ESSAYS ON THE EFFECT OF CLIMATE CHANGE ON AGRICULTURE AND AGRICULTURAL TRANSPORTATION

A Dissertation

by

WITSANU ATTAVANICH

Submitted to the Office of Graduate Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

December 2011

Major Subject: Agricultural Economics

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Approved by:

Chair of Committee,	Bruce A. McCarl
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ABSTRACT

Essays on the Effect of Climate Change on Agriculture and Agricultural Transportation.

(December 2011)

Witsanu Attavanich, B.S., Kasetsart University;
M.A., Thammasat University
Chair of Advisory Committee: Dr. Bruce A. McCarl

This dissertation analyzes the impact of climate and atmospheric carbon dioxide (CO_2) on crop yields and grain transportation. The analysis of crop yields endeavors to advance the literature by statistically estimating the effects of atmospheric carbon dioxide (CO_2) on observed crop yields. This is done using an econometric model estimated over pooled historical data for 1950-2009 and data from the free air CO_2 enrichment experiments. The main findings are: 1) Yields of soybeans, cotton, and wheat directly respond to the elevated CO_2, while yields of corn and sorghum do not; 2) The effect of crop technological progress on mean yields is non-linear; 3) Ignoring atmospheric CO_2 in an econometric model of crop yield likely leads to overestimates of the pure effects of climate change and technological progress on crop yields; and 4) Average climate conditions and climate variability contribute in a statistically significant way to average crop yields and their variability.

To examine climate change impacts on grain transportation flows, this study employs two modeling systems, a U.S. agricultural sector model and an international grain transportation model, with linked inputs/outputs. The main findings are that under climate change: 1) The excess supply of corn and soybeans generally increases in Northern U.S. regions, while it declines in Central and Southern regions; 2) The Corn Belt, the largest producer of corn in the U.S., is anticipated to ship less corn; 3) The importance of lower Mississippi River ports, the largest current destination for U.S. grain exports, diminishes under the climate change cases, whereas the role of Pacific Northwest ports, Great Lakes ports, and Atlantic ports is projected to increase; and 4) The demand for grain shipment via rail and truck rises, while demand for barge transport drops.

DEDICATION

I dedicate my dissertation to my grandfathers, Jirote Attavanich and Cho Sae Heng, and grandmothers, Pongphan Attavanich and Engsokmeng Sae Heng, whom I wish could have lived to see the accomplishment of this work. I also dedicate this work to my wife, Patra Attavanich, and my wonderful daughter, Punteri Pamela Attavanich, for being there for me during my doctoral study. Both of you have been my best cheerleaders. In addition, this dissertation is dedicated to: my parents, Mana and Viyada Attavanich; my two sisters, Niluborn and Nitima; my mother-in-law, Suchada Saelim; and my father-in-law, Manus Udomjitpittaya.

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Being proud of succeeding in doing something special surely happens to everyone. This time, this feeling happened to me. For almost two years I tried to finish this dissertation. Sometimes I was full of inspiration, and sometimes I just had no energy to keep on. However, doing this dissertation has made me realize that education is not just making people literate, but also training them to think systematically and teaching them how to cooperate with other people. My dissertation, however, would not have been achieved unless there had been assistance from my doctoral committee and other people. Therefore, I would like to take this opportunity to express my sincere thanks to all of them.

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NOMENCLATURE

AMS	Agricultural Marketing Service
AP	Appalachia
ARS	Agricultural Research Service
ASM	Agricultural Sector Model
BEA	Business Economic Area
CB	Corn Belt
CO_2	Carbon Dioxide
CRD	Crop Reporting District
CS	Consumer Surplus
D	Delta States
ENSO	El Niño–Southern Oscillation
EPIC	Environmental Policy Integrated Climate
ERS	Economic Research Service
FACE	Free Air Carbon Dioxide Enrichment
FAPRI	Food and Agricultural Policy Research Institute
FAS	Foreign Agricultural Service
FASOM	Forest and Agricultural Sector Optimization Model
FGLS	Feasible Generalized Least Squares
FOB	Free on Board
FSA	Farm Service Agency

GCM	Global Circulation Model
GHG	Greenhouse Gas
IGTM	International Grain Transportation Model
IPCC	Intergovernmental Panel on Climate Change
LS	Lake States
MLE	Maximum Likelihood Estimation
MT	Mountain States
NASS	National Agricultural Statistics Service
NE	Northeast
NOAA	National Oceanic and Atmospheric Administration
NOPA	National Oilseed Processors Association
NP	Northern Plains
NRI	National Resource Inventory
OLS	Ordinary Least Squares
PAC	Pacific
PDSI	Palmer Drought Severity Index
PCP	Posted County Prices
PPM	Parts Per Million
PS	Producer Surplus
ROW	Rest of the World
SC	South Central
SE	Southeast

SP	Southern Plains
SRES	Special Report Emissions Scenarios
STB	Surface Transportation Board
TTI	Texas Transportation Institute
US	United States
USDA	United States Department of Agriculture
WAOB	World Agricultural Outlook Board
WLS	Weighted Least Squares

TABLE OF CONTENTS

Page

LIST OF FIGURES

LIST OF TABLES

Page

CHAPTER I

INTRODUCTION

The global concentration of CO_2 in the atmosphere has increased markedly from a preindustrial level of 280 ppm (IPCC 2007a) to 394 ppm in mid 2011 (NOAA 2011d). Globally we have also seen climate shifts with rising temperatures and altered precipitation patterns among other items. The IPCC asserts that human activities as manifest in the form of CO_2 and other GHG emissions are likely (probability > 90%) causal factors contributing to climatic change. The growing GHG emission trend raises concerns of further climate change. IPCC (2007a) projects:

- Increases in hot extremes, heat waves, droughts, rainfall intensity and heavy precipitation events.
- Increases in the amount of precipitation in the high latitudes, with decreases in most subtropical land regions plus an increased risk of droughts in those regions.

Such changes are anticipated to significantly affect agriculture since its production is highly influenced by climate conditions (IPCC 2007b; Mendelsohn, Nordhaus, and Shaw 1994; Deschenes and Greenstone 2007; McCarl, Villavicencio, and Wu 2008; Schlenker and Roberts 2009).

This dissertation follows the style of *American Journal of Agricultural Economics*.

The above IPCC projections in turn imply alterations in crop yields and their variability. For example, more frequent extreme events may lower long-term yields by directly damaging crops at specific developmental stages, or by making the timing of field applications more difficult, thus reducing the efficiency of farm inputs (e.g., Antle et al. 2004; Porter and Semenov 2005). On the other hand, the effects of CO_2 fertilization and technological progress will likely be positive contributors (e.g., Reilly et al. 2002; Long et al. 2006; McCarl, Villavicencio, and Wu 2008). However in the long term studies of observed changes in mean yield and its variability, CO_2 has been excluded because it has increased monotonically over time and thus cannot be statistically separated from technological progress. One part of this study as explained below looks at CO_2 effects on crops using a mixture of observed and experimental data to try to identify the aggregate effect of CO_2.

Under changing climate, the most immediate reaction of agricultural producers will likely be adaptation. Several studies project that crop production will increase in high latitudes and decline in low latitudes (IPCC 2007b; 2007c; Smith and Tirpak 1989; Adams et al. 1990; Reilly et al. 2002; Reilly et al. 2003). Research suggests that current zones where crops are suitable may shift northward (Reilly et al. 2003). Northward shifts have occurred in U.S. crops with southern parts of wheat belts becoming northern parts of corn-producing region as is already being observed in North Dakota.[1] Such developments will have an effect on the volume of grain production and the demands

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[1] From 1990 to 2009, wheat acres have reduced from 60 percent of the cropland in North Dakota to 45 percent, while corn acres have increased from 5 to 10 percent of cropland and soybean acres have risen from 2 to 20 percent of crop land in North Dakota (Upper Great Plains Transportation Institute 2011).

placed on the transportation system since wheat yields on average are 44 bushels/acre, while corn yields average around 165 bushels/acre (USDA-NASS 2011).

Given these northward shifts caused by climate change plus differences in the typical destinations of grain shipments for different commodities, there will be likely changes in the pattern of interregional grain transportation flows, demand for transportation capacity, and associated infrastructure on selected transport corridors. Thus a second question investigated by this dissertation will involve the effects of climate change induced crop production pattern shifts on grain transportation movements.

Objectives

This dissertation will pursue two objectives related to the overall problem of understanding the implications of projected climate change and greenhouse gas emissions on agriculture:

- To understand how past climate and associated CO_2 concentrations have influenced past crop yields separating out CO_2 effects from technological progress effects. In addition to project the future consequences of projected climate change and CO_2 on future yields, market outcomes and welfare.
- To understand how climate change induced crop yield effects shift cropping patterns and associated demands on the transport system plus the use of alternative modes of transport.

Plan of Dissertation

In pursing the above objectives this dissertation contains three main essays (Chapters II-IV):

The first essay, Chapter II, reports on an investigation of the effects of changes in climate and atmospheric CO_2 concentration on U.S. mean yield and its variability for major crops including corn, sorghum, soybeans, winter wheat and cotton. In addition, the investigation will address the impacts of projected climate change on yields, market outcomes and welfare.

The other essays, Chapters III and IV, report on the transportation related investigation. Chapter III reports on the climate change related analysis of the effects of climate change on cropping patterns and grain transportation flows. Chapter IV reports on the structure and empirical specification of the transport model constructed to pursue the grain transport part of the study

The first and last chapters provide introduction and overall concluding comments respectively.

CHAPTER II

IMPLICATIONS OF CLIMATE CHANGE, CO_2, AND TECHNOLOGICAL PROGRESS ON AGRICULTURAL PRODUCTION AND MARKETS

Introduction

Recent studies including those by IPCC (2007a; 2007b) indicate that GHG emissions and resultant atmospheric concentrations have led to changes in the world's climate conditions including temperature and precipitation. The implications of climate change and atmospheric GHG concentrations for crop yields and economic welfare have been addressed in many studies (see the reviews in IPCC).

A wide variety of findings have arisen regarding the effect of climate change on crop yields. Many studies find that climate change alters mean crop yields (e.g., Reilly et al. 2002; Schlenker and Roberts 2009; Huang and Khanna 2010), while Greenstone and Deschenes (2007) find a statistically insignificant relationship between climate change and mean crop yields. However, a few studies have addressed the contribution of climate change to yield variability (Chen, McCarl, and Schimmelpfennig 2004; Isik and Devadoss 2006; McCarl, Villavicencio, and Wu 2008). A few studies have also taken into account climate variability and extreme events as factors affecting crop yield and its variability (Semenov and Porter 1995; Porter and Semenov 2005; McCarl, Villavicencio, and Wu 2008; Huang and Khanna 2010).

Generally, crop yield studies have been done in two different ways using observed yield data (e.g., McCarl, Villavicencio, and Wu 2008; Schlenker and Lobell

2010) or via crop simulation (e.g., Parry et al. 2004; Tubiello et al. 2002). The observed yield data strategies have been argued by some to be more accurate as they include farmer adaptations (e.g., Schlenker and Lobell 2010). However they are missing a major factor in the form of CO_2 effects since traditionally it is widely accepted that time is a proxy for technological progress and CO_2 and time are highly correlated not allowing identification of their separate effects. Paradoxically CO_2 is widely acknowledged as a major growth stimulating factor for some crops and a drought response factor for others. Consequently, the estimates of climate change effects from observed data are almost certainly biased. The analysis reported in this paper attempts to resolve this difficulty by merging historical data with the recent unique dataset of the response of crop yield to elevated CO_2 obtained from the FACE experiments.[2]

Thus, this chapter reports on a simultaneous analysis of the impact of climate variables, crop production technology, and atmospheric CO_2 on mean yield and yield variability of five major crops including corn, sorghum, soybeans, winter wheat and cotton, in the U.S. merging state-specific, historical data for 1950-2009 with the dataset from the FACE experiments. In addition, the study investigates the implications of projected climate change GCM cases for yields, market outcomes and welfare distribution.

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[2] In the FACE experiments, air enriched with CO_2 is blown into the rings where crops are grown in the real field (not in the chamber). Then, a computer-control system uses the wind speed and CO_2 concentration information to adjust the CO_2 flow rates to maintain the desired CO_2 concentration. Finally, crop yield in the elevated CO_2 rings are compared to that in the control rings with non-elevated CO_2 (ambient) environment. Details of the FACE experiments are provided in Long et al. (2006).

Literature Review

Concerns about the impacts of climate change on agricultural production, especially crop yields, have led to a number of statistical studies over historical yields with mixed findings.

Climate, Crop Yield, and Its Variability

A majority of studies have focused on the effect of temperature and precipitation on crop yields (Lobell and Asner 2003; Chen, McCarl, and Schimmelpfennig 2004; Greenstone and Deschenes 2007; McCarl, Villavicencio, and Wu 2008; Schlenker and Roberts 2009; Huang and Khanna 2010; Schlenker and Lobell 2010). In terms of temperature, using growing season temperature and employing the Just and Pope (1978; 1979) stochastic production function, Chen, McCarl, and Schimmelpfennig (2004) examine state-level panel data and find that yields of corn, cotton, sorghum, and winter wheat are adversely affected by growing season temperature. Greenstone and Deschenes (2007) find that yields of corn and soybeans are negatively correlated to growing degree days. Schlenker and Roberts (2009) find similar results and find a non-linear effect of temperature on yields of corn, soybeans, and cotton. A similar result is illustrated by Huang and Khanna (2010). Unlike other studies, McCarl, Villavicencio, and Wu (2008) incorporating the interaction term of temperature and U.S. regions in their model to capture the heterogeneity of temperature across U.S. regions, they find that the effect of temperature on crop yields depends on location.

Regarding precipitation, using yearly precipitation, Chen, McCarl, and Schimmelpfennig (2004) find that precipitation enhances yields of corn, cotton, soybeans, winter wheat, and sorghum, while it has a negative impact on wheat as also found in Isik and Devadoss (2006) and McCarl, Villavicencio, and Wu (2008). An inverted-U shape relationship between corn and soybean yield and precipitation is found in Schlenker and Roberts (2009). Similar results for corn, soybeans, and wheat are found in Huang and Khanna (2010), who employ monthly precipitation.

While a majority of climate impact studies relies on changes in means of climate variables, a few studies consider climate variability and extreme events. Using standard deviation of temperature as a measure of variation in temperature, McCarl, Villavicencio, and Wu (2008) find that increased variation has a negative impact on yields of all crops. Similar results were found for corn and soybeans by Huang and Khanna (2010). Variability measures reflecting precipitation intensity and drought severity were employed in McCarl, Villavicencio, and Wu (2008). They find that the increase in precipitation intensity decreases all crop yields, while an increase in their drought measure decreases cotton yield, but increases yields of corn, soybeans, sorghum, and winter wheat.

Moreover, a few studies estimate the relationship between climate and yield variability. McCarl, Villavicencio, and Wu (2008) find that increase in yearly total precipitation reduces the variability of sorghum and soybean yields, while Chen, McCarl, and Schimmelpfennig (2004) find an opposite result. Chen, McCarl, and Schimmelpfennig (2004) also conclude that temperature increases the yield variation for corn, soybeans, and winter wheat, while it reduces the yield variation for cotton and sorghum. McCarl, Villavicencio, and Wu (2008) also find no statistically significant relationship between the drought index and crop yields. Precipitation intensity increases the variability of sorghum yield.

This study will investigate the relationship between climate and yield variability using Just and Pope (1978; 1979) stochastic production function. In addition, we consider climate variability and extreme events as factors affecting crop yield by incorporating variables of yearly precipitation intensity, number of days that maximum temperature exceeds 32 degree Celsius, and the drought index. Moreover, the study also controls for the effect of the El Niño-Southern Oscillation (ENSO).[3] Furthermore, we construct an alternative index of yearly precipitation intensity based on the IPCC (2007a) in particular the percent of annual total precipitation due to events exceeding the 1961-1990 95th percentiles.

For a temperature extreme measure unlike McCarl, Villavicencio, and Wu (2008) and Huang and Khanna (2010), who used the standard deviation of temperature, we utilize the number of days that maximum temperature exceeds 32°C based on Mearns, Katz, and Schneider (1984) depicting that days with abnormally high temperatures can harm crop growth and yield, which may not be captured by the mean and standard deviation of temperature. We use 32°C as a threshold based on evidence in Thompson (1975); Mearns, Katz, and Schneider (1984); and Schlenker and Roberts (2009).

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[3] The ENSO, which refers to fluctuations in both sea-surface temperatures (SSTs) in the eastern equatorial Pacific and in sea-level pressures in the southern Pacific (Southern Oscillation Index, SOI), is one of the most important controlling factors in global interannual climate variability (Hastenrath 1995; Phillips et al. 1999).

It is worth noting that empirical studies show mixed results regarding the effect of crop acreage on yield. Kaufmann and Snell (1997) and Huang and Khanna (2010) find that an increase in acreage decreases corn and wheat yield, respectively, while Chen, McCarl, and Schimmelpfennig (2004) and McCarl, Villavicencio, and Wu (2008) find that an increase in crop acreage increases corn, soybean, wheat, and sorghum yield, but decreases cotton yield.

The growing season is often a fixed national assumption for a crop in crop yield studies. For example, McCarl, Villavicencio, and Wu (2008), and Chen, McCarl , and Schimmelpfennig (2004) define the growing season period of corn, soybeans, sorghum, and cotton as between April to November and winter wheat between November and March in all states. Greenstone and Deschenes (2007) use the period of April 1-September 30 to quantify growing season degree-days of corn and soybeans. Unlike these studies, this study uses a state specific growing season definition for each crop based on USDA crop progress data. The data show that growing seasons for a crop vary across states. This method likely reflects an adaptation strategy, early or delayed planting crops that farmers customarily make in response to changing climate. Previous studies that fix periods of growing seasons are likely to obtain overestimate the damages of climate change.

Crop Yield, Technical Change, and CO_2

As a result of technical change in crop production technology such as the development of new varieties and management practices, crop yields increase over time. Such technical change generally improves future crop yields, offsetting possible negative impacts of climate change (see for example, McCarl, Villavicencio, and Wu, 2008; Huang and Khanna 2010). These studies usually utilize a linear or quadratic time trend as a proxy for developments in crop production technology. This method may lead to incorrect estimates of the real effect of crop production technology on crop yields since CO_2, a major factor of crop growth, is omitted in their models as previously stated in the introduction section.

This research attempts to remove the CO_2 effect from the technical change estimation by introducing a dataset on the response of crop yield to elevated CO_2 obtained from the FACE experiments (Long et al. 2006). Merging in the FACE dataset increases the range of CO_2 concentrations inherent in the data and reduces the correlation between time and CO_2 concentration. This allows us to differentiate the real effect of time – a proxy for technical change and the atmospheric CO_2 concentration as they influence crop yields.

Early studies related to the response of crop yield to atmospheric CO_2 were reviewed by IPCC (2007b). The evidence they gathered suggests that the crop yield reduction induced by climate change will be offset by the fertilization effect of rising CO_2 concentrations. C-3 crops are more responsive than C-4 crops to rising CO_2. However, most of the information about crop responses to elevated CO_2 arises from studies in controlled-environment chambers, which has been argued to be an upwardly biased measure of yield response (Long et al. 2006). Recent studies (e.g., Ottman et al. 2001; Ainsworth and Long 2005; Leakey 2009) are of the free-air-CO_2-enrichment (FACE) experiment type. Long et al. (2006) show that for each crop, yield change observed in FACE experiments was well below (about half) that predicted from chambers. They reveal that, across FACE studies, yields of C-3 crops including soybean and wheat increase by about 14 and 13 percent, respectively at 550 parts per million of CO_2 relative to ambient CO_2, while they find no significant relationship between yields of C-4 crops (corn and sorghum) and CO_2.

Moreover, Leakey (2009) finds that unlike C-3 crops, for which there is a direct enhancement of photosynthesis by elevated CO_2, C-4 crops only benefit from elevated CO_2 under drought stress. Kimball (2006) analyzes data from the FACE studies and finds an increase in yields of cotton, wheat, and sorghum at elevated CO_2 relative to ambient CO_2. Under ample water, the values range from 21-81 percent for cotton, 8-17 percent for wheat, and -11-1 percent for sorghum, while under lower water, values range from 50-51 percent for cotton, 5-12 percent for wheat, and 17-34 percent for sorghum. Amthor (2001) reviews fifty studies from both FACE and chamber studies and concludes that elevated CO_2 stimulates yield of water-stressed wheat, but usually does not fully compensate for water shortage.

Climate Projections and Change in Future Crop Yield

Studies have also projected the change in future crop yield induced by climate change using climate projections from GCM cases. Huang and Khanna (2010) find that with 6°C increases in temperature, yields of corn, soybeans, and wheat are projected to decrease 45, 42, and 26 percent, respectively, in 2100. Using climate projections from Hadley GCM, in the medium term (2020-2049), Schlenker and Roberts (2009) find that yields are projected to decrease about 20-30 percent for corn, 15-25 percent for soybeans and 20-25 percent for cotton. Using Hadley and Canadian GCM cases, McCarl, Villavicencio, and Wu (2008) find that generally in 2030 yields of all crops except sorghum are increased regarding to the projected standard deviation of temperature. Similar to above mentioned studies, our study will project the change in future crop yields. Unlike other studies, this study will employs four of the most recent GCM cases to reflect the uncertainty inherent in such projections.

Model Specification and Methodology

Just and Pope Stochastic Production Function

In order to determine the effects of climate change, crop production technology, and CO_2 fertilization on both the average and variability of crop yields, a stochastic production function approach of the type suggested by Just and Pope (1978; 1979) will be used following Chen, McCarl, and Schimmelpfennig (2004), Isik and Devadoss (2006), and McCarl, Villavicencio, and Wu (2008).

The Just and Pope stochastic production function estimates the relationship between yield and a set of independent variables giving estimates for both mean yield and variability of yield. Following the previous studies this can be estimated from panel data relating annual yield to exogenous variables producing estimates of the impacts of the exogenous variables on levels and the variance of yield. The form of production function is shown in Equation (1).

$$y = f(X,\beta) + \mu = f(X,\beta) + h(X,\alpha)\varepsilon \tag{1}$$

where: y is crop yield; $f(\cdot)$ is the mean function relating X to average yield with β as the associated vector of estimated parameters; X is a vector of explanatory variables. μ is a heteroskedastic disturbance term with a mean of zero. In addition, $h(\cdot)$ is a function that accounts for variable-dependent heteroskedasticity, allowing yield variability as a function of observed covariates with α as the corresponding vector of estimated parameters. Under the assumption that the error term ε is distributed with mean zero and unitary variance, $h^2(\cdot)$ is the yield variance.

In this estimation, like in many other studies, this study employs crop planted acreage, yearly growing season mean temperature, yearly total precipitation, time trend and its square. However, this study includes a richer specification allowing estimation with respect to CO_2, extreme climate measures, ENSO events and climate variability measures. The study also adds regional considerations incorporating interaction terms between region and temperature; region and precipitation; and region and ENSO events. Furthermore, this study adds a dummy variable for the observations arising from the FACE experiments.[4] Finally, this study pools data from 1950 - 2009 and separate time invariant state-specific effects into a constructed panel.

In general, there are two methods that have been employed to estimate the function. Just and Pope (1978, 1979) present a three-step FGLS method and others have

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[4] It is equal to 1 if the data collected come from the FACE experiments, and equal to 0 if data come from the observational data.

used a MLE approach. Saha, Havenner, and Talpaz (1997) illustrate that the MLE is more efficient than the three-step FGLS estimation for small samples in Monte Carlo experiments. Nevertheless, this study employs a three-step, FGLS estimation because we have a large number of observations. Moreover, the MLE approach depends heavily on the correct specification of the likelihood function (McCarl, Villavicencio, and Wu 2008). As a robustness check, the study also estimates the production function using the MLE approach[5] and find that the estimates from the two approaches are slightly different from each other.

The procedure to estimate the three-step FGLS estimation can be explained as follows. In the first step, we estimate the model

$$y = f(X,\beta) + \mu \tag{2}$$

using OLS regression and then obtain residuals ($\hat{\mu}$). In the second step, we regress the logarithm of squared residuals on X.

$$ln(\hat{\mu}^2) = h(X,\alpha) + \varepsilon \tag{3}$$

Then, we obtain the predicted values of those residuals and exponentiated them. These values are consistent estimators of variances. In the final step, we estimate the original model by weighted least square (WLS) using the squared root of the predicted variances as weights.

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[5] The log-likelihood function of equation (1) are:

$lnL = -\frac{1}{2}\left[n * ln(2\pi) + \sum_{i=1}^{n} ln(h(X_i,\alpha)^2) + \sum_{i=1}^{n} \frac{(y_i - f(X_i,\beta))^2}{h(X_i,\alpha)^2} \right]$ under the assumption that

$y_i \sim N(f(X_i,\beta), h(X_i,\alpha)^2)$ and $\varepsilon_i \sim N(0,1)$.

$$(4) \qquad yh^{-1/2}(X,\hat{\alpha}) = f(X,\beta)h^{-1/2}(X,\hat{\alpha}) + \mu h^{-1/2}(X,\hat{\alpha})$$

Crop Yield Simulation

To investigate the implication of future climate change on crop yield and its variability, we employ our estimated coefficients from the three-step FGLS estimation together with future climate change projected by standard GCM cases used in the 2007 IPCC Assessment Report, consisting of GFDL-CM 2.0, GFDL-CM 2.1, MRI-CGCM 2.3.2a, and CNRM-CM3.[6] We utilize the IPCC SRES A1B, which is characterized by a high rate of growth in CO_2 emissions and most closely reproduces the actual emissions trajectories during the period since the SRES were completed (2000-2008) (van Vuuren and Riahi 2008). A1B scenario group, in our opinion, is more preferred to those in the B1 and B2 scenario groups since currently actual emissions have been above the A1B scenario projections. At the same time, there has been considerable interest and policy development to encourage non-fossil fuel energy, which is consistent with the A1B scenario vs. A1F1 or A2 (Beach et al. 2009).

Economic Modeling of Climate-Induced Shifts in Crop Yields

To explore the market outcomes and welfare implications of climate-induced shifts in yields across the U.S., we plug in our projected percentage changes of mean crop yields into the ASM, in which crop allocation decisions are based on the relative returns associated with the climate scenarios modeled. ASM model has been developed

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[6] The first two models are developed by the Geophysical Fluid Dynamics Laboratory (GFDL), U.S. The third model is developed by the Meteorological Research Institute, Japan. The last model is developed by National Centre of Meteorological Research, France.

by McCarl et al. (Baumes 1978; Burton 1982; Adams, Hamilton, and McCarl 1986; Adams et al. 1990; Chang et al. 1992; Adams et al. 1996; McCarl and Schneider 2000; Schneider 2000; Adams et al. 2005; Schneider, McCarl, and Schmid 2007; Beach et al. 2009). This model has been used in a large number of climate change–related studies including Adams et al. (1999), Reilly et al. (2002), Reilly et al. (2003), Beach, Thomson, and McCarl (2010), and McCarl (2011).

In brief, ASM is a price-endogenous, spatial equilibrium mathematical programming model of the agricultural sector in the U.S. It includes all states in the conterminous U.S., broken into 63 subregions for agricultural production and 10 market regions for agricultural sector as shown in Table A1 in Appendix A. It also incorporates land transfers and other resource allocations within the U.S. agricultural sectors. ASM is a component of the forest and agricultural sector optimization model (FASOM) and as such is described in Adams et al. (2005), Beach et al. (2009) and Beach, Thomson, and McCarl (2010). The model framework is summarized in Appendix A.

