Leveraging statistical learning theory to characterize the U.S. water consumption

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Abstract

Access to accurate estimates of water withdrawal is requisite for urban planners as well as operators of critical infrastructure systems to make optimal operational decisions and investment plans to ensure reliable and affordable provisioning of water. Furthermore, identifying the key predictors of water withdrawal is important to regulators for promoting sustainable development policies to reduce water use. In this paper, we developed a rigorously evaluated predictive model, using statistical learning theory, to estimate state-level, per-capita water withdrawal as a function of various geographic, climatic and socio-economic variables. We then harnessed the data-driven predictive model to identify the key factors associated with high water-usage intensity among different sectors in the U.S. We analyzed the predictive accuracy of a range of parametric models (e.g., generalized linear models) and non-parametric, flexible learning algorithms (e.g., generalized additive models, multivariate adaptive regression splines and random forest). Our results identified irrigated farming, thermo-electric energy generation and urbanization as the most water-intensive anthropogenic activities, on a per-capita basis. Among the climate factors, precipitation was also found to be a key predictor of per-capita water withdrawal, with drier conditions associated with higher water withdrawals. Results of the first-order sensitivity analysis indicated changes between +/-10% in the future water withdrawal across the U.S., in response to precipitation changes, by the end of the 21st Century under the business-as-usual scenario. Overall, our study highlights the utility of leveraging statistical learning theory in developing data-driven models that can yield valuable insights related to the water withdrawal patterns across expansive geographical areas.

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[1] [1] [2] [3] [4]

- U.S.
-
- U.S. (±10%)
  RCP8.5

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$$= \left[- \hat{ }( ) \right]^2$$
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Th[illegible]

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$= ( ) + ;$ ... $( )$ ... (i.e., ...

$$= \int ( ) \hat{ }( ) ( ) \qquad (2)$$

$( )$ ...

(Hastie, Tibshirani, & Friedman, 2009).

(e.g., ... (e.g., ... (GAM), ... (MARS) ... (RF)) ... (RF) ...

(2001), ...

$$(\ ) = \frac{1}{\ } \sum_{i=1}^{m_{tree}} {}_{i}(\ ) \qquad (3)$$

[illegible] $_i$ [illegible] — [illegible] (e.g., [illegible]). T[illegible] [illegible] ([illegible]) [illegible] $_i$ [illegible] T[illegible] ([illegible]) [illegible] ( ) [illegible]

R[illegible] (H[illegible], 2009). T[illegible] T[illegible] T[illegible] T[illegible] T[illegible] (OOB) [illegible] (i.e., [illegible]) [illegible]

$$= \frac{1}{\ } \sum_{i=1}^{n} (_{i} - \hat{}_{i}')^2 \qquad (4)$$

[illegible] $\hat{}_i'$ [illegible] OOB [illegible] th [illegible] (L[illegible] & W[illegible], 2002). S[illegible] (PDPs) [illegible] PDP [illegible] $_j$ [illegible] (i.e., [illegible]). M[illegible] PDP [illegible] (H[illegible] [illegible], 2009):

$$(\hat{}_j)(_j) = \frac{1}{\ } \sum_{i=1}^{n} (\hat{}_j)(_j \quad _{-j;i}) \qquad (5)$$

[illegible] $\hat{}_j$ [illegible] ; [illegible] (i.e., [illegible]) ; [illegible] $_{-j}$ [illegible] $_j$. T[illegible] PDP [illegible] $_{-j}$ [illegible] $\hat{}$ [illegible] $_j$ is [illegible] $_{-j}$ [illegible]

T[illegible] 1 [illegible] T[illegible] [illegible] M[illegible] (MARS) [illegible] (RF) [illegible] (MLR) [illegible] (GAM) [illegible] T[illegible] Table 1 [illegible] A[illegible] MARS [illegible] RF [illegible]

[illegible] RF [illegible] In [illegible] 2×10^{16}.

Fig. 4 [illegible] RF [illegible]

In [illegible] 2005 [illegible] 2006–2010. [illegible] Fig. 4 [illegible] RF [illegible] RF [illegible] MARS [illegible]

[illegible] (e.g., MLR) [illegible] GAMs [illegible] RF [illegible] MARS [illegible] MARS [illegible] (Friedman, 1991) [illegible]

[illegible] (2010), [illegible] RF [illegible] Fig. 5.

