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### Title

Assessing the Impacts of Urban Water Use Restrictions at the District Level: A Case Study of California's Drought Mandate

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1                   **ASSESSING THE IMPACTS OF URBAN WATER USE**  
2                   **RESTRICTIONS AT THE DISTRICT LEVEL: A CASE STUDY**  
3                   **OF CALIFORNIA’S DROUGHT MANDATE**

4                   María Pérez-Urdiales<sup>1</sup> and Kenneth A. Baerenklau <sup>2</sup>

5                   **ABSTRACT**

6                   This paper estimates feasible water savings for a sample of nine urban water districts  
7                   in California during the height of the 2012-16 drought, just prior to the implementation of  
8                   mandatory water use reductions, using household production theory and stochastic frontier  
9                   analysis. Estimates of feasible savings are compared to mandated reductions and actual  
10                  reductions in each district. Although the mandated reductions were generally feasible, our  
11                  results show that they had asymmetric impacts across districts and tended to impose larger  
12                  burdens on some disadvantaged groups.

13                  **Keywords:** Water Conservation, Mandatory restrictions, Efficiency Analysis, Stochastic  
14                  Frontier Analysis

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## INTRODUCTION

Although droughts are part of regular climate cycles, their frequency and intensity has increased in recent decades across many parts of the world, such as Southern Europe, Africa, Eastern Asia, Southern Australia and Western United States (Spinoni et al., 2014; Cook et al., 2018). With such related increasing concerns about water scarcity, a variety of water conservation policies have been adopted and/or expanded by urban water districts in drought-prone regions. Some approaches are more voluntary in nature, such as messaging campaigns, social norming (i.e. publishing average neighborhood use on each household billing statement), and rebate programs to encourage adoption of water efficient technologies. Others are harder for households to avoid or ignore, such as scarcity pricing and mandatory water use restrictions with penalties for non-compliance. Scarcity pricing has advantages from the perspective of economic efficiency, but often is viewed as inequitable because water is an essential good at low levels of use. Thus, districts often resort to use restrictions under extreme water scarcity. Such restrictions may target type of use (such as washing sidewalks and driveways), time of use (such as irrigating during the day), or total amount used (often referred to as rationing).

A common mandatory water restriction is rationing by percent reduction, in which the amount of allocated water is defined as a percentage of water use in a baseline period before the drought. During California's recent drought (2012-16), which was particularly severe (Mount et al., 2016), the State Water Resources Control Board (State Board) imposed mandatory percent reductions on more than 400 large urban water districts in April 2015. These mandatory restrictions were imposed because of the low level of statewide water savings achieved in 2014, when California Governor Jerry Brown had requested a 20% voluntary reduction in urban areas. After achieving only half of this requested cutback, followed by a record-low snow-pack in the winter of 2015, the State Board imposed mandatory water restrictions to reduce statewide urban water use by 25% relative to 2013 levels. District-level targets ranged from 4 to 36% relative to water use in 2013. To meet these targets, some dis-

42 tricts changed the emphasis of their water conservation actions from voluntary approaches,  
43 like information campaigns, to more severe actions such as penalties, aggressive pricing, and  
44 customer-level water use prohibitions (McCann et al., 2017).

45 As noted by Mitchell et al. (2017), the State Board achieved its overall goal but the  
46 mandate had asymmetric impacts on residents throughout the state. For example, Mitchell  
47 et al. (2017) notes that compliance with the mandate was more difficult for some districts,  
48 especially those with higher targets. Moreover, after the drought, most but not all districts  
49 reported that the mandate had strained relationships with their customers (McCann et al.,  
50 2017). In one high-profile case, the board of directors for a southern California water district  
51 was recalled and replaced due to extreme customer dissatisfaction (Stevens and Lin, 2016).  
52 These observations are consistent with those by Lund and Reed (1995), who argue it can  
53 be challenging for districts and their customers who have already adopted long-term water  
54 conservation strategies to comply with restrictions by percent reduction.

55 In addition, many water districts felt that the State Board had over-reached, usurped  
56 local control, and undermined their pre-existing drought contingency plans. In some cases,  
57 state intervention effectively stranded available water supplies that districts had previously  
58 paid to secure. The inability to sell this water produced unanticipated financial stresses  
59 in such districts. In other cases, customers who had previously undertaken conservation  
60 efforts at the behest of their water district were “rewarded” with a rate increase needed to  
61 compensate for lost revenue and pay for fixed operating expenses (Mitchell et al., 2017).

62 Although the State Board has since adopted a new approach based on stress-testing that  
63 allows for greater local control, analysis of the impacts of the mandate can help inform  
64 debates on the use of mandatory percent reductions and centralized versus decentralized  
65 water conservation authority. The logic for centralized control in California is that most  
66 urban residents are served by a large interconnected statewide water system and thus a major  
67 drought is best addressed through coordinated, collective action to promote cooperation and  
68 reduce shirking - i.e., an equitable sharing of the burden. The logic for decentralized control

69 is that the state already requires districts to develop and implement individual drought  
70 contingency plans, and each district is in the best position to monitor and respond to its  
71 own local conditions. If some districts make preventative drought-related investments, then  
72 they should be able to reap the benefits when droughts occur. Committing to local control  
73 incentivizes such investments, thus reducing the need for (what is perceived as) more blunt  
74 state intervention. The State Board attempted to equitably share the burden through a  
75 mostly formulaic approach to setting individual mandate levels that it felt was fair and  
76 responsive to local conditions. However, the anecdotal evidence mentioned above suggests  
77 that this approach was not entirely successful.

78 The present study contributes to this discussion in two ways. First, we quantify the  
79 district-level impacts of California’s statewide conservation mandate across a sample of ur-  
80 ban water suppliers. Second, we investigate how the impacts correlate with socio-economic  
81 characteristics. We accomplish this with stochastic frontier analysis and show how this  
82 method also could be used by water districts to gauge the conservation potential of a cus-  
83 tomer base, and thus to evaluate the feasibility of various conservation targets.

84 In order to address the first objective, we estimate a local measure of potential water use  
85 efficiency during the year prior to the state mandate. In doing so, we identify the potential  
86 water savings in a given district conditional on household characteristics and available conser-  
87 vation technologies during that period. Water use efficiency is measured using a household  
88 production theory approach in which households produce water services using water and  
89 other marketed goods as inputs. In this context, we can estimate a water demand frontier  
90 that allows us to compute the level of efficiency in water use and potential water savings  
91 at the time of the mandate. The second objective is achieved by regressing the difference  
92 between the estimated efficient water use and the mandated conservation target on a set  
93 of socioeconomic and demographic characteristics. This allows us to see how the relative  
94 feasibility of the mandated reductions correlate with district-level traits.

