THREE ESSAYS ON CLIMATE CHANGE ADAPTATION AND IMPACTS:

ECONOMETRIC INVESTIGATIONS

A Dissertation

by

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ABSTRACT

Climate change, biofuels, agricultural policies and other factors may well be changing farmer decisions and extreme events like wildfires. We use discrete choice models to examine how climate is influencing decisions on crop mix and land use choice along with natural wildfire incidence. Using panel data, we consider the effect of climate change across space on the censored choice of both major land uses and agricultural crop mix plus on the probability of wildfire.

In terms of land use and crop mix, we use a two-step linearized spatial logit model to portray major land use transitions and a fractional dependent variable model to examine crop mix selection. The models include socioeconomic, environmental, and spatial factors. Our results indicate that climate significantly affects land use transitions and crop mix allocations. These results indicate that farm level adaptation to climate change is ongoing in a spatially heterogeneous manner. Generally crops are moving north and west plus up in elevation while climate change causes crop land to transition into grassland.

For wildfire, we examine how wildfire risk is affected by climate and other factors using a fractional regression considering state unobserved factors. We examine risks of both human and naturally caused wildfires. We explore the importance of factors such as climate, demographics, and physical characteristics on fire risks. We find that climate conditions play a significant role in determining wildfire risks in the US

but have regionally heterogeneous effects on human and naturally caused fires. This implies each caused fire can be better dealt with by using separate approaches.

DEDICATION

To my family

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1. INTRODUCTION

Climate change influences agricultural productivity, crop mix, land use and wildfire incidence across the landscape (Preisler, et al. 2004; Gan 2005; McCarl, Villavicencio and Wu 2008; Seo and Mendelsohn 2008a; Feng, Krueger and Oppenheimer 2010; Davis and Kilian 2011; Hertel 2011; Yue, et al. 2013). Such effects stimulate both human and natural adaptations. On the human side farmers adapt by modifying crop mix, land use, and many other forms of management. In natural systems fire may result in a natural adaptation changing over vegetation type. In this dissertation, we will examine climate change effects on these human and natural (wildfire) adaptations.

In terms of agricultural adaptation, previous studies have found that crop mix change and land usage shifts are a potential source of farmer adaptation. Lands can go from crops to livestock as has been found in Mu, McCarl and Wein (2013) and Seo (2010) while crop mixes may change and agricultural land may move to or from forest (Reilly, et al. 2003; Seo and Mendelsohn 2008b; Choi and Sohngen 2009; Langpap and Wu 2011; Souza-Rodrigues 2014).

Understanding the importance of the climate drivers and the response in terms of chosen adaptations provides important insights into how climate change affects agriculture and how agriculture may adapt to future change and what infrastructure needs may arise in the future (Bootsma, Gameda and McKenney 2005; Coles and Scott 2009; Hatfield, et al. 2011; Attavanich, et al. 2013). Adaptation behaviors directed toward reducing or exploiting the effects of the altered climate in the North American agriculture have been observed. This has taken the form of locational shifts in planting areas, varietal selections, altered planting periods and altered crop mix (Bootsma, Gameda and McKenney 2005; Howden, et al. 2007; Coles and Scott 2009; Mendelsohn and Dinar 2009; Nadler and Bullock 2011; Paudel and Hatch 2012). Here we pursue further analysis of how cropping and agricultural land is affected and will be affected. The analysis will be carried out in two essays.

In the first essay, presented in section 2, we examine how climate influences crop mix on crop lands. We will estimate the relationships between climate attributes and crop mix shifts based on historical data at the US county level. To look at crop mix, we inspect how crop land use shares by crop vary regionally with climate by applying a fractional dependent variable model considering climate, socioeconomic, environmental, and geophysical factors. In this analysis we will look at not only longitude and latitude but also elevation. This study also projects major crop mix shifts in terms of spatial patterns based on IPCC climate change projections.

In the second essay, presented in section 3, we will examine US land use transitions using a spatial econometric approach on crop land grasslands, forest, and developed land usages.

In terms of climate change impacts, in the third essay presented in section 4, we will assess a form of natural adaptation where climate change may stimulate more wildfires. In particular, we examine responses in terms of the incidence of human-caused and nature-caused wildfires in forest lands in the US. To do this, we estimate a model with fractional dependent variables and spatial heterogeneity. We also project future wildfire risk under the climate change projections.

Across all of these studies, we will conduct spatial, econometric, data driven analysis with the dependent variable being changes in the probability of an item (incidence of a crop, amount of land in a land use or likelihood of a wildfire). This will be done in a panel data setting using various fractional multivariate models.

2. CLIMATE CHANGE ADAPTATION IN CROP MIX IN THE UNITED STATES

Agricultural crop mix change is often discussed as a response to changing climate. Previous studies found that crop mix change shift is one potential source of farmers' adaptation to climate change (Adams, et al. 1990; Reilly, et al. 2003; Bootsma, Gameda and McKenney 2005; Nadler and Bullock 2011; Attavanich, et al. 2013). Usually the researchers only highlight changes in corn and soybeans, which are the largest crops in the US. However, other crops in the US are also important when it comes to the crop mix changes because they can be substitutes or complements plus some have superior heat tolerating properties.

Crop simulation models have been used to estimate changes in crop yields considering agronomic factors such as soil quality, climate, and management practices as in Rosenzweig and Parry (1994). This method carries with detailed information on the relationship between geophysical factors and climate. However, approaches of this kind involve potential limitations in that they generally neglect farmers' adaption behavior not always portraying changes in management practices or only including as exogenous sensitivity cases.

Although it is still controversial whether the US agriculture will experience a net gain or loss under the projected climate (Mendelsohn, Nordhaus and Shaw 1994; Deschênes and Greenstone 2007), some studies argue that decreases in yield of US corn under increasing temperature will occur and that adaptation behavior against climate change has occurred (Butler and Huybers 2013). Schlenker and Roberts (2009) also pointed out that there are winners and losers in crop yields in the US. Some previous studies used econometric estimations on crop selections under exogenous weather conditions with profit function approaches (Mendelsohn, Nordhaus and Shaw 1994; Mendelsohn, Nordhaus and Shaw 1996; Kurukulasuriya and Mendelsohn 2008; Seo and Mendelsohn 2008a). However, the methods have not been broadly applied to the agricultural sector across the whole US region covering a variety of crops, especially using data from recent years.

This study examines crop mix shifts based on historical US county level data. We will estimate proportional land use shares by applying fractional regression considering most of the major crops in the US. We consider climate, price and spatial effects. In this endeavor we will extend the literature considering more crops than previously examined and also will look at shifts in crop elevation using county data.

2.1 Background on Estimation Approach

Farmers are assumed to choose crop mix based on maximizing expected profits across all the land areas they own or manage. In doing this, producers are assumed to use information on market signals in the form of input and output prices as well as expectations on climate and policy. Crop producers are assumed to be price-takers. In other words, the choice decisions by land owners or managers are assumed as optimal choices prior to harvest, given the information they can acquire.

Land uses for each crop are a proportion between zero and one of the total crop land area. Estimating the proportional response can be done by using a linear probability model which has a drawback that the estimated probability is not confined in the unit interval. Another possible method is a logit or logarithm transformation of the relative shares as done in Wu and Brorsen (1995) and Hardie and Parks (1997) but in doing this several problems arise that will be discussed below.

Models estimating proportional land uses often have difficulty with zero observations where a crop is not used in a region and thus has zero land area. Logit transformations over data with zeroes cause numerical problems because they lead to results that are negative infinity or undefined. For example, a logit transformation is defined as $\ln(\pi/(1-\pi))$ for the case of a single fractional response π, which extends to a logarithm transformation of the relative expected shares being assumed as $\ln(\pi_j/\pi_J)$, where π_j is a share for crop j $(j = 1,2, \ldots, J-1)$, and J is the reference crop for the case of multiple responses. Miller and Plantinga (1999) assumed that the aggregate data do not usually suffer from the zero land area. However, we have multiple zero planted acre cases in this study because some crops are not planted in some regions due to climate and water availability. For example, crops like cotton and rice are produced only in lower latitudes while wheat, barley, oats, and rapeseed are produced only in higher latitudes.

We need to utilize an approach to deal with the structural zeroes when a logit transformation is to be employed. There are some possible ways to avoid this problem but none of them are considered the best method. First, we can add some small values to zeroes so the data can be transformed using logarithms or log ratios as done in Timmins (2006). However, when the distribution is highly skewed to zero, this type of transformation can change the distribution of the variable so it may make inference severely biased. The second method is that adding a small number to the zero and subtracting a small number from non-zeroes, in which the relative magnitude between the data points is unchanged as discussed in Aitchison (1982). However, this also causes a changed distribution with fat tails. Third, we can estimate the model with the data with zeroes present by using fractional regressions will be discussed below.

Estimating models with fractional response variables including zero proportions has been discussed in a variety of studies (e.g., Papke and Wooldridge 1996; Sivakumar and Bhat 2002; Bhat and Gossen 2004; Papke and Wooldridge 2008; Koch 2010; Mullahy and Robert 2010; Kala, Kurukulasuriya and Mendelsohn 2012; Murteira and Ramalho 2013). In the field of economics, this work began when Papke and Wooldridge (1996) proposed estimation in such a case with maximum quasi-likelihood estimation (QMLE) in a generalized linear model (GLM) employing a logit link function, as suggested by McCullagh and Nelder (1989). Papke and Wooldridge (2008) later utilized a panel data approach that could accommodate the zeros using GLM with a probit link function and generalized estimating equations (GEE) with an exchangeable correlation matrix.

Fractional regression models have been discussed in the literature (Papke and Wooldridge 1996; Sivakumar and Bhat 2002; Mullahy and Robert 2010; Ramalho, Ramalho and Murteira 2011) but they have not been widely used in spite of their robustness.

Another issue is that this study involves multiple crops and land uses. Although Papke and Wooldridge (1996, 2008) employ QMLE to deal with the fractional dependent variable, their studies are limited to a single dependent variable. Consequently, we are interested in estimating the equations with multinomial fractional dependent variables (multivariate; polytomous) cases.

A multinomial logit (MNL) and a nested logit (NL) are widely used in the literature on land use changes (Plantinga, Lubowski and Stavins 2002; Lubowski, Plantinga and Stavins 2006, 2008; Seo and Mendelsohn 2008a; Langpap and Wu 2011). However, the MNL approach is known to suffer from the independence of irrelevant alternatives (IIA) problem[1] at times (McFadden 1974; Wooldridge 2010) and the NL approach has a drawback regarding how to group the relevant choices and an inability to deal with zero-one extreme values. Their underling random utility theory does not support using aggregate data very well. Also, MNL and NL generally do not fit the model with fractional dependent variables as efficiently as the QMLE approach (Murteira and Ramalho 2013).

Some studies have attempted this by using approaches such as multivariate binomial, beta, and Dirichlet regressions (Mullahy 2010; Ramalho, Ramalho and Murteira 2011; Murteira and Ramalho 2013). In the multinomial setting, full information maximum likelihood (FIML) estimation can be used with extreme value

[1] A popular example describing this problem is the blue-bus-red-bus (auto-bus) case. IIA implies that if commuters chose between car and red bus with the equal probability 0.5 and then when the third transportation mode, blue bus (another brand of bus travel), was added, they would choose red bus, blue bus, and car with the same probability 1/3. This example is unrealistic since the commuters are not likely to consider the color of the bus as long as the service quality is equivalent between the travel brands.

distribution such as Dirichlet regression (Woodland 1979). Nevertheless, as indicated in Murteira and Ramalho (2013), the QMLE for the fractional response variables is more robust than the regression based on Dirichlet distribution when the research interest lies on the conditional effect of the independent variables on the mean of the dependent variable. Furthermore, the Dirichlet distribution allows the predicted values to fall outside the unit interval so it is not the case for this study.

2.2 Empirical Model Specification

We use the fractional multinomial logit estimation method to estimate how the climate, geophysical, and socioeconomic factors affect land allocations for major crops in the US as it has the ability to deal with zero land share data.

To estimate land use shares, the quasi-likelihood method can be used following Papke and Wooldridge (1996) and Wooldridge (2010). In particular suppose y is a fractional variable bounded between zero and one. Then, let the sequence $\{(\mathbf{x}_{it-1}, y_{it}): i = 1,2, \dots, N, t = 1,2, \dots, T\}$ represent land use shares (y) and values of explanatory variables ($\mathbf{x}$) in time (t) and region (i). The explanatory variables include climate, geophysical, and socioeconomic factors in time $t-1$. Because land use decisions are made before the current return is realized, choice depends on previous information. Thus, we assume the following holds:

(1) $$\mathrm{E}(y_{it}|\mathbf{x}_{it-1}) = G(\mathbf{x}_{it-1}\boldsymbol{\beta})$$

where $G(\cdot)$ is a known function that makes the predicted dependent variable y lie between zero and one with $0 < G(z) < 1$ for all $z \in \mathbb{R}$. For example, the functional forms of $G(z) \equiv \Lambda(z) \equiv \exp(z)/(1+\exp(z))$ (logistic function) or $G(z) \equiv \Phi(z)$ (standard normal cumulative distribution function) limit the range of the predicted value of y. The logistic functional form will be used for $G(\cdot)$ since it allows simple estimation approaches and can be extended to a spatial multinomial logit framework as we will do in the next section.

To estimate this, a quasi-likelihood Bernoulli log-likelihood function can be formed following Nelder and Wedderburn (1972) and Gourieroux, Monfort and Trognon (1984) in the following fashion:

(2) $$l_{it}(\boldsymbol{\beta}) \equiv y_{it} \log[G(\mathbf{x}_{it}\boldsymbol{\beta})] + (1-y_{it}) \log[1-G(\mathbf{x}_{it}\boldsymbol{\beta})].$$

The above method represents the case of each individual who chooses only one commodity at a time.

To implement the estimation with multiple crops, we use the maximum quasi-likelihood estimation for multinomial fractional regression following Koch (2010), Kala, Kurukulasuriya and Mendelsohn (2012), and Murteira and Ramalho (2013). This yields predicted crop land use shares that fall into the unit interval. In turn, the conditional mean for land use share with J cropping alternatives can be expressed as:

(3) $$\mathrm{E}\left(s_{ijt}\middle|\mathbf{x}_{it-1}\right) = G_j(\mathbf{x}_{it-1};\boldsymbol{\beta}) = \frac{\exp\left(\mathbf{x}_{it-1}\boldsymbol{\beta}_j\right)}{\sum_{k=1}^{J}\exp(\mathbf{x}_{it-1}\boldsymbol{\beta}_k)}, \qquad j = 1,\ldots,J$$

where s_{ijt} is the observed land share for crop j in county i in time t. We then normalize on one item setting $\boldsymbol{\beta}_J = \mathbf{0}$**,** which allows identification yielding:

(4) $$\mathrm{E}(s_{ijt}|\mathbf{x}_{it-1}) = G_j(\mathbf{x}_{it-1};\boldsymbol{\beta}) = \frac{\exp(\mathbf{x}_{it-1}\boldsymbol{\beta}_j)}{1+\sum_{k=1}^{J-1}\exp(\mathbf{x}_{it-1}\boldsymbol{\beta}_k)}, j = 1,\ldots,J-1$$

and

$$\text{(5)} \qquad \mathrm{E}(s_{ijt}|\mathbf{x}_{it-1}) = G_J(\mathbf{x}_{it-1};\boldsymbol{\beta}) = \frac{1}{1+\sum_{k=1}^{J-1}\exp(\mathbf{x}_{it-1}\boldsymbol{\beta}_k)}\ .$$

Estimation using the above equations causes the conditional expected land shares to add up to one ($\sum_j s_j = 1$) and to fall in the unit interval ($s_j \in (0,1)$) given that $\Pr\left(s_j = 0\middle|x\right) \geq 0$ and $\Pr\left(s_j = 1\middle|x\right) \geq 0$ for $j = 1,2,\dots,J$.

In this case the specific quasi-maximum likelihood function is

$$\text{(6)} \qquad L = \prod_{i=1}^{N}\prod_{j=1}^{J} G\left(\mathbf{x}_{it-1};\boldsymbol{\beta}_j\right)^{s_{ijt}}$$

and the log-likelihood function of the predicted dependent variable s is

$$\text{(7)} \qquad \begin{aligned} l_i(\boldsymbol{\beta}) = {} & s_{i1t}\log[G(\mathbf{x}_{it-1};\boldsymbol{\beta}_1)] + s_{i2t}\log[G(\mathbf{x}_{it-1};\boldsymbol{\beta}_2)] + \cdots \\ & + s_{iJt}\log\left[G\left(\mathbf{x}_{it-1};\boldsymbol{\beta}_J\right)\right]\ . \end{aligned}$$

Maximizing yields the following first order condition that can be solved to obtain estimates for the parameters:

$$\text{(8)} \qquad \frac{\partial l_i(\boldsymbol{\beta})}{\partial \boldsymbol{\beta}_j} = \sum_{i=1}^{N} \mathbf{x}'_{it-1}[s_{ijt} - G_j(\mathbf{x}_{it-1};\boldsymbol{\beta})] = 0\ .$$

Assuming that the model is correctly specified, the quasi-maximum likelihood estimator is consistent since the log-likelihood function is a member of the linear exponential family (LEF) (Gourieroux, Monfort and Trognon 1984; McCullagh and Nelder 1989).

As discussed in Murteira and Ramalho (2013), the multivariate fractional regression does not generally suffer the problem of independence of irrelevant alternatives which is common in the standard multinomial logit because it identifies the ratio of the conditional means between alternatives, $G_j/G_k = \exp(\mathbf{x}_{it-1}\boldsymbol{\beta}_j)/\exp(\mathbf{x}_{it-1}\boldsymbol{\beta}_k)\ \ (j \neq k)$, which is functionally independent from the ratio of the other pairs.

Note that, as indicated in Papke and Wooldridge (2008), when using QMLE we need to ensure the standard errors are robust to arbitrary standard errors. To make the standard errors robust to misspecification of conditional variance and arbitrary serial dependence, we used heteroskedasticity-consistent robust standard errors as also discussed in Papke and Wooldridge (1996).

Estimates from discrete response estimation methods pose inherent difficulties in interpreting coefficients because the parameter estimates give changes relative to the reference group. The scale of coefficients is different among each model and thus the parameter estimates cannot be compared in magnitude but just in terms of signs for relative alternatives. In this case, even though the coefficients are positive, that is not necessarily indicate that there are positive marginal impacts of the explanatory variable on the expected proportion. For instance, if the parameter of the corn price in the barley equation is positive, it just means that the probability of choosing barley rather than corn increases. It does not explain the relationship between barley and other crops such as sorghum or soybeans when corn price increases.

To compare the magnitude of different models or equations, we use the concept of the average marginal effect (AME). The average marginal effects indicate the marginal impacts of change of one unit of the explanatory variables on the choice decisions on the vector of crop planted acres (Long and Freese 2006). For continuous explanatory variables, the average marginal effect of m-th explanatory variable on the expected probability of land share for crop j is calculated as the mean of marginal effects evaluated at each observation and is expressed as

$$\text{(9)} \qquad \frac{\partial \mathrm{E}[s_{ijt}|\mathbf{x}_i]}{\partial x_{it-1}^m} = N^{-1}\sum_{i=1}^{N}\left(\beta_j^m G_j(\mathbf{x}_{it-1};\boldsymbol{\beta}) - G_j(\mathbf{x}_{it-1};\boldsymbol{\beta})\sum_{k=1}^{J-1} G_k(\mathbf{x}_{it-1};\boldsymbol{\beta})\beta_k^m\right)$$

where s_{ij} is the observed land use share for crop j in county i and x_i^m is the value of one of the continuous explanatory variables in county i. For discrete explanatory variables, the average marginal effect is calculated as

$$\text{(10)} \qquad \frac{\Delta \mathrm{E}[s_{ijt}|\mathbf{x}_{it-1}]}{\Delta x_{it-1}^m} = N^{-1}\sum_{i=1}^{N}\left(G\left(\mathbf{x}_{it-1}^{-m}\boldsymbol{\beta}_j^{-m} + \boldsymbol{\beta}_j^m\right) - G\left(\mathbf{x}_{it-1}^{-m}\boldsymbol{\beta}_j^{-m}\right)\right)$$

where $\mathbf{x}_i^{-m}$ indicates the other explanatory variables besides x_i^m in county i.

2.3 Data and Variables Used

In the estimations, the dependent variable is a vector of proportions, $\mathbf{s}_i = (s_{i1}, s_{i2}, \dots, s_{iJ})'$, which gives the land use shares across the J crops in a region i. The crops are assumed mutually exclusive. A base crop is used as the reference point in the fractional multinomial logit. We cover ten major crops, which consist of about 96% of harvested crop lands, for 2693 counties in 41 United States[2] as shown in the Appendix

[2] Excluded states or territories are Alaska, American Samoa, District of Columbia, Guam, Hawaii, Puerto Rico, and Virgin Islands. From the 48 contiguous U.S., Connecticut, Delaware, Maine, Massachusetts, New Hampshire, Rhode Island, and Vermont are excluded because the croplands are too small or lack of data.

(figure A-1) and years from 1975 to 2011 (from 1976 to 2012 for the share variables). For the estimations, $J = 10$ and alfalfa hay is considered the base crop. The total number of observations is 99,641. Missing values are filled with linear interpolation when the region has some missing observations in analyzed periods.

Crop rotations can be used to improve soil fertility and crop yield. However, data on the exact practices being used are difficult to obtain and assuming they are repeated widely the longer run effects can be captured on average by observations over time on annual acreage. Thus, we assume that the crop acreages implicitly include crop rotations as well as crop switching or selection. Descriptions and sources of the included variables are summarized in table 1. The dependent variables are land shares for crops and the explanatory variables consist of climate, geophysical, and socioeconomic factors that will be discussed below.

Planted acres, harvested acres, and crop yield data were drawn from USDA NASS Quick Stats (U.S. Department of Agriculture 2013d) on a county basis from 1975 to 2012. The crops used are barley, corn, upland cotton, rice, sorghum, soybeans, winter wheat, durum wheat, spring wheat, and alfalfa hay. Although hay is a perennial and would not a readily respond to current conditions, it is reasonable to assume that it responds to the 5-year average values of the explanatory variables. Wheat types vary across geographic regions and exhibit different responses to climate. Thus, we separately estimate the effects on the proportion of the three types of wheat. For example, spring wheat is the most tolerant to cold weather and is used in the coldest regions while winter wheat is used in warmer areas.

Table 1. Descriptions and Sources of Variables

Variables	Description	Source
% Barley	Land share for barley planted acres (%)	USDA NASS
% Corn	Land share for corn grain planted acres (%)	USDA NASS
% Cotton	Land share for upland cotton planted acres (%)	USDA NASS
% Rice	Land share for rice planted acres (%)	USDA NASS
% Sorghum	Land share for grain sorghum planted acres (%)	USDA NASS
% Soybeans	Land share for soybean planted acres (%)	USDA NASS
% Wheat(winter)	Land share for winter wheat planted acres (%)	USDA NASS
% Wheat(spring)	Land share for spring wheat planted acres (%)	USDA NASS
% Wheat(durum)	Land share for durum wheat planted acres (%)	USDA NASS
% Hay(alfalfa)	Land share for alfalfa hay harvested acres (%)	USDA NASS
Temperature	5-year average of annual mean temperature (°C)	USHCN
Precipitation	5-year average of annual total precipitation (100mm)	USHCN
Temperature SD	Standard deviation of Temperature	USHCN
Precipitation SD	Standard deviation of Precipitation	USHCN
Altitude in 100m	Altitude from the sea level (100m)	SSURGO
Soil quality	Weighted average of reverse-order land capability classifications (1 = least suitable for cultivation; …; 8 = most suitable for cultivation)	SSURGO
PDSI	Palmer drought severity index (> –4.0 = extreme drought; …; (–0.5,0.5) = normal ; …; < 4.0 = extreme wet spell)	NOAA CDO
Irrigation rate	Irrigation rate of crop land (%)	USDA NASS
Log(Population density)	Logarithm of population density (persons in an acre)	CENSTAT
Log(Planted acres)	Logarithm of total planted acres	USDA NASS
Net return - Barley	Net return of barley production per acre	Calculated
Net return - Corn	Net return of grain corn production per acre	Calculated
Net return - Cotton	Net return of upland cotton production per acre	Calculated
Net return - Rice	Net return of rice production per acre	Calculated
Net return - Sorghum	Net return of grain sorghum production per acre	Calculated
Net return - Soybeans	Net return of soybean production per acre	Calculated
Net return - Wheat(winter)	Net return of winter wheat production per acre	Calculated
Net return - Wheat(spring)	Net return of spring wheat production per acre	Calculated
Net return - Wheat(durum)	Net return of durum wheat production per acre	Calculated
Net return - Hay(alfalfa)	Revenue of alfalfa hay production per acre	Calculated

Note: Net return for each crop ($/acre) is calculated as state price ($/unit) × county yield (unit/acre) – national cost ($/acre) for each crop.

Price received by farmers ($ per unit of commodity) and Yield (unit of commodity per acre) were also drawn from QuickStats but on the state level. Missing values for price are filled with the price from an adjacent location. Production cost data were drawn from USDA ERS Commodity Costs and Returns report (U.S. Department of Agriculture 2013a). Because classifications used in the cost and returns data differ over time and across crops, the variable costs were calculated into classes making them compatible. For example, ‘hired labor’ is considered as a cash expense before the 2003 data for barley but it is considered to be in allocated overhead after 2003. All the costs and prices are normalized by the Producer Prices Received Index (U.S. Department of Agriculture 2013c) into 1990 constant dollar values.

Revenue ($ per acre) data were calculated as Price received ($ per unit of commodity) multiplied by Yield (unit of commodity per acre). Net returns ($ per acre) were calculated as Revenue minus Variable (Operating) cost. Counties with observations of omitted or zero total harvested acres were excluded from the estimation.

We included geophysical factors to control for the location-specific characteristics. Land capability classification (Klingebiel and Montgomery 1961) is used as a measure of suitability of soil condition for crop production as discussed in Lubowski, Plantinga and Stavins (2006). The land capability that is averaged out across parcels at the county level is named soil quality.

Palmer drought severity index (PDSI) was drawn from National Oceanic and Atmospheric Administration (NOAA)’s National Climatic Data Center (NCDC) at the climate division level (Vose, et al. 2014). PDSI is based on the balance of moisture supply and demand and indicates the severity of a wet or dry spell with negative values indicating dry spells and positive values indicating wet spells.

Since the PDSI does not consider the influence of irrigation, we also include proportion of irrigated land by county. The irrigation rate of agricultural land was calculated using the quantity of irrigated acres drawn from the USDA Census of Agriculture (1969–2012) (U.S. Department of Agriculture 2014).

Monthly, county level, climate data were obtained from the United States Historical Climatology Network (USHCN) (Menne, et al. 2012). Included climate variables are annual average temperature and annual total precipitation, as well as their squared values as we assumed nonlinear trends in development of yield and profits with respect to climate variables. As shown in Mendelsohn, et al. (2007), both climate normals and inter-annual variations are likely to play an important role in crop mix selection. Thus, in this study, standard deviations of temperature and precipitation are also included to reflect temporal fluctuations of climate variables.

Temperature and precipitation are important factors in determining land use allocations and are thus included as explanatory variables. There are some other candidates such as growing degree days and growing seasonal precipitation, as used in Lee and Sumner (2015). Because the historical data and projected values on the variables are not available and our model have multiple crops that have different growing seasons, this study only deals with regional average temperature and precipitation and their variations for estimations and projections.

Some previous studies on crop land allocation have used parcel level data from the Natural Resources Inventory (NRI) but the Natural Resources Conservation Service (NRCS) has not publicly provided those data since 1997. Thus, we instead use county level data from NASS for fractional land uses for each crop.

Data were classified into regions. The farm production regions by USDA Economic Research Service (ERS) were used. Before 1995, ERS used ten farm production regions to classify the region and after 1995, they use nine farm resource regions. Because this study focuses on the locational shifts of the crop variations, we use the older farm production regions as the geographic categories. The regional classifications are shown in figure 1 for the farm production regions based on the data from U.S. Department of Agriculture (2013b).

The means and standard deviations of the dependent and independent variables by region are shown in table 2. The descriptive statistics for the variables show different characteristics between the regions.

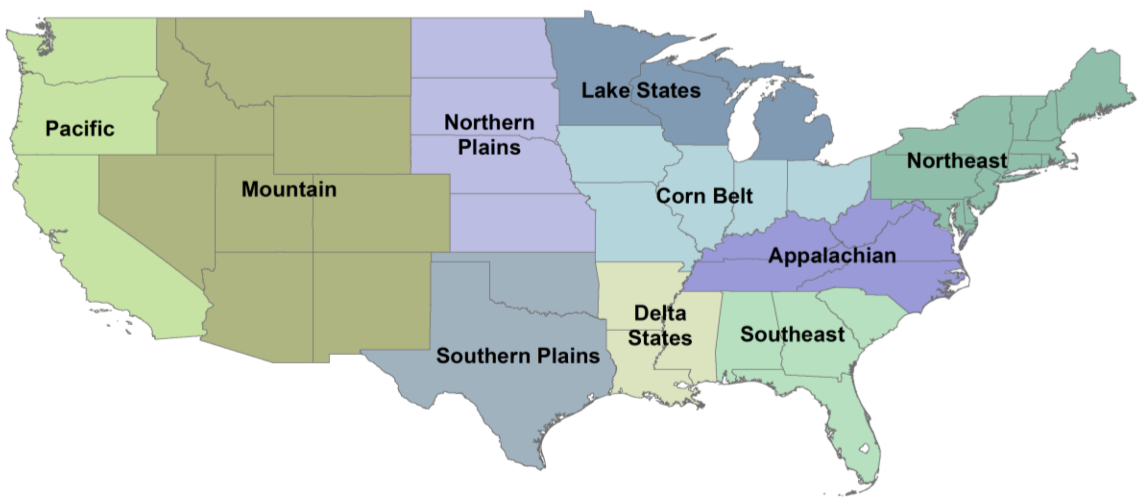


Figure 1. Farm production regions

Source: Data from U.S. Department of Agriculture (2013b)

Table 2. Means and Standard Deviations of Variables by Region

Variable	Appalachian		Corn Belt		Delta States		Lake States		Mountain		Northeast	
% Barley	0.028	(0.037)	0.002	(0.006)	0.001	(0.009)	0.025	(0.053)	0.111	(0.119)	0.023	(0.038)
% Corn	0.375	(0.169)	0.429	(0.147)	0.134	(0.118)	0.481	(0.194)	0.071	(0.109)	0.483	(0.127)
% Cotton	0.031	(0.096)	0.002	(0.023)	0.119	(0.148)	0.000	(0.000)	0.019	(0.084)	0.000	(0.000)
% Rice	0.000	(0.000)	0.001	(0.015)	0.063	(0.130)	0.000	(0.000)	0.000	(0.000)	0.000	(0.000)
% Sorghum	0.021	(0.036)	0.022	(0.051)	0.106	(0.106)	0.000	(0.000)	0.021	(0.054)	0.003	(0.005)
% Soybeans	0.262	(0.187)	0.393	(0.138)	0.433	(0.190)	0.206	(0.170)	0.000	(0.000)	0.145	(0.164)
% Wheat(winter)	0.149	(0.098)	0.085	(0.088)	0.144	(0.101)	0.053	(0.070)	0.199	(0.224)	0.076	(0.074)
% Wheat(spring)	0.000	(0.000)	0.000	(0.000)	0.000	(0.000)	0.043	(0.118)	0.085	(0.144)	0.000	(0.000)
% Wheat(durum)	0.000	(0.000)	0.000	(0.000)	0.000	(0.000)	0.001	(0.004)	0.011	(0.051)	0.000	(0.000)
% Hay(alfalfa)	0.135	(0.185)	0.066	(0.108)	0.000	(0.000)	0.190	(0.215)	0.484	(0.300)	0.269	(0.183)
Temperature (°C)	13.611	(1.786)	10.880	(1.778)	17.410	(1.644)	6.741	(1.586)	8.798	(3.972)	9.844	(2.149)
Precipitation (100mm)	12.234	(1.586)	10.131	(1.438)	14.270	(1.733)	7.887	(1.198)	3.627	(1.433)	10.938	(1.325)
Temperature SD	0.513	(0.196)	0.675	(0.239)	0.499	(0.168)	0.806	(0.311)	0.658	(0.305)	0.566	(0.233)
Precipitation SD	2.014	(0.713)	1.792	(0.685)	2.591	(0.927)	1.309	(0.516)	0.779	(0.375)	1.636	(0.609)
Altitude (100m)	2.276	(1.649)	2.493	(0.714)	0.876	(0.714)	3.004	(0.708)	14.827	(4.768)	2.290	(1.491)
Soil quality	4.453	(1.087)	5.768	(0.913)	4.865	(0.921)	5.202	(1.091)	2.670	(1.352)	4.574	(0.952)
PDSI	0.206	(0.863)	0.675	(0.874)	0.239	(0.824)	0.668	(1.123)	0.010	(1.501)	0.400	(0.823)
Irrigation rate	0.008	(0.021)	0.013	(0.047)	0.102	(0.179)	0.027	(0.056)	0.145	(0.188)	0.026	(0.063)
Log(Population density)	4.734	(0.917)	4.593	(1.074)	4.163	(0.813)	4.464	(1.252)	2.291	(1.579)	5.584	(1.134)
Log(Planted acres)	9.535	(1.339)	11.526	(1.222)	10.154	(1.639)	11.211	(1.339)	10.485	(1.404)	10.272	(1.098)
Net return - Barley (100$/acre)	0.235	(0.355)	0.086	(0.341)	–0.018	(0.098)	0.428	(0.411)	1.003	(0.748)	0.386	(0.338)
Net return - Corn	1.004	(0.749)	1.584	(0.846)	0.707	(0.813)	1.203	(0.822)	1.039	(1.225)	1.470	(0.734)
Net return - Cotton	0.168	(0.773)	0.013	(0.218)	0.478	(1.387)	0.000	(0.000)	0.204	(0.926)	0.000	(0.000)
Net return - Rice	0.000	(0.000)	0.019	(0.210)	0.510	(0.951)	0.000	(0.000)	0.000	(0.000)	0.000	(0.000)
Net return - Sorghum	0.314	(0.431)	0.681	(0.541)	0.585	(0.413)	0.000	(0.000)	0.208	(0.534)	0.103	(0.328)
Net return - Soybeans	1.011	(0.630)	1.706	(0.621)	0.910	(0.503)	1.328	(0.571)	0.000	(0.000)	1.265	(0.722)
Net return - Wheat(winter)	0.761	(0.431)	0.964	(0.449)	0.652	(0.347)	0.826	(0.429)	1.053	(0.936)	0.896	(0.420)
Net return - Wheat(spring)	0.000	(0.000)	0.000	(0.000)	0.000	(0.000)	0.447	(0.453)	0.860	(0.921)	0.000	(0.000)
Net return - Wheat(durum)	0.000	(0.000)	0.000	(0.000)	0.000	(0.000)	0.239	(0.430)	0.346	(0.883)	0.000	(0.000)
Net return - Hay(alfalfa)	2.155	(1.811)	3.197	(1.392)	0.000	(0.000)	1.798	(1.412)	3.203	(1.786)	3.270	(1.042)
Number of counties	411		491		202		219		264		158	

Note: Standard deviations are in parentheses. All of the crop net returns per acre are in 1990 constant hundred US dollars. SD indicates sample standard deviations of each climate variable.

