Water Resources Management (2021) 35:3431–3445
https://doi.org/10.1007/s11269-021-02902-7

Variational Mode Decomposition Hybridized With Gradient Boost Regression for Seasonal Forecast of Residential Water Demand

Taís Maria Nunes Carvalho[1] · **Francisco de Assis de Souza Filho**[2]

Received: 22 February 2021 / Accepted: 3 July 2021 / Published online: 7 July 2021

Abstract
Climate variability highly influences water availability and demand in urban areas, but medium-term predictive models of residential water demand usually do not include climate variables. This study proposes a method to predict monthly residential water demand using temperature and precipitation, by combining a novel decomposition technique and gradient boost regression. The variational mode decomposition (VMD) was used to filter the water demand time series and remove the component associated with the socioeconomic characteristics of households. VMD was also used to extract the relevant signal from precipitation and maximum temperature series which could explain water demand. The results indicate that by filtering the water demand and climate signals we can obtain accurate predictions at least four months in advance. These results suggest that the climate information can be used to explain and predict residential water demand.

Keywords Water demand · Seasonal forecast · Gradient boosting · Variational mode decomposition

1 Introduction

A primary concern of climate change and variability is how they will affect water demand and availability in the next decade (Milly et al. 2008; Jiménez Cisneros et al. 2014). Spatial and temporal variability of precipitation and temperature might cause changes in the intensity and frequency of extreme events (Orlowsky and Seneviratne 2012). In urban systems, there is also the additional challenge of increasing urbanization and water use. Water resources planning should address accurate prediction of water demand, whether the

✉ Taís Maria Nunes Carvalho
taismarianc@gmail.com

Francisco de Assis de Souza Filho
assissouzafilho@gmail.com

[1] Ph.D. Student, Dept. of Hydraulic and Environmental Engineering, Universidade Federal Do Ceará, Campus do Pici, Bloco 713, Fortaleza, CEP 60455-760, Brazil

[2] Dept. of Hydraulic and Environmental Engineering, Universidade Federal Do Ceará, Campus do Pici, Bloco 713, Fortaleza, CEP 60455-760, Brazil

objective is to expand the capacity of the supply system or to implement water conservation measures (Olmstead 2014).

Accurate forecasting of residential water demand is of special importance for the decision-making process, as researchers have shown it to be correlated with climate (Maidment and Miaou 1986; House-Peters and Chang 2011; Adamowski et al. 2013; Chang et al. 2014). Specifically, it presents an inverse relationship with precipitation and a direct relationship with temperature (House-Peters and Chang 2011; Adamowski et al. 2013). Many other elements influence water demand patterns, such as demographic, social, and economic aspects of households (Chang et al. 2017; Chu and Quentin Grafton 2019; Villarin and Rodriguez-Galiano 2019; Lee and Derrible 2020; Carvalho et al. 2021). These variables are associated with water demand trends and are usually predicted with scenario-based simulations.

Past research has indicated that water demand is strongly dependent on past use (Duerr et al. 2018) and that it can be predicted only one month in advance. However, they also concluded that medium- and long-term forecasts could be improved by adding covariates. Short-term water demand forecasting, i.e. hourly to daily forecast, has been well explored. Lee and Derrible (2020) evaluated twelve statistical models for residential water demand prediction, including eight machine learning techniques; gradient boost regression outperformed all the models. In their study, two scenarios of data availability were compared, and the one with a higher number of socioeconomic and climate exogenous variables provided better predictions.

Several studies have explored climate influence on residential water demand (Adamowski et al. 2013; Parandvash and Chang 2016; Zubaidi et al. 2020; Rasifaghihi et al. 2020; Fiorillo et al. 2021). Parandvash and Chang (2016) used a structural time series regression model to assess the effect of climate change on per capita water consumption and projected an increase of up to 10% in the water demand of Portland, in the United States, for the 2035–2064 period. Adamowski et al. (2013) and Zubaidi et al. (2020) used decomposition techniques—wavelet transform and singular spectrum analysis, respectively—to detect interactions between climate and water demand. They found that decomposing time series into different components is a useful approach for filtering relevant information from exogenous variables. Haque et al. (2014) and Rasifaghihi et al. (2020) provided long-term probabilistic forecasts of urban water demand, considering future climate projections. Some authors have investigated the joint influence of weather and socioeconomic aspects of households on water consumption (Fiorillo et al. 2021).

To the best of our knowledge, the current models in the literature are not able to address the influence of climate on the medium-term forecast of water demand in dry regions. Our objectives are to (i) remove low-frequency variability and noisy signals from temperature and precipitation time series, (ii) extract the seasonal component of water demand, and (iii) design a model able to predict residential water demand up to 12 months in advance, considering the influence of precipitation and temperature variability. We do this by using an innovative approach that combines an intrinsic and adaptive decomposition method coupled with a regression machine learning model and use Fortaleza, Ceará – a region frequently affected by drought – as a case study. The variational mode decomposition (VMD) method used in this study was designed to concurrently estimate the components of a signal and properly deal with noise (Dragomiretskiy and Zosso 2014). VMD was applied to extract the seasonal component of water demand, removing the signals unrelated to climate variability, and relevant signals from