95 Using a sample of nine districts located throughout California, we find evidence that the

96 mandated conservation targets were generally feasible, but also hit some districts, and some  
 97 typically disadvantaged groups, harder than others. These findings support claims of some  
 98 water districts that the state’s approach, while well-intentioned, did not adequately account  
 99 for local conditions and fell short of achieving an equitable sharing of the conservation  
 100 burden. We also show that the household production approach may be effective for districts  
 101 needing a method to estimate contemporaneous water use efficiency potential, and to assess  
 102 the feasibility of water reductions in a short-run context such as drought emergencies.

## 103 **MEASURING EFFICIENCY IN WATER USE**

### 104 **The water demand frontier approach**

105 The household production theory approach proposed by Becker (1965) offers a useful  
 106 framework for measuring efficiency in water use. To implement this framework, we assume  
 107 that consumers obtain utility from water services produced in the household using inputs of  
 108 market goods such as water and capital. As in Filippini and Hunt (2011, 2015), an input  
 109 (water) demand frontier function can be derived from a cost minimization problem as:

$$110 \quad \min_W P_W W + P_K K \tag{1}$$

such that  $T(W, W, K) = 0$

111 where  $WS$  is a vector of water services, which are produced using inputs  $W$  and  $K$ , i.e.,  
 112 water use and a vector containing other inputs, respectively.  $P_W$  and  $P_K$  are the input prices  
 113 for each of the previously defined inputs, and  $T$  represents the technologies available to the  
 114 household. This cost minimization problem is assuming that the other inputs  $K$  are fixed,  
 115 and therefore, it identifies the level of water use that minimizes the cost of producing water  
 116 services  $WS$  given the level of other inputs  $K$  and the available technology.

117 In order to solve this cost minimization problem, Filippini and Hunt (2011) propose a  
 118 non-radial measure of efficiency that allows one to identify the potential reduction of only one  
 119 input, as opposed to the standard input oriented radial measure, in which the contribution

120 of each input to technical efficiency is equiproportionate. The differences between these two  
121 measures are explained in Figure 1 by plotting an isoquant and an isocost line. The isoquant  
122 represents all technically efficient combinations of  $W$  and  $K$  used to produce a given level  
123 of  $WS^*$ . The isocost line illustrates all the input combinations that share the same cost.  
124 Having this in mind, the point  $x^*$  where the isocost is tangent to the isoquant represents the  
125 cost-minimizing combination of inputs, that is,  $W^*$  and  $K^*$ . A household using  $W_1$  and  $K_1$  to  
126 produce  $WS^*$  is both technically and cost inefficient. Since the standard input oriented radial  
127 measure implies an equiproportionate reduction of each of the inputs, the level of technical  
128 inefficiency using this measure is defined as the ratio of the distance from the origin to the  
129 technically efficient point  $\theta x_1$  and the distance from the origin to input combination  $x_1$ .  
130 Similarly, cost efficiency is measured as the ratio of the distance from the origin to  $\beta x_1$   
131 and the distance from the origin to  $x_1$ , implying a different input allocation. However, as  
132 discussed by Filippini and Hunt (2015), with the non-radial measure, the inefficiency is the  
133 difference between the cost-minimizing water use  $W^*$  and the observed water use  $W_1$ .

134 We obtain the non-radial measure by estimating a single conditional water demand fron-  
135 tier function for each water district, anticipating that households within the same district are  
136 more similar to each other in terms of water conservation technologies and habits, and thus  
137 neighbors provide a more meaningful efficiency benchmark than residents from other parts  
138 of the state. Blasch et al. (2017) note that this frontier function represents the minimum  
139 amount of water needed to produce a desired level of water services, given input prices, for  
140 a household in the sample that uses the most efficient production technology. Households  
141 not consuming on the frontier are considered inefficient, and the level of inefficiency can be  
142 measured as the distance to the efficient frontier.

143 Following Filippini and Hunt (2011), we use the stochastic frontier approach introduced  
144 by Aigner et al. (1977). The reader may wonder why we do not use data envelope analysis  
145 (DEA). DEA is a deterministic method to estimate efficiency, and therefore it does not  
146 consider an error term in the estimation. In the case of household level data, we can expect

147 a high level of unobserved heterogeneity that could lead to misleading efficiency estimates.  
 148 Therefore, we follow seminal papers in the energy literature to estimate efficiency such as  
 149 Filippini and Hunt (2011, 2015) and use a stochastic frontier model. The water demand  
 150 frontier function can be specified as:

$$151 \quad \ln W_{it} = \alpha + \beta_1 \ln P_{Wit} + \beta_2 WS_{it} + v_{it} + u_{it} \quad (2)$$

152 where  $W_{it}$  is the water use for household  $i$  and period  $t$ ,  $P_{Wit}$  is the average price of  
 153 water, and  $WS_{it}$  is a vector of water services (defined later in the Data Section) produced in  
 154 the household,  $v_{it}$  is a noise term, assumed to be normally distributed, and  $u_{it}$  is a one-sided  
 155 non-negative random disturbance representing the inefficiency term.

156 All households in our sample face Increasing Block Rates (IBR), which present a simul-  
 157 taneity concern as the marginal price increases (decreases) with the quantity consumed. To  
 158 estimate the stochastic frontier model in Equation (2) while correcting for this problem of  
 159 price endogeneity, we use Corrected Two-Stage Least Squares (2SLS) (Amsler et al., 2016),  
 160 which is a generalization of corrected ordinary least squares (COLS). In this case, we first  
 161 estimate Equation 2 by 2SLS using a set of instruments  $Z$  to obtain the 2SLS estimates  $\hat{\alpha}$ ,  
 162  $\hat{\beta}_1$  and  $\hat{\beta}_2$ . Then, we construct the correct 2SLS residuals as:

$$163 \quad e_{it} = \ln W_{it} - \hat{\alpha} - \hat{\beta}_1 \ln P_{it} + \hat{\beta}_2 WS_{it} \quad (3)$$

164 Importantly, we do not construct the residuals using  $\ln \hat{P}_{it}$  from the 2SLS. As indicated  
 165 by Amsler et al. (2016), once we construct  $e_{it}$  we calculate the second ( $\hat{\sigma}_e^2$ ) and the third  
 166 ( $\hat{\mu}'_3$ ) moments of the residuals, and we calculate  $\hat{\sigma}_u^2$  and  $\hat{\sigma}_v^2$  as:

$$167 \quad \hat{\sigma}_u^2 = \left( \frac{\pi}{4 - \pi} \sqrt{\frac{\pi}{2}} \mu'_3 \right)^{2/3} \quad (4)$$

$$168 \quad \hat{\sigma}_v^2 = \hat{\sigma}_e^2 - \frac{\pi - 2}{\pi} \hat{\sigma}_u^2 \quad (5)$$

169 To solve for  $\sigma_u^2$  and  $\sigma_v^2$  in terms of sample quantities,  $\mu'_3 < 0$ . If  $\mu'_3 > 0$ , we face the “wrong  
170 skewness” phenomenon (Waldman, 1982). Simar and Wilson (2009) indicate that this issue is  
171 not an estimation failure, but a finite sample problem that occurs when the variance ratio of  
172 the inefficiency component to the composite error is small. Following Amsler et al. (2016),  
173 in such cases we set  $\sigma_u^2 = 0$ . Once we calculate  $\sigma_u^2$  and  $\sigma_v^2$ , we correct the intercept as  
174  $\tilde{\alpha} = \hat{\alpha} + \sqrt{\frac{2}{\pi}} \hat{\sigma}_u$ , and the COLS estimates are  $\tilde{\alpha}$ ,  $\hat{\beta}$ ,  $\hat{\sigma}_u^2$  and  $\hat{\sigma}_v^2$ .