Data

Observational Data

The state-level dataset we use contains annual crop yields and planted acreage of corn, soybeans, sorghum, cotton, and winter wheat across the U.S. from 1950 – 2009. The data were drawn from the website of USDA-NASS (USDA-NASS 2011). We encounter missing observations over the relevant time period for each crop, and of course not all states grow all crops. State-level climate data, total precipitation, seasonal growing season temperature, and seasonal PDSI[7] are obtained from the website of NOAA (NOAA 2011a). We also construct variables, on state-yearly precipitation intensity, number of days in each state that maximum temperature exceeds 32°C, and the crop-growing-season ENSO phases[8] by state using data from thousands of climate stations across U.S. provided from NOAA (NOAA 2011b; 2011c). Our state-yearly precipitation intensity can be calculated as follow.

$$(5) \qquad PrecipIntensity_{tr} = \frac{\sum_{i \in S} totalprecip_{itr}}{\sum_{i} totalprecip_{itr}} * 100$$

where i indexes days; t indexes period (year); r indexes states of the U.S.; S is the set containing days that have total precipitation exceeding the 1961-1990 95th percentiles; $PrecipIntensity_{tr}$ is the percent of total precipitation due to events exceeding the 1961-1990 95th percentiles in year t at state r; $totalprecip_{itr}$ is the total precipitation of ith day in year t at state r.

The observational data on atmospheric CO_2 concentration are those collected from Mauna Loa (Hawaii) and are drawn from NOAA (NOAA 2011d). We also encounter missing observations on climate data in some states. Nevertheless, when missing observations were present in a given state, we used the available data instead of deleting that state from the estimation which would cause an unbalanced panel.

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[7] The PDSI is a standardized measure of surface moisture conditions, ranging from about -10 to +10 with negative values denoting dry condition and positive values indicating wet condition (Palmer 1965).

[8] We thank Dr. Chi-Chung Chen, professor in the Department of Applied Economics, National Chung-Hsing University, Taichung, Taiwan for his useful suggestion related to the selection of ENSO phases.

Free-Air CO_2 Enrichment (FACE) Experimental Data

The FACE experimental data is merged with the observational data to allow us to do an estimation of the effect of CO_2 fertilization on crop yields. For our study, Arizona and Illinois are only two states in U.S. that have applicable FACE experiments datasets. In Arizona, the experiment is done on cotton, wheat, and sorghum, while in Illinois the experiment is done on corn and soybeans.[9] Cotton was planted in 1989, 1990, and 1991. Wheat was planted in 1993, 1994, 1996, and 1997. Sorghum was planted in 1998 and 1999. Corn was planted in 2004 and 2008. Lastly, soybeans were planted from 2002-2007. Each crop is planted under ambient CO_2 and elevated CO_2 environments. There are generally 4-5 rings (replicates) for each experiment in each year.

Empirical Results

A Major Difficulty of the Historical Agricultural Yield Studies and a Solution

Except the PDSI and dummy variables, all other variables enter the estimation in logarithmic form.[10]

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[9] We thank Dr. Bruce A. Kimball and Dr. Donald R. Ort from USDA-ARS and Dr. Lisa Ainsworth, and Dr. Andrew Leakey from SOYFACE, University of Illinois at Urbana Champaign in providing us the FACE experimental datasets.

[10] For robustness, the observational data were tested for unit roots, although after we pool observational and the FACE experimental data together, our data does not fully have a panel data structure. Using Fisher-type test (Choi 2001) and Levin-Lin-Chu (LLC) (Levin, Lin, and Chu 2002) test, all series except CO_2, which is I(1), are stationary in the level, I(0). However, after we apply the panel unit root tests to the residual of the model, the residual is stationary in the level, I(0), implying that our model might not be encountered with the problem of spurious regression (Granger 1981). We thank Dr. David Bessler for his useful suggestion.

Once the data were assembled we calculated the correlation matrix among variables. We find that before including the FACE experimental data, there is a very high correlation (about 0.99) between the time trend and the CO_2 concentration. However once the FACE data are included, the correlation drops substantially as shown in Table 1. We also will investigate the effect of reduce the scope of our estimation to the regions, where the FACE data arose to get an indication whether adding other regions biases the results.

In Table 1, we also separately summarize crop yields and CO_2 concentration statistics in the observational data and the data set augmented with the FACE experimental data. We find that yields of crops from the FACE experiments are higher than those from the observational data. Another important finding is that the standard deviation of the CO_2 in the FACE experimental data is about four times higher thus, might allow us to simultaneously estimate both the effect of CO_2 fertilization and the effect of time as a proxy for crop technological progress.

Table 1. Statistics of Crop Yields and CO_2 Concentration, and Correlation Coefficients between Time Trend and the CO_2 Concentration Before and After Incorporating the FACE Experimental Data

			Soybeans	Cotton	Wheat	Corn	Sorghum
Sample Size	Number of Observations		1,422	724	1,869	1,928	814
	Number FACE observations		48	40	50	15	32
Correlation Coefficient	Before Including the FACE		0.9883	0.9906	0.9889	0.9880	0.9885
	After Including the FACE		0.7574	0.5910	0.7285	0.9046	0.6827
Crop Yields	Observational Data	Mean	28.34	596.51	41.88	96.60	55.51
		Std. Dev.	8.40	237.60	16.85	41.573	20.41
		Min	6.00	120.00	5.00	10.50	10.00
		Max	54.50	1,469.00	110.00	215.00	109.00
	FACE Experimental Data	Mean	57.46	1348.66	114.16	159.04	69.98
		Std. Dev.	12.28	569.76	21.088	22.15	33.59
		Min	32.09	295.31	63.89	130.25	10.26
		Max	83.26	2,376.77	152.75	193.18	113.99
CO_2	Observational Data	Mean	347.22	348.37	348.87	346.25	347.52
		Std. Dev.	22.24	21.60	21.48	22.56	21.86
		Min	310.70	311.90	310.70	310.70	310.70
		Max	387.35	387.35	387.35	387.35	387.35
	FACE Experimental Data	Mean	464.48	458.00	456.40	458.00	464.50
		Std. Dev.	86.80	93.35	90.84	89.26	98.18
		Min	373.17	350.00	370.00	370.00	363.00
		Max	552.00	550.00	550.00	550.00	566.00

Note: 1) Unit of CO_2 concentration is parts per million.
2) Yields of all crops are in bushels/acre, except for cotton yield, which has unit in lbs/acre
3) Mean, Std. Dev., Min, and Max are the mean value, standard deviation, minimum value, and maximum value, respectively.

Determinants of Crop Yields

As stated in the previous section, all variables other than the PDSI variable are studied in their logarithm form to reduce the heterogeneity of the variance and to provide a convenient economic interpretation (elasticities). We use the PDSI in a non log fashion since it ranges from -10 to +10. The variables that we use and their description are shown in Table 2.

Table 2. Variables and Their Description

Variables	Description
Acreage	Land area devoted to a particular crop in a given year in acres
CO2	CO_2 concentration in parts per million in a given year
CO2 X PDSI	Interaction term between CO_2 and the PDSI index[11]
Trend	Time trend where the data range from 1950 to 2009
Trend^2	Square of time trend
Temperature	Average growing season temperature in degrees centigrade
Days_temp>32C	Number of days growing season temperature exceeds 32 ºC
PDSI	Palmer Drought Severity Index
Precipitation	Annual total precipitation in inch
Precip Intensity	Constructed annual precipitation intensity[12]
Temp X D2_NE, *Temp X D3_NP,* *Temp X D4_SE,* *Temp X D5_SP,* *Temp X D6_MT,* *Temp X D7_PA,*	Interactions between average growing season temperature and regional dummy variables[13] where the dummy variables are • *D2_NE* for the northeast • *D3_NP* for Northern Plains • *D4_SE* for Southeast • *D5_SP* for Southern Plains • *D6_MT* for Mountains • *D7_PA* for Pacific • *D1_C* for Central (base)

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[11] This study includes this interaction term due to the fact that rising CO_2 indirectly increases the efficiency of water use of crops via reduction in stomatal conductance in times and places of drought stress (Long et al. 2006; Leakey 2009).

[12] representing the percent of total precipitation due to events exceeding the 1961-1990 95th percentiles (see equation 5).

[13] Regional dummy variables follow the farm production regions defined in the USDA-ERS.

Table 2. Continued

Variables	Description
Precip X D2_NE, *Precip X D3_NP,* *Precip X D4_SE,* *Precip X D5_SP,* *Precip X D6_MT,* *Precip X D7_PA*	Interactions between annual precipitation and regional dummy variables where the dummy variables are as just defined above.
D2_NE X LaNina *D2_NE X Neutral* *D3_NP X LaNina* *D3_NP X Neutral* *D4_SE X LaNina* *D4_SE X Neutral* *D5_SP X LaNina* *D5_SP X Neutral* *D6_MT X LaNina* *D6_MT X Neutral* *D7_PA X LaNina* *D7_PA X Neutral*	Interactions between the regional dummies and the ENSO event for the year as to whether it is a Neutral, El Nino or La Nina year. Note the intercept represents an El Nino year in the Central region
DummyFACE	Dummy variable for whether this observation is from the FACE experiments
Constant	Constant in the regression

We estimate the model using the three-step FGLS estimation procedure. To capture the unobserved effects that are invariant overtime, we include state dummies as typically done in fixed effects models (see for example McCarl, Villavicencio, and Wu 2008). We check the correctness of our model specification using the link test[14] provided in STATA. We find that the square term of the predicted values of the mean and variance of yield are statistically insignificant for each crop even at the 10 percent level, implying that our model specifications passed the link test, and hence are well specified.

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[14] If a regression equation is correctly specified, we should be able to find no additional independent variables that are significant except by chance. One kind of specification error is called a link error, implying that dependent variable needs a transformation or "link" function to properly relate to the independent variables (Tukey 1949; Pregibon 1980).

Effects on Mean Yield

The estimated coefficients of the mean yield regression from the three-step FGLS estimation are provided in Table 3.[15] They are from the second-stage of our WLS estimation with predicted standard deviations as weights. To save space, estimated coefficients of individual state dummies are not reported here.

For CO_2 concentration effects on crop yields, we find that average yields of the C-3 crops (soybeans, cotton, and winter wheat) are positively correlated with the CO_2 concentration with 1% statistical significance, while yields of C-4 crops (corn and sorghum) are not affected as expected. However, yields of corn and sorghum are negatively correlated to the interaction between CO_2 concentration and PDSI (results are consistent with drought yield stimulation of CO_2 as in Ainsworth and Long (2005), Long et al. (2006), and Leakey (2009)). That is, yields of C-3 crops (soybeans, cotton, and wheat), directly and positively respond to elevated CO_2 via photosynthesis process, while C-4 crops do not. However, C-4 crops indirectly benefit from elevated CO_2 in times and places of drought stress meaning that the higher the level of drought stress, the greater the yields of C-4 crops. Unlike other crops, cotton and wheat in our study do not likely benefits from drought stress condition. This result is similar to what is concluded in Amthor (2001), who finds that elevated CO_2 stimulates yield of water-stressed wheat, but usually did not fully compensate for water shortage.

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[15] Using the MLE approach with the same specification and likelihood function as shown in Footnote 5, its estimated coefficients were found to be close to the coefficients estimated using the three-step FGLS estimation. Moreover, we perform our robustness check for corn considering only the Central region. Our estimated coefficients on atmospheric CO_2 with and without the restricted region are very similar.

Table 3. Estimated Coefficients from Mean Crop Yield Regressions

Variables	Soybeans	Cotton	Wheat	Corn	Sorghum
Acreage	0.028***	0.0129***	0.012***	-0.007	0.052***
	(0.0039)	(0.0058)	(0.0040)	(0.0054)	(0.0051)
CO2	0.309***	1.310***	0.241***	0.181	0.116
	(0.0820)	(0.1740)	(0.0431)	(0.1350)	(0.1682)
CO2 X PDSI	-0.078***	0.155***	0.0454***	-0.042**	-0.075***
	(0.0143)	(0.03104)	(0.0053)	(0.0168)	(0.0272)
Trend	0.011***	-0.0019	0.018***	0.040***	0.037***
	(0.0006)	(0.0015)	(0.0006)	(0.0007)	(0.0012)
Trend^2	-0.00002***	0.00014***	-0.00007***	-0.00014***	-
	(8.94E-06)	(0.00002)	(7.89E-06)	(8.94E-06)	(0.000016)
Temperature	1.189***	0.755	0.055	1.348***	1.177***
	(0.1565)	(0.8707)	(0.1240)	(0.1632)	(0.4227)
Days_temp>32C	-0.028***	-0.075***	0.0003	-0.017***	-0.072***
	(0.0019)	(0.0094)	(0.0016)	(0.0015)	(0.0059)
PDSI	0.474***	-0.900***	-0.269***	0.253***	0.450***
	(0.0841)	(0.1824)	(0.0317)	(0.0987)	(0.1596)
Precipitation	-0.006	-0.256**	-0.194***	-0.0157	-0.240***
	(0.0304)	(0.1084)	(0.0275)	(0.0334)	(0.0636)
Precip Intensity	-0.006*	-0.022***	-0.012***	-0.003	-0.0002
	(0.0035)	(0.0078)	(0.0032)	(0.0032)	(0.0055)
Temp X D2_NE	-1.311***		0.718***	-2.484***	-9.272***
	(0.2974)		(0.1873)	(0.3263)	(2.2730)
Temp X D3_NP	0.456	5.962***	-0.666***	-0.254	1.278***
	(0.3094)	(2.0887)	(0.2466)	(0.2773)	(0.4942)
Temp X D4_SE	-2.435***	1.610*	-1.317***	-3.841***	-1.776***
	(0.3130)	(0.9222)	(0.2350)	(0.3417)	(0.5282)
Temp X D5_SP	-3.512***	0.83	-2.427***	-1.799***	-1.919***
	(0.4209)	(0.9555)	(0.3579)	(0.6512)	(0.5363)
Temp X D6_MT		-0.470	-0.730***	-0.025	-4.030***
		(1.1538)	(0.1875)	(0.2579)	(0.6797)
Temp X D7_PA			0.192	-1.609***	
			(0.3151)	(0.2576)	
Precip X D2_NE	0.0597		-0.0214	-0.043	-0.254
	(0.0378)		(0.0391)	(0.0522)	(0.2202)
Precip X D3_NP	0.258***	-0.148	0.458***	0.325***	0.856***
	(0.0404)	(0.2572)	(0.0537)	(0.0434)	(0.0669)
Precip X D4_SE	0.217***	0.224**	0.074**	0.211***	0.303***
	(0.0384)	(0.1066)	(0.0381)	(0.0463)	(0.0710)
Precip X D5_SP	0.045	0.265**	-0.122***	0.320***	0.310***
	(0.0451)	(0.1065)	(0.0458)	(0.0659)	(0.0660)

Table 3. Continued

Variables	Soybeans	Cotton	Wheat	Corn	Sorghum
Precip X D6_MT		0.122 (0.1135)	0.507*** (0.0325)	0.052 (0.0381)	0.570*** (0.0897)
Precip X D7_PA			0.294*** (0.0444)	-0.056 (0.0344)	
D2_NE X LaNina	0.025*** (0.0149)		0.028*** (0.0010)	-0.001 (0.0142)	-0.430** (0.1793)
D2_NE X Neutral	0.031** (0.0134)		0.003 (0.0089)	0.048*** (0.0135)	-0.041 (0.0817)
D3_NP X LaNina	-0.064*** (0.0152)	-0.192** (0.0872)	0.018 (0.0212)	-0.029** (0.0121)	0.019 (0.0211)
D3_NP X Neutral	0.007 (0.0152)	-0.063 (0.0702)	-0.062*** (0.0185)	-0.022* (0.0131)	-0.003 (0.0220)
D4_SE X LaNina	-0.016* (0.0102)	-0.081*** (0.0165)	0.001 (0.01050)	-0.013 (0.0110)	0.024* (0.0142)
D4_SE X Neutral	-0.008 (0.0100)	-0.084*** (0.0146)	0.001 (0.0088)	-0.037*** (0.0108)	-0.006 (0.0131)
D5_SP X LaNina	-0.060*** (0.0134)	-0.095*** (0.0172)	-0.020 (0.0154)	-0.011 (0.0216)	-0.047*** (0.0142)
D5_SP X Neutral	-0.014 (0.0144)	-0.084*** (0.01467)	-0.006 (0.0129)	-0.028 (0.0205)	0.013 (0.0113)
D6_MT X LaNina		0.013 (0.0327)	0.033*** (0.0109)	-0.042*** (0.0117)	0.064 (0.0397)
D6_MT X Neutral		0.028 (0.0254)	0.004 (0.0097)	-0.036*** (0.0081)	0.114*** (0.0369)
D7_PA X LaNina			0.005 (0.0180)	-0.051*** (0.0091)	
D7_PA X Neutral			0.021 (0.0182)	-0.042*** (0.0090)	
DummyFACE	0.684*** (0.0769)	-0.006 (0.2058)	0.170*** (0.0569)	-0.258** (0.1115)	0.512*** (0.1444)
Constant	5.410*** (-1.3004)	-11.041*** (1.7896)	7.198*** (0.8889)	11.923*** (1.5328)	4.483** (1.8528)

Note: 1) ***, **, * are significant at the 1, 5, and 10 percent level, respectively and standard error in parentheses.

2) Regional interacted dummies: D1_C –Central- (Indiana, Illinois, Iowa, Michigan, Missouri, Minnesota, Ohio, Wisconsin); D2_NE –Northeast- (Connecticut, Delaware, Maine, Maryland, Massachusetts, New Hampshire, New Jersey, New York, Pennsylvania, Rhode Island, Vermont); D3_NP –Northern Plains- (Kansas, Nebraska, North Dakota, South Dakota); D4_SE –Southeast- (Alabama, Florida, Georgia, Kentucky, North Carolina, South Carolina, Tennessee, Virginia, West Virginia); D5_SP -Southern Plains- (Arkansas, Louisiana, Mississippi, Oklahoma, or Texas); D6_MT –Mountains- (Arizona, Colorado, Idaho, Montana, Nevada, New Mexico, Utah, Wyoming); D7_PA –Pacific- (California, Oregon, Washington).

Now we examine the results for the time as a proxy for technical change as it influences mean crop yields. The results indicate that the effect of crop technological progress is generally non-linear with an inverted-U shape. In particular the yields, excepting those for cotton, exhibit diminishing technical change over time. To investigate the effect of ignoring CO_2 concentration, we consider two model specifications, one with (our main model) and one without (alternative model) the CO_2 concentration. We then compare the estimated trend in crop yields between these two specifications as shown in Figure 1. Except for sorghum, the estimated trend in crop yields from the model without the CO_2 variable is greater than the model with CO_2 variable particularly in the future period.[16] Cotton has the biggest difference of the estimated trend of crop production technology on its yield between these two specifications.

As a robustness check, we also compare our estimates of yield growth with previous studies, which did not include the CO_2 variable in their model as shown in Table 4. Comparing the partial derivative of crop yields with respect to time trend at year 2000 across all studies, in general the effect of crop technological progress from our model without CO_2 concentration is in the range of previous studies. However, its effect from our model with CO_2 variable is generally lower than that from previous studies and our model without CO_2. For example, in cotton, its yield increases 8.2 and 11.29 lbs/acre/year in the model with and without CO_2, respectively.

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[16] We fix all variables at their 2008 levels and vary time variable from 1950-2100.

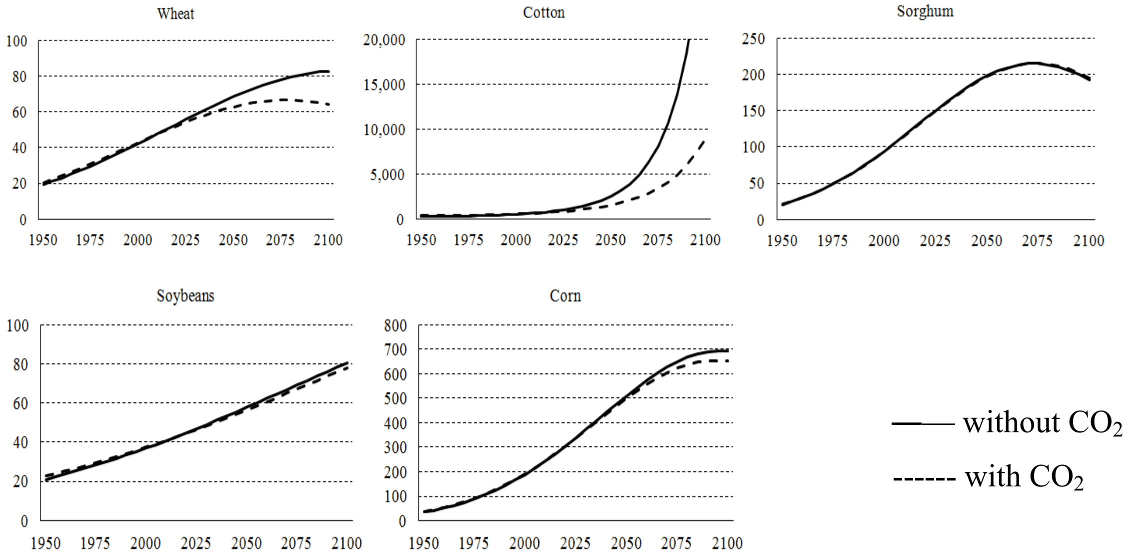

Figure 1. Estimated trend of crop yields

Note: Unit of all crops is in bushels/acre, except for cotton, which has unit in lbs/acre.

Table 4. Comparison of Estimates of Crop Production Technology

	Corn		Soybeans		Wheat		Sorghum		Cotton	
	w CO_2	w/o CO_2	w CO_2	w/o CO_2	w CO_2	w/o CO_2	w CO_2	w/o CO_2	w CO_2	w/o CO_2
Huange and Khanna (2010) (1994-2007)	-	3.26	-	0.29	-	0.64	-	-	-	-
McCarl et al. (2008) (1960-2007)	-	1.89	-	0.39	-	0.67	-	0.40	-	11.56
Chen et al. (2004) (1973-1997)	-	3.30	-	0.35	-	0.63	-	0.11	-	10.11
Our Study (1950-2009)	2.49	2.55	0.29	0.33	0.62	0.63	0.32	0.35	8.20	11.29
% change/year	2.57	2.63	0.91	1.00	1.84	1.85	0.65	0.71	1.30	2.05

Note: 1) Unit of all crops is in bushels/acre/year, except for cotton, which has unit in lbs/acre/year.
2) w CO_2 and w/o CO_2 is the model with and without CO_2 variables included, respectively.
3) The study period of each paper is in parenthesis.
4) The estimated results in the last row are the rate of technological change.
5) All estimates are calculated in year 2000.

In Chen et al. (2004) and McCarl et al. (2008), its yield increases 10.11 and 11.56 lbs/acre/year, respectively. We also calculate the rate of change of crop technological progress and find that, in all cases, the model with the CO_2 variable has the rate of change of crop yields lower than the model without CO_2 as shown in the last row of Table 4. This indicates that ignoring the degree to which CO_2 concentration is contributing to yield increases over time and ignoring its effects, is likely to overestimate the effect of technological progress on crop yields.

Next we examine the effect of climate on mean crop yields. Before we start, it is worth noting that the coefficient of variable "Temperature" represents the effect of temperature on crop yields for the base region (Central), while coefficients of its interaction terms reflect the difference between the effect of temperature over a given region and the Central region. Notice that in Table 3, the interaction terms between temperature and dummy variables of U.S. regions are not uniformly present in all models. This is because of some crops are not grown in some regions. The same is true for interactions involving "Precipitation". Finally, the coefficients of interaction terms between the ENSO phases (El Nino, La Nina, and Neutral) and the dummy variables of U.S. regions reflect the difference between the effects of ENSO phases in a particular region from that in the Central region.

Main findings regarding the effect of climate on mean crop yields are as follow:

- We find that mean temperature has a positive effect over Central (C) and Northern Plains (NP) regions for most crops. It is negative for winter wheat in NP and shows no significant effect for cotton and winter wheat in the Central region. It has negative relative effect for most other regions excepting a positive effect for winter wheat in Northeast (NE), cotton in Southeast (SE), and corn in the Mountain (MT) regions.

- For the effect of extreme high temperature, we find that the higher the number of hot days (number of days that maximum temperature exceeds 32°C) the lower the yields of all crops (except for winter wheat), consistent with the notion that a short period of abnormally high temperatures can have a significant harmful effect on final yield.
- For the effect of total yearly precipitation on crop yields, we finds a statistically significant relationship for the interaction of precipitation and region, implying that crop yield is differentially affected by precipitation across U.S. regions. This might be because this study controls for ENSO events. We find that precipitation has a negative effect over the wetter Central (C) and Northeast (NE) regions with no significant effect for soybeans and corn in both regions. It has positive relative effect for the drier NP region (with a Negative for cotton which is a minor crop in that region). We find mixed results in the remaining regions.
- Precipitation effects are also covered through the PDSI, and precipitation intensity variables. For the effect of drought stress, as represented by the PDSI, an increase in its value (implying wetter condition) directly increases yields of soybeans, corn, and sorghum, while it decreases winter wheat and cotton yield. This is the same finding as in McCarl, Villavicencio, and Wu (2008) for all crops, but winter wheat. However, if we include its indirect effect because of the

interaction between drought stress and the CO_2 concentration, we find that its effect on yields of soybeans, corn, and sorghum tends to decrease, while its effect on yields of cotton and wheat-winter tends to increase as CO_2 increases.

- For precipitation intensity, we find it is harmful to soybeans, cotton, and wheat, although its effect from our model is smaller than that found in McCarl, Villavicencio, and Wu (2008).
- We examine the effect that ENSO events have on crop yields and find that in general its effect is heterogeneous across regions and phase. We find that during the La Nina and Neutral phases, crop yields of soybeans, winter wheat, and corn in NE are slightly higher than that in Central region during the El Nino phase (base), but lower for sorghum. Crop yields in NP, SP, and PA are generally slightly lower than that in Central region during the El Nino phase, but higher for sorghum in SE during La Nina phase. Mixed results are discovered in MT region. Above results are consistent with what have been found in Wolter, Dole, and Smith (1999).

Our results also reveal that the planted acreage of all crops except corn is positively correlated with the mean crop yield 1% statistical significance indicating that yields increases as planted acres expand. In that regard our results are similar to Chen, McCarl, and Schimmelpfennig (2004) and McCarl, Villavicencio, and Wu (2008) for soybeans, wheat, and sorghum, but for cotton and corn.

Effects on Yield Variability

Now, we turn attention to factors affecting the variability of crop yields. The estimated coefficients of the log crop yield variance regressions estimated in the second stage OLS are shown in Table 5. The interpretation of a positive coefficient in this table implies that an increase in the associated variable leads to a higher yield variance and vice versa. Notice that for all crops, the joint significance test rejects the null hypothesis that the variability of crop yields are not determined by all explanatory variables in the model, implying that the crop yields are heteroskedastic being determined by the independent variables as also found in McCarl, Villavicencio, and Wu (2008) excepting for cotton in their study.

Notable findings are that:

- Expansion of crop acreage decreases the variance of soybeans and corn yields.
- The increase in the CO_2 reduces the variation of winter wheat and corn.
- There exists a U-shape relationship between time as a proxy for crop production technology and the variance of corn yield where increases in time increase the variance of corn yield at an increasing rate as argued in Hazell (1984).
- The increase in temperature decreases the volatility of soybean yields in the Central region, while it increases relative variability of yields of soybeans and winter wheat in NE and SE, respectively. It also decreases relative variability of yields of winter wheat and sorghum in NE and NP, respectively.
- Higher incidence of the number of days that the maximum temperature exceeds 32°C increases the variance of winter wheat.

