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Consequences of climate change on food-energy-water systems in arid regions without agricultural adaptation, analyzed using FEWCalc and DSSAT

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A R T I C L E I N F O

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A B S T R A C T

Effects of a changing climate on agricultural system productivity are poorly understood, and likely to be met with as yet undefined agricultural adaptations by farmers and associated business and governmental entities. The continued vitality of agricultural systems depends on economic conditions that support farmers' livelihoods. Exploring the long-term effects of adaptations requires modeling agricultural and economic conditions to engage stakeholders upon whom the burden of any adaptation will rest. Here, we use a new freeware model FEWCalc (Food-Energy-Water Calculator) to project farm incomes based on climate, crop selection, irrigation practices, water availability, and economic adaptation of adding renewable energy production. Thus, FEWCalc addresses United Nations Global Sustainability Goals No Hunger and Affordable and Clean Energy. Here, future climate scenario impacts on crop production and farm incomes are simulated when current agricultural practices continue so that no agricultural adaptations are enabled. The model Decision Support System for Agrotechnology Transfer (DSSAT) with added arid-region dynamics is used to simulate agricultural dynamics. Demonstrations at a site in the midwest USA with 2008–2017 historical data and two 2018–2098 RCP climate scenarios provide an initial quantification of increased agricultural challenges under climate change, such as reduced crop yields and increased financial losses. Results show how this finding is largely driven by increasing temperatures and changed distribution of precipitation throughout the year. Without effective technological advances and operational and policy changes, the simulations show how rural areas could increasingly depend economically on local renewable energy, while agricultural production from arid regions declines by 50% or more.

1. Introduction

Food-Energy-Water (FEW) challenges emanate from ongoing and accelerating changes in surface temperatures (Campbell, 2020; Lesk et al., 2016). Crop production is being affected, especially in the world's arid regions, as crop water requirements increase even as precipitation patterns shift in many regions globally (Dore, 2005; Li et al., 2019; Zhang et al., 2019). Consequently, the economic viability of Small Town And Rural (STAR) economies and the ability to reach United Nations Global Sustainability Goals (UN SDGs) such as No Hunger (SDG 2) are threatened. Policymakers are responding with interventions and incentives aimed at controlling carbon emissions, the primary source of climate change (Chaves and Pereira, 1992; Crowley and Berner, 2001). Their effectiveness has been shown to be positively correlated with stakeholder engagement in the processes of defining and implementing the incentives and interventions (Miller, 2014). Stakeholders are defined to encompass business owners, civic society, and civic leaders in communities of focus, as well as scientists, engineers, and knowledge resource providers supporting program implementation, monitoring and evaluation.

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The intervention policies' outcomes and their sustainability are uncertain due to knowledge gaps in feedback mechanisms (Forrester, 1971) and in accounting for trade-offs and synergies across alternatives (Liu et al., 2017). The lack of effective system-level tools to facilitate stakeholder engagement is another barrier to adoption of suggested policy solutions (Dai et al., 2018; Liu et al., 2018). FEWCalc (Food-Energy-Water Calculator) contributes to addressing these knowledge gaps and adoption barriers by providing stakeholders with a tool to assess synergies and trade-offs under alternative climate and production decisions. It has the flexibility of focusing on a single stakeholder or exploring synergies and trade-offs across the whole system.

Climate-change driven increases in water and food insecurity pose challenges to reaching the Sustainable Development Goals (SDGs; Supplemental Appendix A) related to food, energy, and water: "zero hunger" (Goal 2), "affordable and clean energy" (Goal 7), and "clean water and sanitation" (Goal 6). Surface temperatures are rising and historically rare extreme weather conditions are becoming more frequent (Campbell, 2020; Lesk et al., 2016). Increasing temperatures are already increasing crop water requirements and shifting precipitation patterns (Dore, 2005; Li et al., 2019; Zhang et al., 2019). These changes may directly affect global food security (Wheeler and von Braun, 2013). Moreover, shifting regulations and restrictions on carbon emissions may alter the menu of available adaptation options, thus increasing the uncertainty facing decision makers, including farmers and policymakers.

Food-Energy-Water (FEW) challenges require improved approaches to engage rural agricultural communities to create sustainable and viable economies and communities. The multi-scale, trans-disciplinary scope of the FEW nexus creates system-level problems best served by participatory, systems-level solutions. To be effective and to be adopted by the stakeholders normally most impacted, solutions need to involve a broad range of stakeholders, including scientists and engineers, local officials, small business owners, and private citizens. However, the effectiveness of solutions is limited by knowledge gaps in our understanding of the synergies and tradeoffs involved (Liu et al., 2017) and the lack of effective system-level tools to facilitate stakeholder involvement in identifying solutions and the resulting higher likelihood of adoption (Dai et al., 2018; Liu et al., 2018). FEWCalc provides an innovative and accessible tool for farmers and other decision makers in addressing these issues.

This work presents FEWCalc results that address the question of how agricultural productivity and income are likely to be impacted by climate change. Details about FEWCalc data input and output, how to download and run FEWCalc, and the equations used in FEWCalc, are described in the Supplemental appendices and references cited therein.

1.1. Background

Irrigated areas currently produce 30 to 40% of the world's food, and 70% of global water withdrawals are for agricultural purposes (FAO, 2014; Kovda, 1977; WWAP, 2012). Much of this water is derived from groundwater. For example, groundwater accounts for up to 40% of irrigation water across China's dry northern region and as much as 70% in some locations (Calow et al., 2009). In India, approximately 90 million rural households depend on groundwater irrigation and areas irrigated with groundwater account for 70–80% of the value of irrigated production (World Bank, 1998; Zaveri et al., 2016). In the USA, groundwater from the Central Valley aquifer of California and the High Plains aquifer (HPA) in the middle of the country supply as much as 16% and 30% of the nation's irrigation water, respectively (Dieter et al., 2018; Maupin and Barber, 2005).

Agricultural water demands need to coordinate with other demands. In the USA, thermoelectric power plants accounted for 41% of total water use in 2015, which exceeded the 37% used for agriculture (Maupin, 2018). An important underlying dynamic is that power plant water use is mostly non-consumptive, though effluent warmth may limit its uses (Dieter et al., 2018). In contrast, most agricultural use is consumptive – that is, the water used for irrigation is transferred to plants or other parts of the hydrologic cycle such as the atmosphere, and, thus, only a small percentage is available to serve local water needs again. The renewable energy sources considered in this work use no water and thus place no additional burden on water in agricultural areas.

