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Risk assessment of Cryptosporidium intake in drinking water treatment plant by a combination of predictive models and event-tree and fault-tree techniques

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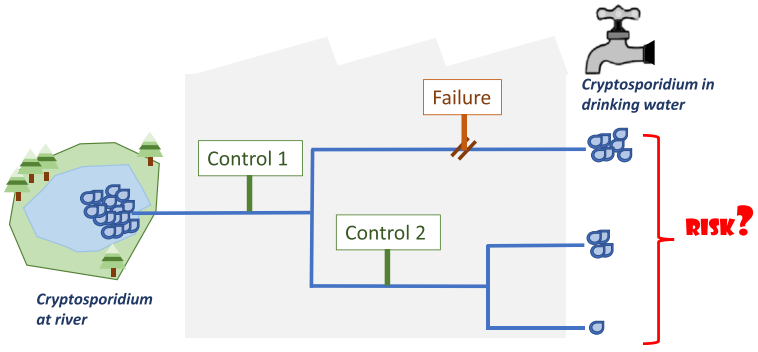
HIGHLIGHTS

- Predictive modelling, event tree and fault trees analysis were combined to quantify the risk of *Cryptosporidium* in drinking water.
- Normal and abnormal process conditions have been considered to simulate the evolution of *Cryptosporidium* along the water chain.
- Controls in the water process are integrated in the risk calculation.
- The risk information enabled to know which measures was the most effective in the control of *Cryptosporidium*.

GRAPHICAL ABSTRACT



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ABSTRACT

Risk-informed decision making permits a more effective water safety management. In this framework, this article introduces the rationale and proposes a new approach to carry out a quantitative risk assessment along the water chain, from river source to tap water, by integrating predictive modelling combined with event-tree and fault-tree techniques. The model developed by this approach could not only account for normal but also for abnormal process conditions in the water treatment plant, as well as assess the real impact of the applied safety controls, such as turbidity control. A sensitivity study was conducted to determine the effect of considering a typical drinking water treatment plant (DWTP), i.e. coagulation, sedimentation and filtration with two turbidity controls (on intake and after filtration) on the risk of infection due to exposure to *Cryptosporidium* in tap water. The results showed that, with the current effectiveness of turbidity reduction in the DWTP, the first control did not minimise the annual risk of *Cryptosporidium* infection (3.6E-04) and only limiting turbidity after filtration to below 0.01NTU provided a clear reduction in risk (7.7E-05) at the cost of rejecting 60 % of the water after the control. The lowest risk was found when turbidity reduction was set at 4 logs (8.48E-06), although this means that the effectiveness of turbidity reduction should be greatly improved. It was therefore concluded that supplementing the current treatment with alternative barriers such as UV or ozone disinfection and/or implementing direct control of *Cryptosporidium* concentration should be considered.

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1. Introduction

Cryptosporidium is a critical diarrhoeal pathogen, considered to be one of the major causes, after rotavirus, of morbidity and mortality in children under five years old (Kotloff et al., 2013; Abeywardena et al., 2015; Platts-Mills et al., 2015). Although, infections of healthy individuals without symptoms or with only mild symptoms are common, patients with a poor immune system may develop profuse life-threatening watery diarrhoea, with a mortality rate of up to 70 % in HIV-infected patients (Khan et al., 2018). Its ubiquitous presence in the environment, persisting for months in moist soil and water, and its resistance to standard chlorination disinfection have made this protozoan parasite one of the most dangerous microorganisms in drinking water (Lamy et al., 2020; Daraei et al., 2021). In fact, despite investments in the sanitation infrastructure and water quality legislation, developed countries continue to experience outbreaks of waterborne diseases, for example Europe had confirmed 10,739 cases of *Cryptosporidium* in 2019 (ECDC (European Centre for Disease Prevention and Control), 2020).

Quantitative Microbial Risk Assessment (QMRA) is a widely recognised tool to support safety management decisions. In the context of pathogens in drinking water, QMRA is increasingly being applied by international agencies, governments and the scientific community as a basis for informed decisions on health risks and to assess the effectiveness of the water treatment plan. The conventional QMRA consists of the following steps: hazard identification, exposure assessment, dose-response assessment and risk characterization (Haas et al., 2014; WHO, 2016; Health Canada, 2019).

Predictive modelling (PM) has become established in assessing microbial exposure as a scientific discipline that can formulate stochastic processes which make it possible to predict the evolution of the microbial load as a function of possible intrinsic and extrinsic parameters, such as pH, activity, temperature, or irradiation (Doménech et al., 2010a). PM has also been used to predict the dose-response relationship, in which a pathogen's infective load predicts the possible health effects on the population and provide the necessary information to assess the full extent of the disease burden attributable to pathogens in drinking water (US EPA, 2005; WHO, 2016).

Some of the most recent examples of the use of PM in water were those carried out by Gao et al. (2020) who assessed copper toxicity in zebrafish larvae, or Brester et al. (2020), who forecast abundance of bacteria in microbial communities in the water pipeline. Oliver et al. (2016), concluded that applying PM provided information on the dynamic concentration of faecal indicator organisms in water and their relationships with water, soil and catchment management. The Scottish Environment Protection Agency (SEPA) has developed the first EU real-time bathing water quality predictions at 10 sites throughout Scotland since 2004 (Stidson et al., 2012). Herrig et al., 2015 developed a multiple linear regression model to predict faecal indicator organisms in the Lahn River (Germany), concluding that two of the main advantages were that it provided a cost-effective tool and the timeliness of determining water quality improved significantly. Although all these authors highlighted the advantages of using PM in risk assessment, they also recognised some of its models' limitations, such as the short data collection period, the variability and uncertainty of the input data, the difficulty of detecting and quantifying the causative microorganisms or the proportionality in some of the coefficients that they used.

Focusing on predictive models for *Cryptosporidium*, the relationship between oocyst removal and turbidity, the efficiency of coagulation/sedimentation steps in a full-scale water treatment plant and the presence of protozoa have been extensively studied (LeChevallier et al., 1992; Nieminski and Ongerth, 1995; States et al., 1997; Lopes, 2008; Bastos et al., 2013). In these cases, the main limitations were due to the limited follow-up programmes, the performance of the recovery procedure steps and the low recovery rates obtained (WHO, 2009).

