Global resilience analysis of combined sewer systems under continuous hydrologic simulation

Mayra Rodriguez a, Guangtao Fu b, David Butler b, Zhiguo Yuan c, Lauren Cook a,∗

a Department of Urban Water Management, Swiss Federal Institute of Aquatic Science and Technology, Dübendorf, Switzerland
b Centre for Water Systems, University of Exeter, Exeter, United Kingdom
c City University of Hong Kong, Hong Kong, China

1. Introduction

Combined sewer systems (CSS) are pipe systems that collect both wastewater and stormwater (Butler et al., 2018). During heavy rainfall, these systems can become overloaded and discharge untreated wastewater into nearby water bodies, leading to pollution and water quality issues (Mailhot et al., 2015). Managing and reducing these discharges from combined sewer overflows (CSOs) has become a priority of public authorities worldwide, due to increased attention towards water quality (European Commission, 2000; UK Government, 2021; United Nations, 2018). In the face of emerging pressures such as climate change and urbanisation, the issues associated with CSOs are likely to increase (e.g., water quality and ecological impacts on receiving waters) (Astarane-Imani et al., 2012; IPCC, 2022; Roseboro et al., 2021). Therefore, there is an agreement that CSS need to be redesigned to support resilience (Butler et al., 2017; Marlow et al., 2013; Ofwat, 2015; UNESCO World Water Assessment Programme, 2018)—i.e., the ability to minimise failure magnitude and duration under exceptional conditions (Butler et al., 2014).

The lack of a common approach to resilience analysis and quantification of CSOs’ impact presents a challenge for implementing strategies for their reduction and resilience enhancement of CSS systems. Several resilience frameworks and assessment methodologies have been proposed to evaluate resilience (Butler et al., 2014, 2017; Hashimoto et al., 1982; Hollnagel, 2015; Liu et al., 2012; Vugrin et al., 2011). For water systems, the Safe and SuRe framework suggests that failures in systems occur due to threats, which lead to a level of service impacts and societal consequences (Butler et al., 2014, 2017). Within the framework, a “middle state” approach (from system failure to impact) involves identifying all the possible ways that a closed system can fail (e.g., pipe and pump failure), irrespective of whether the cause is a known or unknown threat. The Global Resilience Analysis (GRA) is a middle-state method that has been used to quantify resilience based on system performance (Diao et al., 2016; Mugume et al., 2015). In this method, the GRA has been applied to quantify flooding resilience (Mugume et al., 2015; Sweetapple et al., 2018; Wang et al., 2019a)
and general resilience (Sweetapple et al., 2022), but CSOs have usually been neglected in the analysis. In GRA, by framing resilience as “resilience to any system failure,” resilience is assessed as a function of system performance under different failure scenarios.

However, resilience, as defined by Butler et al. (2014), refers to a defined performance target in response to a threat, i.e., an operational goal. Therefore, a key shortcoming in the GRA method is the threat (e.g., rainfall) is not linked to the impact (e.g., CSOs). To address this, the threat-based analysis, also called the “top-down” approach (from threats to impacts), can be integrated with middle-state approaches, previously done in climate change adaptation studies (Ekström et al., 2013; Pulido-Velazquez et al., 2022). The top-down approach focuses on the identification of potential threats that could impact the system and has traditionally been used in risk analysis (Butler et al., 2017; Pulido-Velazquez et al., 2022). Integrating the top-down approach into the GRA can thus provide valuable insights to ensure the delivery of the required level of service, particularly when interested in increasing resilience to a particular threat. A top-down approach allows for differentiation between threats that produce the same impact and similar threats that produce different impacts (Butler et al., 2017; Diao et al., 2016), which is particularly relevant to the ongoing research on the relationship between CSO characteristics and their relationship with rainfall patterns (Mailhot et al., 2015; Yu et al., 2022). In this manner, the effects of different rainfall patterns, dry/wet periods and long-term periods could be incorporated into the resilience analysis by using continuous simulation (Grimaldi et al., 2012; Hoes and Nelen, 2005; Willems et al., 2012).

