Investigating the Influence of Weather on Water Consumption: A Dutch Case Study

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ABSTRACT

Water availability is a major concern of modern societies. As the pressure of fulfilling increasing demands under an uncertain climate increases, the need to understand how weather changes influence water consumption becomes of the utmost importance. This case study is based on nine locations in the Netherlands, each with different societal and household characteristics. Consumption in each location was temporally disaggregated based on the time of day, time of the week and season. Results indicate that water consumption is primarily influenced by temperature and radiation during evenings and working days of spring and summer months. Results also indicate that the water consumption in affluent residencies with gardens in countryside locations is more sensitive to weather changes.

Keywords: water demand, smart meters, weather

1 Introduction

Water is essential for the preservation of life as well as the environmental welfare and economic growth and ensuring a secure water supply for the future is a topic of primary concern.

However, understanding water demand is a challenging task due to the nature and quality of the available data, the numerous factors that influence water consumption, as well as the various forecast horizons and spatial scales [6].

A lot of research has been dedicated to the drivers of water consumption, with the weather being consistently found in the literature among the factors that are most commonly used in order to explain demand variability [1, 3, 10]. Among the weather variables investigated (temperature, relative humidity, rainfall, wind velocity), consumption was found to be more sensitive to changes in humidity, followed closely by temperature [2].

In addition, temporal and seasonal patterns in water consumption have also been widely observed and used for management and forecasting purposes [4]. Consumption shows a high seasonal variability, including high peaks in demand due to summer sprinkling, while winter demands remain relatively homogeneous [5]. In addition, demand follows a diurnal pattern, with high demand occurring during the morning and evening hours [9]. This study tests the assumption that the impact of weather on water demand is not univariate but changes based on the type of property, the individual characteristics of consumers, as well as the temporal characteristics.

2 Data

2.1 The Area

The available data comes from 9 locations in the Netherlands, all with different household and societal characteristics (Table 1). The aggregated consumption of all houses in each location was recorded using smart meters at 1 minute intervals, from 1 July 2016 till 31st July 2017, by the Evides Water Company. Evides invests in data collection and management on a regular basis in order to be prepared for changes in the network. The household and socio-economic characteristics of each location were derived from data publicly available by the Dutch bureau of statistics [8].

Locations 1 to 3 are in the countryside, 4 to 6 are in the outskirts of a city, and 7 to 9 are in cities. Locations 1, 3, and 4 consist mainly of luxurious homes with gardens, locations 5, 6, and 8 consist of flats and apartments, whereas location 7 has mainly luxurious houses and locations 2 and 9 houses with gardens. Each location contains between 109 and 138 houses (Table 1).

However, consumption recordings are not available for all locations and days in the data. While most locations have adequate amount of data, locations 2 and 7 have approximately 4 months of data each, distributed over December to March, and May to July, respectively. Since the availability of consumption data for location 2 is mainly over the winter period, it is unlikely that any weather effect on consumption will be identified, whereas consumption at location 7 which was recorded during spring and summer could correlate better with weather variables.

Table 1. Description of the main characteristics of each location.

Locations	Description	Number of houses
1	luxurious homes with gardens, many senior citizens	115
2	terraced houses with gardens, mixed family composition	142
3	luxurious homes with garden, many double-income households	109
4	luxurious homes with garden, mainly double-income households and families with children	138
5	apartments, mainly double-income households and families with children	-
6	senior citizen flats	125
7	luxurious terraced houses	112
8	cheaper apartments, low income households	117
9	cheaper terraced houses with garden, mainly families with children	119

2.2 The Climate

Weather over the same period recorded at the Rotterdam weather station of the Royal Netherlands Meteorological Institute (KNMI) was also used in the analysis [7]. The Rotterdam station was chosen due to its proximity to all locations for which data was available. Six weather variables, maximum temperature (°C), global radiation, precipitation amount and duration, relative humidity and potential evapotranspiration were initially processed and analyzed (Figure 1).

Results show that maximum temperature is generally higher in the summer, with an average of 22°C, whereas it is considerably lower in the spring and autumn. For radiation, summer shows the highest values followed by spring, autumn, and winter. The same applies to evapotranspiration, which is strongly correlated to radiation. Relative humidity shows equally low values for spring and summer that get higher in autumn and even higher in the winter with an average value of 90%.

