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. This study does not attempt to establish causal relationships, but does observe that cities in states with arid climates and higher partisan voting index (PVI) tend to adopt more conservation measures. Within a state, cities with large and rapidly growing populations and higher PVI than the rest of the state tend to adopt more conservation measures. Economic factors and climatic differences between cities do not correlate with the number of measures adopted, but they 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.

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 central cities of the 22 largest metropolitan statistical areas (MSAs) in the extended Southwestern United States [*Hess et al.*, 2016]. 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).

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.

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.

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 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.

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 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.

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 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 monthly average temperature (T) and monthly total precipitation (P) for the period 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]. 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. 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]. We obtained RPI for MSAs and states in 2014 from the *U.S. Bureau of Economic Analysis* [2016b]. 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]. 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 vote share than the national average and negative PVI a greater Republican vote share (Tables S1–S2 and Datasets S1–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 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.

The distribution of MSA population in 2014 was skewed, with a few large cities producing an asymmetric fat tail (Figure S1), so we deemed the natural logarithm of population a more suitable predictor for a regression analysis [*Gelman and Hill*, 2007, pp. 59–61].

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

2.3 Regression Analysis

We applied Bayesian hierarchical varying-intercept 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 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].

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$_i$,

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

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, 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.

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, and δ is a random noise term that represents state-level variations not accounted for by the regression model. We constrain δ to sum to zero in order to keep the model identifiable [*Stan Development Team*, 2016, Ch. 23].

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, 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 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.

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. 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.

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

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

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

and

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

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 sampled four Markov chains for 1000 iterations each, after 1000 warm-up iterations, which yielded a total of 4000 samples. 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.

To facilitate interpretation, we 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 $p = 0.5$). The corresponding change in VWCI, requirements, or rebates is given by $\beta' N_{\text{action}}$ or $\gamma' N_{\text{action}}$.

We tested VWCI for overdispersion by comparing binomial and beta-binomial models using leave-one-out cross-validation (LOO) (Tables S3–S4), the Widely Applicable Information Criterion (WAIC) (Tables S5–S6), and 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 hierarchical model over a single-level regression on MSA-level covariates.

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.

3 Results

Regressions for VWCI, requirements, and rebates (Figure 3; Tables S7–S9) all show important correlations between PVI and urban water conservation at both the state and MSA levels. State-level aridity also correlates with all three conservation scores. Variations of aridity from one MSA to another within a state have a pronounced correlation with requirements, but not with VWCI and rebates. At the MSA level, faster population growth and larger population correlate with higher values for all three conservation scores. RPI and surface-water dependence do not correlate meaningfully with the conservation indices at the state level, except in the case of RPI and rebates, and are negligible at the MSA level.

States 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 (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 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.

Two differences that stand out among the three measures are that state-level variation in RPI and MSA-level variation in aridity do not correlate meaningfully with total VWCI and correlate differently with requirements versus rebates: state-level RPI correlates more strongly with rebates than with requirements and MSA-level variations in aridity correlate more strongly with requirements than with rebates.

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 (Figures. S2–S4).

3.1 Robustness checks

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).

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.

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.

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

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].

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 associated both with characteristics of the physical environment and 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 correlation between PVI 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.

The state climate (aridity) shows clear correlations that are consistent across all three conservation scores. The correlations between MSA-level aridity and VWCI and rebates are much smaller 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 correlation with requirements, with cities that are drier than the state average tending to adopt more requirements.

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 correlation with VWCI and requirements is small and 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, correlations of all three scores with RPI are negligibly small and consistent with zero.

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 correlation with VWCI; 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 correlation with total VWCI, but 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 correlate with the number of conservation policies adopted, but with the kinds of policies adopted.

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.

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.

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 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 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, are more likely to adopt water conservation policies.

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.

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.

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 cited and listed in the references or included in the supplementary information. The complete VWCI data set with co-

variates 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.

References

Associated Press (2006). Many state legislative races are uncontested. Retrieved from http://www.nbcnews.com/id/15446775/ns/politics/t/many-state-legislative-races-are-uncontested.

