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Weather extremes, infrastructure, and its impacts on U.S. corn and soybean basis levels

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Weather extremes, infrastructure, and its impacts on U.S. corn and soybean basis levels

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1. Introduction

The margin between corn and soybean prices at collection points in the Midwest and the Gulf price reflect the costs of moving these bulk commodities from crop production regions to export facilities. These margins, or crop basis, depend on many factors, including the transportation network, costs of moving goods along that network that are often associated with fuel prices and barge availability, network disruptions, storage costs, and the volume of material being moved (Davis & Hill, 1974; Hart & Olson, 2017; Jiang & Hayenga, 1997; McKenzie, 2005; McNew, 1994; O'Brien, 2009). These factors can be affected by temperature and precipitation: weather affects yield in the region and around each collection point, grain quality, and traffic on rivers and other routes. Climate change projections suggest changes in these conditions, yet the implications for basis have not been studied.

This study estimates how precipitation and temperature affected the gap between local price and Gulf port price and infers stresses to the crop delivery infrastructure. It further analyzes the ways climate change could challenge existing infrastructure and affect basis. The empirical application focuses on corn and soybean basis in the central region of the United States. To achieve the study objectives, we use over a decade of weekly basis data from many hundreds of collection points and other data to estimate how weather conditions can affect volumes moving through the network, disrupt local operations, or impede barge traffic and consequently the margins between local and export prices. These steps put us in a position to simulate how changes to regional precipitation and temperature can affect the distribution network and change corn and soybean basis in the central region in the future.

The usefulness of this study for transportation is to estimate how climate change could stress the existing infrastructure system for moving grains and oilseeds from the main growing regions in the heartland to the Gulf port. The historical relationships between weather and basis are used to estimate how the different weather patterns that are expected would have affected basis. Would the changes in precipitation and temperature have stressed the transportation network or facilitated the Herculean task of moving crops from the Midwest to the key export port? Would the new weather patterns have changed local conditions at collection points, crop production, or river water level in ways that increase or decrease crop producer prices in the Midwest relative to the port price?

The remainder of this report is organized as follows: section 2 is devoted to a description of the methods used to conduct the analysis. A discussion of the data is given in section 3. Finally, section 4 presents the results and section 5 concludes.

2. Methodology

This study mapped weekly temperature and precipitation changes to crop basis in the central states with a view to infer impacts on transportation costs or capacity problems, such as river conditions that affect barge traffic. The effects of temperature and precipitation on crop basis of collection points in the central region were assessed in a muti-step procedure (figure 1).

A central step was to estimate a fixed effects panel data model that explains changes in basis as a function of local precipitation, flooding and low water level proxies, crop yields, and control variables (figure 1, box 2). Control variables were diesel price, ethanol intensity, and merchandise exports. The fixed effects control for any time-invariant elevator-specific omitted variables that are correlated with basis. The basis regression included three possible mechanisms for weather to affect the local-port price gap. First, local precipitation represents the immediate impact of a normal or abnormal weekly rainfall at each crop collection point on the local cash price. Second, the effect of river flooding and low water level on basis could disruption grain transportation as explained above. Third, yield deviations from trend captures the local crop supply shock effect on basis. Nonlinearities were included in the analysis (in the case of local precipitation and yield) to capture the effect of extreme rainfall events and very large changes in crop supply on basis.

In a supporting step, the crop yield and river water level were estimated to capture the indirect impacts of weather through these variables. The first link was examined from the perspective that weather conditions affect both the planting dates and progress of a crop which can in turn impact crop yields (figure 1, box 4). For instance, changes in precipitation and temperature patterns, such as warmer and wetter weather with climate change, can shift when crops are planted, when during the year the weather affects plant growth, and the supplies that hit the market and must move through the US crop distribution network. Therefore, a model that estimates the impacts of precipitation and temperature on planting progress was developed.

The second link was to estimate corn and soybean yields on growing season weather (figure 1, box 3). The temperature and precipitation in selected weeks after planting (based on planting progress data) are used to estimate yield at the county level. The relationships included nonlinear effects to capture sensitivity to extreme conditions as well as a trend that represents long-run factors. Thus, weather effects of yield occur in two steps: first, weather affects when the crop is planted and, second, the weather measured in certain weeks after planting has nonlinear impacts on yield. A change in weather can affect both when the crop is planted – and, consequently, when after during the year the growing crop is sensitive to weather conditions – and the growth of crops.

As part of this step, river water level was also estimated (figure 1, box 5). A moving average of precipitation in the relevant basin was used to estimate water level at three key points along relevant rivers. The water level can be compared to trigger values used to indicate whether the water is too high or too low to permit normal barge traffic.

As a final step, the econometric findings of the basis, planting progress (and inferred yield), and water level estimations along with data on climate change scientists' projections of temperature and precipitation were used in an analysis that simulated the impact of projected climate change temperature and precipitation scenarios on basis (figure 1, lower half). The multi-step process described above was performed separately for corn and soybean basis in the dataset.

In summary, this study focuses on three mechanisms that drive the impacts of precipitation and temperature on corn and soybean basis: a) local precipitation (i.e. precipitation at a collection point that could cause disruptions and affect local basis due to differences in collection, storage, and marketing patterns), b) river traffic (i.e. high and low water days that can impact barge traffic and as a result grain transportation), and c) crop volume (i.e. as shaped by planting progress and yield which can be affected by changes in temperature and precipitation and shift change crop supply patterns). More details on the econometric estimation of the relationships discussed here and shown in Figure 1 are provided in the appendix.