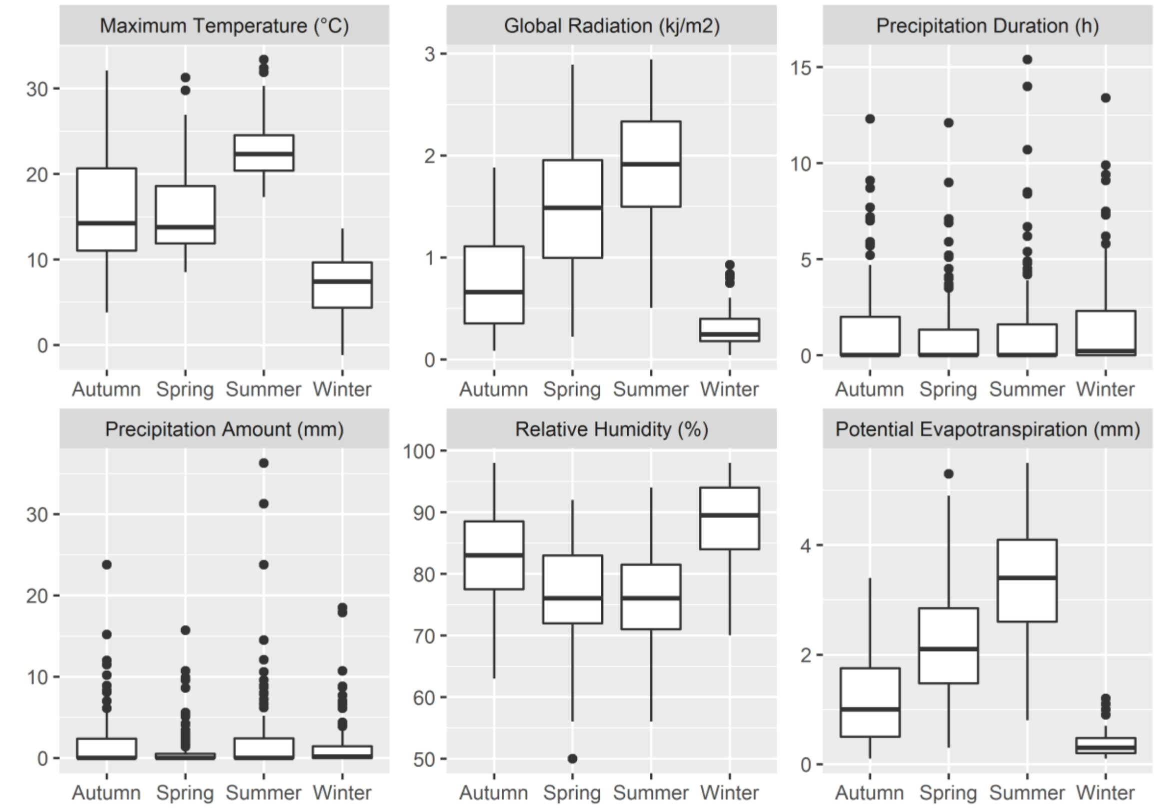

Figure 1. Boxplots of six weather variables as they were recorded at the Rotterdam weather station from 1/7/2016 – 31/7/2017.

Lastly, the summer months show a surprising precipitation amount with record highs, whereas spring is the driest season. Precipitation duration is more evenly distributed among the seasons with winter and autumn demonstrating the longest events, whereas spring is also the season with the lowest precipitation duration.

Potential evapotranspiration has a very high degree of correlation with global radiation, therefore it is not included in the following.

3 Methodology

As it was already mentioned, there are significant temporal variations in water demand patterns. Thus, the influence of the weather was assumed to be different, based on the type of water use that occurs at each time. In order to confirm or reject this assumption, three temporal criteria, the season, day of the week and time of the day, were used in order to create segmentations of consumption (Table 2).

Based on the season, consumption was divided into summer, spring, autumn, and winter, based on the type of day it was divided into weekday demand as opposed to weekends and holidays, and based on the time of the day, it was divided into morning, afternoon, evening, and night consumption. A summary of the temporal segmentation categories is demonstrated in Table 2. For each segmentation characteristic, one category was included ("All") that contained all other categories. The end result when accounting for every possible category combination was 75 (5x3x5) different temporal aggregations of consumption.

