WORKING PAPER:
Does the Structure of Water Rights Impact Agricultural Production During Droughts?
A Spatiotemporal Analysis of California’s Central Valley

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Abstract

California’s Central Valley region has been called the “bread-basket” of the United States as much of the country’s produce is grown there. 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 as the current California drought enters its fifth year.

Presumably, the dynamics of water use over the course of a drought are dependent on the legal structure of water rights in the state as well as variations in the natural landscape. 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 appropriated; pre-1914 appropriations over recent appropriations, has the potential to constrain agricultural production, particularly for junior water rights holders. Interestingly, while California water code for surface waters is well-established, ground water use has gone largely unregulated (the first set of state groundwater regulations are set to roll out in 2017). The unstructured nature of access to groundwater is expected to play a major role in short term mitigation of drought impacts by agricultural producers, offsetting the constraints presented by the highly structured surface water rights.

In this study we use Bayesian multilevel spatiotemporal modeling techniques to examine the influence of the structure of water rights in the California Central Valley on agricultural production during the drought. Total vegetative production (TVP), computed using a remotely sensed metric of vegetation health known as the Enhanced Vegetation Index, is used as a proxy for agricultural production. We assess the extent to which the legal structure of water rights and the nature of water use affect agricultural production across watersheds from 2005 to 2015. Using R-INLA, we account for spatial processes operating at multiple scales (watershed and farmland parcel) that have the potential to influence the effects of water right structures on TVP. In addition to presenting the findings regarding the effects of water rights structures on agricultural production, we discuss the benefits and limitations of spatiotemporal modeling and the implications of our study for long-term agricultural and water policy in California’s Central Valley.

Keywords: Drought, Water Rights, R-INLA, Spatiotemporal models
1 Introduction/Background

1.1 California’s Central Valley is one of the most productive agricultural systems on the planet, making California the country’s biggest agricultural production state (Diffenbaugh et al., 2015). The region has been in a state of prolonged drought since the mid-2000s and under severe drought conditions since 2011 (Howitt et al., 2015). The continued drought conditions have significantly strained agricultural production throughout the valley with an estimated economic cost of $2.7 billion in 2015 alone (Howitt et al., 2015). In response to constrained surface water supplies, many farmers have started pumping groundwater to irrigate fields. In 2015 an estimated 6 million acre-feet of groundwater was pumped for agricultural irrigation to offset about 70% of surface water supply shortages (Howitt et al., 2015). However, 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 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. Unfortunately, future climate projections for the region also suggest that surface water supply shortages are likely to increase in frequency and duration, leading to significantly more water rights curtailments (Schwartz, 2015; Mann and Gleick, 2015). 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.

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 (Schwartz, 2015). Riparian rights are water rights belonging to a land owner and apply to 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, n.d.). However, riparian rights do not entitle a water user to divert water to storage (for use during the dry season) or 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 exempted from the 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, n.d.; Schwartz, 2015).

Appropriative water rights are rights that divert water far from the original stream system for use on land that is not classified as riparian (CA SWRCB, 2016b; Sawyers, n.d.). 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 year (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.

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Appropriative 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, n.d.). 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, n.d.)

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). 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).

In this paper, we present analyses that explore the role of surface water rights on agricultural production throughout the drought while controlling for other forms of water access such as precipitation and groundwater, as well as factors relevant to the agricultural system including crop diversity and land use. We apply Bayesian multilevel modeling techniques that account for spatiotemporal random 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 as well as temporal, spatial, and spatiotemporal patterns in the region. In this preliminary study we examine the validity of two hypotheses:

H1: Areas with more senior status water rights (Riparian and Pre-1914 rights) will, on average, exhibit higher levels of agricultural production than areas with more junior rights (Post-1914 Appropriative rights) when compared across space.

H2: Areas with more senior status water rights will show, on average, decreasing agricultural production over the course of the drought, but less of a decrease than is experience by areas with more junior water rights.
2 Methods

2.1 Study extents

In order to investigate the effects of water rights on agricultural production over the course of the drought a large spatiotemporal dataset was compiled (Table 1). Annual data for each year of the current drought (2007 to 2015) were obtained for the entire Central Valley with outcome, control, and predictor variables available at one of two different spatial scales: field-level (farmland patches) or watershed level. For the analyses described below this dataset was clipped to the subset of fields and watersheds 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 1 displays the spatial extents of the area of study.