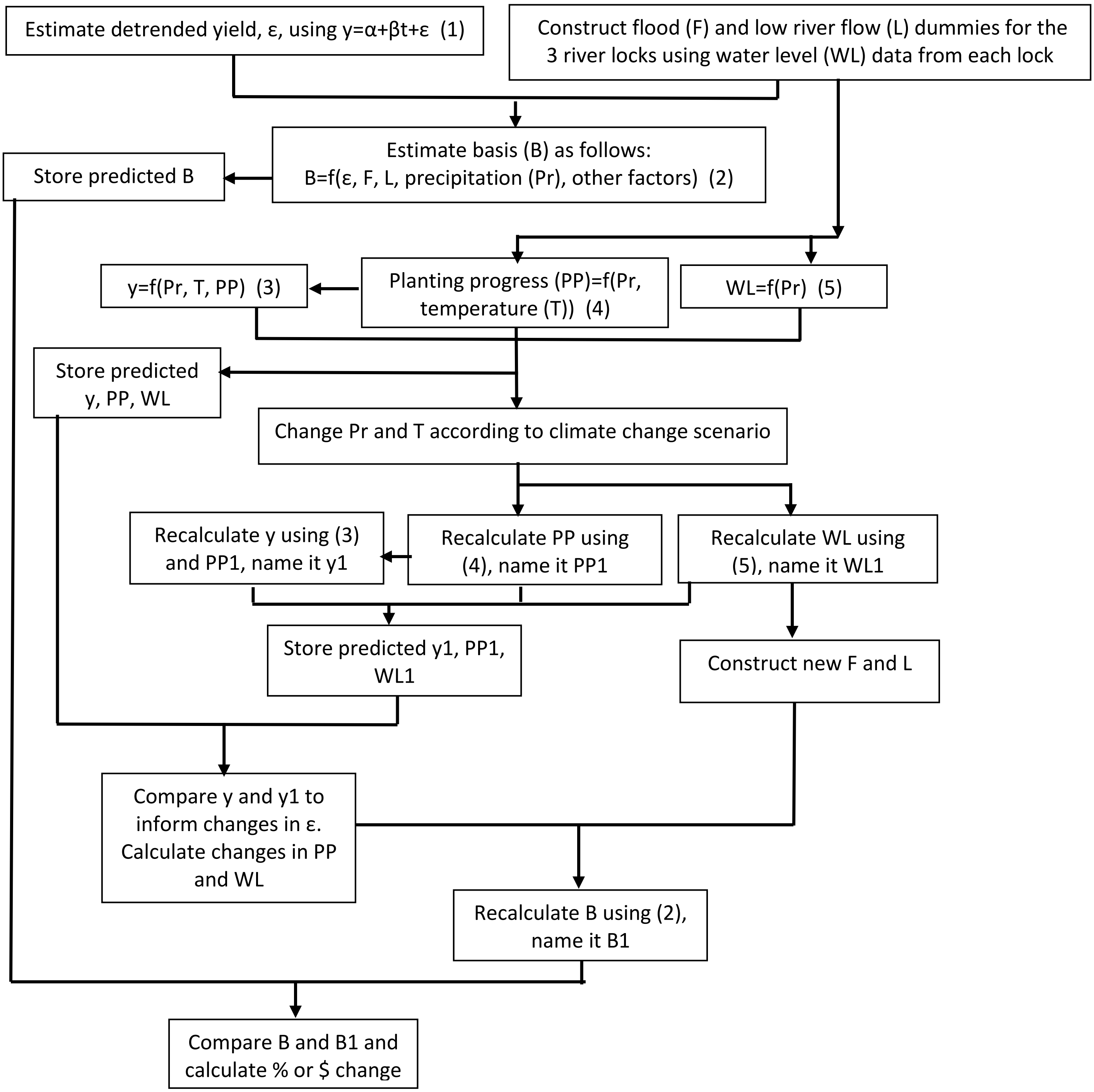

Figure 1. Chart flow of simulation process.

3. Data

Data on corn and soybean basis and yields, grain collection points' location, daily precipitation and temperature, and data on control variables were collected for all states of the upper Mississippi river basin. The basis data are daily observations (transformed to weekly values) for 2,209 and 1,963 corn and soybean elevators over the period 2008-2020 and were retrieved from Refinitiv Thomson Reuters database. The geographic distribution of sample elevators is shown in Figure 2. Yield data are county-specific and were retrieved from USDA-NASS while daily climatic data were collected from the National Weather Service database. The control variables include data on historic ethanol intensity measures linked to the corn and soybeans buyers in our dataset (provided from an OCE collaborator), diesel price, the value of merchandise exports, and share of soybean exports to China (applying only to the soybean basis regression). Moreover, water level data and river closures were retrieved for two navigation locks in the Mississippi river and one each in the Ohio and Illinois rivers. The water level and river closure data reported by the National Weather Service Advanced Hydrological Prediction Service in conjunction with the relative location of the grain collection points under investigation were used to construct proxies for river flooding or low water levels that can impact grain transportation and, as a result, basis. Table 1 presents summary statistics of the variables used in the basis estimations

Finally, data on climate change scenarios related to temperature and precipitation levels in the states under investigation were retrieved from the National Center for Atmospheric Research (NCAR, 2022). Three climate change scenarios were available (i.e. low, medium low, medium high, and high scenario, see Figures A1-A2 in the appendix). The simulation results presented in the results section below concern the “high” scenario. The simulation results for rest of the climate change scenarios are included in the appendix.

Table 1. Summary statistics of the variables used in the empirical analysis.

Variable	Units	Corn		Soybeans	
		Mean	St.dev	Mean	St.dev
Basis	dollars/bushel	-0.803	0.237	-1.154	1.108
Ethanol	million galons/km2	0.016	0.013	0.016	0.013
Diesel	$/gallon	3.101	0.625	3.096	0.627
Local precipitation	inches	0.485	0.712	0.489	0.710
Positive yield shocks	Unitless	7.930	10.085	2.129	2.859
Negative yield shocks	Unitless	-8.008	15.67	-1.945	3.458
Export	ten billion $	12.439	1.465	12.417	1.475
Share of soybean exports to China	ratio	.	.	0.553	0.101
Miss. 1 flood	count/week	0.018	0.280	0.018	0.287
Miss. 2 flood	count/week	0.019	0.356	0.020	0.361
Illinois flood	count/week	0.102	0.764	0.088	0.711
Miss. 1 low	count/week	1.606	2.899	1.649	2.925
Miss. 2 low	count/week	1.304	2.656	1.364	2.702
Illinois low	count/week	0.369	1.471	0.313	1.360

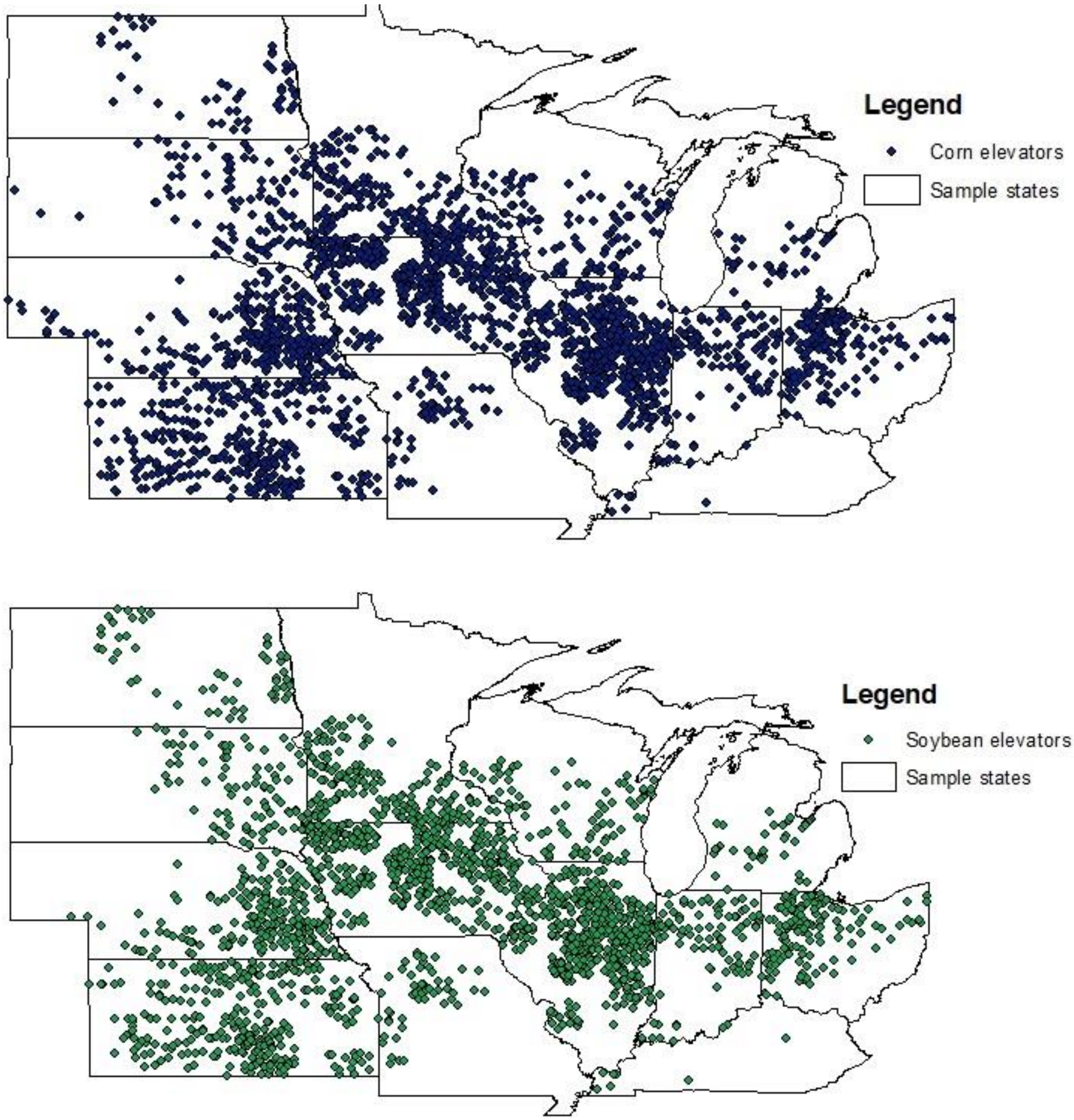

Figure 2. Geographic distribution of the sample corn and soybean elevators.

