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Vulnerability Assessment of Sewer Networks

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Abstract

Urban storm water management faces significant challenges due to climate change, especially in cities with aging combined sewer systems. Many of these networks, which are over a century old, are increasingly strained by urban growth and changing climate patterns. This strain often results in capacity limitations and a heightened risk of surface overflow events. Although detailed sewer network data and occasional records of surface overflows exist, the lack of calibrated and regularly updated simulation models remains a significant hurdle in assessing network integrity. This study aims to address this challenge by introducing a methodology to evaluate sewer network vulnerability. Two distinct approaches are proposed for generating vulnerability indices for individual sewer sections. The first involves comparing theoretical capacity values among adjacent sewer segments, while the second establishes a probabilistic index for surface overflow occurrences in each section. Computational results from both approaches closely align with real surface runoff records, demonstrating their reliability in assessing network performance. By employing these methodologies, stakeholders are provided with a systematic framework to identify high-risk sewer segments and prioritize necessary network enhancements. These approaches support informed decision-making in urban infrastructure development and resilience planning, addressing the complex interplay of urbanization and climate change.

1 Introduction

This study aims to introduce a methodology for risk management of storm sewer networks that relies exclusively on the intrinsic properties of network elements, without dependence on hydraulic simulations or flow measurements.

Numerous studies have explored methodologies for risk management in storm sewer networks, employing various approaches ranging from hydraulic simulations to data-driven techniques. In this section, we review relevant literature that aligns with our scope, highlighting key advancements and gaps addressed by our proposed methodology.

A systematic review of scientific literature regarding the impacts of climate change on wastewater infrastructure was conducted by Li et al. (2023). Their study developed a typological adaptation strategy for city-level decision-making in various income contexts to address climate change challenges for wastewater systems.

Shen et al. (2024) introduced a novel topological index to analyse capacity issues in storm water networks, identifying critical pipes using a sewer-road integrated model. Valizadeh et al. (2019) defined a hydraulic performance index for individual pipes and for the whole network, based on temporal flow rate and flow depth, as a measure of resilience.

An increasing number of risk studies now rely on data-driven methods instead of traditional deterministic calculations. For instance, Leitao et al. (2017) developed a stochastic method for flood risk

evaluation based on the condition of sewer inlets.

The EPA SWMM (Storm Water Management Model) is a globally utilized 1D simulation model for storm water networks (Shen et al., 2024), capable of modelling LID (Low Impact Development), green, and grey infrastructure simultaneously. Detailed surface flood effects require 2D simulations, which can be coupled with the 1D sewer model. Donglai et al., (2022) and Lee et al. (2024) optimized such couplings. However, deterministic hydrodynamic models often exhibit uncertainties due to data limitations (Min and Tashiro, 2024). Combining deterministic models with machine learning methods like LSTM (Long short-term memory) neural networks has shown promise, incorporating inputs like infiltration, rainfall, evaporation, and surface runoff simulated by SWMM (Chenchen et al., 2023). Simplified neural learning models can also predict flooding risks (Safaei-Moghadam et al., 2024).

The vulnerability of sewer networks has traditionally been examined using hydrodynamic models as the highlighted SWMM based researches. Some other studies employ geometric approaches, such as centrality measures in graph theory (Ganesan et al., 2020). Network structure also matters; loop-type networks are often more resilient than tree-type ones (Zang et al., 2017).

Physical parameters of subcatchments can also predict sewer flood risks (Ofwat, 2019). Morphometric and statistical analyses of watersheds provide flood susceptibility insights (Ahmed et al., 2023). Road vulnerability can be assessed based on the amount of water present and the hazard posed by precipitation volume (Safaei-Moghadam et al., 2024). El-Rawy et al. (2023) applied a multi-criteria approach for flood hazard assessment, using basin geometry to produce a flash flood sensitivity index.

Hydraulic efficiency of sewer networks can be assessed through constraints like pipe fullness, flow velocity, slope, downstream diameter increases, and connection elevations (Anwer et al., 2024).

The reviewed physical model simulations exhibit uncertainty due to several factors, including unknown model parameters, insufficient data on load, network, and subcatchments, as well as the use of simplified representations for complex real-world processes. Additionally, these models require measurement data for proper calibration.

On the other hand, data-driven models typically demand large datasets, where data selection plays a crucial role. Their computational requirements are high, and surface flooding is often influenced by local factors that are either unknown or highly uncertain. While predicting localized flood events is challenging, assessing flood risk at a regional scale is generally more feasible.

Despite extensive research on flood risk evaluation, few studies focus on assessing storm sewer network vulnerability solely based on network element properties, without relying on hydraulic simulations or flow measurements.

