Assessing the effectiveness of irrigator-driven groundwater conservation programs to drought: a case study of the northwestern Kansas Local Enhanced Management Areas

Authors: Wayne Ndlovu[a,b*], Sam Zipper[a,b*], Timothy Foster[c]

Affiliations:

a. Kansas Geological Survey, University of Kansas, Lawrence KS 66047
b. Department of Geology, University of Kansas, Lawrence KS 66045
c. School of Engineering, University of Manchester, Manchester, UK

*Correspondence to waynedndlovu5@gmail.com and samzipper@ku.edu

Highlights:

- Evaluated groundwater conservation program in heavily-stressed High Plains aquifer
- We used difference-based bias correction to improve AquaCrop model performance.
- Bias-corrected corn and sorghum models used to assess management effectiveness.
- Current pumping allocations make GMD-4 LEMA ineffective for conserving water.
- Improved water use efficiency can lower water use, even during drought.

Manuscript submitted to Agricultural Water Management for peer review, August 2025

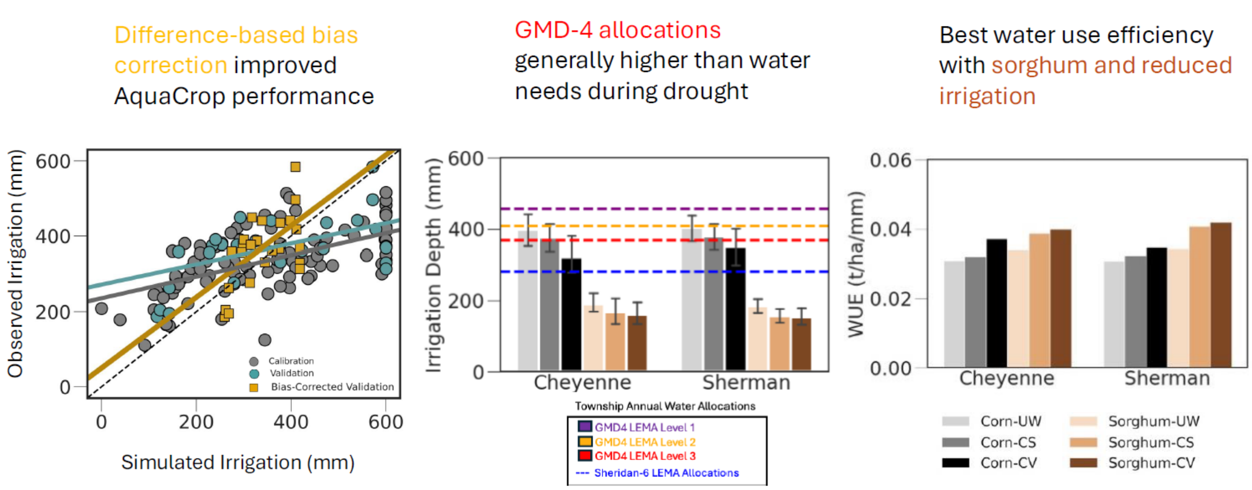
Abstract

Groundwater pumping for irrigation has led to declining groundwater levels in agricultural areas around the world, including the U.S. High Plains Aquifer. Here, we used a process-based crop model, AquaCrop, to assess the effectiveness of different irrigation management strategies during a synthetic multi-year drought. We focused on the Groundwater Management District 4 Local Enhanced Management Area (GMD-4 LEMA), a regional groundwater conservation program in the northwestern Kansas portion of the High Plains Aquifer. We first calibrated corn and sorghum AquaCrop models to simulate yield and irrigation using the Particle Swarm Optimization algorithm, and then applied a novel difference-based bias correction method to improve performance. We found that the corn models outperformed the sorghum models, likely due to limited observational sorghum data. However, both models performed satisfactorily during drought periods. We then evaluated the effectiveness of the groundwater conservation program in reducing water use during a synthetic five-year drought under three irrigation strategies. During the synthetic drought, corn irrigation requirements were roughly double those of sorghum. However, even simulated corn irrigation needs were generally less than current water allocations, supporting past work that suggests the current GMD-4 LEMA water allocations are ineffective for conserving water. Model simulations also indicated that water conservation strategies could reduce annual irrigation requirements without a substantial reduction in crop yield through improved water use efficiency, suggesting that lower allocations would be a feasible approach to reduce irrigation and slow groundwater decline rates.

Keywords:

AquaCrop, High Plains aquifer, groundwater management, model calibration, drought, irrigation

Graphical Abstract



1. Introduction

Groundwater resources across the globe are under threat due to unsustainable pumping rates and changes in climate (Gorelick & Zheng, 2015). Negative impacts of groundwater level declines include streamflow depletion (Lapides et al., 2023; Zipper, Brookfield, et al., 2024), land subsidence (Miller et al., 2020; Teatini et al., 2006), increased groundwater extraction costs (Turner et al., 2019), saltwater intrusion (Peters et al., 2022), and overall decreased water quality (Dorjderem et al., 2020). As the climate continues to change and drought occurrences become more frequent (Chang & Bonnette, 2016; Cook et al., 2018; Dube et al., 2022), humans, natural ecosystems, and industries that rely on groundwater are faced with major challenges. Groundwater depletion is particularly challenging when there is limited ability to increase recharge, as is the case in some regions of the U.S. High Plains Aquifer (HPA). The HPA underlies 450,000 km^2 of land covering parts of eight states (Colorado, Kansas, Nebraska, South Dakota, Wyoming, New Mexico, Oklahoma and Texas; "High Plains aquifer | U.S. Geological Survey," 2024) and supplies about a third of the water used for irrigation in the US (Haacker et al., 2019). Continued depletion of the HPA poses a significant threat to food production, the US economy, and the livelihood of farmers (Deines et al., 2020).

Potential solutions to groundwater depletion can be classified into cognitive, technological, and structural fixes (Zwickle et al., 2021). Cognitive fixes aim to educate irrigators on the impacts of declining aquifer levels, while technological and structural fixes involve introducing more efficient irrigation techniques and changing the factors that influence an irrigator's behavior, respectively (Zelelew & Alfredsen, 2013). Groundwater management policies are an example of structural fixes that have been implemented to address aquifer depletion, and can be classified as either top-down or bottom-up practices. In top-down policies, a centralized government organization formulates rules, while bottom-up policies allow water users to develop self-governance strategies (Marston et al., 2022). Some have argued that top-down management practices tend to be less effective as irrigators have less input on the strategies which often leads to mistrust between the irrigators and governing organizations (Marston et al., 2022). Additionally, Kiparsky et al. (2017) raised concerns about fairness and inefficiency of top-down management. On the other hand, bottom-up governance tends to promote collaboration among water users due to interdependence since one user's actions affects the common pool resource and other's ability to use it (Feltman, 2024). However, some have argued that bottom-up management practices are primarily driven by political and economic feasibility, rather than scientific knowledge, of the solution (Andresen, 2015), and therefore it is unknown how effective they may be.

Effective design of groundwater conservation programs is further challenged by climate change. Groundwater management programs based on current and historical water use practices may not perform as effectively in future climate conditions. Climate change-induced droughts are projected to lower crop productivity in Kansas due to shortening of the crop growing season and limited water availability (Araya, Kisekka, Vara Prasad, et al., 2017). However, the extent to which existing groundwater conservation programs are effective, and whether they could be enhanced through alternative irrigation strategies, remains unknown. To address this knowledge gap, crop models can be used to simulate crop water productivity under varying climate and management scenarios. Here, we use the AquaCrop crop water productivity model to simulate crop yield and water use during a synthetic extreme drought to assess the effectiveness of a bottom-up groundwater conservation program in the Northwest Kansas Groundwater Management District 4 (GMD-4), which overlies a heavily depleted portion of the HPA. Our study asks the overarching questions, how effective are current agricultural water management practices for reducing groundwater withdrawals and what management strategies would be effective at reducing groundwater use while resilient to severe drought? To answer these questions, our study has three objectives:

1. Conduct a sensitivity analysis of the AquaCrop model to determine influential parameters with respect to simulated yield and water use for irrigated corn and sorghum
2. Calibrate and validate the AquaCrop model for irrigated corn and sorghum crop productivity and irrigation requirements
3. Assess the effectiveness of different irrigation and crop choice strategies for groundwater conservation programs under a synthetic multi-year drought.

2. Study area: GMD-4 LEMA

GMD-4 is a 12,623 km^2 district overlying the HPA in semi-arid northwestern Kansas and includes ten counties (Fig. 1). Soils in the GMD-4 include the Ulysses-Colby Association (deep, grayish-brown to dark grayish-brown silt loams), which is found in the western region, and the Holdrege-Ulysses Association (deep to moderately deep, dark grayish brown silt loams and moderately deep gray clays) in the eastern region ("Northwest Kansas Groundwater Management District No. 4: Revised Management Plan," 2021). Annual precipitation is relatively low, averaging 432 mm (17 inches) in the western counties and 533 mm (21 inches) in the eastern counties.

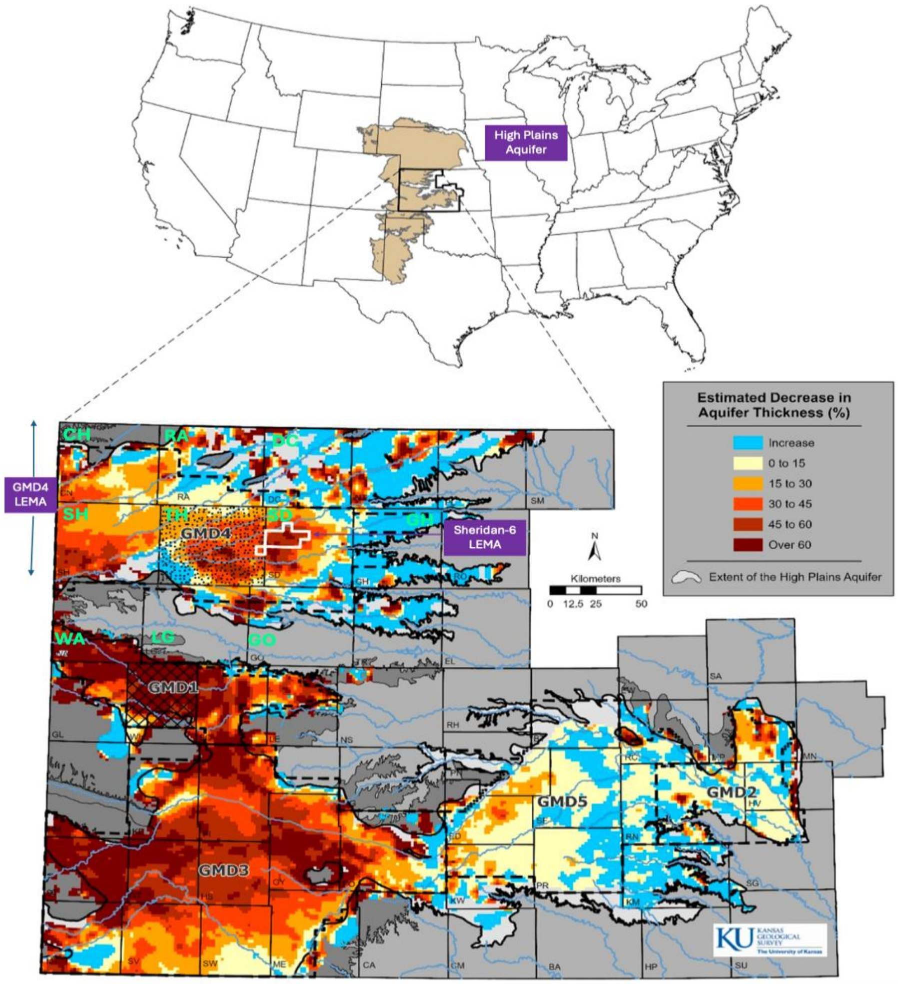


Figure 1. Map showing the High Plains Aquifer and measured decreases in aquifer thickness in the Groundwater Management Districts in Kansas since the onset of widespread pumping for irrigated agriculture. The GMD-4-LEMA is made up of 10 counties in northwest Kansas (CH-Cheyenne, RA-Rawlins, DC-Decatar, SH-Sherman, TH-Thomas, SD-Sheridan, GH-Graham, WA-Wallace, LG-Logan, and GO-Gove). The Sheridan-6 LEMA is represented by the solid-white line. Figure modified from Whittemore, Butler, & Wilson, (2023) under CC-BY license.

Groundwater levels in GMD-4 have declined substantially since the onset of widespread irrigation in the area (Fig. 1). In 2012, irrigators in parts of Sheridan and Thomas counties (a 255 km^2 area within GMD-4) formed a novel groundwater conservation program called a Local Enhanced Management Area (LEMA), commonly known as the Sheridan-6 LEMA (Orduña Alegría et al., 2024). The Sheridan-6 LEMA was a bottom-up groundwater conservation program, designed by irrigators and enforced by the state, in which each water right was allocated a five-year (2013-2017) total of 1397 mm (55 inches) per irrigated ha with some variations based on water right. This translated to an overall 20% pumping reduction from historic (2002 - 2012) average use (Deines et al., 2021; Drysdale & Hendricks, 2018). Assessment of the first cycle (2013 - 2017) of the Sheridan-6 LEMA showed that it was a major success: there was an overall 67% decrease in the rate of water table decline and evidence for increases in crop profitability due to (1) enhanced irrigation efficiency through the use of soil moisture sensors, (2) switching from water intensive corn and soybeans to more drought tolerant sorghum and wheat, and (3) prioritizing highest net profits over highest yields (Butler et al., 2018; Deines et al., 2019, 2021; Orduña Alegría et al, 2024; Whittemore, Butler, Bohling, et al., 2023). The Sheridan-6 LEMA has subsequently been renewed for additional five-year cycles for 2018-2022 and 2023-2027. However, the first LEMA cycle was characterized by average to wetter-than-average weather conditions (Fig. S3) and the LEMA has not yet been stressed by a severe and prolonged multi-year drought.

The success of the Sheridan-6 LEMA led to the creation of a district wide LEMA covering the rest of GMD-4 in 2018. However, the goals and groundwater allocations within the GMD-4 LEMA differed significantly from those of the Sheridan-6 LEMA. In the GMD-4 LEMA, groundwater levels measured between 2004 and 2015 were used to group areas with similar annual groundwater decline rates into township groups. Water allocations were then set based on a combination of historic groundwater decline rates (with lower allocations for areas with higher decline rates) and position within GMD-4 (with lower allocations in the eastern portion of the district where mean annual precipitation is higher). As a result, 49 townships were identified and five-year water allocations ranged from 2286 mm (90 inches) to 1638 mm (64.5 inches) (Fig. 2). For irrigators within the Sheridan-6 LEMA, the more stringent limits of the Sheridan-6 LEMA superseded these township-level allocations.

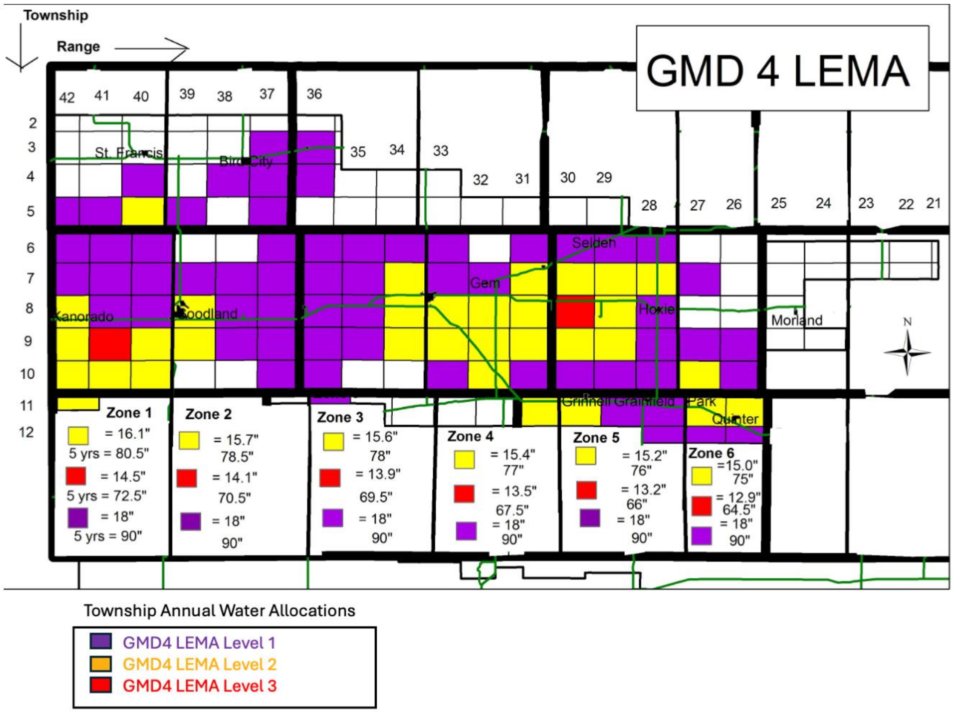


Figure 2. Map showing the GMD-4 LEMA zones (vertical lines with the zone number at the bottom) and water allocations. The LEMA allocated are set at the resolution of townships, which are 9.7 x 9.7 km (6 x 6 miles) squares of land defined as part of the Public Land Survey System. The purple boxes represent the GMD-4 LEMA Level 1 allocations (townships with a 0.5% - 1.0% average annual decline), yellow boxes the GMD-4 LEMA Level 2 allocations (townships with a 1.0% - 2.0% average annual decline), and the red boxes the GMD-4 LEMA Level 3 allocations (townships with +2.0% average annual decline). Figure modified from map prepared by Shannon Kenyon.

