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Using advanced metering infrastructure data to evaluate consumer compliance with water advisories during a water service interruption

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ABSTRACT

Water main breaks disrupt services provided by utilities and result in Water Service Interruptions (WSIs). Water utilities can manage WSIs through water advisories, which request that consumers limit their water use. The performance of water advisories depends on consumer compliance and decisions to conserve water. This research explores customer compliance with water advisories using water consumption data collected through Advanced Metering Infrastructure (AMI). AMI provides high temporal and spatial resolution of water consumption data, which is analyzed to identify changes in water use behaviors. This research explores water use changes during a major water main break in Orange County, North Carolina, that caused a significant WSI, limiting water supply for more than 80,000 people. Customers were asked to reduce water use to essential purposes only and to boil water over the course of two days in November 2018. This research analyzes hourly consumption data to evaluate water consumption trends during the WSI and in response to water advisories. Statistical analysis is used to estimate the number of consumers who complied with utility notifications and to evaluate the volume of water saved. Regression analysis is applied to explore compliance across different user segments. Results provide insight about the level and variation of water conservation that can be expected during a WSI.

1. Introduction

Water main breaks are a recurring issue that interrupt essential water services and pose a hazard to property and public health. A leak or burst in a water main can flood roadways and damage infrastructure. Pipe breaks lead to loss of pressure, allowing microbial, chemical, and physical contaminants to enter the drinking water system. More than 240,000 water pipes break per year in the U.S., wasting over two trillion gallons of treated drinking water (ASCE, 2017).

Water providers must take actions to minimize the duration and extent of a water service interruption (WSI) by locating leaks through, for example, acoustic loggers, ground penetrating radar, and hydrophones, and allocating crews to repair breaks (Puust et al., 2010). Water supply and distribution is a sociotechnical system and is impacted by both the performance of physical infrastructure and the decision-making of operators and consumers (Zechman, 2011; Berglund, 2015). For example, water reuse programs must align public acceptance and adoption with the availability of advanced treatment technologies (Muthukumaran et al., 2011; Kandiah et al., 2019), and drought mitigation requires activities to enhance supply and encourage water conservation (Quesnel et al., 2018). In a similar way, the outcomes of a water main break rely on the response of water consumers, and water shortages can be mitigated by requesting that consumers curb demands. Water advisories direct consumers to reduce water use to essential purposes only, do not use water, or boil water before use (Vedachalam et al., 2016). Water advisories are typically distributed via conventional news media and phone calls and may be further dispersed in a community through social media, online platforms, and word-of-mouth (Bradford et al., 2017). The actions of consumers to limit water use and conserve water can assist in maintaining water pressure in a pipe network, preventing system contamination and the need for subsequent boil water orders (O'Shay et al., 2022).

Customer compliance with water advisories is critical in improving the outcomes of a WSI. Although water utilities have generally been considered trustworthy sources (Lindell et al., 2010), compliance may be influenced by beliefs, risk tolerance, and level of community awareness (Castleden et al., 2015; Bradford et al., 2017; Quesnel and Ajami, 2017; Bolorinos et al., 2020; Booysen et al., 2019). People may be unaware of their susceptibility to waterborne illnesses and fail to associate advisories with health risks (Castleden et al., 2015). Commuters

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may be unaware of local water orders to reduce water use (Strickling et al., 2020). Compliance with water advisories decreases when recommended actions take time, finances, or skill to execute (Lindell et al., 2010, 2016). Previous research studies listed above implemented surveys that explore behaviors during WSIs and characterize water conservation based on self-reported data. The research described in this manuscript explores quantitative methods to evaluate household water use and compliance with water advisories during a WSI, based on analysis of water consumption data reported by Advanced Metering Infrastructure (AMI). AMI deploys connected smart meters at residential and nonresidential accounts reporting subhourly household water consumption. As part of a smart city paradigm, AMI generates high resolution consumption data for improving water system management by characterizing daily water demand profiles (Pesantez et al., 2020, 2022), developing real-time network models (Creaco et al., 2022), and providing feedback to consumers to encourage water conservation (Gurung et al., 2014; Liu et al., 2015). AMI datasets provide an unprecedented resource to characterize consumer response to WSIs.

1.1. Consumer behavior during water service interruptions

Studies indicate that consumers respond with varying levels of compliance to official communications about WSIs (Castleden et al., 2015; Bradford et al., 2017; Quesnel and Ajami, 2017; Bolorinos et al., 2020; Booysen et al., 2019). Message content, timely receipt, and information source are major factors in compliance (Vedachalam et al., 2016). The intention or decision to reduce water use during a hazard is influenced by individual beliefs, media consumption, environmental concern, and ability to conserve water (Quesnel and Ajami, 2017; Bolorinos et al., 2020). Bradford et al. (2017) used interviews with utility officials and household surveys to evaluate the effectiveness of drinking water advisories. They found variation in adherence to advisories based on the neighborhood of residence, notification frequency, and information source (Bradford et al., 2017). Community compliance is also related to the duration of the hazard: 62% of the sample reported adhering to utility communications regarding a short term, urgent water quality issue. For long-term, chronic exposure to lead pipes, less than 30% of respondents reported always following the recommended guidelines for water use (Bradford et al., 2017). The timing and phrasing of the utility message can also affect compliance. Booysen et al. (2019) found that after a "Level 5″ water use restriction was issued in Cape Town, South Africa, water consumption increased, potentially due to confusion over the meaning of the alert. The most significant water use reductions occurred when media outlets focused on "Day Zero", the day when Cape Town taps would run dry (Booysen et al., 2019). News reports about boil water orders often do not deliver clear risk communication that is required for compliance (O'Shay et al., 2022). Surveys conducted in Boston, Massachusetts and College Station, Texas assessed perceptions of the information source and of protective actions, such as buying bottled water, treating water with bleach, or boiling water (Lindell et al., 2010, 2016). Findings indicate that water utility personnel are perceived as trustworthy (Lindell et al., 2010). However, the public still may not fully perceive the risks of water contamination, and might ignore calls to take protective actions, particularly if those actions are costly and take time or skill to execute (Lindell et al., 2010, 2016). Probabilistic models were developed to simulate consumer response to water advisories based on survey results and capture how compliance emerges based on the source of information, targeted messages, and media (Shafiee et al., 2018; Strickling et al., 2020). These modeling studies demonstrate the potential cascading effects of compliance: when individual decision-making and word-of-mouth are included in modeling a contamination event, the spread and location of a simulated contamination plume changes compared to models that consider contaminant fate and transport alone (Shafiee and Zechman, 2013). Combining infrastructure-based response actions with water advisories can provide high levels of public health protection (Shafiee and Berglund, 2017).

