Droughts and Aggregate Economic Profitability Indicators for the U.S. Farm Sector

Tatiana Borisova, Tia McDonald, Clayton Winters-Michaud, Noah Miller, and Jonathan Law[1]

[1] The authors are: Tatiana Borisova: Agricultural Economist, Tia McDonald: Research Agricultural Economist, Clayton Winters-Michaud: Research Agricultural Economist, Noah Miller: Research Agricultural Economist, Jonathan Law: Agricultural Economist, Farm Economy Branch, Resource and Rural Economy Division, the Economic Research Service, U.S. Department of Agriculture. Corresponding authors: Tatiana Borisova (tatiana.borisova@usda.gov) and Tia McDonald (tia.mcdonald@usda.gov).

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Abstract

USDA Economic Research Service (ERS) releases estimates of farm sector income, informing the public on the financial performance of the U.S. agriculture sector. This paper uses the ERS estimates for 1968–2019 state-level annual farm sector net income to explore the effect of droughts on the U.S. agricultural sector, and to evaluate the distribution of the drought impacts among the U.S. regions. We also examine the extent to which the government safety net, including direct government payments and federal crop insurance program indemnities, compensates for the impacts of the drought on farm sector profitability. Panel-data fixed effect regression models are estimated, with the drought indicators constructed from the county crop damage days reported in the Spatial Hazard Events and Losses Database for the United States (SHELDUS™). We show that market net farm income (NFI) is negatively correlated with the drought indicators. Our preliminary results also suggest that a significant share of damages to sector performance are offset by federal crop insurance program indemnities. Finally, our results show that the drought's impacts and the effects of the government safety net may be distributed differently among the regions.

Key words: U.S. agricultural sector, calendar-year state-level net farm income, drought days, panel data regression analysis, government payments, federal crop insurance program indemnities.

As one of the 13 principal federal statistical agencies in the United States (U.S.), the U.S. Department of Agriculture's Economic Research Service (USDA/ERS) produces forecasts and estimates of the U.S. farm sector income and finances. USDA/ERS releases annual, state-level estimates of net farm income and their components, including commodity value of production, Government direct farm program payments, and production expenses. USDA/ERS data and analysis are used by USDA and other farm sector stakeholders, including lenders, agribusinesses, and farm organizations, to inform their perspectives on the financial health of the U.S. agricultural economy. The U.S. Congress, the Secretary of Agriculture, and numerous public and private entities rely on ERS farm income forecasts and estimates for a variety of uses – from aiding in legislation and USDA program development to helping states assess their local farm economies.

Most of the state-level calendar year financial indicators are available starting in 1949 (see U.S. Department of Agriculture, Economic Research Service [USDA/ERS], 2023a), and given this comprehensive nature and long time series, studies have used USDA/ERS farm sector income and wealth statistics to evaluate the impacts of significant events affecting U.S. agriculture. For example, Boehlje et al. (2013) used the data to discuss "boom and bust" cycles in agricultural industry and explore past financial performance of the sector. More recently, Giri et al. (2022) used USDA/ERS forecasts and estimates to examine 2020 farm sector financial ratios before and after the onset of the Coronavirus (COVID-19) pandemic, showing that at the national level, all solvency, liquidity, and profitability ratios for the U.S. agricultural sector for 2020 were weaker than their respective average ratios obtained from 2000 to 2019 data.

In this paper, we use USDA/ERS state-level annual farm sector net income (USDA/ERS, 2022) to examine drought impacts on U.S. agriculture. Extreme weather events, such as droughts and heat waves, are becoming more frequent in the changing climate caused by anthropogenic greenhouse gas emission. While many effects of climate change on agriculture are still uncertain, Pörtner et al. (2022) assign a high level of confidence to the expert conclusions that climate change leads to negative effects on crop quality and it shifts the distribution of crops and livestock losses. These changes affect livelihood in rural communities and pose global food security risks (Pörtner et al., 2022).

While some extreme weather events have localized impacts (e.g., hurricanes and floods), the weather dynamics, such as the jet stream and cyclones and anticyclones, can lead to co-variability of weather across regions (Kornhuber et al., 2020). Many events can affect vast expanses and therefore, they can be reflected in aggregate, state- or national-level, indicators (e.g., see the national-level analysis of weather effect on crop production and agricultural productivity in Lesk et al., 2016, and Ortiz-Bobea et al., 2021).

Many of the past studies focused on the effects of droughts and heat waves on crop yields (e.g., Schlenker & Roberts, 2006, Lobell et al., 2013, Teixeir et al., 2013, Lesk et al., 2016, and Miller et al., 2021), while the analysis of financial measures and weather and climate events is relatively sparse (Ortiz-Bobea et al., 2021). Yet, weather impacts on agricultural profitability can deviate from the impacts on yield because of market-based price changes that can support profits, and due to the adaptation adjustments by producers, including changing mixtures of crops and livestock commodity production, altering agricultural inputs and costs, and other adjustments. For example, Kuwayama et al. (2019) report negative and statistically significant effects of drought on crop yields but little to no effects of droughts on farm income at the county level.

In times of drought, payments from the government safety net may offset the effects of drought on farm profit.[2] Government safety net "is a collection of programs that provide risk protection and financial support to U.S. farmers in times of low farm prices and natural disasters" (p. 1, Rosch, 2021; see also Rosch, 2015). Federal crop insurance program may play a unique role in supporting farm income during droughts since the crop insurance indemnifies revenue or yield, which we may expect to be impacted by weather related shocks like drought[3]. This may account for the fact that since 2000, 42.1 percent of total Federal crop insurance program indemnities were in response to drought or high temperature events (USDA/ERS, 2023d). Furthermore, government safety net has been evolving, and its role in offsetting financial impacts of drought may also be changing over time. A major change in the federal crop insurance program resulted from the Federal Crop Insurance Reform and Department of Agriculture Reauthorization Act of 1994, which increased premium subsidies and required farmers to purchase crop insurance as a condition for supporting commodity support payments (Rosch, 2021). While this requirement to purchase crop insurance was only active for one year (the Federal Agriculture Improvement and Reform Act of 1996 removed it), the result was a dramatic increase in the insurance participation. Under 100 million acres were insured in 1994, while over 200 million acres were insured in 1995, with high levels of participation persisting into 2023 (USDA/ERS, 2023d).

The objectives of this paper are to explore the drought effects on state-level, annual market net income measures for the U.S. agricultural sector, and to evaluate the distribution of the drought

[2] Following the sector-level accounting in USDA/ERS (2023a), net farm income is comprised of the value of production, farm-related income (including total commodity insurance indemnities), expenses and payments to stakeholders, net Government transactions (including direct government payments), and capital consumption.
[3] This is in contrast to many historic and current government programs, many of which support prices. Historic examples of such programs include deficiency payments (1987-1996), direct and countercyclical payments (2002-2007). Similarly, the 2014 Farm Bill introduced Agriculture Risk Coverage (ARC) and Price Loss Coverage (PLC), where PLC is triggered by price decreases, whereas ARC is triggered by revenue.

impacts among the U.S. regions. We also explore if the government safety net, including direct government payments and federal crop insurance program indemnities, may partially alleviate the impacts of the droughts on the sector's profitability. Finally, we investigate if the drought effects and the role of the government safety net changed over time. In particular, given the significant changes in the federal crop insurance program and related expansion in the enrolled acreage in 1995, we compare the results of the analysis for two time period: pre-1995 and 1995+.

Method and Data

Conceptual Model

Agricultural profit from production and sales of commodities on the market, $market\ \pi$, can be presented as the difference between gross revenues and expenses, as follows:[4]

$$market\ \pi = p(q(w))\ q(w)\ - c(q(w)) \tag{1}$$

where *w* refers to weather event (drought in this study), *q(w)* denotes quantity produced, which is a function of weather, and *p* and *c* refer to price and costs, which depend on quantity and therefore, weather.

