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Microbial risk assessment of sustainable urban stormwater management practices

DISSERTATION

submitted in partial satisfaction of the requirements

for the degree of

DOCTOR OF PHILOSOPHY

in Environmental Engineering

by

Keah-Ying Lim

Dissertation Committee:

Professor Sunny Jiang (Chair)

Professor Stanley Grant

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2016



*Dedicated to my parents, Lim Ing Ngak and Voon Chiew Hwa,  
and uncle, Lim Eng Chu,  
who have sacrificed a lot to provide for me.*

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# CURRICULUM VITAE

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University of California, Irvine, Irvine, CA

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- **Lim, KY.**, S. Shao, P. Jian, S.B. Grant, S.C. Jiang “Evaluation of the dry and wet weather recreational health risks in a semi-enclosed marine embayment in Southern California.” To be submitted to *Water Research*.
- Wu, Y., **KY. Lim**, S.C. Jiang “Assessment of Cryptosporidium and norovirus risk associated with de facto reuse in Trinity River, Texas.” Submitted to *Microbial Risk Analysis*.
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- Jiang, S.C., **KY. Lim**, X. Huang, D. McCarthy, A.J. Hamilton (2015) “Human and environmental health risks associated with urban stormwater harvesting.” *WIREs Water*, **2(6)**, .683-399
- **Lim, KY.**, A.J. Hamilton, S.C. Jiang (2015) “Assessment of public health risk associated with viral contamination in harvested urban stormwater for domestic applications.” *Sci. of the Tot. Environ.*, **523**, 95-108.
- **Lim, KY.**, S.C. Jiang (2013) “Reevaluation of health risk benchmark for sustainable water practice through risk analysis of rooftop-harvest rainwater.” *Water Res.* **47**, 7273-7286.



- Dickinson, G., **KY. Lim**, S.C. Jiang (2013) “Quantitative microbial risk assessment of pathogenic vibrios in marine recreational waters of Southern California.” *Appl. Environ. Microbiol.* **79(1)**, 294-302.
- **Lim, KY.**, C.Q. Surbeck (2011). “A multi-variate methodology for analyzing pre-existing lake water quality data.” *J. Environ. Monit.*, **13**, 2477-2487.
- **Lim, KY.**, S.E. Wilson, E. Woolsey, C.Q. Surbeck (2010). “Evaluation of a community-scale drinking water treatment system.” *Int’l Journal for Serv. Learning in Engr.*, **5(2)**, 17-31.

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## **ABSTRACT OF THE DISSERTATION**

Microbial risk assessment of sustainable urban stormwater management practices

by

Keah-Ying Lim

Doctor of Philosophy in Engineering,

University of California- Irvine, 2016

Professor Sunny Jiang, Chair

Sustainable Urban Water Management (SUWM), a new approach to manage stormwater as a water resource instead of nuisance, has the potential to supplement the diminishing traditional water supplies as well as reducing surface water pollution from storm runoff. Uncertainties of public health risks represent one of the main barriers for the smooth transition to SUWM approach as urban stormwater is known to be highly variable in water quality and is less studied than the conventional water supplies. My research is aimed at improving our state-of-knowledge for the public health risks associated with the SUWM practices. Using the Quantitative Microbial Risk Assessment (QMRA) framework as my main research tool, I investigated the risk implications of three SUWM scenarios: 1) rainwater harvesting, 2) stormwater harvesting, and 3) discharging stormwater into recreational water. As household-level rainwater harvesting is the most readily implementable SUWM approach, I first investigated the public health risks associated with using the rooftop harvested rainwater for household produce irrigation—a reasonable scenario considering the relatively clean water quality of rainwater. My result showed that the risk associated with consuming produce irrigated by harvested rainwater exceeded the EPA’s benchmark for safe drinking water, but is still at least ten-fold lower than when reclaimed water is used for the same purpose. To investigate the risks associated with capturing, treating, and reusing urban stormwater collected from urban developments, I examined three non-potable household applications: 1) toilet-

flushing, 2) showering, and 3) foodcrop irrigation. My results showed that harvested stormwater is only safe for toilet-flushing under the circumstances considered. However, interpretations of the risks also differ depending on the risk benchmark used for comparison. In my final case study, I adopted a new contamination source apportionment QMRA method to investigate the recreational health risks associated with discharging stormwater into a popular recreational beach. My results showed that sewage contamination of urban stormwater is the governing factor for elevated risks in the water. However, the risk levels are within the acceptable risk set by the U.S. EPA in most of the cases in spite of the violation of water quality standard due to contribution of fecal bacteria from non-human sources. The overall finding of my research demonstrated that the QMRA is a powerful tool to provide a scientific basis for SUWM decisions. The risk outcomes can be used to set the appropriate public health risk management guidelines and water legislation that are necessary for the progress of SUWM practices.

## **CHAPTER 1: Introduction**

## 1.1 Background

The rapid population growth and urban sprawling, drastic climate change, and depletion of natural resources have been engendering doubts on the water sustainability of cities in developed nations. Accompanying with these changes are the increasing awareness of ‘green issues’ by the general public, which circulate around the community well-beings, ecological health, and sustainable development. These green issues transcend the traditional focus placed on the public health alone— issues that developing and undeveloped nations are still striving to achieve. Altogether, these issues have driven the concept of a new urban water cycle that push for: **1) the optimal and gradual ‘naturalization’ of urban developments close to its pre-development state,** **2) the enhancement of water security through developing alternative water supplies from sources traditionally considered as nuisance,** and **3) the efficient use of resources that hinged around using green and decentralized systems;** these three central objectives collectively constitute an revolutionary water management approach that is frequently referred to as ‘Sustainable Urban Water Management (SUWM)’ with many similar terms (e.g. Integrated Urban Water Management, Total Water Cycle Management’, and ‘Water Sensitive Urban Design’) describing the same approach [1].

SUWM is propounded to be the successor of the traditional urban water service provision model that is no longer the answer to sustain the urban populations in our increasingly complicated world. The overarching principle of SUWM lies in the integrated management of every urban water source generated in the local region, which is purported to make the most efficient use of water from various stages of the urban water cycle to enhance social, ecological, and economic sustainability. With that being said, the central theme to SUWM is to change the way stormwater is currently managed; it is beneficial to capture and reuse stormwater than releasing/losing it to the environment. It can also be argued that SUWM is merely an extension towards the ill-designed stormwater infrastructure that only focused on flood-control and had resulted in the degradation of urban waterways or the infamous ‘urban streams syndrome’ [2]. In

remediating the urban stream syndrome, SUWM proposes to use a combination of decentralized green systems in the form of biofilters, constructed wetlands, rain tanks, and/or rain gardens to control the frequency, timing, magnitude, pollution, and amount of urban runoff and stormwater at its origin before discharging into the urban waterways, which sometimes entails the capture and/or treatment of the water as alternative water supply for non-potable purposes. The successful implementation of these green systems will, however, require more systematic planning that links all the water sources and interdisciplinary science together to avoid negative repercussions as were experienced through the building of stormwater pipe networks.

The transition from the current urban water systems to that embodying the objectives of SUWM has been slow, mainly due to the difficulties in replacing the legacy infrastructure (e.g. the extensive network of pipelines underground) and the ‘lock-in’ effects of the traditional water systems on both institutional (e.g. water management policies) and technological level (e.g. understanding for the performance of the water system). More specifically, the traditional water management framework currently used in the United States embraces separate management of each water source (e.g. potable water, wastewater, and urban runoff) by different water agencies and local jurisdictions with little-to-no collaboration and communication among the parties— this fragmented nature of water governance means transitioning to a SUWM framework would be a gradual change (instead of a radical one) that is bounded by the legacy infrastructures, such as retrofitting of vetted SUWM solutions based on the buried pipe networks under old cities. As such, developing alternative water resources from urban runoff and stormwater to complement conventional water supplies are expected to be aided by a hybrid of innovative SUWM solutions and current water infrastructure, accompanied by the gradual integration of the separated water governance.

The lack of confidence in SUWM shown by water practitioners is also stemmed from the lack of knowledge and understanding of these solutions, whereby the SUWM systems are not tested widely and adequately in real-world settings and may have heavy implications on the water management issues that

follow [3]. This is not surprising, as **the management of public health risk** has been the foremost factor in deciding how water should be managed, treated, and distributed to the public; transitioning to an urban water system that abide by the principles of SUWM (balancing of green issues with public health) can potentially put the public health safety into uncertain risks as the reliability of SUWM systems are not well-understood. For context, virtually all households in the United States are only receiving water that meets the national drinking water quality standards through a single pipe distribution system, in which the potable water is used for all indoor and outdoor purposes that include toilet-flushing and lawn irrigation. This has in turn shaped the general public's perception of "unsafe water" for non-potable water that is only treated adequately for its purpose (an overlapping objective of SUWM), but that does not meet the national drinking water quality standards.

Public health risks are usually represented by microbial infection/illness risks, which are attributed to the presence of human pathogens in untreated or partially treated water. Human pathogens have the potential to cause a widespread effect as was evidenced by the historical waterborne disease outbreak, such as the Milwaukee Cryptosporidiosis outbreak in 1993 that had caused illnesses among an estimated 403,000 people due to the exposure to water treated by a malfunctioning public water treatment facility [4]. Moreover, microbial infections are acute in nature (as opposed to chronic effects due to most chemical exposure) and have additional risk that may be recurred through secondary transmission (from person to person); these characteristics of microbial risk warrant it as the dominant factor for health risk management of stormwater. In order to convince water practitioners of the benefits of adopting the SUWM approach, it is important to demonstrate the provision of adequate public health safety if alternative water sources and innovative water systems (e.g. green systems) are to replace or even complement the traditional urban water management approach [5].

## 1.2 Research motivation/ questions

The main motivation of this research is to narrow and fill in the knowledge gap to better understand the public health risks associated with various stormwater usages in cities adapting to the SUWM approach.

Emphases were placed on the public health risks associated with the management of stormwater as a water supply, which is increasingly becoming a realistic solution for many water-stressed urban regions in developed nations. Research questions were formulated based on the state of SUWM adoption in the cities of southwestern United States and how it can be progressed, which include the public health policies needed for regulating the use of stormwater harvested through SUWM approach, future research needs for a better risk assessment, and the health risk associated with discharging stormwater as a nuisance. The stage of each research question is set in the U.S., wherein examples from other countries with richer experience as SUWM adopters, particularly Australia [6], are occasionally drawn for comparison. The **Quantitative Microbial Risk Assessment (QMRA) framework** is used as the main tool for answering my research questions and facilitate discussion of the results.

A brief breakdown of my specific research questions is as followed:

1. Are the public health risks associated with using untreated rainwater harvested from the rooftop of houses appropriately regulated using the U.S.EPA annual infection risk benchmark for safe drinking water?

Rainwater is naturally the top candidate to be adopted as the first alternative water supply using the SUWM approach, which is due to the relatively clean quality of rainwater (before it hits the ground) and the ease of harvesting it. In practice, rainwater is harvested from the rooftop, as was practiced in the past centuries by mankind. Harvested rainwater is generally understood to be relatively clean compared to stormwater and wastewater, and is used domestically for many non-potable purposes; some people even use it for potable purpose. However, the public's perception of rooftop-harvested rainwater as an



alternative water supply and the guidelines for managing and using harvested rainwater varies regionally [7]. There is no federal regulation or water quality guideline for harvested rainwater, which makes it difficult to justify the usability of harvested rainwater. In such circumstances, the health risk benchmark for safe drinking water established by the U.S.EPA usually serves as the golden rule for assessing the safety of using the water, as was adopted by numerous studies that investigate the microbial risk of reclaimed water-irrigated crops (e.g. [1, 8, 9]). However, it maybe inappropriate to make such a comparison as the annual infection risk benchmark used for regulating the safety of drinking water supply is a very stringent benchmark that is developed based on a set of conservative assumptions (in QMRA) that only applies for drinking water scenario. The adoption of such benchmark, therefore, might mistakenly interpreted the rooftop-harvested rainwater to be unsafe for many non-potable uses. As such, it is necessary to evaluate the appropriateness of using the health risk benchmark for assessing the safety of harvested rainwater, especially in the context of developing rainwater harvesting guidelines and establishing legal enforcement.

2. Are the health risks associated with non-potable usage of treated stormwater harvested from a developed urban watershed controlled adequately using the SUWM approach?

Urban runoff and stormwater present valuable water resources whose water quality might not be as good as harvested rainwater, but with much plentiful water quantity that can augment a significant portion of the conventional water supplies. Yet, stormwater harvesting is scarcely practiced around the world, wherein many of the water-stressed regions in Australia are pioneering the relatively new water practice. Stormwater is generally harvested from a local water catchment area, where the water is filtered and captured by SUWM systems (e.g. biofilters and constructed wetlands) before being further polished by conventional water treatment processes (e.g. microfiltration, ultra-violet disinfection) and piped for human uses. Harvested stormwater is mostly piped separately from the drinking water supply pipeline, similar to the purple pipes for reclaimed water in California, to indicate the lesser water quality of the

harvested stormwater. Based on the experience of Australia, harvested stormwater is generally accepted by the public for non-potable purposes that involve little water contact with human [6]. As stormwater harvesting is a fairly new water practice, little is understood for the microbial risk related to its uses. There is an urgent need to understand the microbial risks that are associated with the propounded non-potable uses of harvested stormwater, facilitated by a modeling framework that can be further improved with availability of better data or modified depending on the specific stormwater harvesting circumstances (e.g. recharging aquifer vs. direct uses).

3. What are the recreational health risks associated with discharging urban stormwater into a popular recreational beach?

Urban stormwater that is not harvested is usually conveyed and discharged efficiently to receiving water body through networks of stormwater drainage systems. The receiving water bodies for stormwater are sometimes popular recreational destination for coastal cities, wherein the water quality of the beach is regulated by federal agencies (i.e. U.S. EPA) for safe recreational activities. However, the enforced recreational water quality guidelines, the **U.S.EPA recreational water quality criteria (RWQC)**, are developed for wastewater-impacted water bodies that are designated for recreational uses [10]. Many recent studies have pointed to that such criteria are not applicable for water bodies that do not receive wastewater effluent, wherein the criteria are based on the level of fecal indicator bacteria (FIB), such as enterococcus (ENT), that are not always of human sewage origins (e.g.[11-14]). Yet, these non-point source affected water bodies are prone to violating the water quality criteria, especially for water bodies that have poor water circulation. Stormwater and urban runoff discharging to such water bodies are propounded to be the main contributor of fecal indicator bacteria that do not necessarily indicate high health risk of recreating in the water. As such, there is a practical need to reassess the recreational health risk of the non-point source (i.e. stormwater and urban runoff) affected water bodies, facilitated by a

modeling framework to guide the development of a more robust and flexible water quality criteria applicable to all types of recreational waters.

These three research questions are aimed at linking the public health risks that are associated with various ways of stormwater management together. Specifically, by forgoing the capture and reuse of stormwater, the public health risks are merely transferred from the intended users of harvested stormwater to beach goers who visit beaches impacted by the stormwater. It is important to understand the magnitude of the public health risks that are attributed to these stormwater management options. Ultimately, it is hoped this dissertation will help in paving the road towards the optimal balance of the different risks (i.e. public health, green issues, water security, etc) associated with each stormwater management decision, which is the key ingredient for a healthy progression/transition towards the SUWM approach.

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## **CHAPTER 2: Literature Review**

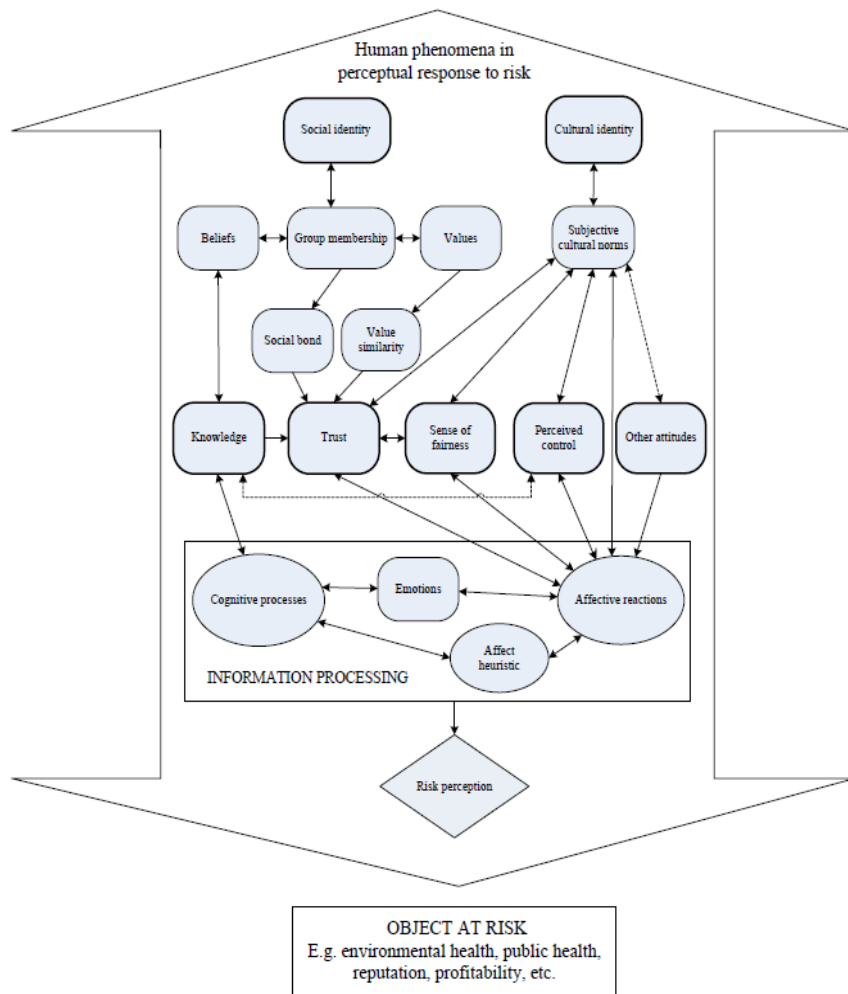
## 2.1 Risks and how they are perceived

Risk, by definition, is the likelihood for the occurrence of an event with negative consequences that can be triggered by any kinds of actions (including non-actions). Risks are ever present and can present themselves in different forms (e.g. financial risk, operational risk, health risk) that are usually interrelated to one another. It is important to understand how the different risks change in response to an action.

Risks and rewards are the main driving factor for one to act or make changes. The rationale for one to take risk is generally explained by the former's expectation for much greater rewards should the risk involved be overcome, mitigated, or avoided. Risk in any form is also subjected to variation in importance depending on the risk perceptions of the stakeholders, which is influenced by the knowledge base and the cultural worldviews of the stakeholders [1]. For example, while the main benefits of adopting SUWM water systems in a local region as perceived by the ecologists could be the preservation/restoration of ecological features of urban waterways, traditional water practitioners might view the change as potential threats that can disrupt the equilibrium of the current urban water system (e.g. benefits of non-action far outweigh that of making uncertain changes). Both parties have a fair share of rationales to support their stands—the benefits of SUWM are mostly established on theoretical basis that are not tested adequately, yet the current urban water systems are also starting to fail the test of time with many real-life examples as evidence. In real-life situation, risks and benefits are to be balanced among many confounding factors that are much more complicated than the simple example described above.

In the context of SUWM adoption, it must be recognized that the decision-makers (to or not to adopt SUWM) take responsibility of all the potential negative consequences associated with any action they took, the magnitude of which is very different from that of SUWM advocates (who may offer technical advice for the adoption of SUWM, but do not hold significant stakes in the outcomes) [2]. This expectation of possible repercussion usually overwhelms those of the positive expectations, especially in

the risk-averse water industry. Moreover, the long history behind the development of the current urban water management system that embraces separated management of water supplies, wastewater, and stormwater has made the current system difficult to penetrate without an objective and transparent framework to facilitate the discussion of the SUWM implementations among the multiple stakeholders (i.e. apportionment of responsibilities).



Framework showing influences on risk perceptions, drawn from the literature.  $\longleftrightarrow$  Relationship demonstrated empirically.  
 $\dashleftarrow \dashrightarrow$  Inferred relationship.

Figure 2.1 Factors that influence risk perceptions of stakeholders (Adopted from [1]).

Intuitively, the optimal standpoint lies along a continuum between the different extremes, in which the overall risks and benefits are balanced to ensure that they are not transferred disproportionately to the stakeholders [3]. As such, a framework that involves the quantification of risks and benefits corresponding to a set of different actions provide a tangible measure for stakeholders to understand their options and help with decision-making (e.g. expensive and unsustainable technologies for lower health risk versus cheaper and sustainable technology for higher health risk) [4]. This type of framework also conveys a sense of fairness to all the stakeholders—all the chain reactions of one action are quantified in terms of risks (or costs) and rewards (or benefits)—, wherein the impacts of confounding factors that yield the quantified outcomes of risk and benefits are/can be negotiated among the stakeholders themselves. When applying this framework to SUWM, the apportionment of responsibilities, such as financial funding, operation, and maintenance of the SUWM systems, can also be agreed upon and assigned systematically among the stakeholders.

Table 2.1 The different criteria of risk (and cost) related to SUWM and methods for evaluating them. (Adopted from [4]).

The priority set of criteria and the associated methods for evaluation for the systems analysis project of the research programme “Sustainable Urban Water Management”

Criterion	Method for evaluation
Health and hygiene criterion	
Risk for infection	Microbial risk assessment
Social and cultural criterion	
Acceptance	Action research and assessment scales
Environmental criteria	
Eutrophication	Life-cycle assessment, computer-based modeling, material-flow analysis, and exergy analysis
Spreading of toxic compounds to water	
Spreading of toxic compounds to arable soil	
Use of natural resources	
Economical criterion	
Total cost	Cost-benefit analysis
Functional and technical criterion	
Robustness	Functional risk analysis



## 2.2 Quantitative Microbial Risk Assessment

The Quantitative Microbial Risk Assessment (QMRA) is an objective and transparent risk assessment framework that incorporates the best-available science and knowledge for assessing microbial risk [5]. As risk is probabilistic in nature, the quantitative nature of QMRA provides a tangible measure for the risk itself. The root of QMRA can also be traced back to the development of the U.S. EPA Surface Water Treatment Rule (SWTR), wherein the selection of treatment technique as supported by QMRA results has since been used to guide water treatment facilities with the production of safe drinking water and form part of the National Primary Drinking Water Standards [6].

In general, QMRA can be broken down into the four main steps as followed:

- 1) **Hazard identification:** Step used in describing the negative health effects associated with the potential microbial hazards (which may present in sources like surface water, biosolids, etc)
- 2) **Exposure assessment:** Step used in describing the potential and magnitude of human exposure to the microbial hazard (due to human application of the sources containing microbial hazards)
- 3) **Dose-response assessment:** Step aimed at the mathematical characterization of health risk outcome (e.g. infection, illness) as a function of the level of exposure to the microbial hazard
- 4) **Risk characterization:** Step aimed at integrating the information gathered in the first three steps to yield an estimate of the health risk, usually characterized in a certain metric (e.g. infection case per year) for further interpretation of the result

Each of the four steps in QMRA are supplemented by scientific and quantitative data, which usually lead to a set of mathematical expressions to model the microbial risk in question (see Figure 2.2). While QMRA is generally understood to be a tiered risk assessment approach, it is not uncommon for the steps to overlap one another—elements of risk management approach are often incorporated in QMRA (see Figure 2.3). For example, the mathematical modeling nature of the QMRA can facilitate multiple “what-if” scenarios, where input parameters can be adjusted to reflect the variation of risk in response to an

action; this flexibility is useful in the ranking of competing risk management options. The tiered nature of QMRA also makes presenting the variabilities and uncertainties in input parameter(s) a natural and easy process, wherein sensitivity analysis of these uncertainties to the QMRA output is important for a better risk assessment.

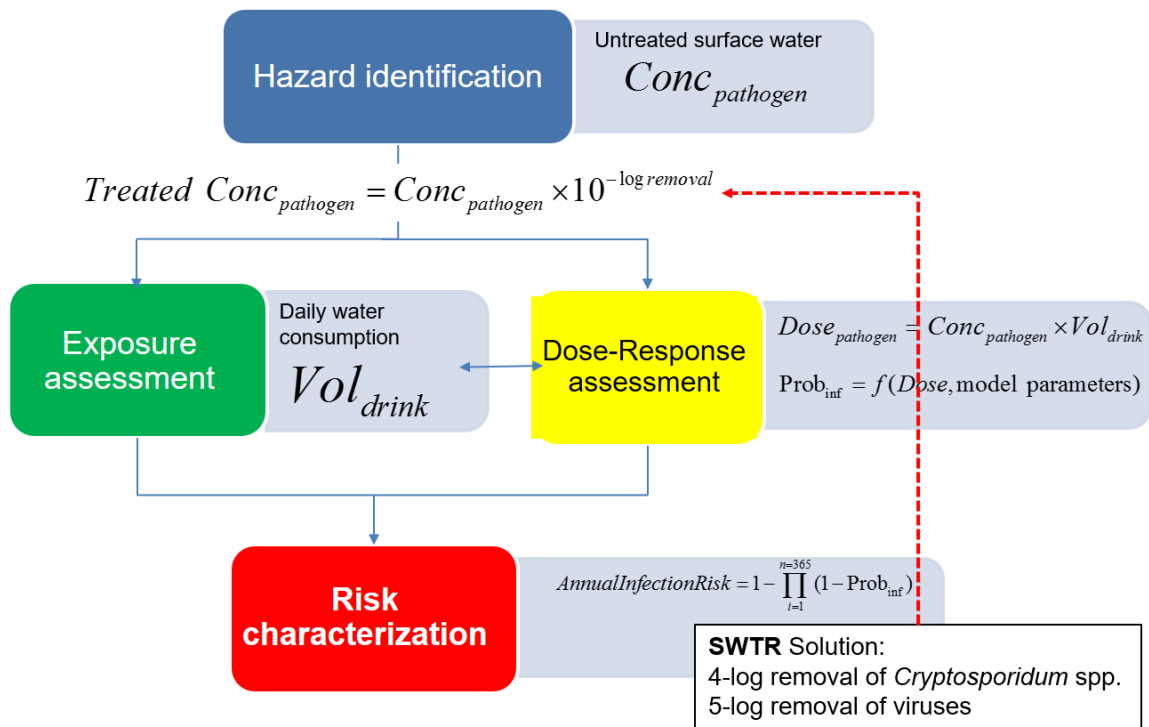


Figure 2.2 A depiction of the QMRA workflow that led to the development of SWTR.

The following subsections describe each of the QMRA steps in details that are sufficient to understand the QMRA framework, particularly for the context of urban water management. For more exhaustive details, interested readers are referred to the excellent QMRA textbook [5] that was co-authored by the founding fathers/mother of QMRA.

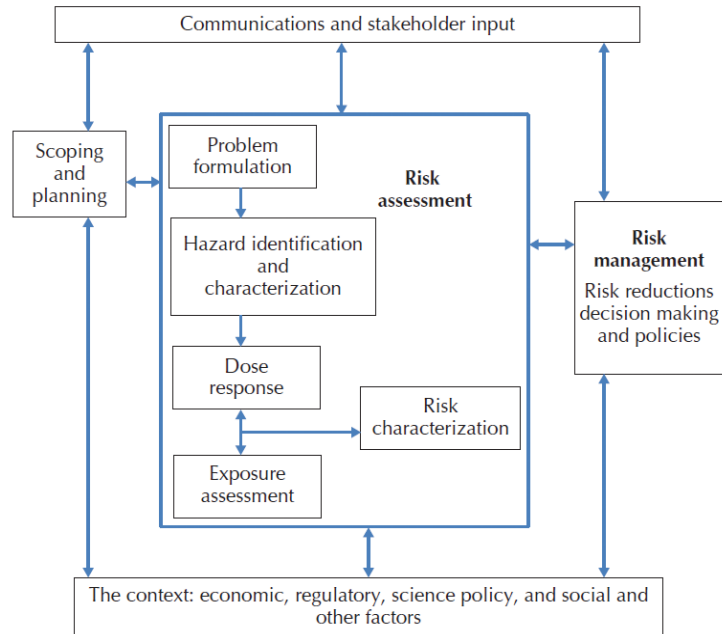


Figure 2.3 Interactive risk assessment and risk management framework showing the different elements that are incorporated into QMRA (Adopted from [7]).

### 2.2.1 Hazard identification

In the hazard identification step, the origin, impact, and magnitude of the microbial hazards are first identified and understood. This step is usually facilitated through consulting epidemiological and clinical literature that may contain information about disease outbreaks (e.g. waterborne cholera outbreak in London [8]), the suspected culprits (the reference pathogens), and the mode of transmission of the hazard (e.g. intake of water, air, fomites). In the context of waterborne disease transmission, this is usually facilitated by first understanding how microbial hazards can be introduced into the water at different stage of a water cycle. Microbial hazards are usually derived from animal and human origins, usually through feces. As such, it is important to identify the different pathways that feces can be introduced into water, especially in an urban watershed setting (see Figure 2.4).

In the U.S. and most developed nations, the primary waterborne pathogen groups of concern are protozoa, bacteria, and viruses [9] due to one or more of their following characteristics [10]:

1. they are shed into the environment in high numbers and/or have low infectious dose (high infectivity),
2. they can multiply under certain environment conditions outside their hosts,
3. they are highly resistant to environmental inactivation and treatment processes.

As many waterborne pathogens maybe present in the water at the same time, a target pathogen from each of the three pathogen groups (i.e. protozoa, bacteria, viruses) is usually selected to be the reference pathogen in a QMRA, which are relatively easy to detect/quantify, have the lowest infectious dose, highest resistance to environmental inactivation and water treatment processes, and/or the heaviest impacts on human health.

