

## ENVIRONMENTAL STUDIES

# Changes in water consumption linked to heavy news media coverage of extreme climatic events

Kimberly J. Quesnel<sup>1,2</sup> and Newsha K. Ajami<sup>2,3\*</sup>

Public awareness of water- and drought-related issues is an important yet relatively unexplored component of water use behavior. To examine this relationship, we first quantified news media coverage of drought in California from 2005 to 2015, a period with two distinct droughts; the later drought received unprecedentedly high media coverage, whereas the earlier drought did not, as the United States was experiencing an economic downturn coinciding with a historic presidential election. Comparing this coverage to Google search frequency confirmed that public attention followed news media trends. We then modeled single-family residential water consumption in 20 service areas in the San Francisco Bay Area during the same period using geospatially explicit data and including news media coverage as a covariate. Model outputs revealed the factors affecting water use for populations of varying demographics. Importantly, the models estimated that an increase of 100 drought-related articles in a bimonthly period was associated with an 11 to 18% reduction in water use. Then, we evaluated high-resolution water consumption data from smart meters, known as advanced metering infrastructure, in one of the previously modeled service areas to evaluate breakpoints in water use trends. Results demonstrated that whereas nonresidential commercial irrigation customers responded to changes in climate, single-family residential customers decreased water use at the fastest rate following heavy drought-related news media coverage. These results highlight the need for water resource planners and decision makers to further consider the importance of effective, internally and externally driven, public awareness and education in water demand behavior and management.

## INTRODUCTION

The California drought that began in late 2011 dramatically stretched the state's water supplies as high temperatures coupled with low, infrequent precipitation events caused severe water shortages (1). In response, state and local government agencies implemented various short- and long-term regulatory and fiscal measures to mitigate impacts of the drought on the state's water supply availability and reliability (2). These actions, coupled with the anomalous severity of the drought (3), led state, national, and international media outlets to heavily cover California's water crisis (4), raising public awareness of the state's water supply shortfall. Are these unprecedented political actions, media coverage, and public interest associated with changes in water use behavior?

Public education and awareness has been shown to increase consumer resource conservation, including water savings (5–7), especially when long-term consequences are included in outreach messages (8). While newspaper readership has declined in recent years (9), news media remains one of the most prevalent and ubiquitous sources of information for the public. Newspapers often “set the agenda” for topics of the day (10), and mass media influences public awareness, community perceptions, and social attitudes (11, 12), especially surrounding environmental issues (13, 14). News media, including coverage of the water sector, often follows legislative or regulatory events and/or political actions, and political appointees are frequently quoted in newspaper coverage of high-profile issues (15, 16). In addition, social media has become an important component of the news information ecosystem, with activity often mimicking that of print news. For example, one study found that journalists and Twitter users had similar attitudes and coverage of the 2010 BP oil spill (17). There is a multidirectional relationship

between news media, public awareness, and political actions with the agendas of each influencing one another (13, 18); thus, newspaper coverage can be an appropriate metric of a topic's societal prominence (19).

In the water sector, however, news media remains an understudied public education outlet that could provide insight into community behavior (20). Media coverage and its link to public awareness, public opinion, and behavior has been studied in the context of energy (21–23) and climate change (18, 24, 25) but has received less attention in the water sector. Limited research on water-related news media primarily focuses on content analysis, examining the themes, sentiments, and tones of newspaper articles (15, 16, 26). Some of these studies have also looked outside traditional news sources. For example, one study examined the comments section of drought-related articles to find public preference for drought mitigation strategies (27), whereas another looked into the role of social media in drought-related communications between decision makers and the public (28).

Furthermore, few researchers have measured the volume of water-related news articles to understand drought saliency. One study investigated the relationship between hydrologic conditions and the number of drought-related newspaper articles, finding that news coverage mostly paralleled actual drought conditions, with higher coverage and more detailed content during more intense droughts (29). Recently, researchers used media volume to help construct a yearly narrative and timeline of water transitions in Miami, Florida, concluding that news media coverage generally followed overall trends in utility-level water supply stress and changes in per-capita water consumption (19). However, there exists a gap in knowledge about the quantitative relationship between news media coverage and water use behavior.

Because people get information about extreme environmental events and associated political actions through news media, which is tightly linked to public interest and awareness levels, we hypothesize that newspaper coverage about the recent historic California drought is linked to changes in residential water demand. Here, we test the idea that exceptional drought media coverage occurred concurrently with customers altering

Copyright © 2017  
The Authors, some  
rights reserved;  
exclusive licensee  
American Association  
for the Advancement  
of Science. No claim to  
original U.S. Government  
Works. Distributed  
under a Creative  
Commons Attribution  
NonCommercial  
License 4.0 (CC BY-NC).

<sup>1</sup>Department of Civil and Environmental Engineering, Stanford University, 473 Via Ortega, Room 314, Stanford, CA 94305, USA. <sup>2</sup>ReNUWit Engineering Research Center, Stanford University, 473 Via Ortega, Room 117, Stanford, CA 94305, USA. <sup>3</sup>Woods Institute for the Environment, Stanford University, 473 Via Ortega, Room 218B, Stanford, CA 94305, USA.

\*Corresponding author. Email: newsha@stanford.edu

their water use behavior either permanently, for example by replacing lawns with drought-tolerant landscaping, or temporarily, such as by letting lawns go brown. We developed this hypothesis after engaging with a number of local water utilities who anecdotally described to us how they were experiencing unexplained drops in water demand despite limited changes in conservation programming. We worked closely with the Bay Area Water Supply and Conservation Agency (BAWSCA), a regional public coordinating agency, throughout this study to ensure that we adequately captured the realities of the study region.

Our research, accordingly, inserts media coverage into water demand modeling, measuring coverage as the volume of articles from national and state news sources about drought in California. First, we modeled average (per account) bimonthly (every 2 months) single-family residential (SFR) water demand for 20 water service areas represented by BAWSCA (fig. S1). These diverse service areas with different water use, climate, and demographic patterns (30, 31) were examined to gain deeper insight into how media interacts with other modes of influence for varying populations. We modeled demand for 10 years from July 2005 to June 2015, a period purposefully chosen to encompass two droughts (2007–2009 and 2011–2015).

Next, we examined customer-level smart meter data for SFR and nonresidential commercial irrigation (COMM-IRR) customers in the city of Redwood City, California (a BAWSCA member agency), from July 2010 to December 2015 to identify changes in water use patterns at a fine temporal scale across two sectors. We constructed a time series of average weekly water demand for each sector and applied an additive seasonal decomposition to unpack water demand trends and patterns. A breakpoint algorithm was then used to discover when and if structural changes in water use trends and seasonality occurred in each sector. We compared these breakpoints to drought conditions, as defined by the Palmer Drought Severity Index (PDSI) (32), and news media coverage time series to illuminate the context in which breakpoints occurred.

