Accounting for the Impacts of Changing Configurations in Temperature and Precipitation on U.S. Agricultural Productivity

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Abstract:

The objective of this study is to investigate how changing configurations in temperature and precipitation are transmitted to productivity growth in the U.S. agricultural sector. In doing so, we account for farm heterogeneity in production possibilities and the considerable variations in weather and other physical characteristics of the environment. In contrast, the received literature on productivity growth assumes that firms share the same production possibilities and only differ with respect to their level of inefficiency. We do this by implementing a Random Parameters approach in a Stochastic Production Frontier framework. The resulting parameter estimates are used to decompose a multiplicative TFP index that yields measures of technological progress, technical efficiency change, environmental, and scale-mix efficiency. Our results indicate that even after accounting for knowledge stocks generated from investments in research and development there are significant reductions in productivity growth, primarily driven by weather anomalies.

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Keywords:

agronomic weather measures, environmental effects, total factor productivity, stochastic production frontier, U.S. agriculture

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1. Introduction

There is growing evidence that climate change will have significant impact on global agricultural production (Lobell, Schlenker, and Costa-Roberts 2011; IPCC 2014). CO_2 emissions have increased 46% since 1990 and this trend has resulted in a major decline in the global resource base for food production thus exacerbating food insecurity (United Nations 2013). Global population currently stands at 7 billion and is projected to rise to 9.7 billion by 2050 (United Nations 2015). Of immediate concern is how to provide food and sustenance to this rapidly growing population. Agricultural production will have to rise by 70% in order to meet 2050 projected food demand (FAO 2011). Beyond food production, the climate change phenomenon may take on other global security dimensions. Indications are that environmental disasters attributed to climate change, such as rising sea levels, floods, drought, and frequent and more intense storms are likely to cause large-scale disruption, massive loss of life and property, overwhelm disaster relief efforts, lead to wide-spread public unrest, large-scale refugee flows and even the failure of some fragile nations (Busby 2008; Femia and Werrell 2016; Werrell and Femia 2017).

Though the agricultural sector constitutes a small proportion of the U.S. GDP, climate change impacts raise major concerns given the significance of this country's role in global food markets. In 2016 the U.S. generated approximately 35% of global corn supply, 33% of global soybeans and close to 33% of global dairy products (U.S. Department of Agriculture 2017). Moreover, extreme weather events attributed to anthropogenic sources have exposed climate related stresses and demonstrated vulnerabilities in agriculture (Hatfield et al. 2014). An increasingly integrated global food system means that any climate shocks in the U.S. agricultural sector would be transmitted worldwide, thus raising the specter of food insecurity globally (Hatfield et al. 2014). Similarly, any negative shocks to world food systems as a result of climate change are likely to increase the reliance of U.S. agricultural output in meeting global shortfalls.

Several studies have considered the projected impacts of climate change on U.S. agriculture (e.g., Mendelsohn, Nordhaus, and Shaw 1994; Schlenker, Hanemann, and Fisher 2006; Deschenes and Greenstone 2007; Schlenker and Roberts 2009; Roberts, Schlenker, and Eyer 2013; Burke and Emerick 2016) and their conclusions have yielded a wide range of expected effects on U.S. agriculture. Whereas some studies present evidence that climate change might be beneficial to the farm sector as profit-maximizing economic agents adapt to a changing climate (e.g., Mendelsohn, Nordhaus, and Shaw 1994; Deschenes and Greenstone 2007), others anticipate mild impacts (Mendelsohn and Dinar 2003), a mixture of results due to a lack of significant climate trends in the United States (Lobell, Schlenker, and Costa-Roberts 2011) and significant declines in agricultural yields for major U.S. field crops such as corn, soybeans, and cotton (Schlenker and Roberts 2009; Roberts, Schlenker, and Eyer 2013; Burke and Emerick 2016). Nevertheless, the studies that present beneficial impacts due to climate change have been criticized for various reasons. The study by Mendelsohn and colleagues has been criticized for applying cross-sectional data while implicitly assuming a perfectly elastic supply of irrigation water (Cline 1996) and for overstating the potential benefits of warmer weather (Darwin 1999). The study by Deschenes and Greenstone (2007) has been criticized for data and coding errors in weather variables and input-output data, the climate change scenario that is used to simulate impacts predictions, and standard errors that are biased due to spatial correlation (Fisher et al. 2012).

Regarding the potential for adaptive mechanisms, some studies have considered regional adjustments in crop and livestock production (Mendelsohn, Nordhaus, and Shaw 1994), the role of irrigation in ameliorating reduced precipitation (Schlenker, Hanemann, and Fisher 2005), future irrigation demand under shifting climatic conditions (Marshall et al. 2015), and shifting growing seasons and planting dates in order to minimize the effects of rising temperatures during key stages in corn production (Ortiz-Bobea and Just 2013). In addition, there is evidence that long-run adaptation in the agricultural sector appears to have mitigated less than half of the short-run effects of extreme heat (Burke and Emerick 2016). Notwithstanding, the U.S. farm sector continues to adapt to climate change via various mechanisms, such as crop rotation, fertilizer management and water management, and these strategies appear to have mitigated some of the negative consequences of climate change (Hatfield et al. 2014).

The primary objective of this study is to investigate how changing configurations in temperature and precipitation are transmitted to U.S. agricultural productivity growth. In doing so, we combine county-level agricultural input-output data, with agronomic measures of weather (growing degree days, harmful degree days, vapor pressure deficit and growing season-precipitation), characteristics of the production environment (e.g., clay and sand content, salinity levels, moisture capacity, soil permeability levels, length of slope), and knowledge stocks generated from cumulative public expenditures in research and development. These variables are incorporated into a stochastic production frontier model and the parameter estimates are subsequently used to construct a total factor productivity (TFP) index. Decomposition is then implemented in order to generate yield TFP measures that isolate and explicitly account for weather effects, technological progress, technical efficiency, and scale and mix efficiency changes. These measures provide a better understanding of U.S. agricultural productivity growth.

Climate shifts vs. random weather fluctuations

In this study, we make a distinction between random fluctuations in weather and climate shifts. Whereas climate refers to the distribution of outcomes over long intervals (e.g., over several decades), weather on the other hand refers to a particular realization from a climate distribution. Hence, *weather variation* refers to shorter-run temporal fluctuation in temperature and precipitation within a given geographic area (Dell, Jones, and Olken 2014, p. 741). The central argument is that changing climate causes fluctuations in weather, and that weather has a direct biophysical impact on agricultural output (Nelson et al. 2014). In this sense, "climate is perceived to be predictably variable, so that a farmer can make adjustments ex-ante while daily weather is unpredictable, so that a farmer must cope with it ex-post" (Seo 2013, p. 113). Thus, because weather fluctuations constitute unanticipated shocks on output, these are more difficult to address and are easier to discern using panel data models.

Therefore, our identification strategy relies on exploiting within-county year-to-year fluctuations in weather variables in order to identify their effects on agricultural output. Unlike the use of long-run climate variables, which are likely to be fixed over the duration of the panel, hence serially-correlated with time-invariant characteristics of the production environment (Fisher et al. 2012), year-to-year fluctuations in weather are random and better identify the effects of changes in climatic conditions on economic outcomes (Burke and Emerick 2016).

