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Seasonal-trend and multi-objective ensemble learning model for water consumption forecasting

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Agenda

- Introduction
- Objectives and Contribution
- Datasets
- Methodology
- Results
- Conclusion
- References

Source: https://www.fostercity.org/publicworks/page/water-consumption-customer-portal

Introduction

- Water demand plays a key role in the urban planning;
- Seasonal and trend are the main features of water demand;
- These features make the forecasting process hard;
- Ensemble methods can deal with it and enhance the forecasting accuracy.

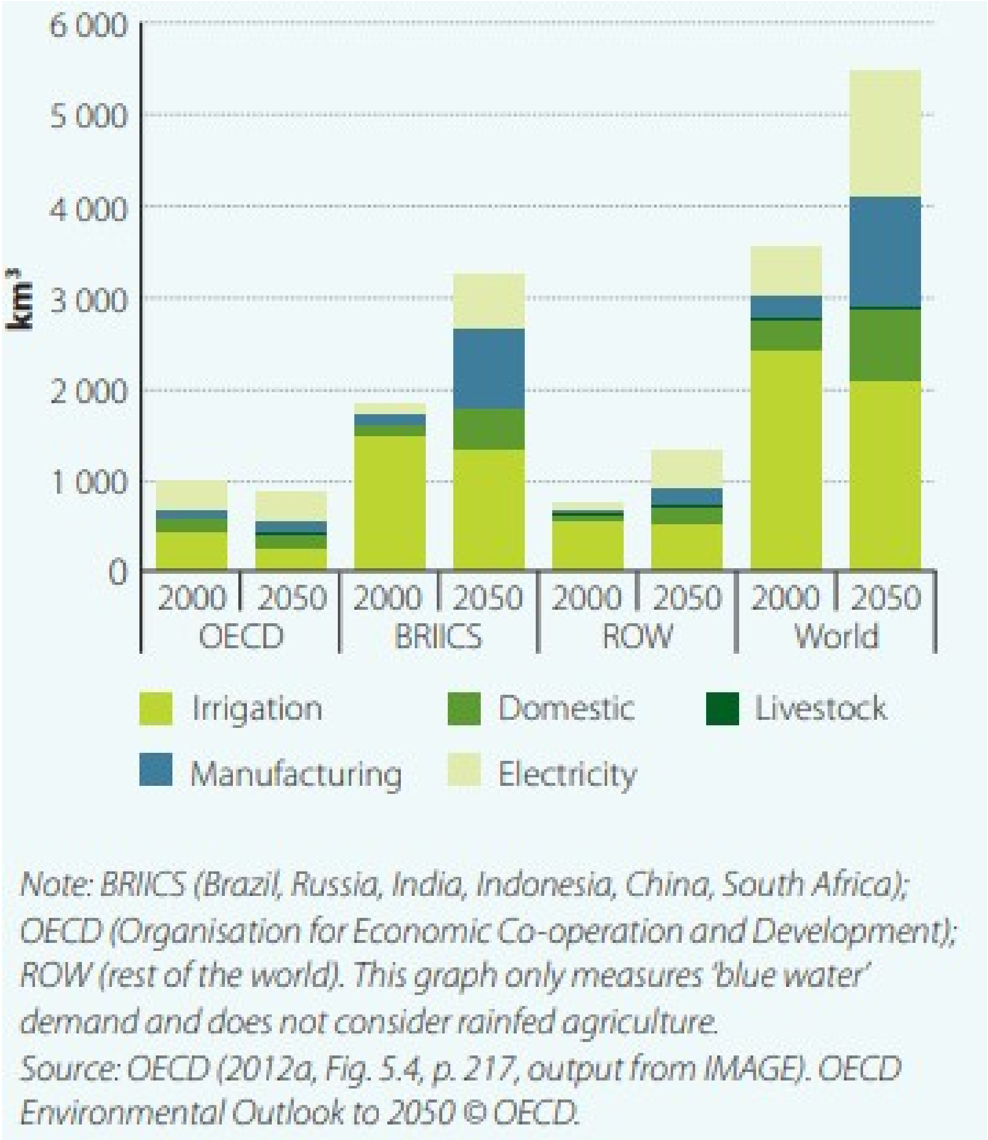

Figure 1: Global Water demand (km³) in 2000 and 2050

Source: https://unesdoc.unesco.org/ark:/48223/pf0000231823

Introduction

The objective is to propose an ensemble learning model to forecasting multi-step-ahead, one up to three-months-ahead water demand for Brazilian states;

