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Assessing Risk of Injection of Reclaimed Water into the Biscayne Aquifer for Aquifer Recharge Purposes

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Abstract

The recharge of non-potable water into a drinking water aquifer is one means to overcome decreasing groundwater supplies and maintain availability of these resources for current and future generations. However, health concerns exist regarding the use of waters of "impaired quality" such as reclaimed wastewater for aquifer recharge. The objective of this study is to evaluate the potential risk to drinking water from the use of reclaimed water for recharge purposes using computational modeling with MODFLOW and MT3D groundwater transport simulation based on an actual situation using rotavirus as a surrogate. The results from the simulation showed that after seven months, the risk of contamination based on concentration contours from the injection well to the production wells was stabilized below 10^{-6}.

Keywords

Potable Reuse, Risk, Rotavirus, Groundwater Contamination

1. Introduction

Surface waters supply the majority of people connected to water utilities, but these same surface waters are used many times over for water supplies, irrigation, industrial and waste disposal. Therefore, their quality can be suspect. Groundwater resources are often thought of as being of higher quality than surface. These groundwater supplies have the benefits of being more drought resistant and more protected than surface waters, and as a result, they are easier to treat. However, unlike surface waters that recharge with rain, many aquifers are confined from the surfaces and are therefore far less responsive to precipitation.

As a result, aquifer levels are falling in many areas of the world (Reilly et al., 2008). As populations have grown in areas with less access to surface waters, the demand for groundwater has increased, putting pressure on groundwater supplies. Higher demands have caused aquifers to be mined, creating potential risk for large populations, a condition that exists for many areas of the world, putting millions of people are at risk.

The widespread expansion of groundwater supplies corresponds to the availability of electricity in rural areas to run pumps, which make formerly dry areas available for farming and development. The reduction of available water due to aquifer mining, threatens the economic and social wellbeing of those that rely on these supplies. For these areas, a solution to their water supply issues is to inject water into aquifers to replenish or maintain water levels. Florida is one of many places that face this risk.

While Florida has not yet faced the critical water shortages experienced in California and Texas, population growth continues to put increasing pressure on Florida's water resources. Given its generally flat topography, Florida's ability to use and store surface waters is limited. The result is the wet season rains cannot be stored for dry season use. Storage issues are compounded by nutrient runoff, algal blooms and other water quality impairment issues. Aquifer storage and recovery (ASR) has been helpful on the west coast of Florida, but it has been less successful on the east coast and central part of the state (Bloetscher et al., 2014; Bloetscher et al., 2015). The need for large volumes of water also exceeds the ASR potential (Bloetscher et al., 2014; Bloetscher et al., 2015). As a result, Florida is already facing an increasing need for innovative water supply source management solutions, including indirect (and potentially direct) potable reuse, that can be an effective part of the integrated water management approach.

The use of such injection programs offers significant potential for improving many of the world's water supply problems, particularly in places like Florida where millions of gallons of treated wastewater are discharged to rivers, streams, oceans and deep injection wells each day, some of which could be diverted for aquifer recharge or protection programs (Bloetscher, 2001). However, these water supplies are of lower quality than the native groundwater in most cases, creating concern among regulators of groundwater contamination. Most of the regulatory concerns have resulted from the perceived risks of adverse health effects from pathogens such as viruses, organic contaminants, metals and nutrients. Solutions to treat the water can be developed, but measuring the risk remains a challenge using current methods. Contaminant transport of nutrients and organics has been modeled, but less so with pathogens, and in no case was an analysis of the risk of pathogen migration undertaken. The question is what level of treatment is needed?

The concern is focused on potentially impairing potable water supplies with various contaminants, a violation of underground injection control rules created as part of the Safe Drinking Water Act (anti-degradation rules), creating the possibility of contaminants being recovered in water supply wells during extraction. In a discussion with Florida regulators, heavy metals are not perceived as being highly mobile in the aquifer system, and the minor concentrations of organics remaining in reclaimed water often decay (or are consumed by aquifer microflora (Bloetscher, 2001). However, they were concerned about pathogens because of 673 waterborne illness outbreaks that occurred in the United States between 1946 and 1980, 44% were attributable to groundwater sources (Asano, 1985). The statistics are similar for the subsequent 25-year period (Blackburn et al., 2004; Lee et al., 2002; Liang et al., 2006; Yoder et al., 2008; Bloetscher & Plummer, 2011; Keswick et al., 1982). Pathogen occurrence rate may be much higher in aquifers with high organic content, which encourages microbial growth (Bloetscher et al., 1997; Meeroff et al., 2008). Because reclaimed wastewater containing viruses may be injected into the ground, regulators fear the injection program will increase the likelihood of groundwater-related illnesses (Yates et al., 1987).

The objective of this study is to evaluate the potential to develop risk contours for aquifer recharge programs using reclaimed water for aquifer recharge. For purposes of this investigation, the term "risk" is defined as the probability of occurrence of an infection as a result of withdrawal of a contaminant introduced into the aquifer by an injection project. The process outlined herein could be replicated for areas outside southeast Florida. The results will build on the prior Hazen and Sawyer (2000) and Bloetscher (2001) work in this field. However, because regulatory agencies are unwilling to permit injection of pathogens into a drinking water aquifer, the results here provide insight, albiet untestable insight, into microbial risk from injection programs.

