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**Marlon Vieira Passos**

marlonvp@kth.se

Stockholm Environment Institute

**Jung-Ching Kan**

Stockholm Environment Institute

**Georgia Destouni**

Stockholm University

**Karina Barquet**

Stockholm Environment Institute

**Luigia Brandimarte**

KTH Royal Institute of Technology

**Zahra Kalantari**

KTH Royal Institute of Technology

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# Simulating Cascading Flood Impacts on Urban Infrastructure Systems in Malmö

Marlon Vieira Passos[1,2*], Jung-Ching Kan[1,2†], Georgia Destouni[3,2†], Karina Barquet[1†], Luigia Brandimarte[2†], Zahra Kalantari[2,3†]

[1*]Stockholm Environment Institute, Stockholm, Sweden.
[2]Department of Sustainable Development, Environmental Science and Engineering, KTH Royal Institute of Technology, Stockholm, Sweden.
[3]Department of Physical Geography, Stockholm University, Stockholm, Sweden.

*Corresponding author(s). E-mail(s): marlonvp@kth.se;
Contributing authors: jungching.kan@sei.org;
georgia.destouni@natgeo.su.se; karina.barquet@sei.org;
luigia.brandimarte@abe.kth.se; zahrak@kth.se;
†These authors contributed equally to this work.

**Abstract**

Interconnected urban infrastructures are increasingly vulnerable to environmental hazards, where local failures can cascade across systems, disrupting essential services. This study introduces TRIGGER, a novel methodological framework coupling flow-based network modeling with Large Language Models (LLMs) to systematically translate technical cascading failure metrics into socially meaningful information. Furthermore, the framework provides a quantitative approach to evaluate and compare the systemic effectiveness of large-scale nature-based adaptation measures in mitigating indirect service losses. Applied to Malmö, Sweden, TRIGGER simulates interdependencies among electricity, water, emergency services, and port operations under three flood scenarios. Results demonstrate that the integrated LLMs effectively translate complex numerical data into contextualized narratives, successfully scaling qualitative severity to the magnitude of disruptions and abstracting large datasets to reduce cognitive load for

decision-makers. The framework also quantifies mitigation potential of nature-based solutions, showing that widespread green roofs could substantially reduce service disruptions. By translating complex failure chains into actionable insights, TRIGGER supports urban planners in advancing from siloed risk management toward proactive, cross-sectoral climate adaptation.

**Keywords:** Climate adaptation, network analysis, utility networks, port operations, emergency preparedness

# 1 Introduction

As societies evolve, they become more interdependent, leading to potential cascading vulnerabilities in the provision of essential services [1]. National and local economies depend on resilient infrastructure to drive growth and support beneficial societal outcomes [2, 3]. Despite this, current methods for managing urban systems often lack a holistic view and fail to fully address the interconnected nature of critical services and how a disaster can cause cascading failures across the integrated infrastructure system [2]. Environmental hazards such as floods can damage the physical integrity of critical infrastructures (CIs), indirectly affecting people and the economy beyond areas initially exposed to the hazard. For instance, the floods that devastated parts of Germany and Belgium in July 2021 destroyed road and railway infrastructure, which not only isolated communities but also severely hampered rescue and repair operations [4]. The 2024 floods in Valencia severely disrupted essential services, including electricity and telecommunications, and inflicted widespread damage on infrastructure such as roads, railways, bridges, and public buildings [5]. The lack of road access and power supply obstructed waste management operations [6]. Extreme weather can also affect business activities with strategic importance to the local economy such as port infrastructure, disrupting trade and logistics [7]. A deeper understanding of these cascading impacts can enhance emergency preparedness and urban resilience, thereby helping to mitigate associated economic and social consequences [8].

Methodologies for assessing cascading impacts on infrastructure are primarily categorized into empirical, agent-based, system dynamics, economic theory based, and network-based approaches [9]. Each approach addresses the complex interdependencies between systems, bringing a distinct set of strengths and limitations. Network-based approaches can be further classified as topology or flow-based. While topology-based approaches assess system vulnerability through graph connectivity metrics like degree and betweenness centrality [10], flow-based approaches integrate physical governing laws to realistically simulate the redistribution of flows following a disruption and can identify potential subsequent failures triggered by component overloads, which are fundamental properties of cascading failures [11, 12].

Given the nature of systemic impact propagation along infrastructures, it is crucial that cascading impact analysis considers the interdependencies between multiple systems. Recent studies provide integrated methodologies for real-world applications of physics-based cascading impact simulation in interconnected electricity-water [12–15], water-transport [16], and electricity-water-transport networks [17]. Despite the robustness of these approaches, two critical limitations remain.

First, existing flow-based cascading infrastructure assessment frameworks predominantly focus on technical metrics without systematically translating these dynamics into socially meaningful, decision-relevant indicators. There is a shortage of frameworks demonstrating the effects of cascading impacts to specific users in terms of service type, location, and number of people affected, assisting local planners to make more informed decisions to enhance community resilience [1, 18]. Although advances in generative AI can improve communication for urban planners by delivering information in a relatable manner and elucidating intricate concepts for individuals of diverse backgrounds and levels of expertise [19], existing frameworks for cascading infrastructure impact assessment have not yet incorporated generative language models.

Second, although multi-system cascading simulations are increasingly sophisticated, existing approaches seldom quantify the effectiveness of adaptation measures in mitigating cascading impacts across interconnected networks. Failure to address these indirect cascade impacts could introduce blind spots in adaptation planning, weaken adaptive capacity, and constrain risk mitigation within existing governance regimes [20].

To address these research gaps, this study presents TRIGGER (*Tracking Ripples in Infrastructure Grids to Guide Enhanced Resilience*), a novel flow-based network modeling framework to investigate how infrastructure failures from environmental hazards can trigger cascading disruptions across multiple interconnected systems. This approach estimates potential electricity and water shortages, as well as reduced capacity of municipal and business services. Large language models (LLMs) were employed in the framework to interpret and contextualize quantitative results into insights to assist local planners in terms of specific types of impacts, number and location of residents affected. Scenarios including adaptation measures are included to quantify and compare their mitigative effects. This study aims to provide a framework to support urban planning and policy decisions by prioritizing investments on solutions that minimize potential social impacts from environmental hazards. The presented framework utilizes global open-source infrastructure models and datasets which can be complemented and refined depending on local availability. Hazard inputs such as inundation maps are necessary to identify assets that would be initially disrupted in the hazard scenarios. The application of the framework allows the investigation of various aspects related to cascading impacts at municipal scales. In this study, an application to a specific case in Malmö is presented as a proof-of-concept to validate the framework. Through this application, the following overarching research questions (RQs) were explored to demonstrate the framework's transferability to urban planning::

1. How can flow-based infrastructure models be coupled with Large Language Models (LLMs) to systematically translate technical cascading failure metrics into socially meaningful indicators for municipal services?
2. How can a multi-system simulation framework be utilized to quantitatively evaluate and compare the systemic effectiveness of large-scale nature-based adaptation measures in mitigating indirect service losses?

The paper is organized into six sections. Section 2 discusses the adopted methodology to implement the framework. Section 3 introduces the case study site, hazard scenarios, and infrastructure interdependencies considered. Section 4 presents the results corresponding to the posed research questions. The implications for urban adaptation are discussed in Section 5, and the key conclusions are summarized in Section 6.

# 2 Methods

To understand how critical services are distributed in urban areas and to identify potential cascading vulnerabilities, the TRIGGER framework was implemented for the study site. This approach acts as a digital twin of a city infrastructure, simulating the flow of essential resources like electricity, water, and emergency services across the urban landscape. The approach involved five key stages: collection of infrastructure and demand data (simulation input), creating baseline scenario and hazard scenarios, and analysing the results to identify key CI disruptions and provide climate adaptation recommendations (simulation output). The analytical framework is represented in Figure 1.