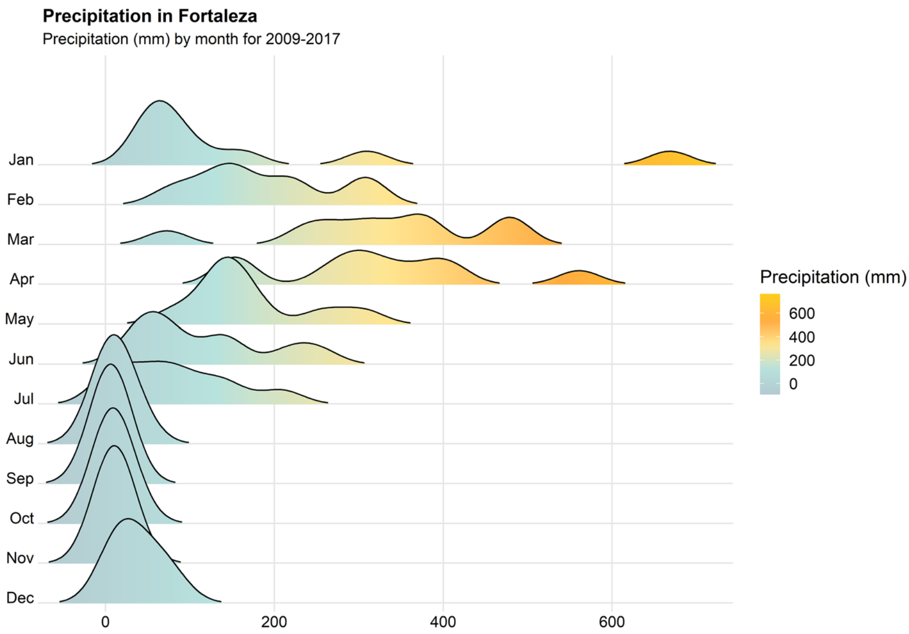

Fig. 1 Monthly average precipitation in Fortaleza for the period between 2009 and 2017

temperature and precipitation time series. Gradient boost regression was employed to capture the relationship between filtered signals of water demand and climate, which is long known to be nonlinear (Maidment and Miaou 1986).

The study offers some important insights into tactical decisions on urban water supply planning. The predictive model can be coupled with seasonal climate forecasts to assess future water demand and to guide the decision-making process.

2 Study Area and Data

The city of Fortaleza was used as a case study for the proposed model. Fortaleza is in the Northeast region of Brazil and is the fifth most populated city of the country, with over 2.6 million inhabitants. The region suffers from high climate variability and recurrent droughts, directly affecting Fortaleza's water supply. The most recent drought lasted seven years, starting from 2012 until 2018 (Pontes Filho et al. 2020). The rainy season occurs between February and May (Fig. 1) and the maximum temperature ranges from 30 to 33 °C during the year (Fig. 2).

Monthly residential water demand data from 2009 to 2017 was provided by the Water and Wastewater Company of Ceará. Data was provided at the household level, in cubic meters per month, and it was averaged over the number of consumers. Precipitation and maximum temperature time series were obtained from a conventional meteorological station maintained by the Brazilian National Meteorology Institute.

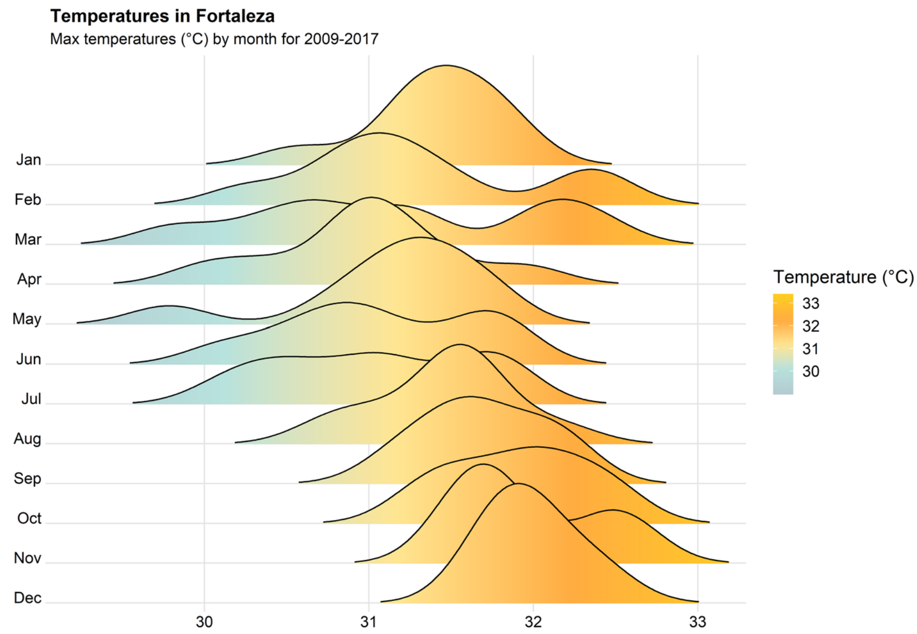

Fig. 2 Monthly maximum temperature in Fortaleza for the period between 2009 and 2017

3 Methods

3.1 Variational Mode Decomposition

Signal decomposition is a useful approach for filtering and capturing information from time series. The empirical mode decomposition (EMD) (Huang et al. 1998) is a famous time–frequency analysis used to process nonstationary and nonlinear series. Although this technique is simple and robust, there are a few limitations, such as the mode mixing problem, due to intermittent signals and noise, and the endpoint effect (Gao et al. 2008). In addition, EMD lacks an appropriate mathematical theory basis. Some methods have been developed to solve these problems, such as the ensemble EMD (EEMD) (Wu and Huang, 2009), the complementary EEMD (Yeh et al. 2010), and the complete EEMD with adaptive noise (Torres et al. 2011). However, they were not able to address the mode mixing issue for all signals.

The variational mode decomposition is a non-recursive decomposition method developed by Dragomiretskiy and Zosso (2014) to properly address the sensitivity to noise and sampling of EMD. The VMD algorithm decomposes a signal into intrinsic mode functions (IMF), which are amplitude-modulated frequency-modulated signals. Each mode is assumed to be compact around its center frequencies and they are concurrently estimated. The constrained variational problem solved by VMD to decompose a time series is given by the following equation:

$$min_{\{u_k\},\{\omega_k\}}\left\{\sum_k \|\partial_t\left[\left(\delta(t)+\frac{j}{\pi t}*u_k(t)\right)\right]e^{-j\omega_t t}\|_2^2\right\} s.t. \sum_k u_k = f \qquad (1)$$

where $\{u_k\}$ are the estimated modes, and $\{\omega_k\}$ their center frequencies, k is the number of IMFs, δ is the Dirac function, t is the time, $j^2=-1$ and * denotes convolution. For a complete description of the algorithm, see Dragomiretskiy and Zosso (2014).

VMD has three main parameters: the number k of IMFs, the quadratic penalty term α, and the convergence tolerance ε. To find the parameter k, we followed the approach suggested by Zuo et al. (2020), which is based on the observation of the center frequency of the last IMF. After defining an initial value for k, we look at the amplitude spectrum; if this decomposition mode presents the aliasing phenomenon, k is reduced by one and the analysis is repeated. A sensitivity analysis was performed to choose the best values for the quadratic penalty and the tolerance.