2. Methodology

2.1. Prior Methods for Treatment and Analysis of Injection Programs for Reuse

In the late 1990s, the injection of reclaimed wastewater (filtered, high level disinfection) into a shallow aquifer formation for saltwater intrusion control was pursued by the City of Hollywood, FL. A series of injection tests were performed (with potable water), and the results were used by Hazen and Sawyer (2000) and Bloetscher (2001) to create a numerical groundwater simulation model developed to address the differential density issues associated with groundwater movement at the saltwater interface along oceans and other large saltwater bodies.

In the 20 years since that project was initiated, the regulations for indirect potable reuse (whereby purified water would be returned to the surficial aquifer or a deeper brackish aquifer) requires higher levels of treatment, usually consisting of micro/ultrafiltration (MF/UF), reverse osmosis (RO), and UV advanced oxidation (UVAOP). Within the past 10 years, nearly a dozen Florida communities have undertaken pilot studies of potable reuse, including: Sunrise, Plantation, Miami-Dade County, Davie, Pembroke Pines, Hollywood, and Clearwater. Two of these pilot studies were conducted in Southeast Florida in anticipation of the pending Ocean Outfall Rule, which bans ocean disposal of treated wastewater by 2025. A key component of these feasibility studies centered around nutrients, pathogens and microconstituents removal efficiencies, all of which were specifically evaluated in Pembroke Pines (Bloetscher et al., 2011, 2013).

While several of these projects have proven the concept from a treatment perspective, there are two concerns: 1) the cost of the treatment and 2) the aggressiveness of the treated water when using RO. Reverse osmosis for wastewater treatment is relatively expensive to pursue, and so utilities would like to avoid using it if possible. In addition, the Pines studies (Bloetscher et al., 2011, 2013) found that the treatment processes utilized to address microconstituent removal produce nearly distilled, deionized water quality, post-treatment is important to minimize impacts in aquifer recharge projects and protect the injected purified water from aggressively leaching naturally occurring trace metals. Therefore, post-treatment is needed to restore minerals so that the water does not dissolve metals from piping, tank materials, or the native formation (Bloetscher et al., 2011, 2013). A cost/benefit analysis raises the question that if a lesser treatment, say reclaimed quality water used for irrigation of gardens, crops and landscaping was injected, how much risk would there likely be to the public, and how would it compare to full treatment? Risk assessment is one way to address the cost/benefit question.

2.2. Risk Assessment

Given the regulatory agencies' concern about microbial species and the incidence of illness caused by groundwater contamination, Bloetscher (2001) focused on viral risk in public water supplies. But there are difficulties in determining microbial dose-response for pathogens because of a paucity of data, low-dose infectivity transmission effects, and differences in immune system response. Identification of safe doses pathogen exposure in drinking water through collection of dose-response data is generally not feasible. As a result, Bloetscher (2001) focused on utilitzing predictive Bayesian methods to develop a dose-response for several pathogens that were identified as a major potential risk of infection. Englehardt and Swartout (2006) have previously investigated the use of predictive Bayesian methods for dose-response relationships, and Bloetscher et al. (submitted) appears to provide a convenient solution for the use of sparse data, while permitting the incorporation of additional data as it is generated. When the United States Environmental Protection Agency (USEPA) did perform an analysis on rotavirus movement in the subsurface, the focus was oriented to inactivation (4-log) as opposed to creating risk contours (Azadpour-Keeley et al., 2003). As a result, there are no prior studies that use these principles to test for rotavirus risk movement in groundwater.

To construct a risk assessment for the injection of reclaimed wastewater for aquifer recharge, there are four steps that must be completed. First, the tracer must be identified. Second, a groundwater model needs to be constructed and calibrated. Next, using the groundwater model, a contaminant transport model that includes tracer pathways, decay and retardation terms must be developed. Finally, a dose-response curve for tracer infectivity must be created. To be conservative, the scenario does not consider any treatment of withdrawn water. It was assumed that any result lower than 10^{-6} risk would not pose a concern that would prevent the installation and operation of an injection project.

The tracer used was rotavirus, which is a highly infectious pathogen that has good survivability in the environment compared to other viruses (Yates et al., 1987, 1989). Rotavirus also has a high shedding incidence, high exposure rate and low infective dose (Bhattarai et al., 2017). Rotavirus is a common cause of serious gastroenteritis in humans (Gerba et al., 1996) and is estimated to account for 20% of diarrheal deaths in early childhood in the United States (Maldonado & Yolken, 1990). In this study, rotavirus is selected as a surrogate because dose-response data in human adults indicated that it is the most infective of all the enteric viruses (Maldonado & Yolken, 1990). The concentration of rotavirus in treated effluent water samples was calculated based on secondary treatment with filtration and high level of disinfection (for reclaimed wastewater). Secondary treatment can achieve an average removal of 2.00 ± 1.10 $\log_{10}$ (Li et al., 2011) via adsorption on activated sludge (Gerba et al., 1996). Li et al. (2011) reported the average concentration of rotavirus as 16.6 PFU/L in the primary effluent with a maximum of 300 PFU/L, and the detection rate was 33%. Using disinfection with secondary treatment achieved 2.09 logs of removal, and filtration can achieve another 0.72 logs of removal for a total of 2.8 logs. Chlorine can provide additional disinfection, but to be conservative, 2.8 logs removal was assumed.

