Urban Water Conservation Policies in the United States

Jonathan M. Gilligan[1,2,3], **Christopher A. Wold**[3], **Scott C. Worland**[2], **John J. Nay**[3,4,5], **David J. Hess**[3,6], **George M. Hornberger**[1,2,3]

[1]Department of Earth & Environmental Sciences, Vanderbilt University, Nashville, Tennessee, USA
[2]Department of Civil & Environmental Engineering, Vanderbilt University, Nashville, Tennessee, USA
[3]Vanderbilt Institute for Energy and Environment, Vanderbilt University, Nashville, Tennessee, USA
[4]Information Law Institute, New York University, New York, New York, USA
[5]Berkman Klein Center, Harvard University, Cambridge, Massachusetts, USA
[6]Department of Sociology, Vanderbilt University, Nashville, Tennessee, USA

Key Points:

- Analysis of water conservation policies of 195 cities in 45 states
- Water conservation policies correlate with both environmental and social variables
- Partisan voting patterns at both state and metropolitan levels account for much of the variation

Corresponding author: Jonathan M. Gilligan, `jonathan.gilligan@vanderbilt.edu`

Abstract

Urban water supply systems in the United States are increasingly stressed as economic and population growth confront limited water resources. Demand management, through conservation and improved efficiency, has long been promoted as a practical alternative to building Promethean energy-intensive water-supply infrastructure. Some cities are making great progress at managing their demand, but study of conservation policies has been limited and often regionally focused. We present a hierarchical Bayesian analysis of a new measure of urban water conservation policy, the Vanderbilt Water Conservation Index (VWCI), for 195 cities in 45 states in the contiguous United States. (Added: This study does not attempt to establish causal relationships, but does observe that) (Replaced: ~~Cities~~ replaced with: cities) in states with arid climates and (Replaced: ~~greater tendency to vote for Democratic candidates~~ replaced with: higher partisan voting index (PVI))tend to adopt more conservation measures. Within a state, cities with large and rapidly growing populations and (Replaced: ~~greater propensity than the rest of the state to vote Democratic~~ replaced with: higher PVI than the rest of the state)tend to adopt more conservation measures. Economic factors and climatic differences between cities do not (Replaced: ~~have much effect on~~ replaced with: correlate with) the number of measures adopted, but they (Replaced: ~~impact~~ replaced with: do correspond to) the character of the measures, with arid cities favoring mandatory conservation actions and cities in states with lower real personal income favoring rebates for voluntary actions. Understanding relationships between environmental and societal factors and cities' support for water conservation measures can help planners and policy-makers identify obstacles and opportunities to increase the role of conservation and efficiency in making urban water supply systems sustainable.

← Be clear that we're not claiming to demonstrate causality.

← Tone down use of "Democratic" to address concerns about sensationalistic media coverage.

← Be clear that we're not claiming to demonstrate causality.

1 Introduction

Cities face increasing challenges to their water supply because of complex interactions among drought, infrastructure, population growth, land-use changes, and other natural and human factors. The prospect of climatic change adds to the difficulty of planning robust and sustainable water supply systems, on account both of increasing uncertainty about future supply and demand for water, and also of predicted reductions in water availability in some regions, such as the Southwestern United States [*Melillo et al.*, 2014]. For many years, advocates of soft approaches to managing water resources have stressed the importance of improving the efficiency with which society obtains the water services it requires [*Gleick*, 2002]. Some cities and their associated water-supply systems respond to these challenges by pursuing grand energy-intensive infrastructure projects to draw water from distant or difficult sources, but many have also shown increasing interest in the soft path, managing demand through efficiency and conservation measures, and a number of cities have made impressive progress [*Fleck*, 2016].

A pressing challenge is to identify the characteristics of successful transitions toward sustainable water use and the necessary conditions for those transitions to spread more widely. Studies have investigated urban water conservation policies and several water conservation indices are available, but these either lack comprehensive coverage of water conservation policies or are geographically limited [*Hess et al.*, 2017; *Saurí*, 2013; *Maggioni*, 2014]. Recent research finds that individual perception of water scarcity and preference for policy action to address scarcity depend not only on the actual degree of water scarcity, but also on the person's ideological worldview [*Switzer and Vedlitz*, 2016], but it is not clear how these individual preferences translate into policy action.

The Vanderbilt Water Conservation Index (VWCI) is an integer score representing the number of measures that a city has taken to reduce its water demand, out of a list of 79 possible policy actions [*Hornberger et al.*, 2015; *Hess et al.*, 2016, 2017]. This list includes 31 requirements, such as restrictions on lawn-watering or mandatory use of water-efficient plumbing in new construction and renovations; and 21 rebates offered for voluntary actions, such as purchasing water-efficient appliances. Previously, we assessed this index and performed preliminary quantitative and qualitative analyses on a subset of the (Deleted: ~~22~~) central cities of the (Added: 22) largest metropolitan statistical areas (MSAs) in the extended Southwestern United States [*Hess et al.*, 2016]. (Added: That preliminary analysis found that propensity to adopt water conservation measures depended both on characteristics of the physical environment (precipitation) and on socio-economic and political characteristics of the MSA (partisan voting and cost of living).) ← Edited for conciseness.

(Deleted: ~~Our preliminary analysis of the 22 largest MSAs in the Southwest found that propensity to adopt water conservation measures depended both on characteristics of the physical environment (precipitation) and socio-economic and political characteristics of the MSA (partisan voting and cost of living). The Cook Partisan Voting Index for an MSA had, by a large margin, the greatest predictive power for adopting water conservation~~

~~measures. This finding was supported by qualitative analysis, which suggested that political association of water conservation with general "environmentalist" politics created political differences in the ways that cities respond to the physical fact of water scarcity.~~)

← Break this paragraph up: Put a brief summary into the previous paragraph, and incorporate details into the following discussion of the PVI.

(Added: We represented the partisan political leanings of states and MSAs by the Cook Partisan Voting Index (PVI) [*Wasserman*, 2013]. The index measures the difference between the percentage of the two-party vote received by Democratic presidential candidates in a city or MSA and the percentage received in the national election. Positive or negative values measure the city's or state's preference for the Democratic or Republican candidates, respectively, relative to the national average.)

← Provide explanation of what PVI is.

(Added: Municipal water conservation policies are chosen by city officials, so it may seem curious to measure partisan leanings with respect to presidential elections. However, presidential votes have the advantage of providing a uniform scale because voters across the country choose between the same candidates, whereas the differences between Democratic and Republican candidates for city and state positions vary considerably from one city or state to another, with narrow ideological differences in some elections and wide differences in others. Assessing partisan leanings in state and local elections becomes more complicated and difficult when we consider that the vast majority of American cities hold non-partisan city-council elections [*Svara*, 2003] and more than one third of state-legislature races are uncontested by one of the major parties [*Klarner*, 2015; *Associated Press*, 2006]. Moreover, detailed vote counts are not readily available for municipal- and state-level elections as they are for presidential elections. For all these reasons, presidential voting patterns are widely used to gauge regional variations in partisan leanings. Finally, we note that the rate of split-ticket voting has declined rapidly and consistently since the late 1980s [*Fiorina*, 2016] and that even voters who self-identify as independent are found to align consistently with one party or the other [*Hawkins and Nosek*, 2012], so we believe that presidential votes are good indicators for comparing the partisan leanings that voters bring to state and local elections across the United States.)

