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Editorial

Relating agriculture, energy, and water decisions to farm incomes and climate projections using two freeware programs, FEWCalc and DSSAT

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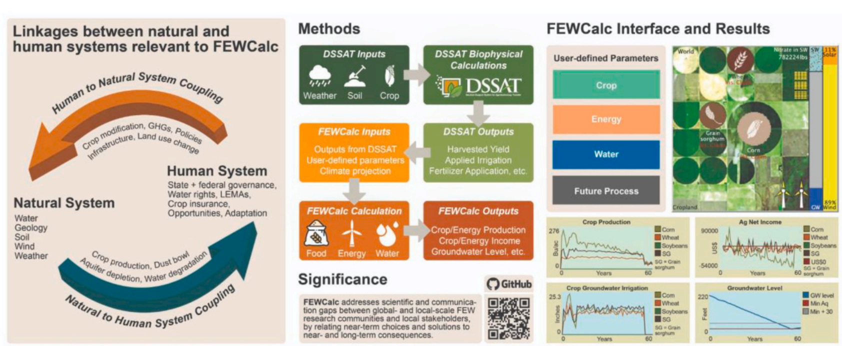
HIGHLIGHTS

- Crop production and water use results from the DSSAT model with arid regions package.
- ABM adds renewable-energy, water quantity and quality, climate change, and farm economics.
- FEWCalc enables users to relate current choices to near- to long-term implications.
- Intuitive GUI makes FEWCalc accessible to non-technical stakeholders.

GRAPHICAL ABSTRACT



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ABSTRACT

CONTEXT: The larger scale perspective of Integrated Assessment (IA) and smaller scale perspective of Impacts, Adaptation, and Vulnerability (IAV) need to be bridged to design long-term solutions to agricultural problems that threaten agricultural production, rural economic viability, and global food supplies. FEWCalc (Food-Energy-Water Calculator) is a new freeware, agent-based model with the novel ability to project farm incomes based on crop selection, irrigation practices, groundwater availability, renewable energy investment, and historical and projected environmental conditions. FEWCalc is used to analyze the interrelated food, energy, water, and climate systems of Finney County, Kansas to evaluate consequences of choices currently available to farmers and resource managers.

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OBJECTIVE: This article aims to evaluate local farmer choices of crops and renewable energy investment in the face of water resource limitations and global climate change. Metrics of the analysis include agricultural and renewable-energy production, farm income, and water availability and quality. The intended audience includes farmers, resource managers, and scientists focusing on food, energy, and water systems.
METHODS: Data derived from publicly available sources are used to support user-specified FEWCalc input values. DSSAT (Decision Support System for Agrotechnology Transfer) with added arid-region dynamics is used to obtain simulated crop production and irrigation water demand for FEWCalc. Here, FEWCalc is used to simulate agricultural and energy production and farm income based on continuation of recent ranges of crop prices, farm expenses, and crop insurance; continuation of recent renewable-energy economics and government incentives; one of four climate scenarios, including General Circulation Model projections for Representative Concentration Pathway 8.5; and groundwater-supported irrigation and its limitations.
RESULTS AND CONCLUSIONS: A 50-year (2018-2067) climate and groundwater availability projection process indicates possible trends of future crop yield, water utility, and farm income. The simulation during more wet years produces high crop production and slower depletion of groundwater, as expected. However, surprisingly, the simulations suggest that only the Drier Future scenario is commercially profitable, and this is because of reduced expenses for dryland farming. Although simulated income losses due to low crop production are ameliorated by the energy sector income and crop insurance, the simulation under climate change still produces the worst annual total income.
SIGNIFICANCE: FEWCalc addresses scientific, communication, and educational gaps between global- and local-scale FEW research communities and local stakeholders, affected by food, energy, water systems and their interactions by relating near-term choices to near- and long-term consequences. This analysis is needed to craft a more advantageous future.

1. Introduction

Small towns and rural (STAR) agricultural communities produce much of the food for an increasingly urban world. Yet they face serious problems such as declining populations, increasing challenges resulting from disadvantageous changes in farm economic conditions, and exacerbating climatic conditions. Many STAR communities in the USA have been diversifying their economies over the past 50 years in efforts to sustain their viability (Bureau of Economic Analysis, 2020). Increasingly, they are taking advantage of their wide open, low density areas to diversify into renewable energy production. Yet the expertise needed to consider such alternatives is largely unavailable to many stakeholders.

FEWCalc (Food-Energy-Water Calculator) makes expertise accessible to local stakeholders whose decisions will lead their communities into more viable futures by enabling clearer understanding of tradeoffs and possibilities. This introduction briefly reviews other attempts to create similar models and the systems included in FEWCalc, including climate change, water resource degradation and depletion, renewable energy opportunities, and public policy priorities. It then briefly outlines how FEWCalc fits into two broad approaches to research on food, energy, and water system decision-support capabilities.

The linkage of the FEW system has been studied and conducted mostly at the academic level using different approaches and aspects (Endo et al., 2017). For example, some FEW studies previously focused on land use optimization (Nie et al., 2019), nutrient flow (Yao et al., 2018), environmental security for livelihood (Biggs et al., 2015), food-energy tradeoff (Cuberos Balda and Kawajiri, 2020), and water-energy-food production and consumption (Guijun et al., 2017) using distinct analytical tools such as MATLAB Simulink, crop models, and agent-based models. Most previous works have not connected all three FEW components together with other variable factors (e.g., climate projection and economics). Some of the more developed efforts at simulating all or part of food-energy-water systems are CLEWS (Climate, Land, Energy, Water and Soil) (IAEA, 2009; Villamayor-Tomas et al., 2015; Welsch et al., 2014), WEAP (Water and Energy Assessment Program) (Stockholm Environment Institute, 2021), and ITEEM (Li et al., 2021). FEWCalc represents a broader set of options than these alternatives and is open-source freeware, readily available on GitHub to serve as a foundation for future development.

Climate change is apparent through surface rising temperatures and historically extreme weather conditions that are becoming more frequent (Campbell, 2020; Lesk et al., 2016). Climate-change driven increases in water and food insecurity pose emerging and long-term challenges. Increasing temperatures are already increasing crop water requirements and shifting precipitation patterns and may directly affect global food supply quantity and quality going forward (Dore, 2005; Li et al., 2019; Wheeler and von Braun, 2013; Zhang et al., 2019). Moreover, shifting regulations and restrictions on carbon emissions may alter the menu of available adaptation options. FEWCalc enables users to evaluate the impact on agricultural production of climate change by choosing future General Circulation Model (GCM) projections and other future climate scenarios.

Water scarcity is an immediate and enduring challenge in many regions, which can in part be addressed with groundwater reserves. Irrigated areas currently produce 30–40% of the world's food, and 70% of global water withdrawals are for agriculture (FAO, 2014; Kovda, 1977; WWAP, 2012). Farmers and policy makers in some regions are recognizing the need to collaborate to extend the usable lifetime of their local water resources by reducing irrigation rates (Hardin, 1968; Kansas Department of Agriculture, 2021; California Water Boards, 2020). Groundwater is important: for example, in China's dry northern region, groundwater accounts for as much as 70% of irrigation in some locations (Calow et al., 2009). In India, it accounts for 70–80% of the value of irrigated production and supports 90 million rural households (World Bank, 1998; Zaveri et al., 2016). Groundwater from the Central Valley aquifer of California and the High Plains aquifer (HPA) supply as much as 16% and 30% of irrigation water in the entire USA (Dieter et al., 2018; Maupin, 2018; Maupin and Barber, 2005). FEWCalc includes irrigation derived from groundwater and the generally hidden and delayed effect of declining groundwater on agricultural production.

Producing wind and solar energy could contribute to the diversification and viability of STAR communities' economy in three principal ways. (1) Renewable energy exported to existing load centers has been profitable for farmers participating in land-lease programs with power producers (Weise, 2020). (2) FEWCalc is designed to investigate how the direct investment by rural landowners in renewable energy production changes their economic situation (Epley, 2016; Hill et al., 2017; Phetheet et al., 2019). Although in the area used to demonstrate FEWCalc wind turbines tend to be more profitable than solar panels (Fu et al., 2017), both technologies are included in FEWCalc to generalize its utility. (3) More affordable local renewable energy could be used to attract and retain businesses to create and grow jobs (Hill et al., 2019). FEWCalc addresses option 2 and provides a foundation for option 3.

Effective policies supporting current and evolving local, regional, national initiatives in the food, energy, and water nexus are imperative to ensure the sustainable viability of STAR communities. These will be influenced by institutional, economic and socio-cultural attitudes, and subjective perceptions (Cash et al., 2006). Farm income, as a major income in STAR communities, can be affected by these policies. To this end, FEWCalc simulates the effects of crop insurance and selected renewable energy incentive programs on farm incomes.

As a tool focused on how decision-makers perceive the viability of their communities or businesses, FEWCalc bridges the gap between two dominant research themes — Integrated Assessment (IA), and Impacts, Adaptation, and Vulnerability (IAV) (Table 1). The themes have been converging as the value of integrated, multi-scale approaches to climate research has become apparent (Absar and Preston, 2015; de Bremond et al., 2014; Huber et al., 2014; Kraucunas et al., 2015; Rosenzweig et al., 2014). The standardized, multi-scale Shared Socioeconomic Pathways (SSPs) scenario framework (O'Neill et al., 2014) relates economic and technological choices to carbon emissions, and is thus closely related to Representative Concentration Pathways (RCPs) levels used in FEWCalc. FEWCalc supports carbon emission mitigation through developing greater local familiarity with renewable energy production and greater research-level familiarity with the challenges of local stakeholders. Fig. 1 shows how the major components of the FEW system form a natural and human system of concern to IA and IAV, showing how they can be thought of as a collection of heterogeneous and autonomous individuals interacting cooperatively and competitively with one another and the environment (Bert et al., 2015; Hu et al., 2018).

Unresolved scale and human connection issues still limit the utility and relevance of IA and IAV models (Ericksen, 2008; Ericksen et al., 2009; Vervoort et al., 2014). For example, national policies could be rendered ineffective for want of local-level adaptation and mitigation options, and local-level efforts could be stymied by national policy or global market conditions. Climate, weather, hydrology, politics, energy, and economics are all important and interact across multiple societal scales, including jurisdictional, institutional, and managerial ones (Cash et al., 2006; Allan et al., 2015; Endo et al., 2017), so that FEWCalc exists within the context of national- and global-scale dynamics (Ericksen et al., 2009). Proper support and coordinated action are required for successful outcomes such as those achieved by Sustainable Groundwater Management Act (SGMA) in California and the LEMAs in Kansas. The FEWCalc model can be thought of as addressing three key needs identified by Vervoort et al. (2014): (1) engage diverse stakeholders across multiple levels; (2) move beyond analysis of single interventions toward system-wide measures that act across multiple spatial, temporal, and geographic scales; and (3) develop long-term capacity for collaborative decision making.

Table 1
Summary IA and IAV approaches to technology and policy analysis.

Description	IA (Integrated Assessment)	IAV (Impacts, Adaptation, and Vulnerability)
Typical topic	Climate policy impacts[1]	Climate change effects and responses[2]
Geographic Scale	Regional (U.S. State) – Global	Local (town, farm, ecosystem)
Temporal Scale	Long-term up to ~100 years	Few years or less
Scenario (assumptions about the future) and Policy (adaptations) Development	Global scale, cross-cutting, generalized, little inclusion of stakeholder values.	Narrower focus, more detailed, often has explicit representations of stakeholder values.
Interdisciplinary Focus	Broad	Narrow
Perspective	General impacts and adaptation possibilities. Projection/qualitative results.	Specific impacts and adaptation measures. Prediction and quantitative results.

