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Reliability of pathogen control in direct potable reuse: Performance evaluation and QMRA of a full-scale 1 MGD advanced treatment train

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ABSTRACT

To safely progress toward direct potable reuse (DPR), it is essential to ensure that DPR systems can provide public health protection equivalent to or greater than that of conventional drinking water sources. This study collected data over a one-year period from a full-scale DPR demonstration facility, and used both performance distribution functions (PDFs) and quantitative microbial risk assessment (QMRA) to define and evaluate the reliability of the advanced water treatment facility (AWTF). The AWTF's ability to control enterovirus, *Giardia*, and *Cryptosporidium* was characterized using online monitoring of surrogates in a treatment train consisting of ozone, biological activated carbon, microfiltration, reverse osmosis, and ultraviolet light with an advanced oxidation process. This process train was selected to improve reliability by providing redundancy, defined as the provision of treatment beyond the minimum needed to meet regulatory requirements. The PDFs demonstrated treatment that consistently exceeded the 12/10/10-log thresholds for virus, *Giardia*, and *Cryptosporidium*, as currently required for potable reuse in California (via groundwater recharge and surface water augmentation). Because no critical process failures impacted pathogen removal performance during the yearlong testing, hypothetical failures were incorporated into the analysis to understand the benefit of treatment redundancy on performance. Each unit process was modeled with a single failure per year lasting four different failure durations: 15 min, 60 min, 8 h, and 24 h. QMRA was used to quantify the impact of failures on pathogen risk. The median annual risk of infection for *Cryptosporidium* was 4.9×10^{-11} in the absence of failures, and reached a maximum of 1.1×10^{-5} assuming one 24-h failure per process per year. With the inclusion of free chlorine disinfection as part of the treatment process, enterovirus had a median annual infection risk of 1.5×10^{-14} (no failures) and a maximum annual value of 2.1×10^{-5} (assuming one 24-h failure per year). Even with conservative failure assumptions, pathogen risk from this treatment train remains below the risk targets for both the U.S. (10^{-4} infections/person/year) and the WHO (approximately 10^{-3} infections/person/year, equivalent to 10^{-6} DALY/person/year), demonstrating the value of a failure prevention strategy based on treatment redundancy.

1. Introduction

The primary focus of all drinking water systems is to provide a safe water supply from the standpoint of public health. From this perspective, reliability, or the consistent protection of public health, is the most important goal (Pecson et al., 2015; Tchobanoglous et al., 2015). Modern constraints are forcing a re-evaluation of the strict separation of wastewater and drinking water, a fact particularly evident in the rapid growth of the planned reuse of

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wastewater for potable applications (Gerrity et al., 2013; NRC, 2012; Trussell et al., 2013). To ensure reliability, planned potable reuse projects supplement traditional design elements—e.g., treatment and monitoring—with an additional layer of protection in the form of an environmental buffer. Passage through a buffer, such as an aquifer or reservoir, further improves water quality through both dilution and additional treatment, while retention in the environment provides time for treatment excursions to be detected and corrected before water reaches the public (CDPH, 2014; NRC, 2012). Potable reuse has the potential to greatly expand existing supplies (NRC, 2012), but maximizing its potential assumes that future projects can be created that do not employ an environmental buffer. These so-called direct potable reuse (DPR) projects offer numerous potential benefits in terms of costs, water quality, and geographic distribution (Tchobanoglous et al., 2011). The critical hurdle to the implementation of these new projects, however, is the age-old concern: can we *reliably* produce safe water?

The goal of this study was to assess the public health reliability provided by a potential DPR treatment train in terms of pathogen control. The analysis was based on a year's worth of continuous on-line data collected from a full-scale, 1 million gallon per day (mgd, or 3785 m^3/d) potable reuse treatment train. The treatment train was built on the premise that reductions in certain potable reuse design elements—namely, the environmental buffer—could be compensated with enhancements in treatment and monitoring (Pecson et al., 2015). Accordingly, this study placed greater reliance on monitoring and the treatment of the nitrified, tertiary feedwater through ozone (O3), biological activated carbon (BAC), micro- or ultrafiltration (MF/UF), reverse osmosis (RO), and a UV-based advanced oxidation process (UV/AOP). One unit process that was not incorporated into the performance evaluation was chlorine disinfection.

The treatment train was designed to provide a high degree of reliability through redundancy and robustness. Redundancy refers to the provision of treatment beyond the minimum needed for public health protection (Pecson et al., 2015), a strategy that enhances reliability by reducing the likelihood that the treatment train will fail to meet the minimum requirements. In this context 'redundancy' does *not* refer to the provision of standby capacity, although this is also an important design feature of reliable systems. Robustness refers to the use of multiple treatment barriers, which provides benefits in two ways. By distributing the role of contaminant removal between several processes, a multiple barrier approach reduces the impact of any single process failure thereby reducing the chances of a complete, or catastrophic, system failure. Selecting barriers with different forms of contaminant control—physical, chemical, and biological—also improves the system's ability to mitigate the wide range of potential contaminants. The main focus of this study was the control of microbiological contaminants, as they pose the greatest acute threat to public health in water reuse (NRC, 2012; Trussell et al., 2013).

Starting in the 1980s, regulatory and health organizations began using risk-based water quality targets as the basis for regulations and guidance. Since the 1989 Surface Water Treatment Rule, federal and state drinking water regulations in the U.S. developed risk-based water quality targets for three pathogen groups: enteroviruses, *Cryptosporidium* oocysts, and *Giardia* cysts (EPA, 1989, 1998, 2006a; Regli et al., 1991). These same pathogens are also frequently used as potable reuse standards with the individual states (Texas Water Development Board, 2015; CDPH, 2014; Crook et al., 2013). A risk-based goal of 10^{-4} infections per person per year is frequently used as the basis for developing pathogen log removal targets in the U.S. (CDPH, 2014; EPA, 1989; Regli et al., 1991). There is general agreement that this same *de minimis* risk target should be used in potable reuse projects in the U.S. (CDPH, 2014; Crook et al., 2013; Tchobanoglous et al., 2015; Trussell et al., 2013). This value is in line with the 10^{-6} disability adjusted life years (DALYs) per person per year used by the WHO and other countries, as it represents an equivalent risk of acute gastrointestinal infection of approximately 10^{-3} infections per person per year, specifically for rotavirus and *Cryptosporidium* (Natural Resource Management Ministerial Council, 2008; World Health Organization, 1996; World Health Organization, 2006). Both goals were used in this study in assessing the adequacy of public health protection of the DPR treatment train.