← Explain why why we use a measure (PVI) derived from presidential vote shares, rather than something that uses vote shares from state and local elections

(Added: Our previous analysis found that the PVI for an MSA had, by a large margin, the greatest predictive power for adopting water conservation measures *Hess et al.* [2016]. The importance of PVI was supported by qualitative analysis, which suggested that political association of water conservation with general "environmentalist" politics created political differences in the ways that cities respond to the physical fact of water scarcity.)

We subsequently expanded our database to the central cities in 197 MSAs in 47 states [*Hess et al.*, 2017], which comprise more than half of the 382 MSAs in the United States [*U.S. Census Bureau*, 2016] and here, we present the first quantitative analysis of the larger database, analyzing relationships between environmental and societal characteristics of 195 cities across the contiguous United States and those cities' propensity to adopt water conservation policies. This analysis considers state-level as well as MSA-level variables. We identify which variables (Replaced: ~~best explain~~ replaced with: correlate most strongly with) variations in water conservation policy regimes, how effects at the state level moderate city-level effects, and whether these effects manifest differently when we consider specific aspects of water-conservation policy, such as requirements and rebates. This analysis may help water managers and policy makers to anticipate how receptive a given city might be to adopting different conservation measures.

← Be clear that we're not claiming to demonstrate causality.

2 Data and Methods

2.1 Vanderbilt Water Conservation Index

The full VWCI data set provides detailed information about both the number and nature of urban water conservation policies, which allows hierarchical analysis to examine the relationships between water conservation scores and hydroclimatological and societal characteristics at both state and MSA levels. Our complete database includes Anchorage, AK, and Honolulu, HI, but for this analysis we chose to include only cities within the contiguous United States (195 cities in 45 states, Figure (Replaced: ~~S1~~ replaced with: 1)) because both climatic and socio-political characteristics of Alaska and Hawaii may be very different from those of the contiguous states, and also because state-level variables that average over the enormous area of Alaska and across the multiple Hawaiian islands may render them less suitable for our hierarchical treatment.

← Bring map figure from SI to main paper to help readers easily see the geographic distribution of MSAs.

VWCI scores range from 3 to 53 with a mean of 18.7 and a median of 15 (Figure 2a; Table S1). The number of requirements ranges (Deleted: ~~from~~)from 0 to 23 with a mean of 5.6 and a median of 4 (Figure 2b) and the number of rebates ranges from 0 to 15 with a mean of 2.7 and a median of 2 (Figure 2c).

The 20 cities with the greatest VWCI scores are in states in the Western U.S., with the exception of two cities in Florida and one in New York (Tables 1, S1). Cities with similar total VWCI scores, such as New York and Salt Lake City vs. Tampa and Vallejo, El Paso vs. Miami, and Riverside vs. Fresno, may have very different relative contributions from requirements and rebates.

The relative contributions of rebates and requirements to VWCI varied considerably (Tables 1, S1), and our previous qualitative research indicated that there might be a preference for rebates over requirements in more politically conservative cities [*Hess et al.*, 2016; *Brown and Hess*, 2017]. Consequently, in addition to the VWCI score we also analyzed the number of rebates and the number of requirements in a city's portfolio of conservation policies.

2.2 Explanatory Variables

We obtained values for the MSA-level (Replaced: ~~average annual average~~ replaced with: monthly average) temperature (T) and (Added: monthly) total precipitation (P) for the period (Replaced: ~~1970~~ replaced with: 1900)–2014 from the University of Delaware's gridded climate reanalysis [*Matsuura and Willmott*, 2015a,b] and for state-level from the National Climatic Data Center's divisional temperature and precipitation records for the Continental U.S. [*Vose et al.*, 2014]. (Added: We calculated the mean annual temperature and precipitation over a 30-year interval from 1985–2014.) We obtained populations for MSAs and states in 2010 and 2014 from the *U.S. Census Bureau* [2016] and used them to calculate average annual rates of population growth. (Added: An important economic indicator is real personal income (RPI), which represents the average personal income in the city or state, adjusted for inflation and the regional cost of living [*U.S. Bureau of Economic Analysis*, 2016a].) (Replaced: ~~Per-capita real personal income (RPI) for MSAs and states in 2014 were was obtained~~ replaced with: We obtained RPI for MSAs and states in 2014)from the *U.S. Bureau of Economic Analysis* [2016b]. (Replaced: ~~The~~ replaced with: We obtained the) fraction of the public water supply taken from surface water sources (henceforth, surface-water fraction) from the U.S. Geological Survey's water use report for 2010 [*Maupin et al.*, 2014]. (Replaced: ~~The Cook Partisan Voting Index (PVI) was calculated~~ replaced with: We calculated the Cook Partisan Voting Index (PVI))using state- and county-level presidential votes, averaged over the 2008 and 2012 elections [*Wasserman*, 2013; *CQ Press*, 2016]. Positive PVI indicates a greater Democratic

← Present the time extent of the entire data set, rather than just the years we extracted from that data set.

← Explain interval used to calculate aridity averages.

← Explain what the RPI variable indicates and why we used it.

vote share than the national average and negative PVI a greater Republican vote share (Tables S1–S2 and Datasets S1–(Replaced: ~~S2~~ replaced with: S4)).

We began with the covariates listed above, but adopted a modified set based on preliminary results: The regression coefficients for T and P showed collinearity. This, together with a desire for parsimony, led us to replace them with the Köppen aridity index: $P/(T+33)$, with P in millimeters and T in Celsius. The Köppen index is (Replaced: ~~deemed an especially reliable index of aridity~~ replaced with: derived from mean annual temperature and precipitation and correlates reasonably well with other aridity indices that incorporate evapotranspiration) [*Quan et al.*, 2013]. Larger values of this index correspond to wetter conditions and smaller values to drier conditions.

← Give a clearer description of what the Quan paper said and why we chose the Köppen index, as opposed to a more detailed one that uses evapotranspiration.

The distribution of MSA population in 2014 was skewed, with a few large cities producing an asymmetric fat tail (Figure S(Replaced: ~~2~~ replaced with: 1)), so we deemed (Added: the) natural logarithm of population (Replaced: ~~more suitable~~ replaced with: a more suitable predictor) for a regression analysis [*Gelman and Hill*, 2007, pp. 59–61].

(Added: We tested for robustness by comparing this regression to alternate regression analyses that used different predictors and different prior distributions.)

← Address questions about possible alternate covariates, such as economic inequality, population density, MSA area, etc.

2.3 Regression Analysis

We applied Bayesian hierarchical varying-intercept (Added: logistic) regression to each of the three conservation scores (VWCI, number of requirements, and number of rebates) with the following explanatory variables: the Köppen aridity index, surface water fraction, PVI, RPI, metropolitan population, and population growth rate. The hierarchical structure of our regression model, which nests cities and MSAs within states, reflects the fact that water resources extend beyond MSA boundaries and that state-level policies affect local actions, both by constraining local ordinances and regulations, and by encouraging or requiring counties and cities to adopt various types of conservation measures.