Failures in the safety conditions of drinking water can occur along the entire chain “from river to tap”, directly affecting consumers' exposure to pathogens. In this context PM by itself is not enough to account for such faulty conditions. Fault-tree analysis (FTA) combined with PM is often used to predict the pathogens' evolution in failure conditions. Kelley and Allison (1981) proposed a comprehensive approach to preventing hazards and threats in a water treatment plant. Sadiq et al. (2008) used FTA to determine the main causes of inadequate water quality in urban water distribution, concluding that the pollution of source water, corrosion of system components and failures in the water treatment plant were the basic events in the occurrence of the top event. Similarly, Lindhe et al. (2009) determined that water pollution and failure in the water treatment plants were the basic events that led to poor water quality in the urban water distribution network. Tchorzewska-Cieslak et al. (2012) described the possible scenarios of using FTA for the failure of urban water-supply networks and pointed out that water-contamination in water pipelines were a consequence of incorrect technical conditions, human error or changes in temperature. Stein et al. (2017) proposed FTA as a management tool, since it provides information on the relationships among the underlying events and their effects on the top event in a small water treatment plant and to support decision-making.

Gachlou et al., 2019 studied the risk assessment of river basins by FTA and proposed that corrective actions should be chosen considering the importance of the basic and intermediate events to increase the reliability of the river basin. Viñas et al. (2022) integrated fault tree analysis (FTA) to provide input to the QMRA by modelling the interactions between the different events that can lead to failure in drinking water distribution networks and provide a framework for estimating the risk of cross-connection infection and backflow. However, even though FTA permits considering the effect of system failures on the evolution of the pathogens, it does not consider other important events that form part of the entire chain “from river to tap”, for example safety controls, health controls, etc. at critical points within the chain for water safety or quality. Thus, combining PM and FTA does not provide a complete picture of the whole set of events and their relationships throughout the stages of the process or the water chain, for which event-tree analysis (ETA) can be used to overcome this drawback.

ETA is a graphical representation of an inductive logic method that makes it possible to identify the different sequences that can be generated from a single initiating event, for example, as in this study, contaminated DWTP inlet water, and to determine its possible results or consequences. Doménech et al. (2010a, 2010b) proposed an approach based on a combination of traditional PM, FTA and ETA techniques for exposure assessment within a QMRA framework, which included failures and other events along the food chain to better estimate the real impact of these events and deviations/faults in consumers' exposure to pathogens.

This paper introduces the fundamentals and proposes a method that combines PM, ETA and FTA in the framework to assess exposure to pathogens in drinking water. The combination of exposure assessment and the dose-response to these pathogens obtain a QRMA model and assess the risk to the consumer. In a case study, the consumer risk was quantified due to the presence of *Cryptosporidium* in tap water controlled indirectly through reducing turbidity and continuous turbidity monitoring at water collection and after the filtration stage. The proposed QMRA model accounts for both normal and abnormal variations in the parameters throughout the water chain, from the river source to the tap, and assesses the real impact of deviations or failures on the water treatment plant and controls. A sensitivity study was also conducted to illustrate the impact of the controls and filtration effectiveness on the water treatment plant.

2. Material and methods

2.1. System description

A case study was carried out at the “La Presa” DWTP (Manises, Valencia-Spain), which collects water from the River Turia and supplies drinking water to a population of 859,885. The input water, or first stage, includes the source of water collection, which may come from several sources including rivers, as in this study, underground or from a well, among others. The second stage includes the treatments carried out in the DWTP to make the water safe. The Manises treatments include coagulation, sedimentation, filtration and disinfection with chlorine. The second stage is distribution, which consists of a regulation tank and the distribution network, both intended to provide an uninterrupted supply of drinking water

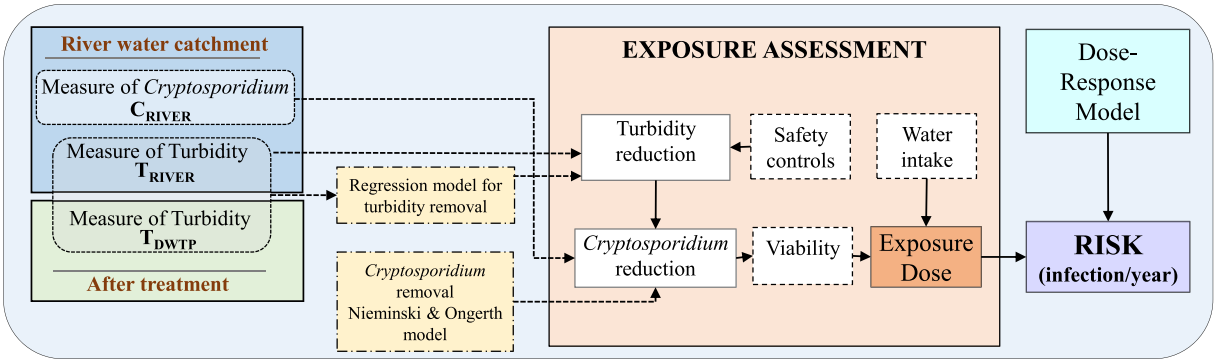

Fig. 1. QMRA modelling steps for predicting *Cryptosporidium* oocyst infection risks after DWTP treatment considering safety controls.

to consumers. Finally, the consumers can directly access tap water without any heat treatment before consumption.

The water is analysed at different points along the chain to assess the quality: first, in the river basin, before water enters the DWTP, as the river water may be contaminated above the acceptable levels. Another important monitoring point is after treatment to verify its effectiveness. In both cases the control is carried out at the DWTP and so both controls have been considered in this study. The Public Health Administration also carries out water controls after distribution from the DWTP to check water safety parameters in the distribution pipeline and at taps with public access, which are not included in this study, which focusses only on the DWTP.

2.2. QMRA modelling

Fig. 1 gives an overview of the QMRA model as well as data and steps in the sequence considered to quantify the *Cryptosporidium* infection risk. As can be seen, turbidity is continuously monitored in real time in the river water and after treatment.