2 Methodology

The methodology for vulnerability assessment was developed based on the Climate Impact and Vulnerability Assessment Scheme (CIVAS) model outlined by the Intergovernmental Panel on Climate Change (Parry, 2007). Adopting Hungarian national guidelines (Kajner, 2016), these principles were applied to the drainage system of Budapest, Hungary. A CIVAS model tailored for sewer vulnerability was designed, using CIVAS terminology for drainage systems (Fig. 1).

The sewer system's "Exposure" is represented by precipitation over the catchment area. Precipitation, a variable natural phenomenon, is characterized by height, intensity, and duration—key parameters for sewer networks. These factors vary across sections, with different rainfall patterns imposing varying loads.

The “Expectable Impact” of precipitation is an increase in sewer water levels. During intense rainfall, the total capacity of the system may be exceeded, leading to pressure build-up and potential surface flooding if the water level rises above ground level. The influential loads on specific sections of the sewer network are determined through modelling. Relationships between subcatchments, sewers, and flow timing require a comprehensive model of the entire sewer network. By analysing historical and empirical data, it becomes possible to identify overloaded sections and the rainfall events that caused pluvial flooding.

Different sewer sections respond differently to rainfall events, depending on their “Sensitivity”. Sections with shallower slopes experience more rapid water level increases. In areas with deeper topography, surface runoff is greater, and sewers located closer to the surface face higher flooding risks. Capacity is determined by sewer dimensions; constricted sections lead to increased water levels. Pipe direction and elevation also influence vulnerability, as backflow can occur. Drainage conditions of the catchment areas, such as land coverage, slope, and infiltration capacity, also impact flow rates into the sewers. Sections with high coverage and slope but low infiltration are more prone to flooding. Urban features like downtown areas, underpasses, or industrial facilities may exhibit greater sensitivity to flooding.

"Adaptation Strategies" means long-term solutions for capacity problems. Periodic rehabilitation of existing sewers and even the separation of combined systems into wastewater and storm water networks can increase their adaptive capacity.

“Adaptation Capacity” can be improved with various interventions, including water control, diversion, and storage solutions. Blue-green infrastructure, such as rain gardens and residential reservoirs, can reduce the load on drainage systems.

Study Area

The study area for sewer vulnerability assessment encompasses the entire city of Budapest, the capital of Hungary. The stormwater network spans approximately 3,200 km, with 79% operating as a combined system. The total subcatchment area covers 507 km².

Sewer Capacity Methodology

The first method to assess vulnerability focuses on sewer capacity. The maximum flow rate of each sewer section is calculated. Vulnerable sections are identified where capacity decreases between connected segments, particularly where lower sections have smaller capacities than upstream sections.

This vulnerability index reflects design and construction issues in the sewer network. It accounts for expected loads and includes extreme exposures, such as unanticipated pluvial floods. Locations where sewer capacity issues correlate strongly with actual flooding are highlighted.

Multi-Factor Vulnerability Assessment

The second method utilizes historical flooding data (2010–2023) and network sensitivity factors. Following the CARE-S (Computer Aided Rehabilitation of Sewer Networks) methodology (Saegrov et al., 2006), a probabilistic index is calculated.

Factors such as material, diameter, slope, and construction year were grouped into classes. Historical flooding data were matched to the nearest sewer section, and the flooding ratio was normalized across the network. The flood "probability" for each section was derived by averaging class flooding ratios and multiplying them by the network-wide flooding ratio.

This probability, while not a classical probability value, effectively characterizes vulnerability.

3 Result and Discussion

3.1 Results Based on Sewer Capacities

The full-section total flow is determined by two main variable parameters: diameter and slope. Budapest has over a hundred types of sewer sections (e.g., circular, egg-shaped). A "substitute" diameter can be assigned to each diameter for calculation purposes.

Similar examinations were carried out for diameters, slopes and total flow. That is, if the diameter of the upper sewer section is greater than that of the lower section, capacity problems can be anticipated there. Similarly, a decrease in slopes or total flow also indicates vulnerability.

In Fig. 2, pluvial flooding reports are marked with yellow crosses. Sections where capacity problems can be inferred based on diameter, slope, or total flow are marked in red. For slopes and total flow, only differences of at least 5x and 2x, respectively, were taken into account because considering simple smaller or larger conditions would have resulted in many more capacity locations, which only represent minor total flow problems based on the correlation calculations detailed below. Even so, as shown in Fig. 2, there were still many more sections with slope and total flow problems than with diameter problems.

To compare pluvial flooding and capacity problem locations and calculate their correlation, density maps were created for both datasets. Figure 3 illustrates pluvial flooding points and density maps. Grey lines

represent the sewers, indicating that where there are no pluvial floods, it may also indicate a lack of sewers.

The correlation results between pluvial flooding and capacity problems are summarized in Table 1.