The regression (Replaced: ~~models each city's conservation score (VWCI, requirements, or rebates) as the result of a beta-binomial process (an overdispersed analogue to a binomial process) [*Gelman et al.*, 2014, pp. 437–38]. This model characterizes each city i by a probability p_i for adopting water conservation policies. In a pure binomial process, each policy would~~

~~have the same probability p_i of being adopted in city i, but the beta-binomial process allows for greater dispersion of scores by drawing the probability for each action separately from a beta distribution with mean p_i. The probability p_i is modeled using a hierarchical varying-intercept logistic regression on both state-level and MSA-level covariates:~~ replaced with: analysis follows standard textbook treatments [*Gelman and Hill*, 2007; *Gelman et al.*, 2014]. Each city's conservation score (VWCI, requirements, or rebates) is an integer count out of a maximum number of possible actions. We model this as a quasi-binomial process, in which each policy action a_j for city i is adopted independently with a probability p_{ij}. In a pure binomial process, each policy in city i would have the same probability p_i of being adopted. However, the VWCI data was over-dispersed relative to a pure binomial so our model uses a beta-binomial process, which allows for greater dispersion of scores by drawing the probabilities p_{ij} for the different actions in city i from a beta distribution with mean p_i [*Gelman et al.*, 2014, pp. 437–38].)

← Added extensive description of the regression analysis, and be explicit in our references to standard textbook treatments.

(Added: We model the cities' mean probabilities p_i with a hierarchical varying-intercept logistic regression in which MSAs are nested within states and VWCI depends on both state-level and MSA-level covariates. For city i, located in state$_i$,)

← Clearer description of the regression parameters.

$$\text{Score}_i \sim \text{beta-binomial}(N_{\text{action}}, \phi p_i, \phi(1 - p_i)), \tag{1}$$

where

$$p_i = \text{logit}^{-1}(y_i), \tag{2}$$

$$y_i = \alpha_{\text{state}_i} + \textstyle\sum_j \beta_j x_{ij}, \tag{3}$$

$$\alpha_{\text{state}_i} = \alpha_0 + \textstyle\sum_k \gamma_k w_{\text{state}_i,k} + \delta_{\text{state}_i}, \tag{4}$$

N_{action} is the number of possible conservation actions (79 for VWCI, 31 for requirements, and 21 for rebates), β is a vector of MSA-level regression coefficients, x is a matrix of MSA-level covariates, (Added: and α_{state_i} is the intercept of the MSA-level regression for all cities in state$_i$. We do not include a noise term in Equation 3 because random variations related to the probabilities p_i are incorporated in the beta-binomial process [*Gelman and Hill*, 2007, p. 321]. The inverse logit function maps the real numbers onto the interval $(0, 1)$, thus transforming y_i to a probability. The overdispersion of conservation scores is parameterized by ϕ: as $\phi \to \infty$, the distribution of conservation scores approaches a binomial distribution, and the smaller ϕ is, the greater the overdispersion.)

← Detailed descriptions of the regression parameters and explain why we did not explicitly model noise in the probabilities

(Added: In modeling α_{state}, α_0 is the mean intercept across all states,) γ is a vector of state-level regression coefficients, w is a matrix of state-level covariates, (Added: and) δ is a random noise term that represents state-level variations not accounted for by the regression model (Deleted: ~~, and ϕ parameterizes the overdispersion, relative to a binomial distribution. As $\phi \to \infty$, the distribution approaches a binomial distribution~~). We constrain δ to sum to zero in order to keep the model identifiable [*Stan Development Team*, 2016, Ch. 23].

← Clarify α_0 parameter.

(Added: Standardizing independent variables to put them on a common scale serves both to facilitate comparing the relative importance of variables whose natural scales are vastly different [*Gelman et al.*, 2008; *Gelman and Hill*, 2007, pp. 55–57], and also to improve computational performance [*Stan Development Team*, 2016].)State-level covariates were rescaled to have means of zero and standard deviations of 0.5. Where the same covariate appeared at both the state and MSA level, (Replaced: ~~the MSA-level covariate was rescaled~~ replaced with: we addressed multicollinearity between state-level and MSA-level variables by rescaling the MSA-level covariate) to the same scale as its state-level counterpart and (Replaced: ~~the state-level value was subtracted~~ replaced with: subtracting the state-level value), so that MSA-level covariate represented the difference between the MSA and the state-average. Covariates that only appeared at the MSA level were rescaled so the mean over all 195 MSAs was zero and the standard deviation 0.5. (Deleted: ~~Standardizing the independent variables served both to facilitate comparison of the relative importance of variables whose natural scales are vastly different [*Gelman et* al., 2008; *Gelman et* al., 2007], and also to improve computational performance [*Stan Development Team*, 2016].~~)

← Explain clearly the point of standardizing independent variables.

← Clarify the rescaling procedure for independent variables.

(Added: Because there are no previous quantitative comprehensive analyses of urban water conservation policies, we represent our ignorance at the outset by choosing weakly-informative priors, so the regression results are almost entirely determined by the data, and are only weakly constrained by the priors.) (Replaced: ~~We represent δ as normally distributed and use weakly informative Cauchy priors for the coefficients and parameters [*Gelman et* al., 2008].~~ replaced with: We follow *Gelman et al.* [2008]'s analysis of weakly-informative priors for logistic regression by choosing Cauchy priors with a scale of 2.5 for the parameters corresponding to the standardized variables (α_0, β, and γ). We represent δ as normally distributed with a scale defined by the hyperparameter σ with a positive half-Cauchy hyperprior [*Gelman et al.*, 2008]. For ϕ, we parameterized the Cauchy priors *ad-hoc*, based on the data, and setting the scales by trial and error to make the

← Explain our choice of priors.

prior distribution wide enough that it did not noticeably constrain the posterior.) ← Explain that our choice of Cauchy priors follows established practice and be clearer about the source for this choice.

$$\alpha_0, \beta, \gamma \sim \text{Cauchy}(0, 2.5), \tag{5}$$

$$\delta \sim \text{normal}(0, \sigma), \tag{6}$$

$$\sigma \sim \text{positive half-Cauchy}(0, 2.5), \tag{7}$$

and

$$\phi \sim \begin{cases} \text{Cauchy}(50, 20) & \text{for VWCI.} \\ \text{Cauchy}(15, 10) & \text{for requirements and rebates.} \end{cases} \tag{8}$$

(Deleted: ~~The posterior distributions were considerably narrower than the priors, and were not sensitive to changing the scales of the priors.~~)

We implemented the statistical model in the Stan probabilistic programming language [*Carpenter et al.*, 2017], which generates a Hamiltonian Monte Carlo sampler. We used R to prepare the data and call the sampler [*R Core Team*, 2016]. We (Replaced: ~~ran each chain for 2000 iterations (1000 for warm-up and 1000 for sampling),~~ replaced with: sampled four Markov chains for 1000 iterations each, after 1000 warm-up iterations,) which yielded a total of 4000 samples. (Added: The means and medians of the posterior distributions for regression coefficients β and γ, were equal within ± 0.01 (Tables S7–S9). Code to reproduce the analysis is included in the supporting information.) ← Clearer explanation of the Markov-Chain Monte Carlo sampling.

