Model-Based Deficit Irrigation of Maize in Kansas

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MODEL-BASED DEFICIT IRRIGATION OF MAIZE IN KANSAS

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ABSTRACT. *Maize is the dominant irrigated crop in Kansas. In recent years, as a result of declining groundwater levels in the Ogallala aquifer and diminished well capacities, farmers are turning to deficit irrigation strategies. This study demonstrates the potential of model-based optimization for determining adequate soil water depletion levels. CERES-Maize was used as surrogate crop, while the AquaCrop model was used in an optimization procedure that determined the optimal water depletion levels. A multi-objective optimization framework was used to determine several combinations of optimal water depletion levels based on ten years of historical weather, and these combinations were tested using an additional 50 years of historical weather. The results show that, although imperfect modeling and weather fluctuations caused the actual yield to be different from the target yield, the fluctuations around the multi-year averages were not significantly larger when testing the irrigation schedule with the CERES-Maize model than when testing it with the AquaCrop model that had been used to develop the irrigation schedule.*

Keywords. *AquaCrop, Center-pivot irrigation, CERES-Maize, Multi-objective optimization.*

Groundwater levels in the Ogallala aquifer, which is the main source of irrigation water in Kansas and other parts of the U.S. South and Central High Plains, have been declining due to water withdrawals exceeding mean annual recharge (McGuire, 2004). Farmers with diminished well capacities that cannot meet full crop water needs are turning to limited or deficit irrigation strategies. In addition to hydrologic constraints, new institutional water policies that limit the amount of water that can be pumped, such as the Local Enhanced Management Areas (LEMA) and Water Conservation Areas (WCAs), have also led farmers to adopt deficit irrigation (Rogers et al., 2016). The new water policies have been driven by the desire to extend the usable life of the Ogallala Aquifer.

Maize is the dominant irrigated crop in Kansas. For example, of the 1,166,017 ha irrigated in 2015, 605,005 ha were under maize, representing 52% of all total irrigated land in 2015 (KDA, 2016). The interest in maize can be attributed to several factors, including high water productivity compared to other grain crops and high economic value due to demand from cattle feeders and ethanol producers. In water-limited environments, Schneekloth et al. (2004) recommended adoption of the following practices for maize: reduce the amount of land irrigated in order to meet full crop water needs, irrigate more land under deficit irrigation, rotate maize with winter crops, reduce soil water evaporation through residue management and reduced tillage, implement irrigation scheduling targeting critical growth stages, and timely termination of irrigation toward the end of the growing season to allow the crop to use stored soil water. Kisekka et al. (2017) noted that finding a mix of deficit irrigation strategies that optimize water productivity and economic returns for a majority of years under erratic climatic conditions is not trivial, and they demonstrated how crop models could be applied to optimize irrigation water management.

Over 90% of irrigated land in Kansas and other areas of the U.S. Central High Plains is under center pivots (Rogers and Lamm, 2012). The main source of water to center pivots is groundwater, and the major constraints to irrigation scheduling are institutional water policies and irrigation capacities. Howell et al. (2012) provided a review of irrigation capacity and its importance in determining irrigation frequency. To minimize evaporation losses, most farmers in the U.S. South and Central High Plains apply at least 25 mm during each irrigation event. For center pivot systems with diminished well capacities, this means that the center pivot takes several days to complete one revolution. Farmers using subsurface drip irrigation (SDI) are able to apply smaller amounts more frequently, but the percentage of land currently under SDI is limited.

Crop models provide a fast and inexpensive way to assess deficit irrigation strategies. Numerous studies have demonstrated the use of crop simulation models for optimizing irrigation scheduling (Rogers and Elliott, 1989; Rinaldi 2000; Bergez et al., 2001; Nijbroek et al., 2003; Saseendran et al., 2008; Cai et al., 2011; DeJonge et al., 2011, 2012; Linker et al. 2016; Kisekka et al., 2016; Araya et al., 2017). Rogers and Elliott (1989) applied the cost/loss (C/L) risk analysis

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ratio to determine the need for irrigation of grain crops in the Oklahoma Panhandle and reported that the C/L ratio resulted in decreasing water application as irrigation cost increased or crop value decreased, making this a useful approach under limited water compared to purely biophysical irrigation scheduling triggers such as evapotranspiration or soil water. Rinaldi (2000) reported successful use of the EPIC model for optimizing irrigation scheduling for sunflower in southern Italy. Bergez et al. (2001) developed MODERATO, a crop simulation model that was linked to a decision model for optimizing maize irrigation scheduling in France. They noted that determining suitable thresholds to optimize yield or other environmental aspects proved difficult and recommended integrating biophysical crop simulation models and decision tools with optimization algorithms. Nijbroek et al. (2003) used the CROPGRO-Soybean crop simulation model for determining optimal irrigation schedules for variable-rate irrigation zones based on 25 years of historical weather data in the southeast Coastal Plain. They showed that variable-rate irrigation (applying different amounts to meet the crop water needs of each zone) was more profitable than applying the same amount uniformly to all zones. Saseendran et al. (2008) applied the CERES-Maize model (Jones et al., 2003) to optimize irrigation scheduling based on growth stage for maize in northeastern Colorado. DeJonge et al. (2011, 2012) also reported successful use of CERES-Maize for optimizing irrigation scheduling for maize in Colorado. Cai et al. (2011) developed a framework for real-time optimization of irrigation scheduling based on the soil-water-atmosphere-plant (SWAP) biophysical model, an optimization algorithm and NOAA's probabilistic forecasts of rainfall. They tested the framework using five years of data from Mason County, Illinois, and reported that crop simulation-optimization irrigation scheduling based approaches were superior to simple rule-based irrigation scheduling.

More recently, Linker et al. (2016) used the AquaCrop model and optimization procedures to determine optimal deficit irrigation strategies for cotton, potato, and tomato. Kisekka et al. (2016) used three years of experimental data, the CERES-Maize model, and long-term weather data to generate optimum deficit irrigation scheduling recommendations for maize in Kansas. Araya et al. (2017) used the Agricultural Production Systems sIMulator (APSIM) model to develop irrigation scheduling recommendations based on growth stage for winter wheat in Kansas.

Most of the prior studies on optimizing irrigation scheduling using crop simulation models focused on retrospective evaluation of irrigation scheduling options based on experimental data and long-term weather data (Saseendran et al., 2008; DeJonge et al., 2011; Araya et al., 2017). Very little work is documented in the literature on using crop simulation models as tactical in-season irrigation scheduling decision support tools (Linker et al., 2016). In commercial production systems, soil water sensors or evapotranspiration monitoring are typically used to guide irrigation scheduling, but the uncertainty associated with soil water sensor measurements has limited their wide-scale adoption. Similarly, the uncertainty associated with crop coefficients under deficit irrigation has also impacted the adoption of evapotranspiration-based irrigation scheduling.

