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**Key Points:**

- A new regional hydroeconomic optimization modeling framework is proposed for mixed irrigation regimes using AquaCropOS
- Optimal deficit irrigation strategy is economically better than full irrigation by reducing the cost and energy for groundwater pumping
- Crop simulation module and optimization module are linked using Bayesian Hierarchical Model to reduce computation time

**Supporting Information:**

Supporting Information may be found in the online version of this article.

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# Understanding the Food-Energy-Water Nexus in Mixed Irrigation Regimes Using a Regional Hydroeconomic Optimization Modeling Framework

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**Abstract** Understanding the nexus between food, energy, and water systems (FEW) is critical for basins with intensive agricultural water use as they face significant challenges under changing climate and regional development. We investigate the food, energy, and water nexus through a regional hydroeconomic optimization (RHEO) modeling framework. The crop production in RHEO is estimated through a hierarchical regression model developed using a biophysical model, AquaCropOS, forced with daily climatic inputs. Incorporating the hierarchical model within the RHEO also reduces the computation time by enabling parallel programming within the AquaCropOS and facilitates mixed irrigation—rainfed, fully irrigated and deficit irrigation—strategies. To demonstrate the RHEO framework, we considered a groundwater-dominated basin, South Flint River Basin, Georgia, for developing mixed irrigation strategies over 31 years. Our analyses show that optimal deficit irrigation is economically better than full irrigation, which increases the groundwater pumping cost. Thus, considering deficit irrigation in a groundwater-dominated basin reduces the water, carbon, and energy footprints, thereby reducing FEW vulnerability. The RHEO also could be employed for analyzing FEW nexus under potential climate change and future regional development scenarios.

## 1. Introduction

The availability of food, energy, and water resources is critical for sustained growth of human civilization (Scanlon et al., 2017). The production, consumption, and security of food, energy, and water (FEW) are inextricably linked as global food production accounts for 85.8% of global water withdrawal (D'Odorico et al., 2018). The agricultural production also has significant energy consumption with food-related energy use in the United States representing 16% of the national energy budget. Food systems are also linked to energy systems as crops serve as feedstock for bio-fuel production. The supplies of these interconnected resources are becoming less secure as global demand for FEW resources continues to increase (Cai et al., 2018). We are at a critical junction in identifying sustainable pathways without irreversibly compromising the environmental and biophysical resources (Rockström et al., 2009). Despite international initiatives such as Sustainable Development Goals, we still have to overcome significant challenges in sustainably managing the FEW systems acknowledging the interdependencies among them (Fuso-Nerini et al., 2018). The linkages between the FEW nexus have been extensively studied recently resulting in the development of sectoral and inter-sectoral models and tools for analyzing the nexus (McCarl et al., 2017; D'Odorico et al., 2018; Sušnik & Staddon, 2021).

The FEW nexus has been studied by researchers from diverse fields—environmental management, economics, statistics, social sciences, and systems modeling, etc. (Albrecht et al., 2018). This has contributed to a wide range of FEW nexus methods, such as, scenario analysis, life cycle assessment, decision support systems, input-output analysis, cost-benefit analysis, integrated assessment models, network analysis, regression statistics, and hydroeconomic modeling (Albrecht et al., 2018; Cai et al., 2018; Howitt et al., 2012; Kimaite, 2011; Yuan et al., 2018). The objectives of studying the nexus have varied from understanding the interactions among different sectors to optimal resource allocation leading to diverse definitions and foci of nexus studies (Sušnik & Staddon, 2021). Recent reviews of nexus research advocate the use of nexus concept as an analytical tool to inform policy amongst others (Albrecht et al., 2018). Two approaches—system dynamics modeling (SDM) and especially integrated assessment modeling (IAM)—have shown the potential for holistic modeling of the nexus by breaking disciplinary silos (Sušnik & Staddon, 2021). SDMs produce a unique model for each application based on based on the primary concepts of flows, feedback loops and time delay (Feng et al., 2016) and their flexibility has resulted in

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their application in nexus studies. The model development in SDMs requires initial conceptualization of linkages, stakeholder inputs, domain knowledge and data availability (Bakhshianlamouki et al., 2020; Naderi et al., 2021). IAMs use different methodological approaches and apply different system boundaries depending on the application (Krey et al., 2019). Hydroeconomic modeling developed for integrated water resources management as a solution-oriented tool and can work with limited data availability (Harou et al., 2009). Several important research gaps and opportunities still exist in modeling the food-water nexus especially in linking component crop, water, and food systems to analyze nexus's inter-sectoral relationships and improve understanding of management intervention (Hameed et al., 2019; McCarl et al., 2017).

Recent studies have called for developing regional relationships of water-and-food and water-and-energy dependencies to improve FEW resource allocation (Cai et al., 2018). Hydroeconomic models represent hydrologic engineered systems with explicit consideration of economic nature of water demands and costs and have been shown to be useful in providing integrated assessments (Harou et al., 2009). Often hydroeconomic models are custom-built to incorporate the locally relevant relationships between resources, demands, and costs. Thus, the design choices of hydroeconomic models vary between simulation and optimization, deterministic and stochastic formulations, and modular and holistic submodel integration (Harou et al., 2009). Hydroeconomic models have been adopted widely to advance efficiency and transparency in water use due to their solution-oriented nature and have been used to facilitate resource allocation amongst users. Traditionally, hydroeconomic models aimed at modeling agricultural demands have been limited to regions where irrigated agriculture is the largest water use supporting local economies in arid regions (Howitt, 1995; Howitt et al., 2012). The use of hydroeconomic models in mixed agricultural regimes of rainfed agriculture with supplemental irrigation has been limited.

Positive mathematical Programming (PMP) is a popular method to calibrate hydroeconomic models using deductive reasoning for optimal portfolio analysis of policy changes on cropping patterns. In PMP, a production function between yields and input variables (i.e., water availability) is utilized to optimize input use such that net returns to land and management are maximized. The cost function in PMP formulation may be linear and/or non-linear to account for heterogeneity in inputs, as done by Howitt et al. (2012). Hence, PMP is highly suitable for irrigated arid basins where precipitation peak is off from the irrigation season and the farmer has information over water availability based on reservoir levels or snowpack information (Howitt, 1995; Howitt et al., 2012). However, traditional PMP approaches have limitations in modeling stochasticity in hydrologic component and economic environment (Maneta & Howitt, 2014) which limits extending it to mixed agricultural regimes, which receive significant amount of water through rainfall and supplemental irrigation from groundwater (Graveline, 2016; Heckelei & Wolff, 2003). Maneta and Howitt (2014) recently analyzed PMP models for mixed irrigation regimes under synthetic experiments, but did not consider real-world remote sensing data and other inputs and emphasized that extension of PMP for mixed agricultural regimes remains to be extensively studied. Another limitation of PMP models is that it estimates the yield using crop production function, which does not incorporate within-the-season rainfall variability for estimating crop yield, thereby limiting its ability to develop drought-resistant strategies (e.g., deficit irrigation based on intra-year rainfall variability), which can be useful intervention under a changing climate (Torres et al., 2019). Towards this, we propose a novel regional hydroeconomic optimization (RHEO) model inspired from PMP formulation to estimate crop yield and the associated costs from a biophysical model, AquaCropOS, by incorporating intra-annual variability in precipitation for mixed irrigation regimes.

Crop yield estimation is a critical component of hydroeconomic model, which typically uses empirical production function for linking crop yield to inputs. Crop yield can be obtained through empirical production function/model (e.g., PMP), crop-growth simulation model, and meta-model. Empirical production function describes the interaction between observed crop yields and other factors) (e.g., climate, fertilizer application and management practices (Amikuzuno & Donkoh, 2012; Traore et al., 2013; J. Wang & Baerenklau, 2014; Kukal & Irmak, 2018). However, empirical models do not describe the underlying bio-physical mechanisms and do not consider intra-seasonal climate variability, thereby having limited potential to perform well outside the calibrated domain (Soltani, 2013). Crop simulation models are mathematical models to simulate the growth, development, and yield of a crop for a given set of environmental conditions and management practices (Foster et al., 2014; Monteith, 1996) and properly calibrated models estimate the crop-water production relationships with reasonable accuracy (Foster & Brozović, 2018). Many crop simulation models have been developed in recent decades, for example, DSSAT (J. W. Jones et al., 2003), APSIM (Keating et al., 2003), Hybrid-Maize (Yang et al., 2004). These models require detailed input data and information about crop growth which are usually not available

(Foster et al., 2017). The Food and Agriculture Organization of the United Nations (FAO) developed AquaCrop, a multi-crop model requiring relatively fewer inputs, to address this data availability limitation (Foster et al., 2017; Vanuytrecht et al., 2014). However, the improvement in process-oriented biophysical models to estimate the impacts of climate change on crop yields (see e.g., Esteve et al., 2015; Hristov et al., 2020; Marshall et al., 2015) has not yet resulted in their integration with economic models. A direct integration of daily outputs from biophysical models to seasonal scale profit optimization models results in multiple iterations to identify optimal water and land resource allocations amongst crops. Existing approaches such as lookup tables have been useful in addressing this computational challenge, however, these approaches cannot be easily extended to other regions (Rouhi Rad et al., 2020; S. Li et al., 2021).

The agriculture in the southeastern United States of America (US) has historically been rainfed but has been experiencing a steady increase in irrigated acreage in recent decades (Das Bhowmik et al., 2020; Edwards & Smith, 2018). This changing mixed irrigation pattern combined with the increasing urbanization and population has intensified the competition and conflict for water both within the basin as well across the basin (Ruhl, 2009). This increased usage amidst changing climate could stress future water availability in the eastern US (Ruhl, 2009). One potential way to reduce the water stress is to consider deficit irrigation strategies which have been evaluated for surface water and groundwater irrigated regions (Araya et al., 2016; Foster & Brozović, 2018; Paredes et al., 2014). Deficit irrigation has been a widely used strategy to improve irrigation efficiency to reduce water and carbon footprint of agriculture particularly in groundwater-dominated agriculture towards optimally utilizing water and energy availability for maximizing crop yield by improving irrigation efficiency, that is, ratio of increment in crop yield to total supplied water for irrigation (Foster & Brozović, 2018; Ziolkowska, 2015). Gonzalez-Alvarez et al. (2006) used pumping cost as a proxy for water price and observed that farmers use less water for irrigation when it is more expensive to pump due to increased fuel prices. The streamflows and groundwater extraction in the study region are closely linked and improved groundwater withdrawal strategies can be useful during droughts to prevent excessive withdrawals (Mitra et al., 2016; Seo et al., 2018). Development of such strategies using climate projections for mixed irrigation regimes can prevent excessive withdrawals especially during droughts to protect streams and river flows (Mitra et al., 2016; Seo et al., 2018). This would reduce the FEW vulnerability in stressed water and energy resources due to continually increasing population and irrigation development under changing climate.

We propose the RHEO model to understand how various irrigation practices could be developed for sustainably managing FEW resources in an expanding groundwater-irrigation dominated basin. We use the proposed model to address the following research questions that are of critical importance to the FEW nexus:

- How does the integration of crop-simulation module and profit maximization perform in a mixed irrigation regime?
- Does the proposed RHEO framework capture the inter-annual variability in crop yields?
- Do deficit irrigation strategies improve yield with reduced water availability and reduced energy availability in mixed irrigation regime under different inter-annual climatic conditions?

To investigate the above research questions, we consider the Southern Flint River Basin (SFRB) in Georgia, US, which is part of one of the major river basins, Apalachicola-Chattahoochee-Flint, in the Southeast US. Agriculture in the SFRB forms an important part of the regional economy in terms of regional revenue and jobs supported. Furthermore, the SFRB has experienced increased municipal, agricultural and industrial water demands in recent years. Mullen et al. (2009) noted that farmers in Georgia would be mildly responsive to changes in the unit cost of water, and the response would come more in the form of intra-seasonal water use than through adjustments in crop selection. We utilize the National Agricultural Statistics Service (NASS) census and survey data along with the open-source formulation of FAO's AquaCrop by Foster et al. (2017) enhanced with parallel programming for estimating crop yield for major crops. We also utilize RHEO to identify water limiting conditions that can promote application of deficit irrigation strategies for revenue maximization under mixed irrigation regime.

