Effects of the Structure of Water Rights on Agricultural Production During Drought: A Spatiotemporal Analysis of California’s Central Valley

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Key Points:
- Seniority in surface water access improves agricultural productivity on cultivated lands.
- Agricultural productivity in areas with more junior surface water access is less sensitive to changes in drought stress.
- Greater seniority in surface water access reduces sensitivity of cultivation decisions to changes in drought stress.
Abstract

California’s Central Valley region has been called the “bread-basket” of the United States. The region is home to one of the most productive agricultural systems on the planet. Such high levels of agricultural productivity require large amounts of fresh water for irrigation. However, the long-term availability of water required to sustain high levels of agricultural production is being called into question following the latest drought in California. In this paper, we use Bayesian multilevel spatiotemporal modeling techniques to examine the influence of the structure of surface water rights in the Central Valley on agricultural production during the recent drought. California is an important place to study these dynamics as it is the only state to recognize the two dominant approaches to surface water management in the United States: riparian and appropriative rights. In this study, Bayesian spatiotemporal modeling is employed to account for spatial processes that have the potential to influence the effects of water right structures on agricultural production. Results suggest that, after accounting for spatiotemporal dependencies in the data, seniority in surface water access significantly improves crop health and productivity on cultivated lands, but does not independently affect the ability to maintain cultivated extent. In addition, agricultural productivity in watersheds with more junior surface water rights show less sensitivity to cumulative drought exposure than other watersheds, however the extent of cultivation in these same watersheds is relatively more sensitive to cumulative drought exposure.

1 Introduction

California’s Central Valley is one of the most productive agricultural systems on the planet [Diffenbaugh & Swain, 2015]. This system requires massive amounts of water to function; the agricultural sector accounts for 77 percent of the state’s water use [Swain et al., 2014]. The Central Valley experienced a state of prolonged drought starting in the mid-2000s that escalated to severe drought conditions lasting from 2011 until 2017 [Howitt, Medellín-Azuara, & MacEwan, 2014; U.S. Drought Monitor, 2017]. The persistent drought conditions significantly strained agricultural production throughout the valley with an estimated economic cost of $2.7 billion in 2015 alone [Howitt, MacEwan, Medellín-Azuara, Lund, & Sumner, 2015]. Research suggests that future changes in climate will continue to impact surface water availability, ultimately affecting plant growth rates as well as irrigation timing and runoff [Mann & Gleick, 2015; Schwarz, 2015]. These changes will likely increase legal mandates curtailing surface water use. In a study of the Sacramento-San Joaquin Delta, Schwartz [2015] estimates that water rights curtailments between 2030 and 2059 may last 20% longer and occur with 10% greater frequency than they have in the past. These changes, coupled with rapidly increasing population growth and shifts in agricultural demand will place significant strain on agricultural systems in the Central Valley in the future, threatening national food security.

In the Central Valley, increased pumping of groundwater has enabled many farmers to continue to cultivate in spite of the current drought [Christian-Smith, Levy, & Gleick, 2015; Famiglietti et al., 2011]. Rates of groundwater depletion in the Central Valley have increased dramatically throughout the drought, exceeding groundwater recharge rates and putting future groundwater use at risk [Famiglietti et al., 2011; Howitt, MacEwan, Medellín-Azuara, Lund, & Sumner, 2015; Medellín-Azuara et al., 2015]. If current pumping rates continue the region’s groundwater supplies may be over-drafted and the ability of farmers to use groundwater to mitigate surface water shortfalls during drought will be increasingly limited. Farmers have also engaged in water transfers among agricultural users, fallowing of land, and diversification.
towards less water-intensive crops [Christian-Smith et al., 2015]. These farm-level adaptive practices are fairly short-term responses to water scarcity; they leverage current technology, institutions, and infrastructures to address drought. Growing evidence suggests that California may enter a period of prolonged water stress in the future requiring more significant adaptation; therefore, it is important to assess the impact of how the institutions governing resource use impact agricultural responses to water scarcity [Hertel & Lobell, 2012; Zilberman, Dinar, MacDougall, Brown, & Castillo, 2002].

This paper focuses on the impact of the legal institutions governing California’s surface water on a remotely sensed metric of agricultural productivity and the likelihood of a field being left fallow during the recent drought in California’s Central Valley. California is an important place to study these dynamics as it is the only state to recognize the two dominant approaches to surface water management in the United States: riparian and appropriative rights. The unique hierarchical legal structure of these surface water rights in California facilitates exploration of the impact of these distinct ways of managing surface water on agricultural systems. We hypothesize that during periods of extreme water stress, such as the recent drought, seniority in access to surface water significantly improves local capacity to cultivate and maintain crop health, and also decreases sensitivity to increasing precipitation deficits. In what follows, we discuss the nature of surface water rights and groundwater in California (Sections 1.1 and 1.2) and outline the conceptual framing of the analyses conducted (Section 1.3). In Section 2, we describe the methods and novel dataset used in this study. Section 3 describes the statistical analyses conducted while Section 4 discusses the empirical results. In Section 5 the implications of the study for water management in a changing climate and limitations of the study are discussed.

1.1 Understanding surface water rights in California

Surface water access in the Central Valley is governed by a complex hierarchy of water rights. California is the only state to recognize both riparian and appropriative rights [Schwarz, 2015]. Riparian rights are water rights belonging to a land owner and apply to the use of naturally flowing water within, or adjoining, a parcel of land [California State Water Resources Control Board (CA SWRCB), 2016a]. As riparian rights do not require licenses or permits and generally are not lost by non-use or transitions in land ownership, they are considered as “senior” to appropriative water rights [CA SWRCB, 2016b; Sawyers, 2005]. However, riparian rights do not entitle a water user to divert water to storage (for use during the dry season) or to apply the water outside of the watershed in which the parcel of land lies [CA SWRCB, 2016b]. While water diversion under riparian rights are by law limited to the amount of water which can be put to reasonable and beneficial use, because they are exempt from California State Water Resources Control Board (CA SWRCB) oversight diversion amounts are rarely quantified unless a stream system statutory adjudication process takes place [CA SWRCB, 2016a; Sawyers, 2005; Schwartz, 2015].

Appropriative water rights are rights that divert water from the original stream system for use on land that is not classified as riparian [CA SWRCB, 2016b; Sawyers, 2005]. Like riparian rights, appropriative rights are limited to the amount of water which can be put to reasonable and beneficial use, however as permitted and licensed rights, the diverted quantities of water are generally subject to more scrutiny than riparian rights. In addition, any appropriative right may
be lost if the right is not exercised for a period of five years (prescriptive period). In times of water shortage riparian water rights holders typically have higher priority access to water than appropriative rights holders, where each riparian right is given equal priority [CA SWRCB, 2016b; Sawyers, 2005].