The turbidity measured in the river (T_{RIVER}) by a turbidity meter (HI 93703, Hanna Instruments) had an average value of 5.56 NTU (nephelometric units of turbidity), a median of 3.59 NTU, a minimum value of 0.324 NTU and a maximum of 850 NTU. The company's criterion for self-control is that if the turbidity exceeds 100 NTU the water is rejected, which occurs with a mean probability of 0.15 %. The average turbidity after treatment (T_{DWTP}) was approximately 0.16 NTU, ranging from 0.01 to 1.51 NTU. A second control rejects the treated water when turbidity exceeds 0.1 NTU, which occurs with a mean probability of 0.066 %. These results show that although the turbidity values are usually within the established control values, there is a real probability of exceeding them and therefore underline the need to ensure the proper functioning of control systems to guarantee the safety of the water distributed to households.

Cryptosporidium concentration in the river water was measured by the immunomagnetic separation–immunofluorescence assay (US EPA, 2005, 2012) for 43 weeks in the Manises DWTP. A total of 129 samples were taken. *Cryptosporidium* was present in 16.67 % of the river samples, giving values ranging between 4 and 150 oocyst/100 L and a median of 15 oocyst/100 L.

Table 1 shows the turbidity distribution functions obtained after fitting the measured results for water before and after treatment, plus river oocyst concentration on @ Risk 8.0 software (Palisade, Newfield).

The turbidity data before and after the treatment were used to obtain the turbidity reduction and then fitted to a quadratic regression model on Statgraphics Plus 5.1 program software to obtain an rT turbidity reduction predictive model. Considering the determination coefficient (R^2) as well as the overall significance levels ($p \leq 0.05$), the obtained rT model explains 84 % of the results. To include the uncertainty involved in determining rT, a normal distribution was adjusted in which 0 and 0.2869 were the mean and deviation parameters, respectively (UrT).

The next step is to determine the oocyst concentration after treatment. Previous studies have demonstrated that oocyst concentration reduction is positively correlated with turbidity reduction (Dugan et al., 2001; Hsu and Yeh, 2003; Burnet et al., 2014). A similar conclusion was obtained by Macián-Cervera (2015) in the Manises DWTP. Values obtained in this research showed that the Nieminski & Ongerth predictive model (1995) fitted well with the reduction of oocyst concentration as a function of turbidity reduction. However, not all the oocysts will be infectious, so that infection viability is considered in order to obtain the oocyst infective load per litre. Next, the exposure dose is assessed considering the water intake, e.g. litres per day. As can be seen in Fig. 1, the risk of infection is obtained by combining the exposure dose assessed and the dose-response model.

2.2.1. Exposure assessment combining predictive modelling, plus event and fault trees

Fig. 2 provides a schematic view of the stage-based model developed to represent the evolution of *Cryptosporidium* in water, from the river catchment until consumption. This model is used to determine the exposure dose to *Cryptosporidium* in tap drinking water and is based on the principles introduced in Doménech et al. (2007, 2008, 2009, 2010a, 2010b), where event tree analysis (ETA), fault tree analysis (FTA) and predictive modelling (PM) were combined for exposure assessment within QMRA. As can be seen, a branching of the tree occurs according to whether or not a certain condition is satisfied, represented by a branching event within the tree. We adopted the standard of associating the upper branch to the non-fulfilment of the pre-established condition and the lower branch to the complementary condition, i.e. fulfilment. In the case study, turbidity of raw

Table 1
Distribution functions of Cryptosporidium and turbidity in water (Own data).

Parameter	Description	Distribution function	5th	Mean	95th
T_{RIVER}	River water turbidity (NTU)	Loglogistic (0.324;3.268;2.299)[a]	1.23	4.89	12.09
T_{DWTP}	Water turbidity after DWTP (NTU)	Loglogistic (−0.017;0.173;7.699)[a]	0.10	0.16	0.24
C_{RIVER}	River water Cryptosporidium (oocyst/100 L)	Exponential (43.143)[b and c]	2.21	43.143	129.24

[a] Loglogistic (shape; scale; location) parameters.
[b] Exponential (rate) parameter.
[c] This distribution corresponds to the oocyst/100 L concentration of the 16.67 % positive samples found contaminated with *Cryptosporidium*.

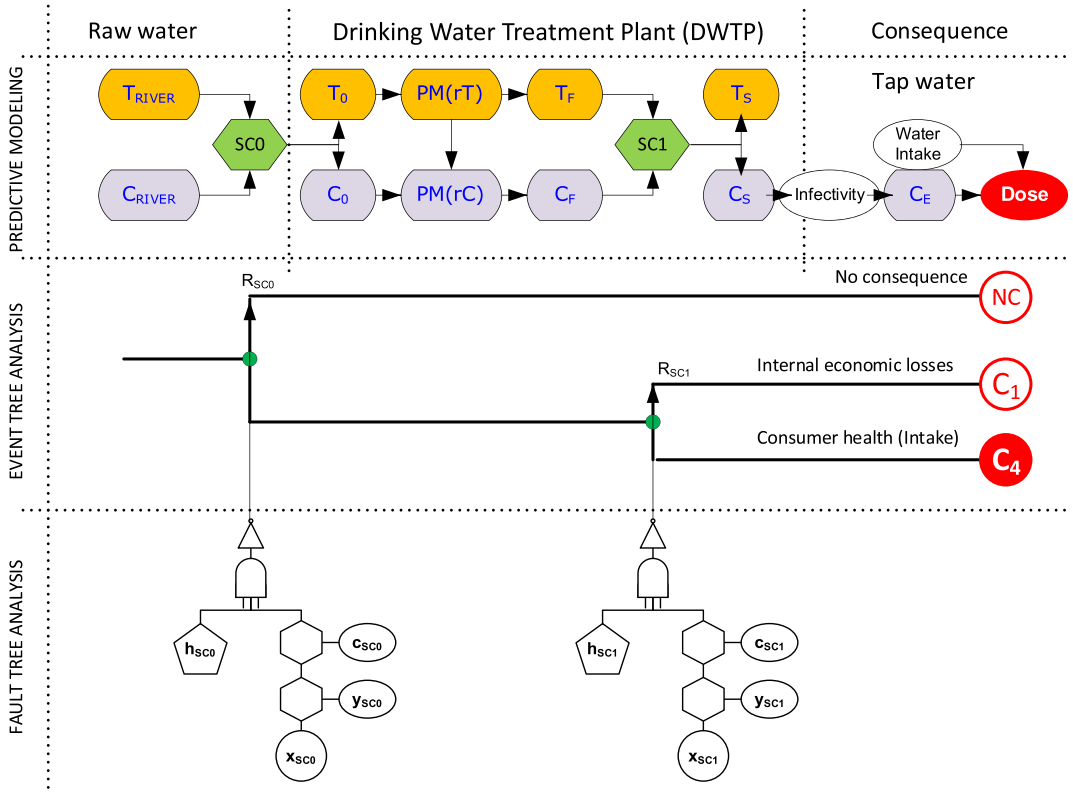

Fig. 2. PM, ETA and FTA combination model to assess *Cryptosporidium* risk.

water (T_{RIVER}) was continuously monitored at self-control SC0 with the pre-established condition that turbidity must be lower than a given threshold value, e.g. 100 NTU. If the turbidity value was higher than the pre-established condition the water was rejected (upper branch). Otherwise (lower branch), the water was accepted with turbidity up to T_0 and went through the conventional treatment consisting of coagulation, flocculation, sedimentation and granular filtration.