3. Methods

To assess the effectiveness of the GMD-4 LEMA under severe drought, we used a process-based crop model (AquaCrop) trained on historical data. In this section, we describe the AquaCrop model, the input and observational data used, and the calibration and model bias correction methods used, and the drought scenarios simulated.

3.1 AquaCrop Model

A number of carbon-, radiation-, and water-driven crop models have been used to simulate crop productivity using mathematical relations that link the crop, environmental, and management conditions. Common crop models used for assessing irrigation and yield response to variable climate and management conditions include AquaCrop (Steduto et al., 2009), DSSAT (Jones et al., 2003), APSIM (McCown et al., 1996), EPIC (Cavero et al., 2000), AgroIBIS

(Kucharik, 2003), and ARCWHEAT (Weir et al., 1984). These types of models have been applied to address a variety of management-relevant questions in irrigated landscapes, including the impacts of limiting irrigation on crop yield (Araya et al., 2016; Araya, Kisekka, Vara Prasad, et al., 2017), the effects of rooting depth and planting density on crop yield (Nyakudya & Stroosnijder, 2014), evaluating drivers of drought resilience (Zipper et al., 2015; He et al., 2014), and quantifying the impacts of projected climate change on crop yield (Onyekwelu et al., 2024; Reilly et al., 2003).

The AquaCrop model is a widely-used crop water productivity model developed by the United Nations Food and Agriculture Organization. AquaCrop uses a soil water balance approach at the daily timestep to calculate the growth and water requirements for agricultural crops (Raes et al., 2009). Crop growth and irrigation requirements are determined primarily by the soil water depletion in the root zone. For irrigated crops, the user can set a soil moisture threshold (*smt*) to trigger irrigation. The *smt* is defined as a percentage of the Total Available soil Water (TAW), which is the depth of plant available water in the root zone at field capacity (W_{FC}) after subtracting out the depth of plant available water at permanent wilting point (W_{PWP}) as shown in Eq. 1:

$$TAW = W_{FC} - W_{PWP} \qquad (1)$$

The irrigation depth is then calculated based on the soil water depletion as described in the Supplementary Material. The crop growth is simulated daily by first estimating canopy cover (*CC*) followed by the growth of above-ground crop biomass which is estimated using the product of the ratio of the daily ratio of transpiration (*Tr*) to reference evapotranspiration (*ETo*) and the normalized water productivity (*WP**). From biomass (*B*), crop yield can then be calculated as the product of the reference harvest index (*HI0*), *B*, and the harvest index adjustment factor for stress (*fHI*) such as soil water depletion and excess heat or cold (Eq. 2):

$$Crop\ Yield\ (Y) = fHI * B * HI0 \quad (2)$$

In this study, we used AquaCrop-OSPy, which is the open source Python implementation of AquaCrop (Foster et al., 2017; Kelly & Foster, 2021), referred to as ‘AquaCrop’ throughout the manuscript for brevity. A more detailed description of AquaCrop is provided in the Supplemental Material and associated references.

3.2 Data Sources

The required input for the AquaCrop model includes daily meteorological data (precipitation, minimum temperature, maximum temperature, and reference evapotranspiration), crop parameters, management parameters, and soil data (Xing et al., 2017). Since this study focused on regional groundwater conservation patterns, we consolidated the field-scale level input data and calculated the county level average soil and average daily meteorological conditions as described below. For the 2006-2020 study period, we used a cultivated field dataset

(Gao et al., 2017) to extract the dominant annual crop type from the United States Department of Agriculture National Agricultural Statistics Service (USDA NASS) Cropland Data Layer (CDL) (“USDA National Agricultural Statistics Service Cropland Data Layer,” 2023) and irrigation status from the Annual Irrigation Maps - High Plains Aquifer (AIM-HPA) dataset as in Zipper, Kastens, et al., (2024). Since our study focused on irrigated corn and sorghum, we averaged soil type from the Probabilistic Remapping of SSURGO (POLARIS; Chaney et al., 2016) dataset and daily meteorological data from the Gridded Surface Meteorological (gridMET; Abatzoglou, 2013) dataset. Planting dates for each year were defined based on the annual planting dates in the northwestern Kansas region since field-specific planting dates were not available (“USDA - National Agricultural Statistics Service - Charts and Maps - County Maps,” 2023).

To calibrate and evaluate the model’s performance, we used observed irrigation and crop yield data for each county. Irrigation depths in the GMD-4 region were extracted from the Kansas Water Information and Management and Analysis System (WIMAS) well data (“WIMAS,” 2023) a statewide pumping database that irrigators are required to submit annual pumping volumes, crop types, and irrigated acreage. Following methods by Obembe et al., (2023), we first excluded wells that reported irrigation on areas <40 acres or >500 acres, and those with irrigation depths outside of the 1st and 99th percentile, to eliminate outliers that may be linked to misreported or misrecorded data. For each county and year, we then calculated the annual median irrigation depth for corn and sorghum. We eliminated counties where the specified crop (corn or sorghum) was grown less than three times over the entire study period to ensure a more robust analysis.

We obtained annual county level yield data for the 2006 to 2020 period for the 10 counties in the GMD-4 area from the Kansas State - Extension Yield Correlation Tool (https://www.agmanager.info/crop-insurance/crop-insurance-papers-and-information/kansas-yield-correlation-tool) which uses data reported by the United States Department of Agriculture Risk Management Agency (USDA-RMA), and the United States Department of Agriculture National Agricultural Statistics Service (USDA-NASS; “USDA/NASS QuickStats Ad-hoc Query Tool,” 2023). We compared the two yield datasets and excluded any counties or years where the difference between them exceeded 10% to account for potential errors in the reported data since the two data sources are aggregated in different ways. Due to multiple missing observations in the USDA NASS dataset, the USDA-RMA data was used as the primary dataset. For instances where there were missing observations in the USDA-RMA dataset, the USDA-NASS was used to fill the gaps and complete the dataset. We eliminated the years and counties where hail and freeze caused significant crop losses, since these processes are not simulated by AquaCrop. To do this, we removed county-years from the dataset where losses due to hail and/or freeze exceeded $1,000,000 as reported in the loss data from the United States Department of Agriculture Risk- Management Agency (USDA-RMA; “Cause of Loss | RMA,” 2023).

3.3 Sensitivity Analysis, Calibration, and Bias Correction

The AquaCrop model was calibrated using observed yield and irrigation depth data reported between 2006 and 2020 in the ten GMD-4 counties (Fig. 1). We first used the Sobol Method (Sobol, 1993) to identify influential model parameters for simulating crop yield and irrigation requirements, and then used a Particle Swarm Optimization (PSO) algorithm to calibrate parameters that were identified as sensitive and applied a difference bias correction method to improve model performance (Fig. 3).

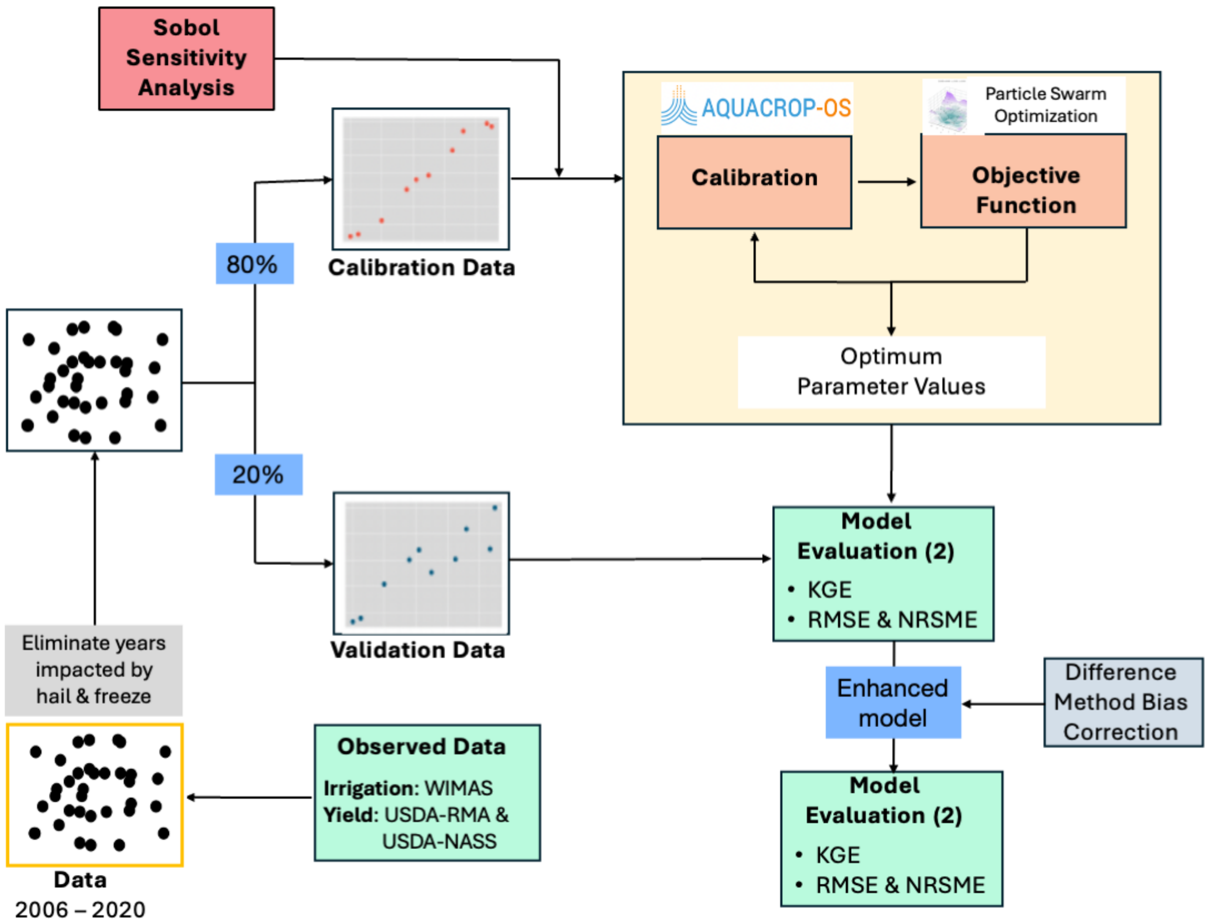


Figure 3. Methodology for calibrating the AquaCrop model integrating sensitivity analysis, model calibration, and bias correction.

3.3.1 Sensitivity analysis

Our sensitivity analysis was intended to identify parameters with the greatest influence on simulated corn and sorghum yield and irrigation under dry, normal, and wet meteorological conditions. We used 12 scenarios which were a factorial combination of the meteorological condition (dry, normal, or wet year, defined based on the lowest, median, and highest annual precipitation during the model period), crop type (corn or sorghum), and response variable (irrigation or yield). For each sensitivity analysis scenario, the Sobol method (Sobol, 1993) was applied to crop parameters related to (1) crop development and transpiration, (2) biomass and yield, (3) water stress, and (4) management using the *SALib* Python package (Herman & Usher, 2017). We evaluated a total of 12 parameters for corn and 8 parameters for sorghum (Table S1). Parameter ranges used in this study were obtained from the model documentation (Raes et al., 2023) and previous studies in the surrounding regions (Araya et al., 2016; Araya, Kisekka, Lin, et al., 2017; Masasi et al., 2019). For example, the maximum daily and seasonal irrigation depths during the calibration period were 6.5 mm and 600 mm for corn, and 6.5 and 450 mm for sorghum based on field observations from Kansas State Research and Extension (Ciampitti et al., 2022, 2023) and each crop's maximum observed irrigation depths from WIMAS. For parameters included in the sensitivity analysis, we analyzed the first, second and total indices, which were summed to define the total sensitivity index (ST). To distinguish between the influential and non-influential parameters, we defined a threshold: parameters with ST greater than 10% of the maximum ST from each scenario were defined as influential. Please refer to the Supplementary Material and Ndlovu (2024) for more details on the sensitivity analysis methods and findings.

3.3.2 Calibration using Particle Swarm Optimization (PSO)

PSO is a bio-inspired global optimization algorithm based on the social behavior of biological organisms such as a flock of birds or a school of fish (Kennedy & Eberhart, 1995; Reynolds, 1987). In PSO, each particle in the swarm moves in a multidimensional search space over a given time, which is determined by the number of iterations. Each particle in the search space represents a potential solution which optimizes the objective function (Umapathy et al., 2010). The particle swarm optimization (PSO) algorithm was used because it is easier to implement, has fewer parameters, converges faster, and requires fewer computational resources than other global optimization methods (Liu et al., 2022; Noel, 2012).

The user specifies the population size of the 'swarm.' For each particle within the swarm, initial parameter values are randomly generated from a uniform distribution within the user specified bounds. The PSO implementation followed methods documented in previous studies (Poli et al., 2007; Wagner et al., 2020) to estimate coefficients for parameters identified as influential by the sensitivity analysis (Table 1) that maximized model fit to observed county-resolution crop yields and irrigation depths. We used a swarm size of 100 with 500 as the maximum number of iterations. Other required PSO parameters were ω (set to 0.5 following Eberhart & Shi, 2001), c_1 and c_2 (set to 2). For c_1 and c_2, values that are less than or equal to two are mostly used (Anandakumar & Umamaheswari, 2018). The algorithm was set to terminate when the minimum change in swarm's best position and objective value were $1\text{x}10^{-8}$ and 0.1, respectively, or when the maximum number of iterations was reached. We defined the weighted least square's objective function as follows:

$$S(b) = \sum w_y[y_{tc} - y_{tc}(b)]^2 + \sum w_i[i_{tc} - i_{tc}(b)]^2 \qquad (3)$$

where:

w = weight of the observation where w_y and w_i are the weights for yield and irrigation depth, respectively. The weights are calculated as 1/variance.

y = observed yield (t/ha)

$y(b)$ = simulated yield (t/ha)

i = observed irrigation depth (mm)

$i(b)$ = simulated irrigation depth (mm)

tc = summations done over all counties and years in the training data

Table 1. Influential model parameters used in model calibration (see Supplementary Material for details on parameter selection and ranges). Highlighted rows indicate parameters considered only for corn and the remaining parameters were used for both corn and sorghum.

