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The Water Footprint of Fuel Ethanol

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Abstract

Biofuels (i.e., biomass-derived fuels) play a key role in discussions in the United States about energy security, agriculture, taxes and the environment. Although their potential to reduce our dependence on foreign oil and to mitigate climate change is still being debated, biofuels constitute a renewable domestic resource, offer advantages to air quality improvement, and provide alternative revenue for agricultural producers. In 2007, Congress enacted the Energy Independence and Security Act (EISA), which mandates the production of 36 billion gallons per year (BGY) of biofuels by 2022, including 15 BGY of corn-derived ethanol. This large increase in demand for biofuels requires immediate consideration and mitigation of unintended environmental impacts.

Specifically, there is concern that the potentially high water demand for biofuel production could result in added pressure to already scarce water resources across the country and become, in many cases, the main limiting factor to biofuel production. The extent of the impact created by different crops and across agricultural regions is unknown but could potentially be large. In addition, climate change could ameliorate or worsen the water footprint of biofuels through several mechanisms. First, it could either reduce or increase rainfall and water availability. Secondly, water use by crops will change as a result of the combination of several factors influenced by climate change (notably temperature, precipitation and CO₂ concentration in the air), which interact in complex ways. Finally, climate changes will be markedly regional and biofuels production is also highly concentrated in one particular region of the United States, potentially magnifying the effects on water

resources of large scale production.

To answer these important questions, we calculated the water requirements for biofuel production from multiple cash crops (i.e., corn, soybean, switchgrass, sorghum, potatoes, and sugarbeet), taking into consideration the region they are currently grown. This is done through a life cycle analysis (LCA) methodology and based on existing US Department of Agriculture (USDA) and industry statistics. We also estimated the effects of climate change in the water demand of corn, the most prominent biofuel crop, using a large-scale distributed agricultural model and projections of climate change from coupled General Circulation Models (GCMs). Climate projections from five different models were used to include a wide range of future climate scenarios. This approach is necessary given the large differences in projected precipitation that exist between different climate models. The magnitude of projected increase in water requirements varied across the five simulations but the trend was consistently upwards in all of them.

Overall, this thesis will enhance decision making by contributing with a tool that can provide spatially distributed projections of water requirements for biofuel crop agriculture. The location of future biofuel crop acreage is unknown at this time, which precludes accurate discernment of where and to what extent water shortages are likely to occur. Nevertheless, model simulations underscore the importance to consider irrigation requirements and water resources availability prior to selecting biofuel crops and where to grow them to avoiding straining regional water resources and jeopardizing future biofuel production.

Specifically, our analyses show that the consumptive water demands

associated with biofuel crop agriculture ranges from 500 to 4,000 liters of water for liter of fuel ethanol produced under current climatic conditions. Simulations with corn showed that by mid century corn crops in traditionally irrigated areas of the High Plains might require significantly more water (up to 40% in some areas) and that biofuels production now taking place in traditionally rainfed areas of the Midwest might require irrigated water supplies, potentially placing a major strain on water resources in that region, if not analyzed and managed properly. This analysis suggests that U.S. biofuels policy will have to be adjusted in the coming years to avoid exacerbating the substantial pressures that climate change are expected to have on certain regions of the United States and on national food production. In particular, the Ogallala Aquifer, the main source of irrigation water in the High Plains, is already experiencing significant water table drops and could be significantly threatened by a continuation of current biofuels policy in the context of projected climate change outcomes.

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Ch1.

Introduction

Biofuels (i.e., biomass-derived fuels) are playing a key role in discussions about energy security, agriculture, taxes and the environment. Although their potential to reduce our dependence on foreign oil and to mitigate climate change is still being debated, biofuels offer advantages to air quality improvement, constitute a renewable domestic resource, and provide alternative revenue for agricultural producers.

Increased biofuel production could exert a significant demand for water to irrigate fuel crops, which might in turn result in increased pressure over regional water resources and threaten water security. Effects on water resources will be region-specific. In already water-constrained areas, the choice of biofuel crops could lead to significant long-term impacts. In addition, climate change could impact both water resources and crop water use, but the effects are uncertain and will probably

vary across the regions.

The nexus between energy, water and climate has traditionally been overlooked, despite its significance at both the regional and national scales. A resilient society requires combined management of water and energy resources. This is especially relevant in the case of pursuing a large-scale biofuel production but the information necessary for this combined planning might not be available.

This study attempts to evaluate the implications to national water resources of escalation and long-term production of biofuels. It calculates the current volumes of water required to produce biofuels, how they are expected to change due to climate change, and to what extent detrimental impacts can be mitigated through management strategies.

This effort should result in an important contribution: government and policy makers will be provided with a method for assessing relationships between water and transportation biofuels at a regional resolution. Thus, decision-making would be enhanced. Far from being a topical issue, this method can be applied to any alternative scenarios (crop choice, scale, climate change projections) that might need to be considered. Therefore, this project could have a high translational value.

General background

In December 2007, Congress enacted the Energy Independence and Security Act (EISA) and created a new Renewable Fuel Standard (RFS) that mandates the escalation of renewable fuel from 9.0 billion gallons per year (BGY) in 2008 to 36 BGY in 2022, of which 15 BGY are to be derived from corn (US Congress, 2007).

The increase in volume of biofuel production will require significant increases in water demand, which could add more pressure to already stressed water supplies in some areas of the country (National Research Council “Water Implication of Biofuels in the US”, 2008). The water footprint of biofuels (WFB) is defined here as the amount of water needed to produce a unit of biofuel (e.g., Liters of water per L of biofuel), and is critical to the assessment of biofuels sustainability. The high water demands of biofuels crops could, in many cases, be the single limiting factor to biofuel production.

Water demand occurs at the different stages of life cycle of biofuel production: water is used in the agriculture of biofuel crops (i.e. agricultural water) and in the processing of crops to biofuel (i.e. process water). At the agricultural phase, a high variability in estimates can be expected as a result of:

1. The wide variety of feedstocks available (which have different evapotranspiration requirements), and
2. Regional variability in the conditions that affect water use (e.g., soil type, rainfall, climate).

Not all water use, however, is equal in terms of impact to regional water resources: there is a difference to be made between consumptive water use and withdrawals. In agricultural systems, water consumption is determined by evapotranspiration, whereas withdrawals refer to irrigation withdrawals. Consumptive uses are more useful to evaluate contributions to water scarcity, whereas irrigation withdrawals are more appropriate to assess potential impacts on water pricing, water distribution logistics, and legal cases of water rights.

The effects of climate change on plant productivity and resource (water and nutrient) use can also be significant. Increased CO₂ concentration might have a stimulatory effect on primary productivity, and increasing temperatures are conducive to accelerating crop growth and therefore shortening the growth season (Reilly et al., 2002). Precipitation might be either reduced or increased on average, but areas with increased average annual precipitation might get it less frequently and more intensely, appearing too early or too late, or too abundant, thus reducing crop productivity unless appropriate irrigation and drainage systems are put in place (Reilly et al., 2002). Although the effects of climate change on crop productivity have been assessed before (Lobell et al., 2008, Parry et al., 2004, Reilly et al., 1999), its effects on plant water and nutrient demand remain mostly unexplored.

Finally it is possible that certain easy-to-adopt adaptation strategies (e.g., adaptation to earlier onset of growing season, precision irrigation, and precision fertilization) could contribute to mitigating the potential detrimental effects of climate change on water requirements to grow biofuel feedstocks, and thus must be evaluated.

The analysis involves scenario construction and a high degree of spatial analysis, which requires the use of a spatially explicit (distributed) agricultural model. However, the use of distributed modeling as decision support systems (SSD) requires careful consideration of model uncertainty, which is dominated by the uncertainty of large input data requirements.

Objectives, Hypotheses and Significance.

This research seeks to provide scientific input to water resources planners and energy policy makers. First, by evaluating the water footprint of biofuels , defined as the amount of water needed to produce a volume unit of biofuel from a life cycle analysis perspective, and then by using a spatially distributed model that evaluates the combined effect of projected changes in pertinent climate factors (CO₂, temperature, and precipitation) on biofuel crops productivity, and evaluate the extent to which we can mitigate impacts to the WFB with an optimal management strategy.

Specific tasks include:

- 1. Estimate the water and nutrient requirements associated with all life stages of biofuel production. Study variability in estimates as a function of choice of feedstock and region of feedstock agriculture.**

We hypothesize that water requirements to produce biofuels are relatively large and mainly associated with the agriculture of feedstock production, but that there will be large variability across feedstocks and across agricultural regions.

- 2. Evaluate the implications of the EISA-mandated increase in biofuel production on water resources, availability and water quality degradation under current climate conditions.**

We hypothesize that EISA-induced water requirements will represent a significant increase in total regional water use and possibly contribute to water scarcity in some regions of the US.

3. Evaluate the suitability of GEPIC, a large-scale distributed biophysical model, to simulate changes in biofuel water use induced by climate change.

We hypothesize that the ability of GEPIC to provide spatially distributed projections will demonstrate it is a superior decision support system than single site models, which are devoid of spatial information (i.e., EPIC).

4. Estimate long-term climate change effects in yields, consumptive water, nutrient, and irrigation plant efficiencies under two adaptation scenarios: 1) "I Adaptation" (adaptation to seasonal shift plus precision fertilization and irrigation), and 2) "NoI Adaptation" (adaptation to seasonal shift plus precision fertilization. No irrigation water available).

We hypothesize that climate change can induce increases in resource demands (water and nitrogen) for corn agriculture and reduce corn productivity, which might jeopardize EISA's goal of energy independence, and that these detrimental effects can be partially palliated by adaptation strategies, such as changing planting and harvesting dates to adapt to changes on growing season onset and duration, and adaptation to changes in water and fertilizer demands.

Significance

The socioeconomic and environmental issues related to the impending increased production of biofuels are very broad and complex, and are subject to considerable speculation and polarization, which reflects a need for scientific input. This project will provide answers to timely and critical questions such as:

- How will unit water requirements to produce biofuels from different crops (e.g., Liters of water per L of ethanol) change as a result of climate change? Will the unit irrigation and total evapotranspiration requirements increase or decrease, and by how much?
 - Where these changes will be most pronounced, and what areas in the contiguous USA are more vulnerable to experience EISA-related water shortages?
- Can three specific aspects of precision agriculture (i.e., changing planting and harvesting dates to adapt to changes on growing season onset and duration, adaptation to changes in water, and adaptation to changes in fertilizer demands) save water and mitigate these impacts?

Thesis organization

Chapter 2 provides background information and a review of past peer-reviewed research in the field.

Chapter 3 describes the LCA methodology used to calculate the current water footprint of biofuels, as well as its strengths and limitations.

Chapter 4 shows the results of the LCA, identifies which phases of production are most critical for water use and evaluates the variability across different feedstock and regions. It also discusses the potential implications to water resources, including a discussion on hypoxia and Conservation Reserve Program (CRP) land. The findings in this chapter have been published in:

- Dominguez-Faus, R., Powers, S.E., Burken, J.G., and Alvarez, P.J.. *The Water Footprint of Biofuels: A Drink or Drive Issue*. *Env. Sci. Technol.* 43(9): 3005–

3010, 2009.

(Featured in the news of Science Magazine, and requested by institutions such as the National Energy Renewable Lab (NERL), the Government's Office of Accountability (GOA) and the United Nations Environmental Programme (UNEP)).

- Baker Institute for Public Policy white paper. *The Fundamentals of a Sustainable U.S. Biofuel Policy*. Rice University (2010)
- Powers, S.E., R. Dominguez-Faus, P.J.J. Alvarez, *The water footprint of biofuel production in the United States*. *Biofuels*. (2010) Vol. 1. No. 2. (Pages 255-260)

Chapter 4 describes the modeling methodology, including a description of calibration efforts and model accuracy, reliability and efficiency. Chapter 5 discusses model data uncertainty reduction efforts and Chapter 6 discusses the results obtained from simulations of corn productivity and resource use under different management and climate scenarios for future decades (2040-2070). Chapter 7 reconnects the results with the original objectives, summarizes the significance and limitations of this study, and recommends future lines of investigation.

Background and Literature Review

EISA

In December 2007, The U.S. Congress enacted the Energy Independence and Security Act (EISA) to reduce energy dependence on foreign oil. EISA included a Renewable Fuel Standard (RFS) that increases the volume of renewable fuel to be blended in transportation fuel from 9 billion gallons per year (bg) in 2008 to 36 bg in 2022, when it will represent a 7% share of the total transportation fuel.

EISA biofuel feedstocks include corn, soybean, grasses and short rotation woody crops (SRWC) as well as other crop and crop-derived cellulosic materials, although any other biomass material containing sugar or starches can be converted into ethanol through fermentative processes. Corn ethanol is currently the most abundant biofuel with the highest escalation rate, with a statutory cap of 15 billion gallons per year (bg) that must be reached by 2015. EISA also mandates EPA to

conduct a triennial analysis on the overall environmental implications of biofuel production based on scientific studies like the one presented in this thesis (EISA. US Congress, 2007).

These mandatory periodic reviews reflect the considerable uncertainty that exists as to whether biofuels present an overall environmental benefit or detriment. On the one hand, biofuels are believed to reduce criteria pollutant emissions during fuel combustion when ethanol is added to gasoline as an oxygenate, and they have a potential net reduction effect of greenhouse gas (GHG) emission when substituting conventional fossil transportation fuel, as CO₂ emitted during the combustion of biofuels is offset by CO₂ uptake during photosynthesis. However, recent studies have revealed that when the entire life cycle of biofuel (production, distribution and consumption) is taken into account larger GHG emissions might result due to impacts directly and indirectly derived from biofuel production (i.e., direct or indirect land use changes, and agriculture machinery use)(Searchinger et al., 2008, Fargione et al. 2008)

At the time this thesis was started, a considerable amount of research had been devoted to analyzing the impacts of increased use of biofuels on air quality, GHG emissions or even aspects relevant to both the environment and economics, such as the net energy values (NEV) or net energy balances (NEB) (Dias de Oliveira et al., 2005, Farrell et al., 2006). However, the water quantity aspects of biofuel production had been overlooked and, if anything, only found in the “grey” literature (not peer reviewed).

Water supply and stresses

In 2008, the National Research Council (NRC) expressed concerns over water implications of biofuel production, expanding the traditional environmental impact analysis to include water quantity (NRC “Water Implications of Biofuels”, 2008). NRC asked what are the water requirements to grow produce biofuels and whether climate change could significantly affect those water requirements. Dennis Keeney, an emeritus professor and former director of the Leopold Center for Sustainable Agriculture of the University of Iowa, wrote that (Keeney, D., 2008):

“Water is becoming the most critical natural resource for food production and we could end up with a biofuel industry that is taking water from food production ... perhaps the next energy policy act should also insist on a water footprint analysis of all biofuels”

Many water resources in the nation are already experiencing water stress. According to a Government Accountability Office (GAO) survey in 2003, 36 state water managers expect water shortages in their states by 2013 (Johnsons Foundation “Charting New Waters”, 2010). Examples of conflicts, economic losses and legal actions as result of water stresses abound: The Ogallala Aquifer (a.k.a. The High Plains Aquifer) provides irrigation water to the each of the eight states it underlies (USGS Circular 1223, 2002), a region that supplies one fifth of the total annual U.S. agricultural harvest. Water level declines of a 150 ft have been observed in some parts of Texas (USGS Circular, 1223, 2002), which resulted in local water supplies and irrigation shut downs. Over the past years, the Western States from the Rockies to the Pacific Coast are experiencing moderate to extreme droughts

(National Climatic Data Center, 2004). Although the East seems to overall be getting wetter, precipitation is less frequent and more intensive, making irrigation a requirement to meet crop's seasonal water requirements. Texas experienced the driest spring on record in 2003, and a nuclear plant temporary closed during a drought in 2008 (Johnsons Foundation "Charting New Waters", 2010).

The insufficient protection of water resources in the US stems from an overly complex system of water governance, which is the source of numerous conflicts among states. In 2008, Kansas took legal action against Nebraska based on allegations that Nebraska farmers used 98 billion liters more than their allotment of the Republican River in 2004 and 2005 (as ruled by the Supreme Court in 2003). Meeting the Kansas demand meant shutting off irrigation to an estimated 485,000 ha of Nebraska farmland. Other examples of water conflicts include fights over the Apalachicola-Chattahoochee-Flint River system between Alabama, Georgia and Florida, efforts in the Great Lakes states to protect lake levels and reduce water exports to other areas, disputes over the Klamath River by Oregon and California, and other issues in the Sacramento Delta, the Rio Grande River and Colorado River. In the West, Native America water rights disputes abound (USGCRP, "Global Climate Change Impacts in the US: Water Resources", 2009). These conflicts highlight how crucial is for Congress to evaluate the consequences of the EISA mandate and to take appropriate action.

In addition to current disputes for existing water supplies, water demand is on the rise. Between 1950 and 2005, water use for public supply tripled while the population doubled (Johnsons Foundation "Charting New Waters", 2010) and

presently, energy, agriculture and public supply rank as the top three water users in US, and account for 48%, 34%, and 11% of the US total (1), respectively. Although the trend seems to have been recently inverted as a result of conservation measures, environmental regulation, and increased efficiencies (USGCRP, "Global Climate Change Impacts in the US: Water Resources", 2009). The population increased by 5 percent between 2000 and 2005 whereas public supply withdrawals increased by just 2 percent (Johnsons Foundation "Charting New Waters", 2010). US population is projected to increase from 307 to 392 million by 2050, a 27 percent increase (US Census Population Projections, 2009), which will result in increased water demand for public supply energy production, and agriculture. Thermoelectric generation is expected to increase by 22% between 2005 and 2030 (DOE "Energy Demands on Water", 2006), and irrigation water requirements could significantly increase to meet higher crop demands to produce more biofuel, food and feed.

Impact of biofuel production on water resources

The production potential of biofuels depends on availability and reliability of water, which will have a markedly regional component. At the time this thesis was started in 2007, only a few and incomplete estimates on the water demands of biofuel production existed. In 2006, DOE provided a first estimate of 3 to 4 gallons of water per gallon of ethanol produced (DOE "Energy Demands on Water", 2006). This, however, referred to process water only (i.e., water used in converting the feedstock to biofuel) and ignored the much larger water requirements for growing the feedstocks. In 2007, a NREL report (Phillips et al., 2007) documented that ethanol production from wood chips required 1.9 gallons of water per gallon of ethanol for a

water conservation best-case scenario of thermochemical conversion and active water minimization strategies. This estimate also refers to process water and not feedstock agriculture related water. In comparison, petroleum refining consumed 2 to 2.5 gallons of water per gallon of gasoline. (DOE "Energy Demands on Water", 2006) None of this estimates allocated any credit to co-products: distilled dry grain solids (DDGS) in the case of corn ethanol or kerosene and diesel in the case of gasoline. DOE also estimated that coal fired power plants used about 9.5 gallons per minute per megawatt (MW), which translates to 3.4 million gallons per day for a 250 MW power plant, and that nuclear power plants used 25 percent more water than an equivalent coal-fired power plant (DOE "Energy Demands on Water", 2006)

The University of Arizona dedicated its October 2007 issue of the journal "Southwest Hydrology" to the water-energy nexus, and reported estimates of water requirements for electricity production from different sources including biofuels. This report identified that water withdrawals associated with the cultivation of bioenergy crops could be as high as 130 gallon of water per KWh, higher than any other energy generation related process (Cohen, 2007).

In 2008, King and Webber (2008) investigated the water intensity for light duty vehicle (LDV) travel. They found that the water intensities of LDVs operating on biofuels derived from irrigated crops in the United States were 28 and 36 gallons of water per mile driven (gw/mile) for corn ethanol (E85) for consumption and withdrawal, respectively. For soy derived biodiesel the average consumption and withdrawal rates are 8 and 10 gw/mile. This compared to consumptive (<0.15 gw/mile) and withdrawal (<1 gw/mile) rates when using conventional petroleum

based gasoline and biodiesel.

Most of the information available is related to electricity production or to biofuel process water only. No estimates of water uses during the cultivation of feedstocks were available (except for a undetailed estimation in Southwest Hydrology), but feedstock agriculture is poised to be one of the most water intensive biofuel phases. As I will show in this thesis, water requirements for a typical sugar cane or corn ethanol refinery are around 2 to 10 liters of water per liter of ethanol produced (National Research Council 2008), while consumption (evapotranspiration) water requirements to produce enough feedstock to make one liter of ethanol in the U.S. range from 500 to 5,000 liters depending on what crop is used to produce it, as will be shown in this thesis. Additionally, any plans that involve intensification of agriculture will have important effects on water consumption. This is very relevant to biofuel policy because biofuel feedstock cultivation, usually row-crop agriculture, is the most water-intensive of the stages of biofuels production by far. No regional analyses were performed either, only national averages were calculated, but a high regional variability can be expected that will have to be accounted for. In most cases, no distinction between consumptive water and withdrawals was provided, even though this is a critical point: withdrawals only are not necessarily a good measure of potential contribution to water scarcity. Thus, it is important to differentiate between water withdrawals and water consumption when discussing water use. Water withdrawals (water taken from a source) are more easily measured, but they do not necessarily correspond with water consumption (water lost from the resource system that will be unavailable for other uses). Part of

the water withdrawn for a given purpose will be consumed, while part of it will be returned to the system and available for re-use. Examples of water consumption are evaporation (E) losses from cooling towers in power generation, and evapotranspiration (ET) losses from biophysical systems, such as agricultural systems. Different economic activities have different impacts on both withdrawals and depletion of water. In the US, power generation is responsible for 34% of total national withdrawals while only for 3.3% of total national water consumption, whereas agriculture accounts for 48% of total water withdrawals and for as much as 80% of total water consumption. (Sandia National Laboratories 2006; Hutson et al. 2004; Gollehon and Quinby, 2006).

In the first part of this thesis, I estimate the water footprint of biofuels, defined as the amount of water needed to produce a volume unit of biofuel. I do this for multiple feedstocks and for each growing region in the US. Both consumed water (based on ET) and withdrawn water (irrigation) are independently measured. Nutrient and land requirements are also estimated. The unit volume of biofuel is chosen because it can easily be translated to gasoline displacement potential. This is done by taking into account differences in irrigation at the state level using legacy data on water use, plant yield, and biofuel yields. The data is incorporated in the framework of a Life Cycle Analysis methodology that allows distinction between the different phases of biofuel production and use. More details on the methodology used in this first phase of research are available in chapter 3.

Effects of climate change on water use

Another source of potential uncertainty is how future climate will affect water resources and how plants grow and use water. Climate change could either reduce or increase rainfall and water availability, and plant growth and plant water use co-adjust in response to combinations of atmospheric CO₂, soil nutrients, precipitation and temperature.

The effects of climate change on water consumption are indirect, and depend in part on changes in atmospheric CO₂ concentrations and temperature, which will differentially impact plant growth responses and ET, as well as regional precipitation patterns. These interrelations are detailed below.

Growth response to CO₂

Under the current scientific paradigm, CO₂ is a nutrient and will increase productivity only in cases where CO₂ is the limiting factor to growth, according to Leibniz's law of the minimum. As plant productivity increases, so does the demand of other factors (nutrients, water), which will become the new limiting factors. This will have implications on the amounts of additional fertilizer required under high atmospheric CO₂ concentrations. Yield response to CO₂ has traditionally been investigated with enclosed experiments, and more recently with free-air carbon enrichment (FACE) experiments. FACE experiments represent better actual field conditions as they do not limit growing space, alter microclimate, or limit precipitation and pest access, and because the scale is more comparable to agronomic trials (Ainsworth et al., 2008). Enclosed studies found that C3 plants

(soybean and wheat) yields are more susceptible to changes in CO₂ concentrations than C4 plants (corn and sorghum), with a 30% and 10% increase respectively to a doubling CO₂ (350-700 ppm) and C3 weeds show larger responses than soybean. In general, FACE experiments corroborate trends obtained from enclosure studies but show that yield responses are smaller than reported in enclosure studies (USGCRP "Global Climate Change Impacts: Agriculture", 2009). The US Global Change Science Program (USGCSP) estimates an increase of 4% in both biomass and grain yield of corn is likely. EPIC parameterization is based on enclosure studies experimental data. Consequently, there is a possibility that this study overestimates yields as a result of increasing CO₂ concentrations in future scenarios.

