Sensing Drinking Water: Towards Real-Time Technology to Monitor, Control, and Study Drinking Water Quality at the Tap

by

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Dedication

For all the educators who inspired my love of water and science.

For people who fight and advocate for equitable, high-quality, reliable water service, as well as those who have been and are affected every day by the lack of it.

For my family, friends, and Emily.

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Abstract

A new generation of drinking water management tools that incorporate real-time sensing and data-driven control stand to transform our interactions with drinking water systems in a more comprehensive way. Sensors have been lauded for their promise to revolutionize drinking water management, but the adoption of real-time data technologies lags behind other infrastructure sectors and their value as a tool in the management of drinking water systems is still unknown. Using low-cost sensors, programmable microcontrollers, and wireless communications, this work introduces a suite of next-generation tools to monitor drinking water quality throughout distribution systems and building plumbing in real-time.

To advance the goal of adopting sensor networks for drinking water distribution systems, this work first introduces a novel open-source, end-to-end wireless platform for the real-time monitoring of drinking water systems capable of measuring pH, oxidation-reduction potential, electroconductivity, temperature, and pressure. Second, the applications and value of these tools are evaluated in three unprecedented real-world deployments in Ann Arbor and Ypsilanti, Michigan, USA and in Mexico City, Mexico with a total cumulative 34 sites – resulting in the largest deployment effort of a wireless sensor network to measure drinking water quality directly in residential taps.

In each of these deployments, we demonstrate the detection of phenomena that would have been missed through existing, low-throughput monitoring approaches. The deployment in Ann Arbor emphasizes the importance of real-time measurements in a drinking water distribution system, highlighting shifts in neighborhood-scale electroconductivity (a proxy for total dissolved

solids) that would have been missed as part of established sampling procedures. The deployment in Ypsilanti actively measured with ORP the decay of free chlorine after overnight stagnation in building plumbing. The Mexico City deployment demonstrates highly variable water quality and supply in intermittent systems and characterizes the variability of chlorine concentrations between continuous and intermittent portions of the city.

Manual flushing of building plumbing is commonly used to address water quality issues that arise from water stagnation. Autonomous flushing informed by sensors has the potential to aid in the management of building plumbing. To further our understanding of water quality in building plumbing and develop smart flushing practices, an experiment was designed to flush the tap twice per day in buildings with free chlorine (Ypsilanti) and chloramine (Ann Arbor). The overnight decrease in ORP measured in Ypsilanti was not observed when tap water was automatically flushed. Results from the experiment also show that a "smart" flushing protocol could be informed by temperature signals to detect when flushing is done, potentially leading to water savings.

Lastly, sensor nodes are used to better understand the spectrum of intermittent water supply and its impacts on the experience of water quality. This study goes beyond the technology application by using a combination of anthropology and statistical methods to understand the effects of intermittent water supply on public health at the household level. The analysis demonstrates that dynamics in water supply and water quality are key factors in shaping people's water quality experience.

As we embark on unprecedented water challenges around the world, including natural and anthropogenic pressures in water resources, real-time water quality monitoring systems should be considered as part of a new generation of information-driven infrastructure to support drinking water management and research as shown in this dissertation.

Chapter 1
Introduction

There are unprecedented and increasing challenges to fresh water around the world, including natural and anthropogenic pressures on water resources [1,2]. Addressing these pressures means using water and resources more efficiently. Real-time water quality monitoring can help support information-driven infrastructure that helps drinking water management and research [3–6], but the adoption of real-time data technologies, including sensors, wireless communications, and adaptive control lags behind other infrastructure sectors [4]. Ongoing calls to increase drinking water monitoring have largely gone unanswered over the last twenty years [7–9], but aging infrastructure, emerging contaminants, and increased urbanization may provide the impetuses necessary to improve monitoring in our drinking water systems.

Innovations in sensors, microcontrollers, and data services are underpinning a broader smart cities movement that includes real-time traffic surveillance to reduce traffic congestion [10], air quality monitoring to alert of environmental exposures, and watershed automation to prevent flash floods [11]. To date, however, the value and possibility of sensors as tools in the management of drinking water systems remains largely underutilized. Ultimately smart drinking water systems are built with sensors and the resulting data could transform infrastructure management and foster collaborations with users in real-time.

A number of key knowledge gaps hinder the ability to enable this vision of smart drinking water systems. First and foremost, water utilities have lacked the necessary tools to measure drinking water systems continuously at the scale of individual taps. Without these tools, there is a paucity of data on the dynamics of water quality at the tap, and how to effectively counter sudden degradation of water quality experienced in household and building plumbing. With respect to the drinking water users, there is a need to understand how household water dynamics are experienced by residents, and if "smart water" technology can improve drinking water experiences. Finally, in the wake of rapid urbanization and diminishing water resources, information is needed on how water supply issues (i.e. intermittency) will affect the performance of household drinking water sensor technologies.

The drinking water quality experiences shape confidence, trust, and are known to be rooted in complex interactions between the built environment and social constructs [12]. Trends show increasing per-capita consumption of purchased water [13], often reported to have worse water quality, and bottled products, including sugared drinks [14,15], which have led to global obesity and diabetes type 2 epidemics [16]. Trust in water quality is a complex subject requiring cross disciplinary research. Sensors and real-time technology stand to fill a gap that describes an otherwise invisible infrastructure that could help explain links between water quality and trust; however, the social constructs and the complexity of surrounding built environments are best studied through ethnography [17]. Ethnography is a tool designed to study people in naturally occurring surroundings with the goal of capturing social meanings and ordinary activities. In the context of drinking water quality experiences, ethnography is needed to collect data in a systematic manner without meaning being imposed on people externally [17].

The goal of this dissertation is to enable the study, control, and management of drinking water systems using wireless sensor networks (Figure 1.1). This dissertation begins to close the knowledge gaps described above and will ultimately serve as the foundational work for the development and adoption of "smart" drinking water systems. The three research chapters address three different aspects of drinking water data:

Chapter 2: The development and deployment of a reliable low-cost sensor node network leveraging cloud platforms.

Chapter 3: The first experimental autonomous building flushing protocol using the wireless sensor networks from Chapter 2

Chapter 4: An analysis of the experience of water quality and supply at the household level in Mexico City.

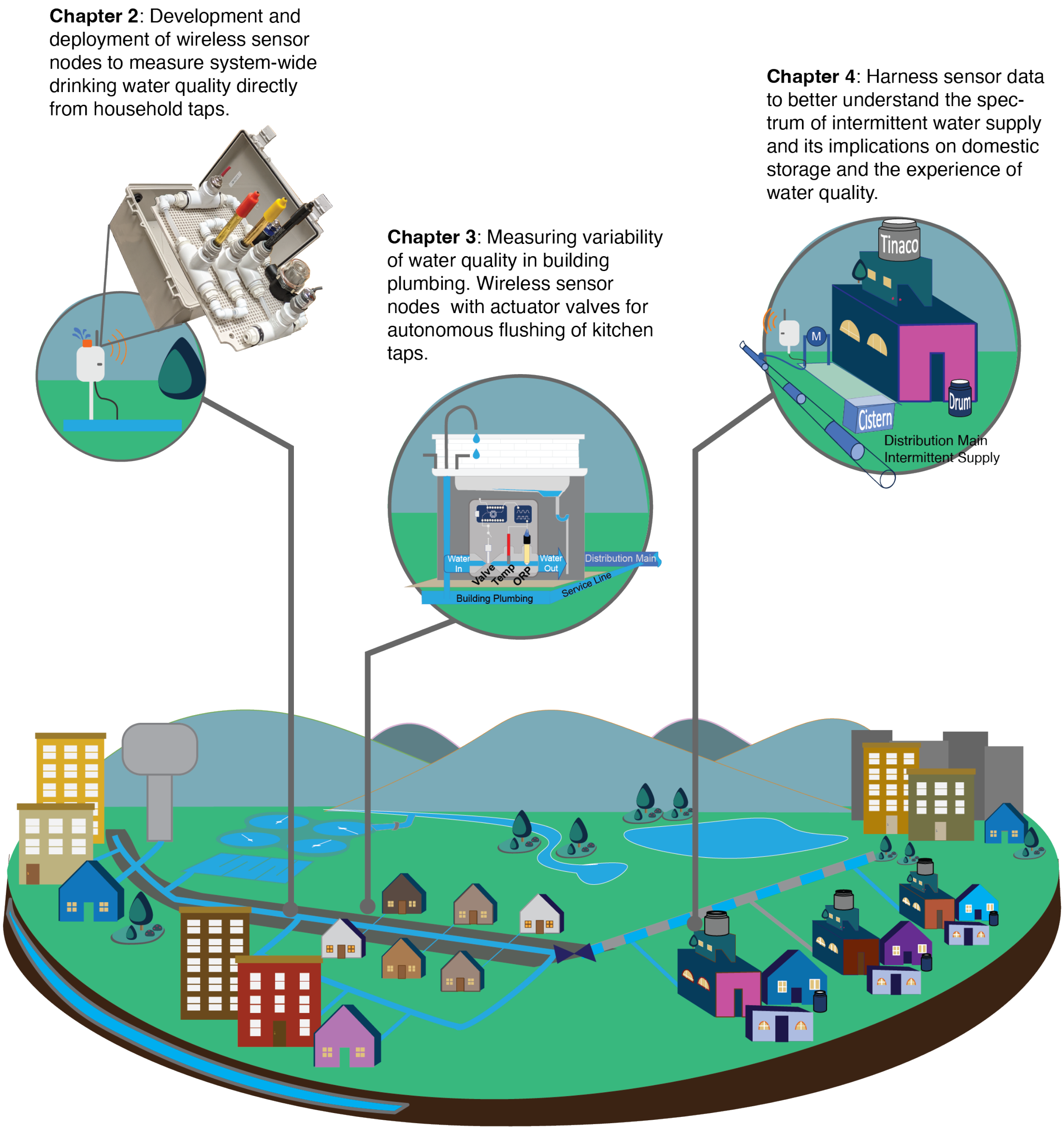

Figure 1.1: Drinking water distribution system components and research areas

1.1 Background and Significance

1.1.1 Drinking water quality monitoring: From grab sampling to online sensing.

Under current safety guidelines and regulations (WHO, USEPA), drinking water utilities physically collect grab samples throughout the distribution system. The samples are subsequently analyzed in a laboratory for various management drivers, including safety, treatment efficiency, and quality of service. The frequency of samples depends on the size of the system measured by population and the severity of the health-related risk of each contaminant, with fecal contamination and residual disinfectant concentrations typically setting the minimum required grab samples (Table 1.1). Plans for spatial distribution of grab samples are drafted by each community water system. It is often recommended that sampling sites be representative of water quality throughout the distribution system, including end-of-system and low-pressure zones, population density, and where multiple water sources enter the system. Sampling frequency and spatial distribution are important factors in monitoring plans, but comprehensive or scientifically-driven protocols that include spatial and temporal resolution based on grab samples continue to be sparse. Rather, it is much more common to sample water quality at set locations on a regular schedule (e.g. every month or every few weeks).

Table 1.1: Minimum grab sample monitoring frequency for fecal contamination and disinfectant residual analysis

System Size[#] (Population)	*WHO Guidelines for Drinking Water Quality [18]*	*USEPA Total Coliform Rule [19] and Stage 1 Disinfectants and DBP Rule [20]*
	Samples per year	Samples per year
5,000	12	60
500,000	720	2,520
>3.96M	1,550	5,760

[#] More ranges in the source tables; [*] Residual disinfectant analysis is done with each fecal sample.

Manual sampling and analyses are labor and resource intensive. For many service providers, this represents an enormous effort. As such, many providers are often not able to comply [21]. Additionally, important information can be missed through grab sampling plans if changes in water quality happen day-to-day, especially health-based parameters that are known to change during distribution, such as disinfectant residual, turbidity, and microbial counts. Studies on the trade-offs between grab-sample and online monitoring approaches have concluded that grab sampling plans are not adequately capturing dynamics at locations with higher disinfectant variability [22,23]. The development of online continuous monitoring technologies stands to fill two pain points, namely, by helping resource-constrained service providers to increase their sampling capacity [21] and by adding spatiotemporal resolution to capture highly variable dynamics [9].

Online continuous monitoring tools can be easily integrated into water safety plans to increase the spatiotemporal resolution of water quality measurements. Recent work with online continuous measurements has been successful in detecting anomalies in water quality. For example, pilot- and lab-scale studies have developed algorithms that locate simulated leaks and main breaks using high-frequency pressure measurements [24–26]. Organic, inorganic, and biological contaminants have been detected in controlled lab-scale experiments through relative changes in physical parameters, such as free and total chlorine, pH, ORP, EC, and chloride [27–30]. The US EPA has also noted that the operational benefits of sensor-based monitoring can eliminate frequent site visits, data processing and reporting [21]. Pilot studies in collaboration with drinking water utilities have been implemented in large cities of the United States [31] describing challenges to large-scale deployments such as cost of maintenance [30], storage of big data sets, and sensor reliability [6]. Several resources are now available through the EPA for utilities to implement online water quality monitoring technologies, from system design to data processing [32]. To date, however, cities and municipalities have not yet implemented sensors at a large scale.

Most online monitoring has relied on wired infrastructure that drives up cost and hinders spatial coverage. The development of wireless platforms has the potential to extract the most spatiotemporal value out of online monitoring systems. The rapid development in wireless communication technologies has been driving a collective movement called the *Internet of Things [10],* opening the door for reduced-cost solutions for data communication. Wireless Sensor Networks leverage these technologies to deploy sensors in difficult-to-access locations to monitor infrastructure systems, track environmental phenomena, and control municipal services [9]. Wireless Sensor Networks also have the advantage of encrypted security and the web services readily available for cloud-hosted data processing. Several wireless platforms that include water quality sensors have been designed [25,26,33–35], but only two were deployed and tested in full-size distribution systems (Table 1.2) – PipeNet in Boston, MA, USA [25] and WaterWiSe in Singapore [26]. While these two studies demonstrated reliability of network data communication, with water quality probes included as a proof of concept, the main priority was hydraulic monitoring for leaks, main breaks, and high-frequency transient events. There is therefore a need for the investigation and deployment of wireless sensor networks focused on drinking water quality.

In addition to showing promise for monitoring drinking water distribution systems, wireless sensor networks may help manage water quality inside building plumbing. Building plumbing can cause elevated levels of lead and copper [36] and elevated levels of *Legionella* spp [37,38] at the tap. Approaches to decrease contamination at the tap include flushing fixtures, adding residual disinfectant, controlling water temperature, or cleaning and replacing fixtures [37].

Management protocols for building plumbing are complicated by the large variability in water quality dynamics from building to building. In the United States, guidelines and regulations exist for health, institutional, and federal buildings, but lack guidance in all other buildings (including residential single-family houses). A recent systematic review of guidelines concluded that recommendations on pipe materials, flushing frequency, and minimum disinfectant residual are inconsistent and lack a scientific basis [37]. To that end, there is a need for scientifically based knowledge and tools for managing drinking water quality in buildings. Taps inside buildings can be retrofitted with water quality sensor nodes and provide real-time data, both to further our understanding of the variability in quality due to building pluming, and to make management decisions in real-time.

Building plumbing water quality remains an active area of academic research [39]. Focus has been placed on understanding the role of water age, temperature, contact surface area, pipe and fixture materials affect the physicochemical [40,41] and biological [42] composition of water at the tap. To date, research involving continuous on-line measurements to study water quality is limited to three recent efforts (Table 1.2). One study applied internet-connected on-line sensors in different stories of an institutional building to measure and predict chlorine residuals based on floor occupancy [43]. Another study looked at tap water usage based on temperature signals from thermostatic mixing valves inside a hospital drinking water system [44]. The third study used online water quality and flow measurements from all three floors of a residential building hot and cold water fixtures in order to study the variability in water use and its effects on quality [45]. All three studies found spatial and temporal quality variations within each building and determined that sensors are valuable for increased monitoring and decision making. The third study specifically called for more affordable continuous monitoring tools (after spending $100,000 USD in sensors, special fixtures, and installation) at building taps to uncover more findings and broaden our understanding of water quality deterioration and its implications to public health [45]. A reliable and compact solution to deploy water quality sensors inside buildings would provide insights where drinking water is ultimately used.

Table 1.2: Selected development and applications of wireless sensor networks in drinking water

Project	*Deployment*	*Parameters Monitored*	*Major applications*
PipeNET [25]	Distribution System	Pressure, pH	Hydraulic and water quality monitoring of transmission and distribution systems including capturing transient pressure events and pH
WaterWISE [26]	Distribution System	Pressure, pH	On-line hydraulic modeling, leak and burst detection experimentation and operational event analysis
Saeta et al [43]	Building Plumbing	pH, conductivity, temperature, ORP, dissolved oxygen, free chlorine	Assess water quality patterns inside a seven story building and predict chlorine residual based on building occupancy
Salehi et al [45]	Building Plumbing	*Taps:* water flow, temperature *Service Line:* water flow, temperature, chlorine residual, turbidity, pH	Investigate temporal and spatial variations of drinking water chemical quality in a net-zero energy green building.
Whiley et al [44]	Building Plumbing	Temperature	Monitoring real-time temperature fluctuations in thermostatic mixing valves located in a hospital that were linked to flow events and their relation to microbial water quality.
Chapter 2 of this dissertation [46]	Building Plumbing	*Taps and service line:* pressure, pH, conductivity, ORP, temperature	System-wide monitoring of drinking water quality. Assess value of increased spatiotemporal resolution featuring event detection with conductivity, water quality variability due to intermittent supply, and differences in water quality across system.
Chapter 3 of this dissertation	Building Plumbing	*Taps:* Temperature and ORP	Understand variability of water quality in building plumbing as measured with ORP in systems with free chlorine and chloramine. Autonomous flushing to counter degradation.
Chapter 4 of this dissertation	Building Plumbing	*Service Line:* pressure, pH, conductivity, ORP, temperature	Harness high-resolution pressure and water quality data to understand the experience of water quality at the household level in Mexico City.

1.1.2 Intermittent water supply, domestic storage, and the experience of water quality

As global water resources become increasingly strained from anthropogenic and environmental stressors [47], highly urbanized communities around the world will face more water shortages. As a result, an increasing number of water supply systems may be forced to provide drinking water on an intermittent basis. In many cities, especially in developing countries, intermittent water supply systems are already prevalent, with an estimated 1 billion people globally receiving intermittent water supply [48]. Intermittent water systems are known to pose public health risks and thus may contribute to the estimated 1,560 annual deaths that are caused by the consumption of tap water contaminated with fecal material [49]. Intermittent water supply may also be linked to chronic disease through reduced water availability, exposure to trace contaminants, and consumption of alternative beverages.

Under the specific lens of Civil and Environmental Engineering, intermittent water systems have been largely studied on their effects on drinking water quality and public health [50]. For example, "first flush" events have been characterized as having high turbidity, low disinfectant residual, and high microbial activity after water sits in the pipes during the intermittent periods [48,51,52]. The pressure cycling that occurs in intermittent systems produces structural stresses on water mains reducing their service life, while also promoting soil and groundwater intrusion into the water mains [52]. Additional issues such as backflow, high demand, and the negative pressures caused when pumps are used to extract water from the supply system, are common characteristics of intermittent systems that pose risks to public health and system integrity [52].

Compared to research on the effects of intermittency on system integrity and public health, relatively little research has focused on how households manage intermittent systems [50,52]. Intermittency is managed by people with domestic water storage [53]. Domestic storage provides the stability for daily needs, but may cause water quality deterioration. In particular, studies have observed chlorine residual decay and microbial communities regrowing during domestic storage [53]. The latter specifically leading to higher risk of illness associated with fecal contamination in containers without proper lids, improper handling, and poor maintenance [51,54,55].

Intermittent water supply is disruptive to people's daily lives, as well as mental and physical health. The frequency of cutoffs may have characteristic attributes describing the service – predictable, irregular, and unreliable [50] – reflecting the inherent complexity of intermittent systems. Their impact to system integrity, public health and domestic storage needs is well documented. However, many of the implications of intermittent systems remain to be explored at the household level, partially because of the complexity of the systems, the difficulty to obtain data at the household level, and the unknown extent of mediated effects. The need to manage intermittent supplies can lead to economic, physical, or emotional burdens to household members. For example, purchasing trucked water to supplement public supply, carrying buckets where needed, or cleaning storage tanks [50,52]. Understanding the requirements of domestic water management placed in households in relation to the spectrum of intermittency may help engineers and policy makers understand the mediated effects of intermittency on "less immediate" public health and socioeconomic outcomes.

Novel sensing techniques can be leveraged to uncover the temporal granularity associated with intermittent systems and make deductions of the associated dependencies for domestic storage; however, studying intermittency requires interdisciplinary research. Water quality and hydraulics expertise is necessary to understand the physics governing intermittency and domestic water infrastructure. Direct observation is necessary to uncover the deeper layers and mediated effects of intermittent water supply on domestic life, chronic health effects, and the experience of water quality at the household level. Importantly, human-based observations are needed to link supply dynamics and water quality to the experience of the water consumer, including the management of domestic infrastructure. Ethnography, an anthropological tool that combines rigorous observation with social analysis provides a means to gather data on the impact of water intermittency on households. Combining smart sensor technologies to characterize water supply, and quality, with fine grained observation of household experiences across intermittent water systems provides us with a continuum of information with which we can study the effects of intermittency at the household level. Without the continuum of information, sensors alone could not explain human behaviors, the same way that household observations could not explain the dynamics of water supply and quality.

1.2 Research Outcomes and Aims

To fill the knowledge and data gaps discussed in this introductory chapter, this work establishes next-generation tools to monitor drinking water distribution systems and building plumbing systems. The use of low-cost sensors, programmable microcontrollers, wireless communications, and cloud-based data analytics will enable real-time monitoring protocols that are deeply integrated into adaptive water management plans. Ultimately this research will result in the acquisition of higher resolution data streams that better inform the state of water availability and quality. This dissertation provides insight on the dynamics of water quality in full-scale distribution systems and in real building plumbing systems with different residuals and over time. Additionally, by combining sensing technology data and ethnographic data, this dissertation provides insights from intermittent systems that link variability of water supply to dependencies and effects at the household level. Toward these outcomes, this dissertation is split into three chapters.

In Chapter 2 two real-world studies are summarized – one in Ann Arbor, Michigan and another in Mexico City, Mexico. A total of 29 combined sites in both cities resulted in the largest deployment effort of a wireless sensor network to measure drinking water quality directly in residential taps. The added value of wireless sensor networks and importance of increased spatiotemporal measurements of drinking water quality at the tap are discussed. Specifically, in Ann Arbor we show a system-wide electroconductivity event, and in Mexico City we show the spatial variability in drinking water quality as measured with ORP.

In Chapter 3 we deploy sensor nodes under the kitchen sink of single-family houses in Ann Arbor and Ypsilanti, Michigan. In Ann Arbor, the drinking water is supplied with chloramine disinfection residuals and in Ypsilanti, the drinking water is supplied with free chlorine residuals. High resolution ORP and temperature measurements are summarized to quantify the variability in water quality associated with building plumbing. An experiment was designed to flush the tap twice per day and the impacts to water quality as measured with ORP are discussed. We then show how a "smart" flushing protocol could be informed by temperature signals to detect when flushing is done, potentially leading to water savings. In this chapter we explore the benefits and drawbacks of using ORP sensors in real-time to study building plumbing water quality, this includes an evaluation of the sensor when measuring free chlorine or chloramine under decaying and transient conditions. Altogether this chapter improved the understanding of the variability of water quality in single-family households building plumbing and how to use real-time data and control to autonomously flush the tap. Suggestions are presented for future work on the development of autonomous building plumbing flushing systems.

In Chapter 4 we focus on harnessing a multi-faceted data set including rich ethnographic observations from an intensive nine month field work from 60 households in Mexico City, and real-time data to better understand the spectrum of intermittent water supply and its impacts on the experience of water quality through domestic water storage. Our analysis demonstrates that dynamics in water supply and water quality affect how people interact with water at the household level, ultimately shaping their water quality experience. Using data from the sensor node deployments in Chapter 2 and a rich ethnographic data set, this chapter explores the implications of rapid urbanization, depleting water resources, and climate change on drinking water at the household level. This chapter uses a unique combination of methods from various fields in addition to the use of sensor networks to answer the research questions. First, rich ethnographic data was methodically coded to extract insights about water management and hypothesize connections between intermittency to the experience of water quality. Second, factor analysis is used to build latent constructs associated with household storage, intermittency, water quality, and the experience of water quality. And lastly linear regression is used to quantify the hypothesized pathways linking the constructs. We show that while the water quality of supplied water shapes the experience of water quality, the need to manage intermittency through domestic storage also influences the experience of water quality.

Finally, chapter 5 presents a summary of results, highlights the key takeaways, and poses a number of future research questions to promote the continuation of this work.

Chapter 2

Wireless Sensors for Measuring Drinking Water Quality in Building Plumbing: Deployments and Insights from Continuous and Intermittent Water Supply Systems

2.1 Publication Information

This chapter was adapted from its published version for this dissertation. For citation please use the following information:

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2.2 Abstract

Despite continued calls to increase the monitoring of drinking water systems, few communities and utilities have adopted modern, distributed, and real-time monitoring systems. Measurements of drinking water quality are often only made at the treatment plant, with limited grab sampling taking place throughout the distribution system. At the building level, where most of the public's exposure to drinking water takes place, the capacity to make continuous measurements to characterize water quality dynamics has been almost impossible. Innovation in sensors, microcontrollers, and data services is underpinning a broader smart cities movement, but their value as a tool in the management of drinking water systems is still unclear. In this paper, we

present a new open-source wireless sensor platform, which allows water quality to be measured at the tap. Our internet-connected devices transmit data back to cloud hosted services, where they can be analyzed in real-time. We provide examples of large-scale deployments within buildings in Ann Arbor, MI, USA and Mexico City, Mexico. In each of these studies, we demonstrate the detection of phenomena that would have been missed through existing, low-throughput monitoring approaches. The deployment in Ann Arbor emphasizes the importance of real-time measurements in a drinking water distribution system, highlighting shifts in neighborhood-scale electroconductivity (a proxy for total dissolved solids) that would have been missed as part of established sampling procedures. The Mexico City deployment demonstrates highly variable water quality and supply in intermittent systems and characterizes the variability of chlorine concentrations between continuous and intermittent portions of the city.

2.3 Introduction

Despite continued calls to increase the monitoring of drinking water systems [7–9], few communities and utilities have adopted comprehensive, distributed and real-time monitoring systems [6]. Sensors have been lauded for their promise to revolutionize drinking water management, but the adoption of real-time data technologies lags behind other infrastructure sectors [4]. As we embark on unprecedented water challenges around the world, including natural and anthropogenic pressures on water resources [1,2], real-time water quality monitoring systems should be considered as part of a new generation of information-driven infrastructure to support drinking water management and research [3–6].

In most countries, federal regulations require public water managers to monitor treated drinking water to support safety and public health. Such monitoring typically includes quantifying the concentrations of disinfectant residuals, disinfection by-products, lead, copper, total coliforms, and some waterborne pathogens at the entry points of and throughout the distribution system. In the United States, nearly 100 contaminants are required to be monitored periodically [19], and regulations are regularly updated based on public health risk [56]. Because water quality characteristics change throughout distribution, most parameters are required to be monitored by collecting water from different locations in the distribution system (e.g. residual disinfectant, total coliforms), while a few contaminants are monitored at the tap due to the impact plumbing materials have on water quality (i.e. lead and copper)[19]. The required residual disinfectant and total coliforms monitoring frequency for a public water system depends on the number of people served, ranging from 480 samples per month in the largest systems (>3.96 M people) to once per month for the smallest systems (<1000 people) [19]. Manual sampling and analyses are labor and resource intensive, which limits the number of measurements that can be collected. Achieving a high spatiotemporal measurement resolution, therefore, is not possible with grab sampling and important information can be missed if water quality varies across the distribution system or changes from day to day [9].

Innovations in sensors, microcontrollers, data communications, and web services have allowed for the rapid expansion of wireless sensor networks, which are increasingly used to monitor, model, and control municipal services as part of a broader smart cities movement [9,10]. The fields of stormwater and wastewater management [57,58], transportation [59], and power distribution [60], for example, have improved performance and lowered operational costs through the adoption of real-time analytics and control. There is an equally exciting opportunity to harness these technologies for a better understanding of drinking water systems.

A number of sensor platforms for drinking water have been evaluated over the past decade [25,26,33–35,61]. Most recently, a study used multiple sensors to study water quality in different stories of an institutional building to predict chlorine residuals at each floor based on floor occupancy [43]. Organic, inorganic, and biological contaminants have been detected in lab-scale experiments using high frequency sensor data from free and total chlorine, pH, oxidation-reduction potential (ORP), electroconductivity (EC), and chloride probes [27–30]. To our knowledge, no studies have measured water distributions at the scale of an entire city, nor at the residential tap level. Despite the demonstrated benefits of real-time monitoring, cities and municipalities have not yet implemented sensors at a large scale.

To date, most examples of using wireless sensor networks to monitor drinking water rely on single-site demonstrations or short-term deployments. Challenges to large-scale deployments include the maintenance cost of the systems [30], the management and storage of real-time, high-frequency data, and the uncertainty of sensor behavior [6]. PipeNet [25] in Boston, MA, USA and WaterWiSe [26] in Singapore are examples of large-scale deployments that demonstrated the reliability of node network data communications and detected leaks and pipe bursts with high-frequency pressure sampling. These two systems also included pH sensors as a proof of concept for water quality monitoring. In the PipeNet, WaterWiSe, and Skadsen et al [30] deployments sensors were placed into distribution system pipes or reservoirs. A reliable and compact formfactor to deploy water quality sensors in buildings would provide insights where drinking water is ultimately used.

Drinking water quality changes throughout the distribution system, as well as inside building plumbing. Variables like water age, temperature, pipe and fixture materials, and pipe surface area to volume ratio have effects on the physicochemical and biological composition of water at the tap [37,39]. This is part of the reason why some contaminants, such as lead and copper, are required to be monitored at the tap [36]. Additionally, granular data at the building level could provide information about water quality across intermittent water supply systems. Intermittent water supply is often unreliable and inconsistent, and has been shown to pose risks to public health [48,52]. An estimated one billion people worldwide depend on intermittent water supply, and that number is projected to increase significantly in the next decades [48,49].

To advance the goal of adopting sensor networks for drinking water distribution systems, this paper introduces a novel open-source, end-to-end wireless platform for the real-time monitoring of drinking water systems capable of measuring pH, ORP, EC, temperature, and pressure (Figure 2.1). We provide results and observations of two large-scale wireless sensor network deployments, one within buildings in Ann Arbor, MI, USA and one within homes in Mexico City, Mexico. Our specific objective is to evaluate the performance of this platform in-situ and to summarize practical deployment considerations for others interested in carrying out similar studies.