4. Results

4.1 The determinants of basis

The results of basis estimation are presented in Table 2.

Results indicate that the coefficients of local precipitation and its squared term are statistically significant for both corn and soybean models. More specifically, higher local precipitation increases corn/soybean basis at a decreasing rate, indicating an inverted U-shaped relationship. The marginal effect of local precipitation on basis is presented in Table A1 in the appendix. These effects imply that a one -inch increase in local rainfall causes an average increase in corn and soybean basis by about one cent, ceteris paribus. Strong rainfall might disrupt local deliveries for the week, causing a small uptick for the basis of the fewer crop producers who make the trip.

Corn volume, as reflected in positive and negative yield residual variables, is shown to have a significant effect on mainly corn basis. As expected, higher corn yield, as reflected by the positive yield residual variables, decreases corn basis at a decreasing rate, ceteris paribus. Higher crop yield reflects a higher crop supply and more pressure on the infrastructure to ship corn out of the region. Thus, if crop demand remains constant then this leads to lower local price for a given port price. In contrast, a lower corn yield and lower volumes supplied causes less stress on the infrastructure network and higher basis. All that said, statistical results for the soybean yield do not conform entirely to expectations. Atypically high soybean yields can have higher basis and particularly low soybean yields can have low basis, according to the nonlinear terms – although these are not all statistically significant. The outcome might reflect the relative volumes of crops in the event that the soybean crop is not as voluminous and consequently has less potential to strain the distribution network relative to corn or other factors. In any case, reductions in soybean yields below expectations tend to have a positive impact on basis, as expected.

The water level dummies show the expected negative effect on basis in both corn and soybean models. This finding implies that rivers can be so high that they prevent barge traffic or too low for normal volumes, and this could negatively affect local price relatively to a given port price.

Table 2. Basis regression results

	Dependent variable	
VARIABLES	Corn basis	Soybean basis
Ethanol intensity measure	1.004***	1.275
	(0.231)	(0.979)
Diesel price	-0.0922***	-0.0808***
	(0.00157)	(0.00409)
Local precipitation	0.00785***	0.00964***
	(0.000712)	(0.00250)
Local precipitation^2	-0.000884***	-0.000522*
	(0.000214)	(0.000289)
(+Yield residual)	-0.00149***	0.00128
	(0.000267)	(0.00134)
(-Yield residual)	-0.00636***	-0.00148
	(0.000191)	(0.00160)
(+Yield residual)^2	-1.01e-05	0.000153
	(7.74e-06)	(0.000128)
(-Yield residual)^2	-4.11e-05***	0.000580***
	(3.16e-06)	(0.000103)
Export	0.00245***	0.00162
	(0.000503)	(0.00116)
Share		-0.347***
		(0.0749)
Mississipi1*flood	-0.0144***	-0.0365***
	(0.000707)	(0.00706)
Mississipi2*flood	-0.00359***	-0.0204***
	(0.000321)	(0.00307)
Illinois*flood	-0.00255***	-0.0128***
	(0.000215)	(0.00376)
Mississipi1*low	-0.00276***	-0.00825***
	(0.000255)	(0.00106)
Mississipi2*low	-0.000734***	-0.00946***
	(0.000182)	(0.00138)
Illinois*low	-0.00711***	-0.0107***
	(0.000279)	(0.000881)
Constant	-0.583***	-0.741***
	(0.00537)	(0.0159)
Observations	739,436	664,006
R-squared	0.157	0.007
Number of elevators	2,664	2,379
Fixed effects	Yes	Yes

Note: *** and * denotes statistical significance at the 1% and 10% level, respectively.

Among the control variables, the ethanol intensity measure positively affects corn basis (only), as expected, and is significant at the 1% level. Corn basis strengthens by $1 with every thousand gallons/per sq. miles increase in ethanol intensity. This could be explained by the increased demand for nearby cash sales of corn due to the expanded ethanol intensity in the area surrounding the local elevator. Diesel price, which can be considered as a non-river transportation cost proxy, is found to have a positive and statistically significant effect on both corn and soybean basis. This finding might be contrary to theoretical expectations. The diesel price effect is an average for a large region, but obscures a potential wide range based on distances within the region. As such, if we sought to explore the effects of this variable further then we might consider delineating further the pathways from collection points to port to evaluate distances travelled by roads, rail, or barges. Merchandise exports, which reflects broader demand for crops and goods and consequently for distribution services, is shown to be positively related to corn basis, keeping all other things constant. Higher demand for corn can increase local price relative to a given port price and with crop supply being constant. In the soybean model, the share of soybean exports to China is found to have a negative impact on basis. This variable is included largely to reflect the shifts in soybean trade flows from the Pacific Northwest to other ports during the U.S.-China trade dispute. The shift in soybean volumes towards the Gulf port caused strain on the distribution system and reduced the soybean basis.

4.2 The impact of weather variables on planting progress and yield

Table 3 presents the results of the planting progress regressions. In both corn and soybean models, planting progress at the start of each week is estimated to be positively related to the three-week moving average temperature and negatively precipitation in the preceding week. These findings imply that sustained warmer weather allows earlier planting on the one hand, while more precipitation slows planting progress.

Table 3. Planting progress regression results

	Dependent variable	
	Corn progress	Soybean progress
MV of temperature	0.276***	0.274***
	(0.006)	(0.005)
L1 precipitation	-0.154***	-0.202***
	(0.057)	(0.050)
Trend	0.013	0.031***
	(0.011)	(0.010)
Constant	-37.933*	-75.739***
	(22.767)	(19.751)
Fixed effect	Yes	Yes
Observations	1,351	1,426
R2	0.620	0.670
Adjusted R2	0.616	0.667

Note: *p<0.1; **p<0.05; ***p<0.01

Moving to the results of the yield regressions (Table A2 in the appendix), the nonlinear effects of weekly precipitation on yield bear elaboration. If precipitation is about normal, then more precipitation generally leads to an increase in yield at a decreasing rate. There are exceptions, such as the effect or precipitation in the first week after planting which is negative for corn or soybeans. For other weeks if precipitation rises above average levels then the impact of additional rain on crop yield becomes negative. In some instances, particularly in the later part of the growing phase, more rain tends to cause more yield even if the weekly rate is far above average. The effect of temperature on crop yields is more mixed, with an increase in temperature from the mean value in earlier and later weeks of the growing season showing a positive and a negative effect on crop yields, respectively,. For corn, these relationships hold for a wide range of temperatures, but soybean yield impacts of temperature changes are more sensitive to the starting value. Recall that changes in yields are expected to have an inverse impact on basis because of how the volume of crops produced, particularly voluminous corn, can increase or decrease stress in the distribution network.

Regarding the river water level regressions results, and consistent with expectations, we found that higher precipitation is related to higher river water level (Table 4).