Parameter	Description	Units
Crop Development and Transpiration		
ccx	maximum fractional canopy cover size	-
rtx	maximum effective rooting depth	m
kc	crop coefficient when canopy is complete but prior to senescence	-
Biomass and Yield		
wp	water productivity normalized for reference ET0 and CO2	g/m2
hi	reference harvest index	-
hipsveg	coefficient describing positive impact of restricted vegetative growth during yield formation on HI	-
Management		
smt1	soil moisture threshold during crop emergence and canopy growth	%
smt2	soil moisture threshold during crop maximum canopy	%
smt3	soil moisture threshold during crop canopy senescence	%

While the focus of our scenario analysis is severe drought, we incorporated all counties and years with available data into our calibration and validation to increase the data available for calibration purposes, thereby reducing equifinality, and because we do not expect these parameters to be different in drought years. We randomly split the observed yield and irrigation data into calibration and validation using an 80:20 split. We also used multi-model analysis and model selection (Barnhart et al., 2020; Hill & Tiedeman, 2005; Poeter & Hill, 2007) to (1) compare alternative models and (2) quantify the uncertainty of the model calibrations. Following recommendations by Hill & Tiedeman (2005), fifteen alternative models were developed through a factorial combination of the (1) three initial soil water contents (*field capacity (FC)*, *saturation (SAT)* and *wilting point (WP)*) and (2) five random model input realizations. From these, we selected the best overall model for each crop to simulate irrigation depth and crop yield, which used *FC* for initial soil water content (Fig. S1, Fig. S4, Fig. S5, Table S3, Table S4). Model performances were evaluated using the Kling-Gupta Efficient (KGE; Gupta et al., 2009), root mean squared error (RMSE), and RMSE normalized by the mean (NRMSE).

3.3.3 Difference method for bias correction

Environmental systems are complex, and even calibrated models have inevitable limitations due to poorly constrained parameters, processes, or model conceptualization (Saltelli et al., 2020). In our study, we are simulating crop productivity and irrigation applications across the scale of a county, which integrates thousands of different fields and makes it impossible to precisely specify a uniform and representative set of parameters for all fields. Additionally, some parameters are unknowable from existing data. For example, unobserved heterogeneity in soil properties or irrigation system efficiency would be likely to affect crop growth and sensitivity to rainfall variability and crop models are unable to represent factors such as cooling effects from irrigation that might limit impacts of lower rainfall on yields. As a result, crop models can be subject to equifinality in which a single parameterization is unknowable (Lamsal et al., 2018).

While calibration limitations are commonly addressed via bias correction in hydrological and climate models (Acharya et al., 2013; Bosompemaa et al., 2025; Fang et al., 2015; Jaiswal et al., 2022), bias correction has not been widely applied to crop models, despite the potential to improve model simulation outputs. However, a handful of studies suggest that bias correction can improve simulated crop yields for several other crop models, such as the GLAM model (e.g. Watson et al., 2014; Yang et al., 2016; Ramirez-Villegas et al., 2017), while post-hoc yield scaling has also been employed successfully in large-scale regional or global applications of AquaCrop such as by Mialyk et al. (2022) and Su et al. (2025).

We have not, however, observed bias correction methods applied jointly to yield and irrigation estimation in a regional crop model. Here, we evaluated the ability of the difference method of bias correction, which establishes a correction factor based on the difference between the observed and simulated data (Kaur & Kaur, 2023), to improve crop yield and irrigation simulation performance. We selected the difference method because it produced lower errors and was more efficient in a comparison of multiple bias-correction models for climate projections (Kaur & Kaur, 2023). We implemented the difference method by establishing two additive correction factors; one for the predicted annual crop yield and another one for the irrigation. Both crop yield and irrigation were bias-corrected with a correction factor as follows:

$$Y^*_{pred} = Y_{pred} + \hat{C} \qquad (4)$$

where Y^*_{pred} and Y_{pred} denote the bias-corrected and calibrated model predictions for crop yield or irrigation. $\hat{C}$ is the correction factor or estimated model residuals, which is calculated for all the years and counties using the linear relationship between the model predictions (Y_{pred}) and the model residuals:

$$\hat{C} = mY_{pred} + b \quad (5)$$

where m and b are the slope and intercept of the regression line, respectively. Fig. 4 shows an example of the relationship between residuals and simulated values that is used to develop the relationship in Eq. 5. We used a linear regression since we observed a strong linear relationship between simulated values and the residual (Fig. S4 and Fig. S5), though the method would be adaptable to other functional forms.

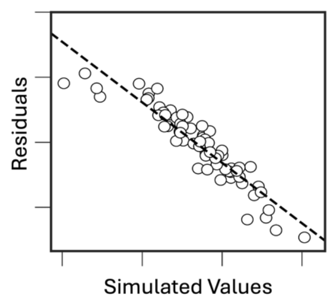


Figure 4. The relationship between simulated values and model residuals used to establish the correction factor for bias correction. Specific relationships for all models are shown in Fig. S4 and Fig. S5.

3.4 Assessing LEMA effectiveness during drought

To simulate the potential effectiveness of the GMD-4 LEMA to severe drought, we used historic (2006 - 2020) meteorological data from the region to create a synthetic dataset with the five lowest growing season precipitation years during the study period (2012, 2020, 2006, 2013, and 2007; Fig. S3). For a spin-up prior to the drought, we also included five randomly selected non-drought years (Fig. S3). We then used the bias-corrected corn and sorghum models to simulate crop yield and irrigation requirements during spin-up and synthetic drought period, and assessed the impact of different water management strategies on crop productivity and irrigation requirements during the synthetic drought.

As discussed in Section 2, the LEMA operates on a five-year water allocation system and water allocations vary spatially (Fig. 2). To assess the impacts of water conservation on crop yield and irrigation requirements during the drought period, we evaluated three irrigation strategies: Conservative (CV), Current Status (CS), and Unlimited Water (UW). We defined the CS scenario as the calibrated and bias-corrected models, which reflect the current irrigation practices. The target irrigation requirements under the CV and CS scenarios were based on regional irrigation practices. We then reduced the *smt* thresholds by 10% to create the CV scenario, and increased the *smt* thresholds by 10% and increased the maximum allowable seasonal irrigation to create the UW scenario (Table 2). The model defaults for maximum seasonal irrigation were used for the UW scenarios. The other model parameters remained unchanged from the calibration process.

Table 2. Irrigation strategies used to assess the effectiveness of the LEMA. The LEMA is represented by the CS parameter values from the model calibration. The soil moisture threshold (SMT) values are decreased and increased by 10% under Conservative (CV) and Unlimited Water (UW) conditions, respectively to represent variations in conservation strategies.

Parameter	**Conservative (CV)**	**Current Status (CS)**	**Unlimited Water (UW)**
Max Irrigation (Corn)	600 mm	600 mm	1000 mm
Max Irrigation (Sorghum)	450 mm	450 mm	1000 mm
SMT	Calibrated value - 10%	Calibrated value	Calibrated value + 10%

4. Results and Discussion

4.1 Sensitivity analysis

Results from the sensitivity analysis showed that there were more influential parameters for crop yield compared to irrigation depth (Table 3, with sensitivity indices plotted in Fig. S2A, Fig. S2B). This is likely because yield simulation is more complex than irrigation simulation in AquaCrop; the equations governing yield production begin with water balance calculations prior to seed germination and continue through to the estimation of yield based on biomass towards the end of the plant growing cycle. For irrigation, the only influential parameters were *rtx* and the *smt* parameters. The *rtx* parameter controls the rooting depth, which defines the depth to which soil water can be used by the plant, and the *smt* parameters all determine when and how much water is applied to the crop. For corn and sorghum yield, the biomass and yield formation parameters (*wp* and *hi*) and a stress parameter (*hipsveg,* which links restricted vegetative plant growth to yield changes) were influential in addition to *smt* values. Additionally, we identified the canopy development and senescence parameters (*ccx*, *rtx*, and *kc*) as sensitive, aligning with findings from past studies (Lu et al., 2021; Ran et al., 2022). To calibrate the model for each crop, we used the influential parameters identified for yield or irrigation across any of the three meteorological scenarios (Table 3, last row). Influential parameters were calibrated while non-influential parameters were fixed to simplify the model calibration.

Table 3. List of sensitive parameters for irrigation depth and crop yield under different meteorological conditions. The bold final row indicates the full list of parameters used to calibrate the models. Parameters are defined in Table 1.

Variable and Scenario	Sensitive Parameters (Corn)	Sensitive Parameters (Sorghum)
Irrigation, dry year	*rtx, smt1, smt2, smt3*	*rtx, smt1, smt2, smt3*
Irrigation, normal year	*rtx, smt1, smt2, smt3*	*rtx, smt1, smt2, smt3*
Irrigation, wet year	*rtx, smt1, smt2*	*rtx, smt1, smt2*
Yield, dry year	rtx, smt1, smt2	rtx, hi, smt1, smt2
Yield, normal year	ccx, rtx, kc, wp, hi, smt1, smt2, smt3	ccx, wp, hi, smt2, smt3
Yield, wet year	ccx, rtx, kc, wp, hi, hipsveg, smt1, smt2	ccx, rtx, kc, wp, hi, smt1, smt2
Parameters used in calibration	**ccx, rtx, kc, wp, hi, hipsveg, smt1, smt2, smt3**	**ccx, rtx, kc, wp, hi, smt1, smt2, smt3**

4.2 Model calibration and bias correction

4.2.1 Overall model calibration and bias correction

For corn, KGE for simulated irrigation depth indicated that the skill of the model ($-0.01 \leq$ KGE ≤ 0.04; Fig. 5, Table S3) exceeded the performative benchmark of KGE = -0.41 (Knoben et al., 2019). Furthermore, the corn irrigation RMSE were comparable between the calibration (127 mm) and validation (138 mm) stages, which indicated that the model was not subject to overfitting. Due to the similar RMSE, the NRMSE was also similar in the calibration and validation steps. While the models performed satisfactorily in simulating irrigation depths during calibration and validation, we observed poor KGE values for corn yield during both stages (KGE ≤ -0.41; Table S3). Despite the fair NRSME values (NRMSE < 0.3) for yield during these stages, the RMSE values were high (3.2 t/ha $\leq$ RMSE $\leq$ 3.5 t/ha) and above those reported in the literature, which ranged between 0.14 t/ha and 1.77 t/ha (Ahmadi et al., 2015; Heng et al., 2009; Paredes et al., 2014; Sandhu & Irmak, 2019). The performance of the sorghum models were generally worse for both irrigation and yield compared to the corn models (Fig. 5). For sorghum irrigation, we observed 'acceptable' KGE values (KGE ≈ 0.07) and high RMSE (133 mm $\leq$ RMSE $\leq$ 143 mm) and NRMSE ($0.62 \leq$ NRMSE ≤ 0.85) values during the calibration and validation stages (Fig. 5, Table S4). For sorghum yield, KGE values were poor while RMSE and NRMSE were less than 2.6 t/ha and 0.38, respectively during both stages.

We observed a significant improvement in the model performances for both crops and variables after applying the bias correction (Fig. 5). For the corn and sorghum models, there was high correlation between the simulated values and the residuals prior to the bias correction process (yield $r^2 \geq 0.66$; irrigation $r^2 \geq 0.86$; Fig. S4, Fig. S5), which meant that the modified difference bias correction approach was effective at improving model performance without any additional data beyond simulated outputs. The bias correction of the corn model resulted in fair crop yield and irrigation performances with 'medium' KGE and 'fair' NRMSE values (Table S3). After bias-correction, the corn models (RMSE = 1.2 t/ha (yield) and 79 mm (irrigation), NRMSE = 0.10 (yield) and 0.22 (irrigation)) still outperformed the sorghum models (RMSE = 1.0 t/ha (yield) and 87 mm (irrigation), NRMSE = 0.15 (yield) and 0.41 (irrigation)), but for both crops and variables the bias-corrected results provide the best match with observations compared to non-bias-corrected model output. For corn yield, the RMSE and NRMSE were 1.2 t/ha and 0.10, respectively within the range observed in other studies (Ahmadi et al., 2015; Heng et al., 2009; Paredes et al., 2014; Sandhu & Irmak, 2019). The bias correction of the sorghum model improved all the fit metrics and led to crop yield RMSE (1.0 t/ha) values that were closer to the 0.5 t/ha - 0.7 t/ha range reported by Masasi et al., (2019) and Fazel et al., (2023). However, the bias correction compromised the sorghum model's ability to accurately simulate variations in observed values. Hereafter, models without bias correction are referred to as ‘calibrated models’ and their simulation results as ‘calibrated’, while those with bias correction are denoted as ‘bias-corrected models’ and their simulation results as ‘bias-corrected’.

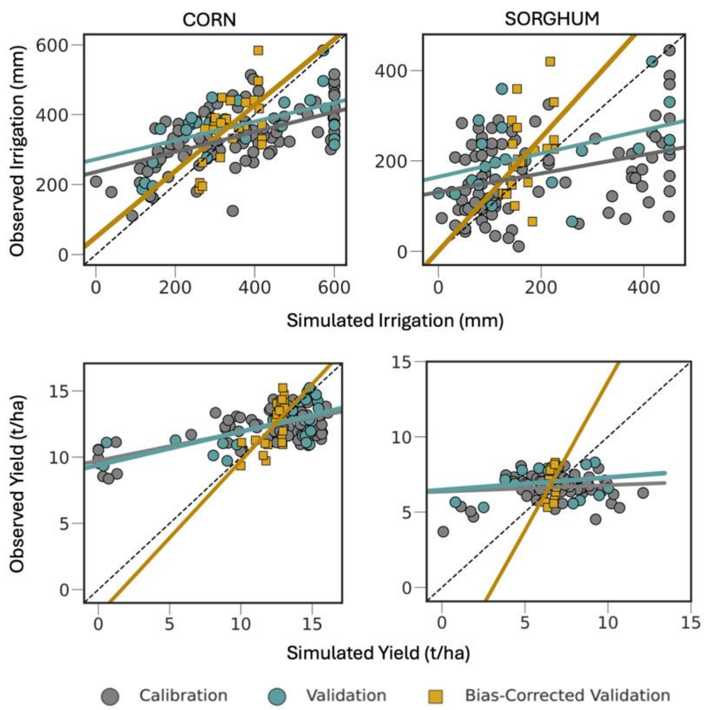


Figure 5. Comparison of simulated and observed corn (left column) and sorghum (right column) irrigation (top row) and yield (bottom row) during the calibration, validation, and bias-correction steps.

4.2.2 Spatial and temporal variability in performance

4.2.2.1 Corn model

The corn model successfully captured the general temporal pattern observed in the irrigation depths but tended to overestimate the variability of the fluctuations (Fig. 6A). For example, in 2008 and 2020, as well as between 2011 and 2013, there were significant differences between the observed and calibrated irrigation depths in counties located in the central and eastern parts of the region (Gove, Logan, Rawlins, Sheridan and Thomas). In contrast, the bias-corrected model more accurately simulated the temporal dynamics in irrigation, though it tended to underestimate variability compared to observations. In the western counties (Cheyenne and Sherman) with higher observed irrigation rates, the bias-corrected model underestimated irrigation depths from 2006 – 2017, while it did the same in Wallace between 2006 and 2008. The irrigation bias-correction was most effective for counties in the central and eastern part of GMD-4, specifically Gove, Graham, and Decatur (Fig. 6A).

There were fewer fluctuations in the observed corn yield across all counties over the study period (Fig. 6B). During the extremely dry years, such as 2011 and 2012, the calibrated model underestimated yield (<2 t/ha) and overestimated irrigation requirements (Fig. 6) due to high temperature stress (above 35ºC). This is due to a combination of (1) a reduction in the potential harvest index due to heat stress during the flowering period and (2) water stress during a high crop water demand period. Given the proportional relationship between *hi* and yield, (Eq. 2), reductions in *hi* result in lower yield. Moreover, temperatures above 30ºC slow plant growth by limiting photosynthesis (Miller, 2018) and reducing grain fill (Zhao et al., 2022). Although the calibrated model underestimated irrigation applications between 2017 and 2019 in Gove and Graham counties, the simulated yields were generally comparable to the observed yields. Since the amount of irrigation applied is a function of both physical conditions (weather, soil) and human decisions (management strategy, resource availability), this suggests difficulties in simulating farmer behavior differences between years, which would not be well-captured by a crop model unless it explicitly simulates time-varying decision-making processes (i.e., Lin et al., 2024), or limitations related to soil hydrology that are causing incorrect relationships between irrigation, soil moisture, and crop water stress (Heng et al., 2009; Sandhu & Irmak, 2019a). During these years, the bias-correction model substantially improved the match between simulated and observed yields.