Table 1
Results of Capacity Problem Methods

Comparative Data	Correlation Value
Pluvial flooding — sewer diameter problems	0.73
Pluvial flooding — sewer slope problems	0.60
Pluvial flooding — sewer total flow problems	0.60

The correlation factor shows how much the decrease in diameter, slope, or total flow along the flow direction correlates with the occurrence of pluvial flooding. The correlation factor was also calculated for different degrees of decrease in diameter, slope, and total flow along the flow direction, and the decrease causing the maximum correlation was selected. Capacity problems exist in a significant portion of sewer sections, e.g., for total flow, in over a quarter of sewers, as shown in an average map excerpt (Fig. 4).

There was no correlation increase with increasing difference in diameter. For slopes, the maximum correlation occurred at a 5x difference. For total flow, it occurred at a 2x difference. Thus, actual pluvial floods, i.e., exposures, were included in the vulnerability index by selecting the maximum difference.

For better visibility, capacity problems were shown on density maps and pluvial floods were marked as points in Fig. 5. As with the correlation coefficients provided in the Table 1, similar relationships between pluvial floods and various capacity problems (diameter, slope, total flow) can be observed in the figures. Therefore, the vulnerability of the sewer network is well characterized by the locations of sewer capacity reductions.

3.2 Results based on multi-factor vulnerability assessment

For the multi-factor analysis, we utilized the 13 factors listed in Table 2 for every sewer section, based on the data available for the entire sewer network, of which the last 3 were calculated values.

Table 2
Factors Used for Multi-Factor Analysis

Factor name	Factor value	Was it used in the final result?
Length	0–700m	X
Construction year	1850–2023	X
Pipe material	36 types	-
Drainage system type	Combined, wastewater, stormwater	-
Diameter	Equivalent diameter calculated from section area, 5–480cm	X
Counter slope	0–50%	X
Collector type	Main collector, collector, lateral	-
Road type	Under secondary road, under main road, under public transport route	-
Paved transportation	Under railway, tram line, metro line	-
Depth	0.2–8.1m	-
qot_ratio	Ratio of full section water flow in upper/middle/lower sections, the larger the ratio, the "riskier", 0–45	X
d_ratio	Ratio of diameter in lower/middle/upper sections, the smaller the ratio, the "riskier", 0.1–11.0	X
Slope change	Change in slope in upper/middle-lower sections, positive value indicates "riskier" -0.75 – +0.65	X

Within each factor, we formed classes. Flood events were assigned to the nearest sewer. We calculated the normalized flood ratio for each class. Then, considering all factors, we calculated flood ratios for each sewer section, which we then multiplied by the flood ratio calculated for the entire network to obtain a flood "probability" for each section. In Fig. 6, the red and bold sewer sections indicate the highest vulnerability, where flooding is most likely. Changes from red (through orange-yellow-green) towards blue indicate a decrease in vulnerability.

To calculate the correlation between floods and "probabilities," we identified the 1000 most vulnerable sewer sections, as the number of available flood events is of this order of magnitude. Density maps were prepared for the selected locations. In Fig. 7, the red colour scale indicates increasing vulnerability in the respective 1km x 1km squares.

Among the factors listed during the correlation analysis, those designated in Table 2 proved to be decisive. The correlation between the thus calculated probabilities and historical floods was slightly higher than with the capacity-problematic method, at 0.77.

3.3 Discussion

Our approach to vulnerability assessment was shaped by the available data, specifically the sewer network structure and historical surface flood records. In contrast, most reviewed studies rely on significantly more complex and data-intensive models, often introducing greater uncertainties. However, insights from these models informed our methodology. The achieved correlation values validate the effectiveness of our cost-efficient approach, demonstrating its practical applicability.

4 Conclusions

The two developed and applied vulnerability assessment methods yielded similar results. We demonstrated how to calculate vulnerability without network simulation models, that is, how to predict potential capacity issues and their locations. We presented results achieved without using physical models, without model construction, parameterization, measurement, or calibration. Despite the limited but reliable available data, our analysis demonstrated that meaningful vulnerability assessments could still be conducted effectively.

By applying the described vulnerability assessments, flood events can be predicted with greater reliability, especially with longer and more detailed datasets. More comprehensive datasets on the timing, duration, and extent of historical flood events would have been beneficial, but were not available for the investigations presented here.

Network simulation models could further improve the prediction of hydraulic capacities. Of course, this would require significantly more data and calibration measurements. With sufficient and reliable data, machine learning programs could also be applied.

The vulnerability of drainage systems can be reduced by improving the network's adaptability. Adaptive techniques could also be integrated into simulation models. By incorporating blue-green infrastructure elements, forecasting loads, and using real-time control methods, effective interventions can be designed and applied even within existing networks.

Declarations

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Data Availability Statement: Data will be made available on request.

Author contributions:

All authors contributed to the study conception and design. All authors read and approved the final manuscript.

Ethical Approval: Not applicable.

Consent to Participate: Not applicable.

Consent to Publish: All authors read and approved the final manuscript.