Table 2. Continued

Variable	Northern Plains		Pacific		Southeast		Southern Plains		All regions	
% Barley	0.029	(0.054)	0.156	(0.186)	0.011	(0.028)	0.020	(0.042)	0.031	(0.073)
% Corn	0.252	(0.218)	0.128	(0.179)	0.243	(0.159)	0.108	(0.133)	0.285	(0.216)
% Cotton	0.001	(0.006)	0.036	(0.127)	0.187	(0.216)	0.152	(0.216)	0.053	(0.137)
% Rice	0.000	(0.000)	0.050	(0.180)	0.000	(0.000)	0.016	(0.081)	0.009	(0.060)
% Sorghum	0.086	(0.105)	0.026	(0.085)	0.083	(0.087)	0.176	(0.170)	0.056	(0.102)
% Soybeans	0.151	(0.173)	0.000	(0.000)	0.293	(0.183)	0.065	(0.130)	0.219	(0.208)
% Wheat(winter)	0.246	(0.265)	0.327	(0.250)	0.184	(0.123)	0.418	(0.283)	0.183	(0.205)
% Wheat(spring)	0.089	(0.174)	0.056	(0.079)	0.000	(0.000)	0.000	(0.000)	0.024	(0.090)
% Wheat(durum)	0.022	(0.090)	0.014	(0.074)	0.000	(0.000)	0.000	(0.000)	0.004	(0.038)
% Hay(alfalfa)	0.124	(0.153)	0.207	(0.278)	0.000	(0.000)	0.045	(0.081)	0.137	(0.214)
Temperature (°C)	9.617	(2.886)	12.277	(3.709)	17.308	(1.419)	17.576	(2.380)	12.489	(4.301)
Precipitation (100mm)	6.299	(1.945)	5.890	(4.137)	12.931	(1.644)	8.462	(3.109)	9.473	(3.640)
Temperature SD	0.793	(0.313)	0.489	(0.229)	0.489	(0.184)	0.539	(0.163)	0.613	(0.265)
Precipitation SD	1.324	(0.637)	1.370	(0.975)	2.148	(0.849)	1.909	(0.879)	1.718	(0.856)
Altitude (100m)	5.934	(2.548)	4.263	(3.703)	1.434	(0.902)	3.963	(3.354)	4.087	(4.441)
Soil quality	5.386	(0.894)	3.018	(1.474)	4.941	(0.765)	4.807	(0.883)	4.752	(1.352)
PDSI	0.852	(1.505)	–0.102	(1.229)	–0.081	(0.964)	0.529	(0.915)	0.394	(1.118)
Irrigation rate	0.077	(0.129)	0.198	(0.201)	0.031	(0.050)	0.036	(0.099)	0.052	(0.119)
Log(Population density)	2.671	(1.264)	4.088	(1.838)	4.558	(0.981)	3.508	(1.462)	4.042	(1.522)
Log(Planted acres)	12.034	(0.783)	10.234	(1.718)	9.495	(1.333)	10.471	(1.523)	10.618	(1.577)
Net return - Barley	0.193	(0.333)	0.832	(0.607)	0.021	(0.244)	0.017	(0.308)	0.260	(0.500)
Net return - Corn	1.103	(1.011)	1.776	(1.658)	0.558	(0.909)	0.577	(1.094)	1.080	(1.033)
Net return - Cotton	0.040	(0.397)	0.622	(1.701)	0.528	(1.318)	–0.235	(1.216)	0.132	(0.917)
Net return - Rice	0.000	(0.000)	0.482	(1.478)	0.000	(0.000)	0.112	(0.555)	0.072	(0.465)
Net return - Sorghum	0.515	(0.536)	0.408	(0.698)	0.224	(0.355)	0.422	(0.457)	0.383	(0.507)
Net return - Soybeans	1.184	(0.752)	0.000	(0.000)	0.814	(0.496)	0.476	(0.595)	0.970	(0.779)
Net return - Wheat(winter)	0.647	(0.359)	1.730	(0.911)	0.621	(0.353)	0.389	(0.372)	0.796	(0.572)
Net return - Wheat(spring)	0.192	(0.363)	0.855	(0.956)	0.000	(0.000)	0.000	(0.000)	0.172	(0.486)
Net return - Wheat(durum)	0.177	(0.350)	0.703	(1.377)	0.000	(0.000)	0.000	(0.000)	0.098	(0.450)
Net return - Hay(alfalfa)	2.319	(1.011)	2.589	(2.328)	0.000	(0.000)	2.873	(2.526)	2.239	(1.916)
Number of counties	317		100		253		321		2693	

Note: Standard deviations are in parentheses. All of the crop net returns per acre are in 1990 constant hundred US dollars. SD indicates sample standard deviations of each climate variable.

The regions with the largest land shares for corn are Appalachian, Corn Belt, Lake States, Northeast, and Northern Plains. The largest crop share in Delta States and Mountain are soybeans and alfalfa hay, respectively. The largest land share in Pacific and Southern Plains regions is for winter wheat. Northern Plains region has the largest crop lands. Corn Belt and Northern Plains have the most suitable lands for cultivation as measured in land capability classification. Note that we have multiple cases with zero crop mix shares which generally reflect that not all crops are planted in all regions but may also may result from rounding or confidential observations. For example, rice is only observed in Corn Belt, Delta States, Pacific, and Southern Plains regions.

2.4 Estimation Results

The estimations are conducted employing the following conditional mean function:

$$\text{(11)} \qquad \mathrm{E}(s_{ijt}|\mathbf{c},\mathbf{x},\mathbf{z};\boldsymbol{\beta}^c,\boldsymbol{\beta}^x,\boldsymbol{\beta}^z) = G(\mathbf{c}_{it-1}\boldsymbol{\beta}^c + \mathbf{x}_{ijt-1}\boldsymbol{\beta}^x + \mathbf{z}_{ij}\boldsymbol{\beta}^z)$$

where $G(\cdot)$ has a multinomial logit functional form, s_{ijt} indicates land use share for crop j in county i at time t, $\mathbf{c}_{it-1}$ indicates climate variables at time $t-1$ in county i, $\mathbf{x}_{ijt-1}$ implies time-varying variables such as net return and other socioeconomic factors at time $t-1$ in county i, and $\mathbf{z}_{ij}$ indicates time-invariant county fixed variables in county i for crop j. The climate variables consist of 5-year average of temperature of precipitation and their standard deviations. The averaged values are used to incorporate the generalized longer run pattern of climate and such a practice models farmer longer run reactions and avoids excessive fluctuations caused by anomalies in some years. The standard deviations formed over five years are also included to model reactions to climate variations. The time-varying factors include five year averages for net returns for crops, irrigation rates, population density, and total planted area. Time-invariant factors include soil quality, altitude of planted areas, drought index, and other county-specific factors.

Although our model does not explicitly deal with the panel structure of data, testing for the existence of autocorrelation and cross-sectional correlation in terms of linear estimations can mitigate misinterpretations of the estimates. The results of unit root tests in panel data following Breitung (2001) show that the dependent and independent variables do not suffer from autocorrelation and contemporaneous correlation except for the share of soybeans and the net return of barley.

Using the quasi-maximum likelihood method over the above functional form, the estimated results for average land share allocation are presented in table 3. We tested several specifications regarding the temperature and precipitation terms. In the testing, since the estimation was done by QMLE with robust clustered variance-covariance matrix, the conventional Hausman test could not be used. Instead, we used the Akaike information criterion (AIC) and Bayesian information criterion (BIC) to compare models. The lower AIC or BIC is considered the better fitted model when the same data are used in the compared models. AIC and BIC are calculated as $\mathrm{AIC} = 2k - 2\ln(L)$ and $\mathrm{BIC} = \ln(N)k - 2\ln(L)$, respectively, where k is the number of parameters estimated (model degrees of freedom), L is the maximized likelihood, and N is the number of observations. The BIC penalize the number of parameters more strongly than the AIC does as the number of observation increases the BIC.

Table 3. Fractional Multinomial Logit Estimation Results

	% Planted acres (Base: Hay(alfalfa))				
Variables	Barley	Corn	Cotton	Rice	Sorghum
Temperature	–0.075	–0.040	3.757***	–0.425	0.851***
	(0.060)	(0.051)	(0.289)	(0.320)	(0.086)
Temperature squared	0.008***	0.006***	–0.092***	0.028***	–0.014***
	(0.003)	(0.002)	(0.008)	(0.010)	(0.003)
Precipitation	–0.069	0.389***	0.024	0.698***	–0.041
	(0.083)	(0.041)	(0.092)	(0.191)	(0.072)
Precipitation squared	–0.000	–0.013***	0.003	–0.012	0.001
	(0.005)	(0.002)	(0.004)	(0.007)	(0.003)
Temperature SD	–0.013	–0.224***	–0.880***	–0.513***	–0.089
	(0.071)	(0.036)	(0.078)	(0.176)	(0.059)
Precipitation SD	0.227***	–0.005	0.086***	–0.133**	0.146***
	(0.042)	(0.019)	(0.029)	(0.055)	(0.026)
Altitude	–0.062***	–0.065***	0.124***	0.021	0.060***
	(0.014)	(0.012)	(0.030)	(0.080)	(0.021)
Soil quality	0.130***	0.294***	0.431***	0.146	0.477***
	(0.042)	(0.033)	(0.063)	(0.182)	(0.050)
PDSI	–0.012	–0.051***	–0.137***	0.023	0.063***
	(0.013)	(0.010)	(0.024)	(0.048)	(0.016)
Irrigation rate	0.517	1.282***	1.800***	6.823***	0.614
	(0.376)	(0.297)	(0.415)	(0.510)	(0.405)
Log(Population density)	0.060*	0.044**	–0.099**	0.028	–0.095***
	(0.031)	(0.022)	(0.044)	(0.111)	(0.034)
Log(Planted acres)	0.218***	0.255***	0.757***	0.797***	0.261***
	(0.038)	(0.029)	(0.048)	(0.091)	(0.041)
Net return - Barley	0.637***	–0.088	–0.792***	–0.164	–0.299***
	(0.103)	(0.070)	(0.131)	(0.323)	(0.102)
Net return - Corn	–0.026	0.396***	0.120**	0.161	–0.052
	(0.051)	(0.036)	(0.061)	(0.135)	(0.049)
Net return - Cotton	–0.281***	–0.056	0.262***	–0.422***	–0.140**
	(0.073)	(0.053)	(0.059)	(0.101)	(0.057)
Net return - Rice	0.408	0.582*	0.389	1.647***	0.741**
	(0.358)	(0.319)	(0.323)	(0.330)	(0.331)
Net return - Sorghum	0.380**	0.381***	0.037	1.777***	1.279***
	(0.152)	(0.069)	(0.115)	(0.245)	(0.100)
Net return - Soybeans	–0.934***	0.247***	–0.421***	–1.412***	–0.176**
	(0.086)	(0.050)	(0.107)	(0.228)	(0.076)
Net return - Wheat(winter)	0.140	0.044	0.059	–0.842**	–0.482***
	(0.096)	(0.071)	(0.137)	(0.358)	(0.107)
Net return - Wheat(spring)	–0.109	–0.207**	–1.046*	–6.985***	–0.669**
	(0.086)	(0.095)	(0.579)	(0.725)	(0.280)
Net return - Wheat(durum)	0.475***	0.305***	0.146	0.179	–0.065
	(0.089)	(0.091)	(0.146)	(0.302)	(0.140)
Net return - Hay(alfalfa)	–0.372***	–0.316***	–0.318***	–0.618***	–0.391***
	(0.032)	(0.016)	(0.031)	(0.104)	(0.022)
Constant	–2.975***	–5.574***	–44.538***	–16.250***	–12.668***
	(0.659)	(0.477)	(2.376)	(2.566)	(0.740)
Number of counties	2693				

Note: County-clustered robust standard errors are shown in parentheses and *, **, and *** indicate statistically significance at 10%, 5%, and 1% levels, respectively.

Table 3. Continued

	% Planted acres (Base: Hay(alfalfa))			
Variables	Soybeans	Wheat(winter)	Wheat(spring)	Wheat(durum)
Temperature	0.556***	0.827***	–0.071	–0.849***
	(0.062)	(0.083)	(0.075)	(0.091)
Temperature squared	–0.015***	–0.018***	–0.005	0.034***
	(0.003)	(0.003)	(0.004)	(0.004)
Precipitation	0.331***	0.067	–0.418***	0.722
	(0.056)	(0.065)	(0.078)	(0.454)
Precipitation squared	–0.007***	–0.003	0.017***	–0.134***
	(0.002)	(0.003)	(0.005)	(0.051)
Temperature SD	–0.025	–0.103*	0.247***	0.033
	(0.039)	(0.055)	(0.056)	(0.121)
Precipitation SD	0.029	0.017	0.076	–0.086
	(0.020)	(0.022)	(0.046)	(0.137)
Altitude	–0.349***	0.025	–0.185***	–0.263***
	(0.018)	(0.015)	(0.016)	(0.036)
Soil quality	0.466***	0.293***	0.275***	0.218*
	(0.041)	(0.047)	(0.056)	(0.126)
PDSI	–0.019	0.039***	–0.011	0.042
	(0.014)	(0.014)	(0.016)	(0.031)
Irrigation rate	0.802**	–0.144	0.288	0.378
	(0.321)	(0.384)	(0.395)	(0.872)
Log(Population density)	0.041	–0.057*	–0.133***	0.039
	(0.028)	(0.032)	(0.044)	(0.078)
Log(Planted acres)	0.575***	0.528***	0.544***	0.535***
	(0.034)	(0.037)	(0.056)	(0.122)
Net return - Barley	–0.689***	–0.189**	–0.060	0.921***
	(0.078)	(0.085)	(0.111)	(0.280)
Net return - Corn	–0.150***	0.136***	–0.215***	–0.138
	(0.039)	(0.041)	(0.060)	(0.131)
Net return - Cotton	–0.078	–0.210***	0.022	–0.254**
	(0.055)	(0.060)	(0.078)	(0.118)
Net return - Rice	0.772**	0.724**	–5.862***	–0.237
	(0.332)	(0.341)	(0.706)	(0.516)
Net return - Sorghum	0.337***	0.024	–0.691***	0.709**
	(0.078)	(0.082)	(0.230)	(0.334)
Net return - Soybeans	0.765***	–0.534***	–1.184***	–2.135***
	(0.064)	(0.069)	(0.119)	(0.382)
Net return - Wheat(winter)	–0.158**	0.274***	–0.143	–0.526
	(0.077)	(0.085)	(0.106)	(0.325)
Net return - Wheat(spring)	0.437***	–0.168	0.981***	–1.396***
	(0.111)	(0.103)	(0.113)	(0.265)
Net return - Wheat(durum)	0.610***	0.178	0.397***	0.879***
	(0.107)	(0.112)	(0.080)	(0.150)
Net return - Hay(alfalfa)	–0.447***	–0.330***	–0.356***	–0.361***
	(0.020)	(0.020)	(0.035)	(0.060)
Constant	–13.125***	–12.509***	–3.758***	–2.500
	(0.582)	(0.618)	(0.711)	(1.539)
Number of counties	2693			

Note: County-clustered robust standard errors are shown in parentheses and *, **, and *** indicate statistically significance at 10%, 5%, and 1% levels, respectively.

Applying these tests, we found that the model including climate squared terms is more desirable than the model without the squared terms. We also find that the inclusion of the net return variables improves the model. On the other hand, we did not see significant improvement in including year dummies for time fixed effects. Thus, the year dummies are excluded.

Average marginal effects (AME) estimates in table 4 show the following:

- All of the major crops are statistically significantly affected by changes in temperature and precipitation except the case of precipitation on cotton. Upland cotton, rice, sorghum, and winter wheat are more likely chosen when the 5-year average temperature increases. On the other hand, barley, corn, soybeans, spring wheat, durum wheat, and alfalfa hay are less likely chosen when the temperature goes up.
- When annual precipitation increases, the proportions of planted acres for corn, rice, and soybeans increase with the proportions for barley, sorghum, hay, and all types of wheat declining.
- Larger variations in temperature reduce land allocations for corn, cotton, and rice and larger standard deviations of precipitation decrease the proportions of planted acres for corn, rice, winter wheat, and hay. This implies that changes in land allocations for some crops are more sensitive to climate variations.

Table 4. Average Marginal Effects on Proportions of Planted Acres

Variables	Barley	Corn	Cotton	Rice	Sorghum
Temperature	–0.0015***	–0.0190***	0.0145***	0.0024***	0.0098***
	(0.0004)	(0.0010)	(0.0007)	(0.0004)	(0.0006)
Precipitation	–0.0032***	0.0106***	0.0008	0.0019***	–0.0054***
	(0.0008)	(0.0015)	(0.0008)	(0.0003)	(0.0008)
Temperature SD	0.0020	–0.0258***	–0.0311***	–0.0019*	0.0053**
	(0.0018)	(0.0033)	(0.0028)	(0.0011)	(0.0021)
Precipitation SD	0.0058***	–0.0075***	0.0021**	–0.0011***	0.0058***
	(0.0011)	(0.0017)	(0.0009)	(0.0003)	(0.0008)
Altitude	–0.0002	0.0117***	0.0087***	0.0008*	0.0064***
	(0.0004)	(0.0020)	(0.0011)	(0.0005)	(0.0008)
Soil quality	–0.0028***	–0.0044	0.0034	–0.0015	0.0076***
	(0.0011)	(0.0033)	(0.0021)	(0.0011)	(0.0017)
PDSI	–0.0002	–0.0089***	–0.0058***	0.0003	0.0040***
	(0.0003)	(0.0012)	(0.0008)	(0.0003)	(0.0006)
Irrigation rate	0.0015	0.1427***	0.0452***	0.0366***	–0.0072
	(0.0078)	(0.0308)	(0.0120)	(0.0031)	(0.0119)
Log(Population density)	0.0021***	0.0093***	–0.0036**	0.0002	–0.0042***
	(0.0008)	(0.0023)	(0.0015)	(0.0007)	(0.0012)
Log(Planted acres)	–0.0026***	–0.0312***	0.0132***	0.0019***	–0.0093***
	(0.0008)	(0.0028)	(0.0015)	(0.0005)	(0.0013)
Net return - Barley	0.0221***	0.0470***	–0.0204***	0.0017	0.0003
	(0.0024)	(0.0066)	(0.0045)	(0.0019)	(0.0034)
Net return - Corn	–0.0030**	0.0753***	0.0017	0.0007	–0.0082***
	(0.0013)	(0.0044)	(0.0021)	(0.0008)	(0.0017)
Net return - Cotton	–0.0061***	0.0061	0.0160***	–0.0023***	–0.0029***
	(0.0014)	(0.0039)	(0.0012)	(0.0005)	(0.0010)
Net return - Rice	0.0140***	0.0237	–0.0122***	0.0061***	0.0071**
	(0.0053)	(0.0158)	(0.0026)	(0.0006)	(0.0031)
Net return - Sorghum	0.0067*	0.0252***	–0.0146***	0.0087***	0.0511***
	(0.0038)	(0.0052)	(0.0036)	(0.0015)	(0.0032)
Net return - Soybeans	–0.0221***	0.0302***	–0.0169***	–0.0094***	–0.0068***
	(0.0021)	(0.0053)	(0.0037)	(0.0014)	(0.0026)
Net return - Wheat(winter)	0.0038*	0.0135	0.0037	–0.0049**	–0.0258***
	(0.0022)	(0.0082)	(0.0047)	(0.0021)	(0.0039)
Net return - Wheat(durum)	–0.0011	–0.0389***	–0.0325	–0.0419***	–0.0211
	(0.0019)	(0.0129)	(0.0236)	(0.0052)	(0.0138)
Net return - Wheat(spring)	0.0075***	–0.0020	–0.0057	–0.0009	–0.0174***
	(0.0017)	(0.0096)	(0.0039)	(0.0017)	(0.0040)
Net return - Hay(alfalfa)	–0.0036***	0.0011	0.0018*	–0.0015**	–0.0028***
	(0.0008)	(0.0016)	(0.0011)	(0.0006)	(0.0007)

Note: Standard errors via delta method are shown in parentheses and *, **, and *** indicate statistical significance at the levels 10%, 5%, and 1%, respectively.

Table 4. Continued

Variables	Soybeans	Wheat (winter)	Wheat (spring)	Wheat (durum)	Hay (alfalfa)
Temperature	–0.0062***	0.0214***	–0.0039***	–0.0012***	–0.0164***
	(0.0009)	(0.0009)	(0.0005)	(0.0002)	(0.0009)
Precipitation	0.0164***	–0.0091***	–0.0052***	–0.0010***	–0.0059***
	(0.0012)	(0.0018)	(0.0007)	(0.0003)	(0.0014)
Temperature SD	0.0268***	0.0090*	0.0055***	0.0002	0.0101***
	(0.0024)	(0.0047)	(0.0009)	(0.0004)	(0.0032)
Precipitation SD	0.0011	–0.0031**	0.0008	–0.0005	–0.0034**
	(0.0012)	(0.0015)	(0.0008)	(0.0005)	(0.0016)
Altitude	–0.0472***	0.0157***	–0.0021***	–0.0007***	0.0071***
	(0.0021)	(0.0017)	(0.0003)	(0.0001)	(0.0008)
Soil quality	0.0252***	–0.0028	0.0016*	–0.0000	–0.0262***
	(0.0030)	(0.0039)	(0.0008)	(0.0004)	(0.0028)
PDSI	0.0005	0.0087***	–0.0001	0.0002*	0.0012
	(0.0013)	(0.0013)	(0.0002)	(0.0001)	(0.0008)
Irrigation rate	–0.0151	–0.1407***	–0.0030	–0.0004	–0.0605**
	(0.0224)	(0.0327)	(0.0059)	(0.0030)	(0.0244)
Log(Population density)	0.0065***	–0.0080***	–0.0025***	0.0003	–0.0001
	(0.0022)	(0.0027)	(0.0007)	(0.0003)	(0.0019)
Log(Planted acres)	0.0326***	0.0232***	0.0049***	0.0006	–0.0333***
	(0.0023)	(0.0029)	(0.0009)	(0.0004)	(0.0025)
Net return - Barley	–0.0750***	0.0114*	–0.0018	0.0034***	0.0114**
	(0.0054)	(0.0066)	(0.0018)	(0.0010)	(0.0058)
Net return - Corn	–0.0543***	0.0059	–0.0051***	–0.0005	–0.0126***
	(0.0033)	(0.0038)	(0.0010)	(0.0005)	(0.0026)
Net return - Cotton	–0.0000	–0.0219***	0.0023**	–0.0007*	0.0096**
	(0.0026)	(0.0034)	(0.0012)	(0.0004)	(0.0045)
Net return - Rice	0.0362***	0.0424***	–0.1068***	0.0052***	–0.0160
	(0.0081)	(0.0116)	(0.0112)	(0.0017)	(0.0279)
Net return - Sorghum	0.0021	–0.0450***	–0.0159***	0.0028**	–0.0213***
	(0.0045)	(0.0057)	(0.0037)	(0.0012)	(0.0063)
Net return - Soybeans	0.1215***	–0.0860***	–0.0158***	–0.0056***	0.0111**
	(0.0050)	(0.0060)	(0.0021)	(0.0015)	(0.0043)
Net return - Wheat(winter)	–0.0281***	0.0460***	–0.0027	–0.0018	–0.0036
	(0.0063)	(0.0082)	(0.0017)	(0.0012)	(0.0055)
Net return - Wheat(durum)	0.1147***	0.0011	0.0204***	–0.0056***	0.0058
	(0.0137)	(0.0128)	(0.0019)	(0.0010)	(0.0067)
Net return - Wheat(spring)	0.0560***	–0.0142	0.0022**	0.0021***	–0.0277***
	(0.0093)	(0.0087)	(0.0009)	(0.0005)	(0.0073)
Net return - Hay(alfalfa)	–0.0202***	–0.0022	–0.0020***	–0.0002	0.0297***
	(0.0015)	(0.0016)	(0.0006)	(0.0002)	(0.0014)

Note: Standard errors via delta method are shown in parentheses and *, **, and *** indicate statistical significance at the levels 10%, 5%, and 1%, respectively.

- The average marginal effects of own net returns for all of the crops show positive signs at the 1% statistical significance level. It implies that higher own net return increases the land allocation for the specific crop. Thus, the net return variables are advised to be included because omitting the variables may overestimate or underestimate the effects of climate factors.
- As population density in the county increases, the marginal effects are mixed. Specifically, barley, corn, and soybeans are grown in more populated areas. On the other hand, upland cotton, sorghum, winter wheat, and spring wheat are more likely chosen in less populated areas.

The predicted proportions of crop planted acres over the 5-year average temperature are shown in figure 2. Around the 1975–2010 mean (12.5 degrees Celsius), we find that warming causes increasing proportions of upland cotton, rice, sorghum, and winter wheat. On the other hand, the predicted proportions of barley, corn, soybeans, spring wheat, durum wheat, and alfalfa hay decrease as the annual mean temperature increases. The figure follows the results of the average marginal effects. Nonlinear relationships between predicted proportions for crops and increasing temperature are shown as expected. For instance, winter wheat start decreasing as the temperature goes beyond 15 degrees Celsius and soybeans start decreasing beyond 12 degrees Celsius. Figure 2 also shows the regional differences in that the predicted proportions for each crop above and below the mean temperature indicate the responses of crop allocations in regions with higher and lower temperature.

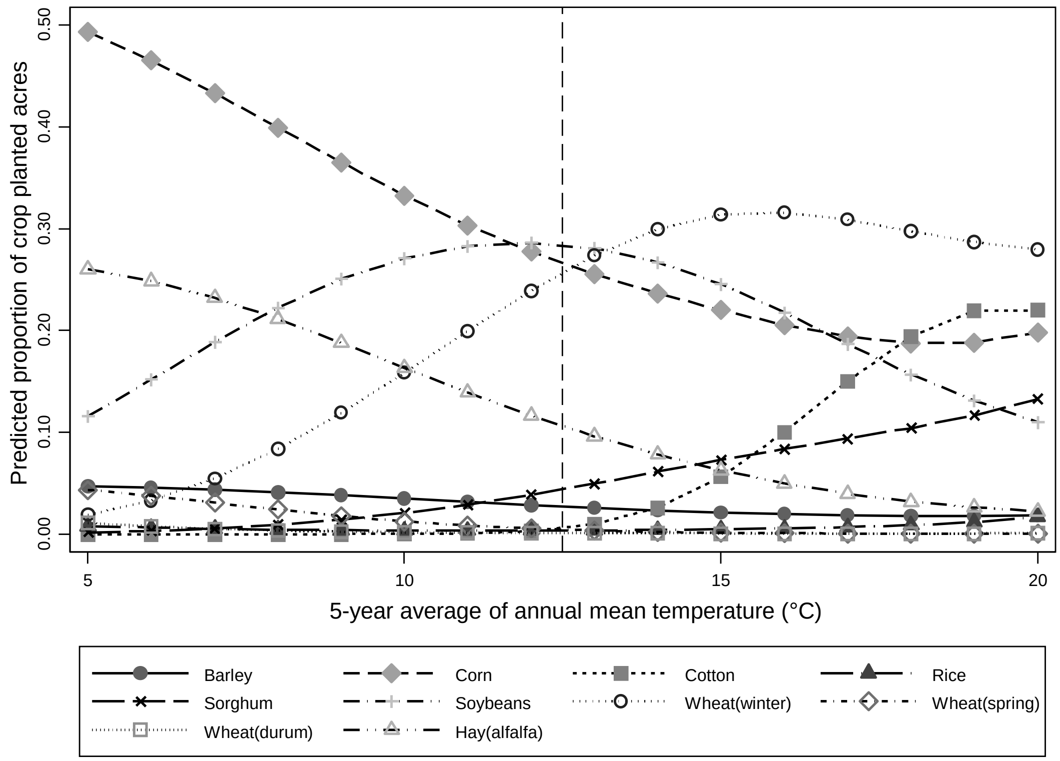


Figure 2. Predicted proportions of crop planted acres over temperature

Note: Predicted proportions are evaluated holding other variables including precipitation at their observed values. Annual mean temperature over 1975–2011 has mean (12.5 degrees Celsius) shown as a vertical dashed line and standard deviation (4.30).

Figure 3 contains results on the changes in crop choice under changes in precipitation. Around the 1975–2011 mean of the annual precipitation (947 mm), more precipitation causes increasing proportions of corn, rice, and soybeans. On the other hand, from the mean precipitation, more precipitation makes the predicted proportions of barley, sorghum, winter wheat, spring wheat, durum wheat, and alfalfa hay smaller. The figure also follows the results of the average marginal effects. We see the change in land share proportions is nonlinear to a unit change of precipitation. The further the deviation from the mean temperature and precipitation goes the larger the crop mix change.

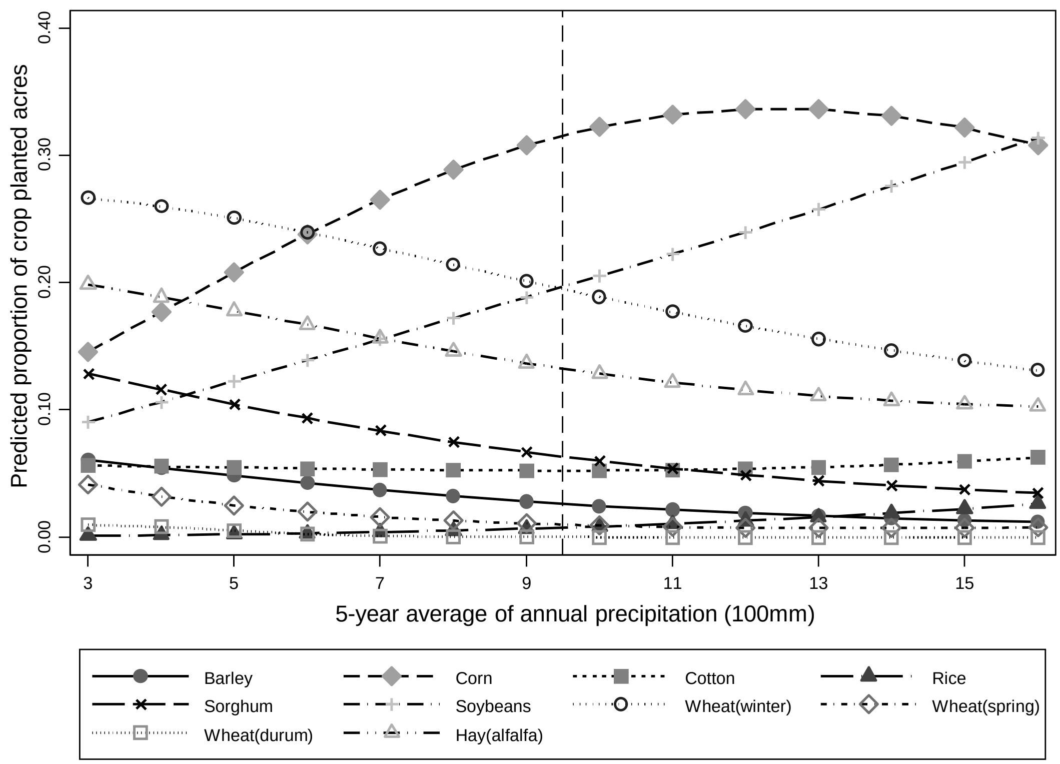


Figure 3. Predicted proportions of crop planted acres over precipitation

Note: Predicted proportions are evaluated holding other variables including temperature at their observed values. Annual total precipitation over 1975–2011 has mean (947 mm) shown as a vertical dashed line and standard deviation (364).

2.4.1 Estimation Results by Region

Farmers in various locations produce different crops depending on economic, agronomic, social, and other location specific characteristics. We estimate the same model with subsampled counties separately by the ERS farm production regions. Some crops that are not planted at all in some regions were excluded from the estimation for the specific regions. We show the average marginal effects of temperature and precipitation on the proportions of planted acres by region in the Appendix (table A-1). With the locational figures, the results are also summarized in figure 4 for the marginal effects of temperature and precipitation on the choice of planted crops. Based on the results in figure 4, we find that when the annual temperature increases:

- The proportion of planted acres for barley increases in the Northeast region but decreases in the Delta States, Lake States, Mountain, and Northern Plains regions. This indicates that the overall share of barley is likely to decrease because the major areas for barley production (Northern Plains and Mountain) are negatively affected by the increase in temperature.
- The proportion of planted acres for corn decreases in the Corn Belt and Northern Plains regions which are the major areas for corn production. However, the proportion increases in the other regions such as Delta States, Lake States, Mountain, Southeast, and Southern Plains. Thus, the increasing temperature has mixed effects on different regions but the total amount of corn production is likely to drop because the major areas are negatively affected by the increasing temperature.
- The proportion of upland cotton planted acres increases in all of the regions. This implies that the overall share of upland cotton is likely to increase especially in the major areas for cotton production (Southern Plains and Southeast) regions.

Pacific		
Barley	.	(–)
Corn	.	(+)
Cotton	.	.
Rice	(+)	(+)
Sorghum	.	[+]
Wheat(winter)	(+)	.
Wheat(spring)	.	.
Wheat(durum)	.	.
Hay(alfalfa)	(–)	[–]

Mountain		
Barley	(–)	.
Corn	(+)	(+)
Cotton	(+)	.
Sorghum	(+)	[+]
Wheat(winter)	(+)	(+)
Wheat(spring)	(–)	(–)
Wheat(durum)	.	(+)
Hay(alfalfa)	(–)	(–)

Northern Plains		
Barley	(–)	(–)
Corn	(–)	(+)
Cotton	(+)	(+)
Sorghum	(+)	(–)
Soybeans	(–)	(+)
Wheat(winter)	(+)	(–)
Wheat(spring)	(–)	(–)
Wheat(durum)	(–)	(–)
Hay(alfalfa)	(–)	.

