Spatial impact of green infrastructures on urban drainage resilience

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Highlights

- Application of exploratory spatial data analysis to understand the impact of green infrastructure location on the resilience enhancement of the sewer system.
- Results show differences in spatial autocorrelation and spatial clusters for different green infrastructure types and indicators, highlighting trade-offs in the placement in particular locations.
- The proposed framework can be used as a tool for green infrastructure planning, helping towards a systematic approach for resilience-performance design and planning.

Introduction

Due to deeply uncertain threats to the urban environment (i.e. climate change, urbanisation and socio-economic pressures), the need for resilience in drainage systems is deemed essential (Mugume et al. 2015). Previous research has shown that green infrastructure, nature-based stormwater management solutions, can contribute to the enhancement of resilience in sewer systems (Sweetapple et al. 2018, Wang et al. 2019). Although being a promising alternative to stormwater practices, they present various challenges in their application. There is a gap in the understanding of their relationship to resilience performance enhancement in the sewer system, and the underlying spatial patterns on their impact.

This study, based on Rodriguez et al. (2021), proposes the application of exploratory spatial data analysis (ESDA) to understand the impact of green infrastructure (GI) location on resilience enhancement in urban drainage systems. The impacts of GI on the resilience to sewer flooding and Combined Sewer Overflows (CSOs) are considered. The objectives are: (i) the detection of spatial autocorrelation between GI location in a sewer system and its impact on resilience, (ii) the identification of spatial clusters and spatial outliers of high and low resilience impact, and (iii) the identification of the differences in the spatial relationships and spatial heterogeneities when using different types of GI and resilience indicators. These objectives work towards a resilience-performance orientated GI design and planning and a systematic approach to revealing the link between resilient properties and resilience performance in urban drainage systems.

Methodology

The proposed framework, shown in Figure 1, consists of four key elements: the GI types and modelling approaches, the resilience assessment, the location sensitivity analysis, and the exploratory spatial data analysis.

The GI types considered are bioretention cell, green roofs, and permeable pavement. The Global Resilience Analysis (GRA) (Butler et al., 2017; Diao et al., 2016; Mugume et al., 2015) is used for resilience assessment, as it provides a performance-based and quantitative measurement of resilience. The impact of GI in the system is evaluated by the reduction in sewer flooding and CSOs, both in magnitude and duration. These are noted as SF_M and SF_D for sewer flooding magnitude and duration, and CSO_M and CSO_D for CSO magnitude and duration respectively.

The ESDA methods used for the analysis of the location effects are based on the methods developed by Anselin (2007) and were performed using PySAL (Rey and Anselin, 2007). The analysis consists of visualisation, global spatial autocorrelation, and local spatial autocorrelation. Box maps are used for an initial visualization and exploration of the data. The assessment of the global spatial dependence of each of the variables is performed using the global Moran's *I* statistic (Ord and Getis, 1995). Six spatial weights matrices were used to test the robustness of the Moran's *I* test results. Local Indicators of Spatial Association (LISA) (Anselin, 1995) are used for spatial cluster and spatial outlier detection and based on this, the values are categorised into five main categories: high-high (HH), low-low (LL), high-low (HL), low-high (LH), and non-significant (ns) observations.

The case study used is a catchment in the United Kingdom, consisting of 220 sub-catchments with a total area of 73.3 ha, and the combined sewer system consists of 487 conduit links and associated junction nodes, 3 storage tanks, and one outfall node. The hydrologic-hydraulic simulations were performed using the US EPA Stormwater Management Model (SWMM), and the Python interface PySWMM.

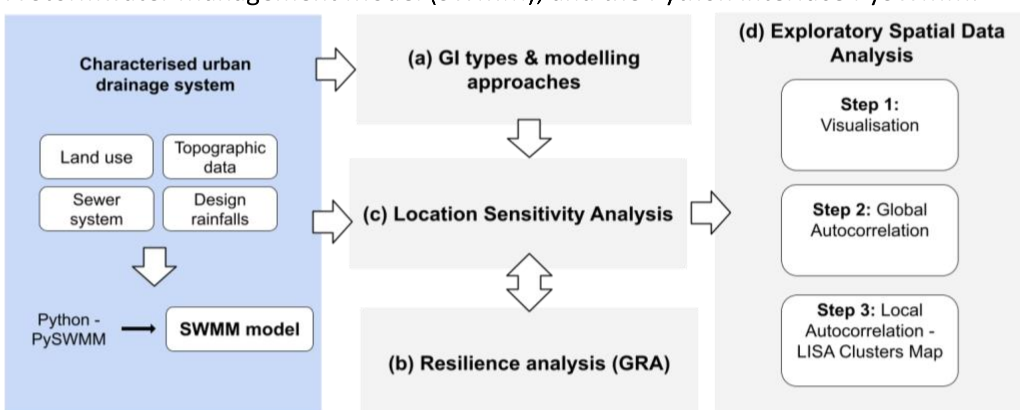

Figure 1. Adapted from Rodriguez et al. (2021). Framework for the application of exploratory spatial data analysis to assess the relationship between GI location and resilience enhancement. (a) GI types and modelling approach. (b) Resilience assessment using Global Resilience Analysis (GRA) (Adapted from [2]). (c) Location Sensitivity Analysis. (d) Exploratory Spatial Data Analysis.