Growth response to temperature

Crop yield responses to rising temperatures are more difficult to evaluate, as plants need different optimum temperatures at different phases of life cycle. Higher temperature, explains the CCSP report, generally means faster development that might translate in smaller plants and shorter reproductive phase (lower grain yields). Also, temperatures above 35°C are lethal to pollen viability and photosynthesis rate is reduced at temperatures above 38°C. The reports also indicate that temperature changes in some parts of the day are more relevant than others to grain yield. Nighttime temperatures, which are projected to continue to increase in the future, can increase the respiration rate, thus reducing the amount of carbon accumulated during the daylight photosynthesis available for grain production. The SSCP concludes that a temperature rise over the next 30 years of 1.2°C in the

Midwest might decrease yield by about 4% under irrigated or water-sufficient management (temperature stress only). Although the combined effect of CO₂ and T has been sparsely studied for corn, sorghum, another C₄ plant, showed a negative interaction of CO₂ with temperature for grain set, as temperature sensitivity of yield was significantly greater at elevated CO₂ than at ambient temperatures. However, this was not shown for photosynthesis, thus while a negative impact on grain yield is possible, a possible positive overall impact on biomass is also likely.

ET response to CO₂

Higher CO₂ reduces stomatal conductance that in turn reduces ET, but CO₂ induces larger leaves and larger transpiration area. Based on experimental data, the CCSP reports a potential significant effect of 1 to 4% reduction in current ET rates in different species with an increase to 440 ppm atmospheric CO₂ equivalents in the future.

ET response to temperature

Higher temperatures will induce more ET, unless other compensatory factors such as higher humidity are present. The CCSR concludes that higher CO₂ concentrations can enable some water conservation, but temperature stresses could reverse or slow the trend, as plants need to transpire more water to maintain cooler temperatures.

Combined responses

In summary, CO₂ increases plant yield and water use efficiency, but

temperature might reduce plant yields and reduce water efficiency. The responses are non linear and the combined effects are hard to predict. It has been found that many crops growth respond positively to elevated CO₂ and low warming levels, but negatively to higher levels of warming. Effects are difficult to generalize, since effects change across phenological phases and climate parameters variability is different across different geographic regions.

Changes in precipitation

Although precipitation projections are among the most uncertain climate model estimates, it is generally assumed that a warmer atmosphere will hold larger amounts of moisture, which will produce more overall precipitation. In the Midwest, Northeast, and Alaska total precipitation is expected to increase the most, while precipitation might decrease in the West (Hatfield, J.L., 2002). As a result, renewable water availability (as measured by streamflow) might increase in the future in some areas. Climate models consistently project that the East will experience increased runoff (which accumulates as streamflow) while there will be substantial declines in the interior West, especially the Southwest (Hatfield, J.L., 2002). In the West and some areas in Northeast, where snowpack dominates, the timing of runoff will continue to shift to earlier in the spring and flows will be lower in late summer. Snowmelt dominated runoff is occurring 20 days and 14 days earlier than 50 years ago in the West and the Northeast respectively, with climate projections indicating up to 60 and 14 days earlier appearance in the next 30 years. (Hatfield, J.L., 2002). A

change in the temporal distributions of rain and temperature has an influence in the different phases of plants grow (phenology).

Adaptation strategies

There are easy-to-adopt adaptation strategies to limit the extent of climate change impacts. The most notable effects of climate change will be changes in growing season onset and duration, and changes in resource (irrigation and fertilizer) requirements. Farmers currently adapt to those aspects as needed and it is expected that they will continue to do so in the future. For instances, by planting and harvesting sooner or later, and by applying more or less resources (irrigation and water) to maintain yields.

Agricultural Systems Models

The complexity of plant-water-climate interactions and the regional variability of climate parameters can only be evaluated through modeling. Models can also incorporate the effects of inputs on each phonological phase of development provided they incorporate processes at adequate time scales (i.e., daily). Models can also be used to evaluate the effects of different management strategies as a mean of adapting to potential effects of climate change.

Many agricultural systems models exist which simulate one or more of the physiological processes of interest as a function of environmental and managerial variables. However, EPIC is chosen because it includes all processes of interest and because is capable of simulating these processes with relatively simple equations and a relatively small number of parameters (Liu et al., 2010) when compared to other

models.

Why use GEPIC

The choice of model must be guided by which one among the available ones includes the following desirability traits:

- 1) Capable of assessing yield response to combinations of precipitation, temperature, atmospheric CO₂ and soil chemistry.
- 2) Capable of assessing ET response to combinations of precipitation, temperature, atmospheric CO₂ and soil chemistry.
- 3) Capable of assessing nutrient response to combinations of precipitation, temperature, atmospheric CO₂ and soil chemistry.
- 4) Adaptative management options
- 5) Accounting for both spatial and temporal distribution of driving forces.
 - Account for spatial heterogeneity of input variables
 - Effects on all phases of phenological development
- 6) Reduced process parameterization

Based on these criteria, the best available model (used in this thesis) is GEPIC, which is a GIS adaptation by Dr. Junguo Liu of the United State Department of Agriculture (USDA) Environmental Policy Integrated Calcluator (EPIC) model (Liu et al., 2007). EPIC was selected by Dr. Liu among a range of crop models - such as DSSAT, WOFOST, CropSyst, YIELD, CENTURY, CropWat, and APSIM - based on the following characteristics: flexibility for the simulation of different crops under a variety of climatic conditions, ability to simulate ET and yield, availability of and easy access to the model, different time and space scales, and technical feasibility for the

integration with GIS (Liu et al., 2007). The model was modified after 1992 to include ET response to CO₂.

GEPIC equations

A detailed description the equations and processes used in GEPIC can be found in Appendix A. What follows below is a general description of some of the equations that are relevant to this study.

The growth model of EPIC estimates yields by taking temperature, CO₂ and radiation values as inputs. Unlike temperature and CO₂, which are fed into the model by the user, radiation is calculated internally by GEPIC from latitude, longitude, angle of sun in a given day of the year, and soil cover albedo. Actual radiation will be affected by cloud cover, which is not explicitly accounted for in GEPIC.

Plant water use is based on potential evapotranspiration estimations, which can be achieved through four different methods: Penman (Penman, 1948), Penman-Monteith (Monteith, 1965), Priestly-Taylor (Priestley, 1972), and Hargreaves (Hargreaves and Samani, 1985). The Penman-Monteith method is the only one that accounts for CO₂ effects on stomatal conductance and ET reduction, and thus is the most adequate for climate change studies. However, this method requires inputs on relative humidity and wind speed, which are not available for future climate projections. Thus, in this study we use the Hargreaves method, which does not require those inputs.

Previous Studies with GEPIC

The single site version of EPIC, in which no spatial distribution is incorporated, has been widely used, both in the US and globally. The most notable uses include a 1988 national drought assessment, soil loss tolerance studies, and multiple examples of global climate change analysis (Gassman et al. 2004).

GEPIC is a recent iteration of EPIC that takes the basic functionality of EPIC and incorporates spatial distributions (Liu et al., 2009). The region of interest is divided into a regular grid, and the simulation model is run for each of the grid units or cells independently (Phillips and Marks, 1996). The advantage that GEPIC offers over the single site version of EPIC is that spatially explicit input data is incorporated and thus large heterogeneous areas can be simulated in parallel. Spatially explicit input data (e.g., soil parameters) is inputted through maps. Input variables that have both a spatial and temporal component (e.g. climate data) can be managed through gridded time series. The resolution of the model is limited by the resolution of the input datasets, which in this study is 0.5 arc-degree.

Uncertainty

All predictive models will experience one or more of the following sources of uncertainty: a) conceptual model b) parameters, c) input data uncertainty (temporal and spatial).

Conceptual and parameter model uncertainty

Conceptual model uncertainty arises from: 1) Errors in the theory or an incomplete understanding of the processes that are modeled, and 2) Errors in the mathematical representation of the modeled processes.

Parameters represent the relationship between the dependent and independent variables in a predictive model. Models might require calibration of model parameters (i.e., parameterization) if they are used outside the domain for which the statistical relationships were initially described. This is the case of empirical models, but not the case of mechanistic models, as the latter are based on processes governed by universal physical laws. In EPIC, the core model of GEPIC, yield (grain yield) and biomass (overall plant yield) productivity are calculated semi-empirically and evapotranspiration (ET) is calculated mechanistically. The plant growth model was developed and parameterized for both the region (USA) and crop (corn) of interest (Gassman et al., 2004), and thus needs no further calibration for this study. The hydrologic module in GEPIC is mechanistic (based on physical laws) and therefore needs no calibration.

Parameter and conceptual uncertainty in GEPIC has been estimated from single site studies that used EPIC as a model, because in these cases data uncertainty is minimal (input and validation data are measured ad-hoc for the purpose of the simulation) and model uncertainty is dominated by parameter and conceptual uncertainty. Niu et al (2009) examined the reliability of the EPIC model in simulating grain sorghum yields in the U.S. Great Plains under different climate scenarios and

noticed that model accuracy might be compromised in extreme water- and nitrogen-stressed conditions (Niu et al., 2009).

As explained earlier, EPIC parameterization inaccuracies of yield response to CO₂ might result in overestimation of yields in future scenarios. A correction factor to GEPIC estimates could be applied but it would have to take into account that future yields increments are not due to CO₂ only, but also to temperature changes. GEPIC could also overestimate future ET because it does not incorporate CO₂ effects on ET. A correction factor could be applied to ET estimations, but careful consideration of the fact that ET response to both CO₂ and ET would be required.

Input data uncertainty

Data uncertainty occurs when the data does not accurately represent the conditions of the sites being simulated. Uncertainty of spatial data is endemic to distributed modeling, in which the spatial reality is approximated by a regular grid. Errors arise, for example, when the values are interpolated from irregular networks of data collection or administrative units, or when they are aggregated/disaggregated from different resolutions. In addition, datasets can be constructed from data sources of limited accuracy. For example, irrigation datasets are based on surveys to farmers and thus the obtained information might be more indicative of farmers water use needs in order to keep their water rights rather than being reflective of actual plant irrigation requirements.

In the spatially explicit GEPIC, uncertainty associated with input datasets is more relevant than uncertainty associated with parameters and conceptual model. In this thesis, some of the actions taken to minimize data uncertainty include:

- 1) When possible, use peer-reviewed datasets. These datasets are published by specialized datacenters, normally university-based, and are generally spatially and temporarily distributed datasets. Raw data for these datasets is collected in different ways, from surveys to satellite measurements. They are specialized in spatial and temporal statistics, and account for issues of spatial and temporal correlation, extrapolation, geometry, topology, natural variability and measurement error.
- 2) When datasets need to be created *de novo*, data from federal agencies was used. Whenever possible, measurements from physical instruments were preferred to survey data.

The uncertainties associated with future climate projections are important, and will be discussed separately in the next section.

Future climate uncertainty

Emission scenarios uncertainty

Climate models simulate future climates and are based on assumptions of carbon emissions rates. The Special Report on Emission Scenarios (SRES) of the International Panel on Climate Change (IPCC, 2000) defines four families of emission scenarios based on different combinations of energy use, population growth, and policies leaning towards either environmental or economic protection. In this thesis, the climate projections based on the A2 scenario family are preferred over the others (A1, B1 and B2). The SRES defines the world described in the A2 family as “A *very heterogeneous world with prevalent self-reliance and preservation of local identities.*”

Fertility patterns across regions converge very slowly, which results in continuously increasing global population. Economic development is primarily regionally oriented and per capita economic growth and technological changes are more fragmented and slower than in other storylines". A2 is a high emission scenario, but the rate of accumulation is slower than the highest emission scenario A1. In the A2 scenario, cumulative CO₂ emissions will reach 600 and 1850 GtC by the middle and end of the 21st century, respectively. This would result in an increase in CO₂ concentrations from current 380 ppm to 575 and 870, by the middle and end of the 21st century respectively (Nakicenovic et al., 2000).

Climate model uncertainty

Climate models simulate atmospheric dynamics (atmospheric motion) and physical processes (radiation, surface processes and hydrological cycles). Past versions of General Circulation Models (GCMs) for the most part included Atmospheric processes only. Extreme events, such as droughts and floods are correlated to large-scale, ocean-atmosphere interactions known as ENSO (El Niño Southern Oscillation) in the Australian region, southern Africa and in the American continent. For this reason, Atmospheric GCMs were unable to predict variability on extreme events such as droughts or floods (Jakeman et al., 1993). More recently, coupled Ocean-Atmosphere GCMs (OAGCMs) have been developed which overcome this technical limitation. In this thesis, climate projections from five OAGCMs participating in IPCC Fourth Assessment Report (AR4) (IPCC, 2007) are included:

- The second generation Coupled Global Climate Model (CGCM2) from the

Canadian Center for Climate Model and Analysis.

- The second generation of the Commonwealth Scientific and Industrial Research Organization (CSIRO2) from Australia's National Science Agency.
- The fourth version of GCMs by the Max Plank Institute of Meteorology from the University of Frankfurt, Germany (Echam4).
- The third generation of GCMs by the Hadley Center for Climate Prediction and Research from UK Met Office (HadCM3).
- The Parallel Climate Model (PCM), a joint collaboration of Los Alamos National Laboratory (LANL), the Naval Postgraduate School (NPG), the US Army Corps of Engineers Cold Regions Research and Engineering Lab (CRREL), and the National Center for Atmospheric Research (NCAR) in the United States.

Global GCMs have a grid resolution of about 500 km. Thus, smaller-scale meteorological phenomena, like tropical cyclones, might not be adequately simulated. In addition, certain details of the terrain and the nature of Earth's surface, which greatly affect simulated patterns of precipitation and surface temperature, are not well represented either (Jakeman et al., 1993). Specifically, models have difficulties with regions with high and step terrain, and often over predict long-term averages in those regions (Jakeman et al., 1993). The authors of the Fourth US National Assessment of Climate Change Synthesis Report on the effects of climate change on agriculture acknowledge that the studies might be unable to predict the negative effects of excess water conditions on crop yield for these reasons (Reilly et al., 2002).

The confidence on future climate predictions is based on the level of agreement between models. GEPIC was run with climate data from five different global GCMs and the results were averaged to obtain a single projection for each cell. The confidence in these results is determined by the standard deviations from the mean at each cell.

In order to reduce the effect of short-term climate variability and to limit the biases introduced by short-term extreme events (i.e. droughts or floods) a time integration to produce a stable climatology of 10-year is typical among climate change studies and has been adopted in this study.

LCA methodology

This chapter describes the LCA methodology and sources used to accomplish the first objective of this study: Estimate the water and nutrient requirements associated with all life stages of biofuel production in the present period. The methodology is presented here in the same format that was published in the supporting information to the peer-reviewed paper *The Water Footprint of Biofuels: A Drink or Drive Issue*. Dominguez-Faus, R., Powers, S.E. , Burken, J.G., and Alvarez, P.J.. *Env. Sci. Technol.* 43(9): 3005–3010, 2009.

Supporting Information Prepared for

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Water and land footprint calculations

To estimate water requirements, distinguishing between withdrawals and consumptive use is important, the former meaning the overall amount of water diverted from a water body for a particular use (*e.g.*, irrigation) regardless of whether it is returned or not, and the later meaning the water not directly returned to the system but consumed during the process, (*e.g.*, evapotranspiration).

To calculate the consumptive water use of biofuels in the U.S. for selected crops, we used the virtual water content of crops grown in the U.S. from the UNESCO's report "The Water Footprint of Nations" 2004 (Chapagain et al., 2004). Cellulosic crops used as biofuel feedstocks (*e.g.*, switchgrass) were not included in the report, and consequently its evapotranspiration requirement was obtained from a combination of studies across the U.S. geography (Chapagain et al., 2004, Kiniry et al., 2005, McLaughlin et al., 1999) (Table1)

ET values were converted to water consumed per liter of biofuel produced by factoring in ethanol conversion yields for the respecting crops (Table 2), which were obtained from industry statistics or pilot scale tests when possible. When such

statistics were nonexistent, such as with cellulosic feedstocks, we assumed an efficiency of 80% of the theoretical ethanol yield according to NREL. This assumption was made on the basis that the actual corn ethanol yield (ORNL, 2008) is about 80% of the theoretical (DOE, 2008).

Table 1. Virtual water content and average yields of selected crops in the U.S and calculated values for an ethanol volume basis

	<i>Virtual Water Content</i>	<i>Water footprint based on ET</i>
	<i>m³/tonne</i>	<i>L water/ L ethanol</i>
<i>Maize</i>	489	1,262
<i>Potatoes</i>	105	777
<i>Sugar cane</i>	103	1,266
<i>Sugar beet</i>	84	812
<i>Sorghum</i>	782	2,018
<i>Soybean*</i>	1,870	4,185
<i>Switchgrass</i>	N/A	1,401

* Soybean is used to produced biodiesel rather than ethanol, and this value represents energy-equivalent liters of ethanol (obtained by multiplying by 0.64, which is the ratio of energy content of ethanol to that of biodiesel if using 6.18 KWh per liter of ethanol and 9.58 KWh per liter of biodiesel as provided by Oak Ridge National Laboratory quick-reference list of conversion factors(ORNL, 2008))

Table 2. Ethanol yields from different feedstocks

Crop	L/tonne	Source
Sugar cane	81	The Feasibility of Ethanol Production from Sugar cane in the U.S. (Shapouri et al., 2006)
Potatoes	135	Ethanol Production for Automotive fuel Usage (Mays et al., 1979)
Sugar beet	103	The Feasibility of Ethanol Production from Sugar cane in the U.S. (Mays et al., 1979)
Corn	387	NREL average yield (not theoretical) (DOE-NREL, 2008)
Sorghum	387	The Feasibility of Ethanol Production from Sugar cane in the U.S. (Shapouri et al., 2006)
Switchgrass	311	80% of theoretical ethanol yield calculator (DOE-NREL, 2008)
Poplar tree	294	80% of theoretical ethanol yield calculator DOE (DOE-NREL, 2008)
Soybean	447	Biodiesel and Petroleum Diesel Life Cycles (Sheehan et al., 1998)

Estimation of overall water withdrawals (*i.e.*, irrigation) for different crops used statistics on irrigation from different regions of the U.S., thus taking into account the regional variability. We estimated how many of liters of irrigation water are needed to produce one liter of ethanol from seven different crops, for each of the major producing states (which altogether accounted for 80% or more of the total U.S. production for that crop), and calculated a weighted average with the following formula:

$$x^j = \frac{x_1^j w_1^j + x_2^j w_2^j + \dots + x_n^j w_n^j}{w_1^j + w_2^j + \dots + w_n^j} \quad (1)$$

Where:

x^j is the U.S.-weighted average of irrigation water requirements of ethanol for crop j (L irrigation water/ L irrigated ethanol);

x_i^j is irrigation requirement per liter of ethanol for crop j in state i (L irrigation water/ L irrigated ethanol); and

w_i^j is the weight of the state-specific value, (*i.e.*, the percentage of U.S. production of a particular crop j attributable to state i)

n is the number of states accounting for $\geq 80\%$ of the total U.S. production for that crop.

Rankings of top producing states for each crop were obtained from the National Agricultural Statistics Service (NASS) of the USDA for the year 2003 to match the 2003 Farm and Ranch Irrigation Survey (FRIS) by the USDA (NASS, 2008), the latest available, from which irrigation water uses for each crop, and irrigated harvest yield for traditional crops used as feedstocks were obtained. Data on irrigation of sugar cane was not available through the FRIS 2003 and we used personal communications from faculty at the University of Florida (Whitty et al., 2005) and Louisiana State University (Salassi et al., 2008). Irrigation data for switchgrass was not available and harvest yields were obtained from the same experiments from which ET data were found (Table 1) Since no irrigation water was applied to cellulosic feedstocks in those experiments, no irrigation was assumed in this study, but we acknowledge that irrigation might happen in the future if they are grown as fuel crops.

The estimation of the x^j (U.S. weighted average) and x_i^j (state specific) values required factoring in ethanol conversion yields (Table 2), feedstock harvest yields, irrigation water requirements and fertilizer application rates. Land requirements were estimated using the same method and dataset used for water irrigation requirements.

A summary of all required agricultural input data and results by state and as a weighted national average can be found in Tables 7 and 8 for traditional crops. The standard deviations depicted as error bars in Figure 1 were calculated from the pool of state-specific x_i^j values for each crop.

Nitrogen and pesticide requirements

Nitrogen requirements were estimated using the same method used for water irrigation and land requirements. Error bars correspond to the standard deviation of the pool of results for the states considered. The latest available fertilizer (nitrogen) application rates (Tables 7 and 8 were obtained from the 2000 and 2003 Field Crops Agricultural Chemical Usage database from NASS (NASS, 2008) for all crops except for potatoes and sugar cane, which were not available. A national average for potato fertilizer application rate was obtained from an Economic Research Service (ERS) of the USDA (Padgitt et al., 2000) while nitrogen data for sugar cane were obtained from independent sources for each of the major producing states (Padgitt et al, 2000) Fertilizer use of cellulosic feedstocks (Table 10) was inferred from the same sources from which irrigation and harvest yields data were obtained (see above).

Pesticide data were obtained from the USDA NASS agrichemical usage data, which provides total pesticide usage for the Nation and total harvest mass for specific crops (NASS, 2008). The most recent data set for most of the crops (corn, potatoes, soybeans) was available for 2005. The most recent sorghum values were from 2003. Switchgrass data was from Pimentel & Patzek, who suggest that 3 kg/ha pesticide used (Pimentel and Patzek, 2005). This application is typically only in the first year and so the normalization to the ethanol volume produced assumed one year of pesticide application for eight years of switchgrass harvest. No data were available for the sugar crops. Pesticide use data were normalized to liters of ethanol (or ethanol equivalents) using the method described above.

The pesticide data show the sum of herbicides, insecticides and fungicides (Table 3). The high application value for potatoes is largely due to the use of sulfuric acid at harvest time to kill plant shoots to make the harvest easier. Other common pesticides include atrazine and alachlor for corn and glyphosphate, used primarily on soybeans. The use of glyphosphate on corn is growing rapidly due to the switch to over 50% of corn acreage being planted with "Roundup Ready" corn (Corn and Soybean Digest, 2008). Note that glyphosphate is the active ingredient in this commercial herbicide.

Table 3. Pesticide use data

Crop	Year of data	Harvested area (1000 ha)	Total U.S. Pesticide Use				Pesticide Application	
			herbicide (tonne)	insecticide (tonne)	fungicide (tonne)	other (tonne)	application (kg pest./ha)	g pest./ L e
Corn	2005	30,947	71,625	2,204	42	0	2.39	0.66
Potatoes	2005	342	634	445	2,515	30,923	100.94	15.29
Soybeans	2005	26,237	35,085	1,086	87	0	1.38	2.57
Sorghum	2003	3,426	6,995	120	0	0	2.08	1.24
Switchgrass	--	--	--	--	--	--	3.00	0.08

* assumed 3 kg/ha pesticide in first year, averaged over total 8-year harvest

The estimated pesticide application for switchgrass assumes 3 kg/ha of broadleaf herbicides (e.g., atrazine and 2,4-D) used in the first year only for switchgrass establishment. The impact of these agricultural pesticides on water quality continues to be studied and is often hotly debated. For example, in a study in 2003, atrazine was implicated as an endocrine disruptor contributing to mutations in frogs even at very low concentrations (Hayes et al., 2003). More recent studies, however, have shown this to not be the case (Oka et al., 2008).

Water uses of various energy-related processes

Water is needed to produce energy. In Table 1 (in Chapter 4) we show water uses of various processes related to electricity production and oil extraction and refinement, which were obtained from the DOE Report to Congress “Energy Demands on Water Resources” (DOE, 2006) and “The Water and Energy Nexus”

article (Cohen, R., 2007). We added to this list the irrigation water requirements of corn ethanol and soybean biodiesel obtained in this study (Table 11). We converted the data given in different units to liters per Mega-Watt-hour (L/MWh) for easy comparison. We assumed energy contents of 1,700 KWh per barrel of petroleum, 6.18 KWh per liter of ethanol and 9.58 KWh per liter of biodiesel, and that a barrel of oil is contains 42 U.S. gallons as provided by Oak Ridge National Laboratory (ORNL) quick-reference list of conversion factors (ORNL, 2008)

Table 4. Water uses of other energy related processes

<i>Process</i>	<i>gal/MWh</i>	<i>L/MWh</i>
Petroleum extraction	3-10	10-40
Oil refining	20-40	80-150
Oil shale surface retort	45-180	170-681
NGCC* power plant, closed loop cooling	60-8,000	227-30,300
Coal Integrated Gasification Combined-Cycle	~230	~900
Nuclear power plant, closed loop cooling	~250	~950
Geothermal power plant, closed loop tower	500-1,100	1,900-4,200
Enhanced Oil Recovery	~2,000	~7,600
NGCC*, open loop cooling	7,500-20,000	28,400-75,700
Nuclear power plant, open loop cooling	25,000-60,000	94,600-227,100
Irrigated corn ethanol**		2,270,000 - 8,670,000
Irrigated soybean biodiesel**		13,900,000 - 27,900,000

* Natural gas combined cycle

** From data in Table 8

EISA implications

In order to obtain water, land and nitrogen requirements of the 57 billion liters of ethanol (15 billion gallons per year), we multiplied this value for the weighted averages of this requirement calculated on a liter-of-biofuel basis from Table 11. Weighted averages are calculated from 2003 agricultural statistics, and current industry ethanol yields (Table 2) as found in the literature.

