Analysis of Uncertainty in Water Management

and Wastewater-based Population Health Assessments

by

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ABSTRACT

Uncertainty is inherent in predictive decision-making, both with respect to forecasting plausible future conditions based on a historic record, and with respect to backcasting likely upstream states from downstream observations. In the first chapter, I evaluated the status of current water resources management policy in the United States (U.S.) with respect to its integration of projective uncertainty into state-level flooding, drought, supply and demand, and climate guidance. I found uncertainty largely absent and discussed only qualitatively rather than quantitatively. In the second chapter, I turned to uncertainty in the interpretation of downstream observations as indicators of upstream behaviors in the field of Wastewater-Based Epidemiology (WBE), which has made possible the near real-time, yet anonymous, monitoring of public health via measurements of biomarkers excreted to wastewater. I found globally, seasonality of air and soil temperature causes biomarker degradation to vary up to 13-fold over the course of a year, constituting part of the background processes WBE must address, or detrend, prior to decision-making. To determine whether the seasonal change in degradation rates was introducing previously unaccounted for uncertainty with respect to differences in observed summertime and winter-time populations, I evaluated demographic indicators recorded by the Census Bureau for correlation with their distance from all major wastewater treatment plants across the U.S. The analysis identified statistically significant correlation for household income, education attainment, unemployment, military service, and the absence of health insurance. Finally, the model was applied to a city-wide case study to test whether temperature could explain some of the trends observed in monthly observations of two opiate compounds. Modeling suggests some of

the monthly changes were attributed to natural temperature fluctuation rather than to trends in the substances' consumption, and that uncertainty regarding discharge location can dominate even relative observed differences in opiate detections. In summary, my work has found temperature an important modulator of WBE results, influencing both the type of populations observed and the likelihood of upstream behaviors disproportionally magnified or obscured, particularly for the more labile biomarkers. There exists significant potential for improving the understanding of empirical observations via numerical modeling and the application of spatial analysis tools.

DEDICATION

First and foremost, to BQT.

And to everyone else who has made the experience not only possible, but profoundly rewarding.

…Ну вот и пошёл инженер (DBA гусь), наконец-то строя из себя девушку…

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LIST OF SYMBOLS

k	thermal diffusivity at target saturation
k_0	thermal diffusivity of dry soil
a	difference between the highest thermal diffusivity at the optimal water content and the thermal diffusivity of dry soil
b	half-width of the peak of the thermal diffusivity as a function of water content curve
θ	actual volumetric water content
θ_0	optimal water content
$T_{soil\,(D,t_{year})}$	soil temperature at given time of the year and depth below ground surface
T_{mean}	mean monthly air temperature
T_{amp}	amplitude: equal to half of the difference between the maximum and minimum monthly temperature
D	soil depth at which temperature is calculated
α	soil thermal diffusivity
t_{year}	time elapsed from the beginning of the year until the time of interest
t_{shift}	mid-point of month with the lowest surface temperature (elapsed time from Jan 1)
ΔT	heat loss or gain in wastewater flowing in a pipe from interaction with soil and air
q_{wa}	thermal heat loss between wastewater and air
q_{ws}	thermal heat loss between wastewater and soil
m	mass flow rate of wastewater
c_p	thermal heat capacity
R_1	initial half-life
T_1	initial temperature at which initial half-life was derived,
R_2	half-life at calculated temperature,
T_2	calculated temperature to which initial half-life is adjusted to,
Q_{10}	factor of temperature-dependence of rate change.

CHAPTER 1

INTRODUCTION

Few infrastructures provide more anonymous, resource-efficient access for continuous, near-real time monitoring of the health of large urban populations than the municipal wastewater collection system. By its nature, wastewater is an ideal matrix for the study of daily consumption and metabolism. Wastewater-based Epidemiology (WBE) has been used to monitor population-scale consumption of various illicit and recreational substances, medications, and exposure to environmental toxins and contaminants. More recently, WBE has been explored as a tool for monitoring dietary choices and overall nutrition as well as the impact of air quality and temperature on public health. Although many of the proposed dietary and mental and physical health biomarkers have yet to be fully tested in wastewater matrices, the field is rapidly moving towards the evaluation of antibiotic resistance and changes in microbiome. In short, over the last decade, WBE has been shown to be an effective, increasingly viable method for the evaluation of human health at large scales, with analytic techniques developed to identify even minute volumes of substances of interest. These advances have positioned practitioners of WBE to consider larger, and longer-lasting longitudinal studies.

While WBE has emerged as a non-invasive, non-intrusive, technique attractive for its protection of the anonymity of groups of individuals monitored, WBE studies are structurally vulnerable to uncertainty as to the size and type of population represented by the measurements collected at central monitoring points downstream of the contributing individuals.

In this dissertation, I attempt to further bracket this uncertainty by integrating modeling into the interpretation and future design of field- and lab-based wastewater-based epidemiology (WBE) studies. The results of these modeling experiments are intended to inform future WBE efforts two-fold. On the front end, modeling experiments can lead to better-designed monitoring studies, such that the selection of biomarkers of interest and population estimate methods are matched to a study area and its hydraulic and demographic characteristics. On the back end, these models can assist in better interpreting experimental results obtained in the field, such that decision-making is less skewed by biases in the data which are the result of non-experimental factors, like ambient conditions.

Hypotheses

The underlying hypothesis being tested in this dissertation is that 1) seasonal air and soil temperature, by modulating the temperature of wastewater and the speed with which wastewater temperature achieves equilibrium, will result in different rates of in-sewer degradation for any biomarker of interest; that in turn, this will lead to 2) different upstream extents and minimum initial mass loads observable at downstream sampling locations; and finally that 3) these seasonal differences in degradation rates can result in statistically-significant changes in populations observable at the same sampling location, and 4) that temperature-related seasonality can be observable in field measurements of substances with public health significance, such as opiates.

Objectives

The objectives of this dissertation are as follows:

a) To identify to what extent wastewater temperature is expected to fluctuate over the course of a year across the world, and what impacts these fluctuations are expected to have on the degradation rates of biomarkers, the maximum distal reach of WBE observation, and the population captured by downstream sampling,

b) To identify to what extent the seasonal change in distal reach resulting from the acceleration or retardation of biomarker degradation in response to seasonal changes in wastewater temperature can lead to the observation of demographically distinct populations at the same sampling location in winter versus summer months, and,

c) To test, on a local scale, whether the proposed model of temperature dependence may explain some of the monthly differences observed in a real-world year-long opiate monitoring study, and to extrapolate the impact seasonal differences in degradation may have on estimates of per-capita opioid consumption.

CHAPTER 2

ON THE NEED TO INTEGRATE UNCERTAINTY INTO U.S. WATER RESOURCES PLANNING

Abstract

A changing climate is expected to inject uncertainty into water resource management decision making. We examined the latest publicly available, state-level guidance regarding the management of water supplies and demands concerning risks associated with drought, flooding, and climate change. We found state-level guidance supplementing the federally backed flood mitigation program to be updated most regularly (54% in the last 5 years; 84% in the last decade). Yet, the underlying floodplain mapping data these local planning efforts rely on are acknowledged by the Federal Emergency Management Agency (FEMA) to be chronically outdated. Drought planning guidance was found to be most outdated (16% last updated in the last 5 years; 18% almost two decades ago), and across the U.S., almost universally (94%) reactive (emergency response) rather than proactive (mitigation or management). Although 79-94% of states provide some level of guidance regarding water supply and demand, the projections themselves may significantly predate the guidance. Many (70%) U.S. states still lack climate change impact guidance, particularly non-coastal states and those impacted by increased water scarcity rather than flooding. Strategies are rare (4%) for addressing the impacts of increased variability and uncertainty to meet inelastic demands with finite supplies. We conclude significant gaps exist in planning to address known or projected risks of climate-related impacts. Specific recommendations, including the

implementation of a nationwide water census, are provided to improve both the data and knowledge base of water management and reduce current vulnerabilities.

Introduction

Today's global and local climates deviate from historical records collected over the past two centuries, a fact that poses new challenges. Human activities are affecting climate (Easterling et al. 2000; Short et al. 2012; UNFCCC 2015; Marotzke et al. 2017; Cai et al. 2019) and introducing a new level of uncertainty into forecasts. Recent analyses indicate that even if all anthropogenic greenhouse gas emissions were to cease immediately, the impacts of legacy emissions would continue for some time (Meishausen et al. 2011). Thus, our climate is already altered (Milly et al. 2008; Cubasch et al. 2013; Yang et al. 2015) and historical records are becoming less illustrative of future climate events (Rummukainen 2012). While climate change mitigation is important, near-term adaptation by human populations is unavoidable (Hanemann et al. 2012).

Water resources are an important aspect of climate change. As the extent and frequency of extreme climate events increases, the probability grows of unprecedented and potentially irrevocable changes in planetary processes (Alexander et al. 2006). These changes will challenge communities around the world to adapt their use and governance of water, both regionally and locally (Mujumdar 2013; Liu et al. 2018). Experts have observed the emergence of more extreme weather patterns, with direct implications for water resources management (Kunkel et al. 2013; Westra et al. 2014; Peterson et al. 2013; Janssen et al. 2014; Vose et al. 2014; Wuebbles et al. 2014; Hirsch and Archfield 2015; O'Gorman 2015; Seeley and Romps 2015; Feng et al. 2016; National Academies of Sciences, Engineering and Medicine 2016; Pathak et al. 2017). An altered climate will change the distribution and magnitude of water supplies and influence the distribution and magnitude of anthropogenic water demands, particularly for agriculture and power production, and ecologic water demands, particularly via evapotranspiration (Huntington 2006).

Until recently, we had been designing infrastructure and crafting policies under the premise that natural fluctuations in hydrologic parameters fall, and will continue to fall, within an unchanging envelope of variability. This unchanging variability is known as the principle of stationarity (Milly et al. 2008). Under stationarity, while the day-to-day value of any particular hydrologic parameter may be more or less difficult to predict, the overall range – and thus overall uncertainty – in the expected range of parameter values can be known from historic records. Thus, in the past, regulations relied heavily on historical climate records to assess risk and plan for uncertainty in largely deterministic ways (Huskova et al. 2016; Pahl-Wostl 2007; Liu et al. 2013).

Uncertainty in the water sector, like in other physical systems, is composed of epistemic and aleatoric components (Der Kiureghian and Ditlevsen 2009; Beven 2013; Jiang et al 2016; Gardoni 2017). The former is a function of our imperfect ability to measure every input and thus, there being some uncertainty associated with our outputs. The latter relates to the highly variable behavior of some systems. For instance, rainfall characteristics (frequency, intensity, duration) may fall within known bounds, but the amount of daily rainfall a year from today can be effectively considered random. That is why many rainfall generators rely on descriptive statistics sampled from an observation record to regulate mean storm recurrence and intensity, but use random processes to generate the discrete pulses themselves (Rodriguez-Iturbe et al. 1987; Rodriguez-Iturbe et al. 1988; Heneker, et al 2001; Willems 2001; De Michele and Salvadori 2003; Furrer and Katz 2008; Muller et al. 2009; Serinaldi 2009; Ailliot et al. 2015; Ben Alaya et al. 2015; So et al. 2015; Shamir et al. 2015; Shamir 2017; Shahraki et al. 2019). Epistemic uncertainty may be easier to reduce (e.g., by investing in finer-resolution weather satellites; expanding stream gauge and soil moisture sensor networks; implementing SCADA systems to collect data on water use in real-time), but it may be more difficult to quantify a priori, since it is an unknown unknown. By contrast, we may not have the means of reducing aleatory uncertainty (e.g., some variability in climate will remain regardless of recent climate change), however, we can describe and quantify it using probabilistic methods.

A growing body of work is demonstrating the aleatory component of uncertainty is increasing and that water resources management decisions made under past climate normals are failing to satisfy the reality of a changing climate (Huskova et al. 2016; Wilbanks and Fernandez 2014; Shamir et al. 2015; Sharma and Wasko 2019). Increasingly, we are seeing changes in runoff, streamflow, and precipitation that are large enough to push hydroclimate beyond the range of historical behaviors (Seager et al. 2007; U.S. Climate Resilience Toolkit; IPCC 2014). Uncertainty around the excess or deficit of water is negatively coupled with economic prosperity and political stability, particularly in transboundary settings (Albrecht et al. 2017; Movilla-Pateiro 2016; Salman 2007; Giordano et al. 2014; Conti 2014; Eckstein 2013; Bernauer 2002; Gerlak et al. 2011; Megdal and Scott 2011). That uncertainty will matter more than ever before as the era of stationarity comes to an end (Milly et al. 2008).

Are we doing what is necessary to adapt to this change? How prepared are we to plan, design, and invest in the face of escalating uncertainty? The objective of this paper is to address these questions by:

(A) exploring where increased climate uncertainty may impact and impair water resource planning;

(B) assessing how prepared we are today to face future challenges;

(C) highlighting areas in which we stand to improve our preparedness; and

(D) providing recommendations for moving forward.

Methodology

A search of U.S. state-level drought, flood management, supply, and demand guidance documents was conducted between late Summer and early Fall 2018. A database was created to provide citations for the latest-available guidance documents analyzed and included in this study. These data were joined to state shapefiles retrieved from the U.S. Census Bureau in Fall 2018. Risk maps, providing an indication of projected risks associated with drought, flooding, supply, and demand were adapted from the U.S. Environmental Protection Agency's EPA's Climate Change Impacts and Risk Analysis (CIRA) project data (EPA 2015). To better demonstrate the implications of future uncertainty on the complexity of planning efforts, the range of impacts across each of the projections (projections include the outputs of different global climate models, such as IGSM-CAM (MIT's Integrated Global System Model (IGSM) coupled with the National Center for Atmospheric Research Community Atmosphere Model (CAM); see Monier et al. 2013) vs MIROC (University of Tokyo's Model for Interdisciplinary

Research on Climate; see Watanabe et al. 2011), as well as the impacts of no-action vs. some emission mitigation) were mapped. Projected climate impacts, mapped to the county level, were adapted from Hsiang et al. 2017.

Results and Discussion

Where We are Today

The review uncovered significant gaps in states' preparedness with respect to water resource planning and uncertainty (Figure **Error! No text of specified style in document.**-1, Table **Error! No text of specified style in document.**-1). Compared with drought, supply and demand, and climate change guidance, state-level flooding guidance supplementing the federally backed flood mitigation program has been most recently updated (54% in the last 5 years; 84% in the last decade). Yet, the underlying floodplain mapping data these local planning efforts rely on are acknowledged by the Federal Emergency Management Agency (FEMA) to be at least in part, chronically outdated (DHS 2017). Particularly in rapidly developing and inland (vs. coastal) parts of the country, FEMA struggles to keep up with the compounding effects of climate and land use change (ASFM, 2011; DHS 2017). Drought planning guidance is almost universally (94%) reactive (emergency response) rather than proactive (mitigation or management). Only 16% of states had updated their drought guidance in the last 5 years, whereas 18% continue to rely on guidance published almost two decades ago. Although 79-94% of states provide some level of guidance regarding water supply and demand, the projections themselves may significantly predate the guidance. 70% of US states still lack climate change impact guidance, particularly inland, non-coastal states and those which will suffer from increased water scarcity rather than flooding.

Finally, we find uncertainty too-rarely (as few as 20%) mentioned, and even more seldom adequately explained. As few as 4% of guidance offer strategies for addressing or mitigating the impacts increased variability and uncertainty will have on the states' ability to fulfill demands with finite supplies.

Hsiang et al. (2017) perform their analysis using only one global circulation model (GCM). However, because they map their projections to the county level, the data nevertheless provides a good illustration of the spatial variability that state-level guidance must address. In reviewing the projected risks associated with climate-related impacts to the water sector, we find the threats – and uncertainty – unevenly distributed across the U.S. The southeastern United States is projected to be the strongest-hit by climate-related impacts to the water sector (Hsiang et al. 2017). The figure communicates net economic impacts, at the county level, related to climate change. Some counties in the U.S. were found to have no detrimental impact, or even a positive economic impact, from a changing climate. Thus, we make a determination of no risk. However, lacking a planning process or guidance may pose a risk in itself. Further, if for instance, increased agricultural productivity or tourism offsets the impacts of increased storm surge, the net impact may show no risk, even as there is a very real impact when the results are disaggregated. This is a limitation to any composite measures of risk, however, and particularly when applied to something like climate change in the water sector, in which components act in opposite direction (e.g., drought vs flooding).

The uncertainty pertaining to our current best estimates is generally largest in the southeastern United States, and smallest in the northeastern United States. Although northern in-land states are not, as a whole, particularly well (or better) prepared, these states are projected to face a lesser magnitude of risk with respect to future drought around which there is greater agreement between different GCMs. Adequate preparation plans may be simpler to develop than in regions, such as the southeast, where there exists more uncertainty around the magnitude and direction of impact of climate on water resources. With the exception of California and Florida, states least prepared for climate change (in terms of the lack of climate change planning guidance), are at risk for higher damages associated with climate change as a percentage of income (Hsiang et al. 2017).

Hawaii and Alaska were part of the planning guidance document review. The results of this effort are shown in Table **Error! No text of specified style in document.**-1. However, the bulk of national-level climate modeling for the U.S. has, to date, been limited to the contiguous states. State-level climate modeling studies for Hawaii and Alaska that used a methodology consistent with that used for the continuous U.S. studies were not available. Thus, the two states are not shown in Figure **Error! No text of specified style in document.**-1.

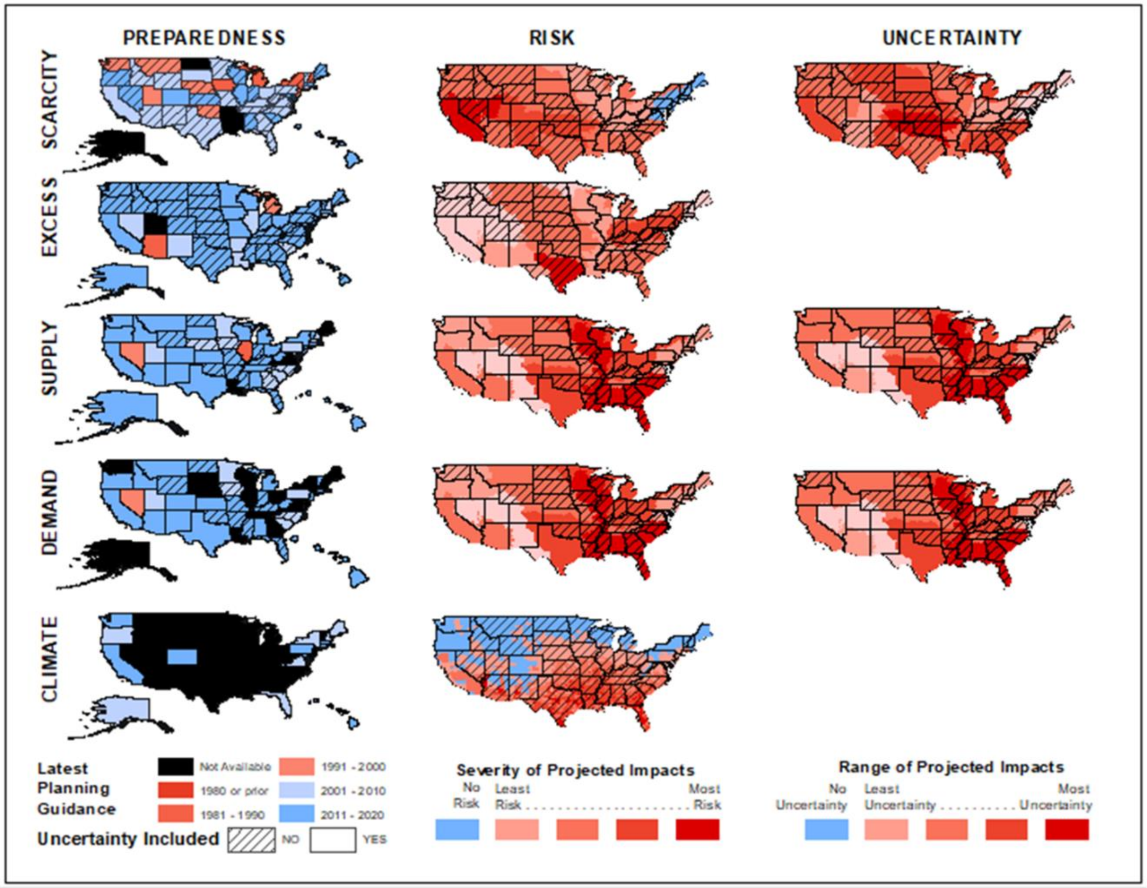

Figure **Error! No text of specified style in document.**-1. Existing water resource planning efforts do not adequately address climate-induced uncertainty and risks. Nationwide there exists a mismatch between levels of preparedness and projected risk, particularly in the Southeast and Midwest.