The rest of the paper is organized as follows: Section 2 describes the study region and data sources. Section 3 explains the formulation of the crop growth simulation model, deficit irrigation strategies, and regional hydro-economic optimization model. Section 4 describes the baseline and optimization scenarios to identify key irrigation strategies for the region. Section 5 presents the study's results, which is followed by the discussion section (Section 6) summarizing the potential for application of the proposed RHEO methodology to other basins. Finally, Section 7 lists the main conclusions of this study.

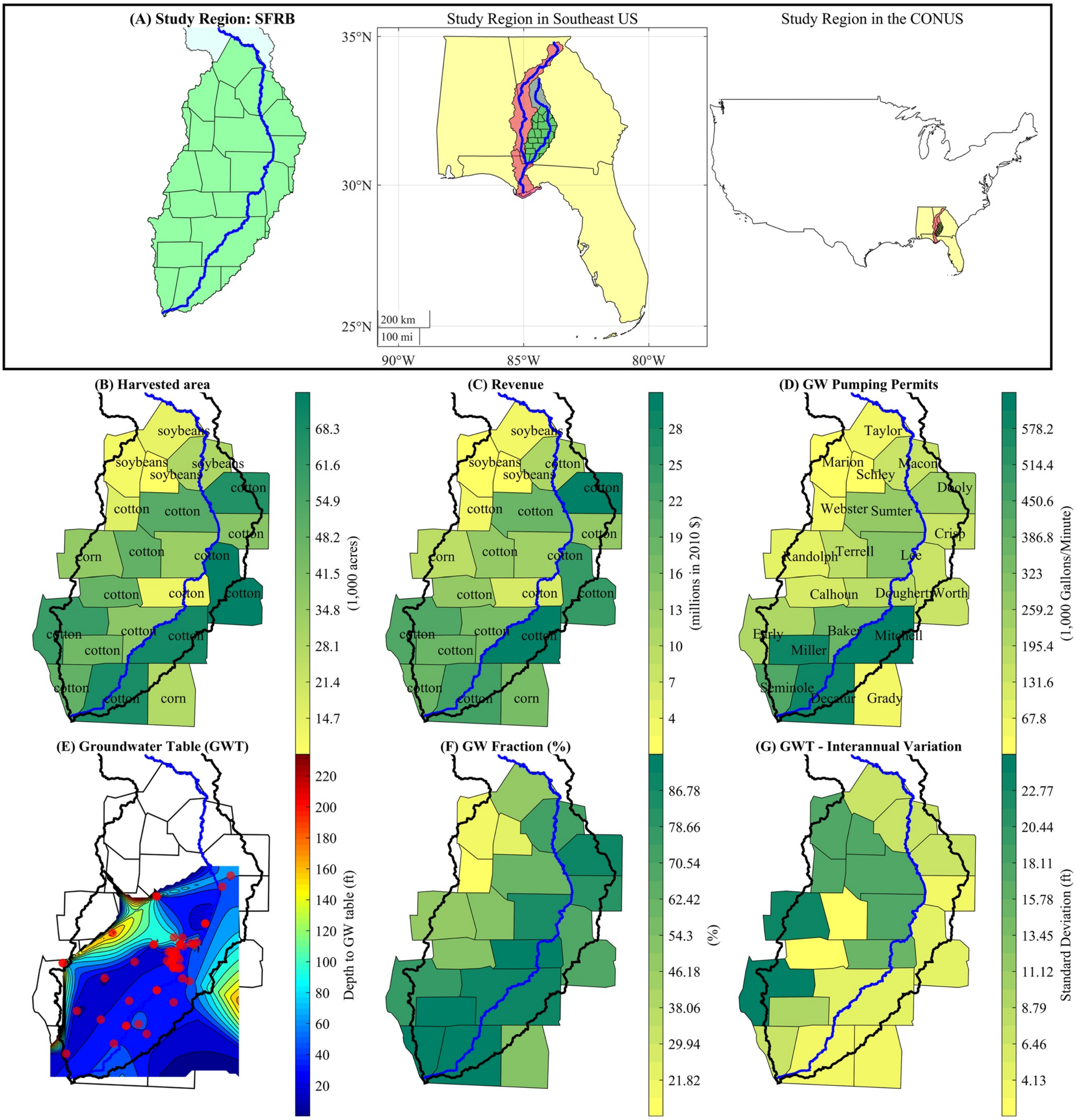


**Figure 1.** Study region: (a) Location of study region; (b) Mean harvested area; (c) Average annual agricultural revenue (inflation adjusted to 2010 dollar value); (d) Countywise groundwater pumping permits issued (thousand gallons per minute); (e) Groundwater observation wells (red circles) and interpolated average groundwater table (feet below ground level); (f) The share of groundwater withdrawals (%) in total freshwater supplied for irrigation; and (g) inter-annual variation in mean annual groundwater table. The labels in (b) and (c) denote the crop with highest harvested area and revenue respectively.

## 2. Study Region and Data

### 2.1. Flint River Basin

The Flint River is one of the three major rivers of the Apalachicola-Chattahoochee-Flint River Basin located in Georgia, Alabama, and Florida (Figure 1a). Average annual rainfall over this sub-basin ranges from 48 to 54 inches/year, most of which falls between November and April (Kimaite, 2011). Agriculture is one of the most important economic sectors, most of which depends heavily on supplemental irrigation. The agriculture sector annually contributes about $6 billion in direct and indirect economic benefits to the sub-basin's economy (Kimaite, 2011). Agricultural irrigation comprises around 90% of the total water needs of the region during the April-September growing season. More than 70% of the irrigation (403,000 acres) relies on groundwater from the Floridian aquifer with only 160,000 acres being irrigated from surface water (Figure 1f). Agricultural surface-water and groundwater-withdrawals peak at 250 million gallons per day (mgd) and 950 mgd respectively at the peak of the irrigation season during a drought year (Georgia Environmental Protection Division, 2006). The SFRB has experienced significant growth in number of farmers switching to irrigation from rainfed farming (Das Bhowmik et al., 2020). Agricultural groundwater (GW) withdrawal is a significant use in the basin and especially during droughts, it is used to provide supplemental irrigation. The Georgia Environmental Protection Division has had to suspend issuing new permits and pay farmers not to irrigate during long droughts (most recently in 2013) (Georgia Water Coalition, 2017). The Division had taken out more than 33,000 acres out of irrigation for a total cost of approximately $4.5 million in 2001 (Georgia Environmental Protection Division, 2006). H. Wang et al. (2010) observed that interannual variability of summer precipitation in the southeastern US has intensified in the recent decades (1978–2007) leading to stronger summer droughts. This variability is expected to further intensify based across all emission scenarios (2050–2099) (L. Li & Li, 2015) leading to exacerbated socio-economic impacts intensified by high population numbers and significant water usage (Binita et al., 2015). This will result in higher amounts of supplemental irrigation by the farmers to avoid crop failure due to heat and insufficient soil moisture (Smith & Edwards, 2021). Furthermore, the long term decreasing trend in precipitation and increasing trend in potential evapotranspiration are expected to increase the agricultural water demands (Zhang, 2011). This increased water use will call for further regulations for management of GW pumping in the basin. The SFRB has also experienced significant growth in agricultural production over the past few decades. Agriculture in southern Georgia, where SFRB is located, was revolutionized by the implementation of center pivot irrigation systems throughout the 1970s in an effort to combat the effects of drought on yields. Irrigation changed crop selection decisions, stabilized production and yields, and enabled the use of systems for the application of fertilizers, herbicides, and pesticides, decreasing the risk to agricultural producers (Mullen, 2019). We focus on the following four major field crops for this study: corn, cotton, sorghum, and soybeans for this study as they account for 65% of cultivated acreage in the SFRB. The major crops grown in the SFRB by harvested acreage and production value are shown in Figures 1b and 1c. These four crops contribute >60% of total harvested acreage in each county.

### 2.2. Agricultural Production Data

We use the annual county-level data of crop yield per unit area and harvested acreage from US Department of Agriculture (USDA) NASS survey database to calibrate AquaCropOS (discussed in Section 3.1). The data was acquired through the Quick Stats API service (https://quickstats.nass.usda.gov) for the period 1980–2010. The state-level irrigated (and rainfed) acreage and irrigated (and rainfed) yield per unit area information at five-year intervals (1987–2012) were obtained from USDA NASS census database through the Quick Stats API. The 5-yearly agricultural census also provides the water applied per acre for irrigated crop which is used to calibrate AquaCropOS (AQ) for full irrigation scenario. Annual county-level yields from agricultural commissioner's reports were not available in the public domain. The production budgets for the crops have been obtained through University of Georgia's Extension service (UGA, 2021).

The Official Code of Georgia states that no person shall make any withdrawal, obtain, or utilize groundwater in excess of 100,000 gallons per day for any purpose without obtaining a permit from the Georgia Environmental Protection Department (EPD) (https://www.legis.ga.gov/api/legislation/document/20092010/103008). The issued permits are available publicly through the EPD's website (https://epd.georgia.gov/watershed-protection-branch-lists). The EPD estimates that FRB has approximately 4.8% undocumented permits in addition to total 7,064 issued permits (Georgia Water Coalition, 2017). We have aggregated the permits to county scale to obtain a maximum limit on county-wise water withdrawals for setting up the RHEO (Figure 1d). However, this is a conservative limit as smaller farmers can still pump water without applying for permits.

The census provides detailed estimates of crop yields under no irrigation, partial irrigation, and full irrigation, while the surveys do not mention yield under different irrigation types. The comparison of survey and census crop yields shows that the survey estimates are close toward rainfed agriculture and hence we assume the annual yield values to be rainfed yields. The NASS yields have a strong chronological trend due to technological improvements (e.g., high-yield seed, fertilizer application and management practices) over the decades. Hence, we de-trend by assuming linear chronological trend in the annual NASS yield timeseries for each crop and county. The detrended NASS yield timeseries is then compared to the AquaCropOS rainfed yield and the mean bias value is removed. The best available information on irrigated agriculture in SFRB is available from University of Georgia Cooperative Extension Service which conducts surveys at one to three year intervals (Harrison & Hook, 2005). These surveys provide information on type of irrigation system (i.e., center pivot/linear, travelers, and drip/trickle, etc.), irrigation depth, energy source (natural gas, diesel, and electric, etc.). We assume the patterns in SFRB follow general trends observed in Georgia agriculture. These surveys indicate that the composition of energy sources has changed significantly over from 1980s when diesel engines comprised more than 80% of all power units to electric motors comprising more than 80% of all power units (Harrison & Skinner, 2012).

### 2.3. Meteorological Data

We utilize the gridded precipitation and temperature data set of 1/8° from Maurer et al. (2002) and gridded evapotranspiration data set of 1/4° from GLEAM project v3.3a (Martens et al., 2017) for 1980–2010 period. The gridded data for evapotranspiration, precipitation, and temperature was aggregated to county level. The groundwater table information was obtained from the active wells in US Geological Survey (USGS) Active Groundwater Level Network (https://waterdata.usgs.gov/nwis/gw). The pumping costs are calculated based on historic time series of groundwater levels from the USGS well data. More than 70% of the total irrigation water demand in the SFRB are met by groundwater (Figure 1f).

## 3. RHEO Methodology

An overview of proposed Regional HydroEconomic Optimization framework, RHEO, is shown in Figure 2 to describe key variables and processes. Following sections (3.1–3.5) provide detailed formulation of each component.

### 3.1. Crop Simulation Model: AquaCropOS

AquaCrop is a multi-crop model developed by FAO to simulate crop yield under different climatic and soil conditions and management practices. It has been successfully calibrated and validated across a wide range of climatic and agricultural practices (Vanuytrecht et al., 2014). AquaCrop is designed to model crop yield at the single field scale (point simulations) and has been typically used to calibrate and validate statistical models at the farm level. However, its requirement of few input variables and parallelization capability has allowed AquaCrop to model mean crop yields at various spatial scales ranging from point to county and regional scales. Recently, studies have focused on simulating crop yields beyond farm levels using AquaCrop such as: (Foster & Brozović, 2018; Silvestro et al., 2017). To scale up single simulations beyond a field or farm up to the regional level, high resolution input data of weather, crop, soil, and management practices are required (Soltani, 2013). However, the use of AquaCrop for these applications requires a large number of simulation runs, involving the generation of large amount of input and project files, and complex interpretation and analysis of the results (Vanuytrecht et al., 2014).

