A sampling approach for storm events with focus on micropollutants at combined sewer overflows

Une approche de l'échantillonnage aux déversoirs d'orage pour l'estimation des rejets de micropolluants

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RÉSUMÉ

Les rejets des stations d'épuration (STEP) ainsi que les rejets unitaires de temps de pluie et les rejets d'eaux de pluie des zones urbaines et des autoroutes constituent une voie d'entrée des micropolluants dans les masses d'eau de surface. Un échantillonnage représentatif des événements pluviaux constitue la première étape pour estimer les charges émises en micropolluants. Les informations issues des estimations de charges et de la détection des voies principales peuvent être utilisées pour développer des mesures d'atténuation adéquates pour réduire les rejets de ces substances. Cet article présente une stratégie d'échantillonnage pour que des auto-échantillonneurs génèrent des concentrations moyennes événementielles (CME) représentatives des rejets unitaires de temps de pluie sous des dynamiques de flux élevé pendant des orages. Les données de prévision immédiate des pluies sont associées à des données de haute résolution en ligne de 44 orages historiques pour un rejet unitaire dans un bassin versant urbain de la ville de Graz, afin de définir une relation pluie-ruissellement pour la prévision à court terme des orages à venir. Un classement des événements est développé et utilisé pour choisir des réglages dynamiques d'échantillonneurs pour cinq orages en 2012. Les effets d'un volume d'échantillonnage nécessaire pour les analyses chimiques en laboratoire et une limite de débit selon le réglage sélectionné sont en cours de discussion. Nous démontrons que l'utilisation de réglages d'échantillonneur dynamiques augmente la probabilité de générer des échantillons composites représentatifs, par rapport à un réglage statique des échantillonneurs.

ABSTRACT

The effluent of waste water treatment plants (WWTPs) as well as combined sewer overflows (CSOs) and stormwater discharges from urban areas and highways represent entry path for micropollutants in surface water bodies. Representative sampling of storm events constitutes the first step to estimate emitted micropollutant loads. The obtained information from load estimations and main path detection can be used to develop suitable mitigation measures to reduce the discharge of these substances. This paper introduces a sampling strategy for auto-samplers to generate representative event mean concentrations (EMC) of CSO discharges under high flow dynamics during storm events. Rainfall nowcasting data is combined with high resolution online data of 44 historical storm events at a CSO in an urban catchment in the city of Graz to define a rainfall-runoff relation for short-time prediction of upcoming storm events. A developed event classification is used to select predicted dynamic sampler settings for five storm events in 2012. The effects of a required sampling volume for chemical lab analytics and a flow limit depending on the selected setting are discussed. It is shown that using dynamic sampler settings increases the probability to generate representative composite samples compared to the usage of a static sampler setting.

KEYWORDS

Auto-sampler, CSO, EMC, Micropollutants, Nowcasting, Storm events

1 INTRODUCTION

The implementation of the EU Water Framework Directive (European-Comission, 2000) requires a comprehensive analysis of pollution entry paths to surface water bodies. Therefore flow and pollution measurements are required for the assessment of mitigation strategies for critical entry paths.

In the past the focus was mainly set on the effluent of waste water treatment plants (WWTPs) where detailed historical data of emitted organic and inorganic substances is available. However, only limited information on the influence of other essential entry paths such as combined sewer overflows (CSOs), stormwater discharges from urban areas and highways exists. Pollutants are washed out from the atmosphere through precipitation or can be washed off from urban surfaces like roads, metal roofs or veneers. Substances accumulated during dry weather can be remobilized during rainfall events from urban surfaces or in sewer pipes. In combined sewer systems these substances can emit to surface water bodies via CSO discharge. A characteristic of these entry paths is the complex and highly dynamic flow behaviour during rainfall events. Compared to the relatively low flow dynamics of WWTPs, discharge in the combined sewer system can vary by a factor up to 1:200 or more (Butler and Davies, 2000). This causes problems for the sampling approach and the high variability between events makes the selection of auto-sampler settings difficult or in extreme events impossible.

