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Climate Change Would Increase the Water Intensity of Irrigated Corn Ethanol

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Supporting Information

ABSTRACT: Changes in atmospheric CO_2 concentrations, temperature, and precipitation affect plant growth and evapotranspiration. However, the interactive effects of these factors are relatively unexplored, and it is important to consider their combined effects at geographic and temporal scales that are relevant to policymaking. Accordingly, we estimate how climate change would affect water requirements for irrigated corn ethanol production in key regions of the U.S. over a 40 year horizon. We used the geographic-information-system-based environmental policy integrated climate (GEPIC) model, coupled with temperature and precipitation predictions from five different general circulation models and atmospheric CO_2 concentrations from the Special Report on Emissions Scenarios A2 emission scenario of the Intergovernmental Panel on Climate Change, to estimate changes in water requirements and yields for corn ethanol. Simulations infer that climate change would increase the evaporative water consumption of the 15 billion gallons per year of corn ethanol needed to comply with the Energy Independency and Security Act by 10%, from 94 to 102 trillion liters/year (tly), and the irrigation water consumption by 19%, from 10.22 to 12.18 tly. Furthermore, on average, irrigation rates would increase by 9%, while corn yields would decrease by 7%, even when the projected increased irrigation requirements were met. In the irrigation-intensive High Plains, this implies increased pressure for the stressed Ogallala Aquifer, which provides water to seven states and irrigates one-fourth of the grain produced in the U.S. In the Corn Belt and Great Lakes region, where more rainfall is projected, higher water requirements could be related to less frequent rainfall, suggesting a need for additional water catchment capacity. The projected increases in water intensity (i.e., the liters of water required during feedstock cultivation to produce 1 L of corn ethanol) because of climate change highlight the need to re-evaluate the corn ethanol elements of the Renewable Fuel Standard.

INTRODUCTION

Fuel ethanol production in the U.S. is rapidly increasing after the adoption of the Energy Independence and Security Act (EISA) of 2007.[1] By 2022, 136 billion liters per year (bly) [36 billion gallons per year (bgy)] of biomass-derived fuel will be blended with conventional motor fuels in the U.S. From those, up to 57 bly (15 bgy) will be derived from corn. In 2012, the U.S. experienced the hottest July and most severe drought on record in 50 years, resulting in a 12% decrease in corn production.[2,3] This crop shortfall underscores the vulnerability of feedstock-specific mandated fuel targets to extreme weather conditions that could become more frequent and of higher intensity as a result of long-term climate change.

The interdependence between energy production and water resources has been emphasized in recent studies.[4−12] When reporting water use, both evapotranspiration (ET) and withdrawal estimates are relevant. ET affects the water supply, because more ET translates into less runoff and less local recharge, while withdrawals relate to water demand. A combination of larger ET (temporal reduction of supply) and larger irrigation (more demand) can result in a less sustainable situation. In comparison to other energy sources, biofuels have large water requirements. Those are associated with feedstock cultivation.[8] For example, corn ethanol might require about

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1600 L of ET water (lw) per liter of ethanol (le), while 1 L of gasoline requires only about 3 L.[4,8]

When irrigated, corn ethanol uses between 350 and 1400 L of irrigation water per liter of ethanol, depending upon where it is grown. If 20% of the 118 million metric tonnes of corn (4 billion bushels or 44% of the annual production) used to produce 45 bly (12 bgy) of ethanol in 2011 continues to be irrigated at a weighted average of 800 lw/le,[13] it would require 7 trillion liters of irrigation water/year (tly). Currently, this represents only 4.4% of all irrigation withdrawals in the U.S. (corn is primarily grown in the rain-abundant Midwest, whereas the irrigation-intensive Western states cultivate mainly other crops) and 1.5% of all national water withdrawals.[14−16]

Biofuel crops are vulnerable to droughts (i.e., termporary water scarcity) and to long-term climate-induced water stress. Consequently, a sustainable biofuel policy should consider how climate change would alter both water supply and demand and, in turn, how related changes in water availability will impact the production of biofuel crops.

Different aspects of global climate change (e.g., CO_2 concentrations in air, temperature, and precipitation) are known to affect ET, irrigation demand, and crop yields,[17−21] but the combined effects of these variables are relatively unexplored at the scale required for national policy decision-making. The effects of climate change on crop productivity and plant water demand and the hydrologic cycle have been addressed to some extent before.[17−20,22,23] However, few studies if any considered the effects of climate change on both crop productivity and water use as proposed here.[1,23] We consider these effects at temporal and spatial scales and resolutions that are relevant to U.S. bioenergy policy and that enable more accurate modeling of plant physiology. Specifically, we consider plant response to relevant environmental factors and generate geographically distributed information on corn yields, ET, and irrigation requirements under present conditions and on a 40 year horizon. In doing so, we discern specific challenges of the EISA of 2007, which expanded the Renewable Fuel Standard (RFS).