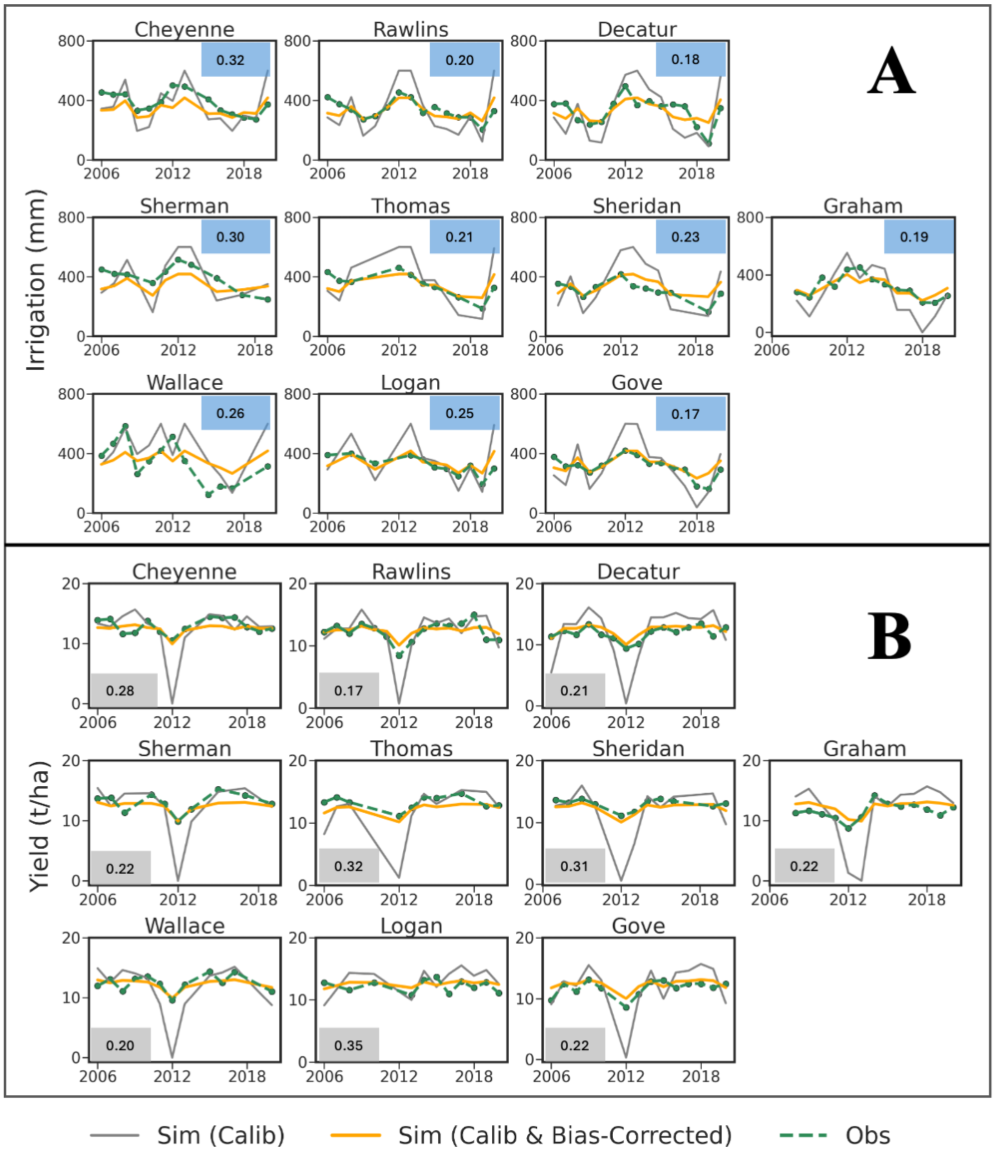


Figure 6. Comparison of observed, calibrated and bias-corrected irrigation and yield for corn over the 2006 - 2020 period for each county in the study domain. The blue and gray boxes show the bias-corrected NRSME values for irrigation and crop yield, respectively. The panels are arranged based on the location of the counties (Fig, 1).

4.2.2.2 Sorghum model

The performance of the sorghum model was impacted by the limited availability of observational data for irrigation and yield (Fig. 7). For example, the number of annual observed irrigated sorghum fields ranged from one to seventeen. Compared to corn, there were more fluctuations in the observed sorghum irrigation depths as well as lower overall irrigation rates, possibly due to the smaller overall amount of sorghum being grown in the area (Zipper, Kastens, et al., 2024) and therefore observed data being more subject to variability in the irrigation practices of sorghum growers and the influence of potential outliers. We believe this contributed to the model's difficulties in accurately capturing the dynamics of sorghum growth (Fig. 7). Our analysis shows that the calibrated model tended to overestimate irrigation depths (Fig. 7A). For example, in 2008 and 2011, the calibrated model failed to simulate the decreases in irrigation depths in Cheyenne, Sherman and Sheridan, and instead simulated sharp increases (Fig. 7A). Additionally, some of the calibrated irrigation depth peaks were out of phase with the observed data such as those in Gove, Sheridan and Thomas. Although the performance of the calibrated model was generally poor across most counties, its performance in Graham County was exceptional and closely matched the observed data (Fig. 7A). Similar to corn yield, the drought in 2012 led to low simulated crop yields and high simulated irrigation depths (Fig. 7). However, due to sorghum's greater tolerance to water stress (Lamm et al., 2014), simulated sorghum yields were generally more stable than those for corn.

Generally, the sorghum bias correction eliminated the major peaks in the simulated data, which led to the underestimation of the irrigation depths during dry years, when irrigation is higher, and overestimation of irrigation depths during wet years, when irrigation is lower (Fig. 7A). Across the nine counties with irrigation data, the bias correction resulted in significant improvements in Thomas and Sheridan counties, beginning in 2011, when irrigation depths became consistent. Although the calibrated model failed to closely match most of the observed yields, it had more variability which matched some of the trends in the observed data (Fig. 7B). The bias-correction yield model lowered the magnitude of the residuals for the study period, but it also eliminated the model's ability to capture the fluctuations in irrigation and yield. Overall, the bias-corrected sorghum model outperformed the calibrated model particularly during the drier periods (2006, 2007, 2012, 2013 and 2020), suggesting it is appropriate to use in our synthetic drought scenario.

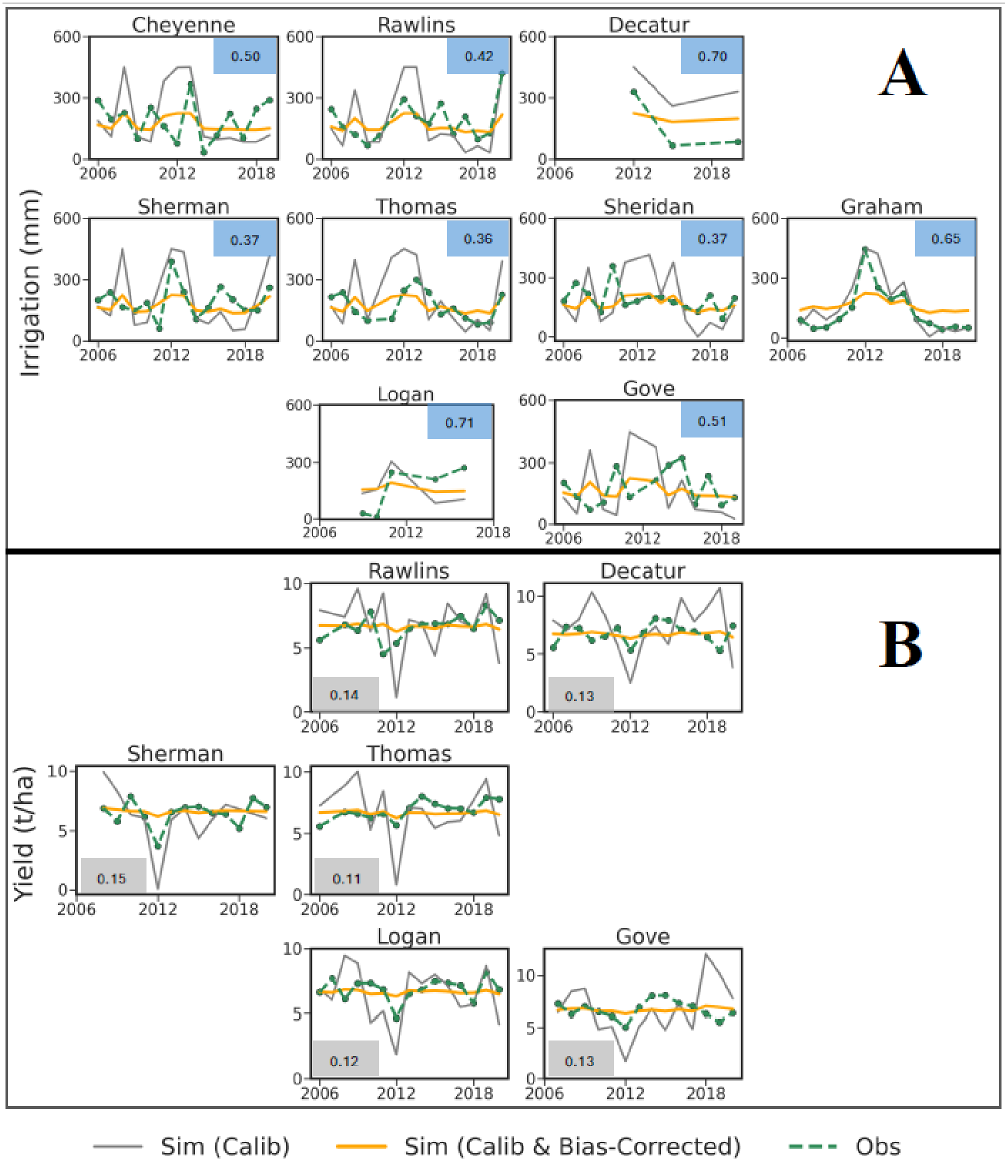


Figure 7. Comparison of observed, calibrated and bias-corrected irrigation and yield for sorghum over the 2006 - 2020 period for each county in the study domain. The blue and gray boxes show the bias-corrected NRSME values for irrigation and crop yield, respectively. The panels are arranged based on the location of the counties (Fig. 1).

4.2.3 Utility of bias-corrected models

Bias-correction is a valuable tool to improve model performance in other disciplines that investigate complex environmental systems, such as climate modeling and hydrology, but rarely used in crop modeling. Since the focus of our modeling exercise was assessing the potential effectiveness of the GMD-4 LEMA during severe drought conditions, we specifically examined the bias-corrected models' capabilities during dry periods. As discussed in previous sections, the bias-corrected corn model performed satisfactorily throughout the study period (Fig. 6). During extreme drought periods such 2012 and 2013, the bias-corrected model accurately simulated the decrease in crop yield. For most counties in the central and eastern parts of the GMD-4 region, the increase in irrigation depths was correctly simulated. However, for counties in the west (Cheyenne, Sherman, and Wallace), which had slightly higher observed irrigation depths, the bias-corrected model underestimated the irrigation requirements by about 50 mm (approximately 8-13% of observed irrigation values). On the other hand, improvements in the bias-corrected sorghum model were not as strong, as discussed in Section 4.2.2, which led to less variability in biased corrected values than observed data (Fig. 7). While alternate bias correction approaches, such as a non-linear or segmented difference-based bias correction may have provided a better fit, the relationships between residuals and simulated sorghum yield were highly linear except at the very highest residuals, where they flattened off (Fig. S5). This suggests that the incorporation of additional variables for model calibration or application of alternate bias-correction functional forms may be able to address these extreme years and improve performance. For sorghum yield, the bias-corrected model simulated values of about 6 t/ha while the observed yield ranged between 3 t/ha and 8 t/ha. In countries that experienced a major increase in pumping rates during the 2012 drought (Sherman and Graham), the model severely underestimated the irrigation requirements by close to 200 mm. However, in 2006 and 2007 which had low precipitation, the differences between the observed and bias-corrected crop yield and irrigation depths were within acceptable ranges and generally less than 1.5 t/ha and 50 mm, respectively. Since the bias-corrected corn model successfully captures most spatial and temporal patterns, we conclude that it can be effectively used in studies investigating regional agricultural water management objectives, including those focused on crop-water productivity during extreme drought.

Our analysis accounted for various sources of model uncertainty, such as the uncertainty due to initial soil moisture conditions, input parameters and the calibration optimization algorithm used. However, disentangling the proportions of uncertainties from each source remains challenging for crop models, particularly since they are primarily calibrated and assessed relative to year-end values (yield and irrigation). Since many different factors interact to determine these year-end values, crop models are subject to model equifinality, meaning that multiple model parameterizations can provide similar performance (Lamsal et al., 2018). Therefore, it is therefore difficult to determine precisely which specific uncertainties the bias correction method addresses. Although several bias correction methods have been proposed in previous literature (Section 3.3.3), a major limitation is that they typically require large datasets and daily-scale data. Given that our study is based on limited annual data, these methods were not feasible for our analysis. Studies such as that by Roberts et al. (2017) further demonstrate the potential benefits of combining statistical models with process-based crop simulation models, in particular to account for impacts of unobserved heterogeneity in model inputs and uncertainties in model parameterization and structure. Overall, our results suggest that bias-correction can be a potentially valuable tool to improve the ability of models to simulate observed irrigation and crop yield dynamics.

4.3 Effectiveness of different water management strategies during severe drought

4.3.1 Variation in yield, irrigation, and water use efficiency

We evaluated the effectiveness of different irrigation management strategies (UW, CS, and CV; Table 2) by comparing irrigation (Fig. 8), yield (Fig. 9), and water use efficiency (Fig. 10) averaged over our simulated synthetic drought scenario using the bias-corrected models for the counties in the GMD-4 LEMA. We compared simulated irrigation to the average annual GMD-4 and Sheridan-6 LEMA allocations to assess how each management strategy compared to authorized water withdrawals. In our study, irrigation begins earlier in the UW scenario due to soil moisture thresholds (SMTs) for triggering irrigation being 10% higher than in the CS scenario, while it is delayed in the CV scenario due to SMT values being 10% lower than in the CS scenario. As a result, irrigation is highest during the UW scenario and lowest during the CV scenario. We observed relatively minor differences in the corn irrigation depths between the three scenarios, with average differences between UW and CV scenarios of ~70 mm. The differences among years was greatest during the driest years and caused by variation in the timing and depth of irrigation application events, which was ultimately driven by the root zone water balance's role in triggering irrigation (Ndlovu, 2024). For sorghum, irrigation depths during the CS and CV scenarios showed little variation.

Overall, the GMD-4 LEMA water allocations tended to be greater than the irrigation requirements for both corn and sorghum in most zones and irrigation management scenarios. Only townships in Zone 1 and 5 exceeded the Level 3 allocations under the corn UW scenario. However, after accounting for the model uncertainty, corn irrigation under CS and UW scenarios exceeded the GMD-4 LEMA Level 2 allocation limits in several zones. Corn cultivation under the three scenarios resulted in irrigation application depths that were higher than the Sheridan-6 LEMA allocations in all zones. Sorghum, on the other hand, required substantially less water than corn did for each scenario. As a result, under sorghum cultivation none of the water allocation thresholds were exceeded.

Although there were differences in the corn irrigation application rates across the three scenarios, their impact on crop yield was relatively small. Within a given county and management zone, the crop yield differences for both corn and sorghum were less than 1.0 t/ha (Fig. 9). Comparing across all six zones, for a given irrigation strategy, the simulated crop yields were similar (10 t/ha – 13 t/ha range) across counties. While some of the similarity may be linked to the bias correction process, in particular for sorghum (Fig. 7), the bias-corrected crop models were generally able to simulate yield reductions during drought (Fig. 5, Fig. 6), suggesting that the simulated yield dynamics are reasonable. However, dynamics that may occur during a severe multi-year drought but were not reflected in crop yield data during our calibration and validation period may not be captured here. In general, sorghum yield was approximately half of corn yield, reflecting the lower overall yield potential of this crop. The maximum corn yield was 13 t/ha while the maximum sorghum yield was 7 t/ha.

Crop water use efficiency (defined here as simulated yield per mm of simulated irrigation) generally showed consistent patterns between crop type and irrigation management scenarios (Fig. 10). Among crops, water use efficiency was higher for sorghum than for corn. Comparing irrigation scenarios for a given crop, the greatest water use efficiency generally occurred in the CV scenario. In the easternmost portion of the domain (Zones 5 and 6), the water use efficiency for UW sorghum tended to still be greater than for CV corn, indicating the dominant control of crop type over water use efficiency variation. In the western counties, such as Zones 1-3, CV corn tended to have a greater water use efficiency than UW sorghum, but lower than CS sorghum.