3.2 Gradient Boosting Regression

Gradient Boosting is a statistical model for function estimation based on a sequential ensemble of weak learners (Friedman 2001). In this method, the weak learner – usually a decision tree – is first used to predict an output variable y with a set of explanatory variables **x**. Then, the weak learner (g_n) is used to predict the residuals of the initial model, and this procedure is repeated until the loss reaches a threshold or a maximum number of models is built (N). Predictions are multiplied by a learning rate or shrinkage parameter ν to slow down the procedure and to increase the number of weak learners in the model:

$$f_n(x) = \nu * g_n(x) \tag{2}$$

The learning rate can vary between 0 and 1 but usually ranges from 0.1 to 0.3 (or less). The predicted value is added to the output of the previous model:

$$F_n(x) = F_{n-1}(x) + f_n(x)$$

Loss is minimized following a functional gradient descent algorithm. For regression tasks, the usual loss function is the mean squared error:

$$L(f) = \frac{1}{2}(y - F(x))^2 \tag{3}$$

The gradient descent algorithm is used to optimize the parameters of the predictive model by finding the local minimum of the loss function:

$$f_n(x) = -\frac{\partial L(f)}{\partial F} \tag{4}$$

The main parameters of the gradient boosting model are: (i) the number of trees, which defines the number of iterations; (ii) the tree depth, which influences the complexity of the tree; (iii) the learning rate, and (iv) the minimum number of observations in a node to result in splitting. In this study, we set the learning rate to 0.1 and the number of observations per node to 10. We tested different combinations of the tree depth (1, 2, and 3) and the number of trees (50, 100, and 150). The model parameters were tuned using fivefold cross-validation: the combination of parameters that provide the best performance across the cross-validation results is chosen.

3.3 Hybrid VMD-GBR Model

To check the stationarity of the signals, the Augmented Dickey-Fuller (ADF) test was performed. This test assumes a unit root for the univariate time series, i.e., it tests the null hypothesis that α = 1 in the following equation:

$$\Delta Y_t = c + \beta t + \alpha y_{t-1} + \phi_1 \Delta Y_{t-1} + \phi_2 \Delta Y_{t-2} + \cdots + \phi_p \Delta Y_{t-p} + e_t \tag{5}$$

The inputs for the predictive model were selected using the mutual information (MI) between the signals of the weather variables and the filtered water demand and the partial autocorrelation function (PACF) plots of each decomposed signal of water demand. The PACF approach is commonly used for streamflow forecasting (Ali et al. 2020; Feng 2020). The confidence interval for the PACF corresponds to $[-\frac{1.96}{\sqrt{n}}, \frac{1.96}{\sqrt{n}}]$, where n is the length of the training set; the significant lags are the ones that fall out of this interval.

The MI metric accounts for the interactions between two random variables without assuming linearity or continuity. Basically, the larger the value of MI, the closest the relationship between the variables and the amount of information that one contains about the other. MI is based on the concept of Shannon entropy, which measures the uncertainty of a variable. The MI between two variables X and Y is expressed as:

$$I(Y;X) = \sum_{x \epsilon X} \sum_{y \epsilon Y} (x, y) log\ log \left(\frac{p(x, y)}{p(x)p(y)} \right) \tag{6}$$

The methodology of the VMD-GBR model can be summarized as follows:

Step 1: Decompose the water demand, precipitation, and maximum temperature time series into additive intrinsic mode functions using VMD. The parameter k is defined by observing the power spectrum of the last IMF of each decomposed signal, which should not present a center frequency alias (Zuo et al. 2020). The quadratic penalty term α and the convergence tolerance ε are chosen with sensitivity analysis on model performance.

Step 2: Estimate the deterministic component of the signals of water demand using the Augmented Dickey-Fuller (ADF) test and reconstruct the time series using only the remaining signals.

Step 3: Detect the most relevant IMFs of the weather variables by calculating the mutual information between each of them and the reconstructed signal of water demand. These will be inputs for the predictive model.

Step 4: In addition to the IMFs selected in the previous step, choose the lagged inputs for the predictive model by observing the partial autocorrelation function of the water demand IMFs. The IMF corresponding to the trend component is not included in this analysis.

Step 5: Normalize all data using the min–max normalization:

$$x_{norm} = \frac{x - min(x)}{(x) - min(x)} \tag{7}$$

Step 6: Split the dataset into training and testing (here, we used 80% for model training and 20% for testing). The input variables are the lagged IMFs of water demand and the most relevant IMFs of weather variables. In this study, different combinations of the model parameters were tested, namely, the number of trees, the tree depth, shrinkage, and the number of observations in the terminal nodes. The parameters are tuned using fivefold cross-validation in the training dataset and the model performance is evaluated using the testing dataset.

3.3.1 Performance Assessment

Model performance was evaluated with three measures: R-squared, Mean Absolute Error (MAE), and Root Mean Squared Error (RMSE).

$$R^2 = \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y}_i)^2} \tag{8}$$

$$MAE = \frac{\sum_{i=1}^{n}|\hat{y}_i - y_i|}{n} \tag{9}$$

$$RMSE = \sqrt{\sum_{i=1}^{n}\frac{(\hat{y}_i - y_i)^2}{n}} \tag{10}$$

where y_i is the observed water demand at month i, $\hat{y}_i$ is the predicted water demand at month j, and n is the number of months in the prediction horizon.

4 Results and Discussion

The residential water demand time series was decomposed into four signals to avoid the aliasing effect observed in the last IMF when k was set to five (Figs. 3 and 4). Following the same approach, the precipitation and maximum temperature time series were decomposed into three IMFs each (Figs. 5 and 6).