Water turbidity after treatment, T_F, is checked again at the second turbidity control, SC1, with the pre-established condition that turbidity must be lower than another more restrictive threshold value, e.g. 0.1 NTU. As in the previous control, if turbidity does not fulfil the condition, the water is rejected (upper) and otherwise water with turbidity T_S goes to the chlorination disinfection stage. In this study, this stage was not considered due to the low effectiveness of chlorination to reduce *Cryptosporidium* (Betancourt and Rose, 2004; WHO, 2016). T_S thus represents the water turbidity after DWTP and considering the safety controls. As can be seen in Fig. 2, three types of consequences are derived from the ETA model according to the branching: NC or no consequence for water with high turbidity at the SC0 control prior to DWTP, which is rejected; C_1 or economic losses for the DWTP when water is reprocessed because of an unacceptable turbidity level after DWTP at SC1; and C_4 or health consequences when drinking water reaches the consumer and possibly contaminated by *Cryptosporidium*.

The ETA is complemented by the FTA technique to evaluate whether or not the pre-established condition is satisfied at controls SC0 and SC1. Thus, in Fig. 2, the upper branch of each branching condition in the even tree can be interpreted as the "top event" of a fault tree, which represents a Boolean function R(i) giving the rejection condition or non-fulfilment of the control condition, labelled *i*. This rejection function is a logic function associated with the top branch event representing the fulfilment of the stage rejection condition, which provides one of two possible output values {0, 1}. Output

Table 2
Variables and models of interest for exposure assessment.

Param	Description	Value	Units	Source
T_0	Input water turbidity	$T_{RIVER}\cdot(1-R_{SC0})$	NTU	This study (Table 1)
C_0	Input water Cryptosporidium concentration	$C_{RIVER}\cdot pC_0\cdot(1-R_{SC0})$	Oocyst/100 L	This study (Table 1)
pC_0	Probability of contaminated water with Cryptosporidium	Uniform (0,1) < 0.1667	–	Own data
R_{SC0}	Input water rejection	$h_{S0}\cdot c_{S0}\cdot x_{S0}\cdot(1-y_{S0})$	–	This study (Table 3)
T_F	Water turbidity after filtration	$T_0\cdot rT\cdot UrT$	NTU	
$Log_{10}(rT)$	Turbidity removal by filtration (rT)	$-1.98 - 0.897\cdot\log_{10}(T_0) - 0.008\cdot\log_{10}(T_0)^2$	–	Own model
$Log_{10}(UrT)$	Turbidity removal uncertainty (UrT)	N (0; 0.2869)	–	Own model
C_F	Cryptosporidium concentration after filtration	$C_0\cdot rC$	Oocyst/100 L	
$Log_{10}(rC)$	Cryptosporidium removal vs turbidity	$0.963\cdot\{Log_{10}(rT) + Log_{10}(UrT)\} + 1.10$	–	Nieminski and Ongerth, 1995
T_S	Water turbidity after turbidity control	$T_F\cdot(1-R_{SC1})$	NTU	
C_S	Cryptosporidium concentration after turbidity control	$C_F\cdot(1-R_{SC1})$	Oocyst/100 L	
R_{SC1}	Water rejection by turbidity control	$h_{S1}\cdot c_{S1}\cdot x_{S1}\cdot(1-y_{S1})$	–	This study (Table 3)
I	Viability of Cryptosporidium	Beta(2.60, 3.40)	–	Pouillot et al., 2004
C_E	Concentration of infective Cryptosporidium in tap water	$C_S\cdot I$	Oocyst/100 L	
V	Tap water intake	Lognorm(0.6;0.8;1.2)[a]	L/day	AECOSAN (Agencia Española de Consumo, 2016
D	Intake dose of infective Cryptosporidium in tap water	$C_E\cdot V/100$	Oocyst/day	

[a] Lognorm (50th;75th;95th) percentile.

Table 3
Probabilistic models and data.

Variable	Description	Self-control SC0	Self-control SC1
h	Control Active (1/0)	{0, 1}	{0, 1}
c	Operation condition	Uniform (0,1) ≤ Pr{S0}	Uniform (0,1) ≤ Pr{S1}
	Operation value	Pr{S0) = {0; 1}	Pr{S1} = {0; 1}
x	Control variable	$T_{RIVER} \geq T_{RL}$	$T_F \geq T_{FL}$
	Threshold value	T_{RL} = {100, 50} [NTU]	T_{FL} = {1, 0.1, 0.01} [NTU]
y	Success condition	Uniform (0,1) > b	Uniform (0,1) > b
1-y	Failure condition	Uniform (0,1) ≤ b	Uniform (0,1) ≤ b
b	Failure probability	6.53E-4	6.53E-4

R(i) = 0 means the stage monitoring system "accepts" the control condition, whereas R(i) = 1 and "rejects" it. h_i is a logic variable that represents the activation or inactivation of the control-monitoring system: $h_i = 1$ when it is active and $h_i = 0$ in the opposite case, while c_i is a logic variable representing the operation condition that enters its left-hand side "inhibit gate", which is used to represent the condition under which the monitoring system is operational. This condition is used here to model the type of monitoring adopted, for example continuous monitoring is represented by $c_i = 1$. Logic variable x_i represents the rejection condition imposed through the control variable, e.g. turbidity at SC0 higher than 100 NTU, while $1\text{-}x_i$ represents the acceptance condition. Finally, logic variable y_i indicates that monitoring can detect and warn about possible deviations, while $1\text{-}y_i$ represents a physical failure in the monitoring system.