## 2.1 Data collection

The modeling process started by defining the study area using the official administrative boundaries of the study site. This geographic footprint served as the limit area for

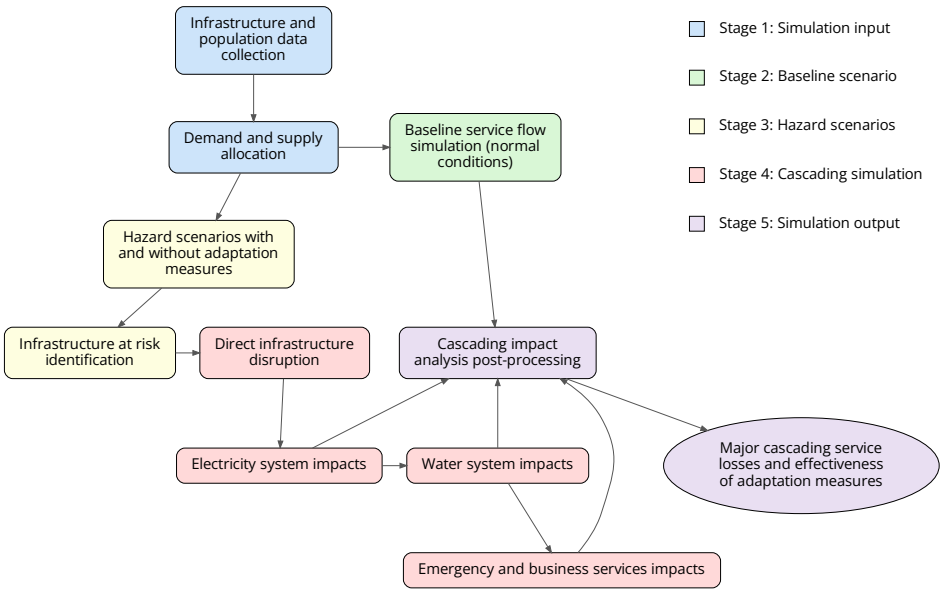



**Fig. 1** Methodological flowchart of the TRIGGER framework.

all subsequent data and analysis. OpenStreetMap (OSM) [21], a global collaborative mapping project, provided the locations of key public infrastructures. This foundation layer can then be enhanced with official information from municipality officials, governmental agencies, or utility companies. The base network data was obtained using the Python library OSMnx [22]. To ensure a more realistic simulation, a data cleaning step was performed to connect isolated road segments to the main network, creating a single, fully connected transportation grid. An underlying assumption is that the pipelines and cables for water and electricity distribution follow the transportation network.

To understand the demand placed on critical services by residents, we applied the Global Human Settlement Population Layer, a global satellite-based dataset that projects the population distribution for the year 2025 with approximately 100-meter resolution [23]. A key challenge was determining how many people rely on each part of the overall network. To solve this, we applied the Voronoi geospatial allocation

method [24]. For every road intersection in the model, we calculated its local service area, creating a mosaic of small zones covering the entire city. We then calculated the population within each zone and assigned that number as the residential demand to its nearest node in the transportation network. Therefore, the road nodes represented residential demands in the model. This technique effectively translated population density into a direct load on the infrastructure network.

For commercial and industrial facilities, demand for services like freshwater and electricity was adopted based on their type and function, using established engineering standard average consumption data [25, 26] and more specific local sources [27]. All demand and supply units have been normalized as per capita residential demand units, adopting 4 MWh/year [28] and 51 $m^3$/year [29] per capita residential demands of electricity and freshwater, respectively. For transport-based networks, the allocated demand was equivalent to the assigned population at road nodes. For all systems, the total allocated demand was divided equally between all supply nodes, to guarantee that the total demand of a service was equal to the total supply. Figure 2 shows the adopted average electricity and water demand values for each infrastructure type. These are global demand reference values used to build synthetic networks and can be further refined for specific local conditions. Among all building types, the consumption of water and electricity is the largest at the port within the study site, due to heavy machinery and support of extensive shipping and cruising activities.

## 2.2 Service flow and failure simulation

The simulation of cascading failures began by identifying which infrastructure assets are directly exposed to flooding in each hazard scenario. We overlaid the infrastructure model with detailed flood inundation maps. An asset was flagged as exposed if the projected floodwater depth at its location exceeded a predefined threshold. This process generated a list of all infrastructure components directly inundated by floodwaters in each hazard scenario. This threshold was chosen as a conservative estimate

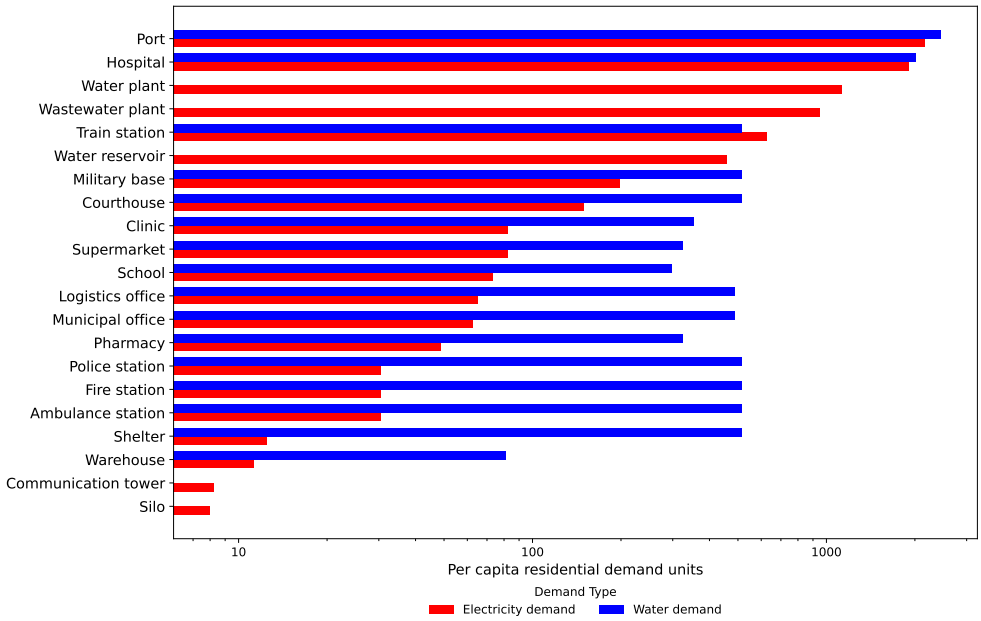



**Fig. 2** Adopted electricity and water demand for each infrastructure type.

for when functionality is likely to be compromised, particularly for transportation and electrical equipment. It was assumed that vehicles cannot drive on roads with flood depths exceeding 30 centimeters [30], and that pipelines and cables would be disrupted at the same depth or higher.

For transportation networks, the minimum cost flow algorithm was applied using Google's *OR-Tools* software [31] to find the most efficient paths from suppliers, like a hospital or fire station, to consumers represented by road nodes with allocated demand proportional to the assigned residential population. For transportation-based services, the capacity to transmit services at exposed network edges was set to zero, effectively removing it from the operational network. Since the minimum cost flow algorithm becomes unfeasible under disrupted conditions, dummy edges with extremely high cost were introduced in the model to maintain stability, by allowing a last resort flow path of critical services. The inaccessible network nodes were considered as nodes with unmet demand. Figure 3 demonstrates the minimum cost flow algorithm application

for undisturbed and disrupted networks, showing how this technique is applied to quantify hazard impacts on the distribution of flow and node accessibility.