Study Scope and Objective

The objective of the present study was to investigate the potential of model-based deficit irrigation scheduling under conditions as realistic as possible, i.e., assuming that only an imperfect crop-soil model and historical weather data were available to determine the irrigation schedule. Note, however, that this study considered only the effect of soil water storage on yield, while additional factors, particularly nutrient availability, were considered optimal. The two drawbacks commonly mentioned when considering model-based irrigation scheduling are that (1) this approach relies on an imperfect soil-crop-atmosphere model and (2) the future weather cannot be forecasted with high accuracy. This article presents a systematic investigation of the impact of these two factors using maize in Kansas as a case study. The impact of model imperfectness was investigated by calculating irrigation schedules with one model and testing them using a different model. Conceptually, this second model should be viewed as a replacement for the actual crop because conducting actual experiments for the extended period considered here (60 years) is not feasible. Clearly, this second model is also imperfect. However, for the sake of this study, the important point is that the two models differ, rather the accuracy of each model by itself. Irrigation schedules were obtained using an optimization approach inspired by the approach described by Linker et al. (2016) in which the AquaCrop model was embedded. The Root Zone Water Quality Model 2 (RZWQM2) model with the embedded DSSAT-CSM CERES-Maize crop growth module was used as the crop surrogate for testing these irrigation schedules. Both models were simulated with daily time steps. The impact of weather fluctuations was investigated using ten years of weather for determining the irrigation schedules and then testing these irrigation schedules on an additional 50 years.

Materials and Methods

CERES-Maize

RZWQM2 (ver. 4.0) with the embedded DSSAT-CSM CERES-Maize crop growth module has been calibrated and validated using experimental data, as reported by Kisekka et al. (2017). A more detailed description of RZWQM with embedded CERES-Maize is provided by Ma et al. (2006). Cultivar coefficients for maize in western Kansas and other soil physical and hydraulic parameters were reported by Kisekka et al. (2017). In the present study, this model was used to simulate crop development and yield response to various irrigation schedules. For all simulations, planting was done on May 5 at a seeding rate of 76,000 seeds ha^{-1} and 76 cm row spacing, and planting depth was 5 cm. Fertilizer was applied as surface broadcast preplant at a rate of 269 kg N ha^{-1} as urea-ammonium nitrate.

AquaCrop

AquaCrop is a water-driven model distributed and supported by FAO that offers a good compromise between accuracy and simplicity. The AquaCrop package includes sets of default parameter values for various soils and crops (including maize), but the user is expected to perform local model calibration. A detailed description of the model's conceptual structure, inputs, and outputs is provided by Raes et al. (2009). In the present study, simplistic calibration of AquaCrop was performed using a small database generated with the CERES-Maize model. This database was created by running the CERES-Maize model with 20 irrigation treatments and the weather data recorded in 2010. The irrigation treatments were obtained using the default AquaCrop maize model and the multi-objective optimization procedure described by Linker and Sylaios (2016). The AquaCrop model (growing degree days version) was run with the same irrigation treatments, and adjustments of parameter values were done by trial and error until the agreement between CERES-Maize and AquaCrop simulated yields was deemed acceptable. This trial-and-error approach was preferred over more rigorous approaches based on sensitivity analysis and error minimization (e.g., Ioslovich et al., 2004; Linker et al., 2004) for two reasons: (1) in practice, the AquaCrop model should be calibrated using actual crop measurements from field experiments, and it seems unlikely that the quality and frequency of these measurements would be sufficient for applying sensitivity-based approaches; and (2) we did not wish to achieve an unrealistically good agreement between CERES-Maize (surrogate for the actual crop) and the AquaCrop model used to develop the irrigation strategies, which would have voided the analysis related to the robustness of the results.

OPTIMIZATION

From a phenology point of view, the maize growing season is traditionally split into 12 periods (table 1). For optimization purposes, some of the shortest periods were merged, resulting in only nine periods. Each of these periods was associated with a (constant) water depletion level in the root zone at which irrigation would be triggered. Following current practices, each irrigation event consisted of 25 mm. Deficit irrigation (DI) thresholds were determined by solving the multi-objective problem: maximize yield and minimize irrigation. The computations were performed using the algorithm of Herrero et al. (2007) in Matlab 2016a with AquaCrop v41.

Multi-Objective Optimization

The weather data recorded in the years 2000-2009 were used to determine optimal irrigation strategies. Two optimization approaches, which can be viewed as special cases of implicit stochastic optimization and explicit stochastic optimization (Labadie, 2004), were investigated:

Approach A: Single-year optimization

In this approach, the DI threshold combinations were optimized separately for each year, namely:

$$\text{Find } (t_1, t_2, t_3, t_4, t_5, t_6, t_7, t_8, t_9) \qquad (1)$$

$$\text{such that } (-Y, n) \rightarrow \min$$

where t_1 to t_9 are the depletion levels at which irrigation is triggered in periods 1 through 9, Y is the yield predicted by AquaCrop, and n is the number of irrigation events (which is a direct outcome of the irrigation thresholds).

The optimization problem defined in equation 1 was solved ten times, each time using historical weather from a different year. For each year, solving equation 1 yielded a number of [yield, seasonal irrigation] combinations that were optimal in the sense that, for each combination, yield could be increased only by increasing irrigation (the so-called Pareto front). The sequence of DI thresholds corresponding to each of these combinations was then tested on all ten years, and the performance of each sequence was quantified in terms of the average yield and seasonal irrigation.

Approach B: Multi-year optimization

In this approach, the DI threshold sequence was optimized simultaneously for all ten years, namely:

$$\text{Find } (t_1, t_2, t_3, t_4, t_5, t_6, t_7, t_8, t_9) \qquad (2)$$

$$\text{such that } \left(-\frac{\sum_{i=1}^{N} Y_i}{N}, \frac{\sum_{i=1}^{N} n_i}{N} \right) \rightarrow min$$

where N is the number of years ($N = 10$), and subscript i has been added to emphasize that yield and irrigation are now calculated for all N years.

Operational Constraints

Because, in practice, water delivered by a center pivot has an irrigation frequency that is constrained by irrigation capacity, this limitation had to be included in the optimization procedure. There is a wide range of irrigation capacities, depending on well yield. In the present study, as an example, we assumed a limited well capacity of 76.3 m^3 h^{-1} irrigating a typical area of 51 ha, which is common in the U.S. High Plains. This system would require seven days to complete a full rotation applying a depth of 25 mm. Accordingly, a seven-day gap between irrigation events was imposed when solving the optimization problems (eqs. 1 and 2). This was achieved in the following manner. At each iteration:

1. An AquaCrop simulation was run using the DI threshold combination under investigation, and the corresponding irrigation schedule was extracted from the output file.
2. The irrigation schedule was scanned iteratively (starting at the first irrigation event on day D), and any event planned within days D to D+6 was delayed to day D+7.
3. When no more irrigation events needed to be rescheduled,

Table 1. Phenological growth stages of maize.

Growth Stage	Days after Emergence From	Days after Emergence To	Period Length (days)	Optimization Period
-	Sowing	0	Variable	
VE-V3	1	11	11	1
V4-V5	12	18	7	
V6-V11	19	28	10	2
V12-V14	29	42	14	3
V15-V18	43	53	11	4
VT (tasseling)	54	58	5	5
R1 (silking)	59	61	3	
R2 (blister)	62	73	12	6
R3 (milk)	74	81	8	7
R4 (dough)	82	87	6	
R5 (dent)	88	97	10	8
PM (maturity)	98	115	18	9

the updated irrigation schedule was saved as the AquaCrop irrigation file.

4. A new AquaCrop simulation was run using the updated irrigation file, and the output of this simulation was associated with the DI threshold combination under investigation.

