Research Paper

Models for forecasting water demand using time series analysis: a case study in Southern Brazil

Danielle C. M. Ristow, Elisa Henning, Andreza Kalbusch and Cesar E. Petersen

ABSTRACT

Technology has been increasingly applied in search for excellence in water resource management. Tools such as demand-forecasting models provide information for utility companies to make operational, tactical and strategic decisions. Also, the performance of water distribution systems can be improved by anticipating consumption values. This work aimed to develop models to conduct monthly urban water demand forecasts by analyzing time series, and adjusting and testing forecast models by consumption category, which can be applied to any location. Open language R was used, with automatic procedures for selection, adjustment, model quality assessment and forecasts. The case study was conducted in the city of Joinville, with water consumption forecasts for the first semester of 2018. The results showed that the seasonal ARIMA method proved to be more adequate to predict water consumption in four out of five categories, with mean absolute percentage errors varying from 1.19 to 15.74%. In addition, a web application to conduct water consumption forecasts was developed.

Key words | ARIMA, exponential smoothing, forecasting water demand, time series

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HIGHLIGHTS

- Monthly urban water demand forecasts are conducted by analyzing time series.
- A case study in Southern Brazil is presented.
- A web application to conduct water consumption forecasts is proposed, which can be used in other regions and countries.

INTRODUCTION

Population growth, urbanization, industrialization and improved life standards have led to increased demand for drinking water in urban areas (Bai *et al.* 2014; Nunes *et al.* 2019). According to Billings & Jones (2008), water demand forecast supplies a basis for operational, tactical and strategic decision-making and can help improve the performance of water distribution systems by anticipating consumption values. Forecasting models generally facilitate understanding water consumption behavior (Stoker & Rothfeder 2014),

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besides helping the development of water-saving strategies (Babel Gupta & Pradhan 2007), energy and adequate destination for effluents (Herrera *et al.* 2010). In addition, understanding and managing water, in an urban context, is considered a critical factor for achieving sustainability (Marlow *et al.* 2013).

Forecasting monthly water consumption is important for efficient operation and management of an existing water supply system (Boubaker 2017). Furthermore, water demand can be seen as a dynamic system and requires mathematical modeling (Boubaker 2017). As stated by Donkor *et al.* (2014), there is a series of forecasting methods and choosing one directly depends on the quantity and quality of the data, desired forecast horizon and the availability of time and resources. Employing methods for modeling time series is quite widespread as there are two advantages: (i) the methods are simpler than the others and they are based on the premise that historical behavioral trends regarding series are maintained with time (Adamowski & Karapataki 2010); (ii) they are direct methods, forecasting without considering other external variables that quite often can be complex and uncertain (Zhai *et al.* 2012).

The objective of this study is to evaluate water consumption forecast models using time series analysis in a case study in the city of Joinville, Southern Brazil. In addition, a web application is proposed, which can be used in other regions and countries. The web application is expected to assist in planning water supply systems and managing water demand in regions with limited resources. According to Zhai *et al.* (2012), forecasting water demand has become an essential component in planning and managing water resources, as it supplies a simulated view of the future and contributes to identify an appropriate water supply–demand balance. The significance of this study arises from its application in monthly urban water consumption forecasts, easily replicated in any location using the proposed web application. The application was created with the open-source R language (R Core Team 2020) and the Shiny web application framework (Chang *et al.* 2020). In addition, other advantages of the proposed methodology are the application of classic forecasting methods, the use of free software, easy training of people and also the possibility of adapting the methodology to other situations to predict water consumption. This paper is structured in four sections, including the Introduction. The Methodology is presented in the next section, and the Results and discussion and Conclusions are presented in the last two sections.

METHODOLOGY

The application of time series forecasting models to predict monthly urban water consumption in the short term, the objective of this study, involves using low computational cost procedures to evaluate modeling techniques to choose more efficient forecasting models for the analyzed data set. The analysis of a set of actions based on the theoretical reference from the preliminary study was used to select forecasting models in a case study, in order to anticipate future water demand scenarios.

Knowing such scenarios is crucial for the management of local water resources, which includes ensuring water quality (Brentan *et al.* 2017), planning strategies to promote water savings and increasing resilience in the face of adverse situations that can compromise water supply (Billings & Jones 2008; Tiwari & Adamowski 2015). Figure 1 shows the methodology adopted in this study. The statistical analysis is conducted using the software R (R Core Team 2020), with the forecast package (Hyndman *et al.* 2020).