Table 5. Estimated Coefficients from Log Crop Yield Variance Regressions

Variables	Soybeans	Cotton	Wheat	Corn	Sorghum
Acreage	-0.281** (0.1106)	-0.096 (0.1085)	0.011 (0.1109)	-0.522*** (0.1150)	-0.093 (0.1208)
CO_2	-1.813 (1.7603)	-2.477 (1.7379)	-2.831* (1.5493)	-5.350* (3.0889)	-1.010 (1.7425)
CO_2 *X PDSI*	-0.063 (0.4326)	0.137 (0.5526)	0.190 (0.2058)	-0.027 (0.4230)	-0.039 (0.5714)
Trend	-0.002 (0.0191)	-0.015 (0.029)	-0.011 (0.0160)	-0.074*** (0.0148)	-0.029 (0.0238)
Trend^2	0.0002 (0.0003)	0.0002 (0.0004)	0.0003 (0.0002)	0.0011*** (0.0002)	0.0003 (0.0004)
Temperature	-22.575*** (5.6790)	-15.859 (15.8596)	-0.880 (3.4657)	-1.863 (5.0896)	13.311 (9.8555)
Days_temp>32C	0.225*** (0 .0723)	0.116 (0.2043)	0.085* (0.0528)	0.054 (0.0512)	0.278* (0.1424)
PDSI	0.420 (2.5444)	-0.835 (3.2516)	-1.165 (1.2162)	0.148 (2.4822)	0.444 (3.3514)
Precipitation	-1.542 (1.0738)	-1.035 (2.0071)	1.427* (0.8226)	-2.148** (0.9132)	-2.208 (1.3849)
Precip Intensity	0 .152 (0.1304)	0.084 (0.1501)	0.149* (0.0912)	-0.042 (0.0883)	0.200 (0.1368)
Temp X D2_NE	34.053*** (10.2678)		-12.067* (7.0394)	17.809 (8.5947)	-6.738 (60.0009)
Temp X D3_NP	5.624 (9.5418)	4.832 (26.1447)	-5.863 (5.6480)	-11.968 (8.1306)	- (12.7683)
Temp X D4_SE	11.102 (9.1176)	35.009 (17.6074)	16.519** (6.7243)	12.471 (9.5224)	-11.700 (13.1818)
Temp X D5_SP	17.151 (11.2194)	9.551 (18.1257)	7.366 (8.9693)	6.436 (10.8458)	15.073 (13.0952)
Temp X D6_MT		15.747 (20.8440)	1.324 (5.2046)	-9.327 (7.6126)	-5.970 (11.5075)
Temp X D7_PA			-6.432 (8.7626)	0.401 (10.8799)	
Precip X D2_NE	-1.317 (1.3693)		-1.962 (1.3832)	0.748 (1.2742)	-3.618 (5.2080)
Precip X D3_NP	-0.166 (1.3038)	6.268 (3.6472)	-2.322* (1.2359)	1.234 (1.2288)	-3.821** (1.5858)
Precip X D4_SE	-1.652 (1.1925)	0.292 (2.01535)	-1.971* (1.1411)	0.439 (1.1690)	0.143 (1.6866)

Table 5. Continued

Variables	Soybeans	Cotton	Wheat	Corn	Sorghum
Precip X D5_SP	-1.648	1.607	0.171	2.387**	0.345
	(1.2628)	(2.0062)	(1.1956)	(1.1544)	(1.4553)
Precip X D6_MT		1.482	-2.979***	1.047	0.327
		(2.0745)	(0.9584)	(1.0735)	(1.5007)
Precip X D7_PA			-1.214	1.334	
			(1.2052)	(1.1619)	
D2_NE X LaNina	-0.662*		-0.029	0.193	1.219
	(0.3726)		(0.3897)	(0.3391)	(2.6136)
D2_NE X El Nino	-1.323***		-0.307	0.158	-1.512
	(0.3614)		(0.3699)	(0.3256)	(1.7593)
D3_NP X LaNina	-0.307	0.682	-0.130	0.271	-1.664***
	(0.4435)	(1.1928)	(0.4251)	(0.4179)	(0.4637)
D3_NP X Neutral	0.000	-0.013	-0.518	0.942**	-0.681
	(0.4178)	(0.9422)	(0.4012)	(0.3858)	(0.4396)
D4_SE X LaNina	-0.038	-0.737**	-0.054	0.029	0.161
	(0.2980)	(0.3439)	(0.2798)	(0.2855)	(0.3877)
D4_SE X Neutral	0.067	-0.463	-0.663**	0.085	0.155
	(0.2793)	(0.2953)	(0.2638)	(0.2759)	(0.3678)
D5_SP X LaNina	0.0567	-0.028	0.840**	0.536*	0.885***
	(0.3707)	(0.3964)	(0.3706)	(0.3318)	(0.3348)
D5_SP X Neutral	0.440	0.011	0.489	0.507	0.383
	(0.3565)	(0.3348)	(0.3470)	(0.3204)	(0.3112)
D6_MT X LaNina		0.622	-0.079	1.078***	-0.378
		(0.6531)	(0.2990)	(0.3187)	(0.6747)
D6_MT X Neutral		0.544	-0.142	0.595**	-0.413
		(0.5350)	(0.2768)	(0.2898)	(0.6273)
D7_PA X LaNina			-0.766	-0.222	
			(0.4820)	(0.4547)	
D7_PA X Neutral			-0.230	0.304	
			(0.4341)	(0.4071)	
DummyFACE	-2.744	0.142	1.444	-8.388***	1.452
	(2.1505)	(3.5337)	(1.5697)	(2.3200)	(2.0657)
Constant	68.131**	-67.504*	-51.114*	-7.442	1.037
	(-34.1210)	(38.6709)	(26.3072)	(40.2063)	(43.1475)
F(df1,df2)	F(56,1413)	F(42,737)	F(75,1842)	F(76,1866)	F(49,796)
Prob > F	3.65***	1.91***	2.52***	5.89***	3.23***

Note: 1) ***, **, * are significant at the 1, 5, and 10 percent level, respectively and standard errors are in parentheses.

2) Definitions of variables are provided in Table 2 and the note in Table 3.

- Considering the effect of precipitation on the variability of crop yields, we find that higher precipitation increases the variability of winter wheat, while it decreases variability of corn yield in the Central region. Higher precipitation also decreases the variation of winter wheat yield in NP, MT, and SE, and sorghum yield in NP, while it increases the volatility of corn yield in SP region.
- Precipitation intensity increases the variance of winter wheat.
- We find the heterogeneity of the variance of crop yields across regions due to the ENSO phases. For example, the variability of yields of winter wheat, corn and sorghum during the La Nina phase is higher than during the El Nino phase in SP.

Simulation of the Impacts of Climate Change on Future Crop Yields

To investigate the implications of future climate change on crop yield and its variability, we employ our estimated coefficients from Tables 3 and 5 with future climate change projections from GCM cases. We also use the projected PDSI and the probability of future ENSO phases from Dai (2010) and Timmermann et al. (1999), respectively. According to Timmermann et al. (1999), the current probability of ENSO event occurrence (with present day concentrations of greenhouse gases) is 0.238 for the El Niño phase, 0.250 for the La Niña phase and 0.512 for the Neutral phase. They also project that probabilities for these three phases will change under increasing levels of GHGs assumed under IPPC projections. In their work the, ENSO event frequency is forecasted to become 0.339, 0.310, and 0.351 for El Niño, La Niña and Neutral, respectively.

We simulate the projected percentage change by 2050 of mean crop yield and its standard deviation in four scenarios. The first scenario is the base scenario in which all climate change and CO_2 variables are fixed at their average values during 1980–2009. The second scenario is the situation in which the CO_2 variable changes, but other climate variables are fixed at their mean level. The third scenario is the case in which all of the climate variables change, but the CO_2 variable is hold at its mean level. The second and third scenarios aim to measures the partial effect of the CO_2 fertilization and climate change, respectively. In the last scenario, both climate and CO_2 are changed, which is different from a majority of previous studies that often quantify only the partial effect of a single climate variable. We report the simulated percentage change of mean yields and their standard deviation of year 2050 averaged from our four GCM cases as shown in Table 6.

For the partial effect of CO_2 fertilization (Scenario1), we find that if atmospheric CO_2 continues to increase, yields of all crops are likely to be higher in the future in all regions. CO_2 concentration is likely to increase yields of C-3 crops (soybeans, cotton, and winter wheat) more than yields of C-4 crops (corn and sorghum). The most advantaged crop is cotton. We find that as atmospheric CO_2 increases from 367 to 550ppm, yields of wheat, soybeans, cotton, corn, and sorghum are projected to increase 12, 13, 63, 8, and 4 percent, respectively. Our estimated magnitudes of the CO_2 fertilization effect generally agree to what are reviewed in Long et al. (2006) and found in Leakey (2009), implying that the stimulation of yield obtained from chamber studies

Table 6. Average Percent Change of Mean Yields and Their Standard Deviation in 2050 under Selected Scenarios

	% Change in Mean Yields					% Change in Standard Deviation of Yields				
Region	Corn	Sorghum	Soybeans	Cotton	Wheat	Corn	Sorghun	Soybeans	Cotton	Wheat
	Scenario 1: Change in CO_2 but no climate change									
NP	5.61	1.63	9.37	84.65	12.83	-67.80	-19.83	-32.76	-38.47	-42.57
SP	7.23	3.80	11.89	77.49	12.03	-67.62	-19.40	-32.20	-39.98	-43.44
LS	6.33		10.67		11.90	-67.70		-32.49		-43.54
CB	5.76	2.47	9.79	83.23	12.20	-62.88	-19.75	-27.21	-39.17	-43.27
D	7.56	4.63	13.14	76.68	11.09	-67.59	-19.24	-31.91	-40.14	-44.41
NE	7.07	1.78	13.17		11.41	-67.69	-18.34	-31.57		-44.20
SE	8.37	5.86	14.37	71.97	10.57	-67.51	-19.01	-31.62	-40.82	-44.93
AP	7.78	4.51	13.48	74.19	10.85	-67.55	-19.27	-31.82	-40.59	-44.70
PA	8.75				10.04	-67.47				-45.62
MT	7.09	2.89		52.79	10.89	-67.64	-19.14		-31.49	-44.42
	Scenario 2: Climate change but no change in CO_2									
NP	13.08	39.91	10.06	13.82	1.58	-12.77	1723.52	34.15	92.42	-11.29
SP	-24.42	-10.28	-8.07	-1.09	21.72	-8.17	511.16	365.44	-22.30	-37.63
LS	-0.72		-4.56		8.60	75.60		71.47		-12.05
CB	0.57	-0.89	-0.15	-4.68	-2.72	-0.89	59.01	-22.51	-21.15	26.91
D	-18.05	-11.82	-17.30	4.02	-6.85	6.51	502.85	201.37	-23.44	5.85
NE	0.23	-15.35	5.05		-6.30	-17.69	4.86	-14.25		-1.48
SE	3.19	0.57	2.32	1.31	-6.71	-0.14	10.06	3.40	18.88	35.32
AP	3.49	-1.24	2.61	0.72	-4.86	-9.76	-3.98	-6.13	11.73	20.05
PA	1.59				-0.78	17.57				36.93
MT	-0.84	-21.38		24.96	-3.72	25.50	104.73		-33.82	65.37
	Scenario 3: Change in climate and CO_2									
NP	22.28	47.21	25.79	96.23	12.33	-71.68	1375.66	-8.30	14.86	-51.20
SP	-18.32	-5.52	4.93	70.64	34.55	-70.19	394.50	218.11	-53.97	-65.70
LS	7.24		8.88		20.01	-43.00		17.17		-51.67
CB	8.16	4.15	12.76	65.27	7.54	-63.03	28.46	-43.10	-53.19	-30.22
D	-11.43	-7.14	-5.52	79.34	2.91	-65.42	387.72	106.01	-54.67	-41.87
NE	8.36	-11.33	19.93		3.51	-73.32	-13.74	-41.19		-45.92
SE	11.57	6.02	16.97	74.50	3.01	-67.58	-10.98	-29.29	-29.63	-25.70
AP	11.81	3.94	17.14	74.11	5.15	-70.71	-22.43	-35.84	-33.77	-34.03
PA	9.85				9.71	-61.82				-24.71
MT	7.17	-17.33		86.37	6.36	-59.26	69.39		-55.22	-9.10

Note: 1) NP –Northern Plains- (Kansas, Nebraska, North Dakota, South Dakota); SP –Southern Plains-(Oklahoma, Texas); LS –Lake States-(Michigan, Minnesota, Wisconsin); CB –Corn Belt-(Illinois, Indiana, Iowa, Missouri); D –Delta States-(Arkansas, Louisiana, Mississippi); NE –Northeast-(Connecticut, Delaware, Maine, Maryland, Massachusetts, New Hampshire, New Jersey, New York, Pennsylvania, Rhode Island, Vermont); SE –Southeast- (Alabama, Florida, Georgia, South Carolina); AP –Appalachia- (Kentucky, North Carolina, Tennessee, West Virginia); PA –Pacific- (California, Oregon, Washington); MT –Mountain-(Arizona, Colorado, Idaho, Montana, Nevada, New Mexico, Utah, Wyoming)

2) Numbers in table are averaged from 4 GCM cases; GFDL-CM 2.0, GFDL-CM 2.1, MRI-CGCM 2.3.2a, and CNRM-CM3 (see also Footnote 6).

is overestimate the real effect of the CO_2 fertilization.[17] Therefore, most models used to predict future crop yields should be aware of using the assumption regarding the effect of CO_2 fertilization on crop yields from chamber studies. Lastly, we find that a higher atmospheric CO_2 in the future decreases the standard deviation of yields of all crops in all regions.

Fixing the atmospheric CO_2 at its mean level and varying climate, we find that climate change has a positive effect on yield on all crops in the NP and SE regions (excepting a negative for winter wheat in the SE), while it has negative effect on yield of almost all crops in the SP, CB, and D regions and a positive effect for winter wheat in SP, corn in CB, cotton in D). We find mixed results in other remaining regions. For yield variability, the climate change increases the standard deviation of crop yields in D, MT, and SE (Decrease for cotton in D and MT, and corn in SE). We find mixed results in other remaining regions.

Under the situation that climate and CO_2 are both changed, the effect of CO_2 fertilization generally outweighs the effect of climate change on mean crop yields in NP, LS, CB, SE, AP, and PA. On the other hand, yields of corn and sorghum will be decreased in SP and D. Moreover, in 2050, yield variability of all crops are projected to reduce in all regions, except sorghum and cotton in NP, sorghum and soybeans in SP and D, soybeans in LS, sorghum in CB and MT.

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[17] In their study, as atmospheric CO_2 increases from 367 to 550ppm, yields of wheat, soybeans, and C-4 crop (corn and sorghum) are projected to increase 13, 14, and 0 percent, respectively, while chamber studies find that yields of wheat, soybeans, and C-4 crop are forecasted to increase 31, 32, and 18 percent, respectively.

Implications of the Change in Yields on Market Outcomes and Welfare Distribution

After incorporating our projected percentage changes of mean crop yields in the previous section into the ASM, market outcomes (including crop prices and their planted acreage) and the welfare distribution across regions are reported in Tables 7 and 8, respectively. Our first finding is that prices of all crops tend to decrease in 2050 compared to the base scenario, where there is no change in climate and atmospheric CO_2 as shown in Table 7. This finding is consistent with results in the previous section, which reveals that yields of all crops are projected to increase in almost all U.S. regions and this is possibly greater than the increase in the demand for crops. Next finding is that planted acreage of all crops in NP, except winter wheat, is projected to increase with the highest percentage change in soybeans and corn, respectively. This result is consistent to what is shown in scenario 3 of Table 6 that yields of almost all crops increase the most in NP. On the other hand, planted acreage of all crops in SP, LS, D, SE, and MT is simulated to decrease (increase for cotton in SP and MT, and corn in D and SE). Mixed results are found in remaining regions. Percentage of planted acreage of corn, sorghum, soybeans, cotton, and winter wheat is projected to increase the most in AP, CB, AP, MT, and PA, respective. Summing up across U.S. regions, only planted acreage of soybeans is projected to increase in 2050.

Our last finding is related to the regional welfare distribution as shown in Table 8. In all regions, consumer surplus (CS) is projected to increase slightly due to the CO_2 fertilization and climate change, while producer surplus (PS) changes are heterogeneous across U.S. regions. Producer surplus in SP, D, and PA tend to increase, while it is

Table 7. Average Crop Acreage and Price Change with/without Change in Climate and CO_2

	Crop Acreage without Change in Climate and CO_2 (million acres)				
Region	Corn	Sorghum	Soybeans	Cotton	Wheat
Northern Plains	12.05	4.91	9.10	0.000	4.12
Southern Plains	0.71	3.76	2.05	1.82	0.01
Lake States	7.04	0.00	7.54	0.00	0.36
Corn Belt	25.99	3.33	25.71	1.61	1.90
Delta States	0.43	0.43	5.79	2.24	0.00
Northeast	0.66	0.01	0.80	0.00	0.00
Southeast	0.85	0.22	1.93	0.47	0.00
Appalachia	1.29	0.61	2.52	7.84	0.00
Pacific	0.30	0.23	0.00	0.10	0.11
Mountains	0.63	0.58	0.00	0.12	2.91
Total	49.95	14.08	55.44	14.20	9.41
Region	Percentage Change in Acreage with Change in Climate and CO_2				
Northern Plains	9.59	2.20	14.01	—	-7.16
Southern Plains	-13.76	-0.52	-37.43	16.42	-62.15
Lake States	-19.25	—	-19.53	—	-53.27
Corn Belt	-7.98	29.17	-3.37	151.31	-45.82
Delta States	10.82	-52.47	-2.79	-13.40	—
Northeast	3.46	-15.84	1.83	—	—
Southeast	3.77	-77.40	-11.62	-64.58	—
Appalachia	169.51	-82.15	168.26	-96.15	—
Pacific	-14.29	-96.03	—	106.47	23.14
Mountains	-36.92	-47.32	—	533.08	-15.24
Total	-0.73	-2.42	3.66	-32.65	-18.87
Scenario	Major Crop Prices				
	Corn	Sorghum	Soybeans	Cotton	Wheat
Without Change in Climate and CO_2	2.61	7.95	9.93	260.31	4.56
With Change in Climate and CO_2	2.42 (-7.16)	7.22 (-9.19)	9.34 (-5.89)	217.88 (-16.30)	3.82 (-16.15)

Note: 1) Numbers in parentheses represent the percentage change.
2) "—" means no data available.
3) Numbers in table are averaged from 4 GCM cases; GFDL-CM 2.0, GFDL-CM 2.1, MRI-CGCM 2.3.2a, and CNRM-CM3 (see also Footnote 6).

Table 8. Impact of Change in Crop Yields Due to Change in Climate and CO_2 on Regional Welfare in US$ Billion

	Without Change in Climate and CO_2			With Change in Climate and CO_2		
Region	CS	PS	Total Welfare	CS	PS	Total Welfare
Northern	41.47	7.78	49.25	41.62	6.12	47.74
				(0.38)	(-21.38)	(-3.06)
Southern	157.86	3.61	161.47	158.46	3.75	162.20
				(0.38)	(3.82)	(0.46)
Lake States	139.82	4.82	144.65	140.35	4.30	144.65
				(0.38)	(-10.82)	(0.01)
Corn Belt	273.08	14.68	287.76	274.11	12.39	286.50
				(0.38)	(-15.62)	(-0.44)
Delta States	73.11	1.92	75.03	73.39	2.03	75.42
				(0.38)	(5.94)	(0.52)
Northeast	424.38	0.94	425.33	425.99	0.86	426.85
				(0.38)	(-8.70)	(0.36)
Southeast	176.68	1.16	177.85	177.35	1.12	178.47
				(0.38)	(-3.90)	(0.35)
Appalachia	176.74	1.79	178.52	177.41	1.47	178.87
				(0.38)	(-17.93)	(0.20)
Pacific	275.66	5.42	281.08	276.71	5.63	282.34
				(0.38)	(3.86)	(0.45)
Mountains	104.75	4.08	108.83	105.15	3.83	108.98
				(0.38)	(-6.19)	(0.13)
Total	1,843.55	46.21	1,889.76	1,850.54	41.49	1,892.03
				(0.38)	(-10.21)	(0.12)

Note: 1) Numbers in parentheses represent the percentage change. “CS” and “PS” are defined as consumer’s surplus and producer’s surplus, respectively. Total welfare is the summation of the consumer’s and producer’s surplus.

2) Numbers in table are averaged from 4 GCM cases; GFDL-CM 2.0, GFDL-CM 2.1, MRI-CGCM 2.3.2a, and CNRM-CM3 (see also Footnote 6).

projected to decrease in remaining regions. In total, it decreases about $ 4.72 billion. Summing up PS and CS, we find that total welfare is projected to drop only in NP and CB. Overall the total U.S. welfare is increased about $ 2.27 billion compared to the base scenario.

Conclusions

This study estimates effects of climate variables, crop production technology, and atmospheric CO_2 on yields of five major crops including corn, sorghum, soybeans, winter wheat and cotton, in the U.S. using both historical data and the unique dataset from the FACE experiments. We also investigate their impacts on future crop yields and their variability. Finally, we explore market outcomes and welfare implications of economic units across U.S. regions.

We find that yields of C-3 crops, soybeans, cotton, and wheat, positively respond to the elevated CO_2, while yields of C-4 crops, corn and sorghum do not. However, we find C-4 crops indirectly benefit from elevated CO_2 in times and places of drought stress. The effect of crop technological progress on mean yields is non-linear with inverted-U shape in all crops, except cotton. Our study also reveals that ignoring the atmospheric CO_2 in econometric model of crop yield studies is likely to overestimate the effect of crop production technology on crop yields.

For climate change impact, the average climate conditions and their variability are found to contribute in a statistically significant way to both average crop yields and their variability. If all climate and CO_2 variables are changed simultaneously in the future, the effect of CO_2 fertilization generally outweighs the effect of climate change on mean crop yields in many regions.

In terms of market outcomes and welfare distributions, prices of all crops tend to decrease in 2050. Planted acreage of all crops in NP, except winter wheat, is projected to increase, while it tends to decrease in SP, LS, D, SE, and MT for almost all crops. In all regions, consumer surplus (CS) is projected to increase, while producer surplus (PS) is heterogeneous across U.S. regions, but in total it decreases about $ 4.72 billion. Overall the total U.S. welfare is increased about $ 2.27 billion compared to the base scenario.

Several clear implications arise:

- Climate change affects the mean and variance of crop yields and this may need to be considered by policy makers and risk management groups such as crop insurance companies.
- Given CO_2 is likely to increase, it may be worth devoting relatively more scarce research funds to C-4 crops as C-3 crops will receive CO_2 stimulation. Moreover, the returns to agricultural research may merit by reevaluation taking into account the effect of the CO_2 fertilization.
- Similar to FACE studies (e.g., Long et al. 2006), most models used to predict future crop yields should be aware of using the assumption of CO_2 fertilization from chamber studies since it may overestimate the real effect of CO_2 fertilization on crop yields.
- Yields are differentially affected regionally and thus adaptation efforts may need to be targeted to more vulnerable regions.

CHAPTER III

THE EFFECT OF CLIMATE CHANGE ON TRANSPORTATION FLOWS AND INLAND WATERWAYS DUE TO CLIMATE-INDUCED SHIFTS IN CROP PRODUCTION PATTERNS

Introduction

U.S. grain production plays a crucial role in supplying global and local demand for food, feed, and biofuels. In the 2009/2010 crop year, the U.S. supply of corn, soybeans, and wheat accounted for about 39, 31, and 9 percent of the respective world supplies. The U.S.'s share of the international export market was about 52, 44, and 18 percent for corn, soybeans, and wheat, respectively (USDA-WAOB 2011).

A highly efficient, low-cost transportation system is a major factor determining U.S. competitiveness. Barges, railroads, and trucks bridge the gap between U.S. grain producers, and domestic and foreign consumers. Not only is agriculture a very large user of the transportation system, accounting for 22 percent of all transported tonnage and 31 percent of all ton-miles generated via all modes in 2007, but grain is also the largest user of freight transportation in agriculture (Denicoff et al. 2010).

According to Marathon and Denicoff (2011), from 1978 to 2007, total U.S. grain shipments increased 92 percent with corn transportation accounting for 63 percent of all grain movements in 2007 followed by movements of soybeans and wheat (19 percent and 14 percent, respectively). During 2002-2007, inland grain transportation via truck and rail was the principal channel accounting for about 85 percent, while inland water transportation via barge represented 15 percent of grain tonnage. Although inland water transportation has a small share of all movements, it is a major route to export markets accounting for about 48 percent of all tonnage.

Adjustments in transport will occur in the future and climate change is one likely driving force. Recent studies including those by IPCC (IPCC 2007a; 2007b) indicate that the world's climate conditions are changing and are projected to continue to do so. Such changes are expected to substantially impact agriculture (e.g., IPCC 2007b; Mendelsohn, Nordhaus, and Shaw 1994; Deschenes and Greenstone 2007; Schlenker and Roberts 2009), with the most immediate reaction of agricultural producers being adaptation.

Several studies indicate that crop production will increase in high latitudes and decline in low latitudes (e.g., IPCC 2007b; 2007c; Adams et al. 1990; Reilly et al. 2003). Research suggests that crop suitability zones may shift more than 100 miles northward (Reilly et al. 2003). In the U.S., northward shifts in the crop production mix have already been observed with more corn planted in North Dakota among other changes[18] (Upper Great Plains Transportation Institute 2011). Such developments will have increase regional volumes of grain production and the demand placed on the transport system since corn yields are about four times greater than wheat (USDA-NASS 2011).

Given these northward shifts caused by climate change plus differences in the typical destinations of grain shipments for different commodities, there will be likely changes in the pattern of interregional grain transportation flows, and demand for

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[18] In 1990, roughly 60 percent of the crop land in North Dakota was planted to wheat. In 2009, this number was 45 percent. Over the same period, corn acres have increased from 5 to 10 percent of cropland.

transportation capacity. To our knowledge there have not been studies focusing on implications that climate change induced crop production alterations have for the transportation system. Thus the objective of this chapter is to investigate the effect of climate change on interregional grain transportation flows and mode choice.

The remainder of this chapter is organized as follows. In section 2, we review the existing literature on adaptation patterns of U.S. crop production to climate change and the impact and the effect of climate change on the transportation system. Section 3 describes our analytical approach including model components, data, and linkage procedures. Section 4 presents empirical findings. Finally, section 5 concludes by discussing climate change implications for the U.S. grain transportation system.

Literature Review

This section concentrates on two aspects of the literature, namely the climate change related studies relevant to crop mix adaptation and studies on the transport system.

Crop Mix Adaptation to Climate Change

There are a number of ways that land use can be affected by climate change. For example, climate change alters land values and land productivity through changes in the productivity of crops, forests, pastures, and livestock. Land use can also be affected by climate change-induced alteration of spatial and temporal distribution and proliferation of pests and diseases (e.g., see the discussion in Reilly et al. 2002 and recent reviews in Aisabokhae et al. 2012).

A number of studies have examined how climate change influences the migration of crop mixes as an adaptation response. Crop production is expected to increase in high latitudes and decline in low latitudes since increases in precipitation are likely in the high latitudes, while decreases are likely in most subtropical regions (e.g. Adams et al. 1990; Reilly et al. 2003). This effect has also been observed in the results of Reilly et al. (2003) who construct the geographic centroid of production for maize (corn) and soybeans and plot their movements from 1870 (1930 for soybeans) to 1990. They find that both U.S. maize and soybean production shifted northward by about 120 miles during the analyzed period. An updated result is presented in Beach et al. (2009), who find soybean production trending northwest between 1970 and 2007 shifting northward by about 3.6 miles per year on average over this timeframe.

