

A Case Study on Water Demand Forecasting in a Coastal Tourist City

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Outline

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- Motivation
- Case Study
- Experimental Setup
- Results and Discussion
- Final Remarks

Motivation

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- Water demand is susceptible to variations
 - Economic, demographic and climatic
- Different forecasting windows and goals
 - Short-term (hours, days)
 - Optimize water treatment / reservoir levels
 - Long-term (months, years, decades)
 - Infrastructure Planning

Motivation

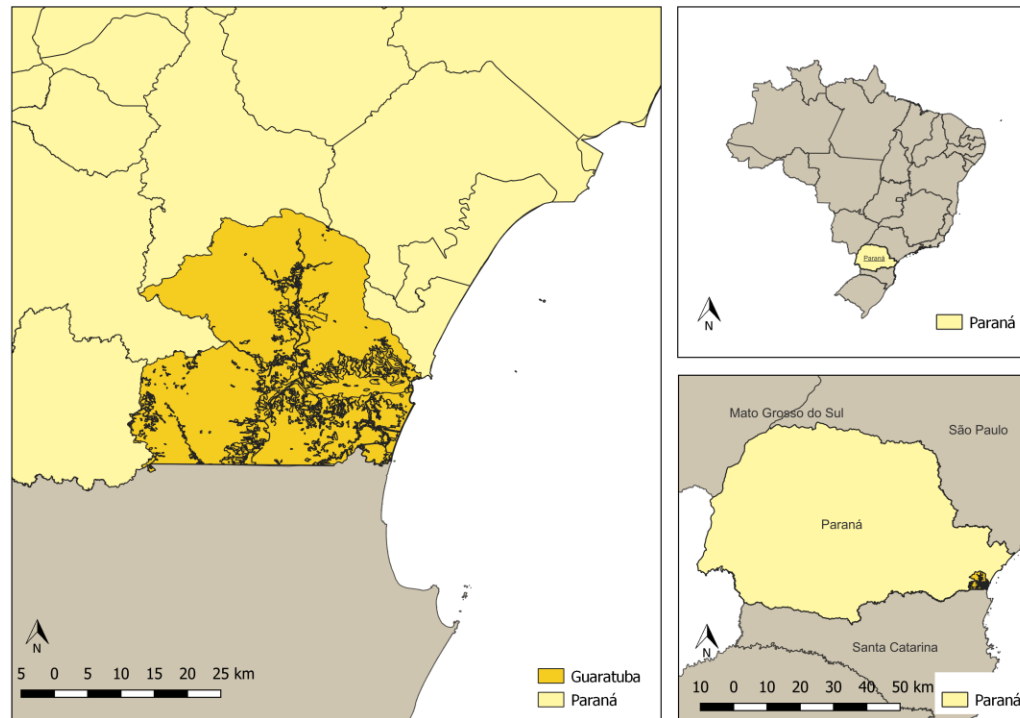
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- In touristic cities such a planning becomes more urgent
- We evaluated statistical methods (ARIMA / SARIMA)
 - One week ahead, daily forecasts
- Comparison with previous study based on regression models
- Related work employed ARIMA/SARIMA as baselines, mostly with auto tuned parameters (which we believe is not fair)

Case Study

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- Guaratuba - Paraná



Vieira et al.; Machine learning for water demand forecasting: Case study in a Brazilian coastal city. Water Practice and Technology 1 May 2024; 19 (5): 1586–1602. doi: <https://doi.org/10.2166/wpt.2024.096>

1 milhão de pessoas passaram a virada no Litoral do Paraná, estima Polícia Militar

As praias do Litoral receberam cerca de 1 milhão de pessoas na virada de 2023 e 2024, segundo estimativas de público da Polícia Militar do Paraná divulgadas nesta segunda-feira (1). A prainha de água doce de Porto Rico, na Costa Noroeste, recebeu aproximadamente 30 mil turistas na virada do ano.