1.2. Advance metering infrastructure applications

AMI systems provide utilities with continuous, high resolution measurements of water consumption at household meters, reporting at sub-hourly frequencies (Gurung et al., 2014; Guerrero-Prado et al., 2020). Cities including Los Angeles, Boston, and London have invested in multimillion dollar smart metering programs (Thames Water, 2021). It is anticipated that 45% of cities worldwide will implement internet-enabled water management by 2024 (Yesner et al., 2018). Guerrero-Prado et al. (2020) reviews different types of AMI data applications, including demand forecasting (Candelieri, 2017; Chen et al., 2011; Pesantez et al., 2020), leak detection (Britton et al., 2013; Kermany et al., 2013; Luciani et al., 2019), and consumer demand classification (Davies et al., 2014; McKenna et al., 2014; Garcia et al., 2015, Ebeid et al., 2017). Hourly and sub-hourly water consumption data collected through AMI have been analyzed to evaluate changes in user consumption based on price changes (Yang, 2017) and to assess daily use patterns and peaking factors (Gurung et al., 2014). High resolution consumption data has been analyzed to model demands and improve simulation and management of water distribution networks (Creaco et al., 2021; Fiorillo et al., 2020). AMI data can be analyzed in real-time to help managers respond to hazards that impact water distribution. For example, when Winterstorm Uri rendered widespread power outages and frozen pipes across Texas in February 2021, Arlington Water Utilities analyzed AMI data to identify hotspots where customers were lacking water service and establish locations to distribute bottled water (Nhede, 2021).

Studies which focus specifically on using AMI data to identify changes in demands often focus on long-term hazards, such as drought (Quesnel and Ajami, 2017; Booysen et al., 2019; Bolorinos et al., 2020). A few studies focus on how water use is affected by communication from utilities about consumption based on AMI data. For example, more frequent water use information and comparisons with past water consumption or neighbors' water consumption can encourage conservation (Cominola et al., 2021; Liu et al., 2015). AMI data was analyzed to explore how disruption of daily activities due to social distancing measures during the COVID-19 pandemic changed diurnal water use patterns (Abu-Bakar et al., 2021; Pesantez et al., 2022; Berglund et al., 2022). Seasonal changes, particularly air temperature, can also influence the volume of water consumed by households (Xenochristou et al., 2019).

Research studies have utilized AMI datasets that vary in the number of smart meters that are included in the dataset, the spatial distribution of meters, and the period over which data are collected. Some studies focus on a small set of meters at spatially explicit apartment or school buildings (Kermany et al., 2013), midsize community studies comprised of 50 to 100 representative meters (Pesantez et al., 2020; McKenna et al., 2014), and longer duration studies of meters representing large communities or regions, including Alicante, Spain (Garcia et al., 2015), southwestern U.K. (Xenochristou et al., 2019), Redwood City, California (Quesnel and Ajami, 2017), and Sydney, Australia (Davies et al., 2014). These studies evaluate data from hundreds of meters, and only a few encompass more than 1500 smart water meters (Xenochristou et al., 2019; Garcia et al., 2015).

1.3. Research gap and study objective

Consumer response to water utility advisories has been explored using survey methods, which does not provide insight about compliance with defined reductions or the volume of water that is saved during advisories. The advent of smart cities technologies and smart metering creates a new opportunity to observe individual account-level behavior and water consumption at a high resolution and quantitatively assess reductions in water consumption. This objective of the research described in this manuscript is to explore an AMI dataset to quantify account-level water consumption and compliance during a WSI. The AMI dataset used in this research characterizes water use during a WSI that occurred in November 2018 in Orange County, North Carolina, in which a major water main burst. Water service to more than 21,000 customer accounts was interrupted, and water customers were advised to reduce water use to essential purposes only (OWASA, 2018). The AMI dataset describes water use at more than 16,000 water meters and is supplemented by occupancy information and lot-level characteristics for a sub-set of meters. This exploratory analysis develops unique insight about consumer behaviors during a WSI through quantifying the level of compliance based on verifiable data and evaluating measured volumes of conserved water. This study explores one of the largest AMI datasets reported to date in literature. Utilities can apply outcomes from this research to gain insight about household compliance, management and communication strategies, and system pressure during water infrastructure hazards durins WSIs.

2. Materials and methods

This study explores a large AMI dataset and characterizes household water consumption during a WSI by analyzing changes in water use behaviors from typical usage and estimating compliance with advisories to reduce water use. Variables are summarized in Table 1.

2.1. Estimating essential use

During a WSI, utilities issue advisories asking consumers to limit demands to essential use only. This research uses information from the World Health Organization (WHO) to estimate minimum uses for basic water purposes and data from a U.S.-based study to estimate minimum requirements for toilet flushing. Water use for bathing is not included beyond water requirements for basic hygiene. Estimates from the WHO guidelines indicate water for survival, including food and drinking, is 3.0 L per person per day; basic hygiene requirements are 6.1 L per person per day; and basic cooking requirements are 6.1 L per person per day (WHO, 2013). According to a U.S. study conducted by the Water Research Foundation (WRF) on residential end uses of water, use in toilet fixtures account for 24% of indoor water use (Water Research Foundation, 2016). Based on this study, toilet flushes are included at an additional 6.1 L per flush with a frequency of five flushes per person per day (30.3 L per person per day). In total, the essential water use is 45.5 L per person per 24-hour period.

Table 1
Summary of nomenclature.

Name	Variable symbol	Definition
Total consumption	$W_{i,p}$	Total household water consumption at meter i during a period p
Total event consumption	E_i	Total household water consumption during a WSI
Hourly consumption	$c_{t,i,p}$	Water consumed during time step t at meter i for period p
Mean previous consumption	MPC_i	Average consumption for a group of previous time periods of duration D at meter i
Water savings	S	Approximate net volume of water saved across all meters
Occupancy	O_i	Number of persons living in the household at meter i
Essential Use Threshold per capita	EUT	Volume of water necessary for essential use purposes per person during a period of duration D
Essential Use Threshold per meter	EUT_i	Volume of water necessary for essential use purposes during a period of duration D for meter i
Compliance metric	d_i	Difference between household total water use during a WSI and essential use threshold at meter i
System-wide compliance	C	Percent of meters in compliance with the essential use during a WSI
Standardized variate for total consumption	$Z_{i,E}$	Standardized variate for total consumption $W_{i,E}$ during event E for a normal distribution of consumption with $\mu = MPC_{i.}$
Standardized variate for advised consumption	$Z_{i,EUT}$	Standardized variate for advised consumption during WSI based on EUT_i for a normal distribution of consumption with $\mu = MPC_{i.}$
Total use percentile	$F_{i,E}$	Percentile associated with $Z_{i,E}$
Advised use percentile	$F_{i,EUT}$	Percentile associated with $Z_{E,i}$