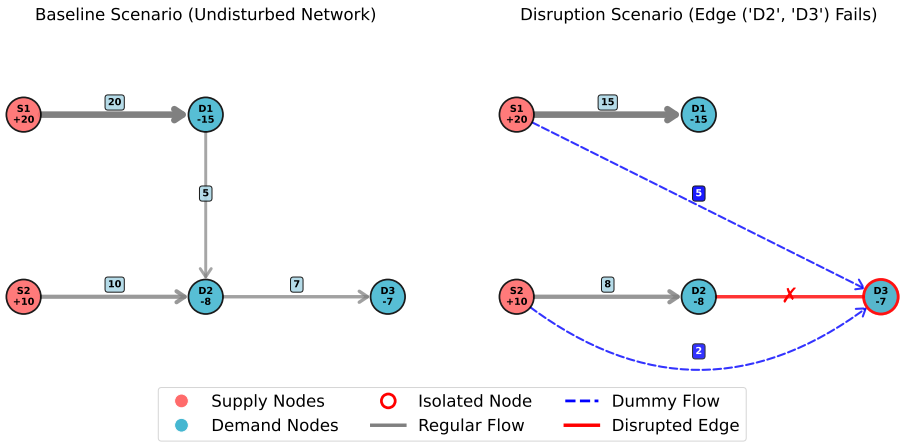



**Fig. 3** Comparison of minimum-cost flow solutions between baseline and disrupted networks.

For electrical power networks, a synthetic model was generated using the *pandapower* library [32] to analyze cascading failures. Initially, a hierarchical grid was constructed by modeling graph nodes as 20 kV electrical buses and edges as power lines with electrical properties corresponding to their real-world road classifications. To enhance realism and resilience, this distribution network was integrated into a robust, multi-level backbone featuring a redundant 110 kV high-voltage ring with multiple external grid connections and an enhanced medium-voltage ring that interconnects all substations with parallel, high-capacity lines. Customer demands were modeled as electrical loads, calibrated in aggregate to a specified target peak load. The target load for calibration was set so that all demands are met in the baseline case, but a disruption at a single substation caused a blackout area. This ensured that the synthetic network was neither under or over-designed. The core of the analysis was an iterative algorithm that began by applying initial component disruptions and then repeatedly calculated the alternate current (AC) power flow. If the calculation converged without

overloads (defined as >110% capacity), the grid is deemed stable. If it converged but with overloads, the most critical overloaded components were disconnected to simulate protective relay actions, and load was shed in any resulting small, isolated network islands. A failure to converge represented a large-scale blackout, prompting the algorithm to identify the largest remaining energized portion of the grid and record all demand outside this area as unmet. This iterative process of solving the power flow, mitigating overloads, and managing blackouts continued until the grid stabilizes or a maximum number of iterations was reached, ultimately quantifying the full impact of the initial disruptions.

For water distribution systems, a physics-based hydraulic model was built using the software *Water Network Tool for Resilience* [33] to analyze system failures. The process began by constructing a synthetic hydraulic network where graph nodes were represented as junctions or reservoirs, and edges as pipes with diameters assigned hierarchically based on their corresponding road classification. To realistically model supply constraints, each reservoir was equipped with a dedicated pumping station whose capacity was sized to handle a proportional share of the total system demand plus a safety margin, ensuring that the loss of a single source had a significant but not catastrophic impact. Disruptions were then applied to this model by closing specified pipes. This simulated a clean break where the pipe was immediately isolated by valves, resulting in no water loss to the environment. Alternatively, for source failures, the disruption was simulated by closing the pump associated with a target reservoir. Following the application of these failures, a hydraulic simulation was executed to determine the network response. The primary output was a quantitative assessment of service interruption, calculated as the unmet demand at each customer node, which represents the difference between the required demand and the actual volume of water delivered under the stressed, post-disruption conditions.

## 2.3 Post-processing using large language models

An algorithm was developed to systematically process and interpret the large volume of data generated across multiple hazard scenarios and infrastructure systems. The primary objective of this procedure was to ensure a scalable and objective method for translating technical quantitative outputs into contextualized information for improved prioritization of impacts and communication with planners. The core of the algorithm was a computational loop that iterates through the simulation output for each infrastructure system under each hazard scenario. For every combination, the algorithm reads the quantitative output data, specifically focusing on the unmet demand metric to quantify service disruptions.

To identify the most critical impacts, a filtering process is applied to isolate the infrastructure nodes experiencing the most severe consequences, defined as those within the top one percentile of unmet demand. This filtered, high-impact data, is then submitted to LLMs for qualitative synthesis. The threshold for high-impact disruptions is defined as those affecting more than 100 people, while impacts exceeding 1000 people are classified as extreme. To ensure a structured and consistent analysis, the LLMs are provided with a standardized prompt containing the methodological context of the study and the formatted quantitative data. This prompt directed the model to produce a formal narrative identifying key vulnerability patterns and the broader implications of service disruptions. In this study, the textual analysis was performed using the models *Google Gemini 2.0 Flash* and *NVIDIA Nemotron Nano 9B V2* [34].

The resulting textual summaries for each scenario were compiled into a preliminary structured report. This automated output serves as a first-pass analysis, systematically highlighting the key impacts across all simulations. The full prompt used to generate the analysis is provided in the Supplementary Material (Appendix A) for reproducibility.

To systematically evaluate the LLM's ability to contextualize and interpret the infrastructure simulation data, a quantitative text analysis was performed comparing the model's textual outputs against the underlying original datasets. The evaluation focused on four specific metrics:

- Semantic threat scaling: A predefined dictionary of 14 hazard-relevance keywords (e.g., *catastrophic, critical, cascading, systemic, collapse*) was established. The frequency of these keywords in each LLM response was quantified (Severity Score) and plotted against the maximum normalized unmet demand using linear regression. This assessed the model's ability to scale language intensity alongside numerical impact.
- Output consistency: The total word count of the LLM's generated text was calculated for each prompt and grouped by the specific hazard scenario (MHW, EV, EN) to evaluate the predictability and consistency of the output length.
- Data abstraction: Regular expressions were utilized to extract the exact number of unique infrastructure node IDs explicitly cited by the LLM in the text. This count was plotted against the actual number of nodes comprising the top 1% of unmet demand to measure the model's capacity to summarize and group large datasets rather than exhaustively listing them.
- Infrastructure system prioritization: The mean Severity Score was aggregated and ranked by infrastructure system category. This determined whether the LLM inherently differentiated the severity of operational loss based on societal function.

# 3 Case study

## 3.1 Study site

Malmö municipality lies on Sweden's southwestern coast within Skåne County, fronting the Öresund Strait. Skåne County features extensive coastal areas, with Malmö itself

boasting a long coastline that highlights the importance of climate resilience and adaptation measures in the region to protect against extreme weather events. The geographic limits of this study are the administrative boundary of Malmö Municipality retrieved from OSM (Figure 4).