Table **Error! No text of specified style in document.**-1. Current preparedness of U.S. states to deal with uncertainty related to climate change

Scarcity (Drought)	• 45 U.S. states have a state-wide drought plan; 5 do not (AK, AR, LA, MS, ND). • 9 states (AK, AR, IA, LA, MI, MS, MT, NH, NJ, NY, ND, OK, UT, and WA) last issued or updated their current drought plans prior to 2000. • 8 states (DE, HI, IN, ME, MD, OR, SC, WI) have drought plans issued in the last 5 years. • 10 states mention uncertainty in drought guidance (CA, CO, HI, IL, IA, KY, MI, OH, SD, UT) • 40 states do not include any language around uncertainty associated with planning for and anticipating the timing, duration, intensity of droughts. • Most states (up to 47) provide drought guidance that is reactive rather than proactive

Excess (Flooding)	• 49 U.S. states provide state-level flood guidance; 1 state (Utah) does not. • 27 states have flood guidance published or updated in the last 5 years. • 42 states have flood guidance published or updated in the last 10 years. • 34 states do not include uncertainty in any form in their flood management guidance. • Of the 16 states (AK, AZ, AR, CA, IL, IA, LA, MD, MA, MN, MO, NV, NH, NM, OH, WI) that do mention uncertainty associated with the timing, spatial distribution, duration, or intensity of flooding forecasts, 14 do not provide any additional or site-specific guidance for addressing the uncertainty beyond the FIMA boilerplate suggestion of voluntarily incorporating an extra 1 foot of freeboard (height above a minimum estimated base flood elevation) during the initial construction process) as a factor of safety. • 2 states (AZ, CA) are unique in that they go beyond the federal boilerplate language and offer additional guidance on the uncertainty associated with flooding. Arizona provides a matrix of recommended and inadvisable calculation methods based on risk level; California elaborates on the sources of uncertainty with flooding mapping and flood management, esp. when hazards are projected over the long term.

Supply	• 47 states have some form of state-wide water supply guidance; 3 states (LA, ME, VA) do not. • 25 states have state-level water supply guidance published or updated in the last 5 years – however, the supply estimates on which this guidance relies on have not necessarily been updated in the last 5 years. • 39 states have state-level water supply guidance published or updated in the last 10 years – however, the supply estimates on which this guidance relies on have not necessarily been updated in the last 10 years. • 25 states acknowledge that there exists uncertainty with respect to water supplies, particularly for projections at longer time scales; another 25 of 50 states do not.

Demand	• 35 states have some form of state-wide water demand guidance; 15 states (AK, GA, IL, LA, ME, MD, MA, NH, NY, OH, SD, TN, VA, WA, WI) do not. • 19 states have state-level water demand guidance published or updated in the last 5 years – however, the demand estimates on which this guidance relies on have not necessarily been updated in the last 5 years. • 29 states have state-level water demand guidance published or updated in the last 10 years – however, the demand estimates on which this guidance relies on have not necessarily been updated in the last 10 years. • 22 states acknowledge that there exists uncertainty with respect to water demands, particularly for projections at longer time scales; another 28 of 50 states do not.

Climate Impacts	• Only 15 (AK, CA, CO, CT, FL, HI, ME, MD, MA, NH, NY, OR, PA, VA, WA) have issued guidance and planning materials pertaining to climate change and its impacts on water resources; 35 states have no such guidance. • Of those 15 states with state-level climate change guidance, only 1 (California) is in a semi-arid region of the country. • Of those 15 states with state-level climate change guidance, only 1 (Colorado) is non-coastal. • Of those 15 states with state-level climate change guidance, only 3 (CA, HI, PA) were last published or updated in the last 5 years. • In existing guidance, there is significant recognition and acknowledgment of uncertainty – both in the climate projections themselves, and in climate's changing impact on water supplies and demands as well as the occurrence of episodes of drought and flooding.

These findings overlie a national under-investment in water resources. Funding for water-resource infrastructure lags what is necessary to maintain and modernize existing assets. The American Society of Civil Engineers estimates across the nation, the deficits amount to $105 billion for water and wastewater infrastructure, $15 billion for inland waterways and marine ports, $39.4 billion for dams, and $70 billion for levees (ASCE 2017). With federal and state-level funding for infrastructure declining, the burden to address these deficits falls to municipalities and local utilities. Although 80% or more of the spending in the water sector is currently occurring at the municipal level

(Koehler 2018), many communities lack the tax base to address their part of the nearly $230 billion national water sector deficit (ASCE 2017).

Promising Forward Progress

With respect to better understanding (quantifying) variability and uncertainty

As modern water infrastructure continues to become more reliant on automation via SCADA (Supervisory Control and Data Acquisition) control systems, utilities around the country are beginning to apply their SCADA systems to tasks like preventative maintenance and leak detection. Data reported by American Water Works Association suggests non-revenue water (lost and unaccounted for water) rates are as high as 43% in major U.S. cities and over 85% in rural communities (Arcadis and Bluefield 2018; American Water Works Association 2018). The implementation of SCADA for preventative maintenance and leak detection is doubly beneficial, as it helps better manage water in the face of increasing risk of water scarcity (Figure **Error! No text of specified style in document.**-1) and prevents the $230 billion backlog of investment in water resources infrastructure from growing as a result of premature asset failures.

Some utilities are already moving beyond these more basic tasks, by implanting SCADA in conjunction with analytics tools for predictive purposes. The Tarrant Regional Water District (TWRD) in Texas is leveraging machine learning technology in addition to SCADA to track real-time energy market conditions and the energy consumption of energy-intensive assets used in daily operation of its water conveyance system. The energy management optimization tool includes an alert system for energy market conditions, a capability to proactively simulate power consumption impact of operational changes before they are implemented, and a platform to integrate asset performance levels (Arcadis 2018). While SCADA systems do not replace expert operators they can, and do, supplement them. Coupled with the appropriate analytics and alert levels, SCADA can improve the ability of utilities to respond to frequent fluctuations or rapid spikes in operational parameters and to carry out probabilistic decisions by mining data collected by the SCADA system in the past.

With respect to developing tools for communicating uncertainty to decision makers

Dynamic simulation tools have been recommended for environmental resource management for several decades (Costanza and Ruth 1998; Simonovic and Fahmy 1999; Stave 2003; Winz et al 2009; GoldSim 2016). The availability of object-oriented, modular, GUI-based platforms to build hitherto computationally complex system-dynamics models has increased participation by utilities and governmental agencies (GoldSim 2016). These software tools are being used to develop comprehensive models which are capable of simulating long-term planning horizons, numerous competing demands, and alternative supply and demand scenarios, while remaining interactive and informative to stakeholders with various levels of modeling expertise. In Arizona, the Central Arizona Project Service Area Model (CAP:SAM) was developed by CAP staff and is used to aid the management of the Central Arizona Project (CAP 2017). The Central Arizona Project (CAP) is tasked with managing and delivering all the state’s off-river allocation of the Colorado River (up to 1.5 million acre-feet per year) to municipal and industrial users, agricultural entities, and Native American tribes, serving 80% of the state’s population in the process (Hanemann 2002). CAP:SAM projections incorporate variable rates and patterns of growth, shortage levels, effluent reuse patterns, aquifer recharge and recovery plans, and complex supply portfolio management decisions (Emanuel et al.; Seasholes et al.). The model is successful not only in its ability to provide a central repository for large amounts of disparate data, but as a cohesive and more easily digestible tool for CAP planners to communicate with water users and decisionmakers about issues facing the state's water resources. Similarly, in California, the CalLite model was developed through a partnership between the California Department of Water Resources and the U.S. Bureau of Reclamation to simulate operation of California's State Water Project and Central Valley Project (Islam et al. 2010). CalLite is used to screen proposed water management projects throughout California and provides a platform for rapid and interactive policy evaluations which can be revised in collaboration with stakeholders and decisionmakers.

The more these probabilistic models are built in-house by the water resource management agencies themselves, the more likely they are to be used, because 1) consensus regarding the need for these tools, their major assumptions, and critical capabilities and has been reached; 2) sufficient institutional capacity to run, interpret, maintain, and update the models has been developed; and 3) ownership in the process and product will prolong the period of time the models will be maintained.

With respect to implementing policies to manage the impacts of uncertainty

Whereas official redactions to water right law are slower in coming, across the country voluntary programs are emerging. Conserve to Enhance (Schwarz and Megdal 2008) and the Verde River Exchange Water Offset Program (Cronin et al. 2017) are two successful examples. Conserve to Enhance (C2E) is a voluntary municipal water conservation program; each billing cycle, participating households or businesses are notified of monthly savings they accrued as a result of their voluntary conservation efforts. Participants may then elect to donate the value of the savings to the C2E grant pool. Funds are disbursed annually as grants for projects which enhance local water resources and the environment, such as stream restoration, rainwater harvesting, or stormwater control. The Verde River Exchange was established in 2016 to provide local groundwater users a mechanism by which to reduce the impact of groundwater pumping on the Verde River. Without forfeiting or gaining long term water rights, participants may purchase annual credits from other Exchange participants who elect to withdraw less than their allotted share during a given water year. It is the first voluntary groundwater mitigation program in operation in the U.S. (Cronin et al. 2017). Neither program negates the uncertainty associated with future water supplies and demands. However, as a tool encouraging conservation and promoting the idea of banking water (whether legally or physically) for lean times, these programs can buffer communities from the impacts of short-term water-stress while capacity for longer-term solutions is developed.

Across the country, new rainfall intensity-duration-frequency (IDF) curves are being calculated, new design storms are being generated, and new materials are being specified in response to a changing climate (PANYNJ 2018). Updated design manuals and master plans reflect these changes. However, little-to-no retrofitting of existing infrastructure does. Insofar as infrastructure is concerned, funding is the principal bottleneck. However, in May 2018, the Governmental Accounting Standards Board issued an Implementation Guidance Update that opens new funding mechanisms for green infrastructure (GASB 2018). Under the new GASB guidance, not only the initial installation, but also the ongoing maintenance of green infrastructure like green roofs or permeable pavements, will be considered capital assets if they are part of water utilities' distributed infrastructure. As assets, these line items can be funded via bonds, thus opening new, deeper funding sources than what exists for operation and maintenance activities under previous standards.

Evidence from other large federal water-related investments suggest that the move towards smaller and more privatized funding in the water sector will continue. Change in FEMA policy may be forthcoming to address the agency's $24 billion debt (Palmer 2017), as it shifts its strategy away from funding rebuilding efforts and towards relocation (Moore 2017). If privatized, the non-subsidized cost of insuring home in flood zone could discourage sprawl into low-lying flood-prone areas by market forces rather than regulation.

Finally, some cities are beginning to move towards developing guidelines for both qualitative and quantitative cost-benefit analyses that consider more novel categories such as ecosystem services, service losses, stress and anxiety, and quality of life and health benefits, recommending sensitivity analyses, and pricing ecosystem services as they relate to making communities more resilient to the impacts of climate change (NYC ORR 2019; FEMA 2016). NYC planners in particular are promoting the integration of flexible adaptation pathways, particularly for infrastructure projects with a useful life exceeding 50 years (NYC ORR 2019).

Remaining Gaps

In planning for drought, the prevalent lack of discussion of uncertainty may be attributed in part to the fact that drought forecasts are usually made on much shorter time scales than projections of water supply and demand or flooding, which helps reduce the uncertainty associated with the forecasts. Drought forecasts are made on time scales ranging from one to four months (NOAA CPC). By contrast, projections of supply and demand rely on assumptions made for much longer timescales. For instance, Arizona state statutes require the demonstration of 100-year assured water supply which necessitates forecasting supply and demand 100 years into the future (A.R.S. § 45-576). We have expanded this section to include the discussion provided above as well as the references cited. Secondly, most current state-level drought guidance is reactive rather than proactive. It is aimed at addressing drought once the state of emergency is declared, rather than planning for it, or anticipating its occurrences in the future.

In flood management, the universal recommendation for additional freeboard (height above a minimum estimated base flood elevation) during construction does provide some buffer for unforeseen flooding events. However, freeboard elevations are calculated based on FEMA base flood elevation maps which for many communities, particularly in non-coastal areas which represent the majority of the country's landmass, are outdated. In areas, like the northeastern U.S., undergoing rapid land development and/or rapidly changing climate normals (averages of climatological variables including temperature and precipitation (Arguez et al. 2012)), one foot of additional freeboard based on outdated flood elevation maps may be insufficient to prevent flooding.

Of the 25 states whose water supply guidance acknowledges that there exists uncertainty with respect to water supplies, particularly for projections at longer time scales (Table **Error! No text of specified style in document.**-1), none describe practical suggestions, infrastructure tools, or legal mechanisms to help mitigate its effects. The 25 states which do acknowledge the existence of uncertainty do not quantify it. Lacking even an order of magnitude estimate of the envelope of uncertainty around a state's current water supply estimates and projections makes planning efforts more brittle, as these plans are tailored to a narrower set of future scenarios than are plausible.

Water demands are also subject to uncertainty, particularly in the context of long-term planning (USBR 2011). Similarly to water supply, we find uncertainty in water demand estimates and projections not quantified in the reviewed state-level guidance even by the 22 states whose planning guidance does acknowledge the existence of uncertainty (Table **Error! No text of specified style in document.**-1, Figure **Error! No text of specified style in document.**-1). Socioeconomic drivers behind water demands are as important as the biophysical drivers behind water supply, but much of the knowledge exists outside of the water sector (USBR 2011). Further, in many states, de minimis users (especially of groundwater) are legally exempt from reporting their water use. Thus, there is also un-represented uncertainty with respect to historic and current water demand that we can estimate only by indirect indicators such as population and per capita daily water consumption estimates (themselves subject to uncertainty).

Finally, there is a lack of coverage and a lack of diversity in the types of climate-related water resource impacts that are being addressed across the nation at present. For instance, because coastal states are over-represented among those with climate planning guidance, more guidance is available for adapting to sea level rise and flood surge than to drought. Such guidance will be of little assistance to states tasked with developing climate impact plans in which scarcity is a more probable risk (Figure **Error! No text of specified style in document.**-1). With the exception of California and New York, most available state-level climate change guidance documents do not offer up any concrete steps to address uncertainty.

Recommendations

Table **Error! No text of specified style in document.**-2. Recommendations for U.S. states to deal with uncertainty related to climate change.

Scarcity (Drought)	• For states with no drought response guidance (AK, AR, LA, MS, ND), develop such guidance. • For states with pre-2000 guidance (AK, AR, IA, LA, MI, MS, MT, NH, NJ, NY, ND, OK, UT, and WA), consider the likelihood of the plans' obsolescence and update as needed. • Expand drought planning to include adaptation and mitigation strategies (that acknowledge the uncertainty around the timing, duration, and intensity of drought events) rather than simple emergency response measures. • Develop and include in planning guidance tiered shortage levels that occur as a state of drought is approached; tie these to legal mechanisms which provide the state progressive authority to begin emergency-level regulation of water demands in advance of absolute drought conditions.

Excess (Flooding)	• Collaborate with FEMA to develop guidance language around the limitations of FEMA flood maps and floodplain delineations to aid public and developers in interpreting the assurances and limitations of these models more correctly. Refer to current CA and AZ approaches for examples (Table **Error! No text of specified style in document.**-1). • Integrate, where appropriate, ecological engineering and green infrastructure options into flood management recommendations as an additional tool for managing uncertainty in addition to (or if appropriate, instead of) the standard 1-foot freeboard. This can be more effective on a local level and would not duplicate federal-level efforts by FEMA. Just as freeboard provides a factor of safety (buffer) against the uncertainty around flood elevations, green infrastructure (e.g., as permeable pavements, swales and berms, constructed/managed wetlands, vegetated buffers, greenways, etc.) provides additional capacity to contain storm/floodwater that happens to exceed design assumptions. • Seek to integrate land use (zoning, general plans) and water resource planning where possible to address floodplain problems proactively rather than reactively by decreasing the amount and value of infrastructure constructed in vulnerable areas.

Supply	• For water supply planning, integrate land use and water resource planning to better steward land representing critical supply sources (e.g., streams, mountain fronts, areas with snowpack); Better integrate demographic data (population growth projections) into water use planning to prevent over-development and over-allocation in areas with known water supply limitations. • On monthly and annual scales, track how projected volumes of renewable water supplies for key watersheds have compared to actual availability of snowpack, streamflow, or other indicators of concern. • Use discrepancies to re-calibrate the models used to generate projections, adjusting the conceptual model (projection assumptions) if required. If needed, use discrepancies to direct investment in better tools and additional data collection for watersheds or processes (e.g., streamflow; snowpack) which are more poorly simulated by predictive models. • Quantify the uncertainty associated with water supplies, both seasonally and annually. • Consider how poor water quality may impact water supply and incorporate into projections as a reduction in water available to serve municipal, agricultural, industrial, and/or ecological needs: if infrastructure and funding are not available to remediate or treat water

	such that it can be used to meet existing productive demands, it is effectively unavailable as a source of supply. • Identify and quantify how upstream water management decisions may affect downstream availability (particularly in transboundary settings). • In conjunction with demand planning, review all allocations which rely on supply predictions; identify the sensitivity of unmet demand (or new surplus) to anticipated changes in supply – particularly at the upper and lower bounds of the envelope of uncertainty calculated for water supply.

Demand	• To improve demand planning, conduct a water census to establish baseline; require all water users to report their annual water use, regardless of exemption status (e.g., domestic/de minimis users, Native American reservations, federal lands) or water source (e.g., surfacewater vs groundwater vs reclaimed water). Repeat every n-years, basing census frequency on growth, overall supply availability, and amount of risk and uncertainty acceptable to constituents. • Use water census to generate n-year water priorities and cutback programs subject to the limits of state jurisdiction; integrate into emergency drought response and tiered shortage plans. • Evaluate alternative demand alternatives whenever possible, to better understand how closely to over-allocation the system is operating (e.g., when demand exceeds supply). • For states which do not track de minimis users, initiate efforts to document the number of users and locate their water abstractions in space. Subsequently, require annual reporting of de minimis users' withdrawals. • For states with larger seasonal fluctuations in water demands (e.g., related to climate, water use sector (i.e. agricultural vs large urban), and demographics (i.e., snowbird populations vs lack thereof), consider requiring reporting on annual or seasonal, rather than annual, time scales.