Future agricultural, energy, and water systems are influenced by current and evolving local policies and policies in different jurisdictions, the practices of supporting institutions and businesses, economic and socio-cultural attitudes and subjective perceptions (Cash et al., 2006). There are some promising efforts to promote sustainable groundwater use, such as California's 2014 Sustainable Groundwater Management Act (SGMA) and northwest Kansas' 2013 Sheridan-6 (SD-6) Local Enhanced Management Area (LEMA) (KDA, 2018; KWO, 2020). To date, these programs have not had visible adverse effects on the affected agricultural sectors. For example, in the case of northwest Kansas, reductions of almost 20% in groundwater withdrawals have had a neutral effect on farm net incomes. The reduction in withdrawals has reduced average annual water-level declines by more than 54% over ten years, from 46 cm (2008–2013) to 21 cm (2013–2017). In some locations in Sheridan-6, groundwater levels have increased.

Many farmers and STAR community residents understand that their way of life is threatened and action is needed. However, consensus on the path forward is elusive, at least in part, because the scale, complexity, and importance of the issues make it difficult for individual stakeholders to answer a key question: "What could this mean for me?" Effective, enduring solutions, such as LEMAs in Kansas, require technical knowledge and also the inclusion of community knowledge, perspectives, and values in decision processes. Knowledge gaps are pervasive across many STAR communities as their leaders grapple with alternative strategies to address the existential risks that confront them.

Many of the communities facing groundwater depletion have economies based almost entirely on agriculture. A possible adaptation to water scarcity is to expand the economic base of STAR communities. Diversifying local economies could enable investment in emerging agrotechnological solutions and improved use of the limited water resources.

One promising opportunity for community economic diversification is renewable energy. Many water-stressed areas of the world are also rich in renewable energy resources. For example, in the central USA, renewable energy exported to existing load centers has been profitable for farmers through participation in land-lease programs from which they can derive considerable annual income (Weise, 2020).

One example of diversification based on renewable energy, and the one FEWCalc is designed to investigate, is for landowners, such as farmers, to invest directly in renewable energy production by owning wind turbines and solar panels, and thus take on both additional risk and greater income potential (Epley, 2016; Hill et al., 2017; Phetheet et al., 2019). A successful application of renewable energy to diversify STAR economies would have the potential to positively influence SDGs, especially SDG 7 (affordable and clean energy).

To close these critical knowledge gaps, the Food-Energy-Water Calculator (FEWCalc) (Phetheet et al., in review) relates present agricultural, energy, and water decisions to long-term dynamics and consequences. Including renewable energy production addresses in part the concern that agricultural production alone may not be able to maintain STAR communities given resource challenges and competitive global markets. An advantage is that alternative energy production from wind and sunlight that exist in these regions may be exploited by the community without placing greater demands on the already challenged water resources.

In this work, we use FEWCalc to investigate the impacts of global effects on local systems. We include an analysis of 20 General Circulation Models (GCMs) and discuss how linking FEWCalc with global-scale integrated assessment models could have synergistic benefits that would improve both local- and global-scale modeling.

The analysis conducted here can be viewed as advancing existing scholarship on two separate but complementary research streams: the typically large space and time scale Integrated Assessment (IA) and the generally more narrow and locally focused Impacts, Adaptation, and Vulnerability (IAV) (Absar and Preston, 2015; van Ruijven et al., 2014; Weyant, 2017). Historically, the IA and IAV communities focused on different research topics, however, these research streams have been converging as the value of integrated, multi-scale approaches to climate research has become apparent. As a tool focused on bringing longer-term perspectives to present-day decision makers, FEWCalc bridges the gap between the IA and IAV communities.

The standardized, multi-scale Shared Socioeconomic Pathways (SSPs) scenario framework (O'Neill et al., 2014) relates economic and technological choices to carbon emissions. As such, it supports research in the IA and IAV communities. Also, FEWCalc supports emissions mitigation through developing greater local familiarity with the development of renewable energy capacity, and greater research-level familiarity with the challenges of local stakeholders.

For FEWCalc, the freeware model Decision Support System for Agrotechnology Transfer (DSSAT) model (Araya et al., 2019; Jones et al., 2003, 2017a, 2017b; Sharda et al., 2019) is used to calculate crop yields and irrigation demand because of its capabilities and popularity. DSSAT requires daily weather data (maximum and minimum air temperature, precipitation, and solar radiation), soil data (physical and chemical properties of soil profile horizons), and crop management practices (cultivars, planting practices, irrigation, fertilization, etc.). DSSAT produces the simulated values of crop production, irrigation rates, and fertilizer demand used in FEWCalc.

The agent-based model (ABM) framework NetLogo was used to construct FEWCalc (Anderson and Dragićević, 2018; Guijun et al., 2017; Hu et al., 2018; Tisue and Wilensky, 2004; Wilensky, 1999). Because dynamic modeling system had its roots in business and expanded to urban and environmental problems (Forrester, 1971; Meadows, 2008; Morecroft, 2015; Sterman, 2000), and use in the food-energy-water nexus has only emerged recently (Al-Saidi and Elagib, 2017; Memarzadeh et al., 2019; Phetheet et al., in review; Schulterbrandt Gragg et al., 2018). FEWCalc is designed to engage stakeholders using the framework of farm incomes. In this article, we use FEWCalc to assess local impacts of global drivers.

1.2. Test case: the high plains aquifer

This work uses data from Garden City, Kansas, USA (Fig. 1) and the surrounding Finney County, which occupies 3375 km^2 (1303 mi^2). Both are located in the northern part of the Arkansas River Basin, in the southern HPA of the USA. The HPA consists of the Ogallala aquifer and its overlying aquifer units. Because irrigation is largely drawn from fossil water, estimates for the lifespan of the southern HPA is on the order of centuries, with high spatial heterogeneity producing much shorter lifespans locally (Scanlon et al., 2012).

The area's water problems are typical of arid agricultural regions around the world. Large-scale irrigation over many decades is the primary cause of depleting groundwater resources and an increasing number of now dry irrigation wells (Buchanan et al., 2015). Reduced pumping and technological advances could extend the life of the region's agricultural economy. However, a primary disincentive for reducing pumping now is the immediate economic impact of diminished irrigation. People, from local farmers to political leaders, are searching for viable ways forward. The region's potential to develop renewable energy, its declining water resources, and its rich, 70-yearlong 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.