To facilitate interpretation, we (Replaced: ~~report~~ replaced with: follow the recommendations of *Gelman and Hill* [2007, pp. 81–82] by reporting) rescaled regression coefficients: $\beta' = \beta/4$ and $\gamma' = \gamma/4$, which represent the approximate change in the probability p corresponding to a two-standard-deviation change of the covariate near the midpoint of the logistic function (where $p = 0.5$) (Deleted: ~~[*Gelman and Hill*, 2007, pp. 81–82]~~). The corresponding change in VWCI, requirements, or rebates is given by $\beta' N_{\text{action}}$ or $\gamma' N_{\text{action}}$. ← Clarify where we get the rescaled regression coefficients from.

We tested VWCI for overdispersion by comparing binomial and beta-binomial models using leave-(Replaced: ~~on~~ replaced with: one)-out cross-validation (LOO) ((Replaced: ~~Table S3~~ replaced with: Tables S3–S4)), the Widely Applicable Information Criterion (WAIC) ((Replaced: ~~Table S4~~ replaced with: Tables S5–S6)), and (Replaced: ~~graphical~~ replaced with: visual) inspection of the distribution of posterior predictions of the mean, standard deviation, maximum, and minimum of VWCI over the cities in our data set

[*Gelman et al.*, 2014; *Vehtari et al.*, 2017]. All three methods favored the overdispersed beta-binomial model. These tests also strongly favored a (Replaced: ~~hierarchial~~ replaced with: hierarchical) model over a single-level regression on MSA-level covariates.

(Added: We also considered a hierarchical varying-slope model, but with an average of only 4.3 MSAs per state there were too few degrees of freedom to adequately constrain 6 additional regression coefficients for each state.) ← Explain why we did not consider a varying-slope model.

3 Results

(Deleted: ~~In comparing magnitudes of regression coefficients β and γ (see Section 2), we refer to the average value of the posterior (means and medians were equal within ±0.01; see Tables S5–S7). Where the 95% highest-density interval of the posterior overlaps zero, we refer to the effect as ambiguous because it is consistent with zero and its sign cannot be determined with confidence.~~) ← We moved paragraph that originally appeared here to the previous section.

Regressions for VWCI, requirements, and rebates ((Replaced: ~~Figures 2–3; Tables S5–S7~~ replaced with: Figure 3; Tables S7–S9)) all show (Replaced: ~~that PVI is an important predictor of~~ replaced with: important correlations between PVI and)urban water conservation at both the state and MSA levels. (Replaced: ~~Aridity matters at the state level for~~ replaced with: State-level aridity also correlates with)all three conservation scores. ← Be clear that we're not claiming to demonstrate causality. Variations of aridity from one MSA to another within a state have a pronounced (Replaced: ~~effect on~~ replaced with: correlation with) requirements, but (Replaced: ~~make only small and ambiguous contributions to~~ replaced with: not with) VWCI and rebates. At the MSA level, faster population growth and larger population (Replaced: ~~are associated~~ replaced with: correlate) with higher (Replaced: ~~scores on~~ replaced with: values for) all three conservation scores. (Deleted: ~~Effects of~~) RPI and surface-water dependence (Replaced: ~~are mostly ambiguous~~ replaced with: do not correlate meaningfully with the conservation indices) at the state level, (Deleted: ~~with uncertainty making it difficult to say anything definite~~) except in the case of RPI and rebates, and are negligible at the MSA level.

States with (Replaced: ~~more positive~~ replaced with: greater) (Democratic-leaning) PVI have greater propensity to adopt conservation policies, as do MSAs whose PVI is greater (more likely to vote Democratic) than the rest of the state. States with drier climates ((Replaced: ~~negative~~ replaced with: lower) aridity) also have greater propensity for conservation. MSAs with large and rapidly growing populations also tend to score higher on all three measures.

For all three conservation scores, the largest (Replaced: ~~effects~~ replaced with: correlations) were for state-level, as opposed to MSA-level, characteristics, but the posterior distributions show considerable overlap so it is important not to over-interpret the ranking of coefficients.

← Be clear that we're not claiming to demonstrate causality.

Two differences that stand out among the three measures are that state-level variation in RPI and MSA-level variation in aridity (Replaced: ~~each has ambiguous effects on~~ replaced with: do not correlate meaningfully with) total VWCI and (Replaced: ~~different effects on~~ replaced with: correlate differently with) requirements versus rebates: state-level RPI (Replaced: ~~affects rebates more strongly~~ replaced with: correlates more strongly with rebates) than (Added: with) requirements and MSA-level variations in aridity (Replaced: ~~affect requirements more strongly~~ replaced with: correlate more strongly with requirements) than (Added: with) rebates.

← Be clear that we're not claiming to demonstrate causality.

Regression residuals for VWCI range from −15.1 to +17.3, with a root-mean-square value of 5.3 (Figure 4 and Table 2). There is no indication of multicollinearity creating worrisome correlations among the coefficients ((Replaced: ~~Figures. S3–S5~~ replaced with: Figures. S2–S4)).

3.1 Robustness checks

(Added: We chose our explanatory variables based on theoretical considerations, as described by *Hess et al.* [2016]. To test the robustness of our analysis, we compared the results described above to three kinds of alternate regression analyses for the VWCI (See discussion of robustness, Figures S5–S6, and Tables S3–S6 in Supporting Information).)

← Add robustness checks and discussion of possible alternate predictor variables, such as population density, MSA area, and economic inequality, different averaging periods for calculating MSA aridity, and different priors.

(Added: First, we tested whether conservation policies might be more responsive to recent extreme events, such as drought, by varying the period over which we averaged the aridity index. Second, we repeated the regression analysis substituting MSA population density for the total population or including the MSA area and Gini index of income inequality as additional predictors. In all of these analyses, regression coefficients β and γ were consistent with the original model. The information criteria were also consistent with one another. In all of these analyses, the original set of covariates received the best scores by a small and insignificant margin.)

(Added: Finally, we tested for sensitivity to the functional form of the prior distributions and found only small and insignificant changes when we changed scales and replaced Cauchy priors for α, β, and γ with normal priors.)

(Added: We conclude from this that the results of our analysis are robust against many changes of time-spans, explanatory variables, and assumptions about priors.)

(Added: There are myriad other potential explanatory variables, but we worried that exploring a large set of alternative models and choosing the one that performs best might unintentionally become an exercise in "p-hacking" due to "garden of forking paths" effects [*Gelman and Loken*, 2014]. Because of these concerns, we chose to confine our analysis to the original set of variables, which we chose for theoretical reasons [*Hess et al.*, 2016].) ← Explain why we did not extend this analysis to consider a more comprehensive set of alternate explanatory variables

4 Discussion

This analysis identifies distinguishing characteristics of cities across the contiguous United States that embrace water conservation policies, and allows us to differentiate state-level from MSA-level effects. We find that water conservation is (Replaced: ~~driven~~ replaced with: associated) both (Replaced: ~~by~~ replaced with: with) characteristics of the physical environment and (Replaced: ~~by~~ replaced with: with) political and demographic characteristics of cities and states.