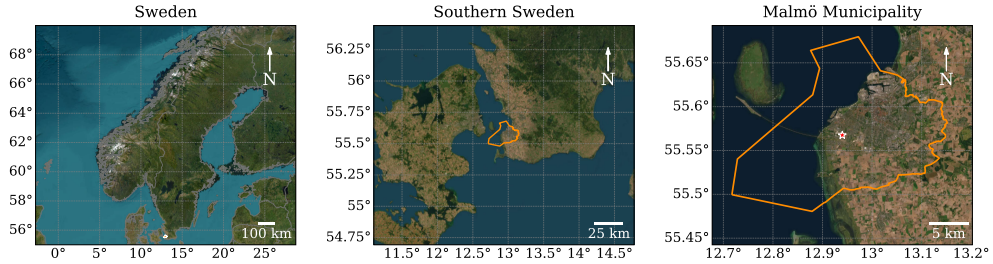



**Fig. 4** Malmö municipality boundaries considered in this study.

Physically, Malmö is characterized by flat terrain and urbanized waterfronts. The proximity to Öresund contributes to seasonal precipitation patterns, making stormwater management and green infrastructure critical for flood control and urban resilience [35].

Socio-economically, Malmö's coastal areas are prominent tourism sites for recreation and cultural experiences, supported by a hospitality sector and connectivity to Copenhagen via the Öresund Bridge. This tourism role, alongside a diverse economy transitioning from shipbuilding to innovation and services, heightens the area's visibility and economic significance within Sweden's southern coastal zone [36, 37]. The Copenhagen–Malmö Port, located in the municipality, is of major importance to the local economy, primarily because it is a leading cruise ship destination and provides freight services [27, 38].

Malmö has experienced significant pluvial flooding in recent years. An extreme cloudburst delivered up to 122 mm of rainfall in approximately six hours on August 31$^{st}$ 2014, overwhelming the city's combined and separated sewer systems and leading to widespread basement inundations, structural damages to residential buildings,

displacement of households, and disruptions to the main hospital, schools, and transportation infrastructure [39]. This unprecedented event, characterized by a return period exceeding 200 years in some areas, resulted in over 1,000 insurance claims for direct damages to residential properties, with total payouts surpassing 600 million SEK [40].

## 3.2 Hazard scenarios

An engineering report prepared for Malmö Municipality [41], outlines three distinct climatic hazard scenarios designed to simulate flood-prone areas in the year 2125 (Figure 5). These scenarios are based on the RCP 8.5 climate projection, a high-emissions scenario, and combine different intensities of rainfall with varying sea levels to stress-test the local infrastructure. The scenarios were abbreviated as EN (Extreme Rainfall), EV (Extreme Water Level), and MHW (Mean High Water/1-year Rain).

The scenario models consider two key factors: the sea level in the Öresund and the amount of rainfall over Malmö. The sea levels are calculated for areas north and south of the Öresund Bridge, as these regions experience slightly different conditions. The rainfall is modeled via a standardized method for simulating intense, short-duration rainfall, with a climate factor of 1.3 applied to account for the expected increase in precipitation intensity in a future climate.

The EN scenario simulates the impact of a severe cloudburst event. It combines a 100-year return period rainfall with a future mean sea level projected for the year 2125. This scenario is designed to test the capacity of the city's drainage systems and identify areas prone to flooding from intense, heavy rain when sea levels are at a normal future average.

The EV scenario models a major storm surge event. It combines an extreme future sea level, corresponding to a 200-year return period, with a relatively common 1-month return period rainfall. This scenario is intended to identify areas vulnerable to coastal




**Fig. 5** Flood extent maps for each hazard scenario.

flooding when the sea level is exceptionally high, coupled with moderate rainfall that can exacerbate flooding by preventing drainage into the sea.

The MHW scenario represents a more frequent, yet still significant, combination of events. It uses a future sea level corresponding to the average of the highest daily tides, combined with a 1-year return period rainfall. Although the individual components are less extreme than in the other scenarios, their combination is considered to have a return period of over 200 years. This scenario helps identify areas at risk from flooding during more common high tides when accompanied by significant rainfall.

### 3.3 Adaptation scenarios

Adaptation scenarios integrating five nature-based solutions from a previous assessment study in Malmö were considered to demonstrate how the cascading impact model can assess the effectiveness of these adaptation measures in reducing systemic disruptions [42]. The runoff reduction figures corresponding to land cover changes for each solution were estimated using USDA Curve Number method within the InVEST software [43, 44]. The large-scale nature-based solutions include green roofs, street-tree planting, parking-area de-sealing, and enhanced park vegetation. The following specific adaptation measures were considered:

- *GreenRoof*: This is the nature-based solution with the largest potential area, affecting 816 hectares or 5.2% of the city. The primary change involves covering 61% of the existing building footprints with green roofs.
- *ParkingAreas*: This scenario has the smallest area of land cover change, impacting 159 hectares, which is 1.0% of the city's area. The main outcome is a 3.2% reduction in impervious surfaces.
- *Parks*: This scenario focuses on enhancing vegetation in existing urban parks and results in land cover changes over 399 hectares, approximately 2.5% of the city

area. This leads to a significant 16.1% increase in tree cover and a 4.0% decrease in impervious surfaces.

- *StreetTrees*: This scenario involves the addition of over 52000 new trees. This results in a 12.1% increase in tree coverage compared to the current conditions and a 4.5% decrease in impervious surfaces over a change area of 224 hectares (1.4%).
- *GreenDream*: This comprehensive scenario involves the largest total land cover change, affecting 1588 hectares or 10.0% of the city. It combines several interventions, leading to a 27.9% increase in tree cover, an 11.5% reduction in impervious surfaces, and the installation of green roofs on 61% of the building area.

In this study, the inundation maps for each flood scenario were modified to assess nature-based solutions using a simplified flood depth reduction factor $(1 - RR_{NBS}) / (1 - RR_{LC})$, where $RR_{NBS}$ is the runoff ratio of the nature-based solution and $RR_{LC}$ is the runoff ratio of the current land cover without solution. This factor represents the relative change in water retention.

## 3.4 Infrastructure interdependency modeling

To elucidate the systemic vulnerabilities of urban infrastructure to flooding events, an integrated interdependency model was developed for the city of Malmö, as illustrated in Figure 6. This model considers relationships between key infrastructure systems, facilitating the identification of critical nodes and potential cascading failure pathways that could be triggered by flood-induced disruptions.

The model is structured around four primary systems: the electricity system, the water distribution system, emergency services, and port operations. These are interconnected flows to represent the interdependencies of various municipal, commercial, and logistical facilities on a core set of infrastructure providers. The service flows for each system are calculated as explained in Section 2.2, using specialized power and

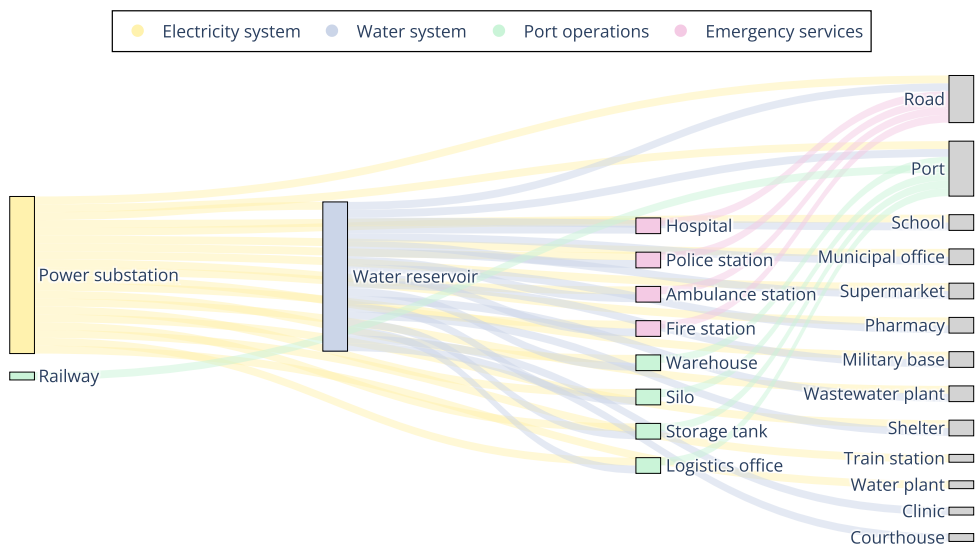



**Fig. 6** Interdependency model designed for Malmö municipality.

water flow modeling and minimum cost flow algorithm for emergency services and port operations, which are transportation-based.

