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Heat in the Heartland: Crop Yield and Coverage Response to Climate Change Along the Mississippi River

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Abstract

Farmers may adapt to climate change by substituting away from the crops most severely affected. In this paper we estimate the substitution caused by a moderate change in climate in the US Midwest. We pair a 10-year panel of satellite-based crop coverage 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. We find the change in expected crop coverage and then we link those changes to the expected changes from an estimated climate dependent yield equation. Ceteris paribus, we find that climate induced changes in yield are offset by land coverage changes for rice and cotton but they are strongly amplified for corn and soy.

Keywords Adaptation · Climate change · Crop choice · Yield · Production

JEL Classification Q15 · Q54

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1 Introduction

Crop yields per acre (hereafter yield) for corn and soybeans in the US 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). There are similar findings in Africa (Lobell et al. 2011) and China (Chen et al. 2016). In addition to the yield effect, there is also a crop coverage response to climate change. Crop coverage is the area of land used to produce a given crop in a given year. Farmers may grow crops that are better suited to the new weather conditions. That is, they increase or decrease the amount of land devoted to a particular crop. The coverage response effect may offset or reinforce the yield effect on crop production. Since farmers' adaptation behavior is an important factor that affects crop production, in this paper, we study both crop yield and crop coverage in light of both weather and soil conditions along the Mississippi-Missouri river system, in order to project climate-related changes in crop production. This paper is the first to forecast the land coverage effects of projected climate change.[1]

The dominant crop types along the Mississippi River are corn, soy, cotton and rice in the south and corn and soy in the colder north. Farmers grow crops with characteristics matching the landscape characteristics. As evidence, one sees cotton in the warmer, wetter south, wheat in drier regions, corn in the wetter parts of the Midwest, and so on. Based on temperature alone, coverage response to higher temperatures should result in the northward spread of cotton and rice, substitution of shorter-season crops (e.g., soy) for longer-season crops (e.g., corn), and the conversion of non-crop land in the south. However, soil properties are also a major determinant of which crops can be grown and the crop's ultimate yield. If all crops suitable to local soils are negatively affected by warming, it is possible that farmers are left with no better alternative crop, not considering new technology or new crops being introduced into the region. 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. We estimate the changes in crop coverage within the limits imposed by soil conditions.

Modern econometric studies of crop 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 is a large literature elaborating on this basic model, but it mostly focuses on the effect of price, cost, or risk of growing crops rather than changes in climate.

The major contribution of this paper is to project land use change on a 4 km square basis as a function of changes in climate. The other contributions of this paper are the methodological innovations, elaborated as follows. (1) We use a limited dependent variable regression with a ratio transformation function to simultaneously deal with the problems of that crop coverages are proportions and that our crop coverage data have many data points with zero coverage. There are previous researchers (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, Berry's logit is not suitable for the data that have many zero data points as is the case in land use models over a large landscape. The model design in this paper satisfies the constraint of proportion dependent variable, has the advantage of linearity in parameters,

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[1] Burke and Emerick (2016) show that long run and short run responses to temperature change have been very similar, so that adaptation mitigated less than half of the change. Hornbeck (2012) examines the land use adjustments to the Dust Bowl.

and is good for the data with many zero points. (2) We use a local regression framework to address the problem of that land use may be correlated across space. A spatial error estimator can address the spatial correlation problem, but is not consistent in nonlinear regressions, like the limited dependent variable regression we use in this paper. The key problem is that the homoscedasticity assumption is violated by the spatial correlation in errors. Therefore, 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 that would lead to spatial correlation. (3) We include the interaction terms of moisture and heat to address the fact that a dry warming is likely to be more harmful than warming with moisture. (4) Utilizing the fine-level panel data on weather and soil, we explicitly model the effects of weather and soil. Modeling the effect of weather is key for simulating the effects of climate change; and modeling the effect of soil allows us to estimate the changes in crop coverage within the limits imposed by soil conditions. In contrast, studies interested in price response use place fixed effects to account for these factors and so cannot shed light on the role of soil in climate change adaptation. (5) Since our focus is on climate, not on price, we can use year fixed effects to account for both price and non-price incentives to grow crops. 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. However, since our focus is on climate, we use year fixed effects to account for both prices and government programs. The year fixed effects also would account for differences in input prices and any effects of variables that are common across space. For instance, the American biofuels program is also subsumed in the year fixed effects. In addition, many researchers (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. Given that the risk of growing a crop can be taken as constant, which is a good approximation in a short time series, we use crop fixed effects to account for this factor.

As for estimating the effect of climate change on crop yield, recent literature, particularly Schlenker and Roberts (2009), worked at the county level and quantified the effects of weather on yield. 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. Lobell et al. (2011) and Chen et al. (2016) did a similar analysis for Africa and China, respectively. These studies find that warmer climates negatively affect crop yield. Their work is noteworthy for the use of a great deal of spatial and temporal detail in their weather data, while the effects of soil are subsumed in the place fixed effects. Utilizing a much finer level of data and also a great deal of spatial and temporal detail in both weather and soil data, we explicitly model the effects of both weather and soil in the yield regression. It allows us to predict the crop yield losses to climate change, within the limits of soil conditions.

In this paper, we estimate the coverage response of corn, soy, cotton and rice to two climate change scenarios. We also estimate the change in yields implied by these same scenarios to see whether yield change and coverage change offset or reinforce each other. Like Schlenker and Roberts (2009), we find reductions in yield due to climate change. For corn and soybean, we find that coverage is also reduced; this exacerbates the yield loss and shifts the supply curves of corn and soybean further inward. For rice and cotton, we instead find increases in

coverage; this compensates for yield loss and shifts the supply curves of rice and cotton back toward its original position.

The remainder of the paper is organized as follows. Section 2 summarizes the data on land use, soil conditions, weather, climate change scenarios, and crop yields for the states along the Mississippi-Missouri river corridor. Section 3 establishes the econometric system and presents the estimation results. Section 4 simulates crop coverage responses to climate change. Both Sects. 5 and 6 predicts crop production losses to climate change. Section 5 holds crop coverage fixed, while Sect. 6 considers both yield effect and coverage response. Section 7 concludes.

2 Data

Both yield and crop coverage are estimated as functions of weather, soil, and time trends or time fixed effects. Data on land cover, soil characteristics, weather, and climate change scenarios are matched on a 4 km by 4 km grid to create the primary data set. Data on crop yield are at the county level. 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: Wisconsin, Iowa, Illinois, part of Missouri, Arkansas, and Mississippi.[2] Given that corn and soy are mainly grown in the three northern states (Wisconsin, Iowa, and Illinois), and rice and cotton are mainly grown in the southern states (Missouri, Arkansas, and Mississippi), the six states are divided into the groups of north and south accordingly. The summary statistics of all the variables for the two groups are presented in Table 1.

2.1 Crop Coverage

Land cover data is derived from the Cropland Data Layer (CDL) available annually from 2000 to 2010 (USDA NASS) for the six states.[3] They are divided 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 coverage 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, Arkansas and Mississippi. For corn, the average percent coverage from 2002 to 2010 is 27.5% in the north (the three northern states: Wisconsin, Iowa, and Illinois), while it is only 5.5% in the south (the three southern states: Missouri, Arkansas, and Mississippi). For soy, the coverage is 20.9 and 29.4% in the north and the south, respectively. There is little cotton and rice in the north, while in the south, cotton takes 10.3% of the agricultural land and rice takes 11.8%.

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[2] There is currently insufficient land cover data to extend our analysis to other states.

[3] 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 and Seffrin 2006).