Table 5. Footprint of 15 BGY.

<i>Metric</i>	<i>Quantity</i>	<i>Benchmark for Comparison</i>
Fuel Requirement	56 Billion Liters Ethanol (15 BGY)	7% of 2006 annual gasoline consumption
Amount of feedstock	143 Million tonnes (5.8 Billion bushels)	44 % of the 2007 U.S. corn production
Land	16 Million ha (39 Million ac)	9% U.S Cropland
Irrigation water*	6×10^{12} L (1.6×10^{12} gallons)	3.23 % of current irrigation water use in the U.S. (Compare to 1.23 Trillion gallons withdrawn per year in Iowa for all uses)
Nitrogen fertilizer	2.5 million tonnes (5.5×10^{12} lbs)	19% of the N fertilizer used for all crops in the U.S. (~\$2.2 billion)

*Assuming 19% of corn is irrigated

Alternatively, we can calculate the footprint associated the additional expansion from 2007 baseline, which would be of 9.5 BGY instead of 15BGY if we consider that 5.5 BGY were produced in 2007. We obtain the 2007 baseline value as follows: The Renewable Fuel Association (RFA) (<http://www.ethanolrfa.org/industry/statistics/>) reports two values of ethanol production for the year 2007: 6.5 BGY (Historic US Ethanol Production), and 5.5 BGY (Energy Industry Overview). If we take that 2,117 million bushels were used to produce ethanol in 206-2007 (USDA long term projections at

<http://www.ers.usda.gov/publications/oce081/>) and factor in the conversion yield of ethanol (2.53 gal/bu, or 387 L/tonne, Table 2), we obtain 5.4 BGY. For our calculations we assumed 5.5 BGY were produced in 2007 per the RFA Energy Industry Overview, resulting in an additional 9.5 BGY needed to meet the 15 BGY mandate by 2015.

Table 6. Footprint of 9,5 BGY.

<i>Metric</i>	<i>Quantity</i>	<i>Benchmark for Comparison</i>
Fuel Requirement	36 Billion Liters Ethanol (9.5 BGY)	4.5% of 2006 annual gasoline consumption
Amount of feedstock	93 Million tonnes (3.6 Billion bushels)	28 % of the 2007 U.S. corn production
Land	10.3 Million ha (25 Million ac)	5.7% U.S Cropland
Irrigation water*	3.8×10^{12} L (1×10^{12} gallons)	2 % of current irrigation water use in the U.S. (Compare to 1.23 Trillion gallons withdrawn per year in Iowa for all uses)
Nitrogen fertilizer	1.5 million tonnes (3.5×10^{12} lbs)	12% of the N fertilizer used for all crops in the U.S. (~\$2.2 billion)

*Assuming 19% of corn is irrigated.

The results shown in both tables 5 and 6 assume current trends in harvest and fermentation yields, as well as irrigation rates and irrigation acreages. While alternative scenarios can be built using projected increases in agricultural and industrial yields; this scenario can be considered as a baseline for comparisons.

Table 7. Summary of U.S. agricultural statistics for non-leguminous crops.

From NASS 2003, FRIS 2003 (Table 27), and Field Crops Agricultural Chemical Usage 2000 and 2003, 2002 Census of Agriculture (Volume 1, Chapter 2, Table 24), necessary to obtain the following statistics: % of U.S. production, % of irrigated area, % area fertilized with nitrogen, Irrigated Yield (Yirr), Ratio irrigated to non-irrigated yield (Yirr/Ynon-irr), Irrigation rate (I-rate), Nitrogen application rate (N-rate). The environmental footprint results are presented as: Liters of water per liter of irrigated ethanol (*Lw/Lie*), land used per liter of ethanol (*m²/Le*), and grams of Nitrogen fertilizer used per Liter of fertilized ethanol (*gN/Lfe*).

	US prod. ¹	Irrig. Area ²	Fert. Area ³	Yirr ⁴	Yirr/ Ynon-irr ⁴	I-rate ⁵	N-rate ⁵	Water ⁶	Land ⁷	Nitrogen ⁸
CORN	(%)	(%)	(%)	(bu/ac)		(ac-ft/ac)	(lb/ac)	(Lw/Lie)	(m ² /Le)	(g N/Lfe)
Iowa	19	1	93	171	1.17	0.5	133	367	2.62	39.0
Illinois	18	2	98	174	1.07	0.6	161	432	2.51	45.3
Nebraska	11	61	95	186	2.14	1.2	130	809	2.82	41.0
Minnesota	10	3	95	169	1.30	0.6	122	445	2.82	38.5
Indiana	8	4	99	169	1.18	0.5	154	371	2.82	48.6
Ohio	5	0.12	100	143	1.02	1.6	164	1,402	2.64	48.5
South Dakota	4	4	92	169	1.52	1.0	98	742	3.70	40.7
Wisconsin	4	3	99	171	1.50	0.7	102	513	3.19	36.4
Missouri	3	9	99	158	1.39	0.6	169	476	3.81	72.1
Kansas	3	54	99	178	3.12	1.4	133	986	3.43	51.1
Michigan	3	9	99	165	1.35	0.5	123	380	3.21	44.3
Texas	2	36	98	184	3.61	1.6	146	1,090	3.49	57.0
US		19	96							
							U.S. Weighted average	566	2.85	44.0
							Standard deviation	340	0.45	9.9
SORGHUM	(%)	(%)	(%)	(bu/ac)		(ac-ft/ac)	(lb/ac)	(Lw/Lie)	(m ² /Le)	(g N/Lfe)
Texas	37	16	63	68	N/A	1	90	1,843	7.62	61.0
Kansas	32	6	97	93	N/A	0.9	76	1,213	9.14	37.7
Nebraska	8	5	99	113	N/A	1.3	86	1,442	6.63	35.1

Arkansas	4	27	N/A	90	N/A	0.6	N/A	836	5.02	N/A	
US		11	82								
								U.S. Weighted average	1,523	8.08	49.2
								Standard deviation	422	1.73	14.3
SUGAR CANE	(%)	(%)	(%)	(Tonnes/ha)		(in)	(Kg/ha)	(Lw/Lie)	(m²/Le)	(g/Lfe)	
Florida	52	98	N/A	88	N/A	44.75	163	1,684	1.40	22.7	
Louisiana	37	0	N/A	59	N/A	N/A	112	N/A	2.09	23.4	
US		48	N/A								
								U.S. Weighted average	1,684	1.70	23.1
								Standard deviation	N/A	0.49	0.5
SUGAR BEET	(%)	(%)	(%)	(Ton/ac)		(ac-ft/ac)	(Kg N/ha)	(Lw/Lie)	(m²/Le)	(g N/Lfe)	
Minnesota	33	1	100	24	N/A	-	135	N/A	2.09	19.5	
Idaho	20	100	97	29	N/A	2.7	224	1,224	1.48	24.3	
North Dakota	17	6	94	20	N/A	2.2	146	1,417	2.11	17.1	
Michigan	11	N/A	100	21	N/A	0.5	105	313	2.26	34.4	
US		24	98								
								U.S. Weighted average	1,081	1.97	22.2
								Standard deviation	590	0.35	7.7
POTATOES	(%)	(%)	(%)	(CWT/ac)		(ac-ft/ac)	(Kg/ha)	(Lw/Lie)	(m²/Le)	(g N/Lfe)	
Alaska	37	100	N/A	109	3.63	0.50	N/A	923	3.14	N/A	
Idaho	27	100	N/A	349	N/A	2.10	N/A	1,211	1.92	N/A	
Washington	20	95	N/A	535	1.54	2.30	N/A	865	1.15	N/A	
US		96	100								
								U.S. Weighted average	1,051	2.38	58.8
								Standard deviation	185	1.01	N/A

¹ See sample calculation 1.

² See sample calculation 2.

³ See sample calculation 5.

⁴ See sample calculation 3 (find % irrigated corn area for all states in table 9).

⁵ See sample calculation 4.

⁶ See sample calculation 5.

⁷ See sample calculation 6.

⁸ See sample calculation 7.

Table 8. Summary of U.S. agricultural statistics for soybean (a leguminous crop that is not frequently fertilized with N

From NASS 2003, FRIS 2003 (Table 27), and Field Crops Agricultural Chemical Usage 2000 and 2003, 2002 Census of Agriculture (Volume 1, Chapter 2, Table 24), necessary to obtain the following statistics: % of U.S. production, % of irrigated area, % area fertilized with nitrogen, Irrigated Yield (Yirr), Ratio irrigated to non-irrigated yield (Yirr/Ynon-irr), Irrigation rate (I-rate), Nitrogen application rate (N-rate). The environmental footprint results are presented as: Liters of water per liter of irrigated ethanol (*Lw/Lie*), land used per liter of ethanol (*m²/Le*), and grams of Nitrogen fertilizer used per Liter of fertilized ethanol (*gN/Lfe*).

	<i>US prod. (%)</i>	<i>Irrig. Area (%)</i>	<i>Fert. Area (%)</i>	<i>Yirr (bu/ac)</i>	<i>Yirr/Ynon-irr</i>	<i>I-rate (ac-ft/ac)</i>	<i>N-rate (lb/ac)</i>	<i>Water (Lw/Lie)</i>	<i>Land (m²/Le)</i>	<i>Nitrogen (g N/Lfe)</i>
Illinois	15	2	11	46	1.24	0.6	15	2,038	13.86	14.9
Iowa	14	0	15	42	1.24	0.4	49	1,488	15.77	55.4
Minnesota	10	1	8	43	1.43	0.6	17	2,180	16.02	19.5
Indiana	8	1	7	43	1.16	0.4	29	1,454	13.49	28.1
Nebraska	7	42	32	55	1.72	1	14	2,841	12.66	12.7
Ohio	7	0	19	53	1.29	-	20	N/A	13.32	19.1
Missouri	6	7	12	43	1.30	0.5	26	1,817	17.38	32.4
South Dakota	5	2	29	43	1.54	0.8	14	2,907	18.64	18.7
Arkansas	5	58	3	43	1.39	0.8	61	2,907	13.32	58.3
North Dakota	4	1	43	38	1.27	0.7	32	2,878	17.68	40.6
US	-	7	18							
<i>U.S. Weighted average</i>								1,935	12.42	29.3
<i>Standard deviation</i>								618	2.16	16.5

Table 9. Percentage irrigation acreage of corn in 2003.

	<i>Total harvested acres 2002</i>	<i>Harvested acres irrigated 2002</i>	<i>% irrigated 2002¹</i>
Alabama	176,122	11,990	6.81%
Alaska	(N/A)	(N/A)	(N/A)
Arizona	27,838	27,838	100.00%
Arkansas	238,554	145,351	60.93%
California	168,354	168,192	99.90%
Colorado	708,197	634,015	89.53%
Connecticut	3,010	(N/A)	(N/A)
Delaware	161,421	43,747	27.10%
Florida	26,790	9,404	35.10%
Georgia	252,176	99,179	39.33%
Hawaii	4,383	4,383	100.00%
Idaho	42,209	(N/A)	(N/A)
Illinois	10,742,787	211,167	1.97%
Indiana	5,123,291	180,305	3.52%
Iowa	11,761,392	86,261	0.73%
Kansas	2,494,179	1,346,807	54.00%
Kentucky	1,043,990	8,195	0.78%
Louisiana	461,782	130,968	28.36%
Maine	2,660	(N/A)	(N/A)
Maryland	406,841	31,940	7.85%
Massachusetts	2,573	(N/A)	(N/A)
Michigan	2,007,021	180,261	8.98%
Minnesota	6,556,082	178,457	2.72%
Mississippi	496,219	123,232	24.83%
Missouri	2,677,491	246,315	9.20%
Montana	11,642	11,642	100.00%
Nebraska	7,344,715	4,505,579	61.34%
Nevada	7,344,715	4,505,579	61.34%
New Hampshire	880	(N/A)	(N/A)
New Jersey	66,128	4,465	6.75%
New Mexico	48,096	47,904	99.60%
New York	450,664	4,262	0.95%
North Carolina	700,045	23,716	3.39%
North Dakota	991,390	54,445	5.49%
Ohio	2,869,951	3,387	0.12%
Oklahoma	182,777	99,457	54.41%
Oregon	19,308	19,116	99.01%
Pennsylvania	790,111	3,277	0.41%
Rhode Island	41	(N/A)	(N/A)
South Carolina	240,085	14,932	6.22%
South Dakota	3,165,190	123,229	3.89%
Tennessee	593,564	7,286	1.23%
Texas	1,815,560	658,177	36.25%
Utah	14,999	14,999	100.00%
Vermont	5,130	(N/A)	(N/A)
Virginia	335,692	12,953	3.86%
Washington	73,703	73,038	99.10%
West Virginia	29,123	(N/A)	(N/A)
Wisconsin	2,862,031	83,602	2.92%
Wyoming	34,095	33,507	98.28%
United States	75,574,997	14,172,559	18.75%

¹ See sample calculation 2.

Table 10. Yields, evapotranspiration, land and fertilizer requirements for Switchgrass.

<i>Location</i>	<i>ET (m³/ha)</i>	<i>Y (Tonne/h a)</i>	<i>N-rate (KgN/ha)</i>	<i>ET Water (Lw/Le)</i>	<i>Land (m²/Le)</i>	<i>Nitrogen (g N/Lfe)</i>
West Nevada		10	56		3.29	18.4
Knoxville, TN		16	110		2.01	22.1
Stephenville, TX	6,564	14	200	1,517	2.31	46.2
Hope, Arkansas	5,962	17	200	1,161	1.95	38.9
Ames, Iowa	7,622	13	200	1,943	2.55	51.0
Clinton, Louisiana	8,540	26	200	1,041	1.22	24.4
Columbia, Missouri	7,702	13	200	1,910	2.48	49.6
Florence, SC	8,539	22	200	1,239	1.45	29.0
Beeville, TX	6,386	21	200	1,000	1.57	31.3
<i>Average</i>				1,401	2.09	34.6
<i>Standard deviation</i>				396	0.93	10.6

Table 11. Irrigation, land, and nitrogen requirement for biofuel production in the U.S. from different crops.

	<i>Land Use</i>		<i>Water Use</i>		<i>Fertilizer Use</i>	
	<i>m² land /Le</i>	<i>STDEV</i>	<i>L irrigation water/ L irrigated ethanol produced</i>	<i>STDEV</i>	<i>g N/L fertilized ethanol</i>	<i>STDEV</i>
Corn grain	2.8	0.45	566	340	44.0	9.9
Potatoes	2.4	1.01	1,051	185	58.8	N/A
Sugar cane	1.7	0.49	1,684	N/A	23.1	0.5
Sugar beet	2.0	0.35	1,081	590	22.2	7.7
Sorghum	8.1	1.73	1,523	422	49.2	14.3
Soybean*	8.1	1.40	1,256	401	29.7	5.1
Switchgrass	2.1	0.93	N/A	N/A	34.6	10.6

* As energy-equivalent liters of ethanol (i.e., multiplied values per L biodiesel by 0.62)

Sample calculations

1. Percentage of U.S. corn production attributable to Iowa in 2003.

We obtained the 2003 harvested corn acreage from “US & State Data–Crops” and then divided the Iowa harvested corn acreage by the total US harvested corn acreage.

Data available at:

http://www.nass.usda.gov/Data_and_Statistics/Quick_Stats/index.asp

State	Harvested (1,000 ac)	% US Production
Iowa	11,900	19
United States	70,944	100

2. Percentage of irrigated cropland for each crop.

we obtained % of irrigated acreage for each crop using data from Volume 1, Chapter 2, table 24 from the 2002 Census of Agriculture for each crop and for each state, available at:

http://www.agcensus.usda.gov/Publications/2002/Volume_1_Chapter_2_US_State_Level/index.asp

State	Total harvested acres 2002	Harvested acres irrigated 2002	% Irrigated 2002
Iowa	11,761,392	86,261	0.73%

3. Irrigated corn yield (Yirr) and Ratio of irrigated to non-irrigated corn yield (Yirr/Ynon-irr).

We obtained data from Table 27 of the FRIS 2003, downloadable from the 2002 Census menu at <http://www.nass.usda.gov/Quick Stats/> or at <http://www.agcensus.usda.gov/Publications/2002/FRIS/index.asp>.

In Iowa, the average irrigated corn yield was 171 bu/ac while the average non-irrigated corn yield was 146, which results in a ratio of 1.17.

<i>State</i>	<i>Yirr (bu/ac)</i>	<i>Y nonirr (bu/ac)</i>	<i>Yirr/Ynonirr</i>
Iowa	171	146	1.17

4. Irrigation and nitrogen application rates and percentages of area irrigated/fertilized.

We obtained irrigation rates from Table 27 of FRIS 2003, and fertilizer application rates from the 2000 and 2003 Field Crops Agricultural Chemical Usage database available at <http://www.agcensus.usda.gov/Publications/2002/FRIS/index.asp>, and <http://usda.mannlib.cornell.edu/MannUsda/viewDocumentInfo.do?documentID=1001>, respectively.

<i>State</i>	<i>I-rate (ac-ft/ac irrigated)</i>	<i>% irrigated</i>	<i>N-rate (lb/ac fertilized)</i>	<i>% fertilized</i>
Iowa	0.5	1	133	93

5. Water footprint of biofuels based on irrigation.

2003 Irrigation rates (ac-ft/ac) were divided by 2003 irrigated yields (bu/ac). Ethanol conversion efficiencies were factored in and unit conversions performed to finally obtain the water footprint based on irrigation (Lw/Le). The example below shows data for ethanol from corn grown in Iowa.

<i>State</i>	<i>Water applied (ac-ft/ac)</i>	<i>Irrigated yield (bu/ac)</i>	<i>Ethanol yield (L ethanol/Tonne grain)</i>	<i>Irrigation water footprint (Lw/Lie)</i>
Iowa	0.5	171	387	367

6. Land footprint of biofuels.

Ethanol conversion efficiencies were factored in with 2003 corn yields to obtain the land footprint of biofuels (m²/Le). The example below shows data for ethanol from corn grown in Iowa.

<i>State</i>	<i>2003 Average yield (bu/ac)</i>	<i>Ethanol yield (L ethanol/Tonne grain)</i>	<i>Land footprint (m²/Le)</i>
Iowa	157	387	2.69

7. Nitrogen footprint of biofuel.

2003 Nitrogen application rates (lb N/ac fertilized) were divided by 2003 fertilized yields (bu/ac). Ethanol conversion efficiencies were factored in and unit conversions performed to finally obtain the grams of nitrogen per liter of ethanol from fertilized land (gN/Lfe).

<i>State</i>	<i>Average N-application rate (lb/ac fertilized)</i>	<i>Average yield (bu/ac)</i>	<i>Ethanol conversion efficiency (L ethanol/Tonne grain)</i>	<i>Nitrogen footprint (gN/Lfe)</i>
Iowa	133	171	387	39.04

LCA Results

This chapter describes the results obtained with a LCA methodology and current USDA and industry statistics. A distinction between agricultural water requirements (water needed to grow the feedstocks) and process water requirements (feedstock processing to corn) is made. The high regional and feedstock variability is evaluated. Biofuel water requirements are compared to the requirements of other energy production processes. The contents of this chapter are presented as they were published in the peer-reviewed paper *The Water Footprint of Biofuels: A Drink or Drive Issue*. Dominguez-Faus, R., Powers, S.E., Burken, J.G., and Alvarez, P.J.. *Env. Sci. Technol.* 43(9): 3005–3010, 2009. This paper was produced in collaboration with two more authors, which contributed with a discussion on biofuel production implications to land use change and water quality of the Gulf of Mexico.

The Water Footprint of Biofuels: A Drink or Drive Issue.

Dominguez-Faus, R., Powers, S.E., Burken, J.G., and Alvarez, P.J..
Env. Sci. Technol. 43(9): 3005–3010, 2009.

Ensuring inexpensive and clean water is an overriding global challenge noted as one of the Millennium Development Goals of the United Nations. This challenge will likely be intensified by the increasing demand for biomass-derived fuels (i.e., biofuels) for transportation fuel needs, because (1) large quantities of water are needed to grow the fuel crops, and (2) water pollution is exacerbated by agricultural drainage containing fertilizers, pesticides and sediment. These potential drawbacks are balanced by biofuels' significant potential to ease dependence on foreign oil and improve trade balance(s) while mitigating air pollution and reducing fossil carbon emissions to the atmosphere. In the U.S., the Energy Independence and Security Act of 2007 (EISA) mandated the annual production of 56.8 billion L of ethanol (15 billion gal/yr [BGY]) from corn by 2015 and an additional 60.6 billion L (16 BGY) of biofuels from cellulosic crops by 2022 (DOE Ethanol Myths and Facts, 2008), a total that represents 15% of the gasoline used in the U.S. in 2006 on an energy basis. The EISA requirements virtually guarantee a large increase in biofuel production. Furthermore, this mandated and subsidized change will occur largely free from the market pressures and environmental constraints that would normally apply. Although the continued rate of growth in ethanol production in the current economic recession is uncertain, its growth rate vastly outpaced most U.S. industries in 2008, with record amounts of ethanol produced (>9 billion gallons) (Dinneen, R., 2009) and a corn harvest only slightly behind the 2007 record production (USDA Corn Grain

Quick Stats, 2008). Continued growth could have far-reaching environmental and economic repercussions, and it will likely highlight the interdependence and growing tension between energy and water security.

Developing a sustainable national biofuels program requires careful consideration of logistical concerns (e.g., suitable production and distribution infrastructure) and of unintended environmental impacts. Numerous recent studies have considered the latter, with a primary focus on air quality (Gaffney et al., 2001; Graham et al., 2008; Pouloupoulos et al., 2002), land use (Donner et al., 2004; Searchinger et al., 2008; Secchi et al., 2007), and net energy value (Dias de Oliveira et al., 2005; Farrell et al., 2006; Groode et al., 2006; Lavigne et al., 2007; Pimentel et al., 2005; Shapouri et al., 2008). These studies generally reflect beneficial environmental tradeoffs for biofuels compared to fossil fuels, with a few notable exceptions that recently considered greater CO₂ emissions associated with massive deforestation in tropical regions (Searchinger et al., 2008; Dias de Oliveira et al., 2005; Fargione et al., 2008). However, the effect of increased biofuels production on water security has not been subjected to the same scrutiny (Water Implications of Biofuels Productions in the United States, NRC, 2008). As biofuels production increases, a growing need exists to understand and mitigate potential impacts to water resources, primarily those associated with the agricultural stages of the biofuel life cycle (e.g., water shortages and water pollution) – herein referred to as the *water footprint*.

Are We Ready for Fifty Gallons of Water per Mile Driven?

The water requirements of biofuel production depend on the type of feedstock used and on geographic and climatic variables. Such factors must be considered to determine water requirements and identify critical scenarios and mitigation strategies. Feedstock cultivation, usually row-crop agriculture, is the most water-intensive of biofuel production stages. For example, evapotranspiration water requirements to produce enough feedstock to make one liter of ethanol in the U.S. range from 500–4000 L (Figure 1) while processing water requirements for a typical sugar cane or corn ethanol refinery are only 2–10 liters of water per liter of ethanol produced (Lw/Le) (Water Implications of Biofuels Productions in the United States, NRC, 2008). Nevertheless, the water used in biofuel processing and other stages in biofuel production is often withdrawn from local point sources and can have localized impacts on water quality and quantity.

The water requirements associated with driving on biofuels can be significant (King et al., 2008). Assuming conservatively a volumetric water to ethanol ratio of 800 (e.g., for irrigated corn ethanol from Nebraska, which excludes processing water requirements), and that a car can drive 16 mi on one gallon of ethanol (or 2/3 of the mileage from gasoline), this represents about 50 gallons of water per mile driven (gwpm) (or 0.02 miles per gallon of water [mpgw]). To illustrate the variability of the irrigation water requirement as a function of the crop used and where it is grown, this value could decrease to 23 gwpm (~0.04 mpgw) for irrigated corn grown in Iowa, or increase to 90 gwpm (~0.01 mpgw) if irrigated sorghum ethanol from

Nebraska is used, or to 115 gwpm (~ 0.009 mpgw) if the sorghum is grown and irrigated in Texas.