The injection well used for this transport modeling was estimated to deliver 1 million gallons per day into the recharge zone (200 feet below ground level). For the worst-case scenario, the detection rate was assumed to be 100%; thus the approximate concentration level was 2 million PFU per 1 million gallons of injection water. Note that Li et al. (2011) evaluated a water treatment plant with reverse osmosis membranes and did not detect any rotavirus after treatment, so they could not perform an analysis. Results for wastewater treated with reverse osmosis followed by ultraviolet radiation and advanced oxidation by Bloetscher et al. (2011, 2013) also did not find any presence of rotavirus after treatment either.

2.3. Groundwater Model

The City of Hollywood is located in southeast Broward County, Florida. It is Broward County's third-largest municipality with a population of about 140,000 permanent residents, 50,000 seasonal residents and various commercial and industrial customers of its water supply. The main source of drinking water for the city is the Biscayne aquifer, which is a shallow, productive aquifer. However, extensive drainage practices during the wet season and the increased population demand during the tourist season adversely affect the supply of water, which results in frequent water shortages. Protection or recharge to the aquifer would help the City sustain its existing groundwater supplies.

The City of Hollywood's model of injection is the most robust in southeast Florida. The groundwater model for the City of Hollywood study (Hazen & Sawyer, 2000) was initially analyzed using the finite-difference groundwater model (MODFLOW) by the U.S. Geological Society. For the study of contaminant transport, MT3D simulations were used to illustrate the effect of propagation of contaminants using rotavirus as a surrogate (Zheng & Bennett, 1995). MODFLOW and MT3D were used to predict groundwater movement in the vicinity of the injection zone and the impact on inland wellfields. Hazen and Sawyer (2000) used a modification to MODFLOW to address the buoyancy of freshwater called SEAWAT. The SEAWAT model was calibrated to actual field data for groundwater levels and rainfall over a 24-month period. The SEAWAT output was then used as input to a contaminant transport software package (MT3D) to track movement of the tracer in the formation. The contaminant contours were then used to assess the potential risk to consumers.

For this project the groundwater model was re-created using Groundwater Vistas, a groundwater modeling system with comprehensive graphical analysis tools was used to combine these packages in a post-processing software environment (Rumbaugh, 2004). In addition to MODFLOW, SEAWAT and MT3D, Groundwater Vistas includes a contaminant transport subprogram. For the input module, the number of rows and columns was set at 65 and 85, respectively. The uniform X spacing and uniform Y spacing was 500 feet. This gave a total modeled area of 32,500 by 42,500 ft^2 (see **Figure 1**). Note that the columns and rows were further subdivided in the vicinity of the recharge wells for better model resolution. The grids were developed to simulate the spatial variability of depth and the hydrologic effects of surface and groundwater bodies and compared against actual, calibrated results as developed by Bloetscher (2001) and Hazen and Sawyer (2000). There were 5 layers representing hydrologic differences in the soil characteristic; however, layers were assumed to be in the same conditions throughout the whole area of the model, which reduces the complexity and computational difficulty of the model.

Once the grid was established, hydrogeologic and hydrochemical conditions were required to set-up the groundwater transport model in the defined domain. The primary geologic parameters were locations of model boundaries and thicknesses of geologic units (see **Table 1**). Physical and chemical parameters such as reaction coefficients, porosity, specific yield, storage, transmission and hydraulic conductivity were developed by Hazen and Sawyer (2000) in their calibrated model of the wellfield.

The South Florida Water Management District's DBHYDRO web-portal (https://www.sfwmd.gov/science-data/dbhydro) was used to gather the initial parameters for rainfall data for calculation of recharge in **Table 2**, while the

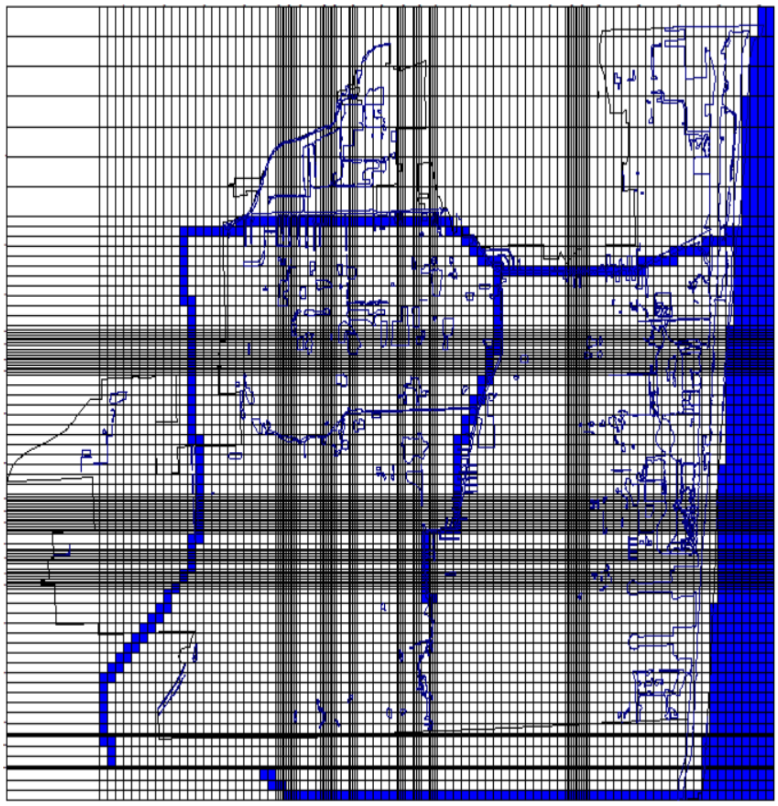

Figure 1. The initial grid used for modeling the aquifer in the Hollywood area. On the right is the Atlantic Ocean.

