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Citation for the original published paper (version of record):
Bergion, V., Lindhe, A., Sokolova, E. et al (2021). Accounting for Unexpected Risk Events in Drinking Water Systems. Exposure and Health, 13(1): 15-31.
http://dx.doi.org/10.1007/s12403-020-00359-4

Exposure and Health
https://doi.org/10.1007/s12403-020-00359-4

ORIGINAL PAPER

Accounting for Unexpected Risk Events in Drinking Water Systems

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Received: 16 August 2019 / Revised: 3 February 2020 / Accepted: 9 May 2020

Abstract

Unexpected risk events in drinking water systems, such as heavy rain or manure spill accidents, can cause waterborne outbreaks of gastrointestinal disease. Using a scenario-based approach, these unexpected risk events were included in a risk-based decision model aimed at evaluating risk reduction alternatives. The decision model combined quantitative microbial risk assessment and cost–benefit analysis and investigated four risk reduction alternatives. Two drinking water systems were compared using the same set of risk reduction alternatives to illustrate the effect of unexpected risk events. The first drinking water system had a high pathogen base load and a high pathogen $\log_{10}$ reduction in the treatment plant, whereas the second drinking water system had a low pathogen base load and a low pathogen Log_{10} reduction in the treatment plant. Four risk reduction alternatives were evaluated on their social profitability: (A1) installation of pumps and back-up power supply, to remove combined sewer overflows; (A2) installation of UV treatment in the drinking water treatment plant; (A3) connection of 25% of the OWTSs in the catchment area to the WWTP; and (A4) a combination of A1–A3. Including the unexpected risk events changed the probability of a positive net present value for the analysed alternatives in the decision model and the alternative that is likely to have the highest net present value. The magnitude of the effect of unexpected risk events is dependent on the local preconditions in the drinking water system. For the first drinking water system, the unexpected risk events increase risk to a lesser extent compared to the second drinking water system. The main conclusion was that it is important to include unexpected risk events in decision models for evaluating microbial risk reduction, especially in a drinking water system with a low base load and a low pathogen $\log_{10}$ reduction in the drinking water treatment plant.

Keywords Decision support · Quantitative microbial risk assessment (QMRA) · Cost–benefit analysis (CBA) · Dose–response · Risk management · Water quality modelling

Introduction

Contaminated drinking water can cause waterborne infections (Guzman-Herrador et al. 2015) and result in a considerable cost to society due to health effects and related monetary effects (Lindberg et al. 2011). Microbial risks in drinking water systems are mainly related to gastrointestinal disease resulting from infection by various pathogens (e.g. *Campylobacter*, *Salmonella*, EHEC, norovirus, rotavirus, *Cryptosporidium* and *Giardia*) (WHO 2016). Microbial risks in drinking water systems can be divided into two main components (Assmuth et al. 2016). Firstly, a base microbial risk level caused by pathogen sources with a predictable contribution and a continuous or reoccurring temporal distribution (wastewater discharge, annual manure spreading, etc.). Secondly, microbial risks related to unexpected risk events occurring with an uneven, less predictable temporal distribution and with typically short and varying durations (spill accidents with faecal matter containing pathogens, extreme weather events, combined sewer overflows, technical system failures, etc.).

To describe the total risk, a set of events must be identified to describe possible scenarios that may occur and cause problems. In Fig. 1, the base load (UR_0) represents the base risk level that occurs on an annual basis. UR_1, UR_2…UR_n represent unexpected risk events occurring irregularly and occasionally. These unexpected risk events are part of the total risk in a drinking water system. In drinking water

Electronic supplementary material The online version of this article (https://doi.org/10.1007/s12403-020-00359-4) contains supplementary material, which is available to authorized users.

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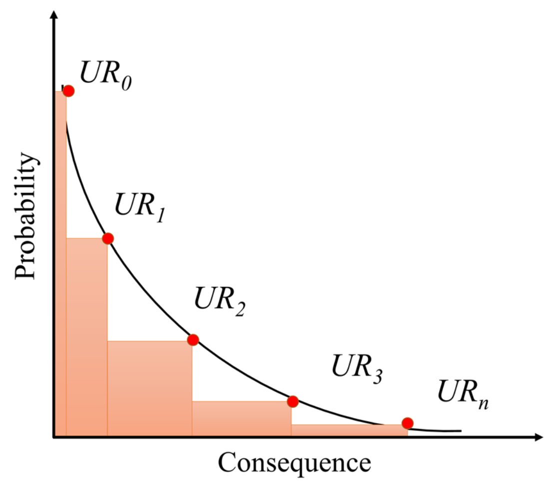

Fig. 1 Example of a risk graph illustrating the total risk from regularly occurring risk events and unexpected risk events occurring irregularly and occasionally

distribution systems, unexpected risk events have been investigated to a certain extent (e.g. Viñas et al. 2018), but there has been less focus on the drinking water catchments and the adoption of a holistic approach, which would include all parts of a drinking water system. The use of a risk graph to illustrate the total risk has been described, including examples such as nuclear power and dam failures (Ale et al. 2015), but not in this type of drinking water setting. In the risk graph in Fig. 1, the area under the curve illustrates the total risk. Risk reduction alternatives aim to reduce the total risk, i.e. the graph area, either by reducing the base load, reducing the unexpected risk events, or reducing both. The graph shape varies and is dependent on the types of unexpected risks in the system.

The total microbial risk level in drinking water systems is thus affected by unexpected risk events. Despite this, drinking water producers in Sweden commonly perform risk analysis based solely on the average base load (UR_0) or adapt a worst-case scenario with the highest risk (UR_n) to serve as a dimensioning event. In the first case, the risk level may be underestimated, while in the second case the risk level may be overestimated. To supply safe water to drinking water consumers, microbial risks in drinking water systems need to be managed and, depending on the system, risk reduction measures may need to be implemented. However, implementing these measures is costly and available resources must be used efficiently. It may thus be of great importance to consider unexpected risk events to provide holistic decision support.

Earlier studies have set up models for evaluating the microbial risks in drinking water systems (e.g. Bartram et al. 2009; Bergion et al. 2017; Schijven et al. 2011, 2013, 2015) and related economic effects (e.g. Baffoe-Bonnie et al. 2008; Bergion et al. 2018b; Juntunen et al. 2017). In general, it can be concluded that unexpected risk events have a short duration, hence the importance of analysing the risk using an appropriate time resolution. In addition, unexpected risk events related to climate change are likely to increase in the future, highlighting the importance of accounting for future changes in risk and decision models (Schijven et al. 2013). Accounting for both the base risk and unexpected risk events has been identified as important for integrated water management on a qualitative level (Assmuth et al. 2016), although to our knowledge there is no detailed quantitative description available of how to perform this. On the other hand, looking only at the risk assessment and omitting any decision analysis, Westrell et al. (2003) reported that the microbial base risk caused the majority of annual infections. Risk management will be dependent on thorough identification of relevant events to be included. Furthermore, this inclusion of unexpected risk events facilitates analyses aimed at investigating whether dimensioning risks are part of the base load or part of the unexpected risk events.

The main contribution and novelty of this study was to enable inclusion of unexpected risk events in the decision analysis for prioritising microbial risk reduction in drinking water systems using a scenario-based approach. An existing risk-based decision model was used as a starting point for this work (Bergion et al. 2018b). To achieve the aim, further features were added to the decision model:

- The risk was calculated on a daily basis, to take account of variation in the daily risk level and the occurrence of unexpected risk events.
- Hydrological modelling was added to the already applied hydrodynamic model to simulate the fate and transport of pathogens in the catchment.
- Unexpected risk events were included using a scenario-based approach.

To illustrate the expanded decision model, it was applied to two drinking water systems with distinctly different characteristics. The comparison facilitated the investigation of unexpected risk events and their impact on drinking water systems with different preconditions.

Methods

The risk-based decision model (Bergion et al. 2018b) is based on quantitative microbial risk assessment (QMRA), including source characterisation, hydrological modelling, hydrodynamic modelling, groundwater modelling and dose–response models. Hydrological modelling describes the processes within the catchment and contribution from land sources to the lake, hydrodynamic modelling estimates the pathogen fate and transport within the lake, and groundwater modelling estimates the pathogen removal in the artificial groundwater recharge. The hydrodynamic modelling and the groundwater modelling were used to estimate the $\log_{10}$ pathogen removal in the lake and in the artificial groundwater recharge, respectively. The decision model is also based on cost–benefit analysis (CBA) to enable evaluation of risk reduction alternatives in order to determine the alternative that is most profitable for society. In this study, risks were calculated using an updated version of the decision model (Bergion et al. 2018b) and the risk was expressed in terms of probability of infection, lost quality-adjusted life years (QALYs) and the number of infections. The risk cost was calculated using a unit value per lost QALY and a unit value per infection. Details on the decision model and related assumptions can be found in (Bergion et al. 2018b) and in the supplementary material, Table S1. A schematic illustration of the decision model is presented in Fig. 2.

