The Impact of Drought on Farmland Values through a Hedonic Price Analysis of Farmland Transactions in Contiguous US

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Abstract

The negative economic impacts of climate change on the agricultural sector have more commonly been explored through hedonic analysis of extreme temperatures on farmland values. Changing patterns of precipitation have received relatively less attention despite being an extremely important factor for crop productivity. We explore this knowledge gap via a hedonic price analysis of actual farmland transactions that occurred on contiguous US between 2019-2020. We use two constructs of "drought" and find that regions facing higher frequency of droughts are likely to also have farmlands with lower land values.

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1. Introduction

Climate change can have implications for the agricultural economy through diminished crop yields and livestock productivity due to rising temperatures, frequent and severe droughts, and other extreme weather events. The seminal literature in economics has tried to capture the effect of climate change on the agricultural economy using Ricardian analysis (Mendelsohn, Nordhaus, and Shaw (1994); Schlenker, Hanemann and Fisher (2006); Deschênes and Greenstone (2012) among others). This literature finds a negative impact of rising temperatures on agricultural productivity (Schlenker and Roberts (2009)) and subsequently on the capitalized value of this productivity represented by farmland prices. The focus of much of this literature has remained on exploring the impact of rising temperatures. However, climate change can manifest in several forms of anomalous weather events. Chief among these, that have potentially severe implications for agriculture, are droughts. Droughts are periods of extreme water scarcity that can be caused by a combination of below average precipitation and high temperatures and that lead to loss in crop and livestock production.

Few studies have attempted to study the impact of drought on the agricultural economy for the contiguous US. Kuwayama et al. (2019) explore the effect of drought measured through the US drought monitor on crop yields and crop revenue and find their results aligned with previous studies that showed a negative impact on agriculture. Since the study explores the impact on crop yields and revenues, it provides evidence on the immediate impact of a drought within a growing season. It does not, however, capture the long-term effect of rising temperatures and lower precipitation (which is the goal of a Ricardian analysis). Secondly, the US drought monitor, suffers from certain drawbacks. First, it is measured at a county level which precludes exploring within-county heterogeneity. Secondly, the drought index is used by governing agencies to provide disaster assistance in times of drought and thus maybe correlated with unobservables that determine land prices, leading to biased estimates.

Hornbeck and Keskin (2014) compare the yield sensitivity to drought between regions with and without access to irrigation through the Ogallala Aquifer in United States. The study utilizes the Palmer Drought Sensitivity Index (PDSI) as a measure of drought. The index incorporates both temperature and precipitation into a single index and measures drought from the perspective of a water budget (i.e. demand and supply of water). However, the PDSI is calculated at a fixed timescale and is often best suited to measure long-term hydrological droughts (Guttman, 1998) as opposed to agricultural droughts.

Outside of the United States, Fezzi and Bateman (2015) have explored the multiplicative effect of temperature and precipitation on a rich dataset of farmlands across the Great Britain. They find that the negative effects of rising temperatures are mitigated somewhat if they are accompanied with higher precipitation. The context of their study may limit the results to geographical areas that experience cold and humid weather (such as the Great Britain). The US provides a suitable opportunity to explore this relation across more heterogeneous climatic conditions.

In this study we explore this knowledge gap via the following analysis. We study the impact of “droughts”, as measured below, on farmland values obtained from actual farmland transactions that occurred in the US between 2005-2019. The hedonic analysis allows us to measure the long-term economic impact of drought on the agricultural sector through its capitalization into farmland values. We measure drought in two ways. One, using the Standard Precipitation and Evapotranspiration Index (SPEI), a more recently developed drought index, akin to the PDSI but with the additional benefit of being a multi-scalar index. The SPEI incorporates the water budget approach, utilizing both temperature and precipitation data and can be computed at various time-scales depending upon the purpose of the study (Vicente-Serrano, Beguería and López-Moreno (2010)). For example, most agricultural droughts are computed over the period of 3-6 months period (Wang et al. (2020)). Second, by computing the multiplicative effect of precipitation and temperatures on land values following Fezzi and Bateman (2015). We also incorporate information on winter season precipitation, which is considered important for plant growth in the West.