Appropriate rights are themselves subject to an internal hierarchy that is often described as "first in time, first in right" whereby rights holders with the oldest claim have higher priority access to water [CA SWRCB, 2016b]. In California, appropriative rights are divided into two categories, Pre-1914 and Post-1914 rights. Pre-1914 appropriative rights are non-riparian rights for which there is evidence that the right was claimed prior to the creation of a state-wide permitting system in 1914 [CA SWRCB, 2016b; Sawyers, 2005]. These rights, similar to riparian rights, are not subject to CA SWRCB oversight and are senior to Post-1914 appropriative rights. Post-1914 appropriative water rights are subject to a great deal of oversight and are granted by the CA SWRCB only after demonstration of both unappropriated water availability and applicant ability to beneficially use that water. Priority of water access among Post-1914 appropriative rights holders is granted based on the date the water right permit application was filed, where the most recent rights are the first to discontinue use in times of water shortage [CA SWRCB, 2016b; Sawyers, 2005].

While some farmers hold the rights to the surface water they use for irrigation, much of the surface water in California is distributed via contracts between a farmer with no legal water rights and a second party who holds the original water right, but does not directly use the water [Medellín-Azuara et al., 2015; Sawyer, 2005]. While private water contracting is common, the largest water contractors, and holders of the largest share of water rights, are the state and federal government [California Department of Water Resources [CA DWR], 2017a; Sawyer, 2005]. The California Department of Water Resources (CA DWR) and the U.S. Bureau of Reclamation (USBR) collectively hold an estimated 219 water rights with more than one thousand points of diversion across the state, and are estimated to supply approximately 25% of irrigation water in any given year [Medellín-Azuara et al., 2015]. This water is diverted to water contract holders via the State Water Project (SWP) or the Central Valley Project (CVP), which are managed by CA DWR and USBR, respectively, and include large-scale water conveyance structures, such as the California Aqueduct [CA DWR, 2017b; Medellín-Azuara et al., 2015; USBR, 2017a].

As the SWP and CVP transport water across watersheds, and sometimes over great distances, water right point of diversion locations for contracted water are not necessarily directly associated with the location of water use. However, it is required that points of rediversion from natural and artificial water ways be reported to the California Water Resources Control Board suggesting that some records do exist that link contracted water to areas near the location of water use [California Water Boards, 2017]. Contract water is typically used for municipal and agricultural uses and the contracts are often made with local governments and large irrigation management districts, but may be also held by individuals and small trusts [CA DWR, 2017b; Medellín-Azuara et al., 2015; USBR, 2017b]. While those who contract for water with a second party do not have a direct legal claim to water, and their use of water may be restricted by the nature of their contract with the water right holder or a local distributor of water (such as an irrigation management district), the water they receive is associated with a legal water right and is subject to the same restrictions and privileges granted to that class of water rights.
1.2 Groundwater in California

Groundwater plays a critical role in the California agricultural system as during a typical year groundwater supplies about 30% of irrigation water, while during drought years this share can increase to over 50% [Medellín-Azuara et al., 2015]. However, while increased groundwater extraction has been a prevalent response to recent droughts in California, a growing body of research suggests that this is not a sustainable response to projected future changes in water availability [Famiglietti et al., 2011; Howitt, MacEwan, Medellín-Azuara, Lund, & Sumner, 2015]. At present, there is no state-wide groundwater use permitting and regulation process and the only regulation of groundwater use is limited to basin-specific court adjudication in a few regions [CA SWRCB, 2016b]. The Sustainable Groundwater Management Act, signed into law in 2014, requires High and Medium Priority basins subject to critical conditions of overdraft to be managed under a groundwater sustainability plan by January 31, 2020, leaving groundwater basins vulnerable to increased pumping rates over the next few years [CA DWR, 2015; Medellín-Azuara et al., 2015]. Lack of groundwater monitoring is also a significant issue in the region with about a quarter of High and Medium priority basins inadequately monitored under the California Statewide Groundwater Elevation Monitoring Program (CASGEM) [CA DWR, 2014; Medellín-Azuara et al., 2015]. Groundwater use is therefore constrained primarily by groundwater aquifer location and depth, the ability to drill new wells, and pumping costs [Mukherji & Shah, 2005; Schlenker, Hanemann & Fisher, 2007].

1.3 Modeling agricultural production during water scarcity

In this study, a farmer’s cultivation decision (what and how much to plant) during times of water stress is conceptualized as a function of expectations of water availability, recent weather trends, the portfolio of cultivation options available to the farmer, and expected crop values. Similarly, the health and productivity of cultivated crops is seen to be dependent on the choice of crop grown, weather conditions during the growing season, and access to and availability of water to apply to the cultivated crops. We hypothesize that the legal structure of surface water rights in the state is one of the factors at play in both farmer decision-making and crop productivity.

California water code prioritizes water allocations based on the stated purposes of water use, the type of water right, and the timing of appropriation. The structure of these prioritizations, e.g. domestic use over irrigation; Riparian over Appropriative; Pre-1914 appropriations over recent appropriations, has the potential to inform farmer cultivation decisions and constrain the amount of water available for application to fields, particularly for junior water rights holders. Therefore, we hypothesize that during periods of extreme water stress, such as the recent drought, seniority in access to surface water significantly improves local capacity to cultivate and maintain crop health and productivity. In addition, we predict that access to senior appropriative water rights will decrease agricultural sensitivity to cumulative meteorological drought stress relative to riparian and junior rights. In what follows, we apply Bayesian spatiotemporal modeling to a novel dataset to test these hypotheses.
2 Methods and Data

That water shortages have a negative impact on agricultural production is a logical and somewhat obvious deduction. However, analysis of the impacts of water shortages on agricultural production, including factors influencing access to water, is a non-trivial task. One of the largest contributors to heterogeneity in water stress impacts on the health and productivity of agricultural systems is location. Vegetation health exhibits strong autocorrelative spatial dependency that can be difficult to account for in regression analyses and which, if not considered, has the potential to bias results. In addition, temporal dependency, differences in crop type, the sources of water used for irrigation, the complexity of the physical water distribution system, and the scale of cultivation activities also contribute to variations in the impacts of drought on agriculture.

In water resources research, simulation models of water use dynamics are commonly employed. There are many examples of agricultural water use models for California’s Central Valley that employ simulation strategies. Medellín-Azuara et al. [2015] merge a model of economic and agricultural production (SWAP) with a groundwater use model (C2VISim) to estimate the economic costs of pumping groundwater during the drought, finding higher vulnerability in regions without access to wells and uncertain access to surface water. Schwartz [2015] uses a series of linked models to estimate future water rights curtailments, finding that many more water rights holders will be affected by curtailments in the future. While simulation studies provide valuable information, it is prudent to assess the conclusions of simulations using alternate methods.