AquaCropOS is an open-source version of FAO's AquaCrop 4.0 and allows for parallel execution to speed up scenario evaluation. AquaCropOS was developed by Foster et al. (2017) for Matlab programming environment and has been successfully applied across the globe in agricultural studies. We calibrate AquaCropOS for the given weather, soil, and crop characteristics at the county level for all the 21 counties in the basin. The AquaCropOS crop growth simulation model is first manually calibrated for the four major crops for the 1980–2010 period using climate data (Maurer et al., 2002), soil data from USGS land surveys in Worth county in the following manner. We assign an initial value to AquaCropOS model parameters based on reported values in the literature for the selected geographical region, perturb the parameters and compare the AquaCropOS yield to the observed NASS yields. We obtain a time series of AquaCropOS yield for 31 years (one growing season in each year, fallow for the rest of the year) and calculate the sum of squared differences between AquaCropOS yields and NASS detrended yields. The set of parameters for which we obtain minimum sum of squared differences is selected (Figure 2b).

We employ auto parameterization of AquaCropOS parameters to scale it from a single county to all the counties in the basin. Auto parameterization is suitable as a limited number of environmental and management factors

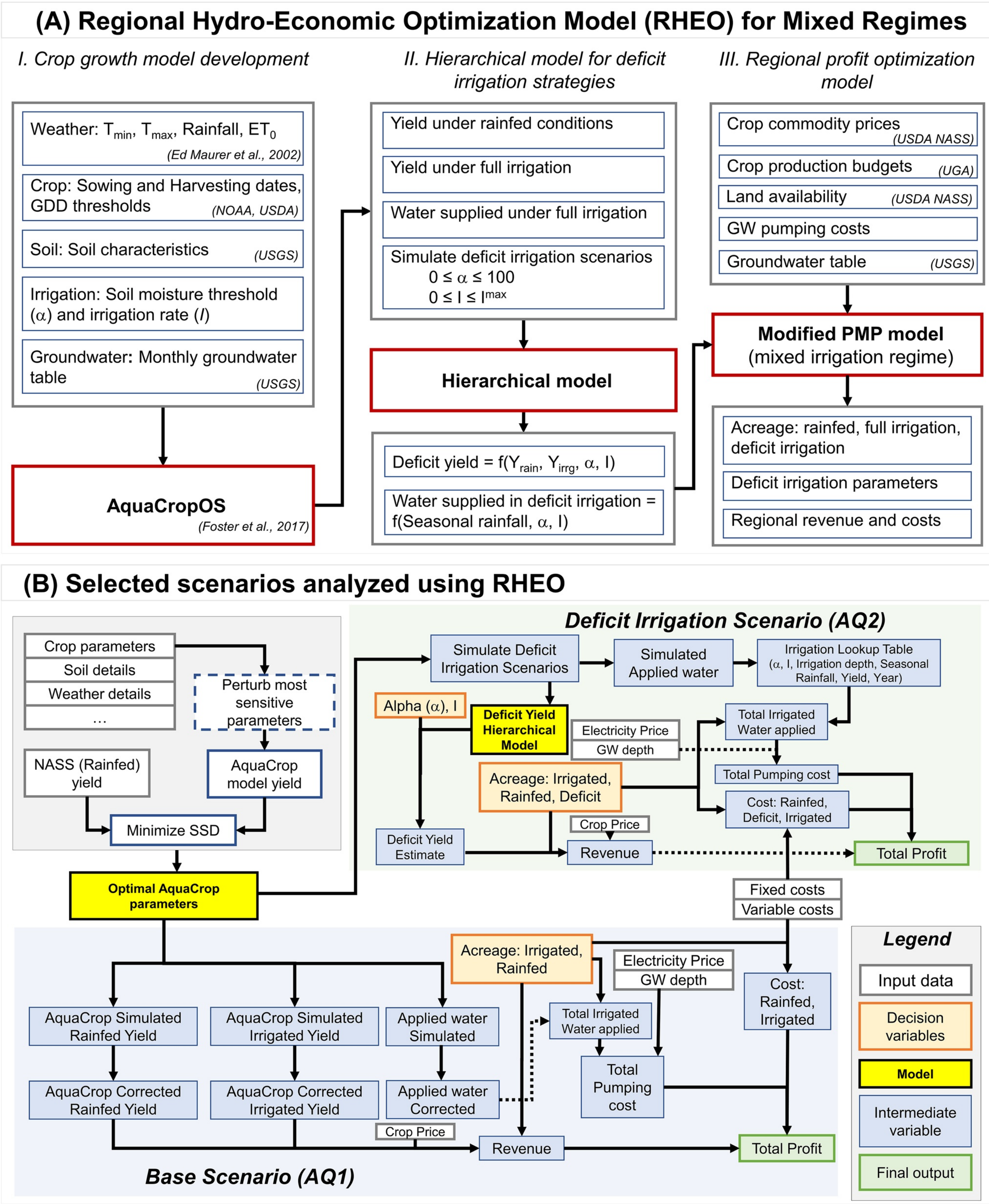


**Figure 2.** (a) Overview of proposed three-part framework: (i) Calibrate crop growth simulation model, (II) Simulate deficit irrigation and develop hierarchical model, and (III) Develop regional profit maximization model with acreage and deficit irrigation parameters as the decision variables. (b) Detailed explanation of the optimization algorithm to simulate AQ1 and AQ2 scenarios.

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determine crop growth in most regions (Soltani, 2013). We utilize the list of AquaCrop variables having significant influence on crop yields identified by Silvestro et al. (2017) for auto parameterization. We also note that the crop yields in the neighboring counties are significantly cross-correlated possibly due to relatively small variation in soil and weather conditions (see Figure S1 in Supporting Information S1).

Worth county was selected for manual calibration as is the largest county in terms of acreage in the SFRB (8.38% of total harvested area in SFRB; Figure 1b) and is irrigated primarily by groundwater. Webster county was selected as geographically it is far away from Worth county and has different irrigation characteristics (surface water dominated irrigation) than Worth County. Initially, the parameters values for Worth counties are taken as starting input. We then algorithmically perturb the most sensitive parameters, evaluate the AquaCropOS yield and compare the correlation against detrended NASS time series. This approach is inspired from gradient descent method. We run the algorithm multiple times to ensure it does not converge to one local minima.

### 3.2. Bias-Correcting AquaCropOS Yields Using Reported NASS Yields

We calculate the difference between NASS rainfed yields and NASS irrigated yields in census years and use these differences to generate the annual irrigated yields timeseries through linear interpolation. We now use these NASS irrigated yield estimates to correct the bias in the simulated AquaCropOS irrigated yields. We also utilize the acreage information on rainfed agriculture and irrigated agriculture from the USDA censuses. We assume that the ratio of rainfed to irrigated acreage gradually changes between census years for each crop and each county and thus piecewise linear interpolation has been used. We then calculate the weighted yield from rainfed and irrigated yields with rainfed and irrigation acreage values as the weights. This acreage weighted estimate of yield is compared to NASS detrended yield to evaluate AquaCropOS performance.

### 3.3. Pumping Costs for Irrigated Agriculture

The irrigation in SFRB is predominantly through groundwater (Figure 1f). The irrigation is mostly done through center pivot system (Georgia Environmental Protection Division, 2006). The farmers use a mix of diesel and electricity to pump groundwater. We have limited the study to electricity-driven pumps to estimate the pumping costs as past electricity prices are typically available from Energy Information Administration. The electric pumps comprise more than 80% of all power units in the region (Harrison & Skinner, 2012). The pumping cost is directly related to the energy, which is calculated based on the volume of water pumped, the depth of groundwater table, motor and pump efficiencies, and the pressure at pump discharge. The groundwater table depth is based on the monthly USGS well network (Section 2.3). Pressure at pump discharge is assumed to be 60 psi (138.43 feet) as suggested by the NASS census. The efficiency of electric motors ranged from 85% to 92% in 2010s. The electric pump and electric motor efficiencies in this study are assumed to be 0.7 during the study period (Harrison & Skinner, 2012). The representative electricity cost of \$0.11/kWh is assumed based on the Georgia Power report (https://www.georgia-power.com/content/dam/georgia-power/pdfs/electric-service-tariff-pdfs/SAS-11.pdf , accessed 1 February 2022). This could be considered as the lower bound on the total cost of pumping as we don't have detailed information on efficiency. The pumping cost for one acre-foot (\$/ac-ft) is calculated in the following manner:

$$\text{UPC} = 1233.48 \times \rho_w \times g \times \left(h_{\text{GW}} + h_{\text{discharge}}\right) \times (p_{elc}) / \left(3.6 \times 10^6 \times \mu_p \times \mu_m\right) \tag{1}$$

where, $\rho_w$ = water density (1,000 kg/m$^3$), $g$ = acceleration due to gravity (9.81 m/s$^2$) $h_{\text{GW}}$ = GW depth in meters, $h_{\text{discharge}}$ = pressure at pump discharge in meters, $p_{elc}$ = electricity cost in \$/kWh, $\mu_p$ = pump efficiency (=0.7), and $\mu_m$ = motor efficiency (=0.7). 1 acre-feet equals 1,233.48 cubic meters.

### 3.4. Hierarchical Mathematical Model for Deficit Irrigation

The deficit irrigation strategy is defined as irrigating lesser than the total water requirement of the crop and has been globally applied especially during water scarcity periods (Araya et al., 2016; Foster & Brozović, 2018; Paredes et al., 2014). Deficit irrigation can be achieved through multiple irrigation strategies by controlling the rate and timing of water application. Figure 3 illustrates the conceptual formulation of deficit irrigation using AquaCropOS. AquaCropOS allows to control the rate of water (mm/day) and also offers multiple scheduling options to control the frequency of irrigation which ensures filling the soil to its field capacity (i.e., maximum possible saturation) (Foster & Brozović, 2018). We adopt a soil moisture-deficit scheduling approach, in which irrigation happens when soil moisture goes below a specified threshold ($\alpha$), instead of a fixed interval

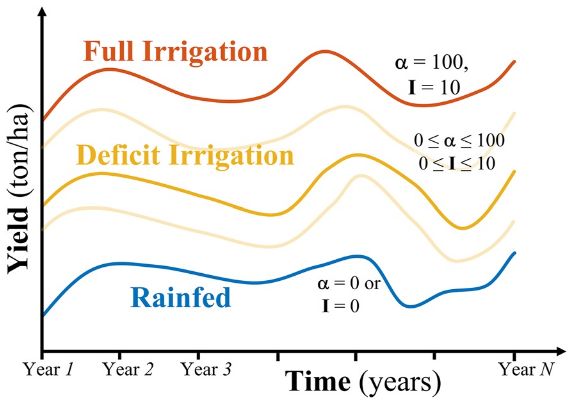


**Figure 3.** The conceptual model of deficit irrigation: crop yield under deficit irrigation (yellow lines) varies between yield under rainfed (blue line) and full irrigation (orange line) for different values of deficit irrigation parameters ($\alpha$ and $I$).

as it automatically incorporates rainfall events and helps avoiding irrigation following rainfall events.

