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Uncertainty analysis of an irrigation scheduling model for water management in crop production

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ABSTRACT

Irrigation scheduling tools are critical to allow producers to effectively manage water resources for crop production. To be useful, these tools need to be accurate, complete, and relatively reliable. The current work presents an uncertainty analysis and its results for the Mississippi Irrigation Scheduling Tool (MIST) model, showing the margin of error (uncertainty) of the resulting irrigation advice arising solely from the propagation of measurement uncertainty through the MIST calculations. The final relative uncertainty in the water balance value from MIST was shown to be around 9% of that value, which is in the normal range of the margin of error and acceptable for agronomic systems. The results of this research also indicate that accurate measurements of irrigation and rainfall are critical to minimizing errors when using MIST and similar scheduling tools. While developed with data from Mississippi, the results of this uncertainty analysis are relevant to similar tool development efforts across the southern and southeastern United States and other high-rainfall areas, especially for locations lacking high-quality co-located weather stations.

1. Introduction

Irrigation scheduling is a method of applying water for irrigation of crops based on calculated crop water needs. It improves water management while maximizing crop yields. Modeling and simulation of irrigation requirements to ensure effective water management has been employed in many regions, and a number of irrigation schedulers have been developed (Cancela et al., 2006; Dağdelen et al., 2006; Fortes et al., 2005; Grassini et al., 2011; Popova and Pereira, 2008). The Mississippi Irrigation Scheduling Tool (MIST) was designed for the needs of producers in the Mississippi River Valley Alluvial Flood Plain, a region colloquially known as the Delta (Sassenrath et al., 2013a). Continued and expanding reliance on ground water for irrigation by crop producers has begun to deplete the alluvial aquifer in the Delta, imperiling future availability of groundwater resources (Powers, 2007). To provide accurate irrigation scheduling for this area, MIST uses daily weather data to calculate the evapotranspiration using standard equations (Allen et al., 2006), and determines daily soil water balance using a checkbook method (Andales et al., 2011).

As with all models, there are differences between in-field reality and model results. Simplifying assumptions useful in models for one region and a specific crop are frequently not appropriate in other regions or for different crops. Therefore, it is necessary to adjust any model to regional climate and crops, and to examine the accuracy of model predictions. Several researchers have evaluated and measured uncertainty in other irrigation scheduling systems (Burt et al., 1997 and Molden et al., 1990), and Chaubey et al. (1999) examined the uncertainty due to regional rainfall. Allen et al. (2011) researched common uncertainty errors arising from measurements of evapotranspiration, and Snyder et al. (2015) proposed improvements on estimates of evapotranspiration to account for microclimates. Pereira et al. (2015) also investigated and updated formulations of crop coefficients and estimates of

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evapotranspiration to improve accuracy. Popova et al. (2006) validated their irrigation modeling system for crops and conditions in Bulgaria. Prats and Picó (2010) performed a similar type of uncertainty analysis of the irrigation scheduling model, using aMonte Carlo method where the uncertainties of the various parameters were considered. Monte Carlo type analysis is useful for analyzing the statistical inference between parameters, but it is computationally expensive due to the convergence test, which requires significant sampling from random distribution and calculation of the equation. Therefore, this method is difficult to use for decision making tools such as an irrigation scheduling tool from a practical standpoint. On the other hand, Taylor series method, the mathematical technique that we use in this manuscript, includes analytical derivations so that the solutions can be obtained through computationally inexpensive calculations.

In this study, we focused on determining the uncertainty of MIST predictions by calculating the propagated uncertainties of input data through the underlying model, one aspect of overall validation of the MIST model. All observational data have measurement and observational uncertainties, and complex sequences of calculations can in some cases result in very large uncertainties in the final number (prediction). Previous research examined potential inaccuracies in the weather database used in the water balance calculations and irrigation decision (Sassenrath et al., 2012), and the spatial variability of rainfall patterns (Sassenrath et al., 2013b). Uncertainty analysis quantifies the degree of error arising from uncertainties in input data (typically measurement uncertainties) during the model calculations. The standards for determination of uncertainty analysis are based in quality assessment methodologies and guidelines developed and revised over time by consortiums of researchers and engineers (e.g., BIPM, 2008; AIAA Standard, 1995). Coleman and Steele (2009) further refined the uncertainty methodology, delineating uncertainties into those that are caused by variability (random) and those that are not (systematic), and their approach is the basis of this analysis.