The data used in this research study refer to the micrometered monthly water consumption per water-consuming unit, in the urban environment of the city of Joinville, from January 2013 to December 2017. The municipal water supply company provided the data sorted into four consumption categories: residential, commercial, industrial and public. Residential water consumer units are defined as follows: all real estate properties are exclusively used for dwelling purposes. The industrial category refers to all production and/or transformation activities, businesses, housing developments and condos in the construction phase with a built area greater than 750 m^2. The commercial category refers to a real estate property used to perform commercial/business activities and/or provide a service. The public category is considered as units where the water supply is used for public municipal, state and federal administration purposes.

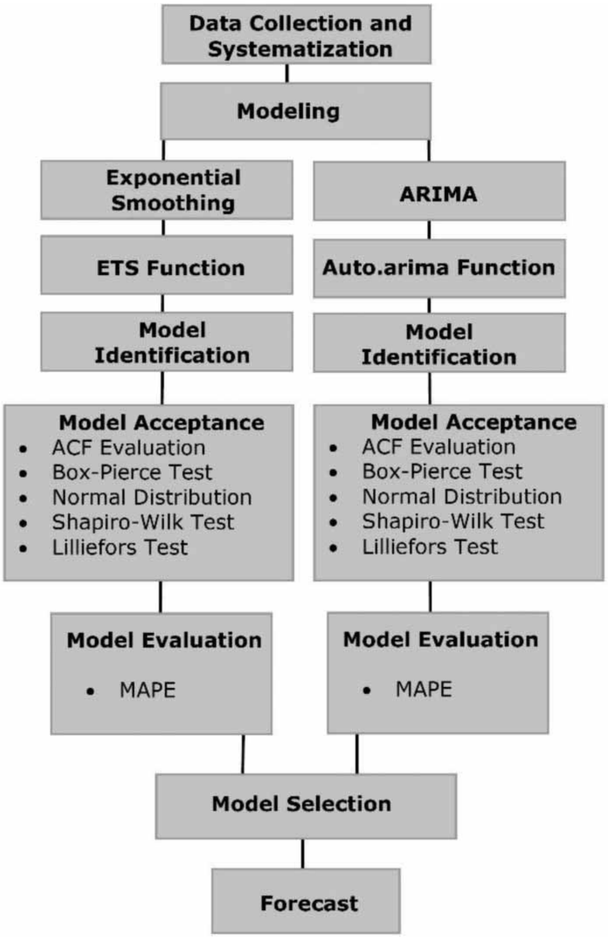

Figure 1 | Methodological steps.

This work also included the modeling of a total water consumption category, which deals with urban consumption, considering the sum of all categories. Linear interpolation was used to impute missing data and to replace outliers. The modeling and forecasting were performed using the forecast package (Hyndman *et al.* 2020). Two forecast models were developed for each consumption category: one employs exponential smoothing state-space models (ETS) and the other is performed through the Box–Jenkins methodology (ARIMA models). Automatic procedures were applied to choose the forecast package, and the model selection is based on the lowest value of the Akaike Information Criterion (Hyndman *et al.* 2020).

A forecasting model is only considered adequate if the residuals are normally distributed and do not display any autocorrelation. The autocorrelation function (ACF) graph was used to check for autocorrelation. Also, the Box–Pierce test considers the number of lags as equal to 10 for non-seasonal series, or equal to 2m, with m corresponding to the seasonal period. The residual normality was evaluated through the Shapiro–Wilk and Lilliefors tests. The adopted significance level (α) was 5%.

The forecast accuracy was measured based on the smallest mean absolute percentage error (MAPE). The MAPE was defined as the main model selection criterion for this research study, as it is considered relevant to compare the forecast models (Arandia *et al.* 2016), and it is easily interpreted and widely used in water demand modeling studies (Al-Zharani & Abo-Monasar 2015; Yalçintaş *et al.* 2015; Arandia *et al.* 2016). After modeling, a 6-month water consumption forecast was performed. The predicted results were compared to the actual consumption data for each category from January to June 2018, to gauge model accuracy. The models bearing the lowest MAPE value were chosen as the most adequate.