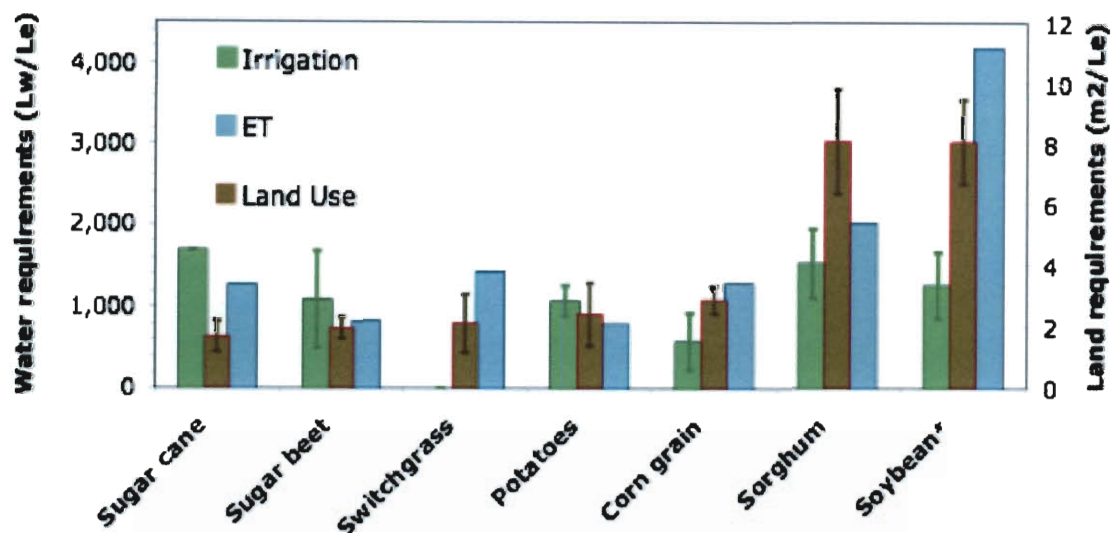


Figure 1. Evapotranspiration, irrigation, and land requirements to produce one liter of ethanol (Le) in the U.S. from different crops.

Weighted average \pm one standard deviation for top producing States, from USDA and other pertinent statistics as described in the Supplemental Information section. Irrigation averages correspond to irrigated land only, while evapotranspiration and land averages correspond to total planted land. *Note that soybean is used for biodiesel production, and its water and land requirements were estimated for an energy-equivalent volume of ethanol.

To minimize the water footprint of biofuels, it is important to recognize that some crops yield more biofuel energy with lower requirements for agricultural land, fertilizer and water, and that consumptive water (evapotranspiration) requirements

tend to increase with land requirement (Figure 1). Thus, from a water supply perspective, the ideal fuel crops would be drought-tolerant, high yield plants grown on little irrigation water. Currently, evapotranspiration requirements for fuel crops range in the U.S. from about 800 Lw/Le for potatoes to about 4200 Lw/Le for soybean (Chapagain et al., 2004). To put these numbers in perspective, large quantities of water are also needed to produce energy from traditional sources (e.g., to pump petroleum out of the ground, generate steam to turn turbines, or nuclear power plants cooling water). However, the water requirements to produce an equivalent amount of energy from biofuels are comparatively large and more consumptive (Table 12).

Table 12. Water requirements for energy production by different processes.

<i>Process</i>	<i>L/MWh</i>
Petroleum extraction	10-40
Oil refining	80-150
Oil shale surface retort	170-681
NGCC* power plant, closed loop cooling	230-30,300
Coal IGCC**	~900
Nuclear power plant, closed loop cooling	~950
Geothermal power plant, closed loop tower	1,900-4,200
Enhanced oil recovery	~7,600
NGCC*, open loop cooling	28,400-75,700
Nuclear power plant, open loop cooling	94,600-227,100
Corn ethanol irrigation	2,270,000 - 8,670,000
Soybean biodiesel irrigation	13,900,000 - 27,900,000

* Natural Gas Combined Cycle

**Integrated Gasification Combined Cycle

Figure 1 shows that both corn grain, which is the most common fuel ethanol crop in the U.S., and switchgrass, which is a lignocellulosic crop, compare favorably to other fuel crops regarding water and land requirements. In fact, the theoretical

irrigation water requirement for prairie-grown switchgrass is zero. Nevertheless, despite intensive research activity on plant genomics and metabolic engineering to facilitate conversion of lignocellulosic feedstock into biofuels, current technology is not yet economically feasible to meet our large biofuel requirements from such feedstocks (Biomass to Chemicals and Fuels: Science, Technology and Public Policy; Energy Forum, Baker Institute, 2008). Consequently, an initial reliance on corn ethanol appears unavoidable to reach the current EISA mandate.

Will the Biofuels Mandate Cause Water Shortages?

Expansion of corn acreage and associated irrigation requirements will have different consequences depending on where it occurs. Rainfall can satisfy most of the agricultural water requirements for biofuel production in some regions (e.g., Iowa, where only about 1% of the corn acreage is irrigated with less than 400 Lw/Le, or Ohio which irrigates less than 1% of the corn but uses 1400 Lw/Le [Table 7 in previous chapter]), while other regions rely primarily on irrigation (e.g., Nebraska where 61% of corn acreage is irrigated and uses about 800 Lw/Le, as detailed in previous chapter). This spatial variability, as well as temporal variability in rainfall, makes it difficult to predict how increased irrigation requirements will exacerbate competition for water and create local water shortages. Nevertheless, some general inferences can be made at a national level.

The mandated annual production of 57 billion L (15 BGY) of fuel ethanol from corn by 2015 represents a requirement of 44% of the 2007 U.S. corn production. To estimate the corresponding impact on irrigation requirements, we assumed that the

percentage of the total corn acreage that would be irrigated remains at the 2002 level of 19% (Table 7 in previous chapter), and that 566 Lw/Le are needed for irrigation (2003 weighted-average irrigation requirement, Figure 1). Accordingly, the irrigation water demand attributable to the mandate is about 6 billion m³/yr which represents about 3% of total irrigation water use in the US in 2000 and is higher than the total water withdrawals (all uses) for the state of Iowa (Hutson et al., 2004). This preliminary analysis does not consider changes in water requirements due to potential displacement of crops of different water intensity, or how advances in biotechnology and improvements in harvest yields and conversion efficiencies might affect this demand. Note that about 5.5 BGY of corn ethanol are already being produced towards meeting the EISA mandate thus, the incremental demand for irrigation water is lower than the above estimate. Nevertheless, regional impacts to water resources as a result of corn ethanol irrigation are already being experienced.

Most biofuel feedstock expansion is occurring in the Midwest (USDA 2008 Acreage Report, USDA, 2008). In Nebraska, irrigated corn area surpassed all time highs in 2007 and 2008, with over 3.64 million ha planted. That area is also experiencing all-time water deficits and legal actions have been taken by Kansas, based on allegations that Nebraska farmers in 2004 and 2005 used 98 billion L more of the Republican River's allotments permitted by the Supreme Court in 2003. Meeting the Kansas demand would mean shutting off irrigation to an estimated 485,000 ha of Nebraska farmland (US Water News Online, 2008). The Ogallala Aquifer is also being drawn down at record rates, with an average draw down of 4 m across the 8-state region it underlies, and water levels have dropped by over 40 m in

some areas (McGuire, V.L., 2007). These trends are expected to continue to increase as ethanol production increases.

But floods are common in the Midwest, so why is water availability a concern?

Extreme hydrologic events (droughts or floods) can impact feedstock production and availability. The 2008 floods and heavy rains in the Midwest washed away about 2% of the nation's corn crop (USDA 2008 Acreage Report, USDA, 2008). However, the nation-wide corn production from 32 million ha (79.3 million acres) is projected to be about 312 million t (12.3 billion bu), down 6% from the 2007 record, but up 17% from 2006 (USDA Forecasts Robust Corn and Soybean Crops, USDA, 2008).

According to the U.S. Climate Change Science Program (Karl et al., 2008) extreme hydrologic events have become more frequent and intense in the past 50 years in the U.S., and this trend is likely to persist. Thus, in addition to the existing temporal and geographical distributions in water availability, the potential change in these distributions and its uncertain effects on crop yields and crop water demand confounds our ability to determine the implications of biofuel in future water supplies.

Regardless of climate change, the competition for water between sectors will intensify in the near future. Energy and agriculture already rank as the top two sectors in U.S. water withdrawals, accounting respectively for 48% and 34% of the total (Hutson et al., 2004). The Energy Information Administration's (EIA) predicts

that thermoelectric generation from coal, natural gas, nuclear and other fuels will increase by 22% between 2005 and 2030 (Energy Demands on Water Resources; Report to Congress on the Interdependency of Energy and Water; DOE, 2006), for example. Combined with a biofuel-induced increase in agricultural water use of 6.2×10^{12} L by 2015 (Table S5 in SI), the potential to create water shortages and conflicts cannot be dismissed.

How Will Water Quality Be Affected by the Biofuel Mandate?

The overall water footprint associated with biofuels must recognize the impact of increased agricultural activity on water quality as well as water consumption. To meet the mandated increased production of biofuels, increased agricultural activity such as tilling more land and higher agrichemical application is inevitable, as are some adverse impacts that range from local groundwater degradation to eutrophication of distant coastal waters (Galloway et al., 2003; Rabalais, N.N., 2002). Annual row crops such as those typically used as biofuel feedstocks are especially prone to cause soil erosion and nutrient run off to surface water, with corn having the highest nutrient application rate and highest nutrient loading to surface waters on a per land area basis (Hypoxia in the Northern Gulf of Mexico, EPA, 2008). Furthermore, marginal lands that require even higher fertilizer application and are more susceptible to erosion and runoff may be pressed into agricultural service to take advantage of beneficial crop prices: use of marginal lands would increase impacts on water quality.

Projecting fertilizer use on current lands.

As shown above for water usage, agrichemical application rates vary widely among crops. Figure 2 presents the application rates for nitrogen fertilizer and pesticides available for bioenergy crops in a manner that normalizes the application rates to biofuel production potential. From the perspective of the total nutrient use, the nitrogen (N) fertilizer demand attributable to the 15 BGY mandate is about 2.2 million t/yr (Table 5 in Chapter3), which is about 16% of the value used annually for all crops in the U.S. (Conservation Reserve Program: Summary and Enrollment Statistics, USDA, 2008).

The high fertilizer application rates, especially for row crops in the Midwestern U.S., provide the greatest fluxes of N and phosphorus (P) to local waterways and the Mississippi River basin (Powers, S.E., 2007) and are therefore considered one of the primary contributors to the growing hypoxic zone in the Gulf of Mexico, (>20,700 km² in 2008) ('Dead Zone' again rivals record size 2008, LUMCOM, 2008). The discharge of nutrients from the Mississippi River to the Gulf of Mexico has been measured by the U.S. Geological Survey (USGS) for decades (Figure 3) (Hypoxia in the Northern Gulf of Mexico, EPA, 2008). The total nitrogen (TN) load is comprised primarily of dissolved inorganic nitrogen (DIN), with organic and particulate nitrogen forms contributing 36% ($\pm 8\%$ over 30-year history) of the TN load.

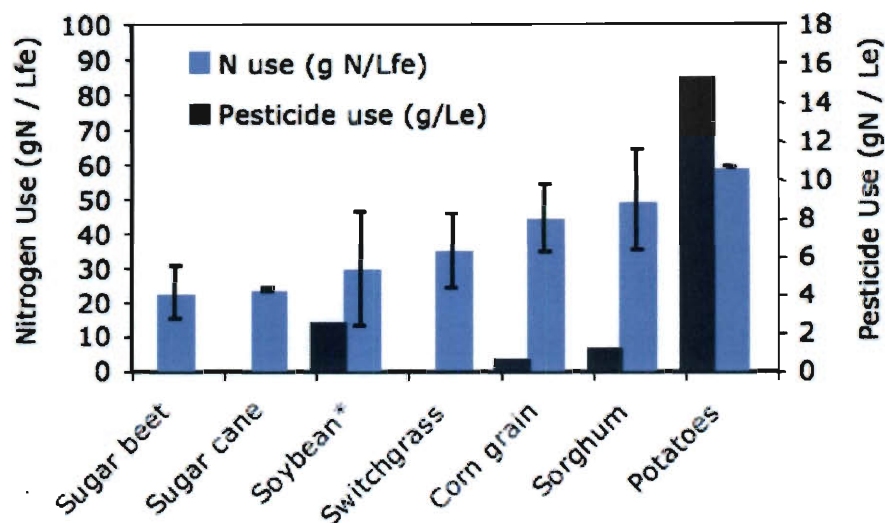


Figure 2. Nitrogen and pesticide requirements for producing one liter of ethanol in the U. S. from different crops.

Data are based on FRIS 2003 and NASS agricultural chemical usage datasets from the USDA. Data for pesticide application is not available for all crops.

*Soybean is used for biodiesel production; its requirements were estimated for an energy-equivalent volume of ethanol. In addition, soybean is a leguminous plant and only about 18% of the total soybean crop comes from N-fertilized fields. See details in the Chapter 3, Table 8.

In 2001, the Mississippi River/Gulf of Mexico Watershed Nutrient Task Force completed an integrated assessment of the hypoxia problem, which led to a goal of reducing the size of the hypoxic zone to 5000 km² by 2015 (Action Plan for Reducing, Mitigating, and Controlling Hypoxia in the Northern Gulf of Mexico, EPA, 2001). Recent estimates suggest that a 45% reduction in TN exports would be required to meet this goal (Hypoxia in the Northern Gulf of Mexico, EPA, 2008; solid black line in Figure 3). Donner and Kucharik employed a rigorous agricultural and process-based dynamic ecosystem model to predict the DIN load that will result from expanding production to meet the 15 BGY corn ethanol goals (Donner et al., 2008). The symbols

included in Figure 3 for the year 2015 are their predictions for the mean (\pm 95% confidence interval) DIN exports. The anticipated increase in corn cultivation would increase the annual average DIN load by 10–18%, which greatly exceeds the DIN export load targets. The role of P discharges in the formation of the hypoxic zone in the Gulf of Mexico has also been reassessed (Sylvan et al., 2006); resulting in a new goal for a 45% reduction in total phosphorus (TP) exports (Figure 3). Nutrient loads to the Gulf of Mexico are highly dependent on the annual rainfall in the upstream Midwest each year (Goolsby et al., 2000), total nutrient application, and land usage for crops. For corn and soybean row crops, the average N discharged from the fields to surface waters through runoff, sediment transport, tile drainage and subsurface flow represents 24–36% of the N fertilizer applied, although this fraction can range from 5–80% in extreme years of drought (e.g., 1988, 2000, Figure 3) and flooding (1983, 1993) (Powers, S.E., 2007). Land use and crop selection can greatly change the amount reaching surface waters. Nutrient discharges are greatest in the more humid corn and soybean regions across Illinois, Indiana, and Ohio (Donner et al., 2004; Donner et al., 2008; Goolsby et al., 2000; Burkart, et al., 2006). The presence of tile drainage in these areas of higher rainfall increases transport fluxes. In a modeling study comparing tile drained and non-drained soils in Iowa showed that the fraction of N fertilizer lost to surface waters ranged from an average of 8% in non-drained fields to 36% in tile drained fields (Powers et al., 2008). The eastern regions of the Corn Belt contribute less to the water consumption aspect of the water footprint, but they contribute more to the water pollution component of the overall water footprint.

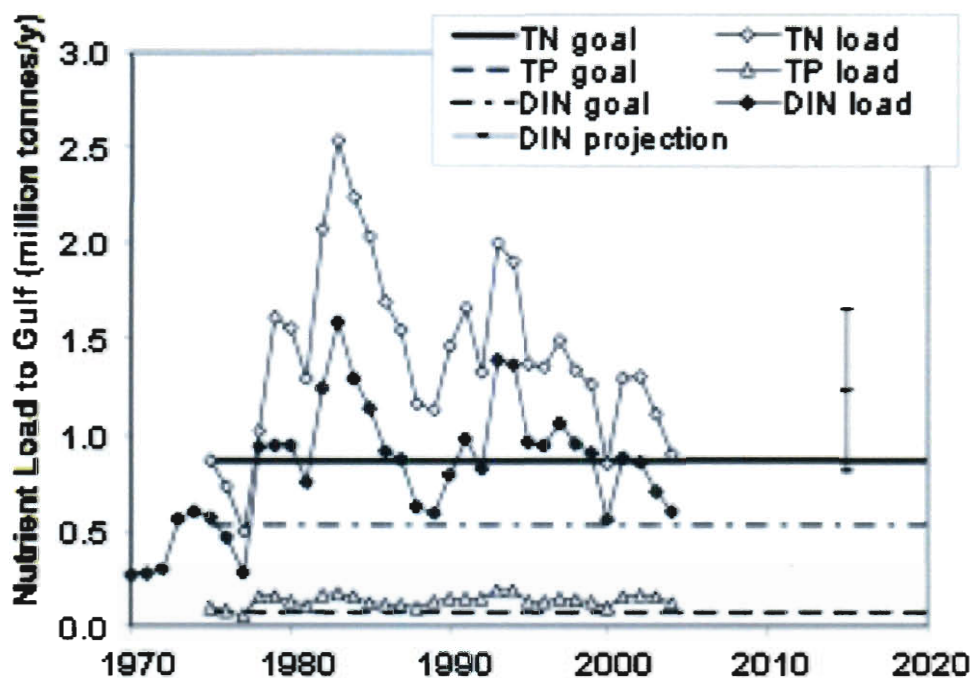


Figure 3. Annual Nutrient loads from the Mississippi River at the St. Francis (USGS station number 07373420) and Atchafalaya River (07381495) sampling points.

The horizontal lines represent the goals for nutrient discharges defined to reduce the size of the hypoxic zone to 5,000 km² (Galloway et al., 2008). The 2015 symbols are projected DIN loads given increased biofuel crop production (Hypoxia in the Northern Gulf of Mexico, EPA, 2008).

Less information is available regarding nutrient losses from other potential biofuel crops. The U.S. EPA Chesapeake Bay office (Biofuels and the Bay, Chesapeake Bay Commission, 2007) modeled the potential changes in nutrient loads resulting from increased biofuel production in the watershed, and projected a substantial reduction in N loads to the Chesapeake Bay if farmland is converted to switchgrass with no fertilizer (~11,500 t/yr). In comparison, the Bay program partners are striving to reduce loads by 41,000 t from all sources. Thus, these changes will contribute substantially to that goal.

The assumption that no fertilizer would be used on the switchgrass fields in the Chesapeake Bay region is inconsistent with other reports that recommend between zero and several hundred kilograms of N fertilizer per hectare, with an average of 32 kg N/ha in available field trials (see Chapter 3). These discrepancies exist because of the lack of data associated with switchgrass cultivated as a cash crop, the uncertain relationship between fertilizer application and increased yields, and lack of field measurements quantifying the fate of the fertilizer in the soil, air, and water after application. Switchgrass uses applied N efficiently (Parrish et al., 2005), and appears able to obtain N from sources that other crops cannot tap. The long-term impacts on soil productivity are as yet unknown. In areas with sufficient rainfall, annual sustainable switchgrass yields of 15 t/ha may be achievable by applying 50 kg N/ha (Parrish et al., 2005). The modeling study by Powers *et al.* assumed a much higher average fertilization rate for switchgrass grown in Iowa (0 kg/ha in year 1 to 260 kg/ha in years 6-8), and predicted that the average total N discharge to surface water would be 7.8 kg N/ha, representing 4.2% of the N fertilizer applied (Powers et al., 2008). Although the fertilization rates were high in some years, a much lower fraction of fertilizer is lost to surface water with switchgrass than with corn.

Land use changes that could impact water quality.

Prior to the current ethanol mandate and subsidies, fuel crops were generally grown where it was most economically and environmentally sound to do so. This was in part due to the conservation reserve program (CRP), which pays farmers not to utilize highly erodible and minimally productive lands. CRP contracts are ranked

and selected based on the Environmental Benefits Index (EBI) to target retiring land from row crop production, which has the greatest detriment in terms of erosion, runoff, and leaching of nutrients. In 2007, over 14 million ha were enrolled in the CRP, producing notable reductions in pollutant loads to surface water, including reductions of 187 million t of sediment erosion, 218,000 t of N and 23,000 t of P (Hypoxia in the Northern Gulf of Mexico, EPA, 2008). The program was also reported to sequester an estimated 45 million t of carbon (C)/yr (Conservation Reserve Program: Summary and Enrollment Statistics, USDA, 2008). Farmers are encouraged to plant CRP lands with native grasses or short rotation woody perennials including willow and poplar, which could also serve as biofuel crops. This selective planting clearly shows benefits of these crops on surface water quality, the overarching goal of the CRP.

Re-enrollment of lands in the CRP is dropping however, and participants requested early release from CRP contracts to take advantage rapidly rising biofuels crop prices, largely driven by the EISA mandate and federal subsidy in the form of the blender's credit. In 2007, Secchi and Babcock estimated that over 526,000 ha of Iowa farmland would likely be pulled from the CRP and put into a corn/soybeans rotation if corn prices hit \$196/t (\$5/bu) (Secchi et al., 2007). In June 2008, corn rose to nearly \$314/t (\$8/bu), well beyond the upper range modeled only one year earlier. Corn prices and futures stabilized through 2008 between \$157–196/t (\$4–5/bu) and overall 2008 averaged just over \$160/t (\$4/bu) at the upper end of the 2007 estimates and well above the stable average or peaks of the previous two decades before the EISA mandate. The average price in 2005 was only \$74/t

(\$1.9/bu) (National Statistics: Corn, Field, NASS, 2009). Although CRP contracts are established on a 10–15 yr basis, enrollment in the program is already decreasing. CRP enrollment dropped by more than 840,000 ha in 2008 and another 410,000 ha as of January 2009. Due to the erodible and less-productive nature of most land enrolled in the CRP, removing land from the program for row crop production will likely lead to a non-linear increase in erosion and nutrient loading to surface waters. This trend is likely to continue as over 2.2 million ha are due to expire in the next three years, and the new farm bill also decreased the maximum area to be in the CRP by about 1.2 million ha (CRP Contract Summary and Statistics, USDA, 2009). One proposal to avert removal of land from the CRP program is to increase CRP payments, which totaled more than \$1.6 billion 2007 (Conservation Reserve Program: Summary and Enrollment Statistics, USDA, 2008). However, some analysts suggest that even doubling the payments would not be sufficient to retain land in the CRP (Secchi et al., 2007).

Policy Measures to Mitigate the Water Footprint of Biofuels

The current and ongoing increase in biofuel production could result in a significant increase in demand for water to irrigate fuel crops, which could worsen local and regional water shortages. A substantial increase in water pollution by fertilizers and pesticides is also likely, with the potential to exacerbate eutrophication and hypoxia issues in inland waters and coastal areas including Chesapeake Bay and the Gulf of Mexico. This in turn would cause undue financial hardship the fishing industry as well as negative impacts to these vital, biodiversity-

rich, ecosystems. Such threats to water availability and water quality on local to national scales represent a major obstacle to sustainable biofuel production and will require careful assessment of crop selection and management options. It is important to recognize that certain crops such as switchgrass and other lignocellulosic options deliver more potential biofuel energy with lower requirements for agricultural land, agrichemicals and water.

Climatic factors such as frequency of droughts and floods are beyond human control, but as the wide range of estimated nutrients discharged to surface waters shows, clearly some important variables are within our control. These include crop selection, tillage methods, and location. As more biofuel production is integrated into the agriculture sector it will be important to adopt land-use practices that efficiently utilize nutrients and minimize erosion, such as co-cropping winter grains and summer biomass crops. These land use choices should also focus on establishing riparian buffers and filter strips to serve a dual purpose in erosion control and biomass production. Similarly, a CRP-like program should be considered to promote cellulosic biofuel crop planting in marginal lands to prevent excess erosion and runoff while allowing producers to benefit from historically high commodity prices. CRP-like payments would then help to balance societal goals with ecological benefits and provide financial viability for the farmers making the land use choices. Finally, increasing charges for irrigation water for biofuel crops to market rates should be considered to promote fuel crop agriculture in areas where rainfall can supply the majority of the water requirements and to reflect the true value of water resources in the price of biofuels. Policies and programs should be coordinated to avoid the

current situation where some efforts (ethanol subsidies, mandates) bid against other programs (CRP) though both are funded by taxpayers with the common goal of environmental protection.

Overall, we cannot expect a major shift in our energy supply from the oil fields of the Middle East to the farm fields of the Midwest to occur without some detrimental impacts. Evaluating the water footprint of this shift is a critical first step to provide input to policy makers to implement a robust and environmentally sustainable national biofuels program. Clearly, the energy and water interdependence will play a key role in our ability to grow the crops needed for biofuel production without causing significant damage to the economy and the environment. However through energy conservation and careful agricultural methods and water usage planning, we can have our drive and drink our water too.

GEPIC Modeling Methodology

The second half of this thesis is dedicated to 1) Assessing the adequacy of GEPIC as a decision support system (DSS), 2) Estimating the effects of climate change on water requirements of corn ethanol, and 3) Estimating the potential of adaptation strategies (shifting of growing season, precision irrigation and precision fertilization) to palliate negative effects of climate change. This chapter describes the methodologies used to meet those goals.

