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Characterization of sources of microbiological contamination in the Seine River during the Paris Olympics 2024 using inverse modeling

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Abstract
Rivers provide many ecosystem services. However, in densely populated urban areas, they are polluted by multiple sources including combined sewer overflows (CSOs). By studying the behavior of the combined sewer system, whose capacity can be saturated during heavy rainfall episodes, it is possible to anticipate these contamination periods. In addition, by using an inverse method (quantifying causes from effects), it would be possible to determine the quantity of contaminants released by the CSO. In this paper, we present the design of the method on the study site of the Seine River, in Paris. The spatial extension of the combined sewer network is described by a directed graph. Temporal consistency is achieved through event definition. The use of these data for CSO assessment would make it possible to anticipate contamination and guide decisions to contain it.

Highlights
- Modeling CSOs discharging behavior using graph representation of the sewage network.
- Solve inverse problem to assess CSOs discharged fecal concentration from downstream measurements in river.
- Consistency of model output with observations during the Olympic Games

Introduction
Rivers are central to human activities. They provide water for basic needs (drinking, fishing, agriculture), economic development (transportation, hydropower, defense among others in the past), and well-being (recreational bathing, surrounding cooling)(Haarstrick and Sharma, 2024). They are also the habitat of numerous ecosystems (Giller and Malmqvist, 1998). However, the water quality of these rivers has deteriorated as a result of human activity. The anthropogenic context defines the type of contaminants to be found in the water courses. When it comes to bathing, the European Union commission selected the Fecal Indicator Bacteria (FIB) to characterize water quality (European Parliament and Council of the European, 2006). FIB indicate the presence of pathogens, also present in the intestines of warm-blooded animals. These pathogens are harmful to human health. Modeling

water quality enables us to anticipate and better manage: (i) bathing times, (ii) pumping times for drinking water, (iii) human pressures on biodiversity.

Methodology

Rainfall events saturate the combined sewer system, causing sewerage to be discharged into the receiving environment. This leads to a deterioration in water quality in rivers. The objective of the current work is to quantify the contribution of different sources of microbiological contamination. To achieve this objective, we follow the methodological framework illustrated in Figure 1 (colored letters make reference to data description in Figure 2). The first step is to break down the data into events. An event begins with the cause, the rain, and ends with the consequence, the contamination.

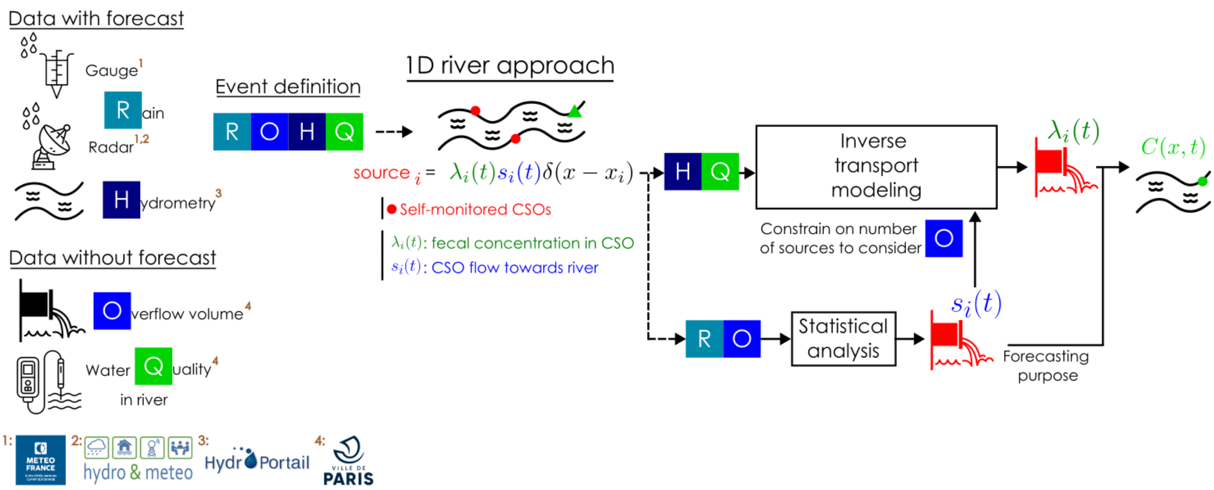

Figure 1. Methodological framework.

A one-dimensional river approach is chosen to begin. The sources considered are monitored storm overflows (monitoring criterion based on contamination potential). Sources are modeled as follows:

$$\text{source}_i = \lambda_i s_i(t)\delta(x - x_i),$$

for source i in position x_i (x being the spatial variable) discharging contaminated water to the receiving environment at a flow rate $s_i(t)$ with a concentration λ_i in contaminants (supposed constant per event in first approach), δ a Gaussian distribution. Discharge data are available for the monitored CSOs, but not the contaminant concentration. The modeling is a two-step process:

1. Model the function linking flow to precipitation and catchment data. A first approach consists of a binary output function indicating flow or not. The aim is twofold: predictive capacity and limiting the number of sources to be considered for contaminant concentration studies.
2. Estimate the concentration of bacteria in the spill based on downstream microbiological measurements. This will be based on downstream microbiological measurements.