The water intensity[4] denotes here the liters of water required during feedstock cultivation to produce 1 L of corn ethanol (lw/le), thus recognizing that the agricultural stage of the fuel ethanol life cycle exerts a significantly higher water demand than fuel processing and use.[4−12] Water requirements are estimated per liter of biofuel rather than per unit area to facilitate extrapolation to biofuel volumetric production targets. We make a distinction between irrigation water intensity (IWI), which is based on irrigation water estimates, and evaporative water intensity (EWI), which is based on plant ET estimates. The later affects water supply, because the more water that is evapotranspired, the less it will replenish the supply, while the former relates to water demand.

Simulations were run using geographic information system (GIS)-based environmental policy integrated climate (GEPIC),[24] a geographically distributed agronomic model, thus enabling consideration of spatial heterogeneity of environmental factors through the use of distributed data sets. A daily time step as a basis for calculations incorporates the effects of daily weather variability and its effects on plant physiology throughout all growing phases. To account for climate modeling uncertainty, we run GEPIC with different temperature and precipitation data sets. To account for climate interannual variability, simulated water use and crop productivity were averaged over a 10 year period. We first construct a scenario based on recorded climate data for 1995−2004 (baseline). This is compared to simulations for the period 2050−2059 (future scenario). Through this approach, we infer how water requirements in relation to corn-irrigated agriculture for ethanol production will evolve as a result of climate change and, thus, fill a critical knowledge gap for formulating sustainable biofuel and water resources policy. We acknowledge, however, that the expansion of irrigation will only take place if commercial, legal, and economic circumstances warrant it. The evaluation of these non-environmental factors is a good subject for future inquiry.

■ METHODOLOGY

General Modeling Approach. GEPIC[23−25] is based on the environmental policy integrated climate (EPIC) model,[13,26] a United States Department of Agriculture (USDA) agronomic model. The reliability of EPIC at the field and regional scale has been demonstrated by more than 100 studies, including simulations of corn cultivation in the U.S.A.[23−30] Using GEPIC, we combine the power of EPIC to simulate the effects of environmental inputs on each phenological phase of development, with the power of distributed modeling.

The region of interest (continental U.S.) is divided in a 0.5 arc-degrees (about 55 km at the equator) grid, and GEPIC is run independently in each cell of the grid (assuming homogeneous conditions). Atmospheric CO_2 concentrations were set to 369 ppm_v in the baseline period (1995−2004) and 532 ppm_v in the future period (2050−2059) according the International Panel on Climate Change (IPCC) Special Report on Emissions Scenarios (SRES) A2 emission scenario, which is characterized by a steady population increase until 2050 and a high regional heterogeneity in economic development.[28] Five climate data sets are used to account for climate modeling uncertainty. These data sets are described in Table S1 of the Supporting Information, corresponding to simulations by five different general circulation models (GCMs) (CGCM, CSIRO, ECham, Hadley, and PCM), and downscaled using MOD-AWEC.[29] The five-model mean and coefficient of variation (CV) (i.e., standard deviation divided by the mean) are calculated at each cell for each output variable. The CVs indicate deviations between estimates with the five different climate data sets and are taken in this study as a measure of agreement (the lower the CV, the higher the agreement). Final data analysis is performed with R statistical packages, version 2.15.0 (64-bit).

The above considerations address input data uncertainty rather than model uncertainty. The GEPIC model was selected because of the history of successful application of its core model EPIC, which has been developed, calibrated, and applied in the U.S. and elsewhere for studies in multiple crops and locations over 30 years.[23−30,32]

Management interventions (irrigation, fertilizers, and pesticides) are assumed to be infinitely available in our simulations and are applied on demand to eliminate any plant stress caused by water or nutrient scarcity and potential pests. Infinite availability means plant growth will not be limited by such factors, which helps discern how climate change would affect irrigation water intensity. Planting and harvesting seasons are timed through a feedback process aimed at optimizing productivity.[30] ET is calculated using a modified Hargreaves equation[31] that closely matches predictions by the Penman−Monteith equation, which incorporates the effects of CO_2 on ET.[32] Model equations and detailed information on input variables are described in detail in Table S1 of the Supporting Information. We focused on the 10 states that contribute to 84% of U.S. corn production (Table S2 of the Supporting Information), grouped into three USDA farm regions:[33] Northern Plains (South Dakota, Nebraska, and Kansas), Corn Belt (Iowa, Illinois, Missouri, Indiana, and Ohio), and Great Lakes (Minnesota and Wisconsin) states.