Publicação
01/01/2024 - 13:50

Editoria
[Verão Maior Paraná](#)

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▶ 0:00 / 3:17



1 milhão de pessoas passaram o virada no Litoral do Paraná, estima Polícia Militar
Foto: PMPR

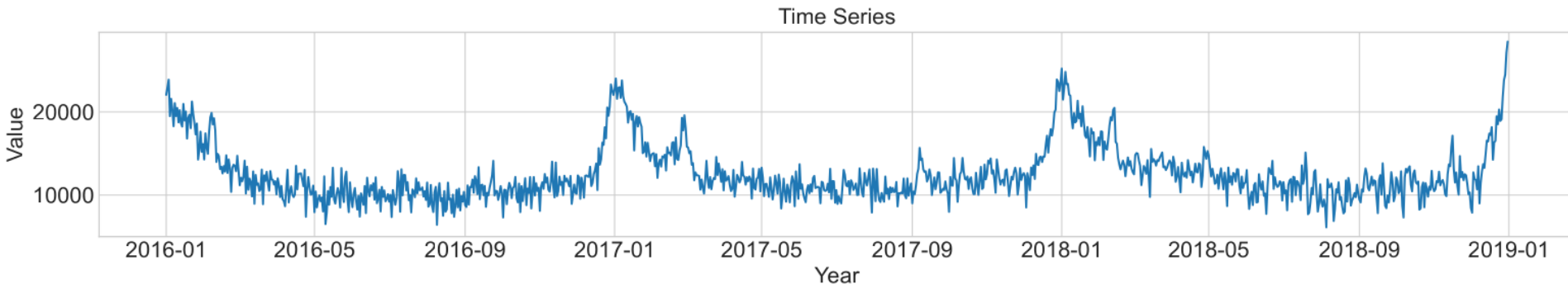
COMPARTILHE:



Case Study

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- Daily water consumption in m³



- Four year dataset from SANEPAR (2016 – 2019)
- We actually considered produced water, not consumed
 - Correlated, but not the same

Case Study – Exploratory Analysis

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Determination of ARIMA and SARIMA parameters

- Performed time-series decomposition
- Autocorrelation Function (ACF)
- Partial Autocorrelation Function (PACF)

Experimental Setup

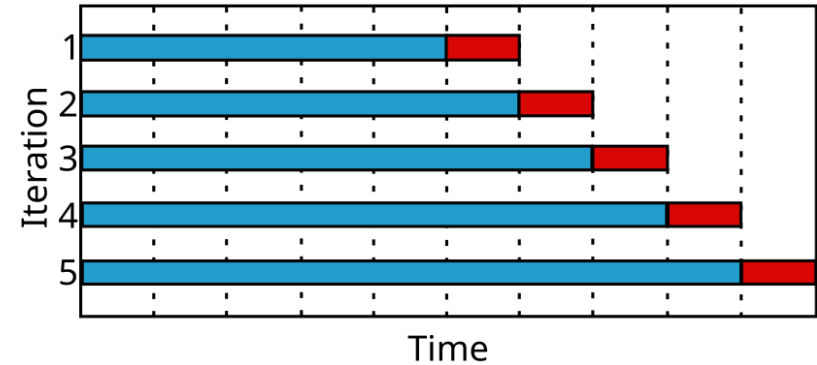
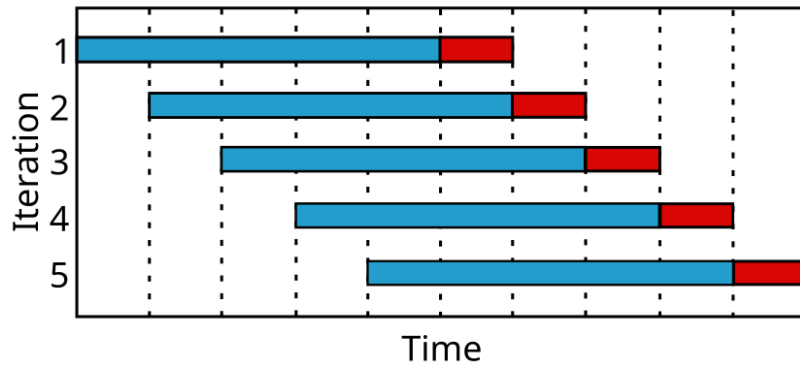
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- Data was split into
 - Train (2016 and 2017)
 - Validation (2018)
 - Test (2019)

Model	Hyperparameter	Search Space
ARIMA	p	(2, 3, 8)
	d	(0, 1)
	q	(3, 4, 28, 38)
SARIMA	p	(2, 3, 6)
	d	(0, 1)
	q	(3, 4, 6)
	P	(2, 3)
	D	(0, 1)
	Q	(1, 3, 4)
	s	(7)

Experimental Setup

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Window Type	Window Size		Sliding Steps
	Train	Test	
Sliding Window (SW1Y)	365 days	7 days	7 days
Sliding Window (SW2Y)	730 days	7 days	7 days
Expanding Window (EW)	*	7 days	7 days

Results – Model Selection

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- Regarding the validation set
- For each method, we observed
 - Best / Average / Worst
- Check the whether parameter tuning matters
- Best model selected for further comparison