Quantitative microbial risk assessment (QMRA) has been used to estimate pathogen risk in drinking water for over two decades (Gale, 2001; Haas and Eisenberg, 2001; Haas et al., 1999; Nadebaum et al., 2004; Regli et al., 1991; Westrell, 2004; Westrell et al., 2003). Fewer QMRA studies have been conducted on indirect potable reuse (Asano et al., 1992; Tanaka et al., 1998) and DPR (Amoueyan et al., 2017; Ander and Forss, 2011; Barker et al., 2013; Soller et al., 2016). One of the limitations of previous QMRA efforts was the lack of full-scale performance data. The use of site-specific treatment performance data is preferable to using general log removal credits since actual treatment efficacy can vary widely between plants (Smeets, 2010). The goals of this study were to (1) develop a robust data set on DPR treatment performance through continuous, year-long surrogate monitoring of a full-scale operating facility, and (2) use probability distribution functions (PDFs) from the data and QMRA to assess the ability of the treatment train to meet the risk-based targets, and produce a water that provides public health protection.

2. Materials and methods

2.1. Demonstration facility

The advanced water treatment facility (AWTF) treatment train consisted of ozone (O_3), biological activated carbon (BAC), micro- or ultrafiltration (MF/UF), reverse osmosis (RO), and a UV-based advanced oxidation process (UV/AOP). This train was tested from April 2015 to April 2016 at the Demonstration Pure Water Facility located at the North City Water Reclamation Plant (NCWRP) in San Diego, California. Design criteria for each unit process are provided in the Supplementary Information section. The feed water to the AWTF was nitrified, filtered tertiary effluent from the NCWRP. While pathogen removal performance of the NCWRP was not quantified in this study, the high degree of treatment provided upstream of the AWTF provides a number of benefits in terms of the consistency and quality of the feed water (Tchobanoglous et al., 2015). Demonstration of post-disinfection with free chlorine was not considered necessary.

2.2. Data collection

To increase system reliability, enhancements were made both in treatment and monitoring. Online monitors placed throughout the treatment train provided continuous information on process performance. Most processes were designed with monitoring redundancy to ensure that treatment performance was reliably demonstrated and to minimize the time when the system went "dark" or unmonitored. Pathogen removal performance was continuously quantified using on-line monitoring of surrogates (Table 1). While pathogen removal through BAC is likely to occur, it is not included in Table 1 due to (1) the lack of studies characterizing and confirming the degree of removal achieved, and (2) the absence of an accepted surrogate framework for the awarding of pathogen removal credit.

All data were collected at 10-s intervals and passed from the unit

Table 1
Summary of pathogen surrogates and measurement strategies for each unit process. V = enterovirus; C = *Cryptosporidium*; G = *Giardia*.

Unit Process	Pathogen – Surrogates	Measurement Location/Strategy	Basis for LRV Calculation
Ozone	C – Ozone CT[a] V/G – based on *Crypto* removal	3 O_3 residual monitors along length of contactor	*Crypto* log removal based on drinking water framework using the extended T_{10} method for calculating ozone CT (USEPA, 2006a,b).[b] 6-log virus and *Giardia* credit applied if CT providing 1 or more logs of *Crypto* was achieved.
MF/UF	C/G – Effluent turbidity and pressure decay test (PDT) V – no credit	Continuous indirect integrity verification with effluent turbidity; daily direct integrity test with PDT	Crediting based on membrane filtration guidance manual, including compliance with effluent turbidity limits and maximum allowable values for PDT (USEPA, 2005b)
RO	V/G/C – total organic carbon (TOC) and electrical conductivity (EC) removal	TOC and EC meters on influent and effluent	Pathogen log removal credits based on measured reductions in TOC and EC, per the California groundwater replenishment regulations (CDPH, 2014)
UV/AOP	V/G/C – UV intensity, power, and transmittance	All parameters measured in UV process	6-log credit for each pathogen group assuming minimum values of each surrogate parameter are achieved, in line with California groundwater replenishment regulations (CDPH, 2014)

[a] CT is the product of ozone residual concentration (C) and contact time in the ozone contactor (T).
[b] Modified method approved by the California Division of Drinking Water.

process's programmable logic controllers (PLC) to a central PLC. From the central PLC, data were passed to a human machine interface (HMI) and then to a central server, where they were stored. Additional discussion of the data processing procedures is provided in the Supplemental Information.

2.3. Creating performance distribution functions

Process performance probability distribution functions (PDFs) were developed using the collected data. For each process, an established methodology from either drinking water or potable reuse was used to calculate the treatment performance in terms of $\log_{10}$ removal values (LRVs), as summarized in Table 1. The PDF of each unit process was fit with a parametric distribution; the methods used to create and model the PDFs are further described in the Supplemental Information.

2.4. Risk analysis

The four steps of risk assessment are (1) hazard assessment, (2) exposure assessment, (3) dose-response analysis, and (4) risk characterization (Haas and Eisenberg, 2001). As a starting place, the hazard assessment (Step 1) focused on the pathogens currently regulated in existing U.S. federal and state drinking water and reuse regulations—enterovirus, *Giardia*, and *Cryptosporidium* (CDPH, 2014; EPA, 2005a; Haas et al., 1996; NWRI, 2015). Of the protozoan pathogens, only *Cryptosporidium* was used for the analysis because it is smaller and more resistant to disinfectants than *Giardia*, and thus provides a conservative estimate of *Giardia* removal through the AWPF (Crook et al., 2013). Enterovirus was chosen to align with U.S. regulations for viral pathogen control. While there is a growing interest in norovirus, it was not selected for a number of reasons, including (1) uncertainty associated with the selection of a dose-response model, (2) the lack of regulatory direction on the appropriate dose-response to utilize, (3) the absence of a culture method to assess norovirus infectivity, and (4) uncertainty related to the use of molecular methods to assess norovirus infectivity (NRC, 2012; Olivieri et al., 2016; Van Abel et al., 2017). The remaining three steps of the risk assessment are shown in Fig. 1 and further described below.

