Using climate scenarios to evaluate future impacts on the groundwater resources and agricultural economy of the Texas High Plains

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ABSTRACT

This study evaluated the impacts of future climate scenarios on the groundwater resources and agricultural economy of the Texas High Plains, using Hale county as a case study. Climate change impacts were incorporated into regional economic models using weather projections to develop crop response functions from crop models. These projections are based on quantitative projections of precipitation, potential evapotranspiration, and temperature trends driven by simulations from the latest IPCC AR4 climate models (Community Climate System Model (CCSM), Geophysical Fluid Dynamics Laboratory (GFDL), UK Met Office Hadley Model (HadCM3), and Parallel Climate Model (PCM)) under two specific emissions scenarios, A1B (mid-range) and A1FI (higher). Results indicated that for both the emission scenarios, saturated thickness, water use per cropland acre, and irrigated acreage declined under climatic predictions by all four models. At the end of the 90 year horizon, the A1B scenario resulted in a decline in average net income per acre as predicted by the CCSM and HadCM3 models, while the GFDL and PCM models predicted an increase in average net income per acre. Under the A1FI scenario, the CCSM, GFDL, and PCM model projections led to increased average net income per acre, while climate projections under the HadCM3 model indicated a decline in average net income per acre at the end of the 90 year horizon.

Key words | climate change, climate scenarios, economic models, groundwater, net revenue, Texas High Plains

INTRODUCTION

The agricultural industry is strongly impacted by the macro and micro-climate under which it operates. Climate and weather forces play a critical role in the existence, development, and sustainability of any regional economy that is dependent on agriculture. The vulnerability of the agricultural industry and agriculture-based economies is more evident in areas that are provided for solely by the groundwater resources in their region. The Texas High Plains is representative of economies driven by irrigated agriculture and groundwater resources have been the major source of irrigation when compared with surface water resources. The most important and dependable source of groundwater for irrigation purposes in this region is the Ogallala Aquifer which has been witnessing severe declines in its water levels on account of heavy withdrawals for irrigated agriculture in the region. Given that precipitation and temperature changes profoundly impact the longevity and recharge of the aquifer which impacts the agriculture in the area,
future climate change impacts have emerged as a focal point of interest for this region.

After the publishing of the first assessment of climate change by the Intergovernmental Panel on Climate Change (IPCC 1990), increasing efforts have been channeled toward analyzing the impact of climate change on agriculture (Antle & Capalbo 2010). In the IPCC assessment report (IPCC AR4) for the USA, it is indicated that the most profitable cropping systems may not change much, but the impact on transitional areas like the Great Plains may be variable (IPCC 2007). For example, in the Texas High Plains, if climate change impacts of higher temperatures are accompanied by decreased precipitation, the already marginal crop and pastureland could experience reduced productivity (Antle & Capalbo 2010). Also, as mentioned in the US Global Change Research Program’s report for the year 2009, regional climate impacts are anticipated to adversely affect the groundwater resources of the Texas High Plains. Specifically, by the end of the century a temperature increase in the range of 2.5–13°F from the 1960–1979 baseline has been predicted for the Texas High Plains area (Karl et al. 2009). Projections of rising temperatures, higher evaporation rates, and more sustained droughts brought on by climate change pose an impending threat for the sustainability of the regional economy of the Texas High Plains, which is heavily dependent on groundwater resources.

According to Karl et al. (2009), in 1990 the Ogallala Aquifer in the eight-state area of the Great Plains contained 0.41 billion hectare meter of water of which Texas had about 12%, or approximately 51.29 hectare meter, of water in storage. Currently, an annual average of 19 billion gallons of groundwater is pumped from the Ogallala Aquifer. Since 1950, water levels in the entire aquifer have declined an average of 13.97 m, equivalent to a 9% decrease in the storage volume of the aquifer. It has also been observed that in areas of low recharge, utilizing heavy irrigation, depletion levels are more pronounced, from 30.5 to 77 m (Karl et al. 2009). The general belief is that the outcome of these climatic changes happening in the groundwater resource supply will most likely have a significantly negative impact on the agricultural economy of the Texas High Plains, which mainly depends on irrigation. It therefore becomes imperative to examine the effect of anticipated climate changes on crop production and evaluate the economic effects of these changes on the agricultural crop mix to predict the profitability of crops grown in the area in future time frames. As understood from the facts mentioned above about the study area, a continuous decline in groundwater levels requires that the researchers and policy-makers correlate this decline with factors influencing agricultural production. This study could in fact be the first step and will add to the existing literature toward understanding possible measures to extend the economic life of the Ogallala Aquifer in the study area and maintain the viability of a regional economy which critically depends on agriculture.

The objectives of this study are twofold. The first objective is to develop crop production function parameters for Hale County in the Southern High Plains of Texas. This is achieved by incorporating climatic predictions from a combination of climate models and future emission scenarios as inputs for crop models. The second objective is to estimate county level changes in farm income, crop mix, and associated water use from the aquifer, by incorporating the production function parameters in the economic optimization models over three time frames.

LITERATURE REVIEW

Climate change impacts on agricultural production can be measured through farm-level profitability by evaluating changes in crop yields and changes in input costs, especially irrigation costs. The effects are also measured through changing aquifer levels which are primarily impacted by changing amounts of withdrawal for irrigation. From an economic standpoint, the profitability and net returns from irrigated farming will be the parameters of concern for the producers of the region, and therefore their correlation with variables of climate change leaves policy-makers and researchers searching for options to reduce drastic impacts of such anticipated vicissitudes. Several studies in recent decades have estimated potential economic impacts of climate change on US agriculture. Among various studies which are of relevance to the study region is an early study by Rosenzweig & Reibsame (1989), which focused on the question of how agriculture in the Great Plains (focusing on Nebraska, Kansas, Oklahoma, and Texas) is
sensitive to climate fluctuations and would be at risk from global warming. The results from this study indicated that climate change would cause reductions in regional agricultural production. The study also concluded that irrigated acreage in the Great Plains could increase and that the demand on the Ogallala aquifer could go up by 15%.

Recent economic studies have brought forth great improvement in the ability to analyze US food production under climate change, primarily by studying farm sector adaptation to changing climatic conditions. Reilly et al. (2001) utilized an end-to-end approach to assess the effects of climate change on various agricultural crops. They presented climate change scenarios for the future derived from general circulation models, with crop models designed to capture the effects of climate change and elevated atmospheric CO2 concentrations (350 parts per million by volume (ppmv) for the base, 445 ppmv for the year 2030, and 660 ppmv for 2090) on crop yields at different national and state level sites in the USA representing major agricultural production areas. The future climate scenarios were generated by two climate models, the Hadley and Canadian models, and the decision support system for agrotechnology transfer (DSSAT) family of models was used to simulate cotton, wheat, corn, potato, soybean, sorghum, rice, and tomato, while other crop models were used to simulate specific crops. The results of the study indicated that the weighted average yield impact for many crops grown under dryland conditions across the entire USA was positive under both the Canadian and Hadley scenarios. The study also found that changes in irrigated yields for the grain crops showed a lower level of increase than dryland yields. In a recent study by Tubiello & Rosenzweig (2008), it was found that moderate warming (up to 28°C) in the initial part of this century may positively impact crop and pasture yields in the temperate regions, while reducing crop yields in the semiarid and tropical regions. They also concluded that further warming that is expected for the latter part of the century will likely reduce crop yields in all regions.