[illegible] (HDD), [illegible] U.S.

In [illegible] Fig. 5.

[illegible] (M[illegible], 2014).

C[illegible] D[illegible] (i.e., [illegible] 600) [illegible] H[illegible] i.e., HDD 3000 [illegible] N[illegible] C[illegible] U.S., [illegible] N[illegible] D[illegible], M[illegible], [illegible] (T[illegible]) T[illegible]

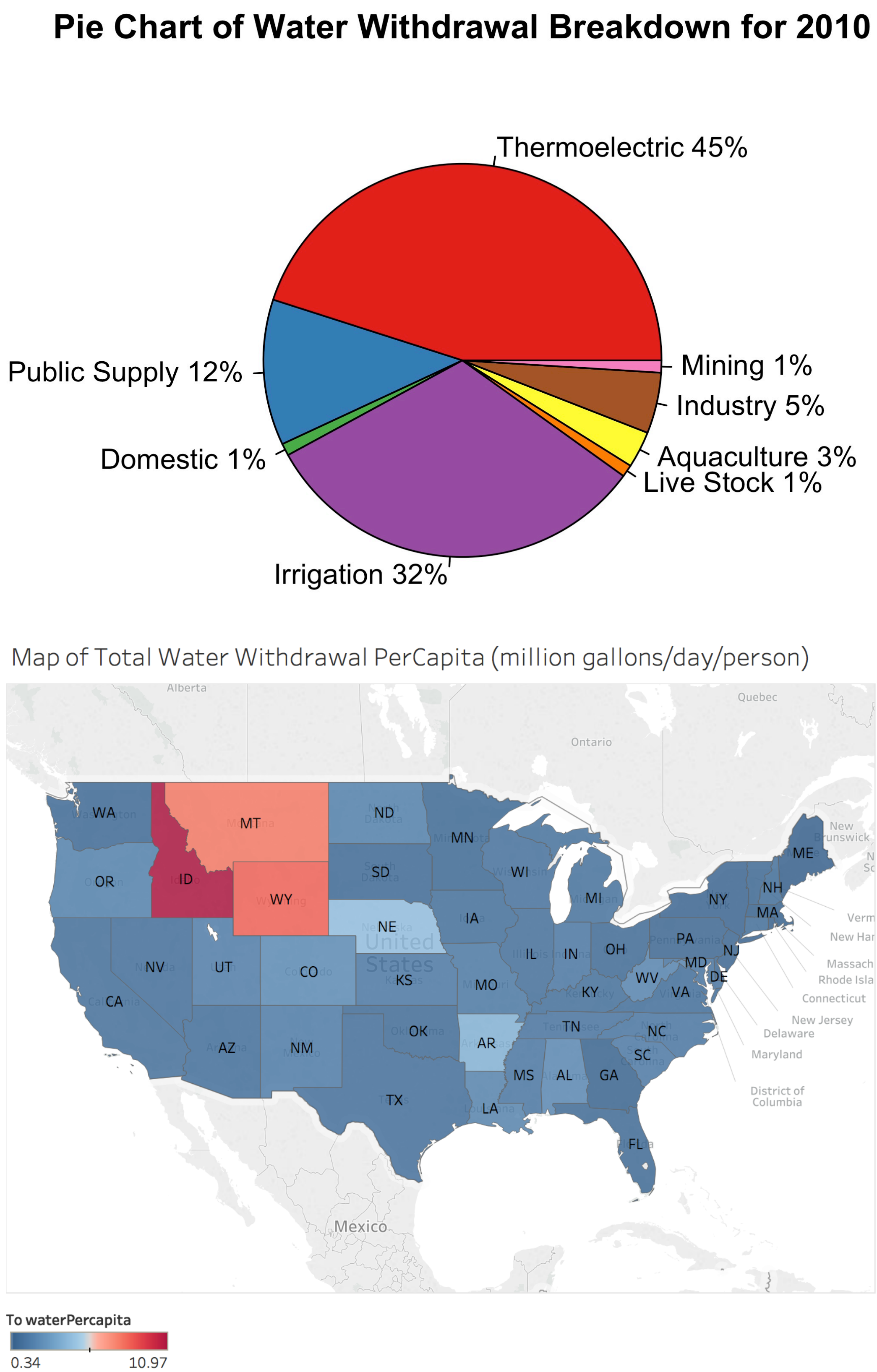
[illegible] O[illegible] U.S. ([illegible] ±10%), [illegible] ([illegible]) [illegible] ([illegible]) [illegible] RCP8.5 [illegible]. I[illegible] (e.g., HDD [illegible]) [illegible] (e.g., [illegible]); [illegible] ([illegible]) [illegible]