A drought can result in a reduction in quantity ($\frac{\partial q}{\partial w} < 0$), and using equation (1), marginal changes in the profits in response to the drought can be expressed as follows:

$$\frac{\partial\ market\ \pi}{\partial w} = \frac{\partial p}{\partial q}\ \frac{\partial q}{\partial w}\ q + p\ \frac{\partial q}{\partial w}\ - \frac{\partial c}{\partial q}\frac{\partial q}{\partial w} \tag{2}$$

The first term is the <u>*increase*</u> in gross revenue due to potential commodity price increase. It can mitigate (a part of the) profit losses due to lower production (Deschênes & Greenstone, 2007). The

[4] In this paper, we modify the stylized model from Deschênes & Greenstone (2007) to represent changes in the sector net incomes.

second term in equation (2) measures the *reduction* in the gross revenue due to drought-induced quantity changes. The third term in equation (2) is the change in production expenses, $\frac{\partial c}{\partial q}\frac{\partial q}{\partial w}$, due to the reduction in quantity. The relative sizes of the three components and the ultimate effect of droughts on profits depend on the elasticity of the supply and demand curves.

The conceptual model (1)–(2) does not account for the safety net made available to producers by the federal Government, such as the federal crop insurance program, agriculture disaster assistance programs, or other government programs. Potential effects of government payments on agricultural supply are discussed, for example, in Burfisher & Hopkins (2004), Goodwin & Mishra (2005), Moro & Scokai (2013), and Weber et al. (2016). If we denote government payments as *GP*, the total agricultural net income, π, can be expressed as the sum of the market profit and government payments:

$$\pi = market\ \pi(w) + GP(w) \tag{3}$$

where government payments *GP* depend on the weather events, *w*. Note that this dependence can be direct (e.g., when ad hoc payments are made in response to drought-related yield losses) or indirect (e.g., when droughts and supply shortage cause increase in prices and reductions in income support program payments). The effect of droughts on this net income can be conceptualized as follows:

$$\frac{\partial\ market\ \pi}{\partial w} = \frac{\partial p}{\partial q}\ \frac{\partial q}{\partial w}\ q + p\ \frac{\partial q}{\partial w}\ - \frac{\partial c}{\partial q}\frac{\partial q}{\partial w} + \ \frac{\partial GP}{\partial w} \tag{4}$$

In this paper, we examine to what degree the government safety net can have offset drought-related reductions in profits, $market\ \pi$. In other words, we evaluate and compare the changes in market profits, $\frac{\partial\, market\, \pi}{\partial w}$, as well as changes in government payments, $\frac{\partial GP}{\partial w}$, in response to droughts, and we do that for two time periods, pre-1995, and 1995 and after.

Method

A panel-data regression model was used to examine the correlation between sector market net income, π, and droughts:

$$market\ \pi_{it} = \alpha_0 + \beta_1 w_{it} + c_i + \lambda_t + u_{it} \tag{5}$$

where $marekt\ \pi_{it}$ is the state-level, annual market net farm sector income; *i* indexes states; *t* refers to year, and w_{it} includes weather indicators (i.e., county drought days, as explained below). In this equation, α_0 is a constant, c_i is state fixed effect, λ_t is year fixed effect, and u_{it} is assumed to capture the remaining uncertainty.[5] The inclusion of state and year fixed effects controls for time invariant state-level factors, like geographic location, and time varying factors common to all states, like macroeconomic conditions.

To explore the effect of the government safety net (SN), we run the same model(s) but with the dependent variable being federal crop insurance program indemnities and direct government payments:

$$SN_{kit} = \alpha_0 + \beta_2 w_{it} + c_i + \lambda_t + u_{it} \tag{6}$$

where *k* refers to the type of safety net considered, specifically, direct government payments or federal crop insurance program indemnities.

[5] Here, u_{it} is assumed to be normally distributed; various model specifications are compared, including those accounting for potential heteroscedasticity ('robust' option in Stata's *xtreg*) and clustering of the errors by state ('cluster' option in Stata's *xtreg*).

We further seek to understand the expanded importance of the federal crop insurance program indemnities in supporting farm incomes in times of drought, especially in response to the 1995 expansion in the federal crop insurance program participation. To do this we estimate models based on the first (1968–1994) and second (1995–2019) halves of the sample:

$$market\,\pi_{it} = \alpha_0 + \beta_1^{94}\,w_{it}^{94} + \beta_1^{95}\,w_{it}^{95} + c_i + \lambda_t + u_{it} \quad (7)$$

The difference between coefficients β_1^{94} and β_1^{95} would reflect empirically the changes over time in $market\,\pi$ response function to the droughts. A similar model was estimated with the states' $indemnities$ and $direct\ Govenrent\ payments$ as the dependent variables (i.e., with the coefficients in the two periods denoted β_2^{94} and β_2^{95}).

Finally, the following steps were used to examine the regional distribution of drought impacts on $market\,\pi$ and income from safety net programs, focusing on the more recent years (1995-2019). First, region-specific effect of droughts on $market\,\pi$ was examined using the following model:

$$market\,\pi_{it} = \alpha_0 + \beta_{1j}^{95} w_{it}^{95}\,h_j + c_i + u_{it} \quad (8)$$

where, as before, w_{it}^{95} identifies drought events occurring in t^{th} year and i^{th} state. However, the regression coefficients β_{1j}^{95} are interacted with each USDA-ERS farm production region. Specifically, in equation (8), j refers to the region that includes ith state, and h_j represents a dummy variable which is equal to zero unless the state belongs to region j (and in this case, h_j=1).

Second, a model similar to model (8) was estimated with the dependent variable being the states' federal crop insurance program indemnities and government payments–to explore the potential difference in the regional effects of the government safety net programs:

$$SN_{kit} = \alpha_0 + \beta_{2j}^{95} w_{it}^{95} h_j + c_i + \gamma_{jt} + u_{it} \quad (9)$$

This regional analysis is limited to the more recent years (1995-2019) to focus on the effect of changes to the federal crop insurance program and the effects of newly implemented government safety net programs.

Profits can vary significantly among the states (USDA/ERS, 2023a), and therefore, changes in $market\ \pi$ due to drought can differ among states. For example, if a drought results in the losses of a half of planted acreage or contraction in available livestock water or forage, this loss results in larger reductions in profits for the states with a greater planted acreage. To account the variation in profits due to extent of the agricultural activity in the state, models (4)–(8) are controlling for planted acres. All the models were estimated in Stata/MP 17.0 (StataCorp LLC, 2023).

Data

In this study, we explore the effect of droughts on state-level, calendar year net farm income (NFI) indexed to 2022 dollars (USDA/ERS, 2022). NFI is a fundamental measure of U.S. farm sector finances and profitability, and one of the most frequently cited USDA statistics (McGath et el., 2009).[6] For the state *i* and calendar year *t*, USDA/ERS calculates NFI as follows:

$$NFI_{it} = Value\ of\ Crop\ and\ Animal/Animal\ Products_{it} + \\ Direct\ Government\ Payments_{it} + Farm\ Related\ Income_{it} - Total\ Expenses_{it} \qquad (10)$$

Note that the value of production (i.e., the first term in the equation) includes 'calendar year' subscript *t*, which references the year that the commodity was produced, rather than when it was marketed. This value of production also accounts for the value of non-cash items, such as

[6] Other financial indicators released as a part of ERS Farm Income and Wealth Statistics include: net cash farm income, value added by U.S. agriculture, return to operators, farm balance sheet, selected financial ratios, and average farm-level net cash income. See USDA ERS - Data Files: U.S. and State-Level Farm Income and Wealth Statistics .

agricultural products consumed on the farm. In turn, direct government payments are those made by the Federal Government directly to farmers and ranchers with no intermediaries. Government payments do not include Federal Crop Insurance Corporation (FCIC) indemnities (listed as a separate component of farm related income) and USDA loans (listed as a liability in the farm sector's balance sheet) (USDA/ERS, 2023c). Most direct government payments to farmers and ranchers are typically administered by the USDA under the Farm Bill or other authorities; though they can also include supplemental programs authorized by Congress. Examples of program categories included into direct government payments in USDA/ERS (2022) are historical commodity programs, conservation programs, countercyclical and countercyclical-type programs, fixed payments, marketing loan benefits, and supplemental and ad hoc disaster assistance (Wakefield, 2022). Among the direct government payment categories, supplemental and ad hoc disaster assistance payments are expected to be the most directly related to the adverse weather impacts, including droughts. However, ERS (2022) separately identifies this category only since 1998. Therefore, for this paper, we consider the total direct government payments, and do not disaggregate them into the specific programs.

