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Real-Time Irrigation Scheduling Based on Weather Forecasts, Field Observations, and Human-Machine Interactions

A. Jamal[1], X. Cai[1], X. Qiao[2], L. Garcia[3], J. Wang[3], A. Amori[4], and H. Yang[4]

[1]Faculty of Civil and Environmental Engineering, University of Illinois at Urbana-Champaign, Urbana, IL, USA, [2]Panhandle Research & Extension Center, University of Nebraska-Lincoln, Lincoln, NE, USA, [3]Faculty of Chemical and Biochemical Engineering, University of Iowa, Iowa City, IA, USA, [4]Faculty of Agronomy and Horticulture, University of Nebraska-Lincoln, Lincoln, NE, USA

Key Points:

- Simulation-optimization, data assimilation, and human-computer interaction are integrated into a real-time irrigation scheduling tool
- Human-computer interaction facilitates practical application of the tool through farmer's engagement
- Using the tool leads to more accurate state estimations and higher profits in comparison to traditional techniques and practices

Correspondence to:

X. Cai,
xmcai@illinois.edu

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Abstract

Real-time irrigation schedules have been shown to outperform predetermined irrigation schedules that do not consider the present state and requirements. However, implementing real-time irrigation scheduling requires reliable present soil-crop-atmosphere dynamics and weather predictions; moreover, enabling farmers to adopt recommended water applications remains challenging as they rely on personal experience and knowledge. Farmers and computer-based tools are rarely connected in a closed-loop and farmers' feedback are usually not incorporated into a real-time modeling procedure. To resolve these critical issues, this paper addresses the feasibility of a real-time irrigation scheduling tool (RTIST) based on weather forecasts, field observations, and human-machine interactions. RTIST integrates a simulation & optimization model, a data assimilation (DA) technique, and a human-computer interaction method, and enables optimality, accuracy, and applicability of the tool. The principle of the RTIST is to engage farmers directly into computer modeling, and support irrigation scheduling decisions jointly based on model provided information and farmers' own justification. The optimization and simulation are validated by running the tool on two crop fields, showing the accuracy of present estimation and future prediction of soil moisture and leaf area index, taking advantage of field observation and DA. The applicability of RTIST is tested via virtual irrigation exercises with a group of farmers for a corn field in Eastern Nebraska. RTIST with farmers' direct engagement shows increased productivity in comparison to traditional practices. Especially, farmers' feedbacks show interest in using the tool in real-world irrigation scheduling and providing meaningful suggestions to improve the tool for real-world application.

1. Introduction

Agriculture is the largest water resources consumer, as irrigation constitutes 70% of the world's freshwater withdrawals; even though, more regions will face water scarcity due to environmental and economic limitations (Jeong et al., 2020; Michelon et al., 2020). Therefore, farmers need to make optimal decisions on irrigation scheduling, that is, determining the irrigation timing and amount for both water saving and crop yield increase. As more field-specific data are revealed along the crop growing season, real-time irrigation schedules have been shown to outperform predetermined irrigation schedules that do not consider the present water requirement and water availability for a crop (Jamal et al., 2018, 2019). However, a main challenge of implementing real-time irrigation scheduling is to represent the soil-crop-atmosphere dynamics at present and/or future predictions (Hejazi et al., 2014). Reliable employment of the dynamics via accurate simulation with consideration of uncertainty is crucial for real-time irrigation scheduling. Meanwhile, how to incorporate farmers' experience and knowledge in irrigation schedule development is also crucial for the acceptance and utilization of a model-recommended irrigation schedule. By resolving these critical issues, this paper addresses the feasibility of a real-time irrigation scheduling tool (RTIST) based on weather forecasts, field observations, and human-machine interactions. Relevant studies on the optimality, accuracy, and applicability of an irrigation schedule to real-world practices are reviewed as follows.

1.1. Optimality

Various studies employ real-time irrigation scheduling using rule-based approaches, in which the irrigation is determined according to the current field conditions and a set of predetermined rules. For instance, Hashemi and Decker (1969) derived irrigation scheduling rules that helped keep the soil moisture above 50%. Meanwhile, several studies showed that incorporating weather forecasts in irrigation scheduling could increase the

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profitability of irrigated agriculture (Allen & Lambert, 1971; Cai et al., 2011; D. Wang & Cai, 2009). The superiority of weather forecasts in irrigation scheduling lies in applying current decisions while exploiting the information from the upcoming weather (e.g., by waiting for a forthcoming rain event rather than applying the whole amount currently needed for irrigation). For example, D. Wang and Cai (2009) showed superior profits from using weather forecasts within rule-based irrigation scheduling in comparison to only using current soil moisture in corn fields in Illinois. The irrigation was applied when a set of condition on the soil moisture and the probability of rain on the forecast period is met. When the irrigation was applied, the soil moisture was bringed to the field capacity. In particular, weather forecasts are incorporated into irrigation scheduling via stochastic optimization techniques, which showed the advantage over rule-based techniques and conventional methods in terms of profit maximization (Bergez et al., 2002; Jamal et al., 2018; D. Wang & Cai, 2009).

1.2. Accuracy

Irrigation scheduling is mostly based on an agro-hydrological simulation model to evaluate the impacts of different irrigation application plans. The simulation approach includes models of soil water balance (Mateos et al., 2002), water dynamics (Shang et al., 2004), and crop simulation (Bergez et al., 2002). These models are able to describe in detail the crop growth, which enables the evaluation of user-defined irrigation schedules by comparing simulation results of evapotranspiration, crop yield, as well as water consumption. Recent studies employed coupled simulation-optimization models to address the irrigation scheduling problem (Allam et al., 2016; Jamal et al., 2019; Linker, 2021; Singh, 2012). Within this approach, the coupled models are used to determine the optimal irrigation scheduling under given objectives (e.g., maximizing profits) and constraints (e.g., limiting irrigation amounts). However, the limited accuracy of these simulation models presents a barrier to the use of the models for real-world irrigation scheduling practice.

With growing data availability at the crop field scale from various sources such as remote sensing and in-situ sensing, using field observations of the environment (e.g., soil moisture) and the crop status (e.g., leaf area index [LAI]) has been shown to improve the modeling accuracy of crop water requirement and availability, crop growth, and the soil-crop-atmosphere dynamics (Hu et al., 2019). In particular, data assimilation (DA) is an efficient approach to improving state estimation by combining information from field observations and simulation models in a real-time manner (Reichle, 2008). While remote sensing and satellite data can work successfully in DA of LAI (Charoenhirunyingyos et al., 2011; Ines et al., 2013), soil moisture remote sensing has some limitations in terms of temporal and spatial resolution (Jamal & Linker, 2020). In addition, remote sensing does not provide data on deep soil layers along the root zone, which is important for crop growth simulations. Furthermore, remote sensing cannot penetrate through dense vegetation (Ines et al., 2013). Therefore, direct pointwise sensor observations installed at several depths (e.g., Dong et al., 2015; Lü et al., 2011) are complementary to remote sensing data for crop and environment modeling at the field scale.

1.3. Applicability

Last but not least, despite numerous trials to improve its applicability, real-time irrigation scheduling studies are rarely applied in real life. One of the main reasons is that farmers do not like to be replaced but like to be involved (Rose et al., 2018). In addition, the experience of farmers implicitly includes many factors which are difficult to include in computer-based models, such as responses to policies (Bontemps & Couture, 2002) and various impacts of farmers' age, education, attitude, and knowledge toward the irrigation scheduling problem (Karami, 2006). Therefore, the involvement of farmers is necessary for not only improving computer-based tools in terms of reality but also for the final acceptance for use (Yohannes et al., 2019). However, farmers' suggestions as feedback to the computer-based tools are usually not incorporated into a real-time modeling procedure (Rose et al., 2016; Tapsuwan et al., 2015). In general, despite the existing efforts to reduce the gap between farmers and computers in irrigation scheduling (Pande & Savenije, 2016; van Emmerik et al., 2014), incorporating farmers' insights and experiences into computer models is still limited (Bierkens, 2015). Therefore, the direct incorporation of the farmers' insights and experiences into an irrigation scheduling decision support model can contribute to the realism of the model (O'Keeffe et al., 2018). At each decision point, the farmers' involvement with computer-based tools that provide estimations of current and predicted variables (e.g., crop yield) can profoundly contribute to the implementation of such tools in real life (Linker, 2021). As adopted by several works on agriculture (Rose et al., 2018), reservoir operation systems (Zhang et al., 2020), and others, in this work, a real-time irrigation scheduling model based on "online" human-computer interaction between the model and the user is presented.

This study integrates a simulation & optimization model, a DA technique, and a human-computer interaction method to generate a RTIST. This integration enables providing the daily optimal irrigation amounts based on weather forecasts. This framework will be based on crop and environment simulation models improved by assimilating field observations. The framework will involve farmers in day-by-day irrigation decision-making crossing the crop growth season to assure the applicability of the tool. The uniqueness of the framework is thus expressed in its optimality, accuracy, and applicability. The performance of the framework is examined by an interactive workshop with a group of farmers and in a real-world case study in corn fields in Eastern Nebraska, US.

2. Methodology

2.1. Overview

The proposed RTIST framework consists of four sub-models: (a) stochastic optimization, (b) soil-crop simulation, (c) DA, and (d) human-computer interaction. Daily irrigation amounts are inferred in real-time, based on probabilistic weather forecasts, current field conditions, and crop growth predicted by Soil Water Atmosphere Plant (SWAP) model (Kroes et al., 2017). However, the recommended irrigation amounts by the simulation-optimization model are not assumed to be used by default; instead, the actually applied irrigation amounts are decided day-by-day via a human-computed interactive method, which combines the computer optimality and farmers' experience, knowledge, and behavior. In this paper, farmers are directly interacting with the computer by accepting or modifying the recommended irrigation. The ultimately applied irrigation amount (after the interaction with the farmer and his final decision) is used as input for the simulation model enhanced by the DA module within a "closed-loop." This module aims to update the current states, the soil hydraulic parameters and LAI related crop parameters of the simulation model as detailed in the remainder.

The RTIST framework is illustrated in Figure 1. The computer model (simulation-optimization) runs by rolling daily time windows. In each of the time windows (t), it assimilates the observation of LAI and soil moisture at several depths, and adopts the actual irrigation application taken by farmers (which can be the same or different from the model's recommended optimal value at time window t) at the end of the time window, and then moves to next time window ($t + 1$) to generate a new recommended irrigation based on the updated soil moisture and crop growth status and the weather forecast with a certain length of forecast horizon (e.g., a 3-day period is tested in this study). Meanwhile, farmers check the recommended application from the model during each time window and decide to take it or use a different one based on their justification. This procedure is continued over all time windows till the end of the crop growing season. In this framework, observed data, irrigation farmers' choices, and computer models are coupled in the human-computer interactions (Figure 1), and the framework directly links framers with a real-time optimization-simulation model. This kind of "online" and "closed-loop" interaction between the model and users rolls over the time windows during the irrigation season.