During the first drought in the study period from water years 2007 to 2009, the state experienced record low precipitation coupled with increased demand from urban areas, prompting the first ever declaration of statewide drought emergency in California's modern history in February 2009 (33). Then, just 2 years later, from water years 2011 to 2015, the state experienced the driest 4-year period in recorded history, with drought conditions continuing through 2016, prompting another statewide emergency declaration in January 2014 (34). In response to worsening drought conditions, California's governor declared the state's first ever mandatory water use restrictions in April 2015, requiring a collective 25% statewide reduction in potable urban water use through Executive Order B-29-15 (35). The State Water Resources Control Board then adopted, by resolution, specific details of how utilities were to achieve these goals, with a start date of 1 June 2015 (36). We therefore do not model water use for the BAWSCA service areas after 30 June 2015 (assuming a short lag in response to new programs) because the goal was not to examine the impact of those restrictions on water use, but instead to focus on media as a prompt for voluntary water conservation. We do, however, examine water use trends in Redwood City through 2015 to determine whether there were any changes in water demand trends after the restrictions were implemented.

The objectives of this study were as follows: (i) to construct a timeline of news media coverage about the California drought and correlate this coverage with public interest as measured by internet search frequency; (ii) to determine whether media coverage of the California drought explains variance in SFR water consumption for populations with varying demographic profiles; and (iii) to

evaluate breakpoints in water use trends for SFR and COMM-IRR sectors in the context of drought conditions and media coverage. By evaluating the relationship between news media and water use during a highly publicized drought, the findings of this study may better inform water managers' responses to future droughts, emphasizing the importance of raising public awareness and using effective communication methods to reach customers.

## RESULTS

### News media coverage of the California drought

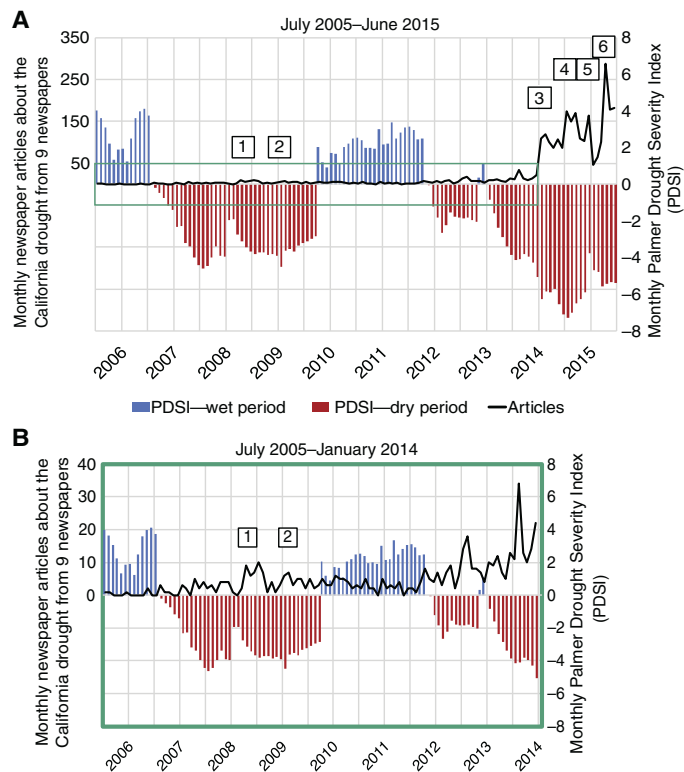
We used newspaper article volume as a quantitative variable in water demand modeling to account for news media coverage of drought. To calculate the volume of newspaper articles, we used the Articulate algorithm (see Materials and Methods) (37). First, a time series analysis shows that the 2007–2009 drought received limited media attention, with a few articles published in the summer of 2008 after Governor Schwarzenegger declared an emergency proclamation for selected Central Valley counties and even fewer written after the statewide emergency declaration in 2009 (33). This low coverage is likely due to other political events such as the great recession and presidential election that overshadowed the drought event (19).

The data set then shows that news media coverage of the recent historic drought was extraordinarily high, with coverage starting in 2012 and 2013 and then rapidly increasing in January 2014, with the first spike in coverage after Governor Brown declared the second statewide drought state of emergency (35). From January 2014 to June 2015, there were four distinct peaks corresponding directly to political or significant weather events (Fig. 1), highlighting the link between political actions and media interest and confirming findings from previous studies that mass media coverage of the water sector tracks events (15, 16). Because media heavily covered the most recent drought but less so the previous drought, the early drought period provides a base case for water use behavior with limited media exposure during drought.

### Public awareness and news media coverage

Is this media attention truly indicative of public awareness and education? To answer this question, we investigated the relationship between mass media and public interest using Google Trends as a proxy for drought awareness. Google Trends is a free online tool that shows the rate of Google searches for a word or term over a certain period at country, state, and regional geographic levels (38). The number of searches is provided in relative terms; the period with the most searches for that term is assigned a value of 100, and all other observations are scaled in comparison to that peak. Google Trends has been shown to provide useful insights into public behavior (39, 40) and has been extensively used in academic research, especially to study health phenomena (41). We acknowledge the potential demographic bias in using internet searches as a metric for public attention because socioeconomic status, age, and geographical factors influence internet use (42). However, given that more than 85% of Americans currently engage with the internet (42), examining search data can provide a good general representation of issue salience (43).

For this study, we extracted data from Google Trends on how relatively often the term "California drought" was entered into the Google search bar each month over the period of July 2005 to June 2015 in the San Francisco Bay Area region of California. The number of drought-related newspaper articles was transformed to a scale of 1 to 100 to match the relative terms of the Google searches. The

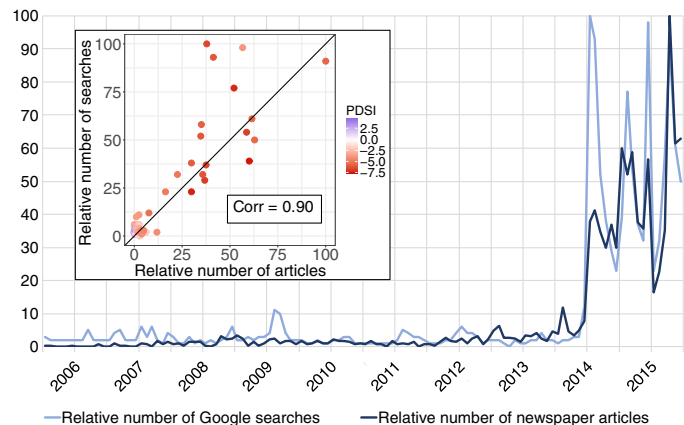


**Fig. 1. Volume of newspaper articles discussing water- and drought-related issues in California and drought classification as represented by the PDSI.** (A) Media coverage for the entire study period, highlighting heavy coverage of the later drought. (B) Zoomed-in view of media coverage before January 2014, before the first spike in coverage but including coverage of the start of the recent historic drought. Prominent drought events are as follows: (1) June 2008: Governor Schwarzenegger's emergency proclamation for selected Central Valley counties; (2) February 2009: Governor Schwarzenegger declares Drought State of Emergency; (3) January 2014: Governor Brown declares Drought State of Emergency; (4) July 2014: Outdoor water conservation regulation; (5) December 2014: Rain event; and (6) April 2015: Mandatory statewide water use restrictions.

Pearson correlation coefficient between Google Trends and newspaper article volume was 0.90 ( $P < 0.001$ ), confirming the significant and positive relationship between Google searches and mass media coverage found previously by one study examining issue coverage in the *New York Times* (44). Examining the two variables as time series reveals that peaks occurred simultaneously, with spikes matching significant political actions and/or storm events (Fig. 1), further demonstrating the connection between public interest and newspaper coverage (Fig. 2).