Estimating the yield using AquaCropOS is computationally intensive and time consuming and thus directly integrating the running into the profit maximization module of RHEO is infeasible. Thus, we develop a Bayesian hierarchical model (BHM) to estimate the yield under deficit irrigation strategies with $\alpha$ and $I$ as decision variables within the RHEO by linking the deficit yield from the BHM as a function of rainfed and fully irrigated yield. To develop the BHM regression, we estimate crop yield from AquaCropOS for the four major crops considered under deficit irrigation scenarios based on the irrigation control parameters: $\alpha$ (%) = 0 (never irrigated), 5, 15, 25, 35, 50, 60, 80, 100 (very frequently irrigated) and I (mm/day) = 0, 2, 4, 6, 8, 10. This generates a table with the following columns: year, alpha ($\alpha$), I, irrigation water applied, crop yield (termed as deficit yield) for each year (1980–2010) for all the four crops for the Worth County. The simulation to estimate crop yield under these deficit irrigation combinations takes approximately 4 hr on a 12-core Intel® Core i7-8700 CPU (3.2 GHz) for the four crops for one county for 31 years. We now develop a hierarchical model for deficit yield as predictand with hierarchy in terms of the irrigation intensity ($I$ and $\alpha$):

$$Y^{\mathrm{def}}(t) = a_1 + a_2 \times Y^{\mathrm{rain}}(t) + a_3 \times Y^{\mathrm{irrg}}(t) + \epsilon_0 \forall t = 1, 2, \ldots, 31 \tag{2a}$$

$$a_1 = a_{11} + a_{12} \times \alpha + a_{13} \times I \tag{2b}$$

$$a_2 = a_{21} + a_{22} \times \alpha + a_{23} \times I \tag{2c}$$

$$a_3 = a_{31} + a_{32} \times \alpha + a_{33} \times I \tag{2d}$$

where, $t$ denotes the year of study = 1, 2, …, 31, $Y^{\mathrm{rain}}(t)$ and $Y^{\mathrm{irrg}}(t)$ denote yield under rainfed and full irrigation conditions. The coefficients ($a$) of above relationship are estimated using a single-step Bayesian with uninformative priors. The convergence of Markov chain Monte Carlo was checked through visual inspection. The point estimates of coefficients ($a_{ij} \forall i,j = 1, 2,3$) were obtained from median value of the generated posterior distributions. The details on parameter prior distributions and burn-in period are provided in Table S1 in Supporting Information S1. The BHM model apart from being useful in reducing the time required in running the RHEO, it also allows us to explicitly consider deficit irrigation parameters as decision variables. The BHM is developed for each crop for two counties, Worth and Webster, and validated for one county with the other. Since the performance of the BHM was similar through spatial validation, separate model for each county was not developed as the performance of the model is going to be similar even if developed separately. This little spatial is variation is expected as the crop yields in the neighboring counties are significantly cross correlated (see Figure S1 in Supporting Information S1). This is possibly due to small variation in soil and weather conditions in this small sub-basin. The parameter values for the Webster County are used in the rest of the analysis.

### 3.5. Regional Profit Maximization Model

The decision variables of the non-linear profit optimization module include the county acreage under rainfed, full irrigation, and deficit irrigation and two parameters, $\alpha$ and $I$, of deficit irrigation which respectively represent frequency and intensity of irrigation. The combination of o deficit irrigation parameters can simulate various irrigation scenarios such as no irrigation, frequent intense irrigation, and infrequent intense irrigation. The objective function of RHEO consists of total fixed cost, total variable cost, pumping cost, crop commodity price, and constrained with observed maximum acreage from NASS and withdrawal permits from Georgia Environmental Protection Division. The RHEO is formulated for the SFRB consisting of 21 counties as presented below:

#### 3.5.1. RHEO Objective Function

$$\max_{\left\{A^{\mathrm{rain}}_{i,c,t}, A^{\mathrm{irrg}}_{i,c,t}, A^{\mathrm{def}}_{i,c,t}, \alpha_{i,c,t}, I_{i,c,t}\right\}} \sum_t \sum_c \sum_i \left(\mathrm{REV}_{i,c,t} - \mathrm{PC}_{i,c,t} - \mathrm{TVC}_{i,c,t}\right) \tag{3a}$$

**Table 1**
*Details of the Scenarios Analyzed in This Study*

| # | Scenario | Yield and acreage | Cases included | Decision variables | Purpose and relevant equations |
|---|---|---|---|---|---|
| 1 | NASS | NASS yields, NASS acreage | Rainfed + Irrigated | N.A. | Simulate the revenue, profit by assuming mixture of rainfed agriculture, and irrigated agriculture for the observed NASS acreage. Equations: 1, 3, 4, 5, 6 |
| 2 | Baseline (AQ1) | AQ yields, NASS acreage | Rainfed + Irrigated | | Simulate the expected regional revenue and profits under observed rainfed and irrigated acreage for AquaCropOS bias-corrected yields. Equations: 1, 3, 4, 5, 6 |
| 3 | AQ2 | AQ yields, Computed optimal acreage | Rainfed + Irrigated + Deficit | $A^{\text{rain}}, A^{\text{irrg}}, A^{\text{def}}, \alpha^{\text{def}}, I^{\text{def}}\ \forall$ each crop | Optimal regional revenue, profits by allocating area under rainfed, full irrigation, and deficit irrigation agriculture. The acreage is kept close to observed acreage. Equations: 1, 2, 3, 4, 5, 7 |
| 4 | AQ2-M | | Rainfed + Irrigated + Deficit | | Optimal regional revenue and profits by allocating area under rainfed, full irrigation, and deficit irrigation agriculture. Equations: 1, 2, 3, 4, 5 |
| 5 | AQ2-IR | | Rainfed + Irrigated | $A^{\text{rain}}, A^{\text{irrg}}\ \forall$ each crop | Expected additional regional revenue and profits under fully irrigated agriculture. Equations: 1, 2, 3, 4, 5, 8 |

$$\mathrm{REV}_{i,c,t} = p_{i,t}\, Y_{i,c,t}^{\mathrm{rain}}\, A_{i,c,t}^{\mathrm{rain}} + p_{i,t}\, Y_{i,c,t}^{\mathrm{irrg}}\, A_{i,c,t}^{\mathrm{irrg}} + p_{i,t}\, Y_{i,c,t}^{\mathrm{def}}\, A_{i,c,t}^{\mathrm{def}} \tag{3b}$$

$$\mathrm{PC}_{i,c,t} = \mathrm{UPC} \times \left( \mathrm{WP}_{i,c,t}^{\mathrm{irrg}} \times A_{i,c,t}^{\mathrm{irrg}} + \mathrm{WP}_{i,c,t}^{\mathrm{def}} \times A_{i,c,t}^{\mathrm{def}} \right) \tag{3c}$$

$$\mathrm{TVC}_{i,c,t} = \omega_{i,t}^{\mathrm{rain}} \times A_{i,c,t}^{\mathrm{rain}} + \omega_{i,t}^{\mathrm{irrg}} \times A_{i,c,t}^{\mathrm{irrg}} + \omega_{i,t}^{\mathrm{def}} \times A_{i,c,t}^{\mathrm{def}} \tag{3d}$$

where, $i$ represents the index of major crops grown in the county: Corn (1), Cotton (2), Sorghum (3), Soybeans (4), $c$ represents the index of county (1, 2, …, 21), $t$ represents the index of year (1, 2,…, 31), $REV_{i,c,t}$ denotes the revenue generated for crop $i$ in county $c$ in year $t$, $PC_{i,c,t}$ denotes the pumping costs for crop $i$ in county $c$ in year $t$, and $TVC_{i,c,t}$ denotes the total production cost except pumping for crop $i$ in county $c$ in year $t$. $A_{i,c,t}^{\text{rain}}$, $A_{i,c,t}^{\text{irrg}}$, and $A_{i,c,t}^{\text{def}}$ denote the acreage of crop $i$ in county $c$ in year $t$ under rainfed, fully irrigated, and deficit irrigation regimes. $\alpha_{i,c,t}$ and $I_{i,c,t}$ denote the frequency and intensity of irrigation for the deficit irrigation regime for crop $i$ in county $c$ in year $t$. $Y_{i,c,t}^{\text{rain}}$, $Y_{i,c,t}^{\text{irrg}}$, and $Y_{i,c,t}^{\text{def}}$ represents the crop yield of crop $i$ in county $c$ in year $t$ under rainfed, fully irrigated, and deficit irrigation regimes. $p_{i,t}$ denotes the price per unit production (pounds or bushels) for crop $i$ in year $t$. Deficit crop yield ($Y_i^{\text{def}}$) is calculated based on the hierarchical model (Equation 2). *UPC* denotes the cost of pumping one acre-feet of water (Equation 1). $\mathrm{WP}_{i,c,t}$ denotes the total irrigational water supplied (pumped) per acre for crop $i$ in county $c$ in year $t$. $\omega_{i,t}$ represents the total production cost per acre excluding pumping for each crop $i$ in year $t$) (see Table S2 in Supporting Information S1).

### 3.5.2. Resource Constraints

*Land resource availability*

$$\sum_i \left( A_{i,c,t}^{\mathrm{rain}} + A_{i,c,t}^{\mathrm{irrg}} + A_{i,c,t}^{\mathrm{def}} \right) \le A_{c,t}^{\max} \forall\, c = 1, 2, ..., 21 \;\&\; t = 1, 2, \ldots, 31 \tag{4a}$$

$$A_{c,t}^{\max} = \sum_i \left( A_{i,c,t}^{\mathrm{observed}} \right) \forall\, c = 1, 2, ..., 21 \;\&\; t = 1, 2, \ldots, 31 \tag{4b}$$

*Water availability*

$$\sum_i \left( W\,P_{i,c,t}^{\mathrm{irrg}} + W\,P_{i,c,t}^{\mathrm{def}} \right) \le W\,P_c^{\max} \forall\, c = 1, 2, ..., 21 \;\&\; t = 1, 2, \ldots, 31 \tag{5}$$

where, $A_{c,t}^{\max}$ is defined as the total observed acreage for all crops in county, $c$, for the given year, $t$, from NASS. $W\,P_c^{\max}$ is defined as the amount of water that can be pumped in the given season based on the water permits issued in county, $c$. The profit maximization model is formulated with a non-linear objective function and linear constraints and solved with the Sequential Quadratic Programming (SQP) using "fmincon" function in MATLAB programming language. The solution of each scenario for four crops in 21 counties for 31 years took approximately 1 hr on a 12-core Intel® Core i7-8700 CPU (3.2 GHz) running with 10 parallel nodes. The detailed flowchart in Figure 2b describes RHEO's optimization algorithm. The profit maximization module of RHEO is described in detail in Figure S2 in Supporting Information S1.

## 4. Experiments/Scenarios

### 4.1. RHEO—Simulation Scenarios

We consider five scenarios listed in Table 1 to understand the impact of policy decisions on cropping patterns and regional profits. We use the observed acreage and yields from NASS (Equation 6) in the first scenario to estimate the yearly baseline profits for each crop and acreage without any optimization. We term this scenario (#1 in Table 1) as NASS scenario as it provides regional profits from RHEO under NASS-reported cultivated acreage and yields. We repeat this scenario using bias corrected AquaCropOS yields and observed NASS acreage and term as AQ1 (#2 in Table 1). We use AQ1 as the baseline to compare results of optimization scenarios. Scenarios NASS and AQ1 assume zero acreage under deficit irrigations based on the prevalent irrigation

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practices in the region during the study period. The commonly used technology such as high pressure, high angle impact sprinklers were not highly efficient and less water intensive practices such as soil-moisture based irrigation were not followed (Gonzalez-Alvarez et al., 2006; Harrison & Hook, 2005). The comparison of the RHEO performance from baseline (AQ1) and NASS scenario provides information on underestimating/overestimating the regional profits using AquaCropOS yields. These two simulation scenarios are followed by optimization scenarios to investigate the various deficit irrigation strategies.

