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Climate Change and Agricultural Risk Management Into the 21st Century

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Abstract

Programs that help farmers manage risk are a major component of the Federal Government's support to rural America. Changes to this risk—and thus to the Government's fiscal exposure—are expected as weather averages and extremes change over the coming decades. This study uses a combination of statistical and economic modeling techniques to explore the mechanisms by which climate change could affect the cost of the Federal Crop Insurance Program (FCIP) to the Federal Government, which accounts for approximately half of Government expenditures on agricultural risk management. Our approach is to compare scenarios of the future that differ only in terms of climate. Using weather scenarios for 2060-99 from general circulation models, we project decreases in corn and soybean yields and mixed changes to winter wheat yields, compared to a baseline scenario in which climate is identical to that of the past three decades. We use an economic model of the U.S. agricultural sector to estimate how projected yield changes may induce farmers to change what and where they plant, and the resulting impacts on production and output prices. These ingredients allow us to explore drivers of change in the cost of the FCIP's Revenue Protection program, which is used as a heuristic for potential farm safety net programs that could exist in the future. Differences between the scenarios are driven by increasing prices for the three crops studied, caused by relatively lower production in the presence of inelastic demand, as well as by changing volatility in both yields and prices.

Keywords: climate change, risk management, machine learning, agriculture, Regional Environment and Agriculture Programming, REAP, model, crop insurance, semiparametric neural networks, general circulation model

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About the Authors

Andrew Crane-Droesch, Elizabeth Marshall, Stephanie Rosch, and Steven Wallander are agricultural economists with USDA, ERS. Joseph Cooper and Anne Riddle are former ERS economists whose contributions to this report were made when they were with ERS.

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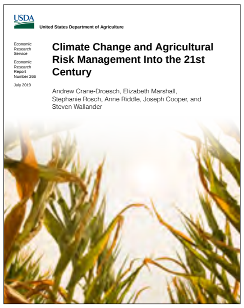

Climate Change and Agricultural Risk Management Into the 21st Century

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What Is the Issue?

The Federal Government implements a number of programs that mitigate risk in agriculture, including the Federal Crop Insurance Program (FCIP), Agriculture Risk Coverage (ARC), Price Loss Coverage (PLC), and several others. The FCIP provides subsidized insurance, while other programs provide payments to farmers in response to adverse production or market conditions. Together, the costs of these programs have averaged about $12 billion annually over the past decade. Year-to-year fluctuations in these costs are heavily influenced by weather variability, which affects yields and prices. The Federal Government's cost exposure is expected to increase as weather averages and extremes change over the coming decades.

This study uses statistical, geophysical, and economic models to explore the mechanisms by which climate change could affect future costs of farm safety net programs to the Federal Government. This approach first simulates the potential impact of climate change on yields of major commodities, then quantifies the implications of yield change on planting decisions and prices, which in turn affects the cost of risk management programs. This allows for analysis of three different pathways by which cost increases could occur: (1) the direct impact of climate on yield risk, (2) the indirect effect of yield risk on price risk, and (3) the impact of changed average yield, production, and price on the total value insured (liabilities). While farm safety net policies change over time, this study uses the current version of the FCIP's Revenue Protection program as a heuristic: a program that reduces both yield and price risk as past programs have, and as future policies may.

What Did the Study Find?

Of the mechanisms considered, changes to total liabilities are more influential than price volatility and yield volatility on the cost of the FCIP's premium subsidies to the Federal Government, though all were found to be significant. All climate scenarios considered suggest that climate change would lower domestic production of corn, soybeans, and wheat relative to a future scenario with climate identical to that of the past three decades. All else equal, this implies that prices would be higher than they would otherwise, which implies higher premiums and, consequently, higher subsidies. Foreign supply or demand changes that are driven by climate change would mitigate or exacerbate this effect, though this analysis does not model production in the rest of the world.

ERS is a primary source of economic research and analysis from the U.S. Department of Agriculture, providing timely information on economic and policy issues related to agriculture, food, the environment, and rural America.

Changes to yield and price volatility also strongly influence the cost of FCIP premium subsidies, but the direction in which these factors would change is less certain. Yield volatility increases under most (but not all) climate scenarios and crops, increasing the frequency and/or depth of losses, and thus increasing premiums and subsidies. On the other hand, changes to price volatility differ by crop and scenario.

Much depends on the severity of future warming. This study compares two scenarios representing differing future rates of greenhouse gas emissions and, consequently, differing severities of climate change. Under the moderate emissions scenario, the cost of today's FCIP would be about 3.5 percent higher than under a future with a climate similar to that of the recent past. Under the higher emissions scenario, this cost increase is 22 percent.

These estimates would be higher if the analysis did not account for adaptation to climate change. While not all possible forms of adaptation are included, this study explicitly accounts for how farmers may change what they plant, where they plant it, and how they manage it in response to changes in expected yields and prices. If the study did not include adaptation in its models, the estimates of cost increases would jump to 10 percent and 37 percent, under the moderate and severe greenhouse gas concentration scenarios, respectively.

How Was the Study Conducted?

Detailed historical weather and yield data are used to train statistical models—semiparametric neural networks—to predict yields of corn, soybeans, and winter wheat. These models are then used to project yields under simulated weather data for the period 2060-99, which is used to approximate a distribution of possible weather for the year 2080. The study uses simulations from five different climate models to represent uncertainty in the response of the climate to greenhouse gas emissions, and two scenarios for each corresponding to moderate and higher emissions.

Next, projected yields are used as inputs to ERS's Regional Environment and Agriculture Programming Model (REAP), an economic model that simulates the co-movement of planted acres, yields, and prices. REAP simulates how farmers would change what they grow – and where they grow it – in response to changes in yields and prices. Finally, the output of the economic model is used to simulate the cost of the FCIP for corn, soybeans, and winter wheat for 2080, which is taken as a representative year in the second half of the 21st century.

Climate Change and Agricultural Risk Management Into the 21st Century

Climate, Agriculture, and Agriculture Risk Management

Agriculture is directly dependent on weather and uniquely exposed to weather risk. While farmers have coped with weather variability since the advent of agriculture, the 1930s saw the beginning of Federal support of agricultural risk management in the United States. Today, the Federal Crop Insurance Program (FCIP), managed by the USDA Risk Management Agency (RMA), is one of the most common tools that farmers use to manage weather risk, along with programs such as Agriculture Risk Coverage (ARC), Price Loss Coverage (PLC), and others administered by the USDA Farm Service Agency (FSA).

While the weather on any given day may be difficult to predict beyond a few weeks, the range of what is possible and what is likely have been remarkably consistent throughout most of the history of the United States. Exceptions such as 1816's "year without a summer" (Stommel and Stommel, 1979) and the Dust Bowl of the 1930s (Schubert et al., 2004) serve as contrast to the relative climatic stability that American agriculture has mostly enjoyed for nearly 250 years.

Evidence has accumulated in recent years, however, that long-term temperature averages are shifting with the buildup of heat-trapping gases in the atmosphere (Wuebbles et al., 2017). In addition to average temperature, shifts in seasonal patterns of temperature, precipitation, and other variables have been observed (Wuebbles et al., 2017). While weather consistent with the long-term historical record will continue to occur, some forms of weather that had previously been rare or extreme are projected to become increasingly likely, while other forms increasingly rare. Changes in weather variability around a shifted average remain uncertain (Huntingford et al., 2013). Specific rates of temperature change are projected to vary spatially, along with changes to other variables, such as precipitation (Wuebbles et al., 2017).

These changes have already begun to affect agriculture in the United States and globally and will continue to do so in proportion to the amount of warming experienced over the coming decades and centuries (Porter et al., 2014). Substantial research has focused on the impact of climate change on crop yields (Rosenzweig and Parry, 1994; Schlenker and Roberts, 2009) and on adaptation to climate change (Lobell et al., 2008; Marshall et al., 2015; Annan and Schlenker, 2015; Burke and Emerick, 2016). While studies differ in important respects and focus on different issues within this overall domain, there is a general consensus that crop yields are likely to decline unless improvements in agricultural technology are able to keep pace with growing weather stress.

This study aims to quantify how climate change could affect the cost of U.S. agricultural risk management programs toward the end of the 21st century. We study the FCIP specifically—though its cost in an average year is approximately equal in magnitude to "shallow-loss" programs like ARC and PLC—as it provides a useful heuristic for agricultural risk management programs generally. While specific policies and programs are likely to change over time, any program that seeks to manage agricultural risk is likely to have many of the same key features as the current program.

Our approach first assesses the impact of climate change on yields, then quantifies the implications of yield change on production and prices, which, in turn, affects the cost of the program. We do so through a system of chained models, integrating agronomic, economic, and policy models with statistical/machine learning tools. These models are combined to provide joint projections of yields, acreages, and prices, which allow us to project the costs of present levels of coverage in the FCIP for the year 2080, which we take as a representative year for the second half of the 21st century. We focus on corn, soybeans, and winter wheat, three crops that make up 55 percent of agricultural land use, but 65 to 75 percent of the total premium subsidy costs of the FCIP (USDA, 2018).

Overview of the Federal Crop Insurance Program

Established in 1938, the Federal Crop Insurance Program (FCIP) provides insurance to farmers to compensate for crop losses due to natural causes such as drought, flooding, diseases, and pests. Policies can be purchased for a wide variety of field crops, vegetables, fruits, aquaculture, and forage crops, with endorsements[1] available for some crops to account for differences in practices, such as irrigated or organic production.

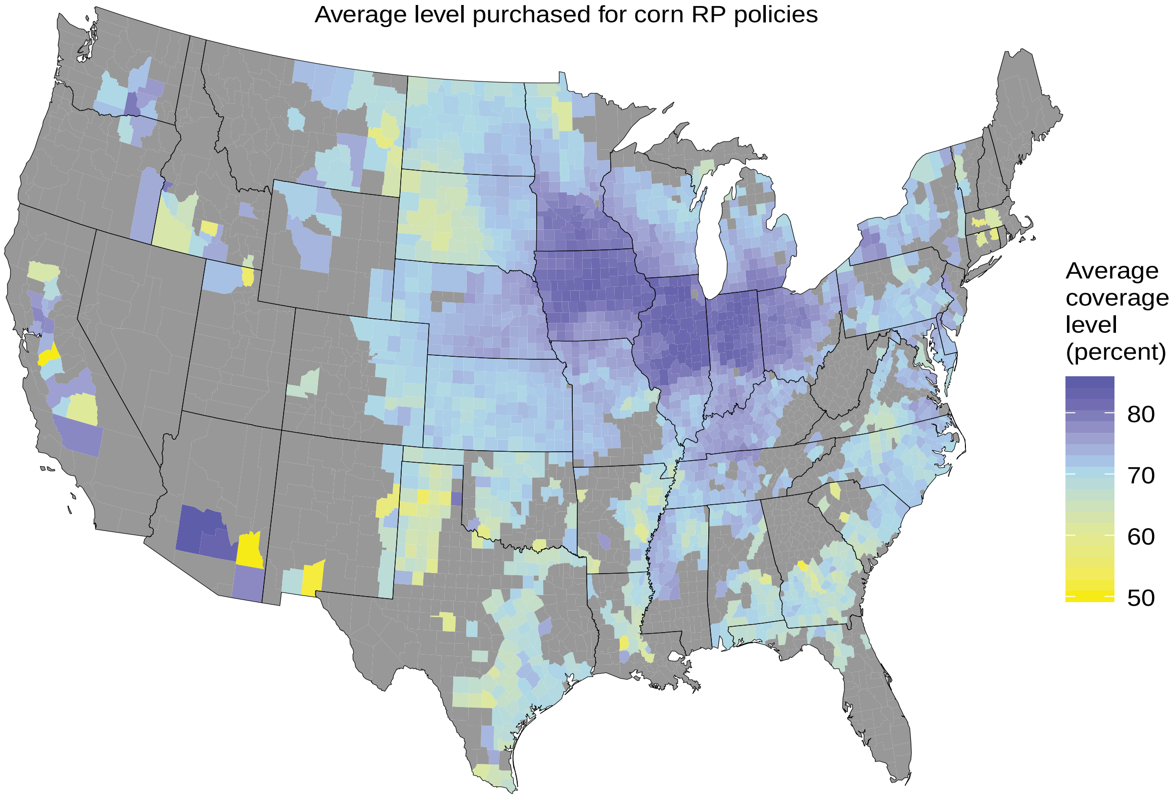
The FCIP offers policies covering different types of farm risk. The most commonly sold policies are Yield Protection (YP), which indemnifies farmers against production losses relative to a farm-specific target yield, and Revenue Protection (RP), which indemnifies farmers against revenue losses relative to a farm-specific target revenue amount. RP policies were introduced in 1996 and since 2003 have been the most popular policy sold for field crops, including the three on which we focus. Other types of commonly purchased policies covering field crops include group and index-based policies, which indemnify farmers against a yield or revenue loss relative to an area-based target.

Crop insurance policies are sold in discrete coverage levels in 5-percent increments, ranging from 50 percent to 85 percent of the target yield or revenue. The maximum possible coverage level offered in each county varies based on type of commodity and policy. The minimum possible coverage, referred to as catastrophic coverage, or CAT, is the same for all crops and counties. CAT coverage insures 50 percent of the target yield and reimburses at 55 percent of the expected market price. Farmers can choose higher levels of yield or price coverage; those higher levels of protection, and all coverage purchased through RP policies, are referred to as “buy-up” coverage. Figure 1 shows an example of the variation in average coverage levels for all corn RP policies per county in 2016. Coverage levels are highest in the Corn Belt.

[1] An endorsement is a set of contract terms that modifies the standard crop insurance policy for different types of practices or coverage limits. USDA’s Risk Management Agency (RMA) offers many types of endorsements to the Common Crop Insurance Policy Basic Provisions for production practices, specific commodities such as cottonseed or malting barley, Supplemental Coverage Option (SCO), and more. More details can be found at the RMA website.

Figure 1

Spatial distribution of average county coverage levels (percentage of risk covered) purchased for corn Revenue Protection policies, in 2016



Note: RP = Revenue Protection. Minimum possible average coverage is 50 percent; maximum possible average coverage is 85 percent.

Source: USDA, Economic Research Service calculations based on USDA, Risk Management Agency data, 2018.

RMA attempts to price crop insurance policies on an actuarially fair basis and then subsidizes the premiums (see box "Example of Federal Crop Insurance Premium Calculation"). Excluding administrative and operating costs, the premium for an actuarially fair insurance policy is equal to the expected value of losses insured under the policy. This expected loss is a function of the value of the loss multiplied by the probability of the loss. As such, premiums increase when there is more yield variability or when the value of insured crops increases.

Example of Federal Crop Insurance Premium Calculation

Consider a hypothetical 100-acre field that has a typical yield of 150 bushels per acre. Assume a futures contract price of $3.50 per bushel and a crop insurance policy with 75 percent coverage. The expected total output for that field would be 15,000 bushels, with an expected market value of $52,500. The insured yield for that field would be 0.75 × 150 bushels/acre = 112.5 bushels per acre, and the insured liability for that field would be 112.5 bushels/acre × 100 acres × $3.50/ bushel = $39,375.

If this field had an 8-percent chance of producing 100 bushels per acre instead of the typical yield, the total value of the loss would be (112.5 - 100) × 100 × 3.50 = $4,375, and the expected value of the loss would be 0.08 × $4,375 = $350. An actuarially fair policy would charge $350 ($3.50 per acre) to fully insure against this loss. RMA subsidies would cover 55 percent of the actuarially fair premium for a policy with 75 percent coverage. Therefore, the cost to the farmer for insuring an expected loss of $350 would be (1 - 0.55) × 0.08 × $4,375 = $157.50 (or $1.58 per acre).

This hypothetical example is a stylized depiction of the true method of determining crop insurance premiums. In this example, we assume that yields have only 2 values: 100 bushels per acre or 150 bushels per acre. This assumption was made to simplify calculating the actuarially fair premium and to highlight the connections between expected market value, insured liability, and subsidized premium costs paid by farmers. In reality, yields can take on a wide range of values, and the true method used by RMA to determine actuarially fair premiums accounts for the full range of possible yields and losses in the calculations.

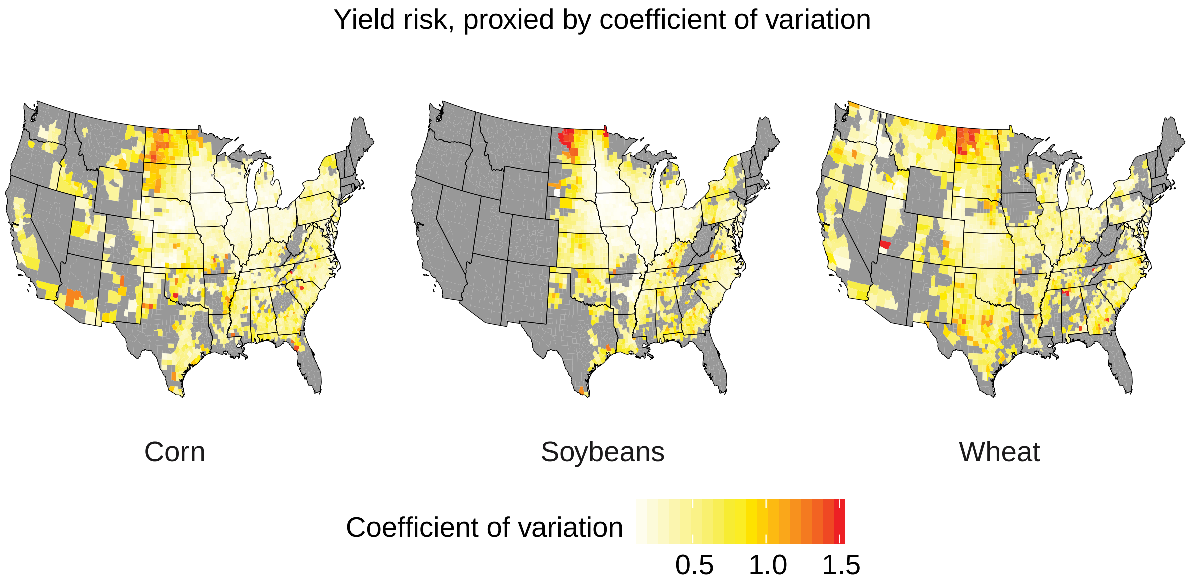
Expected losses are determined on the basis of average yields and losses at the county level and adjusted for each policyholder based on his or her actual historical yields. The extent of county-level yield risk varies by crop and location (see fig. 2) and is proxied by the coefficient of variation (CV),[2] which scales the variability by the average. A higher CV indicates greater variation in yield relative to the average over the time period, which we interpret as an indication of greater risk. Corn and soybean production is least risky by this measure in the central Corn Belt. Winter wheat is cultivated in more counties than corn or soybeans, but has a similar range of yield variability across counties as soybeans. Average yield variability for all three crops is strongly correlated within counties.

While a thorough description of the Federal Crop Insurance Program is beyond the scope of this report, additional information about the FCIP can be found in O’Donoghue et al. (2016).

[2] Coefficient of variation = $CV(x) = \frac{StandardDeviation(x)}{Mean(x)}$. As such, the CV scales the variability of a phenomenon by its average magnitude.

Figure 2

Coefficient of variation—a close proxy for risk—for county-average corn, soybean, and wheat yield, 1996-2015



Note: Counties with fewer than 5 years of reported yields are not displayed.

Source: USDA, Economic Research Service calculations based on USDA, National Agricultural Statistics Service measures of county-average yields.

Scenarios, Methods, and Data

This section provides an overview of the methodology that we used. Broadly, we link a suite of models:

1. **Yield models:** Using a combination of machine learning and agronomic simulation models, we train a model to predict historical crop yields using historical weather. We then use these models to generate projections of yield and yield variability over 2060-99, by feeding weather simulations from climate models through the fitted yield models. The years 2060-99 are taken as plausible realizations for 2080, which we take as a representative year in the second half of the 21st century.

2. **Economic models:** We use ERS's Regional Environment and Agriculture Programming Model (REAP), an economic model that simulates producer crop choice, land use, and price response for the U.S. agricultural sector, to simulate acreage allocation and market price under alternative yield scenarios. Iterative runs of this model are used to determine joint yield and price distributions for corn, soybeans, and winter wheat across the country.