Table 2.2 Selected waterborne pathogens of concerns (Modified from [9] with the source therein).

Pathogen group	Pathogen name	Source	Disease	Effects	Contribute to % of total outbreaks (1986-2000)	
					Drinking water (surface water source)	Recreational Water
Protozoa	<i>Cryptosporidium</i>	Human, animal and bird feces	Cryptosporidiosis	Diarrhoea, death in susceptible populations	10.42	4.21
	<i>Giardia lamblia</i>	Human, animal and bird feces	Giardiasis	Mild to severe diarrhoea, nausea, indigestion	41.67	4.21
Bacteria	<i>Campylobacter</i>	Domestic, wild animal feces	Campylobacteriosis	Acute diarrhoea	2.08	N/A
	<i>Escherichia coli O157:H7 (enteropathogenic)</i>	Cattle feces	Gastroenteritis	Vomiting, diarrhoea	6.25	12.63
	<i>Legionella pneumophila</i>	Aquatic environments	Legionellosis	Acute respiratory illness	N/A	N/A
	<i>Salmonella (1,700 serotypes)</i>	Domestic and wild animal, human feces	Salmonellosis	Diarrhoea	N/A	N/A
	<i>Vibrio cholerae</i>	Sediments, shellfish asymptomatic human carriers	Cholera	Extremely heavy diarrhoea	N/A	N/A
Virus	Adenovirus (48 serotypes; types 40 and 41 are of primary concern)	Humans	Respiratory disease	Acute respiratory disease, pneumonia, conjunctivitis, gastroenteritis	N/A	N/A
	Norovirus	Humans	Gastroenteritis	Vomiting, diarrhoea	N/A	4.21

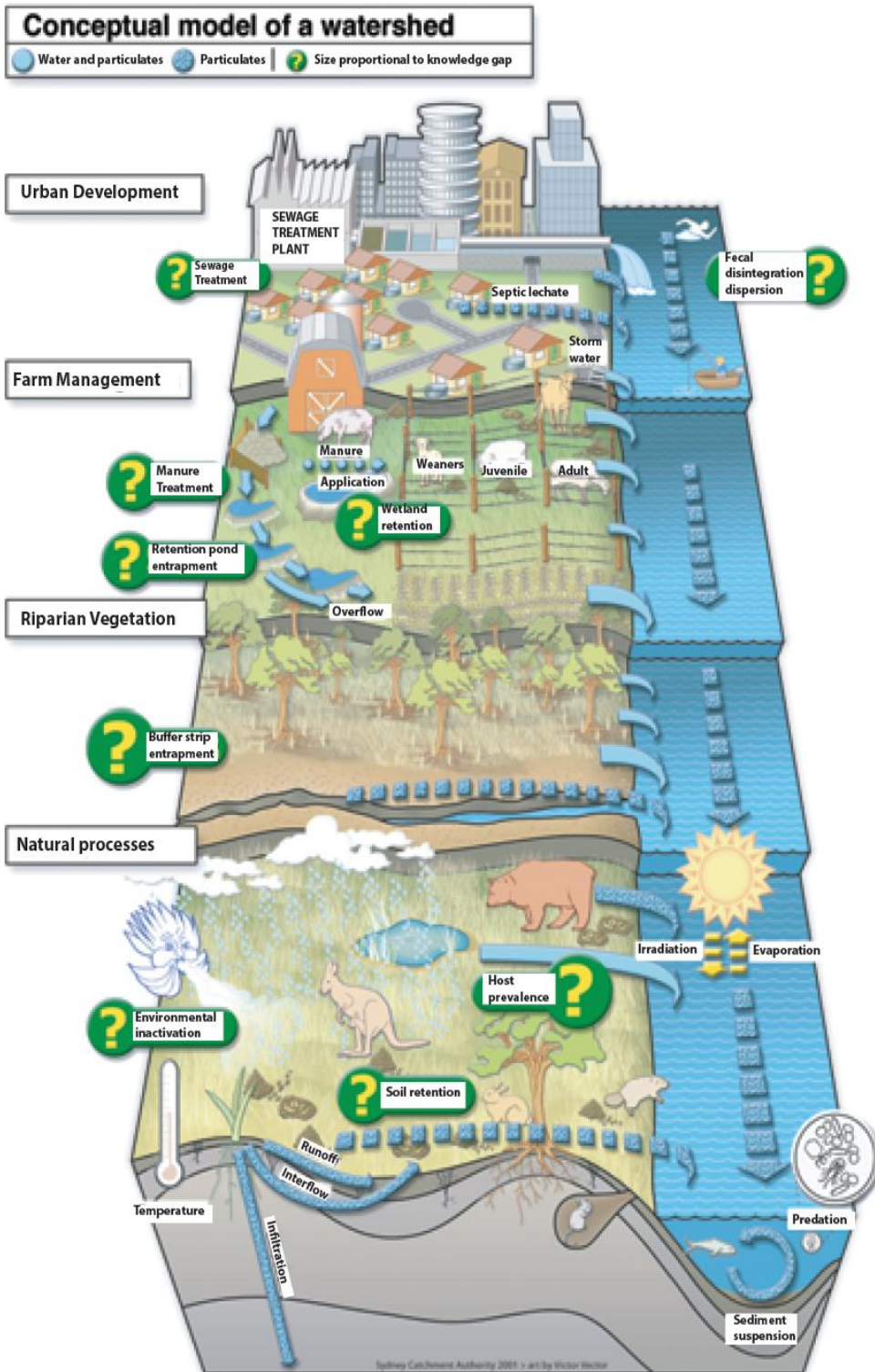


Figure 2.4 Fate of pathogen transmitted through feces in a watershed (Adopted from [11], Text enhanced for clarity).

### 2.2.3 Exposure assessment

The exposure assessment step involves understanding how the waterborne pathogens can be transmitted to susceptible parts in a human body (i.e. skin, respiratory tracts, or gastrointestinal tracts) to induce infection, which are often complicated and can take more than one route or medium (See Figure 2.5). For example, consider the application of treated wastewater for foodcrop irrigation:

- 1) pathogens in the water can be transfer onto the foodcrops, which presents a transmission route to human who consume the foodcrops.
- 2) should the wastewater is applied using spray irrigation, the water would be aerosolized and carried in the wind, which could be inhaled by occupational personnel working near the farm.

The transmission route of pathogens to human do not necessarily involve direct water contact, but are often facilitated by water as a medium.

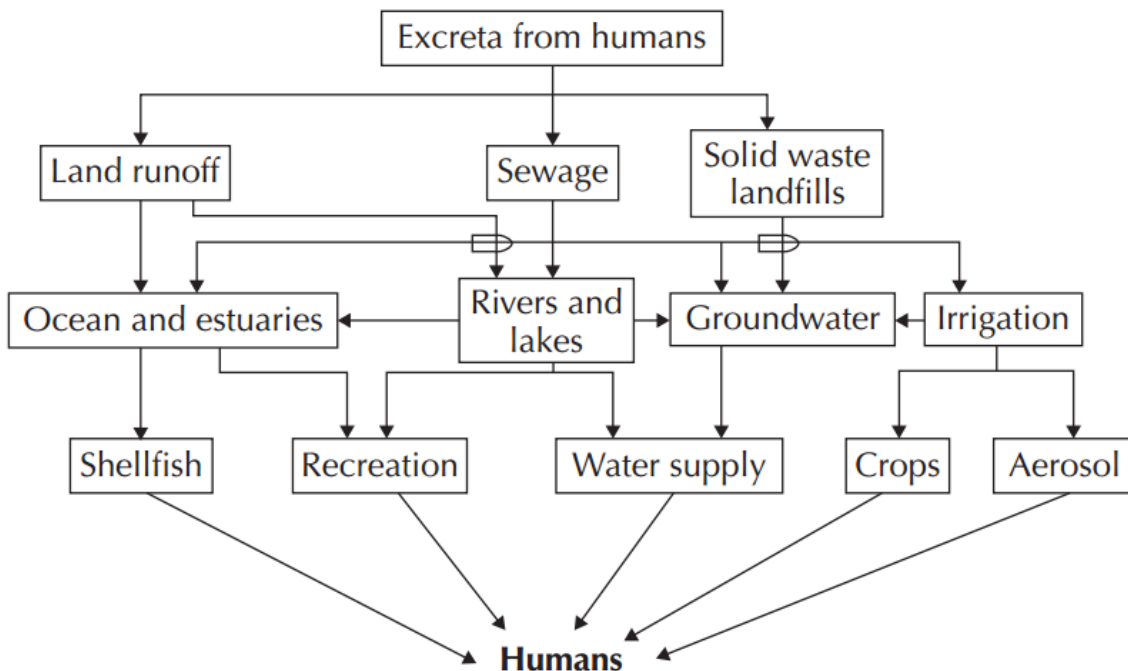


Figure 2.5 Routes of enteric pathogens transmission through the environment (Adopted from [5]).

Waterborne pathogens may also have different dominant infection pathways, which should be reflected on this part of the QMRA. For example, opportunistic pathogens such as *Legionella pneumophila* that are known for causing respiratory diseases generally induce infection in human through the respiratory pathways, but not the gastrointestinal pathway (acidic conditions in the gastrointestinal tracts are likely hostile to respiratory illness-causing pathogens) [12, 13]. The magnitude of human exposure to pathogens are generally characterized by relevant human behavioral patterns that can potentially facilitate the pathogen transmission to human. For example, the level of human exposure to pathogens through drinking water can be estimated as the mathematical product of the pathogen concentration in the water and volume of daily water consumption (See Figure 2.2). Likewise, the magnitude of human exposure to airborne pathogens can be assessed through understanding the breathing intensity and patterns of human and the concentration of the pathogens in the air.

In general, a control measure is usually incorporated in this step of the QMRA, such as the inactivation of target pathogen through a vetted treatment process (e.g. chlorination of water) to measure the effectiveness of the measure in controlling human exposure to the pathogen.

#### **2.2.4. Dose-response assessment**

The dose-response assessment step entails characterizing the mathematical relationship between the probability of infection (or illness) and the target pathogen dose administered to human subjects. The most common basis used for developing dose-response model is based on the theoretical assumption that any single target pathogen that is ingested by (or in any form of administration) human subject can induce an infection in human with a certain probability (i.e. the infectivity), which can be seen as the probability of the target pathogen overcoming the defense mechanisms of and colonizing (multiply in great numbers) the host [5]. This theory has been used in developing “single-hit” models, which usually take the form of exponential function, hypergeometric function, and the Beta-Poisson function (approximated hypergeometric function).

Table 2.3 The most common dose-response model.

Model form	Model Formula	Infectivity parameters
Exponential	$P = 1 - e^{-r \times D}$	$r$
Beta-Poisson	$P = 1 - \left\{ 1 + \frac{D}{\beta} \right\}^{-\alpha}$ or $P = 1 - \left\{ 1 + \frac{D \times \left( 2^{\frac{1}{\alpha}} - 1 \right)}{N_{50}} \right\}^{-\alpha}$	$\alpha, \beta, N_{50} = \beta \cdot \left( 2^{\frac{1}{\alpha}} - 1 \right)$
Hypergeometric	$P = 1 - {}_1F_1(\alpha, \alpha + \beta, -D)$	$\alpha, \beta$

\* $P$  is the probability of infection (or illness),  $D$  is the target pathogen dose

The resulting mathematical model, more commonly known as dose-response model, is usually developed based on clinical trial data that characterize the successful infection rate (or illness) of human or animal subjects that are administered with varying target pathogen doses— a higher pathogen dose generally leads to a higher infection rate, but maybe constrained by immunities that are inherent among the human population [14]. As clinical trial study using human subjects are complicated by ethical issues and are limited to human exposure to target pathogens that do not cause serious symptoms (i.e. fatality), outbreak data are sometimes used in place of clinical trial data in the development of dose-response models [15, 16].

Table 2.4 Selected examples of infection dose-response models for different target pathogens.

Reference pathogen	Form of model	Model parameters	Reference
<i>Cryptosporidium spp.</i>	Exponential	$r=0.09$	[17]
<i>Giardia lamblia</i>	Exponential	$r=0.0199$	[18]
<i>Campylobacter jejuni</i>	Beta-Poisson	$\alpha=0.145, \beta=7.59$	[19, 20]



<i>E. coli</i> O157:H7	Beta-Poisson	$\alpha=0.4, \beta=45.9$	[21]
<i>Salmonella enterica</i>	Beta-Poisson	$\alpha=0.3126, \beta=2884$	[18]
Norovirus	Hypergeometric	$\alpha=0.04, \beta=0.055$	[22]

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Dose-response assessment is also one of the most critical components of any QMRA model, as the availability of target pathogen dose-response models usually decide the options available for quantifying the microbial risks. Some of the dose-response models with infection as the health outcomes are presented in Table 2.4.

### 2.2.5 Risk characterization

The risk characterization step involves estimating the probability of infection or illness (risks) as a function of the magnitude of human exposure to the hazards as determined in the exposure assessment step. This also entails converting the risk outputs into metrics that are comparable risk benchmark or health-based target as set by regulatory agencies (see Table 2.5). These benchmarks can also vary depending on the hazard source being managed, such as drinking water versus recreational water versus reclaimed water. For example, the U.S. EPA set a risk benchmark for safe drinking water based on annual infection risk of <1 infection case per 10,000 people, which is supposedly a standard that is guaranteed by water treatment plants that supply water to households. Likewise, the same government agency also set a different risk benchmark to characterize the safety of waters that are designated for recreational uses, wherein a “safe” recreational water is expected to guarantee an illness risk of less than 32 illness cases per 1000 recreators engaging in activities with a lot of water contact [23]. Most often, comparison with such benchmarks usually helps in facilitating the next step or the risk management strategies, such as the establishment of the “treatment technique” rule for managing microbial risks (similar to Maximum Contaminant Level for contaminants) of drinking water. In this case, the

requirement for “treatment technique” is a legally enforceable standard for which many water treatment plant can comply with, in contrast to measuring target pathogens that are inherently difficult procedures that require skilled expertise and expensive to perform.

Table 2.5 Risk benchmark: What is the acceptable risk? (Adopted from [24] and source therein).

Risk Target	Medium	Source	References
Annual $10^{-4}$ infection	Drinking water	Preamble to the surface water treatment rule in the United States; drinking water legal limit for the Netherlands	[27, 28, 40]
8/1000 per swim event highly incredible gastrointestinal illness	Recreational water	USEPA recreational guidelines based on epidemiological risks associated with odds ratios for swimmers compared to nonswimmers	[41]
$7.7 \times 10^{-4}$ TR rotavirus, $10^{-2}$ for <i>Ascaris</i>	Reclaimed water	Benchmark is for annual tolerable risk (TR) for diarrhea per person in developing countries given the incidence of diarrheal diseases in developing countries at 0.8–1.3 per person per year. <i>Ascaris</i> based on its high prevalence in developing countries	[42–44]

### 2.3 QMRA applications

The robust, intuitive, and flexible nature of QMRA has seen it been widely adopted for understanding the risks associated with environmental transmission of microbial hazards, which often involves probabilistic and low level of exposure that are potent enough to induce negative health effects. Examples of QMRA applications ranged from understanding and assessing the risk associated with wastewater reuse for different scenarios [25], land application of biosolids [26], and recreational health risks [27]. In the same manner, understanding the public health risks that are associated with the sustainable management of urban stormwater should also be aided through the application of QMRA.

Intuitively, all the components in each of the four steps in a QMRA are active research area wherein the state-of-knowledge keep improving overtime. QMRA itself is an embodiment of interdisciplinary research that put pieces of information together to form a bigger picture that is otherwise not perceivable. A major aspect of QMRA is its tendency to present uncertainties and variabilities associated with the risk in question, which should be viewed as its major strength than weakness as risk itself is a random event that should not viewed as a static measure with absolute certainties. Through questioning specific uncertainties and variabilities in a QMRA model, the asker is also undergoing a process of conceptualizing the risk, which is an essential step for improving the risk estimation (through more directional research) and/or devising risk management strategies. Ultimately, a main goal of QMRA is achieved when the discussion among the stakeholders is facilitated through the transparent and objective framework of QMRA, wherein the results are used for informed decision-making. All these have made QMRA an appropriate tool for achieving my overall research objective of understanding the public health risks associated with sustainable urban stormwater management practices and also the relevant knowledge gaps that maybe filled for progressing the practice.

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**CHAPTER 3:   Reevaluation of health risk standards for sustainable water  
practice through risk analysis of rooftop-harvested  
rainwater**

### 3.1 Abstract

Health risk concerns associated with household use of rooftop-harvested rainwater (HRW) constitute one of the main impediments to exploit the benefits of rainwater harvesting in the United States. However, the benchmark based on the U.S. EPA acceptable risk level of  $\leq 1$  illness case per 10,000 people per year ( $\leq 10^{-4}$  pppy) for assessing safe application of water may be unnecessarily stringent for sustainable water practice. In this study, I challenge the current risk standard by quantifying the potential microbial risk associated with consumption of HRW-irrigated home produce and comparing it against the current risk benchmark. Microbial pathogen data for HRW and exposure rates reported in literature are applied to assess the potential microbial risk posed to household consumers of their homegrown produce. A Quantitative Risk Assessment (QMRA) model based on worst-case scenario (e.g. overhead irrigation, no pathogen inactivation) is applied to three crops that are most popular among home gardeners (lettuce, cucumbers, and tomatoes) and commonly consumed raw. The illness risks of household consumers attributed to consumption of these home produce vary with the type of produce. The lettuce presents the highest risk, which is followed by tomato and cucumber, respectively. Results show that the 95<sup>th</sup> percentile values of illness risk per intake event of home produce are one to three orders of magnitude ( $10^{-7}$  to  $10^{-5}$ ) lower than U.S. EPA risk benchmark ( $\leq 10^{-4}$  pppy). However, annual illness risks under the same scenario (multiple intake events in a year) are very likely to exceed the risk benchmark by one order of magnitude in some cases. Estimated 95<sup>th</sup> percentile values of the annual risk are in the  $10^{-4}$  to  $10^{-3}$  pppy range, which are still lower than the  $10^{-3}$  to  $10^{-1}$  pppy risk range of reclaimed water irrigated produce estimated in comparable studies. I further discuss the desirability of HRW for irrigating home produce based on the relative risk of HRW to reclaimed wastewater for irrigation of food crops. The appropriateness of the  $\leq 10^{-4}$  pppy annual risk benchmark as the absolute standard for assessing safety level of HRW-irrigated fresh produce is questioned. Consequently, the need of an updated approach to assess appropriateness of sustainable water practice for making guidelines and policies is proposed.

## 3.2 Introduction

Increasing scarcity of readily available water and energy resources, population growth, aging water infrastructures, and extreme weather phenomena have presented daunting challenges to global water securities in recent years [1, 2]. Sustainable water resource management, such as wide-scale adoption of low-impact development (LID) and green infrastructures, could be one of the key solutions to alleviate these heavy burdens [3]. LIDs, for example, rain gardens, vegetated rooftops, permeable pavements, and rainwater tanks, are decentralized, onsite stormwater management tools which can be applied to both existing developments and new ones for preserving and/or restoring pre-development hydrological features and reducing pollution loads to aquatic environments.

Harvesting rainwater from rooftops to supplement household or local water needs represents one of the simplest, yet effective LIDs that define sustainable practice suitably. Here, a distinction is made between harvested rainwater (HRW) and stormwater. HRW is rainwater that falls onto rooftop of buildings and is collected directly into a rain storage tank. Stormwater, on the other hand, is rainwater that falls onto catchment areas such as roads and pavements, and therefore collects much more pollutants before discharge into any streams or stormwater collection systems. Extensive use of HRW as alternative water supplies has been very common in cities of many developed countries such as Australia, Germany, and Japan. For example, many urban regions in Australia harvest rainwater from rooftop for both potable (less common) and non-potable purposes [4].

In the United States, health risks associated with using HRW represent one of the greatest concerns for the public, who have accustomed to using potable water for every end-use and deemed any lesser quality water unsafe. Skeptical city officials who adopt rainwater tanks do not recommend the use of stored rainwater for household purposes, opting to discharge them after storm events as a mean to manage/reduce stormwater pollution [5]. Lack of governmental agencies-established guidelines for safe usage of HRW is a main contributing factor for varying perspectives across different agencies in the nation regarding the best practice to utilize their stored rainwater [6]. As of the end of 2012, only 12 out



of 50 states in the U.S. have their own rainwater-harvesting laws [7] that deal with different aspects of the practice (encouraging or prohibiting the practice, and/or restrict HRW usage options, etc). This trend shows the diverse opinions at both state and local level regarding rainwater harvesting and also the lack of scientific studies to support the practice [3].

It is apparent that the current water policy or lack of an adequate water policy in the U.S. has obstructed the progress of sustainable water practices. Transition of water management have been slow due to the lack of support for adopting new standards that conflict against existing (but often outdated) standards, which were established decades ago. Sustainable water practices such as application of HRW for various end-uses often find themselves disadvantaged to be benchmarked against stringent standards such as the safe drinking water standards. The science behind the establishment of the latter was based on risk assessment paradigms, but this risk-based approach has seldom been applied to other sustainable water practices for non-potable uses. It is therefore proposed to guide sustainable water practices using the same strategy, where risk assessment serves as the main tool to answer the appropriateness of each practice [8].

Putting this into context, urban agriculture in densely populated cities such as New York City is rapidly growing due to the adoption of LIDs to manage stormwater, and the recognition of the long forgotten idea of using HRW for irrigating crops [9]. However, most HRW quality reported in literature did not comply with the US EPA safe drinking water standards [10]. HRW collects chemical pollutants from dry deposits, microbial pathogens from feces of birds, rats and other wild animals resting/nesting on the rooftops. These pathogens washed into the storage tank by rain could also potentially multiply in it. Thus, using HRW for irrigating crops could result in (chemical and microbial) contamination of the crops. Epidemiological data have indicated that foodborne disease outbreaks are most prominent where there are continuing sources of infection, for example, serving of contaminated food in restaurants [11]. If restaurants in New York City decided to use their city-grown HRW-irrigated crops for preparation of raw salads, there exist risks of foodborne disease outbreak. Nevertheless, in a comparative analysis, prior to

the rise of urban agriculture in New York City, people may be eating raw vegetables irrigated with secondary-treated effluents imported from countries with uncertain sanitary practices [12]. Such dichotomy argues for reevaluation of health risk standards for sustainable water practice.

Here, I attempt to assess the appropriateness of using untreated HRW to water lawns and/or gardens, which is generally practiced in the United States [6]. The National Gardening Association (NGA) estimated in a 2008 survey that 31% of US households participated in food gardening [13]. Produce that are eaten raw and fresh, such as salad greens, tomatoes, were recognized vectors for foodborne diseases [14, 15]. It is believed that home gardeners have varying knowledge in terms of how to grow their own produce as compared to the industrial standards. Specific irrigation methods and sterilization process were usually employed by the latter based on the crops grown in order to reduce the microbial contamination of the produce. However, an average home gardener might lack such awareness and could increase the microbial risks of eating raw home produce. For example, cultivar of tomatoes grown in commercial farms usually has thicker skins to resist against fruit cracking which could create opening for pathogen intrusion [16]. Home gardeners lacking the logic behind this might opt to grow thin-skinned tomatoes and over-irrigate them to the point of cracking and thus increase the probability of contamination.

A QMRA framework is applied to assess the potential microbial health risks associated with using HRW to irrigate homegrown-produce in the United States. A probabilistic-based risk model is built to estimate range and likelihood of the risk in question. Three types of produce, tomatoes, cucumber, and lettuce, which are commonly consumed raw as fresh salads, are selected for the study. They are also some of the most popular home produce in the U.S.. According to NGA, 86% home gardens grow tomatoes, 47% grow cucumber, and 28% grow lettuce [13]. The risk outcomes are then compared to the US EPA risk benchmark of  $\leq 1$  illness case per 10,000 persons per year (hereafter, represented as:  $\leq 10^{-4}$  pppy) and the relative risk is estimated using the comparative risk study of food crops irrigated using reclaimed wastewater.

This study discusses the strength of using comparative risk analysis to assess appropriateness of a water practice independently of risk benchmark set for a different water use (e.g. drinking purpose). It entails the strength (and pitfalls) of risk assessment tools for appraising sustainable water practice.

### **3.3 Materials and methods**

For the purpose of relative risk estimation, I structured my QMRA risk model in a fashion similar to the risk model used by Hamilton *et al.* [17], in which real measurements collected from different sources (as opposed to simplistic assumptions used in a screening-level QMRA) are used to assess the risk of reclaimed-water irrigated vegetables. It should be noted that the definition of reclaimed water used in Hamilton *et al.* refers to non-disinfected secondary effluent of different wastewater treatment plants in Southern California. Thus, their outcomes may be regionally bound. Our risk model incorporates home produce production and consumption behavior of the U.S. population, which are based on nation-wide survey responses from home-gardeners to characterize the risk of whole population.

As with most risk assessment studies, assumptions were made based on worst-case scenarios in our risk model, which are: 1) No environmental inactivation of pathogens on food crops, 2) Overhead irrigation that maximize pathogen exposure to edible portion of the crops, 3) Intake rate of each crop is solely attributed to consumption of raw crops, and 4) Annual risk assumes that home gardeners eat homegrown produce daily (e.g. 365 exposure events annually). These assumptions are also justified through the general understanding that home gardeners would hand-irrigate their crops everyday and would harvest their crops only when they need it (i.e. for preparation of raw and fresh salads immediately after harvesting). And, as a result, the scenario maximizes the water exposure to the edible portion of the crops and minimizes any possible inactivation of pathogens attached on the crops. Considering human habits, this worst-case scenario is not far fetched. Similar assumptions were used by Hamilton *et al.* [17],

where differences are marked by their use of enteric viruses as the sole target pathogen, and pathogen inactivation varies by duration of environmental exposure.

### **3.3.1 Hazard identification**

The potential microbial hazards of HRW were reported in numerous literature [18-23]. based on the presence of pathogens in rainwater tanks. Pathogens including *Giardia* spp., *Cryptosporidium* spp., *Salmonella* spp., *Campylobacter* spp., *Legionella pneumophila*, and *Clostridium perfringens*, as well as fecal indicator organisms such as *E. coli* and enterococci were found in rainwater tanks tested in Denmark, Netherland, France, Greece, Australia, and USA. It is noted that the HRW sampling methods, pathogen detection and quantification methods used in each study were different from one another. Configuration details of rainwater collection systems, such as installation of first-flush diverters and filtration systems were only reported by a few studies. Due to the large uncertainties of these data, most of them can only serve to identify the potential risks in HRW. The study by Ahmed *et al.* [18] is the only literature reporting the concentration of target pathogens in HRW stored in rainwater tanks and detailing the sampling and detection/quantification method of the target pathogens. As such, I used their pathogen concentration data as the generic surrogate for pathogen concentration in HRW.

### **3.3.2 Potential risk**

Pathogens are known to possess different surviving mechanisms and resistance to sunlight, chlorination etc. For example, *Campylobacter* can be easily inactivated when exposed to the air, but if introduced into the soil (e.g. through drip irrigation) directly without sunlight exposure, they can survive in the root zone for at least a month [24]. Likewise, *Salmonella* is reported to persist up to weeks under greenhouse conditions and even replicate to high densities on the surface of tomatoes [25]. Moreover, internalization of pathogens in fruits/vegetables through capillary action from calyx of fruits into its core,

through wound or bruise on its surface was reported in literature [26]. Due to the presence of pathogens in HRW, pathogens of different types could attach on the surfaces of home produce or internalize it, depending on the crop types (e.g. exposed or protected) and irrigation method (e.g. overhead irrigation, spray irrigation, drip irrigation) used. The risk is the greatest for home produce with exposed edible portion that are eaten raw as salads (e.g. tomatoes, lettuce, cucumber, etc.).

### 3.3.3 Target pathogens

*Salmonella spp.* and *Giardia lamblia* were used as target pathogens for the analysis due to the availability of data and their importance in waterborne/foodborne human health risk. *Salmonella* and *Giardia* are known to cause gastroenteritis with varying symptoms and are well-recognized to be transmitted through ingestion of contaminated food and water [27]. Symptoms associated with Salmonellosis are characterized by the abrupt onset of diarrhea, abdominal pain, prostration, chills, fever, and vomiting [28]. Giardiasis is characterized by abrupt onset of self-limiting, foul-smelling, watery diarrhea, along with abdominal cramps, flatulence, and steatorrhea [28].

The abundance of *Salmonella spp.*, and *Giardia lamblia* as reported by Ahmed *et al.* [18] were first collected using binary PCR assay for the presence of the target pathogens and followed by quantitative PCR (qPCR) for pathogen quantification in positive binary PCR samples. A total of 214 samples were tested using binary PCR, which provide good statistical confidence in terms of the samples size. The lower qPCR detection limit of each target pathogen was also reported, and is used to represent the upper range of binary PCR with negative outcome. Details of the data treatment are described in the Monte-Carlo simulation in section 2.8.

### 3.3.4 Pathogen transfer to home produce

The transfer of pathogens to home produce is modeled based on the amount of water that is absorbed by home-produce upon irrigation. Water retention rate varies among different types of crops, which could be a function of crop geometry, surface area properties (e.g. charge, smoothness, etc.), crop type (root, exposed, or protected), and irrigation method (e.g. surface- or subsurface-irrigation). Shuval *et al.* [29] conducted a laboratory test to measure the amount of water that can be absorbed by cucumber and lettuce. The experiment measured the increase in weight of the vegetable after submerging them in water for varying period of time. The weight increase of crops translated to an average of  $0.36 \pm 0.12$  mL water absorbed by 100 grams of cucumber (n=26), and an average of  $10.8 \pm 1.9$  mL water/ 100 grams lettuce (n=12). Likewise, the water retention rate of tomato were converted from the relative weight increase of tomato submerged in packinghouse flumes and dump tanks, which ranged from 0.04 to 1.66 mL of water/ 100 grams of tomato [30].

