Supporting Information

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National Percentages of Significant Correlations

The percentage of significant TFPC–climate correlations differs radically before and after 1980 (Fig. S1). As climate indicators, we used PR, TA, TN, and TM. In 1951–1980, autumn temperatures correlated most significantly to TFPC, with positive correlations over 28.2% (TA), 21.7% (TN), and 15.2% (TM) of grids. Spring temperatures showed negative correlations in fewer areas, with significant correlations in only 11.4% (TA), 9.5% (TN), and 5.1% (TM) of grids. Few areas saw TFPC–temperature correlation in summer or winter. A negligible number of grids had opposite correlations (negative autumn and positive spring). Few grids showed any correlation between TFPC and precipitation. Precipitation had positive effects for only 4.0% of grids in both summer and autumn, and exhibited negative effects for an additional 3.5% of grids in autumn. The general lack of significant correlations suggests that TFPC in this period has little sensitivity to climate variability, except that warmer autumn temperatures are associated with measured productivity increases.

The TFPC–climate relationships changed substantially in 1981–2010. Summer temperatures had the largest percentage of correlated grids, with negative correlations for 36.7% (TA), 31.7% (TN), and 33.9% (TM), with an additional 5.1 to 6.1% showing positive correlations. Spring temperatures showed the second-largest percentage, with positive correlations over 23.0% (TA), 12.0% (TN), and 26.5% (TM), and no negative correlations. Thus, cooler summer and warmer spring temperatures were associated with measured agricultural productivity increases in many locations. Winter and autumn had modest numbers of grids with negative TFPC–temperature correlations, respectively, 11.0%, 18.6%, 6.9% and 17.6%, 8.7%, 15.1%, and no positive correlations. Although TA remained the largest player in summer and autumn, TM became more important in spring, and TN was more influential in winter. Additionally, precipitation showed a more significant impact in this later period, with 9.1% of grids having positive correlations in summer and 10.4% (7.4%) of grids showing negative correlations in winter (spring). The drastic increase in the number of significant correlations during the growing seasons suggests that TFP sensitivity to climate is radically enhanced in 1981–2010 compared with the earlier period.

Because the three temperature variables are highly correlated, our subsequent analyses focused on TA, which generally exhibited larger percentages of significance. As shown in Fig. 2, the correlation patterns with TA were mostly inclusive of those with TN and TM. The two exceptions were winter TN and spring TM, which played larger roles than TA in 1981–2010. Given negligible correlations with winter and spring PR in 1951–1980, Fig. 2 instead shows correlations with winter TN and spring TM in 1981–2010. Even in these two cases, TA clearly captured the core pattern of the correlation.

Evolving Effects of Climate Variation

Fig. S2 shows the percentage of significant TFPC-climate correlations in each 20-y period, in running 10-y increments. These reveal a clear transition between the correlation patterns before and after 1980 (as depicted in Fig. S1 and described in *National Percentages of Significant Correlations*). For example, negative temperature correlations in summer increased sharply between 1971–1990 and 1981–2000, and negative temperature correlations in spring were entirely replaced by positive correlations following the 1971–1990 period. One noteworthy pattern is that, over recent decades, spring and summer positive temperature correlations decreased, whereas summer negative temperature correlations increased. This pattern suggests that temperatures in agricultural regions may have started moving beyond the optimum temperature thresholds, with increasingly negative impacts on TFPC. Precipitation changes were relatively small in each period, except that, in 1991–2010, negative precipitation correlations decreased in spring and winter, whereas positive correlations increased in autumn.

Changes in Sectoral Contributions to TFP

Substantial changes in US agricultural economy between 1951 and 2010 likely affected the relationship between TFPC and climate. The USDA partitions agricultural production into three categories: crops, livestock, and farm-related goods and services. At the national level, the relative values of these sectors have shifted significantly over time (Fig. S3). In particular, crop products became more important in recent decades, at the cost of reducing the contribution of livestock products. The growing reliance on crop production likely caused TFPC sensitivity to increase, because crops are generally more sensitive to weather than livestock. From 1951 to 1980, crops and livestock consistently reflected inverse tendencies (such that, when one increased, the other decreased) to maintain a total of ∼98% of the total value. After 1980, they become less correlated, largely due to the increasing importance of farm-related goods and services, which rose to between 2.5% and 6.6% of total value in 1981–2010. The greater role of farm-related goods and services may have also factored into the increased climate sensitivity seen in the later period.