The MI metric indicated that the second IMF of both maximum temperature and precipitation were the ones to contain the most information on the water demand series (Table 1). The autocorrelation functions of these signals present a seasonal pattern

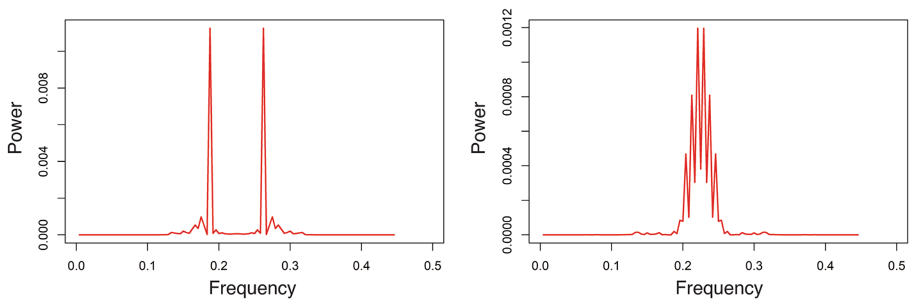

Fig. 3 Power spectrum of IMFs 4 (left) and 5 (right) of water demand time series. The aliasing effect can be observed in the IMF5, where the center frequency overlap

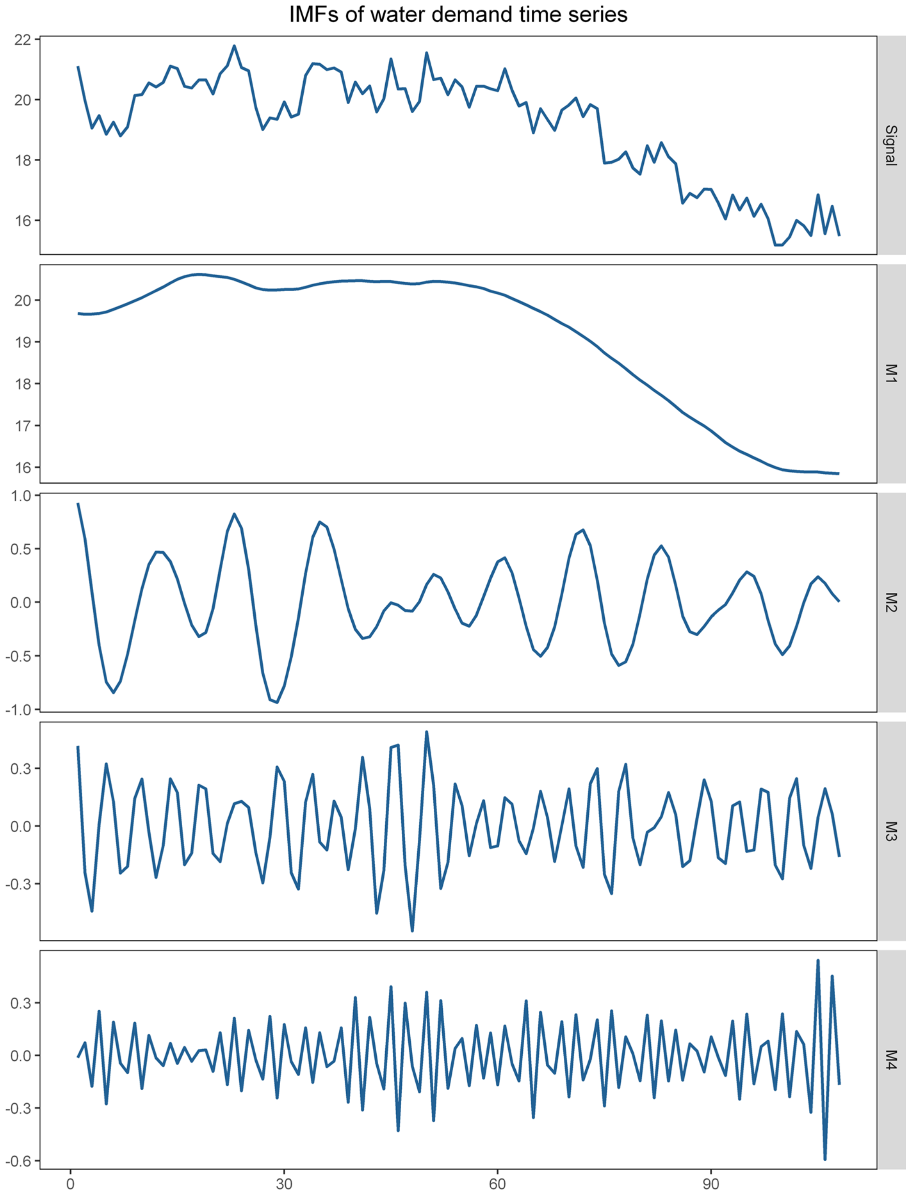

Fig. 4 Original and decomposed signals of water demand time series

where the peaks and the troughs are six months apart, while the third IMF does not seem to have a seasonal pattern. This might indicate that the last IMF of each series contains noise and thus could not directly influence demand patterns, while the second corresponds to a periodic signal.

The second IMF of water demand decomposition corresponds to the trend component. The decreasing trend in residential water demand after 2015 could be associated