The proposed method is characterized by several advantages. First, using stochastic optimization rather than deterministic optimization takes into account the uncertainty involved in the weather forecast. Second, including Soil-Water-Atmosphere-Plant (SWAP) model in the irrigation scheduling as a well-validated hydro-agronomic model provides a solid physical basis for the decision process; in particular, including DA adjusts the modeled states from time to time to ensure the reliability of the simulated state variables. Third, farmer intervention is crucial for the practical application of the tool. Some existing works include stochastic weather forecasts (e.g., Jamal et al., 2018; Linker, 2021); some include DA for irrigation scheduling modeling (e.g., Han et al., 2012; Ines et al., 2013); some include DA, deterministic optimization, and farmer intervention together with simple simulation models (X. Li et al., 2023). The uniqueness of the proposed method of this work lies in the inclusivity of all the mentioned advantages in one holistic framework, as shown in Figure 1.

2.2. Real-Time Simulation-Optimization Model

Weather forecasts play an important role in irrigation scheduling, especially the forecasts that extend to more than a few days (Cai et al., 2011; Jamal et al., 2018, 2019). However, since the forecasted weather might differ from actual weather, a probabilistic weather forecast can help handle this problem in the context of

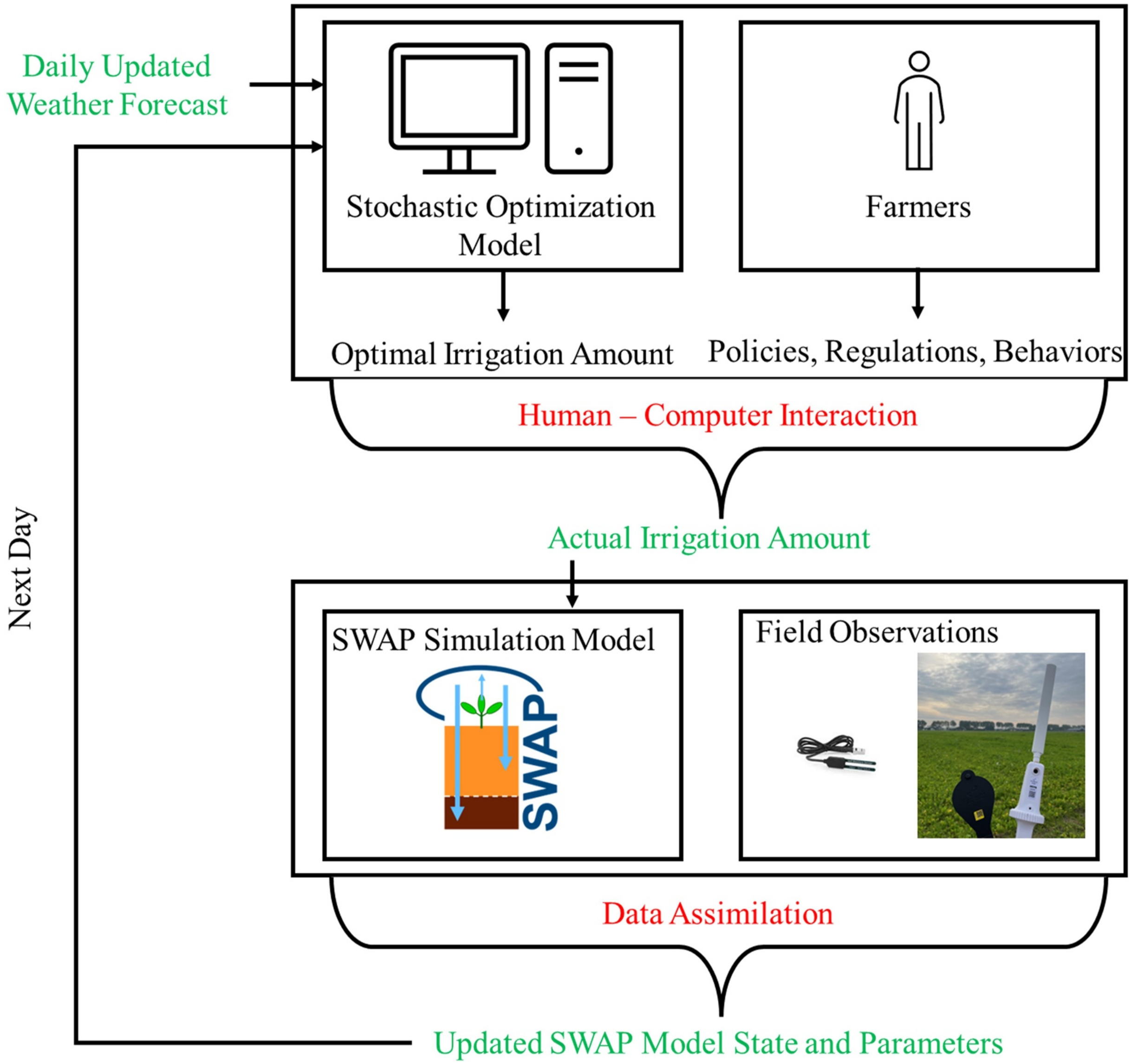

Figure 1. Overall framework of RTSIT composed of stochastic optimization, soil-crop simulation, data assimilation, and human-computer interaction.

stochastic optimization with multiple scenarios characterized by probabilities of occurrence. The scenarios can be obtained based on probabilistic forecasts (e.g., National Oceanic and Atmospheric Administration probabilistic forecasts; D. Wang & Cai, 2009; Cai et al., 2011). In this study, the probabilistic forecasts were generated by a mean of Weather Research Forecast (WRF; J. Wang et al., 2022) and a standard deviation that was heuristically calculated based on historical calculation of the error of WRF forecast. Gaussian distribution was used for sampling the scenarios of the variables except for the rain where Gamma distribution was used. More details are in Section 3.

Optimization methods and algorithms are used to infer the optimal irrigation amounts based on a predefined objective function and constraints (Cai & Rosegrant, 2004; J. Li et al., 2020; Wen et al., 2017). In this study, the SWAP model is used as a simulation model, which simulates physical processes at a field level related to soil heat flow, solute flow, soil water flow, crop growth, macropore flow, and interaction with groundwater and/or surface water system. Within the simulation-optimization framework, SWAP is coupled with an optimization algorithm in which several irrigation amounts are examined by employing simulations based on current field status and future forecasts (Cai et al., 2011; Jamal et al., 2018, 2019). A detailed description of the SWAP model can be

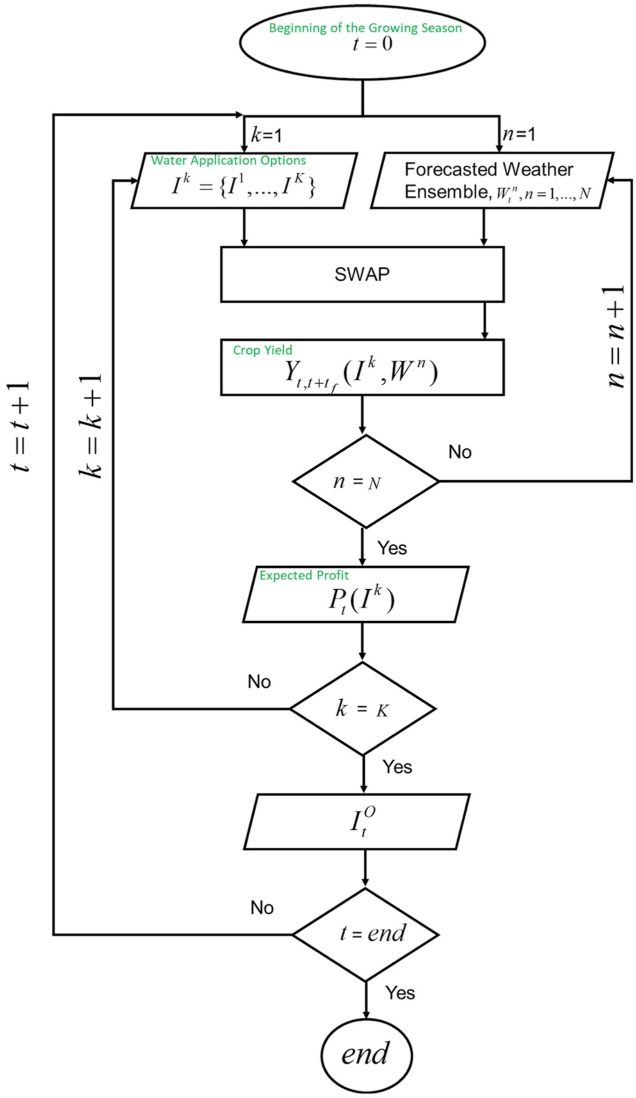

Figure 2. The simulation-optimization framework. The framework is composed of three loops with time (t, crossing the irrigation season), weather forecast scenarios (n), and water applications (k).

found in van Dam (2000). SWAP is run using several irrigation amounts on day t under each weather scenario and the expected profit is calculated using the model outputs, as follows:

$$P_t\left(I^k\right) = \sum_{n=1}^{N} \mathrm{Pr}_n \cdot \left(Y_{t,t+t_f}\left(I^k, W_t^n\right) \cdot Y_p - I^k \cdot \mathrm{PWR}_t\right) \tag{1}$$

$$Y_{t,t+t_f}\left(I^k, W_t^n\right) = \mathrm{SWAP}\left(s_t, p_t, I^k, W_t^n\right)$$

where $P_t(I^k)$ is the expected profit at time step t with irrigation amount I^k, Pr_n is the probability of occurrence of the nth weather ensemble member, t_f is the weather forecast length, $Y_{t,t+t_f}\left(I^k, W^n\right)$ is the expected yield when running the SWAP model from time t until $t + t_f$ using the nth weather ensemble member and I^k irrigation, s_t is the state variable at time t (e.g., soil moisture, LAI, and yield), p_t is the model parameters set at time t, W_t^n is the nth weather ensemble member at time step t, Y_p is the yield price, PWR_t is the water price, and N is the size of the weather forecast ensemble. The recommended irrigation amount results in the highest profits:

$$I_t^O = \underset{I^k}{\mathrm{argmax}}\left(P_t\left(I^k\right)\right) \tag{2}$$

where I_t^O is the optimal (recommended) irrigation amount at time t (day). t is basically run from the beginning of the growing season ($t = 0$) until the end of the growing season. Figure 2 describes the simulation-optimization framework.

