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Multi-scale Modelling of Urban Water Demand under Urban Development and Societal Uncertainties: The Case Study of Milan, Italy

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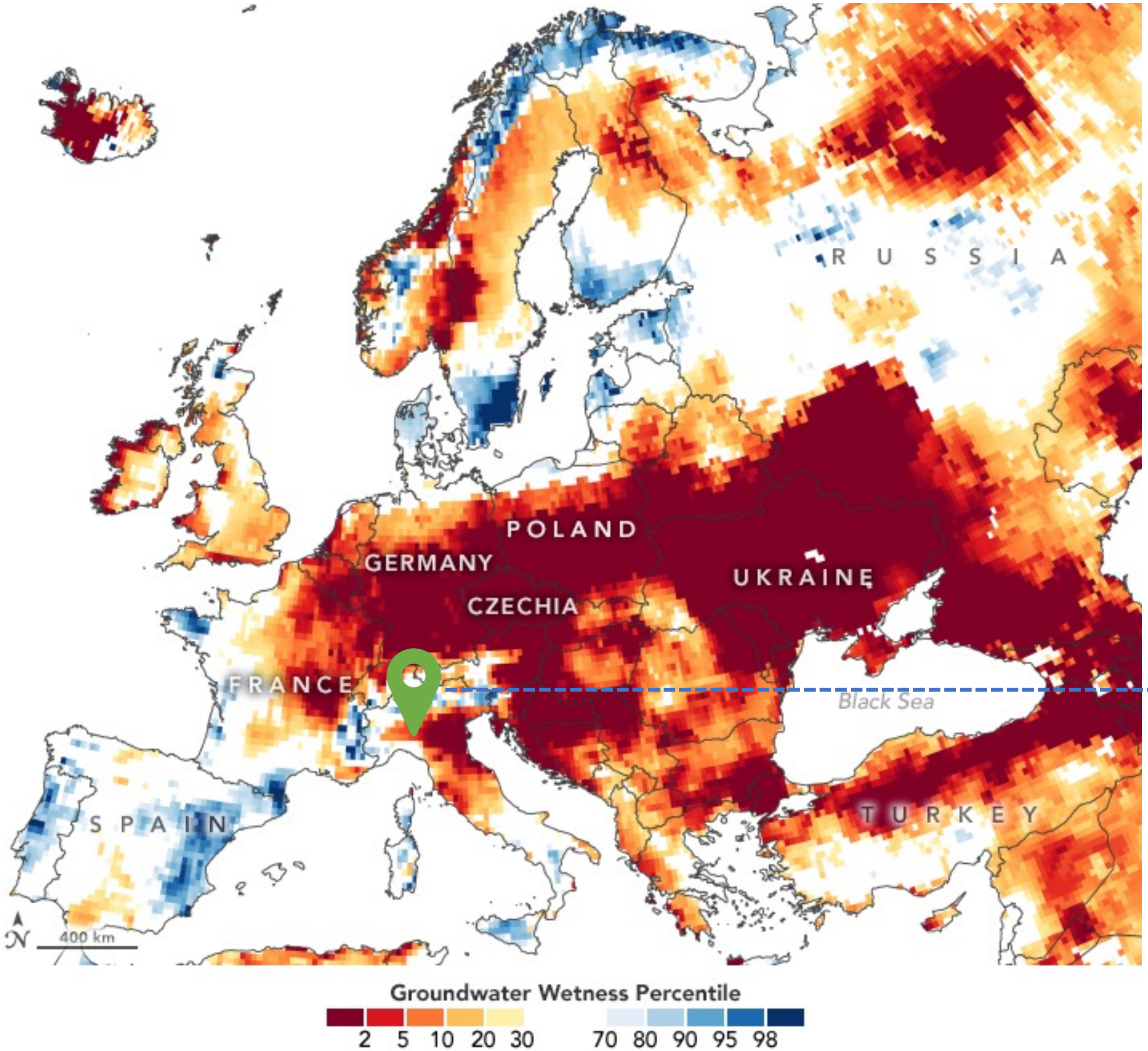
Outstanding Student & PhD candidate Presentation contest