Evaluation of GEPIC model as Decision Support Systems

General modeling approach

As discussed in Chapter 2, GEPIC is a distributed version of the model EPIC, a well-established biophysical model created at Blackland USDA and Texas A&M Research Extension (Williams et al. 1989). GEPIC has been improved for multiple cash crops in the US over the past 30 years. It includes a crop growth module that calculates crop yields with semi-empiric equations, and a hydrology module that uses mechanistic equations to calculate evapotranspiration (ET). All equations are described in Appendix A. EPIC can simulate single sites with homogeneous field conditions are assumed. A watershed/farm version of EPIC exists that can simulate multi-field site conditions (APEX). GEPIC can be used with large-scale projects (national to global) with inherent high spatial heterogeneity more relevant to this study.

In this study, the region of interest (Continental US) is divided in a 0.5 arc-degrees grid and the process model (EPIC) is run independently for each cell of the grid. Homogeneous conditions are assumed in each cell. Simulations were run at a spatial resolution of 0.5 arc-degrees (30 arc-minutes, or about 50 km at the equator), which results in about 4,000 cells that cover the entire conterminous US, from which about 2,000 contain corn acreage. Spatially explicit input values are introduced in the form of maps (grids or rasters) through a GIS interface. Preparation of quality input datasets is the most time consuming step in this simulation effort.

GEPIC can simulate multiple agricultural variables through the interactions of a crop growth, hydrology and nutrient cycling modules. In this thesis, I am estimating corn grain yield, corn stover yield, ET and irrigation water use, and nitrogen use associated with the production of ethanol. GEPIC can simulate the effects of environmental variables in the different phenological (life cycle) phases of plant development as growth is simulated with daily time steps. Results corresponding to annual estimates are computed as the accumulation of daily estimations based on length of growing season. The length of the growing season is determined by inputting planting and harvesting dates. Alternatively, harvesting date can be calculated as a function of a potential heat unit (PHU) value, which is inputted by the user and is distinctive for each crop. A sensitivity study performed in 2005 found that the input that the model was particularly sensitive to was the Potential Heat Unit (PHU) (Xanthoulis, F. R., 2005). Correctly assigning the length of the growing season has a major impact accuracy of results.

The daily potential increase in biomass depends on intercepted photosynthetic radiation and biomass energy conversion. Radiation is estimated by GEPIC from latitude, longitude, day of the year, and land-cover albedo. Biomass conversion efficiency (BE) is calculated from CO₂ concentration, vapor pressure deficit and crop-default parameters. Daily biomass accumulation might be reduced by stresses, and is computed by multiplying potential biomass by a regulating factor, determined by the lower of the four stresses calculated in EPIC: water, aeration, temperature, or nutrient (Williams, 2008)

Crop yield is obtained by multiplying biomass by harvest index (HI), the ratio of

economic yield (grain or fruit) to total plant biomass. Stover yield can be calculated by multiplying biomass by (1-HI). HI is crop-dependent and has relative low variability across regions but HI is also modified by the model if a shorter than normal growing season or by some stress occur.

Plant evapotranspiration (ET_p), the potential water consumed by the plant, is computed as a function of potential evapotranspiration (PET) and leaf area index (LAI). Soil evaporation (ET_s) is computed as a function of PET and a soil cover index (EA). PET can be estimated in EPIC with four different equations: Penman (Penman, 1948), Penman-Monteith (Monteith, 1965), Priestly-Taylor (Priestley, 1972), and Hargreaves (Hargreaves and Samani, 1985). Penman-Monteith is the only method that incorporates CO₂ effects on stomatal conductance and thus in evapotranspiration. Penman-Monteith requires solar radiation, air temperature, wind speed and relative humidity as inputs. Unfortunately, future climate projections do not include the variables wind speed and relative humidity, thus estimation of climate change effects on ET can only be done with Priestley-Taylor or Hargreaves. This study uses the Hargreaves method, which does not require these inputs. The Hargreaves method estimates PET as a function of extraterrestrial radiation and air temperature according to the formula:

$$E_o = 0.0032 \left(\frac{RAMX}{HV} \right) (T + 17.8) (T_{mx} - T_{mn})^{0.6}$$

Irrigation and nitrogen can be applied as a fixed volume and fixed rate. Alternatively, a total annual volume to be dispensed with an automatic scheduling

triggered daily by water and nutrient stress factors is available. The latter is more representative of precision irrigation and fertilization, as only the exact volume required, as determined by daily plant stress, is applied. A thorough description of process equations can be found in the EPIC/APEX manual version 0604. (Williams, 2008).

Data uncertainty

In this study, model uncertainty is dominated by data uncertainty. This is because:

1) The model has been extensively used and parameterized for corn agriculture in the US (Williams et al., 1990). Although further calibration of the model would be required in studies that require absolute values of yields and a high degree of accuracy, it has been concluded that the uncalibrated model can be reliably used to estimate the magnitude of changes associated with the long-term impacts of different cropping systems and management practices (Gassman et al., 2004), which is the use given to GEPIC in this study.

2) The study presented here is a distributed modeling study. Distributed models are extremely useful tools to aid decision making because they incorporate spatial heterogeneities and provide large amounts of spatially relevant information. However, it is the characteristic of distributed models to suffer from high input data uncertainty. Input data is introduced as distributed datasets (DD), which might not accurately represent reality for several reasons: First, the input DD can be at different spatial resolutions (i.e., one value per state vs. one value per county).

Second, grid regular geometries might not accurately represent real spatial variability, which is presented in irregular forms (i.e. county boundaries, soil distribution). In addition, agricultural systems, as any living system, experience large inter annual variability, which contributes uncertainty to datasets.

Data on climate, soil conditions, elevation and slope, irrigation and fertilization, and planting and harvesting dates (or PHU) are required. The success in obtaining good results will greatly depend on using DDs that accurately represent actual site conditions for each cell.

Whenever possible, peer-reviewed datasets (for which an attempt to reduce uncertainty has already been made) were used. This was the case of several input DDs (soil, climate, dem, slope, planted area) and the validation dataset (yields). In the case of unknown variables (*planting and harvesting dates/PHU, fertilization, irrigation, and plant coefficients*), peer-reviewed DDs do not exist, and had to be created ad-hoc for this simulation effort.

The following groups of input variables exist:

1. Fixed variables with known spatial distribution: peer-reviewed distributed datasets are available. In the present study, this category includes data on soil composition, elevation, slope and planted area. These variables are fixed across all simulations.
2. Fixed variables with unknown spatial distribution: plant coefficients (e.g., *harvest index*) are not subject to change across time, but they are heavily dependent on the planted variety, whose spatial distribution is unknown.

3. Adaptable variables with unknown spatial distribution: irrigation, fertilization, and planting and harvesting dates (or PHU) are, like variables in category 2, also unknown at the high spatial resolution required for GEPIC inputs for all past and future crops. In addition, these inputs (unlike unknown variables) can be modified to represent adaptation strategies to minimize the impacts of climate change stressors. A sensitivity study performed in 2005 found that the input GEPIC is most sensitive to is the PHU (Xanthoulis, F.R., 2005)
4. Climate: climate plays a central role in this research project. Because of its importance, climate is considered a separate category. In practice, we will determine the input values for all other variables before we turn to evaluate the impact of climate change, the main goal of this thesis.

Distributed (cell level) datasets for known inputs (category 1) were obtained from previously published studies; in contrast, datasets for unknown (categories 2 and 3) inputs had to be created as described below.

Input distributed dataset creation

Input DD for categories 2 and 3 were created from the scarce available sources in the literature (see Appendix B for details). Source data formats differed from the desired DD format in spatial resolution (i.e. state or national averages vs. cell values), geometries (county geometry vs. grid geometry) and temporal accuracy (i.e. one-year value only where a longer term average is required). The quality of the

each created DD was tested by running the model with the input dataset (iDD) and comparing the resulting simulated yield output dataset (oDD) to a recorded yield dataset (rDD).

The use of a peer-reviewed rDD was required because the rDD also suffers from uncertainties. The rDD was obtained from the Center for Sustainability and the Global Environment (SAGE) of the University of Wisconsin-Madison, a peer-reviewed dataset (Monfreda et al., 2008). The SAGE dataset contains the 5-year average (1997-2002) of corn yields at the 0.5 arc-degrees resolution. Using an average rather than single year results is required to limit the effect of agricultural inter-annual variability. Reported yield variability is not only due to climatic variability, which is incorporated in the model, but also to crop rotations and cropping practices (i.e., corn is rotated with soybean, land can be laid fallow or converted altogether to other crops), which incorporate uncertainties in reported areas and yields for those cells experiencing changes. The peer-reviewed dataset is preferred because these uncertainties are minimized and is considered to be representative of corn agriculture in the US throughout the years. Creating a new rDD would require particular care of uncertainties introduced.

Data uncertainty of the created input DD was minimized but not eliminated. The quality of the created iDD was tested by observing the overall model quality after each sequential increase of input dataset resolution. The overall model quality was evaluated by examining the bias, reliability, and efficiency of the model. Model bias (systematic error: under prediction or over prediction) can be evaluated quantitatively with the mean of Relative Errors (mRE), calculated with equations 1

and 2, where $Ysim_c$ and $Yobs_c$ are simulated and observed yields for cell c respectively. A negative value of RE indicates under-estimation whereas a positive value indicates over-estimation.

$$mRE = \frac{\sum_i^n RE_c}{n_c} \times 100 \quad (1)$$

$$RE_c = \frac{Ysim_c - Yobs_c}{Yobs_c} \times 100 \quad (2)$$

Model reliability (Eq 3) is the probability to produce accurate results, and is calculated as the proportion of cells that produce absolute error below 30%.

$$Rel = \frac{\sum_{cells} [AbsRE < 30\%]}{n_c} \quad (3)$$

Four categories of accuracy are established based on AbsRE levels:

- Very accurate (AbsRE < 7%)
- Accurate (7% < AbsRE < 30%)
- Unacceptable (30% < AbsRE < 50%)
- Extremely unacceptable (AbsRE > 50%)

This classification is based upon the facts that:

- 1) 7% and higher accuracy levels are achieved with EPIC (single site model), for which model error is dominated by conceptual and parameter uncertainty (Wang et al. 2005).
- 2) 20 - 30% accuracy levels are the accepted standard in regional studies with EPIC/APEX, for which the model error type that dominates is data uncertainty. (Niu et al., 2009).
- 3) A somewhat larger error can be expected in GEPIC induced from a larger data error inherent to large-scale gridded datasets.

Overall model accuracy can also be assessed visually by plotting simulated results against recorded observed data, where a resemblance to a 1:1 line represents a perfect accuracy level (no error). Model efficiency, whether the distributed results provide more information than the average of the results, is evaluated quantitatively in this thesis with the Nash-Sutcliffe model efficiency coefficient (NS). The Nash-Sutcliffe efficiency coefficient evaluates whether a distributed model gives a better estimation than the mean of the observed dataset and is calculated according to the formula:

$$NS = 1 - \frac{\sum_{n=1}^c (Y_s^n - Y_o^n)^2}{\sum_{n=1}^c (Y_o^n - \bar{Y}_o)^2} \quad (4)$$

Where the nominator represents residual variance (simulated minus observed) and the denominator represents data variance. Nash-Sutcliffe (NS) efficiencies can range from $-\infty$ to 1. An efficiency of 1 ($NS=1$) corresponds to a perfect match of simulated yield to the observed data. An efficiency of 0 ($NS=0$) indicates that the model predictions are as accurate as the mean of the observed data, whereas efficiency less than zero ($-\infty < NS < 0$) occur when the observed mean is a better predictor than the model.

Table 13. Input data resolution change during model evaluation efforts.

	Run 1 ^a	Run 2 ^a	Run 3 ^b	Run4 ^b	Run 5 ^b	Run 6 ^b
Planting date	National average	State Averages	*	State Averages	Cell level	*
Harvesting date (HD) or PHU	National average HD	State Averages HD	National Averages PHU	State averages PHU	Cell level	*
Maximum Fertilizer volume (kg/ha)	National average	State averages	*	*	*	*
Maximum irrigation volume (mm)	National average	State averages	Cell level	*	*	*
Plant coefficients	National average	*	*	*	*	Cell level

* Indicates no resolution increase from previous run

Shading indicates run when the dataset was changed for the last time

^a Run 1 and 2 were carried out under fixed harvesting schedules.

^b Run 3-6 were carried out under automatic harvesting schedules based on PHU

There were cells for which errors were unacceptable even after the dataset calibration process was ended (because no more increases in spatial resolution are relevant). It is important to bear in mind that data uncertainty was minimized but not eliminated. Model residuals (observed-simulated) were plotted against the different inputs in an attempt to discern the causes of remaining error.

Input distributed dataset final selection

The final selection of created and peer-reviewed input DDs to be used in simulations with GEPIC can be found in table 14.

Table 14. Parameter information, sources and grid resolution of peer-reviewed and input DDs used in this study.

GIS map	Input Variables	Source	Grid Resolution
Current Climate	Maximum temperature (°C) Minimum temperature (°C) Precipitation (mm)	Daily climate dataserries from CRU Ts 2.1 for years 1901-2002 adapted to GEPIC Daily climate dataserries from CRU Ts 2.1 for years 1901-2002 adapted to GEPIC (Mitchell and Jones, 2005) (Liu et al., 2009)	0.5 arc-degrees on a global scale
Future Climate	Maximum temperature (°C) Minimum temperature (°C) Precipitation (mm)	Daily climate dataserries adapted to GEPIC for the years 2040s-2070s based on cGCMs (Liu et al., 2009)	0.5 arc-degrees on a global scale
Soil	Depth (m) % sand % silt Bulk density (kg/m ³) pH Fraction of organic C content Fraction of CaCO ₃	ISRIC- WISE International Soil Profile Data Set (Batjes, N.H., 2006)	0.5 arc-degrees
Land use	Area (m ²) planted with crop	Rain-fed and irrigated harvested areas MIRCA2000 Version 1.1 dataset (Portmann et al., 2010).	0.5 arc-degrees
DEM	Elevation (m)	GTOPO30 DEM from the United States Geological Survey (USGS) EROS Data Center	30 arc-seconds aggregated to 0.5 arc-degrees
Slope	Slope	HYDRO1K digital raster slope map, which defines the maximum change in the elevations between each cell and its eight neighbors (USGS, 2000).	30 arc-seconds aggregated to 0.5 arc-degrees
Irrigation	Irrigation (mm)	USDA Farm and Ranch Irrigation Survey 2003	State level rasterized to a 0.5 degree grid
Fertilization	Fertilizer (kg/ha)	State-wise data for 18 major corn-growing states was obtained from US Department of Agriculture Economic	State level rasterized to a 0.5 degree grid

Research Service (USDA ERS, 2009).			
Planting dates	Julian day	Center for Sustainability and the Global Environment (SAGE) dataset at the University of Wisconsin (Sacks et al., in press).	0.5 degree grid
PHU	PHU	Folberth et al., (under revision)	0.5 arc-degrees
Crop coefficients	HI	Folberth et al., (under revision)	0.5 arc-degrees

Simulations

GEPIC was run with the peer-reviewed and calibrated input datasets described in table 14 to evaluate climate effects and adaptation strategies. The model was run only at the cells that comply with AbsRE <50%. Three rounds of simulations were carried out: one with current (baseline) and two with future (climate change scenarios) climate data.

Baseline – current climate data

Current climate simulations were carried out with climate records for the years 1990-2000 from CRU adapted to GEPIC (Mitchell and Jones, 2005, Liu et al., 2009). The results of this simulation represent baseline conditions to which results from climate change scenarios will be compared. The 1995-2005 period is selected because a 10-year average is required for time stabilization of climate as explained in the background section (Chapter 2), and this period is the latest available data adapted for GEPIC. Atmospheric CO₂ concentrations in this period were set to 369 ppm (IPCC AR4, 2007).

Climate change scenarios – future climate projections

For future climate simulations, I used climate projections for the years between 2040 and 2070 adapted to GEPIC (Liu et al., 2009) from five different Ocean-Atmosphere General Circulation Models (OAGCMs): CGCM2 (Canadian), CSIRO2 (Australia), ECHAM4 (Germany), HadCM3 (UK), and PCM (US). For each cell, the results obtained with the five different models were averaged to obtain a single future estimation. The agreement between the different model estimates was measured by the Standard deviation or interquartile range (IQR) and taken as an approximate measure of likelihood of the climate change projections. To obtain stable climate results 10-year averages of the outputs for the decade 2050s were calculated. Atmospheric CO₂ concentrations were set to 532 ppm according to predictions from the International Panel on Climate Change (IPCC, 2001).

Adaptation strategies

Two rounds of future climate simulations were carried out. A first round was carried under the assumptions that farmers will adapt to a shifting season by changing planting and harvesting date accordingly, and will compensate for any changes in irrigation and fertilizer demand. Results from this round of simulations are referred from now on as “Future with Irrigation” (I) and correspond to impacts due to temperature stresses only, as water and nutrient stresses will be palliated through farming. A second round of future climate simulations was carried under the assumption of no irrigation, henceforth referred to as “Future without irrigation” (NoI). Results obtained in this second round corresponded to a situation in which climate induced water stress is not mitigated, thus these results reflect both

temperature and water stresses.

Comparison of baseline and climate change scenarios (I, NoI)

Comparing future results to baseline conditions will determine the changes in productivity and water and nutrient demands of biofuels created by climate change in the context of different adaptation strategies (I and NoI). The difference between I and NoI adaptation scenarios will give a direct estimation of the importance of water availability on biofuel production. The spatial distribution of the model results will also allow me to identify water “hot spots” where biofuel production would be most affected by shortages in water supply.

Input DD creation and data uncertainty minimization

GEPIC uncertainty is dominated by data uncertainty. For the simulations presented here, whenever possible peer-reviewed distributed datasets were used to minimize this type of uncertainty. However, peer-reviewed distributed datasets were not available for certain input variables: planting and harvesting dates or PHU, and crop coefficients.

Distributed datasets (DD) were created for these inputs (planting dates, harvesting dates or PHU, and crop coefficients) based on available data from USDA. This was the best data available, but not deprived from large degree of uncertainty (spatial and temporal). Previous sensitivity analyses show that GEPIC is more

sensitive to PHU (Xanthaloulis, F.R., 2005) if automatic scheduling is used and it will be very relevant to establish appropriate DD of PHU.

After creating a new dataset and using it with the model, model uncertainty was evaluated by comparing model outputs distributed datasets (oDD) to recorded outputs distributed datasets (rDD). Higher resolution iDDs were consecutively created in an attempt to further reduce data uncertainty, until a limit of spatial resolution imposed by the validation dataset was reached (0.5 arc-degrees)

Model performance was evaluated through the estimation of model accuracy (cell to cell) and through overall model quality, evaluated by examining the bias, reliability, and efficiency of the model, as described in Chapter 5.

Description of Input Distributed Dataset Creation and potential uncertainty.

Maximum annual fertilizer and irrigation volumes

Tabular data for maximum annual fertilizer volume for 18 states was obtained from the Economic Research Service (ERS) of the US Department of Agriculture (USDA) corresponding to year 2002. States with no data were given a value of 152 KgN/ha (136 lbs/ac), as this was the average fertilization volume calculated from available states. Tabular data was downloaded from the USDA library hosted by Cornell University and converted into a vector map and to a raster map with GIS software ArcView 9.1. Raw state corn irrigation data was obtained from USDA FRIS

corresponding to 2002 year, converted into a state shapefile (vector) and finally to a raster file (Figure 1)

Potential contribution to uncertainty: Errors can arise for inadequate spatial or temporal resolution of fertilizer data. The highest spatial resolution achieved was state resolution although fertilizer application volumes might vary within the states. Additionally, where states had no recorded data and an average value was used. While data for the other years of simulation (1997-2002), was available to some extent, year 2002 data was selected because 1) It included the largest amount of states (18) and 2) for most states 2002 saw the highest volume of fertilizer applied, representing a conservative case of using as much nitrogen as possible. Further inaccuracies can arise from the fact that data come from a survey, which is a subjective method of data gathering, and from conversion of vector to raster geometry.

Recorded corn yields.

A published peer-reviewed raster dataset available from the Center for Sustainability and the Global Environment (SAGE) of the University of Wisconsin (Monfreda et al. 2008) (Figure 2).

Harvested area

The model produces a result for the whole cell assuming homogeneous conditions across the cell. As such, it also assumes the whole cell is planted with corn when in reality it is not and computes a total biomass produced in the cell. This introduces considerable error as not the entire cell is covered with crops and we need to adjust to the actual level of harvested acreage. The harvested area dataset is

used to compute production proportionally to the area that is actually harvested. A peer reviewed published dataset (Portmann et al 2010). (Figure 3)

Planting date

Prior to this study, a unique day of planting was used for the entire country. The date was introduced directly in EPIC field operation files. I started using the model in this setting, to find out that results were very poor. Planting, however, occurs at different times in different regions so using a single value for the whole country is not appropriate. A modification of the model was introduced so planting dates were introduced through raster maps in GIS instead of through the parameter file in UTIL. This way, a field operation file with specific planting dates was created for each state. Results were still unsatisfactory and we attributed it to the fact that planting dates corresponded to records of 1997. We can expect planting to occur in different dates in different years so we acquired existing published and peer-reviewed data on planting date (Figure 4).

Harvesting date or PHU

This date determines the end of the growing season and thus the end of the simulation. The accumulated biomass to this date will be the reported biomass. There are two modes of setting the harvesting date: Fixed and Automatic. In Fixed mode, a specific date is used. In the automatic mode, harvesting will occur at plant maturity as calculated with a function of potential heat units (PHU) values, which are crop and climate specific and need to be introduced by the user. Each day that ambient temperature surpasses a plant base temperature is accounted as a heat unit. When the accumulated heat units equal the PHU value, the model assumes plant has

achieved maturity and is ready for harvest, and model stops the simulation. Originally I tried the fixed harvest schedule hoping this would represent actual management conditions that would be used as a baseline scenario. Unfortunately the spatial and temporal resolution of the input data was low and the simulation results under these settings were very unsatisfactory. I then turned to simulate under automatic schedule setting (harvest will occur when plant is mature as calculated by the model as a function of PHU) since it will closely resemble what farmers do.

Originally, one single value of PHU was used for the whole country. The one value was suggested by Jimmy Williams, the developer of EPIC, with the acknowledgement that local values might be needed for each cell instead. One PHU value was indeed insufficient since PHU values depend on crop type and climate conditions, and thus vary geographically. A modification of the model was introduced so it could run under 3 and then 9 different PHU values consecutively. Spatial resolution of PHU values was progressively increased from one to three to ~2000 values (one for each cell). (Figure 5)

Soil.

Soil parameters and spatial distribution of soils from the ISRIC-WISE database (Batjes, 2006) and the Digital Soil Map of the World (FAO,1990)

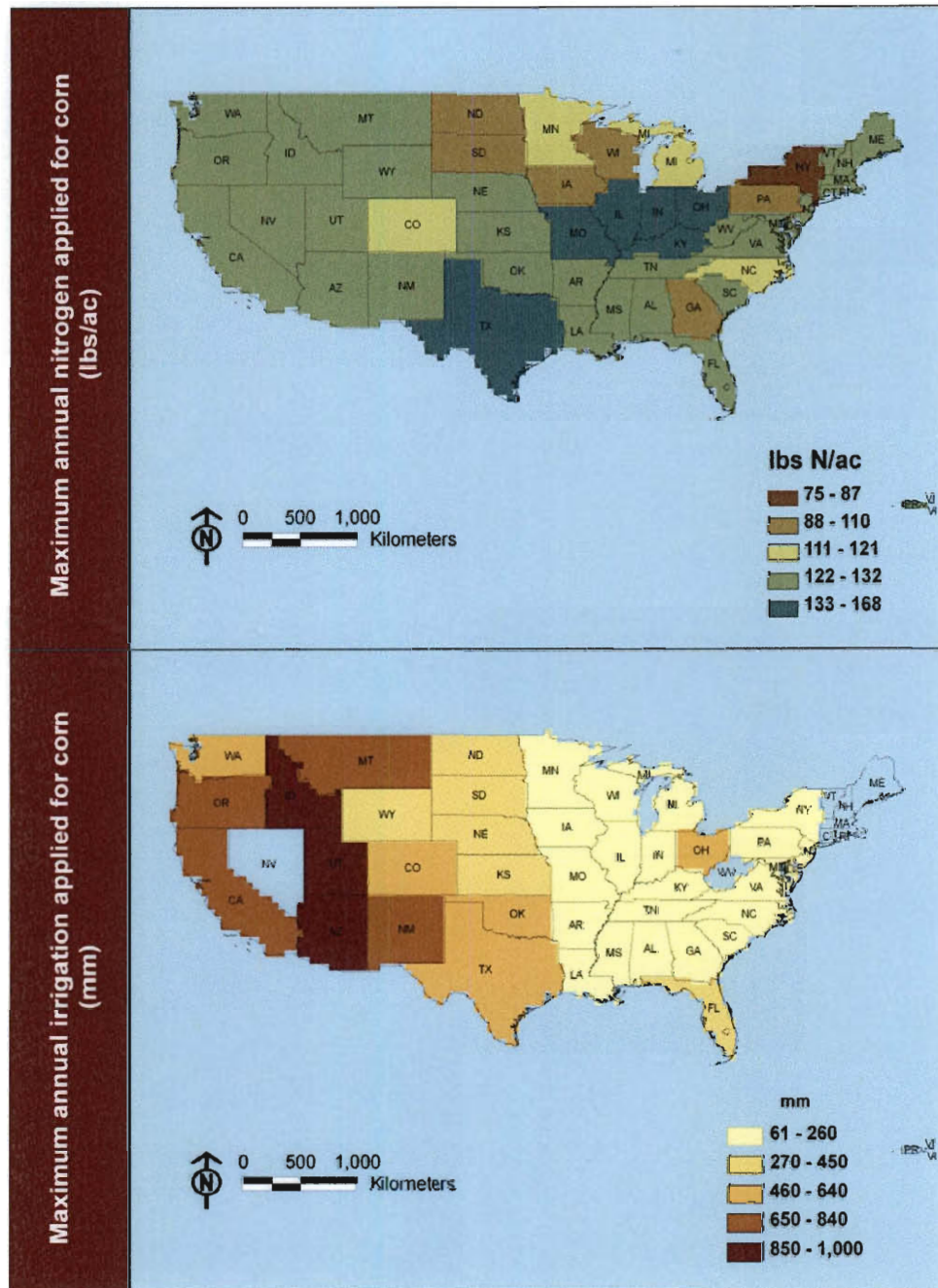


Figure 4. a) Annual fertilizer use. b) Annual irrigation use.