Table 2. Temporal segmentation of analysed consumption data.

TEMPORAL SEGMENTATION		
Season	Day of the Week	Time of the Day
All	All	All
Summer	Weekends and Bank Holidays	Morning (06.00-12.00)
Spring	Working Days	Afternoon (12.00-18.00)
Autumn		Evening (18.00-24.00)
Winter		Night (24.00-06.00)

Each location (9 in total) was considered separately, whilst there was also one category including aggregated consumption from all locations. This resulted in 10 location categories, therefore the final number of segmentations was 750 (75x10).

For each segmentation category (750) and each weather variable (5), a linear model was fitted on the data that described the best fit between consumption and a weather variable for each day in the data. Segmentations that included less than 35 days of data were excluded from the dataset, as the sample was considered insignificant. In addition, models that resulted in an R^2 correlation coefficient of less than 20%, a p-value of more than 5%, or a gradient less than the mean gradient among all segmentations for the corresponding weather variable were also excluded from the data.

4 Results and Discussion

Results show that temperature and radiation are the most influential weather variables, followed by relative humidity, while there were no significant correlations identified between daily precipitation duration or precipitation amount and water consumption (Figure 2).

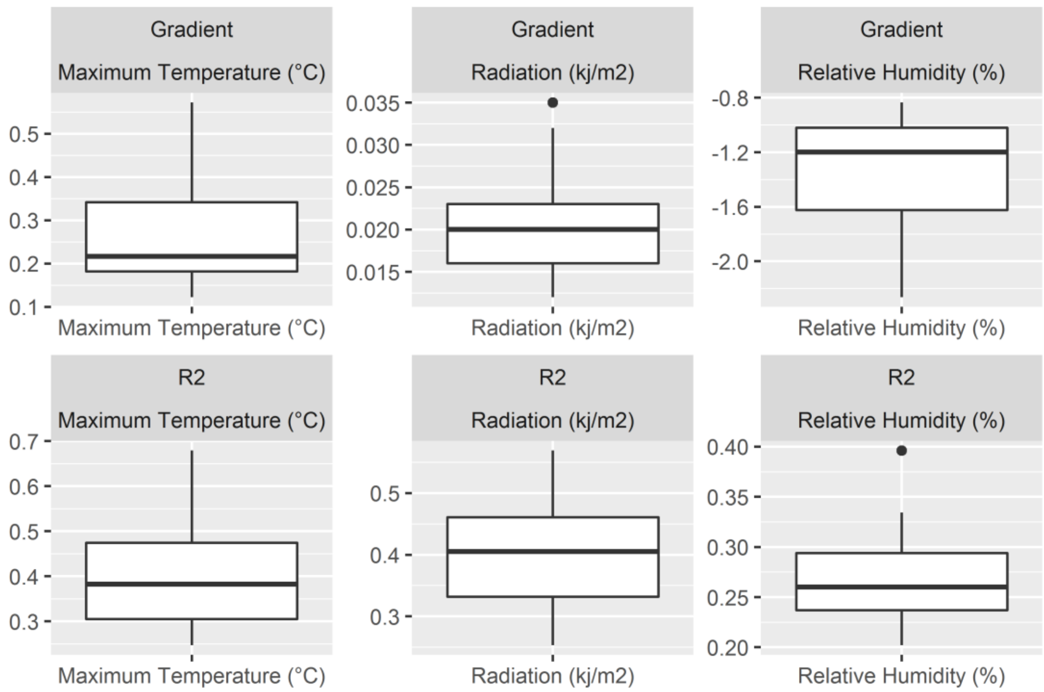

Figure 2. Boxplots showing the distribution of the R^2 and gradient values of all the aggregations that resulted in an R^2 >20%, a gradient greater than the mean and a p value<0.05.

Figure 2 shows the R^2 and gradient values that were identified among the best performing segmentations, i.e. the ones that achieved a correlation greater than 20% and gradient greater than the mean. The total number of these segmentations for each weather variable were 81, 72, 48, 1, and 0 for radiation, maximum daily temperature, relative humidity, precipitation duration, and precipitation amount, respectively.

The R^2 correlation coefficient between maximum temperature and consumption as well as radiation and consumption for these aggregations averages at approximately 40%, while the correlation between relative humidity and water demand is at the much lower 26% (Figure 2).