RESULTS AND DISCUSSION

Joinville is located in the northeastern region of the state of Santa Catarina, Southern Brazil. Its territorial area is 1,127.946 km^2 (IBGE 2018). The population of Joinville was 569,645 in 2016, and the estimated total population was 577,077 in 2017 (IBGE 2018). According to the updated Köppen–Geiger classification, the predominant climate in the region is classified as warm temperature, fully humid, with hot summer (Kottek *et al.* 2006).

The time series on residential water consumption in Joinville can be observed in Figure 2(a). A continuously increasing trend can be observed in the analyzed period, as well as some seasonality, as the highest consumption values are registered in the months of summer (the end and beginning of each school year), and the lowest during the months of winter. Figure 2(b)–2(d) show the data series on commercial, industrial and public water consumption in Joinville, respectively. Figure 2(c) shows the industrial water consumption series graph. An increasing trend could be observed during the first years, which was reverted in 2015, possibly because of the drop in industrial

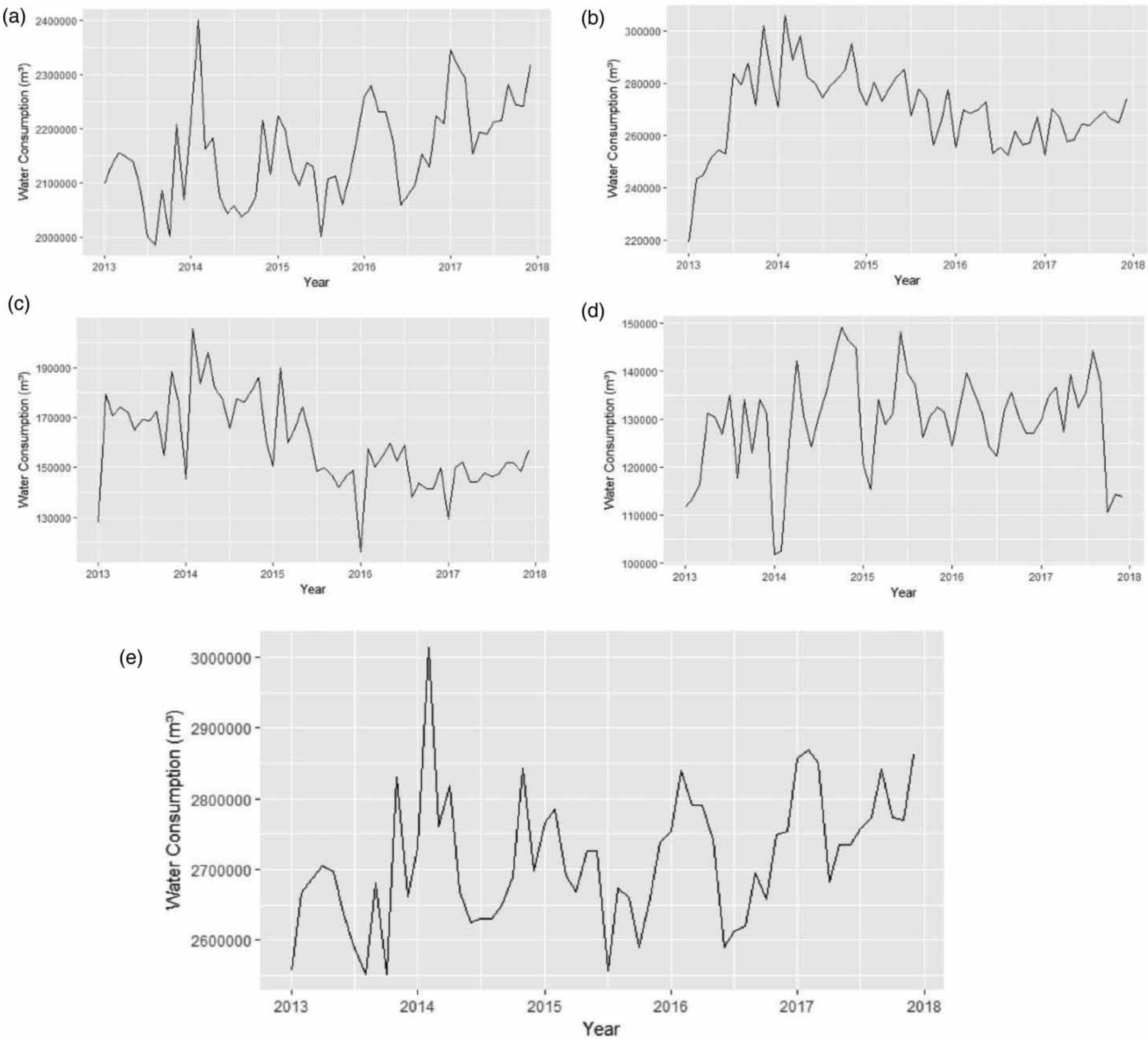

Figure 2 | Time series on residential (a), commercial (b), industrial (c), public (d) and total (e) water consumption in Joinville from January 2013 to December 2017.

