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Estimating Market Implications From Corn and Soybean Yields Under Climate Change in the United States

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Jayson Beckman, Maros Ivanic, and Noé J Nava[1]

Abstract

The United States is one of the largest producers and exporters of corn and soybeans globally partly because of yields that are among the highest in the world. However, a changing climate could affect these yields, which could ultimately affect production and the availability of products for export. In this report, the authors estimate that U.S. corn yields could increase 3.1 percent and soybean yields could decrease 3.0 percent in 2036 relative to 2016, based on climate projections. These results are driven primarily by the increased frequency of periods of extreme heat and declines in precipitation in counties east of the 100th meridian part of the United States. These estimates are then used in a simulation model to explore the market implications from these yield projections, and those results indicate that these yield changes could affect U.S. production and ultimately trade. The estimated growth in U.S. corn yields increases corn production that could ultimately affect the amount of corn the United States has available to export. Holding yields in other countries fixed, the model indicates that U.S. corn exports increase 0.36 percent (the equivalent of $63 million). The decline in soybean yields decreases production, leading to a 1.17-percent drop in U.S. exports (the equivalent of $319 million) based on 2016 exports.

Keywords: agricultural productivity, climate change, crop yields (bushels per acre), corn, soybean, trade

About the Authors

Jayson Beckman, Maros Ivanic, and Noé J. Nava are agricultural economists with the Market and Trade Economics Division, USDA, Economic Research Service.

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A report summary from the Economic Research Service — *October 2023*

Estimating Market Implications From Corn and Soybean Yields Under Climate Change in the United States

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What Is the Issue?

The Intergovernmental Panel on Climate Change (IPCC) climate scenarios indicate U.S. climate pattern changes such as rising temperatures and mild declines in precipitation toward the middle of the 21st century. Some outlooks for the United States predict declines in crop yields due to warming temperatures and the increased likelihood of extreme weather events such as droughts and floods, suggesting that U.S. agricultural production and exports might be affected. However, there have not been many studies that examine how past yields and their relationship with weather could help inform future yields, and how this can affect agricultural production and exports. That is, trade outlooks are often conducted using climate and crop model simulations–such as that from the Agricultural Model Intercomparison and Improvement Project (AgMIP)–rather than work that links historical yields with historical changes in climate, such as those coming from econometric studies. The authors' approach to estimating yields in this report is based on historical outcomes. This approach highlights the need to consider data at a finer resolution for those data associated with climate change, as yield estimates vary by county.

What Did the Study Find?

The authors estimated changes in corn and soybean yields in 2036 relative to 2016 for the counties east of the 100th meridian part of the United States. These estimates incorporated evidence on the interaction between weather variations and past crop yield growth. Here are several findings:

- The direction and magnitude of climate effects vary by U.S. county.
- Results indicate that increasing temperatures will likely reach extreme levels that could hinder crop growth during the growing season.
- Similarly, results indicate that precipitation during the growing season will likely decline further and affect crop growth.
- Crop yield projections highlight opposite effects for corn and soybeans as follows:

- Corn yields in the United States increase 3.1 percent (bushels per acre).
- Soybean yields decrease 3.0 percent in yields (bushels per acre).

- The analysis considered the main corn and soybean growing regions, which are east of the 100th meridian part of the United States. Yield projections varied by region, including:
  - North and South Dakota, Kansas, and Nebraska experience sharp declines in crop yields of 14.5 percent for corn and 7.1 percent for soybeans.
  - Midwestern States such as Illinois, Missouri, Iowa, and Wisconsin experience crop yield gains of 1.2 percent for soybeans and 5.7 percent for corn.
  - Indiana, Kentucky, and Tennessee experience yield gains for corn of 5.4 percent and yield declines for soybeans of 5.8 percent.

A global economic model was used to examine how these yield changes could affect U.S. agricultural production and trade patterns. Among the findings:

- Production increases 0.11 percent across all U.S. corn-producing States. The model indicates that producers allocate less land to corn due to the increase in yields. U.S. corn exports increase 0.36 percent, the equivalent of $63 million based on 2016 exports.
- U.S. soybean production decreases 0.93 percent due to the decrease in yields, while exports decline 1.17 percent. Producers allocate more land to soybeans in the model, to compensate for the decrease in yields.

How Was the Study Conducted?

The authors used a multistep approach that connects crop yield projections under climate change with a global economic model. In the first step, a geographically weighted regression (GWR) estimator was used to estimate county-specific marginal effects of climate change on corn and soybean yields for counties east of the 100th meridian part of the United States. The estimation procedure assumed that farmers adapt to climate change through new technologies and adopt different managerial practices over the projected future period that are consistent with differences in yields achieved over 1996 to 2016.

The study projects out into 2036 and shows how yields might change based on changes in climatic data. The analysis is conducted independently for each crop. In the next step, the Global Trade Analysis Project-Agro-Ecological Zone (GTAP-AEZ) economic model, which incorporates agro-ecological zones (AEZs) into the GTAP framework, is introduced. Yield projections are incorporated into the GTAP-AEZ model to study how domestic yield changes could affect U.S. agricultural production and trade while holding trading partner yields constant. That is, the effect of climate change on production is held constant in the rest of the world (ROW) to analyze how trade is affected by projected U.S. production responses to projected climate change.

Estimating Market Implications From Corn and Soybean Yields Under Climate Change in the United States

Introduction

U.S. corn and soybean production experienced steady gains in agricultural productivity over the last three decades due to acreage expansion and technology adoption (Saavoss et al., 2022). U.S. production of corn was 110 bushels per acre (bpa) in 1992, reaching 177 bpa in 2020, while U.S. production of soybeans was 33 bpa in 1992, reaching 52 bpa in 2020, turning the United States into a world-leading producer of corn and soybeans. In 2020, the United States produced 360 million tons of corn, contributing more to the global supply than China, India, and Russia combined (305 million tons). Similarly, the United States produced 127 million tons of soybeans in 2020, which was surpassed by Brazil's 149 million tons in 2020[1] (Colussi & Schnitkey, 2021). Corn and soybeans are also important export commodities for the United States. Traditionally, soybean exports were the highest value U.S. exports, accounting for between 11 and 17 percent of all U.S. agricultural exports from 2017 to 2021. Corn traditionally has been in the top five of all agricultural commodities exported. In 2021, corn's export value of $18.7 billion was second only to soybeans ($27.4 billion). Combined, the 2 commodities accounted for 26 percent of all U.S. agricultural commodity exports in 2021 (USDA, Foreign Agricultural Service (FAS), 2021).

The increase in U.S. corn and soybean productivity has been partially achieved by increasing yields (see box titled "Productivity and Yields"). Schnitkey et al. (2022) note that U.S. corn yields have been growing since the late 1930s, and evidence suggests that they are increasing between 1.9 and 2.0 bushels per year. Schnitkey et al. (2022) point out that U.S. soybean yields have been increasing over time, although both the corn and soybeans yields for the United States decreased in 2022 relative to the trends projected in their report.

Productivity and Yields

Yields are a part of broader measure of productivity, which is often labeled as total factor productivity (TFP). TFP accounts for a larger set of inputs into production and considers technical efficiency change. The data presented by USDA, Economic Research Service (ERS) (2022a) for the United States and by USDA, ERS (2022b) for the rest of the world are some examples of data on TFP. However, TFP by agricultural commodity is difficult to measure. As such, yields are often used as a measure of agriculture productivity. In a broad sense, yields measure the quantity of crops grown on an amount of land.

Along with acreage planted, productivity determines the changes in production to the agricultural sector. That is, acreage planted can remain the same, and an increase in productivity will increase the amount of agricultural production. Given that research literature often focuses on yields when discussing how a future climate might affect agricultural markets, the authors of this report do the same.

[1] Colussi & Schnitkey (2021) predict the U.S.-Brazil gap to continue towards the end of the decade with Brazil producing 173 million tons of soybeans with the United States producing 147 million tons.

The most recent Intergovernmental Panel on Climate Change (IPCC) report noted that the planet will continue to warm and experience more frequent extreme weather events. Numerous agricultural outlooks (e.g., Burke & Emerick, 2016; Challinor et al., 2014; Deschênes & Greenstone, 2007; Mendelsohn et al., 1994; Porter et al., 2019; Schenker & Roberts, 2009; Roberts et al., 2013) suggest that these changes in the climate will likely cause agricultural productivity and yields to decline toward the middle of the century. They note that an increase in the frequency of extreme weather events, such as droughts, floods, and heat-waves, and shifts in climatic conditions may prevent the optimal growth of some crops.[2] But the effects of climate change on yields are expected to differ across commodities. For example, Zhao et al. (2017) estimate that global rice yields will likely decrease 3.3 percent compared to 3.6 percent for soybeans, 6.9 percent for wheat, and 8.6 percent for corn as a result of a 2-degree (Celsius) rise in global mean temperature from 2029 to 2058.

A changing climate could affect the United States' standing as a global leader in agricultural production and trade. If climate change affects yields, it will ultimately affect how much the United States can grow and export. Although there is a good deal of information on yields and yield projections in the research literature, much of it is not very detailed—often providing the change in yield by the whole country. However, yield changes can be and will be (as the authors show) heterogenous, depending on where the crops are grown and the projected change in climate for that area. To fully understand the potential effects to the United States, a more detailed picture of yield changes is needed. As such, the authors estimated the potential changes to corn and soybean yields by county, considering differences in weather for each area (see box titled "Data on Crop Yields, Historical Weather, and Climate Change"). Using a middle-of-the-road IPCC climate scenario for 2036, this report connects climate-induced crop yield projections with a computable general equilibrium (CGE) model to determine how U.S. markets and trade could be affected by a changing climate.

[2] Several mitigation strategies have been proposed, including building resilience in the food system by connecting regions through trade (Dall'erba et al., 2021), but import-dependency may bring its own challenge in the form of supply chain disruption in the domestic market of agricultural commodities (Nava et al., 2022).

Data on Crop Yields, Historical Weather, and Climate Change

Data for this study came from three main sources:

- Data for corn and soybean yields come from the USDA's yearly survey on crop yields. These numbers were generated by dividing total bushels per total acreage for each of the counties considered in this report.

