RESEARCH ARTICLE

Impact of *Escherichia coli* from stormwater drainage on recreational water quality: an integrated monitoring and modelling of urban catchment, pipes and lake

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Abstract
In recent years, recreational waterbodies are increasingly favoured in urban areas. In spite of the growing concerns for maintaining the required bathing water quality, the impacts of stormwater drainage are still poorly controlled. In this context, this study originally develops an integrated urban catchment-pipes-lake monitoring and modelling approach to simulate the impacts of microbial quality from stormwater drainage on recreational water quality. The modelling system consists of three separated components: the urban catchment component, the 3D lake hydrodynamic component and the 3D lake water quality component. A series of processes are simulated in the model, such as rainfall-discharge, build-up, wash-off of *Escherichia coli* (*E. coli*) on urban surfaces, sewer flows, hydrothermal dynamics of lake water and transport and mortality of *E. coli* in the lake. This integrated model is tested for an urban catchment and its related recreational lake located in the Great Paris region. Continuous monitoring and samplings were performed at the stormwater drainage outlet and three different sites in the lake. Comparing the measured data with simulation results over 20 months, the modelling system can correctly represent the *E. coli* dynamics in the stormwater sewer systems and in the lake. Although uncertainties related to parameter values, pollution sources and *E. coli* mortality processes could be further discussed, the good performance of this modelling approach emphasizes a promising potential for urban bathing water quality management.

Keywords *Escherichia coli* · Recreational water · Urban stormwater drainage · Integrated monitoring and modelling · Process-based modelling · Build-up and wash-off

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Introduction

In recent years, recreational waterbodies are increasingly attractive and frequented in urban areas. This worldwide trend requires minimum standards for achieving and maintaining high water quality at all times to ensure the protection of public health. In accordance with the European Bathing Water Directive (Directive 2006/7/EC), the concentration of faecal pathogens has to be monitored in order to take appropriate management actions in case of non-compliance with the requirements. Present in the gut microbiota of humans and warm-blooded animals, *Escherichia coli* (*E. coli*) is commonly used as an index of faecal contamination (Edberg et al. 2000), which indicates the presence of pathogens causing gastrointestinal infections (WHO 2003). Depending on the risk of infection, the Directive 2006/7/EC classifies bathing waters as excellent, good, sufficient or insufficient.

In spite of the growing concerns for maintaining the required quality of the bathing waters, the impacts of several pollution sources are still poorly controlled, particularly the pollution from urban stormwater discharges. In many municipal areas, urban stormwater is conveyed in separated sewer systems and discharged directly to receiving waters without any treatment. The typical levels of *E. coli* in stormwater greatly exceed the existing recreational water guidelines (Marsalek and Rochfort 2004); this may degrade the bathing water quality and even cause severe public health risks, especially during heavy precipitation periods.

The distribution and fate of *E. coli* released into the urban lakes can be generally described as a combination of die-off and dilution (McLellan et al. 2007; McCarthy et al. 2012). However, it is still unfeasible to track the spatial-temporal distributions of this faecal indicator organism with monitoring data. Many modelling approaches have been reported in scientific literature for simulating the transport and fate of *E. coli* in recreational waters. Existing models can be mainly categorized into two classes: the data-driven approaches and the deterministic models. The data-driven models, for example, artificial neural networks (ANN) (Kashefipour et al. 2005; He and He 2008), random forest (Parkhurst et al. 2005; Jones et al. 2013) and other regression-based models (de Brauwere et al. 2014; Brooks et al. 2016), attempt to relate *E. coli* concentrations with various environmental factors such as rainfall, solar radiation, water temperature, salinity and population density. Although acceptable results are reported using these methods, their performance will continue to be questionable if they are applied to extrapolate patterns outside the range of case-specific measured data, and they cannot reproduce the spatial-temporal dynamics of *E. coli* processes. The deterministic models aim to fully capture the changing dynamics for describing the complex interactions between catchments, rivers and water bodies (e.g. Bedri et al. 2014; Huang et al. 2017). Nevertheless, most published deterministic models are focused on coastal bathing waters. Very limited research exists for urban catchments and their receiving lakes. Moreover, the fate of *E. coli* is mainly simulated by using a constant decay rate, and rare studies have considered the mortality of *E. coli*.

In this context, this paper proposes an integrated deterministic and spatially distributed urban catchment-lake model for simulating the generation, transport and mortality processes of *E. coli* from an urban catchment including the drainage network to a receiving recreational lake. Two widely used models are comprised in the modelling system, including (i) the sub-catchment based and one-dimensional sewage network model SWMM (Rossman 2010) and (ii) the three-dimensional model Delft3D (Deltares 2016). This integrated modelling chain is tested for an urban catchment and its related recreational lake located in the Great Paris region. Extensive hydrodynamic and water quality data from detailed monitoring survey are used for model calibration and validation.

Materials and methods

Study area description

The study area is located in the southeast of Paris (Créteil, Val-de-Marne, France) (Fig. 1a) and consists of an urban catchment of 95 ha and a recreational lake of 42 ha (Lake Créteil) (Fig. 1b).

The study catchment is a typical urbanized area in the Paris region, characterized by its high population density ($\approx 8{,}000$ inhabitants/km^2) and low surface permeability (about 10% of the areas are permeable surfaces). The average slope is approximately 2%. During rainfall events, stormwater runoff is collected by a separated drainage system. The total length of the network is 17.6 km, with a single outlet on the eastern side of Lake Créteil (Fig. 1b). Besides, a flow valve is installed at the end of the stormwater sewers to divert dry weather flow into the wastewater networks, avoiding the discharge of waste water from cross-connections between the separated pipes.

The receiving waterbody, Lake Créteil, is an important outdoor leisure centre in the Paris region (boating, sailing, angling, etc.), with a park of 0.62 km^2 on the western bank of the lake. Apart from the stormwater drainage of the urban catchment, Lake Créteil is mainly fed by groundwater, which flows from the Marne River to the Seine River (Fig. 1a), due to a 1-m difference in the normal levels of the navigation reaches (Soulignac et al. 2017). The lake water level can be regulated by a fixed gate on the western bank. The mean depth of Lake Créteil is 4.5 m, with the southern part deeper than the northern part, reaching a maximum depth of 6.5 m. The total volume of the lake is about 1.9×10^6 m^3.

Since the boundary conditions of Lake Créteil are well controlled with constructed isolation dams, the *E. coli* patterns in the receiving water body are strongly influenced by the stormwater drainage of the connected urban catchment. This study area is therefore specifically suited for assessing the impact of stormwater quality on urban lakes.

Sampling methodology

Measuring equipment in stormwater sewer

From Oct. 10th to Nov. 5th 2013, hereafter referred to as the sewer monitoring period, a monitoring and auto-sampling system is set up at the downstream end of the main stormwater sewer, before it divides into two parallel pipes towards the outlet. Water depth and water flow rate are recorded at a 2-min time step. An autonomous controller is connected both to a flow meter (Mainstream IV, Hydreka Inc.), which measures

Fig. 1 **a** Location of the study area in Créteil, France. **b** Zoomed-in view of the urban catchment, recreational lake, storm sewer system and monitoring and sampling points
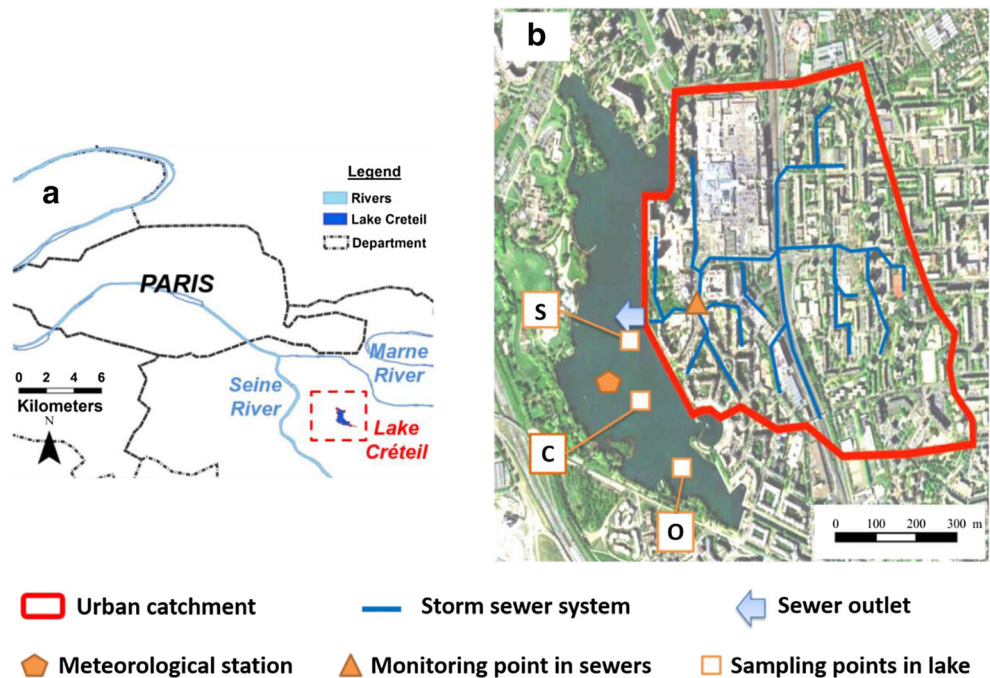
water depth and mean flow velocity, and to an auto-sampler (HACH Sigma SD900). The discharge is then automatically estimated by considering water height, flow velocity and pipe shape. When the sewer water depth is higher than 0.15 m, the controller receives a positive signal to activate its 'water height flag', and starts to count the water volume registered by the flow meter. If the 'water height flag' remains activated, the controller sends positive signals to the auto-sampler for sampling 125 mL water at 64 m³ water volume interval. Water samples gathered during a rainfall event are mixed and stored in a large container and then collected on the following day of every rainy day and reserved at 4 °C up to 4 h prior to laboratory processing. This approach allows to collect representative stormwater flow samples of each rainfall event.