Integrating a top-down approach linking threat and impact can help develop effective strategies to enhance resilience and reduce CSO impact. Among the different interventions in CSS to enhance resilience, decentralised stormwater strategies that mimic natural processes, such as “green infrastructure” (GI) (e.g., green roofs, bioretention cells, permeable pavements) (Browder et al., 2019; Fletcher et al., 2015; Matsler et al., 2021), are gaining popularity. Research has demonstrated the efficacy of GI under various precipitation conditions, with some studies showing significant reductions in CSO volume (24–100% reduction) through the implementation of different GI types under different spatial allocations (Casal-Campos et al., 2015, 2018; Joshi et al., 2021; Lucas and Sample, 2015; McClymont et al., 2020; Rodriguez et al., 2021; Roseboro et al., 2021). Conflicting findings on the effectiveness of GI in reducing CSOs suggest a need for further exploration of GI’s relationship with CSS resilience performance, as current literature lacks clear characterisation in this regard.

This study proposes a method for quantifying the resilience performance in CSS by expanding the existing GRA to a top-down approach, linking threats (i.e., rainfall) to impact (i.e., CSOs) under continuous and long-term simulation. Specifically, this study evaluates the resilience performance of GI (green roofs, permeable pavements, and bioretention cells) in reducing CSOs in Fehraltorf, Switzerland, through the application of the proposed method. This approach contributes to the literature by characterising the consequences of rainfall as a threat to CSS and their link to CSOs, supporting the effective implementation of GI that promotes the resilience of cities.

**2. Extension of the global resilience analysis**

Fig. 1 presents an overview of the framework to quantify resilience under continuous simulation, expanding the existing GRA to a top-down approach. The six steps presented (i.e., rainfall indices definition, CSO performance metrics, metric calculation based on continuous simulation, correlation analysis, stress-strain curve generation and computation of resilience index) are explained in the following subsections.

**2.1. Step one: Characterisation of the system’s threat and definition of rainfall indices**

In the proposed extension of the GRA, “stress” is defined as a measure of the threat or load that is put on the system (e.g., rainfall intensity), which differs from the original version of GRA, where the stress represents the magnitude of a system failure. The impact, or how the system reacts to a given threat magnitude is the “strain” (e.g., CSO volume).

The first step characterises the system stress using rainfall indices, which are standardised indicators to characterise climate variability and rainfall features (Alexander et al., 2019). The indices allow us to understand the critical qualities of rainfall patterns, such as the central tendency, magnitude, proportion or frequency of extremes, or the frequency of wet or dry periods (Cook et al., 2019). The indices are used to portray the stress in the GRA “stress-strain” curves and allow the analysis of system performance in the face of extreme events required in the study of resilience.

The rainfall indices used in this study (Table 1) were developed by
Cook et al. (2019) and are based on the recommendations of the Expert Team on Climate Change Detection and the World Climate Research Programme (Peterson et al., 2001). Each index was calculated using yearly rainfall, based on historical time series. Different statistical factors (as shown in column “variation” in Table 1) were used to represent the variation of each metric.

### 2.2. Step two: Identification of the system’s strain and performance metrics

Based on the resilience definition by Butler et al. (2014, 2017), resilience has two main components: magnitude and duration. Resilience addresses the dynamic system performance under threats (e.g., excessive rainfall), such as the system’s ability to resist, respond and recover. In the literature, CSO discharges are characterised by the total discharge volume, frequency of spills, and duration of discharges, or its counterpart, time free of spills (Abdelatif et al., 2015; Casal-Campos et al., 2018; Fu and Butler, 2012; Joshi et al., 2021; Lau et al., 2002).

New CSO performance metrics based on similar concepts to the rainfall indices can be developed to address, not only the principal components of resilience, but also the dynamics of system performance. Presented in Table 2, these metrics are used to represent system strain. They are classified according to the main components of resilience (failure magnitude and duration) and phases of dynamic system performance under threats (resistance, absorption, recovery). The volumes selected for the metric number of days with CSO discharges higher than n m³ were selected based on the CSO volume comparison found in Quaranta et al. (2022).