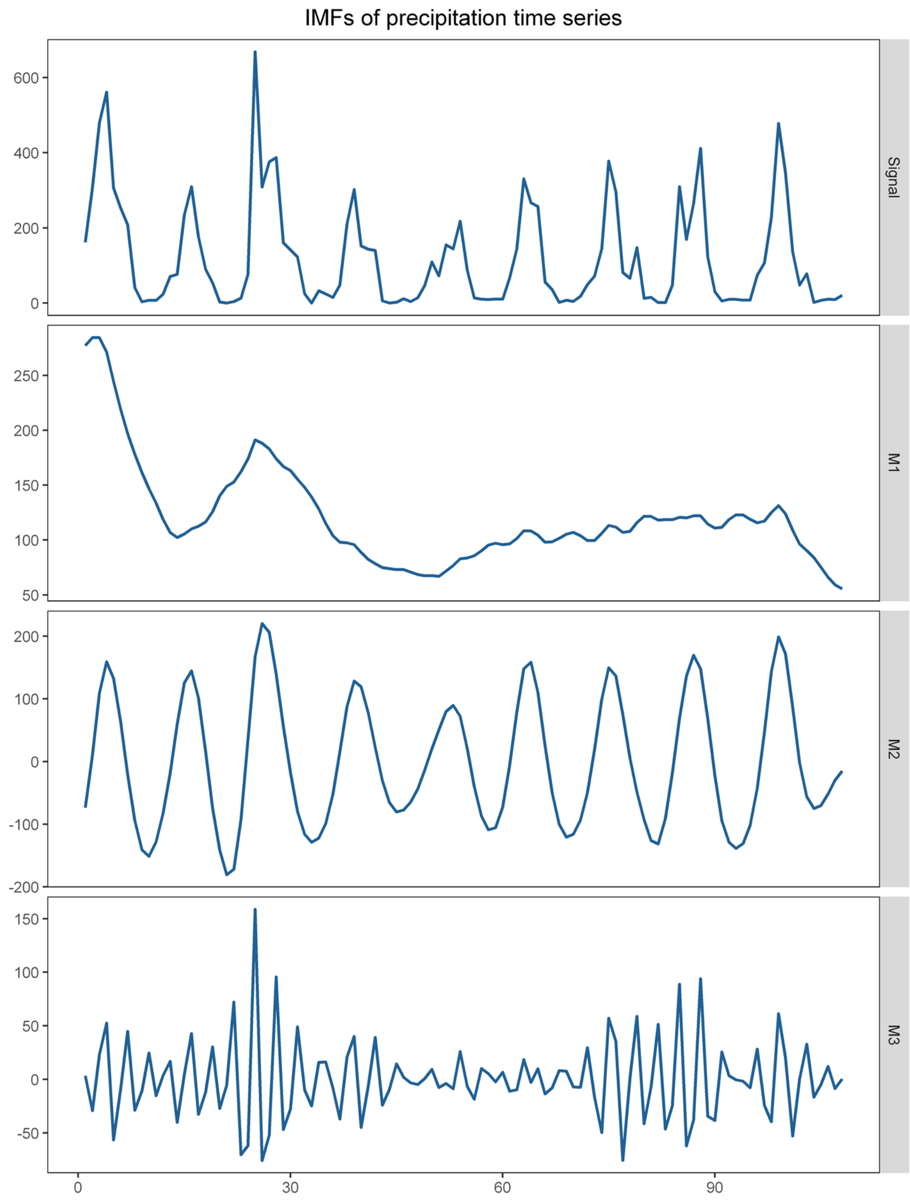

Fig. 5 Original and decomposed signals of mean precipitation time series

with conservation attitudes. After the 2012–2018 drought, the local water company implemented a contingency tariff to encourage a reduction of at least 20% in consumption. Socioeconomic factors, such as income, water price, and household composition could also be associated with changes in water demand trends, as pointed out in previous studies (Parandvash and Chang 2016; Zubaidi et al. 2020). Demand-side measures and even mass media coverage of extreme events can also affect the behavior of this

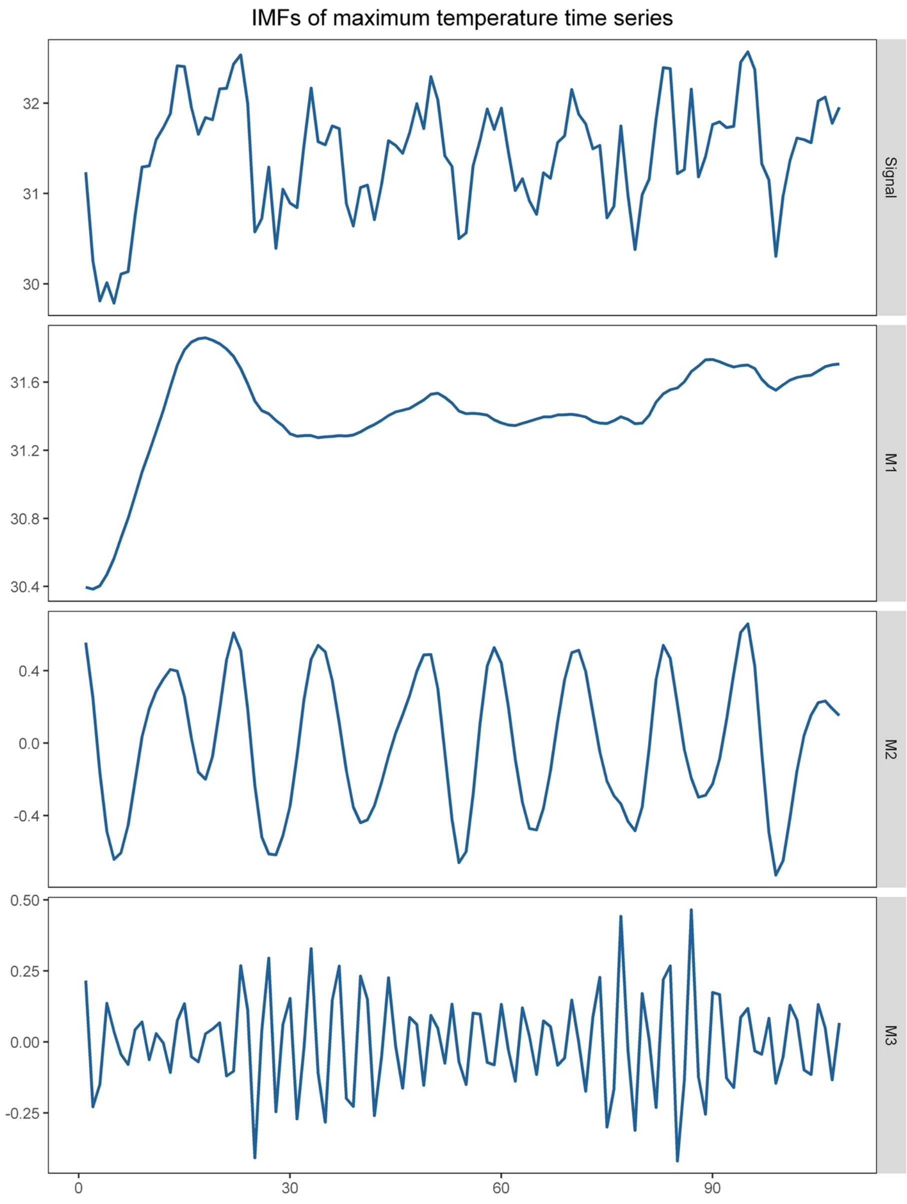

Fig. 6 Original and decomposed signals of maximum temperature time series

particular signal of water demand (Bolorinos et al. 2020). Modeling this component was beyond the scope of this study.

