Crop Adaptation to Climate Change

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Abstract Farmers may adapt to climate change by growing different crops. This type of adaptation may offset the negative effects of climate change on crop yields. However, adaptation may be restricted by soil conditions. Even in the case of substantial warming the actual amount of adaptation could be small. In this paper, we pair a 10-year panel of satellite-based crop coverage in the Midwest with spatially explicit soil data and a fine-scale weather data set. Combining a proportion type model with local regressions, we simultaneously address the econometric issues of proportion dependent variables and spatial correlation of unobserved factors. Based on the estimates of crop choice, we predict the future crop distribution under several climate change scenarios. We find that rice and cotton spread northward, the average shares of corn and soy decrease in the north and increase in the south. We also find that crop shifting patterns vary across quality levels of soils. There is less crop adaptation on better soils than on soils with lower quality.

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1 Introduction

Crop yields are forecasted to decrease by 30-46% before the end of the century even under the slowest (B1) climate warming scenario (Schlenker and Roberts 2009). Farmers may adapt to the expected yield changes by growing crops more suited to the new climate. Predicting adaptation behavior, i.e. the change in cropping patterns, is therefore an important part of evaluating the effect of climate change on food and fiber production. In this paper, we look at the potential adaptation to climate change, using currently grown crops, for a group of US states situated in a north-south transect along the Mississippi-Missouri river system. Together the states comprise a major agricultural region with a considerable diversity of weather and soil. The selected states are also among the few for which more than 10 years of fine scale satellite-based crop coverage data are available.

Along the Mississippi River, the dominant crop types are corn, soy, cotton and rice in the south and corn and soy in the colder north. Based on temperature alone, adaptation to higher temperatures should result in the northward spread of cotton and rice and substitution of shorter-season crops (e.g., soy) for longer-season crops (e.g., corn). However, agricultural crop coverage is not determined by temperature alone, or even rainfall and temperature taken together. Soil properties are a major determinant of which crops can be grown and what the crop's ultimate yield is. It is very plausible that, even in the face of the same level of warming, crop shifting patterns will be very different across soils of different qualities. The purpose of this paper is to show how weather and soil determine crop location and how, in the face of warmer weather, crop adaptation varies across quality levels of soil.

Modern econometric studies of crop land coverage began with Nerlove's (1956) examination of crop share response to crop prices. His estimating equations are of the form that coverage is a function of lagged coverage, crop price, input prices and other variables. There are many ways to elaborate on this basic model. (1) In many countries (e.g., the United States and European Union), the incentive to grow crops in addition to the price is government payments. As these programs change year to year and have different marginal effects for different farmers, it is not possible to have a fully satisfactory treatment of the price variable. If the focus, as was Nerlove's focus, is on price response, parsing the true incentive effects is a serious problem. If the focus is on climate, the standard solution is to use year fixed effects to account for both prices and government programs. The year fixed effects also would account for differences in input prices. (2) Many authors (Just 1974, Chavas and Holt 1990, Lin and Dismukes 2007) think that the risk of growing a crop, perhaps the variance or lower semi-variance, is an important determinant of crop choices. So long as the risk of growing a crop is taken as constant, which is a good approximation in a short time series, crop fixed effects account for this factor. (3) Crop coverages are proportions and therefore should sum to one. Indeed there are authors (Lichtenberg 1989, Wu and Segerson 1995) who use discrete choice models for crop share decisions. Berry's logit (1994) is an appealing discrete choice model for shares that are not zero or one, because it is linear in the parameters and errors. However, our crop coverage data has many data points with zero coverage. To deal with a great number of zero shares, we use a limited dependent variable regression with a transformation function which will be described in detail later. (4) Land use can be correlated across space, either as a spatial lag or spatial error process. A spatial lag process is natural in housing developments, where the land use on the next plot does influence that on the subject plot. A spatial error process corresponds to unmeasured factors that influence yield that vary slowly over space. For instance, the persistence of summer fog along a coast might not be captured by measured low temperature, since the fog also produced moisture. All adjacent coastal areas would be similarly affected. The spatial correlation in errors does not cause inconsistency to OLS estimate, but for nonlinear regressions, such as logit, tobit, etc., the key problem is that the homoscedasticity assumption is violated by the spatial correlation in errors. We use a local regression framework so that all parameters and the variances can vary across the landscape and account for unmeasured place specific phenomenon. (5) Crop coverage in cross section is determined by climate and soil. Studies interested in price response use place fixed effects to account for these factors. Because these are the factors that interest us, we use measured climate and soil variables. We also include the interaction terms of moisture and heat, because a dry warming is likely to be more harmful than warming with moisture.

Recent literature, particularly Schlenker and Roberts (2009), working at the county level, quantified the effects of weather on yield. Their work is noteworthy for the use of a great deal of spatial and temporal detail in their weather data. In their studies, the effects of soil are subsumed in the place fixed effects. The general tenor of their results is that high temperatures are very harmful to yields and so climate change projections for the United States result in large yield deficits in response to an increase in the number of hours of 29°c plus temperatures for corn, 30°c for soybeans, and 32°c for cotton. Lobel et al. (2011) did a very similar analysis for Africa, though they emphasize the interaction of moisture and heat. These studies find that warmer climates negatively affect yield.

One potential response of farmers to climate change is to shift the location of crops, in turn planting crops with characteristics better matching the new landscape characteristics. This type of adaptation is evident on crop landscape maps. One sees cotton in the warmer, wetter south, wheat in drier regions, corn in the wetter parts of the Midwest, and so on. The choice of crops to fit climate may offset the negative effects of increasing temperature on crop yields, but it may be limited by soil conditions. Where crops of a certain type can be grown and what their maximum potential yields may be are determined not only by weather but also by soils. If all crops suitable to local soils are negatively affected by warming, it is possible that farmers are left with no better crop to substitute to. That is, adaptation happens only when the substitution crop fits in the local soils and the current crop is harmed so much that it is less profitable than the substitution crop. In this paper, we show that, due to soil restriction, adaptation makes some difference, but that it does not undo the negative effects of higher temperature.

The remainder of the paper is organized as follows. Section 2 summarizes the data on land use, soil conditions, weather, and climate change scenarios for the states along the Mississippi-Missouri river corridor. Section 3 describes estimation issues and establishes the econometric system. Section 4 presents the estimation results. Section 5 simulates crop adaptation to climate change. Section 6 concludes.

2 Data

Geospatially explicit data on land cover, soil characteristics, weather, and climate change scenarios are matched on a 4km by 4km grid to create the primary data set. The states included in the analysis are those along the Mississippi-Missouri river corridor for which there are at least 10 years of land cover data: Iowa, Illinois, Mississippi, and part of Wisconsin, Missouri, and Arkansas. There is currently insufficient land cover data to extend our analysis to other states. Summary statistics are provided in Table 1. Each variable in the table is described in detail below.

Land use

Land cover data is derived from the Cropland Data Layer (CDL) available annually from 2000 to 2010 (USDA NASS) for the six states. The CDL is generated based on Resourcesat-1 AWiFS, Landsat 5 TM, and Landsat 7 ETM+ satellites and has a ground resolution of 56 or 30 meters, depending on the year and sensors used (Mueller & Seffrin, 2006).

We divide land cover into major crops, other crops, non-crop and wild, urban, and water bodies. The major crops include corn and soybean for Iowa, Wisconsin, and Illinois; and corn, soybean, rice, and cotton for Missouri, Arkansas, and Mississippi. The category of non-crop and wild land includes pasture, forest, improved pasture, etc. Conservation reserve lands should fall within this category as they do not have crops. We define agricultural land as the sum of major crops, other crops, and non-crop and wild land. Because urban and water bodies are very difficult to convert into crop land, we do not include them in discussion in this paper. Therefore, we define the share of major crops as the area of major crops divided by area of agricultural land.

Figure 1 shows the shares of corn, soybean, rice, and cotton along the corridor. Corn grows mainly in the colder north, while soy crops are more widely distributed. Rice and cotton concentrate along the river in Missouri and Arkansas. For corn, the average percent coverage from 2002 to 2010 is 34.3% in the north (the three northern states: Wisconsin, Iowa, and Illinois), while it is only 2.9% in the south (the three southern states: Missouri, Arkansas, and Mississippi). For soy, the coverage is 26.4% and 14.1% in the north and the south, respectively. There is little cotton and rice in the north, while in the south, cotton takes 4.5% of the agricultural land and rice takes 5%.

Soil Characteristics

For soil data we focus on two types of variables, both derived from the USDA's U.S. General Soil Map (STATSGO2). First, the underlying soil data include percent clay, sand, and silt, water holding capacity, pH value, electrical conductivity, slope, frost-free days, depth to water table, and depth to restrictive layer. Soil variable averages are spatially weighted from irregular polygons for each grid cell.

Second, we use a classification system generated by the USDA – Land Capability Class (LCC). A LCC value of one defines the best soil with the fewest limitations for production, and progressively lower LCC classifications signify more limitations on the land for agricultural production. The LCC integer scores decline incrementally to eight, where soil conditions are such that agricultural planting is nearly impossible. The use of LCC codes add explanatory power to the raw soil characteristics because these codes were assigned with knowledge of past yields that depend on characteristics not present in our data set. The distribution of LCC levels is shown in Figure 2. Together with Figure 1, we see that prime agricultural soils are absent in southern Iowa and so largely is the corn-soy complex. Similarly, more optimal soils hug the river in Missouri and Arkansas, and so do rice and cotton.

Weather Variables

For weather data we use PRISM data processed by Schlenker and Roberts (2009) to a 4km by 4km spatial resolution, with a daily level of temporal resolution. The dataset includes both temperature (highs and lows) and precipitation. Figure 3 shows the observed weather condition in the planting season (from April to June)[2] from 2002 to 2010 and the growing seasons (from April to November) from 2002 to 2009. The observed temperatures are warmer in the south and the precipitation levels are appreciably larger. Average temperature in the growing season ranges from 12° to 25°c from the top of Iowa to the bottom of Mississippi, a distance of 1600 km. Total rainfall in a growing season is also variable across this landscape with a high of 130 cm and a low of 30 cm, highest in the southeast and lowest in the northwest.

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[2] Planting season and growing season vary across crops. In the six states along the Mississippi-Missouri river corridor, the planting season is from April to May for corn, rice, and cotton, and from May to June for soybean. The harvest season is October for rice and corn, and November for cotton and soybean. Growing season is defined as the period between planting season and harvest season.

Because this study has so many cross-sectional data cells, we are able to use a great deal of detail from the weather data. Two time periods of weather data are used for each crop year. (1) The planting season data, which farmers know before they actually plant. A cold wet spring, for instance, would delay planting and make a shorter season crop more desirable than a longer season crop. Compared to corn, soy is more tolerant of being planted late and more dependent on daylight hours, so it can make up time easily. When the planting season is late, farmers are more inclined to plant soy. (2) Past weather is used as a proxy for expected weather. We do not find much gain from including past weather beyond one season, though, in terms of predicting current weather, quite a few lags of past weather are statistically significant. For parsimony, we limit the lags of past weather to one.