### 2.3. Step three: Metrics calculated after continuous hydrologic simulation

The calculation of the performance metrics is based on the analysis of time series obtained from hydrologic-hydraulic models. These models characterise system response over time, enabling consideration of antecedent soil moisture conditions between consecutive storm events, evapotranspiration (ET), and groundwater processes. Metrics are calculated for all the outfalls in the sewer system, as well as, at a system level.

### 2.4. Step four: Correlation analysis and the selection of the most indicative rainfall indices

Since rainfall indices characterise different aspects of rainfall patterns, they differ in their effect on system performance, and consequently in the CSO performance metrics. As in Cook et al. (2019), the selection of metrics is performed using correlation analysis and the rainfall index chosen is based on the strongest absolute correlation for each CSO performance metric. As the relationship between rainfall indices and the CSO performance metric is not necessarily linear, the Spearman’s rank-order correlation, a non-parametric version of the Pearson correlation coefficient, is used. Spearman’s rank order measures the strength and direction of association between two variables instead of the strength and direction of the linear relationship measured by the Pearson correlation coefficient (Freedman et al., 2007). The null hypothesis, i.e., the test for statistical significance, is rejected by calculating the p-value, and the correlation is considered statistically significant if the p-value is less than 0.05 (Freedman et al., 2007).

### 2.5. Step five: Generation of stress-strain curves and calculation of resilience indicators

The area under the curve can be used as a proxy for resilience when comparing different states of the system and plausible interventions to enhance resilience. A smaller area represents a higher resilience under the stress-strain curve, indicating a lower system strain over a range of conditions (Butler et al., 2017; Mugume et al., 2015).

Since the results are a set of points, a continuous stress-strain curve is obtained using polynomial regression for each CSO performance metric i and its selected, representative rainfall index (Step 4). To facilitate comparison among metrics that use different units, the CSO performance metrics obtained from the best-fitted polynomial regression and rainfall indices are normalised relative to the system or outfall baseline. With the normalised values, the area under the curve ($\int_{area}^{area} area \\cdot strain \, darea$) for each CSO performance metric i is calculated using the trapezoidal rule (Press et al., 2007). Further information on polynomial regression, normalisation, and the area under the curve calculation can be found in Supplementary Information (SI) S1.

To create a metric for resilience, the following equation is used,
\[ \text{Res}_i = \frac{1}{1 + \text{AUC}_{\text{stress-strain curve}i}} \]  

[1]

The value represents the resilience of each CSO performance metric \( i \) to rainfall. The inverse transformation is applied to ensure that a higher \( \text{Res}_i \) equates to a higher resilience when considering the corresponding CSO performance metric. This transformation forces the resilience indicator to be between zero and one, where one indicates perfect resilience (no loss of functionality under any rainfall) and zero means that the system fails under all rainfall types. The metric is unitless.

2.6. Step Six: Computation of a CSO resilience index

To aid decision-making processes, compare different interventions, and further understand the system, a CSO resilience index, \( \text{Res}_{\text{CSO}} \), is used to illustrate the general resilience level of the system. The resilience indicators from Step 5 are aggregated into a single index using the weighted sum approach following (Casal-Campos et al., 2018),

\[ \text{Res}_{\text{CSO}} = \sum_i w_i \ast \text{Res}_i \]  

[2]

where \( \text{Res}_{\text{CSO}} \) represents the CSO resilience index as a weighted summation of the resilience indices \( \text{Res}_i \), \( i \) represents each CSO performance metric considered in this study, and \( w_i \) is the relative weight for each CSO performance metric. The metric is unitless. One indicates a perfectly resilient system, while zero indicates system failure under all rainfall events. In this study, all the weights \( (w_i) \) are considered equal; however, the weights could be adjusted based on the importance of the performance metrics in the CSS and on receiving waters.

