ESTIMATING THE IMPACT OF DROUGHT ON AGRICULTURE USING THE U.S. DROUGHT MONITOR

YUSUKE KUWAYAMA, ALEXANDRA THOMPSON, RICHARD BERNKNOPF, BENJAMIN ZAITCHIK, AND PETER VAIL

We estimate the impacts of drought, as defined by the U.S. Drought Monitor (USDM), on crop yields and farm income in the United States during the 2001–2013 time period. Our empirical strategy relies on panel data models with fixed effects that exploit spatial and temporal variability in drought conditions and agricultural outcomes at the county level. We find negative and statistically significant effects of drought on crop yields equal to reductions in the range of 0.1% to 1.2% for corn and soybean yields for each additional week of drought in dryland counties, and 0.1% to 0.5% in irrigated counties. Region-specific results vary, with some regions experiencing no yield impacts from drought, while yield reductions as high as 8.0% are observed in dryland counties in the Midwest for every additional week of drought in the highest USDM severity category. Despite this impact on crop yields, we find that additional weeks of drought have little to no effect on measures of farm income. While precipitation and temperature explain most of the variability in crop yields, we find that the USDM captures additional negative impacts of drought on yields.

JEL codes: Q1, Q15, Q25, Q54.

Key words: Drought, agriculture, irrigation.

Recent years have seen an increased interest in the economic impacts of droughts in the United States as a result of disasters such as the 2012 Midwest drought and the 2011–2017 drought in California. This attention has been reinforced by predictions that droughts will become more frequent and more severe in the future with the progression of climate change (Intergovernmental Panel on Climate Change; IPCC 2014). While droughts have the potential to affect an entire regional economy, the agricultural sector is particularly vulnerable (Climate Change Science Program 2008; Walthall et al. 2012). Droughts are associated with below-average precipitation, which can affect crop yields, and reduce surface water and groundwater supplies, which can affect irrigation and livestock watering. Furthermore, droughts are associated with periods of above-average temperatures that can exacerbate hydrological and biophysical stress. These impacts can lead to a decrease in revenues from crop and livestock sales, changes in production costs—or both—possibly reducing net farm income and negatively affecting communities that are dependent on agriculture.

Despite this interest in the economic impacts of drought, few studies have quantified the impact of droughts on physical measures such as crop yield, or monetized measures, such as farm income. One reason for this lack of research is that there is no universally accepted quantitative definition of drought. Instead, drought is often defined qualitatively as a deficit of water relative to normal conditions as referenced by water supply demand and management (Wilhite 2000;

Yusuke Kuwayama is a fellow and Alexandra Thompson is a research associate, both at Resources for the Future. Richard Bernknopf is a research professor in the Department of Economics, University of New Mexico. Benjamin Zaitchik is an associate professor in the Department of Earth and Planetary Sciences, Johns Hopkins University. Peter Vail is a research assistant at Resources for the Future. The authors wish to thank Sara Pesko for excellent research assistance, and David Brookshire, Molly Macauley, Kevin Patrick, Matthew Rodell, seminar participants at the University of Florida and the University of Nebraska-Lincoln, and three anonymous referees for valuable comments and suggestions. This project was completed with financial support from the National Aeronautics and Space Administration, NNX09A01G. Correspondence to be sent to: kuwayama@rff.org

Amer. J. Agr. Econ. 101(1): 193–210; doi: 10.1093/ajae/aay037
Published online July 10, 2018

Lloyd-Hughes 2014). As a result, what constitutes a drought varies across regions and time periods, and is also a function of the local socioeconomic context, including factors such as the composition of the local economy, access to infrastructure, and household income levels and distribution. At the same time, governments at the federal, state, and municipal levels often use some form of composite drought index instead of individual thresholds for hydrologic measures (e.g., precipitation or reservoir levels) for informing drought-related policies such as State of Emergency proclamations and eligibility for drought disaster assistance. Furthermore, public sector drought policies in the United States act as triggers for the distribution of a significant amount of public resources to agricultural communities. For example, in fiscal year 2014, the federal government designated $873 million across 11 western states for drought-related crop insurance and programs that were a result of drought emergency declarations (Mount et al. 2016).

In the United States, the composite drought index most often used by policymakers is the U.S. Drought Monitor (USDM). The USDM consists of a weekly map that indicates which regions of the country are currently in drought, as well as the intensity of those droughts. It is used by a variety of federal agencies including the USDA and the Internal Revenue Service (IRS), as well as state government agencies, primarily for programs related to the agricultural sector (National Drought Mitigation Center; NDMC 2016). Given the key role that the USDM plays in U.S. drought policy in the agricultural sector, evidence regarding the relationship between USDM drought categorizations and realized agricultural outcomes is desirable.

In this paper, we estimate the impacts of drought, as defined by the USDM, on crop yields and farm income in the United States during the 2001–2013 time period. Our analysis makes two main contributions to the literature. First, to our knowledge, this is the first study to confirm that drought information from the USDM is correlated with observed agricultural outcomes. This evidence is valuable because the USDM plays a critical role in decisions regarding the allocation of financial resources in response to drought. Furthermore, by quantifying the impacts on crop yields and farm income that are associated with USDM drought categorizations, we provide useful information for policymakers who are designing USDM-based eligibility requirements for drought assistance. Our second contribution is to add to existing evidence regarding the effect of weather and climate on agricultural outcomes. While precipitation and temperature have received significant attention as determinants of current and future agricultural output, quantitative evidence on the effect of drought as an extreme event is scarce. Drought, as defined by the USDM and other composite drought indices, is driven not only by precipitation and temperature measures; it is also determined by indicators such as soil moisture, streamflow, vegetation indices, reservoir and lake levels, groundwater levels, and snowpack. These other dimensions of drought can generate impacts on farm income beyond those that are identified for below-average precipitation or above-average temperatures.

Our analysis is based on a panel dataset that was constructed by matching crop yield data from the USDA's National Agricultural Statistics Service (NASS), and farm income data from the Bureau of Economic Analysis (BEA) to drought intensity categorizations in the USDM at the county level. Our empirical strategy relies on panel data models with fixed effects that exploit spatial and temporal variability in drought conditions and crop yield and farm income, allowing us to estimate an average nationwide impact as well as impacts in specific regions. These estimates reflect the impact of an additional week of drought on crop yield and annual farm income, inclusive of all the on-farm activities that are available to agricultural producers that help mitigate the biophysical impact of drought on crops and livestock. We run separate regressions for irrigated and dryland counties because we expect the effect of drought on agricultural outcomes to vary between these two types of counties.

For the average dryland county, we find negative and statistically significant impacts of drought on crop yields equal to reductions in the range of 0.1% to 1.2% for corn and soybeans for each additional week of drought. Impacts in irrigated counties are smaller in magnitude, ranging from 0.1% to 0.5% for each additional week of drought. Region-specific results are mixed, with some regions experiencing no yield impacts from drought, while yield reductions in dryland counties in the midwest are as high as 8.0% for corn and 3.1% for soybeans for every additional week of exceptional drought, the highest level of drought severity in the USDM categorization. We find that additional weeks of drought have little to no effect on the value of cash receipts and production expenses, perhaps due to farmers receiving higher prices as a result of drought-induced local scarcity in agricultural commodities. Finally, we find that precipitation and temperature explain most of the variability in crop yields during the time period of our analysis, but the USDM does capture additional negative impacts of drought on yields.

The paper proceeds as follows. The next section contains a brief review of existing studies on the relationship between droughts and agricultural outcomes and a description of the USDM and its current use in federal drought policy. This is followed by sections describing our data and empirical strategy, respectively. In the next section, we present our estimates for the effect of drought on crop yields and farm income, while the final section concludes.

Background

Droughts and Agricultural Outcomes

From a biophysical standpoint, the effects of drought on crops are well studied, particularly in the context of potential future impacts due to climate change. In addition to retrospective analyses of past droughts on crop productivity (e.g., Ciais et al. 2005; Zhao and Running 2010), biophysical research on droughts and crops has addressed the benefits of drought tolerance practices (e.g., Cattivellia et al. 2008; Craine et al. 2013) and the role of extreme heat (e.g., Lobell et al. 2013). The effects of drought on livestock have also been studied, with a focus on developing countries and the role of livestock acting as a buffer against income shocks from drought (Fafchamps, Udry, and Czukas 1998; Kinsey, Burger, and Gunning 1998; Kazianga and Udry 2006).