Further, McCarl et al. (2008) used time series techniques to analyze how climatic variability impacts crops. The overall results from this study indicated that yields for corn, cotton, soybeans, and winter wheat will increase, while yield for sorghum may decline under the Hadley model. In one of the early studies specifically for Texas, McCarl et al. (1993) employed models of crop and livestock response to weather and changing CO2 concentrations, under scenarios generated through the Hadley and Canadian models. Under climatic conditions as predicted by both models for the Texas High Plains and Texas South Plains, cotton yields showed substantial increases in the range of 13–101% from baseline toward 2090. Sorghum yields followed a similar trend with yield increases in the range of 23–47%. Corn yields declined for the Texas High Plains under both models. For the Texas South Plains, the Hadley model showed an increase in corn yields, in contrast to a decline as predicted by the Canadian model. Most recently, Attavanich & McCarl (2011) estimated the effects of climate variables, crop production technology, and atmospheric CO2 on yields of five major crops including corn, sorghum, soybeans, winter wheat, and cotton, in the USA using state level historical data. The results of the study indicated that, for the USA, the yields of C-3 crops, soybeans, cotton, and wheat, positively respond to the elevated CO2, while yields of C-4 crops, corn and sorghum do not. However, the study also pointed out that C-4 crops like corn indirectly benefit from increased CO2 especially when the crop is subject to drought stress.

Several past studies have used economic optimization models to evaluate the impacts on groundwater resources and the regional economy of the Texas High Plains. In one of the pioneer studies for this region, Feng (1992) used a combination approach of utilizing diverse kinds of models to optimize the use of the remaining groundwater stock in the Ogallala aquifer. The study included three optimization models, a dynamic programing model, a profit maximization model, quadratic programing models, and one bio-simulation model of crop growth. The results indicated that irrigated cotton was found to be superior to irrigated corn and irrigated sorghum under the dynamically efficient proportion of crop combination for the specified conditions of the area. Also, it was found that groundwater supply was not the factor causing the decline in irrigated acreage in Lubbock County and irrigation systems with lower efficiency could also be the major reason for the recent decline in irrigated acres. Arabiyat et al. (1999) incorporated a dynamic optimization model to evaluate the effects of introduction of new irrigation technologies and
biotechnology on the use of groundwater and calculated the net present value of agricultural returns for Swisher, Hale, and Lubbock Counties in the Texas High Plains. This study concentrated on utilizing these improvements for sustaining irrigated agriculture and reducing water depletion from the Ogallala Aquifer. The study concluded that advancement in technology and the controlled judicious use of groundwater had significant potential to contribute to the sustainability of agriculture in the Texas High Plains. Recently, Johnson et al. (2004, 2009) used a dynamic optimization model along with an input/output model and studied the impacts of different policy alternatives on the saturated thickness of the Ogallala Aquifer and economy of Texas High Plains. The study compared a baseline scenario with three policy alternatives for response to aquifer depletion using a planning horizon of 50 years. These alternatives were a production fee on water extracted, a water pumping quota restriction, and a water drawdown restriction. The results showed that the baseline scenario resulted in the most rapid exhaustion of the water supply and caused the most dramatic decrease in net income for the economy over time. The production fee alternative showed little change from the baseline and the drawdown restriction resulted in slightly lower net income than the quota restriction. They further concluded that the aquifer drawdown restriction could be considered the most effective alternative because it projected the best equivalence between producer profit, water conservation, and subsequent effects on the regional economy.

EXISTING GAPS

From the review of existing literature as discussed above, the following gaps have been identified which this study attempts to fill:

1. Prior studies conducted for the study region of the Texas High Plains have individually addressed the implications of climatic changes on agricultural crops of importance using crop models. On the other hand, the economic optimization studies for the region have predicted long-term impacts on the groundwater resources based on current depletion rates and production practices. However, there remains a gap of following an integrated approach that combines crop responses under climatic predictions for future scenarios with hydro economic models to forecast water use and impacts on the regional agricultural economy.

2. In addition, there is a high emphasis in the study region on groundwater management due to the depleting levels of underground water reserves aggravated by insufficient recharge, as mentioned previously in the introduction section. Past studies have suggested water policy alternatives for groundwater management and have majorly relied on the assumption that future climatic conditions would be the same as past conditions, following historical trends. However, with observable changes in climate being noticed and anticipated in the future, it is crucial to prepare our current agricultural systems for adapting toward future climate shocks and to conserve the existing groundwater resources for long-term sustainable use by the farming community. Therefore, the impacts of climatic variability on water resources should also be an integral part of policy decisions about long-term water allocation and withdrawal planning. This information can be used further to recommend the most suitable irrigation practices for the farming community, and the type and acreage of crops to be grown. Using the integrated approach described earlier, a significant contribution of this study will be to augment the information available to both producers and policy-makers in the region for effective management planning of scarce groundwater resources, by incorporating future climatic conditions.

FRAMEWORK OF STUDY AND METHODS

With regard to agricultural irrigation (with groundwater as the primary source) and its optimal use, climatic factors and their direction of change in the future are variables of interest for policy-makers and producers of the Texas High Plains. The study of impact of climatic factors in the future and quantification of the same in terms of agricultural parameters provides an insight toward groundwater management policies that may be incorporated in the future management plans. This can determine the current quantity in use and the cost-benefit aspects of groundwater usage for
an individual producer, as well as on a regional scale. In
order to incorporate climate variability in future water
resource allocation in the agricultural sector, several factors
must be considered, and a sequential approach should be
imparted to the study (Chung et al. 2009). This involves a
clear understanding of the direct effects of climate change
on groundwater availability in the area, followed by linking
climatic variability to agricultural production, irrigation
practices, water application for irrigated crops, and crop
mix of the area. Finally, it summarizes the changes in the
economic aspects of farm production in terms of profitabil-
ity and viability for the future planning periods. Figure 1
outlines these factors and describes the sequential approach
for incorporating the effects of climate variability into econ-
omic aspects of agricultural production and water resource
planning in the study area.