Next, farm-related income accounts for various cash and non-cash farm-related income. The gross imputed rental value of farm dwellings is non-cash income, and it accounts for one third of farm-related income (on average for 2012-2021, adjusted for inflation). Important for this analysis is that farm-related income also includes federal commodity insurance indemnities, which contributes 18% of total farm-related income, on average, for 2012-2021 (based on data from USDA/ERS, 2023a, adjusted for inflation).[7] In this paper, federal crop insurance program

[7] Note that the levels of the "Federal commodity insurance indemnities" in USDA/ERS (2023a) are based on the national Summary of Business from USDA/RMA (undated), while the authors used information from USDA/RMA (2023). However, authors analysis shows that the indemnity levels from these two information sources are highly correlated and they are generally close.

indemnities are based on the "Summary of Business" reports from the USDA/RMA (USDA/RMA 2023), because USDA/ERS (2022) do not separately identify the indemnities until 2008.

In total, the value of crops and animal/animal products, direct government payments, and farm-related income constitute gross farm income, and therefore, NFI is the difference between gross farm income and total expenses. Total expenses are a comprehensive accounting of the sector expenses, specifically: farm origin inputs (feed, livestock and poultry, and seed), manufactured inputs (e.g., pesticides, fertilizer, fuel, and electricity), other intermediate expenses (e.g., repair and maintenance, machine hire and custom work, and marketing, storage, and transportation), labor expenses, interest expenses, net rent to landlords, property taxes and fees, and capital consumption (which is a measure of economic depreciation).[8] Among these expense categories, NFI also includes non-cash expenses, such as expenses associated with operator dwellings, non-cash employee compensation, and a measure of economic depreciation (capital consumption). Additional discussion of NFI is available in USDA/ERS (2023b).

When calculating the farm profitability less government payments (i.e., "market NFI"), we exclude federal crop insurance program indemnities and direct government payments:

$$market\ NFI_{it} = NFI_{it} - Direct\ Government\ Payments_{it} - Federal\ Insurance\ Indemnities_{it} \quad (11)$$

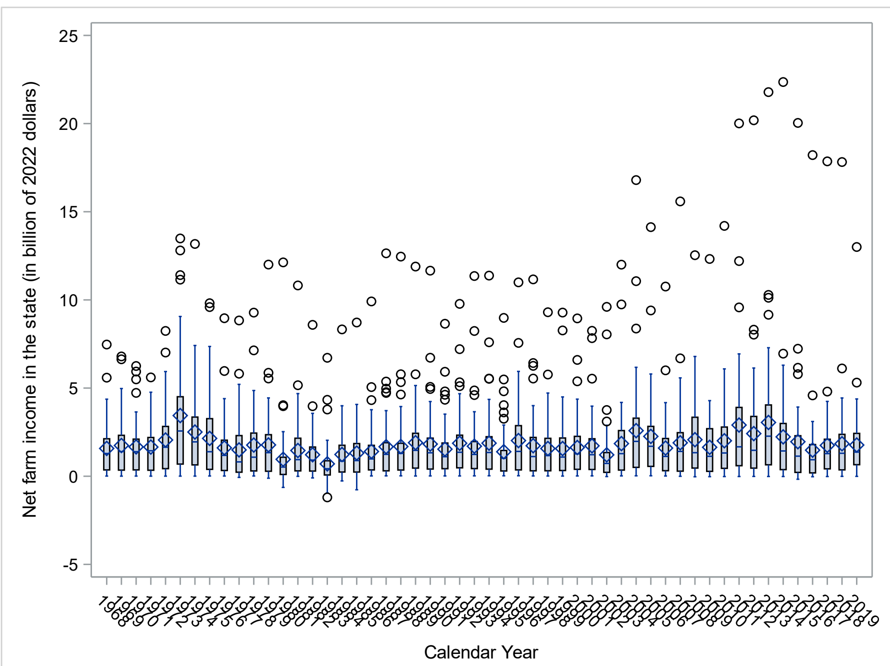
For this analysis, nominal NFI, direct government payments, and federal crop insurance program indemnities were adjusted for inflation using the U.S. Bureau of Economic Analysis Gross Domestic Product Price Index (BEA API series code: A191RG). The values are rebased to 2022 using the deflator from USDA/ERS (2022).

[8] An itemized list of sector-level expenses is available in the ERS data product "Production expenses (usda.gov)".

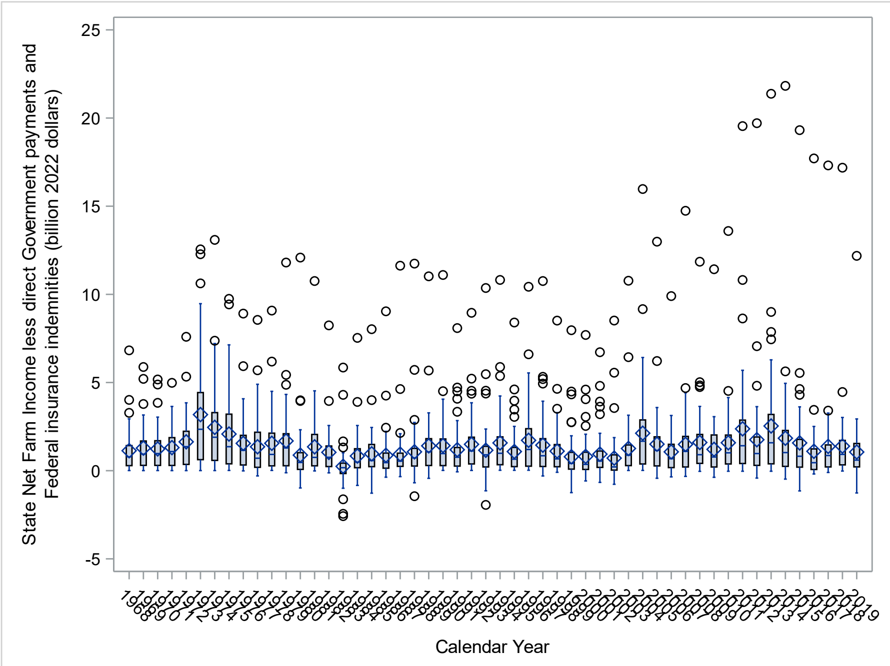
Figures 1(a) and 1(b) show variability in the state-level calendar year NFI and market NFI, by year. Panel (a) shows that the average and median state/calendar year NFI has been relatively stable since 1968 (in inflation-adjusted terms), but that there is wide cross-state variation for any given year, and this state-to-state variation has increased over time. The same applies to the market NFI. Comparison of panels (a) and (b) shows that government payments and federal crop insurance program indemnities eliminate a few of the negative NFI observations, pulling up the mean NFI for most of the years. The variation in the NFI and market NFI among the states can be partially explained by the difference in the acreage of the major agricultural crops.