Lake States		
Barley	(–)	(–)
Corn	(+)	(+)
Soybeans	(+)	(–)
Wheat(winter)	.	.
Wheat(spring)	(–)	(–)
Wheat(durum)	(–)	(–)
Hay(alfalfa)	(–)	(+)

Northeast		
Barley	(+)	.
Corn	.	.
Sorghum	.	(+)
Soybeans	(+)	.
Wheat(winter)	(+)	(–)
Hay(alfalfa)	(–)	.

Corn Belt		
Barley	.	(+)
Corn	(–)	.
Cotton	(+)	(+)
Rice	(–)	(+)
Sorghum	(+)	.
Soybeans	(+)	(–)
Wheat(witer)	(+)	.
Hay(alfalfa)	(–)	(+)

Appalachian		
Barley	.	(–)
Corn	.	(–)
Cotton	(+)	(+)
Sorghum	[+]	.
Soybeans	(+)	(+)
Wheat(winter)	(+)	.
Hay(alfalfa)	(–)	(–)

Southern Plains		
Barley	.	(+)
Corn	(+)	(+)
Cotton	(+)	(–)
Rice	(–)	.
Sorghum	(+)	.
Soybeans	(–)	(+)
Wheat(winter)	(–)	[–]
Hay(alfalfa)	(–)	.

Delta States		
Barley	(–)	.
Corn	(+)	.
Cotton	.	[–]
Rice	(+)	[–]
Sorghum	.	(+)
Soybeans	(–)	.
Wheat(winter)	.	[–]

Southeast		
Barley	.	(–)
Corn	(+)	.
Cotton	(+)	(+)
Sorghum	[+]	.
Soybeans	(–)	(–)
Wheat(winter)	.	.

Figure 4. Average marginal effects of temperature and precipitation on proportions of planted acres by region

Note: By region, the first column, the second column, and the third column indicate crop name, marginal effects of temperature, and marginal effects of precipitation, respectively. The signs in ( ) and [ ] are statistically significant at the 5% and 10% levels, respectively. The major regions for each crop have crop names in bold face.

- Both of the major regions for rice production (Pacific and Delta) show increases in the proportion of planted acres for rice when it gets hotter. However, the Corn Belt and Southern Plains regions show decreases in the proportion of rice planted acres. This indicate that the nearby areas of the Delta region are negatively affected by the increasing temperature.
- The proportion of planted acres for grain sorghum increases in all of the regions including the major areas (Southern Plains and Northern Plains).
- The proportion of soybeans planted acres in the southern regions decreases but the proportions in the northern regions increases with an exception of soybean decreases in the Northern Plains. This indicates that the overall temperature increase may cause the soybean production regions to move north.
- The proportion of winter wheat planted acres in the Southern Plains decreases but all of the other northern regions increases when it gets hotter. This implies that the overall temperature increase may cause the winter wheat production regions to move north. The proportion of spring wheat in all of the major planted regions (Pacific, Mountain, Northern Plains, and Lake States) and durum wheat in the major planted regions (Northern Plains and Lake States) decreases when temperature increases. The decreased spring wheat and durum wheat might cause Canada to increase planted acres for spring wheat and durum wheat. However, this study does not see the effects since the analysis is bounded in the US.

- The proportion of planted acres for alfalfa hay decreases in all of the regions. This indicates that the overall share of alfalfa hay production is likely to drop.

Based on the results in figure 4, we find that when the annual precipitation increases:

- The proportion of planted acres for barley increases in the Southern Plains and Corn Belt but decreases in all of the major regions for barley production. This indicates that the barley production is likely to drop but it may move to central regions.
- The proportion of planted acres for corn grain decreases in the Appalachian region but increases in all of the other regions including major areas for corn production. This indicates that the increasing precipitation may lead to the overall increases in share of corn planted acres.
- The proportion of upland cotton planted acres decreases in the Southern Plains and Delta States which are the major areas for cotton production. However, the Corn Belt, Northern Plains, and Southeast regions show increasing share of cotton planted acres. Specifically, among the major areas (Southern Plains, Delta States, and Southeast), only the Southeast shows the increases in share of cotton planted acres. This implies that the major production regions may move east when the precipitation increases.
- The proportion of planted acres for rice increases in the Pacific region but decreases in the Delta. It indicates that the rice production may move west under increased precipitation in the regions.

- The proportion of grain sorghum planted acres decreases in the Northern Plains region which is one of the major areas for sorghum production. However, the Delta, Mountain, and Pacific regions show increasing share of sorghum production when the annual precipitation increases. Another major area for sorghum production, Southern Plains, is not significantly affected by the increasing precipitation.
- The proportion of winter wheat increases in the Mountain but decreases in the eastern and central regions. This implies that the planted acres for winter wheat might move west if precipitation increases or east if precipitation declines.
- The proportion of spring wheat planted acres decreases in all of the regions when the precipitation increases.
- The proportion of planted acres for durum wheat increases in the Mountain region but decreases in the other central regions. This implies that the production region for durum wheat might move west.
- The proportion of alfalfa has spatially mixed results to increases in precipitation. In the Appalachian, Mountain, and Pacific regions, the proportion decreases but in the Corn Belt and Lake States regions, the proportion increases.

2.4.2 Predictions with Climate Change Scenarios

Using the climate outcomes from the Representative Concentration Pathways (RCP) of the Coupled Model Intercomparison Project Phase 5 (CMIP5), the predicted proportions are evaluated at the mean current value of each region. The pooled model predicts the expected proportions of the major crops across the national land area in the US. The regional models yield region-specific predictions of the cropland proportions.

We obtained the projected temperature and precipitation outputs from six different climate models including CanESM2, CCSM4, CESM1-CAM5, GFDL-CM3, HadGEM2-ES, and MPI-ESM-MR. We obtained these from the Archive of CONUS 1/8 degree BCSD (Bias-Corrected and Spatially Downscaled) (Brekke, et al. 2013). Mean near-surface air temperature and monthly mean of the daily precipitation were obtained for the Representative Concentration Pathways (RCP) 2.6, RCP 4.5, and RCP 8.5 scenarios. We then averaged out the outputs of the six different climate models under each RCP[3]. RCPs indicate a possible range of radiative forcing values in the year 2100 relative to pre-industrial values (+2.6, +4.5, and +8.5 Watts per square meter for RCP 2.6, RCP 4.5, and RCP 8.5, respectively). The grid data were converted to county-level data using the mean of the grid-point values inside each county.

As presented in table 5 and table 6, all of the regions exhibit increasing temperature and precipitation except for Pacific temperature (lowest in 2020–2050) and Southern Plains precipitation (lowest in 2020–2050). In general, the greater the radiative forcing the higher the temperature and the more the precipitation.

[3] Although there are four scenarios including RCP 6.0, we excluded the scenario because some models (CanESM2 and MPI-ESM-MR) do not report it.

Table 5. Mean Temperature by Climate Scenarios and Regions

Regions	Mean temperature (°C)						
	Base	RCP 2.6		RCP 4.5		RCP 8.5	
	1975–2010	2020–2050	2051–2099	2020–2050	2051–2099	2020–2050	2051–2099
Appalachian	13.60	15.40	15.78	15.53	16.68	15.64	17.95
Corn Belt	10.88	12.89	13.29	12.96	14.25	13.13	15.54
Delta States	17.40	19.11	19.36	19.20	20.24	19.31	21.37
Lake States	6.73	8.81	9.34	8.87	10.39	9.05	11.78
Mountain	8.80	9.26	9.57	9.28	10.55	9.43	11.89
Northeast	9.83	11.40	11.97	11.58	12.95	11.71	14.29
Northern Plains	9.62	11.46	11.81	11.50	12.78	11.64	14.04
Pacific	12.28	11.96	12.41	11.94	13.18	12.13	14.33
Southeast	17.30	18.97	19.28	19.09	20.10	19.18	21.30
Southern Plains	17.56	19.43	19.68	19.51	20.53	19.67	21.73
All regions	12.48	14.11	14.48	14.19	15.41	14.34	16.67

Table 6. Mean Precipitation by Climate Scenarios and Regions

Regions	Mean precipitation (100mm)						
	Base	RCP 2.6		RCP 4.5		RCP 8.5	
	1975–2010	2020–2050	2051–2099	2020–2050	2051–2099	2020–2050	2051–2099
Appalachian	12.24	12.85	13.38	12.81	13.49	13.07	13.98
Corn Belt	10.10	10.23	10.59	10.26	10.66	10.41	11.22
Delta States	14.29	14.68	15.17	14.66	15.22	14.65	15.63
Lake States	7.88	8.05	8.25	8.21	8.33	8.25	8.62
Mountain	3.63	4.76	4.89	4.71	4.98	4.83	5.09
Northeast	10.91	11.23	11.63	11.27	11.63	11.29	11.99
Northern Plains	6.28	6.48	6.68	6.42	6.67	6.55	6.99
Pacific	5.91	8.72	8.80	8.60	8.90	8.77	8.86
Southeast	12.97	13.91	14.49	13.91	14.75	14.09	15.13
Southern Plains	8.48	8.30	8.39	8.06	8.35	8.08	8.49
All regions	9.47	9.95	10.27	9.92	10.34	10.04	10.69

Based on the estimation results, we obtained the predicted crop share proportions under the RCPs in two different periods, namely 2020–2050 and 2051–2099 plus 1975–2012. We used other non-climate items fixed at the average 1975–2010 level so that we can get the predicted proportional change of crop land share affected by only climate change.

We show the predicted change in land allocations for crops under each RCP scenario in table 7. The results indicate that the proportions of land allocation for corn, barley, durum wheat, spring wheat, and alfalfa hay are expected to decrease in the periods 2020–2050 and 2051–2099 under all the climate scenarios, with the proportions of planted acres for upland cotton, rice, sorghum, soybeans, and winter wheat increasing. Thus, the estimation results and simulated predictions show that the heat tolerant crops in general are expected to have increased planted acres in the next decades. Although the increasing or decreasing planted acres show monotonic patterns, the rate of shifts is more severe in moderate and extreme scenarios (RCP 4.5 and RCP 8.5) than the optimistic scenario (RCP 2.6). The global mean temperature in the RCP 2.6 scenario is expected to decline after the peak around 2030. However, the US crops are not likely to benefit from the optimistic situation because the expected proportions for all the crops have the expected values between 1975–2010 and 2051–2099.

Table 7. Land Allocation Changes for Crops from 1975–2010 to 2020–2050 and 2051–2099 under RCP 2.6, 4.5, and 8.5 Scenarios

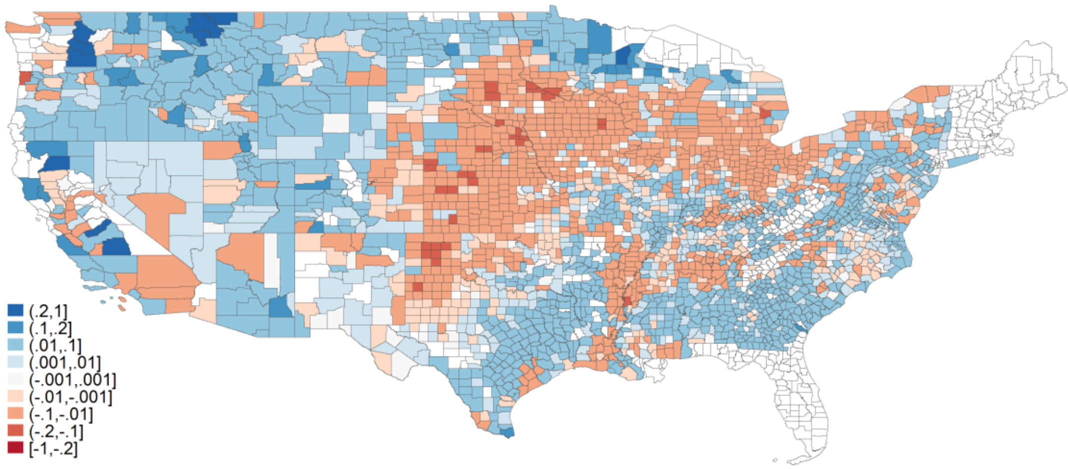
Crop	RCP	2020–2050	2051–2099	Average
Barley	2.6	–0.7%	–0.7%	–0.7%
	4.5	–0.7%	–0.9%	–0.8%
	8.5	–0.7%	–1.0%	–0.8%
Corn	2.6	–1.1%	–1.7%	–1.4%
	4.5	–1.2%	–3.0%	–2.1%
	8.5	–1.4%	–4.2%	–2.8%
Cotton	2.6	2.9%	3.4%	3.2%
	4.5	3.0%	4.6%	3.8%
	8.5	3.2%	5.8%	4.5%
Hay (alfalfa)	2.6	–2.0%	–2.6%	–2.3%
	4.5	–2.1%	–3.8%	–3.0%
	8.5	–2.3%	–5.4%	–3.9%
Rice	2.6	1.1%	1.4%	1.2%
	4.5	1.1%	2.1%	1.6%
	8.5	1.2%	3.5%	2.3%
Sorghum	2.6	0.5%	0.6%	0.5%
	4.5	0.6%	1.3%	0.9%
	8.5	0.7%	2.1%	1.4%
Soybeans	2.6	–1.8%	–1.5%	–1.7%
	4.5	–1.9%	–2.7%	–2.3%
	8.5	–1.8%	–4.2%	–3.0%
Wheat (durum)	2.6	–0.1%	–0.1%	–0.1%
	4.5	–0.1%	–0.1%	–0.1%
	8.5	–0.1%	0.0%	–0.1%
Wheat (spring)	2.6	–1.0%	–1.2%	–1.1%
	4.5	–1.0%	–1.5%	–1.3%
	8.5	–1.1%	–1.9%	–1.5%
Wheat (winter)	2.6	2.2%	2.5%	2.3%
	4.5	2.3%	4.0%	3.2%
	8.5	2.4%	5.4%	3.9%

Note: The values in percentage are calculated as the predicted value in 2020–2050 and 2051–2099 minus the historical value of 1975–2010, respectively, under different RCP scenarios.

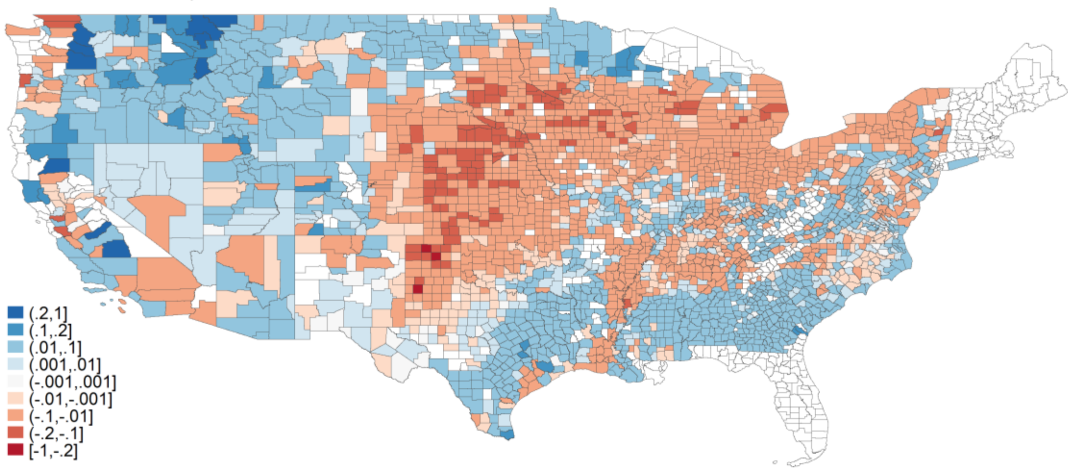
To illustrate the regional change in land allocations for specific crops, we provide maps drawn from the predicted allocations of land shares under the climate scenarios. Figure 5 shows the difference of predicted land share for crop by county from 2010 to 2030, 2050, and 2070, respectively. The blue and red shades indicate increases and decreases in proportions of the land for corn, respectively, from 2010 under the RCP 2.6 scenario. The bolder the color, the more the changes in magnitude of proportions. We find decreasing corn land share in the Corn Belt region and increasing the land share in other regions over time.

In figure 6, the same projection under the RCP 8.5 scenario shows a greater decrease in land share for corn in the Corn Belt and increasing share in the other regions than the case under the RCP 2.6. This result also follows the result from the marginal effects estimates and here we see the regional differences. Under the RCP 2.6 and RCP 8.5 scenarios, the changing predicted shares for corn show similar patterns but the RCP 8.5 outputs lead to more severe changes. For other crops, we find the similar changes between the RCP 2.6 and 8.5 scenarios. Thus, we show some predicted differences of share for some crops under the RCP 8.5 scenarios.

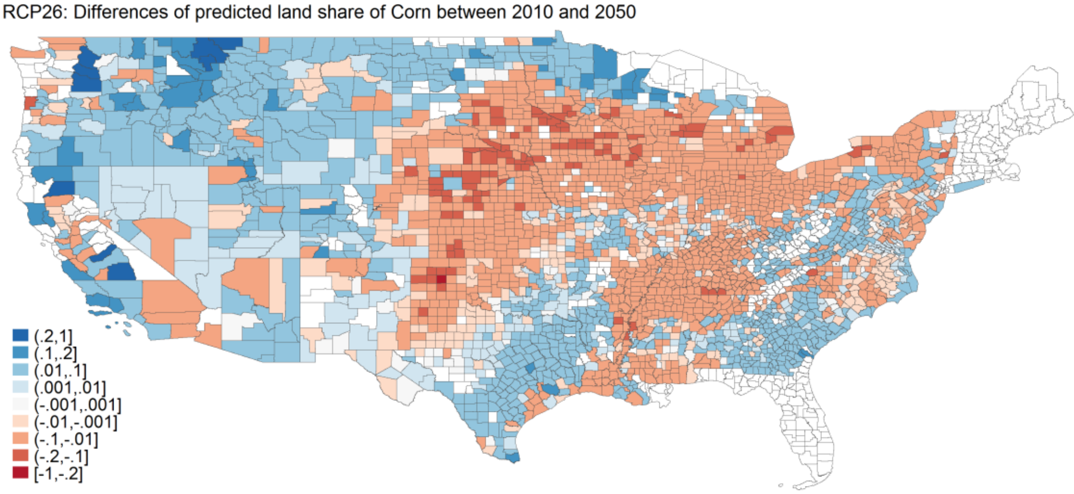
Figure 7 shows noticeable pattern of the land proportions for cotton increasing in the northern areas and decreasing in the southern regions as the year increases. In figure 8, land proportion for soybeans production is also projected with the similar pattern to the cotton lands, increasing in the northern areas and decreasing in the southern areas although the major production regions are different from the lands for cotton. The projected results for other crops by region are available in the Appendix (tables A-2).



RCP26: Differences of predicted land share of Corn between 2010 and 2030



RCP26: Differences of predicted land share of Corn between 2010 and 2050



RCP26: Differences of predicted land share of Corn between 2010 and 2070

Figure 5. Differences of predicted share of corn from 2010 to 2030, 2050, and 2070 under RCP 2.6

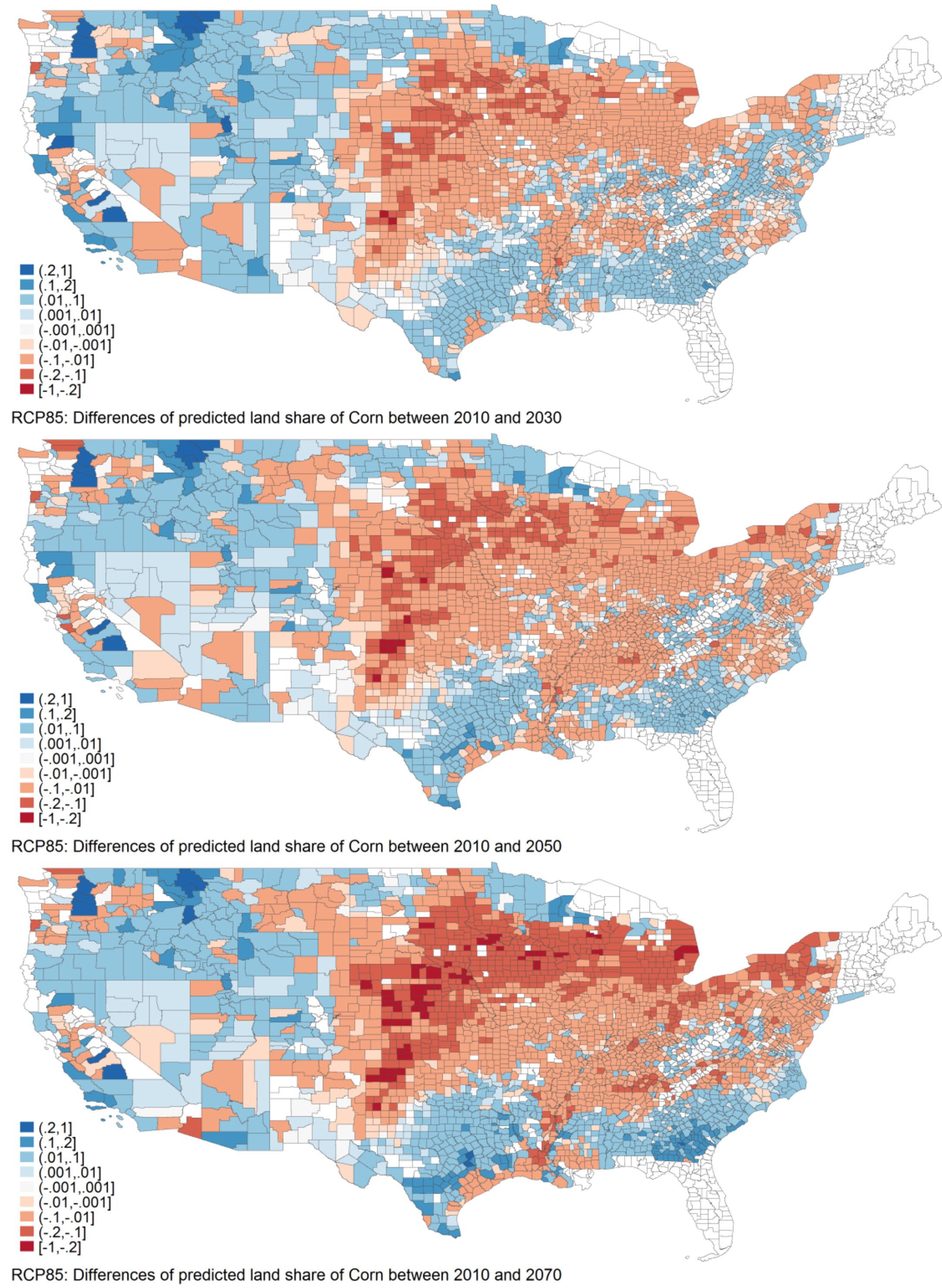
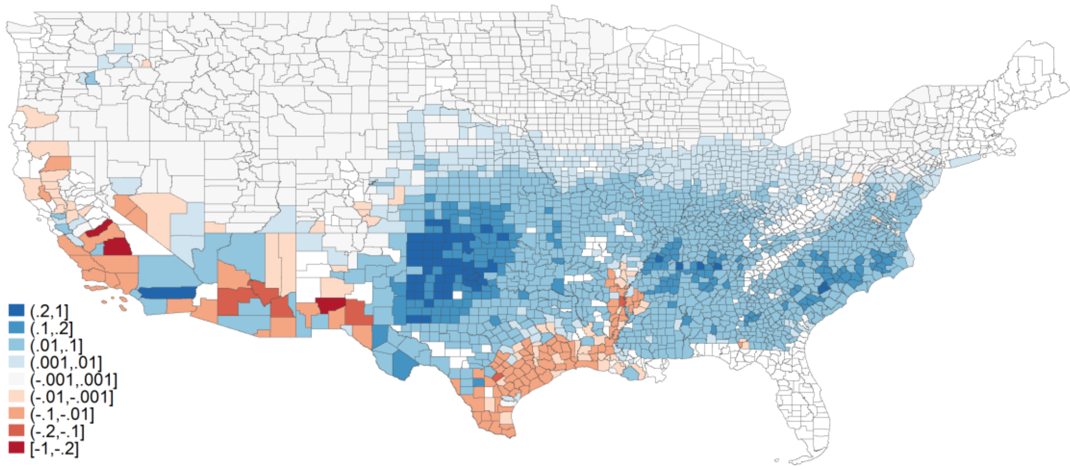
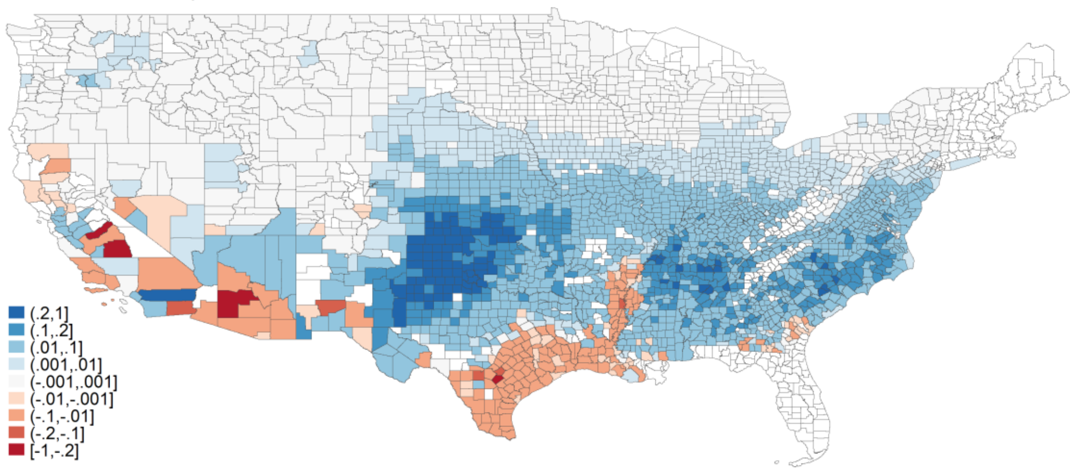


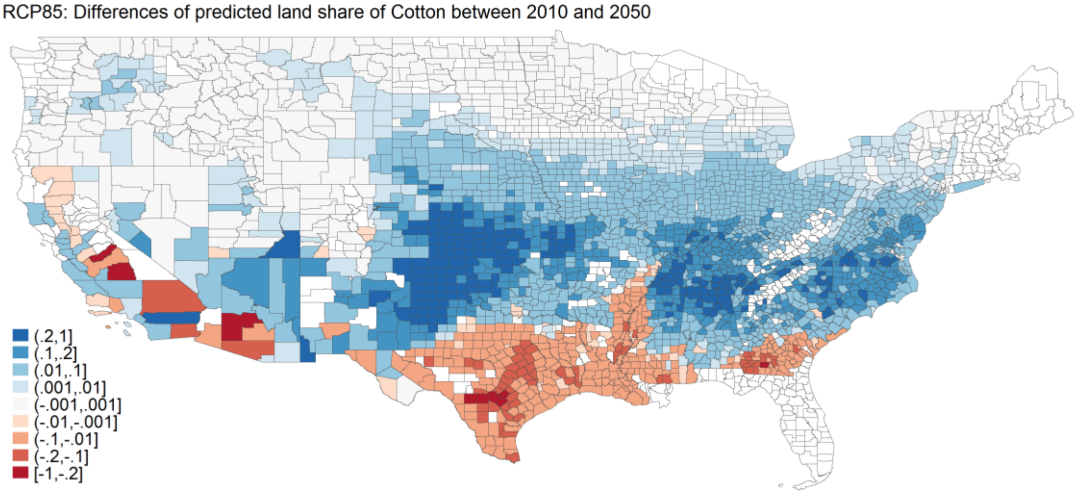
Figure 6. Differences of predicted share of corn from 2010 to 2030, 2050, and 2070 under RCP 8.5



RCP85: Differences of predicted land share of Cotton between 2010 and 2030



RCP85: Differences of predicted land share of Cotton between 2010 and 2050



RCP85: Differences of predicted land share of Cotton between 2010 and 2070

Figure 7. Differences of predicted share of cotton from 2010 to 2030, 2050, and 2070 under RCP 8.5

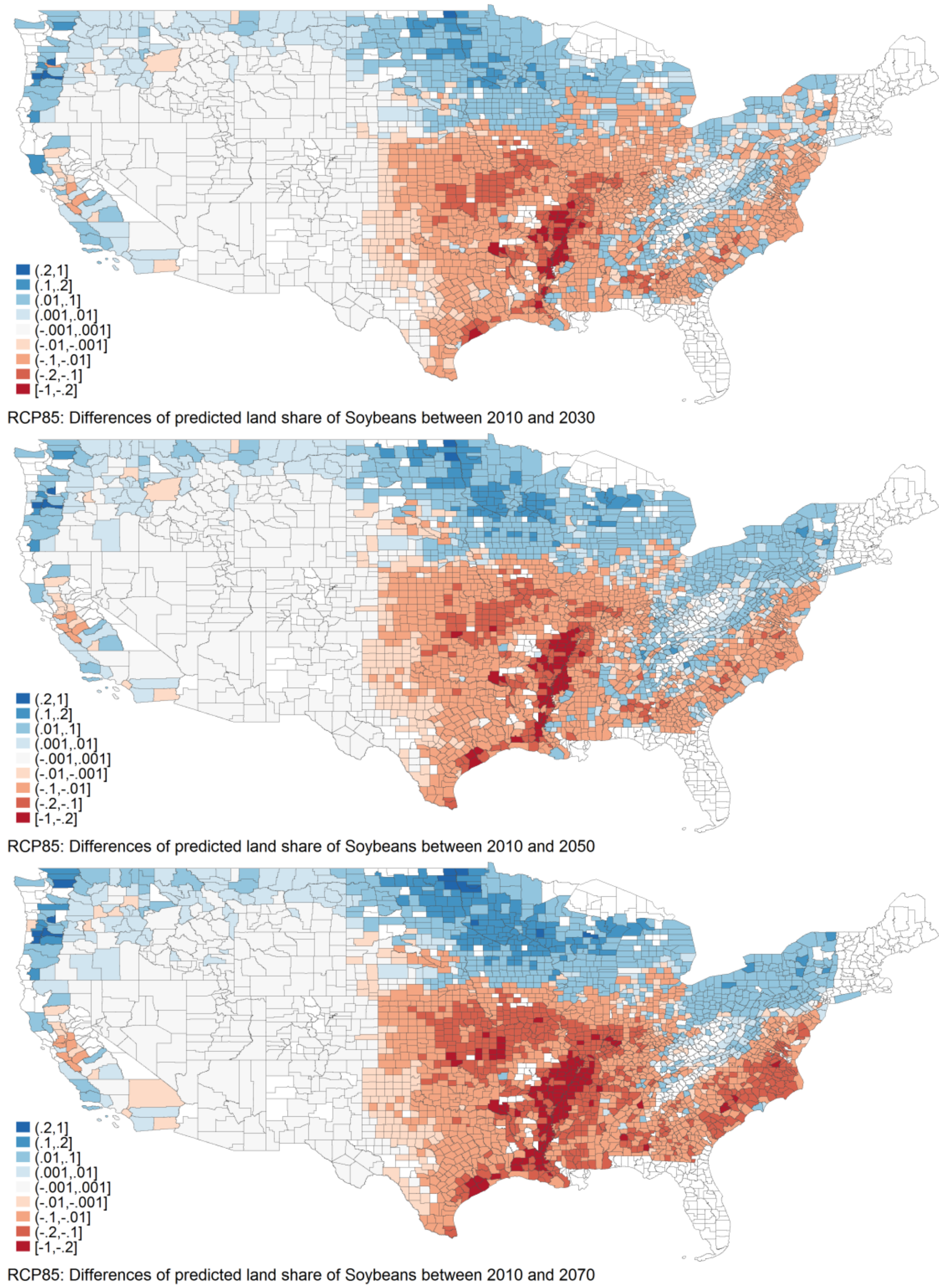


Figure 8. Differences of predicted share of soybeans from 2010 to 2030, 2050, and 2070 under RCP 8.5

2.4.3 Climate Change Adaptation via Shifting Croplands

Based on the estimates of the fractional multinomial logit, we examine the shifting pattern of expected geographic centers with production quantity weighted for each crop using a procedure like that in Reilly, et al. (2003) although we also look at elevation. In particular, we examine shifts in the geographic center (centroid) which is defined as the geographic center of planted area by crop. We use production amounts as weights to calculate weighted average of latitude, longitude, and elevation. The change of centroid can represent the global spatial shifts of production of each major crop.

The weighted averages of location variables (latitude, longitude, and elevation) by using production quantity as weights can be calculated as:

$$(12) \quad \overline{loc}_t = \sum_{i=1}^{N} w_{it} \times loc_i = \frac{\sum_{i=1}^{N} q_{it} loc_i}{\sum_{i=1}^{N} q_{it}} \quad \text{for each } t$$

where the normalized weight is $w_{it} = q_{it}/\sum_{j=1}^{N} q_{jt}$, the production quantity is q_{it}, and the location variables set is $loc_i = \{longitude_i, latitude_i, elevation_i\}$, consisting of longitude, latitude, and elevation in county i. We estimated the predicted production quantity of crop j in county i in time t as $\hat{q}_{it}^{j} = f_{it}^{j} G(\mathbf{x}_{it}; \widehat{\boldsymbol{\beta}}) A_{it}^{j}$ where the f_{it}^{j} is the yield of crop j in county i in time t, $G_j(\mathbf{x}_{it}; \widehat{\boldsymbol{\beta}})$ is the predicted probability of allocating land for crop j, and A_{it}^{j} is the total planted acre. During the period 1980–2010, the historical values for yield and total planted acre are used. During the period 2010–2050, given the other variables are assumed as maintained at the level in the year of 2010, climate-related variables based on the values of the Coupled Model Intercomparison Project Phase 5 (CMIP5) simulation outputs of temperature and precipitation are used to estimate the production quantity. The weighted averages of locations were calculated separately for each crop at time period t by using the county level data.

The shifting pattern of geographic centers of production for some major crop (corn, soybeans, winter wheat, and alfalfa hay) are shown in figures 9–12. The figures for other crops are shown in the Appendix (figures A-2–A-7). With the RCP 2.6 and RCP 8.5 outputs assumed for temperature and precipitation during 2020–2090, the figures exhibit the pattern of changing weighted average elevation for each crop over the years 1980–2090. It considers not only the proportions of each crop land but also the production quantities. Thus, this implies the shift of production-weighted average of geographic center for each crop.