Figure 1: Spatial extent of agricultural watersheds in California's Central Valley for 2007 through 2014.
2.2 Data

2.2.1 Agricultural production 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 an outcome at the field-level. To capture field-level production dynamics, we computed an index of total vegetative production (TVP) using remotely sensed measures of vegetation health. This proxy for agricultural production was computed for one kilometer square pixels using the NASA Moderate Resolution Imaging Spectroradiometer (MODIS) Terra MOD13A2 Enhanced Vegetation Index (EVI) dataset (NASA LP DAAC, 2015), a measure frequently used as an estimate of the health of agricultural crops (Cai and Sharma, 2010; Galford et al., 2008; Sakamoto et al., 2005). The full time series for each pixel-year was smoothed using a Savitzky-Golay filter and the TVP was computed as the integral of the smoothed EVI time series. A histogram of all TVP values is shown in Figure 2. Higher values of TVP indicate higher amounts of vegetative production over a year.

![Histogram of all TVP values](image)

Figure 2: Histogram of all TVP values

2.2.2 Predictor 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, et al., 2009; Kollet and 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 the watershed level to reflect watershed-level patterns of surface water access. The legal structure of water rights is represented by three variables that give the percent of all PODs within a watershed that are classified as Riparian, Pre-1914 and Post-1914 Appropriative (henceforth referred to as simply “Appropriative”) water rights (Figure 3).

![Figure 3: Mean of water rights structures over the course of the drought by watershed.](image)

2.2.3 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. Recent work conducted in Sri Lanka has suggested that farmers in crop diverse areas are more likely to engage in sharing of mitigation and adaptation strategies and/or crop switching during water shortages to minimize losses, therefore the diversity index is intended to control for local knowledge transfer (Burchfield and Gilligan, 2016). This metric also 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. The CropScape data from USDA were aggregated for each watershed-year using the diversity indexing method described by Turner et al. (1989) where diversity is described by a linear sum of the proportion of a landscape area that is covered by each crop type. To control for spatiotemporal variations in the effects of the drought we also computed the average annual Standardized Precipitation Index (SPI) 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). The SPI is measure of meteorological drought (a deficit in precipitation) that is given over a specified time period (in this case we use a 9-month SPI) 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. In addition, we control for both the fragmentation of surface water and the physical complexity of the distribution network in each watershed using the computed density of surface water right PODs for each watershed (Figure 4).
To control 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 land use categorical variable computed from the CropScape dataset (USDA National Agricultural Statistics Service, 2016). The CropScape data for each year was aggregated into six generalized categories of land use: barren and fallow, non-edible grasses, grains, row crops and vegetables, fruits and nuts, and uncultivated cover. 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 (Figure 5).

Figure 4: Mean density of water rights PODs in each watershed (count/square kilometers) over the course of the drought.

Figure 5: Land use classification for farmland fields in 2014.
The second field-level dataset is the estimated annual change in local groundwater elevation. 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 increasing groundwater withdrawals, and in an attempt to avoid missing and incomplete data issues, we applied spatiotemporal kriging to the CASGEM groundwater elevation point dataset using the R package ‘spacetime’ (GeoTracker GAMA, 2016; Gräler et al., 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 Benedikt, Pebesma, and Heuvelink (2016) we tested the fit of a number of variogram structures to our data and found a simple-sum metric model to best fit our data. The point data was then kriged through space-time to generate a 5 kilometer monthly gridded groundwater elevation dataset (Figure 6) which was compared to a held-out dataset of groundwater elevation observations for verification purposes.

![Figure 6: Average of predicted groundwater elevation (ft. above mean sea level) for each 5km grid over the drought.](image)