Spatial resolution: State. Temporal resolution: year 2002.

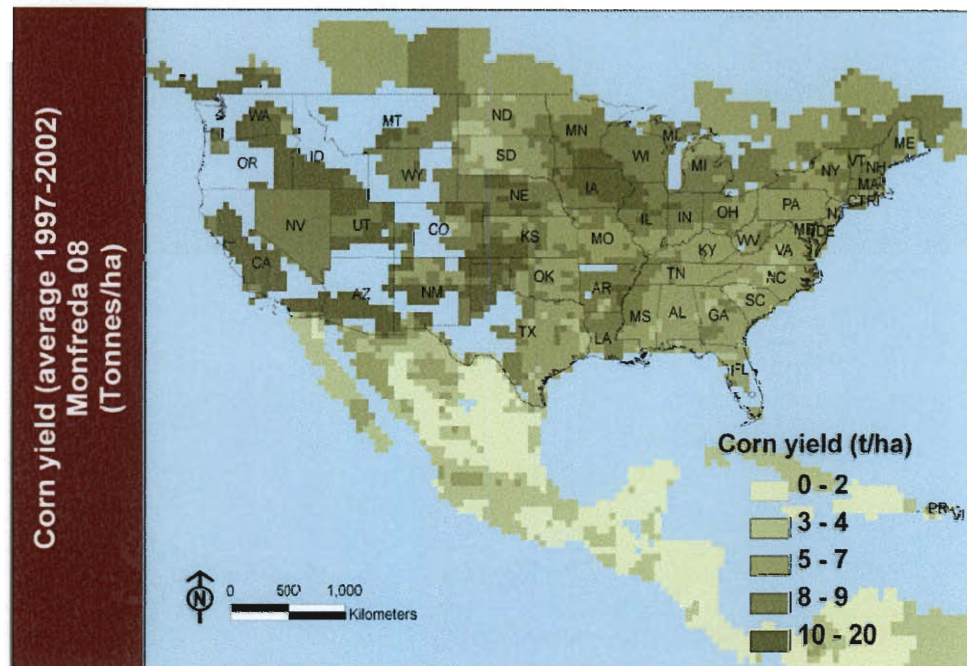


Figure 5. Total corn yield raster published by (Monfreda et al., 2008).

Spatial resolution: cell. Temporal resolution: 1997-2002 averages.

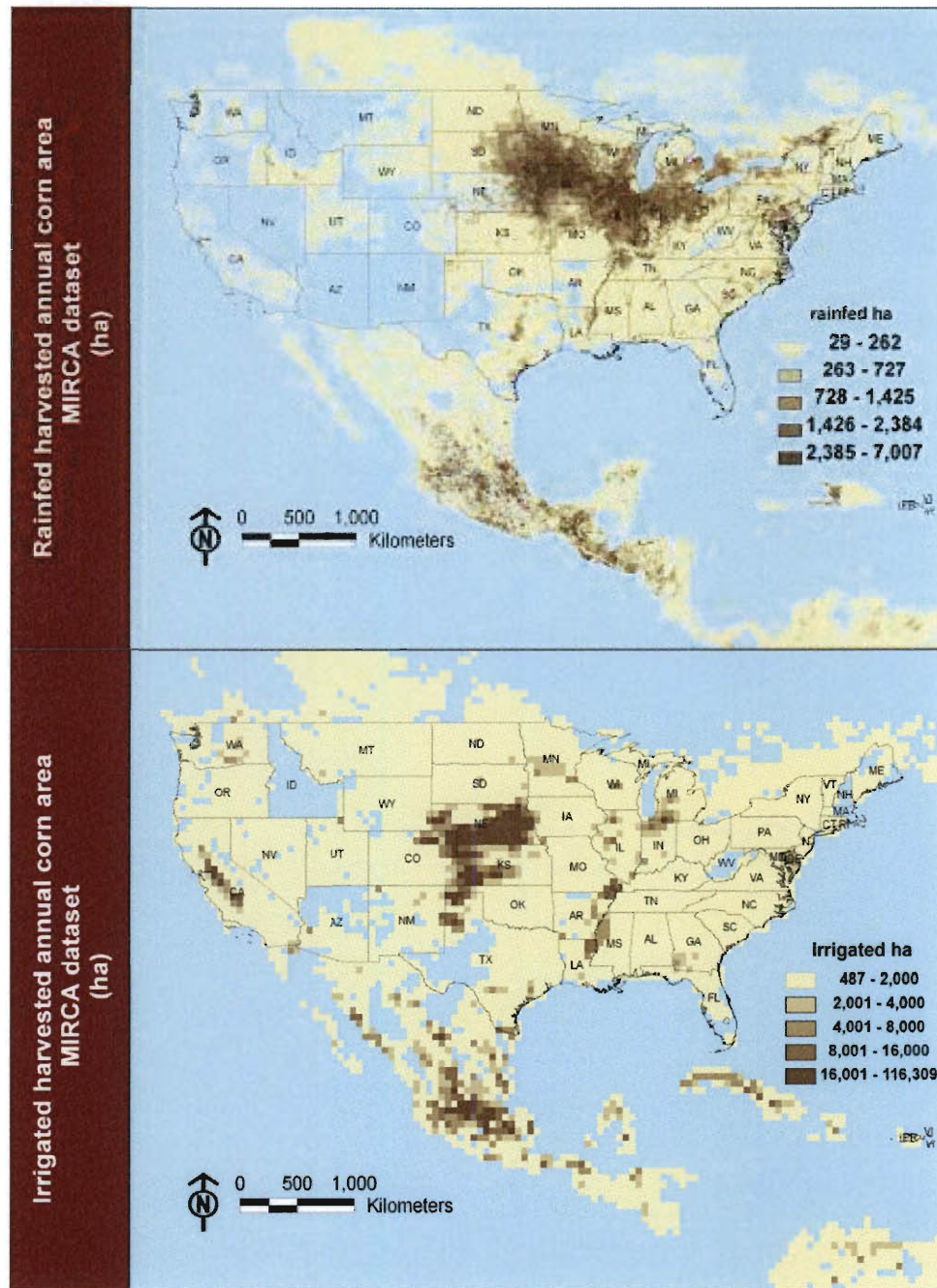


Figure 6. MIRCA2000 version 1.1 datasets for irrigated and non-irrigated corn areas. Spatial resolution: 0.5 degree raster. Temporal resolution: 1998-2002 average.

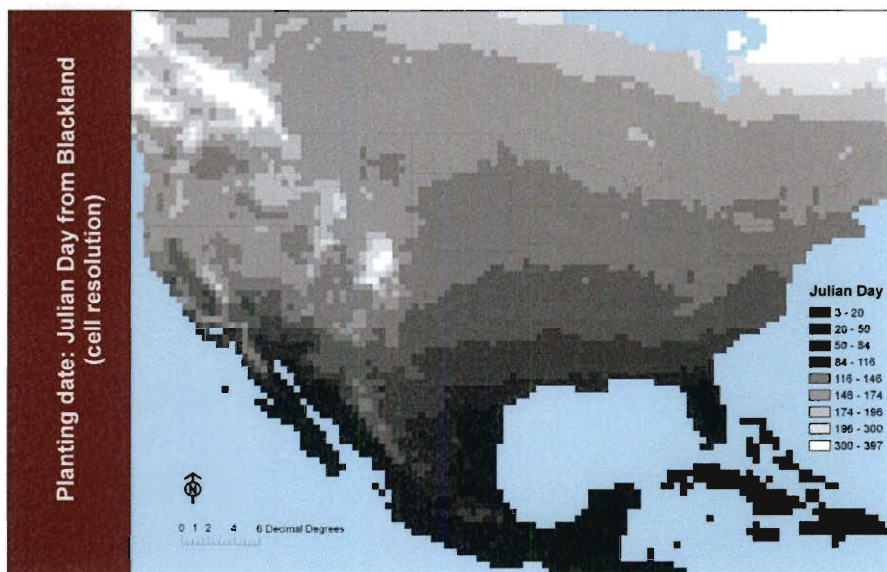


Figure 7. Planting date from SAGE (Sacks et al., 2010).

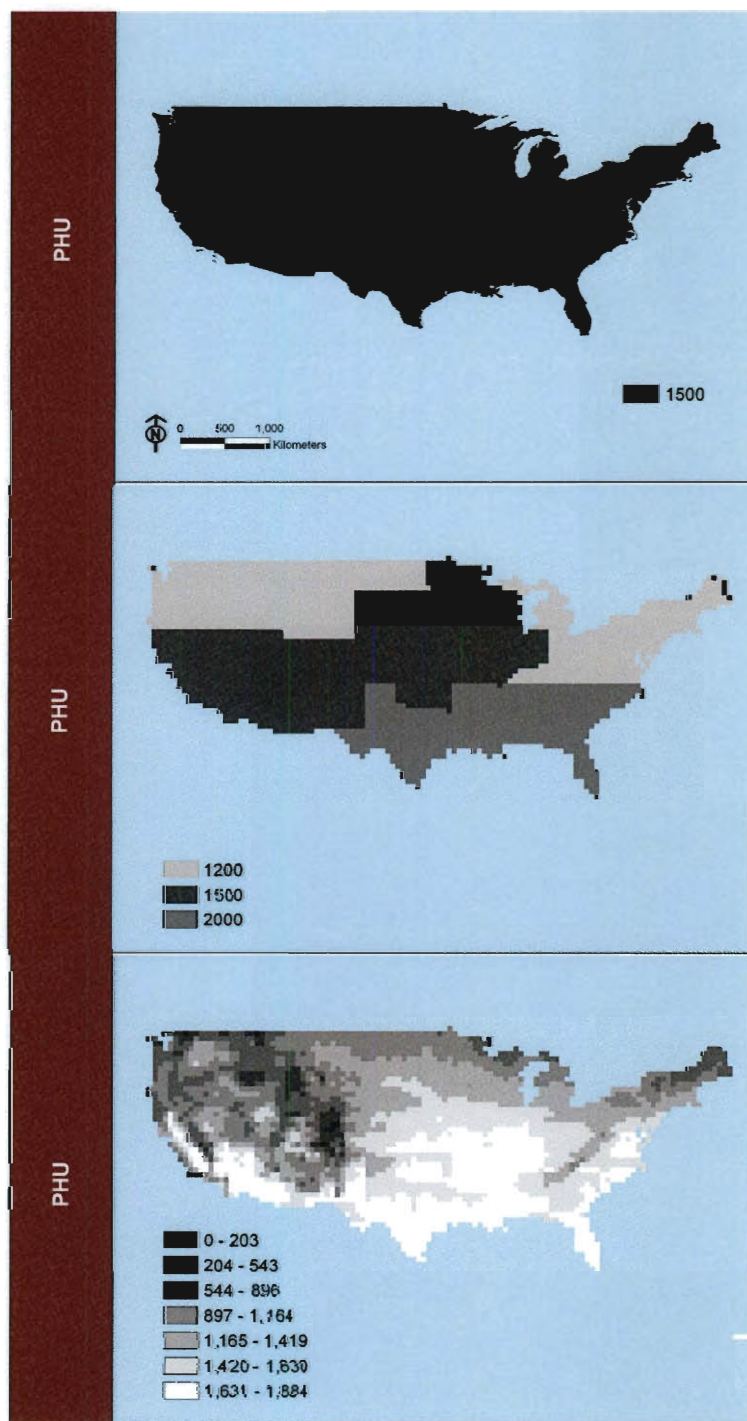


Figure 8. PHU increased resolution from one single value to cell distribution.

Run performance evaluation

Table 15 describes the changes in dataset resolution performed in each run. Table 16 shows bias, reliability, and efficiency of calibration runs and figure xx shows plots of simulated yields against recorded yields for each run.

Table 15. Description of datasets used in each run.

	Run 1	Run 2	Run 3	Run 4	Run 5	Run 6
Planting date	National average	State averages (1997)	*	State-level Julian day	Cell-level dataset	
Harvesting date (HD) or PHU	National average HD	State averages HD (1997)	PHU (1 national value)	State-level PHU	Cell-level PHU dataset	
Maximum fertilizer volume (kg/ha)	National average	State averages (2002)	*	*	*	*
Maximum irrigation volume (mm)	National average	State averages (2002)	Unlimited		*	*
Plant coefficients	National average	*	*	*	*	Cell-level dataset

* Indicates no resolution increase from previous run

Shading indicates when the run for which dataset was changed (calibrated) for the last time

^a Run 1 and 2 were carried out under fixed harvesting schedules.

^b Run 3-6 were carried out under automatic harvesting schedules based on PHU

Table 16 . Summary of quality evaluation criteria: Model average, bias (mean error), reliability, and NS efficiency.

	Obs	Run 1	Run 2	Run 3	Run 4	Run 5	Run 6
Yd Ave (T/Ha)	7.3	4.57	4.60	7.47	7.43	7.42	7.58
Bias		-31%	-31%	11%	9%	10%	12%
Reliability		34%	35%	50%	56%	56%	57%
NS Efficiency		-2.11	-2.09	-1.03	-0.55	-0.46	-0.43

Runs 1 and 2 were simulated with fixed schedules. Run 1 used 1997 national average planting and harvesting dates and Run 2 used 1997 state specific dates. Model reliability remained low in both runs and model consistently under projected yields by 31%. Increasing the spatial resolution of planting and harvesting dates did not result in better predictions. This could be due to the fact that planting and harvesting dates are varied from year to year to adjust growing season to climate variability and one year data might not represent well this variability. Model efficiency remained very low (about -2). Model reliability was increased to 50% and NS efficiency to -1.03 when automatic harvesting based on PHU was introduced in run 3. This could be explained by the fact that a PHU harvesting scheduling represents reality better than a fixed date, as farmers will harvest based upon observation of crop evolution rather than on a prefixed date. Under this setup, model overestimates yields by about 10%. In Runs 1 and 2, irrigation data from the 2002 Farm and Ranch Irrigation Survey (2002) were used but in Run 3, maximum irrigation volume was set to “unlimited”. In EPIC irrigation is both an input and an output. The model estimates daily irrigation demands and will apply irrigation until a maximum irrigation volume is accrued. Using an unlimited irrigation volume might

have also impacted the results, as one-year data might not accurately represent the five-year average reflected in the validation dataset. In Run 4, state values of planting dates and PHUs were introduced and model reliability was increased to 56%. NS efficiency was increased significantly (-0.55) but remained negative. In Run 5, planting date and PHU resolution was increased from state level to cell level. Reliability was not increased but NS efficiency was to (-0.46), although it remained still negative. In Run 6, a distributed dataset of plant coefficients was introduced, which resulted in a slight increase in model reliability (57%) and NS efficiency (-0.43).

The biggest increases in model reliability and model efficiencies were experienced when automatic schedule was introduced for the first time in Run3, and when state values of PHU were introduced in Run 4. Model efficiencies were increased slightly when distributed dataset (cell level) of PHU was introduced in Run 5 and when a distributed dataset of crop coefficients was introduced in Run 6.

Model efficiency remained negative in all runs, indicating the model is not representing all the spatial variability better than an area-average would. However, the error map of the last run displayed in fig 10 suggests that the model could be efficient over large areas of the country if not over the entire dataset.

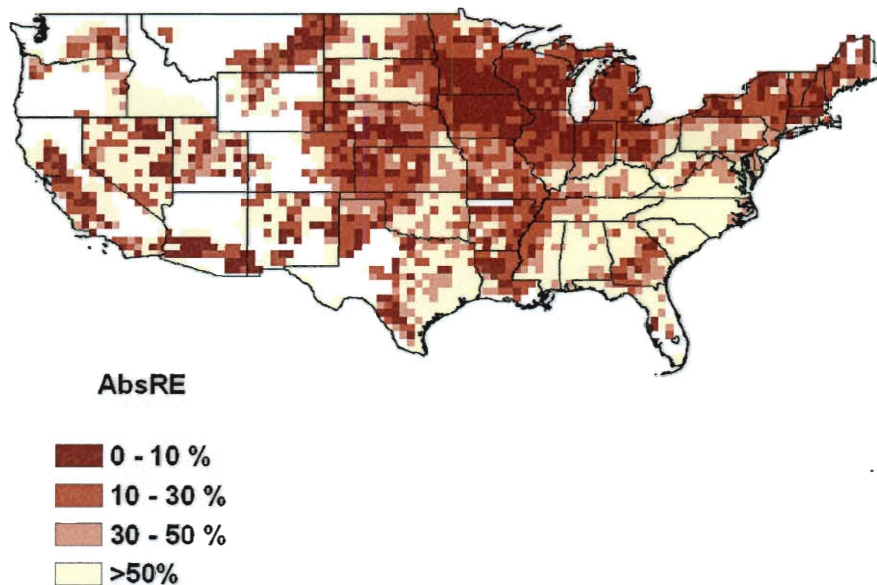


Figure 9. GEPIC final distribution of error.

Cells without AbsRE values do not contain corn crops.

Figure 10 shows that a certain degree of error prevailed in about 40% of the areas evaluated even after Input DD were created to its maximum resolution. This indicated data uncertainty was not eliminated in these areas. To understand whether any input factors still had a relationship with the simulation error we performed a residual analysis by examining whether a linear correlation existed between the simulation error of the high spatial resolution dataset and the different input factors (PHU, planting date, and planted area.).

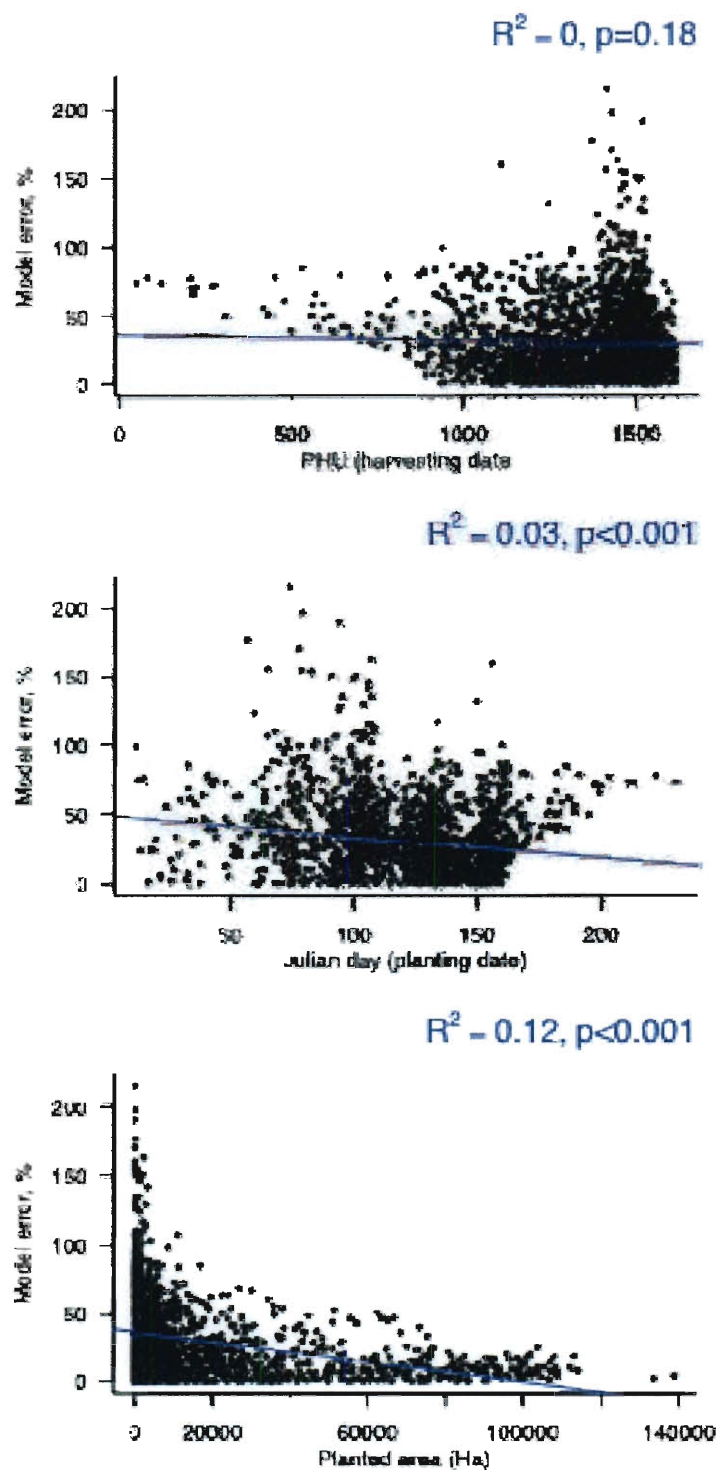


Figure 10. Residuals analysis. Y-axis shows residuals and x-axis shows a) PHU, b) Planting date, and c) Planting area.

Grey lines are the result of the linear fit. There is no statistical correlation between error and PHU ($p=0.18$), which indicates that little uncertainty decreases could be derived from more accurate datasets. There is a significant tendency towards smaller errors with later planting dates ($p=0.001$). There is a relationship between model error and size of planted areas in cell ($p=0.001$), with smaller areas generating larger errors. Indeed, the relationship was evident when visually comparing error maps with farmland density maps (Fig 12).

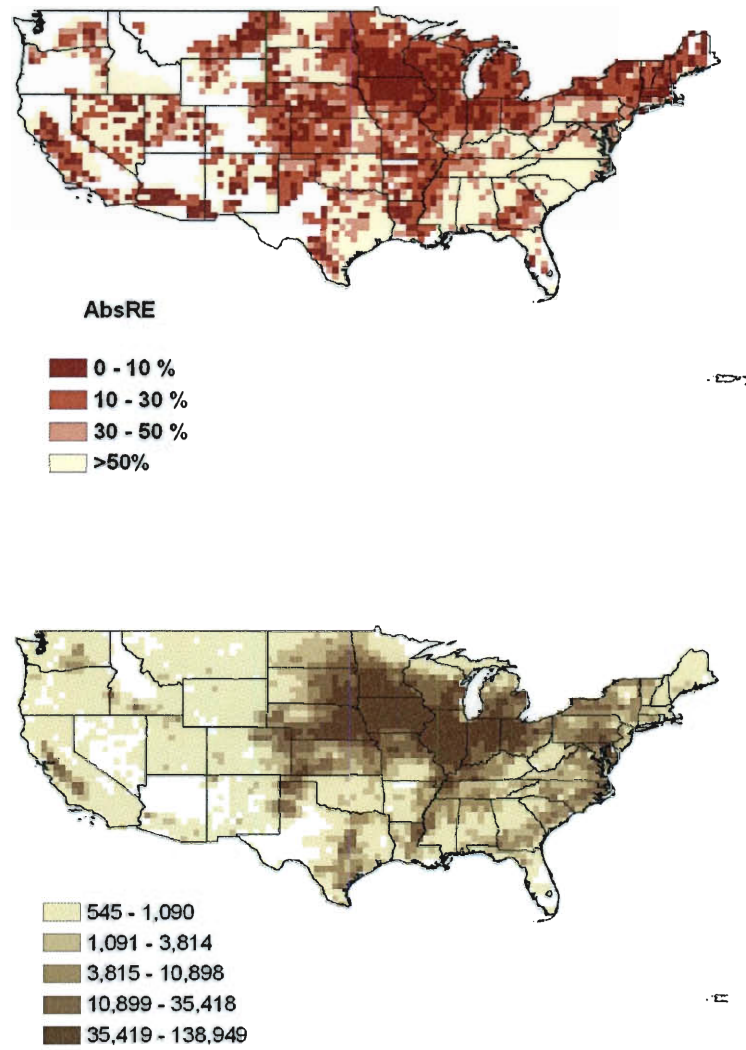


Figure 11. a) Model error, b) Farmland area.