[1] Weyant (2017).
[2] Absar and Preston (2015) and van Ruijven et al. (2014).

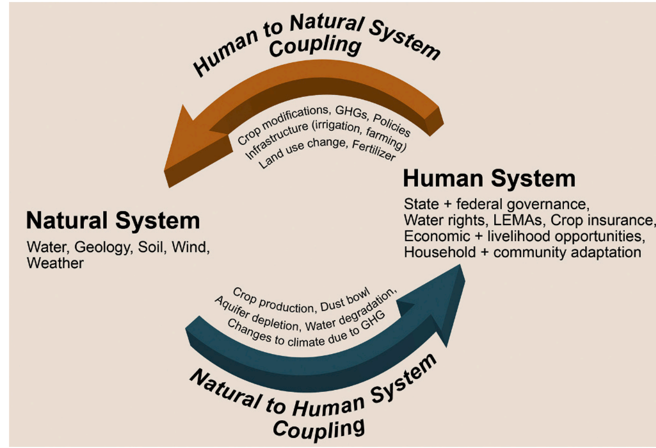

Fig. 1. The linkages between natural and human systems relevant to FEWCalc (modified from K. Rogers, East Carolina University, personal communication, 2017; NSF [National Science Foundation], 2018). LEMA (Local Enhanced Management Area) is a governance structure used in the state of Kansas, USA, to limit water use from a depleted aquifer.

FEWCalc is an agent-based model (ABM) constructed using NetLogo (Hu et al., 2018; Tisue and Wilensky, 2004; Wilensky, 1999), designed to integrate complex real-world systems and evaluate future policy decisions (Anderson and Dragićević, 2018; Guijun et al., 2017). ABMs have been used in business (Forrester, 1971; Morecroft, 2015), urban problems (Sterman, 2000), and environmental evaluations (Meadows, 2008) and recently for the FEW nexus (Al-Saidi and Elagib, 2017; Memarzadeh et al., 2019; Schulterbrandt Gragg et al., 2018). Most of this recent research has been conceptual or focused on regional applications. Focus on individual stakeholders is rare (Ravar et al., 2020; Shannak et al., 2018) and mostly limited to urban systems (Bieber et al., 2018; Guijun et al., 2017). FEWCalc is novel and contributes to the emerging ABM literature using the NetLogo platform.

The purpose of this study is to develop a scientific tool able to represent a real-world complex system composed of agriculture, energy production, and water use under complicated climate and economic conditions, and use it to reveal unexpected interactions within this system of systems that are important to stakeholders. The rest of this article, along with online appendices A-D, describes the methods and data using in FEWCalc and its utility in a scientific investigation of the roles played by water scarcity and climate change in the productivity and economics future of a typical STAR community.

2. Methods

In this section, the FEWCalc workflow is briefly introduced, and FEWCalc components and related equations are described using a Finney County, Kansas test case to provide motivation and examples. The Decision Support System for Agrotechnology Transfer (DSSAT) model (Araya et al., 2019; Jones et al., 2003; Jones et al., 2017a, 2017b; Sharda et al., 2019) was chosen for the agrosystems simulations based on its capabilities, availability, and feasibility. Selected DSSAT and FEWCalc inputs, outputs, and equations are listed here; more detail is provided in appendices A, B, and C. Default values for user-controlled FEWCalc variables are provided in Table D.1. As programmed, all costs are in US dollars.

2.1. *Workflow and case study from the high plains aquifer, USA*

The workflow of FEWCalc with inputs from DSSAT is shown in Fig. A.1, including components representing agriculture, energy, and water. Climate data and crop choices are entered using the weather data DSSAT input or WeatherMan (Pickering et al., 1994). DSSAT is then executed to provide input needed for FEWCalc via files in a comma-separated values format (CSV files). The final results are presented in graphs as shown in Fig. A.1. Selected graphs are presented in the Results section of this article. The time discretization of DSSAT is one day. FEWCalc time is incremented annually and simulation length is defined by the user, with simulations of 60 to 90 years being common.

FEWCalc is developed and tested using data from Finney County, Kansas, USA (Fig. 2). The High Plains aquifer (HPA) consists of the Ogallala aquifer and its overlying aquifer units. The area's water problems are typical of arid agricultural regions around the world: Large-scale irrigation over many decades has depleted groundwater resources and produced now dry irrigation wells (Buchanan et al., 2015). The region's potential to develop renewable energy, its declining water resources, and its rich, 70-year-long time series of historical data makes it an ideal candidate for exploring opportunities to sustain farmers' economic well-being under alternative agricultural and energy production choices using FEWCalc.

DSSAT is tested by comparing calculated values for crop production and irrigation to observed field data (see Appendix A) obtained from the United States Department of Agriculture's (USDA) National Agricultural Statistics Service (NASS), Kansas State University's Department of Agronomy, and the Kansas Department of Agriculture (KDA). FEWCalc is tested through comparisons with values obtained through the literature and expert elicitation.

2.2. Weather, climate, and projections

Daily weather data for air temperature, precipitation, and solar radiation are used as input to DSSAT (Tsuji et al., 1994) and acquired as described in Appendix A.

A 10-year period from 2008 to 2017 is used as the historical base period for this work. This 10-year period is presented in the context of data since 1950 in Fig. 3, in which wet and dry periods are identified using the Palmer Drought Severity Index (PDSI) (Palmer, 1965). The base period was chosen because a generally complete set of weather and agricultural data is available, and because wet, moderate, and dry years are included in that period of time (see Fig. 3). This variability is used to create future climate scenarios.

The four 60-year long scenarios used to demonstrate FEWCalc are listed in Table 2. All scenarios have the same 10-year (2008 to 2017) temperature, precipitation, solar radiation, and agricultural price conditions, and differ for the following 50 years. **Scenario 1**, Repeat Historical tests the time progression in FEWCalc, and allows users to focus on the impact of groundwater declines and energy production. **Scenarios 2 and 3** are dominated by wetter or drier years to create wetter and drier "futures". The weather data are chosen from the 10-year base set of years. So, for example, if those 10 years are numbered 1, 2, …, 10, years 8, 9, and 10 are wet (Fig. 3). Going forward, 7 of each 10 years will be selected from the three wet years. The other 3 of each 10 years are chosen from the 4 moderate base years (years 1, 2, 3, and 7). The random sequence of moderate to wet years results in increased crop production with no significant loss of yield. **Scenario 4** is based on 20 General Circulation Model projections out to 2098 (Fig. A.5), though only the values through 2067 are used in the FEWCalc demonstration provided in this work. Projected crop prices are described in Section 2.3.2.

Scenario 4 uses DSSAT results in which runs use projected air temperature, precipitation, and solar radiation from 20 downscaled GCMs to represent years 2008 to 2067 (Taylor et al., 2009, 2012). Results from the 20 DSSAT runs are averaged and used in FEWCalc. RCP 4.5 and 8.5 results are available in FEWCalc — see Appendix B for a discussion of RCP. FEWCalc results using the RCP 4.5 and 8.5 scenarios are compared in Phetheet et al. (2021). Results from the more severe RCP 8.5 are presented in this article.

2.3. Calculations for agriculture

FEWCalc starts with the assumption that the decision maker is already in business as a farmer and, for the demonstration provided here, produces crops in the Garden City area of Finney County, Kansas. FEWCalc envisions a farmer considering investments in renewable energy as a diversification strategy to improve farm incomes, which have been extremely variable in the last decade. The environmental conditions and resources are as described in Sections 2.2 and 2.5. Therefore, FEWCalc's focus is on farm operations and renewable-energy investment decisions. Methods for simulating crop production, crop net income, and crop insurance are presented below. To communicate results to stakeholders, this article presents both English and metric units. DSSAT uses metric units. In this section, metric units or appropriate conversion factors are listed to facilitate cross-referencing to DSSAT results.

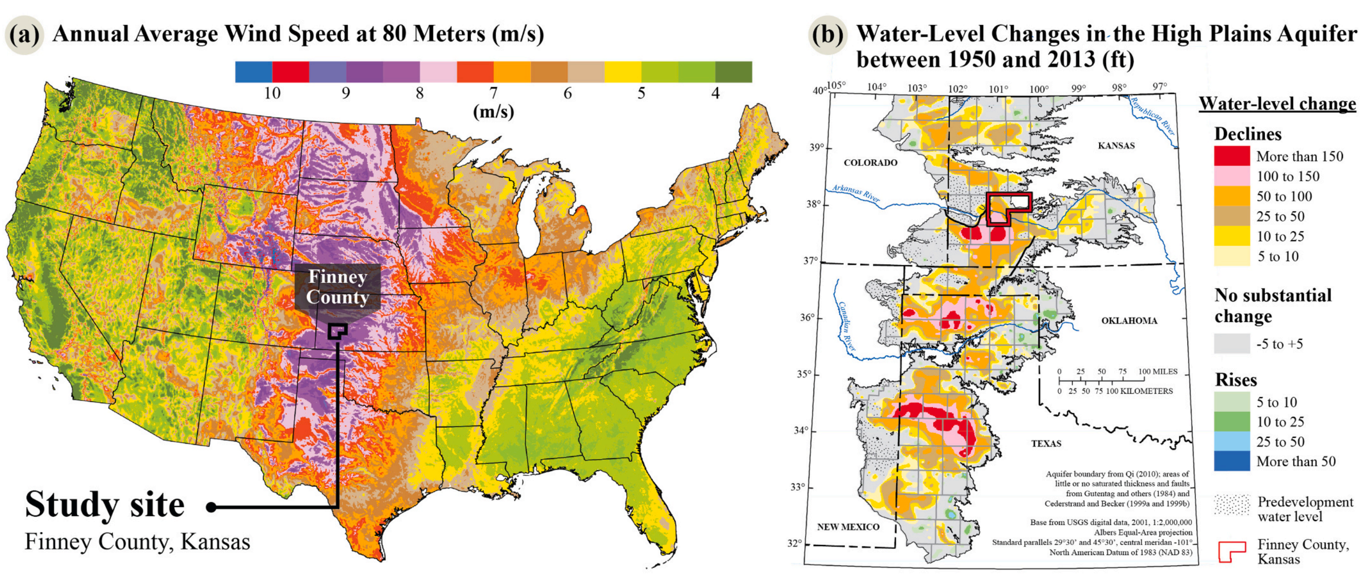

Fig. 2. (a) Average annual wind speed map for the Continental USA (modified from NREL, 2011). Finney County has very high average wind speeds (shown here) and moderate solar energy supplies (not shown). (b) High Plains aquifer water-level changes (modified from McGuire, 2014).