3. **Policy models:** We calculate crop insurance premiums and attendant subsidies under the yield and price simulations for each scenario.

Together, these ingredients allow us to project the likely impact of climate change on crop yields, then model how farmers and markets would respond to these changes, and then compute the implications of these changes on the cost of the Federal Crop Insurance Program. Our results should be interpreted as "all else equal" differences between scenarios in response to changing weather. Each climate scenario assumes identical technological and economic environments in order to isolate the effect of different weather realizations driven by a changed climate. While dynamic assessment of how climate, technological, and economic change will interact over time is an important area for future research, it is beyond the scope of the present report. For more details on the methodology beyond what is presented here, see Appendix A.

Climate Change Scenarios

Future climate scenarios used in our analysis were taken from five climate models: the Hadley Centre Global Environment Model (HadGEM), the Community Climate System Model (CCSM), the Canadian Earth System Model (CanESM), the Model for Interdisciplinary Research on Climate (MIROC), and the Goddard Institute for Space Studies model (GISS). These models were all run under the auspices of the Coupled Model Intercomparison Project (Taylor et al., 2012) and differ in their methods for numerically representing the physics of the atmosphere.

Like many climate change impacts studies, we use multiple models to capture the uncertainty about the evolution of the climate system in response to emissions of greenhouse gasses. Each model is driven by the same emissions scenarios, but the resultant climates that they simulate differ to a substantial degree. While they all share certain characteristics—notably, increase in average temperature with increasing concentrations of greenhouse gasses—they differ in the spatial patterns of temperature change, precipitation change, and degree of average warming.

The emissions scenarios—termed “representative concentration pathways” (RCP) (Van Vuuren et al., 2011)—represent possible future emissions pathways to the year 2100. We use RCP4.5 and RCP8.5, which represent stabilization of greenhouse gas concentrations at double pre-industrial levels and continuation of recent rates of increase in greenhouse gas concentrations, respectively. RCP4.5 can be interpreted as a simulated climate future in which some amount of climate change mitigation occurs, and RCP8.5 can be interpreted as one in which no mitigation occurs.

Each climate model/scenario combination is treated independently for the purpose of simulating the future cost of the FCIP. We present results disaggregated by climate model and emissions scenario, and sometimes the “ensemble mean” estimate of various outcomes of interest, which is the estimate averaged over estimates calculated using only individual climate models.

Methods and Data

The machine-learning algorithm used to predict yield response to weather is a semiparametric variant of a feed-forward neural network (Crane-Droesch, 2018). We use machine learning, in general——and neural networks specifically——because they offer better predictive performance than classical econometric and statistical methods. In particular, the semiparametric neural network variant that we use nests standard econometric models of yield response to weather, following approaches used in Schlenker and Roberts (2009). Thus, we are able to incorporate insights from econometric methods while leveraging larger datasets and recent advances in machine learning and artificial intelligence. See appendix B for more information.

Our statistical models were fit to historical yield and weather data spanning 1981 through 2013. Annual county-level yield data by crop was taken from the USDA, National Agricultural Statistics Service Quick Stats database (NASS, 2017). Irrigated and dryland yields were modeled separately. Where irrigated and dryland yields were not explicitly reported, we used data from the USDA Census of Agriculture to determine if a region’s crops were primarily irrigated or primarily dryland. Yield data were then re-allocated from county-level resolution to the coarser REAP model regions using an acreage-weighted and spatially weighted average of county-level yields.

To estimate how yields within a region vary across crop rotations and tillage types, we use the Environmental Policy and Integrated Climate (EPIC) model (Williams 1989). EPIC is a crop systems model, developed and maintained by researchers at Texas A&M University and elsewhere. This output is then fed into the REAP model, which simulates how producers and markets would adapt to changes in expected yields.

The REAP model is initialized with a baseline scenario developed for Marshall et al. (2015). In that study, reference conditions were developed based on expert advice, literature, and a modified extrapolation of the USDA 10-year baseline forecast and reflect a continuation of historic trends (population, diet, demographics, and other socioeconomic factors), but without climate change. As the climate scenarios alter yields over space, the REAP model simulates how acreage would shift from this baseline.

Projection of future yields based on past relationships between weather and yields implicitly assumes that the relationship between weather and yield will remain constant over time. If greater severity of climate change leads to decreasing sensitivity of yield to climate, then the assumption of constant sensitivity would lead to a downward bias in yield projections into the future. Despite the theoretical plausibility of this potential source of bias, recent empirical studies don’t yet support it

(Burke and Emerick, 2016; Lobell et al., 2014). Furthermore, we emphasize that our main purpose in scenario-building is the exploration of the factors mediating their differences, in order to understand the mechanisms by which climate change could affect Federal agricultural risk management programs.

Policy Simulation

Simulated future yields, acreages, and prices under five climate models and two emissions scenarios—together with a baseline scenario of recent climate—allow us to compute premiums, indemnities, and ultimately the cost of the FCIP into the future.

We recognize that policies change over time. As noted above, we simulate the current FCIP into the future not because we expect the suite of Federal farm safety net programs to necessarily continue in their precise current form. Rather, we use the current incarnation of the FCIP as a heuristic—a program that protects against yield and price risk, as past policies have and as future policies may.

Finally, we simulate only the costs associated with subsidizing the program, excluding administrative and overhead costs of implementing it, or overwriting gains. While we cannot rule out the possibility that these may vary with climate, we have no reason to believe that this would be so, and such an analysis is beyond the scope of this report.

Results

This section details the main results of the analysis, beginning with yield impacts, continuing with adaptive response by markets and farmers to those impacts, and concluding with an analysis of the potential implications of these dynamics on the cost of the FCIP.

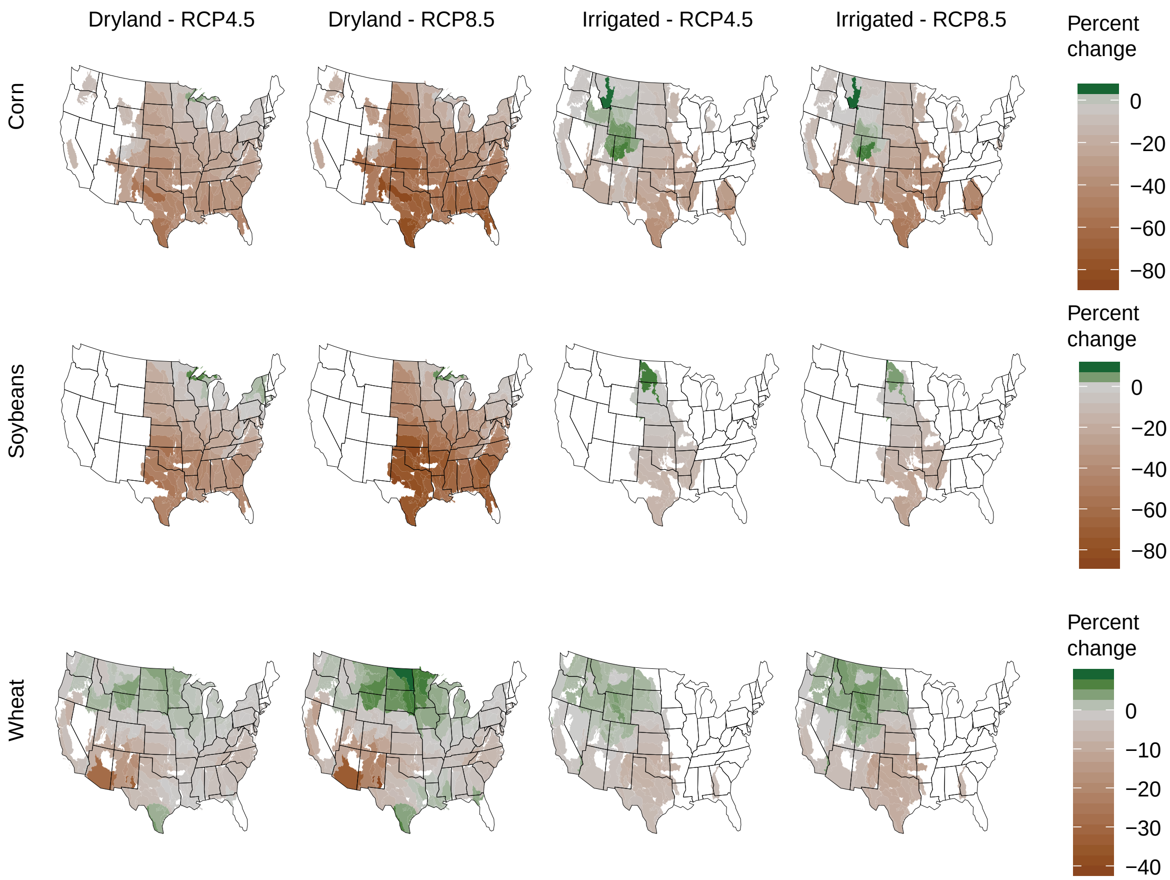
Projected Yields

On average, climate models project declining average corn and soybean yields, while changes to winter wheat are modest and variable. Figure 3 shows maps of percentage change in yield from historical baselines for corn, soybeans, and winter wheat, disaggregated by irrigated and dryland production, for RCP4.5 (some mitigation, less warming) and RCP8.5 (no mitigation, more warming). Losses are generally largest in the southern United States and in dryland production. This is consistent with the known vulnerability of corn and soybean yields to extreme heat, which is projected to increase across all climate scenarios (Schlenker and Roberts, 2009). Increases are observed in some northerly areas, but never above 10 percent. Declines are larger in RCP8.5 than RCP4.5, with the exception of winter wheat, where increases are larger in northern parts of the country with greater warming. This is likely a function of the fact that winter wheat is not exposed to summer heat (see section “Variable Importance” in appendix B). Yield changes in irrigated production are generally smaller than in dryland production.

Yield riskiness, computed as the interannual coefficient of variation of yields, is projected to increase to varying degrees for dryland corn and soybeans under both emissions scenarios, while changing little or declining in many areas under irrigated production (fig. 4). As with projections for average yields, projections for winter wheat yield risk are less pessimistic, with risk declining in many areas. Given that we proxy risk with the coefficient of variation, increases in risk can stem either from more variance between years while yield is held constant, or lower expected yields where variance between years is held constant, or a combination of both.

Figure 3

Projected changes to expected yields averaged across climate model simulations of the period 2060-99

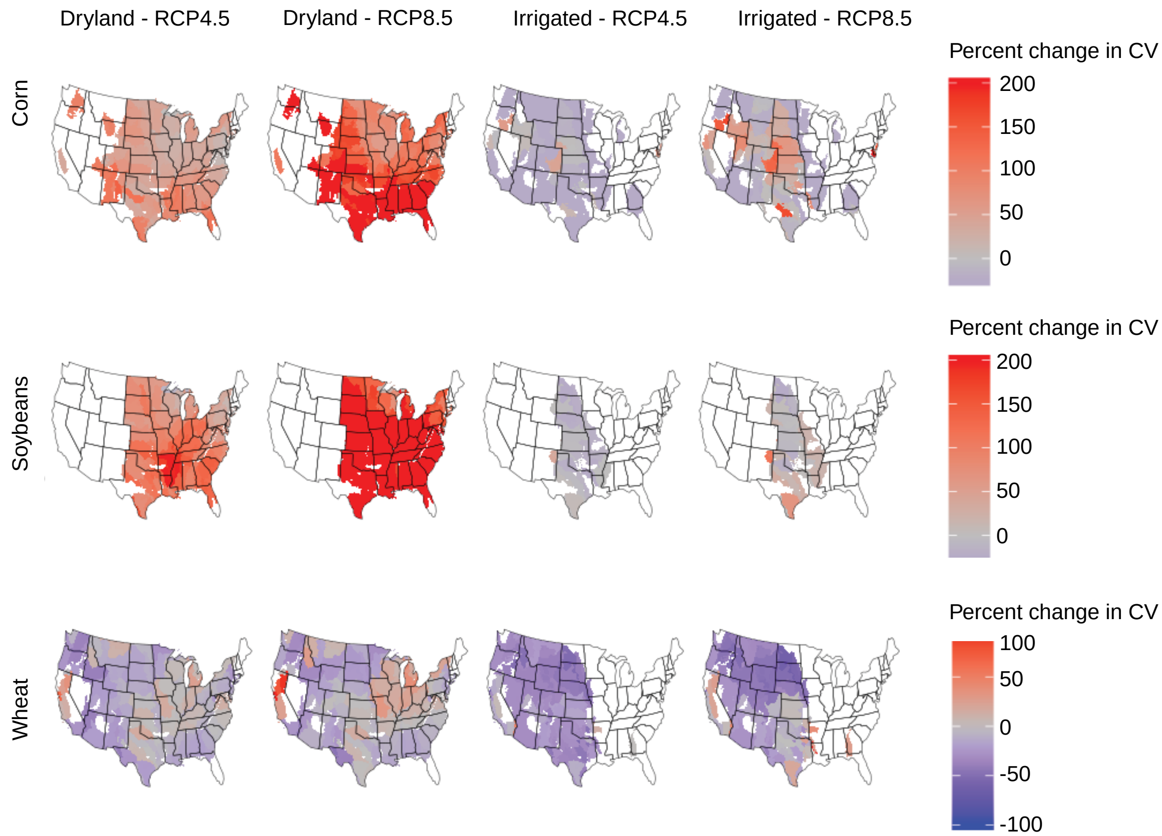


Note: RCP4.5 and RCP8.5 refer to lower and higher greenhouse gas concentration scenarios, respectively.

Source: USDA, Economic Research Service.

Figure 4

Projected percentage changes to yield riskiness—proxied by coefficient of variation (CV)—averaged across climate model simulations of the period 2060-99



Note: RCP4.5 and RCP8.5 refer to lower and higher greenhouse gas concentration scenarios, respectively.

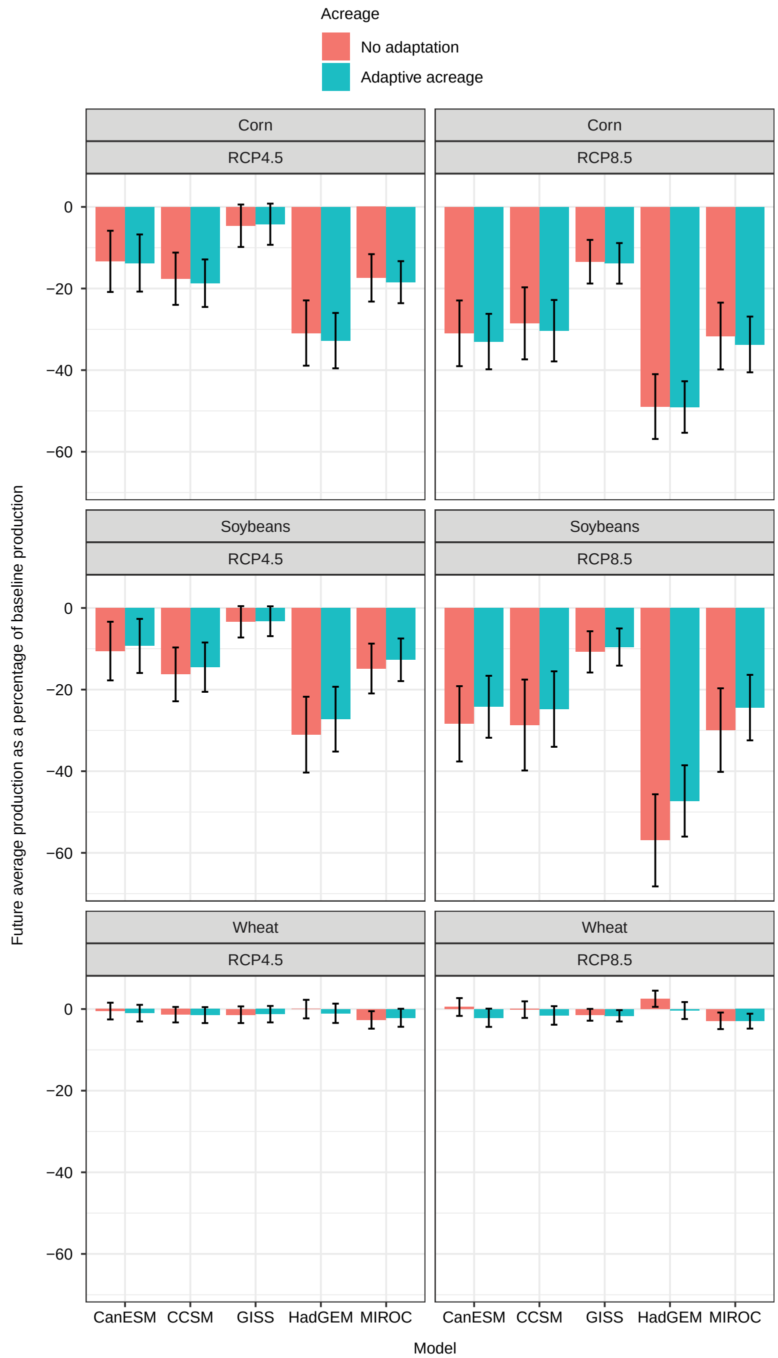
Source: USDA, Economic Research Service.

Acreage, Production, and Price

Adaptation in the form of shifting locations and methods of production has the potential to mitigate overall production declines, as well as change levels of interannual production volatility. We explore the importance of adaptation by running REAP twice—once in which acreage is held fixed to baseline values (which are projections out to 2080 based on the dynamics underlying the USDA baseline (Marshall et al., 2015)) and once in which acreage is allowed to shift in response to new expected yields. These are termed "no adaptation" and "adaptive acreage." Their implications for total production are shown for each climate model in our analysis in figure 5. There is substantial heterogeneity in the magnitudes of yield projections by climate model for corn and soybeans, whose impacts are largely parallel, and some heterogeneity in winter wheat, where impacts are small. In corn, total production is very similar between the adaptive acreage and no-adaptation scenarios, though average declines tend to be slightly larger under the adaptive acreage scenario. In soybeans, losses are larger in the no-adaptation scenario, and decreasing in proportion to the degree that no-adaptation production declines from baseline.

Figure 5

Projected changes in production of corn, soybeans, and winter wheat—with and without adaptation in planted acreage—for each climate model used in the analysis



Note: Error bars reflect modeled interannual variability in production, which is reflective of yield risk and related to price risk. RCP4.5 and RCP8.5 refer to lower and higher greenhouse gas concentration scenarios, respectively. CanESM, CCSM, GISS, HadGEM, and MIROC refer to different climate models. They are shown individually to represent variability across models. See subsection "Climate Change Scenarios" in section "Scenarios, Methods, and Data" for more detail on the models used.

Source: USDA, Economic Research Service.

The dynamics observed under the “adaptive acreage” scenario are driven by yield change (mapped in fig. 3) as well as the movement of planted acreage in response to expected yield change (mapped in fig. 6). The REAP model alters acreage in response to changes in expected yields and prices under climate change, which leads to substantial shifts in where production is located, how much acreage is planted, and how crops are grown. The model projects that national acreage in corn, soybeans, and wheat will decline under both emissions scenarios, though there is substantial variability across regions (table 1 and figure 7).