Lake Créteil monitoring

Lake Créteil is equipped with high-frequency monitoring sensors and a meteorological station (PME Inc, LakeESP) from May 12th, 2012, to Jan. 31th 2014, hereafter referred to as the lake monitoring period. Meteorological variables such as wind speed and direction, precipitation, air temperature, air pressure, relative humidity (Vaisala, WXT520) and net radiation (Kipp and Zonen NR Lite2) are measured every 30 s. Since the study area is quite small (< 1 km²), which corresponds to only one grid of a typical C-band radar (1-km resolution) and dozens of grid cells of an X-band radar in Paris region (250-m resolution) (Paz et al. 2020), rainfall is considered homogeneous within the Créteil basin. The underwater chain is equipped with temperature sensors (NKE, SP2T) at different depths, also with a sampling time-step at

30 s. These datasets and the measured lake bathymetry are used for the hydrodynamic modelling of the lake (Soulignac et al. 2017).

E. coli concentration measurement

During the sewer monitoring period, on-site experiments are carried out in Lake Créteil at station S, C and O (Fig. 1b) on the following day of each rainfall to collect water samples for laboratory analysis. *E. coli* concentrations of the collected lake and sewer water samples are enumerated by the microplate method, according to the French standard method NF ISO 9308-3. Raw or diluted samples are spread in 96-well microplates containing a dehydrated culture medium. After an incubation period of 48–72 h at 44 °C ± 0.5 °C, the microplates are examined under ultraviolet light at 366 nm. The results are expressed as the most probable number (MPN), which is a statistical estimate of the density of microorganisms. The detection limit of < 0.075 MPN mL⁻¹ water sample is estimated. Moreover, a monthly *E. coli* monitoring program of Lake Créteil is performed from January 2012 to December 2013 (Roguet et al. 2018), which covers the lake monitoring period.

Event-based and continuous simulations

Using rainfall intensity measurements at every 30 s, different rainfall events can be identified by dry period intervals longer than 90 min, meaning no rain intensity data recorded during 90 min. And a valid rainfall event should have a total water depth more than 1 mm. Based on these criteria, four different rainfall events can be recognized for the sewer monitoring

period. Event-based simulations are performed for these rain-fall events, calibrated and validated by using the continuous measurements of stormwater sewer discharge, *E. coli* event mean concentration (EMC) of stormwater sewer flow and the *E. coli* concentration at three points in Lake Créteil on the following day of each event. In addition, a continuous simulation is performed for the lake monitoring period with the calibrated parameters; monitored water temperature at different depths and monthly *E. coli* concentration in the lake are used to evaluate the model performance. Simulation periods, comparison measurements for assessing model performance and characteristics of the studied rains are illustrated in Table 1.

Model description

Overview of the integrated modelling system

The integrated modelling system consists of three separated components: the urban catchment component, the 3D lake hydrodynamic component and the 3D lake water quality component. Urban catchment processes are simulated by the SWMM model (Rossman 2010). Faeces of urban animals (dogs, cats, birds, etc.) are considered to be continuously accumulated on urban surfaces (roads, roofs, sidewalks, etc.) in dry weather periods (build-up). During rainfall events, these pollutants are removed with surface runoffs (wash-off) and then transported in the stormwater drainage network into the receiving lake. The in-lake processes are simulated with the Delft3D modelling suite (Deltares 2016), respectively, hydrodynamics by the FLOW module and *E. coli* transport and mortality processes with the WAQ module.

Python scripts are developed in order to automatically link the different modelling components by interfacing the involved state variables. However, feedback among different components, such as a downstream condition in the stormwater outlet due to the lake water level, are not permitted yet by the current version of modelling. A schematic of the integrated model is presented in Fig. 2.
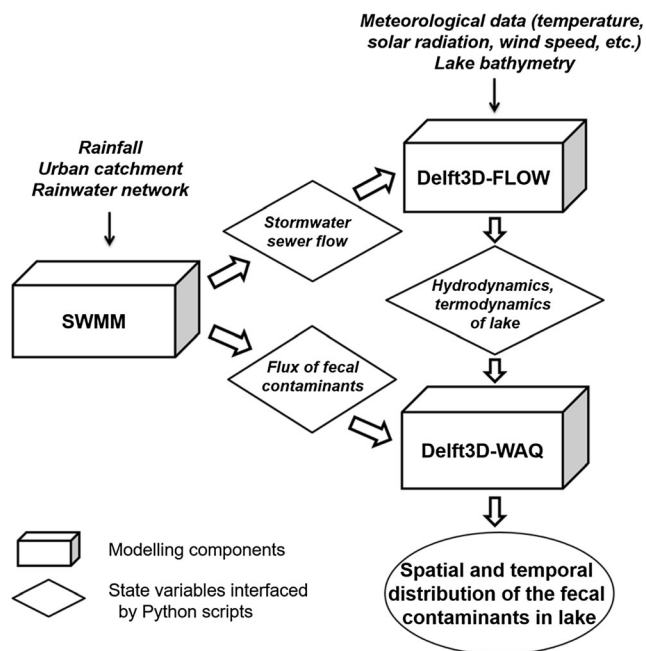

Fig. 2 Scheme of the integrated modelling system

Urban catchment component

The urban catchment is divided into 21 sub-catchments according to the administrative divisions of residential, commercial and industrial zones. The surface runoff of each sub-catchment is simulated with a non-linear reservoir because of the simplicity and robustness of this approach. The surface storage is taken into account as an initial hydrological loss. The impervious area represents 40–80% of different sub-catchments and the infiltration in pervious areas being described by the Green and Ampt (1911) equations. Rainfall-runoff routing is solved by coupling the continuity equation with the Manning equation. Water flow in sewer networks is computed by 1D kinematic wave equations with finite-difference scheme, whereas ponding is not allowed for the manholes since it is not an issue for the study period, and this research focuses on *E. coli* simulations under normal rains.

Table 1 Simulation periods, comparison measurements for assessing model performance and characteristics of the studied rains

Simulation period	Comparison measurements	Rains	Precipitation depth (mm)	Duration	Calibration/validation
Sewer monitoring period: 10/10–11/05/2013 (event-based simulations)	Stormwater sewer discharge; *E. coli* EMC of stormwater sewer flow; *E. coli* concentration in the lake after rains	10/14/2013	4.8	1.3 h	Calibration
		10/16/2013	3.4	1.4 h	Validation
		10/20/2013	5.9	0.4 h	Validation
		11/03/2013	11.7	8.2 h	Validation
Lake monitoring period: 05/12/2012–01/31/2014 (continuous simulation)	Lake water temperature at different depths; monthly *E. coli* concentration in the lake	05/12/2012–01/31/2014	1046	628 days	Validation

The build-up and wash-off processes of *E. coli* are calculated at the scale of each sub-catchment. The build-up during a dry period follows an exponential growth curve (Eq. 1), and the wash-off rate depends on the runoff discharge and the amount of the remaining substances at each time-step (Eq. 2) (Rossman 2010).

$$Build\_up = C_1\left(1 - e^{-C_2 t_{dry}}\right) \tag{1}$$

$$dM/dt = -C_3 q^{C_4} M \tag{2}$$

where

Build _ up is the mass of *E. coli* accumulated on the surface during a dry period (MPN m^{-2});

t_{dry} is the time of dry weather periods (days);

C_1 is the maximum possible build-up of *E. coli* (MPN m^{-2});

C_2 is build-up constant rate (day^{-1});

dM/dt is the wash-off rate (MPN m^{-2} h^{-1});

C_3 is the wash-off coefficient (mm^{-1});

C_4 is the wash-off exponent (-);

q is the runoff flux rate over sub-catchment (mm h^{-1});

M is the remaining *E. coli* at each time step (MPN m^{-2})

For *E. coli* routing, the pipes are considered continuously stirred tank reactors (CSTR). The concentration of *E. coli* in pipes at the end of a time step is found by integrating the conservation of mass equation over this time step.