To aggregate this monthly dataset to an annual time-step, we computed the annual change in groundwater elevation from January to January for each pixel-year in our dataset. This value of annual change in groundwater elevation was extracted to each field-year.
<table>
<thead>
<tr>
<th>Variable</th>
<th>Data Source</th>
<th>Spatial Data Type/ Spatial Resolution/ Temporal Resolution</th>
<th>Data Transformation</th>
<th>Spatial Scale in Analyses</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>Agricultural Land</td>
<td>CA Farmland Mapping and Monitoring Program</td>
<td>Spatial Polygons/ Sub-watershed/ Biennial</td>
<td>NA</td>
<td>NA</td>
<td>Land classified as farmland or grazing land.</td>
</tr>
<tr>
<td>TVP</td>
<td>NASA LP DAAC: MOD13A2</td>
<td>Raster/ 1km pixel/ 16 day</td>
<td>Calculated integral of annual time series for each pixel and year.</td>
<td>Field</td>
<td>Total vegetative production. (Proxy for agricultural production.)</td>
</tr>
<tr>
<td>Land Use</td>
<td>USDA CropScape</td>
<td>Raster/ 30m pixel/ Annual</td>
<td>Aggregated categories into six general land use types.</td>
<td>Field</td>
<td>Crop or land cover type.</td>
</tr>
<tr>
<td>Groundwater Elevation</td>
<td>GeoTracker GAMA</td>
<td>Point/ NA/ Daily</td>
<td>Spacetime kriging used to interpolate groundwater elevations (in ft above msl) to a 5km grid on a monthly time step. Annual groundwater elevation change was calculated for each grid cell and year.</td>
<td>Field</td>
<td>Annual change in local groundwater elevation (ft).</td>
</tr>
<tr>
<td>Water Rights Density</td>
<td>CA SWRCB: eWRIMS</td>
<td>Point/ NA/ Daily</td>
<td>Calculated as the count of all surface water right PODs per square kilometers of watershed area.</td>
<td>Watershed</td>
<td>Density of all surface water right PODs in a watershed.</td>
</tr>
<tr>
<td>Percent Riparian</td>
<td>CA SWRCB: eWRIMS</td>
<td>Point/ NA/ Daily</td>
<td>Count of Riparian status water right PODs in a watershed divided by the count of all surface water right PODs in the watershed.</td>
<td>Watershed</td>
<td>Percent of all surface water right PODs in a watershed that have Riparian status.</td>
</tr>
<tr>
<td>Percent Pre-1914</td>
<td>CA SWRCB: eWRIMS</td>
<td>Point /NA/ Daily</td>
<td>Count of Pre-1914 status water right PODs in a watershed divided by the count of all surface water right PODs in the watershed.</td>
<td>Watershed</td>
<td>Percent of all surface water right PODs in a watershed that have Pre-1914 status.</td>
</tr>
<tr>
<td>Percent Appropriative</td>
<td>CA SWRCB: eWRIMS</td>
<td>Point</td>
<td>Count of Post-1914 Appropriative water right PODs in a watershed divided by the count of all surface water right PODs in the watershed.</td>
<td>Watershed</td>
<td>Percent of all surface water right PODs in a watershed that have Post-1914 Appropriative status.</td>
</tr>
<tr>
<td>Crop Diversity</td>
<td>USDA CropScape</td>
<td>Raster/30m pixel/ Annual</td>
<td>Calculated index of watershed crop diversity. (Turner et.al., 1989)</td>
<td>Watershed</td>
<td>Diversity of crops grown in a watershed.</td>
</tr>
<tr>
<td>SPI</td>
<td>AghaKouchak and Nakhijiri</td>
<td>Raster/ 1/8th degree grid/ Monthly</td>
<td>Annual average of monthly SPI.</td>
<td>Watershed</td>
<td>Index of the 9 month precipitation deficit.</td>
</tr>
</tbody>
</table>
2.3 Statistical Analysis

2.3.1 Multi-level structure. The importance of multi-level structuring on the dependent variable (TVP) was tested by fitting a three-level null model and calculating the interclass correlation coefficient (ICC). The null model takes the form,

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

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 assumed to follow a Gaussian likelihood distribution, and for the null model we model all random effects using a random Gaussian correlation structure (iid). The interclass correlation coefficient was calculated as the proportion of the total variance attributable to between unit variance at levels \( i \), \( j \), and \( k \). 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 (8 years, ~62,000 fields, and 849 watersheds) we prioritize consideration of processes occurring at levels \( i \) and \( k \) to reduce the computational demands of model estimation.