In order to account for adaptive mechanism we incorporate knowledge stocks generated from cumulative public expenditures in agricultural research and development (R&D). Such public expenditures differ across states, thus this is akin to introducing an exogenous spatially heterogeneous time trend, which ensures that the relationship of interest is identified by local shocks (Dell, Jones, and Olken 2014). Moreover, this approach of incorporating the potential for adaptation via knowledge stocks created from expenditures in public goods helps to allay the '*dumb-farmer*' scenario (see Mendelsohn, Nordhaus, and Shaw 1994, p. 754) which is used to characterize a typical farmer that is unresponsive to changing climatic conditions.

The rest of this paper is organized as follows: Section 2 presents the analytical framework as well as the theoretical foundation for the random parameters stochastic production frontier. Section 3 illustrates the methodology that is used to decompose a total factor productivity index. In section 4 we introduce the data. We present the results in section 5 and finally present the concluding remarks.

2. Analytical Framework

The evaluation of the effects of year-to-year fluctuations in weather on agricultural output is conducted in two stages. The first stage involves an estimation of a Random-Parameters Stochastic Production Frontier in order to capture spatial and temporal firm-level effects. The second stage consists of the decomposition of a total factor productivity (TFP) index in order to capture the growth effects. We proceed by assuming a representative decision-making unit (DMU) that has access to a period-and-environment specific technology set that characterizes all feasible input-output combinations under a set of environmental conditions. This period-*t* technology under conditions characterized by environment z is given as:

(1) $$T^t\,(z) = \{\,(x, q) \in\, \mathfrak{R}_+^{M+N}\!: x \text{ can produce } q \text{ in environment } z \text{ in period } t\}$$

We also assume that the standard theoretical properties of a regular period-*t* technology hold (O'Donnell 2016, p. 330). We proceed by introducing subscripts *i* and *t,* into the notation that characterize firm and time, respectively, such that, q_{it}, x_{it}, and z_{it} now represent output, a vector of inputs and a vector of environmental characteristics for DMU *i* in period *t*, respectively.

Consider a Cobb-Douglas stochastic production frontier that represents the unknown technology and that captures the level effects of weather, which is expressed as:[1]

$$(2) \qquad \ln q_{it} = \sum_{i=1}^{I} \phi_i + \gamma_h \ln g_{ht} + \sum_{m=1}^{M} \beta_{mit} \ln x_{mit} + \sum_{j=1}^{J} \rho_j \ln z_{jit} + v_{it} - u_{it}$$

where: q_{it} is a measure of firm-level output; g_{ht} represents state-level knowledge stocks generated from cumulative expenditures in research and development (R&D); $x_{1it}, \ldots, x_{6it}$ are land, labor, capital, intermediate materials and livestock, irrigation; $w_{1it}, \ldots, w_{4it}$ are weather variables (i.e., growing degree-days, harmful degree days, vapor pressure deficit, and growing season precipitation); $z_{1it}, \ldots, z_{9it}$ represent physical characteristics of the production environment (i.e., fraction of land under clay and sand, permeability of the soil, susceptibility to erosion, length of slope); v_{it} is an unobserved variable representing statistical errors and is distributed $v \sim N(0, \sigma_v^2)$; and finally, u_{it} is a nonnegative technical efficiency effect with distributional parameters $u \sim N^+(0, \sigma_u^2)$.

Total Factor Productivity

Total factor productivity (TFP) is defined as the ratio of aggregate output to aggregate inputs used over a given period (Solow 1957; Jorgenson and Griliches 1967; O'Donnell 2016). In the single output case, which is the case in this study, the multiplicative index that compares TFP of firm *i* in period *t* with the TFP of firm *k* in period *s* is the Total factor productivity index denoted as:

$$(3) \qquad TFPI^M(x_{ks}, q_{ks}, x_{it}, q_{it}) = \frac{q_{it}}{q_{ks}} \prod_{m=1}^{M} \left(\frac{x_{mks}}{x_{mit}}\right)^{b_m}$$

[1] We do not appeal to the more flexible and commonly used translog specification because it fails to satisfy some regularity conditions that are necessary in order to guarantee the existence of a regular metatechnology that conforms to economic theory (see O'Donnell 2012, 2016).

where $b_1, \ldots, b_M$ are any nonnegative weights such that $\sum_{m=1}^{M} b_m = 1$. Furthermore, $b_m = \bar{\beta}_m / \sum_{m=1}^{M} \bar{\beta}_m$, where $\bar{\beta}_m$ is the estimated mean of the random parameters. By substituting the antilogarithm of the right-hand side of equation 2 into equation 3, we obtain the full expression of the TFP index as follows:

(4) $TFPI^M(x_{ks}, q_{ks}, x_{it}, q_{it})$

$$= \left[\frac{exp(\sum_{h=1}^{H} \gamma_h g_{hit})}{exp(\sum_{h=1}^{H} \gamma_h g_{hks})}\right] \left[\prod_{j=1}^{J} \left(\frac{z_{jit}^{\rho_{jit}}}{z_{jks}^{\rho_{jks}}}\right) \prod_{m=i}^{M} \left(\frac{x_{mit}^{\beta_{mit}-b_m}}{x_{mks}^{\beta_{mks}-b_m}}\right) \left(\frac{exp(\phi_i)}{exp(\phi_k)}\right)\right] \left[\frac{exp(u_{it})}{exp(u_{ks})}\right] \left[\frac{exp(v_{it})}{exp(v_{ks})}\right]$$

The TFPI in (4) above decomposes into the following six components. The first term is a technology index (TI) that captures technological progress as a result of cumulative R&D expenditures. The argument is that the R&D investments result in new knowledge that is productivity enhancing. The second component is an environmental effects index (EI) that captures the contribution of observed time-varying weather fluctuations and other physical characteristics of the production environment to TFP. The third term is the output-oriented scale efficiency index (OSEI), a component that measures productivity gains linked to economies of scale. The fourth term is an Agricultural index (AI) that measures the effect of unobserved time-invariant characteristics of the production environment. The fifth term is an output-oriented technical efficiency index (OTEI) that captures movements towards and away from the frontier. And the last term is a statistical noise index (SNI) that accounts for measurement errors and other sources of statistical noise.

Data

The data consists of a panel of county-level input-output data drawn from the U.S. Department of Agriculture, Census of Agriculture for the years 1987, 1992, 1997, 2002, 2007 and 2012. The 'State and County rankings' volume that is published alongside every census report is used to select 340 of the top agricultural counties across all the 48 conterminous states, based on the total market value of agricultural products sold in 2012. Figure 1 illustrates the spatial location of the agricultural counties used in this analysis. Aggregation at the county-level can be justified based on past research that finds evidence that U.S. agricultural producers behave collectively as if they were price-taking, and profit-maximizing firms (e.g., Williams and Shumway 1998). The output variable is the total value of agricultural sales. The input variables include: agricultural land in acres; livestock (number of dairy cows, beef cows, hogs, sheep, horses, poultry) converted into animal equivalents using an approach that accounts for the feed requirements of each animal type (USDA 2000); value of machinery and equipment; hired and contract labor hours; and expenditures on intermediate materials (fertilizer, chemicals, electricity and gasoline). The market value of agricultural products sold that represents the output variable is converted into constant-2016 dollar values using agricultural price indexes constructed by the USDA (USDA 2016b). The variable representing the value of machinery and equipment is constructed using the perpetual inventory method, which imputes net additions to the capital stock (e.g., Christensen, Jorgenson, and Lau 1973; Griliches 1980; Madsen 2007; Madsen and Islam 2016). Using 1987 as the base year, any changes in machinery and equipment values are considered to reflect net investments in capital. These figures are then adjusted to 2016 dollars.

