Climate Change Impacts on US Agriculture and Forestry: Benefits of Global Climate Stabilization
Supplementary Material

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Additional Detail on Climate Projections

The base framework used to project future climate, the NCAR Community Atmospheric Model linked with the MIT Integrated Global System Model (IGSM-CAM), is presented in Monier et al. (2013). Monier et al. (2014) also provides a summary of the simulations and details on the regional projections of climate change used in this study. To evaluate the influence of natural variability, the two emissions scenarios (Reference and Policy) were simulated in IGSM-CAM using five different ensemble members that differ in their stochastic wind stress forcing of the IGSM ocean component and in the initial conditions of the CAM model, for a total of 10 different climate simulations. The use of these initial conditions for each scenario enables the evaluation of the effect of natural variability in the climate system for a plausible range of outcomes. Throughout the main paper, the FASOM estimates presented for IGSM-CAM represent the average of the results for each of the five initializations per scenario.

The IGSM-CAM, which projects a relatively wetter future for the Eastern and Central regions of the contiguous United States, only represents one general circulation model (GCM). To develop a balanced set of regional patterns of climatic change, the IGSM pattern scaling methodology was applied to a second GCM to help bound the potential climate change impacts (see Monier et al. 2014, for methodological details). This approach preserves all of the CIRA socioeconomic and emission drivers, but replaces the CAM climate projections with those from a comparatively drier GCM: the Model for Interdisciplinary Research on Climate (MIROC3.2-medres).

Both sets of climate simulations project changes in a wide variety of climatic variables needed for simulating the impacts of climate change on crop yields and forest productivity, including changes in daily average/minimum/maximum temperature, precipitation, CO₂ concentration, and solar radiation. Monier et al. (2014) discusses how the IGSM-CAM simulations compare to the pattern-scaled MIROC projections, as well as the limitations of both methods. Waldhoff et al. (2014) further describes the rationale for selection of the emission scenarios and climate projection methods.

Finally, slightly different techniques were used in bias correcting the IGSM-CAM versus IGSM pattern scaled model outputs, based on constraints of the available data. For IGSM-CAM, the bias correction component of the Bias Correction and Spatial Disaggregation (BCSD) approach was employed. The methodology used to generate the BCSD projections closely follows that outlined by Maurer et al. (2007) and the Bureau of
Reclamation (2013) as part of a project jointly funded by multiple U.S. agencies to bias correct and downscale climate and hydrology projections based on the CMIP3 and CMIP5 archives. The approach requires first resolving the GCMs and baseline to a common spatial resolution and then bias correcting the GCM outputs. The bias correction step involved three datasets for each unique grid cell-GCM run combination: (1) observed baseline (NLDAS) between 1980 and 2009, (2) modeled baseline between 1980 and 2009, and (3) modeled projections between 2010 and 2115. Quantile maps were first developed between the observed and modeled baselines for each grid cell and month, relating the empirical cumulative density functions (CDF) of the observed and modeled baselines. These quantile maps provide the "bias correction" through which each modeled projection value is adjusted to be statistically consistent with the observations. This general process was applied to develop bias corrected IGSM-CAM projections of daily precipitation, minimum average daily temperature, maximum average daily temperature, and atmospheric pressure. For the three remaining variables needed for the Penman Monteith PET calculation -- solar radiation, wind speed, and humidity -- projected time series were constructed synthetically by binning historical data and randomly selecting values from those bins according to the projected sequences of precipitation and temperature. This approach insured statistical consistency between the bias-corrected projections.

Bias correction of the IGSM pattern scaled outputs required a different approach. The outputs of the IGSM pattern scaling approach were changes in temperature and precipitation from the historical baseline to each of the four eras (30-year periods centered around 2025, 2050, 2075, and 2100). These changes, which were captured as absolute differences for temperature and ratios for precipitation for each grid cell and month, were linearly interpolated into annual time series between 2010 and 2115. These interpolated time series were then applied to the NLDAS series, which was repeated to form a 106-year time series that was compatible with the series of projected changes. This procedure developed bias corrected series of temperature and precipitation, and the remaining variables (minimum average daily temperature, maximum average daily temperature, atmospheric pressure, solar radiation, wind speed, and humidity) were developed using the same binning approach as described for IGSM-CAM above.
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Waldhoff S, Martinich J, Sarofim M, DeAngelo B, McFarland J, Jantarasami L, Shouse K, Crimmins A, Ohrel S, and Li J 2014 Overview of the Special Issue: A multi-model framework to achieve consistent evaluation of climate change impacts in the United States. *Climatic Change* doi:10.1007/s10584-014-1206-0
2. **Additional Information on EPIC Crop Modeling Methods**