**Modeling SFR water use**

To determine drivers of SFR water use, semi-log ordinary least squares (OLS) multiple linear regression models were developed (see Materials and Methods), where the natural logarithm of average bimonthly water use was modeled as a function of temperature, precipitation, PDSI, average price, unemployment, median household income, and media volume. To capture service area diversity, spatially explicit climate (45), unemployment (46), and demographic (47) data were used (see the Supplementary Materials). Four models were generated—one pooled model with all 20 service areas and three models based on service area clusters. These clusters were generated using a *k*-means clustering method based on service area income and water demand levels (see Materials and Methods) (48). Cluster A service areas have higher in-



**Fig. 2. Public interest as measured by Google searches for the term California drought and news media coverage of water- and drought-related issues in California.** The inset figure shows the high correlation between the two metrics, where the black line figure is 1:1. Google search data is provided by Google Trends on a relative 1 to 100 scale. The number of newspaper articles from nine sources was transformed to match the scale of the search data set.

come, higher water use profiles; cluster B service areas have medium income, medium water use profiles; and cluster C service areas have lower income, medium water use profiles (see the Supplementary Materials). Table 1 presents the variability of SFR water consumption as explained by the models. All models were significant, as shown by *F* statistics ( $P < 0.001$ ). Variance inflation factors for each variable in each model were less than 2, indicating no collinearity.

Volume of newspaper articles was highly significant ( $P < 0.001$ ) in all four models. The coefficient in each model was between  $-0.0011$  and  $-0.0018$ , indicating that an increase of 100 drought-related articles in a bimonthly period was associated with a decrease in SFR water use per account of 11 to 18%. This finding confirms that heightened media coverage and corresponding increased public engagement are related to residential water use behavior. These results demonstrate the correlation not only between water demand and news media coverage but also between water demand and the composite of the political, social, and economic drought-related activities conveyed by the news media (18).

We also find that unemployment was significant ( $P < 0.01$ ) and negative in all models including the high-income cluster model, indicating that fluctuating unemployment rates, which rose steeply from 2008 to 2010 before slowly declining to pre-recession rates in 2015, explain some variance in water demand over the 2005–2015 decade. The downward water use trends from 2008 to 2010 could have been partly driven by rising unemployment rates that prompted customers to save water for economic reasons, whereas water use drops from 2013 to 2015 could be explained by political actions and increased public attention to severe drought conditions and water supply shortages.

Temperature was highly significant ( $P < 0.001$ ) and positive in all four models, which conforms to well-established findings in the literature (49). Precipitation was not significant in any models, matching studies that show that temperature is more explanatory of water use than rainfall (50, 51). PDSI was significant in the pooled models, but not in the clustered models. This result could indicate that PDSI plays a role in regional water conservation but is less important in relation to other factors when characterizing utilities based on demographic clusters. Price was not significant in the cluster A model, parallel to previous findings that lower income households respond to price more than higher income households do (52).

**Table 1. SFR water demand model outputs.** \* $P < 0.05$ , \*\* $P < 0.01$ , \*\*\* $P < 0.001$ .

	Pooled model	Cluster A model (highest income, high WU)	Cluster B model (medium income, medium WU)	Cluster C model (lowest income, medium WU)
<b>Model information</b>				
Number of observations	1200	180	660	360
F statistic	301.2*** (df = 7; 1192)	101.9*** (df = 7; 172)	204.5*** (df = 7; 652)	108.4** (df = 7; 352)
<b>Coefficients</b>				
Intercept	1.417***	2.057***	1.749***	2.462***
Temperature (°C)	0.082***	0.132***	0.073***	0.054***
Precipitation (mm)	$-3.5 \times 10^{-6}$	$-4.2 \times 10^{-4}$	$-1.3 \times 10^{-4}$	$-9.3 \times 10^{-5}$
PDSI	-0.012**	-0.007	-0.006	-0.003
Average price [2015\$/hundred cubic feet (CCF) water]	-0.058***	-0.005	-0.035***	-0.077***
Unemployment rate (%)	-0.031***	-0.041**	-0.036***	-0.018***
Median household income (2015\$/1000)	0.009***	0.001*	0.005***	0.002**
Number of newspaper articles about the California drought from nine sources	-0.0018***	-0.0015***	-0.0016***	-0.0011***
<b>Model performance metrics</b>				
Adjusted $R^2$	0.64	0.80	0.68	0.68
RMSE	12.9	11.7	4.0	3.1
PBIAS	-7.0%	-2.1%	-1.9%	-1.3%
AIC	583.2	18.2	-265.2	-323.8

Metrics were calculated to evaluate and compare model performance. The cluster A model had the highest adjusted  $R^2$  of 0.80, whereas cluster B and C models both had adjusted  $R^2$  of 0.68, and the pooled model had the lowest adjusted  $R^2$  of 0.64. Clusters B and C had the lowest root mean squared error (RMSE) values, mimicking the overall lower water use in these service areas. The percent bias (PBIAS) for all models was negative, indicating that each model consistently underestimated water demand, with the pooled model being the most biased of all four models. Akaike information criterion (AIC) values and adjusted  $R^2$  values showed that the three cluster models outperformed the pooled model, emphasizing the importance of creating data-driven models tailored to service areas or regions based on their varying populations and water use behavior.

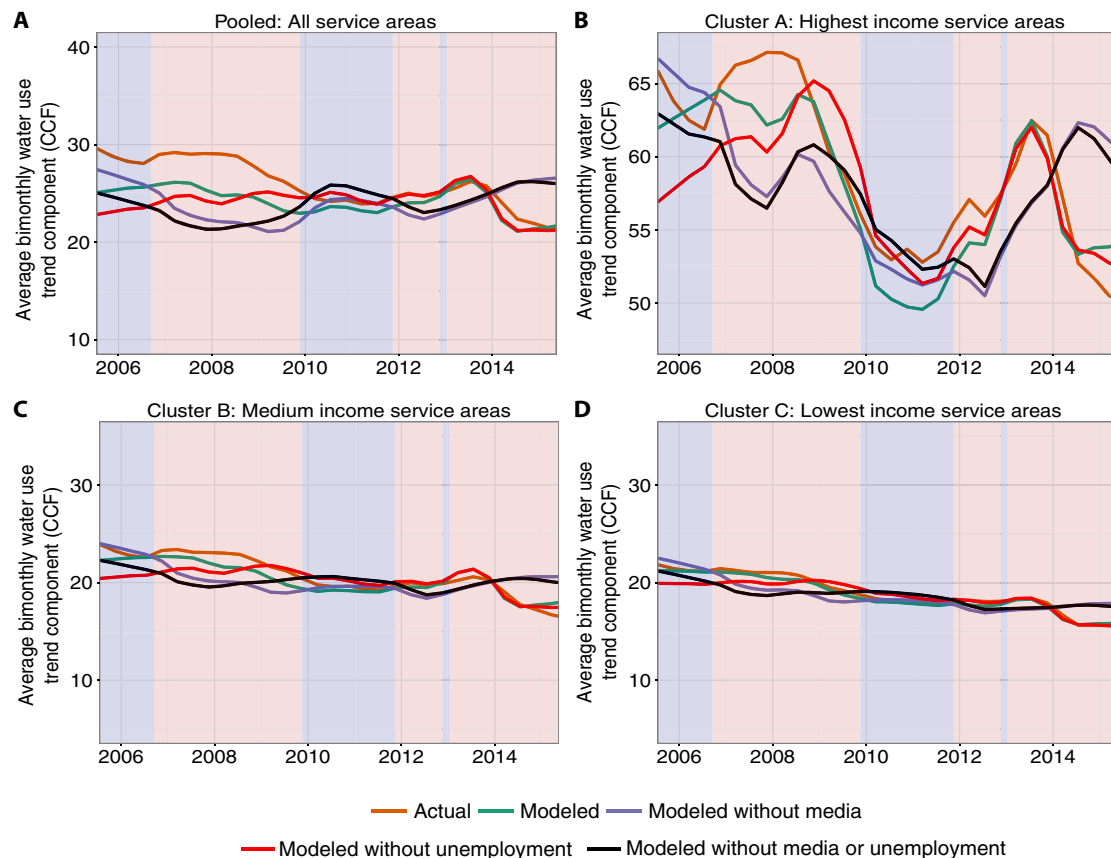
Three counterfactual scenarios were developed using the same models as above but without news media coverage and/or unemployment as covariates. For each pooled and clustered data set, analysis of variance (ANOVA) showed a significant difference ( $P < 0.01$ ) between all three counterfactual models compared to the original models, rejecting the null hypothesis that media and unemployment do not explain additional variance in SFR water use. An additive seasonal decomposition was then applied (see Materials and Methods) to find the trend components of (i) actual average water demand, (ii) average water demand predicted by models with media, (iii) average water demand predicted by models without media, (iv) average water demand pre-