CMIP5 Climate Simulations

To represent future climate change, we chose CMIP5 simulations, which were used in the fifth Assessment Report of the Intergovernmental Panel on Climate Change (37) and in the latest National Climate Assessment (NCA) (38) of the US Global Change Research Program. The CMIP5 archive contains simulations of the 20th century using best estimates of the temporal variations in external forcing factors (such as greenhouse gas and volcanic aerosol concentrations, and solar output), as well as projections of the 21st century following four RCPs: RCP2.6, RCP4.5, RCP6.0, and RCP8.5, with the numbers indicating the 2100 radiative forcing increase relative to preindustrial levels in watts per square meter. Following the selection for the next quadrennial NCA on impacts, vulnerability, and adaptation responses to climate change, we used the projections under RCP4.5 and RCP8.5, which produce end-of-century global mean temperature increases of 4.2 °F and 8.3 °F, respectively, compared with a base period of 1901–1960 (38). To depict the perceivable range of uncertainty due to climate sensitivity, we used all available simulations based on these two RCPs, for, respectively, a total of 86 and 54 realizations from 34 and 26 different coupled general circulation models (GCMs). We averaged all realizations from each GCM into a single contribution so that all GCMs were weighted equally in the final ensemble. Because the historical simulations switch to future projections after 2005, we chose 1976–2005 as the reference for the present-day climate base, and calculated future climate change as differences from this reference. These differences, averaged over the key regions and seasons, were used as future changes of the climate indices in regression model **2** to project potential TFPC responses.

Key Contributors to the Future US TFP Declines

The largest contributor to the climate penalty is the projected increase in summer temperature over the agricultural heartland

($TA_{JJA.AH}$). This explains a fraction of the modeled total TFPC variance in the range of 0.05, 0.13, and 0.41 for the 25th, 50th, and 75th percentiles, respectively, of all CMIP5 climate projection realizations. The second-largest contributor is the projected increase in autumn temperature across California, Oregon, Nevada, Arizona, and New Mexico ($TA_{SON.CX}$), with the corresponding fraction range of 0.05, 0.14, and 0.26. The third-largest contributor is the spring temperature in the Southwest ($TA_{MAM.SW}$), with a range of 0.00, 0.02, and 0.14. The fourth-largest contributor is the projected increase in summer temperature in California and Nevada ($TA_{JJA.CN}$), with a range of 0.02, 0.03, and 0.11. All four of these top factors are related to the warming trend. The first two enhance the heat stress on crop growth, and so reduce productivity. The third and fourth have a reverse effect, possibly because warmer springs and summers may favor regional agriculture such as wine grapes. Precipitation comes in fifth, with the small projected decrease in amount and increase in variability in summer along the arc in the transition zone ($PR_{JJA.TZ}$) contributing a range of 0.01, 0.02, and 0.05.

Projected Rate and Uncertainty of Future TFP Loss

The exact rate of TFP loss depends on the climate scenario used, and has a wide spread due, primarily, to uncertainty in climate projections. However, two patterns are evident under all scenarios: The future climate penalty reduces TFP at greater rates than it has grown in recent decades, and the rate of loss increases significantly over time.