Degree days are calculated from daily highs and lows using a fitted sine curve to approximate the amount of hours the temperature is at or above a given threshold (Baskerville & Emin, 1969). As in Schlenker and Roberts (2009), we bin the weather data into degree days at a given temperature and above. We draw on their work and other literature to reduce the number of bins to just those at critical thresholds. However, we expand the number of classifications of temperature to account for the month in which it occurs. We expect, for instance, that hot temperatures are not as harmful in autumn as they are in the middle of the growing season.

Climate Change Scenarios

Climate change scenarios are taken from Climate Wizard.[3] Two models are considered: (1) Ensemble average, SRES emission scenario: A1B; and (2) Ensemble average, SRES emission scenario: A2. Both models predict temperature and precipitation in change and in level for the end of the century (2080's). The comparison baseline is the average temperature and precipitation between 1961 and 1990. Future degree days are processed in two steps:

[3] Source: http://www.climatewizard.org/

first, future temperature highs and lows are generated by adding changes to original highs and lows; then the degree days are calculated based on the future highs and lows.

Figure 3 shows climate change scenarios, along with the observed weather condition in the growing season in 2009 and the planting season in 2010. The observed temperatures are warmer in the south and the precipitation levels are appreciably larger. Average temperature in a growing season ranges from 12° to 25°c from the top of Iowa to the bottom of Mississippi, a distance of 1600 km. Total rainfall in a growing season is also variable across this landscape with a high of 130 cm and a low of 30 cm, highest in the southeast and lowest in the northwest. The A1B model predicts a 4°c increase in temperature on average in the north, and a 3.5°c increase in the south. The A2 model predicts a similar warming pattern, but 0.5°c warmer than A1B's prediction. The A1B model also predicts an 18 cm decrease in total precipitation in a growing season in the north, and a 5 cm decrease in the south. The A2 model predicts a similar drying pattern with a very similar magnitude.

3 The Econometric System

Within each of our 4km grid cells, n, we observe the fraction of land in year t that was allocated to crop (or other use) i: S_{int}. There are M crops. If we imagine that each hectare of our grid cells has a crop choice, then on that hectare the crop with the highest revenue will be chosen. As a result, the fraction of the crop chosen in a grid cell will be a proportion type model.

(1) $$S_{int} = \phi\big((\boldsymbol{\beta_1}'\boldsymbol{X_{1nt}} + d_{1nt}), \dots, (\boldsymbol{\beta_M}'\boldsymbol{X_{Mnt}} + d_{Mnt})\big)$$

where $\boldsymbol{X_{int}}$ is a vector of determinate factors of revenue from planting crop i on plot n at year t, $\boldsymbol{\beta_i}$ is a vector of coefficients and d_{int} is an error term. $\phi()$ is a suitable transformation with its domain on the unit interval. When all of the shares are strictly within the unit interval, using logit as the transformation and rearranging terms gives a linear estimation equation

(Berry 1994): $log(S_{int}) - log(S_{0nt}) = \boldsymbol{\beta_i}'\boldsymbol{X_{int}} + d_{int}$. To deal with the fact that many plots do not have a certain crop (i.e., many S_{int} are zeros), we use a ratio transformation and we get

(2) $$\frac{S_{int}}{S_{0nt}} = \boldsymbol{\beta_i}'\boldsymbol{X_{int}} + d_{int}$$

In order to predict shares as a function of the independent variables, we sum the share ratio over S_i (recall that the shares sum to one) and solve for S_{0nt}

(3) $$S_{0nt} = \frac{1}{1+\sum_{j=1}^{M}(\boldsymbol{\beta_j}'\boldsymbol{X_{jnt}}+d_{jnt})}$$

Substituting (3) into (2), we get

(4) $$S_{int} = \frac{\boldsymbol{\beta_i}'\boldsymbol{X_{int}}+d_{int}}{1+\sum_{j=1}^{M}(\boldsymbol{\beta_j}'\boldsymbol{X_{jnt}}+d_{jnt})}$$

The estimation strategy is that first we estimate equation (2) by Tobit, accounting for the zero shares. Then we simulate d_{jnt} $(j = 1, \dots, M)$ by taking draws from a left truncated normal distribution with mean 0, standard deviation σ_{jnt} and truncation at $-\boldsymbol{\beta_i}'\boldsymbol{X_{jnt}}$. Finally, we calculate S_{int} for each draw and take the averages.

Because the scale of this study encompasses more than a thousand kilometers, there are conditions that are unaccounted for in our variables that change across the landscape. This spatial correlation can induce heteroscedasticity, which would make straightforward tobit estimation inconsistent. We know of two feasible estimation strategies. One strategy is to estimate a linear probability model with a Spatial Error Model (SEM) correction for the errors. In the linear probability model, OLS would be consistent and the SEM would serve to produce the correct standard errors and a more efficient estimate of the coefficients. The limitation is that the prediction is not guaranteed to be between 0 and 1. The other solution is to estimate local Tobit models, each for only one county and its neighbors. The spatial correlation is taken care of because the coefficients and the variances are free to vary across the landscape. Neighbors of county i are defined to be counties whose centroids are within 70 km distance of the centroid of county i. 70 km is chosen based on Moran's I tests. The tests show that the spatial correlation in error decrease exponentially and beyond 70 km it is lower than 10^{-3}. Within 70 km, a county has 8 neighbors on average and each county has about 100 4km grid cells. Therefore, each regression has about 900 observations.

Next, we consider what explanatory variables should be included. The Nerlovian adaptive price expectations model (Nerlove 1956) assumed that farmers have rational price expectations based on their information set, and described it in three equations. Braulke (1982) derived a reduced form from the three equations by removing the unobserved variables. Choi and Helmberger (1993) combined this reduced form and farmer's demand functions, and based on their work, Huang and Khanna (2010) described the crop share as a function of the lagged share, climate variables, economic variables, risk variables, population density, and time trend. Hausman (2012) included most of these explanatory variables, and also futures prices, substitute crop share and crop yield. To follow the literature,[4] we include lagged crop share, lagged substitute crop share, weather in the current planting season and the last growing season, and soil conditions as explanatory variables. We include the interaction term of heat and moisture to account for the possibility that dry warming is much more harmful than warming with moisture (Lobell, et al. 2011) . We also include year fixed effects to account for both output and input prices and government programs. This leads to the following specification:

(5)
$$\frac{S_{int}}{S_{ont}} = \alpha_i + \beta_i S_{int-1} + \boldsymbol{\gamma_i}'\boldsymbol{SS}_{int-1} + \boldsymbol{\varphi}_i^{'}\boldsymbol{Soil}_n + \boldsymbol{\theta}_{1i}^{'}\boldsymbol{GDD}_{nt-1} + \boldsymbol{\theta}_{2i}^{'}\boldsymbol{PDD}_{nt} + \boldsymbol{\theta}_{3i}'\boldsymbol{GP}_{nt-1} + \boldsymbol{\theta}_{4i}^{'}\boldsymbol{PP}_{nt} + \boldsymbol{\theta}_{5i}^{'}\boldsymbol{PreDD}_{nt} + \boldsymbol{\theta}_{6i}^{'}\boldsymbol{PreDD}_{nt-1} + \mu_t + \varepsilon_{int}$$

[4] For reviews of share response literature, see Askari and Cummings (1977) and Nerlove and Bessler (2001) .

where S_{int} is the share of crop i planted at grid cell n in year t. $\boldsymbol{SS}_{int-1}$ is a vector of substitute crop shares planted in year $t-1$. $\boldsymbol{Soil}_n$ is a vector of soil conditions, including all the soil characteristics described in the data section. $\boldsymbol{GDD}_{nt-1}$ is a vector of degree days by month in the last growing season (April through November in year $t-1$). $\boldsymbol{PDD}_{nt}$ is a vector of degree days by month in the current planting season (April through June in year t). The critical temperatures in a planting season include 10 ^{o}c and 15 ^{o}c. 10 ^{o}c is the base temperature limit of rice, corn, and soybean development, while 15 ^{o}c is the base temperature limit of cotton development. The critical temperatures in a growing season include 10 ^{o}c, 15 ^{o}c, 20 ^{o}c, 25 ^{o}c, 29 ^{o}c, and 32 ^{o}c. Temperatures higher than 29 ^{o}c are harmful to corn, 30 ^{o}c to soybean, and 32 ^{o}c to rice and cotton (Schlenker and Roberts 2009). $\boldsymbol{GP}_{nt-1}$ is a vector of precipitation by month in the last growing season. $\boldsymbol{PP}_{nt}$ is a vector of precipitation by month in the current planting season. $\boldsymbol{PreDD}$ are vectors of interactions of degree days above 30 ^{o}c and precipitation levels in the same month. All months in the current planting season and the last growing season are included.

4 Estimation Results

We run separate regressions for each crop and each county. In sum, we have 1022 sets of estimates (368 counties; 2 main crops for the northern states and 4 main crops for the southern states). We test the significance of soil, precipitation, and degree days. The F-test results are shown in Table 2. Soil, precipitation and temperature are significant at the 1% significance level in most of the regressions for corn, soy, and cotton, while they are significant in half of the regressions for rice. Rice only covers about 4% of the land in the southern states, while the land for other use covers about 80% of the land. It is not surprising that the coefficients for rice are not statistically significant, given that the dependent variable is the ratio of rice share and the share of other land use. In a linear probability model, using just rice share, all coefficient groups are significant, so the lack of significance is likely because of the inability to predict the “other” category. Cotton covers a small portion of land as well, however cotton responds more strongly to weather than rice. Therefore, the coefficients are significant in the regressions for cotton, while they are not in the regressions for rice.

Based on the estimates, we predict crop share changes for two scenarios. In one scenario, daily temperature increases by one degree for all months in 2009 and 2010. In the other scenario, monthly precipitation decreases by one centimeter in all the months, and temperature increases as above. We are interested in both short-run and long-run adaptation, therefore we check the crop share changes in 2010, which is the year when the weather shock happens, and in 2015, allowing the weather shock to take its full effect. The predicted crop share changes are summarized in Table 3. In the short run, one-degree warming decreases corn share by 0.007 in the north and increase corn share by 0.003 in the south, which means 0.7% less land (a 2% decrease) in the north and 0.3% more land (a 7% increase) in the south is covered by corn. Although corn in the north and corn in the south are affected by warming differently, corn in total is affected negatively, because it mainly grows in the north. One-degree warming also decreases soy share in the north and increase soy share in the south. It indicates that 2.1% less land (a 8% decrease) in the north and 2.8% more land (a 18.1 increase) in the south is covered by soy. One degree warming increases rice share by 0.031 (a 57.5% increase in the south) and cotton share by 0.023 (a 57.3% increase in the south). It suggests that warming favors rice and cotton. By comparing the crop adaption in the north and in the south, we find that both average shares of corn and soy decease in the north, while all the main crop shares increase in the south. This finding contradicts the general hypothesis that warming benefits the north agriculture. It suggests how warming affects crops depends on more detailed weather and soil factors.