Table 1. Initial geohydrological parameters for each model layer.

Layer of aquifer	Depth from surface (ft)	Hydraulic conductivity x direction K_x (gpd/ft^2)	Hydraulic conductivity y direction K_y (gpd/ft^2)	Hydraulic conductivity z or vertical direction K_z (gpd/ft^2)	Storage Coefficient (dimensionles)	Specific yield of aquifer or drainable porosity (ratio)	Porosity of formation (ratio-% voids)	Leakance (1/d)	Transmissivity (gpd/ft)
1	13	800	160	16	0.015	0.015	0.15	0.45	130,000
2	37	1000	200	20	0.015	0.015	0.15	0.45	37,000
3	40	10000	2000	200	0.00015	0.00015	0.15	0.45	400,000
4	60	10000	2000	200	0.00045	0.00045	0.15	0.13	600,000
5	60	100	20	2	0.015	0.015	0.15	0	6000

physical conditions of the soil were adapted from Hazen and Sawyer (2000) as shown in Table 3.

It was assumed that the injection wells will be operated continuously, thereby reaching equilibrium by:

$$\overline{c}\left(x, y, z, t=\infty\right) \tag{1}$$

However, the model cannot function when the time element is infinity; therefore, the two years with recharge via rainfall from Table 2 was used as an estimate of steady state. An appropriate decay rate (0.1027 day^{-1}) as defined by

Table 2. Two-Year Precipitation Data 2011-2012 (DBHYDRO, SFWMD).

Month	Monthly Precipitation (in)	Annual Cumulative Precipitation (inches)	Recharge Rate (2/3 if rainfall)	Recharge (ft/day)
1	1.37	1.37	0.0761	0.0025
2	0.17	1.54	0.0094	0.0003
3	2.54	4.08	0.1411	0.0046
4	3.31	7.39	0.1839	0.0061
5	2.85	10.24	0.1583	0.0051
6	2.2	12.44	0.1222	0.0041
7	7.79	20.23	0.4328	0.0140
8	7.91	28.14	0.4394	0.0142
9	7.96	36.10	0.4422	0.0147
10	16.43	52.53	0.9128	0.0294
11	2.91	55.44	0.1617	0.0054
12	2.44	57.88	0.1356	0.0044
1	0.55	0.55	0.0306	0.0010
2	3.79	4.34	0.2106	0.0075
3	2.43	6.77	0.1350	0.0044
4	10.09	16.86	0.5606	0.0187
5	11.62	28.48	0.6456	0.0208
6	7.53	36.01	0.4183	0.0139
7	10.24	46.25	0.5689	0.0184
8	14.29	60.54	0.7939	0.0256
9	8.73	69.27	0.4850	0.0162
10	4.69	73.96	0.2606	0.0084
11	0.54	74.50	0.0300	0.0010
12	1.89	76.39	0.1050	0.0034

Table 3. Biscayne aquifer flow model input parameters (Hazen & Sawyer, 2000).

Layer	Name	Transmissivity (ft^2/day)	Vertical Conductivity (dimensionless)	Layer Thickness (ft)	Initial Head (ft, NGVD)	Storativity (ft^3/ft^3)
1	Upper Zone 1	25 - 1249	0.02 - 0.08	15 - 22	0 - 4.5	0.18 - 0.5
2	Upper Zone 2	1000 - 3000	0.02 - 0.08	5 - 15	0 - 4.5	0.0002 - 0.0006
3	Biscayne Aquifer 1	100,000 - 500,000	0.08 - 0.15	30 - 50	0 - 4.5	0.00004 - 0.0001
4	Biscayne Aquifer 2	100,000 - 500,000	0.08 - 0.15	30 - 50	0 - 4.5	0.00004 - 0.0001
5	Lower Zone 1	2000 - 13,000	0.02 - 0.09	50 - 60	0 - 4.5	0.0002 - 0.0006

Bhattarai et al. (2017) was incorporated.

The baseline condition from two years of observations and precipitation data was used to model the groundwater flow with MODFLOW under the assumption of transient conditions. The flow rate of the injection well (Q = 1 MGD) and production wells (Q = 12 MGD) were assumed to be constant throughout the two-year period of simulation. The model used monthly time steps and actual rainfall in **Table 2** for calibration. The baseline condition model was compared against historical City of Hollywood records for groundwater table level elevations in DBHYDRO and the monitoring wells in Dania Beach and Hollywood.

At this point, the contaminant transport model, MT3D, using rotavirus as a contaminant tracer was introduced. A three-dimensional solute transport simulation in MT3D was conducted to predict the contaminant movement within the groundwater aquifer. Analysis included not only the contaminant transport mechanism reaction, but also a rate of decay and dispersion radius from the injection source. The output data was migrated to ArcGIS to visualize the risk contours.