Table 1 Summary statistics

Variable	North				South			
	Mean	SD	Min	Max	Mean	SD	Min	Max
Dependent variable: coverage shares (%, from 2001 to 2010)	(Obs = 256,575 cell year)				(Obs = 42,660)			
Corn	0.275	0.196	0.000	0.983	0.055	0.087	0.000	0.774
Soy	0.209	0.162	0.000	1.000	0.294	0.186	0.000	0.955
Rice	–	–	–	–	0.103	0.133	0.000	0.801
Cotton	–	–	–	–	0.118	0.173	0.000	0.982
Dependent variable: yield (from 1950 to 2013)	(Obs = 14,509 county year for corn, 11,784 for soy)				(Obs = 6965 for corn, 4826 for soy, 1455 for rice, 1131 for cotton)			
Corn (Bu/Acre)	98.975	43.803	0.247	206.630	79.009	39.163	1.464	203.846
Soy (Bu/Acre)	35.816	11.535	0.326	63.576	29.211	8.256	5.000	56.990
Rice (Lb/Acre)	–	–	–	–	5324.411	1102.702	2400.000	8322.223
Cotton (Lb/Acre)	–	–	–	–	603.471	200.773	60.000	1172.727
Soil condition	(Obs = 27,418 cell)				(Obs = 4272)			
Percent clay (%)	23.075	9.046	0.024	57.700	35.601	12.918	2.910	62.900
Percent sand (%)	31.392	22.467	0.059	95.300	18.656	9.463	2.627	84.600
Percent silt (%)	44.501	15.662	0.014	73.600	45.231	13.960	3.530	73.598
Water holding capacity	0.168	0.030	0.000	0.450	0.162	0.025	0.015	0.220
pH	6.309	0.632	0.020	7.700	6.116	0.630	0.638	7.511
Slope	4.603	5.004	0.009	48.000	2.817	3.851	0.137	19.862

Table 1 continued

Variable	North				South			
	Mean	SD	Min	Max	Mean	SD	Min	Max
Electrical conductivity	0.013	0.074	0.000	1.000	0.000	0.000	0.000	0.000
Frost free days	151.034	29.133	0.000	213.750	233.261	37.076	0.000	302.704
Depth to water table	71.321	43.718	0.000	201.000	54.379	22.347	21.000	189.233
Depth to restrictive layer	172.426	48.866	3.300	201.000	185.638	43.649	18.000	201.000
Percent of land in Class 1 (%)	0.005	0.052	0.000	1.000	0.014	0.097	0.000	1.000
Percent of land in Class 2	0.618	0.428	0.000	1.000	0.264	0.362	0.000	1.000
Percent of land in Class 3	0.218	0.343	0.000	1.000	0.445	0.430	0.000	1.000
Percent of land in Class 4	0.049	0.184	0.000	1.000	0.132	0.301	0.000	1.000
Percent of land in Class 5	0.056	0.197	0.000	1.000	0.018	0.111	0.000	1.000
Percent of land in Class 6	0.051	0.189	0.000	1.000	0.019	0.113	0.000	1.000
Percent of land in Class 7	0.002	0.031	0.000	1.000	0.108	0.277	0.000	1.000
Percent of land in Class 8	0.001	0.027	0.000	1.000	0.000	0.000	0.000	0.000

Table 1 continued

Variable	North				South			
	Mean	SD	Min	Max	Mean	SD	Min	Max
Weather variables								
Planting season (April through June from 2002 to 2010)	(Obs = 711,873)				(Obs = 115,164)			
Temperature (daily average, celsius)	15.180	5.038	2.637	27.585	21.153	4.022	11.728	28.932
Precipitation (monthly average, CM)	10.265	3.905	1.450	37.160	11.988	4.082	2.090	28.540
Growing season (April through November from 2001 to 2009)								
Temperature (daily average, celsius)	15.192	6.554	− 2.387	28.918	20.891	5.494	5.763	30.408
Precipitation (monthly average, CM)	9.003	4.146	0.150	33.310	10.525	4.116	0.500	28.540
Climate change scenarios (based on 2009 and 2010 weather)	(Obs = 27,367)				(Obs = 4260)			
A1B								
Planting season (April through June)								
Temperature (change, celsius)	4.078	0.113	3.702	4.235	3.708	0.176	3.362	4.008
Precipitation (change, CM)	1.353	0.282	0.000	2.238	− 0.222	0.607	− 1.191	1.098

Table 1 continued

Variable	North				South			
	Mean	SD	Min	Max	Mean	SD	Min	Max
Growing season (April through November)								
Temperature (change, celsius)	4.078	0.113	3.702	4.235	3.708	0.176	3.362	4.008
Precipitation (change, CM)	0.650	0.102	0.000	0.969	−0.243	0.262	−0.674	0.484
A2								
Planting season (April through June)								
Temperature (change, celsius)	4.735	0.107	4.098	4.894	4.187	0.178	3.826	4.531
Precipitation (change, CM)	1.248	0.466	0.000	2.444	−0.314	0.452	−1.134	0.673
Growing Season (April thourgh November)								
Temperature (change, celsius)	4.735	0.107	4.098	4.894	4.187	0.178	3.826	4.531
Precipitation (change, CM)	0.706	0.184	−0.100	1.176	−0.340	0.191	−0.625	0.237
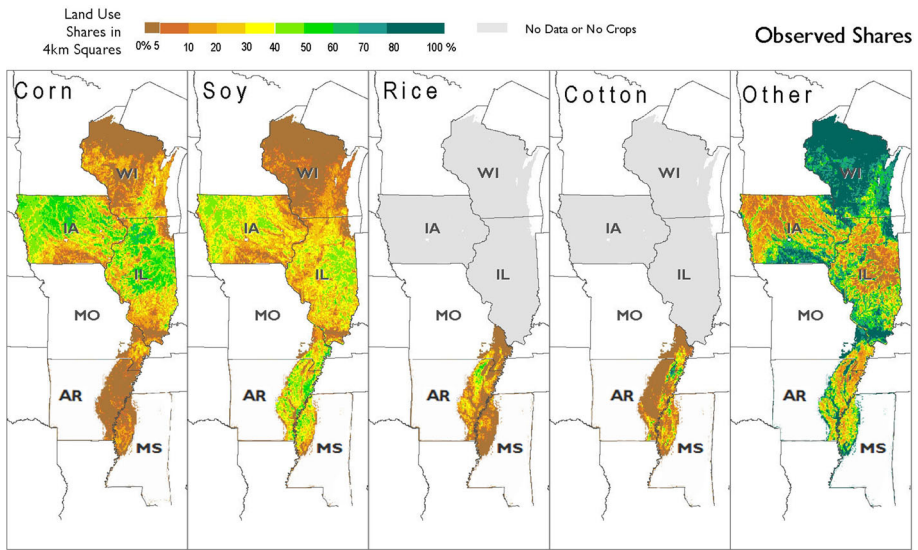
Fig. 1 Observed crop coverage along the Mississippi-Missouri River system. *Notes*: graphs display observed coverage shares for corn, soy, rice, cotton, and other land use, in the six states along the Mississipppi-Missouri river corridor. They are average shares over 2001–2010

2.2 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[4] (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 increase 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 spatial distribution of LCC levels is shown in Fig. 2. Together with Fig. 1, we see that prime agricultural soils are absent in southern Iowa and most parts of Wisconsin 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.

2.3 Weather Variables

For weather data we use PRISM data processed by Schlenker and Roberts (2009) to a 4 km by 4 km spatial resolution, with a daily level of temporal resolution. The dataset includes both

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[4] LCC codes are based on physical measurements only. One reason why we don't reproduce it with our variables is that it is based on the soil series, which is categorical and we don't use. http://www.nrcs.usda.gov/wps/portal/nrcs/detail/national/about/history/?cid=nrcs143_021436.

Fig. 2 Distribution of land capabilty classification (LCC) levels. *Notes*: land capability class (LCC) one is the best soil, which has the fewest limitations. Progressively lower classifications lead to more limited uses for the land. LCC eight means soil conditions are such that agricultural planting is nearly impossible
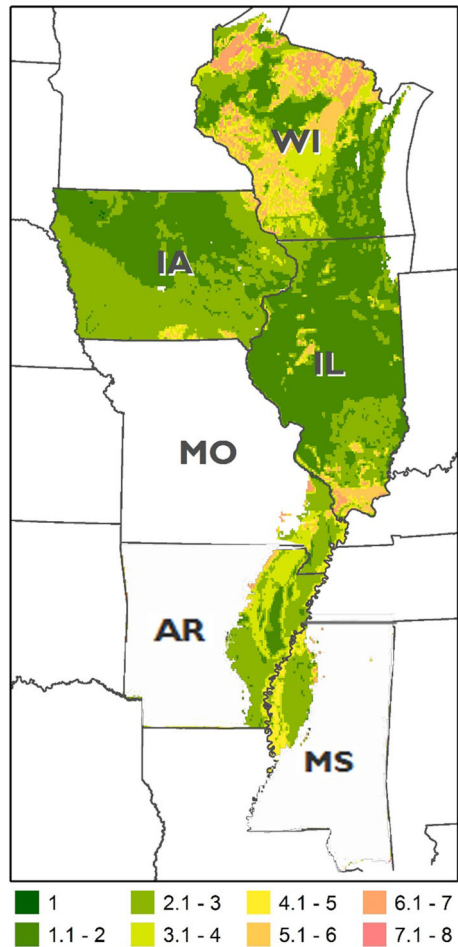
temperature (highs and lows) and precipitation. Two time periods of weather data are used for each crop year. (1) The planting season data are known by farmers before they actually plant. A cold wet spring, for instance, would delay planting and make a shorter season crop more desirable than a longer 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.

Figure 3 shows the observed weather condition in the planting season (from April to June)[5] from 2002 to 2010 and the growing seasons (from April to November) from 2001 to

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[5] Planting season and growing season vary across crops and regions. 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 (included) and harvest season (included).