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Figures

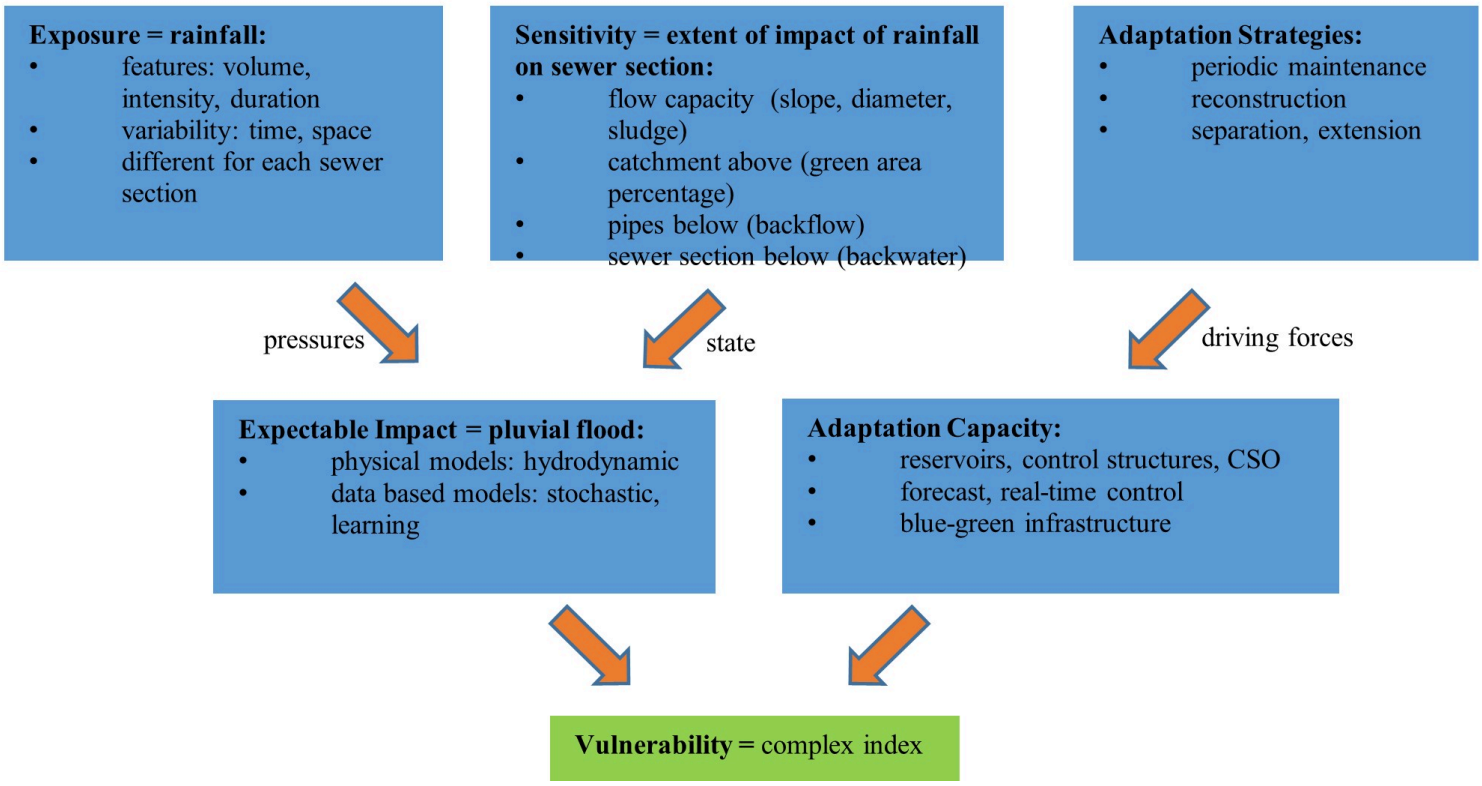


Figure 1

Sewer vulnerability based on CIVAS model.

