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An Automated Data-Driven Irrigation Scheduling Approach Using Model Simulated Soil Moisture and Evapotranspiration

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Abstract: Given the increasing prevalence of droughts, unpredictable rainfall patterns, and limited access to dependable water sources in the United States and worldwide, it has become crucial to implement effective irrigation scheduling strategies. Irrigation is triggered when some variables, such as soil moisture or accumulated water deficit, exceed a given threshold in the most common approaches applied in irrigation scheduling. A High-Resolution Land Data Assimilation System (HRLDAS) was used in this study to generate timely and accurate soil moisture and evapotranspiration (ET) data for irrigation management. By integrating HRLDAS products and the crop growth model (AquaCrop), an automated data-driven irrigation scheduling approach was developed and evaluated. For HRLDAS ET and soil moisture, the ET-water balance (ET-WB)-based method and soil-moisture-based method were applied accordingly. The ET-WB-based method showed a 10.6~33.5% water-saving result in dry and set seasons, whereas the soil moisture-based method saved 7.2~37.4% of irrigation water in different weather conditions. Both of these methods demonstrated good results in saving water (with a varying range of 10~40%) without harming crop yield. The optimized thresholds in the two approaches were partially consistent with the default values from the Food and Agriculture Organization and showed a similar trend in the growing season. Furthermore, the forecasted rainfall was integrated into this model to see its water-saving effect. The results showed that an additional 10% of irrigation water, which is 20~50%, can be saved without harming the crop yield. This study automated the data-driven approach for irrigation scheduling by taking advantage of HRLDAS products, which can be generated in a near-real-time manner. The results indicated the great potential of this automated approach for saving water and irrigation decision making.

Keywords: irrigation management; HRLDAS; water conservation; threshold optimization; yield estimation

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Citation: Zhao, H.; Di, L.; Guo, L.; Zhang, C.; Lin, L. An Automated Data-Driven Irrigation Scheduling Approach Using Model Simulated Soil Moisture and Evapotranspiration. *Sustainability* **2023**, *15*, 12908. https://doi.org/10.3390/su151712908

Academic Editors: P. V. Vara Prasad, Prakash Kumar Jha and Surendra Singh

Received: 14 July 2023
Revised: 8 August 2023
Accepted: 24 August 2023
Published: 26 August 2023

1. Introduction

Crop cultivation is the primary source of food, fiber, and biofuel supplies in the U.S. and the world. Crop cultivation consumes a significant amount of freshwater and energy, mainly through irrigation. According to a World Bank report [1], irrigated agriculture accounts for 17% of all the arable lands, which is about 277 million ha. However, this relatively small fraction of cropped land produces approximately 40% of the world's gross agricultural output [2]. Although irrigation plays a crucial role in significantly boosting crop yields, leading to increased farmer income and improved food security, it accounts for up to 80% of water consumption in the United States and over 90% in various Western states [3]. Fueled by increasing competition from the urban and industrial sectors for scarce water resources, high agricultural water consumption, and water wastage, freshwater has become a scarce resource in many parts of the U.S. and around the world. Moreover, with a steady population growth worldwide and limited land area, it will become more difficult in the future to meet food production requirements with limited water resources despite all the efforts towards sustainable agriculture [4]. On the other hand, excessive irrigation frequently occurs at the field scale, leading to the wastage of valuable water and energy resources, agricultural run-off, and pollution of the surface and groundwater. Additionally, this practice results in the depletion of water sources and soil nutrients, and it can also cause soil salinization, thus harming agricultural sustainability. Given these challenges, the need for effective irrigation management becomes even more critical to enhance water use efficiency (WUE) and overall productivity, and to save water for future use [5].

Irrigation scheduling is the process of determining and optimizing the amount and timing of irrigation activities. The primary objective of irrigation scheduling is to achieve specific management goals, such as improving crop yield, reducing water wastage, and preventing environmental issues. Over the past few decades, several methods have been proposed to schedule and quantify the necessary depth of individual irrigation applications [6–8]. According to what the scheduling rests upon, four types can be distinguished: (1) Evapotranspiration, water balance (ET-WB)-based, (2) soil moisture-based, (3) plant-water-index-based, and (4) simulated model-based. These scientific irrigation management approaches are based on timely and accurate data on crop conditions, soil properties, and weather patterns to make well-informed irrigation decisions. Such data-driven approaches have proven to be highly effective in determining the suitable timing and depth of irrigation for crop growth [6]. Among these methods, ET-WB-based methods are the optimal choice due to their economical, straightforward implementation, and reasonably accurate characteristics. Other types of methods demand specific preparations before their implementation: the installation of sensors and monitoring systems in the field, the research and validation of thresholds to trigger irrigation, and/or model calibration via previous field experiments.

Despite all the data-driven methods that are proposed and researched, farmers and water managers mostly adopt traditional methods in their irrigation operations. For example, only 30% of farms in Nebraska utilized scientific approaches or subscribed scheduling services in a 2018 survey [9]. One of the reasons that hinders the wide application of data-driven scientific methods is that most of these methods involve a chain of data-processing steps. To make an irrigation decision using these methods, farmers must collect soil moisture or ET data from models, install field sensors or satellite sensors, determine a threshold to trigger irrigation, and keep track of the weather conditions to adjust the amount of irrigation during the crop growth season. Moreover, farmers without the required knowledge and specialized analysis skills may encounter difficulties in processing soil moisture and ET data in this manner. Our goal in this study was to automate the data-driven irrigation scheduling process based on model simulation data, thus providing stakeholders with irrigation decision-making information in a timely and easy manner.

In order to automate the data-driven approach and thus promote its utilization in applications, it is important to obtain dynamic data in near-real time with regional, state, or even national coverage using either modeling or remote sensing. Root-zone soil moisture (RZSM) (~top 1 m) and ET are key parameters for irrigation scheduling. Crop growth depends on RZSM, which is depleted mainly by ET and replenished mainly by precipitation and irrigation. Even though the significance of soil moisture in crop growth and irrigation management has been acknowledged [10], obtaining accurate soil moisture data remains challenging due to the lack of routine high spatial resolution (<1 km) observation of soil moisture at the continental scale. The model-simulated soil moisture and ET are important data sources for quick decision-making support in irrigation management as they can be generated in a near-real-time manner. A High-Resolution Land Data Assimilation System (HRLDAS) [11] from the National Center for Atmospheric Research (NCAR) has been developed to fill this gap by simulating the evolution of land surface states at field scales. HRLDAS was utilized in a NASA-funded agricultural pest management decision support system to generate real-time soil moisture and temperature data [12]. These forecast products were made available to farmers in the Central and Great Plains regions through the NCAR partner Meteorlogix, assisting them in making informed decisions regarding their agricultural activities.

In this study, HRLDAS soil moisture and ET during the dry season (2020) and wet season (2019) were utilized to schedule irrigation activities, demonstrating its application possibility in irrigation scheduling for saving water and improving crop yields. By integrating HRLDAS products and a crop growth model (AquaCrop), it is possible to find the best threshold to trigger irrigation activity for maximum crop output. Based on the typical four crop growth stages, four thresholds were determined to represent the dynamic nature of crop water demand during the growing season. For HRLDAS ET and soil moisture, the ET-WB-based method and soil-moisture-based method were applied accordingly to examine the water-saving effect. Furthermore, short-term rainfall forecasts were integrated to prevent unnecessary irrigation from the incoming rainfall.