Herein we examine the uncertainty in all equations and other parameters used by MIST in the calculation of the water balance. We compare the calculated values with trends, and then evaluate the uncertainty associated with all the parameters in the water balance modeling. This gives us an indication of the sources of errors in the measured parameters used in the daily water balance calculations and the contributions of the error sources to the total uncertainty of the daily water balance. This information will be used in subsequent studies to validate the model against soil moisture measurements. The following sections describe the uncertainty analysis methodology (Section 2), the results and discussion (Section 3) deduced from the uncertainty analysis of the MIST web-based application, and conclusions (Section 4) of the current research.

2. Methodology

2.1. Crop growth and data collection

Three crops (corn, *Zea mays*, cotton, *Gossypium hirsutum*, and soybean, *Glycine max*) were grown with common production and irrigation practices, and critical data was recorded and quality assured for use in the uncertainty calculations. Crops were grown at the USDA-ARS Mechanization Farm near Stoneville, MS from 2005 to 2012 using standard agronomic practices for several different planting dates. Plant measurements included emergence date, growth stage, leaf area index and yield. Plant growth was assessed as plant height and plant growth stage based on published stages of development; leaf area index was measured with a LAI Plant Canopy Analyzer (LiCor, Lincoln, NE). Alternatively, canopy development was measured as percent of incoming sunlight intercepted by the crop canopy using a light bar (LiCor, Lincoln, NE). Yield from small plots was measured at harvest by weight, and on large plots or production farms by using yield monitors on commercial scale harvesting equipment. Soil nutrient and textural composition were analyzed at the Mississippi State University soil testing lab. Soil water content was measured near the rooting zone throughout the growing season using Watermark Soil Moisture Sensors (Irrometer, Inc., Irvine, CA) placed at 15 cm increments to a depth of 1 m. The Watermark sensors measure soil water tension as resistance changes in a solid state electrical resistance sensing device embedded in a granular matrix. Additional measurements were made in production fields in 2010, 2011 and 2012 in collaboration with cooperating producers.

Weather parameters were downloaded from the Mississippi Delta Weather Center network of weather stations as previously described (Sassenrath et al., 2012). Measured weather parameters were tested for accuracy and used to calculate daily reference evapotranspiration rates according to the modified Penman–Monteith method (Allen et al., 2006) in an Excel spreadsheet (Microsoft, Inc.). Crop coefficients were developed from measured crop growth parameters (plant height, leaf area, and percent light interception) as described in Sassenrath et al. (2013a) and Allen et al. (2006). The MIST daily soil water balance was determined for each research and production field using a water balance method (Allen et al., 2006; Andales et al., 2011). All measured, calculated, and constant input parameters for the soil water balance calculations are given in Table 1.

2.2. Uncertainty methodology

Uncertainties in a measured variable can arise from a variety of sources such as an imperfect instrument calibration process, incorrect standards used for calibration, or influence on the measured variable due to variations in ambient temperature, pressure, humidity and vibrations. Uncertainties can also result from unsteadiness in an assumed “steady-state” process being measured, and undesirable interactions between the transducers and environment (Coleman and Steele, 2009). The uncertainties that arise due to variability or randomness of a measured quantity (such as water balance on a given day) are referred to as random standard uncertainty. Uncertainties that do not arise from random variability are called systematic standard uncertainty. The systematic uncertainty can include calibration (bias), data acquisition, data reduction, or conceptual errors.

The systematic standard uncertainty can be calculated either through Taylor’s Series Method (TSM) or Monte-Carlo Method (MCM). With TSM, the uncertainty U_x can be calculated through a root sum of random uncertainty s_x and systematic uncertainty as specified by Coleman and Steele (2009):

$$U_x = \tau\sqrt{s_x^2 + b_x^2} \quad (1)$$

where τ is the normalized deviation from the mean value for a standard Gaussian distribution.

$$P(\tau) = \frac{1}{\sqrt{2\pi}}\int_{-\tau}^{\tau} e^{-\tau^2/2} d\tau \quad (2)$$

For example, for $P(\tau) = 0.95$ or 95% of the confidence, τ is approximately 2 and for $P(\tau) \approx 0.68$ or 68% of the confidence, τ is approximately 1. Here, we use $\tau = 2$ for 95% confidence so that the true value of w_t, for any given day in the calculations, is expected to lie within the bounds of 95% of the time. Similar to Eq. (1),