2.4.1. Exposure assessment

The exposure assessment was limited to the ingestion of treated waters. Exposure to pathogens from the consumption of potable reuse water was quantified in 15-min increments. This interval was selected after considering the minimum amount of time that off-spec water could be produced and distributed (and eventually consumed) before a failure response action could be initiated to halt its distribution. A 15-min interval was selected as a reasonable minimum time interval based principally on the use of on-line

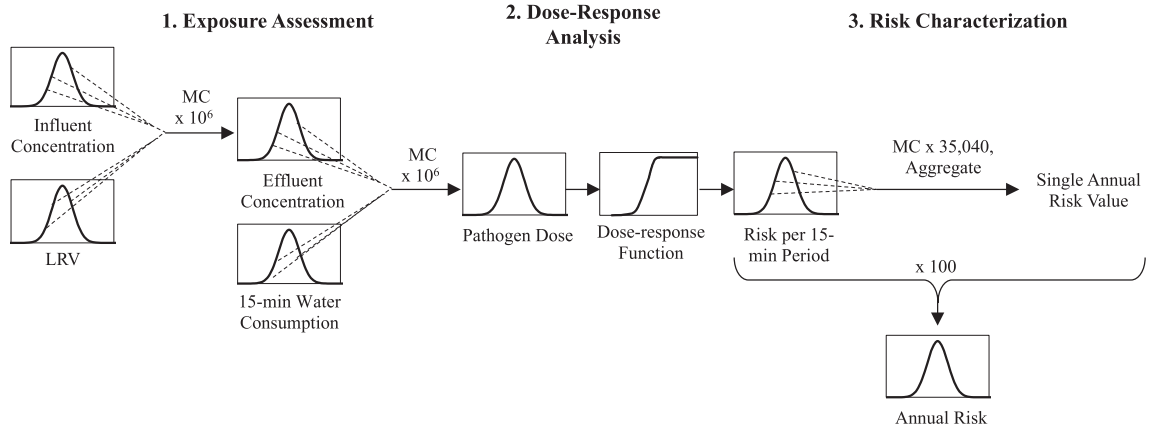

Fig. 1. Summary of risk assessment methodology.

monitoring that provides a "continuous" (i.e., at least one reading every 15 min) assessment of process performance. Note that in this study performance data were collected at a significantly higher frequency (i.e., every 10 s), a situation that could justify the use of even shorter intervals in the failure analysis. Nevertheless, a 15-min interval was selected under the assumption that future regulations will require monitoring no less than once every 15 min.

The impact of longer duration failures was also assessed. The pathogen dose consumed during each period was calculated as the product of the pathogen concentration in the final product water—a function of the pathogen concentration entering the AWTF and the removal performance through the AWTF—and the volume consumed over the period of interest.

2.4.1.1. Influent pathogen concentration. The analysis focused exclusively on the performance of the AWTF to quantify its role in the overall reduction of risk. Consequently, the risk analysis began with raw wastewater and calculated the reduction in risk due to treatment at the AWTF alone. This approach would therefore identify the gap in treatment that would need to be met—e.g., at the wastewater or drinking water treatment plant—to reduce pathogen concentrations down to an acceptable level. Raw wastewater concentrations for both enterovirus and *Cryptosporidium* were modeled based on data collected by Rose et al. (2004) in the influent to several water reclamation facilities. Both data sets are lognormally distributed. The mean and standard deviation of each distribution was used to generate sample influent concentrations (see Table 2).

2.4.1.2. Treatment performance. As in Olivieri et al. (1999), Monte Carlo (MC) simulations were used to generate individual process performances using the parametric distributions, and were subsequently summed together to obtain values for the performance of the overall treatment train. One million simulations were performed to estimate the overall distribution of AWTF pathogen removals. Although it was not tested at the demonstration facility, chlorine disinfection was incorporated into the treatment performance modeling since it can be included in such facilities at minimal cost and, because the TOC is so low, with minimal risk of chlorinated disinfection byproducts. EPA currently credits 4-log virus inactivation with CT values of 3 mg-min/L at 20 °C (EPA, 2003), and recent studies have shown greater than 6-log inactivation of MS2 virus in membrane filtered effluents at CT values as low as 2 mg-min/L (Pecson et al. submitted). Consequently, it was assumed that 6-log virus inactivation could be consistently achieved. The free chlorine PDF was therefore equivalent to that used for UV/AOP. No credit was given for the more resistant *Giardia* cysts or *Cryptosporidium* oocysts.

2.4.1.3. Quantifying exposure. Effluent concentrations of virus and *Cryptosporidium* from the overall treatment train were calculated using Equation (1). Both the influent concentration (C_{inf}) and the treatment LRV were generated with 10^6 MC simulations, resulting in a distribution of effluent concentrations with 10^6 values.

Table 2
Lognormal distribution parameters for enterovirus and *Cryptosporidium* influent concentrations (per L).

Pathogen	Lognormal Mean	Lognormal Standard Deviation
Enterovirus	3.19	1.71
Cryptosporidium	2.72	1.85

$$C_{eff} = \frac{C_{inf}}{10^{LRV}} \quad (1)$$

The resultant distributions of virus and *Cryptosporidium* concentrations were converted to a distribution of doses according to Equation (2):

$$Dose = C_{eff} * \frac{Volume\ consumed\ \ (L)}{Person - 15\ mins} \quad (2)$$

Tap water consumption ("*Volume consumed*" in Equation (2)) was modeled as a lognormal distribution with mean and standard deviation of 7.492 and 0.407 mL/day, respectively, corresponding to a median consumption of 1.8 L/person/day (Roseberry and Burmaster, 1992). This distribution has been used in other risk assessments performed in the context of drinking water (Haas and Eisenberg, 2001; Westrell, 2004). It was assumed that all of the consumed tap water originated at the DPR facility. This assumption is worst-case since DPR product water may also be blended with other source waters and diluted in the distribution system prior to consumption.

2.4.2. Dose-response analysis

The beta-Poisson dose-response function was used to model *Cryptosporidium* risk, rather than the exponential model utilized by EPA in the Long Term 2 Enhanced Surface Water (EPA, 2006a). A recent analysis of *Cryptosporidium* dose-response models by Messner and Berger (2016) indicates that the fractional Poisson, beta-Poisson, and exponential with immunity may be more appropriate for predicting the probability of *Cryptosporidium* infection given that these models estimate a higher level of risk at low doses. At the low concentrations of *Cryptosporidium* that are relevant to this study, the Beta-Poisson distribution is the most conservative and was the one selected for the analysis (see Section 3.3 for results of sensitivity analysis). The dose-response equation used is given in Equation (3):

$$P_{inf} = 1 - \left[1 + \frac{Dose}{\beta}\right]^{-\alpha} \quad (3)$$

where P_{inf} is the probability of infection, α and β are the beta-Poisson parameters (see Table 3), and dose is each of the 10^6 simulated ingested doses calculated above in Equation (2). The result of this equation is a distribution of 10^6 15-min risk values for *Cryptosporidium* infection.

To maintain consistency with the Surface Water Treatment Rule, virus infection modeling was based on a rotavirus model using a beta-Poisson dose-response curve (Regli et al., 1991). See Table 3 for the beta-Poisson parameter values used.

2.4.3. Risk characterization

To evaluate the public health protection provided by the DPR train under study, the annual risk of infection was estimated and compared to the *de minimis* goals of one infection in 10,000 persons per year and one in 1000 persons per year. The dose-response

Table 3
Summary of dose-response functions and parameters used for risk analysis.