Under the different radiative forcing level, the production-weighted averages of latitude, longitude, and elevation are not significantly different in the crop production. However, after 2050, the differences between the scenarios are intensified. As shown in IPCC (2013), the climate model scenario outputs have diverging patterns at increasing rates especially after the year of 2050, which conforms the crop land shifting pattern in this study.

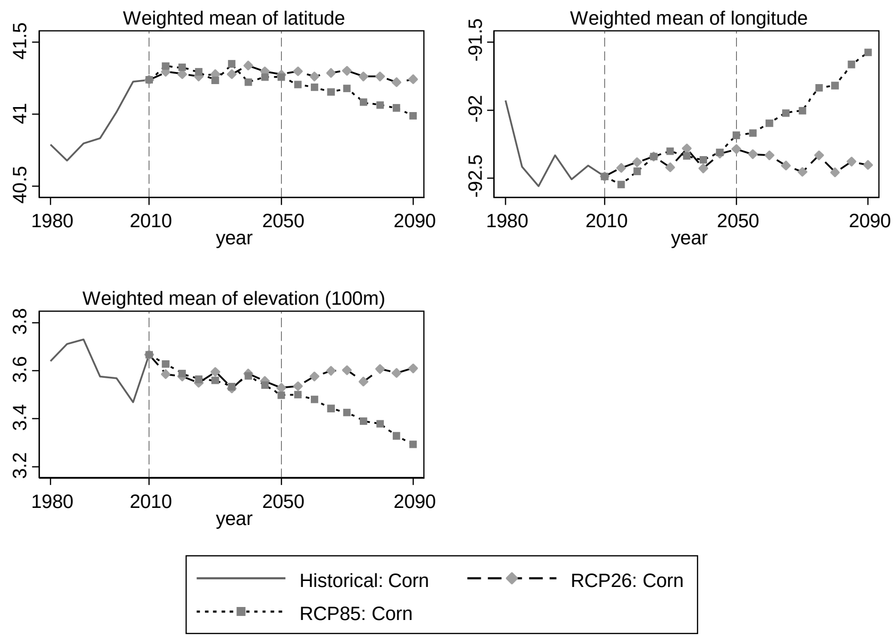


Figure 9. Weighted mean of location change for corn, 1980–2090

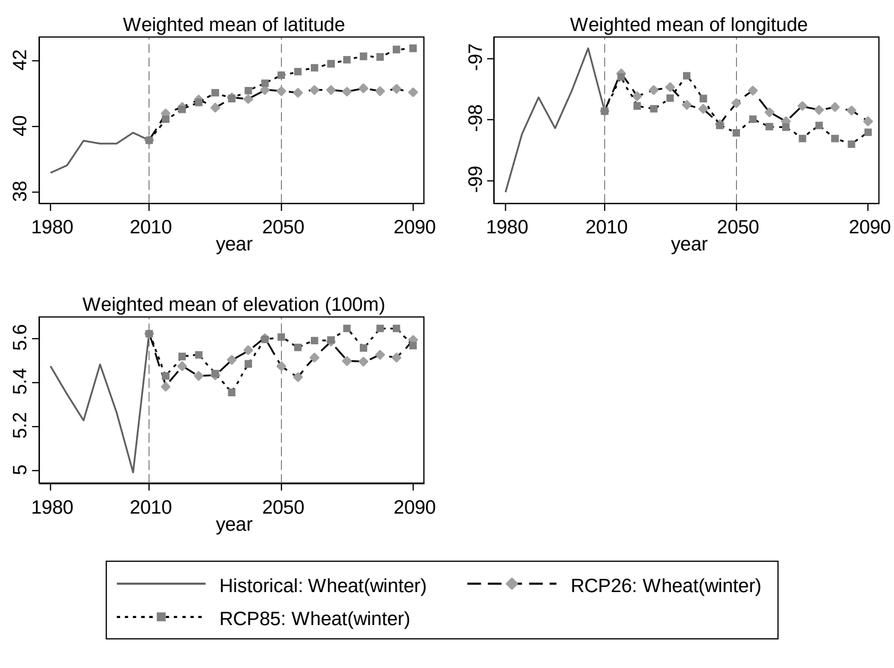


Figure 10. Weighted mean of location change for winter wheat, 1980–2090

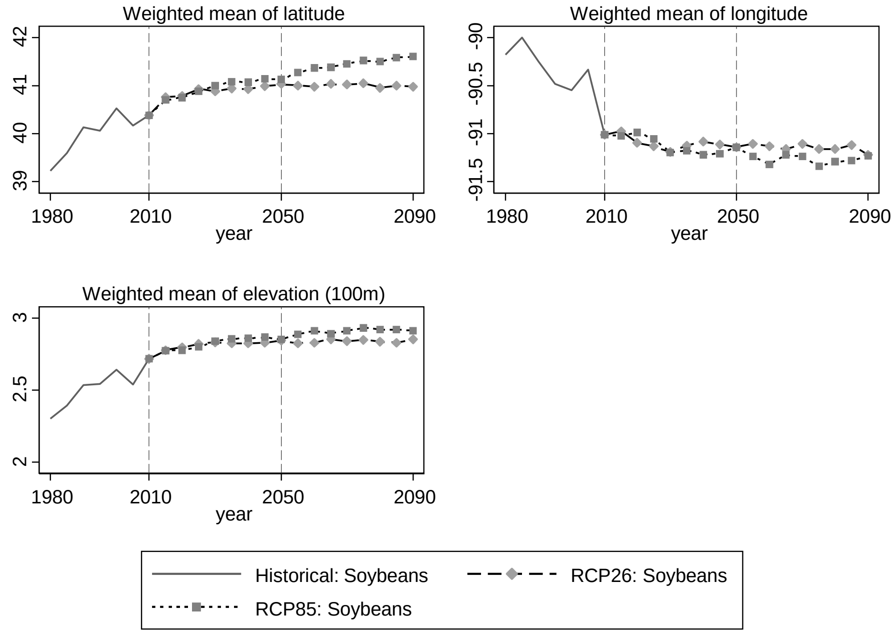


Figure 11. Weighted mean of location change for soybeans, 1980–2090

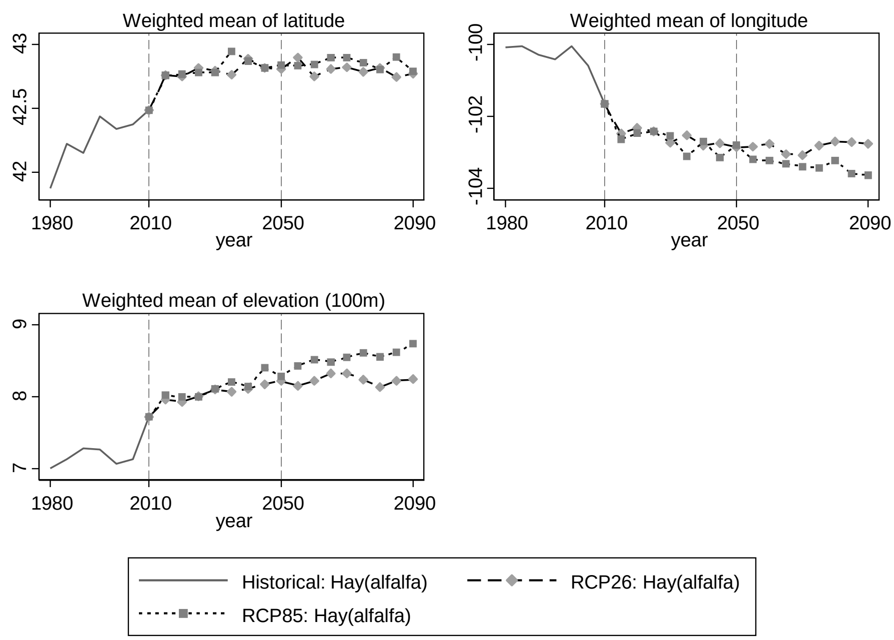


Figure 12. Weighted mean of location change for alfalfa hay, 1980–2090

Among the four largest crops in the US, corn only shows moving south in the RCP 8.5 scenario. In terms of latitude, under RCP 2.6 scenario, all the crops have stable production-weighted mean latitudes. This implies that under the optimistic scenario, the crop land allocation adaptation on climate change may be less uncertain in shifting patterns. The weighted means of elevation in most crops show increasing pattern under RCP 8.5. It implies that adapting climate change would occur by moving the crop planted to higher places. The higher temperature may allow most of the crops to be planted in the current lands which are not suitable for cultivation at the moment but suitable when the temperature increases. However, weighted mean of elevation for planting corn comes to the lower places under the projected climate change. It might be because corn productions in the Corn Belt region are likely declining under the projected climate change so the weighted average elevation decreases but the production amount is expected to increase thanks to the increasing production in other areas.

Under the RCP 2.8 and RCP 8.0 outputs of climate variables, we have similar shifting pattern of crop productions. In general, almost all of the crops have moved north given other things do not change. While the crop land moving pattern has not been thoroughly studied in the literature, we estimated the magnitudes and directions of expected crop mix changes. This can be extended to a broader area or just be more specific for a local area.

2.5 Concluding Remarks

The primary goal of this study was to examine how climate influences land use choice among major crops in the US. In doing this, this study applies fractional regression. Furthermore, this study examines crop mix shifts considering the price effects.

We find that when the annual temperature goes up, the overall proportions of cotton, rice, sorghum, and winter wheat are likely to increase with barley, corn, soybeans, spring wheat, and durum wheat declining. We also found that increased precipitation reduces barley, sorghum, hay, and all types of wheat but increases corn, rice, and soybeans. We also find that most of the major crops except for corn are expected to move north and to higher altitude under climate change scenarios.

Although we estimated the crop mix allocations affected by various factors, there might be some omitted variables to explain the changes. We assumed that farmers are risk-neutral price takers in crop land allocations and crop yield is stable over time. Furthermore, although our results include the existing crops, we do not explain some recent crops not settled in the past. Also, we did not explicitly model the price changes by national and local policies such as Farm Bill and state-specific agricultural policies. Thus, further research would be better conducted by considering risk aversion, explicit policy impacts, spillover effects, and flexible model to include newly introduced crops as well as dynamic crop yields.

3. CLIMATE CHANGE AND MAJOR LAND USE CHANGES IN THE UNITED STATES: A SPATIAL ECONOMETRIC APPROACH

The relationship between climate change and major land use changes have been in the subject of a number of studies. The results of these studies indicate that climate and policy factors stimulate direct and indirect land use changes along with changes in greenhouse gas emissions (Lambin, Geist and Lepers 2003; Solecki and Oliveri 2004; Lubowski, Plantinga and Stavins 2006; Timmins 2006; Lubowski, Plantinga and Stavins 2008; Searchinger, et al. 2008; Mendelsohn and Dinar 2009; Hertel, et al. 2010; Plevin, et al. 2010; Alig 2011; Haim, et al. 2011; Mu, Wein and McCarl 2013). These studies have examined the possible impact of policy factors such as carbon sequestration and conservation programs on land use changes. However, as Dale (1997) argued that climate factors are likely to affect human adaptation as a way of land use changes, temperature and precipitation also tend to play a significant role in land use decisions. Reilly, et al. (2003) also highlighted climate and policy factors that influence agricultural land use and cause changes under simulated future climate change.

Lubowski, Plantinga and Stavins (2008) investigated the determinants of land use change including climate factors. However, they did not account for potential spatial effects that would give poor results in estimating land use changes as explained in Flores, et al. (2008). Rashford, Walker and Bastian (2011) examined land conversion from grassland to cropland and its economic returns but they did not consider the potential factors of climate change. Likewise, most of the previous studies have operated either over large geographic areas relying on aggregate data or local areas with detailed data but allowing little inference to broader settings.

The main objective of this study is to extend the literature by examining the determinants of land use changes in the recent years with detailed data, using a spatial econometric method. In addition, we use the latest climate model based scenarios to project future changes in land use allocation in the US.

3.1 Major Land Use in the US

The national land use cover database 2011 (NLCD 2011) provides detailed data on US land transitions between recent years (Homer, et al. 2007; Fry, et al. 2009; Fry, et al. 2011). The NLCD classifies land cover into water, developed, barren, forest, shrubland, herbaceous, planted/cultivated, and wetlands. We reclassified them into six categories that are cropland, grassland, forest, urban, water, and others following the USDA report of major uses of lands in the US (Nickerson, et al. 2011). The matched classifications are shown in table 8.

Table 8. Matched Land Use Classifications

Classification in this study		NLCD 2001–2011 Classification
Cropland	82	Cultivated Crops
	81	Pasture/Hay
Urban	24	Developed, High Intensity
	22	Developed, Low Intensity
	23	Developed, Medium Intensity
	21	Developed, Open Space
Forest	41	Deciduous Forest
	42	Evergreen Forest
	43	Mixed Forest
Grassland	71	Grassland/Herbaceous
	52	Shrub/Scrub
Water	11	Open Water
	12	Perennial Ice/Snow
Other	31	Barren Land
	95	Emergent Herbaceous Wetlands
	90	Woody Wetlands

Note: Detailed descriptions of each classification are provided in the Appendix (table A-3).

Recent US land use transitions among the major categories described above are shown in table 9. In the period 2002–2012, the land areas for crop and forest decreased while the amount in the urban lands, grasslands, and water/ice lands increased. During the periods, the remote sensing data show that urban land does not generally convert back to other land uses once it is developed. The largest transitions out of croplands were movements into urban lands during 2002–2012. Also, note that there was a net movement from forest to grasslands during those periods. Major movements of grasslands involved conversion to forest in the 2002–2012 period. Most croplands remained with 99.3% unchanged during 2002–2012. Likely the higher recent prices influenced this greater retention.

Table 9. Land Use Transitions between 2002 and 2012 (Million Acres)

	To 2012						
From 2002	Crop	Urban	Forest	Grass	Water	Other	2002 Total
Crop	439.161	2.108	1.058	1.771	0.371	0.771	445.240
Urban	0.000	107.234	0.001	0.004	0.001	0.002	107.242
Forest	0.566	1.279	478.866	22.088	0.108	0.904	503.813
Grass	2.274	1.159	7.153	696.907	0.404	1.238	709.134
Water	0.140	0.024	0.028	0.266	102.684	0.919	104.061
Other	0.301	0.444	0.243	1.152	0.907	123.895	126.941
2012 Total	442.442	112.248	487.349	722.189	104.475	127.728	1996.431

3.2 Spatial Econometric Specification

Some recent studies examined spatial effects on land use (e.g., Chakir and Le Gallo 2013 for France; Li, Wu and Deng 2013 for China) using methods which account for spatial interaction or spatial dependence. In our analysis, we assume that common physical and economic conditions across nearby areas affect land use decisions in those areas, with diminishing effects as physical distance increases. We assume that latent variables depend on spatially lagged values of the latent variables. The assumption implies that the propensity to change land usage in an area relies on the propensity to change land uses in neighboring areas. For example, if a farmer is in close proximity to similar land uses nearby, she may benefit from lower costs to find labor with the skills desired by the particular land use. Additionally, a large proportion of a particular land use in a region may help lower costs to obtain the information required to improve overall productivity plus lead to close by suitable marketing infrastructure. As pointed out in Flores, et al. (2008), ignoring spatial autocorrelation in estimating land use changes can lead to poor predictions.

For the estimation, we use a two-step linearized GMM estimator for the major land use change in the US. Unlike the crop mix case, the six land uses (crop, forest, grass, urban, water, and other) cover the complete 48 contiguous United States. The predicted proportion of each land use implies the global share of the land in the lower 48 States so it indicates not just local proportions but also global proportions of the total US land. However, our preliminary results from the estimation with the county level data have insignificant results for some spatial dependence. Thus, we explicitly incorporate the spatial interactions between contiguous areas only on the estimation for the major land uses at the 10 × 10 km cell level.

Following Li, Wu and Deng (2013), we assume that the expected conditional mean of allocations across parcels of land in nearby areas is affected by common factors including common climate, common land quality, information spillovers, technology adoption, and labor transfers plus other factors that generate spatial externalities.

Adding spatial dependence into the conditional mean function of fractional multinomial regression model, the equation can be expressed as:

$$\text{(13)} \quad \mathrm{E}(s_{ijt}|\mathbf{x}, w) = K_j(\mathbf{x}_{it-1}, w_{im}; \boldsymbol{\beta}, \rho) = K\left(\sum_{m \neq i} \rho_{jt} w_{im} s_{mjt} + \mathbf{x}_{it-1} \boldsymbol{\beta}_{jt}\right)$$

where $K(\cdot)$ is the multinomial logit function, ρ_{jt} is a spatial lag parameter ($|\rho_{jt}| < 1$), implying the degree to which the propensity to have land use j in nearby areas. The explanatory variables $\mathbf{x}$ include geophysical and socioeconomic factors plus the lagged proportional land use share in time $t - 1$ to control for potential endogeneity as done in Li, Wu and Deng (2013). In the above equation, w_{im} implies the spatial relationship between land areas i and m. By construction, spatial relation term in a single region is zero ($w_{ii} = 0,\ i = i$). The specification in $K(\cdot)$ including spatially lagged dependent variables is often referred to as a spatial lag model (LeSage 2008).

In turn the conditional mean function is expressed in a stacked form across areas as

(14) $\mathrm{E}\left(\mathbf{S}_{jt} \middle| \mathbf{X}, \mathbf{W}\right) = K\left(\rho_{jt}\mathbf{W}\mathbf{S}_{jt} + \mathbf{X}_{t-1}\boldsymbol{\beta}_{jt}\right)$,

where $\mathbf{S}_{jt} = \left(s_{1jt}, \dots, s_{Njt}\right)'$ and $\mathbf{X}_{t-1} = (\mathbf{x}_{1t-1}, \dots, \mathbf{x}_{Nt-1})'$. The reduced form of the above equation is $\mathrm{E}\left(\mathbf{S}_{jt} \middle| \mathbf{X}, \mathbf{W}\right) = K\left(\left(\mathbf{I}_N - \rho_{jt}\mathbf{W}\right)^{-1}\mathbf{X}_{t-1}\boldsymbol{\beta}_{jt}\right)$, where $\mathbf{I}_N$ is an N-dimensional identity matrix. An important aspect of the spatial lag model is the spatial multiplier, which can be implied by expanding the inverse term in this reduced form: $\mathrm{E}(\mathbf{S}_{jt}|\mathbf{X}, \mathbf{W}) = K\left(\mathbf{X}_{t-1}\boldsymbol{\beta}_{jt} + \rho_{jt}\mathbf{W}\mathbf{X}_{t-1}\boldsymbol{\beta}_{jt} + \rho_{jt}^2\mathbf{W}^2\mathbf{X}_{t-1}\boldsymbol{\beta}_{jt} + \cdots\right)$. Thus, the value of s_{ijt} in area i relies not just on $\mathbf{x}_{it-1}$ but also on $\mathbf{x}$ at other areas $(-i)$, with locations further discounted by powers of ρ_{jt}. This represents the diminishing nature of the spatial multiplier effects in the spatial lag model. Specifically, if a unit change were induced in a given explanatory variable x_{it-1}^k at every location, the effect on s_{ijt} would amount to $(1 - \rho_{jt})^{-1}\beta_{jt}^k$ (Kim, Phipps and Anselin 2003).

Although specification for spatial weight matrix $\mathbf{W}$ is an empirical question as discussed in LeSage (2008) and Li, Wu and Deng (2013), we use a row-normalized first queen contiguity matrix. $\mathbf{W}$ is defined as a $N \times N$ matrix where $\sum_{m=1}^{N} w_{im} = 1$ and $w_{im} > 0$ if areas i and m share common borders or vertices; $w_{im} = 0$ otherwise. The global nature of the spatial multiplier effect allows such specification capturing spatial reactions between any two locations through higher powers of $\mathbf{W}$. Let $(\mathbf{I}_N - \rho_{jt}\mathbf{W}) \equiv$

$\mathbf{\Psi}_{jt}$. Then the variance-covariance matrix of $\mathbf{S}_{jt}$ is proportional to $[(\mathbf{\Psi}_{jt})'(\mathbf{\Psi}_{jt})]^{-1}$. Let σ_{ijt}^2 be the diagonal elements of $[(\mathbf{\Psi}_{jt})'(\mathbf{\Psi}_{jt})]^{-1}$ matrix, and let $\mathbf{x}_{ijt-1}^{*} = \mathbf{x}_{it-1}\sigma_{ijt}^{-1}$ and $\mathbf{X}_{jt-1}^{**} = (\mathbf{\Psi}_{jt})^{-1}\mathbf{X}_{jt-1}^{*}$. Under the assumption analogous to the maximum quasi-likelihood estimation, the share of area i can be derived as follows:

$$(15) \qquad p_{ijt} = \mathrm{E}\left(s_{ijt} \middle| \mathbf{x}_{ijt-1}^{**}\right) = \frac{\exp\left(\mathbf{x}_{ijt-1}^{**}\boldsymbol{\beta}_{jt}\right)}{\sum_k \exp(\mathbf{x}_{ikt-1}^{**}\boldsymbol{\beta}_{kt})}$$

where changes in land use in area i between $t-1$ and t are intrinsically captured by the left-hand side variable $p_{ijt}, j = 1, \ldots, J$ and the right-hand side vector of the land proportions at period $t-1$.

The estimation approach is similar to the fractional multinomial logit. However, we do not use that approach as the fractional multinomial logit model with integration of spatial effects can be computationally challenging, especially in a large sample as discussed in Klier and McMillen (2008). Thus, we use the linearized spatial logit approach for the spatial general method of moments estimator suggested by Li, Wu and Deng (2013) and Klier and McMillen (2008). The approach uses a two-step estimation. The first step is to estimate the model by standard multinomial logit in setting $\rho = 0$ to linearize the model around a reasonable starting point. Then the initial estimates are formed for $\boldsymbol{\beta}$ (coefficients), $u = s - p$ (generalized residual), $\mathbf{g}_{ijt}^{\beta} = \partial p_{ijt}/\partial \boldsymbol{\beta}_{kt}$ (gradient terms for β), and $g_{ijt}^{\rho} = \partial p_{ijt}/\partial \rho_{kt}$ (gradient terms for ρ). Based on $\mathbf{g}_{ijt} = (\mathbf{g}_{ijt}^{\beta\prime}, g_{ijt}^{\rho})'$, we calculate $u_{ijt}^{1} \equiv u_{ijt}^{0} + \mathbf{g}_{ijt}^{\beta}\boldsymbol{\beta}_t^{0} + \mathbf{g}_{ijt}^{\rho} \cdot \mathbf{0}$ which are used for the following two-stage least squares since $u_{ijt}^{0} + \mathbf{g}_{ijt}^{\beta}\boldsymbol{\beta}_t^{0} + \mathbf{g}_{ijt}^{\rho} \cdot \mathbf{0} \approx u_{ijt} + \mathbf{g}_{ijt}^{\beta}\boldsymbol{\beta}_t + \mathbf{g}_{ijt}^{\rho} \cdot$

$\boldsymbol{\rho}_t$. In the second step, regress $\mathbf{G}_{jt} = (\mathbf{g}'_{1jt}, \dots, \mathbf{g}'_{Njt})'$ on instruments $\mathbf{Z} =$ $(\mathbf{X}, \mathbf{WX}, \mathbf{W}^2\mathbf{X}, \dots, \mathbf{W}^5\mathbf{X})$ and then regress the calculated terms $[u^1_{11t}, \dots, u^1_{NJ-1t}]'$ on $(\widehat{\mathbf{G}}'_{1t}, \dots, \widehat{\mathbf{G}}'_{J-1t})'$ by using two-stage least squares. The estimated coefficients $\widehat{\boldsymbol{\beta}}$ and $\hat{\rho}$ are the spatial multinomial logit estimates.

Note that the coefficients from the spatial econometric models are not directly interpreted because the model is nonlinear. That is also due to the fact that the explanatory variables are not independently determined by the equation but depend on the interactions with the variables in other observations through the weight matrix.

Following Li, Wu and Deng (2013), the marginal effects of covariates with respect to the expected share of land uses are calculated as:

$$\text{(16)} \qquad \frac{\partial p_{ijt}}{\partial x_{it-1}} = p_{ijt}\left(\frac{\boldsymbol{\beta}_{jt}}{\sigma_{ijt}} \odot \left(\mathbf{I}_N - \rho_{jt}\mathbf{W}\right)^{-1} - \sum\nolimits_k \frac{\boldsymbol{\beta}_{kt} p_{ikt}}{\sigma_{ikt}} \odot \left(\mathbf{I}_N - \rho_{kt}\mathbf{W}\right)^{-1}\right)$$

where $\odot$ is an element-by-element product operator.

The marginal effects of each independent factor on land use are direct marginal effects as shown in LeSage and Pace (2009). We can estimate the indirect marginal effects that are formed from the total marginal effects (the row sum or column sum of marginal effects) minus direct marginal effects. This can be viewed as spillover effects or indirect effects as termed in LeSage and Pace (2009).

3.3 Data and Chosen Variables

We summarize the descriptions and sources of included variables in table 10. The estimation procedure is similarly specified to the crop land allocation case in the previous section but with spatial terms. Again the assumption is used that land use decisions by land owners or managers are made to maximize profit or utility. The 30m-by-30m level land use data come from National Land Cover Database (NLCD) of Multi-Resolution Land Characteristics (MRLC) Consortium: in particular, for 2001 (Homer, et al. 2007), for 2006 (Fry, et al. 2011), and for 2011 (Jin, et al. 2013). The National Land Cover Database data contains the transitions from and to land uses. However, the 1992 and post 2001 data sets have different imagery, legends, and methods. Thus, we used the data for the 2001, 2006, and 2011 periods, which make the transition data comparable across all the periods.

The number of national land parcel cells is approximately 16.8 trillion, which makes it hard to compute so we will go to a larger scale of aggregation. Also, all of the other data we have are highly aggregated data compared to the cells so we can reduce the sample size to take advantage of feasible computation without much of loss of information. We aggregated the cells into 10×10km cells. Although this will prevent capturing the heterogeneity within the 10 by 10 km cells, it allows us to capture the interaction between cells.

Census data for economic and social factors were obtained for 2002, 2007, and 2012 from the USDA Census of Agriculture and the general US Census. The data include agricultural land asset value, median housing value of owner-occupied units, farm proprietor income, non-farm proprietor income, and population estimates. When the data for a specific year are not available, the data from a succeeding or preceding year were used.

Table 10. Descriptions and Sources of Variables for Major Land Use Change

Variables	Description	Aggregation Level	Source
% Crop	Share of croplands (%)	10×10km	MRLC[a]
% Grass	Share of grasslands (%)	10×10km	MRLC[a]
% Forest	Share of forest (%)	10×10km	MRLC[a]
% Urban	Share of urban land (%)	10×10km	MRLC[a]
% Water	Share of water/ice (%)	10×10km	MRLC[a]
% Other	Share of other lands (%)	10×10km	MRLC[a]
Temperature (°C)	5-year average of annual mean temperature (degrees Celsius)	10×10km	USHCN[b]
Precipitation (100mm)	5-year average of annual total precipitation (100mm)	10×10km	USHCN[b]
Temperature SD	Standard deviation of Temperature in 5 years	10×10km	USHCN[b]
Precipitation SD	Standard deviation of Precipitation in 5 years	10×10km	USHCN[b]
Altitude (100m)	Altitude from the sea level (100m)	10×10km	SSURGO[c]
Slope	Slope of land (degrees)	10×10km	SSURGO[c]
Soil quality	Soil quality based on land capability classification (Index)	10×10km	SSURGO[c]
Irrigation rate (%)	Irrigation rate of crop land (%)	County	NASS[d]
Ag. land value ($/acre)	Agricultural land asset value including buildings ($/acre)	County	NASS[d]
Farm income (1000$/acre)	Farm income (1000$/acre)	County	CENSTAT[e]
Non-farm income (1000$/acre)	Non-farm income (1000$/acre)	County	CENSTAT[e]
Housing value ($)	Logarithm of Median value of owner housing ($)	County	CENSTAT[e]
Log(Population density) (per acre)	Logarithm of population density (persons in an acre)	County	CENSTAT[e]

[a] Multi-Resolution Land Characteristics (Environmental Protection Agency, National Oceanic and Atmospheric Administration, United States Forest Service, United States Geological Survey, Bureau of Land Management, National Park Service, National Aeronautics and Space Administration, U.S. Fish and Wildlife Service, National Agricultural Statistics Service, U.S. Army Corps of Engineers, and United States of Department of Agriculture)
[b] United States Historical Climatology Network, National Climatic Data Center, National Oceanic and Atmospheric Administration
[c] Soil Survey Geographic Database, Natural Resources Conservation Service, United States of Department of Agriculture
[d] National Agricultural Statistics Service, United States of Department of Agriculture
[e] United States Census Bureau

The time-invariant land characteristics data are obtained from the soils data base SSURGO data (Soil Survey Staff 2014) of the Natural Resources Conservation Service, United States Department of Agriculture (USDA-NRCS). This includes data on land capability classes (LCC) in which class 1 and class 8 imply the most desirable and the least desirable for cultivation, respectively, and figure 13 presents the LCC in non-irrigated lands. For ease of interpretation, we converted LCC to a weighted averaged continuous variable, Soil Quality (1: least desirable; 8: most desirable), as shown in the estimation results.

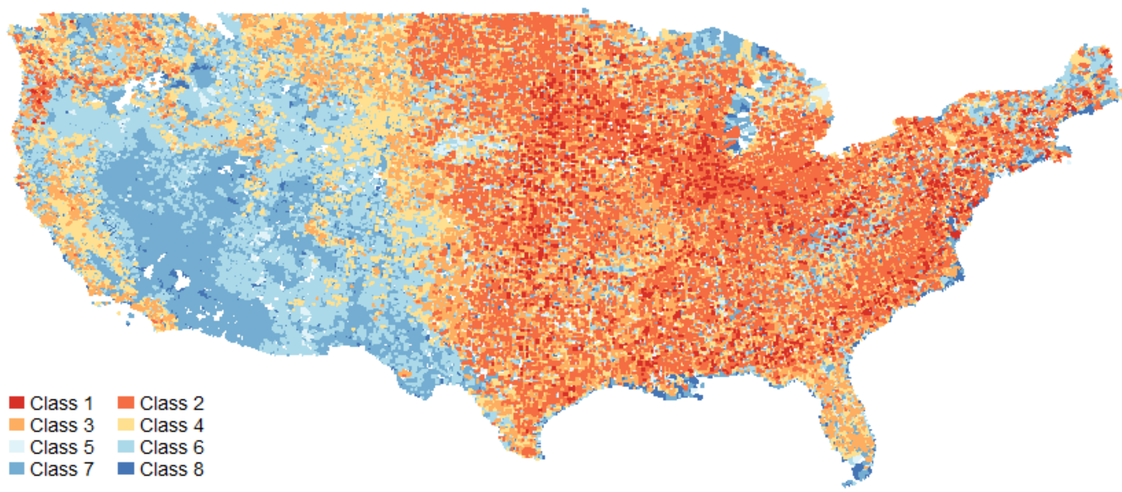


Figure 13. Land capability classification (Non-irrigated)

Source: Data from Klingebiel and Montgomery (1961) and Soil Survey Staff (2014).
Note: Class 1 is most suitable and Class 8 is least suitable for cultivation.

The base county and state maps (*tl_2008_us_county00* and *tl_2008_us_state00*) were obtained from the TIGER products (U.S. Census Bureau 2008). The 10×10 km map was based on the TIGER maps and gridded by using *fishnet* function in ArcGIS software (ESRI 2013).

Climate variables such as annual mean temperature, annual mean of monthly minimum temperature, annual mean of monthly maximum temperature, and annual total precipitation are obtained from United States Historical Climatology Network (USHCN). The variables are spatially interpolated between weather stations for the finer scale data. We then calculated the mean and standard deviations of observations of the climate variables in a 5-year window.

3.4 Estimation Results

We estimate the land use transitions with the data at the10 $\times$ 10 km cell level. The included explanatory variables are the same as the county level data except for the geophysical data including altitude, slope, land capability class and climate data including temperature and precipitation as shown in table 10.

Unlike the county level estimation, the estimation here includes more than 60,000 observations so it needs much more computing power to compute the marginal effects. Due to the computing memory constraints for the full weight matrix, we used sparse matrices using the algorithm implemented in MATLAB (Gilbert, Moler and Schreiber 1992; Mathworks 2014) since the values in the contiguity weight matrix is highly banded around the diagonal. For example, when locations are sorted in terms of latitude and longitude, a candidate for the starting point is the left-upper location. It leads to banded matrix which can be expressed as a much smaller dimension since the diagonal elements and most of the off-diagonal elements are zero. We can then manipulate the sparse or banded matrix with much smaller memory. The banded sparse weight matrices were constructed by using a Stata (StataCorp 2013) command, *spmat*, written by Drukker, et al. (2013).

Using finer scale micro-level data can relax assumptions of common behavior compared to using aggregate-level data although it requires much more computing power. One of the assumptions underlying the land use change estimation is that all the decision makers behave identically at the same area. Accordingly, the county level data cannot show spatial dependence within a county but the micro level data can.

We present results from the fractional multinomial logit and the spatial multinomial logit in table 11 for the period 2002–2007 and table 12 for 2007–2012. The results show that the coefficients are generally robust between the models. However, the spatial lag parameter estimates are all positive and significant at the 1% level. This implies that the estimates without spatial lag terms can lead to a misspecification error and thus the estimates can be biased (Pace and LeSage 2010).