Proposed model is composed by

- season and trend decomposition,
- some machine learning models, and
- **multi-objective** optimization;

The main contribution is the combination of different techniques including time-series pre-processing, non-linear forecasting models, and multi-objective optimization to develop an efficient forecasting model.

Datasets – Water demand (m³) for Brazilian Cities

- Datasets for two Brazilian cities, Palmas and Pato Branco;
- There are 152 monthly observations from January 2000 to August 2012 provided from the Water and Sanitation Company of Paraná;
- The data was split into Training and Testing sets in the proportion of 70% and 30%, respectively;
- Time series cross-validation is applied in training set to tune the models’ hyperparameters.

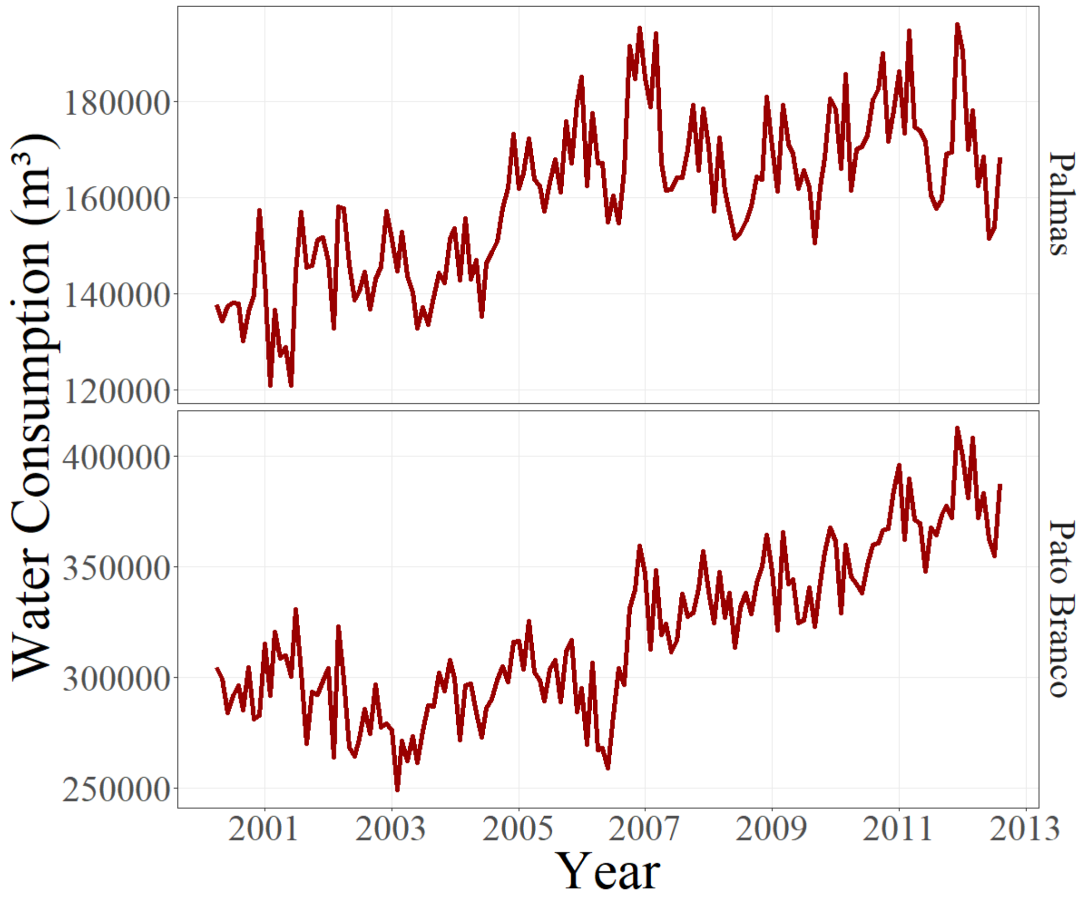

Figure 2: Water demand (m³) time series.