Metrics Generated in This Study. High-resolution spatial distributions of three output variables generated with the model are relevant for this study: grain yield (tonne/ha), ET (mm), and irrigation (mm). These output variables are used to calculate the water intensities of biofuels (EWI and IWI, measured as lw/le) as follows: The EWI is estimated by dividing ET (lw/ha) by ethanol yields per area (le/ha), which are a combination of crop yield (tonne/ha) and an average corn-to-ethanol conversion rate of 387 (le/tonne).[34] The IWI (lw/le) is estimated by dividing irrigation rates (lw/ha) by ethanol yields per area (le/ha). Subsequently, differences (Δ) in intensities between the baseline and the future estimates are calculated. Positive changes in water intensity (shown in red) indicate that more water is needed to produce a unit volume of ethanol. Conversely, negative changes (shown in blue) indicate less water is needed to produce a unit of ethanol.

Model Evaluation. We evaluate model accuracy, bias, reliability, and efficiency by comparing simulated and recorded distributed data sets of yields. Although this study focuses on irrigated corn, total yields (from irrigated + rain-fed acreage) were simulated for validation purposes, because independent distributed (grid) data are only available for total yields.[35] Additionally, state-aggregated simulated irrigated yields were compared to USDA state data for the 2000−2005 period.[8,14] We also compared state-aggregated simulated irrigation rates with USDA state data for the same period,[14] as well as the 10-states aggregated ET estimated in this analysis with two national means obtained from other studies.[36,45] Irrigation efficiency factors are not reported in the USDA irrigation data but generally range from 60 to 95%.[38] We used an average irrigation efficiency of 73% as a surrogate factor in our simulations based on the best published data available.[4,39] Note that recorded irrigation values include all uses of irrigation (e.g., salt leaching or fertilizer application), whereas irrigation estimated by the model refers exclusively to the physiological water needs of the plant. Finally, it is important to recognize that the decision to irrigate is influenced by legal (e.g., state-specific water rights) and economic constrains, which are not considered by the model. These factors represent a hurdle to irrigation data validation and interpretation of simulated results.

Model accuracy was tested by examining cell−cell absolute relative error (AbsRE) with

$$|\mathrm{RE}|_c = \left| \left(\frac{Y_{\mathrm{sim}_c} - Y_{\mathrm{obs}_c}}{Y_{\mathrm{obs}_c}} \right) \times \right| 100 \qquad (1)$$

where Y_{sim_c} is the simulated yield in cell c in tonne/ha and Y_{obs_c} is the observed yield in cell c in tonne/ha. High accuracy levels (5−7%) can be achieved with EPIC (single cell model), where model error is dominated by conceptual and parameter uncertainty.[40] In contrast, 20−30% accuracy levels are the acceptable standard in regional studies with APEX[24,41] (a watershed scale version of EPIC), where model error is dominated by data uncertainty. Such uncertainty is for the most part irreducible and is determined by the quality of available information.[24,25,41]

Model bias (systematic error: under- or overprediction) was evaluated quantitatively with the mean of relative errors (mRE) calculated with

$$\mathrm{mRE} = \frac{\sum_i^c \mathrm{RE}_c}{n_c} \qquad (2)$$

where RE_c is the relative error in cell c as calculated with eq 1 and n_c is the total number of cells. A negative value of mRE indicates underestimation, whereas a positive value indicates overestimation.

Model reliability (Rel), defined as the probability to produce accurate results, corresponds to the proportion of sites that produce an absolute error below 30%. It was calculated as

$$\mathrm{Rel} = \frac{\sum \mathrm{cells}[|\mathrm{RE}| < 30\%]}{n_c} \qquad (3)$$

where the number of cells with $|\mathrm{RE}| < 30\%$ is divided by the total number of cells n_c.

Model efficiency was evaluated quantitatively with the Nash−Sutcliffe (NS) model efficiency coefficient.[42,43] The NS coefficient is used in distributed modeling because it evaluates whether a distributed model gives a better estimation of data spatial variability than the mean of the observed data set. It is calculated as

$$\mathrm{NS} = 1 - \frac{\sum_{n=1}^c (Y_{\mathrm{sim}_c} - Y_{\mathrm{obs}_c})^2}{\sum_{n=1}^c (Y_{\mathrm{obs}_c} - \overline{Y}_{\mathrm{obs}_c})^2} \qquad (4)$$

where $\overline{Y}_{\mathrm{obs}_c}$ is the mean of the observed yields. In eq 4, the nominator represents residual variance (simulated − observed) and the denominator represents data variance (observed − observed mean). NS efficiencies can range from $-\infty$ to 1. An efficiency of 0 (NS = 0) indicates that the model predictions are as accurate as the mean of the observed data. An efficiency of 1 (NS = 1) indicates that the model variance is equal to the data variance and identifies the model as a good predictor of regional variability, whereas efficiency less than zero indicates that the model is not a better predictor of the regional variability than the observed mean.[27,43]

Uncertainty Considerations. Despite a long process of input data error reduction,[47] an absolute relative error (AbsRE) greater than the 30%, which is the threshold that is commonly accepted in regional studies,[41] prevailed in 18% of the cells within the major growing regions (Figure 1). Nevertheless, about one-half of the remaining cells had a relatively low AbsRE (<10%). The correlation between GEPIC modeling uncertainty and low cultivated area has been previously demonstrated[30] and is related to irreducible data uncertainty.