3. Application of the modified GRA to a case study in Switzerland

3.1. Case study and combined sewer system model

The municipality of Fehraltorf, Switzerland is a residential and industrial, pre-alpine catchment located 15 km east of Zurich (Federal Office for Statistics, 2022). As shown in Fig. 2, Fehraltorf’s drainage area and two neighbouring municipalities (Russikon and Rumlikon) are connected to the CSS, which is conveyed together to a wastewater treatment plant (WWTP) (maximum capacity: 180 Ls\(^{-1}\)). The WWTP and the CSO structures discharge to the Luppmen river, where long-lasting discharges lead to severe environmental and ecological impacts (Krejci et al., 1994). The CSS model was implemented in US EPA Stormwater Management Model (SWMM) (Rossman, 2015). The model characteristics and its automatic calibration are described in detail in Rodriguez (2022).

3.2. Quantification of the resilience baseline

The modified GRA is applied to Fehraltorf over 38 years between 1982 and 2020. The hydrologic-hydraulic simulation of the system was conducted in SWMM (Rossman, 2015) using 10-min historical rainfall data from a station located 15 km from Fehraltorf (MeteoSwiss, 2022). The rainfall indices are calculated for each year of historical data, resulting in 38 data points per rainfall index. Each CSO performance metric is calculated individually from the simulated time series for each CSO outfall junction (\( n = 6 \)). CSO metrics are also calculated at the system level by summing the time series across all junctions and then calculating each metric in the same manner as the individual outfalls.

As discussed in Section 2.5, only the rainfall indices most indicative of system performance are selected to represent system stress. In this study, the rainfall indices that show a strong (−0.79 to −0.51 or 0.51 to 0.79)
used in practical applications and literature (Wang et al., 2017) and they in each subcatchment. These GI types are selected as they are commonly (the outfall before the WWTP) and RUB 80 (an outfall related to an in RUB 128 (a midstream outfall, Fig. 2), as can be observed in Fig. 3 a1, e1. GI also affect different urban land uses and involve different hydrolog maximum spatial extent (Table 3), which is defined by the land-use type systems resilience

3.3. Quantification of green infrastructure impact on combined sewer systems resilience

In addition to quantifying baseline resilience, different GI scenarios are considered for the same period and the same historical rainfall data from MeteoSwiss. Three different types of GI (bioretention cells “BC”, green roofs “GR”, and permeable pavements “PP”) are implemented at a maximum spatial extent (Table 3), which is defined by the land-use type in each subcatchment. These GI types are selected as they are commonly used in practical applications and literature (Wang et al., 2017) and they can be explicitly modelled in SWMM (Rossman and Huber, 2016). These GI also affect different urban land uses and involve different hydrological processes (Rossman, 2015; Rossman and Huber, 2016). The implementation of GI at the full spatial extent is unlikely to be met in practice due to various limitations such as ownership of the land, building types, and characteristics of the catchment itself (i.e., soil types and ground-water level). However, this approach represents the best possible case within each subcatchment and serves as a benchmark to compare their effectiveness in the different locations in the catchment. The GI SWMM modelling and parameters are explained in the SI S2.

4. Results and discussion

4.1. System baseline and CSO discharge assessment

Fig. 3 presents the simulated hydraulic performance for the six outfalls and the system in the Fehraltorf CSS over the period from 1982 to 2020. The results illustrate the variability in performance between the different outfalls and the evaluated metrics. The most critical outfall in the system in terms of total discharge volume (both total and per event) is RUB 128 (a midstream outfall, Fig. 2), as can be observed in Fig. 3 a1, e1 and f. The outfalls with the next highest yearly volumes are RUB 59 (the outfall before the WWTP) and RUB 80 (an outfall related to an industrial area) (Fig. 3a1). These outfalls show comparatively low total duration (Fig. 3b1) and low spill frequency (Fig. 3c1), which means that these outfalls have shorter, but larger CSO discharge events than other outfalls, contrary to what would be generally expected (more volume, more duration). Along the same line, despite SK 102 (the most upstream outfall) and RUB 40a (another midstream outfall) having small total discharge volume compared to the other outfalls, they show the highest yearly CSO discharge duration and frequency (Fig. 3b1) (Fig. 3c1). Their discharge events tend to last longer (Fig. 3c and d) and happen more often, but with a smaller volume discharged into the creek. The system mimics performance in the most critical outfall, but the other outfalls are still relevant depending on the flow of the receiving waters (for example, creeks with small flows, like in the case of Fehraltorf, would still be impacted by low CSO volume). This variability highlights the importance of investigating several metrics and outfalls when analysing CSO discharges. Overall, considering different outfalls in the system, and not just the system itself (subplots 1 versus 2) is important to understand the spatial particularities of the CSS, as not all outfalls behave similarly.