3D lake modelling

The Delft3D-FLOW model (Deltares 2016) solves the Navier-Stokes equations for an incompressible fluid, under the shallow water and the Boussinesq assumptions. The system of equations consists of the horizontal equations of motion, the continuity equation and the transport equation of heat. This set of partial differential equations in combination with an appropriate set of initial and boundary conditions is solved on a finite difference grid with current velocities defined on cell faces and scalar variables at cell centres. Following the settings in Soulignac et al. (2017), the horizontal surface of Lake Créteil is meshed with 981 Cartesian cells of 20 m × 20 m, and the Z-model is used with 18 horizontal layers of height 33 cm. Monitored values of wind direction and speed, air temperature, relative humidity and precipitation, as well as the recorded values of hourly incident solar radiation and cloud cover at the nearest weather station located at Orly Airport, 10 km west of the lake, are used to force the simulations. Water level variations are neglected as they never exceeded 3% of the water height over a simulation period.

The transport and fate of *E. coli* in the lake are simulated with Delft3D-WAQ (Deltares 2016). For modelling purpose, it is supposed that *E. coli* is a stand-alone substance: (i) it is present only in the water column, (ii) it does not accumulate in

the sediment or resuspend from it, (iii) it does not grow in the water and (iv) only the transport and mortality processes are simulated. These hypotheses simplify the real-world processes, making the physically based modelling of *E. coli* dynamics possible for urban lakes. Processes of *E. coli* in Lake Créteil is computed by advection-dispersion-mortality equation (Eq. 3). In each cell of the 3D model, advection-dispersion of *E. coli* is computed by the conservation of mass equations (please refer to Deltares (2016) for more details), while the mortality of *E. coli* is related with temperature and solar radiation (Eqs. 4 and 5).

$$\frac{\partial C}{\partial t} = \text{advection} + \text{dispersion} - \text{mortality} \tag{3}$$

$$\text{mortality} = \left[km_b \cdot ktmrt^{(T-20)} + km_{rd}\right] \cdot C \tag{4}$$

$$km_{rd} = k_{rd} \cdot DL \cdot fuv \cdot I0 \cdot \frac{(1 - e^{-\varepsilon \cdot H})}{\varepsilon \cdot H} \tag{5}$$

where

C is the concentration of *E. coli* in a 3D-cell (MPN m^{-3})

km_b is the basic mortality rate of *E. coli* (day^{-1});

$ktmrt$ is the temperature coefficient of the mortality rate (-);

T is the water temperature (°C);

km_{rd} is the radiation dependent mortality rate (day^{-1});

k_{rd} is the radiation related mortality constant (m^2 W^{-1} d^{-1})

DL is the fraction of daytime in 24 h (-);

fuv is the fraction of UV radiation as derived from visible light (-);

I_0 is the daily solar radiation as visible light at the water surface (W m^{-2});

ε is the background extinction of UV radiation (m^{-1});

H is the water depth (m);

Model calibration and uncertainty analysis

Calibration of SWMM model are first performed for hydraulic/hydrologic parameters and then for build-up/wash-off parameters. The Nash-Sutcliff efficiency coefficient (NSE) (Nash and Sutcliffe 1970) is used to assess the model performance (Eq. 6). NSE can range from −∞ to 1. An efficiency of 1 (NSE = 1) corresponds to a perfect match of modelled discharge or *E. coli* concentration to the observed data.

$$NSE = 1 - \frac{\sum_{t=1}^{T}\left(Q_s^t - Q_m^t\right)^2}{\sum_{t=1}^{T}\left(Q_m^t - \overline{Q_m}\right)^2} \tag{6}$$

where

T is the simulation period;

t is the modelling time-step;

Q_s^t is the simulated discharge or *E. coli* concentration at time t;

Q_m^t is the measured discharge or *E. coli* concentration at time *t*;

$\overline{Q_m}$ is the mean of measured discharge or *E. coli*;

A simple and robust bisection approach is applied to estimate the optimized value of each parameter. Given the initial interval of each parameter, the bisection method cuts the interval into two halves and check which half interval has the larger NSE value. This method keeps cut the interval in halves until the resulting interval is small; the optimized parameter value can be then approximately equal to any value in this final interval. When calibrating one parameter, we fix other parameters to their optimal values or the mid-point of the initial interval if the calibration is not performed yet.

For urban catchment hydrological simulations, we calibrate the manning's n roughness and the initial loss for impervious and pervious surfaces, respectively. The initial intervals for these parameters and other default values of hydraulic/hydrologic parameters can be referred to (Rossman 2010). Initial intervals of *E. coli* build-up and wash-off parameters are shown in Table 2.

An exploratory uncertainty analysis is performed to represent the impacts of wash-off/build-up parameters on *E. coli* concentration. Since simulations for the integrated water quality modelling is computational expensive (particularly for the 3D lake module), a stochastic parameter sampling approach is repeated for ten simulations of each event-based modelling and the continuous modelling. The analysed parameters are considered uniformly distributed in the initial intervals defined in Table 2. For each rain, we randomly pick-up ten parameter sets in these intervals and implement simulations. The uncertainty of the analysed simulation period can be then expressed by the 95% confidence interval of the simulated *E. coli* concentrations.

Results

Water flow and *E. coli* concentration at drainage outlet

The hydraulic/hydrologic and build-up/wash-off parameters of the SWMM model are calibrated for the rain of 10/14/2013 and then validated with the other three rainfall events, as well as the sewer monitoring period (10/10–11/05/2013).

The optimized *n*-manning values are 0.015 for impervious areas and 0.15 for pervious areas, and the initial loss is 0.5 mm for impervious areas and 2 mm for pervious areas. Optimized build-up and wash-off parameter values of *E. coli* are shown in Table 2.

Water flow simulations at stormwater outlet

As seen in Fig. 3, the performance of the water flow simulation was quite satisfactory (NSE > 0.7 for all rainfall events). The hydrological dynamics in urban catchment is correctly represented by the SWMM model. The model can be then used for event-based and long-term simulations of *E. coli* dynamics.

Event mean concentrations of *E. coli*

As shown in Fig. 4, the simulated EMC of *E. coli* can correctly represent the measured values at the drainage outlet for the four sampled rainfall events. This consistent result confirms the validity of using the presented modelling approach for simulating the generation and transfer of faecal contaminants in urban catchment. Following thermal-hydro dynamics of the receiving waterbodies, the discharged *E. coli* may lead to the degradation of water quality in potential bathing areas of the lake, confirming the necessity to evaluate the impacts of stormwater drainage on recreational water quality in urban areas.

However, it can be noted that the modelling uncertainty of *E. coli* is significant in stormwater sewer flows. Uncertainties related to build-up and wash-off parameters can be up to two orders of magnitude, while the analytical uncertainty of measured values is less than one order of magnitude. These results suggest that further field studies could be operated in order to reduce the initial intervals of parameter values. Moreover, the reliability of this modelling approach could be tested for different urban catchments.

Long-term variations of *E. coli* in stormwater sewers

Long-term simulations are performed for the period from May 12th, 2012, to Jan. 31th, 2014, using the optimized parameters. Water flow rate and *E. coli* fluxes are computed at 5 second time-step, simulated results are reported every 2 min.

Table 2 Initial intervals and optimized values of the build-up and wash-off parameter for *E. coli*