*Figure 1. State Net Farm Income Variation, by Year**

a) Net Farm Income (NFI_{it})



b) Market Net Farm Income (market NFI_{it})

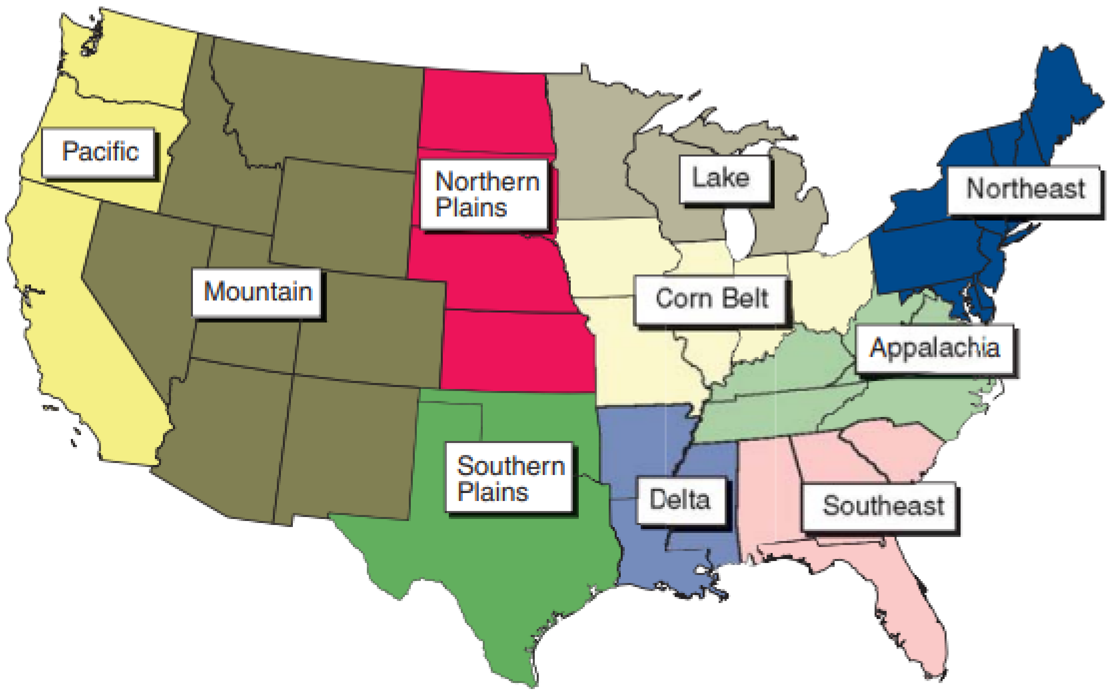


* In these box-and-whiskers plots, the rhombuses in the boxes indicate the group means; and the horizontal lines inside the boxes are the medians (i.e., 50th percentiles). The two horizontal lines that constitute the top and bottom of the boxes are the 25th and 75th percentiles respectively; and the distances between them are the Inter Quartile Ranges (IQRs). The whiskers are calculated as 1.5 IQR. Observations falling beyond 1.5 IQR are represented with small circles.

Source: USDA Economic Research Service.

To account for the effects of the factors that may impact entire regions, each state was assigned to one of the eleven USDA/ERS Major Land Use Regions (Figure 2). Further, the total planted area for the major crops was used as an indicator of the size of the agricultural industry in the state. The differences in the planted area may help explain part of the variation in market NFI, and drought impacts among the states. The planted area for the following 15 crops were considered: barley; beans, dry edible (including chickpeas); corn; cotton; hay (acres harvested); oats; peanuts; potatoes; rice; rye; sorghum; soybeans; sugar beets; sunflower; wheat. The total planted acreage for the states annually for 1968-2019 was acquired from USDA/NASS (2023). Note that this list of crops does not include specialty crops, and therefore, the extent of the agricultural industry in large specialty states, like California or Florida, can be misrepresented.

Figure 2. USDA/ERS Major Land Use Regions



* Alaska and Hawaii are grouped into the Far West Region (not shown on the map).

Source: USDA Economic Research Service. Copied from: Lubowski et al. (2006).

Various drought indicators were considered for this research. Below, we present the analysis based on the drought measure constructed from the drought hazard data in the Spatial Hazard Events and Losses Database for the United States (SHELDUS^{TM}; version 20, released on 2/1/2022, see ASU/CEMHS 2022). The analysis using an alternative drought-related weather definition is presented in Appendix A, and the results are generally consistent with those presented in the main part of the paper.

SHELDUS™ loss and hazard data are derived from the National Center's for Environmental Information *Storm Data* (see National Oceanic and Atmospheric Administration, National Centers for Environmental Information [NOAA/NCEI], 2022), with hard copies used for 1960-2009 and digital data imports since 2010. NOAA/NCEI *Storm Data* includes only significant weather phenomena that have sufficient intensity to cause loss of life, injuries, significant property damage, and/or disruption to commerce are documented[9] (see National Oceanic & Atmospheric Administration, National Weather Service [NOAA/NWS], 2021). For drought events, NOAA/NCEI *Storm Data* uses the definitions of five drought categories from University of Nebraska-Lincoln, National Drought Mitigation Center [UNL/NDMC] (2023) and includes Extreme (D3) and Exceptional (D4) droughts. For illustration, Extreme (D3) droughts can lead to *major* crop/pasture losses and widespread water shortages, while Exceptional (D4) droughts may result in *exceptional and widespread* crop/pasture losses, as well as water emergencies (UNL/NDMC, 2023). In addition, Severe (D2) droughts are also included in *Storm Data* for locations east of the Rocky Mountains (NOAA/NWS, 2021). Given Severe (D2) droughts, crop or pasture losses are likely, water shortages are common, and water restrictions are imposed (UNL/NDMC, 2023).[10] NOAA/NCEI *Storm Data* reports droughts for forecast zones (NOAA/NWS, 2021), which are usually the same as the counties, but can also subset counties to reflect weather differences within a county (e.g., due to differences in elevation; see NOAA/NWS, 2023).

[9] The database also includes rare, unusual, weather events that generate media attention, and other significant meteorological events, such as record maximum temperatures or minimum precipitation that occur in connection with another event (NOAA/NWS, 2021).

[10] Nationwide, NOAA/NCEI *Storm Data* also includes drought events of lesser classification "if they cause significant impacts to people, animals, or vegetation" (p. A-11, NOAA/NWS, 2021).

SHELDUS™ contains only events reported in NOAA/NCEI *Storm Data* that cause losses: fatalities, injuries, and property/crop damage. And while NOAA/NCEI *Storm Data* report the droughts for the forecast zones, SHELDUS™ distributes the events to the counties by overlapping county and forecast zone boundaries while accounting for the changes in forecast zone and county definitions over time. Drought hazard data from SHELDUS™ go back to 1968 and contain information on the date of an event and affected location (county and state).

For use in the analysis, county drought days reported for each event were summed to the total for the year and state:

$$w_{it} = \sum_m \sum_v d_{mv} \tag{12}$$

where m indexes counties in ith state, v refers to drought events included in SHELDUS™ for mth county in tth year, and d_{mv} is the number of days with drought crop damage for vth event in mth county in year t. Drought days d_{mv} are based on SHELDUS™. Note that the number of counties in the state influences the drought indicator w_{it}; in this study, we assume that larger number of counties indicate larger states and therefor, greater extent of the drought. In other words, we assume that the average size of the counties is approximately equal across states. Modeling results with alternative strategies to construct drought variable from SHELDUS™ are presented in Appendix B.