The mean gradient for each weather variable shows what weather change is required for consumption to be increased by 1 m^3/day. On average, an increase of 5°C in maximum temperature, 50 kj/m^2 in radiation or 0.8% in relative humidity will result in an increase of 1 m^3/day in water demand according to Figure 2.

Next, the occurrence of each segmentation category among the highest performing segmentations was recorded as a percentage of the total. Results highlight the strong temporal variability of weather induced demand (Figure 3).

Segmentation Categories	Radiation	Relative Humidity	Maximum Temperature
Season			
All	30%	35%	24%
Summer	26%	46%	32%
Spring	26%	0%	31%
Autumn	19%	19%	14%
Winter	0%	0%	0%
Day of the Week			
All	42%	35%	43%
Weekends	10%	10%	12%
Working days	48%	54%	45%
Time of the day			
All	26%	29%	24%
Morning	10%	12%	19%
Afternoon	12%	12%	12%
Evening	49%	46%	42%
Night	2%	0%	3%

Figure 3. Percentage of occurrence of each segmentation category among the highest performing segmentations.

While the effect of the relative humidity is particularly prominent during the summer, the effect of temperature and radiation are equally strong during the spring and summer months. On the other hand, the influence of all three weather variables is the highest during evenings of working days.

When looking at Figure 1, it seems that maximum temperature in the area for that year was similar for spring and autumn, although it was a lot higher for the summer months. However, according to Figure 3, the influence of maximum temperature is similar for the summer and spring months, whereas it is a lot smaller for autumn. This indicates that the difference in the weather influence comes from certain habits that relate to different seasons rather than higher temperatures. This could be due to gardening habits, as flowers typically grown in the Netherlands require watering after they bloom in early spring, whereas they do not require any water after planting in autumn. In addition, as it was already mentioned, spring was by far the driest season, which could also be a contributing factor.

Finally, the influence of the weather in each location was assessed. Results show that luxurious homes with gardens in countryside locations (locations 1 & 3) show the highest sensitivity to weather changes (Figure 4), followed by luxurious homes with gardens in the outskirts of cities (location 4). Luxurious homes without gardens as well as cheaper houses with gardens in city locations show a relatively smaller correlation to the weather (locations 7 & 9, respectively). Consumption in apartments and flats shows no significant correlation to weather changes, whether in the city or the outskirts (locations 5, 6, and 8). No significant correlations were identified for location 2, however, data for this location were deemed inadequate and thus no conclusions can be drawn.

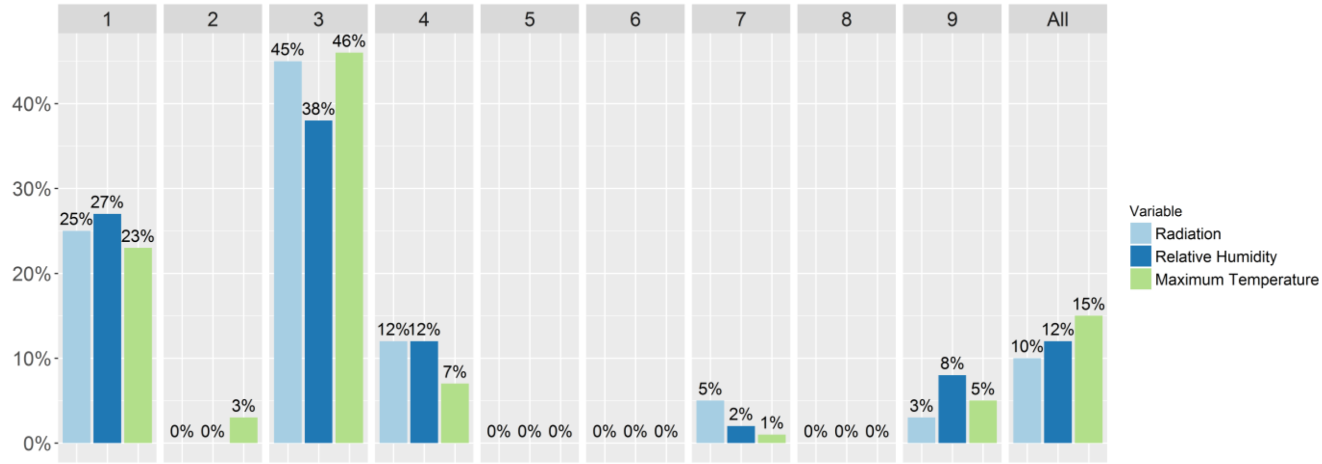

Figure 4. Percentage of occurrence of each location among the highest performing segmentations for each weather variable.