2. Study Area and Materials

This study uses data from a variety of sources, as documented below. In addition to the hourly updated model simulation products, annual data on crops and soil are also necessary for irrigation scheduling. The automation of irrigation scheduling in 6 agricultural sites has been performed for the growing seasons of 2019–2020. Most of the data are currently visualized and made available to the public on the WaterSmart Data Information Portal (WaterSmart DIP) [13] (https://geobrain.csiss.gmu.edu/watersmartport/web/ (accessed on 13 July 2023)) covering Nebraska, as this study is mainly focused on Nebraska (Figure 1). Nebraska is selected as the study area because it is the largest irrigation state in the U.S. and one of the leading states in terms of its agricultural output. According to the 2017 Census of Agriculture [14], Nebraska had the highest amount of irrigated land among all states in the U.S., encompassing 8.6 million acres of irrigated croplands, which accounted for 14.8% of all irrigated cropland in the country. Because of its semiarid climate condition, crop yields in Nebraska farms are quite sensitive to subtle differences in irrigation scheduling, which, therefore, makes Nebraska an ideal area to test our irrigation scheduling approaches.

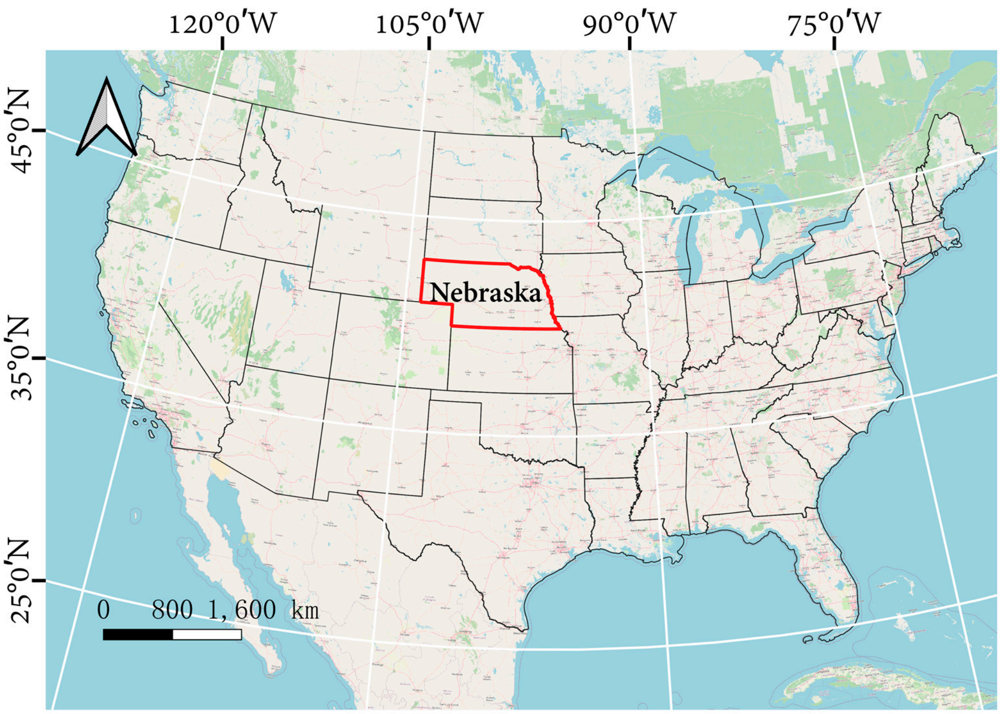
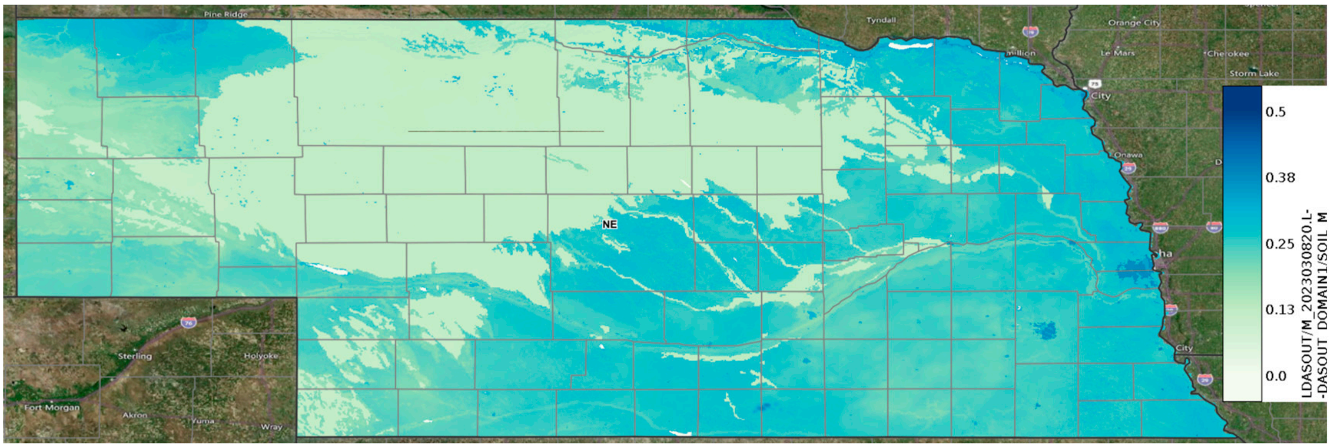


Figure 1. The location of Nebraska.

2.1. Soil Moisture and ET Map

Soil moisture and ET are the key parameters in most irrigation decision-making methods. The HRLDAS generates hourly maps of soil moisture and ET at a spatial resolution of 500 m covering Nebraska from 2019 to the present in a near-real-time manner.

Figure 2a,b show sample maps of the hourly updated HRLDAS soil moisture and the daily ET accumulated from hourly HRLDAS ET, which are visualized on the WaterSmart DIP.



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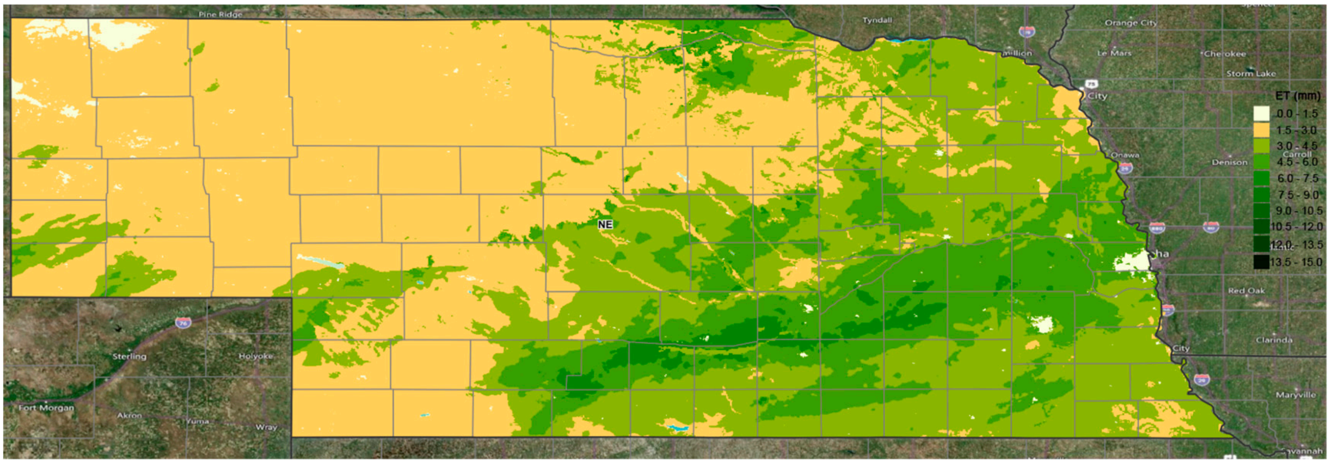