2.3.2 Bayesian model specification. In this preliminary study the measured TVP was fit to a multi-level linear growth model with covariate-year interactions, which can be expressed generally as:

\[ y_{ijk} = \beta_{0jk} + \beta_{1jk} \text{year} + \beta_{20k} X + \beta_{30k} X \times \text{year} + \beta_{4jk} C + e_{ijk} \quad (2.0) \]

where, \( \beta_{0jk} \) is an intercept term, \( \beta_{1jk} \) represents the linear effect of drought duration on TVP, \( \beta_{20k} \) is a vector of coefficients that describe the effects of water rights structure at the watershed level, \( X \) is a vector of predictors (Percent Riparian, Percent Pre-1914, and Percent Appropriative), \( \beta_{30k} \) is a vector of coefficients that describe the effect of interactions between predictors and drought duration, \( \beta_{4jk} \) is a vector of coefficients for controlling variables, \( C \) is a vector of controlling variables (SPI, land use category, agricultural diversity, and annual groundwater elevation change) and \( e_{ijk} \) is a random effect accounting for within field variability. Additional spatial,
spatiotemporal, and temporal structures were added to this base model to account for variance across space and time. For all analyses the temporal index, year, was centered at zero to represent years of drought duration since 2007, and all continuous control variables were scaled to a mean of zero and standard deviation of one to ease interpretation of the intercept.

In order to account for spatial and spatiotemporal effects 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 (R-inla). In all models spatial effects at the watershed level ($u_{00k}$) 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 addition of a random intercept term (see equation 1.3) such that the mean value of TVP (when year is zero and all covariates and controls equal zero) is allowed to vary across watersheds (see Figure 10).

A parameteric space-time interaction was also added to all models to allow the linear effect of year on TVP to vary across watersheds. This addition can be expressed as

$$\beta_{1jk} = y_{100} + u_{10k}$$

(3.0)

where $y_{100}$ is the mean effect of year on TVP and $u_{10k}$ is a random effect term representing variability in that effect across watersheds. The random effect term $u_{10k}$ was modeled with an exchangeable (iid) structure.

Model A includes the base model shown in equation 2.0 and the two above mentioned random effects. Model B adds an additional temporal random effect which is modeled using a first order autoregressive structure for year to account for non-linearity in the mean TVP trend over time. Model C adds a non-structured (iid) spatial effect at the field level ($u_{0jk}$) to Model B. The intercept term in this model then includes random effects at both the field and watershed levels and can be expressed as

$$\beta_{0jk} = \beta_{00k} + u_{0jk} + u_{00k}$$

(4.0)

Median estimates of posterior parameters and their corresponding 95% Credibility Intervals (0.025 quantile and 0.975 quantile) were extracted from R-INLA and are presented in the Results section below.

3 Results

Over the time period 2007 to 2014 California experienced continued varying degrees of drought conditions over large portions of the state, including the Central Valley. Figure 7 illustrates the spatial extent and relative severity of the meteorological drought conditions in 2007 and 2014.
Examination of the mean TVP across space over time (Figure 8) indicates that on average the negative effects of the drought on vegetation health were mitigated (most likely by increased groundwater pumping) as TVP did not significantly change over time.

However, it is also apparent, after examining Figure 9, that TVP is highly varied across space. These spatial variations in TVP exhibit clustering at a regional scale with lower TVP generally found around the more mountainous edges of the Central Valley.
Figure 9: TVP at the farmland field level in 2007 (left) and 2014 (right).

The random intercept at the watershed level appears to match well with general observed TVP trends through space (Figure 10).

Figure 10: Posterior median of the random intercept by watershed with upper and lower 95% credibility intervals for Model B.

Results of the Bayesian multi-level spatiotemporal models given as the median estimates of posterior parameters and their corresponding 95% Credibility Intervals (0.025 quantile and 0.975 quantile) are summarized in Table 2. Model fit among the candidate models was compared using marginal log-likelihood, $AIC$ (Akaike information criterion), and $BIC$ (Bayesian information criterion) and is also presented in Table 2. All three model fit statistics indicate that Model B
provides a better fit than Model A. While both log-likelihood and AIC for Model C indicate a better fit than Model B, the BIC for Model B suggests that Model B provides a better, more parsimonious fit than Model C. In addition, the standardized residuals for Model B were mapped to ensure that no obvious spatial trends remained unaccounted for (Figure 11). For the remainder of this paper results and interpretation will be provided for Model B.

Figure 11: Standardized residuals for Model B for years 2007 (left) and 2014 (right).