Crop productivity was simulated in EPIC (Environmental Policy Indicator Climate, ver. 1120), an agricultural ecosystem model that simulates biophysical and biogeochemical processes as influenced by climate, landscape, soil, and management conditions (Williams, 1995), such as plant growth and productivity, C and nutrient cycling, soil erosion, and greenhouse-gas emissions. The plant growth sub-model of EPIC is a revised version of Crop Environment Resource Synthesis model (Williams et al., 1989; Jones et al., 1991). It employs the concept of radiation-use efficiency by which a fraction of daily photosynthetically-active solar radiation is intercepted by the plant canopy and converted into plant biomass. Daily gains in plant biomass are affected by vapor pressure deficits, atmospheric CO$_2$ concentrations, environmental controls and stresses. EPIC is parameterized for about 120 plant species including food crops, native grasses, and trees, and traces all salient terrestrial water cycling processes including snowmelt, surface runoff, infiltration, soil water content, percolation, lateral flow, water table dynamics, and evapotranspiration (Williams, 1990). It was modified by Stockle et al. (1992a,b) to simulate the influence of increasing atmospheric CO$_2$ concentrations on plant growth and crop yield.

A modified version of the CENTURY carbon model (Parton et al., 1994) by Izaurralde et al. (2006; 2007) is used to simulate soil carbon (C) and nitrogen (N) transformations among soil organic matter pools.

EPIC has been applied in climate impacts studies on a number of occasions, most recently as part of the Agricultural Model Intercomparsion Project (AgMIP) maize and wheat model intercomparisons (Asseng, 2013) (Bassu et al., 2014). Previous climate impacts applications with EPIC have ranged from regional (Chavas et al. 2009) to national (Izaurralde et al. 2003; Thomson et al. 2005a,b) to global (Schneider et al., 2011) in scale. EPIC has been widely validated in the United States for major crop systems (Izaurralde et al. 2003; Thomson et al. 2005a-b; Zhang et al. 2015) and been used for a range of additional applications such as assessing environmental benefits of the Conservation Reserve Program (FAPRI et al. 2007).

EPIC simulates agricultural production at the farm-scale. For national scale simulations we use the geospatial modeling system developed by Zhang et al. (2010, 2015) to produce unique combinations of crop, soil, and weather conditions from Natural Resources Inventory (NRI) statistics (2000a,b) originally applied in EPIC by Potter et al (2004) (SOM Table 1). We selected a discrete set of soils representing at least 80% of agricultural soils in each of the 2100 8-digit hydrologic units in the continental United States (USGS, 1987). Approximately 1400 of these have some crop production in the baseline period (1988-2012). Crops were simulated for their
current and an extended range (defined by a 100km buffer) to account for the potential of shifts in production regions due to climate change. Crops were simulated under both rainfed and irrigated conditions, with the exception of rice and potato which were always irrigated.

Adaptation to climate change is not specifically parameterized; however, some features of these simulations can be considered automatic adaptations. Crop planting and harvesting dates vary based on accumulation of heat units throughout the growing season, which allows for adaptation to changing growing season length. In addition, the long term, 135 year continuous simulation necessitated allowing EPIC to automatically apply fertilizer to meet crop N demand with a maximum application of 250 Kg N ha$^{-1}$. Irrigation was similarly allowed to be automatically applied when plant water stress occurs for the irrigated scenarios. These automatic applications vary based on plant stress, allowing fertilizer and water applications to adapt to changes in climate conditions.