Brown, K. P., & Hess, D. J. (2017). The politics of water conservation: Identifying and overcoming political barriers to successful policies. *Water Policy*, *19*, 304–321. https://doi.org/10.2166/wp.2016.089.

Carpenter, B., Gelman, A. Hoffman, M. Lee, D., Goodrich, B., Betancourt, M., Brubaker, M. A., Guo, J., Li, P., & Riddell, A. (2017). Stan: A probabilistic programming language. *Journal of Statistical Software*, *76*, 1–32. https://doi.org/10.18637/jss.v076.i01.

CQ Press (2016). Voting and elections collection. Retrieved from http://library.cqpress.com/elections/.

Fiorina, M. P. (2016). *The (re)nationalization of Congressional elections* (Essays on Contemporary Politics 7). Stanford, CA: Hoover Institute. Retrieved from https://www.hoover.org/sites/default/files/research/docs/fiorina_renationalizationofcongressionalelections_7.pdf.

Fleck, J. (2016). *Water is for Fighting Over and Other Myths about Water in the West*. Washington, DC: Island.

Gelman, A., & Hill, J. (2007). *Data Analysis using Regression and Multilevel/Hierarchical Models*. New York, NY: Cambridge.

Gelman, A., & Loken, E. (2014). The statistical crisis in science. *American Scientist*, *102*, 460–465.

Gelman, A., Jakulin, A., Pittau, M. G., & Su, Y.-S. (2008). A weakly informative default prior distribution for logistic and other regression models. *Annals of Applied Statistics*, *2*, 1360–1383. https:\\doi.org/10.1214/08-AOAS191.

Gelman, A., Carlin, J. B., Stern, H. S., Dunson, D. B., Vehtari, A., & Rubin, D. B. (2014). *Bayesian Data Analysis*, 3rd ed. Boca Raton, FL: CRC.

Gleick, P. H. (2002). Water management: Soft water paths. *Nature*, *418*, 373–373, https://doi.org/10.1038/418373a.

Hawkins, C. B., & B. A. Nosek (2012). Motivated independence? implicit party identity predicts political judgments among self-proclaimed independents. *Personality and Social Psychology Bulletin*, *38*, 1437–1452. https://doi.org/10.1177/0146167212452313.

Hess, D. J., Wold, C. A., Hunter, E., Nay, J. J., Worland, S., Gilligan, J., & Hornberger, G. M. (2016). Drought, risk, and institutional politics in the American Southwest. *Sociological Forum*, *31*, 807–827. https://doi.org/10.1111/socf.12274.

Hess, D. J., Wold, C. A., Worland, S. C., & Hornberger, G.M. (2017). Measuring urban water conservation policies: Toward a comprehensive index. *Journal of the American Water Resources Association*, *53*, 442–455. https://doi.org/10.1111/1752-1688.12506.

Hornberger, G. M., Hess, D. J., & Gilligan, J. (2015). Water conservation and hydrological transitions in cities in the United States. *Water Resources Research*, *51*, 4635–4649. https://doi.org/10.1002/2015WR016943.

Klarner, C. (2015). Competitiveness in state legislative elections: 1972–2014. *Ballotopedia*. Retrieved from https://ballotpedia.org/Competitiveness_in_State_Legislative_Elections:_1972-2014.

Maggioni, E. (2014). Water demand management in time of drought: What matters for water conservation. *Water Resources Research*, *51*, 215–139. https://doi.org/10.1002/2014wr016301.

Matsuura, K., & Willmott, C. J. (2015a). *Terrestrial Air Temperature: 1900–2014 Gridded Monthly Time Series (Version 4.01)* (Department of Geography, University of Delaware). Retrieved from http://climate.geog.udel.edu/~climate/html_pages/Global2014/README.GlobalTsT2014.html.

Matsuura, K., and Willmott, C. J. (2015b). *Terrestrial Precipitation: 1900–2014 Gridded Monthly Time Series (Version 4.01)* (Department of Geography, University of Delaware). Retrieved from http://climate.geog.udel.edu/~climate/html_pages/Global2014/README.GlobalTsP2014.html.

