws}); referred to as the non-water-stressed baseline temperature, and (b) the temperature of a non-transpiring canopy (T_{dry}); referred to as the upper limit baseline temperature. Ideally, the CWSI ranges from 0 to 1, where 0 represents a well-watered condition and 1 represents a non-transpiring, water-stressed condition, hence providing intuitive crop water status quantification as a simple tool for irrigation scheduling (King and Shellie, 2016).

Two forms of the CWSI are currently available. The first is the empirical CWSI, originally introduced by Idso et al. (1981). In their empirical approach to quantifying the CWSI, T_{nws} and T_{dry} were determined by developing a linear relationship for the canopy-air temperature difference and the vapour pressure deficit (VPD). It has however been shown that T_{mws} is crop growth stage dependent and also dependent on the agro climatic zone in which the crop is being grown (Jones, 1999). The stable weather conditions required for the application of the original approach to quantifying the CWSI is also seldom encountered in humid regions where weather conditions are highly variable in the short term (Maes and Steppe, 2012). Artificial wet and dry reference surfaces have been successfully applied to estimate T_{nws} and T_{dry} under the same environmental conditions as T_c for the calculation of an empirical CWSI (Grant et al., 2007; Möller et al., 2007). These include the use of wet and dry filter papers, leaves sprayed with water and those covered with petroleum jelly, and plots maintained as well watered and water stressed. However, the required maintenance of these artificial surfaces limit their potential use for automation in a precision irrigation system including periods during which high frequency data acquisition is required (Maes and Steppe, 2012).

The use of theoretical equations of CWSI based on the energy balance model of Jackson et al. (1981) involves the combination of T_c and meteorological measurements to compute the CWSI. This approach eliminates the need to acquire separate measurements of T_{nws} and T_{dry} . It is however limited by the need to estimate net radiation and aerodynamic resistance, and also requires large model input parameters (Agam et al., 2013b). The energy balance model proposed by Jones (1999) requires less model input parameters and the baseline temperatures computed using the model have been demonstrated to show excellent agreement with the measured temperatures of artificial reference leaf surfaces under minimal wind conditions (Fuentes et al., 2012). It has further been demonstrated as producing a robust quantification of the CWSI and eliminates the need for artificial reference surfaces (Ben-Gal et al., 2009). However, the model requires ancillary measurement to reliably estimate equation parameters including the boundary layer resistance to heat and water vapor which limits the potential of its application in commercial crop production.

Baseline temperature prediction models which have limited data requirements and straightforward calculation will, therefore, enhance the adoption of the CWSI as a practical irrigation monitoring tool. Maes and Steppe (2012) noted that this could be realized through improvements in the prediction of the baseline temperatures employed in the empirical CWSI approach. Including air temperature, solar radiation, wind speed and VPD as predictors in multiple linear regression models (MLR) has been found to improve the predictions of the baseline temperatures (Payero and Irmak, 2006). King and Shellie (2016) also reported improved predictions of the baseline temperatures using an artificial neural network (ANN), with air temperature, solar radiation, wind speed and VPD applied as input variables. The plant response will typically vary over the growth season due to crop growth and various adaptation processes (Boonen et al., 2000). Dhillon et al. (2014) showed that baseline temperature prediction models for tree crops varied as the season progressed. Hedley et al. (2014) noted that adaptive monitoring systems which are able to account for the temporal variability in plant response and water requirements would improve the performance of irrigation management tools. The ANN and MLR approaches however fail to consider the time-varying nature of the plant systems as their model parameters are assumed to remain constant once identified.

Dynamic models provide a possible approach for accounting for the time-varying nature of the plant system in the prediction of the baseline temperatures. Dynamic models have been successfully applied in simplifying and modelling complex environmental and biological processes (Taylor et al., 2007; Young, 2006), predicting time-varying biological responses (Kirchsteiger et al., 2011; Quanten et al., 2006), and in many other irrigation decision support applications (Delgoda et al., 2016; Lozoya et al., 2016). To the best of our knowledge, a dynamic model has not ever been used to predict T_{nws} or T_{dry} for calculation of a CWSI. A dynamic model is particularly well suited for predicting T_{nws} and T_{drv} because the time varying nature of the system under study can be taken into account through and adaptive and online estimation of the model parameters. This means the model parameters are updated recursively using all new incoming data from the system. Predicting plant canopy temperature may involve an understanding of the timing of the opening and closing of the stomates (Al-Faraj et al., 2000). A dynamic model is however able to implicitly account for the stomatal response by the inclusion of the time delay associated with each model input parameter.

The objectives of this paper are to exhibit the potential of using a dynamic model to predict T_{mvs} and T_{dry} (baseline temperatures) and demonstrate the applicability in calculating an empirical CWSI for a lettuce crop (*Lactuca sativa*) grown under greenhouse conditions. Performance of the dynamic model was evaluated by comparing the model predicted baseline temperatures with measured baseline temperatures. The calculated empirical CWSI values were also compared with theoretical CWSI values.

2. Theoretical background

2.1. Empirical CWSI

The empirical CWSI introduced by Idso et al. (1981) hereafter referred to as $\text{CWSI}_{\text{E}},$ is defined as

$$CWSI_{E} = \frac{T_{C} - T_{nws}}{T_{dry} - T_{nws}}$$
(1)

where T_C (°C) is the actual canopy surface temperature under given environmental conditions, T_{dry} (°C) is the upper limit for canopy temperature and equates to the temperature of a non-transpiring canopy such as would occur if the stomata were completely closed as a result of drought, while T_{raws} (°C) is the non-water stressed baseline representing the typical canopy of a well-watered crop transpiring at maximum rate.

Therefore, the temperature of a plant transpiring without soil water shortage can be assumed to represent T_{mus} and the temperature of a plant canopy from which all transpiration has been blocked, for example using petroleum jelly, can be assumed to represent T_{dry} . This is similar to the methodology employed by Rojo et al. (2016) to calculate an empirical CWSI for grape and almond trees. In their study, T_{mus} and T_{dry} were measured using a well-watered tree and a simulated dry canopy.

2.2. Theoretical CWSI

The theoretical CWSI proposed by Jackson et al. (1981) hereafter referred to as CWSI_T is calculated as

$$CWSI_{T} = \frac{(T_{c} - T_{a}) - (T_{c} - T_{a})_{LL}}{(T_{c} - T_{a})_{UL} - (T_{c} - T_{a})_{LL}}$$
(2)

where T_c-T_a is the canopy-air temperature difference, $(T_c-T_a)_{LL}$ is the lower baseline representing a non-stressed canopy, transpiring at potential rate and $(T_c-T_a)_{UL}$ is the upper baseline representing a stressed, non-transpiring canopy. The lower and upper baselines are given as

$$(T_c - T_a)_{UL} = \frac{r_a I_c}{\rho_a c_p} R_n \tag{3}$$

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