- Historical weather data were collected from the Parameter-elevation Regressions on Independent Slopes Model (PRISM). Daily minimum temperature, maximum temperature, and total precipitation to construct agronomy-relevant heat and humidity indicators were gathered. The heat measure was based on the cumulative growing degree days (GDD) and extreme degree days (EDD) temperature (Burke & Emerick, 2016). The temperature of 30 °C was used as the measure of GDD as temperatures above this can be stressful to corn plants (Minnesota Department of Natural Resources, 2023). Soybeans can experience heat stress at 29.4 °C (Farm Progress, 2023). The measure of precipitation was cumulative precipitation over the growing season. In contrast to GDD and EDD, which have thresholds that divide growing temperature from harmful temperature, precipitation does not have such a threshold, so the same approach was used as in previous studies and focused on cumulative precipitation (Burke & Emerick, 2016).

- The climate scenario used future weather forecasts employed in the most recent IPCC report, which assumes increases in global temperature of 1.5–3.0 °C above pre-industrial levels. The National Aeronautics and Space Administration (NASA) collects and makes available all weather forecast simulations employed in the most recent Intergovernmental Panel on Climate Change report through its NASA Earth Exchange Global Daily Downscaled Projections (NEX-GDDP) database (Thrasher et al., 2012). The chosen climate models are known as CanESM5, TaiESM2, MIRO6, and ACCESS-CM2 and are based on the "middle of the road" assumptions for the Shared Socioeconomic Pathway (SSP2-4.5) climate scenario that considers moderate adjustments to the economy that have a medium-level climate change mitigation effect relative to more aggressive SSPs. Despite that all climate models are based on the same fundamental assumption previously described (e.g., SSP2-4.5), these models may produce slightly different results based on the empirical decisions made by climate scientists. Therefore, weather variables are processed while considering the unit of measure may change across data sources by averaging the results from each of these climate models (Dall'erba et al., 2021).

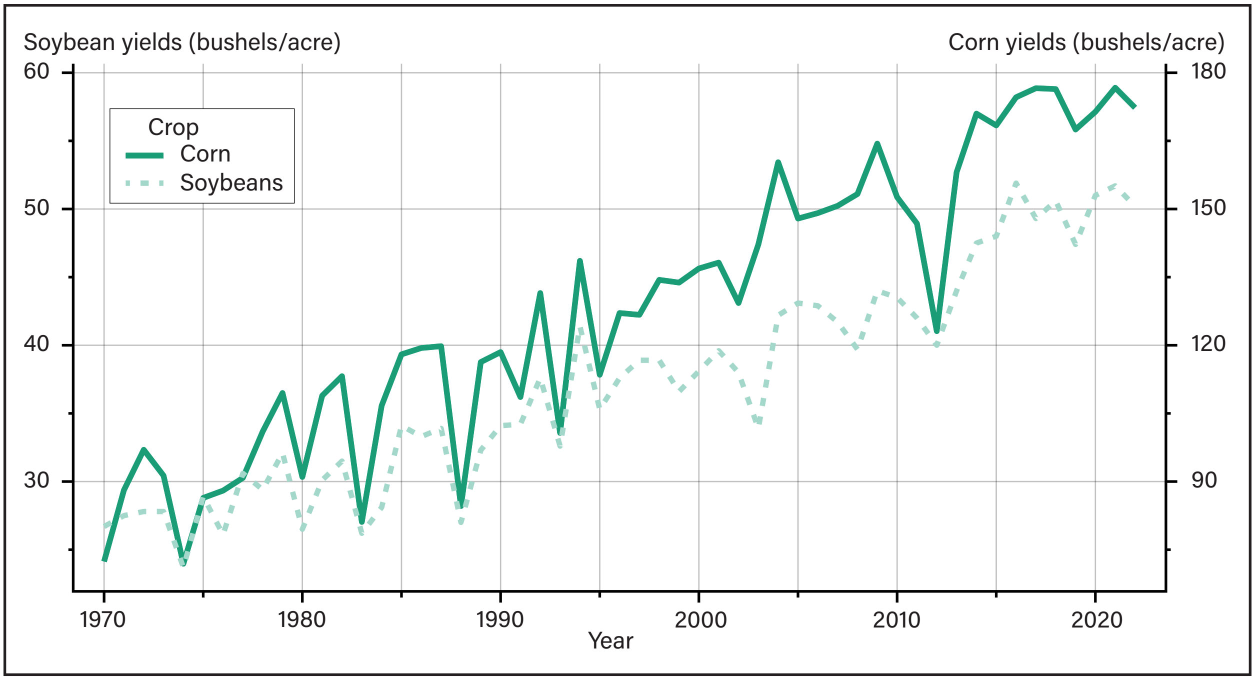
U.S. Corn and Soybean Yields Between 1996 and 2016

U.S. farmers are among the most productive globally partly because of yields that are among the highest in the world. For example, data from the Food and Agriculture Organization of the United Nations (FAO) (2023) indicate that U.S. corn yields are the highest in the world (recall that these were 177 bpa), while corn yields for China (the second-largest producer) were 93.98 (bpa).[3] Soybean yields are more comparable among major producers, but the United States still had the largest yields (52 bpa versus 48.77 bpa for Brazil,

[3] Data from the Food and Agriculture Organization of the United Nations (2023) is in metric tons per hectare. The authors converted the numbers for bushels per acre by assuming that 1 metric ton per hectare = 14.8697 bushels per acre.

the second-most productive soybean producer).[4] Figure 1 indicates that U.S. corn and soybean yields have increased over time. Corn and soybean yields have doubled since 1970, but there has been somewhat of a plateauing for the last couple of years. Schnitkey et al. (2022) attribute this to drought in some States and lackluster yields in others. This report's authors noted that drought could be a function of a changing climate.

Figure 1
Historical yields for U.S. corn and soybeans, 1970 to 2022

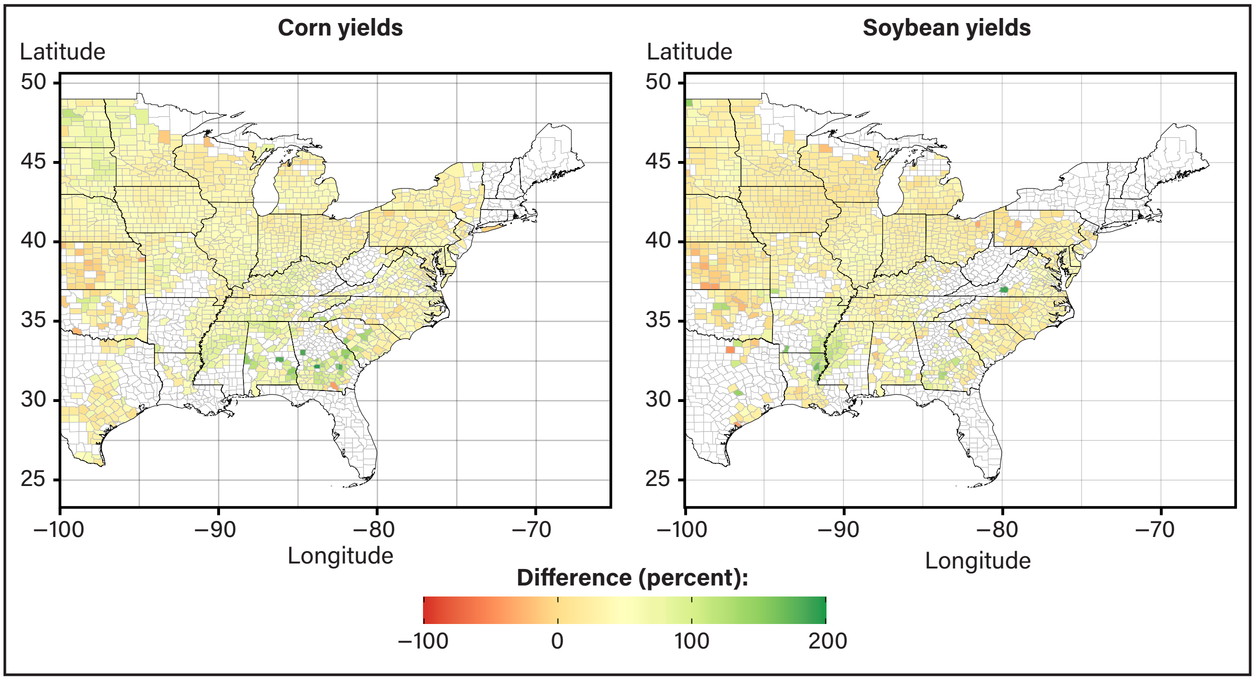


Source: USDA, National Agricultural Statistics Service, 2023.

Despite the overall increase in U.S. corn and soybean yields, they are not uniform across all States and across time. To show this, figure 2 describes the spatial distribution of changes in corn and soybean yields from 1996 to 2016. While some U.S. counties had a decrease in corn and soybean yields between 1996 and 2016 (most noticeably in Oklahoma and Kansas), most counties' increase was between 25 and 50 percent. The upper parts of the Midwest, especially Illinois, Iowa, and Minnesota, had crop yield improvements. Counties in these regions are traditionally large producers of cereals and oilseed. Only a handful of counties (one in North Dakota and a few in Alabama, Georgia, and South Carolina) experienced crop yield growth above 100 percent. In contrast, soybean yield growth above 100 percent is found along the Mississippi Delta, with a few exceptions outside this region. For this report, counties were dropped if they did not produce corn or soybeans in either 1996, 2016, or both years. Florida and some New England States were not analyzed because USDA did not report corn and soybean production in those States during the analysis years.

[4] As we indicated earlier, total production in the United States was 127 million tons in 2020, which was only exceeded by Brazil with 149 million tons.

Figure 2
Corn and soybean yield changes for U.S. counties east of the 100th meridian, 1996–2016



Note: The 100th meridian is often defined in the literature to divide irrigated crops (West) from rain-fed crops (East).

