Determining climate effects on US total agricultural productivity

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The sensitivity of agricultural productivity to climate has not been sufficiently quantified. The total factor productivity (TFP) of the US agricultural economy has grown continuously for over half a century, with most of the growth typically attributed to technical change. Many studies have examined the effects of local climate on partial productivity measures such as crop yields and economic returns, but these measures cannot account for national-level impacts. Quantifying the relationships between TFP and climate is critical to understanding whether current US agricultural productivity growth will continue into the future. We analyze correlations between regional climate variations and national TFP changes, identify key climate indices, and build a multivariate regression model predicting the growth of agricultural TFP based on a physical understanding of its historical relationship with climate. We show that temperature and precipitation in distinct agricultural regions and seasons explain ~70% of variations in TFP growth during 1981–2010. To date, the aggregate effects of these regional climate trends on TFP have been outweighed by improvements in technology. Should these relationships continue, however, the projected climate changes could cause TFP to drop by an average 2.84 to 4.34% per year under medium to high emissions scenarios. As a result, TFP could fall to pre-1980 levels by 2050 even when accounting for present rates of innovation. Our analysis provides an empirical foundation for integrated assessment by linking regional climate effects to national economic outcomes, offering a more objective resource for policy making.

total factor productivity | agricultural economy | economic growth | climate impacts | crop yield

A long-standing challenge of climate impact assessment has been to determine how climate has influenced the agricultural economy, and how its effects may change in the future. Climate affects agriculture regionally, depending not only on local weather factors but also on specific crops, livestock, and related goods and services, as well as agricultural systems, infrastructures, and interventions. Aggregating these disparate and potentially contradictory regional impacts into larger-scale economic outcomes is particularly difficult because the ultimate consequences are influenced by market fluctuations and policy incentives. As a result, understanding of how climate has influenced the agricultural economy is limited, making projection of the future under climate change extremely uncertain.

This uncertainty is reflected in the lack of consensus regarding the overall impacts of climate change on US agriculture (1, 2). In general, studies follow two approaches, both focusing on partial productivity measures or local economic indicators. One approach seeks to determine the impact of weather shocks on common partial productivity measures such as crop yield (3–7). These studies tend to show that weather variability substantially influences local crop production. The other approach aims to identify the impact of weather patterns on economic returns to farmers in the form of land values or measured profitability. Some such studies document small impacts (8, 9), and others document more significant effects (10, 11). However, because both these approaches are based on local climate effects, select agricultural products, and/or short time frames, they have limited ability to characterize how climatic factors may influence overall US agricultural performance. Long-term, national studies are needed to understand the aggregate climate effects on agricultural growth patterns in the past, and to more credibly project future changes.

Currently, impact analyses of the potential economic consequences of climate change often refer to results from integrated assessment models (IAMs), which use functions that translate the impacts of temperature increase into economic damages. However, these damage functions depend on assumptions about the link between climate and economy that are difficult to verify. Consequently, they vary substantially between different models (12), and have been criticized as subjective (13–15). Improving these functions, and thus the credibility of the projections, requires understanding the connection between regional climate and national productivity.

We therefore take an objective, upscaling approach to quantify the effects of 60 y of regional variations in climate variables across the continental United States on the national total factor productivity (TFP) of agriculture. TFP represents the ratio of measured output (such as crops, livestock, and goods and services) per unit of

Significance

Projections of the economic consequences of climate change are valuable for policy making but generally rely on integrated assessments that cannot account for highly localized climate effects. Most agricultural climate impact studies focus on local effects or partial productivity measures insufficient to capture national economic outcomes. Here, we directly link climate variables in specific US regions to total factor productivity (TFP). We quantify the national economic consequences of past climate variations, identify critical agricultural regions with national significance, and project future changes in TFP under different climate scenarios. We provide a physical understanding of these climate–economic links, show that the agricultural economy is becoming increasingly sensitive to climate, and lay a more concrete foundation for informed decision-making.

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measured inputs (such as land, labor, capital, and resources), and thus is an important indicator of the efficiency of the agricultural system (16). Growth in productivity (i.e., growth not accounted for by increases in inputs) has been a primary driver of the US agricultural economy over the last century. Total inputs to US agriculture have remained relatively constant, whereas aggregate agricultural output grew at an average rate of 1.50% per year from 1948 to 2011 (17, 18). Consequently, TFP has grown at an annual rate of 1.43% since 1948 (19). Thus, the United States is now getting roughly 2.5 times as much agricultural product from the same resource base as it was in 1948. Typically, this increase in productivity is attributed to technological innovation (18–23) and, in particular, to the sustained US policy of public investment in research and development (24, 25). However, this interpretation does not factor in any climate influence on TFP.

The remarkable long-term growth of TFP in recent decades has overshadowed substantial year-to-year fluctuations (Fig. 1) that have not been well explained. These fluctuations are primarily due to changes in aggregate output emerging from variability in exogenous shocks such as weather, market, and policy fluctuations. Until ~1970, US agriculture seemed to manage such shocks well, maintaining relatively consistent TFP growth from year to year. Since then, however, TFP growth rates have been highly variable. Some of this enhanced variability is explained by specific exogenous events, such as the 1973 energy crisis and the US government's 1983 Payment-In-Kind (PIK) program. On the other hand, some of the variability has been casually associated with extreme weather events such as severe droughts and floods in key agricultural areas (26). For example, TFP rates declined sharply in 1993, when persistent heavy rain and thunderstorms caused drastic flooding in the Midwest. Although these events undoubtedly caused substantial damage to agriculture, there has been little quantification of the actual relationships between TFP growth and weather fluctuations or to explain their underlying physical mechanisms. Because temperature and moisture are external physical inputs that affect both plant and animal growth, variability in agricultural production is naturally connected to climatic drivers (27). If climate adversely impacts agricultural production, there seems little doubt that it will manifest itself in either diminished or increasingly variable TFP growth. Understanding that impact is essential for designing agricultural policies to help maintain and promote sustainable US agricultural growth.

This study examines the impact of climate patterns on overall US agricultural performance, based on long records of the most updated data. We use TFP change from the previous year (TFPC) as an indicator of economic growth. Examining TFPC rather than TFP itself allows us to avoid stationarity issues in regression analysis and focus on its relationship with interannual climate variations. Additionally, from a policy perspective, it is important to understand the variability of TFP around the long-term trend. TFPC has been traditionally attributed to technological improvement, but we hypothesize that climate has also been a significant factor in explaining its variability. We therefore assume that TFPC is composed of a constant growth term representing long-term trends and a variable term representing interannual fluctuations. The growth term includes technological contributions and other long-term factors such as the effects of adaptation and CO_2 fertilization (increased photosynthesis due to higher atmospheric CO_2 concentrations) on crop production. We currently cannot separate or specifically quantify these trends, but treat them together as a constant. The variable term represents the effects of interannual changes, primarily due to climate anomalies, but also encompassing short-term impacts such as agricultural and trade policies.