2.3. Data Assimilation

Data assimilation techniques can help estimate the states and model parameters of a complex system using observations to adjust the modeled state variable value, as well as refining associated parameters. Particle Filter (PF) has shown several advantages over other widely used techniques such as ensemble Karman Filter in different studies on nonlinear dynamic systems. PF estimates states and parameters based on running an ensemble of models (or particles) in parallel, and each particle is associated with a weight that indicates for its probability to represent the posterior distribution (Douc & Cappé, 2005; Moradkhani et al., 2012).

Nonlinear dynamic systems in a discrete formation are described as follows:

$$\begin{aligned} x_t &= f(x_{t-1}, u_t, \theta_t) + \omega_t \\ y_t &= h(x_t) + \nu_t \end{aligned} \tag{3}$$

where $f(\cdot)$ denotes the model, $h(\cdot)$ denotes the operator of the observations, x_t denotes the state variable at time t, u_t is the forcing data at time t, θ_t is the vector of the model parameters at time t, and y_t is the vector of the observations at time t. ω_t and ν_t are the process and observations noises, which are usually assumed to be white noises with covariance Q_t and R_t, respectively.

When observations become available, the posterior of the states and parameters are calculated based on the Bayesian theorem as follows:

$$p(x_t, \theta_t / y_{1:t}) \propto p(y_t / x_t, \theta_t) \cdot p(x_t / \theta_t, y_{1:t-1}) \cdot p(\theta_t / y_{1:t-1}) \tag{4}$$

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An analytical solution for the posterior is only feasible for specific cases such as a linear process with Gaussian noise and therefore the need for posterior approximation. PFs estimate the posterior based on the ensemble of particles and their corresponding weights. The weights are calculated based on the Bayesian theorem as follows:

$$w_t^i = \frac{w_t^{i-} \cdot p\left(y_t / x_t^i, \theta_t^i\right)}{\sum w_t^{i-} \cdot p\left(y_t / x_t^i, \theta_t^i\right)} \tag{5}$$

where w_t^{i-} is the weight of the ith particle in the prior distribution, and $p\left(y_t / x_t^i, \theta_t^i\right)$ is the likelihood. The prior weights are equal to the posterior weights from the previous time step. When applying resampling the weights are set to be equal.

Well-known problem of PFs are filter degeneracy and sampling impoverishment, in which low weights of the particles and low sample diversity occur, respectively (Abbaszadeh et al., 2018; Moradkhani et al., 2012). Among the newest versions of PF that alleviate these problems is the version provided by Jamal and Linker (2020). This method consists of a PF combined with Markov Chain Monte Carlo (MCMC) and evolutionary operators of crossover and mutation with the PF. Integrating MCMC with PF helps eliminate the low weights particles and maintain particles that have higher weights and probabilities of survival. This operation can help solve the problem of filter degeneracy. However, this method only eliminates particles with low weights without generating new particles with high weights. Therefore, evolutionary operators are used to ensure the sampling of new particles based on the high weights particles. As shown in Jamal and Linker (2020), this integration can alleviate the impoverishment problem.

In this study, DA is applied on daily basis to improve the estimations of the current states and the model parameters, which leads to improved future predictions. At each time step (daily), soil moisture at several depths and crop LAI (from sensors) are used to update the field-level state and the model parameters. The updated state and parameters are related to the soil and crop that are highly correlated to the observations. The soil parameters are the van Genuchten–Mualem model parameters, and the crop parameters are the maximum relative increase in LAI, lower threshold temperature for the aging of leaves, light use efficiency for real leaf, and efficiency of conversion into leaves. More details are in Section 3. Note that LAI and soil moisture play an important role in the crop yield estimation by controlling several processes such as plant canopy interception and evapotranspiration, and by linking soil, atmosphere, and plant together (Bai and He, 2015; Charoenhirunyingyos et al., 2011; De Wit & Van Diepen, 2007).

DA will not only connect field observation and modeling but also close the loop between the simulation-optimization model and farmers' decisions by assimilating new field observations of soil moisture and LAI that are updated with farmers' actual irrigation application at the present day to the model for updating the water and crop simulation, as detailed in the following.

2.4. Human-Computer Interaction: Graphical User Interface and Experiments

The essential difference between the method presented in this work and the direct use of optimization lies in the "online" incorporation of farmers' choices, which brings in farmers' experiences, knowledge, and behaviors on irrigation. Farmers' irrigation decision and their willingness to follow the model-suggested solution vary by person, crop, and area. To address this issue, some studies used machine learning methods and historical records to train a "mental model" that attempts to mimic irrigation scheduling decisions (Sun et al., 2017; Yang et al., 2020); however, limited understanding and representation of farmers' behaviors hinder the effective use of such a computer-based mental model. The construction of a computer-based human mental model to mimic irrigation farmers' behaviors is not the purpose of this paper. Instead, RTIST provides a framework for farmers to interact with a computer model *directly*. RTIST allows farmers to decide if they want to adopt the model-recommended water application or use their choice based on their experiences and priorities with consideration of the model recommendation. Framers' choices can involve multiple factors, including crop types, personal experiences, and responses to policies and regulations. The human-machine interaction is designed for a specific irrigated crop in a particular area, with consideration of farmers' experiences on the land.

A Graphical User Interface (GUI) is designed to facilitate the human-machine interaction, as shown in Figure 3. At the beginning, farmers are asked to provide some inputs such as if they conduct irrigation with fertilization

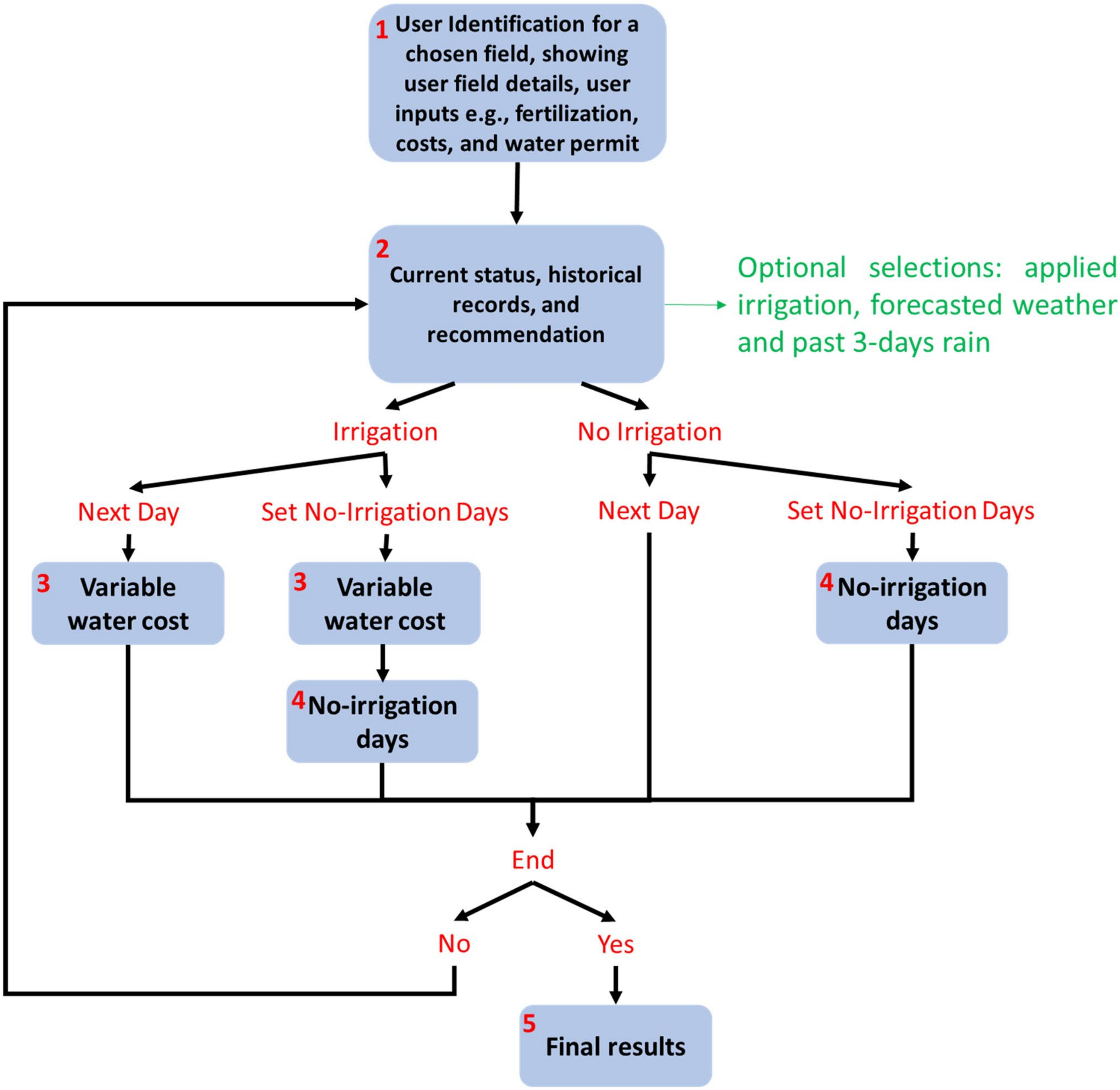

Figure 3. The flowchart of the Graphical User Interface designed for the human-machine interaction. The window number at each stage is shown in bold red.

at the beginning of the season, what are the variable and constant water application costs, and how much is the seasonal irrigation amount limit if existing. Following that, at the interaction for a particular day, farmers are provided with several pieces of information based on observation, forecast and model simulation, including the status of the field, irrigation application up to the day, rain in the past several days, and weather forecast in the next several days. Following reviewing these information pieces, farmers are given the model-recommended irrigation amount for the day; they decide whether to accept the recommendation or do something different by choosing different amount of irrigation application (including no irrigation on that day). Whenever irrigation is applied, farmers provide other inputs such as current variable water cost, which will enable more realistic cost assessment of an irrigation application. At the end of an interaction, farmers can choose to have a no-irrigation period (a number of days following the current day), in which the tool assumes no-irrigation and no farmers' intervention. The computer model keeps simulating the water and crop states based on observation and forecast during the period and interacting with farmers in some days chosen by farmers. For any day with farmer-computer interaction, farmers will be asked to choose the "no-irrigation period" after the current day, and the interaction will come back at the end of the no-irrigation period. Such interactions continue to the end of the irrigation season. The final window shows farmers the total amount of water application, crop yield, and profit.