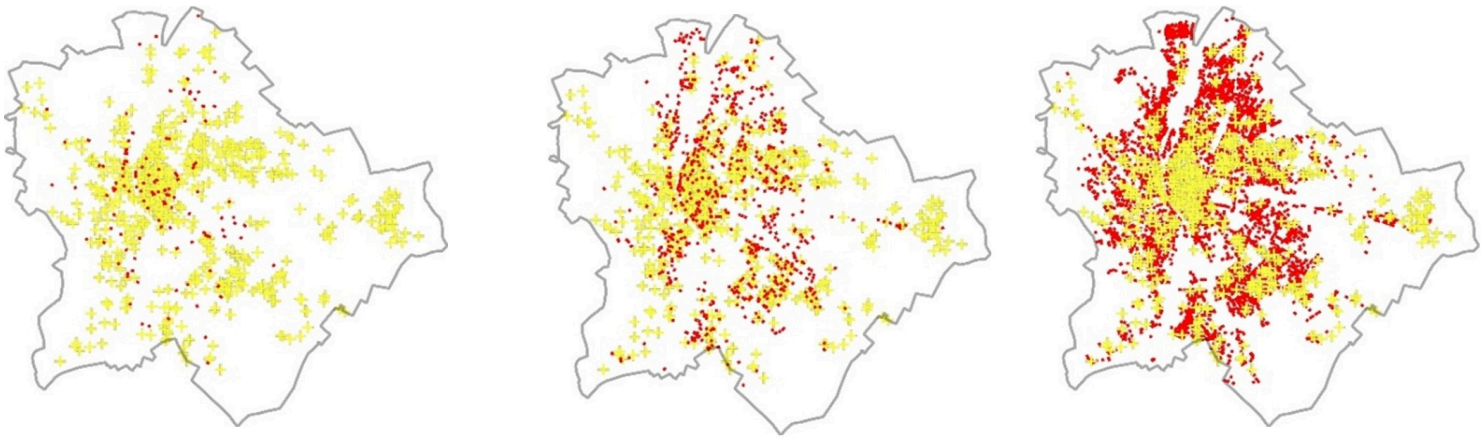


Figure 2

Floods (yellow) and locations of capacity problems (red) based on diameter, slope and total flow.

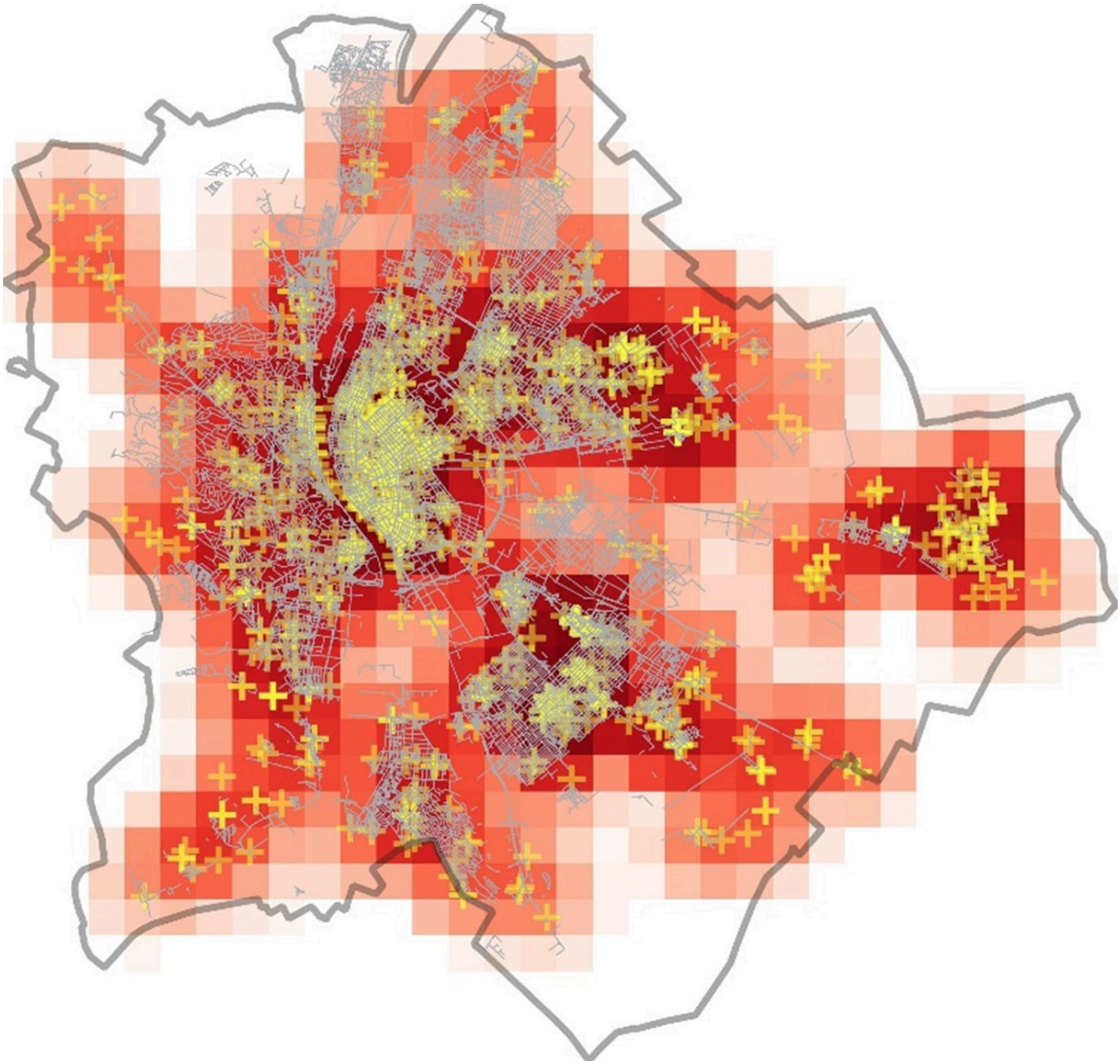


Figure 3

Floods depicted as point data and on a density map.