We first analyze the correlation of national TFPC with seasonal and geographic distributions of climate variables, focusing on daily average surface air temperature (TA) and daily cumulative precipitation (PR) anomalies, to identify which have important and statistically significant relationships, and when and where these relationships exist. We then objectively define a set of key regional climate indices that have statistically significant relationships with TFPC. We attempt to explain the biophysical mechanisms associated with these relationships, and, finally, develop a multivariate regression model to predict national aggregate agricultural TFP growth.

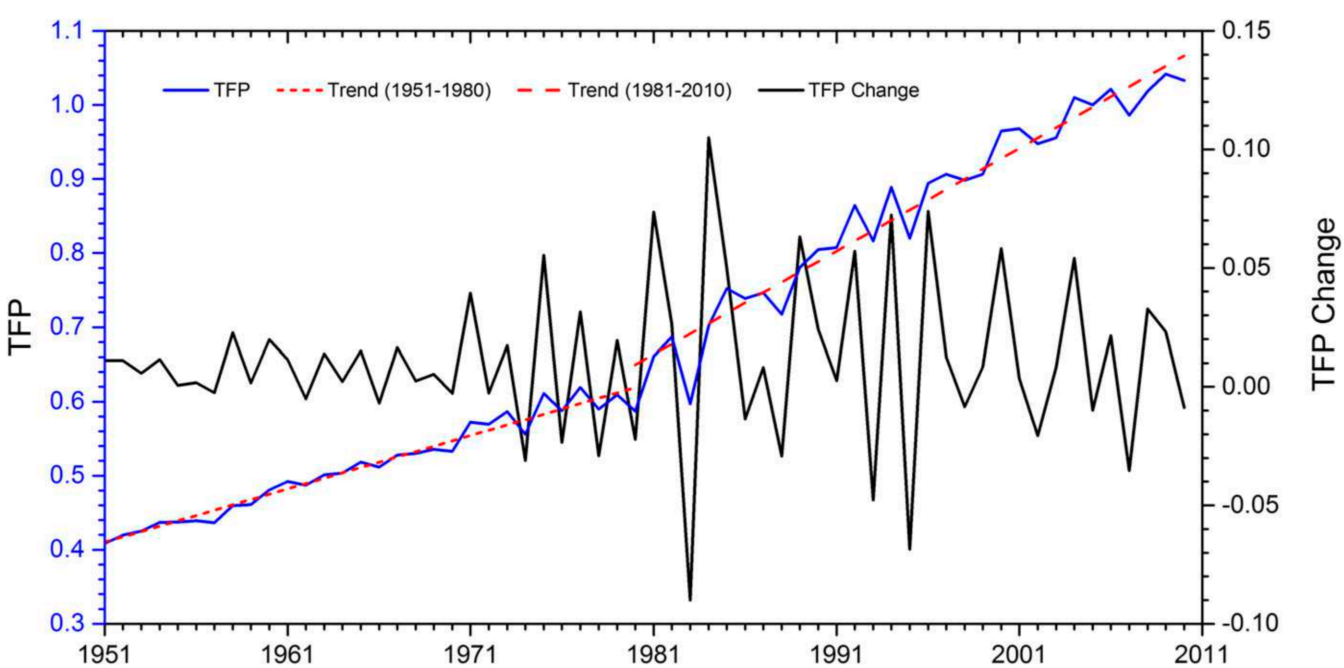

Fig. 1. Evolution of US agricultural TFP. The productivity itself (TFP: blue, scale on right) and its change from the precious year (TFPC: black, scale on left) during 1951–2010, as well as TFP's linear trend estimates for 1951–1980 and 1981–2010 (red dashed). The measured TFP values are relative to year 2005 (= 1), as in the raw data.

Results

Regional Climate Correlations to National TFPC. Fluctuations in TFP were relatively minor from 1951 to 1980, but became much stronger from 1981 to 2010, even as the overall TFP trend increased (Fig. 1). These two periods also exhibited radically different TFPC–climate relationships. In 1951–1980, TFPC had little response to climate variability, whereas, in 1981–2010, there was a drastic increase in the number of significant correlations during the growing seasons, suggesting that TFPC became much more sensitive to climate. (Comparisons of correlations by each period are given in *National Percentages of Significant Correlations* and Fig. S1.) We examined the geographic distribution of the 30-y correlations to identify key areas where regional climate indices significantly affect national TFPC. These key regions are outlined and labeled in Fig. 2, which depicts TFPC correlations to TA and PR anomalies by period and season. For convenience, relationships are described below in terms of positive TFPC or as TFP increases. Analogous relationships can be inferred for negative TFPC.

In 1951–1980, warmer autumns over Texas and across the Northeast through the Midwest and mid-Atlantic regions were associated with higher measured agricultural productivity (Fig. 2*D*). In Texas, cotton was the most valuable crop during this period. Cotton yields are higher in warmer autumns or longer harvesting seasons, and less precipitation also facilitates harvesting. Similarly, in the Midwest, Northeast, and mid-Atlantic regions, warmer autumns mean an extended growing season that aids harvest and allows more crops (especially corn and soybeans) to achieve full maturity and productivity. On the other hand, cooler springs in Nevada, Utah, Arizona, and the coastal regions of California and New Mexico were more productive (Fig. 2*B*). Cooler springs in these regions reduce soil moisture losses and irrigation needs, increasing available moisture for the subsequent summer months when crop needs are greatest. In addition, some regions had positive correlations with summer precipitation, but these were scattered across several central and southeastern states (Fig. 2*G*). Increased water availability raises crop yields, especially over dry lands where irrigation was previously less common than it currently is.

TFPC–climate correlation patterns in 1981–2010 were drastically different. In summer, productivity growth was associated with cooler temperatures over the US agricultural heartland (Midwest, Northeast, mid-Atlantic, and surrounding areas), but with warmer temperatures in California and its border areas (excluding much of the Central Valley) (Fig. 2*K*). Growing evidence indicates that hot temperatures in excess of optimal thresholds for growth can be very harmful to major grain crops such as corn, soybeans, and wheat (3–5, 28, 29). Heat stress can also negatively affect confined animal (dairy, beef, swine, and poultry) operations, increasing production costs and capital expenditures (30), reducing meat and milk production, and lowering animal reproduction rates (31). The situation in California is complicated by the large variety of crops, which leads to a wide range of dependences on seasonal climate conditions. For example, cotton, grapes, lettuce, and tomatoes are more productive in a warmer spring; strawberries and walnuts favor a cooler autumn; and hay yields are higher in a drier winter (32). In the Central Valley, higher temperatures are less beneficial, as summers are already warm (Fig. 2*K*), but they may have been favorable for the dramatic expansion of the wine industry in the northern areas in the late 20th century. These dependences may explain the TFPC correlation patterns in California and other