Fig. S4 shows the projected TFP loss rate under RCP4.5 and RCP8.5, including the mean rate and the range due to uncertainty in climate and the regression analysis. Rates were calculated as compound annual growth rates from 2010 to 2040, the year by which 75% of models project a TFP drop off to pre-1980s levels. Based on the ensemble mean, the climate penalty of RCP4.5 will reduce TFP by ~2.84% per year through 2040. Given uncertainty in climate projections, as represented by the 25th and 75th percentile of model results, the loss rate may be between 1.75% and 5.19% per year. The rate increases significantly over time. From 2010 to 2020, the mean rate loss is 0.69% per year, with the 75th percentile GCMs still showing slight TFP growth. In 2020–2030, the loss rate rises to 2.40%, followed by an even greater increase to 5.38% per year in 2030–2040. Using 870 28-y submodels that represent regression-based uncertainty, rates are slightly higher, with average yearly losses of 2.97% from 2010 to 2040 (including climate-based uncertainty, the estimates range from 1.48 to 5.60%).

Under the RCP8.5 scenario, the mean loss rate is 4.34% per year, or between 2.52% and 13.32% per year considering the effects of climate uncertainty. Again, this rate strongly increases over time, moving from 1.37% per year in 2010–2020 to 3.26% in 2020–2030, and finally rising to 8.25% from 2030 to 2040. The submodel results somewhat increase the mean projected TFP loss to 4.55% per year, with a climate-based uncertainty range of 2.17 to 14.43%. We believe that the main model is a more reliable indicator, because it uses the entire available sample.

Under both RCPs, projections in the later years have additional uncertainty. The model is built on observed regional climate anomalies, which are linked to measured economic responses. Once future climate changes exceed the magnitude of historical anomalies, the observed past relationships may no longer hold true, and the model may no longer be applicable. This may already be evident in the later years of our projection.

Differences Between Projections of Yield and Productivity

Past studies of yield, which is a partial productivity measure, are difficult to compare even among themselves, because they vary widely in respects such as location, crop type, reference period, and climate projection used. We calculate that published values in such studies tend to reflect crop yield losses in the range of 0.3 to 1.7% per year (5, 7, 39). Our results suggest that TFP loss will be significantly higher than these yield loss projections, likely due both to the inherent physical differences between yield and productivity measures and to differences in our analytical approach.

First, yield and productivity are equivalent only when there is a single input and a single output. Yield measures the returns per unit land, and is thus a measure of land productivity. Productivity measures consider all inputs required to generate all outputs, and therefore may respond to climate very differently. For example, farmers may respond adaptively to anomalously warm or dry years by increasing their use of irrigation, or using sprinklers to cool their livestock. To the extent that they are successful in mitigating the effect of the heat, their yield would remain the same. Productivity, however, would drop, because it considers the added aggregate input of the increased water use, pumping, and electricity costs. Similarly, adaptations, such as decreased acreage or increased use of fertilizer, pesticides, or livestock medication, may mask yield losses but will be reflected in decreased productivity. As a result, TFP loss may be higher than yield loss, because it reflects the added costs of maintaining yield under less beneficial climate conditions.

Second, our analytical approach differs significantly from those of most partial productivity studies, which tend to be limited to certain crops, conditions, and locations. For example, Schlenker and Roberts (5) project the effect of temperature changes on corn, soy, and cotton yields, whereas Lobell et al. (7) project the effect of changing monthly temperature maximums and specific humidity on Midwestern corn yields. In reality, crops are (and will be) affected by combinations of these factors, which are often specific to particular locations. Studies based on dynamic crop models (39, 40) may not capture the actual response of the agricultural–economic system to climate change. On the other hand, our TFPC model represents the observed relationships between the US agricultural economy and climate variations, and uses these as an analog to project future productivity change. Additionally, many yield studies tend to substantially overestimate the effects of carbon fertilization in their crop models, compared with open-air field measurements (41). This overestimation of the beneficial effects of carbon fertilization may also contribute to the smaller yield loss projections.

Furthermore, productivity accounts not only for crop responses to climate change but also for changes in livestock and agriculture-related goods and services. We have found no studies looking at the latter, and few studies looking directly at climate effects on livestock yield, despite the fact that heat and humidity have documented effects on livestock health and production (42). Existing studies find a wide range of impacts, but these tend to be strongly dependent on location, and are often estimated in terms of individual animal responses [for example, the average milk loss per dairy cow (43)], and do not account for larger-scale changes such as altered herd sizes.