Table 11. Estimates of Land Use Allocations, 2002–2007

	Land share 2007									
	Fractional multinomial logit					Spatial multinomial logit				
Covariates	Crop	Grass	Forest	Urban	Water	Crop	Grass	Forest	Urban	Water
Temperature	–0.0002	0.0276***	0.0196***	0.0153***	–0.0411***	0.0042***	0.0232***	0.0187***	0.0166***	–0.0354***
Precipitation	–0.0116***	–0.0743***	–0.0067***	–0.0255***	–0.0039	–0.0180***	–0.0657***	–0.0151***	–0.0261***	0.0065*
Temperature SD	–0.7744***	–0.9277***	–0.0549*	–0.7624***	–0.3555***	–0.7086***	–0.8044***	–0.1691***	–0.6652***	–0.4346***
Precipitation SD	–0.1116***	0.1310***	–0.0346***	–0.0305***	0.0047	–0.0859***	0.1115***	–0.0258***	–0.0280***	–0.0011
Altitude	–0.0219***	–0.0038***	0.0214***	–0.0181***	–0.0434***	–0.0191***	–0.0051***	0.0172***	–0.0157***	–0.0264***
Slope	0.0014***	0.0060***	0.0067***	0.0022***	0.0066***	0.0026***	0.0057***	0.0063***	0.0021***	0.0073***
Soil quality	0.0182***	0.0110***	0.0209***	0.0069***	0.0023	0.0163***	0.0126***	0.0193***	0.0068***	0.0010
Irrigation rate	–0.5473***	–0.2352***	–0.5877***	–0.6596***	–0.0088	–0.5131***	–0.2093***	–0.5435***	–0.6427***	0.0917
Ag. land value	0.0213*	–0.0965***	0.0147	0.0914***	–0.0658***	0.0200***	–0.0789***	0.0046	0.1128***	–0.1275***
Farm income	–0.3202***	0.0053***	–0.0000	0.0040**	–0.0036	–0.2049***	0.0048*	–0.0028	0.0052	–0.2012***
Non-farm income	–0.0458***	0.0409***	0.0151*	–0.0632***	0.0198*	–0.0456***	0.0420***	0.0104**	–0.0577***	0.0458***
Housing value	–0.4499***	–0.0749***	0.0201	–0.2455***	–0.2159***	–0.3742***	–0.0811***	–0.0088	–0.2076***	–0.2383***
Population density	0.0915***	0.0025	0.0179***	0.1559***	0.0204*	0.0787***	0.0117***	0.0253***	0.1227***	0.0345***
Share of crop	10.4119***	6.2685***	5.9784***	7.7404***	3.7272***	9.9662***	5.9115***	5.7138***	7.5797***	3.7069***
Share of grass	6.6656***	9.6786***	5.9282***	6.7593***	3.3545***	6.3720***	9.1156***	5.6304***	6.5957***	3.4519***
Share of forest	6.4098***	6.9197***	10.0230***	6.8763***	3.8746***	6.2662***	6.5251***	9.5966***	6.7744***	3.8038***
Share of urban	6.5377***	4.8558***	6.0867***	11.6991***	5.4337***	6.2158***	4.3657***	5.7980***	11.5153***	5.3844***
Share of water	4.2380***	3.7647***	4.4576***	5.8827***	9.6582***	4.0215***	3.2571***	3.9130***	5.7843***	9.5273***
Constant	–0.4995***	–3.4276***	–6.0916***	–4.7260***	–1.1443***	–1.1596***	–3.2753***	–5.2991***	–5.1118***	–0.5809**
Spatial lag (WX)						0.0552***	0.0841***	0.0449***	0.0316***	0.0472***
Observations			68978					68978		

Note: *, **, and *** indicate statistical significance at the levels 10%, 5%, and 1%, respectively.

Table 12. Estimates of Land Use Allocations, 2007–2012

	Land share 2012									
	Fractional multinomial logit					Spatial multinomial logit				
Covariates	Crop	Grass	Forest	Urban	Water	Crop	Grass	Forest	Urban	Water
Temperature	0.0009	0.0320***	0.0256***	0.0236***	–0.0355***	0.0055***	0.0268***	0.0224***	0.0218***	–0.0259***
Precipitation	–0.0252***	–0.0620***	–0.0288***	–0.0191***	–0.0331***	–0.0243***	–0.0523***	–0.0329***	–0.0191***	–0.0217***
Temperature SD	–0.2661***	–0.3665***	0.1556***	0.1009***	0.0604	–0.2236***	–0.2620***	0.1077***	0.0826***	0.1970***
Precipitation SD	0.0137**	0.0895***	0.0254***	0.0227***	0.1006***	0.0143***	0.0670***	0.0267***	0.0232***	0.0979***
Altitude	–0.0055***	0.0127***	0.0310***	0.0032*	–0.0245***	–0.0027***	0.0090***	0.0275***	0.0042***	–0.0056*
Slope	0.0019***	0.0068***	0.0072***	0.0032***	0.0081***	0.0030***	0.0064***	0.0068***	0.0031***	0.0085***
Soil quality	0.0163***	0.0108***	0.0197***	0.0058***	0.0058	0.0145***	0.0123***	0.0190***	0.0057***	0.0039
Irrigation rate	–0.7925***	–0.4460***	–1.0266***	–0.7858***	–0.2521***	–0.7073***	–0.4036***	–0.9658***	–0.7825***	–0.0194
Ag. land value	0.1198***	–0.0097	0.1018***	0.1770***	–0.0076	0.1006***	0.0020	0.0913***	0.2017***	–0.0377*
Farm income	–0.3040***	0.0329***	0.0204**	0.0319***	0.0013	–0.3453***	0.0335***	0.0351***	0.0420***	–0.1254***
Non-farm income	–0.0332***	0.0265***	0.0030	–0.0546***	0.0164**	–0.0303***	0.0274***	0.0013	–0.0493***	0.0259***
Housing value	–0.4885***	–0.0966***	–0.0319**	–0.2336***	–0.2011***	–0.3916***	–0.0943***	–0.0455***	–0.2289***	–0.2144***
Population density	0.0772***	–0.0152***	0.0171***	0.1305***	–0.0123	0.0644***	–0.0024	0.0187***	0.1056***	–0.0041
Share of crop	10.6111***	6.3789***	5.9045***	7.8573***	3.6298***	10.1149***	5.9446***	5.5714***	7.7643***	3.6512***
Share of grass	6.8252***	9.7883***	5.7980***	6.8323***	3.0658***	6.4946***	9.1029***	5.4305***	6.7488***	3.2602***
Share of forest	6.4818***	6.9516***	9.9192***	6.8251***	3.6051***	6.3066***	6.4884***	9.3915***	6.7860***	3.5175***
Share of urban	6.7538***	5.1062***	6.0060***	11.7150***	5.3303***	6.4107***	4.5651***	5.6614***	11.6079***	5.2830***
Share of water	4.6929***	3.9158***	4.5805***	6.2050***	9.8287***	4.2454***	3.1620***	3.9649***	6.1788***	9.7565***
Constant	–1.2291***	–4.2654***	–6.1660***	–6.2515***	–1.6543***	–1.9910***	–4.0896***	–5.4994***	–6.2930***	–1.6149***
Spatial lag (WX)						0.0590***	0.1018***	0.0529***	0.0262***	0.0393***
Observations			68978					68978		

Note: *, **, and *** indicate statistical significance at the levels 10%, 5%, and 1%, respectively.

The spatial dependence estimates are summarized in table 13. Comparing the period 2002–2007 with the period 2007–2012, the share of cropland, grassland, and forest is becoming more dependent on land use patterns in the nearby areas over time with the urban lands less dependent. The spatial dependence terms are mostly stable over time but there is negative growth rate of the dependence for urban lands and water. Decreasing spatial dependence in urban areas might be because the allocation of US lands is somewhat irreversible so that the changes have become less sensitive to the spatial interactions with nearby areas since once a parcel goes to urban lands it almost never comes back to other land uses. The result differs from the findings of other works (Zhang 1993; Li, Wu and Deng 2013) which find increasing spatial dependence over time in China. Whether the country characteristic affects the decreasing spatial dependence or the other structural changes have occurred should be further investigated by the data in longer periods.

Table 13. Estimated Spatial Lag Parameter to the Final Land Usage

	Crop	Grass	Forest	Urban	Water
2002–2007	0.0552***	0.0841***	0.0449***	0.0316***	0.0472***
2007–2012	0.0590***	0.1018***	0.0529***	0.0262***	0.0393***

Note: *** implies statistical significance at the 1% level.

Table 14 contains estimates of the average marginal effects from the spatial multinomial logit for the years 2002–2007 and 2007–2012. We find the marginal effects of the explanatory variables are mostly consistent across time. Namely:

- Higher temperatures lead to a decrease in the share of croplands with the effects growing over the years. Increases in precipitation leads to an increase in the cropland share but over time this is declining. Also, larger variations in temperature and precipitation generally decrease in the cropland use share, implying that higher volatility appears to reduce the land share for crops.
- Higher temperatures lead to an increase in the share of land in grassland with the effect growing over time. Increases in precipitation lead to less land in grasslands but the effect is declining over the years.
- Soil quality significantly affects shares of cropland with the effect declining over time but does not affect those of grassland. This may indicate that crop and grazing lands are less dependent on the land or soil quality as technology advances.
- Irrigation rates have positive impacts on allocating lands to grasslands with negative impacts on crop, forest and urban lands. This implies that irrigation may be limited by water and the remaining lands may be in grasslands.
- Higher asset values for cropland have positive impacts on crop land use share but negative impacts on grassland use. However, farm income decreases cropland share but increases grassland share. This may imply that croplands response more to a longer run value such as asset value but less to a short run value like annual income while grasslands do in opposite direction

Table 14. Marginal Effects on Land Use Allocations in Spatial Multinomial Logit, 2002–2007 and 2007–2012

	Crop	Grass	Forest	Urban	Water
From 2002 to 2007					
Temperature	–0.0011***	0.0014***	0.0008***	0.0003***	–0.0008***
Precipitation	0.0015***	–0.0053***	0.0022***	0.0000	0.0005***
Temperature SD	–0.0224***	–0.0436***	0.0499***	–0.0071***	0.0001
Precipitation SD	–0.0111***	0.0162***	–0.0046***	–0.0006***	0.0001
Altitude	–0.0019***	–0.0004***	0.0029***	–0.0005***	–0.0004***
Slope	–0.0002***	0.0002***	0.0003***	–0.0001***	0.0001***
Soil quality	0.0004***	–0.0002	0.0009***	–0.0003***	–0.0002***
Irrigation rate	–0.0157***	0.0263***	–0.0242***	–0.0111***	0.0078***
Ag. land value	0.0034***	–0.0098***	0.0025***	0.0055***	–0.0022***
Farm income	–0.0191***	0.0086***	0.0067***	0.0037***	–0.0026***
Non-farm income	–0.0055***	0.0060***	0.0012**	–0.0024***	0.0009***
Housing value	–0.0288***	0.0081***	0.0179***	–0.0019***	–0.0019***
Population density	0.0044***	–0.0040***	–0.0020***	0.0036***	–0.0001
Share of crop	0.4417***	–0.0750***	–0.0810***	0.0384***	–0.0353***
Share of grass	–0.0009	0.4040***	–0.1066***	0.0219***	–0.0347***
Share of forest	–0.0443***	–0.0416***	0.4225***	0.0054***	–0.0380***
Share of urban	0.0682***	–0.1488***	0.0550***	0.2737***	0.0029***
Share of water	0.0267***	–0.0622***	0.0273***	0.0876***	0.1030***
From 2007 to 2012					
Temperature	–0.0014***	0.0015***	0.0008***	0.0004***	–0.0007***
Precipitation	0.0009***	–0.0030***	0.0000	0.0005***	0.0001**
Temperature SD	–0.0173***	–0.0265***	0.0282***	0.0078***	0.0044***
Precipitation SD	–0.0026***	0.0049***	–0.0014***	–0.0004**	0.0012***
Altitude	–0.0015***	–0.0002**	0.0025***	–0.0002***	–0.0002***
Slope	–0.0002***	0.0002***	0.0003***	–0.0001***	0.0001***
Soil quality	0.0003**	–0.0001	0.0009***	–0.0003***	–0.0001**
Irrigation rate	–0.0121***	0.0341***	–0.0521***	–0.0070***	0.0096***
Ag. land value	0.0039***	–0.0095***	0.0041***	0.0061***	–0.0018***
Farm income	–0.0358***	0.0147***	0.0127***	0.0066***	–0.0012*
Non-farm income	–0.0033***	0.0044***	0.0003	–0.0020***	0.0005***
Housing value	–0.0286***	0.0092***	0.0152***	–0.0020***	–0.0011***
Population density	0.0041***	–0.0045***	–0.0012***	0.0034***	–0.0006***
Share of crop	0.4570***	–0.0723***	–0.1031***	0.0461***	–0.0380***
Share of grass	0.0135***	0.4185***	–0.1373***	0.0290***	–0.0396***
Share of forest	–0.0308***	–0.0382***	0.4030***	0.0095***	–0.0427***
Share of urban	0.0825***	–0.1332***	0.0267***	0.2779***	–0.0001
Share of water	0.0427***	–0.0906***	0.0254**	0.1019***	0.1069***

Note: *, **, and *** indicate statistical significance at the levels 10%, 5%, and 1%, respectively, based on the standard errors using the delta method.

- Non-farm income has negative impacts on land use for planting crops and urban areas and positive impacts on grasslands and forest. It is noted that the non-farm income is defined the total income minus the farm income by county and as this increases there would be greater labor allocation away from the farm so it is reasonable that the more labor intensive cropland decreases due to the higher non-farm incomes.

- Moving land to urban lands and grasslands from other land uses are possibly affected by the specific type of non-farm incomes so the overall incomes might not separate the effects. This may also reflect a greater demand for environmental amenities as income grows.
- Higher median housing values decrease the probability of allocating lands to crops and urban uses but increase the probability of allocation lands to forest. It implies that the high-valued housing units are likely to be placed out of crop or urban lands.
- More populated areas increase the land allocation for crop and urban lands. This implies that as population grows, grassland and forest may be converted to crop or urban lands. This also indicates the crop lands and urban lands may be placed nearby for the cropland to be urbanized in the future. This result is also consistent with the observed positive correlation between cropland values and proximity to urban areas as discussed in Nickerson, et al. (2012).
- Land share in the previous period affects land usage in the current period. In specific, increases in the previous forest share have negative impacts on land use shares for crops and grass in the current period and vice versa. This may imply that as the region becomes more forested, that crop and grass lands tend to move

more rapidly into forest lands. We also find that when any land shares in the previous period increases, the urban land share in the current period still increases. This indicates that urban lands are likely to be developed from any lands in the previous period as well as the previous urban lands.

Overall, temperature and precipitation are found to have the largest effects on use of cropland and grassland. Generally, increasing temperature affects an increase in grassland share and a decrease in cropland but increasing precipitation leads to declining share of cropland and increasing share of grasslands. Given the most areas are expected to experience higher temperatures, the cropland is likely to decline but the grassland is likely to increase in the next decades.

We computed the root mean squared errors (RMSE) to compare the predictions to the observed values among models. In specific, the predicted values with fractional multinomial logit and spatial multinomial logit estimations are compared. As shown in table 15, the predicted values from spatial multinomial logit estimation have smaller RMSE to the sample observations except the croplands in both 2002–2007 and 2007–2012 periods. This may imply that observed cropland shares tend to be distributed more clustered around the mean. This also indicates that in linear models it might be appropriate not to employ spatial dependences.

Table 15. Root Mean Squared Errors of Predicted Shares

Land Share	RMSE of predicted to observed shares: Fractional MNL	Spatial MNL
2002–2007		
Cropland	0.04736	0.04803
Grassland	0.05413	0.05248
Forest	0.05722	0.05578
Urban	0.02711	0.02667
Water	0.02907	0.02873
Other	0.04019	0.03952
2007–2012		
Cropland	0.04732	0.04770
Grassland	0.05520	0.05399
Forest	0.05804	0.05720
Urban	0.02675	0.02641
Water	0.02951	0.02899
Other	0.03973	0.03899

3.5 Projected Land Use Allocations as Climate Change Adaptation

Based on the estimation results, we provide some predictions on major land use allocations as adaptation to climate change under counterfactual and future climate scenarios. The counterfactual simulation is conducted under the assumption that the historical climate has been fixed at the level of 1900–2000 average value in 2012 and the future climate scenarios reflect the temperature and precipitation values from the global climate models. The former may indicate what was likely to happen if the climate change was absent and the latter may indicate what is likely to happen if the climate change occurs in the next decades.

3.5.1 Counterfactual Simulation

We conducted a counterfactual simulation under the assumption that the temperature and precipitation would have stayed the 1900–2000 average values in 2012. We presented the average marginal effects of temperature on the land use allocations but the effects are averaged over the space. Thus, we also show the counterfactual allocations of major land uses by region in figure 14, given the counterfactual predicted values based on 1900–2000 average temperature and precipitation. In the figures, the growth rate between observed and counterfactual shares are evaluated at the year 2012 as differences of share of observed in 2012 and share of counterfactual in 2012 divided by share of counterfactual in 2012. Under the 1900–2000 normal, the expected proportion of cropland in 2012 would have been likely to be larger than the observed values in most areas. In contrast, grasslands would have been less allocated if the temperature and precipitation stayed the historical normal. As the marginal effects show the opposite response of cropland and grassland to temperature and precipitation, the counterfactual allocations show opposite, if not exact, growth rate under the historical mean.

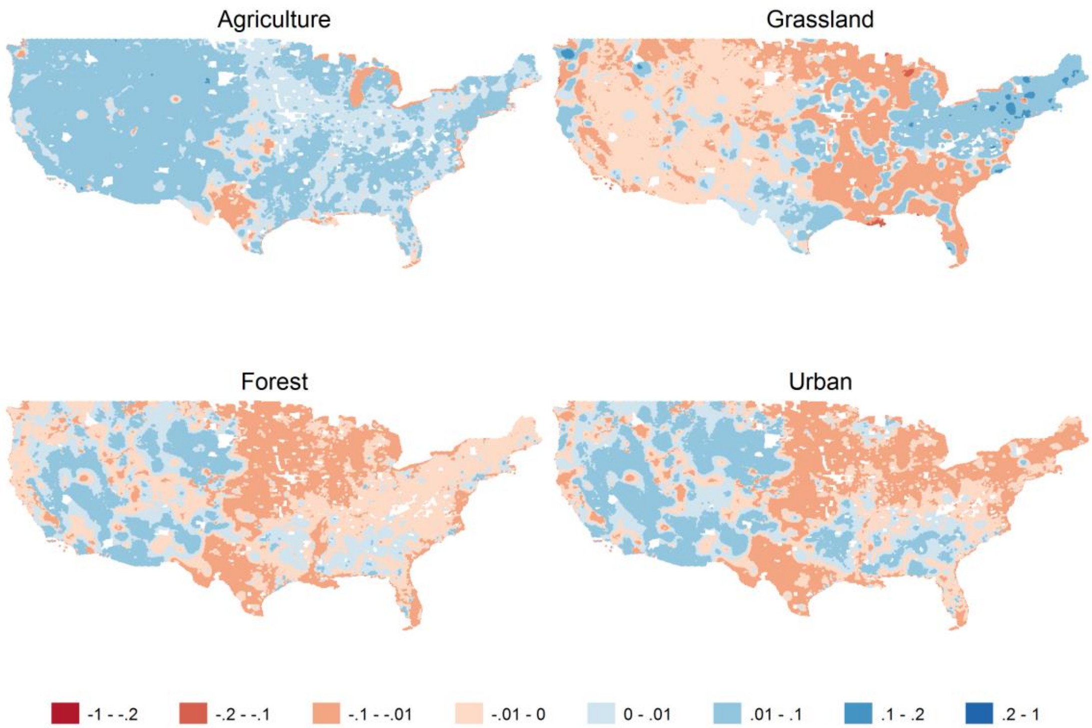


Figure 14. Counterfactual growth rate of predicted shares with historical climate normal 1900–2000 in 2012

Note: Blue cells indicate more allocations for each land usage than the values in 2012 under 1900–2000 average climate and red cells indicate less allocations.

3.5.2 Climate Scenarios

Using the temperature and precipitation estimates from the Representative Concentration Pathways (RCP) of the Coupled Model Intercomparison Project Phase 5 (CMIP5), we simulated the land use allocations in 2030, 2050, 2070, and 2090. We obtained the projected temperature and precipitation outputs from six different climate models including CanESM2, CCSM4, CESM1-CAM5, GFDL-CM3, HadGEM2-ES, and MPI-ESM-MR. We obtained these from the Archive of CONUS 1/8 degree BCSD (Bias-

Corrected and Spatially Downscaled) files available at "Downscaled CMIP3 and CMIP5 Climate and Hydrology Projections". RCP 2.6 scenario implies optimistic conditions with the lowest level of greenhouse gas emissions while RCP 8.5 scenario indicates pessimistic conditions with the highest level of GHG emissions. Since we focus on the climate effects on the land use changes, we simplified the assumption that the market values are exogenously determined although they are likely to be endogenous to commodity production and consumption. That is, the predicted values of land use allocation demonstrates the marginal change of the land uses when the other variables are stable in the current condition. Unlike the counterfactual simulation, we evaluate the expected growth rate of share in the future years from 2012 to show how the land allocations would adapt to the altering climate over the years.

Figure 15 shows the growth rate of land share for crops under the values of temperature and precipitation under the RCP 2.6 scenario. Because the RCP 2.6 scenario implies the least increases in GHG and the least change in climate, the change in land use shares over the future years are not much variant. In figure 16, using the same prediction under RCP 8.5 results in noticeable changes in expected land shares compared to the RCP 2.6 result. The shares of cropland are expected to decrease in the Eastern and Central areas and to increase in the southwest, Mountain and Pacific areas over the years. Although the patterns resemble each other, the figures show more rapid decreases in cropland share under the RCP 8.5 than the RCP 2.6.

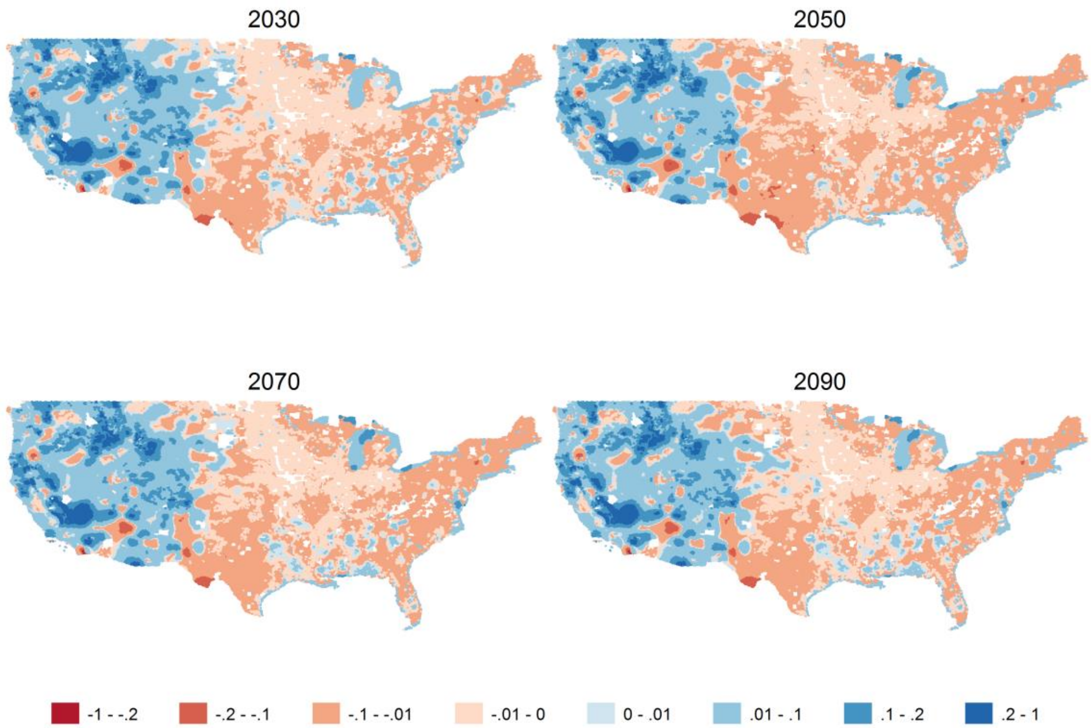


Figure 15. Cropland growth rate under RCP 2.6 scenario from 2012

Note: Blue cells indicate more allocations for each land usage compared to the values in 2012 under RCP 2.6 scenario in 2030, 2050, 2070, and 2090 and red cells indicate less allocations.

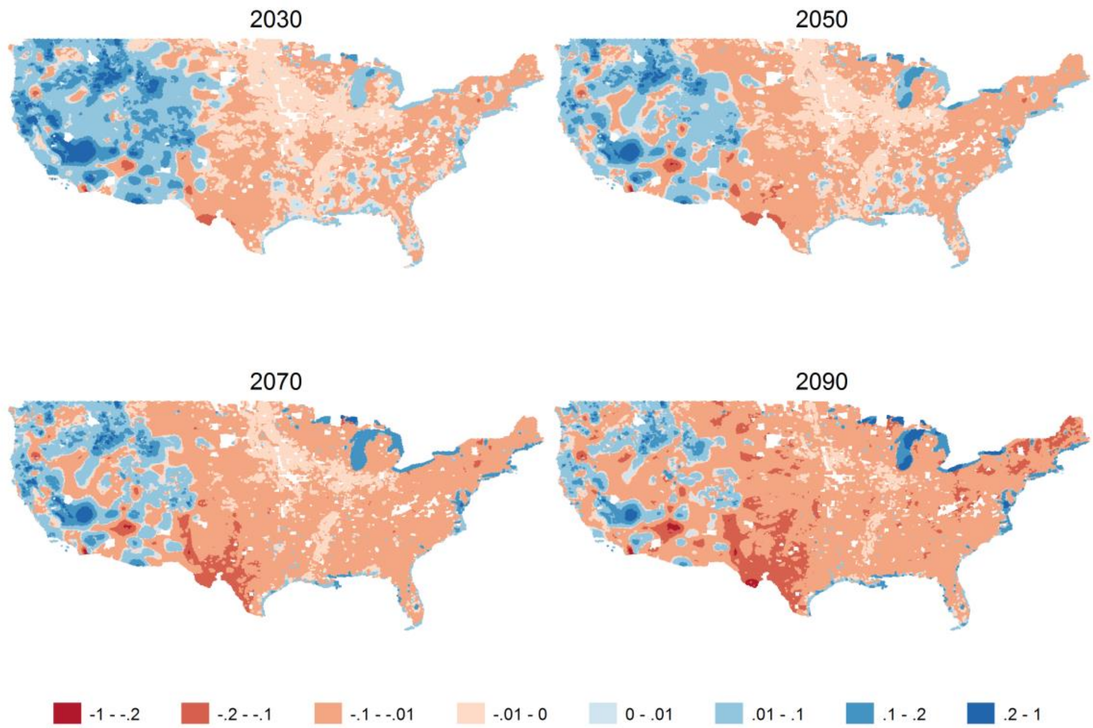


Figure 16. Cropland growth rate under RCP 8.5 scenario from 2012

Note: Blue cells indicate more allocations for each land usage compared to the values in 2012 under RCP 8.5 scenario in 2030, 2050, 2070, and 2090 and red cells indicate less allocations.

Figures 17–18 present the growth rate of share for grasslands under RCP 2.6 and RCP 8.5 in 2030, 2050, 2070, and 2090 compared to 2012. Over the years, Southeastern and Western areas are expected to have less shares for grassland due to climate change. As in the case of croplands, expected shares for grassland under RCP 8.5 increase or decrease more rapidly than those under RCP 8.5 particularly in Texas and the Great Plains. Because the RCP 8.5 climate estimates change more rapidly than those of RCP

2.6, the other land use shares such as forests and urban areas are also expected to change more severely under the RCP 8.5.

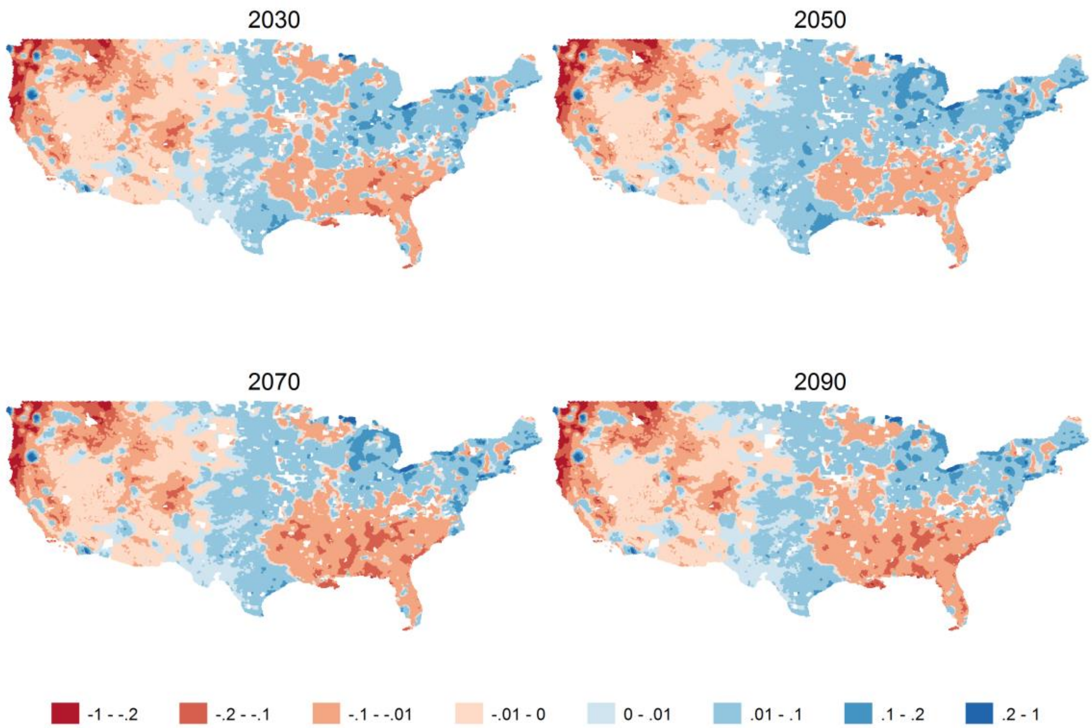


Figure 17. Grassland growth rate under RCP 2.6 scenario from 2012

Note: Blue cells indicate more allocations for each land usage compared to the values in 2012 under RCP 2.6 scenario in 2030, 2050, 2070, and 2090 and red cells indicate less allocations.

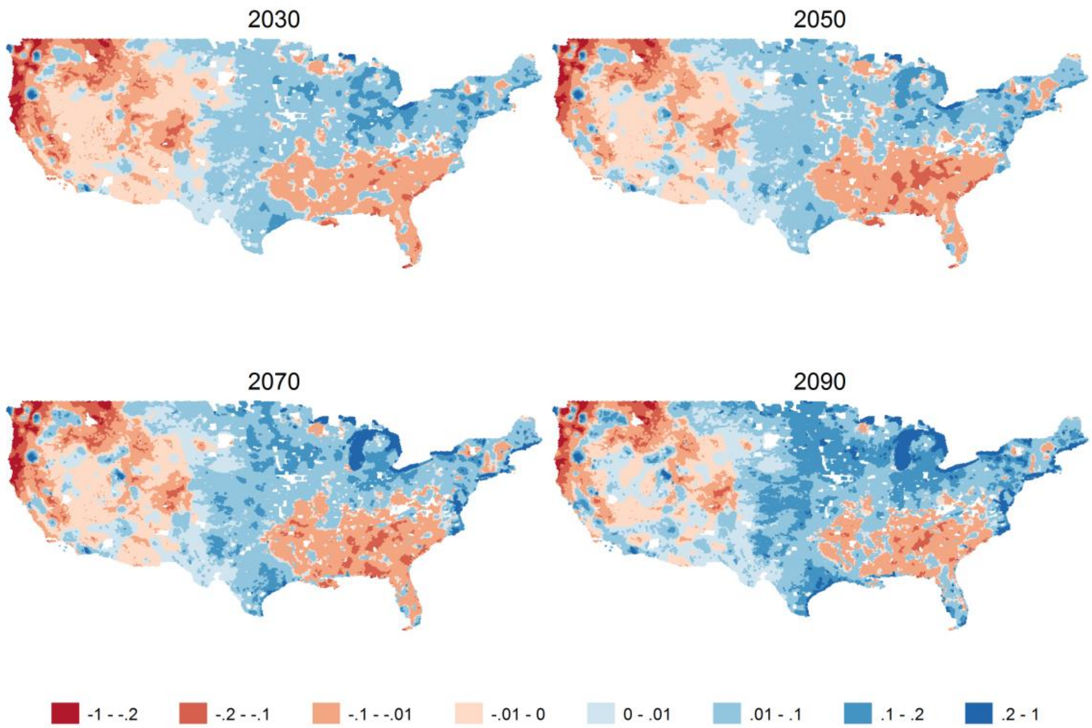


Figure 18. Grassland growth rate under RCP 8.5 scenario from 2012

Note: Blue cells indicate more allocations for each land usage compared to the values in 2012 under RCP 8.5 scenario in 2030, 2050, 2070, and 2090 and red cells indicate less allocations.

3.5.3 Marginal Effects of Land Use Transitions

We also estimated the land use transitions model with the fractional multinomial logit model because some transitions between land uses turn out insignificant spatial autocorrelations. Also, RMSE of the predicted probabilities of transitions are smaller in the fractional MNL result. Thus, we rely on the fractional MNL results to estimate the transitions. To save space, we only present the marginal effects of average temperature and precipitation. Because the changed probability is constructed as the land use changes from A usage to B usage divided by B usage, we multiply the B usage shares at the initial state to the marginal effects to identify the changed magnitude. We estimate the marginal effects of all the variables in 2002–2007, 2007–2012, and 2002–2012 periods. However, the transitions lead to too many marginal effects estimates so we focus on the temperature and precipitation between 2002 and 2012 here.

Table 16 shows that increasing temperature significantly decreases the probability of maintaining the initial land uses for all usage except the urban lands. Specifically, cropland is likely to change most significantly to grassland and urban lands under increasing temperature. Grassland is likely to be converted to forest and urban lands the most in higher temperature. The probability of urban lands to be remained may not respond to the changed temperature.

The result indicates that under increasing temperature, the croplands is highly likely to convert to grassland and the grasslands are likely to convert to forests and the forests are likely to convert to grasslands. Thus, cropland would be likely to change to other land uses significantly and grasslands and forests are mostly converted to each other.

Table 16. Marginal Effects of Temperature on Land Use Transitions, 2002–2012

	Final land use				
Initial land use	Cropland	Grassland	Forest	Urban	Water
Cropland	-0.052^{***}	0.023^{***}	0.011^{***}	0.016^{***}	0.002
Grassland	0.004^{***}	-0.072^{***}	0.043^{***}	0.018^{***}	0.004^{***}
Forest	0.000	0.066^{***}	-0.076^{***}	0.010^{***}	0.000^{*}
Urban	0.000	0.000	0.000^{***}	0.000	0.000^{**}
Water	0.000^{*}	0.005^{***}	0.001^{***}	0.001^{***}	-0.012^{***}

Note: Marginal effects are multiplied by the 2002 shares and by a hundred. ***, **, and * indicate statistical significance at the levels 1%, 5%, and 10%, respectively.