Table 1

Acreage change by farm producton region, crop, and climate scenario

	Baseline acreage			RCP4.5 acreage change (Percent)			RCP8.5 acreage change (Percent)		
FPR	Corn	Soybeans	Wheat	Corn	Soybeans	Wheat	Corn	Soybeans	Wheat
AP	4.55	4.20	1.24	-0.120	-0.048	0.012	-0.207	-0.100	0.027
CB	47.44	38.62	3.23	-0.038	-0.028	-0.052	-0.090	-0.077	-0.109
DL	2.48	5.06	0.61	-0.144	-0.025	-0.340	-0.251	0.015	-0.469
LA	17.16	12.11	1.76	0.012	0.025	0.000	0.006	0.029	0.008
MN	1.69	0	6.23	-0.202	NA	-0.095	-0.235	NA	-0.172
NP	25.28	15.01	17.02	-0.130	-0.102	-0.018	-0.206	-0.183	-0.029
NT	3.33	1.35	0.49	-0.047	-0.020	-0.019	-0.099	-0.061	-0.086
PA	0.51	0	2.29	-0.079	NA	-0.030	-0.136	NA	-0.017
SE	0.81	0.81	0.33	-0.163	-0.082	0.070	-0.252	-0.174	0.053
SP	2.51	0.21	6.57	-0.254	-0.320	-0.005	-0.337	-0.464	-0.059
Total U.S.	**105.77**	**77.37**	**39.78**	-0.067	-0.036	-0.034	-0.121	-0.078	-0.066

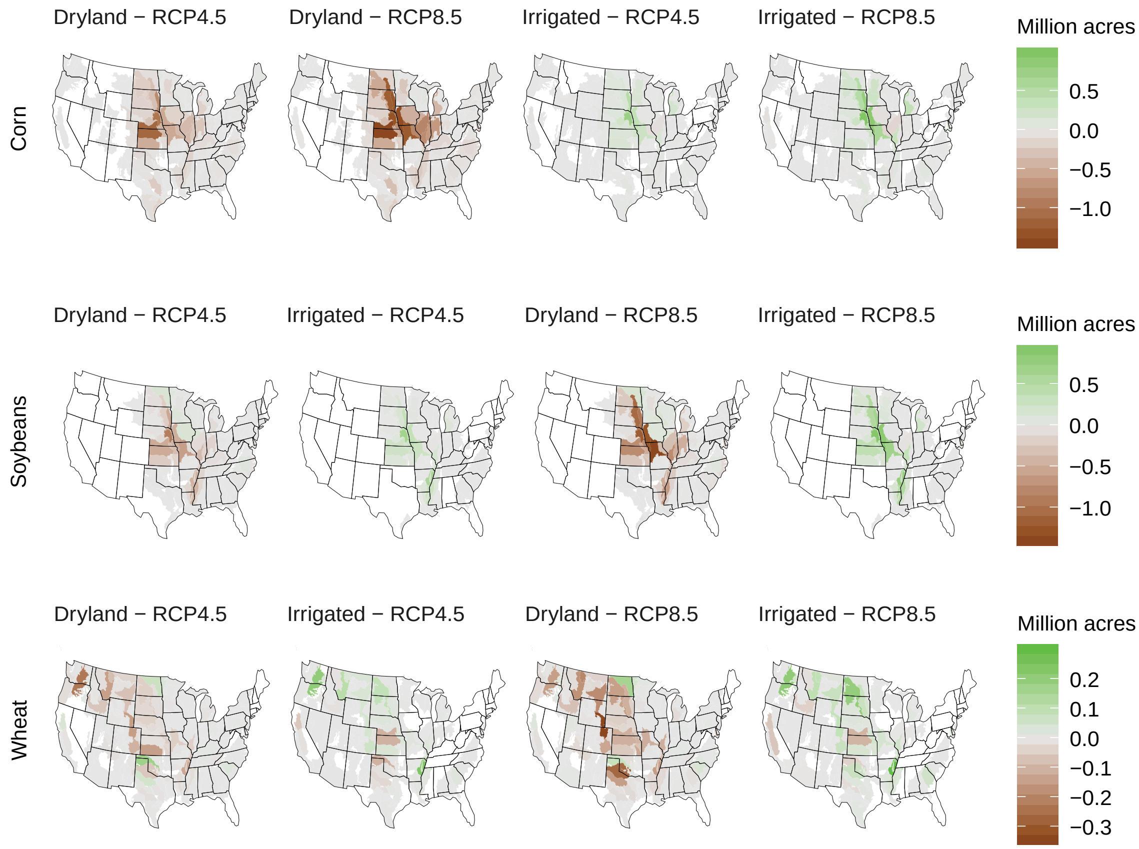
Note: RCP4.5 and RCP8.5 refer to lower and higher greenhouse gas concentration scenarios, respectively. FPR = Farm Production Regions. AP =Appalachia, CB = Corn Belt, DL = Delta, LA = Lake, MN = Mountain, NP = Northern Plains, NT = Northeast, PA = Pacific, SE = Southeast, SP = Southern Plains. NA = not available.

Source: USDA, Economic Research Service.

For all three crops, the model also projects movement out of dryland production and into irrigated production. This movement helps mitigate total declines in production, particularly for corn and soybeans, where in some regions substantial declines in dryland yields are accompanied by less substantial decreases, or in some cases increases, in irrigated yields.

Figure 6

Projections of change to planted acreage by crop and emissions scenario, for dryland and irrigated production, averaged across climate models

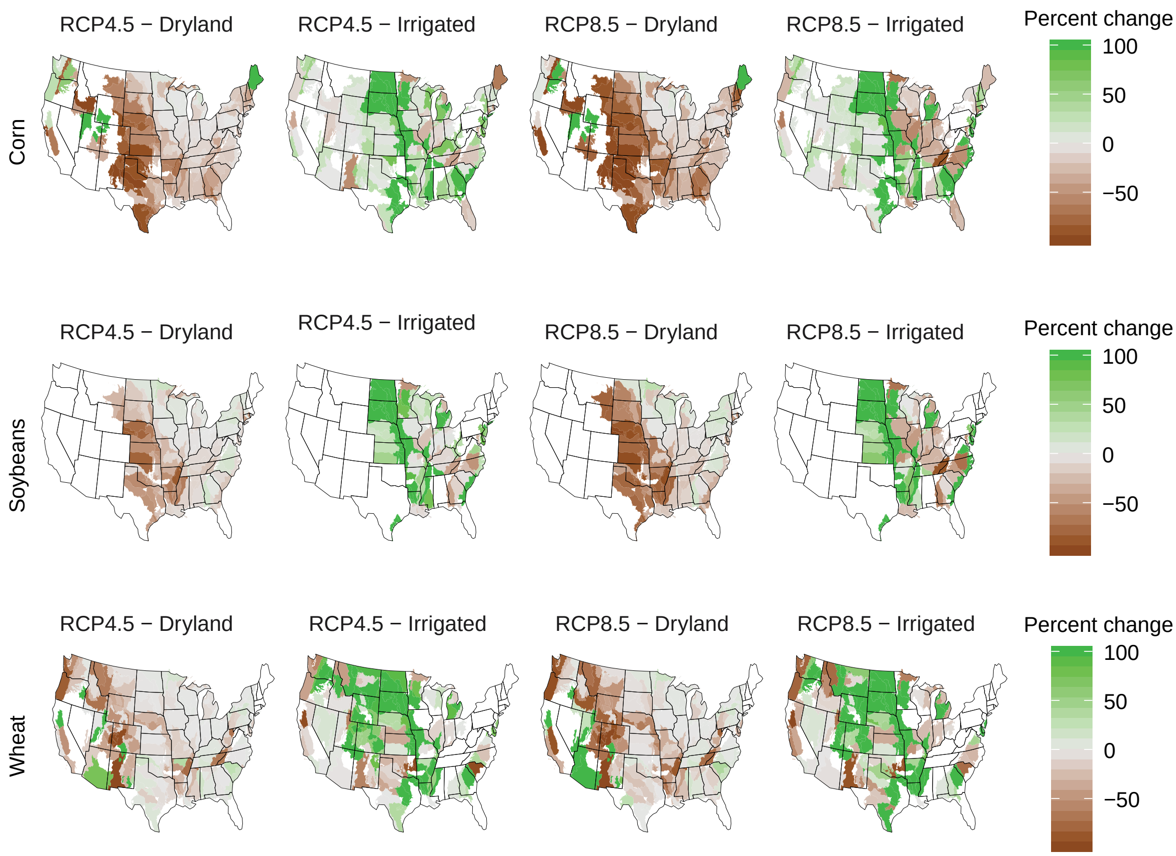


Note: RCP4.5 and RCP8.5 refer to lower and higher greenhouse gas concentration scenarios, respectively.

Source: USDA, Economic Research Service.

Figure 7

Projections of percentage change to planted acreage by crop and emissions scenario, for dryland and irrigated production, respectively



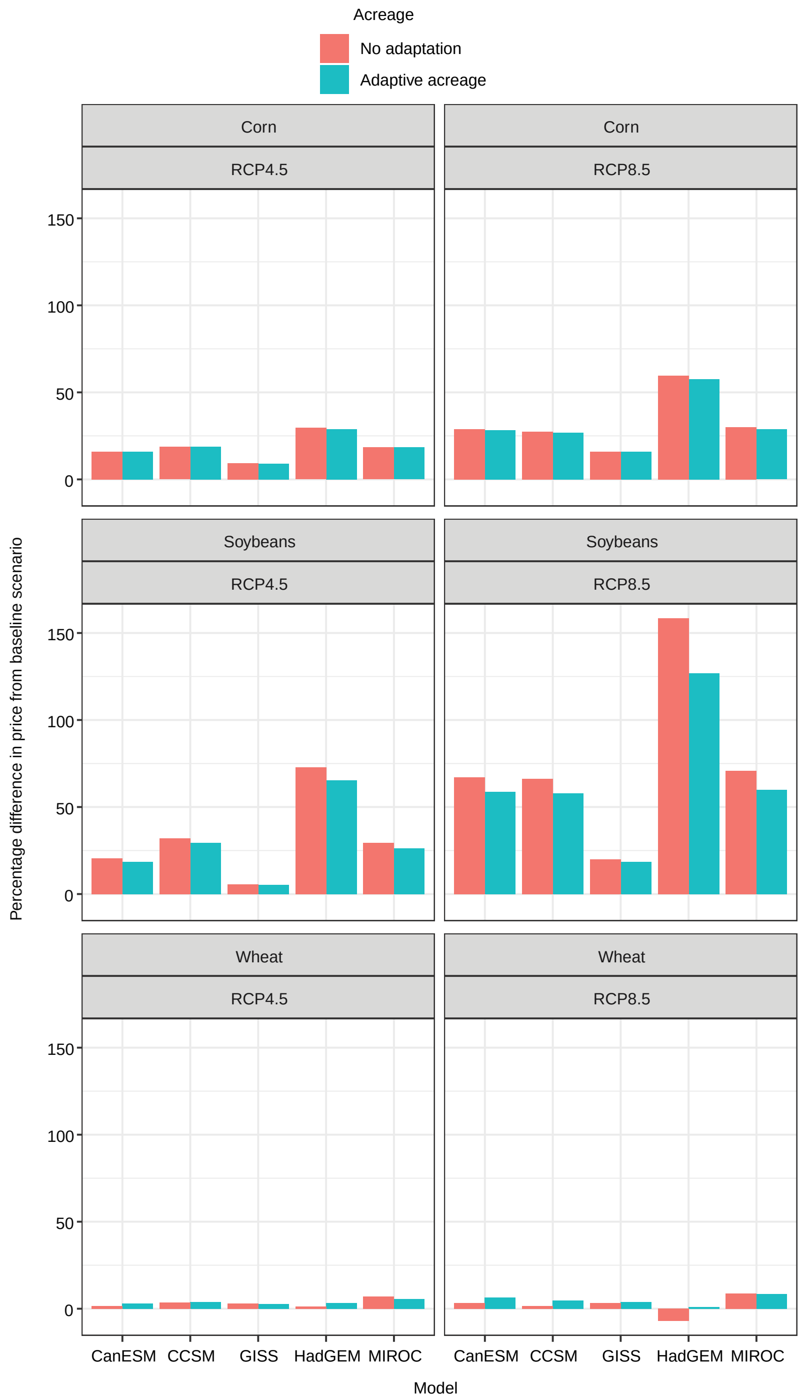
Note: RCP4.5 and RCP8.5 refer to lower and higher greenhouse gas concentration scenarios, respectively.

Source: USDA, Economic Research Service.

Differing levels of production would also affect prices for crops. REAP models this by solving for the new set of prices that allow agricultural markets to clear under the alternative weather and associated yield and production outcomes. This is shown in figure 7. Like projections of production, projections of average price exhibit substantial heterogenity across climate models, with greater increases in price for those combinations of climate model and emissions scenario for which production decline is more severe (fig. 5). Under RCP8.5, average prices for corn under both adaptive acreage and no adaptation generally increase by about 25 percent over baseline, while prices generally increase by over 50 percent for soybeans. Because average prices are driven by average production, the most pessimistic climate models in terms of yield show the largest increases in price. This implies larger liabilities to be insured, which is a major driver of increases in the cost of the FCIP Revenue Protection program (discussed below). Price increases also imply declines in the consumer surplus derived from agricultural products.

Figure 8

Projected price differentials between the climate change and no climate change scenarios by crop, emissions scenario, and climate model, for the fixed-acreage and adaptive acreage scenarios



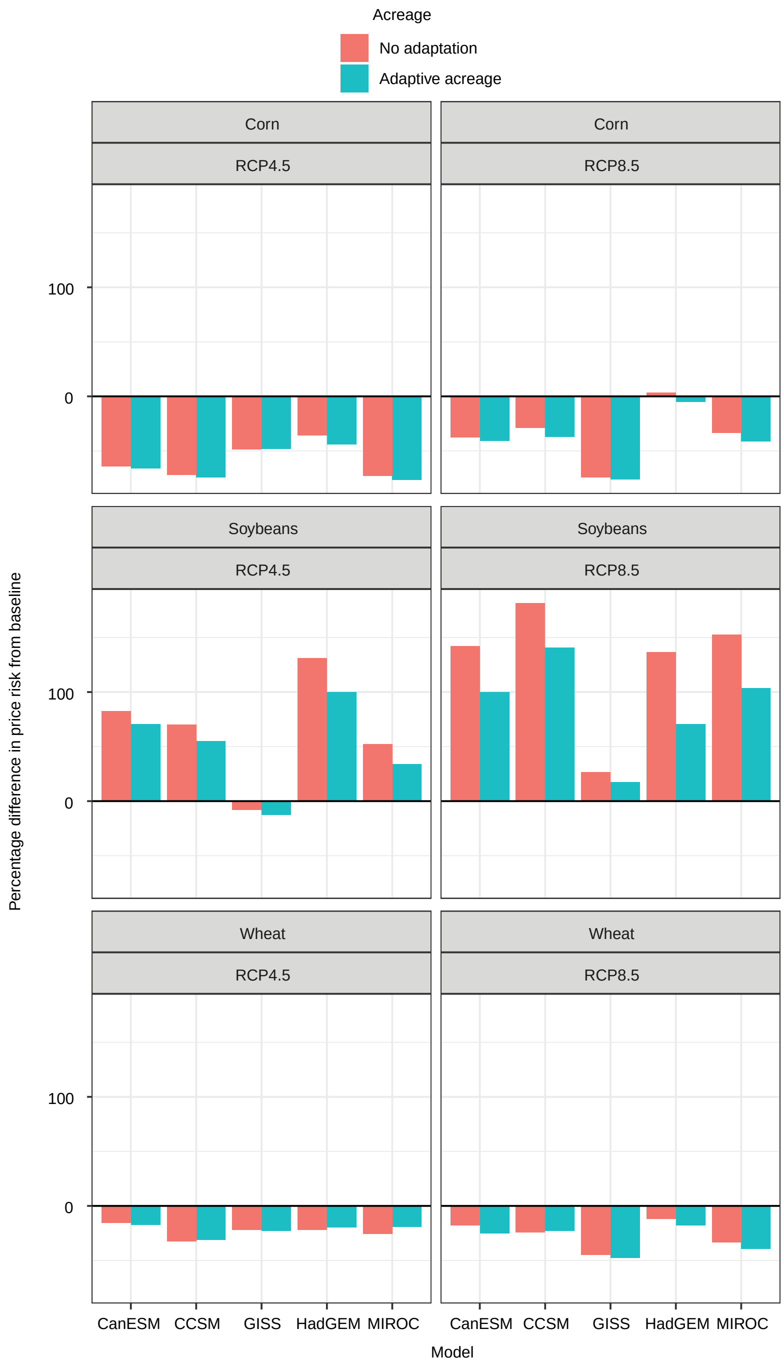
Note: RCP4.5 and RCP8.5 refer to lower and higher greenhouse gas concentration scenarios, respectively. CanESM, CCSM, GISS, HadGEM, and MIROC refer to different climate models. They are shown individually to represent variability across models. See subsection “Climate Change Scenarios” in section “Scenarios, Methods, and Data” for more detail on the models used.

Source: USDA, Economic Research Service.

Changes to yield volatility, changing price levels, and changing methods and locations of production also imply changes in price risk—a key component of the riskiness of revenue, which is what the RP program insures. Changes in price risk under climate change, as measured by changes in the coefficient of variation, are shown in figure 8. Our results indicate substantial heterogeneity by crop: price risk for corn and wheat declines, while it increases for soybeans. Risk, which we proxy with CV (the standard deviation divided by the mean), is determined by average prices and price variability, which largely arises from yield variability. Soybean price risk rises because soybean price variability increases faster than average soybean prices. The opposite is true for corn and wheat, in which average prices increase faster than price variability. This is partially explained by increasing soybean yield risk, which is projected to increase more severely than the two other crops considered.

Figure 9

Projected price risk differentials (difference in the interannual CV of price) between the climate change and no climate change scenarios for corn, soybeans, and winter wheat by crop, emissions scenario, and climate model, for the fixed-acreage and adaptive acreage scenarios



Note: Risk is proxied by the coefficient of variation (CV), the standard deviation of prices divided by their mean. RCP4.5 and RCP8.5 refer to lower and higher greenhouse gas concentration scenarios, respectively. CanESM, CCSM, GISS, HadGEM, and MIROC refer to different climate models. They are shown individually to represent variability across models. See subsection “Climate Change Scenarios” in section “Scenarios, Methods, and Data” for more detail on the models used.
Source: USDA, Economic Research Service.

Impacts on Revenue Protection Premiums and Subsidy Costs

The Revenue Protection (RP) program of the Federal Crop Insurance Program (FCIP) insures farmers against risks to revenue, which is determined both by yields and prices. As we saw in the previous sections, the climate change scenarios projected average corn and soybean yields decline, average prices increase, yield risk increases, and price risk varies by crop, compared to the baseline. Winter wheat, on the other hand, is much less affected. Here we combine these factors to project RP premiums at the county level based on these scenarios.