Thus, the human-computer interaction enables farmers to learn and make their choices based on the information and recommendation provided by the model. DA plays a key linkage between farmers' decisions on irrigation applications and the simulation-optimization model. Via the DA, the state variables (soil moisture and LAI) and parameters of the SWAP simulation model are updated using the real-time field observation of soil and crop, as well as daily updated weather forecast, which provides more reliable support for generating the optimal irrigation application in a specific day crossing the entire irrigation season. Furthermore, it is assumed that farmers have some recapitulation about their choices during the interactions with the computer model and bring some learning to the next irrigation season. This learning process is further discussed in the following.

Experiments are designed to test RTIST with irrigation farmers to have their feedback about the usefulness of the tool and the improvement needed. This can be conducted via a "fire drill" of a virtual irrigation exercise (VIE). In a workshop set up for the experiments, RTIST modelers and invited farmers go over the interactions described above through a hypothetical, computer-generated VIE. Being analogy to the so-called virtual drought exercises (VDEs, Loucks and van Beek, 2005), a good VIE will raise important issues and provide experiences that can be applied in real irrigation practices. The VIE follows the three stages of VDE as described in Loucks and van Beek (2005)—briefing, gaming and debriefing. The briefing will define the objectives of the exercise and provide a brief tutorial about the interaction process including some explanation of the windows (Figure 3). The gaming portion of VIE allows participants (modelers and irrigation farmers) to play a "dry run" of the modeling tool. A single farmer or a small group of farmers can participate in one experiment, where the groups can discuss their responses to the model outputs and make a choice together. The same experiment will be conducted simultaneously with multiple individual farmers or farmer groups so that the results from different farmers can be compared. Through this gaming stage, it is important for participants to perform "self-observation," that is, knowing the consequence of their decisions (e.g., no-irrigation may end with soil dryness; an irrigation application may coincide with a major rainfall event in the next few days). Such self-observation will contribute to the final debriefing stage that translates participants' actions and perceptions into "lessons learned" via some recapitulation of their choices during the experiments. In addition, for modelers to refine RTIST, a survey can be conducted at the end of the workshop, asking for users' feedback on the experiments including their experiences in irrigation scheduling decisions and suggestions to improve RTIST (see Appendix for the survey questions and responses).

3. Case Study

RTIST was tested on two maize fields located in east Nebraska (98.22°W, 42.02°N; 98.2°W, 41.95°N) in the crop season of 2019. Current weather was collected daily from Elgin station of the Automated Weather Data Network operated by the High Plains Regional Climate Center, located at 98.19°W, 41.94°N. The real-time weather forecast was made using the Weather Research and Forecast model with Chemistry (WRF-Chem, Fast et al., 2006; Grell et al., 2005), which provides 72-hr prediction of meteorology and air quality for the study domain at 4 km resolution, four times per day. The WRF-Chem configuration we have here followed our past studies (Ge et al., 2014, 2017; J. Wang et al., 2013, 2022; Zhang et al., 2020). The 1° × 1° National Center for Environmental Prediction Final Analysis data at 0000, 0600, 1200, and 1800 UTC were used in real time for initializing and specifying the temporally evolving lateral boundary conditions. For each model run (i.e., four times per day), the prediction was made for the following 72 hr, and the hourly outputs were archived. Therefore, for a given hour on a given day, there are multiple realizations of the forecasts made in the past 72 hr at the interval of every 6 hr (J. Wang et al., 2022). Assuming equal weights for all the simulations, the average value for all the simulated minimum temperature, maximum temperature, relative humidity, and wind speed and the summation of the simulated precipitation and the radiation were calculated and used as the mean of the WRF forecast. A standard deviation of the WRF was calculated as the difference between the forecasted values (from WRF) and the observed values in 2018. The obtained standard deviations are 0.31 mm, 0.54 mJ m^{-2}, 0.23°, 0.14°, 0.12%, 0.37 m s^{-1} for the rain, minimum temperature, maximum temperature, relative humidity, and wind speed. Then, 10 scenarios were sampled from Gaussian distribution for all the weather variables, except for rain where Gamma distribution was used.

Daily soil water content and LAI observations were assessed at the field. The soil water content observations were collected directly from the study fields using three time-domain reflectometry probes and data loggers that were installed at three sampling zones at each of the testing fields. On each of the sampling locations, three probes were vertically installed at soil depths of 10 and 18 inches. The probes were installed at the location with the lightest soil type (and therefore the lowest water content in the field), so that the irrigation amounts at these locations would be sufficient for other locations. Data loggers were automated to constantly collect soil moisture data at a temporal resolution of 30 s, which are aggregated to a daily time period. The LAI observations were collected using a remote sensing product iLAI-2200C plant canopy analyzer (model LAI-2270, LICOR Bioscience, Lincoln, Nebraska, USA), which are updated every 2 weeks. Each field was divided to three sampling zones, and five samples were collected from each zone. The average of all samples is used as the final LAI measurement. Polynomials with a degree of six were fitted to the available LAI observations in three periods with an equal length to interpolate the daily observations. The three periods were chosen as corresponding periods of the time from emergence to the full canopy, full canopy to the beginning of leaf senescence, and leaf senescence to maturity (about 40 days each). The observations of soil moisture and LAI are used in the DA to update the crop and soil state and parameters that are highly correlated to the observations. The state includes several variables such as LAI, soil moisture at the whole soil profile, and root depth. The soil parameters are the van Genuchten–Mualem model parameters, and the crop parameters are the maximum relative increase in LAI, lower threshold temperature for the aging of leaves, light use efficiency for real leaf, and efficiency of conversion into leaves.

According to the reports of California Soil Resource Lab at UC Davis and UC-ANR (Walkinshaw et al., 2021), the soils of the test fields are sandy-loam to loamy-sand soils of seven layers, with less than 6% slopes with any of the soil layers. The soil hydraulic parameters in the SWAP model were initialized according to the soil reports, and the soil slopes were assumed as 0%. The crop parameters were used as the default parameter set provided in the SWAP model. The planting date is 25 April 2019. The fields are irrigated with sprinklers. The average water price is 40 USD/in-acre and the crop price is 3 USD/Bushel.

Using these test fields, the tool performance was assessed. A workshop for the model experiments was organized by the Agriculture Extension of the University of Nebraska at Lincoln to test the interactions with farmers. Ten farmers from Nebraska attended the workshop (Table A1). A survey was conducted during the workshop to seek feedback from farmer participants (Table B1).

4. Results

This section first discusses the RTIST performance by comparing the optimized irrigation schedule (without human intervention) to the actual applications, with detailed result analysis on the influence of the DA on soil moisture and LAI. Following that, the results from the RTIST experiment workshop are presented and the influence of human-machine interactions are discussed.

4.1. Tool Performance

4.1.1. Data Assimilation

Here the effectiveness of DA is shown by comparing the estimations of LAI and soil moisture with and without using DA. In this test, the actual field irrigation schedule and the actual observations were used. The irrigation schedules together with the precipitation amounts are presented in Figure C1 in Appendix C. The error difference is used as a comparison indicator, which constitutes of the difference between the error with and without using DA under each of the two cases. For LAI, the error difference is calculated according to the difference between the absolute error of estimation of LAI (the absolute difference between the estimated LAI and the measured LAI) with DA and without DA; for soil moisture, the error difference is calculated as the absolute difference between the average (over the number of observations) error of the estimation of soil moisture (the absolute difference between the estimated soil moisture and the measured soil moisture) with DA and without DA. The results of the current state estimations are presented in Figure 4. Values below 0 indicate a lower error with the tool with DA than the case without. The results are shown only after the LAI assimilation has begun (i.e.,

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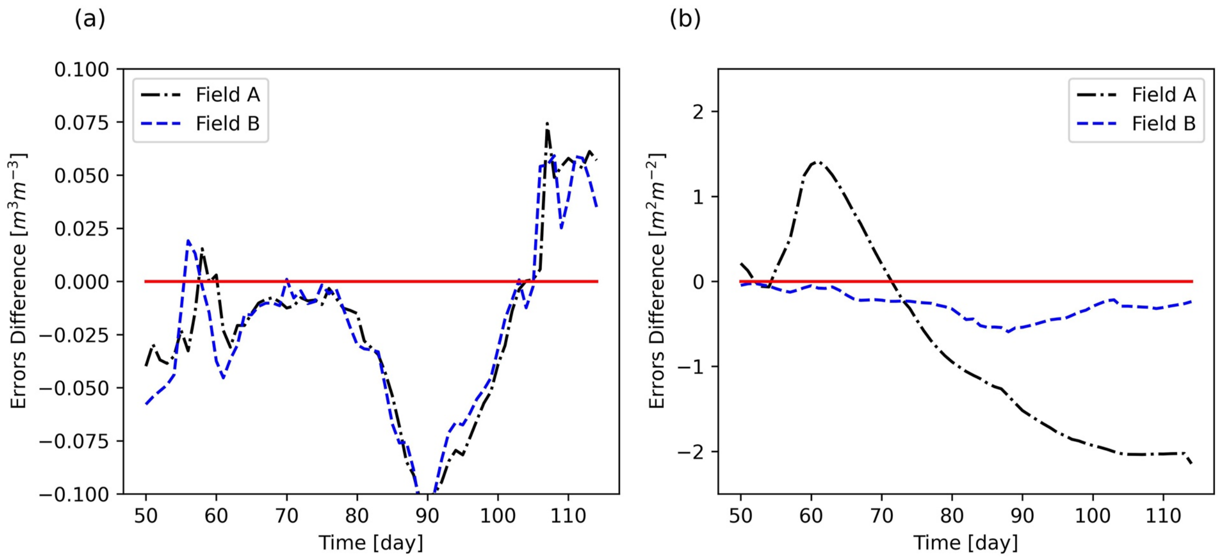

Figure 4. The error difference for (a) soil moisture and (b) leaf area index estimated at the current time step.

after the crop emergence), as leaves do not exist in the early days and the assimilation process did not commence. The improvement of the estimations of both LAI and soil moisture over time is clearly shown. At most of the time steps, both LAI and soil moisture are better estimated with DA. The results of soil moisture are similar on both fields, while better LAI estimations were observed on Field A using DA. This is due to the lower LAI in early periods (days 50–60) in Field A and the lower errors of DA, which led to a better convergence of DA with more accurate estimations in comparison to Field B (see Figure D1 in Appendix D). However, the convergence of LAI is more consistent than soil moisture due to two reasons. First, the negligible LAI correlation with other measured state variables. For example, a slight modification of LAI within the assimilation process can lead to a direct change of the estimated LAI which can easily match the estimated LAI with the measured LAI. On the other hand, the state of measured soil moisture at one depth has a high correlation with the state of measured soil moisture at other depths. Due to this correlation, the correction of the soil moisture at one depth using DA is accompanied with changing the value of correlated soil moisture at other depths. Therefore, an improvement in the estimation of the state of soil moisture at one depth might be accompanied by a degradation at other depths which may result in no improvement in the whole soil moisture estimation (see Figure D2 in Appendix D). Hence, in general, estimating soil moisture on the whole soil profile can be more challenging than LAI. Second, soil moisture improvement is highly dependent on the changing dynamics with the changing irrigation amounts and precipitation. For example, when low irrigation amount and precipitation occur (as the case in days 90–110), new (low, in comparison to past periods) dynamics exist and no information is available for improving the estimations. A sufficiently long period for DA is required to improve the accuracy of the simulation model and converge to satisfactory estimations.