### 3.3.5 Intake rate of home produce

The best available consumer-only intake rate of home produce by home gardeners was estimated based on the 1987-1988 Nationwide Food Consumption Survey (NFCS) by Moya and Phillips (2001)[31, 32]. In their study, they estimated the distributions for unadjusted intake rate of individual home-produced food items (e.g. lettuce, tomato, and cucumber). The term “unadjusted” does not account for food-preparation and post-cooking losses, and therefore, serve as a maximum estimate. This assumption closely represents crops eaten in its raw form, such as tomatoes and lettuce, which are usually sliced for salad preparation with relatively negligible discarded portion.

The intake rate of home produce is adjusted based on body-weight and expressed as grams of home produce  $\cdot$  kg body weight<sup>-1</sup>  $\cdot$  day<sup>-1</sup> (g HP  $\cdot$  kg BW<sup>-1</sup>  $\cdot$  day<sup>-1</sup>). Empirical distributions of each home produce intake rate were generated from percentile values of the data reported. As the intake rate of home-produce is adjusted according to body weight, the distributions of body weight of US population

were referred to based on a study by Kahn and Stralka [33]. Empirical distributions of the overall US population's body weight were generated from the data reported, which are based on the USDA's 1994-1996, 1998 CSFII (Continuing Survey of Food Intake by Individuals).

### 3.3.6 Dose of pathogens ingested

Pathogen ingestion is estimated using pathogen concentration in HRW, intake rate, body weight, and volume of HRW retained per mass of produce [17]. Each of the parameter is assumed to be independent of each other. It is expressed as:

$$d = PConc \cdot Intake \cdot BodyWeight \cdot V \rightarrow (1)$$

where:

$d$  = Dose of pathogens ingested (# pathogens · day<sup>-1</sup>)

$PConc$  = Pathogen concentration in HRW (# pathogens · mL water<sup>-1</sup>)

$Intake$  = Intake rate of home-produce by home gardeners (g HP · kg BW<sup>-1</sup> · day<sup>-1</sup>)

$Body\ weight$  = Body weight of US population (kg BW)

$V$  = Volume of water absorbed per unit mass of home-produce (mL water · g HP<sup>-1</sup>)

Steady state distribution of  $d$  is obtained by 10,000 or more iterations of equation (1) using Monte-Carlo method.

### 3.3.7 Illness risk per day

The risk,  $P_{ill}$ , is quantified as estimated illness case per person per day (or per event if assuming a single consumption event in a day). Different target pathogens have different virulence and infectious dose. Thus, dose-response models are developed for specific target pathogens. Dose-response model use

dose of target pathogens taken in as an input parameter and return a probability of illness. An exponential dose-response model (equation 2) from the literature [34] was used for estimating the illness risk due to exposure to *Giardia*. A beta-Poisson model (equation 3) was used for estimating the risk of exposure to *Salmonella* [27].

$$\text{Exponential model, } P_{ill} = 1 - \exp(-r \times d) \quad \rightarrow (2)$$

$$\text{beta-Poisson model, } P_{ill} = 1 - \left[ 1 + \frac{d}{\beta} \right]^{-\alpha} \quad \rightarrow (3)$$

The  $r$  in the exponential model is the best-fit parameter, which is 0.0198 for *Giardia*. The best-fit parameters  $\alpha$  and  $\beta$  in the beta-Poisson model are 0.3126 and 2884, respectively, for *Salmonella*.

The illness risk due to exposure to target pathogens is calculated using Monte Carlo method for 10,000 or more iterations to obtain steady state distribution of the illness risk.

### 3.3.8 Risk characterization

The results for illness risk per day are further adjusted to annual risk in order to be compared to the US EPA acceptable risk associated with drinking water ( $\leq 10^{-4}$  pppy), which has since been used as a benchmark for foodborne risk associated with irrigation water [17, 29, 35, 36]. The annual risk guideline accounts for the fact that a person engages in a scenario multiple times throughout a year (e.g. 365 exposure events in a year) and the compounded risk effect of multiple exposures needs to be accounted for. I estimated the annual risk of consuming the HRW-irrigated crops by assuming home gardeners consume their home produce daily, which is computed based on the independence theorem according to Haas *et al.* [37]:

$$\text{Annual risk} = 1 - \prod_{i=1}^{n=365} (1 - D(P_{ill})_i) \quad \rightarrow (4)$$



The subscript  $i$  represents the  $i$ -th iteration of equation (4) and  $n$  represents the total number of exposure events in a year (the total number of exposure events in a year).

Again, the distribution of the annual risk is computed using the Monte-Carlo method.

### **3.3.9 Monte-Carlo simulation**

All Monte-Carlo algorithms were written and implemented using MATLAB R2010a (The Mathworks, Inc., MA). Distribution-based input parameters are randomly selected based on their corresponding probability distributions, output parameters (e.g. dose of pathogens ingested, illness risk due to certain target pathogens) are computed between 10,000 and 15,000 iterations until its distribution attained steady state. Reproducibility of the results is checked by small variation (e.g. <1%) in terms of average between replicates of distribution.

In acknowledging that samples falling below pathogen detection limit are not equivalent to absence of pathogens in the samples [38], I used extra steps in treating the sampling of target pathogens concentration in HRW. The binary PCR (positive and negative) data of target pathogens were used to generate a  $m \times n$  binary matrix containing “0”s and “1”s, representing negative and positive results. The percentage of “1”s in each row was selected randomly from the binomial distribution of the binary PCR result for the target pathogen, where probability of selecting a certain percentage is highest at the distribution’s mode and decreasing towards its tail (95% confidence interval). Whenever a random sample of target pathogen concentration is needed, a sample will first be randomly picked from the binary matrix. If a “0” is picked, a uniformly distributed number from the interval [0 1] will be sampled and multiply by the lower qPCR detection limit of the target pathogen to represent the pathogen concentration. Otherwise, a “1” picked would lead to random sampling from the empirical distribution of the target pathogen concentration (observed samples above detection-limit). Uniform distributions (instead of point estimates or normal distribution) are used to minimize the introduction of unwanted bias into the risk model where

information is lacking. A pseudo-algorithm flowchart for the generation of illness risk is shown in Figure 3.1.

### **3.3.10 Sensitivity Analysis**

The uncertainty and variability propagation of each input parameters throughout the risk model is assessed using a sensitivity analysis method. Spearman's rank correlation of the illness risk (model outputs) to each input parameters (e.g. pathogen concentration, water retention rate, etc.) were computed to assess the relative contribution of the latter to the uncertainties/variability of the illness risk. The method was chosen due to its ease of implementation and capability of showing possible strong non-linear correlation of parameters, which were used frequently in similar studies [17].

Table 3.1 Descriptions of parameters used in the risk model.

Parameters	Units	Point estimates	Range and distribution type	Reference
<b>Target pathogen binary PCR detection</b>				
<i>Salmonella</i>	% positive		<i>Binomial</i> ( $n = 214, p = 0.107$ )	
<i>G. Lamblia</i>	% positive		<i>Binomial</i> ( $n = 214, p = 0.098$ )	
<b>Target pathogen lower detection limits</b>				
<i>Salmonella</i>	cells/ 1000 mL	5		Ahmed <i>et al.</i> (2010)
<i>G. Lamblia</i>	cysts/ 1000 mL	0.4375		
<b>Target pathogen quantitative PCR concentration</b>				
<i>Salmonella</i>	cells/ 1000 mL		$P(PConc = 65, \dots, 380)^a$	
<i>G. Lamblia</i>	cysts/ 1000 mL		$P(PConc = 9, \dots, 57)^a$	
<b>Exposure assessment for home-produce intake</b>				
<b>Water retention rate of home-produce</b>				
Tomatoes	mL water/ 100 gram produce		$U(0.04, 1.63)^{b,c}$	Bartz (1988)
Lettuce	mL water/ 100 gram produce		$U(8.9, 12.7)^c$	Shuval <i>et al.</i> (1997)
Cucumber	mL water/ 100 gram produce		$U(0.24, 0.48)^c$	
Body weight of human	kg body weight		Empirical distribution of body weight from populations of all age-groups <sup>a</sup>	Kahn and Stralka (2008)
<b>Home-produce intake</b>				
Tomatoes	g produce/ kg body weight		Empirical distribution of consumer-only intake for all age-groups <sup>a,d</sup>	U.S. EPA (2011)
Lettuce	g produce/ kg body weight			
Cucumber	g produce/ kg body weight			
<b>Dose-response assessment</b>				
<i>Salmonella</i> beta-Poisson model				
$\alpha$	-	0.3126	Best-fit parameter	Haas <i>et al.</i> (1999)
$\beta$	-	2884		
<i>G. Lamblia</i> Exponential model				
$r$	-	0.01982	Best-fit parameter	Rose <i>et al.</i> (1991)

<sup>a</sup>Empirical distribution from data reported in corresponding literature

<sup>b</sup>Converted from % relative weight increase of submerged tomatoes

<sup>c</sup>A uniform distribution is used in the absence of the distribution's descriptive statistics

<sup>d</sup>Data from Table 13-39,-42, and -52 of US EPA Exposure Factors Handbook 2011

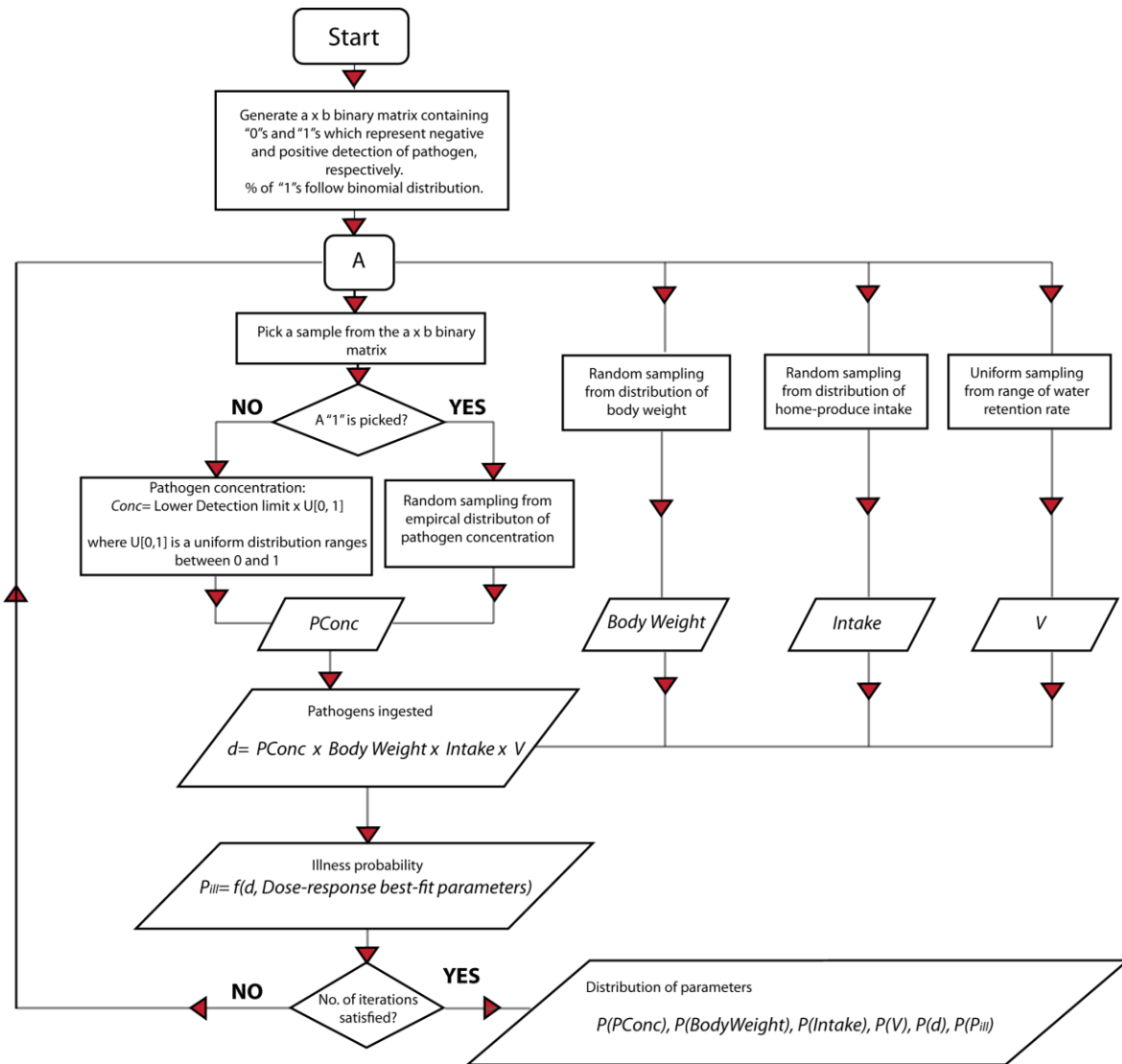


Figure 3.1 Pseudo-algorithm flowchart for estimating illness risk due to consumption of HRW-irrigated home-produce. Node A represents the starting point for each iteration after the first one.

## 3.4 Results

### 3.4.1 Illness risk per day

The estimated illness risks per day (or per intake event) due to consumption of raw produce irrigated with HRW are presented in Figure 3.2 and Table 3.2. The mean value and 95<sup>th</sup> percentile value

of each illness risk is tabulated in Table 3.2. Giardiasis risk are visibly much higher by one to two order(s) of magnitude than Salmonellosis risk (for every crop considered), as shown by the right-shifting trend of the former's cumulative distribution curve in relative to the latter in Figure 3.2. Among the three crops, the ascending order of illness risk is as follows: cucumber < tomato < lettuce. However, the mean intake rate of lettuce is the lowest ( $0.39 \text{ g HP} \cdot \text{kg BW}^{-1} \cdot \text{day}^{-1}$ ) in comparison to that of tomato and cucumber ( $1.18$  and  $1.03 \text{ g HP} \cdot \text{kg BW}^{-1} \cdot \text{day}^{-1}$ ) (Figure 3.5). The higher illness risk of consuming contaminated lettuce is due to the relatively higher water retention rate of lettuce than that of tomato and cucumber. It is also inferred that the illness risk per day (for both pathogens and all home produce) is very unlikely to exceed the propounded acceptable annual risk at  $\leq 10^{-4}$  pppy, with the 95<sup>th</sup> percentile values of the former 1 to 3 order(s) of magnitude lower than the latter.

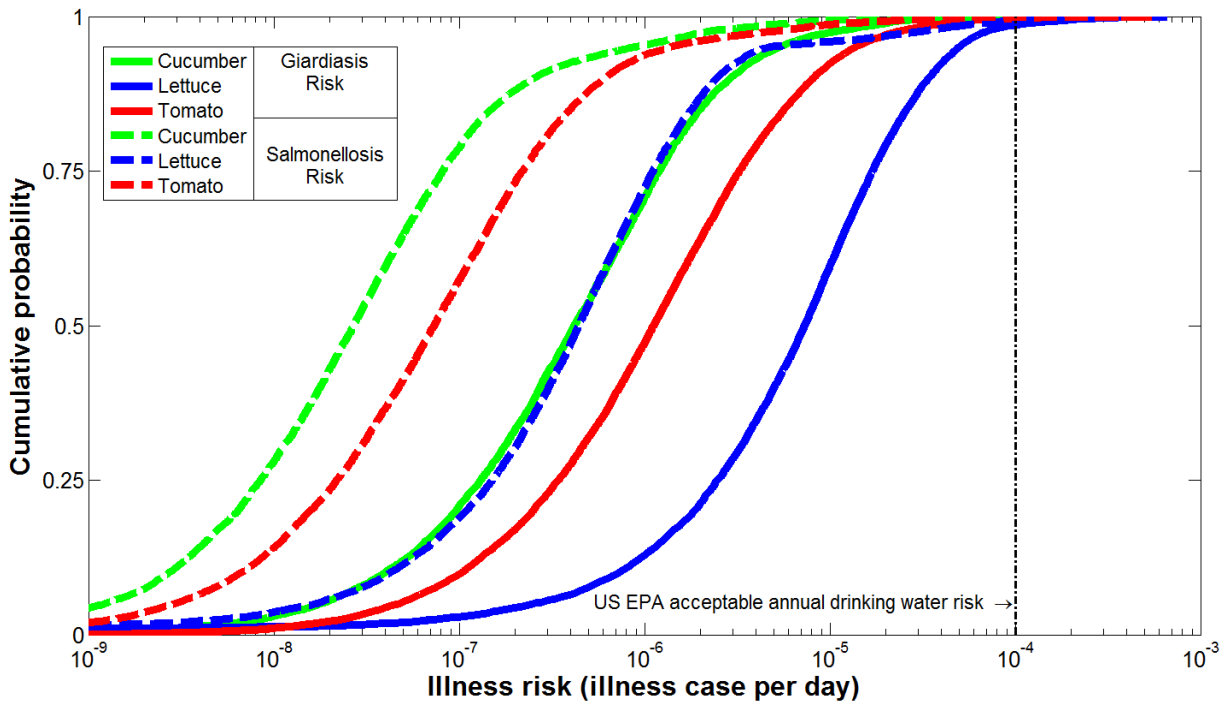


Figure 3.2 Cumulative distribution of Giardiasis risk (solid lines) and Salmonellosis risk (dashed lines) due to consumption HRW-irrigated home-produce. The illness risk is expressed as likely illness case per day.

### 3.4.2 Annual risk

The annual risks of consuming HRW-irrigated home-produce are presented in Table 3.2 and Figure 3.3. Both the mean and 95<sup>th</sup> percentile values of annual Giardiasis risk and Salmonellosis risk (for all crops) are in the range of  $10^{-4}$  to  $10^{-3}$  order of magnitude. Figure 3.3 shows probability density (normalized histogram, in increment of  $\log_{10}(0.05)$ ) of the annual risk associated with each crop. The lower x-axis limit of the graph is represented by the U.S. EPA risk benchmark ( $\leq 10^{-4}$  pppy), suggesting it is unlikely to be met by all the HRW-irrigated home-produce. However, a comparison of the annual risk of HRW-irrigated crops with that of reclaimed-water-irrigated crops [17] shows that the former is one to two orders of magnitude(s) lower than the latter.

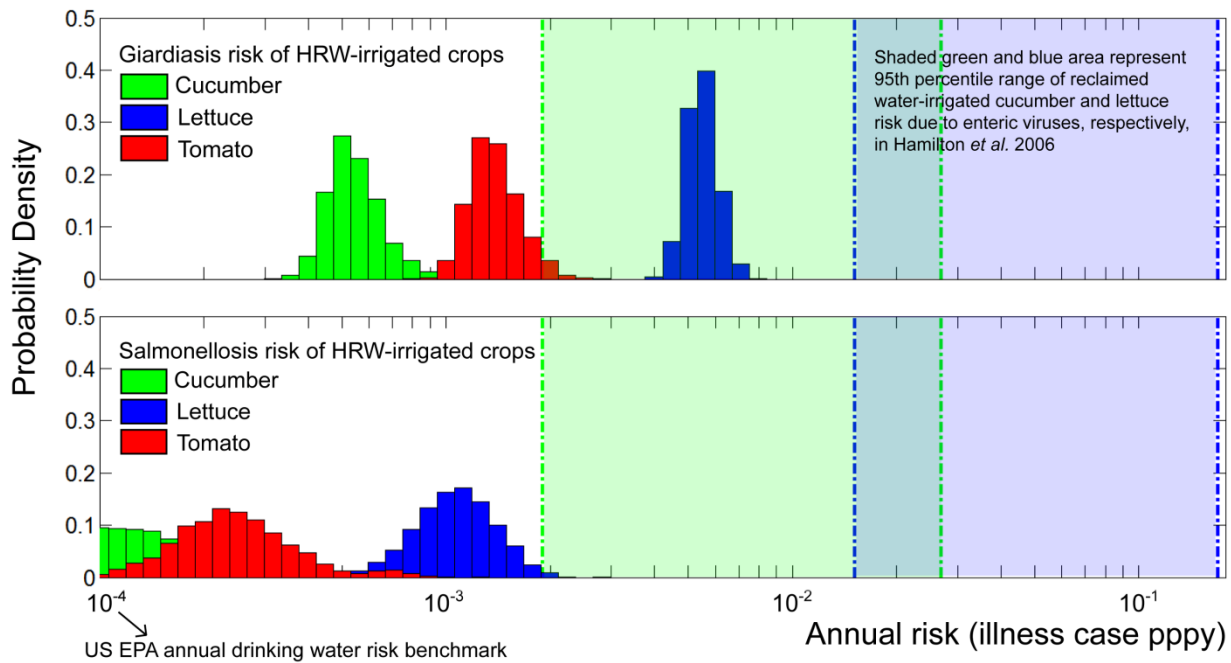


Figure 3.3 Distribution of annual Giardiasis risk (top panel) and Salmonellosis risk (bottom panel) due to consumption HRW-irrigated home-produce. The probability density is estimated as normalized histogram. The lower x-axis limit is the propounded acceptable annual risk benchmark at  $\leq 1$  illness case per 10,000 people per year. Shaded regions in the figure shows the 95<sup>th</sup> percentile range of the annual risk of reclaimed-water-irrigated crops estimated by Hamilton et al. 2006.

Table 3.2 Summary descriptors for the illness risk associated with consumption of each home-produce.

	Illness Risk per day		Annual Risk		
	Mean	95 <sup>th</sup> percentile	Mean	95 <sup>th</sup> percentile	95 <sup>th</sup> percentile range for reclaimed water-irrigated crops (Hamilton <i>et al.</i> 2006) <sup>a</sup>
Giardiasis					
Cucumber	1.52 x 10 <sup>-6</sup>	5.37 x 10 <sup>-6</sup>	5.53 x 10 <sup>-4</sup>	7.58 x 10 <sup>-4</sup>	1.9 x 10 <sup>-3</sup> ~ 2.7 x 10 <sup>-2</sup>
Lettuce	1.51 x 10 <sup>-5</sup>	4.96 x 10 <sup>-5</sup>	5.49 x 10 <sup>-3</sup>	6.50 x 10 <sup>-3</sup>	1.5 x 10 <sup>-2</sup> ~ 1.7 x 10 <sup>-1</sup>
Tomato	3.84 x 10 <sup>-6</sup>	1.37 x 10 <sup>-5</sup>	1.40 x 10 <sup>-3</sup>	1.87 x 10 <sup>-3</sup>	-
Salmonellosis					
Cucumber	3.76 x 10 <sup>-7</sup>	8.60 x 10 <sup>-7</sup>	1.39 x 10 <sup>-4</sup>	2.80 x 10 <sup>-4</sup>	1.9 x 10 <sup>-3</sup> ~ 2.7 x 10 <sup>-2</sup>
Lettuce	3.01 x 10 <sup>-6</sup>	4.63 x 10 <sup>-6</sup>	1.09 x 10 <sup>-3</sup>	1.62 x 10 <sup>-3</sup>	1.5 x 10 <sup>-2</sup> ~ 1.7 x 10 <sup>-1</sup>
Tomato	7.35 x 10 <sup>-7</sup>	1.38 x 10 <sup>-6</sup>	2.67 x 10 <sup>-4</sup>	4.95 x 10 <sup>-4</sup>	-

<sup>a</sup>Result for annual risk of enteric virus infection based on secondary effluent of four different wastewater treatment plants in Southern California, environmental exposure of 1 day, and viral kinetic decay of 0.69 day<sup>-1</sup>.

### 3.4.3 Sensitivity Analysis

The relative contribution of each input parameters to the uncertainties/variability of illness risks are summarized in Figure 3.4 and 3.5. Significance of each parameter is characterized by its Spearman's rank correlation coefficient with illness risk,  $|r_s|$ , where a higher value indicates greater contribution to the uncertainties/variability of illness risk and vice versa. In general, consumption rate of home produce ( $|r_s| > 0.60$ ) accounts for most of illness risk's uncertainties/variability. It should, however, be noted that consumption rate is a product of intake rate (body weight-adjusted) and body weight. Separate consideration of intake rate and body weight shows that intake rate still accounts for a large share ( $|r_s| > 0.52$ ) of illness risk's uncertainties/variability whereas body weight shows a lesser contribution ( $|r_s| < 0.34$ ). Pathogen concentration in HRW is another large contributor of illness risk's uncertainties/variability ( $|r_s| > 0.53$ ). Although water retention rate of lettuce and cucumber ( $|r_s| < 0.11$ ) represents a minor contributor to the uncertainties/variability of the illness, the same is not observed for tomato's ( $|r_s| > 0.38$ ). This observation is explained by the wide variation of water retention rate of tomato (0.04~ 1.63 ml/100g tomato). Not much difference in terms of parameter sensitivity is observed for the prediction of Giardiasis and Salmonellosis risk.

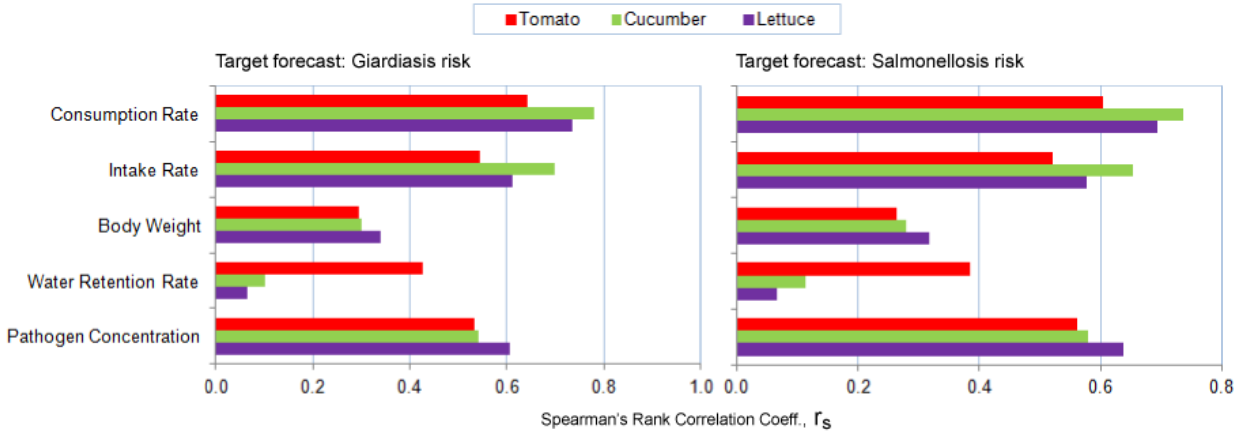


Figure 3.4 Sensitivity analysis chart of input parameters for estimating Giardiasis risk per day (Left panel) and Salmonellosis risk per day (Right panel). Consumption rate = Intake rate  $\times$  Body weight.

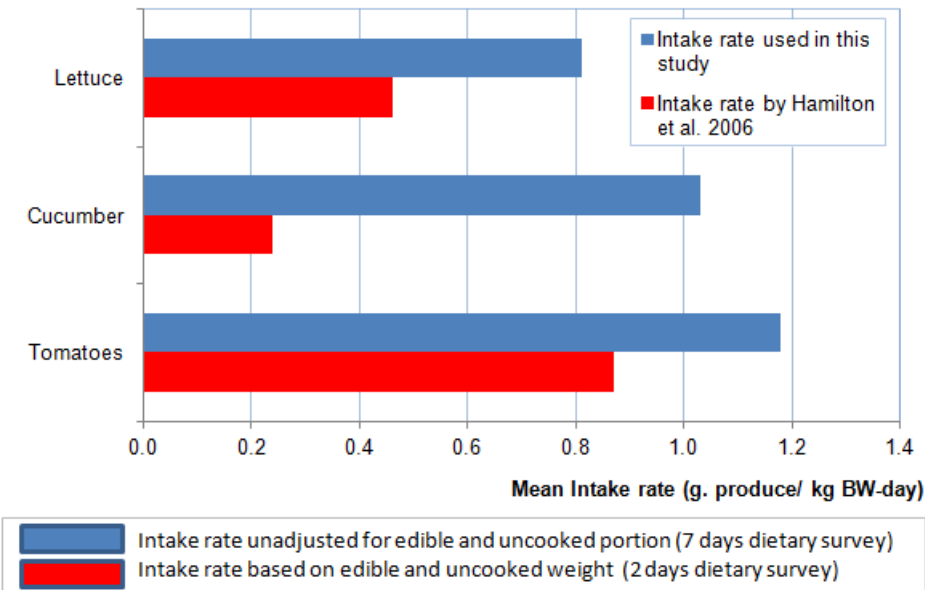


Figure 3.5 Comparison of the mean intake rate used by Hamilton et al. (2006) in their QMRA with the mean intake rate used in this study. Notice that the latter is unadjusted for edible and uncooked weight, but is based on a longer survey period. The former reports more specific intake rate, but were based on two non-consecutive days of survey.



## 3.5 Discussion

Emerging water and energy issues have heightened people's awareness to conserve and use their water wisely. HRW represents an easy source of relatively clean water that most average households can harvest and benefit from. However, the lack of uniform guidelines across the nation for safe usage of HRW has hampered the wide adoption of the rainwater harvesting practice [6]. QMRA was the main driving force for the development of the Surface Water Treatment Rule established by U.S. EPA in 1989 for guiding the safe treatment of drinking water [39, 40]. The same approach should, in principle, be used for establishing safety guidelines of HRW usage.