Our previous qualitative analysis of the 22 largest southwestern MSAs suggested that partisan differences over water conservation are more muted at the MSA-level than at the state and national level [*Hess et al.*, 2016], but while the quantitative analysis of that data showed that PVI played a large role, it could not distinguish state-level from MSA-level effects. Here, we find that for all three conservation scores (total VWCI, requirements only, and rebates only), PVI is important at both the state and MSA levels. The (Replaced: ~~effect of~~ replaced with: correlation between) PVI (Replaced: ~~on all~~ replaced with: and the) three conservation scores appears to be greater at the state level than at the MSA-level, but the posterior distributions of state-level and MSA-level coefficients overlap too much to permit much confidence in this ranking. ← Be clear that we're not claiming to demonstrate causality.

The state climate (aridity) shows clear (Replaced: ~~effect~~ replaced with: correlations) that are consistent across all three conservation scores. The (Replaced: ~~effects of~~ replaced with: correlations between) MSA-level aridity (Replaced: ~~within a state on~~ replaced with: and) VWCI and rebates are much smaller (Deleted: ~~, ambiguous,~~) and consistent with zero. We interpret this as reflecting the fact that urban water supplies often draw from sources, such as river networks, watersheds, and aquifers, that cover large areas and which may be shared by many cities and many categories of users. However, aridity has a clear (Replaced: ~~effect on~~ replaced with: correlation with) requirements, with cities that are drier than the state average tending to adopt more requirements.

← Be clear that we're not claiming to demonstrate causality.

RPI measures the real purchasing power of per-capita personal income, adjusted for inflation and regional variations in the cost of living [*U.S. Bureau of Economic Analysis*, 2016a], and thus reflects prosperity. At the state level, greater RPI correlates with lower conservation scores on all three measures, but the (Replaced: ~~effect~~ replaced with: correlation with VWCI and requirements) is small and (Replaced: ~~ambiguous (consistent with zero)~~ replaced with: consistent with zero), whereas it is large and clearly nonzero for rebates. Perhaps this reflects greater political support for choosing rebates over requirements when households have less disposable income with which to pay for conservation actions. At the MSA-level, (Replaced: ~~variations of RPI within a state~~ replaced with: correlations of all three scores with RPI) (Replaced: ~~have negligibly small effects, which are~~ replaced with: are negligibly small and) consistent with zero (Deleted: ~~, on all three scores~~).

← Be clear that we're not claiming to demonstrate causality.

What emerges in the big picture is that cities in states with higher (more Democratic-leaning) PVIs and more arid climates tend to adopt more conservation measures, including more requirements and more rebates. State-level RPI does not have a clear (Replaced: ~~effect on~~ replaced with: correlation with) VWCI(Replaced: ~~, but RPI appears to affect the composition of conservation policies, with lower RPI corresponding to a greater reliance on rebates.~~ replaced with: ; but when we look at the composition of policies, states with lower personal income tend to rely more heavily on rebates.)Within a state, cities in MSAs with greater PVI than the state average and those with large and rapidly growing populations tend to adopt more total conservation measures, including more rebates and requirements. Variations in aridity from one MSA to another within a state do not have an appreciable (Replaced: ~~effect on~~ replaced with: correlation with) total VWCI, but (Replaced: ~~they do affect the composition of policies, with MSAs whose climate is~~

← Be clear that we're not claiming to demonstrate causality.

~~more arid than the state average tending~~ replaced with: more arid MSAs tend) to favor requirements over other conservation measures.

Brown and Hess [2017] report on detailed interviews with decision-makers from four cities, including San Antonio and Phoenix, which have the largest and ninth-largest residuals, respectively (Table 2). This merits some discussion: San Antonio has a low predicted VWCI in part because of its low (Republican-leaning) PVI. However, federal policy may have contributed to San Antonio having a much higher VWCI than predicted by our regression: San Antonio's options for increasing its water supply are constrained by the settlement of a lawsuit over endangered species, which requires the U.S. Fish and Wildlife Service to restrict withdrawals from the Edwards Aquifer [*Brown and Hess*, 2017]. Phoenix has a much lower water conservation index than predicted. One contributing factor may be the city's access to water from the Colorado River, by means of the Central Arizona Project, which significantly relieves the water stress that might be expected from the region's hydroclimatology [*Brown and Hess*, 2017].

One should be cautious about using using qualitative data based on historical conditions to explain unusual observations or deviations from a model, but these two examples illustrate the rich complexity of water conservation policy and suggest that in future research, mixed-methods approaches can be valuable, combining statistical analyses with detailed case studies of selected cities to study both the patterns that represent what cities have in common and the distinctive individual characteristics of different cities.

In comparing the findings of this analysis to those of our previous preliminary analysis of the 22 largest MSAs in the Southwest, both studies identified PVI as a very important predictor of water conservation policies, but with its much smaller and less diverse sample, the previous study could not identify other effects after controlling for PVI, and it could not quantitatively distinguish state-level from MSA-level effects of PVI or other covariates. Here we observe clearly that variations in both environmental and societal characteristics at the state level are relevant to policy adoption; that within a state, variations from MSA to MSA of PVI, population, and population growth are consistently important; and that MSA-level variation in climate does not (Replaced: ~~affect~~ replaced with: correlate with) the number of conservation policies adopted, but (Replaced: ~~affects~~ replaced with: with) the kinds of policies adopted.

(Added: We emphasize that this study investigates associations and correlations, which are not necessarily causal. We only consider water policies at one point in time, which limits both our ability to assess causality and to assess the effectiveness of the policies at curtailing water consumption. Thus, this study only considers the number of policies cities adopt, and cannot speak to how effective those policies are. We expect that extending this work longitudinally would provide a richer understanding of conservation policy adoption and policy effectiveness.)

← Be clear that we're not claiming to demonstrate causality.

5 Conclusion

An integrated perspective that draws on social science and natural science variables shows that the adoption of urban water conservation policies cannot be explained by considering only hydroclimatological factors, such as aridity and the surface water fraction. Societal variables, such as political leanings, are also important.

(Replaced: ~~This analysis finds that for the most part hydroclimatological variables are important at the state level, but not at the MSA level, whereas PVI is important at both the state and MSA level.~~ replaced with: We find that correlations between hydroclimatological variables and conservation policies are greater at the state level than at the MSA level, and that state-level aridity is the only hydroclimatological variable (Replaced: ~~that~~ replaced with: whose effect) is consistently clearly distinct from zero across all the conservation measures. PVI, on the other hand, is consistently important at both the state and MSA levels.)Economic well-being has smaller correlations with policies, but (Replaced: ~~appears to affect which~~ replaced with: does correlate with the) categories of conservation policies a city is likely to favor. These results suggest that large, rapidly growing, and more politically liberal cities, and cities in arid and politically liberal states, (Replaced: ~~will be~~ replaced with: are) more likely to adopt water conservation policies.

← Be clear that we're not claiming to demonstrate causality.

(Replaced: ~~Policy~~ replaced with: We conclude that policy) rationales for water conservation and proposals for specific conservation measures would likely benefit from taking into account the complex mix of factors revealed by integrated social and natural science research.