Table 2 shows the variables and models used in the case study to represent the evolution of *Cryptosporidium* in water from the river catchment to consumption based on integrated PM-ETA-FTA modelling. The PM turbidity reduction model achieved with the treatment was derived from plant data, as explained in the previous section. The rest of the variables and models used to assess exposure are all included in Table 2.

Table 3 shows the probabilistic models and data adopted to represent the performance of the control and monitoring system carried out in the water treatment plant. The rejection conditions given in Table 2 are obtained using the data provided in Table 3, according to the ETA + FTA model depicted in Fig. 2.

2.2.2. Dose-response model and risk quantification

After obtaining the exposure dose, we calculated the individual per-day infection probability (see Table 4), in which r is the infectivity constant of the exponential dose-response model and D is the intake dose of infective *Cryptosporidium* in tap water. The probability of infection per year was then calculated from the probability of individual infection per day. Finally, the Population becoming ill per year was estimated by multiplying the per-year infection probability by the probability of illness after infection and the population supplied by the DWTP.

2.3. Simulation procedure and scenarios

The risk of infection/illness from *Cryptosporidium* was quantified by simulation for different scenarios in a procedure composed on a spreadsheet model in Microsoft Excel and Add On @Risk 8 software (Palisade, Newfield). The propagation of *Cryptosporidium* along the chain and the risk to consumers was simulated by a standard Monte Carlo method with Latin Hypercube sampling in 20 repetitions of 100,000 iterations per simulation in each scenario. (see Table 5).

The first scenario (NoC) represents the absence of controls in the DWTP. In scenarios 2 (SC0_100) and 3 (SC0_50), the plant controls incoming water turbidity, only rejecting water over 100NTU or 50NTU, respectively. In scenarios 4 to 9 (SC1_1, SC1_0.1, SC1_0.05, SC1_0.03, SC1_0.02, and SC1_0.01), the DWTP controls both incoming water, rejecting values in excess of 100NTU, and post-filtration treatment. In scenarios 10(rT_3log) and 11 (rT_4log), the DWTP monitors the same factors as in scenario 5 but fixing DWTP turbidity reduction after filtration to 3 or 4 logs, respectively.

3. Results

3.1. Exposure assessment

Table 6 shows the results of the concentration of oocysts in the different stages of the DWTP in the different scenarios. The river water in all scenarios started at 4.31E + 01 oocyst/100L. However, as *Cryptosporidium* was present only in 16.67 % of the samples, the first column in Table 6 (C_{RIVER_ALL}) gives the average concentration of *Cryptosporidium* in the DWTP prior to the first control (SC0), after which only water turbidity below 100 NTU or 50NTU (scenarios 2 and 3, respectively) was accepted. *Cryptosporidium* concentration after SC0 (column C_0) showed slight differences between the scenario without initial control (7.19 oocyst/100L) and with control (from 7.17 to 7.21 oocyst/100L). This may be due to turbidity being below this limit in 99.8 % of the cases and the average 5.71 NTU was far from the control threshold, so that the incidence of the SC0 control was extremely low. Column C_F in Table 6 shows the oocyst concentration after treatment (sedimentation, coagulation and filtration). This value was obtained by applying the Nieminski & Ongerth model (1995), which predicts the concentration of *Cryptosporidium* as a function of the turbidity removed after filtration. As can be seen, the only differences are in scenarios 10 and 11, in which turbidity was fixed at 3 or 4 logs, respectively, instead of the function obtained from plant data and represented in Table 2, $\log_{10}(rT)$, which resulted in an average turbidity reduction of 2.653 log. Column C_S gives the oocysts in 100L of filtered water after being accepted by the SC1 control, which rejects water over a pre-set value (T_{FL}). The oocysts in 100L of water after SC1 were thus around or below those in filtered water.

Oocyst concentration was higher than 0.05 (scenarios 4 to 6). Similar reductions were found in scenarios 7 and 8, where water values between 0.02 and 0.03NTU were rejected. Important but similar reductions were found in scenarios 9 and 10. However, in scenario 11 the lowest concentration of *Cryptosporidium* was obtained (8.02E-05 oocysts/100L), with filtration set at 4 logs. Finally, the *Cryptosporidium* exposure dose in oocyst/day was obtained by applying the probability of infection to the C_S column and the water consumption distribution, shown in Table 2.

3.2. Risk assessment

The process without control and catchment turbidity control showed similar infection risk values (around 3.6E-04), even when the intake turbidity was limited to 50NTU, nor were there large differences of risk in scenarios 4–6 (3.64E-04, 3.60E-04 and 3.42E-04, respectively), in which turbidity

Table 4
Dose-response model and risk quantification.

Variable	Description	Parameters	Source
$P_{inf/day}$	Probability of infection per day	$1\text{-}e^{-r \cdot D}$	Haas et al., 1999; Health Canada, 2019
r	Scale factor	Uniform (0.004, 0.2)	US EPA, 2006; WHO, 2011 (Mohammed and Seidu, 2019)
$P_{inf/year}$	Probability of infection per year	$1\text{-}(1\text{-}P_{inf/day})^{365}$	WHO, 2016
$P_{ill/inf}$	Probability of illness after infection	0.7	WHO, 2016
$P_{ill/year}$	Probability of illness per year	$P_{inf/year} \cdot P_{ill/inf}$	WHO, 2016
P	Population	859,885	Own data
PI_{year}	Population becoming ill per year	$P_{ill/year} \cdot P$	Health Canada, 2018

Table 5
Sensitivity study conditions according to scenario. Parameters considered were: threshold values (T_{RL} and T_{FL}) in both controls, i.e. water collection (SC0) and after treatment (SC1), respectively, and the turbidity removed by filtration, considering either variable (Log10(rT)) or fixed at a reduction of 3 or 4 logs.