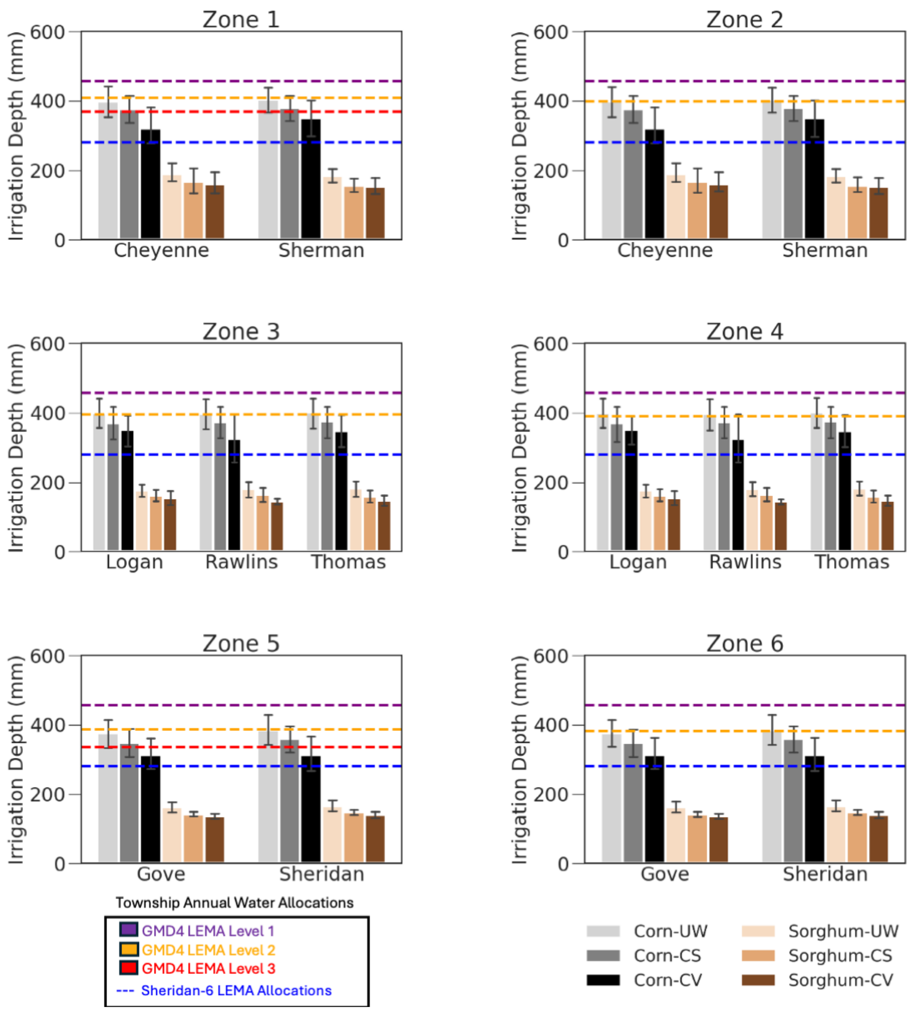


Figure 8. Predicted annual irrigation depths for corn and sorghum during synthetic drought simulation under UW, CS, and CV irrigation scenarios. The horizontal lines represent the GMD-4 LEMA allocations (Level 1 to 3) in the six zones within the GMD-4 LEMA shown in Figure 2. The blue line represents the Sheridan-6 LEMA annual allocation based on the 55 inches/5-year LEMA cycle allocation. Error bars represent the irrigation RMSE values from the bias-corrected models.

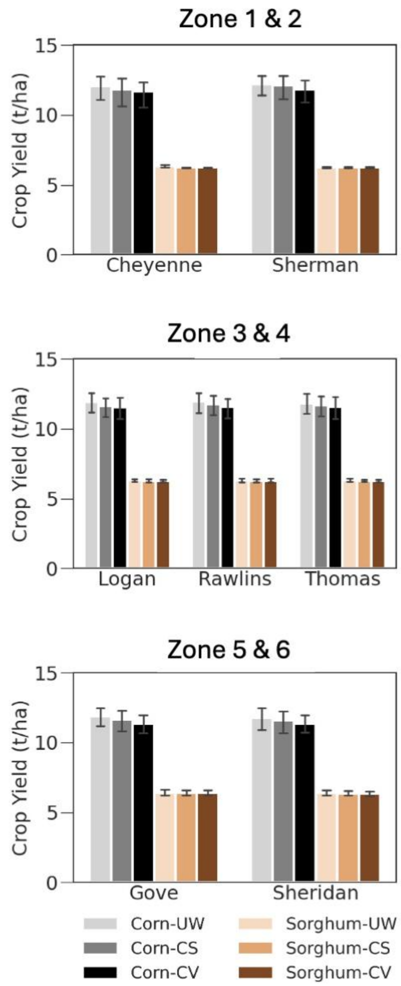


Figure 9. Predicted annual crop yield for corn and sorghum during synthetic drought simulation under UW, CS, and CV irrigation scenarios. Error bars represent the crop yield RMSE values from the bias-corrected models.

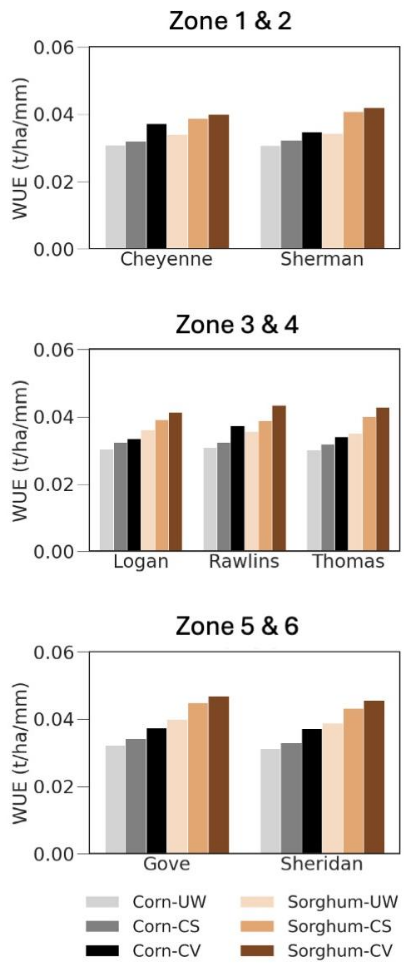


Figure 10. Predicted annual crop yield water use efficiency (WUE) for corn and sorghum during synthetic drought simulation under UW, CS, and CV irrigation scenarios.

4.3.2 Assessment of effectiveness

Comparing the simulated annual irrigation demands for corn and sorghum under CV, CS and UW scenarios to the annual GMD-4 LEMA pumping limits shows that this LEMA is ineffective, meaning that the limits would not promote reductions in water use because they are generally higher than existing crop requirements (Fig. 8). In most townships and zones, the GMD-4 LEMA can effectively support corn irrigation, which requires approximately 400 mm on average, under all three scenarios, without exceeding the GMD-4 LEMA Levels 1 to 3 pumping limits (Fig. 8). However, these corn irrigation requirements exceeded the lower average annual allocations of the Sheridan-6 LEMA (279.4 mm; 11 inches), which has effectively reduced water use (Orduña Alegría et al., 2024; Whittemore et al., 2023). These findings suggest that corn cultivation under the current GMD-4 LEMA allocations would be ineffective at conserving groundwater during prolonged droughts. This aligns with a previous assessment of the effectiveness of GMD-4 and Sheridan-6 LEMA conservation practices, which showed that the

Sheridan-6 LEMA was more effective at reducing water use than the GMD-4 LEMA (Whittemore et al., 2023). Their study shows that the first GMD-4 LEMA achieved very little water conservation while the two Sheridan-6 LEMA cycles led to a 27.4% reduction in total irrigation groundwater use decrease in water table decline rates from 0.43 m/year (1.4 ft/year) during the pre-LEMA to 0.18 m/year (0.6 ft/year) during the LEMA (Whittemore et al., 2023). In contrast, the GMD-4 LEMA water allocations, which were generally higher than the average irrigation water use during the pre-LEMA period, have only affected a few irrigators with high irrigation rates due to the LEMA restrictions (Whittemore et al., 2023).

Our study also provides evidence that switching to sorghum cultivation offers significant benefits for overall groundwater conservation. During droughts, sorghum utilizes about half of the GMD-4 LEMA Level 2 allocations (~180 mm) under all scenarios compared to corn which requires ~90% of the allocations. Furthermore, sorghum cultivation requires irrigation application rates that are within the Sheridan-6 LEMA allocations, making it a sustainable option for water resource management in the region. While yield is also lower for sorghum compared to corn, it typically has a greater overall water use efficiency in the region (Fig. 10). However, we acknowledge that apart from crop water use, farmers in the region also select crops based on economic returns, available government programs including crop insurance, crop adaptability in the area and overall crop production (Hu & Beattie, 2019; Klocke et al., 2012; Zipper, Ifft, et al., 2024). Based on an irrigator's priority, preference may be given to corn which is used as feed grain for the beef and dairy industry and also for ethanol production (Bhattarai et al., 2020).

We also found that both crops had relatively little yield sensitivity to the three irrigation application rates (CV, CS, and UW) that we tested (Fig. 9). This may be due to one of several factors, including the relatively small (10%) changes in *smt* values between irrigation strategies, issues with model calibration, or dampened sorghum yield variability caused by bias correction (see Section 4.2). However, other studies have also shown that sorghum is both more water stress tolerant and less responsive to irrigation compared to corn (Lamm et al., 2014). In one study, Klocke et al., (2012) found total irrigation depths of 25 mm produced 91% of yields from the 200 mm irrigation treatment. (Eck & Musick, 1979) also indicated that sorghum yield was not affected by 13 to 15 days of water stress; however, yield reductions of about 27% and 50% were observed after 27 to 28 and 35 to 42 days of stress, respectively. We found that reducing corn irrigation by up to 70 mm between the UW and CV scenarios led to crop yield differences that were less than 1.0 t/ha (Fig. 9). A field study done in Kansas showed that limiting irrigation by about 60 mm - 70 mm led to average yield that was 95% of the full irrigation treatment (Klocke et al., 2012). Similarly, in Texas, 75% (413 mm) and 100% (550) irrigation treatments resulted in similar end of season crop yield for one of the irrigation sprinkler methods (Schneider & Howell, 1998). Moreover, the overall yield difference between the 75% and 100% irrigation treatments across all four sprinkler methods was only 1.5 t/ha (Schneider & Howell, 1998). Therefore, our results highlight the potential to improve water use efficiency by reducing crop irrigation rates without significant yield losses, even during prolonged droughts.

5. Conclusions

This study sought to understand the current and potential effectiveness of an innovative groundwater conservation program. To accomplish this, the goals of this study were to calibrate the corn and sorghum AquaCrop models for GMD-4 LEMA using sensitivity analysis, the PSO algorithm, and a novel bias-correction approach; and use the calibrated models to assess the effectiveness of different irrigation management strategies relative to local LEMA water allocation limits during a synthetic five-year drought. From this analysis, the key findings were:

1. In GMD-4, AquaCrop was better at simulating corn irrigation and yield compared to sorghum. The worse sorghum performance is likely due to limited observational data, leading to challenges in model calibration. However, both models had some limitations in capturing the spatial pattern of the observed data, particularly the higher irrigation requirements in the western portion of GMD-4.
2. The incorporation of a residual-based difference method for bias correction substantially improved irrigation and yield simulation performance for both crops. Overall, the difference method bias correction worked better for corn models, which had fewer variations in observed data, than for sorghum models. Performance improvements were particularly notable during the extremely dry periods, such as the 2012 drought. This suggests that bias-correction may be a useful tool for crop modeling in complex and poorly-constrained systems.
3. Under our synthetic drought simulations, all three water management scenarios were able to maintain high crop yield. Simulated irrigation depths during the synthetic drought were generally below the GMD-4 LEMA water allocations, suggesting that the high water allocations may be ineffective for conserving water. However, the corn irrigation requirements exceeded the Sheridan-6 LEMA allocations, which have been effective in promoting groundwater conservation in the region.
4. During the multi-year severe drought scenario, there was a relatively small impact of decreasing irrigation application on crop yield for both crops. This highlights the potential to reduce crop irrigation rates without significant yield losses during extended droughts through improved water use efficiency.

Acknowledgments

This work was supported by the National Science Foundation (NSF) [grant number RISE-2108196], with additional support from the National Aeronautics and Space Administration (NASA) [grant number 80NSSC22K1276] and U.S. Department of Agriculture (USDA) [grant number 2025-68012-44235]. TF was also supported by Innovate UK [award number 10044695], as part of the UK Research and Innovation and European Commission funded project 'TRANSCEND: Transformational and robust adaptation to water scarcity and climate change under deep uncertainty'. We appreciate useful feedback and suggestions from Jim Butler, Rick Devlin, Mary Hill, Malena Orduña Alegría, Greg Tucker, and Brownie Wilson. We acknowledge computing time on the CU-CSDMS High-Performance Computing Cluster and appreciate computing support from Mark Piper. This manuscript is adapted from Ndlovu's M.S. thesis, available at https://www.proquest.com/dissertations-theses/assessing-effectiveness-resilience-groundwater/docview/3160666385/se-2

Data Statement

Data and code from this study are available on the HydroShare repository: https://www.hydroshare.org/resource/297e1cfd67ec4baca164b0974921eeb8/

Author Contributions

Ndlovu: Conceptualization, Data curation, Formal Analysis, Investigation, Methodology, Software, Validation, Visualization, Writing – original draft, Writing – review & editing

Zipper: Conceptualization, Funding acquisition, Methodology, Project administration, Resources, Supervision, Writing – review & editing

Foster: Funding acquisition, Methodology, Software, Writing – review & editing

References

Abatzoglou J. T. (2013). gridMET. Retrieved December 7, 2022, from https://www.climatologylab.org/gridmet.html

Acharya, N., Chattopadhyay, S., Mohanty, U. C., Dash, S. K., & Sahoo, L. N. (2013). On the bias correction of general circulation model output for Indian summer monsoon. *Meteorological Applications*, *20*(3), 349–356. https://doi.org/10.1002/met.1294

Ahmadi, S. H., Mosallaeepour, E., Kamgar-Haghighi, A. A., & Sepaskhah, A. R. (2015). Modeling Maize Yield and Soil Water Content with AquaCrop Under Full and Deficit Irrigation Managements. *Water Resources Management*, *29*(8), 2837–2853. https://doi.org/10.1007/s11269-015-0973-3

Anandakumar, H., & Umamaheswari, K. (2018). A bio-inspired swarm intelligence technique for social aware cognitive radio handovers. *Computers & Electrical Engineering*, *71*, 925–937. https://doi.org/10.1016/j.compeleceng.2017.09.016

Andresen, S. (2015). International Climate Negotiations: Top-down, Bottom-up or a Combination of Both? *The International Spectator*, *50*(1), 15–30. https://doi.org/10.1080/03932729.2014.997992

Araya, A., Kisekka, I., & Holman, J. (2016). Evaluating deficit irrigation management strategies for grain sorghum using AquaCrop. *Irrigation Science*, *34*(6), 465–481. https://doi.org/10.1007/s00271-016-0515-7

Araya, A., Kisekka, I., Vara Prasad, P. V., & Gowda, P. H. (2017). Evaluating Optimum Limited Irrigation Management Strategies for Corn Production in the Ogallala Aquifer Region.