dicted by models without unemployment, and (v) average water demand predicted by models without media or unemployment (Fig. 3).

In every scenario, water demand predicted by models with media followed observed trends more closely than demand predicted by models without media, further demonstrating model improvement when media was included. The divergence between actual demand and demand predicted by models without media is particularly pronounced after 2013. As media coverage started to increase, water demand decreased and the models with media correctly captured the downward trend, but the models without media forecasted increasing demand. Demand predicted by models without unemployment closely followed actual water use starting in 2011, after the recession, but deviate before and during the recession. This output highlights the role of economic conditions in water demand when unemployment rates are high, including in affluent communities.

### Water use trends

Water use data from smart meters, known as advanced metering infrastructure (AMI), from the city of Redwood City, one of the service areas modeled in the previous section, were further examined to investigate water use trends on a finer temporal scale from July 2010 to December 2015. After preprocessing and aggregating daily customer-level water use to weekly service area-level average water use (see the Supplementary Materials), an additive seasonal decomposition method was applied to



**Fig. 3. Actual and predicted water use trends in BAWSCA service areas.** (A) Performance of the pooled models compared to measured demand. (B to D) Model performance for each service area cluster. Red shading indicates dry periods and blue shading indicates wet periods, as defined by PDSI.

parse the time series into seasonal, trend, and residual components (see Materials and Methods) (53). Then, the BFAST (Breaks for Additive Seasonal and Trend) breakpoint algorithm (54, 55) was used to detect shifts in the trend and seasonal components to determine when demand changes occurred in SFR and COMM-IRR sectors (see Materials and Methods; Fig. 4). Results show that all slopes between trend breakpoints are negative, indicating downward water use trends during the entire study period. The first two trend breakpoints in both sectors occurred around the same time. The first structural changes in demand occurred in the summer of 2011 (weeks 23 and 24, June) which coincides with the middle of a wet period as defined by the PDSI. The second structural changes occurred in the spring of 2013 (weeks 10 and 6, March and February, respectively) after a brief wet spell but amid the 2011–2016 drought.

After the first two breakpoints, SFR and COMM-IRR customers show different patterns, indicating differing responses to changing climatic and political events. At the beginning of 2014 (week 5, January/February), SFR customers again changed water consumption behavior, coinciding with the Governor's drought state of emergency declaration and the increase in news media coverage, but this trend is not evident for COMM-IRR customers. Examining the linear trend slopes during each of these time periods, we see that for COMM-IRR customers, water use decreased at the fastest rate during a wet period (2010–2011), whereas SFR customers decreased use at the fastest rate after media coverage began (2014) (Table 2).

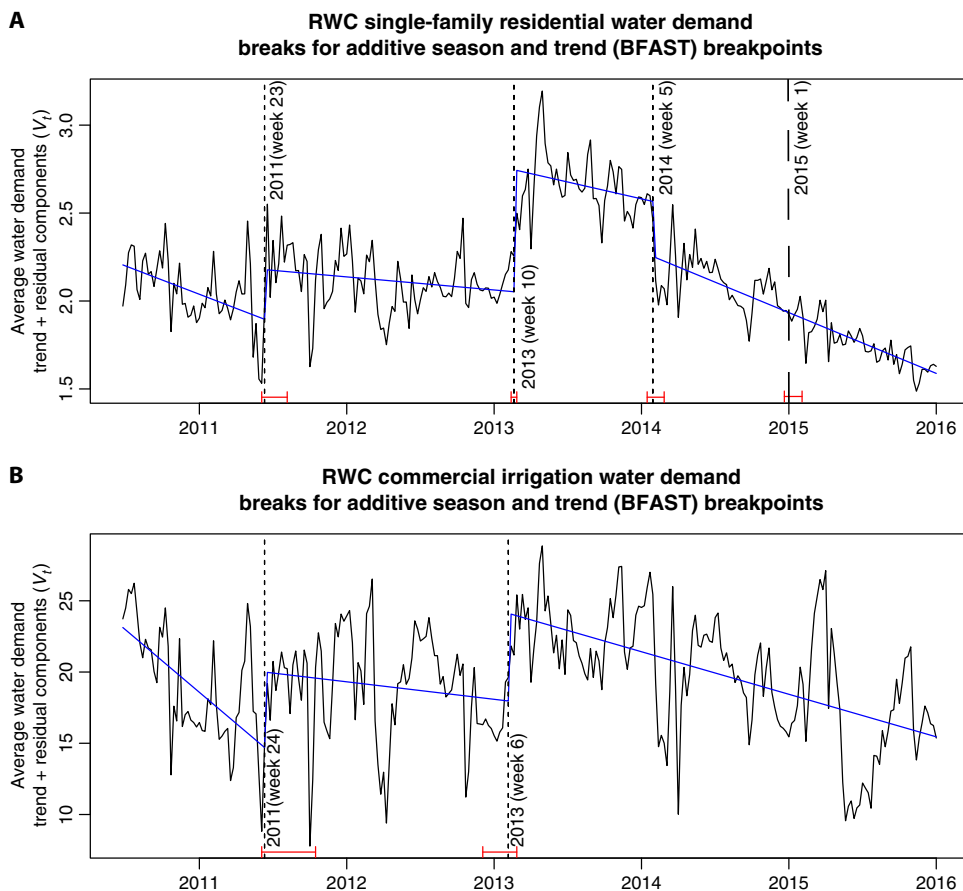
The BFAST method was also used to detect changes in seasonality during the study period. No seasonal breakpoints were detected in the

COMM-IRR time series, yet a seasonal breakpoint was detected in the SFR time series during the first week of 2015, indicating that not only did the trend of water use behavior pivot starting in the beginning of 2014, but as the drought progressed, the underlying seasonality changed as well, as the difference between winter and summer water use became less accentuated. Furthermore, although this analysis extends through the end of 2015, many months after the water use restrictions were enacted, no trend or seasonal breakpoints were detected after January 2015, indicating that the downward trend in water use was already progressing before the statewide mandate.