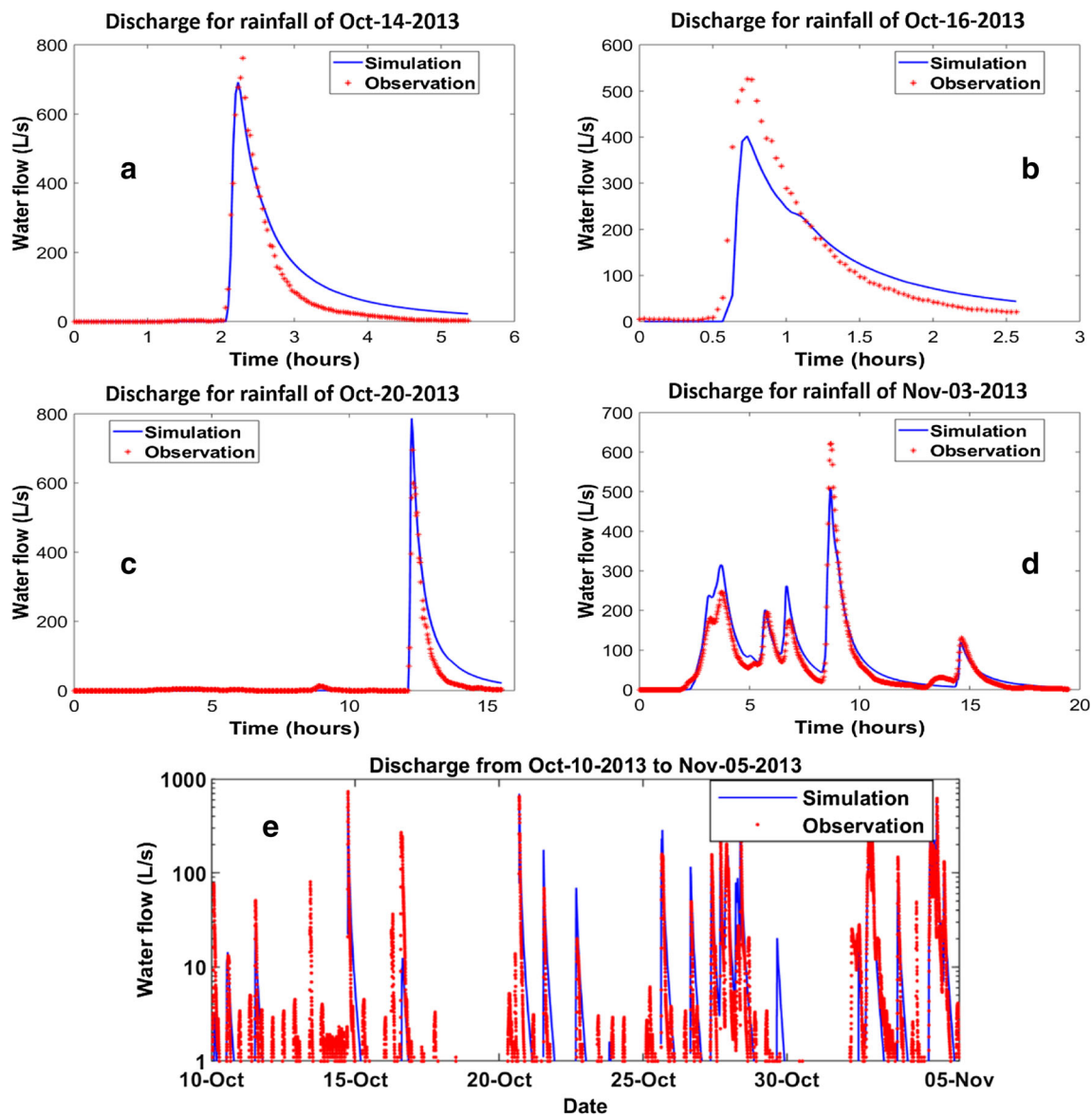| Symbol	Units	Definition	Initial interval	Optimized value
C_1	$MPNm^{-2}$	Maximum possible build-up of *E. coli*	10^{10}–10^{16}	10^{14}
C_2	day^{-1}	Build-up constant rate	0.6–2.0	1.2
C_3	mm^{-1}	Wash-off coefficient	1.0–3.0	2.0
C_4	-	Wash-off exponent	1.0–2.0	1.1

Fig. 3 Water flow simulations at stormwater drainage outlet. Simulations (solid blue line) are compared with continuous measurements (red asterisks). Parameters are calibrated for the event of 10/14/2013 (**a**) and validated for the event of 10/16/2013 (**b**), 10/20/2013 (**c**), 11/03/2013 (**d**) and a long period from 10/10 to 11/05/2013 (**e**)

Rainfall intensity, water volume and *E. coli* mass from stormwater drainage are shown in Fig. 5.

The stormwater discharge entering Lake Créteil can be up to 1×10^4 m^3 per day for heavy rain periods; it is negligible compared with the total water volume of the lake, which is approximately 2×10^6 m^3. However, during rain events, the total influx of *E. coli* into the lake is at a maximum of 4×10^{13} MPN per day. Considering the EU 'good water quality' threshold (1000 MPN/100 mL) with a homogeneous distribution assumption, this limit is consistent with 2×10^{13} MPN of *E. coli* in the entire lake. Showing that the urban stormwater discharge may impact the microbial quality of the lake. In that case, insight into the distribution of *E. coli* from stormwater sewer discharge is required for a good management of urban bathing water quality.

Hydrodynamics and *E. coli* distribution in Lake Créteil

Coupling the SWMM model and Delft-3D model at a 2-min time-step, the hydrothermal dynamics and *E. coli* transport in Lake Créteil are simulated. Simulations are performed with the calibrated values of drag coefficient (0.0015) and Secchi depth (1 m) presented in (Soulignac et al. 2017). Forcing variables such as wind direction and speed, air temperature, relative humidity, precipitation, solar radiation and cloud cover are defined according to in situ monitoring and recordings of the nearest weather station. The background concentration of *E. coli* in the lake is set to 5 MPN/100 mL based on the average *E. coli* concentration over a monthly monitoring of the points S, C and O. Since very few measured
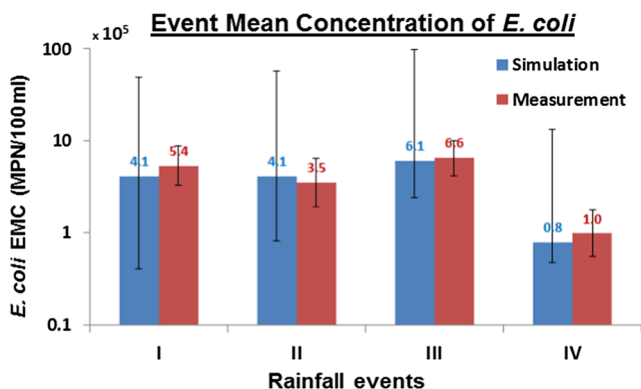
Fig. 4 Event mean concentration (EMC) of *E. coli* in stormwater sewer flows, for rains of 10/14 (I), 10/16 (II), 10/20 (III) and 11/03/2013 (IV). Simulated EMC (blue bars) are compared with the measurements (red bars). Error bars indicate the modelling uncertainty related to parameter values (blue bars) and the analytical uncertainty of measured values (red bars)

data is available for defining *E. coli* characteristics in Lake Créteil, water quality parameters are defined following Deltares (2016) (Table 3).

Measured and simulated water temperature

An accurate simulation of water temperature thermal stratification and mixing of water column is required for water quality modelling in the lake. In order to verify the model

performance, its ability to reproduce the water temperature and the thermal regime was assessed. In Fig. 6, the hourly mean profiles of observed water temperature in the middle of Lake Créteil (point C) are compared with the simulation results for the period from 05/12/2012 to 01/31/2014. The mean absolute error (MAE; Eq. 7) between simulated and measured temperature at different depths are calculated for the three monitoring points (S, C, O), shown in Table 4.

$$MAE = \frac{1}{n} \sum_{i=1}^{n} |(S_i - M_i)| \tag{7}$$

where n refers to the number of simulated-measured temperature data pairs; S_i and M_i represent the simulated and measured water temperature, respectively.

According to Table 4, for this simulation period of 20 months, the MAE between simulated and measured water temperature is varied from 0.4 to 0.7 °C at the three points and different depths, indicating a good modelling performance for representing the thermal dynamics of the lake. Water temperature is slightly better reproduced in the middle of the lake (point C) and worse reproduced on the surface water (0.5 m). This phenomenon is because that the water condition is more stable in the middle of the lake, where it is less influenced by stormwater inflows (point S), outflows (point O) and fluctuations on the water surface caused by wind and human activities. In Fig. 6, several stratifications are observed during the study period. The stratification period varies

Fig. 5 a Observed hourly rainfall intensity and simulations of **b** daily stormwater discharge entering Lake Créteil and **c** daily total influx of *E. coli* entering Lake Créteil
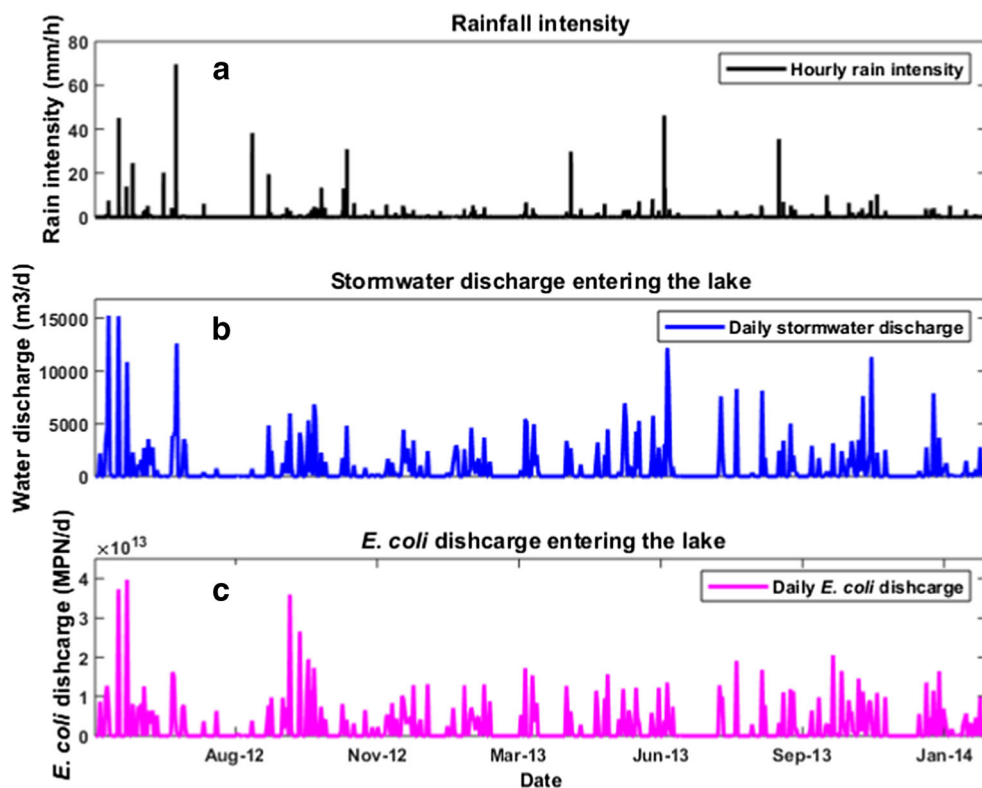
Table 3 Parameters for modelling *E. coli* dynamics