To estimate the emissions of pollutants to surface water bodies a representative sampling of storm events is necessary. This requires an appropriate parameterisation of the used sampling equipment. Since suitable auto-sampler settings are highly dependent on flow dynamics, only a limited number of events can be sampled representatively with the same settings at a specific location (see e.g. Harmel et al. 2003 or Ort and Gujer, 2006).

In the national research project SCHTURM (micropollutant emissions of urban catchments out of WWTPs, stormwater discharges and CSOs) the main focus is on the estimation of micropollutant emissions from several entry paths to surface water and ground water bodies during storm events in Austria. The aim is to estimate certain micropollutant loads from these entry paths for the whole of Austria to accomplish a relatively comparison of the main entry paths of investigated substances like heavy metals (Pb, Cd, Cr, Cu, Ni, Zn, Hg), phthalates, PAHs, hormones (estradiol), pesticides (diuron) and several industrial chemicals.

In this work a new dynamic strategy for the parameterisation of auto-sampler systems in CSOs during storm events is introduced. A rainfall nowcasting system for short-time prediction of the flow dynamics is used to predict the auto-sampler settings for upcoming storm events. The method allows a maximisation of the number of representative composite samples per relevant storm event and it can consequently provide better insights into the dynamics of micropollutant discharges during storm events. The goal is to generated composite samples for whole storm events providing representative event mean concentrations (EMCs) for the estimation of pollution loads under the constraint of a minimum sample volume required for further lab analytics.

2 MATERIALS AND METHODS

2.1 Catchment and measurement station

2.1.1 Catchment description

The investigated urban catchment “Graz-West R05” is located in the western part of the city of Graz, Austria. The city of Graz, divided by the Mur River with a mean runoff of about 120 m³/s, lies on 353 m altitude. The average annual rainfall depth is 830 mm. The catchment has a total area of approximately 456 ha including about 126 ha of impervious surface. The extension from East to West is about 4.8 km, population density is 43 inhabitants/ha. The overall length of the combined sewer system in this catchment is 46.5 km with 1 363 single sewer pipes in a wide range of circular profiles of 150 mm diameter up to oval cross sections of 1300/1950 mm. An in-sewer storage with a volume of 2 300 m³ is installed in the system. At the catchment outlet the sewer system is connected to the main sewer collector of Graz. At that point the CSO-R05 is situated. Discharge to the Mur River starts with an inflow to the CSO-R05 of about 600 L/s. For further information refer to Gamerith et al. (2011).

2.1.2 Measurement and sampling equipment

A sewer monitoring station is located directly at the CSO-R05. The flow in the discharge channel is calculated from the measured flow velocity and water level using an ultrasonic sensor, situated on the bottom of the channel. Additional, an in-situ ultraviolet-visible (UV/VIS) spectrometer probe (Langergraber et al., 2003) is situated in the CSO-chamber to measure concentrations of selected water quality parameters. Data is measured online with a temporal resolution of one minute for hydraulics and also for pollutant concentrations of the water quality parameters TSS (total suspended solids) and COD (chemical oxygen demand).

For sampling a peristaltic auto-sampling system of the type American Sigma 900 MAX (American Sigma, USA, www.hach.com) was used, connected to the flow meter sending an impulse every 1 m³ to the auto-sampler.

Available historic data since 2009 including 44 storm events allowed a detailed a-priori analysis of the flow conditions during dry weather and storm weather conditions at the CSO-R05. The flow variability ranges from 40 L/s in dry weather conditions up to approximately 15 m³/s in wet weather conditions. The maximum measurable flow of the flow meter is limited with approximately 7 000 L/s. For more details on the measurement station refer to Gruber et al. (2004).

2.2 Storm event sampling

2.2.1 Selected sampling mode

As stated in the introduction, the goal of the introduced sampling procedure is to generate representative event mean concentrations (EMCs) for micropollutants in CSO discharge to calculate mean pollution loads out of composite samples using an auto-sampler system.