Background: Urban water scarcity has emerged as one key problem in sustainable water management and demand-side management is regarded as a key complementary measure to supply-side interventions



Source: NASA, June 2020

Milan, Italy

Case study: Urban water demand in Milan, Italy

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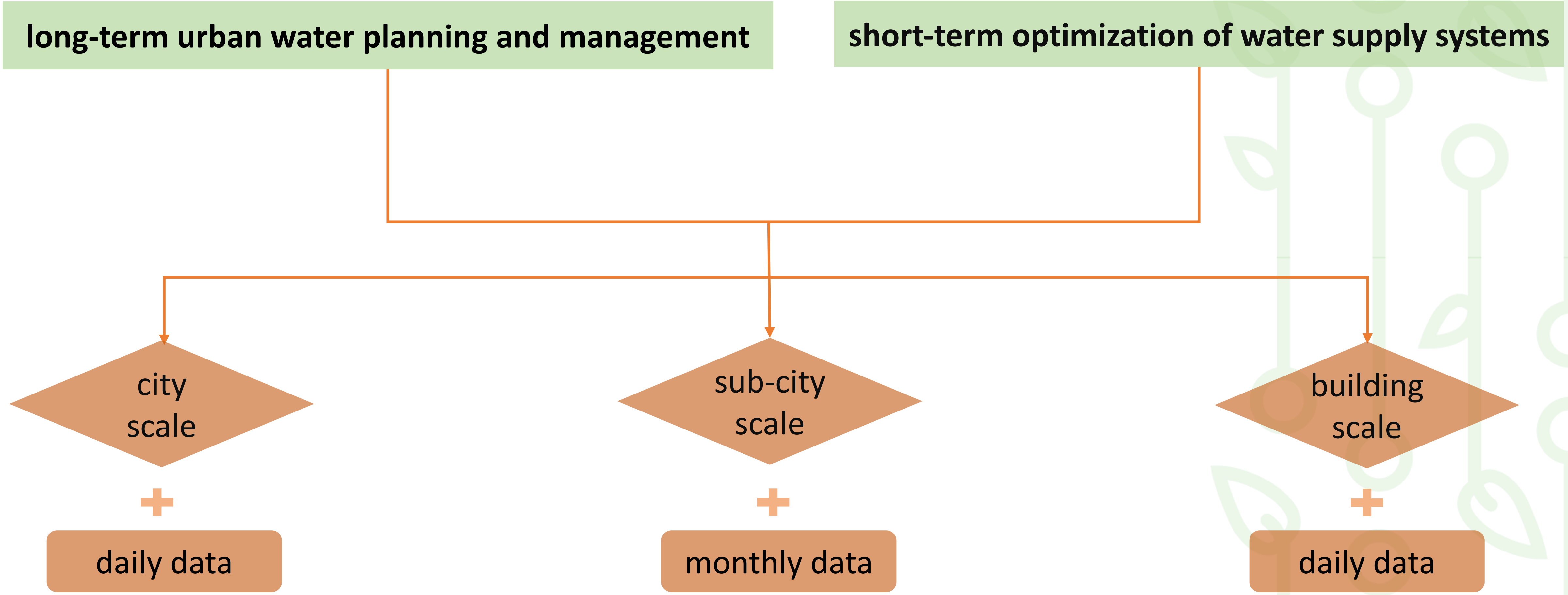
- Municipal water is 100% from groundwater
- 28 pump stations are activated and serve in total more than 50, 000 water users
- Smart meters have been used to monitor water consumption at the building level

Methodology

- **Descriptive modelling of water use change across scales**
- **Predictive modelling of water demand**



Methodology

- **Descriptive modelling of water use change across scales**
- **Predictive modelling of water demand**

feature selection → Light Gradient Boosting Machine

clustering → Hierarchical Clustering

demand forecasting → Time series models, Artificial Neural Networks, Support Vetor Regression, Light Gradient Boosting Machine, Long Short Term Memory Networks + wavelet analysis

CITY SCALE + DAILY DATA (2017-2019)