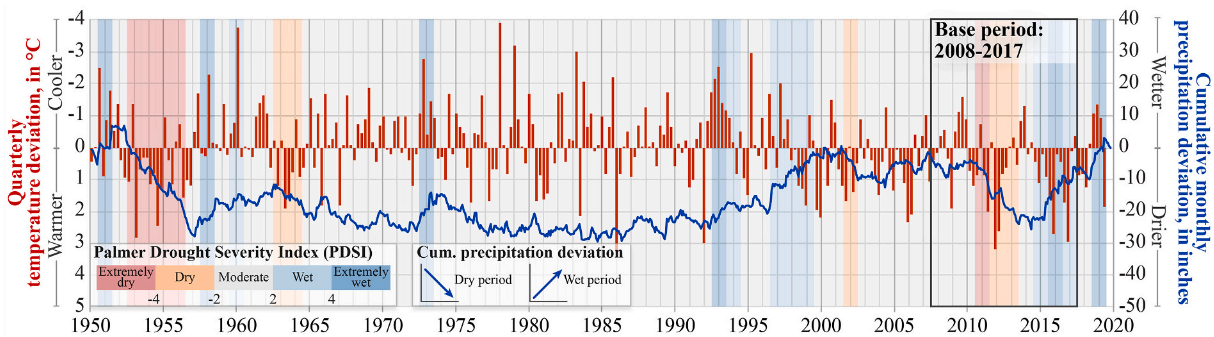

Fig. 3. Annual average PDSI, monthly cumulative precipitation deviation, and quarterly temperature deviation data from January 1950 to September 2019. Monthly and quarterly base values are listed in Table A.13. The 2008–2017 base period used in this work is highlighted. The axes for precipitation and temperature deviation are scaled so that conditions producing drought (high temperature and low precipitation) produce downward pointing bars of temperature deviation and downward sloping trend of cumulative precipitation deviation.

Table 2
Simulation scenarios used to represent climate conditions in DSSAT for the 50-year projection period (2018-2067) that follows the 2008–2017 historical base period in the FEWCalc simulations.

Name	DSSAT Temporal Progression of T, P, and S[1]
Scenario 1. Repeat Historical	Repeat conditions from 2008 to 2017 for all 50 years of the projection period.
Scenarios 2 & 3. Wetter/Drier Future	Use more wet or dry years from 2008 to 2017, respectively to create a correlated random 50-year projection. The Wetter Future is similar to this area in the 1990s; the Drier Future is similar to this area in the 1950s.
Scenario 4. GCM-simulated RCP8.5 T, P, and S Changes[2]	Apply GCM-simulated climate for the 50-year projection period

[1] T, temperature, in degrees Celsius; P, precipitation, in inches per year; S, solar radiation, in watts per square meter.
[2] GCM, General Circulation Model.

2.3.1. *Crop production*

The crops commonly produced in Kansas are corn, winter wheat, soybeans, and grain sorghum, all of which FEWCalc incorporates into the simulations (Table A.2). Fig. A.3 shows Kansas crop production, planted acres, crop prices, and, to represent expenses, gasoline prices in the USA from 1866 to 2019. The increase in productivity per acre is apparent by comparing Fig. 4a and b. Although soybeans are generally not produced in Finney County due to unfavorable soil and heat conditions, they are retained in the software because it is a common crop throughout the USA Midwest, and hence allow for other locations to use FEWCalc without major changes.

DSSAT simulations are conducted using a one-day time step. Results are accumulated to produce annual results for FEWCalc. Datasets are prepared using DSSAT built-in software programs XBuild and SBuild (Fig. A.1). XBuild allows users to specify management options such as cultivars, planting date, and plant population. SBuild assembles physical and chemical soil data. The soil database available in DSSAT was developed by the International Soil Reference and Information Centre for the project "World Inventory of Soil Emission Potentials (WISE)". The WISE database is one of the most comprehensive soil databases, with samples well distributed globally (Gijsman et al., 2007).

In this work, the DSSAT Seasonal Analysis is used and simulations represent individual growing seasons. In this mode, by default, DSSAT starts each spring with soil water content at field capacity (SDUL). However, for this area, drier conditions are likely. As such, for this study, DSSAT is started each year with soil water content equal to (SDUL + SLLL)/2, where SLLL is the water content at the wilting point. The simulations are started one week before planting to allow the precipitation record to affect soil moisture at planting.

The long periods of interest in this work were simulated using the DSSAT Biophysical Analysis part of the Seasonal Analysis option. Outputs such as harvest yield, applied irrigation, and applied fertilizer are calculated based on parameters defined in Table A.2; the values were chosen based on the cited references.

2.3.2. *Crop income after variable costs*

Revenue from crop production is the product of crop output and price per acre, and acres planted. Because farmers often produce more than one crop per year, production costs may be shared across more than one crop. Therefore, net farm income from crop production is the difference between gross revenue from crop production less total variable costs. Future crop yield, crop prices, and input costs are all uncertain (Fig. 4a and c). While production variability may be attributed to weather and other production vicissitudes, price variability is driven by global market conditions and trade and other policies (USDA, 2020). No attempt to project this process is made in FEWCalc since no individual farmer or group of farmers influence prices. However, the Midwest USA is a large enough producer of global corn and sorghum to affect global prices (USDA, 2020). This means higher supplies during good weather years often depress prices and vice versa. Although western Kansas is a major wheat production area in the USA, it is not large enough to influence global prices. These conditions define how prices are treated in FEWCalc.

The FEWCalc base period (2008–2017), has three wet, three dry, and four average years, and is used to create projected climate conditions as described in Section 2.2. For corn and grain sorghum, the following procedure is used. In Scenario 1, the base period prices along with the climate data (temperature and precipitation) are repeated in sequence five times to create the 50-year projections. For Scenarios 2 and 3, the base period is used to define 10 sets of annual climate and crop-price data and selections are made from this 10-member set (with replacement) to create wetter and drier futures. For Scenario 4, prices are assigned based on precipitation: Less than 17 in. of precipitation is considered a dry year and price is selected randomly from one of the three dry years; 20 in. or more is treated as a wet year and price is selected randomly from one of the three wet years.

For wheat, local conditions do not dominate world crop prices, so prices do not remain associated with the local climate data. The 10 annual prices from 2008 to 2017 are assigned to each year for the period 2018–2067 randomly and independently of the climate data.

Total annual crop income after variable expenses is computed as:

$$Income_{C\_t} = \sum_{i} \left[\left(p_{i\_t} \times q_{i\_t} \right) - w_{i\_t} \right], i = 1, 2, \ldots, \mathrm{N} \quad (1)$$

Where $Income_{C\_t}$ is crop income after variable expenses earned for each year t in US dollars per acre, and i identifies an acre; p_{i_t} is the market price per bushel, q_{i_t} is the yield (bushels/acre from DSSAT) and w_{i_t} is the variable production costs per acre for the crop planted on acre

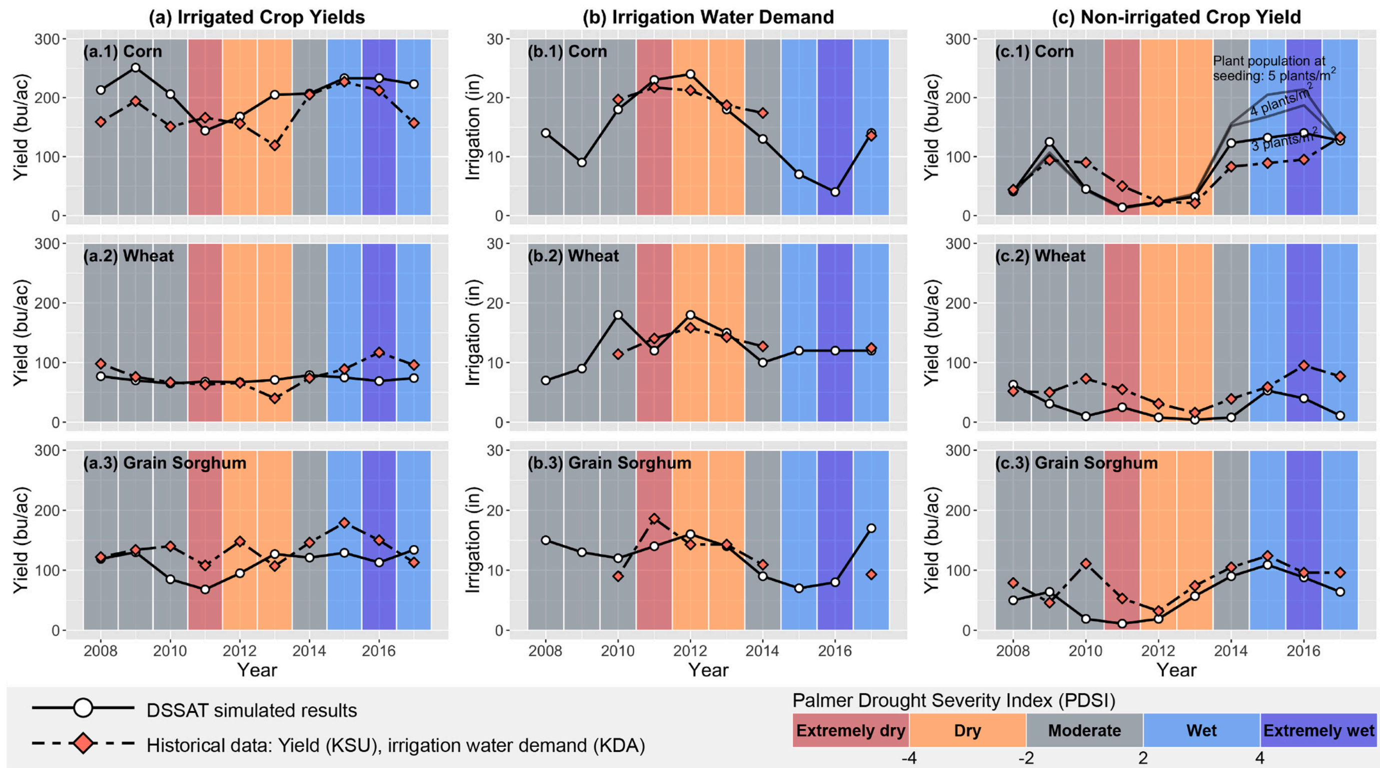

Fig. 4. Comparison of the DSSAT results (solid lines) and historical data (dashed lines) between 2008 and 2017 for corn, wheat, and grain sorghum. (a) Irrigated crop yields, (b) Irrigation water demand, (c) Non-irrigated crop yields. (Crop yield data from the Department of Agronomy, Kansas State University, irrigation data from KDA, and simulated results are in Tables A.4, A.11, B.1 and B.2). Conversion: 1 bu./ac corn or grain sorghum = 62.77 kg/ha, 1 bu./ac wheat = 67.25 kg/ha, and 1 in = 2.54 cm. Moisture adjustments have been applied (see Table A.10).

i. The items making up the variable production costs are irrigation, fertilizer, herbicide, pesticide, labor, rent, and crop insurance; details are listed in Tables A.5 to A.8. As noted in Table A.7, six of the included costs are not strictly variable costs. They are included to reflect what is thought to be a fair representation of operating costs for irrigated and unirrigated farming.

2.3.3. *Crop insurance*

Agricultural farm income support takes many forms which may or may not improve financial stability (Mishra and Cooper, 2017). FEWCalc includes the option of insurance for crop yield. General characteristics of crop-yield insurance are described by Edwards (2011) and RMA (2020). Crop-yield insurance is purchased to protect against potential losses of crop yield from natural disasters, and especially droughts. In practice, insurance companies will increase premiums if indemnities are high, so over the long term, farm incomes will not be increased by crop insurance. However, the insurance does mitigate income declines in exceptionally bad years. In FEWCalc, the crop prices and premiums from the 2008–2017 base period are maintained, and years and values of indemnities are noted. How crop insurance is represented in FEWCalc is described in Appendix C, Eqs. C.1 to C.4.

2.4. *Calculations for renewable energy*

Renewable energy calculations for wind turbines and solar panels are calculated in FEWCalc. Users control the number and installed capacity of wind turbines and solar panels, and their degradation rates, lifespan, capital costs, and tax credits.

The version of FEWCalc presented here considers farmer-owned energy production facilities that serve both local electric loads and electricity sale to the grid. These are not represented explicitly, the FEWCalc input is simply the resulting average value obtained from the electricity produced. Section 2.4.1 describes this process.