To the best of our knowledge, this is the first study that attempts to explore the impact of drought on farmland values for the contiguous US. We also add to literature using data based on real transactions of farmlands as opposed to county level survey data. There are two main advantages of this data as compared to county level survey data. First, by using a revealed preference measure of value, we avoid hypothetical bias that may arise from using the land-owner’s measure of land value (Bigelow, Ifft and Kuethe (2020)). Secondly, by using more fine-scale data, we are able to exploit within-county heterogeneity in weather and soil conditions.

2. Data

We conduct our analysis using data on a repeated cross section of 404,735 parcel-year observations of farmland transactions in the US between 2005-2019. These were obtained from Corelogic Inc. We match this data set with current weather and long-term climate variables such as average daily temperature, growing degree days (GDD), extreme degree days (EDD), and total growing season precipitation. Following Schlenker et al. (2006) and Schlenker and Roberts (2009), GDD is computed as the total number of heat units during the growing period (1st March to 30th August) between 10-29 degree Celsius. The GDD so defined is considered to affect the growth of field crops positively by contributing to the cumulative temperature received by them during the growing period. We expect this effect to translate to higher farmland values in our study. EDD is defined as the total number of heat units during the growing period that recorded temperatures beyond the 29-degree Celsius mark. Temperatures beyond this critical threshold are expected to affect the plant growth negatively. We expect this effect to translate to lower farmland values in our project. The long-term climate variables are computed by taking rolling averages of current weather variables (measured over 10 and 25-year periods to check for robustness). This data is obtained from gridMET which is available at the spatial resolution of 4km by 4km. Information on the SPEI was extracted the from the gridded data derived from spatially interpolating data from the Global Historical Climatology Network (GHCN) and made available by the National Oceanic and Atmospheric Administration's (NOAA) National Centers for Environmental Information (NCEI). The raw SPEI values were used to construct drought measures, which are explained in detail below. In the future we aim at controlling the following other variables: (i) Measure of irrigation (Xie, Gibbs and Lark (2021)) (ii) Measures of soil characteristics obtained from SSURGO and (iii) Distance from urban centers (US Census data).

3. Method

Measuring drought

1. *Drought measured using SPEI*: We obtained information on measured drought designations as per the categorization of the SPEI laid down by the US Drought Monitor (USDM) (Monitor (n.d.)). While the USDM categorizes drought into four categories depending on the intensity of drought, for simplicity, we pool all four drought categories

into one single indicator of drought. Droughts can also be classified into short term or long term droughts (Monitor (n.d.)). Short term droughts (those covering <6 months) are most likely to have an immediate effect on agricultural production. Long term droughts that last more than 6 months are likely to affect hydrological and ecological characteristics of the landscape. Depending upon the purpose of the study, the SPEI can be computed over different time scales (1 to 72 months). For the purpose of this study, we focus on short-term droughts that affect agricultural production and thus rely on the 6-month SPEI in this study. We construct two drought indicators, one for the growing season and another for the winter season.

Growing season drought =1 if parcel was drought designated as per the US Drought Monitor's categorization during the growing period of interest (March-August of current year), 0 otherwise.

Winter season drought =1 if parcel was drought designated as per the US Drought Monitor's categorization during the off-season of interest (September of last year – Feb of current year), 0 otherwise.

The drought designations were then aggregated into 25 year rolling counts in order to facilitate the estimation of long-term effects of agricultural drought. For example, for the year 2005, we count the number of times during the last 25 years (1980-2004) the parcel was drought designated as per our definition.

2. *Drought as measured by the multiplicative effect of precipitation and temperature*: Temperatures beyond a threshold that is critical for plant growth can be detrimental for agricultural production. The interaction of the long-term rolling averages of EDD and total precipitation helps us measure drought. We use post-estimation analysis to compute the average partial effect of precipitation at different intensities of EDD.