production in the state (IBGE 2018). The total category included the sum of all the consumption categories, and it is displayed in Figure 2(e). The series displays a growth trend until mid-2014, with a drop in consumption until mid-2015, when it starts growing again, maintaining that trend until the end of the analyzed period. Data seasonality was also observed, with a consumption drop during the coldest months and high consumption being registered in the months of summer. The lowest value was observed in January 2013 (2,551,517 m^3), and the highest was in February 2014 (3,014,547 m^3).

The lowest residential water consumption was observed in mid-2013 (1,986,054 m^3), while the highest was at the beginning of 2014 (2,400,832 m^3). The initial analysis confirmed the data displayed normal distribution ($p = 0.6436$). The first model produced for the residential category employed the exponential smoothing method. The model defined by the software was an ETS (M, A, A) with a

Table 1 | Summary of results obtained from modeling

Category	Method	Type	MAPE in sample (%)	MAPE out of sample (%)
Residential	ETS[a]	(M, A, A)	1.95	1.89
Commercial	ETS	(M, Ad, N)	2.89	2.34
	ARIMA[a]	(1,1,0) (1,0,0) [12]	2.83	2.08
Industrial	ETS	(A, N, A)	4.43	6.65
	ARIMA[a]	(0,1,1) (0,1,1) [12]	4.65	4.58
Public	ARIMA[a]	(0,0,1) (1,0,0) [12] with non-zero mean	5.32	15.74
Total	ARIMA[a]	(1,1,1) (1,0,1) [12]	2.19	1.19

[a]Selected model.

multiplicative error, additive trend and additive seasonality (Table 1). The residuals were normally distributed according to the Shapiro–Wilk test ($p = 0.2374$) and the Lilliefors test ($p = 0.6918$), and there was no autocorrelation according to the Box–Pierce test ($p = 0.5351$). The seasonal ARIMA (SARIMA) was the second model for the residential category, defined as ARIMA (1,0,0) (1,1,0) [12] with drift. The normality tests indicated that the model residuals do not represent a normal distribution, so it was discarded. In the Shapiro–Wilk test, the calculated *p*-value was 0.03008, and the Lilliefors test showed a *p*-value of 0.0001031. The model shows no evidence that its residues are autocorrelated, according to the Box–Pierce test ($p = 0.9891$).

Regarding commercial water consumption, the lowest consumption (219,056 m^3) was observed at the beginning of 2013, and the highest (305,956 m^3) in February 2014. Regarding seasonality, the highest and lowest consumption peaks are in the months of summer. Consumption rises in the period before the end of the year and school recess, decreases in the recess period of some local companies and increases again as activities resume. There is also a decrease of consumption in the colder months. The Shapiro–Wilk test shows that the series has a normal distribution ($p = 0.3271$). The adjusted smoothing model was an ETS (M, Ad, N) with a multiplicative error, additive smoothened trend and no seasonality. The residuals display normal distribution in the Shapiro–Wilk and Lilliefors tests ($p = 0.8447$ and 0.4635, respectively). The model residuals are not autocorrelated, according to the Box–Pierce test ($p = 0.6571$). The SARIMA model for the commercial category was defined as a SARIMA (1,1,0) (1,0,0) [12]. The residuals met the requirements, as they displayed normality (Shapiro–Wilk $p = 0.1635$ and Lilliefors $p = 0.1758$) and did not present autocorrelation (Box–Pierce $p = 0.7988$).