Crop growth simulation models are research tools that
are generally applied in assessing the relationship between
crop productivity and environmental factors and have
been shown to be efficient in determining the response of
crops to changes in weather and climate (Adejuwon 2002).
A variety of crop models are available to study the effects
of changing climate on crop production. Examples of such
models include EPIC (Williams et al. 1989), CERES (Ritchie

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Figure 1 | Incorporating climate variability into economic aspects of agricultural production and water resource planning.
et al. 1989), GAPS (Butler & Riha 1989), SOYGRO (Jones et al. 1989), DSSAT crop model (Jones et al. 2003; Hoogenboom et al. 2010), and IBSNAT (IBSNAT 1989). In most cases these crop models have been developed in particular regions, and therefore the choice of crop models in a study is guided by the local cropping patterns and production practices.

Effects on crop production of changing climate as well as CO₂ emission changes have been a major part of prior assessment studies regarding climate change impacts (e.g. Rosenberg & Crosson 1993; Rosenzweig & Parry 1994) and are followed in this study as well. The basic approach involves predicting climatic conditions from climate models and incorporating them into the crop models. To ensure uniformity in results, the soil type and profile description for a particular study area are specified when running the crop models. Simulations are run for important crops in the study area under both non-irrigated and irrigated conditions for future time frames, and crop response is recorded in the form of yield responses for each crop under dryland and irrigated conditions. These yield responses are used to derive the production functions for each crop and are used as inputs to the economic models for planning and predicting future cropping patterns and farm revenue in the study regions.

Farm-level adjustments to climate change depend on the technological potential (different varieties of crops and irrigation technologies); soil, water, and biological response; and the capability of farmers to adapt to climate change (Gleick 1997). It is imperative to understand the fit of these models with changes in climatic variables, represented by change in crop yields as these changes directly impact farm profitability in a region. Also, in irrigated farming the amount of water applied to the crop during the growing season using irrigation techniques as applicable to the area will account for the variability in crop yields on a unit area as well as the region. This function of representing the variability in climate in terms of economic parameters of production is carried out by the economic models.

The economic modeling approach provides a detailed analysis of the movement and adaptation of cropping patterns and associated profitability in an agricultural production system. This improves the ability to adapt and improve the scientific understanding of plant responses. It is therefore a necessary step to link the yield response details of crop response models with equally detailed models specifying economic options for adapting to climate change. The simplest form of evaluating these changes will be in the form of changes in net revenue, net present value of net returns over the study period, changes in irrigated acreages, and movement in crop mix. These changes should be considered a part of any policy development process by the planners of agricultural water use policy in the current and future time frames. This will assist in mitigating to some extent, the anticipated climatic disruptions by way of prior adjustments in groundwater resource use planning.

**CASE STUDY**

**Description**

The primary focus of this research concentrates specifically on a high groundwater use area, the Southern High Plains of Texas. Groundwater is the main source for irrigated agricultural production in the area, and irrigated cotton and corn are cultivated under large acreages, besides dryland sorghum and wheat. It is to be noted that a substantial portion in this area overlies the Ogallala aquifer, which is the main groundwater source for irrigated agricultural production. Hale County is chosen as a representative county, which is located in the Texas Southern High Plains (Figure 2). There are a total of 266,672 cropland acres in the target area of which 192,778, or 72%, are irrigated. The average saturated thickness of the aquifer currently is approximately 24.38 m in Hale County with average depth to water approximately 65.84 m (Texas Tech University Center for Geospatial Technology 2010). On average, 77% of the irrigated acreage is devoted to cotton production, and 23% to irrigated corn production. For the purpose of this analysis, it is assumed that all of the irrigated acres use center pivot irrigation technology, although subsurface drip (SDI) acres are on the rise. There are three sequential steps that are used in this study to accomplish the objective of evaluating the economic impacts of future climate change scenarios.
Selection of GCM and scenarios

The first step is the selection and use of climate models for future climate projections. Among the various emission scenarios described in the IPCC Special Report on Emission Scenarios (Nakicenovic et al. 2000), this study uses the higher A1FI and mid-range A1B scenarios. Although both of these scenarios are characterized by rapid economic growth, the A1FI emphasizes fossil-fuels, while A1B has a balanced emphasis on all energy sources. The four atmosphere ocean general circulation models used in the research are a part of the latest IPCC AR4 archive: the Community Climate System Model version 3, Parallel Climate Model version 1 (PCM), both developed by the National Center for Atmospheric Research; the UK Met Office Hadley Model, HadCM3, and the Geophysical Fluid Dynamics Laboratory (GFDL) CM2.1. From previous studies, it has been concluded that the magnitude of temperature-driven trends in the future is generally projected by the above models to be higher under the A1FI and A1B emission scenarios (Hayhoe et al. 2007, 2012). The specific selection criteria for these specific models are explained here. First, only well-established models were used which have been evaluated extensively in the peer-reviewed scientific literature. Next, it was imperative for the models to include the greater part of the IPCC range of uncertainty in climate sensitivity (2–4.5°C; IPCC 2007). Finally, it was crucial that the models have continuous daily time series of temperature and precipitation archived for both of the emission scenarios (Hayhoe et al. 2012). The General Climate Models (GCM) selected for this analysis are the only four models for which continuous daily output for the A1B and A1FI scenario simulations was available (Hayhoe et al. 2012).

The selected GCMs are employed to predict a set of future climate projections under the two emission scenarios. This research follows the selection criteria chosen by Cayan et al. (2009) for future climate projections, where a climate projection is defined as a GCM simulation of 21st century climate conditions for a future greenhouse gas emissions scenario. This should be selected on the ability of the climate projections to adequately represent the El Niño Southern Oscillation climate patterns, predictions of drought periods, and annual patterns of monthly mean temperature and precipitation for the study region. Other factors considered for selection are daily outputs for air temperature, precipitation, and available climate model and application documentation.

The projected future trends are specifically observed for primary climate characteristics and indicators of change as provided by variables like seasonal temperatures and rainfall (Hayhoe et al. 2007). High-resolution daily temperature and precipitation projections from these four climate models and two scenarios downscaled using a statistical asynchronous regression model based on long-term daily
station observations from Plainview TX (located in Hale county) are used individually to generate crop response functions using crop models over three time frames: near future (2010–2039), mid future (2040–2069), and distant future (2070–2099). From the above approach, 24 climate projections were used to predict future climate changes for the study county. These projections were provided by the Texas Tech Climate Science Center for the purpose of this study. The sequence of steps described above has been modified from the framework described by Chung et al. (2009).

Downscaling

Grid-scale variability in temperature and precipitation for each model and scenario was downscaled to the location of the weather station in the study region located in Plainview, TX (K. Hayhoe, personal communication, 2011. www.depts.ttu.edu/artsandsciences/csc/). Regression coefficients for estimating secondary meteorological variables from the downscaled daily minimum temperature ($T_{\text{min}}$), maximum temperature ($T_{\text{max}}$), and precipitation ($P$) values were calculated using daily Texas Tech University Mesonet data during 2002–2011. Daily dew point temperatures were derived from daily $T_{\text{min}}$ and $T_{\text{max}}$ values and an annual aridity index via Equation (4) of Kimball et al. (1997). Daily surface shortwave radiation was estimated from the downscaled $T_{\text{min}}$, $T_{\text{max}}$, and $P$ via Equation (4) of Hunt et al. (1998). Daily wind run values were stochastically generated via a multivariate regression on daily temperature anomalies adapted from Parlange & Katz (2000).