## DISCUSSION

The 2011–2016 California drought was unprecedented not only hydrologically but also in terms of widespread political action and publicity. By quantifying anomalously high drought media coverage, corresponding public interest, and changes in water use behavior, our study showed that news media coverage was correlated with changes in urban water use in the San Francisco Bay Area from 2005 to 2015. Water demand models revealed that the volume of drought-related news articles published by highly circulated newspapers explained variance in SFR water use for service areas of all demographic profiles examined in this study. This correlative relationship was further confirmed in our second analysis, which showed that residential water use decreased at the fastest rate after media coverage of the drought ramped up.

The 2007–2009 drought received some media attention, but less so considering the concurrent economic recession and presidential election.



**Fig. 4. Breakpoints as identified by the BFAST method on trend and seasonal components of seasonally decomposed water use. (A)** Breakpoints for SFR customers. **(B)** Breakpoints for COMM-IRR customers. The short dashed vertical lines in both plots denote trend breakpoints, whereas the long dashed vertical line in (A) denotes a seasonal breakpoint. The  $y$ -axis  $V_t$  represents the average water use  $WU_t$  minus the seasonal component  $S_t$ , that is, the trend  $T_t$  plus the residual component  $\epsilon_t$  (see Materials and Methods). Red lines show 95% confidence intervals.

**Table 2. Slopes between Redwood City water use trend breakpoints.**

SFR customers with AMI				
Time period [year (week)]	2010 (26)–2011 (23)	2011 (23)–2013 (10)	2013 (10)–2014 (5)	2014 (5)–2016 (1)
Slope	–0.322	–0.074	–0.191	–0.346
COMM-IRR customers with AMI				
Time period [year (week)]	2010 (26)–2011 (24)	2011 (24)–2013 (6)	2013 (6)–2016 (1)	
Slope	–8.76	–1.23	–2.99	

The recent historic drought, however, received abnormally high coverage, with sometimes hundreds of newspaper stories being published nationally in a single month. Although the recent historic drought began in 2011, widespread news media coverage started picking up slowly in 2012, ramped up in 2013, and reached the highest levels in 2014 and 2015. Examining peaks in media coverage and corresponding public interest, as measured by Google search frequency, confirmed that widespread political actions stimulated news media coverage and interest in the drought. For example, the catalyst for the first peak in media coverage in 2014 was the declaration of drought by Governor Brown.

As we confirmed, during times of extreme hydrologic events such as drought and flooding, heightened public awareness can result in behavioral changes (56); yet, utilities cannot replicate widespread political actions or news media coverage. However, this knowledge that public education and awareness play a key role in water use behavior can help water managers design better and more effective conservation campaigns and long-term education and outreach efforts (57). If customers are connected to their water use, local water resources, and the urban water cycle, they may be more likely to value the role of utilities in providing them this vital resource. Customers may

then change both their short-term and long-term behavior, for example, they may participate in voluntary demand management or may be more willing to accept changes in water management strategies, such as the inclusion of alternative water sources or price structures.

Because this is the first study to use media volume as an explanatory variable in water demand modeling, there is a large potential for future work exploring the intersection of water use and mass media. Examining this relationship at finer spatial and temporal scales could reveal the daily and weekly periods in which heightened media coverage is related to changes in water demand. In addition, looking at multifamily residential, commercial, industrial, and institutional water use sectors and drought media coverage could provide new information for utilities and water managers, especially for service areas with more nonresidential customers.

One potential next step for this study would be to include social media outlets, such as Twitter. Social media platforms and their adoption are advancing at a rapid rate, but still remain less prominent than print (58, 59) and often follow print media trends (17). Yet, as social media becomes increasingly prevalent, it will be critical to compare the influence of various media types, evaluating how social media and traditional media interact with one another and are associated with public awareness, environmental attitudes, and resource consumption. Like traditional news media, social media has been shown to track extreme events (60), and is also important for relaying information to the public, including during the recent California drought (28). Social media is also a tool that water agencies can use to engage their customers.

Examining newspaper coverage of water- and drought-related issues in the context of water demand highlights the relationship between public awareness and education on water use behavior. Utilities and water managers can put this research into action by incorporating more effective customer education and outreach efforts into conservation campaigns. As droughts become more frequent and water scarcity continues to be an issue in the western United States and around the world, interdisciplinary studies such as this one that explore the social factors influencing water demand will become increasingly important.

## MATERIALS AND METHODS

### Data

Information on data sources for clustering and water demand modeling can be found in the Supplementary Materials.

### Newspaper articles

To measure news media coverage of drought in California, the Articulate software package was used (37). The package, written in Python, interfaces with the Google Custom Search Engine (CSE) application programming interface to query the Google search bar for articles from a specific newspaper website for specific keywords within a time frame of interest. Articulate only extracts articles and excludes all comments, ads, or banners, whereas Google CSE filters duplicates. The Articulate python package has been shown to produce results that statistically mirror those from proprietary databases such as ProQuest (37).

Nine national and California-based daily newspapers were chosen on the basis of circulation (61): *Wall Street Journal*, *New York Times*, *USA Today*, *Los Angeles Times*, *San Jose Mercury News*, *The Sacramento Bee*, *The Orange County Register*, *The San Diego Union-Tribune*, and *San Francisco Chronicle* (captured by SFGate, the free online sister site of the *San Francisco Chronicle*). The keywords used in the search bar were “California drought,” “California droughts,” “drought in California,” “droughts in California,” and a combination of “California,” “drought(s),” and a water-related term “water

conservation,” “rainfall,” “snowpack,” “climate,” “weather,” “aqueducts,” “reservoirs,” “aqueduct,” “reservoir,” “rain and snow,” or “snow and rain” to exclude irrelevant articles (for example, “California sports team experiences a winning drought”). These search terms were based on initial investigation of algorithm outputs. Articulate produced two outputs: one tallied spreadsheet of the number of articles sorted by source and date, and one spreadsheet with a database of information including title, date, and news source for every article counted. The number of articles in each month from each source was recorded and tallied for each period. Article titles and associated information were checked manually for relevance.

### K-means clustering of BAWSCA service areas

Because water demand often exhibits regional differences, we grouped service areas using a *k*-means clustering algorithm

$$J = \sum_{j=1}^K \sum_{i=1}^n \|x_i^{(j)} - c_j\|^2 \quad (1)$$

where *J* is the objective function, *K* is the number of clusters, *n* is the number of observations to be clustered (20 service areas), *x<sub>i</sub>* is observation *i*, and *c<sub>j</sub>* is the centroid for cluster *j*.

Clustering service areas can provide insight into how various factors are related to water use for different groups, revealing useful information that can be used to better understand how different populations behave, to design conservation campaign strategies, and to predict behavior (62). Regional water demand modeling can also benefit from clustering because it addresses the challenge of scale—aggregate water demand models that assume homogeneity can mask important water use relationships, whereas individual agency or sub-agency models can create data management issues (63).