Testing with AquaCrop and CERES-Maize

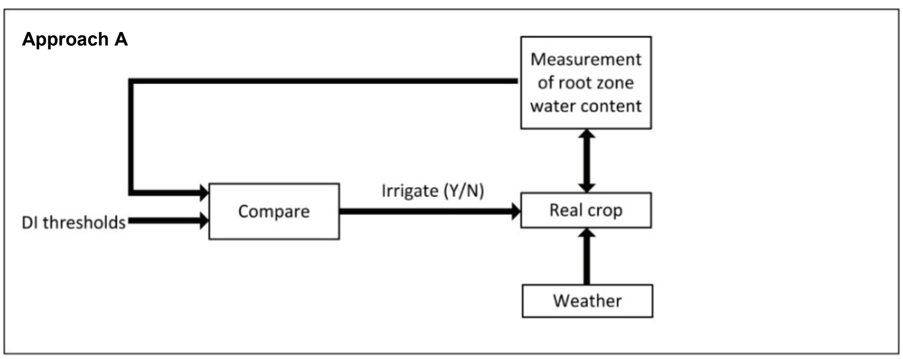
Selected optimal irrigation strategies were tested using the weather for the years 1950-1999, both with AquaCrop and with RZWQM2 (ver. 4.0) with the embedded DSSAT-CSM CERES-Maize crop growth module. As mentioned above, a seven-day gap was imposed between irrigation events, and each irrigation event consisted of 25 mm.

The goal of the tests with AquaCrop was to investigate the performance (robustness) of the DI strategies obtained using ten years of weather over a wide range of actual weather conditions, under the unrealistic assumption that the model used to determine the DI strategies is perfect. The goal of the tests with CERES-Maize was to estimate the performance of these DI strategies if they were applied in the field.

When testing the DI strategies with CERES-maize, implementation was simulated in two ways: implementation of the irrigation thresholds, and implementation of the irrigation events generated by AquaCrop. These two approaches are shown conceptually in figure 1. Approach A corresponds to a situation in which (continuous) measurements of the root zone water content are available, and irrigation events are triggered by these measurements. In approach B, instead of using actual soil water measurements, a model is run in parallel to the actual crop, and irrigation events are triggered by the soil water content predicted by the model. In the present study, the "crop/soil model" run in parallel to the "real crop" was the AquaCrop model embedded in the optimization procedure. Figure 1 underscores the advantages and disadvantages of each approach. The first approach requires measurements of the root zone water content, which are not easy to perform in the field, especially because the whole soil water profile is needed and the definition of the root zone should match the one in the model used to determine the DI thresholds. On the other hand, in the second approach, irrigation is affected by the imperfectness of the crop/soil model and of the weather information used to estimate the root zone water content, but this method allows the farmer to implement deficit irrigation without the need for a soil water sensor.

RESULTS AND DISCUSSION

This section is organized as follows. First, the calibration of the AquaCrop model is presented. This model is then used to determine optimal DI strategies using the weather for the years 2000-2009. Selected DI strategies are then tested for the weather for the years 1950-1999, first with AquaCrop (i.e., assuming perfect modeling) and then with CERES-maize. Finally, a discussion of the main results is presented.



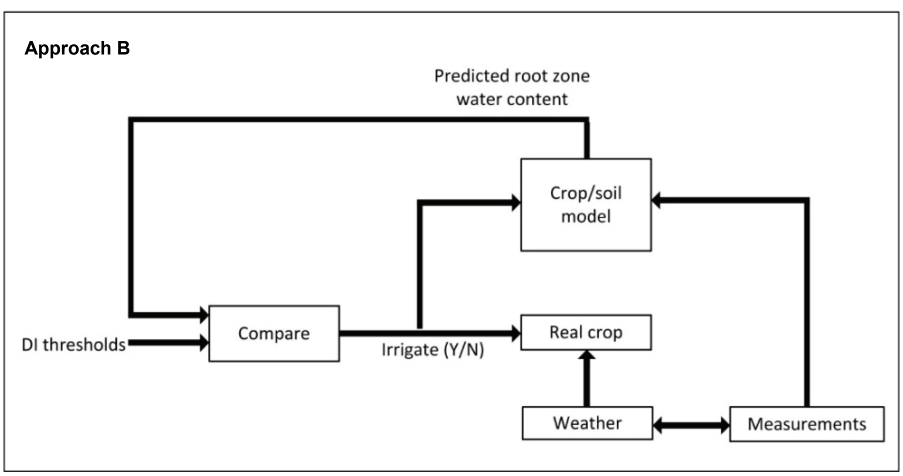


Figure 1. Schematics of the two implementation approaches: (approach A) implementation of the optimal thresholds using soil water measurements, and (approach B) implementation of the irrigation events generated by a crop model running in parallel to the actual crop.

Table 2. AquaCrop crop parameters that were adjusted to obtain satisfactory agreement between AquaCrop and CERES-Maize.

Parameter	Original Value	Calibrated Value
Length of growing cycle in rowing degree days	1700	1740
Soil water depletion factor for canopy expansion, upper threshold	0.14	0.12
Soil water depletion factor for canopy expansion, lower threshold	0.72	0.78
Shape factor for water stress coefficients for canopy expansion	2.90	3.50
Soil water depletion fraction for stomatal control, upper threshold	0.69	0.60
Shape factor for water stress coefficients for stomatal control	6.00	4.50
Soil water depletion factor for canopy senescence, upper threshold	0.69	0.62
Shape factor for water stress coefficients for canopy senescence	2.70	3.00
Crop coefficient when canopy is complete but before senescence	1.05	1.20
Minimum effective rooting depth	0.30	0.20
Maximum effective rooting depth	2.30	2.10
Normalized water productivity	33.7	32.0
Reference harvest index	48	47
Growing degree days from sowing to emergence	80	135
Growing degree days from sowing to maximum rooting depth	1409	1508
Growing degree days from sowing to start of senescence	1400	1476
Growing degree days from sowing to maturity	1700	1740
Growing degree days from sowing to flowering	880	967

Calibration of AquaCrop

The soil parameters were set according to the corresponding values in CERES-Maize: saturation = 45%, field capacity = 33%, wilting point = 15%, K_{sat} = 68 cm d^{-1}, thickness = 2.30 m (uniform profile). The crop parameters that were adjusted are listed in table 2. Figure 2a shows a comparison of the yields predicted by CERES-Maize and the calibrated AquaCrop mode. There was good agreement between the models, except at very low yields. Figure 2b shows the soil water contents (up to 2.3 m) predicted by the two models. Although AquaCrop captured the general behavior, there was a clear tendency toward overestimation during the second part of the season. As explained above, no attempt was made to obtain better agreement between the yields and soil water contents predicted by the two models.

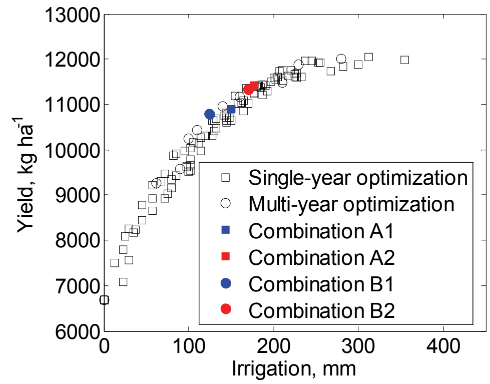


Figure 3. Results for years 2000-2009. Average irrigation versus average yield for all deficit irrigation thresholds combinations obtained by optimization.