Summary of models performance given as correlation coefficient (R^2), fitted Root Mean Square Error (RMSE; million gal/day/person), and Leave one out cross validation (LOOCV) RMSE. Each model is trained and tested using all available data records for the period 1991-2010.

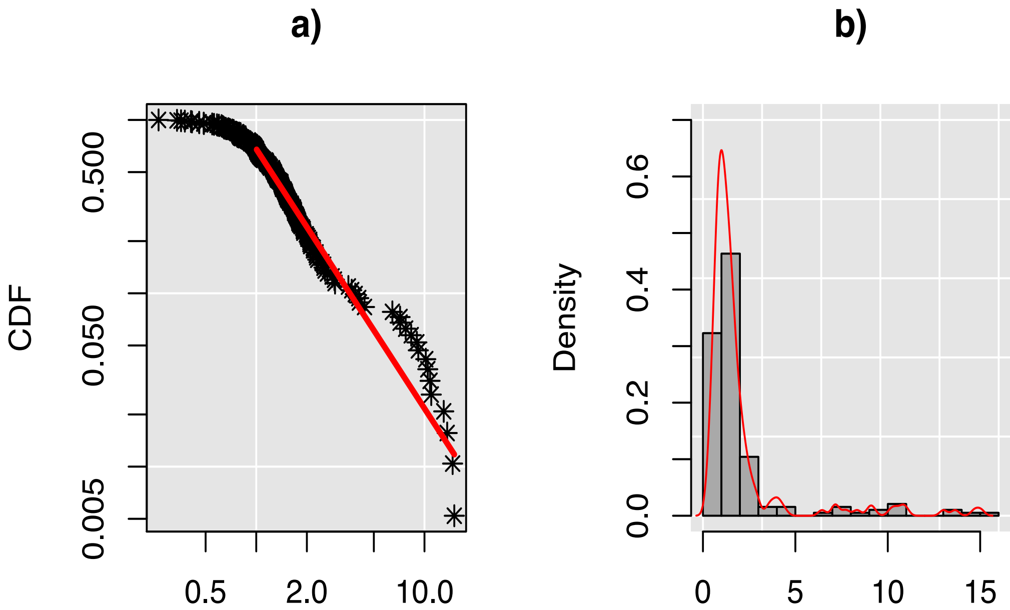
Model	R^2	RMSE	LOOCV RMSE
[illegible]	–	2.60	2.62
[illegible]	0.57	1.71	1.84
[illegible] (GAM)	0.61	1.62	1.62
[illegible]	0.85	0.99	1.40

Summary of models predictive accuracy. Each Model is trained using 1991-2005 data and tested using 2006-2010 data. Summary performance is presented here in terms of correlation coefficient (R^2), fitted Root Mean Square Error (RMSE; million gal/day/person), Leave one out cross validation (LOOCV) RMSE, and prediction RMSE (for the test data). See Appendix D for more details on LOOCV-RMSE.