Case study

The study site covers the city of Paris (see Figure 3). It is crossed by the Seine River. This area is densely urbanized. Within dense urban catchments, fecal contamination is due to sewer networks, whose functioning is illustrated in Figure 2 (colored symbols make reference to data location in Figure 3).

Radar rainfall has been produced on the base of Météo France radar at Trappes. The polar data with a range resolution of 240 m have been clutter-corrected for the Paris area and adjusted with available rain gauges from Météo France. The resulting rainfall amounts were intersected with the catchments as shown in figure 3 in order to provide areal rainfall amounts, with a time step of 5 minutes. For data retrieval, the open data facility of Météo France was used.

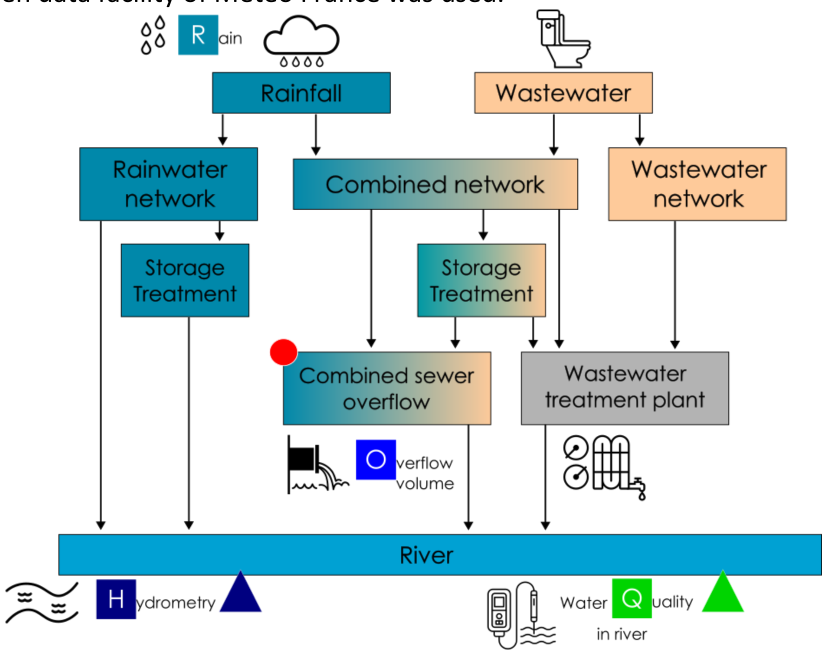

Figure 2. Functioning of wastewater drainage network (modified from Chocat et al., 2021).

Results and discussion

A first step was to collect the data shown in Figure 3: concerning sources (location, hourly discharge volume for those in Paris), river (hydrometric data, water quality from ColiMinder instrument every 2 hours (Cazals, 2019)), study site (urban catchment areas) and rainfall (radar rain on the catchment areas and a rain gauge to the south-east of Paris). As contamination is due to rainfall events, we split the temporal data to reflect this notion of events (based on threshold consideration and a minimum inter-event duration between events).

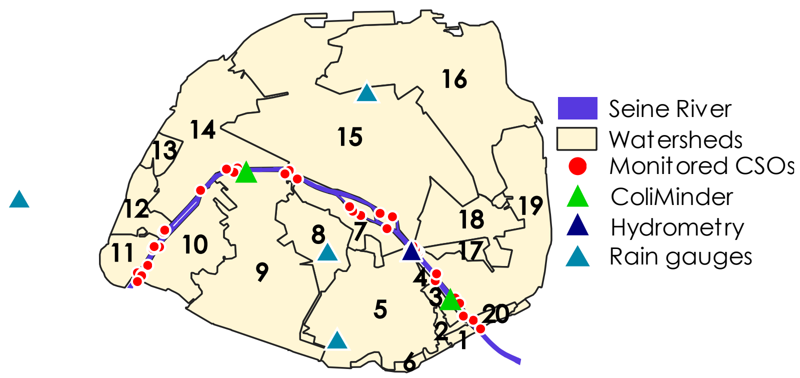

Figure 3. Map of the study site with data location

Based on sewer network map, we created a directional graph representing the wastewater transport from one catchment to another. This highlights which rainfall variables to consider regarding the CSO location. Rainfall event characteristics are extracted for all parent (upstream in the graph) catchments. At first approach we model sewer network behavior regarding pulses, that are single peaks of rain producing or not peak of overflow. This for each CSO separately. We represent the discharging function in time by a triangular function. Its description is based on two size parameters (total discharge volume and maximum flow rate) and two time parameters (initial time and time of the maximum). To retrieve those variables of interest, we create linear combination of rainfall event characteristics (maximum intensity, total depth, etc.). We Finally compare the gain using weather radar data over gauges.