Results of 1 day-ahead prediction on daily water consumption in 2017-2019 show the avantage of hybrid wavelet decomposition machine learning models

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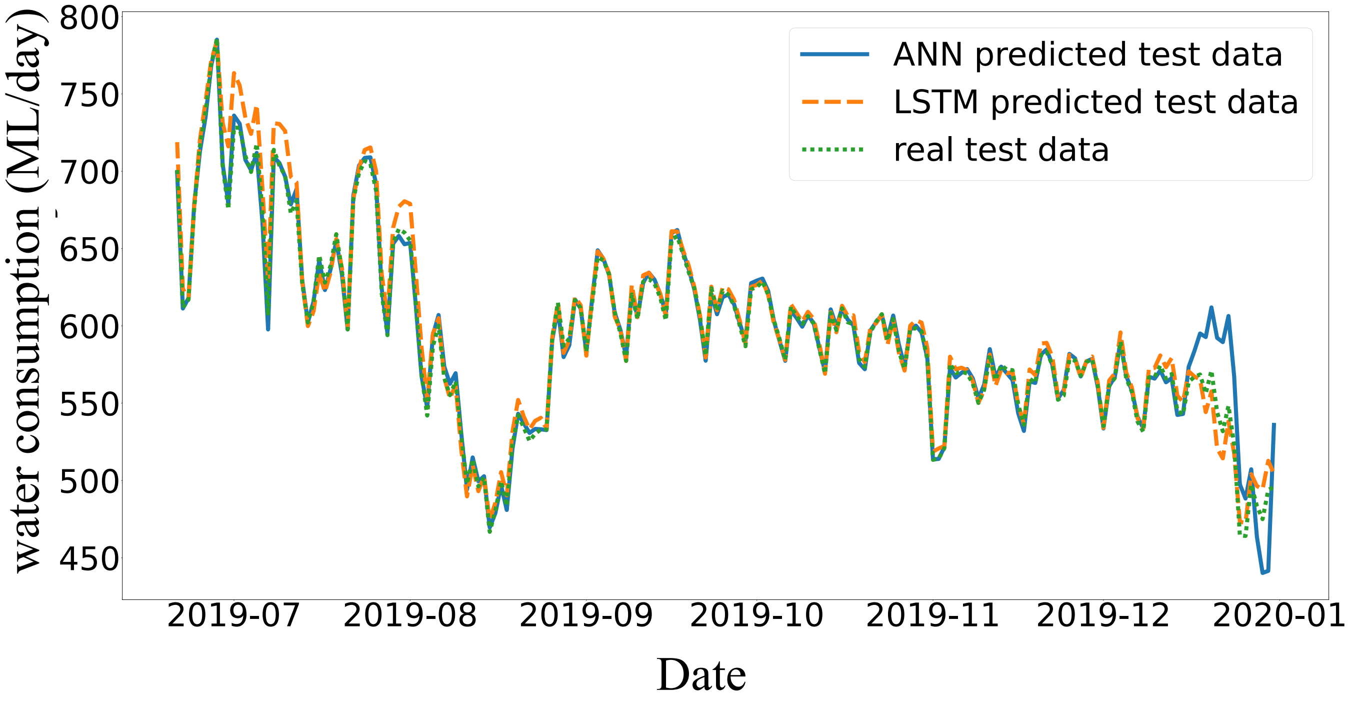

Models	$RMSE(ML)$	$MAE(ML)$	$MAPE(\%)$	R^2
		Training Phase		
SARIMAX	19.285	13.716	2.3	0.828
SVR	18.101	14.025	2.3	0.837
ANN	15.126	10.990	1.8	0.886
LightGBM	8.629	6.516	1.1	0.963
LSTM	10.373	6.274	1.1	0.947
WA-SVR	16.435	13.895	2.3	0.873
WA-ANN	**2.556**	**1.927**	**0.3**	**0.997**
WA-LightGBM	2.627	2.032	**0.3**	**0.997**
WA-LSTM	4.666	3.158	0.5	0.990
		Test Phase		
SARIMAX	15.460	11.284	1.9	0.906
SVR	19.546	14.747	2.5	0.896
ANN	18.058	13.273	2.3	0.911
LightGBM	20.524	14.510	2.5	0.885
LSTM	24.942	17.630	3.0	0.810
WA-SVR	20.721	14.193	2.4	0.886
WA-ANN	10.913	**4.874**	**0.9**	0.968
WA-LightGBM	16.637	12.038	2.1	0.926
WA-LSTM	**9.596**	6.300	1.0	**0.974**