Table 4. River water level regression results

	Dependent variable:		
	Canton	Dubuque	Illinois
MV of precipitation	3.714***	1.916***	3.897***
	(0.157)	(0.118)	(0.218)
Constant	6.399***	6.978***	12.539***
	(0.126)	(0.094)	(0.201)
Observations	4,674	4,678	4,666
R2	0.107	0.054	0.064
Adjusted R2	0.107	0.053	0.064

Notes: *p<0.1; **p<0.05; ***p<0.01. For the estimation of water level for Canton and Dubuque lock points, precipitation variables are average of precipitation of three states (i.e. Minnesota, Iowa, and Wisconsin). In the case of the Illinois lock point, the precipitation variable reflects precipitation of Illinois state.

4.3 Climate change simulation results

The climate change simulation process simulated the impact of projected climate change temperature and precipitation scenarios on basis. This was achieved by using the econometric results of the basis, planting progress, yield, and water level estimations and actual climate scenarios reflecting estimates of state-level changes in temperature and precipitation. As noted earlier, the climate change simulation results presented below concern the “high” climate change scenario of NCAR. Results for the rest of the NCAR climate change scenarios (which have led in general to qualitatively similar conclusions) are included in the appendix. The simulation is conducted by adjusting historical weather as though the predicted climate change impacts given to us had already happened, then mapping the new precipitation and temperature data to the intermediate and final variables to estimate the basis level with these new weather patterns.

High climate change scenario simulation results for this case for river water levels are not presented in detail here, but are reported in the appendix (Table A3). The water level at all three key points is increased in all four of the climate change scenarios that we incorporate, leading to fewer low water days and potentially more high water days, on average. The results of this exercise highlight an interesting consideration: the high climate change scenario globally might not be the most extreme scenario for this region. The so-called “medium-high” indicate to us a greater increase in regional precipitation than in the “high” case that we explore in the main text of this report.

Yield simulations are reported in detail in the appendix (Tables A4-A7) and summarized as follows. The warmer temperatures suggested to us by the high climate change scenario lead to faster planting of corn (Table A4) and an earlier start to soybean planting (Table A5), as well. This change shifts forward the growing season. Growing season weather is consequently affected by both starting earlier for a share of the crop and also by the climate change effects on precipitation and temperature during that period. For corn yield (Table A6), the simulated positive impact of precipitation and negative impact of temperature largely balance given the high climate change scenario parameters (and other scenario assumptions, as well), and corn yield changes are modest. The negative temperature effect overwhelms the positive precipitation effect on soybeans, however, and the yield is off by about half a bushel (-1%) in the high climate change case (Table A7).

Table 5 presents the simulation results of corn and soybean basis. Corn basis decreased by 0.05 cents on average as a result of climate change (i.e. future changes in temperature and precipitation). Precipitation is shown to be the main driver of this finding. In fact, expected temperature changes in this scenario alone would suggest a mild strengthening in corn basis. On the other hand, soybean basis was found to increase by 2.6 cents on average due to the combined change in future temperature and precipitation. Temperature change is the main driver of soybean basis change while precipitation alone would weaken basis in this scenario somewhat.

Tables A8 and A9 in the appendix show how basis distribution changes as a result of climate change. Regarding corn basis, it is observed that, in most cases, climate change shifts the lower and central portions of the distribution to the left (i.e. to more negative values). The upper end of the corn basis distribution increases in these scenarios. On the other hand, climate change shifts the soybean basis distribution to the right (i.e. to less negative values). In both cases, the range widens with more positive impacts occurring when basis is already high and less positive or even negative impacts occurring when basis is already low.

Table 5. Changes in basis due to climate change

	Corn	Soybean
Historical Basis	-0.8019	-1.1527
Simulated basis_Temperature change only	-0.8012	-1.1265
Simulated basis_Precipitation change only	-0.8028	-1.1286
Simulated basis_Temperature and precipitation change	-0.8024	-1.1268

Note: Historical basis is the observed average basis over the period 2008-2020.

Tables 6 and 7 decompose the effect of climate change on basis according to three mechanisms through which weather is expected to affect basis. These mechanisms are local precipitation, river traffic (i.e. flood and low river water level dummies), and crop volume (i.e. yield residuals). Results show that for both crops, changes in yield (triggered by climate change) contribute the most to basis change. For soybeans, the yield loss amounts to about half a bushel across the distribution of outcomes given the regression results and the input from the high climate change projections (Table A8), implying lower pressure on the distribution infrastructure and higher basis.

Table 6. Summary statistics of the corn basis decomposition results.

	5th percentile	1st quartile	Median	Mean	3rd quartile	95th percentile
Historical basis	-1.1906	-0.9450	-0.8000	-0.8019	-0.6504	-0.4286
Local precipitation effect	-0.0009	-0.0010	-0.0005	-0.0006	-0.0005	0.0000
Yield effect	-0.0137	-0.0080	-0.0026	-0.0006	0.0038	0.0217
Flood/low river water level effect	-0.0009	-0.0010	-0.0005	-0.0006	-0.0004	0.0004

Table 7. Summary statistics of the soybean basis decomposition results.

	5th percentile	1st quartile	Median	Mean	3rd quartile	95th percentile
Historical basis	-1.7192	-1.3765	-1.1652	-1.1527	-0.9157	-0.6144
Local precipitation effect	-0.0004	-0.0011	-0.0012	-0.0010	-0.0010	-0.0010
Yield effect	0.0274	0.0209	0.0217	0.0257	0.0296	0.0346
Flood/low river water level effect	-0.0004	-0.0013	-0.0012	-0.0009	-0.0009	-0.0008

The impacts on the entire range of basis values can also be important, not just the average impact. Does the climate change scenario cause the basis to vary more, or less? Does the climate change scenario shift the distribution, or cause the extreme values at one end of the distribution to change more? Do the results suggest different stress to the transportation infrastructure during times of extreme weather than observed in the past? The local effect widens the corn and soybean basis distribution by pulling down the lower end, but the central values also move lower. Thus, local precipitation appears to disrupt processes in a way that reduces average basis and low-end risks, although the sizes of these changes are not big if expressed as a percent of historical basis. The corn yield changes cause very little change in average basis for this crop, but widen the range as the high climate change scenario expands the risks of a high or low corn crop and consequently varies the degree of stress on the distribution system. For soybeans, the high climate change scenario causes less yield and consequently less strain on the system, shifting the entire range of basis. The river water level changes in this climate scenario cause a degree of widening in corn basis while the entire soybean basis range is moved lower with the central values reduced the most. Taking all impacts into account, the high climate change scenario widens the range of basis for corn and soybeans and increases the basis overall for soybeans, suggesting that the extremes become more extreme relative to normal conditions and there is generally a lower volume of soybeans to move given the scenario assumptions.

Other climate change scenarios can generate different results. However, the data available to us that relate to the precipitation and temperature impacts in this region tend to have similar implications for basis. Soybean basis rises by \$0.020 to \$0.035, depending on the scenario and the point in the distribution. Corn basis changes range is -\$0.014 to +\$0.023. The ranges widen in either case; greater uncertainty in basis is a simulation result in all four climate change scenarios for both crops. Precipitation and temperature impacts interact or overlap in these simulations, and are not additive.

Different climate change information could lead to different results. The cases we use are published and readily available, but climate change impacts are presumably more uncertain than these four scenarios alone imply. Moreover, if the seasonal patterns change radically, such as much greater rainfall at times that have been dry in the past, then the impacts could be quite different, as well. Our focus on historically estimated relationships allows us to quantify impacts of projected climate change, but a large shock would presumably cause at least some adaptive behaviors that could cause past relationships to no longer be relevant. That said, while some of the changes we estimate are important, they do not seem so dramatic as to cause restructuring of agricultural commodity production, distribution, or use in this region. One might suppose that a greater risk is that climate change has large impacts (positive or negative) on other growing regions, creates new growing regions, or affects crop demand, but this perspective overlooks our focus on a price margin – the local-to-port price comparison – not overall crop price levels. Our focus on the basis helps us set aside some possible complications.