(Added: We also expect that further integrated interdisciplinary research along these lines can produce a more detailed understanding of the number and character of conservation policies that different kinds of cities are likely to adopt, which would be relevant and useful for decision makers.)

← Be clear that we do not aspire to be the last word, but that there is a lot of potential for future research to consider other interdisciplinary questions about water conservation policies.

Acknowledgments

This material is based upon work supported by the National Science Foundation under Grant #EAR-1416964. The authors thank Christopher Fonnesbeck for helpful discussions and suggestions. All data used for this paper are (Deleted: ~~properly~~) cited and listed in the references or included in the supplementary information. (Replaced: ~~The complete VWCI data set, together with the code (R scripts and Stan models) used for this analysis, will also be posted publicly on github prior to publication.~~ replaced with: The complete VWCI data set with covariates is available on figshare at `https://doi.org/10.6084/m9.figshare.5714944`, and `https://figshare.com/s/278fb7278d174163a2a9`. The code (R scripts and Stan models) used for this analysis, will be posted publicly on github prior to publication.)

← URL and DOI for data used in this paper, which we have posted to figshare.

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Tables

Table 1. Cities with the twenty highest VWCI scores. Req. = requirements, Reb. = rebates. A complete list of all 195 cities appears in Table S1.

Rank	City	VWCI	Req.	Reb.	Req./Reb.
1	Los Angeles, CA	53	23	13	1.77
2	San Diego, CA	52	19	15	1.27
3	Santa Rosa, CA	50	19	15	1.27
4	Oxnard, CA	49	23	11	2.09
5	San Jose, CA	48	22	12	1.83
5	Santa Cruz, CA	48	20	11	1.82
7	Austin, TX	47	19	11	1.73
8	San Antonio, TX	46	19	8	2.38
9	Albuquerque, NM	45	19	12	1.58
9	Riverside, CA	45	15	13	1.15
11	Fresno, CA	44	22	8	2.75
12	Denver, CO	43	19	8	2.38
13	San Francisco, CA	42	18	9	2.00
14	Las Vegas, NV	40	18	7	2.57
14	Salinas, CA	40	19	6	3.17
16	El Paso, TX	38	19	3	6.33
16	Miami, FL	38	14	8	1.75
18	Fort Collins, CO	37	9	8	1.12
18	Stockton, CA	37	14	8	1.75
20	New York, NY	35	19	2	9.50
20	Salt Lake City, UT	35	18	2	9.00
20	Tampa, FL	35	14	5	2.80
20	Vallejo, CA	35	14	6	2.33

Table 2. Cities with the ten largest residuals from VWCI regression.

Rank	City	VWCI	predicted VWCI	residual
1	San Antonio, TX	46	28.7	17.3
2	McAllen, TX	15	30.1	−15.1
3	Oxnard, CA	49	33.9	15.1
4	Austin, TX	47	32.5	14.5
5	Santa Maria, CA	23	35.7	−12.7
6	San Diego, CA	52	39.4	12.6
7	Santa Rosa, CA	50	37.4	12.6
8	College Station, TX	30	18.0	12.0
9	Phoenix, AZ	21	32.5	−11.5
10	Houston, TX	18	29.0	−11.0

Figure Captions

Figure 1. Map of cities with VWCI scores.

Figure 2. Distribution of VWCI, requirements, and rebates.

Figure 3. Scaled regression coefficients for VWCI, requirements, and rebates: γ refer to state-level regression coefficients and β to MSA-level ones. For a scaled coefficient of 0.1, a two-standard-deviation change in the predictor corresponds to VWCI changing by about 8 for a city with a VWCI of around 40, the number of requirements changing by about 3 for a city with around 16 requirements, and a the number of rebates changing by about 2 for a city with around 10 rebates. The points represent the median of the posterior, the thick lines the 66% highest-density interval (HDI), and the thin lines the 95% HDI. Coefficients are grouped by state vs. city level and then ordered within each group by absolute value of the median for the VWCI analysis.

Figure 4. Predicted versus actual VWCI. Cities with the ten largest residuals are labeled. Cities in California, Florida, and Texas are indicated by color (these states contain 27% of the MSAs in our data set)

List of Changes

Added: This study does not attempt to establish causal relationships, but does observe that, on page 2, line 24.

Replaced: ~~Cities~~ replaced with: cities, on page 2, line 25.

Replaced: ~~greater tendency to vote for Democratic candidates~~ replaced with: higher partisan voting index (PVI) , on page 2, line 26.

Replaced: ~~greater propensity than the rest of the state to vote Democratic~~ replaced with: higher PVI than the rest of the state , on page 2, line 29.

Replaced: ~~have much effect on~~ replaced with: correlate with, on page 2, line 32.

Replaced: ~~impact~~ replaced with: do correspond to, on page 2, line 33.

Deleted: ~~22~~, on page 3, line 70.

Added: 22, on page 3, line 70.

Added: That preliminary analysis found that propensity to adopt water conservation measures depended both on characteristics of the physical environment (precipitation) and on socio-economic and political characteristics of the MSA (partisan voting and cost of living)., on page 3, line 71.

Deleted: ~~Our preliminary analysis of the 22 largest MSAs in the Southwest found that propensity to adopt water conservation measures depended both on characteristics of the physical environment (precipitation) and socio-economic and political characteristics of the MSA (partisan voting and cost of living). The Cook Partisan Voting Index for an MSA had, by a large margin, the greatest predictive power for adopting water conservation measures. This finding was supported by qualitative analysis, which suggested that political association of water conservation with general "environmentalist" politics created political differences in the ways that cities respond to the physical fact of water scarcity.~~ , on page 3, line 75.

Added: We represented the partisan political leanings of states and MSAs by the Cook Partisan Voting Index (PVI) [*Wasserman*, 2013]. The index measures the difference between the percentage of the two-party vote received by Democratic presidential candidates in a city or MSA and the percentage received in the national election. Positive or negative values measure the city's or state's preference for the Democratic or Republican candidates, respectively, relative to the national average., on page 4, line 83.

Added: Municipal water conservation policies are chosen by city officials, so it may seem curious to measure partisan leanings with respect to presidential elections. However, presidential votes have the advantage of providing a uniform scale because voters across the country choose between the same candidates, whereas the differences between Democratic and Republican candidates for city and state positions vary considerably from one city or state to another, with narrow ideological differences in some elections and wide differences in others. Assessing partisan leanings in state and local elections becomes more complicated and difficult when we consider that the vast majority of American cities hold non-partisan city-council elections [*Svara*, 2003] and more than one third of state-legislature races are uncontested by one of the major parties [*Klarner*, 2015; *Associated Press*, 2006]. Moreover, detailed vote counts are not readily available for municipal- and state-level elections as they are for presidential elections. For all these reasons, presidential voting patterns are widely used to gauge regional variations in partisan leanings. Finally, we note that the rate of split-ticket voting has declined rapidly and consistently since the late 1980s [*Fiorina*, 2016] and that even voters who self-identify as independent are found to align consistently with one party or the other [*Hawkins and Nosek*, 2012], so we believe that presidential votes are good indicators for comparing the partisan leanings that voters bring to state and local elections across the United States., on page 4, line 89.