We created clusters based on two dominant characteristics of each agency—average bimonthly water consumption per account and median household income (48). To determine the optimal number of service area clusters, a sum of squared error (SSE) scree plot was generated for *K* = 1 to *K* = 10; a bend in the plot was identified at *K* = 3, which is the final solution presented in fig. S2A. The Welch two-sample *t* test verified that mean bimonthly water use and median household income were both significantly different among all clusters (all values of *P* ≤ 0.001). Examining other demographic variables provided further insight into cluster characteristics (fig. S2B).

### BAWSCA water demand model

We modeled water demand using semi-log OLS multiple linear regression, a common technique for examining the factors affecting water use (49)

$$\ln(\text{WU}_{\text{SFR } i,t}) = \beta_{0,m} + \beta_{1,m} \text{temp}_{i,t} + \beta_{2,m} \text{precip}_{i,t} + \beta_{3,m} \text{PDSI}_t + \beta_{4,m} \text{price}_{i,t} + \beta_{5,m} \text{unemployment}_{i,t} + \beta_{6,m} \text{income}_{i,t} + \beta_{7,m} \text{media}_t \quad (2)$$

where for each model *m* and a given service area *i* at bimonthly time period *t*, **WU** is average SFR water demand per account, **temp** is average daily temperature, **precip** is cumulative precipitation, **PDSI** is the Palmer Drought Severity Index, **price** is the average monthly price per hundred cubic feet (CCF) of water paid by an SFR customer, **unemployment** is average city-level unemployment rate, **income** is median household income, **articles** is the number of newspaper articles from nine highly circulated newspapers, and the β values are the model coefficients.

Water use was transformed to the natural logarithm for two purposes: first, to account for the higher variability in water use exhibited by higher-volume users, which is true in the BAWSCA case study given the high seasonality of water use by high-income water users (64–66), and second, to interpret the output, where a unit change in the covariates corresponds to a percentage change in water use (67). Four multiple linear regression models ( $m = 4$ ) were created—one pooled model including all service areas and one model for each of the three service area clusters. The data set included 1200 observations: 10 years of 60 bimonthly observations ( $t = 60$ ) for 20 service areas ( $i = 20$ ).

### Seasonal decomposition

Water consumption in the San Francisco Bay Area is highly seasonal, which can make detecting trends difficult; because demand has a relatively constant periodicity, we applied an additive seasonal decomposition to water demand time series, iteratively partitioning the data into seasonal, trend, and residual components using a locally weighted regression smoother (Loess) procedure (53)

$$WU_t = S_t + T_t + \varepsilon_t \quad (3)$$

where  $WU_t$  is the water use observation at time  $t$ ,  $S_t$  is the seasonal component at time  $t$  with period  $s = 6$  for bimonthly data or  $s = 52$  for weekly data,  $T_t$  is the unobserved trend component at time  $t$ , and  $\varepsilon_t$  is the unobserved residual component. We applied this method in BAWSCA service areas to compare actual demand trends with demand trends predicted by models with and without media and/or unemployment as covariates. In the city of Redwood City, we decomposed average weekly SFR and COMM-IRR water consumption from AMI (see the Supplementary Materials) to determine water use trends at a finer temporal scale.

### Redwood City breakpoint analysis

We used a breakpoint method to detect changes within the water use trend and seasonal components in Redwood City, where the number and locations of the breaks were not user-specified and instead estimated on the basis of model constraints and trend behavior. We used the BFAST method that was developed by Verbesselt *et al.* (55, 68) to detect change in remote sensing applications, and has been used in the water sector by Hester and Larson (54) to discover breakpoints in water demand trends in three North Carolina cities. Following these studies, we use the STL (Seasonal Decomposition of Time Series by Loess) package and the BFAST and strucchange packages in *R* (53–55). We apply a 16% minimal segment size between breakpoints and a harmonic seasonal model to account for the seasonality in water demand.

### SUPPLEMENTARY MATERIALS

Supplementary material for this article is available at <http://advances.sciencemag.org/cgi/content/full/3/10/e1700784/DC1>  
Demand modeling  
Breakpoint analysis  
fig. S1. BAWSCA service areas.  
fig. S2. K-means clustering of service areas.  
table S1. BAWSCA service area cities and proxies used for unemployment.