Many studies conclude that climate change would affect crop yields and result in northward shifts in cultivated land (e.g., Adams et al. 1990; Reilly et al. 2002; Reilly et al. 2003). For example, Reilly et al. (2002) find substantial shifts in regional crop production with LS, MT, and PAC regions showing gains in production, while SE, D, SP, and AP regions generally losing production acres. More recently McCarl (2011) estimates changes of crop acreage in the U.S. under 2030 climate scenarios with adaptation. He finds decreased acreage for cotton, soft white and hard red spring wheat, barley, hay, sugar cane, sugar beets, processed tomatoes, and processed oranges; but increased acreage for soybeans, hard red winter wheat, rice, potatoes, fresh tomatoes, and fresh citrus.

The Effect of Climate Change on Transportation System

Changing climate raises critical questions for the transportation sector in the U.S. Several studies analyze how transportation would be affected by changes in weather and climate extremes (e.g., Peterson et al. 2008; Koetse and Rietveld 2009; Humphrey 2008). Koetse and Rietveld (2009) survey concludes that flooding of coastal roads, railways, transit systems, and runways due to rising sea levels coupled with storm surges may be some of the most worrying factors. They review previous studies and find that countries at higher longitudes will become more suitable for food production, with countries at lower longitudes, becoming suitable. This would likely result in an increase in grain trade flows from developed to developing countries.

Savonis, Burkett, and Potter (2008) study climate change implications for the Gulf Coast finding that seven of the ten largest commercial ports (by tons of traffic) may be inundated over the next 50 to 100 years due to sea level rise (up to 122 cm), with 27 percent of the major roads, nine percent of the rail lines, and 72 percent of the ports being at risk. They also find that combined effects of increases in mean and extreme high temperatures are likely to affect the construction, maintenance, and operations of transportation infrastructure and vehicles.

Several studies find that watersheds supplying water to the Great Lakes are likely to experience drier conditions, resulting in lower water levels and reduced capacity plus higher cost to ship agricultural and other commodities (Millerd 2005; 2011; Chao 1999; Easterling and Karl 2001). Millerd (2005) finds that the impacts vary between commodities and routes. For grains, the annual average shipping cost from the upper lakes to the St. Lawrence River is found to increase by about 11 percent in 2050 compared to 2001. Millerd (2011) projects an increase in the U.S. vessel operating costs of grains and agricultural products for Great Lakes movement ranging between 4.15–4.95, 7.96–9.30, and 21.71–22.62 percent by 2030, 2050, and under a doubling of CO_2 scenario, respectively. However, many studies find that warming temperatures are likely to result in more ice-free ports, improved access to ports, and longer shipping seasons (e.g., Great Lakes Regional Assessment Team 2000; Kling and Wuebbles 2005), which could offset some of the resulting adverse economic effects from increased shipping costs (Millerd 2011; Humphrey 2008).

Based on the above studies, climate change potentially affects physical transportation infrastructures and costs, which could lead to changes in overall transportation flows of commodities.

Model Components, Data, and Process Overview

In order to examine changes in transportation flows due to shifts in crop production patterns under alternative climate scenarios, we first estimate northward shifts in crop mix and then calculate the implications for trade flows. In order to achieve this, we link two modeling systems. The systems and their link are described below.

Agriculture Sector Model (ASM)

The first model simulates the location of crop production under climate change scenarios. It is based on the ASM model developed by McCarl et al. (Baumes 1978; Burton 1982; Adams, Hamilton, and McCarl 1986; Adams et al. 1990; Chang et al.

1992; Adams et al. 1996; McCarl and Schneider 2000; Adams et al. 2005; Schneider, McCarl, and Schmid 2007; Beach et al. 2009; Beach, Thomson, and McCarl 2010) as explained in Chapter II and Appendix A. It will be run twice once with and once without climate change to see what the implications are.

International Grain Transportation Model (IGTM)

A grain transportation model will be used to examine the transportation implications of climate change induced crop mix shifts. This model (IGTM) was constructed for this study and is explained in Chapter IV. IGTM depicts world grain trade in corn and soybeans and contains a detailed representation of internal transport system in the U.S. IGTM follows a price-endogenous, spatial equilibrium, mathematical programming framework. The theoretical underpinnings of the model can be found in Samuelson (1952), and Takayama and Judge (1971). Briefly, IGTM simulates quarterly grain production, consumption, prices, and storage. It also predicts quarterly transportation flows by modes consisting of truck, rail, barge, lake vessel, and ocean-going ship from and to 303 U.S. regions (largely crop reporting districts) going through 42 intermediate shipping points where modes can be changed and also depicts world trade. World trade is modeled on quarterly basis with 118 foreign exporting and importing countries/regions.

IGTM's basic geographic unit for U.S. regions is crop reporting districts (CRD).[19] IGTM does not take into account transport flows within crop reporting

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[19] The geographic scale of non-U.S. region is the country level except for Canada and Mexico.

districts, mainly accomplished by truck [20] but rather is limited to interregional trade. As a result, the role of truck mode in this study is generally smaller than what it could be. The structure of IGTM and full model description are provided in Chapter IV.

Developing Climate Change Induced Crop Mix Shifts with ASM

ASM has been used on at least 10 occasions to look at climate change implications starting with Adams et al. (1988), Adams et al. (1990), and Reilly et al. (2002) and ranging through the recent work by McCarl (2011). The same procedures were used herein and are most explicitly detailed in McCarl (1999). The specific adjustments incorporated in the model for the purposes of present study are as follows:

- Crop yields were altered under climate change scenarios based on the estimates developed by Beach et al. (2009). The latter were obtained from runs of the Environmental Policy Integrated Climate (EPIC) model[21] over four IPCC 2007 A1B scenarios.[22] The data used from these were estimated percentage changes in irrigated and dryland yields plus irrigation water use.
- Levels of inputs such as fertilizer, energy, labor, and insecticides were varied with crop production changes. For example, if yields are higher more inputs are needed and *vice versa*. Farm level evidence suggests that the change in input use is less than proportional to the yield change. The estimated relationships vary by

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[20] In general, truck is more advantageous than rail and barge for short distance, while for middle to long distance its competitiveness drops compared to rail and barge.

[21] first developed by Williams et al. (1984)

[22] namely those from the GFDL-CM 2.0 model; the GFDL-CM 2.1 model, the Meteorological Research Institute Coupled Atmosphere-Ocean General Circulation Model (MRI-CGCM 2.2) and the Coupled Global Climate Model (CGCM 3.1)

crop, but the change for most crops was on the order of a 0.4% change in input use for a 1.0% change in yield based on results in Adams et al. (1999).

- Climate change can have implications for livestock principally through changes in appetite and the distribution of energy between maintenance and growth. Animal yields were modified based on the data in Adams et al. (1999).
- The amount of feedstuffs and other inputs change when livestock productivity changes. We assume that feedstuff use is strictly proportional to the volume of animal products produced. The use of the non-feed inputs changed by 0.5% for every 1.0% change in livestock yields.
- Climate change effects on water supply and, in turn, the amount of irrigation water available for agriculture was calculated using data from the water component of the U.S. national assessment (Gleick et al. 2000 as explained in McCarl 1999).
- Climate change effects on grass growth and thus the effective supply of pasture and animals that can be supported on Western grazing lands was altered based on EPIC hay simulation results.
- Pesticide treatment cost was raised using the results from Chen and McCarl (2001).

Changes of corn and soybean yields under climate change from GCM cases for the period of 2045–2055 are shown in Figure 2 and Figure 3, respectively.[23] Dryland

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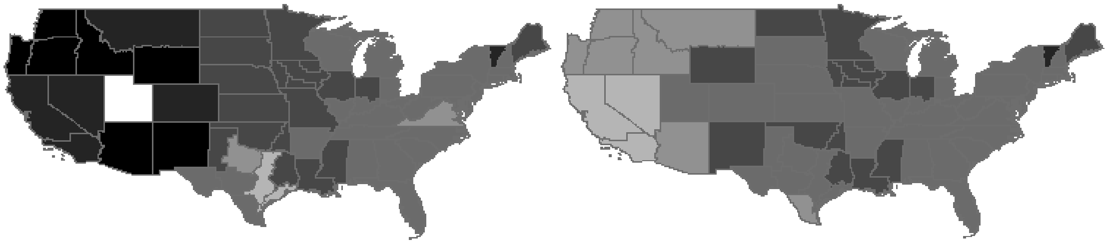
[23] Beach et al. (2009) present more details.

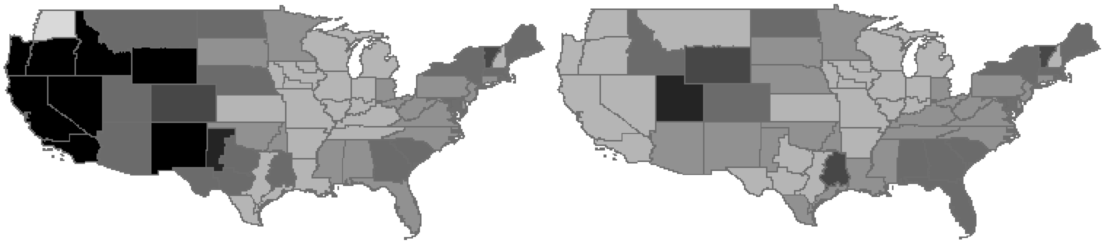
corn yield is expected to increase in almost all states in the Rocky Mountains, Pacific Southwest and Pacific Northwest West in all GCM cases, while it is projected to decrease in almost all states in the southern parts of the Corn Belt. MRI-CGCM 2.2 provides the most optimistic projections for corn yield changes both on dry- and irrigated land. For dryland, various degrees of yield increase are projected across the U.S. regions except for Utah, some regions of Texas, and Virginia. For irrigated land, small increases in corn yield are predicted. On the other hand, GFDL 2.1 presents the most pessimistic projections for changes in both dryland and irrigated corn yield. In particular, under this model irrigated corn yield is projected to decrease almost everywhere (Figure 2).

Results from MRI-CGCM 2.2 provide the most optimistic projected change in soybean yield. On the other hand, GFDL 2.1 generates the most pessimistic projections as illustrated in Figure 3. The variation in soybean yield changes across models is generally larger than that of corn yields. In particular, soybean yields are projected to drop by more than 20 percent in a large part of Corn Belt, Southwest, and South Central regions in GFDL 2.0 and GFDL 2.1. On the other hand, various degrees of yield increases are projected in all GCM cases in almost entire northern part of the U.S (Great Plains, Northern part of the Rocky Mountains, Lake States, and Northeast).



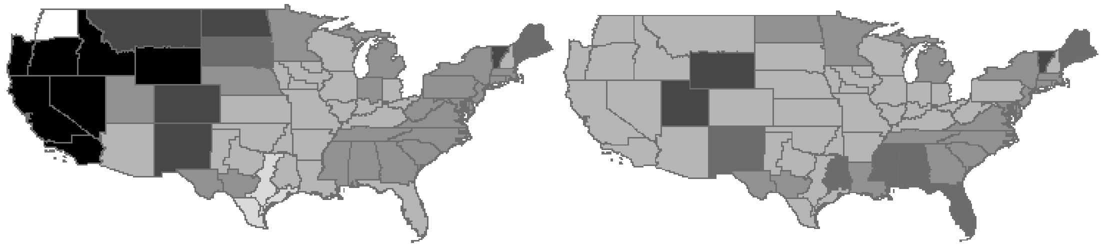
MRI-CGCM2.2 Dryland Corn - Percentage Change in Yield

MRI-CGCM2.2 Irrigated Corn - Percentage Change in Yield



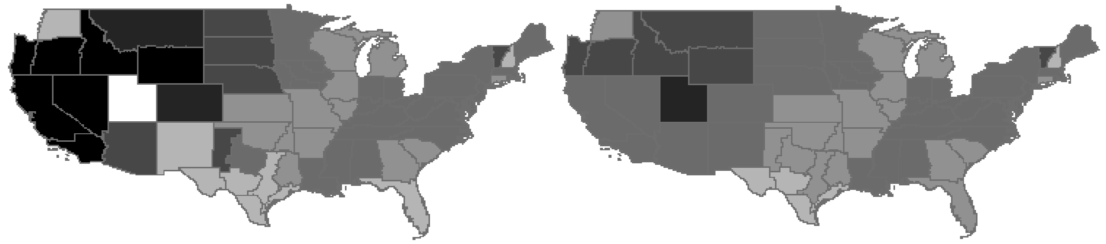
GFDL 2.0 Dryland Corn - Percentage Change in Yield

GFDL 2.0 Irrigated Corn - Percentage Change in Yield



GFDL 2.1 Dryland Corn - Percentage Change in Yield

GFDL 2.1 Irrigated Corn - Percentage Change in Yield

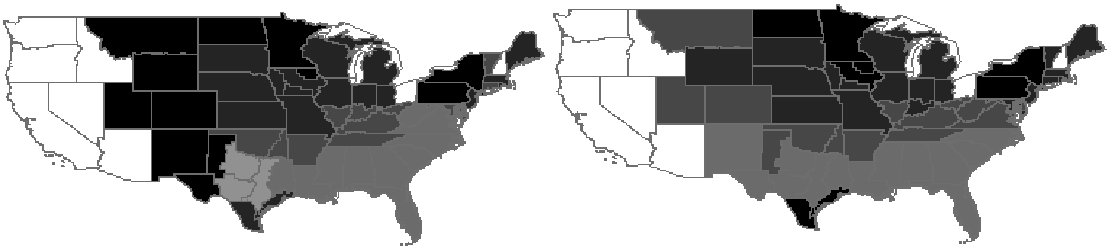


CGCM3.1 Dryland Corn - Percentage Change in Yield

CGCM3.1 Irrigated Corn - Percentage Change in Yield

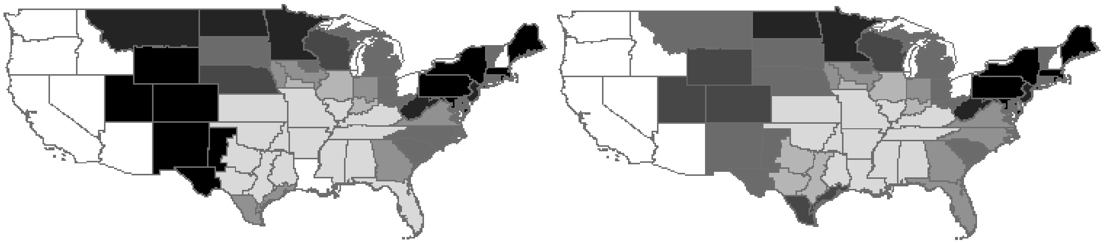
□ -40 < ▨ -40 - -21 ▨ -20 - -6 ▨ -5 - -1 ▨ 0 - 5 ▨ 6 - 20 ■ 21 - 40 ■ > 40

Figure 2. Percentage change in dryland and irrigated corn yields under different GCM cases simulated for the 2045-2055 period



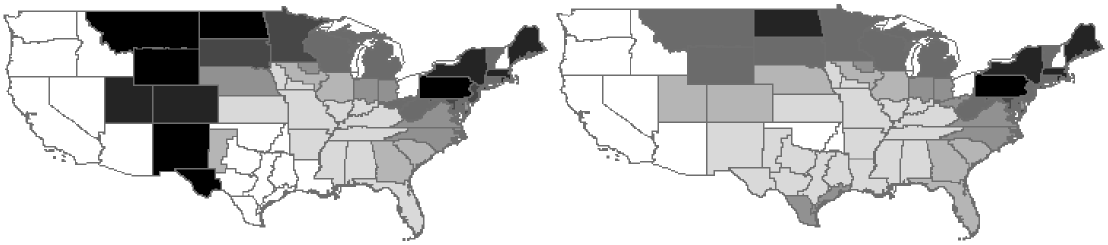
MRI-CGCM2.2 Dryland Soybeans - Percentage Change in Yield

MRI-CGCM2.2 Irrigated Soybeans - Percentage Change in Yield



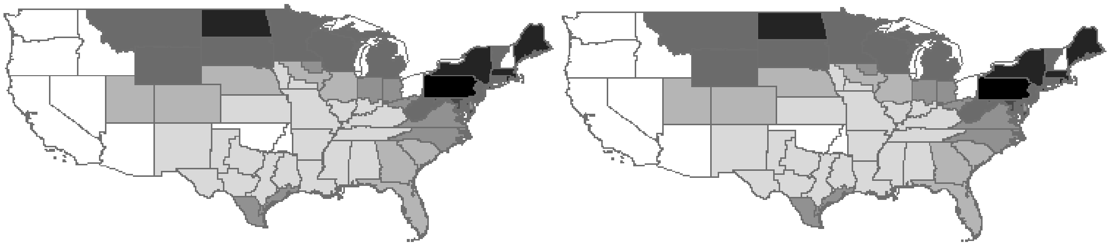
GFDL 2.0 Dryland Soybeans - Percentage Change in Yield

GFDL 2.0 Irrigated Soybeans - Percentage Change in Yield



GFDL 2.1 Dryland Soybeans - Percentage Change in Yield

GFDL 2.1 Irrigated Soybeans - Percentage Change in Yield



CGCM3.1 Dryland Soybeans - Percentage Change in Yield

CGCM3.1 Irrigated Soybeans - Percentage Change in Yield

□ -20 < ▨ -20 - -11 ▨ -10 - -6 ▨ -5 - -1 ▨ 0 - 5 ▨ 6 - 10 ■ 11 - 20 ■ > 20

Figure 3. Percentage change in dryland and irrigated soybean yields under the different GCM cases simulated for the 2045-2055 period

Linking the Models

In order to examine the transport implications of climate change we run ASM for a baseline and several climate change cases (procedures identified below) and then incorporate the resulting changes in grain production patterns into IGTM by appropriately shifting regional excess supplies in order to examine the effects on transport flows.[24] The linkage between the models is implemented as follows.

ASM represents production in 63 regions in the U.S. Although this is a fairly fine level of spatial detail for economic analysis, it is not sufficiently detailed for the grain transportation model in which 303 U.S. regions are analyzed. Therefore, downscaling is required in order to incorporate ASM results into IGTM.[25] To do this we follow a downscaling procedure developed by Atwood et.al (2000) and later employed in Pattanayak et al. (2005). The procedure allocates the 63 region crop mix to the component counties in each region using a multi-objective programming downscaling model that minimizes the deviations between the crop mixes based on the ASM solution and those observed in 1970-2007 data drawn from the Census of Agriculture, U.S. Bureau of Census, USDA-NRI, and USDA county crops data after accounting the crop migration due to climate change as discussed below.

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[24] Due to the uncertainty of factors in the future such as technological progress, economic growth, and policies related to transportation, agricultural and energy, this study fixes all parameters and demand for grains to their current level (base year). Also we did not include feedback in ASM in the form of IGTM generated transportation cost shifts. The study allows only the possibility of northward shift of crop production patterns and the change in grain yields.

[25] Development of a CRD-level counterpart to the ASM crop mix would not be necessary if we could use CRD as the ASM spatial specification. However, not only would such a model be very large but developing/maintaining production budget, crop mix and resource data for such a scale would be a monumental undertaking.

The fundamental choice variable in the downscaling model is the acres of each crop allocated to each irrigation status in each county. The choice variable is constrained so it matches the land area shift in ASM, but minimally deviates from the observed data. More specifically, eight criteria listed below minimally deviated from the model:

- Total modeled acres farmed in a county do not exceed maximum observed.
- Total modeled acres farmed in a county are at least as high as the minimum observed.
- Total modeled irrigated acres in a county do not exceed maximum observed.
- Total modeled acres of an individual crop in each county does not exceed maximum observed.
- Total modeled acres of an individual crop in each county are at least as high as the minimum observed.
- Total acres allocated to each crop by irrigation status across all counties in an ASM region have to equal the totals that were in the ASM solution for the region.
- Total acres farmed in a county are constrained to minimally deviate from an interpolated county crop mix developed by interpolation between the periodic NRI and census data using agricultural statistics for the whole state following McCarl (1982).
- The ratio of total acres of an individual crop relative to total acres of the same crop in all adjacent counties is required to equal the historical average ratio between the counties.

The downscaling model chooses the county land allocation minimizing the sum of the deviations from all of the above criteria. This model is run for 14 crops in ASM.[26] The resulting crop mix and total production numbers at the county level are then aggregated to the CRD level and passed to IGTM. However, our study cannot rely purely on deviations from historical data since climate change introduces the possibility of crop expansion into new production areas[27] (Figure 4), depicting national production of corn and soybeans moving about 100 and 138 miles northwest during 1950-2010. To account for this possibility, the study applies a method based on econometric results developed by Adams et al. (1999) where a proportion of the acreage in each county for shift of the crop mix in the immediately Southern area was identified and such shifts then allowed in the historical Census, NRI and USDA data as explained in Appendix B.

Then we employ results from the downscaling model to calculate the CRD level grain supplies using the climate change-adjusted yields and the CRD acreage data arising from each climate change scenario. We then form excess supply/demand by subtracting the CRD-level grain demand[28] from grain supply. The generated excess demands and supplies of grain in each CRD are then entered into IGTM.

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[26] including barley, corn, cotton, forage production, oats, peanuts, potatoes, rice, rye, sorghum, soybeans, sugarbeets, tomatoes, and wheat.

[27] The regionalizing downscaling of Atwood et al. (2000) disaggregated the solution of crop mixes and crop acreage from sector model to the county level by fixing crop mix and crop acreage solutions close to the county level historical crop mix, which cannot fully account for items which are expected to fall significantly outside the range of historical observation.

[28] Demand for grains in the IGTM is estimated using 2007/2008 marketing year. Demand for corn is the summation of seed use, consumption for feed purposes, and consumption for food, alcohol, and industrial use, while demand for soybeans includes soybean crush and seed, feed, and residual use (please see more details in Chapter IV).

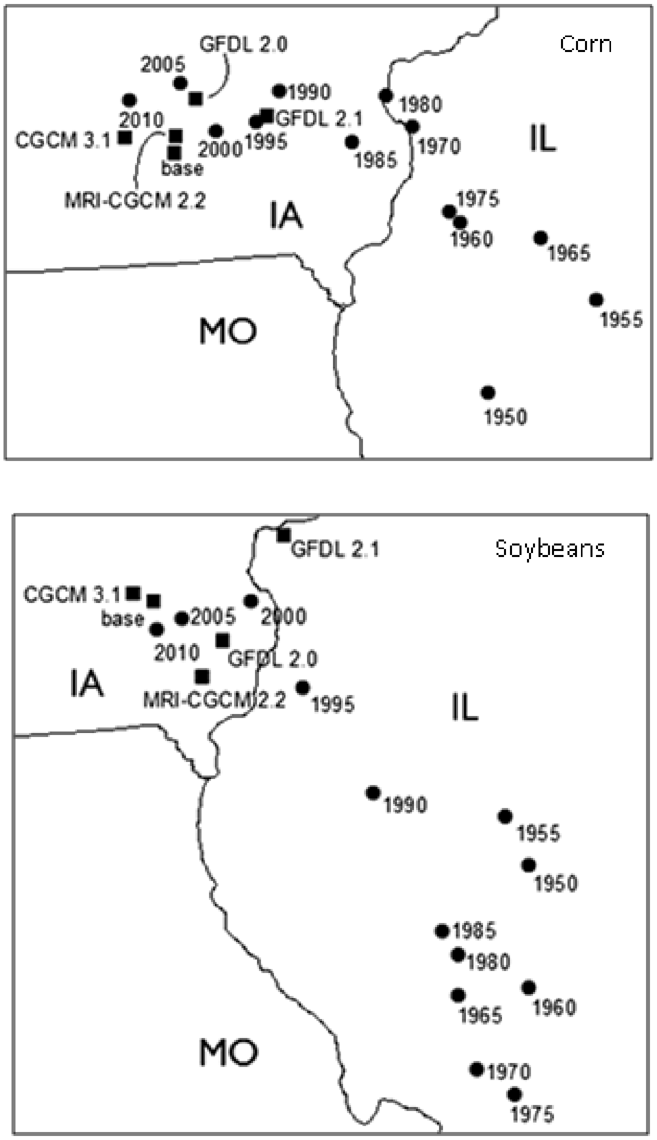

Figure 4. Production-weighted central location of U.S. grain production in 1950–2010 based on historical data, under the baseline scenario in 2007/2008, and under climate change scenarios from GCM cases in 2050[29]

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[29] The difference between production and supply of grains in this study is the beginning stock. That is, the summation of production and beginning stock of grains is the supply of grains. In the analysis of transportation flows it is necessary to take into account both production and beginning stock of the commodity.

Results

Two types of results arise, the first involves the magnitude of the crop mix shifts and the second the transport implications. Both are presented.

Crop Mix Shifts

The projected changes in the overall crop mix under different climate scenarios are summarized in Table 9. The results are generally consistent with the simulated change in crop yields as presented in the previous section. GFDL 2.1 projects a decrease in crop production due to the projected drop in crop yields, thus leading to the rise in crop prices. In contrast, MRI-CGCM 2.2 predicts the increase in overall crop production, which leads to the decrease in crop prices. Corn production is projected to increase only under MRI-CGCM 2.2, while soybean production is projected to increase in three out of four GCM cases. Total national cropland use increases with the expansion of irrigated land and contraction of dryland. Dryland corn production remains constant in all GCM cases, while for soybeans it tends to increase (except under GFDL 2.1). On irrigated land, both corn and soybeans are projected to increase (except under GFDL 2.1 for soybeans).

Supply Locations of Grains

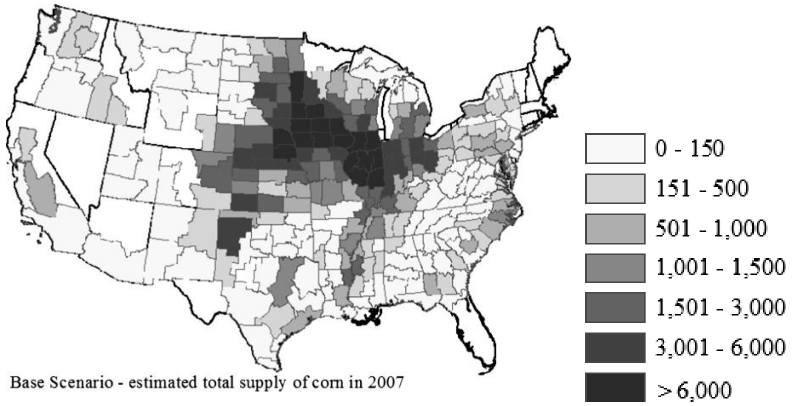
Estimated total supplies of corn and soybeans for the baseline scenario and GCM cases simulated in 2050 are shown in Figure 5 and Figure 6, respectively.