Journal of Irrigation and Drainage Engineering, *143*(10), 04017041. https://doi.org/10.1061/(ASCE)IR.1943-4774.0001228

Araya, A., Kisekka, I., Lin, X., Vara Prasad, P. V., Gowda, P. H., Rice, C., & Andales, A. (2017). Evaluating the impact of future climate change on irrigated maize production in Kansas. *Climate Risk Management*, *17*, 139–154. https://doi.org/10.1016/j.crm.2017.08.001

Bhattarai, B., Singh, S., West, C. P., Ritchie, G. L., & Trostle, C. L. (2020). Water Depletion Pattern and Water Use Efficiency of Forage Sorghum, Pearl millet, and Corn Under Water Limiting Condition. *Agricultural Water Management*, *238*, 106206. https://doi.org/10.1016/j.agwat.2020.106206

Bosompemaa, P., Brookfield, A., Zipper, S., & Hill, M. C. (2025). Using national hydrologic models to obtain regional climate change impacts on streamflow basins with unrepresented processes. *Environmental Modelling & Software*, *183*, 106234. https://doi.org/10.1016/j.envsoft.2024.106234

Butler, J. J., Whittemore, D. O., Wilson, B. B., & Bohling, G. C. (2018). Sustainability of aquifers supporting irrigated agriculture: a case study of the High Plains aquifer in Kansas. *Water International*, *43*(6), 815–828. https://doi.org/10.1080/02508060.2018.1515566

Cavero, J., Farre, I., Debaeke, P., & Faci, J. M. (2000). Simulation of Maize Yield under Water Stress with the EPICphase and CROPWAT Models. *Agronomy Journal*, *92*(4), 679–690. https://doi.org/10.2134/agronj2000.924679x

Chaney, N. W., Wood, E. F., McBratney, A. B., Hempel, J. W., Nauman, T. W., Brungard, C. W., & Odgers, N. P. (2016). POLARIS: A 30-meter probabilistic soil series map of the contiguous United States. *Geoderma*, *274*, 54–67. https://doi.org/10.1016/j.geoderma.2016.03.025

Chang, H., & Bonnette, M. R. (2016). Climate change and water-related ecosystem services: impacts of drought in california, usa. *Ecosystem Health and Sustainability*, *2*(12), e01254. https://doi.org/10.1002/ehs2.1254

Ciampitti, I., Carcedo, A. J. P., Diaz, D. R., Onefre, R. B., Lancaster, S., Whitworth, R. J., & Aguilar, J. (2022). *Kansas Sorghum Management* (No. MF3046). Kansas State University.

Ciampitti, I., Correndo, A., Lancaster, S., Diaz, D. R., Aguilar, J., Sharda, A., et al. (2023). *Kansas Corn Management* (No. MF3208). Kansas State University.

Cook, B. I., Mankin, J. S., & Anchukaitis, K. J. (2018). Climate Change and Drought: From Past to Future. *Current Climate Change Reports*, *4*(2), 164–179. https://doi.org/10.1007/s40641-018-0093-2

Deines, J. M., Kendall, A. D., Butler, J. J., & Hyndman, D. W. (2019). Quantifying irrigation adaptation strategies in response to stakeholder-driven groundwater management in the US High Plains Aquifer. *Environmental Research Letters*, *14*(4), 044014. https://doi.org/10.1088/1748-9326/aafe39

Deines, J. M., Schipanski, M. E., Golden, B., Zipper, S. C., Nozari, S., Rottler, C., et al. (2020). Transitions from irrigated to dryland agriculture in the Ogallala Aquifer: Land use suitability and regional economic impacts. *Agricultural Water Management*, *233*, 106061. https://doi.org/10.1016/j.agwat.2020.106061

Deines, J. M., Kendall, A. D., Butler, J. J., Basso, B., & Hyndman, D. W. (2021). Combining Remote Sensing and Crop Models to Assess the Sustainability of Stakeholder-Driven Groundwater Management in the US High Plains Aquifer. *Water Resources Research*, *57*(3), e2020WR027756. https://doi.org/10.1029/2020WR027756

Dorjderem, B., Torres-Martínez, J. A., & Mahlknecht, J. (2020). Intensive long-term pumping in the Principal-Lagunera Region aquifer (Mexico) causing heavy impact on groundwater quality. *Energy Reports*, *6*, 862–867. https://doi.org/10.1016/j.egyr.2019.11.020

Drysdale, K. M., & Hendricks, N. P. (2018). Adaptation to an irrigation water restriction imposed through local governance. *Journal of Environmental Economics and Management*, *91*, 150–165. https://doi.org/10.1016/j.jeem.2018.08.002

Dube, K., Nhamo, G., & Chikodzi, D. (2022). Climate change-induced droughts and tourism: Impacts and responses of Western Cape province, South Africa. *Journal of Outdoor Recreation and Tourism*, *39*, 100319. https://doi.org/10.1016/j.jort.2020.100319

Eberhart, R. C., & Shi, Y. (2001). Tracking and optimizing dynamic systems with particle swarms. In *Proceedings of the 2001 Congress on Evolutionary Computation (IEEE Cat. No.01TH8546)* (Vol. 1, pp. 94–100 vol. 1). https://doi.org/10.1109/CEC.2001.934376

Eck, H. V., & Musick, J. T. (1979). Plant Water Stress Effects on Irrigated Grain Sorghum. I. Effects on Yield. *Crop Science*, *19*(5), cropsci1979.0011183X001900050009x. https://doi.org/10.2135/cropsci1979.0011183X001900050009x

Fang, G. H., Yang, J., Chen, Y. N., & Zammit, C. (2015). Comparing bias correction methods in downscaling meteorological variables for a hydrologic impact study in an arid area in China. *Hydrology and Earth System Sciences*, *19*(6), 2547–2559. https://doi.org/10.5194/hess-19-2547-2015

Fazel, F., Ansari, H., & Aguilar, J. (2023). Determination of the Most Efficient Forage Sorghum Irrigation Scheduling Strategies in the U.S. Central High Plains Using the AquaCrop Model and Field Experiments. *Agronomy*, *13*(10), 2446. https://doi.org/10.3390/agronomy13102446

Feltman, B. (2024). *Sustaining Water Resources and Communities Through Local Collaborative Governance* (Ph.D.). Michigan State University, United States -- Michigan. Retrieved from https://www.proquest.com/docview/3047749156/abstract/897AD25806E74ADFPQ/1

Foster, T., Brozović, N., Butler, A. P., Neale, C. M. U., Raes, D., Steduto, P., et al. (2017). AquaCrop-OS: An open source version of FAO's crop water productivity model. *Agricultural Water Management*, *181*, 18–22. https://doi.org/10.1016/j.agwat.2016.11.015

GMD 4 LEMA. (2024). Retrieved October 23, 2024, from https://gmd4.org/LEMA.html

Gorelick, S. M., & Zheng, C. (2015). Global change and the groundwater management challenge. *Water Resources Research*, *51*(5), 3031–3051. https://doi.org/10.1002/2014WR016825

Gupta, H. V., Kling, H., Yilmaz, K. K., & Martinez, G. F. (2009). Decomposition of the mean squared error and NSE performance criteria: Implications for improving hydrological modelling. *Journal of Hydrology*, *377*(1), 80–91. https://doi.org/10.1016/j.jhydrol.2009.08.003

Haacker, E. M. K., Cotterman, K. A., Smidt, S. J., Kendall, A. D., & Hyndman, D. W. (2019). Effects of management areas, drought, and commodity prices on groundwater decline patterns across the High Plains Aquifer. *Agricultural Water Management*, *218*, 259–273. https://doi.org/10.1016/j.agwat.2019.04.002

He, Y., Hou, L., Wang, H., Hu, K., & McConkey, B. (2014). A modelling approach to evaluate the long-term effect of soil texture on spring wheat productivity under a rain-fed condition. Scientific Reports, 4, 5736. https://doi.org/10.1038/srep05736

Heng, L. K., Hsiao, T., Evett, S., Howell, T., & Steduto, P. (2009). Validating the FAO AquaCrop Model for Irrigated and Water Deficient Field Maize. *Agronomy Journal*, *101*(3), 488–498.

Herman, J., & Usher, W. (2017). SALib: An open-source Python library for sensitivity analysis. *Journal of Open Source Software, 2(9). Doi:10.21105/Joss.00097*.

High Plains aquifer | U.S. Geological Survey. (2024). Retrieved September 10, 2024, from https://www.usgs.gov/mission-areas/water-resources/science/high-plains-aquifer

Hu, Y., & Beattie, S. (2019). Role of Heterogeneous Behavioral Factors in an Agent-Based Model of Crop Choice and Groundwater Irrigation. *Journal of Water Resources Planning and Management*, *145*(2), 04018100. https://doi.org/10.1061/(ASCE)WR.1943-5452.0001033

Jaiswal, R., Mall, R. K., Singh, N., Lakshmi Kumar, T. V., & Niyogi, D. (2022). Evaluation of Bias Correction Methods for Regional Climate Models: Downscaled Rainfall Analysis Over Diverse Agroclimatic Zones of India. *Earth and Space Science*, *9*(2), e2021EA001981. https://doi.org/10.1029/2021EA001981

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

Kansas Mesonet · Soil Moisture. (2024). Retrieved September 28, 2024, from https://mesonet.k-state.edu/agriculture/soilmoist/#tab=chart-tab

Kaur, K., & Kaur, N. (2023). Comparison of bias correction methods for climate change projections in the lower Shivaliks of Punjab. *Journal of Water and Climate Change*, *14*(8), 2606–2625. https://doi.org/10.2166/wcc.2023.503

Kelly, T. D., & Foster, T. (2021). AquaCrop-OSPy: Bridging the gap between research and practice in crop-water modeling. *Agricultural Water Management*, *254*, 106976. https://doi.org/10.1016/j.agwat.2021.106976

Kennedy, J., & Eberhart, R. (1995). Particle swarm optimization. In *Proceedings of ICNN'95 - International Conference on Neural Networks* (Vol. 4, pp. 1942–1948 vol.4). https://doi.org/10.1109/ICNN.1995.488968

Kiparsky, M., Milman, A., Owen, D., & Fisher, A. T. (2017). The Importance of Institutional Design for Distributed Local-Level Governance of Groundwater: The Case of California's Sustainable Groundwater Management Act. *Water*, *9*(10), 755. https://doi.org/10.3390/w9100755

Klocke, N., Currie, R., Tomsicek, D., & Koehn, J. W. (2012). Corn Yield Response to Deficit Irrigation. *Transactions of the ASABE*, *55*. https://doi.org/10.13031/2013.41526

Knoben, W. J. M., Freer, J. E., & Woods, R. A. (2019). Technical note: Inherent benchmark or not? Comparing Nash–Sutcliffe and Kling–Gupta efficiency scores. *Hydrology and Earth System Sciences*, *23*(10), 4323–4331. https://doi.org/10.5194/hess-23-4323-2019

Kucharik, C. J. (2003). Evaluation of a Process-Based Agro-Ecosystem Model (Agro-IBIS) across the U.S. Corn Belt: Simulations of the Interannual Variability in Maize Yield. Retrieved from https://journals.ametsoc.org/view/journals/eint/7/14/1087-3562_2003_007_0001_eoapam_2.0.co_2.xml

Lamm, F., Rogers, D., Aguilar, J., & Kisekka, I. (2014). Deficit Irrigation of Grain And Oilseed Crops. In *ResearchGate*. Retrieved from https://www.researchgate.net/publication/268982644_Deficit_Irrigation_of_Grain_And_Oilseed_Crops

Lamsal, A., Welch, S. M., White, J. W., Thorp, K. R., & Bello, N. M. (2018). Estimating parametric phenotypes that determine anthesis date in Zea mays: Challenges in combining ecophysiological models with genetics. *PLOS ONE*, *13*(4), e0195841. https://doi.org/10.1371/journal.pone.0195841

Lapides, D. A., Zipper, S., & Hammond, J. C. (2023). Identifying hydrologic signatures associated with streamflow depletion caused by groundwater pumping. *Hydrological Processes*, *37*(4), e14877. https://doi.org/10.1002/hyp.14877

Lin, C.-Y., Orduña Alegría, M. E., Dhakal, S., Zipper, S., & Marston, L. (2024). PyCHAMP: A crop-hydrological-agent modeling platform for groundwater management. *Environmental Modelling & Software*, *181*, 106187. https://doi.org/10.1016/j.envsoft.2024.106187

Liu, M., He, J., Huang, Y., Tang, T., Hu, J., & Xiao, X. (2022). Algal bloom forecasting with time-frequency analysis: A hybrid deep learning approach. *Water Research*, *219*, 118591. https://doi.org/10.1016/j.watres.2022.118591

Lu, Y., Chibarabada, T. P., McCabe, M. F., De Lannoy, G. J. M., & Sheffield, J. (2021). Global sensitivity analysis of crop yield and transpiration from the FAO-AquaCrop model for dryland environments. *Field Crops Research*, *269*, 108182. https://doi.org/10.1016/j.fcr.2021.108182

Marston, L. T., Zipper, S., Smith, S. M., Allen, J. J., Butler, J. J., Gautam, S., & Yu, D. J. (2022). The importance of fit in groundwater self-governance. *Environmental Research Letters*, *17*(11), 111001. https://doi.org/10.1088/1748-9326/ac9a5e

Masasi, B., Taghvaeian, S., Gowda, P. H., Warren, J., & Marek, G. (2019). Simulating Soil Water Content, Evapotranspiration, and Yield of Variably Irrigated Grain Sorghum Using AquaCrop. *JAWRA Journal of the American Water Resources Association*, *55*(4), 976–993. https://doi.org/10.1111/1752-1688.12757

McCown, R. L., Hammer, G. L., Hargreaves, J. N. G., Holzworth, D. P., & Freebairn, D. M. (1996). APSIM: a novel software system for model development, model testing and simulation in agricultural systems research. *Agricultural Systems*, *50*(3), 255–271. https://doi.org/10.1016/0308-521X(94)00055-V

Mialyk, O., Schyns, J.F., Booij, M.J. & Hogeboom, R.J. (2022). Historical simulation of maize water footprints with a new global gridded crop model ACEA. *Hydrology and Earth System Sciences*, 26(4).923-940.

Miller, J. (2018). Corn Reproduction and High Temperatures | Delaware Agronomy Blog. Retrieved October 7, 2024, from https://sites.udel.edu/agronomy/2018/07/06/corn-reproduction-and-high-temperatures/

Miller, M. M., Jones, C. E., Sangha, S. S., & Bekaert, D. P. (2020). Rapid drought-induced land subsidence and its impact on the California aqueduct. *Remote Sensing of Environment*, *251*, 112063. https://doi.org/10.1016/j.rse.2020.112063

Ndlovu, W. (2024). Assessing the Effectiveness and Resilience of Groundwater Self-Management Practices Using AquaCrop: A Case Study of the Northwestern Kansas Local Enhanced Management Areas. Retrieved March 16, 2025, from https://www.proquest.com/docview/3160666385

Noel, M. M. (2012). A new gradient based particle swarm optimization algorithm for accurate computation of global minimum. *Applied Soft Computing*, *12*(1), 353–359. https://doi.org/10.1016/j.asoc.2011.08.037

Northwest Kansas Groundwater Management District No. 4: Revised Management Plan. (2021). GMD4. Retrieved from https://gmd4.org/Management/GMD4-MgtPro.pdf

Nyakudya, I. W., & Stroosnijder, L. (2014). Effect of rooting depth, plant density and planting date on maize (Zea mays L.) yield and water use efficiency in semi-arid Zimbabwe: Modelling with AquaCrop. *Agricultural Water Management*, *146*, 280–296. https://doi.org/10.1016/j.agwat.2014.08.024

Obembe, O. S., Hendricks, N. P., & Jagadish, S. V. K. (2023). Changes in groundwater irrigation withdrawals due to climate change in Kansas. *Environmental Research Letters*, *18*(9), 094041. https://doi.org/10.1088/1748-9326/acf147

Onyekwelu, I., Zipper, S., Welch, S., & Sharda, V. (2024, December 24). Quantifying Climate Change Impacts on Maize Productivity Under Different Irrigation Management Strategies: A High-Resolution Spatial Analysis in the U.S. Great Plains. SSRN Scholarly Paper, Rochester, NY: Social Science Research Network. https://doi.org/10.2139/ssrn.5069870

Orduña Alegría, M. E., Zipper, S., Shin, H. C., Deines, J. M., Hendricks, N. P., Allen, J. J., et al. (2024). Unlocking aquifer sustainability through irrigator-driven groundwater conservation. *Nature Sustainability*, *7*(12), 1574–1583. https://doi.org/10.1038/s41893-024-01437-0

Paredes, P., de Melo-Abreu, J. P., Alves, I., & Pereira, L. S. (2014). Assessing the performance of the FAO AquaCrop model to estimate maize yields and water use under full and deficit irrigation with focus on model parameterization. *Agricultural Water Management*, *144*, 81–97. https://doi.org/10.1016/j.agwat.2014.06.002

Peters, C. N., Kimsal, C., Frederiks, R. S., Paldor, A., McQuiggan, R., & Michael, H. A. (2022). Groundwater pumping causes salinization of coastal streams due to baseflow depletion: Analytical framework and application to Savannah River, GA. *Journal of Hydrology*, *604*, 127238. https://doi.org/10.1016/j.jhydrol.2021.127238

Raes, D., Steduto, P., Hsiao, T., & Fereres, E. (2023, August). Reference Manual, Annexes – AquaCrop, Version 7.0.