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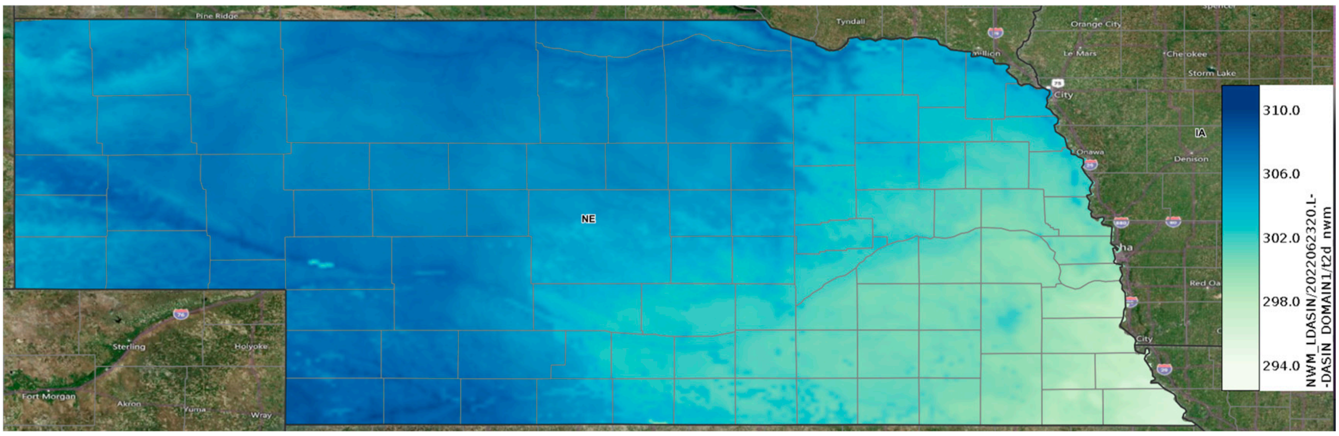

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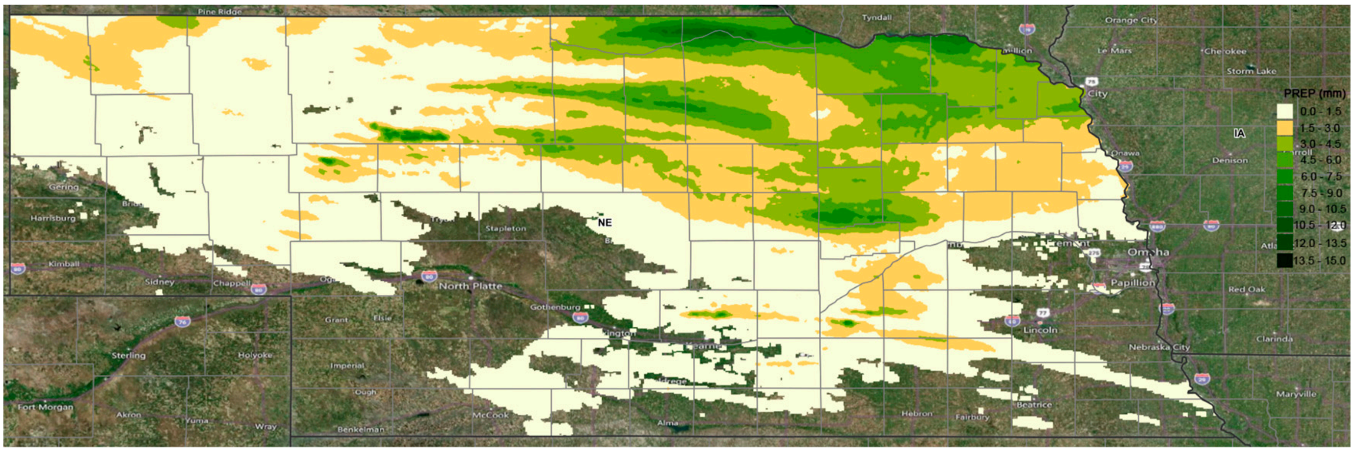
Figure 2. *Cont*.



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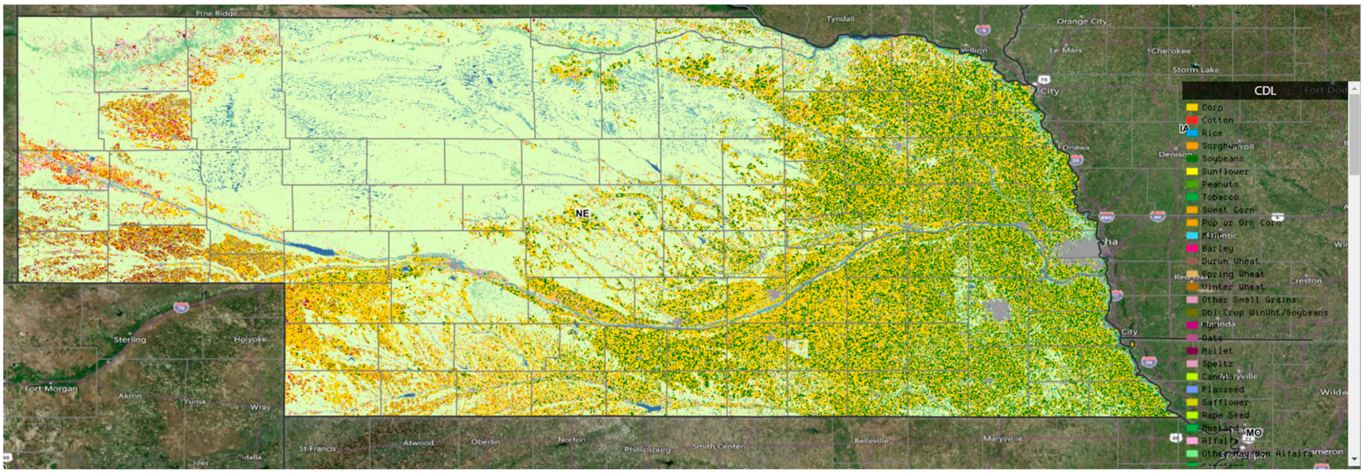


(**e**)

Figure 2. Visualized example maps of used data in Nebraska (from https://geobrain.csiss.gmu.edu/watersmartport/web/ accessed on 13 July 2023). (**a**) Soil moisture; (**b**) ET; (**c**) temperature; (**d**) precipitation; (**e**) CDL.

HRLDAS is the merging of a data assimilation system and a land surface process model. The underlying land model within HRLDAS is the community Noah-Multiparameterization Land Surface Model (Noah-MP LSM) [15]. It uses multiple options for many key land-atmosphere interaction processes affecting hydrology and vegetation to achieve accurate surface energy and water transfer processes. Noah-MP considers the surface water infiltration, runoff, and groundwater transfer and storage. It predicts vegetation growth by combining a photosynthesis model and a carbon allocation model that distinguishes between C3 (e.g., soybean) and C4 (e.g., corn) plants.

The HRLDAS obtained the surface forcing from the National Water Model standard analysis configuration [16]. This configuration used meteorological forcing data sourced from the Multi-Radar/Multi-Sensor System (MRMS) Gauge-adjusted and Radar-only observed precipitation products, along with short-range Rapid Refresh (RAP) and High-Resolution Rapid Refresh (HRRR) data. Additionally, stream-gauge observations from the United States Geological Survey (USGS) were assimilated into the model. The initial values were derived from the North American Land Data Assimilation System (NLDAS) analysis. The HRLDAS has been running from 2019 to the present at 500 m spatial resolution for the Nebraska region, and the output is saved in hourly intervals. The HRLDAS was configured for NLDAS to have 4 soil moisture layers with thicknesses (from top) of 10 cm, 30 cm, 60 cm, and 100 cm, for a total soil column depth of 2 m. For assessing the data quality, the model soil moisture products were compared with site-based soil moisture measurements and gridded soil moisture maps from our previous study [17].

