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Optimization of sampling regimes to monitor runoff events

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Abstract
Urban runoff threatens freshwater quality making it important to understand pollution sources and pathways. Measuring every pollutant in real-time is unfeasible, hence the need for in-situ grab sampling. Integrating real-time sensor data, rainfall forecasts and runoff models can optimize automated grab sampling beyond the current capabilities of autosamplers. This study evaluates two sampling strategies to optimize sampling times: (1) rainfall-volume based strategy which triggers sampling by accumulated rain volume (mm) or intensity (mm/h), (2) rainfall-runoff based strategy that triggers sampling by peak flow trigger (m^3/s) estimated using a hydraulic model. Both strategies account for “no-event days”, the number of days with no runoff. Events of interest, here defined as first flush events resulting from heavy rains following consecutive days without rain, are identified. Different combinations of trigger parameters were tested, the sampling times from each strategy are evaluated based on whether the events of interest have been sampled, and the number of samples generated in those events. We highlight the potential of optimized sampling strategies in improving water quality monitoring. The ability to remotely trigger auto samplings, enables tailored measurements based on the specific data requirements or research questions.

Highlights

- Provides targeted sampling strategies for more effective water quality monitoring
- Optimized two grab sampling strategies and their parameter configurations

Introduction
Freshwater quality is highly impacted by urban runoff, requiring mitigation measures based on the understanding of pollutant types, sources and pathways. Continuous measurement of all water quality parameters is challenging, making in-situ grab sampling essential for pollutant identification and detailed analysis. But its efficiency depends on the sampling strategies, particularly during storm events that transport heavy pollutant loads and rapidly altering flow patterns. Accurate sampling during these events depends on rainfall distribution requiring precise and timely sampling to record water quality changes (Bertrand-Krajewski et al., 2021). Current offline sampling approaches that rely on local sensor data lack to account for factors such as prolonged no rain days or the temporal variability of storm events. Because auto-samplers can be triggered remotely, IoT offers improved accuracy by combining real-time observations, rainfall predictions and near-real-time urban runoff modelling (Van Hoey et al., 2024). Due to the increased complexity, optimizing sampling strategies and

trigger parameters to target sampling during events of interest can be challenging. This study focuses on testing the performance of two sampling regimes and their parameter settings in triggering samples during rain events. The effectiveness of scheduled samples is evaluated by assessing whether the scheduler precisely targets rain events of interest and evaluating the number of samples in the events of interest versus the total number of proposed samples.

Methodology

Sampling strategies

The sampling strategies are part of an integrated hardware and software implementation that relies on the MQTT protocol for bidirectional communication. (Van Hoey et al., 2024). Rainfall forecasts (forecast window 2h, temporal resolution 5min) from Buienradar from Nov 2023 – Oct 2024 (https://www.buienradar.be/) are used as input for the sample scheduler. Figure 1 (A) illustrates the rainfall-volume based strategy that assumes a direct response of water flow to the forecasted rainfall and schedules samples based on three key parameters: the rain volume trigger (activates sampling when the sum of accumulated volume of forecasted rain exceeds a set threshold), the rain intensity trigger (activates sampling when the maximum intensity of forecasted rain exceeds a set threshold) and "no-event days" , the required amount of dry days before a new set of samples can be taken. Figure 1 (B) depicts the rainfall-runoff based strategy that uses a hydraulic model to estimate flow from forecasted rain enabling to implement flow-based sampling. This allows the comparison of the different sampling strategies and test if the use of a hydraulic model results in a better capture of events of interest. A flow peak trigger is used to initiate sampling when the modelled flow exceeds a certain threshold while also applying the "no-event days" concept. A brute force optimization of parameters, rain volume trigger (0.2–1.8 mm) and rain intensity trigger (0.2 -1.8 mm/h) in 0.2 intervals, and "no-event days" (0 – 3 days) is performed; the resulting sampling times for each parameter combination are evaluated against the events of interest.

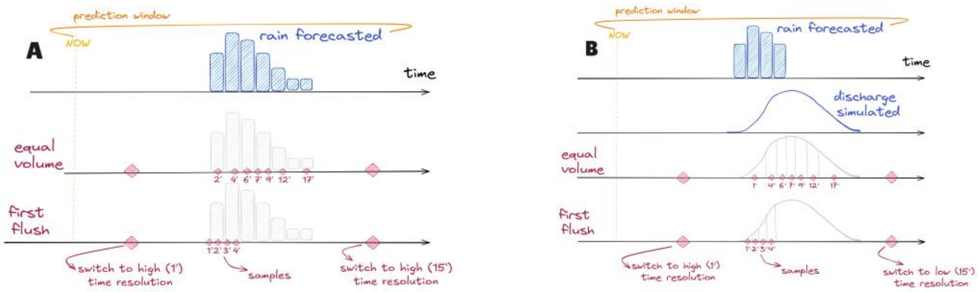

Figure 1 Illustration of the two sampling strategies. (A) rainfall- volume strategy (B) rainfall-runoff based strategy