Since the SWAP model is used for predictions within RTIST, it is important to examine the accuracy of the predictions provided by the simulation model. The prediction capability of both soil moisture and LAI state in a future period (i.e., 3 days ahead, as used in this study) using the DA enhanced SWAP modeling is examined, where the daily average error difference is also used. Overall, using DA, the estimations in most of the growing period are superior to the method with no assimilation in both fields (as shown in Figure 5, all error differences are below 1.0). The results of the predictions follow the results of the current state estimations as shown in Figure 4 to some extent. For LAI, the current estimation was better than the prediction at the beginning, as the direct influence of the modification of the current LAI using crossover and mutation can be higher than the influence of modifying the crop parameters on LAI during the assimilation process. This direct LAI modification, as the driver of the improvement in LAI, might hinder the parameter estimations. This can be alleviated by lowering the amplitude of the crossover and mutation parameters applied to LAI (Jamal & Linker, 2020). The values of soil moisture at different depths and the LAI are presented in Figures D3 and D4 in Appendix D.

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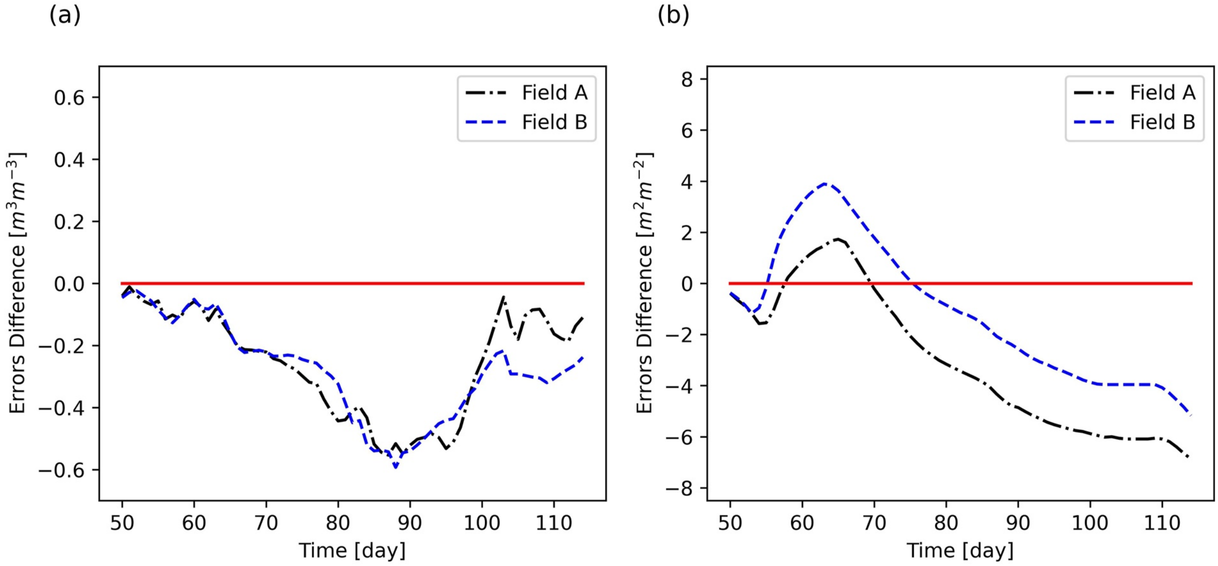

Figure 5. The error difference for (a) soil moisture and (b) leaf area index, predicted for the *future time periods*.

4.1.2. Optimization

The RTIST was tested on two fields (namely field A and field B) in east Nebraska and the optimized irrigation schedules from the simulation-optimization model are compared to the actual schedules which were applied by farmers in the real fields, as shown in Figure 6 together with the rain during the crop growing season. In both fields, the optimized and the actual schedules both have irrigation applications mainly in the second part of the growing season, as the evapotranspiration increases. However, the optimized applications occur over a relatively narrow range with especially low rainfall. This emphasizes the importance of exploiting the rainfall possibilities from some incoming days using weather forecasts. This also indicates that in the real world, farmers' decisions might not be well informed by weather forecasts. In addition, the low amplitude of the optimized irrigation applications shows that an accurate timing might substitute for applying large irrigation amounts (Table 1). Increasing the crop yield while decreasing the water usage with the optimized schedule shows the possibility to improve the actual schedule. However, it is not realistic for farmers to fully accept the optimized schedule due to the impacts

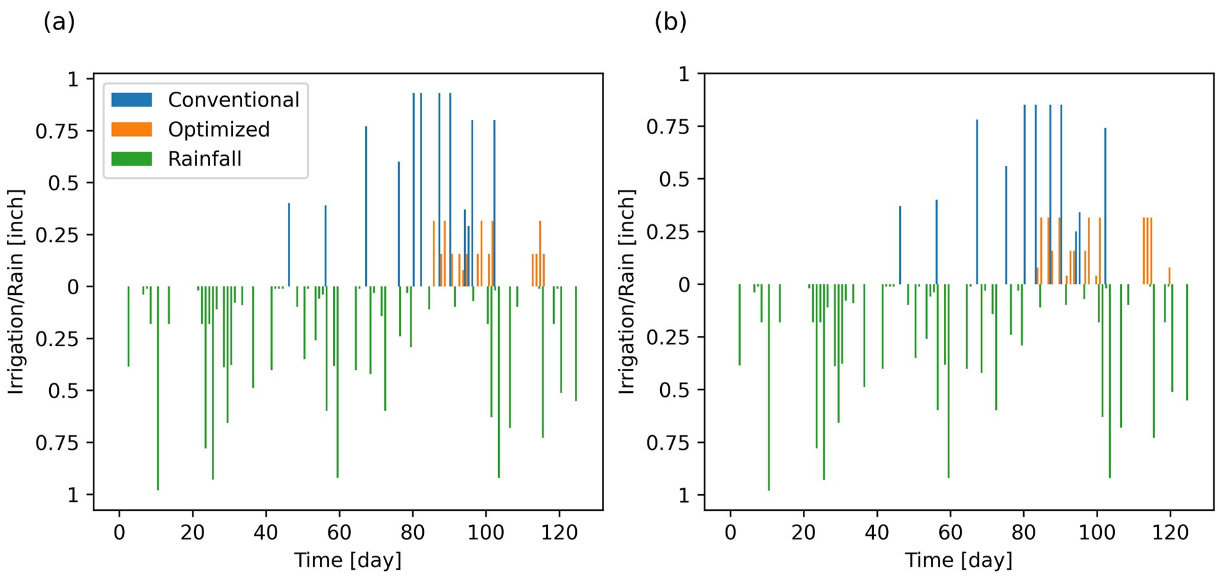

Figure 6. The conventional and optimized irrigation schedules with rainfall events in (a) Field A and (b) Field B.

Table 1
Seasonal Irrigation Amount, Dry Matter and Profit Using Optimized and Actual Methods for Field A and Field B

Field	Method	Irrigation (inch)	Dry matter (bushel/acre)	Profit (USD/acre)
Field A	Actual	8.1	324	648
	Optimized	3.1	365	971
Field B	Actual	6.9	335	729
	Optimized	3.4	373	983

of farmers' behaviors, policies, as well as incomplete knowledge and limited knowledge delivery to farmers (Rose et al., 2018).

It should be noted that a 3-day probability-based weather forecast is used for the current simulation-optimization model. The stochastic optimization approach is compared with a deterministic approach, in which a single-scenario weather forecast, rather than multiple probabilistic WRF forecasts, is used. No improvement is observed between the two approaches, owing to the low uncertainty of the forecasts with a short period of 3 days. The importance of the stochastic approach is manifested by longer forecast periods and higher uncertain conditions (Cai et al., 2011; Hejazi et al., 2014). A future work may include forecasts that have heading time of up to 2 weeks, as suggested by Cai et al. (2011) and Hejazi et al. (2014).

4.2. Human-Machine Interaction

Multiple runs of RTIST and the GUI were conducted with invited farmers via a VIE that took place at the University of Nebraska-Lincoln with farmers from different sites in Nebraska. In this workshop the farmers interacted with the tool through the GUI by running a test field case study from the site in east Nebraska (the same site as Field A and Field B, but a different field). The experimental results, discussions between modelers and farmers during the human-machine interactions, and the survey at the end of the experiments show the interest, involvement, learning, and feedback for the tool improvement from the farmer participants. Each of the VIE took about 1 hr.

4.2.1. Farmers Intervention

The test field was run in the workshop with two groups of farmers, with each group including 4 farmers. Here the final irrigation schedules from two groups (named Group 1 and Group 2) are compared to the schedule without any intervention (i.e., assuming farmers accept all model recommendations), and shown in Figure 7. Furthermore, the irrigation schedule that was applied in the real field is presented. Group 1's choices were closer to the model recommendations than Group 2, but both groups modified the recommendations. Both groups chose to irrigate toward the end of the growing season. Group 2 started to irrigate earlier than the model and Group 2. In addition, both groups decided to irrigate in the first week, which differs from the model recommendation of no-irrigation. This is because both groups of farmers have experience of combined fertilizer and water application during the seed stage. Based on this result, RTIST was modified to add a choice of applying water and fertilizer in the seed stage (see more about the tool modification based on farmers' feedback in Section 4.2.3).