Crop response modeling

The next step is to incorporate climatic indicators for individual weather stations in crop response models. The specific crop model used in this study is a biophysical model (the DSSAT crop modeling suite) for obtaining responses of selected crops to climate, soil, and nutrients with varying irrigation levels as the focus is on water resource management (Nelson et al. 2009). For this study, in order to obtain the crop responses, individual crop specific information is incorporated into DSSAT (Jones et al. 2003; Hoogenboom et al. 2010). The DSSAT crop-simulation model is a detailed process model that could be used to study response and development of specific crop varieties, at different stages (Nelson et al. 2009). The major inputs to the model are daily weather data, including maximum and minimum temperature, solar radiation, and precipitation, soil characteristics, physical and chemical characteristics of the field, crop variety, planting date, plant spacing, and inputs such as fertilizer and irrigation levels (Nelson et al. 2009). This study uses the latest version 4.5 of the DSSAT crop model (Jones et al. 2003; Hoogenboom et al. 2010). One major advantage of using DSSAT is that it also allows for CO$_2$ fertilization effects, which is an important aspect of plant growth and response (Nelson et al. 2009). Next, we established a functional relationship between yield and applied irrigation water for major crops in the study area. In order to estimate this relationship, separate runs were drawn for cotton and corn under different levels of irrigation application using DSSAT.

Given the required daily weather inputs, DSSAT cropping simulations were conducted for each year of 1960–2099 based on each model’s downscaled output for both emission scenarios. For each site, climate model, scenario, and year four crops – corn, cotton, sorghum, and winter wheat – were modeled. Cotton, sorghum, and winter wheat were simulated under dryland conditions. Corn and cotton were also modeled under irrigated conditions. In each simulation, initial soil moisture was set to 70% of field capacity and initial soil nitrogen was set at 96 kg/ha. The models were run in a mode that assumed water stress to be the yield-limiting factor with nitrogen and other soil nutrients being maintained at optimal levels. Cultivars used were cotton – Deltapine 77, corn – generic long season variety, winter wheat – Newton, and sorghum – ATx399XRTx430.

Irrigation

In the irrigated model runs total growing season irrigation was defined based on climatological irrigation demand ($ID_c$) calculated over the periods 1960–2009, 2010–2039, 2040–2069, and 2070–2099. Irrigation demand was defined as total crop evapotranspiration ($\Sigma ETc$) calculated over the growing season via the FAO-56 single crop coefficient method (Allen et al. 1998) minus growing season precipitation ($\Sigma P$). This is formulated as $ID_c = \Sigma ETc - \Sigma P$. During each year $ID_c$ for each crop was calculated at Plainview.
and Amarillo using the downscaled $T_{\text{min}}$, $T_{\text{max}}$, and $P$ values and secondary meteorological variables calculated via the references cited above. Additional secondary variables, e.g. outgoing long-wave radiation, were calculated via formulas found in Allen et al. (1998). ID$_c$ for each crop was defined as the median of the ID values calculated at the two locations during each period. Thus, for example, during 1960–2009 the ID$_c$ for cotton was defined as the median of the 100 cotton ID values calculated from the Plainview and Amarillo data.

**Environmental CO$_2$**

Environmental CO$_2$ levels in each year’s simulations for the A1B and A1FI scenarios were defined as the scenario average of annual CO$_2$ calculated over the same periods used to define climatological irrigation demand (Table 1). Each year’s cropping simulation during those periods assumed the average CO$_2$ value of the scenario assumed in the associated climate model simulation. Thus, for example, all of the cropping simulations driven by the downscaled daily weather under the A1B scenario during 1960–2009 assumed the 1960–2009 A1B scenario mean (346.4 ppm).

The yield predictions obtained are used to generate regression equations for each crop, where $Y$ is the yield per acre and $X$ is the water application rate. It was observed that the cotton yields showed a cubic response function, while the corn yields followed a quadratic trend.

The established equation for cotton is represented as

$$Y = \beta_0 - \beta_1X + \beta_2X^2 - \beta_3X^3$$  \hspace{1cm} (1)

Table 1 | CO$_2$ levels assumed in the decision support system for agrotechnology transfer simulations

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Period</th>
<th>CO$_2$ level (ppm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>A1B</td>
<td>1960-2009</td>
<td>346.42</td>
</tr>
<tr>
<td>A1FI</td>
<td>1960-2009</td>
<td>346.24</td>
</tr>
<tr>
<td>A1B</td>
<td>2010-2039</td>
<td>436.66</td>
</tr>
<tr>
<td>A1FI</td>
<td>2010-2039</td>
<td>437.58</td>
</tr>
<tr>
<td>A1B</td>
<td>2040-2069</td>
<td>549.66</td>
</tr>
<tr>
<td>A1FI</td>
<td>2040-2069</td>
<td>601.46</td>
</tr>
<tr>
<td>A1B</td>
<td>2070-2099</td>
<td>664.23</td>
</tr>
<tr>
<td>A1FI</td>
<td>2070-2099</td>
<td>838.10</td>
</tr>
</tbody>
</table>

Similarly, the dryland yields for cotton, sorghum, and wheat were also calculated through the crop models, by letting crop responses to be determined by rainfall. Corn in the region must be irrigated; therefore, the dryland yields for corn were not used in this analysis. The irrigated production functions and dryland yields were calculated individually to represent the three time periods under different climate models and scenario combinations.

**Dynamic programing**

The final step comprised employing a dynamic programming approach using economic optimization models to predict the behavior of the farming system, net revenue, and associated water use from the aquifer over a stipulated planning horizon. The framework of the optimization model used in this study was originally developed by Feng (1992) and has been expanded and modified by Johnson et al. (2004, 2009) and Wheeler et al. (2008). Optimization models are developed using dynamic programming for individual counties under each weather station to provide a comparative analysis of economic results for each weather station. The basic principle that guides the model is determining the optimal allocation of available groundwater in order to maximize the net returns from crop production. Wheeler et al. (2006) developed the basic framework for the dynamic optimization models specifically for two different irrigation systems, i.e. low energy precision application (LEPA) and furrow irrigation. These models were developed for the study area that comprised the Southern Ogallala region in the states of Texas and New Mexico. This research utilizes the same framework for optimizing NPV, with the difference that only LEPA irrigation is taken into consideration. The specific model for the purpose of this study is a nonlinear dynamic model with the incorporation of crop production functions for irrigated crops as well as dryland yields as derived from DSSAT. An approach that utilizes nonlinear dynamic programming in combination with General Algebraic Modeling Systems (GAMS) (Brooke et al. 1998)
is used in this study to facilitate multiple runs of the model. The optimization model with the incorporated production functions and dryland yields estimates the optimal water requirements for irrigation and the resulting net returns from crop production for major crops in the study county over the three time frames. A 5% discount rate is used to calculate the net present value for each time period in the study county.