The additional relevant inputs were defined based on the PACF of the decomposed signals of water demand (Fig. 7). Previous water demand has a great influence on future consumption and climate variables alone would not be able to provide accurate predictions. The final dataset had 12 input variables.

Table 1 Mutual information between each decomposed signal and filtered water demand time series

Max Temperature			Precipitation		
IMF_1	IMF_2	IMF_3	IMF_1	IMF_2	IMF_3
0.07	0.22	0.06	0.07	0.11	0.05

A sensitivity analysis on the performance of the VMD-GBR model for 1-month ahead predictions indicated the most suitable values for the quadratic penalty term and the convergence tolerance, set to 10 and 10^{-5}, respectively. Table 2 indicates the R^2 values for different combinations of both parameters. After defining these parameters, the model was tested for predictions with leading times varying between one and twelve months.

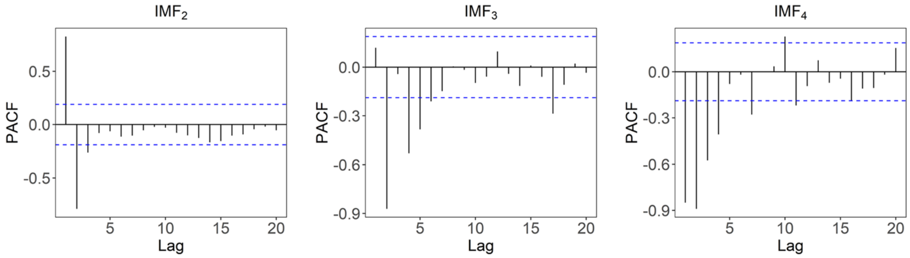

Fig. 7 Partial autocorrelation plots of water demand IMFs

Figure 8 presents the scatter plots of the testing set for each leading time. As it would be expected, the performance is worse as the leading time increases, but the model presents accurate predictions for 1, 2, 3, and 4-months ahead of water demand. Table 3 shows the R^2, RMSE, and MSE for each leading time. The VMD-GBR model successfully addresses climate variability in water demand prediction and reassures previous findings that residential consumption is driven by precipitation and temperature patterns (Adamowski et al. 2013; Parandvash and Chang 2016; Zubaidi et al. 2020).

Table 2 R^2 for different combinations of VMD parameters

α	ε						
	10^{-5}	10^{-6}	10^{-7}	10^{-8}	10^{-12}	10^{-15}	0
10	0.719	0.714	0.705	0.705	0.705	0.705	0.705
20	0.680	0.697	0.697	0.697	0.697	0.697	0.697
50	0.711	0.700	0.700	0.700	0.700	0.711	0.700
100	0.675	0.675	0.675	0.675	0.675	0.675	0.675
200	0.710	0.710	0.710	0.710	0.710	0.710	0.717
500	0.323	0.323	0.323	0.323	0.323	0.323	0.323
600	0.307	0.307	0.307	0.307	0.307	0.307	0.307
700	0.276	0.276	0.276	0.276	0.276	0.276	0.276
800	0.282	0.283	0.283	0.283	0.283	0.283	0.283
900	0.273	0.273	0.273	0.273	0.273	0.273	0.273
1000	0.272	0.266	0.266	0.266	0.266	0.266	0.266
2000	0.192	0.185	0.185	0.185	0.185	0.185	0.185

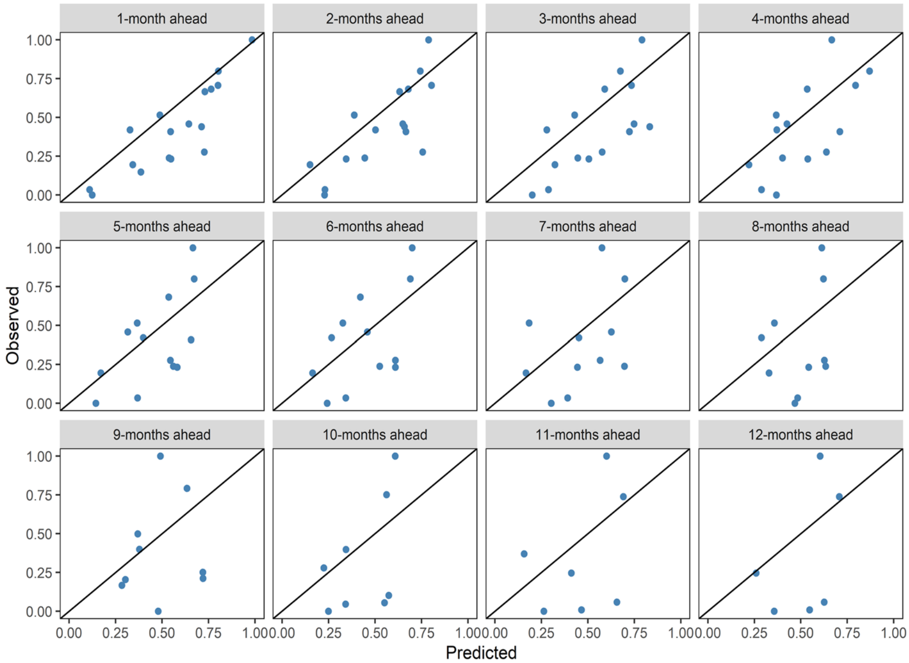

Fig. 8 Scatter plots of the normalized fitted values of the VMD-GBR model and normalized observed data for the testing period for each leading time

The importance measure of the input variables provides insight into the influence of climate variables in the prediction (Fig. 9). Although there is a large variance in the mean average MSE of the IMFs of temperature (tmpIMF2) and precipitation (precIMF2), they are amongst the top-ranked variables. This result confirms the hypothesis that residential water demand is driven by climate patterns.