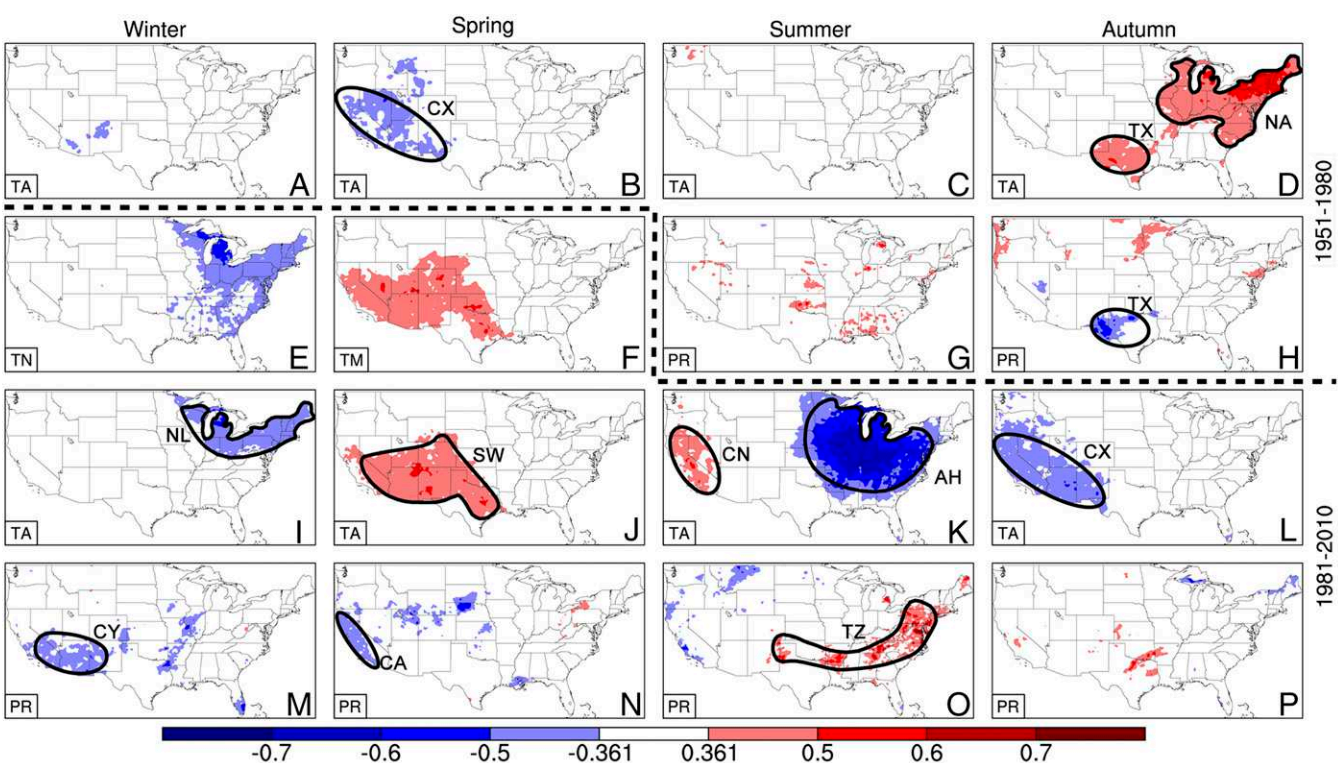

Fig. 2. Geographic distributions of TFPC–climate correlations. Regions defining key climate indices are outlined and labeled. In 1951–1980, TFPC correlated with cooler springs in CX (*B*), warmer autumns in NA and TX (*D*), and dryer autumns in TX (*H*), as well as scattered areas of TA and PR (*A*, *C*, and *G*). Winter and spring PR in 1951–1980 are not shown, as there were no significant correlations; they are replaced by 1981–2010 winter minimum temperature (*E*) and spring maximum temperature (*F*). In 1981–2010, TFPC correlated to cooler winters in NL (*I*), warmer springs in SW (*J*), cooler AH and warmer CN summers (*K*), and cooler autumns in CX (*L*), as well as to dryer winters in CY (*M*), dryer springs in CA (*N*), wetter summers in TZ (*O*), and scattered regions in autumn (*P*). Statistically insignificant correlations between ±0.361 are not depicted.

southwestern states (Fig. 2 *J*–*N*): spring (+), summer (+), and autumn (−) TA, and winter (−) and spring (−) PR.

Two additional differences distinguished 1981–2010 from the earlier period. First, areas where summer precipitation positively correlated with TFPC were no longer scattered across the country, but were concentrated along an arc stretching from the Northeast through the mid-Atlantic to the Texas High Plains (Fig. 2*O*). This arc rests in the transition zone between the Corn and Cotton Belts, neither of which exhibited strong correlations, likely because rainfall is generally abundant in the Corn Belt and water deficits in the Cotton Belt are offset by wide application of irrigation. The transition zone, on the other hand, consists of heavy grazing lands where pasture depends mainly on rainfall without irrigation support. Increased summer rainfall in the region may increase forage grass yields or reduce feed stock prices, increasing TFP for livestock production. Second, TFPC was negatively correlated with winter TA in broad areas straddling the Northeast and Lake States (including Ohio, Indiana, Michigan, and northern Wisconsin) (Fig. 2*I*). In these areas, early growing season soil moisture derives from winter snowfall that melts slowly during the spring. Warmer winter temperatures lead to snow melt and runoff throughout winter, depleting soil moisture to begin the growing season. Coupled with hotter summers, this process can dramatically reduce crop productivity. Most of these areas had no correlation with winter temperatures in 1951–1980. Coincidentally, in that earlier period, similar areas showed positive correlations in autumn.

To determine the evolving effects of climate variation, we performed a running correlation analysis over 20-y periods. These TFPC–climate correlation patterns, in general, reflect a clear transition between those observed in 1951–1980 and 1981–2010 (details are given in *Evolving Effects of Climate Variation* and Fig. S2). The results reinforce the finding that climate dependence significantly increased after 1980. In recent decades, positive temperature correlations noticeably weakened over time, and negative correlations strengthened. These changes suggest that the impacts of climate on TFPC became increasingly negative as agricultural production passed optimum temperature thresholds.

In summary, US agricultural TFPC correlated significantly with both temperature and precipitation in certain seasons over broad regions. These regions are all areas of major US agricultural production, including crops, livestock, and nursery products. Most of the observed statistical relationships are biophysically intuitive and seem to correspond with current understanding of how climate influences US agricultural production. We used seasonal temperature and precipitation averages over 10 significant regions (AH, TZ, SW, NL, CX, CN, CY, CA, NA, and TX, as defined in Fig. 2) to construct indices of key regional climate factors that affect TFPC. Based on these climate indices, we developed regression models for each period to capture TFPC–climate relationships. Model **1** simulates 1951–1980, and model **2** represents 1981–2010. We then compared their simulations to historical records to establish model creditability and determine the role of climate in US agricultural productivity.

Historical TFPC–Climate Dependence Simulations. Model **1** explains almost 50% of the total TFPC variance from 1951 to 1980, while model **2** represents around 70% of variance from 1981 to 2010. This finding matches well with previous estimates that, from 1979 to 2008, more than 60% of yield variability can be explained by climate variability (33); it also suggests that agricultural productivity has become more sensitive to climate in recent years.