Two drinking water systems were investigated. For the first system, settings for the Vomb drinking water system (Vomb DWS) were used, as described in Bergion et al. (2018b). The second system (Alt. DWS) was based on the Vomb DWS, although the artificial groundwater recharge was replaced by a treatment step resulting in much lower pathogen removal. Additionally, the Alternative Lake Vomb was assumed to provide less pathogen removal compared to Lake Vomb. It was also assumed that the base load for the alternative system was 1% of the base load of the Vomb DWS. The Alt. DWS was set up to be representative for many drinking water systems in Sweden in terms of the treatment steps and the resulting $\log_{10}$ removal of pathogens.

Microbial risks included in the base load (UR_0) were wastewater discharges and combined sewer overflows (CSOs) from on-site wastewater treatment systems (OWTS) and wastewater treatment plants (WWTP), manure application on farmland and grazing farm animals. The OWTSs and WWTPs were added as point sources to the tributary discharges into the lake. The manure application and grazing farm animals were added using the SWAT (Soil and Water Assessment Tool) hydrological model set up for the catchment. Note that the wild animals were not accounted for in the model. Also included were unexpected risks from a precipitation event with a 10-year return period (UR_1), emergency CSOs (ECSO) (UR_2) and an accident resulting in a large manure discharge directly into the lake (UR_3).

The decision model was illustrated by investigating four risk reduction alternatives: (A1) installation of pumps and a back-up power supply to remove CSOs and ECSOs; (A2) installation of UV treatment in the drinking water treatment plant (DWTP); (A3) connection of 25% of the OWTSs in the catchment to the WWTP; and (A4) a combination of A1–A3. The risk reduction alternatives were compared to a reference alternative (A0), where no risk reduction measures were implemented.

By defining uncertainty distributions for the input data, Monte Carlo simulations (@risk version 7.6.0) could be used to also present uncertainties in the results. The risk model, including the added model features, is presented below.

Quantitative Microbial Risk Assessment

Source Characterisation

The daily average pathogen (p) concentration in OWTSs ($c_{\mathrm{OWTS},i,p}$) (#/L) contributing to the pathogen count in tributary i was calculated as in Bergion et al. (2018b) using epidemiological statistics. Details can be found in the supplementary material.

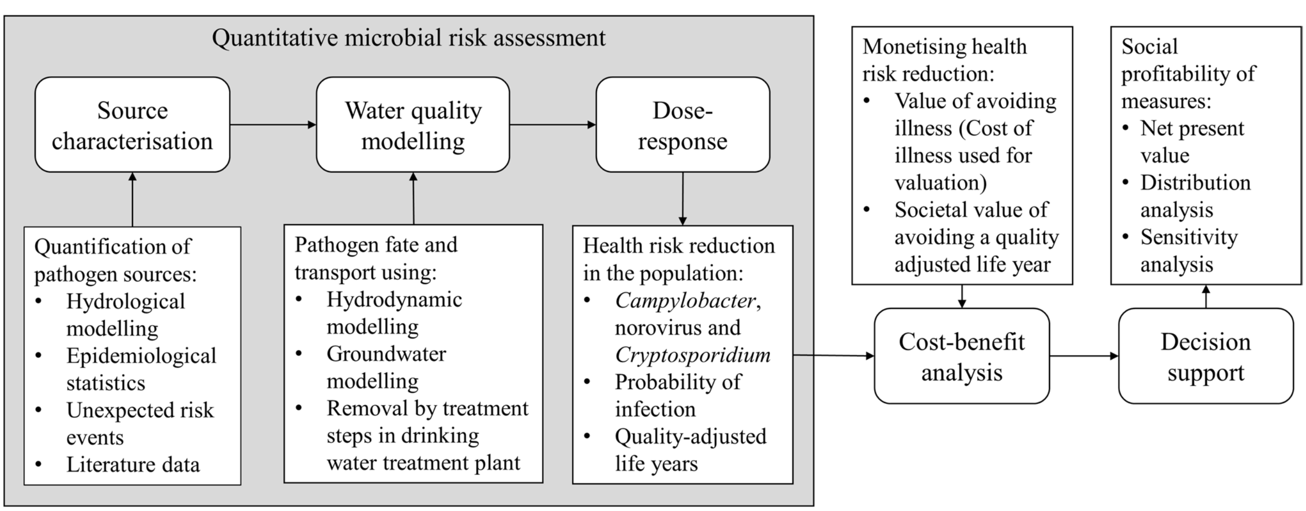

Fig. 2 Schematic illustration of the decision model and how different methods are connected

The contribution of WWTP discharge ($c_{\mathrm{WWTP},i,p}$) (#/L) to the pathogen concentration in tributary i was calculated as:

$$c_{\mathrm{WWTS},i,p} = \frac{c_{\mathrm{WW},p} \cdot 10^{-R_{\mathrm{WWTP},p}} \cdot Q_{\mathrm{WWTP}}}{Q_i + Q_{\mathrm{WWTP}}} \tag{1}$$

where $c_{\mathrm{ww},p}$ (#/L) was the literature value of pathogen (p) concentration in wastewater, $R_{\mathrm{WWTP},p}$ ($\log_{10}$ removal) was the pathogen removal in the WWTP reported in the literature (Supplementary Table S1), Q_i was the average daily flow in tributary i, and Q_{WWTP} (L/Day) was the average daily wastewater production. The $c_{\mathrm{ww},p}$ was approximated to a log normal distribution with μ/σ LN(17200/13200) for *Campylobacter* (Stampi et al. 1993) and LN(3947233/190.7) for norovirus, respectively. For *Cryptosporidium*, the $c_{\mathrm{ww},p}$ was set at a point value of $10^{3.4}$, estimated by the authors based on observed oocyst concentrations during the Östersund waterborne outbreak in 2010 (PHAS 2011).

Based on Ottoson et al. (2006), the pathogen removal in WWTP was included using uniform distribution with min/max of 2/3, 0.5/1.5 and 0.5/2.5 for *Campylobacter,* norovirus and *Cryptosporidium*, respectively.

The contribution by CSOs ($c_{\mathrm{CSO},i,p}$) (#/L) to the tributary pathogen concentration was estimated using the same literature values as for WWTP discharge, though it was assumed the CSOs would not undergo any treatment:

$$c_{\mathrm{CSO},i,p} = \frac{c_{\mathrm{WW},p} \cdot Q_{\mathrm{CSO}}}{Q_i + Q_{\mathrm{CSO}}} \tag{2}$$

where Q_{CSO} (L/Day) was the volume of wastewater discharged from the CSO. Based on CSO frequencies and volumes for the last five years, it was assumed that one CSO with a volume of 139,500 L occurred each year. The timing of the CSO was assumed to be during the summer months, coinciding with the grazing period but not with manure application. This was assumed since standard practice is to avoid manure application in temporal proximity to heavy rain due to the loss of nutrients and the fact that the ground cannot cope with heavy vehicles.

Hydrological Modelling

The contribution of grazing activities and manure application (note that only *Cryptosporidium* was considered for these two pathogen sources) to the pathogen concentrations in the tributaries was estimated using the Soil and Water Assessment Tool (SWAT) (Nietsch et al. 2011), which was set up for the Vomb catchment. The model included transport from land sources to water and die-off processes during land transport and in the watercourse. The number of farm animals, dairy cows (5279), calves (6967), heifers and steers 1–2 years (7416) and heifers > 2 years (3257), was based on reported statistics for the municipality of Sjöbo for 2016 (Swedish Board of Agriculture 2019). The amount of manure produced during indoor periods, and later applied to farmland during manure application, was calculated in the manner presented in (Bergion et al. 2017). 1591, 308, 411 and 411 kg manure per hectare was applied to fields on 15 April, June, August and October each year, where proportions were based on (Statistics Sweden 2012). It was assumed that the grazing animals (excluding calves) grazed for 153 days, starting on 1 May and the daily contribution from grazing was 88 kg per hectare. Based on literature values for herd prevalence and excretion, the number of *Cryptosporidium* oocysts in manure was estimated to 4400 (oocysts/g) (Sokolova et al. 2018, Table S2).

The SWAT model was calibrated and validated based on the observed monthly average flow for the Eggelstad gauging station (SMHI 2018). Calibration was performed for 2009–2013, and validation for 2014–2017. The Nash Sutcliffe Efficiency (NSE) index was used to determine the fit between simulated and observed water flow. The SWAT-CUP software was used, applying the General Likelihood Uncertainty Estimation (GLUE) approach, simulating 1000 iterations (Abbaspour 2013). Calibration and validation of the water flow resulted in an NSE index of 0.75 and 0.78, respectively. These are considered to be very good results, since the NSE index can range from $-\infty$ to $+1$, where a value above 0.5 is considered good, and a value above 0.75 is considered very good (Moriasi et al. 2007). Final parameter values are presented in supplementary material, Table S3. Calibration and validation of the pathogen concentrations were not possible as no observations were available.

SWAT model results for the grazing months May–September during the simulation period 2009–2017 were used as input for the risk-based decision model. Daily *Cryptosporidium* oocyst concentrations were randomly resampled from the SWAT model output to represent the variations in *Cryptosporidium* oocyst concentrations due to the variations in hydrometeorological conditions during this period.