Regarding industrial water consumption, there was a substantial consumption decrease during the summer vacation period observed in the series, due to seasonality. The minimum consumption was observed at the beginning of 2016 (116,044 m^3), and the maximum (205,387 m^3) in February 2014. The data display normal distribution ($p = 0.2776$). The model developed for the category with the application of the exponential smoothing method was an ETS (A, N, A) with additive error, without any trends and additive seasonality. In the analysis stage, statistical tests indicated that there is normality in the distribution of residuals confirmed by the results of the Shapiro–Wilk test ($p = 0.3166$) and the Lilliefors test ($p = 0.1352$). The Box–Pierce test indicated that the residuals are not autocorrelated ($p = 0.81$). A SARIMA (0,1,1) (0,1,1) [12] model for the industrial category was defined by the software applying the Box–Jenkins methodology. The results from the statistical tests confirmed that the model residuals are not autocorrelated ($p = 0.881$). The residual distribution normality was confirmed by the Shapiro–Wilk test ($p = 0.294$).

The public water consumption data series displays seasonality and an accentuated consumption drop during the summer vacation months and presents some reduction during the coldest months. The lowest consumption value was in January 2014 (101,699 m^3). The maximum consumption also occurred in 2014 (149,150 m^3), but in October. The adjusted model for public water consumption in Joinville with the application of the exponential smoothing model was an ETS (M, N, N) with multiplicative error, without any trends and no seasonality. The residuals met normality (Shapiro–Wilk $p = 0.1399$ and Lilliefors $p = 0.2326$). Despite the result of the Box–Pierce test ($p = 0.4297$), the ACF graph (not shown in this paper) indicates two lags that exceed the limit of the dashed lines, indicating that the exponential smoothing model residuals may be autocorrelated. Therefore, the exponential smoothing model cannot be considered adequate for making water consumption predictions for the public category in Joinville during the analyzed period. The second model developed for the public category was a SARIMA (0,0,1) (1,0,0) [12] with non-zero mean. The residuals were displayed as white noise, without autocorrelation ($p = 0.9918$) and distributed normally (Shapiro–Wilk $p = 0.6039$ and Lilliefors $p = 0.2426$).

The model for the total water consumption in Joinville, adjusted by using the exponential smoothing method, was an ETS (A, N, N) with an additive error, no trends and no seasonality. The graphs and statistical tests indicated that the residuals from the models were displayed as white noise. However, the Box–Pierce test indicated that the residuals displayed autocorrelation ($p = 0.03948$). The adjusted SARIMA model for the total category was identified as ARIMA (1,1,1) (1,0,1) [12]. The residuals displayed normal distribution in the Lilliefors test ($p = 0.4886$) and no autocorrelation ($p = 0.7686$).

Table 1 presents the overall characteristics of the adjusted models for each category. Each model's accuracy was evaluated after modeling, based on the MAPE calculation, considering the in-sample (model calibration) and out-of-sample (model validation) forecasts.

The exponential smoothing model developed for the residential category proved adequate for forecasting consumption in the city of Joinville, with 1.89% test MAPE. The SARIMA models proved to be adequate for the commercial and industrial categories, displaying some small errors. The structure of the models could capture some specificities and standards from the series.

For the public category, the model produced by the exponential smoothing method was rejected because it contained two lags exceeding the dashed lines in the residual ACF graph, despite the Box–Pierce test considering the absence of autocorrelation with a p-value of 0.4297, and normality tests indicating a normal distribution. In this category, the SARIMA model was considered qualified to generate the predictions, as it has normally distributed residuals with no autocorrelation. In the training stage, the MAPE was 5.32%. However, in the accuracy-check stage, the calculated MAPE was 15.74%, indicating that the ARIMA model was not as effective in capturing the series structure, showing a better performance in adapting to the observed data curve than in the forecast itself.

Analyzing the model's acceptance criteria, in the total category, only the SARIMA model was considered adequate for the predictions (out-of-sample MAPE = 1.19%). Comparing the obtained results, the models developed by the ARIMA method performed better in four out of five analyzed categories. Only in the residential category did the exponential smoothing method produce a more assertive model. The ARIMA model for the residential category could be improved through previous mathematical series-data transformations, to make the pattern more consistent across the data set (Hyndman & Athanasopoulos 2020). As automatic modeling was the objective of this work, with a minimum interference from the predictor, such transformations were not applied. The forecasts were performed for all model categories for a 6-month horizon. The actual water consumption series, the values adjusted by the model, the punctual forecasts and the respective confidence intervals ranging from 80 to 95% (light gray) are presented in Figure 3. The blue line represents the forecasts from January to June 2018.