4.2. Correlation analysis and selection of rainfall indices

As there is clear variability in system performance among the different metrics, there is also variability in the characteristics of rainfall influencing this performance. The relationship between CSO performance (strain) and rainfall (stress) is quantified as the correlation of the indices and metrics at a system level (Fig. 4). The total number of rainfall indices showing a strong or very strong correlation are presented at the bottom of the figure.

All the CSO performance metrics strongly correlate with at least two rainfall indices, which is in line with previous research (Jean et al., 2018; Malhotra et al., 2015; Schroeder et al., 2011). Only the rainfall indices that show a strong or very strong correlation in five or more outfalls are presented in Fig. 4 (all rainfall indices are presented in SI S3). In line with the results by Cook et al. (2019), the rainfall indices with the strongest correlation in the highest number of outfalls and highest strengths in the correlation are related to the central tendency or extremes, e.g., total precipitation for the central tendency and 95th percentile of hourly rainfall for the extremes.

The identified relationships highlight the importance of continuous simulation analysis and show its advantage over an event-based approach, as it allows accounting for a variety of storm profiles, rainfall patterns, and intensities characterised by the rainfall indices. The analysis of CSO discharges showed the need to consider rainfall “extremes”, which are more relevant than rainfall “totals”. This is reflected in the most indicative rainfall indices for each CSO performance metric, presented in Table 4. While these rainfall indices are representative of the Fehraltorf CSS, they may not represent other CSS. Thus, rainfall indices should be selected depending on individual system characteristics, the needs of the stakeholders, and the criticality of each outfall in the system (from a performance, social, environmental, or economic point of view). The rainfall spatial distribution and variation are not considered in this study, but could influence the correlation indices in different locations.

4.3. Generation of stress-strain curves and calculation of resilience indices

4.3.1. Stress-strain curves for baseline and green infrastructure implementation

The resulting stress-strain curves based on the best-fitted polynomial regression for each CSO performance metric and its corresponding rainfall index at a system level are presented in Fig. 5. The stress-strain curves are presented for the system baseline (black) as well as with the addition of green infrastructure at a maximum spatial extent, including BC (blue), PP (yellow) and GR (green). A comparison of the stress-strain curves for individual outfalls is presented in SI S4.

In the baseline, most of the fitted stress-strain curves show acceptable goodness of fit for the models (r² > 0.5). Generally, all stress-strain curves are positively increasing, implying that as the rainfall index increases, so does the stress in the system, as would be expected. Five
Fig. 3. CSO performance metrics (1982–2020) for the outfalls (left) and the system (right), including (a) totcso, (b) durcso, (c) evdurmean, (d) freq, (e) maxdcso, (f) dischnd50, (g) dischnd1000, and (h) incddmean.
curves are linear, while two are quadratic (spill frequency and inverse consecutive days without CSOs). The frequency of spills and the inverse of days without spills peak in the middle and later plateau or decrease. This trend does not mean that the CSO discharge volume decreases (the opposite is shown in Fig. 5a). Instead, the decrease in higher rainfall index values can be explained by how the CSO discharge behaviour changes: higher volume yet lower duration (Fig. 5a–b) means lower frequency and more days without spills. This phenomenon is also observed in individual outfalls as previously explained in Section 4.1.