A surprisingly small number of studies conduct *ex post* estimations of the economic cost of droughts on the agricultural sector. For example, Riebsame, Changnon, and Karl (1991) present a detailed narrative of the 1988–1989 drought in the United States, including a quantitative impact analysis that yields an estimated crop loss of $15 billion due to output and price changes in corn, barley, grain sorghum, oats, soybeans, and wheat. However, the authors note that because of high prices resulting from the drought, non-drought area production, inventory sell-offs, and irrigation, net agricultural income in 1988 rose slightly from the previous non-drought year despite the crop losses. The authors also find that negative impacts for specific individuals and regions were substantial. Wheaton et al. (2008) evaluate drought impacts on agriculture by comparing production values during the 2001–2002 Canadian drought to that in benchmark years. Estimated crop production value losses were in the range of $1.7 to $2.4 billion depending on the region, while impacts on cash receipts were smaller due to inventory adjustments.

Horridge, Madden, and Wittwer (2005) take an agricultural production function approach to estimate the impacts of the 2002–2003 Australian drought, aggregating values from 38 sectors and 45 regions. The authors find significant aggregate effects from agriculture on the national economy, despite the relatively small role of the sector in Australia, with income losses of up to 20% and a 1.6% reduction in Gross Domestic Product. More recently, Howitt et al. (2014, 2015) and Medellín-Azuara et al. (2016) estimated the economic impact of drought in California on the state's agricultural sector. Using an economic optimization model of crop choice that includes regional water availability constraints, the authors calculated the net water shortage (5 million acre feet) to result in significant losses in crops ($2 billion) and dairy and livestock ($553 million), as well as additional groundwater pumping costs ($1.3 billion) and lost jobs (43,000) in 2014, 2015, and 2016. Unlike these previous *ex post* studies, which estimate costs to the agricultural sector for entire drought events, our econometric approach yields estimates of economic impact for marginal increases in the duration and intensity of droughts. This information may be useful for policymakers who need to allocate scarce financial resources for drought assistance and emergency programs.

A different strand of research addresses specific types of farmer adaptation to drought. For example, Cavatassi et al. (2011) investigate whether farmers in Ethiopia adopt modern, drought-tolerant varieties of sorghum as a risk reduction strategy in the face of drought. Moreover, Ding, Schoengold, and Tadesse (2009) investigate the relationship between drought and flood events and the likelihood that farmers will adopt conservation tillage practices, using county-level data from Iowa, Nebraska, and South Dakota. While our data do not allow us to observe the evolution of specific on-farm practices in response to changes in drought conditions, our estimates can be interpreted as including the mitigating effects of some of these practices, namely, those that can be adopted in response to the onset of a drought.

Our paper is perhaps most similar to a group of studies that addresses the relationship between agricultural outcomes and specific weather components, such as precipitation and temperature. The main goal of these studies is to use these estimated relationships to predict the effects of future climate change on U.S. agriculture. Mendelsohn, Nordhaus, and Shaw (1994) adopt a hedonic approach by modeling farmland values and rents as a function of temperature, precipitation, soil type, and other physical and socioeconomic variables. The authors then use uniform precipitation and temperature increases to simulate how agricultural farmland values would vary under climate change, finding effects that are highly nonlinear and that vary by geography and season. Schlenker, Hanemann, and Fisher (2005) refined this approach by differentiating irrigated from rainfed agriculture, finding statistically significant differences in coefficient estimates. Deschênes and Greenstone (2007) take a different approach by exploiting year-to-year weather fluctuations rather than climate differences across counties, and by using yields and profits as outcome variables instead of farmland values, concluding that climate change impacts will be neutral or possibly positive due to adaptation. However, Fisher et al. (2012) find different results when replicating the Deschênes and Greenstone (2007) analysis while including inventory adjustments and correction for data irregularities. The replication finds significant negative economic impacts of climate change on agricultural production. As mentioned earlier, our analysis differs from these studies because our explanatory variables consist of drought categorizations that are actively used in federal drought policy, and reflect a larger universe of weather and hydrologic conditions.

The U.S. Drought Monitor

The USDM is an expert-based national map of drought conditions that is produced jointly by the USDA, the National Oceanic and Atmospheric Administration (NOAA), and the National Drought Mitigation Center (NDMC) on a weekly basis.[1] The maps designate general drought areas as being in one of five intensity classes, ranging from "abnormally dry" (abbreviated as D0), "moderate drought" (D1), "severe drought" (D2), "extreme drought" (D3), and "exceptional drought" (D4). Each intensity class is associated with its probability of occurrence, expressed as a percentile, on the basis of a 1932–2001 data record of drought indicators (Svoboda et al. 2002; Houborg et al. 2012). Table 1 lists the percentiles associated with each drought intensity class; the classification scheme indicates, for example, that droughts of intensity D3 or worse have a 5% chance of occurring in any given location.

Table 1. Categories of Drought Intensity Used by the U.S. Drought Monitor

Category	Drought Intensity Level	Percentile
D0	Abnormally dry	20 to $\leq$ 30
D1	Drought, moderate	10 to $\leq$ 20
D2	Drought, severe	5 to $\leq$ 10
D3	Drought, extreme	2 to $\leq$ 5
D4	Drought, exceptional	$\leq$ 2

The USDM is not strictly a drought index, but rather a composite product developed from a suite of climate indices and numerical models, as well as from input from regional and local experts. The six key physical indicators used by the USDM authors are a drought index (specifically, the Palmer Drought Severity Index), percentiles from a soil moisture model, daily streamflow percentiles, the percent of normal precipitation, a standardized precipitation index, and a remotely-sensed vegetation health index (Svoboda et al. 2002). The authors also rely on supplementary indicators such as humidity and temperature departure from normal, reservoir, and lake levels, surface water supply indices, snowpack, and groundwater levels. The authors then seek input and verification from regional and state climatologists, agricultural and water resource managers, National Weather Service field employees, and others to help ground-truth the maps based on local

[1] The USDM map for any given week can be accessed at http://droughtmonitor.unl.edu/.

knowledge of drought conditions and impacts. All of this information is subjectively incorporated into a final map of drought intensity categorizations that are considered with reference to their historical frequency of occurrence for a location and time of year, so that categorizations reflect local impacts and vulnerability (Svoboda et al. 2002).

The fact that the USDM is a composite product developed by a panel of experts may make it less "objective" than specific weather indicators such as precipitation and temperature. However, drought is driven by multiple environmental stresses that may combine in ways that are not entirely predictable and that may cause cascading impacts (National Research Council; NRC 2007). The USDM has the benefit of incorporating many more types of information that can improve understanding of drought conditions. In addition, the USDM is a timely and easily interpreted data product, making it readily usable by regulators, producers, and the general public in drought-related decisions.

Another drawback of using the USDM to determine the impacts of drought on agriculture is that it includes a measure of vegetation health. In the context of our empirical analysis, the inclusion of vegetation health may make our regressors endogenous. Because of the way the USDM is developed, it is impossible to determine how much emphasis is placed on vegetation, and as a result, it is impossible to determine the degree to which the endogeneity is problematic for estimation. Nonetheless, to the extent that the USDM is used to inform drought policy, our empirical results can help decision makers understand how USDM categorizations relate to agricultural outcomes.

Despite its drawbacks, the USDM is formally used to inform several major drought management decisions. As of 2012, the USDA's Secretarial disaster designation process provides for nearly automatic designation for a county when, during the growing season, any portion of the county is classified by the USDM as being affected by a drought with an intensity level of D2 for eight consecutive weeks, or a higher drought intensity level for any length of time (USDA 2015). In addition, the USDA has utilized the USDM to determine drought disaster assistance program eligibility in programs such as the Livestock Forage Disaster Program (LFP), the Livestock Assistance Grant Program (LAGP), Commodity Credit Corporation surplus stock sales, and emergency loans through Emergency Disaster Designations and Declarations.