175 After obtaining these parameters, we predict the inefficiency term using the point esti-  
176 mator in (Kumbhakar and Lovell, 2000, p.142):

$$177 \quad WE_i = E(\exp\{-u_i\} | e_i) = \left[ \frac{1 - \Phi(\sigma_* - \mu_{*i}/\sigma_*)}{1 - \Phi(\mu_{*i}/\sigma_*)} \right] \exp\left[-\mu_{*i} + \frac{1}{2}\sigma_*^2\right] \quad (6)$$

178 where  $\mu_{*i} = \epsilon_i \sigma_u^2 / \sigma^2$  and  $\sigma_*^2 = \sigma_u^2 \sigma_v^2 / \sigma^2$  and  $\Phi(\cdot)$  is the standard normal cumulative distri-  
179 bution function. A water use efficiency score ( $WE$ ) of 1 indicates the household is efficient,  
180 and a water use score below 1 indicates that the household could reduce water use by  $(1 -$   
181  $WE)$  by adopting water use habits and/or technologies currently used by the most efficient  
182 households. Because we estimate a water demand frontier function for each water district,  
183 this measure is relative to the most efficient households in a given household’s water district.

### 184 **Efficient and mandate-level water use**

185 Once we estimate the efficiency scores, the efficient level of water use for each household  
186 in each month can be computed as:

$$187 \quad \text{Efficient Water use}_{it} = \text{Actual water use}_{it} \times WE_{it} \quad (7)$$

188 Moreover, we can then compute the mean efficient water use for each district by month,  
189 and then calculate the distance between the log of this measure and the log of the state  
190 mandated conservation target assigned to each district:

$$191 \quad \text{Feasibility}_{dt} = \log(\text{Mandate Water use}_{dt}) - \log(\text{Efficient Water use}_{dt}) \quad (8)$$

192 This distance measure can be viewed as a feasibility indicator for each district in each  
193 month. If the mandated conservation target is higher than efficient use, then the target is  
194 “feasible” given current water use habits and technologies employed by the most efficient  
195 households in a given district. If the target is less than efficient use, then the target is not  
196 feasible in this sense. Rather, novel habits and technologies not currently used by even the  
197 most efficient households would be needed to meet such a target. Thus, the measure provides  
198 a sense of the reasonableness or fairness of each conservation target. This enables assessment  
199 of whether the targets were generally feasible and achievable. Moreover, we can regress this  
200 measure on socioeconomic, demographic, and seasonal variables to assess how these might  
201 be correlated with feasibility.

## 202 **DATA DESCRIPTION**

203 Our data set is consists of household level data from nine water districts in California  
204 from May 2014 to June 2015, that is, the drought’s so-called voluntary conservation period.  
205 We remove households reporting consumption levels equal to 0, as likely being unoccupied.  
206 Moreover, we balance the panel to consider households observed for the entire period of  
207 analysis. This period immediately precedes the mandate period to provide an accurate  
208 picture of technologies in use going into the mandate.

209 Figure 2 shows counties including water districts in the analysis (in gray). These counties  
210 span the most populous regions of central and southern California. At the request of the  
211 water districts that have generously shared their data with us, we do not specifically identify  
212 any individual district. The household-level data set includes water use, water prices and  
213 housing characteristics such as the number of bathrooms in the house and household irrigated  
214 areas. These data were merged with socioeconomic and demographic characteristics at the  
215 district level from the American Community Survey (ACS) of the US Census, and with  
216 data on evapotranspiration from the California Irrigation Management Information System  
217 (CIMIS).

218 Table 1 shows some descriptive statistics by water district of variables used to estimate

219 the water demand frontiers. For the dependent variable we use monthly water use (*water*  
220 *use*) measured in cubic meters ( $\text{m}^3$ ). For water services, i.e., the outputs to be produced by  
221 the household, we use the number of bathrooms (*Bathrooms*) as a proxy for indoor water  
222 services, and as proxies for outdoor water services, the amount of irrigated area (*Irrigated*  
223 *area*) measured in square meters and the average monthly evapotranspiration rate (*ET*).  
224 The evapotranspiration rate is an indicator of weather variability, and therefore, the need for  
225 outdoor water services. We consider this indicator rather than precipitation or temperature  
226 because Baerenklau et al. (2014) found that it captures more than 90% of weather variability  
227 for another application involving CIMIS data. The year each house was built (*Year Built*) is  
228 included to control for housing characteristics that may affect their ability to produce water  
229 services. Last, we include the average water price (*Avg P*). The district with the highest  
230 water use also has the largest average irrigated area, but this district also shows a high  
231 standard deviation in this variable, i.e, there is more variability within the district. This  
232 district also has the highest average price. While this can be due to higher marginal prices  
233 for each block, it may also reflect that households in this district tend to consume in a higher  
234 block and so are charged a higher rate. Districts with less water use and water services (both  
235 indoor and outdoor) tend to be more urban.

236 Table 2 shows descriptive statistics for variables considered in the second stage regression  
237 for our feasibility measure. For this regression, we consider a set of socioeconomic and  
238 demographic characteristics at the district level obtained from the US Census. Specifically,  
239 we include median household income (*Income*), median age (*Age*), the percent of population  
240 under 10 (*Pop<10*) and over 75 years of age (*Pop>75*), the percent of population identifying  
241 as Hispanic, (*Pop Hispanic*), the percent of population with bachelors degrees (*Pop bachelor*),  
242 and the mandatory water restriction assigned to the district (*Mandate level*). We also include  
243 three seasonal dummy variables: *winter* for December-February, *spring* for March-May, and  
244 *summer* for June-August. Last, we include a monthly time trend  $t$  that controls for temporal  
245 changes in water consumption observed during the period of analysis. Several variables had

246 high dispersion, such as *Income*, *Pop Hispanic*, and *Pop bachelor*. This indicates that districts  
247 considered in the analysis are quite heterogeneous, and we might expect differences in their  
248 ability to respond to mandatory restrictions.