Closer agreement between modeled and measured TFPC represents a more significant climate contribution. In the first period (1951–1980), TFPC fluctuations increased and model–measurement correspondences became tighter after ∼1971 (Fig. 3). The increased role of climate was likely due to the accelerated growth of crop production, because demand for crop exports surpassed that for livestock in the mid-1970s (18) (*Changes in Sectoral Contributions to TFP* and Fig. S3). As crop production is generally more sensitive to adverse weather events than livestock production, TFPC containing a larger contribution from crops fluctuates more and corresponds more closely to climate variations. Close model–measurement agreement

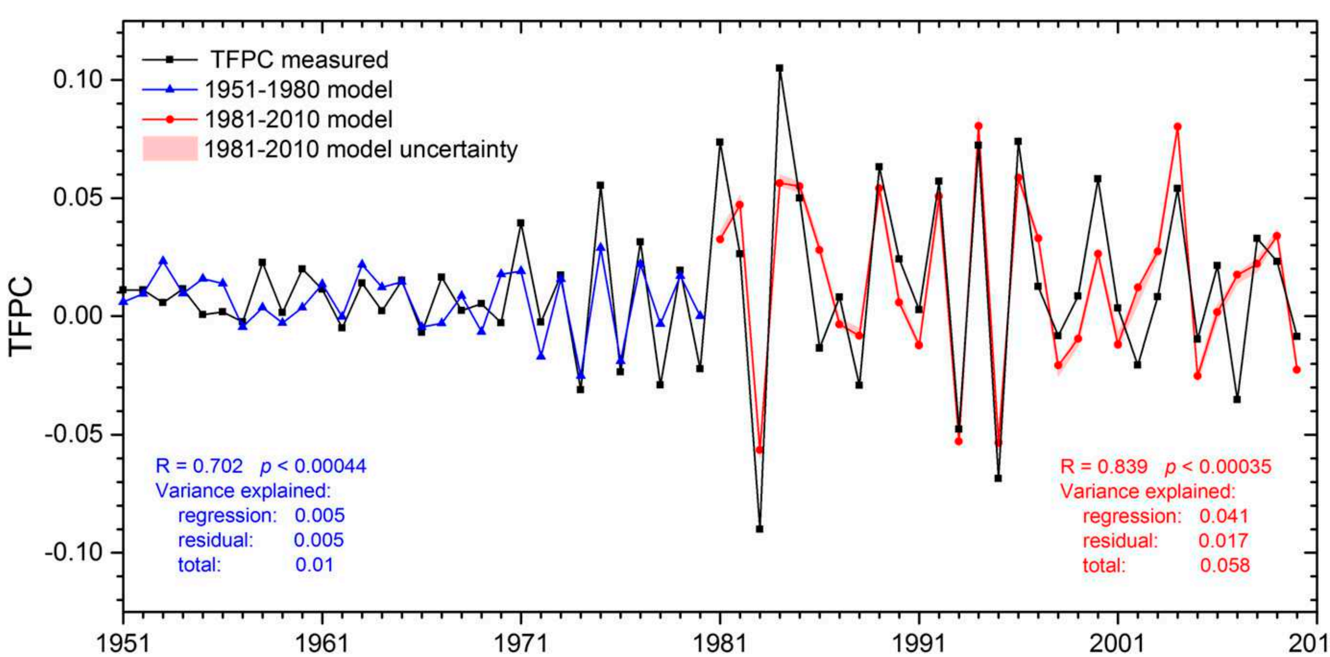

Fig. 3. Measured and simulated TFPC variations. The simulations include those by model **1** for 1951–1980 and by model **2** for 1981–2010. Also shown are the correlation coefficient (R) of the simulated with measured TFPC, the *p* value of the regression, and the explained, residual, and total variance for each period. The shaded area represents uncertainty in the 1981–2010 regression model, showing the 25th to 75th percentile range of submodel simulations when using 28-y bootstrap samples.

continued into the second period (1981–2010), indicating that agricultural TFPC became more strongly dependent on regional climate variations.

Larger departures of modeled from measured TFPC imply more influence from external nonclimate factors. The relatively large departures early in the second period likely stem from the significant impact of policy interventions in the early 1980s on measured agricultural productivity. In particular, the large swing in model departures between 1983 and 1984 is mainly associated with the 1983 PIK program, which encouraged farmers to reduce crop production in return for in-kind payments from government stores. The immediate effect was a drastic reduction in productivity (by close to 15 to 16%) as production fell but the input base remained relatively fixed. Productivity then snapped back and grew by almost the same amount immediately afterward, as output returned to normal with a relatively fixed input base. TFP growth skyrocketed as a result. Similarly, a large departure in 1986 may have been related to the Food Security Act of 1985 that reduced the influence of government price supports in favor of a more market-oriented farm policy (18). Since this policy-driven period, commodity prices have been largely based on market supply and demand.

Another significant departure began around 1998, with noticeable phase shifts in 2002 and 2007. It is possible that US agriculture was significantly changed by the production of oil crops, which saw the highest average growth rate among all crops from 1998 onward (18). Soybeans are the second-most important US field crop after corn. They transitioned from being overwhelmingly used for animal feed to accounting for ∼90% of total US oilseed production. This shift may have altered crop contribution to TFPC. In addition, recent mandate-driven demand for biofuels resulted in the conversion of almost 40% of the US corn crop to energy production, and so shifted land use from food to energy (34) and contributed to high crop prices. Further exploration is needed to determine the actual causes of these departures.

The United States has a long history of heavy public investment in agricultural research and development, which has contributed to sustained US agricultural productivity growth and an increasing supply of US agricultural products (23). Both farmers and consumers have reaped the benefits. Sustained investment in research and development is undoubtedly critical to maintaining long-term growth. However, variability in agricultural TFP growth, which consists almost entirely of variability in aggregate output growth, is also critical to sustainability. Our findings suggest that this variability over 1981–2010 is closely linked to climate variability in important crop-producing areas.

So far, the aggregate TFPC effects of regional climate trends have been relatively small. Observed trends in the climate indices have not all been significant, and their positive and negative effects on TFPC have partially canceled. Using model **2**, we calculated that the climate trends have caused a net TFP loss of 0.0003846 per year, which has been outweighed by a technological gain of 0.014865 per year. Thus, TFP has continued to grow at a significant rate. However, these key crop-producing areas are projected to see significant changes in climate in the coming years, including increased warming trends, decreased water availability, and enhanced extremes (28, 35). If the measured statistical relationships reflect reality, these changes could have important consequences for the long-term TFP growth of US agriculture.