The LFP, which was made a permanent program by the U.S. Agricultural Act of 2014, provides eligible livestock producers payments that are equal to 60% of their monthly feed costs. Producers are eligible for one monthly payment if they own or lease grazing land or pastureland located in a county rated by the USDM as having, during the normal grazing period, a D2 drought for eight consecutive weeks or more, and additional monthly payments for weeks in D3 or D4 drought (USDA 2017a). Between 2011 and 2016, more than $6 billion in LFP funds were awarded (USDA 2017b). The LAGP, the predecessor to the LFP, awarded $50 million in 2007 alone (USDA 2006). Persistent drought conditions between 2001 and 2003 in the central United States prompted a Commodity Credit Corporation (CCC) sell-off of surplus dry milk to supplement feed supplies to impacted livestock producers. Eligibility for these sales hinged on USDM drought designations; if on March 11 2003, any part of a county was included in the D4 category, or if it was in the D3 category and experienced D4 sometime between September 3 2002 and March 11 2003, surplus dry milk sales were available to producers in the county (USDA 2003). Automatic disaster designations triggered by the USDM authorize emergency loans to producers in affected counties as well as in adjacent counties; more than $56 million in emergency farm loans were provided in the 2015 and 2016 fiscal years (although not all loans are related directly to drought; USDA 2017c). The IRS also uses the USDM to determine the time frame for waiving gains from livestock replacement purchases due to drought (U.S. Department of Treasury; USDT 2016). Finally, the private sector uses the USDM in order to make decisions about resource allocation that may be affected by the regional and temporal distribution of drought (Bernknopf et al. 2018). In many states, USDM categorizations are combined with location-specific levels of its component metrics and serve as triggers for action in drought preparedness plans.

Data

The key explanatory variables in our data set are based on observations of USDM drought categorizations, precipitation, and temperature for 3,080 counties for every year between 2001 and 2013. Our dependent variables are county-level yields of corn and soybeans, and measures of farm income per agricultural acre. Yield and farm income data are not available for all counties for all years, so the number of county-year observations varies across our econometric specifications.

USDM Data

Weekly USDM drought intensity categorizations do not necessarily follow county boundaries. Given our interest in drought's effects on agricultural outcomes, we develop annual county-level USDM measures that reflect drought occurrence in agricultural areas within counties during the twelve months preceding the end of the growing season. Specifically, for each week, we quantify the percentage of county agricultural area experiencing each USDM drought category using a geographic information system (GIS). Values for each drought level are summed from October of the previous year to September of the current year, representing the general time window during which crops are affected by drought. County agricultural areas were determined by aggregating agricultural land cover categories observed in the 2008 Cropland Data Layer.[2] Thus, our drought variables are defined as the number of weeks that a county experiences a drought of a given severity level, where each week is weighted by the percentage of the county's agricultural area affected by that level of drought during that week. For example, our drought variable $D1_{ist}$, representing exposure to drought intensity level D1 for county i in state s year t, can be expressed as

$$(1)\; D1_{ist} = \sum_{w}(\text{proportion of county } i \text{ agricultural area in D1 drought during week } w)$$

where w is the index for weeks falling between October of year $t-1$ and September of year t. Used as an explanatory variable in a regression, the coefficient associated with this variable can be interpreted as the effect of an additional week of D1 drought covering all of the agricultural area in the county.

Summary statistics for the aggregated USDM data are presented in the upper portion of table 2. As would be expected, the average number of weeks that counties are assigned to a particular drought intensity class is smaller for more intense drought classes. In addition, some regions of the United States have experienced greater variability in drought conditions relative to other regions. Figure 1 is a map that illustrates regional differences in the variability of drought conditions observed over the time period covered by our USDM data. The map shows that counties with the most variable drought conditions are located along a band starting in Texas and extending northward through the High Plains. A portion of the Southeastern United States also exhibits high variability in drought. Because our econometric specifications rely on the use of county fixed effects, our coefficient estimates will be driven by the relationship between drought and agricultural outcomes in these high-variability counties.

Crop Yield Data

In order to evaluate the effect of drought (as designated by the USDM) on agricultural production, we utilize corn and soybean yield data, available annually from 2001 through 2013 from NASS.[3] Yield variables represent crop-specific ratios of total county production to total county acres harvested.[4] Yield data, while surveyed annually, are not available for every county-year. Missing observations represent county-years with no production, county-years with a sufficiently small number of producers such that information is not disclosed for privacy reasons, or county-years that simply were not surveyed.

Farm Income Data

Farm income data were obtained from the Bureau of Economic Analysis (BEA) for the

[2] The 2008 Cropland Data Layer can be accessed at: https://nassgeodata.gmu.edu/CropScape/.

[3] NASS crop yield data can be accessed at: https://quickstats.nass.usda.gov/.

[4] Existing studies on the impacts of weather on agricultural outcomes use either harvested acres (e.g., Annan and Schlenker 2015) or planted acres (e.g., Deschênes and Greenstone 2007) to calculate crop yields. There is little guidance in the literature on which acreage measure is preferable. We use harvested acres, which is the default choice in reporting by NASS and the Food and Agriculture Organization of the United Nations (FAO).

Table 2. Summary Statistics

Variable	Mean	Std. dev.	Minimum	Maximum	Observations
# weeks in D0 (weighted by % agricultural area affected)	8.47	7.34	0	50.98	40,040
# weeks in D1 (weighted by % agricultural area affected)	5.66	7.11	0	51.05	40,040
# weeks in D2 (weighted by % agricultural area affected)	3.87	6.8	0	52	40,040
# weeks in D3 (weighted by % agricultural area affected)	2.26	5.84	0	52	40,040
# weeks in D4 (weighted by % agricultural area affected)	0.8	3.55	0	51.15	40,040
Cash receipts from marketings plus value of inventory change (in thousands of U.S. dollars)	100,858	201,018	0	5,033,282	9,240
Production Expenses (in thousands of U.S. dollars)	94,441	161,973	0	3,661,699	9,240
Cash receipts from marketings plus value of inventory change / farm acres (in thousands of U.S. dollars)	0.5	0.97	0	44.47	9,126
Production Expenses / farm acres (in thousands of U.S. dollars per acre)	0.48	0.81	0	37.04	9,126
Soy yield (bushels per acre)	37.59	10.44	0.7	68.5	21,247
Corn yield (bushels per acre)	126.04	37.12	4.5	244	25,188
Maximum harvested irrigated cropland acres / Harvested cropland acres	0.19	0.3	0.000015	1	2,909
Soybean moderate heat degree days (Celsius and days, thousands)	1.9	0.54	0.22	3.22	40,027
Corn moderate heat degree days (Celsius and days, thousands)	1.87	0.52	0.22	3.15	40,027
Soybean extreme heat degree days (Celsius and days, hundreds)	0.49	0.59	0	6.1	40,027
Corn extreme heat degree days (Celsius and days, hundreds)	0.71	0.74	0	7.06	40,027
Precipitation (meters)	0.56	0.23	0.01	1.51	40,027

Note: Monetary values expressed in 2009 U.S. dollars.

three USDA Census of Agriculture years that overlap our USDM data timeframe: 2002, 2007, and 2012. Although the BEA provides farm income estimates for every year, only census-year data were used because they are the only years for which farm income estimates are consistently based on census data and not interpolated or imputed (Bureau of Economic Analysis; BEA 2015). We choose two outcomes of interest that reflect farm revenues and costs, both of which can be affected by drought through a variety of channels: (*a*) total cash receipts from marketings plus the value of inventory change; and (*b*) production expenses.

We rely on BEA farm income data instead of census data because BEA provides estimates of the value of inventory change, which has been shown to be an important component of farmer decision making in the presence of weather fluctuations (Riebsame, Changnon, and Karl 1991; Wheaton et al. 2008; Fisher et al., 2012). The major field crops in the United States are often stored by farmers in years with high yields or low prices, and these stocks are depleted in years of high prices or low yields. Similarly, livestock producers may alter their herd sizes in reaction to market or weather conditions. Total cash receipts from marketings combined with the value of inventory change represents revenues generated by commodities produced under the current year's conditions. Since these data constitute total county values, they are normalized by the total county agricultural acres for that year; data on agricultural

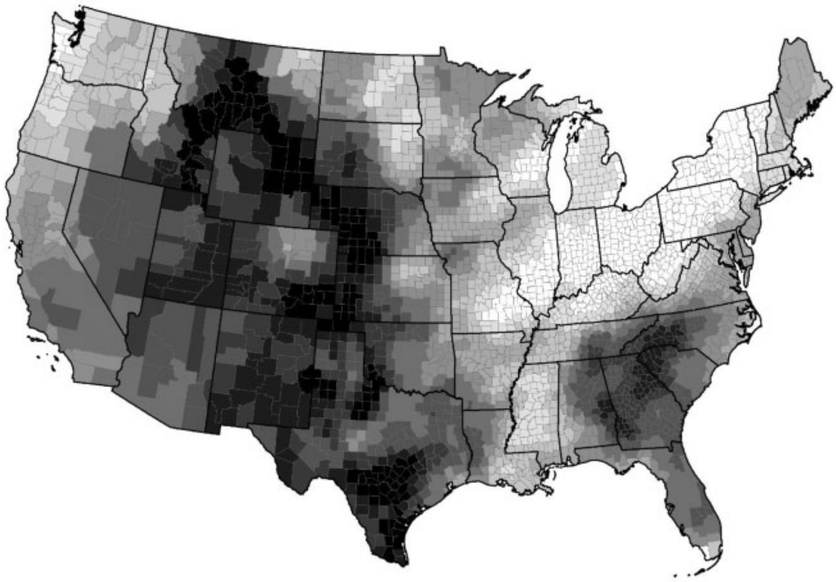

Figure 1. Variance of weighted drought index based on USDM drought classifications 2001 through 2013

Note: Weighted drought index is calculated by summing annual drought variables after they have been multiplied by a factor corresponding to severity (e.g., weeks in D0 is the identity and weeks in D4 is multiplied by five). The figure illustrates the regional variance of drought 2001 through 2013. The greatest variation occurs in the Western and Southeastern United States (darker shades).

acres are also available from NASS. Thus, we explore the effect of drought on revenues from current production and production expenses per agricultural acre.[5] Although our farm income measures are only available for three years, county coverage is better than for our crop yield data, covering most counties in the lower 48 states.