	• In approving new water claims, utilize a moving target (x years of demonstrated uninterrupted water supply with y% certainty); base timeframe on type of right, consider requiring a re-issuance of rights in n-years to balance the need for some certainty for development and consumer protection with an understanding that excessively long projections may have unacceptably wide margins of uncertainty.
Climate Impacts	• More critically consider steps to adaptation and mitigation rather than just acknowledging impacts may occur. • Document changes to climate normals across the state; if data are lacking, design and implement monitoring networks and analysis protocols to collect and interpret these data moving forward. • Update specific guidance documents, such as stormwater conveyance design manuals, in which assumptions related to probable precipitation, temperature, or other hydrologic indicators are based on climate normals. • Identify key infrastructure and planning tools designed for climate normals which are significantly exceeded by current and/or projected climate; identify adaptation or mitigation measures to increase their resilience; retrofit, retire, or reinforce as needed.

Additionally, to continue making meaningful strides towards identifying sources of uncertainty, quantifying their impacts, and taking appropriate steps towards mitigating negative externalities we recommend the community continue working to close the gap in climate models. Despite advances, the need for better data and better climate models remains (DWR 2008). Divergence of GCM-based projections of water supply and flood risk leads to lack of clear guidance for decision makers and operators. While projected variability (more erratic climate) may be a legitimate reality, projected divergence between GCMs is not. When resources are under-allocated towards determining which projection scenarios are more likely, costly water resources infrastructure (already subject to a $230 billion deficit) is over-engineered, and additional uncertainty is passed along to challenge decision makers. The climate science community should continue to make strides in how it curates, reviews, and ranks the outputs of its modeling efforts.

Conclusions

In the United States, our survey of state-level planning guidance found states currently under-prepared or entirely unprepared to address the impacts clime change will have on our ability to manage drought, flooding, supply and demand. Coastal states lead the nation with respect to climate planning, but the lessons learned may not be transferable to those in-land – particularly in semiarid regions projected to face increased aridity rather than coastal flooding. We find that although uncertainty has begun to leak into the vernacular of state-level planners (with 10 out of 50 states-level guidance acknowledging the presence of uncertainty with respect to drought planning, 16 of 50 for flooding, 25 of 50 for water supply, 22 of 50 for water demand, and 15 of 50 for climate impacts), the magnitude of the uncertainty is not quantified nor are its sources explicitly identified. To that end, we recommend the water community embrace a planning process that is more tolerant of variability, work to map and quantify uncertainty, and wherever possible, increase the amount of empirical data that projections, as well as other design and planning tools, are based on. Doing so will improve the nation's ability to plan, design, and invest in the face of escalating uncertainty.

CHAPTER 3

MODELING WASTEWATER TEMPERATURE AND ATTENUATION OF SEWAGE-BORNE BIOMARKERS GLOBALLY

Abstract

Accurate modeling of in-sewer degradation of sewage-borne epidemiological biomarkers requires information on local wastewater temperature. We applied a deterministic, physical model to map theoretical wastewater temperature on a monthly scale worldwide and incorporated in the model estimated changes in the decay rate of 31 biomarkers of public health relevance frequently used in wastewater-based epidemiology (WBE). Over the course of a year, 75% of the world's global wastewater temperatures were estimated to fall into the temperature range of 6.9 to 34.4°C. These modeling results were in good agreement with empirical observations (*n*=400), as indicated by coefficients for Pearson (0.81; 0.76) and Spearman (0.86; 0.78) correlations for annual minima and maxima, respectively. Application of the Q_{10} rule for biochemical reaction rates showed that, depending on wastewater temperature, half-lives of sewage-borne biomarkers will change significantly (range: 27%-7,010%) from the baseline at ambient conditions (21±1°C; 100%). Importantly, these temperature-related modulations of in-sewer biomarker decay changed the size of the area observable by WBE; in the extreme, changes in the distal reach observable by WBE can be as large as 49-fold over the course of a year at a given location. This first model of spatial and temporal variability in wastewater temperature has multiple suggested applications, including (*i*) utility for explaining literature-reported discrepancies in the detectability and levels of sewage-borne biomarkers, (*ii*) identification of optimal and sub-optimal wastewater-borne

biomarkers depending on their varying half-lives over the course of the year at the sampling location of interest, and (*iii*) estimating the effective size of the sewershed capture zone in WBE studies.

Introduction

Wastewater-based epidemiology (WBE) has been used successfully to study the behavior and chemical consumption of populations at large scales, without the expenses and privacy concerns associated with traditional human subject studies (Zuccato et al. 2008, Castiglioni et al. 2011; Van Nuijs et al. 2011; Rodríguez-Álvarez et al 2015, McCall et al. 2016, Ort et al. 2014; Choi et al 2018; Gracia-Lor et al. 2018). These studies have been performed at different scales, from neighborhood-wide (Gushgari et al 2018) to city-wide (e.g., Hernández et al 2015, Tscharke et al 2016, Andrés-Costa et al 2014, Kim et al 2015, Baz-Lomba et al 2016) to nationally (e.g., Du et al 2015, Mackuľak et al 2014, Castiglioni et al 2015, Been et al 2016, Zuccato et al 2016, Yu et al 2015) to internationally (e.g., European Union - Ort et al 2014). While fewer international campaigns have been undertaken (e.g., Ryu et al 2016), WBE remains highly relevant for global analysis as well. The SCORE monitoring network has provided a wealth of information primarily for European companies (Van Nuijs et al 2018). In the United States, the Human Health Observatory at Arizona State University represents another shared resource constituting both a sample repository and a sampling network allowing studies to reach back in time as well as around the globe (Venkatesan et al 2015). The importance and challenge of appropriately accounting for biomarker degradation has been characterized previously (McCall et al. 2016; Devault et al 2017; Ramin et al 2018;

Thai et al 2019; Plósz et al 2013; Chen et al 2014; O'Brien et al 2017) and is relevant at any scale but particularly in global locations experiencing significant temperature fluctuations. Few other studies have explored half-lives of biomarkers in wastewater at non-standard temperatures (Cormier et al 2015; Senta et al 2014), and no studies have explored temperatures higher than 22°C.

The temperature of wastewater around the world is only anecdotally known, and observations are recorded predominantly at the downstream end of sewer networks at the intake locations of wastewater treatment plants, whereas the majority of the residence time of wastewater-borne biomarkers is spent in the low-flow reaches upstream in the deep underground (Elías-Maxil 2015).

Prior work on temperature gradients in sewers has been done in the field of construction for the purpose of establishing the feasibility of, and methods for, the recovery of thermal energy from wastewater (Dürrenmatt and Wanner 2008; Dürrenmatt and Wanner 2014; Silva 2012; Cipolla and Maglionico 2014; Hofman et al 2014; Brueckner et al 2014; Abdel-Aal et al 2015; Elías-Maxil 2015; Mattsson et al 2017; Bertrand et al 2017; Elías-Maxil et al 2017; Pelda and Holler 2018). However, because these models were developed for localized, design-oriented application, many of even the more parsimonious ones are too dependent on knowing detailed three-dimensional construction information for a sewer network to enable global analysis – information that often is not known or not available to researchers performing WBE and UMM studies.

The present study was designed to address this gap by providing robust monthly estimates of long-term average wastewater temperature around the world and monthly estimates of the in-sewer decay rate of 31 biomarkers of physical and mental health, as well as the effective reach of the wastewater monitoring effort. WBE studies typically make use of a mixture of target biomarkers consisting of parental compounds (e.g., medications), their characteristic metabolites, and supplemental analytes tracked to enable an estimation of the count of people (population size) reflected in a sample.

The 31 biomarkers selected in this study include licit and illicit drugs (e.g., heroin, morphine, amphetamine, ecstasy, methamphetamine) and their metabolites as well as antibiotics, birth control hormones, and other medications used for treatment of seizures and depression. Together or separately, tracking of these signature compounds in wastewater may allow to estimate spatial and temporal patterns in substance use and disease prevalence. The stimulants caffeine and nicotine also were included, as these may serve a dual purpose of providing insights into community behavior and the size of the contributing population (Senta et al 2015). At ambient temperatures, the half-lives of these substances are known to range from minutes to weeks (McCall et al 2017, Senta et al 2014; Cormier et al 2015; Benotti and Browawell 2009; Baz-Lomba et al 2016; Berset et al 2010; Castiglioni and Zuccato 2011).

Methodology

Global Air and Soil Texture Data

Air temperature (monthly average, minimum, and maximum for 1970-2000) was derived from WorldClim Version 2.0 (Fick and Hijmans 2017), downloaded at 10-minute spatial resolution (approximately 100 square miles). Soil texture (topsoil and subsoil USDA soil texture classification) was derived from the Harmonized World Soil Database, version 1.2 (FAO 2012). Soil water content by soil texture was estimated with the upper limit of water content set to the Field Capacity and the lower to the Permanent Wilting Point (Datta el al. 2017).

Wastewater Temperature Estimation

Wastewater temperature was estimated from calculations of soil temperature at depth, in turn based on monthly statistics regarding air temperature observed between 1970-2000. A unifying deterministic model was developed and implemented in QGIS 3.6.1 (QGIS Development Team, 2019). The wastewater temperatures were used to calculate adjusted biomarker half-lives to identify the impacts on signal loss and capture area.

The thermal diffusivity, k, per USDA soil texture class was calculated as:

$$k = k_0 + a\, exp\left(-0.5\, \left(\frac{ln\left(\frac{\theta}{\theta_0}\right)}{b}\right)^2\right) \qquad \textit{Equation}$$

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where k_0 is the thermal diffusivity of dry soil, a is the difference between the highest thermal diffusivity at the optimal water content θ_0 and the thermal diffusivity of dry soil, b is the half-width of the peak of the $k(\theta)$ curve, and θ is the actual volumetric water content (Arkhangelskaya and Lukyashchenko 2018).

The minimum depth of cover for sewer pipes may be estimated at 3 m based on a review of design guidelines for different climate conditions (Anchorage Water and Wastewater Design Manual, 2018; El Paso Utilities, 2016; EPCOR 2019; Orange County Sanitation District, 2012). Although the actual depth to cover may greatly exceed the minimum and extend down to 12 meters or more (Caughey 2013; WSSC 2008), the actual depth to cover was parameterized at 6.1 meters to represent a more globally applicable upper mean.

Soil temperature at sewer depth was calculated as shown in *Equation* ***Error! No text of specified style in document.****-2*:

$$T_{soil\,(D,t_{year})} = T_{mean} - T_{amp} * exp\left(-D\sqrt{\frac{\pi}{365 * \alpha}}\right) * cos\left(\frac{2\pi}{365}\left(t_{year} - t_{shift} - \frac{D}{2}\sqrt{\frac{365}{\pi * \alpha}}\right)\right)$$

Equation ***Error! No text of specified style in document.****-2*

where T_{mean} is the mean monthly air temperature, T_{amp} is the amplitude equal to half of the difference between the maximum and minimum monthly temperature, D is the soil depth at which temperature is calculated (equal to the depth of cover), α is the soil thermal diffusivity, t_{year} is the time elapsed from the beginning of the year, and t_{shift} is the time to the mid-point of the month with the lowest surface temperature (Kusuda and Achenbach 1965; Florides and Kalogirou 2005).

Wastewater temperature was calculated from soil and air temperature based on an initial estimate of domestic wastewater discharge temperature (17.8-31.2°C; based on an assumed range of 25-75% hot water and temperatures of 13°C and 50°C for unheated and heated indoor water. The in-pipe heat loss or gain was calculated as:

$$\Delta T = \frac{q_{wa}+q_{ws}}{mc_p}$$

Equation ***Error! No text of specified style in document.****-3* *with* $q_{wa} = \frac{1}{R_{wa}}(T_{water} - T_{air})$ *Equation*

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and $q_{ws} = \frac{1}{R_{ws}}(T_{water} - T_{soil})$ *Equation*

Error! No text of specified style in document.*-5*

where ΔT heat loss or gain in wastewater flowing in a pipe from interaction with soil and air; q_{wa} is the thermal heat exchange between wastewater and air; q_{ws} is the thermal heat exchange between wastewater and soil; m is the mass flow rate of wastewater (estimated with a density of 1,000 kg/m^3); c_p is the thermal heat capacity, and T_{water}, T_{soil}, and T_{air} are the initial temperatures of wastewater, and the surrounding soil, and air, respectively. The thermal resistivity between wastewater and air (R_{wa}) was estimated at 0.04 m^2/℃, thermal resistivity between wastewater and soil (R_{ws}) was estimated at 0.5 m^2/℃, and specific heat capacity for water (c_p) was estimated at 4.2 kJ/kg℃ (Abdel-Aal et al 2013; Abdel-Aal et al 2015).

The adjusted biomarker half-lives were based on the calculated wastewater temperature, a series of initial biomarker half-lives lives reported at ambient temperatures, and the Arrhenius Equation as shown in Equation 3-6:

$R_2 = R_1 \times Q_{10}^{\left(T_2 - T_1 / 10℃\right)}$ *Equation*

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where R_1 is the initial decay rate, equal to the negative natural log of two divided by the initial reported half-life (Laidler 1984). When solving for the half-live, yields Equation 3-7:

$$t_{\frac{1}{2},2} = t_{\frac{1}{2},1} \times \frac{ln(2)}{ln(2) \times Q_{10}{}^{\left(T2-T1/_{10℃}\right)}}$$ *Equation*

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where $t_{1/2,1}$ is the initial half-life, T_1 is the temperature at which initial half-life was derived, $t_{1/2,1}$ is the half-life at seasonally- and spatially-adjusted wastewater temperature calculated in this study, T_2 is the calculated temperature to which initial half-life is adjusted to, and Q_{10} is a factor of temperature-dependent of rate change, ranging between 2 and 3 for most biologic systems, estimated at 2.5 for all 31 biomarkers.

For estimating time to extinction, where N_t is the detection limit and N_0 is the load measured in wastewater, the exponential decay equation can be rewritten as Equation 3-8:

$$t = \frac{t_{1/2}\, ln\left(\frac{N_t}{N_0}\right)}{-ln\ 2}$$ *Equation*

Error! No text of specified style in document.*-8*

Temperature-dependent Change in Relative Distal Reach

To understand how the observed range in calculated wastewater temperature impacts the expected distance a marker can cover between the point of introduction and point of observation in the sewer pipe (relative distal reach), the exponential decay equation can be rewritten to solve for travel time (Equation 3-9), which is the dividend of length and flow velocity (Equation 3-10). Thus, for a constant flow velocity (v), initial biomarker discharge quantity (N_0) and analytical detection limit (the minimum $N(t)$ that could be observed by WBE sampling), the monthly calculated wastewater temperatures result in maximum and minimum observable sewer reaches which vary by a factor of up to 260 globally over the course of the year (Table **Error! No text of specified style in document.**-3), relative to published half-lives reported for transformations at ambient temperatures. Performing the same calculation to obtain the estimated range of half-lives at monthly-varying wastewater temperatures results in transformations which range from no change to a factor of 49 for a given location over the course of a year.

$t = \log_{N_0}\left(\frac{N(t)}{0.5}\right)^{t_{1/2}}$ *Equation*

Error! No text of specified style in document.*-9* $L/v = \log_{N_0}\left(\frac{N(t)}{0.5}\right)^{t_{1/2}}$

Equation ***Error! No text of specified style in document.****-10*

$L = v\log_{N_0}(2N(t))^{t_{1/2}}$ *Equation*

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$L_{annual\ min} = v\log_{N_0}(2N(t))^{0.44t_{1/2}} = 0.27t_{1/2}v\log_{N_0}(2N(t))$ *Equation*

Error! No text of specified style in document.*-12* $L_{annual\ max} =$

$v\log_{N_0}(2N(t))^{19.36t_{1/2}} = 70.10t_{1/2}v\log_{N_0}(2N(t))$ *Equation* ***Error! No text of specified style in document.****-13*

$\Delta L = L_{max} / L_{min} = \frac{19.36t_{1/2}vlog_{N_0}(2N(t))}{0.44t_{1/2}vlog_{N_0}(2N(t))} = \frac{70.10}{0.27} = 260$ *Equation*

Error! No text of specified style in document.*-14*

Temperature-dependent Effective Area Observable by Wastewater-based Epidemiology

To transform the change in maximum sewershed reach into an estimate of observable area, the length (L) can be approximately equated to a radius (r), such that sewershed area is estimated to be half of the area of a circle whose radius (radial extent) is defined by the maximum observable extent, L (Equation 3-15 through Equation 3-18).

$$A = \frac{1}{2}\pi r^2 \cong A = \frac{1}{2}\pi L^2$$ *Equation*

***Error! No text of specified style in document.**-15*

$$A_{annual\ max} = \frac{1}{2}\pi {L_{max}}^2$$ *Equation*

***Error! No text of specified style in document.**-16*

$$A_{annual\ min} = \frac{1}{2}\pi {L_{min}}^2$$ *Equation*

***Error! No text of specified style in document.**-17*

$$\Delta A = A_{max}/A_{min} = \frac{1}{2}\pi {L_{max}}^2 / \frac{1}{2}\pi {L_{min}}^2 = {L_{max}}^2/{L_{min}}^2 = (\Delta L)^2$$ *Equation*

***Error! No text of specified style in document.**-18*

Illustrative Change in Population Captured

To estimate the impact of changing observable sewershed extent on the capture of population over the course of a year, estimated population density for the year 2020 was multiplied by the change in observable area (Equation 3-19). Population density (number of persons per square kilometer) was based on a 15-arcminute (approximately 30 km) resolution download of The Gridded Population of the World, Version 4 (GPWv4): Population Density Adjusted to Match 2015 Revision of UN WPP Country Totals (CIESIN 2018).

$$\Delta\, population = density \times \Delta A \cong density \times \Delta L^2$$ *Equation*

***Error! No text of specified style in document.**-19*

Results

Global-scale seasonal wastewater temperature

Assuming a sewer burial depth of 6.1 meters (~20 feet), soil water moisture parameterized as the average between field capacity and permanent wilting point, a wastewater flow volume of about 11 liters per second (0.25 million gallons per day) with a density of 1,000 kg/m^3, and an initial wastewater temperature of 17.8°C, model output places 75% of the world's global wastewater temperatures in the range of 6.9 to 34.4°C (Figure **Error! No text of specified style in document.**-1).