Weather Measures

Data on contemporaneous temperature and precipitation are derived from the Parameter-Elevation Regressions on Independent Slopes Model (PRISM) Climate Group. The PRISM incorporates a climate-mapping system to generate temperature and precipitation information at ‘2.5 by 2.5’ mile grid cells for the entire United States and accounts for the effects of elevation, coastal proximity, temperature inversions, and terrain induced air-mass blockage (Daly et al.

2008, 2012; Daly, Smith, and Olson 2015). The weather measures are used to construct estimates that comprise growing degree-days, harmful degree-days, vapor pressure deficit, and growing season precipitation. We discuss each measure below.

Growing Degree-Days

Schlenker and Roberts (2009) argue that the true underlying relationship between temperature and yield is nonlinear and is best-characterized using growing degree-days. From an agronomic perspective, each crop species relies on ambient weather conditions from planting to harvesting and has a temperature range that is considered optimal for crop development (Hatfield et al. 2014). Growing degree-days capture the accumulated exposure of crops to heat between given upper and lower bounds during the growing season (Roberts, Schlenker, and Eyers 2013; Burke and Emerick 2016). We use daily maximum and minimum temperatures as well as PRISM's inverse-distance squared weighting interpolation methods to obtain estimates for each '2.5 by 2.5' mile grid in the county and thereafter we average over the grids in each county. The growing degree-days are obtained by calculating the number of degrees above a lower threshold and below an upper threshold and sum across all the days in the growing season, April to September. (see Roberts, Schlenker and Eyer 2012). Furthermore, growing degree-days are constructed for each county in the dataset based on the predominant field crop in the county for each of the census of agriculture years: 1987, 1992, 1997, 2002, 2007 and 2012.

Harmful Degree-Days

Agronomists also recognize that beyond certain thresholds, higher temperatures are likely to negatively affect crop development (Hatfield and Prueger 2015). Therefore, we incorporate into the model a non-linear measure that captures the number of days within the growing season with extreme temperatures. This measure is expected to capture the yield-decreasing range, and thus we refer to this as harmful degree-days (e.g., Schlenker, Hanemann and Fisher 2006; Schlenker, Roberts and Eyers 2013).

Vapor Pressure Deficit

Vapor pressure deficit (VPD) is the difference between the amount of moisture currently in the air and how much moisture the air can hold when it is completely saturated. It captures the potential of the surrounding air to pull moisture from the foliage through transpiration (Ficklin and Novick 2017). Rising temperatures lead to higher levels of vapor pressure deficit between the saturated foliage and the ambient air, which then leads to higher rates of evapotranspiration, which is the amount of water that is lost from the leaf surface. Plants respond to higher rates of VPD by reducing stomatal conductance in order to prevent excessive water loss and this in turn limits plant carbon uptake, thus leading to wilting and stunted growth (Ficklin and Novick 2017). Conversely, when the air is fully saturated with humidity, leaves transpire less, leading to low VPD. This reduces the rate of transpiration thus limiting the ability of the plant to take up essential minerals, which may lead to mineral deficiencies and plant susceptibility to disease pathogens (Ficklin and Novick 2017). Both scenarios may lead to reduced crop development and yields. We incorporate measures of averages of daily maximum and minimum VPD over the growing season for all counties in the dataset using PRISM's inverse-distance squared weighting interpolation methods in order to obtain estimates for each '2.5 by 2.5' mile grid in the county (see Daly, Smith, and Olson 2015).

Growing Season Precipitation

Finally, we include a measure of cumulative precipitation over the growing season, April to September. This measure is split into two: spring precipitation (April-June) and summer precipitation (July-September), which capture cumulative precipitation in the early growing season and the latter half of the growing season, respectively.

Irrigation

As mentioned above, in the absence of adequate rainfall, additional water can be supplied via irrigation. According to the U.S. Geological Survey (USGS 2014), the agricultural sector was the second largest consumer of water resources in United States. Combined water withdrawals used in irrigation, livestock and aquaculture accounted for approximately 115,000 million gallons per day, with 62.4 million acres of land under irrigation in 2010 (USGS 2014). Estimates of volumetric measures of water applied in agriculture at the county-level are obtained from the U.S. Geological Survey and are available for the years 1985, 1990, 1995, 2000, 2005 and 2010.[2] Cubic spline interpolation methods are used to match the irrigation data with the input-output data (e.g., Yang and Shumway 2016).

Soil Quality

We conjecture that agricultural production is likely to be impacted by topography and soil characteristics. Therefore, we incorporate into the model information on the physical attributes of the land, obtained from the National Resource Inventory of the U.S. Department of Agriculture. This information comprises data on soil samples obtained from soil surveys. It also contains detailed information on the land characteristics such as measures of susceptibility to soil erosion (k-factor), estimates of susceptibility to floods, length of slope, permeability, fraction of land cover under clay and sand, level of moisture capacity, and salinity of the soil. Similar measures of soil characteristics have been used in other studies of climate change (e.g., Deschenes and Greenstone 2007; Schlenker, Hanemann and Fisher 2006).

[2] U.S. Geological Survey data on irrigation are constructed from estimates of all secondary sources of water used for agriculture and does not indicate if these volumetric measures are obtained from groundwater or surface water sources.

Research and Development

New technologies (i.e., new methods for transforming inputs into outputs) are discovered through research and development (R&D). Public R&D expenditures are incorporated into the stochastic production frontier in order to capture technological progress. This is an improvement over the common practice of measuring technological change using a simple time trend. The state-level public expenditures dedicated to agricultural research used in this study are similar to those used in Huffman and Evenson (1992), Huffman and Evenson (2006), and Huffman (2010) [3]. The R&D expenditure data are originally extracted from the Current Research Information System (CRIS) that is maintained by the National Institute for Food and Agriculture (NIFA). The data consist of outlays dedicated to agricultural research that are allocated via the USDA's Agricultural Research Service and Economic Research Service, State Agricultural Experiment Stations (SAES), and Schools of Veterinary Medicine.

The R&D stocks are constructed as a weighted sum of previous years flows using a 35-year lag. This 35-year lag captures the time frame from when the initial R&D investment is made and consists of: a research lag, when experimental work is done; a development lag, that precedes the commercial phase; and finally an adoption lag, when the new variety is adopted by farmers, and net benefits increase until they reach a maximum (Alston et al. 2010, p. 244). The trapezoidal form for the lag distribution that is used to characterize the weights to be applied to past research expenditures is taken from Huffman and Evenson (2006) and Huffman (2010). These data has been used in various studies, most recently by Wang et al. (2012, 2013) and by Jin and Huffman (2016).

[3] We are grateful to Professor Wallace Huffman (Iowa State University) for sharing the dataset on R&D expenditures.

Furthermore, investments in R&D should also account for transfer of technology across geopolitical boundaries, that is spillover effects, because new knowledge created in one geopolitical entity can have impacts elsewhere (Alston et al. 2010). We expand R&D measures by incorporating estimates of spillover effects. This way, the R&D stock in each state is a function of its own stock of knowledge, as well as spillover stocks of knowledge from other states that have a similar mix of outputs (see Alston et al. 2010, p:274). Summary statistics of all the variables incorporated in the stochastic production frontier model are provided in Table 1.