2009.[6] The observed temperatures are warmer in the south and the precipitation levels are larger. Monthly average temperature in the growing season ranges from 9 to 24 °C from the top of Wisconsin to the bottom of our study areas in Mississippi, a distance of 1600 km. Monthly average rainfall in a growing season is also variable across this landscape with a high of 17 cm and a low of 7 cm, highest in the southeast and lowest in the north.

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 and 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.

2.4 Climate Change Scenarios

Climate change scenarios are taken from Climate Wizard.[7] 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 (2080s). The comparison baseline is the average temperature and precipitation between 1961 and 1990.

Figure 4 shows the two climate change scenarios. The A1B model predicts a 4.1 °C increase in temperature on average in the north, and a 3.7 °C increase in the south. The A1B model also predicts a 1.35 cm increase in monthly precipitation in a planting season in the north, and a 0.65 increase in a growing season; while in the south the A1B model predicts a 0.22 cm decrease and a 0.243 cm decrease in a planting season and a growing season respectively. The A2 model predicts similar warming and drying pattern, but 0.6 °C warmer and 0.1 cm drier than A1B's prediction.

Future degree days are processed in two steps: 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.

2.5 Yield Data

For the yield equations, the county-level data (1950–2010) of non-irrigated planted area and production on non-irrigated land is from USDA. Yield is defined as non-irrigated production divided by non-irrigated planted area for corn, soy, and cotton. For rice, non-irrigated planted area and production are not reported, because rice has to be irrigated. So for rice, yield is defined as total production divided by total planted area.

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[6] We have ten year's land use, soil and weather information from 2001 to 2010. Growing season weather enters regressions as a lag variable. For 2001, there is no lagged land use data or lagged weather data, so 2001 is dropped from the regressions. Regressions for 2002 to 2010 use the growing season weather from 2001 to 2009.
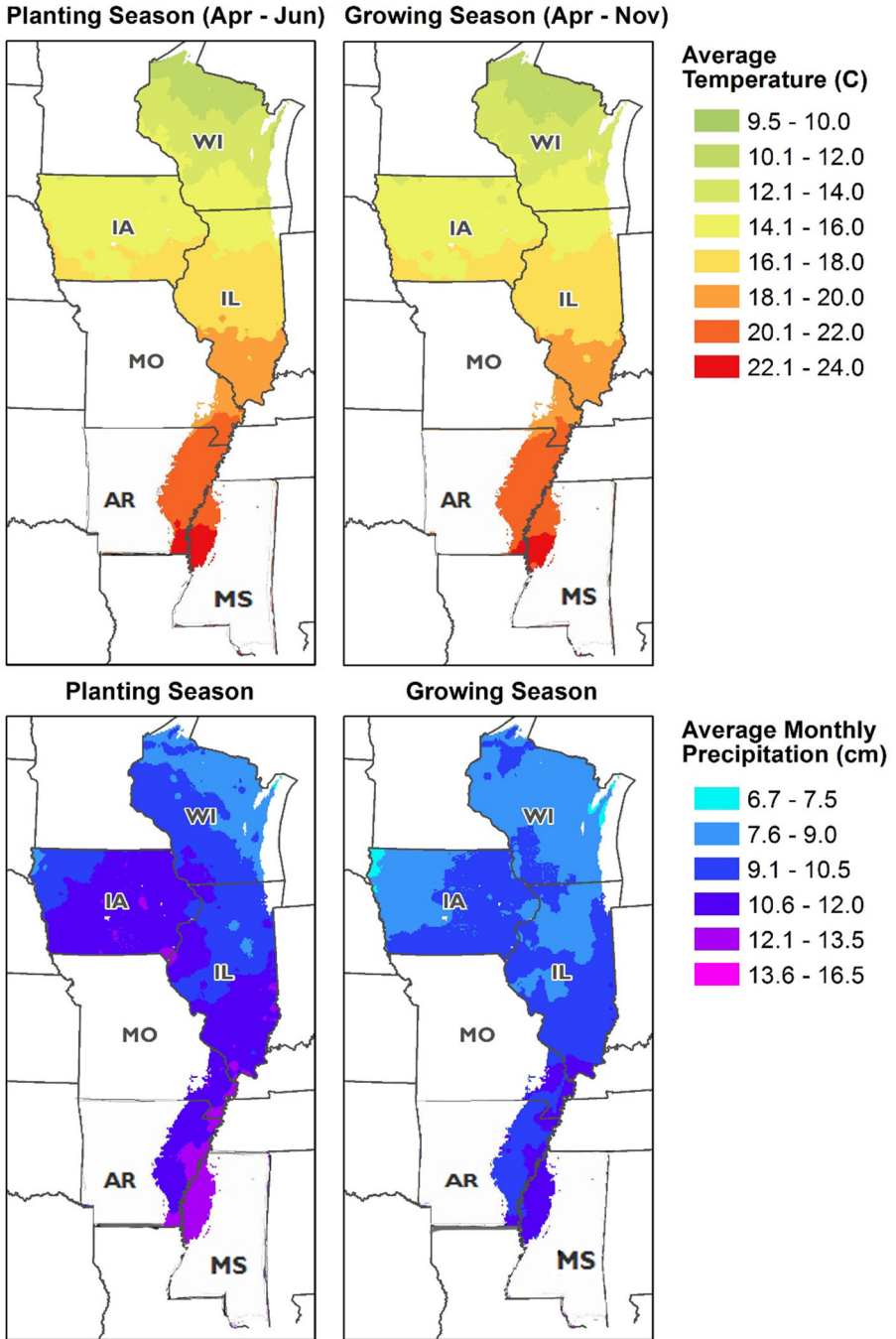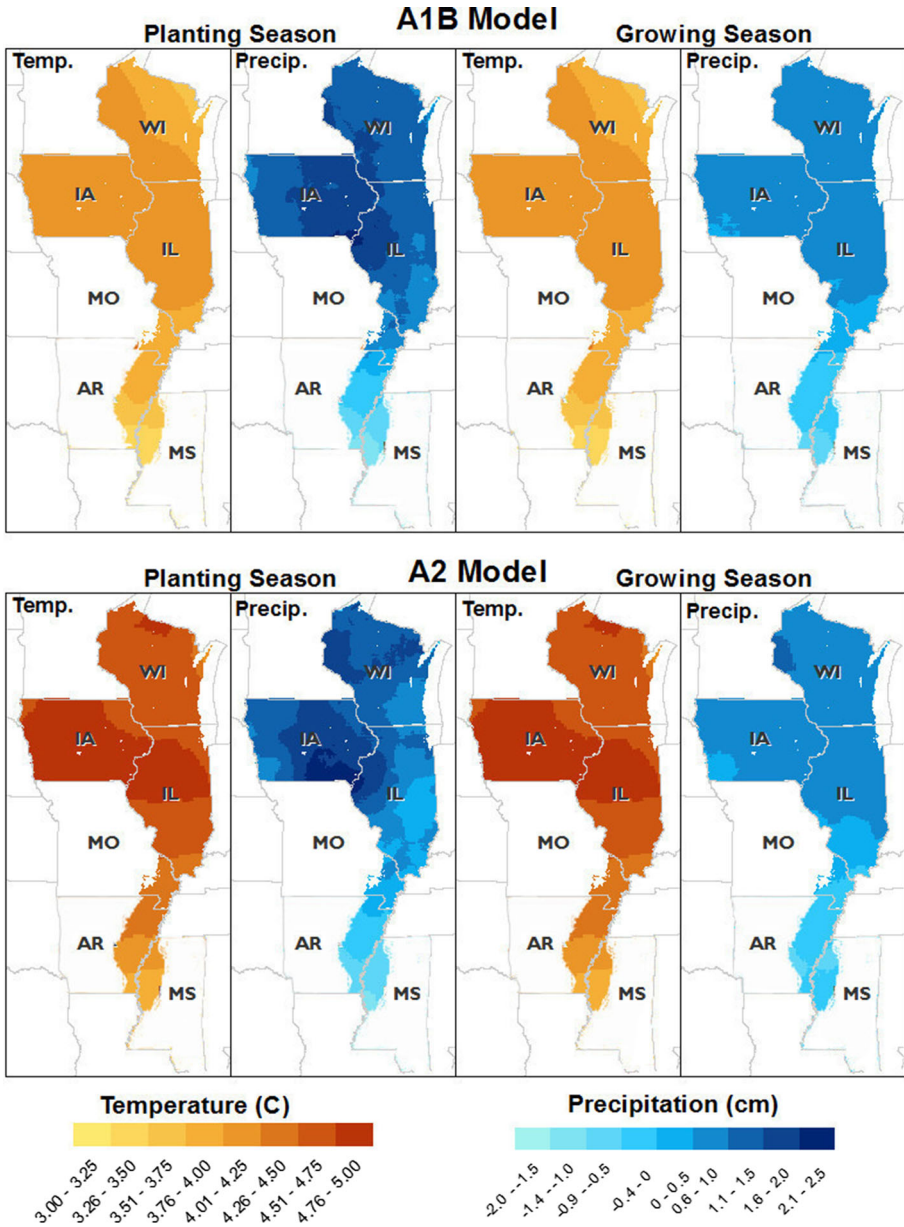
[7] Source: http://www.climatewizard.org/.