2.2. Meteorological Forcing Data

The weather data used to drive the HRLDAS were obtained from the National Water Model (NWM, https://water.noaa.gov/about/nwm (accessed on 13 July 2023)) [16] and Global Forecast System (GFS, https://www.ncei.noaa.gov/products/weather-climate-models/global-forecast (accessed on 13 July 2023) [18]. Both models provide 8 forcing variables: precipitation rate, surface pressure, shortwave radiation, longwave radiation, u-wind, v-wind, temperature, and specific humidity. These variables were clipped to Nebraska and regridded to a spatial resolution of 500 m. NWM provides near-real-time data while GFS variables are forecasted 4 times a day for the following 120 h. Among the 8 variables, we focused most on the precipitation rate when making an irrigation decision. All these data are visualized and made available to the public on WaterSmart DIP. Figure 2c,d display sample maps of the hourly temperature from NWM and the daily rainfall accumulated from the hourly NWM precipitation variable, respectively.

2.3. Crop Types and Soil Properties

Different crop has a different crop evapotranspiration (ET_c), which requires different amounts of irrigation during the growth process. In this research, crop type is identified using the annually released Cropland Data Layer (CDL) [19,20], which contains crop and other specific land cover classifications obtained using remote sensing for the conterminous United States. A rapid in-season mapping of corn and soybean fields, which are the two major crops in Nebraska, is currently available using historical CDL data [21]. This greatly promotes our irrigation scheduling for an entire state. Figure 2e illustrates the annual CDL layer for the year 2022.

Soil properties are considered to be relatively static conditions for a region and are usually updated annually based on soil surveys. The physical and chemical soil properties considered here include soil texture, electrical conductivity, available water-holding capacity, and permanent wilting point. The UC Davis team has aggregated the current U.S. Department of Agriculture (USDA) National Cooperative Soil Survey (NCSS) soil survey data within 800 m grid cells to generate nationwide soil property maps, and the gridded data products are all available on the web application programming interface (API) of soil properties [22].

3. Automation of the Irrigation Scheduling: The Methodology

When initially introducing a scientific (versus experience-based) irrigation scheduling method to a certain crop field, the ET-WB method proves to be straightforward to implement and demonstrates its effectiveness when field weather data and Food and K_c curves a specific crop recommended by the Agriculture Organization (FAO) for are accessible. The ET-WB method remains feasible even in cases where soil properties are not known, as long as the accumulated daily soil water deficit calculated by ET estimates is promptly replenished. For example, irrigations can be scheduled at regular intervals (e.g., every 3 days or twice a week) to satisfy the soil water deficit calculated by ET estimates [23]. In the ET-WB-based method, the daily soil water deficit is calculated using the basic soil water balance equation. On a daily basis, D_c, the soil water deficit in the root zone on the current day, can be estimated using the following simplified accounting equation:

$$D_c = D_p + ET_c - P - Irr, \tag{1}$$

where D_p is the soil water deficit on the previous day, ET_c is the crop ET for the current data, P is the gross precipitation for the current day, and Irr is the net irrigation amount infiltrated into the soil for the current day.

Irrigation events are scheduled when accumulated D_c exceeds the set threshold, which is the Management Allowed Depletion (MAD) in default. While we can calculate D_c using the water balance equation, it should be noted that D_c represents the discrepancy between the field capacity and current soil water content. Thus, D_c is an estimation of the true deficit in the field, which can be calculated more directly by subtracting the current soil water content from the field capacity of the root zone when the measurement of current soil water content is available.

The ET-WB-based method is more popular than the soil-moisture-based method because determining D_c based on the current soil water content is limited by its dependency on the accuracy and reliability of the soil moisture content readings from soil moisture sensors, which are required to be installed before application in the field. This laborious requirement for farmers hampers the wide application of soil-moisture-based methods. However, if there are accurate measurements of field-scale soil moisture, the soil-moisture-based method is more straightforward. Soil-moisture-based approaches use an Available Water Content threshold (AWC_{th}), whereas the triggering threshold in the ET-WB-based method is defined using MAD. $AWC_{th} = 1 - MAD$ holds for the same field in the same growing season, as both methods describe a single real value, whether it is determined by site-specific field experiments [24] or a default value drawn from FAO-56 [25].

HRLDAS provides ET_0 based on the NWM parameters during the growing season. Thus, daily ET_c and water deficit can be estimated during the growing season. Irrigation is scheduled when the accumulated water depletion exceeds the thresholds we set. The amount of irrigation water is set to refill the soil water content slightly below the field capacity to avoid percolation and increase the WUE. Furthermore, HRLDAS-derived soil moisture at a spatial resolution of 500 m can be directly used in soil-moisture-based irrigation decision making, as it effectively captures the seasonal evolution of soil moisture. Irrigation and yield information of eight corn farms during the 2019 and 2020 growing seasons with its crop growing states is provided by the University of Nebraska-Lincoln. These farm sites are located closely in Nebraska, with a similar size of 800 m $\times$ 800 m; thus, they are influenced by the same climate conditions at most times. The soil texture of these experimental sites is sandy loam, which indicates that they have a similar field capacity and wilting points. As shown in Table 1, corn was planted around the end of April and the beginning of May, and we can observe that more water was irrigated in 2020, whereas their yields in 2019 and 2020 are similar.

Table 1. Total irrigation amount (mm) and yield (ton/ha) in the 8 study sites.

Site Name	Planting Date	Total Irrigation Amount (mm)	Yield (ton/ha)
East	2 May 2019	181.6	13.5
Home	4 May2019	191.5	13.9
Kelly	25 April 2019	206.8	13.4
Links	24 April 2019	198.1	12.8
North	8 May 2020	251.0	13.3
Home	1 May 2020	278.4	13.6
Kelly	1 May 2020	278.4	13.7
Johnson	25 April 2020	276.4	13.9

To simulate the dynamic nature of crop water demands, an analysis of the crop growth stage and identification of patterns in them are necessary. GDD, or Growing Degree Days, is a measure of heat accumulation used in agriculture to determine the crop growth stages [26,27]. It is based on the principle that plants grow and develop in response to temperature, with warmer temperatures generally accelerating their growth. By tracking the accumulation of GDD over time, farmers and researchers can determine when a crop reaches key growth stages, such as emergence, flowering, and maturity. This information can be used to plan irrigation, fertilizer application, and other management practices, and to predict yield and harvest timing. Four typical crop growth stages are identified in this paper based on GDD: initial stage, development stage, mid-season stage, and late-season stage.

Based on the growing state dates and temperature record during the growing season, the accumulated GDD in different stages of corn in the test fields are calculated. These accumulated GDD values are further used to determine the start point and duration of the four stages in other fields without information on crop state dates [28].

The main focus of this study is to schedule irrigation based on model-simulated ET and soil moisture and evaluate its water-saving effect without harming crop yield. The FAO developed a crop growth model, AquaCrop [29,30], which can estimate crop yield in response to available water. Compared to other crop growth models, only a few parameters are required for yield estimation in AquaCrop. It simulates plant water stress (soil moisture) based on the input weather and ET data. Integrating AquaCrop as a yield estimator, it is possible to determine four thresholds in four crop stages instead of a single fixed threshold as in traditional methods. Although several studies have demonstrated that AquaCrop is a reliable tool capable of reasonably accurately predicting both total biomass and final yield under various irrigation strategies, ranging from no water stress to mild or severe water stress [7,31–33], it is important to note that the accuracy of the yield estimates and irrigation recommendations depend on the accuracy and representativeness of the model inputs, including weather data, soil characteristics, crop parameters, and management practices [34]. Therefore, it is important to carefully validate the inputs and outputs of the model before relying on them to make irrigation decisions. One approach to validation is to compare the simulated soil moisture (SM) data from AquaCrop with independent data from other models to assess the accuracy and reliability of the AquaCrop output. AquaCrop is first calibrated for these farms in Table 1 to acquire good-quality yield estimations and then used to simulate the yields of these farms when different irrigation schedules are derived. To validate the accuracy and reliability of the AquaCrop model, we use the same inputs as that of HRLDAS to compare their soil moisture outputs, assuming there is no irrigation during the season.