The posterior Bayes estimates for Model B indicate that all the water rights structures have a positive main effect on TVP and that these effects change significantly over time. However, it is apparent that the main effect of Percent Riparian ($\beta_2$) is highly variable across space as the Bayes 95% credibility interval for this coefficient includes zero. This partially supports hypothesis H1 that areas with more senior water rights will exhibit, on average, higher TVP levels than areas with more junior rights. The interaction effects for Percent Riparian and Percent Pre-1914 with time are both significantly positive, while the interaction effect for Percent Appropriative is significantly negative, supporting hypothesis H2. The mean estimated TVP over time based on Model B is shown in Figure 12 and appears to track well with the observed TVP values over time.
Table 2: Posterior Bayes estimates for spatiotemporal models evaluating field level TVP in the Central Valley.

<table>
<thead>
<tr>
<th></th>
<th>Model A</th>
<th>Model B</th>
<th>Model C</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \gamma_{000} )</td>
<td>0.5246 (0.5213, 0.5279)</td>
<td>0.4735 (0.4273, 0.5196)</td>
<td>0.5212 (0.4296, 0.5895)</td>
</tr>
<tr>
<td>( \gamma_{100} )</td>
<td>-0.0077 (-0.0083, -0.0071)</td>
<td>-0.0053 (-0.0157, 0.0051)</td>
<td>-0.0055 (-0.0202, 0.0104)</td>
</tr>
<tr>
<td>( \beta_2 )</td>
<td>0.0770 (0.0690, 0.0850)</td>
<td>0.0051 (-0.0024, 0.0126)</td>
<td>-0.0170 (-0.0221, -0.0119)</td>
</tr>
<tr>
<td>( \beta_3 )</td>
<td>0.0229 (0.0133, 0.0325)</td>
<td>0.0174 (0.0076, 0.0273)</td>
<td>-0.0315 (-0.0375, -0.0255)</td>
</tr>
<tr>
<td>( \beta_4 )</td>
<td>0.0126 (0.0065, 0.0188)</td>
<td>0.0105 (0.0044, 0.0166)</td>
<td>0.0272 (0.0230, 0.0314)</td>
</tr>
<tr>
<td>( \beta_5 )</td>
<td>-0.0115 (-0.0131, -0.0099)</td>
<td>0.0023 (0.0011, 0.0036)</td>
<td>0.0044 (0.0034, 0.0055)</td>
</tr>
<tr>
<td>( \beta_6 )</td>
<td>-0.0071 (-0.0093, -0.0050)</td>
<td>0.0068 (0.0051, 0.0086)</td>
<td>0.0082 (0.0067, 0.0097)</td>
</tr>
<tr>
<td>( \beta_7 )</td>
<td>0.0024 (0.0014, 0.0035)</td>
<td>-0.0021 (-0.0029, -0.0013)</td>
<td>-0.0026 (-0.0033, -0.0018)</td>
</tr>
</tbody>
</table>

Marginal Log-Likelihood | 388418.34 | 407226.88 | 584293.52 |
AIC | -772431.74 | -81076.42 | -1046127.48 |
BIC | -7.48E+05 | -7.86E+05 | -3.66E+05 |

\( \gamma_{000} \): Intercept, \( \gamma_{100} \): Year fixed effect, \( \beta_2 \): Percent Riparian, \( \beta_3 \): Percent Pre-1914, \( \beta_4 \): Percent Appropriative, \( \beta_5 \): Percent Riparian-Year interaction, \( \beta_6 \): Percent Pre-1914-Year interaction, \( \beta_7 \): Percent Appropriative-Year interaction

Figure 12: Mean of fitted values (TVP estimates) with fitted value standard deviations (dashed red lines) across space over the course of the drought for Model B.
4 Discussion