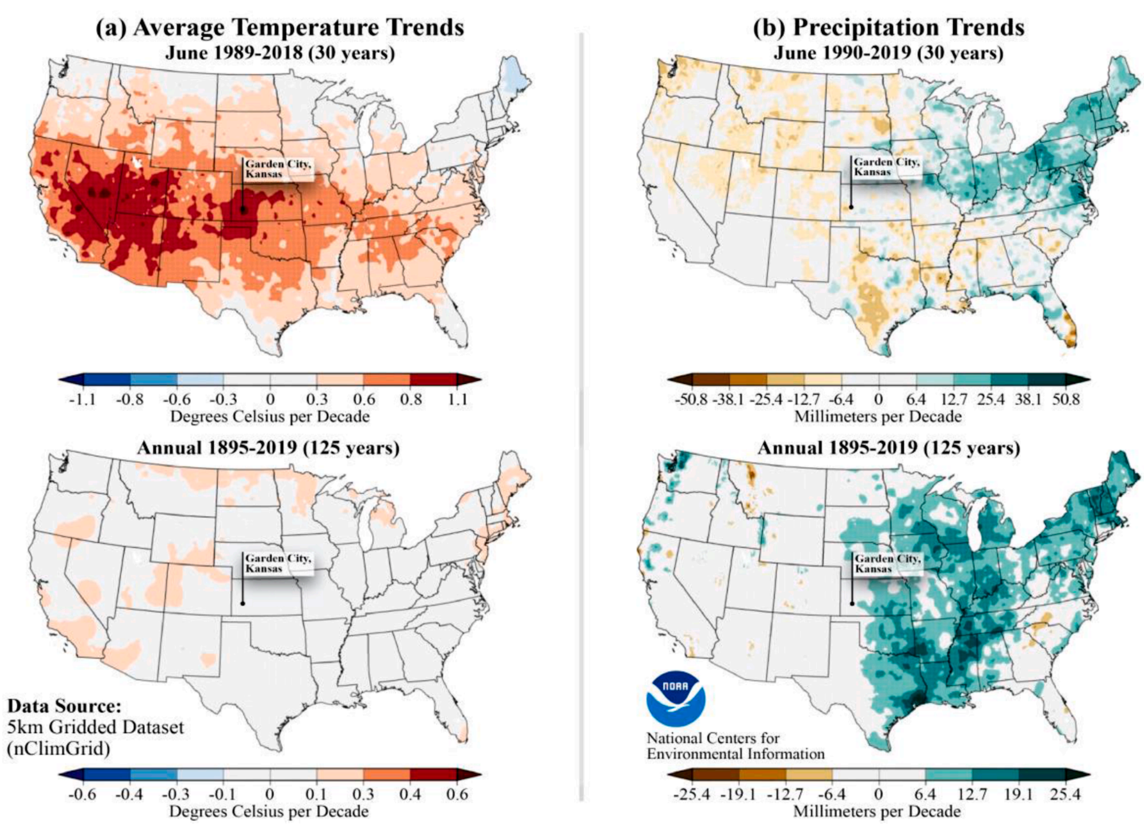

Fig. 1. (a) Temperature and (b) precipitation trends maps for the Continental United States. Historical trends are shown for June (row 1) and annual data (row 2) (modified from NOAA, 2020). Annual average maps and maps for additional months are available at https://www.ncdc.noaa.gov/temp-and-precip/us-trends.

2. Data and methods

The FEWCalc workflow and calculations are described by Phetheet et al. (in review). As programmed, all costs are in US dollars. Here, the climate data used in this study are discussed, followed by a brief description of how agriculture, water, and renewable energy are simulated.

2.1. Weather, climate, and projections

Daily weather data for air temperature, precipitation, and solar radiation are used as input to DSSAT (Tsuji et al., 1994). In this work, solar radiation refers to the total downwelling short-wave radiation that reaches the surface, including both direct and diffuse components. Daily temperature and precipitation data for the 10-year base period 2008 to 2017 were obtained from a weather station at Garden City Regional Airport, Finney County, Kansas (37°55′38′′N, 100°43′29′′W) and can be accessed from the National Oceanic and Atmospheric Administration's (NOAA) National Centers for Environmental Information (NCEI). Thirty-minute solar radiation data at a 4-km horizontal resolution were acquired from the National Solar Radiation Database's (NSRDB) Data Viewer provided by the National Renewable Energy Laboratory (NREL) (Sengupta et al., 2018). WeatherMan (Pickering et al., 1994) is used to import, harmonize, and error-check the daily weather data.

Two scenarios are considered in this work. Both are 91 years long and begin with the historical weather data from the 10-year base period 2008 to 2017. This 10-year period is presented in the context of data since 1950 in Fig. 2, in which wet and dry historical periods are identified using the Palmer Drought Severity Index (PDSI) (Palmer, 1965). The 2008–2017 base period provides a complete set of weather and agricultural data and includes wet, moderate, and dry years (Fig. 2). For the remaining 81 years of the two scenarios, 2018 to 2098, air temperature, precipitation, and solar radiation are defined using projections from global climate models based on Representative Concentration Pathways (RCPs) 4.5 or 8.5 (IPCC, 2014).

To compare with the base period and project into the future, we use data produced as part of the Coupled Model Intercomparison Project Phase 5 (CMIP5) (IPCC, 2014), which was downscaled using the method of Multivariate Adaptive Constructed Analogs (MACA) developed by Abatzoglou & Brown (2012). Model data for Garden City, Kansas, was obtained for the ~4-km grid cell corresponding to our meteorological station and can be downloaded from https://climate.northwestknowledge.net/MACA/data_csv.php. MACA provides downscaled versions of both RCPs 4.5 and 8.5 as alternative future pathways for global greenhouse gas concentrations. RCP 4.5 is an intermediate emission scenario where emissions peak around 2040 and then decline (Thomson et al., 2011). In RCP 8.5, emissions rise throughout the projection period, and this scenario produces the most warming among the RCPs (Riahi et al., 2011). RCPs 4.5 and 8.5 correspond to a 5–95% likelihood range of global temperature increases of 1.1–2.6 °C and 2.6–4.8 °C, respectively (IPCC, 2014). While the plausibility of RCP 8.5 has been a source of vigorous discussion in the climate community (Hausfather and Peters, 2020; Moss et al., 2008), projections based on current policy suggest a central estimate of 3.2 °C of warming by 2100 and a 10% chance of at least 4.4 °C of warming (Rogelj et al., 2016). In addition, current policy implies future outcomes are likely to reside on the higher end of this range. As such, both RCPs 4.5 and 8.5 are included in FEWCalc to bracket potential impacts given uncertainty in future climate policy, and model structure and parameter values.

2.2. Agricultural, energy, and water calculations

For agriculture, DSSAT is used to calculate irrigated and dryland crop yield and irrigation water demand using temperature, precipitation, and solar radiation values measured for 2008 to 2017 and the GCM model results for 2008 to 2098. Other variables required by DSSAT and FEWCalc are derived from the historical period 2008 to 2017. This includes, for example, crop-related capital costs, expenses, cultivars, market prices, and operational practices; energy capital costs, expenses, and prices, and operational practices; and groundwater extraction costs and response of groundwater levels to pumping. This approach is taken for two reasons. One is that speculation about what adaptations may occur in the future is highly uncertain. The second is that this analysis provides a baseline estimate of the likely need for adaptation to climate change.