Pathogen	Dose-Response Model	Parameters
Virus	Beta-Poisson[a]	$\alpha = 0.253$ $\beta = 0.426$
Cryptosporidium	Beta-Poisson[b]	$\alpha = 0.116$ $\beta = 0.121$

[a] Ward et al., 1986.
[b] Messner and Berger, 2016.

analysis described in Section 2.4.2 provided the distributions of risk over a 15-min sampling interval. From these, estimates of annual risk were developed by sampling a year's worth of 15-min risk values (35,040 separate events in a one year period) and aggregating them to obtain a single annual risk value using Equation (5) (Haas et al., 1999):

$$P_{annual} = 1 - \prod_{n=1}^{35,040} (1 - P_n) \quad (5)$$

where P_{annual} is a single annual probability of infection, and P_n is a single 15-min risk of infection. This procedure was repeated 100 times to create a distribution of annual risk. This methodology assumes that each 15 min of exposure results in a statistically independent risk of infection, in line with previous risk assessments (Haas and Eisenberg, 2001). An overview of the risk assessment methodology is presented in Fig. 1.

2.4.4. Modeling failures

An analysis of the mechanical reliability of the system studied showed that "critical" failures did not occur, i.e., there were no failures that impacted the pathogen removal performance of the unit processes over the 12-month testing period. Given that this was a one-year study, however, it may not provide sufficient time to witness rare failure events (i.e., those occurring less than once per year) that could impact public health. Underestimating failure rates may lead to risk estimates that do not provide a conservative depiction of public health protection. To account for this, treatment performance was modeled under both baseline (no added failures) and failure scenarios (with added failures).

Assumptions about mechanical failure rates were used to bookend their potential impact on water quality.

- Frequency of failures: in the absence of data, each unit process was assumed to have the same critical failure frequency. A critical failure rate of one per process per year was selected; this failure rate is conservative compared to rates observed at the DPR demonstration facility, in currently operating potable reuse facilities (Tng et al., 2015), and in other AWTF pilot demonstration plants (Olivieri et al., 1998).
- Magnitude of failures: all failures were assumed to drop unit treatment performance to 0 LRV (no removal). This assumption is highly conservative since this type of failure mode is uncommon. Equipment is more likely to fail progressively, e.g., the slow loss of rejection capacity through RO, or the failure of individual UV lamps are more likely to occur than a sudden, complete failure.
- Duration of failures: the duration of a failure is influenced by many factors, including the time to detect, validate, and respond to an event. As such, monitoring frequency and operational response procedures will dictate the duration that off-spec water will be discharged to consumers. Four different durations were used in modeling the impacts of failures—15 min, 60 min, 8 h, and 24 h—to provide a range of estimated risks associated with different failure response strategies.

3. Results and discussion

3.1. Process and treatment train performance results

Cumulative probability distributions characterizing the pathogen removal performance of the four critical control point processes (ozone, MF, RO, and UV/AOP) are shown in Fig. 2. A statistical summary of the unit process PDFs is provided in the Supplemental Information. The results of the distribution fitting for each process/pathogen are given in Table 4.

Process performance was calculated based on the use of surrogate parameters in compliance with existing crediting frameworks (Table 1). It is important to differentiate between the *actual* level of pathogen removal and that which can be rapidly and continuously demonstrated. In lieu of direct pathogen measurements, surrogates are frequently used to provide continuous evaluation of system performance (see Table 1). Oftentimes, these surrogates have lower sensitivity than the microbial methods, and thus cannot demonstrate the same degree of protection as a microbial challenge study. Because they can provide a rapid and continuous demonstration of performance, however, surrogates are used as the basis for the crediting of pathogen barriers. Additional information on the LRV calculation methods can be found in the Supplemental Information.

Recent studies have also evaluated DPR treatment train performance. Amoueyan et al. (2017) evaluated the performance of an alternative, non-RO based DPR treatment train consisting of UF, ozone, BAC, and UV. Comparisons with this study are challenging given the differences in the treatment trains evaluated and the use of point estimates versus distributions to assess process performance. Nevertheless, the point estimates used were in line with the performance distributions shown in Fig. 2. Soller et al. (2016) evaluated a series of DPR treatment trains, including the one evaluated here, but assumed uniform distributions of performance based on a potential range of *actual*—not *demonstrable*—performance. The goal of the current study was to evaluate demonstrable performance, thus the pathogen log removal results presented here are generally lower than the literature ranges used by Soller et al. (2016).

Ozone. Ozone inactivation of *Cryptosporidium* was modeled as an inverse Gaussian distribution (Fig. 2). All values above 6 logs were assigned a maximum of 6 logs to remain consistent with the maximum credit a single process can receive per the California groundwater replenishment regulations (CDPH, 2014). Furthermore, the authors judged that credits above 6 logs should be carefully evaluated, in particular in light of the potential influence of dispersion on performance through reactors (Olivieri et al., 2016). For virus and *Giardia*, the distribution used is a step function, as these pathogens were assigned values of either 0 or 6 LRV depending on whether credit for *Cryptosporidium* was achieved (see Table 1 for further discussion). Given the higher susceptibility of these pathogens, any CT that provided a 1-log reduction in *Cryptosporidium* (≥4 mg-min/L) was credited with 6 logs of *Giardia* and virus inactivation. In reality these organisms would be significantly inactivated in circumstances when *Cryptosporidium* is less than 1 LRV. This nuance was not included in the modeling since *Cryptosporidium* inactivation was always >1 LRV.

MF. The performance curve for MF showed consistently high removal of protozoa, but also exhibited a number of discrete jumps (Fig. 2). This is a result of the different operational scenarios that were tested and their impact on calculated LRV. This calculation includes a number of terms, including the MF system volume (EPA, 2005b). This value varies based on the number of MF modules that were utilized in the skid in service at any given time. During the course of testing, multiple MF flux rates were tested, which required modifying the number of modules in service to maintain the same effluent flow rate. The four different system volume values used directly impacted the MF LRV calculations and resulted in discrete steps in Fig. 2. Because the steps in the distribution are small, MF is still best modeled as an inverse Gaussian distribution.