### REFERENCES AND NOTES

- U.S. Geological Survey, *Drought Impacts* (California Water Science Center, 2016); <http://ca.water.usgs.gov/data/drought/drought-impact.html>.
- California Natural Resources Agency, *California Water Action Plan: 2016 Update* (California Natural Resources Agency 2016); [http://resources.ca.gov/docs/california\\_water\\_action\\_plan/Final\\_California\\_Water\\_Action\\_Plan.pdf](http://resources.ca.gov/docs/california_water_action_plan/Final_California_Water_Action_Plan.pdf).
- N. S. Diffenbaugh, D. L. Swain, D. Touma, Anthropogenic warming has increased drought risk in California. *Proc. Natl. Acad. Sci. U.S.A.* **112**, 3931–3936 (2015).
- J. Terhaar, "Media must make a difference in coverage of California's drought," *The Sacramento Bee*, 18 April 2015; [www.sacbee.com/opinion/opn-columns-blogs/joyce-terhaar/article18722001.html](http://www.sacbee.com/opinion/opn-columns-blogs/joyce-terhaar/article18722001.html).
- B. H. Hurd, Water conservation and residential landscapes: Household preferences, household choices. *J. Agr. Resour. Econ.* **31**, 173–192 (2006).
- D. E. Delorme, S. C. Hagen, I. J. Stout, Consumers' perspectives on water issues: Directions for educational campaigns. *J. Environ. Educ.* **34**, 28–35 (2003).
- C. W. Trumbo, G. J. O'Keefe, Intention to conserve water: Environmental values, reasoned action, and information effects across time. *Soc. Nat. Resour.* **18**, 573–585 (2005).
- P. C. Stern, Effect of incentives and education on resource conservation decisions in a simulated common dilemma. *J. Pers. Soc. Psychol.* **34**, 1285–1292 (1976).
- Pew Research Center, *State of the News Media 2016* (Pew Research Center, 2016); <https://assets.pewresearch.org/wp-content/uploads/sites/13/2016/06/30143308/state-of-the-news-media-report-2016-final.pdf>.
- M. E. McCombs, D. L. Shaw, The agenda-setting function of mass media. *Public Opin. Q.* **36**, 176–187 (1972).
- D. A. Scheufele, J. Shanahan, S.-H. Kim, Who cares about local politics? Media influences on local political involvement, issue awareness, and attitude strength. *Journalism Mass Comm.* **79**, 427–444 (2002).
- R. E. Kasperson, J. X. Kasperson, The social amplification and attenuation of risk. *Ann. Am. Acad. Pol. Soc. Sci.* **545**, 95–105 (1996).
- S. N. Soroka, Issue attributes and agenda-setting by media, the public, and policymakers in Canada. *Int. J. Public Opin. Res.* **14**, 264–285 (2002).
- A. C. Schoenfeld, R. F. Meier, R. J. Griffin, Constructing a social problem: The press and the environment. *Soc. Probl.* **27**, 38–61 (1979).
- J. Wei, Y. Wei, A. Western, D. Skinner, C. Lyle, Evolution of newspaper coverage of water issues in Australia during 1843–2011. *Ambio* **44**, 319–331 (2015).
- A. Hurlimann, S. Dolnicar, Newspaper coverage of water issues in Australia. *Water Res.* **46**, 6497–6507 (2012).
- B. R. Watson, Is Twitter an alternative medium? Comparing gulf coast Twitter and newspaper coverage of the 2010 BP oil spill. *Commun. Res.* **43**, 647–671 (2016).
- M. T. Boykoff, J. M. Boykoff, Climate change and journalistic norms: A case-study of US mass-media coverage. *Geoforum* **38**, 1190–1204 (2007).
- G. Treuer, E. Koebele, A. Deslatte, K. Ernst, M. Garcia, K. Manago, A narrative method for analyzing transitions in urban water management: The case of the Miami-Dade Water and Sewer Department. *Water Resour. Res.* **53**, 891–908 (2017).
- T. J. Troy, M. Konar, V. Srinivasan, S. Thompson, Moving sociohydrology forward: A synthesis across studies. *Hydrol. Earth Syst. Sci.* **19**, 3667–3679 (2015).
- M. Viklund, Energy policy options—From the perspective of public attitudes and risk perceptions. *Energy Policy* **32**, 1159–1171 (2004).
- G. Tsantopoulos, G. Arabatzis, S. Tampakis, Public attitudes towards photovoltaic developments: Case study from Greece. *Energy Policy* **71**, 94–106 (2014).
- R. Langheim, M. Skubel, X. Chen, W. Maxwell, T. R. Peterson, E. Wilson, J. C. Stephens, Smart grid coverage in U.S. newspapers: Characterizing public conversations. *Electr. J.* **27**, 77–87 (2014).
- Y. Sampei, M. Aoyagi-Utsui, Mass-media coverage, its influence on public awareness of climate-change issues, and implications for Japan's national campaign to reduce greenhouse gas emissions. *Glob. Environ. Chang.* **19**, 203–212 (2009).
- K. Akerlof, K. E. Rowan, D. Fitzgerald, A. Y. Cedeno, Communication of climate projections in US media amid politicization of model science. *Nat. Clim. Change* **2**, 648–654 (2012).
- W. Shang, H. Zheng, Z. Wang, Baimaqvzong, Y. Wei, Newspaper coverage of water issues in China from 1950 to 2000. *Water Policy* **17**, 595–611 (2015).
- S. Russell-Verma, H. M. Smith, P. Jeffrey, Public views on drought mitigation: Evidence from the comments sections of on-line news sources. *Urban Water J.* 454–462 (2015).
- Z. Tang, L. Zhang, F. Xu, H. Vo, Examining the role of social media in California's drought risk management in 2014. *Nat. Hazards* **79**, 171–193 (2015).
- J. D. Ruiz Sinoga, T. León Gross, Droughts and their social perception in the mass media (southern Spain). *Int. J. Climatol.* **33**, 709–724 (2013).
- E. R. Levin, W. O. Maddaus, N. M. Sandkulla, H. Pohl, Forecasting wholesale demand and conservation savings. *J. Am. Water Works Assoc.* **98**, 102–111 (2006).
- Bay Area Water Supply and Conservation Agency, *Annual Survey Fiscal Year 2014-15* (Bay Area Water Supply and Conservation Agency, 2016); [http://bawasca.org/uploads/userfiles/files/BAWSCA\\_AnnualSurvey\\_FY2014-15.pdf](http://bawasca.org/uploads/userfiles/files/BAWSCA_AnnualSurvey_FY2014-15.pdf).
- National Climatic Data Center (NCDC), *Climate Data Online: Climate Indices* (National Climatic Data Center, 2016); [www7.ncdc.noaa.gov/CDO/CDODivisionalSelect.jsp#](http://www7.ncdc.noaa.gov/CDO/CDODivisionalSelect.jsp#).