In comparison with the actual data, the per-category demand forecast overestimated consumption by 195,291 m^3, while the total category model forecast underestimated real consumption by 92,549 m^3. These results may indicate that, for the city of Joinville, developing forecasts without categorizing consumption could be more assertive. However, the obtained results were calculated using the assumptions defined in the proposed methods. Thus, making the category-divided consumption forecast should be chosen at the researcher's discretion, depending on the availability of data and the study objectives.

Finally, Figure 4 shows the web application (Petersen et al. 2020) that summarizes the analyses presented in this study.

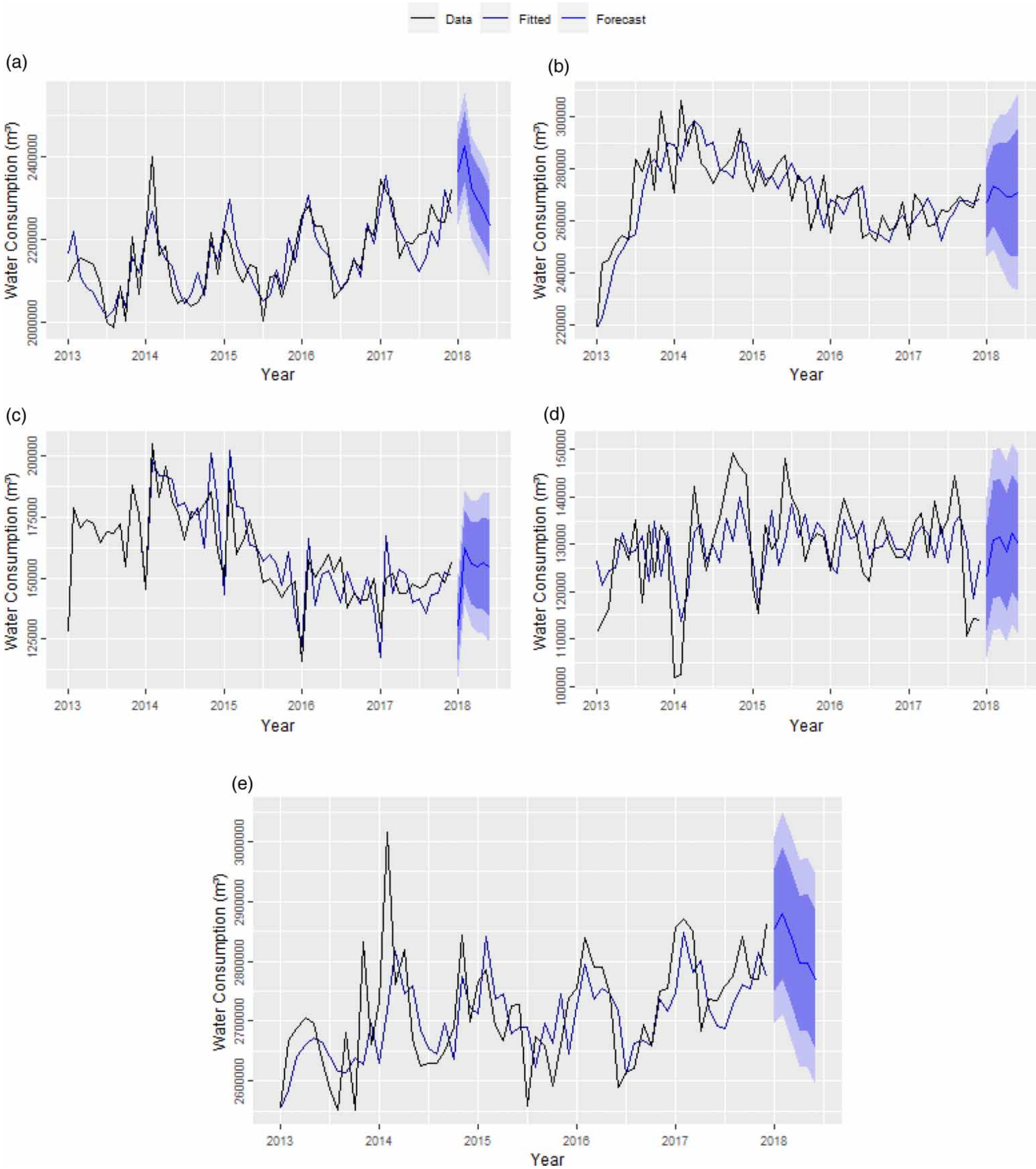

Figure 3 | Forecast graphs on water consumption in Joinville. (a) Residential category for the ETS model; (b) commercial category for the SARIMA model; (c) industrial category for the SARIMA model; (d) public category for the SARIMA model and (e) total category for the SARIMA model. Please refer to the online version of this paper to see this figure in color: http://dx.doi.org/10.2166/washdev.2021.208.