5. Summary and Conclusions

In this study, an examination of the effect of temperature and precipitation changes on corn and soybean basis is provided. The analysis includes a multi-step approach that estimates the links between weather variables and basis. First an econometric model of basis as a function of local precipitation, flooding and low water level proxies, crop yields, and control variables (such as diesel price, ethanol intensity, and merchandise exports) was developed. This model harbors three channels through which weather changes are expected to affect basis, namely, local precipitation (representing the risk of local delivery or loading disruptions and also area supply, demand, and capacity interactions.), river traffic (representing the risk of barge traffic stoppages and reduced barge loading capacity), and crop volume (representing the risk of greater volumes stressing the distribution network capacity). These channels were empirically approximated by developing models to link weather conditions to planting dates and progress of a crop which can in turn impact crop growing periods, and crop growing period weather to yields. We have also developed models to link precipitation to river water level (to test if low- or high-water conditions reduce barge travel). Finally, the econometric results of the basis, planting progress (and inferred yield) and water level estimations along with scientists' future climate change predictions were used in a simulation analysis to predict the impact of climate change on basis.

Results show that changing local weather conditions impact crop basis in the Midwest (measured here as local price less port price) as they interact with the crop delivery infrastructure to change basis. Our results further suggest that warming weather can accelerate planting while precipitation slows planting progress. Taking into account when crops go into the ground, we find that rising precipitation often improves crop yield. Thus, a change in weather patterns towards wetter conditions could potentially increase yields and cause more stress on the crop distribution system. It should be noted however that far above average levels of precipitation could have a negative impact on crop yields (as shown by the non-linear terms of the precipitation variables in the yield regressions) implying less stress on the crop distribution network. Greater rainfall in the Midwest can hamper local operations of grain collection points, such as elevators, and affect river traffic by increasing the frequency of high-water disruptions while reducing the number of low-water days. River conditions are found to have a negative impact on basis of upstream collection points; river water level that leads to barges traveling light or stopping entirely will tend to lower Midwest price relative to the port price as the infrastructure system no longer can move the crops as effectively.

The climate change simulation results show that corn basis decreased and soybean basis increased when accounting for future changes in temperature and precipitation. More specifically, corn basis decreased by 0.05 cents on average in the high climate change scenario, while soybean basis increased by an average of 2.6 cents. The soybean basis change was roughly consistent among climate change scenarios, whereas the corn basis change doubled in one case and reversed sign in another. The distribution of basis widened in either case, with the upper extreme of changes in corn basis approaching those of soybean basis. Soybean basis change was mainly driven by changes in temperature. Regarding the channels through which weather effects operate, it was found that (for both crops) yield (representing crop volume) was the main contributor to basis change. As yield is a proxy for the capacity of the distribution network overall and its sensitivity to atypical yield conditions, the implication is that soybean yields implied by available climate change projections could test this infrastructure going forward. Efforts on rivers to manage high river water levels might have a smaller positive impact on basis given these projections, whereas measures to maintain barge traffic at times of low water might be less well rewarded if precipitation really increases. More generally, the implications might be put to scale as follows. Using the product of basis and average production for 2010/11-2020/21, the average value of Midwest-to-port price gap for corn and soybean was just over $15 billion. The changes reported in this study would imply changes in this value by about a hundred of millions of dollars a year on average, with more at stake in the extreme cases.

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Appendix

1. Element of flow chart: Estimate detrended yield (Figure 1, top left text box)

Detrended yield, ε, is estimated using equation 1:

$$y_{it} = \alpha + \beta t + \varepsilon_{it} \quad (1)$$

where y is state level yield at time t, t is a time trend, α and β are parameters to be estimated, and ε is an error term.

The "Residual" variables, ε, (which is used as an additional explanatory variable in the basis regression below) are errors from the detrended yield. The departure from expected, trend yield could be shocks to the volume relative to the planned capacity, and consequently stress the crop distribution network or alleviate strain on that network.

2. Element of flowchart: Construct flood (F) and low river flow (L) dummies for the 3 river locks using water level (WL) data from each lock (i.e. Figure 1, top right text box)

The water level indicators are set at trigger points for each of the three locations. If water level exceeds the indicator for high water, then the flood dummy (F) takes a value of one. If the water level is below the indicator for low water, then the low water dummy (L) takes a value of one. Dummies are zero otherwise.

3. Element of flowchart: Basis estimation (i.e. Figure 1, equation 2)

Basis estimation is done using the following fixed effects model:

$$\begin{aligned} Basis_{it} = \beta_0 &+ \beta_1 Ethanol_{it} + \beta_2 Diesel_{it} + \beta_3 Precip_{it} + \beta_4 Precip_{it}^2 \\ &+ \beta_5 Residual_{it}^{+} + \beta_6 Residual_{it}^{-} + \beta_5 (Residual_{it}^{+})^2 + \beta_6 (Residual_{it}^{-})^2 \\ &+ \beta_9 Export_{it} + \beta_{10} Flood1_{it} + \beta_{11} Flood2_{it} + \beta_{12} Flood3_{it} \\ &+ \beta_{13} Low1_{it} + \beta_{14} Low2_{it} + \beta_{15} Low3_{it} + \gamma_i + \epsilon_{it} \end{aligned}$$

where $Basis_{it}$ is the weekly average commodity basis quoted by elevator i in period t. This estimation reflects the effect of three mechanisms on basis: local precipitation (as captured by $Precipitation_{it}$), river traffic (captured by the Flood and Low dummies), and crop volume (as captured by the positive and negative Residual variables). Three control variables were also included: ethanol intensity, merchandise exports, and diesel price. In the soybean basis regression and additional control variables was included (i.e. share of soybean exports to China). β_0-β_{15} are parameters to be estimated. γ_i denotes fixed effects and ε_{it} is an error term.

4. Element of flowchart: Estimate WL as a function of precipitation (Figure 1, equation 5)

Estimation of WL for each lock point is performed using the following equations:

$$Canton_t = \beta_0 + \beta_1 \frac{\sum_{k=-4}^{-1} precip_{t+k}}{4} + \epsilon_{it}$$

$$Dubuque_t = \beta_0 + \beta_1 \frac{\sum_{k=-4}^{-1} precip_{t+k}}{4} + \epsilon_{it}$$

$$Illinois_t = \beta_0 + \beta_1 \frac{\sum_{k=-4}^{-1} precip_{t+k}}{4} + \epsilon_{it}$$

For the estimation of water level for canton and Dubuque lock points, precipitation variables (i.e. $precip_t$) are the moving average (of the last four weeks) of precipitation of three states (i.e. Minnesota, Iowa, and Wisconsin). In case of the Illinois lock point, the precipitation variable is the moving average (of the last four weeks) of the precipitation of Illinois state.

5. Element of flowchart: Estimation of planting progress (i.e. Figure 1, equation 4)

Estimation of planting progress is performed using the equation below.

$$ln\left(\frac{progress_{it}}{1 - progress_{it}}\right) = \beta_0 + \beta_1 \frac{\sum_{k=-3}^{-1} Temp_{it+k}}{3} + \beta_2 precip_{it-1} + \gamma Trend_t + \delta_i + \epsilon_{it}$$

The dependent variable in this equation is the percentage of planting progress at the start of each week. Regarding the explanatory variables, temperature (i.e. $Temp_{it}$) is the moving average of air temperature in the last three weeks and is intended to represent the effect of air temperature on soil temperature. The precipitation variable, $precip_{it}$, is defined as the precipitation of the preceding week. This variable reflects the potential that precipitation causes excess soil moisture and inhibits planting. Estimation is performed at the state level.