*Observed crop acreage*.

$$A_{i,c,t}^{\mathrm{rain}} + A_{i,c,t}^{\mathrm{irrg}} + A_{i,c,t}^{\mathrm{def}} = A_{i,c,t}^{\mathrm{observed}}\,\forall\, i, c, t \tag{6a}$$

$$A_{i,c,t}^{\mathrm{rain}}, A_{i,c,t}^{\mathrm{irrg}}, A_{i,c,t}^{\mathrm{def}} \geq 0;\, i = 1, 2, 3, 4;\, c = 1, \ldots, 21;\, t = 1, 2, \ldots, 31 \tag{6b}$$

### 4.2. RHEO—Optimization Scenarios

The optimization scenarios investigate the potential for improvements in regional profit, changes to crop diversity, and changes to groundwater withdrawals. The first optimization scenario, AQ2, investigates the potential increase in regional profit by incorporating deficit irrigation while maintaining the crop diversity. Crop diversity is maintained through two constraints: the acreage allocated to a crop for a county in a given year cannot be changed (increased or decreased) by (a) more than 50% of the observed NASS acreage or (b) more than 5,000 acres. The following additional constraints (Equations 7a–7e) for scenario AQ2 are specified to the model defined through Equations 3–5 in Section 3.5 to maintain crop diversity:

*Maintain crop diversity*.

$$A_{i,c,t}^{\mathrm{rain}} + A_{i,c,t}^{\mathrm{irrg}} + A_{i,c,t}^{\mathrm{def}} \leq 1.5 \times A_{i,c,t}^{\mathrm{observed}}\,\forall\, i, c, t \tag{7a}$$

$$A_{i,c,t}^{\mathrm{rain}} + A_{i,c,t}^{\mathrm{irrg}} + A_{i,c,t}^{\mathrm{def}} \geq 0.5 \times A_{i,c,t}^{\mathrm{observed}}\,\forall\, i, c, t \tag{7b}$$

$$A_{i,c,t}^{\mathrm{rain}} + A_{i,c,t}^{\mathrm{irrg}} + A_{i,c,t}^{\mathrm{def}} \leq A_{i,c,t}^{\mathrm{observed}} + 5000\,\forall\, i, c, t \tag{7c}$$

$$A_{i,c,t}^{\mathrm{rain}} + A_{i,c,t}^{\mathrm{irrg}} + A_{i,c,t}^{def} \geq A_{i,c,t}^{\mathrm{observed}} - 5000\,\forall\, i, c, t \tag{7d}$$

$$A_{i,c,t}^{\mathrm{rain}} + A_{i,c,t}^{\mathrm{irrg}} + A_{i,c,t}^{\mathrm{def}} \geq 0;\, i = 1, 2, 3, 4;\, c = 1, \ldots, 21;\, t = 1, 2, \ldots, 31 \tag{7e}$$

The total harvested acreage of a county in a given year is capped with observed NASS acreage ($A_{c,t}^{\mathrm{max}}$) for all scenarios as specified in Equation 4. The second optimization scenario, termed AQ2-M, investigates the potential maximum increase in regional profits by relaxing above two constraints (particularly Equations 7a–7d) under AQ1 for maintaining crop diversity by not assigning a limit on acreage allocated to any crop. The comparison of results from AQ2 and AQ2-M would help in understanding the impact on crop diversity and groundwater withdrawals.

Finally, the third optimization scenario, termed AQ2-IR, is a modification of AQ2-M wherein deficit irrigation is not allowed. This will help in understanding the potential savings in groundwater withdrawal through adopting deficit irrigation by comparing with AQ2-M. The following additional constraint (Equation 8) for scenario AQ2-IR is specified to the model defined through Equations 3–5 in Section 3.5 to exclude deficit irrigation.

*Prevent deficit irrigation*.

$$A_{i,c}^{\mathrm{def}} = 0;\, \alpha_{i,c} = 0;\, I_{i,c} = 0\,\forall\, i = 1, \ldots, 4, c = 1, \ldots, 21 \tag{8}$$

## 5. Results

### 5.1. Evaluation of AquaCropOS in Simulating NASS Yields

This section describes the performance of AquaCropOS in capturing the inter-annual variability of crop yields. Figure S3 in Supporting Information S1 presents the representative timeseries plots of weighted AquaCropOS

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yields (described in Section 3.2) against detrended NASS yields for each crop for a selected county. AquaCropOS captures the inter-annual variability in crop yields well especially for corn, sorghum and soybeans as Pearson correlation value is significant at 10% significance level. AquaCropOS captures the increases and decreases in the yields due to annual rainfall and temperature conditions (will be discussed in Section 5.5). The spatial performance of the AquaCropOS is shown in Figure 4 using the Pearson correlation between AquaCropOS simulated and observed NASS detrended yields. Pearson correlation is a measure of linear correlation between two datasets. A value of Pearson correlation closer to 0 represents absence of linear correlation and near to $\pm 1$ denotes strong linear correlation. Figure 4 shows the correlation value in counties where the correlation is significant (at 10% significance level). The AquaCropOS model performs well for corn, sorghum, and soybeans with median correlation value of 0.60, 0.58, and 0.55 respectively across the counties (Figures 4a, 4c, 4d). It performs slightly poor for cotton with a median correlation value of 0.48 (Figure 4b).

### 5.2. Validation of Bayesian Hierarchical Model in Estimating Yields From Deficit Irrigation

The calibrated AquaCropOS was run for 105 combinations of deficit irrigation parameters for each county with $\alpha$ ranging from 0% to 100% and $I$ ranging from 0 to 10 mm/day. This resulted in the 105 estimates of deficit yield for each year (1980–2010) with total 3,255 estimates (31 years). The response surface of deficit yield from these 105 estimates is shown in Figure S4 in Supporting Information S1. We now evaluate the performance of parameterized relationship developed using BHM (described in Section 3.4) against the 3,255 deficit yield estimates for each crop from AquaCropOS. We used leave-N-out-cross-validation ($n = 1, 2, 5$) to split data into train and test period for BHM development and validation. The $R^2$ values for this test are provided in Table S3 in Supporting Information S1. The scatter plots in Figure 5 shows that deficit yield estimates from BHM are in agreement with AquaCropOS simulated deficit yields with high $R^2$ values for all four crops: corn (0.85), cotton (0.83), sorghum (0.87), and soybeans (0.81) without any systematic underestimation/overestimation. Furthermore, Figure 5 also shows good model performance under different seasonal rainfall conditions—normal (between 33rd and 67th percentile), above normal (wet; higher than 67th percentile), and below normal (dry; less than 33rd percentile). It should be noted that the variation in deficit yield estimates is higher in drier years compared to normal and wetter years. This is expected as the rainfed yield in dry years will be lower than that in a wet year and application of irrigation will improve the yield until the crop's total water requirement is met. We can thus integrate the BHM model into RHEO instead of directly integrating AquaCropOS to speed up the RHEO.

### 5.3. Performance Analysis of RHEO—Simulation Scenarios

The RHEO model outputs production costs (excluding pumping costs), pumping costs, total water applied, total yields, total revenues, and total profits for each year and for each crop across 21 counties. We initially examine the total revenues and profit for the entire sub-basin as shown in Figure 6 and summarized in Table 2 (all monetary values are given in 2010 dollar value after adjusting for inflation using Consumer Price Index from U.S. Bureau of Labor Statistics). The mean annual regional revenue and annual profits are 365.1 million dollars (2010$) and 190.2 million dollars for the NASS scenario (Figures 6a and 6b, Table 2). The contribution of corn (32%) and cotton (53%) to the total revenue is the highest followed by soybeans (14%). This is due to their large acreage: 26%, 48%, and 24% (of total harvested acreage) for corn, cotton, and soybeans respectively. Sorghum's revenue contribution is quite small (2%) since it is cultivated in a very small acreage (3% of total acreage) (Figure 6g, Table 2).

The simulation of existing conditions using AquaCropOS yields with NASS acreage in AQ1 scenario underestimates (Table 2) the average annual revenue compared to NASS by 65.92 million (18% of total NASS revenue) and underestimates the average annual regional profits by 72.33 million (38% of NASS profit). This is expected as the model yields were calibrated to be conservative to avoid overestimating the yields and associated revenues. This difference in NASS and AQ1 values can be used for bias correcting the results from optimization scenario. The amount of water applied estimates from AQ1 scenario (285,686 acre-feet) does not have any bias compared to NASS scenario (Figure 6f, Table 2). Similarly, the energy used pumping from AQ1 (113.1 Gigawatt hours or GWh) matches with that of NASS (Figure 6e, Table 2). We will use AQ1 as the baseline to compare results of optimization scenarios in the next section.

### 5.4. Performance Analysis of RHEO—Optimization Scenarios

The first scenario, AQ2, maintains crop diversity close to the observed acreage in the simulation scenarios. The average annual revenue and profit for AQ2 represent a gain of 54.02 million dollars in revenue and 60.71 million

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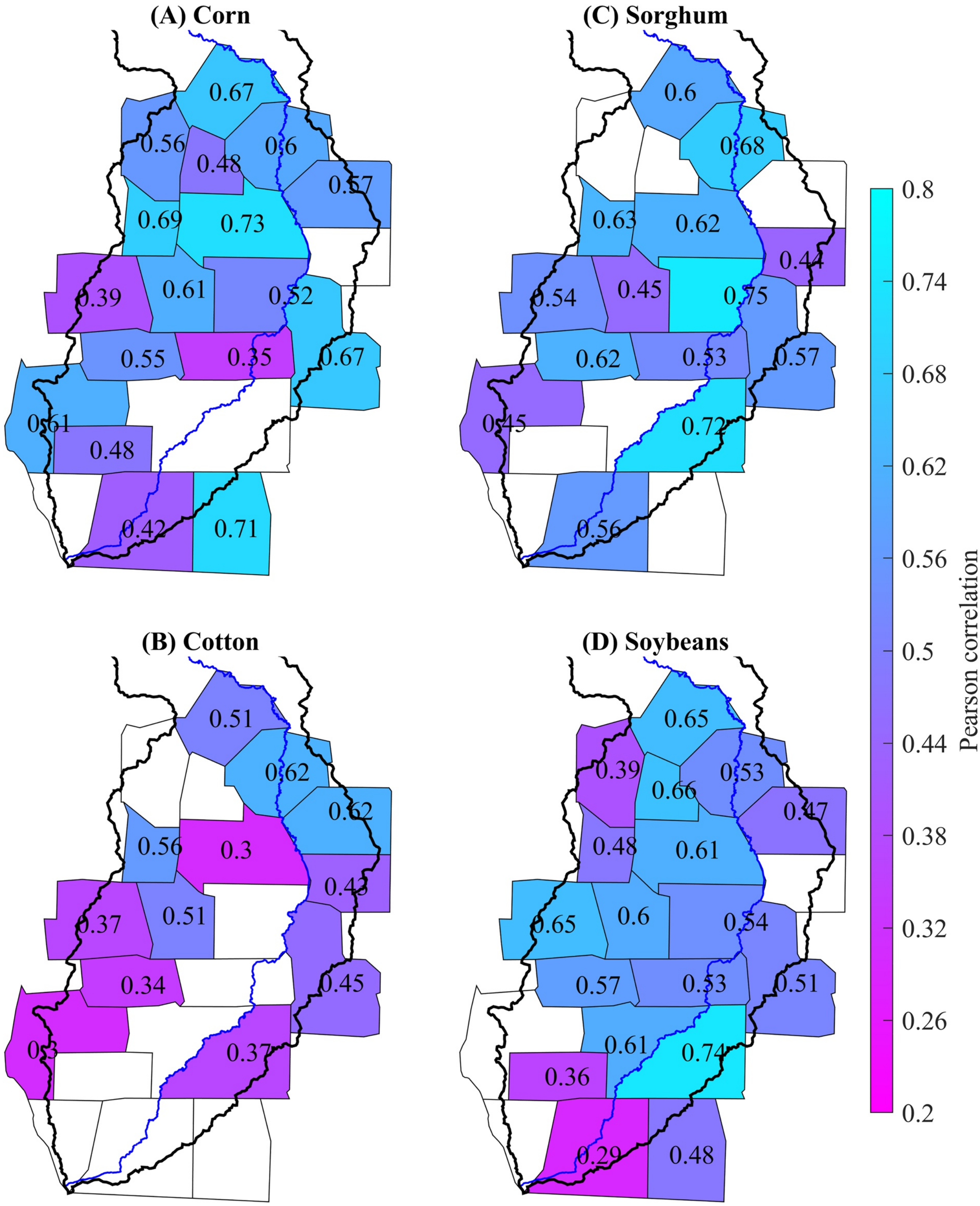


**Figure 4.** The spatial plot of Pearson correlation (significant at 0.10) between simulated crop yields from AquaCropOS and detrended NASS yields for (a) corn, (b) cotton, (c) Sorghum, and (d) soybeans.

dollars in profits compared to baseline (AQ1) scenario (Figures 6a and 6b and Table 2). Thus, the inclusion of deficit irrigation while maintaining crop diversity increased the revenue by 18% and profit by 51% compared to the baseline scenario. Further, the inclusion of deficit irrigation reduces the amount of total annual water pumped by 14.1% compared to the baseline scenario (Figure 6f, Table 2). This is due to the decrease in fully irrigated