Forecasted rainfall is also considered to determine whether and how much irrigation water should be applied. Irrigation is unnecessary if there is unexpected rainfall in the near future. This risk of wasting water due to the uncertainties in future weather conditions could be mitigated by integrating short-term rainfall forecasts into the model. The incorporation of rainfall forecasts into water management can provide farmers with valuable information on upcoming weather patterns, allowing them to adjust their irrigation schedules accordingly and avoid overwatering. This approach not only saves water but also reduces the risk of crop damage due to waterlogging, improves soil health, and reduces the energy consumption associated with pumping and distribution. In this study, the rainfall events over consecutive 5 days within the crop growth period are considered in calculating the total rainfall. The daily rainfall contributes differently to the total rainfall, with a decay factor of 0.9. Based on this, the irrigation amount is rescheduled by reducing the possible total rainfall in the weather forecast. If the total rainfall amount is larger than the originally scheduled irrigation amount, the irrigation event is postponed to a later date.

In this research, we determined the thresholds of irrigation scheduling for four stages in response to fluctuations in crop water demands. To accomplish this, we followed three main steps. First, we randomly selected 100 sets of thresholds for each stage. Second, we used these sets of thresholds to obtain a starting point with the maximum yield. Finally, we optimized the thresholds using the downhill simplex algorithm for the minimum irrigation water for each stage. The downhill simplex algorithm [35] was chosen because it is a simple and efficient optimization technique that does not require knowledge of the gradient of the function being optimized. This method can account for complex relationships between soil moisture and crop yield, which may be difficult to capture when using traditional single fixed thresholds. The resulting thresholds were then used to inform irrigation decisions and optimize water use efficiency. By following these steps, we were able to identify optimal thresholds for each stage of irrigation scheduling, which can help improve crop yield and reduce water waste. Rainfall forecasts from the GFS were further integrated into the irrigation scheduling to improve the efficiency of water usage in irrigation. The overall flowchart is shown in Figure 3.

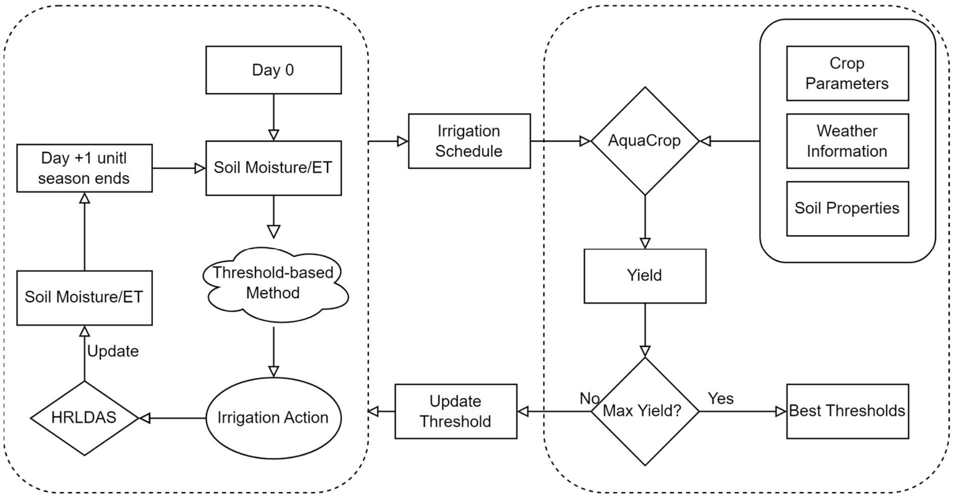


Figure 3. The flow chart of threshold optimization in irrigation scheduling.

4. Results and Discussion

4.1. Validation of AquaCrop

Validating AquaCrop is crucial for reliable yield estimations and irrigation recommendations. Figure 4 illustrates the comparison result of eight corn farms between the model simulations and AquaCrop-simulated soil moisture. At the same site, AquaCrop generated very similar soil moisture to HRLDAS soil moisture, with an average Root Mean Square Error (RMSE) of around 0.013 and an average R2 of around 0.77 (Table 2). This demonstrates the ability of AquaCrop to simulate soil moisture accurately and ensure the reliability of yield estimation. With farmers reporting integrated irrigation information, the yields for the eight study sites were estimated by AquaCrop and compared with actual yields, as shown in Table 3.

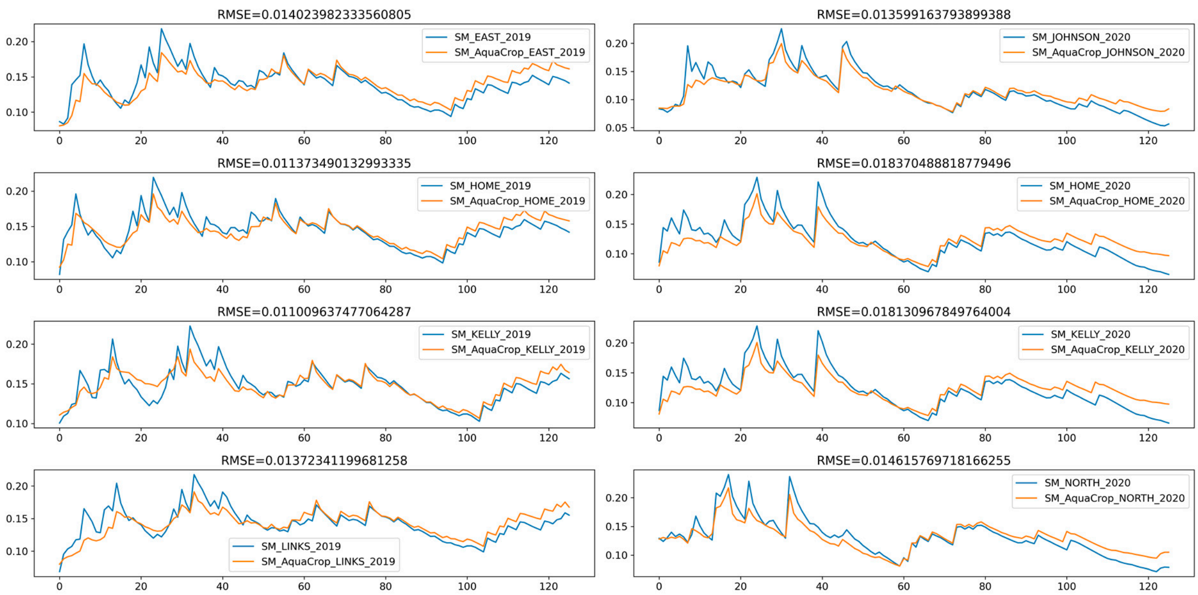


Figure 4. Simulated soil moisture from AquaCrop (orange) and HRLDAS soil moisture (blue) for the 8 study sites in 2019 (**left**) and 2020 (**right**) growing season.

Table 2. Accuracy of soil moisture retrieved from AquaCrop compared to HRLDAS products. RMSE (root mean square error) is in m3/m3. R2 is the correlation coefficient.

Year and Site	RMSE	R2
2019 East	0.0140	0.67
2019 Home	0.0114	0.76
2019 Kelly	0.0110	0.77
2019 Links	0.0137	0.66
2020 North	0.0146	0.87
2020 Home	0.0184	0.75
2020 Kelly	0.0181	0.75
2020 Johnson	0.0136	0.92

Table 3. Yield estimations from AquaCrop and actual yields, both in ton/ha.