Results

Statistical tests and parameter estimates

An important aspect of agricultural production in the United States is the key disparity between the eastern half and the western half. Western states are characterized by a semi-arid climate compared to the sub-continental eastern half (Schlenker, Hanemann, and Fisher 2006). For this reason, western agriculture is heavily dependent on irrigation for primary purposes while eastern states utilize irrigation for supplemental purposes only (Schlenker, Hanemann, and Fisher 2006; Wichelns 2010). We conduct a statistical test to measure if this effect is significant enough to warrant separating the model into a western vis-à-vis an eastern half. A likelihood ratio test of the pooled vs. the restricted model generates a likelihood-ratio statistic of 147.309 with a p-value=0.000 and this provides evidence in favor of a pooled model.

The model represented by equation 2 is estimated using simulated maximum likelihood methods. There are possible concerns regarding the potential for endogeneity in stochastic production frontier models (Mutter et al. 2013; Tran and Tsionas 2013; Shee and Stefanou 2015). A possible source of endogeneity in our model is that input choices may be driven by weather outcomes. A Wu-Hausman test for endogeneity is conducted; where the null hypothesis is that the variable under consideration, in this case irrigation, is exogenous. The logarithms of intra-annual precipitation from 5 years prior are used as instruments. We obtain a Wu-Hausman test statistic=3.30 and a p-value=0.1694; thus, we fail to reject the null hypothesis of exogeneity.

The estimated coefficients are presented in Table 2. The estimates for the conventional inputs (i.e., land, labor, machinery, livestock, intermediate materials, and irrigation), are interpreted as partial output elasticities. The estimated partial elasticities are nonnegative, which is consistent with our assumption of strong disposability of inputs. A Wald test for the null hypothesis of constant returns to scale generates a test-statistic of 39.25 with a p-value = 0.000. Therefore, we reject the null hypothesis that this model exhibits constant returns to scale. In fact, the sum of the coefficients, $\hat{r} = 1.11$, reveals slightly increasing returns to scale. The values of σ_v^2 and σ_u^2 show that the inefficiency component dominates the statistical error component in the overall error term. The estimated coefficient for R&D indicates that stocks generated from the investment in R&D contribute, *ceteris paribus*, 11.05% to agricultural output.

The maximal possible output is affected by the seasonal spread and fluctuations in year-to-year temperature and precipitation as well as characteristics of the production environment, such as soil quality. We conjecture that weather fluctuations impact agricultural output in a non-linear fashion. Hence we model this relationship via measures of growing degree-days, harmful degree-days, vapor pressure deficit; and linearly using a cumulative measure of precipitation during the growing season. Separate Wald tests with the null hypothesis that the weather variables, and the land quality measures are not jointly significant generate F-statistics of 3.98 and 8.79 respectively, with p-values=0.000 in both cases. Therefore, we strongly reject the null hypothesis that the weather variables and the soil quality measures do not belong in the model.

We experiment with multiple specifications for the weather variables. The resulting model that we select minimizes the Bayesian information criteria and consists of level and squared-terms for growing degree-days, harmful degree-days, spring precipitation; a level term for maximum vapor pressure deficit; and the cross product of harmful degree-days and spring precipitation. The impact of growing degree-days, and harmful degree-days indicate weakly positive and negative effects on output respectively. Conversely, the effects of spring precipitation, the square term of growing degree-days, and the interaction term of harmful degree-days and spring precipitation have strongly positive effects on output. On the other hand, maximum vapor pressure deficit, and the square terms for spring precipitation, and harmful degree-days have strongly negative effects on output.

As mentioned above, we include the characteristics of the production environment (e.g., clay content, sand content, permeability, moisture capacity, length of slope, k-factor, flood prone) in order to capture time invariant unobserved effects. Results indicate that counties characterized by greater proportions of clay having strongly positive effects on output. Clay soils are amenable to farming because their small-sized particles have more surface area and create layers in the soil that can hold more water and nutrients. The effects for the other physical characteristics of the soil and land in which agricultural production takes place reveal that counties characterized by higher levels of moisture capacity, and soil permeability also have strongly positive effects on output. On the other hand, the marginal impact of soils characterized by high susceptibility to erosion (k-factor), and wetlands, *ceteris paribus*, have strongly negative effects on agricultural output. In addition, our model comprises a fixed effect that captures unobservables in agricultural production west of the 100th Meridian; which is, the boundary that roughly demarcates the semi-arid climate to the West of the United States where agriculture is heavily dependent on irrigation and hence more vulnerable to shocks due to water scarcity (Schlenker, Hanemann and Fisher 2006; Wichelns 2010). The parameter estimate that captures agricultural production west of the 100th Meridian indicates, *ceteris paribus*, a statistically significant reduction in agricultural output at a rate of 4.3% per annum.

Decomposition of Total Factor Productivity Index

As indicated above, we define total factor productivity index (TFPI) as aggregate output divided by aggregate input. The parameter estimates from equation 2 are used to decompose the TFP index following equation 4 into a technological index (TI), which measures shifts of the production frontier due to the discovery of new technologies; an output-oriented technical efficiency index (OTEI), which measures movements towards or away from the frontier due to the use of different technologies; an output-oriented scale efficiency index (OSEI), that measure productivity gains linked to economies of scale; an environmental effects index (EI), which captures changes in TFP due to year-to-year fluctuations in weather; an agricultural index (AI), which measures changes in TFP due to time-invariant characteristics of the land; and a statistical noise index (SNI) as defined in equation 5.

Moreover, the TFP index that we use is a proper index in the sense that it satisfies several basic theoretical axioms including monotonicity, linear homogeneity, identity, commensurability, proportionality, and transitivity (see O'Donnell 2016). The transitivity axiom, guarantees that we can make a direct comparison of the TFPI of two DMUs and that they should yield the same estimate of TFP change as an indirect comparison through a third DMU (O'Donnell 2012). In this study, all indexes compare the relevant value of any DMU in any particular year against the value of a reference DMU, which is Weld County in Colorado (CO) in 1987.

The way to interpret TFPI is as follows: Fresno county, California (CA), the largest agricultural county according to the 2012 agricultural census generated \$3,782.55 million of agricultural output in 2012. On the other hand, Weld County in Colorado (CO) generated \$1,283.56 million and \$1,415.28 million of agricultural output in 1987 and 2012, respectively[4]. Thus the TFPI that compares Fresno County in 1987 to Weld County in 1987 decomposes as $TFPI_{Fre\ 12, Weld\ 87} = 0.91$ as illustrated in equation 3. In words, Fresno County in 2012 was approximately nine-tenths as productive as Weld County in 1987. A comparison of Weld County productivity in 2012 vis-à-vis 1987 translates as $TFPI_{Weld\ 12, Weld\ 87} = 0.90$. Again in words, Weld County in 2012 was approximately nine-tenths as productive as Weld County in 1987. By the transitivity property we conclude that Weld County in 2012 was as productive as Fresno County in the same year.

Productivity growth is measured as the year-to-year percentage rate of growth in TFP and decomposes as: %ΔTFP = %ΔT + %ΔOSE + %ΔOTE +%ΔE +%ΔAE + %ΔSN, where the right-hand-side components are percentage rates of growth in TFP due to changes in technology (%ΔT), output-oriented scale efficiency (%ΔOSE), output-oriented technical efficiency (%ΔOTE), environmental effects (%ΔE), agricultural effects (%ΔAE) and statistical noise (%ΔSN). For conciseness, we present results of TFP growth by placing each county into one of eight plant-hardiness zones in the contiguous United States as illustrated in Figure 2. These zones, which are based on the average annual minimum winter temperatures, are generated by the U.S. Department of Agriculture for purposes of illustrating regions with varying climatic conditions. Thus each zone is on average, 10°F warmer (cooler) than its neighboring region. Table 3 presents estimated year-to-year percentages rates of growth in TFP and its components

[4] All monetary values are converted to 2016 dollars using the U.S. Department of Agricultural price index generated by the economic research service.

for the counties in our sample over the period 1987-2012. Viewed in concert with Figure 2, we observe that with the exception of Zone 3, which consists of counties in the northern parts of Montana, North Dakota, and Minnesota, all the regions in the United States initially experienced positive TFP growth. Results from the most recent decade 2003-2007, and 2008-2012 reveal significant reductions in TFP growth in all regions. The decline in overall productivity growth was primarily driven by reductions in technological change, output-oriented technical efficiency change, as well as sharp declines in weather effects.