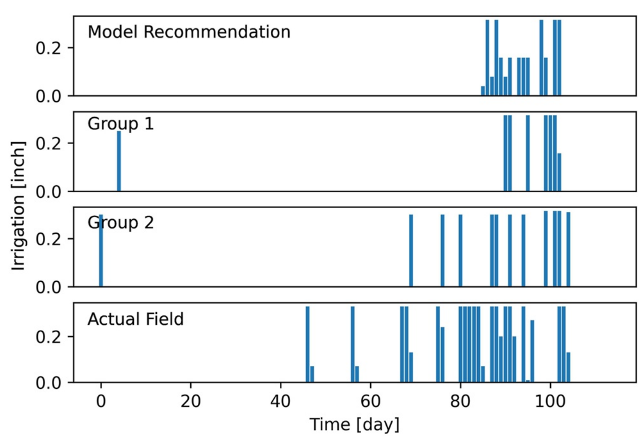

Figure 7. Irrigation schedules based on the model recommendations (without interactions), human-machine interactions with two groups of farmers, and field records.

The total irrigation amounts, crop dry matters, and profits, together with the average no-irrigation period lengths, total no-irrigation days and the number of rejections are presented in Table 2. Overall, the results of the modeled schedule (without interaction) and of the human-machine interactions with Group 1 and Group 2 is better than that of the actual field practices, in terms of saving water, increasing dry matter, and increasing profits. However, Group 1 tended to be more conservative and used less water than the model, while Group 2 used more water. When the human-machine interaction is finished for a particular day, farmers are asked to tell how many days they will wait for considering the next irrigation application. It is found that both groups chose periods of less than a week (6.4 days for Group 1 and 4.1 days for Group 2), with a close total no-irrigation days in the entire season (76 days for Group 1 and 86 days for Group 2). Both groups showed high agreement with the tool (less than 10% rejections); yet one group rejected three times more than the other group. However, similar dry matter was obtained from all the cases; the highest profit was achieved for Group 1 due to less water application and cost than the model and Group 2. The difference in the choices of the two groups indicates the complexity of anticipating farmer behavior, which emphasizes the necessity of involving farmers in the decision-making process.

Table 2
Seasonal Irrigation Amount, Dry Matter, and Profit Resulting From the Various Irrigation Schedules

Case	Irrigation (inch)	Dry matter (bushel/acre)	Profit (USD/acre)	Total no-irrigation days (day)	Average no-irrigation period length (day)	Number of rejections (out of 115 days) (day)
Model	2.71	237	602	–	–	–
Group 1	2.29	235	613	76	6.4	3
Group 2	3.65	237	565	86	4.1	9
Actual field	7.00	240	440	–	–	–

4.2.2. Debriefing

In the debriefing stage following the gaming stage (i.e., the human-machine interactions), farmers and modelers discussed the experiments. In general, the participating farmers thought the tool was informative, encouraging, exciting, and conceptually great. They expressed the willingness to use the tool, after it is finalized, as a decision assistance tool, especially in the form of as mobile phone app. They also provided very helpful suggestions based on their experiences and expectation to refine the tool shown in the VIEs. Some suggestions are highlighted below to show the diverse requirements from irrigation farmers. Some farmers said they were challenged by the water use permit and the timing of applications, which often enforces constraints on their irrigation scheduling. Water cost is also a concern for some farmers since it varies with the energy market. The tool in the experiment assumed farmers made a decision for the current day but some farmers sometimes also like to make a decision in a number of consecutive days (e.g., 5 days).

A specific discussion between the farmers and modelers is about the late irrigation applications appearing in the model recommended schedule (Figure 7). The model determines an irrigation application on a particular day according to the current soil moisture, crop growth status, and the weather forecast. In particular, the threshold soil moisture plays a critical role. In the real world, this threshold varies by farmers. Some farmers in the workshop said they tried to keep the soil close to saturated status all time, however, this wastes water and may not be necessary for crop growth either. For both modelers and farmers, adjusting the threshold soil moisture is a trial-and-error learning process that will be supported by real-world practices.

In addition, some farmers may only consider the current soil and crop status and not the weather forecast, and they may irrigate right before a rainfall event. Thus, farmers may build their trust to the weather forecast via the human-machine interactions over a number of consecutive seasons.

At the end of a dry run, some farmers told the modelers that they might do it differently regarding the model recommendations if they took the experiment again; farmers from different groups exchanged their choices and thoughts during the VIEs. In future real-world use of the established tool, farmers are expected to learn from the interactions season by season so that their decisions can be more informed, especially whether to accept the model recommended application at a particular time; if they decide to apply amount of water different from the model recommended, how different it should be, etc.

The survey conducted at the end of the VIE workshop provides some feedback from farmer participants, as presented in Table B2 in Appendix B. Most of the farmers grow corn and other crops, with a wide range of farm scales, which makes the farmers good representatives of the (especially corn) farmers in Nebraska. Most of the farmers rely basically on current weather conditions. This highlights the importance of the current information in the field (D. Wang & Cai, 2009). In particular, one farmer mentioned that his decision was based on soil moisture probes (PREC University of Nebraska - Lincoln). However, most farmers still showed interest in using forecasts. They suggested showing them the actual weather in the past 3 days to 1 week so that they could have a sense of how reliable the forecasts were and to what extent they should trust the forecast (Shafiee-Jood et al., 2021); they also wondered about the effectiveness of relatively long weather forecast up to one to 2 weeks (Hejazi et al., 2014).

In general, the debriefing results indicate the readiness of farmers to accept scientifically-based tools in irrigation scheduling and their excitement to get involved in human-machine interactions to obtain support in their decisions. In particular, RTIST was demonstrated for corn/maize only during the workshop, and the participants

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expected to see the tool for other major crops. Meanwhile for the RTIST modelers, farmers' feedback led to a more realistic and more effective tool, as discussed in the following.

4.2.3. Tool Modifications Based on Farmers' Feedback

Some comments from the VIEs are related to the threshold soil moisture, which the model uses to decide an irrigation application, variable water cost, maximum applicable water in an application, seasonal and monthly water use permit, relevance of soil moisture to crop stress, and joint fertilization and water applications. These comments are constructive for technical improvement and led to modification of RTIST right after the workshop, as summarized in Table B2, Appendix B. Some comments are related to the provided information, as the farmers showed interest in more information from the model such as water stress, weather forecast reliability, crop growth stages, seasonal results, and excessive water events. Part of the required information is not easily measured (e.g., water stress and growth stage) and can be estimated by the simulation model. Even so, the farmers still thought the information was valuable after the VIE workshop. This highlights the importance of the human-machine interaction in terms of the learning for both the modelers and the participating farmers.

RTIST is under further refinement and modification. As some farmers in the VIEs expected, the final goal is to deliver a smart phone *app* based on RTIST that is accessible for farmers during the irrigation season.

5. Conclusions

In this study, a simulation model, a DA technique, and a human-computer interaction method are integrated into an optimization framework to support real-time irrigation scheduling regarding optimality, accuracy, and applicability of the RTIST. The principle of the RTIST is to engage farmers directly into computer modeling and support farmers' irrigation scheduling decisions jointly based on model provided information and their own justification. This is different from many existing studies that try to mimic farmer's behaviors and decision processes, which is however not realistic for real world applications. RTIST does not propose an "automatic" tool to replace irrigation farmers to conduct irrigation scheduling decisions, but to provide model-based information to support farmers to make the decisions themselves. Meanwhile, in the human-computer interaction framework, farmers' feedback improves the computer model of crop growth with real world irrigation applications.

This integration can help track optimal crop profits based on probabilistic weather forecasts while involving field observations to assure reliable environment and crop simulations in the optimization process. In particular, it is shown that human-computer interaction is important for facilitating the practical application of the tool through farmer's engagements. The tool was tested on maize fields in east Nebraska via VIEs with real world farmers. The accuracy of present estimation and future prediction of soil moisture and LAI is improved by field observation and DA, and the optimization and assimilation procedures are validated with increased crop yield, profit, and water saving. The human-computer interaction of the tool was tested on one field via a workshop with invited farmers. High interest in applying the tool was shown by the farmers, to a large extent due to the informativity of the tool, for example, about the status of crop and field environment. The VIEs show that RTIST with farmers' direct engagement results in increased crop yield, profit, and water saving in comparison to traditional practices. In addition, farmers' feedback from the debriefing stage of the VIEs provides meaningful suggestions to improve the tool (especially the GUIs) for real-world application. The VIEs highlight the necessity for the direct intervention of the farmers in the irrigation scheduling modeling process.

The proposed decision support tool can be affected by non-accurate information due to possible systematic errors with both the model structure and parameterization. However, several features of the proposed framework could help alleviate this issue. First, a reliable and widely used simulation model (i.e., SWAP) was used to simulate soil moisture and crop growth in a real crop field, enhanced by assimilating field observations to reduce modeling errors. Furthermore, the interactions with farmers enable the link between the computer model and the real field condition, which ultimately reflects farmers' actual decisions based on both model recommendation and farmers' experience and justification. Future work should include using more data to validate the crop model simulation (e.g., dry matter) and conduct more interactive experiments with farmers for various crops at various sites.

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Appendix A: Workshop and Survey

The workshop windows and survey, which were introduced to farmers, are presented in this appendix (Figure A1).

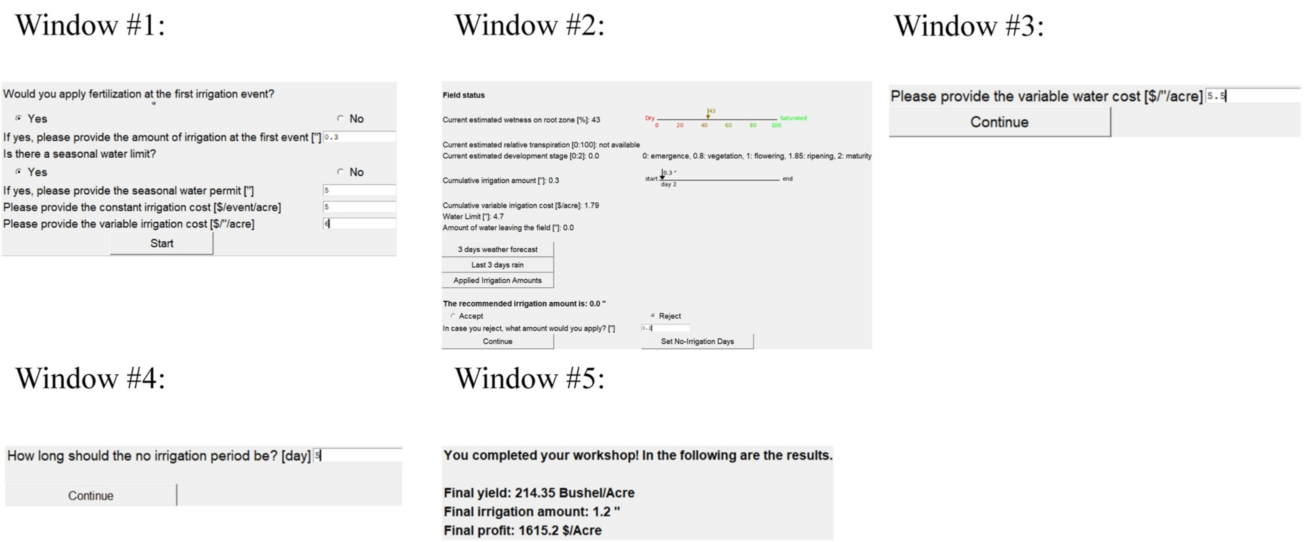

Figure A1. Snapshots of the windows of the workshop.