249 It is worth noting that most of the variables considered in the second stage regression  
250 are related to the ability to reduce water use, as opposed to the variables included in the  
251 first stage that are directly related to the production of water services and the installed  
252 technologies. As discussed by Kay et al. (1994) for the case of agricultural efficiency, dif-  
253 ferences in performance are often due to variation in management. However, management  
254 is not directly measured. For this reason, Rougoor et al. (1998) propose to use personal  
255 aspects (such as socioeconomic and demographic characteristics and abilities) and aspects of  
256 the decision-making process as proxies for the ability of a farmer to influence performance.  
257 Therefore, in this paper we follow a similar approach including “managerial variables” as  
258 determinants of the districts’ ability to meet the mandate.

## 259 **RESULTS**

### 260 **Efficiency in water use**

261 The estimation results for the water demand frontier models for each district are shown in  
262 Table 3. The estimated coefficients have the expected signs for all models and are statistically  
263 significant for most variables. Price elasticities are negative and significant for all districts.  
264 Although they differ in magnitude, elasticity estimates are all within the common range  
265 reported in Sebri (2014).

266 As expected, the proxies for water services *Bathroom*, *ET* and *Irrigated area* have a  
267 positive and significant effect on water use in all models. Moreover, the coefficient for *Year*  
268 *built* is negative and significant in most cases. This negative effect can be explained by newer  
269 houses tending to be more efficiently equipped when initially built.

270 The mean efficiency scores and standard deviations are shown at the bottom of Table  
271 3. We observe that there is some heterogeneity in both the mean score and the dispersion.  
272 Five of the districts show mean efficiency scores ranging from 0.680 to 0.860, indicating

273 that on average these districts could reduce water use by 14%-32%. However, the remaining  
274 four districts suffer from the wrong skewness issue (explained in Section 2) and thus it is  
275 not possible to identify inefficiency during the period of analysis. In order to have a better  
276 understanding of the distribution of efficiency scores, in Figure 3 we show the histograms  
277 of the efficiency scores for the first 5 districts. The vertical lines indicate the 1<sup>st</sup> quartile,  
278 median and 3<sup>rd</sup> quartile in brown, blue and red, respectively. We observe that, while there  
279 are differences in the distributions across districts, at least 25% of the households in each  
280 district have relatively high efficiency scores around 0.9.

281 Figures 4 and 5 compare the evolution of water use by each district during three periods:  
282 the year prior to the voluntary conservation period (the pre-voluntary period, June 2013 -  
283 May 2014), the voluntary conservation period (June 2014 - May 2015), and the mandatory  
284 conservation period (June 2015 - December 2015) (the mandatory period continued into 2016,  
285 however our data set ends in December 2015). Each figure also shows the state-mandated  
286 water use level (with the conservation target shown in parentheses in the figure legend, as  
287 a percent of the pre-voluntary use level) and our estimated efficient water use level. The  
288 panels in the figures are arranged in descending order by mandate level.

289 Generally, the efficient water use levels are below the state-mandated levels in most  
290 months. These positive differences imply the mandated reductions were generally feasible.  
291 However, often in late winter and early spring, mandate levels are below efficient use, so  
292 achieving the mandates without affecting the level of water services would require imple-  
293 menting water use habits and technologies beyond even the most efficient households in  
294 those districts. Two districts show this pattern in summer months, as well.

295 The figures also allow comparison of actual and efficient use. The most meaningful  
296 comparison involves actual use in the voluntary period because our estimate of efficient use  
297 is derived from this data. This comparison shows that actual use during this time exceeded  
298 efficient use for five of nine districts, implying these districts had “room to improve” when  
299 entering the mandate period. However, as noted above, for the remaining four districts, we

300 face the wrong skewness issue (explained in Section 2) and thus cannot identify inefficiency  
301 during the period of analysis. Here, our efficient use estimate coincides with actual use,  
302 implying use was already efficient before the mandate period. This result is not surprising  
303 as the water use during the voluntary period was already near the level required by the  
304 mandate. For these districts the mandate levels were often near or below efficient use.

305 A related comparison is between actual use during the mandate period and efficient use.  
306 In most cases, actual use during the mandate period exceeded efficient use, which makes  
307 intuitive sense. But this is not always the case. Sometimes actual use during the mandate  
308 period fell below our estimate of efficient use. This suggests households were adopting new  
309 habits and technologies as the state transitioned to mandatory cutbacks in water use-habits  
310 and technologies that were uncommon even among efficient households prior to the mandate  
311 period.

312 Further insights can be gleaned by examining the three districts that were assigned a  
313 mandated reduction in the range of 20% to 24%. Two of these districts have relatively  
314 low water use and less seasonal fluctuation. The third has higher overall use and greater  
315 seasonal differences. More interesting is how water use evolved from the pre-voluntary to  
316 the voluntary periods in these districts. The first two districts achieved little conservation  
317 during the voluntary period while the third achieved more. Yet all three were assigned 20-24%  
318 reductions based on the pre-voluntary baseline. Not surprisingly, the mandatory reductions  
319 were more easily achieved (as defined by our feasibility measure) in the first two districts  
320 than in the third, where our efficiency estimate coincides with actual use. This suggests  
321 there were asymmetric impacts of the mandate, and supports arguments that a state-level  
322 approach-even one that was thoughtfully designed to equitably share the burden-did not  
323 adequately capture local conditions.

### 324 **Feasibility and the role of districts' characteristics**

325 To further explore asymmetric impacts, we consider the possibility that observed differ-  
326 ences in feasibility across districts might correlate with observable customer traits. To do

327 so, we regress monthly measures of our difference variable (*Feasibility*) on districts' socio-  
328 economic and demographic characteristics (explained in the Data Section). Negative values  
329 of *Feasibility* indicate that the mandate is below our estimate of efficient water use, implying  
330 the mandate would not be feasible with water conservation habits and technologies already  
331 in use at the time. Conversely, positive values imply more feasible and easily achievable  
332 mandated conservation levels. We also include seasonal dummies as explanatory variables  
333 and a monthly time trend in these regressions. We do this because the preceding analysis  
334 shows that households tend to be less efficient during the earlier months of the analysis,  
335 which includes the summer. Including both seasonal dummies and a trend helps disentangle  
336 these effects.

337 Estimation results for this analysis appear in Table 4. Not surprisingly, *Mandate level* is  
338 strongly negatively correlated with our dependent variable: higher percent reductions occur  
339 with lower feasibility (a higher compliance burden). The time trend  $t$  is positively correlated  
340 with the feasibility measure, indicating that compliance generally becomes easier through  
341 time. This makes intuitive sense to the extent that households change their water use habits  
342 and technologies over time. The seasonal dummies for spring and winter are negatively  
343 correlated, indicating greater difficulty in achieving compliance with the mandate during the  
344 cooler, wetter time of year. This also makes intuitive sense and is consistent with Lund et al.  
345 (2018) who note that landscape irrigation represents a high proportion of urban water use  
346 in California, and reductions during the 2012-16 drought were mostly achieved by reducing  
347 this water use.