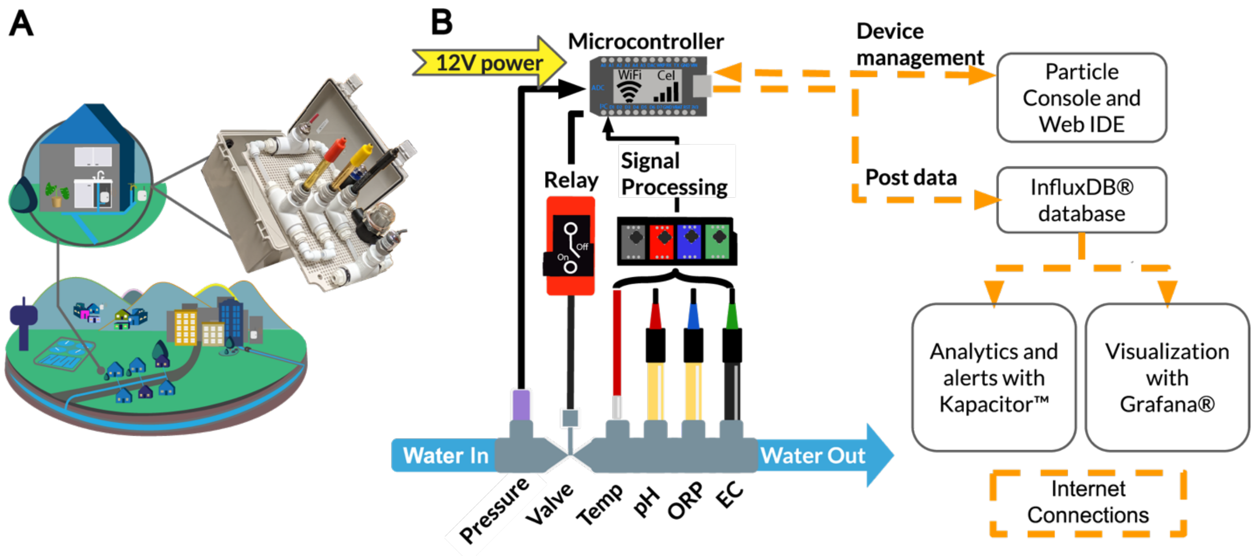

Figure 2.1: Drinking water quality sensing and valve node architecture. A) is the compact formfactor deployed on standard household pipes, such as kitchen sinks or outdoor spigots. The flow cell with the sensors and electronics are contained within the enclosure. B) is the system hardware and cloud architecture including data collection and conditioning within the enclosure and the cloud architecture for data management and visualization.

2.4 Materials and Methods

An open-source wireless sensor node for monitoring drinking water quality was designed and constructed using low-cost commercial sensors and electronics, web services, cloud analytics, and real-time visualization. The design objective was to create a small, portable, and reproducible platform that can be connected to a wide range of complex piping setups used in drinking water distribution, including standard building taps (Figure 2.1-A). With the use of existing in-home internet or cellular connectivity, sensor nodes report data in real-time and are deployable in most buildings and neighborhoods. The system's architecture includes A) hardware and B) cloud services and applications. The hardware includes wireless microcontrollers, analog conditioning circuits, and sensors. The cloud services include a central database, visualization capabilities, and remote management tools. An architecture diagram is provided in Figure 2.1-B.

2.4.1 Hardware

The communications core of the hardware platform was built upon the Particle-series of microcontrollers (Photon and Boron 2G/3G), which can be programmed in C++ and updated over-the-air using a web interface [62]. The node connects to the internet using Wi-Fi or cellular – depending on the connection stability at each site. The core is powered by a DC 12 V power supply, allowing the node to be plugged directly into a nearby wall socket or powered via a 12 V battery. Although the system can operate across lower voltages (3-5 V), 12 V is necessary to open most commercial solenoid valves, which are used to trigger sampling. The remaining electronics, including the microcontroller, carrier boards, and the sensors operate with 5 V delivered by an embedded voltage converter. A backup battery ensures that the nodes remain operational, even when household power goes out.

The sensors communicate with the microcontroller using the I^2C protocol [63]. The sensors are implemented with signal-conditioning circuits (Atlas Scientific EZO™) that facilitate required and customizable sensor operations, such as calibrations, temperature corrections, and measurements. The EZO™ circuits are electrically isolated and mounted on a carrier board designed by ©*Whitebox Labs* [64]. A pressure transducer is connected to the microcontroller's analog to digital converter (ADC) via a voltage divider. The measurement timing and transmission frequency of all parameters can be easily modified remotely to suit a wide range of field conditions. The sensors are described in more technical detail in Appendix A.

The flow cell (housing that exposes the sensors to the water flow stream) was designed to have a low water consumption footprint, to include simple operational requirements using readily available parts, and to be modular. It was built using off-the-shelf plastic tubing and PVC fittings that hold the sensors in place. The arrangement of the flow cell, valve, and the sensors is presented in Figure 2.1-B. The pressure transducer was placed first in line and outside of the flow cell so that pressure can always be measured without actuating the valve. The solenoid valve separates the sensors from the pressurized pipes and only opens to flush new water into the flow cell. The flow cell was designed to exhibit plug flow hydraulics to minimize mixing with previous samples and to prevent the probes from drying. At the time of writing (2021), the cost of materials to build the entire unit was approximately 1,200 USD. The sensor nodes can be built entirely by a single person with limited electronics experience. The plans for building the entire unit are shared on our open-source website: https://github.com/kLabUM/DrinkingWaterNodes.

2.4.2 Cloud Services

The cloud services layer provides storage of sensor data in an online, secure, timeseries database (*InfluxDB*®) and facilitates interactions between user-defined applications (*Kapacitor*™) and visualization tools (*Grafana*®). Node operations push conditioned sensor readings to the database in a custom *JSON* format after each measurement, the user-defined applications query the database for the latest reported readings, and the user can write commands to change the behavior of desired nodes. The cloud architecture also facilitates remote management of individual nodes through Particle's web-based development environment [62].

2.5 Deployments

The sensor nodes (29 nodes in total) were deployed in two cities that differ in size, demographics, and drinking water distribution characteristics. One deployment took place in Ann Arbor, MI, USA and another in Mexico City, Mexico (Figure 2.2). Both deployments took place within residences, at the tap level or entry point into the home. This approach provided us with two distinct data sets to evaluate the sensor system. In each study, we detected phenomena that would have been missed by using existing, low-throughput monitoring approaches. The deployment in Ann Arbor illustrates the importance of collecting real-time measurements in a continuous supply drinking water system that is consistently in compliance with regulations by highlighting shifts in neighborhood-scale EC that would have been missed as part of established monitoring. The deployment in Mexico City results in the first dense and continuous water quality data set available for an intermittent water supply system. The Mexico City data demonstrate highly variable water quality and supply, and variable chlorine concentrations between continuous and intermittent portions of the city. The two cities use different secondary or residual disinfectants, which offered an opportunity to apply ORP sensors in systems with chloramine or combined chlorine (Ann Arbor) and free chlorine (Mexico City).

Figure 2.2: Deployment locations of drinking water quality sensor nodes. A) Map of Ann Arbor, MI, USA, deployments. Ten sensor nodes were deployed within the time period of August 2019 and June 2020. B) Map of Mexico City, Mexico deployments. Nineteen deployment sites were part of the study, which took place between January 2019 and March 2020.

2.5.1 Ann Arbor

The sensor network in Ann Arbor, MI, USA (Figure 2.2-A) was deployed to study spatiotemporal building plumbing water quality in a city with a relatively homogeneous system. Ann Arbor has a population of 120,000 people, covers 75 km^2, and contains 800 km of water distribution pipes. The drinking water is supplied by one drinking water treatment plant that blends surface water (Huron River) and groundwater. The source waters are blended with varying ratios, with higher proportions of surface water during the spring, summer, and fall, and a higher proportion of groundwater during the winter months. The treatment plant provides 400 L per capita per day and finished drinking water is distributed with monochloramine as the residual disinfectant at a concentration of approximately 3 mg/L as Cl_2. The distribution system is divided into five pressure districts, all of which are operated independently and have interconnections to regulate flow, pressure, and water quality. Previous studies have documented the drinking water infrastructure in Ann Arbor, including detailed descriptions of the water treatment train [30,65], the distribution system, and water quality parameters [65,66]. The Ann Arbor drinking water system is part of the 1% of public water systems in the United States that serve more than 100,000 people; more than 50% of the population in the United States is provided drinking water through public water systems within this size range [67].

A total of ten sensor nodes were deployed in four of the five pressure districts at a range of distances between 1.7 and 8.5 km from the treatment plant (as measured from a street layout, not the distribution system). Sensor nodes were placed inside single family homes; two under a kitchen sink, one under a bathroom sink, and seven under a laundry/utility room sink. The deployments lasted from 29 days to 177 days starting in August 2019 and ending in July 2020, and thus included seasonal transitions. The deployment study was interrupted by the COVID-19 pandemic and visits to households were not possible for maintenance or collection of grab samples.

Minor and reversible plumbing modifications were made to accommodate the sensor node water intake and to allow all effluent water to be discharged directly to the closest drain. The sampling protocol was identical for all nodes and throughout the deployment period. It consisted of pressure readings every five minutes, an open valve flushing action of five seconds followed by water quality measurements every 60 minutes. The samples taken represented building plumbing water due to the short amount of time the valve remained open.

2.5.2 Mexico City

The sensor network in Mexico City (Figure 2.2-B) was used to study spatial differences in household water quality and supply dynamics in neighborhoods across the city. Technical information on the operation and management of the drinking water system of Mexico City is not readily available through public channels. Regions of the city have continuous water supplies (70% of grid connections) while others have intermittent water supplies (30% of grid connections) [68]. The city has a population of 9 million, covers 3,773 km^2, and contains 12,500 km of water distribution pipes [68]. The city's drinking water sources consist of 42% surface water and 58% groundwater from 450 wells of various depths tapping into multiple aquifers [69]. There are 58 drinking water treatment plants that supply an average of 200 L per capita per day and distribute water with free chlorine as the residual disinfectant. More information about the Mexico City water situation is available in the Appendix C.

Of the 19 sensor nodes deployed across the city, 13 were placed at homes with continuous drinking water supply and six were in homes with intermittent supply. Of the six sites with intermittent supply, three were supplied water for eight hours per day (daily intermittency) and three were supplied water for a few hours at a time throughout the week (weekly intermittency). The duration of each sensor node deployment ranged from four days to nine months between January 2019 and April 2020. This period encompassed dry winter and spring as well as wet summer seasons.

The sensor nodes were connected to a tap next to the water meter to capture pressure data from the distribution system and to provide the water availability dynamics at locations with intermittent water supply. The sampling protocol included a pressure reading every five minutes, an open-valve flush action of 10 seconds followed by a water quality reading every 60 minutes. When pressure readings were zero, the flushing and water quality readings were postponed until water was available again. In one intermittent home, water quality was measured continuously to evaluate any potential impacts of stagnation in the flow cell.

Grab samples were also collected from each deployment site, ranging from one to three times per location during household visits, and select water quality parameters were measured on-site, including free chlorine (Palintest 7100, DPD method), and pH and EC (Hanna handheld pH-EC combo sensor).

2.6 Results and Discussion

2.6.1 Ann Arbor

The ten sensor nodes in Ann Arbor collected 437,157 pressure readings and 85,405 water quality measurements. The average readings obtained for each of the ten sensor nodes fell in the following ranges: pH: 9.2 – 10.0, ORP: 356 – 669 mV, EC: 558 – 997 uS/cm, and pressure: 24 – 88 psi. A summary of water quality results is provided in Table 2.1.

Table 2.1: Ann Arbor water quality nodes deployment summary statistics per pressure district

pH		EC (uS/cm)		ORP (mV)		Pressure (psi)	
Mean[1]	SD[1]	Mean	SD	Mean	SD	Mean	SD
Northeast							
9.2	0.2	755	55	505	129	24	34
10.0	0.1	774	58	418	14	74	20
West							
9.7	0.0	744	133	409	22	88	2
Gravity							
9.4	0.2	740	59	489	132	55	20
9.5	0.2	832	63	555	94	60	1
9.3	0.2	737	30	493	66	60	2
9.3	0.2	997	352	669	147	59	7

pH		EC (uS/cm)		ORP (mV)		Pressure (psi)	
Mean[1]	**SD[1]**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**
Geddes							
9.5	0.3	717	55	541	100	69	7
9.8	0.0	732	48	424	40	73	5
9.5	0.2	588	272	356	76	50	5

[1]Due to common probe malfunction, pH statistics were calculated using only the first five days of data

The ORP sensors have a "warmup" time (Figure SI-A- 1), requiring an average of three hours to reach equilibrium once deployed. We therefore filtered the full data set to remove start-up data (Figure 2.3-B and Figure SI-A- 1). The resulting ORP data averaged 454 mV, with a range of 300 – 750 mV (Figure 2.3-B). Based on average replicate data reported by Copeland and Lytle [70], at pH 9 and 23 °C, the average ORP value (454 mV) corresponds to a monochloramine concentration of 2.7 mg/L as Cl_2 and the ORP range corresponds to monochloramine concentrations ranging from 0.4 to >4 (out of range) mg/L as Cl_2. Considering the finished water distributed by the Ann Arbor treatment plant has a monochloramine concentration of approximately 3 mg/L as Cl_2, and monochloramine concentrations in the distribution system average 2.55 mg/L as Cl_2 (data provided by the Ann Arbor treatment plant), our ORP results agree with expected monochloramine concentrations. Three nodes exhibited and increase in ORP starting in March 2020 (Figure 2.3-B). All three of these devices were located in the same pressure district.

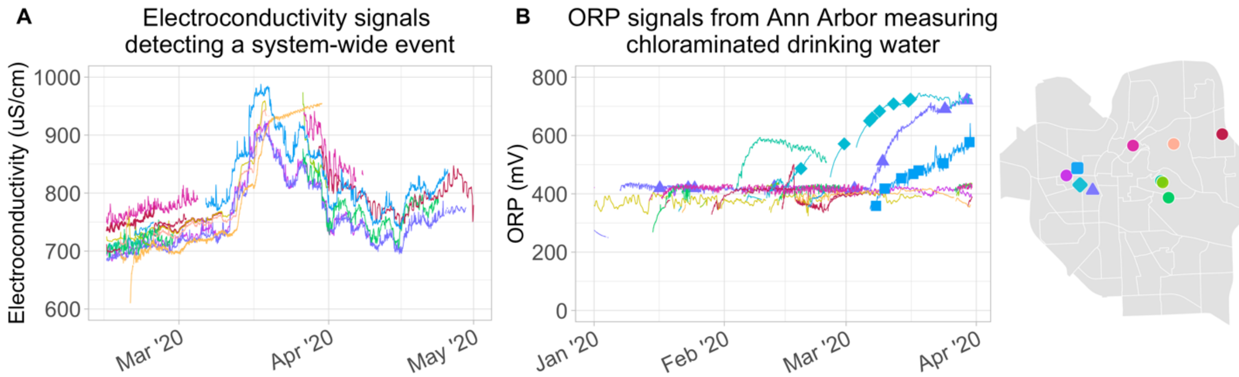

Figure 2.3: Signals from the sensor deployment in Ann Arbor, MI. The time series are color-coded by the site shown in the map. A) EC signals from deployed sensor nodes are shown capturing a system-wide event. B) ORP signals are used as an indicator to monochloramine concentrations. Three signals from the same pressure district exhibited a rise in ORP, shown by the triangular, square and diamond markers. For interpretation of the references to color, the reader is referred to the web version of this article.

The deployment in Ann Arbor highlights the benefits of a sensor network for the purposes of event detection and system-scale monitoring. The network captured events that would have been missed as part of conventional sampling campaigns. For example, the entirety of the Ann Arbor system experienced a rise in EC across a number of weeks (Figure 2.3-A). This period would provide sufficient time to utility personnel to investigate the change in more detail, for example by performing laboratory tests or by running a cross-reference data log to check operational status at the plant. Grab sampling was not possible as part of this study due to the COVID-19 pandemic and stay-at-home orders.

Given that all sensors measured the EC event, a strong case can be made for the occurrence of a system-scale event, compared to if just one sensor node or grab sample would have reported the change. In consultation with Ann Arbor drinking water treatment plant personnel, we believe the increase in EC was related to operational and maintenance changes at the treatment plant, which included changes in source water blend ratio and chemical dose adjustments. While these events did not pose a health risk to the public, our observations highlight the potential benefits of continuous and distributed monitoring for future events. It also emphasizes that water quality parameters do not only vary at the plant, but variations can extend throughout the water system and can be measured at the tap. The sensor nodes continuously measured the event as it developed, capturing a baseline trend, a maximum, a return to baseline conditions, and an additional rise (Figure 2.3-A, Figure SI-A-2). While EC is not a regulated parameter under the U.S. EPA's primary drinking water standards, it still provides aesthetic information about water quality since a typical conversion factor between EC and TDS is *0.5*. TDS (total dissolved solids) is included on the U.S. EPA's list of secondary drinking water standards and is recommended to be below 500 mg/L [71]. This means that the observed peak in Figure 2.3-A (933 uS/cm, 466 ppm TDS) did not reach the threshold of TDS that may negatively influence the taste, smell, or color of drinking water.

Using ORP signals to accurately measure residual disinfectant remains a challenge. Copeland and Lytle [70] reported an increasing variation between ORP duplicate (using two different sensors) measurements of the same solution, at increasing pH values. For a sample with chloramine at a pH of 9, they observed an average and maximum ORP variation of 47 mV and 71 mV. Ann Arbor maintains its chloraminated finished water at a pH slightly above 9, suggesting that ORP measurements across the system may exhibit high variation associated to the probes. The relative fluctuations of ORP signals correspond to changes in disinfection residual, which make the sensors a valuable tool to detect fluctuations in disinfectant residual and assist with flushing strategies during regular distribution system maintenance. For granular decision making, we recommend taking grab samples for ORP checks to complement the real-time sensor node signals.

As shown in Figure 2.3-B, three sensor nodes located in buildings in the same pressure district showed gradually increasing ORP signals. In the context of drinking water, ORP is typically associated with disinfectant concentration because disinfectants are the strongest oxidants present in drinking water. Therefore, this increase in ORP may point to a higher concentration of disinfectant in this neighborhood. Following the event, the ORP sensors were inspected and tested; they did not show any damage nor biofilm growth, and they responded accurately during calibration. This absence of sensor problems suggests that a transient event indeed may have transpired in this neighborhood, but no clear cause could be identified (we verified that no disinfection booster stations are used in Ann Arbor's distribution system). This observation underscores why continuous and distributed sampling is important, as it could be used as a tool to detect water quality regime shifts as they occur.

2.6.2 Mexico City

The 19 sensor nodes deployed across Mexico City resulted in 358,761 pressure readings and 168,685 water quality data points. The average ranges measured by all sensor nodes were as follows: pH: 6.8 – 8.2, EC: 212 – 1064 uS/cm, ORP: 204 – 921 mV, and pressure: 2 – 50 psi. ORP values from each deployment site were compared to free chlorine from grab samples for continuous systems (Table 2.2) and intermittent systems (Table 2.3). EC signals from the sensor nodes are compared to grab samples at each deployment site in Table 2.4. The average pH signals are compared to the respective grab samples per site and shown in Table SI-A-1 in Appendix A.

Table 2.2: Mexico City sensor deployments summary statistics from deployments in continuous systems

ORP Signal (mV)		**Free Chlorine (mg/L as Cl_2)**		
Mean	**SD**	**Mean**	**SD**	**n**
Chlorinated				
795[*]	18	1.06	0.18	3
806[*]	58	1.25	0.18	3
808[*]	25	0.88	0.41	3
688	169[â€]	0.68	0.08	3
922	68	1.34	0.62	2
Not Chlorinated				
257	154	0.04	0.02	2
204	50	0.04	NA	1
Variable Chlorination				
542	159	0.78	0.74	3

ORP Signal (mV)		Free Chlorine (mg/L as Cl_2)		
Mean	SD	Mean	SD	n
493	144	0.17	0.14	2
533	94	0.89	0.56	3
644	156	0.37	0.30	2
736	281	0.00	NA	1

[*]Nodes deployed in the same neighborhood.
[ае] High variability likely attributed to probe lowered sensitivity during deployment period.

For the 13 sensor nodes placed in households with continuous supply, chlorine residuals from grab samples were used to bin the ORP signals into categories of chlorinated, not chlorinated, or having varying levels of chlorination. Measurement time series for these households are categorized and shown in Figure 2.4, with summaries provided in Table 2.2. The ORP averages for chlorinated systems ranged from 688 to 922 mV, with the corresponding average free chlorine concentrations ranging from 0.68 to 1.34 mg/L as Cl_2. The ORP averages in systems categorized as not chlorinated ranged from 204 to 257 mV, corresponding to grab samples that had free chlorine concentrations below the detection limit. The third category — varying levels of chlorination — exhibited average ORP readings ranging from 493 to 736 mV and the free chlorine concentrations in the corresponding grab samples ranging from zero to 0.89 mg/L as Cl_2.

The ORP signals measured in the intermittent households are summarized in Table 2.3. Two of the three ORP signals obtained from the weekly intermittent households averaged 325 and 733 mV, with standard deviations 79 and 137 mV; these were normalized to the duration of intermittency. One of the three ORP signals with weekly intermittency – measuring water quality continuously – resulted in an average of 500 mV with a standard deviation of 219 mV. This means the data among these signals is not necessarily comparable, as the former explains the variability of supplied water only, while the latter explains variability of supplied and stored water. The latter ORP signal is shown in Figure 2.4-C, The variability was caused by free chlorine decay during periods of stagnation in between intermittency periods [48,51,72].

Table 2.3: Mexico City Intermittent Systems

Supply Type	ORP Signal (mV)		Free Chlorine (mg/L as Cl_2)		
	Mean	SD	Mean	SD	n
Weekly Intermittency[*]					
Chlorinated	733[â€]	137	0.17	0.13	3 [â€¡]
Chlorinated	500[â€]	219[Â§]	0.01	0.01	3 [â€¡]
Chlorinated	325[â€]	79	0.12	0.11	2 [â€¡]
Daily Intermittency[*]					
Variable Cl_2	497	151	0.73	0.98	2
Chlorinated	769	75	0.86	NA	1

[*]Determined from pressure data and from interviews with household members.
[â€]Nodes deployed in the same neighborhood.
[â€¡]Grab samples associated with these deployments are from household storage since field visits did not align with water supply hours.
[Â§]Node with continuous measurements. High variability associated to water quality change during storage periods. Statistics not normalized to the intermittency time.

Of the three daily intermittent sites, one signal was determined to be associated to a variable chlorination system based on the high standard deviations from the grab samples and the ORP signal. The second site with daily intermittency shows the highest signal average as well as the lowest standard deviation of all intermittent sites. The third site with daily intermittent supply was removed from the data set because of technical issues.

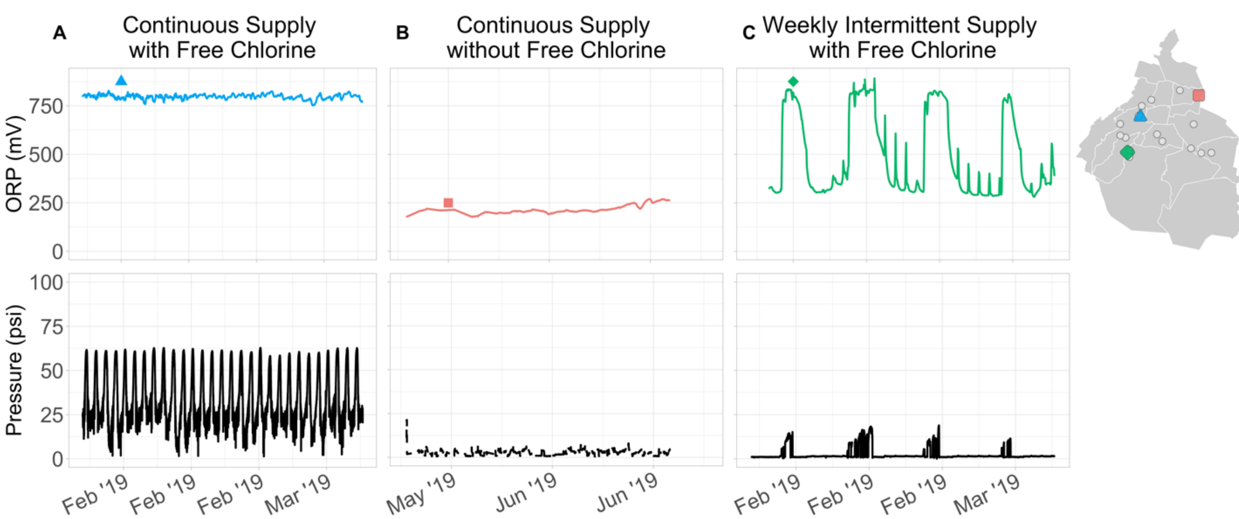

Figure 2.4: ORP and pressure signals from three different deployment sites in Mexico City. ORP and pressure signals from three different deployment sites in Mexico City show the difference in water quality and supply experienced in neighborhoods across the city: A) signal from a continuous supply household in the west of the city with measurable free chlorine and high diurnal pressure variations, B) signal from a continuous supply household located in the east of the city without measurable free chlorine and a consistently low supply pressure – gaps in data due to connectivity issues, and C) signal from a weekly intermittent supply household in the southwest of the city

with measurable free chlorine and chlorine decay during periods of intermittency, spikes in pressure correspond to periods of supply, while the flat line corresponds to periods of no supply.

Use of wireless sensor nodes in Mexico City captured previously unmeasured supply dynamics across a large intermittent system. Intermittency varies across the city and can be highly variable in terms of time and water quality. A grab-sample schedule that captures multiple intermittent events is complicated, may miss the first flush window, and is likely impractical in a city the size of Mexico City. ORP signals from intermittent systems with measurable free chlorine showed high variability throughout the study period. As confirmed by grab samples, the observed ORP variability corresponded with variability of the disinfectant concentrations. Although our data sets are not sufficiently large to allow for a detailed comparative analysis that links ORP to free chlorine concentrations, we found that compared to weekly intermittency sites, one daily intermittent site resulted in higher ORP average and lower standard deviation (Table 2.3), this may be related to less chlorine variability in supplied water when the intermittency periods are shorter. This suggests that the frequency of intermittency plays a role in delivering consistent disinfectant residual concentrations. In other words, the longer the period between water delivery times, the higher the risk of not meeting a particular residual disinfectant concentration target. Generally, the risk of microbial contamination and transmission of illnesses increases as the duration of in-home storage increases [72]. Data from real-time sensor networks could be used to manage risk associated with poor water quality and inform flushing strategies in intermittent systems.

As water resources become more limited and rationed, intermittency may become the new norm for many cities. For example, the water utility of Mexico City expects that, if the amount of government investment into water supply systems does not increase, the proportion of intermittency systems within the city will increase from 30% to 72% over the next decade [68]. Real-time wireless sensor networks provide an opportunity to monitor and manage such systems more closely, which could become increasingly useful as more continuous systems around the world will face greater water demands and a decrease in water resources [48,49,52].

The system in Mexico City is highly heterogeneous due to the multiple water sources and treatment plants that supply the city – surface water, 450 wells and 58 drinking water treatment plants [68]. This heterogeneity was captured through our wireless sensor network, which provided an unprecedented spatiotemporal data set. As seen in Figure 2.4 (A – C), water quality (ORP) varied significantly across the city, as compared to Ann Arbor. The pressure signals show different supply quality that may have impacts on water quality during distribution. Similarly, EC signals varied across the city (Table 2.4). For example, as measured by the grab samples, 11 sites show an average range of 178 – 243 uS/cm, two sites range from 404 – 615 uS/cm, and four sites range from 1030 – 1688 uS/cm. Similar ranges resulted from the EC signals in the sensor nodes.

Heterogeneity across the Mexico City water supply has been studied by Mazari-Hiriart et al. (2019), who provide results from a grab sample campaign [69]. Their findings report varying concentrations of metals, other inorganic contaminants, and biological contaminants. While our wireless sensor network focused on a limited set of physical parameters, our data are consistent with the assessment that the system is highly heterogenous. This is particularly evident when comparing the variability of measurements in Mexico City to those made in Ann Arbor.

Table 2.4: Mexico City electroconductivity

EC Signal (uS/cm)		Grab Sample (uS/cm)		
Mean	**SD**	**Mean**	**SD**	**n**
Continuous				
9^*	1	216	26	3
9^*	1	218	41	3
9^*	0	243	54	3
309	293	232	28	2
296	12	204	6	2
772	1,695	1,688	NA	1
1,065	5,194	1,041	NA	1
8^*	2	224	44	3
278	5,442	1,030	406	2
10^*	1	212	11	2
573	72	615	170	2

EC Signal (uS/cm)		Grab Sample (uS/cm)		
Mean	SD	Mean	SD	n
26*	11	1,031	NA	1
Weekly Intermittent				
8*	5	199	19	3
224	6,334	197	1	2
213	90	178	8	2
Daily Intermittent				
475	35	404	9	2
301	89	181	NA	1
*Early calibration issue, which was subsequently resolved				

Public knowledge about drinking water quality stands at the core of public health around the world. Trends and projections show increasing per-capita consumption of purchased water [13], often reported to have worse water quality, and bottled products, including sugared drinks [14,15], which have led to global obesity and diabetes type 2 epidemics [16]. Trust in water quality is a complex subject requiring cross disciplinary research. Our sensor network deployment in Mexico City is currently being cross-analyzed with qualitative and quantitative data sets studying public trust in drinking water [73,74]. Sensors may serve as an objective tool to help households and utility managers "turn on the lights" on an otherwise invisible infrastructure.

2.6.3 Platform Performance

As measured by data transmission reliability (expected vs delivered data packets), the sensor nodes and cloud architecture successfully collected and delivered data throughout the deployment study. By leveraging proven hardware and commercial cloud services, reliability and server uptime could be maintained without interruption. One of the novel elements of our sensor node and cloud architecture is its ability to be deployed at any location with Wi-Fi or cellular service. Some individual sensor nodes experienced outages, mainly due to instability of residential Wi-Fi. The nodes have a built-in feature to automatically reconnect once Wi-Fi outages resolve. The easy upgrade to cellular connectivity provides added reliability with an extra cost per node and excess data transferred. In terms of cellular coverage, Particle Inc provides a list of countries currently supported through their cellular data plans [75]. Regardless of preliminary connectivity, test should be performed to scout the wireless reliability of each location prior to deployment. Some outages were also caused by residents moving the unit or disconnecting it manually, but not due to the architecture of the system.