Added: Our previous analysis found that the PVI for an MSA had, by a large margin, the greatest predictive power for adopting water conservation measures *Hess et al.* [2016]. The importance of PVI was supported by qualitative analysis, which suggested that political association of water conservation with general "environmentalist" politics created political differences in the ways that cities respond to the physical fact of water scarcity. , on page 4, line 108.

Replaced: ~~best explain~~ replaced with: correlate most strongly with, on page 5, line 120.

Replaced: ~~S1~~ replaced with: 1, on page 5, line 133.

Deleted: ~~from~~ , on page 5, line 139.

Replaced: ~~average annual average~~ replaced with: monthly average, on page 6, line 154.

Added: monthly, on page 6, line 155.

Replaced: ~~1970~~ replaced with: 1900, on page 6, line 156.

Added: We calculated the mean annual temperature and precipitation over a 30-year interval from 1985–2014., on page 6, line 159.

Added: An important economic indicator is real personal income (RPI), which represents the average personal income in the city or state, adjusted for inflation and the regional cost of living [*U.S. Bureau of Economic Analysis*, 2016a]., on page 6, line 162.

Replaced: ~~Per-capita real personal income (RPI) for MSAs and states in 2014 were was obtained~~ replaced with: We obtained RPI for MSAs and states in 2014 , on page 6, line 165.

Replaced: ~~The~~ replaced with: We obtained the, on page 6, line 167.

Replaced: ~~The Cook Partisan Voting Index (PVI) was calculated~~ replaced with: We calculated the Cook Partisan Voting Index (PVI) , on page 6, line 170.

Replaced: ~~S2~~ replaced with: S4, on page 7, line 175.

Replaced: ~~deemed an especially reliable index of aridity~~ replaced with: derived from mean annual temperature and precipitation and correlates reasonably well with other aridity indices that incorporate evapotranspiration, on page 7, line 179.

Replaced: ~~2~~ replaced with: 1, on page 7, line 185.

Added: the, on page 7, line 186.

Replaced: ~~more suitable~~ replaced with: a more suitable predictor, on page 7, line 186.

Added: We tested for robustness by comparing this regression to alternate regression analyses that used different predictors and different prior distributions., on page 7, line 188.

Added: logistic, on page 7, line 191.

Replaced: ~~models each city's conservation score (VWCI, requirements, or rebates) as the result of a beta-binomial process (an overdispersed analogue to a binomial process) [*Gelman et* al., 2014, pp. 437–38]. This model characterizes each city i by a probability p_i for adopting water conservation policies. In a pure binomial process, each policy would have the same probability p_i of being adopted in city i, but the beta-binomial process allows for greater dispersion of scores by drawing the probability for each action separately from a beta distribution with mean p_i. The probability p_i is modeled~~

~~using a hierarchical varying-intercept logistic regression on both state-level and MSA-level covariates:~~ replaced with: analysis follows standard textbook treatments [*Gelman and Hill*, 2007; *Gelman et al.*, 2014]. Each city's conservation score (VWCI, requirements, or rebates) is an integer count out of a maximum number of possible actions. We model this as a quasi-binomial process, in which each policy action a_j for city i is adopted independently with a probability p_{ij}. In a pure binomial process, each policy in city i would have the same probability p_i of being adopted. However, the VWCI data was over-dispersed relative to a pure binomial so our model uses a beta-binomial process, which allows for greater dispersion of scores by drawing the probabilities p_{ij} for the different actions in city i from a beta distribution with mean p_i [*Gelman et al.*, 2014, pp. 437–38]. , on page 7, line 200.

Added: We model the cities' mean probabilities p_i with a hierarchical varying-intercept logistic regression in which MSAs are nested within states and VWCI depends on both state-level and MSA-level covariates. For city i, located in state$_i$, , on page 8, line 217.

Added: and α_{state_i} is the intercept of the MSA-level regression for all cities in state$_i$. We do not include a noise term in Equation 3 because random variations related to the probabilities p_i are incorporated in the beta-binomial process [*Gelman and Hill*, 2007, p. 321]. The inverse logit function maps the real numbers onto the interval $(0, 1)$, thus transforming y_i to a probability. The overdispersion of conservation scores is parameterized by ϕ: as $\phi \to \infty$, the distribution of conservation scores approaches a binomial distribution, and the smaller ϕ is, the greater the overdispersion. , on page 8, line 229.

Added: In modeling α_{state}, α_0 is the mean intercept across all states,, on page 9, line 236.

Added: and, on page 9, line 237.

Deleted: ~~, and ϕ parameterizes the overdispersion, relative to a binomial distribution. As $\phi \to \infty$, the distribution approaches a binomial distribution~~, on page 9, line 239.

Added: Standardizing independent variables to put them on a common scale serves both to facilitate comparing the relative importance of variables whose natural scales are vastly different [*Gelman et al.*, 2008; *Gelman and Hill*, 2007, pp. 55–57], and also to improve computational performance [*Stan Development Team*, 2016]. , on page 9, line 243.

Replaced: ~~the MSA-level covariate was rescaled~~ replaced with: we addressed multicollinearity between state-level and MSA-level variables by rescaling the MSA-level covariate, on page 9, line 248.

Replaced: ~~the state-level value was subtracted~~ replaced with: subtracting the state-level value, on page 9, line 251.

Deleted: ~~Standardizing the independent variables served both to facilitate comparison of the relative importance of variables whose natural scales are vastly different [*Gelman et* al., 2008; *Gelman e* and also to improve computational performance [*Stan Development Team*, 2016].~~, on page 9, line 254.

Added: Because there are no previous quantitative comprehensive analyses of urban water conservation policies, we represent our ignorance at the outset by choosing weakly-informative priors, so the regression results are almost entirely determined by the data, and are only weakly constrained by the priors., on page 9, line 258.

Replaced: ~~We represent δ as normally distributed and use weakly informative Cauchy priors for the coefficients and parameters [*Gelman et* al., 2008].~~ replaced with: We follow *Gelman et al.* [2008]'s analysis of weakly-informative priors for logistic regression by choosing Cauchy priors with a scale of 2.5 for the parameters corresponding to the standardized variables (α_0, β, and γ). We represent δ as normally distributed with a scale defined by the hyperparameter σ with a positive half-Cauchy hyperprior [*Gelman et al.*, 2008]. For ϕ, we parameterized the Cauchy priors *ad-hoc*, based on the data, and setting the scales by trial and error to make the prior distribution wide enough that it did not noticeably constrain the posterior. , on page 9, line 261.

Deleted: ~~The posterior distributions were considerably narrower than the priors, and were not sensitive to changing the scales of the priors.~~ , on page 10, line 277.

Replaced: ~~ran each chain for 2000 iterations (1000 for warm-up and 1000 for sampling),~~ replaced with: sampled four Markov chains for 1000 iterations each, after 1000 warm-up iterations,, on page 10, line 281.

Added: The means and medians of the posterior distributions for regression coefficients β and γ, were equal within ± 0.01 (Tables S7–S9). Code to reproduce the analysis is included in the supporting information. , on page 10, line 284.