Irrigated Acreage Data

In order to explore the potential mitigating effects of irrigation on drought impacts, we collected additional data from NASS that allows us to assign counties to one of two groups: irrigated counties and dryland counties. In order to designate a county as irrigated or dryland, we first take the area of harvested cropland in the county that is irrigated and divide it by the total area of harvested cropland in that county as reported in the 1997, 2002, 2007, and 2012 censuses. This value represents the proportion of harvested cropland in the county that is irrigated in each census year. We then take the largest proportion observed for each county across the four census years and use it as a time-invariant variable that describes the potential for farmland in the county to be irrigated.[6] We define a county to be irrigated if the proportion of harvested cropland that is irrigated is greater than 15%. Counties with dryland farming are those in which the proportion of harvested cropland that is irrigated is less than 15%.[7]

Weather Data

We rely on modeled precipitation and temperature data, developed by Schlenker and Roberts (2009), to determine annual growing season weather conditions in agricultural areas. Specifically, we calculate cumulative precipitation and both moderate and extreme heat degree days (Snyder 1985) between

[5] All monetary figures are expressed in terms of 2009 US dollars.

[6] For some counties, data on irrigated harvested cropland area is not available in all Census years, and as a result, the proportion of harvested cropland that is irrigated cannot be calculated for every Census year. For these counties, we take the maximum value of the proportion of harvested cropland that is irrigated across years in which data are available.

[7] The choice of a 15 percent cutoff for the proportion of harvested cropland that is irrigated is consistent with definitions of irrigated and non-irrigated counties in previous studies, which use cutoffs that range from 5 percent to 20 percent [Schlenker et al., 2005; Deschênes and Greenstone, 2007].

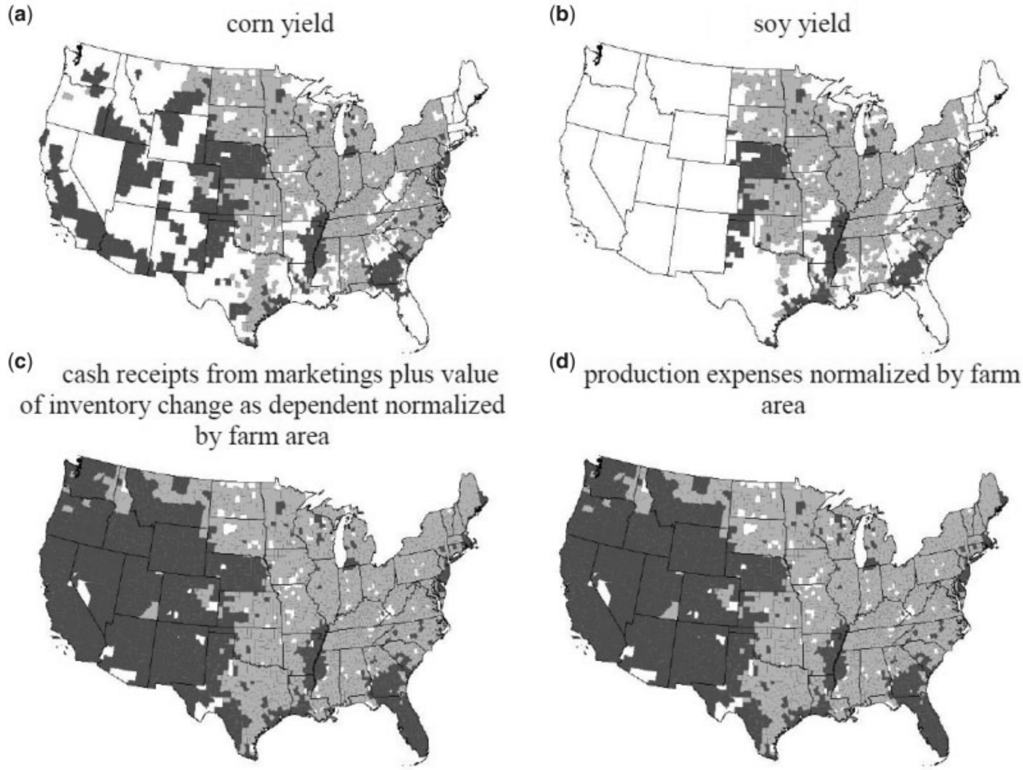

Figure 2. County observations included in regression models employing different dependent variables

Note: Light shades represent dryland counties and dark shades represent irrigated counties

April and September. County averages of daily precipitation and degree days observed in agricultural areas are summed throughout the growing season. Following Annan and Schlenker (2015), we implement different growing degree day temperature thresholds depending on the crop in question. Bounding temperatures for moderate heat degree days for corn and soybeans are 10-29°C and 10-30°C, respectively; extreme heat degree days are those above 29°C and 30°C for corn and soybeans, respectively.

Summary statistics for all agricultural and weather data are presented in table 2. Figure 2 presents four maps that indicate the irrigated and dryland counties that are represented in our corn yield, soybean yield, and farm income regressions. Our panel is unbalanced due to inconsistent availability of crop yield data across years. The empirical analysis presented below is based on this unbalanced panel, although using a balanced panel in which counties with missing years of data are dropped does not lead to significantly different results.

Empirical Strategy

The Impacts of Drought on Crop Yields

Our empirical strategy identifies the net impacts of additional weeks of drought in a given year, at various levels of intensity, on crop yields and measures of farm income at the county-year level, exploiting spatial and inter-temporal variation in agricultural outcomes, drought intensity, and drought duration. First, we consider a parsimonious fixed-effects specification for log crop yield:

$$(2) \quad y_{ist} = \alpha + \mathbf{D}_{ist}{}' \cdot \boldsymbol{\Gamma} + \lambda_t + \varphi_i + g_s(t) + \varepsilon_{ist}$$

where $\mathbf{D}_{ist}$ represents a vector of five variables indicating the area-weighted number of weeks in year t that agricultural areas of county i in state s were categorized as experiencing each of the five USDM drought intensity levels. County fixed effects (φ_i) help obtain unbiased estimates in the presence of unobserved time-invariant characteristics of counties that affect their agricultural outcomes in the face of drought, while year dummies (λ_t) help control for common trends that may be correlated with explanatory variables such as drought occurrence. We also control for the fact that yields are trending upward over time by using a state-specific linear time trend $g_s(t)$. The vector $\boldsymbol{\Gamma}$ contains our coefficients of interest, which capture the effect of an additional week of drought at each USDM intensity level on crop yields. We omit a variable representing the number of weeks that a county is not indicated as being in any drought status, so the coefficients in $\boldsymbol{\Gamma}$ can be interpreted as the impact on crop yields when all of a county's agricultural area is affected by an additional week of drought of a given severity (D0 through D4) relative to not being in any drought at all.

To provide a comparison to models from previous studies that have estimated the relationship between crop yields and weather variables such as temperature and precipitation, we also estimate a version of equation (2) in which we replace the vector of drought variables $\mathbf{D}_{ist}$ with a vector of weather variables, $\mathbf{W}_{ist}$:

$$(3) \quad y_{ist} = \alpha + \mathbf{W}_{ist} \cdot \boldsymbol{\Delta} + \lambda_t + \varphi_i + g_s(t) + \varepsilon_{it}.$$

Following Annan and Schlenker (2015), for our crop yield regressions, our weather variables include (a) the number of degree days of moderate heat, (b) the number of degree days of extreme heat, (c) annual precipitation, and (d) annual precipitation squared. These regressions will help illustrate whether or not the USDM drought variables are superior to the weather variables traditionally used to estimate crop yield outcomes—namely, temperature and precipitation.