The model underpredicts baseline corn total (irrigated + rain-fed) yields on average by 6%, as suggested by a mean relative error of −6.25% (see Table S3 of the Supporting Information). The reliability evaluation shows that the model is a good predictor in about 70% of the cells in the major corn-growing regions (see Table S3 of the Supporting Information). The NS model efficiency coefficient, which indicates whether a distributed model gives a better estimation of data spatial variability than the mean of the observed data set, was 0.59 and positive (see Table S3 of the Supporting Information). Thus, the use of this distributed modeling is useful in representing the regional diversity of the simulated system.

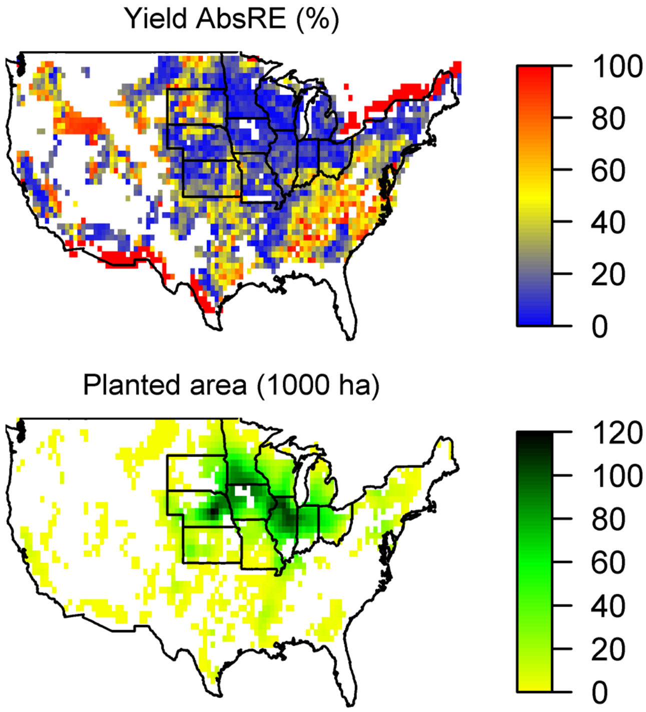

Figure 1. Model error for (a) corn yield (%) and (b) planted corn area (1000 ha). The major growing states that constitute 84% of national production (i.e., Iowa, Illinois, Nebraska, Minnesota, Indiana, Ohio, South Dakota, Wisconsin, and Missouri) are outlined.

