Urban Water Conservation Policies in the United States

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Key Points:

- Analysis of water conservation policies of 195 cities in 45 states
- Water conservation policies correlate with both environmental and social variables
- Correlations with partisan voting patterns explain much of the variation in policy adoption.

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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 tend to adopt more conservation measures. Within a state, cities with more Democratic-leaning voting preferences and large and rapidly growing populations 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 correlate with 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 and consumes 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. However, many have also shown increasing interest in the soft path, which involves 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 studies 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 (more progressive) or Republican (more conservative) candidates, respectively, relative to the national average. Previous studies have indicated that a more Democratic-leaning PVI score is associated with higher environmental policy adoption, including for renewable energy [*Chupp*, 2011] and water-conservation policies [*Hess et al.*, 2016], and conversely that a lower score is associated with higher greenhouse gas emissions from power plants [*Grant and Vasi*, 2017].

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 that 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 a useful measure for gauging 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 measure of Democratic-leaning voting preference (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 this measure was supported by qualitative analysis, which suggested that the 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 the 197 most populous MSAs in the United States [*Hess et al.*, 2017], which span 47 states and comprise more than half of the 382 MSAs in the U.S. [*U.S. Census Bureau*, 2016]. 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. Our goal is to assess differences across MSAs that are correlated with higher or lower levels of water-conservation policy adoption. Our analysis also considers state-level variables because MSA policy adoption can be strongly influenced by state-government actions, such as the California state government's strong policy support for water conservation). We identify which variables correlate most strongly with variations in water conservation policy regimes and whether these effects manifest differently when we consider specific aspects of water-conservation policy, such as requirements and rebates. This 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 VWCI data set reports 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 set of 79 measures for each city makes it possible to construct different variables. In this study, we focus on three variables: the composite VWCI of all 79 policies, the subset of 31 requirements, and the subset of 21 rebates. The requirement scores range from 0 to 23 with a mean of 5.6 and a median of 4 (Figure 2b) and the rebate scores range 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. 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.

The relative contributions of rebates and requirements to VWCI varied considerably (Tables 1, S1)

2.2 Explanatory Variables

We selected explanatory variables with the goal of understanding the relative contribution of political-economic and hydroclimatological factors to policy adoption. We selected one political variable (the Cook Partisan Voting Index, PVI) for reasons described above and one economic variable (real personal income, RPI). We calculated PVI using state- and county-level presidential votes averaged over the 2008 and 2012 elections [*Wasserman*, 2013; *CQ Press*, 2016] (Tables S1–S2 and Datasets S1–S4). Positive PVI indicates that the Democratic share of the two-party vote was greater than the national average, and negative PVI indicates a greater Republican vote share. Income is generally correlated with education and with a range of other variables that are associated with differences in policy adoption, and we reasoned that in poorer regions there may be a preference for rebates and other optional policies. We chose 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].

For the hydroclimatological 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 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].

In addition to the two political-economic variables and the two hydroclimatological variables, we included measures for total population and population growth of the MSA. Our previous research had indicated that larger cities have more capacity to adopt water-conservation policies and that more rapidly growing cities are more concerned with water supply. 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.

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].

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: PVI (Democratic Party preference), RPI (real per-capita income), the Köppen aridity index, surface water fraction, 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. We also considered a hierarchical varyingslope 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.

The regression analysis follows standard textbook treatments [*Gelman and Hill*, 2007; *Gelman et al.*, 2014a]. Each city's water-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 for city i is adopted independently, with the m^{th} action, a_m, having probability p_{im}. In a pure binomial process, each policy in city i would have the same probability p_i of being adopted. The variance of a pure binomial distribution is uniquely determined by its mean and the variance of the VWCI data was greater than a pure binomial distribution could account for, so our model uses a beta-binomial process, which allows for greater dispersion of scores by drawing the probabilities p_{im} for the different actions in city i from a beta distribution with mean p_i [*Gelman et al.*, 2014a, 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 water-conservation policy measures are associated with both state-level and MSA-level covariates. For city i, located in state j,

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

where

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

$$y_i = \alpha_j + \sum_{k \in \text{MSA variables}} \beta_k x_{ik}, \tag{3}$$

$$\alpha_j = \alpha_0 + \sum_{k \in \text{state variables}} \gamma_k w_{jk} + \delta_j, \tag{4}$$

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_j is the intercept of the MSA-level regression for all cities in state j. 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_j, 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].

We standardized the independent variables x and w to put them on a common scale. This 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]. We rescaled the state-level covariates to have means of zero and standard deviations of 0.5, as recommended by *Gelman et al.* [2008] and *Gelman and Hill* [2007, pp. 55–57]: $w_{\text{scaled}} = (w - \mu_w)/(2\sigma_w)$, where w is a state-level covariate, μ_w is the mean over all states, and σ_w is the standard deviation over all states. 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: $x_{\text{scaled}} = (x - w)/(2\sigma_w)$, where x is an MSA-level covariate, w is the state-level covariate for the MSA's state, and σ_w is the standard deviation of w over all states. 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: $x_{\text{scaled}} = (x - \mu_x)/(2\sigma_x)$, as above.