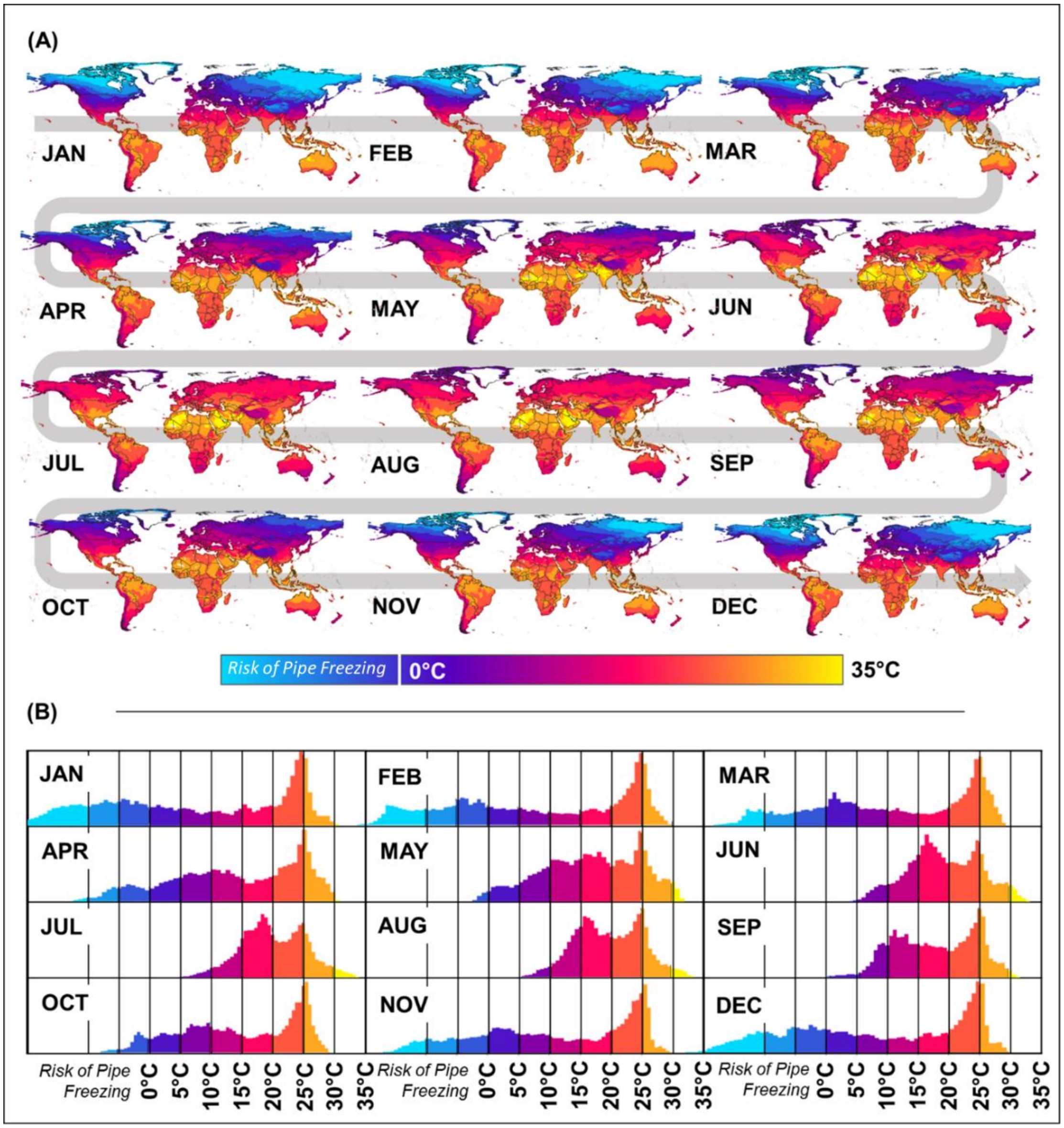

Figure **Error! No text of specified style in document.**-2. Average monthly wastewater temperatures show a wide range between the northern and southern hemispheres (Panel A); the range contracts notably during the months of May to September (Panel B). Note that temperatures below 0°C are artifacts of a model parameterized to represent global average conditions. Sewer depth and thermal resistivity between wastewater and air (R_wa) and between wastewater and soil (R_ws) would, in fact, be higher as a function of deeper burial and pipe insulation designed to prevent pipe freezing and failure.

Implications for biomarker half-lives and observable capture area

The effect of seasonal and spatial variation in wastewater temperature on degradation rates was investigated for a total of 31 sewage-borne biomarkers (McCall et al 2017, Senta et al 2014; Cormier et al 2015; Benotti and Browawell 2009; Baz-Lomba et al 2016; Berset et al 2010; Castiglioni and Zuccato 2011). These included 20 illegal drugs, seven markers of physical health, and four markers of mental health (Table **Error! No text of specified style in document.**-3). Wastewater temperature's modulation of half-life was estimated to deviate from 100% at ambient conditions 21±1°C within a range between 27% and 7,010%, depending on location and season.

Table **Error! No text of specified style in document.**-3. Ambient and range of wastewater temperature-adjusted half-lives for select illegal drugs, and for select biomarkers of physical and mental health.

Compound (Acronym)	**Description**	**$t_{1/2, amb}$ (hr) @ T1 (°C)**	**$t_{1/2, range}$ (hr)**
Illicit Drugs			
6-Acetylcodeine (AC)	Metabolite of Heroin	0.1 @ 22	0.03 - 7.01
6-Monoacetyl-morphine (MAM)	Metabolite of Morphine	0.7 @ 22	0.22 - 49.07
Amphetamine (AMP)	Stimulant	2.2 @ 22	0.71 - 154.21

Compound (Acronym)	**Description**	**$t_{1/2,\ amb}$ (hr) @ T1 (°C)**	**$t_{1/2,\ range}$ (hr)**
Benzoylecgonine (BE)	Metabolite of Cocaine	18 @ 22	5.78 - 1261.74
Cocaine (COC)	Stimulant	8 @ 22	2.57 - 560.77
(±)-3,4-Methylenedioxy-methamphetamine (MDMA)	Ecstasy	38 @ 22	12.20 - 2663.67
Methylenedioxy-pyrovalerone (MDPV)	Stimulant	50 @ 22	16.06 - 3504.83
Mephedrone (MEPH)	Synthetic stimulant drug	14 @ 22	4.50 - 981.35
Cocaethylene (COE)	Metabolite of cocaine and ethanol use	8 @ 22	2.57 - 560.77
2-Ethylidene-1,5dimethyl-3,3-Diphenylpyrrolidine (EDDP)	Major metabolite of methadone	61 @ 22	19.59 - 4275.90
4-Hydroxy-3-methoxy methamphetamine (HMMA)	More potent than MDMA	10 @ 22	3.21 - 700.97

Compound (Acronym)	**Description**	**$t_{1/2, amb}$ (hr) @ T1 (°C)**	**$t_{1/2, range}$ (hr)**
Ketamine (KET)	Dissociative anesthetic	80 @ 22	25.69 - 5607.73
Methamphetamine (METH)	Stimulant	52 @ 22	16.70 - 3645.03
Methiopropamine (MPA)	Stimulant, meth substitute	38 @ 22	12.20 - 2663.67
Methoxetamine (MTO)	Dissociative hallucinogen	173 @ 22	55.56 - 12126.72
Morphine-3-β-D glucuronide (MG)	Metabolite of morphine	7 @ 20	1.87 - 408.51
Norcocaine (NorCOC)	Metabolite of cocaine	7 @ 22	2.25 - 490.68
4-Methoxyamphetamine (PMA)	Serotonergic drug	21 @ 22	6.74 - 1472.03
Methoxymethamphetamine (PMMA)	Stimulant, psychedelic	42 @ 22	13.49 - 2944.06
O-Desmethyltramadol (ODMT)	Opioid	28 @ 22	8.99 - 1962.71
Physical Health Biomarkers			

Compound (Acronym)	Description	$t_{1/2, amb}$ (hr) @ T1 (°C)	$t_{1/2, range}$ (hr)
Carbamazepine (CBZ)	Seizure Treatment	139 @ 22	44.64 - 9743.44
Sulfamethoxazole (SMX)	Antibiotic	480 @ 21.5	147.25 - 32139.68
Ethinylestradiol (EE2)	Birth Control	456 @ 21.5	139.89 - 30532.70
Norethindrone (NOR)	Birth Control	144 @ 21.5	44.18 - 9641.90
17β-Estradiol (E2)	Hormone	31.2 @ 21.5	9.57 - 2089.08
Diclofenac (DCF)	Anti-inflammatory	78 @ 22	25.05 - 5467.54
Tramadol (TRA)	Narcotic / Pain Relief	160 @ 22	51.38 - 11215.47
Physical Health and Population Count Biomarkers			
Caffeine (CAF)	Stimulant / Population Marker	456 @ 21.5	139.89 - 30532.70
Zolpidem (ZOL)	Sedative	64 @ 22	20.55 - 4486.19

Compound (Acronym)	**Description**	**$t_{1/2,\ amb}$ (hr) @ T1 (°C)**	**$t_{1/2,\ range}$ (hr)**
Nicotine (NIC)	Stimulant / Population Marker	233 @ 21.2	69.54 - 15178.12
Norketamine (NorKET)	Antidepressant, sedative	28 @ 22	8.99 - 1962.71
Range of half-life at max and min wasterwater temperatures vs. ambient conditions			***27%-7,010%***

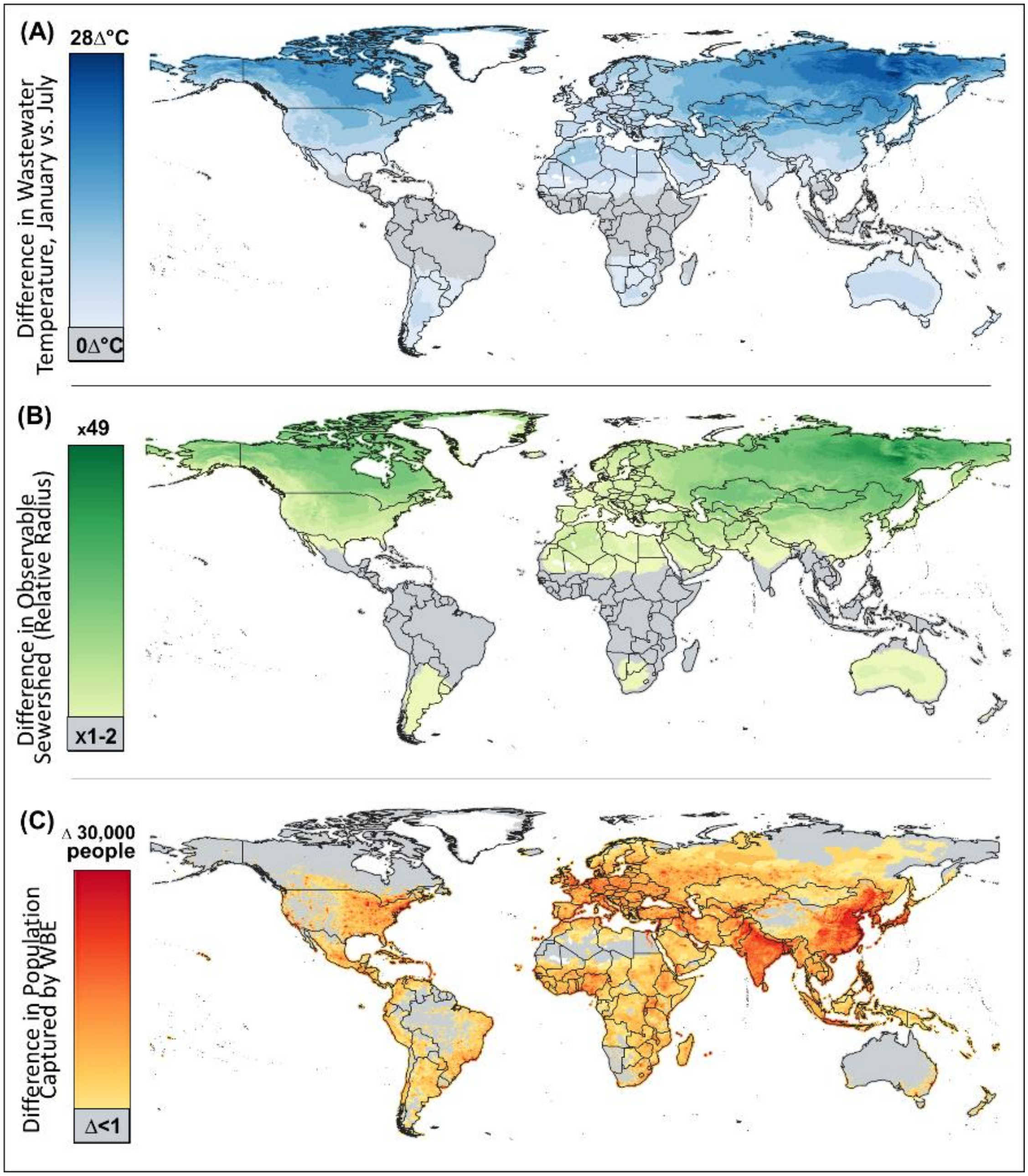

Figure **Error! No text of specified style in document.**-3. Annual fluctuations in wastewater temperature, expressed as the maximum absolute difference (□) between winter and summer extremes (Panel A); holding all other parameters constant, the change in temperature results in a sewershed extent change between 1 (no change over the course of a year) and a factor of 49 (Panel B); overlaid with 2020 global population density, fluctuations in wastewater temperature may translate to up to 30,000 additional people captured by WBE monitoring efforts over the course of a year (Panel C).

Predicted seasonal changes in biomarker degradation vary across the world, with equatorial regions having the highest degradation rates (i.e., highest wastewater temperatures, refer to Figure **Error! No text of specified style in document.**-2) but the smallest variation over the course of a year (Figure **Error! No text of specified style in document.**-3A,B). Inland areas are expected to have more variability than coastal ones. Most extreme fluctuations in theoretical wastewater temperature and observable sewershed extent occur in sparsely populated, or unpopulated regions of the world (Figure **Error! No text of specified style in document.**-3C). However, in densely population regions of the world where past monitoring efforts have taken place, even relatively small factors translate to significant changes in the size of the population observable as a function of wastewater temperature and biomarker decay (Figure **Error! No text of specified style in document.**-3C). The population observed is biomarker dependent. Thus, low-concentration biomarkers may fall below the practical limit of detection (

Table **Error! No text of specified style in document.**-4).

Table **Error! No text of specified style in document.**-4 Observed loading, detection limits, and subsequent effective extinction periods for 11 select biomarkers investigated frequently Castiglioni and Zuccato 2011.

Compound (Acronym)	**Global $t_{1/2}$, range (hr)**	**Loads measured in WW (~N_0)[60]**	**Method detection limit (~N_t)[60]**	**Max time, *t*, before effective extinction (hr)**
6-Acetylcodeine (AC)	0.03 - 7.01	<LOQ to 1.5±2.7 ng/L	2.6 ng/L	0 – 4.9
6-Monoacetyl-morphine (MAM)	0.22 - 49.07	2.0±2.4 to 14±14 ng/L	5.3 ng/L	0 – 118
Amphetamine (AMP)	0.71 - 154.21	<LOQ to 2±3.4 ng/L	5.4 ng/L	0 – 0

Compound (Acronym)	**Global** $t_{1/2}$**, range (hr)**	**Loads measured in WW** $(\sim N_0)$[60]	**Method detection limit** $(\sim N_t)$[60]	**Max time,** t**, before effective extinction (hr)**
Benzoylecgonine (BE)	5.78 - 1261.74	127±12 to 1468±211 ng/L	1.98 ng/L	34 - 12274
Cocaine (COC)	2.57 - 560.77	50±9 to 465±90 ng/L	1.4 ng/L	13 - 4840
(±)-3,4-Methylenedioxy-methamphetamine (MDMA)	12.20 - 2663.67	0.9±1.7 to 28±10 ng/L	6.3 ng/L	0 – 6906
Cocaethylene (COE)	2.57 - 560.77	2.4±2.6 to 12±2 ng/L	0.95 ng/L	0 - 2177
2-Ethylidene-1,5dimethyl-3,3-Diphenylpyrrolidine (EDDP)	19.59 - 4275.90	24±3 to 91±19 ng/L	1.64 ng/L	72 - 25945
Methiopropamine (MPA)	12.20 - 2663.67	<LOQ to 40±17 ng/L	3.7 ng/L	0 – 10509

Compound (Acronym)	**Global $t_{1/2,\ range}$ (hr)**	**Loads measured in WW ($\sim N_0$)[60]**	**Method detection limit ($\sim N_t$)[60]**	**Max time, *t*, before effective extinction (hr)**
Morphine-3-β-D glucuronide (MG)	1.87 - 408.51	<LOQ to 18±3 ng/L	0.63 ng/L	0 – 2067
Norcocaine (NorCOC)	2.25 - 490.68	1.1±1.2 to 8±1 ng/L	1.92 ng/L	0 – 1094

Comparison of calculated wastewater temperature with observations

The theorical wastewater temperatures were compared with nearly 400 observations extracted from 20 studies reporting empirical observations of wastewater temperature for 45 locations around the world (Figure **Error! No text of specified style in document.**-4A,B). While wastewater treatment plant operators routinely measure the temperature of plant influent and effluent, these data are not academically available, and a database of wastewater treatments plants worldwide does not currently exist. Based on the available dataset (n=400), the results show that, as parameterized, the modeled wastewater temperatures are biased to under-estimate the high end (30-40°C) of observed wastewater temperatures. Nevertheless, the modeled temperatures are able to replicate seasonal dynamics well for those instances where such finer-resolution data were available (Figure **Error! No text of specified style in document.**-5).

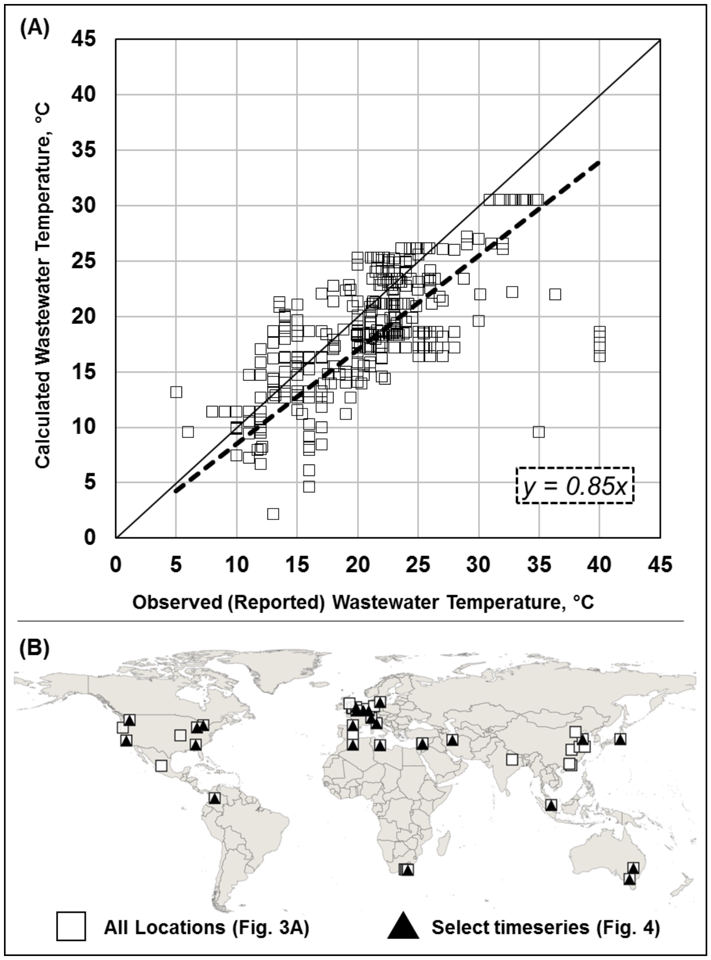

Figure **Error! No text of specified style in document.**-4. All reported observations of wastewater temperature correlated against calculated analogs for equivalent time period and location in space (Pearson correlation = 0.57; Spearman correlation = 0.63) (Panel A); location of all reported wastewater temperature observations shown in Figure **Error! No text of specified style in document.**-4A and select monthly timeseries shown in Figure **Error! No text of specified style in document.**-5 (Panel B).