Future TFP Change Projections. Although the impact of climate on US agricultural productivity seems relatively weak in the 1951–1980 period, TFPC sensitivity to climate variables has greatly increased in more recent times. This increase was accompanied by substantial changes in regional and seasonal correlation patterns. If the behavior observed in 1981–2010 represents the contemporary norm for TFPC responses to regional climate variations, model **2** can be used to evaluate potential TFPC responses to projected future climate changes. This analysis assumes that the effects of technological advances and adaptation practices remain the same as in 1981–2010. In other words, it presumes that agricultural producers would respond to future climate changes as they currently do to interannual climate

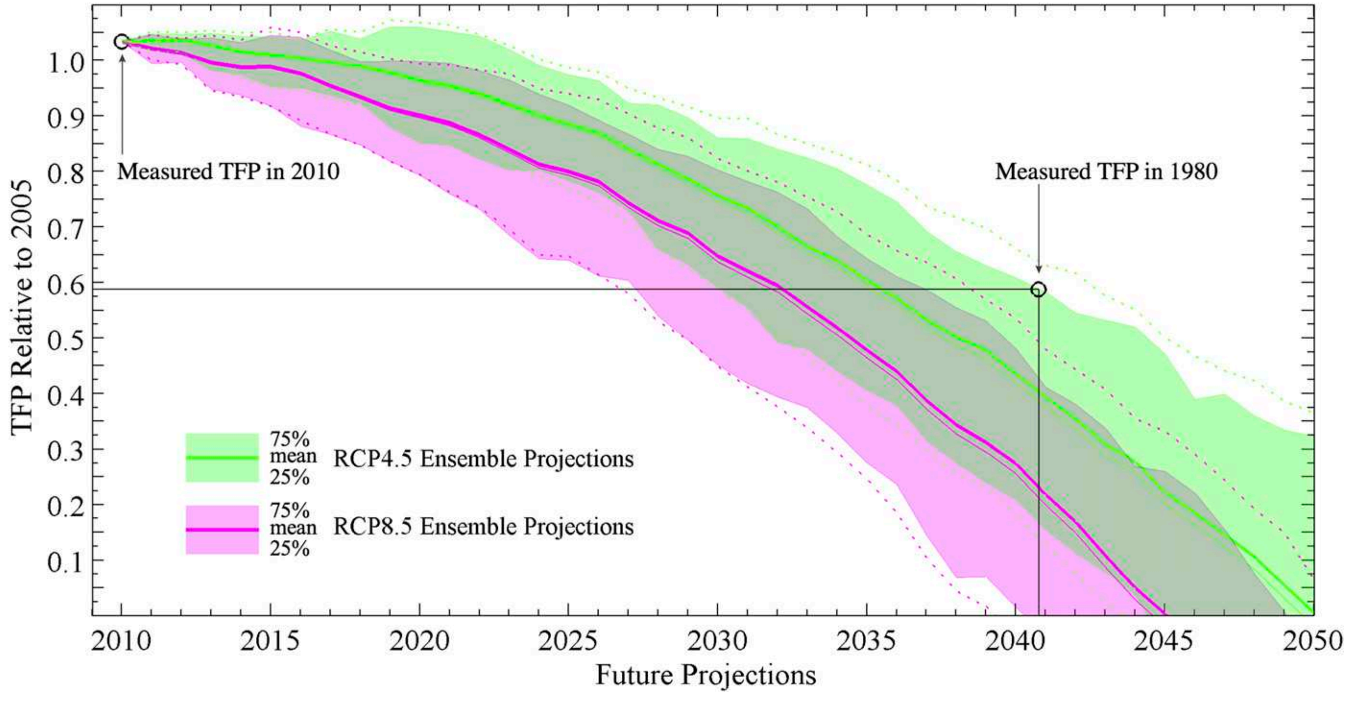

Fig. 4. Projected TFP variations through 2050. The ensembles are based on all available future climate realizations for both RCP4.5 and RCP8.5. The 25th and 75th percentiles represent uncertainty due to variance in climate projections. The measured TFP values in 1980 and 2010 are marked for reference. Submodel simulations were used to estimate uncertainty due to regression; the thin line shows the ensemble mean, and the dashed lines represent its 25th to 75th percentile range.

anomalies. The only differences modeled are future climate changes over these agriculturally responsive regions.

To assess climate change impacts on future TFPC, we adopted the Coupled Model Intercomparison Project Phase 5 (CMIP5) simulations for two representative concentration pathways: RCP4.5 (medium) and RCP8.5 (high), and derived changes to the climate indices in model **2**. A description of the CMIP5 simulation data used is given in *CMIP5 Climate Simulations*. Under both RCPs, TFP is projected to decline continuously, with faster rates after ∼2025 (Fig. 4). To determine key contributors to the future US TFP declines, we performed a factor analysis of model **2** based on projected changes in the regional climate indices, including a range of uncertainties depending on climate sensitivity and RCP forcing. The top four contributors to the decline were all related to the climate warming trend. The largest was the projected warmer summers in the Midwest (region AH), the second was the warmer autumns in scattered regions across the Southwest (CX), the third was the warmer springs in the Southwest (SW), and the fourth was the warmer summers in California and Nevada (CN). The fifth contributor was the projected decreasing amount and increasing variability of summer precipitation in the transition zone between the Corn and Cotton Belts (TZ). Details on the fraction of modeled variance each of these factors contribute, as well as explanations of their tendencies, are given in *Key Contributors to the Future US TFP Declines*.

Because the effects of technological advances, agricultural practices, and long-term factors such as CO_2 fertilization are treated as a constant, the modeled TFP decline represents the penalty arising solely from projected climate changes over the key agricultural regions. Using the ensemble mean projection from 2010 to 2040, the climate penalty will reduce TFP by ∼2.84% per year under RCP4.5 and 4.34% per year under RCP8.5, both larger than the measured TFP growth rate in recent decades. The rates vary significantly due to uncertainty in climate projections, but they show a strong increase over time in both scenarios (*Projected Rate and Uncertainty of Future TFP Loss* and Fig. S4). This penalty must be distinguished from projected decreases in crop yields, because yield and productivity are physically different measures, and the scope and methodology of our study is inherently different from past yield studies (*Differences Between Projections of Yield and Productivity*).

Thus, if technological advances and other adaptations to climate-driven change merely keep pace with recent historical rates, the average climate penalty under RCP4.5 will cause TFP to lose, by ∼2035, all of the gains achieved from 1981 to 2010. To overcome this loss, the effect of technological advances would have to double to sustain US agricultural productivity at the current level. RCP8.5 creates a larger penalty but only hastens the total loss of accumulated TFP growth by ∼3 y. Under either RCP, the projected climate penalty will substantially reduce US agricultural productivity in the coming decades.

These TFP projections must be interpreted in light of limitations in the model's explanatory ability, factors not considered in the model creation, and uncertainties inherent in the climate projections and regression model. First, the model itself describes ∼70% of measured TFPC variance, and the rest remains unpredictable. Because the model is constructed by linking observed regional climate anomalies to measured economic responses, it may no longer be applicable if future climate changes significantly exceed the magnitude of historical anomalies (thus TFP appears to become negative at the end of the simulated period in Fig. 4). Second, the model does not incorporate several factors, some that may decrease climate's impact on TFP, and others that could further enhance it. These factors include the effects of adaptation and regulation, evolving climate sensitivity, and reductions in ability to compensate for climate extremes using processes such as irrigation (*Sources of Modeling Uncertainty*).