Table 9. Summary of Agricultural Activities and Cropland Use

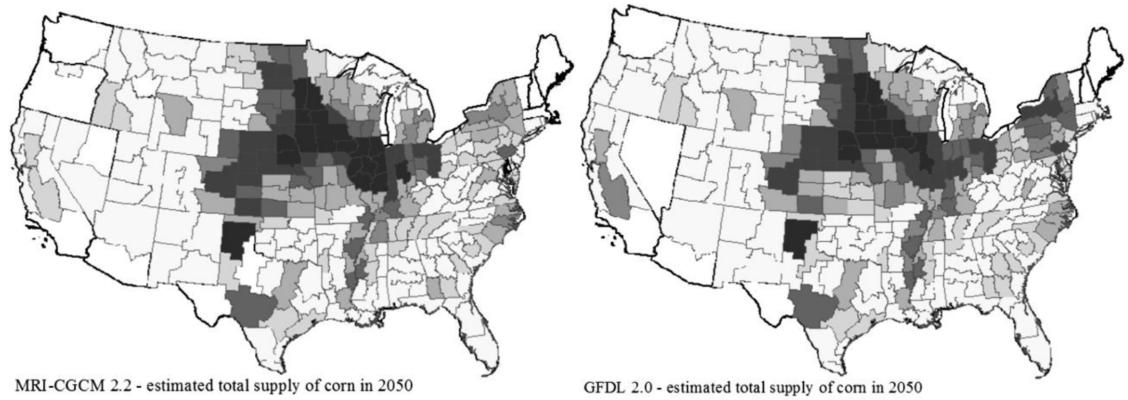
	Baseline	MRI-CGCM 2.2	GFDL 2.0	GFDL 2.1	CGCM 3.1
Agricultural Activities (index: base=100)					
Production of all crops	100.00	117.74	100.79	92.19	106.68
Production of corn	100.00	109.27	93.39	82.84	89.98
Production of soybeans	100.00	130.10	105.87	86.05	103.80
Price of all crops	100.00	94.58	105.72	106.11	100.00
Price of corn	100.00	90.93	103.71	108.01	94.61
Price of soybean	100.00	92.07	100.00	101.19	97.16
Crop Land Use (10,000 acres)					
Corn, irrigated land	999.72	1,205.22	1,369.07	1,367.75	1,431.16
Corn, dryland	6,904.38	6,904.38	6,904.38	6,904.38	6,904.38
Corn, total land use	7,904.10	8,109.60	8,273.45	8,272.13	8,335.54
Soybean, irrigated land	268.46	383.31	363.72	257.74	342.16
Soybean, dryland	4,686.83	5,412.47	4,633.24	4,746.42	4,981.61
Soybean, total land use	4,955.29	5,795.78	4,996.96	5,004.16	5,323.77
All crops, irrigated land	3,838.79	4,175.91	4,093.00	4,321.34	4,191.75
All crops, dryland	26,461.35	26,138.12	26,253.13	26,006.19	26,154.38
All crops, total land use	30,300.14	30,314.02	30,346.13	30,327.53	30,346.13

The principal results are:

- Under climate change, overall supply of corn and soybeans increases in Northern regions, while it tends to decline in some areas in the Southern regions of the U.S. This finding is consistent with the projected increase in temperature across U.S. regions under climate change scenarios (e.g., IPCC 2007a), which could damage crop production in the Southern part, while likely to be beneficial to crop production in the Northern part.

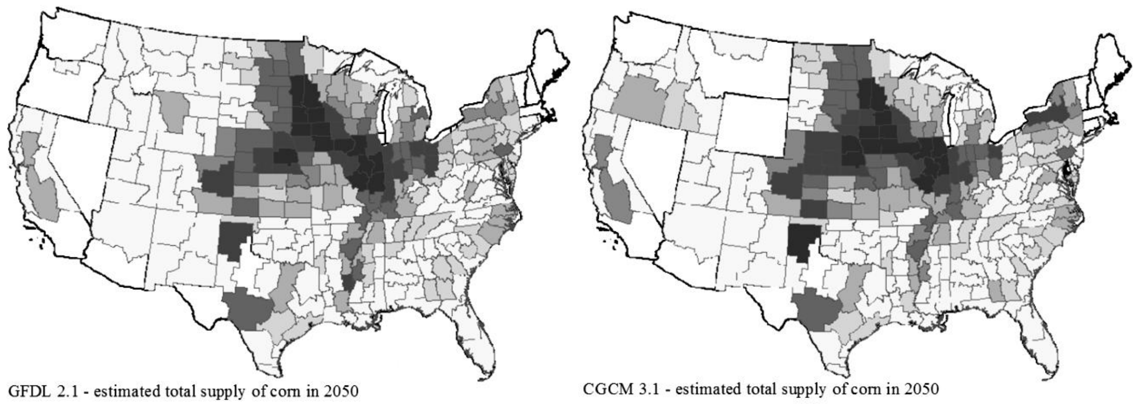


Base Scenario - estimated total supply of corn in 2007



MRI-CGCM 2.2 - estimated total supply of corn in 2050

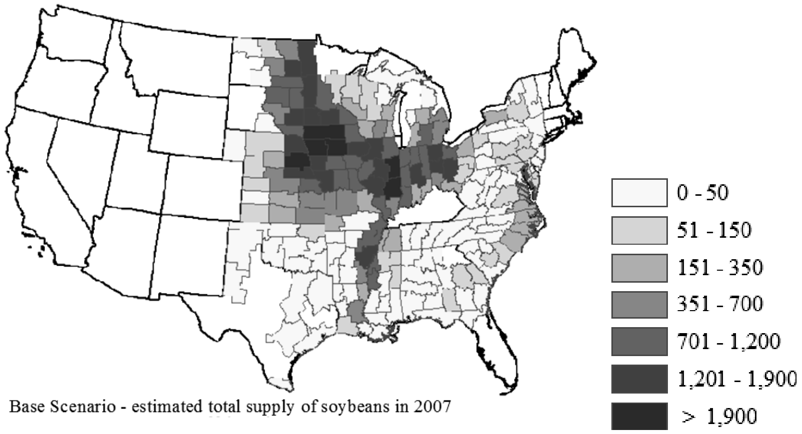
GFDL 2.0 - estimated total supply of corn in 2050



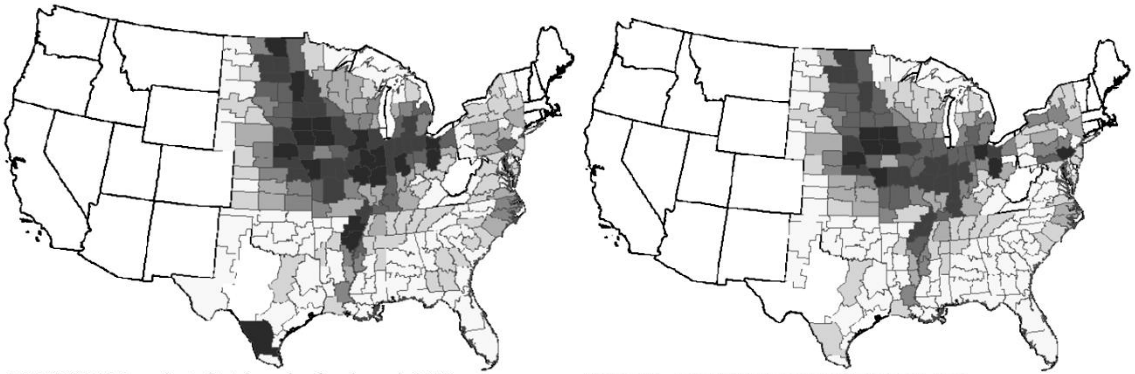
GFDL 2.1 - estimated total supply of corn in 2050

CGCM 3.1 - estimated total supply of corn in 2050

Figure 5. Estimated total supply of corn (1,000 tonnes) for the baseline scenario in 2007/2008 marketing year and under GCM cases in 2050

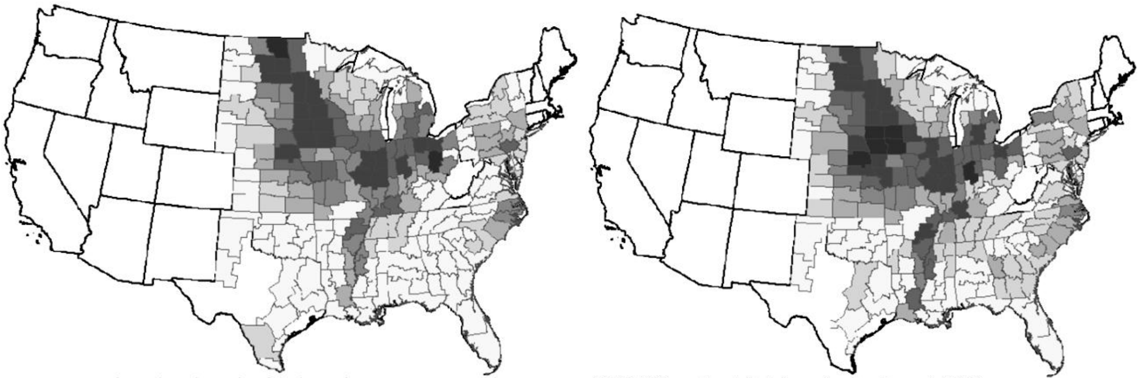


Base Scenario - estimated total supply of soybeans in 2007



MRI-CGCM 2.2 - estimated total supply of soybeans in 2050

GFDL 2.0 - estimated total supply of soybeans in 2050



GFDL 2.1 - estimated total supply of soybeans in 2050

CGCM 3.1 - estimated total supply of soybeans in 2050

Figure 6. Estimated total supply of soybeans (1,000 tonnes) for the baseline scenario in 2007/2008 marketing year and under GCM cases in 2050

- For corn, the GCM cases provide mixed results. Nevertheless, generally corn supply is projected to increase in Colorado, Wyoming, North Dakota, South Dakota, upper Nebraska, Minnesota, Connecticut, New Jersey, New York, Pennsylvania, Rhode Island, and California, while it declines in Arizona, New Mexico, and Kansas.
- For traditional locations of corn especially the Corn Belt, three out of four GCM cases project a decline in corn supply (except for Ohio). Finally, corn is likely to expand into new production areas including Connecticut, Rhode Island, Massachusetts, parts of Idaho, Oregon, Montana, Northern part of Arkansas, Minnesota, Colorado, and California (Figure 5).
- For soybeans, the MRI-CGCM scenario indicates an increase in supply across all U.S. regions, while the other GCM cases provide mixed results. All GCM cases predict an increase in soybean supply in Pennsylvania, New Jersey, North Dakota, Michigan, Indiana, and Texas. On the other hand, supply of soybeans is projected to fall in Maryland, West Virginia, South Dakota, Virginia, Florida, Mississippi, and Oklahoma. Moreover, soybean supply in Corn Belt, a traditional supply location, is predicted to fall under GFDL 2.1 and CGCM 3.1, but rise under MRI-CGCM 3.1 and GFDL 2.0. Finally, this study finds that the supply of soybeans is likely to expand in Kentucky, Northern Minnesota, Georgia, and the Western part of South and North Dakota (Figure 6).
- Figure 4 also shows the supply-weighted centroid of U.S. grain supply under the baseline scenario and climate change scenarios in 2050 from GCM cases. For

corn, we find that by 2050 climate change is likely to induce a further movement in the centroid of about 20 miles. For soybeans, the centroid is projected to shift northward about 18 miles.[30]

Demand Destinations for Grains

Figure 7 shows estimated CRD-level quantity demanded for corn and soybeans in 2007/2008 marketing year. The Corn Belt has the largest share of grain domestic demand accounting for 37 and 59 percent for corn and soybeans, respectively. More than half of the Corn Belt's quantity demanded comes from Iowa and Illinois. Great Plains and Lake States as well as South Central and Southeast regions are also major destinations.

Excess Supply and Demand Locations for Grains

The estimated excess supply and demand for grains are shown in Figures 8 and Figure 9. Although some locations produce a large volume of grains as shown in Figure 5 and Figure 6, after taking into account their local demand for grains (Figure 7) we find a northward shift in locations of excess supply with more southern regions tending toward increases in excess demand.

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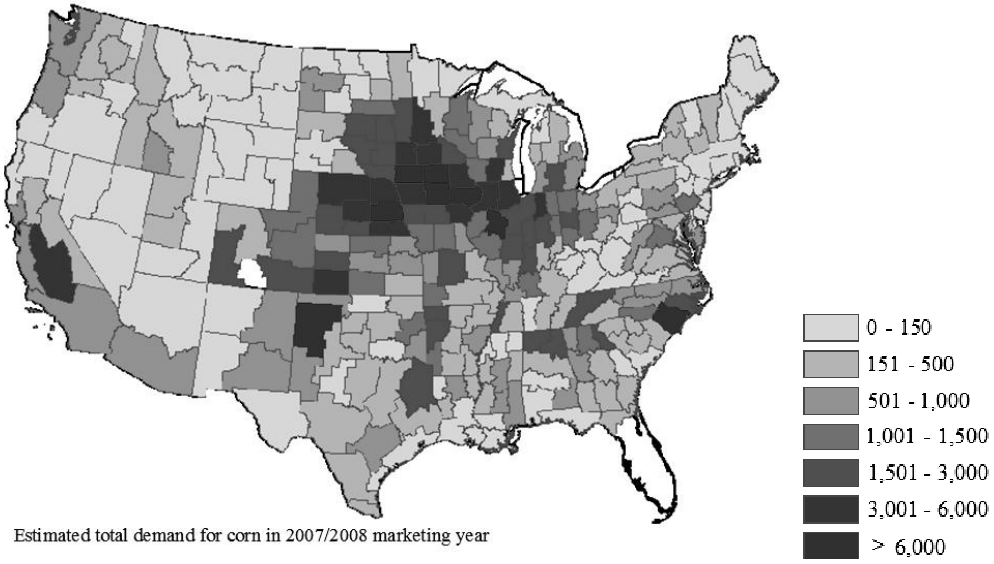
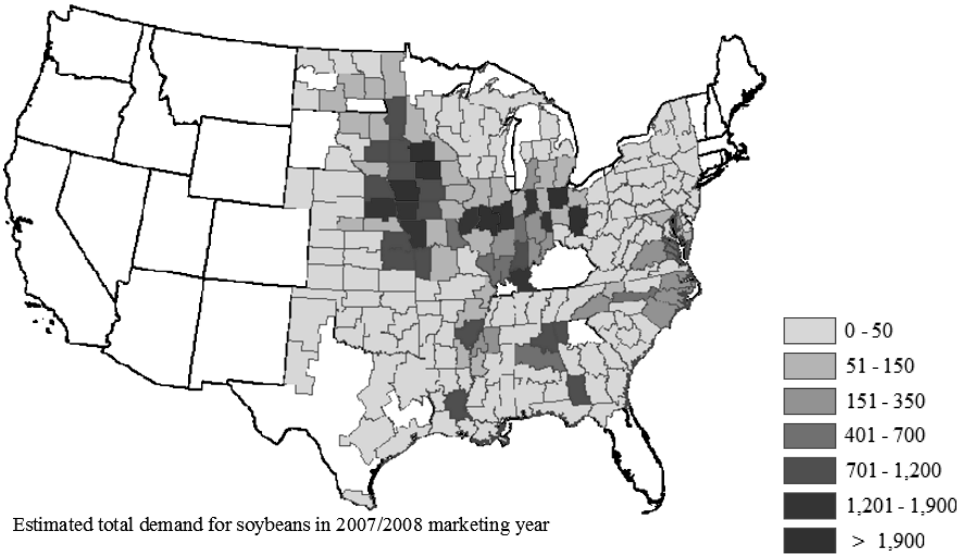
[30] It is worth mentioning that the distances of corn and soybeans movements in this study are lower than what were found in their historical movements as illustrated in the same figure (Figure 4) since this study fixes all factors affecting corn and soybean production such as technological progress to their current level in the base year, and allows only the effect of the northward shift of crop production patterns and the change in grain yields.

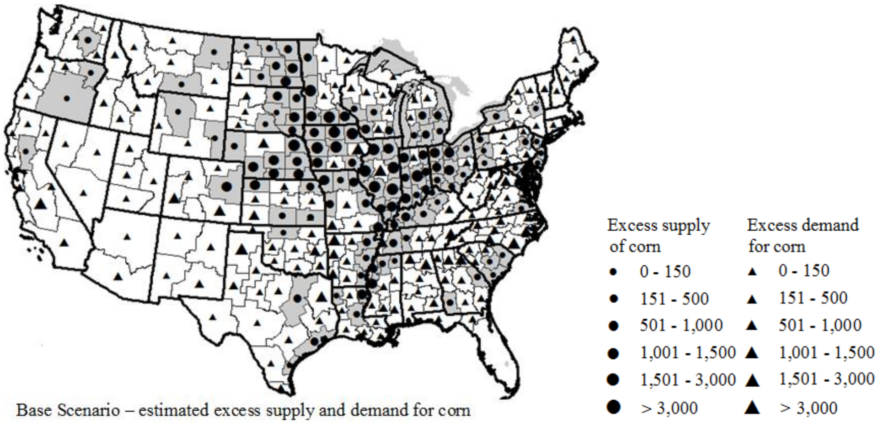


Estimated total demand for corn in 2007/2008 marketing year

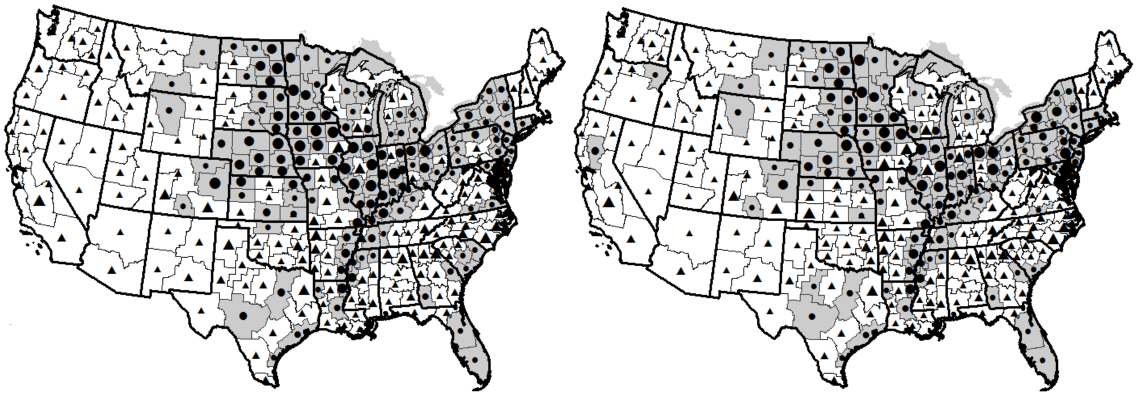


Estimated total demand for soybeans in 2007/2008 marketing year

Figure 7. Estimated total demand for corn and soybeans (1,000 tonnes) in 2007/2008 marketing year

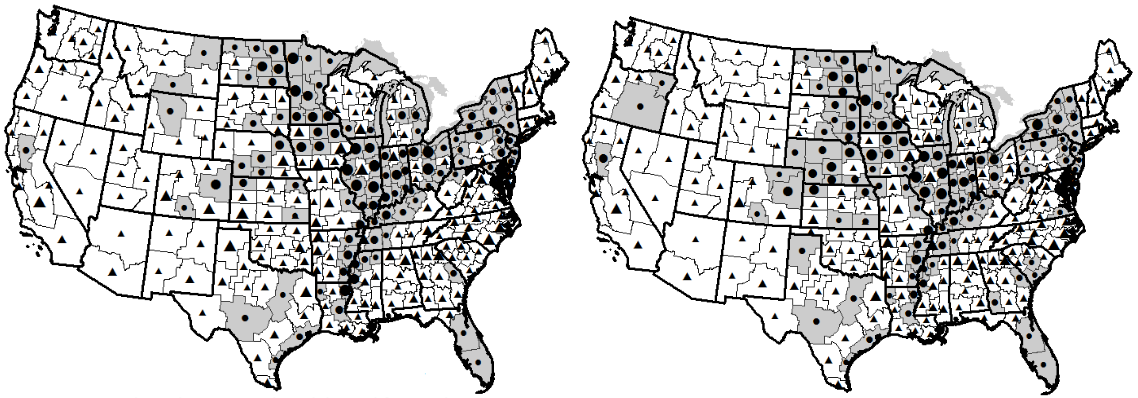


Base Scenario – estimated excess supply and demand for corn



MRI-CGCM 2.2 - estimated excess supply and demand for corn in 2050

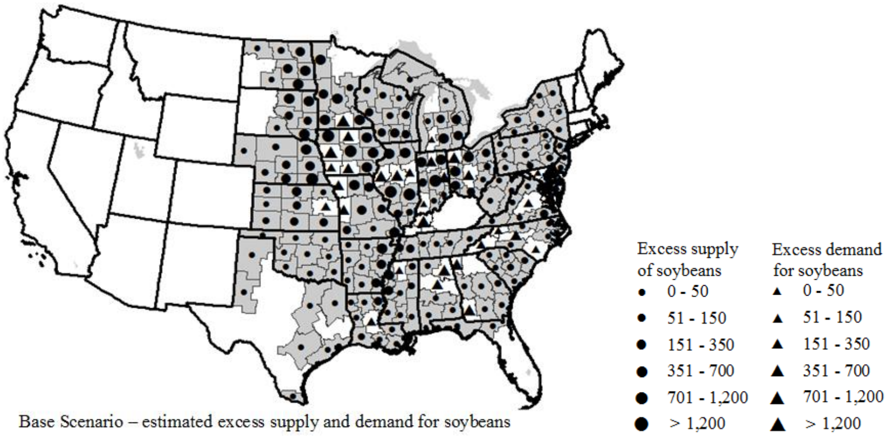
GFDL 2.0 - estimated excess supply and demand for corn in 2050



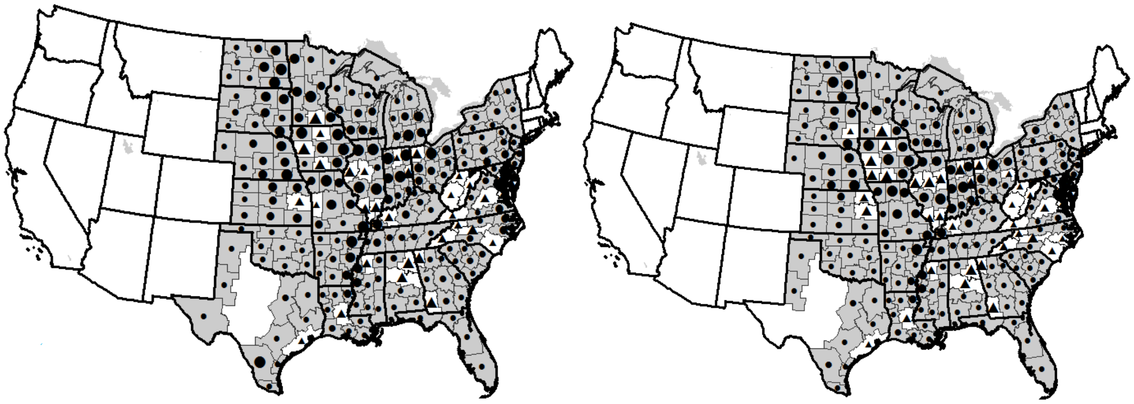
GFDL 2.1 - estimated excess supply and demand for corn in 2050

CGCM 3.1 - estimated excess supply and demand for corn in 2050

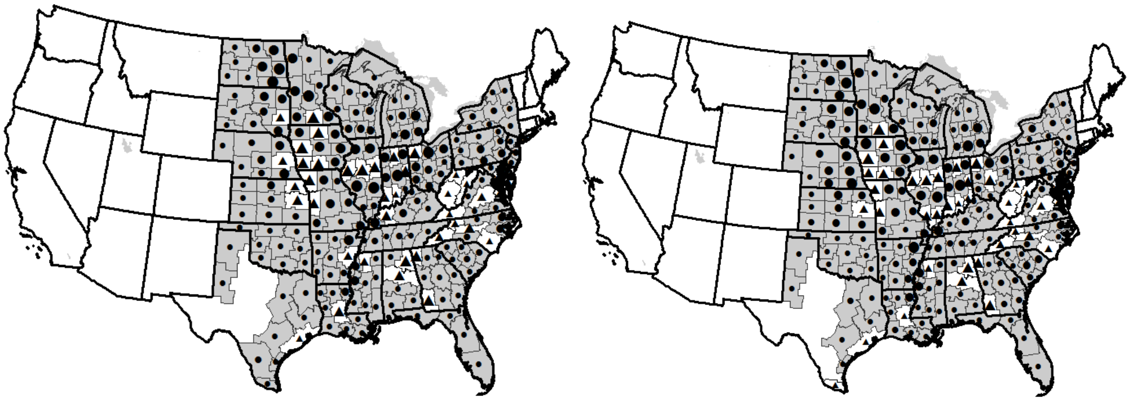
Figure 8. Excess supply and demand for corn (1,000 tonnes) for the baseline scenario in 2007/2008 marketing year and GCM cases in 2050



Base Scenario – estimated excess supply and demand for soybeans



MRI-CGCM 2.2 - estimated excess supply and demand for soybeans in 2050 GFDL 2.0 - estimated excess supply and demand for soybeans in 2050



GFDL 2.1 - estimated excess supply and demand for soybeans in 2050 CGCM 3.1 - estimated excess supply and demand for soybeans in 2050

Figure 9. Excess supply and demand for soybeans (1,000 tonnes) under the baseline scenario in 2007/2008 marketing year and GCM cases simulated in 2050

Transportation Flows

Climate change alters the volume of grain produced in each region and the geographic distribution of excess supply and demand locations are changed and we now examine how these outcomes affect the pattern of grain transportation flows. Table 10 and Table 11 summarize the simulated interregional transportation flows of corn and soybeans, respectively in all GCM cases. See Figure 10 to identify U.S. regions and exporting channels included in flow summary.

Corn Flows

In Table 10, all GCM cases show the Corn Belt, the largest producer of corn in the U.S. and the source to 57 percent of all U.S. interregional corn shipments in the base model to ship less corn in 2050. In particular, all GCM cases show the Corn Belt's shipments to the Pacific[31], Northeast, Rocky Mountains, and Southeast regions and the lower Mississippi River ports to decline. Moreover, three GCM cases show the Corn Belt's corn shipments to the South Central region and Pacific Northwest ports are reduced. Shipments to lower Mississippi River ports comprise 34 percent of the Corn Belt's total shipments in the base model, while about 20 and 15 percent of all shipments in the base model are to the Southeast and South Central regions, hence the Corn Belt's important interregional corn flows are projected to be altered by climate change. GCM cases show no unanimous agreement regarding increasing interregional corn flows from the Corn Belt. However, three GCM cases suggest increased flows to Great Lakes ports,

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[31] Due to the low volume of grain shipments from Pacific Southwest and Pacific Northwest to all excess demand locations and to save the space, we merge these two regions and call them as "Pacific" region.