2.4.1. *Energy net income*

Energy net income for year *t*, $Income_{E\_t}$, is the sum of total net income from wind production (Eq. C.11) and total net income from solar production (Eq. C.21):

$$Income_{E\_t} = Income_{W\_t} + Income_{S\_t} = Energy\_value_t \times (M_{w\_t} + M_{s\_t}) \qquad (2)$$

Calculating $Income_{W\_t}$ and $Income_{S\_t}$ (income from wind and solar energy for year *t*) requires $Energy\_value_t$, the monetary value of all megawatt-hours (MWh) of electricity produced, and used in Eqs. C.13 and C.23. the $M_{w\_t} + M_{s\_t}$ term is the power output in MWh from wind and solar for year *t*. Users can control the average value obtained for that electricity. Usually, this value should be greater than the wholesale price of electricity, which in Kansas and surrounding states is presently (2020) US$20 to US$40/MWh. Higher values would be expected because some of the electricity is worth retail because it allows the generator to avoid retail purchase of energy to, for example, run electric water pumps, or qualify for net-metering. In the Kansas region, retail is presently US$100 to US$130/MWh. In addition, with some restrictions, farmers can enter into Power Purchase Agreements (PPAs) to sell electricity at prices that tend to be between wholesale and retail prices. While electricity prices tend to be less volatile than crop prices, they are still difficult to predict. FEWCalc uses a default $Energy\_value_t$ of US$38/MWh.

The effects of equipment depreciation on net income are simulated using a CSV file that is read by FEWCalc and defines the percent of installed cost to be depreciated, the depreciation taken each year, and the tax rate of 20% to be applied (see Appendix A). This deduction may require a third-party financial partner. This tax savings can be used to increase farmer income or reduce the loan to cover the renewable energy costs.

In Eqs. C.5 and C.15, installed costs for energy production are financed over a period defined by the user as a fraction of the life of the equipment ($Nyears_W$ or $Nyears_S$) and an interest rate (*APR*) that is also defined by the user.

2.4.2. An overview of energy production and regulatory environment

The regulatory environment of renewable energy, including wind and solar, are complex and evolving. Here, we provide a few comments to establish some context for the range of solar and wind energy resources that FEWCalc supports.

Regulation of solar production can depend on capacity, and policy is not well established. Commercial size installed solar capacity is about 1 MW in Kansas (KCC Kansas Corporation Commission, 2019); capacities under 3 MW are commonly classified as small (Green Coast, 2019). States with less total solar capacity tend to have smaller installations: in the three lowest ranked states (including Kansas) solar installations for agricultural use average around 0.0004 MW (Xiarchos and Vick, 2011). In 2019, Kansas had 47 MW of installed solar (SEIA, 2020a). In contrast, neighboring Missouri, with less solar potential but more solar-friendly policies, had 258 MW of installed solar capacity (SEIA, 2020b).

FEWCalc supports the installation of up to 2.4 MW of solar installed capacity, which would require 8000 solar panels with a combined area of 16.6 acres (6.7 ha) (Ong et al., 2013). In southwest Kansas, where an average peak sun hour (*PSH*) is 5.6 h per day, Eq. C.21 suggests that these solar panels would produce about 4906 MWh of electricity per year. Eq. C.11 indicates that it would require about 0.7 2-MW wind towers and 0.9 acres of land (0.4 ha) to produce the same output per year (Denholm et al., 2009). The net revenue gained by this land use would need to be compared with crop revenues as part of deciding whether to make the renewable energy investment. FEWCalc provides the results needed for the user to produce such a comparison.

2.4.3. Financial assumptions — Energy equipment tax incentives and depreciation

Tax incentives and equipment depreciation can produce large tax deductions that exceed what some owners can deduct from their taxes. It can thus be advantageous to contract with a third-party financial partner, called a Tax Equity Investor, who can claim the credit and return much of the value to the owner, depending on the agreement made; typical cost is 6–7% (M. Gilhousen, personal communication, 2020). In FEWCalc, use of the tax incentives (ITC or PTC; see Eqs. C.13, C.15 and C.23) and depreciation often imply that such third-party arrangements are involved. The transaction fee is not included, and the entire value of any tax credit and deduction is applied to the owner as income in the year it is incurred. It could be accumulated to defray the cost of updating equipment, but FEWCalc does not provide for this.

The applicability of ITC and PTC has changed over time and differs with installed capacity and whether wind or solar equipment is installed. FEWCalc includes an adjustable range of options.

2.5. Calculations for water

The only water use represented in FEWCalc is irrigation to support the farm production simulated using DSSAT. The current version of FEWCalc satisfies all water demands using groundwater, and it is assumed that dryland farming is the default production method when groundwater levels are too low. Simulation of crop production and irrigation demand in the arid region considered in this work required modification of the distributed version of DSSAT, and this modification is described below. This is followed by a description of how DSSAT results are used in DSSAT to simulate impacts on groundwater levels and surface-water quality.

2.5.1. DSSAT irrigation calculation for arid regions

Irrigation requirements and frequency of application vary as a function of crop type, crop management, soil properties, and weather conditions (Salazar et al., 2012). In DSSAT, the default irrigation calculations provided too much water and restrictions were needed to match measured water-use data. This was addressed by using the fixed amount automatic mode in DSSAT, as described by I. Kisekka (personal communication, 2019) and as used by Sharda et al. (2019). The approach is described in Appendix C.

2.5.2. Calculating groundwater levels based on water use

In FEWCalc, it is assumed that all irrigation water comes from groundwater. The simplest way to relate the irrigation use per crop area produced from DSSAT to groundwater level change is to divide by specific yield. However, this neglects spatial changes in specific yield, groundwater recharge, and other hydrologic processes, and was found to produce unrealistically fast dewatering of the aquifer. When available, historical data can provide an alternative. Butler et al. (2016) and Whittemore et al. (2016) show that in parts of Kansas, groundwater declines are linearly related to total groundwater pumpage and discuss the circumstances under which this would occur.

For FEWCalc, a two-step process was developed using two linear regressions and reported Finney County data from B. Wilson (personal communication, 2019). The process is described in Appendix A using Fig. A.5.

2.5.3. Nitrogen concentrations in surface water

When nitrogen is applied to fields, a percentage of it remains in the soil until it is moved into surface-water bodies by large storms (USGS, 1999). In the study area, about 10% of the applied nitrogen is thought to be retained for silt loam soil and typical soil temperatures during fertilizer application (Kansas Mesonet, 2017; Sawyer, 2011). Individual storm data are not available, so nitrogen is moved to surface water in wet and extremely wet years as defined using PDSI. For Scenario 4, PDSI data are not available, and nitrogen is moved when annual rainfall exceeds or equals 20 in.. The equations used are presented in Appendix C.

2.6. FEWCalc interface

FEWCalc's NetLogo interface (Fig. D.5) is divided into three main areas. From left to right, the areas include (1) sliders, input boxes, and dropdown menus that allow users to vary model parameters and control the simulation (see Fig. D.6). All inputs are at default values (Table D.1) except ITC_S is set to 30%. (2) In the center, a NetLogo World area shows circular cultivated areas, solar panel and wind turbine installations, and groundwater (GW) quantity and surface-water (SW) quality impacts, and a fraction of energy produced from solar and wind (see Fig. D.8). (3) Eight output plots on the right show FEWCalc results evolving over time.

In years that production conditions trigger an insurance claim, the text “Ins. Claim” appears next to the related crop in the World. The indemnity is shown in the lower right graph. The rust-colored dots are used to represent nitrogen accumulation on fields and its concentrations in surface water (see Section 2.5.3). Each particle represents 10,000 lb. (4500 kg) of nitrogen. Groundwater levels vary as irrigation is applied each year as described in Section 2.5.

3. Results

For the results presented here, the input values are those shown in Fig. D.5, except that the future process is modified for Scenarios 2 through 4. The solar panels occupy about 5.2 acres (2.1 ha), and a similar area is occupied by the wind turbines (Denholm et al., 2009).

Results comparing the DSSAT simulation with historical results are presented in Section 3.1. The four subsequent sections show results from the four climate scenarios listed in Table 2 and support an analysis of climate impacts on crop income in the context of potential farm energy capacity development. Finally, Section 3.6 focuses on financial results from all simulations.

3.1. Comparison with historical data

Crop production and irrigation water use simulated by DSSAT for 2008 to 2017 are compared to historical data in Fig. 4. As in Fig. 3, colors based on PDSI are used to identify dry and wet years. Fig. 4 suggests crop yields and water use are reasonably well represented using DSSAT, though in some years the differences are substantial (for example, non-irrigated grain sorghum yield in 2010).

For non-irrigated corn, the simulated yield was unrealistically large during some wet years, and it was suspected that the plant population per acre was too high. Fig. 4c (top figure) shows the effects of accounting for the plant population at seeding for corn under dryland farming. In this work, a plant population of 13,000 plants/acre (3 plants/m^2) was used.

3.2. Scenario 1: Repeat 10 historical years to create the 60-year simulation

Six ten-year long base periods of precipitation, temperature, and crop prices are repeated consecutively to create the 60-year FEWCalc simulation. The repetition allows analysis for a repeated known historical period; the duplication of results every 10 years indicates that FEWCalc progresses through time correctly. The only change is when groundwater is depleted toward the end of the simulation when dryland farming begins.

Energy solutions are the same for all scenarios and are presented with the Scenario 1 results. Income for wind is high in the first year of operation when tax policy allows 50% of capital costs to be depreciated, though the loan payments continue. Solar income becomes positive after the loan is paid.

3.3. Scenario 2: Wetter future

For the wetter future, FEWCalc randomly chooses a greater percentage (70% instead of the original 30%) of wet years.

3.4. Scenario 3: Drier future

For the drier future, FEWCalc randomly chooses a higher percentage of dry years (70% instead of the original 30%). As compared to the wet scenario (Fig. 5b), Fig. 5c shows that crop production simulated for a dry climate scenario drops in many simulation years.

3.5. Scenario 4: RCP 8.5 temperature, precipitation, and solar radiation changes to create the 50-year future

In Fig. 5d, the first 10 years of crop production reflect historical (2008–2017) climate variability, while years 11 to 60 (2018 to 2067) show GCM results that tend to be smoother because results from 20 GCMs are averaged (Figs. B.1 and B.3).

3.6. Total net income and crop insurance for all four scenarios

Total farm net annual income is shown in Fig. 6a; income from crop insurance (the indemnity) is shown in Fig. 6b. Selected metrics for the four runs are shown in Table 3. Time series shown for the four scenarios in Fig. 5 are discussed in Section 4 of this article.

Scenario 1, for which 2008–2017 weather continues into the future, results in a depleted aquifer and dryland farming. The wetter scenario 2 results in irrigation water lasting more than 60 years. The drier scenario 3 results in irrigation lasting only 45 years. The RCP 8.5 scenario 4 shows marked potential for decreased crop production: With elevated greenhouse gases and temperature conditions crop incomes are reduced. Renewable energy development is important to continued viability and, hopefully, would allow new approaches and technologies to buffer the impacts of climate change.

4. Discussion

FEWCalc is designed to produce the same net income for all scenarios in the base period. Income differences determined by scenario conditions and parameters begin after the base period (Fig. 6a).