The daily maximum *Cryptosporidium* oocyst concentrations in the tributaries ($c_{\mathrm{Manu},i,p}$) (#/L) from April to October simulated in the SWAT model were used as input for manure application. These maximum concentrations were assumed to last for one week after the manure application day. No stochastic input for manure application was used in the Monte Carlo simulations.

The total pathogen (p) concentrations ($c_{\mathrm{TOT},i,p,S}$) in the tributaries (i) for each scenario (S) were calculated as:

$$c_{\mathrm{TOT},i,p,S} = c_{\mathrm{OWTS},i,p} + c_{\mathrm{WWTP},i,p} + c_{\mathrm{CSO},i,p} + c_{\mathrm{Graz},i,p} + c_{\mathrm{Manu},i,p} + c_{\mathrm{UR}} \tag{3}$$

where S corresponded to the different scenarios, i.e. possible combinations of considered events (presented further in Fig. 3. below), and c_{UR} was the contribution from

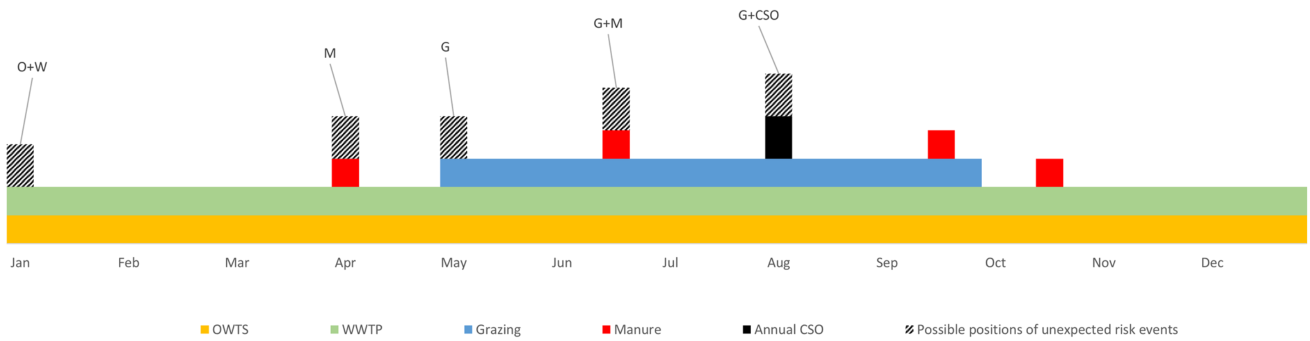

Fig. 3 Schematic illustration of the variation in base pathogen load (solid areas) and the possible positions of unexpected risk events (striped areas). Note that the height of the bars is not to scale. O+W (OWTS and WWTP, included in all scenarios), M (manure), G (grazing), G+M (grazing and manure), and G+CSO (grazing and CSO) represent the five different scenarios of when unexpected risk events could occur in relation to the five different base load levels. Note that the possible positions O+W, M, G, G+M and G+CSO are only examples, and that the actual event can take place on any day when the same base load conditions for each scenario exist

unexpected risk events as explained in the section *Scenario-based approach for including unexpected risk events* below.

Pathogen Removal Based on Hydrodynamic and Groundwater Modelling

The daily drinking water pathogen concentration ($c_{\mathrm{DW},p,S}$) was calculated as:

$$c_{\mathrm{DW},p,S} = \left(c_{\mathrm{TOT,Bo},p,S} \cdot 10^{-R_{\mathrm{LAKE,Bo},p}} + c_{\mathrm{TOT,To},p,S} \cdot 10^{-R_{\mathrm{LAKE,To},p}} + c_{\mathrm{TOT},Bj,p,S} \cdot 10^{-R_{\mathrm{LAKE},Bj,p}}\right) \cdot 10^{-(R_{\mathrm{DWTP}})} \tag{4}$$

where R_{LAKE} was the $\log_{10}$ removal during transport in Lake Vomb from the tributary mouth to the raw water intake for Borstbäcken (Bo), Torpsbäcken (To) and Björkaån (Bj), respectively, R_{DWTP} was the $\log_{10}$ removal in the DWTP plant. The R_{LAKE} was based on Bergion et al. (2018b). The removal in the DWTP was calculated as:

$$R_{\mathrm{DWTP}} = R_{\mathrm{StepI}} + R_{\mathrm{StepII}} + R_{\mathrm{StepIII}} \tag{5}$$

where R_{StepI}, R_{StepII} and R_{StepIII} were the combinations of treatment steps in the specific risk reduction alternative. The $\log_{10}$ removal in the treatment steps was estimated using values reported in the literature (see Table 1). For norovirus, the $\log_{10}$ removal in the artificial groundwater recharge (AGR) was estimated using a groundwater virus transport model (including retention time, attachment of pathogens to soil and pathogen die-off) (Åström et al. 2016). The possible combinations of treatment steps and their removal are reported in Table 1.

Dose–Response Model

The dose–response models used were the same as in Bergion et al. (2018b). The daily probability of infection per person ($P_{\mathrm{inf},p,S}$) (no unit) was calculated using a dose–response model, adapting the Exact Beta Poisson distribution, represented using an exponential function with a beta distribution in the exponent:

$$P_{\mathrm{inf},p,S} = e^{-h_p \cdot D_{p,S}} \tag{6}$$

where S was the scenario (refers to the different scenarios in Fig. 3 below) for that specific day, h_p (no unit) was the infectivity (represented using a beta distribution with α and β for each pathogen), $D_{p,}$ was the pathogen dose for the scenario (S). Values for α/β were 0.024/0.011 (Teunis et al. 2005), 0.04/0.055 (Teunis et al. 2008) and 0.115/0.176 (Teunis et al. 2002) for *Campylobacter*, norovirus and *Cryptosporidium*, respectively.

The annual probability of infection ($P_{\mathrm{inf,ann},p,g}$) (no unit) for each pathogen (p) was calculated for each risk reduction alternative ($g = A0, \ldots A4$) as (WHO 2016):

$$P_{\mathrm{inf},ann,p,g} = 1 - \prod_{1}^{s_1}\left(1 - P_{\mathrm{inf},p,g,S_1}\right) \cdot \prod_{1}^{s_2}\left(1 - P_{\mathrm{inf},p,g,S_2}\right) \ldots \cdot \prod_{1}^{s_i}\left(1 - P_{\mathrm{inf},p,g,S_i}\right) \tag{7}$$

where s_i (days) represents the duration of the scenario (S_i) with the specific daily probability of infection ($P_{\mathrm{inf},p,g,Si}$). Note that the durations ($s_1 + s_2 + \ldots + s_i$) should total 365 days. The annual probability of infection was thus calculated using a separate P_{inf} value for each day of the year.

Table 1 Mean log10 removal for the treatment steps in the drinking water treatment plant for each of the risk reduction alternatives A0–A4

	Step 1[a] (R_{StepI})[b]	Step 2[a] (R_{StepII})[b]	Step 3[a] (R_{StepIII})[b]	Total (R_{DWTP})[c]	Risk reduction
Vomb DWS					
A0	AGR(8.5/7/8.5)	RSF(0.5/0.25/0.5)	–	(9/7.25/9)	–
A1	AGR	RSF	–	(9/7.25/9)	Remove CSO
A2	AGR	RSF	UV(5.3/4.24/3)	(14.3/11.49/12)	Install UV
A3	AGR	RSF	–	(9/7.25/9)	Remove OWTS
A4	AGR	RSF	UV	(14.3/11.49/12)	Combine (A1–A3)
Alt. DWS					
A0	CONV(4/3/5)	–	–	(4/3/5)	–
A1	CONV	–	–	(4/3/5)	Remove CSO
A2	CONV	UV	–	(9.3/7.24/8)	Install UV
A3	CONV	–	–	(4/3/5)	Remove OWTS
A4	CONV	UV	–	(9.3/7.24/8)	Combine (A1–A3)

[a]AGR = Artificial groundwater recharge, RSF = Rapid Sand Filtration, UV = UV disinfection, CONV = Conventional treatment consisting of coagulation, flocculation, floc removal, including sand filtration

[b]Mean $\log_{10}$ removal (*Campylobacter*/Norovirus/*Cryptosporidium*) for the treatment steps. For AGR for norovirus, mean values were based on groundwater modelling of the artificial infiltration system (Bergion et al. 2018b), and for *Campylobacter* and *Cryptosporidium,* estimates of removal per metre in the saturated zone were used. The values were assumed to be normally distributed (μ, σ): *Campylobacter* (8.5, 1.5), norovirus (7, 1), and *Cryptosporidium* (8.5, 1.5). CONV was an estimate for slow sand filtration with approximately 80% of maximum removal reported by Smeets et al. (2006), and set at 4, 3 and 5 $\log_{10}$ removal for *Campylobacter*, norovirus and *Cryptosporidium*, respectively. RSF was based on (Norwegian Water BA 2014) and was assumed to be triangularly distributed (minimum, most likely, maximum): *Campylobacter* (0.4, 0.5, 0.6), norovirus (0.2, 0.25, 0.3), and *Cryptosporidium* (0.4, 0.5, 0.6). UV was based on maximum removal in UV disinfection based on the QMRA tool developed for Swedish drinking water utilities (Abrahamsson et al. 2009) and was assumed to be 5.3, 4.24 and 3 $\log_{10}$ removal for *Campylobacter*, norovirus and *Cryptosporidium*, respectively

[c]Mean total $\log_{10}$ removal (*Campylobacter*/Norovirus/*Cryptosporidium*) for the combination of treatment steps for each risk reduction alternative

Scenario-Based Approach for Including Unexpected Risk Events

The base load risk level (UR_0) included pathogen load from OWTSs, WWTPs, one annual CSO, grazing animals and manure application. UR_1, UR_2…UR_n represented unexpected risk events (here $n=3$). The unexpected risk events are part of the total risk in a drinking water system, as illustrated in the risk graph in Fig. 1.