Table 10. Interregional Transportation Flows of Corn (1,000 tonnes) in 2050 under Different GCM cases Compared to the Baseline Scenario

Source	Destination	Baseline	MRI-CGCM 2.2	GFDL 2.0	GFDL 2.1	CGCM 3.1
Corn Belt	Corn Belt	12,188	11,931	20,680	17,921	18,100
	Great Plains	2,629	396	5,882	4,289	1,297
	Lake States	43	86	243	-	2,955
	Pacific	5,257	5,255	-	-	998
	Northeast	2,114	1,460	525	494	1,173
	Rocky MT	1,481	1,077	9	884	631
	Southeast	16,777	14,768	8,920	12,430	9,872
	South Central	12,382	15,249	9,843	8,565	10,051
	Southwest	2,597	2,679	2,191	3,709	2,094
	Lower Miss Ports	29,114	26,165	6,730	12,861	14,840
	PNW Ports	193	1,057	-	-	-
	Great Lakes Ports	602	1,729	2,946	2,501	497
	Atlantic Ports	-	-	-	724	-
	Interior, Mexico	-	-	-	1,031	-
	All Regions	85,377	81,852	57,969	65,409	62,508
Great Plains	Corn Belt	-	44	-	-	589
	Great Plains	2,831	1,273	2,009	1,508	2,160
	Pacific	1,305	2,651	5,275	1,451	3,689
	Rocky MT	2,598	2,838	1,803	346	1,877
	South Central	-	469	-	-	-
	Southwest	6,284	3,464	1,272	3,132	2,115
	Texas Gulf Ports	-	-	2,437	-	1,735
	PNW Ports	9,746	11,608	13,954	7,386	14,343
	Interior, Mexico	6,347	7,071	5,513	2,370	4,859
	Interior, Canada	226	931	1,460	1,405	1,445
	All Regions	29,338	30,348	33,723	17,599	32,812
Lake States	Corn Belt	1,111	120	-	1,618	-
	Great Plains	227	213	-	2,420	125
	Lake States	2,285	3,654	4,432	3,316	4,658
	Pacific	1,521	1,480	1,586	5,798	1,296
	Northeast	619	-	-	-	-
	Rocky MT	1,457	1,026	1,843	2,241	1,358
	Southeast	1,232	386	-	1,779	-
	South Central	684	696	1,064	-	1,045
	Southwest	-	-	943	2,555	-
	Lower Miss Ports	4,238	2,847	6,433	1,366	4,460
	PNW Ports	1,400	5,283	6,156	6,830	4,461
	Great Lakes Ports	-	72	56	-	68
	Atlantic Ports	543	50	-	71	-
	Interior, Mexico	-	-	-	171	-
	Interior, Canada	1,692	657	-	-	-
	All Regions	17,009	16,484	22,513	28,165	17,471

Table 10. Continued

Source	Destination	Baseline	MRI-CGCM 2.2	GFDL 2.0	GFDL 2.1	CGCM 3.1
Rocky MT	Pacific	-	-	23	-	-
	Rocky MT	1,893	3,207	3,646	3,508	3,076
	All Regions	1,893	3,207	3,668	3,508	3,076
Pacific	Pacific	88	-	698	482	1,367
	Rocky MT	196	-	1	-	157
	PNW Ports	339	-	-	-	452
	All Regions	623	-	699	482	1,977
Northeast	Northeast	1,006	2,447	1,772	2,438	2,595
	Southeast	208	2,518	9,774	3,320	7,164
	Atlantic Ports	-	5	4,441	790	5
	Interior, Canada	389	786	820	775	801
	All Regions	1,603	5,757	16,806	7,323	10,565
Southeast	Northeast	96	-	-	-	-
	Southeast	797	782	289	267	667
	South Central	-	-	-	-	8
	Atlantic Ports	164	126	-	-	78
	All Regions	1,057	908	289	267	753
South Central	Southeast	160	162	752	656	413
	South Central	5,818	5,629	7,950	9,225	7,711
	Southwest	-	-	-	394	-
	Lower Miss Ports	4,892	4,124	4,340	7,079	2,159
	All Regions	10,870	9,915	13,042	17,354	10,283
Southwest	Southwest	404	894	815	702	1,064
	Texas Gulf Ports	1,616	904	385	387	612
	All Regions	2,020	1,798	1,200	1,089	1,676
All Regions	All Regions	149,791	150,269	149,911	141,196	141,124

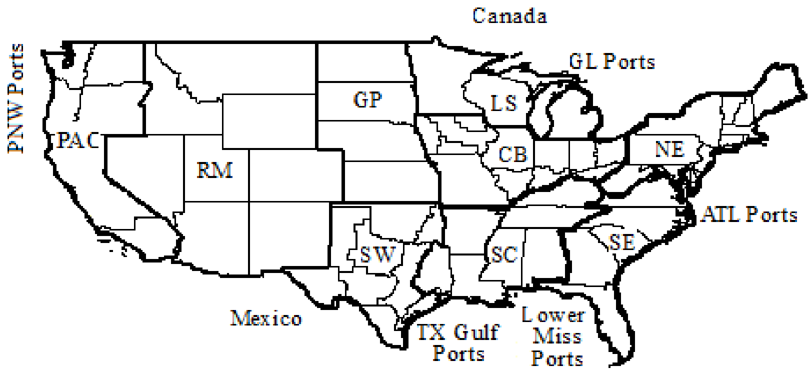

Figure 10. U.S. regions and exporting channels used in the study

Note: CB –Corn Belt; GP –Great Plains; LS –Lake States; RM –Rocky Mountain; PAC –Pacific; NE –Northeast; SE –Southeast; SC –South Central; SW –Southwest; PNW Ports –Pacific Northwest Ports; TX Gulf Ports –Texas Gulf Ports; Lower Miss Ports –Lower Mississippi River Ports; GL Ports –the Great Lakes Ports; and ATL Ports –the Atlantic Ports

Lake States, and back to its own (Corn Belt) region, with shipments back to itself comprising about 14 percent of all Corn Belt shipments.

The Great Plains states, a source to about 20 percent of all interregional corn flows in the base model, is projected to increase corn shipments in three of the four GCM cases. Results under all GCM cases indicate there would be increased shipments to the Pacific region and Canada. Three GCM cases show increased shipments to Pacific Northwest ports comprising about 33 percent of the regions corn shipments. These flows largely come from increased corn supplies in North and South Dakota. All GCM cases concur regarding the Great Plain's declining corn shipments to the Southwest and to own (Great Plains) region, and three GCM cases indicate declining interior shipments to Mexico and to the Rocky Mountains. Importantly, the corn shipments to interior Mexico and the Southwest represent about 22 and 21 percent of the Great Plains corn shipments in the base model, while corn shipments to own region (10 %), Rocky Mountains (9 %) and Pacific (4%) represent lesser flows.

The Lake States rank third among the corn shipping regions sourcing approximately 11 percent of all interregional corn flows in the base model. Three of the four GCM cases results project expanded corn shipments, with all GCM results project expanded regional shipments to own region (Lake States), and Pacific Northwest ports. Further, the solutions under three of the four GCM cases project expanded shipments to South Central and the Great Lakes ports. Noteworthy among expanded interregional flows of the Lake States are those to Pacific Northwest ports with flows projected to increase from 200 to 400 percent as compared to baseline projections, with most of these expanded corn shipments originating in Minnesota. In contrast, the Lake States expanded shipments to its own region (Lake States) are projected to increase 45 to 100 percent. All GCM cases show declining shipments to Northeast, Atlantic ports, and interior Canada, and three of the four GCM cases project declines in shipments to the Corn Belt, Great Plains, and Southeast.

The South Central region, the source of approximately 7 percent of the U.S.'s interregional corn shipments is projected to increase corn shipments in two of the GCM cases. The primary corn shipment (54%) by the South Central states (baseline) is to itself (South Central) and three of the GCM cases project this flow to increase, while the second-ranked flow (45%) is to lower Mississippi River ports and three of the GCM cases project this flow to decrease.

Several additional regions have interesting changes in shipments as a result of climate change. For example, the Northeast region is projected to ship only 1.6 million tonnes of corn in the base model, but this rises to a range of 5.7 to 16.8 million tonnes under 2050 climate change. These expanded shipments are to its own (Northeast) region, Southeast, Atlantic ports, and interior locations in Canada. These expanded flows by the Northeast affect corn shipments by the Corn Belt, Lake States and Great Plains. The Rocky Mountain region is also projected to increase shipments, with virtually all shipments to its own (Rocky Mountain) region.

Discussion

The analysis offers strong evidence that climate change will affect quantities transported over selected transport corridors. For example, the flow of corn from the

Corn Belt to Lower Mississippi River ports to decrease in all cases falling by an estimated 10 to 67 percent. Similarly, all GCM cases show Corn Belt flows to the Southeast to decline from 16.8 million tonnes by an estimated 12 to almost 50 percent, and the analyses further suggest important declines in the Corn Belt’s shipments to the South Central region. In addition, corn flows from the Great Plains to Pacific Northwest ports are projected to increase by as much as 47 percent. For export, the importance of Lower Mississippi ports, the largest destination for corn exports from the U.S. to the rest of the world, is projected to diminish, whereas the role of Pacific Northwest ports is expected to increase.

Climate induced shifts in crop production patterns are likely to generate new transportation flows for corn that do not exist under the current condition. Transportation flows from Illinois to Michigan; Minnesota to New Mexico and Oklahoma; Colorado to Idaho; New York to Maine, North Carolina, and Vermont; Pennsylvania to Delaware and Atlantic ports; and South Dakota to California are examples of these new transportation flows. The increase in excess supplies of corn in the upper regions of U.S. and the decrease in excess supplies of corn in the middle to lower sections of Corn Belt and the Great Plains (Nebraska and Kansas) may be the main reason behind these findings.

Soybean Flows

Table 11 suggests that overall soybean shipments from the Corn Belt, the largest producer of soybeans to regions vary across the GCM cases. However, all GCM cases show unanimous agreement regarding increasing interregional soybean flows from the

Corn Belt to the Southeast and the Northeast, plus the Great Lakes and Atlantic ports. Moreover, three GCM cases demonstrate increasing Corn Belt shipments to the Lakes States, but less soybeans to the South Central region.

The Great Plains rank second among the soybean shipping regions sourcing about 25 percent of all interregional soybean flows. Three of the four GCM cases predict expanded overall soybean shipments from the Great Plains. All GCM cases indicate there would be increased shipments to the Pacific region and three GCM cases show increased shipments to the Pacific Northwest ports due to the expected increase in excess soybean supplies in North Dakota and the northern section of Nebraska. On the other hand, the Plains states are projected to ship lower quantities of soybeans to the South Central region (in all GCM cases), and the lower Mississippi River ports in three of the four GCM cases.

The Lake States, a source of about 17 percent of all interregional soybean flows in the base model, is predicted in three of the four GCM cases to ship greater soybeans. Soybean flows from Lake States to Atlantic ports are expected to rise under all GCM cases with flows projected to increase from 40 to 200 percent as compared to baseline shipment, with most of these increased soybean shipments originating in Michigan. Moreover, three of the four GCM cases project the shipments from the Lake States to the Corn Belt and the Great Lakes ports to increase. On the other hand, the primary soybean shipment by the Lake States (baseline) is to the lower Mississippi River ports (25%) and itself (23%) and three of the four GCM cases predict this flow to reduce. All GCM cases project the Lake States reducing soybean shipments to Southeast region.

Table 11. Interregional Transportation Flows of Soybeans (1,000 tonnes) in 2050 under Different GCM cases Compared to the Baseline Scenario

Source	Destination	Baseline	MRI-CGCM 2.2	GFDL 2.0	GFDL 2.1	CGCM 3.1
Corn Belt	Corn Belt	9,016	6,278	8,447	10,915	10,879
	Great Plains	-	-	271	-	-
	Lake States	443	1,255	1,929	-	1,238
	Northeast	-	2	1	1	2
	Southeast	56	915	313	206	99
	South Central	2,558	1,972	2,587	1,356	874
	Lower Miss Ports	9,192	14,816	10,674	6,066	6,290
	Great Lakes Ports	579	1,586	1,356	1,709	506
	Atlantic Ports	182	-	463	226	-
	Interior, Mexico	-	438	-	-	-
	All Regions	22,026	27,262	26,041	20,479	19,888
Great Plains	Corn Belt	1,008	37	1,233	401	2,115
	Great Plains	397	253	698	1,443	354
	Pacific	18	26	37	30	31
	South Central	495	351	150	-	261
	Southwest	-	35	-	235	-
	Lower Miss Ports	1,069	2,114	24	-	907
	PNW Ports	6,856	7,407	7,836	6,053	8,300
	Interior, Mexico	2,596	2,424	2,626	1,892	2,606
	All Regions	12,439	12,647	12,604	10,054	14,574
Lake States	Corn Belt	836	941	597	2,475	1,357
	Great Plains	-	-	-	102	-
	Lake States	1,899	1,811	1,711	2,502	1,450
	Southeast	835	299	670	740	456
	South Central	-	-	-	213	-
	Lower Miss Ports	2,122	1,993	1,422	995	2,452
	PNW Ports	1,804	2,651	669	831	2,002
	Great Lakes Ports	98	280	117	-	543
	Atlantic Ports	731	2,176	1,007	1,569	1,235
	Interior, Mexico	-	-	-	183	-
	All Regions	8,325	10,151	6,193	9,610	9,495
Northeast	Northeast	62	313	356	385	277
	Southeast	780	780	1,324	965	870
	Atlantic Ports	5	7	65	16	8
	Interior, Canada	156	114	338	94	280
	All Regions	1,003	1,215	2,083	1,459	1,435

Table 11. Continued

Source	Destination	Baseline	MRI-CGCM 2.2	GFDL 2.0	GFDL 2.1	CGCM 3.1
Southeast	Northeast	18	-	-	5	7
	Southeast	554	1,010	252	652	1,020
	Atlantic Ports	225	387	120	328	328
	All Regions	796	1,397	372	985	1,355
South Central	Southeast	1,545	1,581	1,571	1,283	1,513
	South Central	732	682	845	1,582	747
	Southwest	-	1	2	1	1
	Lower Miss Ports	2,832	4,414	4,528	1,073	4,570
	Texas Gulf Ports	10	-	12	-	-
	All Regions	5,119	6,678	6,958	3,939	6,831
Southwest	South Central	3	-	17	-	-
	Southwest	-	-	-	45	1
	Lower Miss Ports	134	1,236	59	17	69
	Texas Gulf Ports	41	869	87	139	6
	Interior, Mexico	45	139	91	340	81
	All Regions	223	2,244	254	541	157
All Regions	All Regions	49,931	61,593	54,505	47,069	53,736

The South Central region, accounting for approximately 10 percent of all interregional soybean flows in the base model, is projected to increase soybean shipments in three of the four GCM cases. Similarly three of the four cases show increasing soybean shipments to the lower Mississippi River ports and itself (South Central), representing 55 and 14 percent, respectively, of the South Central soybean shipments in the base model.

A few other regions have interesting changes in shipments as a result of climate change. The Northeast region is projected to ship soybeans within the region to fill in its own excess demand, and ship higher amount of soybeans to Southeast and Atlantic ports. The Southeast region is projected to ship higher amount of soybeans to their own excess demand locations. The Southeast also ships more soybeans to the Atlantic ports (except under GFDL 2.0). The Southwest is projected to export higher volume of soybeans to Texas Gulf ports (except under CGCM 3.1) and Mexico.

Discussion

Similar to corn, above findings show strong evidence that climate change will affect soybean shipments over selected transport corridors. For example, the flows of soybeans from the Corn Belt to the lower Mississippi ports are reduced up to 34 percent. The analysis further suggests important declines as much as 66 percent by 2050 in the Corn Belt's shipments to South Central region. Furthermore, soybean flows from the Great Plains to Pacific Northwest ports are projected to increase by as much as 21 percent. For soybean export, the role of the lower Mississippi River ports and the Pacific Northwest ports, the first and second largest destinations for current soybean exports, respectively, is inclusive under climate change, whereas the role of small export destinations including the Great Lakes ports, the Atlantic ports, and interior locations in Mexico, is likely to increase.

Similar to corn, climate change is likely to generate higher or new transportation flows for soybean shipments that do not exist under the current conditions. For example, Kentucky would ship soybeans to Alabama, Georgia, North Carolina and lower Mississippi River ports, whereas Maryland would ship soybeans to Atlantic ports and its own excess demand locations. Moreover, Illinois and North Carolina are expected to receive higher amounts of soybeans from itself, and New York, respectively. North Dakota, Ohio, and Michigan are projected to increase their soybean shipments to the

Pacific Northwest ports, the Great Lake ports at Toledo (Ohio), and the Atlantic port at Norfolk (Virginia), respectively.

Demand for Modes of Transportation

Figure 11 shows the shifts in usage modes of transportation for corn, soybeans, and both grains combined under climate change scenarios. Considering both domestic and export shipments, rail has the largest share of grain (both corn and soybeans) transportation between excess supply and demand locations in terms of tonnes and is expected to have an increasing role under climate change scenarios compared to truck and barges. Three out of four GCM cases suggest an increasing demand for trucking of corn, soybeans, and total grain shipments.

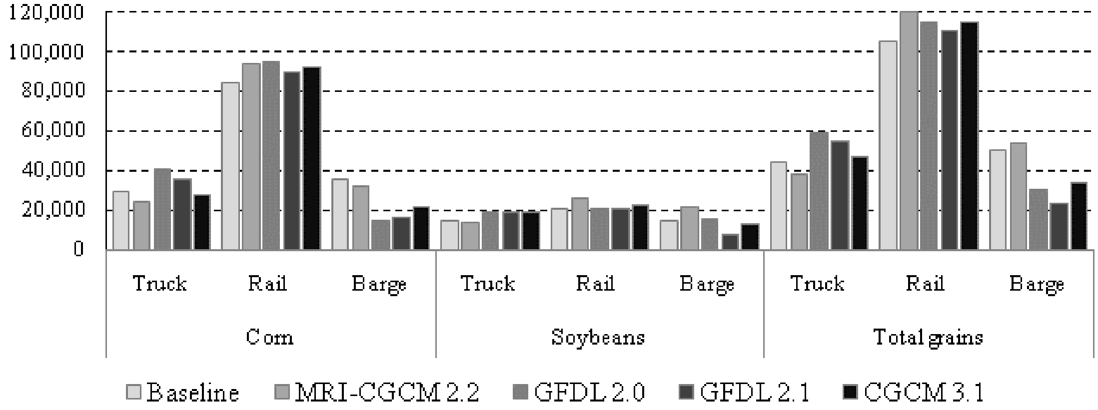

Figure 11. Grain shipments (1,000 tonnes) classified by modes of transportation under different GCM cases in 2050 compared to the baseline

On the other hand, barges are expected to receive fewer grain shipments (under three of the four GCM cases). Demand for barges for corn drops under all GCM cases, while soybean barge shipments are relatively stable. The corn supply reduction in the Corn Belt and lower section of Minnesota is the main reason.

Conclusions

This study investigates the effect of climate change on interregional transportation flows and use of inland waterways in the U.S. Our study finds that overall supply of corn and soybeans would likely increase in the Northern part, while declining in some areas of the Central and Southern U.S. We find the Corn Belt is anticipated to ship less corn to Pacific, Northeast, Rocky Mountains, Southeast, and South Central regions plus the Pacific Northwest and lower Mississippi ports, while the Great Lakes ports and Lake States are expected to receive higher corn shipments.

In terms of export, the importance of lower Mississippi ports is projected to diminish, whereas the role of Pacific Northwest ports is projected to increase. In terms of overall demand for modes of transportation for total grain shipments, demand for rail and truck is expected to rise, while demand for barge mode is projected to drop.

Several clear implications arise:

- Although overall the future demand for barge mode may drop, the upper Mississippi River is likely to receive higher grain transportation shipments due to the predicted increase in the grain supply from the middle to northern parts of Minnesota and North Dakota under climate change. Therefore, enlarging or improving conditions of locks and dams in that segment might be appropriate to speed up passage of barge tows and increase the barge efficiency, which could increase the competitiveness of U.S. grain for export.[32]

- Due to the projected increase in overall demand for rail, many components of the rail infrastructure may need to be upgraded and expanded along the routes that are simulated to have new or higher levels of grain transportation flows. This includes routes from Minnesota and North Dakota to Pacific Northwest ports; New York to North Carolina; Colorado to Idaho; Minnesota to New Mexico and Oklahoma; Nebraska to California; Pennsylvania to Virginia; South Dakota to Texas Gulf ports; Michigan to Atlantic ports.
- To collect grain from rural farmlands in the northern region grain elevators, short line rail track beds and bridge structure could be expanded.[33] To increase the speed of the shipments and their reliability, expanding mainline rail track and increasing the number of sidings should be considered.[34]

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[32] Almost all of locks on the Upper Mississippi River were built between 1930 and 1950, which have standard tows around 600 feet. Standard tows since then have grown from 600 feet to over 1,100 feet. Therefore the standard tow must move through the locks in two passes, requiring break up and reassembly of some tows. Passage through a 1,200-foot lock can take about 45 minutes or less but transiting a 600-foot lock takes approximately 90 minutes, which can produce queuing delays for other barges (Frittelli 2005).

[33] Many short line railroads were formerly part of a main line railroad's network, but they were abandoned by the main line railroad due to low profitability on that route. Before abandonment, the main line railroad typically deferred maintenance on these sections of track. Most importantly and currently, the main line railroads utilize the larger 286,000 pound railcars (Frittelli 2005). Therefore, track beds and bridge structures of these short line railroads cannot support these heavier cars.

[34] A majority of the main line network is single tracked. Currently, railroad main lines (Class I) are experiencing high track utilization rates. Some studies reveal that the privately financed Class I freight railroads are failing to keep pace with the growth in demand for freight transportation capacity (Frittelli 2005).

- Transportation by trucks is also a mode that is projected to receive increasing grain transportation flows. Road infrastructure may need to be expanded and upgraded to accommodate the heavy future truck traffic from areas where grain supply are expected to increase to nearby excess demand locations and ports. Roads in rural areas along the Upper Mississippi River in Minnesota, Ohio River, Arkansas River, and the Lower Mississippi River in Kentucky leading toward nearby barge locations shipped to the lower Mississippi ports; routes in northern parts of Ohio leading toward the Great Lakes ports at Toledo; and roads in Ohio, Pennsylvania, and New York leading toward Atlantic Ports at Norfolk, Virginia, are some of the examples. Finally due to a multifaceted system of grain supply chain, improving intermodal connectors such as truck routes connecting highways with ports and rail terminals might be suitable in those areas.

CHAPTER IV

INTERNATIONAL GRAIN TRANSPORTATION MODEL (IGTM) CONCEPTUAL STRUCTURE AND DOCUMENTATION

Introduction

This chapter describes and documents the transport model used in the previous chapter. Also please note this chapter is written jointly with Zafarbek Ahmedov, who is using the same model in his dissertation. In terms of the chapter it will 1) present detailed description of the INTERNATIONAL GRAIN TRANSPORTATION MODEL **(**IGTM); 2) reveal IGTM's mathematical structure; 3) discuss steps and procedures involved in developing the data set used in the model and 4) present validation information regarding the model.

Model History

The IGTM is the latest version of a model developed by Fuller and colleagues (e.g., Fuller, Fellin, and Grant 1999; Fuller, Fellin, and Eriksen 2000; Fellin et al. 2008). The current version started from a version described in Fellin et al. (2008) with the data updated to reflect the 2007-2008 production year (Vedenov et al. 2010). The current data reflect recent changes in grain demand reflecting growth in the biofuel market along with the cost effects of higher energy prices. The original model and its modified versions have been used in many transportation studies (e.g., Fuller, Fellin, and Grant 1999; Fellin et al. 2001; Fuller, Fellin, and Eriksen 2000; Fuller et al. 2003; Fellin et al. 2008).

The remainder of this chapter is organized as follows. In the second section, the IGTM is briefly described and then the domestic and international excess supply and demand regions for corn and soybeans are described in detail followed by a discussion of domestic and international port locations. Next, we present the mathematical structure of the model and its parameters. The model data, sources, and data processing procedures are discussed in great detail in the fourth section. Finally, in the last section, we compare model-projected results to real world evidences.

Model Description

IGTM is a price-endogenous, spatial equilibrium, mathematical programming model. The IGTM models the world grain trade in corn and soybeans with an objective to maximize the total net welfare, where the total net welfare is determined as sum of producers' and consumers' surplus less the costs associated with transportation, storage, and grain handling activities. The theoretical underpinnings of the model originate from the works of Samuelson (1952), and Takayama and Judge (1971), where Takayama and Judge extended Samuelson’s formulation into multi-commodity quadratic programming problem.

Domestic regional excess demands and supplies, transportation, storage and grain handling rates/charges are modeled at the crop reporting district level in IGTM. Internationally, all foreign trading countries are treated as an excess supply or excess demand region except for Canada and Mexico. Mexico includes five regions (Northwest, Northeast, West, Central, and South) and Canada two regions (East and West). Each region demand, supply, and shipments are modeled on a quarterly basis. In addition, the model depicts modal choice among truck, rail, barge, lake-vessel, and ocean-going ships. In total transportation flows depict grain flows to and from 303 U.S. domestic regions going through 42 U.S. intermediate shipping points and internationally 118 foreign exporting and importing countries/regions.

Each of the domestic and foreign regions in the model is identified either as excess supply or excess demand region plus can be a transshipment region. Excess supply regions have production plus carry-in stocks that exceed consumption, while excess demand regions have consumption that exceeds production and carry-in. The prices for a point that the supply and demand curves are passed through for domestic excess supply regions are average county level country elevator grain prices, while grain prices for foreign excess supply regions are represented by free on board (FOB) ship or rail grain prices. In the domestic portion all grain handling, storage and transportation charges associated with moving grain from country elevators to ports are included in the model.

Grain supply is generated in the fall quarter (northern and southern hemisphere) and carried forward into subsequent quarters incurring storage charges in the domestic and foreign portion of the models. Grain handling costs are incurred at grain storage facilities, such as country elevators, in domestic regions and intermodal transfer facilities (barge loading and unloading facilities, and ports). Interregional trade occurs as a result of the quarterly regional excess demands, transportation costs and sufficient price differentials that provide an incentive for trade.

Shipments in the continental U.S. are modeled as a quarterly and modal dependent transportation network (rail, barge, and truck) that links domestic excess supply regions with barge-loading/unloading sites, domestic excess demand regions and ports where appropriate grain handling and storage charges, and quarterly truck, rail and barge rates apply. Grain barge loading sites on the inland waterways are linked to barge unloading elevators at Texas Gulf ports and barge unloading elevators on the lower Mississippi River, Cumberland River, and Tennessee River by quarterly barge rates.

The barge unloading points on the Texas Gulf and at the lower Mississippi ports incur charges associated with receiving the grain and loading the grain to ocean going vessels, while barge-unloading facilities on Cumberland River and Tennessee Rivers incur costs of receiving and loading grain to truck and rail cars. Domestic excess supply regions are directly linked to excess demand regions and all U.S. ports by truck and rail modes with applicable grain loading (supply region) and unloading charges and quarterly transportation rates. In addition, truck and rail modes connect excess supply regions to river’s barge loading sites or the river's barge unloading elevators to nearby excess demand regions at quarterly rates. Some selected domestic excess supply regions are also linked to foreign excess demand regions in Mexico and Canada with applicable quarterly rail rates. Mexico may also import grain via the ocean port at Veracruz (Southern part of Mexico), which is linked by truck and rail rates to the other five Mexican excess demand regions.

In the base IGTM, the domestic portion includes 126 corn excess supply regions and 181 soybean excess supply regions. It also contains 174 corn excess demand regions and 35 soybean excess demand regions. Geographic regions in the domestic portion of the model are CRDs, generally including ten to twenty counties. The foreign component of IGTM includes 20 corn excess supply regions (exporting countries) and 92 corn excess demand regions (importing countries) as shown in Table 12. For soybeans, internationally, IGTM includes 11 soybean excess supply regions (exporting countries) and 58 soybean excess demand regions (importing countries) as shown in Table 13.

The grain is stored in the excess supply region until it is shipped via the transportation/logistic network to other locations. The stored grain can be shipped to barge loading elevators that are linked to barge unloading elevators. Included in the model are 32 barge loading/unloading sites on the upper Mississippi (7), Illinois (3), Missouri (6), Arkansas (3), Ohio (4), lower Mississippi (5), Cumberland (1), White (1) and Tennessee (2) Rivers. River elevators at these sites are barge-loading facilities with the exception of the two sites on the Tennessee River (Huntsville and Knoxville) and a site on the Cumberland River (Nashville) that may both ship and receive grain. In the base model, the upper Mississippi River elevators are closed above St. Louis during the winter in order to account for river freezing.

Domestic excess supply regions are also linked by quarterly truck and rail rates to the port elevator locations: lower Mississippi, Texas Gulf, Atlantic, Pacific Northwest, and the Great Lakes. In the model, these ports (except for the Great Lakes ports) can ship directly to foreign excess demand regions at quarterly bulk grain carrier rates.