Compared to warming alone, dry warming increase other land use more in the north and decrease other land use less in the south, as shown in Table 3. It shows that dry warming does more damage to crop yields than warming with moisture. Although the averages are different, the difference is small and the share change patterns are similar in the two scenarios, as shown in Figure 4. This indicates that a one centimeter change in precipitation is not large enough to have significant effects on crop adaptation.

Table 3 and Figure 4 also show the crop share changes in the long run. The crop share changes in the long run are larger on average and the distributions have fatter tails. It suggests that it takes time for farmers to fully adjust crop coverage to weather shocks. We also check the crop share changes in 2020 and find that they are very similar to those in 2015. This suggests that five years is long enough for the farmers to complete the adaptation.

To illustrate how crop adaptation varies across landscapes, we map out the long-run share changes in Figure 5 and Figure 6 for the one-degree-warmer scenario and the one-degree-warmer-and-one-centimeter-drier scenario, respectively. The findings are as follows. First, the two scenarios have similar land cover shifting patterns, which confirms the findings in Figure 4. Second, rice and cotton in the south spread toward the north, which is expected, because the north becomes more suitable for rice and cotton. Third, the main crops take land from minor crops and other uses in the south. This suggests that for south a one-degree increase from current temperature is beneficial to the main crops. Finally, by comparing the changing pattern of other land cover to the spatial distribution of LCC levels (Figure 2) and precipitation (Figure 3 Panel B), we find that land with lower quality soils and more precipitation are more likely to be converted into major crop land in face of climate warming.

To further investigate how soil affects crop adaptation, we construct a counterfactual crop share change map for selected counties in Iowa. We choose one county in middle Iowa and one in bottom Iowa according to their similarity in weather and their discrepancy in soil.

As shown in Figure 7, Panel A, in the growing season in 2009, the counties have similar average temperatures which are around 14°c (14.0°c for middle Iowa and 14.7°c for bottom Iowa) and similar precipitation levels, which are around 82 cm (82.7 cm and 82.1 cm, respectively), while soils differ significantly (LCC level 2 vs. LCC level 3 and 6). Despite the similar weather conditions and the same temperature increases, crop adaptations in the two places are different. Changes in shares of corn, soybean, and other land use due to a one degree increase in temperature are mapped out in the first and second row in Figure 7, Panel B, for the middle Iowa county and the bottom Iowa county, respectively. The hypothesis is that, if bottom Iowa had the same soil as middle Iowa, they would have similar crop adaptation. To test this hypothesis, we predict the crop adaptation for the bottom Iowa county assuming that they had the same soil as the middle Iowa county. First, we create the counterfactual for the bottom Iowa county. We take the average soil properties (average LCC, average percent of silt land, and averages of all other soil characteristics) of the middle Iowa county, and the actual temperatures and precipitation levels of the bottom Iowa county. Together they form the weather and soil conditions of the counterfactual land. Second, we predict the crop shares for the counterfactual land. Two things are different from the prediction for the actual bottom Iowa county – soils, and coefficients. Remember that coefficients are changing across landscapes, because we run local regressions. The changing coefficients reflect the fact that crops on landscapes with different soils are affected differently by weather and soil. For example, precipitation on silt soil and sandy soil has different effects on crop yields, because silt soil holds water more effectively than sandy soil. The counterfactual has similar weather and soil to middle Iowa county, so we use the coefficients estimated from the middle Iowa county to predict crop shares on the counterfactual land. Next, we assume the temperature is one degree higher in all months in the current planting season and the last growing season, and again predict the crop shares for the counterfactual land. At last, we find the difference in the shares predicted from the last two steps, and that is our predicted share change due to the one degree increase in temperature. The results are shown in the last row of Figure 7, Panel B. Compared to the first row of the same panel, it shows that the counterfactual land of the bottom Iowa county has similar crop share change patterns as middle Iowa county. Figure 8 shows the distributions of crop share changes for the middle Iowa county, the bottom Iowa county, and the counterfactual land. This confirms the hypothesis above. The middle Iowa county and the bottom Iowa county have different crop share change patterns. However, if the soils in the bottom Iowa county were the same as those in the middle Iowa county, the crop share changes would be similar to the changes in middle Iowa.

5 Climate Change Impacts

Given that farmers need about five years to fully adjust crop types to respond to a weather shock, for the following discussion, we focus on crop share changes in the long run. Crop adaptations under climate change are summarized in Table 4. Four climate change scenarios are compared: (1) A warmer scenario predicted by the A1B model (only temperature changes are considered), (2) A warmer-and-drier scenario predicted by the A1B model (both temperature and precipitation changes are considered), (3) A warmer scenario predicted by the A2 model, and (4) A warmer-and-drier scenario predicted by the A2 model. As shown in Table 4, the four scenarios have similar effects on crop shares. In the north, the average changes range from -0.0343 to -0.0514 for corn, from -0.0906 to -0.0986 for soy, and from 0.1249 to 0.15 for other land use. In the south, the average changes range from 0.0559 to 0.0702 for corn, from 0.1005 to 0.1118 for soy, from 0.0616 to 0.0714 for rice, from 0.0433 to 0.0572 for cotton, and from -0.2728 to -0.2956 for other land use.

The distributions of predicted crop share changes are depicted in Figure 9. Compared to Figure 4, Figure 9 has wider distributions, which is expected because the A1B scenario has larger increases in temperature than a one-unit increase. Spatial variations of crop adaptation under the four scenarios are displayed out in Figures 10 through 13. Figure 10 considers temperature changes only, predicted by the A1B model, while Figure 11 considers both temperature and precipitation changes. The figures show similar land use shifting patterns, which suggests that a drying climate within the predicted magnitude does not significantly worsen the growth condition for crops. Therefore, we conclude that for the Mississippi-Missouri river system, the major concern about climate change is warming, not drying. Figures 12 and 13 consider the scenarios predicted by the A2 model. They are similar to Figures 10 and 11, because the A2 model predicts the same patterns in temperature and precipitation changes as the A1B model does, only with slightly larger magnitudes.

6 Conclusion

This paper examines crop adaptation to climate change in the context of the six states along the Mississippi-Missouri river corridor. We consider the entire distribution of temperatures within each day and each 4km grid cell. We also consider the soil conditions at the 4km grid level. Based on the estimates of crop choices, we predict future crop share distribution under several climate change scenarios. We find that rice and cotton spread north, while the average shares of corn and soy decrease in the north and increase in the south. We also find that the crop shifting pattern is not determined by temperature alone – soil plays an important role as well, as there is less crop adaptation on prime soils than on lower quality soils. Therefore, due to the variation in crop adaption on soils of varying quality, a significant makeover of major crop distribution is not likely to happen.

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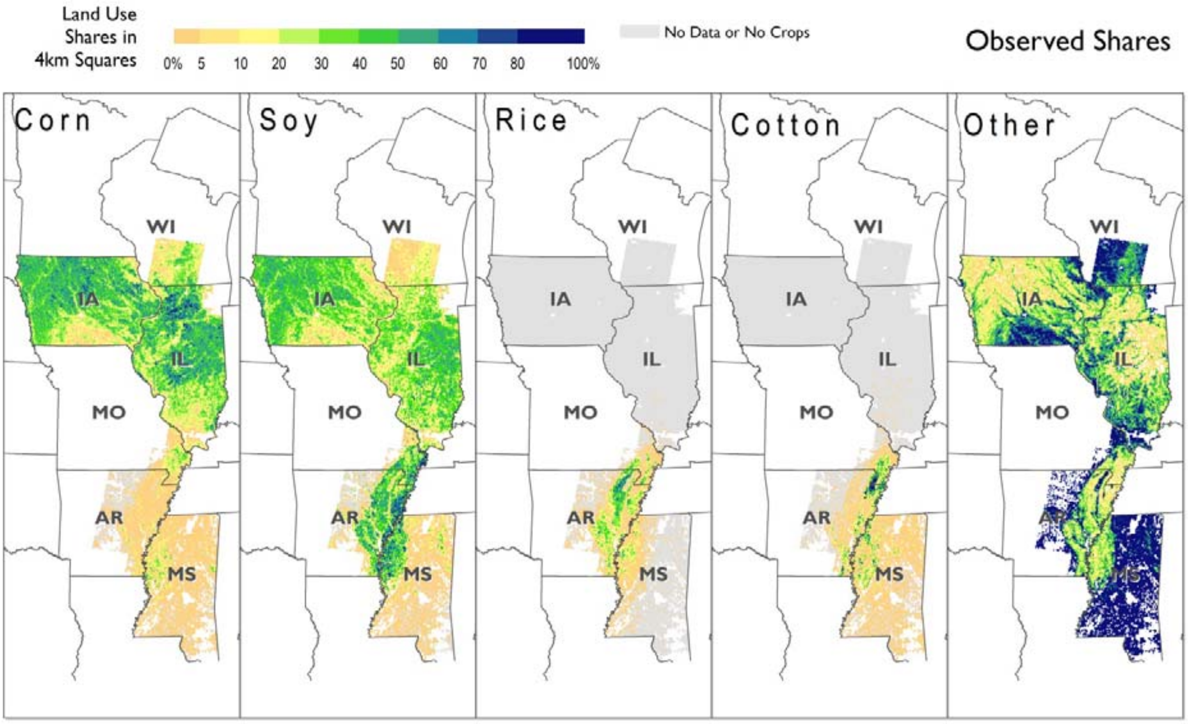
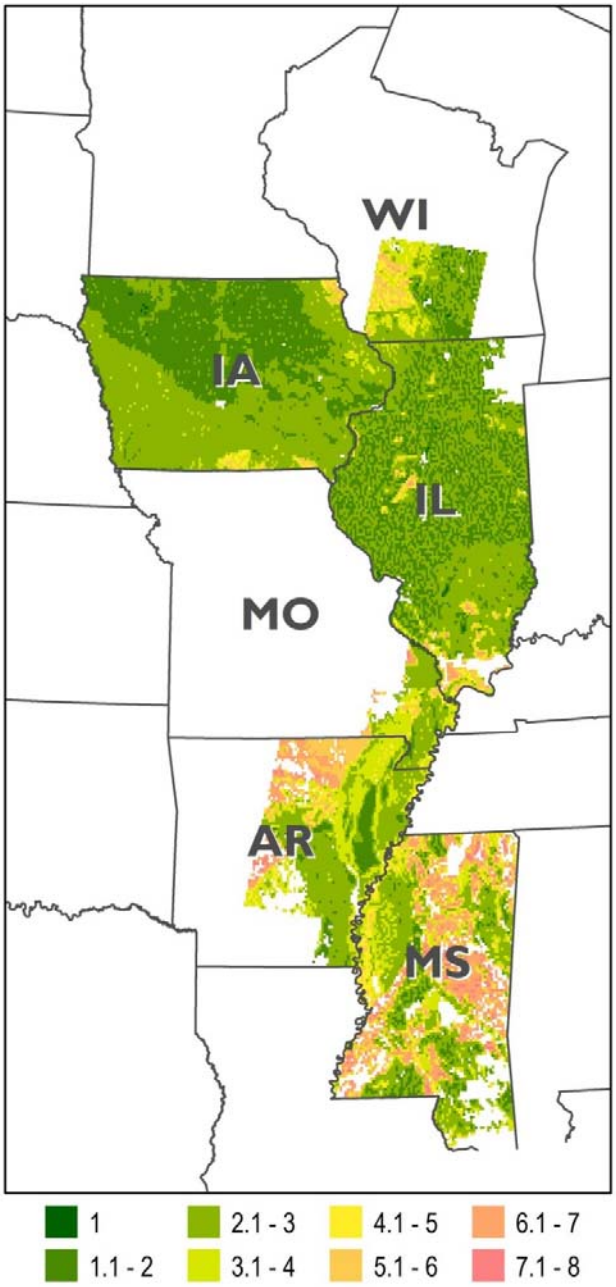
Figures 1: Observed Crop Coverage along the Mississippi-Missouri River System