We recognize that there are various ways that the multilevel model could be configured. Our choice of models was based on the theoretical objective of highlighting MSA-level difference in water-conservation policies. This choice involved three decision criteria. First, we selected the four main variables (Democratic-leaning, income, aridity, and surface water) on theoretical grounds described above with our goal of understanding the relative strength of political and economic factors and hydrogeological factors. The population variables were included as "controls." This choice of variables allowed us to have a balanced approach to sociohydrological factors and to show that policy adoption is not a simple outcome of hydrological factors. Second, we selected the state-government level as the higher level for the model because water conservation policy is frequently driven by state-government organizations and policies. Third, any of the four variables could be included only at the MSA level rather than at both the MSA and state levels, but doing so would tend to bias the model toward an overestimation of MSA-level differences. By using a model that includes these four variables at both the MSA and state levels, and by normalizing the MSA-level variables to state averages, we developed a conservative approach to showing the importance of MSA-level differences. Thus, when we demonstrate MSA-level differences, we do so with a model that would tend to underestimate those differences.

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 S15–S17). 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 of $\beta' N_{\text{action}}$ or $\gamma' N_{\text{action}}$. For example, $N_{\text{VWCI}} = 79$, so if $\beta'_k = 0.1$ for some covariate x_k, then for a city with VWCI of 39 ($p \approx 0.5$), a two-standard-deviation change in x_k would correspond to a change in VWCI of roughly 8.

We tested VWCI for overdispersion by comparing binomial and beta-binomial models using leave-one-out cross-validation (LOO) (Tables S3–S5), the Widely Applicable Information Criterion (WAIC) (Tables S6–S8), and also by 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.*, 2014a,b; *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.

3 Results

With respect to the political-economic variables, regressions for VWCI, requirements, and rebates (Figure 3; Tables S15–S17) all show correlations between adoption of water-conservation policies and Democratic-Party vote share at both the state and MSA levels. States with greater Democratic-leaning PVI scores have greater propensity to adopt conservation policies, as do MSAs with greater Democratic vote-share than the rest of the state. Personal income (RPI) does not correlate meaningfully with the conservation indices at the state level, except in the case of rebates, and it is negligible at the MSA level. With respect to the hydroclimatological variables, state-level aridity also correlates with all three conservation scores with MSAs in drier (low-aridity) states having a greater propensity for conservation. Variations of aridity from one MSA to another within a state have a pronounced correlation with requirements, but not with VWCI and rebates. Surface-water dependence does not correlate meaningfully with the conservation indices at the state or MSA levels.

At the MSA level, faster population growth and larger population correlate with higher values for all three conservation scores. This finding was expected for reasons given above.

For all three conservation scores, the largest effects 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 real personal income (RPI) and MSA-level variation in aridity do not correlate meaningfully with total VWCI. However, they do correlate differently with requirements versus rebates: state-level real personal income 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 -15.2 to $+17.1$, 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

As described above, we chose our explanatory variables for theoretical reasons with the goal of understanding the relative role of political-economic and hydroclimatological differences among MSAs as factors that explain water-conservation policy adoption. 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–S10, and Tables S3–S14 in Supporting Information). We compared the predictive accuracy of the different analyses using information-criteria scores [*Gelman et al.*, 2014b; *Vehtari et al.*, 2017] and also considered whether the regression coefficients produced by the alternate were substantively different from those of the original analysis.

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. Both the regression coefficients and the information criteria were indistinguishable for the different averaging periods (Figure S5, Tables S3 and S6).

Second, we repeated the regression analysis with different sets of covariates: substituting MSA population density for the total population or including the MSA area and Gini index of income inequality as additional predictors (Figure S6, Tables S4 and S7). 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 margin.

We also repeated the regression analysis removing either PVI or aridity (Figure S7, Tables S4 and S7). Removing either of these covariates reduced the quality of fit to the observations, as indicated by information criteria scores. The models with PVI removed showed the worst quality, which indicates that PVI made the greatest contribution to the quality of the fit and had the greatest predictive power of the covariates we considered. It is important to note that there was considerable uncertainty in the information criteria estimates, which makes it difficult to disentangle the specific contributions of each covariate. Therefore, we used information criteria scores primarily to compare the overall predictive accuracy of different model configurations [*Gelman et al.*, 2014b].

In addition to comparing different choices of covariates, we also examined different structures for the regression models: In addition to hierarchical regression models that nest MSAs within states, with different intercepts for different states, we also considered single-level models that considered only MSA-level covariates and used the same intercept for all MSAs, we considered interaction terms between aridity and PVI at both the state and MSA levels (Figure S7, Tables S4 and S7), and we considered an alternative normalization in which the MSA-level covariates were scaled separately from the state-level covariates to have zero mean and 0.5 standard deviation across all MSAs ($x_{\text{scaled}} = (x - \mu_x)/(2\sigma_x)$), rather than representing the scaled difference between the MSA value and the state-level value (Figures S8–S10, Tables S9–S14).