Changes to average premiums by county are shown in figure 9. Changes to premiums reflect changes to riskiness of revenue, which are driven by changes in both yield and price risk, as well as changes in the value of the crop insured. Premiums increase in most areas most substantially for soybeans, which are projected to experience increases in both yield and price risk for most regions, as well as increases in average price. Increases in premiums for corn production arise despite the decline in price risk, due to the substantial increases in yield risk and the increase in corn price. Changes in premiums for winter wheat are small and localized. In many areas, premiums increase the most in places where acreage declines in response to expected yield declines (fig. 6). For corn, this is particularly the case in Kansas and Nebraska. This is a major factor explaining why adaptation is projected to reduce the impact of climate change on the cost of the program (see next section).[3]

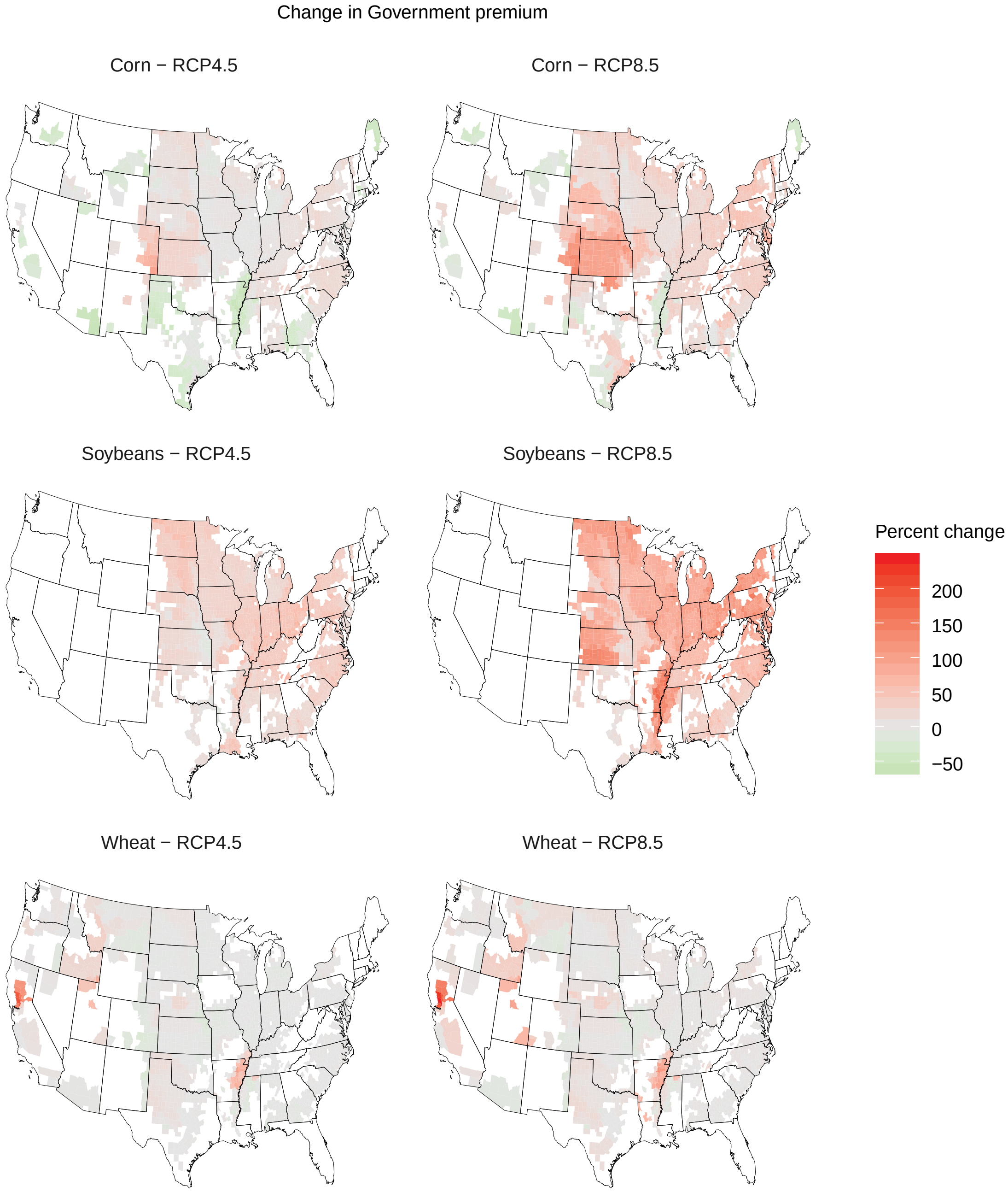
In this study, we hold crop insurance participation, the share of acreage enrolled in the FCIP, and the share of policies at each level of buy-up constant in all scenarios. While greater risk exposure would be expected to increase demand for crop insurance, the expected increase in crop insurance premiums shown would counteract some of the increase in demand. The relative dominance of these two mechanisms is an open empirical question, which we leave to future research.[4] Instead, we hold insurance coverage rates and buy-up levels fixed for the purpose of this analysis. This allows us to directly compute the cost of these scenarios to the Federal Government, where the cost is measured as the portion of total insurance premiums that is subsidized by the Federal Government. This is mapped by county in figure 10.

[3] It is important to note that our modeling framework does not permit us to examine shifts in acreage in response to crop insurance premiums. Furthermore, we hold county-level rates of crop insurance coverage fixed, leaving estimation of crop insurance demand response to changing risk for future research.

[4] Bulut (2018) suggests that uptake declines with premium costs, but this is based on a theoretical simulation model, rather than an empirical study using an approach that is able to abstract away from confounding factors.

Figure 10

Projections of change to average county-level Revenue Protection program premiums averaged over climate models, by crop and emissions scenario

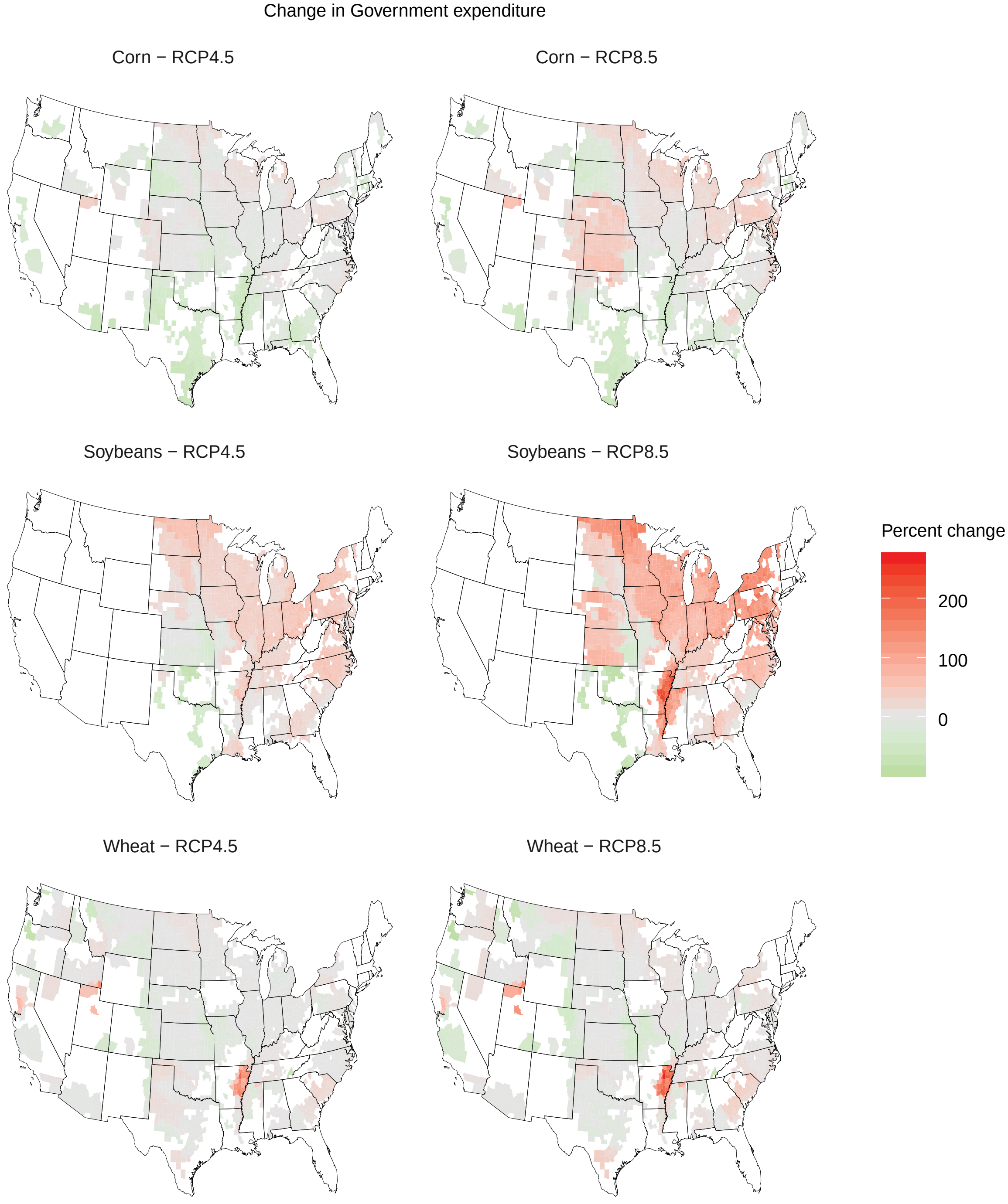


Note: Mapped premiums are computed based on the adaptive-acreage scenario and reflect historical county-level rates of buy-up coverage in addition to changes in underlying revenue risk. RCP4.5 and RCP8.5 refer to lower and higher greenhouse gas concentration scenarios, respectively.

Source: USDA, Economic Research Service.

Figure 11

Projections of change to average Government expenditure, by county, by crop and emissions scenario



Note: Maps represent averages of projections over the five climate models considered. RCP4.5 and RCP8.5 refer to lower and higher greenhouse gas concentration scenarios, respectively.

Source: USDA, Economic Research Service.

Under RCP4.5—the milder emissions scenario—costs to the Federal Government decline for corn in most places, reflecting a combination of reduced premiums in some areas and movement of production out of other areas in which premiums increase. A similar dynamic mitigates the increase in the cost under RCP8.5. Likewise, some movement out of production mitigates cost increases for soybeans, but not enough to avoid increases in the cost of the program in many areas. Changes to the cost of the program for winter wheat are modest and localized.

Because of the decline in insured acreage in Kansas and Nebraska, percentage changes to premiums are larger than percentage changes to the Government's exposure in those areas. Conversely, because of movement of soybean production to parts of the lower Mississippi valley under RCP8.5, increases in costs to the Federal Government are proportionally larger than the increases in expected premiums in those regions.

These results are summarized over the whole country in table 2. The cost of the program for corn declines under the milder emissions scenario (RCP4.5) but increases by approximately $750 million (11 percent) under the warmer scenario (RCP8.5). As discussed above, this decline in program costs under RCP4.5 is explained in part by declining production acreage in areas in which yield risk grows and partially by the decline in price risk for corn. The cost for soybeans increases by approximately $550 million (27 percent) under RCP4.5 and $1.3 billion (65 percent) under RCP8.5, reflecting increases in soybean prices and price risk, as well as more uniform and higher proportional increases in yield risk. Changes in cost for winter wheat are small.

These numbers would be substantially larger if we did not model movement of planted acreage in response to climate change—several hundred million dollars for corn and soybeans, as seen in the bottom panel. The difference for winter wheat is small.

Table 2

Total projected annual cost of the Revenue Protection program ($ millions) and planted acres (millions), assuming that planted acreage adjusts to expected changes in yield driven by climate change (Adaptive acreage) and that acreages are fixed at their baseline levels (No adaptation)

Adaptive acreage Crop	Emissions acenario	Cost of program ($ millions/yr)	Insured acres (Millions)
Corn	Baseline	6,847	76
	RCP4.5	6,628 (-3%)	71
	RCP8.5	7,609 (11%)	66
Soybeans	Baseline	1,991	56
	RCP4.5	2,536 (27%)	55
	RCP8.5	3,282 (65%)	52
Wheat	Baseline	479	20
	RCP4.5	479 (<.1%)	20
	RCP8.5	482 (<.1%)	19

continued

Table 2

Total projected annual cost of the Revenue Protection program ($ millions) and planted acres (millions), assuming that planted acreage adjusts to expected changes in yield driven by climate change (Adaptive acreage) and that acreages are fixed at their baseline levels (No adaptation) — continued

No adaptation Crop	Emissions scenario	Cost of program ($ millions/yr)	Insured acres (Millions)
Corn	Baseline	6,847	76
	RCP4.5	6,875 (2%)	
	RCP8.5	8,179 (21%)	
Soybeans	Baseline	1,991	56
	RCP4.5	2,807 (41%)	
	RCP8.5	3,980 (100%)	
Wheat	Baseline	479	20
	RCP4.5	482 (<.1%)	
	RCP8.5	491 (2%)	

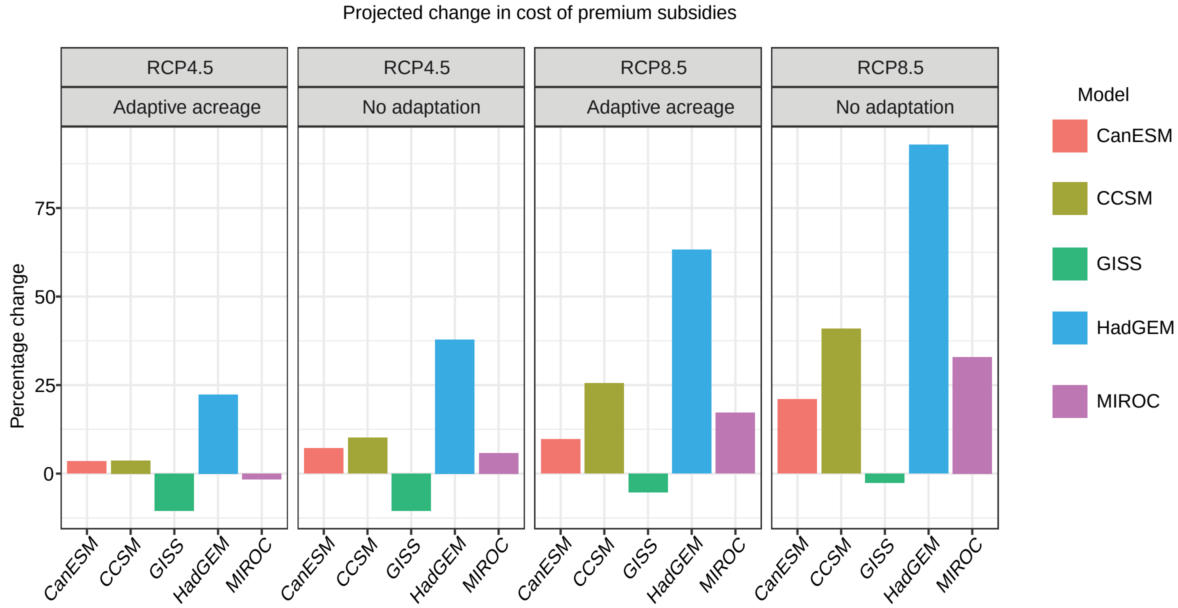
Note: Figures reflect averages across climate models. The baseline acreages were projections out to 2080 based on the dynamics underlying the USDA baseline, developed by Marshall et al. (2015). RCP4.5 and RCP8.5 refer to lower and higher greenhouse gas concentration scenarios, respectively.

Source: USDA, Economic Research Service.

While table 2 presents an average across multiple climate models, figure 11 plots percentage changes in cost by climate model. Costs for the entire program vary substantially by climate model. The most optimistic model (GISS) projects decreases in the cost of the program, while the most pessimistic model (HadGEM) projects substantial increases. While the ranges between models and scenarios are large, we note that recent evidence suggests that more pessimistic climate models have more accurately represented recent warming and may be better guides to the future than less pessimistic models (Brown and Caldeira, 2017). Thus, estimates in table 1 are likely to be underestimates. Furthermore, the Intergovernmental Panel on Climate Change has recently found that the emissions and climate change mitigation policies currently in force imply a trajectory of warming consistent with more pessimistic emissions scenarios (IPCC, 2018). Program cost estimates for RCP8.5 may therefore be more reflective of the climate trajectories that are likely to occur absent substantial changes in emissions and emissions policy globally.

Figure 12

Projected percentage change in the cost of premium subsidies to the Federal Government, relative to the baseline scenario in which future climate is similar to that of the recent past



Note: Subplots represent scenarios in which climate change adaptation does and does not occur (no adaptation versus adaptive acreage) and differing warming severities (RCP4.5 versus RCP8.5). Bars represent different climate models used in the analysis. RCP4.5 and RCP8.5 refer to lower and higher greenhouse gas concentration scenarios, respectively. CanESM, CCSM, GISS, HadGEM, and MIROC refer to different climate models. They are shown individually to represent variability across models. See subsection "Climate Change Scenarios" in section "Scenarios, Methods, and Data" for more detail on the models used.

Source: USDA, Economic Research Service.

Implications for Risk Management Programs

The scenarios presented in the previous sections illustrate potential pathways by which current program costs could change in response to different climate scenarios. We apply state-of-the-art modeling tools and decades of data to this problem. However yields, acreages, and prices could shift in ways that do not correspond with our modeled scenarios, while the structure of Federal agricultural risk management programs could change over time as well. This section explores drivers of change in the cost of the RP program, and from these drivers, it attempts to quantify which aspects of climate change's impact on agriculture would have the most impact on agricultural risk management program costs generally. Thus, it could inform policymakers of the potential consequences of either policy changes or trends in agriculture or markets—recognizing that the scenarios that we simulate are unlikely to come to pass exactly as we have modeled them.

We explore this regressing the output of our simulation models—the average premium—on measures of the factors that influence it: yield risk, price risk, and price levels. Results are presented in table 3. For all three crops, change in average price is a larger determinant of change in the price of premiums than are either yield risk or price risk. The effect of price levels reflects the fact that much of the cost of insurance—and of premium subsidies—is driven by the value of the output that is insured. As climate change impacts total production, premiums and subsidies would increase with the value of that which is insured. Price risk and yield risk are also important for all three crops, to varying degrees. Scenarios with no adaptation generally have larger estimated changes in premiums, relatively larger roles for price risk, and smaller roles for average price in corn and soy.

Table 3

Regressions of simulated county-level crop insurance premiums on simulated yield risk, price risk, and price level, for each of the five climate models, with and without adaptive acreage

	Dependent variable:		
	Log (average premium)		
	Corn	Soybeans	Winter wheat
Log (yield risk)	0.674***	0.501***	0.766***
	(0.010)	(0.008)	(0.031)
Log (price risk)	1.435***	0.510***	0.556***
	(0.024)	(0.017)	(0.028)
Log (average price)	1.549***	0.914***	1.051***
	(0.033)	(0.013)	(0.031)
No adaptation	0.395***	0.443***	0.589***
	(0.039)	(0.020)	(0.040)
Yield risk × no adaptation	−0.054***	0.012***	0.038***
	(0.007)	(0.003)	(0.006)
Price risk × no adaptation	0.183***	0.061***	0.452***
	(0.026)	(0.009)	(0.028)
Average price × no adaptation	−0.119***	−0.126***	0.063*
	(0.034)	(0.006)	(0.033)
Observations	41,074	36,542	39,776
R^2	0.916	0.892	0.971
Adjusted R^2	0.912	0.887	0.970

Note: *p<0.1; **p<0.05; ***p<0.01. Estimated coefficients are interpretable as elasticities, meaning that for a coefficient equal to ß a 1-percent change in an independent variable leads to a ß-percent change in the dependent variable. No-adaptation effects may be taken by adding the no-adaptation interaction term to the main effect. All estimates are conditional on county-level fixed effects. Standard errors, which are adjusted to account for within-county autocorrelation, are given in parentheses. The unit of observation is the county under a given climate model and emissions scenario, and, as such, elasticities are estimates averaged over models and scenarios.

Source: USDA, Economic Research Service.

Discussion

The Influence of Increased Value of Production

While we show that yield risk and price risk are important drivers of the cost of agricultural risk management programs, we also show that climate change could lead to increases in program costs, even if there is no increase in yield or price risk, through changes to the value of total crop production. In fact, this is the most important driver of the change in projected premiums in our simulations. We term this “the liability effect.”

Substantial research has focused on estimating the impact that climate change could have on average crop yields (Rosenzweig and Parry, 1994; Schlenker and Roberts, 2009). While there is some variation in the magnitudes of the estimates, there is general agreement that climate change will reduce average yields and total production for most crops in most regions (all else equal) (Porter et al., 2014), and our estimates are consistent with those projections. Given that demand for most agricultural commodities is relatively inelastic, a decrease in total production would increase prices. Under these circumstances—the change in the quantity demanded is less than the change in price—prices increase proportionately more than the supply decreases.

Supply reductions in the presence of inelastic demand imply increases in the total value of production. Since crop insurance insures a percentage of the value of production, total liabilities for the program would increase in such a scenario. This liability effect was a major driver of increases in program costs during the increase in commodity prices from 2008 to 2012, although in that case, the primary cause was increased demand rather than decreased supply (Glauber, 2013).

Note that the liability effect arises from more than just the average yield changes. Since land allocations are changing, some of the shifts in supply for each commodity are also driven by adaptation. For soybeans, this leads to smaller shifts in supply than would occur without adaptation (see table 2), and, therefore, adaptation also leads to a somewhat smaller liability effect, while for corn, adaptive acreage shifts exacerbate reductions in supply and therefore lead to a somewhat larger liability effect. Ultimately, an increase in program costs due to climate change could occur without any changes in yield volatility or price volatility, though we do project substantial increases in yield volatility for corn and soybeans across most regions.

Caveats and Future Work

A number of caveats apply to this research and to our results. They are detailed below.

Unmodeled Risk

An important feature of increases in yield risk is that they are sensitive to assumptions about the relative shift between changes in yield and non-weather-related risks. For example, changes to weather conditions that induce changes in average yields may also change volatility stemming from pests or disease. This is an important topic for future research. Lacking specific information on the relationship between these factors, we model non-weather-related volatility in yields as constant and uncorrelated with volatility stemming from weather.