348 Regarding the socio-demographic regressors, *Income* has a positive and significant effect  
349 on *Feasibility*. The mandated reductions were more feasible (easier to comply with) wealthier  
350 districts, and more difficult in poorer districts. Districts with an older population, a higher  
351 percentage of children under 10 and adults over 75 also found it more difficult to comply with  
352 their mandated reductions. A similar effect occurred for districts with larger percentages  
353 of Hispanic residents, with feasibility measures being lower in such districts. In each of

354 these cases, a greater compliance burden occurs with traits that often indicates an already  
355 disadvantaged community: lower income, more children and elderly residents to care for, and  
356 a larger under-represented minority population. However, this is not true for our education  
357 variable. The proportion of bachelor's degree holders has a negative and significant effect  
358 on the *Feasibility* variable, indicating greater feasibility in districts with lower educational  
359 attainment.

360 To assess the economic significance of these regression estimates, we report the elasticities  
361 for the socioeconomic and demographic regressors in Table 5. A change in any of these  
362 variables produces an elastic response in our feasibility measure. For example, a 1% increase  
363 in *Age* and *Pop<10* would lead to a 23.6% and 20% decrease in the feasibility measure,  
364 respectively. A 1% decrease in median household income would lead to an 11% decrease in  
365 the feasibility measure. The impact on the feasibility measure of a 1% change in any of these  
366 socio-demographic variables is larger than that of a 1% increase in the mandate level which  
367 produces an inelastic response. These are not trivial differences in policy impacts across  
368 districts.

## 369 **CONCLUSIONS**

370 This paper analyzes the mandatory water restrictions implemented during the 2012-16  
371 California drought by using household production theory and stochastic frontier analysis,  
372 both widely used in the economics literature, including applications to energy consumption.  
373 In general, the restrictions were not excessive, consistent with work by Mitchell et al. (2017)  
374 who observe that most districts achieved their mandated reductions in 2015-16 and that Cal-  
375 ifornia historically has been able to achieve short-term urban water use reductions of around  
376 20%. However, the present work adds important context to these findings by motivating  
377 a measure of water conservation feasibility and using this measure to show that the state  
378 mandate imposed larger burdens on some districts.

379 To further investigate the asymmetric impacts of the state mandate, we regress our feasi-  
380 bility measure against several socioeconomic and demographic characteristics. Although the

381 State Board’s approach to setting the mandate levels did not directly target such charac-  
382 teristics, they nonetheless seem to correlate such that poorer and older communities, those  
383 with more children and/or more elderly residents, and those with more Hispanic residents  
384 were harder hit by the regulations. While speculative, this may be because poorer and older  
385 communities are less able to purchase and install water efficient technologies as a response to  
386 drought. Those with children may find it more challenging to control indoor use and may be  
387 less willing to forego a green lawn. And Hispanic communities may be less likely to receive  
388 water district messages in their native language and thus less likely to be responsive.

389 From a policy perspective and looking ahead to future droughts, our results provide a  
390 rationale for greater local control, to the extent such control could be more responsive to local  
391 conditions and mitigate undesirable differential impacts. Moreover, while our approach could  
392 be implemented by state regulators, water districts have a potential advantage for tailoring  
393 short-term water restrictions as they have immediate access to household level customer  
394 information and a better understanding of heterogeneity within the district. The observed  
395 feasibility of the mandate levels generally increasing during the drought also suggests that  
396 a more flexible approach is warranted - one that adapts conservation targets to changes  
397 in technology and behavior that appear to occur during a drought. In this context, our  
398 methodological approach could be useful for water districts. Rather than setting fixed percent  
399 reduction targets from an arbitrary baseline, our approach would allow districts to assess  
400 conservation potential in near-real-time. This would enable water managers to estimate their  
401 available demand-side “cushion” as water scarcity concerns increase during the onset of a  
402 drought. Analyzing this conservation potential in the context of available reserves could  
403 then help inform policy decisions about actions that might be needed to help customers  
404 install new technologies not currently in use. By regularly updating the calculations, water  
405 managers could judge whether and to what extent percent reductions might be increased in  
406 an ongoing drought without creating excessive burdens for customers.

## 407 DATA AVAILABILITY STATEMENT

408 The data supporting our paper is a large household-level data set that includes monthly  
409 water consumption records and household characteristics considered by the water districts  
410 to be confidential information. The code generated during the study is available from the  
411 corresponding author by request.

## 412 ACKNOWLEDGMENTS

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## 415 REFERENCES

- 416 Aigner, D., Lovell, C., and Schmidt, P. (1977). “Formulation and estimation of stochastic  
417 frontier production function models.” *Journal of Econometrics*, 6(1), 21 – 37.
- 418 Amsler, C., Prokhorov, A., and Schmidt, P. (2016). “Endogeneity in stochastic frontier  
419 models.” *Journal of Econometrics*, 190(2), 280 – 288.
- 420 Baerenklau, K. A., Schwabe, K. A., and Dinar, A. (2014). “The residential water demand  
421 effect of increasing block rate water budgets.” *Land Economics*, 90(4), 683–699.
- 422 Becker, G. S. (1965). “A theory of the allocation of time.” *The Economic Journal*, 493–517.
- 423 Blasch, J., Boogen, N., Filippini, M., and Kumar, N. (2017). “Explaining electricity demand  
424 and the role of energy and investment literacy on end-use efficiency of swiss households.”  
425 *Energy Economics*.
- 426 Cook, B. I., Mankin, J. S., and Anchukaitis, K. J. (2018). “Climate Change and Drought:  
427 From Past to Future.” *Current Climate Change Reports*, 4(2), 164–179.
- 428 Filippini, M. and Hunt, L. C. (2011). “Energy demand and energy efficiency in the oecd  
429 countries: A stochastic demand frontier approach.” *The Energy Journal*, 32(2), 59–80.

430 Filippini, M. and Hunt, L. C. (2015). “Measurement of energy efficiency based on economic  
431 foundations.” *Energy Economics*, 52, S5 – S16.

432 Kay, R. D., Edwards, W. M., and Duffy, P. A. (1994). *Farm management*. McGraw-Hill  
433 New York.

434 Kumbhakar, S. and Lovell, C. (2000). *Stochastic Frontier Analysis*. Cambridge University  
435 Press, U.K., 142.

436 Lund, J., Medellín-Azuara, J., Durand, J., and Stone, K. (2018). “Lessons from California’s  
437 2012-2016 Drought.” *Journal of Water Resources Planning and Management*, 144(10).

438 Lund, J. and Reed, R. (1995). “Drought Water Rationing and Transferable Rations.” *Journal*  
439 *of Water Resources Planning and Management*, 121(6), 429–437.

440 McCann, H., Hanak, E., Baerenklau, K. A., Escrivá-Bou, A., Mitchell, D., and Schwabe,  
441 K. A. (2017). *Building Drought Resilience in California’s Cities and Suburbs*. Public Policy  
442 Institute of California (PPIC), Chapter Appendix B: Results from the PPIC Survey on  
443 Urban Water Suppliers.