The following sampling modes are available in standard auto-samplers (ISO 5667-10, 1992):

- With time-proportional sampling a fixed subsample volume is taken at fixed time intervals. This mode is only representative for low dynamics in flow and pollution concentrations.
- With flow-proportional sampling a variable subsample volume, proportional to the flow, is taken at fixed time intervals. The reliability of sampling is only ensured for a homogenous ratio between pollutant concentration and flow, which is not given in the case of micropollutants (see Ort et al., 2010). In practice the variable subsample volume is limited by the maximum subsample volume of the sampler. This limitation is often reached during highly dynamic events and leads to a cut off of peaks.
- With volume-proportional sampling a fixed subsample volume is taken at variable time intervals, depending on the flow volume. Therefore a constant flow volume, called impulse factor, is used for the parameterisation of the automatic sampling system. Every time the flow meter reaches this constant flow volume, an impulse from the flow meter is sent to the sampler to start taking a subsample.

As stated in ISO 5667-10 (1992) representative sampling of a homogenous stream would best be done by continuously collecting a small, flow-proportional fraction. In practice, however, several problems arise by applying this method as e.g.:

i. The storage volume of the sampling vessel needs to be very large.
ii. Frequent back flushing of the sampling hose is necessary to prevent clogging.
iii. Undesired biodegradation can occur of sampling low flows for long time spans (Ort and Gujer, 2006).

Therefore, in practice the volume-proportional sampling mode is mostly appropriate for taking a representative composite sample of a storm event and was therefore applied in this study. At the considered monitoring station CSO-R05 an installed ultrasonic flow meter measures the flow rate and sends an impulse generated every 1 m³ to the connected auto-sampler. When a defined number of impulses is reached (called impulse factor IF), the auto-sampler is triggered to take a sample.

For further information on different sampling modes see e.g. ISO 5667-1 (2006) or EPA (1992).

2.2.2 Sampling boundary conditions

For the introduced sampling strategy several boundary conditions depending on the sampling mode and the sampling location have to be considered.

It is assumed that the wastewater matrix is homogenous and that the distribution of the pollutants is constant over the whole cross-section. Due to the high flow dynamics during a storm event and the high flow variability between different storm events, auto-sampler settings need adjustment appropriate to the predicted maximum flow of an event.

In volume-proportional sampling an increase in flow leads to a decrease of the time interval between subsequent subsamples. Auto-samplers are limited by a minimum required subsample duration which depends on subsample volume, possible sucking height and sampler type. The minimum required subsample duration defines the maximum flow limit that can be detected. When the maximum flow in the system exceeds this limit, the time until the next sample impulse will be shorter than the time to take the current subsample. As a consequence of this a complete sample could not be generated (see Figure 1) to determine representative event mean concentrations (EMC) for the whole event.

In addition to the maximum flow limit, also the required total sampling volume for subsequent chemical investigations affects the sampling settings. For lab analytics a minimum pre-defined sampling volume is required depending on the investigated pollutants (Bertrand-Krajewski et al., 2000; American Public Health Association, 2005). Especially for an analysis of several micropollutants per sample it's necessary to have sufficient sample volume at disposal. On the other hand the maximum sample volume is limited by the overall volume capacity of the sampling vessel. Thus, the sample settings have to be adjusted accordingly.

To reduce the effort and potential errors in sampler handling, the auto-sampler settings should be constant for the whole event. Therefore, the following points were considered in this study:

- The setting of the sampler consists of two parameters: i) the pre-defined subsample volume Vsubsample of the auto-sampler and ii) the impulse factor IF, which has to be set at the connected flow meter.
- The first subsample has to be taken at the beginning of an event. Otherwise the pollution concentration in the beginning of an event will not be captured until the impulse factor is reached the first time.
- The maximum subsample volume for the developed sampling strategy is limited to 1000 mL, because this volume can still be sampled with the used auto-sampler in this study.
- The very last part of an event cannot be subsampled because the flow meter does not send an impulse to the sampler anymore. This flow volume can reach maximally the defined volume of the impulse factor and is relatively small compared to the entire flow volume of an event.