Recent advances in computational power and Bayesian empirical modeling techniques, which offer advantages over traditional regression methods in consideration of uncertainty in estimates and the ability to accommodate missing data, have made Bayesian modeling approaches more tractable for analyses of complex systems [Blangiardo & Cameletti, 2015; Gelman & Hill, 2007]. Bayesian methods have been found to be particularly useful for analyses of spatial and hierarchically (multi-level) structured data and have been used to examine the space-time dynamics of disease [Schrodle et al., 2011; Raghavan et al., 2016], child malnutrition [Kandala et al., 2001], and wildlife population dynamics [Cosandey-Godin et al., 2015]. More recently the expansion of Laplace approximation-based Bayesian analyses, which are more computationally efficient than traditional Markov chain Monte Carlo-based Bayesian analyses, has led to a rapid increase in examination of spatiotemporal phenomenon in large datasets [Mantovan & Secchi, 2010].

In what follows, we present analyses that explore the role of surface water rights in modifying the effects of drought on a remotely sensed metric of agricultural productivity and the likelihood of a field being left fallow throughout the recent California drought. We apply Bayesian multilevel modeling techniques that account for spatial and temporal effects to estimate the variation in the effects of surface water rights structure over the course of the drought. These techniques allow us to quantify the effects of key predictors after accounting for temporal and spatial patterns in the region. The multilevel approach also allows us to explore factors driving agricultural response to drought at both the watershed and field levels.
2.1 Area of Interest

In order to investigate the effects of the legal structure of surface water rights on agricultural production over the course of the drought a large spatiotemporal panel dataset was compiled (see Table S1 in the Supporting Information for additional information on data sources and formats). Annual data for years 2010-2014 of the recent drought were obtained for the Central Valley with outcome, control, and predictor variables available at one of two different spatial scales: field-level (1km pixels) or watershed level (U.S. Geological Survey hydrologic unit code (12 digit designation). For the analyses described below the dataset was clipped to the subset of fields located in the California Central Valley that have been characterized as agricultural land (farmland or grazing land) in any of the biennial California farmland mapping surveys between 2006 and 2014 [California Department of Conservation, 2016]. Figure S1 in the Supporting Information displays the spatial extent of the area of study, which contains 849 watersheds and 62,050 fields.

2.2 Outcome data

The spatiotemporal resolution of existing agricultural production datasets made public by the U.S. Department of Agriculture is at the county-year scale, however, given the size of counties in California, agricultural production data at this level can mask significant spatial variations that occur at the farmland field and watershed scale. In order to more precisely investigate relationships that link agricultural production to water use we opted for outcomes at the field-level. While data limitations inhibit consideration of the legal structure of water rights at the field-level, the use of the field-level outcome allows us to both account for localized factors such as land-use and to explicitly model the full extent of field-level variation within an area.

To capture field-level production dynamics, we computed an index of total vegetative production (TVP) using remotely sensed metrics of vegetation health. TVP is computed as the integral of the annual smoothed Enhanced Vegetation Index (EVI) time series and represents the relative productivity of that pixel for the year of interest. To compute TVP we extracted measures of the observed EVI from a one-kilometer, 16-day resolution dataset from the NASA Moderate Resolution Imaging Spectroradiometer (MODIS) Terra MOD13A2 dataset [NASA LP DAAC, 2015]. The EVI is measured as:

\[ EVI = G \frac{\rho_{NIR} - \rho_{RED}}{\rho_{NIR} + C_1 \times \rho_{RED} - C_2 \times \rho_{BLUE} + L} \]

where \( \rho \) is atmospherically corrected surface reflectance, \( L \) is the canopy background adjustment, and \( C_1 \) and \( C_2 \) are the coefficients of the aerosol resistance term, which uses the blue band to correct for aerosols in the red band [Huete et al., 2002]. EVI values approaching one indicate higher levels of photosynthetic activity over the 16-day period. The MODIS quality mask was applied to the full dataset, dropping low quality observations. Pixels with more than 50 percent of their values flagged as low quality through time were dropped from the analysis. For the remaining pixels, missing observations were linearly interpolated and the full time series was
smoothed using a Savitzky-Golay filter before computing the annual integral to obtain TVP [Savitzky & Golay, 1964].

The EVI is highly correlated with both leaf area and vegetation fraction estimates [Gumma, 2011; Huete et al., 2002; Sakamoto et al., 2005; Small & Milesi, 2013; Xiao et al., 2006]. A recent study compared MODIS vegetation indices, including EVI, to county-level yield data from the U.S. Department of Agriculture. Crops studied include barley, corn, canola, cotton, potatoes, rice, sorghum, soybeans, sugarbeets and wheat. The EVI was found to correlate strongly with yields across all these crops [Johnson, 2016]. As the integral of the EVI time series, TVP serves as a proxy for cumulative annual vegetative productivity. Integrated vegetation indices such as TVP have been shown to be a good measure of productivity and yield in a number of studies [Mkhabela, Bullock, Raj, Wang, & Yang, 2011; Wang, Rich, Price, & Keple, 2005]. Higher values of TVP indicate higher amounts of vegetative health and productivity over a year [Jönsson & Eklundh, 2002; Jönsson & Eklundh, 2004]. Figure S2 in the Supporting Information provides a representative map of TVP spatial patterns.

In order to probe the effects of the structure of surface water rights on cultivation decisions a binary, field-level outcome was computed that represents whether a field is barren and fallow. This outcome variable was derived from the National Agricultural Statistics Service CropScape dataset [USDA National Agricultural Statistics Service, 2016]. For each year, the mode of the 30-meter resolution CropScape dataset was computed for pixels within each field (1 kilometer TVP pixel) and fields where the mode was categorized as barren and fallow were assigned a value of one while all other fields were assigned a value of zero.

2.3 Surface water rights data

Surface water use explanatory variables that describe the structure of water rights were computed at the watershed level. Watersheds are irregular spatial units that define local hydrologic dynamics that are topology dependent and are often the preferred unit of analysis for water use and water quality studies [Ficklin, Luo, Luedeling, & Zhang, 2009; Kollet & Maxwell, 2008]. Point data identifying the location of surface water right points of diversion (PODs) and the legal status of each POD were downloaded from the CA SWRCB electronic water rights information management system (eWRIMS) [CA SWRCB, 2016c]. Digitized data currently does not exist to link a POD to a specific place of use, so this point data was aggregated to watersheds to reflect watershed-level patterns of surface water access. Use of watershed scale or river basin data aggregations in studies examining access to water and water allocations in relation to water rights are common in the literature, in large part due to the lack of data on water access at the field-level [Grantham and Viers, 2014; Schwarz, 2015; Tidwell et al. 2014].

In this study, the legal structure of water rights is represented by three variables that give the percent of all active agricultural use PODs within a watershed that are classified as Riparian, Pre-1914 Appropriative (henceforth referred to as “Pre-1914”) and Post-1914 Appropriative (henceforth referred to as simply “Appropriative”) water rights (additional information on water rights data processing and aggregation is provided Text S1 in the Supporting Information). We suggest that these newly developed metrics provide a measure of the distribution of legal access to surface water within watersheds. While legally structured differences in field-level access to surface water most certainly exist within watersheds these metrics provide information about the relationship between the tendency towards certain types of legal access within a watershed that
may influence the average level of agricultural production within that watershed. The legal structure of water rights in a watershed is expected to influence farmer cultivation decisions by modifying expectations for water availability during the growing season. The legal structure of water rights is also expected to influence agricultural productivity of cultivated fields by modifying the availability of sufficient surface water to maintain cultivated fields during the growing season. Of the 849 watersheds within the study area, 333 have some Riparian water right PODs, 190 have one or more Pre-1914 right PODs, and 486 have Appropriative right PODs. Additional summary statistics can be found in Table 1. Maps of the spatial distribution of water rights can be found in Figures S3 through S5 in the Supporting Information.