Finally, there is a large degree of modeling uncertainty. Most of this uncertainty arises from climate projections, not only because of forcing differences between the two RCPs but also because of climate sensitivity variations among CMIP5 models. The total loss of the US agricultural productivity gained in 1981–2010 is projected to occur as much as 6 y earlier or later than the ensemble mean, respectively, by 25% higher or 25% lower climate sensitivities of the models. Meanwhile, 75% of the models project that US agricultural TFP will drop to pre-1980s levels by ∼2040 or earlier if the effects of technological advances and agricultural practices continue as in the past (Fig. 4). These ranges are similar under both RCPs. Further, 90% of models project this drop-off to occur by 2043 and 2051 for RCP8.5 and RCP4.5, respectively. Additional uncertainty comes from sampling errors in the regression model, which may alter the mean drop-off point by less than 1 y. Even taking these uncertainties into account, all gains in US agricultural productivity during 1981–2010 will likely be canceled by a climate penalty before ∼2050 if significant adaptation does not occur.

Implications

As the world's leading food commodity producer (20), it is critical that the United States sustain its growth in the future to support increasing domestic and global needs. Therefore, significant adaptation and technological advances are needed merely to maintain the current US agricultural productivity level. Consequently, there is an urgent need for policies to promote such changes, including large increases in research and development investments that can influence technological advances, new regional production practices, and major adaptation and mitigation strategies. These changes are expected to be more cost-effective if made in the agriculturally responsive or climate-sensitive regions identified above.

Although the United Nations' 2015 Paris Agreement set the stage for global action to limit climate change impacts, adaptation and mitigation strategies must be prioritized based on credible knowledge of regional impacts in all sectors. These strategies will be driven by national climate policies, which must be based on a clear understanding of climate impacts on overall economic growth. Strategy-critical information is mainly drawn from IAMs, which typically use a production function with capital and labor as inputs multiplied by a TFP growing factor at a specified rate, and then reduce the output with climate damage function (2). However, such functions vary greatly between different models, and have been criticized for relying on hard-to-validate assumptions about climate–economic linkages (12–15, 36). Our study offers an objective approach to understand the climate–productivity relationship and, in particular, to determine a credible climate damage function for use in IAMs. This approach will improve assessment of agricultural policy responses to global climate change operating at local levels.

Materials and Methods

TFPC–Climate Correlation Analyses. We used the US Department of Agriculture's national-level TFP estimates for 1948–2011 (18) to capture the impacts on aggregate output and aggregate inputs. The geographic distributions of climate data are from the latest observational analysis of PR, TA, and daily minimum and maximum surface air temperature (TN, TM); they are available from 1895 to 2013 on 0.26° grids over the contiguous United States, and were developed by the National Climatic Data Center from measurements at over 12,000 stations.

We analyzed the correlation between the TFPC yearly time series and individual climate variables at every US land grid for each season of two separate 30-y periods, 1951–1980 and 1981–2010. The location-wise correlations measure the temporal correspondences between TFPC and seasonal climate interannual variations, and the contrast between the periods measures their decadal changes. We focused on correlations larger than +0.361 or smaller than –0.361, which are statistically significant at the 95% confidence level assuming yearly independence. We also examined TFPC–climate correlations over five 20-y periods (1951–1970, 1961–1980, 1971–1990, 1981–2000, and 1991–2010) to test the robustness of the results and examine their evolution over time.

TFPC–Climate Regression Models. For each season in each region, we constructed the climate indices by averaging a specific variable (TA or PR) over all of the grids containing statistically significant (positive or negative) correlations. As outlined in Fig. 2, there are 10 seasonally changing regions of significant TFPC–climate correlations, eight in the 1981–2010 period, and four in the 1951–1980 period (two are found in both periods). For 1981–2010, the climate indices are summer TA in the agricultural heartland (AH); summer PR in the arc of the transition zone (TZ); spring TA in the Southwest (SW); winter TA in the Northeast and Lake States (NL); autumn TA across California, Oregon, Nevada, Arizona, and New Mexico (CX); summer TA in California and Nevada (CN); winter PR in southern California, Arizona, and western New Mexico (CY); and spring PR in California (CA). For 1951–1980, the climate indices are autumn TA in the expanded region across the Northeast through Midwest and mid-Atlantic (NA), spring TA across CX, and autumn TA and PR in Texas (TX). We define winter as December–January–February (DJF), spring as March–April–May (MAM), summer as June–July–August (JJA), and autumn as September–October–November (SON).

For each of these seasonal–regional climate indices, yearly anomalies were first calculated in reference to each period mean, and then each period was subject to a regression analysis with TFPC. As a first-order approximation, here we considered only linear, additive TFPC relationships with the anomalies of the climate indices. The interdependences among the responsive climate indices, if any, were included in the stepwise multivariance regression. Nonlinear effects, such as TA- or PR-squared and their product terms, as well as influences from climate anomalies in the previous year(s), were not considered, although both may have introduced uncertainty into the fit model prediction due to an inflated error term.

Using the same units as for the measured TFP data relative to year 2005 (= 1), the stepwise regression model for 1951–1980 is

$$\mathrm{TFPC}[1] = 0.006327 \quad +0.007573\cdot \mathrm{TA}_{\mathrm{SON.NA}} \quad -0.009827\cdot \mathrm{PR}_{\mathrm{SON.TX}} \quad -0.007508\cdot \mathrm{TA}_{\mathrm{MAM.CX}}. \tag{1}$$

Model **1** fits measured TFPC for 1951–1980 with a correlation coefficient of 0.702 ($P < 0.00044$) and a SE of 0.014, explaining 49.34% of the total variance (0.010). The constant term measures the expected TFPC if the climatic variables remain constant at the period mean. Therefore, it helps capture the TFPC that is attributable to other factors such as technical change, adaptation, and innovation. The remaining terms in the fitted regression estimate the impacts of regional climate variations. The three climate indices contribute ~27.64%, 11.59%, and 10.11% of the total variance explained. The fourth climatic index, $\mathrm{TA}_{\mathrm{SON.TX}}$, is not included in the model because it has strong cross-correlations with $\mathrm{TA}_{\mathrm{SON.NA}}$ (+0.551) and $\mathrm{PR}_{\mathrm{SON.TX}}$ (−0.540), and so independently contributes close to zero variance.

Similarly, the regression model for 1981–2010 is

$$\begin{aligned}\mathrm{TFPC}[2] = 0.014865 \quad & -0.010050\cdot \mathrm{TA}_{\mathrm{JJA.AH}} && -0.023636\cdot \mathrm{PR}_{\mathrm{DJF.CY}}\\ & +0.035730\cdot \mathrm{PR}_{\mathrm{JJA.TZ}} && -0.011561\cdot \mathrm{PR}_{\mathrm{MAM.CA}}\\ & -0.014439\cdot \mathrm{TA}_{\mathrm{SON.CX}} && -0.011849\cdot \mathrm{TA}_{\mathrm{MAM.SW}}\\ & +0.004774\cdot \mathrm{TA}_{\mathrm{JJA.CN}}.\end{aligned} \tag{2}$$

Model **2** fits measured TFPC for 1981–2010 with a correlation coefficient of 0.839 ($P < 0.00035$) and an SE of 0.028, explaining 70.41% of the total variance (0.058). Compared with 1951–1980, a greater number of significantly correlated climate variables explain a much larger fraction of TFPC variance, suggesting that climate impacts on TFPC substantially increased in 1981–2010. The constant term is ~2.35 times larger than the value for 1951–1980, indicating that the role of technological advances in US agricultural productivity growth was also considerably enhanced in this period. The impacts from the seven climate indices, listed in the equation in decreasing order, contribute ~38.91%, 14.41%, 5.82%, 4.90%, 4.41%, 1.60%, and 0.36% of the total variance explained. The eighth climatic index, $\mathrm{TA}_{\mathrm{DJF.NL}}$, is not included in the model because it has strong cross-correlations with $\mathrm{PR}_{\mathrm{JJA.TZ}}$(−0.470) and $\mathrm{TA}_{\mathrm{JJA.AH}}$(+0.419), and so independently contributes almost zero variance.