2.2. Estimating compliance and conserved water

The following framework provides an approach to evaluate the level of compliance with an essential purpose only water advisory administered during a WSI. An event window is established to quantify the duration (D) of the WSI. Consumption readings at every time step t for each individual meter i are summed for the duration D to determine the total consumption:

$$W_{i,p} = \sum_{t=1}^{D} c_{t,i,p} \tag{1}$$

where $W_{i,p}$ is total consumption at meter i during a given period p (L); $c_{t,i,p}$ is consumption at time step t and meter i for a given period p (L); and D is the duration of a WSI (hours). In this research, the time step is one hour. The expected volume of water used under normal operating conditions is estimated as the mean previous consumption (MPC_i) for periods without service interruption matching in duration D (hrs.) to the WSI.

$$MPC_i = \frac{\sum_{p=1}^{P} W_{i,p}}{P} \tag{2}$$

MPC_i is the mean consumption over P periods under normal operating conditions at meter i (L). P is the number of periods of duration D (hrs.). The standard deviation ($\sigma_{MPC,i}$) is also calculated over the P periods of water consumption recorded during normal operating conditions.

The total volume of water saved during the WSI is the difference between the consumption during a WSI (E_i) and the mean consumption (MPC_i).

$$S = \sum MPC_i - E_i \tag{3}$$

where S is the net volume of water saved across all meters in a sample set for a specific WSI (L).

Compliance of households is evaluated based on the assumption that the utility broadcasts a water advisory that directs consumers to use water for essential purposes only. The essential use estimate is utilized with the occupancy data to develop thresholds of compliance.

$$EUT_i = O_i \times EUT \times \frac{D}{24} \tag{4}$$

where EUT_i is the Essential Use Threshold at meter i (L/capita/day). EUT is the Essential Use Threshold per person, defined as 45.5 L per person per 24 h period above. O_i is the occupancy at meter i (people). The essential use threshold is used as a metric for the volume of water that should be used by a household of that size during a WSI. Finally, a household is assumed to have complied with the water advisory if the water consumed is less than the threshold:

$$d_i = E_i - EUT_i \tag{5}$$

where d_i is the difference between total use during a WSI (E_i) and the essential use threshold at each household to measure compliance (L). If $d_i \leq 0,$ the household at that meter is considered to have complied with essential use advisories.

2.3. Statistical methods

Water consumption is also evaluated based on how households change water use compared with distributions of past consumption. First, the essential use volume for a duration D is calculated for each meter based on occupancy (EUT_i in Eq. (4)). The essential use volume for each meter is assigned a standardized variate, or Z-score ($Z_{i,EUT}$), based on the mean of P previous normal operating condition periods (MPC_i).

$$Z_{i,EUT} = \frac{MPC_i - EUT_i}{\sigma_{MPC,i}} \tag{6}$$

The standardized variate ($Z_{i,EUT}$) is converted to a percentile ($F_{i,EUT}$), based on a normal distribution of previous consumption values. In a similar way, the consumption during the WSI (E_i) at each meter is also assigned a Z-score ($Z_{i,E}$):

$$Z_{i,E} = \frac{MPC_i - E_i}{\sigma_{MPC,i}} \tag{7}$$

The standardized variate ($Z_{i,E}$) is converted to a percentile ($F_{i,E}$) using a *normalcdf* function, based on a normal distribution of previous consumption values. Z-scores tests are used to assess the fraction of typical use for each household's essential use threshold and actual use during the WSI.

Multiple linear regression is used to determine predictors of d_i, which is a compliance metric as defined above, that estimates the difference between the total use during the WSI (E_i) and the essential use, scaled for household occupancy (EUT_i). Only meters with normally distributed demand profiles are used in the application. Variance inflation factors are tested to confirm that assumptions of multivariate normality and no multicollinearity are met. Independent variables include lot-level characteristics: home size, tax value of the home, total acreage of the metered property, and numbers of bedrooms and bathrooms in the home. Independent variables are reported in diverse units of measurement and are standardized by normalizing each variable. Significant relationships are identified between the explanatory variables and the dependent variable d_i. A stepwise forward regression is performed using the R *step* function. This approach adds each independent variable in order from most to least influential to the model. Stepwise forward regression is used to identify finalized model coefficients and the significance of relationships between independent variables and the variable of interest, compliance (d_i).

2.4. Case study

This research focuses on a WSI that occurred in Orange County, North Carolina in November 2018 (referred to as WSI 2018). The Orange Water and Sewer Authority (OWASA) provides water supply to a population of 86,600 people through service connections at approximately 21,000 residential households (U.S. Census, 2019). In 2016, OWASA began a $6 million infrastructure upgrade for the over 21,000 households, replacing existing water meters that required manual readings with AMI technology that records auto-record hourly water consumption to the nearest gallon (Chapelboro Staff, 2016). By November 2018, more than 16,000 AMI meters were installed, and additional meters were added daily.

On Monday, November 5th, 2018, a major water pipeline leaving OWASA's water treatment plant burst, leading to loss of pressure and decreased storage levels in water tanks, and around 21,000 residential customer accounts servicing more than 80,000 people were asked to conserve water (OWASA, 2018). OWASA isolated and repaired the water main break after more than seven hours, and the event caused a partial road collapse at Jones Ferry Road in Carrboro, NC. Customers received texts and phone calls, and information about the burst was broadcast in social media announcements and by local news media. OWASA communicated three compliance orders: 1) advisories to conserve water to maintain system pressure by limiting water use to essential purposes only 2) advisories to boil water and 3) announcements that lifted water advisories.

2.5. Data description

Data used in this study include hourly water consumption and lot-level land use information, summarized in Table 2 and described as follows. Raw data for research purposes were provided by OWASA, including AMI readings for 16,675 and a database with descriptions of metered households. AMI data were provided for 16,675 water meters, which report hourly readings of water consumption at a resolution of one gallon (3.79 L) during the months of September to December of 2018. Information about occupancy, or the number of occupants, is available for 13,924 of the accounts, and of these meters, 7403 have non-zero, normally distributed demands. Occupancy was reported within the dataset as one, two, three, four, or five+ person households. For the purposes of this analysis, five+ person households are conservatively treated as five-person households. Additional descriptors about household characteristics are available for 4356 water meters, and provide lot-level characteristics, including tax value, year built, total acreage, home square footage, number of bedrooms, and number of bathrooms. The North Carolina State University IRB approved the use of AMI data for this research, pursuant to Protocol 20,414. Further information used in this analysis includes census data for population size and climate data from the United States Geological Survey (USGS, 2020).