Source identification have different meaning according the context. Contamination can be accidental (circumstantial, e.g., linked to a breakage in the drainage network), or structural, as here linked to combined sewer network functioning. In the former, the information to recover is source location, time of release and discharged contaminant load, but with single or few sources. In the latter, the release locations are known beforehand, so the interest is over contaminant load. We propose to retrieve this information using inverse modeling (Barati Moghaddam et al., 2021). It involves studying the cause (wastewater discharge) from the effect (degradation of water quality). Previous studies have been using inverse modeling to retrieve source characteristics in case of known location (e.g. concentration and flow rate in Wang et al., 2022). In the present study, both locations and flow rate are known, so the only unknow are concentrations. To the author's knowledge, no previous studies perform inverse modeling on such scenario. Another contribution of the current work is the possibility to apply inverse methods on real data (Barati Moghaddam et al., 2021).
To model bacterial transport, we developed a 1D numerical river model, based on the advection-dispersion transport equation:

$$\frac{\partial C}{\partial t} + u\frac{\partial C}{\partial x} - D\frac{\partial^2 C}{\partial x^2} + k_T C = \sum_{i=1}^{N} \mathrm{source}_i$$

with u the flow velocity $(m.s^{-1})$, D the diffusion coefficient $(m^2.s^{-1})$, k_T the comprehensive decay coefficient (s^{-1}), N the number of contaminant sources. This numerical model enables us to evaluate methods for solving the inverse problem with synthetic data, before applying it to the real case. We compare two methods:

1. Optimization (gradient descent based). Robust to non-linearities, but more computationally intensive.
2. Deconvolution. The way we model bacterial transport is linear regarding the concentration. Thus, the superposition principle holds (output from combined inputs equals the sum of outputs from individual inputs). Given an event, we run unitary pulses for each discharging source at the associated discharging time. Retrieving the concentration boils down to retrieving pulses heights. This leads us to a linear optimization problem that can be solved by matrix inversion.

Conclusions and future work

To identify contamination sources, a first step is to look after the available data. Most hydrological measurement networks have been designed for operational rather than scientific purposes. The methodology used must be adapted and take this aspect into account if it is to be generalizable. The implementation of new high-frequency instruments, as in Paris, makes it possible to evaluate methods that until now were purely numerical, with no application to real cases. Identifying and forecasting source discharges and contamination load would enable better management of bathing and water supply risks, and better evaluation of mitigation infrastructures.

References

Barati Moghaddam, M., Mazaheri, M., Mohammad Vali Samani, J., 2021. Inverse modeling of contaminant transport for pollution source identification in surface and groundwaters: a review. Groundwater for Sustainable Development 15, 100651. https://doi.org/10.1016/j.gsd.2021.100651

Cazals, M., 2019. Application d'une nouvelle technologie de détection enzymatique pour le suivi en quasi-temps réel de la dynamique d'Escherichia coli dans des eaux récréatives (masters). Polytechnique Montréal.

Chocat, B., Bertrand-Krajewski, J.-L., Barraud, S., 2021. Pollution des rejets urbains de temps de pluie, in: Techniques de l'Ingénieur. p. article W 6800 v2, 38 p.

European Parliament, Council of the European, 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/EEC.

Giller, P.S., Malmqvist, B., 1998. Life in running waters, in: Giller, P.S., Malmqvist, B. (Eds.), The Biology of Streams and Rivers. Oxford University Press, p. 0. https://doi.org/10.1093/oso/9780198549789.003.0004

Haarstrick, A., Sharma, L., 2024. Chapter 8 - Urban river pollution control, in: Shinde, V.R., Mishra, R.R., Bhonde, U., Vaidya, H. (Eds.), Managing Urban Rivers. Elsevier, pp. 131–159. https://doi.org/10.1016/B978-0-323-85703-1.00013-4

Lugão, B.C., Knupp, D.C., Rodriges, P.P.G.W., 2022. Direct and inverse simulation applied to the identification and quantification of point pollution sources in rivers. Environmental Modelling & Software 156, 105488. https://doi.org/10.1016/j.envsoft.2022.105488

Permanoon, E., Mazaheri, M., Amiri, S., 2022. An analytical solution for the advection-dispersion equation inversely in time for pollution source identification. Physics and Chemistry of the Earth, Parts A/B/C 128, 103255. https://doi.org/10.1016/j.pce.2022.103255

Wang, J., Zhao, J., Lei, X., Zhao, T., Wang, H., 2022. Release process identification of non-instantaneous point source pollution in rivers via reverse flow and pollution routing. Environmental Research 213, 113704. https://doi.org/10.1016/j.envres.2022.113704