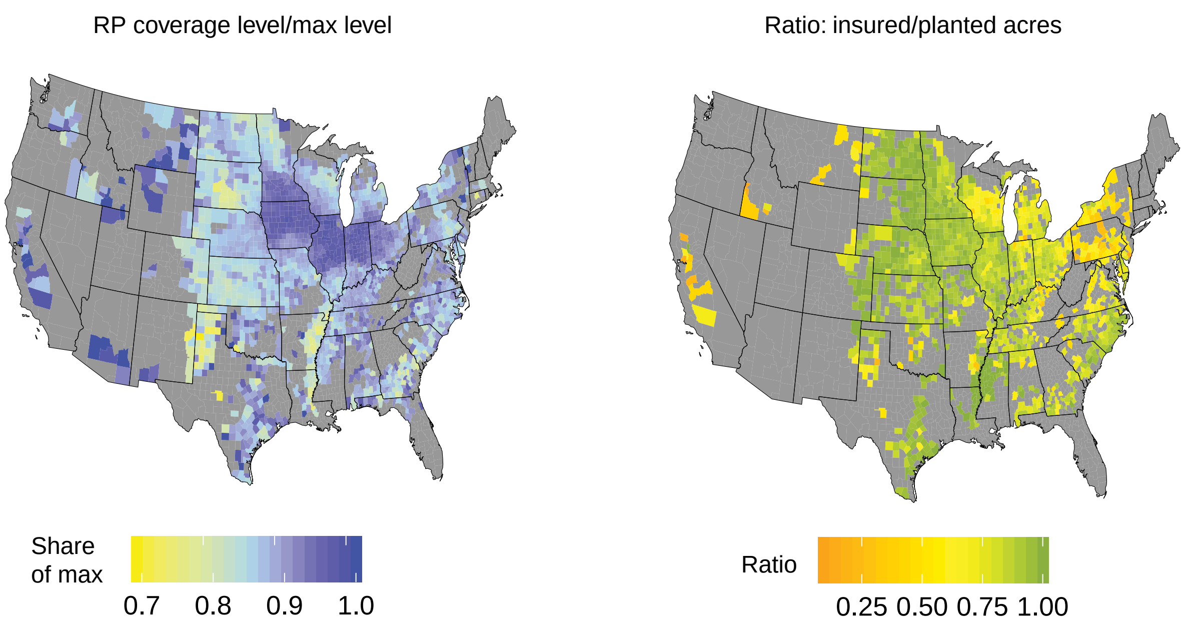
Disease or other disturbance vectors as drivers of yield risk are another important issue. Climate change could increase yield risk through increased exposure to pathogens and pests (Bebber et al., 2013). Climate change could also increase ground-level ozone or increase the frequency of certain kinds of storms (Walthall et al., 2013) in ways that we do not capture here.

Changes in Program Participation

Our analysis of crop insurance expenditures under climate change assumes no demand response to higher crop insurance premium rates. This is a simplifying assumption; farmers would likely demand less insurance at higher prices, but more as its value increases. An analysis of crop insurance purchases in 2016 (OMB, 2016) shows that farmers in lower risk areas—where premiums are less expensive—tended to purchase higher average coverage levels than farmers in higher risk areas (fig. 12). However, farmers in higher risk areas tended to insure a larger fraction of their planted acres than farmers in lower risk areas. Increasing insured acreage as a share of planted acres would increase the projected cost of the crop insurance program under climate change. Decreasing average coverage levels, however, would reduce the projected cost of the FCIP under climate change. The aggregate effect of increasing insured acreage and decreasing coverage levels and participation rates is an important empirical question, but unresolved in the literature; it is unclear which would dominate. This question is left for future research.

Figure 13

Measures of crop insurance participation in corn, for 2016



Note: RP = Revenue Protection. Ratios of average coverage to maximum possible coverage. Ratios of insured corn acres to planted corn acres.

Source: USDA, Economic Research Service analysis of data from USDA, Risk Management Agency.

Ethanol Demand

REAP explicitly models demand for corn for ethanol production. In the baseline scenario, 40 percent of corn production is diverted for this purpose, with lower amounts in climate scenarios in which prices for corn climb. It is possible that underlying demand for ethanol may change with policy changes, which in turn would change corn demand and, thereby, crop insurance premiums though the channel of price levels. This effect would be smaller in the more severe climate scenarios because the climb in prices would lead to less total corn being diverted into ethanol.

Changes in Program Design

There will be several Farm Bills before 2080, and the structure of the crop insurance and commodity support programs could change. This study does not consider alternative program structures, though we emphasize that changes in program design could interact with the impacts of climate change. For example, changes in the share of premiums covered by farmers could change both the share of cropland enrolled and the share of policies that buy up to higher coverage levels. The modeling framework here could provide a foundation for policymakers to analyze the predicted results of such policy changes, although additional modeling of farmer insurance decisions would likely be needed.

Irrigation

Climate change is likely to change the availability of water for irrigation (Marshall et al., 2015). Changes to precipitation and increased average temperature are likely to reduce surface water supplies in many regions and also reduce groundwater availability by altering recharge rates. Increased precipitation could expand supplies in some regions, but increased variability in precipitation (for example, heavier yet less frequent rainfall events) could offset that impact leading to more runoff and less surface water and groundwater storage (Foti et al., 2012).

On the demand side, farmers may expand irrigation in some areas in response to climate change, though this would entail substantial investment in many regions, as well as institutional impediments in others. Expanded irrigation adoption could reduce production risk, or reduction in water supplies could increase production risk. We do not model irrigation supply shocks; incorporation of hydrological modeling could add this texture to the present analysis.

If the irrigation expansion that we have modeled is overly optimistic in its representation of potentially irrigable land, then our results are biased downwards—and estimates of both agricultural risk and cost to the Government might be much higher. First, less irrigation would mean lower average yields and probably lower production, unless the area under cultivation is expanded in the face of declining dryland yields. This would lead to substantially higher prices. Second, production would get riskier because more of it would be under dryland production. Holding our yield models and climate scenarios constant and assuming that all land that is currently irrigated will be irrigable into the future, our results are bounded below at the results derived from the adaptive acreage scenario and bounded above at the no-adaptation scenario. However, Marshall et al. (2015) project that irrigation water supplies are likely to become constrained in areas such as Kansas and Nebraska, where irrigated production accounts for a significant amount of the corn and soybean production in our baseline scenario.

Other Factors Influencing Yield

There are also several other pathways by which yields could change over the coming decades that we do not model. Seed technology is among the foremost of these. Technology will continue to change—perhaps in direct response to climate change (Heisey and Rubenstein, 2015)—though it is unclear how this would be forecasted. A great deal of current research in crop genetics is focused on improving drought tolerance, though there is some evidence that extant gains are not translating to improved drought resistance in practice, as it has also led to higher planting densities (Lobell et al., 2014). While we incorporate increases in average yields under both the baseline and the climate change scenarios, we do not model any trend of changing vulnerability.

International Markets

The REAP model allows for some adjustments in exports and imports of agricultural commodities, but we model the impact of productivity, yield, price, or demand shocks from outside the United States only indirectly, by calibrating price volatility in the future scenarios to approximate the estimated proportion of price volatility stemming from global markets in the baseline (see appendix C). Effectively, we assume that price volatility stemming from international markets scales with domestic price volatility. This might be an optimistic assumption if the rest of the world is impacted by climate change more severely than is the United States. Such a dynamic would increase price risk and price levels, increasing the cost of the program. Conversely, the assumption is overly pessimistic if U.S. production is impacted by climate change to a greater extent than the rest of the world. Future work could extend our methodology by explicitly modeling global agricultural supply and demand responses to climate change (Wiebe et al., 2015; Schmitz et al., 2014; Nelson et al., 2014).

Storage

Price volatility in agricultural markets is substantially dampened by storage. Producers store their production in years with low prices and sell when they become higher. Thompson et al. (2018) find that price volatility stemming from climate-induced yield volatility is likely to be substantially buffered by increases in storage and storage capacity. We do not represent growth in storage with growth in price or yield volatility, though REAP does model grain stocks. While increases in storage would reduce premiums by reducing price volatility, it would not affect average price levels, which are a major driver in the projected growth in program costs.

Conclusion

Climate risk management has always been central to agricultural risk management, though the stationarity of the climate system over the past few centuries has meant that this linkage has been implicit. Long-term shifts in average and extreme weather patterns may render this linkage increasingly explicit, and this report may be considered in that light.

Absent changes to program design, we find that the cost of one Federal agricultural risk management program, the Federal Crop Insurance Program (FCIP), is likely to increase, driven by a combination of increasing overall variability of prices and yields, and higher prices driven by lower supply. Lower supply is due to yield changes that are imperfectly offset by acreage changes, driven by weather that is projected to be less favorable to field crops than a future without climate change, on average, over most of the United States.

While we model some aspects of behavioral adaptation—largely shifts of dryland production into irrigation, and out of production entirely in many regions—we are unable to model every potential means by which the agricultural sector might adapt to coming changes, beyond coarse assumptions regarding overall technical change. If our assumptions about expansion of irrigation are too optimistic, then our results are lower bounds to the true impact of climate change on the cost of Federal agricultural risk management. If agricultural technology is able to become substantially more resilient to adverse weather than it is now, then our results are overestimates of the true impact.

While we explicitly model the FCIP, our results have implications for any agricultural risk management program that provides benefits in response to yield or price shocks. This includes the current versions of the Agriculture Risk Coverage and Price Loss Coverage programs managed by the Farm Service Agency, as well as any hypothetical program that a future Congress might enact, if it shares the basic features of revenue and yield risk mitigation. Any constraints on the growth in production will increase the value of commodities, thereby increasing the cost of insuring them (unless, of course, there are simultaneous decreases in value stemming from lower demand). Yield and price risk increases would also contribute to costs of risk mitigation.

Projections of outcomes into the future remain fraught with uncertainty. While some of these uncertainties will generally be irreducible, substantial scope remains to refine this work. Despite its limitations, this study has employed novel tools for modeling the relationship between weather and yields, and through those yield changes to model the potential impact of climate change on the cost of the Federal Crop Insurance Program. Opportunities for future research include finer scale data, further advancing the modeling approaches used here, and relaxing some of the simplifying assumptions adopted.

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Appendix A: Methodology

This section lays out the methodology that we used. Broadly, we link a suite of models:

1. **Yield models:** Using a combination of machine-learning and agronomic simulation models, we train a model to predict historical crop yields using historical weather. We then use these models to generate projections of yield and yield variability over 2060-99, by feeding weather simulations from climate models through the fitted yield models. The years 2060-99 are taken as plausible weather realizations for the year 2080, which we take as a representative year in the second half of the 21st century.

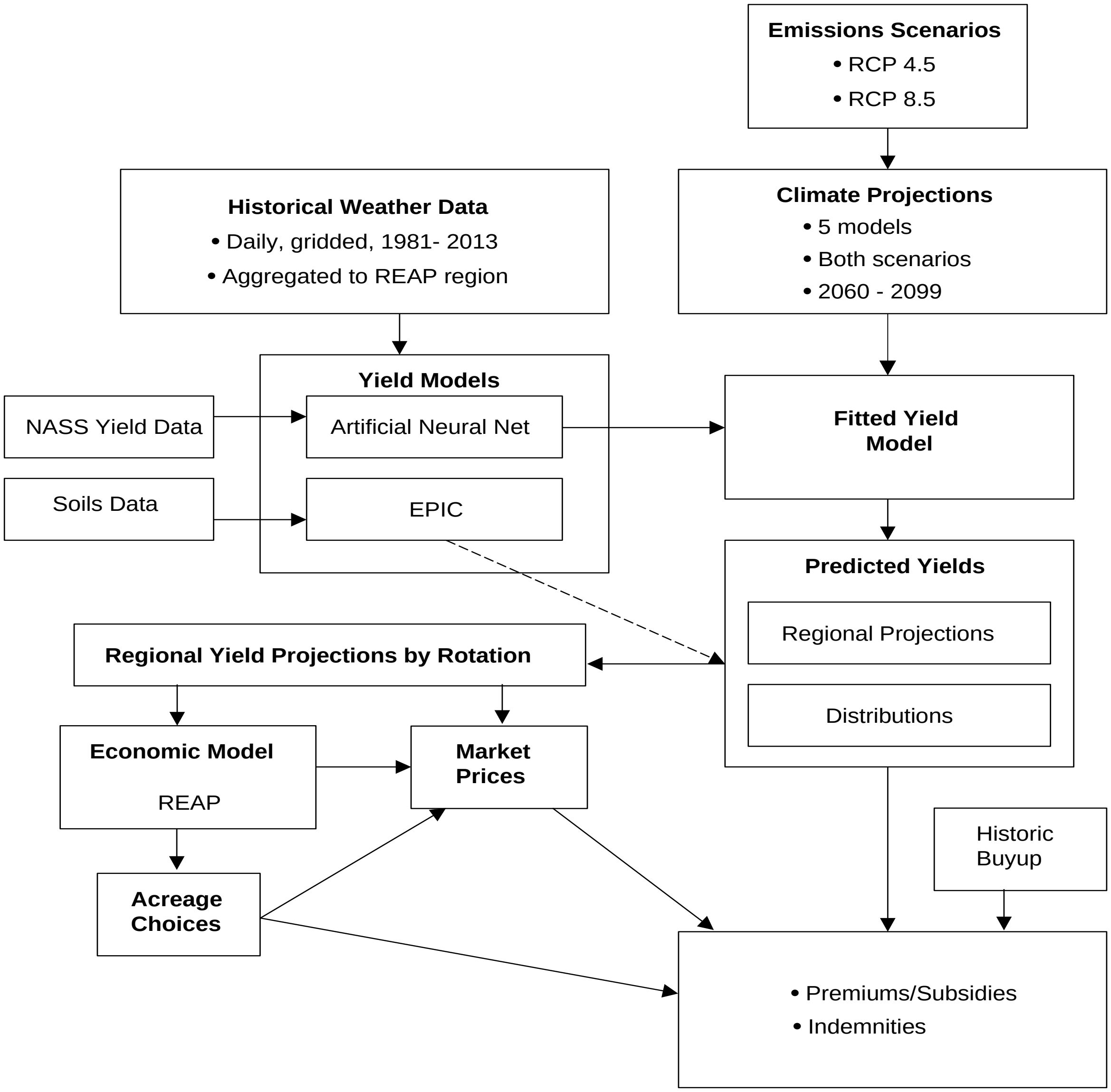
2. **Economic models:** We use ERS's Regional Environment and Agriculture Programming Model (REAP), an economic model that simulates producer crop choice, land use, and price response for the U.S. agricultural sector, to simulate acreage allocation and market price under alternative yield scenarios. Iterative runs of this model are used to determine joint yield and price distributions for corn, soybeans, and winter wheat across the country for each of the weather realizations, and associated yields, from 2060 to 2099.

3. **Policy models:** We calculate crop insurance premiums and attendant subsidies under the yield and price simulations for each scenario.

Figure A.1 describes how these models are linked.

Figure A.1

Schematic of this study's modeling approach



Note: NASS = USDA, National Agricultural Statistics Service. RCP = Representative Concentration Pathway. EPIC = Environmental Policy Integrated Climate (crop) model. REAP = Regional Environment and Agriculture Programming Model. ARC = Agriculture Risk Coverage. PLC = Price Loss Coverage.

Source: USDA, Economic Research Service.

Yield Models

Two complementary frameworks were used to model the relationship between crop yields and weather. A machine learning algorithm is used to predict average yields across entire REAP regions (see box "Machine Learning"), while a process-based agronomic model is used to allocate these yields to specific crop rotations.

Machine Learning

Machine learning is a field of computer science and statistics that gives computers the ability to learn without being explicitly programmed. It is largely (though not entirely) concerned with prediction of events that are unobserved by the modeler at the time of model building. This is distinct from causal inference—the tasks that classical statistics and econometrics are largely focused on—which attempts to discover the causal relationships between variables and outcomes, rather than simply predicting outcomes.

Methods for the two tasks are different, though they build from similar principles. Models used for causal inference commonly aim for simplicity and interpretability. More complex models can be difficult to interpret but are often useful for predicting outcomes that are unseen at the time of model building. In fact, one of the central challenges in building effective predictive models is selecting the optimal degree of model complexity to predict well without overfitting—distinguishing signal from noise.

Models for causal inference are generally evaluated based on theory and assumptions about the underlying phenomena that are driven by subject-matter knowledge. While subject-matter knowledge can certainly be used in predictive modeling, the quality of a model is, rather, evaluated by its ability to accurately predict outcomes that were unseen at the time the model was built. In other words, a good machine-learning model can predict well out of sample, for each individual unit in the sample. By contrast, a good statistical model for causal inference can predict what would happen to the average of an outcome if a specific variable is perturbed, holding all other factors equal. While some causal models can effectively predict individual outcomes, many predictive models cannot be interpreted causally, because their estimates accept some degree of bias in order to reduce variability, thereby improving accuracy. This is known as the "bias-variance tradeoff," and is a fundamental feature of many statistical models that are used for predictive tasks.

Neural networks, which are used for the predictive yield models here, represent the current state of the art in machine learning and artificial intelligence. Neural networks work by representing data in progressively more abstract representations and relating those abstractions to an outcome. These abstractions are discovered automatically in the input data, without being prespecified by the modeler. For example, temperature and precipitation measurements over time can be abstracted as "a hot day," and several hot and dry days can be further abstracted as "drought," which can in turn be correlated with crop yields.

Friedman et al. (2010) provide an overview of machine learning, and Goodfellow et al. (2016) provide an overview of neural networks. We provide more details on our methodology in appendix B.

The machine-learning algorithm used to predict yield response to weather is a semiparametric variant of a feed-forward neural network (Crane-Droesch, 2018). We use machine learning in general and neural networks in particular because they offer better predictive performance than classical econometric and statistical methods. The semiparametric neural network variant that we use nests standard econometric models of yield response to weather, following approaches used in

Schlenker and Roberts (2009). Thus, we are able to incorporate insights from econometric methods while leveraging larger datasets and recent advances in machine learning and artificial intelligence.

Our statistical models were fit to historical yield and weather data from 1981 through 2013. Annual county-level yield data by crop were taken from the USDA, National Agricultural Statistics Service's Quick Stats database (NASS, 2017). Irrigated and dryland yields were modeled separately. Where irrigated and dryland yields were not explicitly reported, we used data from the USDA Census of Agriculture to determine if a region's crops were primarily irrigated or primarily dryland. Yield data were then re-allocated from county-level resolution to the coarser REAP model regions, using an acreage-weighted and spatially weighted average of county-level yields.

Future climate scenarios used in our analysis were taken from five climate models—the Hadley Centre Global Environment Model (HadGEM), Community Climate System Model (CCSM), Canadian Earth System Model (CanESM), Model for Interdisciplinary Research on Climate (MIROC), and Goddard Institute for Space Studies (GISS) model. These models were all run under the auspices of the Coupled Model Intercomparison Project (Taylor et al., 2012) and differ in their parameterizations of atmospheric physics. Each model simulates two warming scenarios. Termed "representative concentration pathways" (RCPs) (Van Vuuren et al., 2011), RCP4.5 represents lower emissions and less warming, while RCP8.5 represents higher warming, driven by a continuation of historical emissions trends.