Maupin, M., Kenny, J., Hutson, S., Lovelace, J., Barber, N., & Linsey, K. (2014). *Estimated use of water in the United States in 2010* (USGS Circular 1405). Washington, DC: U.S. Geological Survey. Retrieved from https://doi.org/10.3133/cir1405.

Melillo, J. M., Richmond, T. C., & Yohe G. W. (Eds.). (2014). *Climate Change Impacts in the United States: The Third National Climate Assessment*. Washington, DC: U.S. Global Change Research Program. Retrieved from https://doi.org/10.7930/J0Z31WJ2.

Quan, C., Shuang, H., Torsten, U., Chunhua, Z., and Liu, Y.-S. (2013). Validation of temperature—precipitation based aridity index: Paleoclimatic implications. *Palaeogeography Palaeoclimatology Palaeoecology*, *386*, 86–95. https://doi.org/10.1016/j.palaeo.2013.05.008.

R Core Team (2016). *R: A Language and Environment for Statistical Computing.* Vienna: R Foundation for Statistical Computing.

Rodden, J. (2016). The geographic distribution of political preferences. *Annual Review of Political Science*, *13*, 331–340. https://doi.org/10.1146/annurev.polisci.12.031607.092945.

Saurí, D. (2013). Water conservation: Theory and evidence in urban areas of the developed world, *Annual Review of Environment and Resources*, *38*, 227–248. https://doi.org/10.1146/annurev-environ-013113-142651.

Stan Development Team (2016). *Stan Modeling Language: User's Guide and Reference Manual*, version 2.14.0. Retrieved from http://mc-stan.org/documentation/.

Svara, J. H. (2003). *Two Decades of Continuity and Change in American City Councils*, Washington, DC: National League of Cities. Retrieved from http://www.skidmore.edu/~bturner/Svara%20citycouncilrpt.pdf.

Switzer, D., and Vedlitz, A. (2016). Green colored lenses: Worldviews and motivated reasoning in the case of local water scarcity. *Environment and Behavior*, *49*, 719–744. https://doi.org/10.1177/0013916516669391.

U.S. Bureau of Economic Analysis (2016a). Real personal income and regional price parities. In *Regional Economic Accounts Methodology* (Report RPP2016). Retrieved from http://www.bea.gov/regional/pdf/RPP2016_methodology.pdf.

U.S. Bureau of Economic Analysis (2016b). *RPI1: Real per-capita personal income.* Retrieved from http://www.bea.gov/iTable/index.cfm.

U.S. Census Bureau (2016). *Metropolitan and micropolitan statistical areas.* Retrieved from https://www.census.gov/data/datasets/2016/demo/popest/total-metro-and-micro-statistical-areas.html/.

U.S. Census Bureau (2017). Gini index of income inequality. In *2014 American Community Survey 1-Year Estimates.* Retrieved from https://www.census.gov/data/datasets/2016/demo/popest/total-metro-and-micro-statistical-areas.html/.

Vehtari, A., Gelman, A., & Gabry, J. (2017). Practical Bayesian model evaluation using leave-one-out cross-validation and WAIC. *Statistics and Computing*, textit27, 1413–1432. https://doi.org/10.1007/s11222-016-9696-4.

Vose, R. S., Applequist, S., Squires, M., Durre, I., Menne, M. J., Williams, C. N., Fenimore, C., Gleason, K., & Arndt, D. (2014). Improved historical temperature and precipitation time series for U.S. climate divisions, *Journal of Applied Meteorology and Climatology*, *53*, 1232–1251. https://doi.org/10.1175/JAMC-D-13-0248.1.

Wasserman, D. (2013). *Introducing the 2014 Cook Political Report Partisan Voter Index.* Cook Political Report. Retrieved from http://cookpolitical.com/story/5604.

Wilson, S. G. and Plane, D. A. and Mckun, P. J. and Fischetti, T. R. & Goworowska, J. (2016). *Patterns of Metropolitan and Micropolitan Population Change: 2000–2010* (Report No. C2010SR-01). Washington, DC: U.S. Census Bureau. Retrieved from https://www.census.gov/library/publications/2012/dec/c2010sr-01.html

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)