Fig. 3 Observed weather conditions

Fig. 4 Climate change scenarios. *Notes*: distribution is over 4 km squares for temperature change to 2080. Annual temperature change is from http://www.climatewizard.org/. Since it's annual, the temperature changes in planting season and growing season are the same. Annual precipitation percent change is from the same source. We convert percent change to change by multiplying the observed precipitations in 2010 for the months in planting season and 2009 for the months in growing season

3 The Econometric System and Regression Results

In this section, we set up the econometric systems for crop coverage response and yield response to weather and soil characteristics. We also present the regression results, based on which we do the simulation under climate change scenarios in the next section.

3.1 Crop Coverage Response Equation

Within each of our 4 km 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 profit will be chosen. As a result, the fraction of the crop chosen in a grid cell will be a proportion type model.

$$S_{int} = \phi\big(\big(\boldsymbol{\beta}'_{\mathbf{1}} X_{\mathbf{1}nt} + d_{1nt}\big), \ldots, \big(\boldsymbol{\beta}'_{\mathbf{M}} X_{\mathbf{M}nt} + d_{Mnt}\big)\big) \tag{1}$$

where X_{int} is a vector of determinate factors of profit 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): $log(S_{int}) - log(S_{0nt}) = \boldsymbol{\beta}'_i X_{int} + d_{int}$. To deal with the fact that many plots do not have a certain crop (i.e., many S_{int} are zeros), we instead use a ratio transformation and we get

$$\frac{S_{int}}{S_{0nt}} = \boldsymbol{\beta}'_i X_{int} + d_{int} \tag{2}$$

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}

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

Substituting (3) into (2), we get

$$S_{int} = \frac{\boldsymbol{\beta}'_i X_{int} + d_{int}}{1 + \sum_{j=1}^{M} \big(\boldsymbol{\beta}'_j X_{jnt} + d_{jnt}\big)} \tag{4}$$

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

Because the scale of this study encompasses more than a 1000 km, some conditions that change across the landscape may not be accounted in our variables. 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 of shares 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,[8] a county has 8 neighbors on average and each county has about 100 4 km 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. 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,[9] we include as explanatory variables lagged crop share, lagged substitute crop shares, weather in the current planting season and the last growing season, and soil conditions. 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:

$$\frac{S_{int}}{S_{0nt}} = \alpha_i + \beta_i S_{int-1} + \gamma_i' SS_{int-1} + \varphi_i' Soil_n + \theta_{1i}' GDD_{nt-1} + \theta_{2i}' PDD_{nt}$$
$$+ \theta_{3i}' GP_{nt-1} + \theta_{4i}' PP_{nt} + \theta_{5i}' PreDD_{nt-1} + \mu_t + \varepsilon_{int} \tag{5}$$

where S_{int} is the fraction of land in year t that was allocated to crop i, SS_{int-1} is a vector of the coverage shares of crop i's substitutes planted at grid cell n in year $t-1$, and soy and corn are substitutes in the north and all four crops are substitutes in the south; $Soil_n$ is a vector of soil conditions at grid cell n, including percent clay, percent sand, percent silt, water holding capacity, pH, slope, electrical conductivity, frost-free days, depth to water table, and depth to restrictive layer, as well as LCC (Land Classification Code); GDD_{nt-1} is a vector of degree days by month in the last growing season (April through November in year $t-1$), and the data are binned at 10, 15, 20, 25, 29, 30, and 32 °C, where 10 °C is degree days $\geq$ 10 °C, etc.; PDD_{nt} is a vector of degree days by month in the current planting season (April through June in year t), and the data are binned at 10 and 15 °C; GP_{nt-1} is a vector of precipitation by month in the last growing season; PP_{nt} is a vector of precipitation by month in the current planting season; $PreDD_{nt-1}$ is a vector of interactions of the inverse of precipitation and the degree days at 32 °C and above in the same month, and all months in the last growing season are included. μ_t and ε_{int} are the year fixed effect and the error term respectively. In sum, Eq. (5) describes the coverage ratio $\left(\frac{S_{int}}{S_{0nt}}\right)$ as a function of lagged coverage shares of the crop of interest (S_{int-1}) and its substitutes (S_{int-1}), soil characteristics ($Soil_n$), weather conditions ($GDD_{nt-1}, PDD_{nt}, GP_{nt-1}, PP_{nt}, PreDD_{nt-1}$), and common shocks that change along years (μ_t).

We run separate land use regression for each crop and each county. In sum, we have 766 sets of estimates (312 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. As shown

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[8] We also tried 130 km to define neighbors in the regressions. It turns out to have smaller maximum likelihood and large minimum Chi square. So we choose 70 km for the regressions.

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

Table 2 F − tests for soil, precipitation and temperature

	Corn (%)	Soy (%)	Rice (%)	Cotton (%)
Regressions with 1% significance level				
Soil	92	88	69	71
Precipitation	76	76	42	54
Temperature	89	87	79	93
Regressions with 5% significance level				
Soil	93	89	75	83
Precipitation	83	84	59	69
Temperature	92	90	79	93
Regressions with 10% significance level				
Soil	93	91	82	84
Precipitation	86	87	65	76
Temperature	93	90	79	94
Number of regressions in total	312	312	71	71

Separate regressions are run for each crop and each county. Corn and Soy regressions are for counties in the six states along the Mississippi-Missouri river corridor (312 counties), while rice and cotton are for counties in the three southern states (71 states)

in Table 2, soil and temperature are significant at the 1% significance level in 69 to 93% of the regressions. Precipitation is significant at the 1% significance level in 42 to 76% of the regressions. These results show that soil, precipitation and temperature are all important determinants of crop coverage.

"Appendix A" explores how a 1-degree change in temperature and a 1-cm change in precipitation affect crop coverage in both short run and long run. The results indicate that rice and cotton in the south spread toward the north, consistent with the fact that rice and cotton are heat-requiring crops; and farmers make different crop adaptations, even when facing same level of climate change, and the reason is soil. The results also indicate that it takes time for farmers to fully adjust crop coverage to weather shocks and 5 years is long enough for the farmers to complete the adaptation. Therefore, in the simulation for the climate change, we consider crop coverage response in 5 years.

3.2 Yield Equation

Yield is estimated at the county level as a function of weather, soil, and time trends. The estimation differs from Schlenker and Roberts (2009) in the use of the interaction term for hot and dry weather and in replacing the county fixed effects with soil variables. It leads to the following yield equation:

$$Y_{ict} = \alpha_i + \boldsymbol{\varphi}'_i \, \boldsymbol{Soil}_c + \boldsymbol{\theta}'_{1i} \, \boldsymbol{DD}_{ct} + \theta_{2i} P_{ct} + \theta_{3i} (P_{ct})^2 + \theta_{4i} \, PreDD_{ct} + \boldsymbol{\theta}'_{5i} \, \boldsymbol{QT} + \varepsilon_{ict} \quad (6)$$

where Y_{ict} is yield of crop i per acre (abbreviated as yield) in county c in year t; $\boldsymbol{Soil}_c$ is a vector of soil conditions in county c, weighted by crop acre over grid cells; $\boldsymbol{DD}_{ct}$ is a vector of degree days in county c in year t, weighted by crop acre over grid cells, and the data are binned at 0, 5, 10, 15, 20, 25, 29, 30, and 32 °C, where 10 °C is degree days > 10 and ≤ 15 °C;

P_{ct} is precipitation in county c in year t; $PreDD_{ct}$ is interaction of the inverse of precipitation and the degree days at 32 °C and above, by year; QT is a vector of linear and quadratic time trends by state; ε_{ict} is the error term. In sum, Eq. (6) describes crop yield (Y_{ict}) as a function of soil characteristics ($Soil_c$), weather conditions (DD_{ct}, P_{ct}, $(P_{ct})^2$, $PreDD_{ct}$), and time trends (QT). Precipitation and its quadratic form are both in the model because of the non-linear relationship between yield and precipitation: When precipitation is low, additional rain or snow relives the drought and therefore increase yield; while when precipitation is high, additional rain or snow may harm the yield (Schlenker and Roberts 2009; Chen et al. 2016).