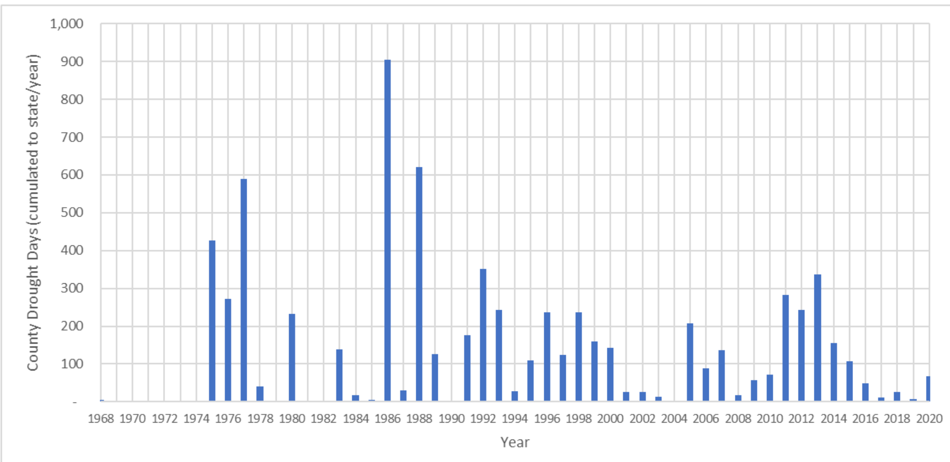
For the analysis of the two time periods (pre-1995, and 1995 and after), we created two drought indicators for each state, w_{it}^{94} and w_{it}^{95}.

Figure 3 shows mean and maximum drought days values, by year, for 52 years in the study period. Based on the mean state drought days, the following periods can be identified as having extensive and prolonged droughts: 1975–1977, 1986–1988, 1992–1993, 1996–1998, and 2011–2013.

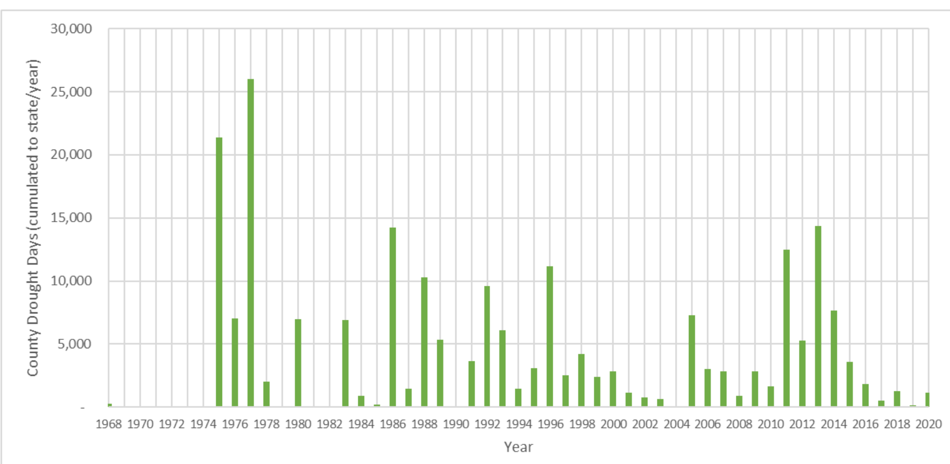
Maximum values confirm this conclusion, but also indicate that in 1975, 1977, 1986, 1996, 2011, and 2013 were very dry in selected states. On the other hand, no droughts were reported in 1969–1974, 1979, and 1981–1982; and only short and localized droughts were observed in 1968, 1985, 1990, 2004, and 2019.

Figure 3. Maximum and Mean Drought Day Indicator Values, by Year

(A) County Drought Days (cumulated to state/year), Mean Values, by Year



(B) County Drought Days (Cumulated to State/Year), Maximum Values, by Year



Source: produced by authors based on data from SHELDUS™ (ASU/CEMHS, 2022).

Results

Regression results suggest a negative association between county crop damage days (cumulated to state/year) and market NFI (Table 1). The first set of results (column 1) only includes state and year fixed effects and suggest that each additional county drought day is associated with approximately $46,000 decrease in market NFI. Other specifications were included to demonstrate robustness. The second column includes state planted acres as an independent variable to control for the size of agricultural activity in each state. The third column includes a year trend in addition to year fixed effects to account for trends in technology advancement over time. The last column includes year trend by region (i.e., interacted variables) to account for any regional-specific changes to technology over time. The consistency in the magnitude of the identified negative relationship between drought and market NFI as more controls are added is suggestive of a robust specification.

However, the regression results in Table 2 show a break in the association between crop damage days and market NFI before versus after the 1995 expansion of federal crop insurance program enrollment. The reason for this disaggregation is not because we necessarily expect to see a difference in the impact of drought on market net farm income, instead we want to assess the extent to which any decreases in market NFI are offset by federal crop insurance program indemnities and government payments. The results suggest that prior to 1995, the effects of federal crop insurance program on market NFI had a high enough variation that we do not see a statistically significant effect.[11] Post 1995, the effect is significant and negative. The results of the federal crop insurance program indemnities post 1995 suggests that of the average decrease in market NFI of

[11] The reason for a lack of statistical significance prior to 1995 may be an indication of less intense droughts or an issue of data quality for historical observations of crop damage.

$187,000 per county crop damage day approximately $101,000 was offset by federal crop insurance program indemnities. The results regarding direct government payments seems to suggest that drought decreases the likelihood of receiving government payments. Because we only have total direct government payments and not payments from specific programs, it is difficult to further investigate the mechanism that might be driving this negative association.[12]

Table 1. Regression Results of Association between County Drought Days (Cumulated to State/Year) and State Market NFI

	(1)	(2)	(3)	(4)
VARIABLES	Market NFI ($ thousand)	Market NFI ($ thousand)	Market NFI ($ thousand)	Market NFI ($ thousand)
County crop damage duration	-46.44***	-48.05***	-48.05***	-48.76***
	(17.02)	(16.70)	(16.70)	(16.85)
Acres planted		0.0280	0.0280	0.00963
		(0.0615)	(0.0615)	(0.0566)
Constant	1.192e+06***	993,458**	1.079e+07	1.072e+07*
	(101,571)	(470,683)	(6.410e+06)	(5.700e+06)
State and year FE	Yes	Yes	Yes	Yes
Year trend	No	No	Yes	Yes
Year trend by region	No	No	No	Yes
Observations	1,961	1,961	1,961	1,961
R-squared	0.276	0.276	0.276	0.296
Number of States	37^{α}	37^{α}	37^{α}	37^{α}

Notes: Robust and State clustered standard errors in parentheses. Significance denotes as *** p<0.01, ** p<0.05, * p<0.1. $^{\alpha}$ only the states east of Rocky Mountains are included, since for these states, SHELDUS™ and NOAA/NWS (2021) are consistent in considering Severe (D2), Extreme (D3), and Exceptional (D4) droughts when reporting crop damage days.

[12] The negative association may be due to the fact that some government payments are based on price targets, where farmers receive payments if prices fall below specified targets. We might not expect prices to fall during times when there is a shock to supply, like drought, which may account for this negative association, however there is more work that needs to be done to fully understand this relationship. There may also be a delay in receiving direct government payments triggered by natural disasters, which may also weaken the association between the level of payments and drought events.

Table 2. Association Between Crop Damage Duration and Market NFI, Federal Crop Insurance Program Indemnities, and Direct Government Payments.

VARIABLES	Market NFI ($ thousand)		Federal crop insurance program indemnities ($ thousand)		Direct government payments ($ thousand)	
	Prior to 1995	1995 and beyond	Prior to 1995	1995 and beyond	Prior to 1995	1995 and beyond
Sum of county crop damage days	-13.07 (24.37)	-186.7*** (28.28)	0.289 (3.446)	101.4*** (12.77)	-13.72 (13.01)	-29.99*** (9.559)
Constant	1.651e+06*** (421,173)	-1.838e+06* (935,691)	-54,250*** (16,093)	956,134*** (146,779)	1.453e+06*** (250,480)	-11,341 (440,896)
Observations	999	962	999	962	999	962
R-squared	0.338	0.250	0.196	0.292	0.436	0.411
Number of States	37	37	37	37	37	37

Notes: Robust and State clustered standard errors in parentheses. Significance denotes as *** p<0.01, ** p<0.05, * p<0.1.