The platform reliably time stamped system-wide events such as the EC event in Ann Arbor, and distributed water quality and supply variations across Mexico City. By making technology more accessible and easier to use, these sensors nodes provide the potential to begin capturing building plumbing dynamics that have so far remained elusive. To our knowledge, our study is the first example of a large-scale deployment in distributed and intermittently supplied households made possible by a built-for-purpose technology.

2.6.4 Constrains, limitations, and practical considerations

This paper presents a first step towards making water quality measurements more accessible through an open source, real-time water quality wireless sensor network. As with any new tool, several new venues remain to be studied before it can become a vetted method. For those interested in carrying out similar studies, a major time barrier should be reduced since the steps of our study are provided in detailed web guides, source code, and blueprints that accompany this paper. While the platform is an end-to-end solution, it cannot be bought as an off-the-shelf product, and will require hands-on construction, calibration, and fine tuning. We expect these practical barriers to be reduced as the community of adopters grows.

The ease of deployment ensured that our team could instrument each household with a sensor node in a single visit of one hour. This feature limited the need for professional installations and reduced the burden on residents. All things considered, we recommend a team of at least two people construct and build a fleet of devices. Given the sporadic need to troubleshoot the nodes or expand their functionality, some basic knowledge of circuits, electronics, and coding is required. A basic undergraduate course in these topics should be sufficient to cover these. Installations require non-intrusive plumbing modifications (e.g. connecting and disconnecting threaded fittings), and system maintenance require data monitoring and field visits. For reference, the ten nodes used in the Ann Arbor deployment were built and tested by two students in two weeks and deployed over a period of two weeks. Recruiting household participants is perhaps the most practical constraint and may require approval by city authorities or an internal review board (IRB). This should be considered as early as possible, as it may take a long time to establish these relationships. For comparison, the nodes used in the Mexico City were deployed over nine months. The limiting factor in Mexico City was coordination with residents, and the sheer logistics deploying and maintaining a system in one of the largest cities in the world. This underscores even further the reliability of the network, as this limits long and unnecessary trips and coordination across large areas.

Our sampling protocol remained static throughout the study period (pressure every five minutes, water quality every hour), we recommend the use of more advanced operational scripts to automatically modify the sampling frequency as needed and to label data points within the script for a more streamlined analysis (e.g. first flush, bulk supply, building vs water main). Groups can do this by taking advantage of the microcontroller's internet features by simply writing new code and uploading it wirelessly to field deployed units.

The limitations of the water quality sensors should be characterized further. When signals show gradual or sudden changes, but grab samples are not available to validate such observations, it remains challenging to draw general conclusions about water quality. pH and ORP signals can drift or spike due to sensor malfunction, but unexpected results may also point to previously unrecognized water quality dynamics at the tap. Spatial redundancy of a deployment is a benefit of our cost effective and distributed approach in such cases, since it is unlikely that multiple sensors will fail in the same neighborhood. Further research is needed to understand the sensor signal dynamics of water quality at the tap. In the meantime, we recommend the deployment of multiple sites within a single study region. Furthermore, the real-time dashboard accompanying the platform should be used daily for quality control (at least in the early weeks of a deployment) to ensure that no major sources of noise or outages are present. As the team becomes more familiar with the individual nuances of their deployment, the need to quality control the data daily will become less important.

ORP and EC sensors showed the most potential in our study, but more detailed process studies are needed to evaluate the strength of the correlation between measure ORP and disinfectant residual. While these specific parameters have been studied in a broad range of water applications, their use as part of real-time drinking water monitoring networks remains uncharted. The sensitivity of ORP sensors to new conditions needs to be further evaluated, since there are existing known relationships between the ionic strength of a solution and the time it takes an ORP sensor to stabilize. Currently ORP sensors can take anywhere between 15 minutes to several hours to reach equilibrium when measuring low ionic strength waters, such as some drinking waters [76]. Because this is the case, real-time ORP measurements will need further operational tuning and technology development to achieve measurements that can be confidently linked to other parameters of interest.

During regular operation, the time to reach ORP sensor stabilization was variable (one to three hours). The Mexico City deployment shows that the sensor stabilization is an initial phenomenon when sensors are first turned on, rather than caused by exposure to water (intermittent vs continuous). While it should be evaluated on a deployment-by-deployment basis, this stabilization period is likely caused by power supply state, which underscores the need for a stable power source and battery backup. Our platform supports this with using a built-in backup battery, which we recommend as a vital component of future deployments. When nodes are reset, the stabilization time period should be accounted for through visual inspection and an initial grab sample.

2.6.5 Research Opportunities

In addition to event detection and monitoring benefits, the EC signals from the Ann Arbor deployment (Figure 2.3-A) show how a study may be conducted to quantify the water age and hydraulic patterns of a distribution system based on the delay and magnitude of the signals. A dedicated sensor node at the treatment plant could serve as the baseline for water quality characteristics, while a deployed sensor network within the distribution system could inform the time and possible flow paths of the water in the distribution system. We see future potential to use these sensor nodes in applications such as water age model calibration using approaches such as the ones published by Rubulis et al. (2011) [77], where EC was proposed as a natural tracer to track the flow of various water sources within the distribution system. Hyoungmin Woo et al. (2019) [78] implement Dynamic Time Warping to computationally find the corresponding elements of various water quality signals that are offset by a time component and signal magnitude. Access and availability to sensors has been a major barrier to release these theoretical approaches, but it is now entirely possible to accomplish this with our platform.

Even when relying on sensors that are lower cost and less maintained than those used at the plant, the option to generate long-term summary statistics and time-series using real-time wireless sensor networks has the potential to provide substantial value. After the sensor network has been deployed and the water quality baseline has been established through summary statistics, specific signals can be queried for relative changes. For example, stable ORP signals can be taken as validation that chloramine concentrations throughout the day and across the city remain within a safe range. If the average and range continuously correspond to previously set values (e.g. 400 $\pm$ 100 mV in chloraminated waters), the wireless sensor network may have the potential to alleviate some of the efforts required in field grab sampling, assuming the regulator would allow for a reduced number of regulatory samples. Furthermore, the real-time data could point to locations of the distribution system that require more attention. Although U.S. EPA regulations in the United States still require mandatory grab samples for compliance, more resources are becoming available for utilities to adopt real-time online water quality tools that can be used to monitor common water quality incidents such as nitrification and corrosion.[79] The sensor node architecture presented in this paper (Figure 2.1) can be modified to address and monitor the parameters that are most relevant to each system and study site.

2.7 Conclusion

Our wireless sensor network shows how a drinking water distribution system can be continuously monitored at the level of building plumbing using a cloud-based architecture. This may present a valuable tool for water quality monitoring, compliance, research, maintenance, warning system design, and operations. Potential allocation of resources for infrastructure projects may benefit from continuous monitoring to ensure that designs meet intended goals. For those wishing to implement and evaluate these technologies, our team has made available all the blueprints and guides as part of a broader effort to open-source water technologies.

2.8 Supporting Information

Details on the methods and deployments specific to each city are described. Summary statistics tables of the signals and grab samples of Mexico City nodes (pH in Table SI-A-1, Pressure in Table SI-A-2). Ann Arbor's deployment results from Figures SI-A-1 and SI-A-2 complement Figures 2.3 A and B.

2.9 Funding Sources

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Chapter 3

Toward the Autonomous Flushing of Building Plumbing: Characterizing Oxidation-Reduction Potential and Temperature Sensor Dynamics

3.1 Abstract

Manual flushing of building plumbing is commonly used to address water quality issues that arise from water stagnation. Autonomous flushing informed by sensors has the potential to aid in the management of building plumbing, but a number of knowledge gaps hinder its application. This study evaluates autonomous flushing of building plumbing with online sensor and actuator nodes deployed under kitchen sinks in five residential houses. Online oxidation-reduction potential (ORP) and temperature data were collected for nine weeks during the winter and summer in houses with both free chlorine and chloramine. ORP levels in houses with free chlorine residuals decreased after overnight stagnation. The overnight decrease in ORP was not observed when tap water was automatically flushed for five minutes at 6:00 h every morning. ORP levels in houses with chloramine residuals did not decrease consistently after overnight stagnation, and daily automated flushes did not have an observable effect on the ORP signals. Additional laboratory experiments were carried out to evaluate ORP signals during chlorine decay and after incremental changes in chlorine, as would be expected in building plumbing conditions. Results from the lab and field deployments suggest on-line ORP sensors may be used to detect free chlorine decay due to stagnating water, but are not as effective in detecting chloramine decay. However, field results also suggest ORP may not respond as expected on a timely manner after free chlorine or

chloramine have been restored, hindering their applicability in developing control algorithms. In this paper we tested twice-daily five-minute automatic flushing and found that it counteracts water quality degradation associated with overnight stagnation in free chlorine systems. An automatic sensor-based flushing is proposed using online temperature sensor data to determine when flushing has reached water from the main. The results suggest that flushing informed by temperature sensors can reduce the flushing time by 46% compared to the preset five-minute static flush.

3.2 Introduction

Drinking water quality deterioration in building plumbing is a public health issue of growing concern. Varying factors in plumbing can affect residual disinfectant levels [80,81], may increase the concentrations of harmful metals like lead and copper in the water [41,82], and can allow biofilms sometimes containing pathogenic microorganisms to grow [83]. To that end, operational guidelines have been developed to address and mitigate risks [84–86]. The most commonly recommended approaches include disinfectant boosters, water heater temperature control, and manual flushing of taps, with the latter typically considered the most practical to implement. However, many of these guidelines are inconsistent and some even lack a scientific basis [37]. This can lead building occupants to falsely believe they are addressing water quality deterioration by following guidelines. Overall, many knowledge gaps exist in our understanding of building plumbing water quality and risk mitigation practices [39].

In the United States, federal regulations require utilities, with the exception of filtered groundwater systems, to maintain a residual disinfectant in drinking water delivered through distribution systems [87,88]. The purpose of the residual disinfectant is to prevent microbial growth and inactivate pathogens that are introduced after the drinking water exits the treatment plant. Federal regulations further require all public water systems to maintain chemical stability of pipe materials in building plumbing through corrosion control measures [36]. Since regulations focus on distribution system water quality and centralized treatment, building managers and residents are left with the responsibility of ensuring adequate water quality at their tap. A common approach is routine flushing, whereby stagnant water in pipes is replaced with fresh water from the distribution system by opening the tap for a certain time period.

Prior studies have found that flushing building plumbing replenishes disinfectant residual, decreases the levels of viable bacteria [89], and reduces the concentrations of dissolved heavy metals like lead and copper [90–92]. Overall, however, existing flushing guidelines are scattered or nonexistent for various building types [37,39]. A universally-accepted guideline does not exist due to variations in plumbing and lack of clear scientific guidance [38].

Guidelines suggest that building managers or residents flush faucets manually and determine flushing duration by gaging temperature changes with their hand or a handheld thermometer [85]. This approach assumes that tap water at room temperature is associated with building plumbing and colder water is associated with the distribution main. Alternatively, flushing can be carried out for 30 seconds to 2 minutes [19§141.154]. However, the time each tap takes to reach the distribution main water depends on many factors and requires flushing from a few seconds to anywhere between ten minutes to longer than one hour [93]. This makes routine flushing practices prone to error, impractical to implement, and unsustainable in regions experiencing water scarcity.

Flushing durations are important since incomplete and inadequate flushing may inadvertently increase lead and copper concentrations mostly originating from service lines [91], but also from fixtures, galvanized steel pipes, solder and other components in building plumbing

[82,94,95]. In addition to concerns with flushing durations, the daily to weekly flushing frequencies found in guidelines may be insufficient in some cases [89,93]. For example, Totaro et al. found that hospital hot water taps needed to be flushed as frequent as every two hours to reduce *Legionella* counts from $10^2 – 10^5$ to 0 cfu/L, despite the presence of total chlorine concentrations ranging from 0 – 0.23 mg/L as Cl_2 [96].

When long, high frequency flushing is required to achieve the desired safety standards, manual flushing may not be feasible. This presents an opportunity for the development of technology-based or automatic flushing mechanisms. Advances in computing, sensing, and electronics have paved the way for infrastructure automation [9,97]. Infrastructure systems are increasingly being retrofitted with sensors and actuators to allow autonomous responses and dynamic management [98]. These technologies now have the potential to measure and automate tap water management at the scale of individual buildings, for example by measuring water quality in real-time to inform when and for how long flushing should take place. Presently, however, most common uses of water technology in buildings are related to conservation [99]. Proximity sensors have become common in public restrooms to flush toilets, urinals, and faucets [99]. Decreasing water use increases water age and may invertedly cause greater contaminant exposures [100]. Verifying this at scale and with high granularity, however, remains challenging as water quality sensors are not deployed at points of use.

Maintaining a residual disinfectant (free chlorine or chloramine) is an important strategy in drinking water system management [101]. Disinfectant sensing technology, however, is currently not applied in public or residential plumbing as there are no readily available commercial products. Direct and reliable measurements of residual disinfectant concentrations via sensors are complicated by operational requirements, cost, and frequent maintenance necessary to provide reliable measurements [102]. Albeit rare, recent studies have deployed disinfectant sensors in institutional and residential plumbing fixtures [43,45] showing that technical implementation is possible. These studies mentioned the high cost of these sensors limiting their widespread adoption and called for the development of sensing technology to facilitate research and management of building plumbing.

Indirect measurements can provide a low-cost alternative to directly measuring a compound of interest in water. Oxidation-Reduction Potential (ORP) sensors measure the oxidation potential set by the strongest oxidant in solution, which in drinking water is the residual disinfectant. Some studies have correlated ORP to disinfectant concentrations in test waters [70,103], and have correlated ORP with biological inactivation [103–105]. The U.S. Environmental Protection Agency (USEPA) recognizes ORP as an important water safety parameter for detecting contamination incidents and monitoring disinfectant residual, and provides resources for utilities and practitioners to develop online real-time monitoring tools [32]. ORP has recently been used to monitor disinfectant levels in chlorinated and chloraminated full-scale drinking water systems [43,46,106]. The potential of ORP sensing in residential and commercial plumbing remains understudied, so it is unclear if these technologies could be used at scale to adaptively manage water quality.

Temperature is another important, but even more indirect parameter for the characterization of water quality in buildings. Temperature plays an important role in the growth of opportunistic pathogens (e.g., *Legionella pneumophila*) in building plumbing (CDC 2022). Temperature sensors are reliable and readily available, and real-time measurements could be used to assess if water from the distribution main has reached the tap during flushing or to monitor if the temperature is above or below the optimal temperature range for *Legionella* growth.

Applications of temperature sensors have included detection of individual flow events at hospital thermostatic mixing valves [44] and automatic shut off of showers when a temperature set point is reached [99]. To our knowledge, no studies to date have directly characterized the value of using in-situ temperature sensors to inform flushing frequency and duration.

Technologically, opening and closing valves based on sensor readings to flush plumbing is feasible. However, the viability of autonomous flushing as a management strategy is underpinned by several knowledge gaps. Toward that end, the goal of this study is to address three key questions, which must be answered before sensor-mediated flushing can be deployed:

1. Does the dynamic response of ORP sensors provide a reliable correlation to estimate tap water disinfectant residual concentrations?
2. How are in-situ ORP and temperature measurements affected by automated flushing at residential taps?
3. Which practical constraints should guide the deployment of sensor-driven flushing of building taps?

3.3 Materials and Methods

Field experiments using the sensors were performed in Ann Arbor and Ypsilanti, Michigan, USA and validation laboratory experiments were conducted at the University of Michigan. The Ann Arbor distribution system serves a population of 120,000 people and chloramine is used as the residual disinfectant [30]. Ypsilanti's distribution system serves a population of 110,000 and receives water from the Great Lakes Water Authority, which uses chlorine as the residual disinfectant [107,108].

3.3.1 Laboratory Evaluation

Prior to field deployments, ORP sensors (Atlas Scientific #ENV-40-ORP) were evaluated under two controlled scenarios in the laboratory to assess operational performance. All laboratory-based experiments were carried out at 22 °C. Experimental solutions for sensor evaluation were prepared with tap water collected in Ypsilanti and Ann Arbor (physicochemical water quality parameters are reported in Table SI-B-1 in Appendix B). All glassware was treated in a chlorine bath (5,000 mg/L as Cl_2 for >1 hour) and rinsed thoroughly prior to use. Residual disinfectant concentrations were measured with a Hach DR900 Colorimeter using the DPD method [109]. Hach Method 8021 was used to measure free chorine and Hach Method 10250 was used to measure total chlorine. The dynamic range for both methods was 0.05 to 4.00 mg/L as Cl_2. Chloramine in Ann Arbor water was assumed to be the sole contributor to total chlorine measurements.

The first scenario sought to characterize how the ORP sensor data correlate to discrete disinfectant concentrations over ranges typically found in building plumbing. Tap water was diluted to concentrations ranging from 0 – 2 mg/L as Cl_2, placed in 250 ml flasks, and the ORP was measured with ORP sensors after a five-minute signal stabilization period. The ionic strength of the diluted samples was kept similar to the tap water ionic strength by matching the chemical composition of dilution water to that of tap water. Dilution water was prepared by adding sodium bicarbonate ($NaHCO_3$), sodium phosphate monobasic (H_2NaPO_4), sodium sulphate (Na_2SO_4 $2H_2O$), calcium chloride ($CaCl_2$ $2H_2O$), and sodium hydroxide (NaOH) in deionized water (DI) to match total alkalinity, total hardness, phosphate, chloride, sulphate, conductivity, and pH of the tap water samples. The results of these experiments were used to model the relationship between each disinfectant concentration and ORP using a local statistical regression (LOESS) in R.

The second scenario focused on the response of the ORP sensors to the gradual decay of residual disinfectant, seeking to reflect conditions corresponding to water stagnating in building plumbing. Tap water samples (4 L) were placed in large conical flasks, continuously stirred, sealed, and covered with aluminum foil. ORP decay for each sample was monitored in a single flask containing three ORP sensors that collected measurements every five minutes. The measurements collected at each timepoint by the three ORP probes were averaged, and the standard deviations were calculated. Aliquots were removed from the flask two times a day for free chlorine and total chlorine measurements. These measurements were discontinued when the residual disinfectant concentration was below the detection limit. The experiments lasted from seven to 21 days and the decay experiment was repeated multiple times for each disinfectant. Decay constants were estimated using first-order exponential decay models (Eq. 3.1) as first order kinetics have been applied previously to model free chlorine and chloramine decay in bulk water and pipes [81,101,110].

$$\ln[Cl]_t = -kt + \ln[Cl]_o \qquad \text{Equation 3.1}$$

where k is the decay coefficient, t is time in hours, $[Cl]_t$ is the residual disinfectant concentration in mg/L as Cl_2 at time t, and $[Cl]_0$ is the initial concentration.

3.3.2 Field Experiment

The wireless sensor and actuator package (Figure 3.1) was designed as described by Martinez Paz et al. (2022). The WiFi enabled package was connected under a standard household sink (Figure 3.1-B), without affecting regular use of the fixture by residents. The device was equipped with an ORP sensor and a thermistor. To make an in-situ measurement of ORP and temperature, a solenoid valve was actuated to fill a flow cell (250 ml) and divert the sampled water into the drain. The wireless system transmitted ORP and temperature to cloud-hosted services, where server-side logic was implemented to trigger new samples or initiate flushing. The same solenoid valve used to take samples was used for flushing by keeping the valve open for a longer period. The sensor sampling frequency was configured remotely, but the device reported ORP and temperature measurements at five-minute intervals. In total, two households in Ypsilanti and three households in Ann Arbor (Table SI-B-2, Figure SI-B-1) were part of the field experiment with a duration of approximately nine weeks per household.

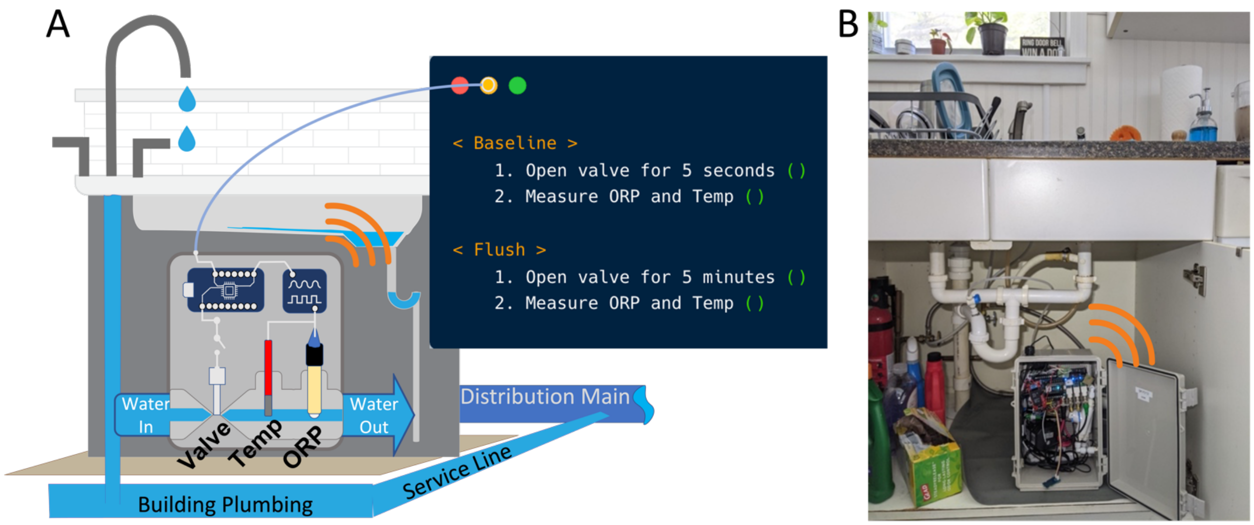

Figure 3.1: Wireless sensor nodes and actuation system deployed under kitchen sink. A valve was actuated to flush water using cloud connected services while temperature and ORP measurements were used to study the resulting water quality dynamics.

ORP and temperature measurements were made at each home and categorized across two scenarios: (1) *Baseline* and (2) *Flush*. In the *Baseline* scenario, water measurements were taken hourly, seeking to characterize baseline use conditions for each home. During the *Flush* scenario, the solenoid was triggered remotely to flush the flow cell for five minutes. The five-minute flushing duration was chosen based on observation that temperature measurements stabilized within a five-minute flush period. Here, we assumed that stabilized temperature readings reflected water arriving from the distribution system at the tap. A fixed schedule for flushing was implemented on the server, triggering the system to flush water at 6:00 h (before waking up) and 17:00 h (before residents returned from work). The flushing flowrate was set at 3 L/min, resulting in approximately 15 liters being flushed each time. After flushing, ORP and temperature measurements were recorded. Measurements were summarized hourly across days to compare trends across the *Baseline* and *Flush* scenarios.

A modified flush scenario was conducted in which the cell was flushed for 15 minutes and the ORP and temperature measurements were recorded every second. This scenario was only triggered for approximately one week per site during the multi-month deployment – a total of 219 high-resolution flushes were collected across all sites. An algorithm was designed to identify flushing stop points on these high-resolution signals based on sensor signal stability. The algorithm used linear regression to calculate the slope of three consecutive measurements using a sliding window. A stable signal was identified when five consecutive slopes were less then $|\pm 0.002|$ °C/sec. The criterion was chosen based on stable signals observed in the data set.

Grab samples were collected from taps during both *Baseline* and *Flush* scenarios between 9:00 h and 17:00 h to characterize the pre- and post-flush residual disinfectant concentrations (Table SI-B-3, Figure SI-B-2). The free chlorine and chloramine concentrations were measured as described above. An additional pair of pre- and post-flush samples from the households in Ypsilanti were collected at 7:00 am to assess the effect of overnight stagnation (Figure SI-B-3). Access limitations prevented similar samples to be analyzed in the Ann Arbor households.

3.4 Results

3.4.1 Laboratory evaluation

The response of the probes to different free chlorine and chloramine concentrations was tested with tap water samples diluted and measured with the probes after a five-minute stabilization period (Figure 3.2). Visualized as a regression, the figure illustrates that ORP provides a linear prediction of free chlorine concentrations in a range of 0.1 - 0.5 mg/L as Cl_2 with slope equal to 834 mV/mg/L as Cl_2 ($R^2 = 0.89$), followed by a plateauing of the signal at > 0.5 mg/L as Cl_2 with an approximate linear relationship with slope of 49 mV/mg/L as Cl_2 ($R^2 = 0.36$). ORP sensors submerged in chloraminated water also exhibited a linear relationship with a slope of 256 mV/mg/L as Cl_2 ($R^2 = 0.70$) in a range of 0.1 – 0.6 mg/L chloramine as Cl_2. The ORP values were not reliable predictors of higher disinfectant concentrations for chloramine. These results for chlorine and chloramine agree with a previous study in which ORP levels plateaued at free chlorine and chloramine concentrations greater than 0.5 mg/L [70]. Copeland and Lytle reported higher ORP variability with increasing pH. Chloramine formation and longevity are known to be more effective at high pH (> 8.5) [101,111], which explains the higher variability in ORP measurements for chloramine samples with a pH value of 9.3 compared to free chlorine samples with a pH value of 7 (Figure 3.2).

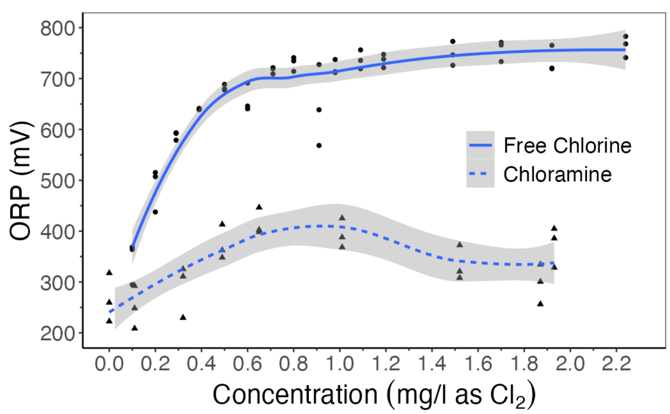

Figure 3.2: Relationship between ORP and residual disinfectant concentrations. Triplicate ORP measurements were taken at different concentrations of free chlorine and chloramine. Solutions were prepared by diluting tap water and then measuring ORP and residual concentrations after five minutes. A LOESS regression model was used to fit the data.

The response of the probes was also tested in laboratory experiments tracking tap water disinfectant and ORP decay over long periods of time, reflecting temporal dynamics that may be observed as water stagnates in pipes (Figure 3.3). In these samples, the initial free chlorine concentrations in Ypsilanti tap water ranged from 0.68 to 1.00 mg/L as Cl_2, and the initial chloramine concentration in Ann Arbor tap water ranged from 1.14 to 2.70 mg/L as Cl_2 (Figure

3.3). ORP decay curves for the water containing free chlorine exhibited a gradual ORP decrease followed by a rapid ORP decline after the free chlorine concentrations reached approximately 0.10 mg/L as Cl_2. This transition occurred after 4 – 8 days. On the contrary, the ORP signals in the samples containing chloramine fluctuated over the first 2-3 weeks even though the chloramine concentrations were decreasing. The ORP signal eventually began to decrease consistently after the chloramine concentrations had decreased by >50%. The ORP sensors reached approximately 260 mV when the chloramine was no longer present. These inconsistent temporal dynamics of the ORP sensors in the decaying chloramine solutions do not support direct conversions from absolute ORP (mV) to chloramine concentrations. A defining feature of the free chlorine ORP signals was the relatively low variability among the triplicate probes submerged in the batch reactor. This was contrary to the replicate probes in the chloramine solutions, which exhibited high levels of signal variability. This higher variability in the chloramine samples is likely related to the complex decay mechanism of chloramine in drinking water [111].

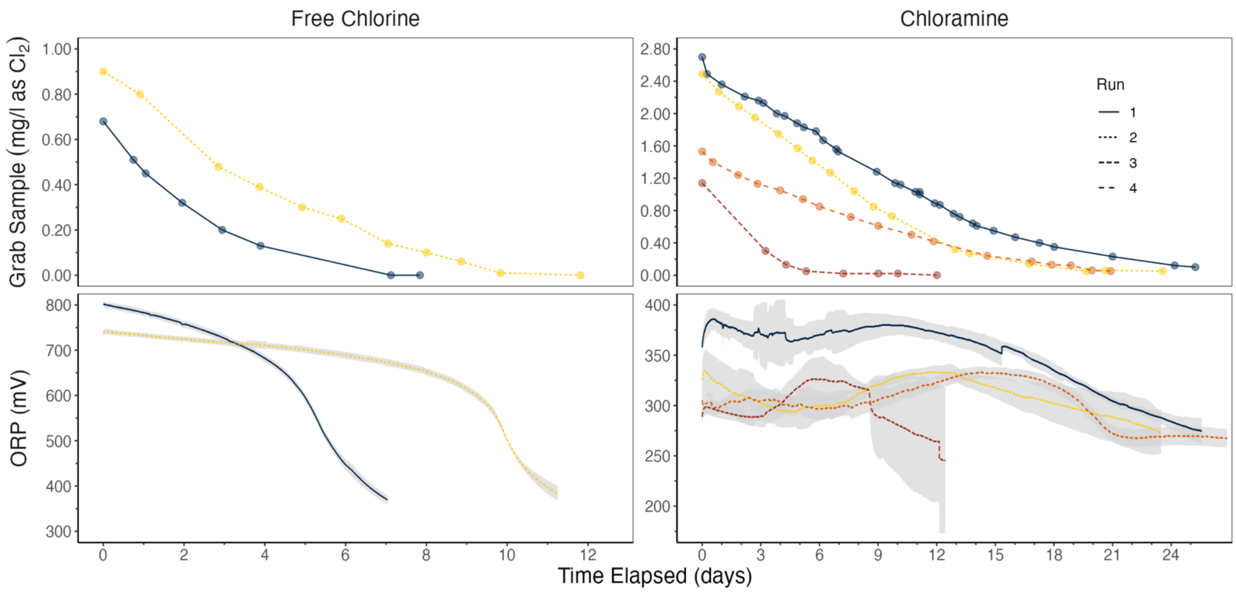

Figure 3.3: Residual disinfectant concentration and ORP decay in batch reactors containing tap water. Top: Results from grab sample free chlorine (left) and chloramine (right) measurements. Data points are connected by lines to clarify replicate experiments. Bottom: ORP results obtained by using the average ORP value of three sensors, with the gray bars indicating the standard deviation.

In systems under surface water influence, the US EPA minimum standard for free chlorine and chloramine concentrations at the entry to the distribution system is 0.2 mg/L as Cl_2, and detectable throughout the distribution system [87]. In the decay experiments (Figure 3.3), 0.2 mg/L as Cl_2 corresponded to 695 mV (σ = 26 mV, n = 9) for free chlorine and 306 mV (σ = 19 mV, n = 12) for chloramine. In the discrete change experiments (Figure 3.2), 0.2 mg/L as Cl_2 corresponded to 476 mV (σ = 11 mV) for free chlorine and 275 mV (σ = 17 mV) for chloramine. These experiments indicate that ORP levels differ in situations where the disinfectant is decaying compared to situations where the probe is exposed to a freshly prepared sample containing residual. The mechanisms behind these observations are not clear, but highlight issues with calibrating sensors solely with freshly prepared residual solutions.