Run	Cod	Threshold value (T_{RL})	Reduction of turbidity	Threshold value (T_{FL})
1	NoC	–	$Log_{10}(rT)$[a]	–
2	SC0_100	100	$Log_{10}(rT)$[a]	–
3	SC0_50	50	$Log_{10}(rT)$[a]	–
4	SC1_1	100	$Log_{10}(rT)$[a]	1
5	SC1_0.1	100	$Log_{10}(rT)$[a]	0.1
6	SC1_0.05	100	$Log_{10}(rT)$[a]	0.05
7	SC1_0.03	100	$Log_{10}(rT)$[a]	0.03
8	SC1_0.02	100	$Log_{10}(rT)$[a]	0.02
9	SC1_0.01	100	$Log_{10}(rT)$[a]	0.01
10	rT = 3log	100	Fixed 3 log	0.1
11	rT = 4log	100	Fixed 4 log	0.1

[a] See Table 2.

was also monitored after filtration, admitting a maximum of 1, 0.1 and 0.05NTU, respectively. In scenarios 7 and 8, with a turbidity limit of 0.03 and 0.02NTU after treatment, a slightly lower risk value was achieved (2.9E-04 and 2.14E-04, respectively). The difference was more marked in scenarios 9 and 10, where the risk was 7.74E-05 in both cases, with the only differences in standard deviation. Scenario 11 reached the minimum infection risk (8.4E-06) and with turbidity reduction set at 4 log, the probability of rejection was zero.

The risk of becoming ill after infection depends principally on the person's sex, age and health status. In this work, the calculation of the risk of becoming ill was obtained by multiplying the risk of infection by the value of 0.7, corresponding to the probability of becoming ill once infected, proposed by the WHO (2016). Fig. 3 shows the annual *Cryptosporidium* risk of illness from tap water for the different scenarios and the probability of the water being rejected. As can be seen, the risk of illness in scenarios 1 to 5 is similar (2.52E-04 - 2.53E-04) and the turbidity content is always accepted. Scenario 6 shows a slight drop in the risk (2.4E-04) accompanied by a low percentage of water rejection (1.5 %) or 0.05NTU after filtration. The probability of water rejection after SC1 increased from 8 % in scenario 7 to 21 % in scenario 8, with scenario 9 reaching the highest probability, around 60 %, when 0.01NTU is exceeded. In scenarios 10 and 11, where the filter stage is designed to reduce turbidity to between 3 logs and 4 logs, the probability of rejection is zero. In terms of the risk of illness risk, scenarios 9 and 10 have the same mean value (5.42E-05) and scenario 11 allowed the maximum risk reduction (5.93E-06).

4. Discussion

Monitoring and control of water safety parameters can be conducted at critical steps of the water supply system. For DWTP catchment waters, turbidity treatment and control are the first barriers, rejecting water that exceeds a fixed value, as in our case study, so that DWTP treatment must be adapted to achieve a reliable process that guarantees water quality and safety. The combination of all three tools provides information on how modifying the controls, acceptance limits and additional measures could improve safety without the need for previous testing. Our findings showed that river water turbidity, continuously measured at the DWTP inlet, was <10 NTU in 95.45 % of the cases. Despite these good results, in 0.20 % of the cases water was rejected due to being over 100 NTU. As Stevenson and Bravo (2019) have indicated, turbidity levels can change slowly over time due to changes in water catchments as part of an underlying trend, but can also rapidly peak over shorter periods, even though they appear to be random. Turbidity peaks are linked to environmental events such as heavy rainfall but can also be a result of operations like pumping. Inherent solution features at the site such as fissures in the aquifer can also cause turbidity (WHO, 2017a). The average turbidity of raw water samples is not related to the presence or concentration of oocysts, since it is possible to find low values (<1 NTU) in some positive samples and register high values (>5 NTU) in water without *Cryptosporidium* (Ramo et al., 2017).

After filtration, the results showed that turbidity values were equal to or <0.25 NTU in 97.62 % of the cases. These values are within the limits established by Teunis.

Directive 98/83/EC, by which the EU member states must ensure that the parametric value of turbidity in drinking water does not exceed 1 NTU. They also agree with the WHO Guidelines for drinking water quality (WHO, 2009, 2017b), which recommend that water treatment systems should be capable of ensuring turbidity does not exceed 1 NTU and 0.3 NTU before disinfection

Table 6
Cryptosporidium concentration through the DWTP stages. Mean ± Standard deviation (1th; 99th percentile).