In general, large errors were associated with smaller planted areas. This could be explained by the fact that conditions in small areas might be misrepresented in the datasets. For example, soil variability can be high inside the cell but homogeneous conditions are assumed inside each cell (see Fig. 13). Soil conditions in a small farm could be well represented or misrepresented whereas big farms will more likely be well represented. Based on residuals in fig 11, small planting areas produced either big or small error but all extreme error was produced in small areas.

A small area represented accurately

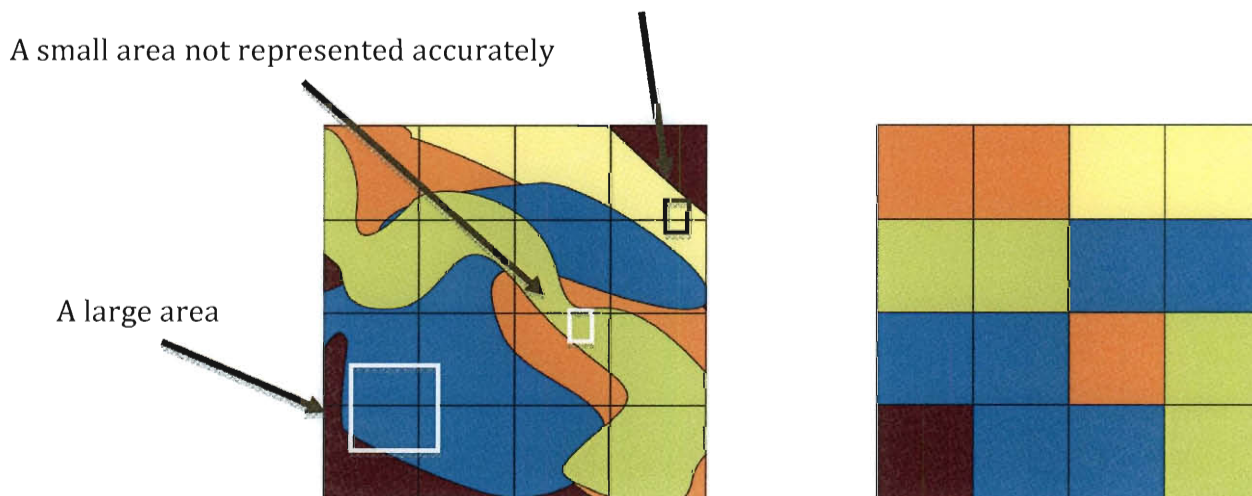


Figure 12. Effect of planted area in accuracy of representation. Left, real spatial distribution of input (i.e. soil); right, raster model input, where only the predominant conditions in the cell are taken into consideration

Small areas could also have an impact on the uncertainty of the recorded yields DD used to evaluate the model. The recorded DD reports a five-year average

instead of a one-year value. This helps to eliminate inaccuracies resulting from high inter annual variability, not only due to climate but also due to rotations and land use changes. Yields in a cell with large planted areas (many farms) will be more consistent across the years because changes related to corn rotations or land use in the different farms are cancelled out, whereas yields in cells with small areas (few farms) are dominated by the changes in these few farms.

Planted area could then be used as criteria for model site selection but this would not be wise because although large errors are normally associated with small areas, not all small areas give large errors.

Based on this discussion, I believe it is fair to assume that model error can be attributed for the most part to dataset uncertainty (data failure to represent reality). Thus, cells for which there is large error (AbsRE >30%) in combinations with small planted area will be eliminated from the simulations. The Midwest and the High Plains, which are the most important corn growing regions, fall within the selected sites.

Regional analysis

The prevalence of negative model efficiencies even after dataset calibration suggested that the scale of the projects could be too large and prompts a regional analysis.

To determine which region could benefit from distributed modeling we split the dataset by the regions showed in figure 14 (ecoregions) and calculated model efficiencies with results for each region. Ecoregions were preferred over

administrative boundaries (e.g. state) because a boundary based on natural conditions seemed more relevant than artificial administrative boundaries.

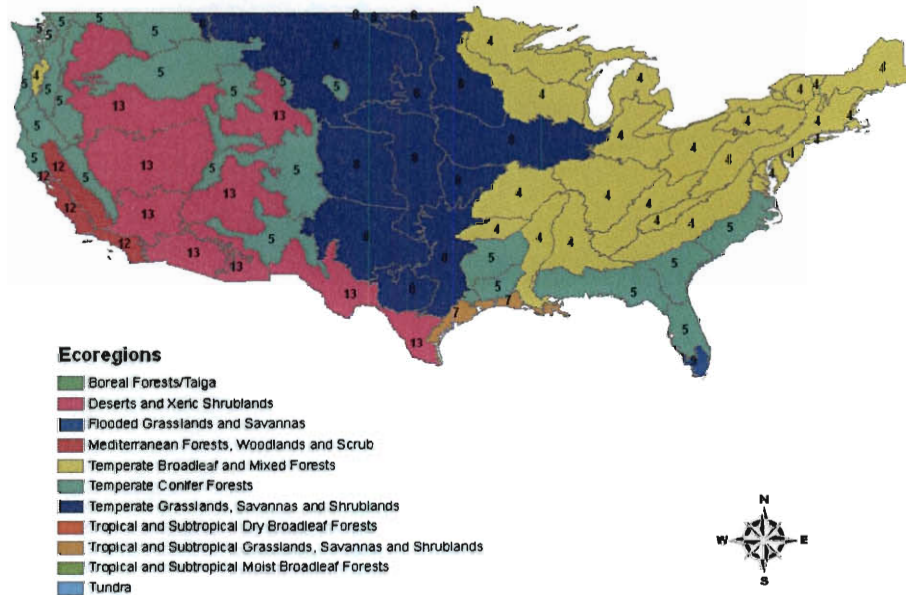


Figure 13. US Ecoregions

The only positive NS efficiency coefficient was found for Region 8 (NS=+0.15), which indicated that distributed modeling is appropriate in this area, and gives better information than that provided by regional average. Region 8 includes large corn growing areas and therefore suits the interest of this analysis.

Table 17. Simulated and Observed mean, and Nash-Sutcliffe efficiency coefficient for all regions.

	Region4	Region5	Region7	Region8	Region9	Region12	Region13
NS Efficiency	-1.17	-1.28	-3.97	0.15	-∞	-4.62	-3.82
Mean Simulated (t/ha)	7.48	7.12	8.24	7.51	9.03	8.19	6.67
Mean Observed (t/ha)	6.66	7.29	5.82	7.54	6.92	10.85	9.71

An additional large amount of planted area occurs in region 4 (ochre) which resulted in low NS efficiencies (-1.17), possibly resulting from the fact that the area is very large and very diverse and contains cells with large planted areas and small planted areas. This indicates that the classification in ecoregions might not be appropriate for the simulations.

For this reason, I will carry out the simulation for all the US regions but will focus on examining the areas of the Midwest and central and northern High Plains, which correspond to the main corn growing areas and which incurred in acceptable error (AbsRE<30%) when evaluated in the previous section.

Model Simulations

This chapter describes the simulations obtained with GEPIC with the input datasets described in the previous chapter. Figure 15 shows error levels that remained after data uncertainty was minimized (although not eliminated) as described in previous chapter.

The discussion in this chapter will be focused on The Midwest, the central High Plains and the regions along the Mississippi River, which include the main corn growing regions in the US and resulted in good agreement when compared to recorded data. Other areas for which results also are in good agreement with recorded data are The Northeast and large areas of the West Coast, but those regions

are not as relevant as they are minor corn growing areas. The Southeast, The discussion will not focus on results for the Southeast and large areas of the Southern and Northernmost High Plains, because of the uncertainties associated with those areas.

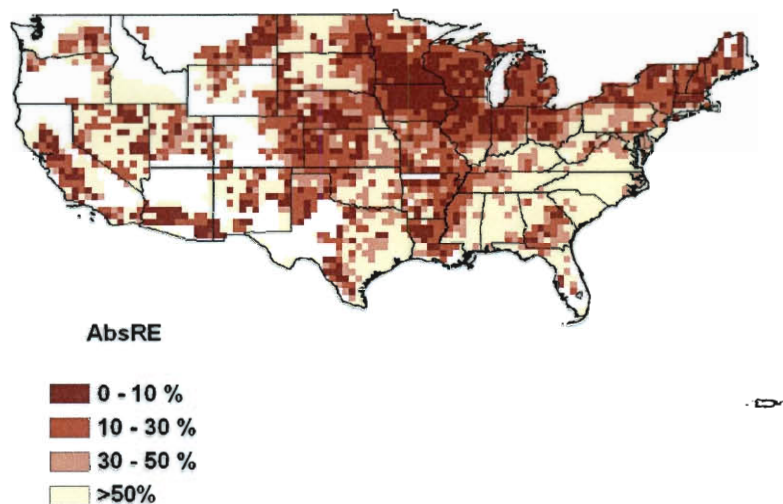


Figure 14. GEPIC simulation error after data uncertainty is minimized (although not eliminated).

Three rounds of simulations were carried out: one for present climate and management conditions (Baseline) and two for future climate with two different management strategies. The first future climate round is based on the assumptions that farmers will adapt to seasonal changes (by changing planting and harvesting date accordingly) and to changes of resource (water and nitrogen) requirements through precision irrigation and fertilization. This first round of simulations reflects the future impacts of temperature stresses only, as water and nutrient stresses will

be palliated through management. The second round of future climate simulations was carried out under the assumption that no irrigation will be available due to water shortages. Results obtained in this second round correspond to a scenario in which climate-induced water stress is not mitigated; thus, these results reflect both temperature and water stresses. The first round of simulations is referred to as “Future with Irrigation” (I) and the second round as “Future without irrigation” (NoI). In each round the model generates spatial distributions of estimates of five output variables: Grain yield (T/Ha), stover yield (T/Ha), consumptive water (L/Ha), irrigation (L/Ha), and fertilizer (Kg/Ha). These output variables are used to calculate biofuel footprints. The consumptive water footprint of biofuels (CWF) is estimated by dividing ET and irrigation estimates (L/Ha) by ethanol yields (Le/Ha). The irrigation water footprint (IWF) is the result of dividing irrigation by ethanol yields. The nitrogen footprint of biofuels (gN/Le) is estimated by dividing nitrogen use (kgN/Ha) by ethanol yields (Le/Ha) and multiplying by 1,000.

The results are presented in three sections: Baseline results, agreement between future simulations, and differences between baseline and future.

Baseline

Figure 16 shows the spatial distribution of corn yield, ET, irrigation and nitrogen generated with GEPIC for baseline conditions. The estimates are very representative of actual conditions: High yields across the country, but particularly high in the Midwest and in California, probably due to high nutrient application in the Midwest and high irrigation activity in California. ET values are larger in the Southeast, which is typical of sub-tropical climates. High nitrogen application prevails in the Midwest

and irrigation water requirements range from less water in the East to more water in the West.

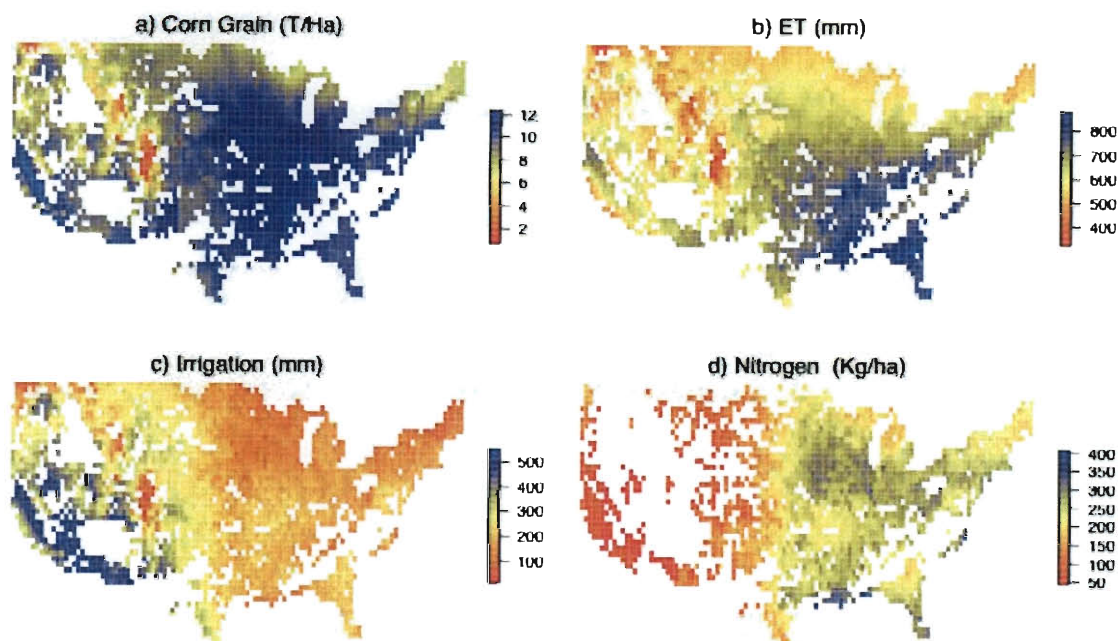


Figure 15. Baseline estimations of a) corn yield (T/Ha), b) ET (L/Ha), Irrigation (L/Ha), and Nitrogen (Kg/Ha).

Figure 17 shows baseline estimations of the water and nutrient footprint of biofuels. Estimations of CWF range from 1,500 to 2,500 Lw/Le. CWF is lowest in the Midwest and higher in the Southeast, Northeast and the Northwest. Low CWF in the Midwest is the results of high corn productivity and moderate uses of consumptive water. In the Southeast, CWF is high despite high levels of corn productivity. This is probably due to higher consumptive water levels typical of hot and humid climates. In the Northwest, CWF is high despite low levels of water consumption because there

are also low levels of corn productivity. Estimations of IWF range from 400 Lw/Le to $1,500 \times \text{Lw/Le}$, and are lower in the eastern and Midwest states and higher in the Western States. This reflects the fact that most agricultural irrigation, including corn agriculture, happens in Western States.

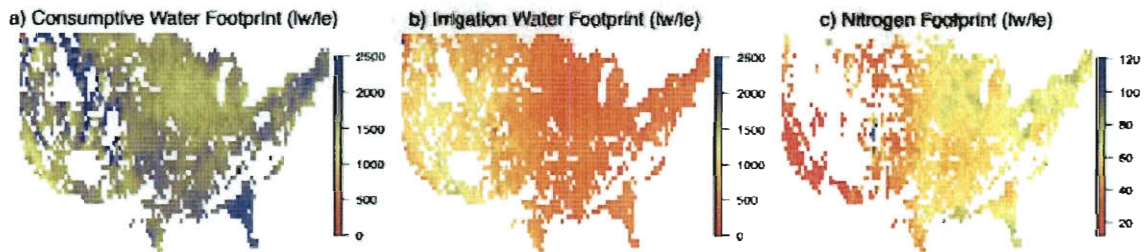


Figure 16. Baseline estimations of a) Consumptive water footprint (CWF) (Lw/Le), b) Irrigation water footprint (IWF) (Lw/Le), and c) Nitrogen footprint (gN/Le).

Footprints calculated from baseline simulations corresponded well with results obtained based on USDA and industry statistics discussed earlier. As reported in Chapter 4, the national average corn ethanol CWF was estimated in $\sim 1,500$ Lw/Le, whereas the average obtained calculated from simulated results was $1,700 (+/- 400)$ Lw/Le. The previous estimation of IWF was $\sim 600 (+/- 340)$ Lw/Le, whereas the national average obtained from simulated results was $675 (+/- 300)$ Lw/Le. NF estimations in Chapter 4 were $50 (+/- 9.9)$ gN/Le whereas the average obtained with simulated results was $54 (+/- 16)$ gN/Le. Previous efforts provided only a national average estimate, whereas the simulations offer the advantage of providing a geographic distribution of estimates, necessary for adequate decision-making.

Agreement between simulations of future periods

Five independent simulations of the future period were carried out with climates projected by five different cGCMs. Reliability of estimates was based on agreement between model outputs. For each output variable, the five-model mean and standard deviation were calculated. The coefficient of variation (CV) was calculated by dividing the standard deviation by the mean, and taken as a measure of disagreement between model estimates. Figure 18 shows cell distribution of five-model mean and coefficient of variation of each output.

Agreement between the five independent future simulations with GEPIC was high for all output variables simulated. The coefficient of variation was relatively low (< 0.1) for simulations of crop yield, ET and nitrogen footprint. Yield agreement was slightly lower in the central areas of the country than the coasts, but was always high (CV=0.08). ET estimations were close (CV= 0.04) in the High Plains and very close in the rest of the country (CV= 0.02). Irrigation estimates had the largest CV among all the output variables but were also relatively small. CV for irrigation ranged from 0.1 to 0.2 in most of the country but were smaller in the West (CV<0.05), suggesting that the models agree most about irrigation in the traditionally irrigated areas of the West. Nitrogen requirement estimates were very uniform across models for most areas. Only small variations (CV=0.1) occurred in some areas of the High Plains. The high agreement between the five independent GEPIC simulations suggested that using the five-global-climate-model mean was appropriate. However, careful considerations were applied to irrigation estimates as they showed the largest disagreement across the five global climate models.

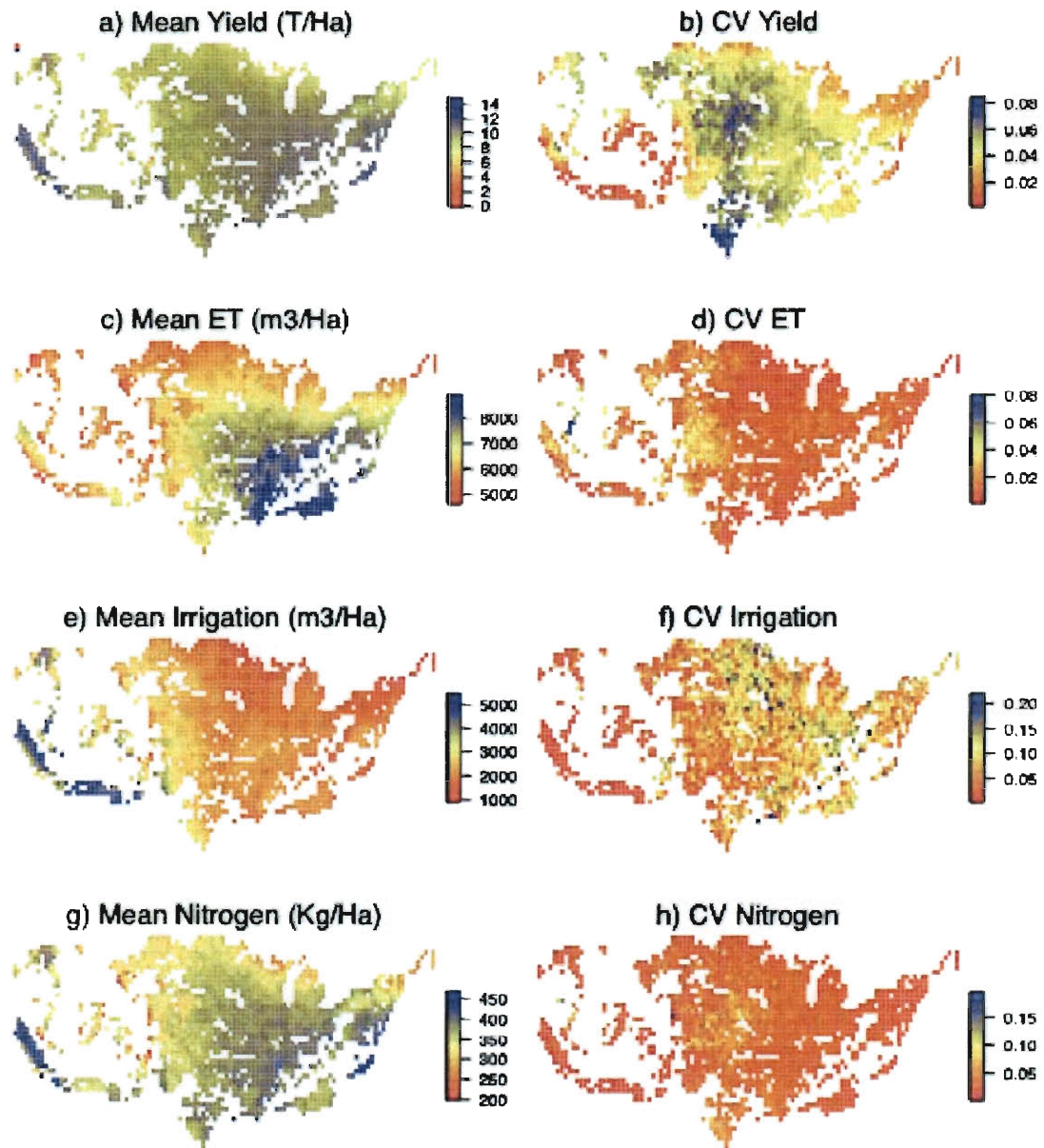


Figure 17. Five-model mean and coefficient of variation (CV) for Yield, ET, Irrigation, and Nitrogen.

Changes from baseline

Differences (Δ) between the baseline and the future period were calculated for the two future scenarios simulated (I and NoI), for three future periods (2040s, 2050s, and 2060s), and for the five output variables (Grain yield, Stover yield, ET, I, and Nitrogen). The three footprints (CWF, IWF and NF) were calculated from the output estimates as explained in baseline section above. Results are evaluated in two groups for simplicity: First, changes in yields and resources (grain yield, stover yield, ET, irrigation, nitrogen), and then changes in footprints (CWP, IP, and NP)

Yield and resource use changes

Figure 19 shows future changes in irrigation, grain yield, stover yield, ET, and nitrogen use compared to baseline for two management scenarios: Irrigation (I) and no Irrigation (NoI). Figure 20 shows changes in irrigation predicted individually with the five different global climate models. Figure 21 shows histograms of output changes for the two management scenarios.

In the future, higher temperatures could drive irrigation (m^3/Ha) demands in the Midwest and the High Plains. While the magnitude of maximum projected increases vary across the five climate scenarios used, significantly the upward trend is consistent across them (Fig. 20). Corn yields (T/Ha) could be slightly reduced (10%) in most parts of the country due to heat stress, but could be reduced up to 50% from a combination heat and water stress (No irrigation available). ET (m^3/Ha) decreases reflect grain decreases (T/Ha) except in the eastern half of the country. Nitrogen demands (kg/Ha) could be decreased to the same extent that yields were decreased.