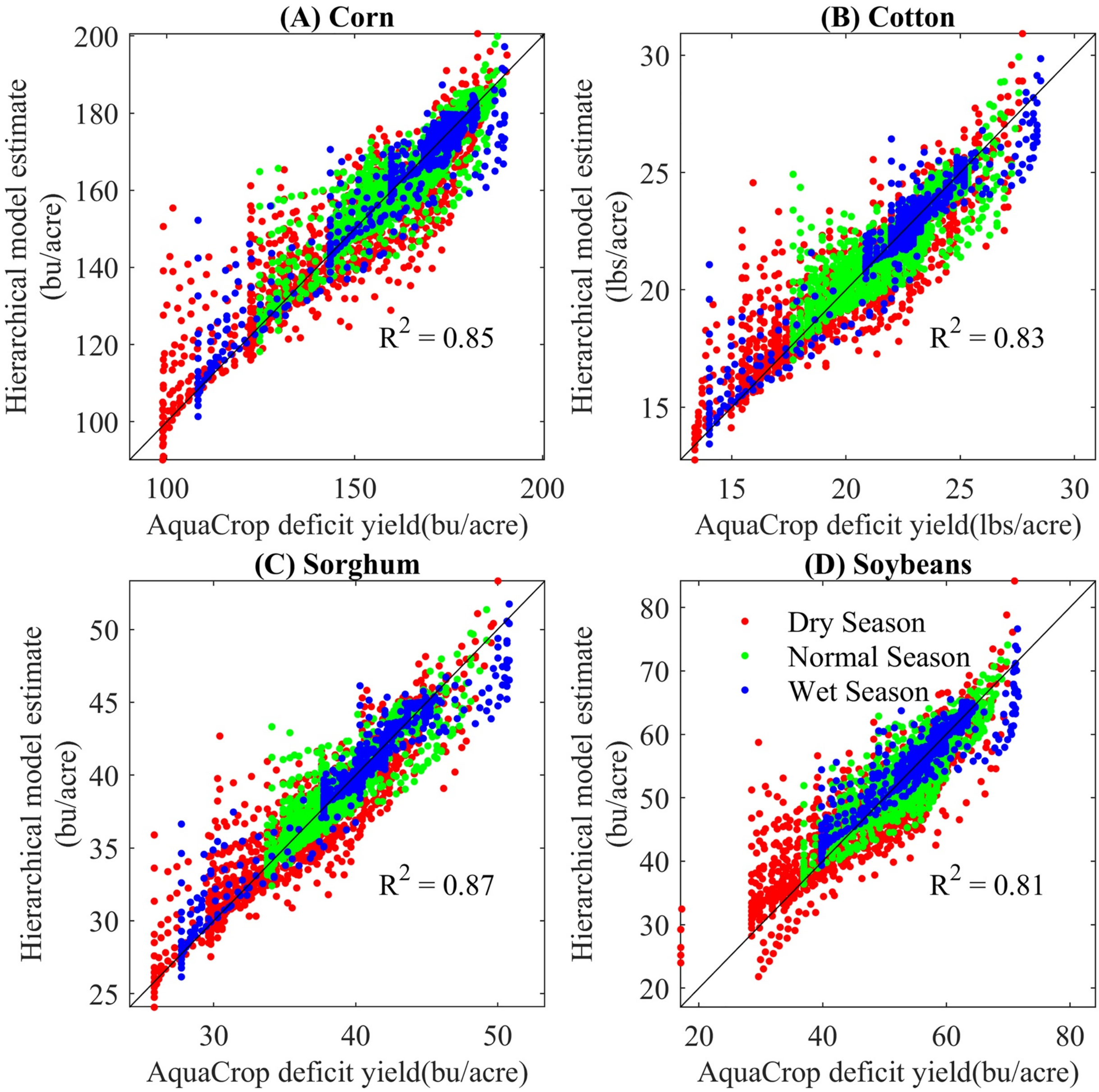


**Figure 5.** The scatter plot between AquaCropOS simulated crop yields and the estimates from the hierarchical model defined in Section 3.4 for (a) corn, (b) cotton, (c) sorghum, and (d) soybeans for Webster County, GA.

acreage (239,344–91,278 acres) and partially allotting it to deficit irrigation (232,907 acres) which uses lesser water per unit area (Figures 6i and 6j).

The AQ2-M provides a maximum bound on regional profits when observed crop diversity is not maintained. We observe 40% and 128% increments in revenue and profits from baseline scenario after correcting (Figures 6a and 6b, Table 2). The difference in profits of AQ2 and AQ2-M scenarios represents the cost of maintaining crop diversity. Thus, relaxing crop diversity constraint can potentially increase the annual regional revenue and profit by 67.1 million and 90.34 million dollars respectively which represents 22.4% revenue and 76.7% profits of baseline AQ1 scenario. The irrigated acreage and acreage under deficit irrigation remain nearly same as AQ2 scenario (Figures 6i and 6j) while the rainfed acreage gets reduced by 32% from the AQ2 scenario (Figure 6h). The other consequence of removing crop diversity is the reallocation of acreage to cotton from corn and soybeans. In terms of total acreage as well as acreage under different irrigation regimes (Figures 6g–6j). Thus, it is possible to increase the average annual revenue albeit with water withdrawals which are 25,507 ac-ft higher than AQ2

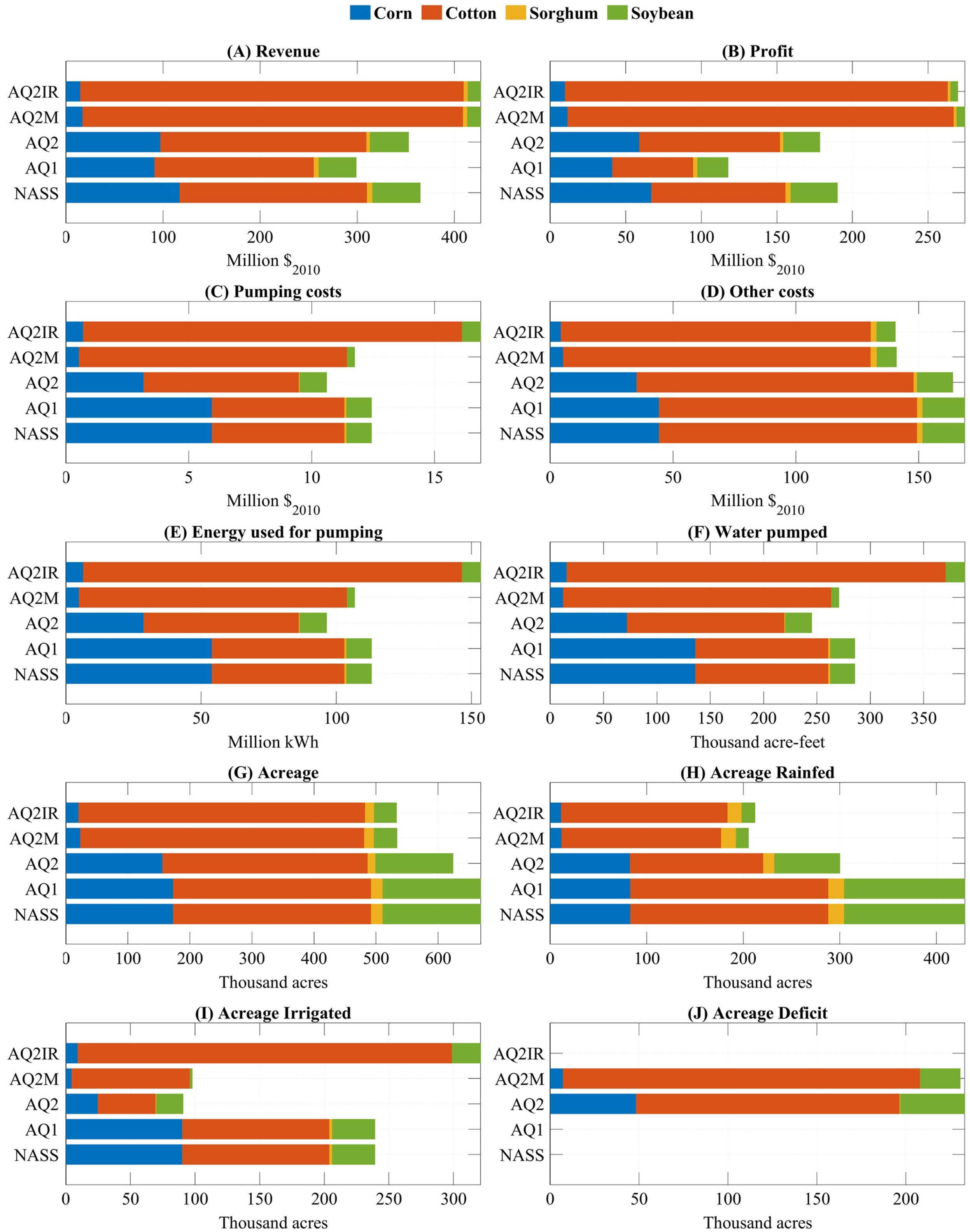


**Figure 6.** Mean annual value of RHEO outputs for five scenarios across 21 counties for 1980–2010 period are shown for (a) revenue, (b) profits, (c) pumping costs, and (d) Other variable costs (inflation adjusted to 2010-dollar value) and for: (e) energy used for pumping water, (f) water pumped in acre-feet, (g) total acreage, (h) rainfed acreage, (i) fully irrigated acreage, and (j) acreage under deficit irrigation.

**Table 2**
*The Mean Annual Values of Regional Profits, Pumping Costs, Allocated Acreage, and Energy Used for Pumping for All Scenarios as Shown in Figure 6*

| | | Revenue | | Profit | | Water applied | | Energy used for pumping | |
|---|---|---|---|---|---|---|---|---|---|
| # | Scenario | (Million 2010$) | % change | (Million 2010$) | % change | (Acre-feet) | % change | (GWh) | % change |
| 1 | NASS | 365.1 | N.A. | 190.2 | N.A. | 285,686 | N.A. | 113.1 | N.A. |
| 2 | Baseline (AQ1) | 299.2 | 0 | 117.9 | 0 | 285,686 | 0 | 113.1 | 0 |
| 3 | AQ2 | 353.2 | 18.0% | 178.6 | 51.5% | 245,283 | −14.1% | 96.5 | −14.7% |
| 4 | AQ2-M | 427.3 | 42.8% | 274.5 | 132.8% | 270,791 | −5.2% | 106.9 | −5.5% |
| 5 | AQ2-IR | 427.4 | 42.8% | 269.9 | 128.9% | 388,797 | 36.1% | 153.5 | 35.7% |

*Note*. % change refers to change with respect to baseline (AQ1) scenario.

which is nearly 9% of baseline pumped water (Figure 6f). These higher water withdrawals are directly linked to increased electricity demand for pumping the water (Figure 6e) with average annual energy used increasing to 106.9 GWh from 96.5 GWh in AQ2 scenario. Thus, the increased revenue comes at the cost of potential savings of 10.4 GWh in energy consumption and 25,507 ac-ft in pumped water.

The final scenario AQ2-IR evaluates the potential impact of not including deficit irrigation in AQ2-M. The total revenue and profits after bias correction are nearly same as that of AQ2-M scenario (Table 2). However, the amount of water pumped increases: 10.4% increment compared to AQ2 scenario (Figure 6f, Table 2) due to the 96% increase in irrigated acreage from baseline (Figure 6i). Thus, the inclusion of deficit irrigation could annually save 118,006 ac-ft of water (3.65 million ac-ft over the 31-year study period). We also analyzed a variant of AQ2IR scenario to further investigate the effect of including deficit irrigation (results presented in Figure S6 in Supporting Information S1). This variant scenario AQ2IR-AQ2 uses same crop diversity acreage constraints as AQ2 scenario (Equation 7) but excludes deficit irrigation (Equation 8). The profits and revenue due exclusion of deficit irrigation (AQ2IR-AQ2) remain very close to AQ2 scenario, but the total water pumped and pumping costs increase by 32%.