### 3.5.1 Benchmarking risk with U.S. EPA risk level

The U.S. EPA drinking water risk standard of  $10^{-4}$  pppy has been widely treated as a benchmark for foodborne risk related to irrigation water due to the lack of specific risk standards for non-potable water applications. In this study, the annual risk associated with consumption of raw crops irrigated using untreated HRW exceeds the commonly accepted U.S. EPA risk benchmark, implying potential human health concerns. However, the validity of this benchmark should be questioned. In fact, Haas *et al.* [37] discussed that a more practical annual risk level people accept unknowingly for food is at  $10^{-3}$ . Petterson *et al.* [36] continued the discussion by reiterating the need for considerable advancement for assessing public health risks from food crops, in which screening-level QMRA result for salad crops irrigated with secondary-treated wastewater significantly exceeds human health risk standards (based on the  $10^{-4}$  pppy risk benchmark). The comparison with U.S. EPA health risk standards is also complicated by the annual consumption rates based on human habits. The drinking water standards are based on the daily consumption of 2 liters of water by a person for 365 days (e.g. 365 exposure events in a year). While this is a justifiable assumption for drinking water consumption, the eating habit of people can vary on a day-to-day basis (e.g. most people probably would not eat the same food every day). The annual risk for food

consumption would need to consider such variation to yield a more reasonable annual consumption rate for the specific produce, at least for food crops eaten raw.

### 3.5.2 Relative risk of HRW to reclaimed water

A comparison of the estimated annual risk between untreated HRW irrigated crops and reclaimed water irrigated crops [17] shows that the former is one to two order(s) of magnitude lower than the latter. Only additional treatment, such as withholding reclaimed water for a week for environmental degradation of pathogens before irrigation of the crops, is able to reduce the annual risk of reclaimed water irrigated crop to the same level as that of HRW irrigated crops. Moreover, non-disinfected secondary effluent is known to contain protozoan pathogens such as *Giardia* and *Cryptosporidium* at much higher detection level (detection frequency of *Giardia* and *Cryptosporidium* in reclaimed water is  $\geq 83\%$  and  $\geq 42\%$  vs HRW of 9.8% and 0.4%, respectively) and concentration than HRW [41, 42]. As such, inclusion of these pathogens in Hamilton *et al.*'s QMRA would likely elevate their estimated annual risks. Although this trend supports the idea of using untreated HRW for irrigating home produce, the 95<sup>th</sup> percentile values for annual risk of HRW irrigated crops are not able to meet the annual risk benchmark of  $\leq 10^{-4}$  pppy by far, which ranges from high  $10^{-4}$  to low  $10^{-3}$  pppy. The annual risk associated with consumption of HRW-irrigated lettuce (95<sup>th</sup> percentile=  $1.6 \times 10^{-3}$  for Salmonellosis and  $6.5 \times 10^{-3}$  for Giardiasis) is, in fact, considered to be highly unsafe if measured against the  $\leq 10^{-4}$  pppy annual risk benchmark.

### 3.5.3 Inferences from sensitivity analysis

Sensitive model parameters can be used as inferences for decision-making. For example, reducing the uncertainties of a sensitive input parameter (e.g. through experiment refinement) can improve risk prediction, and/or derive risk management/mitigation strategies by controlling the phenomenon characterized by a sensitive parameter [27, 43-45].

My sensitivity analysis showed that variations in consumption rate of crops and pathogen concentration are equally significant in predicting illness risk. Variation of water retention rate of lettuce and cucumbers are not as significant as that of tomato in predicting illness risk. While the sensitivity analysis results of Hamilton *et al.* [17] also showed the significance of consumption rate in predicting illness risk ( $|r_s| > 0.49$ ), it was not the case for virus (pathogen) concentration in water ( $|r_s| < 0.22$ ). Nevertheless, consumption rate of crops is deemed as a very sensitive input parameter in both models.

One of the risk management strategies that can be derived from the knowledge of high sensitivity of consumption rate is to reduce consumption of raw crops. In the event that the proposed strategy is impractical (considering the broad health benefit of fresh produce), other sensitive parameters should be explored for solutions. Pathogen concentration in HRW, another highly sensitive parameter to predict illness risk, implies that disinfecting HRW through targeting high-risk pathogens can reduce foodborne risk. Certainly, the examples above are oversimplified, but it showed how our understanding of risk management can be validated and justified by statistical method.

A comparison of the mean intake of each home produce used for my QMRA to the corresponding mean edible and intake of raw crops from all sources (i.e. home-produced or not) used by Hamilton *et al.* [17] shows that the former is marginally higher than the latter (Figure 5). The annual risk estimated for HRW-irrigated home produce is also based on daily consumption of the crops throughout the years (i.e. 365 exposure events), which may be improbable given the different growing season of each crop (although some crops can be grown throughout the year depending on its cultivar and/or where it is grown) and the actual amount of crops that can be grown. This substantiates the possibility that the annual illness risk of HRW irrigated crop may be overestimated due to the uncertainties of estimates for home produce annual intake rate. Indeed, the annual risk can be refined by using alternate days of intake (one intake event per two or more days). However, as with all health risk assessment, any lack of information should be replaced with cautious estimate to assure that the worst-case risk is addressed. The daily intake rate used in this study has included some seasonal variability by averaging the USDA 1987-1988 NFCS

data from all seasons from all regions of the country. Consequently, the risk estimates presented here represent the best state of knowledge.

#### **3.5.4 Interpretation of QMRA**

QMRA model structure, its risk outcomes, and sensitivity test should be used as a tool integrally for decision-making because risk model is constructed based on the best knowledge and available information (parameters and data) at the time of development. There are at times that certain parameters for modeling a phenomenon is challenging due to difficulties and lack of methods to characterize it and modelers have to compromise with a surrogate parameter. A very classic example is the water retention rate by crops, which are used in this study and in many QMRA of crop contamination by irrigation water [17, 35, 36]. The water retention rate is simulated by prolonged water submergence test on the crops to represent a “worst-case scenario”. This is, at best, appropriate for predicting the risk of crops whose edible portion are exposed to contaminated water (e.g. through overhead irrigation). However, this can be considered for risk management strategies by changing the irrigation method from surface irrigation to subsurface irrigation. Additional studies will have to be conducted to substantiate the conclusion, but several studies have already shown that drip irrigation can reduce pathogen exposure to edible portion of above-ground crops (e.g. tomatoes, cucumbers, lettuce) from a detected level to 10 times less or non-detect level in relative to surface irrigation [46, 47].

Another caveat to be addressed in my QMRA is the use of microbial data of HRW collected in Southeastern Australia to represent the microbial quality of HRW in USA. Currently, there are only a few US-based studies [20, 48], which investigate the microbiological quality of HRW. In fact, there has been a lack of thorough investigation of microbiological quality of HRW in developed countries, especially in terms of the data quality and quantities that can be used for standards development [8]. Thus, the interpretation of QMRA and adoption of QMRA result in policy decisions should consider the limitations at the time. QMRA should continuously evolve with the advancement of microbiological measurements,

human behavior changes and availability of new information. The water policy based on the QMRA should also be updated with the QMRA development as illustrated through risk analysis of HRW irrigated home produce.

### **3.6 Conclusions**

Rainwater harvesting systems represent one of the simplest green technologies which have low cost in exchange for a high return. Collection of rainwater also encourages property owners to take “ownerships” of their own water, educating them naturally of the scarcity and characteristics of different water sources. Unfortunately, the benefits of rainwater harvesting in the US are not fully realized due to the lack of studies and wide-scale support given to the area.

Promiscuous use of an established but inappropriate standard as shown in this study can significantly hinder the development of sustainable water practice. While a stringent health risk benchmark is definitely useful as a guidance for human health protection, it can also act as a double-edged sword that increase economic and resource risk of over-treating the water for minimal human benefits. Stringent standards promote the safety level of water uses, but also scare away practitioners in water-related fields who are used to following protocols and guidelines as the golden standard for every water-use. The U.S. EPA annual risk benchmark for safe-drinking water is not appropriate as a singular (absolute) indicator for assessing the safety level of different water end-uses, particularly when sustainable water practice is considered. In supporting this claim, the U.S. EPA had set an acceptable swimming-associated gastrointestinal illness rate of 19 illness case per 1000 swimmers, which is 190 times less stringent than the allowable drinking water risk level [49, 50]. While there are big differences between recreational water and drinking water, in terms of their purposes and controllability over their water quality, the same can be argued for HRW or any sustainable water practices versus drinking water.

As shown in this study, the risk assessment result could be impacted heavily by the quality of data used. Relative risk study of appropriate end-uses of different source water can provide another perspective of the risk and benefits appraisal, and for development of risk standards. Perhaps, as discussed by Haas *et al.* [37], an annual risk of  $\leq 10^{-3}$  pppy for foodborne risk is more recommendable than the standard  $\leq 10^{-4}$  pppy. It is hoped that this study will serve as a platform to drive research needed in the area, provide insights to the establishment of new standards and guidelines for sustainable water practice such as using untreated or treated HRW or other lesser-quality water, such as captured stormwater, for toilet flushing, laundry, and gardening in the near future.

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**CHAPTER 4: Assessment of public health risk associated with viral  
contamination in harvested urban stormwater for domestic  
applications**

## 4.1 Abstract

Capturing stormwater is becoming a new standard for sustainable urban stormwater management, which can be used to supplement water supply portfolios in water-stressed cities. The key advantage of harvesting stormwater is to use low impact development (LID) systems for treatment to meet water quality requirements for non-potable uses. However, the lack of scientific studies to validate the safety of such practice has limited its adoption. Microbial hazards in stormwater, especially human viruses, represent the primary public health threat. Using adenovirus and norovirus as target pathogens, I investigated the viral health risk associated with a generic scenario of urban stormwater harvesting practice and its application for three non-potable uses: 1) toilet flushing, 2) showering, and 3) food-crop irrigation. The Quantitative Microbial Risk Assessment (QMRA) results showed that food-crop irrigation has the highest annual viral infection risk (median range:  $6.8 \times 10^{-4}$ — $9.7 \times 10^{-1}$  per-person-per-year or pppy), followed by showering ( $3.6 \times 10^{-7}$ — $4.3 \times 10^{-2}$  pppy), and toilet flushing ( $1.1 \times 10^{-7}$ — $1.3 \times 10^{-4}$  pppy). Disease burden of each stormwater use was ranked in the same order as its viral infection risk: food-crop irrigation > showering > toilet flushing. The median and 95<sup>th</sup> percentile risk values of toilet-flushing using treated stormwater are below U.S. EPA annual risk benchmark of  $\leq 10^{-4}$  pppy, whereas the disease burdens of both toilet-flushing and showering are within the WHO recommended disease burdens of  $\leq 10^{-6}$  DALYs pppy. However, the acceptability of showering risk interpreted based on the U.S. EPA and WHO benchmarks are in disagreement. These results confirm the safety of stormwater application in toilet flushing, but call for further research to fill the data gaps in risk modeling as well as risk benchmarks.

## 4.2 Introduction

Sustainable urban stormwater management is emerging as one of the solutions to alleviate the negative impact of rapid urbanization. Stormwater harvesting systems are receiving attentions from the water sectors following the revived interest in rainwater harvesting in intermittently drought-ridden regions [1-3]. The rationale for harvesting stormwater for beneficial uses is to capture the excess stormwater before it contaminates the receiving water body and changes the stream hydrology, while providing a new source of water supply that may require less treatment than sewage for various non-potable uses. Development of stormwater harvesting systems as a water source, however, is often impeded by social and institutional barriers resulting from a complicated mix of risk perceptions by multiple stakeholders [4]. While there is an increasing recognition that other associated risks such as technical, socio-economics, and environmental risks also play influential roles in risk management, public health risk has been the focal point of technical risk assessment that guides risk management within the water sector in developed countries.

Stormwater is water that is collected by storm drain systems without any engineered treatment, and can include urban runoff from irrigation, car washes, and rainwater that is intercepted by paved surface. In urban settings stormwater carries a large number of chemical and microbiological pollutants, which have the detrimental impact to coastal water quality (e.g., [5-7]). Stormwater collection systems are usually underground channels that are separated from—but often in close proximity to—sanitary sewer lines. Many of these systems in older cities suffer leakage, which results in unintended cross-contamination of the two types of water [8-10]. A review of stormwater harvesting practices in Australia [3] identified that most of the stormwater (in ~60% of the large-scale systems) collected using conventional urban drainage techniques such as gutters, pipes, and channels, is contaminated by sewage. In spite of the presence of contaminants, harvested stormwater should require less treatment than sewage if it is to be used for non-potable purposes, such as toilet-flushing, irrigation of lawns, car washing, and laundry. Sustainable urban water management systems, frequently termed Low-Impact Development

(LID) systems in the U.S. or Water-Sensitive Urban Design (WSUD) in Australia, are presumed to be able to provide passive treatment of stormwater that is needed for its safe non-potable uses with much less energy requirements than conventional water treatment technologies [3, 11]. These systems include biofilters, rain gardens, bioswales and filter strips, as well as wetlands and ponds. Ultimately, the main concern of using harvested stormwater for household uses lies in the transmission of pathogens to humans, which may translate to disease outbreak in more severe cases.

Human-specific fecal waste markers have been detected in urban stormwater in cities of U.S. [12] and Australia [10, 13, 14], human enteric viruses generally pose the greatest threat to public health [15]. Of these, noroviruses' high potency to cause gastroenteritis [16] and adenoviruses' ubiquitous presence in environmental waters [9] have rendered them two of the most studied viruses. Adenoviruses, double stranded DNA viruses, contain 51 known serotypes. Illnesses associated with adenoviruses range from acute respiratory disease, pneumonia, conjunctivitis, and gastroenteritis, all of which could potentially be transmitted environmentally through non-potable uses of harvested stormwater [17]. Noroviruses are frequently reported as the leading cause of viral gastroenteritis outbreaks worldwide, with some literature estimating that they account for ~50% of all gastroenteritis cases [18, 19].

Direct measurements of viral concentration in stormwater, however, are sparse due to the difficulties facing the quantification technologies, which are often plagued by poor recoveries in environmental water and inhibitory effects of PCR used for detecting viral genomes [20]. My advisor's previous work has shown that viruses were more frequently detected in the receiving water affected by urban stormwater flow than directly from the stormwater itself due to the PCR inhibition and co-concentrated suspended solids [21-24]. In fact, a molecular quantitative analysis of human viruses in stormwater conducted by Rajal et al. [20] yielded results that effectively comprise of non-detects only.

These challenges in enumerating enteric viruses in stormwater have translated to a very poor understanding of removal by basic treatment processes. In fact, the only removal efficacy study for

stormwater treated through a LID system (biofilters in this case) is for the removal efficiency of an indicator virus, F-RNA coliphage [25], and not human-pathogenic viruses.

Consideration of risk associated with stormwater reuse needs to look beyond the water quality itself to include the various ways in which the water is likely to be used. Toilet flushing, showering, and food-crop irrigation are three likely uses, yet they represent distinctly different pathogen-human transmission routes and different infection sites (respiratory vs. intestinal system). Variation within such systems can also be significant. For instance, flush energy associated with different types of toilets can result in marked variation in aerosol production, with high-energy toilets generating larger droplets and greater aerosol production [26]. Rapid gravitational sedimentation or shrinkage of large aerosol droplets usually occurs in the first 15–30 seconds immediately after flushing, and the dynamic regime of aerosol concentration in the air translates to inconsistent results across the literature [26, 27]. Complicating matters further, the deposition rate of aerosols in the respiratory system varies with physical properties of aerosol, such as size, density, and shape, and also the breathing patterns of humans (e.g., breathing cycle, breathing intensity) [28]. While most individuals breathe predominantly through the nose, habitual and obligatory nasal-oral breathers are not uncommon [29]. These are important considerations as our noses retain and remove large deposited particles through mucociliary clearance (up to 83% for 2.5–10 $\mu$ m particles) before they reach human's lower respiratory tract [30, 31]. Particles deposited within macrophages or upon the mucus layer itself are primarily cleared to the gastrointestinal tract, which represents a transmission pathway for pathogens causing gastrointestinal illness [32].

Similarly, the size distribution of aerosols produced by shower heads varies as a function of the water flow rate, water temperature, relative humidity, and also configuration of the shower room (e.g. ventilation) [33]. In addition, an individual's shower temperature preference is greatly influenced by season. Heating shower water can also affect risk. Viruses can be inactivated thermally, the kinetics of which are determined by the water temperature, contact time, and also the types of viruses [34-36]. Conventional water heaters, which heat and store hot water in a tank, can be a potential virus inactivation

system due to the longer contact time, whereas tank-less, on-demand water heaters might contribute to insignificant reduction of viruses due to the very short contact time with the hot water.

Irrigation of food-crops poses a markedly different situation. Water retained on the food-crops can transmit pathogens in the water to cause human enteric infection through ingestion of the crop. Owing to its capacity to trap water on its surface and its popularity among household growers, lettuce has been the subject of previous risk assessments for other types of contaminated water [37-39] but not stormwater.

More broadly, risk modeling for stormwater has received little attention in comparison with other water reuse practices (see [37] and citations within, and more recent examples: [40-42]). QMRA has also been conducted in recreational waters receiving urban storm runoff using screening-level data [43], based on the pathogen numbers inferred from indicator bacteria numbers [44], or using stormwater pathogen data inferred from surface water [45]. These studies suggest that the health risk associated with recreation in stormwater-affected surface water is noteworthy and requires intervention to reduce stormwater impacts on recreational waters. Inherently, harvesting stormwater for non-potable uses also necessitates the evaluation of hazards that are present in stormwater. Given the concern enteric viruses raise to public health, their presence in stormwater, and the rapidly increasing interest in stormwater application for domestic purposes, it is perhaps surprising that to date there has not been a study on health risk assessment of stormwater harvesting practice.

To redress this gap, here I present a QMRA for two viruses of public health significance, norovirus and adenoviruses, for three non-potable applications of LID-treated stormwater: toilet flushing, showering, and food-crop irrigation.

### **4.3 Materials and Methods**

QMRA was conducted following the U.S. National Academy risk assessment framework, which consists of hazard identification, exposure assessment, dose-response assessment, and risk

characterization [46]. The Monte Carlo technique was used to represent the propagation of variability and uncertainties in risk estimation. All calculations were conducted using MATLAB R2012a (The MathWorks Inc., Natick, MA).

### 4.3.1 Hazard Identification

#### 4.3.1a Viral Concentration in Stormwater

Having identified adenovirus and norovirus as the important microbial hazard in stormwater uses, I collected virus data in surface waters affected by urban stormwater runoff as an indirect measure of viral concentration in stormwater after failed attempts to compile meaningful data for stormwater virus load directly (see introduction). The definition for surface water herein is urban tributaries and rivers, which may function as source water for drinking water treatment plants and recreational waters. Urban surface waters are usually affected by storm drain flow. Stormwater can be idealized as undiluted surface water, as in a recent QMRA study [45]. A concentration factor can then be used to estimate viral water quality of stormwater based on that of surface water,

$$C_{virus,storm} = C_{virus,surface} \times F_{conc} \times \frac{1}{R_{eff}} \quad (1),$$

where  $C_{virus,storm}$  is the estimated viral concentration in stormwater (genome copies/ liter),  $C_{virus,surface}$  is the measured viral concentration in surface water (genome copies/ liter),  $F_{conc}$  is the viral concentration factor from surface water to stormwater (unitless) that is adopted from the study of McBride et al [45], and  $R_{eff}$  is the recovery efficiency of virus quantification method (unitless).

With the acknowledgement of the existing limitations and uncertainties, I compiled quantitative virus data in urban surface water for inferring viral concentration in stormwater based on two criteria: 1) quantitative PCR (qPCR) as the detection method and 2) surface water that receives storm-runoff.



Accepted data are derived from different countries and also varied in viral concentration methods, and the qPCR primers and probes used (Table 4.1 and citations within). In the absence of the seasonal data on viral concentration from most regions, seasonal variability was not included in the QMRA and the viral concentrations from all relevant literature were used to provide a broader view of the risk.

Table 4.1 Summary of references used for collecting concentration of viruses in surface water.

<b>Virus</b>	<b>Reference</b>	<b>Virus concentration method</b>	<b>No. of samples</b>	<b>No. of samples below DL</b>	<b>Types of data</b>	<b>Recovery efficiency<sup>a</sup></b>	<b>Recovery target</b>	<b>Primers and Probes reference</b>
Adenovirus	[47]	Adsorption-elution	2	0	Observed value	25%	HAdv2	[48]
	[49]	Adsorption-elution	2	0	Observed value	4.2% (2—6.9%)	HAdv2	[48]
	[50]	Adsorption-elution	18	7	Observed value	-	-	[51]
	[52]	Adsorption-elution	2	0	Geometric mean	-	-	[53]
	[21]	Ultrafiltration	12	4	Median	54% (<0—>100%)	Bacteriophage $\Phi$ HSIC	[54]
	[55]	Ultrafiltration	14	10	Observed value	41% (21—89%)	MS2 coliphage	[56]
	[57]	Skim milk flocculation	12	0	Observed value	65% (24—94%)	HAdv	[48]
	[58]	Adsorption-elution	52	30	Observed value	-	-	[51]
Norovirus GI	[58]	Adsorption-elution	52	23	Observed value	-	-	[59]

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Norovirus					Observed			
GII	[58]	Adsorption-elution	52	20	value	-	-	[59]
	[57]	Skim milk flocculation	7	0	Mean	53% (22— 74%)	NoV GGII	[60]

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<sup>a</sup>Unbracketed numbers are mean recovery efficiency, whereas bracketed numbers are the range of recovery efficiency.

#### 4.3.1b Distribution fit for virus data

A portion of adenovirus and norovirus genogroup I and II (noroviruses GI + GII) data compiled from the literature were reported as non-detects. Instead of applying the commonly used strategy of replacing non-detects with single values (i.e., detection limit value or half of detection limit value) (e.g., [61]), which is known to create biased results, I applied a left-censored data regression technique (Tobit regression) for estimating parameters that characterize the viral concentration distribution [62]. Following inspection of each virus data histogram and based on the knowledge that most environmental and microbial measurement data are distributed log-normally [63, 64], I assumed that adenovirus data follow a unimodal  $\log_{10}$ -transformed normal distribution and norovirus a bimodal  $\log_{10}$ -transformed normal distribution. Thus, the concentrations of adenoviruses ( $C_{Adv,surface}$ ) and noroviruses ( $C_{NoV,surface}$ ) in surface waters (genomic copies/L) are respectively given as

$$\log_{10} C_{Adv,surface} = N(\mu, \sigma) \text{ and} \quad (2),$$

$$\log_{10} C_{NoV,surface} = \alpha \times N(\mu_1, \sigma_1) + (1 - \alpha) \times N(\mu_2, \sigma_2). \quad (3).$$

Non-detects are treated as latent continuous variables,  $C_{virus,surface}^*$ , which have been left-censored, and where

$$C_{virus,surface} = C_{virus,surface}^* \quad \text{if } C_{virus,surface}^* > \rho \text{ and}$$

$$C_{virus,surface} = \text{missing} \quad \text{if } C_{virus,surface}^* \leq \rho,$$

and where  $\rho$  is the detection-limit parameter, which can take different values depending on the virus detection method used in study at hand. There are five different detection-limit values for the compiled adenovirus data. For the purposes of my study, I set the lowest observed value to be the deterministic detection limit value and applied the Tobit regression on the virus data to generate the best-fit.

The maximum likelihood distribution fits for adenovirus and norovirus concentration in surface water (Figure 4.1) indicate that theoretical and empirical probability distribution curves of the data are visually mismatching due to the presence of non-detects and the arbitrarily selected bin sizes for the histograms. Cumulative probability plots of the theoretical (10,000 iteration values) and empirical distribution were thus used to justify the appropriate distribution assumption and good fit of the data. The best-fit parameters are presented in Table 4.2.

In estimating the viral concentration in LID systems-treated stormwater, a 5- $\log_{10}$  viral reduction value was assigned to the estimated viral concentration in harvested stormwater. This reduction value is based on Li et al.'s [25] experimental study of a biofilter's removal efficiency for virus indicators (> 4- $\log_{10}$  removal), plus an additional  $\log_{10}$  removal of virus assigned to the polishing step (i.e., microfiltration) to produce the finished water for domestic applications.

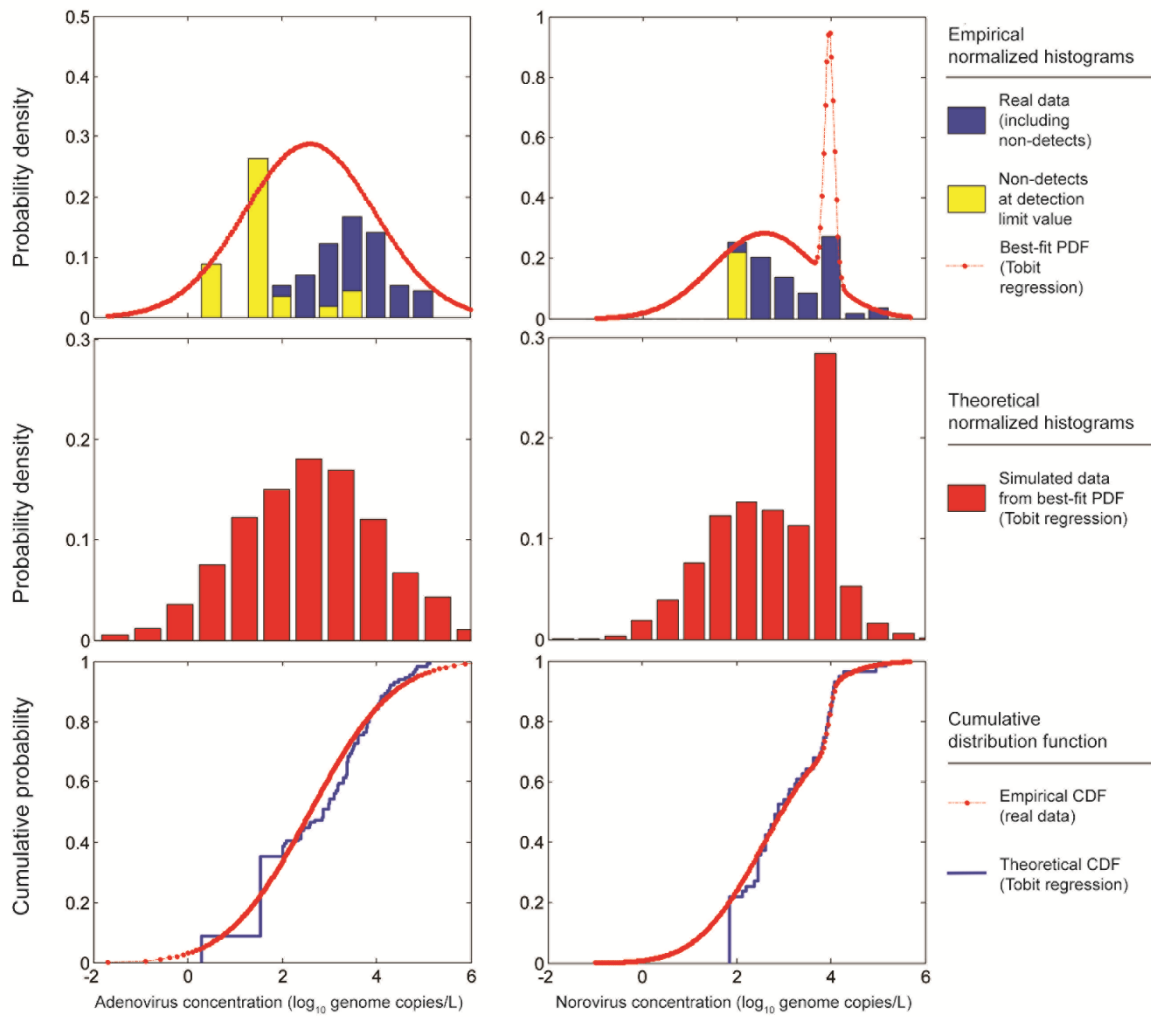


Figure 4.1 Distribution fit for adenovirus and norovirus concentration in surface water based on data reported in literature and compiled in Table 4.1. Left-censored regression technique (Tobit regression) is used to treat the data reported as non-detects.

Table 4.2 List of parameters used in hazard identification of the study.

Description	Unit	Symbol	Point estimate	Probability distribution	Reference
<b>Hazard identification</b>					
Concentration of Adenovirus in surface water	$\log_{10}(\text{genomes/L})$	$C_{Adv,surf}$		N(2.588,1.385)	
Concentration of Norovirus in surface water	$\log_{10}(\text{genomes/L})$	$C_{Nov,surf}$		Bimodal Normal, $0.792 \times$ N(2.578,1.114) $+ 0.208 \times$ N(3.959,0.100)	
Viral concentration factor from surface water to stormwater	unitless	$F_{conc}$	30		[45]
Recovery efficiency of virus quantification method	unitless	$R_{eff}$	0.1		
Log <sub>10</sub> reduction of virus by LID systems <sup>a</sup>	unitless	$\log_{LID}$	5		[25]

<sup>a</sup>Value is justified by assumptions made in Section 4.3.1b

### 4.3.2 Exposure assessment

As the dose-response model for adenoviruses is based on the serotype 4, which causes respiratory infection and transmitted through inhalation route, I estimated adenovirus risk based on the viruses' deposition in human respiratory system. Conversely, norovirus risk was estimated based on inhalation-ingestion route through mucociliary action (assuming all aerosols trapped by our nose are cleared to gastrointestinal tracts) as noroviruses mainly cause gastrointestinal infection. Furthermore, due to the differential deposition efficiencies of aerosols in extrathoracic (nasal and laryngeal) region through nasal versus oral breathing, a distinction was made between the two in my risk assessment.