The groundwater flow model was calibrated using previously known conditions of groundwater table elevation and drawdown from City of Hollywood production wells in the wellfields located on the west side of the City for the period of two years from January 2010-December 2011. **Figure 2** illustrates the groundwater table drawdown levels of the May 2011 dry season from the Groundwater Vistas (GV) simulation, and **Figure 3** depicts the same groundwater drawdowns for the May 2011 dry season in ArcGIS with data imported from GV. The contour lines represent hydraulic head, and color flood represents the drawdown of the groundwater table.

Similarly, **Figure 4** and **Figure 5** illustrate the groundwater table drawdown levels for the September 2011 (wet season) from GV model simulation and GIS, respectively. The approximate minimum value for the hydraulic head is 0.8 feet (dry season) and 1.4 feet (wet season).

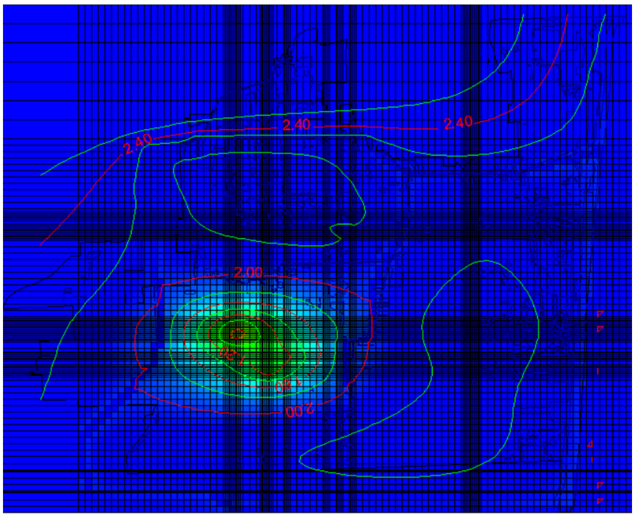

Figure 2. Groundwater table drawdown from May 2011 (Dry Season) in Groundwater Vistas.

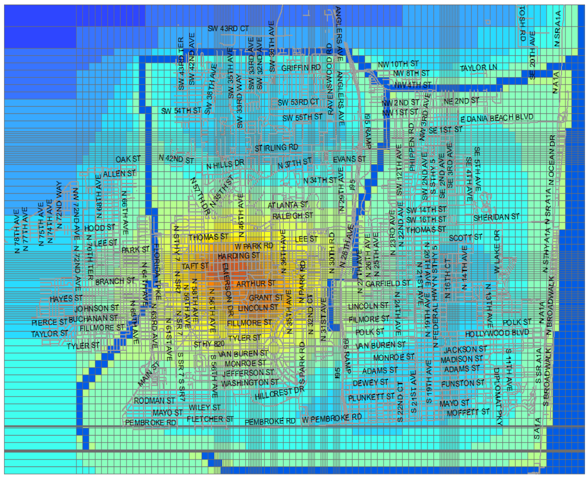

Figure 3. Heat map of groundwater table drawdown May 2011 (Dry Season) in GIS (red is the highest drawdown).

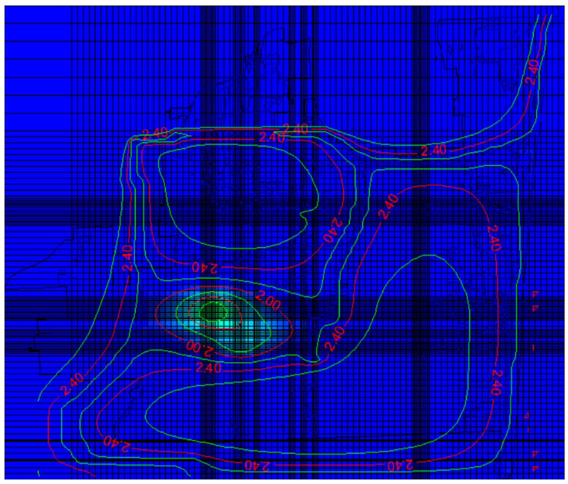

Figure 4. Groundwater table drawdown from September 2011 (Wet Season) in Groundwater Vistas.

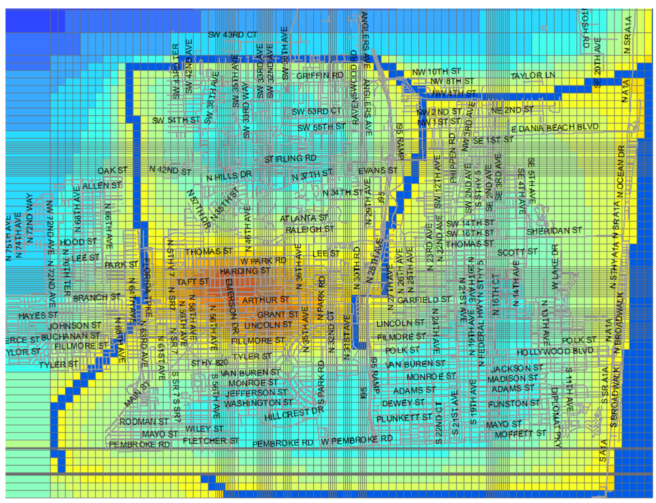

Figure 5. Heat map of groundwater table drawdown from September 2011 (Wet Season) in GIS (red is the highest drawdown).