The individual coefficients are generally significant at the 95% level in the corn and soy equations and more sporadically significant for rice and cotton, presumably because of the much smaller sample size (about 20,000 county years for corn and soy, while only about 2000 county years for rice and cotton). The LCC variables for corn, soy, and cotton show a large advantage to better soils. For cotton in particular, LCC 2 yields less than half of LCC 1. In contrast, rice yields best in the lower rated soils, presumably because very wet soil is good for rice and deleterious for the other crops and so has a low LCC rating. An F-test shows that the soil variables are jointly significant in all crops.

The effect of extreme temperature on yield in this model comes from both the direct effect of the high temperature variable (degree days at 32 °C and above) and from the interaction term (degree days at 32 °C and above times the inverse of precipitation). The latter term accounts for the effect of hot and dry as opposed to just hot weather. The effects of increasing the degree days in the top temperature bin and the effect of increasing precipitation are given in Table 3. Starting with precipitation, the effect of another centimeter of water when there has been average precipitation is near zero for all crops. However, when there is another centimeter of water at minimum precipitation, yield increases by 5.8% for corn, 5.0% for soy, and 4.2% for cotton. Rice is usually irrigated and hence the effect is small and negative. The effects of another degree day in the top temperature bin, at average precipitation, are negative for all crops and strongest in corn with a 1% yield loss. However, when there is another degree day at minimum precipitation, the loss is 1.8% for corn, 1% for soy, 1.4% for cotton, and a slight gain for rice. These results on yield are similar to Schlenker and Roberts (2009) in that very hot weather is deleterious to crop yield.

The detailed regression results for the yield equations are available in "Appendix B".

4 Crop Coverage Responses to Climate Change

Based on the estimation above, we simulate crop coverage response to the climate change A1B scenario. Figure 5 depicts the changes in the geographic distribution of crop coverage. The comparison is the A1B scenario for the late century (2080s) to the actual coverage in 2010.

In the north, the average change for corn is a loss of 9.4 percentage points, starting from a base of 27.5% of the land being devoted to corn. In the figure, corn coverage decreases the most in northern and central Iowa and Illinois near the Mississippi River. These are the places with the highest coverage in corn in the baseline. These negative changes are partially offset by increases in coverage in northeastern Wisconsin. Given the sensitivity of corn to high heat, a hotter climate would be expected to move the corn growing area northward, as shown on the map. For soy, the loss in crop coverage in the A1B scenario is 6.3 percentage points, starting from a base of 20.9% coverage. The pattern follows that of corn; the ratio of

Table 3 Marginal effects of precipitation and temperature on yield

	Corn	Soy	Rice	Cotton
Precipitation at average precipitation	0.0002	0.0032***	− 0.0033***	0.0006
chi2	0.0300	62.8100	52.9600	0.1700
Precipitation at minimum precipitation	0.0583***	0.0496***	− 0.0250***	0.0422**
chi2	25.9500	117.9600	17.3200	4.3900
DDay32 at average precipitation	− 0.0101***	− 0.0033***	− 0.0015***	− 0.0067***
chi2	137.7900	24.0900	9.3600	16.2700
DDay32 at minimum precipitation	− 0.0184***	− 0.0107***	0.0026***	− 0.0142***
chi2	96.0300	170.3500	7.6900	17.1000

***, **,* represent 1%, 5%, 10% significance level, respectively

The reported numbers are partial derivatives of natural logarithm of yield on precipitation and temperature. Therefore, a reported number, for example a, is interpreted as 100a percent change of yield due to one unit change of precipitation or temperature
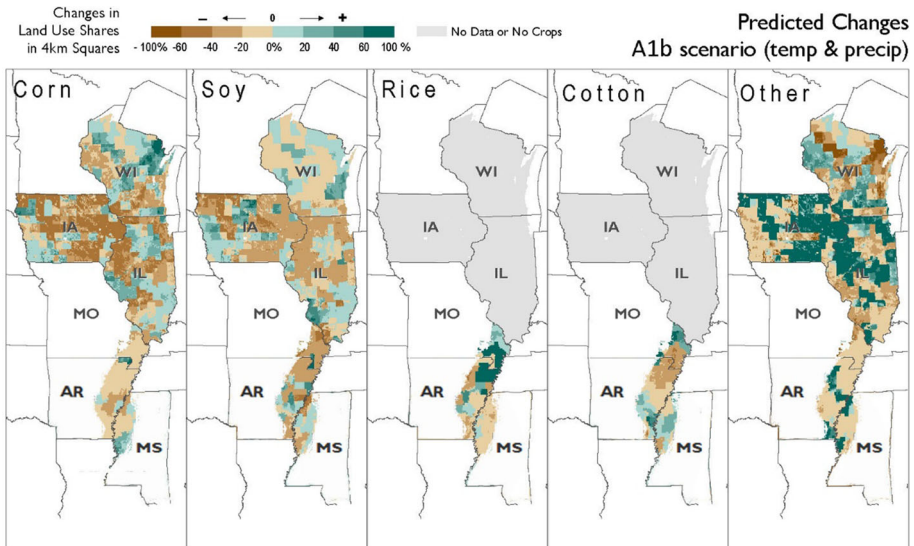
Fig. 5 Predicted crop coverage changes under the A1B scenario. *Notes*: a 20% change reported here means corn (for example) share increases from *a* to *a* + 0.2

soybeans to corn is close to three-quarters in the baseline and remains close to three-quarters in the A1B scenario in the north.

In the south, the change in climate removes most of the remaining corn from the landscape. Corn loses 4.5 percentage points from a base of 5.5% coverage. Soy is more suited to the hot and wet climate. It loses 14.9 percentage points from a base of 29.4% coverage. Rice
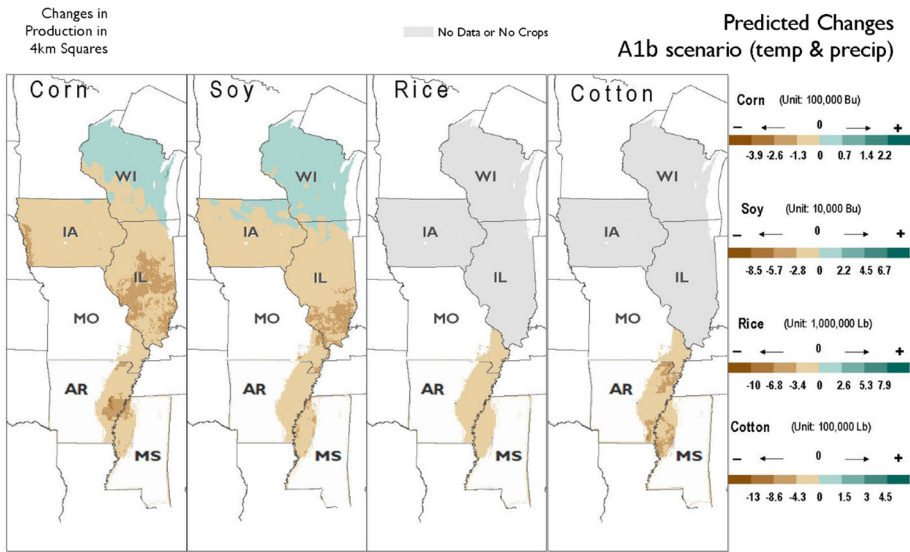
Fig. 6 Crop production loss with coverage fixed under the A1B scenario

and cotton coverage both increase in response to climate change. Rice gains 5.2 percentage points in coverage from a base of 10.3%. Cotton gains a half percentage point from a base of 11.8%. In terms of geographical distribution, the rice area gained is to the north of the cotton area gained. The likely reason that rice is positively influenced by the changed climate in that it is irrigated and not susceptible to damage in hot, dry weather.

"Appendix C" presents the same analysis for the climate change A2 and for temperature change only. We see that the A2 scenario has very similar effects on crop shares. Through comparing temperature change only to both temperature and precipitation changes, we conclude that for the Mississippi-Missouri river system, the major concern about climate change is warming, instead of drying.

5 Crop Production Losses to Climate Change with Crop Coverage Fixed

Figure 6 depicts production losses under the A1B scenario. These losses are predicted holding crop coverage fixed, so they show only the effect of lower yields on production. While Wisconsin gains corn and soy production, all other areas lose. Soy production is positively affected over a larger area compared to corn. The positive effect on soy production includes southwestern Wisconsin and northeastern Iowa. The production losses to both corn and soy are generally greater farther south. As shown in Table 4, the change in total production, holding crop coverage constant, is 20.3% for corn and 6.6% for soy in the north, while these numbers are 83.1% for corn and 58.9% for soy in the south. For rice and cotton in the south, there are production losses for both crops: 18.2% for rice and 59.0% for soy. In sum, only Wisconsin becomes a better climate for growing the major crops.