6. Element of flowchart: Estimation of yield (Figure 1, equation 3)

County-level yield is estimated as a function of precipitation and temperature in certain weeks after planting. Planting progress and raw weather data are used to calculate the precipitation and temperature after planting. We do not use all weeks' data because of multicollinearity in historical data.

$$
\begin{aligned}
Yield_{it} = \gamma_0 &+ \alpha_1 \sum_{w=1}^{52} (\Delta P_{t,w} * Precip_{it,w+1}) + \cdots + \alpha_{15} \sum_{w=1}^{52} \left(\Delta P_{t,w} * Precip_{it,w+15}\right) \\
&+ \alpha_{16} \sum_{w=1}^{52} (\Delta P_{t,w} * Precip_{it,w+1}^2) + \cdots + \alpha_{30} \sum_{w=1}^{52} (\Delta P_{t,w} * Precip_{it,w+15}^2) \\
&+ \beta_1 \sum_{w=1}^{52} (\Delta P_{t,w} * Temp_{it,w+1}) \\
&+ \cdots + \beta_{15} \sum_{w=1}^{52} \left(\Delta P_{t,w} * Temp_{it,w+15}\right) + \beta_{16} \sum_{w=1}^{52} (\Delta P_{t,w} * Temp_{it,w+1}^2) \\
&+ \cdots + \beta_{30} \sum_{w=1}^{52} \left(\Delta P_{t,w} * Temp_{it,w+15}^2\right) + \delta Trend_t + \theta_i + \epsilon_{it}
\end{aligned}
$$

ΔP_t represents the 1st difference of planting progress, which is ($Progress_t - Progress_{t-1}$). For subscripts, 't' represents year, 'w' week, and 'i' represents county. α, β, γ and δ are parameters to be estimated. Trend is a time trend variable that captures technological change over time. θ_ι deno tes fixed effects and ε_{it} is an error term.

7. Additional results

Tables

Table A1. Marginal effects of local precipitation on basis

	5th	25th	50th	mean	75th	95th
Corn	0.0079	0.0078	0.0075	0.0070	0.0067	0.0046
Soybean	0.0096	0.0096	0.0094	0.0091	0.0090	0.0077

Table A2. Yield regression results

Corn				Soybean			
Variable	Coef.	Variable	Coef.	Variable	Coef.	Variable	Coef.
s_prec1	-0.802	s2_prec1	0.627***	s_prec1	-0.968***	s2_prec1	0.109*
	-1.124		-0.241		(0.305)		(0.066)
s_prec3	5.410***	s2_prec3	-1.784***	s_prec3	2.368***	s2_prec3	-0.532***
	-1.454		-0.345		(0.399)		(0.09)
s_prec5	11.394***	s2_prec5	-1.436***	s_prec5	0.675	s2_prec5	-0.268**
	-1.228		-0.259		(0.425)		(0.108)
s_prec7	9.992***	s2_prec7	-3.105***	s_prec7	3.775***	s2_prec7	-0.821***
	-1.521		-0.405		(0.427)		(0.117)
s_prec9	23.998***	s2_prec9	-5.303***	s_prec9	4.468***	s2_prec9	-0.652***
	-1.635		-0.444		(0.453)		(0.126)
s_prec11	24.822***	s2_prec11	-3.819***	s_prec11	4.788***	s2_prec11	-0.524***
	-1.521		-0.381		(0.408)		(0.107)
s_prec13	-1.286	s2_prec13	0.551*	s_prec13	0.818*	s2_prec13	-0.043
	-1.335		-0.323		(0.431)		(0.121)
s_prec15	5.130***	s2_prec15	-0.401	s_prec15	2.438***	s2_prec15	-0.664***
	-1.234		-0.324		(0.324)		(0.085)
s_temp1	2.518***	s2_temp1	-0.014*	s_temp1	-1.045***	s2_temp1	0.009***
	-0.92		-0.008		(0.23)		(0.002)
s_temp6	-2.639***	s2_temp6	0.012**	s_temp6	0.016	s2_temp6	-0.003
	-0.811		-0.006		(0.277)		(0.002)
			2.240***	s_temp12	1.321***	s2_temp12	-0.011***
			-0.062		(0.204)		(0.001)
		year	2.240***			year	0.791***
			-0.062				(0.014)
			-				-
		Constant	4,412.556***			Constant	1,558.541***
			-124.346				(29.226)
		Fixed effect	Yes			Fixed effect	Yes
		Obs.	12,064			Obs.	11,232
		R2	0.751			R2	0.785

Note: s_temp and s_precip denote the linear effects of temperature and precipitation, respectively, on yield. The numbers attached to these variables denote the week of the growing season. Variables starting with "s2" denote non-linear effects of each variable.

Note: indicators of statistical significance are indicated with asterisks. as in other tables representing regression results.

Table A3. Climate change effect on low water and flood days at different river locks.

	Actual	Low	Medium Low	Medium High	High
Canton					
Flood days	0.280	0.281	0.280	0.284	0.281
Low water days	3.990	3.887	3.901	3.873	3.881
Dubuque					
Flood days	0.256	0.256	0.256	0.259	0.256
Low water days	4.707	4.611	4.619	4.592	4.602
Illinois					
Flood days	1.084	1.093	1.090	1.084	1.093
Low water days	1.370	1.256	1.268	1.293	1.256

Notes: The value of flood days shows the average number of days per week during the sample period where river water level exceeds the lock-specific flood threshold (i.e. canton: 18ft, Dubuque:16ft, Illinois:23). The value of low flow days represents the average number of days during the sample period where river water level is below 9ft. The actual reflects historical values whereas the climate change scenarios estimate the incidence of high and low water conditions if projected changes in weather patterns are imposed on the historical data.

Table A4. Climate change effect on corn planting progress under different climate change scenarios

Climate change scenarios	Variables	15th week	18th week	22nd week
Low	Historical progress	0.051	0.389	0.919
	Simulated progress-temperature effect	0.061	0.410	0.932
	Simulated progress-precipitation effect	0.051	0.389	0.919
	Simulated progress-combined effect	0.061	0.410	0.932
Medium-low	Historical progress	0.051	0.389	0.919
	Simulated progress-temperature effect	0.078	0.440	0.944
	Simulated progress-precipitation effect	0.051	0.389	0.919
	Simulated progress-combined effect	0.078	0.440	0.944
Medium-high	Historical progress	0.051	0.389	0.919
	Simulated progress-temperature effect	0.062	0.409	0.931
	Simulated progress-precipitation effect	0.051	0.389	0.919
	Simulated progress-combined effect	0.062	0.409	0.930
High	Historical progress	0.051	0.389	0.919
	Simulated progress-temperature effect	0.087	0.456	0.950
	Simulated progress-precipitation effect	0.051	0.389	0.919
	Simulated progress-combined effect	0.087	0.456	0.949

Table A5. Climate change effect on soybean planting progress under different climate change scenarios

Climate change scenarios	Variables	15th week	18th week	22nd week
Low	Historical progress	0.000	0.097	0.715
	Simulated progress-temperature effect	0.006	0.112	0.741
	Simulated progress-precipitation effect	0.000	0.097	0.715
	Simulated progress-combined effect	0.006	0.112	0.740
Medium-low	Historical progress	0.000	0.097	0.715
	Simulated progress-temperature effect	0.015	0.135	0.771
	Simulated progress-precipitation effect	0.000	0.097	0.715
	Simulated progress-combined effect	0.015	0.135	0.771
Medium-high	Historical progress	0.000	0.097	0.715
	Simulated progress-temperature effect	0.006	0.111	0.739
	Simulated progress-precipitation effect	0.000	0.097	0.715
	Simulated progress-combined effect	0.006	0.111	0.739
High	Historical progress	0.000	0.097	0.715
	Simulated progress-temperature effect	0.021	0.148	0.786
	Simulated progress-precipitation effect	0.000	0.097	0.715
	Simulated progress-combined effect	0.021	0.148	0.786