A third set of crop yield regressions includes both drought variables $\mathbf{D}_{ist}$ and weather variables $\mathbf{W}_{ist}$:

$$(4) \quad \begin{aligned} y_{ist} = {} & \alpha + \mathbf{D}_{ist} \cdot \boldsymbol{\Gamma} + \mathbf{W}_{ist} \cdot \boldsymbol{\Delta} + \lambda_t + \varphi_i \\ & + g_s(t) + \varepsilon_{ist}. \end{aligned}$$

The purpose of these regressions is to examine whether the two types of variables—drought and weather—can explain different aspects of variability in crop yields.

We estimate models (2), (3), and (4) using observed yields of corn as well as soybeans. We run separate regressions for irrigated and dryland counties. Irrigation is known to help counteract the deleterious effects of drought, at least in the short run (Madariaga and McConnell 1984; O'Brien et al. 2001; Hansen, Libecap, and Lowe 2009; Hornbeck and Keskin 2014), and studies have shown that accounting for irrigation in an analysis of the impacts of climate change on U.S. agriculture leads to qualitatively different results (Schlenker, Hanemann, and Fisher 2005, 2006).

It is important to note that while time-invariant characteristics of counties that affect crop yields are controlled for by our fixed effects specifications, the impacts of drought and weather on crop yields estimated in $\boldsymbol{\Gamma}$ and $\boldsymbol{\Delta}$ may include some mitigating factors associated with farmer behavior and relevant institutional, market, and policy environments that change over time differently across counties. For example, farmers may be able to curtail the impacts of drought and weather fluctuations on crop yields within the growing season by the following: increasing irrigation; changing harvest patterns and timing; and augmenting labor, fertilizer, and other production inputs. Other factors that may benefit farmers differentially in the presence of drought include crop insurance payments and government drought disaster assistance.

We forgo specifications of Equations (2), (3), and (4) that implement state-by-year fixed effects in the place of year dummies and state-specific time trends. State-by-year fixed effects may seem appealing because they will help control for state-level inter-temporal shocks such as changes in state-level agricultural policy programs, agricultural markets, or technological change. However, in our empirical context, state-by-year fixed effects have the potential to absorb a significant amount of variance in drought conditions, leading to large standard errors. This concern was highlighted by Fisher et al. (2012), who criticized the use of state-by-year fixed effects by Deschênes and Greenstone (2007) in econometric specifications for identifying the effect of temperature on agricultural yield and profits. As a result, the source of variation in our econometric specification is fundamentally different from that which is used to identify the impacts of weather on agricultural outcomes in existing studies. Studies that have employed the hedonic approach (Mendelsohn, Nordhaus, and Shaw 1994; Schlenker, Hanemann, and Fisher 2005) rely on cross-sectional variation across counties, while Deschênes and Greenstone (2007), who pioneered the panel approach, use both county fixed effects and state-by-year fixed effects such that parameters are identified from the county-specific deviations in weather from county averages after adjusting for shocks common to all counties in a state. We account for potential spatial correlation in the error terms by using an OLS estimator with nonparametric estimation of the variance-covariance matrix for ε_{ist}, developed by Hsiang (2010).

The Impacts of Drought on Farm Income

We also estimate equations (2), (3), and (4) using two measures of farm income—cash receipts from marketings (net of the value of inventory changes) and production expenses—as our dependent variables. The counties and years for which farm income data are available are not the same as those for crop yield data, so results from the farm income regressions are not directly comparable to the results from the crop yield regressions. Other than the fact that they are monetized outcomes, our farm income measures differ from our crop yield measures in that the coefficient estimates may also include the effect of changes in local prices of agricultural commodities due to scarcity that results from droughts, which may increase net farm income if yields and production expenses are not significantly affected. As with the crop yield regressions, our farm income regressions are performed separately for irrigated and dryland counties.

Results

Column 1 in table 3 reports results from the estimation of equation (2) for dryland counties when the dependent variable is log corn yields. The coefficient estimates are all negative and statistically significant, indicating that additional weeks of drought in any severity category are associated with reduced corn yields. The magnitude of this negative impact is larger for additional weeks of drought in higher severity categories and ranges from a 0.1% decrease in corn yields for an additional week of D0 drought up to a 1.2% decrease in corn yields for an additional week of D4 drought.

Column 2 of the same table reports results from the estimation of equation (3) for corn yield outcomes in dryland counties. This regression serves as a check for consistency with the existing literature, which has already addressed the relationship between crop yields and weather variables such as precipitation and temperature. Consistent with these existing studies, we find that degree days of moderate heat are beneficial for crop yields, but degree days of extreme heat are harmful for yields. However, in our data, only the extreme heat variable is statistically significant. Like in previous studies, we find that precipitation has a positive and statistically significant relationship with yields, and the quadratic term for precipitation is negative and statistically significant. The magnitudes of these estimated effects are similar to those presented in studies that use the same temperature and precipitation measures (Annan and Schlenker 2015).

When drought and weather variables are simultaneously included as explanatory variables for corn yield (equation (4)), the coefficient estimates for the number of weeks of D2 and D3 drought remain negative and significant (table 3, column 3). However, the magnitudes of these coefficients are less than half of the magnitudes estimated in the specification that only includes drought variables. At the same time, the magnitude and significance of the coefficients for the weather variables are similar to those estimated in the weather-only regressions. We also note that the R-squared statistic for the drought-plus-weather specification is much closer to the R-squared statistic in the weather-only specification than to the R-squared statistic in the drought-only specification. Collectively, these regression outcomes suggest that precipitation and temperature explain most of the observed variability in crop yields. While the drought variables add little explanatory power in the estimation of equation (4), the statistically significant coefficients for D2 and D3 drought do represent meaningful impacts; that is, even after controlling for precipitation and temperature, an additional week of D2 or D3 drought is associated with reductions in corn yields of 0.3% to 0.5%. Furthermore, a Wald test indicates that the five drought variables are jointly significant at the 1% level. These additional impacts captured by the drought variables suggest that there are

Table 3. Impact of Additional Weeks of Drought and Weather in Agricultural Areas on Log Corn Yield

	Dryland Counties			Irrigated Counties		
	(1) Drought monitor only	(2) Weather only	(3) Drought monitor & weather	(4) Drought monitor only	(5) Weather only	(6) Drought monitor & weather
# weeks in D0	−0.00142[c]		8.37e-05	−0.000939[b]		0.000258
	(0.000425)		(0.000365)	(0.000374)		(0.000349)
# weeks in D1	−0.00318[c]		−0.000441	−0.000394		0.000413
	(0.000519)		(0.000430)	(0.000439)		(0.000393)
# weeks in D2	−0.00622[c]		−0.00284[c]	−0.00135[c]		0.000229
	(0.000735)		(0.000572)	(0.000395)		(0.000381)
# weeks in D3	−0.0109[c]		−0.00484[c]	−0.00125[b]		−0.000311
	(0.00107)		(0.000851)	(0.000512)		(0.000450)
# weeks in D4	−0.0119[c]		−0.00166	−0.00485[c]		−0.000953
	(0.00205)		(0.00140)	(0.000940)		(0.000822)
Moderate degree days (thousands)		0.0724	0.0926		−0.109[a]	−0.110[a]
		(0.0570)	(0.0566)		(0.0569)	(0.0574)
Extreme degree days (hundreds)		−0.571[c]	−0.534[c]		−0.205[c]	−0.203[c]
		(0.0227)	(0.0230)		(0.0169)	(0.0170)
Precipitation (meters)		0.635[c]	0.572[c]		−0.0867	−0.0917
		(0.124)	(0.122)		(0.110)	(0.110)
Precipitation squared		−0.408[c]	−0.381[c]		0.0613	0.0672
		(0.0872)	(0.0862)		(0.0831)	(0.0828)
Constant	4.365[c]	4.420[c]	4.378[c]	4.481[c]	4.939[c]	4.931[c]
	(0.100)	(0.174)	(0.172)	(0.0751)	(0.161)	(0.162)
Observations	17,182	17,182	17,182	5,061	5,061	5,061
R^2 within	0.3043	0.4525	0.4618	0.1936	0.2801	0.2815
R^2 between	0.0525	0.2937	0.3074	0.0043	0.0000	0.0001
R^2 overall	0.1459	0.3273	0.3471	0.0086	0.0268	0.0281

Note: Independent variables included in each specification are labeled in the second row. Standard errors account for potential spatial correlation in the error terms and appear in parentheses. All models include county and year fixed effects and state-specific linear time trends. All drought variables are weighted by the percentage of county agricultural area affected. Significance is denoted as follows: $a = 10\%$ level, $b = 5\%$ level, and $c = 1\%$ level.

hydrologic and climatic factors other than precipitation and temperature that may influence crop yields.