RO. RO exhibited a bimodal performance distribution curve centered around LRVs of 1.3 and 2.1 logs (Fig. 2). The two RO peaks are associated with different monitoring scenarios; TOC removal served as the default surrogate of RO performance with

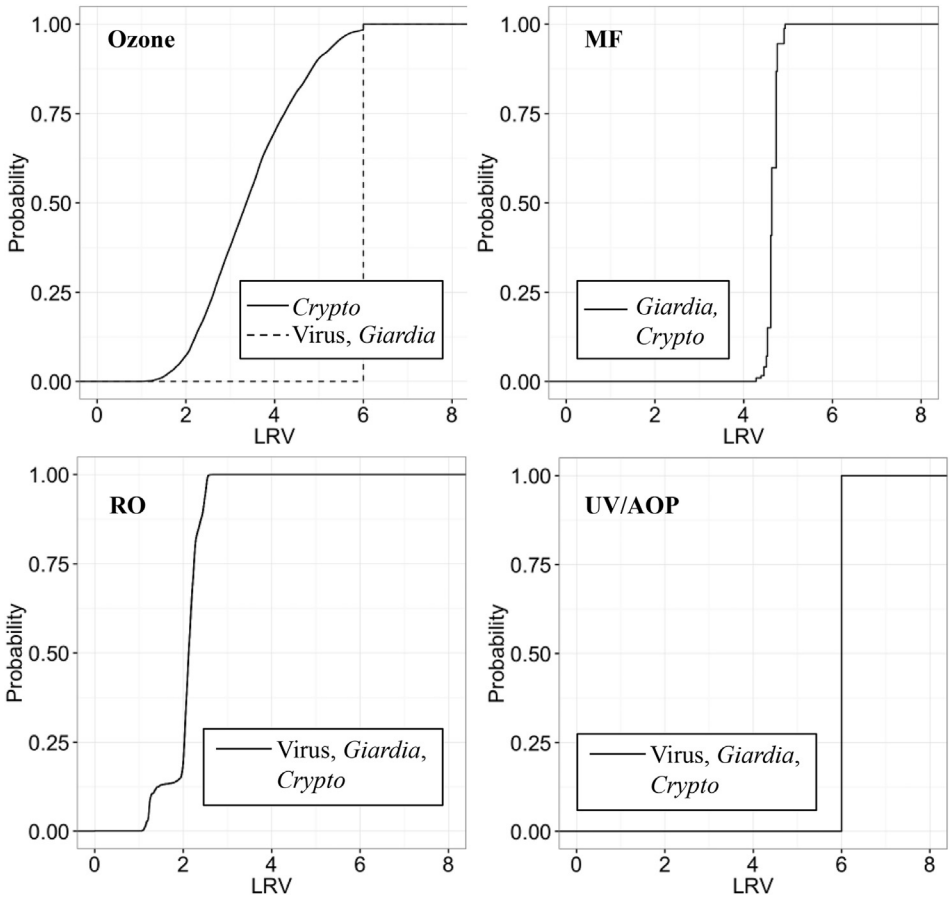

Fig. 2. Process performance probability distributions.

Table 4
Fitted distribution parameters for unit process modeling.

Process	Virus	*Cryptosporidium*	*Giardia*
Ozone	No distribution; LRV is either 6 or 0	Inverse Gaussian μ: 3.38; λ: 29.4[a]	No distribution; LRV is either 6 or 0
RO – TOC[b]	Inverse Gaussian; μ: 2.14; λ: 671.6		
RO – EC[b]	Inverse Gaussian; μ: 1.32; λ: 449.3		
MF	No LRV credit	Inverse Gaussian; μ: 4.68; λ: 12,286	
UV/AOP	No distribution; LRV is either 6 or 0		

[a] Distribution was truncated such that maximum allowed credit is 6 logs.
[b] Bimodal distribution due to EC being used as monitoring backup; 15% of distribution is EC, 85% is TOC.

electroconductivity (EC) used as a backup, redundant monitoring option. TOC was the default because it provides a more sensitive metric of RO performance, leading to higher LRVs compared to EC (2.1 vs. 1.3 log average). During periods when the TOC meter was offline, the performance was based on EC, leading to the bimodal distribution.

UV. To drive AOP reactions, UV systems are designed to provide UV doses in great excess of those needed for pathogen inactivation (EPA, 2006b; NWRI and Water Research Foundation, 2012). The design UV dose for the Demonstration Facility is on the order of 1200 mJ/cm^2, or nearly an order of magnitude greater than those needed for the inactivation of pathogens. In line with current UV/AOP crediting schemes, pathogen removal was assumed to be greater than 6 logs whenever the system met the operational requirements (Table 1 and Fig. 2). Maximum LRVs were capped at 6-logs in line with the maximum credit assignable for a single unit process (CDPH, 2014).

Free chlorine. While free chlorine disinfection was not evaluated at the demonstration facility, it has the potential to provide a significant additional barrier to viruses and, to a limited degree, *Giardia*. Recent studies have shown greater than 6-log inactivation of MS2 virus in membrane filtered effluents at CT values as low as 2 mg-min/L (Pecson et al. submitted). Thus, it is reasonable that full-scale DPR systems will benefit from an additional 6-log virus inactivation credit through this process. While the process was not included in the performance evaluation, it was modeled in the risk assessment (Section 3.2).

Treatment train performance. The performance of the treatment train—as determined from the cumulative performance of the unit processes—is shown in Fig. 3. The treatment redundancy provided by the train is evident from the fact that the processes always provided protection in excess of the minimum treatment requirements.