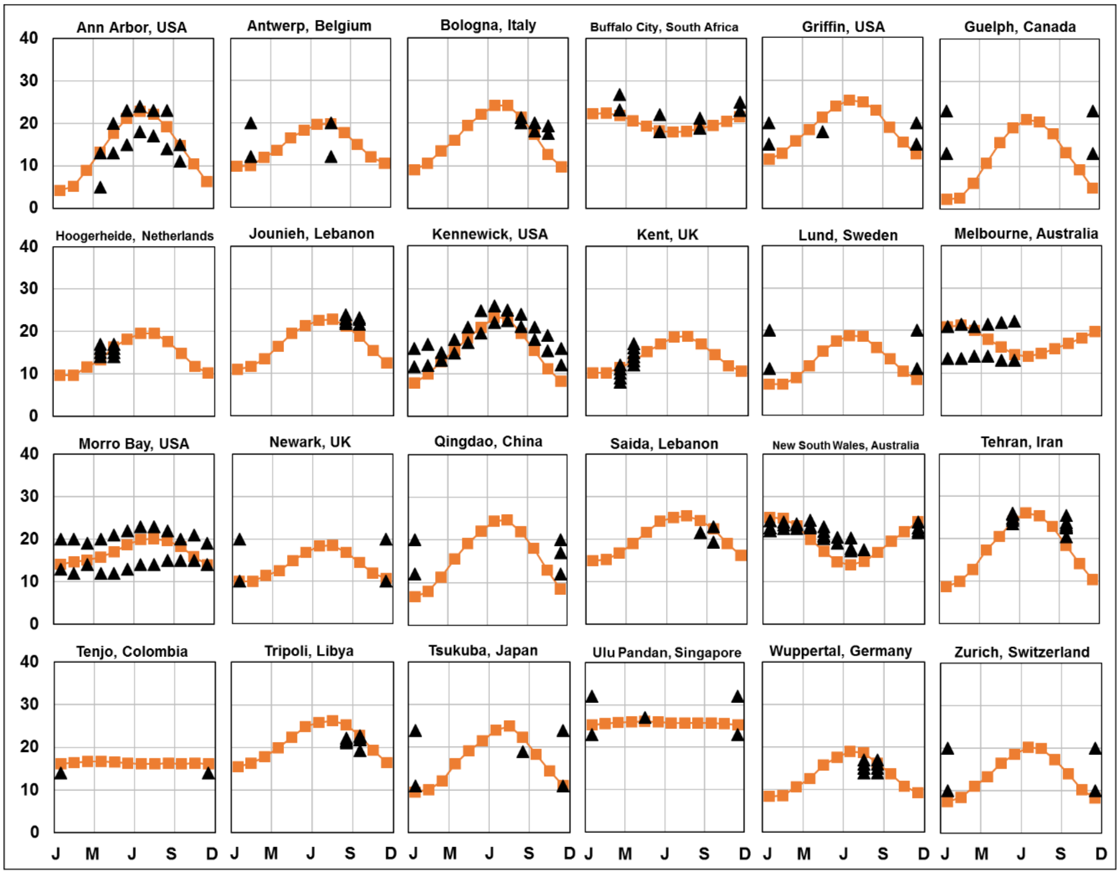

Figure **Error! No text of specified style in document.**-5. Calculated monthly wastewater temperature for 24 locations around the world (Figure **Error! No text of specified style in document.**-4B) as compared to empirical reported wastewater temperature records for the sample location. Empirical observations represent a mixture of monthly or daily values, annual averages, and minimum and maximum annual values.

Discussion

Here we developed, implemented, and validated a framework for estimating biomarker degradation over the course of a year for any location around the world. The model can be used to better guide comparative sewage metrology efforts by identifying optimal sampling locations, times, and biomarkers given their likely degradation in the environment within the study area of interest. Globally, modulations of biomarker half-lives modulated by seasonal wastewater temperature was calculated to range between 27% and 7,010% relative to rates commonly reported for experiments conducted at ambient (21±1°C) conditions. Few other studies have explored half-lives of biomarkers in wastewater at non-ambient temperatures, and no studies have explored temperatures higher than 22°C. Cormier et al. (2015) reported the modulation of half-lives for raw wastewater at 4°C and 21.5°C for 17β-estradiol (3077%), norethindrone (533%), caffeine (342%), sulfamethoxazole (425%). Senta et al. (2014) reported half-life changes for morphine-3-*β*-D glucuronide (257%), 6-acetyl morphine (148%), cocaine (494%), 6-acetyl codeine (150%) at 10°C and 20°C in municipal wastewater. Thus, the theoretical results of this study are consistent with the empirical observations of available parallels. The probable cause for the bias of the model towards the under-estimation of observed temperatures is the under-estimate of the initial wastewater temperature released into the sewer system. Discrete discharges (e.g., a hot shower) will exceed any one long-term average wastewater temperature estimate and lead observed temperatures to rise, particularly if observations are made further upstream in a sewer network where the overall wastewater temperature is not modulated by the aggregation of flows. The observation sample set illustrates some of the limitations in identifying wastewater temperature empirically – observations are scarce, certain regions (and thus, climates) of the world are over-represented compared to others, the relative contribution of wastewater from domestic and industrial sources is not always known, and the associated wastewater flowrate is not always known or reported. Furthermore, many of the observations represent a snapshot in time, which may be overly biased by activity that is less representative of the area on a long-term basis (e.g., a range of 6-35°C captured within the span of a single December day in Ede, Netherlands; Schilperoort and Clemens 2009).

Based on the calculated range in wastewater temperature over the course of a year, and holding initial biomarker loading and analytic detection limit constant, the observable sewershed reach changed up to a factor of 49 between winter and summer months (Figure **Error! No text of specified style in document.**-3B). Wastewater temperature strongly impacts the duration of signal retention, and thus the quality and return-on-investment of sewage metrology and wastewater-based epidemiology campaigns conducted to collect information on the behavior, environmental threats, and human health status of large populations. Additionally, if the population markers degrade as quickly as the biomarker, and the population monitored was homogenously distributed across the sewershed, then the outcome of the seasonal modulation is problematic only in the loss (attenuation during summer months) of signal. However, if the population marker is persistent and the biomarker of interest labile, large biases would result. Of the 31 biomarkers included in this study, population markers caffeine and nicotine were the second- and third-most persistent compounds (Table **Error! No text of specified style in document.**-3). Thus, the variability introduced by the seasonality of wastewater temperature and its modulation of biomarker half-lives, observable sewershed extent, and potential population capture (Figure **Error! No text of specified style in document.**-3, Panels A-C) may in fact be compounded by differences in biomarker decay rates.

If the Q_{10} for the selected population marker (i.e., caffeine; nicotine) and biomarker(s) of interest to a WBE study are equal, then winter and summer per-capita results will not be biased by bias in population estimates, since both will change in unison. This assumes, however, that the population is homogenous around the sampling location, and that the reduced distal reach observable during the hot season captures a population as representative as that observable during the cold season when the reach expands.

Advantages and Limitations

The estimates of wastewater temperature and subsequent biomarker degradation presented in this study are founded on a physically based, entirely deterministic model. The model relies on a relatively few, relatively easy to bracket assumptions, only few of which (e.g., soil water content at time of interest) are time-variant and more challenging to parameterize accurately. Because it is entirely deterministic, the model's limitations are related to the simplifying assumptions used to parameterize it efficiently for a global study. For instance, in this study soil water content was set to the average of field capacity and permanent wilting point, varying by soil texture category, by invariant across climates. Precipitation events or prolonged drought can also push soil moisture outside of this range. At the selected temporal and spatial resolutions (30-year average month, 100 square-mile grid spacing), the model is best suited for understanding regional and seasonal trends.

For use at point or local scale, most parameters are known or can be directly measured. Thus, the model can be used as-is, with more refined inputs providing more reliable outputs, reflective of field conditions at the time of sampling. The model can be easily expanded to a sub-daily timestep by applying empirically derived peaking factors for temperature, such as those presented for a case study in Balogna, Italy (Cipolla and Maglionico 2014).

For refining its use at regional or global scales, future iterations may incorporate: 1) local or regional building codes specifying sewer burial depth requirements for cold regions; 2) the effects of insulated piping on the thermal diffusivity between wastewater and soil in cold regions; 3) a recursive calculation of wastewater temperature based on flow rate, to transition between low-flow upper reaches of a sewer network to high-flow downstream trunk lines arriving at a central wastewater treatment plant; 4) seasonal changes in initial wastewater temperature discharges; and 5) the effects of rainfall-runoff to wastewater temperature based on global precipitation datasets.

Conclusions

According to both empirical and modeling data presented here, wastewater globally is undergoing considerable fluctuations in temperature over the course of the year. This physical change has potentially far reaching consequences for the data quality of wastewater-based epidemiological studies. Assuming constant inputs of biomarkers into a given sewerage system over the course of a year, the concentrations and mass of biomarker compounds detectable at a given monitoring location is predicted to be subject to considerable change as a function of temperature. In addition, the distal reach of wastewater monitoring was determined to change significantly in most regions of the world. This implies that the concentrations and mass loads reported in the literature in longitudinal WBE studies would benefit from a correction for temperature effects. Temperature affects the degradation of compounds, including those of interest to wastewater-based epidemiology studies. To date, most WBE studies have been performed in the northern hemisphere; between the 20^{th} and 40^{th} parallel in North America and Asia, and between the 40^{th} and 60^{th} in Europe. Existing observation-based studies have simply not covered the entire global spectrum of field conditions. If interest in WBE continues to grow and studies expand globally, the resulting observations will come from both more- and less temperate regions, with subsequently greater and lesser seasonal variability in temperature and degradation. In order to account for the potential impact of wastewater temperature in WBE studies, it would be desirable to collect more empirical data on biomarker attenuation in sewage as a function of temperature. Specially, more bench or pilot-scale testing of the temperature-dependence of biomarker degradation rates and the calculation of Q10 rates from empirical results would help demonstrate experimentally the significance of temperature to WBE results. The half-live values used in this work should be viewed as illustrative only and in future studies ideally should be replaced with empirical data that may or may not be specific to the monitoring location and the microbial community of the local sewerage network and wastewater. With respect to the estimates of per-capita consumption or exposure based on de jour population estimates, labile chemical population biomarkers (e.g. caffeine, nicotine, certain pharmaceuticals) are also prone to seasonal temperature-related degradation. This quality makes them even more attractive than de facto (e.g., census-based) population estimates, because the latter would not account for the changing distal reach that is observed during the hotter and colder times of the year. In conclusion, more empirical work is necessary for understanding the temperature-dependence of popular biomarker degradation rates, as this information is largely lacking in the literature but potentially of greater impact on data quality than uncertainties of population estimates in WBE studies.

CHAPTER 4

ANALYZING THE IMPACT OF SEASONAL TEMPERATURE VARIABILITY ON DEMOGRAPHIC GROUPS OBSERVABLE BY WASTEWATER-BASED EPIDEMIOLOGY

Abstract

Over the last decade, wastewater-based epidemiology (WBE) has emerged as a non-invasive, non-intrusive technique to monitor the health and behavior of populations. While attractive for protecting the anonymity of groups of individuals monitored, WBE studies potentially are vulnerable to uncertainty as to the size and type of population represented as a function of wastewater temperature. We used 2017 American Community Survey data and a database of U.S. wastewater treatment plants (WWTPs), to compute the distance between WWTP observational locations and the radial distance to populations of differing demographics. We consistently found at various spatial scales and regions, a non-random relationship between distance and demographics (household income, educational attainment, military service, unemployment, and lack of health insurance), with universally more inclusive study areas in the wintertime compared to summertime sampling. Biomarker degradation slowed by cooler winter temperatures was predicted to increase the effective distal reach of WBE. In addition, the relative contribution of populations nearest and furthest from the WWTP were predicted to be more evenly distributed in winter versus summer. By contrast, summertime WBE data were found to be dominated by populations residing closest to the WWTP. When used in conjunction with appropriate ethical guidelines, results obtained here can aid in designing more equitable WBE sampling campaigns. The approach established here for assessing

radial heterogenicity in the U.S.A. is readily applicable to other parts of the world to improve the robustness and informational value of WBE data.

Introduction

Wastewater-based epidemiology (WBE) has been used to monitor population-scale consumption of illicit substances (Zuccato et al., 2008; Baker et al., 2014; Ort et al., 2018), exposure to environmental toxins and contaminants (Rousis et al., 2016; González-Mariño et al., 2017; Gracia-Lor et al., 2018), and the consumption of recreational substances such as alcohol (Reid et al., 2011; Ryu et al., 2016; Chen et al., 2019), nicotine (Rodríguez-Álvarez et al., 2014; Senta et al., 2015; Lai et al., 2018), and caffeine (Senta et al., 2015; Gracia-Lor et al., 2017a). More recently, WBE has been explored as a tool for monitoring nutrition (Bowes and Halden, 2019) as well as the impact of air quality and temperature on public health (Fattore et al., 2016; Phung et al., 2017). Although many of the proposed diet and health biomarkers have yet to be fully tested in wastewater matrices (Choi et al., 2018a), the field is rapidly moving in the direction of being able to evaluate antibiotic resistance and changes in microbiome (Choi et al, 2018a). In short, over the last decade, WBE has been shown to be an effective, viable method for the evaluation of human health at large scales, with analytic techniques developed to identify even minute volumes of substances of interest (Gracia-Lor et al., 2017b). These advances have positioned practitioners of WBE to consider larger, and longer-lasting longitudinal studies.

Hall et al. (2012) published the first study addressing the ethics of WBE. Later, Prichard et al. (2014; 2016) developed a set of ethical research guidelines for the field.

More recently, others have investigated the privacy (Lancaster et al., 2019; Zipper et al., 2019) and social, political, and ethical impacts of WBE work (Van Hal, 2019). Due to the sensitive nature of the behaviors and conditions being sampled in WBE work, anonymity remains on the forefront of study plans. However, the same factors which make the anonymity of WBE methods both more feasible and attractive than traditional human subject studies mean that more effort is required to ensure that the population observed by WBE remains the same over the course of the experiment(s), and that any changes to that population are accounted for and understood during analysis and subsequent policy or decision-making. For spatial and temporal comparisons to be made effectively, per-capita (population-normalized) results are preferable to bulk loads (Van Nuijs et al., 2011). Uncertainty in population estimates translate directly into uncertainty regarding the calculated daily load of various biomarkers.

Currently, WBE studies attempt to achieve one of two types of population counts. The de jure population is one which represents the long-term population residing within a study area. It is represented by census counts, population surveys, zoning and density maps, and would not include tourist or commuter populations (Zuccato et al., 2016). The de facto population is made up of all persons contributing to the sampled wastewater at the time of sampling. Because the de facto population is more dynamic, there have emerged multiple approaches to its estimation. One of the more traditional is via chemical loading (Thai et al., 2018). Another is using hydrochemical water quality parameters (Lin et al., 2018; Kasprzyk-Hordern, 2019; Zheng et al. 2019). Other alternatives, such as via mobile device data (Thomas et al., 2017; Baz-Lomba et al., 2019), and via genetic biomarkers (Yang et al., 2017) have also emerged. Any counts which depend on analytes found in wastewater, however, are not entirely immune to unrelated phenomena like rainfall, temperature, and other (Ramin et al., 2018; Thiebault et al., 2019). However, these are the easiest to use, since they are co-collected alongside the biomarker of interest, and may be expected to have undergone and been subjected to much of the same conditions in-pipe.

To date, population markers previously used in WBE studies include artificial sweeteners, nicotine (Chen et al, 2014; Senta et al., 2015), caffeine (Senta et al, 2015), pharmaceuticals (Lai et al., 2011; O'Brien et al., 2017), creatinine (Chen et al., 2014; Brewer et al., 2012), cholesterol (Chen et al., 2014), ammonia (Zheng et al., 2017), and DNA (Zheng et al., 2017). While endogenous markers may have a narrower band of variability relative to consumed substances, markers like nicotine, caffeine, alcohol, and artificial sweeteners are doubly attractive also because they can elucidate the consumption patterns of populations in addition to serving to estimate population. Variability in urban populations may impact WBE studies. Due to the attenuation of biomarkers in wastewater during their residence time in the collection system, samples collected downstream inherently represent a subset of the parent compounds released by a subset of the population upstream. If this subset is representative of the population at large, proper population counts alone would suffice to make the per-capita estimates representative of the city as a whole. However, if this over-sampled population subset is significantly different than the population at large, even when properly adjusted per capita, the results are not representative of the total population.

The objective of this study was to examine, using the U.S.A. as a case study, whether the results of WBE studies are vulnerable to seasonal changes induced by variable wastewater temperature, insofar as those changes significantly alter the population sampled over the course of a year. In order to understand the potential impact of degradation loss we examined whether heterogenicity exists and poses a threat as a function of monitoring reach. The United States has documented political, social, and economic differences at the regional level, as well as in public health outcomes (Rentfrow et al., 2013). Prior public health studies have investigated the effects of income inequality (Lynch et al., 1998) and heat exposure (Wu et al., 2013) and mortality, air pollution and life expectancy (Pope et al., 2009; Correia et al., 2013), obesity (Drewnowski et al., 2007; Singh et al., 2008), Parkinson disease (Willis et al., 2010), and disability (Vos et al., 2012), finding regional differences. Thus, regional differences in WBE outcomes could be expected. Consequently, a secondary objective of the study was to establish whether the variability of urban populations changes regionally or as a function of spatial scale. The results of the study can be used by WBE practitioners in conjunction with the ethical guidelines to design more equitable WBE campaigns. The methodology can be applied to studies in other countries and adapted for global analysis, pending data availability.

Methodology

Data

USA Wastewater Treatment Plants

Locations of major wastewater treatment plants across the U.S. were obtained from the U.S. EPA inventory of WWTPs. The GIS dataset contained data on wastewater treatment plants, based on EPA's Facility Registry Service (FRS), EPA's Integrated

Compliance Information System (ICIS) and other datasets (USEPA FRS dataset). The full FRS was filtered based on EPA's determination of major facilities to a total of 13,940 WWTPs which were analyzed in this study.

Demographics

Demographic data at the census block group level were obtained from the 2013-2017 American Community Survey, retrieved from the IPUMS National Historical Geographic Information System, v 13.0 (Manson et al., 2018).

Estimated Seasonal Change in Sewershed Extent

Spatial distributions of wastewater temperature were adapted from Hart and Halden (In Review), which estimated monthly wastewater temperature at a 100-square mile resolution across the world based.

Residence time in sewers and wastewater flow velocities

Kapo et al. (2017) report the national median estimated hydraulic residence time (HRT) for wastewater in the United States. For major treatment plants (treating more than 40 MGD), Kapo et al. calculated a median HRT of 10.5 hours, with the 10th percentile of the population located within a 5.8-hour HRT radius from the WWTP, the 90th within 15.4 hours, and the 99th within 19.1 hours. The constant 0.6 m/s (1.432 mph) travel velocity used by Kapo et al. was used to back-calculate the 10th, 50th, 90th, and 99th percentile travel distances. At 0.6 m/s, the travel distances at these percentiles are 7.8, 14.1, 20.7, and 25.6 miles, respectively.

Calculations

Demographics binned by distance from WWTP

The distance from each census block group polygon to a major WWTP was calculated using Spatial Join in ESRI ArcMap. The attributes and distances from each WWTP were joined to all census block groups and their respective demographic data. Category “bins” were created by creating a new field in which the distance field was rounded up to the nearest whole mile. The nearest whole miles were used as categories/bins. Demographic indicators were averaged across the filtered geographies (national vs state vs county scale; states comprising the U.S. Census regions Northeast, Midwest, South, and West).