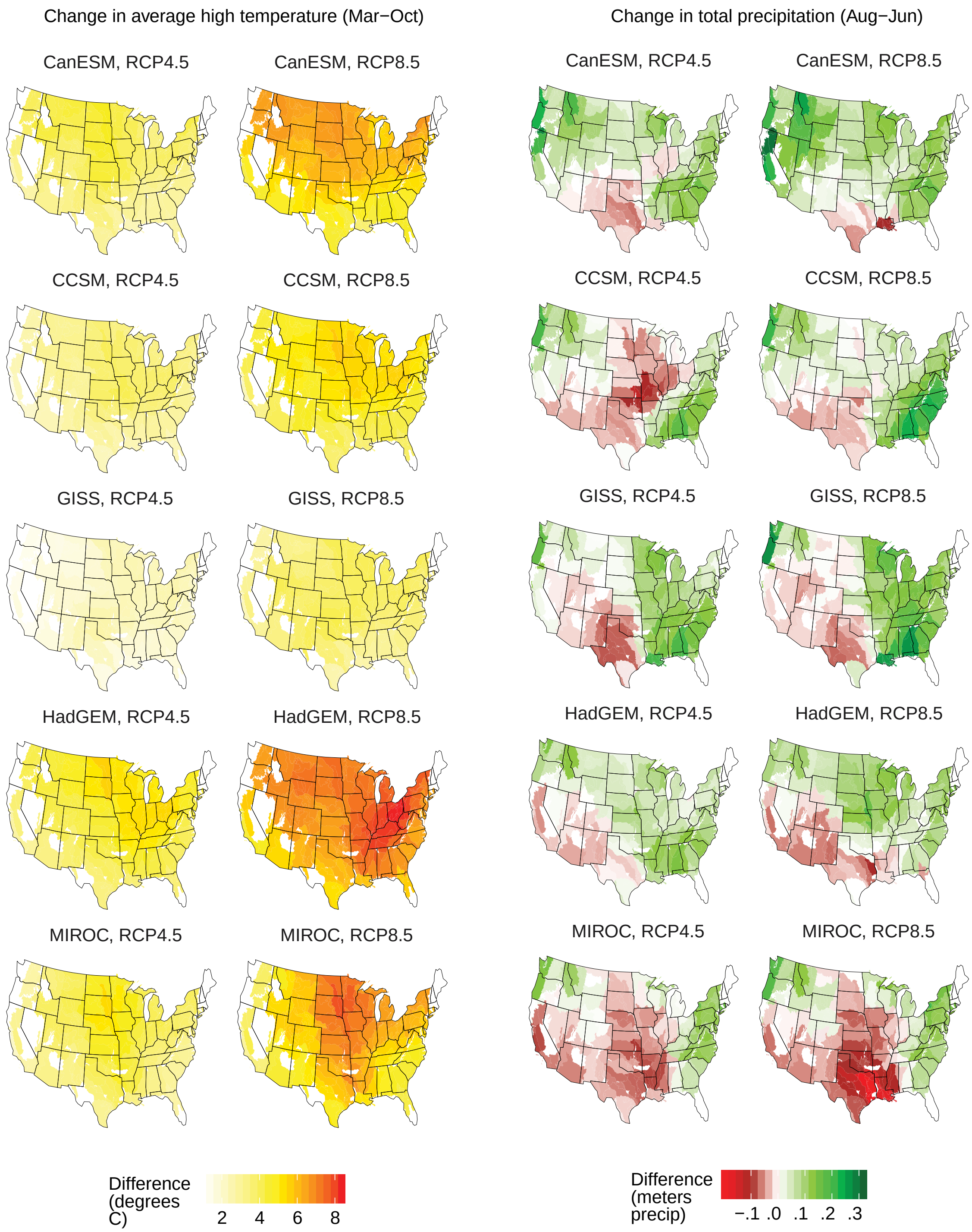
Output from these models is aggregated in the Localized Constructed Analogs (LOCA) dataset[5], which contains downscaled and bias-corrected measurements of minimum and maximum temperature and daily precipitation. We use a version of the dataset, which the U.S. Environmental Protection Agency augmented with minimum and maximum relative humidity, wind speed, and solar radiation, and aggregated to the spatial resolution of the REAP model. Historical weather data for 1981-2013 were also provided by EPA and were processed analogously. For consistency with the REAP model, both historical weather data and climate projection data were aggregated to the spatial resolution of the REAP model.

The neural network provides predictions of average yield for each region and for each climate projection. In addition, it provides estimates of interannual variability (through yearly variation in its predictions) and prediction uncertainty (through root mean squared error in predicting historical yields). In modeling corn and soybean yields, we use weather data from March to October. Because winter wheat has a cropping season that spans years, we define the weather year for wheat as August through June. Key variables from the dataset are summarized in figure A.2. While all models agree that the continental United States warms under RCP4.5 and RCP8.5, they disagree on the degree and spatial pattern of warming.

[5] The LOCA data are housed at http://gdo-dcp.ucllnl.org/downscaled_cmip_projections/dcpInterface.html\#Projections:\%20Complete\%20Archivesunder.

Figure A.2

Differences in mean annual maximum temperature (left) and total annual precipitation (right) between the 1981-2013 baseline and the 2060-99 climate model simulations, for RCP4.5 and RCP8.5, by climate model



Note: The left plot shows differences in average maximum temperature over the March-October period, which was used for modeling corn and soybeans. The right plot shows differences in total precipitation for August-June, which was used for modeling winter wheat. These variables were chosen because they were among the most important in predicting yields (see subsection "Variable Importance" in appendix B.3).

Source: USDA, Economic Research Service analysis of LOCA model run data.

To estimate how yields within a region vary across crop rotations and tillage types, we use the Environmental Policy and Integrated Climate (EPIC) model (Williams, 1989). EPIC is a crop systems model, developed and maintained by researchers at Texas A&M University and elsewhere. EPIC operates on a daily time step and explicitly models crop rotations and crop production under different tillage and irrigation regimes. The rotations included for each REAP production region were identified through analysis of the 2007 USDA Natural Resources Conservation Service's National Resources Inventory data (Marshall et al., 2015).

EPIC is used to model yields for the baseline period 1981-2013 and the years 2060-99 using the same input data that the neural network uses. While the neural network provides more accurate predictions of historical yield, EPIC captures rotation-specific detail, based on a dynamic representation of soils, that the neural networks do not. We use this rotation-specific output to disaggregate the results of the neural networks across rotations and production methods within each REAP region. Specifically, we calculate a separate calibration factor for each crop rotation, tillage, irrigation regime, REAP region, scenario, model, and year as the difference between the acreage-weighted average of EPIC yields within a region and the neural net predicted yield for that region. That adjustment factor is then subtracted from each EPIC crop yield estimate in the region.[6] Calibration thus creates a distribution-preserving shift of EPIC yields, including crop failures if predicted by neural net results. This process incorporates the predictive skill of the neural net approach while preserving REAP's ability to capture variation across production methods and rotations in its land-allocation decisions under climate change.

Acreage and Price Response

We model farmer adaptation to changing climate using REAP, which is a partial equilibrium model of the U.S. agricultural sector. REAP estimates producers' response to shocks, and market response to those producer decisions (see box "The REAP Model").

The REAP Model

The Regional Environment and Agriculture Programming (REAP) model is a static, partial equilibrium optimization model of the agricultural sector that quantifies agricultural production and its associated environmental outcomes for 273 regions in the United States. REAP employs detailed input (derived from the USDA Agricultural Resource Management Survey (ARMS), the National Resources Inventory (NRI), and the Environmental Policy and Integrated Climate (EPIC) model) at the regional level on crop rotations, crop yields, input requirements, costs and returns, and environmental parameters to estimate longrun equilibrium outcomes. Regional production levels are determined for 10 crops, including the 3 crops analyzed here, and 13 livestock categories, and national production levels are determined for 20 processed products. For each REAP region, land use, crop mix, multiyear crop rotations, and tillage practices are all endogenously determined by REAP's constrained optimization process, which implicitly assumes that farmers are risk-neutral actors. Cropland allocations, aggregate input use, and national prices are determined endogenously.

continued —

[6] In REAP regions where there was insufficient data to predict yields using the neural nets, a Farm Production Region average of irrigated or dryland neural net results was used to create the calibration factor.

The REAP Model — continued

The model has been widely applied to address agri-environmental issues such as soil conservation and environmental policy design, environmental credit trading, climate change mitigation policy, and regional effects of trade agreements.

REAP is implemented as a nonlinear mathematical program using the General Algebraic Modeling System (GAMS) programming environment. The goal of the model is to find a welfare-maximizing set of crop, livestock, and processed product production levels subject to land constraints and processing/production balance requirements. Production activities for crops in a region (defined by crop rotation, tillage, and irrigation) are distributed according to a constant elasticity of transformation (CET) relationship; the parameters defining the CET relationship are derived by calibrating them to historically observed acreage distributions.

Shocks based on policy, technical, or environmental scenarios can be introduced as additions of or changes to constraints, modifications of input data assumptions, addition of terms to the objective function, or a combination of approaches. Changes in policy, demand, or production/processing technology can therefore be imposed upon the model and the results examined to determine their effects on the following:

- Regional supply of crops and livestock,
- Commodity prices,
- Crop management behavior and use of production inputs,
- Farm income, and
- Environmental indicators, such as nutrient and pesticide runoff, soil loss, greenhouse gas emissions, soil carbon fluxes, and energy use.

For more information on REAP, see the technical documentation for the model (see Johansson et al., 2007).

REAP allocates agricultural land[7] and distributes the results of production into distinct markets (domestic consumption, export, and feed use) to maximize the economic surplus that arises from agricultural production. REAP models markets for 10 major commodity crops (corn, sorghum, oats, barley, wheat, rice, cotton, soybeans, hay, and silage), a number of livestock products (dairy, swine, poultry, and beef cattle), and other retail products derived from agricultural raw materials. When REAP solves for agricultural production patterns under changed climate, technology, or policy conditions, acreage in each region is distributed among available production enterprises (crop rotations and methods of production) based on relative profitability. To reflect unobserved production considerations that may differ by region, crop, or rotation, allocation decisions are further

[7] While REAP tracks the regional distribution of agricultural land use, it does not attempt to represent what happens on nonagricultural land.

constrained within the model by acreage distribution parameters that reflect historically observed patterns of production.

Climate change impacts in future periods are measured against a “reference” scenario. The reference scenario reflects a plausible future in which patterns of production continue to change in accord with historically observed dynamics (involving changing population, diet, demographics, and other socioeconomic factors), but without climate change. A reference scenario developed for Marshall et al. (2015) for 2080 was used in this report. Design of that future reference scenario was based on a combination of expert input, literature review, and projections based on the USDA’s 10-year baseline agricultural forecast.

We emphasize that we model the impact of climate change on the rest of the world only indirectly. A linear export demand function is estimated in REAP’s calibration process from the extrapolated price and demand, together with a point estimate of elasticity. This export demand function remains fixed across the scenarios. While export can move up and down the curve as prices change, the curve does not shift to reflect potential climate change impacts on the rest of the world. Negative climate impacts on agriculture in the rest of the world, for instance, would presumably increase the export demand at any fixed price; we do not attempt to estimate such shifts. However, we do scale price variability to increase with price levels, as detailed in appendix C. Doing so reflects the possibility that demand shocks—potentially driven by supply shocks in the rest of the world—will have greater impacts on prices when domestic supplies are more constrained. Given its complexity, however, a full treatment of the impact of climate change on global agricultural supply and demand is beyond the scope of this work. To the degree that climate change would increase global demand for corn, soybeans, and wheat, our results on the size of premiums and the cost to the Federal Government of the associated subsidies will be lower bounds on their true costs.

To assess climate change impacts, the REAP model compares optimal production scenarios based on yield predictions derived from climate model output. Each time REAP solves for an optimal production pattern under a climate scenario, it reallocates production acreage to optimize the sum of producer and consumer surplus given the changes in regional yield and crop water use, subject to land and water resource constraints.[8] Farmers’ allocation decisions between crops and production practices (such as irrigation) depend on changes in yields, irrigation costs (through changes in water use), and commodity prices, which are endogenous within REAP.[9] Irrigation expansion is constrained such that areas identified as having groundwater constraints in Marshall et al. (2015) cannot increase irrigated acreage beyond baseline levels.

Prices are determined by demand curves whose elasticities are set to give baseline price volatility approximating the component of historical price volatility that can be attributed to weather (see appendix C). Climate change impacts are then assessed by comparing them to REAP model output driven by yield predictions under the reference scenario.

For this analysis, farmers make planting decisions based on an expected yield for each crop, which is represented by the average of the yield predictions from the neural network over the 40 years in

[8] Those regions identified in Marshall et al. (2015) as likely to experience reductions in groundwater withdrawal in 2080 were modeled as being unable to increase their irrigated acreage.

[9] We model crop insurance participation rates as fixed, in the sense that the proportion of a county insured will remain the same as acreage changes. Acreage choices are not affected by this factor, and modeling the interaction of crop insurance participation rates, coverage levels, prices, and acreage decisions is left to future research.

each scenario. Thus, there is a single pattern of optimal acreage allocation for 2080 for each climate scenario. Once farmers plant, however, the price that emerges from that planting decision depends on the weather that is realized for that year, through the effect of weather on yields. For the reference scenario, REAP estimates a baseline pattern of production, using the expected yields projected for the historical weather conditions, that is calibrated to the 2080 reference production and market conditions described above. The distribution of production and prices under the reference scenario is then calculated by assuming that this pattern of production is in place and imposing upon it each of the annual yield patterns derived from the set of historical weather outcomes.

Under the climate scenarios, it is assumed that any of the simulated weather patterns over 2061-2099 are plausible potential weather outcomes for 2080. Therefore, to generate the potential price distributions associated with each climate scenario for 2080, we fix production acreage at the expectation-optimized level and allow the economic model to re-optimize for each of the 40 potential weather outcomes, as represented by the 40 patterns of regional annual yields calculated from annual weather in each climate projection. We thereby estimate potential distributions of commodity prices, production, and commodity allocation over domestic and international markets for 2080 under each of the climate change projections. Climate change impacts for 2080 are assessed by comparing these outcomes to the REAP model output for the 2080 reference scenario.

Policy Models

Spatial downscaling: Projections of yield from the neural networks are at the spatial resolution of the REAP region, but crop insurance program parameters vary at the county level. We therefore downscale our yield and acreage projections from the REAP region to the county. Because counties are not perfectly nested within REAP regions, we assign to each county a weighted average of the yields in each REAP region with area inside the county, with the weights being proportional to the area of the county within the REAP region.

We compute county-level yield risk as the variance of our yield predictions for the 40 years in each scenario (33 years in the baseline). Variability in county-level yields will generally be an underestimate of farm-level risk, which is what is insured by the FCIP. This is because the county-level distribution is an average over many farmers, and averages are less variable than the data from which they are computed. Failure to account for this dynamic would lead to underestimates of the cost of the programs considered. To inflate this risk to reflect the variability at the farm level, we calculate yield variability expansion factors following the approach of Coble and Dismukes (2008), where the farm-level risk for each county is inferred from current FCIP premiums.

To impute yield variability expansion factors for counties where crop insurance premiums are not available, we fit a random forest[10] (Breiman, 2001) to relate the set of existing county yield variability expansion factors to a number of predictors: latitude, longitude, county area, county perimeter length (tortuosity), average and standard deviation of yield, average acreage in a crop, and proportion of the crop that is irrigated. The random forests explain approximately 84 percent, 81 percent, and 82 percent of the variance in the original inflation factors for corn, soybeans, and wheat, respectively, with geographic coordinates and the mean and standard deviation of yields providing the bulk of the predictive skill for each crop's model.

[10] Random forests are machine-learning algorithms that fit an ensemble of decision trees to a dataset, and average their predictions to form an output. See Friedman et al. (2010) for an overview.

The distribution of yield for a scenario is formed by taking 250 draws from a normal distribution with a mean at the prediction of yield and a standard deviation proportional to the variance of the prediction, inflated by a county-specific factor that is the output of the random forest. For scenarios with 40 years of simulated weather, this provides a mixture distribution comprised of 10,000 simulates. These are multiplied by prices to generate simulated revenue.

Characterizing historical rates of crop insurance coverage and participation: Data from RMA are used to characterize the county-level share of planted acres insured under buy-up policies, as well as the distribution of current RP coverage levels. For each county, we take an average of acres enrolled since 2010 for the three crops that we analyze and divide that by total average planted acreage to compute average enrollment rate. The distribution of coverage levels—from 50 percent through 85 percent coverage—is computed analogously, taking an average over acres in each coverage level divided by planted acreages since 2010. In other words, if the average elected coverage level in a county was 60 percent, 70 percent, and 80 percent over 3 years, we assigned it an average coverage level of 70 percent.

Premium rate calculations and total subsidy estimates: Finally, we compute actuarially fair premiums for RP policies with coverage levels ranging from 50 percent to 85 percent. We model RP because it represents the most important component of the FCIP in terms of Government expenditure and participation, covering the vast majority of corn and soybean policies sold, acres insured, liabilities, and premium subsidies (USDA, 2018). Using the 10,000 simulated draws of yields and prices, we define expected revenue as the mean of all revenue draws. For each draw of yields and prices, we calculate revenue loss as the difference between expected revenue and realized revenue. Then for each coverage level, we calculate the probability of a loss occurring that is at least as severe as the coverage level and the average loss amount. The actuarially fair premium rate per acre for each coverage level is defined as the average loss amount multiplied by the probability of the loss occurring.

Premiums for RP policies are subsidized at different rates for different coverage levels, as shown in table A.1. For each coverage level, we calculate the total subsidy as the subsidy rate multiplied by the actuarially fair premium rate and multiplied by the proportion of acres currently insured at that coverage level. Finally, we sum the total subsidy by coverage level across all coverage levels to create the total subsidy for each county and crop pair.

Table A.1

Subsidies for different levels of RP loss coverage (percent)

Coverage level	50	55	60	65	70	75	80	85
Subsidy rate	67	64	64	59	59	55	48	38

Source: USDA, Economic Research Service using USDA, Risk Management Agency administrative records.

Appendix B: Yield Model

Methods for modeling response of crop yields to weather using semiparametric neural networks are fully described in Crane-Droesch (2018). Briefly, we fit models of the form

$$y_{it}=\alpha_i+\sum_r GDD_{rit}\beta_r+\mathbf{X}_{it}\boldsymbol{\beta}+\mathcal{F}(\mathbf{Z}_{it})+\varepsilon_{it} \quad \text{(B.1)}$$

where i and t represent counties and years, *GDD (growing degree-day)* represents the proportion of the year spent within a temperature interval, r indexes the range of each GDD bin, and $\mathbf{X}$ includes a quadratic in precipitation as well as quadratic time trends by State to account for technological change. The function F is a feed-forward neural network, which represents daily weather data $\mathbf{Z}$ nonparametrically. The parametric component of B.1 is similar to that used by Schlenker and Roberts (2009). A simple feed-forward neural network takes the following form:

$$\mathcal{F}(\mathbf{Z}_{\mathrm{it}})=a(a(a(...a(\mathbf{Z}_{\mathrm{it}}\boldsymbol{\Gamma}_{\mathbf{L}})\Gamma_{\mathrm{L-1}})...)\Gamma_3)\Gamma_2)\Gamma_1$$

Where $\mathbf{Z}_{it}$ are terms that are represented nonparametrically, Γ are parameter matrices with rows equal to the number of inputs to a layer, and columns equal to the number of outputs to a layer. The function $a()$ is applied elementwise to a matrix, which maps the real line to some subset of it. Training the neural network involves choosing the parameter matrices Γ such that $F(\mathbf{Z}_{\mathrm{it}})$predicts the outcome, in linear combination with the parametric component of the model.

The model is fit to minimize an L2-penalized squared-error loss, and training is done by gradient descent, 48 times to datasets comprised of bootstrap samples of unique years in our dataset. The years not selected into each bootstrap sample are used as a test set for each model. We do so because adjacent regions have highly correlated yield and weather, which could lead to overfitting if bootstrap samples of region-years were taken. See Crane-Droesch (2018) for more detail.

This class of model was developed for this project after initial experiments with other machine-learning algorithms showed worse predictive performance than ordinary least squarers (OLS) regressions. While many machine-learning algorithms are nonparametric, OLS' parametric structure could capture time trends, which implicitly represent genetic and other technological change in agriculture—which in turn have been important drivers of yield growth—more efficiently than other models. By the same token, models such as those used by Schlenker and Roberts (2009) rely solely on heat, ignoring other dimensions of climate, both in terms of temporal scale and non-heat phenomena. Our approach assumes that an OLS regression is a useful, yet imperfect, approximation and augments it with a neural network.

Data

An overview of the variables used in the yield model is presented in table B.1.