Notes: Graphs display observed coverage shares for corn, soy, rice, cotton, and other land use, in the six states along the Mississipppi-Missouri river corridor. They are average shares over 2002-2010.

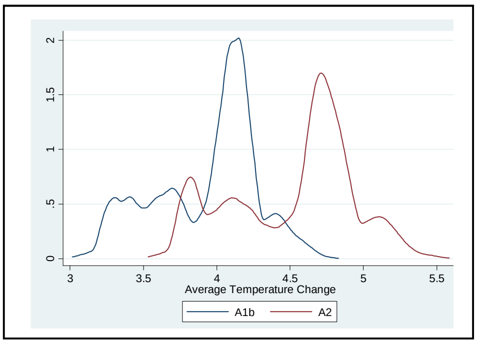
Figure 2: Distribution of Land Capabilty Classification (LCC) Levels

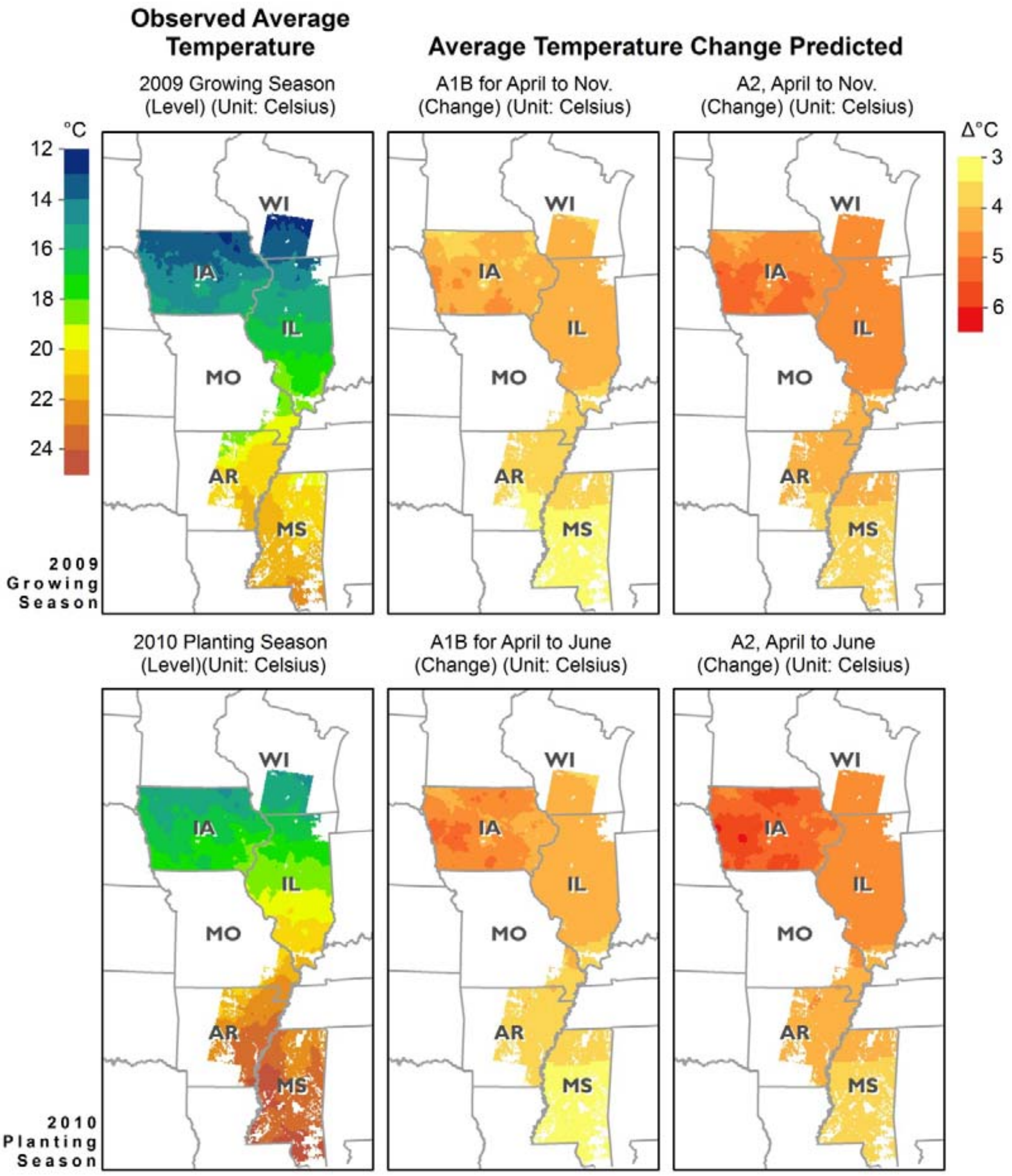


Notes: Land Capability Class (LCC) 1 is the best soil, which has the fewest limitations. Progressively lower classifications lead to more limited uses for the land. LCC 8 means soil conditions are such that agricultural planting is nearly impossible.

Figure 3: Observed Weather Conditions and Predicted Climate Change Scenarios

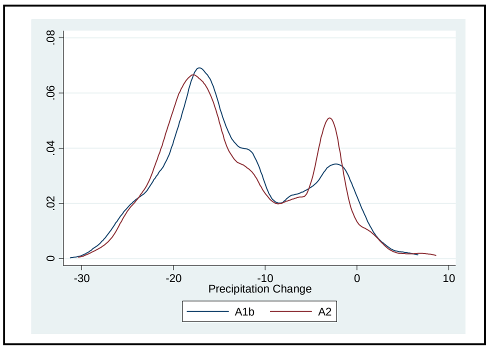
Panel A. Temperature

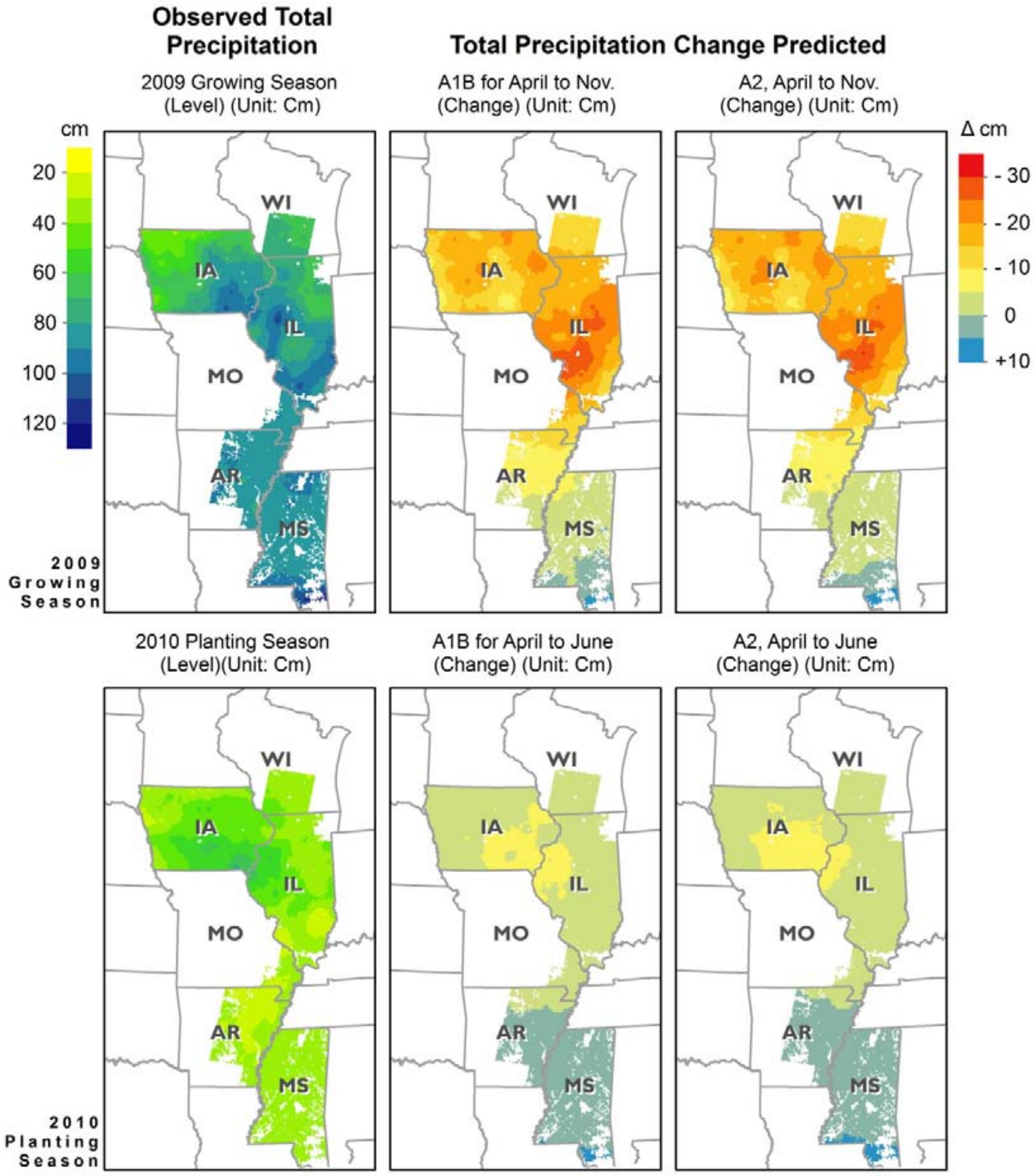




Distribution is over 4km squares for temperature change to 2080.