The first order decay constant (k_d) for free chlorine was $1.35 \times 10^{-2}\ h^{-1}$ (σ = $0.421\ h^{-1}$, n = 2) and for chloramine was $8.25 \times 10^{-3}\ h^{-1}$ (σ = $0.753\ h^{-1}$, n = 4). At these rates, the free chlorine concentrations took 3 – 7 days and the chloramine levels took 4 – 24 days to drop below the US EPA standard of 0.2 mg/L as Cl_2. These decay rate constants were similar to those measured in tap water samples in a beaker or water mains [81,110,112] and are 20-140 times slower than rate constants measured in experimental building plumbing rigs and in real building plumbing systems [81,110,112]. This is likely due to the greater disinfectant demand in premise plumbing systems compared to glass flasks and water main pipe materials. In the case of chloramine, the additional effects of nitrification may also contribute to the discrepancy [81,110,112]. Twenty-fold faster decay rates in building plumbing means that free chlorine and chloramine could decrease from 1.0 to 0.2 mg/L as Cl_2 in roughly seven hours and 15 hours, respectively. Although the decay kinetics observed with ORP sensors (Figure 3.3) are much slower compared to chlorine and chloramine decay kinetics, these calculations along with our bench scale results suggest that ORP sensors may detect low disinfectant residuals due to stagnation. Overall, the laboratory results underscore the need to study the sensors in real household systems.

The laboratory experiments suggest that an absolute ORP measurement may not provide an accurate estimate of decaying disinfectant concentrations in building plumbing. These data, especially in chloraminated systems, demonstrate the challenges with using ORP sensors in systems with high water age for capturing disinfectant decay. On the other hand, experiments using freshly diluted samples (Figure 3.2) suggest that ORP may capture when the disinfectant has been replenished with fresh water from the distribution main.

3.4.2 Field Experiments

Five-minute manual flushes that took place between 9:00 h and 19:00 h resulted in modest improvements in chlorine and chloramine concentrations immediately after flushing (Table SI-B-3, Figure SI-B-2). Specifically, the free chlorine levels increased between 1.4% and 33% and the chloramine concentrations increased between -1% and 18.3%. Larger increases in disinfectant residual concentrations were observed when flushes took place after overnight stagnation, which yielded a 52% and 45% increase for free chlorine systems immediately after flushing (Figure SI-B-3). These data demonstrate that while flushing improves residual disinfectant levels in most cases, it has a larger impact on residual disinfectant levels after long periods of water stagnation.

In most homes, a five-minute flush yielded discernable temperature shifts observed with the in-situ sensors (Figure 3.4), likely corresponding with water arriving in the home from the main. Notably, each household resulted in a unique temperature profile; some households exhibited a rapid temperature change with flushing, whereas others took as long as five minutes of flushing for temperatures to stabilize. The temperature shift was less pronounced in September and October, when differences between indoor and outdoor temperatures are smaller in Southeast Michigan. These high-resolution signals show that temperature changes measured by in situ sensors could be used as an indicator that building plumbing has been flushed and that the household is receiving water from the distribution system. This approach may work better during some parts of the year than others, as the temperature differential may be easier to measure. Of the 219 flushes across the five households that lasted 15-minutes and had high-resolution temperature measurements, 51% of the flushes required less than five-minutes to reach a stable temperature (Figure 3.4). A five-minute flush was equivalent to 15 L, which is roughly 4.7% of the average daily water use per person per day [113]. This water loss is relatively small compared to the water use associated with showering (an eight-minute shower using a low-flow showerhead uses approximately 60 L of water) and corresponds to 2.5 toilet flushes (6 L per flush) [99]. Nevertheless, our experiment highlights an opportunity to reduce the flushing time to save water without changing water quality. Specifically, an average 8-L flush in the summer (46.6% reduction), and 14-L flush in the winter (4.6% reduction), would have been sufficient if temperature sensors would have been used as cutoff indicators. Of note, the flow rate of the sensor node (3 L/min) is lower than faucet flow rates in the US (5.6 – 8.3 L/min)[99]. Depending on each faucet, a manual flush may need less time to reach water mains.

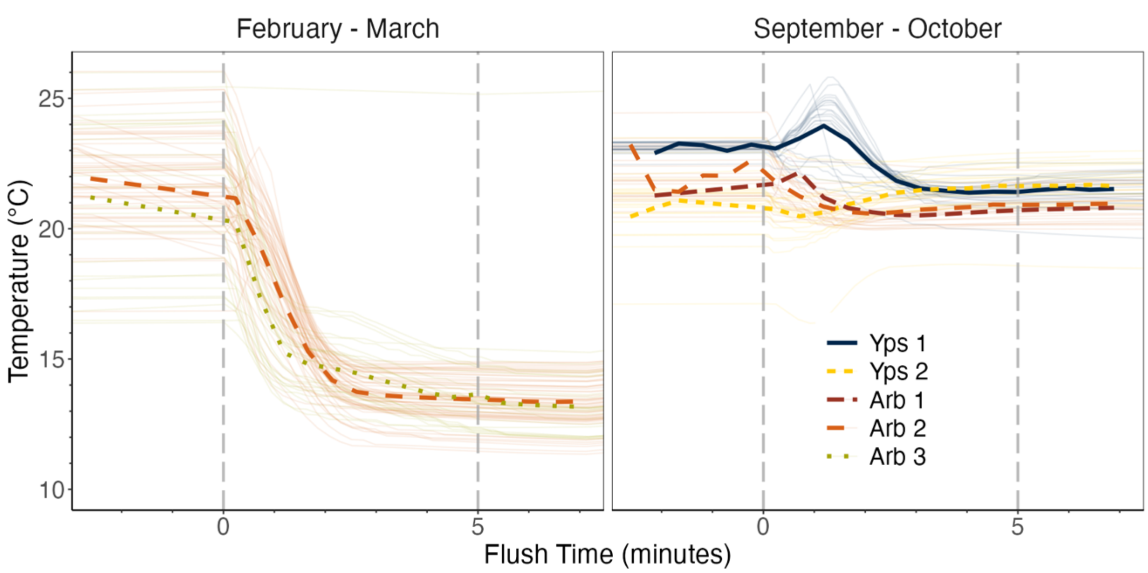

Figure 3.4: Response of temperature sensors during flushing of household taps. Solid lines represent individual flushing events (n = 219), average of lines per site is shown in bold lines, dashed vertical lines represent the start and end of a five-minute flush. Flow rate at 3 L/min.

Similar to the laboratory observations, the ORP sensor readings in homes with chlorinated water increased during a flush (Figure SI-B-4). However, the trends were noisier than the temperature trends. The ORP sensors in homes with chloraminated water resulted in inconsistent trends through flushes, and often exhibited no shift during a flush (Figure S1-B-4). This is likely due to the fact that the chloramine concentrations were typically well above 0.6 mg/L as Cl_2 (Table S1-B-3) and the ORP signals were no longer responsive with our sensors at these concentrations (Figure 3.2).

Water temperatures at the tap generally corresponded with room temperatures throughout the day and averages were slightly higher in the warm periods compared to the cool periods (Figure 3.5). This was expected as homes were often climate controlled. Temperatures dropped the most following the scheduled flushing in the morning. This temperature decrease was larger in the cool months compared to the warm months. Temperatures generally returned to room temperature within an hour of the morning and evening flushes. During the winter, the flush-induced median temperature dip was -5.5 °C, -6.6 °C, and -3.7 °C in *Arb 1*, *Arb 2*, and *Arb 3* from each of their baseline temperatures. During the summer, the impact of flushing on median temperatures was -2.3 °C, -3.8 °C, -2.1 °C, and -3.8 °C in *Yps 1*, *Yps 2*, *Arb 1*, and *Arb 2*, respectively.

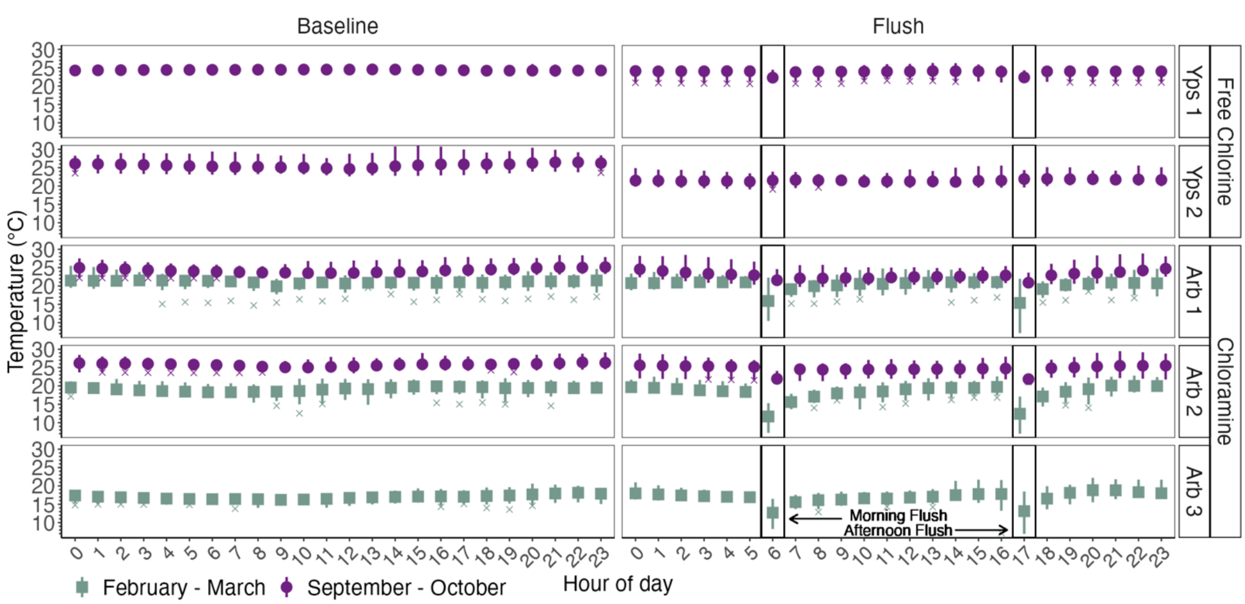

Figure 3.5: Hourly water temperature variability during field experiments, comparing the distribution of temperatures across baseline and flushing scenarios. Summaries include median (Q_2) as circles and squares, whisker

bars extend to $Q_1 - 1.5 \times IQR$ and $Q_3 + 1.5 \times IQR$ or the max/min value of the data set, where IQR is $Q_3 - Q_1$, and minimum values shown as x's if smaller than the whisker bar range.

For homes with free chlorine residuals (Yps1, Yps2), the median ORP values measured by the sensors corresponded to 811 mV and 737 mV (Figure 3.6). A drop in the median ORP was detected in these homes overnight (-17 mV and -27 mV), becoming most pronounced around 8:00 h. The drop in the median at 8:00 h was accompanied by an increase in the variability of the measured signals. This drop aligns with the water stagnation that typically occurs in households overnight. While we did not have access to water usage data, ORP values in homes with free chlorine residuals generally increased in the morning and this aligns with common household water use patterns. Flushing daily at 6:00 h eliminated the ORP minimum observed at 8:00 h when no flushing occurred. Flushing also reduced the variability in measured signals overnight, with the most significant change seen at 8:00 h (IQR shift from 39 mV to 11 mV). The potential use of ORP as an indicator for stagnation is incidentally supported by the observations of extreme outliers when no flushing took place in households (Figure SI-B-5). ORP levels dropped to as low as 242 mV without flushing, and this corresponded with a 3-day household vacancy, as reported by the household residents. ORP outliers were not observed when flushing took place. Combined, our results suggest that ORP sensors can serve as general indicators of improved water quality due to flushing in homes with free chlorine residuals.

In sites with chloramine as the residual disinfectant (*Arb 1*, *Arb 2*, *Arb 3*), the median ORP values measured during the Baseline period were 426 mV, 411 mV, and 416 mV respectively, with aggregate variability between 7 mV and 12 mV. Differences in Baseline ORP between the cold and warm months were minimal, with slightly lower values during September and October in one of the sites (Arb 2). Similar to the results from lab experiments, no strong pattern in ORP could be detected for systems with chloramine residuals. This provides further evidence against using the ORP sensors as dynamic indicators of stagnation in chloraminated systems. The relatively stable ORP values in the chloramine deployments reflect the continuous presence of chloramine, and the lack of hourly trends overnight and throughout the day may be due to the lower chloramine decay rates compared to those of chlorine [80].

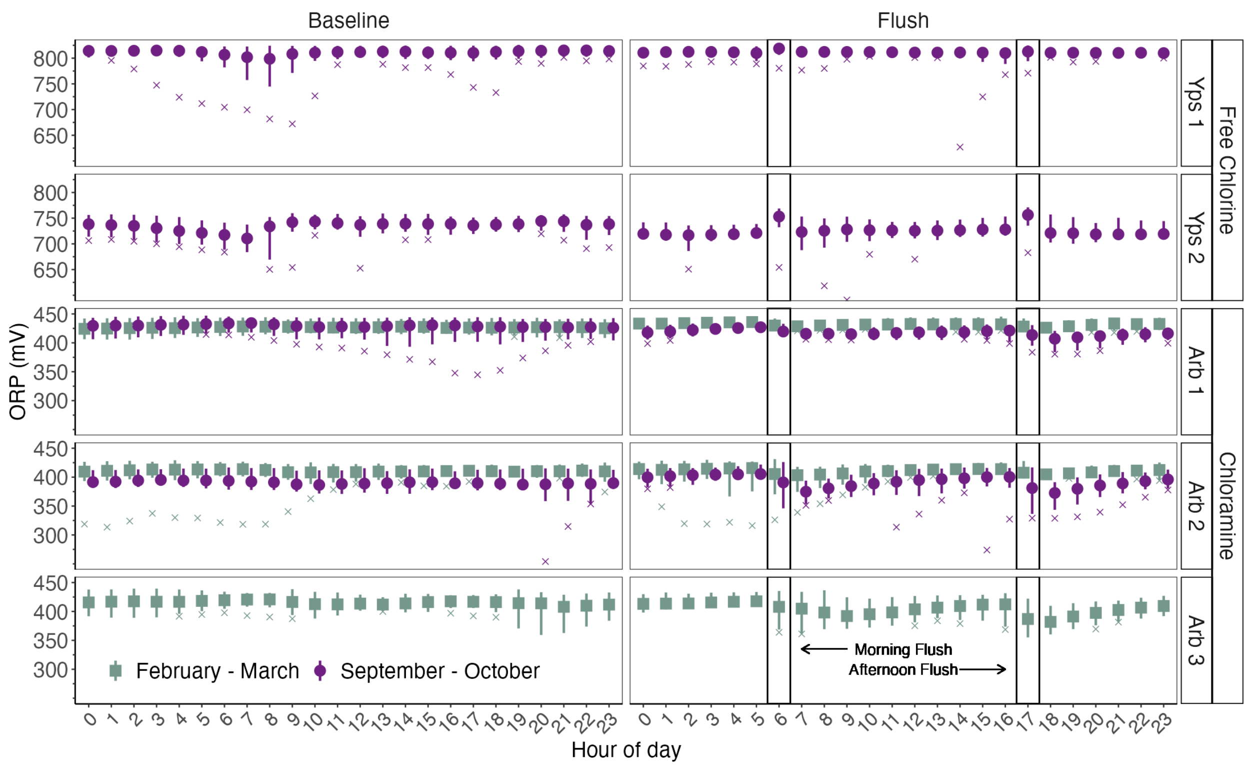

Figure 3.6: Hourly ORP variability during field experiments, comparing the distribution of ORP across baseline and flushing scenarios. Summaries include median (Q_2) as circles and squares, whisker bars extend to $Q_1 - 1.5 \times IQR$ and $Q_3 + 1.5 \times IQR$ or the max/min value of the data set, where IQR is $Q_3 - Q_1$, and minimum values represented as "x" if smaller than the whisker bar range.

3.4.3 Towards autonomous flushing

This study supports several practical guidelines, which could be considered for future "smart" or sensor-mediated flushing. Flushing has the potential to improve disinfectant residual concentrations, but a major barrier to implement flushing involves the need to flush manually. As our study shows, automated flushing could be scheduled during expected times of stagnation (early morning and evening), and the schedule could be adjusted remotely to comply with management goals or observed usage patterns. A flushing device can be constructed with parts that cost under 100 USD, and future work should focus on easy installation methods and training for homeowners and technicians. As with recent advances in home automation, such as smart thermostats, flushing devices could be put into a “vacation mode” while residents are traveling to limit water waste. Flushing devices could be installed in buildings within areas of the distribution system that are of concern, such as high-water age sectors, dead-ends. Since our study locations generally had acceptable disinfectant residual concentrations, future studies should be carried out in locations that experience low disinfectant residuals to further evaluate the potential of automated flushing.

Adding temperature sensors to the flushing system is relatively inexpensive (less than 40 USD additional cost) and could help reduce wasted water from flushing. Thermistors are relatively stable and can last for years without the need for calibration. Since many homes are climate controlled, temperature itself will not be an indicator of stagnation over time. Rather, a change and subsequent stabilization in temperature during flushing could result in the solenoid being shut off earlier than would be the case in a scheduled flush of a fixed duration. In our study, we showed that temperature-mediated flushing could result in 3 – 5 L of water being flushed, as opposed to the 15 L used by the 5-min fixed duration flush. As such, while not adding more complexity to the system in terms of cost and maintenance, temperature-mediated flushing could help conserve water and serve as an indicator that building plumbing has been flushed with water from the main. It should be noted however, that the greatest benefit is expected in non-temperate regions where there is a discernable temperature difference in main to household water.

While adding ORP sensors to the flushing system will provide value in some cases, ORP sensors are relatively expensive (additional 150 USD for parts) and the use of this technology should be closely evaluated for the value it provides. In homes receiving chlorinated water, ORP sensors could serve as indicators that the residual disinfectant has fallen below requirements consistent with distribution system regulations. ORP sensors can also serve as inputs for a residual disinfectant estimation model, as indicated by a linear repones range in the 0 - 0.5 mg/L as Cl_2 free chlorine range in our study. ORP sensors could therefore serve as remote points of water monitoring and allow for water to be flushed only when a setpoint ORP is reached. This could ultimately shift management away from fixed schedule flushing to flushing on an as-needed basis. In this case, temperature sensors could still be used to shut off flushing when the temperature stabilizes. For homes receiving chloraminated water, ORP sensors appear less valuable. They may in some cases serve as an indicator of very low residual disinfectant levels, but the high variability of ORP measurements and the lack of an ORP decrease during chloramine decay make it difficult to justify their value in the context or real-time decisions. Additionally, ORP sensing electrodes are prone to fouling and it is unknown how the probes may operate under different calibration frequencies. Future work should explore their broader value by deploying ORP sensors in distribution systems with known low residual disinfectant levels.

Finally, the sensing technology in this study including the probes, the signal processing circuits, and board carriers were limited to one manufacturer. Despite confirmation in the laboratory, by limiting to one manufacturer questions arise to the reliability and accuracy of the sensors that may be manufacturer-associated. Future research in the application of ORP should take these inherent variabilities in mind and should include measurements with additional sensors. Our study focused on flushing cold water kitchen taps in single-family homes in Michigan, USA. Larger buildings with variable occupancy likely exhibit different water quality dynamics and flushing requirements. Future research should expand to develop and test flushing protocols in different building types based on pre-established baseline dynamics, assess the effect of autonomous flushing on hot water taps, and to measure the effects of automatic flushing on chemical and microbial water quality.

3.5 Conclusions

Toward the goal of supporting the autonomous management of building plumbing water, this study sought to answer questions underpinning sensor-mediated flushing of household water systems. First, we evaluated the dynamic response of ORP sensors to free chlorine and chloramine concentrations in lab experiments under expected building plumbing conditions. Second, we established baseline water quality signals from field deployments using ORP, temperature, and actuator valve nodes, followed by the response of temperature and ORP signals during flushing. The dynamic response of ORP sensors provides information on water stagnation by measuring free chlorine decay and will likely provide the biggest benefit in systems with free chlorine residuals. Results of ORP response to free chlorine may provide viable means by which to detect significant stagnation and support automated flushing. ORP sensors generated high variability in measurements during chloramine decay, but there is potential in detecting very low residual concentrations of chloramine, such as those falling below regulated standards. We showed that flushing generally increases residual concentrations, but since stagnation did not lead to drops below regulated standards in our study, the value of flushing should be evaluated by managers and residents or confined to use cases where residuals are very low. Finally, we provided a set of practical guidelines that could be used in continuing improvement of flushing implementation, for example in the use of temperature sensors to stop flushing when is no longer necessary. Future work should focus on exploring these techniques in multi-story and variable-occupancy buildings, high water age parts of distribution systems with low or without residual. As discussed above, flushing is a recognized and recommended practical solution to water stagnation, ORP and temperature sensors may now be used in real-time to develop better flushing protocols.

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Chapter 4

Intermittent Supply, Domestic Water Storage, and Management Shape Experiences of Drinking Water in Mexico City Neighborhoods

4.1 Abstract

Intermittent water supply affects more than 1 billion people globally. Intermittency is linked to water quality deterioration, and to an estimated 1,560 annual deaths. Additionally intermittency places the burden on households residents to manage domestic water storage. Increased pressures on water resources are expected to increase the prevalence of intermittent water supply. For this reason, this study explores the impacts of intermittency on water quality and water trust at the household level. Using a multi-faceted data set that included ethnographic observations, water sensor data, and drinking water quality measurements collected from field visits to 60 households in Mexico City, we test hypothesized pathways linking intermittency to the management of domestic infrastructure and to the experience of drinking water quality. Statistical tools, including factor analysis and multiple linear regression, were applied to assess several proposed pathways linking intermittency to the experience of water quality. We found that more intermittent systems require more complex domestic storage systems. Systems in households with intermittency included underground storage (cisterns), pumps, and rooftop tanks (tinaco), whereas households with less frequent shutoffs who usually have only a tinaco to manage variability in pressure. Our results suggest that households that are more involved in the day-to-day management of their domestic water infrastructure may report a more positive experience of water quality. Our results also suggest that measured water quality from the public supply is an important determinant

of the experience of water quality at the kitchen tap, regardless of the domestic infrastructure type. These findings are important for developing water trust information campaigns and encouraging utilities and engineers to provide the best water supply and quality service possible.

4.2 Introduction

As global water resources become increasingly strained from anthropogenic and environmental stressors [47], highly urbanized communities around the world will face more water shortages. As a result, an increasing number of water supply systems may be forced to provide drinking water on an intermittent basis. Intermittent water supply systems are already prevalent, presently experienced by an estimated 1 billion people [48,49]. Intermittency is not only a problem of water quantity but also water quality. Intermittency is linked to deteriorating water quality [52,114,115]. As a result, an estimated 1,560 annual deaths are caused by the consumption of tap water contaminated with fecal matter that is linked to intermittency [49].

The effects of intermittency on the integrity of the distribution system, water quality, and illnesses are well documented [51,52,114]. Effects of household management of intermittency, however, are poorly understood due to the complexity of studying the multitude of relationships between physical infrastructure and household dynamics. We anticipate that intermittency has indirect impacts on a number of household-level experiences, including household economics, physical or emotional burdens, chronic health effects, and factors leading to experience, trust, or distrust of publicly supplied water.

Anthropological methods have rarely been used to study intermittency. A review on intermittent water supply found that between 2001 and 2015 only 4 of 126 publications relevant to intermittency had anthropologists in the author list [50]. Typically research at the household level employs surveys to obtain data. Surveys are an efficient tool because they yield large data sets and results with statistical significance. However, the downside of surveys is that pre-determined questions might not fully capture the experience of intermittency. The opposite is true with open-ended ethnographic observations, which gathers data from a much smaller sample size, but which affords the capacity for more fully understanding the phenomena under study. In this study, we use a combination of methods from anthropology, biostatistics, and environmental engineering to explore post-distribution effects of intermittency at the household level. Specifically, we test hypotheses linking intermittency to water quality experience through intermediary factors, such as domestic storage, management, and supplied and tap water quality. Understanding such pathways is critical to develop policy and engineering solutions to the inevitable increase of intermittency. This study combines methods involving both survey and ethnography tools to study intermittency at the household level.

4.2.1 Background

Intermittent water systems are known to compromise drinking water quality, pose risks to public health, and jeopardize system integrity [50]. Pressure cycling produces structural stresses that reduce water mains service life, and promotes soil and groundwater intrusion [52]. Following an off-cycle, "first flush" water is characterized by high turbidity, low disinfectant residual, and high microbial activity [48,51,52]. This compromised water is supplied into building plumbing, domestic storage, and eventually household taps, and this can lead to contaminant exposures. Additional issues such as backflow, high demands, and negative pressure are common characteristics of intermittent systems that pose risks to public health and system integrity [52].

Intermittent systems are broadly managed in binary states, namely on and off. Water availability is generally less than 24 hours per day or less than 7 days per week [115], however intermittency operates on a spectrum, varying in cycle frequency (i.e. daily, semi daily), pressure fluctuations, and unexpected shutoffs [52]. A lack of a systematic definition to classify drinking water intermittency makes it difficult to confidently assess its prevalence, extent of implications, broader public health impacts, and to make comparisons among studies [50]. Recently Galantis et al. proposed a three-level definition to categorize intermittency from least to most disruptive to people's lives – predictable, irregular, and unreliable [50]. Together these definitions highlight the complexity of intermittent systems and studying the impact to system integrity, human health, and the implications to domestic life. Indeed, many of the implications of intermittent systems remain to be explored.

Intermittency is often managed by people in the form of domestic storage [51,53]. Domestic storage, including tinacos (rooftop tanks), and small cisterns (underground storage tank), is a practical solution that counteracts the variability in supply by providing continuous water availability at the tap. Although this storage provides the stability for daily needs, there are some drawbacks. For example, domestic storage is a reinforcer of intermittency [50], meaning that cities and utilities will continue to provide water intermittently to neighborhoods equipped with domestic storage, especially in poorer areas, rather than providing long-term solutions and converting to continuous supply. Furthermore, water quality tends to deteriorate in storage [53,72]. The latter specifically leads to higher risks of illness associated with fecal contamination in storage containers without proper lids, improper handling, and poor maintenance [51,54,55]. Domestic storage is both a need and a liability. It is thus important to minimize the impact of domestic storage on water quality, public health, and socioeconomics while maximizing the stability of water availability with intermittent supply.

Unlike in continuously supplied water systems, the need to work around the unique challenges of intermittent supplies can lead to economic, physical, or emotional burdens to household members. For example, residents often purchase trucked water to supplement public supply, carry buckets of water between the water source and where it is needed, and clean storage tanks [50,52]. Households in intermittent systems ration water use by prioritizing needs and reusing certain water streams. Understanding the requirements of domestic water management placed in households in relation to the spectrum of intermittency may help engineers and policy makers understand the mediated effects of intermittency on “less immediate” public health and socioeconomic outcomes.

How individuals experience their drinking water quality can influence their decision to find alternative drinking water sources. The processes underlying experience of water quality are not fully understood as there are multiple complex interactions among factors including tap water quality, organoleptic experience, prior experiences, information sources, etc. [116,117]. A study comparing a community with continuous water supply to another community with intermittent supply found that residents in the intermittent supply community had a preference for retailed bottled water rather than tap water [54]. This correlation suggests there might be a determinant link between intermittency and experiences of water quality that may influence drinking water source decision making. Previous studies exploring determinants of bottled water preference have found that taste, risk aversion, and income influence decision making [118], but these complex interactions in intermittent systems have not been studied, especially in the context of domestic infrastructure and management as potential mediating factors.

Studying the relationships between factors related to the experience of water quality is difficult because the variables cannot be measured directly (e.g., domestic infrastructure management, water quality experience, etc.). In lieu of direct measurements, latent variables or constructs are made by combining measurable variables. In recent water quality experience studies, latent variables have been used to model multiple linear regression pathways using structural equation modeling [119–121]. These studies found that perceived water quality is largely influenced by flavor, whereas perceived risk and contextual indicators have a weak connection. However, risk perception seems to be a result of external information, past health problems, and water color [119]. These statistical methods have helped pull out valuable insights into the pathways affecting water quality experience. To date, however, these methods have not been applied to study the relationships between intermittency and domestic storage at the household level.

In this study we use exploratory factor analysis to build latent variables relevant to the experience of water quality, intermittency, and infrastructure management and then use multiple linear regression to test hypothesized pathways. Specifically, we hypothesize that intermittency affects water quality experience through intermediary factors, such as domestic storage and management. Additionally, we hypothesize that higher intermittency is met by more variable domestic storage layouts and management, indirectly leading to worse deterioration in water quality and more impact on water quality experience. Through testing this hypothesis, this work will answer the following questions: How can we measure intermittency? How are households adapting to the spectrum of intermittency? What effect is domestic storage having on water quality? And how are these direct factors of intermittency affecting water quality experience? As intermittent systems continue to increase in prevalence, the results of this study provide engineers, policy makers, and utilities information needed to counteract broader public health and socioeconomic issues associated with the consumption of tap water.

4.3 Methods

4.3.1 Constructing hypothesized pathways between variables

The hypothesized direct and indirect pathways between variables are shown in Figure 4.1. In short, we hypothesized that people develop negative experiences of water quality the more they need to manage it. This model allows us to quantify the different pathways through the complex interactions that derive from intermittency. The pathways were informed by field work observations and insights that emerged from the ethnographic research. One of the novelties of this work looks into experience changes, specifically whether or not there is a difference in experience from freshly supplied water to the water coming out of the kitchen tap. We therefore created two variables, namely *Experience of Public Supply Water Quality* and *Experience of Kitchen Tap Water Quality*. The former is freshly supplied from the distribution system while the latter has flowed through domestic storage. An example of how the relationships can be understood is as follows: *Experience of Kitchen Tap Water Quality* is negatively affected by the *domestic infrastructure, intermittency,* and *infrastructure management*. A detailed description and justification for all relationships are provided in Table 4.1.