Methodology

- **STL** (Seasonal and Trend decomposition using Loess);
- Three different algorithms:
  - **GP** (Gaussian Processes)
  - **RIDGE** Regression;
  - **SVR** (Support Vector Regression with Linear kernel);
- Multi-Objective Procedure;
  - **NSGA-II** (Non-Dominated Sorting Genetic Algorithm – version II);
  - **BIAS-VARIANCE** trade-off;
  - **TOPSIS** (Technique for Order of Preference by Similarity to Ideal Solution);
- Performance measures:
  - **RMSE** (Root mean square error);
  - **MAPE** (Mean absolute percentage error);
  - **MAE** (Mean absolute error);

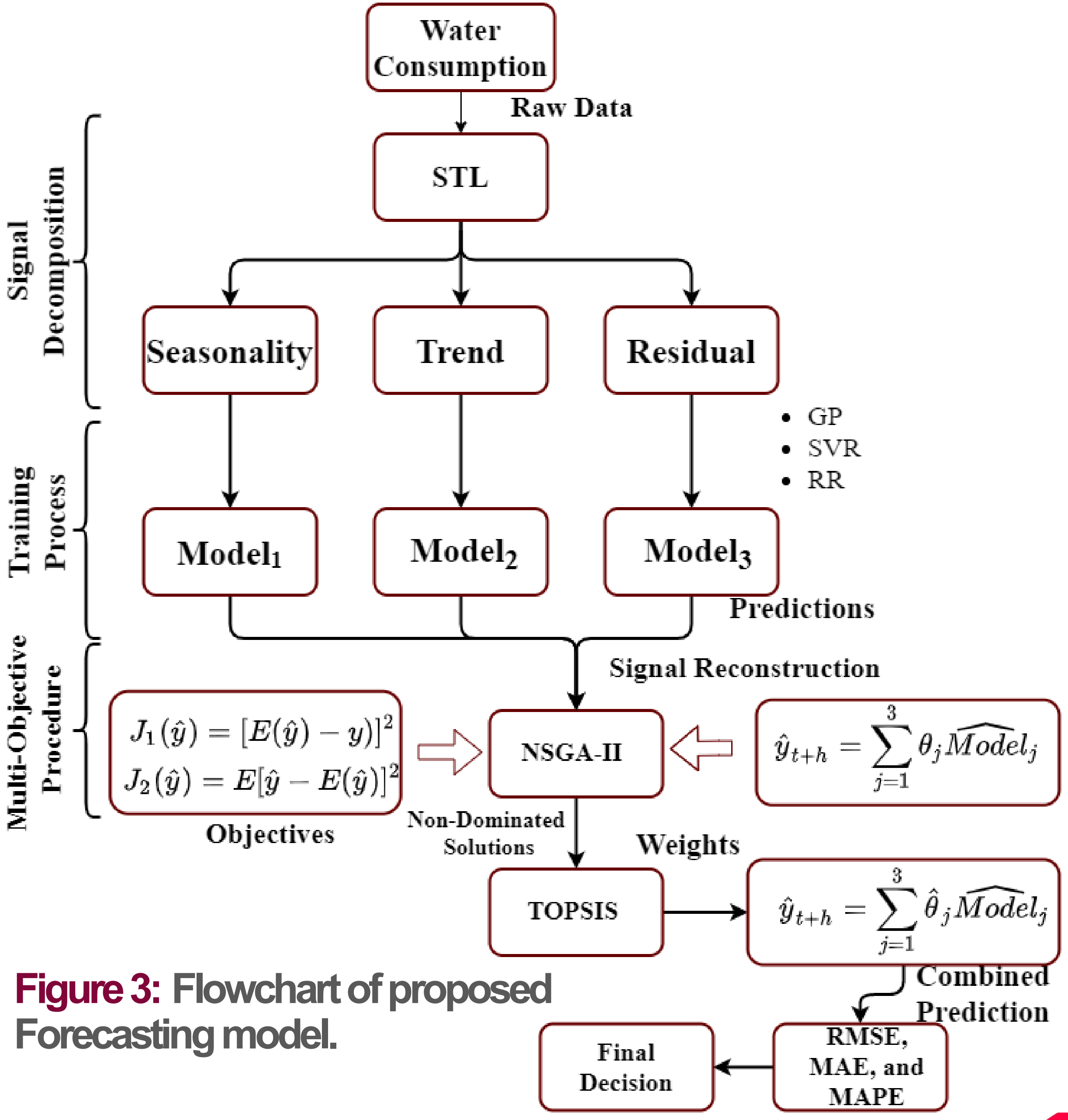

Figure 3: Flowchart of proposed Forecasting model.

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Decomposed water demand time series

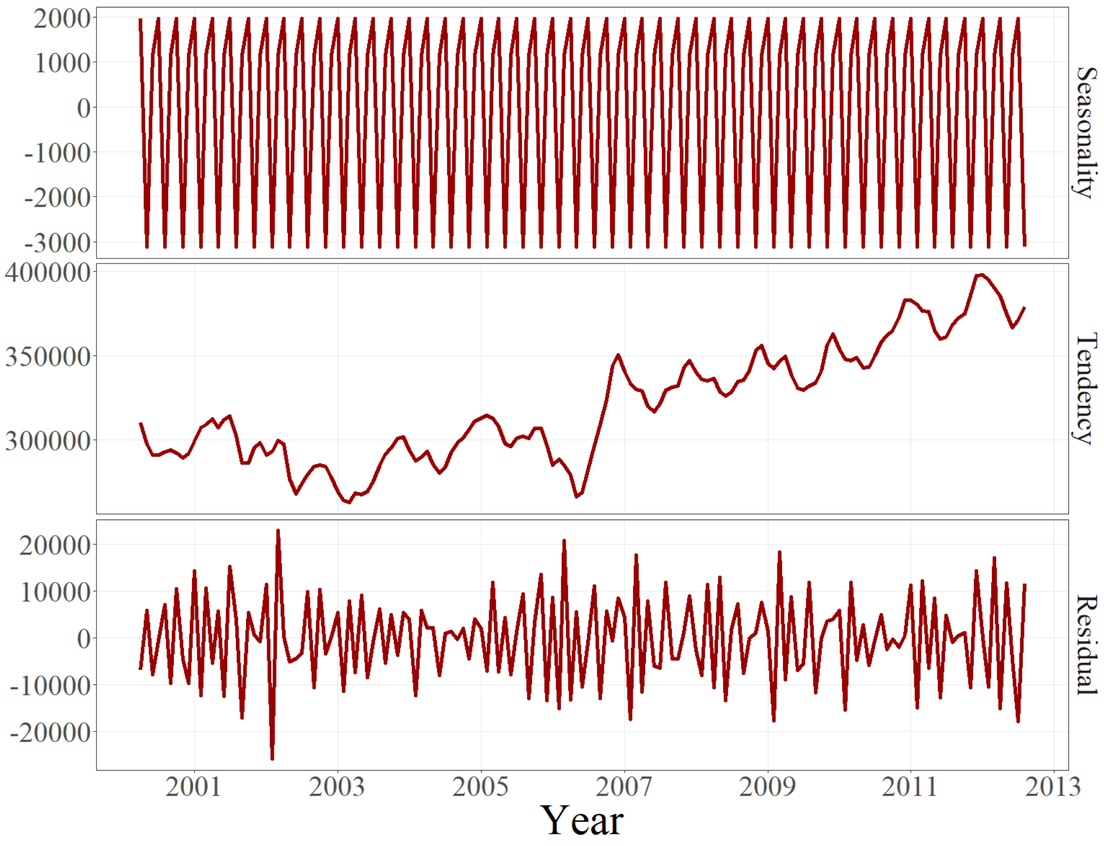

Figure 4: Pato Branco city.