Application of DSSAT to the test case location, and calculation of farm income from agriculture and energy investments including crop insurance, and the impact of irrigation on groundwater supplies calculated in FEWCalc are presented in Supplemental Appendix D and described in detail by Phetheet et al. (in review). Figs. C.5 and C.6 show the FEWCalc input values used in the simulations for which results are presented in this work, except that ITC_S (the investment tax credit for

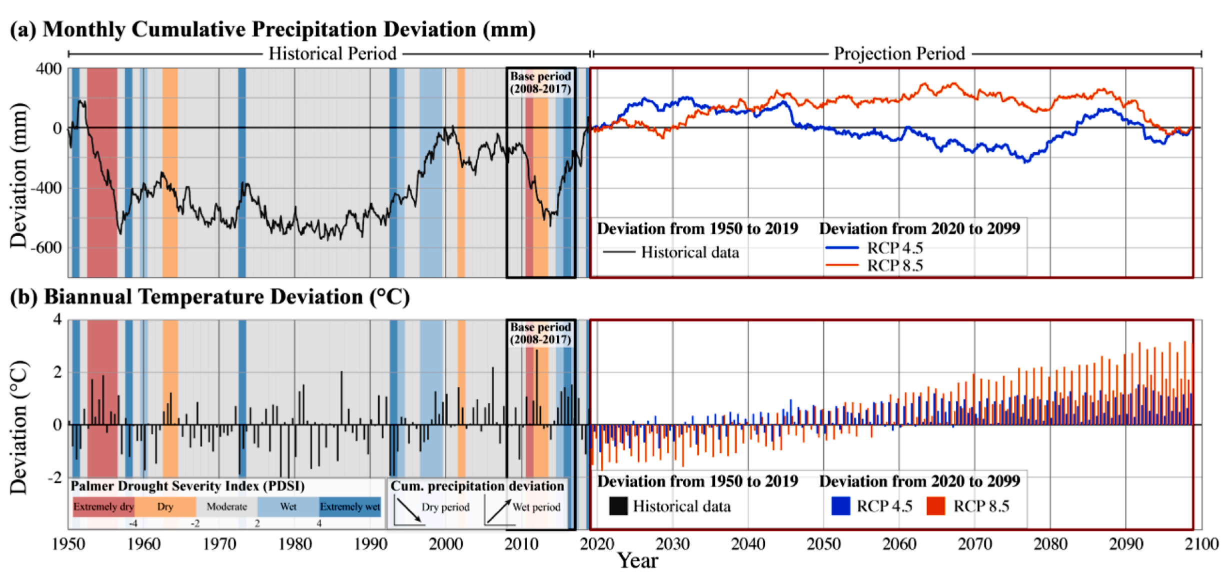

Fig. 2. (a) Monthly cumulative precipitation deviation, and (b) biannual temperature deviation data from 1950 to 2099. For a, the deviations are from monthly average precipitation over the related periods of time – either the historical or projection period RCP. Projections to 2099 are averaged monthly values from 20 global climate model realizations. Because they are averaged, they tend to have smaller variation than the historical data.

solar) is set to 30%. Selected characteristics needed to understand the results presented in this work are listed here.

- Crop prices and expenses and whether global crop prices are correlated with weather conditions in the study area are derived from the 2008–2017 data. Thus, for example, corn and grain sorghum global crop prices tend to be higher during periods of drought in the study area.
- Loss in agricultural production due to climate variability, especially droughts, is insured when crop yield is less than a previous 10-year average yield times the level of coverage defined by users.
- All irrigation water is simulated to come from groundwater. Groundwater levels are calculated to decline in response to irrigation demand based on a two-step, regression-based process. This process is used to relate the simulated water use for irrigation to reported groundwater level changes. If the groundwater level falls below a user-defined threshold that would typically be derived from the subsurface geology, irrigation is no longer supported and dryland farming occurs.
- To represent economic diversification to support rural communities in a way that would reduce carbon emissions, locally owned solar and wind renewable energy resources are simulated. Capital costs, some financial costs, depreciation, equipment performance degradation over time, and some tax incentives typical of the study area are simulated. The user-controlled average energy sales price was set at $38/MWh for the results shown. This price would reflect a combination of net-metering, power-purchase agreements, and wholesale arrangements.
- The impacts of climate change are expected to be greater for agriculture than for energy, and thus are not considered in the energy calculations.

This work uses sets of 20 DSSAT runs in which projected values of air temperature, precipitation, and solar radiation are obtained from 20 downscaled GCMs representing years 2008 to 2098. Results from the 20 DSSAT runs are averaged to obtain irrigated production and water use, and dryland farming production values used in FEWCalc.

3. Results

This section consists of two parts: (1) synthesis and interpretation of climate forcing; (2) consequences for agriculture and water, in the context of potential economic diversification through renewable energy development, using results from DSSAT and FEWCalc.

3.1. Synthesis and interpretation of climate forcing

Analysis of RCP 4.5 and 8.5 climate model outputs are summarized in Figs. 1–4. Evaluation of the climatology of Garden City, Kansas, is needed to understand how response variables in DSSAT and FEWCalc inherit differences from alternative emissions-based scenarios.

Fig. 1a (top) suggests that during the period from 1989 to 2018 the area around Finney County experienced considerable warming in June, a critical month for agriculture. Data from the Garden City airport weather station shown in Fig. A.1 is consistent with the trend identified in Fig. 1a. Temperature trend maps at this station over the same period (not shown) also show increasing annual average temperatures, though the rate of increase is more modest than summertime temperatures. In contrast, an identical analysis using data from 1895 to 2018 (Fig. 1a, bottom) shows little annual temperature change. This implies that lower temperatures prior to 1989 offset more recent increases.

In Fig. 2 (right panel), the values in the projection period are derived from average values from the 20 different GCMs, thus providing a measure of the 21st century climatology of precipitation, temperature, and solar radiation. The historical data (Fig. 2; left panel) is more variable because it is only one realization that represents the actual weather experienced at this site. Unsurprisingly, the values plotted for the projection period suggest a gradual increase in temperature, with the increase being greater for RCP 8.5. Stochastic fluctuations among individual GCMs vary in ways that are more similar to the historical data in the beginning of the projection period, though may be more variable in later years. Further evaluation of this source of variability is beyond