Only noroviruses were accounted for in the risk associated with food-crop irrigation. Although certain serotypes of adenovirus also cause gastroenteritis, there has not been a dose-response model for enteric adenovirus to be used in the QMRA.

#### 4.3.2a Toilet-flushing scenario

The deposition efficiency of aerosols in the human body during toilet flushing is considered based on breathing pattern as indicated by U.S. EPA, which is represented by the inhalation rate for individuals engaging in light activities [65]. These deposition efficiencies were derived empirically by Heyder et al. [28] as a function of particle size and breathing patterns. A breathing rate of 15 L of air/ min, an 8-seconds breathing cycle period (4 seconds each for inspiration and expiration), and 1L of tidal volume were applied. Duration of exposure to the aerosols is defined as the time an individual would stay in the room after flushing the toilet. For simplicity, this exposed duration is set at 1 min and 5 min to represent a range of exposure scenarios.

The dose of adenoviruses ( $Dose_{AdV, toilet}$ ) and noroviruses ( $Dose_{NoV, toilet}$ ) inhaled and deposited in human's system (genomic copies) after flushing the toilet were estimated as

$$\begin{aligned}
Dose_{AdV, \text{toilet}} &= \sum_{i=1}^n C_{AdV, \text{treated}} \times AerosolDose_{diam_i} \times MFR_{air} \times Duration_{toilet} \\
&= \sum_{i=1}^n \left[ C_{AdV, \text{storm}} \times 10^{-\log_{10} LID} \right] \times \left[ C_{aero, diam_i} \times V_{aero, diam_i} \times DE_{B+A, diam_i} \right] \times MFR_{air} \times Duration_{toilet}
\end{aligned} \tag{4}$$

and

$$\begin{aligned}
Dose_{NoV, \text{toilet}} &= \sum_{i=1}^n C_{NoV, \text{treated}} \times AerosolDose_{diam_i} \times MFR_{air} \times Duration_{toilet} \\
&= \sum_{i=1}^n \left[ C_{NoV, \text{storm}} \times 10^{-\log_{10} LID} \right] \times \left[ C_{aero, diam_i} \times V_{aero, diam_i} \times DE_{ET, diam_i} \right] \times MFR_{air} \times Duration_{toilet}
\end{aligned} \tag{5},$$

where  $C_{AdV, \text{treated}}$  and  $C_{NoV, \text{treated}}$  are the concentration of adeno- and noroviruses in treated stormwater (genomic copies/L), is the  $\log_{10}$  reduction of adeno- and noroviruses by LID systems (unitless),  $C_{aero, diam_i}$  is the concentration of aerosols (according to median diameter size,  $i$ ) in the air generated after a single toilet flush (# of aerosols/m<sup>3</sup> of air) and  $V_{aero, diam_i}$  is the volume of spherical aerosol (L/ aerosol),  $DE_{B+A, diam_i}$  and  $DE_{ET, diam_i}$  are the deposition efficiencies of aerosols on bronchial and alveolar region, and extrathoracic region, respectively (unitless),  $MFR_{air}$  is the mean flow rate of air breathed after toilet flushing (m<sup>3</sup> of air/min), and  $Duration_{toilet}$  is the time spent in the room after toilet flushing (min).

#### 4.3.2b Showering scenario

Only conventional water heaters were considered. Shower temperature preferences of 50°C and 60°C were chosen in an attempt to represent variation in this parameter. Assumptions about shower duration, flow rates, and thermal reduction are given in Table 4.3 along with sources to justify these choices. The doses of adenoviruses ( $Dose_{AdV, \text{shower}}$ ) and noroviruses ( $Dose_{NoV, \text{shower}}$ ) inhaled and deposited in a person's system (in genomic copies) during showering were estimated as

$$\begin{aligned}
Dose_{Adv,shower} &= C_{Adv,T_{shower}} \times \frac{AerosolDose_{B+A}}{\rho_{water}} \times Duration_{shower} \\
&= \left\{ C_{Adv,storm} \times 10^{-\log_{LID}} \times \frac{(100 - \%_{hot}) + \%_{hot} \times 10^{-\log_{T,hot}^{Adv}}}{100} \right\} \times \frac{AerosolDose_{B+A}}{\rho_{water}} \times Duration_{shower}
\end{aligned} \tag{6}$$

and

$$\begin{aligned}
Dose_{NoV,shower} &= C_{NoV,T_{shower}} \times \frac{AerosolDose_{ET}}{\rho_{water}} \times Duration_{shower} \\
&= \left\{ C_{NoV,storm} \times 10^{-\log_{LID}} \times \frac{(100 - \%_{hot}) + \%_{hot} \times 10^{-\log_{T,hot}^{NoV}}}{100} \right\} \times \frac{AerosolDose_{ET}}{\rho_{water}} \times Duration_{shower}
\end{aligned} \tag{7},$$

where  $C_{Adv,T_{shower}}$  and  $C_{NoV,T_{shower}}$  are the concentration of adeno- and noroviruses in shower water (genomic copies/L),  $\%_{hot}$  is the percentage of hot water used for mixing with ambient temperature water to produce shower water at the desired temperature,  $\log_{LID}$  is the  $\log_{10}$  reduction of adeno- and noroviruses by LID systems (unitless),  $\log_{T,hot}^{Adv}$  and  $\log_{T,hot}^{NoV}$  are the  $\log_{10}$  reductions of adeno- and norovirus at the temperature of the hot water used for shower water mixing (unitless),  $AerosolDose_{B+A}$  and  $AerosolDose_{ET}$  are the mass of water aerosol deposited in the bronchial-bronchiolar + alveolar-interstitial region and extrathoracic region (g/min), respectively, and  $\rho_{water}$  is the density of water (g/L), and  $Duration_{shower}$  is the showering time (min).

#### 4.3.2c Food-crop irrigation scenario

Lettuce was modeled as the representative vegetable. I assumed that lettuce is watered every two to three days, between which the environmental decay of microbes deposited on the surface of lettuce leaves will occur. Considering the growing period and high perishability of lettuce and also the varying



expertise of home growers, it is unlikely that homegrown lettuce will be consumed daily throughout a year. Thus, I assessed only how the risk varies from one lettuce meal to 90, 180, and 270 meals per year. The environmental decay rate of norovirus GII on savoy spinach was used as a surrogate for estimating the reduction of norovirus on homegrown lettuce during the withholding period between last irrigation and harvesting/consumption of lettuce [66]. Assumptions and relevant sources relating to consumption and water capture on leaf surfaces are given in Table 4.3.

The dose of noroviruses ( $Dose_{NoV}$ ) ingested through intake of raw lettuce (in genomic copies) was estimated as

$$Dose_{NoV} = C_{NoV,treated} \times 10^{-\log_{decay} \times T_{withhold}} \times M_{lettuce:body} \times M_{body} \times V_{lettuce} \quad (8),$$

where  $\log_{decay}$  is the  $\log_{10}$  reduction of norovirus due to environmental decay ( $\log_{10}/\text{day}$ ),  $T_{withhold}$  is the duration of environmental decay,  $C_{NoV,treated}$  is the concentration of noroviruses in treated stormwater  $= C_{NoV,treated} \times 10^{-\log_{decay}}$ , which include the 5- $\log_{10}$  reduction values (genomic copies/L) by LID

treatment. The daily intake of lettuce is calculated as a function of body mass  $= M_{lettuce:body} \times M_{body}$ ,

where  $M_{lettuce:body}$  is the mass of raw lettuce intake per unit body weight per day (grams of lettuce/kg-day)

and  $M_{body}$  is the body weight of U.S. population (kg). The volume of water retained on per unit weight of

lettuce is  $V_{lettuce}$  (L/gram of lettuce).

Table 4.3 List of parameters used in exposure assessment of the study.

Description	unit	Symbol	Point estimate	Probability distribution	Reference
<b>Exposure assessment (Toilet-flushing scenario)</b>					
Concentration of aerosol in air after each toilet flush (at different sampling height)	# of aerosols/cm <sup>3</sup> air	$C_{aero,diam,i}$			
Median diameter	0.6 μm (42 cm above toilet)			Uniform(0,106.9)	[27]
size, $i$	2.5 μm (42 cm above toilet)			Uniform(0, 11.6)	
	2.5 μm (5 cm above toilet)			Uniform(0, 24.5)	
<hr/>					
Deposition efficiency of aerosols in extrathoracic region	unitless	$DE_{ET,i}$	Oral breathing	Nasal breathing	
Aerosol size, $i$	0.6 μm		0	0.04	[28]
	2.5 μm		0.01	0.42	

Description		unit	Symbol	Point estimate		Probability distribution	Reference
Deposition efficiency of aerosols in bronchial and alveolar region		unitless	$DE_{B+A,i}$	Oral breathing	Nasal breathing		
Aerosol size, $0.6 \mu\text{m}$	0.17			0.18			
$2.5 \mu\text{m}$	0.61			0.41			
Mean flow rate of air during a minute of breathing cycle		L of air/min	$MFR_{air}$	15			[65]
Duration spent in restroom after flushing toilet	Mean scenario	min/flush	$Duration_{toilet}$	1			
	Worst-case scenario			5			

### Exposure assessment (Showering scenario)

Description	unit	Symbol	Point estimate	Probability distribution	Reference
Log <sub>10</sub> reduction of Adenovirus through heat inactivation by hot water	unitless	$\log^{AdV}_{T,heat}$			
At T= 50oC			Inf		[35]
At T= 60oC			Inf		
<hr/>					
Log <sub>10</sub> reduction of Norovirus through heat inactivation by hot water	unitless	$\log^{NoV}_{T,heat}$			
At T= 50°C			1.7		[67]
At T= 60°C			5.2		
<hr/>					
Percentage of hot water used for mixing during summer <sup>a</sup>	%	$\%Summer^{hot}_{,T}$			
Hot water at T= 50°C			15		

Description	unit	Symbol	Point estimate	Probability distribution	Reference
			11.3		
at T= 60°C					
Percentage of hot water used for mixing during winter <sup>a</sup>	%	$\%Winter^{hot,T}$			
Hot water at T= 50°C			81.9		
			64.1		
at T= 60°C					
-----					
Mass of water deposited in the extrathoracic region per minute of shower	mg/min	$AerosolDose_{ET}$	Oral breathing	Nasal breathing	
Hot shower (T=43.5°C) at flowrate of :	5.1 L/min		0.659	0.951	
	6.6 L/min		0.637	0.994	
	9.0 L/min		0.852	1.211	[33]
-----					
Cold shower (T=24.5°C) at flowrate of :	5.1 L/min		0.004	0.001	
	6.6 L/min		0.007	0.018	
	9.0 L/min		0.02	0.029	

Description	unit	Symbol	Point estimate		Probability distribution	Reference
Mass of water deposited in the bronchial and alveolar region per minute of shower	mg/min	$AerosolDose_{B+A}$	Oral breathing	Nasal breathing		
Hot shower	5.1 L/min		0.297	0.036		
(T=43.5°C)	6.6 L/min		0.357	0.049		
at flowrate	9.0 L/min		0.364	0.044		
of :						
Cold shower	5.1 L/min		0.005	0.002		
(T=24.5°C)	6.6 L/min		0.008	0.003		
at flowrate	9.0 L/min		0.007	0.001		
of :						
Duration of each shower	min/shower	$Duration_{shower}$	20			

**Exposure assessment (Food crop irrigation scenario)**

Description	unit	Symbol	Point estimate	Probability distribution	Reference
Mass of raw lettuce intake per unit body weight per day	g of lettuce/kg-day	$M_{lettuce:body}$		Empirical distribution of consumer-only intake for all age-groups	[65]
Body weight of U.S. population	kg	$M_{body}$		Empirical distribution of body weight from populations of all age-groups	[68]
Volume of water retained on per unit weight of lettuce	L/ g of lettuce	$V_{lettuce}$		Uniform $(0.24,0.48) \times 10^{-5}$	[69]
Withholding time (between last irrigation and harvesting/eating)	days	$T_{withhold}$		Uniform (0,3)	
Environmental decay rate of norovirus	$\log_{10}/\text{day}$	$\log_{decay}$	0.192		[66]

<sup>a</sup>Assuming that the temperature of tap water is 20°C and 14°C during summer and winter, respectively.

### 4.3.3 Dose-response Assessment

The risk or probability of getting infected through intake of pathogens was estimated using dose-response models based on clinical trial data. The adenovirus dose in genome copies was converted to median tissue culture infective dose (TCID<sub>50</sub>), using 1 TCID<sub>50</sub> equals 700 genomes, to be consistent with that of clinical trial data [30, 45]. All adenovirus genomic copies are included in the assessment to yield the maximal estimate of risk, although only a sub-portion of the 51 adenovirus serotypes are known to cause respiratory illnesses [70]. The dose-infection model is characterized by an exponential function [71]

$$P_{\text{inf,AdV}} = 1 - e^{-r \times \text{Dose}_{\text{AdV}}^{\text{TCID}_{50}}} \quad (9).$$

$P_{\text{inf,AdV}}$  is the estimated infection risk, and  $r$  represents infectivity of the virus and is the best-fit parameter of the model, and  $\text{Dose}_{\text{AdV}}^{\text{TCID}_{50}}$  represents the dose of adenovirus in TCID<sub>50</sub>.

Dose-response model for monodispersed norovirus as also used by other norovirus QMRA to maximize the infection risk outcome and the margin was adopted. This dose-infection was characterized by a confluent hypergeometric function [72]

$$P_{\text{inf,NoV}} = 1 - {}_1F_1(\alpha, \alpha + \beta, -\text{Dose}_{\text{NoV}}) \quad (10).$$

Similar to the dose-infection model for adenovirus,  $P_{\text{inf,NoV}}$  is the infection risk caused by norovirus, whereas  $\alpha$  and  $\beta$  are the fitting parameters of the model.  $\text{Dose}_{\text{NoV}}$  is the dose of norovirus in genome copies.

Both Equation 9 and 10 estimate infection risk, wherein infection does not always translate to illness (symptomatic infection) and is dependent on many factors such as an individual's immunity status, age, medical conditions, and nutrient intake. Higher pathogen dose generally results in higher probability



of illness. In the absence of dose-illness data, as is the case for adenoviruses, probability of illness is estimated as a fixed portion of probability of infection, which is multiplied by a coefficient representing the percentage of illness cases in every infection case. In this study, a value of 0.5 for this coefficient is used for adenoviruses (Table 4.4). For norovirus, a dose-illness model has been developed as a function of pathogen dose intake [72], where conditional dose-dependent norovirus illness risk is expressed as

$$P_{ill, NoV} | P_{inf, NoV} = 1 - (1 + \eta \times Dose_{NoV})^{-r_{ill, NoV}} \quad (11).$$

The best-fit parameters,  $\eta$  and  $r_{ill, NoV}$ , which describe the effects of initial pathogen dose and host's defenses, are also based on that for monodispersed norovirus genome copies.

The general illness risk equation, which applies for both adenoviruses and noroviruses, is expressed as

$$P_{ill, virus} = P_{inf, virus} \times (P_{ill, virus} | P_{inf, virus}) \quad (12).$$

#### 4.3.4 Risk characterization

Two widely-used health risk benchmarks, the acceptable annual infection risk level proposed by the U.S. EPA [73] and the acceptable disability-adjusted life years (DALYs) by WHO, were used for interpreting the magnitude of risk assessment outcomes. The U.S. EPA benchmark is  $\leq 10^{-4}$  infection cases per-person-per-year (pppy), and the WHO benchmark is  $\leq 10^{-6}$  DALYs pppy [74].

The annual infection risk metric is computed based on the theorem of independence of probability as [75]

$$P_{inf, annual_{scenario, virus}} = 1 - \prod_{i=1}^{n=365 \times Freq_{scenario}} (1 - P_{inf, virus_i}) \quad (13),$$

where  $Freq_{scenario}$  represents the number of times an activity is engaged during a day (e.g. one shower event per day), and n represents the total number of times an activity is engaged in a year. For food-crop irrigation,  $n=Freq_{meal}$  as it is highly unlikely that an individual would eat the crop he/she grown every day.

Equation 13 is also used to compute the annual illness risk,  $P_{inf,annual_{scenario,virus}}$ , by substituting per-event illness risk for per-event infection risk (Equation 12). Subsequently, the DALYs metric can be computed from the annual illness risk as [76]

$$DALY_{scenario,virus} = \frac{DALY}{\text{illness case}_{virus}} \times P_{ill,annual_{scenario,virus}} \quad (14).$$

Table 4.4 List of parameters used in dose-response assessment and risk characterization of the study.

Description	unit	Symbol	Point estimate	Reference
<b>Dose-response assessment</b>				
Dose-infection parameter for Adenovirus	-	$r$	0.4172	[75]
Dose-infection parameters for Norovirus		$\alpha$	0.04	[72]
		$\beta$	0.055	
Adenovirus dose conversion factor	TCID <sub>50</sub> /genome copies	$C^{Adv}_{TCID50/GC}$	1/700	[45]
Conditional probability of illness given an infection due to Adenovirus		$P(\text{ill} \text{inf})_{Adv}$	0.5	
Conditional dose-illness parameters for Norovirus		$\eta$	$2.55 \times 10^{-3}$	[72]
		$r_{\text{ill},NoV}$	0.086	
<b>Risk characterization</b>				
Frequency of shower in a day	times	$Freq_{\text{shower}}$	1	
Frequency of flushing toilet in a day	times	$Freq_{\text{flush}}$	4	
Frequency of eating lettuce in a year	times	$Freq_{\text{meal}}$	90, 180, or 270	
DALYs per illness case of Adenovirus disease <sup>a</sup>		$DALYs/\text{illness case}$	0.05340	[77]
DALYs per illness case of Norovirus disease <sup>b</sup>		$DALYs/\text{illness case}$	0.00095	[78]

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<sup>a</sup>Dataset in Table 2 of reference was used. Adenovirus disease burden per 1000 population for age-group <5,6-15,16-64,>65 years old were summed up

<sup>b</sup>DALYs/illness case is computed by dividing total DALYs per year by total number of incidence cases. The values in Table 27 of Kemmeren et al. 2006.

## 4.4 Results

### 4.4.1 Toilet flushing scenario

The viral infection risks from flushing toilet using treated stormwater water are mostly negligible (Figure 4.2). Infection risks for all scenarios are typically order(s) of magnitude (median range:  $1.1 \times 10^{-7}$ — $3.3 \times 10^{-5}$  pppy, 95<sup>th</sup> percentile range:  $2.7 \times 10^{-7}$ — $1.4 \times 10^{-4}$  pppy) less than the U.S. EPA annual infection benchmark of  $\leq 10^{-4}$  pppy. It is noted that norovirus infection risks are up to two orders-of-magnitude or 2  $\log_{10}$  higher than adenovirus infection risk. In terms of breathing style, adenovirus infection risks are within a two-fold difference between oral and nasal breathers. However, norovirus infection risks for nasal breathers are much higher than oral breathers (median:  $3.3 \times 10^{-5}$  pppy vs.  $5.3 \times 10^{-7}$ , 95<sup>th</sup> percentile range:  $1.4 \times 10^{-4}$  pppy vs.  $1.6 \times 10^{-6}$  pppy) due to the nasal breathers' higher indirect ingestion rate of norovirus through mucociliary action. Duration of exposure to aerosols generated by toilet flushing has negligible influence on predicted annual risk, where the difference in risk between one minute exposure and five minutes exposure is within an order of magnitude.

Disease burdens associated with toilet flushing (median range:  $1.0 \times 10^{-20}$ — $5.4 \times 10^{-9}$  DALYs pppy, 95<sup>th</sup> percentile range:  $5.3 \times 10^{-19}$ — $1.4 \times 10^{-8}$  DALYs pppy) are all far below the WHO's recommended threshold of  $\leq 10^{-6}$  DALYs pppy (Figure 4.3).

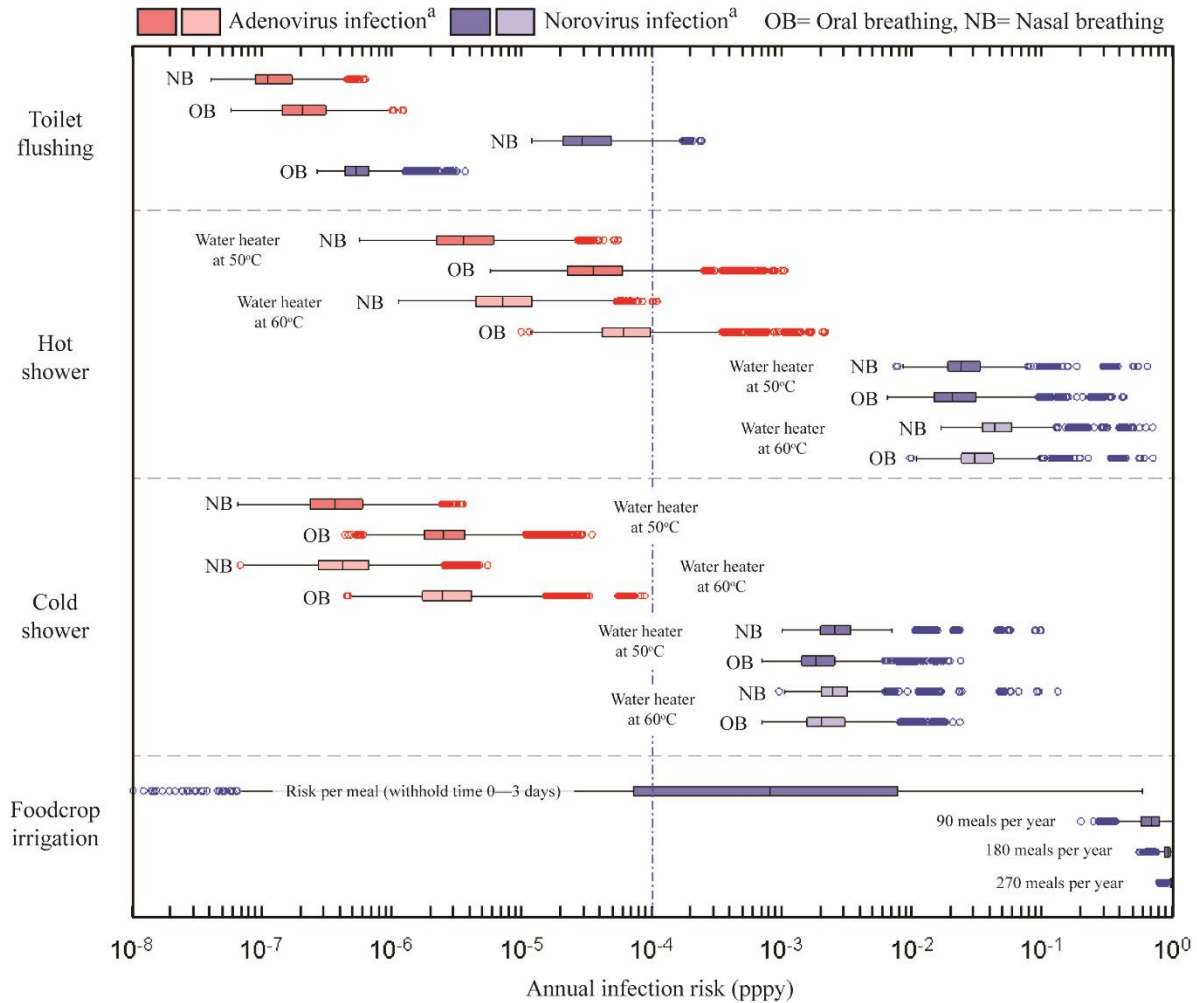


Figure 4.2 Box-and-whisker plot showing the annual adenovirus and norovirus infection risks from using treated stormwater for various water applications. Each box represents the lower, median, and upper quartile (e.g. 25th, 50th, and 75th percentile values) of the distribution, where the whiskers extend  $1.5 \times$  (75th percentile value  $-$  25th percentile value) from each end of the box. Markers graphed outside of each whisker are considered as outliers. The vertical dashed line represents the U.S. EPA annual infection risk benchmark of  $\leq 10^{-4}$  pppy.

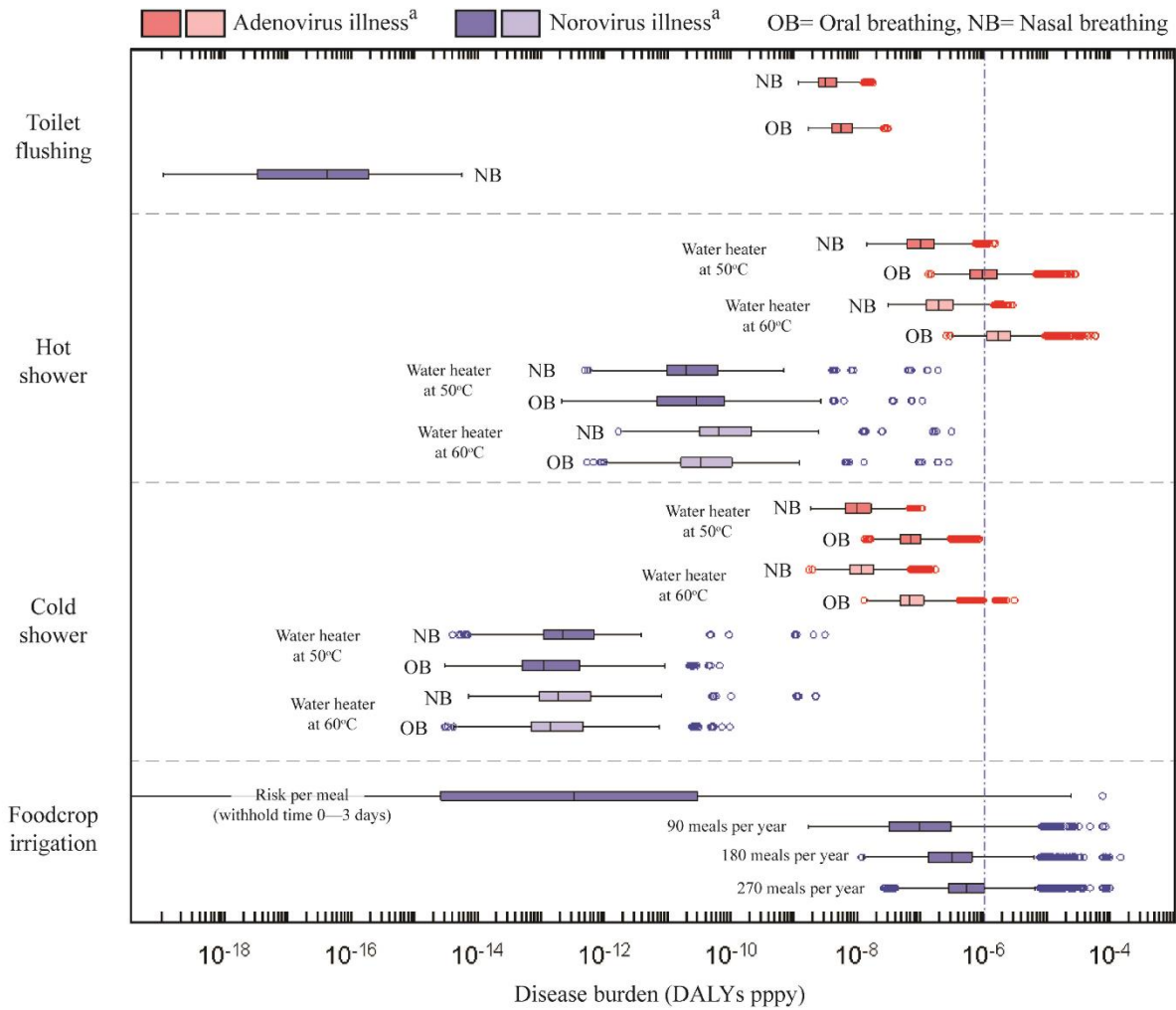


Figure 4.3 Box-and-whisker plot showing the disease burdens of adenovirus- and norovirus-related illness due to using treated stormwater for various water applications. The vertical dashed line represents the WHO recommended benchmark of  $\leq 10^{-6}$  DALYs pppy. Disease burden of norovirus for an oral breather flushing toilet is too low to be graphed.

#### 4.4.2 Showering scenario

Showering risk using treated stormwater differs depending on the virus inhaled, where norovirus infection risks clearly far exceed the U.S. EPA annual infection benchmark and are much higher than adenovirus infection risk (median range:  $3.4 \times 10^{-4}$ — $4.3 \times 10^{-2}$  pppy vs.  $3.6 \times 10^{-7}$ — $6.0 \times 10^{-5}$  pppy, 95<sup>th</sup> percentile range:  $1.6 \times 10^{-3}$ — $2.9 \times 10^{-1}$  pppy vs.  $1.3 \times 10^{-6}$ — $3.5 \times 10^{-4}$  pppy) (Figure 4.2). In comparison, the infection risks of hot showers are a  $\log_{10}$  lower than those of cold showers when all else is equal. The breathing style of an individual does not alter the norovirus infection risk (within a  $\log_{10}$  difference), whereas the adenovirus infection risk of an oral breather is typically a  $\log_{10}$  higher than that of a nasal breather. Risk prediction also is not influenced by different shower water flow rates.

When the infection risks of showering were translated to disease burdens, the opposite trend was observed (Figure 4.3). The disease burdens of norovirus (median range:  $4.1 \times 10^{-15}$ — $6.3 \times 10^{-11}$  DALYs pppy, 95<sup>th</sup> percentile range:  $3.5 \times 10^{-8}$ — $6.1 \times 10^{-8}$  DALYs pppy) all fell below the WHO's benchmark, whereas portion of the disease burdens of adenovirus (median range:  $9.6 \times 10^{-9}$ — $1.6 \times 10^{-6}$  DALYs pppy, 95<sup>th</sup> percentile range:  $3.5 \times 10^{-8}$ — $9.3 \times 10^{-6}$  DALYs pppy) exceeded the benchmark.