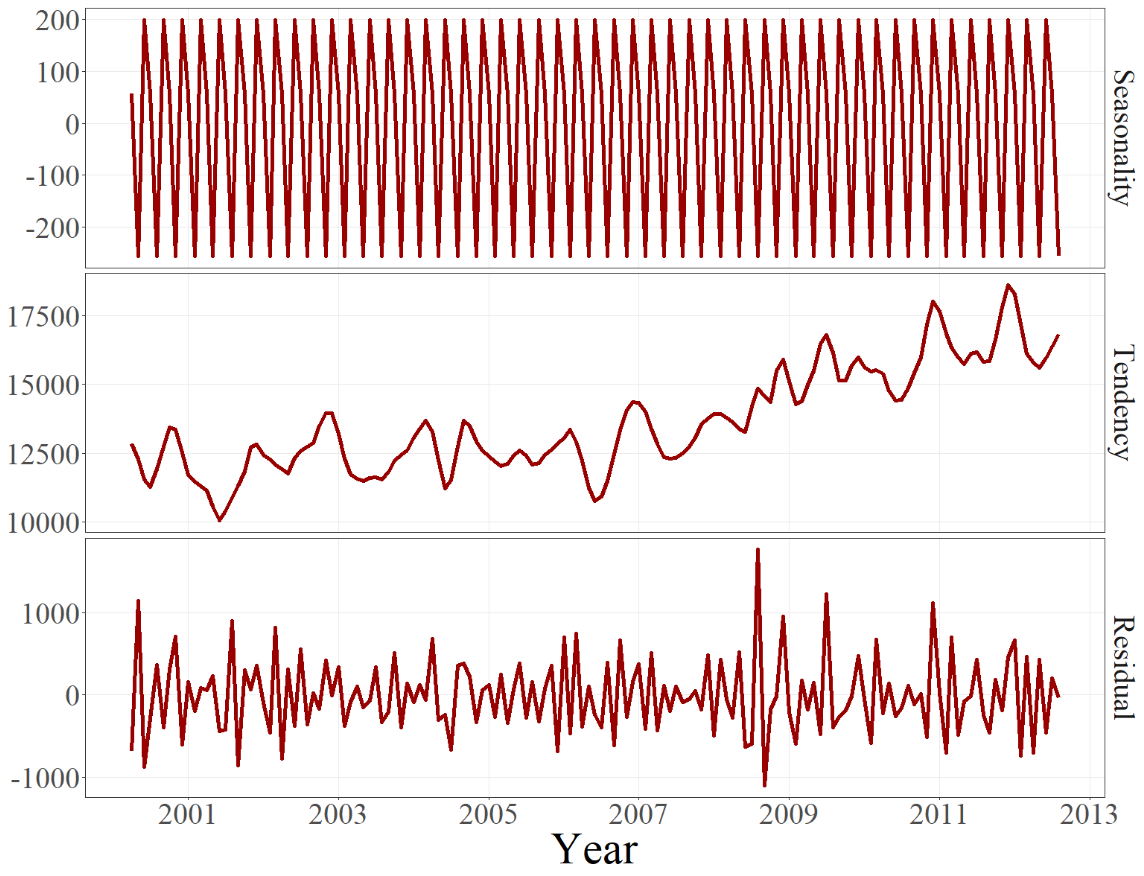

Figure 5: Palmas city.

Results

PERFORMANCE MEASURES OF FORECASTING METHODS.