Estimating equation

This information is used to estimate the following equations:

Equation 1: Using USDM drought designations:

$$lnY_{it} = \alpha + \beta_1 D_{it}^{g} + \beta_2 D_{it}^{w} + s_{st} + c_j + v_t + \epsilon_{it}$$

Equation 2: Using the multiplicative effect of precipitation and temperature

$$lnY_{it} = \alpha + \beta_1 GDD_{it} + \beta_2 P_{it} + \beta_3 EDD_{it} + \gamma GDD_{it} \times P_{it} + \delta EDD_{it} \times P_{it} + s_{st} + c_j + v_t + \epsilon_{it}$$

Y_{it} are real farmland values recorded between 2005 to 2019, GDD_{it} and EDD_{it} are the 25-year rolling averages of growing degree days and extreme degree days, respectively, for parcel i in year t. P_{it} is the 25-year rolling averages of growing season and winter season precipitation, respectively, in parcel i and year t. We control for state trends s_{st}, county fixed effects c_j, and time fixed effects v_t. This allows us to isolate the effect of long-term climate variables on values from other confounding factors (such as the effect of state specific policies and trends, county level time-invariant characteristics, and annual shocks to the entire economy that may also impact land prices). The estimates β_1, β_2, β_3, γ and δ are of primary interest to us. Post-estimation analysis of these estimates can reveal the marginal effects of precipitation at different levels of temperature on the land values. The equations are solved using a Pooled Ordinary Least Squares (POLS) approach.

Post-estimation analysis

Marginal effect of growing season precipitation at different levels of GDD =

$$E\left[\frac{\partial Y}{\partial P} | GDD = x\right] = \beta_2 + \gamma x$$

Marginal effect of growing season precipitation at different levels of EDD =

$$E\left[\frac{\partial Y}{\partial P} | GDD = x\right] = \beta_2 + \delta x$$

4. Results

The regression results are summarized in Table 1. Our results reveal that both long-term higher precipitation and GDD are associated with higher land values, which are in line with existing literature (Table 1, Models 1 and 2) since they are linked mostly with conditions conducive to crop growth. On the other hand, higher EDD values are associated with lower land values (Model 2). Similarly, a one unit increase in count of drought during the growing season is weakly associated with a 0.8% decrease in land values (p<0.1) (Table 1, Model 3). A unit increase in winter season droughts is relatively strongly associated with 1.2% decrease in land values (p<0.05) (Table 1, Model 3). This points towards the importance of winter precipitation in determining soil moisture and agricultural productivity.

Table 1: Pooled OLS of log-land values on 25-yr rolling climate variables

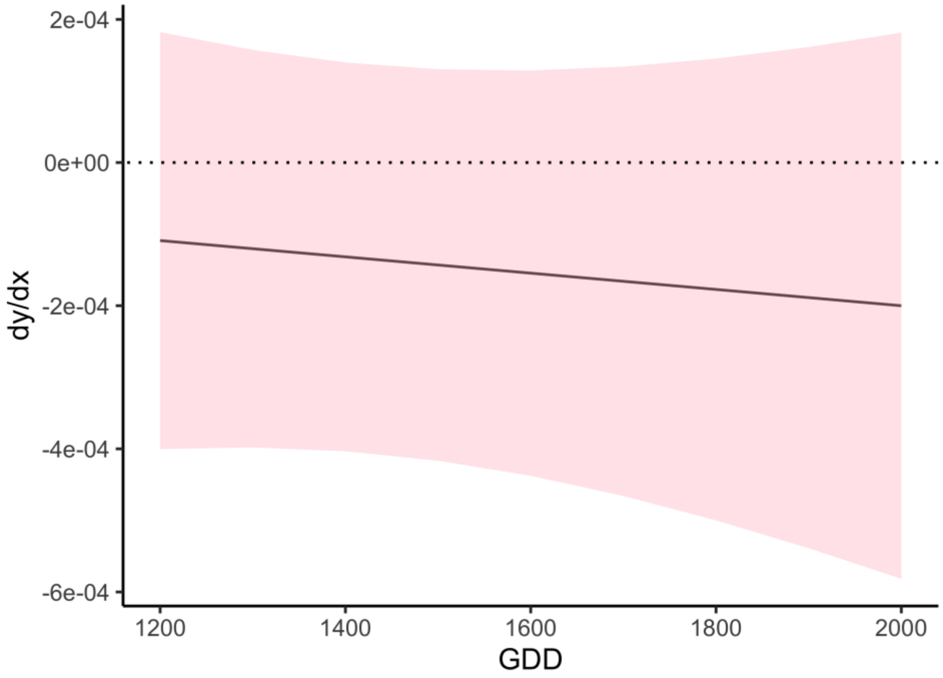
	Model 1	Model 2	Model 3
Precipitation, mm	0.000962***	0.000627**	
	(0.000231)	(0.000283)	
GDD	5.15e-04***	0.001376***	
	(9.25e-05)	(0.000167)	
Precipitation * GDD	-2.44e-07	-1.14e-07	
	(1.53e-07)	(2.39e-07)	
EDD		-0.001485***	
		(0.000272)	
Precipitation * EDD		-2.63e-06***	
		(5.16e-07)	
Growing season drought			-0.00792*
			(0.00455)
Winter season drought			-0.01156**
			(0.00417)
Num.Obs.	404735	404735	404293
State * Year FE	X	X	X
County FE	X	X	X
Year FE	X	X	X