Optimization on Years 2000-2009

The results (average yield vs. average irrigation) obtained with both optimization approaches are shown in figure 3. Approach A (single-year optimization) led to 8 to 12 optimal sequences of DI thresholds per year (depending on the shape of the Pareto front), leading altogether to 99 DI threshold sequences, which were then tested on all ten years. The square symbols in figure 3 show the average performance of each DI threshold sequence on these ten years. *A priori*, there was no assurance that a DI threshold sequence that was optimal on a specific year would be suitable for another year. In this respect, the results in figure 3 are unexpectedly good in the sense that the ten-year average performance of most DI threshold sequences based on a single year are indeed very close to optimal. The average optimal [yield, irrigation] combinations obtained using approach B (multi-year optimization) did not differ substantially from those obtained using approach A. Four combinations, indicated by red and blue symbols in figure 3, were selected for further analysis. These combinations correspond to yields that are 90% and 95% of the maximum achievable average yield. The square and circle symbols correspond to the combinations obtained with approaches A and B, respectively.

The irrigation thresholds corresponding to these four strategies are listed in table 3. Note that these fixed target yields were used only to enable quantitative comparison between the multi-year performances of the various approaches. In practice, the target yield should be adjusted dur-

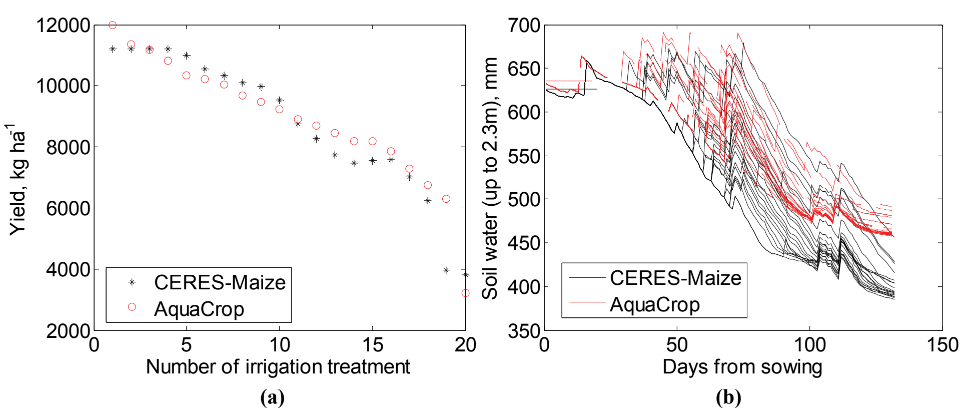


Figure 2. Comparison of the (a) yields and (b) soil water contents predicted by CERES-Maize (stars and solid curves) and AquaCrop (circles and dashed curves) for the 20 irrigation schedules used for calibration.

Table 3. Optimal irrigation thresholds corresponding to the four combinations investigated.

Growth Stage	Optimization Period	Allowable Depletion (mm): Single-Year Optimization: Combination A1 (10,900 kg ha^{-1} average yield)	Combination A2 (11,410 kg ha^{-1} average yield)	Multi-Year Optimization: Combination B1 (10,780 kg ha^{-1} average yield)	Combination B2 11,350 kg ha^{-1} average yield)
VE-V3 V4-V5	1	78	210	159	214
V6-V11	2	211	121	71	103
V12-V14	3	130	56	173	32
V15-V18	4	70	27	14	24
VT (tasseling) R1 (silking)	5	5	58	86	84
R2 (blister)	6	5	7	25	166
R3 (milk) R4 (dough)	7	211	216	200	30
R5 (dent)	8	95	102	190	193
PM (maturity)	9	250	210	230	196

ing the season, taking into account past weather and current crop status. Interpretation of the threshold values in table 3 is not straightforward and should be considered with care, as we observed that, in many cases, delayed irrigation occurred independently of these thresholds due to the seven-day gap imposed between irrigation events. In other words, a high threshold does not necessarily mean that no irrigation occurred during that period. This can be verified in figure 4, which shows the average and minimum-maximum extent of soil water depletion calculated over the 2000-2009 period for all four threshold combinations. In terms of soil water depletion, the differences between approaches A and B are quite minor and much smaller than could be expected from strict implementation of the thresholds listed in table 3.

Testing with AquaCrop on Years 1950-1999

Figure 5 shows the distribution of the results (2D histograms of yield vs. irrigation) when implementing the irrigation thresholds obtained by selecting a target yield of ~10,800 kg ha^{-1} (combinations A1 and B1, as indicated by blue squares and circles, respectively, in fig. 3). Implementing the thresholds recommended by approach A would produce a yield exceeding 9000 kg ha^{-1} on 48 years, with irrigation ranging from 100 to 225 mm. Implementing the thresholds recommended by approach B would produce a yield exceeding 9000 kg ha^{-1} on 44 years, with irrigation ranging from 75 to 175 mm). The yield would exceed 10,000 kg ha^{-1} on 34 years and 28 years for approaches A and B, respectively. The 50-year mean yields are 10,730 and 10,400 kg ha^{-1} for approaches

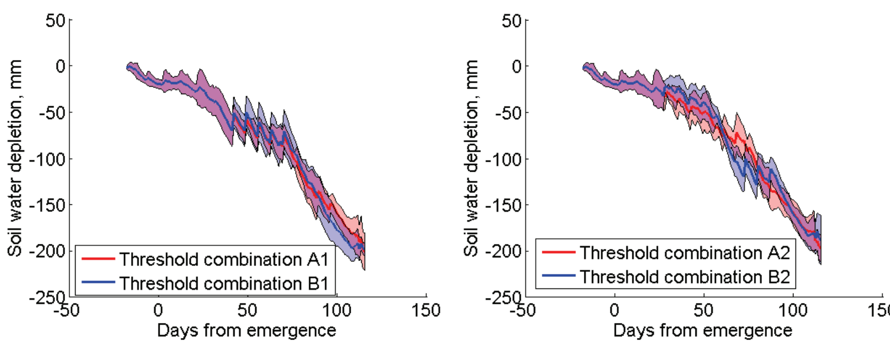


Figure 4. Soil water depletion resulting from the four threshold combinations listed in table 3. Solid lines correspond to the ten-year average, and shaded strips correspond to the minimum-maximum extent.

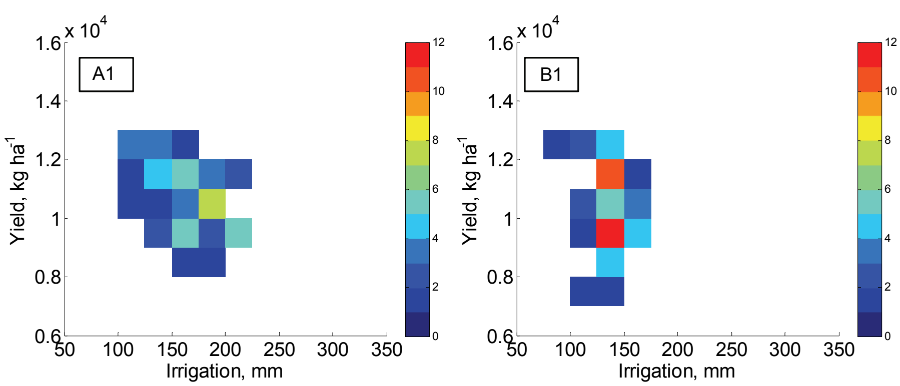


Figure 5. Two-dimensional histograms of yield and irrigation in 1950-1999 using the deficit irrigation thresholds corresponding to the optimal combination approaches A1 and B1 that produced an average yield of 10,800 kg ha^{-1} for 2000-2009 (blue symbols in fig. 3). Color scale indicates the number of years in which the predicted [yield, irrigation] was within the corresponding bin. The results were obtained with AquaCrop.

A and B, respectively, which are within 5% of the yield expectation based on years 2000-2009.