The median (and 5th/95th percentile values) for the log

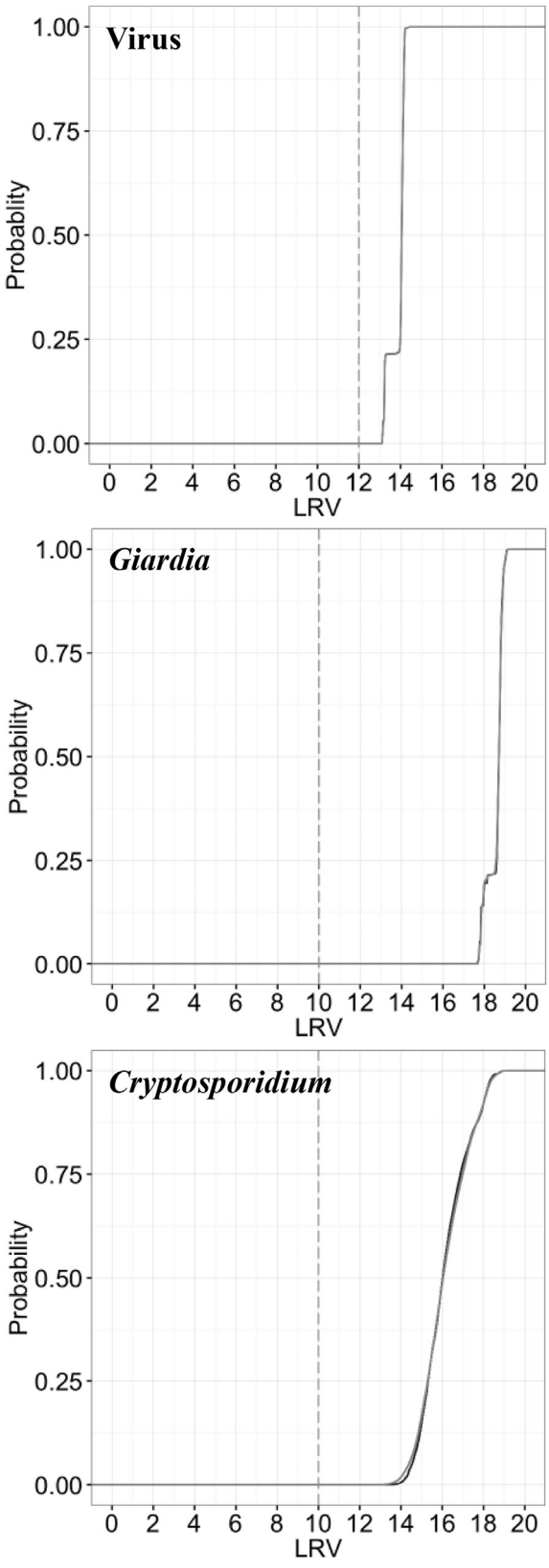

Fig. 3. Treatment train performance probability distributions. Vertical dashed lines indicate indirect potable reuse treatment targets established by California regulations. The grey and black lines represent the modeled and empirical performance of the system, respectively.

removals of each pathogen are as follows: 14.1 (13.2/14.2) for virus; 16.0 (14.5/18.2) for *Cryptosporidium*; 18.7 (17.8/18.9) for *Giardia*. During the yearlong testing there were no critical failures that led to decreased performance in pathogen reduction. This finding aligns with previous studies in both San Diego (Eisenberg et al., 1998, 2001) and Australia (Tng et al., 2015). Nevertheless, there was a distribution of performance due to the "inherent" variability of most engineered systems. This must be considered when designing treatment trains. For example, systems achieving a *mean* level of protection of exactly 12/10/10 will fail to provide 12/10/10 logs of protection half of the time, assuming they have a typical, symmetrical distribution of performance (Pecson et al., 2015). Thus, treatment redundancy above 12/10/10 would be needed if these targets need to be met with a high degree of compliance, e.g., at the 5th or 10th percentile values to ensure that 90–95% of the performance meets or exceeds the treatment minima (Olivieri et al., 2016).

Treatment train interdependence. Interdependence is a concern in engineered systems because it can lead to a "domino effect" where the failure of an upstream unit process cascades to the downstream processes (Salveson et al., 2012). To assess the interdependence of the unit processes, the performance data were compared in two ways: (1) *empirically*, by summing the performance from each unit at a given moment in time, corresponding to the real, observed total treatment train performance, and (2) *probabilistically*, by summing randomly sampled LRV values from each unit process PDF a large number of times (i.e., 1 million samples). If the unit processes were interdependent, the empirical and probabilistic curves would tend to diverge. The empirical curve would incorporate moments when multiple cascading failures co-occurred, leading to periods with low degrees of treatment. This co-occurrence would manifest itself as low degrees of performance in the lower tails of the distribution. The probabilistic curve, however, would not show the same low performance in the tail due to the unlikelihood of randomly selecting multiple treatment failures from each performance curve simultaneously. A comparison of the two curves shows a high degree of overlap, even in the lower LRV range, which supports the assumption of process independence (Fig. 3). This finding, which is in line with previous investigations (Haas and Trussell, 1998; Olivieri et al., 1999), eliminates the need for modeling that incorporates correlation between variables.

The analysis did not take into account the interdependence of processes during critical failures because none were present in the data set. However, it is expected that operational and control criteria would exist at a full-scale DPR facility that would prevent the cascading impacts of critical failures. These controls are often linked to water quality parameters, so that the detection of values outside of an acceptable range leads to a warning or shutdown of unit processes. For example, RO systems are designed to only accept influent water that meets a minimum turbidity threshold; if an upstream MF failure were to occur, the high turbidity filtrate would automatically shut off the RO to prevent damage to the membranes. Similar fail-safe controls are typically included for each unit process. Thus, constraining operation to narrow bands of performance further prevents the interdependence of unit processes.

Impact of failures on PDFs. A failure analysis was included to evaluate the impact of future potential failures on public health protection. Assessing the safety of the performance curves becomes less straightforward when failures are incorporated, since they can cause the curves to cross below the minimum goal. For example, a 1-h failure per unit process per year caused the virus PDF to drop below the 12-log goal 0.03% of the time, with a minimum LRV of 7.2. The *Cryptosporidium* PDF dropped below the 10-log goal 0.007% of the time, with a minimum LRV of 7.5. When the LRV goal is crossed,

a quantitative microbial risk assessment (QMRA) is needed to determine whether the treatment train can still meet the acceptable annual risk goal. Section 3.2 presents the results of the QMRA for all scenarios.

3.2. Risk analysis results

The performance curve from Fig. 3 was used to estimate the risk of *Cryptosporidium* infection from the consumption of treated water. The virus performance curve was modified to include an additional 6-log barrier to account for free chlorine disinfection. As discussed in Section 2.4, this analysis incorporated information on a number of parameters including (1) the distribution of pathogens entering the treatment system in the raw wastewater, (2) the distribution of pathogen removal through the AWTF, (3) the consumption of the treated effluent from the AWTF, and (4) the risk of infection associated with the ingestion of the final product water.

Risk curves were developed to model the annual risk of infection for both virus and *Cryptosporidium* (Fig. 4). These curves confirm that the redundancy included in the DPR treatment train ensures that the annual risk level remains below the 10^{-4} and 10^{-3} risk goals, even when critical failures occur. The rate and magnitude of these failures is understood to be conservative compared to those observed at the DPR demo, in currently operating potable reuse facilities, and in other AWTF pilot demonstration plants (Eisenberg et al., 2001; Olivieri et al., 2016; Tng et al., 2015). The estimated maximum (99th percentile) annual risk of infection was 2.1×10^{-5} for enterovirus and 1.1×10^{-5} for *Cryptosporidium* under the worst-case assumption of a one-day failure event per process per year. When viewed over a 100-year period, the worst-case annual risk levels are still below the target at the maximum, and orders of magnitude below the target at the median (see Table 5).

As shown, a small number of failure events per year can increase the risk in some years by several orders of magnitude (Fig. 4). Despite the fact that such events are rare, even brief failure events (i.e., 15–60 min in duration) can have a significant impact on annual risk, as has been previously observed (Smeets, 2010). Nevertheless, the DPR treatment train evaluated in this study provided sufficient treatment redundancy to maintain the estimated risk from both virus and *Cryptosporidium* below the goals of 10^{-4} and 10^{-3} infections per person per year even when failures occurred.