The application of the cascading model for the Malmö region unfolded in the following sequence to capture how a failure in one sector can trigger failures in others:

1. Initial Disruption: The simulation began with the failure of all assets identified in the exposure analysis.
2. Electricity system impacts: The model first calculated the impact on the electricity grid. It identified which customers (residences, hospitals, water pumps, etc.) would lose electricity due to the initial disruptions.
3. Water system impacts: The water distribution simulation was run accounting for two sets of failures: the initial assets damaged by the flood, plus all the water system components that lost electricity in the preceding step.
4. Emergency services impacts: The accessibility for emergency services (hospitals, ambulance station, fire stations, and police stations) was modelled. This simulation

considered the cumulative impact of all disruptions, including flooded roads and facilities without electricity or water.

5. Port operations impacts: As a final step, the model assessed the functionality of port operations. This simulation evaluated the ability to move goods between key port facilities such as warehouses, silos, and storage tanks within the broader transportation network. It accounted for the cumulative impact of all prior disruptions, including direct flooding of port assets and the loss of critical road or rail access.

# 4 Results

## 4.1 Translating technical cascading metrics into contextualized narratives

A primary methodological advancement of the TRIGGER framework is the coupling of physics-based flow simulations with LLMs to automatically translate abstract, tabular failure data into socially and economically meaningful narratives. To achieve this, an automated post-processing pipeline was executed using a standardized system prompt (Appendix A). The LLM was tasked with interpreting data tables representing the top one percentile of infrastructure nodes experiencing unmet demand and synthesizing them into a structured output containing a "Headline Finding" and a "Detailed Thematic Analysis." For municipal services (detailed in Appendix B), the LLM effectively translated normalized per-capita demand units into estimates of human impact. This translation capability proved equally effective for highly integrated economic hubs, such as port operations (detailed in Appendix C).

To assess the utility of the Large Language Model (LLM) in translating numeric cascading infrastructure impact metrics into actionable insights for urban planning, we quantified the textual outputs across four dimensions: semantic threat scaling, output consistency, data abstraction, and infrastructure prioritization. The results are summarized in Figure 7.

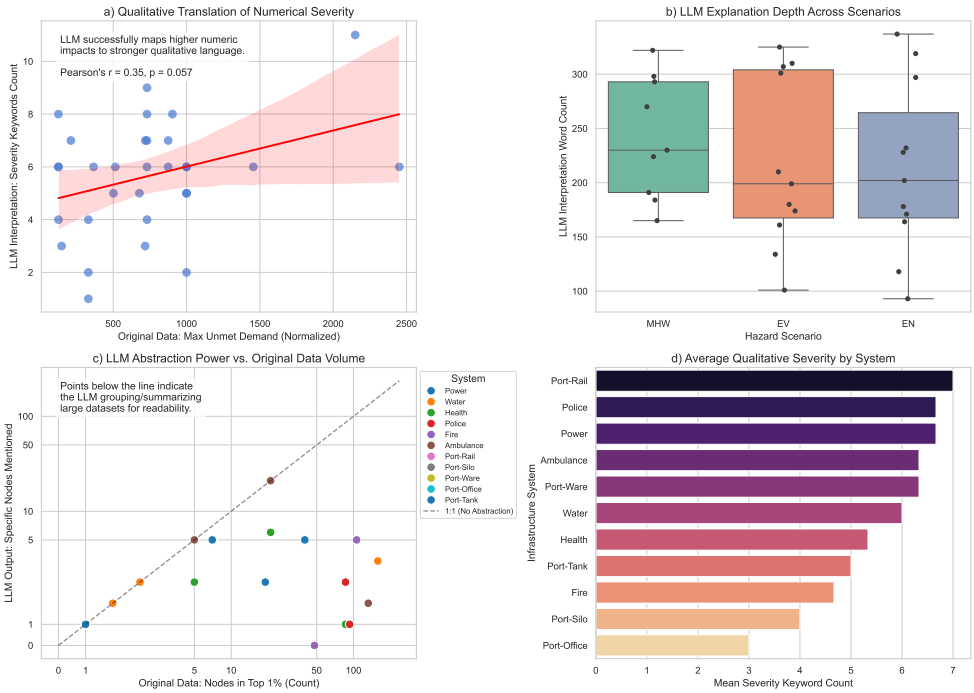



**Fig. 7** Assessment of the utility of the LLM to interpret and translate cascading infrastructure impact metrics.

Figure 7a evaluates the ability of this approach to accurately translate abstract numerical data into contextualized risk by mapping the maximum normalized unmet demand against the frequency of qualitative severity keywords generated by the LLM (such as *catastrophic, cascading, systemic*). The analysis reveals a positive correlation as indicated by the linear trendline. As the numerical severity of the disruption increases, the LLM dynamically scales the intensity of its qualitative warnings. For instance, extreme outlier events exceeding 2,000 units of unmet demand consistently triggered the highest concentrations of severity keywords. This demonstrates that the LLM possesses a robust semantic mapping capability, effectively bridging the gap between numeric thresholds and qualitative hazard descriptions without hard-coded rule sets.

For integration into automated municipal reporting pipelines, generative AI outputs must remain structurally predictable across varying hazard inputs. Figure 7b illustrates the distribution of the LLM's explanation depth—measured by word count—across the three distinct hazard scenarios (MHW, EV, and EN). The boxplots demonstrate a high degree of structural consistency, with the interquartile ranges largely constrained between 160 and 300 words across all scenarios. Despite the distinct impact magnitudes between hazard scenarios, the LLM reliably synthesized textual outputs within stable and accessible lengths. This prevents the generation of verbose, unreadable reports during complex hazard events.

A significant contribution of the LLM lies in its capacity for data abstraction, reducing cognitive load for urban planners. Figure 7c plots the volume of affected nodes (in the top 1% of unmet demand) against the specific number of infrastructure codes explicitly mentioned in the LLM's text. The dashed line indicates a strict parroting behavior, where an AI simply lists the tabular data. The results show that for localized disruptions affecting a small number of nodes (¡10), the LLM successfully identifies and lists specific critical assets. However, during widespread systemic failures affecting 80 to 160 nodes (such as massive residential power or emergency service outages), the model's output flatlines well below the 1:1 threshold. Instead of enumerating hundreds of individual node IDs, the LLM actively specifically mentions only the most critical bottlenecks and groups the rest into broader socioeconomic summaries (for instance, *affecting 50 residential areas*).

The analysis also evaluated whether the LLM applied inherent contextual "general knowledge" regarding the varying societal importance of different infrastructure classes. Figure 7d displays the average qualitative severity score generated per infrastructure system. The language model assigned the highest severity to critical lifelines and central logistical hubs, notably Port-Rail, Police, Power, and Ambulance. Conversely, isolated administrative and static storage assets, such as Port-Office and

Port-Silo, elicited significantly less severe qualitative language despite experiencing high or similar relative unmet demand. This outcome indicates that the LLM does not treat all unmet demand equally. Rather, it successfully contextualizes the data, recognizing that a failure in the power grid or emergency medical services poses a much more immediate and cascading threat to public safety and social welfare than lack of access to an administrative building.