Figure 6 shows the distribution of the results when implementing the irrigation thresholds obtained by selecting a target yield of ~11,400 kg ha^{-1} (combinations A2 and B2, as indicated by red squares and circles, respectively, in fig. 3). In this case, the yield would exceed 10,000 kg ha^{-1} in 44 years if implementing approach A, with irrigation ranging from 100 to 275 mm, and in 39 years if implementing approach B, with irrigation ranging from 125 to 225 mm. Yield would exceed 11,000 kg ha^{-1} in 28 and 27 years for approaches A and B, respectively. The 50-year mean yields are 11,140 and 11,000 kg ha^{-1} for approaches A and B, respectively. In both cases, the average irrigation is 175 mm.

The main questions relative to model-based irrigation scheduling are (1) the impact of model imperfections and (2) the impact of imperfect weather forecasts. The impact of imperfect modeling is discussed in the next section. The impact of imperfect weather forecasts was investigated by comparing the previous results with the results obtained by solving equation 1 for each year. More specifically, solving equation 1 with the weather of a specific year gives a set of [yield, irrigation] combinations such as shown in figure 7 (blue stars). We can extract from these results the [yield, irrigation] combination of the Pareto front that is closest to the desired target yield and measure the deviation between this optimal combination and the result obtained using the irrigation thresholds determined using years 2000-2009. For instance, assuming a target yield of 11,400 kg ha^{-1}, the thresholds previously obtained by approaches A and B (based on years 2000-2009) would have resulted in the [yield, irrigation] combinations shown in figure 7 by square and circle symbols, respectively. These can be compared to the optimal combination (obtained assuming perfect knowledge of the weather) denoted by the triangle. In other words, in this specific example, the fact that the weather was not known in advance and the irrigation thresholds could not be perfectly optimized led to a yield decrease of ~200 to 600 kg ha^{-1}, with or without a reduction of irrigation, depending on the strategy implemented. Figure 8 summarizes the results of the analysis conducted for all 50 years and the four threshold combinations (A1, A2, B1, and B2) and shows 2D-histograms of the deviations from optimality. The strong diagonal patterns show that when irrigation was higher than could have been under ideal conditions, this resulted in yield higher than desired; conversely, when the yield was lower than desired, this was to some point compensated by lower irrigation. Departure from the diagonal pattern occurred mostly with yield reduction lower than 1000 kg ha^{-1}, which in some cases was accompanied by a very large reduction of irrigation.

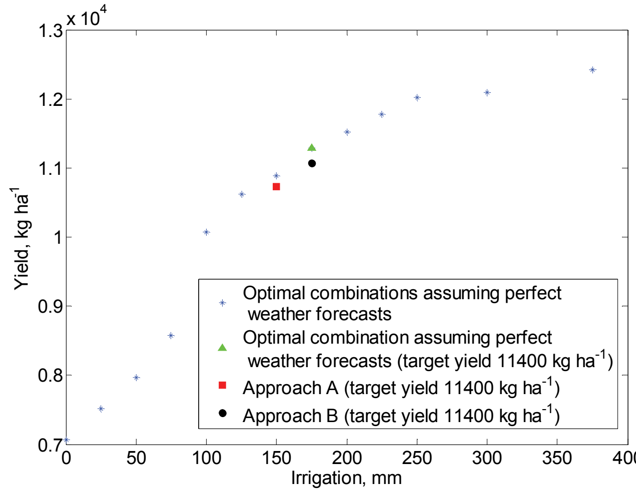


Figure 7. Optimal [yield, irrigation] combinations (Pareto front) for 1985 assuming perfect weather forecasts (stars and triangles) and actual [yield, irrigation] obtained by implementing the deficit irrigation thresholds obtained with approaches A (squares) and B (circles) using weather for 2000-2009 and a target yield of 11,400 kg ha^{-1}.

TEST WITH CERES-MAIZE ON YEARS 1950-1999

Implementation of Irrigation Thresholds

Figure 9 shows the distribution of the results (2D histograms of yield vs. irrigation) when implementing approach A in figure 1, i.e., the optimal thresholds computed with AquaCrop were used to generate irrigation events in CERES-Maize. Compared to the results obtained with AquaCrop (figs. 5 and 6), the most noticeable differences are the higher irrigation and the lack of correlation between the target and actual yields. The average irrigation ranges from 200 to 265 mm (compared to 125 to 175 mm with AquaCrop), and the average yield is 11,000 ±100 kg ha^{-1} regardless of the irrigation strategy chosen.

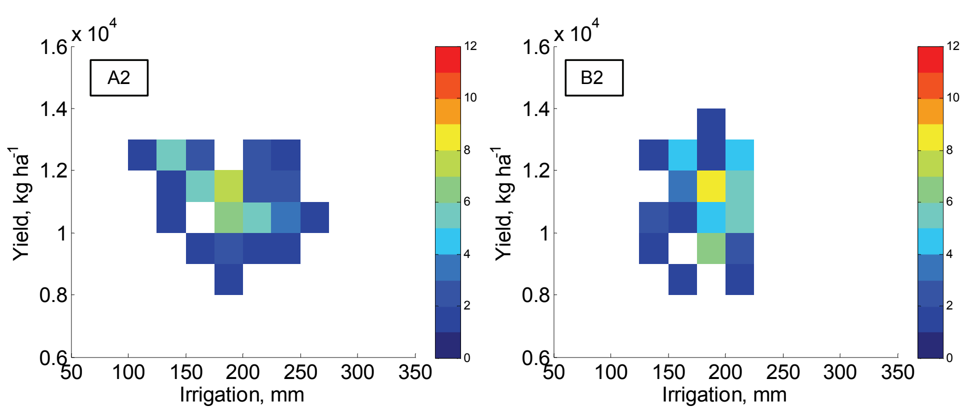


Figure 6. Two-dimensional histograms of yield and irrigation in 1950-1999 using the deficit irrigation thresholds corresponding to the optimal combination approaches A2 and B2 that produced an average yield of 11,400 kg ha^{-1} for 2000-2009 (red symbols in fig. 3). Color scale indicates the number of years in which the predicted [yield, irrigation] was within the corresponding bin. The results were obtained with AquaCrop.