Evaluation of scheduled samples against events of interest

To optimize the sampling times, the proposed sampling times are compared to identified events of interest using independent rainfall measurement data from waterinfo from Nov 2023 – Apr 2024 (https://waterinfo.vlaanderen.be/). Two key conditions are applied to identify events of interest; (1) dry days defined as consecutive timestamps where rainfall falls below 0.1 mm, and (2) the forward sum of rain over the next 2 hours after certain dry days should exceed 1.27 mm (Verstraeten et al., 2006). Spans of consecutive timestamps that meet both conditions are classified as events of interest. The maximum possible events of interest for 0 – 3 dry days are identified. Proposed samples from each strategy are evaluated by checking if they fall in the duration of the events of interest. The percentage of sampled events are computed for each parameter combination of the strategies. Further, the sampling efficiency is computed representing the proportion of the number of samples proposed in the events of interest versus the total number of proposed samples expressed as percentage.

Case study

The protocol is tested by sampling inflow and outflow of a water retention tank with two auto-samplers (type Sigma 900) on a pilot in Wetteren, Belgium (https://stopup.eu/berchem-wetteren/). Urban runoff from a shopping area (shop roofs + parking lots, 5500m^2) is collected in an urban rain shell (URS) retention tank that purifies the water for reuse as play water. The pilot aims to characterize the water in the retention tank and pollution at different moments during rain event. Figure 3 (A) shows the hardware configuration in the field. The IoT logger connected to water quality sensors (water level, electrical conductivity, turbidity) is responsible for the data communication. When the logger receives a trigger from the online service, a pulse is sent to the auto-sampler via a cable to initiate a new sampling. The suction tube takes water from the retention tank to fill the bottles of the auto-sampler. When samples are taken by the auto-sampler, an automatic warning message (via mail) is sent from the online service to collect the bottles and send these to the lab.

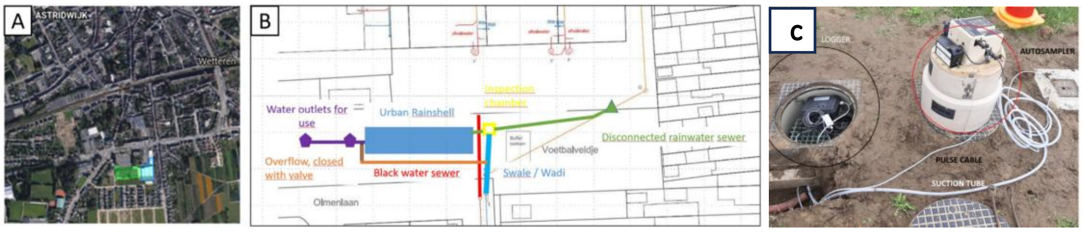

Figure 2 (A) Case study location (B) Schematic overview of Wetteren pilot (C) Hardware configuration on the field

Results and discussion

Figure 3(A) shows the percentage of events of interest that contain proposed samples, using the rainfall-volume based regime for combinations of rain volume and rain intensity triggers and 2 "no-event days". Results for the rest of the "no-event days" are shown in Table (1). Overall, 40% - 87% of the total events of interest are sampled for all the "no-event days" with percentages decreasing as the "no-event days" increase. For 0 and 1 "no-event days", 56% - 87% and 55% to 76% are achieved, respectively with lower thresholds yielding better percentages. For 2 and 3 "no-event days" higher thresholds yield better percentages. 48% - 62% and 40% - 53% of the events of interest contain proposed samples for 2 and 3 "no-event days" respectively. Lower rain intensity triggers exhibit lower percentages while higher rain volume triggers result in better percentages for 2 and 3 dry days. Percentages remain consistent as rain volume triggers increase for the same rain intensity triggers, highlighting rain intensity as the more sensitive parameter. Figure 3(B) shows the sampling efficiency for 2 "no-event days" and efficiency ranges for the other "no-event days" are presented in Table (1). Overall, 8% to 81% sample event coverage is achieved in all the cases with the efficiencies lowering drastically as "no-event days" increase. 8% - 13% of the total proposed samples are in the events of interest compared to the total proposed samples for 3 "no-event days".