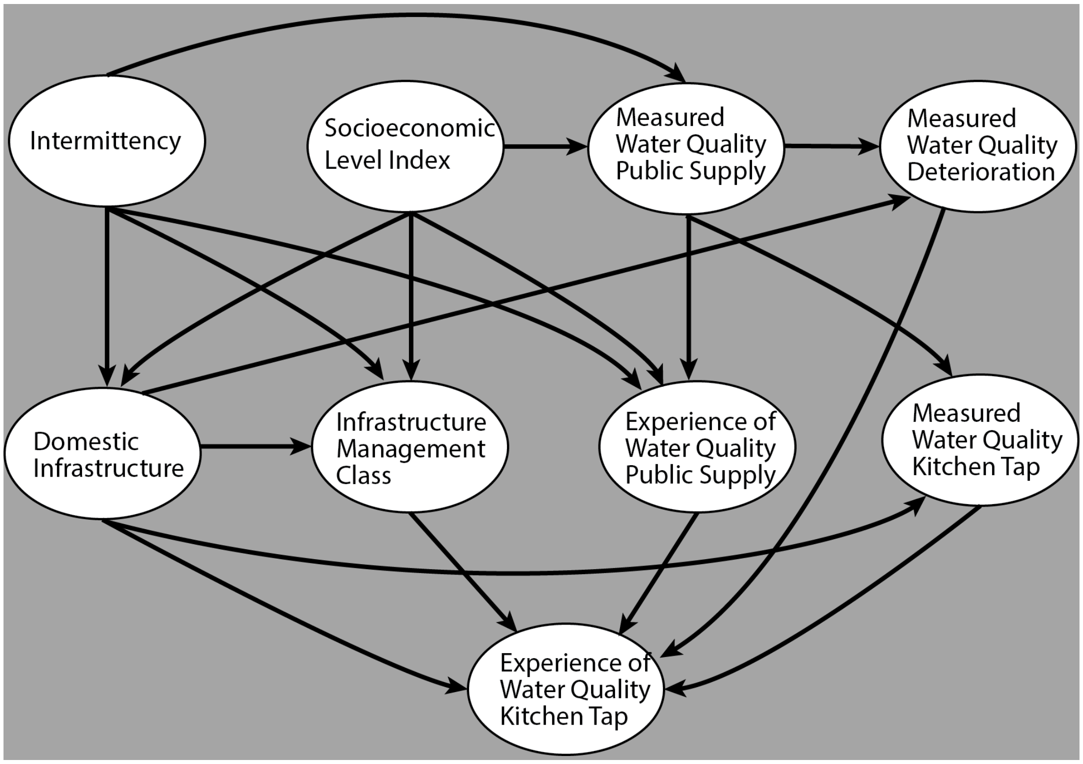


Figure 4.1: Hypothesized pathways linking intermittency to domestic storage, management, water quality deterioration, and experience.

Table 4.1: Hypothesized pathways connecting water supply to water quality experience

Determinant Variable	***Response Variable***	***Justification***
Intermittency	Domestic Infrastructure	Intermittency affects the way the system is built. i.e. need for cisterns, pumps, tinacos, etc. The need for storage comes from the dynamics in water supply. Dynamics of water supply are called "Intermittency" and include characteristics such as daily, weekly, reliable, and low pressure.
	Infrastructure Management Class	The intermittency levels affect how much effort/work residents need to put into the system to make it work. We measured domestic infrastructure management in terms of various tasks and need for tinaco or cistern specifically.
	Experience of Public Supply Water Quality	Intermittency affects the experience/experience of outdoor water quality.
	Measured Water Quality Public Supply	Intermittency is known to affect outdoor water quality during periods of supply, especially the first flush. More intermittency may be measured in lower water quality
Domestic Infrastructure	Infrastructure Management Class	The domestic infrastructure layout affects how much management needs to happen. A more complicated layout may lead to more management.
	Measured Water Quality at Kitchen Tap	The domestic water infrastructure layout may be affecting water quality during storage and flow.
	Experience of Kitchen Tap Water Quality	A more complicated layout in domestic infrastructure may influence residents' experiences of water quality at the kitchen tap after it passed through storage.
	Water Quality Deterioration	Various flow paths available for water to flow, higher water age, affect water quality
Socioeconomic Level	Experience of Public Supply Water Quality	Neighborhood socioeconomics and communication may influence the experience of water quality
	Domestic Infrastructure	More purchasing power leads to more storage and pipe connections for whenever it might be needed
	Infrastructure Management Class	Collective neighborhood economics might be reflected in the need to manage domestic infrastructure
	Measured Water Quality Public Supply	Neighborhood economics might be reflected in the water quality supplied
Infrastructure Management Class	Experience of Kitchen Tap Water Quality	Storage and interaction with storage affects the experience of water quality
	Measured Water Quality Kitchen Tap	Storage and different management tasks affect water quality
Measured Water Quality Public Supply	Water Quality Deterioration	Water quality parameters may deteriorate more than others. Outdoor water quality provides a baseline measurement for each parameter. For example, if free chlorine is present it will deteriorate, but if absent it won't be captured as deterioration.
	Measured Water Quality Kitchen Tap	The indoor water quality can only be as good as the outdoors water quality
	Experience of Public Supply Water Quality	Participants sensory experiences may be related to the measured outcomes of outdoor water quality.
Measured Water Quality Kitchen Tap	Experience of Kitchen Tap Water Quality	Participants sensory experiences may be related to the measured outcomes of indoor water quality

4.3.2 Participants for study

To test the hypotheses we used data collected from January 2019 to March 2020. We recruited participants from 60 households in 46 neighborhoods across 12 out of 16 *Alcaldías* of Mexico City (Figure SI-C-1). 17 of the households were in neighborhoods posted in the 2019 intermittency city memo,[122] 41 of the households were in neighborhoods with continuous water supply, and two were not connected to the grid so they were supplied by trucked water. The selection, recruitment, and data collection of the 60 households was through the multidisciplinary research project "Neighborhood Environments as Socio-Techno-bio systems in Mexico City (NESTSMX)" [123]. Recruited participants were selected from a longitudinal cohort "Early-life exposures in Mexico to environmental toxins" (ELEMENT) [74], that consisted of hundreds of mother-child pairs recruited at birth in social security health clinics of Mexico City. The NESTSMX participant selection criteria were designed to include households in neighborhoods across the city with known differences in water quality and supply.

From January 2019 to March 2020, each of the 60 households was visited in person at least once and up to three times. An additional phone interview was conducted with members of each of the 60 households during the stay-at-home orders and public health Covid-19 crisis in 2020. All data used for analysis in this study originated from information measured, observed, and recorded by the researchers during the visits and phone interviews.

4.3.3 Ethnographic data

Interviews with open-ended questions were designed to give participants opportunities to provide more information and elaboration in their answers while maintaining boundaries and consistency of information across houses. Interviews were recorded and transcribed for each visit. Field notes with detailed descriptions of the conversations, experience, and observations were written by the field team members. Altogether, audio recordings, transcriptions, and field notes comprise the bulk of the ethnographic data. Post-collection analysis of the qualitative data was coded by two researchers that participated in the majority of the visits and were both fluent in English and Spanish. The work was supervised for consistency by a third researcher familiar with the codebook and research objectives of the project.

A codebook (Table SI-C-1) was developed to extract specific information from each household relevant to the experience of water quality and to answer specific questions: 1) What is the experience of water quality coming from the distribution main? and 2) What is the experience of water quality during and after storage? Examples of coded excerpts are provided in Table SI-C-2.

Reports including all instances where the codes were tagged were created for each household. The experience of public supply and kitchen tap water quality was extracted systematically from the reports by assessing mentions of common water quality aesthetics (Table SI-C-3). Each mention was tagged as a "positive" or "negative" connotation as interpreted by the coding researcher. If there was no mention of water quality aesthetics the site was tagged as no mention. Example quotes from the reports (Table SI-C-4) show how some participants described water quality.

4.3.4 Water Tours

During the first visit, the participants walked the researchers through the domestic water storage layout of their household from the service connection point to the kitchen tap. Flow schematics were sketched during the tours including the major components of the water system – all storage units (i.e. cisterns, tinacos, drums), pumps, pipe layouts, bathrooms, and other taps (Table SI-C-5). Points of human input and information needed for decision-making were recorded in the flow diagrams and described in more detail in the field notes. We define human input as physical management tasks required to maintain an operational system with water available at the tap at all times. These tasks could include physical work such as moving filled buckets within the premises or lifting concrete lids to underground cisterns (Table SI-C-5). The compilation of flow schematics, management tasks, and information-driven decisions were used as variables to evaluate the dependency of a system on human input. The combined variables explain how much participants are interacting with their domestic water systems to counteract intermittent water supply. All flow schematics were categorized by specific paths water could take from the public supply to the kitchen tap (Table SI-C-5), a list of tasks is summarized (Table SI-C-6).

4.3.5 Pressure measurements and assessment

Continuous pressure values at the service connection point were measured in 19 households using an on-line pressure transducer. Transducers were deployed for a duration of two weeks to nine months and took measurements every 5 minutes. Details of the deployments and equipment are described in Martinez et al. 2022 [46] and Chapter 2 of this dissertation.

Qualitative assessments of pressure were made for the 60 households and categorized as "adequate" or "inadequate" based on information given by the residents. An "adequate" system was defined as a system with water from the public supply that is continuously available at high pressure and with no dips in pressure that require residents to retrofit the domestic water infrastructure to make up for the low pressure (i.e. with cisterns and pumps). An "inadequate" system was defined as a system whose residents complained about dips and fluctuations in pressure and required upgrades to make water reach the tinaco and indoor taps. Systems that experienced only short dips in pressure due to local peak demand were not considered inadequate.

The numerical pressure values measured in the 19 households were compared with the qualitative data from the household members. Combined, these pressure data provide context into how household members experience pressure dips and fluctuations and how a household may retrofit a system if pressure is consistently low (Figures SI-C-2 – 21).

4.3.6 Water Quality Grab Samples

One liter grab samples were collected during each visit from taps, storage tanks, and bottled water in autoclaved Nalgene bottles. Measurements of water quality were conducted in situ using a handheld probe (Hanna) for pH and conductivity (μS/cm), a field colorimeter (Palintest) for free and total chlorine, total hardness, sulphate, phosphate, chloride, alkalinity, and a turbidity meter for turbidity. After samples were collected and analyzed in-situ, the remaining sample was treated with sodium thiosulphate to quench residual disinfectant and then transported in a cooler to a sterile environment for total and fecal coliform analyses. Samples were filtered through a 0.45 mm pore membrane filter and placed in Membrane Lauryl Sulphate Broth (MLSB), a culture medium selective for coliform growth, then incubated for 24 hours at 35 ˚C for total coliforms and 44 ˚C for fecal coliforms. Samples were processed as soon as possible after each visit, usually within 4-12 hours after collection.

4.3.7 Dimensionality Reduction with Factor Analysis and Latent Class Analysis

Factor analysis was applied to reduce the number of measured and observed variables associated with each household into conceptually cohesive latent variables.

<u>Latent Constructs and Correlation</u>

A latent construct is a cohesive collection of measured or observed variables that seek to describe a phenomenon that cannot be directly measured or observed. It is assumed that the latent construct is responsible for the generation of the observed variables [124]. We used correlation analysis to ensure that our proposed latent constructs were cohesive. High correlations indicate that the variables belong to the same construct, whereas poorly correlated variables (< 0.4) are not likely part of the same construct and were thus removed. For constructs built with ordinal variables we used Polychoric correlation from the R library package *Polycor*. Constructs with continuous variables (e.g. water quality) were treated with Spearman correlation rather than Pearson correlation due to the data containing outliers and exhibiting non-normal distribution.

<u>Exploratory Factor Analysis and Latent Class Analysis</u>

A factor analysis was derived for each latent construct with the Psych library in R and the correlation matrices built for the latent constructs as inputs (Table SI-C-7). Exploratory factor analysis assigns loadings to each variable of the construct based on their correlation. The Ordinary Least Squares algorithm was used to find the minimum residual solution. This approach produces similar solutions to maximum likelihood and is recommended for unmodeled small factors [125,126]. The number of factors expected was determined via "scree" plots of the successive eigenvalues but was limited to two factors where more factors were suggested. The loadings were used as coefficients to measured variables to calculate factor scores.

Latent class analysis was used to classify households based on the management tasks (Table SI-C-6). Bayesian information criterion (BIC) was used to select the appropriate number of classes with the information given. BIC penalizes models that increase maximum likelihood with additional parameters used. Latent class analysis was done in R with the package *poLCA*.

4.3.8 Hypothesis testing with Linear Regression

Linear regressions were used to evaluate the strength of the hypothesized relationships using least-squares to find the best fitting line between factors. Coefficients of determination (R^2), p-values, and coefficients' signs were used to assess the hypothesized relationships. Regressions were built according to the hypothesized paths in Figure 4.1 and Table 4.1. Statistical significance was used to accept ($p < 0.05$) and reject ($p > 0.05$) each hypothesis (Table SI-C-8).

4.4 Results

4.4.1 Summary Statistics

Domestic Storage

We found that 58 of the 60 houses studied had domestic storage. This represented all 46 neighborhoods included in the study. Of the houses with storage, 11 households were in mid- to high-rise apartment buildings where storage is expected due to the need to pump water to reach the top floors, and 2 households were off-grid making storage also needed. This high number of households with domestic storage was unexpected considering only 17 of the 46 neighborhoods appeared in the city's intermittency memo [122]. This was evidence that even houses with continuous supply exhibited some level of domestic storage. The households' median storage capacity per person in single-family buildings and family compounds was 368 L/person, with two off-grid households having as much as 28,000 and 14,000 L/person capacity.

Pressure

Pressure was a recurring theme during interviews, with 25 households mentioning low pressure as a reason to retrofit the household infrastructure to adequately manage the service. The on-line continuous pressure measurements at 19 households in 17 neighborhoods resulted in highly variable profiles across neighborhoods. For the purpose of this discussion, we classified a neighborhood as having adequate or "good" pressure if the average home had an operational threshold of 10.7 psi (7.5 m of head) based on the least amount of pressure to reach tinacos in an average-size construction. In neighborhoods with pressure that was considered good ($n = 17$), the average was 24.2 psi, whereas neighborhoods with pressure that was considered bad ($n = 2$) had an average pressure of 6.5 psi. For perspective, many countries around the world have a minimum recommended pressure of 20 psi (14 m), but it is normal to find operating pressures as high as 50-60 psi to ensure enough pressure for both domestic supply and fire flows [127]. In most households with average pressures that resulted in a good classification, fluctuations between peak and off-peak demand were as drastic as 30 psi. Consequently houses in neighborhoods with continuous water supply often experience intermittency a few hours per day. In the neighborhoods with bad average pressure, pressure was low throughout the day forcing the households to depend on underground storage tanks and pumps to lift water to the rooftop tank.

Domestic Infrastructure Management

A closer inspection of all domestic water system schematics revealed there are common flow patterns among all systems. 43 of the 58 households with storage have a single flow path (i.e. all water flows through the same storage components before reaching the tap), whereas 17 of the systems included two or more flow paths (Table SI-C-6). This built-in system redundancy allows households to operate under varying pressure conditions and with planned and unexpected shutoffs from the distribution grid. We hypothesized this system redundancy makes them more complex, which results in more operational interaction and compromised water quality in comparison to the less complex systems.

Measured Water Quality

Samples from distribution system sampling taps show there is heterogeneity in the supplied water quality across the city. Of the 60 locations, 12 had average free chlorine concentrations below 0.05 mg/L as Cl_2, 4 had average concentrations between 0.05 and 0.2 mg/L as Cl_2, and the remainder had average concentrations above 0.2 mg/L as Cl_2, with an average of 0.85 mg/L free chlorine as Cl_2 (sd = 0.37). The conductivity distribution ranged from 49 to 2,317 uS/cm with three peaks, namely 255 uS/cm (n=47, sd = 81), 716 uS/cm (n = 4, sd=77), and 1,375 uS/cm (n = 7, sd = 506). The spread and multimodal distribution of conductivity suggest there is heterogeneity in water quality across the city, perhaps spatially related to different water sources. Total coliforms were detected in 14 locations at low levels (below 10 cfu/100 ml on average), two locations had high counts (greater than 10 cfu/100 ml on average), and 39 households never had a positive sample. Eight locations had low fecal coliform levels (below 10 cfu/100 ml), one location had high fecal coliform levels (greater than 10 cfu/100 ml), and 46 locations did not have a positive fecal coliform result. For reference, the local drinking water quality regulations require an absence of total coliforms and fecal coliforms [128]. Although total and fecal coliforms are indicator organisms and therefore do not themselves cause a microbiological risk, their presence suggests environmental contamination. Combined with the chlorine and conductivity results, the fecal coliform results highlight the heterogeneity of water quality throughout the neighborhoods. Contextual drinking water sources, distribution, and quality of Mexico City is available in Appendix C.

Samples collected from the kitchen tap had flowed through the domestic storage and exhibited water quality differences from the distribution system. At the tap, 23 households had average chlorine concentrations below 0.05 mg/L as Cl_2, ten households had average chlorine concentrations between 0.05 and 0.2 mg/L as Cl_2, and 24 had average concentrations above 0.2 mg/L as Cl_2, with an average of 0.76 mg/L as Cl_2. Total coliforms were detected in kitchen tap samples from six locations with low levels (below 10 cfu/100 ml in average), three locations had high levels (between 10 and 50 cfu/100 ml average), ten locations had very high levels (> 50 cfu/100 ml), and 36 households did not have a sample positive for total coliforms. In terms of fecal coliforms in tap waters, eight locations had low levels (< 10 cfu/100 ml), and 4 had high levels (>

10 cfu/100 ml), and there was absence of fecal coliforms in 43 locations. Overall, domestic storage corresponded to changes in water quality as seen in the reduction of free chlorine and increase in total and fecal coliforms. Changes in water quality are summarized in Table 4.2.

Table 4.2: Number of locations within ranges of drinking water quality

Source	*Free Chlorine*			*Total Coliforms*			*Fecal Coliforms*		
	Below 0.05	Below 0.2	Above 0.2	Not Detected	Below 10 cfu/100ml	Above 10 cfu/100 ml	Not Detected	Below 10 cfu/100 ml	Above 10 cfu/100ml
Public Supply	12	4	44	39	14	2	46	8	1
Kitchen Tap	23	10	24	36	6	13	43	8	4
Bad Change	11	6	12	3	-8	11	3	0	3

Experience of drinking water and preferences

Of the four parameters we explored in public supply water, color was mentioned by 25 households, chlorine was mentioned in 13, taste and odor in 12, and solids were mentioned in 26 (Table 4.3). This suggests that the public supply influences the overall experience, even though this water has not yet traveled through the domestic storage. From these aggregated mentions across all households, 41 of 60 households had at least one negative comment about public supply water quality. After water flowed through domestic storage, one household mentioned chlorine, two mentioned color, five mentioned the taste and odor, and four mentioned solids (Table 4.3). Of the 60 households, nine mentioned a negative aspect of water quality associated with the domestic storage. This suggests that a smaller number of participants are relating domestic storage to the deterioration of water quality.

Table 4.3: Aggregated mentions of water quality parameters during structured interviews (n=60)

Source	*Chlorine*	*Color*	*Taste/Odor*	*Solids*
Public Supply	13	25	12	26
Kitchen Tap	1	2	5	4

4.4.2 Factor Analysis

All factor analyses, including the loaded parameters and their respective loadings (Table SI-7), resulted from a reduction in dimensionality and the creation of latent variables; these latent variables were subsequently used to test hypothesized pathways.

Measured Water Quality

Seven outdoor and indoor water quality parameters were loaded into two factors with extracted cumulative variances of 51.6% and 53.5% from the parameters. The individual variable loadings into each factor ranged from 0.2 – 1, with pH (0.2) and turbidity (0.3) being the weakest loadings, and free chlorine (1.0), total chlorine (1.0), total coliforms (0.5), fecal coliforms (0.5), and conductivity (0.5) being the stronger ones. The stronger the loadings the more variability within the variable, thus more information can be extracted from it. As described above, free chlorine was highly variable across the neighborhoods, followed by conductivity, and then total and fecal coliforms. Water quality deterioration was calculated by subtracting outdoor from indoor water quality parameters. The two factors resulting from the new variable extracted 48.1% variance from the variables.

Intermittency

To approximate a measurement of intermittency, five variables of water supply (pressure, supply type and frequency, availability confidence, and unexpected shutoffs) were loaded to a single factor. One of the five, *Unexpected Shutoffs*, did not meet the standardized loading (< 0.3) and was therefore removed. The remaining 4 aspects contribute a cumulative variance of 71.5%.

Experience of Water Quality

Four assessments of water quality experience (chlorine, taste and odor, color, and solids) were loaded into a single factor, and information was further split by field visits (V1) and phone interview (V4), for a total of four factors. Factors for *experience of public supply water quality* yielded 50% and 42.4% of the explained variances for V1 and V4 respectively. The individual loadings ranged from 0.1 – 1. The loadings of each variable based on the field visits were different than those from the phone interviews. For example, during the field visits, negative mentions of chlorine had a stronger loading (0.5) than during the phone interviews (0.3). Similarly, loadings of negative mentions of solids during the field visits (0.1) had a smaller effect than the mentions gathered during the phone interview (0.5). This means that the information collected during the visits is different, either due to temporal changes in experienced water quality or due to the less structured nature of collecting data in person through semi-structured conversations.

The factor explaining the *experience of water quality at the kitchen tap* obtained during the field visits was dropped from further analysis due to a low response rate. We believe this is because the conversations during the field visits mostly revolved around the supplied water quality, while in the phone interview we purposedly made distinctions with each question regarding their experience of water quality. The remaining factor originating from phone interviews for kitchen tap water quality had an explained variance of 69.3%, with individual variable loadings ranging from 0.7 (chlorine) to 1.0 (solids).

Domestic Infrastructure Layout and Management

A two-class latent class analysis on management tasks and storage containers resulted in the lowest Bayesian information criterion (BIC). The distinction between the two classes is related to the presence and absence of cisterns and pumps, with 23 households belonging to the class in which cisterns are needed. Of these, 19 manually turn on the pump at frequencies between twice a day to biweekly, and four have installed devices to automate the operation of the pump when needed. The other 37 households operate their systems with a combination of tinacos and miscellaneous containers. Many of the households perform tasks like filling up disconnected containers and disconnecting hoses. We did not observe a direct relationship between the performance of these tasks and whether or not the household had cisterns.

The domestic infrastructure layout, the number of components of the system, and the storage per person were the variables used to approximate the latent construct called Domestic Infrastructure. The factor loadings ranged from 0.3 (storage per person) to 1 (flow schematic). The flow schematic showed more variability and better explained the complexity of the construct than the storage capacity. Together these variables explain 45% of the variance in the construct.

4.4.3 Linear Regressions and Hypothesis testing

Multivariate linear regressions were used to evaluate each hypothesized pathway by regressing latent constructs onto combinations of other latent constructs (Figure 4.1, Table 4.1). For each regression, the significant determinant variables ($p < 0.05$) are plotted in Figure 4.2. Adjusted R^2 are reported at the nodes as the strength of the combined determinants in explaining the variance of the node. Figure 4.2 includes the significant pathways that may link intermittency to the experience of water quality.

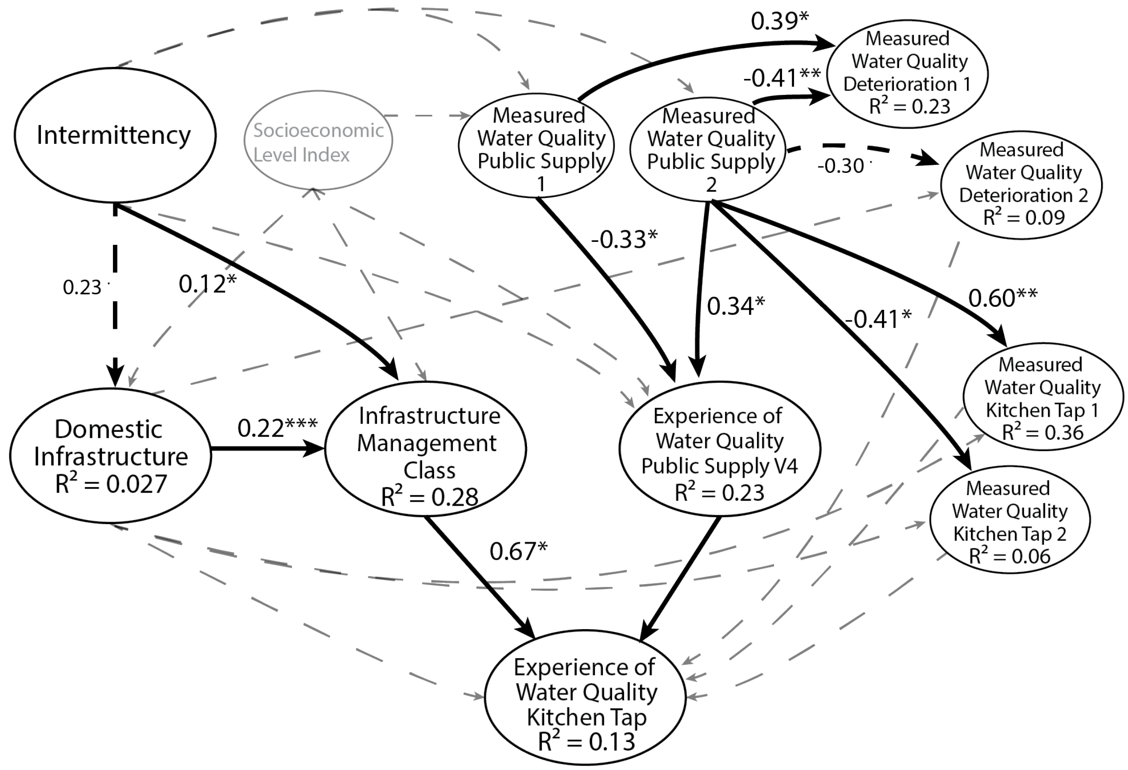


Figure 4.2: Statistically significant pathways linking intermittency to the experience of water quality. Solid lines represent significant pathways, bold dashed lines represent non-significant with $p < 0.1$, and grey dashed lines represent non-significant pathways. Numerical values next to significant pathways are the estimate of the regression with its level of significance (. $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$). Adjusted R^2 includes all possible determinants.

Our latent construct for *Intermittency* has a positive effect on *Domestic Infrastructure* ($p < 0.1$). This means that households experiencing longer periods without water supply, higher fluctuations in pressure, or low pressure altogether, result in domestic systems with more components, flow paths, and storage capacity. *Intermittency* also resulted in a positive effect on *Infrastructure Management* ($p < 0.05$). This means that more intermittent systems influence how a household might be classified based on the components and tasks needed to make the system operational. Furthermore, more intermittent supply may consistently result in a set of tasks strictly associated with cisterns required at the household. These results align with previous studies involving how a household might react to intermittency. For example, households in four intermittent systems in Panama exhibited larger storage capacity in households with more intermittency [72]. Combined, our results and the results of previous studies suggest that more intermittent systems need more domestic infrastructure and more management at the household.

Measured water quality from the public supply was independent from other factors, including *socioeconomic status* and *intermittency*. This suggests that even though the quality of distributed water quality varied across the city the data did not suggest that the neighborhoods experiencing the highest intermittency were also experiencing lower water quality. Measuring the impacts of intermittency on water quality is difficult because most of the impacts occur during the first flush [51]. After water supply is fully restored (i.e. following a shutoff period) water quality is also restored, and domestic storage serves as a buffering agent, meaning that any impacts to water quality associated with the first flush are diluted (or settled in the case of particulates) in storage.

<u>Impact of domestic storage on water quality</u>

The impact of domestic storage on indoor water quality was not statistically significant via regression, however our statistical summary discussed above does explain there were measured changes in water quality. In the regression analysis the strongest variable in explaining the variability in deterioration of water quality was the measured water quality form the public supply. This could mean that regardless of the variability in capacity and layout seen in domestic storage, the water quality in the distribution system is what drives the measured water quality at the kitchen tap. Although the summary statistics of grab samples show there is measurable change in water quality from the public supply to the kitchen tap, the factor analysis and regression analysis suggests there is not a significant change that is explained by domestic storage or management. This suggests that quality is not impacted by people, quality at the kitchen tap is pre-determined by the quality supplied. This analysis is based on a small sample size and may not be conclusive to all domestic storage systems, in particular because this analysis is based on the impact of tinacos and cisterns, which could be considered as safer and more formal than the more improvised solutions such as buckets and drums.

<u>Experience of water quality</u>

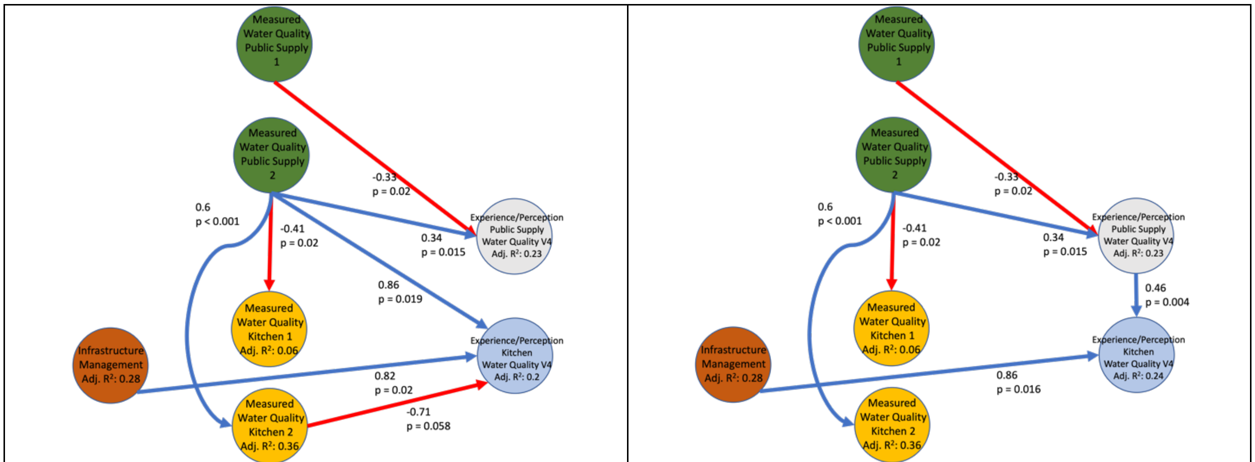
Our results suggest that the experience of public supply water quality is influenced by the actual measured water quality supplied. The first factor of public supply water quality is comprised of fecal coliforms and inversely affects the experience of water quality. In other words, the result suggests that more fecal coliforms are correlated with negative experiences of public supply water quality. The second factor of public supply water quality is comprised mostly of chlorine residual and in part by total coliforms and conductivity. The second factor positively affects the experience of water quality from the public supply, meaning that more chlorine corresponds to a positive experience of supplied water quality. The effect of the two water quality factors interacting together means that even though residents are not measuring these parameters, they are sensing aspects of the water quality associated with these parameters and that this is driving their experience.

We expected chlorine levels to correspond with negative experiences of water quality based on field observations and previous literature [129]. Some participants explicitly mentioned not liking the chlorine in the water because of the taste, odor, and chemical nature of it. This analysis suggests that the presence of chlorine is partially influencing the positive experience. This may not be because a positive experience is explicitly mentioned by people, but rather because adequate chlorine treatment and residual contributes to removing odors and colors, and in preventing microbial growth. In effect, chlorine is treating other organoleptic parameters that shape the experience of water quality, and this highlights the importance of incorporating multiple parameters into latent variables.