It is straightforward to track well-documented recent and past weather shocks and their impacts on U.S. agricultural productivity growth. For example, California's six year drought between 1987-1992 and its most recent drought between 2008-2014 (California Department of Water Services 2015) are picked up in our results as -8.05% and -2.68% declines in weather effects in zone 9 over the periods 1987-1992 and 2008-2012 respectively. In addition the 1988 drought that devastated most of the Midwest region of the United States (Fuchs et al. 2012) is manifested as -8.20% and -2.06% reductions in TFP due to weather effects, in zones 5 and 6 respectively. The primary corn and soybean belt region was also devastated by a severe drought that significantly hampered crops, and pasture development in 2012 (NOAA 2012). Table 4 presents estimated average year-to-year percentages rates of growth in TFP and efficiency changes for all counties in the corn and soybean belt region. The drought that was experienced in the corn and soybean belt in the growing season of 2012 appears markedly as a 3.90% decline in overall TFP change (%ΔTFP) which is primarily driven by: a 1.83% and 0.029% drops due to weather effects (%ΔWE) and agro-ecological change (%ΔAE), respectively; 0.26% decline in technological change (%ΔT); 0.88% drop in output-oriented technical efficiency change (%ΔOTE); and a -1.44% decline for reasons that cannot be identified (%ΔSN).

Conclusion

The third National Climate Assessment report (Hatfield et al. 2014) singles out recent droughts and heavy precipitation as the biggest threats to the U.S. agricultural sector, and notes that crop and livestock productivity will be negatively impacted as critical temperature and precipitation thresholds are met and exceeded. Our general findings are consistent with these reports. Using agronomic weather measures, we find that excessive temperatures as well as heavy precipitation are harmful to crop development.

Shifting patterns in temperature and precipitation as well a general trend towards warming has caused several regions in the United States to face severe declines in agricultural productivity growth. Consequently, it is important and informative to measure agricultural water productivity in order to evaluate the efficient use of water across the United States agricultural sector. We measure water productivity in a way that conforms to the hydrology and agronomy literature.

The main contributions of this study are: we incorporate conventional inputs (i.e., land, labor, capital, livestock, and intermediate materials), agronomic weather measures (growing degree-days, harmful degree-days, vapor pressure deficit, and precipitation), and physical attributes of the land (e.g., soil type, k-factor, soil permeability, salinity, and moisture capacity) into a production function, and subsequently undertake a decomposition of total factor productivity index (TFPI) that isolates the contribution of agronomic weather measures and other environmental factors to productivity growth. In addition we decompose TFPI into various measures: a technology index (TI), which captures the role of cumulative R&D expenditures in generating new knowledge stocks; an Output-oriented scale efficiency index (OSEI), which measures productivity gains linked to economies of scale; an Output-oriented technical efficiency index (OTEI) that captures movements towards and away from the frontier. It is noteworthy to point out that our study is the only one that explicitly incorporate the effects of agronomic weather measures and other agro-ecological conditions into a total factor productivity (TFP) model and the subsequent analysis of productivity growth in U.S. agriculture.

These findings have important implications for public policy. The ability to respond appropriately and in a timely fashion to the adverse effects of climate change is expected to have a significant effect on future agricultural productivity (Malcolm et al. 2012; Hatfield et al. 2014).

Table 1: Summary statistics of variables used in Stochastic Production Frontier

Variable (Unit)	Mean	Std. Dev	Min	Max
Output ('000 $)	259,930.70	387,630.70	1,764.62	3,953,646.00
Land (acres)	440,795.70	423,976.70	1,047.00	3,112,271.00
Livestock (animal equivalent)	42,334.44	59,285.84	29.69	595,766.50
Machinery ('000 $)	146.15	104.64	1.22	1,030.97
Labor (hours)	3,662.06	8,941.37	12.92	96,120.48
Intermediate Inputs ('000 $)	31.29	50.83	12.00	533.03
Irrigation (Mgal/day)	114.65	324.62	0.03	3,411.04
Research and Development ('000)	88,769.51	51,747.18	15,425.16	257,187.30
Weather Variables				
Growing Degree Days	3,433.06	1,111.20	1,516.00	8,078.75
Harmful Degree Days	31.71	34.20	0.00	171.00
Growing Season Precipitation	179.532	19.31318	84.7	244.5
Maximum Vapor Pressure Deficit	15.95	6.60	6.60	55.41
Production Environment Characteristics				
Fraction of Clay	0.17	0.21	0.00	1.00
Fraction of Sand	0.08	0.18	0.00	1.00
Flood Prone	0.12	0.18	0.00	1.00
K-Factor	0.30	0.06	0.02	0.51
Permeability	2.67	2.41	0.25	13.69
Wetlands	0.11	0.11	0.00	0.73
Moisture Capacity	0.18	0.04	0.05	0.30
Salinity	0.01	0.05	0.00	0.64
Length of slope	253.41	230.25	30.51	1631.17

Table 2: Estimates of Random Parameters Stochastic Production Frontier

Variables		**Means for Random Parameters**	**Standard Errors**
Constant	$\bar{\beta}_{1it}$	0.1602***	0.0129
Land	$\bar{\beta}_{2it}$	0.0226*	0.0121
Labor	$\bar{\beta}_{3it}$	0.2665***	0.0074
Machinery	$\bar{\beta}_{4it}$	0.4594***	0.0148
Livestock	$\bar{\beta}_{5it}$	0.1356***	0.0065
Intermediate Materials	$\bar{\beta}_{6it}$	0.1637***	0.0075
Irrigation	$\bar{\beta}_{7it}$	0.0368***	0.0053
Growing degree-days	$\bar{\rho}_{1it}$	0.0173	0.0226
Harmful degree-days	$\bar{\rho}_{2it}$	-0.0113	0.0095
Spring precipitation	$\bar{\rho}_{3it}$	0.2264**	0.1034
Summer precipitation	$\bar{\rho}_{4it}$	0.0026	0.0048
Vapor pressure deficit (Max)	$\bar{\rho}_{5it}$	-0.1108***	0.0196
Growing degree-days squared	$\bar{\rho}_{6it}$	0.5599***	0.1236
Harmful degree-days squared	$\bar{\rho}_{7it}$	-0.0017*	0.0013
HDD*Spring precipitation	$\bar{\rho}_{8it}$	0.0601	0.0609
		Non-random Parameters	
R&D	α_1	0.1141***	0.0143
100th meridian West	γ_1	-0.0349***	0.0111
Clay	γ_2	0.0062***	0.0143
Sand	γ_3	-0.0031**	0.0016
Floodprone	γ_4	-0.0036**	0.0015
Kfactor	γ_5	-0.1181***	0.0341
Permeability	γ_6	0.1016***	0.0213
Wetlands	γ_7	-0.0520***	0.0064
Moisturecapacity	γ_8	0.2225***	0.0387
Salinity	γ_9	0.0043**	0.0021
lslope	γ_{10}	-0.0351***	0.01676
Sigma-squared (v)	σ^2_v	0.0937	
Sigma-squared (u)	σ^2_u	0.1185	
log likelihood		912.622	