3. Results

3.1. Aggregate water consumption

AMI data are analyzed to determine the volume of the change in water use during WSI 2018. First, an event window of 29 h was established to quantify the duration of WSI 2018 by reviewing the timeline of the utility communications, from 11 AM on November 5, 2018, to 4 PM November 6, 2018 ($D = 29$). A dataset of was developed to compare typical use across 29-hour periods (11AM-4PM) that cover two consecutive weekdays. Due to historically different weekday to weekend water use patterns, if the WSI occurred on a weekday, consumption should be compared to other weekdays (Pesantez et al., 2020). Data was obtained covering the period preceding the WSI 2018, ranging from to October 1st, 2018, to November 2nd, 2018. The data are divided into 20 29-hour periods that mirror the WSI 2018 event window. Therefore, the number of periods, P is set at 20 for calculating MPC_i for each meter i in Eq. (2). This period was selected for comparison because of seasonality, and outdoor watering behaviors should be similar for October and November in the piedmont region of North Carolina (Fair and Safley, 2013). The size of the dataset was also restricted by the installation of AMI. At the time of WSI 2018, new meters were deployed daily. For example, while there were 16,675 reporting meters on the day of the event, there were only 15,036 reporting meters on October 1st, 2018.

The hourly volume of water consumed across all households is evaluated to observe system-level changes in water consumption. The total hourly consumption is calculated across 16,675 m for each hour from 6 AM on the first day of the WSI 2018 (Monday, November 5th) to 12 AM on November 7th (Fig. 1). This hourly volume is compared to the hourly distribution of water use for 20 weekday periods of the same the duration of WSI 2018, and the average of the distribution is assumed as the typical use at that hour for these households. Shaved peaks are noticeable in the evening of November 5 and in the morning of November 6. Household water use during WSI 2018 was much lower than typical evening water use among the 16,675 households. The aggregate consumption at 5 PM during WSI 2018 was 185,683 gallons (702,887 L) for these households, 27% less than the average use at 5 PM

Table 2
AMI meter subgroups used in research study.

Dataset ID	Number of meters	Type of data available					
		Online during WSI 2018	Hourly demand data	Non-zero demands	Normally distributed demands	Occupancy data	Household characteristics data
1	16,675	Yes	Yes				
2	13,924	Yes	Yes	Yes		Yes	
3	7403	Yes	Yes	Yes	Yes	Yes	
4	4356	Yes	Yes	Yes	Yes	Yes	Yes

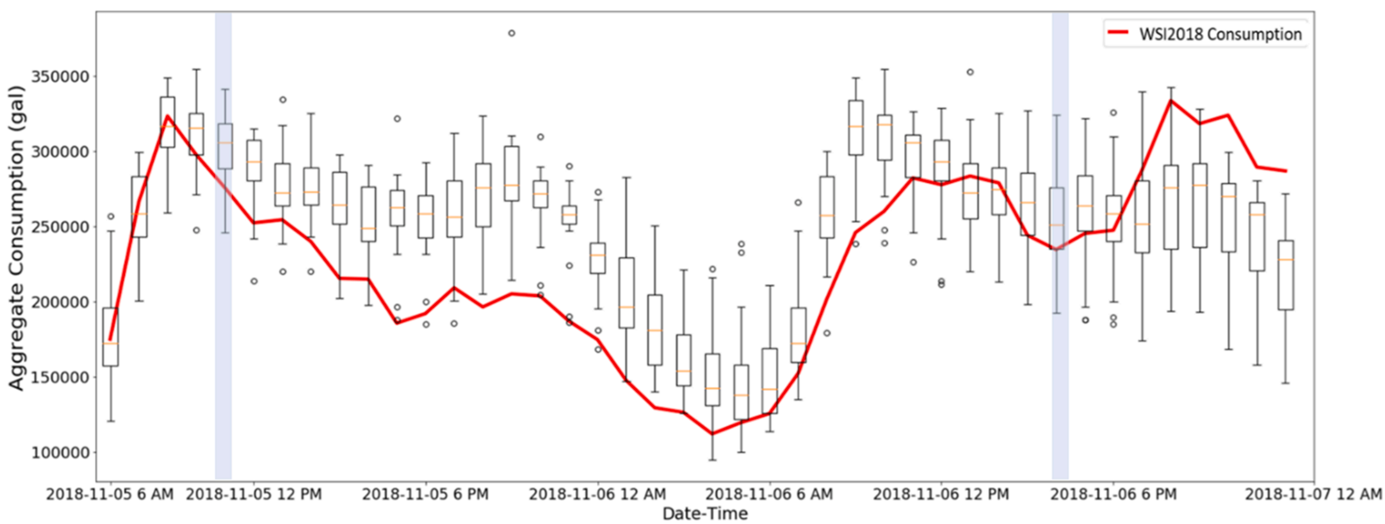

Fig. 1. Water consumption during WSI 2018 compared with water consumption on previous periods. Solid line indicates total consumption during WSI 2018, aggregated across all meters from Dataset 1 (Table 2). Each boxplot represents a distribution of the total volume of water used across all meters, calculated for a set of 20 previous weekdays. Blue shadow boxes indicate the duration of WSI 2018. One gallon is equal to 3.78 L.(For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.).

during normal operating conditions (960,919 L). Peak water use on the evening of November 6th, 2018, after the water advisories were lifted, exceeds the average use by 23%. Consumers resumed water use shortly after water advisories were lifted, and at a higher rate than average, which may indicate that consumers had delayed nonessential water uses, such as dishes and laundry.

3.2. Effect of weather on water consumption

WSI 2018 coincided with a precipitation event that occurred on November 5, 2018, which would reduce outdoor water use, leading to a potentially high estimate of water savings and compliance. Water consumption during WSI 2018 is compared with water consumption on days with similar weather. The rain event on November 5th, 2018, was measured at a depth of 3.94 cm (1.55 inches) at a rain gage in Cane Creek Reservoir, NC, near the Orange County, NC area (USGS, 2020). Climate data were explored to identify days with similar weather to that during WSI 2018 based on the following criteria: (1) $\geq$ 0.254 cm of rain, (2) a temperature range within 15° of that of WSI 2018, and (3) the date of rainfall was a weekday (USGS, 2020). A total of five days met the criteria, including days in October and November of 2018 and 2019 (Table 3 and Fig. 2). A subset of 7403 meters is considered in this analysis, referred to Dataset 3 in Table 1. Fig. 2 shows the total system wide consumption on the five similar weather days (Table 3) compared to the consumption during WSI 2018. Demand for water is much lower in the evening of WSI 2018 compared to the other rainy days at an

Table 3
Weather and consumption information for WSI 2018 and precipitation events in October and November of 2018 and 2019 on Dataset 3.