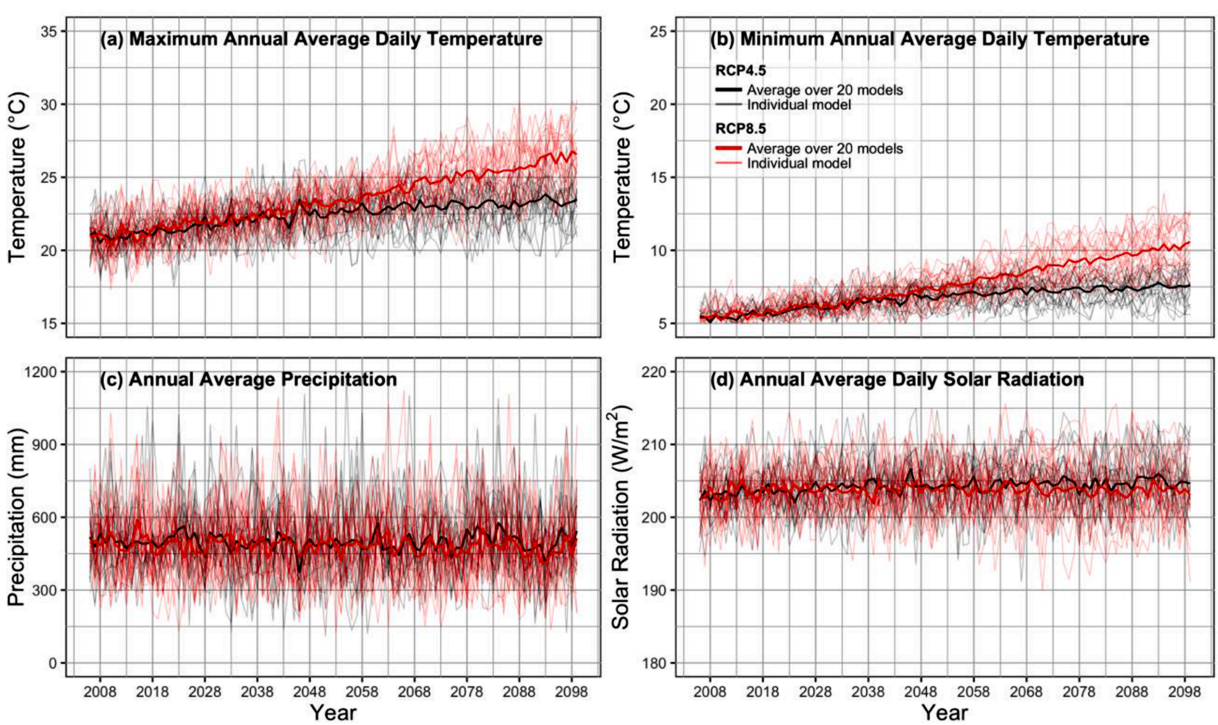

Fig. 3. Comparison of annual average projected weather data between the Representative Concentration Pathway (RCP) 4.5 and 8.5 scenarios obtained from 20 downscaled global climate models between 2006 and 2099.

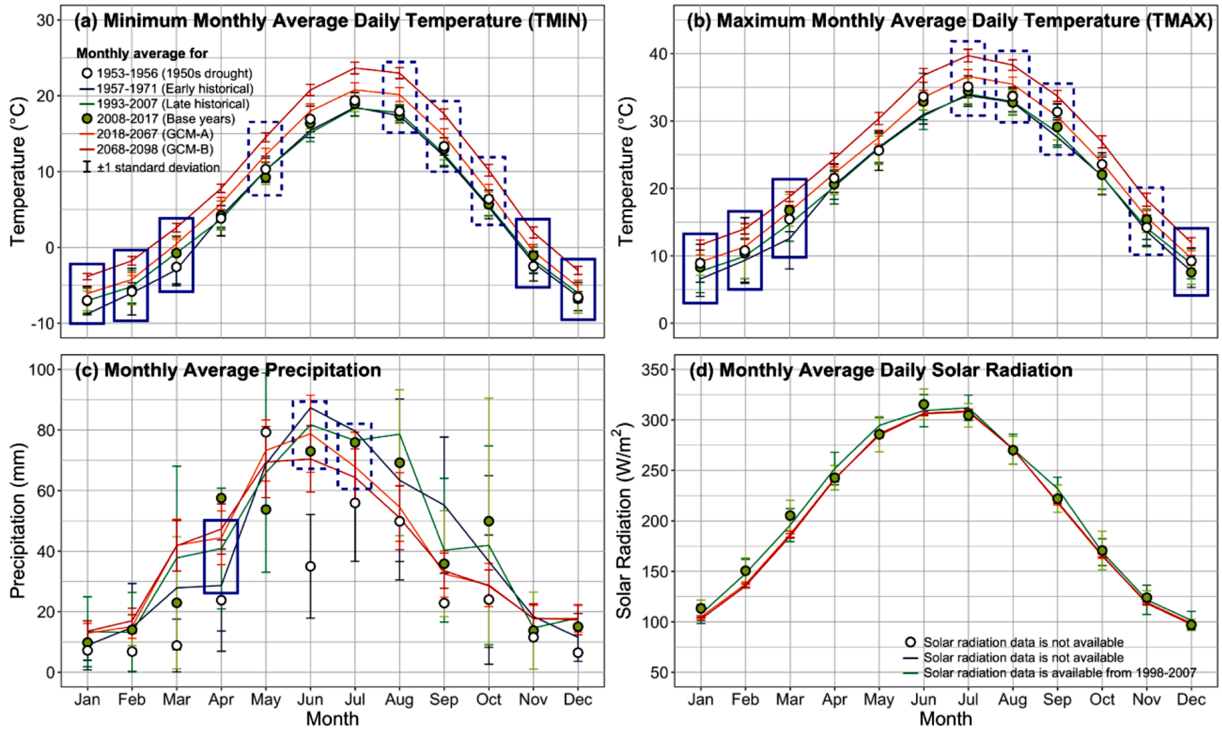

Fig. 4. Historical and projected average monthly weather data for Garden City, Kansas. Two short historical periods of time (4 to 10 years; dots) are provided to show how averages from the 1950s drought of record in the study area and the base period used in this work relate to longer-term averages. Lines are used for four longer data sets – two historical and two projected. The GCM results use RCP 8.5.

the scope of the present study. Mean values plotted for projections in Fig. 2 suggest a consistent increase in temperature. The temperatures start out lower than historical values because of differences in the reference period used for calculating anomalies. Projected precipitation values suggest very contrasting histories for RCPs 4.5 and 8.5 (Fig. 2), though mean annual precipitation is largely invariant over the projection period (Fig. 3). RCP 8.5 produces mostly wet or stable averages until the end of the projection period when there is a dry period. In contrast, RCP 4.5 fluctuates between dry and wet periods with a prominent water deficit between the years 2048 and 2078.

Fig. 3 illustrates the basic differences between the climate scenarios in terms of the variables used to drive DSSAT and FEWCalc. Thin lines represent individual GCM results with bolded lines representing the ensemble average. Trends in minimum and maximum temperature largely mirror global ones, where RCP 4.5 shows increases until ~2040′s at which point it starts to stabilize at ~2 °C of warming, and RCP 8.5 continues to increase throughout the projection period to produce ~5 °C of warming. Importantly, there is not a significant long-term trend in either mean annual precipitation or solar radiation at this site. As such, we interpret changing temperatures as the key driver to DSSAT and FEWCalc results below.