Table 3: Average Percentage change in TFP and its components across U.S. Counties 1987-2012

Region	Year	%ΔTFP	%ΔT	%ΔOSE	%ΔOTE	%ΔWE	%ΔA	%ΔSN
Zone 3	1987-1992	5.766	2.711	-0.365	1.101	2.690	-0.001	-0.370
	1993-1997	-1.526	1.697	0.106	-1.095	-2.445	-0.032	0.242
	1998-2002	5.532	1.033	-0.072	1.913	3.199	0.000	-0.541
	2003-2007	-0.885	0.244	0.511	-0.331	4.617	0.021	-5.947
	2008-2012	-0.276	-0.100	0.606	-0.017	-4.642	0.000	3.877
Zone 4	1987-1992	4.549	2.896	-0.376	0.340	-6.539	-0.013	8.241
	1993-1997	4.230	2.130	-0.097	0.284	1.160	0.031	0.723
	1998-2002	0.093	1.566	0.079	0.197	6.698	-0.032	-8.415
	2003-2007	-0.988	1.038	0.410	-0.439	-0.891	0.008	-1.115
	2008-2012	-0.731	0.589	0.305	-0.475	1.677	0.019	-2.845
Zone 5	1987-1992	4.459	2.941	-0.370	0.317	-8.202	-0.002	9.775
	1993-1997	1.918	2.236	-0.138	0.033	2.697	0.012	-2.923
	1998-2002	0.954	1.507	0.144	0.090	9.586	0.000	-10.372
	2003-2007	0.820	0.438	0.289	-0.109	-2.559	-0.007	2.767
	2008-2012	-3.380	-0.203	0.259	-0.968	0.411	-0.011	-2.869
Zone 6	1987-1992	3.217	2.138	-0.196	0.090	-2.064	0.005	3.243
	1993-1997	2.865	1.517	0.008	0.698	-0.239	0.024	0.856
	1998-2002	1.579	0.834	0.152	0.143	5.538	0.000	-5.088
	2003-2007	-1.323	-0.073	0.285	-0.426	-0.965	-0.014	-0.129
	2008-2012	-2.797	-0.385	0.153	-1.064	1.618	0.000	-3.118
Zone 7	1987-1992	5.273	2.679	-0.190	0.884	-0.636	-0.040	2.576
	1993-1997	2.495	2.008	-0.003	0.235	-1.492	-0.027	1.774
	1998-2002	0.995	1.358	0.165	-0.017	4.019	0.057	-4.588
	2003-2007	-1.391	0.260	0.156	-1.482	-2.784	0.054	2.405
	2008-2012	-1.937	-0.391	0.006	-0.669	1.397	0.000	-2.280
Zone 8	1987-1992	3.486	2.407	0.199	0.244	6.549	0.057	-5.970
	1993-1997	4.257	1.543	0.047	0.805	-7.747	-0.027	9.637
	1998-2002	-1.511	0.843	0.178	-0.621	5.404	-0.031	-7.283
	2003-2007	-0.789	-0.036	0.204	-0.313	4.201	0.013	-4.858
	2008-2012	-1.947	-0.442	-0.095	-0.831	-4.618	0.000	4.039
Zone 9	1987-1992	2.738	2.340	-0.201	0.559	-8.057	-0.149	8.246
	1993-1997	2.960	1.824	0.217	0.281	3.238	0.096	-2.697
	1998-2002	3.007	1.201	0.043	0.221	-3.074	0.000	4.616
	2003-2007	-3.155	0.366	0.182	-1.441	2.576	0.006	-4.844
	2008-2012	-0.999	-0.012	0.260	0.525	-2.687	0.000	0.915
Zone 10	1987-1992	2.085	2.852	-0.206	-0.304	-2.244	0.006	1.982
	1993-1997	3.759	2.169	-0.272	0.835	4.150	-0.026	-3.097
	1998-2002	9.359	1.386	-0.385	0.525	0.074	0.000	7.758
	2003-2007	-6.982	0.265	0.508	-0.887	1.154	0.318	-8.340
	2008-2012	-2.626	-0.306	0.549	-1.480	-3.587	0.000	2.197

Table 4: Average Percentage change in TFP and its components across Corn and Soybean belt

Region	Year	%ΔTFP	%ΔT	%ΔOSE	%ΔOTE	%ΔWE	%ΔA	%ΔSN
Cornbelt	1987-1992	4.427	3.277	-0.313	-0.014	-1.387	0.019	2.846
	1993-1997	3.011	2.636	-0.108	0.609	5.075	0.016	-5.216
	1998-2002	0.985	1.909	0.055	-0.153	0.708	0.000	-1.533
	2003-2007	2.321	0.738	0.251	0.568	4.834	-0.017	-4.052
	2008-2012	-3.905	-0.268	0.548	-0.882	-1.831	-0.029	-1.444