Replaced: ~~report~~ replaced with: follow the recommendations of *Gelman and Hill* [2007, pp. 81–82] by reporting, on page 10, line 288.

Deleted: ~~[*Gelman and Hill*, 2007, pp. 81–82]~~, on page 10, line 292.

Replaced: ~~on~~ replaced with: one, on page 10, line 296.

Replaced: ~~Table S3~~ replaced with: Tables S3–S4, on page 10, line 296.

Replaced: ~~Table S4~~ replaced with: Tables S5–S6, on page 10, line 298.

Replaced: ~~graphical~~ replaced with: visual, on page 10, line 298.

Replaced: ~~hierarchial~~ replaced with: hierarchical, on page 11, line 302.

Added: We also considered a hierarchical varying-slope model, but with an average of only 4.3 MSAs per state there were too few degrees of freedom to adequately constrain 6 additional regression coefficients for each state. , on page 11, line 304.

Deleted: ~~In comparing magnitudes of regression coefficients β and γ (see Section 2), we refer to the average value of the posterior (means and medians were equal within ±0.01; see Tables S5–S7). Where the 95% highest-density interval of the posterior overlaps zero, we refer to the effect as ambiguous because it is consistent with zero and its sign cannot be determined with confidence.~~ , on page 11, line 308.

Replaced: ~~Figures 2–3; Tables S5–S7~~ replaced with: Figure 3; Tables S7–S9, on page 11, line 313.

Replaced: ~~that PVI is an important predictor of~~ replaced with: important correlations between PVI and , on page 11, line 314.

Replaced: ~~Aridity matters at the state level for~~ replaced with: State-level aridity also correlates with , on page 11, line 316.

Replaced: ~~effect on~~ replaced with: correlation with, on page 11, line 318.

Replaced: ~~make only small and ambiguous contributions to~~ replaced with: not with, on page 11, line 319.

Replaced: ~~are associated~~ replaced with: correlate, on page 11, line 321.

Replaced: ~~scores on~~ replaced with: values for, on page 11, line 322.

Deleted: ~~Effects of~~, on page 11, line 323.

Replaced: ~~are mostly ambiguous~~ replaced with: do not correlate meaningfully with the conservation indices, on page 11, line 323.

Deleted: ~~with uncertainty making it difficult to say anything definite~~, on page 11, line 325.

Replaced: ~~more positive~~ replaced with: greater, on page 11, line 328.

Replaced: ~~negative~~ replaced with: lower, on page 11, line 331.

Replaced: ~~effects~~ replaced with: correlations, on page 12, line 334.

Replaced: ~~each has ambiguous effects on~~ replaced with: do not correlate meaningfully with, on page 12, line 339.

Replaced: ~~different effects on~~ replaced with: correlate differently with, on page 12, line 340.

Replaced: ~~affects rebates more strongly~~ replaced with: correlates more strongly with rebates, on page 12, line 342.

Added: with, on page 12, line 343.

Replaced: ~~affect requirements more strongly~~ replaced with: correlate more strongly with requirements, on page 12, line 343.

Added: with, on page 12, line 345.

Replaced: ~~Figures. S3–S5~~ replaced with: Figures. S2–S4, on page 12, line 348.

Added: We chose our explanatory variables based on theoretical considerations, as described by *Hess et al.* [2016]. To test the robustness of our analysis, we compared the results described above to three kinds of alternate regression analyses for the VWCI (See discussion of robustness, Figures S5–S6, and Tables S3–S6 in Supporting Information)., on page 12, line 351.

Added: First, we tested whether conservation policies might be more responsive to recent extreme events, such as drought, by varying the period over which we averaged the aridity index. Second, we repeated the regression analysis substituting MSA population density for the total population or including the MSA area and Gini index of income inequality as additional predictors. In all of these analyses, regression coefficients β and γ were consistent with the original model. The information criteria were also consistent with one another. In all of these analyses, the original set of covariates received the best scores by a small and insignificant margin., on page 12, line 356.

Added: Finally, we tested for sensitivity to the functional form of the prior distributions and found only small and insignificant changes when we changed scales and replaced Cauchy priors for α, β, and γ with normal priors., on page 13, line 364.

Added: We conclude from this that the results of our analysis are robust against many changes of time-spans, explanatory variables, and assumptions about priors., on page 13, line 367.

Added: There are myriad other potential explanatory variables, but we worried that exploring a large set of alternative models and choosing the one that performs best might unintentionally become an exercise in "*p*-hacking" due to "garden of forking paths" effects [*Gelman and Loken*, 2014]. Because of these concerns, we chose to confine our analysis to the original set of variables, which we chose for theoretical reasons [*Hess et al.*, 2016]., on page 13, line 369.

Replaced: ~~driven~~ replaced with: associated, on page 13, line 378.

Replaced: ~~by~~ replaced with: with, on page 13, line 379.

Replaced: ~~by~~ replaced with: with, on page 13, line 380.

Replaced: ~~effect of~~ replaced with: correlation between, on page 13, line 388.

Replaced: ~~on all~~ replaced with: and the, on page 13, line 388.

Replaced: ~~effect~~ replaced with: correlations, on page 14, line 392.

Replaced: ~~effects of~~ replaced with: correlations between, on page 14, line 393.

Replaced: ~~within a state on~~ replaced with: and, on page 14, line 394.

Deleted: ~~, ambiguous,~~, on page 14, line 395.

Replaced: ~~effect on~~ replaced with: correlation with, on page 14, line 399.

Replaced: ~~effect~~ replaced with: correlation with VWCI and requirements, on page 14, line 404.

Replaced: ~~ambiguous (consistent with zero)~~ replaced with: consistent with zero, on page 14, line 405.

Replaced: ~~variations of RPI within a state~~ replaced with: correlations of all three scores with RPI, on page 14, line 409.

Replaced: ~~have negligibly small effects, which are~~ replaced with: are negligibly small and, on page 14, line 410.

Deleted: ~~, on all three scores~~, on page 14, line 411.

Replaced: ~~effect on~~ replaced with: correlation with, on page 14, line 415.

Replaced: ~~, but RPI appears to affect the composition of conservation policies, with lower RPI corresponding to a greater reliance on rebates.~~ replaced with: ; but when we look at the composition of policies, states with lower personal income tend to rely more heavily on rebates. , on page 14, line 416.

Replaced: ~~effect on~~ replaced with: correlation with, on page 14, line 423.

Replaced: ~~they do affect the composition of policies, with MSAs whose climate is more arid than the state average tending~~ replaced with: more arid MSAs tend, on page 14, line 424.

Replaced: ~~affect~~ replaced with: correlate with, on page 15, line 454.

Replaced: ~~affects~~ replaced with: with, on page 15, line 455.

Added: We emphasize that this study investigates associations and correlations, which are not necessarily causal. We only consider water policies at one point in time, which limits both our ability to assess causality and to assess the effectiveness of the policies at curtailing water consumption. Thus, this study only considers the number of policies cities adopt, and cannot speak to how effective those policies are. We expect that extending this work longitudinally would provide a richer understanding of conservation policy adoption and policy effectiveness. , on page 16, line 457.