33. California Department of Water Resources, *California's Drought of 2007–2009: An Overview* (California Department of Water Resources, 2010); [www.water.ca.gov/waterconditions/docs/DroughtReport2010.pdf](http://www.water.ca.gov/waterconditions/docs/DroughtReport2010.pdf).
34. E. Hanak, J. Mount, C. Chappelle, *Just the Facts: California's Latest Drought* (Public Policy Institute of California, 2016); [www.ppic.org/content/pubs/jtf/JTF\\_WaterUseJTF.pdf](http://www.ppic.org/content/pubs/jtf/JTF_WaterUseJTF.pdf).
35. California Department of Water Resources, *Governor's Drought Declaration* (California Department of Water Resources, 2016); [www.water.ca.gov/waterconditions/declaration.cfm](http://www.water.ca.gov/waterconditions/declaration.cfm).
36. California State Water Resources Control Board, *State Water Resources Control Board: Resolution No. 2015–0032* (California State Water Resources Control Board, 2015); [www.waterboards.ca.gov/board\\_decisions/adopted\\_orders/resolutions/2015/rs2015\\_0032.pdf](http://www.waterboards.ca.gov/board_decisions/adopted_orders/resolutions/2015/rs2015_0032.pdf).
37. N. Roby, P. Gonzales, K. Quesnel, N. Ajami, *Articulate: A Search Tool for Quantifying News Media Coverage* (Stanford's Urban Water Policy and Innovation Team, 2017); <https://github.com/Stamford-Urban-Water-Policy-Innovation/Articulate>.
38. Google, *Google Trends*; <https://trends.google.com/trends/>.
39. S. Vosen, T. Schmidt, Forecasting private consumption: Survey-based indicators vs. Google Trends. *J. Forecast.* **30**, 565–578 (2011).
40. H. Choi, H. Varian, Predicting the present with Google Trends. *Econ. Rec.* **88**, 2–9 (2012).
41. S. V. Nuti, B. Wayda, I. Ranasinghe, S. Wang, R. P. Dreyer, S. I. Chen, K. Murugiah, The use of Google Trends in health care research: A systematic review. *PLOS ONE* **9**, e109583 (2014).
42. Pew Research Center, *Who's Not Online and Why* (Pew Research Center, 2013); [www.pewinternet.org/2013/09/25/whos-not-online-and-why/](http://www.pewinternet.org/2013/09/25/whos-not-online-and-why/).
43. J. Mellon, Internet search data and issue salience: The properties of Google Trends as a measure of issue salience. *J. Elect. Public Opin. Parties* **24**, 45–72 (2014).
44. J. T. Ripberger, Capturing curiosity: Using internet search trends to measure public attentiveness. *Policy Stud. J.* **39**, 239–259 (2011).
45. PRISM Climate Group, *Monthly Precipitation and Temperature Data* (Oregon State University, 2012); <http://prism.oregonstate.edu>.
46. Bureau of Labor Statistics, *Local Area Unemployment Statistics* (Bureau of Labor Statistics, 2016); [www.bls.gov/lau/data.htm](http://www.bls.gov/lau/data.htm).
47. U.S. Census Bureau, [www.census.gov](http://www.census.gov).
48. C. Mini, T. S. Hogue, S. Pincetti, Patterns and controlling factors of residential water use in Los Angeles, California. *Water Policy* **16**, 1054–1069 (2014).
49. L. A. House-Peters, H. Chang, Urban water demand modeling: Review of concepts, methods, and organizing principles. *Water Resour. Res.* **47**, W05401 (2011).
50. M. M. Haque, P. Egodawatta, A. Rahman, A. Goonetilleke, Assessing the significance of climate and community factors on urban water demand. *Int. J. Sustain. Built Environ.* **4**, 222–230 (2015).
51. M. S. Babel, N. Maporn, V. R. Shinde, Incorporating future climatic and socioeconomic variables in water demand forecasting: A case study in Bangkok. *Water Resour. Manage.* **28**, 2049–2062 (2014).
52. M. E. Renwick, R. D. Green, Do residential water demand side management policies measure up? An analysis of eight California water agencies. *J. Environ. Econ. Manage.* **40**, 37–55 (2000).
53. R. B. Cleveland, W. S. Cleveland, J. E. McRae, I. Terpenning, STL: A seasonal-trend decomposition procedure based on loess. *J. Off. Stat.* **6**, 3–73 (1990).
54. C. M. Hester, K. L. Larson, Time-series analysis of water demands in three North Carolina cities. *J. Water Resour. Plann. Manage.* **142**, 5016005 (2016).
55. J. Verbesselt, R. Hyndman, G. Newnham, D. Culvenor, Detecting trend and seasonal changes in satellite image time series. *Remote Sens. Environ.* **114**, 106–115 (2010).
56. G. Di Baldassarre, M. Kooy, J. S. Kemerink, L. Brandimarte, Towards understanding the dynamic behaviour of floodplains as human-water systems. *Hydrol. Earth Syst. Sci.* **17**, 3235–3244 (2013).
57. S. Z. Attari, Perceptions of water use. *Proc. Natl. Acad. Sci. U.S.A.* **111**, 5129–5134 (2014).
58. R. K. Nielsen, K. C. Schröder, The relative importance of social media for accessing, finding, and engaging with news. *Digital J.* **2**, 472–489 (2014).
59. A. Ju, S. H. Jeong, H. I. Chyi, Will social media save newspapers? *Journalism Pract.* **8**, 1–17 (2014).
60. Y. Kryvasheyev, H. Chen, N. Obradovich, E. Moro, P. Van Hentenryck, J. Fowler, M. Cebrian, Rapid assessment of disaster damage using social media activity. *Sci. Adv.* **2**, e1500779 (2016).
61. Alliance for Audited Media, *Top 25 U.S. Newspapers for March 2013* (Alliance for Audited Media, 2016); <https://auditedmedia.com/>.
62. A. S. Polebitski, R. N. Palmer, Analysis and predictive models of single-family customer response to water curtailments during drought. *J. Am. Water Resour. Assoc.* **49**, 40–51 (2013).
63. N. Avni, B. Fishbain, U. Shamir, Water consumption patterns as a basis for water demand modeling. *Water Resour. Res.* **51**, 8165–8181 (2015).
64. S. L. Harlan, S. T. Yabiku, L. Larsen, A. J. Brazel, Household water consumption in an Arid City: Affluence, affluence, and attitudes. *Soc. Nat. Resour.* **22**, 691–709 (2009).
65. E. A. Donkor, T. A. Mazzuchi, R. Soyer, J. Alan Roberson, Urban water demand forecasting: Review of methods and models. *J. Water Resour. Plann. Manage.* **140**, 146–159 (2014).
66. K. S. Fielding, S. Russell, A. Spinks, A. Mankad, Determinants of household water conservation: The role of demographic, infrastructure, behavior, and psychosocial variables. *Water Resour. Res.* **48**, W10510 (2012).
67. C. E. Kontokosta, R. K. Jain, Modeling the determinants of large-scale building water use: Implications for data-driven urban sustainability policy. *Sustain. Cities Soc.* **18**, 44–55 (2015).
68. J. Verbesselt, R. Hyndman, A. Zeileis, D. Culvenor, Phenological change detection while accounting for abrupt and gradual trends in satellite image time series. *Remote Sens. Environ.* **114**, 2970–2980 (2010).

**Acknowledgments:** We thank BAWSCA and the city of Redwood City for their time and efforts in providing data and valuable feedback. We would like to thank P. Gonzales for her help throughout the study and N. Roby for his diligence in data processing and development of Articulate. We are grateful for the thoughtful feedback from two anonymous reviewers whose comments helped to improve the quality of the manuscript. **Funding:** This work was financially supported by BAWSCA. In addition, this research was developed under STAR Fellowship Assistance Agreement no. FP-91778101-0 awarded to K.J.Q. by the U.S. Environmental Protection Agency (EPA). It has not been formally reviewed by EPA. The views expressed are solely those of the authors, and EPA does not endorse any products or commercial services mentioned in this poster. Funding was also provided, in part, by the National Science Foundation Engineering Research Center for Re-inventing the Nation's Urban Water Infrastructure (ReNUWit) (Award No. EEC-1028968) and the S. D. Bechtel, Jr. Foundation. **Author contributions:** K.J.Q. and N.K.A. designed the study. K.J.Q. performed the modeling work. K.J.Q. and N.K.A. analyzed the results and wrote the manuscript. **Competing interests:** The authors declare that they have no competing interests. **Data and materials availability:** All data needed to evaluate the conclusions in the paper are present in the paper and/or the Supplementary Materials. Additional data used in this study were acquired under a nondisclosure agreement (NDA) with BAWSCA. Contact the corresponding author ([newsha@stanford.edu](mailto:newsha@stanford.edu)) or the agency ([bawasca.org](http://bawasca.org)) for further information regarding data access.

Submitted 14 March 2017  
Accepted 3 October 2017  
Published 25 October 2017  
10.1126/sciadv.1700784

**Citation:** K. J. Quesnel, N. K. Ajami, Changes in water consumption linked to heavy news media coverage of extreme climatic events. *Sci. Adv.* **3**, e1700784 (2017).

## Changes in water consumption linked to heavy news media coverage of extreme climatic events

Kimberly J. Quesnel and Newsha K. Ajami

*Sci Adv* 3 (10), e1700784.  
DOI: 10.1126/sciadv.1700784

ARTICLE TOOLS	<a href="http://advances.sciencemag.org/content/3/10/e1700784">http://advances.sciencemag.org/content/3/10/e1700784</a>
SUPPLEMENTARY MATERIALS	<a href="http://advances.sciencemag.org/content/suppl/2017/10/23/3.10.e1700784.DC1">http://advances.sciencemag.org/content/suppl/2017/10/23/3.10.e1700784.DC1</a>
REFERENCES	This article cites 50 articles, 5 of which you can access for free <a href="http://advances.sciencemag.org/content/3/10/e1700784#BIBL">http://advances.sciencemag.org/content/3/10/e1700784#BIBL</a>
PERMISSIONS	<a href="http://www.sciencemag.org/help/reprints-and-permissions">http://www.sciencemag.org/help/reprints-and-permissions</a>

Use of this article is subject to the [Terms of Service](#)

---

*Science Advances* (ISSN 2375-2548) is published by the American Association for the Advancement of Science, 1200 New York Avenue NW, Washington, DC 20005. 2017 © The Authors, some rights reserved; exclusive licensee American Association for the Advancement of Science. No claim to original U.S. Government Works. The title *Science Advances* is a registered trademark of AAAS.