The EPIC model simulates CO$_2$ concentration as an important component influencing crop growth. This is a non-trivial difference in this study as the CO$_2$ concentration diverges by up to 400 ppm between the Reference and Policy scenarios. Therefore, we conducted all simulations both with the CO$_2$ pathways from the IGSM and MIROC scenarios, as well as holding CO$_2$ constant at 400 ppm throughout the run period (Table 1). Considering future climate both with and without CO$_2$ increase allows both isolation of the climatic effects, as well as a bounding of the potential future yield response. It is now well known that CO$_2$ fertilization response of crops can be reduced by environmental factors such as ozone damage to crops, pests, diseases and weeds that are not currently simulated by EPIC. Therefore, it is unlikely that increased CO$_2$ will be as ideally beneficial as simulated here. Additionally, the typical levels that have been studied in the free air CO$_2$ experimental (FACE) settings of intact ecosystems have ranged from 475-600 ppmv (Ainsworth and Long, 2005) and have shown the crop response to be lower than – half or less – that observed in chamber studies. These are substantially lower than earlier chamber experiments that determined crop yield increase of an average of 33% under a doubled CO$_2$ scenario, and from which EPIC was developed (Stockle et al., 1992a,b). Additionally, recent work has found that plant response to high CO$_2$ may be reduced with prolonged exposure (Norby and Zak, 2011). Experimental studies of CO$_2$ increases of up to 830 ppm, as simulated here for the Reference scenario, have not been conducted. Considering all these factors, EPIC may be substantially overestimating the positive influence of CO$_2$ at the very high levels considered here.
The full 135 year climate projections of daily weather data from the IGSM-CAM and MIROC climate models were applied directly in EPIC as described below, resulting in a large number of long-term climate impact simulations for each crop and management combination (Table S1).

**Table S1: Sets of scenarios simulated in the EPIC model for each crop.**

| Climate model | Simulation time period | Emission scenario | Crop Management | CO2 conc. in EPIC | Number of Crops in EPIC | IGSM-CAM Ensemble members |
|---------------|------------------------|-------------------|----------------|-------------------|------------------------|--------------------------|
| IGSM-CAM      | 1980-2115              | Reference         | Rainfed        | 400               | 9                      | 5                        |
| IGSM-CAM      | 1980-2115              | Mitigation        | Rainfed        | 400               | 9                      | 5                        |
| IGSM-CAM      | 1980-2115              | Reference         | Irrigated      | 400               | 9                      | 5                        |
| IGSM-CAM      | 1980-2115              | Mitigation        | Irrigated      | 400               | 9                      | 5                        |
| IGSM-CAM      | 1980-2115              | Reference         | Rainfed        | Increasing to 830 | 9                      | 5                        |
| IGSM-CAM      | 1980-2115              | Mitigation        | Rainfed        | Increasing to 460 | 9                      | 5                        |
| IGSM-CAM      | 1980-2115              | Reference         | Irrigated      | Increasing to 830 | 9                      | 5                        |
| IGSM-CAM      | 1980-2115              | Mitigation        | Irrigated      | Increasing to 460 | 9                      | 5                        |
| MIROC         | 1980-2115              | Reference         | Rainfed        | Increasing to 830 | 9                      | 1                        |
| MIROC         | 1980-2115              | Mitigation        | Rainfed        | Increasing to 460 | 9                      | 1                        |
| MIROC         | 1980-2115              | Reference         | Irrigated      | Increasing to 830 | 9                      | 1                        |
| MIROC         | 1980-2115              | Mitigation        | Irrigated      | Increasing to 460 | 9                      | 1                        |

In total, close to two million EPIC simulations were conducted using a parallelized version of the model on the Evergreen cluster. EPIC model results were then transferred to a Linux cluster Postgresql database for further analysis. Results were aggregated to regions that correspond with the FASOM system modeling units for analysis of large scale and long term trends. Crop yield differences over time were calculated as percentage change from the baseline period, 25 years centered around 2000. The future reported years of 2025, 2050, 2075 and 2100 are likewise averages of 25 year periods centered on those reported years.
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Zhang X, Izaurralde RC, Manowitz DH, Sahajpal R et al. 2015 Regional scale cropland carbon budgets: Evaluating a geospatial agricultural modeling system using inventory data. Environmental Modelling & Software 63 (2015): 199-216.
3. Calculation of Changes in Crop Yields used in FASOM-GHG

The EPIC model was simulated on an annual basis for each of the 5 climate model initializations both with and without enhanced CO₂ fertilization, for a total of 10 climate projections. Projections were completed for nine major crops (barley, corn, cotton, hay, potato, rice, sorghum, soybeans, and wheat) in and near their current growing regions under both rainfed and irrigated management. For crops that were not simulated in EPIC, proxy crops were assigned so that they would also have climate change impacts in our scenarios. If no impacts are assigned, it is equivalent to assuming that those crops are not impacted by climate, which may distort the model results.