To determine the effects of sampling errors and examine whether any 1 y or 2 y contributed heavily to the overall results, we created an ensemble of 870 bootstrap samples from the historical data during 1981–2010. This ensemble included all possible 28-y subperiods, with the removal of any combination of two different years without repetition, for a total of 30 × 29 permutations. For each permutation, we repeated the stepwise regression analysis and so constructed 870 submodels corresponding to model **2**. The mean submodel projection differs from that of model **2** by less than a year. We use the 25th and 75th percentiles of the TFPC ensemble of these submodel simulations to represent the range of regression model uncertainty. This uncertainty is small (Fig. 3) and, as shown in Fig. 4, generally widens the spread of future projections by no more than 1 y to 2 y.

To check the robustness of the stepwise regression and avoid possible overfitting, we additionally conducted lasso regressions for both time periods, including all climate indices and minimizing the residual sum of squares. The results differed little from those of the stepwise regressions (*Lasso Regression Analysis*), suggesting that our models are robust.

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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,

$$
\begin{aligned}
\mathrm{TFPC[a]} = 0.006328 \quad & + 0.007243 \cdot \mathrm{TA}_{\mathrm{SON.NA}} && - 0.009420 \cdot \mathrm{PR}_{\mathrm{SON.TX}} \\
& - 0.007562 \cdot \mathrm{TA}_{\mathrm{MAM.CX}} && + 0.000645 \cdot \mathrm{TA}_{\mathrm{SON.TX}} \\
\\
\mathrm{TFPC[b]} = 0.014865 \quad & - 0.0098458 \cdot \mathrm{TA}_{\mathrm{JJA.AH}} && - 0.023616 \cdot \mathrm{PR}_{\mathrm{DJF.CY}} \\
& + 0.034577 \cdot \mathrm{PR}_{\mathrm{JJA.TZ}} && - 0.011355 \cdot \mathrm{PR}_{\mathrm{MAM.CA}} \\
& - 0.014077 \cdot \mathrm{TA}_{\mathrm{SON.CX}} && - 0.011299 \cdot \mathrm{TA}_{\mathrm{MAM.SW}} \\
& + 0.004521 \cdot \mathrm{TA}_{\mathrm{JJA.CN}} && - 0.000889 \cdot \mathrm{TA}_{\mathrm{DJF.NL}}
\end{aligned}.
$$

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.

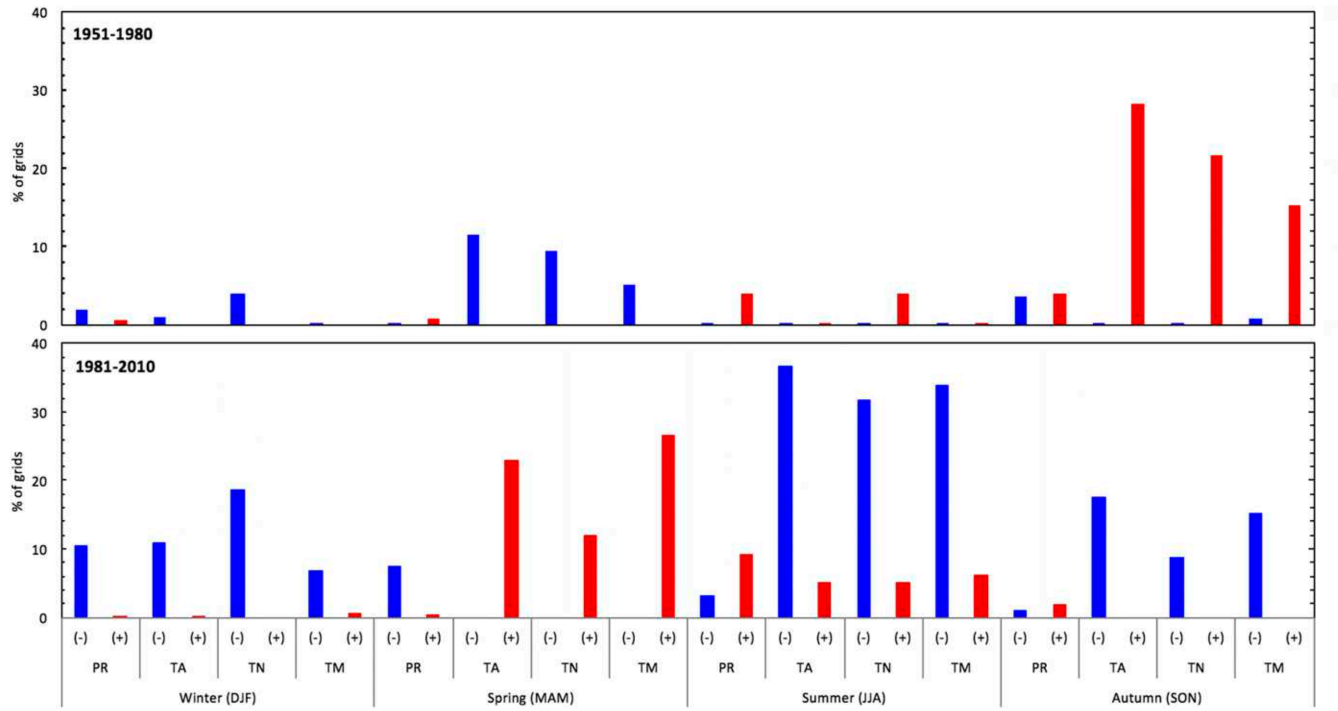

Fig. S1. The percentage of grids over US land that have significant correlations with TFPC. Each bar represents the value for each of the four climate variables in every season, during 1951–1980 (*Upper*) and 1981–2010 (*Lower*). The statistics are separate for positive (+, red) and negative (−, blue)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