Table 12. Foreign Corn Excess Supply and Demand Regions

Regional Status	Region/Country
Excess Supply Regions (Exporting Countries)	Argentina, Australia, Bolivia, Brazil, Burma, Cambodia, China, India, Kazakhstan, Malawi, Moldova, Nigeria, Paraguay, Serbia, South Africa, Tanzania, Thailand, Uganda, Ukraine, and Zambia
Excess Demand Regions (Importing Countries)	Canada East, Canada West, Mexico Northwest, Mexico Northeast, Mexico West, Mexico Central, and Mexico South, Albania, Algeria, Angola, Azerbaijan, Belarus, Belgium, Bosnia Herzegovina, Botswana, Bulgaria, Cameroon, Cape Verde, Chile, Colombia, Costa Rica, Croatia, Cuba, Cyprus, Czech Republic, Denmark, Dominican Republic, Ecuador, Egypt, El Salvador, France, Georgia, Germany, Ghana, Greece, Guatemala, Guyana, Honduras, Hong Kong, Indonesia, Iran, Iraq, Israel, Italy, Jamaica, Japan, Jordan, Kenya, North Korea, South Korea, Kuwait, Kyrgyzstan, Lebanon, Lesotho, Libya, Lithuania, Macedonia, Malaysia, Malta, Morocco, Mozambique, The Netherlands, Nicaragua, Norway, Pakistan, Panama, Peru, The Philippines, Poland, Portugal, Ireland, Romania, Russia, Saudi Arabia, Senegal, Singapore, Slovakia, Somalia, Spain, Swaziland, Switzerland, Syria, Taiwan, Trinidad and Tobago, Tunisia, Turkey, United Kingdom, Uruguay, Venezuela, Vietnam, Yemen, and Zimbabwe.

On the other hand, the Great Lakes ports can only ship grain to Ports at Montreal (Canada) using vessels (lakers). Then the grain is unloaded from lakers at St. Lawrence River elevators in Montreal and subsequently loaded onto large ocean going bulk grain carriers that travel to foreign excess demand regions. The Great Lake ports are assumed closed during the winter months due to freezing.

Table 13. Foreign Soybean Excess Supply and Demand Regions

Regional Status	Region/Country
Excess Supply Regions (Exporting Countries)	Argentina, Australia, Brazil, Canada East, Canada West, Ecuador, India, Paraguay, Uganda, Ukraine, and Uruguay
Excess Demand Regions (Importing Countries)	Bangladesh, Barbados, Bolivia, Belgium, Bosnia Herzegovina, Chile, China, Colombia, Costa Rica, Croatia, Cuba, Denmark, Egypt, France, Germany, Greece, Guatemala, Hungary, Indonesia, Iran, Israel, Italy, Japan, North Korea, South Korea, Malaysia, Mexico Northwest, Mexico Northeast, Mexico West, Mexico Central, Mexico South, Morocco, the Netherlands, Nigeria, Norway, Pakistan, Panama, Peru, the Philippines, Portugal, Ireland, Romania, Russia, Serbia, Singapore, South Africa, Spain, Sweden, Switzerland, Syria, Taiwan, Thailand, Turkey, United Arab Emirates, United Kingdom, Uzbekistan, Venezuela, and Vietnam

Representative foreign ports are associated with foreign corn excess demand regions and include Odessa, Ukraine, for Ukraine and Moldova corn exports; Durban, South Africa, for corn exports from South Africa; Madras, India, for corn exports of that country; Bangkok, Thailand, for corn exports from Burma, Cambodia, and Thailand; Shanghai, China, for corn exports from China; Buenos Aires, Argentina for corn exports from Argentina; and Santos (Sao Paulo), Brazil, for exports from Bolivia, Brazil, and Paraguay. In the soybean portion of the model, most of the same ports are used with the addition of Buenos Aires, Argentina as the representative port for Uruguay. Canada exports through Vancouver and the St. Lawrence River ports (Quebec) plus India shipments via Madras.

Representative foreign ports for foreign corn excess demand regions (importers) include Rotterdam for European Union North; Barcelona, Spain for Western Europe; Bari, Italy for Southeast Europe; Odessa, Ukraine for Eastern Europe; Haifa for East Mediterranean; Algiers for North Africa; Damman for Persian Gulf; Singapore for Southeast Asia; Kaohsiung for Taiwan; Ulsan for Korea; Yokohama for Japan; Veracruz for Mexico; Callao for West South America; Puerto Cortes for Central America; and Maracaibo for Caribbean/North South America. For soybeans, the primary foreign ports and associated excess demand regions include Rotterdam for European Union North; Barcelona, Spain for Western Europe; Bari, Italy for Southeast Europe; Odessa, Ukraine for Eastern Europe; Haifa for East Mediterranean; Dammam for Persian Gulf; Singapore for Southeast Asia; Kaohsiung for Taiwan; Ulsan for Korea; Yokohama for Japan; Shanghai for China; and Veracruz for Mexico.

Structure of the Model

IGTM is a spatial equilibrium model that is of the following form:

$$(6) \qquad \mathbf{Max} - \sum_{i \in l,g,q} \int \boldsymbol{\alpha}(\mathbf{S}_{igq})\mathbf{dS}_{igq} + \sum_{j \in l,g,q} \int \boldsymbol{\varphi}(\mathbf{D}_{jgq})\mathbf{dD}_{jgq} - \sum_{i,j,g,q,m} \mathbf{tc}_{ijgqm} * \mathbf{Transport}_{ijgqm}$$

$$- \sum_{l,g,q} \mathbf{s}_{lgq} * \mathbf{I}_{lgq} - \sum_{l,g,q,m} \mathbf{cul}_{lgqm} * \mathbf{Fromtran}_{lgqm} - \sum_{l,g,q,m} \mathbf{cl}_{lgqm} * \mathbf{Totran}_{lgqm}$$

$$- \sum_{l,g,q,m,m1} \mathbf{CMS}_{lgqmm1} * \mathbf{ModeShift}_{lgqmm1}$$

Subject to

$$(7)\qquad \mathbf{D}_{jgq} + \sum_{m} \mathbf{Totran}_{lgqm} + \mathbf{I}_{lgq} \le \mathbf{S}_{igq} + \sum_{m} \mathbf{Fromtran}_{lgqm} + \mathbf{S}_{igq(-1)} \quad \forall l, g, q$$

$$(8)\qquad \mathbf{Fromtran}_{lgqm} + \sum_{j} \mathbf{Transport}_{ijgqm} + \sum_{m1} \mathbf{ModeShift}_{lgqmm1}$$

$$\le \mathbf{Totran}_{lgqm} + \sum_{i} \mathbf{Transport}_{ilgqm} + \sum_{m1} \mathbf{Modeshift}_{lgqm1m} \quad \forall l, g, q, m$$

$$(9)\qquad \mathbf{I}_{lgq} \le \mathbf{storagecap}_{lg} \quad \forall l, g, q$$

where

l indexes all regions encompassing excess supply and demand regions, barge locations, and ports and is used to identify areas where grain can be transshipped, stored or switch modes;

i indexes excess supply regions, $i \subset l$;

j indexes excess demand regions, $j \subset l$;

g indexes the grains (corn and soybeans);

q indexes quarter of the year;

m indexes the type of transportation modes;

$\mathbf{S}_{igq}$ gives the excess supply in region *i* of grain *g* in quarter *q*;

$\boldsymbol{\alpha}(\mathbf{S}_{igq})$ is the inverse excess supply function in region *i* of grain *g* in quarter *q*;

$\mathbf{D}_{jgq}$ is excess demand in region *j* of grain *g* in quarter *q*;

$\boldsymbol{\varphi}(\mathbf{D}_{jgq})$ is the inverse excess demand function in region *j* for grain *g* in quarter *q*;

$\mathbf{Transport}_{ijgqm}$ is the quantity shipped from excess supply location *i* to excess demand location *j* of grain *g* in quarter *q* by mode *m*;

$\mathbf{I}_{lgq}$ is the amount of grain g stored at region l in quarter q;

$\mathbf{Totran}_{lgqm}$ is the amount of grain g entered into transport from storage or local supply in region l in quarter q by mode m;

$\mathbf{Fromtran}_{lgqm}$ is the amount of grain g removed from transport to meet demand or be entered into storage at region l in quarter q by mode m;

$\mathbf{ModeShift}_{lgqmm1}$ is the amount of grain g in region l that changes mode of transportation from mode m to mode $m1$ in quarter q;

$\mathbf{tc}_{ijgqm}$ is transportation costs ($) per unit of grain shipment from excess supply source i to excess demand destination j of grain g by mode m;

$\mathbf{cul}_{lgqm}$ is the cost of unloading per unit of grain g unloaded at region l in quarter q by mode m

$\mathbf{cl}_{lgqm}$ is the cost of loading per unit of grain g loaded at region l in quarter q by mode m

$\mathbf{CMS}_{lgqmm1}$ is the cost of mode shift per unit of grain g at region l in quarter q from mode m to mode $m1$

$\mathbf{s}_{lgq}$ is the storage costs per unit of grain g stored at region l in quarter q;

$\mathbf{storagecap}_{lg}$ is the storage capacity for grain g in region l

Equation 6 is the objective function. It maximizes the total net welfare, which is determined as the area under the demand curves minus that under the excess supply curves minus grain transportation costs, loading, unloading, mode shift and storage costs. Demand and supply functions in IGTM are assumed to be linear.

Constraints are imposed when maximizing the objective function. Equation 7 is the regional balance constraint for grain going into and out of the transport system in each region in each time period.

Equation 8 is a balance for the grain in the transport system on a particular mode by location, grain, mode, and quarter.

Finally, Equation 9 is the storage capacity constraint for each grain in each region and each time period.

Model Data

Specification of IGTM requires data on the international and domestic excess supply and demand functions; truck, railroad, barge, and shipping rates; and grain storage and loading/unloading charges. This section provides details of these data regarding their sources, a description of the individual datasets, and steps involved to obtain the data used for IGTM.

Excess Supply and Demand Equations

Following Shei and Thompson (1977), we estimate the inverse excess supply equation for each region using estimated excess supply elasticity, quantity exported from the region, and representative price. More specifically, these data were used to estimate the slope and intercept terms of the inverse excess supply equation. In a similar manner, inverse excess demand equations were estimated for each region using excess demand elasticity, quantity imported into region, and a representative price.

As shown in Equation 10, we need own-price demand and supply elasticities, prices and quantities produced, consumed and exported from region to estimate excess supply elasticity. In Equation 11, information on estimated own-price demand and supply elasticities, quantity consumed, produced and imported into region are used to calculate excess demand elasticity.

$$E_{ExS} = E_S(Q_p/Q_e) - E_D(Q_c/Q_e) \tag{10}$$

$$E_{ExD} = E_D(Q_c/Q_i) - E_S(Q_p/Q_i) \tag{11}$$

where

E_{ExS} is the excess supply elasticity for a region

E_{ExD} is the excess demand elasticity for a region

E_S is the own-price supply elasticity for a region

E_D is the own-price demand elasticity for a region

Q_p is the quantity produced for a region

Q_c is the quantity consumed for a region

Q_e is the quantity exported from a region

Q_i is the quantity imported into a region

The study obtains estimated domestic own-price demand and supply elasticities of corn and soybeans from FAPRI at the University of Missouri. We obtain the CRD-level domestic corn and soybean production and aggregate national estimates of domestic corn use and soybean crushing from the databases of NASS and ERS of USDA (USDA-ERS 2009; USDA-NASS 2009). CRD-level soybean crush and corn consumption are estimated using data from various sources including the National Oilseed Processors Association (NOPA), USDA publications, websites of company located in a particular CRD, industry experts, and a FAPRI staff explained in the next section.

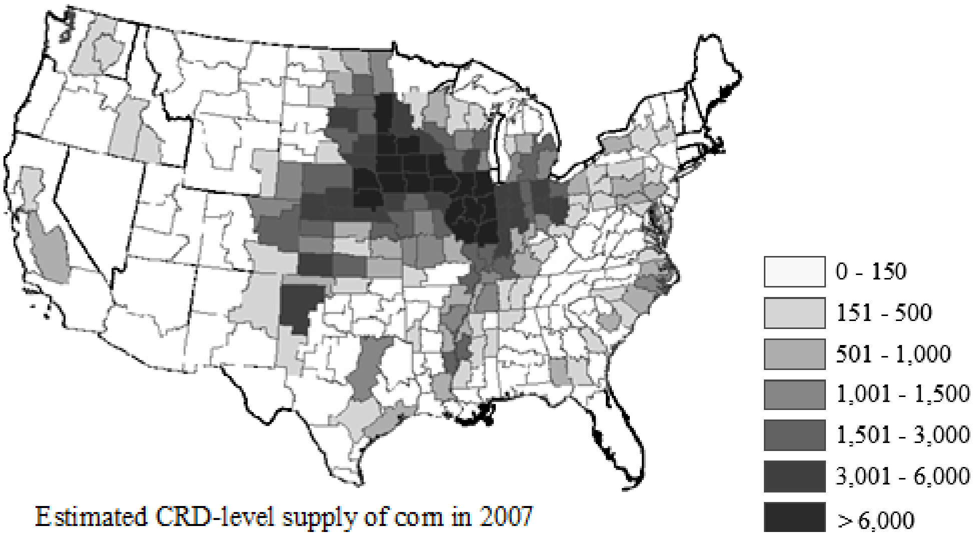
In a similar manner, foreign excess supply and demand elasticities are estimated based on country/region specific own-price demand and supply elasticities obtained from FAPRI. Each country's corn and soybean production, beginning stocks, imports, exports, feed, total disappearance, and ending stocks by crop year are drawn from the Production, Supply and Distribution (PS&D) database compiled by the USDA-FAS (USDA-FAS 2009d). Foreign trade in terms of monthly/quarterly exports and imports of corn and soybean for selected countries is obtained from the FAS Global Agricultural Trade database (USDA-FAS 2009c) and Global Agricultural Information Network (formerly Attaché Reports) database (USDA-FAS 2009b).

Next, regional production and estimated consumption are used to calculate regional corn and soybean export and import quantities. All of the above mentioned data are then used to quantify regional excess supply and demand elasticities. Finally, the regional excess supply and demand equations are derived using calculated regional excess supply and demand elasticities together with regional excess supply and demand quantities and prices for corn and soybeans, which will be discussed in the following subsections.

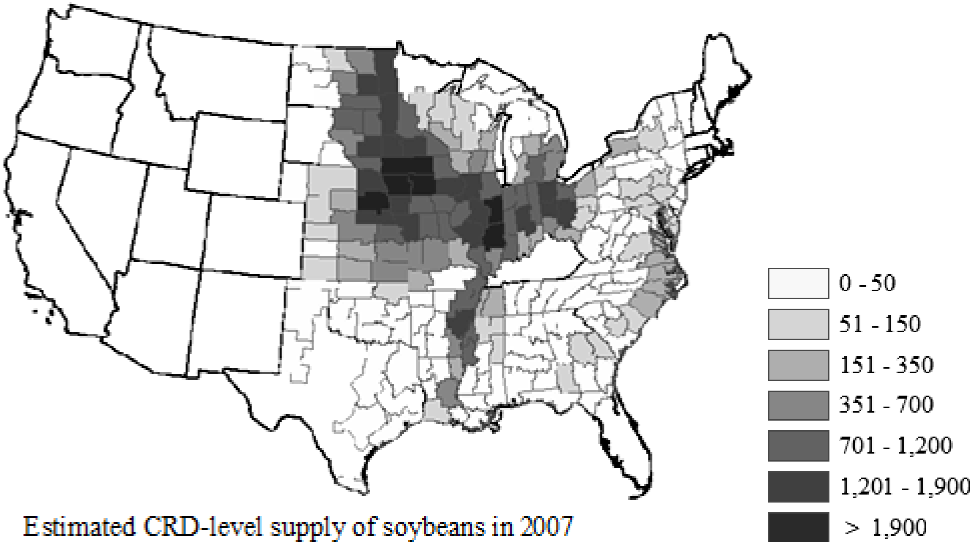
Corn and Soybean Excess Supply and Demand

Domestic excess supply (surplus) and demand (deficit) crop reporting districts for each commodity are identified by subtracting total usage and ending stocks (in bushels) from the production plus initial stocks of a particular commodity. The data are formed for the 2007–2008 marketing year (September 1, 2007 to August 31, 2008). Estimated CRD-level supply of corn and soybeans in 2007 are shown in Figure 12. In general, supply regions of corn and soybeans tend to be concentrated in the Corn Belt (Illinois, Iowa, Indiana, Ohio, and Missouri), Great Plains (Nebraska, Dakotas, and Kansas), and Lake States (Minnesota, Michigan, and Wisconsin) regions.

Total consumption is assumed to be comprised of three categories: 1) Seed use; 2) Consumption for feed purposes; and 3) Consumption for food, alcohol, and industrial use (use for crushing purposes in case of soybeans). Finally, the ending stock is the grain on hand in the end of 2007/2008 marketing year (August 31, 2008). The CRD-level beginning and ending stocks are obtained by multiplying CRD’s share in the total national corn or soybean production with the total national beginning and ending stocks published by USDA. Seed used by each CRD is also obtained in similar fashion by multiplying each CRD’s share in the total national planted acreage of corn or soybeans with the total national seed use during the same planting season.



Estimated CRD-level supply of corn in 2007



Estimated CRD-level supply of soybeans in 2007

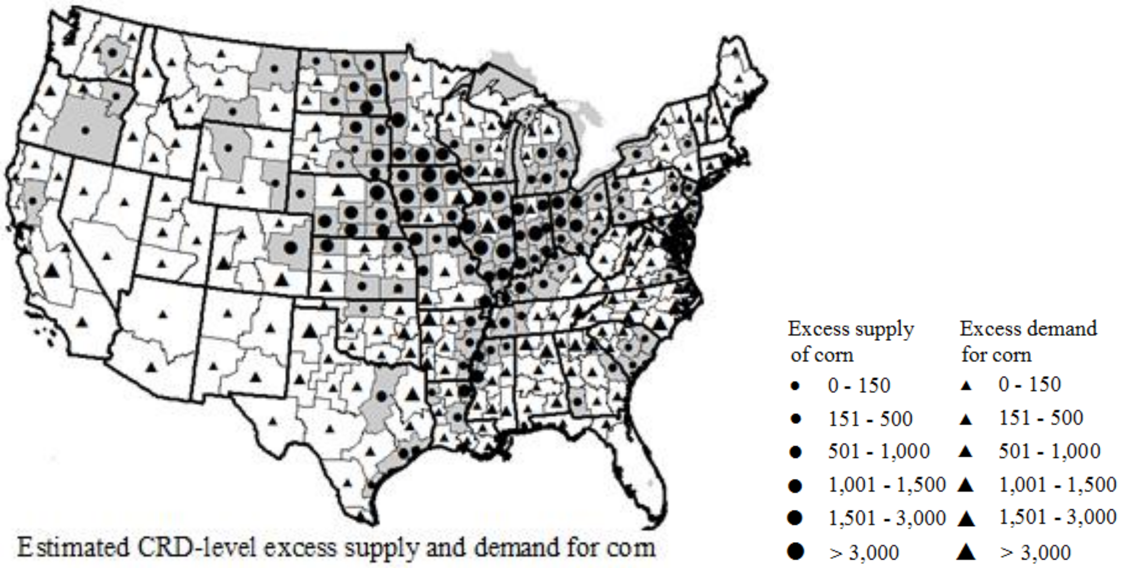
Figure 12. Estimated CRD-level supply of corn and soybeans (1,000 tonnes) in 2007

Corn consumption for food, alcohol, and industrial use in each CRD represents the aggregate consumption of wet and dry corn millers (for food, alcohol, and ethanol production) within each CRD drawn from the websites of company located in a particular CRD, other publicly available data and by industry experts. For soybean, consumption by soybean crushers in each CRD is obtained by multiplying CRD's share in total state crushing with state crush estimates. NOPA publishes soybean crush estimates in terms of seven geographic regions where each region includes an individual state (such as Iowa and Illinois) or groups of states. The state's crushing share within a NOPA region and CRD's share within a state are kept unchanged from the 2003-2004 model (Fellin et al. 2008).

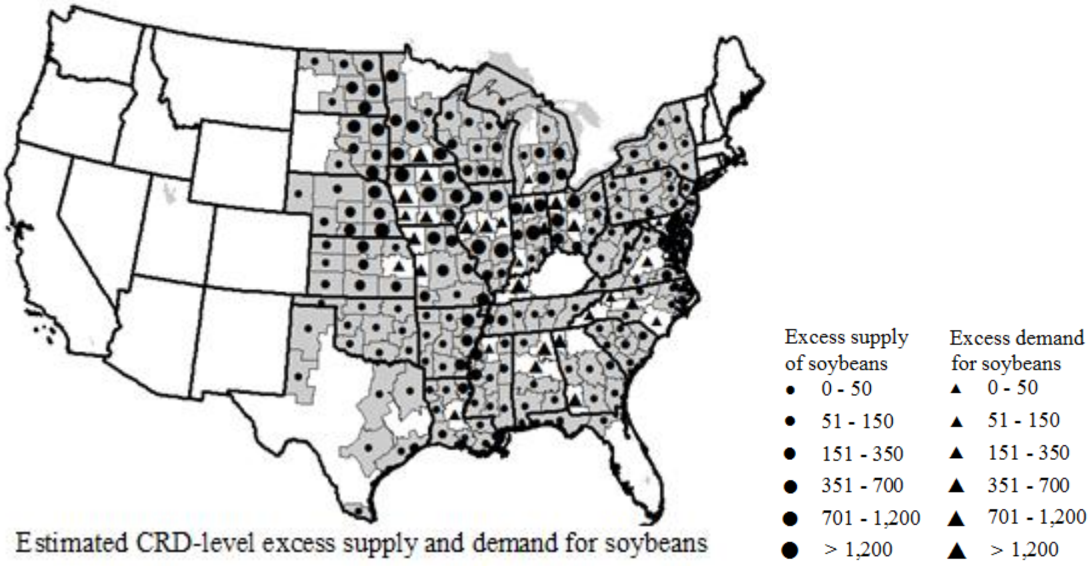
Estimates of corn consumption for feed purposes are based on per animal consumption of corn for each type of animal and number of animals in each CRD. The corn consumption for animal feed – livestock, poultry, and dairy – is estimated based on information on population data and representative rations for the 2007–2008 crop year. Information on livestock and poultry population was obtained from Dr. Edward Yu from the Department of Agricultural Economics, University of Tennessee (formerly with FAPRI) and several USDA publications (USDA-NASS 2008a; USDA-NASS 2008b; USDA-NASS 2008c; USDA-NASS 2008d; USDA-NASS 2008e; USDA-AMS 2009b). Estimated total demand for corn and soybeans in 2007/2008 marketing year are illustrated and discussed in Figure 6 of Chapter III.

Figure 13 shows the distribution of excess supply and demand regions across the U.S. regions. Excess corn supply regions tend to be concentrated in the Corn Belt region even though this area has the largest consumption of corn for feed, food, alcohol, and industrial uses in the U.S. Other important excess demand regions for corn are in the East-Central U.S. (largely in North Carolina), South-Eastern U.S. (primarily Alabama, Georgia, Mississippi, and Arkansas), Texas, and California. Excess soybean supply regions tend to be located in the Great Plains (primarily Dakotas and Nebraska), Lake

States (largely in Minnesota), and Corn Belt. Excess soybean demand regions are generally located in the Corn Belt, and southeastern states.



Estimated CRD-level excess supply and demand for corn



Estimated CRD-level excess supply and demand for soybeans

Figure 13. Estimated CRD-level excess supply and demand for corn and soybeans (1,000 tonnes) in 2007/2008 marketing year

Corn and Soybean Prices

For domestic regions, CRD level quarterly corn and soybean prices are collected from the daily county level Posted County Prices (PCP) from archived datasets of the USDA Farm Service Agency (USDA-FSA 2009). These quarterly prices are represented by quarterly average of three representative county level daily prices in each CRD. Average crop reporting districts contains ten or more counties. The daily PCP rates from only two or three representative counties are chosen to obtain quarterly prices in each CRD due to the extensive manual labor requirement for obtaining data for each individual county. For instance, Alabama CRD 30 contains 16 counties and only three interspersed counties – Jefferson, Pickens, and Tallapoosa – are chosen as a representative sample.

For foreign countries, the FOB ship grain prices were obtained from public information sources as detailed below with the remainder estimated from available price data and shipping rates.[35] For Argentina and Brazil, quarterly FOB prices are used for corn and soybeans. Argentinean corn and soybean quarterly FOB prices are obtained from the official website of Argentinean ministry of agriculture. USDA-AMS report (USDA-AMS 2009b) provides information on soybean prices (in $US/MT) at major exporting regions of Brazil and transportation costs to major exporting ports of the country. Brazilian quarterly FOB port soybean prices are calculated as the weighted average of regional soybean prices times the weighted average transportation charges to

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[35] In order to avoid the possible discrepancy between actual and estimated values of grain handling charges, we decide to use the FOB prices whenever it is possible since they already reflect grain handling charges in these prices.

ports. Finally, the quarterly FOB corn prices ($US/MT) are represented by average monthly corn prices after converting them into U.S. dollars and the data is obtained from the Foreign Agricultural Service reports (USDA-FAS 2009a).

Elasticities

By using own-price elasticities obtained from FAPRI, the long-run excess supply and demand are estimated for both domestic and foreign excess supply and demand regions. Estimated elasticities for the 2004–2005 period were employed in the model due to abrupt fluctuations in prices in 2007-2008 in order to avoid poorly represented long-run elasticities. Domestic corn and soybean elasticity estimates are calculated for each major excess supply and demand CRD regions and for groups of CRDs if they are insignificant players. Similarly, foreign elasticity estimates are calculated for a specific country if it is a major importing or exporting country otherwise adjacent small players are grouped together. For instance, major corn importing countries like Japan, Korea, and Mexico have country-specific elasticity estimates and non-major importing/ exporting countries are pooled into broader geographic region.

Distance Data

The distance data is comprised of three separate distance matrices for truck/rail, barge, and ship transportation modes: (1) Distances (in miles) between domestic, Canadian, and Mexican regions via truck and railroad, (2) Barge distances between barge loading locations with exporting ports, and (3) Inter-port travel distances (in nautical miles) between domestic and international ports plus those between international ports. The distances between each CRD is represented by truck/rail distance matrix and provided by Texas Transportation Institute (TTI). The grain trucking alternative is limited to hauls up to distances of 300 miles and less, since trucking beyond that mileage is not practical or economically feasible for large shipments. Overland shipments to Mexico from the U.S. are linked to three of the five major corn and soybeans excess demand regions and over-the-ocean shipments are linked to the Veracruz port. An internal Mexican distance matrix connects all five major Mexican corn and soybeans excess demand regions with each other and Veracruz.

Separate inter-port distance matrices are constructed for corn and soybeans due to different trade flows between the international regions. For instance, in the corn port distance matrix, all major grain exporting U.S. ports are linked to representative foreign ports, which in turn are connected to other international excess demand and supply regions. In obtaining the port distances the data from World Ports Distances Calculator website is used as the primary data source.[36] The distance between the representative barge locations are based on upper Mississippi River Navigation Charts published by U.S. Army Corps of Engineers (USACE) and other online mapping resources (USACE 2009).

Handling and Storage Charges

The model requires grain storage charges at county elevators and loading/unloading costs associated with each type of transportation mode in each CRD and as well as at domestic intermodal transfer locations. Similar charges are also needed

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[36] http://www.portworld.com/map

in the international portion of the model. The data on handling and storage charges (in $US/metric ton) is obtained from publicly available sources such as U.S. Army Corps of Engineers' publication and industry expert estimates from the National Grain and Feed Association. Whenever available, port FOB grain prices are used in the estimation of excess supply equations for exporting regions, which eliminates the need for explicitly including handling and transportation charges of these regions.