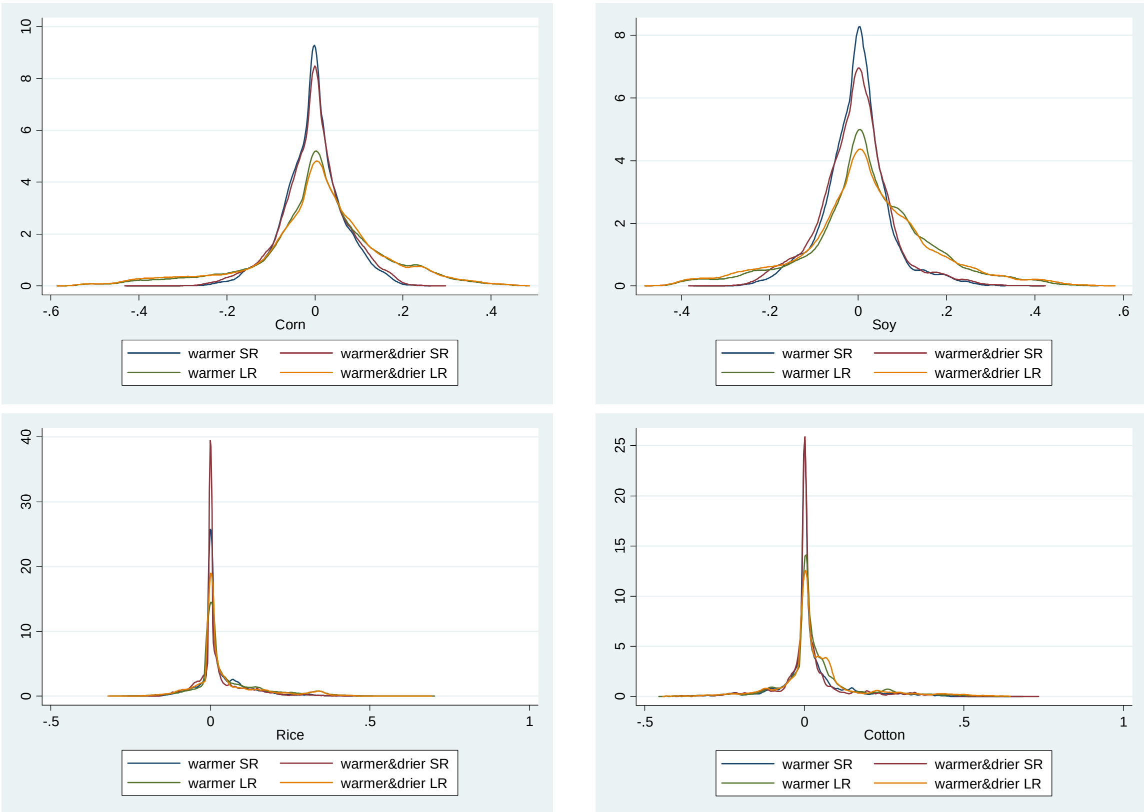
Panel B. Precipitation





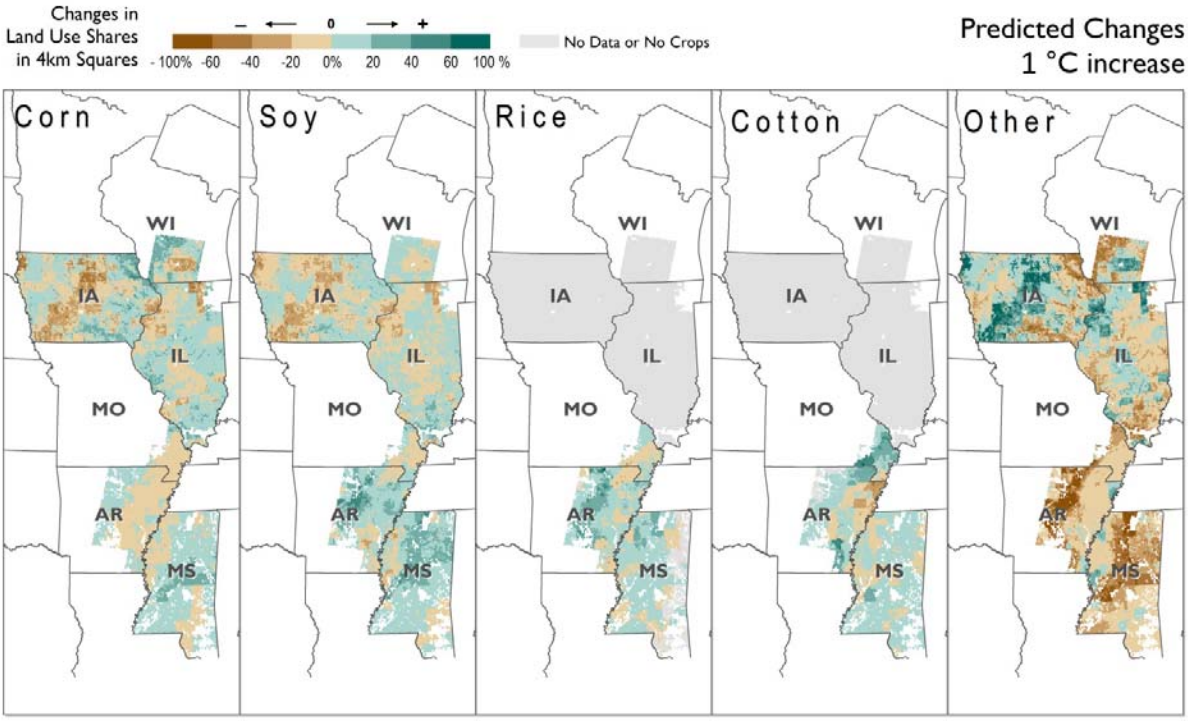
Distribution is over 4km squares for precipitation change to 2080

Figure 4: Distribution of Crop Share Changes with Unit Change in Temperature and Precipitation



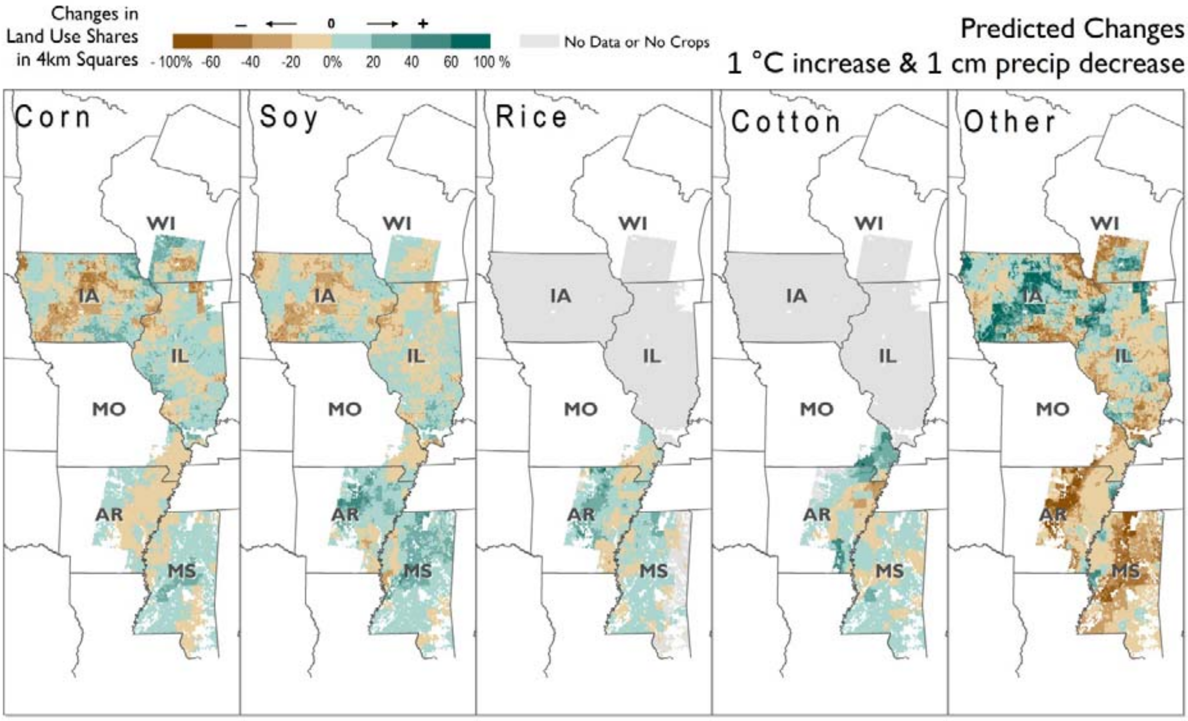
Notes: x-axes are crop share changes. For example, 0.2 in the first panel means corn share increases from a to a+0.2. SR stands for Short Run, which is the year when the weather change happens. LR stands for Long Run, which is five years after the weather change happens. For corn and soy, all six states are included. For rice and corn, only the three south states are included, because there is no rice and cotton in the north.

Figure 5: Crop Share Changes with Unit Increase in Temperature



Notes: a 20% change reported here means corn (for example) share increases from a to a+0.2.