Table 4 Crop production loses through yield and coverage effects

	Corn	Soy	Rice	Cotton
North				
Yield effect (%)	− 20.288	− 6.574	–	–
Coverage plus yield effect (%)	− 42.406	− 32.399	–	–
Base production in 2010	4598.476	1043.889	–	–
South				
Yield effect (%)	− 83.105	− 58.891	− 18.167	− 58.990
Coverage plus yield effect (%)	− 91.274	− 73.848	24.439	− 55.746
Base production in 2010	509.234	393.818	15,007.600	1074.250
Total change in production				
Yield effect	− 1356.150	− 300.548	− 2726.387	− 633.704
Coverage plus yield effect	− 2414.815	− 629.031	3667.674	− 598.849

The reported production is in million bushels for corn and soy and million pounds for rice and cotton

6 Crop Production Loss to Climate Change, Considering Both Yield Effect and Coverage Response

In this section, we answer the central question of the paper: what the production changes will be when farmers adapt to climate change by changing the land use for crops. In these estimates, both crop coverage and yield respond to climate change. These changes can be seen as a shift in the supply curve; prices and other conditions are held fixed. Table 4 and Fig. 7 provide the answer to this question.

Starting in the north, for corn (the first column of the table), 20.3% of production is lost due to the yield effect, and it is more than doubled when yield and crop coverage are both considered. For soybeans, loss from the yield and crop coverage effects together is five times the yield effect alone, despite soy suffering only minor yield effects. The use of the soy–corn rotation and the substitution away from corn is what leads to large coverage responses in soy in the north. Land uses that will increase as corn usage decreases include the major uses for 2010 other than corn and soy. The largest of these uses are grass, forest, wetlands, alfalfa and other hay. There are no other food crops with even 100,000 acres at present.

In the south, the coverage effect reinforces the production losses from the yield effect for corn and soybeans. In the case of corn, the A1B scenario nearly eliminates corn from the landscape; the production change through both effects is 1.1 times the yield effect. Soy is grown independently from corn in the south, unlike the north; both effects together reduce production by 1.3 times the yield effect alone. Because rice gains considerable coverage, it goes from a production loss when considering only yield loss to a production gain when considering both yield and coverage response. For cotton, the increase in coverage slightly mitigates the yield loss. Thus, adaptation by changing the crop landscape within the existing crop collection, particularly the increase in rice and cotton, is noticeable in affecting production changes when facing climate change.
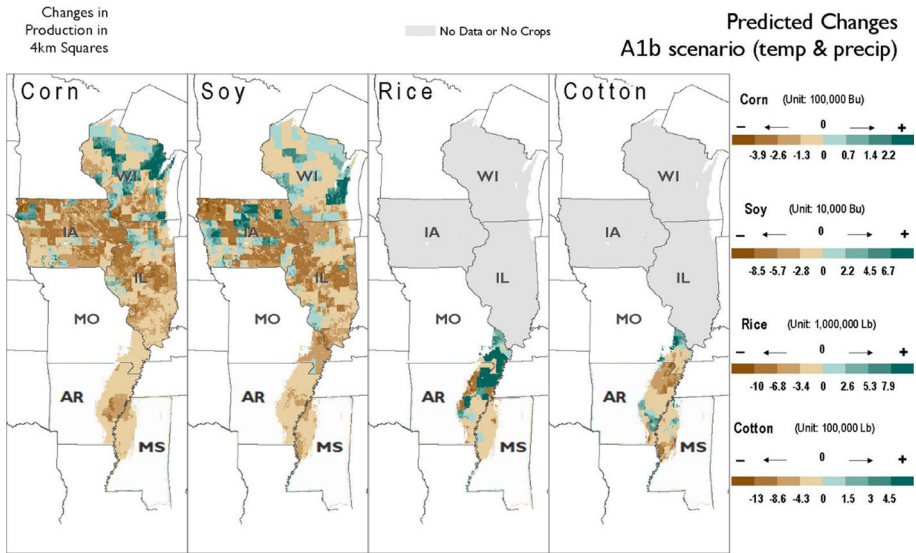
Fig. 7 Crop production loss with both yield effect and coverage response under the A1B scenario

7 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 4 km grid cell. We also consider the soil conditions at the 4 km grid level. Based on the estimates of crop choices, we predict future crop share distribution under several climate change scenarios. We find that adaptation by changing crop choice offsets the production losses caused by lower yields for rice and cotton. For the main food crops, corn and soybeans, however these negative effects are reinforced.

In this paper we have dealt with changes in land use caused by climate. Government programs that are themselves partially a reaction to climate change, like the US Ethanol program, do by themselves induce land use change (Searchinger et al. 2008) For ethanol, these indirect land use changes partially offset the direct land use change from a hotter climate.

While this study shows that, ceteris paribus, the loss in food crop production from corn and soybeans will be exacerbated by substitution away from these crops to other uses, the underlying data on land use does not provide an obvious alternative. In the data pasture and minor crops are lumped together and there are no other food crops that use a substantial part of the landscape. With production losses as big as forecasted in this study, equilibration of the crop supply–demand system would require large changes in price or crops novel to this landscape. Price increases would draw land back into major crop production and might also increase yield through more input (mostly more fertilizer) and technology improvement. Should the equilibration be through price increases, then the quantity of food demanded, which would equal the quantity produced from this landscape, will fall. It is only through the introduction of crops new to this landscape that are more suited to the hot climate that food production can be restored to its current level.

Appendix A: Crop Coverage Response to Unit Change in Weather

Table 5 and Fig. 8 summarize the crop coverage share changes for two scenarios in both short run and long run. In one scenario, daily temperature increases by one degree for all months in 2009 and 2010. In the other scenario, monthly precipitation decreases by 1 cm in all the months, and temperature increases as above. Table 5 shows that in the short run, 1-degree warming decreases corn and soy shares. With 1-degree warming, 1.6% less land (a 5% decrease) in the north and 4.3% less land (a 77% decrease) in the south is covered by corn; 1.2% less land (a 6% decrease) in the north and 0.3% less land (a 1% decrease) in the south is covered by soy. One degree warming increases rice share by 0.042 (a 40% increase in the south) and cotton share by 0.072 (a 61% increase in the south). It suggests that warming favors rice and cotton. Looking at corn and soy, dry warming decreases coverage

Table 5 Crop coverage changes with unit change in temperature and precipitation

	Corn	Soy	Rice	Cotton	Other
North					
Unit changes					
Short-run					
Temperature increase only	−0.0159	−0.0116	–	–	0.0276
Temperature increase and precipitation decrease	−0.0179	−0.0139	–	–	0.0318
Long-run					
Temperature increase only	−0.0455	−0.0340	–	–	0.0795
Temperature increase and precipitation decrease	−0.0496	−0.0390	–	–	0.0886
Average shares	0.2920	0.1969	–	–	0.5111
No. of obs.	27,365	27,365	27,365	27,365	27,365
South					
Unit changes					
Short-run					
Temperature increase only	−0.0428	−0.0028	0.0415	0.0718	−0.0677
Temperature increase and precipitation decrease	−0.0398	−0.0057	0.0197	0.0733	−0.0475
Long-run					
Temperature increase only	−0.0430	−0.0117	0.0294	0.0649	−0.0395
Temperature increase and precipitation decrease	−0.0392	−0.0171	0.0061	0.0688	−0.0185
Average shares	0.0238	0.1025	0.0351	0.0204	0.8737
No. of obs.	4260	4260	4260	4260	4260

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
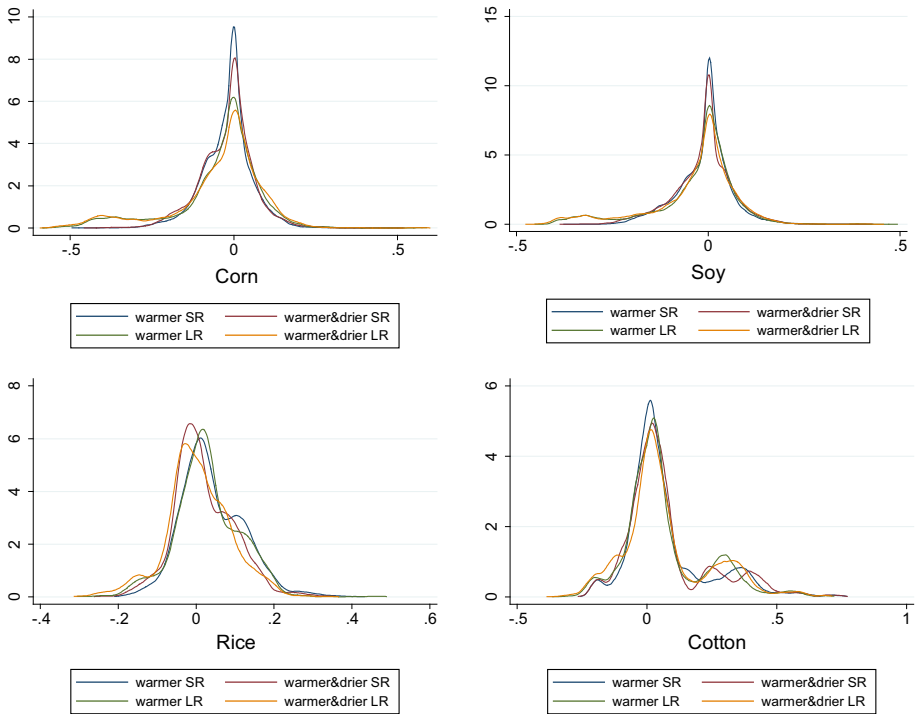
Fig. 8 Distribution of crop coverage changes with unit change in temperature and precipitation. x-axes are crop share changes. For example, 0.2 in the first panel means corn share increases from *a* to *a* + 0.2. SR stands for short run, which is the year when the weather change happens. LR stands for long run, which is 5 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 little rice and cotton in the north