3.3. Discussion

The analysis shows that the DPR treatment train evaluated at this demo facility can meet widely accepted public health protection goals, including both $<10^{-4}$ and $<10^{-3}$ infections per person per year (EPA, 1989; Natural Resource Management Ministerial Council, 2008; World Health Organization, 1996). This finding supports the conclusions from a recent effort by an expert panel for the California State Water Resources Control Board to assess the relative risks of DPR (Olivieri et al., 2016). The treatment train is able to protect public health even in the event of critical unit process failures because it provides a high degree of redundancy in pathogen removal. This redundancy buffers out the impact of failures that reduce unit process performance, and prevents off-spec water from ever leaving the facility. One of the principal benefits of a failure prevention strategy based on redundancy is the breadth of failures it can protect against, from failures in treatment, to monitoring, to source control, and even human (operational) error. The recent California Expert Panel also acknowledged these benefits, and concluded that DPR treatment trains should consist of multiple, independent barriers that provide pathogen control beyond the minimum threshold to protect public health (Olivieri et al., 2016).

The treatment train demonstrated a high degree of treatment redundancy beyond the minimum 12/10/10 LRVs that are required for groundwater recharge and surface water augmentation in California (Fig. 3). It should not be immediately construed that DPR provides a significantly greater degree of protection than IPR, however, based on this analysis alone. The environmental buffer provides numerous benefits, including a substantial amount of protection against pathogens (Amoueyan et al., 2017; NRC, 1998, 2012; Trussell et al., 2015, 2017; Yates et al., 1985). Because these benefits are difficult to quantify, however, the protection provided

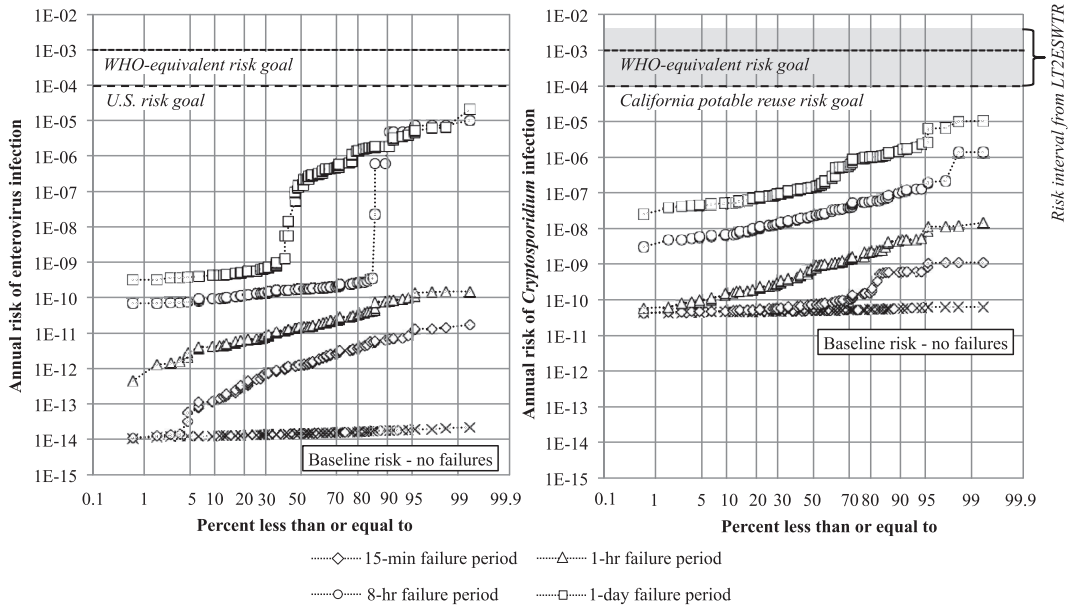

Fig. 4. Results of risk simulation under baseline conditions (no failures) and with up to 1 day of failure per process per year for enterovirus (left) and *Cryptosporidium* (right). Risk targets include U.S. risk goal of 10^{-4} (virus), WHO risk goal of 10^{-3} (equivalent to 10^{-6} DALYs per person per year), California potable reuse risk goal of 10^{-4} (*Cryptosporidium*), and the range of risks associated with compliance with EPA Long Term 2 Enhanced Surface Water Treatment Rule (LT2ESWTR) for *Cryptosporidium*.

Table 5
Summary statistics of annual risk of infection for *Cryptosporidium* and enterovirus under baseline conditions (i.e., no failures) and worst-case conditions (i.e., one-day failure event per process per year).

	Annual Risk of Infection (infections/person/year)					
	Baseline			Worst Case		
	Median	95th percentile	99th percentile	Median	95th percentile	99th percentile
Cryptosporidium	4.9×10^{-11}	5.6×10^{-11}	6.1×10^{-11}	1.4×10^{-7}	2.4×10^{-6}	1.1×10^{-5}
Virus	1.5×10^{-14}	1.9×10^{-14}	2.2×10^{-14}	1.4×10^{-7}	3.8×10^{-6}	2.1×10^{-5}

by them often goes uncredited. Quantifying pathogen removal and inactivation through the environment—such as wetlands, reservoirs, and aquifers—will likely show significant additional protection in IPR settings beyond the explicitly credited treatment at the AWTF and, where applicable, at the downstream drinking water treatment facility.

Failure Assumptions. It was assumed that a maximum of one critical failure per year per process would occur. Based on the demonstration testing, this assumption is conservative given that no critical failures were observed for any of the unit processes over the testing period. This assumed rate of failure is also conservative compared to mechanical reliability values in the literature. A recent Australian study developed mechanical reliability data from several operational potable reuse facilities to model advanced water treatment (AWT) performance, and estimated that the modeled AWT plant would experience 427 failure events over 10 years (Tng et al., 2015). Of these, only 5 percent would have an adverse impact on water quality. This failure rate translates to approximately 2 critical failures among three key unit processes in the treatment train per year. On this same basis, each scenario tested in the current work assumed four failures among four key unit processes per year. Further, Tng et al. (2015) concluded that with effective maintenance strategies, the probability of water quality failures could be as low as one event (total) per year. These results are in line with observations of earlier demonstration scale studies performed at the Aqua II and III plants over 4.5 years in San Diego (Olivieri et al., 1998).

To date, few studies have evaluated the impact of mechanical failures on the performance of potable reuse systems. To improve the modeling of AWT performance, additional data should be collected on the magnitude, frequency and duration of critical failures at full-scale facilities. Future QMRA efforts should incorporate these data as they become available to refine and potentially obtain more realistic estimates of annual risk.

Sensitivity Analyses. Despite the fact that an unprecedented DPR performance data set was utilized, several assumptions were made to quantify the annual risk of infection. The general approach taken was to select conservative values whenever assumptions were required. Table 6 lists the assumptions included in the analysis, many of which utilized the most conservative values possible, e.g., consumption of 100% DPR water, complete failures of unit processes, etc. Sensitivity analyses were used to assess the impact of two key assumptions whose impact on the overall risk findings was less straightforward, namely, daily water consumption and selection of dose-response curves.