Table A1
Survey Questions

#	Questions
1	How many acres of land do you farm or consult?
2	What are the major crops you plant on your farm?
3	For the crop you have (corn in particular), by average, how many irrigation applications do you have in one crop season, or how many inches of water do you apply?
4	Do you use weather forecast (like the public 10-day forecast) in your irrigation decisions?
5	How do you decide when to irrigation and how much to apply? Please choose one or more of the following choices:
	(1) Use my own justification based on observation of plants and soil moisture and weather forecast
	(2) Follow what my neighbors do
	(3) Follow suggestions from crop advisors, district associations, etc.
	(4) Others (please specify)
6	Please describe any positive or negative things (if any) about the real-time irrigation scheduling tool tested in the experiment today
7	Please describe any suggestions you may have for our irrigation scheduling tool

Appendix B: Workshop Results

The results of the survey and the feedback of the farmers in the workshop are presented in this appendix.

Table B1
Survey Results

Farmer #	Q1	Q2	Q3	Q4	Q5	Q6	Q7
1	150	C, B	12–14″	Rely more on current weather	1	It is difficult to coordinate weather to results	–
2	160	C, B, A, O, R, S, G	Once a week	Yes	1, 4: water allotment amount and time from ditch company	Good tool, need variable rate	Increase water amount in an application. Provide when leach happens
3	330	C, A	12″	Rely more on the current rain	1	Very exciting and will validate our real-world work	Fertilizing scheduling is also required
4	450	C, S, B	20 applications, 10″–18″	Yes	1	A good tool to manage irrigation	–
5	800	B	14″	Yes, on the early irrigation period	1, 4: soil monitor	A different tool	–
6	85	A, C, B	5–7 applications, 5″–7″	Yes	1, 4: information from Panhandle Research and Extension Center probes. There is a problem in decision-making that it is made with other farmers who share the land	Disappointed from previous programs. The concept is great and needed especially as it is data-based and informative	Keep up the great work
7	5,500	C, S, B	24 applications, 15″–19″	Yes	1	Soil moisture needs more relevance to actual moisture for crops	–
8	1,800	C, W, S	13–16″	Yes	1, 3, 4: climate view	Very informative	–

Note. C, Corn; B, Beans; A, Alfalfa; O, Oats; R, Rye; S, Sugar beets; G, Grass; W, Wheat.

Table B2
Modifications of the Tool Based on the Farmers' Comments

Comment	Modification
Change the soil moisture scale to give information on the water stress	Water stress was added as the estimated relative transpiration
In the beginning, some amount of water should be applied with fertilizer	Fertilization on the first day was added as an optional choice together with the corresponding irrigation amount
Increase maximum one-time irrigation to 0.8″ or 1″	Maximum irrigation amount was increased to 1″
Add note on the weather forecast reliability (e.g., equal probability for all scenarios)	A note that the scenarios have equal probability was added to the figure of the weather forecast
Show crop growth stages	Instead of LAI, an estimated growth stage was added
Show the actual rainfall during the past 3–7 days	A figure of the actual rainfall for the past 3 days was added
Show crop yield and irrigation at end of the growing season	A window showing the final yield, used water, and profit was added
Farmers were interested in the total budget and monthly budget of water for the growing season as they said it varies from area to area	The variable water cost can be modified each time the irrigation is applied. The total water limit is added to be specified as well
Irrigation is not allowed before a specific date in some cases	No—irrigation period can be chosen anytime during the growing season
Water cost varies from area to area and from month to month	User-defined fixed and variable water cost can be chosen
The time of water leaching out should be provided	Water leaving the field as runoff was added on daily basis

Appendix C: Precipitation and Irrigation for DA

The irrigation schedules together with the precipitation amounts that were used in the DA case study are presented in this appendix.

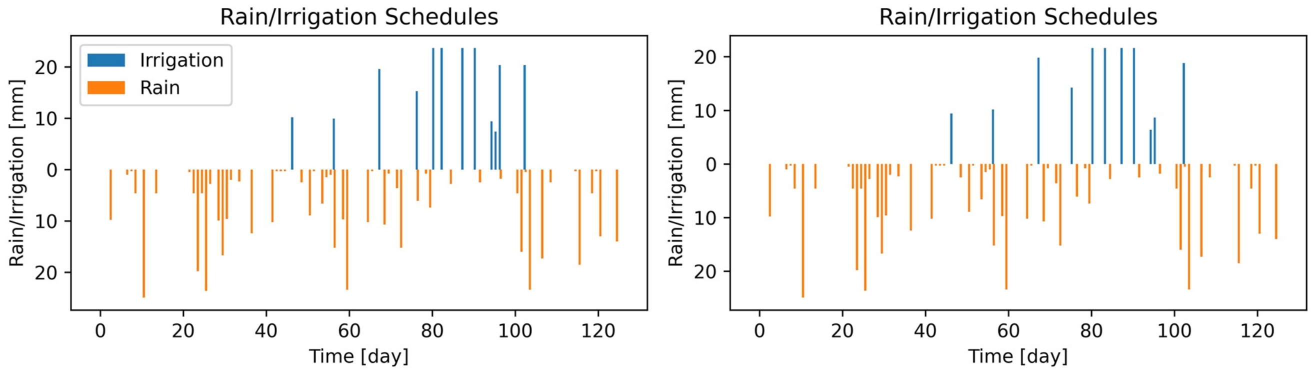

Figure C1. Precipiration and irrigation schedules for field A (left) and field B (right) in the DA case study.

Appendix D: DA Results

DA results for current and predicted estimations are presented in this appendix.

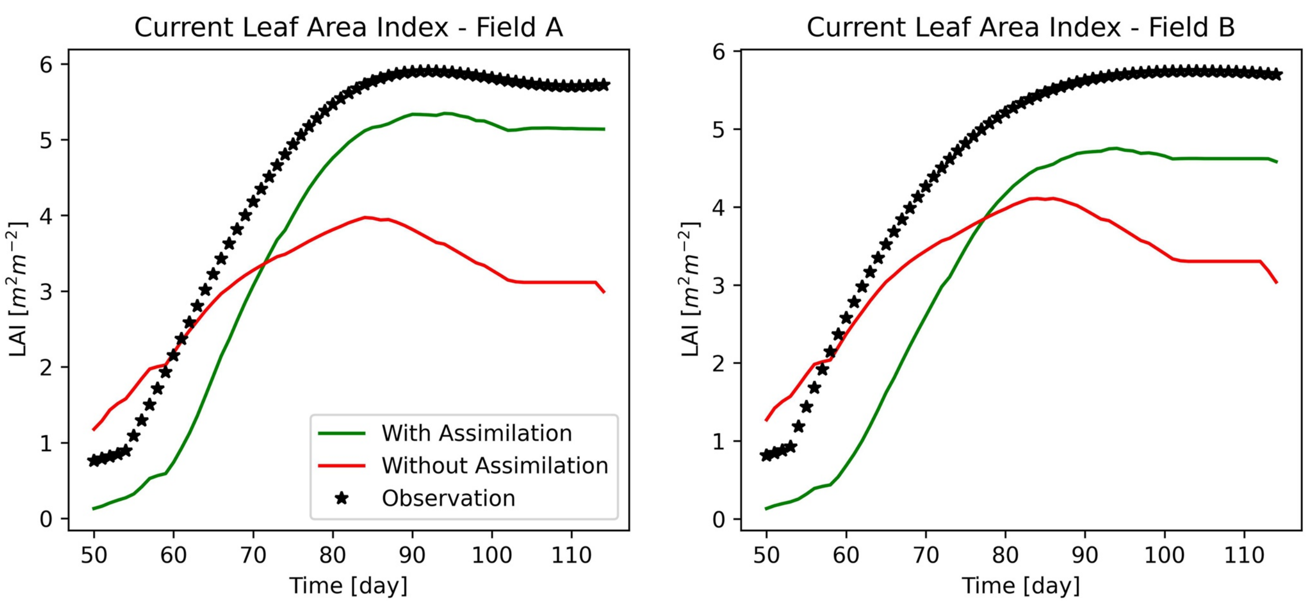

Figure D1. Current leaf area index (LAI) estimations.