more than warming alone in the north, but this pattern does not hold for corn in the south, which is wetter. Figure 8 shows that although the averages in share change are different in the scenarios with and without a change in precipitation, the difference is small and the share change patterns are similar. This indicates that a 1 cm change in precipitation is not large enough to have significant effects on crop adaptation.

Table 5 and Fig. 8 also show that the share changes of corn and soy in the long run are larger on average and the distributions have fatter tails. This indicates that it takes time for farmers to fully adjust crop coverage to weather shocks. The share changes of rice, cotton, and other land use in the long run are larger. We also check the crop share changes in 2020 and find that they are very similar to those in 2015. This suggests that 5 years is long enough for the farmers to complete the adaptation.

To illustrate how crop adaptation varies across landscapes, Fig. 9 maps out the long-run share changes for the 1-degree-warmer scenario and the 1-degree-warmer-and-1-centimeter-drier scenario, respectively. The findings are as follows. First, the two scenarios have similar land cover shifting patterns, which confirms the findings in Fig. 8. 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, mainly rice and cotton, take land from minor crops and other uses in the south. This suggests that a 1-degree increase from current temperature is beneficial to rice and cotton. This is consistent with the fact that rice and cotton
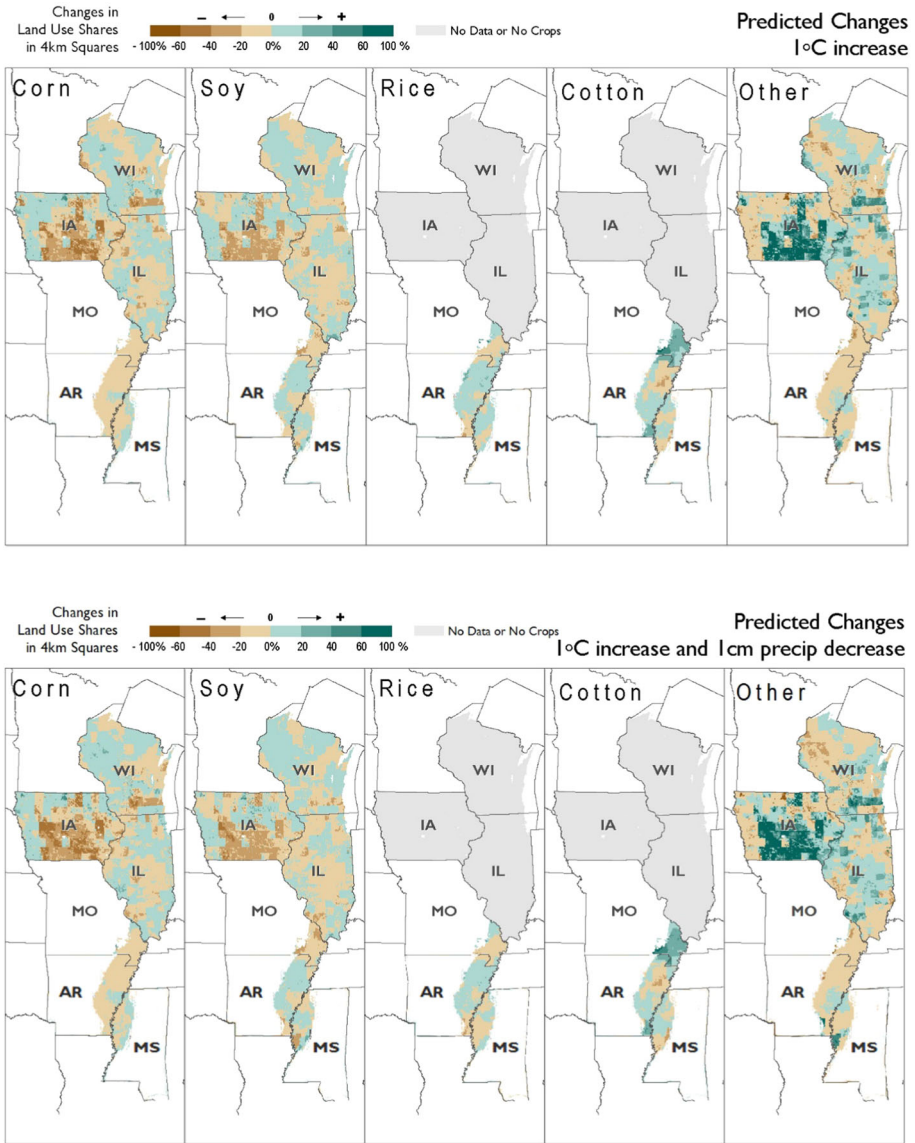
Fig. 9 Crop coverage changes with unit change in weather. *Notes* A 20% change reported here means corn (for example) share increases from *a* to *a* + 0.2

are heat-requiring crops. Last, but not at least, farmers make different crop adaptations, even when facing same level of climate change, and the reason is soil.

Appendix B: Full Regression Results of County Yield Equations by Crop

See Table 6.

Table 6 County yield equations by crop

| Variables	(1) Corn	(2) Soy	(3) Rice	(4) Cotton
Degree days between 0 and 5 °C	0.0035*** (0.0007)	0.0022*** (0.0005)	− 0.0063* (0.0033)	− 0.0276*** (0.0062)
Degree days between 5 and 10 °C	− 0.0032*** (0.0007)	− 0.0053*** (0.0004)	− 0.0025* (0.0014)	0.0096*** (0.0033)
Degree days between 10 and 15 °C	0.0067*** (0.0006)	0.0063*** (0.0004)	0.0023*** (0.0007)	− 0.0030* (0.0018)
Degree days between 15 and 20 °C	− 0.0035*** (0.0004)	− 0.0022*** (0.0003)	0.0011*** (0.0004)	0.0011 (0.0012)
Degree days between 20 and 25 °C	0.0011*** (0.0004)	0.0007*** (0.0003)	− 0.0009* (0.0005)	− 0.0003 (0.0011)
Degree days between 25 and 29 °C	0.0056*** (0.0008)	0.0008 (0.0006)	− 0.0015 (0.0010)	0.0022 (0.0026)
Degree days between 29 and 30 °C	− 0.0420*** (0.0050)	0.0074* (0.0040)	0.0095* (0.0052)	0.0289* (0.0153)
Degree days between 30 and 32 °C	0.0082*** (0.0025)	− 0.0104*** (0.0021)	− 0.0023 (0.0021)	− 0.0154** (0.0063)
Degree days above 32 °C	− 0.0065*** (0.0015)	− 0.0002 (0.0009)	− 0.0032*** (0.0009)	− 0.0035 (0.0029)
Degree days above 32 °C * precipitation	− 0.2471*** (0.0613)	− 0.2182*** (0.0248)	0.1204*** (0.0349)	− 0.2222* (0.1168)
Precipitation	0.0161*** (0.0013)	0.0103*** (0.0008)	− 0.0017 (0.0018)	− 0.0003 (0.0049)
Precipitation square	− 0.0001*** (0.0000)	− 0.0001*** (0.0000)	0.0000 (0.0000)	− 0.0000 (0.0000)
Slope	0.0012 (0.0013)	0.0078*** (0.0009)	0.0069 (0.0064)	0.0281*** (0.0079)
Frost free days	0.0017*** (0.0001)	− 0.0002** (0.0001)	− 0.0001 (0.0003)	− 0.0001 (0.0002)
Electrical conductivity	− 0.2124*** (0.0357)	− 0.2359*** (0.0322)	0.3799 (2.0852)	− 13.3958*** (4.7769)
pH	0.1917*** (0.0105)	0.1063*** (0.0070)	0.0639** (0.0259)	0.0133 (0.0369)
Organic matter	− 0.0470*** (0.0028)	− 0.0161*** (0.0017)	− 0.2158*** (0.0302)	− 0.1693*** (0.0374)
Percent clay (%)	− 0.0396*** (0.0043)	− 0.0017 (0.0028)	− 0.0093** (0.0047)	− 0.0136 (0.0122)
Percent sand (%)	− 0.0350*** (0.0044)	− 0.0025 (0.0029)	− 0.0061 (0.0046)	− 0.0417*** (0.0117)
Percent silt (%)	− 0.0385*** (0.0044)	− 0.0045 (0.0029)	− 0.0027 (0.0046)	− 0.0295*** (0.0114)
Water holding capacity	6.3625*** (0.2312)	3.1518*** (0.1749)	0.7896 (0.5896)	1.3035 (1.0746)
Depth to restrictive layer	0.0007*** (0.0001)	0.0000 (0.0001)	0.0004* (0.0003)	0.0018*** (0.0004)