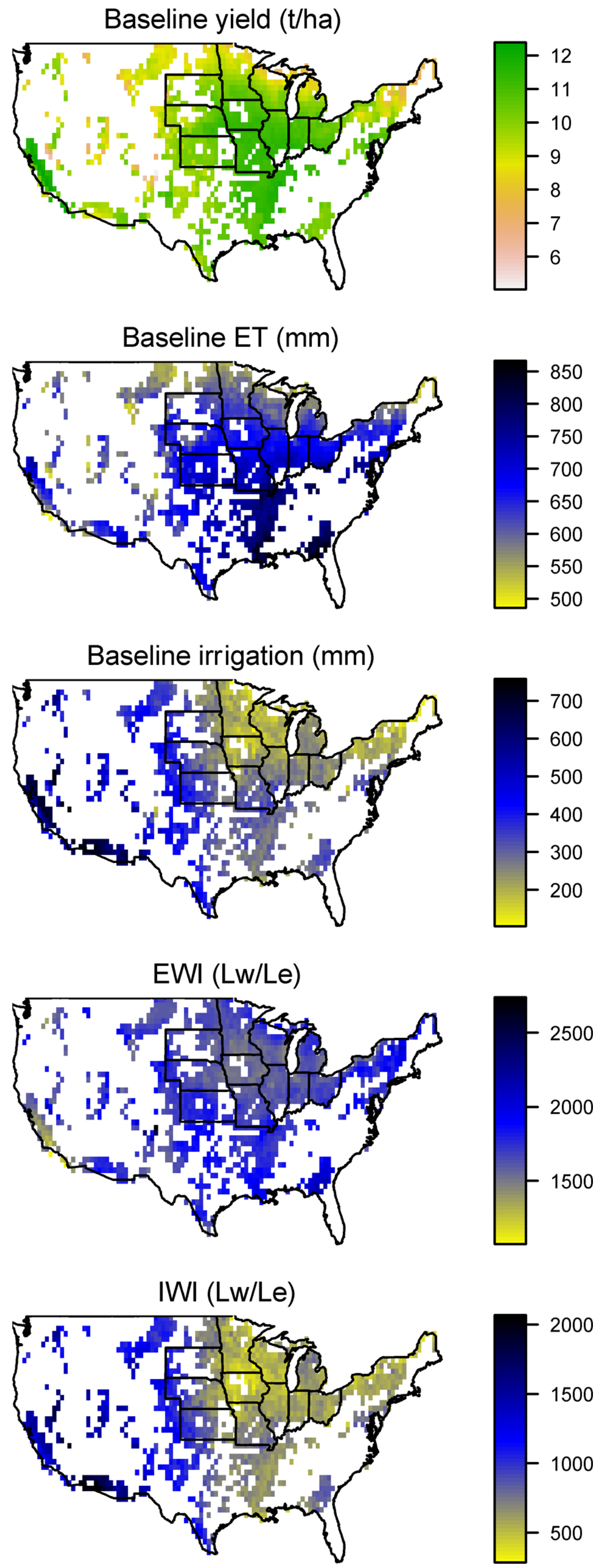

Figure 2. Baseline (1995−2004 average) estimations of yield, ET, irrigation requirements, EWI, and IWI.

On the other hand, simulated irrigated yields for baseline conditions (Figure 2) range from 7 to 13 tonnes/ha, with a 10 state simulated irrigated corn yield average of 10.7 tonnes/ha (Table 1). This compares to an observed national average of 11 tonnes/ha, a 2% deviation, for the simulated period (see Table S4 of the Supporting Information). The irrigated yield is overestimated in Illinois (2%), Iowa (3%), Indiana (4%), Missouri (14%), and Ohio (18%). The yield is underestimated in Kansas (7%), South Dakota (9%), Minnesota (10%), Wisconsin (13%), and Nebraska (13%) (see Table S4 of the Supporting Information).

Simulated baseline irrigation rates in the study area range from 100 to 600 mm (Figure 2). The model underestimates irrigation rates by 1% on average (267 compared to 265 mm recorded values) (see Table S4 of the Supporting Information). Irrigation rates are overestimated for Minnesota by 5%, Wisconsin by 11%, and Nebraska by 12%. Relatively large underestimation occurred for some states (Kansas by 24% and Ohio by 47%), while large overestimation resulted for others (Iowa by 34%, Illinois by 41%, Missouri by 61%, and Indiana by 67%) (see Table S4 of the Supporting Information). Such discrepancies can be attributed to the uncertainties in irrigation efficiencies and irrigation reporting described above.

Baseline ET values range from 500 to 850 mm (Figure 2). While there are no recorded data on ET at the resolution used for this evaluation, the simulated 10 state mean EWI of 1648 lw/le (Table 1) compares to a reported value for the period 1997−2003, corresponding to the U.S. capital region of 1262 lw/le[36] and to a national mean obtained for an undefined period of 1390 lw/le in another study.[45]

The average CV among the five-model future estimates was 0.06 for yield, 0.02 for ET rates, and 0.11 for irrigation rates (see Table S5 of the Supporting Information), meaning that the agreement between projections obtained with the five different climate data sets is higher for yield and ET than for irrigation estimates (Figure 3). This occurs because the purpose of

Table 1. State-Aggregated Model Estimates of Baseline (Subscript B), Future (Subscript F), and Changes (Δ) in Irrigation (*I*), ET, Corn Yield (*Y*), Evaporative Water Intensity (EWI), and Irrigated Water Intensity (IWI)[a]

state	ET_B (mm)	ET_F (mm)	ΔET (%)	I_B (mm)	I_F (mm)	ΔI (%)	Y_B (tonne/ha)	Y_F (tonne/ha)	ΔY (%)	EWI_B (lw/le)	EWI_F (lw/le)	ΔEWI (%)	IWI_B (lw/le)	IWI_F (lw/le)	ΔIWI (%)
Iowa	658	682	3	204	260	28	11	10	−10	1537	1769	15	477	675	42
Illinois	698	727	5	259	267	3	11	10	−9	1610	1854	15	596	681	14
Nebraska	648	641	−1	321	341	6	10	9	−9	1655	1804	9	830	964	16
Minnesota	598	614	3	192	219	14	10	9	−5	1617	1742	8	519	623	20
Indiana	694	724	4	253	262	3	11	10	−7	1624	1813	12	593	656	11
Ohio	689	709	4	249	244	−2	11	10	−3	1680	1787	7	607	612	1
South Dakota	617	605	−2	326	333	2	10	9	−6	1644	1705	4	871	940	8
Wisconsin	590	618	4	190	203	6	9	9	−5	1648	1787	10	534	582	9
Missouri	734	738	1	295	303	3	11	10	−9	1680	1855	10	674	762	13
Kansas	704	689	−2	323	360	11	10	9	−10	1748	1900	9	808	1000	24
all	658	668	1	267	286	7	10	10	−7	1648	1802	10	674	775	15

[a]States are ordered from largest to smaller production. Nebraska and Kansas account for 62% of the total irrigated corn production.

