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Water demand forecasting in the data age

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1. Project Summary

Overall aim: Develop a new methodology for demand forecasting in order to improve accuracy of predictions and obtain improved understanding of water consumption.

3. Methodology and Results

Initial efforts focused in identifying relationships between water consumption and the weather. The methodology adopted evaluates the relationship

Specific objectives:

Utilise smart demand metering and other data (household, socio-economic, temporal, weather)
Quantify the effect that various influencing factors have on consumption (especially the weather)

Compare model efficiency for different

- Aggregations of properties
- Temporal and spatial scales
- Forecast horizons

Quantify uncertainty (accounting for model structural errors)



between consumption data (derived from smart meters) and air temperature in a systematic approach, i.e. varying different aggregations of properties, based on temporal characteristics (time of the day, season, working days), household characteristics (garden size, metering status, rateable value, occupancy rate) and socio-economic data (ACORN). Results indicate varying degrees of correlation, that become stronger for certain times and types of properties (Figure 1).



Figure 1. Correlation between max daily temperature and average daily consumption (averaged across all the properties) for all data (left) and working days and properties with large gardens and high summer consumption (right).

2. Data

Wessex Water: 2,000 properties since 2014

- Smart demand metering data at 30-minute intervals
- Household characteristics



Water consumption correlates stronger with air temperature during **working days, mornings and evenings,** as well as **summer and spring.** People with **bigger gardens** and **higher socio-economic status**, as well as properties with **higher rateable values** and **metered properties** also tend to show a higher correlation (Table 1).

Weekends			Time of day			Season		
FALSE	475	137	morning	268	51	summer	249	41
TRUE	117	19	evening	245	46	spring	199	54
Status			night	150	2	autumn	45	14
Measured	319	67	afternoon	81	4	winter	62	0
Unmeasured	159	25						
Garden Size			ACORN			Rateable value		
Large	183	38	Affluent	263	61	High	283	41
Medium	169	29	Comfortable	152	15	Medium	151	5
Small	106	3	Financially stretched	82	9	Low	71	3

Table 1. The blue columns indicate the number of segmentations that include thecorresponding category of each variable for which the correlation betweenconsumption and air temperature is statistically significant at 99% confidencelevel. The yellow columns indicate the number of segmentations with aSpearman correlation coefficient higher than 0.40.



4. Future Work



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Expand methodology to include additional weather variables (relative humidity, precipitation) while varying the temporal and spatial scale
Apply data-mining techniques on the data in order to identify the most important influencing factors
Use a combination of the acquired knowledge and machine learning methods to develop accurate forecasting models