The model was run with some adaptation measures. For instance, EPIC automatically adjusts planting and harvesting dates based on growing degree days. In addition, fertilizer was automatically applied to meet crop nitrogen demand and irrigation was automatically applied when there was water stress on crops under the runs with irrigation. These automatic adjustments reduce plant stress under climate change. In addition, the model was run for regions near current crop regions to allow for the possibility of shifting crops into new regions. However, the actual determination of changes in area and production practices were determined within the FASOM-GHG model, which accounts for economic considerations.

Results were aggregated to 5-year averages consistent with the 5-year timesteps at which FASOM-GHG solves for the 5 agricultural regions that characterize the continental United States in FASOM-GHG in this study (see Table S-2). The data incorporated into FASOM-GHG were the percentage changes in yields at the timestep/region level based on the differences between EPIC simulations under a fixed climate baseline (no climate change, yields fixed over time) vs. each of the 10 climate projections. These percentage changes in yields were applied to the base yield projections in FASOM-GHG, which are changing over time based on projected rates of yield growth due to technological change.
| FASOM-GHG Aggregated Region | States/Regions Included                                                                                                                                 |
|-----------------------------|--------------------------------------------------------------------------------------------------------------------------------------------------------|
| Midwest                     | All regions in Illinois (IllinoisN, IllinoisS), Indiana (IndianaN, IndianaS), Iowa (IowaW, IowaCent, IowaNE, IowaS), Ohio (OhioNW, OhioS, OhioNE), Michigan, Minnesota, Missouri, Wisconsin |
| Northeast                   | Connecticut, Delaware, Maine, Maryland, Massachusetts, New Hampshire, New Jersey, New York, Pennsylvania, Rhode Island, Vermont, West Virginia         |
| Plains (no forestry included in Oklahoma or Texas regions within the Plains) | Kansas, Nebraska, North Dakota, Oklahoma, South Dakota, All of Texas but the Eastern region (Texas High Plains, Texas Rolling Plains, Texas Central Blacklands, Texas Edwards Plateau, Texas Coastal Bend, Texas South, Texas Trans Pecos) |
| Pacific Northwest, West Side (forestry only) | Oregon and Washington, west of the Cascade mountain range                                                                                               |
| Southern US                 | Alabama, Arkansas, Florida, Georgia, Kentucky, Louisiana, Mississippi, North Carolina, South Carolina, Tennessee, Eastern Texas, Virginia              |
| Western US                  | Arizona, All regions in California (CaliforniaS, CaliforniaN), Colorado, Idaho, Montana, Nevada, New Mexico, Oregon east of the Cascades mountain range, Utah, Washington east of the Cascades mountain range, Wyoming |
4. Calculation of Changes in Forest Yields used in FASOM-GHG

The MC1 model was used to generate potential changes in forest growth rates for use in the FASOM-GHG model. The MC1 variable used was above-ground net primary productivity (NPP) ("afcaccx"). The MC1 vegetation types ("VTYPEyr") were mapped to FASOM-GHG forest types. Because a single MC1 vegetation type may fall into multiple FASOM-GHG types, they were weighted across FASOM-GHG types. For instance, subtropical evergreen needleleaf forest would fall into natural pine as well as planted pine FASOM-GHG types. Therefore, equal weights were assigned to natural pine and planted pine for that MC1 vegetation type when applied the NPP by gridded cell.

Percentage changes in annual values of NPP were generated for each of the climate scenarios with CO$_2$ fertilization over the period 2000-2115 as follows:

\[
\frac{\text{Future NPP} - \text{Historic Average NPP}}{\text{Historic Average NPP}}.
\]

Annual average values were calculated by FASOM-GHG region (see Table S2) based on weighted averages of the gridded percentage change in each FASOM-GHG forest type within each FASOM-GHG region. We then calculated values to be used in each 5-year time step in FASOM-GHG based on 30-year moving averages centered on each 5-year period.
5. **Sensitivity Analysis of CO₂ Fertilization Effects on Crop Yields**

The primary focus in this study has been on the assumption of full CO₂ fertilization effects. The agriculture and forestry literature clearly documents that there will be benefits of CO₂ for plant growth, although there still exists uncertainty regarding the magnitude of this effect. To explore this source of uncertainty, and to estimate the impacts of climate change in isolation from CO₂ benefits, we conducted a sensitivity analysis using the EPIC model to investigate CO₂ fertilization effects on crop yield using the IGSM-CAM climate projections.