By automating this translation process using LLMs, the results demonstrate that the TRIGGER framework can successfully process large volumes of multi-system simulation data and systematically output contextualized risk narratives for specific hazard scenarios and infrastructure systems.

## 4.2 Effectiveness of adaptation measures

To demonstrate how the TRIGGER framework can compare the effectiveness of engineered interventions, Figure 8 shows the estimated reduction of affected residents for different cascading impacts under the three flood hazard scenarios for each adaptation measure. The number of people without access to a service was estimated by summing the total unmet demand expressed in normalized per-capita units across all customer nodes for that service.

Across all three flood hazard scenarios, the *GreenDream* solution consistently showed the most significant estimated reduction in affected residents across almost all services. This is expected, as it is the most comprehensive solution, combining increased tree cover, green roofs, and reduced impervious surfaces. The effectiveness of all solutions was most pronounced in the Extreme Rainfall (EN) scenario, with a dramatically higher number of residents benefiting (reaching an estimated 209059 for water provision) compared to the EV and MHW scenarios, where benefits reached approximately 7400 and 400 residents respectively. The *GreenRoof* solution stood out as a strong alternative, particularly during Extreme Rainfall (EN), where it provided

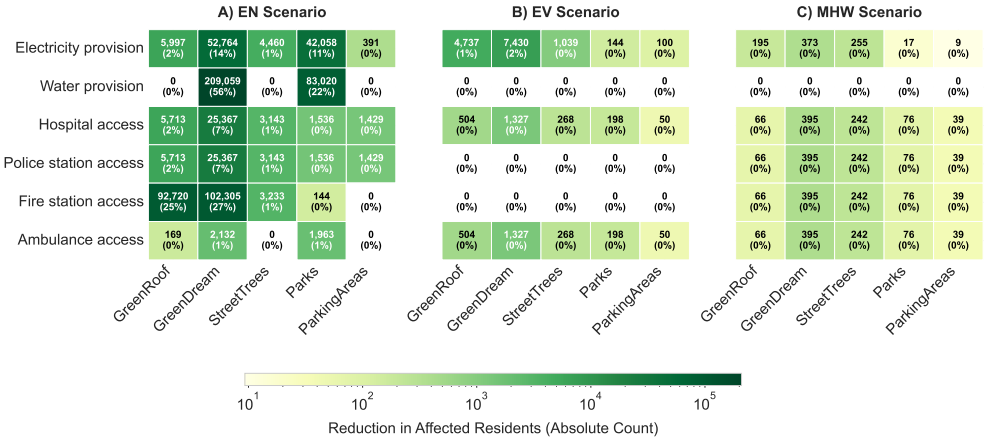



**Fig. 8** Comparison of nature-based solution effectiveness regarding cascading impact reduction under EN (Extreme Rainfall), EV (Extreme Water Level), and MHW (Mean High Water) scenarios.

a massive reduction of 92720 residents affected by fire station access disruptions. The *Parks* solution showed a remarkably high influence on protecting water provision during the EN flooding scenario, safeguarding 83020 residents and proving to be the second most effective solution overall for that specific service. Similarly, the *ParkingAreas* solution, despite its smaller footprint, yielded a substantial benefit of 1429 residents for hospital and police station in the EN scenario. Finally, *StreetTrees* offered consistent, though more moderate, benefits across multiple services and emerged as the second most effective option in the less severe Mean High Water (MHW) scenario, protecting 255 residents regarding electricity provision and 242 for other services. This result highlighted how the best strategy can vary depending on the specific type of flood.

# 5 Discussion

This study presents a novel approach to analyze cascading impacts at local scales on interdependent infrastructure systems arising from destructive hazards such as floods. This approach integrates electricity, water distribution, and transportation models

to simulate the propagation of systemic failures for a range of scenarios. Applying the approach to Malmö municipality made it possible to compare cascading impacts from multiple long-term flood scenarios and to assess the effectiveness of nature-based strategies in mitigating those impacts. Results demonstrate how LLMs can be applied to assist the interpretation of technical cascading impact metrics of municipal and port services for enhanced urban adaptation. The analysis also shows how increasing tree cover, replacing impervious surfaces, and installing green roofs can potentially mitigate those cascading impacts by reducing the number of people directly or indirectly affected by service losses.

To address how flow-based infrastructure models can be coupled with Large Language Models (LLMs) to systematically translate technical cascading failure metrics into socially meaningful indicators (RQ1), this study demonstrates a novel paradigm for bridging the gap between complex network analytics and actionable urban policy. While flow-based models quantify topological vulnerabilities, these technical metrics can be overly abstract for decision-makers. By coupling these outputs with an LLM, the quantitative data is automatically contextualized into narratives of social and economic vulnerability, supporting the robust, collaborative urban contingency plans required to move beyond siloed, single-sector management [45]. In the context of municipal services, the LLM translates technical cascading failures into distinct human impacts. For instance, rather than merely reporting a numerical loss in power distribution, the coupled approach articulates how the failure of a few power substations propagates into critical public safety crises, such as compromised hospitals, halted train stations, and failing wastewater treatment plants. This semantic translation reduces the cognitive load on planners, allowing them to rapidly identify which infrastructural bottlenecks threaten social welfare the most. Consequently, this socio-technical translation prioritizes the protection of these assets for enhanced disaster prevention [46] and provides a narrative justification for strategic decision-making on

resource allocation, such as relocating substations or establishing backup water supplies for emergency preparedness [47]. This coupled approach is equally valuable when evaluating cascading impacts on local port operations. While previous studies have mapped interdependency patterns of risk factors among ports [48], applied geospatial quantifications of cascading effects often remain isolated within technical engineering domains. By employing an LLM to interpret these flow-based logistical disruptions, the analysis demonstrates how local node failures directly threaten the broader economic and supply chain network. The model operationalizes the quantification of systemic risk [49] by explicitly describing how flood-induced logistical bottlenecks restrict port operations. Ultimately, transforming raw geospatial data into socially and economically meaningful indicators helps policymakers clearly communicate vulnerabilities and justify necessary, large-scale strategic investments to increase resilience, such as reinforcing hinterland connectivity and intermodal transportation networks [50].

Regarding the effectiveness of engineered interventions to mitigate impacts originating from cascading failures (RQ2), this study demonstrates how nature-based solutions can assist the functional continuity of essential services, enhancing the absorptive capacity of infrastructure systems to withstand hazards [51]. This contributes to the notion that nature-based solutions should be evaluated and planned as part of social–ecological–technological systems since they are embedded in diverse urban contexts requiring integration with built infrastructure [52]. The results demonstrate that the effectiveness of different engineered interventions would vary substantially depending on the specific flood hazard scenario and the type of infrastructure being protected. This highlights the necessity of a tailored, context-specific approach to implementing green infrastructure for flood risk management [53]. By systematically evaluating the performance of different interventions for a variety of hazard scenarios, the TRIGGER framework provides insights to support investment and mainstream green infrastructure into urban policy [54]. Such a quantitative framework can be useful

for conducting cost-benefit analyses [55] and urban climate adaptation strategies [56]. Ultimately, this data-driven methodology provides planners and policymakers with a tool to prioritize and allocate resources to the most effective adaptation measures, thereby accelerating the creation of more climate-resilient cities.