Results and discussion

The Moran's *I* test for spatial autocorrelation showed significant and positive spatial autocorrelation for the green roof when measuring SF_M and SF_D, and for bioretention cell for the SF_M and CSO_M. For the SF_D and CSO_D, this is also the case when all the GI are simultaneously placed in the same subcatchment. The permeable pavement showed positive spatial autocorrelation only for the SF_D.

Figure 2 shows the LISA clusters maps for the net change in resilience due to GI placement for the indicators with significant global autocorrelation across all the weights considered. There is a contrast between the sewer flooding indicators and CSO indicators, where there is only positive and significant autocorrelation for the bioretention cell when considering CSO_M, and the "all GI" case for CSO_D. This implies that the location of GI in the network impacts the reduction of sewer flooding, but not necessarily the CSO. Furthermore, the difference among the GI types highlights differences in their working mechanisms, as well as providing insights for strategies in their placement in the catchment. The LISA clusters maps show some "conflicting" clusters, which would indicate trade-offs in the resilience enhancement. Finally, there is a disparity in the location of HH and LL clusters, which primarily indicates that the placement of GI on peripheric areas of the network is generally more beneficial in the enhancement of resilience to sewer flooding and CSOs in this catchment.

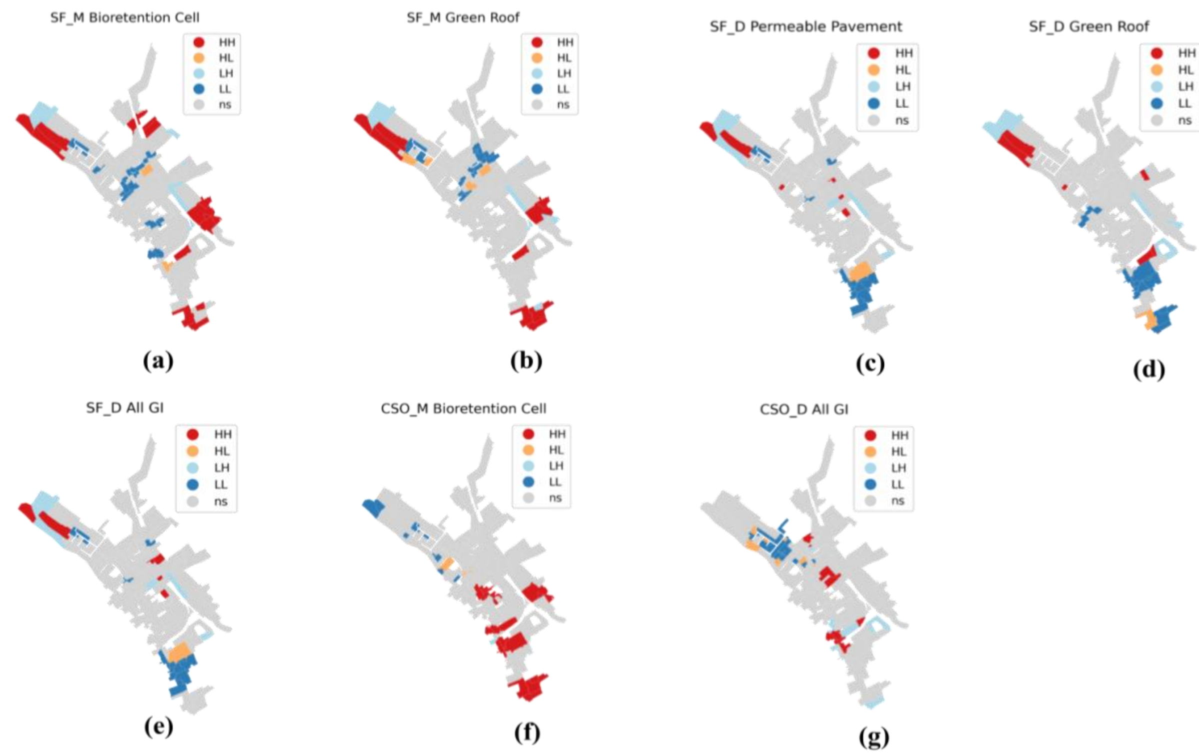

Figure 2. Adapted from Rodriguez et al (2021). LL- low-low cluster. ns: statistically not significant. Low-high cluster. LL- low-low cluster. ns: statistically not significant. (a) Bioretention cell using sewer flooding magnitude (SF_M) as the resilience indicator. (b) Green roof using sewer flooding magnitude (SF_M) as the resilience indicator. (c) Permeable pavement using sewer flooding duration (SF_D) as the resilience indicator. (d) Green roof using sewer flooding duration (SF_D) as the resilience indicator. (e) "All GI" using sewer flooding duration (SF_D) as the resilience indicator. (f) Bioretention cell using CSO magnitude (CSO_M) as resilience indicator. (g) "All GI" using CSO duration (CSO_D) as resilience indicator.

Conclusions and future work

This paper proposed the application of spatial analytical methods for understanding the relationship between GI location in the urban drainage systems and their impact on resilience. The framework could be used in urban planning as a starting point to develop resilience-based infrastructure development plans and stormwater alleviation schemes at an urban scale.

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