Table B.1

Variables used in yield model

Phenomenon	Number of terms	Type of variable	Description
Precipitation	245 (365)	Nonparametric	Daily precipitation
Air temperature	490 (730)	Nonparametric	Daily minimum and maximum air temperature
Relative humidity	490 (730)	Nonparametric	Daily minimum and maximum relative humidity
Wind speed	245 (365)	Nonparametric	Daily average wind speed, taken as the Euclidean norm of northward and eastward wind as reported by METDATA and LOCA
Shortwave radiation	245 (365)	Nonparametric	Daily total solar radiation
Growing degree-days	42	Both	Cumulative time at 1C temperature bands, from 0-40. Additional bins capture the proportion of time spent below 0C and above 40C. These terms enter both the parametric (linear) and nonparametric (neural network) portions of the yield model.
Total precipitation	2	Parametric	Total precipitation over the growing season, and its square
Latitude/longitude	2	Nonparametric	County centroids
Time	1 (2)	Both	Year enters as a quadratic time trend in the parametric (linear) portion of the model, and as a nonparametric term at the base of the neural network
Rotation	93	Nonparametric	Proportions of a region historically under one of 93 distinct crop rotations
Tillage	3	Nonparametric	Proportions of a region historically under conventional, reduced, and no-till tillage.
Friability	1	Nonparametric	Proportion of a region classed as “highly erodible” (Marshall et al., 2015)
Proportion irrigated	1	Nonparametric	Proportion of the region’s farm land under irrigated production.
REAP region	1 (varies)	Parametric	Indicator variable for each of the REAP production regions (estimated as a fixed effect via the “within transformation” at the top layer of the network)

Note: Number of terms reflects the number of variables within a class of variables. This can be large when, for example, there are 245 or 365 observations of daily weather for corn/soybeans (March-October) and winter wheat (August-June). Type of variable reflects whether the variable is part of the linear regression part of the model (parametric) or the neural network part of the model (nonparametric) or both. LOCA = Localized Constructed Analogs. METDATA = Meteorological Data.

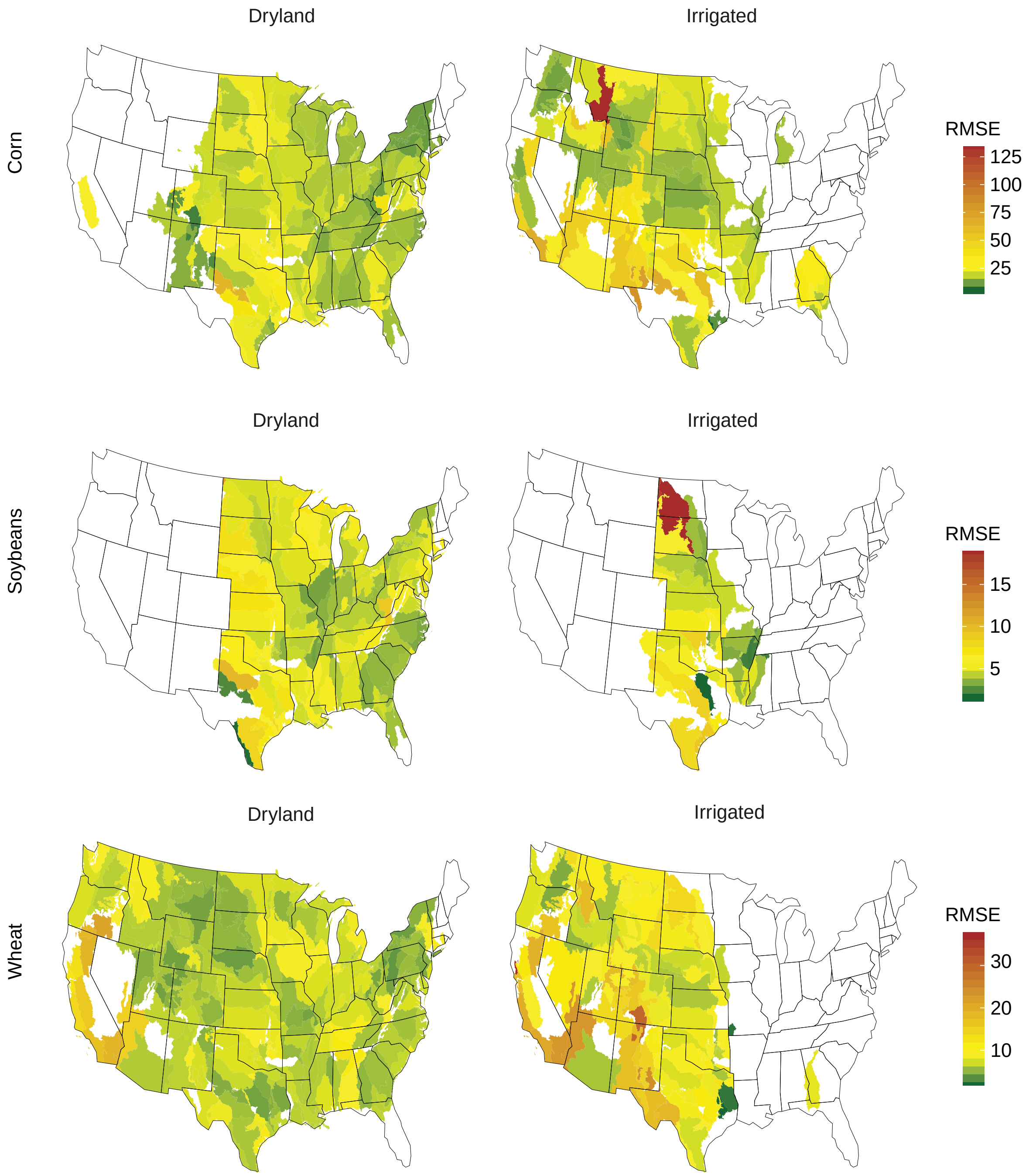
Source: USDA, Economic Research Servive.

Model Fit

Machine-learning methods are assessed by their ability to predict outcomes that were not used in the training of the model. Our use of bootstrap aggregation provides a natural way of doing this. Forty-eight models were fit to bootstrapped samples of the data, with each bootstrap sample being generated by sampling unique years, with replacement. Because this process will oversample some years and omit others, we are able to assess goodness of fit by averaging the yield predictions for each model's set of left-out years. In other words, if model replicates 2, 5, and 38 were not trained on 2012, then our estimate of goodness of fit for 2012 would be based on the average predictions of models 2, 5, and 38. This gives an estimate of generalization error—the error that we expect when the model is applied to entirely new data—rather than in-sample fit. Maps of predictive skill—the average error in out-of-sample-prediction—are given in figure B.1.

Figure B.1

Neural network predictive skill maps

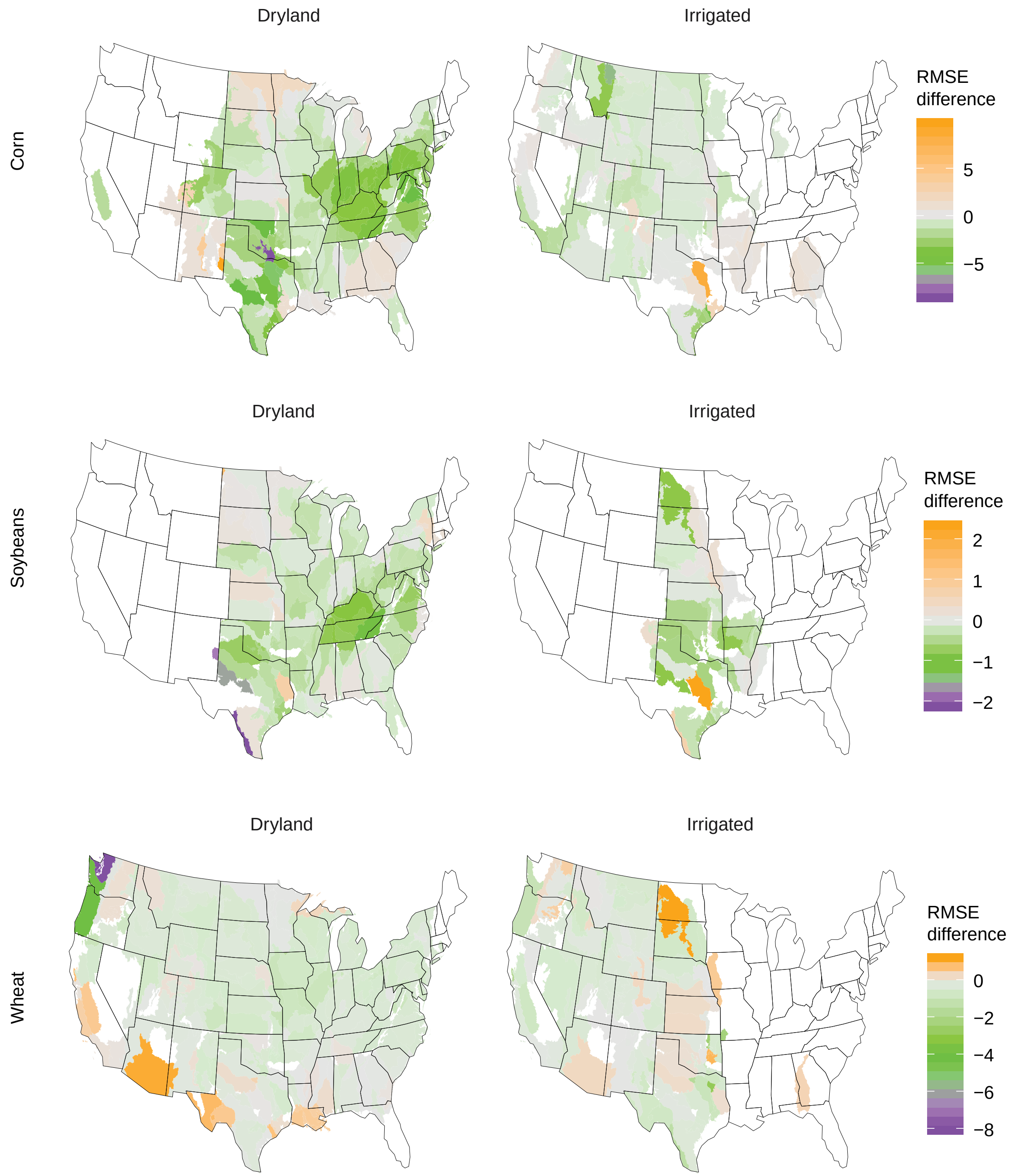


Note: Colors show expected out-of-sample prediction errors, in units of bushels/acre. RMSE = root mean squared error (interpretable simply as average error).

Source: USDA, Economic Research Service.

Figure B.2

Improvement in prediction between neural network and econometric model (difference in RMSE measured in bushels/acre)



Note: RMSE = root mean squared error. Green and purple areas are predicted better by the semiparametric neural network, and orange areas are predicted better by an ordinary least squares regression.

Source: USDA, Economic Research Service.

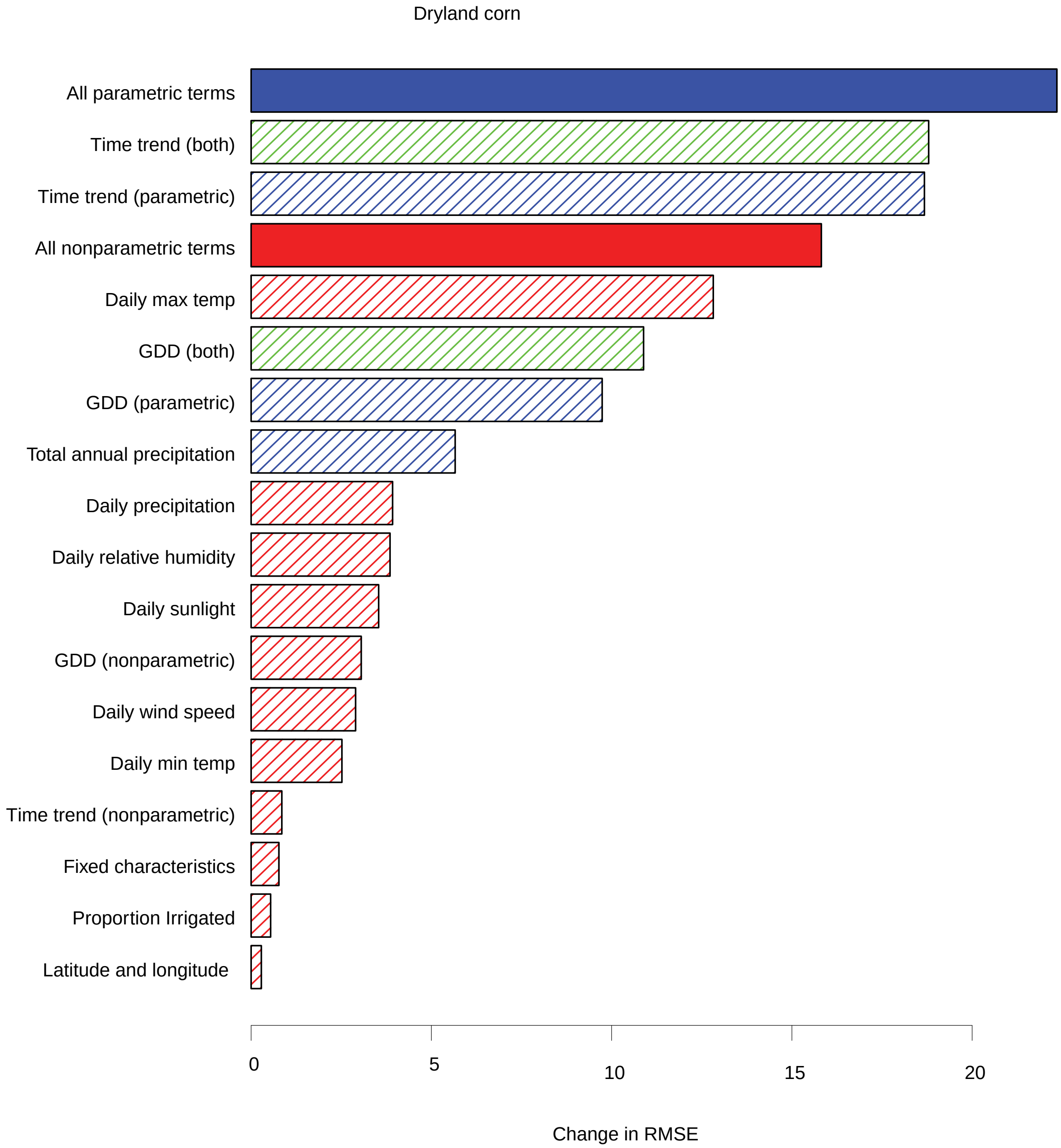
While some regions were better predicted than others, average prediction error for corn was 18.7 and 32.6 bushels/acre, respectively, for dryland and irrigated production. The corresponding prediction errors were 5.1 and 6.2 bushels/acre for soybeans, and 8.4 and 11.8 bushels/acre for winter wheat. For scale, average corn, soybeans, and winter wheat yields are 176.6, 51.6, and 48.8 bushels/acre, respectively. There is little spatial pattern in predictive skill. We compared the neural net to a simple multiple linear regression model, including all of the parametric terms present in the top layer of our neural net. A map of the spatial distribution of that difference is given in figure B.2. The neural net either outperforms or approximately equals the econometric model almost everywhere, though to varying degrees.

Variable Importance

Because neural networks are nonlinear, they are more difficult to interpret than some classical methods. We use permutation tests to determine the degree to which predictive skill decays when a set of variables is randomly permuted, thereby destroying any correlation between it and other variables in the model, including the outcome. This is akin to removing variables from the model, though less computationally expensive. The results of these tests are show in figures B.3-B.8.

Figure B.3

Variable importance for dryland corn, via permutation test

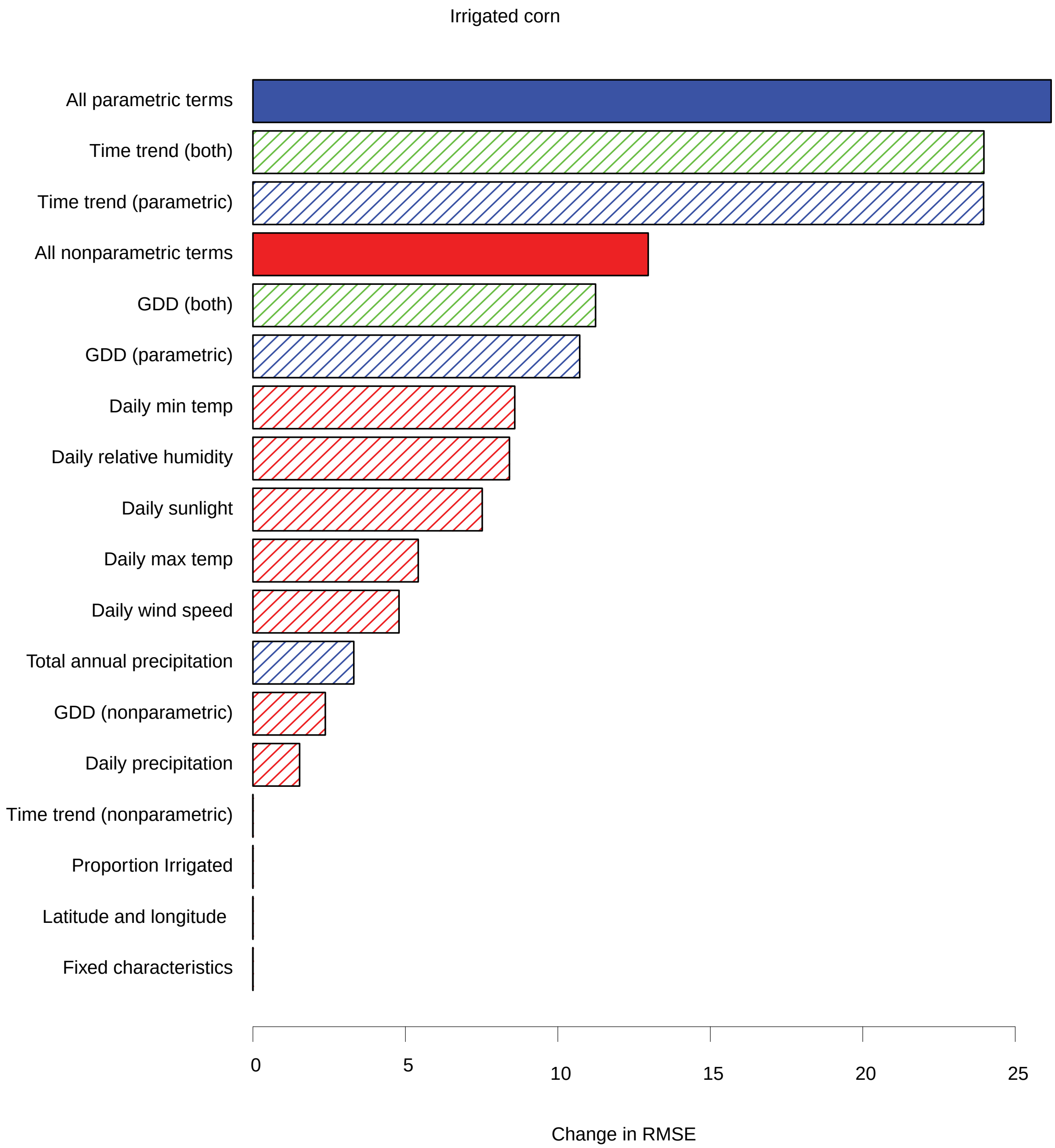


Note: GDD = growing degree days. RMSE = root mean squared error. Each bar reflects the increase in average prediction error (in units of bushels/acre) that would occur if that group of variables were to be removed from the model.

Source: USDA, Economic Research Service.