Different from the application area of other researches mentioned here (Parandvash and Chang 2016; Rasifaghihi et al. 2020; Fiorillo et al. 2021), Ceará has a significant interannual

Table 3 Performance metrics for the VMD-GBR model predictions during the testing period for different leading times

Lead time (months)	R^2	RMSE	MAE
1	0.719	0.197	0.158
2	0.549	0.222	0.188
3	0.463	0.226	0.199
4	0.519	0.213	0.173
5	0.388	0.230	0.192
6	0.295	0.258	0.226
7	0.354	0.258	0.230
8	0.110	0.312	0.278
9	0.233	0.277	0.233
10	0.290	0.319	0.271
11	0.337	0.324	0.271
12	0.324	0.375	0.313

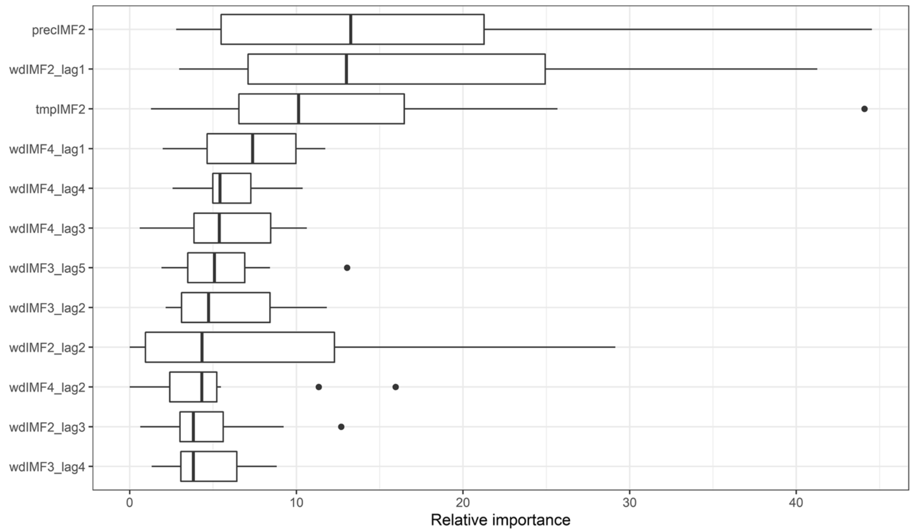

Fig. 9 Boxplot of the increase in MSE obtained when each of the input variables was removed from the dataset, ranked according to the median value of its relative importance

variability of both precipitation and temperature, mainly due to the El Niño South Oscillation and the Interhemispheric Tropical Atlantic Gradient (Hastenrath and Heller 1977). The region also presents intraseasonal variations related to the Madden–Julian Oscillation (Vasconcelos Junior et al. 2018). Although widely studied, these phenomena have complex interactions with precipitation that are still not completely understood by the scientific community. Hence, forecasting models that can properly detect seasonal variability of climate variables and their relationship with water demand can be of great value for operational management decisions and the adjustment of demand-side strategies.

5 Conclusion

This study set out to design a predictive model of monthly residential water demand including climate variability. To do that, we applied a decomposition technique to remove the water demand component associated with socioeconomic and policy characteristics and a machine learning technique to create an autoregressive model. The methodology is applied in Fortaleza, Brazil, a region with an elevated interannual and intraseasonal climate variability.

The results show that applying VMD to filter the water demand signal is an effective approach for removing components that are not directly associated with climate variability. Although the trend component could be associated with a response to drought, that is somehow dependent on climate, the effective implementation of water conservation policies and the change of habits in the households are more related to socioeconomic factors. The VMD-GBR model is suitable for regions affected by extreme events or complex climate variability.

Maximum temperature and precipitation were significant predictors of water demand and including their seasonal components as exogenous variables of the model improved accuracy. The model is appropriated for at least 4 months-ahead predictions, with an average RMSE of 0.193. The methods used in this study may be applied to medium-term planning of water supply systems and to guide operational and tactical decisions of water companies. The VMD-GBR approach can yet be coupled to seasonal climate forecast models and scenario-based predictions of the trend component of water demand. The findings are also useful to assess climate change impacts on future water demand, which could provide insight into policy design.

Authors Contributions All authors contributed to the study conception and design. Material preparation, data collection and analysis were performed by Taís Maria Nunes Carvalho. The first draft of the manuscript was written by Taís Maria Nunes Carvalho and the review and editing was performed by Taís Maria Nunes Carvalho and Francisco de Assis de Souza Filho. All authors read and approved the final manuscript.

Funding This study was supported by the Brazilian Federal Agency for Support and Evaluation of Graduate Education (Grant No. 88887.123932/2015–00); the Brazilian Council for Scientific and Technological Development (Grant No. 441457/2017–7); and the Cearense Foundation for Scientific and Technological Support (Cientista-chefe program).

Data Availability Some or all data and models that support the findings of this study are available from the corresponding author upon request.

Declarations

Conflicts of Interest The authors have no conflicts of interest to disclose.

References

Adamowski J, Adamowski K, Prokoph A (2013) A Spectral Analysis Based Methodology to Detect Climatological Influences on Daily Urban Water Demand. Math Geosci 45:49–68. https://doi.org/10.1007/s11004-012-9427-0

Ali M, Prasad R, Xiang Y, Yaseen ZM (2020) Complete ensemble empirical mode decomposition hybridized with random forest and Kernel ridge regression model for monthly rainfall forecasts. J Hydrol 124647 https://doi.org/10.1016/j.jhydrol.2020.124647

Bolorinos J, Ajami NK, Rajagopal R (2020) Consumption Change Detection for Urban Planning: Monitoring and Segmenting Water Customers During Drought. Water Resour Res 56:e2019WR025812. https://doi.org/10.1029/2019WR025812

Carvalho TMN, Filho F de A de S, Porto VC (2021) Urban Water Demand Modeling Using Machine Learning Techniques: Case Study of Fortaleza, Brazil. J Water Resour Plan Manag. https://doi.org/10.1061/(ASCE)WR.1943-5452.0001310

Chang H, Bonnette MR, Stoker P et al (2017) Determinants of single family residential water use across scales in four western US cities. Sci Total Environ 596–597:451–464. https://doi.org/10.1016/j.scitotenv.2017.03.164

Chang H, Praskievicz S, Bureau PW, et al (2014) Sensitivity of Urban Water Consumption to Weather and Climate Variability at Multiple Temporal Scales: The Case of Portland, Oregon