#### 4.4.3 Food-crop irrigation scenario

Norovirus infection risks from the consumption of stormwater-irrigated raw lettuce varied little (median range: 0.681—0.973 pppy, 95<sup>th</sup> percentile range: 0.881—0.995 pppy) when a range of 90 to 270 meals per year intake frequency was considered (Figure 4.2). The per-event risk had a median of  $8.0 \times 10^{-4}$  pppy and 95<sup>th</sup> percentile value of  $5.2 \times 10^{-2}$  pppy. Despite such a wide range on the event scale, the annual risk (multiple intakes) converged rapidly to the  $10^{-1}$  range.

Again, disease burdens of the food-crop irrigation shed a very different light on the risk interpretation, where the DALYs computed for the different intake frequency (median range:  $9.5 \times 10^{-8}$ —

$5.1 \times 10^{-7}$  DALYs pppy, 95<sup>th</sup> percentile range:  $2.3 \times 10^{-6}$ — $1.8 \times 10^{-5}$  DALYs pppy) frequently fall below that of the WHO's benchmark (Figure 4.3).

## 4.5 Discussions

### 4.5.1 Implications

Models developed in this study conceptualize the health risks associated with LID-treated stormwater in three domestic applications and identify the uncertainties for a more accurate risk assessment. The QMRA predictions rank the viral risks of toilet flushing the lowest while food-crops irrigation the highest. Two of the three stormwater uses are generally above the U.S. EPA annual infection risk benchmark, while toilet flushing is well below the benchmark. It should be noted that U.S. EPA does not enforce the risk benchmark as a legal requirement, which is primarily established for assessment of safe drinking water. Nevertheless, the existence of the benchmark proposed by the authoritative government agency inevitably demands attention from water practitioners, and may also be relevant in a legal context when demonstrating due diligence. In fact, the U.S. EPA benchmark is used in Dutch regulatory processes, which require water authorities to comply with under a QMRA framework [79]. Instead of a yes-or-no compliance, water utilities in the Netherlands use QMRA as a tool for discussion with the regulatory bodies to support decisions about water systems through acknowledging the uncertainties in QMRA. In the same way, the risk assessment outcomes presented here could also be of value in assisting the adoption of alternative water resources for various applications.

Interpreting QMRA results usually draws interesting comparison with how waterborne disease risks are perceived and regulated in different states and countries. Toilet flushing is generally the most acceptable to the public [4, 80]. Flushing the toilet using non-potable water (i.e., seawater, reclaimed water, treated grey water) is practiced in many parts of the world [81] and is supported as being an acceptably safe practice by my risk assessment. Interestingly, the criteria for toilet flushing vary across



states and countries. California, for example, has adopted the most stringent microbial standard for toilet flushing with reclaimed water (California Law, Title 22), which specifies a 7-day median of  $\leq 2.2$  total coliforms/100 mL of reclaimed water. This is three orders of magnitude lower than Japan's reuse criterion of 1,000 total coliforms/100 mL of reclaimed water [82]. It should be noted that the microbial risk of flushing toilet is mostly derived from the aerosolization of human waste and vomitus rather than from the flushing water itself [18, 83]. The disease transmission in public toilet facilities through aerosols (carrying human waste) generated by flushing water has not been investigated.

Showering using water that is not designated for potable-use is not a readily embraced idea for people due to the close contact of showering water with human. The annual risk profiles of showering suggest that viral infection risks are higher during winter, when individuals are more likely to take a hot shower than a cold shower. Aerosols produced using hot water are not only larger in size and quantity, but also more likely to reach infection sites in human body than when cold water is used. This phenomenon, combined with the depressed human immune systems during the cold seasons and tendency for people to stay indoors (i.e. secondary spread), are predicted to lead to higher infection risks during winter [84]. In fact, many norovirus outbreaks had occurred in various geographical locations during winter and is so common in UK that norovirus is sometimes referred to as "winter vomiting bug" [16, 85, 86].

Crop irrigation using reclaimed water is a well-accepted practice, which also makes harvested stormwater a potential water resource for crop irrigation. However, the annual risk profiles of this stormwater practice tell a very different story, where the infection risks exceeded the corresponding risk using non-disinfected secondary effluent for the same purpose [37, 41, 87-89]. This finding, however, is not a total surprise as norovirus is much more infectious and resistant to environmental decay than the enteric virus used in the previous QMRA studies for crop irrigation. Many of these enteric viruses studies have also relied on the use of bacteriophages as surrogate. However, the use of bacteriophages is inappropriate for norovirus as the dose-response model of norovirus is expressed in terms of genome copies, which might be vastly different from the plaque forming units (PFU) for bacteriophages due to the

different principles of science involved behind each quantification method [45]. In fact, norovirus quantified using genome copies are five times more resistant to environmental decay than bacteriophages under comparable experimental conditions [66, 88]. This comparative analysis of risk outcomes offers a basis for judging the safety and adequacy of new water applications. It also implies the need for incorporating updated science into risk assessment, which can be used to revise the findings in past research, and therefore, the current health risk benchmark.

#### **4.5.2 Model Uncertainties**

A large number of factors can influence the model predictions. Firstly, viral concentrations in urban stormwater were deduced from surface water based on dilution factor, quantification recovery efficiency, and PCR inhibitions. The dilution factor of stormwater to surface water could be more accurately assessed with additional hydrological data inputs that usually become available with the development of a stormwater harvesting project [90]. The recovery efficiency of virus in stormwater could be further improved since there is a lack of agreement among the literature values. The value as used in this study is representative of a worst case estimate for public health protection, while the viral concentration data as collected from literature were quantified using different primers and probes that targeting different serotypes of the virus, which may not best inform us of the likely disease/illness it may cause. This factor is reluctantly put aside, but was considered as an uncertainty compiled in the viral concentration distribution. It is recommended that future studies of viral concentration in environmental waters use standardized and uniform quantification methods, so as to produce/reproduce comparable results across different laboratories [91]. This would enable more informative statistical analysis, including Bayesian methods, as recommended by [92] for such circumstances. In spite of the aforementioned data inconsistencies, the virus data as used represent the range of uncertainties that are credible for risk analysis and are reducible with improved knowledge.

Uncertainties associated with virus removal efficiency of LID-treated water were considered by incorporating a safety factor based on a preliminary experimental value of column biofilters' removal efficiency for adenovirus (> 4-log removal) (data not published) and F-RNA coliphages (3.1 to 4.6 log removal) [25]. Thus, my risk analysis presents a “what-if” scenario for treating harvested stormwater. However, more comprehensive studies related to the virus removal efficiency of biofilters and its dynamics (i.e. removal efficiency during wet or dry season) are warranted. The findings of these new studies should then be incorporated into the risk models as poor functioning/maintenance of LIDs could lead to inadequately treated stormwater for its intended usages and may heighten public health risks considerably.

Model uncertainties are also derived from components of exposure models. For example, most individuals are nasal-oral breathers engaging in both types of breathing instead of strictly nasal or oral, which places the annual risk of a typical individual between that of exclusive nasal or oral breathers. The wide range of annual risks observed in my results would reasonably be expected given the large differences in the scenarios considered, and it is likely that actual reuse situations would pose risks somewhere along this continuum.

Dose-response models used for estimating the probability of infection and/or illness are, perhaps, the most important source of uncertainties due to the end point result it generates for risk characterization. Considerable care has to be taken in the culmination of valid inputs for the models and, thus, correct interpretation of the result. In this regard, the complexity of norovirus dose-response model poses a number of data gaps to be filled by future research [72]. In particular, the aggregation state of norovirus in the finished water must be addressed. Dose-infection models for norovirus developed from clinical studies considered the virus aggregation factor [72]. The model that accounts for the aggregation factor treat viruses as aggregates and have higher  $ID_{50}$  than the model for monodispersed viruses (due to the higher efficiency of monodispersed viruses in reaching infection sites to cause infection). Most norovirus QMRAs conducted have ignored the aggregation factor, citing the lack of knowledge of virus aggregation

states in water [45, 93-95]. In fact, aggregation of norovirus is likely rare in the environment due to the high stability of norovirus against aggregation in water near neutral pH and high ionic strength [96], which is characteristic of stormwater [97]. Although aggregated noroviruses are not as infectious as when they are in monodispersed suspended form, the former are much more likely to cause illness in a person they successfully infected (e.g. higher DALYs). Neglecting the aggregation state of norovirus can result in widely different risk results, which potentially contradict risk management decisions depending on the risk metric/benchmark (annual infection or DALYs) used. A more accurate risk assessment can also be aided through understanding the relationship of norovirus quantified in genome copies and infectious units, which currently cannot be assessed due to the lack of a sensitive cell line. The relationship may vary depending on the types of water (e.g. non-disinfected effluent vs. tertiary effluent). As a first start, a study by Hirneisen and Kniel [66] comparing the environmental decay of norovirus GII in genome copies and MNV in PFU showed minor difference (within a  $\log_{10}$  difference) between the two virus quantification methods.

Uncertainties as discussed herein are important in risk characterization. They should be used to guide any future risk assessment for improvement. Uncertainties should also adhere to individual circumstances, which could be unique to each case in the risk analysis.

#### **4.5.3 Comparison of annual infection risks and disease burdens**

Disease burdens are at times used for a broader cost-benefit analysis of microbial risks that encompasses socio-economic terms. The WHO recommends a benchmark of  $\leq 10^{-6}$  DALYs pppy for safe drinking water, but has generated inconsistencies in regard to its adoption in different countries and its comparability with the U.S. EPA annual infection risk benchmark. As a matter of fact, both benchmarks are considered to be overly conservative and impractical by some risk assessors for evaluating the safety of using non-potable water for various water-related activities [76, 98].

The metrics used for both approaches are directly related to each other: annual infection risks are converted to DALYs through incorporation of disease surveillance data such as severity and duration of illness attributable to identified target pathogen. These disease surveillance data are often regionally-bounded and therefore may not be representative of the whole population. The DALYs approach is not commonly used for risk assessment studies in the U.S., and therefore disease burden data specific to the U.S. are less readily available.

In my study, the disease burden of adenovirus is affected by the lack of surveillance data to characterize the true impacts of adenovirus-related illnesses. As presented in Figure 4.3, the DALYs associated with adenovirus-related disease from showering are based on DALYs per illness case derived solely from hospitalized patients, which are heavily scaled upwards (i.e. people who are infected and ill, but with only mild disease symptoms would not visit a hospital) [77]. As a result, adenovirus risks frequently exceeded the WHO's DALYs benchmark, while looked much more "acceptable" in terms of U.S. EPA annual infection benchmark.

The conversion of DALYs from annual infection risks is perhaps most problematic because it requires the knowledge of the portion of ill subjects out of the infected subjects. Many risk assessments have used point-estimate of conditional illness probability to compute DALYs as a simple but not necessarily correct solution. Only Teunis et al. have put forth the idea that illness risk is a function of the dose of target pathogens taken in by an individual [72, 99]. In this regard, I have shown that the computation of DALYs is prone to being influenced significantly by the risk model of choice, where using point-estimate of conditional illness probability can greatly overestimate illness risk, and therefore, DALYs. In contrast, using a dose-dependent illness probability model has shown to moderate the high infection risk of norovirus, which would most likely translate to illness rate that is characteristic of a disease outbreak if point-estimate of conditional illness probability would be used instead. This observation offers a new perspective to evaluate the risk of norovirus (using DALYs), which is disastrous when only infection risk is considered.

The DALYs approach has the potential in adding values to risk management, but is blighted by the lack of data to support its development in the United States. More research is necessary to develop the DALYs approach before it can be used reliably for risk management. The approach should be treated cautiously in a similar manner to U.S. EPA benchmark, and the two should be used as complements rather than in opposition.

## 4.6 Conclusion

QMRA offers a useful tool for estimating the public health risk associated with stormwater harvesting and its applications in domestic households. Among the three non-potable use scenarios assessed in this study, toilet flushing presents the lowest health risk, being negligible in relation to both the U.S. EPA and WHO benchmarks. Showering presents a health risk that clearly exceeds the U.S. EPA benchmark, but complies with the WHO benchmark under certain settings. Consumption of fresh produce irrigated with treated stormwater exceeds both benchmarks. The results also showed the inconsistencies in risk interpretation based on different risk models and acceptable health risk benchmarks. Further improvements in data collection and model refinement are necessary to reduce the uncertainties and inconsistencies associated with the risk outcome. Ultimately, the outcomes of the risk assessment should be used as an educational tool to narrow the gap between perceived risk and estimated risk, instill stakeholders' confidence in stormwater harvesting practice, and protect public health.

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**CHAPTER 5: Evaluation of the dry and wet weather recreational health risks  
in a semi-enclosed marine embayment in Southern California**

## 5.1 Abstract

Recreational beach water quality is currently regulated by fecal indicator bacteria (FIB) for recreational health protection. However, the validity of these indicators is questioned in the recent years. The poor correlations between FIB and human pathogens may lead to “under or over” protection of public health, which can cause either health or economic consequences in the region. A new source-apportionment quantitative microbial risk assessment (QMRA) approach for risk management based on the site-specific condition is proposed and carried out in a small semi-enclosed Southern California Beach, Baby Beach, CA, which has been suffering from chronic elevated level of *Enterococcus* (ENT), especially during the post-storm conditions. The results of the study showed that the median illness risks are meeting the US EPA recreational water quality criteria (RWQC) of 36 illness cases per 1000 bather at 100% of the time during the dry weather condition; and over 93% of the times during the wet weather when the 5% of the stormwater is contaminated by sewage. The results imply that the current FIB water criteria places unnecessary burdens on the recreational water manager to comply with FIB criteria without necessarily managing the recreational water illness (RWI) rate. Optimizing the risk and benefits of recreational beaches requires balancing the RWI with the social-economic value of the beaches. A health risk-based approach as implemented in this study can be an important complement to a better health risk management of a non-point source recreational beach.

## 5.2 Introduction

In the United States, coastal waters designated for recreational uses are required to comply with water quality criteria set by health and regulatory agencies for assuring the health of visitors to the areas [1]. Fecal indicator bacteria (FIB) are used as the primary microbial water quality indicators for managing recreational water illnesses (RWI) due to the long history behind their adoption as well as their ease-of-implementation. However, there have been increasing questions raised regarding the validity of FIB for managing RWI [2, 3]. The presence of FIB in water was traditionally used to infer potential presence of human fecal input, a possible source of human pathogens. Numerous studies have shown that the level of FIB correlated well with the RWI among bathers recreating in waters impacted by human sewage [4, 5]. Yet, increasing evidences also indicate that this correlation is significantly weakened or non-existing for waters impacted by pollution sources other than human sewage [6-9]. These site-specific discrepancies are acknowledged by the U.S.EPA in the 2012 RWQC, which offers beach managers the flexibility to develop site-specific water quality criteria based on epidemiological studies, QMRA, and/or sanitary surveys.

FIB in water can be from both human (i.e. sewage) and non-human hosts (i.e. birds). Traditional methods for quantifying FIB as used for regulatory purposes do not distinguish between the different sources of FIB. FIB originated from non-human hosts are associated with less human pathogens [10]. Regrowth in warm and organic rich environments can also contribute to the elevated level of FIB without the presence of human pathogen [10]. On the other hand, human viruses and pathogenic protozoa are more resistant to inactivation than FIB—they can survive under the conditions that led to removal or reduction of FIB. My advisor's early works and many other studies have shown the absence of human viruses in coastal waters with elevated FIB level, while viruses were detected in beach waters with FIB meeting the water quality standards [11]·[12, 13]. Epidemiological studies also indicated a lack of correlation between FIB and RWI for waters that are affected by non-point source of fecal contamination [6-9]. Despite of this, there were increased odds for bathers (vs. non-bathers) to get sick while recreating



in these waters, suggesting the presence of pathogens in the water at some level. An increasing body of literature has demonstrated that FIB is a poor indicator of RWI, especially at non-point source impacted recreational waters. Consequently, the enforcement of FIB criteria might mislead the interpretation of health risk of the recreational water; causing over or under management of the beach water quality, closure of beaches, harming the socio-economic benefits in the affected regions without the promised health benefits.

The complexity of recreational water quality have urged for an overhaul of the generic FIB criteria, which are expected to include multiple monitoring targets with holistic consideration of the location, hydrometeorologic conditions, historical water quality data, and the possible source of contaminations [13, 14]. A multiple indicator toolbox approach is much more reliable than an approach solely based on FIB indicators, where the latter is incapable to reflect changes in climate such as rainfall patterns, infrastructures that might divert storm or wastewater from the recreational waters, and land-uses that could introduce new contamination source such as cow or chicken feces. For example, a slow and accidental release of municipal wastewater into a recreational water can change the composition of FIB (i.e. FIB from different sources) without changing its FIB level significantly. This expectation can be validated through the use of microbial source tracking (MST) technique, or by the concurrent rise in the level of various microbial indicators (e.g. *C. perfringens* and F+ coliphage) that signifies human sewage contamination [15]. Likewise, rainfall patterns are directly connected to the variation in the source and level of FIB in recreational waters. For a recreational water that receives stormwater during both dry and wet weather, the level of human sewage contamination is dependent on the structure of the stormwater system (i.e. separated from or combined with sanitary sewer systems) and how the stormwater is managed. For example, in some coastal cities of Southern California, urban runoff collected in the storm drains is diverted to wastewater treatment plants during dry weather when there is no rain, but bypassed the diversion during wet weather when storm occurs. Such management actions can change the seasonal FIB level and composition in the recreational waters considerably. These examples illustrate how the

anthropogenic interferences and natural causes can contribute to a very different understanding of FIB level in waters and its risk implications—an important consideration that is not currently addressed in the generic FIB criteria for risk management.

In the face of these issues, several modeling-focused studies were attempted to develop a more robust criteria for RWI in recreational waters that are not (or at least not primarily) affected by point source pollution from human fecal inputs [16-18]. Using the Quantitative Microbial Risk Assessment (QMRA) framework, these studies simulated the range of RWI risks that are likely attributed to different sources of FIB (source-apportionment), such as from seagulls, human, pigs, cows, or mixed sources. The key data needed for the QMRA in these studies are the ratios of FIB to pathogens in the different sources, which are used to determine the level of pathogens (the causative agents for RWI) in the recreational waters based on its FIB level. Instead of the correlation-based statistical approach as used in conventional epidemiological studies that is only applicable for a fixed set of scenario—for example, studies that are carried out in the Great Lake region where major FIB contribution is from human fecal input during dry weather—the QMRA allows for a “what-if” scenario to be incorporated to a risk estimation through appropriate modification in its risk model. This flexibility is important in improving our conceptual understanding of the RWI risk in response to changes that are not addressed in epidemiological data, and in effect, assist in the design of future epidemiological studies. Moreover, results of the QMRA can be “validated” using epidemiological data that are based on the same set of scenario used in the QMRA model [16]. The source-apportionment QMRA, although has been described for hypothetical scenarios, has not been applied in any case study. This research reports application of source-apportionment QMRA to evaluate the RWI risks at a recreational beach impacted by non-point source pollution and demonstrates the value of this approach in recreational water management.

The Baby Beach in Dana Point, California has suffered from chronic high concentration of FIB and is regarded historically as a highly polluted recreational water that is listed by State Water Resources Control Board Clean Water Act Section 303(d) List [19]. To improve the water quality at Baby Beach,

the County of Orange and the City of Dana Point were required to implement Best Management Practices (BMPs) that can comply with the Total Maximum Daily Loads (TMDL) goals as adopted by the San Diego Regional Water Quality Control Board [20]. Beach clean-up and dry weather urban runoff diversion in the area have resulted in water quality improvement and achieved the TMDL goals for total coliforms (TC), fecal coliforms (FC). However, the TMDL goals for Enterococcus (ENT), the key indicator that is required by the U.S. EPA Water Quality Criteria 2012 for managing the marine RWI are still yet to be fulfilled, especially during the wet season condition when the stormwater is not diverted away from the area.

The main objective of this study is to quantify the RWI risks associated with ENT level at Baby Beach by taking consideration of the FIB sources at the Baby Beach. The results lend support to informing the health risk of the beach in the event of non-compliance with the TMDL goals and improve our understanding on a largely unaddressed regulatory issue on the health risk of non-point source recreational waters during wet weather. The outcome of study advocates the adoption of a risk management approach that is based on an acceptable level of illness risk, in addition to using the FIB level as regulatory criteria.

## **5.3 Materials and methods**

### **5.3.1 Site description**

The study site is located at Baby Beach, a small man-made and semi-enclosed beach in Dana Point Harbor, California that has approximately 600 feet long of recreational shoreline (Figure 5.1). Protected by two breakwaters from the Pacific Ocean, the shoreline of Baby Beach is characterized by warm and calm water, which makes the beach a popular family destination that receives an estimated 1 million visitors annually. The catchment basin of Baby beach drains an area of 43.4 acres, which covers

residential and commercial land uses with some undeveloped open spaces. The region receives annual rainfall averaged around 12.8” [21].



Figure 5.1 Study site at the Baby Beach and its surrounding land uses.

In contrary to the seemingly small children-friendly water it offers, Baby Beach had historical high FIB level that are considered as “unsafe” for recreational uses. After the notorious eleven months initial closure of the beach in 1996 and the two months health risk advisory posting at the beach in 2002, massive investigation and measures had been taken to lower the FIB level of the beach [22]. The most notable measure is the construction of a dry weather runoff diversion near the main storm drain line in fall 2005 that resulted in zero runoff to the beach during summer/dry season (April 1<sup>st</sup> to October 31<sup>st</sup> each year) and the installation of media filter vaults for filtering the stormwater when the dry weather diversion is not in effect (November 1<sup>st</sup> to March 31<sup>st</sup> each year).

### 5.3.2 Data source

The ENT level (concentration) in the waters of Baby Beach were quantified weekly using the EPA1600 method [23] since 1995 at four sampling points along the recreational shorelines of Baby Beach (BDP12, 13, 14, 15 in Figure 5.1) by the County of Orange Health Care Agency. A significant decline in the historical ENT level was observed starting in the late 2005 (see Supplementary materials 5.7.2) that coincided with implementation of the dry weather runoff diversion and installation of media filtration system near the main storm drain. The water quality improvements confirm the important impacts of dry weather runoff from the storm drain on the water quality of Baby Beach [24]. Since the objective of my study is to investigate the current RWI risk at the Baby Beach, only ENT data after the implementation of these BMPs collected between August 31<sup>st</sup>, 2005 and April 23<sup>rd</sup>, 2012 were used for the source-apportionment QMRA. The ENT level across the four sampling points were relatively consistent to each other, geometric mean of ENT level across the four sampling points were used to represent the ENT level across the recreational shoreline of Baby Beach.

### 5.3.3 ENT during dry weather condition

#### 5.3.3a Prediction of ENT level during dry weather

During dry weather condition, which is defined as no rain event occurred within the 72 hours prior to the sampling date, two scenarios were considered: **Scenario 1**) storm drain runoff is diverted to sanitary sewer with zero discharge from storm drain to the beach water (April 1<sup>st</sup> to October 31<sup>st</sup>), and **Scenario 2**) storm drain runoff is filtered by media filter vault and discharged to the Baby Beach recreational shoreline (November 1<sup>st</sup> to March 31<sup>st</sup>, no diversion).

Scenario 1 represents that of the dry season in California, defined as the period from April 1 to October 31 annually following the definition adopted by the California AB411 legislation [25]. During this season, rainfall event is rare; the beach water is warmer and attracts the highest number of beachgoers. Due to the small size of the Baby Beach watershed, virtually all dry weather runoff

(max=1.14 m<sup>3</sup>/day) generated in the watershed and received by the stormwater drains was effectively diverted to the neighboring wastewater treatment plant since 2005 [25].

In the absence of storm drain and sewage discharge, the possible sources of ENT at the beach include birds' feces and bathers' shedding. The ENT level of the beach water was elevated on days with high gull and non-speciated bird counts and no preceding rainfall events, suggesting the contribution of birds' feces to dry weather ENT level [26]. This source-apportionment assumption during the dry season is also supported by a source tracking bacteriological study of Baby Beach conducted before the urban runoff diversion and installation of the stormwater filtration system [27]. This trend is expected to be preserved even after the implementation of dry weather runoff diversion because of the presence of high bird feces counts as recorded by the County's janitors [28]. Other factors that could contribute to the variability of ENT level during dry weather condition include tidal waves and human activities that could disturb the beach sediments and reintroduce ENT into the water column [29]. In spite of this possibility, the shedding of bathers recreating in the waters were propounded to be a more significant ENT source than that from beach sediments to influence recreational water quality based on reports in beaches similar to Baby Beach [30, 31].

Scenario 2 represents that of the winter/wet season in California when precipitation is more likely (November 1<sup>st</sup> to March 31<sup>st</sup> in the next year). During this time period, the valve for diverting dry weather runoff from Baby Beach is closed to prevent excess stormwater from overwhelming the sanitary sewer during storm events that may cause backflow of sewage-contaminated stormwater. Instead, the dry weather runoff collected is filtered by a set of media filter vaults before discharging to the Baby Beach. I postulated that the contribution of ENT from dry weather runoff collected in the storm drain during this time period is negligible due to the barrier provided by the media filters and the low dry weather runoff flow. As a consequence, the dry weather ENT sources for Scenario 2 are assumed to be the same as that of Scenario 1. However, the period during Scenario 2 usually coincides with declining beach usages by

the public due to the colder water and air temperature and a general increase in bird densities due to birds migrating to the region, which could change the contribution of ENT by each ENT source [26].

### 5.3.3b ENT source-apportionment for dry weather

In apportioning the ENT source, human shedding during water recreation is assumed to be characteristics of primary sewage, an assumption that is not far-fetched considering the analogy between dilution of bathers' sheddings by beach waters and dilution of human fecal waste by sewer water. Additional evidence of bathers' shedding is supported by natural recreational water disease outbreaks reports in the U.S., where feces in water, ill bathers, and bathers over crowding in recreational waters were identified as the main contributing factors to waterborne outbreaks [32]. Based on a study by Wright et al [33], the microbial loadings (e.g. ENT contribution) from the shedding of a bather are approximately equivalent to one gull fecal event [33]. The ratio of birds-to-visitors count at Baby Beach for Scenario 1 and Scenario 2 as recorded by janitors working at the beach were used to estimate the apportionment of ENT contributed by bird feces and human bathers' sheddings, wherein a single bird count is effectively treated as one gull fecal event. Using the aggregated average of birds and bathers count in each month during the dry season from year 2007 to 2010, it is estimated that 10% of the total ENT level is attributed to gull feces and the remaining 90% to human bathers' shedding under Scenario 1 (dry season runoff diversion in effect). As for Scenario 2 (runoff is not diverted, but filtered), 35% of the total ENT is attributed to gull feces and the remaining 65% to human bathers' shedding.

The ENT level during the dry weather condition can then be decomposed to:

$$\begin{aligned} ENT_{dry} &= F_{dry}^{Gull} \times ENT_{dry} + F_{dry}^{PSew} \times ENT_{dry} \\ &= ENT_{dry}^{Gull} + ENT_{dry}^{PSew} \end{aligned} \quad (1),$$

where  $ENT_{dry}$  is the portion of ENT level during dry weather condition (CFU/100mL),  $F_{dry}^{Gull}$  and  $F_{dry}^{PSew}$  are the portion of ENT level attributed to gulls' feces and primary sewage (surrogate for bathers'

sheddings) during dry weather condition (%), and  $ENT_{dry}^{Gull}$  and  $ENT_{dry}^{PSew}$  are the ENT level attributed to gulls' feces and primary sewage (bather sheddings) during dry weather condition (CFU/100mL).

### 5.3.4 ENT associated with storm events

#### 5.3.4a Prediction of ENT level during post-storm events

In comparison with dry weather conditions, the variability of ENT level during post-storm events are influenced by the rainfall intensity, duration, and the timing of antecedent precipitation. Adding to this highly dynamic pattern of ENT level during storm events is the limited number of data collected during the wet weather condition, which makes the direct application of observational data in source apportionment challenging. In reconciliation of this challenge, I attempted to model the relationship between rainfall and ENT level using nearly seven years of historical ENT and rainfall data. The rainfall data logged by the County of Orange's Palisades Reservoir rain gauge near the Baby Beach (see Figure 5.1) were paired with the  $\log_{10}$ -transformed geometric mean of ENT data (across the four sampling points) according to the sampling date. Subsequently, the association of ENT level with storm events (up to 72 hours prior to the sampling date) were assessed using the Multiple Linear Regression (MLR) technique (See APPENDIX for more details of data treatment). The best-fit model is characterized as

$$\begin{aligned}
 ENT_{gm} &= \alpha + X\beta \\
 &= \alpha + \beta_0 RI_0 + \beta_1 RI_1 + \beta_2 RI_2 + \beta_3 RI_3 + \beta_{12}(RI_1 \times RI_2) + \beta_{23}(RI_2 \times RI_3) \\
 &= 1.19 + 0.91 RI_0 + 1.07 RI_1 + 2.50 RI_2 + 0.20 RI_3 - 5.64(RI_1 \times RI_2) - 3.69(RI_2 \times RI_3)
 \end{aligned} \tag{2}$$

where  $ENT_{gm}$  is the geometric mean of the ENT level at Baby Beach ( $\log_{10}$  CFU/100mL),  $\alpha$  is the intercept of the model and can be interpreted as the dry weather ENT level in  $\log_{10}$  scale,  $RI_i$  are the corresponding rainfall intensities (inches) with the subscript  $i$  represents the day of rain (0, 1, 2, and 3 days) before the  $ENT$  sampling date, and  $\beta_i$  are the corresponding coefficients for the model (including the interaction terms).