**MATHEMATICAL MODELING**

**Model specification**

The objective function maximizes the net returns from production of crops over a time horizon of 50 years, and results are analyzed for the first 30 years (Equation (2)). These runs were carried out for each of the three time periods that represent the near, mid, and far-future planning horizons in the study.

\[
\text{Max NPVs}^{50}_{t=1} = \sum \text{NR}_t (1 + r)^{-t}
\]

where NPV is the net present value of net returns; \( r \) is the discount rate; and \( \text{NR}_t \) is net revenue at time \( t \). The bounds of summation for the net revenue are from 1–50 years.

\( \text{NR}_t \) is defined as

\[
\text{NR}_t = \sum \text{NR}_i = \left[ \sum \text{YC}_i \Omega_{ikt} \Delta t \right] \left[ P_i Y_{ikt} [W_{ikt} + (W_{ipt})] - C_{ikt} (W_{ipt}, X_i, S_{ikt}) \right]
\]

where \( i \) represents crops grown; \( k \) represents irrigation systems used; \( \Omega_{ikt} \) is the percentage of crop \( i \) produced using irrigation system \( k \) in time \( t \); \( P_i \) is the output price of crop \( i \), \( W_{ikt} \) and \( W_{ipt} \) are irrigation water application per acre and water pumped per acre, respectively. \( Y_{ikt} \) is the per acre yield production function, \( C_{ikt} \) represents the costs per acre, \( X_i \) is pump lift at time \( t \), \( S_{ikt} \) represents the saturated thickness of the aquifer at time \( t \). The bounds of summation are 1–4 and 1–2 for \( i \) and \( k \), respectively.

The main equations and constraints of the model are

\[
X_{i+1} = X_i + \left[ \sum \text{RI}_i \Omega_{ikt} \Delta t \right] - ARRjPIA/SY
\]

\[
\begin{align*}
G_P &= \left( S_{ikt}/IST \right)^2 \times (4.42 \times WY/AW) \\
W_T &= \sum \Omega_{ikt} \Omega_{ikt} \Delta t + WP_{ikt}
\end{align*}
\]

\[
\begin{align*}
W_T &\leq G_P \\
PC_{ikt} &= [\text{EF}(X_i + 2.31 \times \text{PSI})EP]/\text{EFF} \times WP_{ikt} \\
C_{ikt} &= VPC_{ikt} + PC_{ikt} + HC_{ikt} + MC_k + DP_k + LC_k \\
\sum \Omega_{ikt} &\leq 1 \text{ for all } t \\
\Omega_{ikt} &\geq 0.9 \Omega_{ikt-1} \\
\Omega_{ikt} &\geq 0
\end{align*}
\]

Equations (5) and (6) update the two state variables, saturated thickness and pumping lift, \( S_{ikt} \) and \( X_i \), respectively, where \( ARR \) is the annual recharge rate in feet (1 foot equivalent to 0.3048 m), \( PIA \) is the percentage of irrigated acres expressed as the initial number of irrigated acres in the county divided by the area of the county overlying the aquifer, and \( SY \) is the specific yield of the aquifer. In Equation (7), \( G_P \) represents gross pumping capacity, \( IST \) represents the initial saturated thickness of the aquifer in year one of the planning horizon, i.e. 2010, and \( WY \) represents the average initial well yield for the county in year one. Constraints (8) and (9) are the water application and water pumping capacity constraints, respectively. Equation (8) represents the total amount of water pumped per acre, \( W_T \), as the sum of water pumped on each crop. Constraint (9) requires \( W_T \) to be less than or equal to \( G_P \). Equations (10) and (11) represent the cost functions in the model. In Equation (10), \( PC_{ikt} \) represents the cost of pumping, \( EF \) represents the energy use factor for electricity, \( EP \) is the price of energy, \( EFF \) represents pump efficiency, and 2.31 feet or 0.7 m is the height of a column of water that will exert a pressure of 1 lb/in\(^2\) (equivalent to 6.89 kPa). Equation (11) expresses the cost of production, \( C_{ikt} \), in terms of \( VPC_{ikt} \).
the variable cost of production per acre, $HC_i$, the harvest cost per acre, $MC_k$, the irrigation system maintenance cost per acre, $DP_k$, the per acre depreciation of the irrigation system per year, and $LC_k$, the cost of labor per acre for the irrigation system. Equation (12) limits the fractional sum of all acres of crops $i$ produced by irrigation systems $k$ for time period $t$ to be less than or equal to 1. Equation (13) limits the annual change in the area of any crop to no more than 10% of the previous year’s area. Equation (14) ensures that the values of the decision variables are non-negative.

**DATA COLLECTION AND ANALYSIS**

Saturated thickness and pump lift by county are based on data from the Texas Tech University Center for Geospatial Technology website (Texas Tech University Center for Geospatial Technology 2010). The recharge rate used in the model on a county basis is obtained from the Texas Water Development Board (Texas Water Development Board 2011). An average estimated specific yield of 0.15 will be used for the entire study area (United States Geological Survey 2011). Specific yield is defined as the volume of water released from storage by an unconfined aquifer per unit surface area of aquifer per unit decline of the water table (Duffield 2014).

The average hydraulic conductivity used in the model for the Ogallala aquifer in Texas is estimated to be 19.81 m/day (United States Geological Survey 2011). Other parameters incorporated in the model are initial acres served per well, maximum allowable withdrawal, and well yield in gal/min (1 gal/min is equivalent to 0.227 m³/hour). Initial acres served per well were calculated by dividing the groundwater irrigated acres by the approximate number of wells for the county.

The county area and the number of acres for each crop are obtained from the US Census Bureau (US Census Bureau 2007). Initial data necessary for the county optimization models included values (representing 2010) for total crop acreage, irrigated crop acreage, and dryland crop acreage which were derived from the Farm Service Agency. The primary crops used in the study were cotton, corn, sorghum, and wheat. Due to minor acreages, initial acreages for dryland corn, irrigated wheat, and irrigated sorghum were not included in the model. The county specific parameters for hydrological and acreage data are presented in Table 2.