In Scenario 1, simulated crop yields for corn and sorghum decline during dry periods (Fig. 4). However, wheat yield remains stable for most simulation years. Wheat and grain sorghum are rarely profitable, and corn is the most profitable crop under the Repeat Historical scenario (Fig. 5a). Repeated historical irrigation water use results in continuous groundwater level decline. This continues well known current trends and in the simulation dryland farming in this area starts in 2065 or, year 58 of the simulation. Crop yields decline after switching from irrigated to dryland cultivation. However, average non-irrigated crop net incomes are higher than irrigated net incomes because dryland farming expenses for all three crops are low enough to make up for lost crop sales. For corn and grain sorghum, the tendency of prices to increase globally when the local yields decline (see Section 2.3.2) could prove even more advantageous than indicated.

For Scenario 2, the 50 years following the base simulation, Fig. 5b shows that crop production improves and groundwater levels drop more slowly, though they continue to drop. Dryland farming is not reached, and FEWCalc maintains irrigation operations for the entire 60-year simulation. However, the downward trend makes it clear that a time will come when dryland farming will be necessary in some years, even with this wetter future simulation.

In Scenario 3, the Drier Future, irrigated corn performed better than other crops, whereas wheat production is low and remains stable during irrigated periods. Corn net income is high because of high crop prices during dry years. The increased irrigation required in drier years accelerates the decline in groundwater levels, and FEWCalc resorts to dryland DSSAT simulations in year 46 (2053), which is 12 and $\geq$ 14 years ahead of Scenarios 1 and 2, respectively.

Table 3 shows that dry scenario 3 yields an annual average agricultural sector profit of US$6818, which is the only commercially successful scenario for agriculture from the simulations. Potential crop price increases caused by reduced production in a drier future are not simulated, and could affect farm profitability and food availability. Because wind energy production is successful in western Kansas, total net income is mostly supported by the energy sector. All scenarios, in turn, have projected positive net incomes and post positive net present value (NPV) using a discount rate of 3.25% for the total farm investment (Table 3). For Scenario 3, farm income with energy sector profit is US $116,142, with an NPV of US$3.1 M. Scenario 4, in contrast, produces the worst average annual total revenue of US$48,003, with an NPV of US $1.6 M.

In Scenario 4, what is thought to be the most likely future scenario results in wheat and grain sorghum are rarely profitable. Irrigated corn's net income is projected to decrease over time and is considerably worse after simulation year 22 (2029). Dryland farming first occurs in year 55 (2062), causing large crop production decline. These results show a large increase in net income for all three crops after shifting to dryland farming as costs decline more than income. The reduced yield would be problematic for the global food system.

The time series in Fig. 5 show the variability in income. For example, in Scenarios 1 and 4, Fig. 5a and d show that corn, wheat, and grain sorghum lose less money with dryland farming than during the irrigation period because of decreased farm expenses and support from crop insurance. For Scenario 2, grain sorghum is the most profitable crop, but it loses money in some simulation years.

In FEWCalc, insurance claims (Fig. 6b) start during any period of transition to dryland farming when the current yield drops below the actual production history. There are other common situations in which crop insurance is indemnified, such as hailstorms and floods, but these are not represented in FEWCalc.

Fig. 5d, B.1, and B.3 results suggest that, overall, RCP 8.5 global

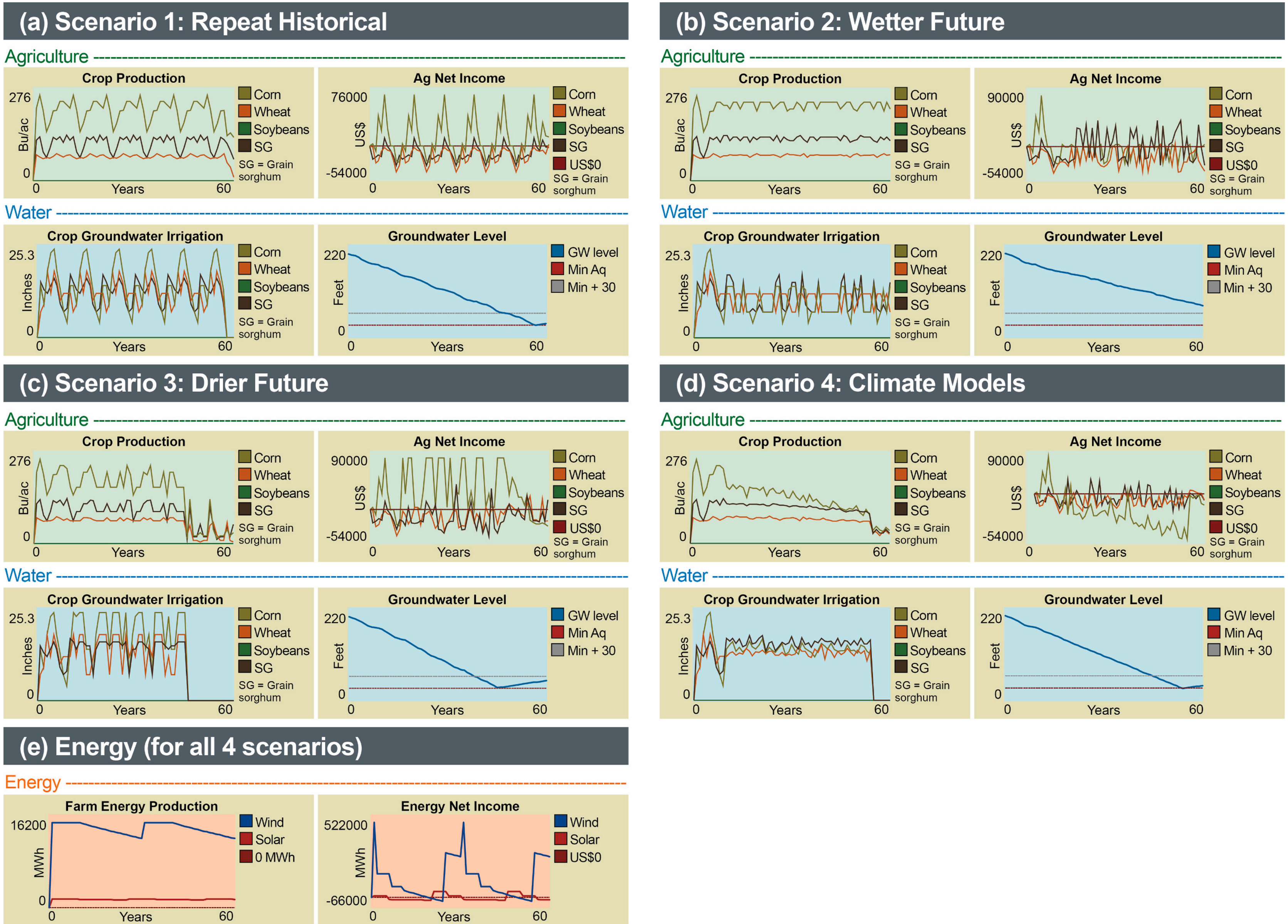

Fig. 5. FEWCalc annual results showing agricultural crop production and net income, energy production and net income, and crop groundwater irrigation and groundwater level for all four climate scenarios. Dashed lines in the charts represent significant values for reference. Abbreviation: bu = bushel, ac = acre, SG = grain sorghum, US$ = US dollar, MWh = megawatt-hour, GW level = groundwater level, Min Aq = minimum available aquifer thickness, and Min + 30 = a level of 30 ft above minimum thickness. Conversion: 1 bu/ac corn or grain sorghum = 62.77 kg/ha, 1 bu/ac wheat = 67.25 kg/ha, 1 in = 2.54 cm, and 1 ft = 0.3 m.

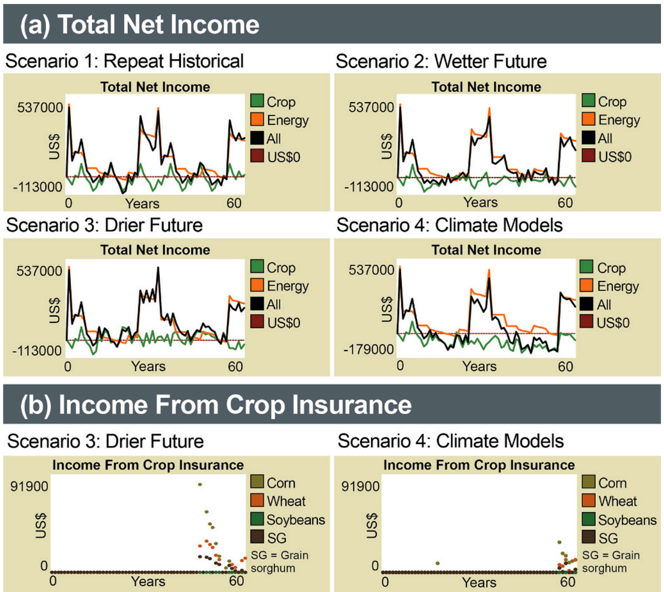

Fig. 6. (a) Total net income and (b) income from crop insurance. The yield-based crop insurance tends are indemnified mostly when farming converts from irrigated to non-irrigated (e.g., year 58 in Scenario 3). Plots for Scenarios 1 and 2 are not shown because annual crop insurance indemnifications were less than $31,000 for Scenario 1 and not indemnified for Scenario 2.

climate change predictions would need to be met with effective technology changes to address crop production trends that slowly decline for the future period. It appears that annual variability would make this trend difficult to discern until reductions are substantial, and history indicates that such obscured consequences tend to make early remedies difficult to implement. While global analyses suggest that delaying action exacerbates both the cost and feasibility of mitigation, how these tradeoffs play out locally requires careful evaluation of how projected changes and uncertainty impact individual FEW systems, a challenge that FEWCalc enables users to address directly for agricultural systems.

For all scenarios, installed solar capacity is initially set at about 9% of the total renewable energy. Higher capital costs and a shorter lifespan make the total cost of solar higher than wind. The slow degradation of wind and solar capacity over time is evident in the energy production graph. Solar power makes money some years because of the simulated tax credit, depreciation, and loan pay off. Wind power production, on the other hand, is generally profitable, in part because of a high wind capacity factor in the study area and the simulated 30-year capital lifespan that makes it easy to cover installation costs.

Overall, the DSSAT results are expected to be adequate for the analysis of renewable energy development and agricultural performance given potential future climate scenarios for which FEWCalc was developed.

The scenarios do not include technological, crop management, crop price, or energy production changes that would be expected to occur. Thus, these results reflect the climate- and market-related pressures to which such changes would need to respond to maintain crop production and farm incomes.

5. Conclusions

This work shows how FEWCalc can provide scientific, engineering, and economic analyses required by stakeholders and policy makers using data from the semi-arid region around Garden City, Kansas. Here we discuss the two points about FEWCalc and provide some final comments.

5.1. *FEWCalc utility for individual, community, and policy maker decision support*

The FEWCalc results for Finney County, Kansas, illustrate many of the general challenges of farming. The main crops are subject to considerable price uncertainty, weather conditions can be harsh and unpredictable, and selected resources have limited availability. As

Table 3

Metrics from the four scenarios for 60 years of FEWCalc simulation (2008–2067). All monetary amounts are in US dollars.