Figure 4 | Web app for forecasting monthly water consumption.

The application allows exploratory data analysis based on descriptive statistics and the construction of the time series graph, the estimation of the exponential smoothing and SARIMA models, the model quality analysis and the conduction of forecasts. The original series, predicted values, forecasts and respective confidence intervals can be viewed in the application. Mathematical models can be useful for many purposes, such as programming, diagnostics, management, control and forecasting in urban water supply systems (Boubaker 2017). Modeling framework and appropriate tools are important for evaluating possible solutions for further decision-making (Goharian & Burian 2018). The Supplementary Material contains the application code and data referring to the analysis carried out in this study. The application source code is open and can be adapted according to local needs, allowing the inclusion of other modeling processes.

CONCLUSIONS

The obtained results demonstrate that the proposed methodology can be easily applied to monthly urban water consumption forecasts in any location, as long as there is enough available consumption data regarding the required number of observations to apply the methods. Other advantages of the proposed methodology are the application of classic forecasting methods, the use of free software, the easy training of people and also how the proposed methodology can be adapted to other situations to forecast water consumption.

The models adjusted correctly to the data, identifying consumption increase and reduction trends, as well as seasonality. When analyzing the recommendation of a specific method to model water consumption in this study, the SARIMA method was more assertive in four out of five analyzed categories (considering model adequacy and the forecast error evaluation).

The residential category was not well adjusted by the SARIMA model, but by observing the results of the total category, formed mostly by residential consumption (about 80%), this model could certainly be improved through mathematical transformations. For the continuity of this work, the manual definition of some model parameters and data manipulation, as well as the creation of prediction error monitoring mechanisms, are suggested. Furthermore, applying other models, such as neural networks and the combination of different models, is another suggestion for future work.

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DATA AVAILABILITY STATEMENT

All relevant data are included in the paper or its Supplementary Information.

REFERENCES

Adamowski, J. & Karapataki, C. 2010 Comparison of multivariate regression and artificial neural networks for peak urban water-demand forecasting: evaluation of different ANN learning algorithms. *ASCE Journal of Hydrologic Engineering* **15** (10), 729–743. doi:10.1061/(ASCE)WR.1943-5584.0000245.

Al-Zharani, M. A. & Abo-Monasar, A. 2015 Urban residential water demand prediction based on artificial neural networks and time series models. *Water Resources Management* **29** (10), 3651–3662. doi:10.1007/s11269-015-1021-z.

Arandia, E., Ba, A., Eck, B. & Mckeena, S. 2016 Tailoring seasonal time series models to forecast short-term water demand. *Journal of Water Resources Planning and Management* **142** (3), 1–10. doi:10.1061/(ASCE)WR.1943-5452.0000591.

Babel, M. S., Gupta, A. D. & Pradhan, P. 2007 A multivariate econometric approach for domestic water demand modeling: an application to Kathmandu, Nepal. *Water Resources Management* **21** (3), 573–589. doi:10.1007/s11269-006-9030-6.

Bai, Y., Wang, P., Li, C., Xie, J. & Wang, Y. 2014 A multi-scale relevance vector regression approach for daily urban water demand forecasting. *Journal of Hydrology* **517**, 236–245. doi:10.1016/j.jhydrol.2014.05.033.

Billings, B. & Jones, C. 2008 *Forecasting Urban Water Demand*, 2nd edn. American Waterworks Association, Denver.

Boubaker, S. 2017 Identification of monthly municipal water demand system based on autoregressive integrated moving average model tuned by particle swarm optimization. *Journal of Hydroinformatics* **19**, 261–281. doi:10.2166/hydro.2017.035.

Brentan, B. M., Luvizotto, Jr, E., Herrera, M., Izquierdo, J. & Pérez-García, R. 2017 Hybrid regression model for near real-time urban water demand forecasting. *Journal of Computational and Applied Mathematics* **309**, 532–541. doi:10.1016/j.cam.2016.02.009.