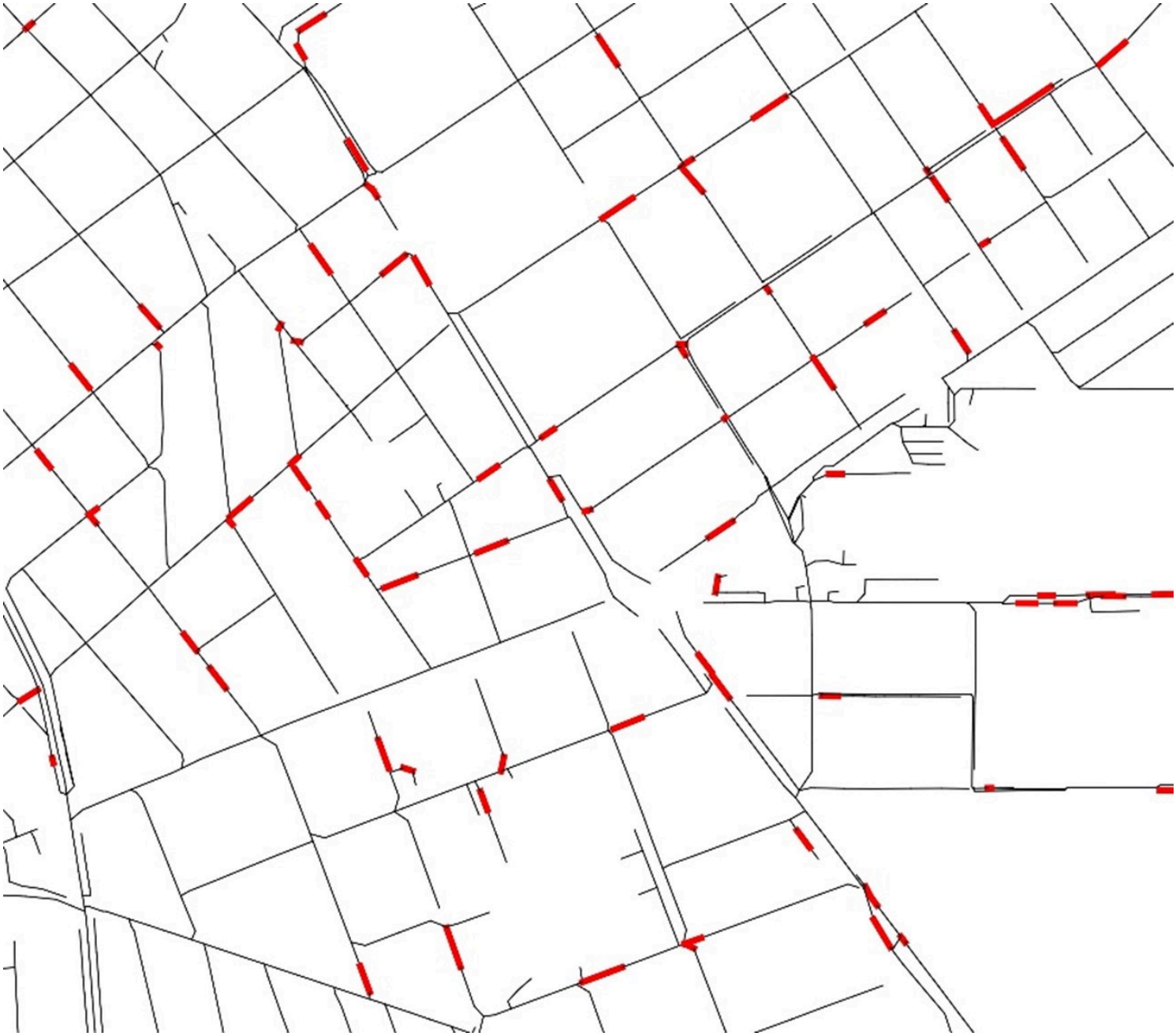


Figure 4

Typical map excerpt of total flow problem locations

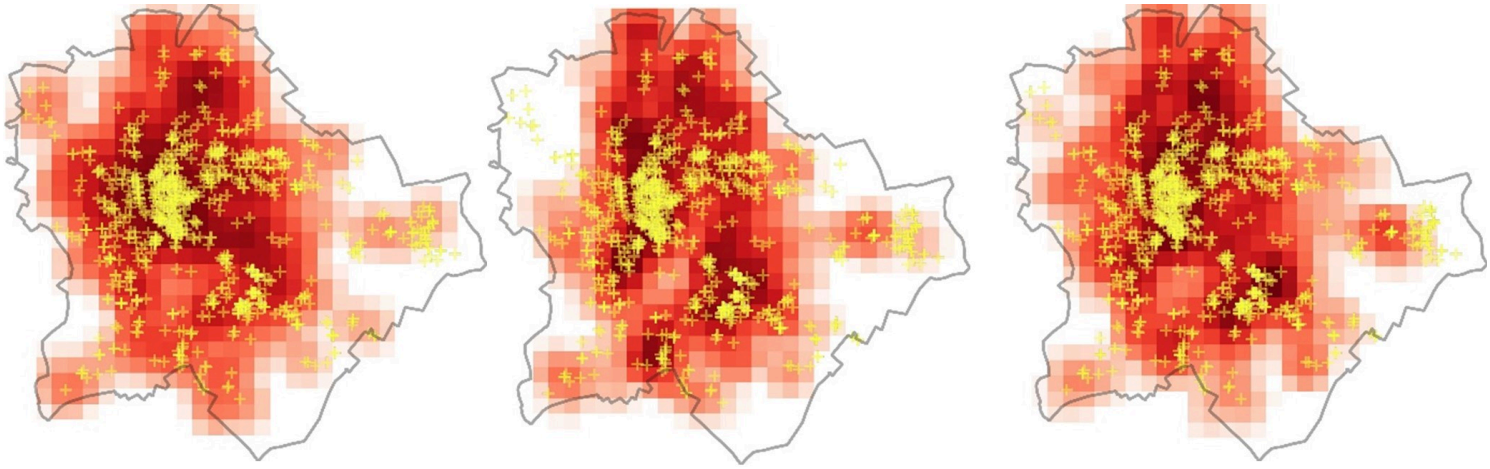


Figure 5

Floods (yellow) and density map of capacity problems (red) based on diameter, slope, and total flow.