The total harvested acreage under optimization scenarios: AQ2, AQ2-M, AQ2-IR is less than baseline AQ1 acreage (Figure 6e) while the total profit is higher than baseline scenario. This is due to the inadequacy of rainfed yield to cover the production costs in some counties and especially in dry years. The RHEO model can allocate zero acreage to a rainfed crop in such an unproductive growing season and thus minimize cost while no such foresight is available to farmer who must decide to allocate acreage in the beginning of the season.

### 5.5. Crop Portfolio and Irrigation Strategies Selection Under Climatic Stresses

The water savings achieved in AQ2-M compared to AQ2-IR shows the usefulness of including deficit irrigation strategy. We now examine the selected crops and selected irrigation strategies during growing seasons with normal rainfall, above normal rainfall (wet years), and below normal rainfall (dry years) for AQ2 scenario. We have reordered the years from the driest to wettest for each county and then plotted the median value of fraction of total acreage under rainfed agriculture, deficit irrigation, and full irrigation in Figure 7. We can note that in the driest years, deficit irrigation is the preferred strategy with more than 40% of acreage under deficit irrigation while rainfed agriculture is the preferred strategy during wettest years with more than 90% acreage (Figure 7). The full irrigation, which occurs in southern counties where groundwater is shallow, is selected occasionally by very few counties. There is no dominant strategy in normal years between rainfed agriculture and deficit irrigation. We also note that supplemental irrigation is suggested with partial/full irrigation during dry years. The acreage allocation amongst the four crops during normal, wet, and dry conditions did not show a clear pattern. The profitability of growing a crop also depends on the crop prices which are influenced by market conditions. Cotton is the preferred crop in almost every year since it is the most cultivated crop across the region followed by corn and sorghum. We have also performed additional analysis by removing the trend in timeseries of inflation adjusted crop price and the results were similar to those presented in this section. Figure S7 in Supporting Information S1 shows the time series of revenue and profit for a selected county (Worth) under rainfed, deficit irrigation, and full irrigation and highlights that deficit irrigation can enable optimal water usage against blanket flood irrigation.

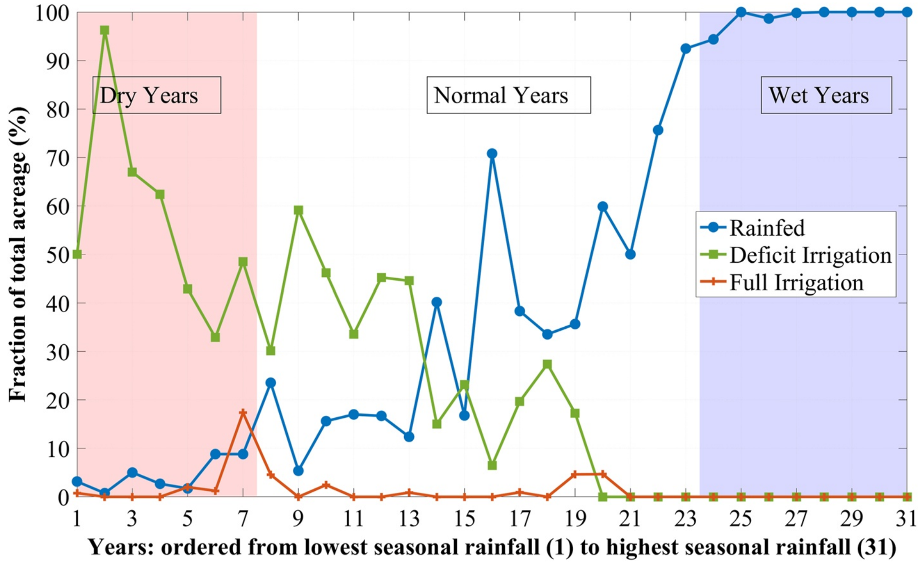


**Figure 7.** Acreage allocation by irrigation practice for the AQ2 scenario. The median fraction values of area under rainfed, deficit irrigation, and full irrigation are shown as line plots. The years have been ordered from driest to wettest using each county's precipitation during the growing period. The seven driest (wettest) years are shown with a red (blue) background.

We now examine how groundwater availability affects the FEW nexus. As the crop yield is non-linearly linked to supplied irrigation water (see Figure S5 in Supporting Information S1), increases in crop yield with each additional unit of supplied water becomes smaller since we approach the upper bound on maximum yield. Thus, these diminishing returns on crop yields with additional supply of water make pumping costs quite significant during normal years and is even more critical during dry years when groundwater table is deep. We carried out additional analysis of how the acreage allocation changes due to deepening of groundwater table in AQ2 scenario. Results in Figure 8 show that when the groundwater table drops past a certain threshold depth, area under rainfed agriculture increases whereas area under deficit irrigation decreases (Figures 8b–8d). It highlights that beyond a threshold the pumping costs surpass the increase in revenue due to irrigated crop yield. Hence, rainfed agriculture and deficit irrigation strategies are more economical than full irrigation (Figure 8). This is particularly true for the study region as there is no pronounced seasonality in rainfall (Petersen et al., 2012).

### 5.6. Crop Portfolio and Irrigation Strategies Under Changing Energy Availability

Groundwater pumping costs are also sensitive to changes in price of diesel and electricity in the lower FRB (Gonzalez-Alvarez et al., 2006) apart from changes in groundwater table. For instance, one could consider the increase in oil price 2022, which led to overall increase production costs in food sector (USDA, 2023). From December 2021 to June 2022, the gas price per gallon almost doubled across the US (EIA, 2023). Hence, we analyze the impact of energy availability on the regional food production through fluctuations in oil price, which could affect energy availability and the associated cost in crop production under normal and dry years. We use RHEO model to study the effect of increased/decreased energy prices on crop portfolio and irrigation strategies in AQ2 scenario. The results from this analysis shown for a selected county (Grady County) in Figure 9 for a potential increase in energy cost up to 300%. The average acreage under rainfed agriculture increases from 18% to 32% in years with below normal seasonal rainfall (Figure 9a) and from 18% to 23% in normal seasonal rainfall years for a trebling of energy prices (Figure 9g). The fully irrigated acreage is more sensitive to energy costs compared to deficit-irrigated acreage in normal and dry years as the fully irrigated acreage for corn nearly halves (Figure 9c). The flexibility in deficit irrigation parameters ($\alpha$ and $I$) allows the deficit irrigation to remain economical (Figures 9d and 9j) even with increased energy costs by lowering the irrigation water quantity per unit area using $\alpha$ and $I$ (Figures 9e, 9f, 9k, 9l). The full irrigation method cannot adjust the irrigation depth per unit area, thereby resulting in reduced acreage cultivated. We can note that deficit irrigation becomes profitable than rainfed agriculture under reduced energy prices (Figure 9a).

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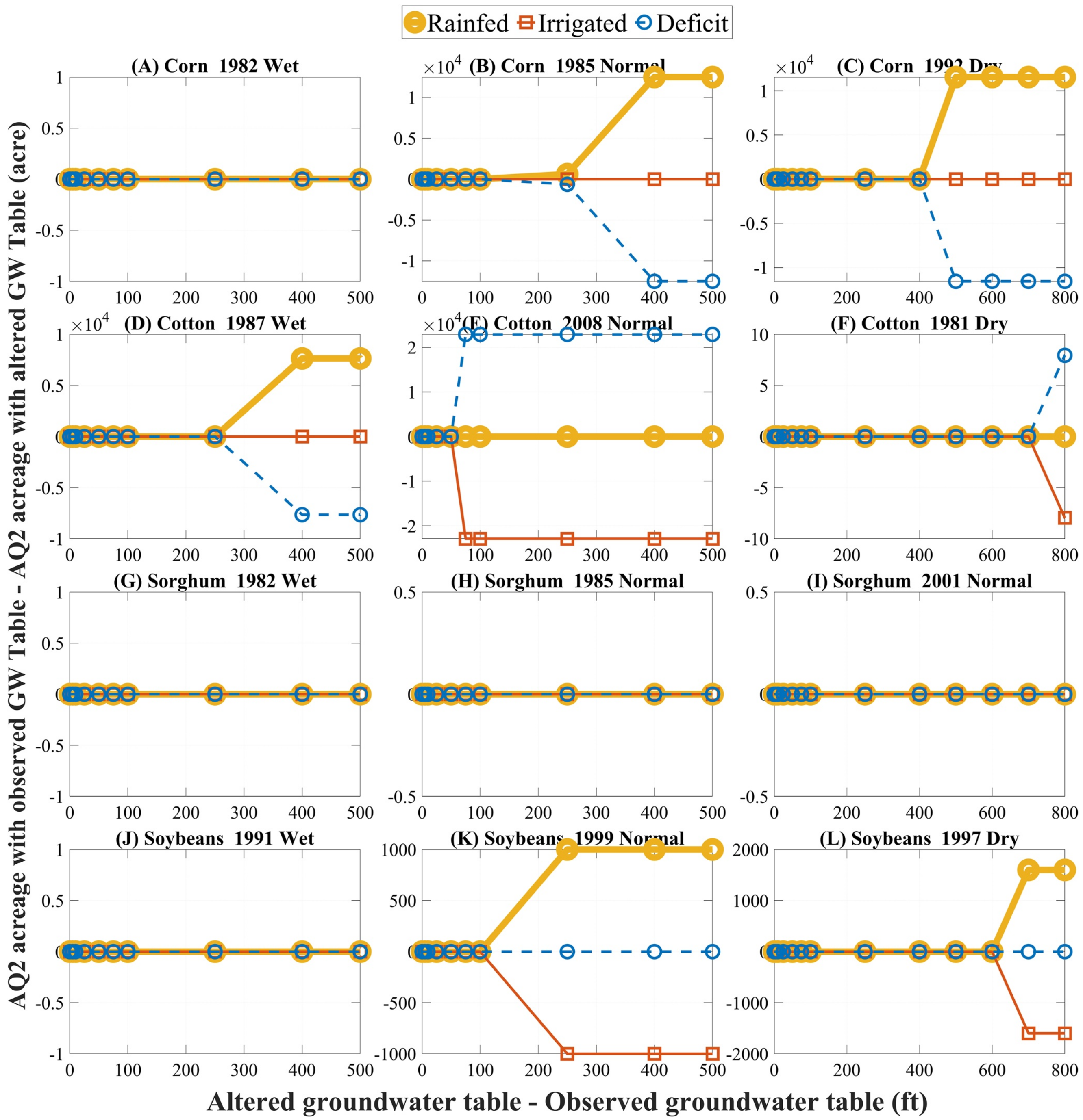


**Figure 8.** The acreage allocation (changes in area in acres) due to deepening of groundwater table for four selected crops under three rainfall conditions (normal-average rainfall, dry-below average rainfall, and wet-above average rainfall) during growing season are shown for Worth County.