It is important to note that the Malmö case study is intended as an exploratory application to demonstrate the potentialities of the proposed framework, rather than as a fully validated operational tool. As such, several simplifying assumptions were necessarily adopted due to data availability and feasibility constraints. Both the electricity and water systems are represented as synthetic, physics-based network models that simplify real-world operational complexity, and do not explicitly represent detailed protection mechanisms, operator interventions, or adaptive control actions. Demand is treated as static and dynamic temporal processes are not explicitly modeled, meaning the findings should be interpreted as indicative of relative system vulnerability and service loss under disruption scenarios, rather than precise quantitative predictions. A deterministic but conservative assumption is that all infrastructure systems would fail if located within flood depths above the adopted threshold; a more realistic approach would consider probabilistic fragility curves [57]. Even though studies have shown that synthetic networks using OpenStreetMap can be realistic representations of actual systems [58, 59], further local calibration and validation against documented disruption data are necessary to demonstrate the accuracy of the simulations conducted for water and electricity systems. Additionally, the runoff reduction indices for nature-based solutions were derived from a previous study considering a 20mm rainfall event [42], potentially overestimating the performance of these measures for more extreme flooding scenarios. In order to mitigate reliability, bias, privacy, and misinformation concerns of LLM applications for disaster-risk management and urban planning [60], AI-generated syntheses are required to be reviewed and supervised to ensure accuracy and contextual relevance before being integrated into actual urban planning policies

[61, 62]. The supervision would combine the efficiency and objectivity of automated processing with essential human oversight, providing a robust method for transforming complex simulation data into actionable insights.

Recommendations for future studies include implementation of the TRIGGER framework for rapid contingency support and infrastructure fault response using real-time hazard datasets [63]. The cascade sequences modeled here assume unidirectional failure propagation, but real-world interdependencies between systems are possibly bi-directional, causing feedback loops. For instance, if water infrastructure is damaged first, this could impair firefighting capacity, which in turn affects the ability of emergency services to respond to electrical fires or short-circuits caused by flooding in substations and potentially extending or worsening electricity outages. All disruptions in the present framework are assumed to propagate instantaneously, whereas in reality, system response and recovery are inherently time-dependent processes. Repair times, crew availability, and resource constraints mean that infrastructure restoration follows a dynamic trajectory rather than a binary failed-or-functional state. Future dynamic models could explicitly incorporate repair timelines, staged restoration sequences, and emergency prioritization schemes, allowing the framework to capture not only the magnitude of service disruption but also its duration and the pace of recovery. Moreover, further model validation in other regions is advised using historical hazard records and documented secondary effects such as power outages, water shortages and critical service losses. The framework can also be extended to other hazard types beyond floods, including wildfires, landslides, and earthquakes. Less immediately destructive hazards such as heatwaves and droughts would require additional refinement to accurately represent how they affect infrastructure components. As LLMs continue to advance, there is potential to test more sophisticated models or even train them specifically to address cascading infrastructure impacts. Future studies could extend this framework by explicitly incorporating temporal dynamics, as longer-duration or

repeated hazardous events are known to produce more severe and persistent impacts by overwhelming coping capacities and enabling secondary and cascading effects to accumulate across interconnected systems, including health, economic, and environmental domains [64].

# 6 Conclusion

As climate hazards intensify and societies evolve, the capacity to analyze and mitigate cascading failures across interdependent infrastructures is increasingly important for effective urban planning. Drawing from infrastructure datasets in conjunction with simulation models for electricity, water, and transportation systems, this study presents the TRIGGER framework to identify cascading vulnerabilities in urban areas. Compared to similar frameworks, this approach elaborates on the social consequences of cascading disruptions, supporting people-centered decision-making. To achieve this goal, the framework leverages LLMs to interpret and describe disruptions for a variety of infrastructure sectors and users. Moreover, the TRIGGER framework novelly compares scenarios with and without adaptation measures in relation to cascading infrastructure impacts.

This study demonstrates that coupling simulation-based infrastructure models with LLMs offers a practical approach for translating technical cascading failure metrics into accessible information for urban planning. While simulation models effectively map how flood disruptions spread across municipal services and port operations, the resulting data can be difficult to interpret directly in policy contexts. Integrating an LLM helps contextualize these outputs by scaling qualitative severity to numerical impacts, summarizing large datasets to reduce cognitive load, and highlighting critical impacts. Consequently, this coupled framework provides a clearer view of systemic interdependencies, illustrating, for example, how local port operations rely heavily on

the stability of the broader logistical network. By converting complex network analytics into readable socio-economic narratives, this approach can assist planners in evaluating vulnerabilities, communicating risks, and comparing adaptation options to support targeted, context-specific disaster preparedness.

While the framework relies on simplifying modelling assumptions, this application exemplifies how it can nonetheless facilitate a shift from siloed sector management to collaborative, cross-sectoral resilience planning for urban planners and policymakers. By explicitly linking adaptation measures to the mitigation of cascading impacts, this framework could support and promote engineered interventions into urban policy. Equipping decision-makers with such integrated simulation tools facilitate enhanced resource allocation so that cities can transition from reactive disaster response to proactive, data-driven adaptation for systemic resilience.

## References


[1] Brunner, L.G., Peer, R.A.M., Zorn, C., Paulik, R., Logan, T.M.: Understanding cascading risks through real-world interdependent urban infrastructure. Reliability Engineering & System Safety **241**, 109653 (2024) https://doi.org/10.1016/j.ress.2023.109653

[2] UNDRR: Principles for resilient infrastructure. Technical report (March 2022). https://www.undrr.org/publication/principles-resilient-infrastructure

[3] Dolan, T.: Systemic Perspectives on National Infrastructure for a Sustainable, Resilient Net Zero Future. Frontiers in Built Environment **7**, 752765 (2021) https://doi.org/10.3389/fbuil.2021.752765

[4] Koks, E.E., Van Ginkel, K.C.H., Van Marle, M.J.E., Lemnitzer, A.: Brief communication: Critical infrastructure impacts of the 2021 mid-July western European flood event. Natural Hazards and Earth System Sciences **22**(12), 3831–3838

(2022) https://doi.org/10.5194/nhess-22-3831-2022

[5] Castro-Melgar, I., Falaras, T., Basiou, E., Parcharidis, I.: Assessment of the October 2024 Cut-Off Low Event Floods Impact in Valencia (Spain) with Satellite and Geospatial Data. Remote Sensing **17**(13), 2145 (2025) https://doi.org/10.3390/rs17132145

[6] Fekete, A., Estrany, J., Ramírez, M.Á.A.: Cascading impact chains and recovery challenges of the 2024 Valencia catastrophic floods. Discover Sustainability **6**(1), 586 (2025) https://doi.org/10.1007/s43621-025-01483-4

[7] Verschuur, J., Koks, E.E., Li, S., Hall, J.W.: Multi-hazard risk to global port infrastructure and resulting trade and logistics losses. Communications Earth & Environment **4**(1), 5 (2023) https://doi.org/10.1038/s43247-022-00656-7

[8] Simpson, N.P., Sparkes, E., De Ruiter, M., Trogrlić, R.Š., Passos, M.V., Schlumberger, J., Lawrence, J., Mechler, R., Hochrainer-Stigler, S.: Advances in complex climate change risk assessment for adaptation. npj Climate Action **4**(1), 74 (2025) https://doi.org/10.1038/s44168-025-00281-y

[9] Ouyang, M.: Review on modeling and simulation of interdependent critical infrastructure systems. Reliability Engineering & System Safety **121**, 43–60 (2014) https://doi.org/10.1016/j.ress.2013.06.040

[10] Vieira Passos, M., Barquet, K., Kan, J.-C., Destouni, G., Kalantari, Z.: Hydrometeorological resilience assessment of interconnected critical infrastructures. Sustainable and Resilient Infrastructure **10**(3), 267–283 (2025) https://doi.org/10.1080/23789689.2024.2446124