A modification to the linear regression was made to test different pathways between measured water quality at the public supply to the experience of water quality in the kitchen tap (Figure 4.3). The results show that there may be multiple pathways, Figure 4.3-A linking measured public supply water quality directly to- and through the measured water quality at the kitchen tap to the experience of water quality at the kitchen tap. While Figure 4.3-B makes the link through the experience of public supply water quality as discussed above and shown in Figure 4.2.

Intermittency affecting the experience of water quality of kitchen tap water

Our hypothesis linking *intermittency* to *experience of kitchen tap water quality* through *infrastructure management* as a mediator was not rejected. We originally anticipated that household members would associate cisterns with poorer water quality and experience due to comments made during field visits about the higher vulnerability of cisterns to contamination than tinacos. However, the effect of interaction was counterintuitive to what was expected. The pathway suggests that more intermittent systems lead to more domestic infrastructure and domestic management, especially the need for cisterns. The pathway also suggested that the houses that depend on a cistern are more likely to have a positive experience of water quality at the kitchen tap, as opposed to houses without the need for a cistern. The effects of this pathway suggest that households with less intermittency (i.e. more continuous supply) are not required to manage water in their household and are more likely to have a negative experience of water quality at the tap. This may be because of differences in supplied water quality by neighborhood, or because people associate domestic storage as an extension of the public supply system and is part of an "invisible" infrastructure, meaning there is no sense of water quality or supply dynamics.



Perc_wq_in_V4 ~ Domestic_infrastructure + LatClass2 + WQ_in_1 + WQ_in_2 + WQ_det_2 + WQ_det_1 + WQ_out_2 + WQ_out_1 + Perc_wq_out_V4 + Perc_wq_out_V1	Perc_wq_in_V4 ~ Domestic_infrastructure + LatClass2 + WQ_in_2 + WQ_in_1 + Perc_wq_out_V4 + Perc_wq_out_V1

Figure 4.3: Different significant paths influencing the experience of kitchen water quality. Different combinations of predictors result in different paths.

4.5 Discussion

Intermittency affects experience of water quality

Within the limitations of the data set and hypothesis testing, these results suggest that a link exists between intermittency and the experience of water quality at the tap through mediating variables. More intermittent systems require more complex domestic infrastructure systems and are determinants of the management class (cisterns vs. tinacos; Figure 4.2). Our hypothesis stated that households interacting more with their systems were more likely to develop negative experiences of water quality at the tap, as it turns out the opposite is true according to our hypothesis testing. Households with cisterns end up developing a better experience of water quality indoors than households that don't. This is counterintuitive based on field-work observations. A possible reason for the outcome is that more interaction with the domestic water infrastructure results in more familiarity with the water and its quality, in this cases people may be extracting information that helps them make decisions, for example when to clean the systems or purchase point-of-use filtering devices. However, these actions are not reflected in our summary data regarding the water source from which people are drinking. When split into the two classes, 28% of households with cisterns are drinking water from the tap and 72% are drinking bottled water, whereas 30% of households without cisterns are drinking water from the tap and 70% are drinking bottled water.

Another possible reason for more management related to a positive experience of water quality is not related to management tasks necessarily (even though that is how its coded). Again, the difference between management is the having a cistern or not, which provides storage and buffering capacity to more intermittent supply. Storage as an equalizer might in this case be related to the outcome of positive experience of water quality at the tap. There may be a sense of ownership which gives people control, autonomy, and a sense of confidence over their experience of water quality. In the same sense, households with only a tinaco or households where superintendents manage the system, do not have a sense of autonomy, control, or access to information regarding the state of the water, negatively affecting their experience of water quality.

Reliable and comprehensive information campaigns regarding water quality and domestic management might be useful tools to address the uncertainty faced by households, regardless of intermittency. Households need information to make decisions about the water they purchase, consume, or treat, and these results might be exposing the effects of the *access to information*. If we think about intermittency as *access to information*, we can extrapolate that households managing intermittency are enabled to search for information on how to better manage, treat, or purchase water. Something that households with continuous systems are not, therefore creating a negative experience of water quality.

Measured public supply water quality affected the experience of water quality

Our data and analysis suggest that the supplied water quality influences water quality experience at the kitchen tap. Utilities must supply water quality that meets the safety regulations for people to have a positive experience of water quality, regardless of their domestic management and storage.

Limitations

The factor analysis and multivariate linear regression used for hypothesis testing can go as far as confirming or rejecting pathways of influence. The significance of the pathways should not be interpreted as direct or indirect causation of an outcome nor as a prediction tool. The R^2 is used as a metric that quantifies how much of the variance in the outcome variable is explained by the explanatory variables, typically for prediction a high R^2 is desired ($R^2 > 0.9$), but as seen in figure 3 the R^2 of various significant paths are rather small. Smaller R^2 means that the combined effect of explanatory variables does not accurately predict the outcome, rather it highlights the complexity of these interactions by showing there are unaccounted and unmeasured factors that are likely interacting in these same pathways. The significance (p-value) of the links shows that a relationship exists between the two variables. Other studies using multivariate linear regression and structural equation modeling have reported R^2 as high as 0.5 for some relationships, and as low as 0.08 for others [121].

The statistical significance in this work is further compromised by the relatively small n ($n = 60$) of the study. For this reason, some of the rejected pathways in this work should not necessarily be excluded from future works. For example, our pathways have shown that measured public supply water quality is independent of socioeconomic level, however, because of the nature of our participant's pool the socioeconomic level of the neighborhoods is mostly uniform, and the incorporation of a broader participant pool may uncover different results.

The power of factor analysis helped us create latent constructs that cannot be measured or observed. Within this framework, factor analysis also helped us understand which measured variables did not belong in the same construct. This is important in the scope of study design because factor analysis helps us understand which variables do not need to be collected. Although, a factor analysis for latent constructs do not tell you that other potential variables do not belong in the same construct. In summary, factor analysis can tell us what not to measure, but it doesn't tell us what to measure.

Finally, a limitation of this work is that all the latent constructs were calculated solely with data extracted from field work data sets. With field work and ethnographic data collection there are vulnerabilities that can carry-over to the analysis, for example, a conversation regarding the experience of water quality might have gone in different directions in the households; Meaning that some households may have mentioned chlorine, taste, and odour, while other households may not. This does not mean that those households did not have anything to say, but that the nature of the conversation went elsewhere. These gaps in the data carry-on throughout the analysis, thus creating a limitation.

Overall, ethnographic field work helped us develop hypotheses, the required data was extracted from the various data streams, then tested using statistical tools. What we have learned is that the ethnographic field work drove the hypothesis development and testing, while the statistical results of this work may be used for a study design with a larger participant pool and a lower ethnographic involvement. Ethnography remains a core part of socio-techno research to uncover household-level trends, challenge system-level assumptions, and develop better research questions.

4.6 Conclusion

In this paper we sought to explore the implications of intermittency beyond the need for domestic storage at the household level. We explored how households manage intermittent supply and how intermittency is related to the experience of water quality at the tap. This work had challenges associated with multidisciplinary research, especially when studying socio-techno systems. Innovative methods from anthropology, engineering, and public health were used to answer questions about measuring intermittency, how households adapt with domestic storage and management, the effects storage have on water quality, and which impact experiences of water quality.

To this end, we built latent constructs that explain various factors associated with intermittency, domestic infrastructure and management, measured water quality and the experience of water quality at the tap. Using linear regression modeling we found one significant pathway linking intermittency to the experience of water quality in the kitchen tap. The pathway is mediated through the need for domestic management, suggesting that households more involved in the management of domestic water have a positive water quality experience, as opposed to households without the need to manage intermittency report a negative experience of water quality. A separate and independent pathway links the public supply water quality to the experience at the tap, showing that the water quality provided through distribution system plays an important role in a positive experience of water quality at the tap.

The implications of these findings are translated to practical applications and interventions in the face of increasingly prevalent intermittent water supply systems. Centralized efforts for water treatment throughout the system are of upmost importance regardless of intermittency. These efforts fall on local governments and public utilities to maintain water treatment plants and distribution systems. To address the pathway linking intermittency to experience of water quality, local information campaigns are needed to facilitate information access about water quality, domestic intermittency management strategies, and risks associated with drinking water.

As intermittency continues to grow, the cross-disciplinary methods used in this study should continue to be considered to uncover more implications, create better interventions, but most importantly – ask better questions.

4.7 Funding

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4.8 Acknowledgements

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This work had not been possible without the continued efforts made by the ELEMENT [74] and Mexico National Institute of Public Health (INSP) teams for establishing, caring for, and maintaining trusting relationships with hundreds of human subjects research participants in Mexico City for more than 20 years. Specifically Ana Benito Vinós, Libni Torres Olascoaga, and Luis F. Bautista.

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Chapter 5
Conclusions

5.1 Overview

The goal of this dissertation was to lay the foundations for the real-time study and management of drinking water systems. To that end, specific contributions of this work tackled practical, technological, and theoretical challenges, which ultimately led to a number of fundamental conclusions.

In Chapter 2 we illustrated that real-time monitoring of drinking water systems have practical applications and potential to quickly expand monitoring of our drinking water systems. In Chapter 3 we uncovered daily residual disinfectant dynamics experienced at the tap, and we showed implementations of real-time flushing are feasible, yield water quality improvements, and could reduce excess water flushed. In Chapter 4 we combined real-time monitoring with ethnographic observations to better understand the dynamics of intermittent water supply and learned that intermittency may be indirectly related to shaping the water quality experience at the tap.

A unique aspect of this dissertation was the focus on household-level taps. Thanks to the built-for-purpose approach and compact size, our platform is the first to be deployed in people's homes. Although most of the work in this dissertation focused on applications and research contextualized around the validity of sensors for subject-area specialists, a large underdiscussed contribution of this work is the feasibility of real-time drinking water quality information for nonsubject area experts. In the context of smart homes, sensors may soon be used to report water quality information to residents with the sole goal of providing objective information about the safety of their water.

Overall, in this dissertation we designed, constructed, and deployed a system built upon low-cost sensors, microcontrollers, and cloud services. Subsequently, we provided two example applications with specific management and research goals. Accessibility to these technologies is increasing both in affordability, reliability, and in implementation – meaning that soon more utilities, researchers, and people will be able to build and deploy their own sensor nodes for custom applications. Our hope is that the foundations laid in this dissertation will help others get a jump start and quickly uncover new grounds on smart drinking water systems. To aid in future efforts, we provide key areas that need further development towards smart drinking water systems.

5.2 Future work

Drinking water distribution systems are increasing in complexity due to sprawling urbanization and changes in water usage patterns. Utilities are constantly trying to understand how their distribution system may behave under various scenarios including fate and transport of chemical contamination, increased water age, and in the case of mixing different water sources to understand how the water quality may be affected throughout the system. Real-time water quality measurements may be used to calibrate models using conductivity and pressure sensors, conductivity as tracer indicator and pressure as a hydraulic correction.

Following the system-wide conductivity event observed in Chapter 2 there are questions remaining to be answered. To begin to understand what the phenomena measured by wireless sensor networks mean, we need to combine our data streams with source water quality, operational and maintenance changes happening at the treatment plant. The treatment plant in Ann Arbor blends ground water and surface water at different ratios throughout the year. These changes may require a change in coagulant chemical dose that may eventually reflect some changes in water quality throughout the system. In a similar note, operational and maintenance schedules may be responsible for some of the changes seen in water quality across distribution systems. In this line of research, it is therefore important to gather information at source waters and treatment plant that may be linked to baseline cyclic behaviors measured at the tap. Close relationships with treatment plant operators and managers are guaranteed to facilitate sharing data and insights for this research.

During the development process of this dissertation, we had conversations with Ann Arbor water treatment plant managers. The objective of the conversations was to find a common interest from the academic research side and the operational side of wireless sensor networks. We found that the application of automatic hydrant flushing needed real-time sensing tools. At the time of these conversations (2021) automatic hydrant flushing devices using fixed timers were being deployed throughout the city, but there was a large need in increased sensing and monitoring to understand the effects of flushing at different flushing frequencies. Flushing plans for the city of Ann Arbor are well documented [130]. An ideal goal of using smart sensors and actuators to flush hydrants is to decide when to start and end flushing. For this a study should be designed to identify the best parameters to understand hydrant flushing. To start, ORP, temperature, color, and turbidity could provide the information necessary. The effects of hydrant flushing should be measured in a similar fashion to how the Chapter 3 study was designed – measuring a baseline followed by a flushing period, and finally a signal processing approach to determine when to start and stop flushing.

Signal processing will continue to be a pain point of real-time monitoring systems. Issues like calibration loss, fouling, signal drifting, physically unlikely measurements, and broken probes, are likely issues that are encountered. Future research on anomaly detection should focus on differentiating noise signals from true events. For this we need to understand baseline behaviors by combining treatment plant operational data and sensors historical data. Additionally, as seen in Chapter 3 with ORP probes, there are sensors with high variation between probes when measuring the same waters, this highlights the inherent complexity of environmental sensing. Research in the area of environmental sensing should also focus on developing measurement confidence tools to assess the validity of measurements.

Building plumbing flushing will be an active area of research. In Chapter 3 we started to make headway into real-time tap water flushing applications in single-family houses. We proposed a smart flushing protocol that automatically stops flushing based on temperature signal stability, but we were not able to deploy and test it. It remains to be determined what can be generalized between a smart flushing real-time control algorithm to a timer. After investigating the variability in ORP at the tap, it may appear that longer periods of stagnation are needed in single-family homes to observe dips in ORP, especially in systems with chloramine residual. An adaptive sensing plan may be developed to reduce the number of samples taken based on the variability of past measurements. This would reduce the load on data collection and processing, and in turn would provide a forecast estimate to when take the next sample.

Next steps in understanding building plumbing water quality and flushing in real-time is the combination of online flow-cytometry and physicochemical parameters. Flow-cytometry is a novel tool used to measure viable bacteria concentrations. Researchers have used it to study the concentration of bacteria in building plumbing [131], source and fate of microorganisms in drinking water distribution systems [132], and to study full-scale ozone disinfection processes in Ann Arbor’s drinking water treatment plant [133]. There is a feasible opportunity to use these tools to understand the impact of flushing on bacteria concentrations in real-time. An experiment similar to the one designed in Chapter 3 may evaluate the effect of building plumbing flushing on bacteria concentrations.

An investigation on how real-time information may induce changes in people's experiences of drinking water. In Chapter 3 we developed an automatic flushing protocol that may provide better water quality at the tap. Then in Chapter 4 our results suggested that more automatic domestic water systems may lead to negative experiences of water quality at the tap. We posit that the lack of information about water quality may be responsible for the negative experiences, thus it would be appropriate to research the changes in water quality experience once real-time information is available at the tap.

In Chapter 4 we have laid the foundations to study in more depth the effects of intermittency on the experience of water quality at the tap. We found evidence that suggests there is a connection linking intermittency to the experience of water quality, however the data set cannot be used to confidently establish these pathways as statistically significant. The next steps are to design a survey that captures these questions more specifically so we can increase the sample size. Finally, a further connection linking the experience of drinking water quality to the desire to treat the water, purchase bottled water, or purchase sugar drinks should be tested. This is the next link associating intermittency to any effects on public health related to water consumption.

Lastly, the deployment of sensors in Chapter 4 left multiple questions unanswered. We now know that intermittency is variable, both in pressure and frequency spatially. We still need to understand how these technologies could be leveraged by homeowners to understand the water supply and quality dynamics experienced at their tap and make informed decisions on how to build and manage their domestic storage systems.

Many technological and theoretical challenges remain, including social, economic, and political barriers to the wider adoption of smart drinking water systems. Smart water systems require highly multidisciplinary teams to continue to evolve. This work was possible through collaborations ranging from engineering, to social, political, and biological sciences, so it is only expected that more multidisciplinary collaborations will continue this work.

Appendices

Appendix A

Supplementary Information for Chapter 2

A.1 Sensors

A.1.1 ORP

The ORP sensor used *(Atlas Scientific #ENV-40-ORP)* and its conditioning circuit *(Atlas Scientific #EZO-ORP)* have a measurement range of +/- 1,019.9 mV with an accuracy of +/- 1 mV, and a response time of one reading per second. The sensors use a silver – silver chloride half-cell with a platinum tip, and a potassium chloride reference solution. The ORP sensors were calibrated with one point using the ZoBell's solution (*Atlas Scientific #chem-ORP)*, which is a standard with an ORP of 225 mV at 25 ^{o}C [134], with a frequency of once per year or once per deployment, whichever occurred first.

The oxidation reduction potential (ORP) is a measurement of the ability of an aqueous environment to oxidize or reduce chemicals [135]. Drinking water containing a disinfectant residual is highly oxidative and the ORP often correlates with different disinfectants and their concentrations [70].

In a water sample with pH 8, the concentration range of free chlorine 0 – 3.5 mg/L as Cl_2 has an ORP range of roughly 199 - 680 mV, while the concentration range of monochloramines 0 – 3.5 mg/L as Cl_2 has an ORP range of 239 - 450 mV [70]. These ORP values are reported in reference to the platinum Ag/AgCl electrode for consistency to the reported values in Chapter 2. The conversion factor to the Standard Hydrogen Electrode is described in Standard Methods 2580

B [134]. All ORP values reported here are in reference to the platinum Ag/AgCl electrode with a 4 M KCl internal solution.

Alternative sensors, such as those that utilize amperometric or colorimetric methods, are advantageous because they can measure specific disinfection compounds. However, the underlying operational requirements tend to be complicated. For example, amperometric sensors require constant flow, constant pressure, and regular membrane replacements [136]. Colorimetric analyzers require frequent reagent refills (6 months) and create waste streams that may require special handling [137]. Both amperometric or colorimetric analyzers need to be recalibrated and cleaned once per month according to most manufacturers. Consequently, these sensors are best suited for applications where regular operational maintenance can be implemented. Measurements of ORP are straight forward and do not require complicated operating protocols. This suits the simple flow cells necessary for sensor deployment in buildings with limited access.

ORP sensors have an ionic-strength dependent equilibrium time. ORP equilibrium is reached faster in higher ionic strength waters than it does in medium to low ionic strength waters. Finished drinking water can have low or medium ionic strengths, depending on the source water quality and the treatment processes. In medium ionic strength water, ORP can take anywhere in between 15 minutes to one hour to reach equilibrium, while in low ionic strength water it can take up to several hours [76].

A.1.2 Electroconductivity

EC is a measure of the water's ability to conduct an electric current and is directly related to the concentration and valence of ions in solution, also referred to as *ionic strength*. EC measurements are correlated with total dissolved solids (TDS), a measure for the combined concentrations of salts and minerals dissolved in the water [135]. Relative changes in EC can be related to sudden events that change the chemical composition of a water sample. Their measurement speed and sensitivity make them suitable for real-time monitoring systems.

The sensor used *(Atlas Scientific #ENV-40-EC-K1.0)* and its conditioning circuit *(Atlas Scientific #EZO-EC)* have a K constant of 1.0 for a measurement range of 5 – 200,000 uS/cm and an accuracy of +/- 2%, and a response time of one reading per second. The sensors were calibrated using two points – 0 (dry measurement) and 1,413 uS/cm (*Atlas Scientific #chem-EC-0.1)*, with a frequency of once per year or once per deployment, whichever occurred first. The measurements were corrected for temperature at the time of collection using the manufacturer's EZO protocols. The sensing area was specifically placed in parallel to the flow of the water to avoid trapped air bubbles and flow short-circuiting.

A.1.3 pH

pH measurements provide information on the activity of hydrogen ions in solution. Hydrogen ions play an important role in the equilibrium and kinetics of chemical reactions that take place in aquatic environments, such as disinfection kinetics, acid-base reactions, metal complexation, and mineral precipitation [135]. The sensor used *(Atlas Scientific #ENV-40-pH)* and its conditioning circuit *(Atlas Scientific #EZO-pH)* have a range of 0 – 14, a resolution of +/- 0.001 and an accuracy of +/- 0.002, and a response time of one reading per second. Calibrations were made using the 7, 4, and 10 standard points (*Atlas Scientific #C-pH-4-7-10*), with a frequency of once per year or once per deployment, whichever happened first. Measurements were corrected for temperature at the time of collection using the manufacturer's EZO protocols.

Maintaining specific pH ranges is of critical importance for achieving effective disinfection. In drinking water distribution systems, where free chlorine is the main residual disinfectant, the pH should be below *7.5*. In systems where monochloramine is the main residual disinfectant, the pH should be above *8.3* [135,138].

A.1.4 Temperature

Temperature influences the kinetics of aquatic chemical and biological reactions [135]. In our sensor nodes, the temperature probes were primarily used to correct conductivity and pH measurements. The sensor used *(Atlas Scientific #PT-1000)* and its conditioning circuit *(Atlas Scientific #EZO-RTD)* have a range of -200 to 850 ^{o}C, an accuracy of +/- 0.15, and a response time of one reading per second.

As the nodes were connected to building plumbing, a room temperature sample usually represented samples from the building, whereas a colder sample indicated water samples from underground water mains. Temperature must be recorded if ORP values need to be referenced back to the Standard Hydrogen Electrode. Temperature measurements were used to correct pH and EC measurements at the time of collection through the EZO temperature-corrected sampling protocols.

A.1.5 Pressure

An analog pressure transducer *(Atlas Scientific #A100-APS)* was included to characterize water supply dynamics. The sensor has a range of 100 psig (689.47 kPa) with a resolution of 0.025 psi (0.17 kPa). The analog signal produced has a range of 0.5 - 4.5 VDC, this signal was stepped down with a voltage divider to get it in a 0.5 – 3.0 VDC and converted with the microcontroller's ADC.

The high-resolution pressure measurements from intermittent systems were used to evaluate the dynamics of water availability in Mexico City households. The sensor node microcontroller interprets the pressure data in real-time and determines if there is water to sample or not. If there was water available, the node took new samples to capture first flush events. In continuous systems the pressure measurements were used to monitor day-to-day hydraulic trends and make spatial comparisons among neighborhoods.

Pressure has an important role in overall system management. For example, pumps are activated once certain pressure threshold is crossed. Although mostly associated with hydraulic operations, pressure is also of interest for water quality. Fluctuations in water pressure are related to the suspended solids at the tap. High water pressure tends to correspond with low velocity, and vice versa. High demand situations increase velocity of water in the distribution system and the flow becomes more turbulent, mixing up previously settled solids and particles [139].

A.1.6 Leak Detector

A water leak detector *(Seeed Studio #SEN11304P)* for the purpose of detecting leaks inside the sensor node was implemented using a microcontroller digital pin. If water was detected in the node enclosure, the sensor triggered a node shutdown until the device could be serviced.

5.2.1 Calibration

The water quality probes (pH, ORP, EC) were calibrated prior to deployments using Atlas Scientific protocols. After calibration and before deployments, each node was tested in a control site where reproducibility was verified by connecting the sensor nodes to the same sampling water source and waited for stable readings. The manufacturer's specifications suggested yearly recalibration of probes and deployments were shorter than one year; therefore, recalibrations were not conducted on probes while they were deployed at a site. For nodes that were deployed at multiple sites over the period of the study, the recalibration protocol per manufacturer specifications was applied in between deployments.

The electroconductivity probes calibration protocol was modified from two-point calibration (84 uS/cm and 1413 uS/cm) to one-point calibration (1413 uS/cm). Under the new protocol the signals reported matched the Hanna handheld probe measurements. In Table 2.4 there is evidence of the values reported by the probe under the two-point and one-point calibrations in comparison to the Hanna handheld probe.

A.2 Sensor node hydraulic limitations impact on water quality signals

Hydraulic conditions within the flow cell created by the fast-closing solenoid valve were likely contributors to pH probe damage. Both pH and ORP probes contain a reference electrolyte and a delicate glass electrode subject to irreversible damage under transient flow and pressure conditions. When damage occurs the signal drifts and it becomes evident that it broke – especially the pH probes. However, there are cases when more than one sensor node in close proximity to one another reports drifting. It is possible in that case to infer there is a water quality change picked up by three nodes such as the one seen in Figure 2.3-A in the main text.

It is recommended to use a motorized ball valve instead of a solenoid valve to avoid the high pressure transients and damaging the probes. For an added cost, there is an option to obtain slow-closing solenoid valves, which have the advantage that will remain in the closed position if failure or power loss should happen.

Furthermore in the specific case of studying low pressure systems, including intermittent systems, it is important to investigate and consider the head loss throughout the node and its implications on the water actually being measured. For example - when a domestic connection pipe is under constant flow to fill an underground cistern, the pressure is not enough to make water flow into a perpendicular branch upstream of the cistern, such as a sampling tap. And thus the question to consider is whether or not the sensor probes are measuring "new" distribution water or node-stagnant water.

A.3 Ann Arbor

Each sensor node was tested for two days in the University of Michigan laboratories to establish a water quality baseline. From the test period in Ann Arbor the resulting average ranges are as follows (min average, max average): pressure (70, 78) psi, pH of (9.31, 9.76), ORP of (336, 425) mV, EC of (649, 818) uS/cm, and temperature of (21, 23) °C. The testing periods of each node were on different dates. Differences and variability in pressure may be attributed to a combination of the day-to-day changes in water supply, differences in ORP, EC, and pH may be inherent variability associated with each probe. Cited studies in this paper have also reported differences between probes when measuring in duplicates [30,70].

A.4 Mexico City

The installation was made with standard and removable connectors (such as a wye with garden hose threads) and the flushed water was collected in a bucket for the resident to use for cleaning or watering the plants. Collecting water in a bucket or flushing directly into a planter was our preferred method (over flushing directly to the drain) because Mexico City residents are acutely aware of water shortages. Unlike Ann Arbor homes, there were usually some household residents at home throughout the day, who could monitor the bucket and use the collected water for domestic tasks. Bucket water collection may not be the best approach in households where residents are away during the day.

We needed to move a number of sensor nodes across multiple sites. We recalibrated and tested the sensor between each deployment. The period of time each sensor node remained deployed was dependent on logistical factors relating to larger parallel health studies who manage the relationships to participant cohorts [74,123]. In total, 15 sensor nodes were used in our Mexico City case study, two were deployed in three locations each, two were deployed in two locations each, nine were deployed in only one location each, one sensor node was not deployed because of technical malfunction, and one sensor node remained deployed in the control site. The decisions for deploying the same sensor node multiple times were based on various factors including field conditions and participants willingness to continue hosting a sensor node.

Each site presented unique challenges and a number of deployment attempts were unsuccessful due to unforeseen circumstances. The team encountered issues such as leaking sampling taps, Wi-Fi or cellular connectivity issues, lack of power source in the vicinity of the water tap, low water pressure unable to flow through our solenoid valve, non-standardized household plumbing, and pets interfering with the deployment setups. We were limited to deployments at single family dwellings in order to avoid neighbor conflict, unwanted handling, and intrusion.

Pressure data varied both spatially and temporally in the continuous systems (Table SI-A-2). Some households exhibited diurnal cycles with large ranges, and other households exhibited consistently low pressures. Some of the systems that were categorized as continuous by the official city's government intermittency schedule [122] exhibited pressure signals that were near-zero at some points of the day.

The ORP signal showed in Figure 2.4-C is highly variable and we believe it is the result of water distributed with free chlorine once per week followed by a period of stagnation where it decays. The intermittency in this particular household did not overlap with one of our field visits and therefore there are no grab samples to confirm the concentration of chlorine during the first flush or during the bulk supply. Instead, the grab samples were taken from a storage tank inside the household, typically 5 days after the last supply day and the free chlorine averages were below the detection limits as mg/L as Cl2. The ORP signal increasing to a level previously associated with free chlorine and grab samples from household storage with low chlorine (several days after supply) are evidence to show that the ORP signal is indeed measuring change in free chlorine over a stagnation period. This shows the duration of intermittency has large implications on water quality at the household level, even if households have enough storage to hold water for a long period of time, the deterioration in water quality will be inevitable.

The classification bins of supply systems (chlorinated, not chlorinated, or having varying levels of chlorination in Tables 2.2 and 2.3) was made depending on the standard deviations of both the ORP signals and the Free Chlorine grab samples. A low variability of both ORP and free chlorine (with a free chlorine mean > 0.5 mg/L as Cl_2) meant a system was chlorinated. A low ORP average with low variability and no measurable chlorine from grab samples – then the system was not chlorinated. Finally, a medium-range ORP signal average, with a high variation would put the system as variable chlorination.

A.5 Figures

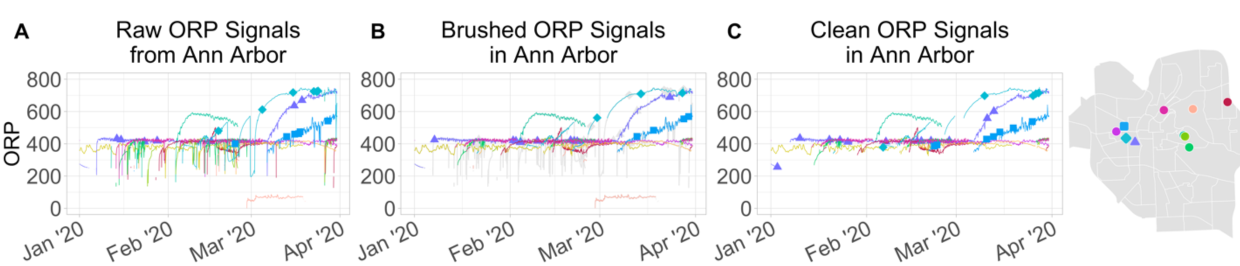


Figure SI-A- 1: ORP signal cleaning and processing from Ann Arbor Deployments. The ORP signals were quality to remove sensor startup values. The ORP sensor exhibited a three hour "warmup" period, which corresponds with the amount of time that the dry electrode and membrane need to be in contact with the water before providing a stable values. Raw values are shows in A. Grayed out values in B reflect data that was removed to produce the final figure C, shown in in the paper.

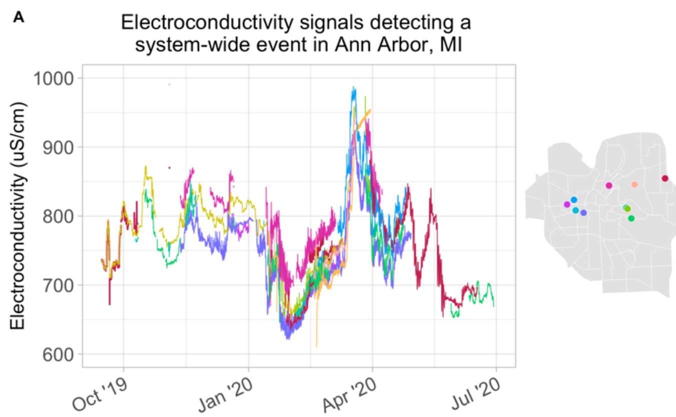


Figure SI-A- 2: Expanded system-wide conductivity event. from October 2019 to June 2020. In the main text Figure 3B shows the same event, but from the dates March 2020 – April 2020. Colors of the timeseries (left) correspond with locations on the map (right). For color reference is advised to refer to the digital online version of this document.