To examine whether differences exist for seasonal patterns of climate variables in alternative climate scenarios, Fig. 4 shows monthly averages for different time intervals (long-term averages as lines; shorter-term averages as points). Climatic trends can be difficult to identify from historical data because of natural variability. As such, solid and dashed boxes are used to highlight when the trends from the climate projections are consistent with historical trends, thus indicating that the anticipated changes are likely already happening. Rectangles identify when two 15-year historical periods (blue and green lines) define the same trend direction as the two GCM projection periods (2018–2067 in orange and 2068–2098 in red) using RCP 8.5. Solid rectangles identify months for which historical changes exceed 5%, and dashed rectangles identify months where historical changes are smaller but still consistent with the direction of the GCM trends. Two key historical periods of a decade or less, shown using points, illustrate conditions during the record drought period 1953–1956 and during the 2008–2017 base period used in this work.

Results shown in Fig. 4 show that there are commensurate increases in temperature in model data at all times of year. This can be gleaned from historical data as well in the winter and shoulder seasons, but only emerges in the climate model data for the summer months. With respect to precipitation, Fig. 4 shows that precipitation will stay the same or increase during winter and spring, and decrease from July to October, resulting in less seasonal variation. With respect to solar radiation, Fig. 4 shows only very slight declines (~5.4 W/m^2) concentrated in the first half of the year. Recall that solar radiation in this model includes both direct and diffuse components and is thus sensitive to the style and timing of cloud cover (NREL, 1992). Solar radiation from climate models is affected by clouds and aerosols, which are some of the largest sources of uncertainty in the energy balance of global climate models (Boucher et al., 2013).

Fig. 4 also shows monthly values for two shorter time periods. The first of these is from the 10-year period between 2008 and 2017 and used as the base period for FEWCalc. While seasonal variations in all climate parameters are noisier than longer-term averages, they are representative of historic values within uncertainty. The second of these is from 1950 to 1956, a very dry historic period that includes the drought of record for this region. Of interest is how the characteristics of this very dry period compare to the characteristics of future projections. Does this ‘extreme’ past event provide clues of what future projections portend? Seasonal temperature patterns over this period were modestly higher over this period, but substantially less than the projected temperature changes associated with climate model projections. This historic drought was largely driven by a deficit in water supply. Overall, precipitation was lower during all months during this period, but is marked by much lower spring and summer precipitation (sans May). This precipitation pattern is only similar, in part, with climate projections of a warmer future (e.g., contrast with higher spring precipitation and lower summer precipitation for both RCPs 4.5 and 8.5). As such, it is unclear how historic droughts driven by reductions in water supply will compare to future ones driven by increased surface temperatures. Anticipating future impacts requires explicit modeling of crop yields under future environmental conditions.

3.2. Consequences evaluated using DSSAT and FEWCalc

The ensemble approach used in this work produces DSSAT results for each of the 20 individual climate models, for the RCPs 4.5 and 8.5. To illustrate, the results for corn are presented in Figs. 5 and 6. Results for wheat and grain sorghum are shown in the Supplemental Appendix B, see Fig. B.1 to B.3. For the 2008–2017 base period, historical data and DSSAT results are provided in addition to the GCM results.

The averages of the 20 DSSAT runs are used in FEWCalc to relate the average agricultural yields and water demands and user decisions about crops and energy investments into profits and resource limits. Results are presented in Fig. 7.

4. Discussion and conclusions

In general, variability of the base period observations and DSSAT model runs are similar to each other and to the GCM model results (Fig. 5). This provides a test of the GCM results and suggests the approach taken in this work is defensible. Fig. 7 shows the FEWCalc results. During the base period (2008–2017), farmers receive the same set of income for both scenarios. Income varies after that period depending on the RCP scenario applied. Results for the two scenarios are similar, with RCP 8.5 results being slightly worse in terms of crop yield being less, water use being more, and agricultural income being less.

These results suggest that larger climate impacts, such as those under RCP 8.5, will have greater negative impacts on the SDG 2 (zero hunger), and SDG 6 (clean water and sanitation).

Results also illustrate the economic difficulties faced by farmers in this region. Low crop prices and increasing costs in recent decades have challenged profitability. The crop prices and expenses used in this work are typical values reported by the Agricultural Extension Service at