Ramirez-Villegas, J., Koehler, A.K. & Challinor, A.J. (2017). Assessing uncertainty and complexity in regional-scale crop model simulations. *European Journal of Agronomy*, 88, 84-95.

Ran, H., Kang, S., Hu, X., Yao, N., Li, S., Wang, W., et al. (2022). A framework to quantify uncertainty of crop model parameters and its application in arid Northwest China. *Agricultural and Forest Meteorology*, *316*, 108844. https://doi.org/10.1016/j.agrformet.2022.108844

Reilly, J., Tubiello, F., McCarl, B., Abler, D., Darwin, R., Fuglie, K., et al. (2003). U.S. Agriculture and Climate Change: New Results. *Climatic Change*, *57*(1), 43–67. https://doi.org/10.1023/A:1022103315424

Reynolds, C. W. (1987). Flocks, herds and schools: A distributed behavioral model. In *Proceedings of the 14th annual conference on Computer graphics and interactive techniques* (pp. 25–34). New York, NY, USA: Association for Computing Machinery. https://doi.org/10.1145/37401.37406

Roberts, M.J., Braun, N.O., Sinclair, T.R., Lobell, D.B. & Schlenker, W. (2017). Comparing and combining process-based crop models and statistical models with some implications for climate change. *Environmental Research Letters*, 12(9), 095010.

Saltelli, A., Bammer, G., Bruno, I., Charters, E., Di Fiore, M., Didier, E., et al. (2020). Five ways to ensure that models serve society: a manifesto. *Nature*, *582*(7813), 482–484. https://doi.org/10.1038/d41586-020-01812-9

Sandhu, R., & Irmak, S. (2019). Performance of AquaCrop model in simulating maize growth, yield, and evapotranspiration under rainfed, limited and full irrigation. *Agricultural Water Management*, *223*, 105687. https://doi.org/10.1016/j.agwat.2019.105687

Schneider, A. D., & Howell, T. (1998). LEPA and spray irrigation of corn - Southern High Plains. Retrieved from https://doi.org/10.13031/2013.17313

Sobol, M. I. (1993). Sensitivity Analysis for Non-Linear Mathematical Models. *Math. Modeling Comput. Exp.*, *1*, 407–414.

Steduto, P., Hsiao, T. C., Raes, D., & Fereres, E. (2009). AquaCrop—The FAO Crop Model to

Simulate Yield Response to Water: I. Concepts and Underlying Principles. *Agronomy Journal*, *101*(3), 426–437. https://doi.org/10.2134/agronj2008.0139s

Su, H., Foster, T., Hogeboom, R.J., Luna-Gonzalez, D.V., Mialyk, O., Willaarts, B., Wang, Y. & Krol, M.S. (2025). Nutrient production, water consumption, and stresses of large-scale versus small-scale agriculture: A global comparative analysis based on a gridded crop model. *Global Food Security*, 45, 100844.

Teatini, P., Ferronato, M., Gambolati, G., & Gonella, M. (2006). Groundwater pumping and land subsidence in the Emilia-Romagna coastland, Italy: Modeling the past occurrence and the future trend. *Water Resources Research*, *42*(1). https://doi.org/10.1029/2005WR004242

Turner, S. W. D., Hejazi, M., Yonkofski, C., Kim, S. H., & Kyle, P. (2019). Influence of Groundwater Extraction Costs and Resource Depletion Limits on Simulated Global Nonrenewable Water Withdrawals Over the Twenty-First Century. *Earth's Future*, *7*(2), 123–135. https://doi.org/10.1029/2018EF001105

Umapathy, P., Venkataseshaiah, C., & Arumugam, M. S. (2010). Particle Swarm Optimization with Various Inertia Weight Variants for Optimal Power Flow Solution. *Discrete Dynamics in Nature and Society*, *2010*, e462145. https://doi.org/10.1155/2010/462145

USDA - National Agricultural Statistics Service - Charts and Maps - County Maps. (2023). Retrieved October 30, 2023, from https://www.nass.usda.gov/Charts_and_Maps/Crops_County/

USDA National Agricultural Statistics Service Cropland Data Layer. (2023). Retrieved October 28, 2023, from https://developers.google.com/earth-engine/datasets/catalog/USDA_NASS_CDL

USDA/NASS QuickStats Ad-hoc Query Tool. (2023). Retrieved September 28, 2024, from https://quickstats.nass.usda.gov/

Watson, J., Challinor, A.J., Fricker, T.E. & Ferro, C.A., (2015). Comparing the effects of calibration and climate errors on a statistical crop model and a process-based crop model. *Climatic Change*, 132(1), 93-109.

Weir, A. H., Bragg, P. L., Porter, J. R., & Rayner, J. H. (1984). A winter wheat crop simulation model without water or nutrient limitations. *The Journal of Agricultural Science*, *102*(2), 371–382. https://doi.org/10.1017/S0021859600042702

Whittemore, D. O., Butler, J. J., & Wilson, B. B. (2023). 2023 Status of the High Plains Aquifer in Kansas.

Whittemore, D. O., Butler, J. J., Bohling, G. C., & Wilson, B. B. (2023). Are we saving water? Simple methods for assessing the effectiveness of groundwater conservation measures. *Agricultural Water Management*, *287*, 108408. https://doi.org/10.1016/j.agwat.2023.108408

WIMAS. (2023). Retrieved October 30, 2023, from https://geohydro.kgs.ku.edu/geohydro/wimas/query_setup.cfm

Xing, H., Xu, X., Li, Z., Chen, Y., Feng, H., Yang, G., & Chen, Z. (2017). Global sensitivity analysis of the AquaCrop model for winter wheat under different water treatments based

on the extended Fourier amplitude sensitivity test. *Journal of Integrative Agriculture*, *16*(11), 2444–2458. https://doi.org/10.1016/S2095-3119(16)61626-X
Yang, H., Dobbie, S., Ramirez-Villegas, J., Feng, K., Challinor, A.J., Chen, B., Gao, Y., Lee, L., Yin, Y., Sun, L. & Watson, J. (2016). Potential negative consequences of geoengineering on crop production: A study of Indian groundnut. *Geophysical Research Letters*, 43(22), 11-786.
Zelelew, M. B., & Alfredsen, K. (2013). Sensitivity-guided evaluation of the HBV hydrological model parameterization. *Journal of Hydroinformatics*, *15*(3), 967–990. https://doi.org/10.2166/hydro.2012.011
Zhao, K., Tao, Y., Liu, M., Yang, D., Zhu, M., Ding, J., et al. (2022). Does temporary heat stress or low temperature stress similarly affect yield, starch, and protein of winter wheat grain during grain filling? *Journal of Cereal Science*, *103*, 103408. https://doi.org/10.1016/j.jcs.2021.103408
Zipper, S., Kastens, J., Foster, T., Wilson, B. B., Melton, F., Grinstead, A., et al. (2024). Estimating irrigation water use from remotely sensed evapotranspiration data: Accuracy and uncertainties at field, water right, and regional scales. *Agricultural Water Management*, *303*, 109036. https://doi.org/10.1016/j.agwat.2024.109036
Zipper, S., Brookfield, A., Ajami, H., Ayers, J. R., Beightel, C., Fienen, M. N., et al. (2024). Streamflow Depletion Caused by Groundwater Pumping: Fundamental Research Priorities for Management-Relevant Science. *Water Resources Research*, *60*(5), e2023WR035727. https://doi.org/10.1029/2023WR035727
Zipper, S., Ifft, J., Orduña Alegría, M. E., Butler, J. J., Marston, L. T., Yu, Q., & Metzger, S. (2024). *Water management challenges and potential solutions related to the U.S. federal crop insurance program* (KGS Open-File Report 2024-11 No. 2024–11) (p. 20). Lawrence KS: Kansas Geological Survey. Retrieved from https://www.kgs.ku.edu/Publications/OFR/2024/OFR2024-11.pdf
Zipper, S. C., Soylu, M. E., Booth, E. G., & Loheide, S. P. (2015). Untangling the effects of shallow groundwater and soil texture as drivers of subfield-scale yield variability. Water Resources Research, 51(8), 6338–6358. https://doi.org/10.1002/2015WR017522
Zwickle, A., Feltman, B., Brady, A., Kendall, A., & Hyndman, D. (2021). Sustainable irrigation through local collaborative governance: Evidence for a structural fix in Kansas. *Environmental Science & Policy*, *124*, 517–526. https://doi.org/10.1016/j.envsci.2021.07.021

Supplementary material

AquaCrop Irrigation Calculation

The irrigation depth (*Irrig Depth*) is calculated daily as follows: the root zone depletion stress indicator is first calculated as the proportion of the soil water depletion (amount of available water that is required to bring to water amount back to FC) and total available water (*TAW*). This stress indicator varies from zero (full stress) to one (no stress). Whenever the root zone depletion is greater than smt_{gs}, the user specified soil moisture threshold for irrigation in each of the four crop growth stages, an irrigation requirement (*Irrig Req*) equal to the soil water depletion is calculated as shown in **Eq. S2**. To account for irrigation efficiency, the irrigation requirement is multiplied by an application efficiency adjustment (*Ieff*), which is expressed as a percentage with higher values indicating greater efficiency (the current model runs with an efficiency adjustment of 85%). The *Irrig Depth* is then calculated as the minimum between the *Irrig Req* and the specified maximum irrigation depth ($Irrig_{max}$) per event (the model default value for $Irrig_{max}$ is 25 mm) using **Eq S3**.

$$\text{Root Zone Depletion } (Dr) > 1 - smt_{gs}/100 \qquad \text{(S1)}$$

$$Irrig\ Req = \max(0, \text{soil water depletion}) \qquad \text{(S2)}$$

$$Irrig\ Depth = \min(Irrig_{max},\ Irrig\ Req * Ieff) \qquad \text{(S3)}$$

Sensitivity Analysis using Sobol Method

The Sobol method (Sobol, 1993) was applied to crop parameters related to (1) crop development and transpiration, (2) biomass and yield, (4) water stress, and (4) management using the *SALib* Python package (Herman & Usher, 2017). We adjusted the maximum irrigation, water stress and temperature stress parameters as shown in Table S2, and the remaining parameters were set to the model defaults for that crop. The maximum daily and seasonal irrigation depths for both crops were estimated based on field studies done by Kansas State Research and Extension scientists (Ciampitti et al., 2022, 2023).

We analyzed the first, second and total indices using the Sobol function from the *SALib* Python package (Herman & Usher, 2017). For both the yield and water use simulations, 2^N and 2^{15} samples were generated from the parameter space where n is a series of one-unit increments from one to ten to ensure model convergence and stability. This sampling scheme creates a total of $n(2k+2)$ model runs where n and k are the number of samples and parameters, respectively. We applied this approach to all the scenarios (for example, irrigated corn and sorghum under dry, normal, and wet conditions) using yield and irrigation water use as individual target outputs for both crops of interest. Due to the large computational needs, we used the Blanca distributed High-Performance-Computing (HPC) system (https://www.colorado.edu/rc/resources/blanca). To distinguish between the influential and non-influential parameters, we defined a threshold:

parameters with total order indices (ST) greater than 10% of the maximum ST from each scenario were defined as influential.

Influence of initial soil moisture conditions on performance

Varying the initial soil water conditions (*field capacity (FC)*, *saturation* (*SAT*) or *wilting point (WP)*) for corn and sorghum did not have a major influence on model fit (Fig. S1). The objective function results were nearly identical for *FC* and *SAT* models, while the *WP* models had higher objective function values (indicating a worse agreement with observations) and more variation within the group. For our analysis, we determined that models calibrated under *FC* conditions produced the lowest objective functions (Fig. S1) and represented the typical soil water content rages in the GMD-4 region ("Kansas Mesonet · Soil Moisture," 2024).

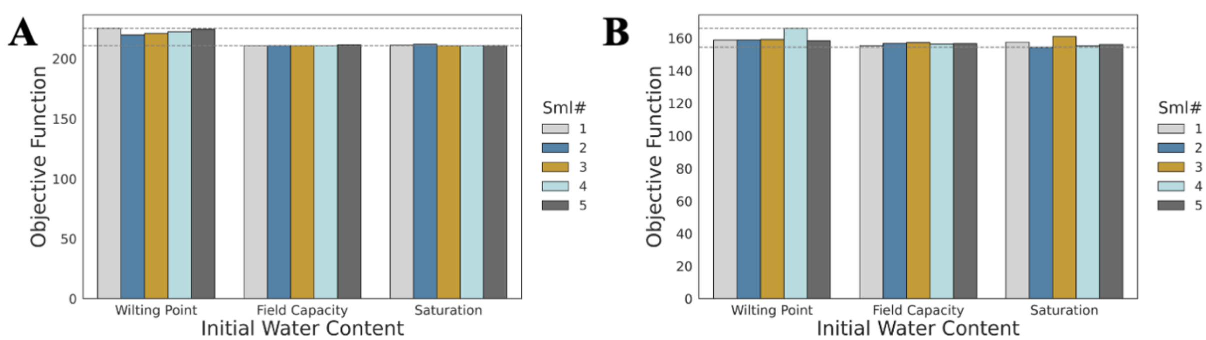


Figure S1. Objective function values for corn (A) and sorghum (B) models from the Particle Swarm Optimization (PSO) calibrations performed using 80% of the observed yield and irrigation depth data. For each initial water content, Sml#1-5 correspond to different random model input realizations (see Section 3.3.2).

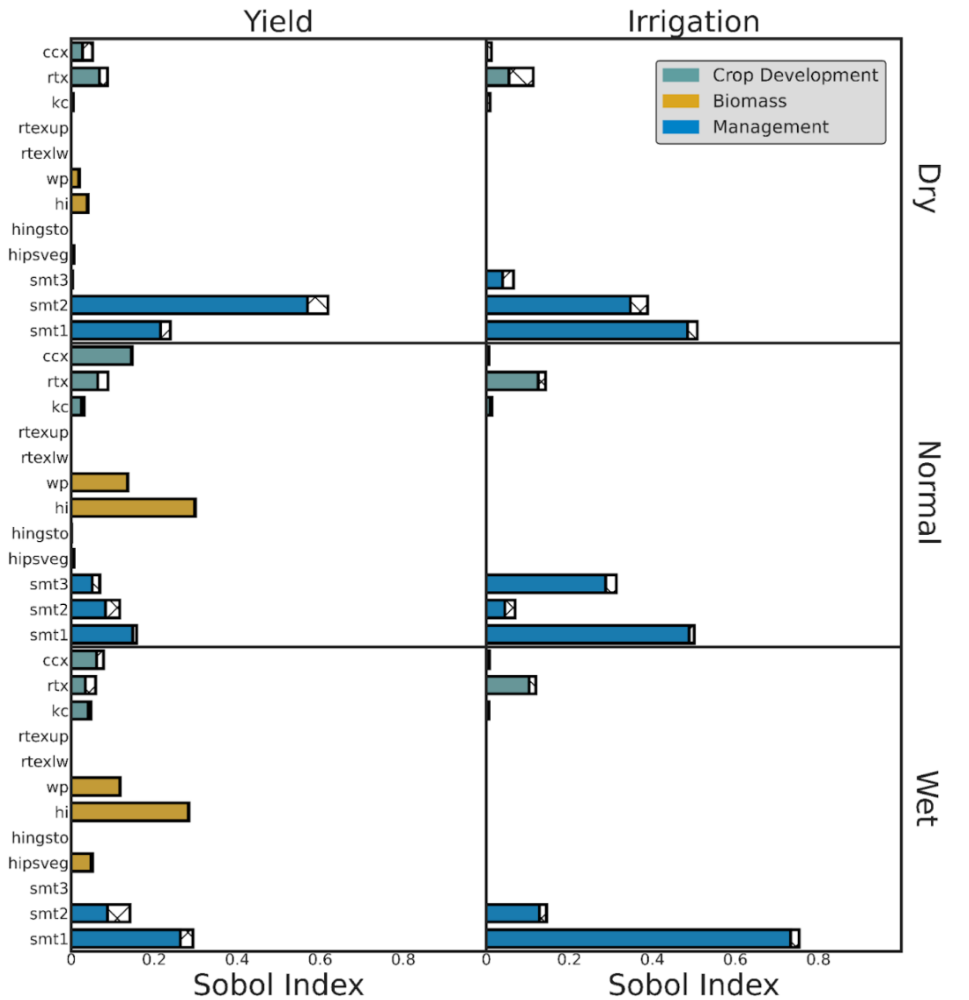


Figure S2A. First and total order indices for corn estimated using the Sobol method. The solid shading represents the first order indices (direct sensitivity of output variable to that parameter) while the diamonds represent the second order indices (parameter interaction effects). The colors are used to distinguish parameters related to crop development, biomass and yield formation and irrigation management.