Columns 4, 5, and 6 in table 3 report results from the estimation of equations (2), (3), and (4) for corn yield in irrigated counties. As would be expected, yields are less sensitive to drought and weather in these irrigated counties relative to the dryland counties. In the drought-only specification (column 4), additional weeks of drought are associated with negative impacts on corn yield at every drought severity level except for D1, but the magnitude of these impacts is smaller than those estimated for dryland counties, with reductions ranging from 0.1% to 0.5%. The weather-only specification (column 5) yields coefficient estimates for degree days of moderate heat and extreme heat that are negative and statistically significant, while the relationships between the precipitation variables and corn yields are not statistically significant. In the drought-plus-weather specification (column 6), the coefficients on the weather variables are very similar to those estimated in the weather-only specification, and the coefficients on the drought variables are not statistically significant. These results suggest that, once controlling for temperature and precipitation, the USDM contributes little to explaining crop yields in irrigated counties.

Our regression results for soybean yields are similar to those for corn yields in dryland counties (columns 1, 2, and 3 in table 4). Drought is associated with lower soybean yields at every severity level, with negative impacts for an additional week of drought ranging from 0.2% to 0.8%. In the weather-only regression, degree days of moderate heat are associated with higher soybean yields, and unlike the case for corn, this relationship is statistically significant. Degree days of extreme heat are harmful for soybean

Table 4. Impact of Additional Weeks of Drought and Weather in Agricultural Areas on Log Soy Yield

	Dryland Counties			Irrigated Counties		
	(1) Drought monitor only	(2) Weather only	(3) Drought monitor & weather	(4) Drought monitor only	(5) Weather only	(6) Drought monitor & weather
# weeks in D0	−0.00184[c]		−0.000119	−0.000127		0.00143[b]
	(0.000446)		(0.000375)	(0.000628)		(0.000574)
# weeks in D1	−0.00602[c]		−0.00266[c]	−0.00216[c]		−0.000498
	(0.000561)		(0.000449)	(0.000713)		(0.000657)
# weeks in D2	−0.00591[c]		−0.00183[c]	−0.00292[c]		−0.00117[a]
	(0.000683)		(0.000526)	(0.000725)		(0.000702)
# weeks in D3	−0.00862[c]		−0.00183[b]	−0.00410[c]		−0.00200[c]
	(0.00109)		(0.000774)	(0.000771)		(0.000696)
# weeks in D4	−0.00657[b]		0.00357[b]	−0.000768		0.00349[c]
	(0.00288)		(0.00182)	(0.00129)		(0.00112)
Moderate degree days (thousands)		0.409[c]	0.418[c]		0.290[c]	0.241[b]
		(0.0576)	(0.0577)		(0.0943)	(0.0939)
Extreme degree days (hundreds)		−0.696[c]	−0.670[c]		−0.300[c]	−0.288[c]
		(0.0235)	(0.0234)		(0.0308)	(0.0307)
Precipitation (meters)		1.490[c]	1.444[c]		0.645[c]	0.682[c]
		(0.114)	(0.115)		(0.178)	(0.173)
Precipitation squared		−0.884[c]	−0.872[c]		−0.345[c]	−0.382[c]
		(0.0793)	(0.0789)		(0.130)	(0.127)
Constant	3.108[c]	1.925[c]	1.928[c]	3.625[c]	2.785[c]	2.876[c]
	(0.157)	(0.170)	(0.173)	(0.215)	(0.311)	(0.309)
Observations	15,366	15,366	15,366	3,391	3,391	3,391
R^2 within	0.2408	0.4732	0.4816	0.1851	0.2863	0.2974
R^2 between	0.0998	0.202	0.2049	0.0044	0.1078	0.0887
R^2 overall	0.1683	0.2896	0.2972	0.0122	0.0205	0.0107

Note: Independent variables included in each specification are labeled in the second row. Standard errors account for potential spatial correlation in the error terms and appear in parentheses. All models include county and year fixed effects and state-specific linear time trends. All drought variables are weighted by the percentage of county agricultural area affected. Significance is denoted as follows: $a = 10\%$ level, $b = 5\%$ level, and $c = 1\%$ level.

yields, and this negative effect is an order of magnitude larger than the beneficial effect of moderate heat degree days, which is consistent with previous literature. In addition, coefficient estimates for both the linear and quadratic precipitation terms are statistically significant and indicate an inverted U-shape relationship with soybean yields. As with corn yields, when drought variables are added to the weather variables as explanatory variables in the soybean regression, the magnitudes of the coefficient estimates for the weather variables are similar to those estimated in the weather-only regression, and coefficients for some of the drought variables remain statistically significant. A Wald test indicates that the five drought variables are jointly significant at the 1% level for soybean yields in dryland counties.

In irrigated counties (columns 4, 5, and 6 in table 4), soy yields are less sensitive to drought and weather variables relative to dryland counties (as was the case with corn yields). In the drought-only specification, negative impacts for an additional week of drought range from 0.2% to 0.4%, while in the weather-only specification, the coefficients for the precipitation and temperature variables are half the magnitudes of those estimated for dryland counties. We struggle to find an intuitive explanation for the positive and significant effect of additional weeks of D4 drought in the drought-plus-weather specifications for both irrigated and dryland counties.

Table 5 reports results from our three econometric specifications, for dryland and irrigated counties, using the log of cash receipts per acre from marketings plus the value of inventory change per acre as the dependent variable. Table 6 reports results from these same specifications using the log of production expenses per acre as the dependent variable. We find

Table 5. Impact of Additional Weeks of Drought and Weather in Agricultural Areas on Farm Income (Log Cash Receipts from Marketings Plus Value of Inventory Change / Farm Acres)

	Dryland Counties			Irrigated Counties		
	(1) Drought monitor only	(2) Weather only	(3) Drought monitor & weather	(4) Drought monitor only	(5) Weather only	(6) Drought monitor & weather
# weeks in D0	0.000253		0.000292	−0.000419		−0.000179
	(0.000215)		(0.000228)	(0.000393)		(0.000379)
# weeks in D1	6.21e-05		0.000179	6.76e-05		8.98e-05
	(0.000216)		(0.000228)	(0.000292)		(0.000330)
# weeks in D2	0.000318		0.000322	−0.000142		0.000246
	(0.000280)		(0.000281)	(0.000323)		(0.000350)
# weeks in D3	−0.00104[c]		−0.000916[c]	0.000221		0.000372
	(0.000313)		(0.000318)	(0.000343)		(0.000337)
# weeks in D4	−0.000288		0.000313	−0.000575		6.89e-05
	(0.000480)		(0.000527)	(0.000558)		(0.000616)
Moderate degree days (thousands)		0.0564	0.0485		−0.134[c]	−0.150[b]
		(0.0360)	(0.0348)		(0.0512)	(0.0587)
Extreme degree days (hundreds)		−0.0283[c]	−0.0258[c]		−0.00746	−0.00657
		(0.00702)	(0.00691)		(0.0103)	(0.0101)
Precipitation (meters)		0.0132	0.00405		−0.00832	−0.00733
		(0.0430)	(0.0437)		(0.0773)	(0.0803)
Precipitation squared		−0.0189	−0.00951		−0.0400	−0.0386
		(0.0328)	(0.0328)		(0.0656)	(0.0686)
Constant	0.105[c]	0.00434	0.0123	0.268[c]	0.616[c]	0.662[c]
	(0.0298)	(0.0932)	(0.0902)	(0.0222)	(0.125)	(0.141)
Observations	6,078	6,078	6,078	2,598	2,598	2,598
R^2 within	0.5079	0.5078	0.5101	0.2918	0.2964	0.2972
R^2 between	0.0757	0.0758	0.0804	0.0108	0.0248	0.0242
R^2 overall	0.1145	0.1148	0.1192	0.0001	0.0059	0.0064

Note: Independent variables included in each specification are labeled in the second row. Standard errors account for potential spatial correlation in the error terms and appear in parentheses. All models include county and year fixed effects and state-specific linear time trends. All drought variables are weighted by the percentage of county agricultural area affected. Significance is denoted as follows: $a = 10\%$ level, $b = 5\%$ level, and $c = 1\%$ level.

that the relationships between drought, weather, and these farm income measures are much less clear than the relationship between drought, weather, and crop yields, with a general lack of statistical significance across coefficient estimates, especially in irrigated counties. In dryland counties, additional weeks of D3 drought are associated with a decrease in cash receipts and additional weeks of D0 and D2 drought are associated with increases in production expenses, but the magnitudes of these effects are very small.