444 Mitchell, D., Hanak, E., Baerenklau, K. A., Escrivá-Bou, A., McCann, H., Pérez-Urdiales,  
445 M., and Schwabe, K. A. (2017). “Building Drought Resilience in California’s Cities and  
446 Suburbs.” *Report no.*, Public Policy Institute of California (PPIC).

447 Mount, J., Chappelle, C., Gray, B., Hanak, E., Howitt, R., Lund, J., Frank, R., Gartell,  
448 G., Grantham, T., Medellín-Azuara, J., Moyle, P., Thompson, B., and Viers, J. (2016).  
449 “California’s water: Managing droughts.” *Report no.*, Public Policy Institute of California  
450 (PPIC).

451 Rougoor, C. W., Trip, G., Huirne, R. B., and Renkema, J. A. (1998). “How to define  
452 and study farmers’ management capacity: theory and use in agricultural economics.”  
453 *Agricultural Economics*, 18(3), 261 – 272.

- 454 Sebri, M. (2014). “A meta-analysis of residential water demand studies.” *Environment,*  
455 *Development and Sustainability*, 16(3), 499–520.
- 456 Simar, L. and Wilson, P. W. (2009). “Inferences from cross-sectional, stochastic frontier  
457 models.” *Econometric Reviews*, 29(1), 62–98.
- 458 Spinoni, J., Naumann, G., Carrao, H., Barbosa, P., and Vogt, J. (2014). “World drought  
459 frequency, duration, and severity for 1951–2010.” *International Journal of Climatology*,  
460 34(8), 2792–2804.
- 461 Stevens, M. and Lin, R. (2016). “Targeted over a rate hike, yorba linda water board incum-  
462 bents likely to be recalled from office.” *LA Times*, LA Times.
- 463 Waldman, D. M. (1982). “A stationary point for the stochastic frontier likelihood.” *Journal*  
464 *of Econometrics*, 18(2), 275 – 279.

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		District A	District B	District C	District D	District E	District F	District G	District H	District I
County	Statistic	San Mateo	Santa Clara	Solano	Alameda	Los Angeles	San Joaquin	Monterey	Los Angeles	San Mateo
Water use (m <sup>3</sup> )	Mean	58.89	36.31	34.85	29.78	39.57	52.36	35.58	20.51	37.28
	Std Dev	82.25	29.84	21.12	21.76	27.23	53.35	30.58	12.74	36.20
	Min	2.83	2.83	2.83	2.83	2.83	2.83	2.83	2.83	2.83
	Max	2217.20	419.09	464.40	563.50	586.16	1826.43	968.43	283.17	1551.76
Bathrooms	Mean	2.75	2.05	1.47	2.40	2.01	2.79	2.45	1.80	1.72
	Std Dev	1.31	0.62	0.65	1.08	0.68	1.01	0.86	0.83	0.78
	Min	1	1	1	1	1	1	1	1	1
	Max	10	5.	8	10	5	10	8	8	8
Irrigated area (m <sup>2</sup> )	Mean	1283.30	360.80	172.90	154.76	237.34	756.19	668.43	201.09	393.06
	Std Dev	1664.61	368.64	102.26	135.35	200.47	966.73	849.93	215.06	320.86
	Min	0.00	3.00	13.68	0.00	8.11	0.00	57.18	0.00	0.00
	Max	8427.49	10176.85	1613.26	2077.94	3406.24	17738.18	20391.28	3999.73	9688.44
ET (cm/month)	Mean	54.83	63.01	68.15	66.19	63.79	54.83	61.22	54.83	59.46
	Std Dev	7.66	16.37	10.96	10.25	11.56	7.66	12.76	7.66	14.42
	Min	33.12	37.41	48.93	47.92	41.13	43.17	42.30	43.17	37.00
	Max	73.91	85.70	84.10	81.32	77.48	64.83	80.42	64.83	78.21
Year Built	Mean	1959	1968	1940	1964	1978	1964	1973	1955	1951
	Std Dev	22	20	16	23	24	19	18	15	16
	Min	1860	1880	1890	1808	1900	1880	1880	1900	1895
	Max	2015	2008	2010	2015	2007	2014	2011	2011	2010
Avg P (\$/m <sup>3</sup> )	Mean	2.61	0.73	0.60	1.90	1.54	1.90	1.92	2.43	1.48
	Std Dev	0.85	0.36	0.19	0.46	0.69	0.69	0.74	0.69	0.70
	Min	1.81	0.31	0.45	1.34	0.85	1.29	1.19	1.68	0.83
	Max	8.56	3.39	2.68	5.34	8.31	7.25	7.32	6.49	6.36
N households		8193	8785	1501	9521	9520	5641	973	9679	6822

TABLE 1: Descriptive statistics by district

Statistic	Mean	St. Dev.	Min	Max
Income (\$1000)	91.014	34.607	41.152	132.652
Age	37.996	4.042	27.748	41.731
Pop <10 (%)	13.660	1.529	11.877	18.010
Pop >75 (%)	5.977	1.119	3.500	7.845
Pop Hispanic (%)	27.762	25.927	7.405	82.047
Pop bachelor (%)	22.683	10.748	5.199	35.359
Mandate level	20.60	6.40	8.00	36.00

TABLE 2: Descriptive statistics for variables in the second stage

TABLE 3: Results

Variables	<i>Dependent variable:</i>								
	log(water use)								
	District A	District B	District C	District D	District E	District F	District G	District H	District I
ET	0.040*** (0.0004)	0.037*** (0.001)	0.015*** (0.0005)	0.017*** (0.0002)	0.008*** (0.0002)	0.022*** (0.0002)	0.017*** (0.001)	0.009*** (0.0002)	0.011*** (0.0003)
Bathrooms	0.226*** (0.002)	0.221*** (0.003)	0.182*** (0.007)	0.186*** (0.002)	0.132*** (0.002)	0.224*** (0.003)	0.140*** (0.008)	0.105*** (0.003)	0.112*** (0.003)
Irrigated area	0.0001*** (0.00000)	0.0001*** (0.00000)	0.0002*** (0.00001)	0.0001*** (0.00000)	0.001*** (0.00001)	0.0002*** (0.00001)	0.0004*** (0.00003)	0.0004*** (0.00002)	0.0001*** (0.00001)
Year Built	-0.001*** (0.0001)	-0.003*** (0.0001)	-0.00000 (0.0002)	0.005*** (0.0001)	-0.001*** (0.0001)	0.0002 (0.0002)	-0.0001 (0.0002)	-0.002*** (0.0001)	-0.002*** (0.0001)
log(Avg P)	-0.659*** (0.051)	-0.684*** (0.063)	-0.537*** (0.029)	-0.815*** (0.019)	-0.482*** (0.032)	-0.305*** (0.019)	-0.314*** (0.031)	-0.136*** (0.015)	-0.315*** (0.026)
Constant	3.129*** (0.235)	7.484*** (0.255)	1.733*** (0.409)	-6.879*** (0.221)	4.622*** (0.175)	1.303*** (0.312)	2.240*** (0.494)	7.157*** (0.225)	7.026*** (0.273)
Efficiency scores									
Mean	0.708	0.726	0.860	0.680	0.857	-	-	-	-
Std Dev	0.185	0.180	0.108	0.204	0.107	-	-	-	-
N	98316	105420	18012	114252	114240	67692	11676	116148	81864