The contaminant transport model showed that rotavirus reached steady state during time step 7 (Month 7-July), which was expected since the decay rate of rotavirus is 0.1027 day^{-1}. The contaminant contours started at the injection well as a point source, propagated through groundwater layers, and widened as time steps increased until reaching equilibrium.

Dose-response assessments require properly identifying the inputs of the hazard of interest. Haas et al. (1999) suggested a number of dose-response models for pathogenic organisms using the assumption of a Poisson distribution (a discrete distribution of the number of unlikely events over a given period of time) combined with the binomial distribution to define the probability that a given person ingests the pathogen, a process that was developed and will be further discussed for this analysis. For microbes, the dose-response algorithms must be combined with estimates of intake exposure. Hence, dose-response data from a number of smaller outbreak data sets are needed to predict the microbial dose required for a direct health response. To address microbial risk, Quantitative Microbial Risk Assessment (QMRA) methods (Beaudequin et al., 2015) were developed to estimate risk from exposure to microorganisms by combining dose-response information with information of the distribution of exposures. However, dose-response algorithms are not precise prediction tools, and the currently applied method is formulaic such that the algorithm's origins and derivation are not well understood. As a result, the idea of applying/extending Bayesian methods to continuous improvement of QMRA dose-response relationships is a sound method to better incorporate uncertainty and variability (Englehardt & Swartout, 2006; Messner et al., 2001; Beaudequin et al., 2015). Predictive Bayesian methods do not require researchers to treat dose-response algorithms as fixed, but they provide a technique to rationally and continually improve the mathematical relationship based on added data.

Bayesian statistical methods are rooted in the concepts of disorder, or thermodynamic entropy, and statistical mechanics (Shannon & Weaver, 1949), assuming a samples space S, with a series of events i, characterized by individual probabilities p_i. Definitive observations play an important role in information entropy theory since once the definitive observation is made, the underlying uncertainty is reduced. The uncertainty defines the confidence in the observation (Englehardt & Lund, 1992). By maximizing information entropy, the most conservative or broadest distribution consistent with the available information can be used (Englehardt & Lund, 1992). The Bayesian approach involves the assignment of probability distributions to the underlying dose-response function. The mean and standard deviation determine the location and scale of the distribution, describing their shape. When little or no data are available to specify the parameters of these distributions, probability distributions can then be assigned to the parameters within the initial distributions. Subjective information may then be used to create these prior distributions until such time as real data is developed or becomes available. Hence subjective data can be incorporated and the prior distributions adjusted as new data emerges. Based on the published rotavirus dose-response data developed by Ward et al. (1986), the value of a, related to the slope on a log-log graph for the Pareto II distribution, was determined through graphical means (Bloetscher, 2001; Englehardt, 1995). The Pareto II distribution has no lower threshold, which is desirable since the dose-response for microbial infection assumes a probability of receiving a given dose (hence numbers less than one) as opposed to a true threshold (i.e. ≥1 organism). In addition, the Pareto distributions are used for high consequence, low likelihood events and have been suggested as an appropriate model by others (Englehardt & Swartout, 2006; Englehardt, 2004; Englehardt & Lund, 1992; Bloetscher, 2001; Furumoto & Mickey, 1967). The methods used by Englehardt and Swartout (2006) were adapted to develop a predictive Bayesian dose-response relationship using the Pareto II distribution probability density function as follows:

$$p(z) = \frac{ak^{a}}{(k+z)^{a+1}} \tag{2}$$

where z is the dose, k is the location parameter (which may be the D_{50} or 50 percentile mortality) and a is a distribution parameter. When the Pareto II distribution is graphed on log-log scale, the slope on the right side is defined as 1-a. The initial value of a was set at 0.4 based on graphing the data from Ward et al. (1986). However, given the uncertainty of one data set, the prior for the Pareto II was assumed to be a gamma distribution with unknown parameters α and β. The location parameter (k) is defined as the dose where the change in slope occurs in the data, which corresponds to where the infection rate changes. This is the point where the fastest rate of increase in the probability of illness occurs in the cumulative density plot (predictive Bayesian). In this case, the values of the variables a and k are not known but can be estimated from data. Englehardt and Lund (1992) generated a solution for Pareto II when a is uncertain and k is assumed. However, the solution for the Pareto II distribution where neither a or k are certain, which is the more typical case for microbial species or synthetic chemicals, has not been similarly solved until now. The maximum likelihood function (L) for the Pareto II distribution (Johnson & Kotz, 1970) is:

$$L(z \mid a, Z_o) = \prod_{J=1}^{J} ak^{a} (k+z)^{-(a+1)} \tag{3}$$

where J is the number of data points of sets. The conjugate prior for a and k are gamma distributions with the following form (Johnson & Kotz, 1970; Arnold & Press, 1989):

$$p(a \mid \alpha, \beta) = \frac{\beta^{\alpha} a^{\alpha-1} e^{-a\beta}}{\Gamma(\alpha)} \tag{4}$$

where both α and β are greater than zero. The binomial distribution is incorporated into the likelihood.