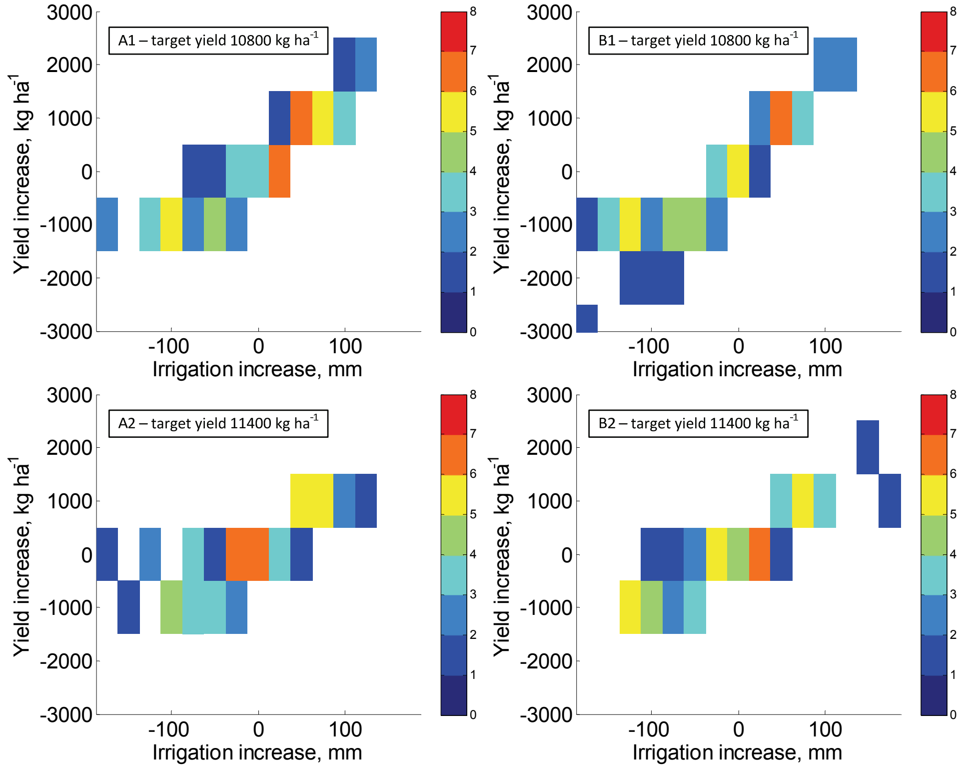


Figure 8. Two-dimensional histograms of deviations from optimality, i.e., deviation from the optimal [yield, irrigation] combination that could be obtained in the same year using perfect weather forecasts. Color scale indicates the number of years in which the [yield, irrigation] deviation was within the corresponding bin. The threshold combination is indicated in the corner of each graph.

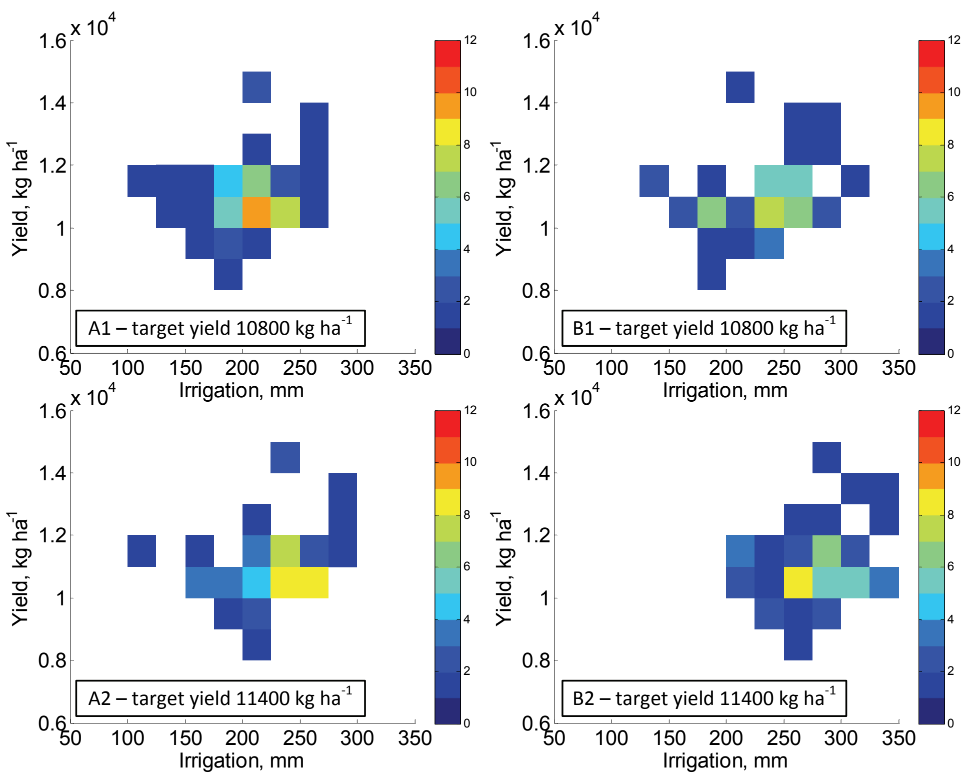


Figure 9. Two-dimensional histograms of yield and irrigation for years 1950-1999. The results were obtained by implementing the optimal irrigation thresholds in CERES-Maize. Color scale indicates the number of years in which the predicted [yield, irrigation] was within the corresponding bin. The threshold combination is indicated in the corner of each graph.

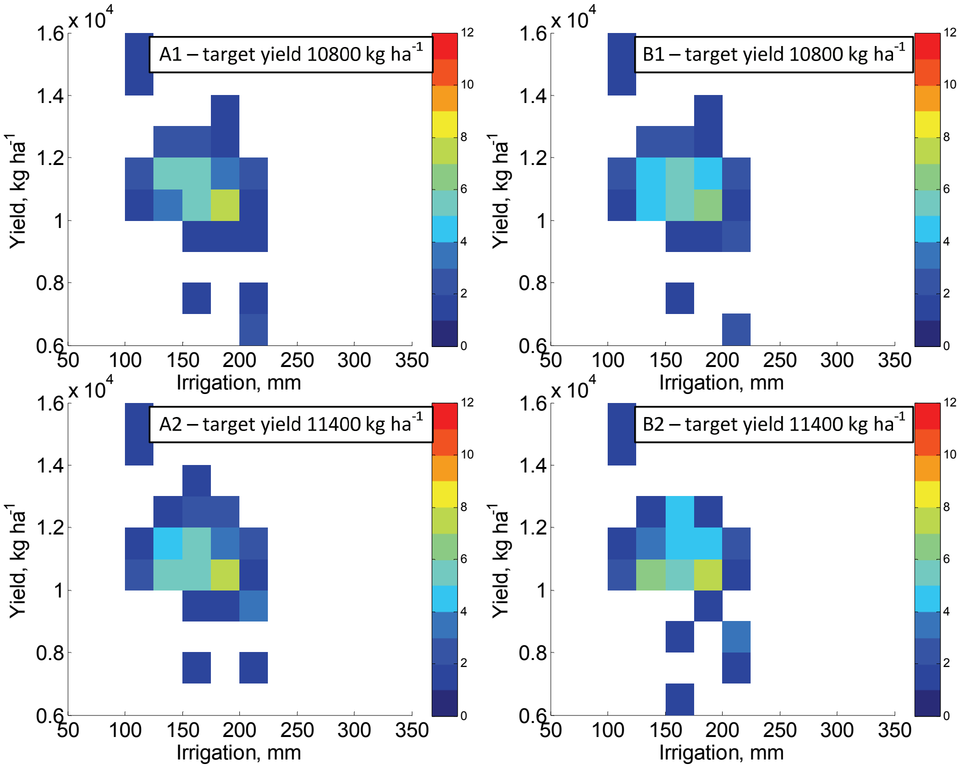


Figure 10. Two-dimensional histograms of yield and irrigation for years 1950-1999. The results were obtained by implementing the irrigation events generated by AquaCrop in CERES-Maize. The color scale indicates the number of years in which the predicted [yield, irrigation] was within the corresponding bin. The threshold combination is indicated in the corner of each graph.

Implementation of Irrigation Events Generated by AquaCrop

Figure 10 shows the distribution of the results (2D histograms of yield vs. irrigation) when implementing approach B in figure 1, i.e., using the irrigation events generated by AquaCrop as inputs to CERES-Maize. As in figure 9, there is no correlation between the target and actual yields, and the average yield was 10,900 ±100 kg ha^{-1} regardless of the irrigation strategy chosen.