Results – Model Selection

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		Model	Evaluation Metrics		
			RMSE $\pm \sigma$	MAE $\pm \sigma$	MAPE(%) $\pm \sigma(\%)$
EW	ARIMA	Best (8,0,38)	1480.51 \pm 805.15	1261.14 \pm 711.8	9.91 \pm 4.24
		Worst (2,0,3)	1955.36 \pm 1172.69	1682.67 \pm 1091.59	12.96 \pm 5.88
		Mean (All)	1741.45 \pm 926.27	1494.52 \pm 828.09	11.81 \pm 5.61
	SARIMA	Best (6,0,6), (2,0,3,7)	1618.21 \pm 893.33	1353.34 \pm 754.17	10.66 \pm 4.9
		Worst (2,1,3), (2,1,4,7)	2032.53 \pm 1063.01	1786.65 \pm 953.22	14.19 \pm 7.14
		Mean (All)	1776.79 \pm 935.03	1525.95 \pm 806.72	12.09 \pm 5.51
SW1Y	ARIMA	Best (8,1,38)	1606.31 \pm 1081.16	1385.81 \pm 959.71	10.78 \pm 5.96
		Worst (2,0,4)	1923.57 \pm 986.1	1651.42 \pm 919.82	13.05 \pm 5.59
		Mean (All)	1764.58 \pm 1022.13	1517.97 \pm 909.44	11.91 \pm 5.92
	SARIMA	Best (6,1,3), (3,0,4,7)	1630.01 \pm 1070.06	1374.61 \pm 932.09	10.61 \pm 5.4
		Worst (3,1,3), (3,1,1,7)	2053.38 \pm 974.55	1761.8 \pm 852.4	13.97 \pm 6.01
		Mean (All)	1810.17 \pm 1027.26	1546.68 \pm 868.25	12.15 \pm 5.51
SW2Y	ARIMA	Best (8,0,38)	1425.35 \pm 918.88	1217.98 \pm 807.72	9.50 \pm 5.08
		Worst (2,0,3)	1994.85 \pm 1216.67	1722.07 \pm 1140.02	13.17 \pm 6.08
		Mean (All)	1737.82 \pm 961.27	1494.01 \pm 857.24	11.78 \pm 5.76
	SARIMA	Best (6,1,4), (3,0,4,7)	1601.85 \pm 885.79	1376.80 \pm 772.35	10.8 \pm 5.13
		Worst (3,1,3), (3,1,1,7)	2023.58 \pm 1089.58	1760.96 \pm 943.46	13.90 \pm 6.6
		Mean (All)	1785.27 \pm 958.85	1533.13 \pm 824.63	12.14 \pm 5.6

Results – Test Set

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- Evaluation on 2019 data
 - Not seen by any of the models before
- Compared w.r.t. Vieira et al. 2024
 - Best ML methods
- In both studies, same windows, data*, pre-processing