One of the main benefits of Pareto is that the parameters a and k are taken to be independent (Arnold & Press, 1989). This simplifies the mathematics compared to intractable solutions suggested by dependent joint priors. The posterior distribution incorporates observations from x into the sample space S. The outcome of the observations conveys additional information about the true content of S through a series of informed assumptions (Aitchison & Dunsmore, 1975). The basis for the information obtained is the influence of the proper distribution, and the attachment of same to the possible distributions for x. Updating the plausibility in light of the observations of the prior using Bayes notation leads to the posterior probability function (Aitchison & Dunsmore, 1975):

$$p(\theta \mid x) = \frac{p(\theta)\, p(x \mid \theta)}{p(x)} \tag{5}$$

where $p(x)$ can be equal to 1. Given that x and θ are often unknowns, they can be estimated using the maximum likelihood estimates or graphical methods (Englehardt & Lund, 1992). The posterior for the bivariate Pareto II is found by:

$$p\left(a,k \mid z_1,z_2,z_3,z_4,\cdots,z_j\right) = L\left(z \mid a,k\right) p\left(k \mid m,\theta\right) p\left(a \mid \alpha,\beta\right) \tag{6}$$

where m and θ are priors for k, and α and β are priors for a which, for this effort, results in:

$$p\left(a,k \mid \theta,m,z_1,z_2,\cdots,z_J\right) = n\theta a^J k^{aJ} \mathrm{e}^{-(a+1)\sum J \ln(z+k)} \mathrm{e}^{-a\theta} \cdot \frac{2^{\frac{1}{a}}-1}{m} \mathrm{e}^{\left(1-2^{\frac{1}{a}}\right)\frac{k}{m}} \tag{7}$$

The predictive Bayesian approach takes the process one step further to create a cumulative density function that will yield risk on a log-log scale. This permits the investigator to find the probability of infection at a given dose. As new information is gathered, from either epidemiological studies or outbreak investigations, the predictive function can be updated to increase the robustness of the dose-response function. This is the benefit of the Bayesian approach: given uncertainty about a density function, $p(y|\theta)$, some data can be deduced from the assessment of $p(\theta|x)$ over θ when the experimental results of x are known (Aitchison & Dunsmore, 1975). This function is:

$$p(y \mid x) = \int_{\theta} p(y \mid \theta)\, p(\theta \mid x)\, \mathrm{d}\theta \tag{8}$$

where the function $p(y|x)$ is the predictive density function. If there are two unknowns, as in this case (a and k), there are two integrations necessary in order to create an equation based on the incident size (z) or in this case the mortality/illness likelihood of the pathogen:

$$p\left(z \mid z_1,z_2,\cdots,z_J\right) = \iint p\left(z \mid a,k\right) p\left(a,k \mid \alpha,\beta,y,z_1,z_2,\cdots,z_J\right) \mathrm{d}a\mathrm{d}k \tag{9}$$

Because of the intrinsic difficulty in solving a predictive Bayesian equation with multiple embedded distributions through double integration, a Markov Chain Monte Carlo (MCMC) program was developed in MATLAB® with uncertain values for a and k using the Metropolitan Hastings protocol with a Gibbs sampler was used to generate mathematical dose-response solution. Using the generated dose-response function, the results of the groundwater tracer model can be used to define the probability of exposure.

Using the mathematical principles described above, **Figure 6** is the resulting dose-response curve for rotavirus. The circles are the actual data from Ward et al. (1986). For this model, the solid line is the beta-Poisson model often employed. The dot-dash is the predictive Bayesian methods developed herein—it is more conservative than the Beta-Poisson model proposed and used by Haas et al. (1996, 1999). The resulting concentrations from the groundwater model were directly translated to risk contours by developing a simple conversion between the risk on the dose-response graph with the concentration contours developed by the MT3D code.

The data from MT3D simulation were exported to GIS as a shape file, which also included concentration levels per contour. Using GIS, each contour color was changed according to its log concentration and translated to a risk contour. Because the groundwater model was based on a drought period, the tracer model (MT3D) will be conservative in its movement (tracers move farther than likely). The tracer concentrations were then converted to risk contours to indicate the impact of rotavirus injection on the aquifer over a two-year period. Note the movement of the organisms ceases within 7 months.

3. Results

After the groundwater modeling data was exported into GIS, the distance between each contour layer and injection well was measured using the measuring tool in GIS. The distance between contours decreased with increasing distance