City	Forecasting Horizon	Criteria	STL-MOO-GP	STL-MOO-SVR	STL-MOO-RR	STL-MOO-HTE	GP	SVR	RR
Palmas	One-month-ahead	RMSE	18205.24	3147.36	3088.05	**3034.19**	10635.46	10701.30	10644.82
		MAE	17960.02	2688.29	2661.23	**2592.85**	8651.98	8636.67	8670.79
		MAPE	10.56%	1.56%	1.54%	**1.51%**	4.97%	4.95%	4.99%
	Two-months-ahead	RMSE	12040.91	7282.46	6165.96	**6063.26**	11590.54	11691.17	11596.86
		MAE	10642.49	5853.94	4587.25	**4486.72**	9867.35	9707.77	9901.96
		MAPE	6.34%	3.49%	2.66%	**2.61%**	5.68%	5.57%	5.70%
	Three-months-ahead	RMSE	10323.38	171811.47	171822.19	**7490.07**	11209.06	11534.52	11190.45
		MAE	8463.93	171207.30	171573.15	**6093.70**	8861.69	9206.96	8850.50
		MAPE	4.82%	99.63%	100.04%	**3.52%**	5.06%	5.25%	5.05%
Pato Branco	One-month-ahead	RMSE	6008.38	36214.36	30162.89	**5119.59**	19224.80	19807.01	17902.26
		MAE	5045.90	35880.22	29834.84	**4331.76**	15879.23	16238.37	14847.18
		MAPE	1.37%	9.96%	8.28%	**1.18%**	4.31%	4.41%	4.05%
	Two-months-ahead	RMSE	10401.89	10475.07	9504.00	**8838.67**	20791.17	21398.96	19101.40
		MAE	7625.56	7435.73	**6651.20**	6725.26	17267.64	17737.44	15671.86
		MAPE	2.07%	2.02%	**1.81%**	1.87%	4.69%	4.81%	4.28%
	Three-months-ahead	RMSE	45702.71	22195.03	362693.16	**15374.36**	22314.41	23507.29	19519.84
		MAE	43937.13	19184.13	362065.51	**12825.63**	19632.81	20657.13	17117.20
		MAPE	12.03%	5.22%	100.00%	**3.51%**	5.32%	5.59%	4.65%

Results – Diebold-Mariano test

STATISTIC OF DM TEST FOR STATISTICAL COMPARISON OF PROPOSED APPROACH VERSUS OTHER MODELS

Model	Palmas			Pato Branco		
	One-month -ahead	Two-months -ahead	Three-months -ahead	One-month -ahead	Two-months -ahead	Three-months -ahead
STL-GP	-19.82***	-4.60***	-3.76***	-3.29***	-1.29	-12.15***
STL-SVR	-1.63*	-1.66*	-30.82***	-22.69***	-1.43*	-6.20***
STL-RR	-0.96	-2.99***	-38.15***	-20.44***	-3.70***	-29.13***
GP	-4.45***	-2.96***	-3.20***	-5.18***	-3.65***	-2.55***
SVR	-4.33***	-2.84***	-3.16***	-5.14***	-3.68***	-2.78***
RIDGE	-4.47***	-2.99***	-3.20***	-5.21***	-3.70***	-2.00**

Note: ***1% significance level; **5% significance level; * 10% significance level.