UR_1 included UR_0 loads and added a rainfall event with a 10-year return period, resulting in additional CSO load and additional load from grazing and manure application. For UR_1, the magnitude of a 10-year rainfall event during a 24 h timeframe (47.3 mm) was calculated using precipitation data for the period 2007–2018 based on the Log-Pearson III distribution (Ojha et al. 2008). The precipitation gauge available in the area has only been in operation since 2007. Proximity to the catchment was considered more important, hence the relatively short data series for the estimation of the 10-year rainfall event. In the SWAT model, fictive precipitation data series in the form of a 10-year rainfall event occurring on the 15th of each month was created. To obtain the maximum pathogen concentrations resulting from a 10-year rainfall event, the maximum concentration based on the modelling results using these fictive data for the 15th of all months with grazing was used, representing the pathogen concentrations in the tributaries during this unexpected risk event.

UR_2 included UR_0 loads and an emergency CSO (ECSO) event, resulting in a high temporary load into the lake. For UR_2, the volume (2,370,000 L) of wastewater discharged by the ECSO was based on an actual event in the catchment, when a technical failure in the sewer network caused untreated wastewater to be discharged. In this simulation the total wastewater volume was assumed to be discharged on one single day.

Table 2 Probability of unexpected risk events occuring during the different scenarios in Fig. 3

Scenario	UR_1[a]	UR_2[a]	UR_3[a]
O + W	NA	198/365	198/365
M	NA	14/365	14/365
G	138/152	138/365	138/365
G + M	14/152	14/365	14/365
G + CSO	NA	1/365	1/365

[a]UR_1 = included UR_0 loads and an added rainfall event with a 10-year return period resulting in additional CSO load and additional load from grazing and manure application. UR_2 = UR_0 loads and an emergency CSO (ECSO) event resulting in a high temporary load into the lake. UR_3 = included UR_0 loads and added pathogen load from a manure transport accident

NA not applicable

UR_3 included UR_0 loads and added pathogen load from a manure transport accident. For UR_3, the manure transport was assumed to occur in close proximity to one of the tributaries, facilitating rapid transport of the manure to Lake Vomb. It was assumed that 25,000 L of manure leaked into the mouth of one of the tributaries. It was assumed that the leak could just as well have occured in any of the tributaries. Only *Cryptosporidium* was assumed to be present in the manure. The *Cryptosporidium* concentration in manure was estimated to be the same as for the hydrological modelling, 4400 (oocysts/g).

UR_1, UR_2 and UR_3 were assumed to have a duration of one day and the probability of occurrence ($P_{\mathrm{occ,UR}i}$) was 0.1, 0.05 and 0.01 for UR_1, UR_2 and UR_3, respectively. The probabilities were based on return period (UR_1), expert judgement (UR_2) and road accident statistics, in combination with expert judgement by the authors (UR_3).

Five different types of base load levels were identified, representing preconditions where unexpected risk events could occur. Examples of these scenarios are schematically illustrated in Fig. 3. The solid areas represent the base load of activities occurring on a regular basis, and the striped areas represent possible positions of the unexpected risk events (UR_1–UR_3) during the different scenarios.

Provided the unexpected risk event is happening, the probability of occurrence during the different scenarios was calculated by dividing the possible days of the specific scenario each year by the number of days per year (Table 2).

The probability of occurrence was equal for all days (365 days) for UR_2 and UR_3, but UR_1 could only occur during the grazing period (152 possible days). It was assumed that each unexpected risk event could occur only once each year, and that different unexpected risk events did not occur simultaneously. UR_1 was assumed to occur during the grazing period, either in combination with manure application or not (Scenarios G or G + M in Fig. 3). It was assumed that the additional CSO load from a 10-year rainfall event was added as an event separate from the annual CSO event, and the possibility of a simultaneous occurrence of an annual CSO and a 10-year rainfall event was thus excluded. Due to practices that avoid manure application in conjunction with heavy rain, this simultaneous occurrence was also excluded. It was assumed that UR_2 and UR_3 could occur during any type of scenario (Fig. 3).

To determine the position of the unexpected risk event, a discrete distribution with the probability weights reported in Table 2 was used in the Monte Carlo simulations. When the position was determined, the additional pathogen concentration was added to the tributary concentrations (Eq. 3) for the duration (one day) of the unexpected risk event.

To calculate the increased annual risk ($\Delta P_{,\mathrm{Inf,ann},p,g,\mathrm{UR}i}$), the addition to the total risk level due to the unexpected risk event (i) was calculated as:

$$\Delta P_{\text{inf,ann},p,g,\text{UR}i} = P_{\text{inf,ann},p,g,\text{UR}i} - P_{\text{inf,ann},p,g,\text{UR0}} \tag{8}$$

where $P_{\text{Inf,ann,p,g,UR}i}$ was the annual probability of infection in the case of a risk event UR_i and $P_{\text{Inf,ann},p,g,\text{UR0}}$ was the probability of infection without any unexpected risk event (UR_0).

The total annual risk ($P_{\text{Inf,ann},p,g,\text{Tot}}$) compriced the base load (UR_0) and the unexpected risk events (UR_1–UR_3) in combination with their respective probability of occurrence, and was calculated as:

$$P_{\text{inf,ann},p,g,\text{Tot}} = P_{\text{inf,ann},p,g,\text{UR0}} + \sum_{i=1}^{3} \Delta P_{\text{inf,ann},p,g,\text{UR}i} \cdot P_{\text{occ,UR}i} \tag{9}$$

where $P_{\text{occ,UR}i}$ was the annual probability of occurrence of unexpected risk events (0.1, 0.05 and 0.01 for UR_1, UR_2 and UR_3, respectively).

The change in annual probability of infection for each risk reduction alternative compared to the reference alternative and the resulting change in QALYs was calculated conservatively, assuming that each infection resulted in illness and using a unit value for the amount of QALYs that corresponded to one infection for each pathogen type, as performed in Bergion et al. (2018b). A *Campylobacter*, norovirus and *Cryptosporidium* infection corresponds to 0.0163, 0.0009 and 0.0035 QALYs, respectively (Batz et al. 2014).

Cost–Benefit Analysis

The total annual (ann) benefits (B_T) from each risk reduction alternative (g) were calculated as:

$$B_{T,\text{ann},g} = B_{H,\text{ann},g} + B_{E,\text{ann},g} + B_{O,\text{ann},g} \tag{10}$$

where B_H was the health benefits, B_E was the environmental benefits, and B_O was other additional benefits. The other benefits were not included as a monetised benefit, but they were identified qualitatively.

The monetisation of the health (H) benefits was estimated using a unit value per gained QALY in each risk reduction alternative (g) each year (ann), calculated as:

$$B_{H,\text{ann},g} = \Delta\text{QALY}_g \cdot \text{DWP}_{\text{ann}} \cdot \text{QALY}_V \tag{11}$$

where $B_{H,\text{ann},g}$ was the annual monetised health benefits (SEK), ΔQALY_g was the annual change in QALYs, the DWP_{ann} (persons) was the drinking water consumer population during that year, and QALY_V (SEK/QALY) was the unit value of one gained QALY. There were 400,000 drinking water consumers in both drinking water systems. Based on a national prognosis of a 30% population increase from 2017 to 2060 (Statistics Sweden 2017), an annual population increase was included in the model. QALY_V was set at SEK 1,220,000 (Svensson et al. 2015).

The annual environmental benefits (B_E) for reducing the nutrient load from wastewater were calculated using a unit value per reduced kg of SEK 53 and SEK 25 for phosphorous and nitrogen, respectively (SEPA 2008), as performed in Bergion et al. (2018b). For $g = \text{A1}$, the annual removal of phosphorous (0.9 kg) and nitrogen (5.3 kg) was calculated as:

$$\text{Nu}_{R,\text{ann},g} = c_{\text{Nu,WW}} \cdot (\text{CSO}_{\text{ann},A1} + \text{ECSO}_{\text{ann},A1}) \tag{12}$$

where $\text{Nu}_{R,\text{ann},g}$ was the annual nutrient (nitrogen or phosphorous) removal, $\text{C}_{\text{Nu,WW}}$ was the maximum measured nutrient concentration in CSO events during the period 2013–2017, $\text{CSO}_{\text{ann},A1}$ was the volume of untreated wastewater discharged during a CSO, and $\text{ECSO}_{\text{ann},A1}$ was the volume of untreated wastewater discharged during an ECSO. For $g = \text{A3}$, the reduction in the phosphorous (651 kg) and nitrogen (4004 kg) load into the lake was calculated based on values from Bergion et al. (2018b).