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Results – Test Set

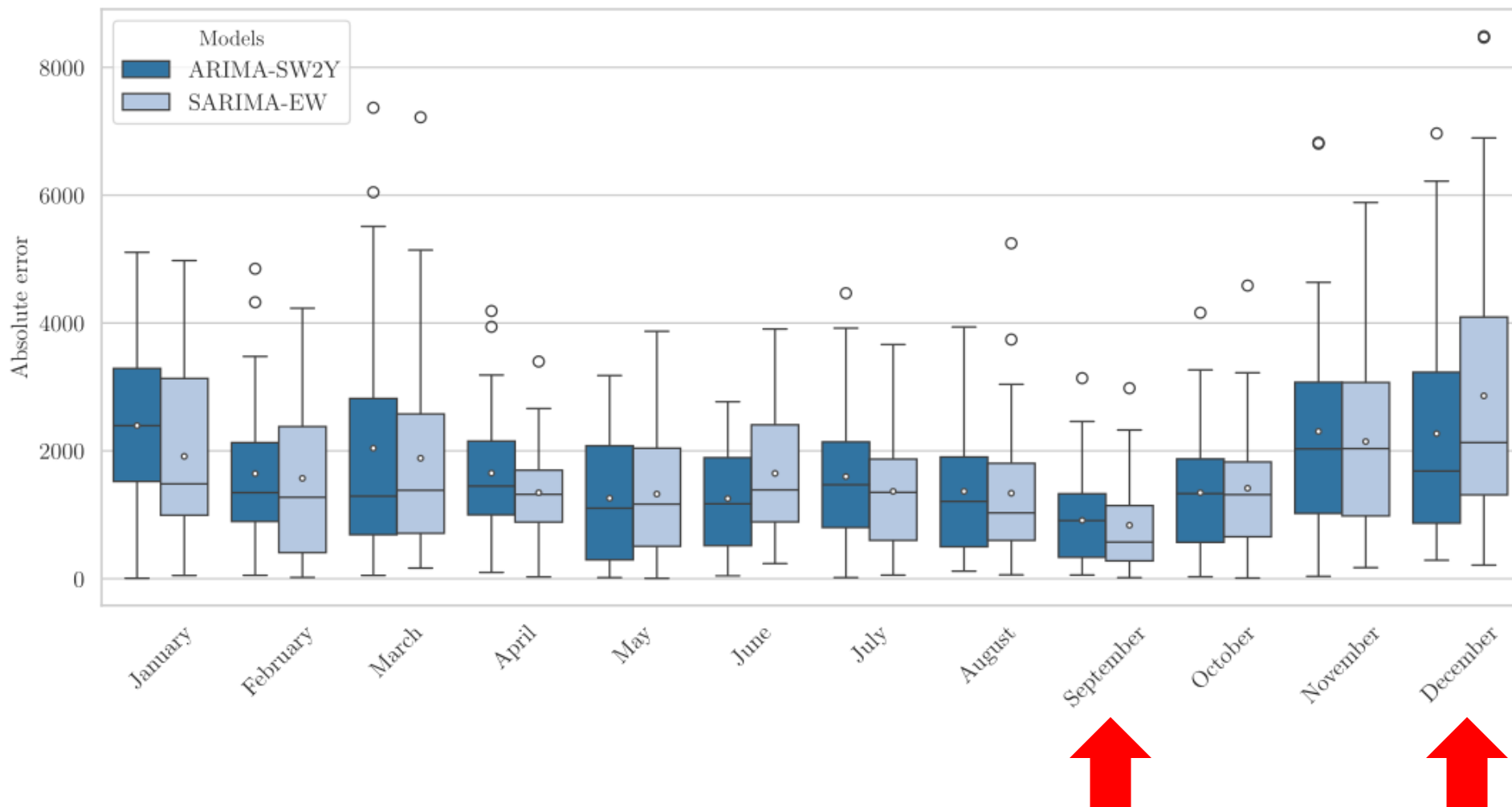
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Model	Evaluation Metrics					
	RMSE	σ	MAE	σ	MAPE(%)	σ (%)
ARIMA-EW	1771.39	1044.06	1523.65	928.79	11.99	6.38
SARIMA-EW	1870.03	962.6	1630.14	893.12	12.81	5.9
MLP-EW	1709.70	593.104	1408.97	515.158	11.81	4.707
ARIMA-SW1Y	1745.08	1165.27	1499.44	999.01	11.52	6.21
SARIMA-SW1Y	2096.22	1096.88	1799.32	991.68	14.0	6.12
KNN-SW1Y	1906.99	969.900	1618.19	954.202	12.47	5.055
ARIMA-SW2Y	1652.67	1078.71	1419.4	975.04	11.15	6.65
SARIMA-SW2Y	1947.23	884.83	1667.8	807.33	13.04	4.93
MLP-SW2Y	1927.41	732.005	1620.15	630.532	13.08	4.916