As described in the main paper, EPIC was simulated with the CO₂ concentration pathways from each GHG emission scenario (reaching about 830 ppm by 2100 under the Reference and 460 ppm under the Policy scenario), as well as with holding CO₂ concentrations constant (referred to as “no CO₂ fertilization”) at baseline levels (400 ppm) in both scenarios throughout the simulation period.

Table S3 summarizes the effects of stabilization under the Policy case relative to the Reference case under CO₂ fertilization and no CO₂ fertilization. As shown, the simulated changes in yields across crops are consistent between the two assumptions regarding CO₂ fertilization.¹

| CO₂ Fertilization       | 2010 | 2050 | 2100 | 2010 | 2050 | 2100 |
|-------------------------|------|------|------|------|------|------|
| Barley, Dryland         | 0.5% | 11.4%| 56.5%| 0.4% | 10.9%| 52.2%|
| Barley, Irrigated       | 0.2% | 6.4% | 35.5%| 0.2% | 6.1% | 32.1%|
| Corn, Dryland           | 0.1% | 4.7% | 22.4%| 0.1% | 4.7% | 23.3%|
| Corn, Irrigated         | 0.1% | 4.6% | 20.8%| 0.1% | 4.5% | 20.1%|
| Cotton, Dryland         | 0.4% | 11.1%| 30.3%| 0.3% | 10.8%| 28.7%|
| Cotton, Irrigated       | 0.0% | 4.8% | 27.0%| 0.0% | 4.7% | 25.8%|
| Hay, Dryland            | -0.2%| -2.7%| -13.8%| -0.2%| -2.5%| -12.4%|
| Hay, Irrigated          | 0.1% | -0.3%| 0.5% | 0.0% | -0.1%| 1.9% |
| Potatoes, Irrigated     | 0.4% | 12.4%| 54.9%| 0.4% | 11.9%| 49.6%|
| Rice, Irrigated         | 0.1% | 5.0% | 18.0%| 0.1% | 4.5% | 14.6%|
| Sorghum, Dryland        | 0.3% | 10.0%| 31.1%| 0.3% | 9.8% | 29.5%|
| Sorghum, Irrigated      | 0.1% | 3.8% | 17.5%| 0.1% | 3.8% | 17.5%|
| Soybeans, Dryland       | -0.1%| 4.7% | 15.7%| -0.1%| 4.7% | 14.8%|
| Soybeans, Irrigated     | 0.0% | 5.5% | 27.2%| 0.0% | 5.6% | 27.4%|
| Wheat, Dryland          | 0.4% | 10.2%| 38.3%| 0.4% | 9.9% | 36.8%|
| Wheat, Irrigated        | 0.3% | 5.5% | 26.6%| 0.3% | 5.5% | 26.6%|

¹ It is worth noting that the response of crops to CO₂ can be reduced by environmental factors such as ozone damage and increases in pest pressure that are not simulated in EPIC, and that studies have not been conducted looking at crop responses to CO₂ concentrations at the levels we are reaching in the Reference scenario (greater than 800 ppm).
6. Effects of Natural Variability

As described in the methods section of the main paper, the influence of natural variability was investigated under the two GHG emissions scenarios (Reference and Policy) using five different ensemble members of the IGSM-CAM climate model. These ensemble members, or “initializations,” differ in their stochastic wind stress forcing of the IGSM ocean component and in the initial conditions of the CAM atmosphere model. This yielded ten different climate simulations – five for each scenario – that were then simulated in EPIC (crop yield), MC1 (timber yield), and FASOM (market model). The use of these initial conditions for each scenario enables the evaluation of the effect of natural variability in the climate system for a plausible range of outcomes.

The EPIC, MC1, and FASOM estimates presented in the main paper represent the average of the results for each of the five initializations per scenario. Table S4 below shows the change in market-adjusted crop yield for each initialization (Policy versus Reference scenario). As shown, the effect of global GHG mitigation across the IGSM-CAM initializations varies modestly, but the sign and magnitude of crop yield change is generally consistent across all five initializations.