Investment costs were assumed to arise in the first year of the time horizon, and operation and maintenance costs were set as an annual cost for the entire time horizon. Costs for A1 were based on reported costs from the municipality of Sjöbo (personal communication), and the costs for A2 and A3 were based on Bergion et al. (2018b). In the Vomb DWS, investment costs were estimated at approximately SEK 1.3 million, SEK 55.5 million, and SEK 36.2 million for A1, A2 and A3, respectively. The investment costs for A4 were the sum of A1, A2 and A3. The annual operation and maintenance costs in the Vomb DWS were assumed to be approximately SEK 0, SEK 0.43 million and SEK 0.2 million for A1, A2 and A3, respectively. The annual operation and maintenance costs for A4 were the sum of A1, A2 and A3. In the Alt. DWS, the investment costs and operation and maintenance costs were the same as for the Vomb DWS with the exception of A3. For A3 for the Alt. DWS, the investment costs were set at SEK 0.36 million, and the annual operation and maintenance costs were set at SEK 2,000. This was 1% of the costs for A3 in the Vomb DWS, since the number of OWTS in the base load was reduced by 99%.

The net present value (NPV) was calculated as:

$$\text{NPV} = \sum_{t=0}^{T} \frac{(B_t)}{(1+r)^t} - \sum_{t=0}^{T} \frac{(C_t)}{(1+r)^t} \tag{13}$$

where B was the benefits for each year; C was the costs for each year; r was the discount rate (3.5%); and t was each specific year during the time horizon T of 50 years.

The health risk reduction potential was also investigated. The maximum health benefits would be achieved if all health risks were reduced to zero. The health benefit potential ($B_{\text{pot.}}$) of each risk reduction alternative was thus calculated as:

$$B_{\text{Pot.}} = \frac{B_{H,g}}{B_{H,\text{Max},g}} \tag{14}$$

where $B_{H,\text{Max},g}$ was the monetary health benefits if all microbial risks were removed.

To account for increased risk in the future, a risk increase factor was used for future risk levels. A 25% increase compared to 2017 was assumed for 2100. This was equivalent to an annual increase of 0.296%. The factor was based on the Swedish Meteorological and Hydrological Institute prognosis of increased future precipitation events (SMHI 2015).

To investigate the impact of including unexpected risk events, the probability of occurrence was set at 0 for UR_1, UR_2 and UR_3 to see the effect on the NPV. This was a decision model that did not include unexpected risk events.

Sensitivity Analysis

The impact of parameters on the pathogen dose for the five scenarios (O + W, G + CSO, M, G and G + M) was investigated using Spearman rank correlation coefficients. The impact of the dose–response model was studied using scatter plots between the two inputs—pathogen dose and infectivity versus the probability of infection. Variation in the *NPV* was reported using the coefficient of variation.

The impact of the discount rate and the choice of health valuation method on the outcome of the risk-based decision model was studied using a manual approach. Two discount rates were tested: 3.5% and 1%. The discount rate of 3.5% was based on the discount rate used by the road administration authorities in Sweden when evaluating large infrastructure projects. The discount rate of 1% was chosen, since the long-term investments that are evaluated in the case study spanned several future generations and this may justify a lower discount rate.

To investigate the sensitivity of the NPV to the health valuation method used, apart from using the value of a QALY, the cost of illness and added cost of disutility, COI(+), was used as a health valuation method in addition to using the value of a QALY (Bergion et al. 2018a). The annual health benefits ($B_{H,\text{ann},g}$) (Eq. 10) were then calculated as:

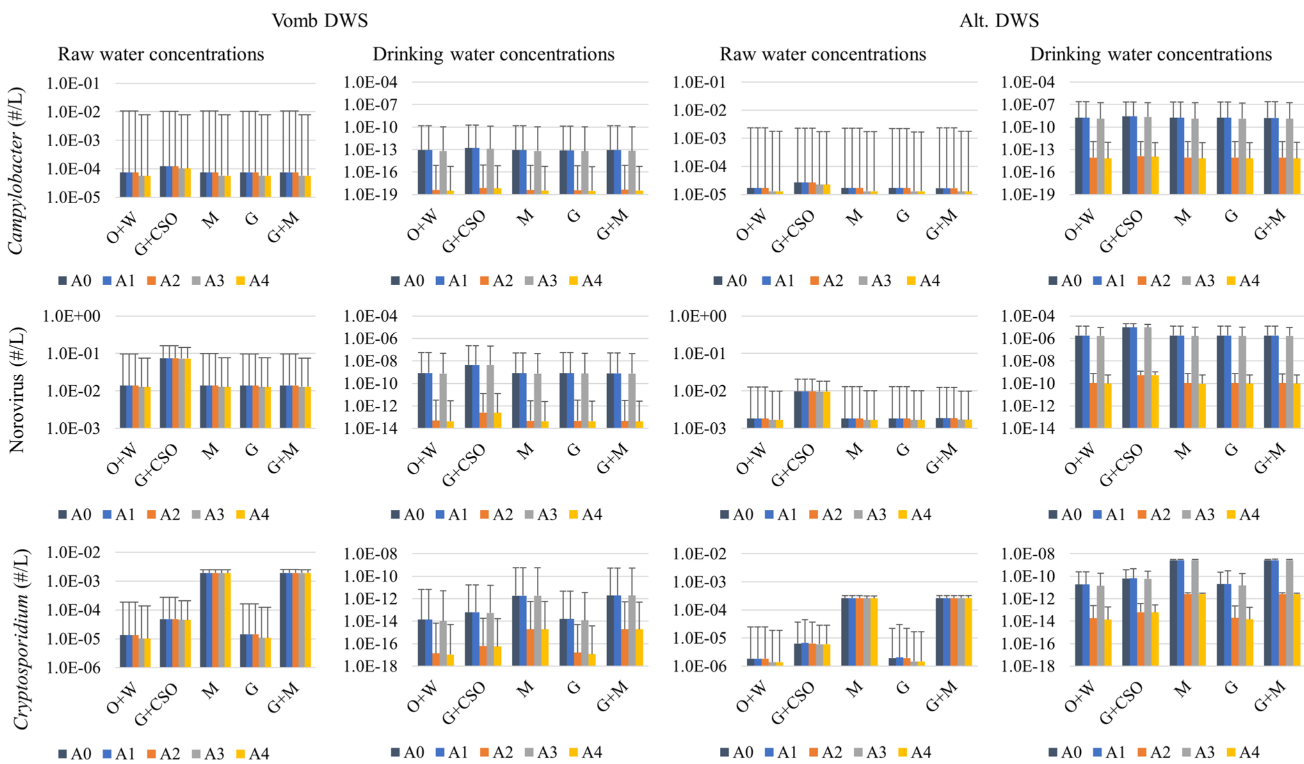

Fig. 4 The simulated 50th percentile (median) of the pathogen concentrations (*Campylobacter*, norovirus and *Cryptosporidium*) in the raw water intake and in the drinking water caused by the base load for the Vomb drinking water system (Vomb DWS) and for the Alternative drinking water system (Alt. DWS). O + W, G + CSO, M, G and G + M represent the five scenarios as shown in Fig. 3. The risk reduction alternatives were as follows: (A0) the reference alternative where no risk reduction measures were implemented; (A1) installation of pumps and a back-up power supply to remove CSOs and ECSOs; (A2) installation of UV treatment in the drinking water treatment plant (DWTP); (A3) connection of 25% of the OWTSs in the catchment to the WWTP; and (A4) a combination of A1–A3. Whiskers represent the 95th percentiles. Note that the risk contribution from unexpected risk events is *excluded* from the results in this figure