SARIMAX, SVR, ANN, and LightGBM models used original selected tabular data for calibration and validation, while LSTM used original time series data for calibration and validation; WA-SVR, WA-ANN and WA-LightGBM used selected wavelet-decomposed tabular data for calibration and validation, while WA-LSTM used selected wavelet-decomposed time series data for calibration and validation.

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Hybrid LSTM model shows promising results on 7 days-ahead prediction on daily water consumption in 2017-2019

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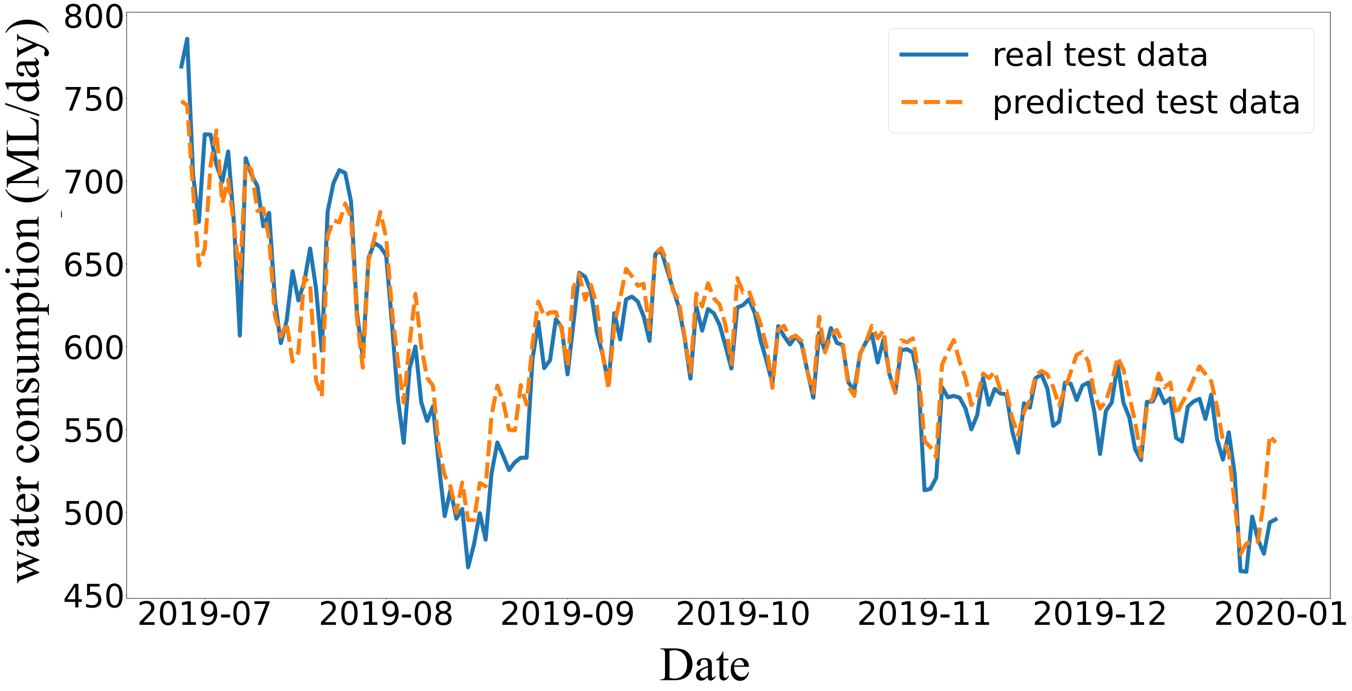