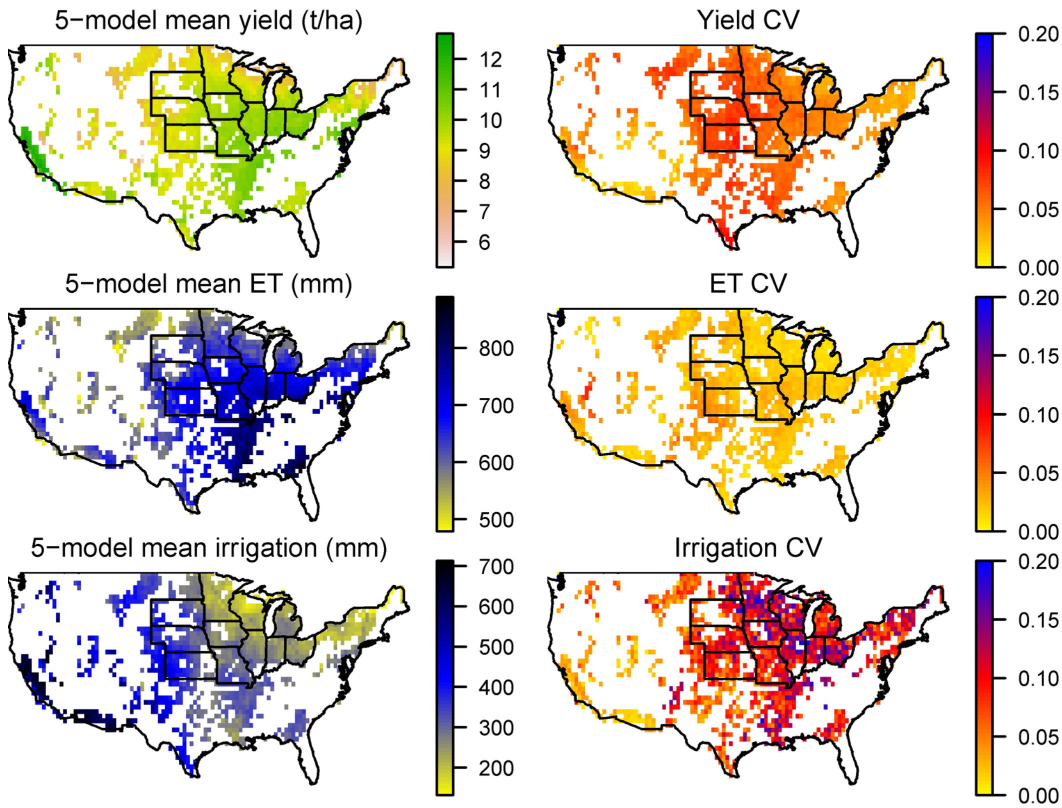

Figure 3. Future (2050s average) mean and CV for corn yield, ET, and irrigation demand simulations with five different climate interpretations (projections by five different GCMs) of the SRES A2 emission scenario.

irrigation in the model is to compensate for insufficient precipitation to maximize yields. Thus, while irrigation estimates are greatly affected by precipitation and variability in precipitation projections by the different GCMs is high[29,46] (thus inducing high variability in irrigation rate estimates), yield and ET rate estimates are affected by the total amount of water provided by both irrigation and precipitation, which vary less because irrigation in the simulations automatically compensates for low precipitation.