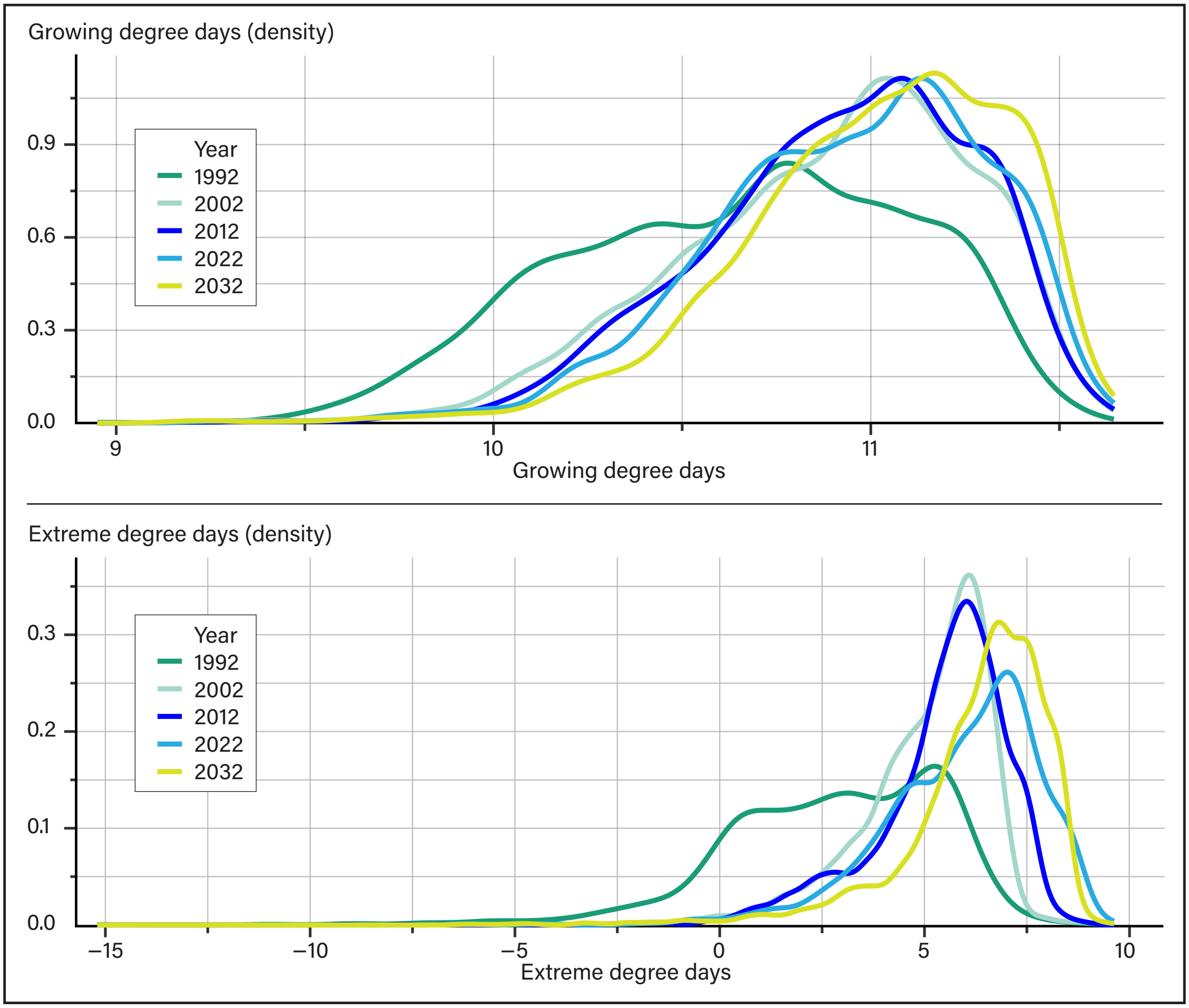
Source: USDA, National Agricultural Statistics Service, 2023.

Past and Future Weather

As mentioned earlier, Schnitkey et al. (2022) attribute part of the plateauing of recent corn and soybean yields to drought in some States. As shown in figure 1, the largest decrease in yields since 1988 was in 2012, which was due to a large-scale drought in many States (USDA, ERS, 2012).[5] To examine how weather has changed over time and how it might change in the future, figure 3 shows warming characteristics for counties east of the 100th meridian part of the United States, where the majority of corn and soybeans are grown. The first plot illustrates growing degree days (GDD), and the second plot illustrates extreme degree days (EDD). Regarding the red distribution as a reference (1992), the line trajectory is skewed to the left in relation to the rest of the years in both illustrations, indicating that 1992 was not a particularly hot year. The lower peak also indicates how relatively cold 1992 was.

[5] There was a large decrease in soybean yields in 2003, but not for corn.

Figure 3
Growing degree days and extreme growing degree days, 1992–2032



Note: Growing degree days and extreme degree days are calculated using 30 °C. Variables are logged base 2, so their interpretation is exponential. The figures illustrate the density distribution (vertical axis) of total U.S. counties with the given level of weather (horizontal axis).

Source: USDA, Economic Research Service, using data from the University of Oregon's PRISM Climate Group and the National Aeronautics and Space Administration (NASA) Earth Exchange Global Daily Downscaled Projections (NEX-GDDP).

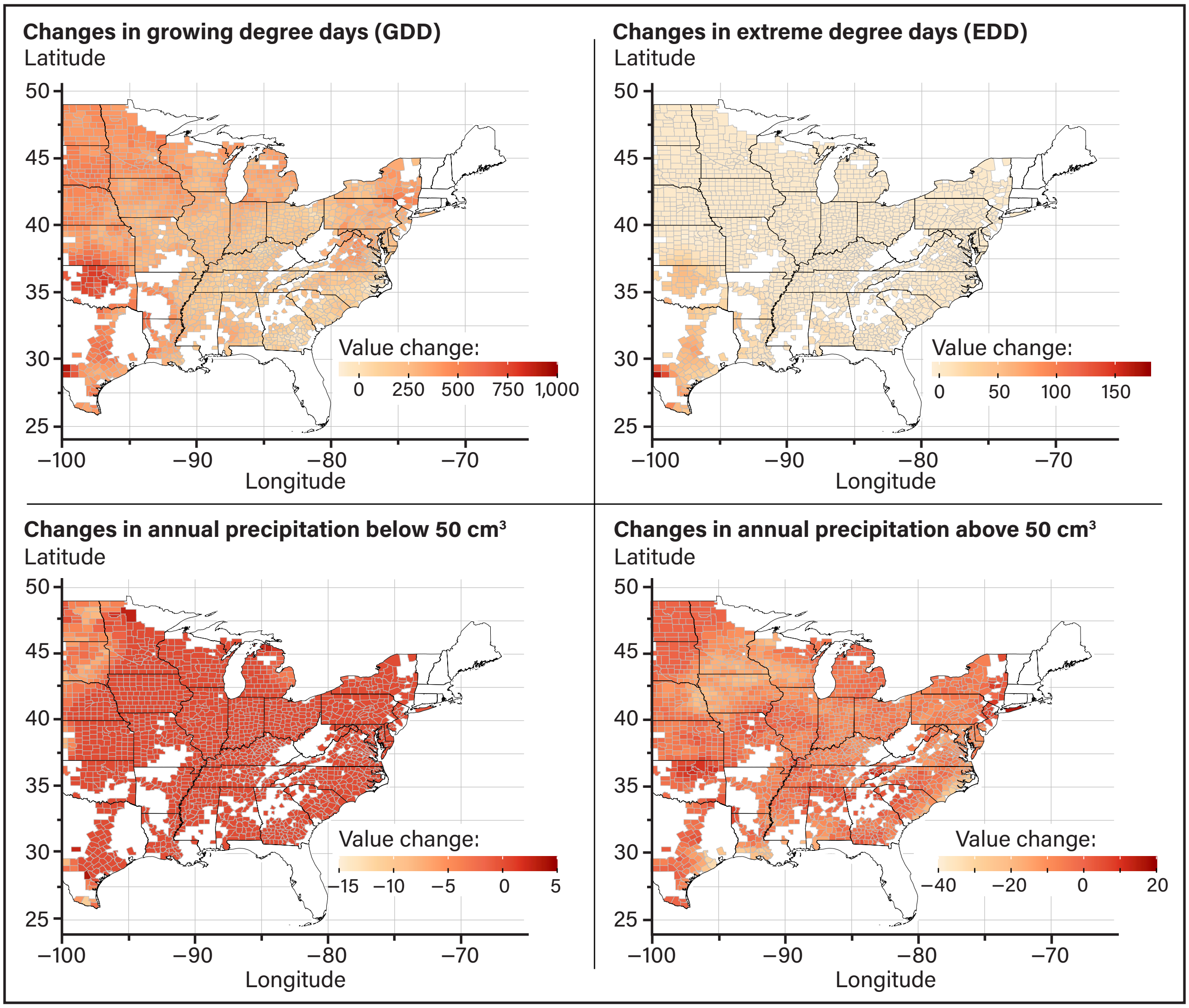
Nevertheless, as time passes, all the distributions noted in the charts in figure 3 shift to the right with higher peaks, illustrating that increasing temperatures are becoming a new norm. Furthermore, a bunching of values can be observed on the right side of the top chart, meaning that the threshold of 30 °C is being surpassed, and extreme degree days (the bottom chart) continue to shift to the right. An important insight to draw from this figure is that extreme heat may become a norm in the next decade.

In figure 4, the authors plot changes in the historical climate (obtained from PRISM) and forecasted climate (obtained from the National Aeronautics and Space Administration (NASA) Earth Exchange Global Daily Downscaled Projections (NEX-GDDP)) for GDD (top-left), EDD (top-right), precipitation below 50 cubic centimeters (cm^3) (bottom-left), and precipitation above 50 cm^3 (bottom-right).[6] Rising temperatures were observed to have two opposite measures of heat crops' growth: A positive one as measured by GDD and a negative one as measured by EDD. The authors noted an absolute increase in the total number of GDD for

[6] The precipitation threshold is based on the model selection as will be shown in the report's appendix.

most U.S. counties, except for some counties in Alabama, Virginia, and Tennessee. These changes, however, are relatively small being as low as -80 while the increases in GDD observed in the rest of the country can be as high as 925 with a mean of 260. Counties that present a decline in GDD, along with increases in EDD, present an exceptional pattern of lower average temperatures during the day, with more hot days above historical records. Similarly, EDD will increase for a large part of counties east of the 100th meridian part of the United States, but the EDD increase is small with a mean of 4 and a high of 174. EDD increases will be the highest for the Southern United States. Having fewer EDD and more GDD in the Northern United States indicates that while climate will become warmer, days with extreme heat will occur less often in 2036. When it comes to precipitation, the data indicate that most of the United States will experience declines in precipitation as manifested in both measures of precipitation decreasing with few exceptions across the country (see box titled "Future Climate Data").