Table 3 provides an indication of the regional distribution of drought impacts and the distribution of federal crop insurance program indemnities and government payments in response to drought. The results suggest a negative association between market NFI and county crop damage days for states in the Corn Belt, Delta States, and the Southern Plains. For the Corn Belt, we estimated that more than 90 percent of the impact on market NFI is offset by federal crop insurance program indemnities and direct government payments. In contrast, for the Delta States and Southern Plains, less than 50 percent of the impact is offset by federal crop insurance program indemnities or direct government payments.

Table 3. Association between Crop Damage Duration and Market NFI, Federal Crop Insurance Program Indemnities, and Direct Government Payments by Region.

	(1)	(2)	(3)
VARIABLES	Market NFI ($ thousand)	Federal crop insurance program indemnities ($ thousand)	Direct government payments ($ thousand)
Crop damage duration interacted with each region:			
Appalachian	46.24	40.05***	-50.60***
	(52.08)	(11.99)	(13.26)
Corn Belt	-539.4**	367.8***	137.6***
	(227.6)	(74.62)	(23.87)
Delta States	-153.8***	34.83*	25.72*
	(26.48)	(20.26)	(14.86)
Lake States	1,063***	-18.75	344.4
	(196.7)	(124.8)	(641.3)
Northeast	84.87	191.6***	-465.8***
	(289.5)	(48.14)	(167.4)
Northern Plains	1.734	640.5***	-14.38
	(650.4)	(135.6)	(113.7)
Southeast	192.7***	46.27***	-77.24***
	(50.34)	(12.30)	(27.75)
Southern Plains	-199.7***	88.79***	-35.56***
	(19.74)	(3.454)	(3.859)
Constant	-1.812e+06*	903,320***	-37,678
	(948,409)	(169,036)	(447,191)
Observations	962	962	962
R-squared	0.257	0.338	0.423
Number of States	37	37	37

Note: The analysis is limited to post 1994. Robust and State clustered standard errors in parentheses. Significance denotes as *** p<0.01, ** p<0.05, * p<0.1.

Discussion and Conclusion

This study explored the drought effects on the state-level, annual net farm income in 1989-2019, using drought days variable constructed from crop damage duration reported in SHELDUS™ v.

20 (ASU/CEMHS, 2022). We found that the market NFI is negatively correlated with the drought indicator post 1995. Our preliminary results suggest that the government safety net, including direct government payments and federal crop insurance program indemnities, can play an important role in alleviating the impacts of the drought on the sector's profitability. Specifically, the increased enrollment in the federal crop insurance program since 1995 may have reduced the impact of droughts on the sector. Finally, our results show that neither drought impacts, nor the effect of the government safety net were uniformly distributed across regions, with the Corn Belt states experiencing the largest impacts from the drought events, on average, while also benefiting the most from the government programs.

This analysis includes several important limitations that should be addressed in future research. The first set of limitations is related to the lack of easily accessible annual data on agricultural land use and land practices that would span the whole study period (1968-2019). While our regression models account for the planted acreage of 15 principal crops, a more comprehensive analysis should account for additional factors, such as the extent of irrigated *vs.* rainfed production (e.g., see discussion in Deschênes & Greenstone, 2007), the total agricultural acreage (e.g., including specialty crops and pasture), and the difference between planted and harvested agricultural acreage.

Another set of limitations is related to the lack of accepted definition of a drought that can match the state and annual level of data aggregation selected for the financial measurements. SHELDUS™ v. 20 (ASU/CEMHS, 2022) has been used because it offers strategies for aggregating the local, short-term drought observations into the state/calendar year drought days. However, even SHELDUS™ v. 20 aggregation procedure was not appropriate for cases other than short-term climate impacts, and drought events lasting more than 366 days would require other methods. In this paper, we use a simple summation of county drought days in each state; we also compared the model estimation results among alternative ways to define the drought variable based on SHELDUS^{TM} v. 20 and Parameter-elevation Regressions on Independent Slopes Model (PRISM) data (see appendices A and B). However, our approach to defining the county drought days is not flexible enough to account, for example, for the differences in the growing season length among the states or crop-specific temperature thresholds. Furthermore, our approach only indirectly accounts for drought intensity. The intensity is accounted for in SHELDUS™ by listing only the drought hazards that resulted in losses, and by relying on *Storm Data* with related selection of droughts with D3 and D4 intensity only. However, the drought intensity is not explicitly listed in SHELDUS™ and therefore, it is not explicitly considered in this analysis. Further, our estimates may be biased towards more recent drought events if the recent events are more abundantly or accurately reported in SHELDUS™ . The study may be underestimating the true effect of droughts if the drought indicator we use included mainly the drought hazards causing urban losses or the hazards affecting densely populated areas (see discussion of similar limitations in the national-level crop production data in Lesk et al., 2016).

Since our study examines the sector-level agricultural profitability at the state level, the local effects of disasters are not reflected in this analysis (see discussion of similar limitations in the national-level crop production data in Lesk et al., 2016). Sub-state agricultural data are more suited for the analysis of local effects (e.g., see Kawayama et al., 2019). Further, we limited our analysis to drought events, and we did not examine the impacts of such events related to climate change as more frequent and intense flooding, extreme cold, hurricanes, and other events. For example, Lesk et al. (2016) did not find significant effects of floods and extreme cold events on crop production at the national level; however, the result may differ if one considers state-level profitability.

Next, our method is not suitable for establishing causality and the mechanisms of climate effects on yield and profitability. The methods we used imply correlations between droughts and reduced state/calendar year NFI. Alternative methods should be used to establish causality, for example, process-based models that can shed the light on the mechanism by which weather can impact plant growth and crop yields (e.g., Lobell et al., 2013). Our method does not allow us to account for various potential effects of climate on agriculture, such as the effects on yields versus the effect on planted and harvested area, or the number of harvests/completed cropping cycles per year (see discussion in Iizumi & Ramankutty, 2015). The behavioral responses and long-term effects of climate change on farmers' activities (such as changing crops or crop varieties to maintain or increase profits in increasingly dry climate, see discussion in Deschênes & Greenstone, 2007) are not examined.

Finally, this study focused on only one measure or agricultural profitability – market NFI. USDA/ERS publishes other sector-level financial measures, such as net cash farm income, inventory changes, value of production, and total expenses, and analysis of these can help decipher at least some mechanisms by which drought affects profitability (e.g., comparing the impact on receipts vs expenses, or the role of adaptation efforts such as holding inventories to reduce losses due to droughts). While this paper explored the total effect of direct government payments, additional analysis is needed to evaluate the role of specific direct government payment programs, such as ad hoc and disaster assistance, in offsetting drought impacts on agricultural profitability.