Crop specific data included commodity prices, variable costs of dryland crop production excluding harvest costs, added variable costs for irrigated crop production, and harvest costs per unit of production as shown in Table 3. Commodity prices used in the analysis were five year averages from 2008 to 2012, using information from the enterprise budgets developed by the Texas Agrilife Extension Service for District 2. The variable costs for dryland crop production and the additional costs for irrigated production were also procured from enterprise budgets developed by the Texas Agrilife Extension Service for Texas District 2 (Texas Agrilife Extension Service 2013). Pumping costs were based on an energy use factor for natural gas of $1.45 \times 10^{-3}$ mcf (equivalent to 1,531 J) per foot (equivalent to 0.3048 m) of lift per acre inch (equivalent to 102.8 cm³), irrigation system operating pressure of 20 lb/in² (equivalent to 137.8 kPa), pump engine efficiency of 75%, and energy price of $8.10 per mcf (Hayhoe et al. 2012). Other costs include the initial cost of the irrigation system of $416 per acre, annual depreciation percentage of 5%, irrigation labor of 1.4 hours per acre, and labor cost of $9.60 per hour (Hayhoe et al. 2012). Annual maintenance

<table>
<thead>
<tr>
<th>Table 2</th>
<th>County specific parameters (hydrologic and acreage data)</th>
</tr>
</thead>
<tbody>
<tr>
<td>County land area (ha)</td>
<td>260,405</td>
</tr>
<tr>
<td>Amount of recharge (m³)</td>
<td>51.4</td>
</tr>
<tr>
<td>Specific yield</td>
<td>0.15</td>
</tr>
<tr>
<td>Initial saturated thickness (m)</td>
<td>24.38</td>
</tr>
<tr>
<td>Initial lift (m)</td>
<td>65.83</td>
</tr>
<tr>
<td>Initial well yield (m³/hour)</td>
<td>41.54</td>
</tr>
<tr>
<td>Maximum allowable withdrawal (ha/m)</td>
<td>45,351</td>
</tr>
<tr>
<td>Initial hectares served per well</td>
<td>16.18</td>
</tr>
<tr>
<td>Initial crop acreages (ha)</td>
<td>Irrigated Dryland</td>
</tr>
<tr>
<td>Cotton</td>
<td>60,173</td>
</tr>
<tr>
<td>Corn</td>
<td>17,902</td>
</tr>
<tr>
<td>Sorghum</td>
<td>0</td>
</tr>
<tr>
<td>Wheat</td>
<td>0</td>
</tr>
<tr>
<td>Total</td>
<td>78,075</td>
</tr>
</tbody>
</table>
cost was set at 8% of initial irrigation system cost, and a real
discount rate of 3% was assumed as mentioned earlier (Ter-
rell 1998; Johnson et al. 2009). Cost calculations included
harvest costs, pumping costs, and total costs of production
for irrigated and dryland crops, and the units for these
costs were in $ per acre.

The results of these models were analyzed for the par-
ameters of saturated thickness, annual net revenue per
acre, pump lift, water applied per cropland acre, cost of
pumping, net present value of NPV, and for shifts in crop
mix over three distinct future time frames, as mentioned pre-
viously. In this manner, this study could be considered as a
starting point to link climate change with its consequent
effect on the availability of water for irrigated agriculture
in the Texas High Plains and associated economic
implications.

RESULTS AND DISCUSSION

In all climate models and scenario combinations, the satu-
rated thickness was reduced from 24.38 m at the beginning
of the period to 9.14 m by the end of the near-future scen-
ario. Saturated thickness at a level of 9.14 m is assumed to
be the minimum saturated thickness that will produce
enough water for irrigation purposes (Mulligan et al. 2013).
Under the A1B scenario, the maximum negative change in
total water use per cropland acre was observed for the HadCM3 model, followed by the
PCM, GFDL, and the CCSM models, respectively. The reduction in total water use per cropland acre can be attrib-
uted to the declines in saturated thickness resulting in
diminished well capacity and increased pumping costs. This
in turn led to heavy reductions for average annual
water use per cropland acre, while water use per irrigated
acre remained relatively constant over the planning horizon
for all models under the A1B scenario.

The percentage of irrigated acres is similarly reduced
from 72% to less than 15% by the end of the near-future
period for all models and scenarios. They further reduce to
less than 1% by the end of the 90-year time frame for all
models and scenarios, indicating a complete switch from
irrigated to dryland production in the study area. The initial
conditions for the crop mix in the county showed 56% under
irrigated LEPA cotton production, 16.5% under irrigated
LEPA corn production, 11% under dryland cotton produc-
tion, 11% under dryland wheat production, and only
5% under dryland sorghum production. The conditions for
crop mix showed a substantial shift under different models
and scenarios with most of the irrigated production shifting
majorly toward dryland cotton production on account of
reduction in water availability with a decline in saturated
thickness, and a high yield response of dryland cotton
toward increasing CO2 concentrations in the future time
periods. Economic results based on climate predictions
under the mid-range scenario (A1B) and the higher range
scenarios (A1FI) are depicted in Tables 4 and 5, respectively.

Net income per acre and economic activity are greatly
impacted by the climate model and scenarios due to the
response of dryland crop yields under different climate
models. Dryland yields for all crops under both scenarios
and all four models increased over the 90-year time horizon,
and the increases were higher under the A1FI scenario
when compared to the A1B scenario. The only exceptions
were the sorghum yields as predicted under the GFDL
model under both scenarios which showed a decline over
the planning horizon. Cotton yield increases surpassed the
increments in yields of other crops and made significant
contributions to increasing net revenue over the planning
horizon under most scenario and model combinations.

Table 3 | County specific parameters (commodity prices and production costs)
| Item | Cotton | Corn | Sorghum | Wheat |
| Average price per unit | $1.51/kg | $186.61/ton | $297.23/ton | $233.3/ton |
| Variable cost of dryland production | $460/ha | $0.00/ha | $215/ha | $178/ha |
| Variable cost of irrigated production | $299/ha | $670/ha | $0.00/ha | $0.00/ha |
| Harvest cost per unit of production | $0.37/kg | $13.39/ton | $22.05/ton | $19.47/ton |
The increase in dryland yields could most likely be attributed to the increasing CO₂ concentrations assumed in modeling dryland yields for future time frames (McCarl et al. 1993; Attavanich & McCarl 2011). A summary of the estimates of dryland yields for each crop under each climate model and policy scenario are presented in Table 6. Dryland yields for corn are not included as corn production in the region requires irrigation and will not produce enough yield to harvest in the absence of adequate irrigation water availability.