Table S4. Differences in Yields of Major Crops by IGSM-CAM Initialization Following Market Adjustments, Policy Case Relative to Reference Case (% change)

| Crop Type          | Initialization 1 |          |          |          | Initialization 2 |          |          |          | Initialization 3 |          |          |          |
|--------------------|------------------|----------|----------|----------|------------------|----------|----------|----------|------------------|----------|----------|----------|
|                    | 2010  | 2050  | 2100  | 2010  | 2050  | 2100  | 2010  | 2050  | 2100  |
| Barley, Dryland    | 2%    | 21%   | 70%   | 1%    | 9%    | 66%   | 5%    | 6%    | 60%   |
| Barley, Irrigated  | 2%    | 16%   | 61%   | 0%    | 12%   | 57%   | 1%    | 9%    | 53%   |
| Corn, Dryland      | 1%    | 8%    | 17%   | 1%    | 4%    | 16%   | 2%    | 3%    | 13%   |
| Corn, Irrigated    | 1%    | 8%    | 16%   | 1%    | 5%    | 15%   | 2%    | 5%    | 12%   |
| Cotton, Dryland    | 1%    | 1%    | 10%   | -1%   | -11%  | 9%    | 0%    | -10%  | 6%    |
| Cotton, Irrigated  | 0%    | 9%    | -8%   | -1%   | 4%    | -15%  | 0%    | 5%    | 9%    |
| Hay, Dryland       | 0%    | 0%    | -4%   | 1%    | -5%   | -13%  | 0%    | -2%   | -13%  |
| Hay, Irrigated     | 0%    | -1%   | 1%    | 0%    | 1%    | 2%    | 0%    | -2%   | 1%    |
| Potatoes, Irrigated| 2%    | 21%   | 55%   | 2%    | 16%   | 51%   | 5%    | 12%   | 72%   |
| Rice, Irrigated    | 1%    | 3%    | 9%    | 0%    | 1%    | 8%    | 0%    | 2%    | 6%    |
| Sorghum, Dryland   | 2%    | 3%    | -5%   | 3%    | -2%   | -7%   | 3%    | 0%    | -8%   |
| Sorghum, Irrigated | 0%    | 11%   | 15%   | 1%    | 8%    | 13%   | 2%    | 6%    | 10%   |
| Soybeans, Dryland  | 1%    | 8%    | 13%   | 1%    | 4%    | 15%   | 2%    | 2%    | 9%    |
| Soybeans, Irrigated| -1%   | 8%    | 23%   | 0%    | 8%    | 25%   | 1%    | 6%    | 29%   |
| Wheat, Dryland     | 2%    | 5%    | 2%    | 2%    | 0%    | 2%    | -1%   | -2%   | -8%   |
| Wheat, Irrigated   | 1%    | 6%    | 8%    | 0%    | 11%   | 21%   | 0%    | 10%   | 27%   |
| Crop Type        | Initialization 4 | Initialization 5 |
|------------------|------------------|------------------|
|                  | 2010  | 2050  | 2100  | 2010  | 2050  | 2100  |
| Barley, Dryland  | 2%    | 15%   | 68%   | 1%    | 5%    | 75%   |
| Barley, Irrigated| 0%    | 8%    | 51%   | 1%    | 11%   | 59%   |
| Corn, Dryland    | 0%    | 2%    | 16%   | 2%    | 3%    | 22%   |
| Corn, Irrigated  | 0%    | 5%    | 15%   | 0%    | 4%    | 17%   |
| Cotton, Dryland  | 2%    | -8%   | 9%    | 4%    | -13%  | 13%   |
| Cotton, Irrigated| 0%    | 5%    | -11%  | 1%    | 5%    | -4%   |
| Hay, Dryland     | 0%    | -9%   | -16%  | -1%   | -7%   | -12%  |
| Hay, Irrigated   | 0%    | -1%   | 2%    | 0%    | 1%    | 2%    |
| Potatoes, Irrigated| 2%  | 15%   | 56%   | 3%    | 10%   | 60%   |
| Rice, Irrigated  | 0%    | 0%    | 10%   | 1%    | 1%    | 9%    |
| Sorghum, Dryland | 1%    | 23%   | -6%   | 0%    | -6%   | -4%   |
| Sorghum, Irrigated| 0%  | 6%    | 15%   | 0%    | 9%    | 13%   |
| Soybeans, Dryland| 0%    | 2%    | 14%   | 2%    | 2%    | 19%   |
| Soybeans, Irrigated| 0%  | 12%   | 27%   | 0%    | 2%    | 23%   |
| Wheat, Dryland   | 2%    | 1%    | 4%    | -1%   | -2%   | -5%   |
7. Additional FASOM-GHG Results