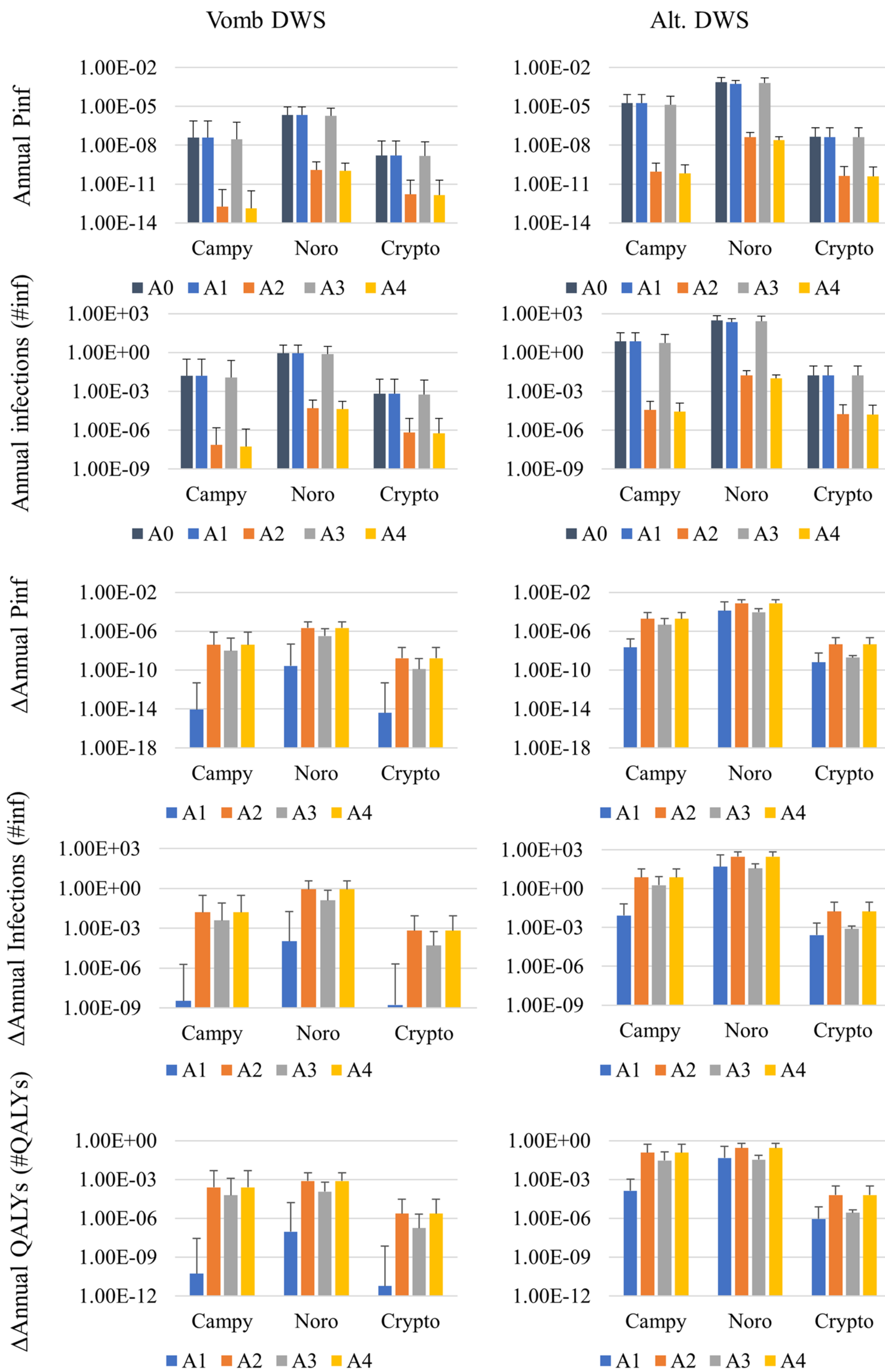

Fig. 5 Risk level in terms of annual probability of infection (Annual Pinf) and number of annual infections (Annual infections) for drinking water consumers for the risk reduction alternatives: (A0) reference alternative where no risk reduction measures were implemented; (A1) installation of pumps and a back-up power supply to remove CSOs and ECSOs; (A2) installation of UV treatment in the drinking water treatment plant (DWTP); (A3) connection of 25% of the OWTSs in the catchment to the WWTP; and (A4) a combination of A1–A3. Reduction in the annual probability of infection (ΔAnnual Pinf), reduction in the number of infections (ΔAnnual Infections), and reduction in QALYs (ΔAnnual QALYs) for the risk reduction alternatives A1–A4 are presented in comparison to A0. Bars represents the 50th percentile (median) and whiskers represent the 95th percentiles. Note that unexpected risk events are *included* in the results reported in this figure

$$B_{H,\mathrm{ann},g} = \sum_{p=\mathrm{Campy,noro,Crypto}} \Delta P_{\mathrm{Inf,ann},p,g} \cdot \mathrm{DWP}_{\mathrm{ann}} \cdot \mathrm{COI}(+)_{V,p} \tag{15}$$

where $\Delta P_{\mathrm{inf,ann,p,g}}$ was the change in annual probability of infection per person resulting from each risk reduction alternative A1–A4 (g), $\mathrm{DWP}_{\mathrm{ann}}$ (persons) was the drinking water consumer population during year y, and $\mathrm{COI}(+)_{\mathrm{V,p}}$ (SEK/infection) was the unit value of one avoided infection for each respective pathogen. $\mathrm{COI}(+)_{\mathrm{V,p}}$ was set at SEK 30,537, SEK 6064 and SEK 26,273 for *Campylobacter*, norovirus and *Cryptosporidium*, respectively (Bergion et al. 2018a).

Results

The results of the QMRA and the CBA are presented below. The manual sensitivity analysis of the impact of the discount rate and the health valuation method are included as part of the results below. The sensitivity analysis using Spearman rank correlation coefficients, scatter plots and coefficient of variation is reported in Supplementary Material (Tables S4, S5, S7 and Fig. S1).

Quantitative Microbial Risk Assessment

The simulated base load pathogen concentrations in the raw water intake and in drinking water for *Campylobacter*, norovirus and *Cryptosporidium* are presented in Fig. 4.

The annual probability of infection and annual number of infections, using the scenario-based approach for including unexpected risk events, are presented in Fig. 5, as are the reduction in the annual probability of infection, the reduction in the number of infections and the reduction in QALYs in comparison to the reference alternative (A0).

Both in US and the Netherlands (Signor and Ashbolt 2009) an annual probability of infection of 10^{-4} has been used as a guideline for an acceptable risk of exposure to pathogens via drinking water. In Sweden, there is no specified acceptable risk level. Consequently, 10^{-4} is used in this study for comparison purposes. Looking at the 50th and 95th percentiles, the Vomb DWS had a microbial risk level below 10^{-4} for all pathogens for all the alternatives, i.e. A0-A4. For the Alt. DWS, looking at the included percentiles the microbial level in A0 was above 10^{-4} for norovirus, but below 10^{-4} for *Campylobacter* and *Cryptosporidium*. For the Alt. DWS, risk reduction alternatives A1 and A3 reduced the norovirus risk level, but not below the acceptable risk level, while A2 and A4 reduced the norovirus risk to below 10^{-4}.

For the Vomb DWS, the unexpected risk events (UR_1–UR_3) contributed 1.5%, < 0.1%, 1.5%, 1.6% and < 0.1% of the total risk for A0, A1, A2, A3 and A4, respectively, (looking at the 50th percentile). For the Alt. DWS, the unexpected risk events contributed 60.1%, < 0.1%, 60.2%, 62.0% and 0.4% of the total risk for A0, A1, A2, A3 and A4, respectively.

For the Vomb DWS, looking at the 50th percentile, the annual number of infections was < 1 for all pathogens and all risk reduction alternatives (A0–A4). For the Alt. DWS, looking at the 50th percentile, the annual number of infections (*Campylobacter*/norovirus/*Cryptosporidium*) was (7.4E0/3.0E2/1.7E−2), (7.4E0/2.1E2/1.7E−2), (3.7E−5/1.7E−2/1.7E−5), (5.5E0/2.6E2/1.6E−2) and (2.8E−5/1.0E−2/1.6E−5) for A0, A1, A2, A3 and A4, respectively.

For the Vomb DWS, the contribution of different pathogens, *Campylobacter*/norovirus/*Cryptosporidium*, to the total annual number of infections (mean) was < 0.1% / > 99.9% / < 0.1% for all the alternatives (A0–A4). For the Alt. DWS, the contribution of different pathogens *Campylobacter*/norovirus/*Cryptosporidium* to the total annual infections was 0.1%/99.9%/< 0.1% for A0 and A3, 0.2%/99.8%/< 0.1% for A1, < 0.1%/99.7%/0.3% for A2, and < 0.1%/99.3%/0.7% for A4.

The annual lost QALYs for each risk reduction alternative and the reduction in annual lost QALYs are presented in Table 3. The reduction in annual lost QALYs in comparison to the reference alternative (A0) represents the avoided QALYs and thus the health risk reduction.

Cost–Benefit Analysis

Net Present Value

The NPVs for A1, A2, A3 and A4 are presented in Fig. 6. The exact figures for the NPV percentiles are reported in the Supplementary Material, Table S6.