Discussion

This discussion focuses on two points: the choice of the optimization approach and the choice of the implementation approach. In both cases, the analysis is based on yield (fig. 11) and water use efficiency (WUE) (fig. 12):

1. Single-year vs. multi-year optimization: For any given model and implementation approach, there was little difference between the results obtained using the irrigation schedules based on single-year or multi-year optimization, both in terms of yield and WUE. The only noticeable exception is WUE of the threshold-based approach, which was lower when using the multi-year strategy for a target yield 10,800 kg ha^{-1}.
2. Implementing thresholds vs. implementing irrigation events (relevant to CERES-Maize only): Implementing the irrigation events recommended by AquaCrop resulted in a higher number of extreme yields (labeled "CERES events" in fig. 11). In terms of WUE, implementing irrigation thresholds led to noticeably poorer results (labeled "CERES threshold" in fig. 12), while implementing the irrigation events recommended by AquaCrop led to WUE very similar to that predicted by AquaCrop.

Further investigation with (ideally) an actual crop or (more realistically) other soil-crop models instead of CERES-Maize should be conducted to corroborate or refute the present results. In addition, the irrigation strategies developed in this work are "one size fits all" in the sense that, for a given target yield, the same irrigation thresholds are used on all years, regardless of the weather. The development of climate-dependent irrigation thresholds (e.g., sets of thresholds for wet, normal, and dry years) was beyond the scope of the present study but should be considered.

Conclusion

This work demonstrated the potential of model-based optimization for managing deficit irrigation of maize in Kansas. However, it must be emphasized that the present study should be viewed only as a proof of concept. The irrigation thresholds reported in this study should not be implemented as-is but should rather be recalculated using a locally calibrated AquaCrop model.

Testing the irrigation strategies derived using ten years of historical weather data on an additional 50 years of weather data showed that when testing the irrigation schedules with the AquaCrop model embedded in the optimization procedure, the multi-year average results were very close to the expectations. Below-average yield was associated with

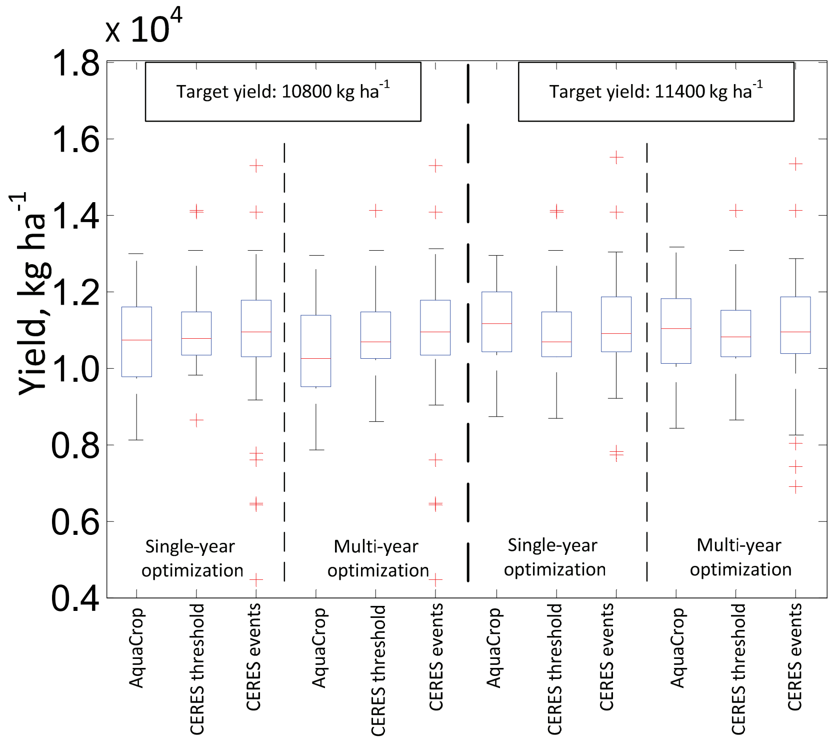


Figure 11. Boxplots of yield for years 1950-1999. Whiskers correspond to the 25th and 75th percentiles. "CERES threshold" and "CERES events" indicate results obtained using approaches A and B, respectively, shown in figure 1.

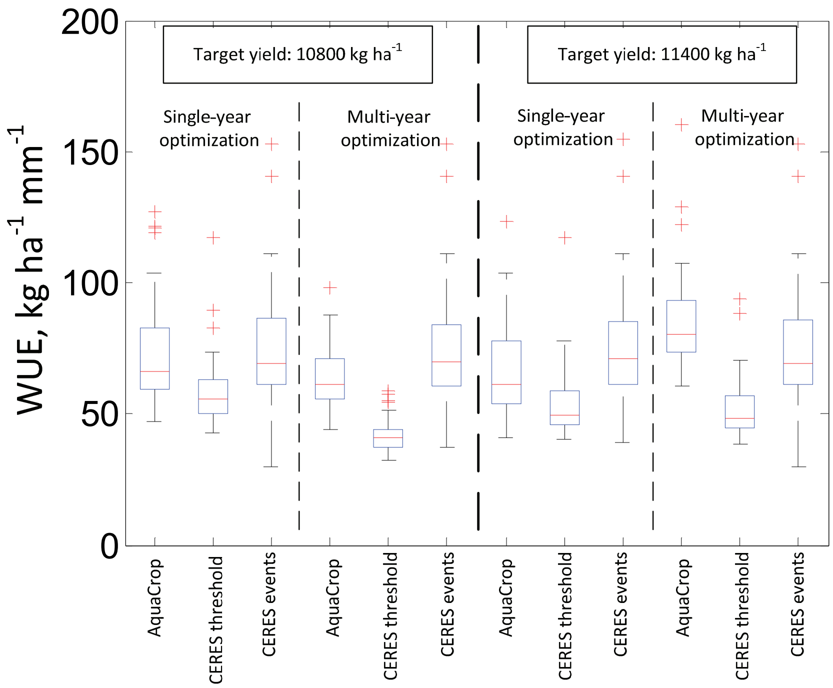


Figure 12. Boxplots of water use efficiency for years 1950-1999. Whiskers correspond to the 25th and 75th percentiles. "CERES threshold" and "CERES events" indicate results obtained using approaches A and B, respectively, shown in figure 1.

lower irrigation, and vice-versa, indicating that little irrigation water was wasted. Clearly, the crop-soil model embedded in the optimization approach is a critical component, and imperfect modeling reduces the overall performance. However, the results reported here show that satisfactory results can be obtained even when this model is overly simplistic and imperfect. In particular, although imperfect modeling (together with weather fluctuations) caused the actual yield to differ from the target yield, the fluctuations around the multi-year averages were no larger when testing the irrigation schedule with the CERES-Maize model than when testing it with the AquaCrop model. Regarding the two optimization approaches developed (single-year vs. multi-year), there was very little difference in terms of overall performance. With regard to implementation, the results show that real-time soil water measurements may not be required to implement the deficit irrigation scheme developed here. In fact, in terms of water use efficiency, better results were obtained when using model estimations (approach A in fig. 1) rather than measurements (approach B in fig. 1). However, using model estimations to drive irrigation also led to a larger number of more extreme yields.

Further investigation should be conducted to determine whether such a purely model-based approach could provide an attractive alternative to non-trivial continuous soil water measurements. Nowadays, crop models can be readily embedded in internet-based platforms that exchange information with local irrigation controllers and sensors in a fully automated manner. Such systems are typically set up by the company that provides the irrigation equipment or by an agriculture extension service, so that farmers' technological proficiency is not an issue. The main obstacle to the implementation of such an approach is that it requires a locally calibrated model. In principle, in modern commercial operations in which irrigation is computer-controlled and sensor readings are recorded automatically, historical data could provide the basis for such calibration. Whether the quantity and quality of the data are sufficient, and how to perform the actual calibration, are critical issues that were beyond the scope of the present study but require further investigation.