Models	$RMSE(ML)$	$MAE(ML)$	$MAPE(\%)$	R^2
Training Phase				
SARIMAX	32.947	23.663	4.0	0.492
SVR	21.228	16.792	2.8	0.776
ANN	21.841	16.060	2.7	0.763
LightGBM	14.042	10.586	1.8	0.902
LSTM	12.841	7.058	1.2	0.919
WA-SVR	13.110	10.195	1.7	0.919
WA-ANN	11.652	8.818	1.5	0.936
WA-LightGBM	**7.209**	5.487	**0.9**	**0.975**
WA-LSTM	7.701	**5.396**	**0.9**	0.972
Test Phase				
SARIMAX	34.391	24.969	4.3	0.526
SVR	29.561	21.784	3.7	0.763
ANN	30.672	22.292	3.8	0.745
LightGBM	31.326	22.699	3.9	0.734
LSTM	45.802	34.152	5.9	0.439
WA-SVR	31.854	16.080	2.9	0.730
WA-ANN	28.362	14.829	2.6	0.786
WA-LightGBM	29.538	20.737	3.6	0.773
WA-LSTM	**18.374**	**13.777**	**2.4**	**0.900**

SARIMAX, SVR, ANN, and LightGBM models used original selected tabular data for calibration and validation, while LSTM used original time series data for calibration and validation; WA-SVR, WA-ANN and WA-LightGBM used selected wavelet-decomposed tabular data for calibration and validation, while WA-LSTM used selected wavelet-decomposed time series data for calibration and validation.