Figure 4
Changes in climate variables in U.S. counties east of the 100th meridian, 2016–36



cm³ = cubic centimeters.

Note: These maps show the spatial distribution of the changes in growing degree days (top-left), extreme degree days (top-right), annual precipitation below 50 cm³ (bottom-left), and annual precipitation above 50 cm³ (bottom-right) for U.S. counties east of the 100th meridian.

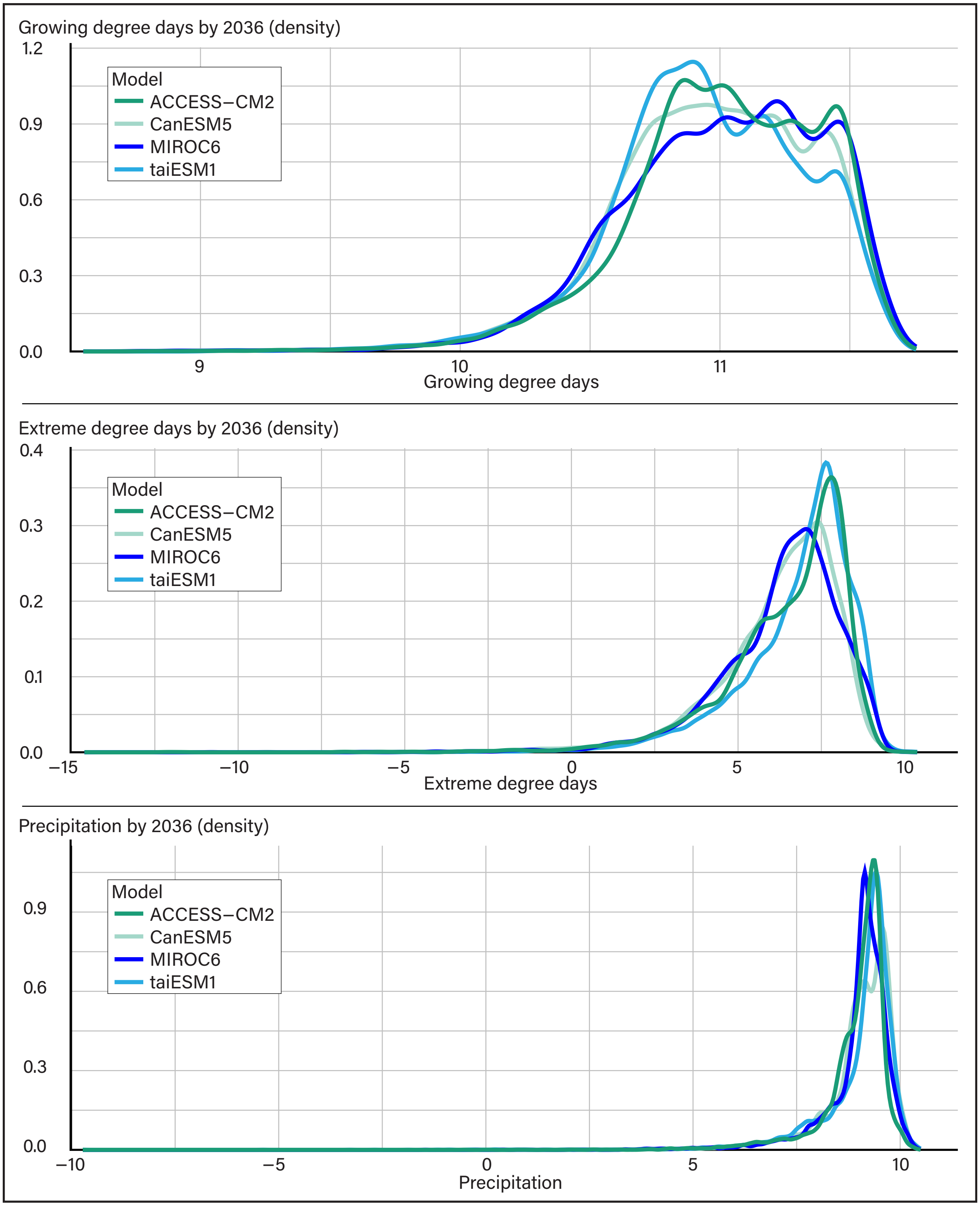
Source: USDA, Economic Research Service, using data from the University of Oregon's PRISM Climate Group, and the National Aeronautics and Space Administration (NASA) Earth Exchange Global Daily Downscaled Projections (NEX-GDDP).

Future Climate Data

In this report, the authors focused on the climate scenario often referred to as the "middle of the road" Shared Socioeconomic Pathway (SSP2-4.5) that accounts for medium challenges to mitigation and adoption of environmentally sustainable practices. There are several climate models available: CanESM5, TaiESM2, MIRO6, and ACCESS-CM2. Differences in models, based on the same SSP2-4.5 assumption, are driven by the decisions on the part of climate scientists' model selection (differences in parameters, regional data, etc.). Figure 5 illustrates forecasted growing degree days (top chart), extreme degree days (middle chart), and precipitation (bottom chart) by the year 2036, where each distribution represents a climate model. The authors did not find significant differences across the climate models.

Despite this, the authors made the empirical decision of how to process all the data. The authors followed common practices adopted by economic practitioners (for a description of the conceptual framework, see Hinne et al., 2020). The authors differentiated between aleatoric and epistemic uncertainty recognizing that all models only present one value per geographical observation such that differences in the models are driven by model selection (e.g., epistemic uncertainty)—i.e., no model is better than the other. That is, the authors averaged each model observation across each geographical area to produce the climate forecast. This approach has been used extensively in the literature (Pierce et al., 2009).

Figure 5
Growing degree days, extreme degree days, and precipitation by 2036



Note: Growing degree days and extreme degree days are calculated using 30 °C. Each density distribution represents a climate model. Variables are logged base 2, so their interpretation is exponential. The figures illustrate the density distribution (vertical axis) of total U.S. counties with the given level of weather (horizontal axis).

Source: USDA, Economic Research Service, using the National Aeronautics and Space Administration (NASA) Earth Exchange Global Daily Downscaled Projections (NEX-GDDP).

Estimating Yields

This study estimated yields by using a crop yield specification that relies on a long-differences approach between the average of two time periods (Burke & Emerick, 2016):

$$\Delta\bar{y}_i = \beta'\Delta\bar{C}_i + \Delta\bar{\epsilon}_i \quad (1)$$

where the variables $\bar{y}_i$ and $\bar{C}_i$ are averages of two time periods for location i for crop yields and climate variables respectively, Δ indicates first-degree differences between those two periods. That is, the authors first calculate an average for each one of the periods of time separately, and subtract one from the other. $\bar{\epsilon}_i$ is the stochastic term associated with such estimation. Time-invariant influences are subsumed in (1) since the estimation relies on differences between 1996–2016. One concern when estimating parameters to investigate climate change impacts is that they must reflect adaptation to climate rather than responses to weather variations (Mérel & Gammans, 2021). Because the differentiation is taken over two distant time periods (20-year periods for this study), estimates from the equality described in (1) can be used to study climate change over the next couple of decades and account for adaptation under the assumption that farmers' adaptation to climate change is the same in the period between 2016 and 2036 as in the period between 1996 and 2016 (i.e., adaptation to climate change is constant) (Burke & Emerick, 2016)[7] [8]

The authors incorporated a cumulative measure of GDD and precipitation during the growing season[9] [10] (April 1 to September 30). This approach remedies the nonlinear nature of crop yields and climate (Schlenker & Roberts, 2006, 2009). Next, the authors followed the work of Nava et al. (2022) by using the Ricardian approach of Mendelsohn et al. (1994) to a locally spatial setting with a geographically weighted regression (GWR) estimator. Following the notation of (1), the equation becomes:

$$\Delta\bar{y}_i = \beta'(\mathrm{u_i}, \mathrm{v_i})\Delta\bar{C}_i + \Delta\bar{\epsilon}_i \quad (2)$$

where $\beta'(\mathrm{u_i}, \mathrm{v_i})$ is a locally varying vector of coefficients associated with climate variables and highlights the strength of the GWR applications as $\mathrm{u_i}$ and $\mathrm{v_i}$ are a location's (i's) latitude and longitude, respectively. With the GWR estimator the authors derived county-specific forecasts since coefficients are estimated at the unit level. The focus was on the two most planted crops produced in the United States: corn and soybeans. Thus, $\Delta y_i = \log(\overline{\omega_b}) - \log(\overline{\omega_a})$ can be written where the subscripts a and b are two time periods, and $(\overline{\omega_b})$ and $(\overline{\omega_a})$

[7] Following the argument of Burke & Emerick (2016), the authors considered the panel specification of (1) $\bar{y}_{it} = \beta_0 + \beta'\bar{C}_{it}$, where β_0 is the constant term and $t \in \{0,1\}$ denote the two time periods that the practitioner is considering. Variables were created using short-run variation by virtue of being "smoothed" variables. Because of the long-differences, $\Delta\bar{y}_i = \bar{y}_{i1} - \bar{y}_{i0}$, not only was the constant term dropped, but the variation left only represents long-run responses to climate, as opposed to weather.

[8] Our empirical strategy assumes that farmers' degree of adaptation to climate change and gains in agricultural productivity that are unrelated to climate for the period of 1996–2016 is similar to that for the period of 2016–36. That is, we should expect, holding climate constant, that if yields increased by 10 percent in 1996–2016, then they should increase by 10 percent in the subsequent 20-year period. An additional form of adaptation that is implicitly embedded in the coefficients of equation (1) is shifting from one crop to another. Our estimation procedure, however, is unable to measure such degree of adaptation. Due to the importance of land use changes to adapt to climate change, we study the role of substitution between our two crops with our GTAP-AEZ framework. We provide our conclusions and results in subsequent sections.