As a single water right may be associated with multiple PODs this metric gives greater weight to water rights with multiple PODs. As water rights are frequently not held by individual farmers, but instead by irrigation management districts who then distribute water via multiple PODs to a number of farmers that contract with the district for water supply, the POD based water rights metrics are intended to capture information about the number of farms receiving water associated with water rights and not just the number of water rights holding institutions and individuals (this assumes that the number of PODs is proportional to the number of water users in a watershed). It should also be noted that due to the lack of information on the point of application of water, these metrics assume that the majority of a water rights users are located within the watershed in which the POD is located, which disassociates a water right from use of water associated with that right occurring in other watersheds (see Text S2 in the Supporting Information for information on contract water representation in the POD dataset).

2.3 Drought severity data

The effect of drought on agricultural production was examined using a measure of cumulative meteorological drought stress which is expected to influence both farmer cultivation decisions (for the following year) and growing-season agricultural productivity (for the current year). This predictor was calculated as the annual sum of the Standardized Precipitation Index (SPI). The SPI is measure of meteorological drought (a deficit in precipitation) that is given over a specified time period (in this case we use 9-month SPI data) and is presented on a normalized scale with a mean of zero and standard deviation of one [AghaKouchak and Nakhijiri, 2012]. Negative values of SPI indicate dry conditions while positive values indicate wet conditions. The cumulative annual SPI predictor (henceforth referred to as “SPI”) was computed for each watershed-year using monthly SPI calculated from the NASA North American Land Data Assimilation System (NLDAS) precipitation data and made available by AghaKouchak and Nakhijiri [2012]. As SPI is a local measure of precipitation deficit it does not account for changes in water availability that are due to precipitation and water storage occurring outside the study area such as alpine snowpack and reservoir storage. In this case, SPI provides a watershed localized measure of negative forcing on soil moisture and streamflow [Whan et al., 2015].

2.4 Crop type data

To account for aspects of field-level agricultural land and water use not attributable to the structure of surface water rights, we included two field-level datasets. The first is a crop type categorical variable derived from the National Agricultural Statistics Service CropScape dataset [USDA National Agricultural Statistics Service, 2016]. This land use categorical variable is
expected to influence the agricultural productivity of cultivated fields. The CropScape data for each year was aggregated into six generalized categories of land use: barren and fallow, grasses, grains, row crops, fruits and nuts, and uncultivated cover (additional information on CropScape data aggregation is provided in Table S2). The mode of the 30-meter resolution CropScape data was computed for pixels within each field (1 kilometer TVP pixel) and this land use category was assigned to each field-year. The average farm size in California is 1.3 kilometers, so while this aggregation approach may mask some intra-farm diversity, it largely captures farm-level variations in land use [California Department of Food and Agriculture, 2016]. Within the final dataset of 62,050 square kilometers of agricultural fields over 5 years, 7.4% of all fields were classified as barren and fallow, 6.1% were classified as grasses, 11.7% were classified as grains, 5.5% were classified as row crops, 16.1% were classified as fruits and nuts, and 53.1% were classified as uncultivated cover. In addition, 37.2% of all fields were classified as barren and fallow at some time during the drought. Figure S7 displays the spatial variation in crop type in a representative year.

2.5 Groundwater data

The second field-level dataset is the depth to groundwater in January of each cultivation year. This provides an estimate of the accessibility of groundwater at a particular location prior to the start of the growing season. The depth to groundwater is expected to influence both cultivation decisions, by modifying expectations for groundwater availability prior to the growing season, and agricultural productivity, by modifying access to groundwater for irrigation during the growing season. The quality of groundwater extraction data in California and across the U.S. is notoriously poor [CA DWR, 2014]. California’s Groundwater Information Center monitors well levels for a subset of wells covering the state through the California Statewide Groundwater Elevation Monitoring Program (CASGEM) program, however the temporal and spatial coverage of this monitoring network is lacking, particularly in key critical regions [CA DWR, 2014]. In order to account for reductions in surface water being offset by groundwater use, and in an attempt to avoid omitted variable bias, we applied spatiotemporal kriging to the CASGEM groundwater elevation point dataset using the R package spacetime to produce a gridded depth to groundwater dataset for the region [GeoTracker GAMA, 2016; Gräler, Pebesma, & Heuvelink, 2016]. This method uses an “exact estimator” to interpolate values for spatial locations and time points for which no data is available using the available space-time information and a provided model of spatiotemporal correlation. Following recommended model-fitting procedures as outlined by Gräler, Pebesma, & Heuvelink [2016], we tested the fit of a number of variogram structures to our data and found a simple-sum metric spatiotemporal model to best fit our data. The point data was then kriged through space-time to generate a 10-kilometer, monthly gridded groundwater elevation dataset which was compared to a held-out dataset of groundwater elevation observations for verification purposes. Our model performed well with a mean normalized RMSE of 0.08 against the held-out observations and a Nash-Sutcliffe efficiency of 0.80. To convert the groundwater elevations to depth to groundwater and aggregate this monthly dataset to an annual time-step, we subtracted the groundwater elevation in January of each year from the ground-level elevation using the elevatr package to estimate depth to groundwater (Hollister and Shah, 2017). This value of depth to groundwater was extracted to each field-year. More information on the groundwater space-time kriging procedure
2.6 Additional control data

To account for agricultural dynamics at the watershed level, we computed an index of agricultural diversity to indicate whether the agricultural system of a watershed tends towards monoculture. This metric captures the complexity of the agricultural system, where areas with less diversity are expected to have a greater amount of permanent or semi-permanent physical irrigation infrastructure in place that might constrain farmer cultivation decisions. The CropScape data from USDA were aggregated for each watershed-year using the diversity indexing method described by Turner, Neill, Gardner, & Milne [1989] where diversity is described as the linear sum of the proportion of a landscape area that is covered by each crop type. As the crop diversity metric is expected to influence pre-season cultivation decisions this variable was lagged by one year.

As access to surface water is expected to influence both farmer cultivation decisions and growing season productivity we also control for physical accessibility and proximity of surface water in each watershed using a measure of the density of agricultural surface water right PODs. This metric was computed by taking the ratio of the total number of agricultural surface water rights PODs in a watershed and the area of all farmland in a watershed and controls for watershed scale variations in agricultural production related to proximity to streams and rivers, where PODs tend to be clustered, that are independent of the legal structure of water rights. In addition, as competition between different types of water uses (e.g. agricultural, municipal, and industrial) during times of water scarcity is expected to influence the availability of surface water for agricultural purposes we computed a metric of completion as the percent of all surface water right PODs in a watershed that are reported to be used for agricultural purposes. This metric is expected to influence both farmer cultivation decisions and growing season productivity within a watershed.