Scenario	C_{RIVER_ALL} (oocyst/100 L)[a]	C_0 (oocyst/100 L) (after SC0[b])	C_F (oocyst/100 L) (before SC1[c])	C_S (oocyst/100 L) (after SC1[c])	Dose (oocyst/day)
1. NoC	7.19E+00 ± 2.39E+01 (0; 1.21E+02)	7.19E+00 ± 2.39E+01 (0; 1.21E+02)	3.45E-03 ± 1.75E-02 (0; 7.10E-02)	3.45E-03 ± 1.75E-02 (0; 7.10E-02)	9.79E-06 ± 5.92E-05 (0;2.07E-04)
2. SC0_100	7.19E+00 ± 2.39E+01 (0; 1.22E+02)	7.18E+00 ± 2.39E+01 (0; 1.21E+02)	3.46E-03 ± 1.78E-02 (0; 7.02E-02)	3.46E-03 ± 1.77E-02 (0; 7.03E-02)	9.80E-06 ± 6.07E-05 (0; 2.06E-04)
3. SC0_50	7.20E+00 ± 2.39E+01 (0; 1.21E+02)	7.16E+00 ± 2.38E+01 (0; 1.21E+02)	3.47E-03 ± 1.76E-02 (0; 7.11E-02)	3.48E-03 ± 1.76E-02 (0; 7.12E-02)	9.88E-06 ± 5.92E-05 (0; 2.09E-04)
4. SC1_1	7.22E+00 ± 2.40E+01 (0; 1.22E+02)	7.21E+00 ± 2.39E+01 (0; 1.22E+02)	3.48E-03 ± 1.74E-02 (0; 7.17E-02)	3.48E-03 ± 1.74E-02 (0; 7.17E-02)	9.86E-06 ± 5.92E-05 (0; 2.09E-04)
5. SC1_0.1	7.18E+00 ± 2.37E+01 (0; 1.21E+02)	7.17E+00 ± 2.37E+01 (0; 1.21E+02)	3.45E-03 ± 1.76E-02 (0; 7.00E-02)	3.44E-03 ± 1.74E-02 (0; 7.00E-02)	9.75E-06 ± 6.06E-05 (0; 2.06E-04)
6. SC1_0.05	7.20E+00 ± 2.38E+01 (0; 1.21E+02)	7.20E+00 ± 2.38E+01 (0; 1.21E+02)	3.47E-03 ± 1.78E-02 (0; 7.07E-02)	3.28E-03 ± 1.63E-02 (0; 6.75E-02)	9.26E-06 ± 5.57E-05 (0; 1.97E-04)
7. SC1_0.03	7.19E+00 ± 2.38E+01 (0; 1.21E+02)	7.18E+00 ± 2.38E+01 (0; 1.21E+02)	3.49E-03 ± 1.80E-02 (0; 7.12E-02)	2.78E-03 ± 1.39E-02 (0; 5.83E-02)	7.84E-06 ± 4.70E-05 (0; 1.70E-04)
8. SC1_0.02	7.22E+00 ± 2.39E+01 (0; 1.22E+02)	7.21E+00 ± 2.39E+01 (0; 1.22E+02)	3.50E-03 ± 1.81E-02 (0; 7.14E-02)	2.04E-03 ± 1.07E-02 (0; 4.55E-02)	5.80E-06 ± 3.66E-05 (0; 1.31E-04)
9. SC1_0.01	7.19E+00 ± 2.39E+01 (0; 1.21E+02)	7.18E+00 ± 2.38E+01 (0; 1.21E+02)	3.46E-03 ± 1.77E-02 (0; 7.07E-02)	7.30E-04 ± 5.27E-03 (0; 2.00E-02)	2.07E-06 ± 1.79E-05 (0; 5.42E-05)
10. rT = 3log	7.19E+00 ± 2.39E+01 (0; 1.22E+02)	7.18E+00 ± 2.38E+01 (0; 1.21E+02)	7.34E-04 ± 2.44E-03 (0; 1.24E-02)	7.35E-04 ± 2.44E-03 (0; 1.24E-02)	2.08E-06 ± 8.37E-06 (0; 4.00E-05)
11. rT = 4log	7.21E+00 ± 2.39E+01 (0; 1.22E+02)	7.20E+00 ± 2.39E+01 (0; 1.22E+02)	8.02E-05 ± 2.66E-04 (0; 1.36E-03)	8.02E-05 ± 2.66E-04 (0; 1.36E-03)	2.27E-07 ± 9.09E-07 (0; 4.38E-06)

[a] Include all samples of input water, i.e., $C_{RIVER\_ALL} = C_{RIVER} \cdot pC_0$.
[b] SC0: Control at water collection from the river.
[c] SC1: Control after filtration.

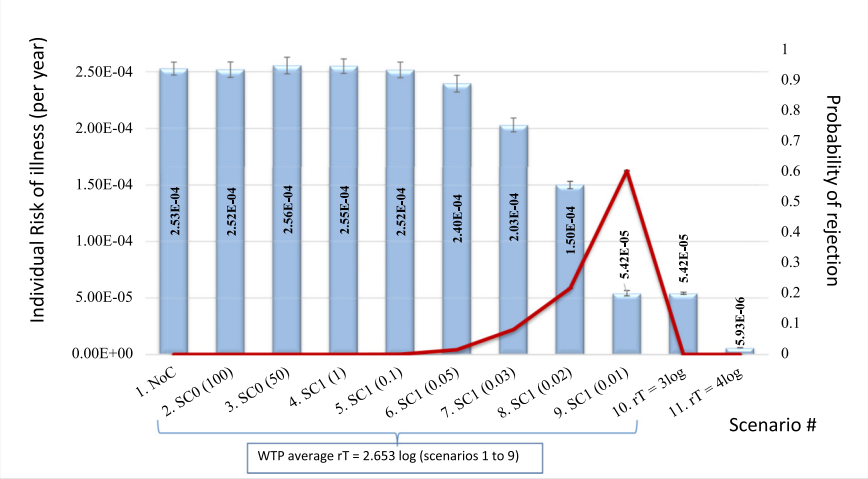

Fig. 3. Consumer risk due to drinking tap water contaminated by *Cryptosporidium* oocyst and probability of rejection of treated water.

by conventional or direct filtration in at least 95 % of daily samples in any month. Turbidity reduction is related to reducing gastrointestinal diseases by 600 % (Muoio et al., 2020). This is particularly important in the present work, as turbidity after filtration has been significantly correlated with *Cryptosporidium* and is considered an indicator of filtration efficiency for the elimination of these pathogens (Dugan et al., 2001; Hsu and Yeh, 2003; Burnet et al., 2014). Many studies have reported that turbidity after filtration should be <0.1 NTU to maximise oocyst reduction, although this does not guarantee the absence of pathogens (Nieminski and Ongerth, 1995).

In the present study, the river water was free of *Cryptosporidium* in 84 % of the samples. In the positive cases, the concentration of oocysts was below 0.0025 oocysts/L in 71 %, although there were high values of up to 1.50 oocyst/L. These results were consistent with a guide for Canadian Drinking Water Quality (Health Canada, 2019) that reviewed *Cryptosporidium* concentrations in surface waters in Canada, concluding that most of the studies range from 0.001 to 1 oocyst/L. These agreed with findings in nine European sites, and one Australian site showed that *Cryptosporidium* was frequently detected at relatively low concentrations, and levels ranged from 0.01 to 0.50 oocysts/L, although on occasions protozoa rose to 4.60 oocyst/L (Dechesne and Soyeux, 2007). Hadi et al., 2019, obtained the minimum, mean and maximum densities of oocysts in river water samples were 0.054, 0.064 and 0.216 oocysts/L, respectively.

Sato et al. (2013) reported that *Cryptosporidium* was detected in 9.2 % of the samples in concentrations between 0.1 oocysts/L and 6 oocysts/L, while Gammie et al. (2000) found that the annual geometric mean ranged from 0.006 to 0.83, although the maximum reached 103 oocysts/L, which was associated with heavy spring runoff. The effects of climate variability and seasonal influence on diarrhoeal disease has been widely studied (Doménech et al., 2017; Bhandari et al., 2020; Aik et al., 2020). Also, *Cryptosporidium* contamination was reported by Mons et al. (2009), who found 45.7 % of positive samples from the Seine and Marne Rivers, with a minimum of 0.05 and a maximum of 24.5 oocyst/L. These results highlight the importance of routine monitoring to characterize source water, as pathogen estimation is limited by the amount of information available on both the uncertainty and the variability of the collected data. Firstly, pathogen densities tend to be small and so may not fully capture the variability inherent to the system. Secondly, the methods available for detecting pathogens do not recover 100 % of the pathogens in the samples and the recovery rate varies between samples (US EPA, 2014).