Table A6. Climate change effect on corn yield under different climate change scenarios

	5th percentile	1st quartile	Median	Mean	3rd quartile	95th percentile
Low scenario						
Historical yield	62.384	114.706	145.105	139.752	170.296	196.879
Simulated yield-temp. effect	62.517	114.479	144.961	139.642	170.183	196.856
Simulated yield-prec. effect	62.968	114.938	145.358	140.102	170.656	197.432
Simulated yield-comb. effect	62.956	114.829	145.285	139.991	170.548	197.292
Medium-low scenario						
Historical yield	62.384	114.706	145.105	139.752	170.296	196.879
Simulated yield-temp. effect	62.266	114.340	144.936	139.522	170.012	196.758
Simulated yield-prec. effect	62.509	114.624	145.026	139.739	170.272	197.035
Simulated yield-comb. effect	62.164	114.223	144.855	139.510	169.981	196.809
Medium-high scenario						
Historical yield	62.384	114.706	145.105	139.752	170.296	196.879
Simulated yield-temp. effect	62.487	114.474	144.993	139.651	170.100	196.814
Simulated yield-prec. effect	62.800	115.047	145.384	140.107	170.619	197.434
Simulated yield-comb. effect	62.927	114.920	145.259	140.004	170.450	197.369
High scenario						
Historical yield	62.384	114.706	145.105	139.752	170.296	196.879
Simulated yield-temp. effect	62.244	114.229	144.824	139.459	169.976	196.694
Simulated yield-prec. effect	63.074	115.198	145.530	140.272	170.832	197.389
Simulated yield-comb. effect	62.897	114.756	145.302	139.969	170.522	197.072

Table A7. Climate change effect on soybean yield under different climate change scenarios

	5th percentile	1st quartile	Median	Mean	3rd quartile	95th percentile
Low scenario						
Historical yield	27.380	39.065	46.613	45.527	52.739	60.556
Simulated yield-temp. effect	27.194	38.854	46.406	45.321	52.530	60.381
Simulated yield-prec. effect	27.446	39.169	46.671	45.613	52.828	60.680
Simulated yield-comb. effect	27.238	38.943	46.477	45.407	52.607	60.473
Medium-low scenario						
Historical yield	27.380	39.065	46.613	45.527	52.739	60.556
Simulated yield-temp. effect	26.878	38.543	46.136	45.031	52.252	60.080
Simulated yield-prec. effect	27.408	39.056	46.602	45.527	52.733	60.570
Simulated yield-comb. effect	26.851	38.551	46.126	45.031	52.235	60.118
Medium-high scenario						
Historical yield	27.380	39.065	46.613	45.527	52.739	60.556
Simulated yield-temp. effect	27.198	38.844	46.427	45.323	52.539	60.342
Simulated yield-prec. effect	27.477	39.146	46.699	45.611	52.808	60.639
Simulated yield-comb. effect	27.274	38.909	46.497	45.406	52.618	60.432
High scenario						
Historical yield	27.380	39.065	46.613	45.527	52.739	60.556
Simulated yield-temp. effect	26.690	38.358	45.973	44.856	52.079	59.895
Simulated yield-prec. effect	27.535	39.198	46.737	45.658	52.877	60.644
Simulated yield-comb. effect	26.857	38.508	46.105	44.985	52.199	59.981

Table A8. Summary statistics for change in corn basis under different climate change scenarios

		5th percentile	1st quartile	Median	Mean	3rd quartile	95th percentile
Low scenario	Historical basis	-1.1906	-0.9450	-0.8000	-0.8019	-0.6504	-0.4286
	Δ basis, Temperature	-0.0130	-0.0073	-0.0018	0.0004	0.0053	0.0233
	Δ basis, Precipitation	-0.0133	-0.0084	-0.0031	-0.0006	0.0041	0.0222
	Δ basis, all climatic variables	-0.0131	-0.0081	-0.0029	-0.0005	0.0041	0.0221
Medium-low scenario	Historical basis	-1.1906	-0.9450	-0.8000	-0.8019	-0.6504	-0.4286
	Δ basis, Temperature	-0.0129	-0.0070	-0.0015	0.0006	0.0054	0.0233
	Δ basis, Precipitation	-0.0132	-0.0076	-0.0020	0.0002	0.0050	0.0232
	Δ basis, all climatic variables	-0.0130	-0.0071	-0.0016	0.0005	0.0052	0.0231
Medium-high scenario	Historical basis	-1.1906	-0.9450	-0.8000	-0.8019	-0.6504	-0.4286
	Δ basis, Temperature	-0.0130	-0.0073	-0.0019	0.0004	0.0053	0.0234
	Δ basis, Precipitation	-0.0144	-0.0089	-0.0034	-0.0010	0.0042	0.0223
	Δ basis, all climatic variables	-0.0143	-0.0087	-0.0034	-0.0009	0.0043	0.0223
High scenario	Historical basis	-1.1906	-0.9450	-0.8000	-0.8019	-0.6504	-0.4286
	Δ basis, Temperature	-0.0128	-0.0069	-0.0013	0.0007	0.0053	0.0232
	Δ basis, Precipitation	-0.0139	-0.0085	-0.0031	-0.0009	0.0040	0.0217
	Δ basis, all climatic variables	-0.0136	-0.0079	-0.0024	-0.0005	0.0041	0.0218

Note: Δ denotes change in basis as a result of changes in temperature, precipitation, or temperature and precipitation. The distribution indicators at the top of the table relate to the basis levels, so these are the change in the 5th percentile basis, 1st quartile basis, median basis, and so on. That is to say, these are not the 5th percentile change in basis, 1st quartile change in basis, median change in basis, or other such indicators of the distribution of the changes.

Table A9. Summary statistics for change in soybean basis under different climate change scenarios

		5th percentile	1st quartile	Median	Mean	3rd quartile	95th percentile
Low scenario	Historical basis	-1.7192	-1.3765	-1.1652	-1.1527	-0.9157	-0.6144
	Δ basis, Temperature	0.0267	0.0202	0.0208	0.0248	0.0284	0.0335
	Δ basis, Precipitation	0.0261	0.0197	0.0204	0.0242	0.0277	0.0319
	Δ basis, all climatic variables	0.0264	0.0201	0.0208	0.0246	0.0282	0.0332
Medium-low scenario	Historical basis	-1.7192	-1.3765	-1.1652	-1.1527	-0.9157	-0.6144
	Δ basis, Temperature	0.0275	0.0208	0.0215	0.0256	0.0294	0.0348
	Δ basis, Precipitation	0.0264	0.0199	0.0204	0.0243	0.0278	0.0324
	Δ basis, all climatic variables	0.0274	0.0208	0.0215	0.0256	0.0294	0.0347
Medium-high scenario	Historical basis	-1.7192	-1.3765	-1.1652	-1.1527	-0.9157	-0.6144
	Δ basis, Temperature	0.0268	0.0201	0.0209	0.0248	0.0285	0.0336
	Δ basis, Precipitation	0.0259	0.0196	0.0205	0.0241	0.0276	0.0321
	Δ basis, all climatic variables	0.0263	0.0199	0.0209	0.0246	0.0283	0.0333
High scenario	Historical basis	-1.7192	-1.3765	-1.1652	-1.1527	-0.9157	-0.6144
	Δ basis, Temperature	0.0277	0.0211	0.0220	0.0262	0.0301	0.0356
	Δ basis, Precipitation	0.0262	0.0197	0.0204	0.0241	0.0276	0.0317
	Δ basis, all climatic variables	0.0275	0.0210	0.0219	0.0260	0.0299	0.0350

Note: Δ denotes change in basis as a result of temperature, precipitation, or temperature and precipitation change.

