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Sensitivity analysis of reference evapotranspiration to sensor accuracy

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ABSTRACT

Meteorological sensor networks are often used across agricultural regions to calculate the ASCE Standardized Reference Evapotranspiration (ET) Equation, and inaccuracies in individual sensors can lead to inaccuracies in ET estimates. Multiyear datasets from the semi-arid Colorado Agricultural Meteorological (CoAgMet) and humid Florida Automated Weather Network (FAWN) networks were evaluated using a local sensitivity analysis (LSA) method which calculated the total error range of each individual sensor, as well as Morris and eFAST global sensitivity analysis (GSA) methods which simultaneously evaluated the full accuracy range of each sensor. Sensitivity of inputs (i.e., temperature, humidity, wind speed, and solar radiation) generally had values within the same range for the FAWN network with solar radiation being the most influential input in the summer, while sensitivity to wind speed for the CoAgMet network was much higher than the other inputs. Due to its simplicity and ease of application, LSA is suggested as a minimal screening method for evaluating input sensor sensitivity. GSA results were highly correlated with each other, but local sensitivity was poorly correlated to GSA methods regarding wind input in Colorado. Uncertainty analysis showed the current configuration of sensors in the CoAgMet network to have a higher range of ET values between 5% and 95% confidence intervals, as compared to the FAWN network. The eFAST GSA method was applied using a hypothetical set of "best case" sensors in both stations (i.e., sensors with the best accuracy between both sites), showing solar radiation to be the most influential input in the high ET months of summer, and the sensitivity in Colorado to wind to be vastly decreased, suggesting that the CoAgMet network could benefit from an upgrade to more accurate anemometers.

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1. Introduction

In irrigated agriculture, accurate and consistent estimates of crop evapotranspiration (ET_c) are vital in terms of water management. At the field scale, ET_c can be used for irrigation scheduling whereas at regional scales knowledge of evapotranspiration (ET) consumption can be used to evaluate irrigation water resources planning and distribution. However, because ET is very difficult to measure directly, it is often estimated using models based on climatic inputs, which individually can be highly variable. The most common method to estimate ET_c is to transform a reference evapotranspiration (grass-based ET_o or alfalfa-based ET_r) by multiplying with a crop coefficient (K_{co} or K_{cr}). The K_c is unique to each crop and reference type, and can vary with several parameters affecting ET such as leaf area, soil and climate conditions, and crop stresses (Doorenbos and Kassam, 1979). While many methods exist to calculate reference ET, physically based approaches such as FAO56 Penman–Monteith (Allen et al., 1998) require more input data but are generally accepted as the most accurate estimation. The American Society of Civil Engineers–Environmental and Water Resources Institute (ASCE–EWRI) created a standardized version of the Penman–Monteith method for reference ET calculation (ASCE, 2005), which has notable advantages with respect to commonality and transferability of K_c values (Irmak et al., 2006).

Field sensor accuracy is of paramount importance when determining reference ET using a physical model. Droogers and Allen (2002) evaluated reference ET estimates using both the Penman–Monteith (Allen et al., 1998) and Hargreaves (Hargreaves and Samani, 1985; Hargreaves et al., 1985) methods. They concluded that the more data intensive (e.g., air temperature, humidity, solar radiation, wind speed) Penman–Monteith method is recommended if accurate weather data collection is feasible and available. If data accuracy is questionable the simpler (e.g., air

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temperature and solar radiation only) Hargreaves method should be considered. While issues such as station siting, proper fetch, and maintaining adequate reference conditions are very important in creating consistent measurement conditions, bias or other measurement errors associated with the sensors themselves can cause tremendous error in the final outputs of the equations. Therefore, it is desirable to fully understand the potential influence of sensor-based measurement error on the final reference ET calculation.

Manufacturers of environmental measurement sensors (e.g., anemometers, pyranometers, temperature/humidity sensors) typically quote an "accuracy" of the device, often in terms of ± a percentage or static value. One way to evaluate and quantify the influence of quoted sensor accuracy on reference ET is through sensitivity analysis (SA), which Saltelli et al. (2004) defined as "the study of how uncertainty in the output of a model (numerical or otherwise) can be apportioned to different sources of uncertainty in the model input." The aim of SA is to determine how sensitive the output of a model is with respect to the elements of the model, which are subject to uncertainty or variability. SA methods are typically classified as local [one-parameter-at-a-time (OAT) and derivative-based] or global (multiple parameters at a time, derivative-based or more often variance-based) (Saltelli et al., 2008; Sobol and Kucherenko, 2009). When the purpose of the SA is to study the effects of several input parameters on the model output responses, local sensitivity analysis (LSA) is more simple but less useful than global sensitivity analysis (GSA) where the output variability is evaluated as the input parameters simultaneously vary in their individual uncertainty domains (Monod et al., 2006; Saltelli et al., 2004). GSA methods, such as Morris (1991), Fourier Amplitude Sensitivity Test (FAST, Saltelli et al., 1999), extended FAST (Saltelli et al., 1999) and Sobol' (1993) can determine not only sensitivity to individual parameters, but sensitivity to interactions between parameters as well. GSA methods are commonly used as auxiliary tools for many different types of simulation models, including hydrologic (Ahmadi et al., 2014), ecological (Ciric et al., 2012; Morris et al., 2014), and crop models (DeJonge et al., 2012; Vazquez-Cruz et al., 2014).