	Scenario 1 (Repeat Historical)			Scenario 2 (Wetter Future)			Scenario 3 (Drier Future)			Scenario 4[4] (GCMs, RCP 8.5)		
	C[1]	W[2]	SG[3]	C[1]	W[2]	SG[3]	C[1]	W[2]	SG[3]	C[1]	W[2]	SG[3]
Average annual crop yield, bushels/acre[4]												
with irrigation	207	71	111	223	75	123	190	71	106	149 (39.8)	72 (4.7)	109 (12.1)
without irrigation	133	35	87	–	–	–	40	23	39	41 (6.3)	31 (5.2)	33 (5.9)
Insurance claims, number of years	3	2	1	0	0	0	8	10	9	7	5	4
Dryland farming starts, year	2065			–			2053			2062		
Dryland farming length, years	3			0			15			6		
Average annual net income, US dollars												
from agriculture	-US$14,197			-US$20,194			US$6818			-US$61,321 (46,734)		
from energy	US$109,324			US$109,324			US$109,324			US$109,324 (122,970)		
total	US$95,127			US$89,130			US$116,142			US$48,003 (146,563)		
Net Present Value (NPV)[5]												
from agriculture	-US$0.4 M			-US$0.5 M			US$0.1 M			-US$1.3 M		
from energy	US$2.9 M			US$2.9 M			US$2.9 M			US$2.9 M		
total	US$2.5 M			US$2.4 M			US$3.1 M			US$1.6 M		

[1] Corn.
[2] Wheat.
[3] Grain sorghum.
[4] For Scenario 4, the standard deviation of the 20 GCM results are presented in parentheses.
[5] Discount rate is 3.25% (prime rate as of June 2020); FEWCalc agriculture and energy finances are combined; for energy, capital costs are explicitly included for energy and depreciated over 10 years assuming a tax rate of 20%, for agriculture, capital costs are applied as listed in Table A.7.

presented here, FEWCalc is applicable directly to farmers in arid regions of the middle part of the USA interested in alternative income sources. The design of FEWCalc has broad applicability for agricultural-energy-water system decision support research and education. Applicability to other regions requires local data, development of a DSSAT model, and adjustment of the FEWCalc input variable values. Little or no programming would be required.

Distributed energy production requires considerable land and rural areas can provide important opportunities, depending on local attitudes and local to national policies. FEWCalc illustrates major input variables relevant to renewable energy development and how local economic impact can be evaluated and projected.

Renewable wind energy development in this area was shown to potentially provide economic opportunities profitable enough to balance farming difficulties and enable the persistence of agricultural production in the region. In part, this is the consequence of the unusually useful wind resources available in this area; other areas will have different advantages and disadvantages that can be evaluated using the framework provided by FEWCalc.

FEWCalc results show that in this area, given current cost and electricity pricing, solar is only profitable with tax incentives and depreciation. In Kansas, the capital costs of solar energy (Fu et al., 2017) are challenging to recover given local solar radiance and electricity prices. As noted previously, an advantage of solar is that it is plentiful on hot summer days when wind velocities are low and electricity demand increases, largely due to increased use of air conditioning. In some cases, this makes solar a very useful addition to a given system despite the challenges of individual profitability. Solar is included in FEWCalc to provide this logistical advantage of solar energy and because tax incentives and even a slight reduction in the price of solar panels could make it a profitable alternative.

FEWCalc illustrates how complicated and interacting systems, as they face new opportunities and challenges — in this case renewable energy, water scarcity, evolving technical innovations, can be assembled into a reasonably realistic, interesting to manipulate, and educational graphical interface. Agent-based modeling using the freeware NetLogo is relatively simple yet flexible enough to perform calculations related to energy, water, nitrate in soils and surface water, crop insurance, and so on, and integrate results from a separate program — in this case DSSAT for agricultural production, water demand, and fertilizer application. The FEWCalc calculations used for energy are expected to be widely applicable. The data-based approach taken for water is expected to be adaptable to other locations with sufficient data; otherwise, this work suggests that greater errors are likely if aquifer water-level response is calculated using estimates of specific yield from pumping wells, a point also noted by Butler et al. (2016) and Whittemore et al. (2016).

The crop production DSSAT model served well when combined with local agricultural expertise and comparison to historical data. The need to use a new irrigation capability designed for arid regions and the poor performance of soybeans in the region were only recognized and explained after comparison to historical data and discussions with local agricultural experts. Lack of these resources would have resulted in substantial errors.

Potential uses of the program not pursued in this work include identifying what thresholds (e.g., crop price, crop production, expenses) and public policies (e.g., tax incentives) are needed to produce profitable opportunities for landowners and agricultural communities. Also, adding technology advances, crop and electricity price changes, and human decision-making characteristics such as avoidance of risk, maximizing profit, and evolution of policies and governmental institutions would improve the human interaction aspects of the simulation.

5.2. FEWCalc impact on IA and IAV gaps

The gaps between the IA and IAV communities that were summarized in Table 1 can be broadly categorized as gaps in the geographic and temporal scale, scenario and policy development, interdisciplinarity, and research perspective. FEWCalc addresses these gaps the following ways:

1) FEWCalc's interface shows the clear connection between current decisions and long-term, interdependent, and interdisciplinary consequences for both non-technical stakeholders and disciplinary specialists. This presentation of information can facilitate discussion across disciplinary boundaries and between scientists and non-technical stakeholders.
2) Metrics such as crop production, farm income, groundwater-level change, and nutrient loading of surface-water bodies, are broadly interesting to many stakeholder communities across a range of geographic scales and/or topical foci. These metrics can serve as a common point of reference for interdisciplinary discussions of their underlying discipline-specific drivers such as climate change, agricultural practices, and renewable energy policy. For example, Fig. 5, depicting the outcomes under Scenarios 1 to 4, could serve as the basis for discussions among different stakeholder communities and become an important focus of communication for topics as wide-ranging as irrigation practices, climate change impacts and adaptation strategies, renewable energy, and farm incomes.
3) Help stakeholders at all levels make better decisions, as follows.
   a) Studies of how local stakeholders use FEWCalc can help researchers gain insight into local values, which will give local stakeholders an implicit voice in scenario development and by implication the national- and global-scale public policy debates that are informed by integrated assessment, such as the Intergovernmental Panel on Climate Change (IPCC) assessment reports and the Paris Agreement.
   b) Inform local stakeholders, which could lead to better feedback and is the only way to achieve more buy-in and support for adaptive measures such as agricultural and energy tax credits and support of technological innovations in irrigation and wind turbine design. Here again, FEWCalc's outputs (Fig. 5) show the connection between global changes and local-stakeholder outcomes, while FEWCalc's intuitive interface allows local stakeholders to explore how their options (e.g., choices about irrigation, crop planting, and energy investment) and outcomes (e.g., farm income) are affected by climate conditions, and local and national public policy.

5.3. Final comments

FEWCalc integrates information from the fields of agriculture, energy, water supply, water quality, climate change, and economics. It uses this information to enable users to explore consequences of interest to farming communities, including farm income, water supply, water quality, and potential opportunities provided by renewable energy development. It also provides a way for anyone interested in their food supply to understand the challenges and opportunities faced by farmers and farming communities.

The version of FEWCalc discussed in this work is constructed of freely available and open-source software that was chosen to facilitate future extensions of FEWCalc. In particular, the use of agent-based modeling using NetLogo means that FEWCalc is well-positioned for expansion to simulate technology advances, behavioral and policy considerations, and the interplay between these important aspects of any natural-human system.

The input to DSSAT is region specific, but DSSAT is used globally and data from other regions would likely provide similar performance as long as some historical data is available for DSSAT model development.

Programs like FEWCalc are well suited to address gaps present between current Integrated Assessment (IA) and Impacts, Adaptation, and Vulnerability (IAV) communities. Said another way, programs like

FEWCalc enable users to envision both near-term impacts and long-term implications of choices made today. Thus, FEWCalc can be used by farmers considering the futures of their farms and communities, laypeople interested in how farms work, and policymakers as they consider potential consequences of regulatory and policy decisions.

Declaration of Competing Interest

None.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.agsy.2021.103222.

References

Absar, S.M., Preston, B.L., 2015. Extending the shared socioeconomic pathways for sub-national impacts, adaptation, and vulnerability studies. Glob. Environ. Chang. 33, 83–96. https://doi.org/10.1016/j.gloenvcha.2015.04.004.

Allan, T., Keulertz, M., Woertz, E., 2015. The water–food–energy nexus: an introduction to nexus concepts and some conceptual and operational problems. Int. J. Water Res. Develop. 31 (3), 301–311. https://doi.org/10.1080/07900627.2015.1029118.

Al-Saidi, M., Elagib, N.A., 2017. Towards understanding the integrative approach of the water, energy and food nexus. Sci. Total Environ. 574, 1131–1139. https://doi.org/10.1016/j.scitotenv.2016.09.046.

Anderson, T., Dragićević, S., 2018. Deconstructing geospatial agent-based model: sensitivity analysis of forest insect infestation model. In: Perez, L., Kim, E.-K., Sengupta, R. (Eds.), Agent-Based Models and Complexity Science in the Age of Geospatial Big Data. Springer International Publishing, pp. 31–44. https://doi.org/10.1007/978-3-319-65993-0_3.

Araya, A., Gowda, P.H., Golden, B., Foster, A.J., Aguilar, J., Currie, R., Ciampitti, I.A., Prasad, P.V.V., 2019. Economic value and water productivity of major irrigated crops in the Ogallala aquifer region. Agric. Water Manag. 214 (September 2018), 55–63. https://doi.org/10.1016/j.agwat.2018.11.015.

Bert, F., North, M., Rovere, S., Tatara, E., Macal, C., Podestá, G., 2015. Simulating agricultural land rental markets by combining agent-based models with traditional economics concepts: the case of the argentine pampas. Environ. Model. Softw. 71, 97–110. https://doi.org/10.1016/j.envsoft.2015.05.005.

Bieber, N., Ker, J.H., Wang, X., Triantafyllidis, C., van Dam, K.H., Koppelaar, R.H.E.M., Shah, N., 2018. Sustainable planning of the energy-water-food nexus using decision making tools. Energy Policy 113, 584–607. https://doi.org/10.1016/j.enpol.2017.11.037.

Biggs, E.M., Bruce, E., Boruff, B., Duncan, J.M.A., Horsley, J., Pauli, N., McNeill, K., Neef, A., Van Ogtrop, F., Curnow, J., Haworth, B., Duce, S., Imanari, Y., 2015. Sustainable development and the water-energy-food nexus: A perspective on livelihoods. Environ. Sci. Pol. 54, 389–397. https://doi.org/10.1016/j.envsci.2015.08.002.

Buchanan, R.C., Wilson, B.B., Buddemeier, R.R., Butler Jr., J.J., 2015. The High Plains aquifer. Kansas Geological Survey, Public Information Circular (PIC), 18, pp. 1–6. http://www.kgs.ku.edu/Publications/pic18/.

Bureau of Economic Analysis, 2020. Employment by county, metro, and other areas. https://www.bea.gov/data/employment/employment-county-metro-and-other-areas.

Butler, J.J., Whittemore, D.O., Wilson, B.B., Bohling, G.C., 2016. A new approach for assessing the future of aquifers supporting irrigated agriculture. Geophys. Res. Lett. 43 (5), 2004–2010. https://doi.org/10.1002/2016GL067879.

California Water Boards, 2020. Sustainable Groundwater Management Act. https://www.waterboards.ca.gov/water_issues/programs/gmp/.

Calow, R.C., Howarth, S.E., Wang, J., 2009. Irrigation development and water rights reform in China. Int. J. Water Res. Develop. 25 (2), 227–248. https://doi.org/10.1080/07900620902868653.

Campbell, M., 2020. Australia's water is vanishing. In: Bloomberg Businessweek. https://www.bloomberg.com/features/2020-australia-drought-water-crisis.

Cash, D.W., Adger, W.N., Berkes, F., Garden, P., Lebel, L., Olsson, P., Pritchard, L., Young, O., 2006. Scale and cross-scale dynamics: governance and information in a multilevel world. Ecol. Soc. 11 (2), 8. http://www.ecologyandsociety.org/vol11/iss2/art8/.