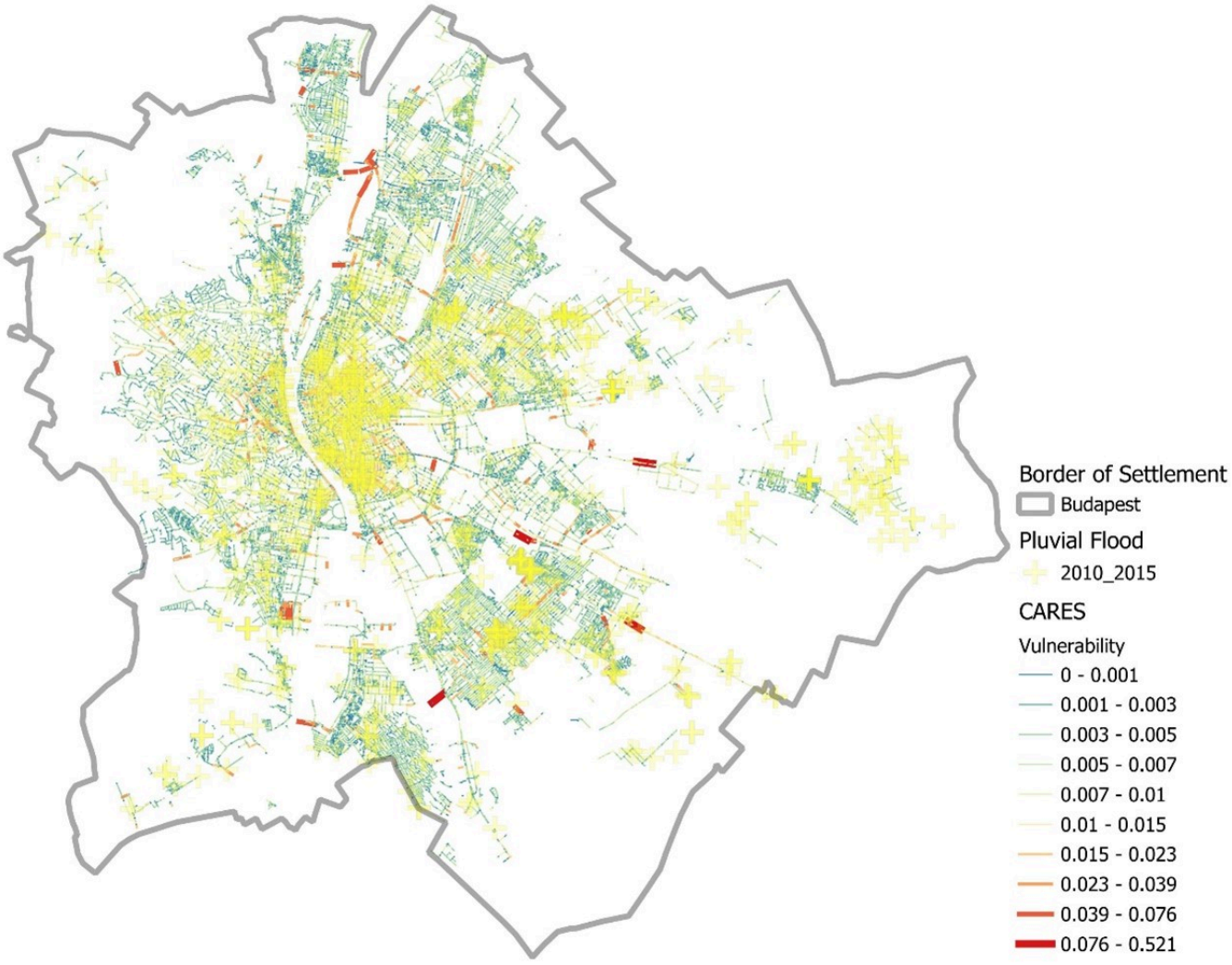


Figure 6

"Probabilities" of Multi-Factor Analysis for Sewers