In setting the scenarios of wet weather, I set the upper limit of rainfall intensity for the MLR model at an arbitrary value of 0.75" since continuous rainfall of very high intensity (i.e.  $\geq 1$ " ) is not common in Southern California. Based on the 72 hours rule of water quality advisory, I consider the ENT level (and the health risk) is influenced by rainfall events occurred 1 day before, 2 days before, 3 days before, and also on the same day as the ENT sampling day. The variations of wet weather scenarios can be defined as a single rainfall event or continuous rainfall (rained continuously for three days before sampling) or rainfall on alternate days. These variations yield 15 different possible combinations of rainfall events. For each of the combination, the rainfall intensity for any rainfall occurrence was set at either 0.2" (moderate rainfall) or 0.75" (heavy rainfall) in order to assess the effects of the rainfall timing and intensity on ENT level and its associated risks.

In order to assure that the predicted ENT level for any scenario does not fall out of the prediction domain, any predicted ENT level that is above 1,000 CFU/100 mL is discarded as supported by the maximum observed ENT level used for the data analysis. Only the mean estimates of ENT level for each wet weather scenario are used for the subsequent source-apportionment QMRA. All computational procedures were conducted using the software package, MATLAB 2014b (Natick, MA).

#### **5.3.4b ENT source-apportionment associated with storm events**

In determining the post-storm source-apportionment, it is necessary to consider cross-contamination of human sewage with the storm runoff collected in the storm drain, even if the storm drains were separated from the sanitary sewer systems. Increasing evidences have shown that urban stormwater systems that are separated from sewage lines can still act as a conduit for sewage due to unforeseen breaches in sanitary sewer infrastructures and/or misconnections of stormwater and sewage pipelines, in which the magnitude of sewage contamination is exacerbated by wet weather flows [34, 35]. For context, the average misconnection rates of stormwater lines to sewage line in the U.S. and Europe were estimated to be 3–4% across the national, regional, and local levels [36]. In assessing the human

sewage contamination in stormwater, human *Bacteriodes* has been used as one of the most successful MST markers to identify human waste among mixed source of human and non-human fecal matters in water samples [37]. Sauer et al. quantified the proportion of the human *Bacteriodes* to the total *Bacteriodes spp.* in several stormwater outfalls in the metropolitan Milwaukee during storm events and found that untreated sewage can make up 10 to 16% of the stormwater at the end of the stormwater pipelines, even when the stormwater pipeline is separated from the sanitary pipelines [35].

In the context of the Baby Beach, the land uses of its watershed explicitly excluded any potential ENT contribution from agricultural animals such as pigs, chickens, and cows that are known to harbor human pathogens. A preliminary tracer study also did not find any existing cross-connection of storm drains and sanitary sewage line during dry weather condition [38]. However, the same result is not guaranteed during storm events as the volume of wet weather flow is several times higher than dry weather flow and has much higher potential to be cross-contaminated with human sewage. Hence, a precautionary measure need to be taken to include human sewage as a contributor of ENT at the Baby Beach during wet weather for recreational health risk assessment purposes.

Based on the available information, the source of ENT for the stormwater portion is assumed to consist of 5%, 10%, or 20% primary sewage from cross contamination of stormwater and sewage, with the remaining portion is considered as non-pathogenic source (i.e. from plants, lawns, and other indigenous sources) that do not contain human pathogens. Although wild and domestic animal feces mixed with the storm runoff are also likely ENT sources, they are much more diffused and likely insignificant in relative to human sewage source in the watershed of Baby Beach. The contribution of wild and domestic animal feces to ENT in storm runoff was not included in this study. The ENT level due to wet weather can then be decomposed to:

$$\begin{aligned}
 ENT_{storm} &= F_{storm}^{PSew} \times ENT_{storm} + F_{storm}^{non-path.} \times ENT_{storm} \\
 &= ENT_{storm}^{PSew} + ENT_{storm}^{non-path.}
 \end{aligned}
 \tag{3},$$

where  $ENT_{storm}$  is the portion of wet weather ENT brought in by the stormwater (CFU/100mL),  $F_{storm}^{PSew}$  and  $F_{storm}^{non-path.}$  are the fraction of ENT level attributed to primary sewage and non-pathogenic ENT source during wet weather condition (%), and where  $ENT_{storm}^{PSew}$  and  $ENT_{storm}^{non-path.}$  are the ENT level attributed to primary sewage and non-pathogenic ENT source from the storm drains during wet weather condition (CFU/100mL).

Therefore, the overall mathematical expression for FIB level during wet weather condition is a combination of two terms: the baseline term assigned to the dry weather ( $ENT_{dry}$ ) that is represented by the intercept term  $\alpha$  of the MLR model (equation 3) and the surplus ENT contribution ( $ENT_{storm}$ ) resulting from the storm that is assigned to sewage and non-pathogenic sources, which can be expressed as

$$\begin{aligned} ENT_{gm} &= \alpha + X\beta \\ &= ENT_{dry} + ENT_{storm} \end{aligned} \quad (4),$$

where  $ENT_{gm}$  is the geometric mean of the ENT level at Baby Beach ( $\log_{10}$  CFU/100mL) estimated using the MLR model and the antecedent rainfall intensities, X.

### 5.3.5 Source apportionment QMRA

The core QMRA methodology, assumptions, and justifications as used in this study is based on the work of Soller et al. unless stated otherwise; the details of which were described in [17, 18]. The illness end-point is characterized by gastroenteritis in bathers. Briefly, the source-specific illness risks as contributed by each ENT source were calculated by the following steps: 1) estimate the dose of each reference pathogen ingested by bathers that are commonly found in a specific ENT source based on its ENT level, 2) estimate the illness risk attributed to each reference pathogen in the ENT source based on the dose-response models for each reference pathogen, 3) summing up the illness risk attributed to all the reference pathogens in each ENT source.

The dose of each reference pathogen in a specific ENT source,  $D_{rp}^S$  (Step 1) is calculated as:

$$D_{rp}^S = \frac{ENT_{weather}^S}{R_{ENT}^S \times 100} \times R_{rp}^S \times P_{rp}^S \times I_{rp}^S \times V \quad (5),$$

where  $ENT_{weather}^S$  is the ENT level in the recreational water contributed by a specific source ( $S$ ) during a certain weather scenario ( $weather$ ) (CFU/100mL),  $R_{ENT}^S$  is the density of ENT in feces (wet mass) (CFU/g) or in sewage (CFU/L),  $R_{rp}^S$  is the reference pathogen level in feces (wet mass), (# of pathogens/g or genome copies/g) or sewage (# of pathogens/L or genome copies/L),  $P_{rp}^S$  is the fraction of human-infectious pathogenic strains in the reference pathogen of a specific source,  $I_{rp}^S$  is the prevalence of infection in the non-human source, and  $V$  is the volume of water ingested (mL).

The parameter values for Equation (5) were based on the literature values adopted and justified in the study by [17] that, unless stated otherwise, are summarized in Table 5.1. Values for  $P_{rp}^{PSew}$  and  $I_{rp}^{PSew}$  are assumed to be 1.0 as primary sewage is derived from human source; reference pathogens found in primary sewage have the maximum infectivity to human. In order to assess the variability of these parameters have on the risk estimates, Monte Carlo simulation was used to generate uniform random samples from the parameter range whenever applicable. The volume of water ingested by bathers,  $V$ , can vary among different sex and age groups [39, 40], but was a relatively insensitive parameter to the overall risk estimate as proven by a sensitivity analysis by Soller et al.[41] and also cross-validated by a separate sub-study on my part (results not shown). For this reason, a point-estimate of 33mL for  $V$ , which correspond to the highest average water volume ingested by swimmers adopted by similar QMRA studies is used for my study [16-18, 41].

The illness risk due to each reference pathogen (Step 2) is calculated based on the published infection dose-response models and morbidity data for inferring the portion of illness cases among

infection cases (see Table 5.2). Illness risk of each reference pathogen,  $Ill_{rp}$ , is computed as the product of infection risk (as a function of pathogen dose) and the portion of illness among each infection case.

In summing up the illness risk due to all the reference pathogen in a single ENT source (Step 3), the

theorem of independence from probability was used [42]:  $P_{ill}^S = 1 - \prod_{rp} (1 - Ill_{rp}^S)$ , where  $P_{ill}^S$  is the

illness risk that is attributed to a single ENT source and  $Ill_{rp}^S$  is the individual illness risk due to a reference pathogen in the ENT source.

As the overall ENT level during any weather condition is attributed by different ENT source (e.g. seagulls and primary sewage), the illness risk from each ENT source is summed up again using the theorem of independence from probability to compute the overall illness risk due to multiple ENT

sources:  $P_{ill} = 1 - \prod_S (1 - P_{ill}^S)$ , where  $P_{ill}$  is the overall illness risk that is attributed to multiple ENT

sources during a weather scenario and  $P_{ill}^S$  is the illness risk that is attributed to a single ENT source.

Table 5.1 Summary of parameters used for Equation 4.

Source	Primary sewage		Gulls			
	Density of ENT or reference pathogen in sewage ( $\log_{10}$ range) <sup>a</sup>	References	Density of ENT or reference pathogen in fecal waste ( $\log_{10}$ range) <sup>b</sup>	Fraction of human-infectious strain	Prevalence of human infection potential	References
<i>Enterococcus</i>	5.8—8	[43, 44]	6.0—8.0	-	-	
<i>Cryptosporidium spp.</i>	-0.3—2.6	[45]	5.5—8.4	None reported	None reported	
<i>Giardia lamblia</i>	0.8—4	[45]	None reported	None reported	None reported	
<i>Campylobacter jejuni</i>	Non-detected—2.3 <sup>c</sup>	[44, 46]	3.3—6.0	1.0	0—0.33	[17, 47]
<i>E. coli</i> O157:H7	Non-detected—3.3 <sup>c</sup>	[48]	None reported	None reported	None reported	
<i>Salmonella enterica</i>	0.5—3	[44]	2.3—9.0	1.0	0—0.33	[17, 47]
Norovirus	3—6	[49, 50]	Not applicable	Not applicable	Not applicable	

<sup>a</sup>The units in  $\log_{10}$  scale as applied to ENT and each pathogen are as followed: CFU/L= *Enterococcus*, *Campylobacter jejuni*, *E. coli* O157:H7, and *Salmonella enterica*, oocysts/L = *Cryptosporidium spp.*, cysts/L= *Giardia lamblia*, and gc/L= norovirus.

<sup>b</sup>The units in  $\log_{10}$  scale as applied to ENT and each pathogen are as followed: CFU/g= *Enterococcus*, *Campylobacter jejuni*, and *Salmonella enterica*, oocysts/g = *Cryptosporidium spp.*

<sup>c</sup>Non-detect is imputed as  $\log_{10}(1)$ , which correspond to “0” on normal scale., for QMRA calculation.

Table 5.2 Dose-response models and parameters used in this study.

Reference pathogen	Form of model	Model parameters	% of infections resulting in illness	Reference
<i>Cryptosporidium spp.</i>	Exponential	$r=0.09$	50%	[51]
<i>Giardia lamblia</i>	Exponential	$r=0.0199$	45%	[42]
<i>Campylobacter jejuni</i>	Beta-Poisson	$\alpha=0.145$ $\beta=7.59$	28%	[52, 53]
<i>E. coli</i> O157:H7	Beta-Poisson	$\alpha=0.4$ $\beta=45.9$	28%	[54]
<i>Salmonella enterica</i>	Beta-Poisson	$\alpha=0.3126$ $\beta=2884$	20%	[42]
Norovirus	Hypergeometric	$\alpha=0.04$ $\beta=0.055$	60%	[55]

### 5.3.6 Risk characterization

The recreational health risks at the Baby Beach during dry weather conditions and post-storm (wet weather) conditions were assessed individually to account for the seasonal variation of ENT sources as a whole.

For dry weather risk assessment, the observed geometric mean of ENT along the Baby Beach shoreline during either of the two dry weather scenarios (with and without diversion) were used separately. The risk calculation for each scenario is repeated for 10,000 times based on uniform random samplings from the corresponding observed ENT level distribution and random samplings of the QMRA parameters as described in section 5.2.5 to represent uncertainties and variability derived from the dry weather ENT level and the QMRA parameters.

For post-storm risk assessments, the mean ENT predicted by the MLR model that corresponds to the wet weather scenarios as described in Section 5.2.4 were used for the risk assessment. In addition, the dry weather ENT source for Scenario 2 is used to represent the baseline ENT level ( $\alpha$ ), as a rainfall event is more likely to occur between November 1<sup>st</sup> to March 31<sup>st</sup> in Southern California. The flowchart for the post-storm QMRA is depicted in Figure 5.2. The risk calculation for each wet weather scenario is repeated for 1,000 times to represent the uncertainties and variabilities of the QMRA parameters.

All computational procedures were performed using the software package, MATLAB 2014b (Natick, MA).



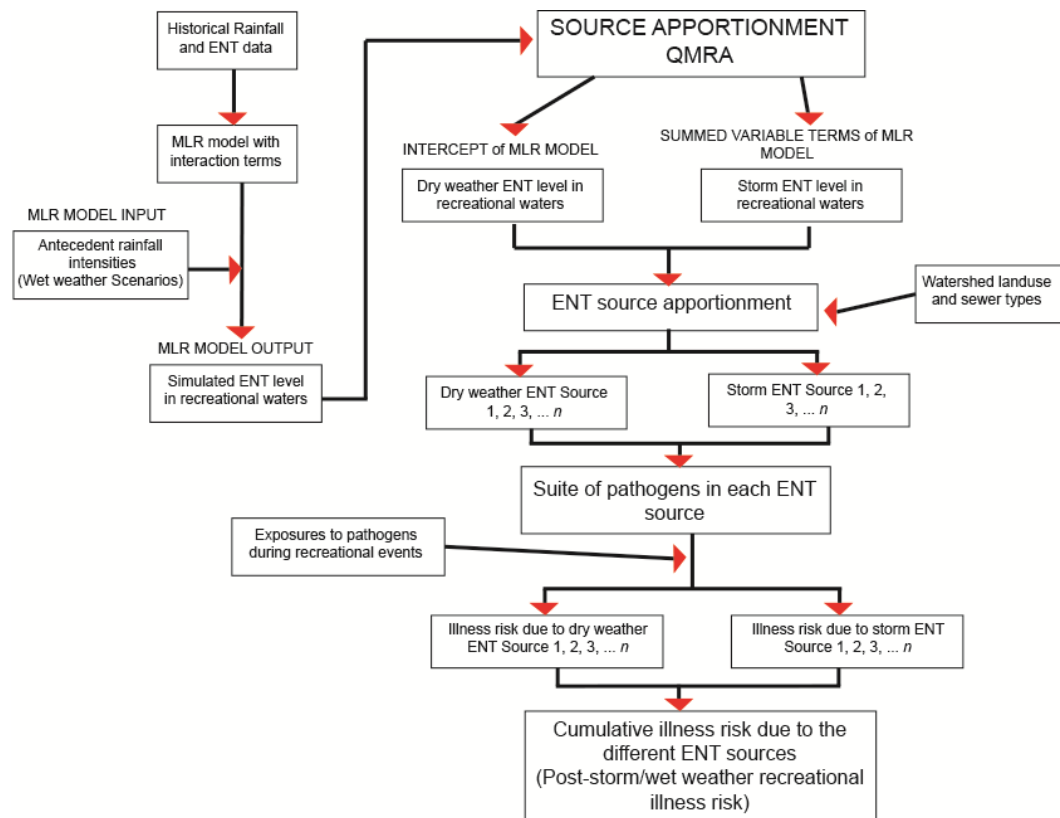


Figure 5.2 Flowchart for estimating post-storm recreational health risks using source-apportionment QMRA.

## 5.4 Results

### 5.4.1 ENT level associated with storm events

The MLR analysis for the relationship between ENT level and rainfall (Figure 5.3) showed that both the timing of antecedent rainfall events and intensities are positively correlated to the ENT level at Baby Beach (See Supplementary materials for more details). The model outputs also indicated that the intercept term of the model is very close to the geometric mean value of the observed dry weather ENT data ( $n=188$ ) (14.6 vs. 15.3 CFU/100 mL), while the geometric mean value of the observed wet weather ENT data ( $n=35$ ) is a close match to the geometric mean value of predicted ENT level based on the same wet weather conditions (35.6 vs 31.1 CFU/100 mL), demonstrating the validity of the model structure.

Further analysis also showed that this close matching of predicted data with observation data is only applicable for conditions after the dry weather runoff diversion (e.g. August 31<sup>st</sup>, 2005 onwards), suggesting that the dry weather storm drain flow into Baby Beach before BMPs installation was significant enough to cause a high ENT level similar to that observed during storm events (Data not shown). The wet weather ENT analysis also indicated that the stormwater filter vaults could not effectively reduce the ENT brought in by the storm runoff, likely due to the large volume of flow.

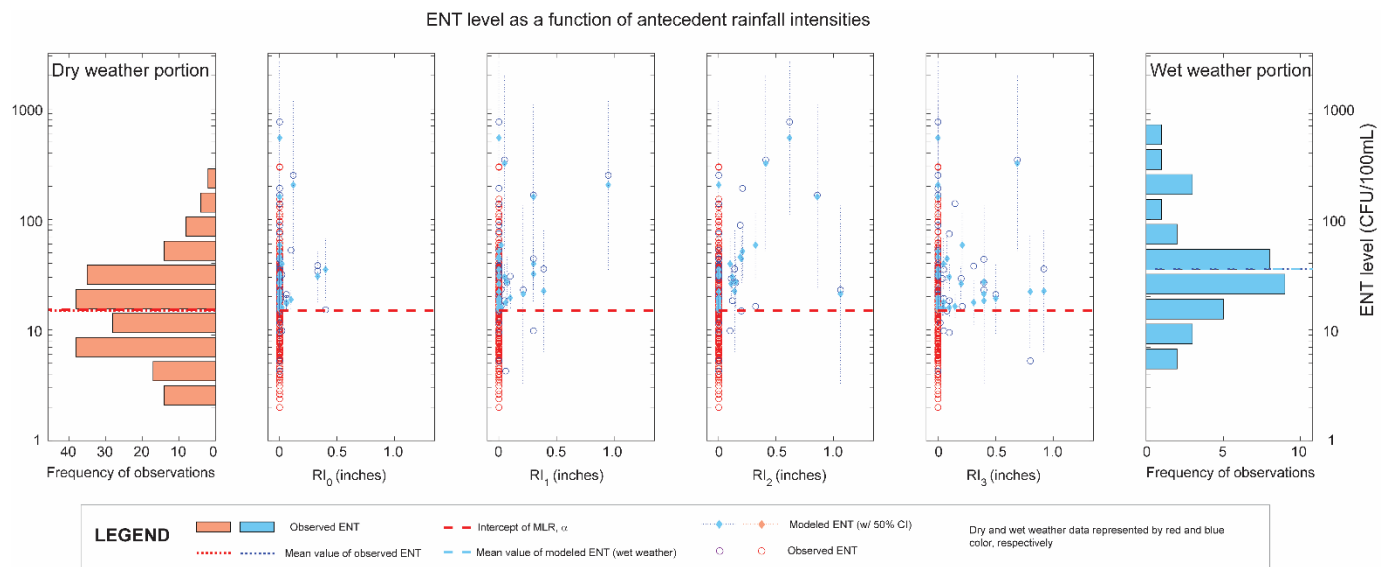


Figure 5.3 Observed and predicted geometric mean ENT in relationship to weather conditions at the Baby Beach recreational shorelines. Dry weather ENT observation is plotted in orange open circle with orange bar histogram displayed on the left side of graph; wet weather ENT observation is plotted in blue open circles with blue bar histogram displayed on the right side of graph. The modeled wet-weather ENT level as a function of antecedent rainfall intensities are plotted in the middle graphs using solid blue diamonds. The histograms also show the matching of mean value of modeled wet weather ENT with wet weather observed ENT mean. The intercept of MLR model is nearly identical to mean value of dry weather ENT.

#### 5.4.2 Recreational illness risk during dry weather conditions

The illness risks of bathers recreating at the Baby Beach during dry weather conditions and the ENT level used in source-apportionment QMRA were shown in Figure 5.4. The boxplot of the dry weather ENT level for Scenario 2 (n=78) shows a wider variation and a slightly higher median ENT level of 19 CFU/100mL than that in Scenario 1 (n=110) of 13 ENT CFU/100mL. Yet, there is no significant difference between the illness risk for both scenarios (median= 2.9 illness cases (IC) per 1000 bathers vs. 4.1 IC per 1000 bathers), both of which are one order-of-magnitude lower than that of the U.S. EPA RWQC risk benchmark at 36 IC per 1000 bathers.

Based on the different ENT source apportionment during Scenario 1 and 2, it is shown that the illness risk attributed to gull fecal source makes up less than 10% of the overall risk for both scenarios. This observation holds even with the much higher ENT contribution of gull fecal source for Scenario 2, which is estimated to be three to four times higher than its dry season counterpart. The illness risk is practically attributed mostly to ENT source of human origin, which is assumed to be originated from bathers' shedding.

For benchmarking purpose and to validate the results, the illness risk that corresponds to the EPA maximum allowed ENT geometric mean threshold at  $\leq 35$  CFU/100mL (assuming primary sewage as the sole ENT contributor) is also calculated using QMRA and plotted in Figure 5.4. The median value of this benchmark risk stands at 11.5 IC per 1000 bathers, which is on the same order-of-magnitude as the RWQC benchmark that is also comfortably covered by the interquartile range of the benchmark risk. This median value can thus be regarded as the QMRA-equivalent of the EPA RWQC.

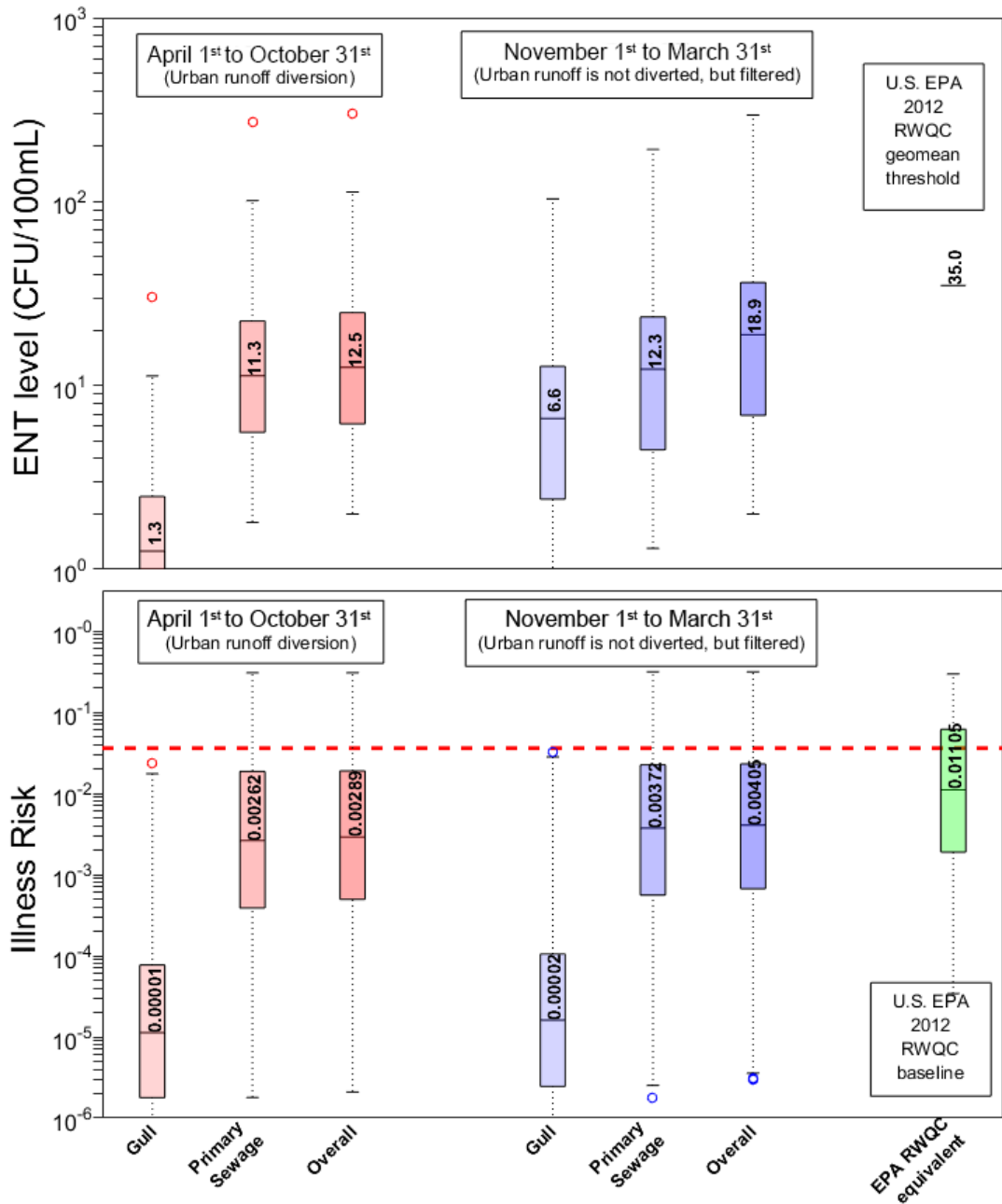


Figure 5.4 Boxplot of observed ENT level (geometric mean across the Baby Beach shoreline) and illness risks during dry weather conditions with (red bar) or without (blue bar) urban runoff diversion. The U.S. EPA RWQC benchmark of 36 illness cases/1000 bathers is represented by the red dashed horizontal line. The green box indicates the QMRA value deduced using the EPA threshold ENT geometric mean of 35 CFU/100ml. Median value of illness risk is indicated by the value in each box. Each box represents the lower, median, and upper quartile (e.g. 25th, 50th, and 75th percentile values) of the distribution, where the whiskers extend  $1.5 \times (75\text{th percentile value} - 25\text{th percentile value})$  from each end of the box. Markers graphed outside of each whisker are considered as outliers.

#### 5.4.5 Recreational illness risk during post-storm conditions

The illness risks of bathers recreating at the Baby Beach during post-storm conditions are shown in Figure 5.5. In general, most illness risks predicated during wet weather conditions are much higher than those during the dry weather conditions, with scenarios exceeding the RWQC risk benchmark (the red horizontal line in Figure 5.5). These exceedances are particularly obvious when there is a high level of sewage contamination in stormwater (i.e. 20% ENT in stormwater is from sewage).

As a sensitivity analysis, I compared the post-storm illness risks that are attributed to different levels of sewage contamination in stormwater (e.g. 5%, 10%, and 20% ENT in stormwater is from sewage, Figure 5.6 and Table 5.3). The result showed that under the different wet weather scenarios, the median values of the post-storm recreational illness risks due to 5% sewage contamination in the stormwater can be up to 8.6 times as high as the illness risk associated with dry weather condition, where 14.3% of the median risk values exceed QMRA-equivalent risk benchmark and 6.7% of the cases exceed RWQC illness benchmark (Table 5.3). The risk is more than doubled when the stormwater contains 10% sewage. At 20% sewage contamination in the stormwater, more than half of median risks exceed the QMRA-equivalent risk and 13.3% exceed RWQC risk benchmark. This result suggests the importance of understanding the level of sewage contamination of the stormwater for managing post-storm recreational health risks.

In addition to the level of sewage contamination, the estimated risks are also significantly influenced by both the timing of a rainfall event and its intensity. The illness risks are proportionate to the rainfall intensities when only one rainfall event occurred within the 72 hours prior to the recreational event. A single heavy rainfall event can potentially result in a post-storm illness risk that is twice as high as that attributed to a moderate rainfall event. This observation is, however, much weaker for a heavy rainfall event that occurred 3 days prior to the recreational event, which verifies the protective nature of the 3-day post-storm advisory rule.

Table 5.3 The influence of the level of sewage contamination in stormwater to the rate of the estimated illness risks in Baby Beach.

Sewage in stormwater	Rate of exceeding	
	Risk based on EPA’s ENT threshold benchmark (35 CFU/100ml) and QMRA-equivalent risk benchmark (11.5 illness/1000 bathers)	Risk based on RWQC (36 illness/1000 bather)
5%	14.3%	6.7%
10%	35.7%	10%
20%	53.8%	13.3%

The illness risks are only proportionate to rainfall events with moderate intensity when it rains daily for 3 days prior to the recreational event. The continuous rainfall events only result in elevated illness risk if the heavy rainfall occurred within 24 hours prior to recreational event, but are otherwise much lower and even below the illness risk under the dry-weather condition. This observation is likely as a result of better circulation of the water due to the turbulent nature of the storm, as compared to the slow input of ENT sources into the waters (and accumulation) during moderate rainfall events. Further study is warranted to confirm this theory.

For post-storm conditions due to rainfall events that occurred on alternating days prior to the recreational event, the illness risks are proportionate to the rainfall intensities. Alternating heavy rainfall events can potentially result in a post-storm illness risk that is two to three times as high as that attributed to alternating moderate rainfall events.