Table 6 continued

Variables	(1) Corn	(2) Soy	(3) Rice	(4) Cotton
Depth to water table	0.0022*** (0.0001)	0.0006*** (0.0001)	− 0.0001 (0.0005)	0.0032*** (0.0010)
Percent of land class 1	0.3630*** (0.0549)	0.2422*** (0.0466)	− 0.0977 (0.1158)	0.9171*** (0.2055)
Percent of land class 2	0.1929*** (0.0279)	0.2051*** (0.0204)	0.2368*** (0.0883)	0.3848*** (0.1249)
Percent of land class 3	0.0950*** (0.0251)	0.1089*** (0.0188)	0.2522*** (0.0835)	0.0792 (0.1179)
Percent of land class 4	0.2969*** (0.0344)	0.1110*** (0.0252)	0.1646** (0.0815)	0.4929*** (0.1093)
Percent of land class 5	0.1142** (0.0530)	0.3850*** (0.0395)	0.2743*** (0.0805)	0.1906 (0.1354)
Percent of land class 6	0.0562* (0.0292)	− 0.0511** (0.0217)	0.2542*** (0.0719)	− 0.1460 (0.1194)
Time trend for AR	− 0.0044*** (0.0013)	0.0312*** (0.0018)	0.0015 (0.0021)	0.0019 (0.0059)
Time trend for IL	0.0365*** (0.0008)	0.0473*** (0.0011)		
Time trend for IA	0.0491*** (0.0009)	0.0523*** (0.0011)		
Time trend for MS	− 0.0175*** (0.0012)	0.0229*** (0.0012)	− 0.0001 (0.0023)	0.0152*** (0.0058)
Time trend for MO	0.0314*** (0.0009)	0.0430*** (0.0011)	− 0.0062*** (0.0023)	
Time trend for WI	0.0311*** (0.0014)	0.0474*** (0.0015)		
Time trend square for AR	0.0005*** (0.0000)	− 0.0003*** (0.0000)	0.0001*** (0.0000)	0.0002*** (0.0001)
Time trend square for IL	− 0.0003*** (0.0000)	− 0.0004*** (0.0000)		
Time trend square for IA	− 0.0004*** (0.0000)	− 0.0005*** (0.0000)		
Time trend square for MS	0.0007*** (0.0000)	− 0.0001*** (0.0000)	0.0002*** (0.0000)	− 0.0000 (0.0001)
Time trend square for MO	− 0.0002*** (0.0000)	− 0.0004*** (0.0000)	0.0003*** (0.0000)	
Time trend square for WI	− 0.0001*** (0.0000)	− 0.0004*** (0.0000)		
Constant	0.0811 (0.5938)	− 0.2476 (0.3810)	14.0369*** (2.2698)	25.2861*** (4.1823)
Observations	24,628	18,361	2068	2399
R-squared	0.7436	0.7465	0.7705	0.5790

***, **,* represent 1%, 5%, 10% significance level, respectively

Appendix C: Predicted Crop Coverage Changes Under the A2 Scenario

Figures 10 displays the spatial variations of crop adaptation under A2 model considering both temperature and precipitation changes. It is similar to the crop adaptation under A1B model, shown in Fig. 5 in the main text. The figures show that in the face of climate change, farmers, in general, will grow less corn and soy, more rice and cotton, and shift rice and cotton towards north.

Figure 11 depicts the distributions of predicted crop share changes under climate change scenarios. Compared to Fig. 8, Fig. 11 has wider distributions, which is expected because the A1B and A2 scenarios have larger increases in temperature than a one-unit increase. It also shows that the four climate change scenarios lead to 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.
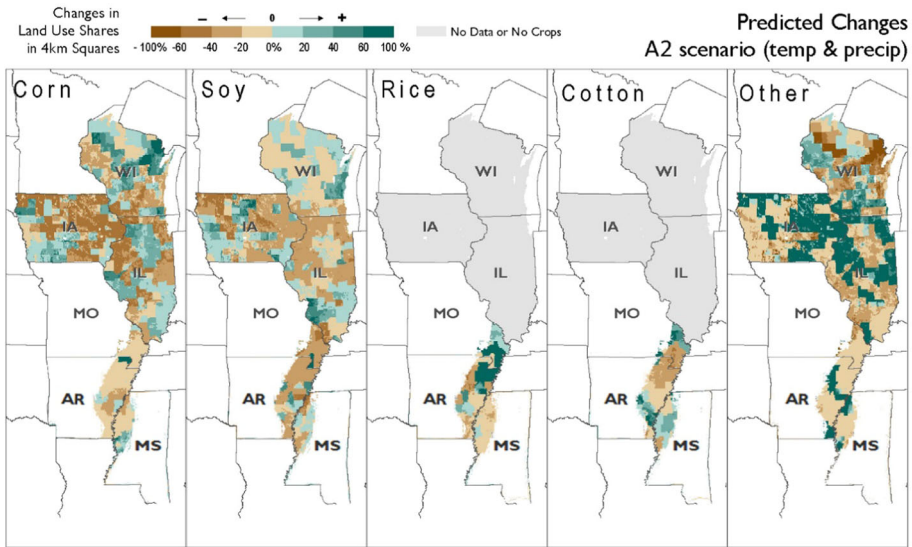
Fig. 10 Predicted crop coverage changes under the A2 scenario. *Notes*: a 20% change reported here means corn (for example) share increases from *a* to *a* + 0.2
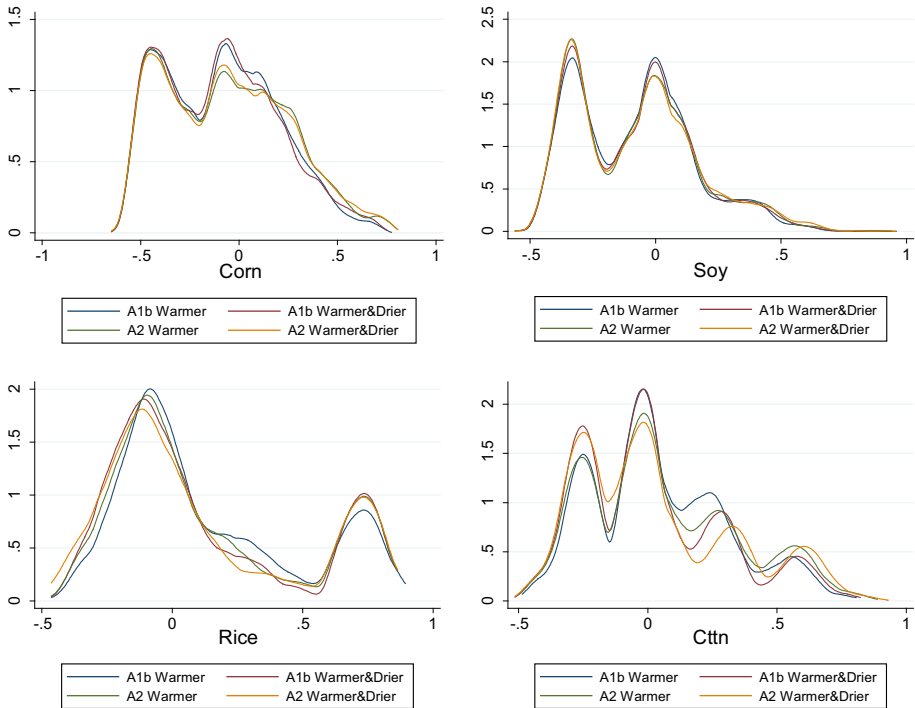
Fig. 11 Distribution of predicted crop coverage changes under climate change scenarios. *Notes*: x-axes are crop share changes. For example, -0.5 in the first panel means corn share decreases from a to $a - 0.5$. For corn and soy, all six states are included. For rice and corn, only the changes in the three south states are included, because there is no rice and cotton in the north

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