Table 3 Annual lost QALYs for each risk reduction alternative, and the corresponding reduction in lost QALYs in comparison to A0

Risk reduction alt[a]	Vomb DWS		Alt. DWS	
	Annual lost QALYs	ΔAnnual QALYs (%)	Annual lost QALYs	ΔAnnual QALYs (%)
A0	4.35E−4	–	2.53	–
A1	4.28E−4	1.49%	1.01	60.1%
A2	2.49E−8	> 99.9%	1.46E−4	> 99.9%
A3	4.02E−4	7.60%	2.45	3.12%
A4	2.28E−8	> 99.9%	5.38E−5	> 99.9%

[a]The risk reduction alternatives were as follows: (A0), no risk reduction measures were implemented; (A1) installation of pumps and a back-up power supply to remove CSOs and ECSOs; (A2) installation of UV treatment in the drinking water treatment plant (DWTP); (A3) connection of 25% of the OWTSs in the catchment area to the WWTP; and (A4) a combination of A1–A3

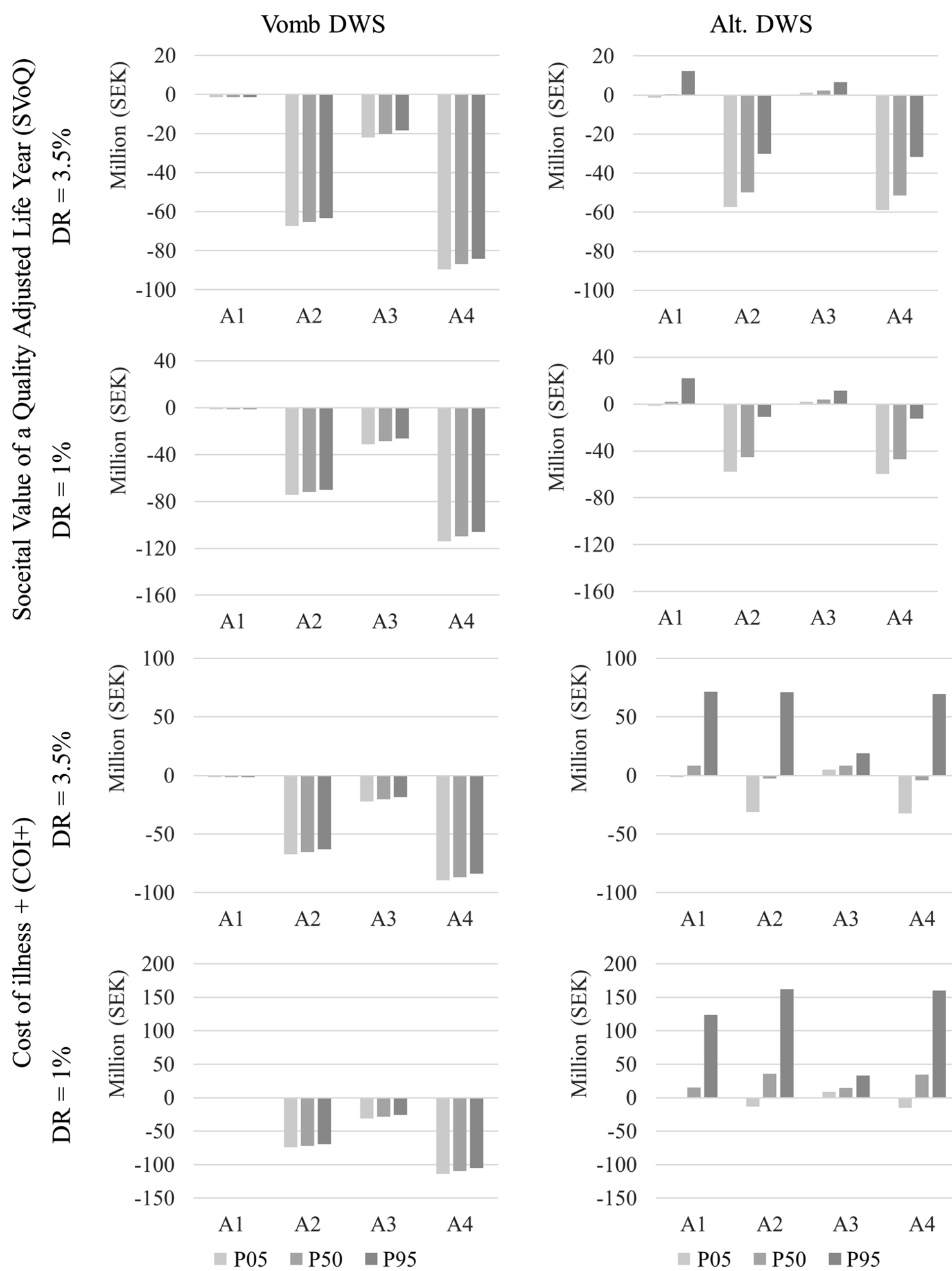

Fig. 6 Net present values for the risk reduction alternatives: (A1) installation of pumps and a back-up power supply to remove CSOs and ECSOs; (A2) installation of UV treatment in the drinking water treatment plant (DWTP); (A3) connection of 25% of the OWTSs in the catchment to the WWTP; and (A4) a combination of A1–A3. Sensitivity analyses of the discount rates (DR) and the choice of health valuation method (societal value of a QALY (SVoQ)) and the cost of illness adding cost of disutility, (COI+) are presented. P05, P50 and P95 are the 5th, 50th and 95th percentiles, respectively

The NPVs for the Vomb DWS were negative for all risk reduction alternatives (< 0.001 probability of a positive NPV). This was consistent when the discount rate was altered and when the health valuation method was altered. Ranking the 50th percentile of the NPVs for the different risk reduction alternatives resulted in the rank order A1 > A3 > A2 > A4. This rank order did not change when using the lower discount rate (1%) or when using the health valuation method COI+.

For the Alt. DWS, the rank order of the risk reduction alternatives based on the NPVs is presented in Table 4 for the 5th, 50th and 95th percentiles.

Probability of Having the Highest Net Present Value and Probability of a Positive Net Present Value

For the Vomb DWS, the probability of having the highest NPV was > 0.999 for A1 and < 0.001 for A2–A4. For the Alt. DWS, the probability of having the highest NPV and the probability of a positive NPV are presented in Table 5.

For the Alt. DWS using the health valuation method SVoQ, A2 and A4 achieved > 99.9% of the maximum possible health benefits (100% would correspond to all risks being reduced to 0), while A1 and A3 achieved < 0.1–37% and 16–17% of the maximum possible health benefits, respectively (ranges from 5 to 95th percentiles). Looking

Table 4 Rank number of the risk reduction alternatives based on the NPVs for the Alt. DWS

Valuation method[b]	Discount rate (%)	Alt. DWS—Rank number of the risk reduction alternative[a] NPVs											
		5th percentile				50th percentile				95th percentile			
		A1	A2	A3	A4	A1	A2	A3	A4	A1	A2	A3	A4
SVoQ	3.5	2	3	**1**	4	2	3	**1**	4	**1**	3	2	4
	1	2	3	**1**	4	2	3	**1**	4	**1**	3	2	4
COI+	3.5	2	3	**1**	4	**1**	3	2	4	**1**	4	2	3
	1	2	3	**1**	4	3	**1**	4	2	3	**1**	4	2

The alternative with the highest rank number is marked in bold

[a]The risk reduction alternatives were as follows: (A1) installation of pumps and a back-up power supply to remove CSOs and ECSOs; (A2) installation of UV treatment in the drinking water treatment plant (DWTP); (A3) connection of 25% of the OWTSs in the catchment to the WWTP; and (A4) a combination of A1-A3

[b]COI+cost of illness and adding disutility, and SVoQ societal value of a quality-adjusted life year, as presented in Bergion et al. (2018a)

Table 5 Probability of having the highest net present value (NPV) and probability of a positive NPV for the Alt. DWS

Valuation method[a]	Discount rate (%)	Alt. DWS—Unexpected risk events included							
		Probability of having the highest *NPV*				Probability of a positive NPV			
		A1[b]	A2	A3	A4	A1	A2	A3	A4
SVoQ	3.5	0.37	< 0.01	**0.63**	< 0.01	0.54	0.01	**> 0.99**	0.01
	1	0.40	0.01	**0.59**	< 0.01	0.59	0.03	**> 0.99**	0.03
COI+	3.5	0.42	0.12	**0.46**	< 0.01	0.64	0.47	**> 0.99**	0.45
	1	0.20	**0.52**	0.29	< 0.01	0.65	0.83	**> 0.99**	0.82
Valuation method[a]	Discount rate (%)	Alt. DWS—unexpected risk events excluded							
		Probability of having the highest *NPV*				Probability of a positive NPV			
		A1	A2	A3	A4	A1	A2	A3	A4
SVoQ	3.5	< 0.01	0.01	**0.99**	< 0.01	< 0.01	0.01	**> 0.99**	0.01
	1	< 0.01	0.02	**0.98**	< 0.01	< 0.01	0.02	**> 0.99**	0.02
CO+	3.5	< 0.01	0.07	**0.93**	< 0.01	< 0.01	0.14	**> 0.99**	0.13
	1	< 0.01	0.33	**0.67**	< 0.01	< 0.01	0.62	**> 0.99**	0.59

The risk reduction alternatives with the probability of having the highest NPV and highest probability of a positive NPV are marked bold

[a]COI + cost of illness and adding disutility, and SVoQ societal value of a quality-adjusted life year, as presented in Bergion et al. (2018a)

[b]The risk reduction alternatives were as follows: (A1) installation of pumps and a back-up power supply to remove CSOs and ECSOs; (A2) installation of UV treatment in the drinking water treatment plant (DWTP); (A3) connection of 25% of the OWTSs in the catchment to the WWTP; and (A4) a combination of A1-A3

at the health valuation method COI+, A2 and A4 still achieved > 99.9% of the maximum possible health benefits, while A1 and A3 achieved < 0.1–49% and 13–15% of the maximum possible health benefits, respectively (ranges from 5 to 95th percentiles).