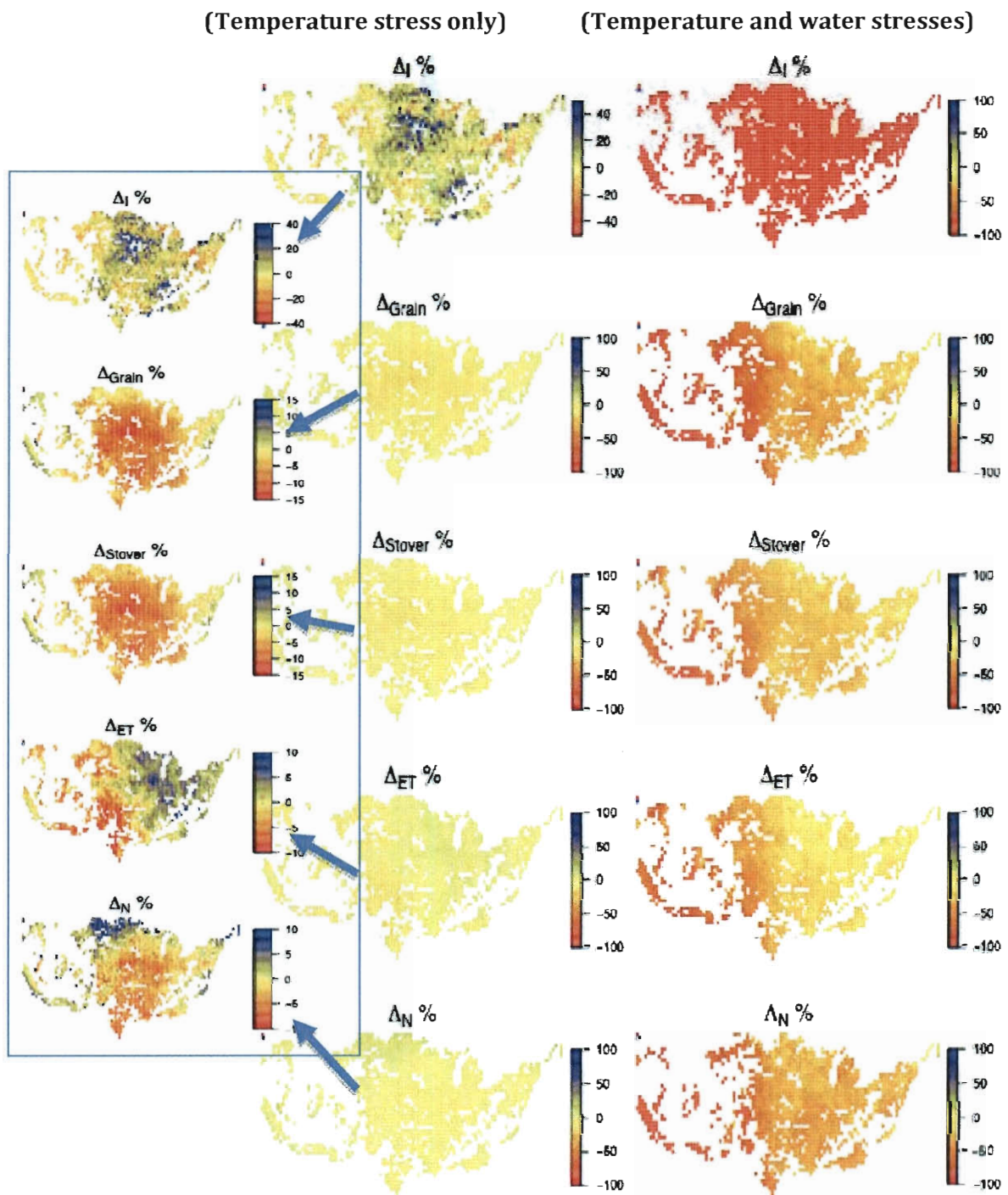


Figure 18. Simulated future changes (%) in grain yield (T/Ha), stover yield (T/Ha), ET (m³/Ha), irrigation (m³/Ha) and nitrogen use (Kg/Ha) compared to baseline for two management scenarios: Irrigation (I) and No irrigation (NoI).

Left panel blowout corresponds to changes under irrigated conditions with an adjusted scale to better display small changes.

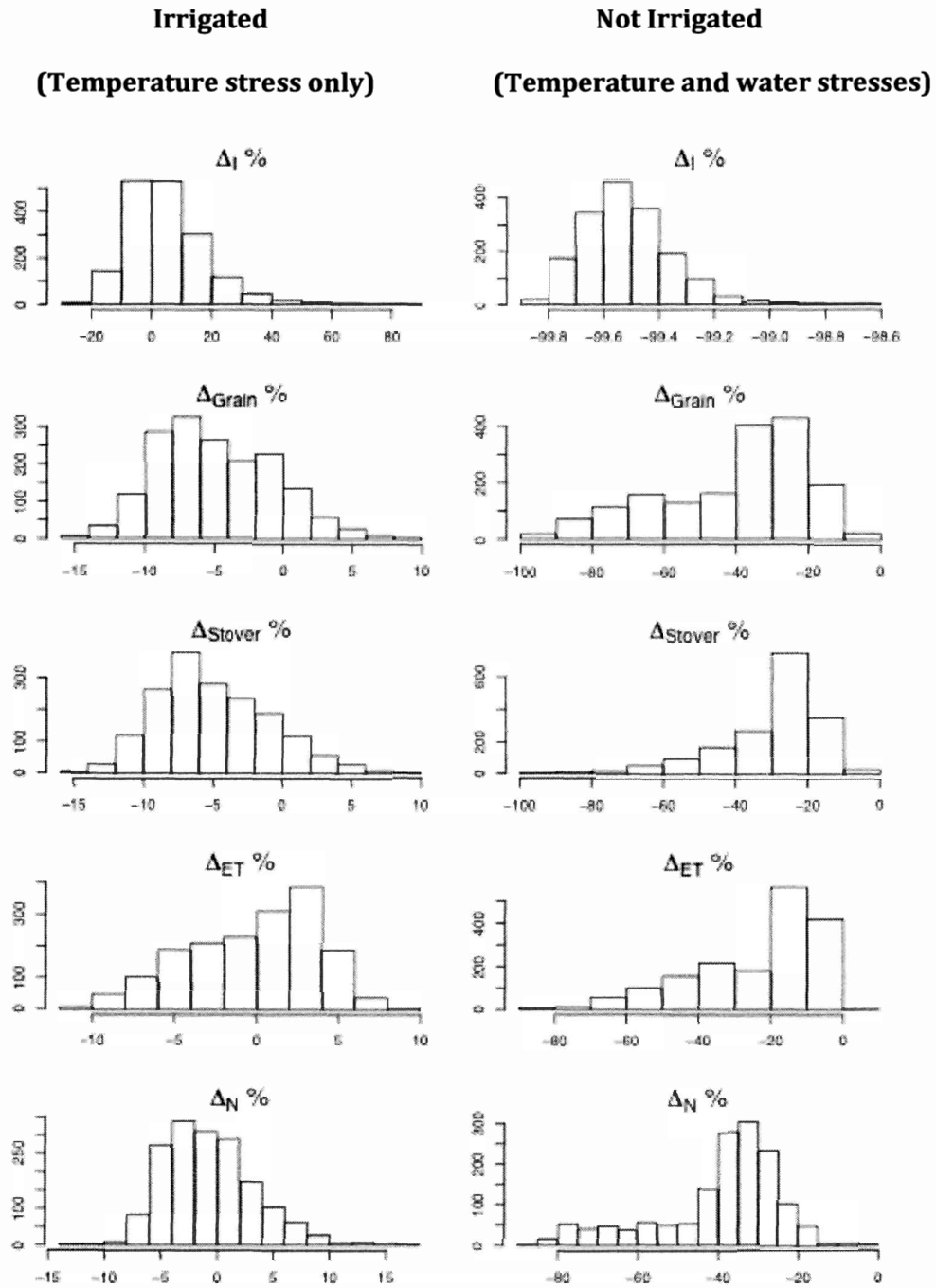


Figure 19. Histogram of changes in variable output compared to baseline in the two management scenarios.

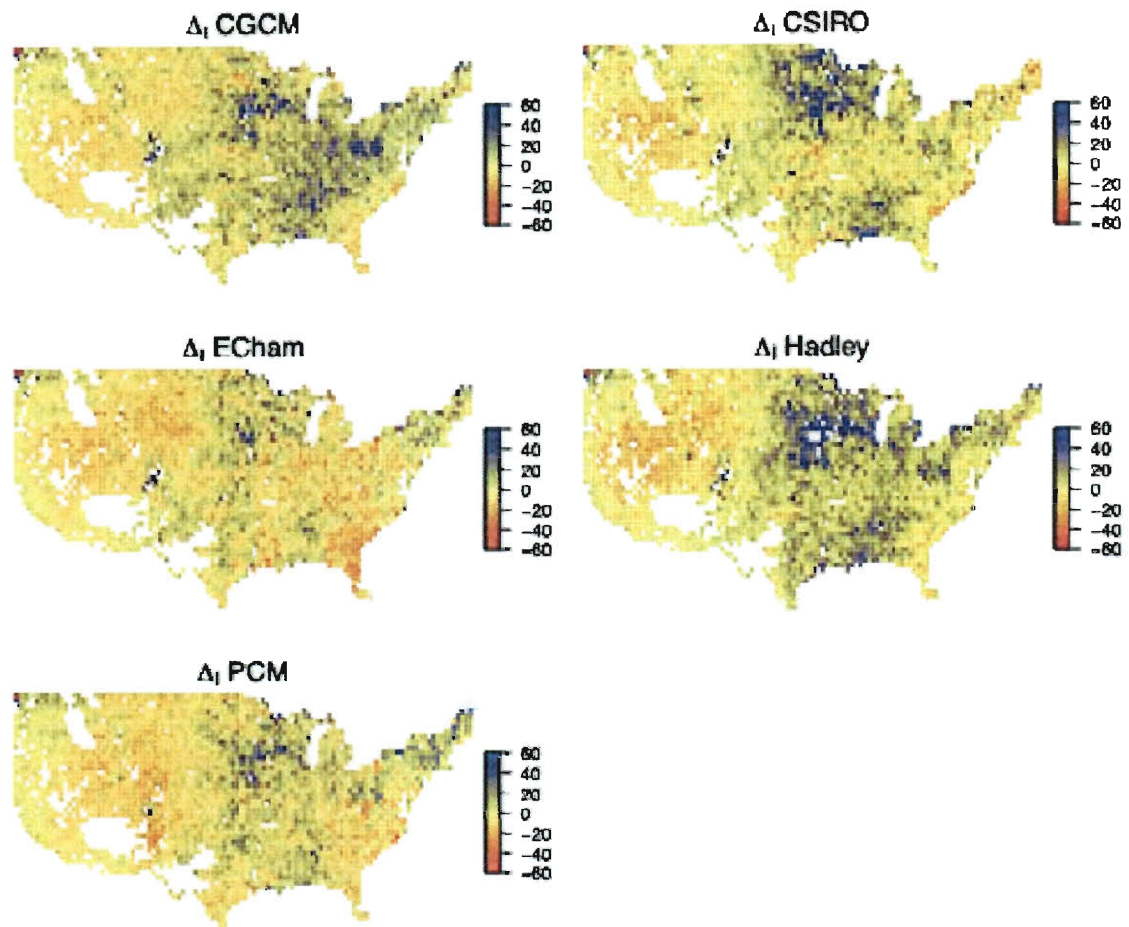


Figure 20. Changes in irrigation between future and baseline periods projected with five different global climate models.

Footprint changes

This section describes information in Figure 22, which shows changes in consumptive water footprint (CWF) (Lw/Le), irrigated water footprint (IWF) (Lw/Le), and nitrogen footprint (NF) (gN/Le). Positive changes in footprints indicate that more ethanol is produced with the same amount of resource (or less resource is needed to produce the same amount of ethanol). Negative changes indicate that more resource is needed to produce a given amount of ethanol. Figure 23 shows histograms of footprint changes in each footprint for the two management scenarios.

Biofuel CWFs (Lw/Le) reflect the combined changes in ET (m³/Ha) and grain yields (T/Ha). Increments in CWF indicate that ET changes more positively than yields. This could happen if ET increases while productivity decreases, or if both ET and productivity experience positive changes but are sharper for ET than for productivity. CWF sharpest increases (20-40%) are found in the Midwest, which could experience a combination of increased ET and decreased yields. CWF increases could be also noticed in the High Plains areas if no irrigation were available. This could happen despite the fact that the lack of irrigation drives ET down, because changes in yields are projected to be more negative than in ET. Biofuel IWF could be increased in the Midwest if additional irrigation demands were not matched by additional in productivity.

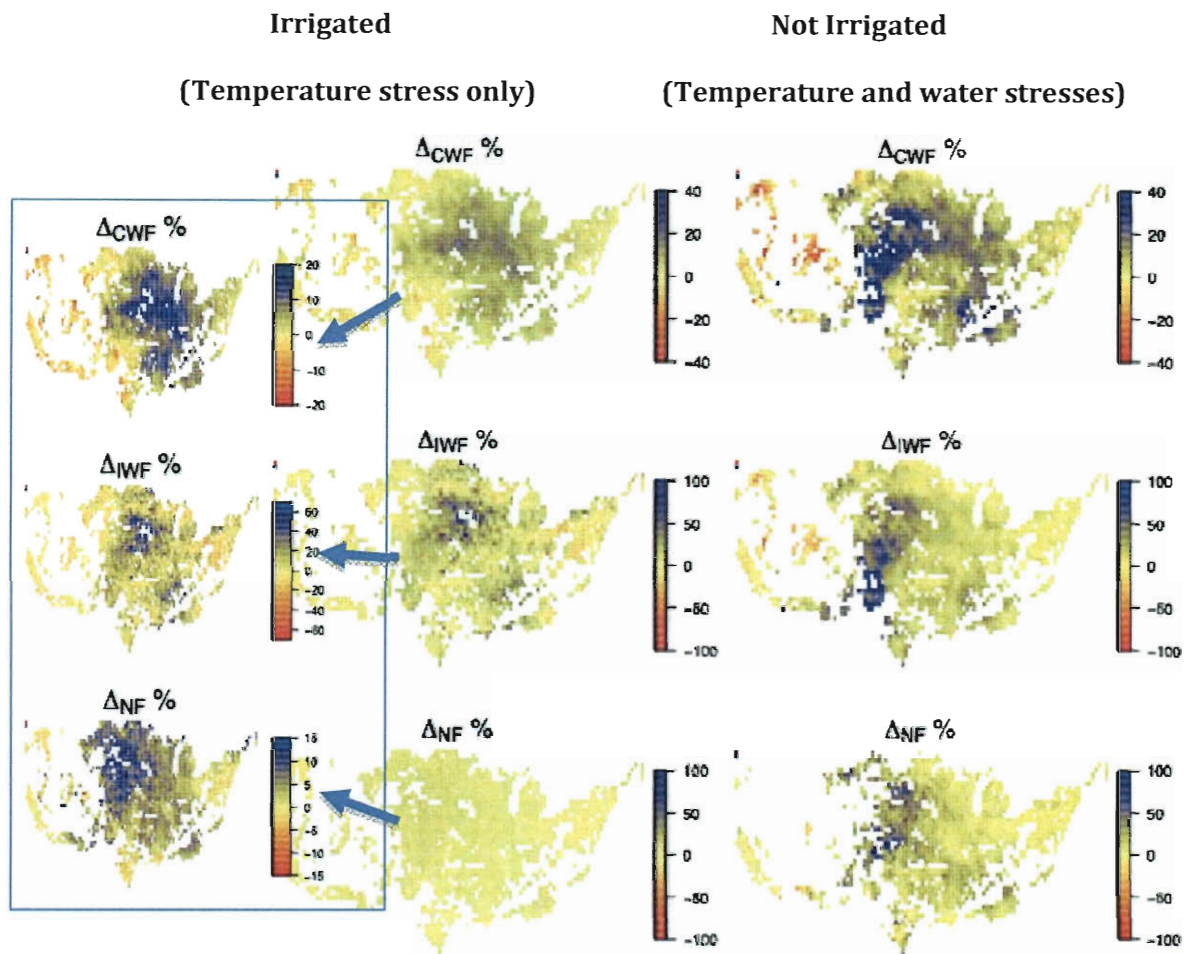


Figure 21. Changes (%) in consumptive water footprint (CWF) (Lw/Le), irrigation water footprint (IWF) (Lw/Le), and nitrogen footprint (NP) (gN/Le) under irrigated and non-irrigated conditions.

The panels in the left column are blowout with their natural scale so small changes are more perceptible

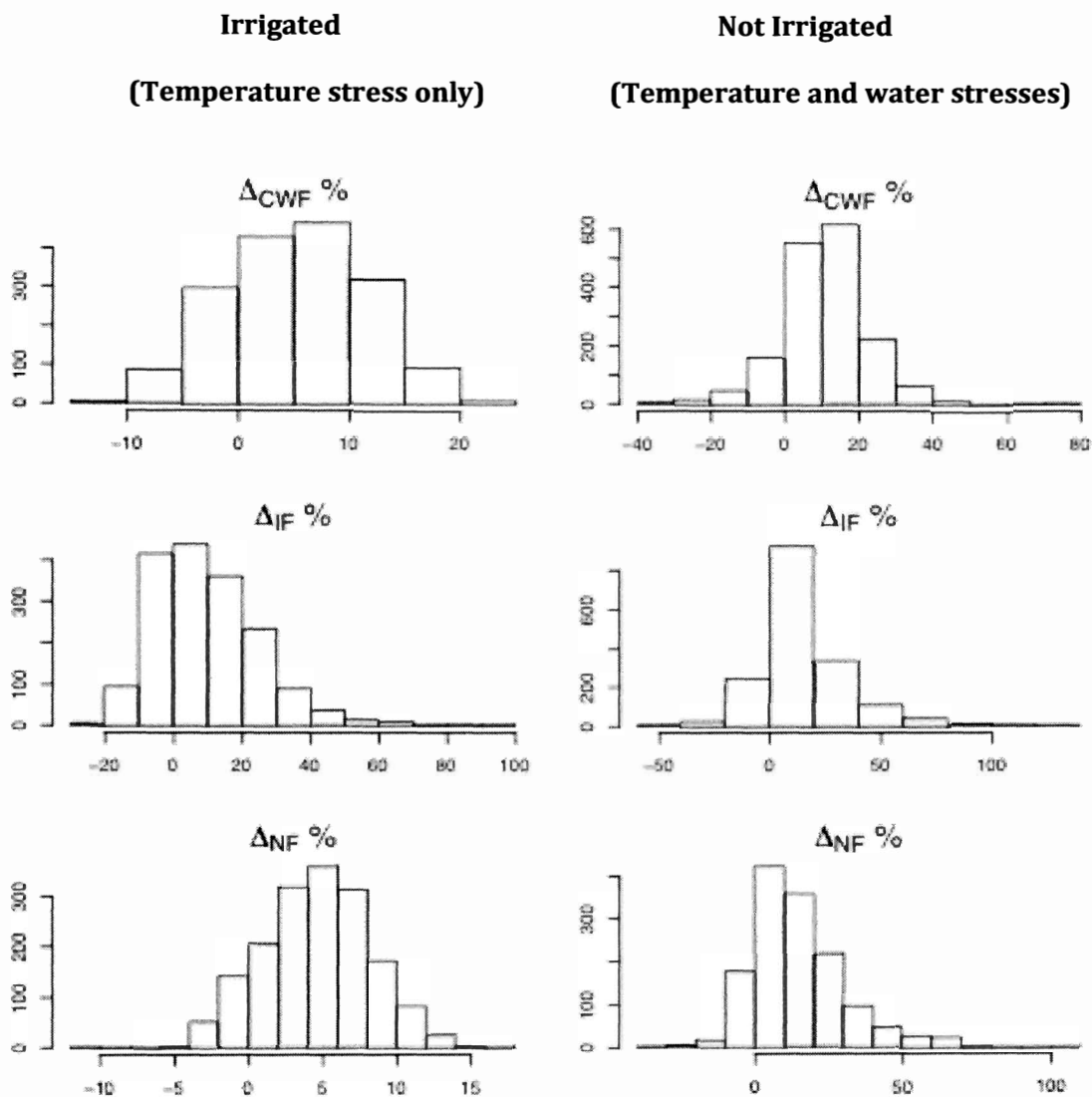


Figure 22. Histograms of CWF, IWF, and NP changes with respect to baseline in two management scenarios.

Sustainability implications

The results suggest that in the Midwest and High Plains, the main corn growing regions, climate change negative effects on plant water consumption could be larger than positive effects on plant yields. The impact of projected increased water footprints has, however, different implications to water scarcity issues in each regions.

The Midwest, an area that for the most part meets crop water demands with rain, might experience an irrigation area expansion despite the fact that more overall precipitation is projected to occur. Projections, however, indicate that rainfall could be more intense but less frequent, with larger periods between rain events in which plants might require irrigation.

In this situation, higher irrigation demands would not necessarily impact regional water supplies, because the excess water from intense rain events could be stored for later irrigation use. This, however, could have implications in water management planning efforts, as this could require an increase in the number of water artificial reservoirs (i.e., dams) in the region.

The High Plains, which is currently the region with the largest irrigated corn acreage, would experience an increase in overall irrigation water requirements. This could have important sustainability implications to the Ogallala Aquifer, the main source of irrigation water in the High Plains, which is already experiencing significant water table drops.

In our previous study (chapter 4) we estimated that producing 56 Billion liters a year (BLY) (15BGY) of biofuel would require 6,000 BLY of irrigation water, based on a water footprint of 566 Lw/Le assuming only 18% of this biofuel (10.8 BLY) were irrigated. The future average water footprint can be estimated in 680 Lw/Le (a 20% increase), which would result in 7,600 Lw/Le if the same irrigated share of corn is maintained. However, since corn agriculture in the Midwest could experience irrigation acreage increase, this figure could change significantly. More accurate projections could be obtained by combining the high resolution data made available through the modeling effort with accurate knowledge of the location of future corn acreage which is unknown at this time.

Conclusions and Recommendations

This research provides scientific input to water resources planners and energy policy makers. The increased demand for fuel ethanol and other biofuels is expected to result in significant increases in water requirements for fuel crop agriculture. This could strain regional water resources and jeopardize future biofuel production, but it is difficult to predict the extent and location of future water shortages because there are many sources of variability and uncertainty, the results of this study suggest that even considering a broad range of varying projections for climate impacts of the US Midwest and High Plains, plant yield and water sustainability impacts are likely to be significant.

Sources of variability that are associated with agricultural choices included the types of feedstock that will be used to produce biofuel and where they would be grown. Sources of uncertainty include the effects of climate on future

evapotranspiration requirements and water availability (e.g., precipitation patterns) for biofuel production, and our choices to adapt to these changes.

A LCA approach was first used to calculate the water footprint of biofuels from different feedstocks in the present period. This provided important information relative to which part of the biofuel production process was more water intensive, and which biofuel crops might be more beneficial from the point of view of water resources. This part of the study revealed that agriculture is the production phase that most significantly uses water on a per liter of biofuel basis, and while effects of increased water demands from biofuel crop agriculture could be noticed at the regional scale, the effects of biofuel processing plants could be more significant at the local level.

Among the different crops that were evaluated for ethanol production, corn was found to be the least irrigated while sorghum and sugarcane required the largest amounts of irrigation water on a biofuel unit base. However, irrigation water is mostly indicative that the area where they are planted enjoys little rain. Consumptive water use is a better measure of water requirements as it represents the water that plants evapotranspire, regardless of whether it is irrigated or rainfed. Large differences between consumptive and irrigated water uses were revealed for most crops. For example, switchgrass had similar consumptive levels to corn, meaning they contribute the same to water scarcity. Switchgrass, however, is rarely irrigated because it is not currently grown as a cash crop, a situation that might change with EISA. Corn had larger consumptive levels than sugarbeets or potatoes, but the two former have in larger irrigation requirements in some instances, which could be the

consequence of being grown in irrigated areas while most of the corn is rainfed. Soybean had the largest consumptive water uses , followed by sorghum and switchgrass, while sugarbeets and potatoes had the lowest.

The metric used (biofuel volume unit) was chosen based upon the method used to calculate overall ESIA effects. EISA overall effects were calculated by extrapolating biofuel unit footprints to the overall biofuel volume mandated. EISA net effects could not be evaluated as accurately because information on landscape changes (what crops or land uses would be substituted by biofuel crops), and their own water footprints, was not available. It might have been more relevant to show footprints in an area basis (rather than biofuel basis) if calculations based on landscape information were available. For instance, irrigation requirements are smaller for corn than for soyben in a biofuel unit basis, but larger in an area basis. The uncertainties about landscape changes will be an obstacle to the evaluation of EISA net effect throughout the completion of this thesis but a back of the envelope calculation was provided to illustrate the magnitude of change that could happen.

The first part of the study generated results of a limited spatial resolution because high spatial resolution statistics were unavailable. Data at high-resolution could only be generated through distributed modeling. A model could also evaluate combined effects of different input variables, which enabled scenario analysis and the evaluation of climate change and management effects, the two largest sources of uncertainty in the study. The drawbacks of distributed modeling are the limited availability of quality-tested distributed datasets. Thus a large effort was undertaken to evaluate input data uncertainty and establish a modeling framework with reduced

uncertainty. Five national-scale simulations were carried out independently with climate predictions from five different global climate models to account for divergences in future climate scenarios. The magnitude of projected increase in water requirements varied across the five simulations but the trend was consistently upwards. The confidence in these results arises from the fact that trends were consistent across simulations with climate data from five different global models.

Model simulations for corn agriculture showed that climate change could likely increase irrigation requirements throughout the High Plains and Midwest regions. The effects could be most detrimental to the High Plains, where irrigated agriculture depends on the Ogallala Aquifer, which is already being depleted, and is prone to droughts. The Midwest could experience an expansion of irrigated land despite having more average precipitation because longer periods between rain events might occur. This, however, would not necessarily impact water availability if excess water from intense rain events were stored for use in between rain periods.

These findings imply that biofuel policy cannot rely on expanding the current practice without careful consideration of evapotranspiration and irrigation requirements and water resources availability. Our simulations also infer the need to periodically revisit biofuel policy to avoid potential unintended impacts to water resources in the High Plains areas (and avert water shortages) and the need for more water management projects in the Midwest to accommodate more intense but less frequent precipitation.

Overall, our GEPIC modeling framework represents a valuable tool to inform energy policy and water resources management because it reduces uncertainty

associated with climate change and agricultural management decisions to understand and mitigate the water footprint of biofuel crop agriculture.

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