Only one relationship is cubic (days with discharge higher than $50m^3$), implying that the wettest rainfall years are prone to a steep (non-linear) increase in CSO discharges. The linear and polynomial equations were cross-validated to ensure they best represent the relationship between stress and strain and that there is no overfitting. However, further efforts to verify the fit robustness could be carried out, including sensitivity analysis of the SWMM model parameters or rainfall period.

When GI is applied to the system, there is generally a change in the polynomial degree and, consequently, a change in the shape of the

![Fig. 4. Correlation analysis between rainfall indices (rows) and CSO performance metrics (columns) for the period from 1982 to 2020. Numbers in grey represent the number of strong or very strong correlations for the CSO performance metric.](image-url)

Table 4
Most indicative rainfall indices at a system level for the historical period (1982–2020).

<table>
<thead>
<tr>
<th>CSO performance metrics</th>
<th>Rainfall Indices</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total Yearly CSO Discharge</td>
<td>Total precipitation ≥ daily 90th percentile</td>
</tr>
<tr>
<td>Total CSO Discharge duration</td>
<td>95th hourly percentile</td>
</tr>
<tr>
<td>Annual spill frequency</td>
<td>95th hourly percentile</td>
</tr>
<tr>
<td>Maximum daily CSO Discharge</td>
<td>Total precipitation ≥ daily 99th percentile</td>
</tr>
<tr>
<td>Number of days with CSO Discharge ≥ 50m³</td>
<td>Total Yearly Precipitation</td>
</tr>
<tr>
<td>Number of days with CSO Discharge ≥ 500m³</td>
<td>99th hourly percentile</td>
</tr>
<tr>
<td>Number of days with CSO Discharge ≥ 1000m³</td>
<td>90th daily percentile</td>
</tr>
<tr>
<td>Inverse of the mean number of consecutive days where CSO Discharge &lt; 0.1 m³</td>
<td>Number of rain days with precipitation &gt; 25 mm</td>
</tr>
</tbody>
</table>
stress-strain curve for most CSO performance metrics. This shows that the system’s relationship with the stresses is altered by including GI strategies. There is also variation in the shape of the stress-strain curve between different GI strategies, highlighting differences in their processes and influence on the CSS. For instance, the BC effectively reduce discharge volume more than the other GI, but they do not provide the highest benefits for the different CSO performance metrics, despite having the largest implementation area. The GR implementation shows the highest benefits for most CSO performance metrics across all the considered ranges of the selected rainfall indices, showing a higher impact on resilience than BC and PP. All the water runoff resulting from the GR was re-routed to previous areas during the simulations, which represents the best-case scenario and constitutes a modelling choice, and may have led to a higher reduction in CSO compared to BC and PP.

In some cases, the GI strategies do not considerably affect CSO duration, frequency, and consecutive days without discharge at the system level. This is largely a result of aggregation to the system level since this is not the case at the individual outfalls (see SI). The benefit of the system-level analysis is the ability to capture the simultaneous discharging of various outfalls — effect, a worst-case scenario. Yet this aggregated approach ultimately reduces detailed, individual relationships. This issue highlights how resilience changes depending on how and where it is measured in the system. Thus, standardised approaches to measure resilience are imperative.

4.3.2. Resilience indices

As shown in Fig. 6, the resilience indicator for each CSO performance metric is calculated as the area under the curve for each stress-strain curve. The resilience index provides a quantitative measure of resilience and a standardised way to compare interventions across a system. Each of the polar plot axes represents one of the resilience indexes derived from each CSO discharge performance metric. A higher resilience index for each performance metric represents higher resilience.

In general, all GI strategies enhance resilience in the Fehraltorf CSS.
However, each strategy affects the outfalls differently, in terms of which CSO performance metric is affected and the magnitude of the effect (see SI S5 for other outfalls plots). As stated previously, GR are the most beneficial strategy when considering all the CSO performance metrics at an outfall and system level. However, the BC shows a higher impact than the GR on the maximum daily discharge.

The differences among the CSO performance metrics highlight the advantages and limitations of placing each GI type in the system. The different GI types could then be used to obtain different performance objectives set by the stakeholder or urban planner, based on the criticalities of each outfall.