**Post-storm recreational health risks**  
(as a function of sewage contamination of stormwater and antecedent rainfall intensities)

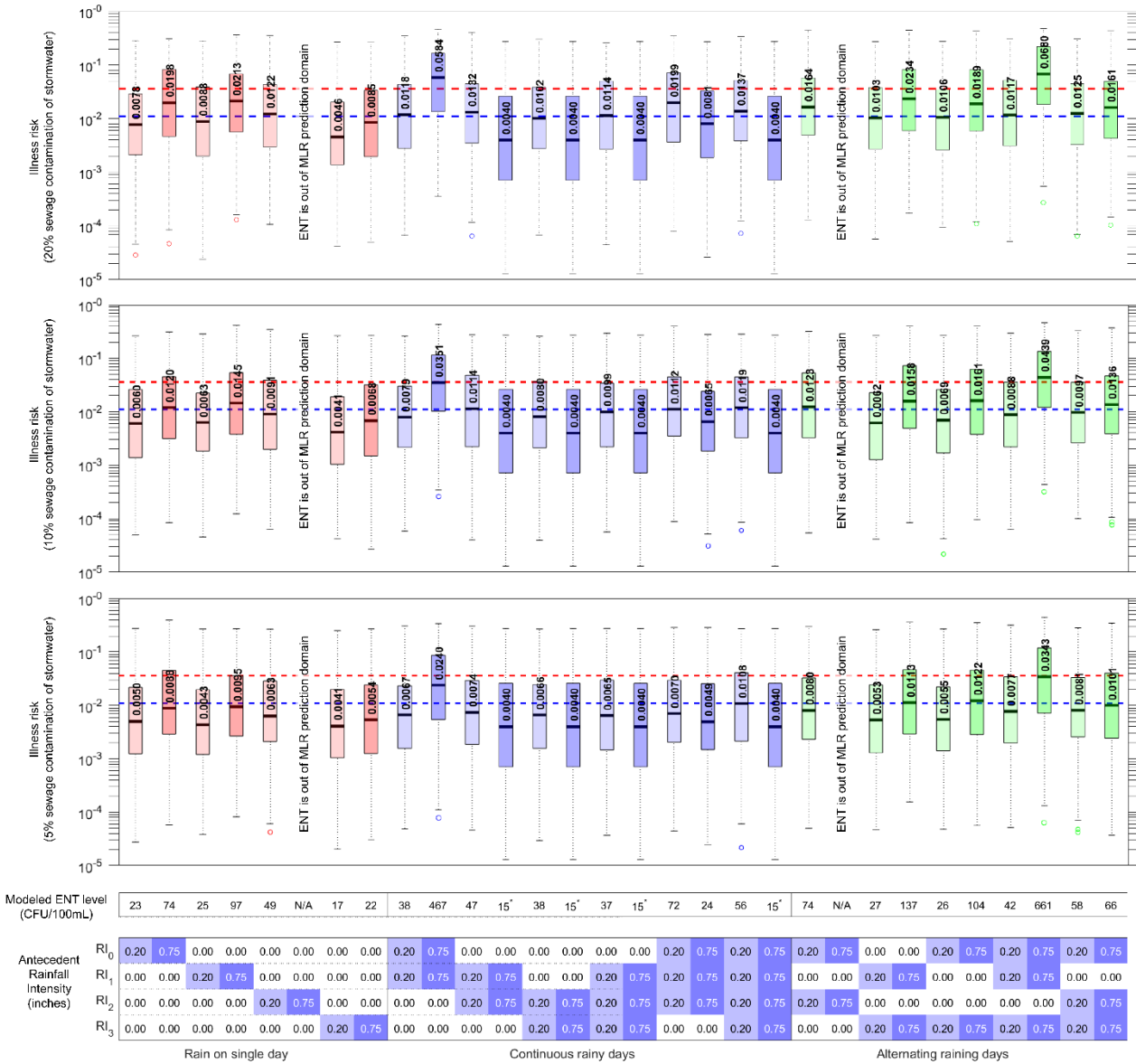


Figure 5.5 Boxplot of wet weather illness risks at Baby Beach for three different levels of sewage contamination of stormwater (in terms of ENT) with different rainfall patterns. Red bars indicate RWI risks due to a single rain event within 72 hours prior to recreation events; blue bars indicate RWI risks due to daily rainfall in the past 3 days prior to recreational events; green bars indicate RWI risks due to alternating raining days in the past 3 days prior to recreational events. Lighter and darker shades indicate results from moderate and heavy rainfall intensity, respectively. The U.S. EPA RWQC benchmark (red line) and the median risk value estimated based on the EPA 35 CFU/100 ml ENT threshold (QMRA-equivalent risk, blue line) are used to compare the risks. The ENT level from MLR model are indicated together with the antecedent rainfalls at the bottom table. For ENT level that is below the dry weather condition (<15CFU/100mL), the risk estimate is imputed as that of dry weather condition.

## 5.5 Discussion

This is the first demonstration of source-apportionment QMRA in understanding of recreational health risk at a non-point source pollution impacted recreational beach. Baby Beach at Dana Point is a small beach with a vast amount of historical data and human interventions in water quality improvements. These past works have set the necessary stage for the source-apportionment QMRA. Other polluted beaches will likewise require site-specific data although the general approaches for source-apportionment QMRA are similar for all beaches.

In evaluating the QMRA outcomes, it is necessary to consider future improvements towards a more accurate and relevant risk assessment. For example, the number of visitors and bird counts at the beach as recorded by the County's janitors were used to estimate the ratio of bather sheddings and gull fecal events in apportioning the dry weather ENT source. However, the portion of visitors who actually recreates in the water and contribute to the ENT level is not known, which led to my conservative assumption of treating all visitors as bathers. The observational biases that are present in the data collected by different personnel (e.g. County's janitors) can also lead to inconsistent results, which were presumably mitigated by using an aggregated average of the data in this study. A more systematic method of data collection following a set of protocols, such as the classification of bathers among beach visitors and the sampling timeframe can therefore ensure consistency of the data and reduce observational bias. Nonetheless, as the total ENT at Baby Beach during the dry season is routinely below the EPA water quality threshold at the Baby Beach, the illness risks fall within the acceptable benchmark regardless of the source of the ENT. The precise contribution of bathers shedding would be more important at other sites when the total ENT exceed the EPA benchmark. Furthermore, the interpretation of post-storm risk result as presented here is very site-specific to the Baby Beach since only the level of sewage contamination in the stormwater is considered and superimposed upon the dry weather conditions. Large watersheds are like to have more complicated sources of ENT, including agriculture and other human sources, which also makes the source apportionment challenging.



The true recreational health risk at Baby Beach is likely much lower than were suggested by the results due to the assumption of level of sewage contamination in stormwater during wet weather conditions. The real amount of sewage as part of the storm runoff collected by stormwater drains of Baby Beach is probably around or less than the 5% assumed in this study, wherein the upper end of 20% was based on the level of sewage contamination of stormwater in the metropolitan watersheds of Milwaukee, Michigan (up to 16%) with a margin of safety. The Baby Beach watershed is much smaller in size with far less complicated storm and sewer lines networks in comparison to the metropolitan Milwaukee.

In a practical context, while the post-storm risks are visibly elevated, fewer visitors would actually swim following storm events. With the exception of avid surfers in search of big waves, the beach visitors during the wet weather conditions decline dramatically due to the low water and air temperature in Southern California region. The low numbers of RWI during the winter rainy months have been documented in a retrospective study of the number of RWI along Southern California coasts [56]. The decline in the number of bathers in water also reduces the bather sheddings, which further reduces the level of risk. In rare occasions though, summer rain could occur especially due to the changing climate. If the stormwater is bypassing the diversion structure as in the case of Baby Beach, beach managers should be prepared for these unexpected circumstances since post-storm illness risks in summer can have much greater socio-economic impacts due to the large number of beach visitors to the beach.

Understanding how the recreational health risks vary with the weather conditions have important risk management implications for the Baby Beach (and any other non-point source influenced beaches) to comply with the wet weather TMDL adopted by the Regional Water Quality Control Board. As was suggested by Surbeck et al. [57], reducing FIB in storm runoff to meet water quality criteria would be impossibly challenging due to water volume generated by storm event and also the many different FIB sources that would cause a shock loading of FIB in the receiving waters. However, the more precise risk of RWI is only depending on the portion of FIB associated pathogens in the storm runoff. As was demonstrated in the present study, with current wet weather ENT level observed in the past 10 years at

baby beach, most of median risks are below the RWQC illness risk benchmark (i.e. 36 IC per 1000 bathers) after the storm events, even at the assumption of 10 to 20% of sewage contamination in the storm runoff to the beach.

The contribution of the source-apportionment QMRA perhaps would be better realized when applied to non-point sources impacted recreational waters that experience persistent heightened level of ENT that of non-human origin. For example, a recreational beach in vicinity of the Baby Beach, the Doheny State Beach, is an exemplar of this case. Although the two beaches were only ~2 km apart from each other, the different hydrological characteristics (e.g. watershed size and embayment around receiving water) in Doheny State Beach have produced a very different response to anthropogenic interferences in mitigating the high pollution level of the water. The FIB level at Doheny State Beach did not reduce as significant as the Baby Beach, which implied that other sources of FIB that enter Doheny State Beach is more significant than those that were diverted away from it. During wet weather conditions, the already high FIB level at Doheny State Beach can rise even more drastically, which can have negative impacts on the region should a TMDL approach for FIB reduction is adopted with less success than expected. Clearly the health risk associated with FIB level of non-point source recreational beaches must be understood further to ensure that the main goal of recreational health protection is actually attained without sacrificing the interests of stakeholders, which include beachgoers themselves and business owners around the regions.

### **5.5.1 The practical value of risk quantification**

By using a regulatory FIB threshold, the RWI risk is only categorized as a dichotomous measure: acceptable or unacceptable; the magnitude of the risk is not understood for facilitating more layered decision-making that optimizes the trade-off between risk and reward (higher human illnesses for higher swimmability and vice versa) [58]. This also ignores the probabilistic nature of RWI risk, wherein the true risk is conditional on many confounding factors that simply cannot be generalized by any number of

epidemiological studies. Moreover, epidemiological studies are very costly to conduct and are not always a suitable option for all types of beaches, especially for a smaller beach with many visitors (i.e.  $\geq 50,000$  visitors annually) that requires the implementation of a robust health risk management plan, but do not receive enough visitors to warrant a reliable epidemiological study.

Under such circumstances, QMRA provides a useful alternative for health risk assessment that allows for scenario explorations through leveraging the findings of epidemiological studies. For instance, the epidemiological study at Doheny State Beach conducted by Colford et al. [7] had supported the importance of identifying ENT source for indicating the RWI risk of recreational waters. In their study, Colford et al. suggested a significant association between FIB and RWI when the berm that block the discharge of urban runoff to the beach is opened, but such association is not significant when the berm is closed. The berm status is likened to the presence/absence of anthropogenic and natural influence (e.g. diversion of/input from wastewater effluent, agricultural runoff, or wet weather runoff) on the water quality of recreational water, which can be used to improve our conceptual understanding of FIB as conditional risk indicators. It is important to note that QMRA only provides us with a conceptual estimate of the risk, whose validity should be supported by hard data that may be provided by epidemiological study whenever feasible or possible.

The practical value of the illness risk estimates derived from QMRA is made more credible when the estimates align with comparable empirical illness cases reported by epidemiological studies, in which a good agreement is usually defined by the order-of-magnitude difference between the illness risk estimate and the empirical illness cases. The difference between the two can only be reduced to a certain extent, explained such that QMRA risk estimates are based on the availability of dose-response models for pathogens that likely do not cover the complete suite of pathogens that are present in the water, yet epidemiological studies are based on illness outcomes of bathers who are likely exposed to a complete suite of pathogens present in the water. Moreover, the definition of illness adopted by the RWQC encompasses more illness symptoms (e.g. various combination of vomiting, diarrhea, stomachache,

and/or nausea) than the gastroenteritis as represented by QMRA, which explains for the lower RWI risk estimate than the empirical RWI cases reported. As such, the RWI risk estimated using the source-apportionment QMRA is reasonably close to the RWI cases as reported by epidemiological study.

Based on these sets of considerations, the source-apportionment QMRA methodology can be further refined and standardized. Through the standardization of the method, it is desirable that an illness risk ruler/standard can be established, which can be used a health risk benchmark for ensuring the adequate recreational safety of non-point sources beaches.

## **5.6 Conclusion**

A new source-apportionment QMRA approach for risk management based on the site-specific condition is proposed and carried out in a small semi-enclosed Southern California Beach to understand the recreational health safety that is currently regulated only by the water quality criteria developed for point-source impacted beaches. The results have demonstrated that the health risks at the beach have been adequately mitigated, even in most of the cases of the post-storm conditions when ENT level are elevated. The medium illness risks are meeting the RWQC 100% of the time during the dry weather condition; 93% of the times during the wet weather when the stormwater is contaminated by 5% of the sewage. The results imply that the current FIB water criteria places unnecessary burdens on the recreational water manager to comply with FIB criteria without necessarily managing the RWI rate. Optimizing the risk and benefits of recreational beaches requires balancing the RWI with the social-economic value of beaches. A health risk-based approach as implemented in this study can be an important complement to a better health risk management of a non-point source recreational beach.

## 5.7 Supplementary Materials

### 5.7.1 Multivariate linear regression of historical ENT and rainfall data

Rainfall events are frequently highlighted as an important meteorological factor in the determination of ENT level in recreational water [14, 59, 60]. As the level of ENT in recreational water is used for assessing RWI risks for both fresh and marine waters, an ENT level prediction model as a function of antecedent rainfall is useful in understanding how the ENT level changes in response to storm events.

Here I fitted historical rainfall and ENT level data for Baby Beach into a Multiple Linear Regression (MLR) model with interaction terms. The MLR model uses antecedent rainfall intensities as predictor variables for predicting the ENT level at Baby Beach as a whole. As the trend of ENT level across the four sampling sites were consistent to one another (Figure A1), the geometric mean values across the four sites were used as a representative ENT level for water along the recreational shoreline of Baby Beach.

In fitting the MLR model, the geometric mean for the ENT level across the four monitoring stations (BDP12, 13, 14, and 15) on each sampling date were  $\log_{10}$ -transformed and paired with rainfall intensity data corresponding to the ENT sampling date, a day before, two days before, and three days before the sampling date. These criteria for selecting the antecedent rainfall were loosely based on the wet weather definition for developing the Baby Beach's wet weather bacterial indicator TMDL, wherein any storm events of  $>0.2$  inches of rain and the following 72 hours after its occurrence is classified as wet weather [22]. Instead of using a clear cut value of 0.2" rainfall for wet weather, I assume that any less intense rainfall can cause a change in ENT level in the receiving water.

In addition, due to the series of structural changes made to mitigate the FIB level of the beach, only data that were collected after Fall 2005—the beginning of dry weather diversion and the most

important change— were used for the model fitting to reduce the uncertainties of the model. A backward deletion stepwise regression approach is then employed to fit the selected dataset into a MLR model with interaction terms. Inclusion criterion for model parameter is based on a p-value of <0.05.

The best-fit model is then characterized as

$$\begin{aligned}
 ENT_{gm} &= \alpha + \beta_0 RI_0 + \beta_1 RI_1 + \beta_2 RI_2 + \beta_3 RI_3 + \beta_{12} (RI_1 \times RI_2) + \beta_{23} (RI_2 \times RI_3) \\
 &= 1.185 + 0.909 RI_0 + 1.070 RI_1 + 2.503 RI_2 + 0.200 RI_3 \dots \\
 &\quad - 5.637 (RI_1 \times RI_2) - 3.685 (RI_2 \times RI_3)
 \end{aligned}
 \tag{1}$$

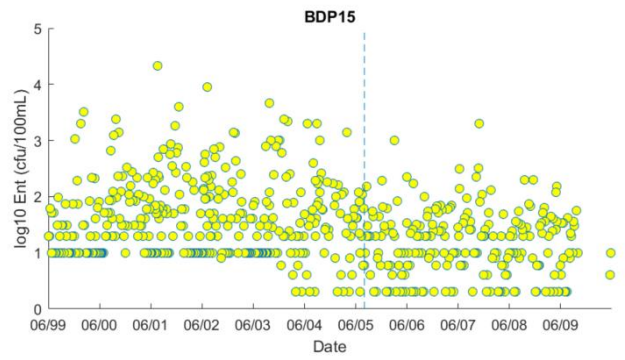
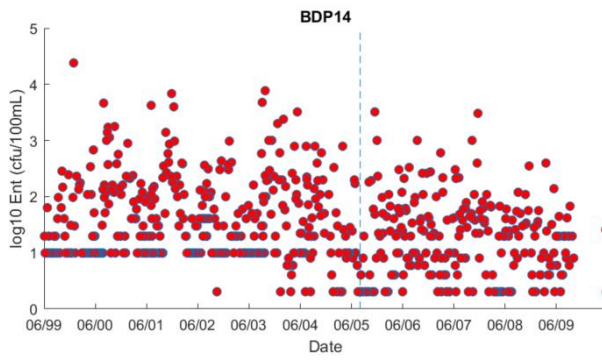
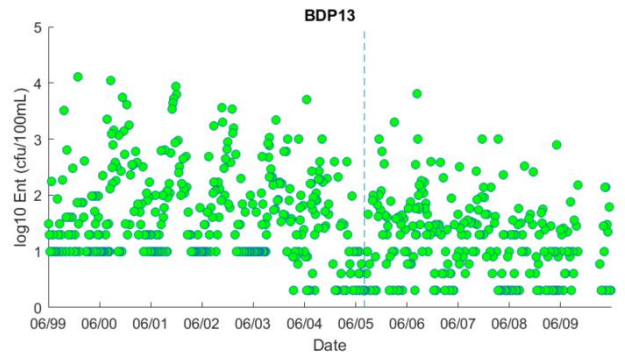
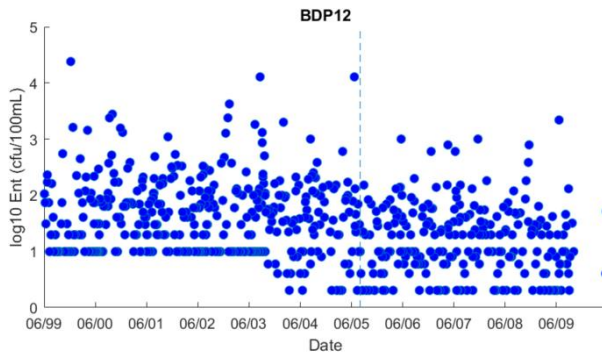
where  $ENT_{gm}$  is the predicted geometric mean of the ENT level at Baby Beach (CFU/100mL),  $\alpha$  is the intercept of the model and can be interpreted as the dry weather ENT level,  $RI_i$  are the corresponding rainfall intensities (inches) with the subscript  $i$  represents the number of days (0, 1, 2, and 3 days) before the ENT sampling date, and  $\beta_i$  are the corresponding coefficients for the model (including the interaction terms).

Instead of using the standard statistical tests (i.e. F-test,  $R^2$ , R as shown in 5.7.3) for supporting the model, interpreting the model on a theoretical basis is more useful. Because the dataset used for fitting the model clearly distinguish between dry and wet weather sample, ENT level for dry weather sample is expected to be relatively constant. In fact, a comparison between the value of the intercept,  $\alpha$ , and the mean value for all dry weather ENT observations (i.e. ENT level with zero rainfall for up to 3 days before the sampling date) yielded a difference of less than 3% on normal scale (<1% on log10 scale). Variation of the observed dry weather ENT level follows a slightly right-skewed distribution that is approximated well using a normal distribution considering the observed ENT level that is below detection limit. Interpreting the model further implies the significance of holistic consideration of rainfall events, intensities, and also the number of days since each rainfall event before the ENT sampling for predicting ENT level in the water. In general, continuous rainfall events of high intensity (>0.2”) that occurred on and/or day(s) before the sampling date are expected to raise the ENT level in the water considerably, with

the rate of rising proportional to the rainfall intensity. It is also observed that a single rainfall event happened 3 days before (with no following rainfall) the ENT sampling event has negative to no effect to the ENT level in the water, whereas a single rainfall happened on the same day (with no preceding rainfall in the past 3 days) as the ENT sampling event causes a great increase in ENT level of the water. The interaction terms suggest that continuous heavy rain in the preceding three days can lower the ENT level considerably, which could be due to the better circulation of waters driven by the heavy rains. Alternatively, it could also imply the limited ENT supplies from the natural environment (e.g. lawns, animal feces, plants, etc.) that were washed off by the continuous heavy rain and into the Baby Beach waters. Detailed modeling efforts based on planned experimental data are, however, required to elucidate these hypotheses [24], which are outside the scope of my work.

The MLR model as fitted is site-specific to Baby Beach and may not be generalizable for all other enclosed beaches. In fact, there is no correlation between ENT level and antecedent rainfall when the data collected before the dry weather diversion were included in the data analysis, where the best-fitted MLR model under such circumstances is a constant model with only an intercept term. This exercise also illustrates the adequacy of a simple model to describe a system that are well-understood or controlled (i.e. dry weather diversion).

### 5.7.2 ENT trend for the four sampling sites at the Baby Beach recreational shorelines





**5.7.3 Statistical summary for MLR model generated by MATLAB (output format edited for consistency)**

$$Y \sim 1 + x1 + x2*x3 + x3*x4$$

Estimated coefficients<sup>a</sup>:

	Estimate	SE	tStat	pValue
(Intercept)	1.1851	0.029875	39.67	8.51E-104
x1	0.90944	0.34834	2.6108	0.0096376
x2	1.0699	0.41142	2.6005	0.009923
x3	2.503	0.56957	4.3945	1.71E-05
x4	0.20038	0.32454	0.61742	0.53758
x2:x3	-5.6373	2.5115	-2.2446	0.02576
x3:x4	-3.6846	1.4501	-2.5409	0.011729
Number of observations:	223			
Error degree of freedom:	216			
R-squared:	0.155			
Adjusted R-Squared	0.133			
F-statistic vs. constant model:	6.92	p-value=	9.26E-07	

<sup>a</sup>x1, x2, x3, and x4 corresponds to the antecedent rainfall variables RI<sub>0</sub>, RI<sub>1</sub>, RI<sub>2</sub>, and RI<sub>3</sub>, respectively.

**5.7.4 Model ENT level as a function of antecedent rainfall intensities vs. observed geometric mean of wet weather ENT level**

Sampling Date			Antecedent rainfall intensities (inches)			
	Observed ENT	Modeled ENT	RI <sub>0</sub>	RI <sub>1</sub>	RI <sub>2</sub>	RI <sub>3</sub>
9/20/2005	15.16	35.39	0.40	0.00	0.00	0.00
10/27/2005	29.19	15.60	0.00	0.00	0.00	0.04
1/4/2006	164.96	160.05	0.00	0.30	0.86	0.00
3/2/2006	5.26	22.15	0.00	0.00	0.00	0.80
3/7/2006	52.66	18.88	0.10	0.00	0.00	0.00
3/23/2006	14.83	43.94	0.00	0.00	0.20	0.08
3/30/2006	251.99	204.49	0.12	0.95	0.00	0.00
4/4/2006	19.20	17.77	0.06	0.00	0.00	0.05
4/27/2006	30.49	19.59	0.00	0.10	0.00	0.00
5/25/2006	20.98	19.29	0.00	0.00	0.00	0.50
7/20/2006	11.56	15.46	0.00	0.00	0.00	0.02
12/14/2006	9.46	16.04	0.00	0.00	0.00	0.10
12/19/2006	88.62	45.78	0.00	0.00	0.19	0.00
12/27/2006	38.37	30.57	0.33	0.00	0.00	0.00
2/14/2007	18.42	30.27	0.00	0.05	0.12	0.10
2/22/2007	139.28	16.41	0.00	0.00	0.00	0.15
3/1/2007	9.90	39.54	0.02	0.30	0.10	0.05
3/22/2007	4.23	17.76	0.00	0.06	0.00	0.00
9/20/2007	43.98	32.07	0.00	0.30	0.00	0.00
9/25/2007	43.54	18.42	0.00	0.00	0.00	0.40

12/3/2007	23.04	21.18	0.00	0.21	1.06	0.40
12/20/2007	757.93	545.75	0.00	0.00	0.62	0.00
1/8/2008	35.71	22.64	0.00	0.39	0.14	0.92
1/23/2008	23.34	16.09	0.00	0.02	0.00	0.00
2/1/2008	35.43	15.67	0.00	0.00	0.00	0.05
2/4/2008	34.14	30.57	0.33	0.00	0.00	0.00
12/18/2008	346.70	323.08	1.39	0.05	0.41	0.69
1/26/2009	16.38	58.33	0.00	0.02	0.32	0.21
2/10/2009	26.88	27.25	0.00	0.07	0.15	0.40
2/19/2009	29.02	26.27	0.00	0.00	0.11	0.20
6/2/2009	74.16	16.04	0.00	0.00	0.00	0.10
10/20/2009	31.65	15.97	0.02	0.00	0.00	0.00
10/28/2010	37.72	17.67	0.00	0.00	0.00	0.31
9/8/2011	191.27	51.38	0.00	0.00	0.21	0.00
4/23/2012	21.00	17.37	0.06	0.00	0.00	0.00
Average	35.58492	31.09492				
Average (log10)	1.551266	1.492689				

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## **CHAPTER 6: Summary**

The SUWM approach embraces the concept of managing stormwater as a water resource. However, stormwater is not well-studied as a source of water supply due to the few number of rainwater harvesting and even much less stormwater harvesting practiced in the developed nations. In furthering the issue, the microbial risk of human contact with stormwater is inferred from several epidemiological studies that reported increased recreational illness risk among bathers recreating in waters near the end of storm drains or receiving stormwater discharge [1-5]. This finding has necessitated the need for a robust public health risk assessment of stormwater harvesting, especially when the harvested stormwater would be used for water applications that involve close human contact with the water.

In treating the captured stormwater, the SUWM approach of using decentralized green systems are frequently propounded to provide adequate treatment of the stormwater for various irrigation purposes that involve little-to-no water contact with human (i.e. golf course irrigation, open space irrigation). Yet, the pathogen treatment efficiency of these decentralized green systems, such as biofilters, are not well understood and are variable with many environmental conditions. As pathogen detection and quantification in the stormwater is difficult, indicator organisms such as *Clostridium perfringens*, *E. coli*, and F-RNA coliphages are commonly used for indicating the presence of different pathogen groups in water (i.e. protozoa, bacteria, virus) to facilitate water quality management [6]. Several studies have suggested that stormwater biofilter's treatment efficiency of indicator organisms vary with the weather regimes (i.e. dry or wet) and also the intermittent dry period between the wet periods [7, 8]. A prolonged dry period, as is characteristic of the climate in the in the southwestern water-stressed urban region of U.S., is found to be detrimental to the removal efficiency of some indicator organisms (i.e. *E.coli*) due to the formation of macropores and fine fissures. A different configuration of the biofilter—such as introduction of a saturated zone at the bottom of the biofilter— is found to moderate this issue, yet it does so by negatively impacting the treatment efficiency of other indicator organisms [8].

These findings do not condemn the benefits of SUWM approach for managing stormwater, but it warrants caution for hopeful adopters who are considering harvesting stormwater for uses beyond that of

irrigation purpose. The functionality of each decentralized system in SUWM must be understood to assess the health issues that are at stake. Likewise, harvesting and using rainwater from the rooftop is a SUWM approach of stormwater management that do not involve the same level of risks for stormwater harvesting due to the limited pollutant source from the rooftop. As was discussed in **CHAPTER 3**, harvested rainwater is much safer than reclaimed water by at least ten folds for foodcrop irrigation scenario even though the quantified risks are higher than the U.S.EPA risk benchmark for safe drinking water; the EPA benchmark alone may not be suitable for developing rainwater harvesting guidelines.

The key questions to ask are the origin of the pollutants and how they can be introduced into stormwater and/or treated using SUWM systems. Unfortunately, these are not straight questions and progress would need to make to fully understand them, which should start with seeing stormwater as a valuable resource and SUWM as a sustainable approach. In **CHAPTER 4**, the assessed risk associated with using harvested stormwater for several indoor non-potable purposes were mostly found to be higher than the same EPA benchmark; it is likely not safe to use harvested stormwater for these purposes. However, this simplified conclusion is blighted by considerable data and knowledge gaps that commensurate with the limited real-world stormwater harvesting practice. In addressing the variable nature of stormwater, it is likely that extra health protection measures—such as the use of conventional water treatment processes—will be necessary for most stormwater harvesting practices that involve non-potable uses of the treated stormwater.

In situation where stormwater is managed by traditional stormwater pipelines (i.e. immediate discharge to environment), the risks are transferred to the environment in many indirect ways, which includes the loss of aquatic ecosystems, the resources (i.e. energy, money) needed for meeting increasing water demand, and the increased recreational health risks, and many more. However, many of these risks are not “tangible” for most people as the risks involve indirect causative linked to untreated stormwater discharge. Elevated health risks of recreating in waters receiving stormwater is perhaps the most relatable one, whereby the SUWM approach of treating stormwater is likely to benefit bathers in the water should

the treated stormwater is discharged to the environment. As such, there is a need for the formulation and adoption of a health risk assessment framework for assessing the recreational health risk that are contributed to stormwater discharge. In **CHAPTER 5**, using the source-apportionment QMRA approach I found the recreational risk associated with urban stormwater discharge into the recreational water is highly dependent on sewage contamination of the stormwater. Sewage contamination of stormwater is a real problem that can be a result of misconnection or aging infrastructure that are leaking. As such, it is postulated that the vetted incorporation of SUWM systems into such urban watersheds would reduce the sewage impacts on the stormwater discharge.

Overall, the transition or incorporation of SUWM approach is a viable approach for improving the water sustainability of urban regions, under the condition that the transition is paced and tempered appropriately by the available and/or necessary knowledge base. In facilitating this transition, a robust and flexible framework that can incorporate the latest knowledge for assessing the available options for incorporating the SUWM approach is needed. The public health aspect of this framework is suitably filled by the QMRA framework, as was partly demonstrated in this dissertation. It is hoped that the research that formed this dissertation would be a stepping stone for driving further progress of the SUWM approach.

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