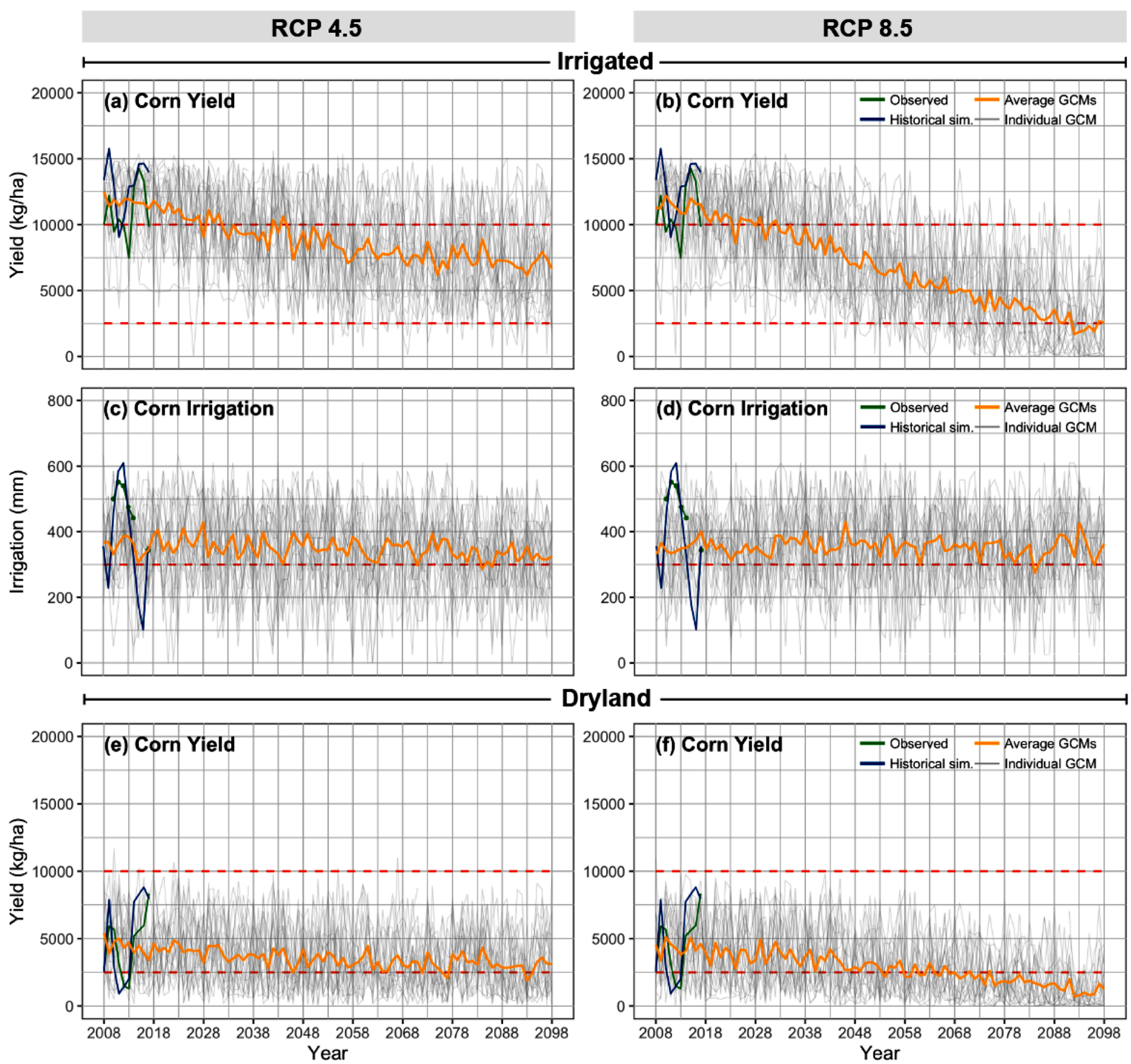

Fig. 5. DSSAT output for corn, including irrigated and dryland conditions. Observed values (2008–2017) were measured by Kansas State University for crop yield (a-b and e-f) and Kansas Department of Agriculture for irrigation water demand (c-d) (green line). Historical simulated values are from DSSAT using historically measured climate variables (blue line). Light gray lines show simulated 2008–2098 results from DSSAT using climate variables from 20 individual downscaled GCMs (gray lines) and the average for all climate models (gold line) under the RCP 4.5 and 8.5 scenarios. Red dashed lines identify selected values to highlight trends. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

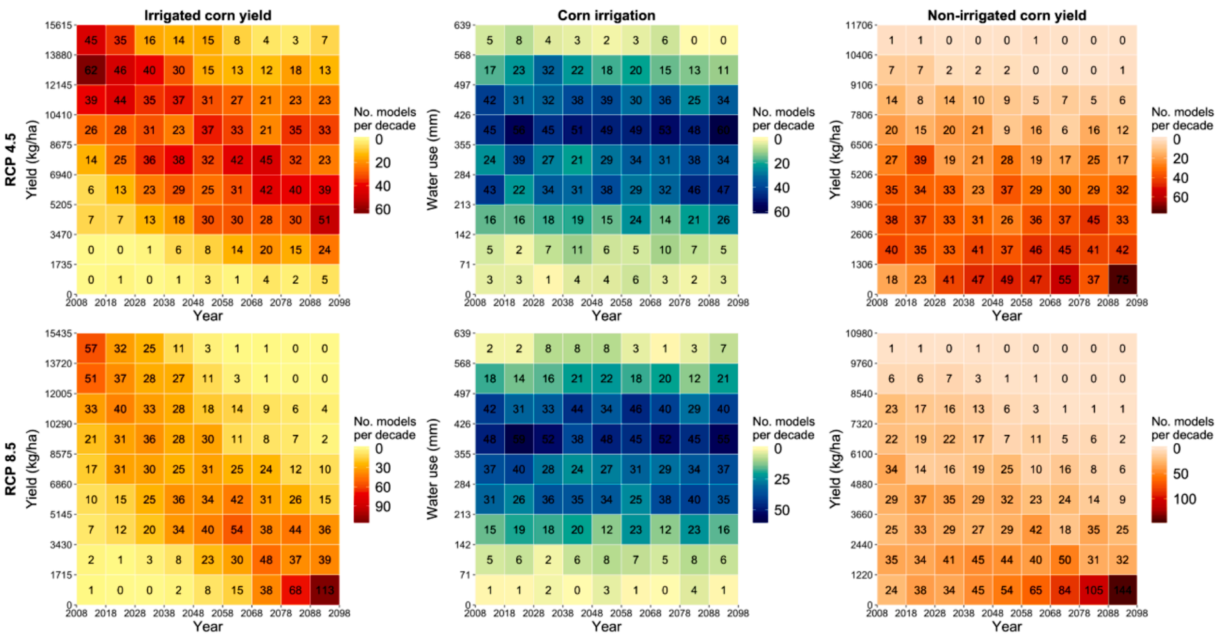

Fig. 6. DSSAT results calculated from 20 GCMs classified based on irrigated corn yield and water use (y-axis), and unirrigated corn yield, per decade (x-axis), shown using heatmaps of number of models. Results are presented for RCP 4.5 (upper row) and RCP 8.5 (lower row).

Kansas State University. The FEWCalc analysis presented here indicates that under normal circumstances making a living in agriculture is difficult, and will become more so under climate change. Success requires creative approaches not represented in the typical conditions simulated here. Our results show that renewable energy development can provide economic support for STAR communities while at the same time promoting SDG 7 (affordable and clean energy).

The results also suggest that climate change is likely to make things even more difficult given a continuation of current crop prices and expenses. RCP 8.5 global climate change predictions would need to be met with effective technology changes to avoid a negative crop production trend from year to year for the future period. Irrigated corn's net income is projected to decrease over time and is considerably worse after simulation year 22 (2029). Net income decreases during the dryland simulation. Farmers will not continue with a strategy that loses money, which suggests that in practice the projections shown would not happen and instead results would be modified by, for example, (1) operational adaptations that increase income under irrigated conditions, (2) increased prices that result in increased income under irrigated conditions, and/or (3) conversion of land to dryland farming with its lower yields and impacts on food security even when groundwater is available for irrigation. In Fig. 7, scenario RCP 4.5, the first dryland farming is applied in year 55 (2062), causing large crop production drops.

The results shown reflect the technology and best practice typical of about 2020. As such, they illustrate the challenges faced by technical innovation and operation adaptation.

Specific aspects of Fig. 7 are discussed in the following paragraphs.

Water. Why is the irrigation demand so unresponsive as yields decline (see also Fig. 5)? The arid-region dynamics add-on used in DSSAT limits the water. In Fig. 7, irrigation increases slowly before the groundwater levels fall below a user-defined threshold and dryland farming begins. Even while water is available, irrigation in this area is conducted in a frugal manner. The arid-region dynamics add-on accounts for this. Without this add-on, DSSAT provides as much water as the crop demands and both crop yields and water use are inconsistent with historic records. Restricting irrigation in this way was important to obtaining the good match shown between the blue and green lines in Fig. 5.

Crop Insurance. Fig. 7 shows that the FEWCalc-simulated insurance claims start during any period of transition to dryland farming when the current yield drops below the actual production history to a crop-dependent factor. For this work, the factors are corn 75%, wheat and soybeans 70%, and grain sorghum 65%. There are other common situations in which crop insurance is indemnified, such as hail storms and floods, but these are not represented in FEWCalc. The results suggest that if a large-scale conversion from irrigated to dryland farming occurs, considerable and perhaps overwhelming demands could be made on yield-based insurance agreements. In such circumstances, the viability of the insurance companies could be problematic.