In order to gain a better insight into the different effect that weather variables have on certain segmentations, daily consumption was plotted against temperature, radiation, and humidity at a daily level (Figures 5-7).

Each point represents one day in the data. The plots on the left hand side include all days (~ 400 days) and all locations (~ 1,000 properties). The plots on the right hand side correlate the weather to consumption occurring only at certain times and/or at certain locations. The red trend line represents the second degree polynomial regression model that best fits the data.

The first thing that becomes clear by Figures 5 to 7 is that the effect of all three weather variables differs significantly for certain times and types of consumers. When looking at the influence of maximum daily temperature, an increase from 20°C to 30°C will cause an increase in consumption of 20 m^3/day, approximately 20%, whereas an equal increase for autumn evenings of working days for location 3 will cause an increase in consumption of approximately 145%. This could be of particular interest when calculating peak demands that occur during the mornings and evenings.

Similarly, an increase in radiation from 2 to 3 kj/cm^2 will likely increase consumption by 20% for all days and locations and by almost 50% for evenings of working days for location 3.

Out of the three weather variables that were found to have the highest correlation to consumption, humidity was the least influential one. Indeed, according to Figure 7, an increase in relative humidity from 80% to 90% will cause an increase in consumption of 5% for all properties and days in the data and an increase of 16% for summer evenings during working days.

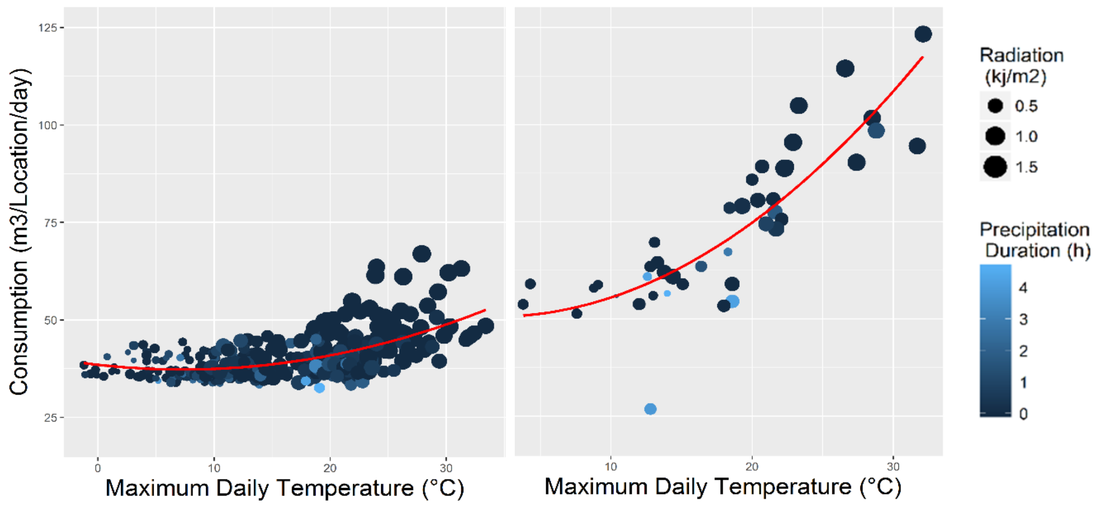

Figure 5. Correlation between maximum daily temperature and average daily consumption for all locations and days (left) and autumn evenings during working days for location 3 (right).