Symbol	Units	Definition	Value
D_x, D_y	m^2 s^{-1}	Dispersion coefficient of *E. coli* in horizontal directions	1
D_z	m^2 s^{-1}	Dispersion coefficient of *E. coli* in the vertical direction	10^{-7}
km_b	d^{-1}	Basic mortality rate of *E. coli*	0.8
$ktmrt$	-	Temperature coefficient of the mortality rate	1.07
ε	m^{-1}	Background extinction of UV radiation	0.08
km_{rd}	m^2 W^{-1} d^{-1}	Radiation related mortality constant	0.086

from a few hours to several days. Alternations between stratification and mixing are correctly reproduced by the model. These results confirm that the present modelling approach is suitable for representing the spatial and temporal variations of the lake's hydrothermal regime.

Spatial-temporal distribution of *E. coli* in Lake Créteil

Simulated *E. coli* concentrations at the three monitoring points are compared with the measurements for the events of October 14th, 16th and 20th and November 3rd, 2013 (Fig. 7). Since on-site samplings in the lake are performed on the following day at 10:00 am of each rainy day, simulated values at the corresponding time are analysed. For each event, using outputs from the ten urban catchment simulations, the uncertainty of *E. coli* simulations at the three points in the lake (S, C, O) can be assessed. These results are shown in Fig. 7.

As shown in Fig. 7, the *E. coli* concentration decreases with the distance from the stormwater outlet (S > C > O). The simulated *E. coli* concentration with optimized parameters are within the confidence interval of the measured values for all the studied rainfall events. Moreover, both simulations and observations are under the EU threshold for a 'good water quality' of bathing water (1000 MPN/100 mL) the day after rainfall events. In this case, lake water quality could recover the good quality threshold for bathing on the day after rains. However, modelling uncertainties are important, particularly for *E. coli* concentration at the point S, which could overpass the EU threshold. Nevertheless, comparing with stormwater sewer flow simulations (Fig. 4), the uncertainty of *E. coli* modelling in the lake is decreased. This result is due to the fixed water quality parameters for the 3D lake modelling. In

order to estimate the duration and range of the impacts of stormwater discharge and to ensure the safety of bathing water, spatial and temporal distribution of *E. coli* in the lake is required. To this end, *E. coli* dynamics in Lake Créteil after the rain of 10/14/2013 is presented as an example (Fig. 8).

As shown in Fig. 8, the central part of the lake close to the sewer outlet always indicates higher *E. coli* levels than the rest of the lake, and it is strongly affected by the stormwater discharge. In a range of 500 m of the sewage outlet, the *E. coli* concentration remains over 10 times higher than the good water quality threshold (1000 MPN/100 mL) 3 h after the end of the rain. After 6–12 h, the *E. coli* are mostly homogeneously distributed in a range of 1 km to the stormwater outlet, while it takes about 24 h for the entire lake to return to a low *E. coli* concentration level. Besides, as the wind direction is mainly from the south during the simulation period, it can be observed that the spread of *E. coli* towards the north of the lake, particularly after 6 h, because of advection process. Moreover, it can be noted that the north and the south border of Lake Créteil are slightly impacted by the stormwater drainage, where the water quality remains at a good level all the time.

Long-term variations of *E. coli* in the lake

For the lake monitoring period (05/12/2012–01/31/2014), simulated monthly mean concentration of *E. coli* with 95% confidence intervals is compared with the monthly observations at the three points (S, C, O) of the lake (Fig. 9).

According to Fig. 9, as expected, the *E. coli* concentrations are higher at the points closer to the stormwater sewer outlet (S > C > O). Moreover, it can be noted that most observed values are within the 95% confidence intervals of the simulated concentrations. These promising results prove the validity of the present modelling approach. Nevertheless, as shown in Fig. 8, the *E. coli* concentration in the lake can change significantly within 24 h; monthly comparisons cannot fully capture the effectiveness of this integrated model. Due to the monthly monitoring setup (always the same day of the month at 9:00 to 11:00 am), not all of the measured *E. coli* concentration can represent the impact of stormwater discharges. Therefore, in order to evaluate the model performance, we only compare the
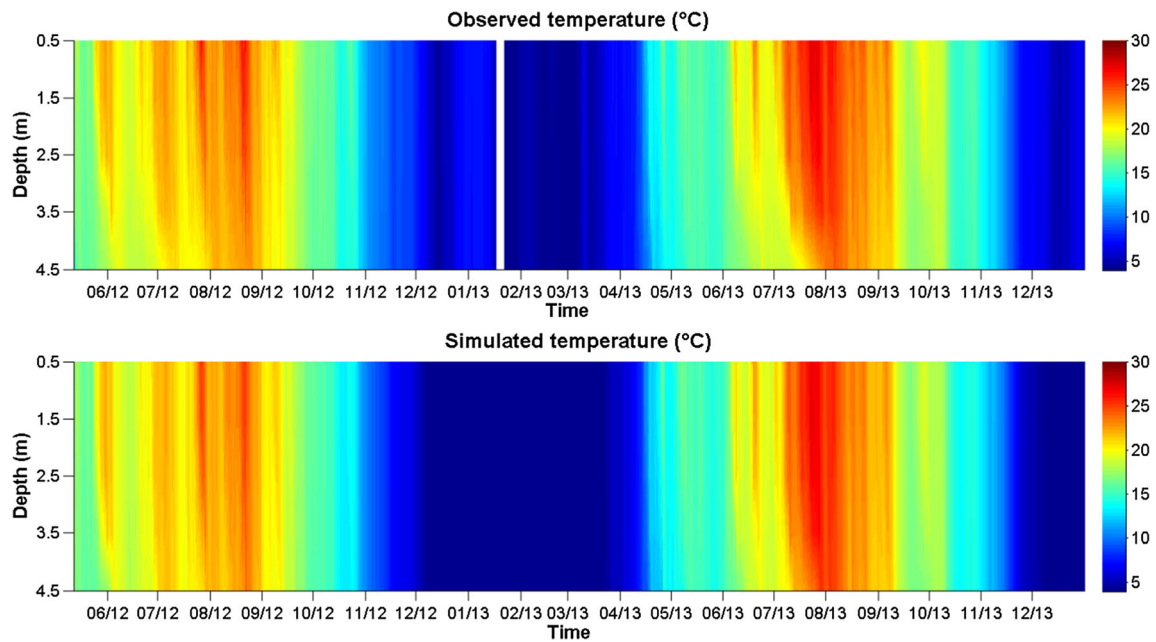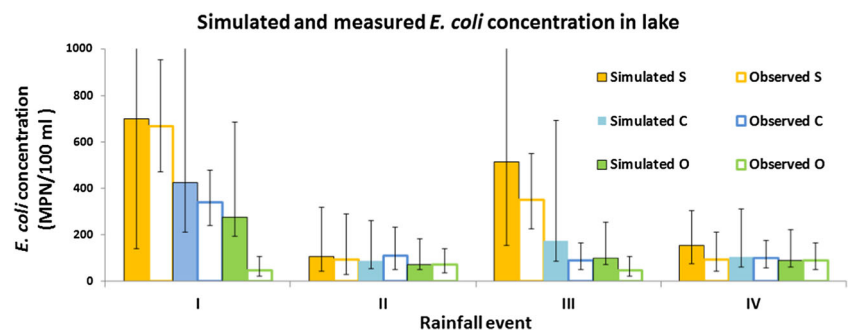
Table 4 Mean absolute error (MAE) of water temperature at points S, C and O and at different depths

Points	0.5 m (°C)	1.5 m (°C)	2.5 m (°C)
S	0.68	0.58	0.59
C	0.47	0.42	0.40
O	0.55	0.51	0.52

Fig. 6 Hourly mean profiles of observed and simulated water temperatures in the middle of Lake Créteil (point C), from May 12th, 2012, to Jan. 31th 2014

measured values within 2 days after rains with the optimized *E. coli* hourly simulations at 10:00 am of the sampling dates. Using all the simulated and measured *E. coli* concentration at the three sampling points (S, C, O), scatter plot of the simulations against the observations is presented in Fig. 10.