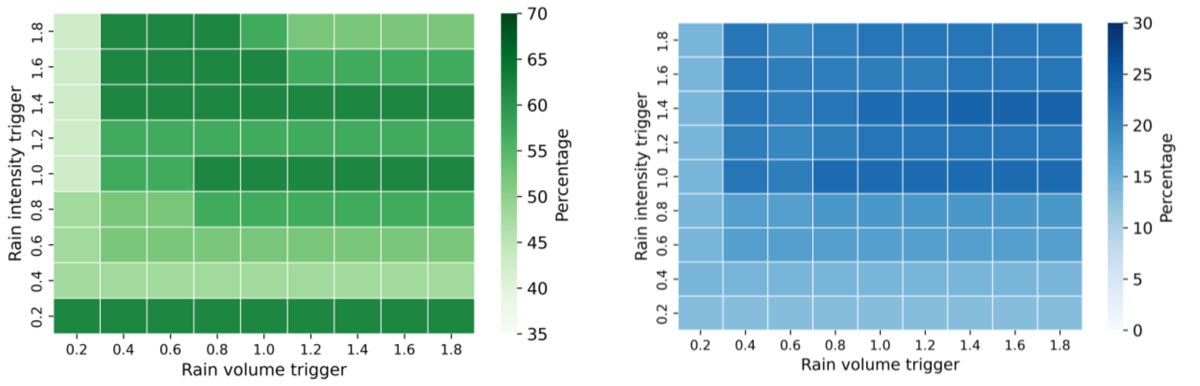

Figure 3. (A) Percentage of events of interest that contain samples and (B) Sampling efficiency for 2 "no-event days" for rainfall-volume based regime

Figure 4(A) shows the percentage of events of interest that contain proposed samples using the rainfall-runoff based regime for combinations of flow peak trigger and 2 “no-event days”. Results for the rest of the “no-event days” are shown in Table (1). Overall, 33% - 81% of the proposed samples are within the events of interest for all “no-event days”. For 0 and 1 “no-event days” 36% - 81% and 33% - 73% are obtained respectively where as for 2 and 3 “no-event days” 43% - 62% and 33% - 67% are obtained with percentages decreasing for flow peak trigger values > 2 m^3/s for all cases. This is due to the high restrictive flow peak trigger value. Figure 4(B) depicts the sampling efficiency for 2 “no-event days” and the results for the other “no-event days” are presented in Table (1). 9% - 75% of of the total samples are in the events of interest compared to the total number of the proposed samples for all “no-event days”. For both strategies the percentages drop siginificantlly as the “no-event days” increase. This is due to the uncertainity of forecasts and the limitation of logics used to define the events of interest.

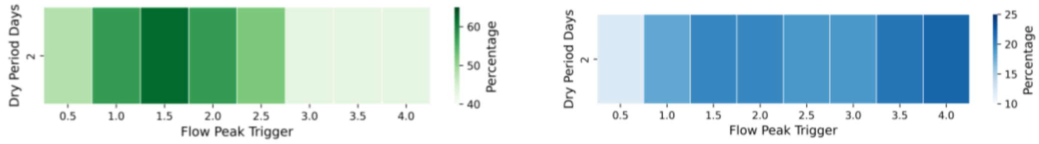

Figure 4. (A) Percentage of events of interest that contain samples (B) Sampling efficiency for 2 “no-event days” for rainfall runoff regime

Table 1. Results of ranges of percentages of events of interest that contain samples and ranges of percentages of sample event coverage for all no event days

	Rainfall-volume based regime		**Rainfall-runoff based regime**	
“No-event days”	Percentages of events of interest	Percentages of sample event coverage	Percentages of events of interest	Percentages of sample event coverage
0	56% - 87%	50% - 81%	36% - 81%	34% - 75%
1	55% - 76%	21% - 41%	33% - 73%	18% - 37%
2	48% - 62%	13% - 24%	43% - 62%	12% - 22%
3	40% - 53%	8% - 13%	33% - 67%	9% - 18%

Conclusions and future work

The auto sampling service triggers samples based on a remotely configured forecast-based sampling strategy. This study focuses on optimizing sampling strategies using rainfall-volume based and rainfall-runoff based regimes with their optimal parameter configurations. Events of interest were independently identified based on measured rainfall data, and the proposed sampling times were compared to determine if they aligned with these events. Various combinations of rain volume and rain intensity triggers with “no-event days” for the rainfall-volume based regime, and flow peak triggers with “no-event days” for the rainfall-runoff based regime were used. The analysis showed that 40% - 87% of the events of interest were sampled when using rainfall-volume based regime. Higher values for rain volume and intensity trigger result in better capturing the events of interest with the rain intensity trigger found to be the most sensitive parameter. Between 33% - 81% of the events of interest were sampled when using the rainfall-runoff based regime with lower flow peak triggers yielding better results. The limitation in this study is the uncertainty in rainfall forecasts and the logics implemented to identify events of interest. To address this, future analysis will include an ensemble of rainfall forecasts which uses multiple forecast models aiming to take better samples in the events of interest. Real time measurements of runoff, turbidity and electrical conductivity will also be included in the definition of events of interest to account for changes in water quality parameters and identify events of interest not solely based on measured rainfall but also measured runoff. Therefore, by optimizing sampling regimes and trigger parameters, events of interest can better be sampled. The outputs of this study are useful inputs in providing an innovative water quality monitoring approach during rain events.

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