Figures

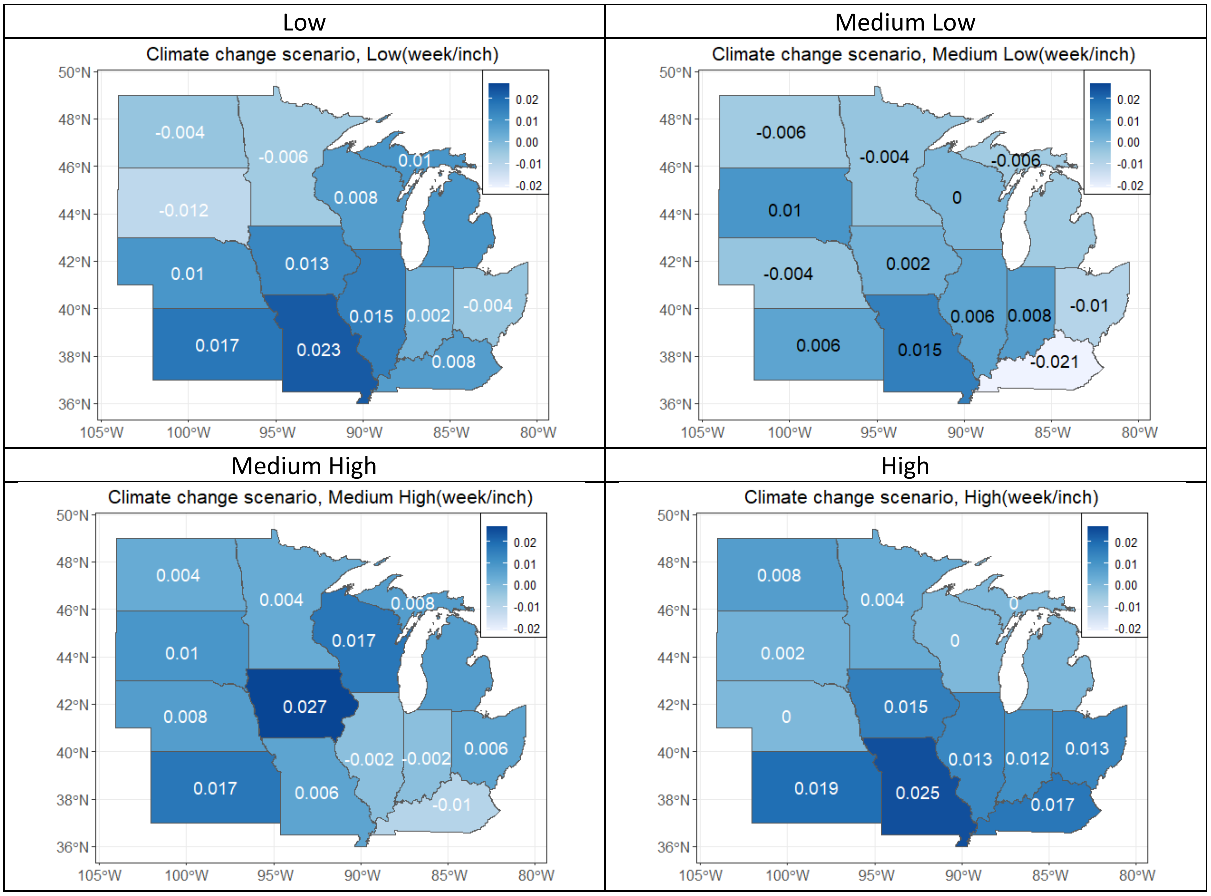

Figure A1. Climate change scenarios for precipitation.

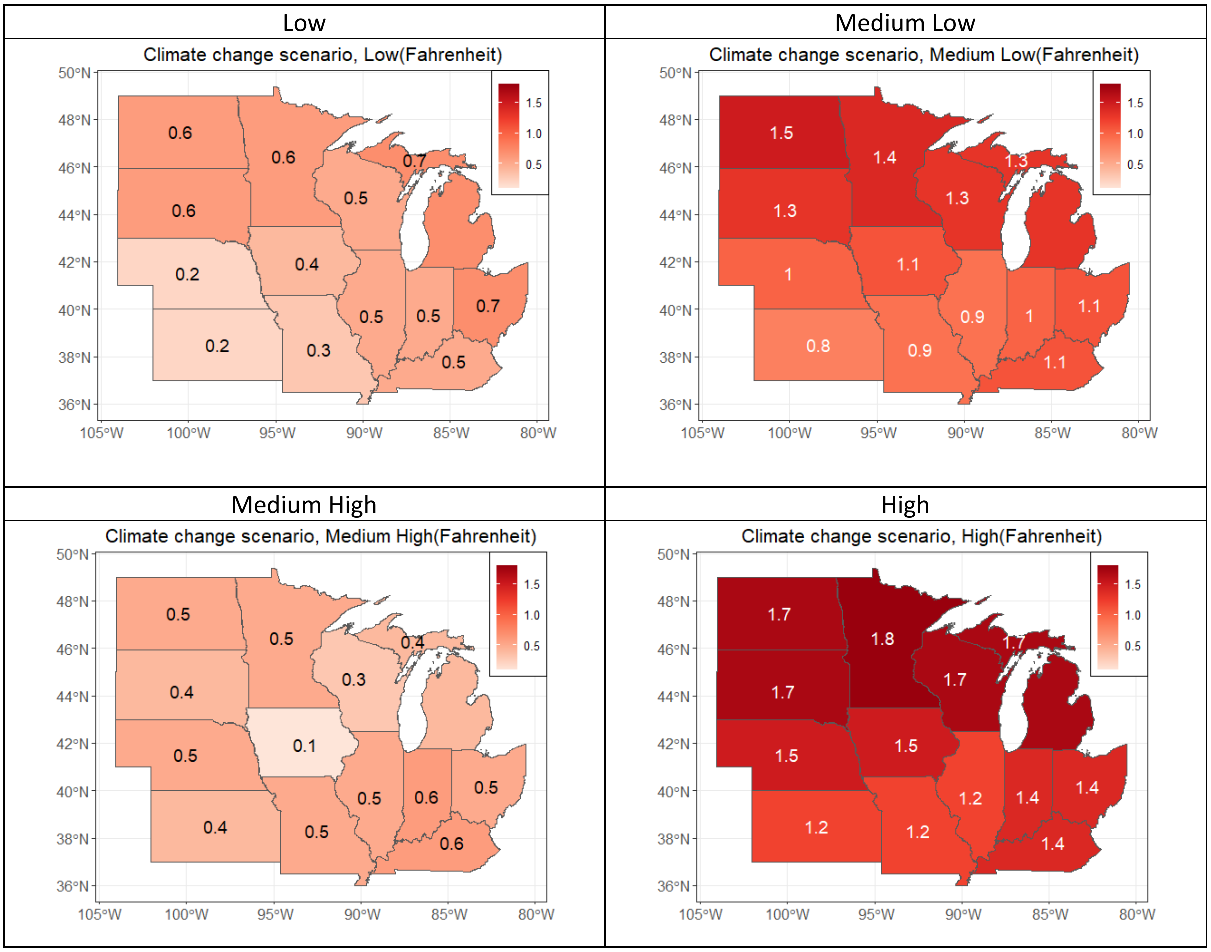

Figure A2. Climate change scenarios for temperature.