Geographically referenced annual data was unavailable for a number of factors thought to be relevant to cultivation decisions and agricultural health and productivity such as surface water availability, climatic conditions, and changes in crop value. In order to take into consideration these omitted variables categorical indexes for year and watershed were included in the dataset so that omitted variable influences that varied with time but not location, or that varied by watershed but remained constant over time could be controlled for using year and watershed specific effects.

3 Statistical Analyses

3.1 Multi-level structure

The importance of multi-level structuring on the growing season agricultural productivity outcome variable (TVP) was tested by fitting a three-level null model and calculating the intraclass correlation coefficient (ICC). The null model takes the form,

$$ y_{ijk} = \beta_{0jk} + e_{ijk} $$  (1.1)
\[ \beta_{0jk} = \beta_{00k} + u_{0jk} \quad (1.2) \]
\[ \beta_{00k} = \gamma_{000} + u_{00k} \quad (1.3) \]

which can be expressed in reduced form as:

\[ y_{ijk} = \gamma_{000} + u_{00k} + u_{0jk} + e_{ijk} \quad (1.4) \]

where \( y_{ijk} \) is TVP for a time-ordered measurement during year \( i \), at field \( j \), in watershed \( k \), \( \gamma_{000} \) is the intercept coefficient, \( u_{00k} \) is a random effect accounting for variability between watersheds \( k \), \( u_{0jk} \) is a random effect accounting for variability between fields \( j \) in watershed \( k \), and \( e_{ijk} \) is a random effect accounting for the remaining within field variability over time. TVP was modeled using a Gaussian likelihood distribution, and for the null model we model all random effects using a random Gaussian correlation structure (iid). The intraclass correlation coefficient was calculated as the proportion of the total variance attributable to between unit variance at levels \( i \), \( j \), and \( k \). The ICC ranges from 0 to 1 where 0 indicates that grouping conveys no information and 1 indicates that all group members are identical [Gelman & Hill, 2007]. The resulting ICCs of 0.2 for level \( i \), 0.3 for level \( j \), and 0.5 for level \( k \) indicate that significant variance is found at each level and suggests that dynamics at all three levels should be taken into consideration. Given the large size of the dataset used in this study (5 years, ~62,000 fields, and 849 watersheds) we prioritize consideration of spatial processes occurring at level \( k \) to reduce the computational demands of model estimation.

3.2 Bayesian model specification

In order to test the hypothesis that seniority in access to surface water improves local capacity to maintain crop health and productivity and reduces agricultural sensitivity to cumulative meteorological drought stress during times of water scarcity the observed TVP was fit to a multi-level mixed-effects model with water right-SPI interactions, which can be expressed generally as:

\[ y_{ijk} = \beta_{0jk} + \beta_{10k}SPI + \beta_{20k}X + \beta_{30k}X \ast SPI + \beta_{4jk}C + s_{00k} + e_{ijk} \quad (2.0) \]

where, \( \beta_{0jk} \) is an intercept term, \( \beta_{10k} \) represents the linear effect of cumulative meteorological drought stress (SPI) on TVP, \( \beta_{20k} \) is a vector of coefficients that describe the effects of water rights on TVP at the watershed level, \( X \) is a vector of water rights predictors (Percent Riparian, Percent Pre-1914, and Percent Appropriative), \( \beta_{30k} \) is a vector of coefficients that describe the effect of interactions between water rights predictors and SPI, \( \beta_{4jk} \) is a vector of coefficients for controlling variables, \( C \) is a vector of controlling variables (year, crop type category, water rights density, competing uses, and depth to groundwater), \( s_{00k} \) is a watershed level spatial effect, and \( e_{ijk} \) is the residual within field variability. Both year and crop type category are modeled as fixed
effects while the watershed spatial effect is modeled as a random effect. All continuous variables were scaled to a mean of zero and standard deviation of one to ease interpretation of the intercept and coefficients.

In order to account for spatial effects in the large spatiotemporal dataset modeling was performed using the R package R-INLA, a Bayesian modeling package utilizing integrated nested Laplace approximations that includes a number of models for spatial and non-linear random effects [Blangiardo, Cameletti, Baio, & Rue, 2013]. Spatial effects at the watershed level were modeled using an intrinsic conditional autoregressive (iCAR) model coupled with an exchangeable (iid) random effect, also known as a Besag-York-Mollié (BYM) model. The addition of the spatial random effects can be interpreted as a random intercept term that accounts for both spatially random differences across watersheds and autocorrelation between neighboring watersheds.

The fit of the above described model (Model A) was compared to a model of only the described linear predictors and interactions using the calculated DIC (deviance information criterion). The proposed model (equation 2.0) showed better performance (see Table S3). In addition, recognizing that the effects of weather are not necessarily linearly related to agricultural production, models adding polynomial terms for SPI were compared with Model A [Schlenker and Roberts, 2006]. While polynomial terms for SPI were found to be significant, the linear effect of SPI, and more importantly, the main effects of the water right predictors and their interaction effects with SPI were not significantly different from those observed in Model A (see Table S4). In addition, the DIC for these models did not offer great improvements over Model A and the range of the full SPI effect for these models remained similar to Model A. Given that the focus of this study is to examine the impacts of the structure of water rights the more parsimonious Model A was selected for further analysis of impacts to agricultural productivity.

In order to test the hypothesis that during periods of extreme water stress, seniority in access to surface water significantly improves local capacity to cultivate crops and decreases the sensitivity of cultivation decisions to cumulative meteorological drought stress, a Bernoulli likelihood model examining the effect of water rights and SPI on the likelihood that a field of agricultural land is classified as barren and fallow was also run. The model (Model B) takes the same basic form as Equation 2.0 (with the addition of the farmland crop diversity control, use of a lagged SPI variable, and minus the land use category control), however, the outcome in this case is binary, where a value of one indicates that a field is barren and fallow and a value of zero indicates the field belongs to some other land use category.