Rain Events		Weather Data				Water Consumption	
Name	Date (Day)	Precipitation (cm) (*inch*)	Max Temperature (C)	Min Temperature (C)	Observed Temperature (C)	Evening peak 8 PM (L)	Next morning peak 8 AM (L
WSI 2018	11/5/2018 (Mon.)	3.94 (*1.55*)	17	11	12	164,042	231,017
Rain Event #1	10/12/2018 (Fri.)	4.90 (*1.93*)	25	12	12	199,299	221,385
Rain Event #2	10/14/2019 (Mon.)	1.40 (*0.55*)	19	13	16	290,976	341,471
Rain Event #3	10/16/2019 (Wed.)	0.38 (*0.15*)	25	6	13	303,894	314,988
Rain Event #4	10/17/2019 (Thur.)	1.19 (*0.47*)	20	5	5	283,936	313,534
Rain Event #5	10/23/2019 (Wed.)	0.51 (*0.2*)	24	8	8	291,006	322,016

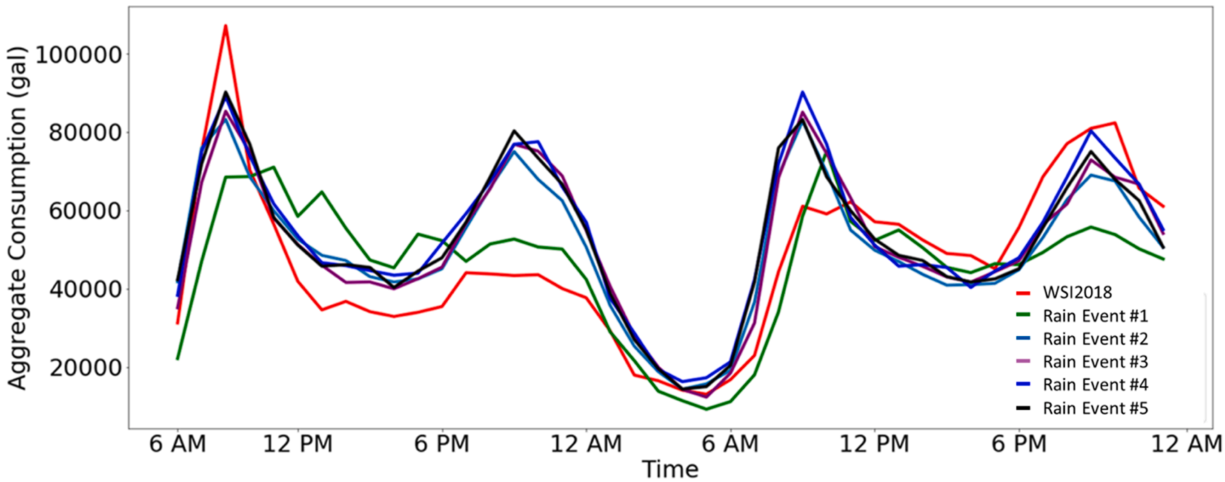

Fig. 2. Water consumption for WSI 2018 and five rain events. Total consumption is summed over 7403 m in Dataset 3 (Table 2), which were online during all rain events. One gallon is equal to 3.78 L.

average of 109,819 L less (Table 3). Similarly, the water use is low on the morning of the second day of WSI 2018 when compared with other days on which it was raining (Table 3). The shaved peaks during WSI 2018 compared to similar weather days verifies that weather is not a major controlling factor in the decreased water use achieved during this event. Rain Event #1 is an exception, when demands only slightly exceed those during WSI 2018 (Table 3, Fig. 2), concurring with hurricane Michael's impact on North Carolina. During this intense storm, thousands of North Carolinians evacuated, sustained damages to their homes, or were under boil water advisories, which contributes to the abnormally low water consumption recorded during Rain Event #1 (Beven et al., 2019; McKenith, 2018).

3.3. Water savings

Water savings during WSI were calculated using a subset of 13,924 AMI meters which were online during WSI 2018 with known occupancy and non-zero demands (Dataset 2 in Table 2). The approximate water savings is 2,046,193 L for this group of meters, and the total known occupants represented is 41,512 people. The AMI meters are a snapshot of OWASA's wider service area, approximately 86,600 people across 21,000 residential accounts. Scaled to the full population, it can be assumed that around 4.28 million L of water was conserved during WSI 2018. U.S. households use approximately 82 gallons per person per day (310 L), which leads to a system wide demand for OWASA of 26.8 million L per day for the duration of WSI 2018. Water savings during WSI 2018 corresponds to a 15.9% reduction in total water use (Dieter et al., 2018).

3.4. Compliance with water advisories based on essential use threshold

Compliance is evaluated based on the essential use estimate (Eq. (4)) for Dataset 3 (7403 meters), which includes all meters with known occupancy values. Based on a per captia *EUT* of 54.9 L per person over a 29 h duration, 30.75% of accounts complied with water advisories during WSI 2018 (Table 4). Compliance may be sensitive, however, to consumer interpretation of essential use. The calculation for *EUT* shown in Section 2.1 uses strict allowances for water consumption, and based on a typical consumption in the U.S. of 82 gallons (310 L) per person (Dieter et al., 2018)), reducing to essential use requires a decrease in consumption by 85%. Individual interpretation of the term essential use can cause low compliance rates, based on the assumptions used to calculate *EUT*. The volume of the *EUT* is increased for a set of increasing volumes, simulating consumers who use water for an additional toilet flush and varying durations of showers. For example, some individuals may

Table 4
Compliance with water advisories using increasing values for essential use. EUT is adjusted to represent households that consume water for end uses beyond the essential uses of basic hygiene, drinking, cooking, and five toilet flushes.

EUT (L/person/29 h) *(gal/person/29hours)*	Additional use type allowed (L/person)	Compliance with *EUT* (%)
54.9 *(14.5)* (base case)	None	30.8
60.9 *(16.1)*	Additional toilet flush (6.1)	34.4
64.3*(17)*	One-minute shower (9.5)	36.1
73.8 *(19.5)*	Two-minute shower (18.9)	39.9
89.3 *(23.6)*	Three-minute shower, and additional toilet flush (34.4)	47.5
102.2 *(27)*	Five-minute shower (47.3)	52.9

choose to shower, which consumes 7.6 L per minute via standard showerheads (US EPA, 2022). Results demonstrate that if essential use allows one 5-minute shower per person during the WSI, then the rate of compliance increases to 52.9% (Table 4). Increasing the volume of the base per captia *EUT* for additional water uses, including an additional toilet flush, one-minute shower, two-minute shower, three-minute shower and additional toilet flush, and a five-minute shower creates a linear increase in system level compliance. Linear regression that uses the six data points shown in Table 4 identifies the following relationship between the *EUT* and system-wide compliance (*C*):

$$C = 0.461EUT + 31.33 \tag{8}$$

where *C* is the percentage of meters complying and consuming a volume of water less than or equal to the *EUT*, where *EUT* is defined as the essential use threshold per capita, as above. The R^2 value for Eq. (8) is 0.997, and this relationship indicates that each additional gallon yields 0.46% more households in compliance. Based on this extrapolation, 100% of households are projected to comply with an *EUT* that is equal to 203.9 L per person, or 149 L per person more than a strict definition of essential use (54.9 L per person). Utilities can use this analysis to develop guidelines to communicate expectations around water conservation during a WSI.