Best ARIMA and SARIMA models in bold

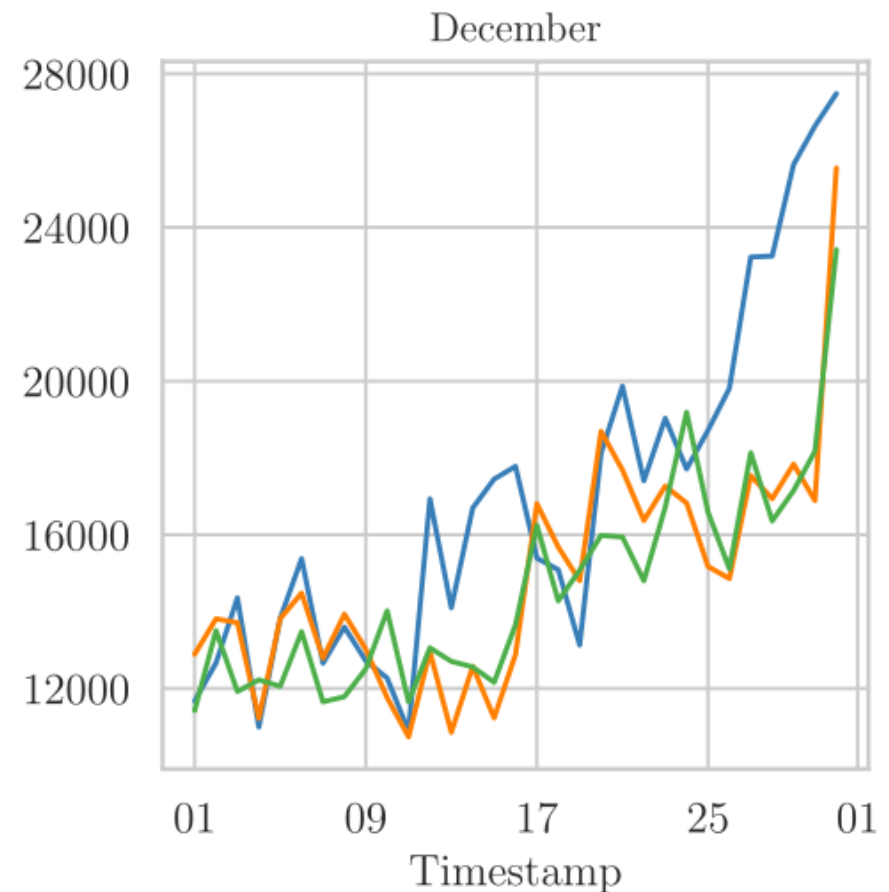
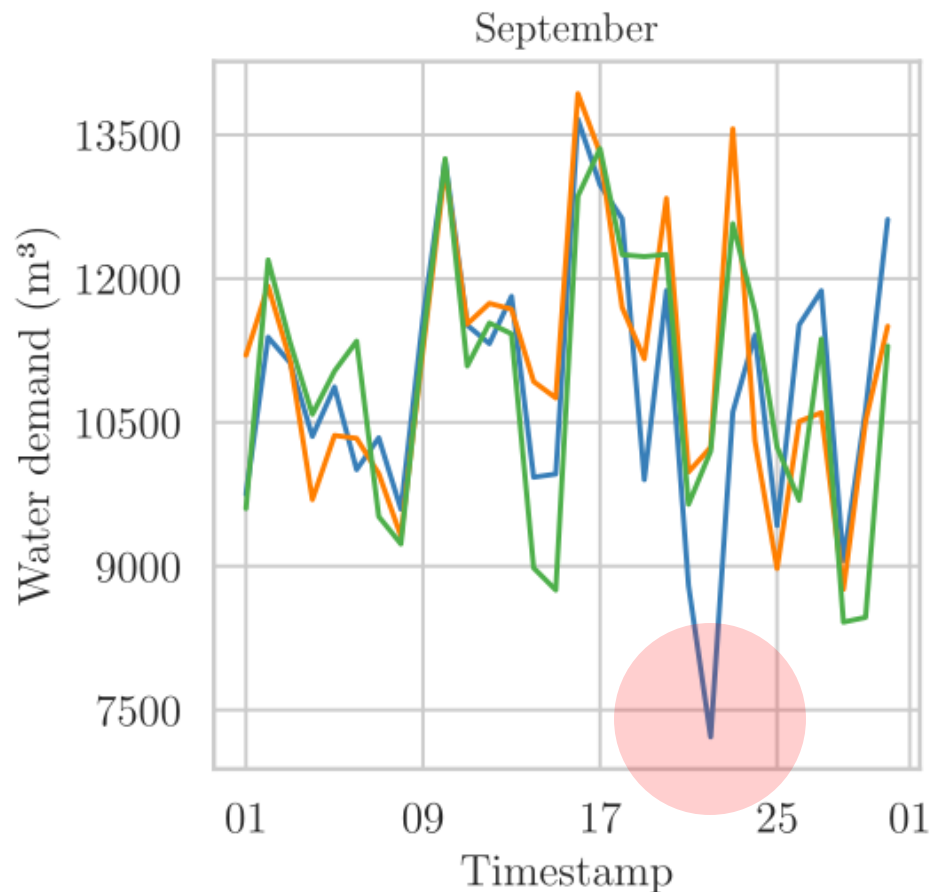
Results – Test Set

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Results – Test Set

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Final Remarks

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- Statistical models provided sound results
- If these are employed as baselines
 - A rigorous analysis of parameters needed
- Previous study from Vieira et al. 2024
 - Regression on same time-series + meteorological data
- Future work considering LSTM and ensemble models

Thanks for the attention

Questions?

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