## 6. Discussion

The FEW nexus is analyzed using hydroeconomic models, which are typically calibrated using Positive Mathematical Programming. We have proposed a novel framework, Regional Hydro-Economic Optimization (RHEO), for integrating a biophysical crop growth simulation into a hydroeconomic model for mixed irrigation regimes (Section 3). RHEO estimates the cultivated area, water-limited crop yield and the associated cost, revenue, and profit with county as the modeling unit (Figure 2) considering both rainfed and irrigated agriculture using rainfall and pumped groundwater as inputs for four different crops over the SFRB. Water-limited crop yields are obtained

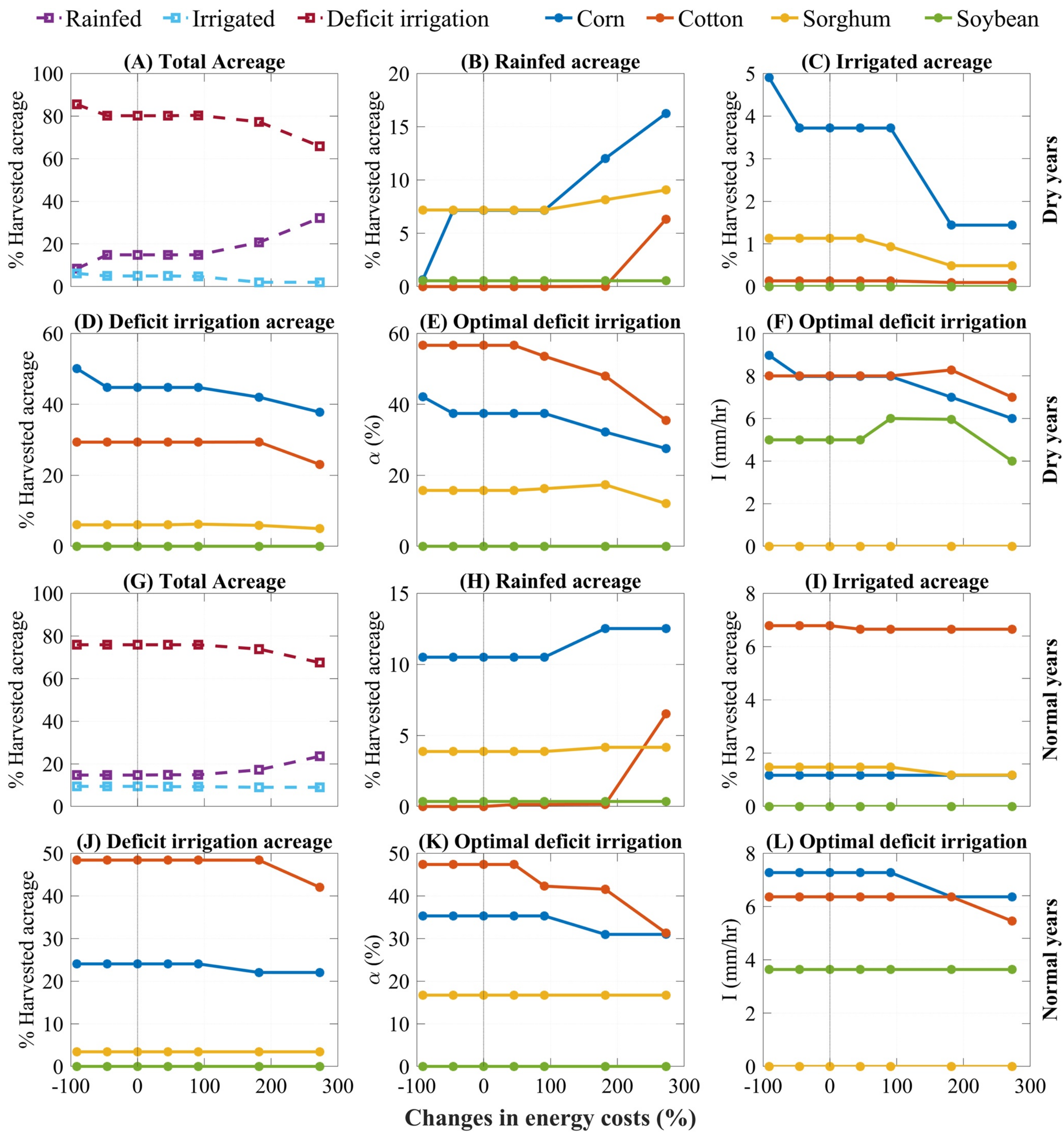


**Figure 9.** The optimal acreage allocation in Grady County using rainfed, full irrigation, and deficit irrigation strategies due to changing costs of energy availability for four selected crops under two rainfall conditions (normal—average rainfall and dry—below average rainfall) during growing season are shown along with the optimal deficit irrigation parameters—$\alpha$ and $I$.

based on a Bayesian hierarchical model (BHM) that estimates the crop yield from rainfed ($\alpha$ and $I = 0$), fully irrigated ($\alpha = 100$ and $I = 10$), and deficit irrigated areas by considering $\alpha$ and $I$ as decision variables within the RHEO (Figure 3). The BHM is pre-developed for the four crops by running the AquaCropOS to estimate rainfed, fully irrigated, and deficit irrigation crop yields under different values of $\alpha$ and $I$. The BHM developed using AquaCropOS nicely captures the interannual variability in crop yields (Figures 4 and 5). Incorporating BHM within the RHEO extends with the following functionalities: (a) estimates the crop yield considering the intra-annual variability in precipitation, (b) provides an indirect to estimate the crop production function using a biophysical model, (c) reduces the computation time by enabling parallel programming within the AquaCropOS and (d) facilitates mixed irrigation—rainfed, fully irrigated and deficit irrigation—strategies. Considering five different strategies (Table 1), RHEO was evaluated on how four different crops could be optimally allocated to understand the FEW nexus—how crop production over a groundwater dominated basin is dependent on energy over the SFRB –for a mixed irrigation regime (Figure 6 and Table 2) and to utilize RHEO for developing deficit irrigation strategies to maximize profit depending on climate variability (Figures 7 and 8) and variability in energy costs (Figure 9). RHEO can also include externalities such as market volatility (fluctuations in crop prices) in addition to the main objective of incorporating inter-annual climatic variability. This could be useful in studying factors such as the negative trend in global crop prices (adjusted to inflation) noted by Haile et al. (2016), Miao et al. (2016), and Wurster et al. (2020) despite increasing crop yield per unit area.

Our study shows similar findings to previous studies (Mitra et al., 2016; Seo et al., 2018) that rainfed and deficit irrigation are preferred over full irrigation in the mixed irrigation regime of SFRB (Figure 7) primarily due to diminishing gains in crop yield with additional supplied water and the increased pumping cost of due to deeper groundwater table in drier years. The model is also capable of optimizing irrigation strategies according to changing groundwater table (Figure 8) and changing energy prices (Figure 9). Previous studies in this region have noted the strong seasonal linkage between precipitation and groundwater table using full-fledged groundwater model (L. E. Jones & Torak, 2006; Mitra et al., 2014, 2016). However, the impact of regional pumping on groundwater level has not yet been looked at partially due to difficulty in modeling a Karst watershed. The RHEO model can allocate zero acreage to a rainfed crop in an unproductive growing season, when rainfed yields fail to cover the production costs, and thus minimize cost. It should be noted that the optimization assumes perfect knowledge about the intra-seasonal variability in climate while no such foresight is available to farmer who must decide to allocate acreage in the beginning of the season. As the analyses in Figures 7 and 8 also provides information on the cropping portfolio and irrigation practices during wet, dry, and normal years, regional agricultural and water managers can utilize RHEO to recommend suitable cropping portfolio at the beginning of the season using seasonal categorical forecasts. They can also recommend updated irrigation practices during the growing season as better sub-seasonal forecasts become available. Thus, RHEO can be valuable for agro and water managers and extension practitioners.

The integration of biophysical and optimization models using proposed hierarchical model is advantageous over existing lookup table approach (Rouhi Rad et al., 2020; S. Li et al., 2021) as it can be extended to regions with similar hydroclimate and can estimate crop yield for potential climatic conditions (e.g., severe drought) by optimizing the deficit irrigation parameters. Data requirements for extending the proposed RHEO framework to regions similar to SFRB is quite possible primarily due to the parsimonious structure of AquaCropOS. Extension to other regions would require manual calibration of AquaCropOS for the given crops and estimation of BHM parameters. In general, it is reasonable to expect a developed hierarchical model using AquaCropOS to be applicable for regions with similar/homogenous climate (e.g., Climate Division). This is achievable as the parameter estimates for most major crop (>20 crops) has been published in the literature for the different geographic regions by FAO and others (Raes et al., 2018; Vanuytrecht et al., 2014). The annual time series of acreage and crop yield per unit area is required in calibrating AquaCropOS for one county/region and then the calibrated parameters could be extended to counties with similar climate. Such annual time series of crop yield per unit area is usually available through governmental agencies (USDA, 2017) or global products such as SPAM which provide multi-year snapshots (IFPRI, 2019) based on survey/census. The spatial resolution of this study can be improved by using remotely sensed acreage information available from USDA Cropscape product and yield information from local agricultural commissioner's reports. Other information related to the crop production costs (Equations 3a and 3d) for the profit maximization is available for major agricultural regions through governmental agencies (USDA, 2022), university extension centers (UGA, 2021) and through global products for food production such as IMPACT and FAOSTAT (FAO, 2021; Robinson et al., 2015). Thus, both the hierarchical model developed from AquaCropOS, and the biophysical hydroeconomic model could be extended to similar climate regions or could be developed for other regions with available data for developing mixed irrigation strategies.

This study used the observed GW data from USGS well network whose spatial coverage varies across the United States. This can be further improved by considering a groundwater withdrawal simulation model (Das Bhowmik et al., 2020; Seo et al., 2018). RHEO can potentially incorporate alternative irrigation strategies such as fixed time interval through AquaCropOS. RHEO can make comparative assessment amongst less efficient high pressure—

high angle sprinkler systems and more efficient soil moisture-based irrigation approaches by varying the pumping efficiency parameter. We were, however, limited by the lack of information on the annual time series about the acreage associated with different irrigation types. However, governmental agencies such as extension services could provide detailed information on pumping units in some regions (Gonzalez-Alvarez et al., 2006; Harrison & Hook, 2005; Harrison & Skinner, 2012; Mullen et al., 2009). The estimates of annual irrigated acreage for some regions such as California and midwestern US (Howitt et al., 2012; Kukal & Irmak, 2018) are available through NASS. However, most regions report irrigated acreage at 5-yearly intervals posing a limitation. This can potentially be addressed by assuming (a) irrigated acreage usually follows total harvested acreage and (b) installing an irrigation system has large initial costs and the area can be assumed to be under irrigation for the upcoming years to be similar within the 5-year intervals. We expect the developed RHEO could benefit in reducing pumping costs for considering deficit irrigation strategies during drought periods, thereby reducing the FEW vulnerability of the region.

## 7. Concluding Remarks

The proposed RHEO framework is demonstrated to estimate the inter-annual variability in crop yields for four major crops - corn, cotton, sorghum, and soybeans—to develop mixed irrigation strategies for the SFRB. The RHEO framework reduces the pumping cost and the associated energy during dry periods by developing deficit irrigation strategies that could reduce the carbon, energy, and water footprints related to agriculture. Linking the crop yield estimates from the biophysical model, AquaCropOS, through the Bayesian hierarchical regression model with the profit optimization model reduces the computation time and also provides an opportunity to model the deficit irrigation parameters ($a$ and $I$) explicitly as a decision variable. The deficit irrigation modeling proposed with the hierarchical model can also reduce FEW vulnerability in regions where groundwater table is deep and/or experiences high frequency of drought. The proposed RHEO framework can thus be a useful platform for regional water managers to study mixed agricultural regimes with supplemental irrigation experiencing strong inter-annual climatic variability and could be considered to investigate the impact of potential climate change on future water availability as well as for analyzing various regional development strategies that includes potential competition of water due to development and growth.

## Data Availability Statement

The datasets used in this work are available in public domain. The timeseries for annual crop yield per unit area, annual harvested area, and annual crop prices for the selected counties may be obtained from U.S. Department of Agriculture (USDA, 2017): Available at https://quickstats.nass.usda.gov/. The county names are given in Figure 1d. The acreage under rainfed agriculture and irrigated agriculture is available in 5-yearly censuses published by U.S. Department of Agriculture (USDA, 2017). The daily climatological forcings (precipitation, minimum temperature, maximum temperature, evaporation) for the AquaCropOS model are available from Maurer et al. (2002) at https://www.engr.scu.edu/~emaurer/gridded_obs/index_gridded_obs.html and Martens et al. (2017) at https://www.gleam.eu/. The monthly groundwater table data may be obtained from U.S. Geological Survey's National Ground-Water Monitoring Network: Available at https://cida.usgs.gov/ngwmn/index.jsp. The AquaCropOS Version 6.0 (Foster et al., 2017) for Matlab may be obtained from http://www.aquacropos.com/. Bayesian statistics were done with *R* (v4.1.2; R Core Team, 2021) using '*rjags*'(v4-13) package. The remaining statistics were performed using Matlab (v2021b) programming language. The time series for observed acreage, observed yield per unit area, yield timeseries from AquaCropOS for rainfed and fully irrigated conditions for all counties along with input files for selected counties for AquaCropOS are available at https://doi.org/10.5281/zenodo.7577701.

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