Further study is needed on the effects of climate on livestock and other agricultural services, as well as its aggregate effects across all sectors, which may not necessarily be linear. For example, livestock yield is tied to feed availability. If crop yields drop below a certain threshold, farmers may curtail livestock herds or on-farm processed goods that become less economically viable. Other farm-related goods and services that are tied to crop yields may have more erratic response curves that include spikes and precipitous declines. Decreases in crop yield will not be consistent across the nation, and regions with sharper drops may exceed the thresholds that make noncrop operations viable, forcing significant changes in these other contributors to TFP.

Our results illuminate a noteworthy difference in productivity and yield responses to climate, with productivity appearing to be significantly more sensitive than previous studies have shown yield to be. We have provided speculation as to the cause of this disparity, but further research is needed to better understand the relationship.

Sources of Modeling Uncertainty

Several factors could influence climate's ultimate effect on TFPC, and should temper interpretation of the model results. Some of these could amplify the TFPC penalty. Increased use of irrigation (primarily in the Southwest, Midwest, and California) during 1981–2010 has, so far, made regional productivity relatively immune to precipitation changes. With many irrigation water sources becoming less plentiful and sustainable (35, 44, 45), future TFP reductions could exceed model predictions. Additionally, our analysis is based on the averaged TFPC–climate relationship observed in 1981–2010, and does not account for evolving climate sensitivity with increasingly negative effects.

On the other hand, adaptation may potentially lower TFP losses through improved technology or changed practices, but these remain unpredictable and are not accounted for by our model. Likewise, we do not consider regulatory effects, which could potentially impact TFP by influencing the quantities and types of domestically produced agricultural commodities. Policies such as the PIK program and biofuel mandates appear to have had some impacts on TFPC, but the general effect of policy has yet to be established, and it is unknown to what degree it will be able to lessen the negative impacts.

Policies such as trade regulations may have indirect effects on agriculture. Our analysis found no persistent correlation between agricultural international trade (as measured by changes in exports, imports, or trade balance) and TFPC. As TFP is a measure of production relative to input use, it is unlikely to be directly impacted by trade. A climate-induced drop in US agricultural TFP could impact the US ability to meet international demands, particularly for coarse grains, with global impacts on trade. However, changes in trade are unlikely to be a viable means of reversing TFP loss.

Lasso Regression Analysis

To reduce overfitting possible in the stepwise regression, we performed a lasso regression analysis by including all climate indices (eight for 1981–2010 and four for 1951–1980) and minimizing the residual sum of squares. The results differed little from those based on the stepwise regression. The lasso regression models for 1951–1980 and 1981–2010 are, respectively,

$$\begin{aligned}\mathrm{TFPC[a]} = 0.006328 \quad & + 0.007243 \cdot \mathrm{TA}_{\mathrm{SON.NA}} && - 0.009420 \cdot \mathrm{PR}_{\mathrm{SON.TX}} \\ & - 0.007562 \cdot \mathrm{TA}_{\mathrm{MAM.CX}} && + 0.000645 \cdot \mathrm{TA}_{\mathrm{SON.TX}}\end{aligned}$$

$$\begin{aligned}\mathrm{TFPC[b]} = 0.014865 \quad & - 0.0098458 \cdot \mathrm{TA}_{\mathrm{JJA.AH}} && - 0.023616 \cdot \mathrm{PR}_{\mathrm{DJF.CY}} \\ & + 0.034577 \cdot \mathrm{PR}_{\mathrm{JJA.TZ}} && - 0.011355 \cdot \mathrm{PR}_{\mathrm{MAM.CA}} \\ & - 0.014077 \cdot \mathrm{TA}_{\mathrm{SON.CX}} && - 0.011299 \cdot \mathrm{TA}_{\mathrm{MAM.SW}} \\ & + 0.004521 \cdot \mathrm{TA}_{\mathrm{JJA.CN}} && - 0.000889 \cdot \mathrm{TA}_{\mathrm{DJF.NL}}\end{aligned}.$$