The information-criteria scores for the single-level models were much worse than for the hierarchical ones. The interaction terms did not produce any important changes in the other regression coefficients, and yielded slightly (but insigificantly) worse information-criteria scores.

The alternate normalization scheme produced posterior estimate for the coefficient of state-level PVI whose median was one third as great as for the original normalization and consistent with zero (Figures S8–S10). We found an 85% posterior probability that the coefficient of the state-level PVI is positive in the alternative normalization, which is suggestive but inconclusive. None of the other coefficients changed much. The information criteria for the alternate normalization were slightly inferior to the original normalization (Tables S9–S14), but the difference was negligible. The MSA-level PVI remains important in both schemes, but it is ambiguous whether it is better to interpret the data as indicating that both the state-level PVI and the difference between the state-level and MSA-level PVI are independently correlated with water conservation policies, or whether the state-level PVI is not correlated with conservation policies, but the MSA-level PVI is. However, we do not think this ambiguity has much practical significance because both models yield similar predictions for propensity to adopt water conservation policies in a given MSA and both find an important correlation with political preferences, although they differ on the importance of state-level preferences.

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

We conclude from these robustness checks that except for the regression coefficient for state-level PVI the results of our analysis are robust against many changes of time-spans, explanatory variables, model-structures, and assumptions about priors and model specifications. Across all of these variations, the political variable measuring vote-shares for Democratic versus Republican presidential candidates, the hydroclimatological variable measuring aridity, and the MSA-level population and population growth rates were consistently and strongly correlated with conservation.

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. This finding suggests the importance of interdisciplinary thinking and analysis in the study of water-conservation policy. The assumption that water scarcity drives water-conservation policy should be broadened to include the political context, at least in the U.S., where water conservation is associated with environmental policy and the Democratic Party.

Water conservation policies are intrinsically political, so it should not be surprising that they correlate with partisan voting patterns. However, partisan voting patterns also correlate with other characteristics, such as population density and income inequality, so it is important to note that the strong correlation of water conservation policies with PVI does not imply that differences in PVI cause cities to adopt different numbers of conservation policies, because PVI could merely be correlated with the truly causal variables. We considered alternate models that incorporated the Gini coefficient of income inequality and the population density as well as models that omitted PVI. Those alternate models did not fit the data as well as the original model, and models that omitted PVI altogether showed the worst performance, although estimates of the information criteria, which we used to compare the models, were too uncertain to rule out any of the alternate models with high confidence.

Because we have only observational data with no natural experiment, we do not believe that it would be possible to try to identify one characteristic as the primary causal factor in determining water conservation policy. Rather, we observe that of the different covariates we considered, PVI appears to be the best predictor in a statistical sense, but we emphasize that it may reflect complicated endogenous relationships between these variables, which we do not attempt to disaggregate.

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 the MSA and possibly also the state level. The correlation between support for the Democratic Party 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 and the different results obtained with the alternate scaling also reduce our confidence in assessing the state-level effect.

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.

Real per-capita income (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 income 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 more arid climates tend to adopt more conservation measures, including more requirements and more rebates. Partisan voting patterns are also important, and while the separate roles of state-level and MSA-level voting are ambiguous, greater support for Democratic Party candidates is clearly associated with adopting more conservation policies. State-level income 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 preference for Democratic candidates 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. Finally, dependence on surface water at either the state- or MSA-level does not correlate with conservation policies.

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 it leans Republican (low 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 partisan political preference (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 political preference, and it could not quantitatively distinguish state-level from MSA-level effects of political preference or other covariates. Here we observe clearly that variations in environmental 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 find that the role of state-level political preference is ambiguous and two formulations are equally plausible: first, that water-conservation policy adoption correlates independently with state-level political preferences and with differences in preference between the state and MSA; and second, that policy adoption correlates only with MSA-level political preferences. In practice, both formulations lead to similar predictions, so we do not expect the ambiguity to affect the practical applications of these results.

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. Political preferences (how much a city or state leans toward the Democratic Party), are consistently significant at the MSA level, but their importance at the state level is ambiguous and depends on the way the statistical model is formulated. Prosperity 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.

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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	28.9	17.1
2	McAllen, TX	15	30.2	−15.2
3	Oxnard, CA	49	33.9	15.1
4	Austin, TX	47	32.7	14.3
5	Santa Maria, CA	23	35.7	−12.7
6	San Diego, CA	52	39.5	12.5
7	Santa Rosa, CA	50	37.5	12.5
8	College Station, TX	30	18.1	11.9
9	Phoenix, AZ	21	32.4	−11.4
10	Houston, TX	18	29.2	−11.2

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 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)