Rail and Truck Rates

In obtaining the domestic rail rates for grain shipments the annual public waybill data for 2007 and 2008 published by Surface Transportation Board (STB) were used as primary data set (USDOT-STB 2007; 2008). STB's annual public waybill data contains detailed information (such as mileage, volume, cost, date and time, etc.) on the shipment of many different agricultural and non-agricultural commodities between Business Economic Areas (BEA). Since the model requires CRD level data, the BEA level rail rates are converted into CRD level rates in order to maintain the spatial consistency of the data explained below.

Based on the waybill data, corridors with high volume of shipments for each commodity are identified in order to obtain representative rail transport charges. In particular, corn waybill data is broken into eight geographic regions where first seven represent seven railroad corridors with high volume of shipments between two (origin-destination) BEA regions or groups of such regions. The last group includes all other corn shipments between regions that are not reflected in any of the seven corridors. The soybean shipments are also categorized in similar fashion and include Pacific Northwest and Gulf of Mexico corridors and a group for all other shipments.

In turn the rail rate per ton-mile for each individual shipment in each of these regions is found by dividing total revenue from the shipment (both with and without miscellaneous charges) by the number of tons and miles of the haul. Then, the quarterly rates ($US/short ton-mile) were calculated as the arithmetic average of rail rates ($US/short ton-mile) within each corridor for each quarter. Quarterly rates for unit train shipments (for shipments equal to or greater than 50 rail cars) were also calculated in a similar fashion. The unit train rates are typically lower than non-unit-train shipment rates. All other rail shipments that are not represented by any corridor are pooled into single general group and the quarterly average rates are calculated for three distinct distance categories. These categories include rail shipments with distances 100 to 500 miles, 501 to 1000 miles, and over 1000 miles. Finally, the obtained rail rates are used for shipments between CRDs, barge locations, and ports by applying the rates from appropriate corridors.

In obtaining the estimates of truck rates for the domestic hauls of 300 miles or less, the quarterly data from the USDA's *Grain Transportation Report* (USDA-AMS 2008a) is used as the primary data source. The per-ton-mile truck rates are estimated by regression analysis. This is applied to the trucking distance matrix to get rates for shipments.

Barge Rates

The barge rates ($US/ Metric ton) are developed for 32 barge loading/unloading locations (mostly along the Mississippi River system) to seven major barge destination locations—Baton Rouge, LA; Glasgow, MO; Huntsville, AL; Knoxville, TN; Memphis, TN; Nashville, TN; and Louisville, KY. The data for barge rates are weekly per ton spot barge tariff rates per short ton published by the USDA (USDA-AMS 2009a). The quarterly barge rates represent average weekly rates within a given quarter at a given barge location. Since the original weekly spot barge tariff rates from AMS do not cover low-volume, small river origin and destination points, the rates for such routes are obtained from the estimates of industry experts and private consultants.

International grain ship rates are estimated using data obtained from the USDA-AMS and the International Grain Council (IGC).[37] The quarterly ship rates are then estimated based on regression using above datasets from these sources and the corresponding distances. Individual rates are estimated for two trading countries if they fall into the list of major grain exporting or importing countries. Otherwise, the rates are estimated for broader geographic regions that represent a group of countries with a representative port city. For example, for most northern EU and Scandinavian countries, Rotterdam, Netherlands is used as a representative port.

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[37] The IGC database provides reasonable coverage of international grain freight rates between major export and import regions. For instance, the data set includes freight rates between U.S. Gulf Coast and Japan, China, Brazil, South Korea, Morocco, and Egypt. However, the IGTM requires more comprehensive data set for estimating ship rates. The rates obtained from USDA-AMS, for important trade routes such as Gulf Coast to Japan and Pacific Northwest to Japan, are also used to complement the IGC data.

Comparison of Historical and Model-Projected Flows

As a way to validate IGTM, this section aims to provide comparison of historical and model-projected transportation flows. Available historical data used to compare with the model-projected results are collected from various sources including the U.S. Army Corps of Engineering, the USDA-AMS, the USDA-FAS, and previous transportation studies in particular recent studies from Marathon and Denicoff (2011) and Denicoff et al. (2010). Because the analysis in Chapter III focuses on the long-term climate change impacts on the transportation system, IGTM is developed and validated in such a way that the model can replicate the general pattern of grain transportation flows in the real world. To represent the general pattern of the flows, we compare model-projected results here with the range of historical flows during a period of time mostly in the recent years depending on the availability of the data instead of choosing a particular year. Overall we find that model-projected quantities of corn and soybeans transportation flows are in the range of their actual quantities of transportation flows as shown in Tables 14 to 17.

Table 14 shows that model-projected quantities and share of corn and soybeans for export classified by modes of transportation are in their historic ranges during 2005-2007. Overall, barge plays an important role for the export of corn and soybeans, which is followed by rail and truck, respectively. For domestic flows classified by modes of transportation shown in Table 15, we find that IGTM's simulated results of corn and soybeans shipped via rail and barge are in their historic ranges except for corn shipped via barge where model-projected quantities are slightly lower than actual quantities. As expected, model-projected shipments of corn and soybeans via truck are lower than their historic ranges estimated by Marathon and Denicoff (2011) since shipments within CRD, mainly accomplished by truck, are not modeled.

In Table 16, model-projected quantities and/or share of corn and soybeans exiting via U.S. port areas are generally in the range of their historic quantities and share. The lower Mississippi River ports and the Pacific Northwest ports are the major destinations for corn and soybean export from the U.S. to the rest of the world. Finally, Table 17 contrasts model-projected shares of corn and soybeans exiting at the lower Mississippi River ports classified by modes of transportation with their ranges of historic shares from 2005-2009. Projections are comparatively close to their historic ranges and this table reveals that almost corn and soybean are shipped via barge to these ports.

Based on these evidences, we concluded the model was adequate for the study conducted in Chapter III.

Table 14. **Historic and Model-Projected Quantities (1,000 tonnes) and Share of Corn and Soybeans for Export Classified by Modes of Transportation**

Mode	Corn		Soybeans	
	Model-Projected Quantities	Range of Historic Quantities	Model-Projected Quantities	Range of Historic Quantities
Truck	5,639 (9)	1,600-6,429 (3-10)	2,019 (7)	1,654-3,998 (5-12)
Rail	21,454 (35)	20,251-22,352 (35-44)	13,282 (46)	11,273-14,169 (40-46)
Barge	34,409 (56)	28,778-34,689 (50-57)	13,395 (47)	15,030-15,242 (46-53)
Total	61,501 (100)	50,629-63,470 (100)	28,696 (100)	28,118-32,824 (100)

Note: 1) Share of corn and soybeans for export in ( )

2) Ranges of historic data of corn and soybeans are from 2005 to 2007 collected from Marathon and Denicoff (2011).

Table 15. Historic and Model-Projected Quantities (1,000 tonnes) and Share of Corn and Soybeans for Domestic Demand Classified by Modes of Transportation

Mode	Corn		Soybeans	
	Model-Projected Quantities	Range of Historic Quantities	Model-Projected Quantities	Range of Historic Quantities
Truck	23,938	148,918-165,570	12,473	43,686-47,910
Rail	62,985	57,657-63,407	7,731	6,382-8,121
Barge	1,365	2,646-2,961	1,034	982-1,302
Total	88,289	209,536-227,106	21,238	43,686-47,375

Note: Ranges of historic data of corn and soybeans are from 2005 to 2007 collected from Marathon and Denicoff (2011).

Table 16. Historic and Model-Projected Quantities (1,000 Tonnes) and Share of Corn and Soybeans Exiting via U.S. Port Areas

Port Areas	Corn		Soybeans	
	Model-Projected Quantities	Range of Historical Quantities	Model-Projected Quantities	Range of Historical Quantities
Lower Miss	38,244 (62.2)	28,839-39,986 (57.4-64.8)	15,349 (53.5)	15,520-23,481 (52.0-59.6)
Texas Gulf	1,616 (2.6)	689-3,071 (1.4-4.0)	51 (0.2)	108-2400 (0.3-6.0)
PNW	11,679 (19.0)	8,480-12,727 (17.0-24.9)	8,678 (30.2)	6,044-10,301 (21.6-29.3)
Great Lakes	602 (1.0)	122-1,707 (0.3-3.1)	677 (2.4)	334-1,112 (1.0-4.0)
Atlantic	707 (1.1)	469-769 (1.0-1.4)	1,143 (4.0)	565-1,389 (1.8-3.4)
Overland	8,655 (14.1)	4,448-7,457 (8.0-14.6)	2,798 (9.8)	3,041-5,449 (7.7-16.6)
Total	61,501 (100)	45,236-63,470 (100)	28,696 (100)	28,034-41,423 (100)

Note: 1) Share of corn and soybeans for export in ( )
2) Ranges of historic data of corn and soybeans are from 2006 to 2010 collected from Marathon and Denicoff (2011) and Grain National Reports from the USDA-AMS (USDA-AMS 2007; 2008b; 2009c; 2010; 2011a)

Table 17. Historic and Model-Projected Share of Corn and Soybeans Exiting at the Lower Mississippi River Ports Classified by Modes of Transportation

Modes	Corn		Soybeans	
	Model-projected share (%)	Historical share (%)	Model-projected share (%)	Historical share (%)
Barge	90	87-91	87	87-89
Truck & Rail	10	9-13	13	11-13
Total	100	100	100	100

Note: Ranges of historic data of corn and soybeans are from 2005 to 2009 collected from Marathon and Denicoff (2011) and the USDA-AMS (2011)

CHAPTER V

CONCLUSIONS, LIMITATIONS AND FURTHER RESEARCH NEEDS

Conclusions

This dissertation examines two aspects of the effects of climate change might have on agricultural yields and grain transportation. Specifically, I analyze:

- The effect of climate change and atmospheric CO_2 on crop yields and their variability of climate variables;
- The effect of projected crop yields, on market outcomes and welfare;
- The effect of climate change on grain production patterns and in turn on grain transportation flows.

In Chapter II, I do an econometric study of the impact of climate variables, time, and atmospheric CO_2 on mean yield and its variability for five major crops merging state-specific, historical data with data from the FACE experiments. To do this a stochastic production function is econometrically estimated over a panel.

I find that yields of C-3 crops, soybeans, cotton, and wheat, positively and directly respond to the elevated CO_2, while yields of C-4 crops, corn and sorghum do not. C-4 crops are found to indirectly benefit from elevated CO_2 in times and places of drought stress. I also find that yield over time is non-linear exhibiting an inverted-U shape for all crops, except for cotton. The analysis also reveals that ignoring the atmospheric CO_2 in econometric model of crop yield studies is likely to overestimate the effect of technological progress on crop yields.

Based on climate change projections, I find that, other things being equal, increases in atmospheric CO_2 lead to higher yields of all crops with cotton being the most advantaged crop. Considering only climate condition change, I find that yields of all crops in the Northern Plains and Southeast regions are projected to increase (except for winter wheat in the Southeast), while yields of all crops in the Southern Plains, Corn Belt, and Delta regions are likely to decline (except for winter wheat in Southern Plains, corn in Corn Belt, and cotton in Delta). When both climate and CO_2 variables change simultaneously, the effect of CO_2 fertilization generally outweighs the effect of climate change on mean crop yields in many regions.

I also explored the effect of climate-induced change in crop yields on market outcomes and welfare implications of economic units across U.S. regions using an agricultural sector model. I find that prices of all crops are likely to decrease compared to the base scenario with production increasing. Planted acreage of all crops in the Northern Plains, except winter wheat, is projected to increase. On the other hand, planted acreage of all crops in Southern Plains, Lake States, Delta, Southeast, and Mountain is simulated to decrease (increase for cotton in Southern Plains and Mountain, and corn in Delta and Southeast). In all regions, consumer surplus is projected to increase slightly due to the CO_2 fertilization and climate change, while changes in producer surplus are heterogeneous across U.S. regions. Finally, the total U.S. welfare is projected to increase by about $ 2.27 billion compared to the base scenario.

Chapter III reports on an investigation of the effect of climate change on interregional grain transportation flows in the U.S. due to climate-induced shifts in geographic crop production patterns utilizing two modeling systems, an agricultural sector model and the international grain transport model (IGTM) developed herein. Chapter IV documents IGTM's detailed description, structure, steps and procedures involved in obtaining the final data set from the raw data set that is used in this model.

The analysis indicates that overall supply of corn and soybeans tends to increase in U.S. Northern regions, while declining in some areas of Cornbelt and Southern parts of the U.S. The Corn Belt, the largest producer of corn in the U.S., is anticipated to ship less corn to the Pacific, Northeast, Rocky Mountains, Southeast, South Central, the Pacific Northwest ports and lower Mississippi ports, while the Great Lakes ports and Lake States are expected to receive higher corn shipments from this region. Furthermore, the importance of lower Mississippi ports, the largest current destination for grain exports to the rest of the world, is projected to diminish, whereas the role of Pacific Northwest ports is projected to increase. Finally, demand for rail and truck is expected to rise, while demand for barge mode is projected to decline.

Limitations and Further Research Needs

This section discusses limitations of the studies in this dissertation and proposes many possibilities of future research as follow:

- In Chapter II, the number of observations from the FACE experiments used for the analysis is small, which could lead to an estimation problem since this small number of observations may not fully distinguish the effect of the atmospheric CO_2 from the time trend. In other words, the correlation coefficient between the atmospheric CO_2 and the time trend is still high. Future research could consider expanding the scope of the study from only the U.S. to include other countries where the FACE experiments have been performed to increase the size of the FACE observations.
- The analysis of crop yield in Chapter II did not distinguish between yields from dryland and irrigated land. Future research could include an explanatory variable that can differentiate the effect of irrigated land since some authors argue that climate change effects need to be assessed differently in dryland and irrigated areas (Schlenker, Hanemann, and Fisher 2005).
- This study in Chapter II provides the projected change in mean crop yields and their standard deviations reflecting the uncertainty. However, the analysis on market outcomes and welfare implications in Chapter III employs the deterministic version of the ASM. Therefore, results provided in the ASM deterministic version may not fully account for the uncertainty from future

climate change. Future research could use the stochastic version of the ASM to better reflect such uncertainty.

- The analysis in Chapter III assumes that there are no climate-induced shifts in geographic crop production patterns of countries other than the U.S. Therefore, results from the current study may not fully reflect the domestic and international patterns of grain transportation flows. Future research could estimate the patterns of shifts in crop production patterns in these countries. Simultaneously, the spatial scale of these countries in IGTM could be disaggregated into more detail level.
- There are many ways that climate change can affect transportation flows and demand for modes of transportation. The study in Chapter III only considers one of many possibilities. For example, climate change may have direct impacts on inland waterways. A large literature find that climate change is likely to: change water levels in the Great Lakes; extend the navigation season in both the Great Lakes and the Upper Mississippi River due to the reduction of lake and river ice cover caused by rising temperature. These alterations could also affect the grain flows. Hence, future research could analyze these changes on the grain transportation flows and demand for modes of transportation.
- Due to time limitations for data collection, there are only two commodities included in IGTM. Namely corn and soybeans are modelled which represents 82 percent of the U.S. grain production. Future work could include wheat and possibly sorghum in the model.

- Although IGTM uses excess supply and demand data from a recent 2007/2008 production year as described in Chapter IV, these datasets could not well represent the current situation, in which there yet more of an increase in demand for corn for bioenergy. This change could lead to change in recent patterns of interregional grain transportation flows. Therefore, updating the datasets to a later year might is a possible extension.

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APPENDIX A

ASM MODEL DESCRIPTION

The ASM framework can be summarized by the following equations.

(A1) $$Max\ -\sum_{j,k}\mathbf{g}_{jk}\mathbf{X}_{jk}-\sum_{k,r}\int\boldsymbol{\alpha}(\mathbf{R}_{rk})\mathbf{dR}_{rk}+\sum_{\mathbf{i}}\int\varphi(\mathbf{Q}_i)\mathbf{dQ}_i$$

$$+\sum_{i,f}\int\boldsymbol{\gamma}(\mathbf{FQD}_{if})\mathbf{dFQD}_{if}-\sum_{i,f}\int\boldsymbol{\beta}(\mathbf{FQS}_{if})\mathbf{dFQS}_{if}-\sum_{i,k,f}\mathbf{USFTC}_{ikf}*\mathbf{USFTRD}_{ikf}$$

$$-\sum_{i.f.f1}\mathbf{FFTC}_{iff1}*\mathbf{FFTRD}_{iff_1}-\sum_{i,k,k1}\mathbf{USTC}_{ikk1}*\mathbf{USTRD}_{ikk1}$$

Subject to

(A2) $$\sum_{j}\mathbf{y}_{ijk}*(\mathbf{1}+\mathbf{dyield}_{ik})*\mathbf{X}_{jk}-\sum_{k}\mathbf{USFTRD}_{ifk}-\sum_{k1}\mathbf{USTRD}_{ik1k}+\sum_{k}\mathbf{USFTRD}_{ikf}$$

$$\sum_{k1}\mathbf{USTRD}_{ikk1}\leq\mathbf{0},\forall i,k$$

(A3) $$\sum_{j}\mathbf{a}_{rjk}*\mathbf{X}_{jk}\leq\mathbf{b}_{rk},\forall r,k$$

(A4) $$\mathbf{Q}_i-\sum_{i,j,k}\mathbf{y}_{ijk}*(\mathbf{1}+\mathbf{dyield}_{ik})*\mathbf{X}_{jk}+\sum_{k,j}(\mathbf{USFTRD}_{ikf}-\mathbf{USFTRD}_{ifk})\leq\mathbf{0},\forall i$$

(A5) $$\mathbf{FQD}_{ik}+\sum_{k}\mathbf{USFTRD}_{ifk}+\sum_{f1}\mathbf{FFTRD}_{iff1}$$

$$-\mathbf{FQS}_{if}-\sum_{k}\mathbf{USFTRD}_{ikf}-\sum_{f1}\mathbf{FFTRD}_{iff1}\leq\mathbf{0},\forall i,f$$

where

i indexes commodities; *f*, *f1* index the rest of the world (ROW)’s regions;

j indexes production processes; k, $k1$ index U.S. regions; r indexes resources;

$\mathbf{g}_{jk}$ is the cost of the jth production process per acre in U.S. region k;

$\mathbf{X}_{jk}$ is the acreage of the jth production process in U.S. region k;

$\boldsymbol{\alpha}(\mathbf{R}_{rk})$ is the inverse U.S. factor supply function for resource r in region k;

$\mathbf{R}_{rk}$ is the resource supply for U.S. region k of resource r;

$\boldsymbol{\varphi}(\mathbf{Q}_i)$ is the inverse U.S. demand function for commodity i;

$\mathbf{Q}_i$ is the U.S. domestic consumption of the ith commodity;

$\boldsymbol{\gamma}(\mathbf{FQD}_{if})$ is the inverse excess demand function for commodity i in importing ROW region f;

$\mathbf{FQD}_{if}$ is the excess demand quantity for commodity i in importing ROW region f;

$\boldsymbol{\beta}(\mathbf{FQS}_{if})$ is the inverse excess supply function for commodity i in exporting ROW region f;

$\mathbf{FQS}_{if}$ is the excess supply quantity for commodity i in exporting ROW region f;

$\mathbf{USFTC}_{ikf}$ is the transportation cost from U.S. region k to ROW region f for commodity i;

$\mathbf{USFTRD}_{ikf}$ is the trade between U.S. region k and ROW region f for commodity i;

$\mathbf{FFTC}_{iff1}$ is the transportation cost between ROW regions f and $f1$ for commodity i;

$\mathbf{FFTRD}_{iff_1}$ is the trade between ROW regions f and $f1$ for commodity i;

$\mathbf{USTC}_{ikk1}$ is the transportation cost between U.S. regions k and $k1$ for commodity i;

$\mathbf{USTRD}_{ikk1}$ is the quantity shipped between U.S. regions k and $k1$ for commodity i;

$\mathbf{y}_{ijk}$ is per acre yield for commodity *i* using *j*th production process of U.S. region *k*;

$\mathbf{dyield}_{ik}$ is the crop yield percentage change due to the change in climate, atmospheric CO_2, and crop production technology;

$\mathbf{a}_{rjk}$ is the amount of resource *r* used in the *j*th production process of U.S. region *k*;

$\mathbf{b}_{rk}$ is the amount of resource *r* available in U.S. region *k*.

Equation A1 is the objective function mixing the price endogenous and spatial equilibrium models. The first line of Equation A1 represents the area under the demand curves for commodity *i* less the area under the regional U.S. factor supply curves for perfectly elastic production costs associated with production process *j* and quantity dependent prices for factor *r* summed across all *k* regions. The next three lines include terms typically used in the spatial equilibrium model. The first two terms of the second line give the area under the ROW excess demand curves minus the area under the excess supply curves for commodity *i* in ROW region *f*. The last term of the second line and terms in the third line provide the summation of the transportation costs between the U.S. and the ROW regions, among ROW regions, and among the U.S. regions involved with trade, respectively. Equation A2 represents the regional balance constraint for goods depicted with a spatial equilibrium trade model in the U.S. Equation A3 is a usual resource constraint for U.S. region *k*. Equation A4 provides the national balance constraint for commodities in the U.S. Equation A5 is the balance constraint for traded goods in the ROW region *f*. ASM regions and subregions are shown in Table A1.

Table A1. ASM Regions and Subregions

Market Region	Production Region (States/Subregions)
Northeast (NE)	Connecticut, Delaware, Maine, Maryland, Massachusetts, New Hampshire, New Jersey, New York, Pennsylvania, Rhode Island, Vermont, West Virginia
Lake States (LS)	Michigan, Minnesota, Wisconsin
Corn Belt (CB)	All regions in Illinois, Indiana, Iowa, Missouri, Ohio (Illinois North, Illinois South, Indiana North, Indiana South, Iowa West, Iowa Central, Iowa Northeast, Iowa South, Ohio Northwest, Ohio South, Ohio Northeast)
Great Plains (GP)	Kansas, Nebraska, North Dakota, South Dakota
Southeast (SE)	Virginia, North Carolina, South Carolina, Georgia, Florida
South Central (SC)	Alabama, Arkansas, Kentucky, Louisiana, Mississippi, Tennessee, Eastern Texas
Southwest (SW)	Oklahoma, All of Texas but the Eastern Part (Texas High Plains, Texas Rolling Plains, Texas Central Blacklands, Texas Edwards Plateau, Texas Coastal Bend, Texas South, Texas Trans Pecos)
Rocky Mountains (RM)	Arizona, Colorado, Idaho, Montana, Nevada, New Mexico, Utah, Wyoming
Pacific Southwest (PSW)	All regions in California (California North, California South)
Pacific Northwest (PNW)	Oregon and Washington, east of the Cascade mountain range

Source: Adam et al. (2005)

APPENDIX B

THE EXTENSION OF ATWOOD ET AL. (2000)'S MODEL

We apply an approach similar to those employed in climate change studies using ASM (as introduced in the section of Model Components, Data, and Process Overview) for the extension of Atwood (2000)'s model to reflect the possibility of crop expansion into new production areas under climate change. First, we construct coefficients for the projected climate-induced crop mix migration in 2050 based on historical crop acreage data from the Agricultural Census and Agricultural Survey provided by the USDA-NASS. Each coefficient provides information regarding the percentage of the crop mix pattern in one CRD that will shift to another CRD. For example, if the coefficient of the projected climate-induced crop migration from Iowa CRD50 to Iowa CRD20 is 0.4, then 40 percent of the crop mix pattern in Iowa CRD50 will have the possibility to shift to Iowa CRD20. We omit presenting these coefficients here due to space limitations. However, these data can be provided by authors upon request. We then follow Equations B1 and B2 quantifying county-level crop acreage, which accounts for the climate-induced shifts in crop production patterns mentioned above.

(B1) $$\mathbf{fipsshift}_{s,crd2,p,c,t} = \mathbf{fipsnoshift}_{s,crd2,p,c,t} * \mathbf{Max}\left\{0,\left(1 - \Sigma_{crd}\, \mathbf{cropshiftcoeff}_{crd,crd2}\right)\right\} + \mathbf{TransferIn}_{s,crd2,p,c,t}$$

(B2)

$$\mathbf{TransferIn}_{s,crd2,p,c,t} = \sum\nolimits_{crd} \left\{ \mathbf{avereagefips}_{s,crd,c,t} * \mathbf{cropshiftcoeff}_{crd,crd2} * \left(\frac{\mathbf{fipsallcrops}_{s,crd2,t}}{\mathbf{fipsallcrops}_{s,crd,t}} \right) \right\}, \forall p$$

where

s indexes ASM regions as shown in Table A1;

crd, $crd2$ index crop reporting districts;

p indexes counties;

c indexes crops;

t indexes crop year;

$\mathbf{fipsshift}_{s,crd2,p,c,t}$ is the acres of crop c in county p in crop reporting district $crd2$ of subregion s at year t accounting for the projected climate-induced shifts in crop production patterns

$\mathbf{fipsnoshift}_{s,crd2,p,c,t}$ is the historical acres of crop c in county p in crop reporting district $crd2$ of subregion s at year t

$\mathbf{TransferIn}_{s,crd2,p,c,t}$ is a term representing the acres of crop c shifting from counties in other regions crd to county p in crop reporting district $crd2$ of subregion s at year t

$\mathbf{cropshiftcoeff}_{crd,crd2}$ is the coefficient of the projected climate-induced crop mix migration in 2050 – specifically, the projected percentage of crop mix pattern in crop reporting district crd that will shift to crop reporting district $crd2$

$\mathbf{avereagefips}_{crd,c,t}$ is the average county-level acreage of crop c in crop reporting district crd in year t

$\mathbf{fipsallcrops}_{crd,t}$ is the average county-level acreage of all crops in crop reporting district crd at year t

The first term on the right hand side represents the remaining original acres of crop *c* in county *p* after part of the original crop mix pattern in crop reporting district *crd2* is replaced by other regions *crd.* The second term represents the acres of crop *c* shifting from counties in other regions to county *p*. The last term on the right hand side in Equation B2 adjusts for the difference in size of the total acres farmed in each county. By using the same method, we also calculate the irrigated acres for individual crops at county level taking into account the climate-induced shifts in crop production ($\mathbf{irracreshift}_{s,crd2,p,c,t}$). Based on the USDA-NASS data, our study assumes that corn and soybean can shift northward up to 120 miles by2050. Moreover, we assume that the total acres of southern crops that are suitable under environment of rising temperature, including orange and grapefruit planted in Arizona, Florida, South Texas, and California, can expand up to two times higher than their historical level by 2050.

Next, we employ the calculated acres of crops that have accounted for climate-induced shifts in crop production patterns ($\mathbf{fipsshift}_{s,crd2,p,c,t}$) to recalculate values for maximum and minimum observed county-level farmed acres, maximum and minimum observed county-level acreages of individual crops, county-level crop mix acreage of individual crops, and total county crop mix acreage demonstrated in Atwood (2000). These terms are represented by $\mathbf{maxuse}_{p}$, $\mathbf{minuse}_{p}$, $\mathbf{maxcrop}_{p,c}$, $\mathbf{mincrop}_{p,c}$, $\mathbf{asmmix}_{p,c}$, and $\mathbf{totalland}_{p}$ respectively. In Atwood (2000), the values for these terms are the historical acres not fully accounting for climate change influence ($\mathbf{fipsnoshift}_{s,p,c,t}$). We also employ the calculated irrigated acres of individual crops that have accounted for climate change ($\mathbf{irracreshift}_{s,crd2,p,c,t}$) to recalculate values for maximum observed total irrigated acres at county level ($\mathbf{maxirracre}_p$). In Atwood et al. (2000), the irrigated acres of individual crops are the historical ones not fully accounting for climate change influence ($\mathbf{irracrenoshift}_{s,crd2,p,c,t}$). With these new values, we solve the Atwood (2000)'s model again and obtain acreage solutions that account for the projected climate-induced shifts in crop production patterns.

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