The sequential order of the climate indices (and thus the relative importance of their contributions) is identical to that of the stepwise regression models **1** and **2**, and the respective coefficients differ only in the fourth or fifth decimal place. These minimal differences result simply from the inclusion of the fourth term ($\mathrm{TA}_{\mathrm{SON.TX}}$) in 1951–1980 and the eighth term ($\mathrm{TA}_{\mathrm{DJF.NL}}$) in 1981–2010. The total root-mean-square error between the lasso and stepwise regression models is 0.000467 for 1951–1980, and 0.001107 for 1981–2010. These errors are negligible compared with the respective total variances of 0.010 and 0.058. Given that the last term in both lasso models TFPC[a] and TFPC[b] explains less than 0.06% of the total variance, we repeated the lasso regression analysis omitting these variables, and the resulting models were identical to the stepwise regression models.

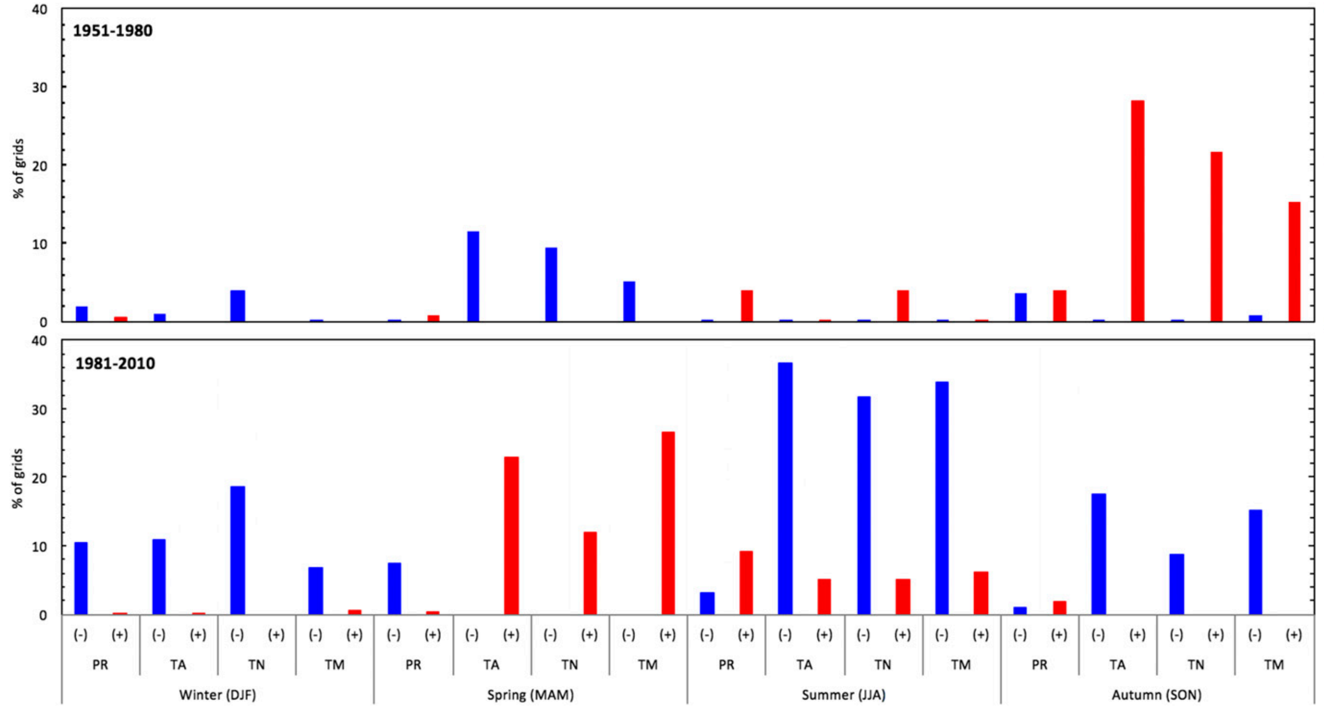

Fig. S1. The percentage of grids over US land that have significant correlations with TFPC. Each bar represents the value for each of the four climate variables in every season, during 1951–1980 (*Upper*) and 1981–2010 (*Lower*). The statistics are separate for positive (+, red) and negative (–, blue) correlations.

