What makes communities resilient to drought?

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Abstract

Drought has affected an unprecedented area of the United States over the past several years. In April 2016, 34 percent of the United States was abnormally dry and 14 percent was in drought.[1] This dryness impacts a large portion of the population: 84.3 million people live in drought-affected areas, and 17.5 million people live in areas experiencing "exceptional drought". [2] But the welfare impacts on the people who live in drought-affected communities are not purely determined by the severity and duration of the drought. What factors predict how severely a drought will impact a community? This paper examines resilience to drought through a two-part analysis. In the first stage, we find the correlation between drought realizations and changes key measures of welfare, including mortality, unemployment, homelessness, and water consumption. Counties with low correlation can be thought of as drought-resilient, while high correlation indicates vulnerability. In the second stage, we examine which characteristics predict resilience. We discuss the predictive power of demographic characteristics such as race, income, age distribution, ..., for the impact of drought on welfare outcomes, with an eye to policy implications.

1 Why resilience matters

Drought has affected an unprecedented area of the United States over the past several years. In April 2016, 14 percent of the United States was in drought and 34 percent was abnormally dry.[3] This dryness impacts a large portion of the population: 84.3 million people live in drought-affected areas, and 17.5 million live in areas experiencing "exceptional drought". [4]

The drought in California demands particular attention given its severity and its impact on national food production. California grows about half of the US's fruit, nuts, and vegetables and 22% of dairy [5]. It has been in severe drought for the past five years. Currently, 90% of the state is in drought. More than 50% is in severe to exceptional drought. [6] Some towns in the Central Valley can no longer supply running water to all their residents. Some communities have undertaken dramatic mandatory water rationing, and Governor Jerry Brown has requested–and achieved–domestic water consumption decreases of around 25%.

But the welfare impacts on the people who live in drought-affected communities are not purely determined by the severity and duration of the drought. Low-income communities, like East Porterville in the CA Central Valley, are more likely to lose tap water than wealthy neighborhoods of Los Angeles. This study sets out to identify the factors that predict how severely a drought will impact a

[1] US Drought Monitor 2016.
[2] US Drought Monitor 2016.
[3] US Drought Monitor 2016.
[4] US Drought Monitor 2016.
[5] EPA State Agricultural Profiles, https://www3.epa.gov/region9/ag/ag-state.html
[6] US Drought Monitor 2016.

community. A better understanding of risk and resilience can support more effective policy to prevent and counteract the welfare impacts of drought.

2 Data

- Drought Monitor
  The United States Drought Monitor combines a set of measures to categorize the severity of droughts in the US. Run in partnership between the National Drought Mitigation Center, the US Department of Agriculture, and the National Oceanic and Atmospheric Administration, a set of 250 experts reviews current data and revises the drought map every week. It was launched in 1999 to as an input for policymakers working on issues concerning water supply and drought.
- NARR

  We use monthly temperature and precipitation from the NCEP North American Regional Reanalysis (NARR) project.
- ACS
- Employment
- Homelessness

3 Model

$$y_{i,t} = \beta_i D_{i,t} + \alpha_i + \tau_i t + \gamma_{s,t} + \epsilon_{i,t} \tag{1}$$

where $D_{i,t}$ refers to the number of days in U.S. Drought Survey bins 2-4 in county i and year t, α_i are county fixed effects controlling for time-invariant differences between counties, τ_i is the coefficient on a county level linear time trend, and $\gamma_{s,t}$ are state-by-year fixed effects controlling for state level time trends common across all counties $i \in s$. Note that the state-by-year fixed effects will non-parametrically account for national trends in the outcome of interest as well as state-level trends. The identifying variation in this model is within-county, annual deviations from the county time trend and from statewide annual average drought levels. Standard errors will need to be corrected for serial correlation over space and time, due to the spatial and temporal nature of droughts (neighboring observations in time and space are not independent draws).

Second Stage:

$$\beta_i = \rho_0 + \boldsymbol{\delta}\mathbf{X}_i + \nu_i \tag{2}$$

Where the β_i come from Eq.(1) for a given outcome; $\mathbf{X}_i$ represents a vector of county characteristics such as urban/rural, mean age, and home ownership; and $\boldsymbol{\delta}$ is a vector of the associated coefficients.

This regression is cross-sectional and therefore not well identified from a causal perspective. Any omitted variable that happens to covary with both the levels of β_i and the variables $\mathbf{X}_i$ will bias the coefficients $\boldsymbol{\delta}$. However, this model will illustrate how "drought resilience" (a low value of β_i) covaries with a set of common county socioeconomic characteristics. The goal with this stage is to gain some insight regarding what characteristics are commonly associated with drought resilience, or the lack thereof. Because county level characteristics likely are correlated over space, we anticipate correcting our OLS standard errors by clustering over space.

4 Discussion

5 Conclusion