Energy. The energy production and income is the same for the two scenarios. Changes in wind speed and solar radiance could affect energy production. Wind speed values produced by global climate models are not considered very reliable and current results for solar radiance indicate little change through 2099, as shown in Fig. 4d. Thus, these effects were not considered in the simulations. The effects of equipment degradation over time are apparent in the slow declines in the production graphs and have a considerable impact on resulting net income. The highest peaks in the wind net income result from favorable capital depreciation rules. The highest solar net incomes occur between when the loan is repaid and the equipment next needs to be replaced.

Results suggest that even the moderate climate change impacts from RCP 4.5 are likely to strain an agricultural system that already has a difficult financial and ecological situation. Larger impacts, such as those in RCP 8.5, would strain STAR communities and their associated agricultural systems even further. These outcomes would have adverse impacts on SDG 2 (zero hunger) and SDG 6 (clean water and sanitation). However, these results suggest that renewable energy development may be a useful mechanism for economic diversification of STAR communities, which would reduce farmers' reliance on agricultural production. If this diversification can be achieved, the resulting renewable energy development will have positive impacts on SDG 7 (affordable and clean energy), and the farmers' reduced dependence on agricultural income may lead to reduced water withdrawals, with consequent positive impacts on SDG 6 (clean water and sanitation). Moreover, the broader economic base provided by renewable energy development may allow some farms to continue agricultural activities at a reduced level beyond the point where they may otherwise have ceased operations, which would reduce adverse impacts on SDG 2 (zero hunger).

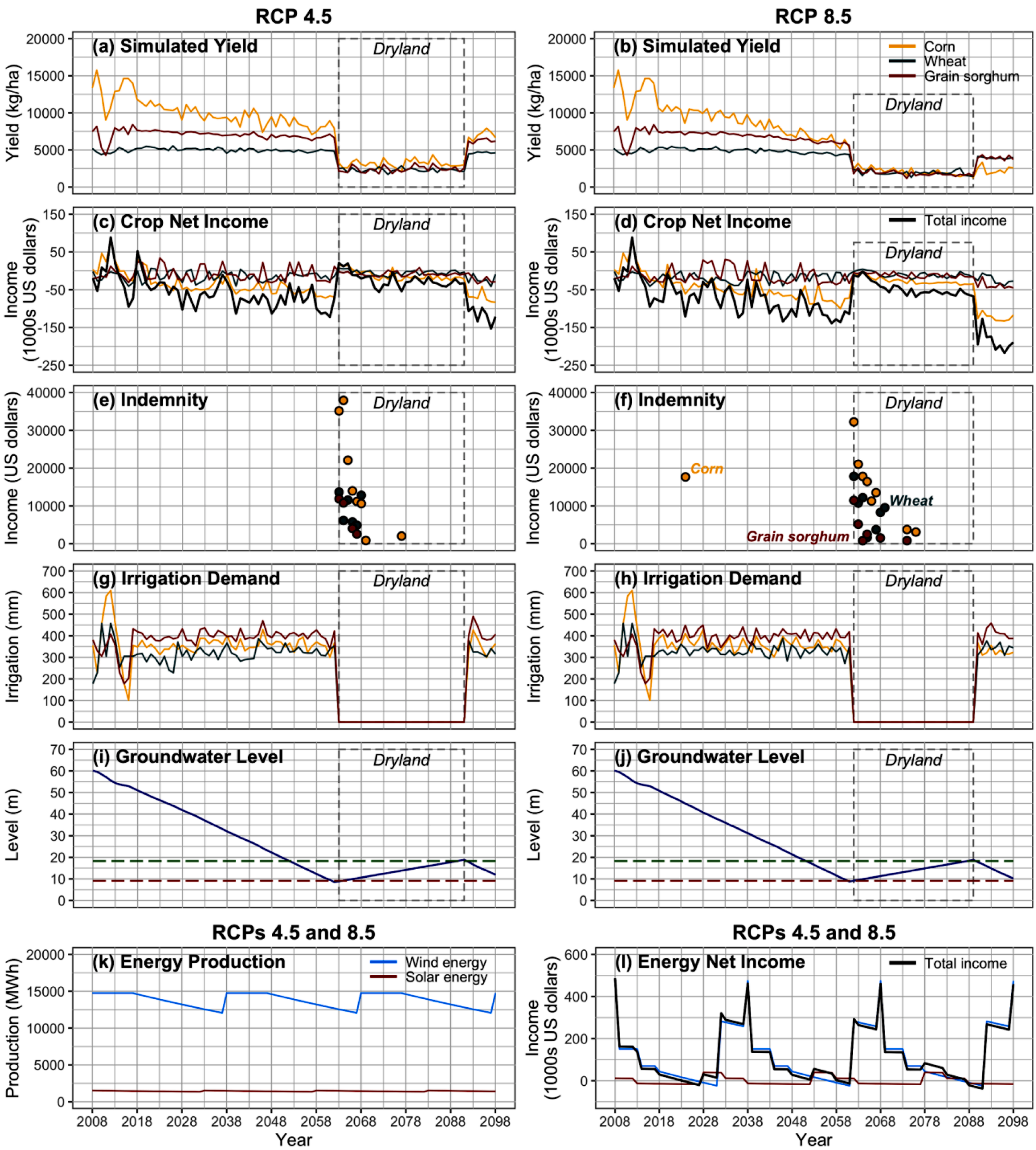

Fig. 7. RCP 4.5 and 8.5 FEWCalc simulated results. The 10-year base simulation is followed by an 81-year projection based on averaging results calculated for 20 downscaled global climate models from 2018 to 2098 under a moderate (RCP 4.5) and high (RCP 8.5) carbon future.

Finally, a few words about the new software developed for this analysis. 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. In this work, FEWCalc was used to evaluate the impact of two climate change scenarios, RCPs 4.5 and 8.5.

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 (ABM) 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. 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. Currently, FEWCalc's input data is based on a particular site with certain climate conditions. To model another area, a new site-specific DSSAT input would be required. Technological development and agricultural adaptation are not presently simulated, and it is assumed that future crop prices and expenses remain in historical ranges. Thus, the simulated results shown address the question of what would happen if current operational conditions continued as climate changes and illustrate the challenges that such changes pose. Addressing different questions would require defining how additional FEWCalc inputs would change over simulated time.

Results suggest that climate change is likely to introduce challenges to an already stressed agricultural system and to achieving the United Nations Sustainable Development Goals.

Instructions for downloading and running FEWCalc and a list of default input variable values are provided in Appendix C of the supplemental materials. The basic equations used in FEWCalc are listed in Supplemental Appendix D.

Credit author statement

Jirapat Phetheet: conceptualization, methodology, software; *Mary C. Hill:* conceptualization, writing - original draft preparation, supervision; *Robert W. Barron:* conceptualization, writing - original draft preparation; *Matthew W. Rossi:* methodology, writing - original draft preparation; *Vincent Amanor-Boadu:* writing - reviewing & editing, *Hongyu Wu:* writing - reviewing & editing; and *Isaya Kisekka:* writing - reviewing & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.resconrec.2020.105309.

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