As indicated in the figure, the simulated *E. coli* concentrations represent correctly the observed values. The Pearson's correlation coefficient is calculated from all the simulations and observations at the three sampling points (S, C, O), resulting $r = 0.89$, p value $= 8.7 \times 10^{-6}$. This encouraging result confirms the validity of the presented modelling approach for simulating the impacts of *E. coli* from stormwater drainage to urban lakes. However, as presented in Fig. 10, only 5 among the 20 monthly observations have rains within 48 h before the sampling dates; a few observed *E. coli* concentrations in the lake were significantly higher than the background concentration (5 MPN/100 mL) during dry weather periods. This phenomenon implies that the microbiological contaminants from sources other than urban stormwater sewer flows may exist.

Discussion

On the use of integrated modelling for bathing water management

Regulated methods for monitoring *E. coli* concentrations take several days from sample collection (Edberg et al. 2000); nevertheless, The EU Bathing Water Directive (EU 2006) requires the provision of appropriate and prompt information to the public, especially in relation to predictable extreme events. Hence, at sites where water quality is affected by the short-term deterioration, results from water quality samples do little to inform the public, particularly for forecasting. The modelling approach is suitable for analysing the impacts of stormwater drainage on bathing water, where the water quality could be degraded immediately after rainfall events.

Many existed studies applied data-driven (or black-box) models to estimate *E. coli* dynamics (e.g. de Brauwere et al. 2014; Brooks et al. 2016). In these models, the output variable is assumed to be a linear or non-linear function of several input
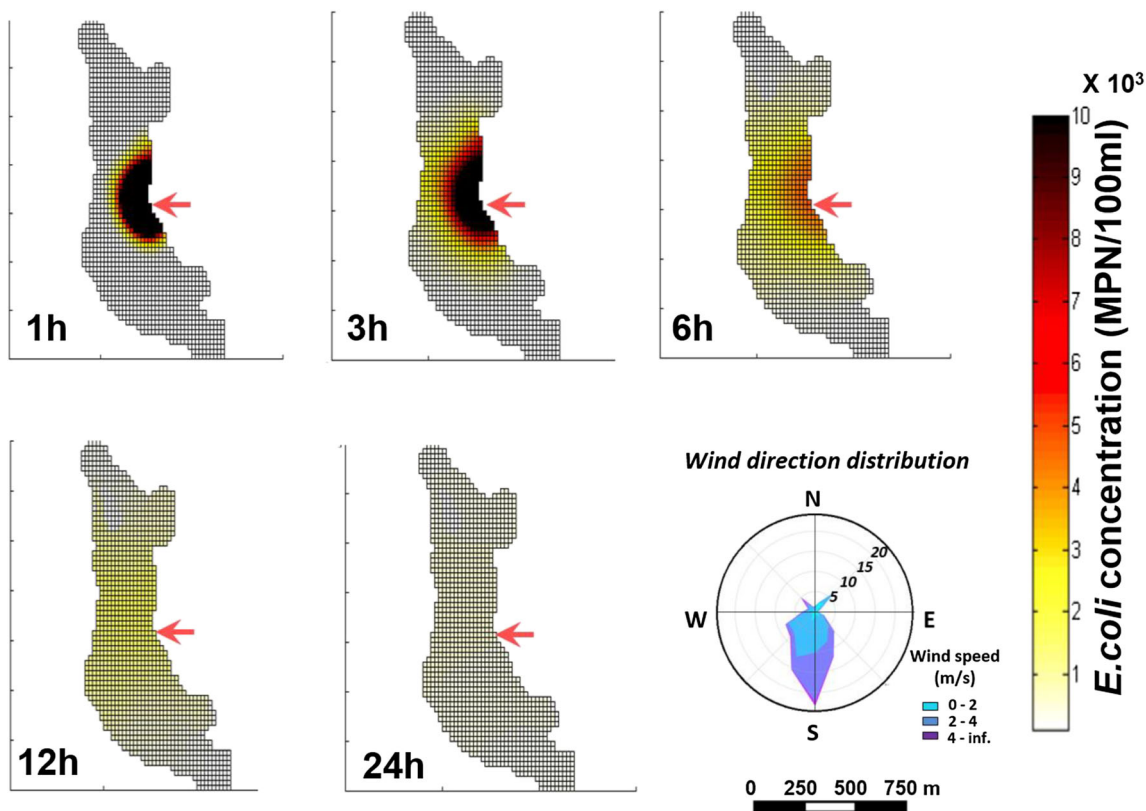
Fig. 7 Simulated (coloured bars) and observed (white bars) *E. coli* concentrations at the three points (S, C, O) in Lake Créteil on the following day at 10:00 am for rains of 10/14 (I), 10/16 (II), 10/20 (III) and 11/03/2013 (IV). Error bars indicate the modelling uncertainty related to parameter values and the analytical uncertainty of measured values, respectively

Fig. 8 Spatial and temporal distribution of *E. coli* in Lake Créteil after the rainfall event of Oct. 14th, 2013. *E. coli* concentration of the surface water are presented. Wind direction distribution during the 24 h are shown as well

Fig. 9 Simulated monthly mean concentration of *E. coli* with the 95% confident intervals and the monthly observations at the three points in Lake Créteil (S, C, O). Simulation period is from 05/12/2012 to 01/31/2014 (please note the that the *y*-axis range of different graphs differs)
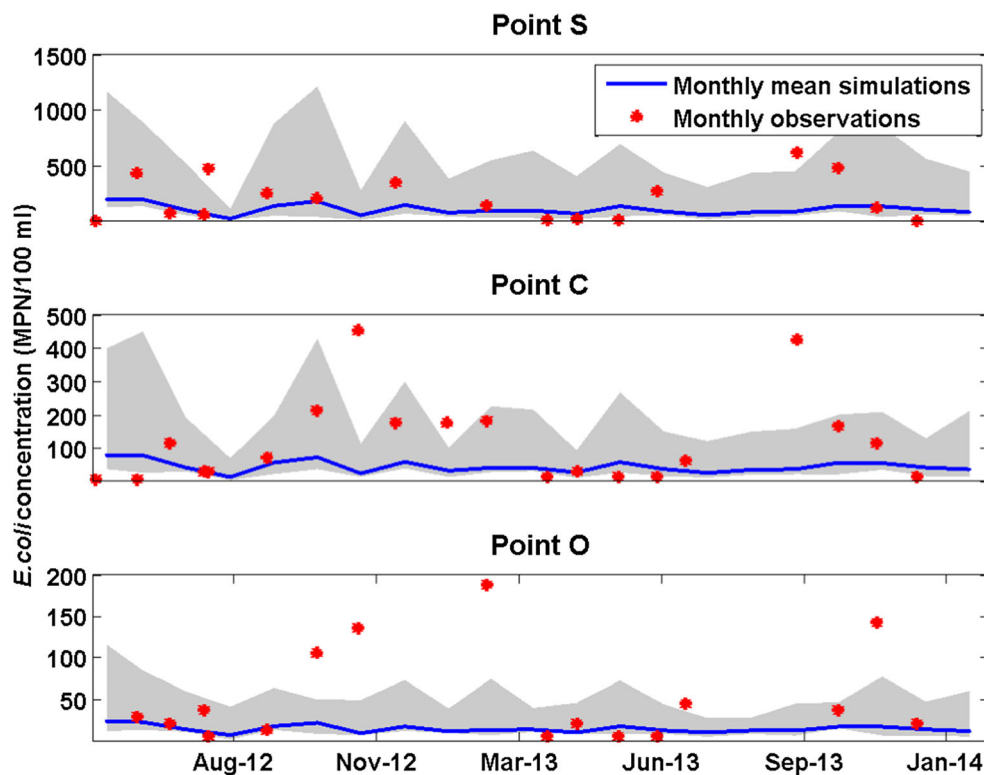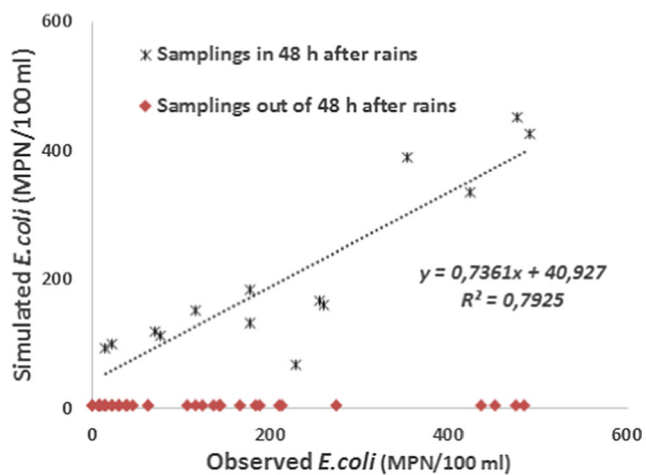
Fig. 10 Scatter plot of simulated and observed *E. coli* concentration on different sampling dates