Two meters are shown in Fig. 3 to demonstrate typical water consumption and compliance during WSI 2018. Fig. 3a shows Meter A, an example of a meter that reports consumption in compliance with an *EUT* equal to 54.9 L/person, and the distribution of consumption ($W_{i,p}$) during 20 previous periods that are 29-hours in duration is also shown. The consumption during WSI 2018 is much lower than the uses during the previous periods and is within the shaded region representing the *EUT*. Meter B shown in Fig. 3b does not report a volume that is

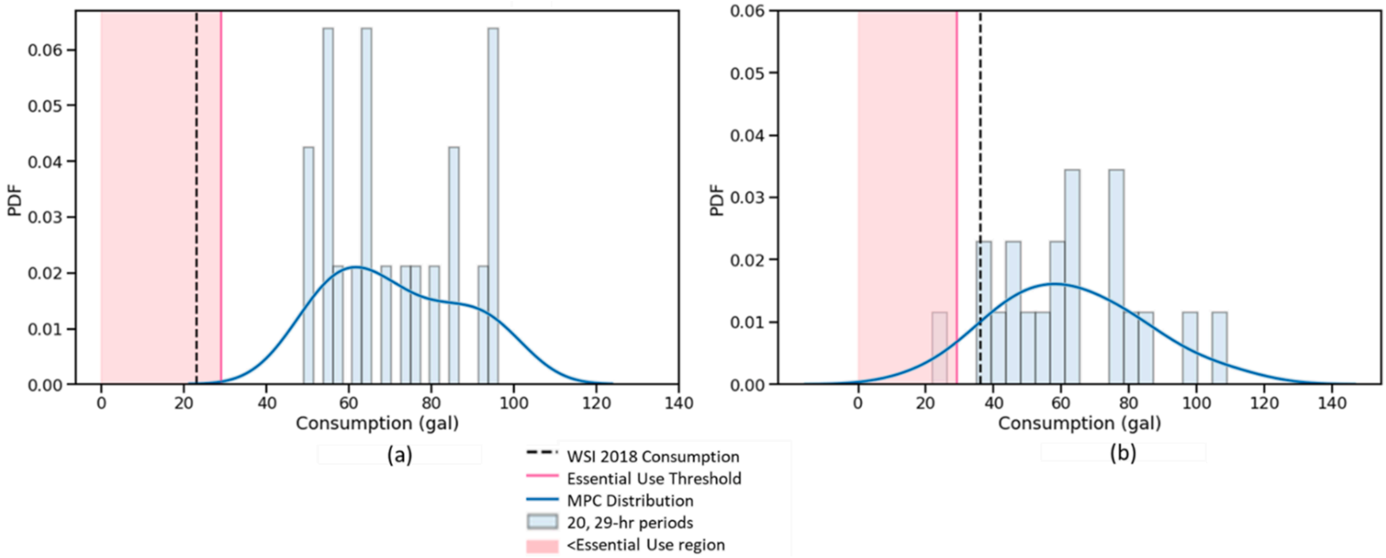

Fig. 3. Consumption during WSI 2018 (black dashed line), typical water use behaviors (curved line and bars), essential use range (shaded region), and essential use threshold (solid line) for two meters: (a) Meter A is a compliant household, and (b) Meter B is a non-compliant household. One gallon is equal to 3.78 L.(For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.).

complying, as the consumption is higher than the *EUT*. For the non-compliant meter (Fig. 3b), water consumption is reduced during the WSI when compared with typical use patterns; however, defining compliance within the context of typical consumption may be insufficient. Highly consumptive meters may reduce their use substantially but consume high water volumes and hinder management during a WSI.

The relationship between typical water consumption and water use during WSI 2018 can be evaluated through calculating $F_{i,E}$, the percentile of the total use during WSI 2018 ($W_{i,E}$) for each meter (Eq. (6)). For a compliant meter, Meter A (Fig. 3a), the value of $F_{A,E}$ is 0.11%, indicating that Meter A significantly reduced their typical consumption, while Meter B (Fig. 3b, $F_{B,E} = 51.0\%$) used a volume of water within the range of typical water use. Similarly, the relationship between the essential use threshold per meter and typical water consumption per meter is assessed by calculating $F_{i,EUT}$, which is the percentile of the EUT_i for each meter (Eq. (7)). While Meter A typically uses higher volumes of water than essential use ($F_{A,EUT} = 0.31\%$), the essential use threshold is closer to the range of typical uses for Meter B ($F_{B,EUT} = 5.5\%$). Values for $F_{i,E}$ and $F_{i,EUT}$ were calculated for each meter in the dataset and plotted as histograms in Fig. 4. The EUT_i falls in low percentiles for many users, indicating that most meters typically use significantly more water than the essential use volume (Fig. 4). As shown by the light gray histogram in Fig. 4, many households used less than the 50-percentile volume of water during WSI 2018. On average, households used in the bottom 33rd percentile of what they typically consume ($F_{i,E} = 33.3\%$). To meet the essential use threshold, however, households would need to use in the lower 22nd percentile of their typical use ($F_{i,EUT} = 21.8\%$). During WSI 2018, OWASA consumers decreased water use from typical levels, but further reductions were needed to reach the essential use threshold.