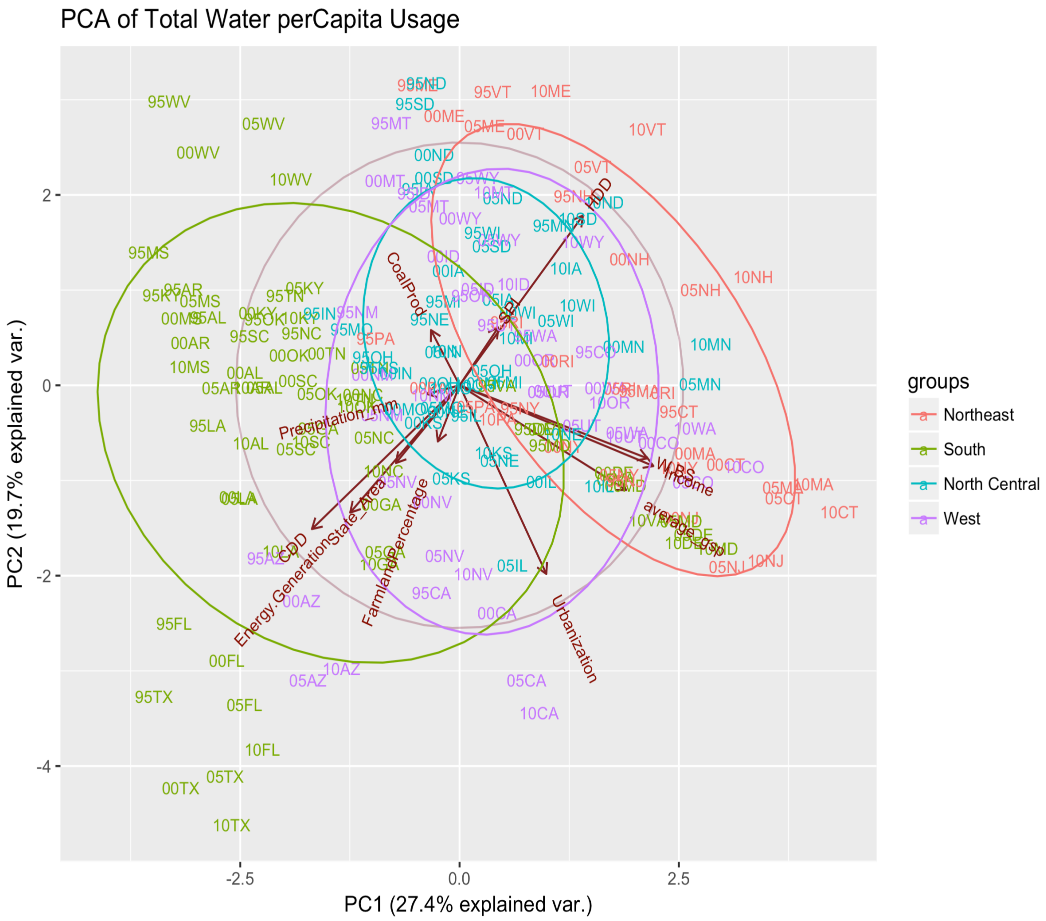
Model	R^2	RMSE	LOOCV RMSE	Prediction RMSE
[illegible]	–	2.75	2.77	2.11
[illegible]	0.59	1.76	2.00	1.52
[illegible] (GAM)	0.65	1.63	1.68	1.31
[illegible]	0.95	0.60	1.57	1.35



i Top: The breakdown of US-wide water withdrawals across the eight major sectors during the period 2006-2010. Bottom: Spatial distribution of the U.S. wide per-capita water withdrawal (in million gallons per-day).



i The empirical distribution of per-capita water withdrawals (in million gallons per day) for the period 1991-2010; (a) the red line shows that power-law fits the tail of the empirical cumulative distribution reasonably well (b) the histogram of per-capita water demand with overlain kernel density line (in red).



i Principal Component Analysis (PCA) biplot of the per-capita water usage (in million gallons per-day) for the period 19952010. The states are color-coded based on their proximity to water bodies and the two digits next to the state codes indicate the year associated with the water use data for the state.

Figure 4. Top: Scatter plot of observed versus estimated values of per-capita water withdrawal (in million gallons per-day) using data of 1995-2010. Bottom: Scatter plot of observed versus predicted values of per-capita water usage (in million gallons per-day) using data of 2006-2010. In the latter case, the models were trained using data of 1995-2005, and the testing was conducted in an independent period of 2006-2010.

RF [illegible]
SPI [illegible]
U.S. [illegible]
USD [illegible] ($)
USGS [illegible]

Acknowledgments

[illegible] NSF [illegible] EES#1555582 [illegible] C4E [illegible] P CCRC) [illegible] ISI-MIP) [illegible] CMIP, [illegible] 3. [illegible] (G [illegible]).

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