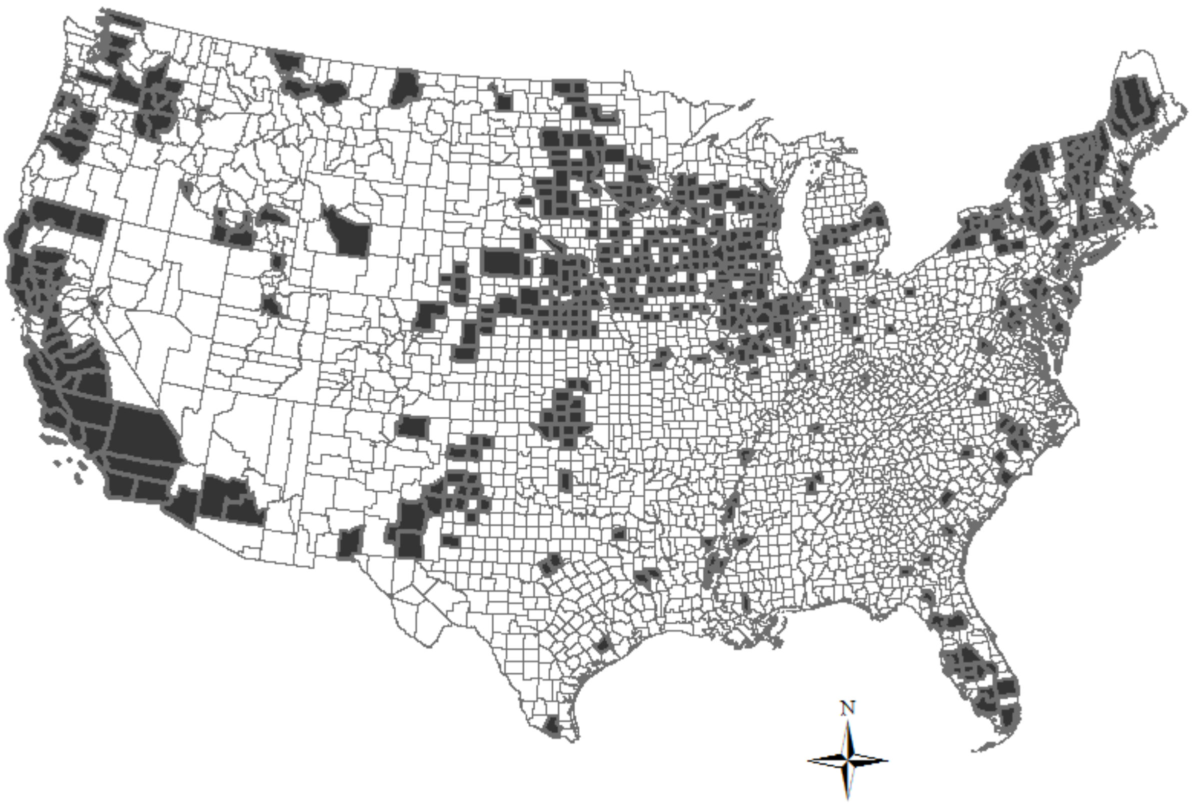

Figure 1: Spatial location of agricultural counties used in analysis

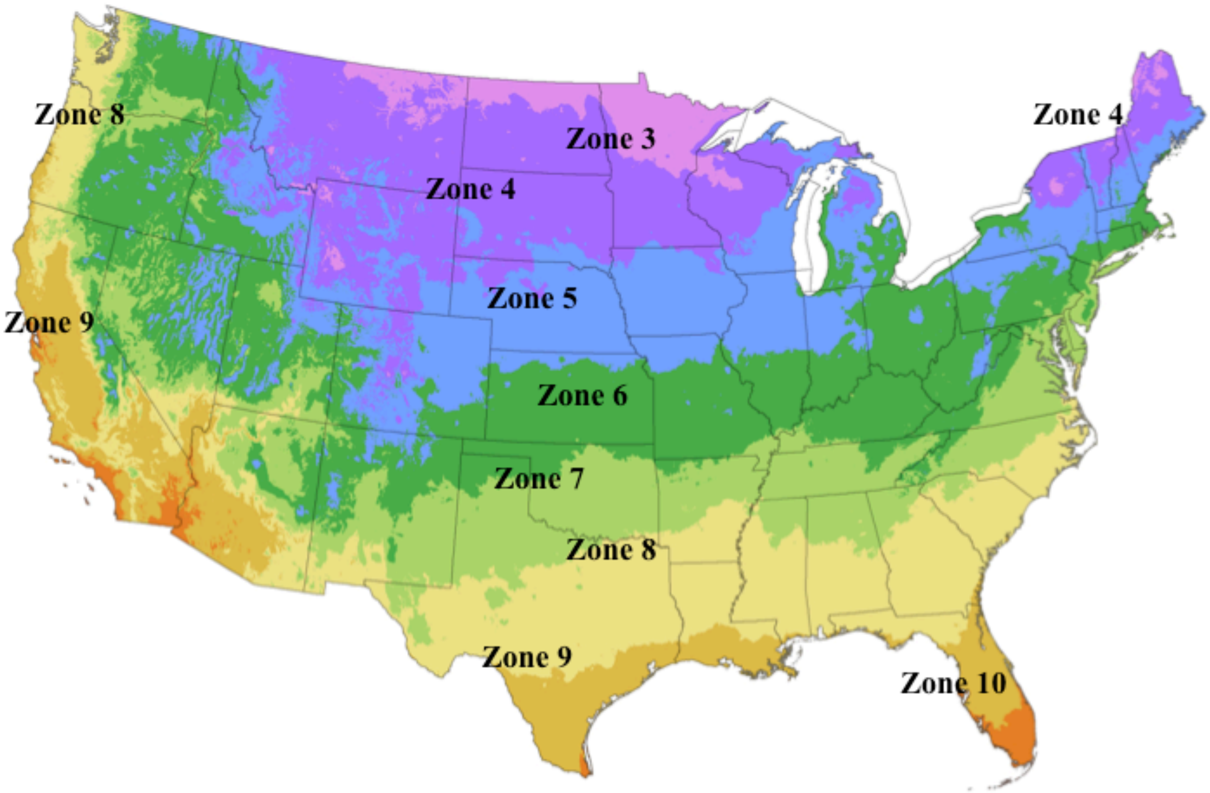

Figure 2: U.S. Department of Agriculture plant hardiness zones

References

Alston, Julian, M., Matthew Andersen A., Jennifer James S., and Philip Pardey G. 2010. *Persistence Pays: U.S. Agricultural Productivity Growth and the Benefits from Public R&D Spending*. 1st ed. Vol. 34. Natural Resource Management and Policy. Springer-Verlag New York.

Burke, Marshall, and Kyle Emerick. 2016. "Adaptation to Climate Change: Evidence from U.S. Agriculture." *American Economic Journal: Economic Policy* 8 (3):106–40.

Busby, Joshua, W. 2008. "Who Cares About the Weather: Climate Change and U.S. National Security." *Security Studies* 17 (3):468–504.

Christensen, L.R, D.W Jorgenson, and L.J Lau. 1973. "Transcendental Logarithmic Production Frontiers." *The Review of Economics and Statistics* 55 (1):28–45.

Cline, Wiiliam, R. 1996. "The Impact of Global Warming on Agriculture: Comment." *American Economic Review* 86 (5):1309–11.

Daly, Christopher, Michael Halbleib, Joseph Smith I., Wayne Gibson P., Matthew Doggett K., George Taylor H., Jan Curtis, and Phillip Pasteris P. 2008. "Physiographically-Sensitive Mapping of Temperature and Precipitation Across the Conterminous United States." *International Journal of Climatology* 28:2031–64.

Daly, Christopher, Joseph Smith I., and Keith Olson V. 2015. "Mapping Atmospheric Moisture Climatologies Across Conterminous United States." *PLOS One* 10 (10):1–33.

Daly, Christopher, Mark Widrlechner P., Michael Halbleib D., Joseph Smith I., and Wayne Gibson P. 2012. "Development of a New USDA Plant Hardiness Zone Map of the United States." *Journal of Applied Meteorology and Climatology* 51:242–64.

Darwin, Roy. 1999. “The Impact of Global Warming on Agriculture: A Ricardian Analysis: Comment.” *American Economic Review* 89 (4):1049–52.

Dell, Melissa, Benjamin Jones F, and Benjamin Olken A. 2014. “What Do We Learn from the Weather? The New Climate-Economy Literature.” *Journal of Economic Literature* 52 (3):740–98.

Deschenes, Olivier, and Michael Greenstone. 2007. “The Economic Impacts of Climate Change: Evidence from Agricultural Output and Random Fluctuations in Weather.” *American Economic Review* 97 (1):354–85.

FAO. 2011. “Safeguarding Food Security in Volatile Global Markets.” Rome, Italy: Food and Agricultural Organization of the United Nations.

Femia, Francesco, and Caitlin Werrell E. 2016. “UPDATE: Climate and Security 101: Why the U.S. National Security Community Takes Climate Risks Seriously.” 30. Briefer. The Center for Climate and Security.

Ficklin, Darren, and Kimberley Novick A. 2017. “Historic and Projected Changes in Vapro Pressure Deficit Suggest a Continental-Scale Drying of the United States Atmosphere.” *Journal of Geophysical Research: Atmospheres* 122:2061–79.

Fisher, Anthony, C, W. Michael Hanemann, Michael Roberts J, and Wolfram Schlenker. 2012. “The Economic Impacts of Climate Change: Evidence from Agricultural Output and Random Fluctuations in Weather: Comment.” *American Economic Review* 102 (7):3749–60.

Griliches, Zvi. 1980. “R&D and the Productivity Slowdown.” *American Economic Review* 70 (2):343–48.

Hatfield, Jerry, L., and John Prueger H. 2015. "Temperature Extremes: Effect on Plant Growth and Development." *Weather and Climate Extremes* 10:4–10.