[9] An ideal measure of crop heat exposure and precipitation relies on mapping temperature and rainfall variations within a day to the crops' exposure to weather. However, this is unpractical outside experimental settings. The next ideal method is to measure the crop's yield growth throughout the growing season (i.e., from planting to harvest) and parametrize an estimation equation that accounts for such time periods. While the authors' weather variables can be calculated for each day, USDA's National Agricultural Statistics Service provides crop yields for the whole growing season for each county. Thus, the authors decided to calculate growing season variables following the work of Burke and Emerick (2016).

[10] It is important to notice that while temperature and threshold selections are informed by the agronomy literature on how the plant responds to heat and precipitation exposure, the direction of the effect may not necessarily correspond to agronomy expectations. The reason is that this study relies on observational data, as supposed to data generated in experimental settings, that may contain unobserved interactions between land characteristics, farmers' managerial decisions as to how and when to adapt to climate change, and other climatic effects affecting the crop growth.

are smoothed yields[11] for each crop in each period. The authors defined smoothed GDD temperature $\overline{GDD_i^{l_0:l_1}}$ but also created a measure of smoothed EDD temperature defined in their $\overline{EDD_i^{l_1:\infty}}$ as l_0 superscripts are a lower limit and an upper limit for which the plant grows with heat exposure is measured in average daily temperature l_1 after, the plant is damaged (Burke & Emerick, 2016). The authors included $\overline{PPT_i^{p<p_0}}$ $\overline{PPT_i^{p>p_0}}$ and denote observed precipitation p_0 below and above a threshold. Precipitation variables are also smoothed. Therefore, the final specification is shown below:

$$\Delta\overline{y}_i = \beta_1(\mathrm{u_i}, \mathrm{v_i})\Delta\,\overline{GDD_i^{l_0:l_1}} + \beta_2(\mathrm{u_i}, \mathrm{v_i})\Delta\,\overline{EDD_i^{l_1:\infty}} + \beta_3(\mathrm{u_i}, \mathrm{v_i})\Delta\,\overline{PPT_i^{p<p_0}} + \beta_4(\mathrm{u_i}, \mathrm{v_i})\Delta\,\overline{PPT_i^{p<p_0}} + \Delta\overline{\epsilon}_i \quad (3)$$

Estimation Results

Table 1 describes the difference of the variables from each period that are associated with the estimation of equation (3). That is, the logged value of corn yields for a county in 2016 is subtracted from the logged value of corn yields for that same county in 1996. As indicated, yields for both crops substantially increased over the 20-year period from 1996 to 2016. Climate variables present a pattern of rising temperatures and mild declines in precipitation. Because acreage is used as weights in the econometric approach, the authors followed the work of Burke & Emerick (2016) and fixed acreages on a reference period. That is, estimates are calibrated using a 20-year period prior to 2016 to project into the subsequent 20-year period. Thus, a reference for acreage is determined despite forecasted values for acreage being unknown, making the interpretation of the crop yield projections the result of changes in productivity rather than changes in acreage.

Table 1
Descriptive statistics for report data

	Mean	SD	Minimum	Maximum	Observations
Log of difference in corn yields	0.36	0.16	-0.49	1.11	1,690
Log of difference in soybean yields	0.28	0.16	-0.61	1.11	1,518
Corn acreage in 2016	30,641	50,420	0	319,973	2,509
Soy acreage in 2016	35,054	54,793	0	588,856	2,509
Difference in growing degree days < 30 °C threshold)	81.83	137.87	-762.46	446.01	2,510
Difference in extreme degree days (> 30 °C threshold)	0.47	6.62	59.13	31.51	2,510
Difference in precipitation below 50 cm^3	0.79	2.33	-3.08	21.65	2,510
Difference in precipitation above 50 cm^3	10.12	8.25	-9.73	54.45	2,510

SD = standard deviation; cm^3 = cubic centimeters; < = less than; > = greater than.

Note: Variables are constructed by first calculating 5-year averages around 1996 and 2016. For example, data for 1996 corresponds to the average from 1994 to 1998, and data for 2016 corresponds to the average from 2014 to 2018. Then the value of 1996 is subtracted from the value of 2016. Observations vary depending on the crop. Acreage for the 2 crops is based on data from 2016.

Source: USDA, National Agricultural Statistics Service (NASS), using data from the University of Oregon's PRISM Climate Group, and the National Aeronautics and Space Administration (NASA) Earth Exchange Global Daily Downscaled Projections (NEX-GDDP).

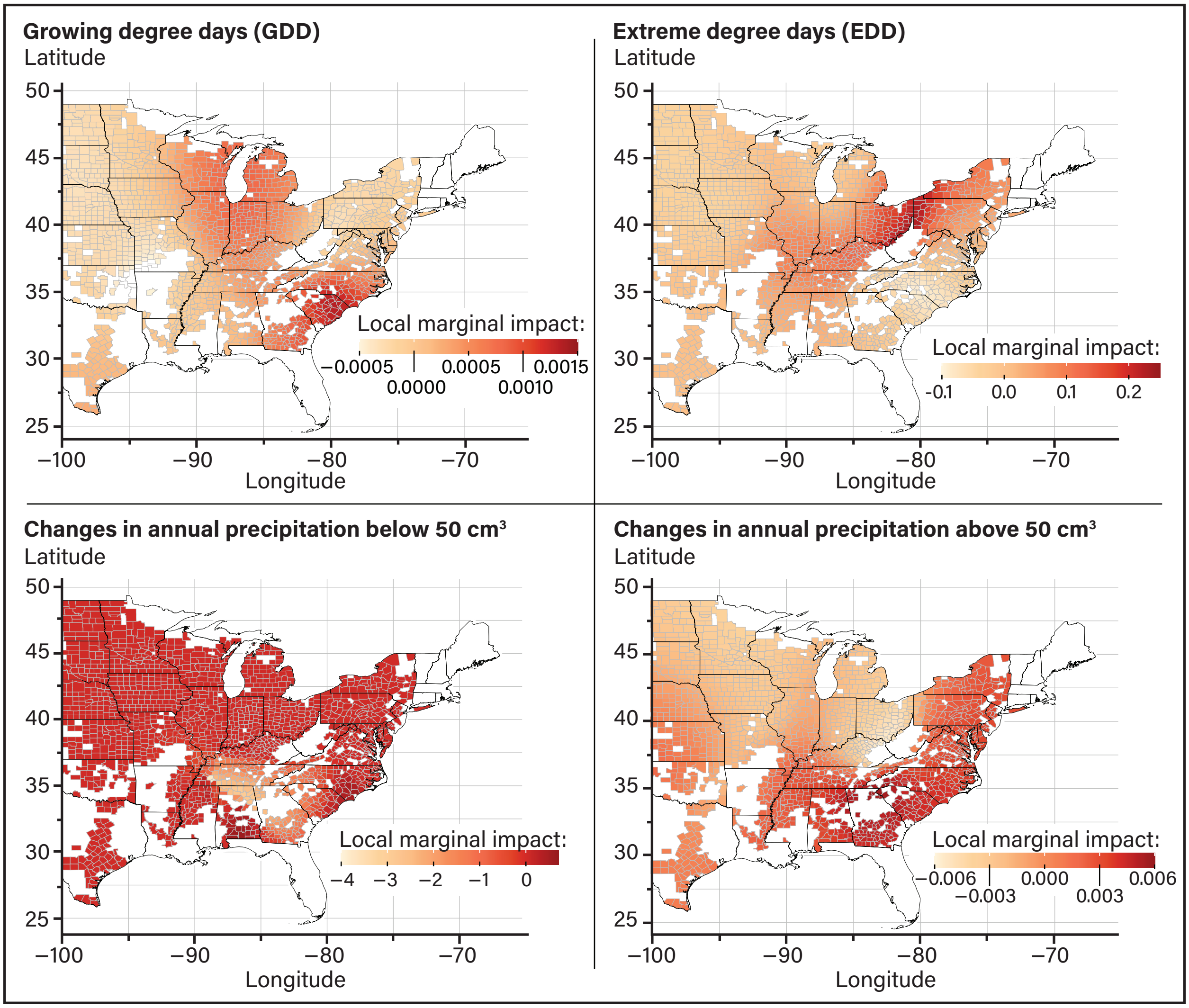
[11] The authors define a smooth variable as an average around the period of interest. For instance, the authors' report focuses on 1996, so an average for 1996 is obtained using the observed values between 1994 and 1998. The importance of having a smooth variable is that the regression focuses on climate rather than weather variations.

Crop Yield Estimates

Crop yield estimates indicate that most counties in North Dakota, Minnesota, Wisconsin, Kansas, Oklahoma, and the States north of Virginia are likely to experience corn yield declines (figure 6) if the cumulative GDD increases due to rising temperatures. The same dichotomy, but with positive values, is found for the Midwest. Illinois, for instance, benefits from overall rise in heat despite the increase in the number of extreme days. This result indicates that Illinois is likely below its optimal temperature level for crop yields. Georgia counties benefit from increases in GDD temperature but are worse off by having a higher amount of EDD temperature. Similar patterns for precipitation are also found.

Figure 6

Spatial distribution of the marginal effects of heat and precipitation on corn yields for U.S. counties to east of the 100th meridian, 2016–36



cm^3 = cubic centimeters.