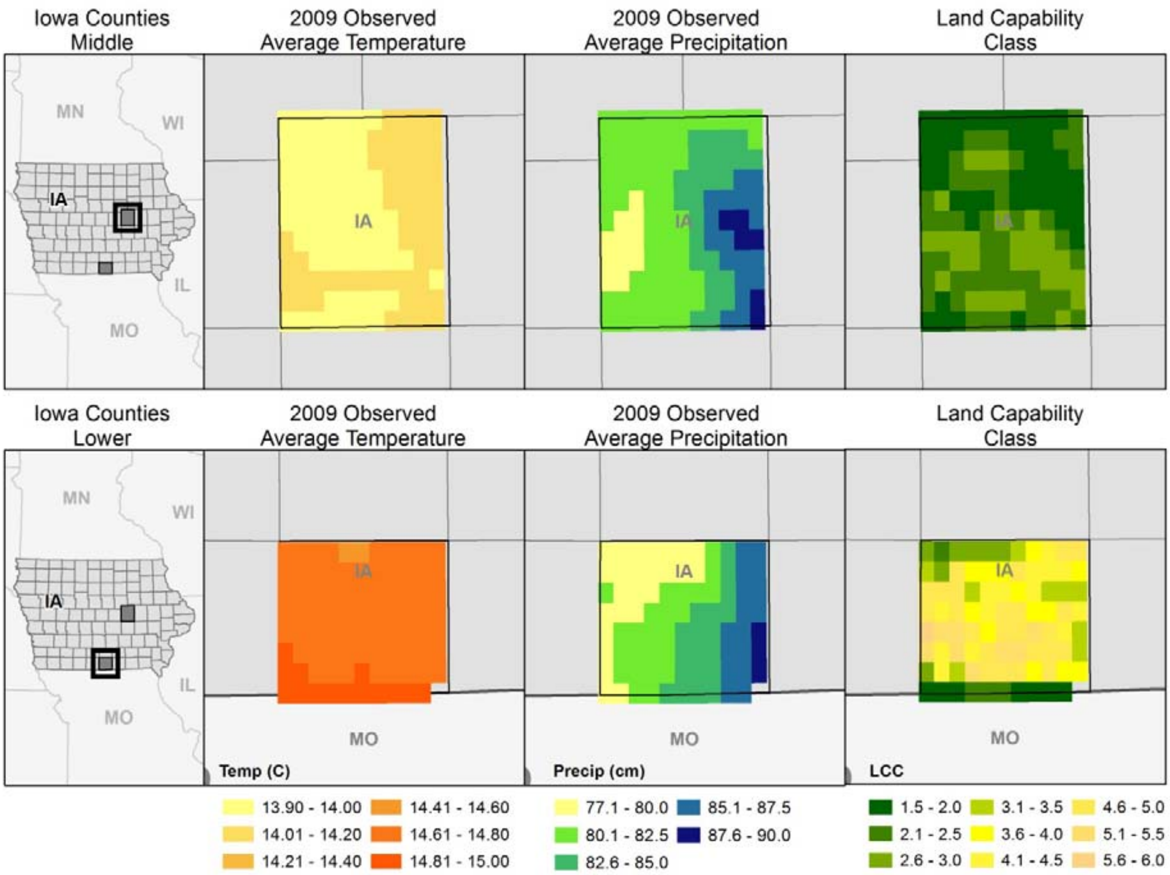
Figure 6: Crop Share Changes with Unit Increase in Temperature and Unit Decrease in Precipitation



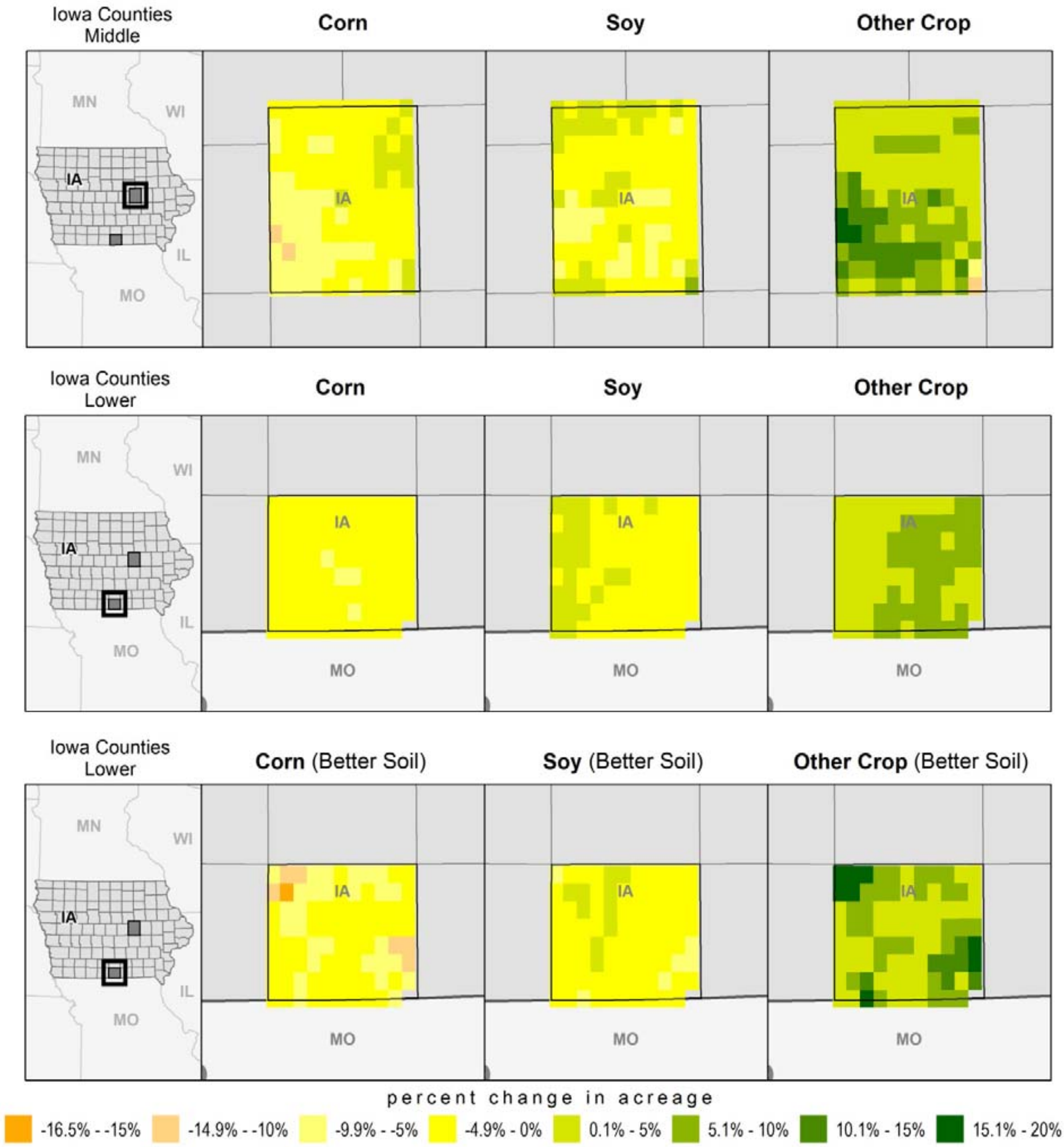
Notes: a 20% change reported here means corn (for example) share increases from a to a+0.2.