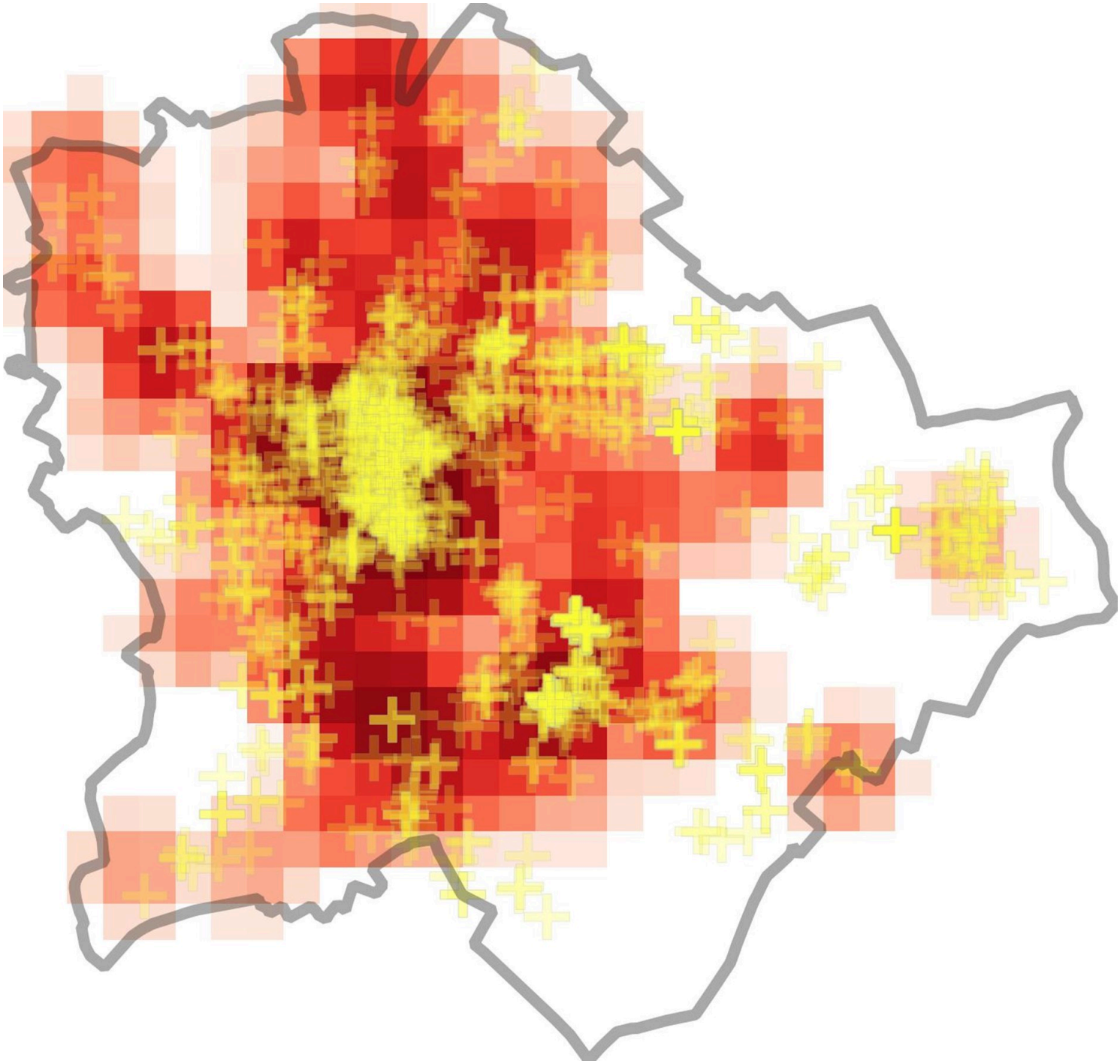


Figure 7

Density Map of "Probabilities" for Multi-Factor Analysis (red) and Flood Points (yellow)