Biomarker Decay: Percent Initial Quantity Remaining vs Hours Elapsed

The adjusted biomarker half-lives were based on the calculated wastewater temperature, a series of initial biomarker half-lives lives reported at ambient temperatures, and the Arrhenius Equation as:

$$R2 = R1 \times Q10^{\left(T2-T1/_{10℃}\right)}$$ *Equation*

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where $R1$ is the initial decay rate, equal to the negative natural log of two divided by the initial reported half-life (Laidler 1984). Thus:

$$t_{\frac{1}{2},2} = t_{\frac{1}{2},1} \times \frac{ln(2)}{ln(2) \times Q10^{\left(T2-T1/_{10℃}\right)}}$$ *Equation*

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where $t_{1/2,1}$ is the initial half-life, $T1$ is the temperature at which initial half-life was derived, $t_{1/2,1}$ is the half-life at seasonally- and spatially-adjusted wastewater temperature calculated in this study, $T2$ is the calculated temperature to which initial half-life is adjusted to, and $Q10$ is a factor of temperature-dependent of rate change, ranging between 2 and 3 for most biologic systems.

For estimating time to extinction, where N_t is the detection limit and N_0 is the load measured in wastewater, the exponential decay equation can be rewritten as:

$$t = \frac{t_{1/2}\, ln\left(\frac{N_t}{N_0}\right)}{-ln\ 2}$$ *Equation*

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Biomarker Decay: fractional contribution as a function of distance

At each time step, the percent initial quantity remaining is divided by the sum of the remaining percentage for all timesteps. Residence time is converted to a distance using a 0.6 m/s travel velocity (Kapo et al., 2017). The result represents the fraction of biomarker that is accumulated at the corresponding distance from the WWTP.

Statistical Analysis

Analyses were performed in ESRI ArcMap 10.6, Microsoft Excel 2016, and R (R-3.6.1). Nonlinear correlation was calculated using the nlcor package in R. nlcor implements a heuristic to calculate the nonlinear correlation between numeric vectors, and to return the p-value of the significance of the calculated correlation. The heuristic adaptively identifies multiple local regions of linear correlations to estimate the overall nonlinear correlation (Ranjan and Najari, 2019).

Results and Discussion

Demographics of populations at different spatial scales

In the United States, the finest level of spatial granularity for which the richest dataset of demographic data is available from the U.S. Census Bureau is the census block group. National, state-, and county-level demographics as a function of census block group distance from a major WWTP are shown in Figure **Error! No text of specified style in document.**-6. The non-linear correlation coefficient (nlcor) between the mean of the demographic indicator and the binned distance to WWTP for each of the panels is shown on the associated panel. Household income is the best-correlated, although education attainment, unemployment, military service, and the absence of health insurance are also significantly correlated with distance. Sex is not correlated at a statistically significant level. One possible explanation for the presence of a non-homogenous distribution of demographic indicators like household income is the zoning and location of “nuisance” public works infrastructure, like wastewater treatment plants or landfills, in less affluent communities. However, wastewater treatment plants are somewhat randomly positioned in different cities, based on topographic considerations and proximity to ready discharge points; historically, rivers, streams, and oceans. It is probable, therefore, that the relationship between indicators of affluence and well-being (e.g., household income, high school graduation, unemployment, health insurance) and proximity to a wastewater treatment plant are bi-directional: less affluent communities are less likely to resist the construction of a new wastewater treatment plant in their midst, and proximity to a plant makes an area less desirable over time. Correlations are highest at the national level, followed by the county level. While the correlation remains statistically significant for the state level, for the state selected (Arizona), it is weakest of the three scales.

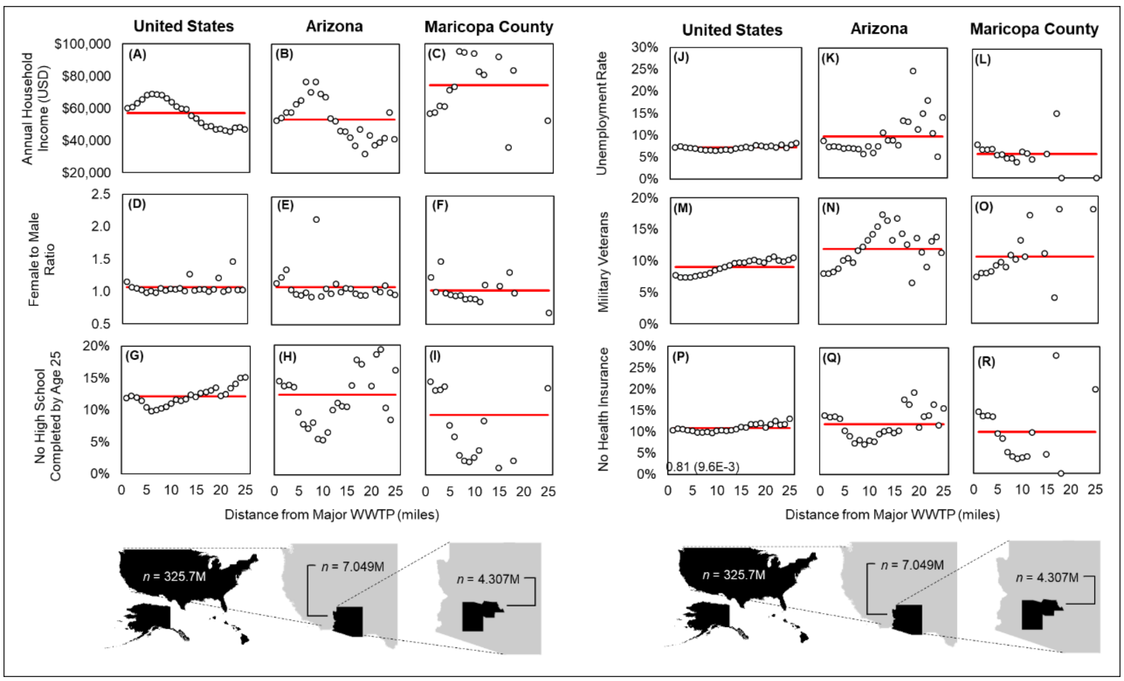

Figure **Error! No text of specified style in document.**-6. National, state, and county-level trends in 6 demographic indicators recorded by the 2017 American Community Survey at the census block group level as a function of distance from a major wastewater treatment plant, and the 2017 population counts (n) captured by the national, state, and county-level categories (sources: U.S. Census Bureau and U.S. EPA FRS). For each spatial scale, the mean value of the demographic indicator shown in red. All demographic indicators other than sex show a non-linear correlation at statistically significant (p<0.05) levels. This indicates that in the U.S.A., heterogeneity exists across different spatial scales (nation, state, county), and seasonal changes in biomarker degradation rates are introducing additional complexity in the interpretation of WBE results intended to represent uniform populations.

Demographics of populations across different regions

Regional demographics as a function of census block group distance from a major WWTP are shown in Figure **Error! No text of specified style in document.**-7. As in the national, state-, and county-level analysis above, household income is most highly correlated with distance. However, all indicators but sex show a statistically significant correlation. Although some variation intra-regionally exists, the overall patterns are generally preserved for each indicator. The nonlinear correlation analysis indicates statistically significant, non-random variability in the demographics of populations served by major WWTPs and their distance from the WWTP.

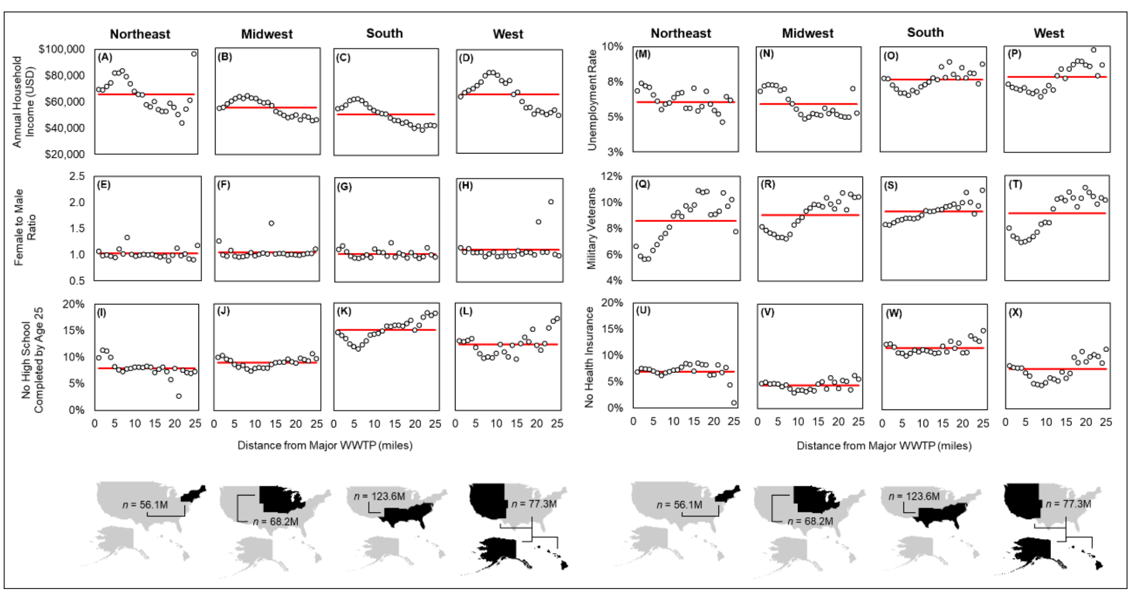

Figure **Error! No text of specified style in document.**-7. Regional trends in 6 demographic indicators recorded by the 2017 American Community Survey at the census block group level as a function of distance from a major wastewater treatment plant, and the 2017 population counts (n) captured by each regional category (sources: U.S. Census Bureau and U.S. EPA FRS). Average shown in red.

Seasonal change in signal decay and population captured by WWTP influent sampling

In the U.S., gravity sewers account for the vast majority (92.5%) of all sewer systems, with force mains accounting for the remaining 7.5% (Morrison et al., 2010). We calculate the signal decay of 17 biomarkers as a function of hydraulic residence time transformed into travel distance to a central sampling point at the WWTP (Figure ***Error! No text of specified style in document.***-8a) using degradation rates (measured in 24-hour, 20°C bench-scale gravity sewer analogs for stress hormones, histamines, and pharmaceuticals, and personal care products (Thai et al., 2019; Choi et al., 2018b; O'Brien et al., 2017). The retention curves are transformed into relative contribution as a function of distance from WWTP sampling point. Applying the monthly wastewater temperature model described in Hart and Halden (In Review), we are able to calculate the adjusted half-life for each biomarker according to the Arrhenius equation to derive maximum and minimum (winter- and summertime) retention curves and the associated contribution by distance (Figure ***Error! No text of specified style in document.***-8b).

Figure ***Error! No text of specified style in document.***-8b demonstrates how WBE measurements of shorter-lived biomarkers such as Ranitidine or Iopromide not only represent a smaller portion of the population during summer months but are also much more strongly biased towards populations closest to the WWTP than wintertime measurements. Assuming uniform initial loading, in this example, July sampling represents primarily the consumption patterns of populations within a 5-mile radius from a WWTP. Based on the median and 90th percentile travel distances, almost 40% of the population would not be represented in July. By contrast, while the capture of Ranitidine and Iopromide in January still undergoes some attenuation with distance, the January sample would be more representative of the service area at large, and up to 99% of the population could theoretically be captured by a single observation made at the WWTP inflow point.

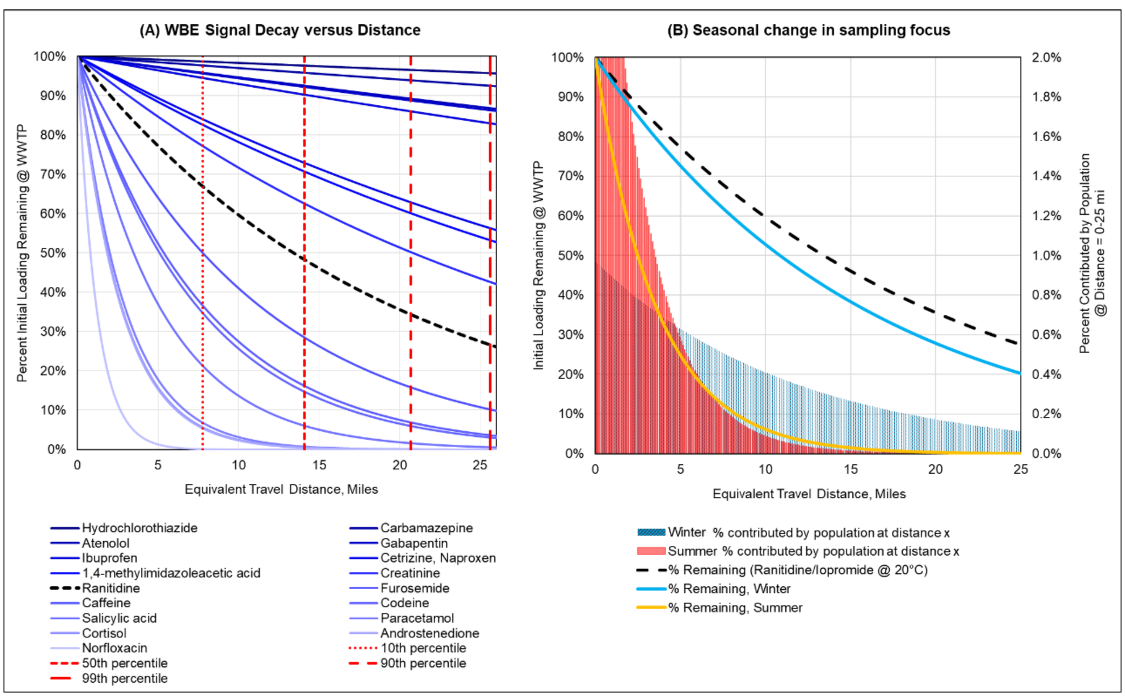

Figure ***Error! No text of specified style in document.***-8. Differences in biomarker half-lives at ambient conditions are magnified by seasonal changes in the temperature of wastewater. As a result, wintertime samples are able not only to capture a larger portion of the population served by a WWTP, but also to bias the results less with respect to populations closer vs. further from the WWTP.

Seasonal change in the demographics of captured by WWTP influent sampling

For chemicals with ambient (20°C) half-lives less than the median hydraulic residence time (10.5 hours), pooled samples represent less than 50% of the population contributing to a major WWTP. During summer months, we find that this applies, in descending magnitude, to Norfloxacin, Androstenedione, Cortisol, Paracetamol, Salicylic acid, Codeine, Caffeine, Furosemide, Ranitidine, and Iopromide (Figure ***Error! No text of specified style in document.***-9). Only those biomarkers which exhibit effectively no degradation over approximately 25 hours (Figure ***Error! No text of specified style in document.***-9) do not bias the results at all. Based on currently reported ambient half-lives under conditions representing pressure and gravity mains, such compounds include, Gabapentin, Carbamazepine, Norethindrone, Tramadol, Carbamazepine, Methoxetamine, Nicotine, Ibuprofen, Hydrochlorothiazide, Ethinylestradiol, Caffeine, Sulfamethoxazole, Fexofenadine, Acesulfame, and Carbamazepine, among others. All other compounds, especially those with half-lives of less than 10 hours, over-represent populations closest to the WWTP with ensuing bias towards associated demographics.

For more quickly degrading biomarkers, longitudinal campaigns that track the health and consumption of populations over the course of a year should not treat winter and summer results as representative of the same population. For this class of biomarkers, the difference in winter versus summertime contributions can be put to good use, however. The steep gradient can be used to study the differences in the consumption patterns of two subsets of the population without the need for additional sampling locations.

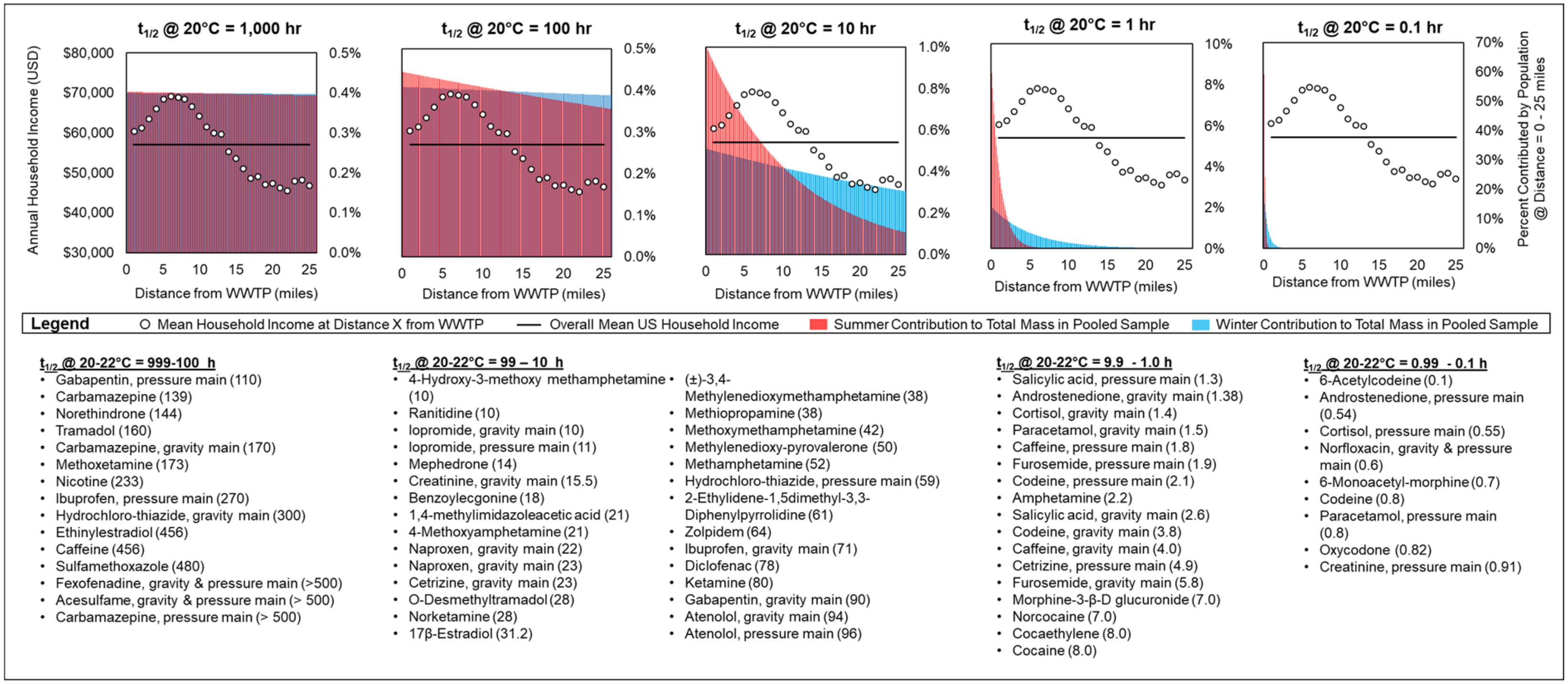

Figure ***Error! No text of specified style in document.***-9. Seasonal differences in population captured by WBE sampling at a WWTP result in varying populations represented by the samples. The effect is magnified for biomarkers with half-lives shorter than 10 hours and attenuated for biomarkers with half-lives over 100 hours. Superimposed on median household income as a function of distance from a major WWTP, the results indicate that wintertime campaigns capture not just a larger number of people, but a qualitatively different population, subject to different economic, social, and likely, Conclusions

There exists a non-random relationship between distance from a major wastewater treatment plant and demographic indicators like household income, educational attainment, military service, unemployment, and the lack of health insurance. In the United States, these patterns appear at various spatial scales (national vs. state vs. county-level) and carry across different regions of the country, despite documented regional differences in political, social, economic, and public health profiles.