The main effects for the three water rights structure covariates indicate that in 2007 watersheds with a larger proportion of water rights with Pre-1914 or Post-1914 Appropriative status had, on average, higher vegetative production levels. More specifically, given a mean for TVP of 0.47 in 2007 ($\gamma_{000}$), a ten percent increase in Pre-1914 water rights ($\beta_3$) in a watershed indicates, on average, a TVP between 0.3 and 0.4 percent higher than the mean TVP. The interaction effects for Percent Riparian ($\beta_5$) and Percent Pre-1914 ($\beta_6$) with time are both significantly positive, indicating that watersheds with a higher percentage of water rights with these statuses fared increasingly better, had higher TVP, than watersheds with a low percentage of those water rights as the drought progressed. In contrast, the interaction effect for Percent Appropriative ($\beta_7$) which is negative, indicates that watersheds with a higher percentage of Appropriative water rights fared increasingly worse, lower TVP, over the course of the drought than watersheds with a lower percentage of these same rights. When the simple slope of TVP regressed on Percent Appropriative over time is examined (Figure 13) it becomes apparent that the strength of the effect of Percent Appropriative on TVP is not significantly different from zero for most years, indicating that on average as the drought progressed the proportion of water rights with Appropriative status in a watershed was not associated with TVP values significantly different from the overall mean.

![Figure 13: Simple slope of TVP regressed on Percent Appropriative water rights over the course of the drought with 95% credibility intervals (red).](image)

The simple slope for TVP regressed on Percent Riparian as a function of time (Figure 14) shows that the effect of increasing the percent of a watershed water rights PODs that have Riparian status is not significant until after 2009 (two years after the 2007 baseline).
Percent Pre-1914 is the only covariate that has a positive main effect and a positive interaction effect with time that are both significantly different from zero. The conditional regression of TVP on Percent Pre-1914 water rights as a function of time (Figure 15) indicates that watersheds where a relatively large proportion of water rights have Pre-1914 status have higher than average TVP and that this advantage increased over the course of the drought.
The expected value of mean watershed TVP for each of the three forms of water rights over the course of the drought when all other covariates and controls equal zero is displayed in Figure 16. This figure illustrates the strongly hierarchial effects of water structure-based water allocation priorities on watershed level vegetative health outcomes. Notably there is little difference in the effect of water rights structure early in the drought indicating that watersheds that primarily had water rights with Appropriate status, on average, had similar TVP levels as watersheds that were composed of mostly Pre-1914 or Riparian status water rights. As the drought progresses and surface water supplies become constrained (note that we control for groundwater pumping using change in local groundwater elevation and precipitation using SPI) watersheds with more Riparian or Pre-1914 rights tend to have higher vegetative production. These effects can be explained by CA SWRCB policies that curtail water diversions to Post-1914 Appropriative water rights holders first when surface water supplies are constrained.

![Figure 16: Conditional regression of TVP on water rights structures as a function of time.](image)

5 Future Work

The work completed thus far provides preliminary results to support the attribution of drought-related impacts to agricultural production to CA SWRCB water allocation decisions based on the legal structure of surface water rights. While preliminary results suggest that agricultural production in California’s Central Valley during drought is least negatively impacted in watersheds in which a large proportion of the surface water rights have Pre-1914 Appropriative status it is less clear if this results in an overall least negative impact to actual crop yields and economic values. Nor does this work suggest that a different water allocation scheme might provide higher overall levels of agricultural production. However, as increasing frequency and duration of water curtailments is expected to occur in the future, and the ability to offset losses in
surface water with groundwater is also expected to be reduced, knowledge about the expected impact of water allocation decisions may help support more comprehensive water use monitoring at the state government level and may assist farmers with junior water rights plan and prepare drought mitigation and adaptation options.

Future work will include examination of the same water rights structures using different model specifications. For example, it should be noted that plots of the fitted values across space (Figure 17) indicate that the spatial distribution of TVP, as well as the true range of TVP values, is not well represented in the selected model.

![Figure 17: Posterior mean of fitted values (estimated TVP) for each field in 2007 (left) and 2014 (right) based on Model B.](image)

As the spatial patterns observed for the random intercept (Figure 10) appear to match well with observed TVP spatial distributions, the spatial patterns observed in the fitted values may indicate that aggregation of water rights information to the watershed level is inappropriate, providing an over-simplified representation of the surface water use dynamics in the Central Valley. The use of a continuous spatial field may more accurately capture spatial dependencies within and between watersheds connected to the same stream system. In addition, a large portion of the variance through time is captured by the autoregressive temporal error term, suggesting that it may be more appropriate to model time, and covariate interactions with time, as non-linear effects. Additional work will examine the role of competition between types of water use (domestic, agricultural, industrial), and the impacts of continued drought conditions of specific crop types, specifically examining the relationship between changes in TVP and agricultural yields at the county level.

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7 References