Chang, W., Cheng, J., Allaire, J. J., Xie, Y. & McPherson, J. 2020 *shiny: Web Application Framework for R.* R Package Version 1.4.0.2. Available from: https://CRAN.R-project.org/package=shiny (accessed 8 May 2020).

Donkor, A., Mazzuchi, T. A., Soyer, R. & Roberson, J. A. 2014 Urban water demand forecasting: review of methods and models. *Journal of Water Resources Planning and Management* **140** (2), 146–159. doi:10.1061/(ASCE)WR.1943-5452.0000314.

Goharian, E. & Burian, S. J. 2018 Developing an integrated framework to build a decision support tool for urban water management. *Journal of Hydroinformatics* **20**, 708–727. doi:10.2166/hydro.2018.088.

Herrera, M., Torgo, L., Izquierdo, J. & Pérez-García, R. 2010 Predictive models for forecasting hourly urban water demand. *Journal of Hydrology* **387**, 141–150. doi:10.1016/j.jhydrol.2010.04.005.

Hyndman, R. J. & Athanasopoulos, G. 2020 *Forecasting: Principles and Practice*, 3rd edn. OTexts, Melbourne. Available from: https://otexts.com/fpp3/ (accessed 22 April 2020).

Hyndman, R., Athanasopoulos, G., Bergmeir, C., Caceres, G., Chhay, L., O'Hara-Wild, M., Petropoulos, F., Razbash, S., Wang, E. & Yasmeen, F. 2020 *forecast: Forecasting Functions for Time Series and Linear Models.* R Package Version 8.12. Available from: https://pkg.robjhyndman.com/forecast/ (accessed 22 April 2020).

IBGE – Instituto Brasileiro de Geografia e Estatística 2018 *Cidades*. Available from: https://cidades.ibge.gov.br/brasil/sc/joinville (accessed 4 April 2018).

Kottek, M., Grieser, J., Beck, C., Rudolf, B. & Rubel, F. 2006 World Map of the Köppen-Geiger climate classification updated. *Meteorologische Zeitschrift* **15**, 259–263. doi:10.1127/0941-2948/2006/0130.

Marlow, D. R., Moglia, M., Cook, S. & Beale, D. J. 2013 Towards sustainable urban water management: a critical reassessment. *Water Research* **47** (20), 7150–7161. doi:10.1016/j.watres.2013.07.046.

Nunes, L. G. C. F., Soares, A. E. P., Soares, W. A. & Silva, S. R. 2019 Water consumption in public schools: a case study. *Journal of Water, Sanitation and Hygiene for Development* **9** (1), 119–128. doi:10.2166/washdev.2019.074.

Petersen, C. E., Ristow, D. C. M., Henning, E. & Kalbusch, A. 2020 *Web Application Developed in Shiny and R to Forecast Monthly Water Consumption Using ARIMA and Exponential Smoothing Models*. Available from: https://elisa-henning.shinyapps.io/water-demand-forecast-master/ (accessed 10 December 2020).

R Core Team 2020 *R: A Language and Environment for Statistical Computing*. R Foundation for Statistical Computing, Vienna, Austria. Available from: https://www.R-project.org/ (accessed 8 May 2020).

Stoker, P. & Rothfeder, R. 2014 Drivers of urban water use. *Sustainable Cities and Society* **12**, 1–8. doi:10.1016/j.scs.2014.03.002.

Tiwari, M. K. & Adamowski, J. F. 2015 Medium-term urban water demand forecasting with limited data using an ensemble wavelet-bootstrap machine-learning approach. *Journal of Water Resources Planning and Management* **141** (2), 532–541. doi:10.1061/(ASCE)WR.1943-5452.0000454.

Yalçintaş, M., Bulu, M., Küçükvar, M. & Samadi, H. 2015 A framework for sustainable urban water management through demand and supply forecasting: the case of Istanbul. *Sustainability* **7** (8), 11050–11067. doi:10.3390/su70811050.

Zhai, Y., Wang, J., Teng, Y. & Zuo, R. 2012 Water demand forecasting of Beijing using the time series forecasting method. *Journal of Geographical Science* **22** (5), 919–932. doi:10.1007/s11442-012-0973-7.

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