Results – Predicted versus Observed water consumption

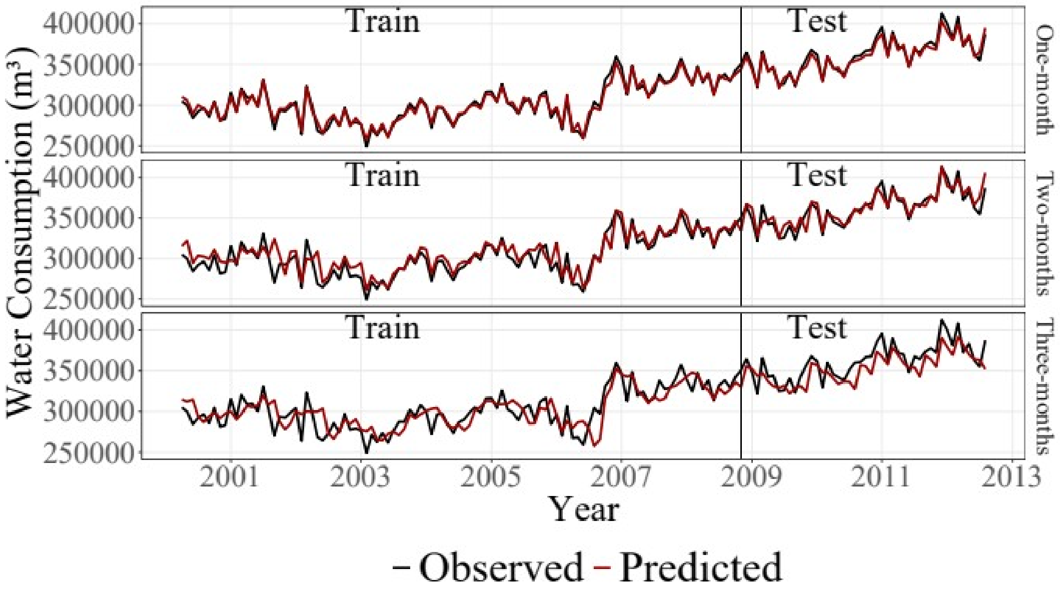

Figure 6: Pato Branco city

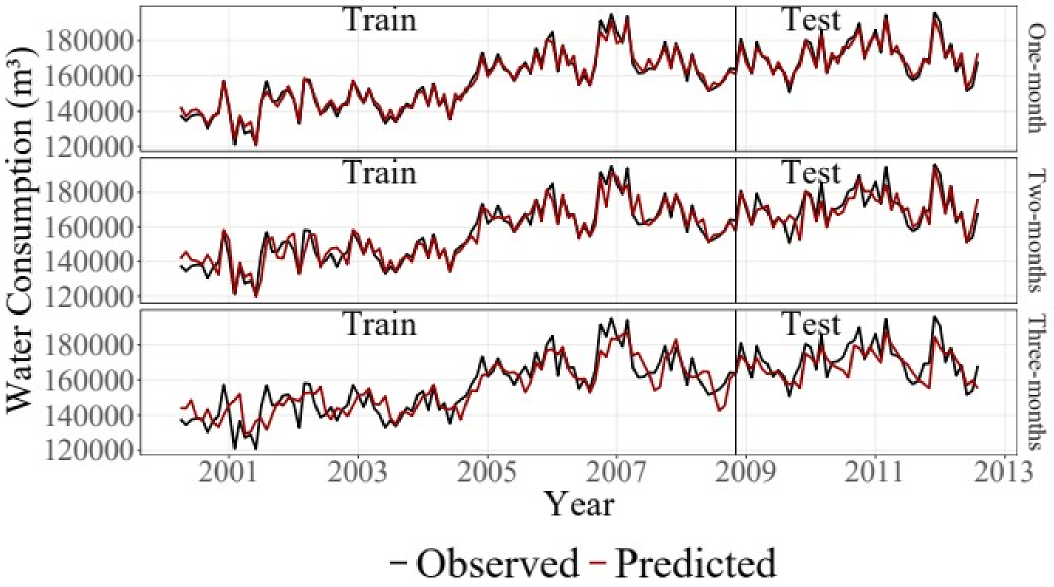

Figure 7: Palmas city

Conclusion

- STL approach allowed to deal explicit with the seasonal behavior of the data and improves the final results regarding not applying decomposition;
- Using heterogeneous ensemble learning model allow to improve the final accuracy concerning the use of a homogeneous ensemble model of components;
- Employing different weights through MOO allow different components contributing in a better way to construct an efficient forecasting model;
- Limitations of the model including: Complexity in relation to single models, and absence of exogenous factors such as climatic and demographic factors;
- Future works intend to using of exogenous factors associated with feature engineering and selection, hybridization of decomposition techniques, and to adopt RF, artificial neural networks, and persistence model to perform comparisons with the proposed framework;

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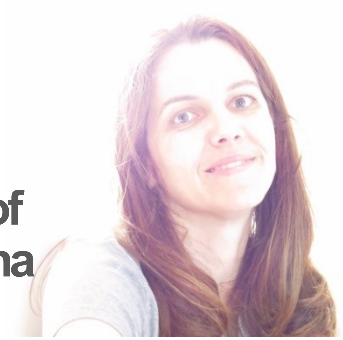

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