3.5. Predicting compliance from household characteristics

Regression analysis is applied to explore if compliance is predictable based on household characteristics. A total of 4356 AMI meters (Dataset

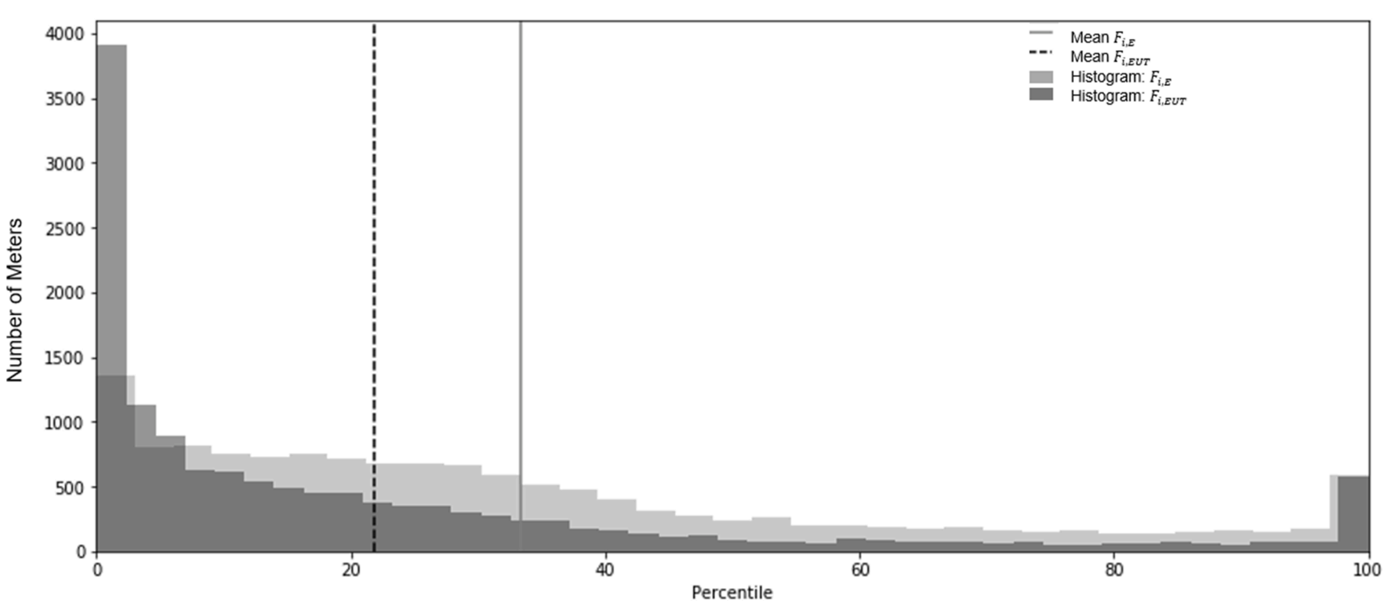

Fig. 4. Histograms of the percentiles of total use during WSI 2018 ($F_{i,E}$: light gray) and percentiles of essential use thresholds ($F_{i,EUT}$: dark gray).

4) were selected for additional statistical analysis based on these criteria: meters were online during WSI 2018, meters report a history of non-zero and normally distributed demands, and household characteristics data are known and available for these meters. The compliance metric, d_i, is the independent variable, which measures the level of compliance to orders to reduce water use to essential purposes. The compliance metric is defined above as the volumetric difference between WSI 2018 consumption and the essential use threshold at each household. A multiple linear regression model is created to predict d_i at each household from potential explanatory variables including mean previous consumption (MPC_i), occupancy, tax value, year built, property acreage, square footage, number of bedrooms and bathrooms of the household. Across Dataset 4, compliance ($d_i \le 0$ for $EUT = 54.9$ L/person) is 24.2%. Because raw data from the AMI meters reports consumption at a resolution of one gallon, the regression is conducted using d_i reported in gallons.

No variance inflation factors for these independent variables exceed 10.0, indicating that multicollinearity is not an issue. A larger, positive value for d_i indicates less compliant behavior - that is, total use during WSI 2018 exceeds the essential use threshold. A significant regression equation predicting the level of compliance was found ($p \le 0.0005$, $R^2 = 0.7665$). *MPC*, occupancy, tax value, square footage of the home and number of bathrooms were significant ($p \le 0.05$), and property acreage was nearly significant ($p = 0.063$) (Table 5). Occupancy and *MPC* are the most significant predictors of the metric d_i (Table 5). As occupancy increases, d_i decreases, indicating that higher occupancy homes are more likely to comply with water advisories. The model also demonstrated that higher tax value homes and more bathrooms are related to decreasing values of d_i (increasing compliance) during WSI 2018. Lower levels of compliance (decreasing values of d_i) are related to high *MPC*, indicating that users that use higher volumes of water on average are less likely to comply with advisories. Larger home sizes are also related to increasing d_i (decreasing compliance) (Table 5).

Stepwise forward regression is performed to determine final model outputs (Table 6). *MPC* and occupancy report the most significant relationships with the compliance metric in the multi-linear regression, and in the stepwise forward regression, *MPC* and occupancy are selected as significant predictors of compliance. Total acreage shows a near significant relationship with the compliance metric and is included in the model found by the stepwise forward regression. The final model reports an R^2 equal to 0.767.

Table 5
Multiple linear regression results for $N = 4356$ m (Dataset 4, Table 1) and $y = d_i$, where d_i is the difference between total use during WSI 2018 and essential use threshold at each household.

	Standardized Coefficient Estimate	Std. Error	Significance	Relationship with d_i
(Intercept)	3.0E-17	7.3E-03	$p > 0.1$	
MPC	8.7E-01	7.4E-03	$p \le 0.0005$	Direct, significant
Occupants	−7.3E-02	7.3E-03	$p \le 0.0005$	Indirect, significant
Tax Value	−4.1E-02	1.5E-02	$p \le 0.005$	Indirect, significant
Year Built	−4.1E-03	8.1E-03	$p > 0.1$	Not significant
Total Acreage	1.4E-02	7.3E-03	$p \le 0.1$	Near significant
Home Square Footage	5.8E-02	1.8E-02	$p \le 0.005$	Direct, significant
Number of Bedrooms	6.5E-03	1.1E-02	$p > 0.1$	Not significant
Number of Bathrooms	−2.9E-02	1.3E-02	$p \le 0.05$	Indirect, significant

Table 6
Final regression model output from stepwise forward regression for $N = 4356$ m (Dataset 4, Table 1) and $y = d_i$, where d_i is the difference between total use during WSI 2018 and essential use threshold at each household.

	Standardized Coefficient Estimate	Std. Error	Significance	Relationship with d_i
(Intercept)	3.2E-17	7.3E-03	$p > 0.1$	
MPC	0.87	7.3E-03	$p \le 0.0005$	Direct, significant
Occupants	−0.074	7.3E-03	$p \le 0.0005$	Indirect, significant
Total Acreage	0.014	7.3E-03	$p \le 0.05$	Near significant

4. Discussion

Previous studies have explored how the public receives, interprets, and complies with water advisories through interviews, surveys, and other social behavioral analyses. This research takes a new approach to measure compliance, and data from AMI meters are analyzed to assess the volume of water consumed when a water main failed and subsequent water advisories disrupted normal water services during WSI 2018. The coinciding nature of the WSI and the AMI data collection presents a unique opportunity to volumetrically assess changes in water use behaviors, quantify compliance with water advisories, and identify household characteristics that support compliance. Other studies utilize smart meter analytics in studies to support plans for network expansion (Candelieri, 2017; Chen et al., 2011; Pesantez et al., 2020) and assess the adoption of drought-conservative behaviors (Quesnel and Ajami, 2017; Booysen et al., 2019; Bolorinos et al., 2020). AMI is an emerging trend, and few studies document and characterize water use changes across a service area. Leveraging new information sources, such as AMI, for water service interruption management is useful as water service providers navigate increasing leaks and failures due to aging infrastructure (ASCE, 2017). This study demonstrates the potential importance of using a large AMI dataset to assess household response to a short-term WSI.