The marginal effects of precipitation on land use transitions are shown in table 17. Increasing average precipitation is likely to increase the probability that the cropland, grassland, urban lands, and water is maintained and thus increasing aridity would stimulate transitions. The probability of converting from cropland to forest and urban lands decreases under increasing precipitation. Grasslands have lower probability to be converted to other uses when precipitation increases. This implies that less precipitation would push the grasslands to other uses, most significantly, to forest. We also find that the urban land change to croplands, grasslands, and forest may not respond to the precipitation. However, unlike the case in temperature change, we do not find monotonic patterns of land use transitions. Because precipitation change differs across regions while temperature change is expected to increase over the regions, the insignificant changing pattern might result from the trade-offs of the effects between heterogeneous regions.

Table 17. Marginal Effects of Precipitation on Land Use Transitions, 2002–2012

	Final land use				
Initial land use	Cropland	Grassland	Forest	Urban	Water
Cropland	0.014*	0.000	–0.005***	–0.009***	–0.002
Grassland	–0.025***	0.097***	–0.054***	–0.011***	–0.007***
Forest	0.003*	0.000	0.000	0.000	–0.008***
Urban	0.000	0.000	0.000	0.000**	0.000**
Water	0.003***	–0.002*	0.001***	0.000	0.004*

Note: Marginal effects are multiplied by the 2002 shares and by a hundred. ***, **, and * indicate statistical significance at the levels 1%, 5%, and 10%, respectively.

3.6 Concluding Remarks

This study employs a spatial econometric method for land use allocations and transitions in the US. We use the linearized multinomial logit framework due to the difficulty of estimating nonlinear discrete choice models when including spatial dependences. The current study extends the previous studies of land use change by using more detailed data while also considering spatial interactions between land areas and focusing on the climate change adaptation via altering land uses.

The results show that the climate significantly affects the land allocations and transitions as do other economic and geophysical conditions. In particular we find that temperature and precipitation affect the land use allocations for cropland and grasslands in the opposite direction. We also find that including spatial dependences in land use allocations improves the land use allocation model. However, we do not find advantages using the spatial autocorrelation term for the land use transitions model. Because the allocation of land shares in the US has been highly stable in the recent years, the land transitions between usages are not readily captured by the spatial dependence and the prediction based on the fractional multinomial logit is shown more robust in the transitions model.

Using the simulated expected shares, we show the regional land responses under the counterfactual case in 2012 under the historical climate normal. We also show the expected shares in the future under the climate scenarios. We find that the patterns of a specific land use change due to the altering climate resemble those of different climate scenarios but the rate of changes are much higher in the climate scenario with more radiative forcing. Generally, we find climate change moves land out of cropping and into grasslands although this is only strongest in certain regions.

Although we estimated the marginal impacts of various factors on land use transitions nationwide, there may be some omitted factors affecting the change. For example, policy changes are a significant factor on land use changes but due to the lack of data, we could not include the factors explicitly in the model. We assumed some state-level or county-level policy impacts implicitly with the spatial information. Also, there might be good approximation of explicit land prices for each usage considering endogenous price changes from market demand and supply of lands. Thus, our model could be further improved by including market factors. Unfortunately, those kind of data are limited especially at the micro level and a system of equations including those factors would be more complicated. Thus, further studies would be better conducted with more detailed panel data and system equations that are not available currently.

4. IMPACTS OF CLIMATE CHANGE ON WILDFIRE RISK IN THE UNITED STATES

Wildfires in the form of uncontrolled occurrence of fire within wild landscapes such as forestlands and grasslands are damaging and of public concern. They are also considered a natural adaptation of an ecosystem to say hotter and drier conditions. Climate change impacts on wildland fire have been discussed conceptually with some regional empirical work in previous studies (Westerling and Swetnam 2003; Gan 2005; Westerling and Bryant 2006; Daigneault, Miranda and Sohngen 2010; Yue, et al. 2013). Here we will attempt to advance the literature by doing a national econometric study examining how climate change may enhance wildfire risk. This will be done using a modified logistic regression over a recent panel data set to discover the effect of climate and other factors on fire risk and then to project the expected change in fire risks under the IPCC (2013) future climate scenarios.

Specifically, we will use an econometric approach to study the impacts of climate variables such as temperature and precipitation on human-caused and lightning-caused wildfire risks in forest lands. We will also include other natural factors and human factors including population, tree mortality, tree removal, and density of biomass. We will employ a fractional regression model over a state level, multiple year, panel data set with heterogeneity considered. Moreover, we will form projections of future wildfire risks in the US based on the IPCC (2013) Representative Concentration Pathways (RCP) climate scenarios.

This study contributes to the literature in several ways. First, we use a panel data approach considering unobservable heterogeneity of each state, which makes the estimates more robust. Second, we employ a fractional multinomial logit to predict incidence of both human-caused and natural, lightning caused fires. Third, we combine recent historical data with the latest IPCC RCP climate scenarios (IPCC 2013; Knutti and Sedlacek 2013) and generate spatially heterogeneous projections of wildfire risks under expected climate change. Fourth, we identify the importance of climatic, demographic and stand characteristic factors as contributors to wildfire risk and understanding of which can possibly aid in setting future forest policy.

4.1 Background on Wildfires in the US

Forestlands have been mainly considered a source of timber production, recreational opportunities, and an environmental amenity (Sorg and Loomis 1984; Garrod and Willis 1992; Pattanayak, Murray and Abt 2002). Also, in the climate change arena they have been mentioned as a carbon sink to mitigate climate change (Richards and Stokes 2004; IPCC 2014). However, increased incidence of wildfires can threaten these roles. Accordingly, the factors increasing wildfire danger has been examined by many previous studies. Climate conditions, human activity, and other variables have been found to affect frequency and severity of wildfire occurrence (Running 2006; Del Genio, Yao and Jonas 2007; Seager, et al. 2007; Price 2009), and the IPCC among others has argued that recent climate change is also contributing (IPCC 2013, 2014). Furthermore, the IPCC also indicates that projected climate change will further increase wildfire activity (IPCC 2013, 2014).

In this study, wildfire risks are defined as ratio of burned area to forested land area. Also, we identify lightning-caused wildfires as natural wildfires, and use those terms interchangeably. National Interagency Fire Center (NIFC) classifies wildfires into lightning-caused fires and human-caused fires among 13 causes such as arson, campfire, equipment use, and smoking (Short 2014). Fires originating due to all other causes excepting lightning are identified as human-caused wildfires.

Currently, the historical average of human- and lightning-caused wildfire risks are given in figure 19 and figure 20, respectively. Generally, we see that the western areas of the US have higher wildfire risks than eastern regions. This might be because the western states are generally drier with large areas of public lands as discussed in Running (2006). The numbers of human-caused and lightning-caused fire occurrences are highest in the Southern area and in the Midwestern area such as Rocky Mountain and Southwest, and Eastern Basin regions, respectively.

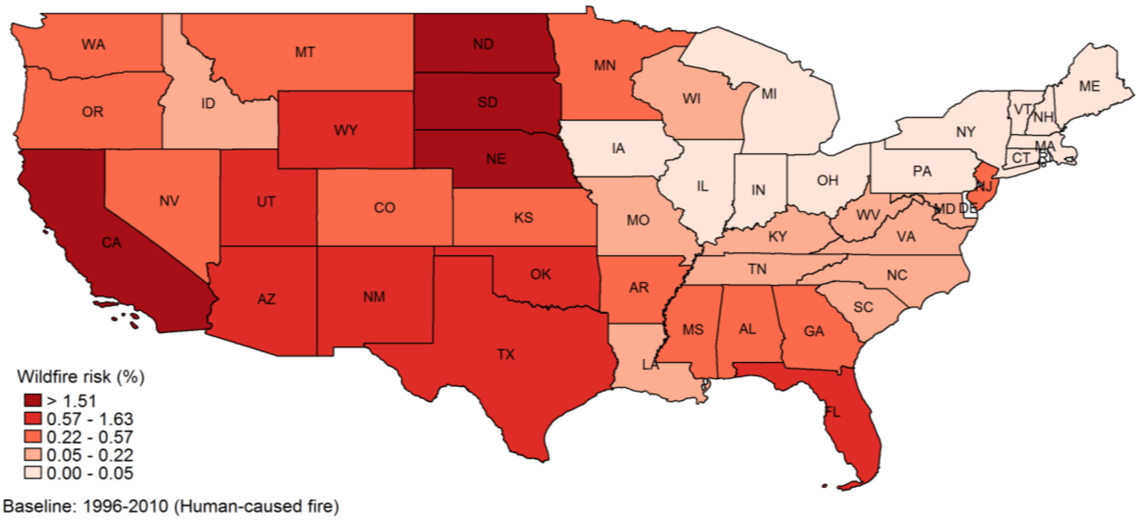


Figure 19. Average human-caused wildfire risk, 1996–2010

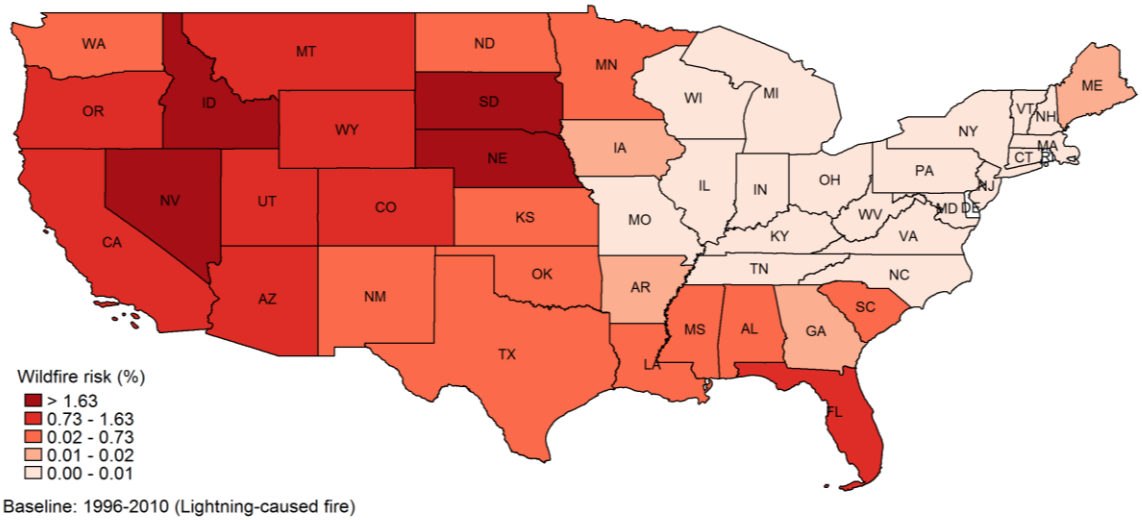


Figure 20. Average lightning-caused wildfire risk, 1996–2010

4.2 Econometric Model Specification

We use a discrete response model method to estimate how human-caused and natural wildfires are affected by climate, physical, and demographic factors. Wildfire risk in this study is estimated as the ratio of area burned to the total forest lands with separate analyses for fires caused by human and lightning. Such a variable is bounded between zero and one and to maintain that restriction we use a fractional model that deals with proportional data (Murteira and Ramalho 2013). There are three alternative cases that would apply to a parcel on an annual basis: human-caused fire, lightning-caused fire, and no fire and the probabilities of these must sum up to one.

To implement the estimation with considering the three cases, we use a maximum quasi-likelihood estimation for multinomial fractional regression approach following Koch (2010), Kala, Kurukulasuriya and Mendelsohn (2012), and Murteira and Ramalho (2013). Furthermore, we utilize fractional regression on panel data as developed by Papke and Wooldridge (2008) and a pooled multinomial logit on panel data as developed by Wooldridge (2010). This method makes predicted fire occurrence proportions for the three cases fall between zero and one.

Our model includes panel data for fire observations at the US state level in states $i = 1, \ldots, N$ and time periods $t = 1, \ldots, T$ where we have data for 46 states and 17 years. In turn the conditional mean for fire occurrence of type j (here j denotes human- and natural lightning-caused fires and no fire) can be expressed as:

$$(17) \qquad \mathrm{E}\left(s_{ijt} \middle| \mathbf{x}_{it}\right) = G_j(\mathbf{x}_{it}; \boldsymbol{\beta}) = G\left(\mathbf{x}_{it}\boldsymbol{\beta}_j\right) = \frac{\exp\left(\mathbf{x}_{it}\boldsymbol{\beta}_j\right)}{\sum_{k=1}^{J} \exp(\mathbf{x}_{it}\boldsymbol{\beta}_k)}, \qquad j = 1, \ldots, J$$

where $G(\cdot)$ is a known function that makes the predicted dependent variable s lie between zero and one with $0 < G(z) < 1$ for any $z \in \mathbb{R}$. s_{ijt} is the observed proportion state i forested lands that end the year in wildfire category j (human-caused fire, natural fire or no fire) in year t. The explanatory variables $\mathbf{x}_{it}$ include climate, physical, and demographic factors in state i in year t.

To consider heterogeneity between states, we include a term (c_i) for unobserved heterogeneity as the following: $\mathrm{E}(s_{ijt}|\mathbf{x}_{it}, c_i) = G_j(\mathbf{x}_{it}, c_i; \boldsymbol{\beta}, \gamma) = G(\mathbf{x}_{it}\boldsymbol{\beta}_j + \gamma_j c_i),\ j = 1, \dots, J$. As introduced by Chamberlain (1980) and Wooldridge (2010), if we assume that $c_i|\mathbf{x}_i \sim N(\psi + \bar{\mathbf{x}}_i\boldsymbol{\zeta}, \sigma_a^2)$ where $c_i = \psi + \bar{\mathbf{x}}_i\boldsymbol{\zeta} + a_i$ and $\bar{\mathbf{x}}_i$ is an average of time-varying variables of $\mathbf{x}_{it}$ over time t for each i, then $\mathrm{E}(s_{ijt}|\mathbf{x}_i) = \mathrm{E}(s_{ijt}|\mathbf{x}_{it}, \bar{\mathbf{x}}_i)$. Because directly estimating this equation is computationally burdensome and does not run without sufficient observations as argued by Wooldridge (2010), we follow Wooldridge (2010) and assume that $\mathrm{D}(c_i|\mathbf{x}_i) = \mathrm{D}(c_i|\bar{\mathbf{x}}_i)$ where $\mathrm{D}(\cdot \mid \cdot)$ is a conditional probability distribution function and then $\mathrm{E}(s_{ijt}|\mathbf{x}_i) = \mathrm{E}(s_{ijt}|\mathbf{x}_{it}, \bar{\mathbf{x}}_i)$ for all j, t. Then, to average out c_i, the specification of the conditional expectation $\mathrm{E}(s_{ijt}|\mathbf{x}_{it}, \bar{\mathbf{x}}_i)$ as the fractional multinomial logit satisfying $s_{it}|\mathbf{x}_{it}, \dots, \mathbf{x}_{iT} \sim multinomial(\mathbf{x}_{it}\boldsymbol{\beta}_1 + \mathbf{x}_i\boldsymbol{\zeta}_1, \dots, \mathbf{x}_{it}\boldsymbol{\beta}_J + \mathbf{x}_i\boldsymbol{\zeta}_J)$. In turn this leads to a pooled fractional multinomial logit estimation including time averaged terms, which averages out the heterogeneity term c_i. This is estimate with a quasi-maximum likelihood method that has robust standard errors makes the estimates robust to arbitrary serial dependence.

We then normalize on one item setting one $\boldsymbol{\beta}_J = \mathbf{0}$ (in this case making the no fire result the base alternative). Subsequently this allows identification as the following:

$$\mathrm{E}\left(s_{ijt}\middle|\mathbf{x}_{it}, c_i\right) = G_j(\mathbf{x}_{it}, \bar{\mathbf{x}}_i; \boldsymbol{\beta}, \boldsymbol{\zeta})$$

(18)
$$= \begin{cases} \dfrac{\exp\left(\mathbf{x}_{it}\boldsymbol{\beta}_j + \bar{\mathbf{x}}_i\boldsymbol{\zeta}_j\right)}{1 + \sum_{k=1}^{J-1}\exp(\mathbf{x}_{it}\boldsymbol{\beta}_k + \bar{\mathbf{x}}_i\boldsymbol{\zeta}_k)}, & j = 1, \dots, J-1 \\ \dfrac{1}{1 + \sum_{k=1}^{J-1}\exp(\mathbf{x}_{it}\boldsymbol{\beta}_k + \bar{\mathbf{x}}_i\boldsymbol{\zeta}_k)}, & j = J \end{cases}$$

where $\bar{x}_i^m = T^{-1}\sum_{t=1}^{T} x_{it}^m$ for each m-th time-varying variable.

Estimation using the above equations causes the conditional expected proportions of area burned due to human and natural causes plus the no fire case to add up to one ($\sum_j s_j = 1$) and to fall in the unit interval ($s_j \in (0,1)$).

In this case the specific log-likelihood function of the predicted dependent variable s is

(19)
$$l_i(\boldsymbol{\beta}) = s_{i1t}\log[G(\mathbf{x}_{it}, \bar{\mathbf{x}}_i; \boldsymbol{\beta}_1, \boldsymbol{\zeta}_1)] + s_{i2t}\log[G(\mathbf{x}_{it}, \bar{\mathbf{x}}_i; \boldsymbol{\beta}_2, \boldsymbol{\zeta}_2)] + \cdots$$
$$+ s_{iJt}\log\left[G\left(\mathbf{x}_{it}, \bar{\mathbf{x}}_i; \boldsymbol{\beta}_J, \boldsymbol{\zeta}_J\right)\right] .$$

Since the log-likelihood function is a member of the linear exponential family (LEF), the quasi-maximum likelihood estimator is consistent (Gourieroux, Monfort and Trognon 1984; McCullagh and Nelder 1989). As suggested in Papke and Wooldridge (2008), we used heteroskedasticity-consistent robust standard errors to make the standard errors robust to misspecification of conditional variance and arbitrary serial dependence.

Because estimates from discrete response estimation methods are difficult to interpret directly, we use the concept of the average marginal effect (AME) as discussed in (Long and Freese 2006). The average marginal effects indicate the marginal impacts of a one unit change in the explanatory variables on the acres in each fire class. For continuous explanatory variables, the average marginal effect of m-th explanatory variable on the expected probability of forest land share burned from cause j is calculated as the mean of marginal effects evaluated at each observation and is expressed as

$$\frac{\partial \mathrm{E}[s_{ijt}|\mathbf{x}_i]}{\partial x_{it}^m} = N^{-1} \sum_{i=1}^{N} \left(\beta_j^m G_j - G_j \sum_{k=1}^{J-1} G_k \beta_k^m \right) \quad (20)$$

where s_{ij} is the observed land share burned by cause j in state i, G_j indicate estimated share on alternative j for each observation and x_i^m is the value of m-th explanatory variables.

4.3 Data and Empirical Model Description

Above we presented the econometric specification with an arbitrary functional form. Here we adopt a specific form which is:

$$\mathrm{E}\left(s_{ijt}\middle|\mathbf{x}_{it}\right) = G_j(\mathbf{x}_{it}, \bar{\mathbf{x}}_i; \boldsymbol{\beta}, \boldsymbol{\zeta}) = G\left(\mathbf{x}_{it}\boldsymbol{\beta}_j + \bar{\mathbf{x}}_i\boldsymbol{\zeta}_j\right) = \frac{\exp\left(\mathbf{x}_{it}\boldsymbol{\beta}_j + \bar{\mathbf{x}}_i\boldsymbol{\zeta}_j\right)}{\sum_{k=1}^{J} \exp(\mathbf{x}_{it}\boldsymbol{\beta}_k + \bar{\mathbf{x}}_i\boldsymbol{\zeta}_k)} \quad (21)$$

where $\boldsymbol{\beta}_j$ and $\boldsymbol{\zeta}_j$ are parameters to be estimated and $\mathbf{x}$ are the independent variables we use to describe factors that alter fire incidence and are denoted as, $\mathbf{x}_{it} = \{x_{it}^1, \dots, x_{it}^q, x_i^{q+1}, \dots, x_i^{q+p-1}, x_i^m\}$. The vector $\mathbf{x}_{it}$ contains both time-varying (q) and time-invariant (p) factors, and $\bar{\mathbf{x}}_i$ includes q time-varying variables averaged out over multiple years for each state.

Several independent variables were considered to contribute to fire incidence. For our study we certainly add climate descriptors as linear terms. We also add non-linear terms to allow increasing and decreasing effects as climate factors change including squared terms for temperature and precipitation. To control for seasonality of wildfire risks, seasonal temperature and precipitation measures. Historically, the Western US has encountered 94% of wildfires and 98% of area burned due to fire between May and October (Westerling and Swetnam 2003; Whitlock, Shafer and Marlon 2003).

We include forest characteristic factors such as tree mortality, tree removal, and aboveground biomass density following Rothermel (1972), Rothermel and Philpot (1973), Anderson (1982), and Gan (2005). After several specification tests, we picked the set of explanatory variables shown in table 18 which also demonstrates descriptive statistics on these variables.

We use the US state-level data for the wildfire incidence and the explanatory factors over 46 states in 17 years. We include population density, annual tree mortality, annual tree removals, and biomass density as time-invariant variables because population density and tree-related variables are changing very slowly and stable in each state. Rather, we consider those variables used for controlling for state-specific characteristics. Although human population density does not rapidly change, most wildfire occurrences have been in populated areas according to the historical records. Tree removals such as harvesting sound trees and amount of aboveground biomass play a role in fuel accumulation and forest structure and operations for the removals may increase wildfire risks. Also, annual tree mortality has impacts on the changes of fuel characteristics since dead trees are more vulnerable to fire risks.

Table 18. Descriptive Statistics of Variables (N = 46, T = 17)

Variable	Mean	Standard Deviation	Min	Max
Dependent variables				
Fire: lightning-caused burned area / forest (ratio)	0.01	0.01	0.00	0.11
Fire: human-caused burned area / forest (ratio)	0.01	0.01	0.00	0.06
Fire: area not burned / forest (ratio)	0.99	0.02	0.88	1.00
Explanatory variables				
Temperature in spring (°C)	10.75	4.63	2.98	21.88
Temperature in summer (°C)	22.17	3.22	16.13	28.87
Temperature in autumn (°C)	12.31	4.14	4.88	23.19
Temperature in winter (°C)	0.48	5.80	–12.85	15.93
Precipitation in spring (hundred mm)	2.45	0.92	0.27	4.91
Precipitation in summer (hundred mm)	2.63	1.16	0.12	6.46
Precipitation in autumn (hundred mm)	2.29	0.97	0.39	4.49
Precipitation in winter (hundred mm)	2.06	1.12	0.24	5.66
Population density (persons / km^2)	63.79	86.8	2.03	440.73
Tree mortality (m^3 / ha)	0.89	0.44	0.05	2.08
Tree removal (m^3 / ha)	1.91	2.06	0.01	8.86
Biomass (hundred tons / ha)	1.03	0.44	0.04	2.07

Note: Number of observations is 782 including 46 states and 17 years.

Data on wildfire occurrence and burned area in the US were drawn from Short (2014) and compiled by year, state, and causes. Forested area data were extracted from National Land Cover Database (NLCD) of Multi-Resolution Land Characteristics (MRLC) Consortium by state: in particular, for 1992–2001 (Homer, et al. 2007; Fry, et al. 2009), for 2006 (Fry, et al. 2011), and for 2011 (Jin, et al. 2013). We used those data to calculate the wildfire risk defined as the ratio of burned area by wildfire to forested lands.

Human population density data were obtained from United States Census Bureau by state and averaged across years. Annual tree mortality, annual tree removal, and total aboveground biomass from 1997 to 2012 by state were obtained from: Smith, et al.

(2001) for 1997, Smith, et al. (2004) for 2001, Smith, et al. (2009) for 2007, and Oswalt, et al. (2014) for 2012, and then averaged out across years because the data series are unstable across survey years and slowly changing and we rather use them as state-specific characteristics.

Historical temperature and precipitation data were obtained from *nClimDiv* which are argued to be improvements on previous estimates by National Oceanic and Atmospheric Administration's (NOAA's) National Climatic Data Center (NCDC) as discussed in Fenimore, et al. (2011) and Vose, et al. (2014). We used the state-level climate variables of *nClimDiv*, estimated by bias-corrected distance weighted average across multiple weather stations. Seasons are defined as: Spring (March to May), Summer (June to August), Autumn (September to November), and Winter (December to February in the following year). We compute the seasonal temperature as the average monthly mean temperature and seasonal precipitation as the sum of the monthly total precipitation data.

4.4 Estimation Results and Discussion

We estimated the lightning- and human-caused wildfires with both the fractional regression and a fixed effects linear regression with heteroskedasticity-robust standard errors (Stock and Watson 2008) for comparative purposes. Estimated coefficients from fractional multinomial logit (FMNL) model are shown in table 19. In the estimation, "no fire" is used for the base case alternative whose coefficients are set to zero to identify the model. The estimates indicate how the alternative would change in probability with respect to the no fire case if one variable increases by one unit. However, it is hard to directly interpret the estimation results of this non-linear model, and thus we compute average marginal effects (AME) with the results shown in table 20.

To show whether AME is estimated appropriately, we compare the two sets of results. We find that the statistically significant AME and FE coefficients have similar patterns except for the case of summer temperature on human-caused fire. Since predicted probabilities in the FE regression are not bounded between zero and one and estimated separately, the estimated results may be biased. Coefficients across regressions are adding up to zero by design due to the unit sum of dependent variables[4]. We focus on the AME estimates in FMNL model because it deals with unobserved factors like panel regression models plus with fractional dependent variables bounded zero and one.

[4] Random effects linear regression shown in the Appendix is also used for comparison but the result is not much different from fixed effects model while the RE model can estimate the coefficients for time-invariant variables. Hausman test that the estimates are indifferent is rejected so we stick to FE model for the purpose with FMNL.

Table 19. Estimates of Lightning- and Human-caused Wildfire Risk, 1996–2012

Covariates	Lightning-caused wildfire Coefficients	Lightning-caused wildfire SE	Human-caused wildfire Coefficients	Human-caused wildfire SE
Temperature - spring (C)	0.507**	(0.212)	–0.119	(0.155)
Temperature squared - spring (°C)	–0.009	(0.010)	0.014*	(0.008)
Temperature - summer (C)	–1.249*	(0.694)	–0.570	(0.485)
Temperature squared - summer (°C)	0.041**	(0.018)	0.020**	(0.009)
Temperature - autumn (C)	–0.004	(0.335)	0.462*	(0.237)
Temperature squared - autumn (°C)	0.004	(0.017)	–0.012	(0.008)
Temperature - winter (C)	–0.074	(0.127)	0.036	(0.077)
Temperature squared - winter (°C)	–0.007	(0.008)	–0.003	(0.004)
Precipitation - spring (hundred mm)	1.231*	(0.715)	–0.320	(0.324)
Precipitation squared - spring (hundred mm)	–0.354*	(0.187)	–0.016	(0.057)
Precipitation - summer (hundred mm)	0.359	(0.393)	0.738	(0.486)
Precipitation squared - summer (hundred mm)	–0.095	(0.073)	–0.101*	(0.056)
Precipitation - autumn (hundred mm)	–1.214*	(0.675)	–2.308***	(0.515)
Precipitation squared - autumn (hundred mm)	0.198*	(0.109)	0.342***	(0.088)
Precipitation - winter (hundred mm)	–0.155	(0.486)	–0.980**	(0.480)
Precipitation squared - winter (hundred mm)	–0.038	(0.069)	0.159**	(0.080)
Population density (persons / km^2)	–0.146***	(0.036)	0.004	(0.003)
Tree mortality (m^3 / ha)	3.530***	(1.189)	–0.478	(0.629)
Tree removal (m^3 / ha)	–0.264	(0.300)	0.117	(0.195)
Biomass (hundred tonne / ha)	–4.473***	(1.516)	0.419	(0.860)
Constant	–87.011***	(24.644)	–34.513***	(10.389)
Quasi-log likelihood	–39.772			
Number of observations	782			

Note: *, **, and *** indicate statistical significance at the levels 10%, 5%, and 1%, respectively. Heteroskedasticity-robust standard errors are in parentheses. Time averaged variables are included in the estimation but suppressed in the table. In the Appendix (table A-5), the full results are shown.

Table 20. Estimates on Wildfire Risk: Average Marginal Effects in Fractional Multinomial Logit and Coefficients in Fixed Effects Linear Regression

	Fractional Multinomial Logit		Fixed Effects Linear Regression	
	Lightning-caused wildfire	Human-caused wildfire	Lightning-caused wildfire	Human-caused wildfire
Covariates	AME	AME	Coefficients	Coefficients
Temperature - spring (°C)	0.00166***	0.00091**	0.00362**	0.00031
	(0.00040)	(0.00041)	(0.00160)	(0.00126)
Temperature - summer (°C)	0.00246***	0.00155**	0.00974*	–0.00800*
	(0.00092)	(0.00065)	(0.00487)	(0.00458)
Temperature - autumn (°C)	0.00039	0.00071*	–0.00150	0.00155
	(0.00057)	(0.00039)	(0.00145)	(0.00124)
Temperature - winter (°C)	–0.00037	0.00014	–0.00012	0.00025
	(0.00063)	(0.00038)	(0.00041)	(0.00044)
Precipitation - spring (hundred mm)	0.00121	–0.00171***	–0.00599*	–0.00539*
	(0.00126)	(0.00065)	(0.00341)	(0.00301)
Precipitation - summer (hundred mm)	0.00043	0.00128	–0.00144	0.00329
	(0.00114)	(0.00115)	(0.00427)	(0.00432)
Precipitation - autumn (hundred mm)	–0.00355*	–0.00528***	–0.01137*	–0.01801**
	(0.00203)	(0.00128)	(0.00609)	(0.00679)
Precipitation - winter (hundred mm)	–0.00119	–0.00235**	–0.00146	–0.00533*
	(0.00157)	(0.00118)	(0.00298)	(0.00299)
Population density (persons / km^2)	–0.00072***	0.00003**	–	–
	(0.00018)	(0.00001)		
Tree mortality (m^3 / ha)	0.01733***	–0.00233	–	–
	(0.00593)	(0.00278)		
Tree removal (m^3 / ha)	–0.00130	0.00054	–	–
	(0.00147)	(0.00086)		
Biomass (hundred tonne / ha)	–0.02195***	0.00211	–	–
	(0.00758)	(0.00384)		
Number of observations	782		782	

Note: Delta-method standard errors for fractional multinomial logit and robust standard errors for fixed effects regression are in parentheses.*, **, and *** indicate statistical significance at the levels 10%, 5%, and 1%, respectively. AME indicates "average marginal effects" in fractional multinomial logit that is comparable to the coefficients of linear models. Full estimation results including random effects regression are included in the Appendix (tables A-6–A-7).

In table 20, the AME results show positive impacts of spring and summer temperature and negative impacts of autumn precipitation on both human- and lightning-caused wildfires significantly at the 10% level. Human-caused wildfire risk increases as autumn temperature increases while lightning-caused fire does not show a significant effect. Increasing spring and winter precipitation significantly plays a significant role in reducing human-caused wildfire. Both caused fires are affected by temperature and human-caused fires are more sensitive to precipitation as discussed in Gan (2005). Seasonal climate changes may alter fuel type and structure due to altered vegetation and fuel moisture as well (Schneider, et al. 2009). Thus, the altered seasonal temperature and precipitation would change the probability of risks on human-caused and lightning wildfires.

The AME estimates also show that the magnitude of the summer temperature is larger than that of other seasonal temperature partially because wildfires occur at the highest frequency and severity in summer. Also, the summer temperature is already higher than others so the marginal increase of temperature would induce intense conditions for wildfire risks such as highly altered fuel moisture.

Human population density has positive impacts on human-caused fire and negative impacts on lightning-caused fire, which implies that populated areas would be more vulnerable to human-caused wildfire. However, the populated areas would be less exposed to lightning wildfire because the degree of efforts on the prevention of catastrophic events may be higher than in non-populated areas plus tree density may be lower.

On lightning-caused fires, increasing annual tree mortality rate has positive impacts. This is not surprising since dead or unsound trees have less fuel moisture and are more combustible. Increasing biomass density has negative impacts on lightning fire risk. This might be because the abundant biomass results from well stocked forests with environmental and high commercial values which are protected by wildlife preventive actions plus tend to be in wetter areas.

Changes in climate conditions would have heterogeneous impacts on both human-caused and natural wildfire risks due to the spatially different responses to temperature and precipitation along with other physical and human factors.

To compare the model predictability, we calculated root mean squared errors of predicted shares based on the estimation results of each model using 1997–2010 as in-sample periods and 2010–2011 as out-of-sample periods. The results are shown in table 21, and FMNL with heterogeneity considered has superior performance to other methods including FMNL without time-averaged covariate **($\bar{\mathbf{x}}$)** terms, FE linear, and RE linear regressions. Since FE shows negative predicted shares of lightning fire (36.2%) and human-caused fire (35.8%) and RE shows negative predicted shares of lightning fire (26.3%) and human-caused fire (24.0%), it is evident that the model predictability of fractional regressions is superior to linear probability model such as FE and RE.

To compare the model performance, we also compare the FMNL regression with the FMNL without the time-averaged terms. According to the McFadden's R2 (FMNL: 0.163; FMNL without $\bar{\mathbf{x}}$: 0.137) and Cox & Snell's R2 (FMNL: 0.020; FMNL without $\bar{\mathbf{x}}$:

0.017), our proposed model performs better than that without controlling for state heteroskedasticity.

Table 21. Root Mean Squared Error based on Estimations in 1997–2010

	RMSE (1997–2010): In-sample		RMSE (2011–2012): Out-of-sample	
Model	Lightning	Human-caused	Lightning	Human-caused
FMNL	0.006	0.004	0.008	0.007
FMNL without $\bar{\mathbf{x}}$	0.008	0.005	0.009	0.008
FE	0.019	0.020	0.020	0.020
RE	0.010	0.007	0.009	0.008

Note: FMNL, FE, and RE indicate fractional multinomial logit, fixed effects ordinary least squares, and random effects generalized least squares, respectively.

4.5 Wildfire Risk under Climate Change

Based on the estimation results and the projected climate change based on the Representative Concentration Pathways (RCP) 4.5 and RCP 8.5 scenarios of Global Climate Models, we projected future changes of wildfire risks in the US.