As water use dynamics in the Central Valley are subject to feedbacks and simultaneity that can lead to endogeneity issues, factors whose values in any year are dependent on processes related to other independent variables or the outcomes (e.g. the amount of groundwater applied to fields is dependent on the crop type and amount of surface water applied to fields) were avoided in the above described models. In addition, due to lack of appropriate data for known factors influencing agricultural productions and other unknown excluded factors, endogeneity due to omitted variable bias was also a concern. In order to test the robustness of our models and identify potential biases in coefficient estimates, a series of models were run testing the sensitivity of our estimates of interest (surface water rights predictors) to the inclusion and exclusion of controlling variables and spatial random effects, while holding the crop type and temporal fixed effects constant. These sensitivity tests were conducted for both Model A and Model B and a subset of the results are provided in Table 2 and Table 3, respectively (complete results are provided in Tables S5 and S6). To test the validity of the random effects assumption
random effects are assumed to be uncorrelated with controlling variables in a regression), Model A was run with fixed effects for watersheds and compared to the same model with spatial random effects. Coefficient estimates for the predictors of interest in the watershed fixed effects and watershed spatial random effects model were not significantly different at the 95% credibility interval, providing confidence that no watershed-scale omitted variables that might significantly bias results remain unaccounted for (see Table S7). Key results of the Bayesian multi-level spatiotemporal models given as the median estimates of posterior parameters are summarized in Table 2 and Table 3 in the Results section (full model results for Models A and B, including 95% Credibility Intervals, are provided in Tables S8 and S9).

4 Results

The posterior Bayes estimates for Model A indicate that cumulative meteorological drought stress and one of the three water rights predictors have a significant effect on agricultural production after accounting for crop type, year, and watershed (Table 2). The effect for SPI indicates that when each water right’s predictor is at zero (its mean), and cumulative drought stress becomes less severe, total annual vegetative production (TVP) shows, on average, slight increases. The water rights predictor Percent Pre-1914 also shows a positive and significant effect on agricultural productivity, while the effect of Percent Riparian and Percent Appropriative water rights are not significant (see Figure 1).

The effect for Percent Pre-1914 water rights indicates that when SPI is zero (at its mean) watersheds with a larger proportion of water rights that are classified as Pre-1914 have, on average, higher TVP (indicating better crop health and productivity) than watersheds with a low proportion of Pre-1914 water rights. In addition, Appropriative water rights have a significant interaction effect with SPI, such that the effect of SPI on TVP is reduced from ~0.06 to ~0.04 when the percent of Appropriative water rights in a watershed increases by one standard deviation. Figure 2 illustrates how the effect of SPI on TVP changes as a function of each water right type. These results rather surprisingly indicate that agricultural productivity in watersheds with a higher proportion of Appropriative water rights is, on average, less sensitive to precipitation deficits than watersheds with a higher proportion of Pre-1914 or Riparian water rights.

Both the primary predictor effect estimates and the interaction effect estimates remain stable in Model A through Model A.3 as control variables are included or excluded when temporal and crop type fixed effects and watershed spatial random effects are held constant, providing some confidence in the robustness of the results. The estimates do shift considerably when the watershed spatial random effects are removed (Models A.4-A.6) suggesting that a significant amount of the variation in the predictors is related to omitted variables correlated with location (e.g. location of contract water districts and volume of water contract allotment).

Surprisingly, the coefficient for the depth to groundwater variable is not significant in Model A. In comparison, the coefficient for depth to groundwater estimated in Model A.4, where watershed spatial random effects are not included, shows that increasing depth to groundwater results in, on average, lower TVP outcomes. This would suggest that after controlling for crop type and year, areas where it may be more difficult or costly to access groundwater are less able to utilize groundwater to offset surface water shortages and maintain crop health. However, variation in this effect seems to occur at the watershed spatial scale and does not vary
consistently over time, leading groundwater effects to be soaked up by the watershed spatial effects. The density of water rights PODs within a watershed is also not significant in Model A. Comparison with Model A.4 where there is no watershed spatial effect indicates that this metric does positively effect TVP outcomes, but that these effects vary primarily across watershed and hence are accounted for with the spatial random effect in Model A. As with the density of water rights and depth to groundwater variables, the percent of all water rights PODs in a watershed that are used for agricultural purposes does not show a significant effect on agricultural productivity in Model A, but does in Model A.4 where its positive effect suggests that watersheds where a greater proportion of water rights go to agriculture are better able to maintain crop health.

The posterior estimates of the marginal distributions for Model B as shown in Table 3 indicate that there is generally a low average likelihood that any agricultural field is classified as barren and fallow. The estimate of the intercept suggests that the chances of a field being barren and fallow given average conditions for SPI in the previous year, water rights predictors, and controls, and after accounting for year and watershed, are about 12 in 1,000. The estimates of the predictor effects can be interpreted as an incremental change in the probability of a field being classified as barren and fallow. The effect of SPI suggests when the water rights predictors equal zero and SPI increases by one standard deviation (decreasing cumulative drought stress), the probability that a field will be barren and fallow decreases by ~8%.

None of the three water rights predictors have a significant main effect on the likelihood that a field is barren and fallow, however all three water rights predictors have significant interaction effects with SPI. The interaction effects can be interpreted as the ratio by which the SPI effect changes due to variations in the water rights predictors. The resulting effect of SPI given an increase of one of the interacting variable can be calculated as the exponentiated sum of the focal predictor (SPI) effect and the interaction effect (this is equivalent to the product of the exponentiated focal effect and interaction effect) [Chen, 2003]. This indicates that increasing the value of the Appropriative water rights predictor from zero to one (from the mean to one standard deviation above the mean) modifies the effect of SPI such that a one standard deviation increase in SPI increases the probability of a field being barren and fallow by ~11% instead of decreasing it by ~8%. Conversely, this implies that in watersheds with a lower percentage of Appropriative water rights, as SPI increases, the likelihood of a field being barren and fallow decreases. A one standard deviation reduction in the percent Appropriative rights corresponds to a reduction in the likelihood of a field being barren and fallow of ~24% when SPI also increases by one standard deviation. The interaction effects for Riparian and Pre-1914 waters are also significant. An increase of one standard deviation in the percent Pre-1914 water rights corresponds to 0.01% increase in the likelihood of a field being barren and fallow when SPI increases by one standard deviation, and an equivalent change in the percent Riparian water rights corresponds to a 1.4% increase in the likelihood of a field being barren and fallow when SPI increases by one standard deviation. These interaction effects suggest that, on average, when cumulative drought stress is more severe, watersheds with a higher than average proportion of senior water rights will be less likely to have barren and fallow fields than watersheds with more junior rights.

While the main effect estimates for the water rights predictors were not significant in Model B the estimates for all controls were significant. The estimate for depth to groundwater suggests that when the depth to groundwater increases by one standard deviation the likelihood
of a field being *barren and fallow* decreases dramatically (~57% less likely). This result is counterintuitive as it suggests that farmers located in areas where it may be more difficult to access groundwater choose to cultivate a greater extent of crops. In order to investigate whether this result reflects the influence of permanent crops such as Almonds, which cannot be left to fallow as annual crops can regardless of groundwater accessibility, and high value crops which may drive increased groundwater use despite increasing pumping costs, a model including a control for type of crop grown in the previous year was run. The results of this model (Table S10) show that while crop type grown in the previous year does strongly influence the likelihood of a field being classified as *barren and fallow* and does significantly change the groundwater effect, it does not produce a meaningful change the groundwater effect. This suggests that the unexpected groundwater effect on cultivation choices is more likely to be related to other factors such as the presence of existing groundwater wells, for which statewide data is not yet publicly available. (As with Model A we note that while we cannot control for all confounding factors in these models the lack of significant movement in the water rights variables of interest when controls are added and removed (see Tables S6 and S10) provides some confidence in their robustness.)