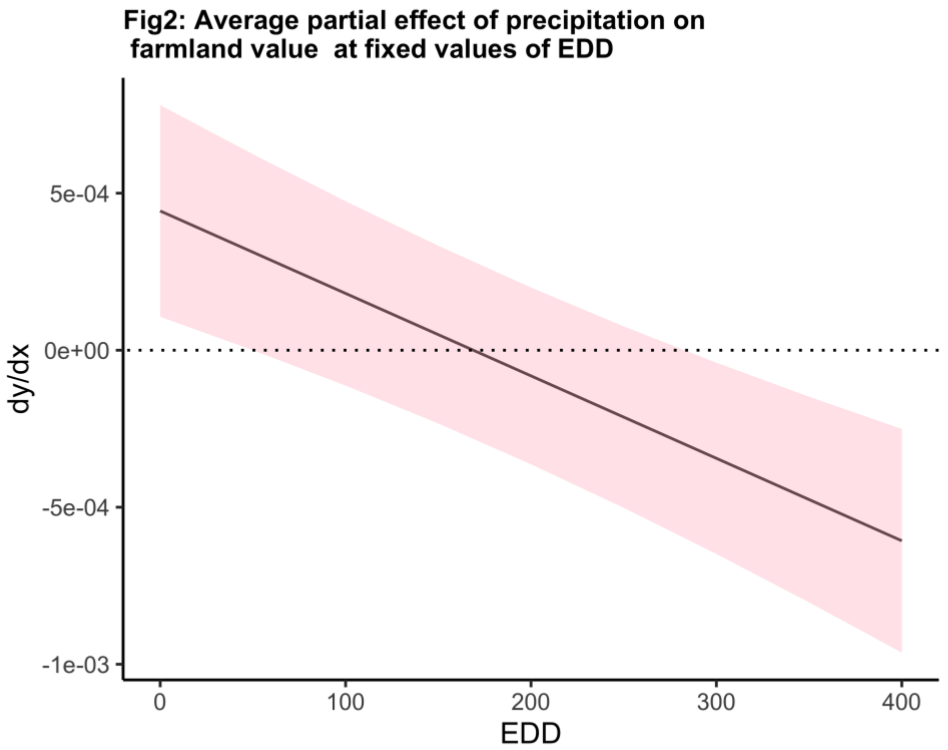
* p < 0.1, ** p < 0.05, *** p < 0.001

Standard errors clustered at county level in parentheses; GDD = Growing Degree Days, EDD = Extreme Degree Days; FE = Fixed Effects; Precipitation, GDD, and EDD are 25-year rolling averages of the corresponding weather variables for the growing season; Drought variables are 25-year rolling counts of drought designation.