variables, and the optimal values for coefficients associated with each of these variables are sought. The main advantage of these models is their ease and flexibility of use, allowing them to be applied for short-term and real-time predictions. Nevertheless, the model reliability and predication performance depend on the complexity of input variables and accessibility of enough data; relevant explanatory variables are extremely site-specific. For instance, Francy et al. (2013) reported that the relations between bacterial concentrations and environmental parameters in Lake Erie differed from year to year, and therefore they suggest using at least 2 years of data for model calibration. Frick et al. (2008) also suggest that these models should be updated and validated regularly in order to account for the changing conditions that would not be covered in the original calibration. The performance of these models varies widely; de Brauwere et al. (2014) reviewed several black box models and found that the R^2 ranges from 0.29 to 0.99, emphasizing their extreme case sensitivity. Since black box models do not include mechanic relationships, they cannot be used for in-depth understanding of the system and cannot be repeatedly applied for different case studies or under changeable conditions, such as land use changes and different management strategies.

Deterministic (or white box) models are capable of investigating the spatial and temporal dynamics of *E. coli* in aquatic systems. An important fraction of the freshwater studies is concerned with catchments, often in rural areas. A significant number of studies used the Soil and Water Assessment Tool (SWAT) (e.g. Chin et al. 2009; Cho et al. 2016) and the USEPA-developed Hydrological Simulation Program—FORTRAN (HSPF) (e.g. Benham et al. 2006). These models use a decay term of *E. coli* depending on solar irradiation. Besides catchment models, some studies developed stream, river or estuary section models. For instance, Bedri et al. (2014) and Huang et al. (2017) couple catchment and coastal models for assessing *E. coli* distributions on coastal beach

areas. However, no existing research integrates urban stormwater discharge model with 3D lake modelling for estimating *E. coli* distributions in urban bathing water. Moreover, uncertainty analysis was barely done in these studies. This is mainly due to the complexity of model set-up and configuration, high uncertainty of pollution sources, expensive computational costs and scarcity of case studies with validated results.

In the present study, deterministic models are used because of the limited availability of in situ measurements. Only a few water samples are collected for measuring *E. coli* concentration in the lake; even less samplings are performed after rains. According to the monthly observations, *E. coli* concentration are generally under 500 MPN/100 mL for all the three monitoring points, showing a good water quality (Fig. 9). On the contrary, simulation results indicate that the *E. coli* concentration can easily overpass this value at a 1-km range of the stormwater outlet within 24 h after rains (Fig. 7). These modelling approach can thus provide more details for the public to make an informed choice on whether and where to use the bathing water. Although the uncertainties linked with parameter values, pollution sources (e.g. waterfowl, cross connection during rains, etc.) and *E. coli* mortality processes could be further discussed, this paper originally challenges the new field of integrated urban catchment-pipe-lake modelling for assessing the impact of stormwater discharge on lake water quality with reasonable assumptions. Moreover, the satisfied modelling performance emphasizes a promising potential for the improvement of urban bathing water quality management.

Future outlook for urban bathing water quality modelling

In order to promote the use of urban bathing water quality modelling in an operational context, considerations for future development can be generally outlined in two aspects: (i) improving the reliability of models by introducing new processes, datasets and calibration approaches; (ii) extending the functionalities of models for practical issues by integrating with socio-economic modules and computer techniques.

The modelling improvements can be considered on the following aspects. First, processes describing pathogenic contaminants from diffuse sources, such as combined sewer overflows, bird faeces and human activities, can be introduced by coupling with distributed urban catchment models (e.g. Hong et al. 2016, 2017; Refsgaard et al. 2010). Second, the description of faecal indicator bacteria (FIB) decay processes can be advanced benefitting from the newly developed rapid bacterial monitoring techniques, by analysing high-frequency measurements of FIB on a time scale of hours or even minutes. Third, more sophisticated calibration and uncertainty analysis could be addressed to enhance the reliability of present model,

for instance, an efficient and robust approach developed by Hong et al. (2019) could be applied to this complex integrated model with limited computational efforts. Finally, as various field studies have reported significant proportions of FIB attached to suspended particles (Pachepsky and Shelton 2011), it may be useful to distinguish the different dynamics of free FIB and those attached to particles: adsorption-desorption processes can be described by appropriate kinetic laws and calculate settling-resuspension processes with settling velocity and erosion formulations. In addition, hybrid models coupling physically based hydrodynamic models with data-driven ecological models is an appropriate approach for certain cases (e.g., Hellweger 2007).

On the other hand, current study uses a single rainfall station as the precipitation forcing for the small Créteil urban catchment (95 ha), which may not be sufficient for urban hydrological simulations at larger scales. Ochoa-Rodriguez et al. (2015) and de Souza et al. (2018) indicate that high spatial and temporal resolutions are required for urban hydrologic applications. Müller and Haberlandt (2018) show that the usage of a single rain gauge and hence spatial uniform rainfall leads to an overestimation of flood events. This overestimation will lead to an overestimation of E. coli load in the lake resulting from the surface runoff. In order to improve the reliability and accuracy of the present modelling approach, the usage of available high-resolution x-band radar data for Paris region (Paz et al. 2020) is a perspective for future studies of urban bathing water quality modelling.

To be extensively used, simulation results need to be rapidly accessible by managers and public; moreover, models should help providing relevant information to make strategic management decisions regarding socio-economic benefits. In perspective, integrated assessments coupling with hydro-ecological simulations can bring together knowledge from a variety of disciplinary sources to solve complex real-world problems, such as using the quantitative microbial risk assessments (QMRAs) for assessing the infection risk from recreational water use and the cost-benefits assessments for evaluating the gains of maintaining the natural bathing water quality. In addition, scenario simulations with the participation of urban water managers and stakeholders can be proposed to evaluate outcomes of different management strategies.

Conclusion

In many municipal areas, urban stormwater sewers are directly connected to receiving water bodies without any treatment; this may degrade the quality of natural bathing waters and even cause severe public health risks. In this paper, we developed an integrated urban catchment-pipes-lake modelling approach to simulate the impacts of E. coli from stormwater sewer flows on recreational water quality. To our knowledge,

it is the first time that such an integrated and spatial distributed approach is developed and applied for urban bathing water quality.

The modelling system couples two widely used models, including SWMM (Rossman 2010) and Delft3D (Deltares 2016), to simulate E. coli processes such as generation, transport and mortality from an urban catchment including the drainage network to a receiving recreational lake. This integrated modelling approach is tested for an urban catchment and its related recreational lake located in the Great Paris region.

Hydrological and E. coli build-up/wash-off parameters of SWMM are calibrated and validated for four rainfall events and a 25-day period. The comparison of measured and simulated E. coli event mean concentration (EMC) at stormwater drainage outlet shows a good modelling performance. The hydrothermal dynamics and E. coli transport in Lake Créteil are simulated by using default parameter values. Simulated E. coli concentrations at three monitoring points are within the confidence intervals of the measurements for the studied rains. Spatial-temporal analysis of E. coli distribution in the lake shows that in a range of 500 m of the stormwater sewer outlet, E. coli concentration remains at a very high level during 3 h after rains, while it takes about 24 h to return to a good water quality level.

A 20-month-simulation is then performed for analysing long-term variations of E. coli in the lake. Comparing the measured and simulated water temperature at different depths of the lake, the modelling system can correctly reproduce the hydrothermal dynamics of Lake Créteil. Moreover, simulated E. coli concentrations at three monitoring points are compared with monthly observations. The good coherence between simulated and measured values confirms the validity of the present modelling approach.

A stochastic parameter sampling approach is applied for preliminarily assessing uncertainties of E. coli simulations related to wash-off/build-up parameters. Uncertainties of E. coli concentration in stormwater sewer flows can be up to two orders of magnitude, while it is decreased for E. coli simulations of the lake, yet still significant. These results suggest that field studies could be operated in order to optimize the initial intervals of parameter values, and the reliability of this modelling approach could be further discussed.

In order to improve the reliability of the present modelling approach, future development can be carried out by introducing new processes, datasets and calibration approaches. We also aim to extend the model functionalities for practical issues by integrating real-time prediction system, socio-economic assessments and participatory scenario simulations.

Compliance with ethical standards

Conflict of interests The authors declare that they have no conflict of interest.