During WSI 2018, OWASA communicated advisories to limit water use to essential purposes only to maintain pressures and prevent contamination. Water savings measures the water reductions achieved by that messaging and helps to evaluate whether the public complied. The aggregate water savings calculated during WSI 2018 indicates there was a 15.9% reduction in total water use (Section 3.3). Additionally, hourly water use during WSI 2018 was much lower during the afternoon of November 5th and morning of November 6th than is typical for OWASA meter's weekday water consumption (Section 3.1). When compared to other rainy days that are reported in the available AMI dataset, water use during WSI 2018 was substantially less (Section 3.2). Consumption was also higher in the hours after water advisories were lifted. Community members may have resumed activities, such as running dishwashers and laundry machines, that were delayed by the advisories. These observations indicate the extent of change in water use during WSI 2018. This research estimated water savings and visualized changes from typical system-wide use trends. Water utilities can use these insights to anticipate the effects of behavioral response to water advisories on system resilience.

This research also defines the threshold for essential water needed per person and found that 30.75% of meters complied to an essential use threshold based on water use estimates adapted from WHO and the WRF (Dataset 2, Table 1). Water consumption during WSI 2018 was on average less than the expected water consumption, falling in the lower 33% of previous consumption (Fig. 4). Further reductions are needed, however, to achieve a strict definition of essential use. Estimates for water for specific end uses as developed by WHO based are typically applied for water use in developing countries, and the definition may not provide an appropriate baseline for interpreting essential use volumes for an affluent U.S. community, such as the community served by OWASA. However, the inclusion of an estimate of volume of water used by modern toilet fixtures as developed by the WRF improves the applicability of the essential use definition (Water Research Foundation, 2016). Additionally, a sensitivity test was conducted in this research to further explore the definition of the essential use volume. Results demonstrated that the percent of households complying increased linearly by 0.46% per each extra liter allowed beyond the essential use definition. For example, 30.75% of OWASA's service area complied with essential use (estimated in Section 2.1) to allow for cooking, hygiene, drinking, and five toilet flushes per person. If this definition is expanded to include a shower lasting about five minutes as an essential water use purpose, increasing the threshold for compliance by about 47 L per person, then more than half of the service area complied. This demonstrates that consumer interpretation of the meaning of essential use can impact the level of compliance. Utilities must seek to provide detailed and specific information in water advisories. This research reports the percent compliance for varying levels of water conservation. This data can be used to manage expected infrastructure performance and system pressure during future WSIs, based on expected behaviors. The relationship between water conservation efforts and the fraction of users who reduce to varying levels of water conservation relies on the communication means and messages that OWASA used during WSI 2018. Further research should explore how the relationship between levels of water conservation and participation is affected by alternative communication methods and messages.

Regression techniques were applied in this research to identify significant predictors related to compliance. Meters with higher typical consumption (*MPC*) tended to have larger values for the compliance metric d_i, indicating water use during WSI 2018 exceeded the essential use threshold. Larger homes with more square footage were also related to increasing values of d_i, or lower levels of compliance. Higher occupancy homes, homes with more bathrooms, and homes of higher tax value were related to decreasing values of $d_{i,\ or\ increasing\ compliance.}$ These households may have a large capacity to reduce demands, and homeowners may understand where they can make significant reductions when alerted. Particularly, homes of higher tax value may have occupants who are more resilient to the economic outfalls of water service interruptions; for example, they have more capital to purchase bottled water for the duration of WSIs. There may be other potential explanatory variables of compliance for which we did not have sufficient data to explore statistically. For example, homes where English is not the primary language spoken are potentially vulnerable to missing critical communications. Additionally, some homes have unique circumstances such as daycare in-home businesses or residents with special medical needs. Identifying the underlying drivers of compliance is important in crafting messages to restrict water use and can be completed in future research through public surveys, interviews, or other behavioral analyses. Utilities can develop targeted communications for large footprint homes in their service area that typically consume high volumes of water (high *MPC*), which had lower compliance based on these results.

AMI adoption is rising globally, and as part of a larger smart city paradigm, the generation of big data can contribute to improved management techniques. AMI enables a new line of research into household-level behaviors. This research conducts one of the largest, community-wide AMI studies on water use behaviors to date. Results provide insights that water utilities can use to better anticipate compliance to advisories during WSIs. Further research is needed to explore how compliance is affected by communication between utility and customers, and new data can be collected and analyzed to ascertain the number of messages received about water advisories, social media interactions, read receipts on texts, the number of customers receiving phone messages and website traffic. These data can be used to analyze how information affects compliance behaviors and to identify groups who pretermit critical water advisories. Future work can couple information about communication with AMI to develop sociotechnical models of changing water demands during a WSI.

5. Conclusion

On November 5th, 2018, a pipe failure in Orange County, North Carolina caused limited water services to more than 80,000 people for 29 h. Water advisories were issued, and this research was conducted to assess compliance with water advisories. In this study, analysis of AMI data from more than 16,000 meters develops insight about water consumption during the water service interruption. Aggregate water demand during the WSI is compared to a distribution of previous water use volumes, and system wide reductions of approximately 15.9% were achieved. Regression techniques were applied to identify several predictors of poor compliance that emerged in the available dataset.

Metrics are applied in this research to approximate the volume of water saved during the WSI and the percent of households complying with an essential purpose only water advisory. Utilities can use these metrics to anticipate system reductions that are achievable in efforts to maintain water network pressure and minimize the introduction of pathogens. Approximately 30% of the households complied with the water advisory.

Aging infrastructure contributes to more frequent pipe breaks, and a drying climate compels efforts to minimize water losses and promote conservation. Utilities need an understanding of household-level responses during water service disruptions to enhance resilience and mitigate consequences. AMI data can be analyzed to gain insight about customer compliance during WSIs and subsequent water advisories. This research contributes to a developing body of work translating large quantities of data generated by smart meters into useful insight for the management and operation of water infrastructure.

Declaration of Competing Interest

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Data Availability

The authors do not have permission to share data.

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