Figure 7: Counterfactual Analysis

Panel A. Similar in Weather and Different in Soil

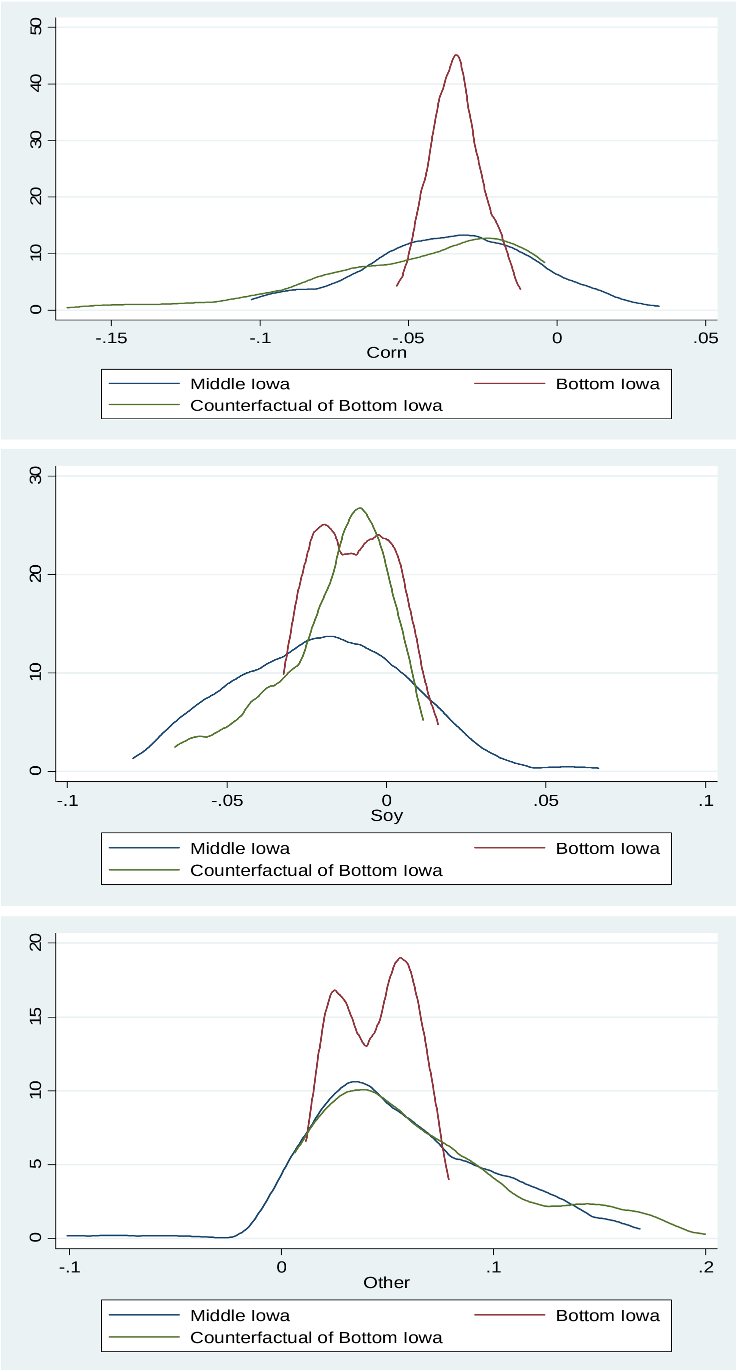


Panel B. Crop Share Changes if Better Soil



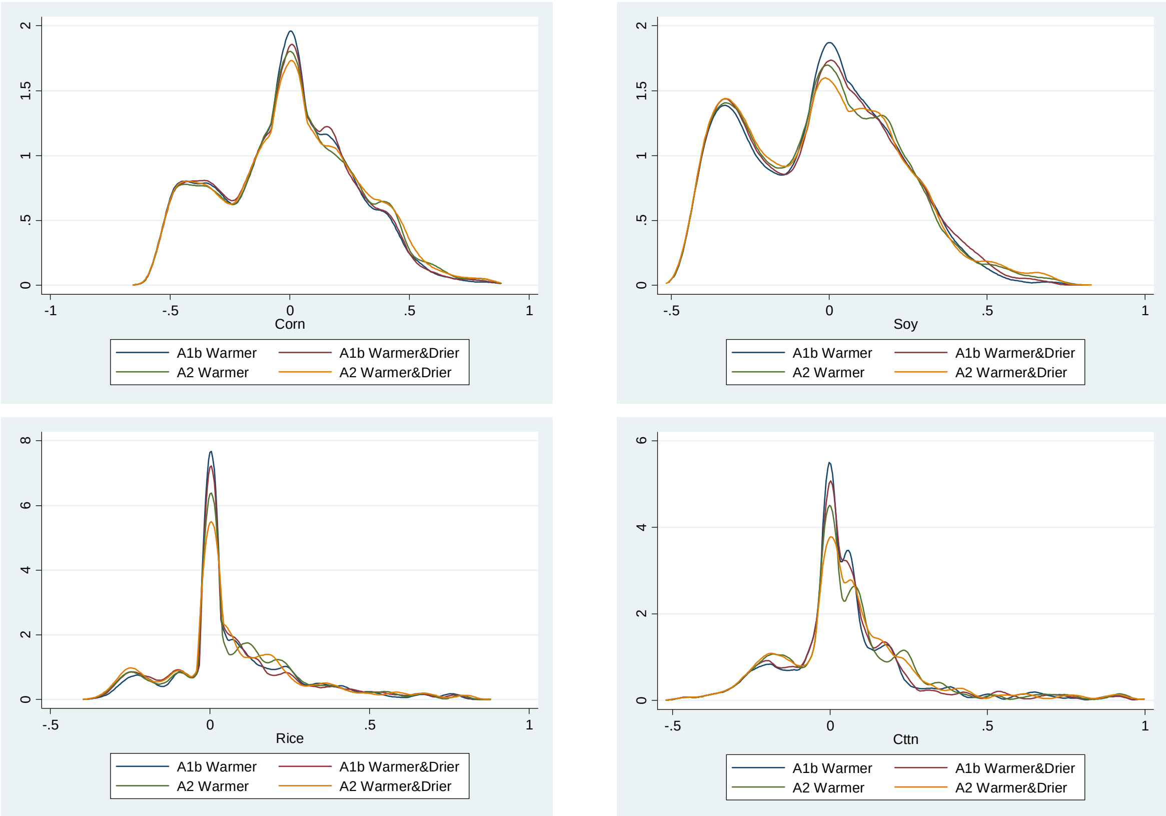
Notes: a 5% change reported here means corn (for example) share increases from a to a+0.05.

Figure 8: Distributions of Crop Share Changes if Better Soil



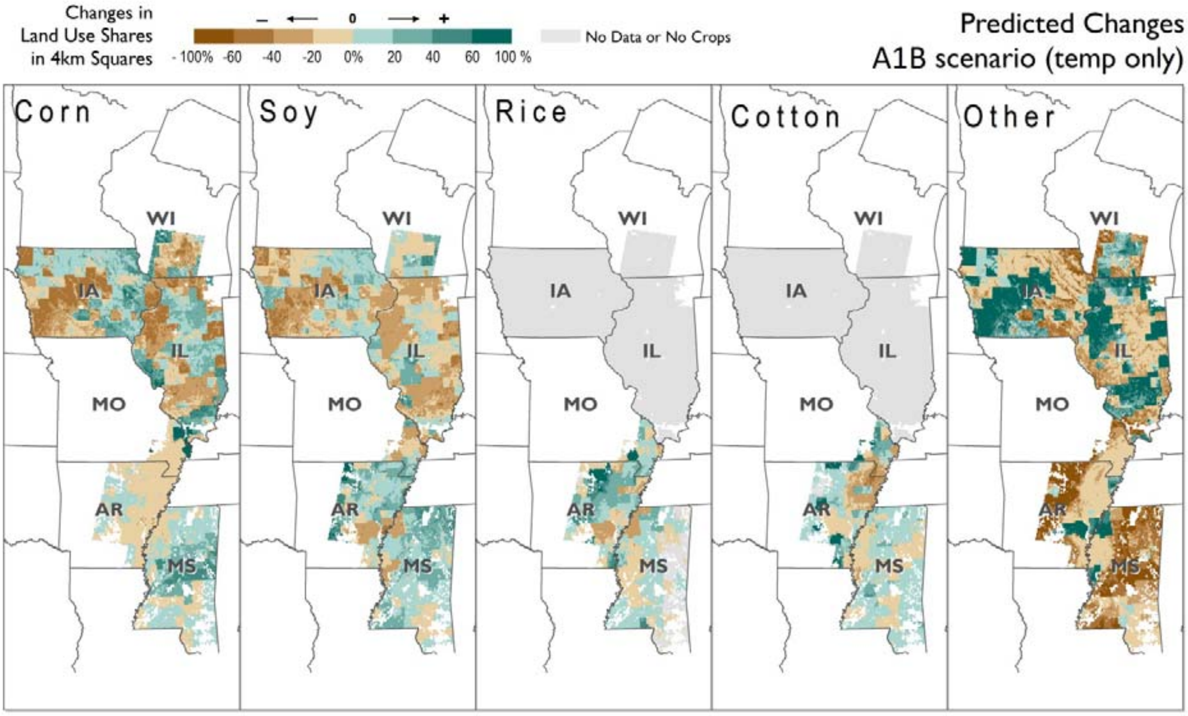
Notes: x-axes are crop shares changes. For example, -0.1 in the first panel means corn share decreases from a to a-0.1.

Figure 9: Distribution of Predicted Crop Share Changes under Climate Change Scenarios



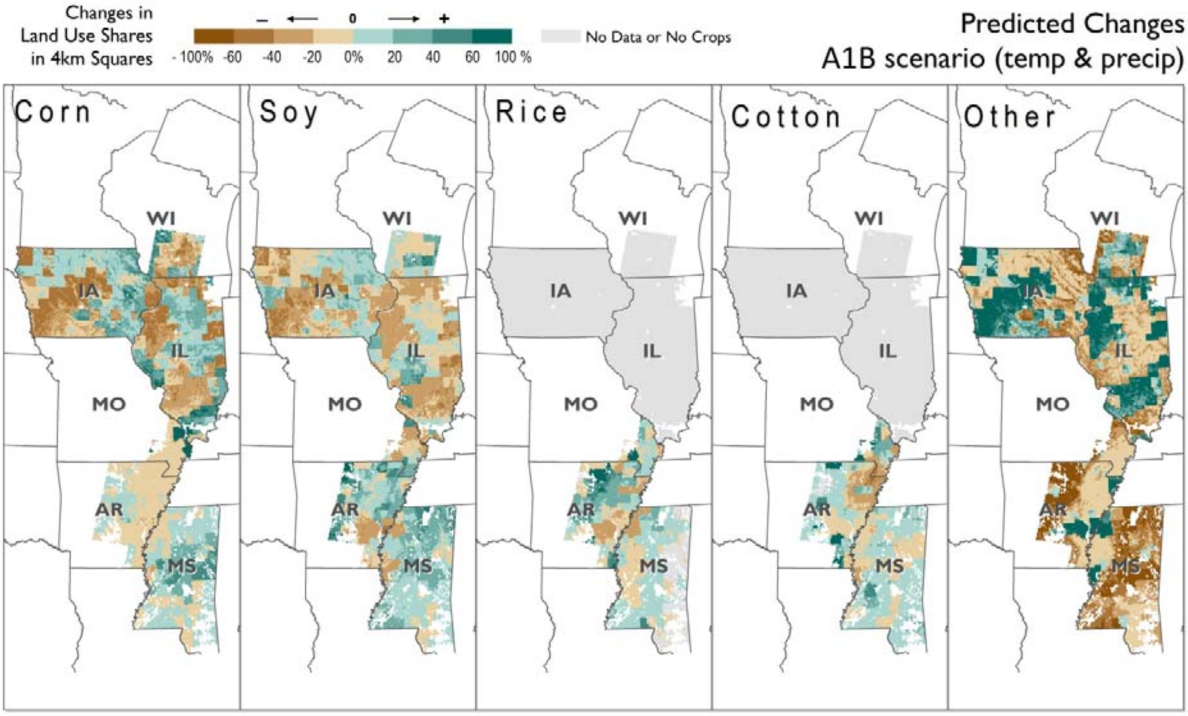
Notes: x-axes are crop share changes. For example, -0.5 in the first panel means corn share decreases from a to a-0.5. For corn and soy, all six states are included. For rice and corn, only the changes in the three south states are included, because there is no rice and cotton in the north.

Figure 10: Predicted Crop Share Changes under the A1B Scenario (Temperature Changes Only)



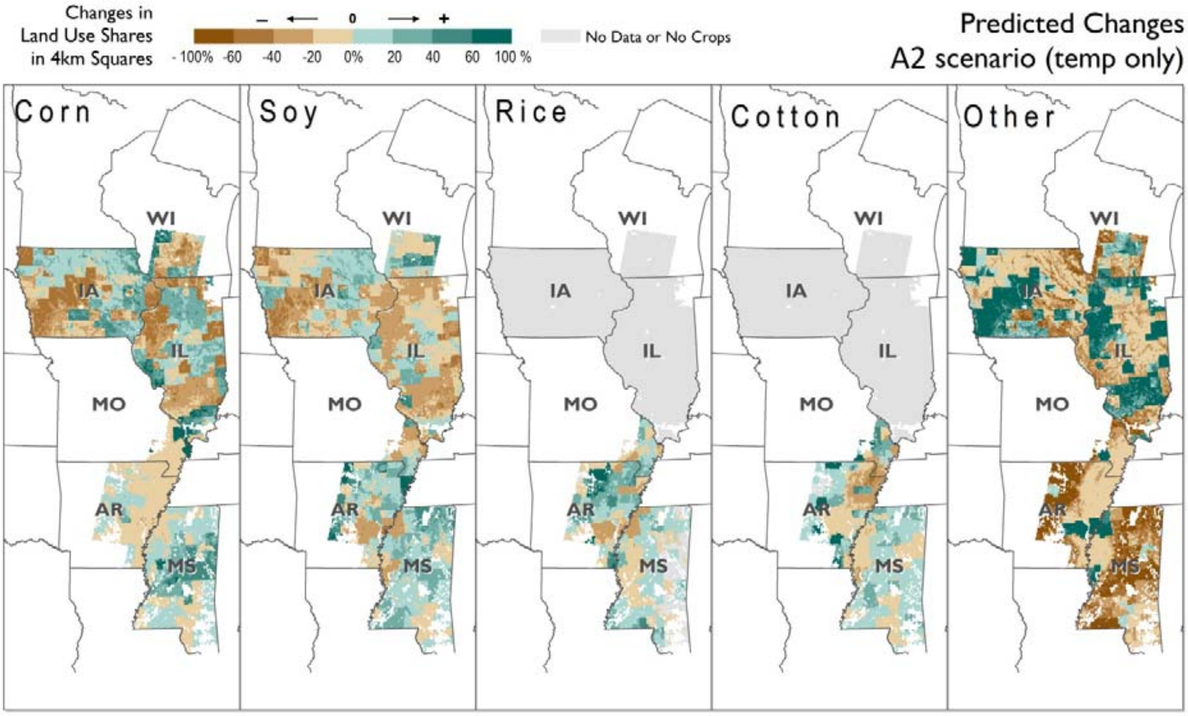
Notes: a 20% change reported here means corn (for example) share increases from a to a+0.2.

Figure 11: Predicted Crop Share Changes under the A1B Scenario (Temperature and Precipitation Changes)



Notes: a 20% change reported here means corn (for example) share increases from a to a+0.2.