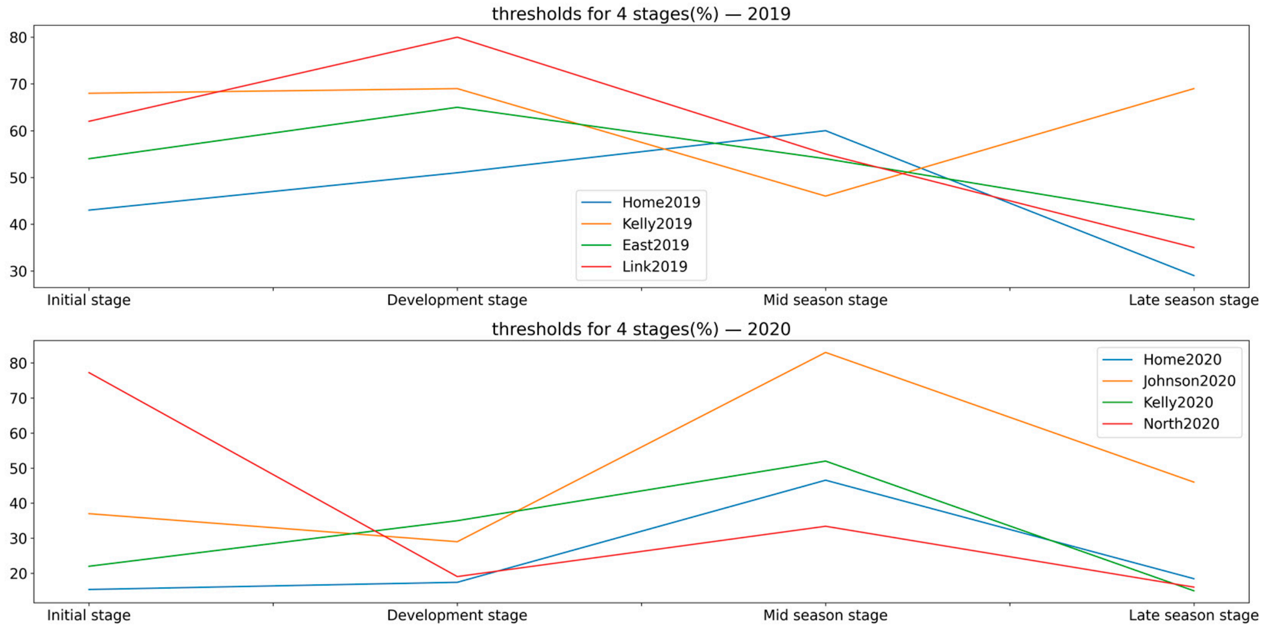
Year and Site	Actual Yield	Estimated Yield
2019 East	13.5	13.6
2019 Home	13.9	14.0
2019 Kelly	13.4	13.3
2019 Links	12.8	12.9
2020 North	13.3	13.4
2020 Home	13.6	13.6
2020 Kelly	13.7	13.8
2020 Johnson	13.9	13.5

Soil moisture in 2019 was generally higher than that in 2020 during the growing season, as shown in Figure 4. This indicates that the weather was drier in 2020 than in 2019, possibly because there was more rainfall in 2019. The RMSE in Table 2 was smaller in 2019 than in 2020, but R2 was slightly lower in 2019, which indicates that AquaCrop simulates the time variation of the soil moisture fluctuations better in a drier year, but may be inferior in capturing the absolute magnitude of soil moisture. High accuracy of yield estimation is observed in Table 2, while in most cases AquaCrop overestimates yield slightly, which may be associated with its feature in modeling crop growth and yield under different levels of plant water stress, assuming that other conditions are all perfect (for example, nutrient management and pest control).

Overall, the validation of the simulated soil moisture and estimated yield demonstrates that AquaCrop can provide an accurate yield estimation when reliable inputs are available. Thus, we can assess our irrigation methods based on yield estimation and optimize thresholds for triggering irrigation to maximize the yield.

4.2. Threshold-Based Irrigation Scheduling

Four crop stages are first determined by the accumulated GDD, and four different thresholds are set to represent the dynamic nature of crop water demands. The ET-WB-based method is first applied based on the HRLDAS-derived daily ET. Figure 5a shows the optimized thresholds in different crop stages for the eight study sites. Overall, the thresholds fluctuate around the FAO recommended value of 50% in the wet season. In the drier season (2020), thresholds are generally lower (float around 40%) than those in the wetter season, and the water demand is highest in the development stage, whereas in the wet season, crops demand more water in the mid- and late-season stages. This is reasonable because, in a dry weather pattern, a lower threshold guarantees timely and more frequent irrigation, which can efficiently prevent crops from experiencing water stress.



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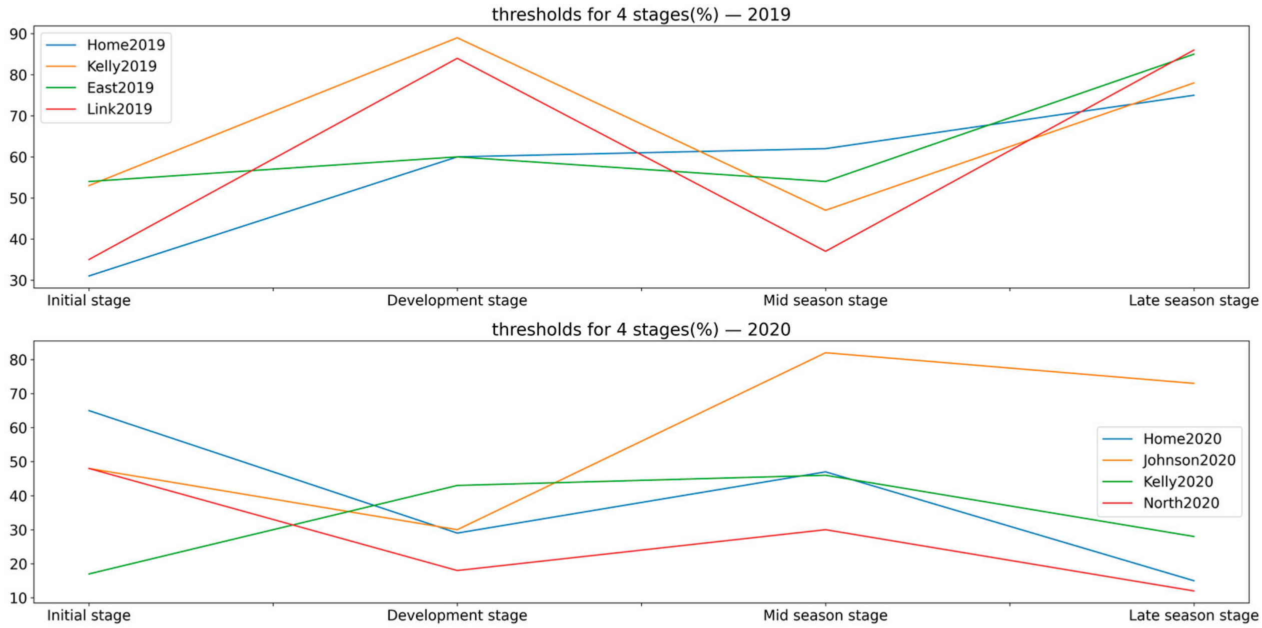


(**b**)

Figure 5. Optimized thresholds in (**a**) ETWB and (**b**) soil moisture irrigation scheduling.