The first sensitivity analysis assessed the impact of assumptions on daily per capita water consumption. Previous QMRAs have used both point estimates and distributions. Four approaches were compared: (1) distribution from Roseberry and Burmaster (1992), (2) distribution from EPA exposure factors handbook (EPA, 2011), (3) constant value of 1 L, as used by the California State Expert Panel (Olivieri et al., 2016), and (4) constant value of 2.5 L, as used by Soller et al. (2016), which is the 90th percentile of the distribution from EPA (2011). The results of the analysis are presented in Table 7,

Table 6
Conservative assumptions included in QMRA.

Parameter	Description
Level of Treatment	Only evaluated LRVs associated with AWTF; did not include potential credits from upstream wastewater treatment plant or downstream drinking water treatment plant
DPR Contribution to Water Supply	Assume that exposed populations are consuming 100% DPR water, i.e., no dilution or mixing with other treated waters
Per Capita Water Consumption	Assumed distribution of tap water consumption based on Roseberry and Burmaster (1992)
Dose-Response	Utilized *Cryptosporidium* dose-response curve that provides higher estimate of risk at low levels of exposure. Utilized dose-response parameters for rotavirus, which results in higher risk estimates for enterovirus
Failure Rate	Assume one critical failure per unit process per year; rate is higher than that observed at the DPR Demo, at other potable reuse facilities, and previous pilot testing
Failure Magnitude	Assume failure leads to LRV credit of 0; most unit processes do not fail suddenly and completely, but progressively decrease in performance

Table 7
Sensitivity analysis of drinking water consumption on annual *Cryptosporidium* risk estimates.

	Median	95th percentile	Maximum
Roseberry and Burmaster (1992)	4.9×10^{-11}	5.6×10^{-11}	6.1×10^{-11}
EPA (2011)	2.8×10^{-11}	3.2×10^{-11}	3.5×10^{-11}
1 L	2.6×10^{-11}	3.0×10^{-11}	3.2×10^{-11}
2.5 L	6.5×10^{-11}	7.3×10^{-11}	7.7×10^{-11}

which summarizes the median and 95th percentile annual risk of infection by *Cryptosporidium* for each method (with no failures). As shown, the Roseberry and Burmaster distribution results in higher risk than the EPA (2011) distribution. The highest risk estimates come from the constant volume assumption of 2.5 L. The authors are comfortable that all of these risk estimates fall well within the overall error in the estimate. The Roseberry and Burmaster distribution was ultimately selected because the preference was to use distributions rather than just set upper bounds.

A sensitivity analysis was also used to assess the impact of different *Cryptosporidium* dose-response functions. Three options were compared: (1) beta-Poisson with parameters from Messner and Berger (2016), (2) fractional Poisson with parameters from Messner and Berger (2016), and (3) exponential with parameters from EPA (2006a,b). The results are summarized in Table 8. As shown, the beta-Poisson dose-response function used in this analysis results in a more conservative estimate of annual risk. The analysis did not incorporate uncertainty in the dose-response parameters themselves.

Considerations for full-scale facilities. This analysis focused on the protection provided by the AWPF in San Diego, but a future full-scale system will provide additional elements to further enhance

Table 8
Sensitivity analysis of dose-response function on annual risk estimates.

	Parameter Values	Median	95th percentile	Maximum
Beta-Poisson[a]	$\alpha = 0.116$ $\beta = 0.121$	4.9×10^{-11}	5.6×10^{-11}	6.1×10^{-11}
Fractional Poisson[a]	$P = 0.737$	3.9×10^{-11}	4.4×10^{-11}	5.0×10^{-11}
Exponential[b]	$r = 0.1$	8.2×10^{-12}	9.2×10^{-12}	1.1×10^{-11}

[a] Messner and Berger (2016).
[b] EPA (2006a,b) – gives range of 0.04–0.16.

system reliability. These include contaminant reduction provided by source control, physical and biological treatment in the water recycling facility providing the source water to the AWPF, and any additional treatment provided subsequent to the AWPF, such as a downstream drinking water treatment plant. Blending of DPR waters with other source waters may also reduce contaminant concentrations. All of these elements will provide additional barriers to contaminants—both microbiological and chemical—that further reduce and manage potential risks.

The addition of free chlorine to the AOP effluent could serve as an additional disinfection step while providing a residual for the control of pathogens and biofilms in the distribution system. Including free chlorine in the risk analysis demonstrated the impressive resistance of the system to failure, and highlights the need for future studies to quantify and compare the degree of redundancy needed to achieve public health protection.

Nevertheless, the design of treatment redundancy may not be driven by considerations of reliability alone. Redundancy also provides operational flexibility, since a failure in one process does not necessarily require an immediate system shut-down or response action. Redundancy provides a margin of safety so that DPR operations staff are not balancing on the edge of compliance, poised to divert off-spec water or shut down the facility at the first sign of a unit process failure. While this risk analysis was *post hoc*, undertaken after the data collection period, it is possible to develop monitoring and control systems that display and integrate unit process and overall treatment train performance in real-time. Such a system could provide a simple and straightforward indication of system status with different symbols corresponding to different levels of system performance. For example, green, yellow, and red lights indicating performance in excess of, approaching, and below minimum removal requirements could provide a simple, unequivocal method to track performance and protect against failures.

4. Conclusions

- The DPR treatment train demonstrated reliable pathogen control that met or exceeded the risk goals used by the U.S., WHO, Australia, and other countries. By providing protection equal to or greater than conventional drinking water sources, DPR should be considered a viable alternative to supplement existing water supplies.
- Treatment redundancy provides operational flexibility, allowing for more time to respond to excursions or failures—in treatment, monitoring, operations—without jeopardizing public health protection. In this train, protection from pathogens was maintained even with a failure rate of up to 1 day of failure per unit process per year.
- The amount of redundancy needed to maintain public health protection from pathogens is related to the frequency, magnitude, and duration of failures. More work is needed to characterize the nature of failures that actually occur at full-scale facilities; this information will aid in quantifying the minimum level of redundancy needed for DPR.
- Pathogen removal crediting is frequently based on the use of conservative surrogate parameters that can be continuously measured. Because these measurements often underestimate the true performance of unit processes, the actual degree of pathogen control may be considerably higher than what can be easily demonstrated. Efforts to better quantify unit process performance should be pursued to improve DPR design and operation.
- Situating the AWPF treatment train within a larger context of reliability features—e.g., robustness, source control, wastewater treatment, effective operations—can offer a reliable path to safe DPR projects.

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Appendix A. Supplementary data

Supplementary data related to this article can be found at http://dx.doi.org/10.1016/j.watres.2017.06.014.

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