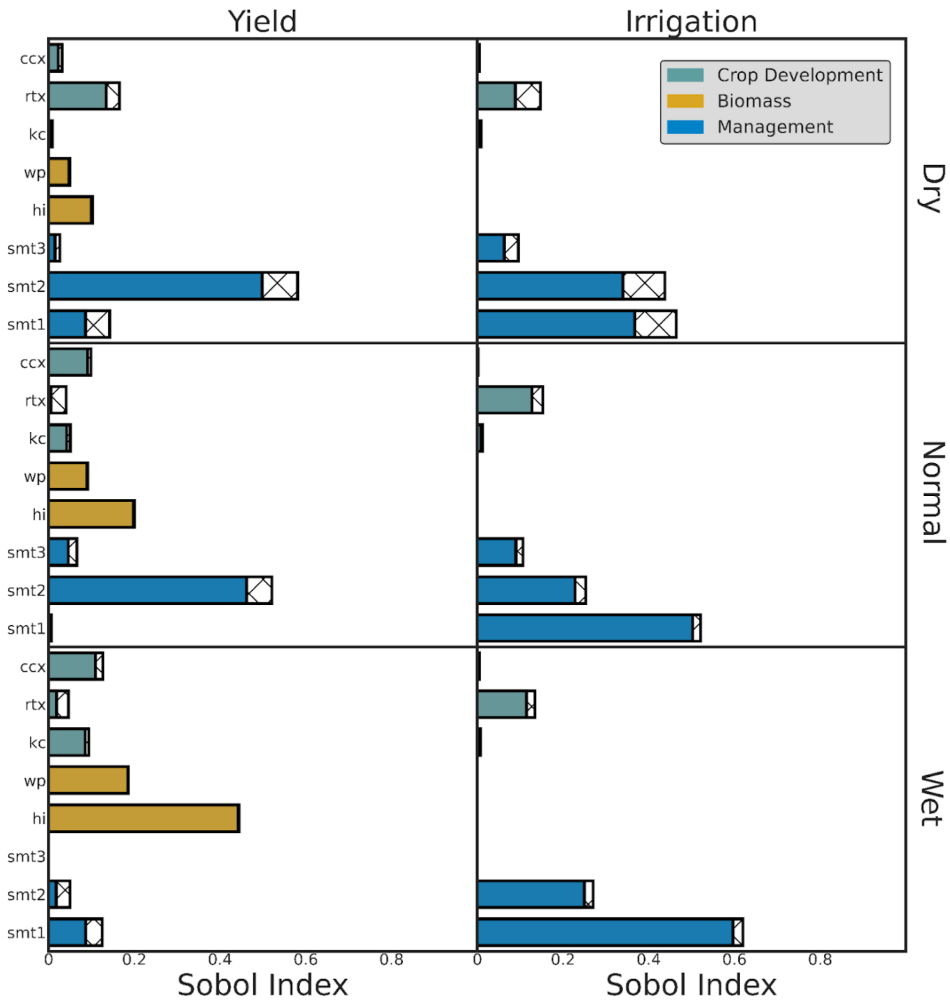


Figure S2B. First and total order indices for sorghum estimated using the Sobol method. The solid shading represents the first order indices (direct sensitivity of output variable to that parameter) while the diamonds represent the second order indices (parameter interaction effects). The colors are used to distinguish parameters related to crop development, biomass and yield formation and irrigation management.

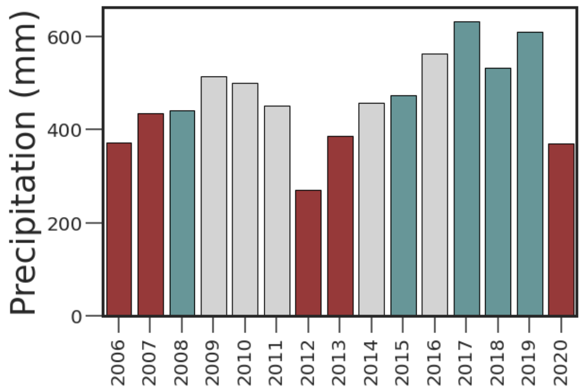


Figure S3. Average irrigation season (Jan – Sept) precipitation in the GMD-4 region. Red bars represent the five driest years over the 2006 - 2020 period. Blue bars represent five randomly selected non-drought years for the model spin up period.

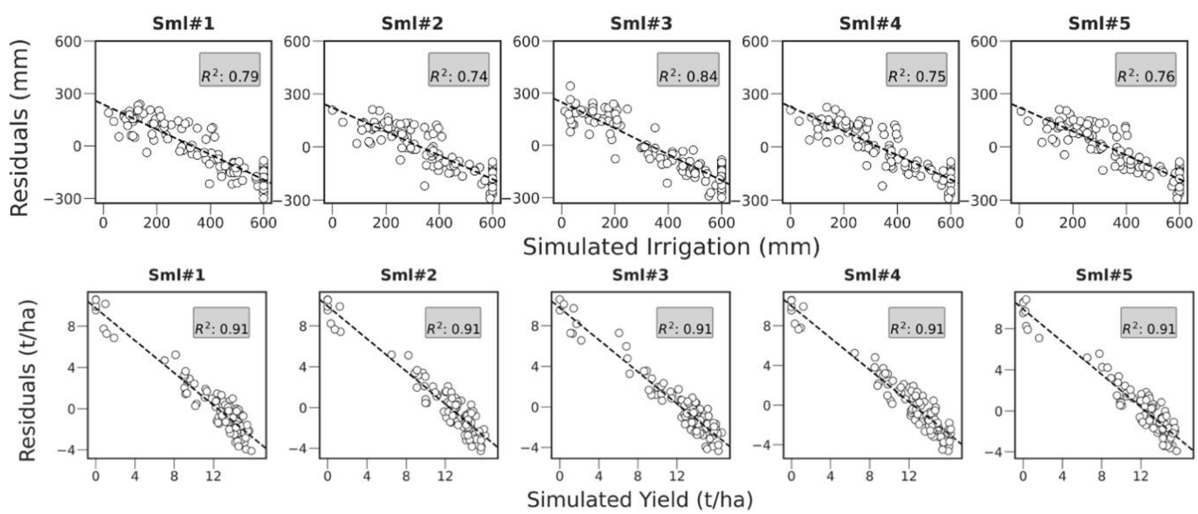


Figure S4. Corn residuals for yield and irrigation as a function of simulated yield and irrigation. These relationships are used for modified-difference bias correction. These results all use field capacity as the initial soil moisture condition, and Sml#1-5 correspond to different random model input realizations (see Section 3.3.2). Sml#2 was selected as the best corn model and used for results shown in the main text. Fit statistics are in Table S3.

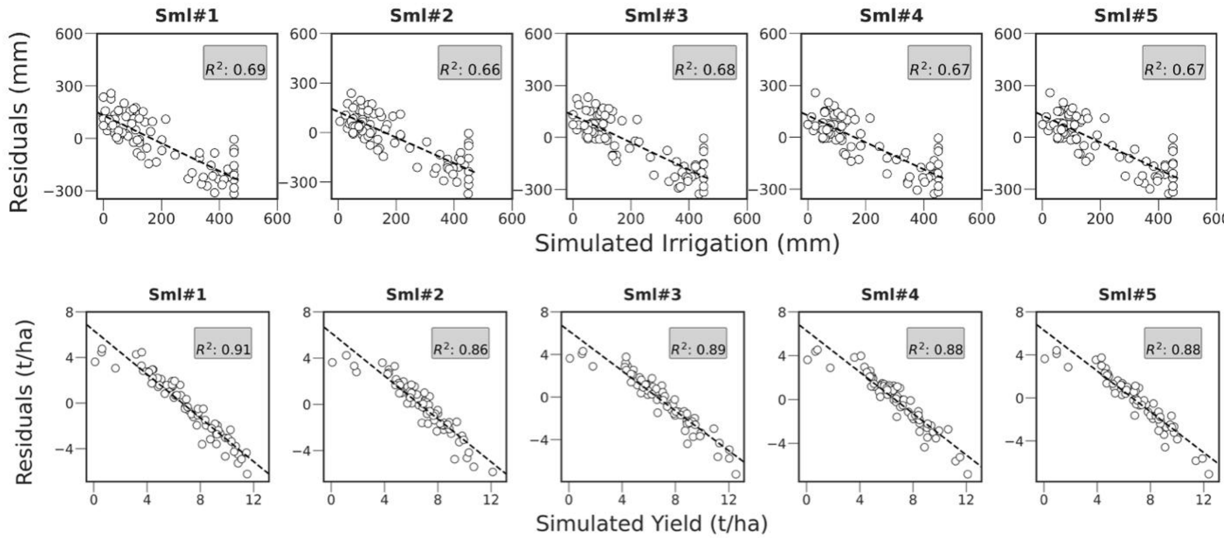


Figure S5. Sorghum residuals for yield and irrigation as a function of simulated yield and irrigation. These relationships are used for modified-difference bias correction. These results all use field capacity as the initial soil moisture condition, and Sml#1-5 correspond to different random model input realizations (see Section 3.3.2). Sml#2 was selected as the best sorghum model and used for results shown in the main text. Fit statistics are in Table S4.

Table S1. Model parameters used for the sensitivity analysis of corn and sorghum. Highlighted rows indicate parameters considered only for corn and the remaining parameters were used for both crops.

Parameter	Description	Units	Lower Bound	Upper Bound
Crop Development and Transpiration				
ccx	maximum fractional canopy cover size	-	0.85	0.99
rtx	maximum effective rooting depth	m	1.2	2
rtexup	maximum water extraction at the top of the root zone	m^3/m^3/day	0.02	0.03
rtexlw	maximum water extraction at the bottom of the root zone	m^3/m^3/day	0	0.01
kc	crop coefficient when canopy is complete but prior to senescence	-	1.0	1.1
Biomass and Yield				
wp	water productivity normalized for reference ET0 and CO2	g/m^2	30	35
hi	reference harvest index	-	0.45	0.55
Water Stress				
hipsveg	coefficient describing positive impact of restricted vegetative growth during yield formation on HI	-	0.5	10.0
hingsto	coefficient describing negative impact of stomatal closure growth during yield formation on HI	-	1.0	20.0
Irrigation Management				
smt1	soil moisture threshold during crop emergence and canopy growth	%	40	80
smt2	soil moisture threshold during crop maximum canopy	%	0	50
smt3	soil moisture threshold during crop canopy senescence	%	0	50

Table S2. Default parameter values used for the corn and sorghum sensitivity analysis.

Parameter	Description	Corn Default Value	Sorghum Default Value
max_irr	maximum depth (mm) that can be applied each day	6.5	6.5
max_irr_season	maximum depth (mm) that can be applied each season	600	450
p_up2	upper soil water depletion threshold for water stress effects on canopy stomatal control	0.45	0.55
p_up3	upper soil water depletion threshold for water stress effects on canopy senescence	0.6	0.85
cdc	canopy decline coefficient (fraction per GDD/calendar day)	1.31	-
tmax_lo	maximum air temperature (degC) at which pollination completely fails	33	-
tmax_up	maximum air temperature (degC) above which pollination begins to fail	38	-

Table S3. Model performance evaluation for corn irrigation depth (mm) and yield (t/ha). Red shading indicates the bias-corrected model with the best fit metrics and blue shading indicates the best model based on the calibration, validation and bias-correction results. For irrigation, Sml#1 and Sml#2 had the best fit metrics after bias correction.

CORN IRRIGATION (mm)				
Model	**Evaluation Metric**	**KGE**	**RMSE**	**NRMSE**
Sml#1	Calibration	-0.22	145	0.43
	Validation	-0.20	157	0.43
	Bias-Corrected Validation	0.41	79	0.22
Sml#2	Calibration	-0.01	127	0.38
	Validation	0.04	138	0.38
	Bias-Corrected Validation	0.41	79	0.22
Sml#3	Calibration	-0.46	164	0.49
	Validation	-0.24	166	0.45
	Bias-Corrected Validation	0.30	83	0.23
Sml#4	Calibration	-0.06	131	0.39
	Validation	0.05	139	0.38
	Bias-Corrected Validation	0.36	81	0.22
Sml#5	Calibration	-0.06	129	0.39
	Validation	-0.01	142	0.39
	Bias-Corrected Validation	0.41	80	0.22

CORN YIELD (t/ha)				
Model	**Evaluation Metric**	**KGE**	**RMSE**	**NRSME**
Sml#1	Calibration	-1.00	3.2	0.26
	Validation	-0.64	3.4	0.27
	Bias-Corrected Validation	0.44	1.2	0.10
Sml#2	Calibration	-1.10	3.3	0.27
	Validation	-0.73	3.5	0.28
	Bias-Corrected Validation	0.44	1.2	0.10
Sml#3	Calibration	-1.10	3.3	0.26
	Validation	-0.71	3.5	0.28
	Bias-Corrected Validation	0.45	1.2	0.10
Sml#4	Calibration	-1.20	3.4	0.27
	Validation	-0.75	3.5	0.28
	Bias-Corrected Validation	0.43	1.2	0.10
Sml#5	Calibration	-1.10	3.3	0.27
	Validation	-0.67	3.4	0.28
	Bias-Corrected Validation	0.43	1.2	0.10

Table S4. Model performance evaluation for sorghum irrigation depth (mm) and yield (t/ha). Red shading indicates the bias-corrected model with the best fit metric and blue shading indicates the best model based on the calibration, validation and bias-correction results.

SORGHUM IRRIGATION (mm)				
Model	**Evaluation Metric**	**KGE**	**RMSE**	**NRSME**
	Calibration	0.00	149	0.89
Sml#1	Validation	-0.01	138	0.65
	Bias-Corrected Validation	0.17	85	0.40
	Calibration	0.07	143	0.85
Sml#2	Validation	0.06	133	0.62
	Bias-Corrected Validation	0.14	87	0.41
	Calibration	0.03	147	0.87
Sml#3	Validation	0.00	137	0.64
	Bias-Corrected Validation	0.16	86	0.40
	Calibration	0.06	144	0.86
Sml#4	Validation	-0.02	139	0.65
	Bias-Corrected Validation	0.15	87	0.41
	Calibration	0.06	143	0.85
Sml#5	Validation	0.00	138	0.65
	Bias-Corrected Validation	0.15	87	0.41
SORGHUM YIELD (t/ha)				
Model	**Evaluation Metric**	**KGE**	**RMSE**	**NRSME**
	Calibration	-1.40	2.7	0.41
Sml#1	Validation	-0.97	2.9	0.41
	Bias-Corrected Validation	-0.17	1.0	0.15
	Calibration	-0.81	2.2	0.33
Sml#2	Validation	-0.69	2.5	0.37
	Bias-Corrected Validation	-0.12	1.0	0.15
	Calibration	-1.20	2.5	0.38
Sml#3	Validation	-1.10	2.9	0.42
	Bias-Corrected Validation	-0.09	1.0	0.15
	Calibration	-0.96	2.4	0.35
Sml#4	Validation	-0.66	2.6	0.37
	Bias-Corrected Validation	-0.14	1.0	0.15
	Calibration	-1.00	2.4	0.36
Sml#5	Validation	-0.82	2.7	0.39
	Bias-Corrected Validation	-0.16	1.0	0.15