■ RESULTS AND DISCUSSION

Projected Climate-Induced Changes from Baseline. The model projects increase in both ET and irrigation water intensity throughout many areas of corn-growing regions as a result of climate change (Figure 4). The overall ET intensity to comply with the 15 bgy of corn ethanol stipulated by EISA would increase by 10%, from 94 to 102 tly based on an increased EWI from 1648 to 1802 lw/le (Table 1). The 10% increase in EWI is the result of a combination of a moderate (1%) average ET rate increase and an average yield reduction of 7% (Table 1). The largest ET rate increases are found in Illinois (5%), Indiana (4%), Ohio (4%), and Wisconsin (4%), while other states might experience small decreases, such as Missouri (2%), South Dakota (2%), and Nebraska (1%) (Table 1). ET generally increases with air temperature, water availability, and length of the growing season. The relatively small simulated ET increases, despite unlimited irrigation and higher temperatures, could be explained by a shortened growing season. This could

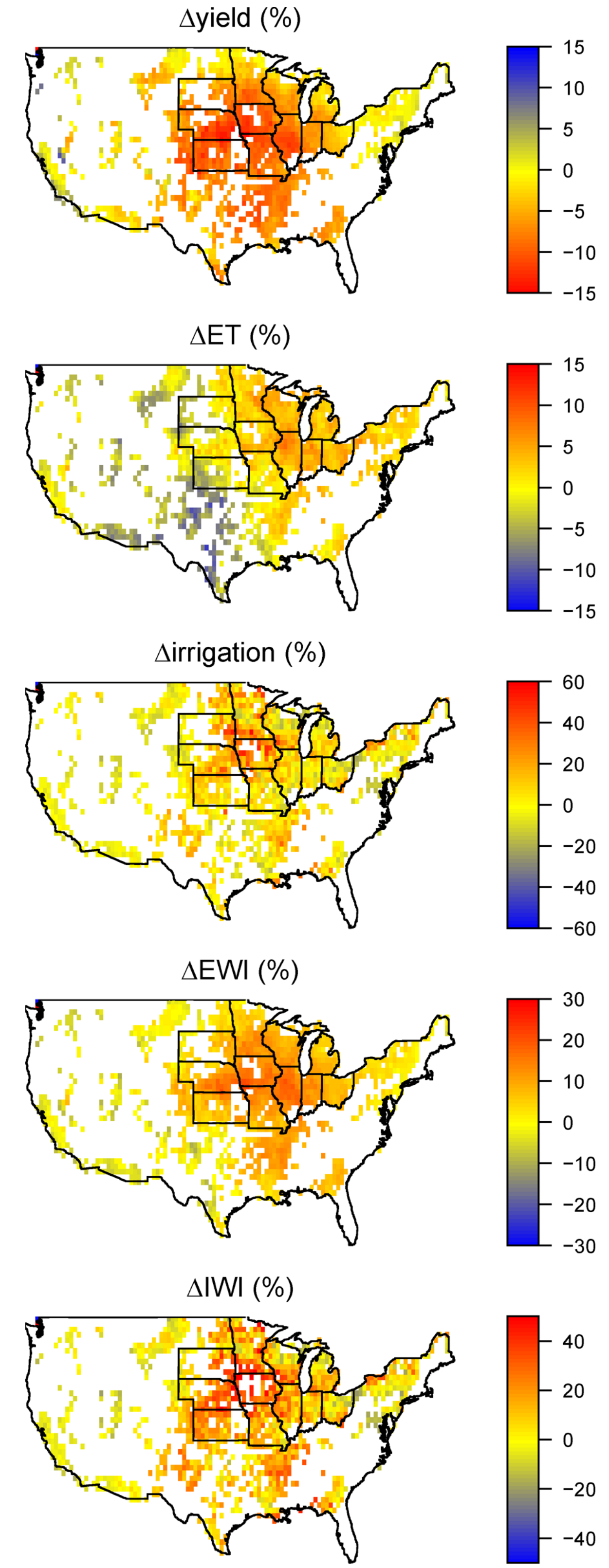

Figure 4. Simulated future (2050s) changes (%) with respect to baseline in yield, ET, irrigation rates, EWI, and IWI. Red indicates a detrimental effect: yield decreases (yield panel), ET or irrigation increases (ET and I panels), and an increase in the amount of water relative to the production of 1 L of ethanol (EWI and IWI panels).

also explain corn yield reductions of 7% on average (Table 1); higher temperatures can also accelerate plant development, producing smaller plants with a shorter reproductive phase, thus contributing to lower grain yields.[18,48−50] The reduction in yield would be experienced in all states considered (Figure 4). The largest corn yield reductions are predicted for Iowa (10%), Kansas (10%), Illinois (9%), Nebraska (9%), Missouri (9%), and Indiana (7%), and the smallest corn yield reductions are predicted for Ohio (3%) (Table 1). This suggests that the detrimental effects of higher temperatures on crop growth are generally more influential than the fertilizing effects of increased atmospheric CO_2 concentrations.