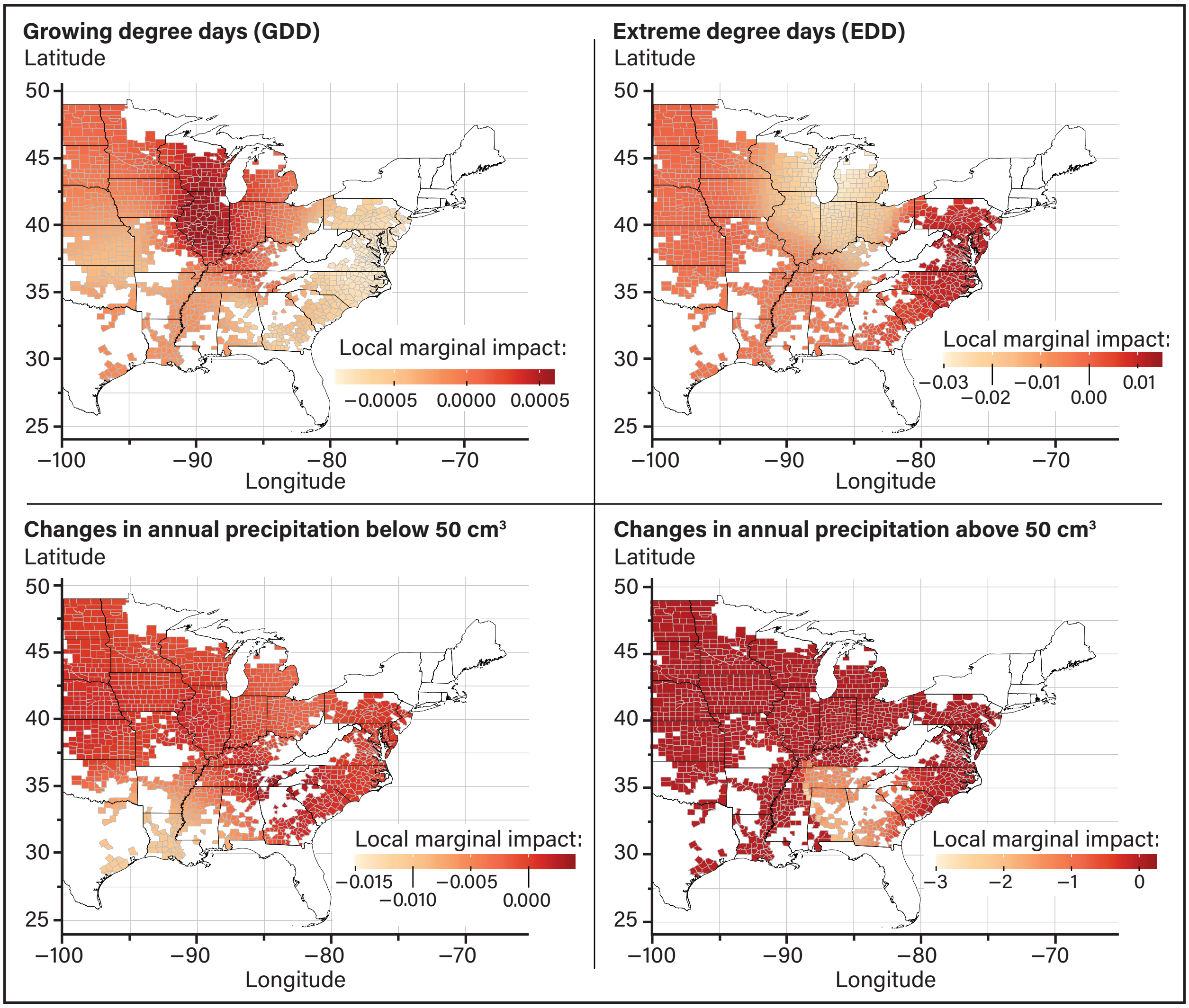
Note: Figure maps the spatial distribution of the marginal effect of growing degree days (top-left), extreme degree days (top-right), annual precipitation below 50 cm^3 (bottom left), and annual precipitation above 50 cm^3 (bottom right) on corn yields for U.S. counties east of the 100th meridian.

Source: USDA, Economic Research Service.

The results for soybean yields show substantial higher variability as described in figure 7. The number of clusters is larger, and negative values are present within clusters of positive values. In contrast, the counties that benefit from heat below the threshold are found to also benefit from heat above the threshold and vice-versa. This result suggests that soybeans may require a larger amount of cumulative GDD for optimal production conditions in places such as Illinois, Indiana, and the northern counties of New York. Precipitation in the Midwest largely follows the same pattern as heat, suggesting that soybeans in the States in this region are prone to floods.

Figure 7

Spatial distribution of the marginal effects of heat and precipitation on soybean yields for U.S. counties east of the 100th meridian, 2016–36



cm^3 = cubic centimeters.

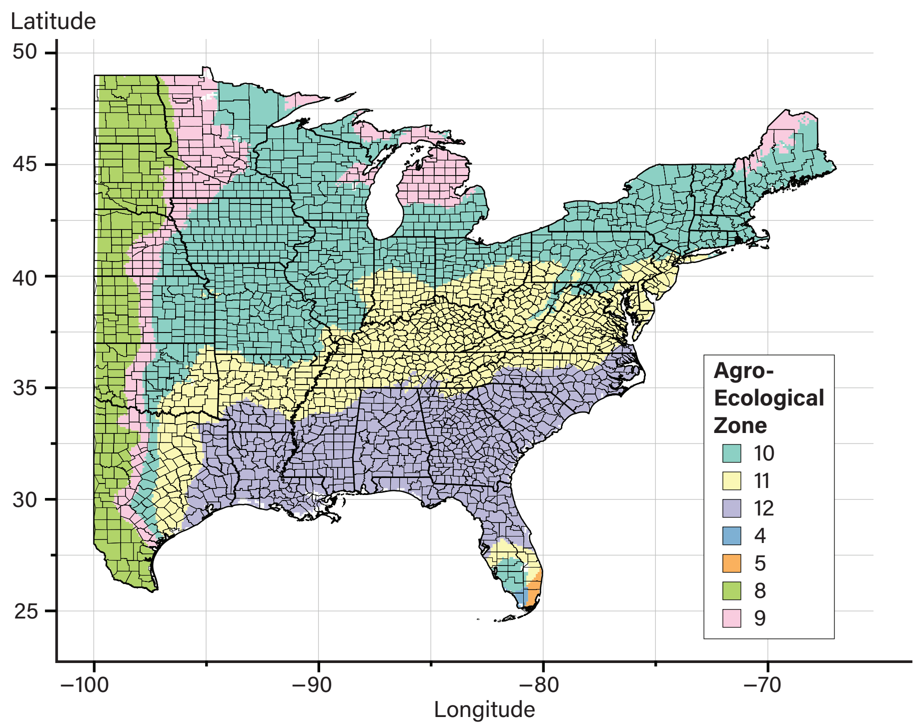
Note: Figure maps the spatial distribution of the marginal effect of growing degree days (top-left), extreme degree days (top-right), annual precipitation below 50 cm^3 (bottom left), and annual precipitation above 50 cm^3 (bottom right) on corn yields for U.S. counties east of the 100th meridian.

Source: USDA, Economic Research Service calculations.

Computable General Equilibrium Model

Once crop yields are determined, a computable general equilibrium (CGE) model is used to estimate their potential economic effects. This model is often used to evaluate the potential outcomes of a technological change, as it provides economy-wide and commodity-specific effects while considering inter-industry linkages. The Global Trade Analysis Project-Agro-Ecological Zone (GTAP-AEZ) model, a global trade model with explicit treatment of subnational land markets, is used to analyze changes in agricultural outputs (Beckman et al., 2020). A concern associated with the use of the CGE model and county-level crop yield projections is that both frameworks consider different spatial units; GTAP-AEZ focuses on land by AEZs[12] and the authors' spatial econometric application produces county-level results. Thus, AEZs are divided for the Eastern (split by the 100th meridian) United States and identify the counties that belong to each AEZ. Figure 8 depicts the AEZs for this region. The AEZ are constructed following the work of Ramankutty & Foley (1999) and Fischer et al. (2021). A county-level shapefile and an AEZ shapefile are used to overlap the two different U.S. projections. Note that AEZs are spread across different States, and some counties have more than one AEZ (e.g., Florida). Because it is impossible to exactly assign crop yield projections from counties into the multiple AEZs, some county projections are assigned to the AEZ that covers the largest territory of the county.

Figure 8
Global Trade Analysis Project-Agro-Ecological Zones across the Eastern United States



Note: The United States has been split by the 100th meridian, as it is commonly done in this literature.

Source: USDA, Economic Research Service.

[12] Agro-Ecological Zones (AEZ) is a method developed by the Food and Agriculture Organization of the United Nations and others to classify similar land types using characterization of climate, soil, and terrain conditions relevant to agricultural production. There are not set units of land across AEZs. See Avetisyan et al. (2011) for information on how the AEZs are incorporated into the Global Trade Analysis Project model.

To make the yield estimates useful for the CGE model, the county forecasts were mapped to AEZs. The crop forecast indicates that overall U.S. soybean yields will decrease 3.04 percent, but that corn yields will increase 3.11 percent (table 2).[13] Results vary across AEZs, including an increase in soybean yields in AEZ 10. This AEZ is where the largest amount of soybean production occurs but given that the overall effect for soybeans is negative, this effect is outweighed by the decrease in other AEZs. Corn has a decrease in yields in AEZ 8, but the total effect is an increase in the crop's yields. Note that this decrease in AEZ 8 is the only zone where yields are estimated to be negative for both crops.

Table 2

GWR yield changes and area harvested from the CGE model, 2016–36

	Soybean		Corn	
AEZ	Area harvested	Yield changes	Area harvested	Yield changes
8	4,438	-7.10	7,103	-14.51
9	3,653	-1.63	4,886	1.13
10	16,096	1.23	18,253	5.68
11	5,740	-5.76	3,997	5.36
12	2,183	-8.04	1,235	2.61
Total	**32,110**	**-3.04**	**35,474**	**3.11**

GWR = geographically weighted regression; CGE = computable general equilibrium; AEZ = Agro-Ecological Zone.

Note: The area harvested is from the Global Trade Analysis Project-Agro-Ecological Zone (GTAP-AEZ) model and is given in thousand hectares (1 hectare = 2.47 acres). Yield changes are from estimations and are provided in percentage changes.

Source: USDA, Economic Research Service.

Three scenarios were used in the global economic model (see box titled "Global Trade Analysis Project-Agro-Ecological Zone" for more details). The first two scenarios introduced the yield shocks for each commodity independently, and the third considered a combined shock. The model introduces the yield shock, which will affect agricultural production as production is determined by acreage harvested multiplied by productivity (i.e., yields for this study). In the soybean shock where the yield change is negative, the model will try to reallocate land to soybeans. That is, the model tries to maintain the shares (or importance) of a given commodity in production (or trade). Given that a large amount of land is allocated to soybeans in the United States, that share conveys that soybeans are important in U.S. agricultural production. This will move land away from other uses up to where shifting land to soybean is no longer economically competitive. For corn, the positive yield change will lead to more corn being produced at the existing acreage, and the United States will likely have an increase in corn production. In the face of international competition, the United States is able to displace some of their exports. Given that a shock to other countries is not specified for this study, their prices remain relatively constant, while an increase in U.S. production leads to a decrease in U.S. prices, making U.S. corn more attractive on the international market. However, this effect only happens to a certain degree. Given that the United States is only able to capture some of the global market, the model will reallocate some of the existing corn land to other uses.