The dryland yields for cotton, grain sorghum, and wheat all increase over the 90-year period, except for grain sorghum under the GFDL model which shows a declining trend in the yields during the study period. Over the 90-year period, estimated yields per acre for the A1FI policy scenario resulted in yield increases for cotton of approximately 72% for CCSM, 48% for GFDL, 28% for HadCM3, and 15% for PCM. Grain sorghum yields under the A1FI scenario resulted in increases of approximately 46% for CCSM, 45% for HadCM3, and 5% for PCM, while the GFDL model predicted climatic conditions resulting in a yield decrease of 11% under the A1FI scenario. Wheat yields showed increments of 55, 42, 21, and 44% for the CCSM, GFDL, HadCM3, and the PCM models, respectively. Estimated yields per acre for the A1B policy scenario result in yield increases for cotton of approximately 48% for CCSM, 33% for GFDL, 37% for HadCM3, and 17% for PCM. Grain sorghum yields under the A1B scenario resulted in increases of approximately 46% for CCSM, 62% for HadCM3, and 22% for PCM, while the GFDL model predicted climatic conditions resulting in a yield decrease of 11% under the A1FI scenario. Wheat yields showed increments of 37, 17, 44, and 43% for the CCSM, GFDL, HadCM3, and 17% for PCM. Grain sorghum yields under the A1B scenario resulted in increases of approximately 46% for CCSM, 62% for HadCM3, and 22% for PCM, while the GFDL model predicted climatic conditions resulting in a yield decrease of 11% under the A1FI scenario. Wheat yields showed increments of 37, 17, 44, and 43% for the CCSM, GFDL, HadCM3, and the PCM models, respectively. Estimated yields per acre for the A1B policy scenario result in yield increases for cotton of approximately 48% for CCSM, 33% for GFDL, 37% for HadCM3, and 17% for PCM. Grain sorghum yields under the A1B scenario resulted in increases of approximately 46% for CCSM, 62% for HadCM3, and 22% for PCM, while the GFDL model predicted climatic conditions resulting in a yield decrease of 11% under the A1FI scenario. Wheat yields showed increments of 37, 17, 44, and 43% for the CCSM, GFDL, HadCM3, and the PCM models, respectively. Dryland yield estimations by crop models are strongly impacted by temperature and precipitation projections for future time frames by different climate models. The GFDL and HadCM3 models tend to have higher temperature increases and greatest precipitation decreases over the 90-year period. The CCSM model predicted the mildest

| Table 4 | Economic results based on climate predictions under the mid-range scenario (A1B) |
|---------|---------------------------------|-----------------|-----------------|-----------------|-----------------|------------------|------------------|
|         | 2010               | 2039               | 2069               | 2099               | % change |
| CCSM model under A1B scenario | | | | | |
| Average saturated thickness (m) | 24.4       | 9.4               | 9.2               | 9.1           | –63 |
| Total water use/cropland acre (m³) | 1,705.59 | 446.39           | 51.40             | 51.40           | –97 |
| Irrigated acres (% of total acres) | 72%       | 15%              | 2%               | 2%           | –98 |
| Average net income per acre ($/ha) | 632.5      | 655.1             | 492.7             | 545.6          | –14 |
| GFDL model under A1B scenario | | | | | |
| Average saturated thickness (m) | 24.4       | 9.4               | 9.4               | 9.4           | –61 |
| Total water use/cropland acre (m³) | 1,705.59 | 446.39           | 5.54             | 0.20           | –100 |
| Irrigated acres (% of total acres) | 72%       | 0.11%            | 0.01%             | 0.0%           | –100 |
| Average net income per acre ($/ha) | 398.7      | 484.5             | 394.3             | 502.4          | 26 |
| HadCM3 model under A1B scenario | | | | | |
| Average saturated thickness (m) | 24.4       | 9.4               | 9.4               | 9.4           | –61 |
| Total water use/cropland acre (m³) | 1,705.59 | 446.39           | 61.24             | 61.24           | –96 |
| Irrigated acres (% of total acres) | 72%       | 14.79%           | 1.60%             | 1.60%           | –98 |
| Average net income per acre ($/ha) | 626.7      | 352.8             | 431.2             | 448.1          | –28 |
| PCM model under A1B scenario | | | | | |
| Average saturated thickness (m) | 24.4       | 9.4               | 9.2               | 9.2           | –62 |
| Total water use/cropland acre (m³) | 1,705.59 | 446.39           | 51.40             | 66.41           | –96 |
| Irrigated acres (% of total acres) | 72%       | 13.25%           | 1.73%             | 1.73%           | –97 |
| Average net income per acre ($/ha) | 519.8      | 466.8             | 637.7             | 637.0          | 23 |
### Table 5 | Economic results based on climate predictions under the higher range scenario (A1FI)

<table>
<thead>
<tr>
<th>CCSM model under A1FI scenario</th>
<th>2010</th>
<th>2039</th>
<th>2069</th>
<th>2099</th>
<th>% change</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average saturated thickness (m)</td>
<td>24.4</td>
<td>9.4</td>
<td>9.2</td>
<td>9.1</td>
<td>-63</td>
</tr>
<tr>
<td>Total water use/cropland acre (m³)</td>
<td>1,705.59</td>
<td>446.39</td>
<td>51.40</td>
<td>45.32</td>
<td>-97</td>
</tr>
<tr>
<td>Irrigated acres (% of total acres)</td>
<td>72%</td>
<td>15%</td>
<td>1.39%</td>
<td>1.39%</td>
<td>-98</td>
</tr>
<tr>
<td>Average net income per acre ($/ha)</td>
<td>438.5</td>
<td>463.1</td>
<td>468.6</td>
<td>685.2</td>
<td>56</td>
</tr>
<tr>
<td>GFDL model under A1FI scenario</td>
<td>2010</td>
<td>2039</td>
<td>2069</td>
<td>2099</td>
<td>% change</td>
</tr>
<tr>
<td>Average saturated thickness (m)</td>
<td>24.4</td>
<td>9.4</td>
<td>9.2</td>
<td>9.2</td>
<td>-62</td>
</tr>
<tr>
<td>Total water use/cropland acre (m³)</td>
<td>1,705.59</td>
<td>446.39</td>
<td>4.17</td>
<td>34.50</td>
<td>-98</td>
</tr>
<tr>
<td>Irrigated acres (% of total acres)</td>
<td>72%</td>
<td>11.87%</td>
<td>0.56%</td>
<td>0.6%</td>
<td>-99</td>
</tr>
<tr>
<td>Average net income per acre ($/ha)</td>
<td>717.2</td>
<td>391.0</td>
<td>402.4</td>
<td>427.8</td>
<td>-40</td>
</tr>
<tr>
<td>HadCM3 model under A1FI scenario</td>
<td>2010</td>
<td>2039</td>
<td>2069</td>
<td>2099</td>
<td>% change</td>
</tr>
<tr>
<td>Average saturated thickness (m)</td>
<td>24.4</td>
<td>9.4</td>
<td>9.2</td>
<td>9.2</td>
<td>-62</td>
</tr>
<tr>
<td>Total water use/cropland acre (m³)</td>
<td>1,705.59</td>
<td>446.39</td>
<td>21.85</td>
<td>27.96</td>
<td>-98</td>
</tr>
<tr>
<td>Irrigated acres (% of total acres)</td>
<td>72%</td>
<td>13.87%</td>
<td>0.65%</td>
<td>0.65%</td>
<td>-99</td>
</tr>
<tr>
<td>Average net income per acre ($/ha)</td>
<td>632.4</td>
<td>611.6</td>
<td>635.9</td>
<td>703.1</td>
<td>11</td>
</tr>
<tr>
<td>PCM model under A1FI scenario</td>
<td>2010</td>
<td>2039</td>
<td>2069</td>
<td>2099</td>
<td>% change</td>
</tr>
<tr>
<td>Average saturated thickness (m)</td>
<td>24.4</td>
<td>9.4</td>
<td>9.2</td>
<td>9.2</td>
<td>-62</td>
</tr>
<tr>
<td>Total water use/cropland acre (m³)</td>
<td>1,705.59</td>
<td>446.39</td>
<td>27.96</td>
<td>21.85</td>
<td>-98</td>
</tr>
<tr>
<td>Irrigated acres (% of total acres)</td>
<td>72%</td>
<td>13.87%</td>
<td>0.65%</td>
<td>0.65%</td>
<td>-99</td>
</tr>
<tr>
<td>Average net income per acre ($/ha)</td>
<td>632.4</td>
<td>611.6</td>
<td>635.9</td>
<td>703.1</td>
<td>11</td>
</tr>
</tbody>
</table>