Cuberos Balda, M., Kawajiri, K., 2020. The right crops in the right place for the food-energy nexus: potential analysis on rice and wheat in Hokkaido using crop growth models. J. Clean. Prod. 263, 121373. https://doi.org/10.1016/j.jclepro.2020.121373.

de Bremond, A., Preston, B.L., Rice, J., 2014. Improving the usability of integrated assessment for adaptation practice: insights from the U.S. southeast energy sector. Environ. Sci. Pol. 42, 45–55. https://doi.org/10.1016/j.envsci.2014.05.004.

Denholm, P., Hand, M., Jackson, M., Ong, S., 2009. Land use requirements of modern wind power plants in the United States. In: NREL Technical Report. National Renewable Energy Laboratory, p. 39. https://doi.org/10.2172/964608.

Dieter, C.A., Maupin, M.A., Caldwell, R.R., Harris, M.A., Ivahnenko, T.I., Lovelace, J.K., Barber, N.L., Linsey, K.S., 2018. Estimated use of water in the United States in 2015. In: U.S. Geological Survey Circular 1441. U.S. Geological Survey, pp. 1–65. https://doi.org/10.3133/cir1441.

Dore, M.H.I., 2005. Climate change and changes in global precipitation patterns: what do we know? Environ. Int. 31 (8), 1167–1181. https://doi.org/10.1016/j.envint.2005.03.004.

Edwards, W., 2011. Yield protection crop insurance. In: Ag Decision Maker (February; pp. 1–2). Iowa State University, University Extension. https://www.extension.iastate.edu/agdm/crops/html/a1-52.html.

Endo, A., Tsurita, I., Burnett, K., Orencio, P.M., 2017. A review of the current state of research on the water, energy, and food nexus. J. Hydrol. Reg. Stud. 11, 20–30. https://doi.org/10.1016/j.ejrh.2015.11.010.

Epley, C., 2016. Turning to turbines: As commodity prices remain low, wind energy leases offer a welcome source of income for farmers. https://www.omaha.com/money/turning-to-turbines-as-commodity-prices-remain-low-wind-energy/article_2814e2cf-83a3-547d-a09e-f039e935f399.htm.

Ericksen, P.J., 2008. What is the vulnerability of a food system to global environmental change? Ecol. Soc. 13 (2), 18. http://www.ecologyandsociety.org/vol13/iss2/art14/.

Ericksen, P.J., Ingram, J.S.I., Liverman, D.M., 2009. Food security and global environmental change: emerging challenges. Environ. Sci. Pol. 12 (4), 373–377. https://doi.org/10.1016/j.envsci.2009.04.007.

FAO (Food and Agriculture Organizations), 2014. Irrigation Areas, Irrigated Crops. Environment. Food and Agriculture Organizations. http://www.fao.org/nr/water/aquastat/didyouknow/print3.stm.

Forrester, J.W., 1971. Counterintuitive behavior of social systems. SIMULATION 16 (2), 61–76. https://doi.org/10.1177/003754977101600202.

Fu, R., Feldman, D., Margolis, R., Woodhouse, M., Ardani, K., 2017. U.S. solar photovoltaic system cost benchmark: Q1 2017. In: In Technical Report. National Renewable Energy Laboratory, pp. 1–59. https://www.nrel.gov/docs/fy17osti/68925.pdf.

Gijsman, A.J., Thornton, P.K., Hoogenboom, G., 2007. Using the WISE database to parameterize soil inputs for crop simulation models. Comput. Electron. Agric. 56 (2), 85–100. https://doi.org/10.1016/j.compag.2007.01.001.

Green Coast, 2019. Solar Farm Land Requirements: How Much Land Do You Need? https://greencoast.org/solar-farm-land-requirements.

Guijun, L., Yongsheng, W., Daohan, H., Hongtao, Y., 2017. A multi-agent model for urban Water-energy-food sustainable development simulation. In: Proceedings of the 2nd International Conference on Crowd Science and Engineering - ICCSE'17, pp. 105–110. https://doi.org/10.1145/3126973.3126991.

Hardin, G., 1968. The tragedy of the commons. Science 162 (3859), 1243–1248. https://doi.org/10.1126/science.162.3859.1243.

Hill, M.C., Pahwa, A., Rogers, D., Roundy, J.K., Barron, R.W., 2017. Developing Community-Focused Solutions Using a Food-Energy-Water Calculator, with Initial Application to Western Kansas. American Geophysical Union, Fall Meeting, December. https://agu.confex.com/agu/fm17/meetingapp.cgi/Paper/256139.

Hill, M.C., Barron, R.W., Amanor-Boadu, V., Pfromm, P., Wu, H., Bloodgood, J., Gray, B. J., 2019. Intelligent Science for Involving Stakeholders in Making Agriculture Sustainable Using Local Renewable Energy. American Geophysical Union, Fall Meeting. https://agu.confex.com/agu/fm19/meetingapp.cgi/Paper/510475.

Hu, M.-C., Fan, C., Huang, T., Wang, C.-F., Chen, Y.-H., 2018. Urban metabolic analysis of a food-Water-energy system for sustainable resources management. Int. J. Environ. Res. Public Health 16 (1), 90. https://doi.org/10.3390/ijerph16010090.

Huber, V., Schellnhuber, H.J., Arnell, N.W., Frieler, K., Friend, A.D., Gerten, D., Haddeland, I., Kabat, P., Lotze-Campen, H., Lucht, W., Parry, M., Piontek, F., Rosenzweig, C., Schewe, J., Warszawski, L., 2014. Climate impact research: beyond patchwork. Earth Syst. Dynam. 5 (2), 399–408. https://doi.org/10.5194/esd-5-399-2014.

IAEA (International Atomic Energy Agency), 2009. Nuclear Technology Review 2009. International Atomic Energy Agency, p. 141. https://inis.iaea.org/collection/NCLCollectionStore/_Public/43/028/43028601.pdf?r=1&r=1.

Jones, J.W., Hoogenboom, G., Porter, C.H., Boote, K.J., Batchelor, W.D., Hunt, L.A., Wilkens, P.W., Singh, U., Gijsman, A.J., Ritchie, J.T., 2003. The DSSAT cropping system model. Eur. J. Agron. 18 (3–4), 235–265. https://doi.org/10.1016/S1161-0301(02)00107-7.

Jones, J.W., Antle, J.M., Basso, B., Boote, K.J., Conant, R.T., Foster, I., Godfray, H.C.J., Herrero, M., Howitt, R.E., Janssen, S., Keating, B.A., Munoz-Carpena, R., Porter, C. H., Rosenzweig, C., Wheeler, T.R., 2017a. Brief history of agricultural systems modeling. Agric. Syst. 155, 240–254. https://doi.org/10.1016/j.agsy.2016.05.014.

Jones, J.W., Antle, J.M., Basso, B., Boote, K.J., Conant, R.T., Foster, I., Godfray, H.C.J., Herrero, M., Howitt, R.E., Janssen, S., Keating, B.A., Munoz-Carpena, R., Porter, C. H., Rosenzweig, C., Wheeler, T.R., 2017b. Toward a new generation of agricultural system data, models, and knowledge products: state of agricultural systems science. Agric. Syst. 155, 269–288. https://doi.org/10.1016/j.agsy.2016.09.021.

Kansas Department of Agriculture, 2021. Wichita County LEMA. https://agriculture.ks.gov/divisions-programs/dwr/managing-kansas-water-resources/local-enhanced-management-areas/wichita-county-lema.