4.4. CSO resilience index

The aggregated CSO resilience indices are presented in Fig. 7 for the system, an upstream outfall (SK 102), a midstream outfall (RUB 128), and the downstream outfall (RUB 59). Although GI increased resilience performance in all the scenarios considered both at a system and outfall level, this increase is low. The resilience performance gains are more important at an outfall level, in particular at the outfall before the WWTP (RUB 59). In the resilience analysis performed, a wide range of rainfall types and profiles are considered (based on real historical time series). This could explain the low improvement in resilience performance under the scenarios considered, as the GI performance tends to decrease for high-intensity and long-duration storms (Webber et al., 2020). Other alternatives to increase resilience performance need to be contemplated, such as combinations of different GI (Wang et al., 2019b) and grey strategies (Casal-Campos et al., 2015). This is beyond the scope of the paper, as the aim is to present a standardised method to measure resilience under continuous simulation.

5. Conclusions

This paper proposed a method to extend the Global Resilience Analysis (GRA) using a threat-based approach in order to quantify the resilience of combined sewer systems (CSS) and the effect of green stormwater infrastructure (GI) on this resulting resilience. Based on results from Fehraltorf, Switzerland, it can be concluded that:

- The use of long-term, continuous simulation to quantify resilience allows for a comprehensive characterisation of resilience performance and its response to rainfall, as it can better represent rainfall variability than design rainfall events in terms of profiles, durations, and intensities.
- Resilience varies in different outfalls, highlighting the importance of considering multiple points in the catchment when analysing resilience. The downstream outfall in Fehraltorf CSS saw the most significant improvement in the CSO resilience index when placing GI in the system. Variations in resilience performance will need to be considered in GI design and spatial deployment.
- The choice of CSO performance metrics is critical in the analysis of resilience, as these metrics must be representative of the problems...
encountered in the system. A range of performance metrics beyond total discharge volume and duration can help identify and explain diverse issues in the system.

- At a system level, the effects of GI on resilience are small. The green roof technologies in Fehraltof CSR are most effective when considering all performance metrics both at the individual outfall and system level.

Future research could implement other threats (e.g., urbanisation-derived changes), as only rainfall is considered in this study. The proposed method could be applied to consider other strains using different performance metrics (e.g., flooding). Different GI spatial extents and distributions could also be considered in future research when applying the modified GRA under climate change scenarios. Given the generality of this method, it could be applied to other catchments with sufficient data and other water management research areas (e.g., water supply, reservoirs, dams) or to the energy sector if the performance metrics are adapted accordingly.

The presented methodology contributes to the existing literature and the field by providing a way to systematically quantify the resilience of combined sewer systems to various rainfall patterns. By doing so, it supports a performance-based implementation of GI and can help decision-makers to understand how green infrastructure alters system resilience in a combined sewer catchment. Consequently, they can make better informed decisions that will effectively bolster the resilience of combined sewer systems.

Author credit statement

Dr. Mayra Rodriguez-Conceptualization; Formal analysis; Investigation; Methodology; Data curation; Software; Validation; Visualization; Roles/Writing - original draft; Writing - review & editing; Prof. Guangtao Fu - Conceptualization; Funding acquisition; Writing - review & editing; Supervision; Prof. David Butler - Conceptualization; Funding acquisition; Writing - review & editing; Validation; SupervisionProf. Zhiguo Yuan - Funding acq; uisition; Writing - review & editing; Prof. David Butler - Conceptualization; Methodology; Supervision; Project administration; Writing - review & editing; Funding acquisition.

Declaration of competing interest

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

Data availability

Data will be made available on request.

Acknowledgements

This research was funded by the QUEX Institute and Eawag. We kindly acknowledge the Australian Centre for Water and Environmental Biotechnology for their support during the development of this study. The authors would like to thank the Urban Water Observatory team at Eawag for providing the SWMM model, meteorological data and flow data of Fehraltof. We would also like to thank the CSCL cluster and Stuart Dennis at Eawag for their help with parallel computing.

References