Post estimation analysis of the interaction terms are summarized in Figures 1 and 2. The interaction of precipitation and GDD does not show any statistically significant impact on land values - the marginal effects were computed at different values of GDD (Figure 1). On the other hand, the precipitation is found to mitigate some of the negative impact of EDD, but only at very low EDD values. This mitigating effect becomes statistically insignificant at higher EDD values and ultimately fails to mitigate the negative impact at values of EDD higher than 300 (Figure 2).

Fig 1: Average partial effect of precipitation on farmland value at fixed values of GDD





We checked for robustness by including current weather variables and by replacing the 25 year aggregates with 10 year aggregates. Our results remain robust to these minor edits. We choose to exclude the current weather variables since they are not likely to influence land values within short time periods. Furthermore, the correlation between current weather and long-term weather variables is very high (~0.75 for precipitation & ~0.9 for temperature) which can lead to difficulty in attributing estimates to either the climatic (long-term) or the weather variables.

Conclusions

This study aims at evaluating the impact of drought on farmland values through a Ricardian analysis. We measure drought in two ways: (i) as the multiplicative effect of temperature and precipitation (a measure that is not as well explored in existing literature), (ii) by utilizing the Standard Precipitation and Evapotranspiration Index (SPEI), an established measure of drought in the agronomic and climatology literature. We find evidence that areas with higher prevalence of droughts, as measured via both constructs, are associated with lower farmland values. The study can add to the knowledge on the potential impact of climate change and the related aridification (such as that observed in South-West US) on the agricultural economy through rigorous empirical evidence using fine-scale data that has not yet been explored in the context of the US.

5. References

Bigelow, D.P., J. Ifft, and T. Kuethe. 2020. “Following the market? Hedonic farmland valuation using sales prices versus self-reported values.” *Land Economics* 96(3):418–440.

Deschênes, O., and M. Greenstone. 2012. “The economic impacts of climate change: Evidence from agricultural output and random fluctuations in weather: reply.” *American Economic Review* 102(7):3761–3773.

Fezzi, C., and I. Bateman. 2015. “The impact of climate change on agriculture: Nonlinear effects and aggregation bias in ricardian models of farmland values.” *Journal of the Association of Environmental and Resource Economists* 2(1):57–92.

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.

Kuwayama, Y., A. Thompson, R. Bernknopf, B. Zaitchik, and P. Vail. 2019. “Estimating the impact of drought on agriculture using the US drought monitor.” *American Journal of Agricultural Economics* 101(1):193–210.

Mendelsohn, R., W.D. Nordhaus, and D. Shaw. 1994. “The impact of global warming on agriculture: A ricardian analysis.” *The American economic review*:753–771.

Monitor, U.D. “Drought classification.” Available at: https://droughtmonitor.unl.edu/About/AbouttheData/DroughtClassification.aspx.

Schlenker, W., W.M. Hanemann, and A.C. Fisher. 2006. “The impact of global warming on US agriculture: An econometric analysis of optimal growing conditions.” *Review of Economics and statistics* 88(1):113–125.

Schlenker, W., and M.J. Roberts. 2009. “Nonlinear temperature effects indicate severe damages to US crop yields under climate change.” *Proceedings of the National Academy of sciences* 106(37):15594–15598.

Vicente-Serrano, S.M., S. Beguería, and J.I. López-Moreno. 2010. “A multiscalar drought index sensitive to global warming: The standardized precipitation evapotranspiration index.” *Journal of climate* 23(7):1696–1718.

Wang, Q., J. Zeng, J. Qi, X. Zhang, Y. Zeng, W. Shui, Z. Xu, R. Zhang, and X. Wu. 2020. “A multi-scale daily SPEI dataset for drought monitoring at observation stations over the mainland china from 1961 to 2018.” *Earth System Science Data Discussions* 2020:1–33.

Xie, Y., H.K. Gibbs, and T.J. Lark. 2021. “Landsat-based irrigation dataset (LANID): 30 m resolution maps of irrigation distribution, frequency, and change for the US, 1997–2017.” *Earth System Science Data* 13(12):5689–5710.