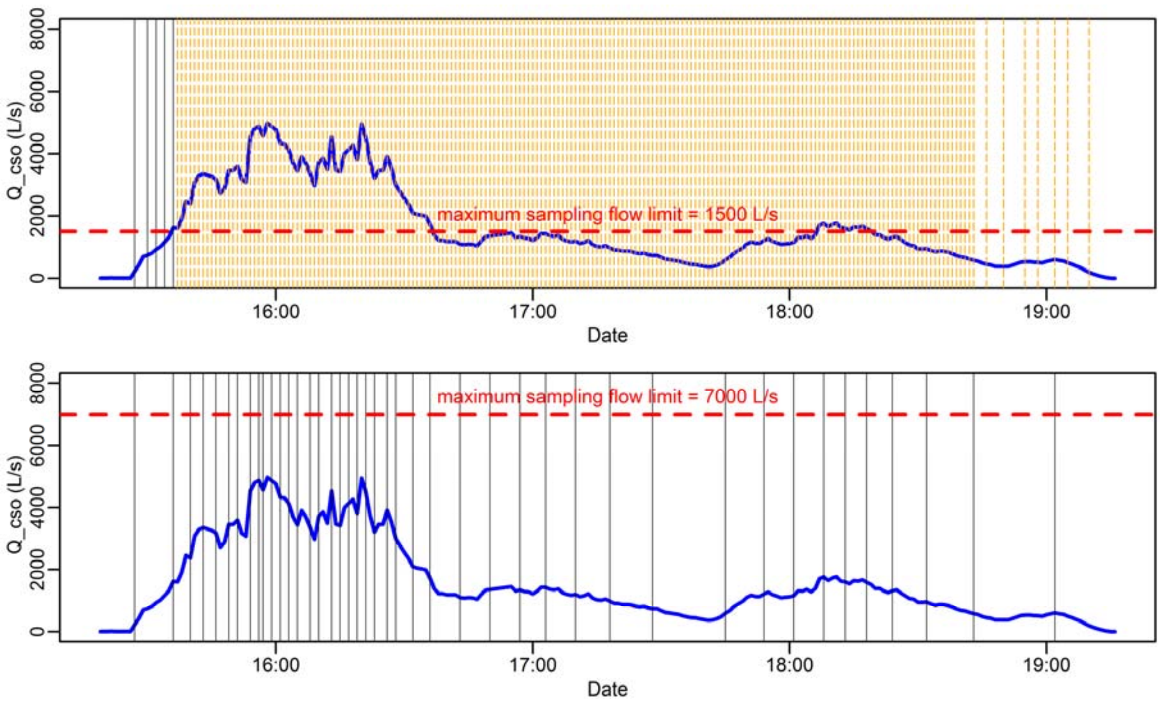

Figure 1: Theoretical sampling of a storm event considering a given maximum sampling flow limit. Upper: Invalid sampling with exceedance of the maximum sampling flow limit of 1 500 L/s. Lower: Valid sampling with a flow limit of 7 000 L/s. Solid vertical lines are indicating valid and complete subsamples, dashed vertical lines are indicating invalid and incomplete subsamples.

2.3 Rainfall nowcasting and runoff estimation

2.3.1 Rainfall nowcasting system

An approach to estimate future storm events is to connect a rainfall nowcasting system with runoff estimation in the catchment. The term "nowcasting" means that the rainfall will be predicted for a time period of a few hours in the future to reach accurate and reliable short-time forecasts. Several studies discussed weather forecasting over the last decades e.g. Austin and Bellon (1974), Browning et al. (1982) or Einfalt et al. (1990). In the past decade research was focused on more accurate nowcasting approaches for short-time predictions like in Golding (2000), Pierce et al. (2000) or Pierce et al. (2004).