The lack of statistically significant responses of farm income measures to drought and weather may be due to the fact that farmers are more able to curtail the impacts of drought on farm income than on yield. This is likely to be the case if local scarcity of agricultural outputs caused by drought raises prices received by farmers.[8] Our measures of farm income—cash receipts from marketings and production expenses—exclude payments from crop insurance and drought disaster assistance programs that may become available to farmers during drought episodes. However, depending on the timing of these payments, farmers may be able to use income from these payments to adjust their on-farm practices in order to offset the negative impacts of drought on crop yields. We also note that our farm income results rely

[8] We are unable to conduct a sub-analysis of the relationship between drought and the price of agricultural commodities at the same level of detail as the rest of our analysis because price data are only available to us at the state level. Regressions using state-level prices of corn and soybeans as dependent variables and drought variables aggregated to the state level as independent variables result in positive and significant effects of drought on corn and soybean prices for D4 drought only, and these coefficient estimates become insignificant once year dummies are included in the specifications.

Table 6. Impact of Additional Weeks of Drought and Weather in Agricultural Areas on Production Expenses (Log Production Expenses/Farm Acres)

	Dryland Counties			Irrigated Counties		
	(1) Drought monitor only	(2) Weather only	(3) Drought monitor & weather	(4) Drought monitor only	(5) Weather only	(6) Drought monitor & weather
# weeks in D0	0.000534[c]		0.000636[c]	2.41e-06		9.46e-05
	(0.000189)		(0.000198)	(0.000367)		(0.000348)
# weeks in D1	−0.000244		−8.91e-05	0.000210		−2.22e-06
	(0.000191)		(0.000199)	(0.000269)		(0.000282)
# weeks in D2	0.000429[a]		0.000565[b]	0.000177		0.000436
	(0.000240)		(0.000240)	(0.000299)		(0.000313)
# weeks in D3	−0.000339		−0.000238	0.000224		0.000283
	(0.000282)		(0.000283)	(0.000322)		(0.000312)
# weeks in D4	−6.06e-05		0.000188	−0.000233		0.000132
	(0.000499)		(0.000526)	(0.000513)		(0.000590)
Moderate degree days (thousands)		−0.0980[c]	−0.113[c]		−0.103[b]	−0.124[b]
		(0.0311)	(0.0302)		(0.0480)	(0.0552)
Extreme degree days (hundreds)		0.00408	0.00703		−0.00204	−0.00172
		(0.00603)	(0.00606)		(0.00951)	(0.00927)
Precipitation (meters)		−0.0187	−0.0202		0.0332	0.0337
		(0.0414)	(0.0413)		(0.0617)	(0.0632)
Precipitation squared		0.0152	0.0227		−0.0926[a]	−0.0912[a]
		(0.0308)	(0.0305)		(0.0505)	(0.0521)
Constant	0.0846[b]	0.342[c]	0.363[c]	0.240[c]	0.517[c]	0.566[c]
	(0.0843)	(0.0333)	(0.0811)	(0.0149)	(0.112)	(0.129)
Observations	6,078	6,078	6,078	2,598	2,598	2,598
R^2 within	0.4959	0.4956	0.498	0.2295	0.2388	0.2396
R^2 between	0.0771	0.0538	0.0533	0.0111	0.0249	0.0219
R^2 overall	0.1116	0.0884	0.0874	0.0000	0.0054	0.0056

Note: Independent variables included in each specification are labeled in the second row. Standard errors account for potential spatial correlation in the error terms and appear in parentheses. All models include county and year fixed effects and state-specific linear time trends. All drought variables are weighted by the percentage of county agricultural area affected. Significance is denoted as follows: $a = 10\%$ level, $b = 5\%$ level, and $c = 1\%$ level.

on only 3 years of data (from 2002, 2007, and 2012), in contrast to the 13 years of data that are available for crop yields. It is possible that the small number of years used in our farm income regressions are not representative of year-to-year fluctuations in farm income due to coincident changes in agricultural policy, the ethanol boom and corresponding increases in crop prices, and the 2012 Midwest drought.

Finally, we estimated equation (2) for corn and soybean yields in dryland and irrigated counties in six different regions of the United States: High Plains, Midwest, Northeast, South, and Southeast.[9] We find that the expected negative relationship between drought and crop yields is consistently observed in dryland counties in the High Plains, Midwest, and South regions but less so in the other two regions. Impacts are particularly large in dryland counties in the Midwest, where an additional week of D4 drought is associated with an 8.0% decrease in corn yields and a 3.1% decrease in soybean yields. These regional results suggest that the USDM may be more useful for identifying communities affected by drought in the High Plains, Midwest, and South. Our results also suggest that drought disaster assistance programs that apply the same eligibility criteria for all regions using USDM categorizations (e.g., a county must have experienced D3 or D4 drought for at least eight consecutive weeks) may not target the farmers who are most vulnerable to drought.

Conclusion

Despite growing interest within the research and policy communities, few studies quantify the effect of drought on agricultural outcomes

[9] We omit the western region of the United States from our analysis due to a lack of crop yield data from counties in this region.

in the United States. In this paper, we estimated the impacts of drought, as defined by the USDM, on crop yields and farm income. We find negative and statistically significant effects of drought on crop yields in the average county, equal to yield reductions in the range of 0.1% to 1.2% for corn and soybean yields for each additional week of drought in dryland counties, and 0.1% to 0.5% in irrigated counties. However, region-specific outcomes vary, with some regions experiencing no yield impacts from drought, while we observe yield reductions as high as 8.0% in dryland counties in the Midwest for every week of drought in the highest severity category. Despite this impact on crop yields, we find that additional weeks of drought have little to no effect on measures of farm income.

Using regression specifications that include weather variables in addition to drought variables, we find that precipitation and temperature explain most of the observed variability in crop yields. However, additional weeks of drought in certain severity categories are associated with negative and statistically significant impacts on crop yields even after controlling for precipitation and temperature. This finding suggests that the USDM contains information regarding impacts on crop yields above and beyond what can be drawn from observing only temperature and precipitation, and serves as evidence to support the official use of the USDM as a complement to weather information for making resource allocation decisions within government drought disaster assistance programs. At the same time, our analysis suggests that the USDM may be more helpful for identifying drought impacts in some regions of the United States and less so in others. In particular, we find that the USDM is more correlated with crop yield outcomes in dryland counties than in irrigated counties, and is more correlated with crop yield in the High Plains, Midwest, and South than in the Northeast and Southeast.

Our analysis focused specifically on the effect of additional weeks of drought on crop yields and components of farm income, but our USDM-based framework can be used to estimate other types of relationships between droughts and agriculture. For example, our econometric approach could be used to estimate the effects of droughts with a longer duration; such an analysis may help policymakers choose the appropriate number of weeks that counties need to be in drought, as categorized by the USDM, before being eligible for drought disaster assistance. More generally, our framework can help policymakers form direct links between the provision of drought disaster assistance and the economic impacts that these programs seek to mitigate.

Building on our results, there are several ways in which future work could delve deeper into the impacts of drought on agriculture. For example, there is evidence that crop production is affected not only by the intensity and duration of a drought, but also its timing with respect to the growing season (Walthall et al. 2012). Future work could examine whether drought categorizations are particularly harmful during certain parts of the calendar year, although this would require careful consideration of the econometric approach as effects are likely to be heterogeneous across regions and crop types. In addition, future work could quantify the degree to which on-farm practices, crop insurance programs, and disaster assistance policies affect observed agricultural outcomes in the presence of drought.

Supplementary Material

Supplementary material are available at *American Journal of Agricultural Economics* online.

References

Annan, F., and W. Schlenker. 2015. Federal Crop Insurance and the Disincentive to Adapt to Extreme Heat. *American Economic Review* 105 (5): 262–6.

Bureau of Economic Analysis. 2015. *Local Area Personal Income Methodology*. Washington DC: BEA.

Bernknopf, R., D. Brookshire, Y. Kuwayama, M. Macauley, M. Rodell, A. Thompson, P. Vail, and B. Zaitchik. 2018. The Value of Remotely Sensed Information: The Case of a GRACE-Enhanced Drought Severity Index. *Weather, Climate, and Society* 10 (1): 187–203.