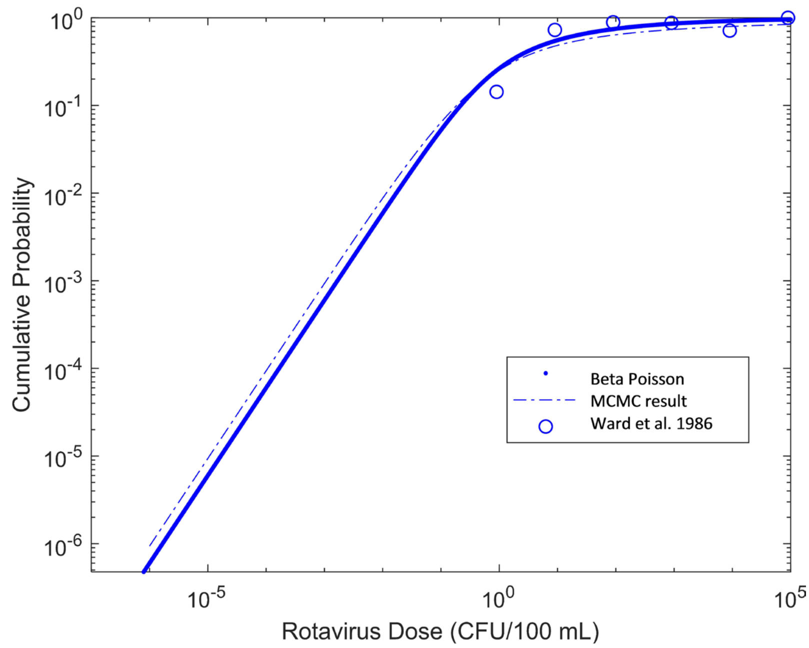

Figure 6. Rotavirus dose-response curve (the dot-dash is the graph of the predictive Bayesian methods developed herein, the Beta Poisson was shown to be the solution to the Pareto II—the model developed herein is more conservative than the beta-Poisson model).

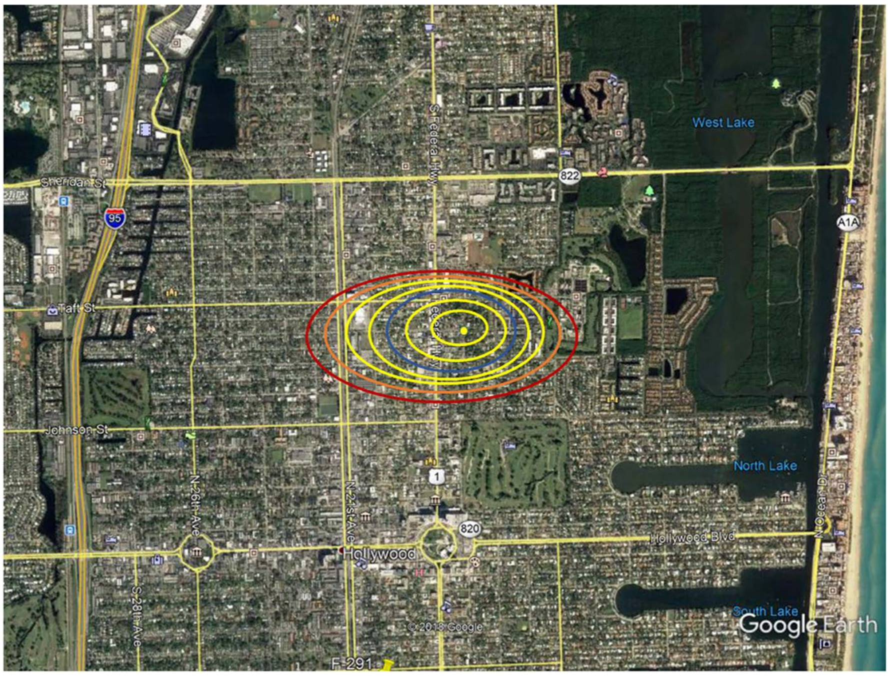

Figure 7. Risk Contours showing that as the water moves away from the injection well, the risk declines (1:10 to 1:10 million; the 1:1000 is the blue contour, 1:1 million is orange and red is 1:10 million).

from the injection point. **Figure 7** shows the resulting risk contours plotted in GIS. Each log reduction in microbial density translates to a one-log decline in risk probability assessment. The closer the distance to the injection well, the higher the risk probability since the microbial density should be higher. The lowest rotavirus concentration contour is 0.7 miles from the injection well, while the City of Hollywood raw water extraction well fields are 3 miles away from the injection site.

4. Conclusion

Several communities have conducted preliminary investigations into the possibility of injecting reclaimed wastewater into an underground source of drinking water to supplement existing supplies. However, utilities have been required to evaluate reverse osmosis treatment as the appropriate treatment prior to injection. due to concerns about aquifer contamination. To date, regulatory agencies are reluctant to permit other less stringent forms of treatment. Furthermore, the potential public health impact of supply augmentation with reclaimed wastewater for irrigation has not been addressed from a risk perspective. In this research, the alternative of injecting treated wastewater was evaluated using rotavirus as a surrogate tracer. For risk analysis purposes, the injectate was reclaimed wastewater with an assumed initial concentration of 2 million PFU of rotavirus per 1 million gallons of injection water. Based on computer modeling of the worst case scenario aquifer situation (dry season involved 24 months of weather records during a recent low rainfall period, and using a predictive Bayesian dose-response relationship), it was found that the 1:1 million risk contour is 0.7 miles from the injection well, which is about 3 miles away from the City of Hollywood's well-fields.

The results of this project stemmed from a long-term effort to develop a Bayesian solution to assess public health risk from pathogens. The goal of the project was to demonstrate the use of risk assessment as a tool to support regulatory agency decisions regarding the potential incidence of illness caused by groundwater contamination, using rotavirus in this case. It should be noted that in the treatability studies (Li et al., 2011), no rotavirus was detected in wastewater effluent treated with reverse osmosis. Regrettably, the conclusion cannot be independently verified without spiking rotavirus in the treated wastewater effluent.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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