Note: \*\*\*p<0.01

TABLE 4: Estimation results - Second stage

	Coefficients	Std. Errors
Intercept	7.51 ***	2.89
t	0.05***	0.01
Summer	0.04	0.04
Spring	-0.52***	0.07
Winter	-0.18***	0.03
Income	0.02***	0.00
Age	-0.11**	0.05
%Pop<10	-0.22***	0.08
%Pop>75	-0.21***	0.06
%Pop Hispanic	-0.01***	0.00
%Pop Bachelor	-0.03***	0.01
Mandate level	-0.006***	0.003

TABLE 5: Elasticities for socioeconomic and demographic characteristics

	Elasticities
Income	11.01
Age	-23.60
%Pop<10	-20.07
%Pop>75	-7.34
%Pop Hispanic	-1.60
%Pop Bachelor	-4.09
Mandate level	-0.85

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5 Evolution of water use for different districts

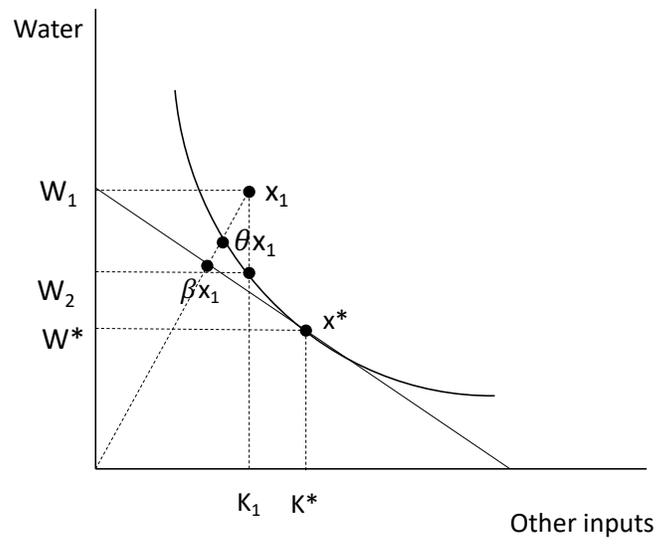
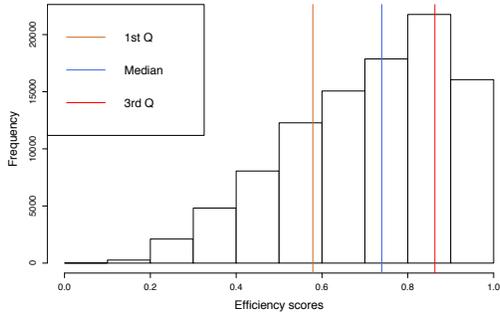


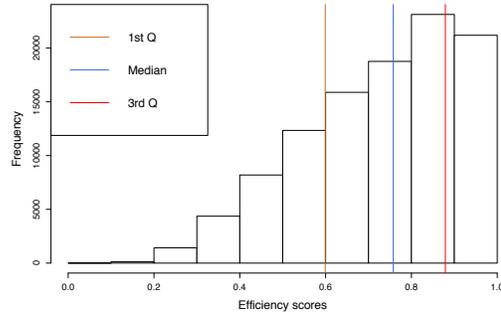
FIG. 1: Cost efficiency



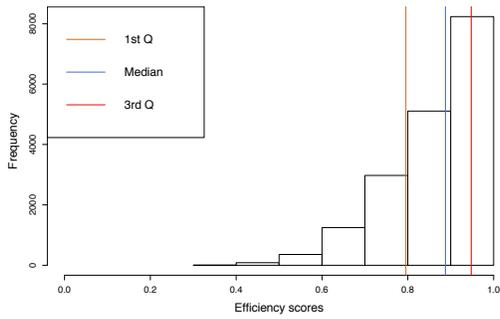
FIG. 2: Distribution of water districts in the analysis



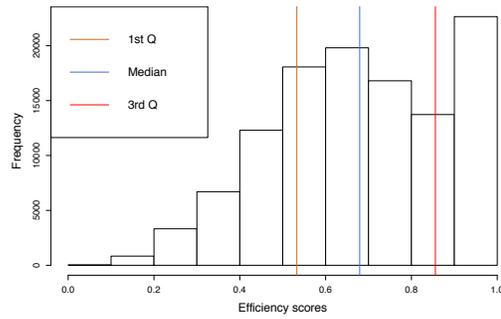
(a) Histogram Efficiency Scores - District A



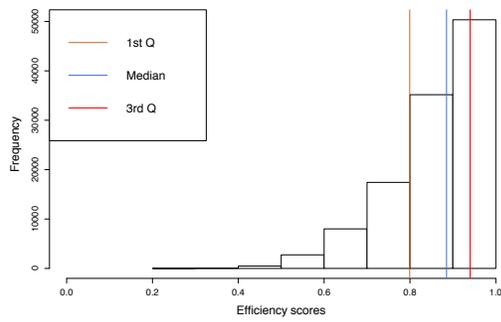
(b) Histogram Efficiency Scores - District B



(c) Histogram Efficiency Scores - District C



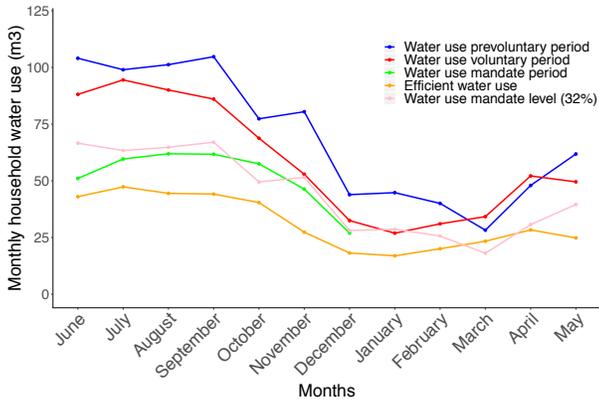
(d) Histogram Efficiency Scores - District D