Cattivellia, L., F. Rizza, F.W. Badeck, E. Mazzucotelli, A.M. Mastrangelo, E. Francia, C. Marè, A. Tondelli, and A.M. Stanca. 2008. Drought Tolerance Improvement in Crop Plants: An Integrated View from Breeding to Genomics. *Field Crops Research* 105 (1–2): 1–14.

Cavatassi, R., L. Lipper, and U. Narloch. 2011. Modern Variety Adoption and Risk Management in Drought Prone Areas: Insights from the Sorghum Farmers of Eastern Ethiopia. *Agricultural Economics* 42 (3): 279–92.

Ciais, P., M. Reichstein, N. Viovy, A. Granier, J. Ogée, V. Allard, M. Aubinet, et al. 2005. Europe-Wide Reduction in Primary Productivity Caused by the Heat and Drought in 2003. *Nature* 437 (22): 529–33.

Climate Change Science Program. 2008. *The Effects of Climate Change on Agriculture, Land Resources, Water Resources, and Biodiversity in the United States*. Washington DC: U.S. Department of Agriculture.

Craine, J.M., T.W. Ocheltree, J.B. Nippert, E.G. Towne, A.M. Skibbe, S.W. Kembel, and J.E. Fargione. 2013. Global Diversity of Drought Tolerance and Grassland Climate-Change Resilience. *Nature Climate Change* 3 (1): 63–7.

Deschênes, O., and M. Greenstone. 2007. The Economic Impacts of Climate Change: Evidence from Agricultural Output and Random Fluctuations in Weather. *American Economic Review* 97 (1): 354–85.

Ding, Y., K. Schoengold, and T. Tadesse. 2009. The Impact of Weather Extremes on Agricultural Production Methods: Does Drought Increase Adoption of Conservation Tillage Practices? *Journal of Agricultural and Resource Economics* 34 (3): 395–411.

Fafchamps, M., C. Udry, and K. Czukas. 1998. Drought and Saving in West Africa: Are Livestock a Buffer Stock? *Journal of Development Economics* 55 (2): 273–305.

Fisher, A.C., W.M. Hanemann, M.J. Roberts, and W. 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.

Hansen, Z.K., G.D. Libecap, and S.E. Lowe. 2009. *Climate Variability and Water Infrastructure: Historical Experience in the Western United States*. NBER Working Paper No. 15558. Cambridge, MA.

Hornbeck, R., and P. Keskin. 2014. The Historically Evolving Impact of the Ogallala Aquifer: Agricultural Adaptation to Groundwater and Drought. *American Economic Journal: Applied Economics* 6 (1): 190–219.

Horridge, M., J. Madden, and G. Wittwer. 2005. The Impact of the 2002-2003 Drought on Australia. *Journal of Policy Modeling* 27 (3): 285–308.

Houborg, R., M. Rodell, B. Li, R. Reichle, and B. F. Zaitchik. 2012. Drought Indicators Based on Model-Assimilated Gravity Recovery and Climate Experiment (GRACE) Terrestrial Water Storage Observations. *Water Resources Research* 48 (7): doi:10.1029/2011WR011291.

Howitt, R.E., J. Medellín-Azuara, D. MacEwan, J.R. Lund, and D.A. Sumner. 2014. *Economic Analysis of the 2014 Drought for California Agriculture*. Davis, CA: Center for Watershed Sciences, University of California.

———. 2015. *Economic Analysis of the 2015 Drought for California Agriculture.* Davis, CA: Center for Watershed Sciences, University of California.

Hsiang, S.M. 2010. Temperatures and Cyclones Strongly Associated with Economic Production in the Caribbean and Central America. *Proceedings of the National Academy of Sciences* 107 (35): 15367–72.

Intergovernmental Panel on Climate Change. 2014. *Climate Change 2014: Synthesis Report. Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*. Geneva.

Kazianga, H., and C. Udry. 2006. Consumption Smoothing? Livestock, Insurance and Drought in Rural Burkina Faso. *Journal of Development Economics* 79 (2): 413–46.

Kinsey, B., K. Burger, and J.W. Gunning. 1998. Coping with Drought in Zimbabwe: Survey Evidence on Responses of Rural Households to Risk. *World Development* 26 (1): 89–110.

Lloyd-Hughes, B. 2014. The Impracticality of a Universal Drought Definition. *Theoretical and Applied Climatology* 117 (3–4): 607–11.

Lobell, D.B., G.L. Hammer, G. McLean, C. Messina, M.J. Roberts, and W. Schlenker. 2013. The Critical Role of Extreme Heat for Maize Production in the United States. *Nature Climate Change* 3 (5): 497–501.

Madariaga, B., and K.E. McConnell. 1984. Value of Irrigation Water in the Middle Atlantic States: An Econometric Approach. *Southern Journal of Agricultural Economics* 16 (2): 91–8.

Medellín-Azuara, J., D. MacEwan, R.E. Howitt, D.A. Sumner, and J.R. Lund. 2016. *Economic Analysis of the 2016 Drought for California Agriculture*. Center for Watershed Sciences, University of California, Davis.

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

Mount, J., E. Hanak, C. Chappelle, B. Colby, R. Frank, G. Gartrell, B. Gray, et al. 2016. *Improving the Federal Response to Western Drought*. San Francisco, CA: Public Policy Institute of California.

National Drought Mitigation Center. 2016. *U.S. Drought Monitor Background*. Lincoln, NE.

National Research Council. 2007. *Understanding Multiple Environmental Stresses: Report of a Workshop*. Washington DC.

O'Brien, D.M., F.R. Lamm, L.R. Stone, and D.H. Rogers. 2001. Corn Yields and Profitability for Low-Capacity Irrigation Systems. *Applied Engineering in Agriculture* 17 (3): 315–21.

Riebsame, W.E., S.A. Changnon Jr., and T.R. Karl. 1991. *Drought and Natural Resources Management in the United States: Impacts and Implications of the 1987-89 Drought*. Boulder, CO: Westview Press.

Schlenker, W., and M.J. Roberts. 2009. Nonlinear Temperature Effects Indicate Severe Damages to U.S. Crop Yields under Climate Change. *Proceedings of the National Academy of Sciences* 106 (37): 15594–8.

Schlenker, W., W.M. Hanemann, and A.C. Fisher. 2005. Will U.S. Agriculture Really 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. *Review of Economics and Statistics* 88 (1): 113–25.

Snyder, R.L. 1985. Hand Calculating Degree Days. *Agricultural and Forest Meteorology* 35 (1–4): 353–8.

Svoboda, M., D. LeComte, M. Hayes, R. Heim, K. Gleason, J. Angel, B. Rippey, et al. 2002. The Drought Monitor. *Bulletin of the American Meteorological Society* 83 (8): 1181–90.

U.S. Department of Agriculture. 2003. *Fact Sheet: Sales of Surplus Non-Fat Dry Milk*. Washington DC: USDA.

———. 2006. *Fact Sheet: Livestock Assistance Grant Program*. Washington DC: USDA.

———. 2015. *Fact Sheet: Emergency Disaster Designation and Declaration Process*. Washington DC: USDA.

———. 2017a. *Fact Sheet: Livestock Forage Disaster Program*. Washington DC: USDA.

———. 2017b. *Livestock Forage Payments as of March 2, 2017*. Washington DC: USDA.

———. 2017c. *Farm Loan Programs Program Data*. Washington DC: USDA.

U.S. Department of Treasury. 2016. *Internal Revenue Bulletin: 2016-42* Notice 2016-60 Extension of Replacement Period for Livestock Sold on Account of Drought. Washington DC: USDT.

Walthall, C.L., J. Hatfield, P. Backlund, L. Lengnick, E. Marshall, M. Walsh, S. Adkins, et al. 2012. *Climate Change and Agriculture in the United States: Effects and Adaptation*. Washington DC: U.S. Department of Agriculture, Technical Bulletin No. 1935.

Wheaton, E., S. Kulshreshtha, V. Wittrock, and G. Koshida. 2008. Dry Times: Hard Lessons from the Canadian Drought of 2001 and 2002. *Canadian Geographer/Le Géographe Canadien* 52 (2): 241–62.

Wilhite, D.A. 2000. Drought as a Natural Hazard: Concepts and Definitions. In *Drought: A Global Assessment*, *Volume* 1, ed. D.A. Wilhite, 3–18. London: Routledge.

Zhao, M., and S.W. Running. 2010. Drought-Induced Reduction in Global Terrestrial Net Primary Production from 2000 through 2009. *Science* 329 (5994): 940–3.