Hatfield, Jerry, L., Gene Takle, Richard Grotjahn, Patrick Holden, R. Cesar Izaurralde, Terry Mader, Elizabeth Marshall, and Diana Liverman. 2014. "Climate Change Impacts in the United States: The Third National Climate Assessment." U.S. Global Change Research Program. Washington, D.C.

Huffman, Wallace, E., and Robert Evenson. 2006. *Science for Agriculture*. 2nd ed. Wiley-Blackwell.

Huffman, Wallace, E., and Robert Evenson E. 1992. "Contributions of Public and Private Science and Technology to U.S. Agricultural Productivity." *American Journal of Agricultural Economics* 74 (3):751–56.

IPCC. 2014. "Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part A: Global and Sectoral Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change." In , edited by C.B Field, V.R Barros, D.J Dokken, K.J Mach, M.D Mastrandrea, T.E Bilir, M Chatterjee, et al., 1132. Cambridge, United Kingdom and New York, NY, USA: Cambridge University Press.

Jin, Yu, and Wallace Huffman E. 2016. "Measuring Public Agricultural Research and Extension and Estimating Their Impacts on Agricultural Productivity: New Insights from U.S. Evidence." *Agricultural Economics* 47 (1):15–31.

Jorgenson, Dale, W, and Zvi Griliches. 1967. "The Explanation of Productivity Change." *The Review of Economic Studies* 34 (3):249–83.

Lobell, David, B., Wolfram Schlenker, and Justin Costa-Roberts. 2011. "Climate Trends and Global Crop Production Since 1980." *Science* 333:616–20.

Madsen, Jakob, B. 2007. "Technology Spillover Through Trade and TFP Convergence: 135 Years of Evidence for the OECD Countries." *Journal of International Economics* 72:464–80.

Madsen, Jakob, B., and Rabiul Islam. 2016. "Exploring the Widening Food Gap: An International Perspective." *Agricultural Economics* 47 (6):645–59.

Malcolm, Scott, Elizabeth Marshall, Marcel Aillery, Paul Heisey W., Michael Livingston, and Kelly Day-Rubinstein. 2012. "Agricultural Adaptation to a Changing Climate: Economic and Environmental Implications Vary by U.S. Region." 136. Washington, D.C.: U.S. Department of Agriculture, Economic Research Service.

Marshall, Elizabeth, Marcel Aillery, Scott Malcolm, and Ryan Williams. 2015. "Agricultural Production Under Climate Change: The Potential Impacts of Shifting Regional Water Balances in the United States." *American Journal of Agricultural Economics* 97 (2):568–88.

Mendelsohn, Robert, and Ariel Dinar. 2003. "Climate, Water, and Agriculture." *Land Economics* 79 (3):328–41.

Mendelsohn, Robert, William Nordhaus D, and Daigee Shaw. 1994. "The Impact of Global Warming on Agriculture: A Ricardian Analysis." *American Economic Review* 84 (4):753–71.

Mutter, R.L, W.H Greene, W Spector, M.D Rosko, and D.B Mukamel. 2013. "Investigating the Impact of Endogeneity on Inefficiency Estimates in the Application of Stochastic Frontier Analysis to Nursing Homes." *Journal of Productivity Analysis* 39 (2):101–10.

Nelson, Gerald, C, Dominique van der Mensbrugghe, Helal Ahammad, Elodie Blanc, Katherine Calvin, Tomoko Hasegawa, Petr Havlik, et al. 2014. "Agriculture and Climate Change in

Global Scenarios: Why Don't the Models Agree." *Agricultural Economics* 45 (1):85–101.

O'Donnell, C.J. 2016. "Using Information About Technologies, Markets and Firm Behaviour to Decompose a Proper Productivity Index." *Journal of Econometrics* 190 (2):328–40.

Ortiz-Bobea, Ariel, and Richard Just E. 2013. "Modeling the Structure of Adaptation in Climate Change Impact Assessment." *American Journal of Agricultural Economics* 95 (2):244–51.

Roberts, Michael, J, Wolfram Schlenker, and Jonathan Eyer. 2013. "Agronomic Weather Measures in Econometric Models of Crop Yield with Implications for Climate Change." *American Journal of Agricultural Economics* 95 (2):236–43.

Schlenker, Wolfram, W. Michael Hanemann, and Anthony Fisher C. 2005. "Will U.S. Agriculture Really Benefit Benefit from Global Warming? Accounting for Irrigation in the Hedonic Approach." *American Economic Review* 95 (1):395–406.

———. 2006. "The Impact of Global Warming on U.S. Agriculture: An Econometric Analysis of Optimal Growing Conditions." *The Review of Economics and Statistics* 88 (1):113–25.

Schlenker, Wolfram, and Michael Roberts J. 2009. "Nonlinear Temperature Effects Indicate Severe Damages to U.S. Crop Yields Under Climate Change." *Proceedings of the National Academy of Sciences* 106 (37):15594–98.

Seo, S. Niggol. 2013. "An Essay on the Impact of Climate Change on US Agriculture: Weather Fluctuations, Climatic Shifts, and Adaptation Strategies." *Climatic Change* 121 (2):115–24.

Shee, A, and S.E Stefanou. 2015. "Endogeneity Corrected Stochastic Production Frontier and Technical Efficiency." *American Journal of Agricultural Economics* 97 (3):939–52.

Solow, Robert. 1957. “Technical Change and the Aggregate Production Function.” *The Review of Economics and Statistics* 39 (3):312–20.

Tran, K.C, and E.G Tsionas. 2013. “GMM Estimation of Stochastic Frontier Model with Endogenous Regressors.” *Economic Letters* 118:233–36.

United Nations. 2013. “Millennium Development Goals Report.” New York: U.N.

———. 2015. “World Population Prospects.” New York: U.N. Department of Economic and Social Affairs, Population Division.

U.S. Department of Agriculture. 2017. “World Agricultural Supply and Demand Estimates.” ISSN: 1554-9089. Washington, D.C.: Economic Research Service.

Wang, Sun Ling, V. Eldon Ball, Lilyan Fulginiti E, and Alejandro Plastina. 2012. “Accounting for the Impacts of Public Research, R&D Spill-Ins, Extension, and Roads in U.S. Regional Agricultural Productivity Growth, 1980-2004.” In *Productivity Growth in Agriculture: An International Perspective*, edited by Keith Fuglie O., Sun Ling Wang, and V. Eldon Ball. Wallingford, U.K.: C.A.B. International.

Wang, Sun Ling, Paul Heisey W., Wallace Huffman E., and Keith Fuglie O. 2013. “Public R&D, Private R&D, and U.S. Agricultural Productivity Growth: DYnamic and Long-Run Relationships.” *American Journal of Agricultural Economics* 95 (5):1287–93.

Werrell, Caitlin, E., and Francesco Femia. 2017. “Climate Change and Security.” *Crisis Response Journal* 12 (3):45–47.

Wichelns, Dennis. 2010. “Agricultural Water Pricing: United States.” Sustainable Management of Water Resources in Agriculture. Organization of Economic Cooperation and Development.

Williams, S.P, and C.R Shumway. 1998. “Testing for Behavioral Objective and Aggregation Opportunities in U.S. Agriculture.” *American Journal of Agricultural Economics* 80 (1):195–207.

Yang, Sansi, and C. Richard Shumway. 2016. “Dynamic Adjustment in U.S. Agriculture Under Climate Change.” *American Journal of Agricultural Economics* 98 (3):910–24.