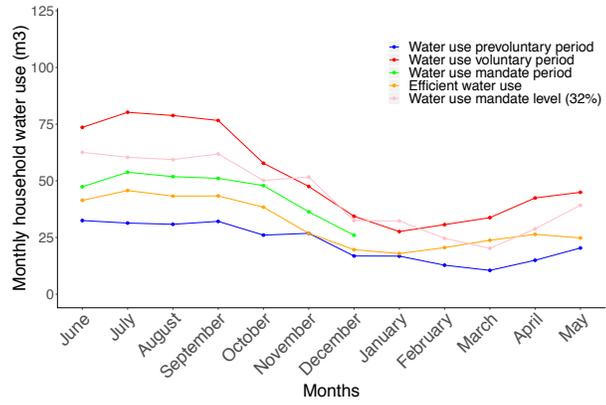
(e) Histogram Efficiency Scores - District E

FIG. 3: Histogram Efficiency Scores

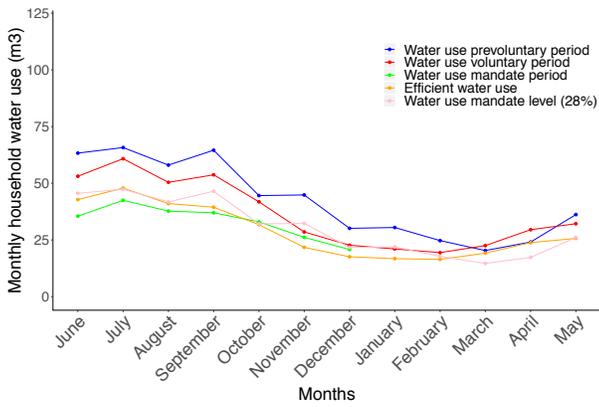
FIG. 3: Histogram Efficiency Scores



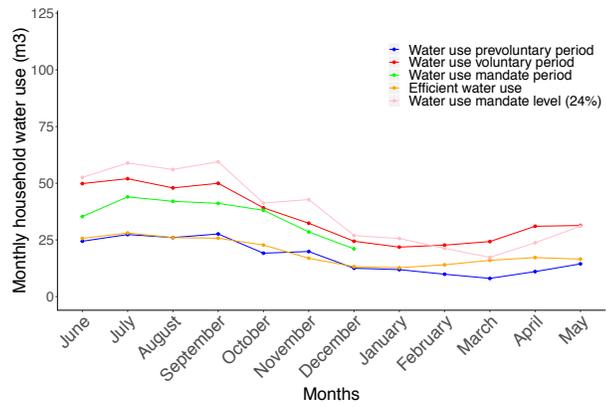
(a) Evolution of water use - District A



(b) Evolution of water use - District B

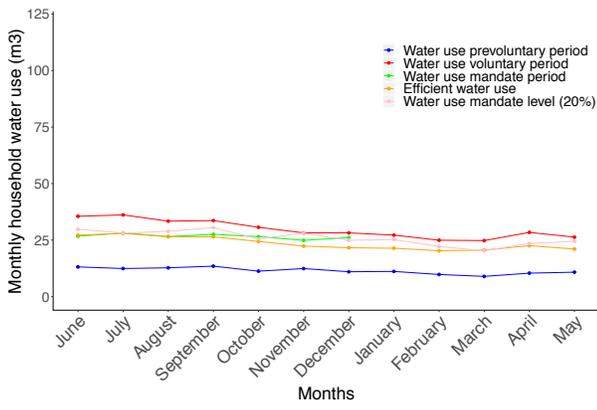


(c) Evolution of water use - District C

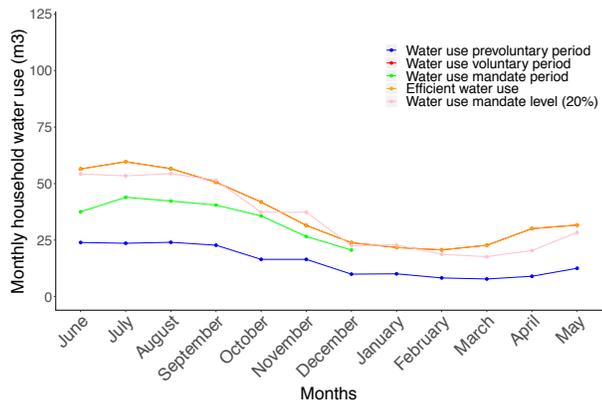


(d) Evolution of water use - District D

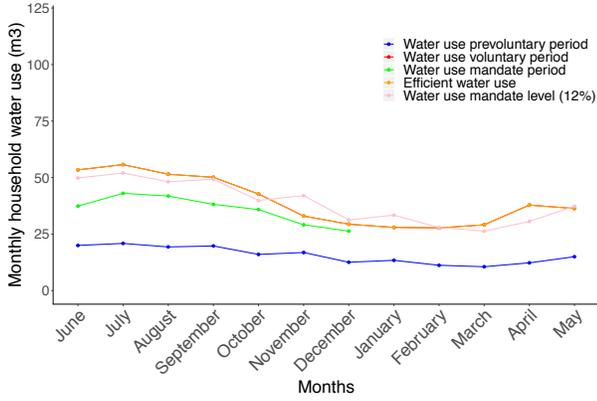
FIG. 4: Evolution of water use for different districts



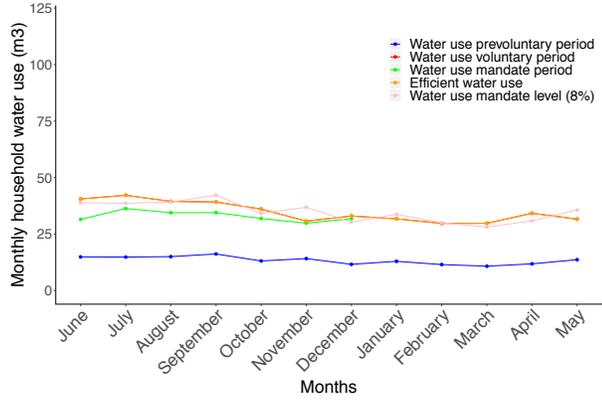
(a) Evolution of water use - District E



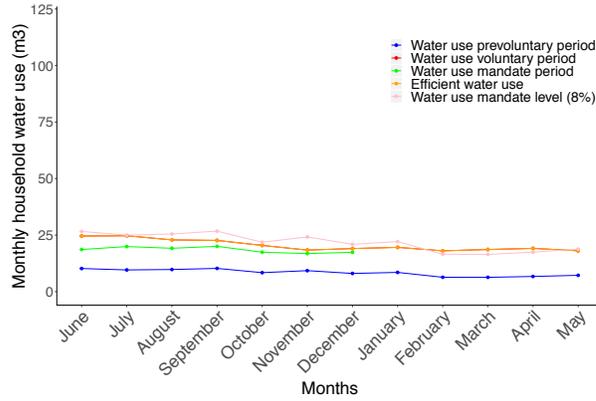
(b) Evolution of water use - District F



(c) Evolution of water use - District G



(d) Evolution of water use District H



(e) Evolution of water use - District I

FIG. 5: Evolution of water use for different districts