A.6 Tables

Table SI-A- 1: pH Summary Statistics of deployment signals and grab samples from Mexico City

pH Signal		pH Grab Sample		
Mean	**SD**	**Mean**	**SD**	**n**
Continuous				
10.66*	1.73	7.30	0.41	3
7.90	0.18	7.45	0.39	3
7.98	0.05	7.82	0.55	3
7.77	0.12	7.31	0.17	2
7.44	0.09	7.46	0.45	2
7.43	0.32	7.60	NA	1
7.98	0.11	7.63	NA	1
5.60*	0.73	7.84	0.65	3
8.20	0.31	7.73	0.23	2
7.86	0.91	7.24	0.08	2
6.81	0.03	7.69	0.01	2
6.89	1.25	7.70	NA	1
Weekly Intermittent				
7.87	0.09	7.56	0.42	3
7.97	0.39	7.40	0.12	3
7.62	0.21	7.80	0.28	2
Daily Intermittent				
7.16	0.16	7.25	0.49	2
7.93	0.26	7.43	NA	1

*Signal likely resulted from damaged probes.

Table SI-A- 2: Pressure Summary Statistics of deployment signals from Mexico City

Pressure Signal (psi)	
Mean	**SD**
Continuous	
48.97	15.59
32.20	12.17
50.82	12.02
18.74	1.09
40.03	14.35
19.25	3.20
18.29	1.74
23.38	1.51
22.67	5.64
34.79	10.83
16.30	3.67
18.52	1.84
Weekly Intermittent	
18.88	4.15
18.64	3.72
4.12	11.82
Daily Intermittent	
21.61	2.56
2.51	4.28

Appendix B

Supplementary Information for Chapter 3

B.1 Tables

Table SI-B- 1: Water quality characteristics for Ypsilanti and Ann Arbor drinking water

City	**Ypsilanti**	**Ann Arbor**
Disinfectant (mg/L as Cl_2)	Free Chlorine 0.69	Chloramine 2.6
pH	6.9	9.3
Conductivity (µS/cm)	224	613
Total Hardness (mg/L as $CaCO_3$)	100	125
Chloride (mg/L)	10.6	117
Sulphate (mg/L)	25.2	51
Alkalinity (mg/L as $CaCO_3$)	71	64
Nitrate (mg/L as N)	0.55 (max)	0.8 (max)
Nitrite (mg/L as N)	Not Detected	0.09
Note: Physicochemical water quality parameters are average values as reported in each system's annual water quality report 2021: https://www.ycua.org/waterreport.pdf https://www.a2gov.org/departments/water-treatment/Documents/water_quality_report_2021.pdf		

Table SI-B- 2: Sites characteristics and deployment durations

Site Name	Household Size: Occupants (bed / bath)	Experiment Durations (days)				
		February – March (Cold)		September – October (Warm)		Total
		Baseline	Flush	Baseline	Flush	
Free Chlorine. Ypsilanti, Michigan.						
Yps 1	1 (2 / 2)	0	0	29	23	52
Yps 2	2 (2 / 1)	0	0	13	14	27
Chloramine. Ann Arbor, Michigan.						
Arb 1	2 (3 / 1)	17	14	22	18	71
Arb 2	5 (4 / 2.5)	17	14	22	21	74
Arb 3	3 (3 / 2)	14	17	0	0	31

Table SI-B- 3: Grab samples summary taken during the study periods.

	Baseline Period							Flush Period						
	First Draw		Full Flush		% Increase			First Draw		Full Flush		% Increase		
	Mean	sd	Mean	sd	Mean (%)	sd (%)	n	Mean	sd	Mean	sd	Mean (%)	sd (%)	n
Free Chlorine														
Yps 1	0.64	0.11	0.78	0.09	26.60	35.62	2	0.59	0.11	0.72	0.05	22.64	15.13	2
Yps 2	0.50	0.01	0.64	0.14	26.55	26.23	2	0.51	NA	0.55	NA	7.84	NA	1
Chloramine														
Arb 1	2.36	0.04	2.52	0.06	6.83	4.31	2	2.23	0.18	2.33	0.17	4.54	1.10	3
Arb 2	2.15	0.25	2.38	0.08	11.50	9.58	2	2.08	0.01	2.07	0.03	-0.24	1.02	2
Arb 3	2.73	NA	2.76	NA	1.10	NA	1	2.68	0.04	2.83	0.02	5.23	2.18	2

B.2 Figures

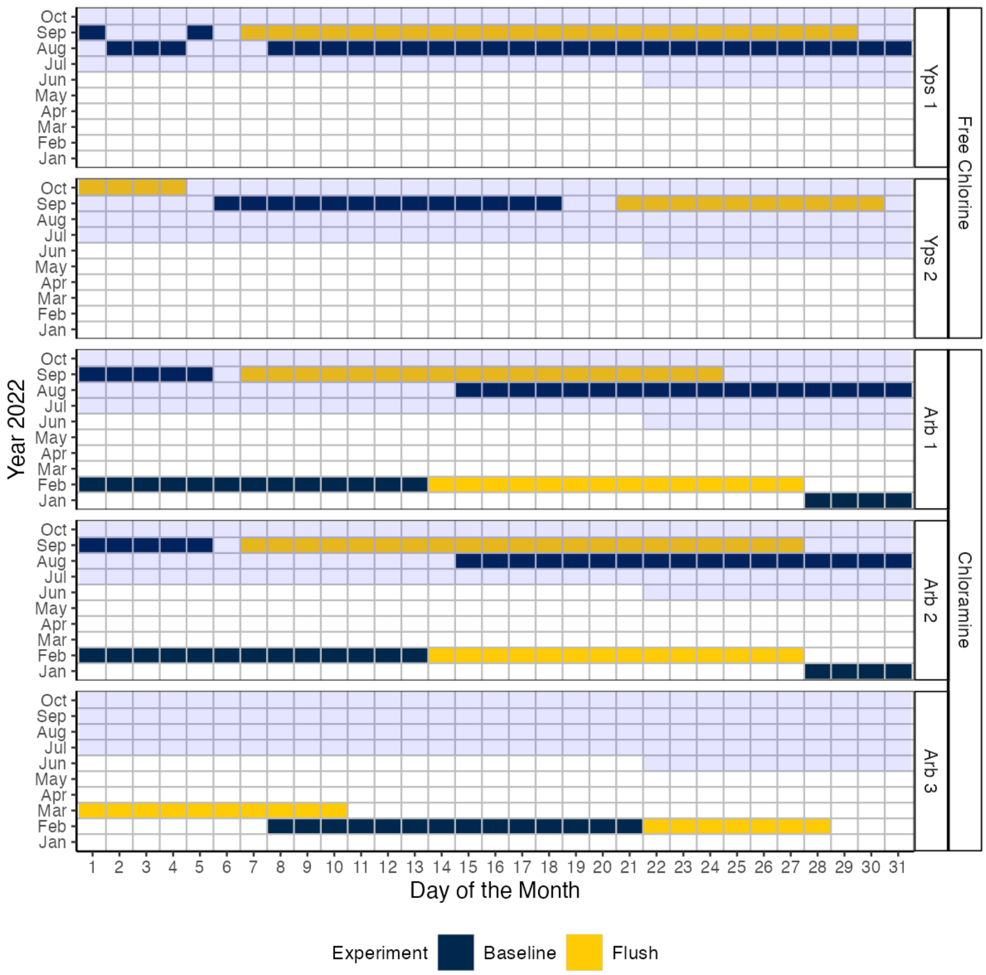


Figure SI-B- 1: Deployment calendar. Shaded squares represent Summer and Fall, blank squares represent Winter and Spring. Colored squares are the dates when the experiments took place. Due to the need to coordinate with homeowners, site access was constrained to specific periods (winter/spring or summer/fall), with two homeowners permitting us to return and measure during both time periods.

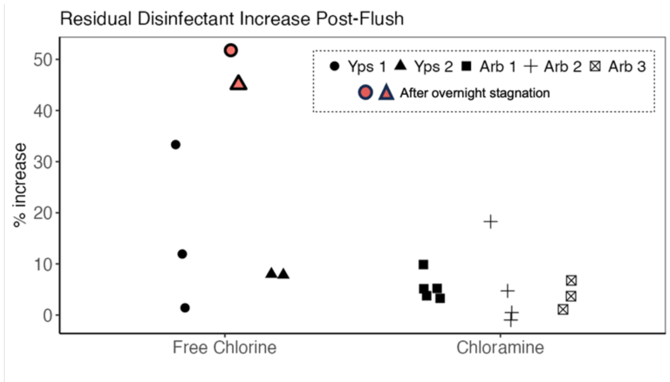


Figure SI-B- 2: Grab samples from the sites shown as percent increase pre- to post flush. Data are grouped by disinfectant to minimize effect of different number of observations per site. Free and total chlorine concentrations were measured using the DPD method.

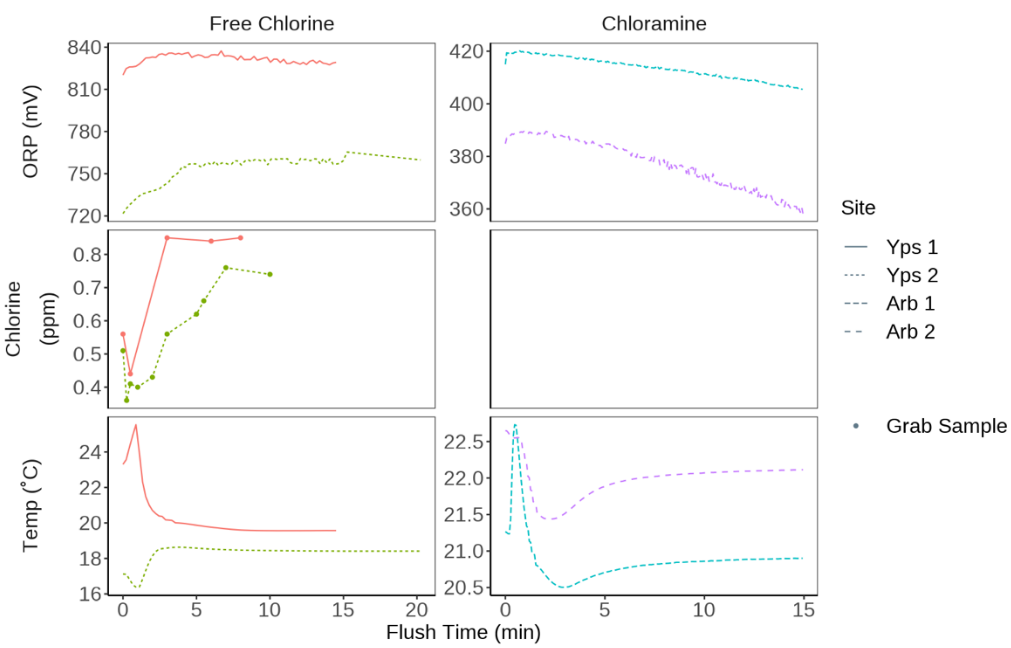


Figure SI-B- 3: Response of ORP, chlorine in grab samples, and temperature to flush after overnight stagnation. . Chlorine grab samples were grabbed every 15 – 30 seconds until change was less than 0.1 mg/L as Cl2 and are connected by lines to highlight trend, ORP and temperature were measured every second for the duration of flushing. Line types (Solid, dash, etc) and color are consistent across sites.

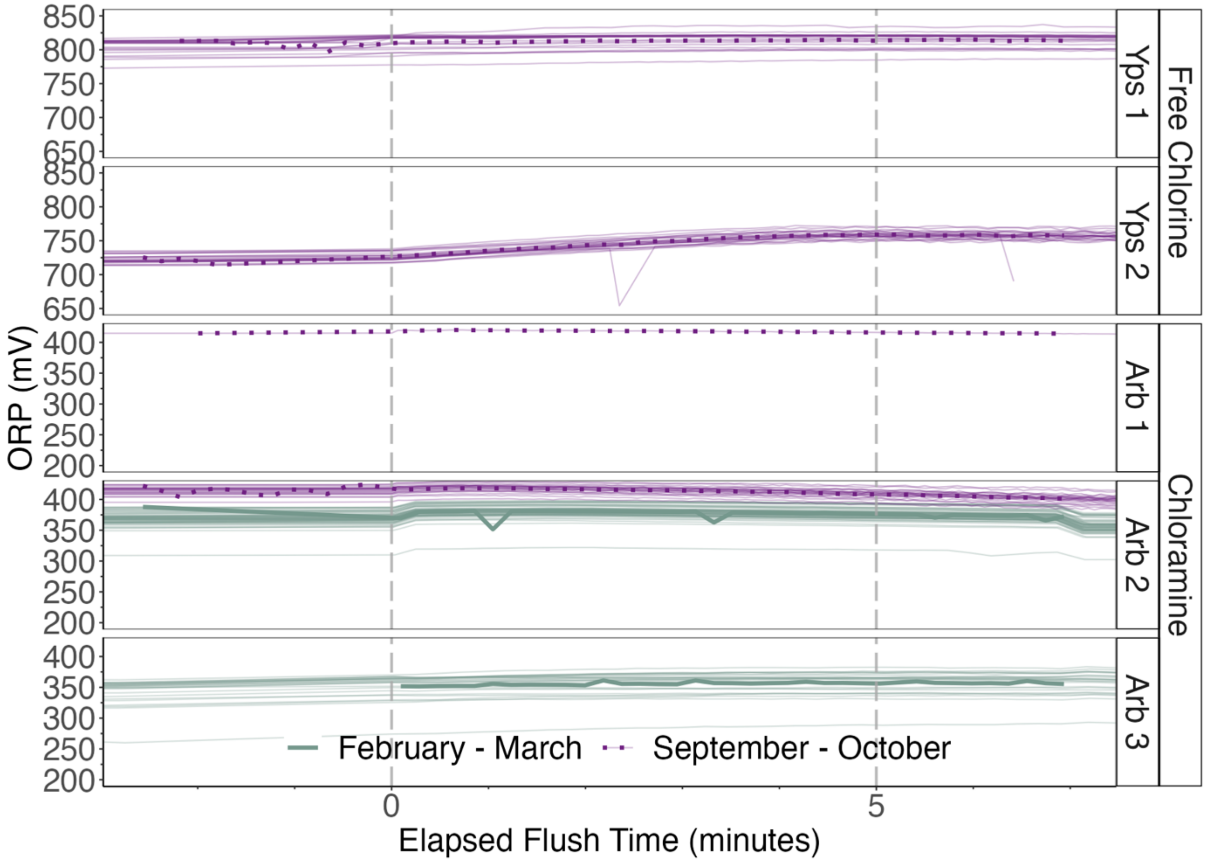


Figure SI-B- 4: Response of ORP sensors during high resolution flushing of household taps. Solid lines represent individual flushing events (n = 219), average of lines per site is shown in bold lines, dashed vertical lines represent the start and end of a 5-minute flushing timer.

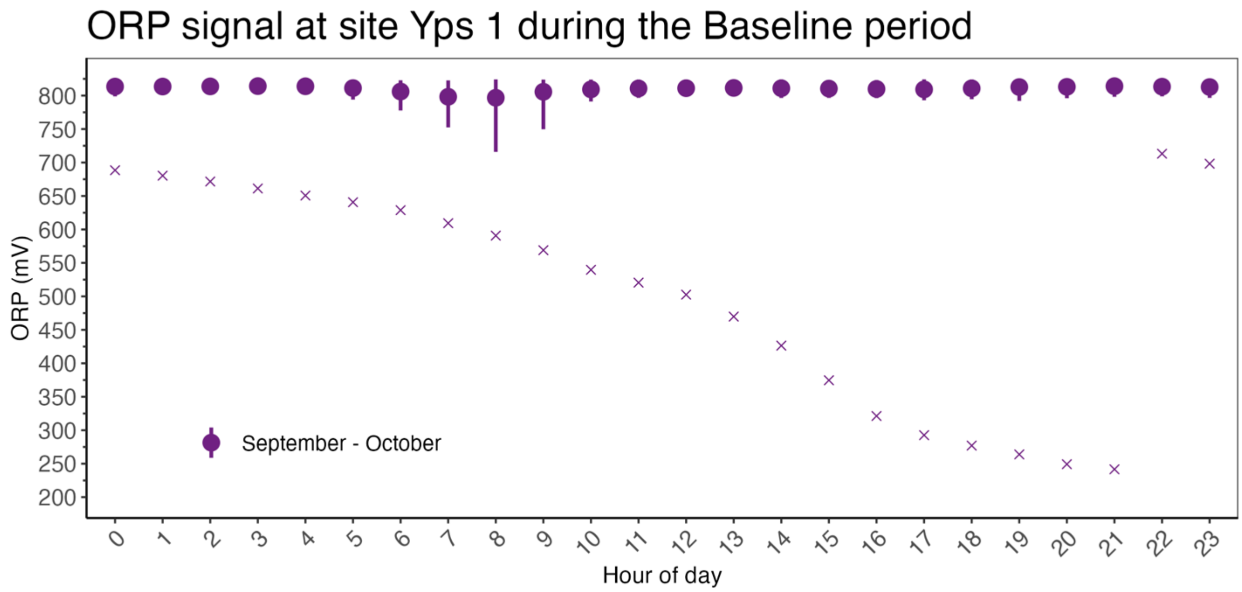


Figure SI-B- 5: Extreme ORP outliers during extended stagnation in a free chlorine kitchen tap. ORP values are given in reference to the Ag-AgCl half-cell. Summaries include median (Q_2) as circles and squares, whisker bars extend to $Q_1 - 1.5 \times IQR$ and $Q_3 + 1.5 \times IQR$ or the max/min value of the data set, where IQR is $Q_3 - Q_1$, and minimum values shown as x's if smaller than the whisker bar range. Data include extreme outliers during No Flush at site *Yps 1*.

Appendix C

Supplementary Information for Chapter 4

C.1 Mexico City, Study location, contextual water situation

With a population of 9 million people within the jurisdictional city boundaries, and 20 million people in the greater metropolitan area, Mexico City is the largest city in Latin America and one of the largest cities globally. As seen in other megacities in the world, water resources and supply are one of the city's biggest challenges. For decades, Mexico City's residents have experienced an ever-changing water landscape, both literally and figuratively, thanks to challenges associated with increased population, depletion of aquifers, and natural disasters. A complete chronology of strategies implemented by the federal and local governments to maintain water supply for the city is described by Tellman et al. and helps understand the challenges the city and residents have adapted to [140]. Mainly a repeating cycle of technical solutions to urban and social problems that create other unforeseen problems years or decades later. Global urbanization trends create more stress on freshwater resources and cities continuously look for adaptation strategies, Mexico City, with a long history of adaptations, serves as an ideal study location to understand the impacts of large-scale water stress on the experience of water supply and the experience of water quality in urban settings.

The water distribution system in Mexico City is supplied with 33% surface and 67% groundwater [68]. A small fraction of the surface water comes from the mountain ranges and natural springs on the west and southwest boundaries of the city, while the bulk of the surface water is imported from the Cutzamala system roughly 140 km west of the city. And while a small portion of groundwater is also imported from the west through the Lerma system, most of the groundwater is extracted from local aquifers through 450 wells distributed across the city [69,141]. The geopolitical governance of water is complex, the federal commission of water resources (CONAGUA) is in charge of treating and allocating water resources outside of the political boundaries of Mexico City, including the Cutzamala and Lerma systems. Inside the city limits the local utility, SACMEX, is in charge of primary distribution systems and allocates water to each of the Mexico City's 16 *alcaldias.* Each *alcaldia's* government operates and maintains the secondary distribution system within their jurisdiction, and determine each neighborhood's water supply schedule [142].

Public information regarding infrastructure assets, treatment trains, disinfectant booster stations, pumping stations, and storage tanks is not available. However, it has been reported in the literature there are varying levels of source water quality [69] and varying levels of distributed water quality across the city at sampling taps [69,143]. This may be directly related to inconsistent levels of treatment at system-entry points, creating a highly heterogeneous system that further amplifies a socioeconomic divides and reinforces city-wide skepticism in distributed water quality, the utility, and the local governments.

C.2 Household Visits Description

When the team arrived to a house for a visit a letter of consent approved by the IRB (Institutional Review Board) at the *University of Michigan* (UofM) and the *Instituto Nacional de Salud Publica* (INSP) was read and signed by the participants. At this time the participants were verbally informed about the goals of the study, the visit structure (or agenda), and the type of information we were there to collect. After a few minutes of introductions, settling down, and small talk, the participants were asked to walk the research team through a "Domestic Water

Infrastructure" tour of their house and to provide descriptions on components' functionality, flow patterns, operational information, and decision-making processes behind managing the system. During the tour water samples were collected from five main points – starting with *outdoor tap* closest to the distribution mains, then following to the *cistern* (underground storage tank), *tinaco* (rooftop storage tank), *kitchen tap*, and their *preferred drinking water* if different than any of the already collected samples (bottled, filtered, boiled, etc.). This part of the visit had the objective to learn directly from the participants how they experience water supply and the adaptive measures required to maintain a functioning water system in their home. At this time, we learned from the participants if they experience pressure fluctuations, water shutoffs, and anything related to water supply in their neighborhood. The collected water samples would be analyzed concurrently during the following structured parts of the visit.

After the tour, team members and participants all convened in the living space, kitchen, or dining area, where the rest of the interview would take place. The interview continued with socioeconomic information about the immediate family members, extended family living in the premises, and about the construction of the house. Then immediately followed into the open-ended questions where themes about water quality, supply, and management experiences were further explored.

NESTSMX Participants

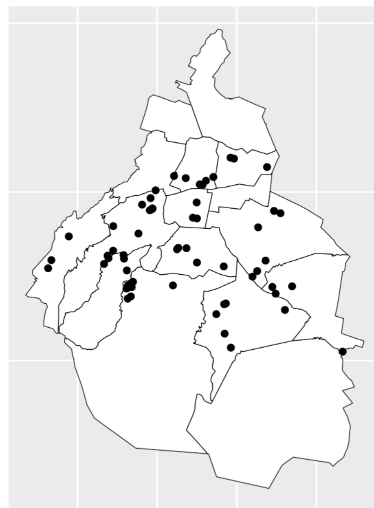


Figure SI-C- 1: Map of Mexico City divided into 16 local governments (alcaldias). Study participants are represented by points.

Table SI-C- 1: NESTSMX Visit Summary

Visit	*n( )*
1	60
2	24
3	7
4 (phone)	56

C.3 Variable Descriptions

C.3.1 Experience of Water Quality

Ethnographic data was coded using codes (Table SI-C-2) that target the experience and experience of drinking water quality before, during, and after passing through domestic storage. During the interview all participants were asked to describe their experience and their take on water quality in their neighborhood. However, a question regarding their experience of water quality during/after storage was not part of the script. These codes were developed post-collection to answer the specific questions relevant to this study.

Table SI-C- 2: Codebook for water quality experience

Code	Description
Water quality experience – public supply	Descriptions of water quality in the public supply or at the point of arrival to the household from the public supply. For example, "the water arrives yellow."
Water quality experience – household	Descriptions of water quality within the household, after it has arrived from the public supply. For example, "water comes out of the kitchen tap yellow."
Water quality related to domestic management/infrastructure	A code to capture all instances where participants attribute a change in their water quality to their household water infrastructure or water management. e.g. "The tinaco pollutes the water."; "I trust the water from the public supply, but not from the tinaco", etc.
Note: When unclear whether a participant is discussing public water management or "within building" or "within household" water management, both "Water quality experience - household" and "Water quality experience - public supply" codes were used. For example, "Yes, we trust the water because they [and they is undefined/unspecified] clean the tinacos" should be coded WQ-household + WQ – public supply + WQ related to domestic management	

Table SI-C- 3: Experience and Experience of Water Quality.

Water Aesthetic	*Justification*	*Examples*	*Levels*	*Numerical Representation*
Chlorine Experience	Participants mention experience of chlorine through smell or taste. Chlorine is good for water safety standards, but some people may perceive it in a negative way.	Question: Do you consider that water quality in your neighborhood is better, worse, or same as other neighborhoods in the city?	Mentioned with good connotation.	1
Color Experience	Color originates from dissolved metals and organic compounds, its a sign of untreated water, high disinfectant demand, and high disinfection by-products		Not Mentioned	0
Taste/Odor Experience	Taste and odor are also indicative of poorly treated water		Mentioned with Bad Connotation	-1
Solids Experience	Suspended solids are indicative of water that has been in contact with soil, either through disturbed pipe material, leaks in the distribution system or not properly closed tanks.			

Table SI-C- 4: Example of coding and water quality experience quotes

<table>
<tr><th></th><th>Codes</th><th>Datatype</th><th>Water Quality Aesthetic</th><th>Connotation</th><th>Quotation ID, Folio</th></tr>
<tr><td rowspan="2">Example 1</td><td>Water quality experience – public supply</td><td>Transcription</td><td>Chlorine

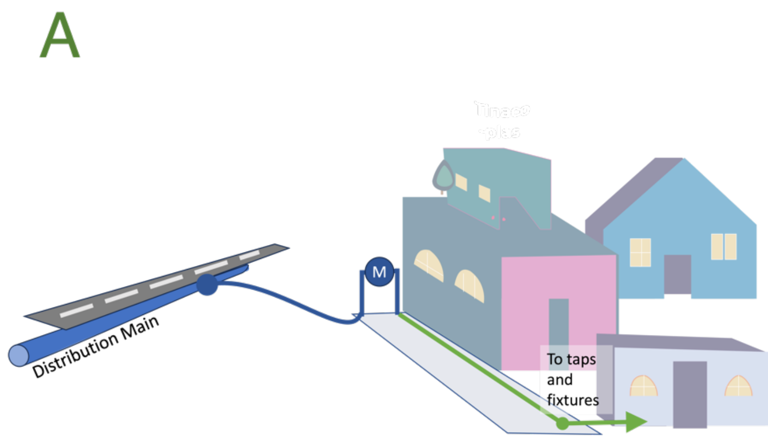
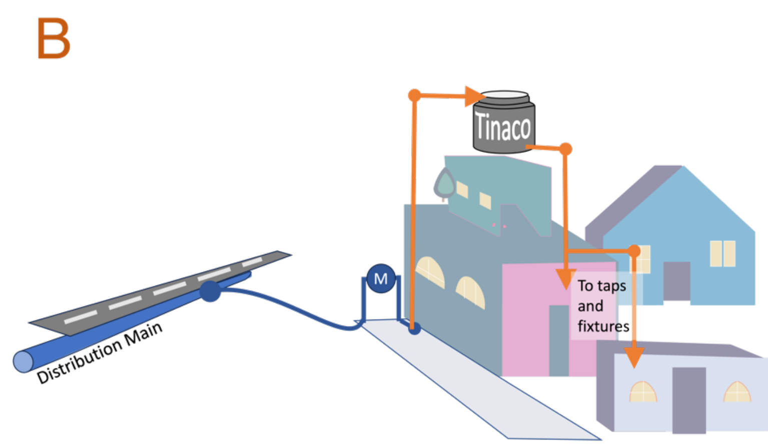
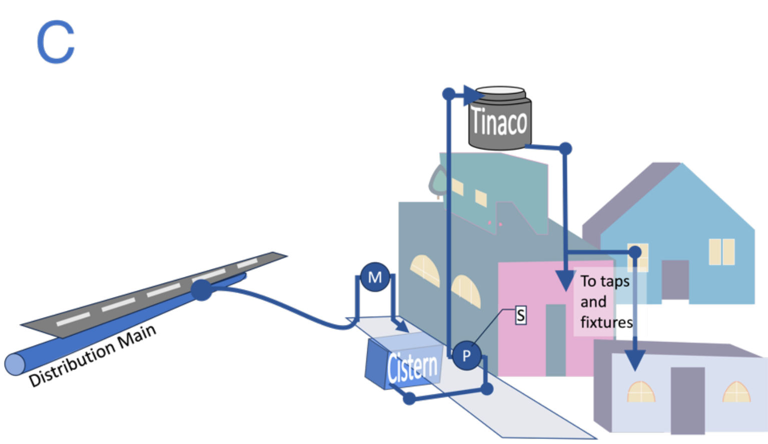
Taste</td><td>Negative