Kansas Mesonet, 2017. Kansas Mesonet Historical Data. http://mesonet.k-state.edu/weather/historical.
KCC (Kansas Corporation Commission), 2019. Electric Supply and Demand Annual Report 2019. Kansas Corporation Commission. https://kcc.ks.gov/images/PDFs/legislative-reports/2019-Electric-Supply–Demand-Report.pdf.
Kovda, V.A., 1977. Arid land irrigation and soil fertility: problems of salinity, alkalinity, compaction. In: Worthington, E.B. (Ed.), Arid Land Irrigation in Developing Countries, 1st ed. Elsevier, pp. 211–235. https://doi.org/10.1016/B978-0-08-021588-4.50034-8.
Kraucunas, I., Clarke, L., Dirks, J., Hathaway, J., Hejazi, M., Hibbard, K., Huang, M., Jin, C., Kintner-Meyer, M., van Dam, K.K., Leung, R., Li, H.-Y., Moss, R., Peterson, M., Rice, J., Scott, M., Thomson, A., Voisin, N., West, T., 2015. Investigating the nexus of climate, energy, water, and land at decision-relevant scales: the platform for regional integrated modeling and analysis (PRIMA). Clim. Chang. 129 (3–4), 573–588. https://doi.org/10.1007/s10584-014-1064-9.
Lesk, C., Rowhani, P., Ramankutty, N., 2016. Influence of extreme weather disasters on global crop production. Nature 529 (7584), 84–87. https://doi.org/10.1038/nature16467.
Li, Z., Li, X., Wang, Y., Quiring, S.M., 2019. Impact of climate change on precipitation patterns in Houston, Texas, USA. Anthropocene 25, 100193. https://doi.org/10.1016/j.ancene.2019.100193.
Li, S., Cai, X., Emaminejad, S.A., Juneja, A., Niroula, S., Oh, S., Wallington, K., Cusick, R. D., Gramig, B.M., John, S., McIsaac, G.F., Singh, V., 2021. Developing an integrated technology-environment-economics model to simulate food-energy-water systems in Corn Belt watersheds. Environ. Model. Softw. 143, 105083. https://doi.org/10.1016/j.envsoft.2021.105083.
Maupin, M.A., 2018. Summary of estimated water use in the United States in 2015. In: US Geological Survey Fact Sheet 3035, p. 2. https://doi.org/10.3133/fs20183035.
Maupin, M.A., Barber, N.L., 2005. Estimated withdrawals from principal aquifers in the United States, 2000. In: US Geological Survey Circular. U.S. Geological Survey, p. 46. https://doi.org/10.3133/cir1279.
McGuire, V.L., 2014. Water-level changes and change in water in storage in the High Plains aquifer, predevelopment to 2013 and 2011–13. In: U.S. Geological Survey Scientific Investigations Report. U.S. Geological Survey, p. 14. https://doi.org/10.3133/sir20145218. No. 5218.
Meadows, D., 2008. In: Wright, D. (Ed.), Thinking in Systems: A Primer. Chelsea Green Publishing.
Memarzadeh, M., Moura, S., Horvath, A., 2019. Optimizing dynamics of integrated food–energy–water systems under the risk of climate change. Environ. Res. Lett. 14 (7), 074010 https://doi.org/10.1088/1748-9326/ab2104.
Mishra, A.K., Cooper, J.C., 2017. Impact of farm programs on farm households in the US. J. Policy Model 39 (3), 387–409. https://doi.org/10.1016/j.jpolmod.2017.04.001.
Morecroft, J.D.W., 2015. In: Morecroft, J.D.W. (Ed.), Strategic Modelling and Business Dynamics. John Wiley & Sons, Inc. https://doi.org/10.1002/9781119176831.
Nie, Y., Avraamidou, S., Xiao, X., Pistikopoulos, E.N., Li, J., Zeng, Y., Song, F., Yu, J., Zhu, M., 2019. A food-energy-Water Nexus approach for land use optimization. Sci. Total Environ. 659, 7–19. https://doi.org/10.1016/j.scitotenv.2018.12.242.
NREL (National Renewable Energy Laboratory), 2011. U.S. Average Annual Wind Speed at 80 Meters. https://windexchange.energy.gov/maps-data/319.
NSF (National Science Foundation), 2018. Dynamics of Coupled Natural and Human Systems. https://www.nsf.gov/pubs/2018/nsf18503/nsf18503.htm.
O'Neill, B.C., Kriegler, E., Riahi, K., Ebi, K.L., Hallegatte, S., Carter, T.R., Mathur, R., van Vuuren, D.P., 2014. A new scenario framework for climate change research: the concept of shared socioeconomic pathways. Clim. Chang. 122 (3), 387–400. https://doi.org/10.1007/s10584-013-0905-2.
Ong, S., Campbell, C., Denholm, P., Margolis, R., Heath, G., 2013. Land-use requirements for solar power plants in the United States. In: NREL Technical Report. National Renewable Energy Laboratory, p. 39. https://doi.org/10.1016/j.rapm.2006.08.004.
Palmer, W.C., 1965. Meteorological Drought. U.S. Weather Bureau, Res. Pap, p. 45. https://www.ncdc.noaa.gov/temp-and-precip/drought/docs/palmer.pdf.
Phetheet, J., Heger, W., Hill, M.C., 2019. Evaluating Use of Water and Renewable Energy in Agricultural Areas: A Coupled Simulation of DSSAT and Agent-Based Modeling. American Geophysical Union, Fall Meeting. https://agu.confex.com/agu/fm19/meetingapp.cgi/Paper/494391.
Phetheet, J., Hill, M.C., Barron, R.W., Rossi, M.W., Amanor-Boadu, V., Wu, H., Kisekka, I., 2021. Consequences of climate change on food-energy-water systems in arid regions without agricultural adaptation, analyzed using FEWCalc and DSSAT. Resour. Conserv. Recycl. 105309. https://doi.org/10.1016/j.resconrec.2020.105309.
Pickering, N.B., Hansen, J.W., Jones, J.W., Wells, C.M., Chan, V.K., Godwin, D.C., 1994. WeatherMan: A utility for managing and generating daily weather data. Agron. J. 86 (2), 332–337. https://doi.org/10.2134/agronj1994.00021962008600020023x.
Ravar, Z., Zahraie, B., Sharifinejad, A., Gozini, H., Jafari, S., 2020. System dynamics modeling for assessment of water–food–energy resources security and nexus in Gavkhuni basin in Iran. Ecol. Indic. 108, 105682. https://doi.org/10.1016/j.ecolind.2019.105682.
RMA (Risk Management Agency), 2020. Actual Production History. In: https://www.rma.usda.gov/en/Policy-and-Procedure/Insurance-Plans/Actual-Production-History.
Rosenzweig, C., Elliott, J., Deryng, D., Ruane, A.C., Müller, C., Arneth, A., Boote, K.J., Folberth, C., Glotter, M., Khabarov, N., Neumann, K., Piontek, F., Pugh, T.A.M., Schmid, E., Stehfest, E., Yang, H., Jones, J.W., 2014. Assessing agricultural risks of climate change in the 21st century in a global gridded crop model intercomparison. Proc. Natl. Acad. Sci. 111 (9), 3268–3273. https://doi.org/10.1073/pnas.1222463110.
Salazar, M.R., Hook, J.E., Garcia y Garcia, A., Paz, J.O., Chaves, B., Hoogenboom, G., 2012. Estimating irrigation water use for maize in the southeastern USA: A modeling approach. Agric. Water Manag. 107, 104–111. https://doi.org/10.1016/j.agwat.2012.01.015.
Sawyer, J., 2011. Estimating Nitrogen Losses. Integrated Crop Management News. https://crops.extension.iastate.edu/cropnews/2011/06/estimating-nitrogen-losses.
Schulterbrandt Gragg, R., Anandhi, A., Jiru, M., Usher, K.M., 2018. A conceptualization of the urban food-energy-water Nexus sustainability paradigm: modeling from theory to practice. Front. Environ. Sci. 6 https://doi.org/10.3389/fenvs.2018.00133.
SEIA (Solar Energy Industries Association), 2020a. Kansas State Solar Spotlight. Solar Energy Industries Association. https://www.seia.org/sites/default/files/2020-03/Kansas.pdf.
SEIA (Solar Energy Industries Association), 2020b. Missouri State Solar Spotlight. Solar Energy Industries Association. https://www.seia.org/sites/default/files/2020-03/Missouri.pdf.
Shannak, S., Mabrey, D., Vittorio, M., 2018. Moving from theory to practice in the water–energy–food nexus: an evaluation of existing models and frameworks. Water-Energy Nexus 1 (1), 17–25. https://doi.org/10.1016/j.wen.2018.04.001.
Sharda, V., Gowda, P.H., Marek, G., Kisekka, I., Ray, C., Adhikari, P., 2019. Simulating the impacts of irrigation levels on soybean production in Texas High Plains to manage diminishing groundwater levels. JAWRA J. Am. Water Res. Assoc. 55 (1), 56–69. https://doi.org/10.1111/1752-1688.12720.
Sterman, J., 2000. In: Sterman, J. (Ed.), Business dynamics: systems thinking and modeling for a complex world, 1st ed. McGraw-Hill Education.
Stockholm Environment Institute, 2021, June 20. WEAP: Water Evaluation and Planning System. SEI. https://www.sei.org/projects-and-tools/tools/weap/.
Taylor, K.E., Stouffer, R.J., Meehl, G.A., 2009. A summary of the CMIP5 experiment design. PCDMI Rep. 33 pp. [Available online at http://cmip-pcmdi .llnl.gov/cmip5/docs/Taylor_CMIP5_design.pdf].
Taylor, K.E., Stouffer, R.J., Meehl, G.A., 2012. An overview of CMIP5 and the experiment design. Bull. Am. Meteorol. Soc. 93 (4), 485–498. https://doi.org/10.1175/BAMS-D-11-00094.1.
Tisue, S., Wilensky, U., 2004. NetLogo: Design and implementation of a multi-agent modeling environment. In: Macal, C.M., Sallach, D., North, M.J. (Eds.), Proceedings of the Agent 2004 Conference on Social Dynamics: Interaction, Reflexivity and Emergence, Chicago, IL. The University of Chicago, pp. 161–184. https://ccl.northwestern.edu/papers/agent2004.pdf.
Tsuji, G.Y., Uehara, G., Balas, S., 1994. DSSAT version 3. In: In International Benchmark Sites Network for Agrotechnology Transfer, Vol. 3. University of Hawaii, Honolulu, Hawaii. http://dssat.info/wp-content/uploads/2011/10/DSSAT-vol3.pdf.
USDA (U.S. Department of Agriculture), 2020. USDA Agricultural Projections to 2029. U. S. Department of Agriculture, p. 114. https://www.ers.usda.gov/webdocs/outlooks/95912/oce-2020-1.pdf.
USGS (U.S. Geological Survey), 1999. The quality of our nation's waters: nutrients and pesticides. In: U.S. Geological Survey Circular, Vol. 1225. U.S. Geological Survey, p. 82. https://pubs.usgs.gov/circ/circ1225.
van Ruijven, B.J., Levy, M.A., Agrawal, A., Biermann, F., Birkmann, J., Carter, T.R., Ebi, K.L., Garschagen, M., Jones, B., Jones, R., Kemp-Benedict, E., Kok, M., Kok, K., Lemos, M.C., Lucas, P.L., Orlove, B., Pachauri, S., Parris, T.M., Patwardhan, A., Schweizer, V.J., 2014. Enhancing the relevance of shared socioeconomic pathways for climate change impacts, adaptation and vulnerability research. Clim. Chang. 122 (3), 481–494. https://doi.org/10.1007/s10584-013-0931-0.
Vervoort, J.M., Thornton, P.K., Kristjanson, P., Förch, W., Ericksen, P.J., Kok, K., Ingram, J.S.I., Herrero, M., Palazzo, A., Helfgott, A.E.S., Wilkinson, A., Havlík, P., Mason-D'Croz, D., Jost, C., 2014. Challenges to scenario-guided adaptive action on food security under climate change. Glob. Environ. Chang. 28, 383–394. https://doi.org/10.1016/j.gloenvcha.2014.03.001.
Villamayor-Tomas, S., Grundmann, P., Epstein, G., Evans, T., Kimmich, C., 2015. The water-energy-food security nexus through the lenses of the value chain and the institutional analysis and development frameworks. Water Alternatives 8 (1), 735–755.
Weise, E., 2020. Wind energy gives American farmers a new crop to sell in tough times. In: Elizabeth Weise. https://www.usatoday.com/story/news/nation/2020/02/16/wind-energy-can-help-american-farmers-earn-money-avoid-bankruptcy/4695670002/.
Welsch, M., Hermann, S., Howells, M., Rogner, H.H., Young, C., Ramma, I., Bazilian, M., Fischer, G., Alfstad, T., Gielen, D., Le Blanc, D., Röhrl, A., Steduto, P., Müller, A., 2014. Adding value with CLEWS – modelling the energy system and its interdependencies for Mauritius. Appl. Energy 113, 1434–1445. https://doi.org/10.1016/j.apenergy.2013.08.083.
Weyant, J., 2017. Some contributions of integrated assessment models of global climate change. Rev. Environ. Econ. Policy 11 (1), 115–137. https://doi.org/10.1093/reep/rew018.
Wheeler, T., von Braun, J., 2013. Climate change impacts on global food security. Science 341 (6145), 508–513. https://doi.org/10.1126/science.1239402.
Whittemore, D.O., Butler Jr., J.J., Wilson, B.B., Butler, J.J., Wilson, B.B., 2016. Assessing the major drivers of water-level declines: new insights into the future of heavily stressed aquifers. Hydrol. Sci. J. 61 (1), 134–145. https://doi.org/10.1080/02626667.2014.959958.
Wilensky, Uri, 1999. NetLogo (and NetLogo User Manual). In: Center for Connected Learning and Computer-Based Modeling. Northwestern University. http://ccl.northwestern.edu/netlogo/.
World Bank, 1998. India—Water resources management sector review: Groundwater regulation and management report. The World Bank, p. 118. http://documents.worldbank.org/curated/en/372491468752788129.

WWAP (World Water Assessment Programme), 2012. The United Nations world water development report 4: managing water under uncertainty and risk. In: UN Water Report. The United Nations Educational, Scientific and Cultural Organization, p. 380. https://unesdoc.unesco.org/ark:/48223/pf0000215644.

Xiarchos, I.M., Vick, B., 2011. Solar Energy Use in U.S. Agriculture Overview and Policy Issues. U.S. Department of Agriculture, pp. 1–86. https://www.usda.gov/oce/reports/energy/Web_SolarEnergy_combined.pdf.

Yao, Y., Martinez-Hernandez, E., Yang, A., 2018. Modelling nutrient flows in a simplified local food-energy-water system. Resour. Conserv. Recycl. 133 (February), 343–353. https://doi.org/10.1016/j.resconrec.2018.02.022.

Zaveri, E., Grogan, D.S., Fisher-Vanden, K., Frolking, S., Lammers, R.B., Wrenn, D.H., Prusevich, A., Nicholas, R.E., 2016. Invisible water, visible impact: groundwater use and Indian agriculture under climate change. Environ. Res. Lett. 11 (8), 84005. https://doi.org/10.1088/1748-9326/11/8/084005.

Zhang, Y., Wang, Y., Niu, H., 2019. Effects of temperature, precipitation and carbon dioxide concentrations on the requirements for crop irrigation water in China under future climate scenarios. Sci. Total Environ. 656 (19), 373–387. https://doi.org/10.1016/j.scitotenv.2018.11.362.