It is important to clarify a few points regarding the interpretation of this study's results. Because the study focused on providing insights regarding how climate change will likely affect the United States, it does not consider changes in other countries. While the aim of this study is not to provide an agricultural outlook,

[13] Most econometric research interested in producing crop yield projections under climate change for the United States focus on producing mid-century results (e.g., between 2050–75). In addition, projections may differ by the goal of the study, the methodology employed, the SSP assumption and even the particular climate change model employed. While we are unable to compare our results directly to what it is found in the literature for these reasons, we find that our results are within the probable scenarios for the mid-century (2025–75) produced in the work of Ortiz-Bobea & Tack (2018).

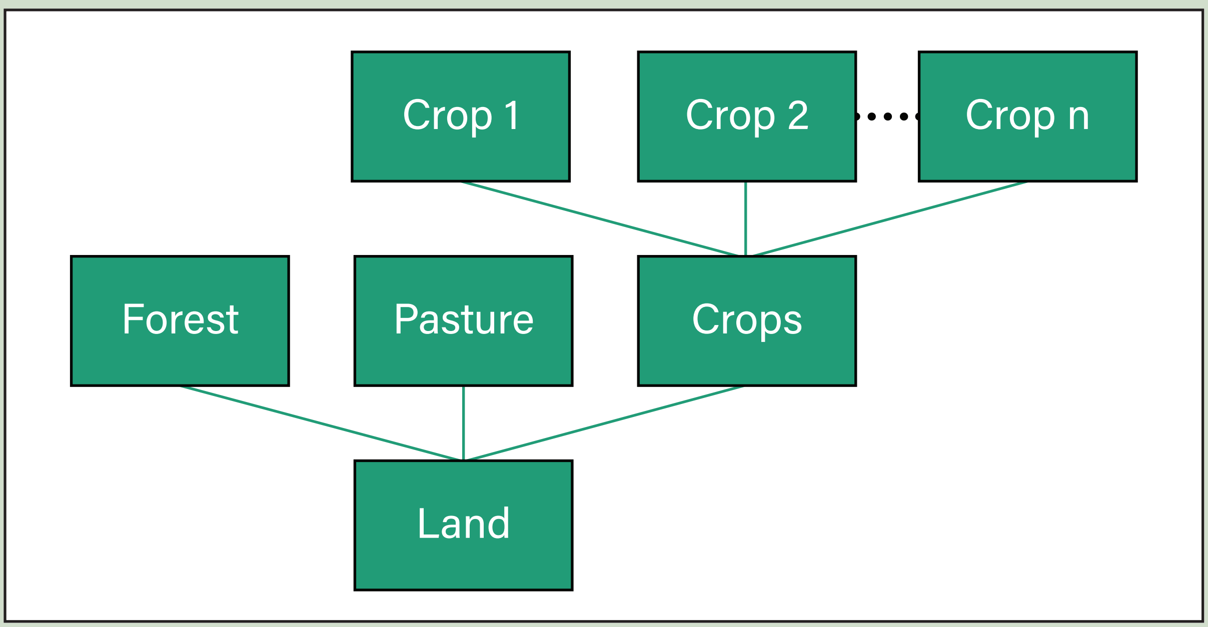
this work could be reproduced for all other regions to provide a global outlook. Doing that, however, is computationally prohibitive since it would require the authors to collect data on crop yields at a detailed level for every country. Nevertheless, another approach for a global perspective could be to use data such as that from the Agricultural Model Intercomparison and Improvement Project (Jägermeyr et al., 2021). A future study could consider using those estimates to understand how climate change affects global yields.

Global Trade Analysis Project-Agro-Ecological Zone Model

The computable general equilibrium (CGE) model was used to incorporate the detailed land-use module of the Global Trade Analysis Project-Agro-Ecological Zone (GTAP-AEZ) model. This captured heterogeneous land quality and provided a more realistic representation of agricultural production. The latest database for the GTAP-AEZ model is from 2014, thus the model results consider how the United States and global economy could be affected from the yield changes, using 2014 as the base. GTAP-AEZ disaggregates land into 18 agro-ecological zones (AEZs) that share common climate, precipitation, and moisture conditions (Hertel et al., 2008). For example, figure 8 indicates that AEZ 10 in the United States stretches across much of the Midwest. The moisture characteristics come from the Global Agro-Ecological Zones (GAEZ) data from the Food and Agriculture Organizations of the United Nations (FAO), and it is used to divide all land into six categories. The temperature characteristic is based on the minimum temperatures and the number of temperatures-adjusted growing days.

Land-use competition is modeled in the AEZ module with a nested constant-elasticity-of-transformation (CET) function. By imposing homothetic separability on the revenue function, the land allocation decision can be split into two sequential stages. In the first stage, the landowner decides on land cover (i.e., whether a given parcel of land will be in crops, forestry, or pasture). In the second stage, crop land is allocated across different uses. The diagram below shows the nesting.

Figure 9
Land allocation in the GTAP-AEZ Model, CGE conceptual framework



CGE =computable general equilirium; GTAP-AEZ = Global Trade Analysis Project-Agro-Ecological Zone.

Source: USDA, Economic Research Service.

Corn Shock

Changing yields lead to changes in where corn and soybeans are grown, which affects production and ultimately trade. Land used for crops in the United States decreases (0.03 percent) and there is a slight increase in land for forest and pasture (table 3). That is, given that yields are increasing for corn, less land is necessary to grow crops in the United States to meet domestic and foreign demand. The decrease in cropland is entirely attributable to corn, as land used for soybeans increases (by 0.03 percent) as does land for other crops (0.35 percent).[14] There is a move of land out of corn in AEZ 8 and AEZ 9, and that land is then reallocated to soybeans and other crops.

The increase in corn yields lead to an increase in U.S. corn production (0.15 percent, table 4), despite the decrease in land used in corn. There is a slight increase in soybeans production (0.01 percent) due to the small increase in land moving to soybeans; and a similar result for the other crops sector (an increase in production of 0.20 percent). As the United States is a major producer of corn, the increase in U.S. production leads to a decrease in production in the rest of the world (0.03 percent).[15]

There are minimal changes in global production of soybeans and other crops since the change in U.S. production of these agricultural products is minimal. As of 2021, the United States is the largest producer and exporter of corn (accounting for about 30 percent of total exports) and the increase in production leads to an increase in exports (0.46 percent), and a decrease in exports in the rest of the world (0.14 percent). The model also estimates a decrease in U.S. imports of corn—the United States does import a small amount due largely to seasonality.

Table 3
GTAP results for land-use change (percent changes), 2016–36

	Corn-only shock U.S. land				Soybean-only shock U.S. land				Combined shock U.S. land		
	Forest	Crops	Pasture		Forest	Crops	Pasture		Forest	Crops	Pasture
	0.01	-0.03	0.01		-0.01	0.01	0.00		0	-0.02	0.01
	Corn	Soybeans	Other crops		Corn	Soybeans	Other crops		Corn	Soybeans	Other crops
	-1.08	0.03	0.35		-0.14	0.31	-0.05		-1.20	0.35	0.31
AEZs				AEZs				AEZs			
AEZ 8	-12.50	3.25	2.52	AEZ 8	0.79	-3.72	0.35	AEZ 8	-11.72	-0.50	2.92
AEZ 9	-0.70	0.69	0.04	AEZ 9	0.17	0.80	-0.18	AEZ 9	-0.49	1.53	-0.16
AEZ 10	1.81	-0.83	-1.38	AEZ 10	-0.82	2.37	-1.18	AEZ 10	1.01	1.54	-2.57
AEZ 11	2.22	-0.18	-0.61	AEZ 11	1.05	-2.25	0.51	AEZ 11	3.33	-2.41	-0.13
AEZ 12	0.24	0.30	-0.17	AEZ 12	1.19	-4.19	0.61	AEZ 12	1.48	-3.86	0.44

GTAP = Global Trade Analysis Project; AEZ = Agro-Ecological Zone. U.S. = United States.

Note: The computable general equilibrium (CGE) model has two stages of land changes. The first stage is the competition for land among forest, crops, and pasture. This is shown in the first row of results. In the second stage, crops areas are then split into use among the different crop types. Results are presented by individual AEZs for each of the crops in the model.

Source: USDA, Economic Research Service.

[14] The GTAP-AEZ model has 20 agricultural sectors in the initial database. Corn is grouped with coarse grains; the authors follow the work by Beckman and Countryman (2021) to split corn out from coarse grains. Corn and the other crops (there are seven others) are kept disaggregated to properly capture land-use changes but the other crops are aggregated in the results for ease of interpretation.

[15] The model has a total of 141 countries/regions. All the other regions are aggregated into the rest of the world (ROW) for ease of explanation of the results.

Table 4
GTAP production and trade results (percent changes), 2016–36

	Production		Exports		Imports	
Corn-only shock						
	U.S.	ROW	U.S.	ROW	U.S.	ROW
Corn	0.15	-0.03	0.46	-0.14	-0.41	0.06
Soybeans	0.01	0.00	0.02	-0.01	0.00	0.00
Other crops	0.20	-0.01	0.47	-0.05	-0.12	0.02
Soybean-only shock						
	U.S.	ROW	U.S.	ROW	U.S.	ROW
Corn	-0.03	0.00	-0.09	0.01	0.09	-0.02
Soybeans	-0.93	0.38	-1.16	0.70	0.61	-0.07
Other crops	-0.02	0.00	-0.04	0.00	0.00	0.00
Combined shock						
	U.S.	ROW	U.S.	ROW	U.S.	ROW
Corn	0.11	-0.02	0.36	-0.12	-0.32	0.04
Soybeans	-0.93	0.38	-1.17	0.71	0.62	-0.07
Other crops	0.18	-0.01	0.44	-0.05	-0.12	0.01

GTAP = Global Trade Analysis Project; ROW = rest of the world. U.S. = United States.

Source: USDA, Economic Research Service.