The farmland crop diversity estimate in Model B suggests that increasing crop diversity slightly reduces the likelihood of fields being *barren and fallow*, and may indicate a shift from cultivation of only a few traditional crops towards cultivation of more acreage of alternative drought-resistant crops in some watersheds. The effects for the controls for surface water access, water rights density and percent agricultural use, indicate that increases in the water rights density and in the amount of water rights associated with agricultural use are correlated with increases in the likelihood of a field being *barren and fallow*. This suggests that farmers in heavily agricultural watersheds that are reliant on surface water were more likely to cultivate less farmland during the drought. When comparing Model B and Model B.2, which has no watershed spatial random effects, it is clear that unlike the model of agricultural productivity (Model A) the estimates of the control variables in the logistic model are relatively insensitive to the addition of spatial effects, suggesting that they are accounting for variance within watersheds and over time. The effect estimates for the water rights predictors in Model B.2 are all significant and for Percent Riparian and Percent Pre-1914 indicate that watersheds with a higher percentage of Riparian or Pre-1914 water rights are less likely to have fields classified as *barren and fallow*. That these effects are not significant in Model B suggests that these effects are not strong after accounting for watershed properties that influence cultivation that are consistent over time.

5 Discussion

Given the importance of governance in creating opportunities to improve the capacity of people to respond to adverse situations, particularly in complex coupled social-ecological systems such as agricultural systems, a better understanding of the impacts of legally institutionalized structures granting and limiting access to surface water may positively inform water managers’ decision-making during times of water scarcity. The models presented in this study represent, to our knowledge, the first attempt to investigate the overall impacts of the legal structure of surface water rights in California on total annual vegetative productivity and the likelihood of a field being left barren and fallow for the entire Central Valley. Starting with the assumption that the legal structure of surface water rights in the state affects agricultural productivity we test the hypotheses that (1) farmers with seniority within the hierarchical legal structure of Californian surface water rights were able to achieve better than average...
agricultural productivity and maintain cultivated extent during the recent drought and that (2) they experienced less sensitivity to cumulative drought stress than did those with junior access to surface water.

The model results partially support the general hypothesis that the legal structure of surface water rights, as represented by the proposed metrics of watershed-scale distribution of water rights types, in the state affects agricultural production. In line with expectations, the model results suggest that areas with a large proportion of the most senior water rights, Pre-1914, did, on average have better agricultural productivity outcomes during the drought than areas with more junior, Appropriative, water rights. However, contrary to expectations, the model results also suggest that areas with a high proportion of junior water rights exhibit less sensitivity to cumulative meteorological drought stress, as decreases in SPI in areas with a high proportion of Appropriative water rights are associated with less severe decreases in agricultural productivity. Conversely, these same watersheds may not experience significant improvements in TVP when local drought conditions improve, perhaps signaling a reliance on distant water sources or a tendency for short-term increases in available surface water to go to higher priority beneficial water uses or senior water rights holders. Significant effects were not found for the main effects of Riparian and Appropriative water rights in spatiotemporal models of agricultural productivity, indicating that any effects of these predictors did not produce sufficient variation in TVP to be differentiated from watershed spatial effects. This may in part be due to the strong influence of groundwater and contract water use for agricultural irrigation that consistently occurs in many watersheds in the Central Valley.

The estimated effect sizes reported for the models examining effects on agricultural productivity may be small, however, it is important to note that these significant effects remain after accounting for variations in watershed characteristics that may influence agricultural productivity, time-invariant watershed-level factors, space-invariant temporal changes, and after controlling for land use decisions in each field. This implies that neither correlation between water rights and type of crop cultivated nor spatial correlation in locations of water rights contribute to the observed water rights effects, which are a reflection of the legal structures governing farmers’ expectations for, and access to, surface water. In addition, it should be recognized that the size of the effect of the water rights predictors on TVP is of a similar magnitude as the linear SPI predictor. That the effect observed for SPI is of such a small magnitude suggests that the short-term capacity of farmers in the Central Valley to mitigate the impacts of drought are considerable. Given likely increases in drought conditions in the area in the future, and state regulations related to sustainable groundwater management, this short-term capacity may be reduced in favor of long-term agricultural system viability, suggesting that the effect of SPI on crop health and productivity may be greater in the future [CA DWR, 2015].

While the results of models examining the role of the legal structure of water rights on agricultural productivity during times of water stress suggest that crop health and productivity was generally higher in areas with a high proportion of Pre-1914 water rights than in other areas, the results of the logistic model examining the likelihood of an agricultural field being left as barren and fallow indicate that the structure of water rights alone does not have a significant direct effect on the likelihood that a field is barren and fallow. However, the interaction effects from the logistic regression suggest that when cumulative meteorological drought stress is more severe, areas with a high proportion of Appropriative water rights are more likely to have barren and fallow fields, while areas with a high proportion of Pre-1914 water rights are least likely to
have *barren and fallow* fields. This finding supports the hypothesis that seniority in access to surface water decreases the sensitivity of cultivation decisions to cumulative meteorological drought stress. Interestingly, the effect of depth to groundwater has a strong and stable effect in the logistic model that indicates that the likelihood of a field being *barren and fallow* is much less in areas where the depth to groundwater is greater. This finding, may reflect the importance of the locations of existing groundwater wells and lack of groundwater pumping restrictions which were not explicitly controlled for in this model.

5.1 Limitations of the study

Accounting for the spatiotemporal dynamics of agricultural response to water availability is a complex task. Despite our best efforts to leverage the power of R-INLA to model complex spatiotemporal error structures, our results remain limited by data resolution and availability [Blangiardo, Cameletti, Baio, & Rue, 2013]. Without data clearly linking points of diversion to farmers’ fields, we can only approximate vegetative responses and cultivation decisions to the general configuration of water rights in the surrounding watershed, and must rely on spatial effects to control for aspects of the agricultural system such as contract water. In addition, these analyses rely on the assumption that the amount of surface water and groundwater applied to agricultural fields can be approximated by metrics of access, availability, and water right priority. Reduction in surface water availability is assumed to be accounted for by year fixed effects, while issues related to dissociation between water right POD locations and point of water use, and between depth to groundwater and locations of actual groundwater wells, are assumed to be accounted for by the spatial random effects. While the use of spatial random and fixed effects can be a powerful tool for addressing issues related to incomplete data, applying these controls successfully and without loss of explanatory power can be difficult. In our analyses incorporation of spatial random effects was associated with a reduction in significant effect estimates. However, the stability of the estimates in the spatiotemporal models when control variables are included or excluded provides some confidence in the robustness of the findings. While models without the spatial random effects provided more significant effect estimates the same level of robustness cannot be claimed as effect estimates do vary significantly with inclusion and exclusion of controls.