### Table 6 | Summary of dryland crop yields under different models and scenarios

<table>
<thead>
<tr>
<th></th>
<th></th>
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<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Cotton (kg/ha)</td>
<td>2010–39</td>
<td>625</td>
<td>629</td>
<td>628</td>
<td>558</td>
<td>607</td>
<td>735</td>
<td>870</td>
</tr>
<tr>
<td></td>
<td>2040–69</td>
<td>1,018</td>
<td>743</td>
<td>813</td>
<td>763</td>
<td>729</td>
<td>941</td>
<td>949</td>
</tr>
<tr>
<td></td>
<td>2070–99</td>
<td>1,075</td>
<td>839</td>
<td>928</td>
<td>763</td>
<td>774</td>
<td>858</td>
<td>1,004</td>
</tr>
<tr>
<td>% change</td>
<td>48%</td>
<td>72%</td>
<td>33%</td>
<td>48%</td>
<td>37%</td>
<td>27%</td>
<td>17%</td>
<td>15%</td>
</tr>
<tr>
<td>Sorghum (kg/ha)</td>
<td>2010–39</td>
<td>1,233</td>
<td>1,009</td>
<td>1,009</td>
<td>1,121</td>
<td>1,233</td>
<td>1,457</td>
<td>1,681</td>
</tr>
<tr>
<td></td>
<td>2040–69</td>
<td>1,569</td>
<td>897</td>
<td>1,009</td>
<td>1,569</td>
<td>1,681</td>
<td>2,018</td>
<td>1,569</td>
</tr>
<tr>
<td></td>
<td>2070–99</td>
<td>2,242</td>
<td>897</td>
<td>897</td>
<td>1,793</td>
<td>1,793</td>
<td>1,793</td>
<td>1,793</td>
</tr>
<tr>
<td>% change</td>
<td>40%</td>
<td>82%</td>
<td>-11%</td>
<td>-11%</td>
<td>60%</td>
<td>45%</td>
<td>23%</td>
<td>7%</td>
</tr>
<tr>
<td>Wheat (kg/ha)</td>
<td>2010–39</td>
<td>2,083</td>
<td>2,688</td>
<td>2,553</td>
<td>1,814</td>
<td>1,881</td>
<td>2,553</td>
<td>2,755</td>
</tr>
<tr>
<td></td>
<td>2040–69</td>
<td>2,889</td>
<td>2,688</td>
<td>2,889</td>
<td>2,284</td>
<td>2,150</td>
<td>2,889</td>
<td>3,695</td>
</tr>
<tr>
<td></td>
<td>2070–99</td>
<td>3,225</td>
<td>3,158</td>
<td>3,628</td>
<td>2,620</td>
<td>2,284</td>
<td>3,695</td>
<td>3,964</td>
</tr>
<tr>
<td>% change</td>
<td>38%</td>
<td>55%</td>
<td>18%</td>
<td>42%</td>
<td>44%</td>
<td>21%</td>
<td>45%</td>
<td>44%</td>
</tr>
</tbody>
</table>
temperature increases and precipitation declines among all climate models. The PCM model, similar to the CCSM model, also predicted precipitation increases into the future time period. Given these projections under both scenarios, the overall trend was that the dryland yields for CCSM and PCM were higher for all crops when compared to the HadCM3 and GFDL models.

CONCLUSIONS

Climate change impacts were incorporated into regional economic models using weather projections to develop crop response functions from crop models. These weather projections were based on quantitative projections of precipitation, potential evapotranspiration, and temperature trends driven by simulations from the latest IPCC AR4 climate models under two specific emissions scenarios, A1B (mid-range) and A1FI (higher) over a 90 year horizon. Hale County was selected as the study region. The major conclusions from this study are mentioned below.

1. Dryland yields of cotton, wheat, and sorghum positively respond to the elevated CO2 under both scenarios and all four models, and the increases were higher under the A1FI scenario when compared to the A1B scenario. The only exceptions were the sorghum yields as predicted under the GFDL model under both scenarios which showed a decline over the planning horizon. Cotton yield increases surpassed the increments in yields of other crops and made significant contributions to increasing net revenue over the planning horizon under most scenario and model combinations.

2. The results of the economic analysis indicated that under both the emission scenarios, saturated thickness, water use per cropland acre, and irrigated acreage declined under climatic predictions by all four models. Significant differences were observed for changes in average net income per acre under predictions by different models. Over the 90 year horizon, the A1B scenario resulted in a decline in average net income per acre as predicted by the CCSM and HadCM3 model, while the GFDL and PCM models predicted an increase in average net income per acre. Under the A1FI scenario, the CCSM, GFDL, and PCM model projections resulted in an increase in average net income per acre over the 90 year horizon, while climate projections under the HadCM3 model indicated a decline in average net income per acre. Overall, under both the emission scenarios, the GFDL model predicted the highest economic returns toward the end of the 90 year time frame.

3. This study faced limitations with regard to the economic model using county average hydrologic data such as saturated thickness, pump lift, gross pumping capacity, and specific yield, where in reality the hydrological characteristics may differ from one part of the county to another. Economic parameters and irrigation technology were assumed to be constant during the planning horizon to emphasize the impacts of the climate change scenarios without the influence of endogenous parameters in the model like prices and input costs. Also, as suggested by Attavanich & McCarl (2011), most crop models (including DSSAT) used to predict future crop yields are faced with the overestimation of the real effect of CO2 fertilization on crop yields, as is the case in this study. Future research efforts will include conducting the analysis on a larger, regional scale and utilizing a varied mix of crops. This will act as an important driver for adjusting regional water management plans with a long-term objective of conserving groundwater resources and maintaining the viability of the regional economy.

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