Soybean Shock

The United States is the second largest exporter of soybeans, accounting for about 40 percent of total exports. While the previous result showed an increase in corn yields, the opposite result occurs for soybeans. The decrease in soybean yields leads to an increase in the total demand for land by U.S. soybean producers by 0.31 percent (table 3). Because of the importance of soybean production in the United States, it might be expected that many of the AEZs would be shifting land from other crops to soybeans to maintain this production. However, there are decreases in land allocated to soybeans in AEZ 8, 11, and 12. The model increased land allocated to soybeans in AEZ 10, which accounts for half of the U.S. soybean area (table 2). This AEZ has an increase in soybean yields, thus the model indicated that the most economically feasible option to try to maintain soybean production is to increase land where yields are also increasing. Table 3 indicates that there is an overall increase in land moving to crops (out of forest), despite a decrease in land used for corn and other crops. Soybeans and corn often compete for the same land. This is evident in the changes across the different AEZs. For example, AEZ 10, which is the main source of corn land (comprising 50 percent of total corn acreage), has a decrease in demand for corn land by 0.82 percent, as land moves to soybeans. The data indicate that the other crops category (encompassing wheat, rice, fruits and vegetables, and horticulture products) does not always compete for the same land as soybeans, but results indicated that land for this category also tends to move in an opposite direction than the change for soybeans.

Although there is an increase in land used for soybean production, the decrease in yields outweigh that change and there is a decrease in U.S. soybean production of 0.93 percent (table 4). And the decrease in land used for corn and other crops leads to a decrease in their production. Overall, the model estimates a decrease in U.S. crop production of 0.03 percent. The decrease in U.S. crop production leads to an increase in soybean production in the rest of the world (ROW) of 0.70 percent. These changes in production lead to a decrease in exports of these products for the United States (ranging from 1.16 percent for soybeans to 0.04 percent for other crops), and an increase in U.S. imports of these products. The United States is a major producer of soybeans and, together with Brazil and Argentina, account for 81 percent of global production.

Combined Shock

Because the two yield shocks are in opposite directions, it is important to examine the net land-use and market/trade impacts. Table 3 indicates that the land-use results from the yield decrease for soybeans outweighs the increase from corn—that is, there is a decrease in land for crops (0.02 percent) and a slight increase in land for pasture (0.01 percent). There is an overall decrease in the demand for land for corn which outweighs the increase in land for soybeans and other crops. Both individual simulations had an increase in land used for soybeans, and this result holds in the combined shock (0.35 percent). Both simulations also had a decrease in land used for corn, and this again holds with a stronger effect in terms of magnitude (1.20 percent). That is, in the combined scenario, land for corn is facing competition from soybeans for land and receiving the benefit of the yield increase. For AEZ 10, where most of corn and soybeans are grown, there is an increase in land demanded for both corn and soybeans, with that land coming from other crops. Other crops do have a decrease in land used in most AEZs; however, the strong increase in AEZ 8 (from wheat) and an increase in land for AEZ 12 (which tends to be plant-based fibers such as cotton) leads to the overall increase in land for the other crops sector.

The market/trade effects combine the two shocks. There is an increase in corn production due to the increase in yields, and a decrease in soybean production due to their yield decrease. For the rest of the world, there is a decrease in corn production due to the increase in the United States, but an increase in soybean production, like the soybean-only shock. The model estimates a decrease in U.S. soybean exports and an increase in corn exports, again following the crops' individual shocks. That is, the indirect effects of land-use change (e.g., corn from the soybeans-only shock) are much smaller than the effects for direct effect for each commodity.

Regarding corn and soybean trade, tables 5a and 5b present the changes by country/region in the model. Results are presented in millions of U.S. dollars using the percentage changes from the model and actual trade in 2016—the year the yield shocks are calibrated to. For corn, the United States has an increase in their exports, and the increase is mostly allocated to the rest of the world ($27 million) and China ($18 million) (table 5a). The total increase in U.S. corn exports is $63 million.[16]

For soybeans, note that the decrease in U.S. exports is felt largely across all importers. The largest decrease, however, is to China ($171 million). Morgan et al. (2022) note that the United States has lost a large amount of market share to Brazil, and the decrease in U.S. soybean yields further exacerbates the decrease in U.S. share. Altogether, results indicated that the United States would lose $319 million of soybean exports. And this loss is mainly picked up by Brazil. Results indicated that Brazil has an increase in soybean exports of $267 million, with $196 million going to China alone. The rest of the world ($40 million) and Argentina ($21 million) are also estimated to have large increases in their soybean exports.

[16] Our study relies on agricultural productivity shocks in the U.S. being affected by climate change, while the rest of determinants remain constant. For instance, our numbers for exports to China is only related to yields. However, exports to China can be affected by other factors such as population growth in China (stagnating) and the rest of the world (increasing in places such as South America and Africa). Furthermore, we do not consider demand patterns changing in the future (such as growing popularity of non-meat alternatives), the role of intermediate and input markets or the expansion of alternative fuel options like biofuels.

Table 5a

Changes to bilateral corn exports in U.S. dollars (millions)

	ROW	China	Japan	South Korea	United States	Mexico	Argentina	Brazil	EU	Ukraine	Egypt
ROW	-4	0	-1	-1	0	-1	0	0	0	0	0
China	0	0	0	0	0	0	0	0	0	0	0
Japan	0	0	0	0	0	0	0	0	0	0	0
South Korea	0	0	0	0	0	0	0	0	0	0	0
United States	27	18	4	4	0	9	0	0	0	0	1
Mexico	0	0	0	0	0	0	0	0	0	0	0
Argentina	-9	0	-1	-3	0	0	0	0	0	0	-2
Brazil	-4	0	-2	-1	0	-1	0	0	-1	0	-2
EU	-1	0	0	0	0	0	0	0	0	0	0
Ukraine	-1	-4	0	0	0	0	0	0	0	0	-1
Egypt	0	0	0	0	0	0	0	0	0	0	0

ROW = rest of the world; EU = European Union. U.S. = United States

Note: Exporters are the rows; importers are the columns. Dollar figures are rounded to the nearest million dollar.

Source: USDA, Economic Research Service, using database information from Trade Data Monitor, Annual Imports and Exports, 2022.

Table 5b

Changes to bilateral soybean exports in U.S. dollars (millions)

	ROW	China	Japan	South Korea	United States	Mexico	Argentina	Brazil	EU	Ukraine	Egypt
ROW	16	6	2	0	1	0	9	0	4	0	1
China	0	0	0	0	0	0	0	0	0	0	0
Japan	0	0	0	0	0	0	0	0	0	0	0
South Korea	0	0	0	0	0	0	0	0	0	0	0
United States	-69	-171	-11	-3	0	-12	0	0	-34	0	-19
Mexico	0	0	0	0	0	0	0	0	0	0	0
Argentina	5	14	0	0	0	0	0	0	0	0	2
Brazil	36	196	2	2	0	9	0	0	20	0	0
EU	2	0	0	0	0	0	0	0	0	0	0
Ukraine	2	0	0	0	0	0	0	0	1	0	0
Egypt	0	0	0	0	0	0	0	0	0	0	0

ROW = rest of the world; EU = European Union. U.S = United States.

Note: Exporters are the rows, importers are the columns. Dollar figures are rounded to the nearest million dollar.

Source: USDA, Economic Research Service, using database information from Trade Data Monitor, Annual Imports and Exports, 2022.

Conclusion

Historical gains in U.S. agricultural productivity elevated the country's status to a global caloric exporter, but future climate patterns raise the question about the ability of the United States to help feed a growing world population expected to be 10 billion by 2050. As such, there has been an increase in research examining the relationship between the changing climate and effects to yields. Most agricultural outlooks predict that corn and soybean yields will decline by the middle of the century, but less is known about how such changes in climate could affect U.S. agricultural production.

This study uses the Intergovernmental Panel on Climate Change (IPCC) climate scenarios that indicate some likely changes for the United States. The data indicate that precipitation changes may not be as substantial as warming temperatures for the country. Rising temperatures can affect crop growth in opposite ways. On one hand, temperature contributes to crop growth in a positive way via growing degree days (GDD). Conversely, extreme temperatures damage crop growth which is captured with extreme degree days (EDD). Therefore, rising temperatures increase the density of GDD, improving crop growth potential, but can also increase the amount of extreme degree days. This report's authors incorporate both measures of the plant's heat exposure to better capture this nonlinear relationship between temperature and crop yields growth. The main results suggest that U.S. agricultural trade patterns will likely experience small deviations in 2036 in relation to a baseline of 2016: Corn exports are expected to increase 0.36 percent and soybean exports are expected to decrease 1.17 percent. While these are small changes, they reflect crop yield growth that will likely stagnate toward the middle of the century, a trend found by this and other studies.

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Appendix

Calibration Results

Geographically weighted regression (GWR) estimators require a choice of bandwidth for their estimation procedure. In addition to bandwidth selection required in the calibration of a GWR estimator, Burke & Emerick (2016) recommended choosing thresholds for the climate variables (as described in table 1). Using the Akaike information criterion (AIC) and three thresholds for each climate variable with a total of nine combinations for each crop, the authors run a minimization calibration algorithm separately. For temperature, 28, 29, and 30 °C are considered. For precipitation, 42, 46, and 50 cubic centimeters (cm3) are considered. Differences in every threshold decision are small (less than 0.01 percent) across each combination of thresholds as they are measured in AIC. These are seen in appendix table A.1. The criteria for choosing the best model was based on the lowest AIC. For corn, the best fitting model was 30 °C and 50 cm^3. For soybeans, it was 28 °C and 50 cm^3. Rather than choosing two different models, the authors considered the combined AIC from both crops and used that threshold for both crops: 30 °C and 50 cm^3.

Table A.1
Calibration statistics across different model specifications considering temperature (rows) and precipitation (columns)

	Corn			Soybeans		
	42	46	50	42	46	50
28	13,948	13,942	13,859	13,148	13,147	13,063
29	13,965	13,962	13,873	13,161	13,160	13,085
30	13,921	13,918	13,819	13,170	13,171	13,094

Note: The table shows Akaike information criterion (AIC) statistics across different models that combine temperature thresholds (in the rows) in degrees Celsius with precipitation thresholds (in the columns) in cubic centimeters for models of corn and soybean yields.

Source: USDA, Economic Research Service.