For projections of wildfire risk in the next decades, we obtained the projections for the years 2015–2099 from six climate models under four RCP scenarios in Coupled Model Intercomparison Project Phase 5 (CMIP5). We obtained these from the Archive of CONUS 1/8 degree BCSD (Bias-Corrected and Spatially Downscaled) files available at: "Downscaled CMIP3 and CMIP5 Climate and Hydrology Projections" (Brekke, et al. 2013). The six Global Climate Models used were CanESM2, CCSM4, CESM1-CAM5, GFDL-CM3, HadGEM2-ES, and MPI-ESM-MR. Mean near-surface air temperature and monthly mean of the daily precipitation were obtained for RCP 4.5 and RCP 8.5 scenarios which are two extreme emission scenarios.

RCPs indicate a possible range of radiative forcing values in the year 2100 relative to pre-industrial values (+4.5 and +8.5 Watts per square meter for RCP 4.5 and RCP 8.5, respectively). A moderate but not extremely low level of greenhouse gas emissions is assumed for RCP 4.5 scenario and a highest level of emissions is assumed in RCP 8.5 scenario. Under the two climate scenarios, we would project the wildfire risk when the emissions are both moderate and extremely high emissions. We then averaged out the outputs of the six different climate models under each RCP. The grid data were converted to state-level data using the mean of the grid-point values inside each state.

The annual wildfire risks by human and nature were estimated up to 2030 and 2050 and compared with the baseline scenario, which is the historical average of fire incidence from 1997 to 2010.

Our projected changes of human-caused and lightning-caused wildfire risks are demonstrated in figure 21 and figure 22, respectively. The differences were estimated as the projected risk in the periods 2015–2030 and 2031–2050 minus the baseline risk in 1997–2010. Human-caused and natural wildfire risks seem complementary to each other in the figures, if not always. Based on both temperature and precipitation varying, some western states encounter decreasing human-caused wildfire risk and some southern states encounter decreasing lightning-caused fire compared to the historical baseline scenario.

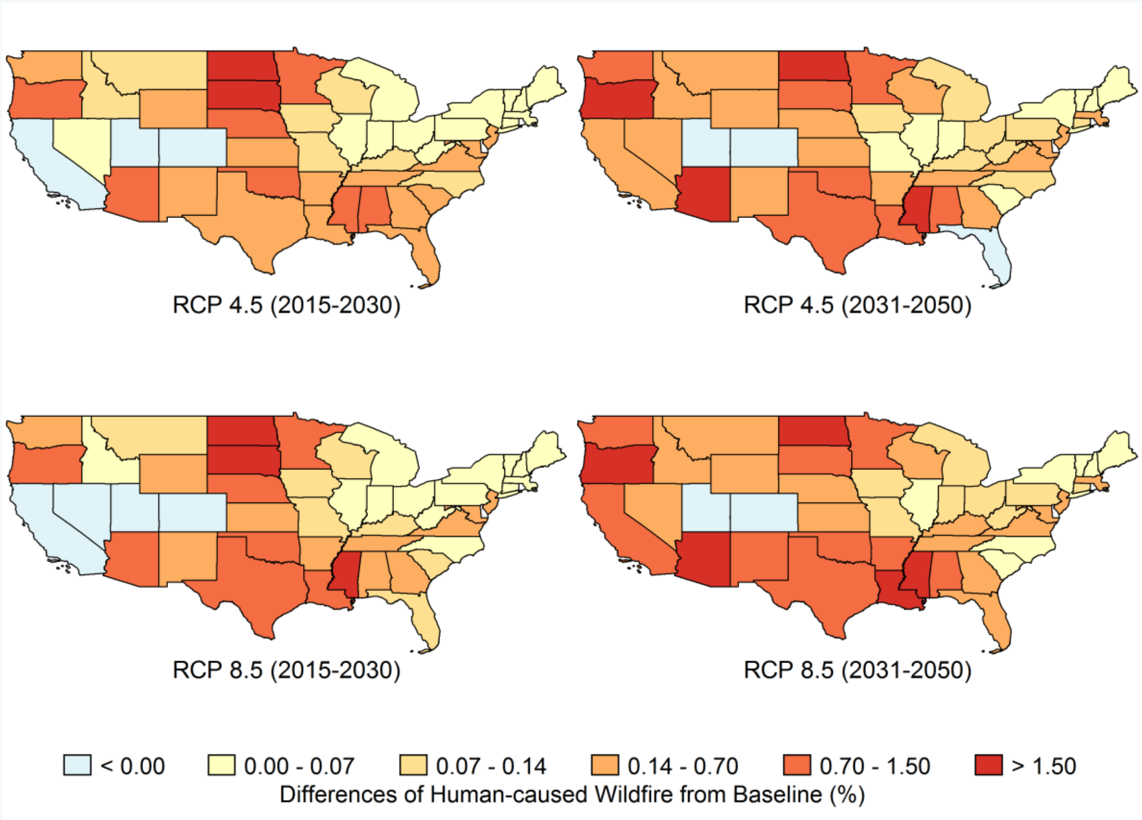


Figure 21. Changes in percent change of human-caused wildfire risk from baseline under RCP 4.5 and 8.5 scenarios, for the periods of 2015–2030 and 2031–2050 relative to 1997–2010

Note: The differences of wildfire risk are calculated by subtracting the baseline (1997–2010) wildfire risk from the projected wildfire risk with the average climatic conditions of the GCMs.

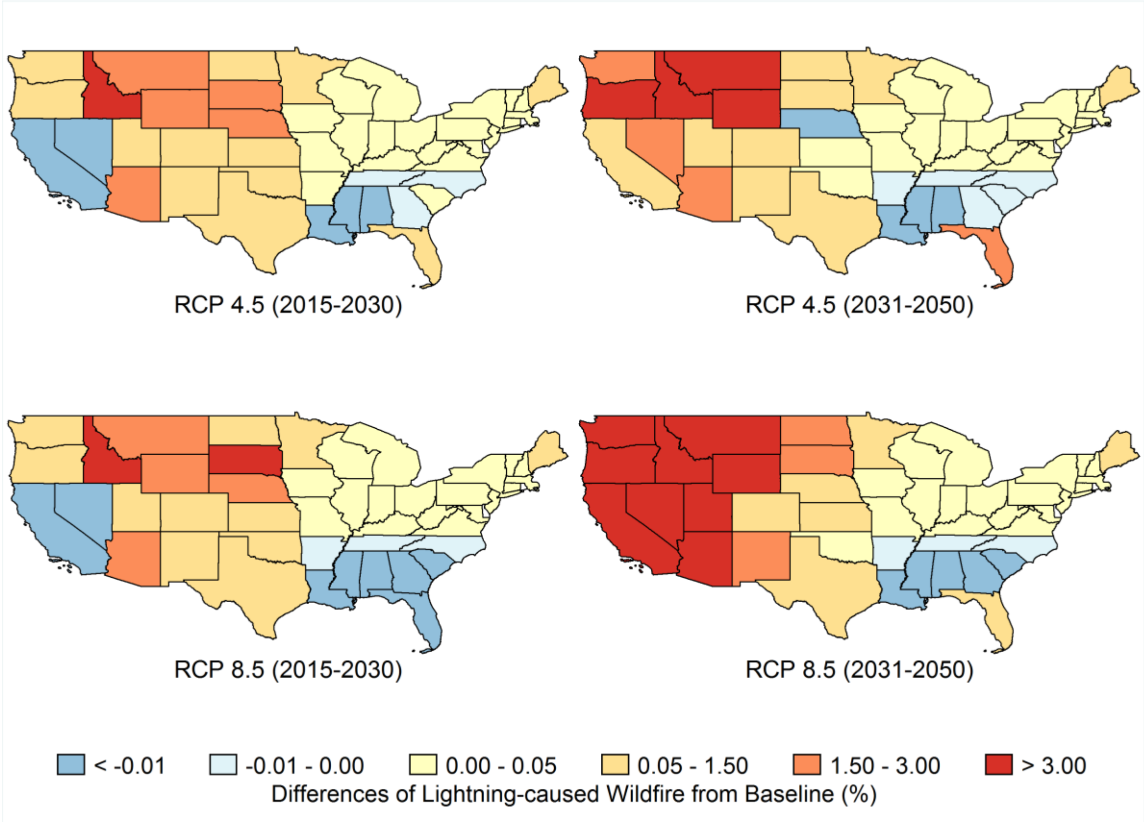


Figure 22. Changes in percent change of lightning-caused wildfire risk from baseline under RCP 4.5 and 8.5 scenarios, for the periods of 2015–2030 and 2031–2050 relative to 1997–2010

Note: The differences of wildfire risk are calculated by subtracting the baseline (1997–2010) wildfire risk from the projected wildfire risk with the average climatic conditions of the GCMs.

However, in most states, wildfire risks from both causes increase under both the RCP 4.5 and RCP 8.5 climate scenarios. To see the long-run impacts of climate change, we also attached a table of average differences in 2010–2050 from the baseline in the Appendix (table A-8). Based on the comparison, the highest increases of human-caused wildfire risk occur in North Dakota, Arizona, and Mississippi under RCP 4.5 and Mississippi, North Dakota, and Louisiana under RCP 8.5 in decreasing order. On the other hand, increases in natural wildfire risk are largest in Oregon, Idaho, and Montana under RCP 4.5 and RCP 8.5 in decreasing order. Although the pattern for human-caused and natural fire risks is consistent for each cause across different climate scenarios, the predicted changes of human-caused fires are more volatile and spatially heterogeneous depending on varying climate conditions than those of lightning-caused fires. This also implies that considering physical factors and spatial differences is needed for effective preventive actions.

Previous literature which found that the most severe effects of altered climate on wildfire in the western US also conform to some of the results of our study. Yue, et al. (2013) found that the biggest driver for wildfires in the next decades would be temperature so the wildfire risks increase if we encounter large increases in temperature over years. Yet, including not just specific regions but nationwide regions in the US, we find that the separate effects of human and natural factors would play a different role in overall wildfire risks. Since the temperature and precipitation changes would differently affect the risks, it would be advised to assess the impacts carefully with considering the human and natural characteristics as well as spatial heterogeneity.

As shown in figure 21, under the RCP 4.6 and RCP 8.5, human-caused wildfire would become more severe in southern regions than Northern Plains states because the southern regions have much higher share of forested lands and are hot already. As shown in the Appendix (figure A-8), the Northern Plains regions show relatively small share of forested lands so the wildfire in forests would be less serious than the southern states which have high share of forested lands. Some states show decreasing human-caused wildfire risks but increases of the risks in the other states become more significant as time advances.

Figure 22 shows that lightning-caused wildfires increase the most in the western states perhaps due to their aridity as has been found in previous literature (Westerling and Swetnam 2003; Westerling and Bryant 2006; Yue, et al. 2013). Under both scenarios, the changes would be more severe in the longer run (2031–2050) in the western states. In southeastern states, lightning wildfires decrease by only a little percent. The non-western states would have relatively small changes in lightning wildfire risks under all scenarios and periods. This also implies that the impacts of climate change on lightning wildfire risk would be much higher in the western states than in the other states.

As previous studies argue, the western states would be affected the most by climate change given their generally warmer and drier characteristics. Accordingly, in terms of fire causality climate change would likely have a more significant impact on lightning wildfires opposed to human-caused wildfires and this is found in our results. Based on the projections, we argue that each caused wildfire would be better managed by considering spatial characteristics and different responses to climate conditions.

4.6 Concluding Comments

We econometrically assess the relationship between forest wildfires, climate, demographics, and forest stand characteristics. The truncated nature of the probability of a wildfire is dealt with a fractional regression model that forces the predicted outcomes to be between zero and one. Human- and lightning-caused fires plus the chance that a parcel will not catch fire probability are simultaneously estimated. Also, average marginal effects of climate, stand characteristics and demographics are estimated. Results are compared with the fixed effects linear regression results. Then we project the wildfire effects of future climate change under the IPCC RCP scenarios.

We find that climate conditions affect the chance of forest wildfires. In particular, we find that increasing spring and summer temperature increases both human and natural wildfire risks but that decreasing spring, autumn, and winter precipitation increases only human-caused fire risks. Also, increases in area population enhance human-caused wildfire risk. Increasing tree mortality and decreasing biomass density are found to increase the wildfire risk caused by lightning.

Predicted future wildfire risk changes under climate change scenarios also show different impacts on the wildfire risks caused by different sources. Although both human-caused and natural wildfire risks in most states would increase under the projected climate change, we find that western states would encounter more intense wildfire risks caused by lightning than other states that would face more human-caused wildfire risk. The findings indicate that different approaches are needed to prevent the two classes of wildfires: for instance, preventive actions to reduce human-caused wildfire in populated areas and to reduce natural wildfire in forests with high tree mortality. We also find that under moderate and extreme climate scenarios, human wildfires are more affected by climate mitigation than naturally caused wildfires.

The study has some limitations and suggests further research. Since the effects are different on human and natural caused fires, we are advised to examine effective preventive actions in different regions. To study the issues, we also need more consistent data across regions nationwide. Forests inherently change very slowly but wildfires can abruptly wipe out the long-life species and highly spoil the efforts on climate change mitigation and environmental protection. The future study would need to incorporate the uncertainty with consistent time series data nationwide.

5. SUMMARY AND CONCLUSIONS

This study examines climate influences on land uses and the incidence of wildfires. Specifically, we look at how climate change is altering human decisions on crop mix, and major land use plus the occurrence of wildfire in the US. This is done using econometric methods over panel data with censored dependent variables in three separate analyses. All look at how probabilities of items are altered by climate and other factors.

In the first and second essays, a crop mix and land use study analysis is done at the county and finer level. We employ a fractional multinomial logit to examine crop mix and predict the way crop mix proportions will shift in the next few decades using the latest climate change scenarios. Also, we examine land use transitions considering spatial dependence with 10×10km cell level data. The results show that that climate significantly affects crop mix and land use transitions. This study also find that climate change adaptation has significant spatial dependence on the nearby area. Under different CMIP5 climate scenarios, most major crops are expected to move north and to higher altitudes except for corn in the next decades. Also, cropland in central and eastern regions and grassland in western and southeastern regions are expected to decrease under the scenarios.

In the second essay, major land transitions and how those are influenced by climate change are considered. We find opposite responses to changing temperature and precipitation on behalf of crop and grass lands. In particular, we find cropped land declines in aggregate as temperatures increase with grasslands increasing but with a degree of response that is heterogeneous by region.

Regarding wildfire incidence in the third essay, we found that human-caused and natural wildfire risks in forested lands respond to climate conditions but in a different manner. Under both moderate and extreme climate scenarios, altering climate has more impacts on human-induced wildfire than natural wildfire. We also find that projected climate change would aggravate the wildfire risks from both cases in most states. Thus, along with mitigating varying climate, a different approach for various regions would be desirable due to the heterogeneous impacts of climate.

In terms of limitations and further research, our study on land use changes can be extended by endogenizing price and cost as well as the crop yield under altered land use and crop mix. Also, we believe greenhouse gas effects may be estimated to deal with mitigation issues in the future research. Furthermore, further studies would be better conducted by using longer and consistent data on land usage and socioeconomic variables at the finer scale than the currently available data. Additionally, the analyses have implicit assumptions on market prices and risk neutral behaviors. Better results on human and natural adaptation to climate change could be obtained with by incorporating market, policy, risk preference, and indirect land use change factors explicitly.

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APPENDIX

This appendix provides information on data descriptions, tables, and figures that are not shown in the main text due to limited space. Headings in the Appendix follow the rule: ***A.c***. The first letter (A) indicates Appendix, and the second number (c) after a period indicates the section number related to the appendix.

A.2 Additional tables and figures in section 2

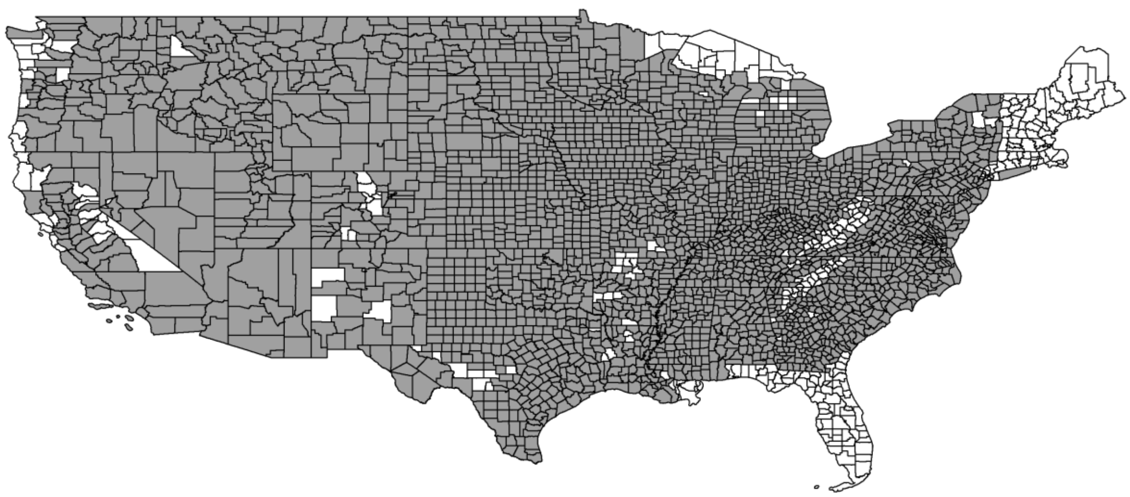

Figure A-1. Sampled counties (N = 2693)

Table A-1. Average Marginal Effects of Temperature and Precipitation on Proportions of Planted Acres by Region

Variable	Barley	Corn	Cotton	Rice	Sorghum	Soybeans	Wheat (winter)	Wheat (spring)	Wheat (durum)	Hay (alfalfa)
Appalachian										
Temperature	0.0005	–0.0060	0.0092***		0.0029*	0.0146***	0.0059**			–0.0272***
	(0.0009)	(0.0047)	(0.0022)		(0.0016)	(0.0042)	(0.0025)			(0.0034)
Precipitation	–0.0040***	–0.0125***	0.0092***		0.0001	0.0114***	0.0034			–0.0077***
	(0.0008)	(0.0036)	(0.0018)		(0.0008)	(0.0031)	(0.0024)			(0.0027)
Corn Belt										
Temperature	–0.0000	–0.0376***	0.0011***	–0.0009***	0.0057***	0.0244***	0.0178***			–0.0120***
	(0.0002)	(0.0029)	(0.0004)	(0.0003)	(0.0008)	(0.0037)	(0.0021)			(0.0027)
Precipitation	0.0007***	0.0047	0.0009***	0.0004***	–0.0000	–0.0098***	–0.0030			0.0049**
	(0.0002)	(0.0032)	(0.0003)	(0.0002)	(0.0006)	(0.0031)	(0.0019)			(0.0022)
Delta States										
Temperature	–0.0008***	0.0142***	0.0056	0.0157***	0.0013	–0.0373***	0.0015			
	(0.0002)	(0.0041)	(0.0063)	(0.0053)	(0.0034)	(0.0069)	(0.0039)			
Precipitation	0.0001	0.0026	–0.0069*	–0.0046*	0.0091***	0.0054	–0.0056*			
	(0.0001)	(0.0030)	(0.0039)	(0.0026)	(0.0025)	(0.0050)	(0.0030)			
Lake States										
Temperature	–0.0078***	0.0177**				0.0479***	0.0032	–0.0046***	–0.0002***	–0.0560***
	(0.0013)	(0.0075)				(0.0054)	(0.0021)	(0.0017)	(0.0001)	(0.0064)
Precipitation	–0.0048**	0.0405***				–0.0441***	–0.0001	–0.0155***	–0.0003**	0.0242***
	(0.0022)	(0.0074)				(0.0062)	(0.0018)	(0.0024)	(0.0001)	(0.0058)
Mountain										
Temperature	–0.0085***	0.0053***	0.0020**		0.0048***		0.0198***	–0.0114***	–0.0012	–0.0109**
	(0.0025)	(0.0019)	(0.0010)		(0.0014)		(0.0039)	(0.0028)	(0.0015)	(0.0046)
Precipitation	0.0073	0.0093**	0.0006		0.0043*		0.0403***	–0.0164***	0.0032***	–0.0486***
Northeast							(0.0075)	(0.0039)	(0.0012)	(0.0088)
Temperature	0.0052***	0.0004			–0.0001	0.0229***	0.0077***			–0.0361***
	(0.0012)	(0.0049)			(0.0002)	(0.0036)	(0.0018)			(0.0052)
Precipitation	0.0021	0.0001			0.0010***	0.0073	–0.0093***			–0.0012
	(0.0019)	(0.0052)			(0.0003)	(0.0051)	(0.0025)			(0.0067)
Northern Plains										
Temperature	–0.0062***	–0.0352***	0.0014***		0.0128***	–0.0072***	0.0670***	–0.0134***	–0.0077***	–0.0115***
	(0.0008)	(0.0026)	(0.0003)		(0.0023)	(0.0019)	(0.0040)	(0.0017)	(0.0013)	(0.0023)
Precipitation	–0.0051***	0.0246***	0.0004**		–0.0086***	0.0409***	–0.0283***	–0.0198***	–0.0101***	0.0060
	(0.0016)	(0.0048)	(0.0002)		(0.0029)	(0.0033)	(0.0063)	(0.0047)	(0.0030)	(0.0044)
Pacific										
Temperature	0.0063	0.0087	–0.0007	0.0039**	0.0007		0.0162**	–0.0028	0.0008	–0.0331***
	(0.0052)	(0.0060)	(0.0012)	(0.0018)	(0.0010)		(0.0082)	(0.0024)	(0.0013)	(0.0087)
Precipitation	–0.0092**	0.0106**	–0.0037	0.0063***	0.0024*		0.0047	–0.0016	0.0002	–0.0097*
	(0.0037)	(0.0050)	(0.0029)	(0.0018)	(0.0014)		(0.0064)	(0.0027)	(0.0021)	(0.0053)
Southeast										
Temperature	0.0004	0.0145**	0.0344***		0.0061*	–0.0447***	–0.0108			
	(0.0015)	(0.0067)	(0.0072)		(0.0037)	(0.0073)	(0.0076)			
Precipitation	–0.0048***	0.0044	0.0099**		0.0011	–0.0116***	0.0010			
	(0.0011)	(0.0035)	(0.0049)		(0.0022)	(0.0041)	(0.0034)			
Southern Plains										
Temperature	0.0013	0.0209***	0.0436***	–0.0059***	0.0274***	–0.0183***	–0.0628***			–0.0062***
	(0.0012)	(0.0039)	(0.0053)	(0.0019)	(0.0041)	(0.0032)	(0.0062)			(0.0016)
Precipitation	0.0032**	0.0122***	–0.0136**	0.0007	–0.0066	0.0167***	–0.0126*			0.0001
	(0.0015)	(0.0030)	(0.0069)	(0.0008)	(0.0057)	(0.0027)	(0.0066)			(0.0021)

Note: Standard errors via delta method are shown in parentheses and *, **, and *** indicate statistically significance at the 10%, 5%, and 1% levels, respectively.

Table A-2. Predicted land use Shares of Crops under Climate Scenarios by Region

	Base	RCP 2.6		RCP 4.5		RCP 8.5	
	1975-2010	2020-2050	2051-2099	2020-2050	2051-2099	2020-2050	2051-2099
Applachian							
Corn	0.489	0.442	0.432	0.438	0.404	0.435	0.370
Barley	0.008	0.005	0.004	0.005	0.004	0.005	0.003
Cotton	0.033	0.056	0.065	0.060	0.086	0.062	0.111
Rice	0.005	0.007	0.008	0.007	0.009	0.007	0.012
Sorghum	0.013	0.020	0.019	0.020	0.023	0.020	0.028
Soybeans	0.303	0.302	0.312	0.300	0.314	0.307	0.327
W.Wheat	0.150	0.168	0.159	0.169	0.159	0.164	0.149
S.Wheat	0.000	0.000	0.000	0.000	0.000	0.000	0.000
D.Wheat	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Corn Belt							
Corn	0.461	0.423	0.407	0.420	0.375	0.413	0.330
Barley	0.001	0.001	0.001	0.001	0.001	0.001	0.000
Cotton	0.003	0.008	0.010	0.009	0.020	0.010	0.040
Rice	0.001	0.002	0.002	0.002	0.003	0.002	0.004
Sorghum	0.011	0.019	0.019	0.019	0.024	0.019	0.028
Soybeans	0.445	0.449	0.466	0.451	0.478	0.459	0.504
W.Wheat	0.075	0.097	0.094	0.097	0.098	0.096	0.093
S.Wheat	0.003	0.001	0.001	0.001	0.000	0.001	0.000
D.Wheat	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Delta							
Corn	0.227	0.215	0.211	0.213	0.201	0.212	0.193
Barley	0.002	0.002	0.002	0.002	0.002	0.002	0.001
Cotton	0.152	0.171	0.175	0.172	0.166	0.171	0.136
Rice	0.044	0.060	0.066	0.061	0.071	0.061	0.080
Sorghum	0.032	0.035	0.034	0.036	0.042	0.038	0.052
Soybeans	0.424	0.402	0.405	0.401	0.416	0.402	0.446
W.Wheat	0.119	0.115	0.107	0.115	0.102	0.114	0.091
S.Wheat	0.000	0.000	0.000	0.000	0.000	0.000	0.000
D.Wheat	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Lake							
Corn	0.672	0.644	0.631	0.643	0.603	0.638	0.561
Barley	0.028	0.022	0.018	0.021	0.014	0.020	0.009
Cotton	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Rice	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Sorghum	0.002	0.003	0.004	0.003	0.005	0.003	0.007
Soybeans	0.197	0.200	0.212	0.205	0.227	0.209	0.251
W.Wheat	0.055	0.107	0.117	0.107	0.140	0.110	0.166
S.Wheat	0.045	0.023	0.018	0.021	0.011	0.020	0.005
D.Wheat	0.001	0.001	0.000	0.000	0.000	0.000	0.000

Table A-2. Continued

	Base	RCP 2.6		RCP 4.5		RCP 8.5	
	1975-2010	2020-2050	2051-2099	2020-2050	2051-2099	2020-2050	2051-2099
Mountain							
Corn	0.133	0.176	0.182	0.175	0.186	0.180	0.180
Barley	0.255	0.268	0.253	0.268	0.209	0.259	0.156
Cotton	0.035	0.031	0.031	0.031	0.041	0.032	0.059
Rice	0.003	0.003	0.003	0.003	0.004	0.003	0.007
Sorghum	0.016	0.024	0.026	0.024	0.030	0.025	0.037
Soybeans	0.010	0.013	0.014	0.013	0.015	0.014	0.017
W.Wheat	0.361	0.370	0.389	0.371	0.439	0.380	0.492
S.Wheat	0.167	0.105	0.092	0.105	0.064	0.098	0.037
D.Wheat	0.020	0.010	0.010	0.010	0.012	0.010	0.015
Northeast							
Corn	0.670	0.639	0.622	0.633	0.593	0.630	0.555
Barley	0.009	0.008	0.006	0.007	0.005	0.007	0.003
Cotton	0.001	0.005	0.007	0.006	0.011	0.006	0.017
Rice	0.000	0.000	0.000	0.000	0.000	0.000	0.001
Sorghum	0.002	0.003	0.003	0.003	0.004	0.003	0.004
Soybeans	0.225	0.221	0.235	0.224	0.246	0.225	0.269
W.Wheat	0.090	0.123	0.126	0.126	0.140	0.127	0.150
S.Wheat	0.003	0.001	0.001	0.001	0.001	0.001	0.000
D.Wheat	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Northern Plains							
Corn	0.262	0.242	0.239	0.241	0.217	0.240	0.190
Barley	0.029	0.026	0.023	0.026	0.018	0.025	0.012
Cotton	0.009	0.028	0.031	0.031	0.057	0.032	0.093
Rice	0.001	0.001	0.001	0.001	0.001	0.001	0.002
Sorghum	0.051	0.079	0.083	0.080	0.095	0.082	0.111
Soybeans	0.149	0.140	0.148	0.139	0.149	0.144	0.158
W.Wheat	0.343	0.400	0.408	0.402	0.419	0.403	0.414
S.Wheat	0.139	0.076	0.061	0.074	0.040	0.068	0.020
D.Wheat	0.016	0.007	0.005	0.006	0.003	0.005	0.001

Table A-2. Continued

	Base	RCP 2.6		RCP 4.5		RCP 8.5	
	1975-2010	2020-2050	2051-2099	2020-2050	2051-2099	2020-2050	2051-2099
Pacific							
Corn	0.334	0.387	0.383	0.383	0.375	0.388	0.352
Barley	0.154	0.141	0.129	0.145	0.108	0.135	0.086
Cotton	0.078	0.060	0.065	0.062	0.074	0.060	0.092
Rice	0.021	0.021	0.024	0.020	0.030	0.023	0.039
Sorghum	0.014	0.017	0.019	0.017	0.021	0.018	0.026
Soybeans	0.028	0.036	0.037	0.035	0.039	0.037	0.040
W.Wheat	0.319	0.296	0.306	0.296	0.323	0.301	0.337
S.Wheat	0.046	0.033	0.027	0.033	0.019	0.030	0.011
D.Wheat	0.005	0.009	0.010	0.009	0.012	0.009	0.017
Southeast							
Corn	0.335	0.315	0.312	0.313	0.301	0.312	0.290
Barley	0.017	0.009	0.008	0.009	0.007	0.009	0.007
Cotton	0.147	0.146	0.149	0.146	0.142	0.146	0.116
Rice	0.015	0.018	0.020	0.018	0.022	0.018	0.024
Sorghum	0.034	0.044	0.044	0.046	0.052	0.046	0.068
Soybeans	0.244	0.291	0.304	0.293	0.323	0.297	0.357
W.Wheat	0.208	0.177	0.164	0.176	0.153	0.172	0.138
S.Wheat	0.000	0.000	0.000	0.000	0.000	0.000	0.000
D.Wheat	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Southern Plains							
Corn	0.162	0.136	0.134	0.133	0.125	0.131	0.115
Barley	0.010	0.011	0.011	0.011	0.011	0.011	0.010
Cotton	0.201	0.202	0.197	0.207	0.201	0.208	0.171
Rice	0.013	0.014	0.014	0.014	0.013	0.013	0.012
Sorghum	0.123	0.193	0.204	0.197	0.237	0.204	0.295
Soybeans	0.106	0.092	0.094	0.087	0.095	0.088	0.101
W.Wheat	0.382	0.346	0.339	0.345	0.306	0.338	0.265
S.Wheat	0.000	0.000	0.000	0.000	0.000	0.000	0.000
D.Wheat	0.004	0.004	0.006	0.006	0.013	0.007	0.031