In this work we apply a practical approved weather nowcasting system of the Central Institute for Meteorology and Geodynamics in Austria (ZAMG). The system INCA (Integrated Nowcasting through Comprehensive Analysis) uses the limited area model ALADIN (see Wang et al., 2006) with a temporal resolution of 1 hour and an area resolution of 5 km. The main input data is collected from a network of 250 automated rain gauges which provide measurements in an interval of 1 min. Additional data comes in a first step from five radar stations allocated in Austria which are operated by the civil aviation administration (Austro Control). INCA operationally works with 2-D radar data synthesized from these five stations, at a time resolution of 5 min. Additional data comes from meteorological satellites. To realize a relation of the weather data to the surface data of Austria a digital elevation model of the Austrian territory in a resolution of 1 km is obtained through bilinear interpolation from the global elevation dataset provided by the US Geological Survey. For nowcasting prediction, motion vectors are computed using a correlation method from consecutive analyses. Then rainfall nowcasting is predicted for a time period of two hours in the future in a rainfall intensity resolution of mm/5min. For a detailed description of the INCA nowcasting system refer to Haiden et al. (2011) and Kann et al. (2012).

The web-based graphical output of INCA rainfall nowcasting is exemplarily shown in Figure 2. The dotted area illustrates the predicted translocation of the storm cell for a time period of two hours in the future. The measured rainfall intensity is graded by colour as shown in the legend below.

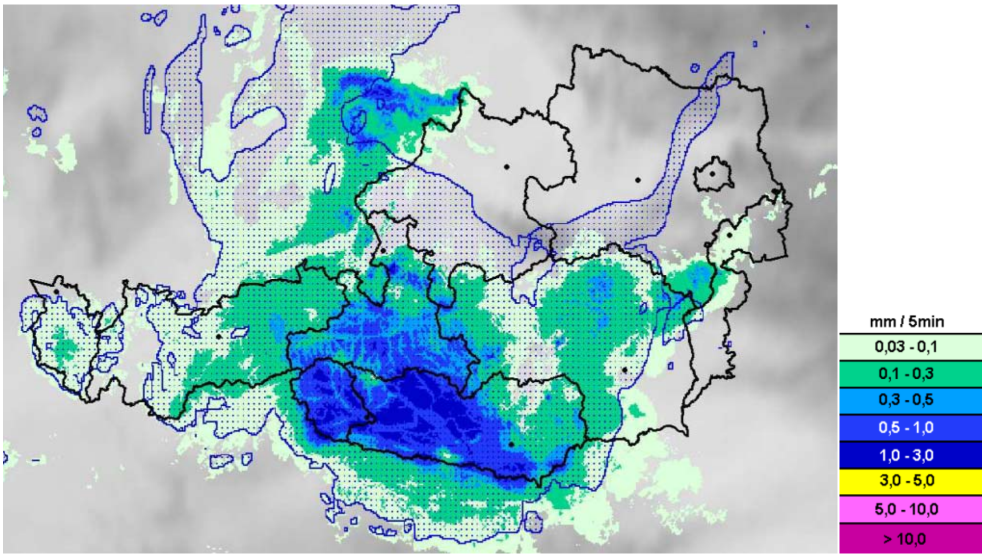

Figure 2: Graphical Output of the web-based INCA rainfall nowcasting system for a storm event with a predicting time period of two hours (Source: http://www.zamg.ac.at, restricted access: 2012-11-28)

2.3.2 Rainfall-runoff relation

An estimation of flow dynamics in the sewer system during a rainfall event from predicted rainfall data is an uncertain task. In the field of event forecasting research work was done e.g. by Kraemer et al. (2005) who combine radar rainfall data with measured flow data in a sewer system. Achleitner et al. (2009) discuss the usability of storm event forecasting based on predicted radar rainfall data by comparing measured with modelled flow data. In consideration of uncertainties they propose a reliable maximum forecast horizon of 90 min. Through the described combination of several data sources the INCA nowcasting system reaches a more accurate rainfall prediction than using radar data only. Therefore a forecast time period of 120 min was chosen in this work.