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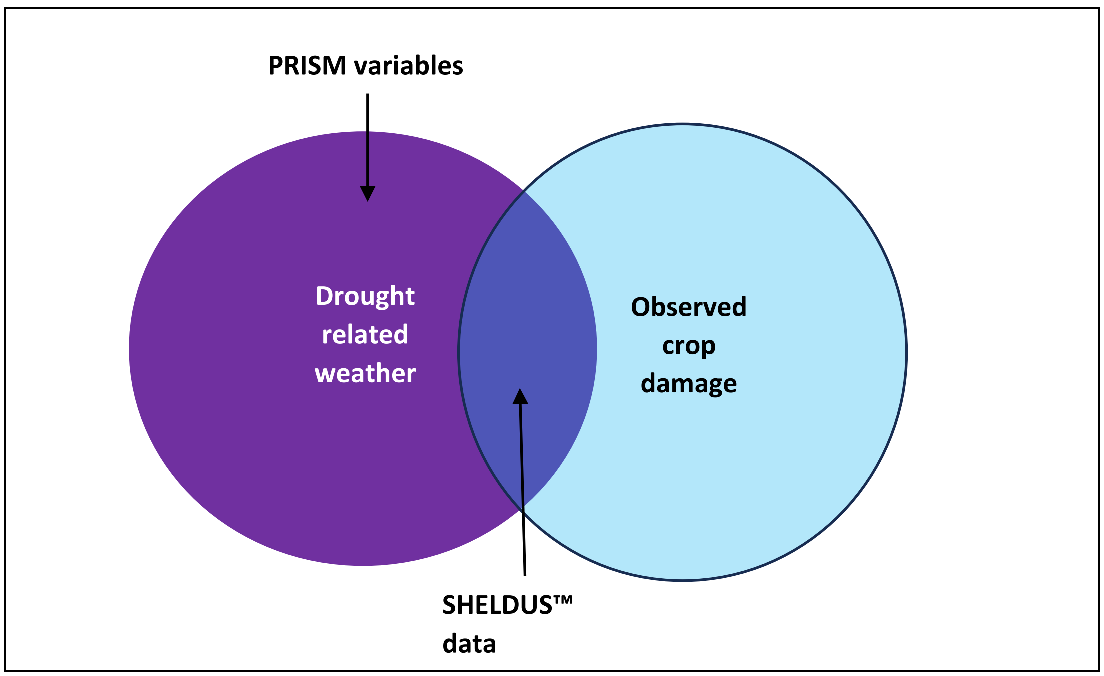
Appendix A. Drought Indicators Based on Parameter-elevation Regressions on Independent Slopes Model (PRISM)

As a robustness check, we examined the drought impacts on sector-level agricultural profitability using the drought indicator constructed from temperature and precipitation data in Parameter-elevation Regressions on Independent Slopes Model (PRISM). Specifically, we rely on the growing degree days and precipitation data created by Schlenker & Roberts (2006, 2009). Growing degree days are generally defined as a fraction of a given day between two temperature boundaries, summed over the entire growing season (Schlenker & Roberts, 2006). The county-level dataset of growing degree days and precipitation was produced by Schlenker & Roberts (2006, 2009) using monthly PRISM and daily weather observations from individual weather stations. For this paper, the county-level growing degree days and precipitation data from Schlenker & Roberts (2006, 2009) were averaged among counties in each state. To match the SHELDUS™ data, the time spans was set to 1968-2019, and the geographical span included the states in contiguous U.S. The growing season was defined as six months (April – September).

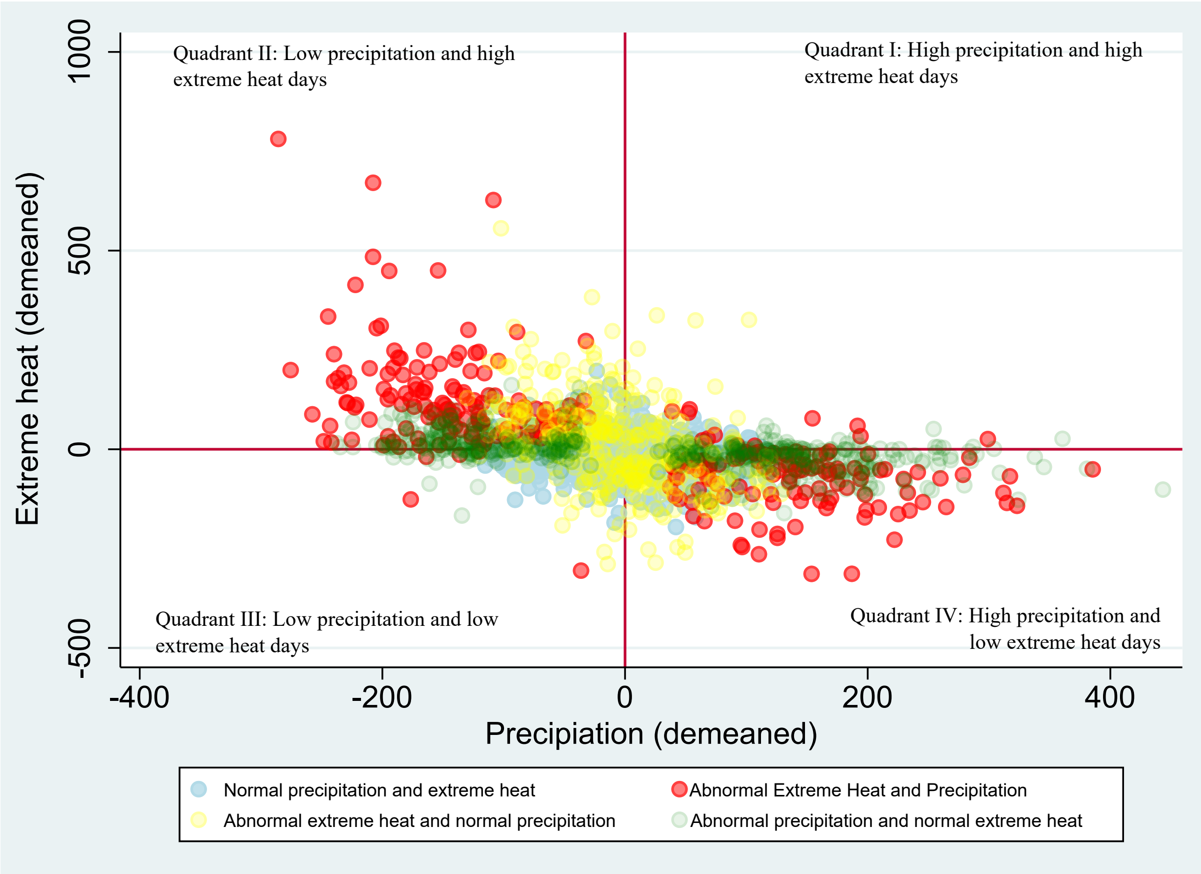
SHELDUS™ data used in this paper represents the overlap between the drought related weather in a specific county and crop damage observation within that county. In contrast, the PRISM growing degree days and precipitation variables can describe drought conditions that may or may not result in observable crop damage (Figure A1). Because drought is often characterized by the interplay between temperature and precipitation, one way to see similarities between the PRISM variables and the SHELDUS™ drought variables is to think about above average and below average precipitation and extreme heat events (where extreme heat are defined as degree-days above 29 degrees Celsius). The average extreme heat degree days and average precipitation values were calculated for each state; these values were subtracted from the extreme heat degree days and precipitation observations for that state, producing “demeaned” annual observations. The demeaned values are displayed in figure A2, where, for example, points to the left of 0, represent lower than average precipitation and point above 0 represent higher than average extreme heat duration. “Normal” years in terms of precipitation and extreme heat can serve as a basis for the comparison. In this analysis, “normal” is defined as observations within one standard deviation of the mean, and the observations outside one standard deviation are classified as “abnormal”.

Figure A1. Schematic Illustration of SHELDUS™ and PRISM data



Source: USDA/ERS; developed by authors of this paper.

Figure A2. Plot of Extreme Heat Duration and Precipitation (Demeaned)



Note: Normal values of extreme heat and precipitation are within one standard deviation of the mean. Abnormal extreme heat defined as values that are more than one standard deviation above (below) the mean. Abnormal precipitation defined as values that are more than one standard deviation above (below) the mean. Source: USDA/ERS, developed by authors, based on data from SHELDUS™ and Schlenker & Roberts (2006, 2009)

Comparison of crop damage duration defined based on SHELDUS™ with the extreme weather variables based on PRISM shows that the two values are tied-in, though they are not identical (Table A1). Specifically, high extreme heat and/or low precipitation (based on PRISM) seem to be related to higher SHELDUS™-based crop damage duration measure. And PRISM-based observations in Quadrant II (high extreme temperature and low precipitation) correspond to the highest average county crop damage duration observations based on SHELDUS™.