Simulations indicate that irrigation rates would increase by 9% on average (Table 1). The largest average increases in irrigation rates are expected in the main corn-growing states, especially in Iowa (27%), Minnesota (16%), Nebraska (10%), Kansas (10%), and South Dakota (9%) (Table 1). Larger increases (up to 60%) could occur in parts of those states (Figure 4). The projected higher irrigation rates can be explained by the higher ambient temperature in combination with unfavorable (in terms of amount and timing) precipitation occurrence, although it should be recognized that precipitation patterns predicted by GCMs are highly uncertain. The combined average increased irrigation rate of 9% and decreased corn yields of 7% translate into an average IWI increment of 19% (Table 1). The largest increase in IWI was projected for Iowa (42%), Kansas (24%), and Minnesota (20%), and the smallest increase in IWI was projected for Ohio (1%) (Table 1). The expected changes in irrigation rates and IWI to produce 1 unit of biofuel correspond to changes as a result of physiological acclimation only.

Of the states evaluated in this study, Nebraska and Kansas are where the largest irrigated corn acreage currently occurs and where the largest irrigation rates are currently applied (see Table S2 of the Supporting Information). Less precipitation and more ET driven by the higher temperatures projected for these regions mean less recharge of the water supply. This study projects a 10% increase in irrigation water demand for corn in both states (Table 1). Currently, irrigation water in this area is obtained primarily from the Ogallala Aquifer, which provides water to seven states and irrigates one-fourth of the grain produced in the U.S.[50] The Ogallala Aquifer is currently used at a faster rate than it is recharged, and a significant decline in the water table (by more than 100 ft in some areas)[51] is observed in many sites, thus increasing the costs of pumping water.[33,50] Surprisingly, these simulations project a reduction in corn yield (9%), despite the (perhaps unrealistic) assumption that irrigation will be applied as needed. In the absence of water, nutrient, and pest stresses, this would be caused by temperature stresses. The increased irrigation water demands to maintain a nonetheless reduced crop production might prove uneconomical for farmers, especially if water pumping is more costly, threatening the ability to meet the mandated biofuel targets domestically without further subsidies.

In the Corn Belt (Iowa, Illinois, Indiana, Ohio, and Missouri) and Great Lakes (Minnesota, and Wisconsin) states, corn agriculture is primarily rain-fed.[14] In this region, the requirements for irrigation would increase between 5 and 25%. In this case, larger irrigation requirements are related to an unfavorable temporal distribution of rain, with more intense but less frequent rainfall and longer rainless periods, especially during the summer months.[17,35] Meeting increased irrigation needs might require the construction of additional water distribution systems or water catchment capacity, which might pose engineering, legal, or economic challenges. The expense of this additional infrastructure might prohibitively increase the cost of meeting the RFS.

Model Limitations. As explained above, we evaluate plant acclimation to CO_2, temperature, and precipitation (environmental parameters) in combination with unlimited resource (irrigation, fertilizer, and pesticide) use and planting and harvesting timing optimization.

It is possible that our simulations overestimate plant growth because plant response to CO_2 is parametrized in GEPIC after enclosure studies, which tend to overestimate productivity compared to free-air carbon enrichment (FACE) studies.[18] It is also possible that we overestimate ET using the Hargreaves equation instead of the Penman–Monteith equation.[31,32] However, distributed modeling is more sensitive to input data uncertainty than to other types of model uncertainty. Another caveat in this analysis is the use of current corn hybrids and ethanol conversion efficiencies in both the baseline and future scenarios. While we acknowledge that biotechnical advances may someday enable higher biofuel yield per area (i.e., by increased grain and/or whole plant yields in combination with enabled cellulosic conversion), there is no conclusive data available about the water requirements of these crops. Finally, it is important to note that, even if irrigation expansion is justifiable based on physical environmental criteria, the degree to which it will actually happen ultimately depends upon non-physical aspects, such as legal and economic, which are not considered in this study.

Policy Implications. Biofuels have received considerable attention in national and international energy policies as alternative renewable fuels. However, the sustainability of biofuels has also been challenged because of potential impacts on water and other resources.[4,8,9,52,53] Concerns have been raised that first-generation biofuel production often uses grain crops as a feedstock, which can negatively impact the availability of the food supply in international markets. To the extent that biofuel expansion in the U.S. would put more pressure on water scarcity and arable lands, it may contribute to food price hikes, as observed from 2006 to 2008.[23,52,54]

We find that changes in climate in certain areas in the U.S. in the coming decades could lead to reductions in crop yields and an increase in irrigation demand. These projections highlight the need to re-evaluate the sustainability of transportation biofuel policy that requires feedstock-specific levels. While we acknowledge that the findings of this study are subject to specific model and data uncertainties, simulations for some areas of the U.S. are sufficiency robust to warrant further investigation. In particular, we recommend additional quantitative analysis on the future role of irrigation requirements for corn production to enable integrated water management.

ASSOCIATED CONTENT

Supporting Information

Details on the GEPIC model equations, input parameters, and relevant statistics. This material is available free of charge via the Internet at http://pubs.acs.org.

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Notes

The authors declare no competing financial interest.

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