In this study we defined the characteristics of a storm event based on the rainfall nowcasting with the three parameters rainfall intensity, expansion of the storm cell and velocity of the storm cell and combine the information of rainfall nowcasting with the runoff information in the catchment. We determined the rainfall-runoff relationship by an analysis of the flow dynamics during several storm events at the CSO-R05 combined with a simultaneous visual analysis of the predictions from the web-based INCA rainfall nowcasting system.

2.4 Historical storm event analysis

To get an overview of the flow dynamics during wet weather conditions a detailed analysis of 44 historical storm events from 2009 to 2011 was done. The start and end of a potential event have to be consistent for the whole research. Effects on different event definitions are discussed for example in Harmel et al. (2003) which are depending on the focus and the location of sampling. During event analysis we observed a measurement inaccuracy of the flow meter at small flows, depending on reflections in the overflow channel and occasionally small backflow from the channel outlet. Thus, we set a minimum limit for reliable flow data to 5 L/s. This flow limit is also used to define start and end of a storm event.

To describe the event dynamics of the investigated CSO the ranges of event duration, the maximum flow and the flow volume are shown in Table 1.

We used the output of that analysis to develop an event classification, depending on the two parameters maximum flow and flow volume. Overall six classes were determined by graduating both parameters in the subclasses small, medium and large.

Table 1: Parameter range of 44 historical storm events from 2009 to 2011

Number of events	Duration range	Maximum flow range	Flow volume range
#	min	L/s	m³
44	24 - 729	148 – 2 208	382 – 24 294

Joining weather nowcasting information with event classification

To get a connection to the event classification, the same graduation (small, medium, large) is also done with the defined rainfall nowcasting parameters (rainfall intensity, expansion of the storm cell, velocity of the storm cell) by visual assessment.

2.5 Sampling strategy

In order to adjust the volume-proportional sampling setting for an upcoming storm event we developed a strategy for volume-proportional sampling as shown in Figure 3.