Table A1. Comparison of Drought and Weather Variables based on SHELDUS™ and PRISM

PRIMS-based definition	Average county crop damage duration (based on SHELDUS™)	Number of observations
High precipitation and		
low extreme heat	4.4	116
normal extreme heat	15.3	263
high extreme heat	56.4	60
Normal precipitation and		
low extreme heat	144.1	182
normal extreme heat	100.6	1384
high extreme heat	163.1	204
Low precipitation and		
low extreme heat	0.0	5
normal extreme heat	280.2	235
high extreme heat	573.1	148

Note: Normal observations are within one standard deviation of the State mean precipitation and extreme heat. Low precipitation is lower than one standard deviation below the mean. High precipitation is higher than one standard deviation above the mean. Low extreme heat is lower than one standard deviation below the mean. High extreme heat is higher than one standard deviation above the mean.

The results of the analysis using PRISM-based variables are comparable with those received with SHELDUS™ data and reported in the main section of this paper. As Table A2 shows, extremely low precipitation and/or high extreme heat days are associated with lower market NFI and higher federal crop insurance program indemnities, offsetting part of the estimated drought impacts. Direct government payments do not show strong correlation with the weather variables, and this can be partially explained by the wide range of programs included into the total government payments (with many of these programs not triggered by natural perils) or the delays in payments.

Table A2. Estimation Results for Weather Variables based on PRISM

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Market NFI ($ thousand)		Federal crop insurance program indemnities ($ thousand)		Direct government payments ($ thousand)	
	Prior to 1995	1995 and after	Prior to 1995	1995 and after	Prior to 1995	1995 and after
High precipitation and normal	-164,362	-186,038	-1,128	10,052	35,961	-12,507
extreme heat days	(104,924)	(152,990)	(5,659)	(21,328)	(29,912)	(24,646)
Low precipitation and normal	-98,226*	-94,274	3,824*	33,649**	-9,381	28,483
extreme heat days	(50,547)	(73,123)	(2,267)	(14,347)	(26,942)	(26,007)
High extreme heat days and	-304,964**	-127,680	-2,836	69,057***	7,583	-45,821**
normal precipitation	(144,750)	(96,026)	(3,495)	(22,620)	(52,753)	(21,675)
Low extreme heat days and	2,542	404,696***	3,277	2,968	-1,591	-108,877***
normal precipitation	(94,823)	(103,697)	(3,740)	(15,537)	(24,170)	(37,139)
Quad I: High precipitation and	62,526	-919,627	-14,588***	-37,608	28,355	92,927
high extreme heat days	(102,224)	(808,276)	(3,850)	(35,064)	(32,969)	(60,936)
Quad II: Low precipitation and	-614,380***	-296,550**	36,767***	208,742***	26,214	-60,600**
high extreme heat days	(135,686)	(114,155)	(10,244)	(59,845)	(66,286)	(24,164)
Quad III: Low precipitation and	464,080***	-393,493*	-15,088***	-90,319**	-26,335	163,647***
low extreme heat days	(73,792)	(211,436)	(3,580)	(41,468)	(29,131)	(44,032)
Quad IV: High precipitation	12,796	-75,768	10,809	63,166	11,221	-5,339
and low extreme heat days	(186,240)	(137,227)	(9,889)	(52,035)	(45,915)	(35,529)
Constant	1.173e+06***	1.157e+06***	5,514	36,370*	448,664***	261,341***
	(88,743)	(112,324)	(3,615)	(20,268)	(31,262)	(21,461)
Observations	1,323	1,274	1,323	1,274	1,323	1,274
R-squared	0.305	0.184	0.174	0.203	0.340	0.375
Number of States	49	49	49	49	49	49

Appendix B. Alternative Drought Variables Constructed from SHELDUS™ Crop Damage Days

In addition to the simple sum of the county crop damage days (CDD), alternative definitions of the drought variables were considered. Specifically, four definitions of a state-level drought variable were examined: 1) simple summation of county crop damage days (results reported in the main part of the paper); 2) sum of county crop damage days weighed by county size; 3) average county crop damage days; and 4) sum county crop damage days interacted with state planted acres. Each of these possible variable constructions has its own limitations. The first measure is a simple summation of crop damage days (CDD) experience by *v* counties in state *i*. This measure will be inflated for states with more (smaller) counties.

$$D_i^1 = \sum_{v=1}^{N_i} CDD_v \qquad \text{(B1)}$$

The second measure weights the county CDD by the size of the county, A_v. This may overstate crop damage in counties with little agricultural activity.

$$D_i^2 = \sum_{v=1}^{N_i} CDD_v * A_v \qquad \text{(B2)}$$

The third measure is the average CDD. This is calculated by summing the CDD in each state and dividing by the, N, number of counties in the state.

$$D_i^3 = \frac{\sum_{v=1}^{N_i} CDD_v}{N_i} \qquad \text{(B3)}$$

One limitation of this measure is that concentrated extreme drought and widespread moderate drought may results in the same D^3 value but could have a different impact on farm income for the state.

The fourth measure interacts state planted acres, P_i, with the simple sum of CDD. Because state planted acres P_i, is the sum of county planted acres p_k, we can write this equation as:

$$D_i^4 = \sum_{v=1}^{N_i} CDD_v * \sum_{n=1}^{N_i} p_n \quad \text{(B4)}$$

One limitation of this construction is that D_i^4 will contain irrelevant elements resulting from distributing these two polynomials, mainly instances when $v \neq n$.

The estimation results for NFI and market NFI for these alternative drought variable definitions is presented in Table B1. The results are generally consistent across the variable definitions and those reported in the main part of the paper.

Table B1. Analysis of NFI and Market NFI Using Alternative Drought Variables Constructed from SHELDUS™ Crop Damage Days

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	NFI ($ thousand)	NFI ($ thousand)	NFI ($ thousand)	NFI ($ thousand)	Market NFI ($ thousand)	Market NFI ($ thousand)	Market NFI ($ thousand)	Market NFI ($ thousand)
	D1 Simple sum CDD	D2 CDD weighted by county size	D3 Average CDD	D4 CDD interacted with state planted acres	D1 Simple sum CDD	D2 CDD weighted by county size	D3 Average CDD	D4 CDD interacted with state planted acres
Pre 1995 x D	-50.48***	-0.0634***	-3,941**	-2.90e-06***	-24.80	-0.0329	-3,132	-1.65e-06
	(11.82)	(0.00964)	(1,592)	(6.49e-07)	(21.52)	(0.0268)	(2,263)	(1.53e-06)
1995 and after x D	-28.57	-0.0338*	-667.1	-1.69e-06*	-117.3***	-0.119***	-11,674	-5.90e-06***
	(25.09)	(0.0196)	(5,271)	(8.73e-07)	(22.16)	(0.0200)	(8,235)	(1.18e-06)
Constant	1.715e+06***	1.715e+06***	1.715e+06***	1.715e+06***	1.192e+06***	1.192e+06***	1.192e+06***	1.192e+06***
	(90,392)	(90,601)	(89,676)	(90,775)	(102,799)	(102,878)	(100,994)	(103,421)
Observations	1,961	1,961	1,961	1,961	1,961	1,961	1,961	1,961
R-squared	0.274	0.275	0.273	0.276	0.278	0.277	0.276	0.279
Number of States	37	37	37	37	37	37	37	37
AIC	59234	59232	59237	59230	59521	59523	59527	59518

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1