Ethical approval The authors declare that the manuscript has not been published previously.

Consent to participate All authors voluntarily to participate in this research study.

Consent to publish All authors consent to the publication of the manuscript.

References

Bedri Z, Corkery A, O'Sullivan JJ et al (2014) An integrated catchment-coastal modelling system for real-time water quality forecasts. Environ Model Softw 61:458–476. https://doi.org/10.1016/j.envsoft.2014.02.006

Benham BL, Baffaut C, Zeckoski RW et al (2006) Modeling bacteria fate and transport in watersheds to support TMDLs. Trans ASABE 49:987–1002. https://doi.org/10.13031/2013.21739

Brooks W, Corsi S, Fienen M, Carvin R (2016) Predicting recreational water quality advisories: a comparison of statistical methods. Environ Model Softw 76:81–94. https://doi.org/10.1016/j.envsoft.2015.10.012

Chin DA, Sakura-Lemessy D, Bosch DD, Gay (2009) Watershed-scale fate and transport of bacteria. Trans ASABE 52:145–154. https://doi.org/10.13031/2013.25955

Cho E, Arhonditsis GB, Khim J, Chung S, Heo TY (2016) Modeling metal-sediment interaction processes: parameter sensitivity assessment and uncertainty analysis. Environ Model Softw 80:159–174. https://doi.org/10.1016/j.envsoft.2016.02.026

de Brauwere A, Ouattara NK, Servais P (2014) Modeling fecal indicator bacteria concentrations in natural surface waters: a review. Crit Rev Environ Sci Technol 44:2380–2453. https://doi.org/10.1080/10643389.2013.829978

de Souza BA, da SR PI, Ichiba A et al (2018) Multi-hydro hydrological modelling of a complex peri-urban catchment with storage basins comparing C-band and X-band radar rainfall data. Hydrol Sci J 63:1619–1635. https://doi.org/10.1080/02626667.2018.1520390

Deltares (2016) 3D/2D modelling suite for integral water solutions - Delft3D User Manual

Edberg SC, Rice EW, Karlin RJ, Allen MJ (2000) Escherichia coli: the best biological drinking water indicator for public health protection. J Appl Microbiol 88:106S–116S. https://doi.org/10.1111/j.1365-2672.2000.tb05338.x

EU BWD (2006) Directive 2006/7/EC of the European Parliament and of the Council of 15 February 2006 concerning the management of bathing water quality and repealing Directive 76/160.

Francy DS, Stelzer EA, Duris JW, Brady AMG, Harrison JH, Johnson HE, Ware MW (2013) Predictive models for Escherichia coli concentrations at inland lake beaches and relationship of model variables to pathogen detection. Appl Environ Microbiol 79:1676–1688. https://doi.org/10.1128/AEM.02995-12

Frick WE, Ge Z, Zepp RG (2008) Nowcasting and forecasting concentrations of biological contaminants at beaches: a feasibility and case study. Environ Sci Technol 42:4818–4824. https://doi.org/10.1021/es703185p

Green WH, Ampt GA (1911) Studies on soil physics. J Agric Sci 4:1–24. https://doi.org/10.1017/S0021859600001441

He L-ML, He Z-L (2008) Water quality prediction of marine recreational beaches receiving watershed baseflow and stormwater runoff in southern California, USA. Water Res 42:2563–2573. https://doi.org/10.1016/j.watres.2008.01.002

Hellweger FL (2007) Ensemble modeling of E. coli in the Charles River, Boston, Massachusetts, USA. Water Sci Technol J Int Assoc Water Pollut Res 56:39–46. https://doi.org/10.2166/wst.2007.588

Hong Y, Bonhomme C, Le M-H, Chebbo G (2016) A new approach of monitoring and physically-based modelling to investigate urban wash-off process on a road catchment near Paris. Water Res 102:96–108. https://doi.org/10.1016/j.watres.2016.06.027

Hong Y, Bonhomme C, den Bout BV et al (2017) Integrating atmospheric deposition, soil erosion and sewer transport models to assess the transfer of traffic-related pollutants in urban areas. Environ Model Softw 96:158–171. https://doi.org/10.1016/j.envsoft.2017.06.047

Hong Y, Liao Q, Bonhomme C, Chebbo G (2019) Physically-based urban stormwater quality modelling: an efficient approach for calibration and sensitivity analysis. J Environ Manage 246:462–471. https://doi.org/10.1016/j.jenvman.2019.06.003

Huang G, Falconer RA, Lin B (2017) Integrated hydro-bacterial modelling for predicting bathing water quality. Estuar Coast Shelf Sci 188:145–155. https://doi.org/10.1016/j.ecss.2017.01.018

Jones RM, Liu L, Dorevitch S (2013) Hydrometeorological variables predict fecal indicator bacteria densities in freshwater: data-driven methods for variable selection. Environ Monit Assess 185:2355–2366. https://doi.org/10.1007/s10661-012-2716-8

Kashefipour SM, Lin B, Falconer RA (2005) Neural networks for predicting seawater bacterial levels. Proc Inst Civ Eng - Water Manag 158:111–118. https://doi.org/10.1680/wama.2005.158.3.111

Marsalek J, Rochfort Q (2004) Urban wet-weather flows: sources of fecal contamination impacting on recreational waters and threatening drinking-water sources. J Toxicol Environ Health A 67:1765–1777. https://doi.org/10.1080/15287390490492430

McCarthy DT, Hathaway JM, Hunt WF, Deletic A (2012) Intra-event variability of Escherichia coli and total suspended solids in urban stormwater runoff. Water Res 46:6661–6670. https://doi.org/10.1016/j.watres.2012.01.006

McLellan SL, Hollis EJ, Depas MM et al (2007) Distribution and fate of Escherichia coli in Lake Michigan following contamination with urban stormwater and combined sewer overflows. J Gt Lakes Res 33:566. https://doi.org/10.3394/0380-1330(2007)33[566:DAFOEC]2.0.CO;2

Müller H, Haberlandt U (2018) Temporal rainfall disaggregation using a multiplicative cascade model for spatial application in urban hydrology. J Hydrol 556:847–864. https://doi.org/10.1016/j.jhydrol.2016.01.031

Nash JE, Sutcliffe JV (1970) River flow forecasting through conceptual models part I — a discussion of principles. J Hydrol 10:282–290. https://doi.org/10.1016/0022-1694(70)90255-6

Ochoa-Rodriguez S, Wang L-P, Gires A, Pina RD, Reinoso-Rondinel R, Bruni G, Ichiba A, Gaitan S, Cristiano E, van Assel J, Kroll S, Murlà-Tuyls D, Tisserand B, Schertzer D, Tchiguirinskaia I, Onof C, Willems P, ten Veldhuis MC (2015) Impact of spatial and temporal resolution of rainfall inputs on urban hydrodynamic modelling outputs: a multi-catchment investigation. J Hydrol 531:389–407. https://doi.org/10.1016/j.jhydrol.2015.05.035

Pachepsky YA, Shelton DR (2011) Escherichia Coli and fecal coliforms in freshwater and estuarine sediments. Crit Rev Environ Sci Technol 41:1067–1110. https://doi.org/10.1080/10643380903392718

Parkhurst DF, Brenner KP, Dufour AP, Wymer LJ (2005) Indicator bacteria at five swimming beaches—analysis using random forests. Water Res 39:1354–1360. https://doi.org/10.1016/j.watres.2005.01.001

Paz I, Tchiguirinskaia I, Schertzer D (2020) Rain gauge networks' limitations and the implications to hydrological modelling highlighted with a X-band radar. J Hydrol 583:124615. https://doi.org/10.1016/j.jhydrol.2020.124615

Refsgaard JC, Storm B, Clausen T (2010) Système Hydrologique Europeén (SHE): review and perspectives after 30 years development in distributed physically-based hydrological modelling. Hydrol Res 41:355–377. https://doi.org/10.2166/nh.2010.009

Roguet A, Therial C, Catherine A, Bressy A, Varrault G, Bouhdamane L, Tran V, Lemaire BJ, Vincon-Leite B, Saad M, Moulin L, Lucas FS (2018) Importance of local and regional scales in shaping mycobacterial abundance in freshwater lakes. Microb Ecol 75:834–846

Rossman LA (2010) Storm water management model user's manual version 5.0. National risk management research and development U.S. environmental protection agency, Cincinnati, OH 45268

Soulignac F, Vinçon-Leite B, Lemaire BJ, Scarati Martins JR, Bonhomme C, Dubois P, Mezemate Y, Tchiguirinskaia I, Schertzer D, Tassin B (2017) Performance assessment of a 3D hydrodynamic model using high temporal resolution measurements in a shallow urban lake. Environ Model Assess 22:309–322. https://doi.org/10.1007/s10666-017-9548-4

WHO (ed) (2003) Guidelines for safe recreational water environments. World Health Organization, Geneva