WBE sampling during the colder months of the year will be universally more inclusive than sampling performed during the hotter months of the year, as a larger proportion of the population can be observed due to slower degradation rates, and also because the difference in the representation of populations at a downstream sampling location is more attenuated than summer-time samples, in which populations closest to the WWTP are represented much more in the composite.

For WBE studies concerned exclusively with passive monitoring of population consumption patterns, health, and stress, we recommend winter-time samples be collected if the study is intended to be representative of the WWTP service area as a whole. For WBE studies which pair interventions with monitoring, our results can help to better target the interventions and interpret their impact.

CHAPTER 5

ASSESSING POTENTIAL IMPACTS OF WASTEWATER TEMPERATURE ON OPIATE CONSUMPTION MONITORING IN TEMPE, ARIZONA, USA

Abstract

In this study, we sought to determine whether it was possible to isolate true changes in community consumption of opiates over the course of a year-long monitoring period from the effects of temperature-related change in degradation rates. Wastewater samples collected at the outfalls of three independent sewersheds and analyzed for total mass of opiate parent compounds codeine and oxycodone were evaluated. Hydraulic residence time and flow rates simulated by an EPA SWMM model were used in conjunction with a physical model representing heat transfer between wastewater, soil, and air, to calculate the expected contribution of temperature on the observed monthly change in measured opiate mass. Modeling results suggest at least some of the monthly changes observed in the measurable concentration of opiates should be attributed to natural, seasonal temperature changes, rather than to actual changes in the substances' consumption. While WBE samples represent pooled populations, such that the exact location and mass of any particular discharge is unknown, hydraulic modeling, in combination with a wastewater temperature model, can be used to bracket the likely effects of ambient conditions (i.e., temperature) on WBE study results.

Introduction

It has been established that wastewater temperature can vary significantly across the world, with a rate of change up to 13-fold between winter and summer at the same location (Hart and Halden, in review). The principal purpose of this study was to determine whether it was possible to isolate true changes in community consumption of opiates by detrending the effects of temperature-related seasonal change in the degradation of the biomarkers.

Methodology

Study area

This study focused on the City of Tempe, Arizona, USA. The city of Tempe covers an area of 104 square kilometers and is land-locked by neighboring cities comprising the metropolitan Phoenix area. It had a population of 185,038 according to the 2017 U.S. Census and a density of 1,779 people per square kilometer. Land use is predominantly residential, with some industrial and commercial activity.

Wastewater sample collection and processing

Wastewater samples were collected over the course of 16 months at 3 locations representing the outfalls of 3 independent (not nested) sewersheds within the City of Tempe collection system. Each month, samples were collected for 7 consecutive days. Each day’s sample represents a composite of a 24-hour period. Samples were processed by liquid chromatography tandem mass spectrometry to derive final observed mass loads of codeine and oxycodone per day, per sewershed.

Data sources and assumptions for model inputs

Data related to the physical layout of the wastewater collection system was obtained from the City of Tempe Water Utilities Department. Wastewater loading was estimated using historic wastewater meter data to derive a per capita wastewater loading rate. Population density estimates were based on Maricopa Association of Governor's Traffic Analysis Zones (TAZ 2019), with residential wastewater loads assigned proportionally to population density and manhole (node) count. Industrial wastewater loads were assigned to the collection system node nearest to the industrial facility, with average flow rates and diurnal curves based on meter data. The EPA SWMM model was set up to simulate a 72-hour period representing typical weekday conditions subject to dry weather flows only. No leakage or infiltration were incorporated into the hydraulic model. The temperature-dependence (Q10) of Codeine and Oxycodone half-lives was assumed to be a constant 2.5.

Table **Error! No text of specified style in document.**-5. Summary of major input datasets and assumptions.

Data Type	**Value**	**Source**
Soil Texture	Loam, Clay Loam, Sandy Loam	USDA NRCS Web Soil Survey
Soil Thermal Diffusivity	Based on soil texture via regression	Arkhangelskaya and Lukyashchenko 2018

Depth to Cover	Varies	Rim minus invert elevation, based on City of Tempe as-builts
Daily wastewater generation, per capita	64.74 gal (0.245 m^3)	City of Tempe Wastewater Master Plan 2016, analysis of meter data, population-weighted average of Alameda, Knox, Carver, and Camelot Lift Stations.
DWF diurnal curves	Varies by basin	City of Tempe Wastewater Master Plan 2016, analysis of meter data
Population	2018 actual population by TAZ polygon	Projections of Population, Housing, and Employment for Maricopa and Pinal Counties, Arizona, by Traffic Analysis Zone, 2019.
DWF per node, industrial	As-is	City of Tempe Wastewater Master Plan 2016, Wilson Engineers.
Initial Wastewater Temperature	30°C	

<table>
<tr><td>Flow Rate</td><td colspan="7">EPA SWMM model output</td></tr>
<tr><td>Q10</td><td colspan="3">2.5</td><td colspan="4">2-3 for biologic systems</td></tr>
<tr><td>Ambient (20°C) half-lives in gravity mains</td><td colspan="3">Codeine: 0.8 hr;
Oxycodone: 0.82 hr</td><td colspan="4">Gao et al. 2017</td></tr>
<tr><td rowspan="5">Average Monthly Air Temperature</td><td rowspan="5">See right, (°C)</td><td colspan="6">2019 US Climate Data, version 2.3</td></tr>
<tr><td>Jan</td><td>Feb</td><td>Mar</td><td>Apr</td><td>May</td><td>Jun</td></tr>
<tr><td>12.3</td><td>14.0</td><td>16.7</td><td>20.4</td><td>25.2</td><td>29.6</td></tr>
<tr><td>Jul</td><td>Aug</td><td>Sep</td><td>Oct</td><td>Nov</td><td>Dec</td></tr>
<tr><td>32.3</td><td>31.7</td><td>28.8</td><td>22.7</td><td>16.2</td><td>11.6</td></tr>
</table>

Calculation of monthly wastewater temperature

Heat loss or gain from a pipe can be expressed as the sum of the convective transfer of energy between wastewater in a pipe and the soil in which the pipe is buried, and because sewers do not flow full, the radiative transfer between wastewater and air as well. This relationship is expressed as:

$\Delta Q = Q_{conv} + Q_{rad}$ *Equation*

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Where Q_{conv} is the convective transfer, in watts; and the Q_{rad} is the radiative transfer, in watts.

First, the convective transfer is calculated as:

$Q_{conv} = \propto A \ (T_{wastewater,initial} - T_{soil})$ *Equation*

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Where $\propto$ is the pipe's convective heat transfer coefficient (estimated at an average 2.493 W/($m^2\cdot$°K) for the study area's collection system); A is the pipe surface area (m^2); $T_{wastewater,initial}$ is the temperature of the wastewater flowing through a pipe (°K); and T_{soil} is the temperature of the soil in contact with the pipe (°K), estimated as:

$$T_{soil} = t_{ave,air} - A_{air}e^{-z\sqrt{\frac{\pi}{\alpha\tau}}} sin\left(\frac{2\pi(\theta-\theta_{lag}}{\tau} - Z\sqrt{\frac{\pi}{\alpha\tau}}\right) + 273.15 \qquad \textit{Equation}$$

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Where $t_{ave,air}$ is the average annual air temperature (°C); A_{air} is its annual amplitude (°C); z is the pipe burial depth (m); α is the thermal diffusivity of the study area's soil (22176 m^2/day, calculated based on soil type from NRRC and texture-diffusivity regressions from Arkhangelskaya and Lukyashchenko 2018); τ is the duration of the annual cycle (365 days); θ is the number of days elapsed since the start of the year; θ_{lag} is the phase lag in soil temperature (set to 0.75 radians based on reported observations for Tempe, Arizona, USA by Kusuda and Achenbach, 1965); and 273.15 is a conversion between degrees Celsius and degrees Kelvin to return T_{soil} in units of °K.

Next, the radiative component of heat transfer is calculated as:

$$Q_{rad} = \epsilon\, A\, \sigma\, \left(\left(T_{wastewater,initial}\right)^4 - (T_{air})^4\right) \qquad \textit{Equation}$$

***Error! No text of specified style in document.**-26*

Where ϵ is the thermal emissivity of the piping material (estimated for the study area's pipe system as 0.92, unitless); A is the pipe surface area (m^2); σ is the Stefan-Boltzmann constant relating emitted power per unit area and thermodynamic temperature, equal to 5.67×10^{-8} $W\cdot m^{-2}\cdot K^{-4}$; $T_{wastewater,initial}$ is the temperature of the wastewater flowing through a pipe (°K); and T_{air} is the air temperature inside the pipe, approximated as surface air temperature (°K).

The sum of convective and radiative transfer from Equation 5-1 (ΔQ) can be related to the rate of temperature change (°C/second) by dividing the net heat transfer by the product of the density (1000 kg/m^3) and specific heat capacity (4200 J/kg°C) of wastewater:

$$\Delta T = \frac{\Delta Q}{mc_p}$$ *Equation*

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To calculate the resulting wastewater temperature at the end of the segment, the rate of temperature change (ΔT, °C/s) is multiplied by the quotient of segment length (m) and segment flow velocity (calculated by the EPA SWMM hydraulic model, m/s):

$$T_{wastewater,final} = \Delta T \frac{L}{v}$$ *Equation*

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Within each pipe segment, the $T_{wastewater,initial}$ subject to in-segment convective and radiative heat transfer is composed of two components: the temperature of any freshly discharged wastewater (temperature associated with DWF loading, estimated at a 24-average of 30°C or 303.15°K), and the temperature of the wastewater passing from the pipe segment immediately upstream. The calculation was performed recursively at a temporal discretization of 1 second, which resulted, at each time step, in a pipe length (m) equal to the wastewater flow velocity (m/s).

Calculation of wastewater temperature-related change in biomarker degradation rates

The degradation over time of a compound of interest present in wastewater can be expected to follow exponential decay, described by the formula as:

$$N(t) = N_0 \left(\frac{1}{2}\right)^{\frac{t}{t_{\frac{1}{2}}}}$$ *Equation*

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Where $N(t)$ is the quantity that still remains and has not yet decayed after a time t (i.e., the amount measured by the sampling campaign); N_0 is the initial quantity of the substance that was excreted and discharged into the wastewater collection system; $t_{1/2}$ is the half-life of the biomarker (codeine, fentanyl, oxycodone), and t is the time elapsed between the time of excretion (time = 0) and time of observation/sample collection (time = t).

The adjusted biomarker half-lives were based on the calculated wastewater temperature, a series of initial biomarker half-lives reported at ambient temperatures, and the Arrhenius Equation as shown in Equation 5-8:

$$R_2 = R_1 \times Q_{10}{}^{\left(T_2 - T_1 / 10℃\right)}$$ *Equation*

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where R_1 is the initial decay rate, equal to the negative natural log of two divided by the initial reported half-life (Laidler 1984). When solving for the half-live, yields Equation 5-9:

$$t_{\frac{1}{2},2} = t_{\frac{1}{2},1} \times \frac{ln(2)}{ln(2) \times Q_{10}{}^{\left(T2 - T1 / 10℃\right)}}$$ *Equation*

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Where $t_{1/2,1}$ is the initial half-life, T_1 is the temperature at which initial half-life was derived, $t_{1/2,1}$ is the half-life at seasonally- and spatially-adjusted wastewater temperature calculated in this study, T_2 is the calculated temperature to which initial half-life is adjusted to, and Q_{10} is a factor of temperature-dependent of rate change, ranging between 2 and 3 for most biologic systems. A value of 2.5 is used in this study.

Modeling and numerical analysis software

Hydraulic modeling to calculate hydraulic residence times (HRTs), volumetric wastewater flow rates, and velocities was performed using the U.S. Environmental Protection Agency's (EPA) SWMM modeling environment (SWMM v.5.1.013; Rossman 2015). ESRI ArcGIS was used to assign dry-weather flow loading to manholes based on TAZ population densities and the results of the City's metering program. NetSTORM v.2019.06 was used to convert the binary output of SWMM 5.1.013 into timeseries of flow and velocity at each pipe segment into a format readable by text editors and GIS software (Heineman 2004). Network Analyst was used in ESRI ArcGIS to perform an accumulation analysis over the pipe network.

Results and Discussion

Impacts of temperature on biomarker mass available for downstream observation

In the absence of seasonal temperature fluctuation, a biomarker discharged to the wastewater collection system at a constant rate would degrade at a rate proportional to its residence time in the system and arrive available for observation at some downstream sampling location at a seasonally invariant rate (Figure **Error! No text of specified style**

in document.-10). Because, however, seasonal changes in air and soil temperature effect the transfer of heat between wastewater and the surrounding environment, the temperature-adjusted degradation rate of such a biomarker will not be constant over a year. As a result, the same hypothetical constant loading upstream will result in different masses available for observation downstream. All else held constant, the degree to which the same seasonality in wastewater temperature will affect downstream observations will increase with increasing hydraulic retention times – i.e., it will be magnified for outfalls serving larger sewersheds, and attenuated in locations serving smaller sewersheds. Failing to account for the role temperature plays in the degradation of biomarkers will lead to the propagation of error into estimates of upstream discharge, consumption, and exposure, and subsequent inferences and decision-making regarding the status of public health and the appropriateness or efficacy of implemented or planned interventions.

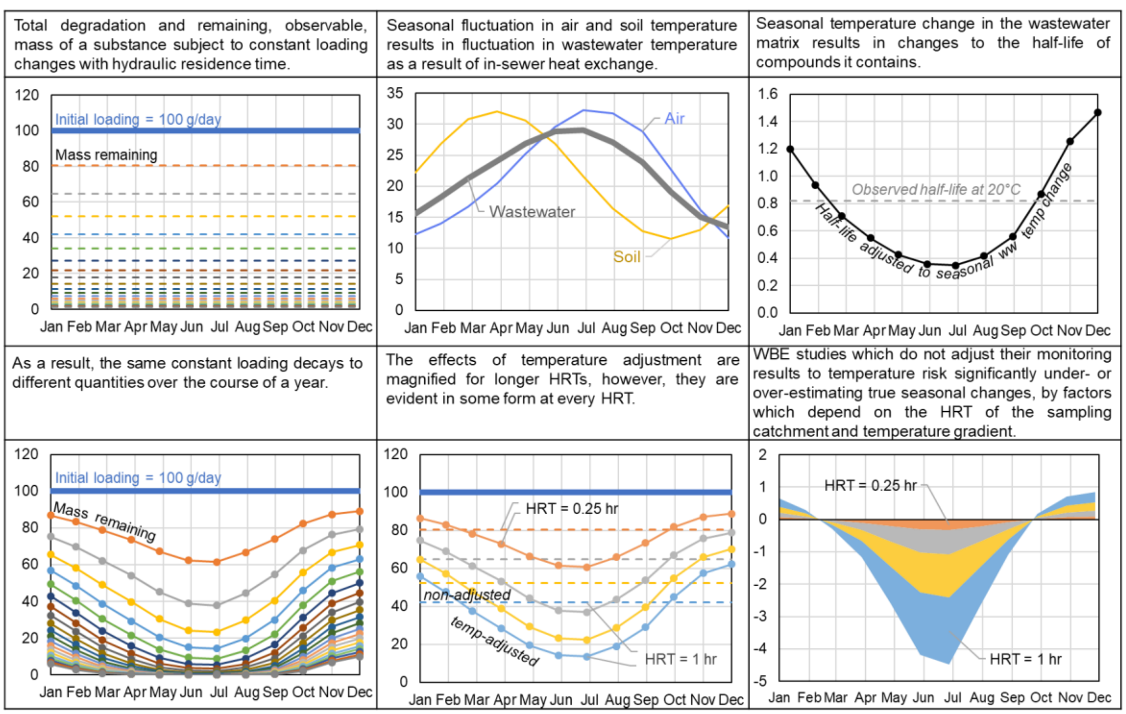


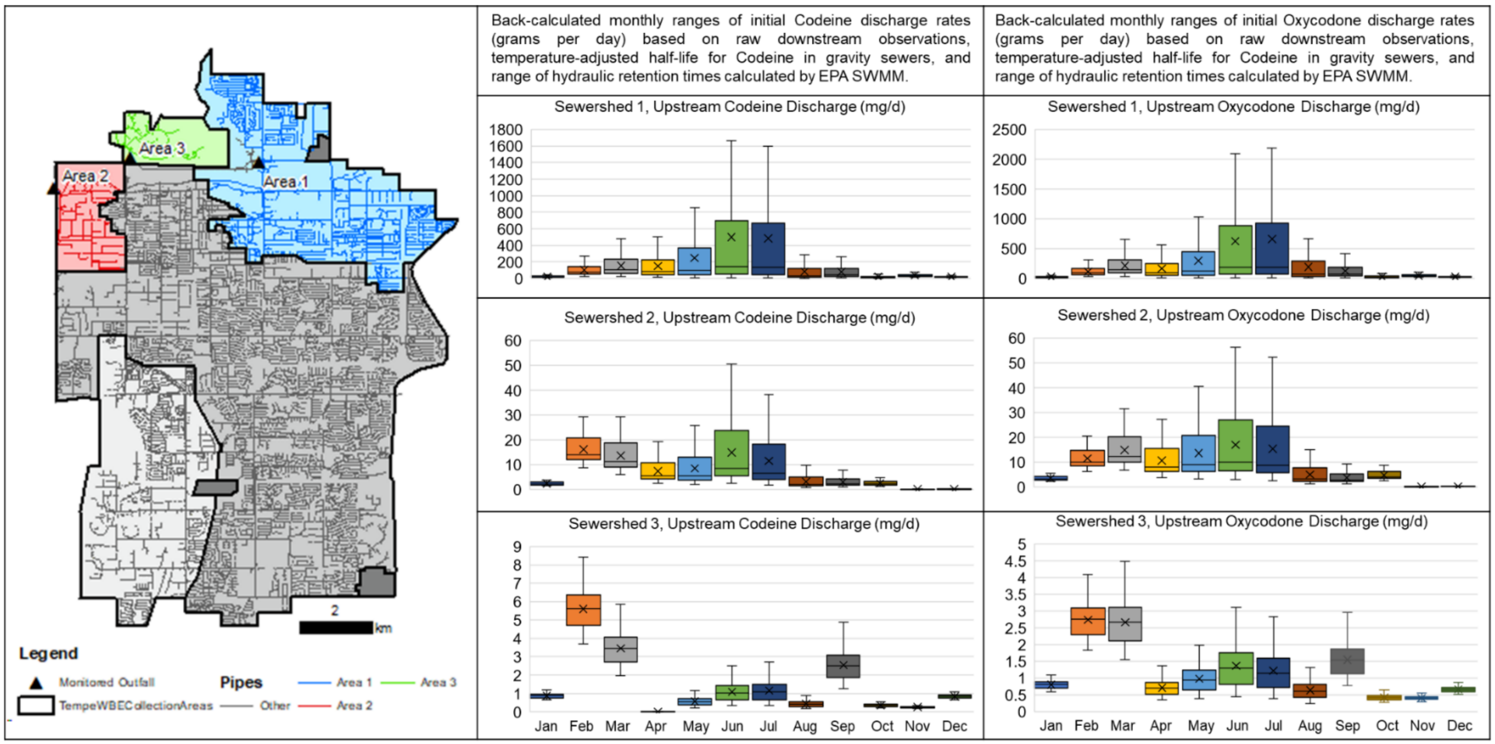
Figure **Error! No text of specified style in document.**-10. The impacts of temperature on biomarker mass available for downstream observation increase with hydraulic retention time. If downstream observations are not adjusted accordingly, estimates of upstream biomarker discharge, and the consumption and exposure of populations to compounds of interests can misrepresent long-term trends.