Several studies have investigated sensitivity analysis of ET estimation equations, typically using derivative-based LSA methods, with widely varying results due to differences in climate, ET models used, and meteorological and/or physical inputs evaluated (Ambas and Baltas, 2012; Bakhtiari and Liaghat, 2011; Beven, 1979; Coleman and DeCoursey, 1976; Eslamian et al., 2011; Gong et al., 2006; Hupet and Vanclooster, 2001; Irmak et al., 2006; Ley et al., 1994a; Liang et al., 2008; Rana and Katerji, 1998). A limited number of studies evaluated two parameters at a time but still used derivative-based methods for evaluating sensitivity (Eslamian et al., 2011; Porter et al., 2012). Monte-Carlo uncertainty analysis of potential ET has even been evaluated on a spatial basis (Phillips and Marks, 1996). However, no study to date has fully utilized variance-based GSA techniques to simultaneously evaluate multiple inputs of ET models. Also, previous studies in the literature somewhat arbitrarily choose an error range for the input parameters, instead of selecting an input error range based on manufacturer quoted sensor accuracy. In one study closely related to this manuscript, Ley et al. (1994b) evaluated the effects of sensor measurement variability in the Kimberly Penman alfalfa ET_r model, finding that at the limits of specified accuracy the greatest ET error was from solar radiation measurement error followed by dew point, maximum temperature, and finally wind speed measurement errors.

The above studies in the literature explore SA of micrometeorological input variables in ET models; however, they are site specific, do not use GSA methods, and rarely use sensor accuracy limits as a basis for comparison. Thus, the primary objective of this study was to evaluate the effect of manufacturer quoted accuracy of required sensors (i.e., temperature, humidity, wind speed, and solar radiation) on short reference evapotranspiration (ET_{os}) calculations using the ASCE Standardized Reference Evapotranspiration Equation. Multiyear datasets from semi-arid (Colorado) and humid (Florida) meteorological sensor networks were evaluated using a LSA method, as well as two GSA (Morris and eFAST) methods. Secondary study objectives were to compare sensitivity results of the three SA methods used in the study, conduct an uncertainty analysis of eFAST results to further quantify ET error range in high ET months, and to perform a final eFAST GSA on both sites using a "best case" (i.e., sensor set with the best accuracy between both sites) set of input sensors in order to directly compare difference in sensitivity between sites due to climate differences.

2. Methods

2.1. ASCE standardized reference ET equation

The ASCE Standardized Reference Evapotranspiration Equation (ASCE, 2005) is intended to simplify the full form ASCE Penman–Monteith method:

$$ET_{sz} = \frac{0.408\Delta(R_n - G) + \gamma\frac{C_n}{T+273}u_2(e_s - e_a)}{\Delta + \gamma(1 + C_d u_2)} \tag{1}$$

where ET_{sz} is the standardized reference crop ET rate for short (ET_{os}) or tall (ET_{rs}) surfaces (mm d^{-1}), R_n is the net radiation flux density at the surface (MJ m^{-2} d^{-1}), G denotes the sensible or soil heat flux density from the surface to the soil (MJ m^{-2} d^{-1}), γ represents the psychrometric constant (kPa °C^{-1}), T is mean air temperature (°C), u_2 is wind speed (m s^{-1}) at 2 m above the ground (relative humidity and dew point are also assumed to be measured at this height), e_s is mean saturated vapor pressure (kPa) computed as the mean vapor pressure as calculated at the daily minimum and maximum temperature, e_a is the actual vapor pressure of the air (kPa), and Δ is the slope of the saturation vapor pressure versus temperature curve (kPa °C^{-1}). Measurements are typically made at 2 m above the ground. C_n and C_d are constants that change with reference type and calculation time step: for hourly time steps C_n is 37 for short reference and 66 for tall reference, whereas C_d is 0.24 (day) or 0.96 (night) for short reference crops and 0.25 (day) and 1.7 (night) for tall reference crops (ASCE, 2005). The variable Δ is computed as:

$$\Delta = \frac{2503\exp\left(\frac{17.27T}{T+237.3}\right)}{(T+237.3)^2} \tag{2}$$

using T as mean air temperature (°C). Saturation vapor pressure e_s (kPa) is given by:

$$e_s = \frac{e^o(T_{\max}) + e^o(T_{\min})}{2} \tag{3}$$

where $T_{\max}$ is maximum daily temperature, $T_{\min}$ is minimum daily temperature, and $e_o(T)$ is a saturation vapor pressure function calculated as:

$$e^o(T) = 0.6108\exp\left(\frac{17.27T}{T+237.3}\right) \tag{4}$$

where vapor pressure is in units of kPa and temperature is in °C. Actual vapor pressure e_a is expressed by:

$$e_a = \frac{e^o(T_{\min})\frac{RH_{\max}}{100} + e^o(T_{\max})\frac{RH_{\min}}{100}}{2} \tag{5}$$

where $RH_{\max}$ and $RH_{\min}$ are maximum and minimum daily relative humidity, respectively. As shown in the above equations, variables Δ and e_s are calculated from temperature, and e_a can be determined by temperature and relative humidity. Thus, simplification of Eq. (1)