With the thresholds determined, irrigation is scheduled based on the water deficit. Compared to the actual yield and total irrigation amount, our irrigation schedule can save roughly 10% of the total irrigation water amount while maintaining a similar yield in the dry season when water demands are high during crop growth, whereas in the wet season with less water demands, roughly 20% of irrigation water can be saved, as shown in Table 4 and Figure 6a. The highest conservation percentage of irrigation water was observed in the Kelly site in 2019, with a slightly reduced yield. The decreased yield may be related to the lowest scheduled amount of irrigation.

Table 4. Yield estimations and total irrigation amount estimated from ET-WB-based and soil moisture (SM)-based irrigation schedule, as well as the water saved compared with the actual irrigation situation.

	Year	2019				2020			
	Site	**East**	**Home**	**Kelly**	**Links**	**North**	**Home**	**Kelly**	**Johnson**
Actual	Yield	13.5	13.9	13.4	12.8	13.3	13.6	13.7	13.9
	Irrigation Amount	181.6	191.5	206.8	198.1	251.0	278.4	278.4	276.4
ET-WB	Yield	13.85	14.2	13.3	12.9	13.3	13.8	13.9	13.7
	Irrigation Amount	149.3	146.1	137.6	157.6	219.1	245.6	249.0	244.8
	Water Saved (%)	17.8	23.7	33.5	20.4	12.7	11.8	10.6	11.4
SM	Yield	13.8	14.1	13.3	12.8	13.3	13.7	13.9	13.8
	Irrigation Amount	137.6	133.3	129.5	147.6	215.0	245.1	254.9	256.4
	Water Saved (%)	24.2	30.4	37.4	25.5	14.3	12.0	8.4	7.2

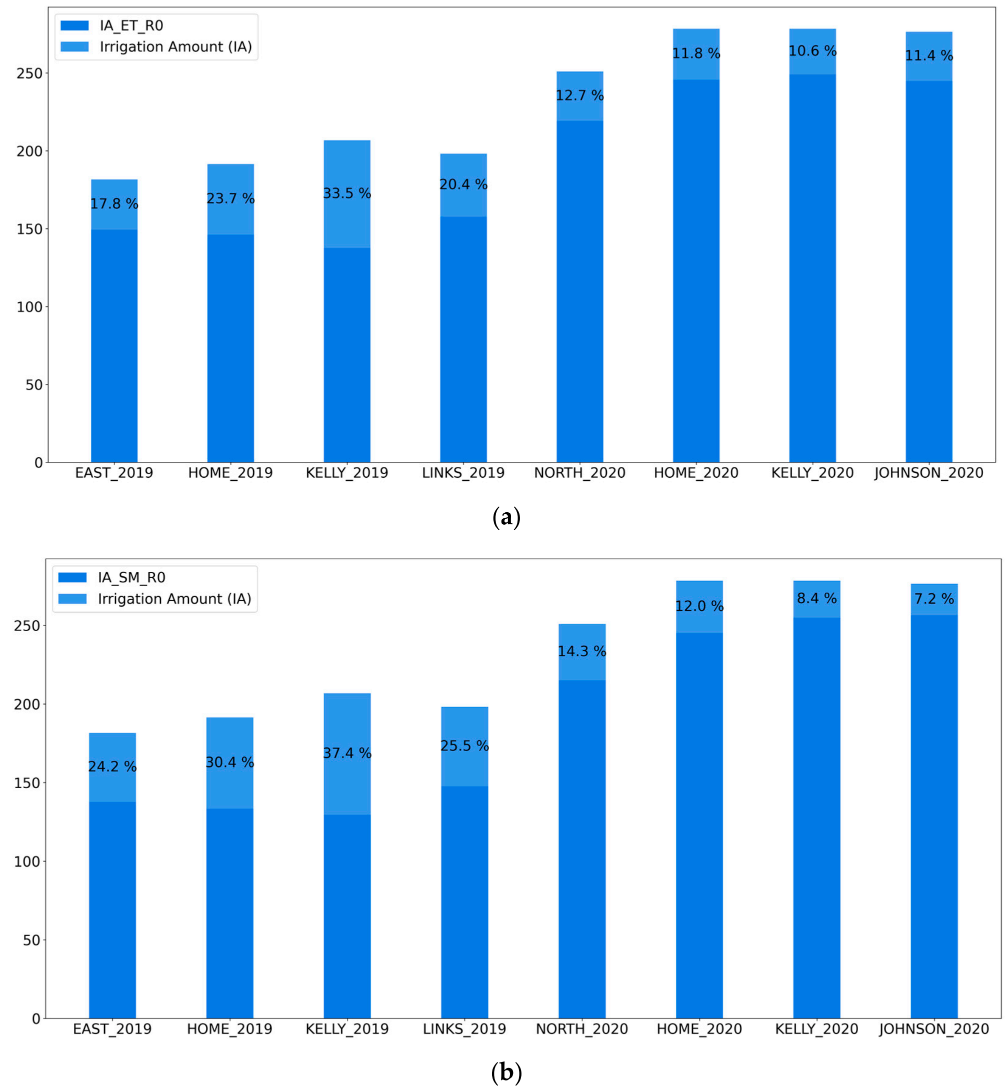


Figure 6. Irrigation amount (mm) saved compared with actual irrigation amount ('IA') using (**a**) ET-WB ('IA_ET_R0′) and (**b**) soil moisture ('IA_SM_R0′) irrigation schedule methods. The percentage number in the figure denotes the water saved compared with the actual irrigation amount.

The same optimization of the thresholds is implemented using the HRLDAS soil moisture, and the results are presented in Figure 5b. The threshold ranges and their tendencies are very similar to those of the ET-WB-based method. The only difference is that in the wet season (2019), the soil-moisture-based method indicates high thresholds in the late season stage, which may be associated with a low water demand from the crop in this stage. This is reasonable because, with adequate rainfall in the wet season, the crop might not require much water during the late season stage, whereas, in the dry season, not enough water supply during the late season may cause yield loss. The low thresholds in the wet season that we obtain from the ET-based method might be caused by accumulative errors in daily soil water deficit calculation.

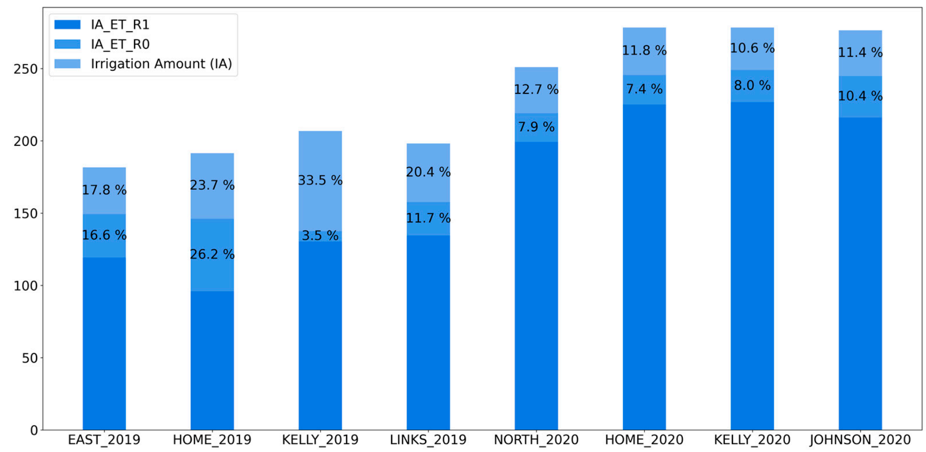
Similar to the ET-based method, the yield and total irrigation amount are then estimated using the AquaCrop model based on the optimized thresholds (Table 4, and Figure 6b). The result is quite consistent with the previous one in the ET-based method, where more water is conserved in the wet season compared to that in the dry season. The slight difference is that in the wet season, although less irrigation water is applied, the estimated yield also decreases a little, whereas, in the dry season, the soil-moisture-based method schedules more irrigation to be applied, and the yield remains at a similar level. Overall, both the ET-WB-based method and the soil-moisture-based method utilizing model simulations of ET and soil moisture exhibit good performance, generating acceptable results for saving water and preventing yield loss.