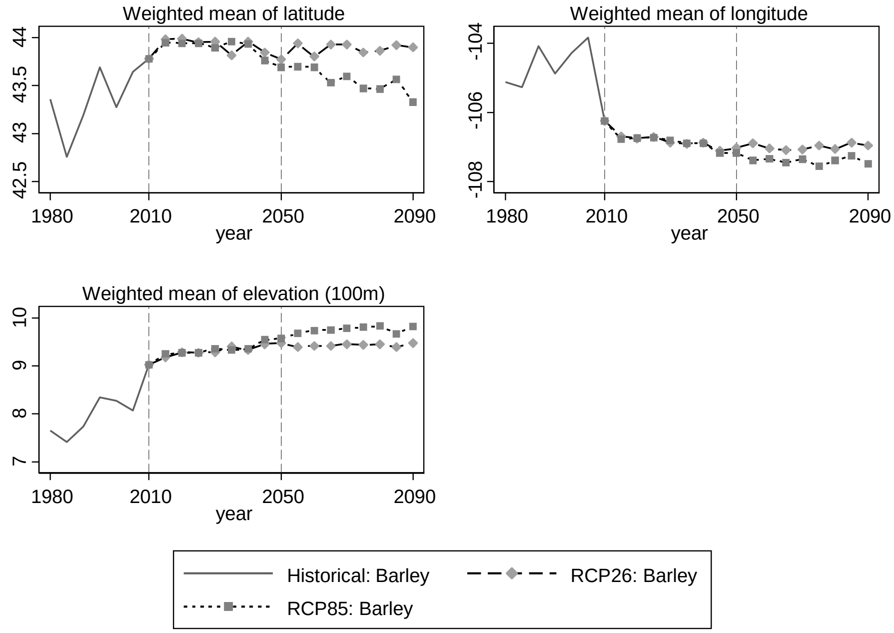

Figure A-2 Weighted mean of location change for barley

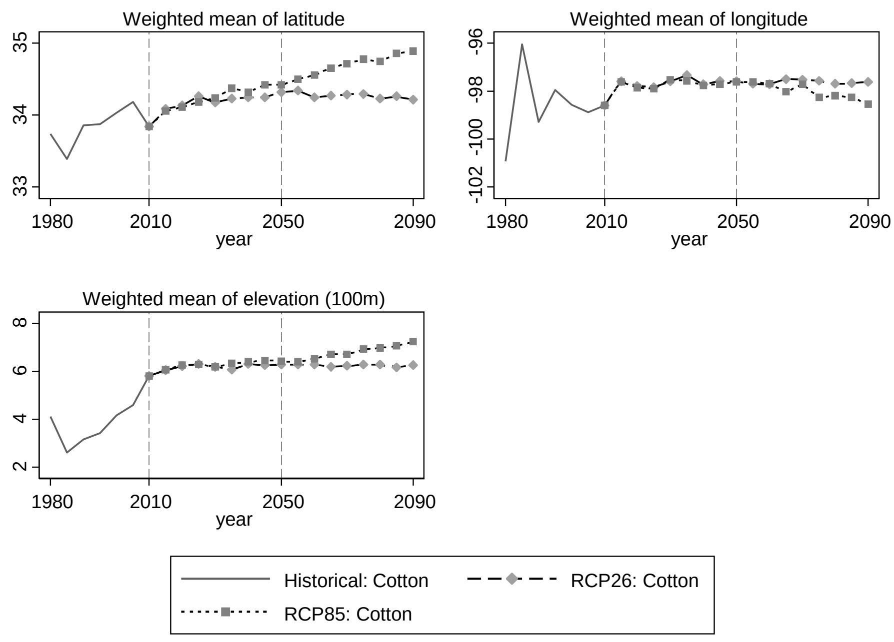

Figure A-3 Weighted mean of location change for cotton

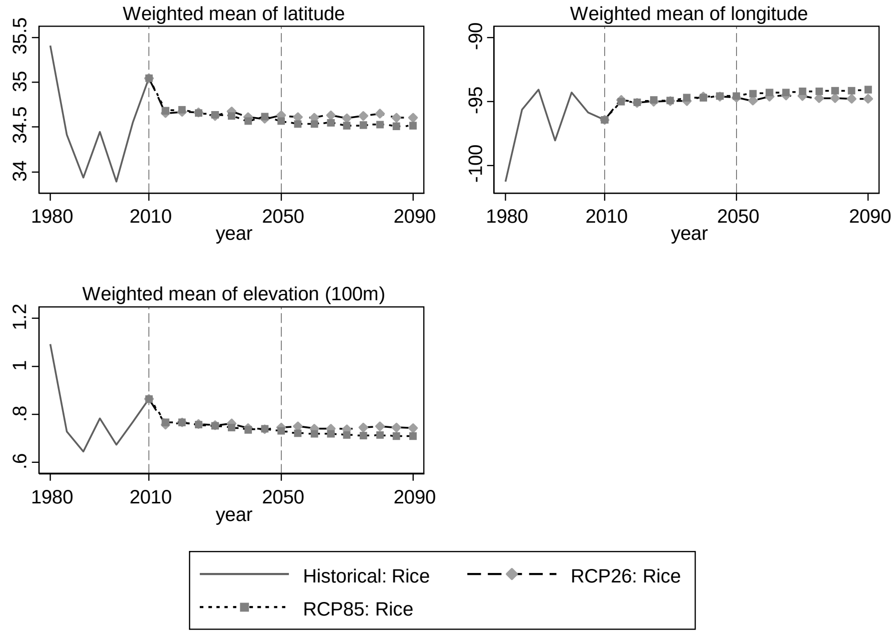

Figure A-4 Weighted mean of location change for rice

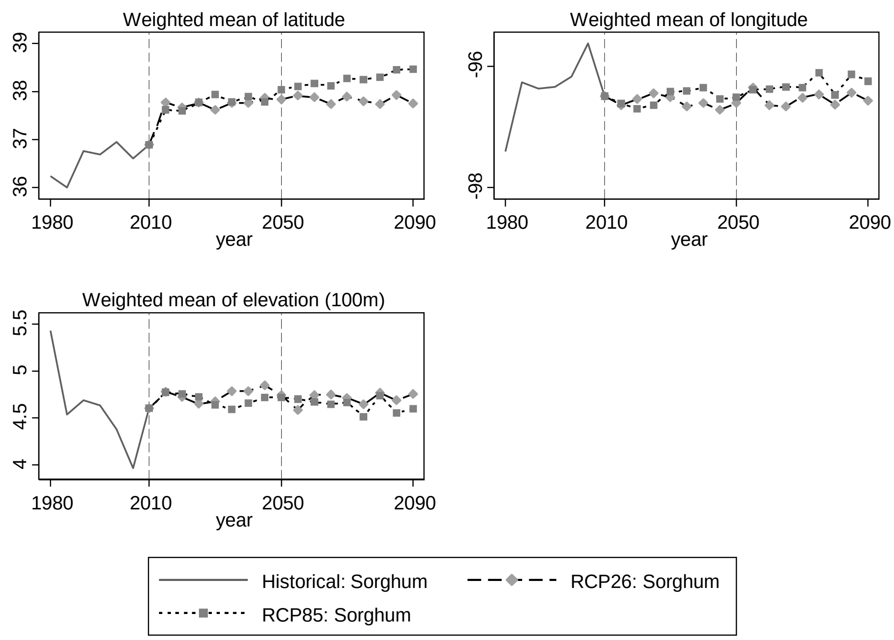

Figure A-5 Weighted mean of location change for sorghum

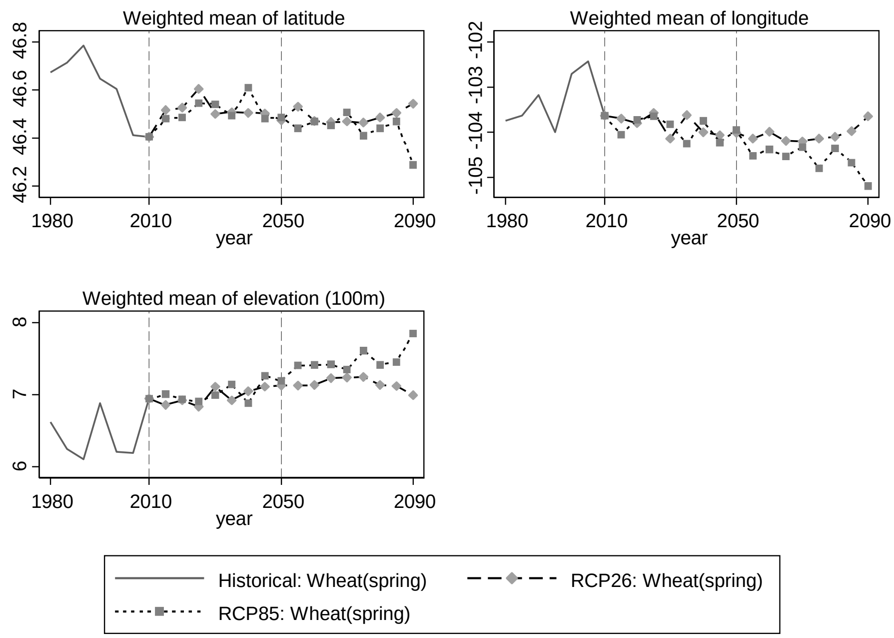

Figure A-6 Weighted mean of location change for spring wheat

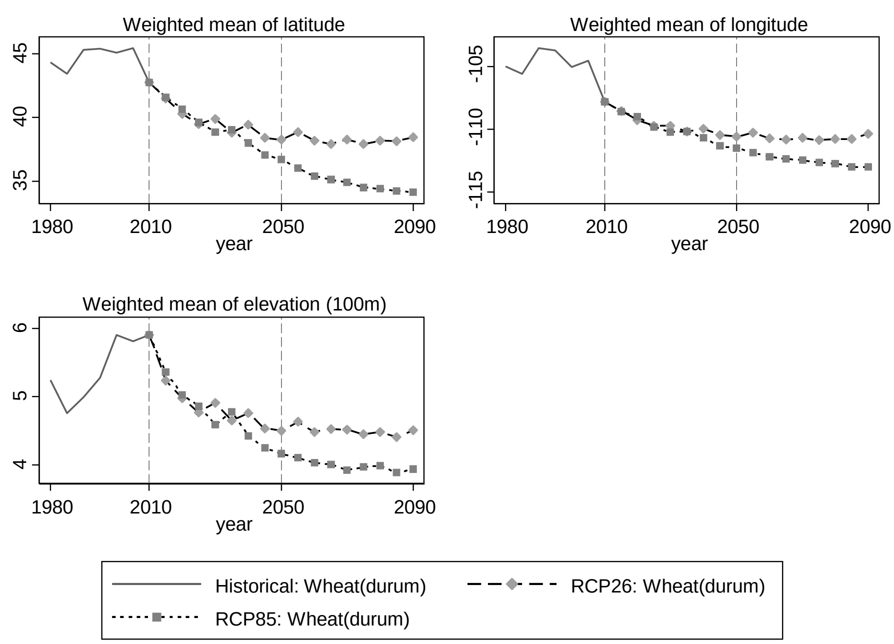

Figure A-7 Weighted mean of location change for durum wheat

A.3 Major land use classifications and micro-level estimates in section 3

Table A-3. National Land Cover Database (NLCD) 2011 Legend

Class\ Value		Classification Description
Water		
	11	**Open Water -** areas of open water, generally with less than 25% cover of vegetation or soil.
	12	**Perennial Ice/Snow -** areas characterized by a perennial cover of ice and/or snow, generally greater than 25% of total cover.
Developed		
	21	**Developed, Open Space -** areas with a mixture of some constructed materials, but mostly vegetation in the form of lawn grasses. Impervious surfaces account for less than 20% of total cover. These areas most commonly include large-lot single-family housing units, parks, golf courses, and vegetation planted in developed settings for recreation, erosion control, or aesthetic purposes.
	22	**Developed, Low Intensity -** areas with a mixture of constructed materials and vegetation. Impervious surfaces account for 20% to 49% percent of total cover. These areas most commonly include single-family housing units.
	23	**Developed, Medium Intensity** – areas with a mixture of constructed materials and vegetation. Impervious surfaces account for 50% to 79% of the total cover. These areas most commonly include single-family housing units.
	24	**Developed High Intensity -**highly developed areas where people reside or work in high numbers. Examples include apartment complexes, row houses and commercial/industrial. Impervious surfaces account for 80% to 100% of the total cover.
Barren		
	31	**Barren Land (Rock/Sand/Clay) -** areas of bedrock, desert pavement, scarps, talus, slides, volcanic material, glacial debris, sand dunes, strip mines, gravel pits and other accumulations of earthen material. Generally, vegetation accounts for less than 15% of total cover.
Forest		
	41	**Deciduous Forest -** areas dominated by trees generally greater than 5 meters tall, and greater than 20% of total vegetation cover. More than 75% of the tree species shed foliage simultaneously in response to seasonal change.
	42	**Evergreen Forest -** areas dominated by trees generally greater than 5 meters tall, and greater than 20% of total vegetation cover. More than 75% of the tree species maintain their leaves all year. Canopy is never without green foliage.
	43	**Mixed Forest -** areas dominated by trees generally greater than 5 meters tall, and greater than 20% of total vegetation cover. Neither deciduous nor evergreen species are greater than 75% of total tree cover.

Table A-3. Continued

Class\ Value	Classification Description
Shrubland	
	51 **Dwarf Scrub -** Alaska only areas dominated by shrubs less than 20 centimeters tall with shrub canopy typically greater than 20% of total vegetation. This type is often co-associated with grasses, sedges, herbs, and non-vascular vegetation.
	52 **Shrub/Scrub -** areas dominated by shrubs; less than 5 meters tall with shrub canopy typically greater than 20% of total vegetation. This class includes true shrubs, young trees in an early successional stage or trees stunted from environmental conditions.
Herbaceous	
	71 **Grassland/Herbaceous -** areas dominated by gramanoid or herbaceous vegetation, generally greater than 80% of total vegetation. These areas are not subject to intensive management such as tilling, but can be utilized for grazing.
	72 **Sedge/Herbaceous -** Alaska only areas dominated by sedges and forbs, generally greater than 80% of total vegetation. This type can occur with significant other grasses or other grass like plants, and includes sedge tundra, and sedge tussock tundra.
	73 **Lichens -** Alaska only areas dominated by fruticose or foliose lichens generally greater than 80% of total vegetation.
	74 **Moss -** Alaska only areas dominated by mosses, generally greater than 80% of total vegetation.
Planted/Cultivated	
	81 **Pasture/Hay** – areas of grasses, legumes, or grass-legume mixtures planted for livestock grazing or the production of seed or hay crops, typically on a perennial cycle. Pasture/hay vegetation accounts for greater than 20% of total vegetation.
	82 **Cultivated Crops** – areas used for the production of annual crops, such as corn, soybeans, vegetables, tobacco, and cotton, and also perennial woody crops such as orchards and vineyards. Crop vegetation accounts for greater than 20% of total vegetation. This class also includes all land being actively tilled.
Wetlands	
	90 **Woody Wetlands -** areas where forest or shrubland vegetation accounts for greater than 20% of vegetative cover and the soil or substrate is periodically saturated with or covered with water.
	95 **Emergent Herbaceous Wetlands -** Areas where perennial herbaceous vegetation accounts for greater than 80% of vegetative cover and the soil or substrate is periodically saturated with or covered with water.

Source: NLCD 2011 Product Legend. MRLC-USDA. http://www.mrlc.gov/nlcd11_leg.php (accessed August 24, 2014).

Table A-4. Micro-level estimation results: land use transitions (2002-2012)

	To land uses in 2012				
From Crop in 2002	Crop	Grass	Forest	Urban	Water
Temperature	**0.0014**	0.0809***	0.0308**	0.0233***	0.0201
Precipitation	**–0.8745*****	–1.1283***	–0.5794***	–0.5029***	–0.8756*
Temperature SD	**0.4525*****	1.1618***	–0.1770	–0.4113**	–0.1744
Precipitation SD	**0.6843*****	3.6926***	0.5588*	0.5016*	2.5054
Drought index	**0.0752*****	–0.2211***	0.0418	0.0579*	–0.0044
Altitude	**–0.0401*****	–0.0013	–0.0047	0.0147	–0.0098
Slope	**0.0097*****	0.0058***	0.0082***	–0.0003	–0.0040
Inverse LCC	**0.0790*****	0.0836***	0.1202***	0.0716***	–0.0361
Irrigation rate	**–1.4050*****	–0.8302***	0.1354	–0.8137***	–0.2228
Asset value of agland	**0.5335*****	0.2447***	0.1855**	0.2316***	0.2214*
Farm income ($/ha)	**0.0000**	0.0000	0.0000	0.0000	0.0000***
Non-farm income ($/ha)	**–0.0001*****	–0.0002	–0.0092***	0.0000	0.0000
Housing value	**–0.6043*****	0.4197***	0.0758	–0.5304***	–0.3757
Housing rent	**0.2898*****	–1.4086***	–0.1842	0.5827**	0.8186
Log(Population density)	**–0.1664*****	–0.1585***	0.0895*	0.2211***	–0.0913
Share of crop 2002	**3.1160*****	–0.0779	0.8170**	0.3877**	0.8532
Constant	**6.5134*****	1.9712***	–1.6468	–0.2571	–2.3011
WX	**0.0860*****	–0.0159	0.9212***	0.7801***	0.5393**

	To land uses in 2012				
From Grass in 2002	Crop	Grass	Forest	Urban	Water
Temperature	–0.0009	**–0.0408*****	0.0222***	0.0698***	0.0107
Precipitation	–2.0713***	**–0.4309*****	–0.1415	–0.7666***	–1.1141***
Temperature SD	0.3230***	**0.3032*****	0.0728	–0.1873	0.0550
Precipitation SD	0.5615*	**–1.3650*****	–0.5313*	–0.4744*	0.8656
Drought index	0.2125***	**0.0905*****	0.0091	0.2265***	0.1396**
Altitude	–0.0151**	**0.0375*****	–0.0624***	0.0455***	0.0216
Slope	0.0067***	**0.0167*****	0.0178***	0.0086***	–0.0058
Inverse LCC	0.0742***	**0.0491*****	0.0519***	0.0254***	0.0053
Irrigation rate	–0.6041***	**–0.8279*****	–0.2607	–0.9131***	–0.5213*
Asset value of agland	0.1499***	**0.2967*****	0.1511***	0.1760***	–0.0004
Farm income ($/ha)	–0.0001***	**0.0000*****	0.0000	0.0000	0.0000
Non-farm income ($/ha)	–0.0001	**0.0000**	–0.0070***	–0.0001***	0.0000***
Housing value	–0.7344***	**–0.4989*****	–0.1886**	–0.5297***	–0.3924
Housing rent	0.5560***	**0.8473*****	0.1138	1.1060***	0.8423**
Log(Population density)	–0.0324	**–0.0722*****	0.0574*	0.3081***	–0.0506
Share of grass 2002	–0.3817***	**1.5331*****	–0.0455	–1.4642***	–1.4510***
Constant	5.8584***	**3.9083*****	0.5029	–3.4750***	–0.1612
WX	0.1289***	**0.0793***	0.7439***	0.6935***	0.3746*

Table A-4. Continued

From Forest in 2002	To land uses in 2012				
	Crop	Grass	**Forest**	Urban	Water
Temperature	–0.0241**	0.0993***	**–0.0259*** **	0.0308***	–0.0737***
Precipitation	–0.2359	–0.4931***	**–0.9058*** **	–0.4979***	–1.6073**
Temperature SD	–0.4277*	0.4186***	**0.2008*** **	0.1365	2.2303***
Precipitation SD	–2.4914***	0.136	**–2.9591*** **	0.9742***	2.0533
Drought index	0.0964**	–0.1410***	**0.2096*** **	0.1804***	0.1895***
Altitude	–0.007	–0.0562***	**–0.0344*** **	0.0284***	0.0356*
Slope	0.0109**	0.0114***	**0.0200*** **	0.0139***	–0.0048
Inverse LCC	0.0989***	0.0725***	**0.0793*** **	0.0538***	0.0561*
Irrigation rate	0.6533***	–1.0215***	**–0.6773*** **	–2.2924***	0.0184
Asset value of agland	0.1677**	0.2950***	**0.5693*** **	0.2460***	0.3579***
Farm income ($/ha)	–0.0002**	0	**0**	0.0000**	0
Non-farm income ($/ha)	–0.0001	–0.0001	**–0.0001** **	–0.0003***	–0.0006
Housing value	–0.6232***	0.1691***	**–0.7552*** **	–0.9148***	–1.8208***
Housing rent	–0.1739	0.3418***	**1.1023*** **	1.2750***	2.1312***
Log(Population density)	0.0945**	–0.2708***	**–0.0398*** **	0.3442***	0.1367*
Share of forest 2002	–0.3481	3.0652***	**2.5466*** **	0.201	–8.7354***
Constant	7.0505***	–5.4449***	**4.4592*** **	–1.3715	4.696
WX	0.0834	0.1903***	**–0.0431** **	0.7597***	0.2615

From Urban in 2002	To land uses in 2012				
	Crop	Grass	Forest	**Urban**	Water
Temperature	–0.0569***	–0.0023	–0.0133	**–0.0549*** **	–0.9769***
Precipitation	–0.5900**	0.4445*	1.2270**	**–0.2613* **	–24.0883***
Temperature SD	1.1226**	0.6552	1.6467*	**0.2695**	–3.3208***
Precipitation SD	–1.3078	–0.3292	–2.3620***	**–1.9813*** **	75.4363***
Drought index	0.0814	–0.1101*	–0.0810	**0.3132*** **	2.9209***
Altitude	0.0132	–0.0054	–0.1657**	**0.0854*** **	1.0166***
Slope	0.0087	0.0071	0.0164***	**0.0182*** **	–0.0459***
Inverse LCC	0.1656***	0.0744***	0.0954***	**0.1202*** **	–0.2871***
Irrigation rate	3.8058***	–0.4270	–6.4412**	**1.7723*** **	5.3959***
Asset value of agland	0.1715	0.4446***	0.4445**	**0.3205*** **	9.1242***
Farm income ($/ha)	–0.0001	0.0000	0.0000	**0.0000**	0.0000
Non-farm income ($/ha)	–0.0011	0.0001	–0.0002	**0.0000**	–0.0050***
Housing value	–0.0547	–0.3374	–0.2884	**–0.4723** **	–7.5423***
Housing rent	–0.3970	0.6401*	0.1274	**0.3721**	14.6306***
Log(Population density)	–0.1966**	–0.4803***	–0.4204***	**–0.2719*** **	–5.4415***
Share of urban 2002	0.7190	0.9136	0.8976	**2.0458*** **	–4.1486
Constant	1.4153	–1.8957	–1.4086	**11.0398*** **	–34.4784***
WX	–0.0126	0.3207*	0.2095	**0.1906*** **	–11.2632***

Table A-4. Continued

	To land uses in 2012				
From Water in 2002	Crop	Grass	Forest	Urban	**Water**
Temperature	–0.0532***	0.0551***	0.0460***	0.0018	**–0.0658*** **
Precipitation	0.9200***	–0.4620***	1.9762***	0.0792	**0.4479*** **
Temperature SD	0.3542	0.7324***	0.4850	0.0792	**0.2375*** **
Precipitation SD	–1.6141**	–0.7868	–3.5816***	–2.6960***	**–2.5012*** **
Drought index	0.1271***	0.1693***	0.0021	0.1905***	**0.0685*** **
Altitude	0.0283**	0.0614***	0.1105***	0.0454***	**–0.0169*** **
Slope	–0.0142**	0.0110***	0.0251***	–0.0039	**0.0133*** **
Inverse LCC	0.0695***	0.0066	0.0695***	–0.0037	**0.0363*** **
Irrigation rate	3.1447***	–0.5370***	–1.4588***	–0.3227	**–0.8305*** **
Asset value of agland	–0.1272*	0.1261***	0.1956**	0.1728**	**0.4334*** **
Farm income ($/ha)	–0.0002**	0.0000	0.0000	0.0000	**0.0000**
Non-farm income ($/ha)	0.0000	0.0000	–0.0001	–0.0001	**0.0000**
Housing value	–0.2293	–0.3557***	0.4982**	–0.8095**	**–0.1084***
Housing rent	–1.1305***	–0.0495	–1.7767***	1.3879**	**–0.1217**
Log(Population density)	0.1066**	–0.0364	–0.0357	0.6435***	**–0.0347** **
Share of water 2002	–2.9856**	–2.6480	18.6570	–9.0126	**0.4885**
Constant	8.2273***	2.2705**	–1.1433	–4.9157***	**3.1908*** **
WX	0.2047***	0.3516***	0.1502*	0.3155***	**0.0545** **

Note: ***, **, and * indicate statistical significance at the 1%, 5%, and 10%, respectively, based on heteroskedasticity-robust standard errors.

A.4 Additional tables and figures in section 4

Table A-5. Full Estimation Results of Fractional Multinomial Logit on Wildfire Risk

	Fire: lightning-caused (%)		Fire: human-caused (%)	
Covariates	Coefficients	SE	Coefficients	SE
Explanatory variables (x_{it})				
Temperature - spring (C)	0.507**	(0.212)	–0.119	(0.155)
Temperature squared - spring (°C)	–0.009	(0.010)	0.014*	(0.008)
Temperature - summer (C)	–1.249*	(0.694)	–0.570	(0.485)
Temperature squared - summer (°C)	0.041**	(0.018)	0.020**	(0.009)
Temperature - autumn (C)	–0.004	(0.335)	0.462*	(0.237)
Temperature squared - autumn (°C)	0.004	(0.017)	–0.012	(0.008)
Temperature - winter (C)	–0.074	(0.127)	0.036	(0.077)
Temperature squared - winter (°C)	–0.007	(0.008)	–0.003	(0.004)
Precipitation - spring (hundred mm)	1.231*	(0.715)	–0.320	(0.324)
Precipitation squared - spring (hundred mm)	–0.354*	(0.187)	–0.016	(0.057)
Precipitation - summer (hundred mm)	0.359	(0.393)	0.738	(0.486)
Precipitation squared - summer (hundred mm)	–0.095	(0.073)	–0.101*	(0.056)
Precipitation - autumn (hundred mm)	–1.214*	(0.675)	–2.308***	(0.515)
Precipitation squared - autumn (hundred mm)	0.198*	(0.109)	0.342***	(0.088)
Precipitation - winter (hundred mm)	–0.155	(0.486)	–0.980**	(0.480)
Precipitation squared - winter (hundred mm)	–0.038	(0.069)	0.159**	(0.080)
Time-invariant variables (x_i)				
Population density (persons / km2): Fixed	–0.146***	(0.036)	0.004	(0.003)
Tree mortality (m3 / ha): Fixed	3.530***	(1.189)	–0.478	(0.629)
Tree removal (m3 / ha): Fixed	–0.264	(0.300)	0.117	(0.195)
Biomass (hundred tonne / ha): Fixed	–4.473***	(1.516)	0.419	(0.860)
Time-averaged variables ($\bar{x}_i$)				
Temperature - spring (C)	1.103	(1.714)	0.868	(0.711)
Temperature squared - spring (°C)	–0.133*	(0.078)	–0.098***	(0.033)
Temperature - summer (C)	10.229***	(2.818)	4.110***	(1.207)
Temperature squared - summer (°C)	–0.262***	(0.076)	–0.061**	(0.026)
Temperature - autumn (C)	–3.653**	(1.692)	–3.625***	(0.934)
Temperature squared - autumn (°C)	0.222***	(0.081)	0.055	(0.038)
Temperature - winter (C)	0.788	(0.729)	1.505***	(0.280)
Temperature squared - winter (°C)	0.038	(0.033)	0.069***	(0.018)
Precipitation - spring (hundred mm)	7.835***	(2.091)	0.486	(0.824)
Precipitation squared - spring (hundred mm)	–1.579***	(0.502)	0.260	(0.198)
Precipitation - summer (hundred mm)	–1.327	(1.568)	–0.306	(0.784)
Precipitation squared - summer (hundred mm)	0.001	(0.294)	–0.174	(0.150)
Precipitation - autumn (hundred mm)	0.518	(1.816)	7.208***	(1.555)
Precipitation squared - autumn (hundred mm)	0.339	(0.330)	–1.404***	(0.306)
Precipitation - winter (hundred mm)	–1.908	(1.376)	–2.195**	(1.004)
Precipitation squared - winter (hundred mm)	0.351	(0.296)	0.303**	(0.143)
Constant	–87.011***	(24.644)	–34.513***	(10.389)
Quasi-log likelihood	–39.804			
Number of observations	782			

Note: ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Robust standard erorrs are in parentheses.

Table A-6. Estimates of Random Effects Linear Regression on Wildfire Risk

	Fire: lightning-caused burned area / forest (%)	Fire: human-caused burned area / forest (%)	Fire: area not burned / forest (%)
Temperature - spring (C)	0.00369**	–0.00004	–0.00378*
	(0.00159)	(0.00106)	(0.00212)
Temperature squared - spring (°C)	–0.00012*	0.00004	0.00009
	(0.00006)	(0.00006)	(0.00011)
Temperature - summer (C)	0.00180	–0.00691*	0.00575
	(0.00369)	(0.00359)	(0.00589)
Temperature squared - summer (°C)	–0.00000	0.00018**	–0.00020
	(0.00008)	(0.00008)	(0.00013)
Temperature - autumn (C)	–0.00310**	0.00017	0.00281*
	(0.00132)	(0.00127)	(0.00161)
Temperature squared - autumn (°C)	0.00005	–0.00002	–0.00002
	(0.00005)	(0.00005)	(0.00007)
Temperature - winter (C)	–0.00040	–0.00027	0.00066
	(0.00031)	(0.00037)	(0.00061)
Temperature squared - winter (°C)	–0.00000	–0.00002	0.00003
	(0.00003)	(0.00004)	(0.00007)
Precipitation - spring (hundred mm)	–0.00433	–0.00046	0.00600
	(0.00326)	(0.00246)	(0.00522)
Precipitation squared - spring (hundred mm)	0.00051	–0.00017	–0.00053
	(0.00053)	(0.00038)	(0.00083)
Precipitation - summer (hundred mm)	–0.00856**	0.00177	0.00634
	(0.00405)	(0.00274)	(0.00537)
Precipitation squared - summer (hundred mm)	0.00112*	–0.00022	–0.00083
	(0.00060)	(0.00040)	(0.00083)
Precipitation - autumn (hundred mm)	–0.01403**	–0.01791***	0.03221***
	(0.00615)	(0.00650)	(0.01106)
Precipitation squared - autumn (hundred mm)	0.00233**	0.00275***	–0.00513***
	(0.00102)	(0.00100)	(0.00179)
Precipitation - winter (hundred mm)	–0.00062	–0.00667**	0.00733*
	(0.00193)	(0.00275)	(0.00393)
Precipitation squared - winter (hundred mm)	–0.00008	0.00112**	–0.00104
	(0.00028)	(0.00049)	(0.00065)
Population density (persons / km2): Fixed	0.00000	0.00000	–0.00000
	(0.00001)	(0.00001)	(0.00002)
Tree mortality (m3 / ha): Fixed	–0.00290	–0.00302	0.00547
	(0.00755)	(0.00410)	(0.00954)
Tree removal (m3 / ha): Fixed	0.00114	–0.00094	–0.00006
	(0.00258)	(0.00167)	(0.00356)
Biomass (hundred tonne / ha): Fixed	0.00763	0.01362***	–0.02206**
	(0.00666)	(0.00506)	(0.01093)
Constant	0.00414	0.08524*	0.90514***
	(0.04002)	(0.04391)	(0.06970)
Number of observations	782	782	782

Note: ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Robust standard erorrs are in parentheses.

Table A-7. Estimates of Fixed Effects Linear Regression on Wildfire Risk

	Fire: lightning-caused burned area / forest (%)	Fire: human-caused burned area / forest (%)	Fire: area not burned / forest (%)
Temperature - spring (C)	0.00362**	0.00031	–0.00393*
	(0.00160)	(0.00126)	(0.00225)
Temperature squared - spring (°C)	–0.00012*	0.00003	0.00009
	(0.00006)	(0.00007)	(0.00011)
Temperature - summer (C)	0.00974*	–0.00800*	–0.00174
	(0.00487)	(0.00458)	(0.00771)
Temperature squared - summer (°C)	–0.00013	0.00023**	–0.00010
	(0.00010)	(0.00011)	(0.00018)
Temperature - autumn (C)	–0.00150	0.00155	–0.00005
	(0.00145)	(0.00124)	(0.00207)
Temperature squared - autumn (°C)	0.00001	–0.00005	0.00004
	(0.00005)	(0.00005)	(0.00008)
Temperature - winter (C)	–0.00012	0.00025	–0.00013
	(0.00041)	(0.00044)	(0.00075)
Temperature squared - winter (°C)	0.00001	–0.00005	0.00004
	(0.00002)	(0.00005)	(0.00005)
Precipitation - spring (hundred mm)	–0.00599*	–0.00539*	0.01137*
	(0.00341)	(0.00301)	(0.00586)
Precipitation squared - spring (hundred mm)	0.00080	0.00065	–0.00145
	(0.00053)	(0.00044)	(0.00089)
Precipitation - summer (hundred mm)	–0.00144	0.00329	–0.00185
	(0.00427)	(0.00432)	(0.00767)
Precipitation squared - summer (hundred mm)	0.00011	–0.00046	0.00034
	(0.00059)	(0.00061)	(0.00110)
Precipitation - autumn (hundred mm)	–0.01137*	–0.01801**	0.02938**
	(0.00609)	(0.00679)	(0.01120)
Precipitation squared - autumn (hundred mm)	0.00180*	0.00278**	–0.00459**
	(0.00101)	(0.00104)	(0.00179)
Precipitation - winter (hundred mm)	–0.00146	–0.00533*	0.00679
	(0.00298)	(0.00299)	(0.00449)
Precipitation squared - winter (hundred mm)	0.00009	0.00092*	–0.00101
	(0.00043)	(0.00055)	(0.00075)
Constant	–0.12514**	0.08752	1.03762***
	(0.05941)	(0.05793)	(0.09386)
Number of observations	782	782	782

Note: ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Robust standard erorrs are in parentheses.

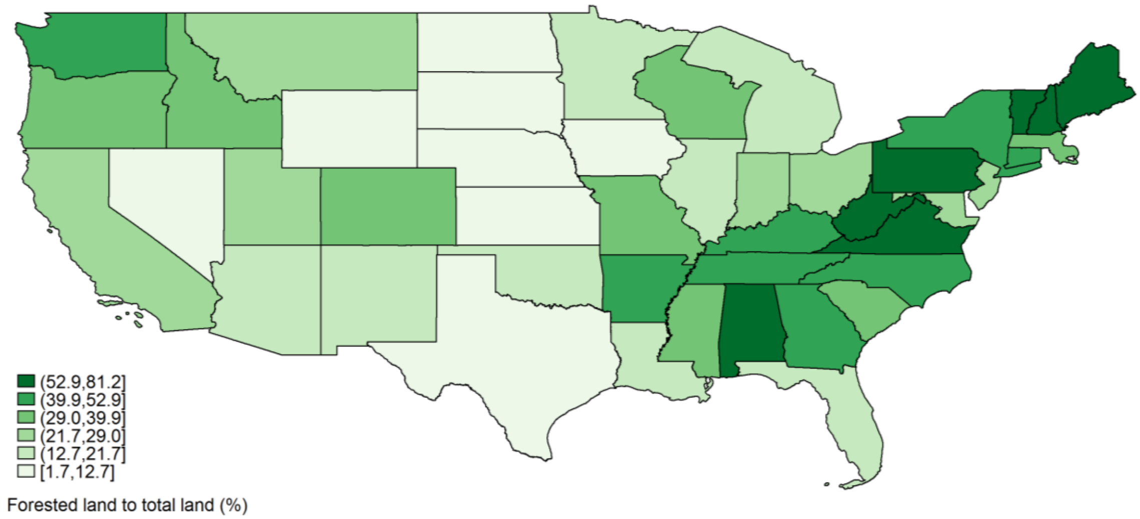

Figure A-8. Forested land share to total land area by state in 2010

Table A-8. Differences of wildfire risks between the baseline in 1997-2010 and the RCP 2.6 and 8.5 scenarios in 2010-2050

	Differences from the baseline (%)			
	Human-caused wildfire		Lightning-caused wildfire	
State	RCP 4.5	RCP 8.5	RCP 4.5	RCP 8.5
AL	0.882	1.062	–0.055	–0.066
AZ	2.165	2.076	2.327	3.562
AR	0.419	0.722	–0.004	–0.006
CA	–0.157	0.496	0.507	2.293
CO	–0.119	–0.114	0.457	0.663
CT	0.072	0.074	0.000	0.000
FL	0.049	0.212	1.776	0.173
GA	0.474	0.547	–0.006	–0.015
ID	0.115	0.113	5.028	6.576
IL	0.040	0.045	0.000	0.000
IN	0.048	0.064	0.000	0.000
IA	0.103	0.103	0.022	0.023
KS	0.398	0.342	0.179	0.210
KY	0.106	0.130	0.001	0.000
LA	0.940	2.327	–0.140	–0.161
ME	0.007	0.007	0.195	0.296
MD	0.308	0.326	0.000	0.000
MA	0.123	0.133	0.000	0.000
MI	0.071	0.100	0.000	0.000
MN	0.819	0.976	0.217	0.269
MS	1.948	2.802	–0.020	–0.022
MO	0.082	0.080	0.002	0.002
MT	0.234	0.152	3.924	4.335
NE	0.749	0.688	1.253	1.440
NV	0.202	0.058	0.665	2.824
NH	0.016	0.018	0.000	0.000
NJ	0.369	0.413	0.000	0.000
NM	0.602	0.709	1.032	1.793
NY	0.040	0.047	0.000	0.000
NC	0.084	0.055	–0.001	–0.002
ND	3.158	2.689	1.035	1.505
OH	0.073	0.107	0.000	0.000
OK	0.856	0.929	0.049	0.056
OR	1.622	1.597	7.333	10.781
PA	0.055	0.074	0.000	0.000
SC	0.101	0.078	0.000	–0.032
SD	1.457	1.546	1.558	2.285
TN	0.284	0.391	0.000	0.000
TX	0.839	1.173	0.400	0.688
UT	–0.196	–0.207	0.875	1.809
VT	0.008	0.009	0.002	0.003
VA	0.217	0.214	0.000	0.000
WA	0.829	0.929	1.913	2.017
WV	0.059	0.087	0.009	0.008
WI	0.122	0.158	0.007	0.007
WY	0.489	0.516	3.482	4.169