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REFERENCES

Araya, A., Kisekka, I., Prasad, V., Holman, J., Foster, A., & Lollato, R. (2017). Assessing wheat yield, biomass, and water productivity responses to growth stage based irrigation water allocation. *Trans. ASABE, 60*(1), 107-121. https://doi.org/10.13031/trans.11883

Bergez, E. J., Debaeke, P., Deumier, J. M., Lacroix, B., Leenhardt, D., Leroy, P., & Wallach, D. (2001). MODERATO: An object-oriented decision tool for designing maize irrigation schedules. *Ecol. Model., 137*(1), 43-60. https://doi.org/10.1016/S0304-3800(00)00431-2

Cai, X., Hejazi M. I., & Wang, D. (2011). Value of probabilistic weather forecasts: Assessment by real-time optimization of irrigation scheduling. *J. Water Resour. Plan. Mgmt., 137*(5), 391-403. https://doi.org/10.1061/(ASCE)WR.1943-5452.0000126

DeJonge, K. C., Andales, A. A., Ascough II, J. C., & Hansen, N. C. (2011). Modeling of full and limited irrigation scenarios for corn in a semiarid environment. *Trans. ASABE, 54*(2), 481-492. https://doi.org/10.13031/2013.36451

DeJonge, K. C., Ascough II, J. C., Andales, A. A., Hansen, N. C., Garcia, L. A., & Arabi, M. (2012). Improving evapotranspiration simulations in the CERES-Maize model under limited irrigation. *Agric. Water Mgmt., 115*, 92-103. https://doi.org/10.1016/j.agwat.2012.08.013

Herrero, J. M., Martinez, M., Sanchis, J., & Blasco, X. (2007). Well-distributed Pareto front by using the epsilon-moga evolutionary algorithm. In *Lecture notes in computer science* (vol. 4507, pp. 292-299). https://doi.org/10.1007/978-3-540-73007-1_36

Howell, T. A., O'Shaughnessy, S. A., & Evett, S. R. (2012). Integrating multiple irrigation technologies for overall improvement in irrigation management. *Proc. Central Plains Irrigation Conf.* (pp. 170-186). Colby, KS: Central Plains Irrigation Association.

Ioslovich, I., Gutman, P.-O., & Seginer, I. (2004). Dominant parameter selection in the marginally identifiable case. *Math. Comput. Simul., 65*(1-2), 127-136. https://doi.org/10.1016/j.matcom.2003.09.012

Jones, J. W., Hoogenboom, G., Porter, C. H., Boote, K. J., Batchelor, W. D., Hunt, L. A., ... Ritchie, J. T. (2003). The DSSAT cropping system model. *European J. Agron., 18*(3), 235-265. https://doi.org/10.1016/S1161-0301(02)00107-7

KDA. (2016). *Kansas farm facts*. Manhattan, KS: Kansas Department of Agriculture. Retrieved from http://agriculture.ks.gov/docs/default-source/ag-marketing/kansas-farm-facts-10052016.pdf?sfvrsn=4

Kisekka, I., Aguilar, J., Rogers, D., Holman, J., O'Brien, D. M., & Klocke, N. (2016). Assessing deficit irrigation strategies for corn using simulation. *Trans. ASABE, 59*(1), 303-317. https://doi.org/10.13031/trans.59.11206

Kisekka, I., Schlegel, A., Ma, L., Gowda, P. H., & Prasad, P. V. V. (2017). Optimizing preplant irrigation for maize under limited water in the High Plains. *Agric. Water Mgmt., 187*, 154-163. https://doi.org/10.1016/j.agwat.2017.03.023

Labadie, J. W. (2004). Optimal operation of multireservoir systems: State-of-the-art review. *J. Water Resour. Plan. Mgmt., 130*(2), 93-111. https://doi.org/10.1061/(ASCE)0733-9496(2004)130:2(93)

Linker, R., & Sylaios, G. (2016). Efficient model-based sub-optimal irrigation scheduling using imperfect weather forecasts. *Comput. Electron. Agric., 130*, 118-127. https://doi.org/10.1016/j.compag.2016.10.004

Linker, R., Ioslovich, I., Sylaios, G., Plauborg, F., & Battilani, A. (2016). Optimal model-based deficit irrigation scheduling using AquaCrop: A simulation study with cotton, potato and tomato. *Agric. Water Mgmt., 163*, 236-243. https://doi.org/10.1016/j.agwat.2015.09.011

Linker, R., Seginer, I., & Buwalda, F. (2004). Description and calibration of a dynamic model for lettuce grown in a nitrate-limiting environment. *Math. Comput. Model., 40*(9), 1009-1024. https://doi.org/10.1016/j.mcm.2004.12.001

Ma, L., Hoogenboom, G., Ahuja, L. R., Ascough, J. C., & Saseendran, S. A. (2006). Evaluation of the RZWQM-CERES-Maize hybrid model for maize production. *Agric. Syst., 87*(3), 274-295. https://doi.org/10.1016/j.agsy.2005.02.001

McGuire, V. L. (2004). Water-level changes in the High Plains aquifer, predevelopment to 2003 and 2002 to 2003. USGS Fact Sheet 2004-3097. Lincoln, NE: U.S. Geological Survey.

Nijbroek, R., Hoogenboom, G., & Jones, J. W. (2003). Optimizing irrigation management for a spatially variable soybean field. *Agric. Syst., 76*(1), 359-377. https://doi.org/10.1016/S0308-521X(02)00127-0

Raes, D., Steduto, P., Hsiao, T. C., & Fereres, E. (2009). Aquacrop - The FAO crop model to simulate yield response to water: II. Main algorithms and software description. *Agron. J., 101*(3), 438-447. https://doi.org/10.2134/agronj2008.0140s

Rinaldi, M. (2000). Application of EPIC model for irrigation scheduling of sunflower in southern Italy. *Agric. Water Mgmt., 49*(3), 185-196. https://doi.org/10.1016/S0378-3774(00)00148-7

Rogers H., D., Aguilar, J., & Kisekka, I. (2016). Adapting the Kansas crop water allocator (CWA) to multi-year use. *Proc. Irrigation Show and Education Conf.* Fairfax, VA: Irrigation Association.

Rogers, D. H., & Elliott, R. L. (1989). Irrigation scheduling using crop growth simulation, risk analysis, and weather forecasts. *Trans. ASAE, 32*(5), 1669-1677. https://doi.org/10.13031/2013.31207
Rogers, H. D., & Lamm, F. R. (2012). Kansas irrigation trends. *Proc. 24th Annual Central Plains Irrigation Conf.* Colby, KS: Central Plains Irrigation Association.
Saseendran, S. A., Ahuja, L. R., Nielsen, D. C., Trout, T. J., & Ma, L. (2008). Use of crop simulation models to evaluate limited irrigation management options for corn in a semiarid environment. *Water Resour. Res., 44*(7), W00E02. https://doi.org/10.1029/2007WR006181
Schneekloth, J. P., Kaan, D. A., & Pritchett, J. (2004). Determining crop mixes for limited irrigation. *Proc. Central Plains Irrigation Short Course Exposition* (pp. 45-52). Colby, KS: Central Plains Irrigation Association.