4.3. Irrigation Scheduling Integrating Short-Term Rainfall Forecasts

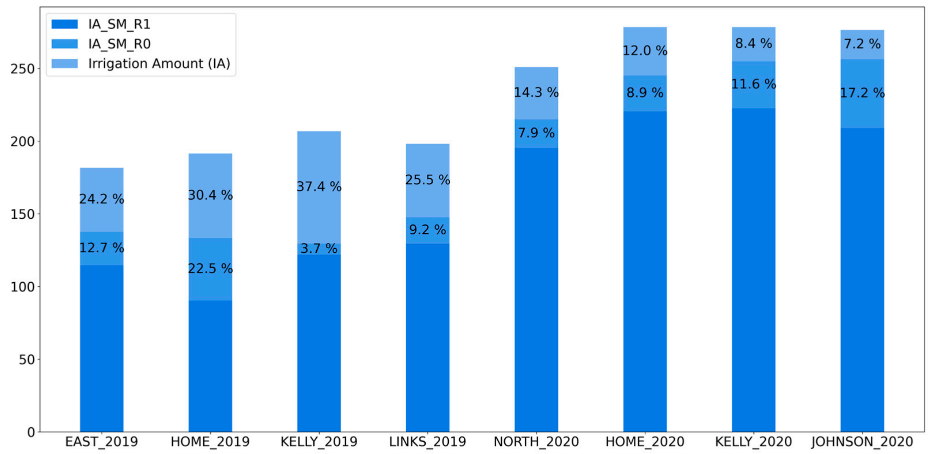
Compared to conventional irrigation scheduling, integrating rainfall forecasts can further save irrigation water without significant yield loss. Figure 7 shows the extra amount of water saved when rainfall forecasts are integrated into irrigation scheduling. An additional 10% of irrigation water is saved during the dry season, and much more of that could be saved in the wet season, totaling around 40%. The final yield from both the ET-WB-based method and the soil-moisture-based method is not significantly reduced (Table 5), although a slight yield reduction of around 0.1~0.2 ton/ha is observed. A higher amount of irrigation water in the wet season can be conserved when short-term rainfall forecasts are considered higher, and more frequent rainfall is the basic feature of wet weather patterns. Even so, integrating the rainfall forecasts still saves a considerable amount of irrigation water in the dry season, which demonstrates its necessity and reliability in irrigation scheduling.

4.4. Future Work

Although the thresholds are optimized for achieving the highest yield and the irrigation scheduling based on these thresholds is proved again in this study to be efficient in water saving, no significant yield improvement is observed. This may be associated with the inherent feature of threshold-based methods that basically determine irrigation time and amount based on the current status; the long-term return of yield is not in their scope. Irrigation scheduling methods based on artificial intelligent algorithms, such as reinforcement learning and deep neural networks, are a good choice for maximum seasonal yield or economic return. Meanwhile, although the irrigation scheduling is automated due to the availability improvement of high-resolution soil moisture and ET data in this study, crop information such as crop planting or emergence date still relies heavily on farmers' reports or inputs. This hampers the promotion of popularizing scientific irrigation scheduling to a larger region and a wider range of users. We used GDD to roughly estimate the crop stages, but this may be unavailable or inaccurate when the local crop stage date and temperature records are missing. Thus, integrating technologies, such as within-season crop emergence date generation [36,37] into the automation process of irrigation scheduling, is a direction for future research.



(**a**)



(**b**)

Figure 7. Irrigation amount (mm) saved using (**a**) ET-WB-based irrigation schedule method, where 'IA_ET_R1' is the irrigation amount when rainfall forecasts are integrated, and 'IA_ET_R0′ is the irrigation amount when rainfall forecasts are not integrated; (**b**) soil-moisture-based irrigation schedule method, where 'IA_SM_R1' is the irrigation amount when rainfall forecasts are integrated, and 'IA_SM_R0′ is the irrigation amount when rainfall forecasts are not integrated. The percentage number in the figure denotes the water saved using the different methods.

Table 5. Yield estimations and total irrigation amount estimated from ET-WB-based and soil moisture (SM)-based irrigation schedule, as well as the water saved compared with the actual irrigation situation using the short-term rainfall forecasts.

	Year	**2019**				**2020**			
	Site	**East**	**Home**	**Kelly**	**Links**	**North**	**Home**	**Kelly**	**Johnson**
Actual	Yield	13.5	13.9	13.4	12.8	13.3	13.6	13.7	13.9
	Irrigation Amount	181.6	191.5	206.8	198.1	251.0	278.4	278.4	276.4
ET-WB	Yield	13.6	14.1	13.3	12.8	13.3	13.7	13.6	13.7
	Irrigation Amount	119.2	95.9	130.3	134.4	199.2	225.0	226.7	216.1
	Water Saved (%)	34.4	50.0	37.0	32.2	20.6	19.2	18.6	21.8
SM	Yield	13.6	14.0	13.3	12.8	13.3	13.6	13.6	13.7
	Irrigation Amount	114.6	90.3	121.8	129.4	195.2	220.4	222.5	208.9
	Water Saved (%)	36.9	52.8	41.1	34.7	22.2	20.8	20.1	24.4

5. Conclusions

Irrigation is an integral part of agriculture. This study proposed an automated data-driven irrigation scheduling approach that utilized HRLDAS soil moisture and ET products, which are generated in a near-real-time manner. Simulations and validations were performed at eight experiment sites in Nebraska. The findings of this study demonstrate the potential of using model simulations in conjunction with threshold-based irrigation scheduling approaches to guide irrigation management and achieve water savings without yield loss. Four dynamic thresholds were determined using a downhill simplex algorithm to represent the varying water demands of crops at different growth stages. AquaCrop was validated to ensure reliable yield estimations before the optimization of the thresholds. The results indicate that all the approaches were effective in reducing water consumption while maintaining crop productivity. Interestingly, the analysis suggests that the potential for water saving may vary depending on the season, with a greater potential for savings in wet seasons compared to dry seasons, with an approximate saving of up to 10%.

To further optimize the water-saving potential of the approach, rainfall forecasts were integrated into the irrigation scheduling. The results indicated that the integration of rainfall forecasts led to even higher water savings, with an additional 20% reduction in water consumption during wet seasons and a 10% more reduction during dry seasons compared to traditional irrigation practices. This approach not only saves water but also helps to avoid invalid irrigation just before subsequent rainfall, which can improve crop health and reduce waterlogging risks. The findings of this study have significant implications for the sustainable management of water resources in agriculture and highlight the importance of incorporating model simulations and weather forecasting into irrigation scheduling.

Author Contributions: Conceptualization, L.D.; Data curation, H.Z. and C.Z.; Formal analysis, H.Z. and L.G.; Funding acquisition, L.D.; Investigation, L.G. and L.L.; Methodology, H.Z.; Project administration, L.D.; Supervision, L.D.; Validation, H.Z. and L.L.; Writing—original draft, H.Z.; Writing—review and editing, H.Z., L.D. and C.Z. All authors have read and agreed to the published version of the manuscript.

Funding: This research was supported by a grant from NSF (Grant #1739705, PI: L.D.).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Publicly available datasets were analyzed in this study. These data can be found here: https://geobrain.csiss.gmu.edu/watersmartport/, accessed on 10 May 2023.

Conflicts of Interest: The authors declare no conflict of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript; or in the decision to publish the results.

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