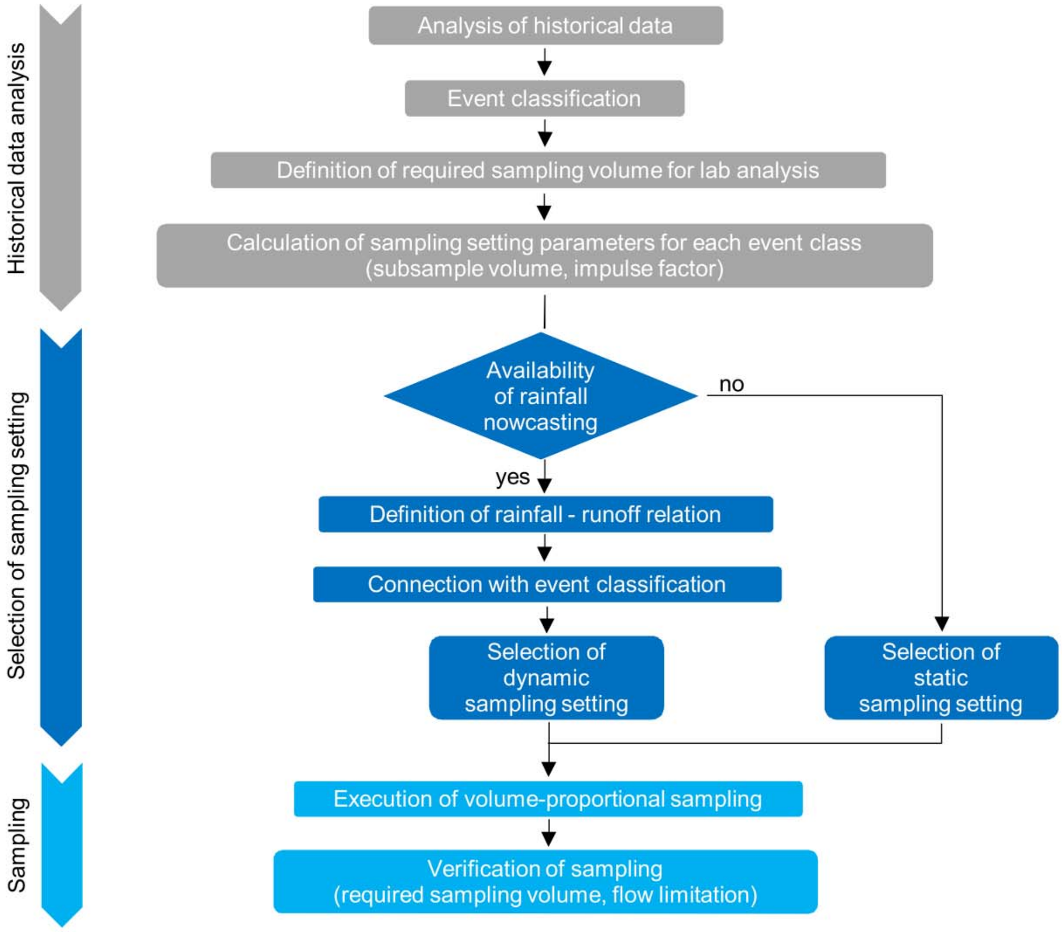

Figure 3: Flow chart of a strategy for volume-proportional sampling of complete storm events

In a first step the historical data is analysed to create an event classification. Depending on the required sample volume for lab analytics the volume-proportional sampling parameters (subsample volume $V_{subsample}$, impulse factor IF) for each class can be calculated by Equation 1 and 2.

$$V_{subsample} = \frac{V_{sample,req} * Q_{max} * t_{subsample}}{V_{event} * 10^3}$$ Equation 1

$$IF = Q_{max} * t_{subsample} * 10^{-3}$$ Equation 2

with:
$V_{subsample}$ ... subsample volume (mL); $V_{sample,req}$ ... required sample volume (L);
Q_{max} ... maximum event flow limitation (L/s); $t_{subsample}$ ... duration to take a subsample (s);
V_{event} ... estimated event flow volume (m^3) ; IF … impulse factor (m^3)

There is a functional relation between subsample volume $V_{subsample}$ and the duration to take a subsample $t_{subsample}$. This relation can be defined by ascertaining the time for taking different subsample volumes. Then a functional relationship can be set up. Often, you will get such information also from the manufacturer of the sampler.

If a rainfall nowcasting system is available, you can set up a relationship between rainfall and runoff. Then you are able use the predicted nowcasting information (rainfall intensity, expansion of the storm cell, velocity of the storm cell) to select an appropriate “dynamic” auto-sampler setting depending on the event classification for an upcoming storm event. Without a nowcasting system you can only use a “static” sampling setting.

After defining an auto-sampler setting you will be able to execute volume-proportional sampling for the next potential storm event. After sampling is completed it is necessary to verify if the sampling was representative and complete. Therefore two criteria have to be checked:

i. The overall sampling volume has to be larger than the required sampling volume for lab analysis.

ii. The maximum measured event flow must not exceed the pre-defined maximum flow limit.

3 RESULTS

Results are shown for five storm events at the CSO-R05. For chemical lab analytics the required total sample volume has been defined with 16 litres. The sampling vessel volume is limited with 25 litres. A functional relation between subsample volume and duration to take the subsample was determined from evaluating the subsample time for different volumes with the following linear model (Equation 3).

$$t_{subsample}(s) = 54 + 20 * V_{subsample}(L)$$ Equation 3

The maximum possible subsample volume of the used auto-sampler is 1000 mL. Sampling of small storm events is not a focus of this work and they would require a more detailed classification. Therefore only events with a maximum flow of more than 600 L/s (effectively leading to a discharge at CSO-R05) and a flow volume of more than 2 000 m³ are considered. The defined boundaries of each class are derived from the historical data analysis of 44 storm events. The subsample volume $V_{subsample}$ and the impulse factor *IF* are calculated with Equation 1 and 2 for each class using the maximum range value of the maximum flow Q_{max} and the minimum range value of the flow volume V_{event}.