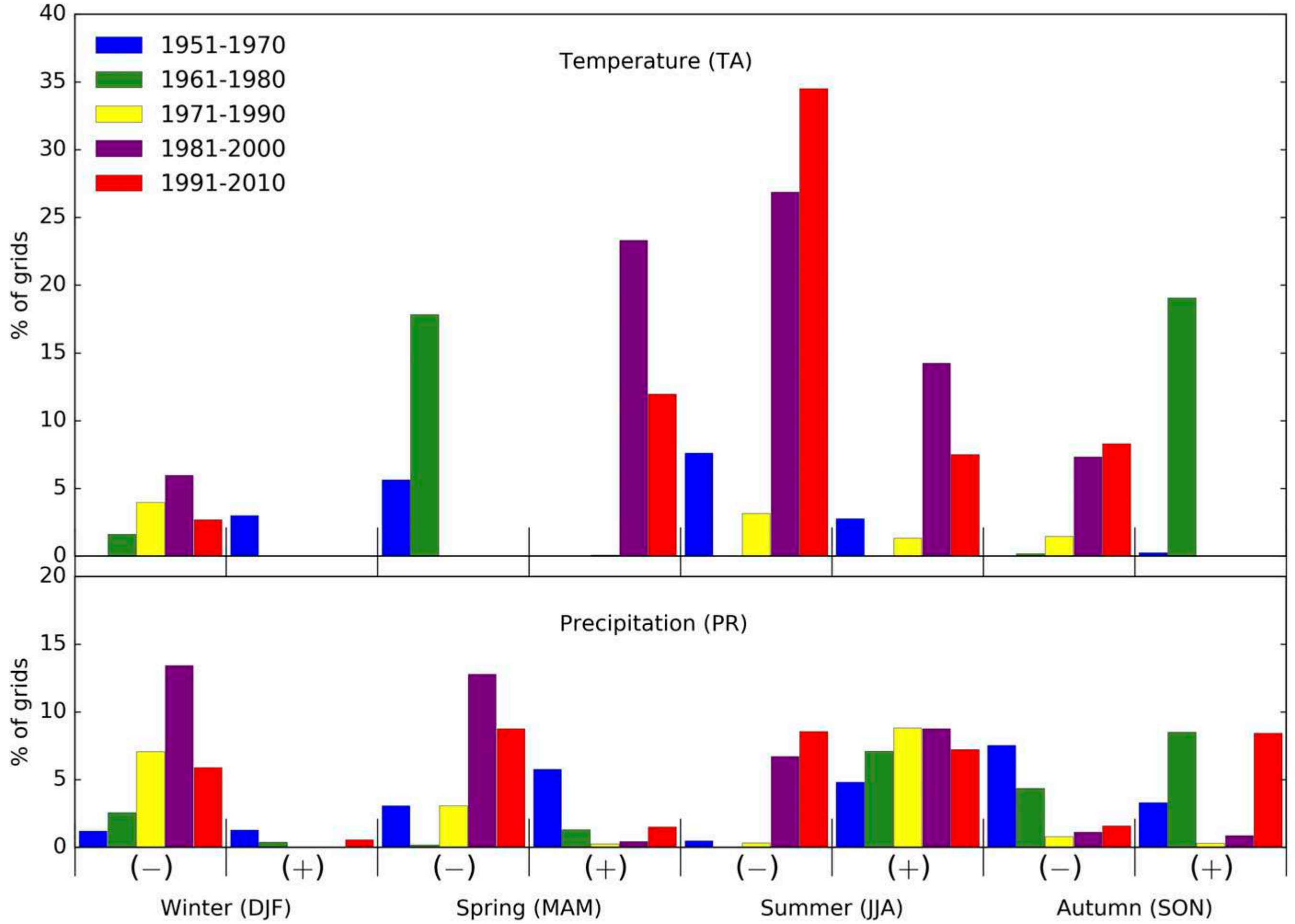

Fig. S2. The percentage of significant TFPC–climate correlations in each 20-y subperiod, including the percentage of grids in which TFPC significantly correlated with temperature (*Upper*) and the percentage of significant correlations with precipitation (*Lower*).

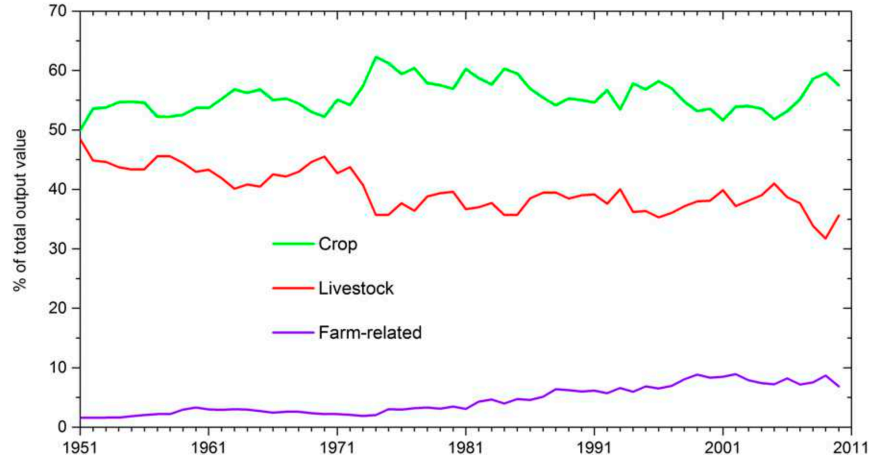

Fig. S3. Variations in the contribution of agricultural sectors to total value. Crops make up the majority of US agricultural value, with livestock (including miscellaneous livestock products not separately identified) seeing a somewhat decreasing role over time, and farm-related goods and services (including 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.

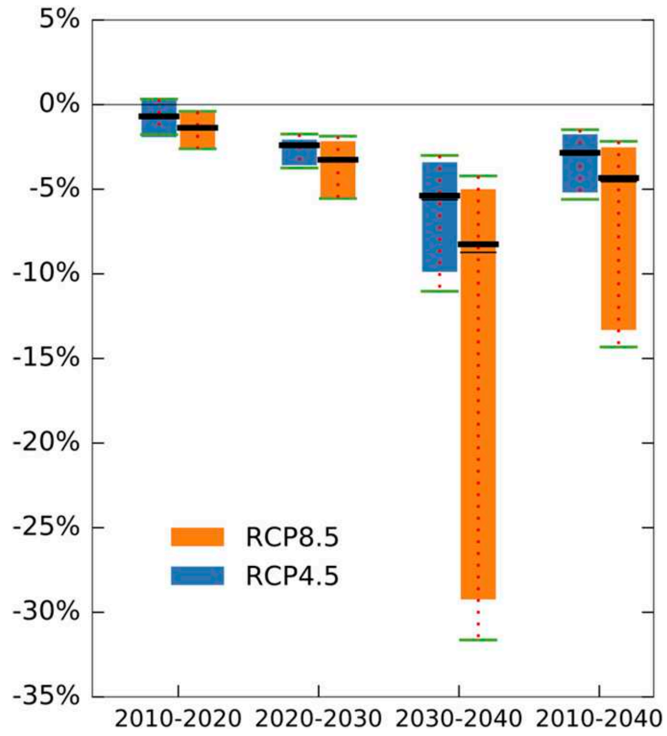

Fig. S4. Compound annual TFP growth rate for each RCP. The range of uncertainty due to climate projections is based on the 25th and 75th percentile GCM results. The dotted lines represent uncertainty in the regression analysis, and are based on 28-y submodels.