Chu L, Quentin Grafton R (2019) Policy Note: Short-term Pain for Long-term Gain: Urban Water Pricing and the Risk-adjusted User Cost. Water Econ Policy 5:1871005. https://doi.org/10.1142/S2382624X18710054

Dragomiretskiy K, Zosso D (2014) Variational mode decomposition. IEEE Trans Signal Process 62:531–544. https://doi.org/10.1109/TSP.2013.2288675

Duerr I, Merrill HR, Wang C et al (2018) Forecasting urban household water demand with statistical and machine learning methods using large space-time data: A Comparative study. Environ Model Softw 102:29–38. https://doi.org/10.1016/j.envsoft.2018.01.002

Feng Z, kai, Niu W jing, Tang Z yang, et al (2020) Monthly runoff time series prediction by variational mode decomposition and support vector machine based on quantum-behaved particle swarm optimization. J Hydrol 583:124627. https://doi.org/10.1016/j.jhydrol.2020.124627

Fiorillo D, Kapelan Z, Xenochristou M et al (2021) Assessing the Impact of Climate Change on Future Water Demand using Weather Data. Water Resour Manag 35:1449–1462. https://doi.org/10.1007/s11269-021-02789-4
Friedman JH (2001) Greedy function approximation: A gradient boosting machine. Ann Stat 29:1189–1232. https://doi.org/10.1214/aos/1013203451
Gao Y, Ge G, Sheng Z, Sang E (2008) Analysis and Solution to the Mode Mixing Phenomenon in EMD. In: 2008 Congress on Image and Signal Processing. IEEE, pp 223–227
Haque MM, Rahman A, Hagare D, Kibria G (2014) Probabilistic Water Demand Forecasting Using Projected Climatic Data for Blue Mountains Water Supply System in Australia. Water Resour Manag 28:1959–1971. https://doi.org/10.1007/s11269-014-0587-1
Hastenrath S, Heller L (1977) Dynamics of climatic hazards in northeast Brazil. Q J R Meteorol Soc 103:77–92. https://doi.org/10.1002/qj.49710343505
House-Peters LA, Chang H (2011) Urban water demand modeling: Review of concepts, methods, and organizing principles. Water Resour Res 47:351–360. https://doi.org/10.1029/2010WR009624
Huang NE, Shen Z, Long SR et al (1998) The empirical mode decomposition and the Hubert spectrum for nonlinear and non-stationary time series analysis. Proc R Soc A Math Phys Eng Sci 454:903–995. https://doi.org/10.1098/rspa.1998.0193
Jiménez Cisneros BE, Oki TNW, Arnell GB et al (2014) Freshwater Resources. In: Field CB, Barros VR, Dokken DJ et al (eds) Climate Change 2014 Impacts, Adaptation, and Vulnerability. Cambridge University Press, Cambridge, pp 229–270
Lee D, Derrible S (2020) Predicting Residential Water Demand with Machine-Based Statistical Learning. J Water Resour Plan Manag 146:04019067. https://doi.org/10.1061/(ASCE)WR.1943-5452.0001119
Maidment DR, Miaou S-P (1986) Daily Water Use in Nine Cities. Water Resour Res 22:845–851. https://doi.org/10.1029/WR022i006p00845
Milly PCD, Betancourt J, Falkenmark M, et al (2008) Stationarity Is Dead: Whither Water Management? Science (80-) 319:573–574. https://doi.org/10.1126/science.1151915
Olmstead SM (2014) Climate change adaptation and water resource management: A review of the literature. Energy Econ 46:500–509. https://doi.org/10.1016/j.eneco.2013.09.005
Orlowsky B, Seneviratne SI (2012) Global changes in extreme events: Regional and seasonal dimension. Clim Change 110:669–696. https://doi.org/10.1007/s10584-011-0122-9
Parandvash GH, Chang H (2016) Analysis of long-term climate change on per capita water demand in urban versus suburban areas in the Portland metropolitan area, USA. J Hydrol 538:574–586. https://doi.org/10.1016/j.jhydrol.2016.04.035
Pontes Filho JD, de Souza Filho F, A, Martins ESPR, Studart TM de C, (2020) Copula-Based Multivariate Frequency Analysis of the 2012–2018 Drought in Northeast Brazil. Water 12:834. https://doi.org/10.3390/w12030834
Rasifaghihi N, Li SS, Haghighat F (2020) Forecast of urban water consumption under the impact of climate change. Sustain Cities Soc 52:101848. https://doi.org/10.1016/j.scs.2019.101848
Torres ME, Colominas MA, Schlotthauer G, Flandrin P (2011) A complete ensemble empirical mode decomposition with adaptive noise. In: ICASSP, IEEE International Conference on Acoustics, Speech and Signal Processing - Proceedings. pp 4144–4147
Vasconcelos Junior FDC, Jones C, Gandu AW (2018) Interannual and intraseasonal variations of the onset and demise of the pre-wet season and the wet season in the northern northeast Brazil. Rev Bras Meteorol 33:472–484. https://doi.org/10.1590/0102-7786333007
Villarin MC, Rodriguez-Galiano VF (2019) Machine Learning for Modeling Water Demand. J Water Resour Plan Manag 145:04019017. https://doi.org/10.1061/(ASCE)WR.1943-5452.0001067
Wu Z, Huang NE (2009) Ensemble empirical mode decomposition: A noise-assisted data analysis method. Adv Adapt Data Anal 1:1–41. https://doi.org/10.1142/S1793536909000047
Yeh JR, Shieh JS, Huang NE (2010) Complementary ensemble empirical mode decomposition: A novel noise enhanced data analysis method. Adv Adapt Data Anal 2:135–156. https://doi.org/10.1142/S1793536910000422
Zubaidi SL, Ortega-Martorell S, Kot P et al (2020) A Method for Predicting Long-Term Municipal Water Demands Under Climate Change. Water Resour Manag 34:1265–1279. https://doi.org/10.1007/s11269-020-02500-z
Zuo G, Luo J, Wang N et al (2020) Decomposition ensemble model based on variational mode decomposition and long short-term memory for streamflow forecasting. J Hydrol 124776 https://doi.org/10.1016/j.jhydrol.2020.124776