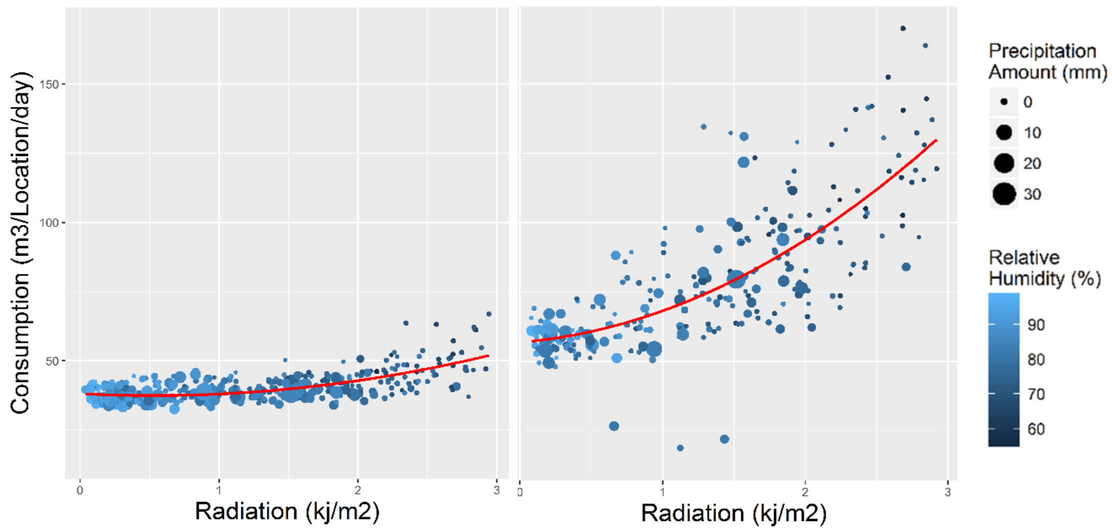

Figure 6. Correlation between total radiation (kj/m^2) and average daily consumption for all locations and days (left) and evenings during working days for location 3 (right).

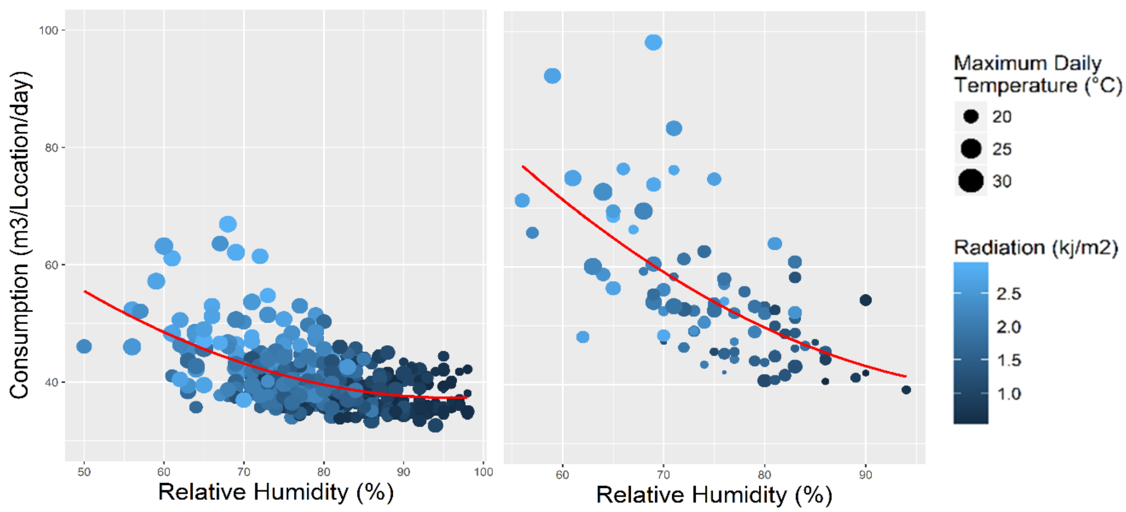

Figure 7. Correlation between humidity (%) and average daily consumption for all locations and days (left) and summer evenings during working days for all locations (right).

5 Summary and Conclusions

The effect of weather on water consumption is a topic of particular interest in the literature, especially under the threat of current and future changes in the climate. This study used consumption, household characteristics, and weather data from 9 locations in the Netherlands in order to investigate the effect of different weather variables during different times and for different types of consumers.

Results showed that temperature and radiation have the biggest influence on consumption, followed by relative humidity. No strong correlations were identified between water consumption and precipitation amount or duration. In addition, results showed that households in countryside locations, as well as houses with gardens and affluent residents during summer and spring evenings of working days are significantly more affected by changes in the weather.

These results can be used in order to better understand water demand and the factors that influence it and can assist in the development of targeted water conservation strategies, as well as improved demand forecasting models.

Acknowledgements

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