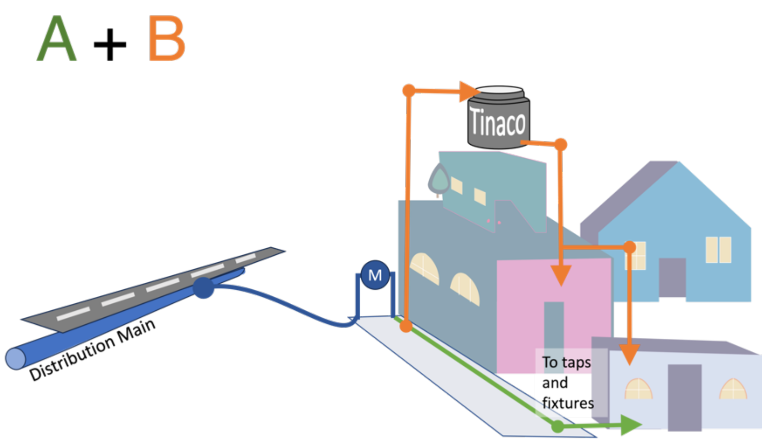
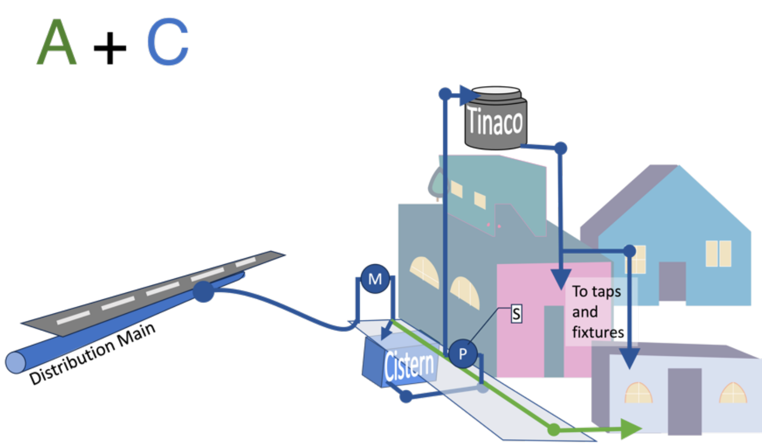
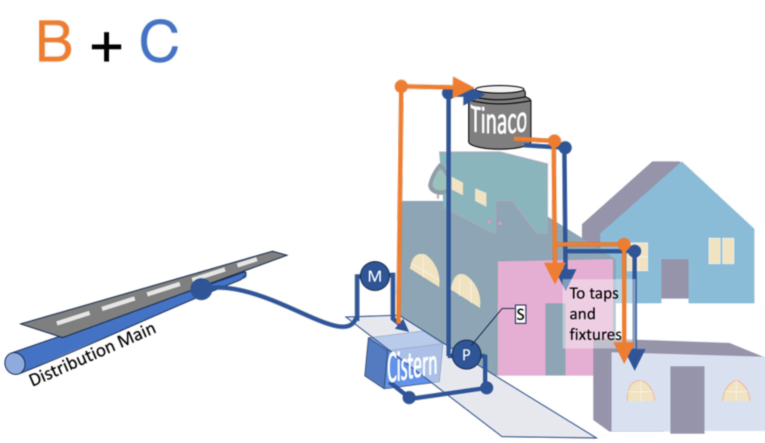
Positive</td><td>3:14
0049
V4</td></tr>
<tr><td colspan="5">Translated text:
Interviewer: Do you consider that water quality in your neighborhood is better, worse, or same as in other neighborhoods? Why?
Participant: I say it is better, because if you taste it, it has a very good taste, I mean I know that water is unflavored, he, he, he, but try it in other places it has chlorine flavor I don’t know and this one does not, it tastes good, it is fresh, good. Ask the neighbors they will say the same he, he, he… sorry.
Original Text:
E: Claro en algunos lugares no la valoran, y la desperdician y en otros no tienen, claro si…..he….okey….usted considera que la calidad del agua en su colonia es mejor, peor o igual que en otras partes de la ciudad de México? P: Yo digo que es mejor E: Porque? P: Porque si prueba esta agua tiene un sabor muy rico, o sea ya sé que el agua es insabora, je, je,je pero prueba en otros lados le sabe a cloro no sé y esta agua no, está rica, está fresca, rica E: Claro si, no si pues incluso a veces? P: Pregúntele a vecinos te van a contestar lo mismo, je, je, je…perdón</td></tr>
<tr><td rowspan="2">Example 2</td><td>Water quality experience – public supply</td><td>Transcription</td><td>Solids Experience</td><td>Negative</td><td>35:1
0263
V4</td></tr>
<tr><td colspan="5">Translated text:
Interviewer: Generally, do you all trust the water coming from the public supply? Why?
Participant: No, because it comes very dirty, I mean very, with dirt, well more with dirt, so that’s why not.
Original text:
E: Generalmente ustedes confían en el agua que viene de la calle, del suministro público? P: No E: Porque? P: Porque viene bien sucia, o sea muy, con tierra…..bueno más seguro con tierra, entonces por eso no</td></tr>
</table>

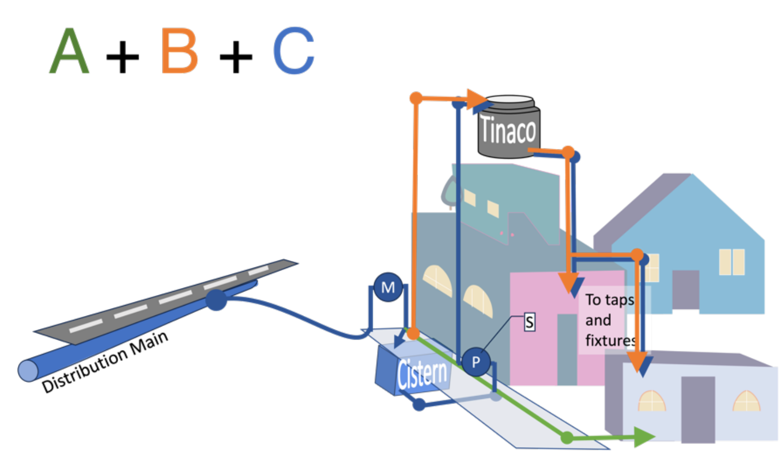
C.3.2 Flow Diagrams

All systems are built using a combination of the same components depending on the needs at each house. Underground storage units (*cisterns*) and rooftop tanks (*tinacos*) are the primary storage elements that are used in response to variable water supply. As opposed to tinacos, which are found almost universally across the city, cisterns are found with less frequency usually in neighborhoods with exceptionally low water pressure but can also be found in apartment buildings and some single-family buildings with added vertical living space. Most houses had very unique set ups and solutions particular to solve their needs, however, at the very core of the flow diagrams there were similitudes among all systems. All households flow diagrams were broken down into 'building blocks' (Table SI-C-5, A – C) of components and flow configurations in order to classify categorically each system. The most basic configurations have a single flow path connecting all components from the service line through the storage, pipes, or pumps, to the taps. We describe increasingly complex systems by adding the most basic configurations that best describe the flow diagram for each household (Table SI-C-5). More complex systems have multiple flow paths, creating situations for residents that require more active interaction with the system for proper operation and creating conditions for increasing water age depending on the primary hydraulic path.

Table SI-C- 5: Domestic infrastructure flow schematics

Domestic Infrastructure Flow Schematic	*Notes*
	n = 7
	n = 10
	n = 26 In some cases this setup is the only one possible due to the height of the building. **Management Tasks**: It is common for the pump to be activated through a light switch, although some *tinacos* are integrated with water level sensors that activate the pump automatically.

Domestic Infrastructure Flow Schematic	*Notes*
	n = 5 Redundancy is added to the system for various reasons. **Stagnation point**: This leads to increased water age in the *tinaco*. **Management tasks**: Some tasks in this set up could include unplugging water hoses to fill up the *tinaco*.
	n = 2 Redundancy same as above, but with a cistern because the pressure is not strong to lift the water. **Stagnation Point**: *Cistern* and *tinaco* if water from “*A*” is primary flow. **Management tasks**: Lift *cistern* lid to check water level. Turn valves to choose where to direct the water after the *cistern*.
	n = 9 Stagnation Points: Cistern if “B” is the primary flow. Management Tasks: Potentially lift cistern lid to check water level. If low and cistern not piped to public supply then connect hose and fill it for a few hours.

Domestic Infrastructure Flow Schematic	*Notes*
	n = 1 Stagnation Points: Cistern if "B" or "A" is the primary flow. Tinaco if "B" and "A" are primary flow. Management Tasks: Potentially lift cistern lid to check water level. If low and cistern not piped to public supply then connect hose and fill it for a few hours. If more than one tinaco, turn valves, turn on pump, until desired tank is full.
M = Meter, P = Pump, S = Light Switch	

C.3.3 Management tasks and system state

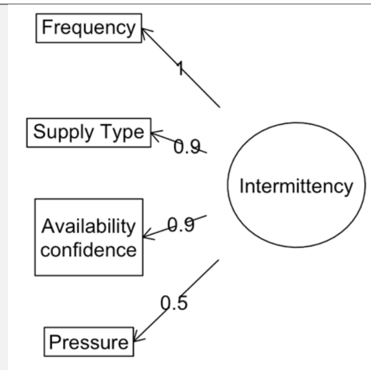
During the domestic infrastructure tours the participant described how the system worked. Generally the narrative used to describe these systems had passive process verbs, as if the water and the flow process was happening autonomously, however most of the systems did not work automatically and rather needed constant human input. The field notes taken during the tours were coded for "water management" and reports were compiled. A short list containing the most reoccurring tasks (Table SI-C-6) was created after reading the reports and for each household a binary indicator was attached to each task. Although not immediately obvious from the task's names, the way in which participants collect information from the system is embedded into the tasks.

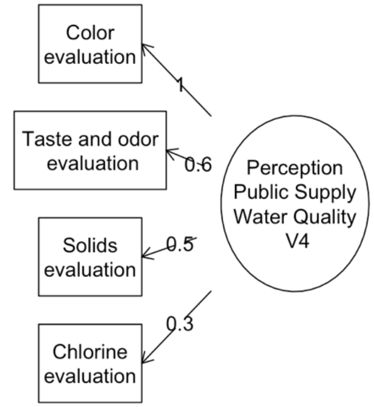
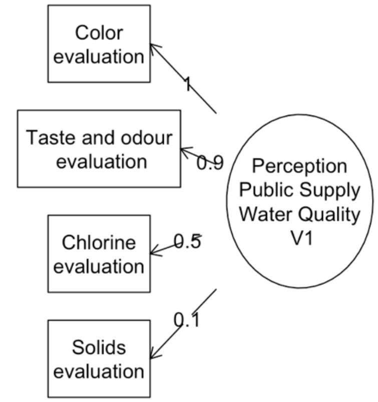
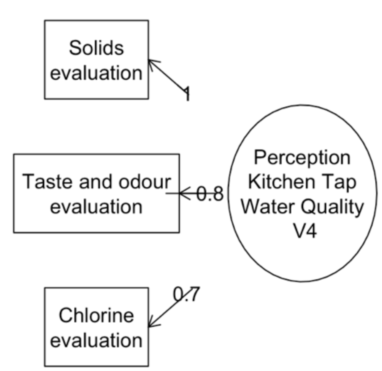
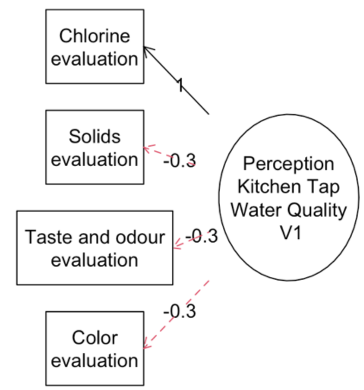
Table SI-C- 6: Management tasks summary

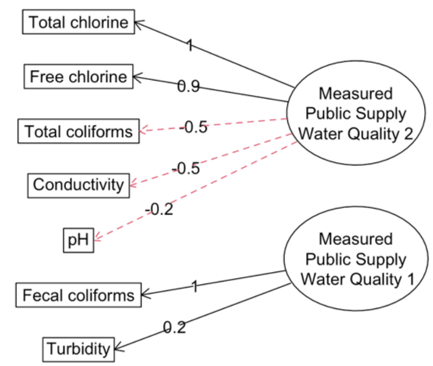
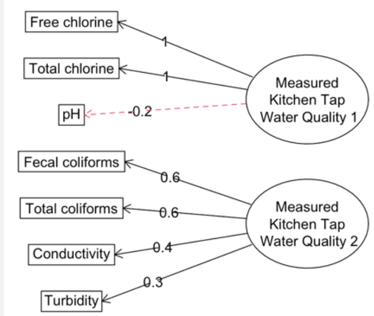
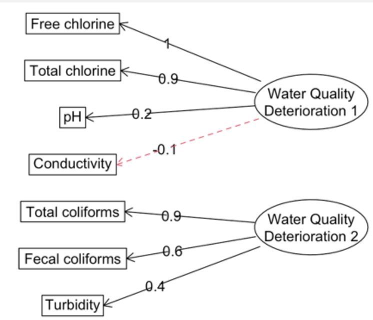
Management Task	*Number of households (n)*
Turn Valves	7
Connect and Disconnect garden hoses	10
Fill Up Disconnected Containers	20
Move Water Containers	4
Turn on/off pump	19
Collect and move preferred water	6
Recycle water task	25

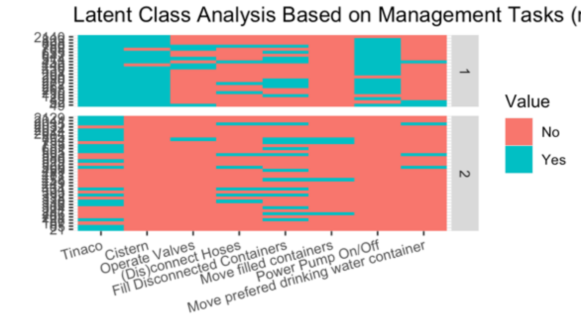
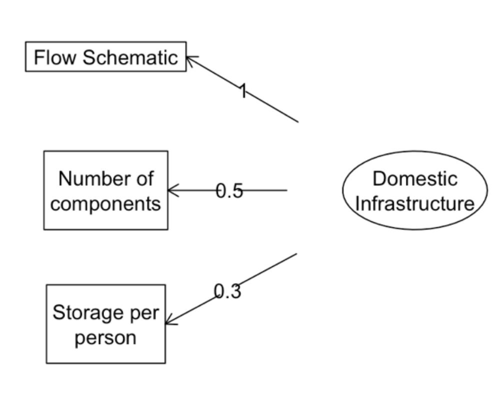
C.4 Latent Constructs and Factor Analysis Results

Table SI-C- 7: Proposed latent constructs and factor analysis

Latent Construct	*Observed Variables*	*Assessing Method*	*Levels*	*Numerical Assignment*	*Factor Analysis Loadings*
Intermittency	Supply Type	City Memo	Continuous	1	
			Off-Grid	0	
			Intermittent	-1	
	Frequency Type	Field Notes	Continuous	2	
			Continuous with regular shutoffs	1	
			Daily	-1	
			Weekly	-2	
	Pressure	Field Notes	Adequate	1	
			Inadequate	-1	
	Availability Confidence	Field Notes	High	1	
			Low	-1	
	Unusual Shutoffs	Field Notes	Yes	-1	
			No	1	
Experience/Experience of Outdoor Water Quality	Chlorine Experience	Field Notes	Mentioned with good connotation	1	
	Color Experience	Field Notes		0	
	Taste/Odor Experience	Field Notes	Not Mentioned	-1	

Latent Construct	*Observed Variables*	*Assessing Method*	*Levels*	*Numerical Assignment*	*Factor Analysis Loadings*
	Solids Experience	Field Notes	Mentioned with bad connotation		 
Experience/Experience of Indoor Water Quality	Chlorine Experience	Field Notes	Mentioned with good connotation	1	 
	Color Experience	Field Notes	Not Mentioned	0	
	Taste/Odor Experience	Field Notes		-1	
	Solids Experience	Field Notes	Mentioned with bad connotation		
Measured Outdoor Water Quality	pH Free Chlorine Total Chlorine	Measured			

Latent Construct	*Observed Variables*	*Assessing Method*	*Levels*	*Numerical Assignment*	*Factor Analysis Loadings*
	Electroconductivity				
	Turbidity				
	Total Coliforms				
	Fecal Coliforms				
	Hardness				
	Sulphate				
Measured Indoor Water Quality	pH	Measured			 
	Free Chlorine				
	Total Chlorine				
	Electroconductivity				
	Turbidity				
	Total Coliforms				
	Fecal Coliforms				
	Hardness				
	Sulphate				
Domestic Infrastructure Management Class	Turn Valves	Field Notes	Yes	1	
	(Dis)connect hoses				
	Fill Up Disconnected Containers				
	Move Water Containers		No	0	
	Turn on/off pump				

Latent Construct	*Observed Variables*	*Assessing Method*	*Levels*	*Numerical Assignment*	*Factor Analysis Loadings*
	Collect and move preferred water				
	Recycle water task				
	Cistern				
	Tinaco	Infrastructure Maps			Note: For the regression the scale was transformed by changing the sign of each class. i.e. (-1, -2)
Domestic Infrastructure	Storage per person	Infrastructure Maps, Field Notes	N/A	100 - 200	
	Number of Components	Infrastructure Maps	N/A	1-5	
	Flow diagrams	Infrastructure Maps, Field Notes	A	1	
			B	1	
			C	3	
			AB	3	
			BC	4	
			AC	4	
			ABC	5	
Socioeconomic Level	Index	ELEMENT	A/B	7	
			C+	6	
			C	5	
			C-	4	
			D+	3	
			D	2	
			E	1	

C.5 Linear Regression Pathway Results

Table SI-C- 8: Linear Regressions Results

<table>
<tr><th>Response Variable</th><th>Determinant Variable</th><th>Regression Summary</th></tr>
<tr><td>Domestic Infrastructure</td><td>Intermittency
Socioeconomic Level</td><td>Call:
lm(formula = Domestic_infrastructure ~ intermittency + amai_8x7,
    data = regression_df)

Residuals:
    Min   1Q Median   3Q   Max
-2.4315 -0.6938 0.2778 0.3552 1.9099

Coefficients:
                Estimate Std. Error t value Pr(>|t|)
(Intercept)   -0.03656   0.41846 -0.087   0.9307
intermittency_1 0.23141   0.12435   1.861   0.0686 .
amai_8x7   0.01295   0.10310   0.126   0.9006

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.9822 on 50 degrees of freedom
Multiple R-squared: 0.0648,	Adjusted R-squared: 0.02739
F-statistic: 1.732 on 2 and 50 DF, p-value: 0.1873</td></tr>
<tr><td>Infrastructure Management Class</td><td>Intermittency
Socioeconomic Level
Domestic Infrastructure</td><td>Call:
lm(formula = LatClass2 ~ intermittency_1 + amai_8x7 + Domestic_infrastructure,
    data = .)

Residuals:
     Min   1Q   Median   3Q   Max
-0.78632 -0.36000 -0.08404 0.34686 0.66570

Coefficients:
                        Estimate Std. Error t value Pr(>|t|)
(Intercept)   -1.68333   0.17757 -9.480 1.15e-12 ***
intermittency_1   0.11926   0.05456   2.186 0.033640 *
amai_8x7   0.01583   0.04375   0.362 0.719104
Domestic_infrastructure 0.22091   0.06001   3.682 0.000578 ***

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.4168 on 49 degrees of freedom
Multiple R-squared: 0.3288,	Adjusted R-squared: 0.2877
F-statistic: 8 on 3 and 49 DF, p-value: 0.0001936</td></tr>
<tr><td>Measured Water Quality Public Supply (factor 1/2)</td><td>Intermittency</td><td>Call:
lm(formula = WQ_out_1 ~ intermittency_1 + amai_8x7, data = regression_df)</td></tr>
</table>

Response Variable	***Determinant Variable***	***Regression Summary***
	Socioeconomic Level	(see below)

```
Residuals:
    Min      1Q  Median      3Q     Max 
-1.1026 -0.5494 -0.3049  0.1281  2.5543 

Coefficients:
                Estimate Std. Error t value Pr(>|t|)
(Intercept)      0.15698    0.41170   0.381    0.705
intermittency_1  0.06170    0.14360   0.430    0.670
amai_8x7        -0.06502    0.10217  -0.636    0.528

Residual standard error: 0.9276 on 44 degrees of freedom
  (6 observations deleted due to missingness)
Multiple R-squared:  0.01459,	Adjusted R-squared:  -0.0302 
F-statistic: 0.3257 on 2 and 44 DF,  p-value: 0.7237
```

Response Variable	***Determinant Variable***	***Regression Summary***
Measured Water Quality Public Supply (factor 2/2)	Intermittency Socioeconomic Level	(see below)

```
Call:
lm(formula = WQ_out_2 ~ intermittency_1 + amai_8x7, data = regression_df)

Residuals:
    Min      1Q  Median      3Q     Max 
-1.9843 -0.8365  0.1879  0.5782  2.0963 

Coefficients:
                Estimate Std. Error t value Pr(>|t|)
(Intercept)      0.37463    0.45270   0.828    0.412
intermittency_1 -0.08783    0.15789  -0.556    0.581
amai_8x7        -0.10263    0.11234  -0.914    0.366

Residual standard error: 1.02 on 44 degrees of freedom
  (6 observations deleted due to missingness)
Multiple R-squared:  0.02335,	Adjusted R-squared:  -0.02104 
F-statistic: 0.5261 on 2 and 44 DF,  p-value: 0.5946
```

Response Variable	***Determinant Variable***	***Regression Summary***
Measured Water Quality Kitchen Tap (factor 1/2)	Domestic Infrastructure Infrastructure Management Class Measured Water Quality Public Supply (factor 1/2) Measured Water Quality Public Supply (factor 2/2)	(see below)

```
Call:
lm(formula = WQ_in_1 ~ intermittency_1 + Domestic_infrastructure + 
    LatClass2 + WQ_out_1 + WQ_out_2, data = .)

Residuals:
    Min      1Q  Median      3Q     Max 
-2.2503 -0.6922 -0.1022  0.6184  2.6029 

Coefficients:
                        Estimate Std. Error t value Pr(>|t|)  
(Intercept)              0.11097    0.67998   0.163   0.8713  
intermittency_1         -0.05744    0.18952  -0.303   0.7636  
Domestic_infrastructure  0.03784    0.20521   0.184   0.8547  
LatClass2                0.04326    0.40546   0.107   0.9156  
WQ_out_1                 0.14091    0.17649   0.798   0.4299  
WQ_out_2                -0.41693    0.17229  -2.420   0.0207 *
---
```

Response Variable	***Determinant Variable***	***Regression Summary***

		`Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1`
		
		`Residual standard error: 1.017 on 36 degrees of freedom`
		`  (11 observations deleted due to missingness)`
		`Multiple R-squared:  0.1788, Adjusted R-squared:  0.0647`
		`F-statistic: 1.567 on 5 and 36 DF,  p-value: 0.1941`

Measured Water Quality Kitchen Tap (factor 2/2)	Domestic Infrastructure
	Infrastructure Management Class
	Measured Water Quality Public Supply (factor 1/2)
	Measured Water Quality Public Supply (factor 2/2)
		`Call:`
		`lm(formula = WQ_in_2 ~ intermittency_1 + Domestic_infrastructure +`
		`    LatClass2 + WQ_out_1 + WQ_out_2, data = .)`
		
		`Residuals:`
		`    Min      1Q  Median      3Q     Max`
		`-1.0249 -0.4704 -0.1122  0.3278  2.4992`
		
		`Coefficients:`
		`                        Estimate Std. Error t value Pr(>|t|)`
		`(Intercept)             -0.43417    0.54182  -0.801    0.428`
		`intermittency_1         -0.07442    0.15101  -0.493    0.625`
		`Domestic_infrastructure  0.17620    0.16352   1.078    0.288`
		`LatClass2               -0.26211    0.32308  -0.811    0.423`
		`WQ_out_1                 0.03957    0.14063   0.281    0.780`
		`WQ_out_2                 0.60561    0.13728   4.411 8.93e-05 ***`
		`---`
		`Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1`
		
		`Residual standard error: 0.8102 on 36 degrees of freedom`
		`  (11 observations deleted due to missingness)`
		`Multiple R-squared:  0.4408, Adjusted R-squared:  0.3631`
		`F-statistic: 5.675 on 5 and 36 DF,  p-value: 0.000587`

Water Quality Deterioration (factor 1/2)	Domestic Infrastructure
	Measured Water Quality Public Supply (factor 1/2)
	Measured Water Quality Public Supply (factor 2/2)
		`Call:`
		`lm(formula = WQ_det_1 ~ Domestic_infrastructure + WQ_out_2 +`
		`    WQ_out_1, data = .)`
		
		`Residuals:`
		`    Min      1Q  Median      3Q     Max`
		`-2.3710 -0.4085 -0.1499  0.4605  2.1022`
		
		`Coefficients:`
		`                        Estimate Std. Error t value Pr(>|t|)`
		`(Intercept)             -0.05943    0.15742  -0.378   0.7079`
		`Domestic_infrastructure  0.15954    0.17598   0.907   0.3703`
		`WQ_out_2                -0.29992    0.15749  -1.904   0.0644 .`
		`WQ_out_1                -0.26729    0.17159  -1.558   0.1276`
		`---`
		`Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1`
		
		`Residual standard error: 1.012 on 38 degrees of freedom`
		`  (11 observations deleted due to missingness)`
		`Multiple R-squared:  0.1585, Adjusted R-squared:  0.09209`

Response Variable	***Determinant Variable***	***Regression Summary***
		`F-statistic: 2.386 on 3 and 38 DF,  p-value: 0.0842`

Water Quality Deterioration (factor 2/2)	Domestic Infrastructure
	Measured Water Quality Public Supply (factor 1/2)
	Measured Water Quality Public Supply (factor 2/2)
		`Call:`
		`lm(formula = WQ_det_2 ~ Domestic_infrastructure + WQ_out_2 +`
		`    WQ_out_1, data = .)`
		
		`Residuals:`
		`     Min       1Q   Median       3Q      Max`
		`-1.60791 -0.63994  0.04282  0.42930  2.61438`
		
		`Coefficients:`
		`                        Estimate Std. Error t value Pr(>|t|)`
		`(Intercept)              0.06388    0.14137   0.452  0.65394`
		`Domestic_infrastructure  0.13945    0.15803   0.882  0.38309`
		`WQ_out_2                -0.41326    0.14143  -2.922  0.00583 **`
		`WQ_out_1                 0.38924    0.15409   2.526  0.01582 *`
		`---`
		`Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1`
		
		`Residual standard error: 0.9091 on 38 degrees of freedom`
		`  (11 observations deleted due to missingness)`
		`Multiple R-squared:  0.2864,       Adjusted R-squared:  0.2301`
		`F-statistic: 5.084 on 3 and 38 DF,  p-value: 0.004667`

Experience of Public Supply Water Quality (Visit 1)	Intermittency
	Socioeconomic Level
	Measured Water Quality Public Supply (factor 1/2)
	Measured Water Quality Public Supply (factor 2/2)
		`Call:`
		`lm(formula = Perc_wq_out_V1 ~ intermittency_1 + amai_8x7 + WQ_out_2 +`
		`    WQ_out_1, data = .)`
		
		`Residuals:`
		`     Min       1Q   Median       3Q      Max`
		`-2.11933 -0.40311 -0.01766  0.34633  2.48162`
		
		`Coefficients:`
		`                Estimate Std. Error t value Pr(>|t|)`
		`(Intercept)     -0.18887    0.48401  -0.390    0.698`
		`intermittency_1 -0.02655    0.16819  -0.158    0.875`
		`amai_8x7         0.05811    0.12065   0.482    0.633`
		`WQ_out_2         0.23670    0.15969   1.482    0.146`
		`WQ_out_1        -0.16656    0.17559  -0.949    0.348`
		
		`Residual standard error: 1.08 on 42 degrees of freedom`
		`  (6 observations deleted due to missingness)`
		`Multiple R-squared:  0.07435,      Adjusted R-squared:  -0.0138`
		`F-statistic: 0.8434 on 4 and 42 DF,  p-value: 0.5056`

Experience of Public Supply Water Quality (Visit 4)	Intermittency
	Socioeconomic Level
		`Call:`
		`lm(formula = Perc_wq_out_V4 ~ intermittency_1 + amai_8x7 + WQ_out_2 +`
		`    WQ_out_1, data = .)`
		
		`Residuals:`

<table>
<tr><th>Response Variable</th><th>Determinant Variable</th><th>Regression Summary</th></tr>
<tr><td></td><td>Measured Water Quality Public Supply (factor 1/2)
Measured Water Quality Public Supply (factor 2/2)</td><td>Min 1Q Median 3Q Max
-1.5749 -0.5588 -0.1128 0.4951 1.8783

Coefficients:
Estimate Std. Error t value Pr(>|t|)
(Intercept) -0.18290 0.40095 -0.456 0.6509
intermittency_1 -0.23383 0.14712 -1.589 0.1203
amai_8x7 0.01409 0.10019 0.141 0.8889
WQ_out_2 0.34068 0.13434 2.536 0.0154 *
WQ_out_1 -0.33992 0.14446 -2.353 0.0239 *

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.8718 on 38 degrees of freedom
(10 observations deleted due to missingness)
Multiple R-squared: 0.3067, Adjusted R-squared: 0.2337
F-statistic: 4.203 on 4 and 38 DF, p-value: 0.006479</td></tr>
<tr><td>Experience of Kitchen Tap Water Quality (Visit 4)</td><td>Domestic Infrastructure
Infrastructure Management Class
Water Quality Deterioration (factor 1/2)
Water Quality Deterioration (factor 2/2)
Experience of Public Supply Water Quality (Visit 1)
Experience of Public Supply Water Quality (Visit 4)</td><td>Call:
lm(formula = Perc_wq_in_V4 ~ Domestic_infrastructure + LatClass2 +
WQ_det_2 + WQ_det_1 + Perc_wq_out_V4 + Perc_wq_out_V1, data = .)

Residuals:
Min 1Q Median 3Q Max
-2.6278 -0.2479 -0.0267 0.1771 2.1562

Coefficients:
Estimate Std. Error t value Pr(>|t|)
(Intercept) 1.195266 0.557452 2.144 0.0400 *
Domestic_infrastructure 0.031077 0.154554 0.201 0.8420
LatClass2 0.676424 0.322887 2.095 0.0444 *
WQ_det_2 -0.067479 0.125021 -0.540 0.5932
WQ_det_1 -0.006574 0.130043 -0.051 0.9600
Perc_wq_out_V4 0.338721 0.159553 2.123 0.0418 *
Perc_wq_out_V1 0.144917 0.130873 1.107 0.2767

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.7615 on 31 degrees of freedom
(15 observations deleted due to missingness)
Multiple R-squared: 0.2733, Adjusted R-squared: 0.1326
F-statistic: 1.943 on 6 and 31 DF, p-value: 0.105</td></tr>
<tr><td>Experience of Kitchen Tap Water Quality (Visit 1)</td><td>Domestic Infrastructure
Infrastructure Management Class
Water Quality Deterioration (factor 1/2)</td><td>Call:
lm(formula = Perc_wq_in_V1 ~ Domestic_infrastructure + LatClass2 +
WQ_in_1 + WQ_in_2 + WQ_det_2 + WQ_det_1 + Perc_wq_out_V4 +
Perc_wq_out_V1, data = .)

Residuals:
Min 1Q Median 3Q Max</td></tr>
</table>

<table>
<tr><th>Response Variable</th><th>Determinant Variable</th><th>Regression Summary</th></tr>
<tr><td></td><td>Water Quality Deterioration (factor 2/2)
Measured Water Quality Kitchen Tap (factor 1/2)
Measured Water Quality Kitchen Tap (factor 2/2)
Experience of Public Supply Water Quality (Visit 1)
Experience of Public Supply Water Quality (Visit 4)</td><td><pre>
-0.62359 -0.31962 -0.18430 0.07664 2.04942

Coefficients:
                       Estimate Std. Error t value Pr(>|t|)
(Intercept)   -0.09682   0.52973 -0.183   0.8562
Domestic_infrastructure 0.21733   0.14867   1.462   0.1545
LatClass2   0.21143   0.30772   0.687   0.4975
WQ_in_1   -0.09508   0.15188 -0.626   0.5362
WQ_in_2   -0.12537   0.14125 -0.888   0.3820
WQ_det_2   0.11353   0.12992   0.874   0.3894
WQ_det_1   0.04158   0.14705   0.283   0.7794
Perc_wq_out_V4   0.10805   0.14775   0.731   0.4704
Perc_wq_out_V1   -0.22151   0.12310 -1.799   0.0824 .

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.694 on 29 degrees of freedom
  (15 observations deleted due to missingness)
Multiple R-squared: 0.1982,   Adjusted R-squared: -0.02302
F-statistic: 0.8959 on 8 and 29 DF, p-value: 0.5325
</pre></td></tr>
<tr><td>Experience of Kitchen Tap Water Quality (Visit 1)</td><td>N/A</td><td></td></tr>
</table>

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