Temperature-corrected estimated upstream daily discharges of codeine and oxycodone

An important source of uncertainty in efforts to translate downstream WBE observations into insights about the upstream populations represented by the pooled sample is that the actual discharge location(s) of substances measured downstream is unknown, and therefore their residence time and degradation are also unknown.

shows the seasonality and range of uncertainty in back-calculated initial daily discharge rates of (N_0, grams per day) of codeine and oxycodone associated with the full range of possible discharge locations in each of the three sewersheds explored in this case study. Larger sewersheds with longer hydraulic retention times afford more variability in potential residence time of the substances in the collection system between point of discharge and point of sampling, and result in greater uncertainty around the back-calculation of initial quantities discharged from those observed at the sampling point (N_t) after time t = hydraulic residence time. This is generally magnified during the summer months when degradation rates increase in response to higher temperatures.

Figure **Error! No text of specified style in document.**-11. Temperature-corrected estimated upstream daily discharges of codeine and oxycodone over the course of a year at three different sewersheds in the study area.



Impacts of discharge location on probability of observable signal at outfall

The role played by the location of biomarker discharge in available observation mass loads is shown in Figure **Error! No text of specified style in document.**-. In Figure **Error! No text of specified style in document.**-, the wintertime and summertime mass of Codeine remaining after an initial discharge of 100 grams per day travels through the collection system is shown for each of the three sewersheds monitored in the case study. Although the same initial mass can decay to one-half to nearly an order of magnitude depending on the location of discharge within the three sewersheds, temperature, particularly during summer months when degradation increases, expands the range. However, unlike the point of discharge which currently cannot be constrained to more than the upper and lower bounds of travel times, the impacts of temperature can be estimated on a finer scale.

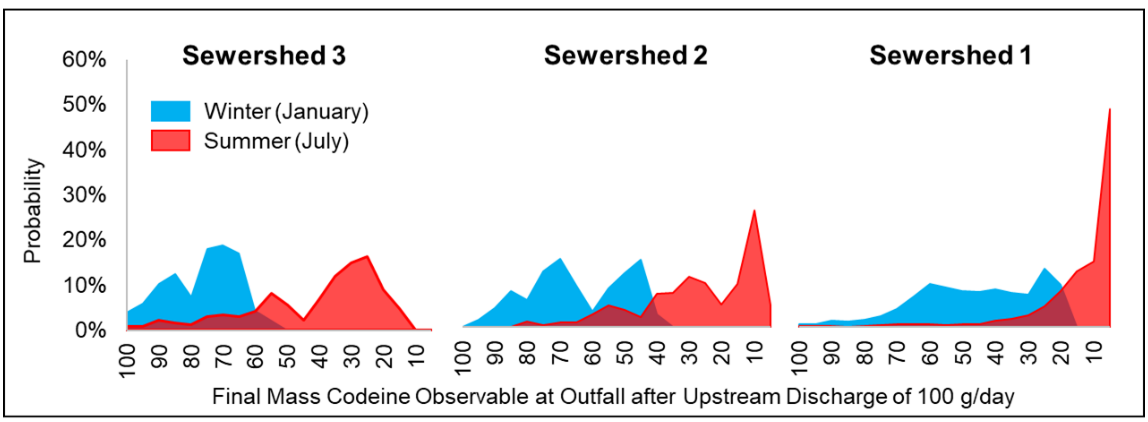


Figure **Error! No text of specified style in document.**-12. Probability distribution of Codeine mass observable at Sewershed 1-3 outfalls if 100 grams per day was discharged at any node upstream in the associated sewershed.

Seasonal changes in the focus of WBE observations

The difference in the outfall sample's makeup during winter and summer months is further illustrated by Figure **Error! No text of specified style in document.-**. In Figure **Error! No text of specified style in document.-**, the wintertime and summertime contributing percentage was assigned to each pipe in the collection system based on its model-simulated HRT and mapped to the associated building footprint. The observable ratio is calculated by dividing the contributing percentage of each pipe segment by the minimum contributing percentage for that sewershed. The ratios have been log transformed. The color coding reflects the ratio between each site's contribution to a sample collected at the outfall, and the contributions of all others in the sewershed.

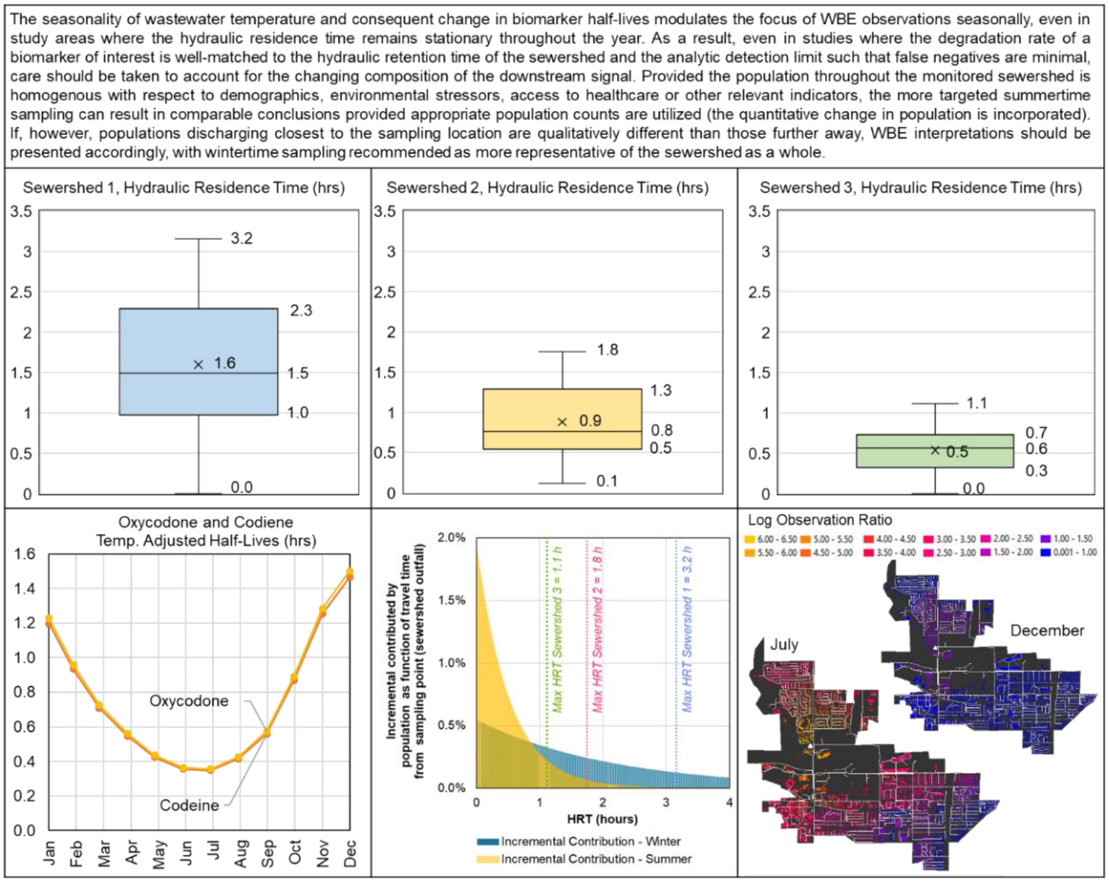


Figure **Error! No text of specified style in document.**-4. Seasonal changes in the focus of WBE observations.

Implications for undetected dosage and its change seasonally

Overall, the case study's monitoring plan is robust in that the half-lives of the compounds of interest, the hydraulic residence time of wastewater in the collection system, the method detection limits, and volumetric flow rates are relatively well-matched, especially in sewersheds 2 and 3. Table 5-5 presents results from a numerical experiment in which a single hypothetical dose of codeine and oxycodone are released into the wastewater collection system at the upstream-most point in each of the three monitored sewersheds, and the concentration remaining after degradation during travel time is compared with the method detection limit. During winter months, the remnants of a single prescription dose of both Oxycodone and Codeine discharged at the upstream-most point in the system will be detectable in sewersheds 2 and 3. During summer months, evidence of a single dose will be detectable only in sewershed 3, and only for Oxycodone. While current WBE method detection limits are precise enough to capture trace amounts of biomarkers on the order of nanograms per liter, there currently remains considerable uncertainty with respect to the timing, concentration, and location of initial compound releases upstream, and their degradation, dilution, or capture prior to arriving at the sampling point downstream. In addition to testing the case study's monitoring design, this numerical experiment also reinforces the role that temperature plays in producing different observable outcomes given the same initial, actual public health-related actions upstream.

Table **Error! No text of specified style in document.**-6. If a single prescription dose of Codeine (30 mg/day) or Oxycodone (10 mg/day) is discharged at the furthest node in the sewershed, its final mass at time $t = max\ HRT$ is as shown for summer and winter conditions based on reported ambient half-lives (0.8 (Gao et al 2017) to 3.8 hours (O'Brien et al 2017) adjusted to seasonal wastewater temperatures estimated by the model. Given the volumetric flow rate at each of the three sewersheds' outfalls (calculated by hydraulic modeling) and the method detection limit for Codeine (0.8 ng/L) and Oxycodone (0.2 ng/L), the maximum non-detectable mass and its equivalent prescription count are shown below. Under these assumptions, a false negative for more than one discharged dose of codeine can occur only in sewershed 1 during both winter and summer months. No false negatives, of either opiate compound would occur in sewersheds 2 and 3

Codeine					**Oxycodone**			
Summer (July)								
Sewershed	Mass Remaining at Outfall (mg)	Conc. at Outfall (ng/L)	Mass Below Method Detection Limit (mg/d)	**Equivalent Non-Detect Prescription Doses**	Mass Remaining at Outfall (mg)	Conc. at Outfall (ng/L)	Mass Below Method Detection Limit (mg/d)	**Equivalent Non-Detect Prescription Doses**
1	0.05-7.98	0.000629-0.0902	70.7-62.7	**2.35-2.09**	0.02-2.74	0.00024-0.031	17.6-14.9	**0.58-0.49**
2	0.91-14.4	0.156-2.45	3.78-N/A	**0.12-N/A**	0.33-4.88	0.056-0.832	0.84-N/A	**0.02-N/A**
3	3.26-18.8	0.556-3.2	0.23-N/A	**N/A**	1.14-6.34	1.20-6.67	N/A	**N/A**
Winter (December)								
1	6.73-21.9	0.0761-0.248	64.0-48.8	**2.13-1.62**	2.32-7.35	0.026-0.083	15.3-10.3	**0.51-0.34**
2	13.1-25.2	2.23-4.29	N/A	**N/A**	4.45-8.43	0.759-1.44	N/A	**N/A**
3	17.7-26.8	18.6-28.3	N/A	**N/A**	5.98-8.97	6.29-9.44	N/A	**N/A**

Limitations and Advantages

Although the EPA SWMM model represents an all-pipes model, it remains a planning-level tool in that the loading is based on long-term average rates. Divergence in the loading from any household at any part of the day from the idealized DWF curves is expected. Thus, while the flow paths are fixed, the actual hydraulic residence time during sampling can diverge from that simulated. More broadly, many variables are responsible for changes in the quantity of a biomarker available for observation at a downstream sampling location. In this study, we focus on temperature-related changes in the rate of exponential decay. When the measured mass of opiates is adjusted by the residual between measured and seasonally expected, the result is suggested to be a more accurate representation of the true nature of monthly differences in opiate consumption. Although simplifying assumptions required for the calculation of the temperature adjustment introduce uncertainty into the adjusted mass, correcting for temperature yields a better estimate of the true magnitude of other variables which impact downstream observations.

Conclusions

In future studies, temperature must be considered when per capita or bulk loads are described. In this case study, in a comparison with field data, we find seasonality in temperature and subsequent degradation rates of opiates cannot be ruled out as an at least partial explanation for observed decrease in summer total mass observed. Because the catchments in this WBE study had relatively short HRTs relative to the half-lives of the opiates sampled, changes in bulk mass are expected to track consistently with changes in per-capita consumption over the course of the year.

However, for WBE campaigns having sparser sampling locations and shorter-lived compounds of interest, during summer months when wastewater temperatures are highest and the persistence of the compounds is lowest, when these bulk masses are adjusted to population to derive per-capita opiate consumption estimates, de-facto population counts (such as those based on census records), or even de-jour counts based on mobile phone data records are likely to over-estimate the population count of people contributing to the sample, resulting in under-estimated per-capita loads. In these instances, population estimates via the analysis of population biomarkers present in sewage, by being subject to the same changes in ambient conditions as the opiates, are more likely to adjust the true observable population appropriately. However, the ideal biomarker will have low variance in its excretion across a population, and will either not vary seasonally, or its variation be thoroughly understood (Gracia-Lor et al 2017). While a number of biomarkers have been proposed and used in WBE studies, an ideal candidate has not yet been definitively identified by the WBE community.

Temperature, along with any other factor that influences biomarker degradation, will play a greater role the longer the biomarker travels between initial excretion and sampling. However, it is possible to estimate seasonal temperature differences – more so, at present, than the location(s) of discharge. Thus, accounting for temperature removes one of the variables in the “black box” and helps to constrain the uncertainty in back-casts of community health from downstream observations of wastewater.

CHAPTER 6

CONCLUSIONS AND FUTURE WORK

In the preceding chapters, my analysis output suggests that temperature plays a significant role in the degradation of many chemicals of concern for wastewater-based epidemiology (WBE) studies, particularly those compounds with half-lives less than a median sewer hydraulic residence time for a given study area.

While temperature is only one of multiple factors causing changes in observable biomarker loads in sewer sampling locations downstream of source releases, I demonstrate that adjusting for its effects is feasible and practical, thereby allowing us to address one of the more easily knowable unknowns. The temperature-adjusted results, in turn, provide wastewater-based epidemiologists with a clearer picture of the remaining magnitude of change that needs to be accounted for in other ways. As a result, we are one step closer to separating the signal (i.e., the "true" changes in the initial excretion of biomarkers and the implications for community health and behavior upstream) from the noise embedded in the downstream observations from factors such as the diluting effects of stormwater intrusion, changes in wastewater pH, or the errors introduced during wastewater sampling or processing.

Expanding the conceptualization of WBE uncertainty by Castiglioni et al. 2013, I propose that the uncertainty in community-scale (rather than per-capita) back-casts from downstream observations can be represented by the propagation of uncertainties:

$$\sum chemical\ analysis + sampling + stability + excretion + uptake \qquad \textit{Equation 6-1}$$

Where stability can be further decomposed into:

$$\sum_{t=0}^{t=\max HRT} t_{0.5} \times (pH + temperature + biofilm + sorption + settling)$$

Equation 6-2

Of these, the most extensively parameterized and empirically measured parameters have been ones related to the role of sampling regime and analytical methods (chemical analysis) on the variability in the mass of compounds measured in wastewater. Some work has been done in estimating compound half-lives, particularly at ambient temperatures. However, currently the number of proposed WBE biomarkers exceeds those tested, and more pilot- and field-scale studies are required overall to validate and bracket observed stabilities under a wider variety of real-world conditions. Other factors, such as the impacts of temperature at non-ambient conditions, or the population-scale variability in the uptake and excretion of compounds present in environmental toxins, foods, personal care products, therapeutic or illicit drugs, have not yet been empirically parameterized.

Key Findings

With respect to whether temperature plays a significant role globally, in Chapter 3, I have found that wastewater globally experiences significant temperature changes annually. Over a year, 75% of the world's wastewater is calculated to range between 6.9 and 34.4°C. Wastewater temperature changes are predicted to impact biomarker fate. Temperature-induced biomarker half-lives may vary 27% to 7,010% from ambient conditions at 21±1°C. The observable distal reach of sewage monitoring may vary up to 49-fold as a result.

With respect to whether demographic patterns may make seasonal variation in degradation rates problematic for the evaluation of long-term (multi-month) WBE studies, in Chapter 4, I have found that statistically significant, non-linear correlations exist between multiple demographic indicators and hydraulic residence time (HRT). For biomarkers with half-lives less than the median U.S. HRT of approximately 10 hours, not only is less than 50% of the population represented in the sample, but the sample is skewed most strongly to represent those living closest to a major wastewater treatment plant. Consequently, current WBE studies may be sampling not just different numbers of people during winter months than they are during summer months, but are capturing, unknowingly, different types (demographics) of people as well. These findings can be leveraged to improve WBE studies in the future, however, by designing monitoring campaigns which compare inter-annual changes between the same season to identify temporal trends, and compare intra-annual changes to identify spatial trends, associated with different population sub-groups.

With respect to the application of the temperature degradation model to a real-world example in the City of Tempe, AZ, USA, in Chapter 5, I have found modeling a possible, practical, and advisable mechanism for understanding the range of uncertainty associated with interpreting downstream observations of wastewater as community consumption of opiates upstream. Adjusted for temperature, the true consumption of codeine and oxycodone by the study area's population remains more constant during the summer months than would be inferred from the experimental data alone. Observed winter-time spikes in the detection of these substances, on the other hand, represent an even greater increase in their use, all else held equal. Finally, even for relatively dense monitoring configurations, in which single prescription-grade doses of the biomarkers of interest can be released at the furthest point upstream and not degrade to false negatives by the time the wastewater arrives at the sampling point, the uncertainty with respect to the actual discharge location within a collection system can dominate the estimation of initial doses back-calculated from downstream observations.

Future Research

A critical simplifying assumption carried through the temperature modeling and its application to real-world opiate observations is that the temperature-dependence of different biomarkers is constant regardless of substance, and can be approximated using the Arrhenius equation, where the rate of degradation increases by a factor of 2.5 for each 10°C rise in wastewater temperature. This bears testing at the bench and field scale, as it is plausible that certain compounds are more sensitive to temperature than others. Determining this temperature dependence empirically may show that another non-linearity needs to be introduced into our conceptual understanding of the relation between direct downstream observations of biomarker concentrations in wastewater, and back-cast estimates of initial discharge and consumption and/or exposure.

A perennial limitation of WBE studies continues to be the difficulty of deciphering between low downstream observations due to low rates of initial excretion, versus higher percentages of degradation – particularly for parent compounds which do not degrade into well-characterized, stable daughter compounds. This class of substances will continue to grow as WBE matures away from the monitoring of illicit drugs and towards more challenging tasks such as characterization of community-scale changes in gut microbiome. By extension, there is also a fundamental difficulty in distinguishing between small loads released close to the sampling point but having undergone little degradation, and larger loads released further upstream and having undergone significant degradation during travel time. Because WBE is ultimately concerned with the upstream behavior and exposure of populations, and not with releases to a downstream environment, that an identical load arrives downstream but has originated from different upstream sources is of interest and not irrelevant. To address these coupled issues, more work is recommended to identify conservative markers that are capable of tracking travel time alongside the biomarker of interest. If such a marker is identified, it can be used to constrain the uncertainty related to the residence time of a particular unit mass of biomarker and thereby more accurately define the initial mass that was released upstream prior to its partial in-sewer degradation.

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