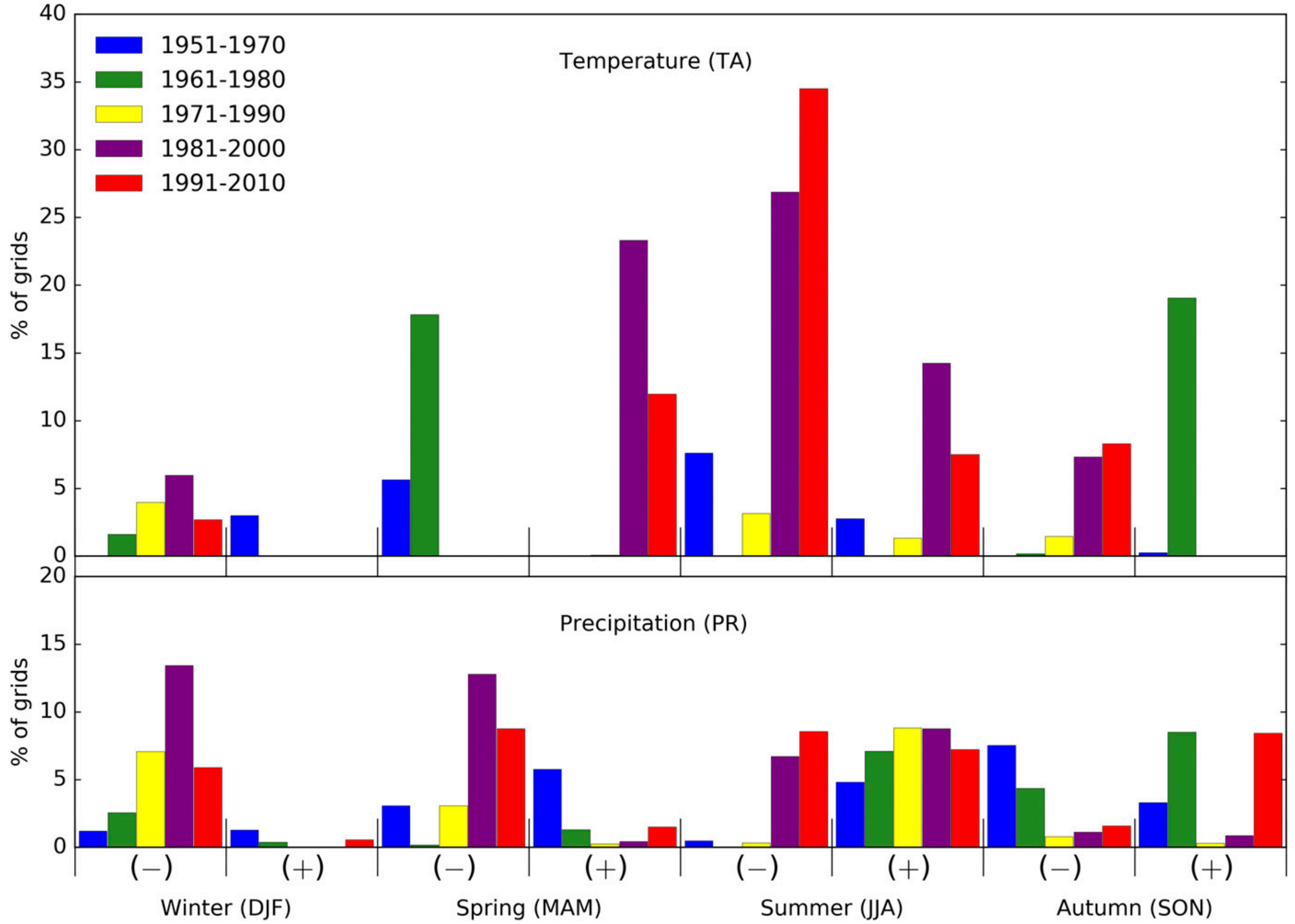

Fig. S2. The percentage of significant TFPC–climate correlations in each 20-y subperiod, including the percentage of grids in which TFPC significantly correlated with temperature (*Upper*) and the percentage of significant correlations with precipitation (*Lower*).