Figure B.4

Variable importance for irrigated corn, via permutation test

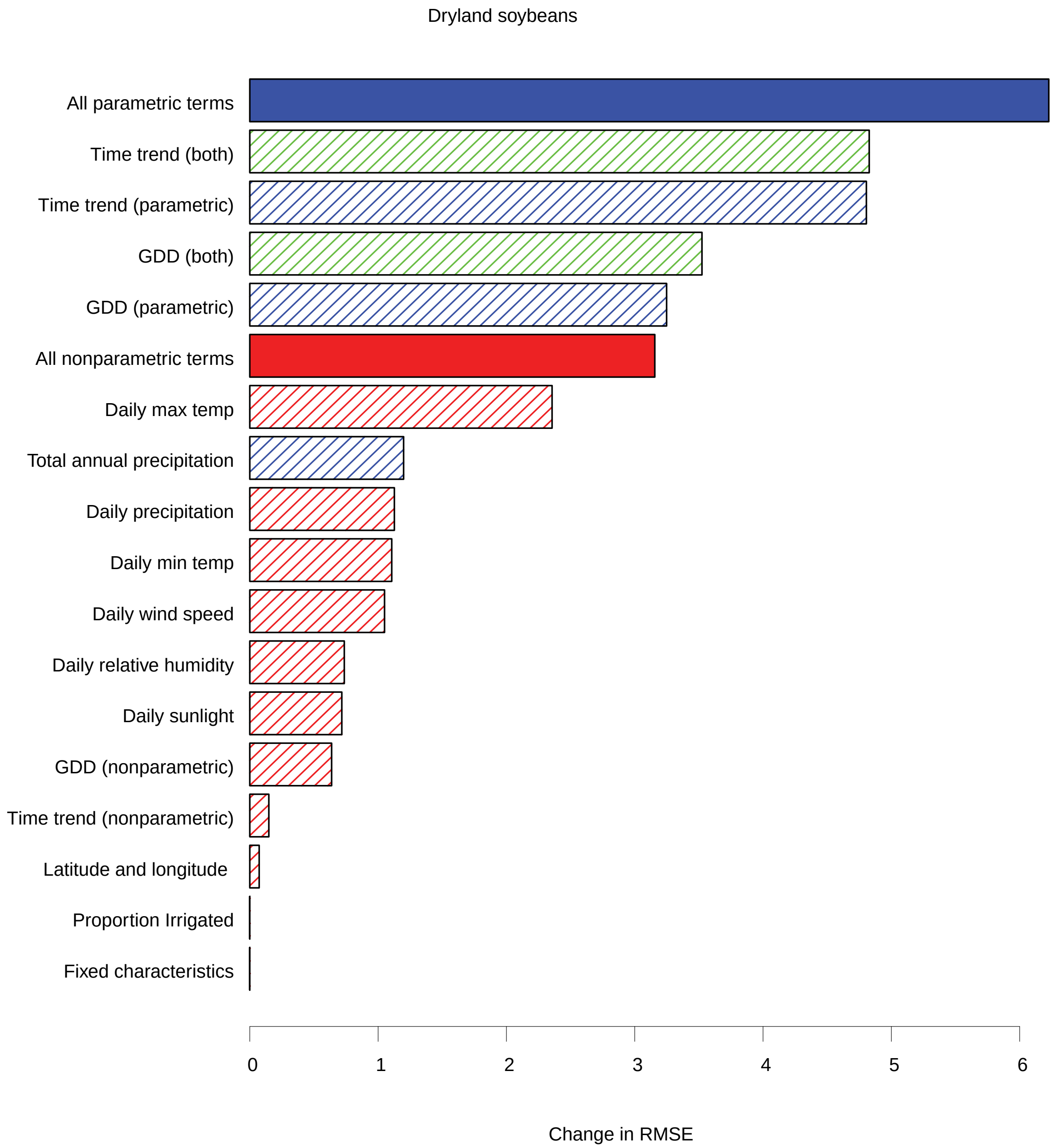


Note: GDD = growing degree days. RMSE = root mean squared error. Each bar reflects the increase in average prediction error (in units of bushels/acre) that would occur if that group of variables were to be removed from the model.

Source: USDA, Economic Research Service.

Figure B.5

Variable importance for dryland soybeans, via permutation test

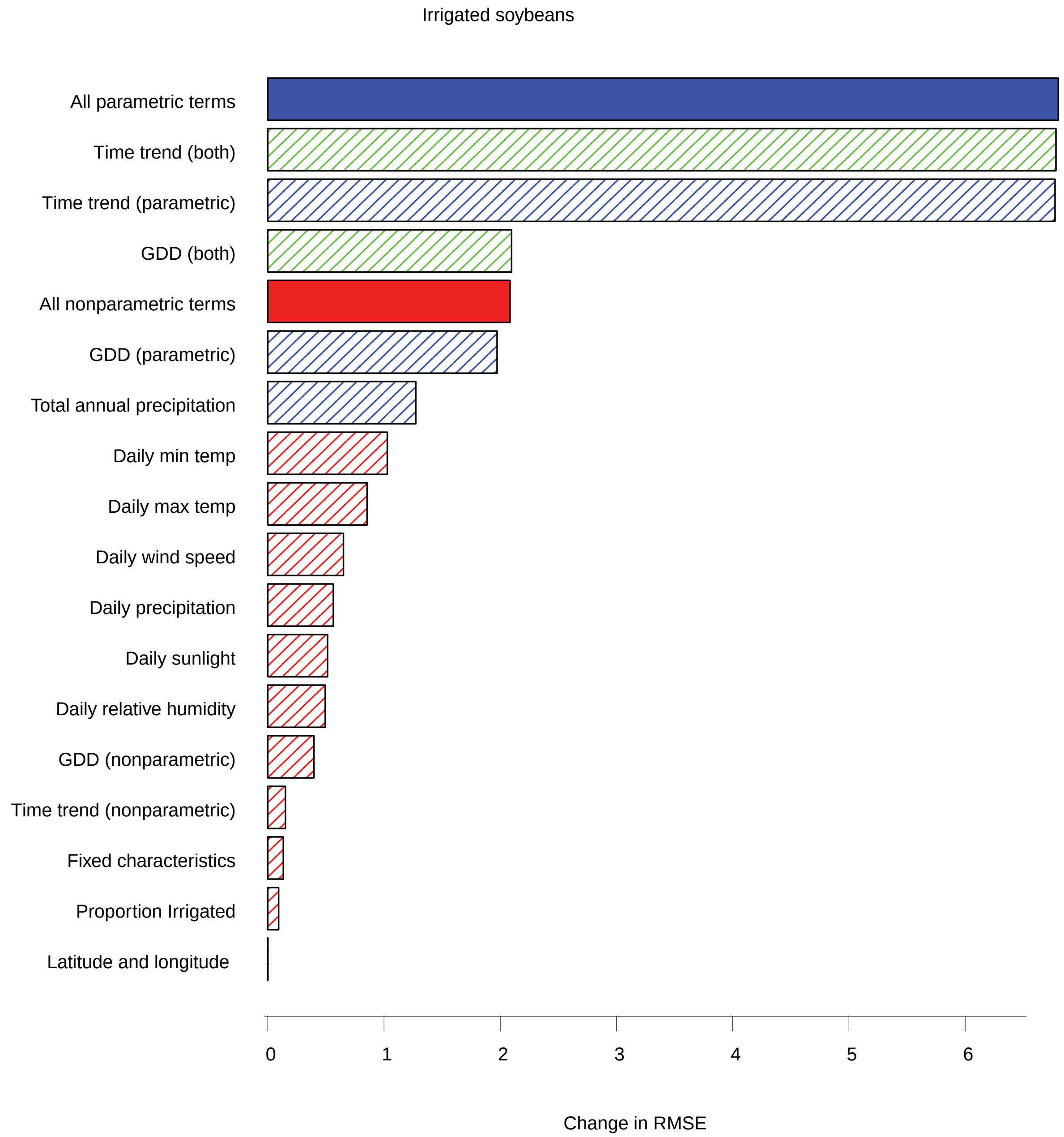


Note: GDD = growing degree days. RMSE = root mean squared error. Each bar reflects the increase in average prediction error (in units of bushels/acre) that would occur if that group of variables were to be removed from the model.

Source: USDA, Economic Research Service.

Figure B.6

Variable importance for irrigated soybeans, via permutation test

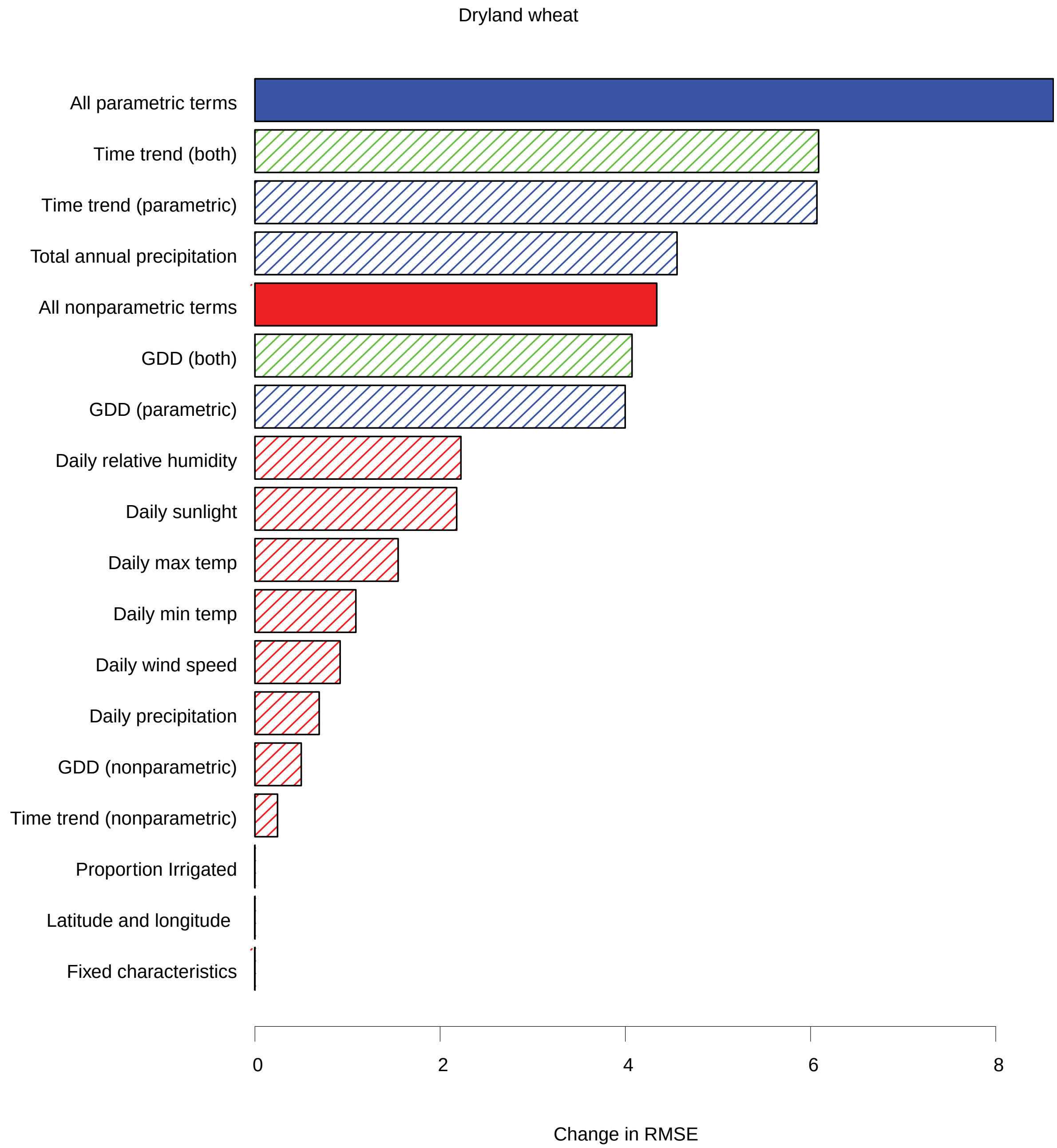


Note: GDD = growing degree days. RMSE = root mean squared error. Each bar reflects the increase in average prediction error (in units of bushels/acre) that would occur if that group of variables were to be removed from the model.

Source: USDA, Economic Research Service.

Figure B.7

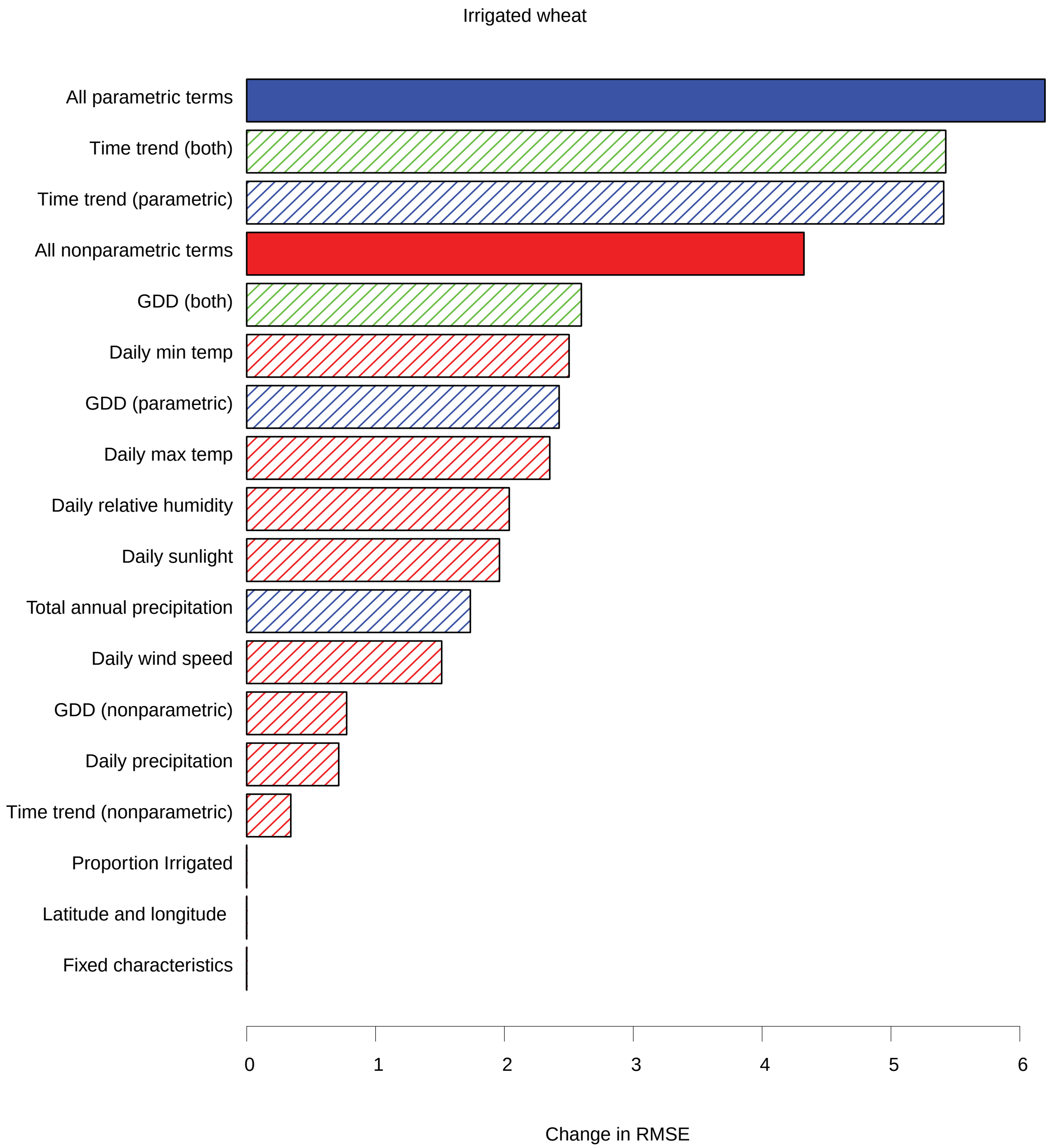
Variable importance for dryland winter wheat, via permutation test



Note: GDD = growing degree days. RMSE = root mean squared error. Each bar reflects the increase in average prediction error (in units of bushels/acre) that would occur if that group of variables were to be removed from the model.

Source: USDA, Economic Research Service.

Figure B.8
Variable importance for irrigated winter wheat, via permutation test



Note: GDD = growing degree days. RMSE = root mean squared error. Each bar reflects the increase in average prediction error (in units of bushels/acre) that would occur if that group of variables were to be removed from the model.
Source: USDA, Economic Research Service.

Across all crops and production systems, variables representing time trends are the most predictive, with the parametric specification of growing degree days the most important for most crops except dryland winter wheat.

Caveats and Assumptions

While the statistical models used here provide a more accurate mapping from weather to yields—as measured by accuracy in predicting historical yields—than alternatives such as deterministic crop models, several shortcomings remain when they are used to project climate change impacts, as we seek to do here.

First, we are able to model the effect of carbon fertilization on crop yields only indirectly. Increasing atmospheric concentrations of carbon dioxide (CO_2) will improve plant growth and drought resistance (all else equal) in a way that may offset some of the negative consequences of climate change, and, this effect has been observed in the recent historical record (Zhu et al., 2016). This effect is difficult to model statistically because there is almost no spatial variation in CO_2 concentrations, and temporal variation is confounded with technological and genetic changes in agriculture (Lobell and Asseng, 2017). Better representation of this phenomenon in statistical yield models is an active area of research (Urban et al., 2015).

Our approach is therefore indirect—carbon fertilization is accounted for in the parametric time trend included in the neural network. While we cannot distinguish the effects of CO_2 fertilization from those of technological change, they will not directly confound our estimates of the relationship between yields and weather in the baseline. However, we are unable to explicitly represent the ways in which increases in CO_2 concentrations may improve water-use efficiency or photosynthetic efficiency.

Another major caveat is that we do not model variability stemming from non-weather factors such as pests or disease. Our analysis implicitly assumes that such "idiosyncratic" risk factors are constant, evenly distributed, and will be unaffected by climate change.[11]

Finally, our framework is not able to model the ways in which yields may themselves be sensitive to the availability of crop insurance. Annan and Schlenker (2015) have found that yields of insured corn and soybeans are more sensitive to extreme heat—by 67 percent and 43 percent, respectively—than uninsured yields, implying that crop insurance changes the behavior of farmers. We are unable to capture this either in our models of expected yields, our models of acreage allocation in response to climate change, or in our simulations of Government expenditure on insurance subsidies.

[11] While this is likely to be untrue to the degree that these factors are correlated with climate variables, we opted not to fit models of conditional heteroskedasticity for two reasons: (1) there was no significant correlation between prediction error (the squared residual) and yield, and (2) variance in the residuals corresponding to specific regions could arise either from true idiosyncratic variability or an inability of our model to capture dynamics specific to that region. Therefore, poorly modeled regions would artificially be considered to be inherently more variable, with consequences for estimated premiums.

Appendix C: Calibration of Prices

In the analysis of weather-driven price risk, we calibrate REAP elasticity parameters so that the price risk arising from domestic yield variability across weather years 1981-2013 approximates the observed price risk over the same historical period.

To estimate within-season price risk—the difference between the expected price prior to planting and the final —we build a method based on the difference between the final marketing-year price (a volume-weighted average of the monthly prices) and the March price for corn and soybeans. For winter wheat, we use the difference between the marketing-year price and the prior September price. As shown in table C.1, the standard deviation of these within-season price differences is a little over half the magnitude of the total price variation in the marketing-year price. This is appropriate since there is considerable year-to-year price variation that is not covered by standard crop insurance.

To decompose the within-season price variation into the portion due to yield risk and the portion due to other market movements (such as international shocks), we regress the within-season price change on the within-season yield change. To calculate the within-season yield change, we estimate a predicted yield based on a linear time trend and take the difference between the final yield and the reported yield. Since the final yield is for harvested acres, this may understate the total yield change since it does not capture changes in unharvested acres. To calculate the variation in within-season price due specifically to yield change (our definition of price risk), we take the predicted price changes from the above model. The standard deviation in the price change explained by yield variability, shown below in the fourth row of data, is about 41 percent of the total standard deviation for corn, 35 percent of the total standard deviation for soybeans, and 32 percent of the total standard deviation for winter wheat. We calibrate the demand elasticities in the REAP model so that the yield shocks resulting from the calibrated EPIC yields for weather years 1981-2013 approximate that amount of price variation. We then add additional price variation into the crop insurance premium calculations to reintroduce variation due to non-yield factors and replicate the standard deviation in the total price changes, as shown in row three.

Table C.1

Historical price statistics related to the calibration of prices used in the analysis

Summary statistics, 1981-2013	Corn	Soybeans	Winter wheat
Mean price (market year)	$ 2.888	$ 7.079	$ 3.871
Standard deviation price	$ 1.259	$ 2.613	$ 1.436
Within-season regression analysis			
Standard deviation price change	$ 0.760	$ 1.410	$ 0.855
Standard deviation predicted price change	$ 0.309	$ 0.494	$ 0.273
Maximum predicted price change	$ 0.815	$ 1.152	$ 0. 787
Minimum predicted price change	-$ 0.515	-$ 1.137	-$ 0.386

Source: USDA, Economic Research Service.