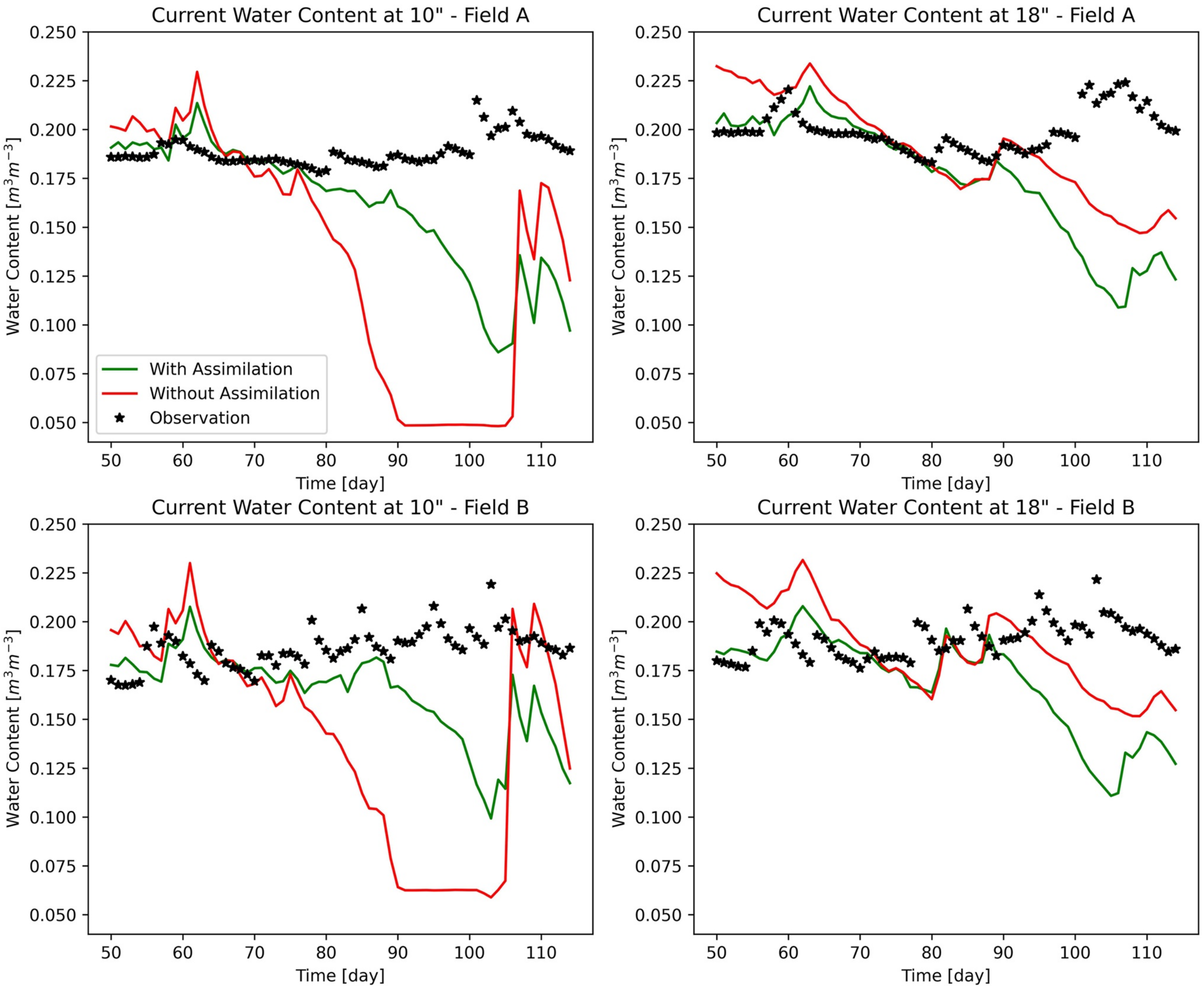

Figure D2. Current soil moisture estimations.

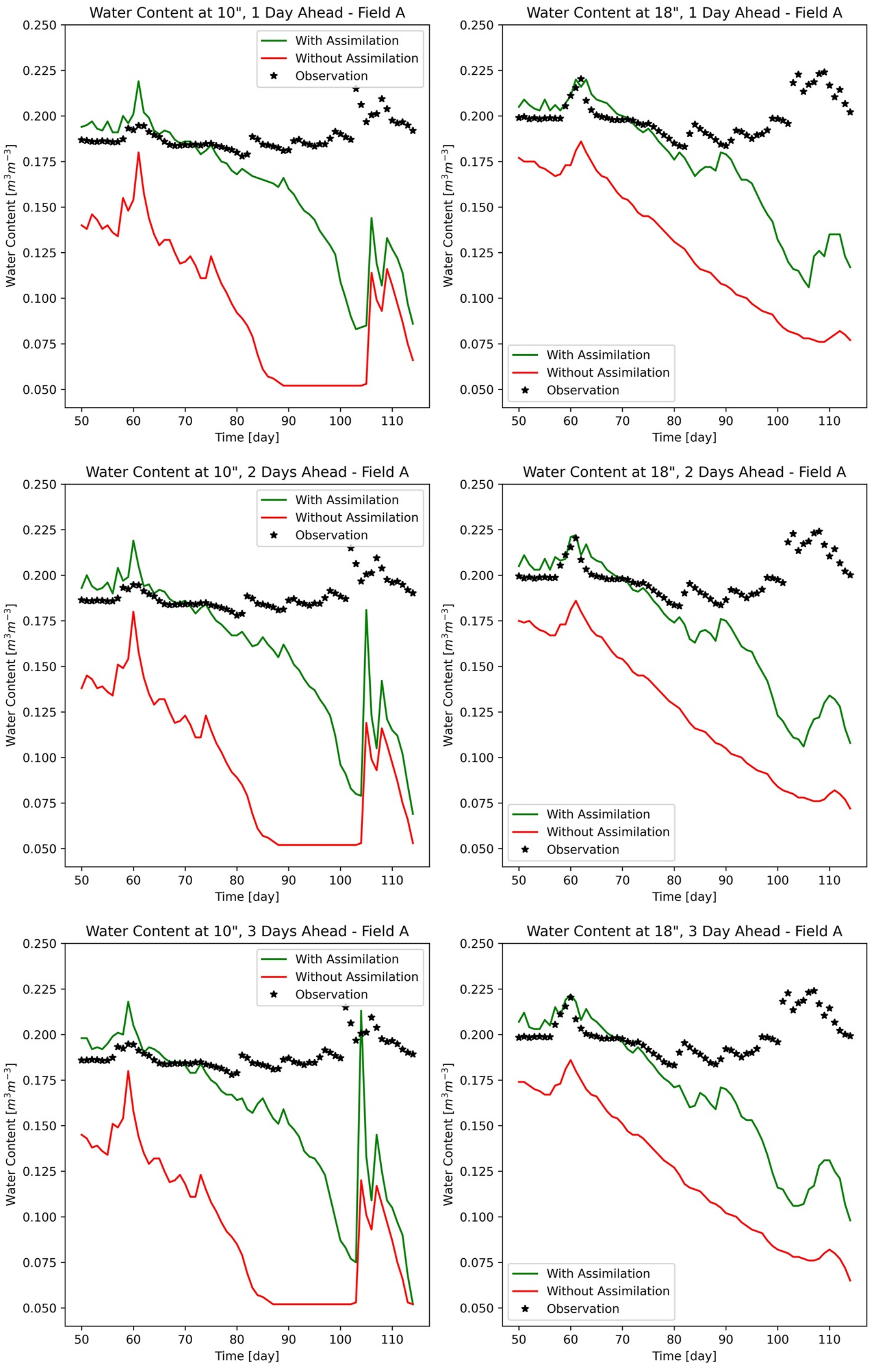

Figure D3. Predicted soil moisture estimations.

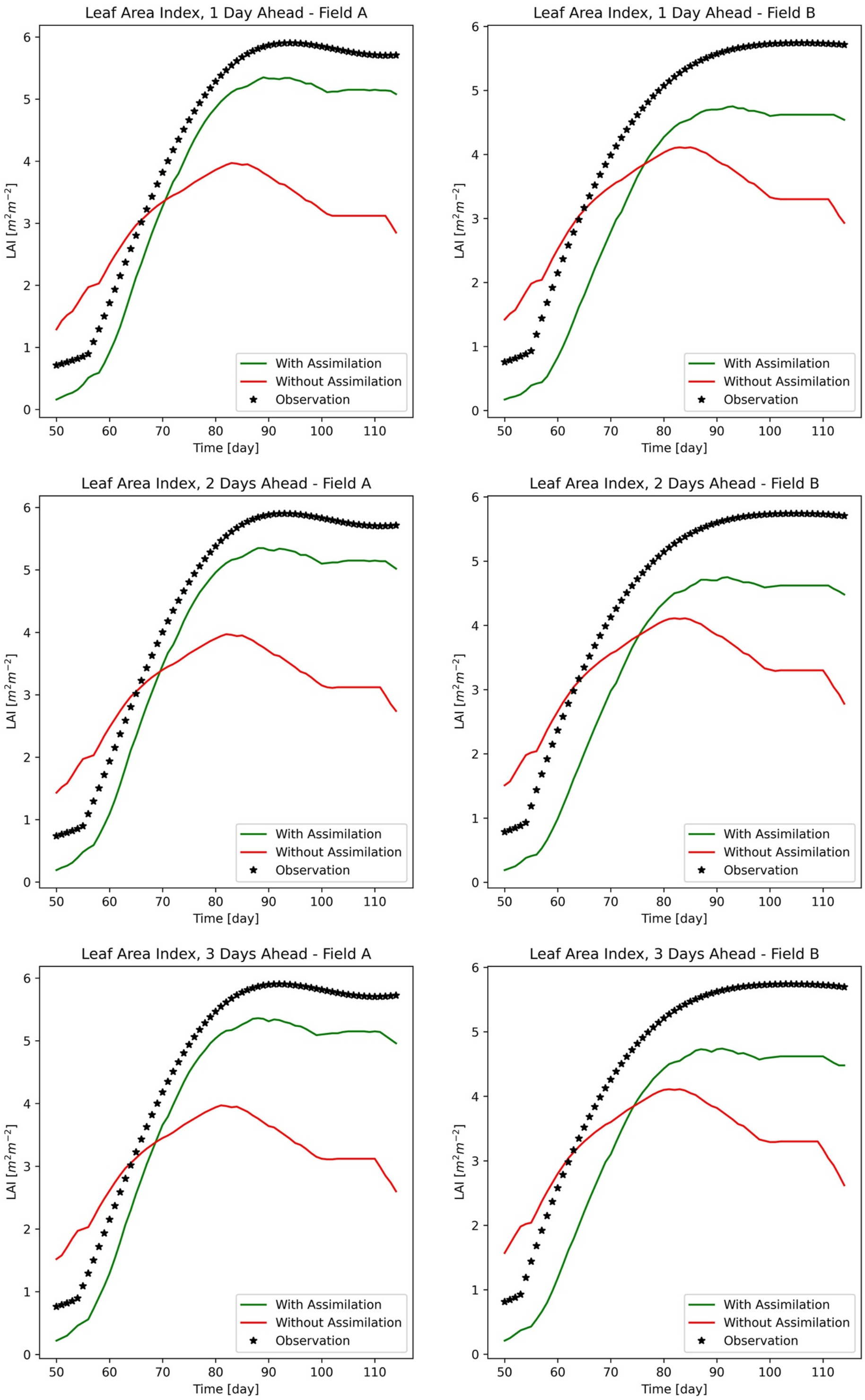

Figure D4. Predicted leaf area index (LAI) estimations.

Data Availability Statement

The software used for the workshop and the case study are available on Mendeley (Case study (Jamal et al., 2023a) and Workshop (Jamal et al., 2023b)).

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