Figure 12: Predicted Crop Share Changes under the A2 Scenario (Temperature Changes Only)



Notes: a 20% change reported here means corn (for example) share increases from a to a+0.2.

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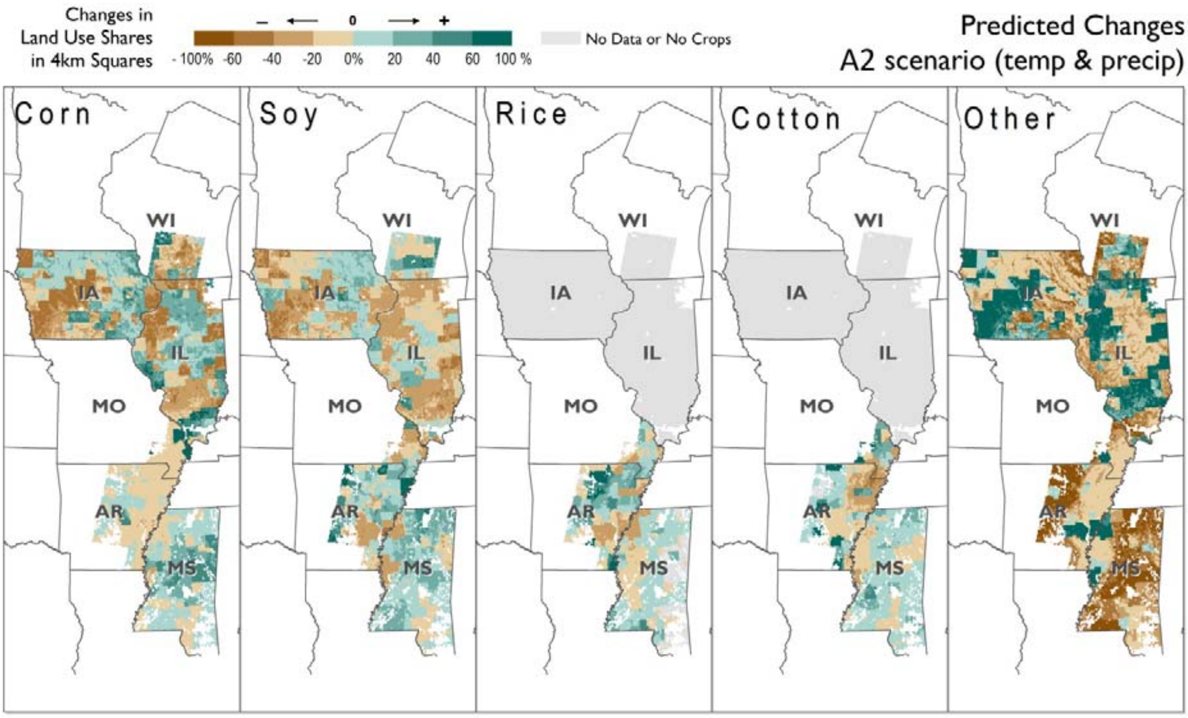
Figure 13: Predicted Crop Share Changes under the A2 Scenario (Temperature and Precipitation Changes)



Notes: a 20% change reported here means corn (for example) share increases from a to a+0.2.

Table 1: Summary Statistics

Variable	North Mean	St.dev.	Min	Max	South Mean	St.dev.	Min	Max
Dependent Variable: Percent Acreage (%)	(Obs = 174825)				(Obs = 91584)			
Corn	0.343	0.179	0	0.983	0.029	0.067	0	0.774
Soy	0.264	0.142	0	1	0.141	0.189	0	0.955
Rice	--	--	--	--	0.045	0.100	0	0.841
Cotton	--	--	--	--	0.050	0.122	0	0.982
Soil Condition	(Obs = 19425)				(Obs = 10176)			
Percent clay (%)	26.447	5.295	1.051	48.600	29.832	11.512	0	62.900
Percent sand (%)	21.560	12.642	0.793	95.300	26.942	14.235	0	84.600
Percent silt (%)	51.181	10.257	1.155	73.600	42.863	13.739	0	73.598
Water holding capacity	0.178	0.022	0.006	0.330	0.157	0.027	0	0.220
pH	6.441	0.511	0.198	7.700	5.591	0.686	0	7.511
Slope	3.435	4.536	0.037	48	7.203	6.394	0	25.400
Electrical conductivity	0.018	0.087	0	1	0.004	0.116	0	5.100
Frost free days	160.041	26.634	0	213.750	207.860	64.116	0	302.704
Depth to water table	79.960	41.173	0	201	62.777	22.750	13.250	201
Depth to restrictive layer	182.668	41.990	3.300	201	175.962	48.510	18	201
Percent of Land in Class 1 (%)	0.006	0.061	0	1	0.008	0.065	0	0.998
Percent of Land in Class 2	0.700	0.386	0	1	0.307	0.377	0	1
Percent of Land in Class 3	0.234	0.351	0	1	0.281	0.385	0	1
Percent of Land in Class 4	0.016	0.106	0	1	0.078	0.231	0	1
Percent of Land in Class 5	0.001	0.018	0	0.707	0.066	0.191	0	1
Percent of Land in Class 6	0.027	0.132	0	1	0.051	0.198	0	1
Percent of Land in Class 7	0.006	0.056	0	1	0.200	0.341	0	1
Percent of Land in Class 8	0	0	0	0	0	0.013	0	0.770

Table 1: Summary Statistics (continued)

Weather Variables								
Planting Season (April through June from 2002 to 2010)	(Obs = 174825)				(Obs = 91584)			
Temperature (Daily Average, Celsius)	15.848	1.540	11.975	20.336	21.044	1.134	16.867	23.960
Precipitation (Total, CM)	32.678	9.969	5.640	74.760	36.311	5.018	16.410	51.130
Growing Season (April through November from 2002 to 2009)	(Obs = 155400)				(Obs = 81408)			
Temperature (Daily Average, Celsius)	16.020	1.623	11.975	22.377	21.270	1.279	16.867	24.868
Precipitation (Total , CM)	74.022	14.814	32.540	127.290	86.839	9.109	56.730	120.550
Climate Change Scenarios	(Obs = 19425)				(Obs = 10175)			
A1B								
Planting Season (April through June)								
Temperature (Daily Average, Celsius)	4.381	0.340	3.868	5.544	3.609	0.261	3.016	4.095
Precipitation (Total, CM)	-3.987	1.060	-7.518	-1.288	1.640	1.925	-3.346	5.533
Growing Season (April through November)								
Temperature (Daily Average, Celsius)	4.151	0.178	3.110	4.829	3.523	0.204	3.016	4.270
Precipitation (Total , CM)	-17.592	4.334	-31.222	-6.461	-4.752	4.811	-23.613	6.639
A2								
Planting Season (April through June)								
Temperature (Daily Average, Celsius)	5.018	0.385	4.393	6.281	4.096	0.263	3.533	4.602
Precipitation (Total, CM)	-3.563	1.674	-8.547	-0.426	1.925	1.696	-2.058	5.969
Growing Season (April through November)								
Temperature (Daily Average, Celsius)	4.788	0.208	3.769	5.585	4.010	0.202	3.533	4.741
Precipitation (Total , CM)	-17.794	4.106	-30.350	-6.087	-4.313	4.305	-21.719	8.605

Table 2: F-tests for Soil, Precipitation and Temperature

Regressions with 1% Significance Level		Corn	Soy	Rice	Cotton
	Soil	93%	89%	54%	82%
	Precipitation	76%	72%	45%	72%
	Temperature	93%	90%	66%	92%
Regressions with 5% Significance Level		Corn	Soy	Rice	Cotton
	Soil	97%	92%	57%	85%
	Precipitation	82%	81%	49%	80%
	Temperature	95%	92%	67%	93%
Regressions with 10% Significance Level		Corn	Soy	Rice	Cotton
	Soil	97%	93%	60%	89%
	Precipitation	85%	84%	54%	83%
	Temperature	95%	93%	67%	93%
Number of Regressions in Total		368	368	143	143

Table 3: Crop Share Changes with Unit Changes in Temperature and Precipitation

			Corn	Soy	Rice	Cotton	Other
North	Unit Changes	Short-Run					
		Temperature Increase Only	-0.0074	-0.0209	--	--	0.0283
		Temperature Increase and Precipitation Decrease	-0.0067	-0.0257	--	--	0.0324
		Long-Run					
		Temperature Increase Only	-0.0010	-0.0181	--	--	0.0192
		Temperature Increase and Precipitation Decrease	-0.0052	-0.0264	--	--	0.0316
	Average Shares		0.3780	0.2623	0	0	0.3597
	No. of Obs.		19425	19425	19425	19425	19425
South	Unit Changes	Short-Run					
		Temperature Increase Only	0.0026	0.0279	0.0307	0.0179	-0.0790
		Temperature Increase and Precipitation Decrease	0.0044	0.0306	0.0225	0.0199	-0.0774
		Long-Run					
		Temperature Increase Only	0.0237	0.1044	0.0545	0.0379	-0.2204
		Temperature Increase and Precipitation Decrease	0.0243	0.1065	0.0451	0.0415	-0.2173
	Average Shares		0.0349	0.1537	0.0534	0.0312	0.7268
	No. of Obs.		10176	10176	10176	10176	10176

Notes: the numbers reported are share changes. For example, -0.0074 means corn share increases from 0.0378 (3.78% of land is covered by corn) to 0.3706.

Table 4: Crop Acreage Changes under Climate Change Scenarios

			Corn	Soy	Rice	Cotton	Other
North	A1B Scenarios	Long-Run					
		Temperature Increase Only	-0.0514	-0.0986	--	--	0.1500
		Temperature Increase and Precipitation Decrease	-0.0479	-0.0970	--	--	0.1450
	A2 Scenarios	Long-Run					
		Temperature Increase Only	-0.0381	-0.0925	--	--	0.1306
		Temperature Increase and Precipitation Decrease	-0.0343	-0.0906	--	--	0.1249
	Average Shares		0.3780	0.2623	0	0	0.3597
	No. of Obs.		19425	19425	19425	19425	19425
South	A1B Scenarios	Long-Run					
		Temperature Increase Only	0.0559	0.1087	0.0700	0.0466	-0.2813
		Temperature Increase and Precipitation Decrease	0.0551	0.1118	0.0616	0.0443	-0.2728
	A2 Scenarios	Long-Run					
		Temperature Increase Only	0.0678	0.1009	0.0714	0.0551	-0.2952
		Temperature Increase and Precipitation Decrease	0.0702	0.1005	0.0677	0.0572	-0.2956
	Average Shares		0.0349	0.1537	0.0534	0.0312	0.7268
	No. of Obs.		10176	10176	10176	10176	10176

Notes: the numbers reported are share changes.