Benefits not included in the NPV were identified and are reported in Table 6. The list does not claim to be complete, although it does include important non-monetised benefits.

Discussion

Previous economic evaluation of microbial risk has focused mainly on the effects (Assmuth et al. 2016; Juntunen et al. 2017) and not compared different risk reduction alternatives. The enhanced risk-based decision model presented here included a detailed analysis of microbial risk reduction alternatives and used CBA for economic evaluation, making it possible to evaluate and compare the alternatives using their societal profitability. The presented decision model enables

Table 6 Benefits not included in the net present value (NPV)

Additional benefits not included in the NPV	A1	A2[a]	A3[a]	A4
Reduced risk of infection for animals (wild and domestic) in the catchment	X		X	X
Reduced risk of infections for recreational swimmers in the catchment	X		X	X
Owners of OWTS relieved of responsibility for treating wastewater			X	X
Increased market value of properties connected to the WWTP			X	X
Reduced CO_2 emissions due to less transport of sludge from OWTS			X	X
Increased opportunities for nutrient recycling	X		X	X
Reduced traffic accidents involving heavy traffic			X	X
Reduced chlorination by-products due to reduced chlorination dose		X		X
Reduced handling and storage of chlorination chemicals		X		X

[a]Based on Bergion et al. (2018b)

an evaluation to be made using an economic perspective, as outlined by the World Health Organization (2001).

Although a strict CBA approach considers only the NPVs, there may be other criteria (legislation, pursuing an opportunity, etc.) that need to be taken into account when determining whether the risk needs to be reduced (WHO 2017). It may be the case that an alternative that reduces the risk to an acceptable risk level needs to be implemented, even though this alternative results in a negative NPV. Given that each risk reduction alternative fulfils the non-monetary criteria, the alternative with the highest NPV rank order should be implemented. This approach combines the two decision criteria of maximising societal benefits and fulfilling legal requirements.

For the Vomb DWS, the probability of a positive NPV was very low for all alternatives. This is mainly because of the high $\log_{10}$ removal in the DWTP and a low probability of infection for the reference alternative. Hence, the risk reduction alternatives could not substantially reduce the risk any further. For the Alt. DWS, $\log_{10}$ removal in the DWTP was lower, and a temporary increase in pathogen load in the raw water thus had a greater effect on the dose to which the drinking water consumers were exposed. This, and the fact that the Alt. DWS had the highest risk compared to the Vomb DWS, resulted in a greater health risk reduction due to the risk reduction alternatives and thus also a higher probability of a positive NPV. However, this large health risk reduction also affects the uncertainties in the NPV. The high $\log_{10}$ removal in the Vomb DWS reduced the dose to a low and similar level in most cases in such a way that, based on the dose–response relationship the effect of additional risk reduction alternatives was almost negligible. For the Alt. DWS, the lower $\log_{10}$ removal resulted in a higher effect from risk reduction alternatives in terms of more avoided infections and thus a greater variation. This suppressing effect of the high $\log_{10}$ removal, in this case the artificial groundwater recharge, can be seen in the uncertainty in the NPV values when comparing the two DWS, resulting in a higher coefficient of variation in the NPV for the Alt. DWS compared to the Vomb DWS (Supplementary Material, Table S7). However, a high degree of uncertainty in the NPV does not automatically mean there is high uncertainty regarding the risk reduction alternative that is the most profitable for society.

The results for the Vomb DWS show that the unexpected risk events did not constitute a high proportion of the total risk. However, for the Alt. DWS, the unexpected risk events were the main contributor to the total risk for both norovirus and *Cryptosporidium*, but not for *Campylobacter*. The importance of unexpected risk events for the outcome of risk reduction measures is dependent on the conditions in the drinking water system. It is important to acknowledge that sub-optimal treatment in the DWTP, especially in combination with other unexpected risk events, may result in high microbial risks to the drinking water consumers (Taghipour et al. 2019). It is thus important to also identify and included unexpected events within the drinking water treatment plant. Where there is a low pathogen base load, as the case for A3 in the Alt. DWS, the contribution of unexpected risk events to the total risk is greater than in situations where the base load is higher. In the Alt. DWS, where there is a lower base load and lower pathogen removal in the DWTP, the unexpected risk events have a greater impact than in the Vomb DWS. When the unexpected risks were excluded, the order of probability of the risk reduction alternatives having the highest NPV changed, and the probability of a positive NPV also changed. In Westrell et al. (2003), where a DWTP with high $\log_{10}$ removal was evaluated, the base load was reported as being the cause of the majority of waterborne illnesses. In this study we confirm these results and add to the discussion that the importance of unexpected risk events is higher in the DWS, where $\log_{10}$ removal in the DWTP is lower.

The stakeholder distribution of costs and benefits for the risk reduction alternatives has not been explored in detail in this study. It has been shown earlier (Bergion et al. 2018b) that including a UV treatment step (A2) distributed all the benefits and costs to the drinking water consumers (assuming the UV treatment is paid for using the drinking water charge). As regards connection of the OWTSs (A3) a discrepancy between the persons bearing the costs and the persons receiving the benefits was identified (Bergion et al. 2018b), where most of the costs were borne by the private owners of the OWTSs and at the same time most of the health benefits were attributed to drinking water consumers supplied with drinking water from Lake Vomb. Distribution of costs is generally not fixed and is arranged according to the settings for the drinking water system, the risk reduction alternative and the specific stakeholders in question.

Even though the presented decision model enables the important inclusion of additional events and conditions typically not considered, further development is possible. For example, the exclusion of the possibility of a 10-year rainfall occurring outside the grazing period could result in an underestimation of the risk. It was based on the fact that most (75%) of heavy precipitation events (2 h intensity) occurs in June, July and August (Hernebring 2006). It is also possible that the risk is underestimated since we assumed that unexpected risk events do not occur simultaneously.

A more accurate description of the inter annual fluctuations of pathogen concentrations in wastewater treatment plant effluent (Westrell et al. 2006) could be a way of achieving a more comprehensive microbial risk assessment.

The 25% risk increase through to 2100 was based on predictions from SMHI for future risk events connected to precipitation. For the purposes of this study, it was assumed that this increase was applicable to all types of risks. However, future work should include additional investigations into how to analyse future changes in risk levels for non-climate-related risk events. Furthermore, ways in which existing models (e.g. Schijven et al. 2013) describing microbial risks in relation to climate change can be included in the decision model should also be investigated.

Hydrological modelling was included to better describe pathogen contribution from grazing animals and the application of manure. In this study, the conversion from deterministic to stochastic results was done using a resampling function. This enables results from all the years in the simulated period to be used as input for the decision model. Future improvements could include investigating other methods for incorporating stochastic hydrological modelling results. The hydrological model was only calibrated and validated for the water flow. For future applications, the water quality component of the model should also be calibrated and validated. For this study, lack of observed pathogen data was the reason for not pursuing these measures. However, during the initial setup of the model (Bergion et al. 2018b) it was confirmed that the norovirus infections spread through drinking water only accounted for a small part of the reported infections in the population. This would be expected and thus provide initial validation of the model. The groundwater modelling was based on a simplified approach using stochastic simulation of an analytical transport and fate model. For future applications, the use of more sophisticated stochastic numerical models should be investigated to take into account aquifer heterogeneities.

Conclusion

Based on the results from the risk-based decision model, it can be concluded that the effect and importance of considering unexpected events is determined by the local preconditions. In drinking water systems with a low pathogen base load and low pathogen removal potential in the drinking water treatment plant, the unexpected risk events have a greater impact compared to drinking water systems with a high pathogen base load and high pathogen removal potential in the drinking water treatment plant. Hence, the risk reduction alternatives aimed at reducing the unexpected risk events will have the greatest effect in the former system rather than the latter.

The results show that unexpected risk events can affect the results of a decision analysis and change the alternative that is most profitable. In the Alt. DWS, excluding the unexpected risks from the decision model resulted in changes in the probability of having the highest net present value and changes in the probability of a positive net present value of the risk reduction alternatives. In addition, the rank order of the NPV of the risk reduction alternatives changed, resulting in a different prioritisation.

In summary, this work has resulted in a comprehensive decision support model, capable of including contributions from both base load and unexpected risk events to the total microbial health risk in drinking water systems. The model can be used in real world systems, and the applications in this study show that a comprehensive model, which includes both base load and unexpected risk events, is needed to provide proper decision support with regard to microbial safety measures.

Acknowledgements Open access funding provided by Chalmers University of Technology. Funding has been provided by the Swedish Water and Wastewater Association through the project *Risk-Based Decision Support for Safe Drinking Water* (Project 13-102). The research is part of DRICKS, a framework programme for drinking water research coordinated by Chalmers University of Technology.

Compliance with Ethical Standards

Conflict of interest No potential conflicts of interest have been identified.

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