7.1 Differences in National Land Cover

The projected differences in yields and prices between the Policy and Reference scenarios, as well as in yield and price variability for both crops and forests, result in changes in acreage allocation over time. Figures S1 and S2 present the average simulated differences in land cover at the national level over the latter half of this century under the two climate model projections (IGSM-CAM and MIROC). Under the IGSM-CAM projections, cropland expands primarily at the expense of cropland pasture, reflecting the greater profitability of growing crops compared to pastureland and forests. Under the MIROC projections, yields are generally higher for both agriculture and forests under the Policy case compared with the Reference. This results in substantially less cropland being used for production relative to the Reference case because demand can be met with considerably less land when yields are so much higher. There expansion of forest and cropland pastures areas as relative returns to those activities rise relative to cropland. In addition to land moving from cropland into other land cover types, there is an increase in idle cropland with the higher yields under the Policy scenarios. Differences in regional land cover type are provided in the figures of the main paper.

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Note that this paper focuses on climate impacts on the United States. If climate impacts on the rest of the world were reflected, then there would likely be substantial trade effects and a potential expansion of US export markets that would keep more cropland in production. Such an assessment is outside the scope of the current study, but is a topic for future research.
**Figure S1. Differences in National Land Cover under the IGSM-CAM Climate Projections, Policy Case Relative to Reference Case (million acres)**

![Graph showing differences in national land cover under IGSM-CAM climate projections.](image)

Note: Cropland Pasture - land of sufficient quality to be classified as cropland, but that is being used as pasture; Forest – private forest; Pasture – pastureland that is not of sufficient quality to be used as cropland without incurring costs of land improvement; Cropland – area of harvested cropland.

**Figure S2. Differences in National Land Cover under the MIROC Climate Projections, Policy Case Relative to Reference Case (million acres)**

![Graph showing differences in national land cover under MIROC climate projections.](image)

Note: Cropland Pasture - land of sufficient quality to be classified as cropland, but that is being used as pasture; Forest – private forest; Pasture – pastureland that is not of sufficient quality to be used as cropland without incurring costs of land improvement; Cropland – area of harvested cropland.
7.2 Differences in National Cropland Allocation

Figures S3 and S4 present differences in land allocation to nine major crops (and an “other crops” category) at the national level between the Policy and Reference scenarios over the 21st century. These results indicate substantial reallocation of the US national crop mix in response to climate change impacts on relative agricultural productivity. Given the projections for larger yields under the Policy scenario compared to the Reference, the trend of decreasing crop area for most crops under the IGSM-CAM projections is consistent with less cropland being needed in order to meet demand. However, the area allocated for hay, cotton, and wheat production increases throughout much of the century. Under the MIROC projections, crop area for wheat increases, especially at mid-century. Acres devoted to all other crops generally decrease across time, consistent with less cropland being brought into production in order to meet demand.

Figure S3. Differences in National Cropland Allocation under the IGSM-CAM Climate Projections, Policy Case Relative to Reference Case (million acres)
7.3 **Differences in Forest Inventory of Hardwoods and Softwoods**

Figure S5 shows the differences in the inventory of hardwoods and softwoods in the contiguous United States through 2100. Changes in forestry-type are more muted in the projections using the IGSM-CAM climate model, showing slight decreases in abundance over time for both hard and softwoods. However, the Policy case under the MIROC climate model results in larger increases in softwoods over time, with slight decreases in hardwoods at the end of the century.
7.4 Changes in Water Use for Irrigation

Figure S6 shows the simulated changes in irrigation water use under each of our scenarios relative to a baseline with no change in climate. Both Reference and Policy cases for IGSM-CAM and MIROC climate conditions result in increases in irrigation water use until 2040, but reductions in irrigated water after that due to general increases in precipitation in later decades this century under our climate change scenarios. As shown in Figure S7, although the Policy scenarios are using less irrigation water than the baseline without climate change, they use substantially more than under the Reference case by the end of the century. Because the climate scenarios being used in this study are resulting in a general increase in precipitation in the United States that becomes greater over time, mitigation results in lower precipitation and greater irrigation demand than in the Reference scenario with the exception of the 2010-2040 period under IGSM-CAM climate conditions.
Figure S6. Difference in National Irrigation Water Use under the IGSM-CAM and MIROC Climate Projections, Policy and Reference Cases Relative to Fixed Climate (% Change)

Figure S7. Difference in National Irrigation Water Use Inventory under the IGSM-CAM and MIROC Climate Projections, Policy Case Relative to Reference Case (% Change)