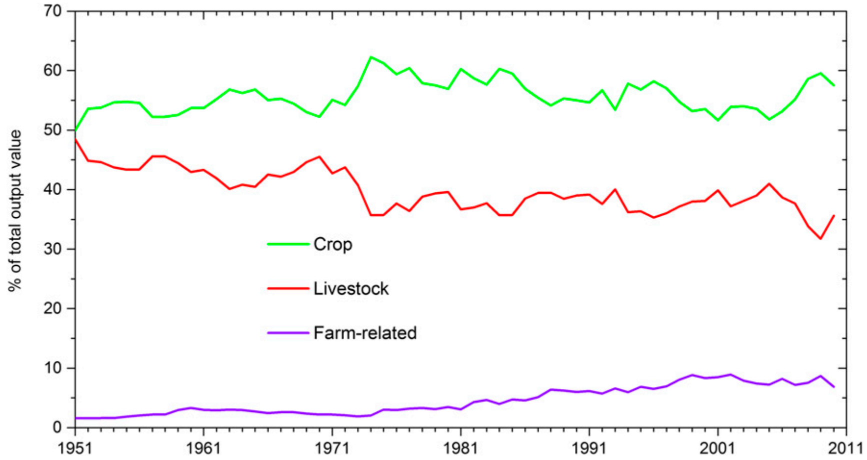

Fig. S3. Variations in the contribution of agricultural sectors to total value. Crops make up the majority of US agricultural value, with livestock (including miscellaneous livestock products not separately identified) seeing a somewhat decreasing role over time, and farm-related goods and services (including nonagricultural or secondary activities closely related to agricultural production for which information on output and input use cannot be separated) increasing in importance in recent decades.

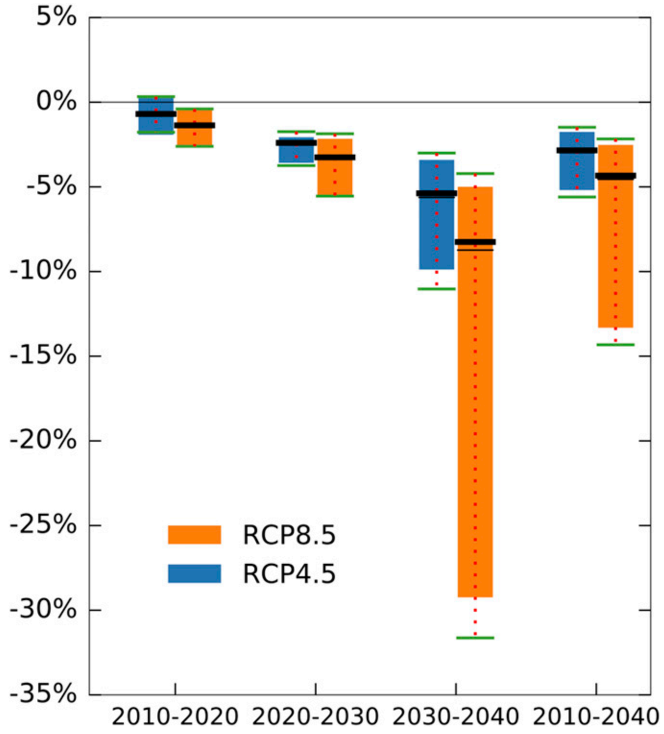

Fig. S4. Compound annual TFP growth rate for each RCP. The range of uncertainty due to climate projections is based on the 25th and 75th percentile GCM results. The dotted lines represent uncertainty in the regression analysis, and are based on 28-y submodels.