In the scenarios studied, filtration succeeded in eliminating the concentration of oocysts by an average value of 3.656 logs, which is the average reduction of water turbidity of 2.65 logs. This value is within the range observed by other authors, who found that the logarithmic extractions of *Cryptosporidium* oocysts after filtration are >1.2 but <4.6, with the median of the means being equal to or >2.34 (LeChevallier and Norton, 1992; Payment and Franco, 1993; Nieminski and Ongerth, 1995; States et al., 1997; Gammie et al., 2000; Betancourt and Rose, 2004; Hadi et al., 2019).

The risk of infection in the current situation of the Manises water company, represented by scenario 5 was 3.64E-04. This value is slightly higher than the target risk for drinking water (1E-04) proposed by the US EPA (US EPA, 2006). Most of the studies that assessed *Cryptosporidium* risk in tap water from rivers treated with coagulation, flocculation, sedimentation and filtration are in line with our findings. Teunis et al. (1997) concluded that the annual risk for several major population centres that received water from the Meuse River (Netherlands) was just over 1E-04. Recently, Eisenberg et al. (2006) published the results of a QMRA of risk of infection in Davenport, Iowa, in the United States, citing the annual risk of infection to be 2.1E-04. Ryu and Abbaszadegan (2008) performed a four-year study on surface waters in central Arizona, USA and found that the infection risk ranged from 4.9E−4 to 6.0E-04. Jaidi et al. (2009) carried out a Monte Carlo model to assess the relative risks of infection associated with *Cryptosporidium* in drinking water, obtaining mean annual risks of 9.33E-04. Aboytes et al., 2004 monitored *Cryptosporidium* in filtered drinking water of 82 surface water treatment plants in 14 US states, obtaining a mean annual risk of infection of 5.2E-03, minimum 9E-04 and maximum 1.19E-02. Higher values were reported by Razzolini, who analysed direct drinking water consumption, concluding that the annual risk of infection in adults in the southeast of Brazil was 4E-03. Similarly, Medema et al. (2003) studied three Dutch communities and found that the annual risks ranged from 3.5E-02 to 1.1E-04. Payment et al. (2000) reported results from 46 communities in Quebec, Canada, obtaining an annual risk ranging from 1.1E-01 to 4.7E-08.

The risk of infection in scenario 5 is similar to those for scenarios 1 to 4, showing that input turbidity control (scenarios 1 to 3) and minimum turbidity control after filtration (scenario 4) had little or no effect on reducing the risk. There was a more marked reduction in turbidity after treatment in scenarios 6 to 9, which were accompanied by a greater probability of water being rejected of up to almost 60 % of cases (scenario 9), which despite reducing the risk to 7.74E-05 would be of little practical use to the company. However, improved turbidity reduction after treatment, e.g., a pre-established turbidity reduction of 3 and 4 logs (scenarios 10 and 11) would greatly reduce the risk to values of 7.74E-05 and 8.48E-06, respectively, without increasing the reprocessing probability but at the expense of improving the current filtering system to achieve the reduction.

The low risk values achieved in scenarios 9 to 11 are comparable to those obtained by other studies in the literature in which the water treatment included ultraviolet disinfection. Thus, Mohammed & Seidu, (2019) studied three drinking water treatment plants in Norway in which UV disinfection was after coagulation/flocculation, sedimentation and rapid sand filtration. The reductions of *Cryptosporidium* achieved with UV treatment ranged from 3.6 to 4 logs, obtaining an annual risk of infection of

between 2.06E-06 and 1.96E-08. Similarly, Health Canada, 2018 reported that the average risk was 3.39E-05 for UV disinfected water UV.

Among the authors who expressed the risk of annual illness, similar values were found by Cummins et al., 2010, who found that in background and extreme level scenarios of coagulation/flocculation, and sedimentation the values reported were 3.69E-05 to 1.28E-02, respectively. Boué et al., 2018 concluded that the mean annual probability of illness in infants mostly varied between 7.30E-04 and 2.52E-02 according to gender and age in months.

5. Concluding remarks

This paper presents a new approach in which predictive modelling, event tree and fault tree analysis techniques are used to simulate the evolution of a pathogen throughout the water chain, addressing the influence of not only normal but also abnormal (i.e. failures) performance of treatment and safety control measures.

The case study quantified the consumer risk due to the presence of *Cryptosporidium* in tap water controlled indirectly through turbidity reduction and continuous turbidity monitoring at water collection and after filtration. It showed the ability of the new approach to reproduce real scenarios and assess oocyst levels after treatment, including the heterogeneity of inputs due to various levels of oocysts in surface water, plant treatment efficiencies, controls during the process and water intake. Uncertainty in the estimation of the oocyst recovery rate, viable oocyst prevalence and the probability of water treatment failure were also considered. As a result, the annual risk of infection in the eleven scenarios studied show the flexibility of the combined techniques to adapt to different circumstances, assess the safety level and contribute to risk-informed decision-making. The use of turbidity only to evaluate the relationship with *Cryptosporidium* contamination is one of the main limitations of this study, but it is current practice in the literature and in real DWTPs. Given the results of the study and that safety objectives are not always met, the possibility of incorporating new treatment stages or even a disinfection stage should be studied to reduce the *Cryptosporidium* concentration to such low levels of turbidity. Alternatively, direct instead of indirect control of oocyst concentration could be more effective in reducing the risk while the water rejection probability would be kept at lower values. This alternative would overcome the limitation introduced above.

The new approach can be used for exposure assessment of other water pathogens, and new treatment measures and safety controls, such as those cited above or others could be considered at any stage of the water chain to assess the real impact of deviations or failures in process conditions and safety controls on the risk to consumers due to the presence of pathogens.

CRediT authorship contribution statement

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Author contribution: Collected data; Other: Experience in the drinking water treatment plant
Ignacio Escuder-Bueno
Author contribution: Other contribution: reviewed the formal framework of risk analysis as applied to civil infrastructures and co-assessed consistency in the outcomes of the practical case

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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