With higher resolution data linking fields to specific water rights, modeling field-level agricultural responses to surface water institutions would be possible. This data, coupled with increased groundwater monitoring could generate crucial research required to understand the complex dynamics of agricultural water use in the Central Valley. As more data becomes available describing access to groundwater and surface water in the region, research can be developed to explore how specific configurations of surface water rights affect agricultural production, how agricultural groundwater and surface water use interact during periods of drought and during years without drought, and how future groundwater policies such as the Sustainable Groundwater Management Act initiative could impact surface water access in the Central Valley. Additional research is also needed to determine how the portfolio of surface water use (e.g. industrial, domestic and agricultural use) influences agricultural response to drought. Knowledge about the impact of these structures on agriculture may help to support more comprehensive water use planning at the state and national levels and may assist farmers in mitigating the impacts of future drought.
6 Conclusion

The work described in this paper advances the use of Bayesian modeling to control for complex dynamics in large socio-environmental datasets. We utilized multilevel Bayesian modeling methods that included consideration of temporal effects and spatially autocorrelated effects to test the hypotheses that farmers with seniority within the hierarchical legal structure of Californian surface water rights were able to achieve better than average agricultural productivity and maintain cultivated extent during the recent drought, and that they also experienced less sensitivity to cumulative drought stress than did those with junior access to surface water. Our results suggest that:

1. Watersheds with a higher proportion of senior water rights had better agricultural health and productivity during the drought than watershed with less seniority in surface water access;
2. That agricultural productivity in watersheds with a higher proportion of junior water rights was, on average, less sensitive to meteorological drought conditions than other watersheds; and
3. That watersheds with a higher proportion of junior water rights were more likely to reduce the extent of cultivation, by allowing fields to fallow in response to increasingly severe meteorological drought conditions.

These results generally suggest that, as expected, seniority in access to surface water granted via the hierarchical legal structure of water rights in California enables farmers to cultivate more land with healthier crops. However, the finding that crop health and productivity in watersheds with relatively more junior water rights are less sensitive to changes in drought conditions may indicate that farmers in watersheds with a large proportion of junior water rights are better prepared to take action to mitigate the impacts of surface water deficits via groundwater pumping and other mechanisms. Considering that watersheds with more junior water rights are more likely to have more barren and fallow fields but also more improved agricultural productivity outcomes when drought severity increases, it may be inferred that farmers in watersheds with more junior access to surface water prioritize maintaining crop health over increasing the extent of cultivation. The findings of this study provide some evidence that the legal structure of surface water rights in California affects the ability of farmers to cultivate crops and maintain crop health during periods of drought, and suggests that attention to the effects of legal institutions governing access to water for agricultural uses should not be neglected in revisions of current water policies and creation of new water policies and institutions.

Acknowledgments, Samples, and Data

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CSV of the compiled dataset used in this work are provided in the Supporting Information; data processing scripts and model code are available at https://github.com/eburchfield/CA_drought or upon request.
References


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<table>
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<th>Mean</th>
<th>Standard Deviation</th>
<th>Minimum</th>
<th>Maximum</th>
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<td>-2.04</td>
<td>3.15</td>
<td>-12.96</td>
<td>8.76</td>
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<td>28.5</td>
<td>33.8</td>
<td>0</td>
<td>100</td>
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<td>Percent Pre-1914</td>
<td>15.6</td>
<td>28.1</td>
<td>0</td>
<td>100</td>
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<td>242.3</td>
<td>0.02</td>
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<td>14.6</td>
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Table 2. Posterior Bayes median effect estimates for models evaluating field level TVP in the Central Valley. Models A-A.3 include watershed spatial random effects and crop type and year fixed effects with inclusion and exclusion of controlling variables. Models A.4-A.6 remove the watershed spatial random effects.

<table>
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<tr>
<th>Variable</th>
<th>Model A</th>
<th>Model A.2</th>
<th>Model A.3</th>
<th>Model A.4</th>
<th>Model A.5</th>
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<td>0.1631</td>
<td>0.1628</td>
<td>-0.1000</td>
<td>-0.0806</td>
<td>-0.1016</td>
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<td>SPI</td>
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<td>0.0624*</td>
<td>0.0623*</td>
<td>0.1081*</td>
<td>0.1113*</td>
<td>0.1120*</td>
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<td>Percent Riparian</td>
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<td>0.0014</td>
<td>0.0008</td>
<td>-0.0661*</td>
<td>-0.0587*</td>
<td>-0.0464*</td>
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<td>Percent Pre-1914</td>
<td>0.0536</td>
<td>0.0540</td>
<td>0.0538</td>
<td>0.0125*</td>
<td>0.0174</td>
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<td>Percent Appropriative</td>
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<td>-0.0517*</td>
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<td>Percent Pre-1914*SPI</td>
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<td>-0.0010</td>
<td>-0.0009</td>
<td>0.0114</td>
<td>0.0109*</td>
<td>0.0166*</td>
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<td>Percent Appropriative*SPI</td>
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<td>-0.0228*</td>
<td>-0.0226*</td>
<td>-0.0798*</td>
<td>-0.0763*</td>
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<td>-0.0428*</td>
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* Indicates effect estimate is significantly different from zero at a 95% credibility level.
Table 3. Posterior Bayes median effect estimates for models of the likelihood of a field being classified as barren and fallow in the Central Valley. Model B is a spatiotemporal model that includes watershed spatial random effects and year fixed effects while Model B.2 removes the watershed spatial random effects.

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<th>Variable</th>
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<tr>
<td>Percent Riparian</td>
<td>0.9804</td>
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<td>Percent Pre-1914</td>
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<td>Percent Appropriative</td>
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<td>Percent Riparian*SPI</td>
<td>1.1023*</td>
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<td>1.0956*</td>
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<td>Water Rights Density</td>
<td>1.0382*</td>
<td>0.9534*</td>
</tr>
<tr>
<td>Percent Agricultural Use</td>
<td>1.1430*</td>
<td>1.0989*</td>
</tr>
<tr>
<td>Farmland Crop Diversity</td>
<td>0.9629*</td>
<td>1.0868*</td>
</tr>
<tr>
<td>Spatial Effects</td>
<td>Yes</td>
<td>No</td>
</tr>
<tr>
<td>DIC</td>
<td>130682</td>
<td>156065</td>
</tr>
</tbody>
</table>

*Anti-logit of the intercept estimate and exponentiated predictor effect estimates are reported. * Indicates effect estimate is significantly different from zero at a 95% credibility level.

Figure 1. Estimated effect of key predictors on TVP. Posterior median (black dot), median ± standard deviation (thick gray line), and 95% credibility intervals (thin gray line) are shown for key predictors.

Figure 2. The effect of SPI on TVP as a function of standardized water rights predictors. The median effect of SPI on TVP as moderated by interactions with Percent Riparian (blue), Percent Pre-1914 (red), and Percent Appropriative (black) water rights are shown as solid lines and 95% credibility intervals are given as shaded areas.