Table 2: Event classification and associated sampling settings

Event class	Maximum flow Q_{max}	Flow volume V_{event}	Sampler setting	Subsample volume	Impulse factor
#	L/s	m³	#	mL	m³
Class 1	600 – 1 500 (small)	2 000 – 3 500 (small)	Setting 1	850	105
Class 2	600 – 1 500 (small)	3 500 – 8 000 (medium)	Setting 2	430	93
Class 3	600 – 1 500 (small)	8 000 – 25 000 (large)	Setting 3	180	87
Class 4	1 500 – 3 000 (medium)	3 500 – 8 000 (medium)	Setting 4	1 000	222
Class 5	1 500 – 3 000 (medium)	8 000 – 25 000 (large)	Setting 5	370	186
Class 6	3 000 – 7 000 (large)	8 000 – 25 000 (large)	Setting 6	1 000	518

Visual analysis of the weather nowcasting system during storm events revealed that predicted rainfall intensity has the most significant influence on the maximum flow. Expansion and velocity of the storm cell mainly influence the flow volume.

An overview of five investigated events is given in Table 3. For each event the selected auto-sampler setting and the total generated sampling volume is stated. The information from rainfall nowcasting is structured as followed:

- Rainfall intensity (mm/5 min): small (0.3 – 1.0), medium (1.0 – 3.0), large (> 3.0)
- Expansion of the storm cell: small, medium, large
- Velocity of the storm cell: slow, fast

Table 3: Sampled storm events in 2012 using rainfall nowcasting to select a dynamic sampling setting

Event	Maximum flow	Flow volume	Rainfall intensity	Expansion storm cell	Velocity storm cell	Sampler setting	**Sample volume**
#	L/s	m³	mm/5min	-	-	#	**L**
Event 1	1 200	5 200	0.3 – 1.0 (small)	medium	fast	Setting 2	**35.2**
Event 2	6 000	21 300	> 3.0 (large)	large	slow	Setting 6	**41.0**
Event 3	2 900	6 800	1.0 – 3.0 (medium)	medium	fast	Setting 4	**30.0**
Event 4	4 000	21 000	1.0 – 3.0 (medium)	large	slow	Setting 5	**41.4**
Event 5	800	7 000	0.3 – 1.0 (small)	medium	fast	Setting 2	**47.7**

Four different dynamic sampling settings were used to generate representative samples of all five storm events. The required total sampling volume was reached for each event. Indeed all samples exceeded the maximum volume of the vessel, but by selecting a specific sampling setting it is ensured that a disproportionately high volume can't be taken and so only one change of the filled vessel to a new one was necessary per event. The verification of the maximum flow limit was done by cross-checking with the specific flow boundaries in Table 2. In addition the dynamic sampling setting ensures that the time span between the subsamples stays relatively short, thereby increasing the reliability of sampling.

As shown in Table 3, using a static sampling setting like setting 2 without rainfall nowcasting would led to a maximum number of only two completely sampled storm events. By selecting other settings it would be only possible to completely sample one of the five investigated events.

4 CONCLUSIONS

It was shown that a combination of a nowcasting system for short-time rainfall prediction and runoff information in a catchment can be used to estimate the flow dynamics of an upcoming storm event at a specific location in the sewer system. A previous analysis of 44 storm events from 2009 to 2011 lead to essential information to determine boundaries for a storm event classification on which the introduced volume-proportional sampling strategy for auto-samplers is set up.

This sampling strategy represents a possibility to generate EMCs of representative and complete samples of whole storm events in consideration of high flow dynamics. Applying this strategy on five storm events from 2012 it could be shown that the probability of a successful event sampling is higher using dynamic settings with rainfall nowcasting than using only static settings for sampling.

The problem of a maximum flow limit exceedance during volume-proportional sampling is discussed and a practical approach for sampling parameterisation to avoid this problem is shown. It is possible to transfer and apply the developed sampling strategy to other catchments.

The linkage between rainfall nowcasting and runoff behaviour was done by visual analysis of the rainfall nowcasting data based on information from available historical storm events. The application of runoff modelling with nowcasting data for the estimation of the occurring flow dynamics could be a topic for further research work to make more objective statements about future expected storm event characteristics.

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