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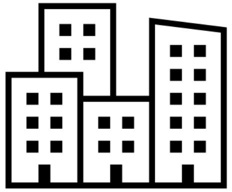
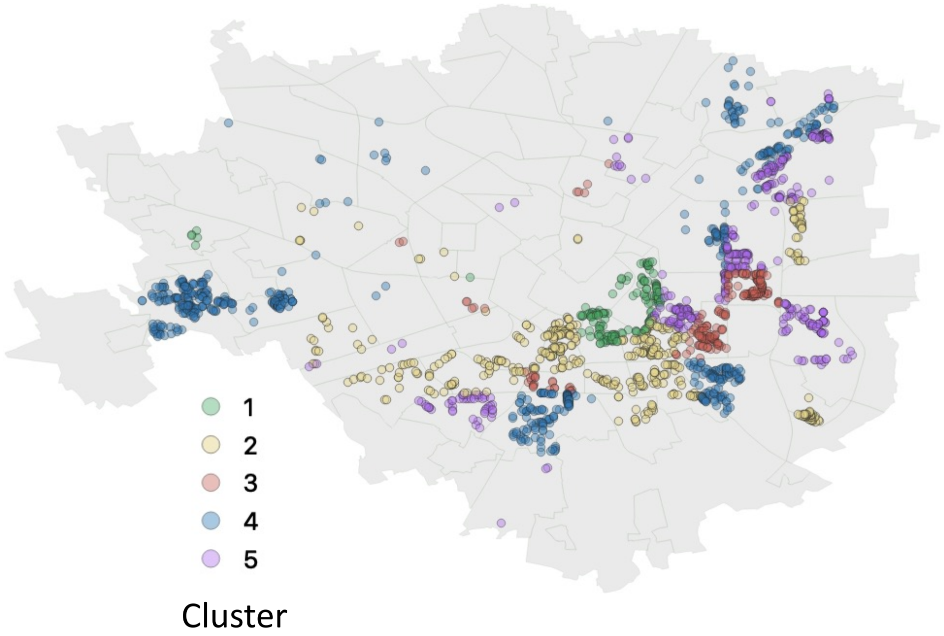
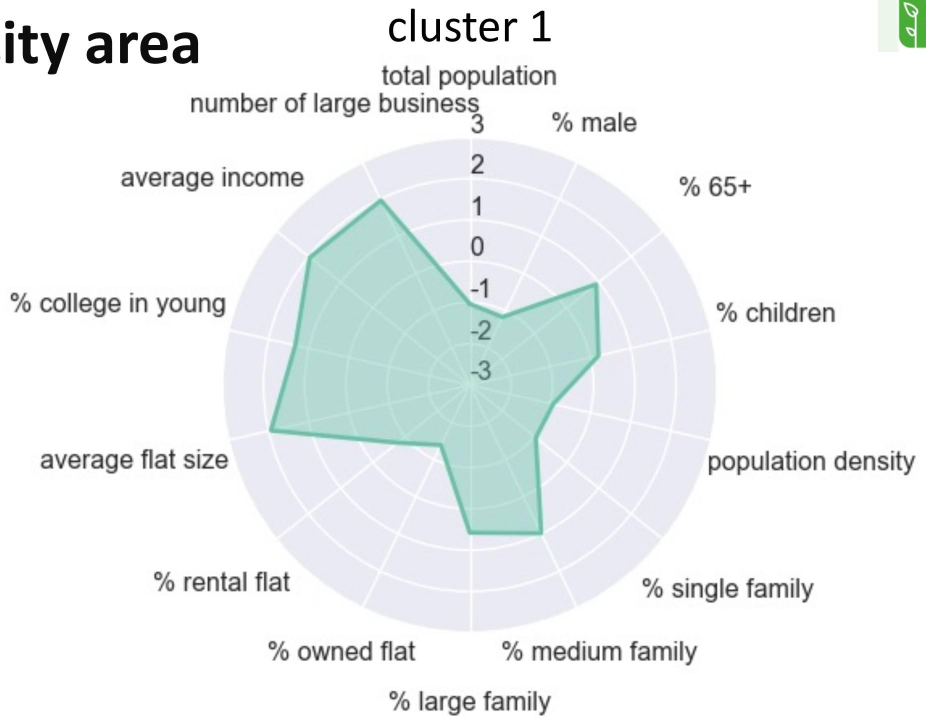
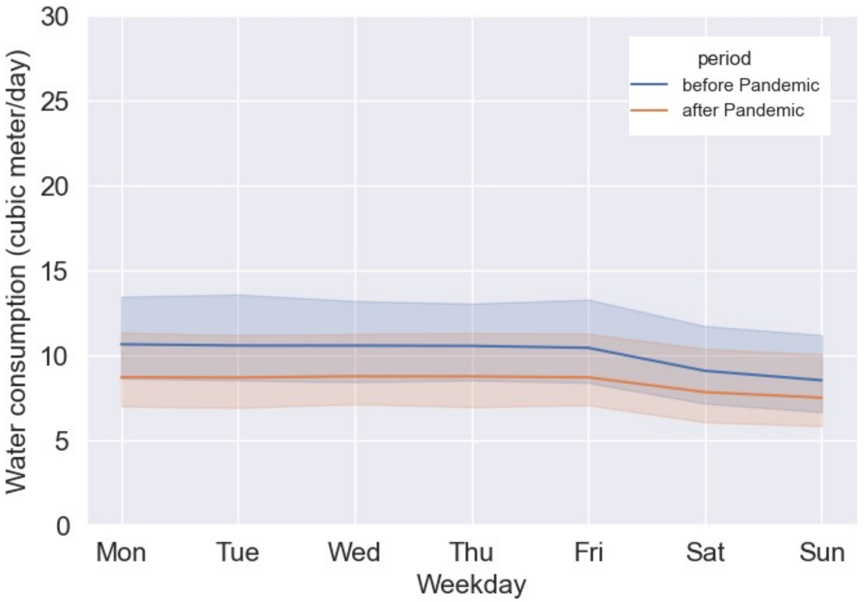


BUILDING SCALE + DAILY DATA (2019-2021)

Hierarchical clustering identifies 5 clusters based on social-demographic and building characteristics of each sub-city area







Representative characteristics of cluster 1:

- multi and large family, elder people
- high income, highly educated
- owned and big dwellings
- less population, low density
- commercial area

Take home messages

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- Urban water demands change differently under the various socio-demographic, economic and building features contexts
- Machine learning/deep learning and advanced data mining tools can contribute to identification of urban water demand change and prediction of future water demand to inform management strategies
- We also acknowledge the challenges of generalization of the data-driven analysis experience due to the case-specific characteristics and quality of data

THANK YOU!

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