[11] Abedi, A., Gaudard, L., Romerio, F.: Review of major approaches to analyze

vulnerability in power system. Reliability Engineering & System Safety **183**, 153–172 (2019) https://doi.org/10.1016/j.ress.2018.11.019

[12] Hoff, R., Sparks, R., Chester, M., Mustafa, A., Johnson, N., Birchfield, A., McPhearson, T., Li, R., Ahmad, N., Searles, I.: Cascading Failure Propagation and Perfect Storms in Interdependent Infrastructures. ASCE OPEN: Multidisciplinary Journal of Civil Engineering **3**(1), 04025001 (2025) https://doi.org/10.1061/AOMJAH.AOENG-0045

[13] Pournaras, E., Taormina, R., Thapa, M., Galelli, S., Palleti, V., Kooij, R.: Cascading Failures in Interconnected Power-to-Water Networks. ACM SIGMETRICS Performance Evaluation Review **47**(4), 16–20 (2020) https://doi.org/10.1145/3397776.3397781

[14] Momeni, A., Dharmawardena, H.I., Prasad, V., Piratla, K.R., Venayagamoorthy, G.K.: Modeling near-real-time multiphase cascading failures across interdependent power, water, and gas infrastructure. Structure and Infrastructure Engineering, 1–17 (2024) https://doi.org/10.1080/15732479.2024.2312267

[15] Li, Y., Zhang, M.: Cascading failure analysis of interdependent water-power networks based on functional coupling. Reliability Engineering & System Safety **259**, 110950 (2025) https://doi.org/10.1016/j.ress.2025.110950

[16] Arrighi, C., Pregnolato, M., Castelli, F.: Indirect flood impacts and cascade risk across interdependent linear infrastructures. Natural Hazards and Earth System Sciences **21**(6), 1955–1969 (2021) https://doi.org/10.5194/nhess-21-1955-2021

[17] Balakrishnan, S., Cassottana, B.: InfraRisk: An open-source simulation platform for resilience analysis in interconnected power–water–transport networks. Sustainable Cities and Society **83**, 103963 (2022) https://doi.org/10.1016/j.scs.2022.103963

[18] Koliou, M., Van De Lindt, J.W., McAllister, T.P., Ellingwood, B.R., Dillard, M., Cutler, H.: State of the research in community resilience: Progress and challenges. Sustainable and Resilient Infrastructure **5**(3), 131–151 (2020) https://doi.org/10.1080/23789689.2017.1418547

[19] Jiang, H., Li, M., Witte, P., Geertman, S., Pan, H.: Urban Chatter: Exploring the potential of ChatGPT-like and generative AI in enhancing planning support. Cities **158**, 105701 (2025) https://doi.org/10.1016/j.cities.2025.105701

[20] Lawrence, J., Blackett, P., Cradock-Henry, N.A.: Cascading climate change impacts and implications. Climate Risk Management **29**, 100234 (2020) https://doi.org/10.1016/j.crm.2020.100234

[21] OpenStreetMap contributors: Infrastructure Datasets Retrieved from OpenStreetMap. https://www.openstreetmap.org (2025)

[22] Boeing, G.: Modeling and Analyzing Urban Networks and Amenities With OSMnx. Geographical Analysis **57**(4), 567–577 (2025) https://doi.org/10.1111/gean.70009

[23] Pesaresi, M., Schiavina, M., Politis, P., Freire, S., Krasnodebska, K., Uhl, J.H., Carioli, A., Corbane, C., Dijkstra, L., Florio, P., Friedrich, H.K., Gao, J., Leyk, S., Lu, L., Maffenini, L., Mari-Rivero, I., Melchiorri, M., Syrris, V., Van Den Hoek, J., Kemper, T.: Advances on the Global Human Settlement Layer by joint assessment of Earth Observation and population survey data. International Journal of Digital Earth **17**(1), 2390454 (2024) https://doi.org/10.1080/17538947.2024.2390454

[24] Virtanen, P., *et al.*: SciPy 1.0: Fundamental algorithms for scientific computing in Python. Nature Methods **17**(3), 261–272 (2020) https://doi.org/10.1038/s41592-019-0686-2

[25] U.S. Energy Information Administration: Table C22. Electricity Consumption Totals and Conditional Intensities by Building Activity Subcategories, 2012. Online Data Table (2016)

[26] U.S. Energy Information Administration: 2012 commercial buildings energy consumption survey: Water consumption in large buildings summary. Technical report, U.S. Department of Energy (February 2017). https://www.eia.gov/consumption/commercial/reports/2012/water/

[27] Copenhagen Malmö Port: CMP Port Annual & Sustainability Report 2022. Annual Report, Copenhagen Malmö Port (June 2023). https://www.cmport.com/wp-content/uploads/2023/06/85836_CMP_Annual_Report_2022_WEB.pdf

[28] IEA: World Energy Statistics and Balances - Data Product. https://www.iea.org/data-and-statistics/data-product/world-energy-statistics-and-balances (2025)

[29] Dadvar, A., Mahapatra, K., Forss, J.: Water Use Behavior in a Multicultural Urban Area in Sweden. Sustainability **13**(15), 8603 (2021) https://doi.org/10.3390/su13158603

[30] Green, D., Yu, D., Pattison, I., Wilby, R., Bosher, L., Patel, R., Thompson, P., Trowell, K., Draycon, J., Halse, M., Yang, L., Ryley, T.: City-scale accessibility of emergency responders operating during flood events. Natural Hazards and Earth System Sciences **17**(1), 1–16 (2017) https://doi.org/10.5194/nhess-17-1-2017

[31] Perron, L., Furnon, V.: OR-tools: Google for Developers. Google. https://developers.google.com/optimization/ (2025)

[32] Thurner, L., Scheidler, A., Schafer, F., Menke, J.-H., Dollichon, J., Meier, F.,

Meinecke, S., Braun, M.: Pandapower—An Open-Source Python Tool for Convenient Modeling, Analysis, and Optimization of Electric Power Systems. IEEE Transactions on Power Systems **33**(6), 6510–6521 (2018) https://doi.org/10.1109/TPWRS.2018.2829021

[33] Villa, D., Hart, D., Klise, K., Bynum, M., Laird, C., Seth, A., Moriarty, D., Hogge, J., Bonney, K.: Water Network Tool for Resilience (WNTR). Sandia National Laboratories (SNL-NM), Albuquerque, NM (United States) (2023). https://doi.org/10.11578/DC.20171025.1707

[34] OpenRouter AI: OpenRouter: The Open-Source Standard for LLM APIs. https://openrouter.ai (2025)

[35] Amirsoleimani, Niloufar: Nyhamnen, Climate Adaptation Regarding Sea Level Rise and Flood. http://lup.lub.lu.se/student-papers/record/9082161 (2022)

[36] Holgersen, S.: The rise (and fall?) of post-industrial Malmö: Investigations of city-crisis dialectics. Doctoral Thesis (compilation), Lund University / Department of Human Geography (2014). https://portal.research.lu.se/en/publications/the-rise-and-fall-of-post-industrial-malm%C3%B6-investigations-of-city/

[37] Mukhtar-Landgren, D.: Problematisations of Progress and Diversity in Visionary Planning: The case of post-industrial Malmö. Nordic Journal of Migration Research **6**(1), 18–24 (2016) https://doi.org/10.1515/njmr-2016-0004

[38] Karimpour, R., Ballini, F., Ölcer, A.I.: Circular economy approach to facilitate the transition of the port cities into self-sustainable energy ports—a case study in Copenhagen-Malmö Port (CMP). WMU Journal of Maritime Affairs **18**(2), 225–247 (2019) https://doi.org/10.1007/s13437-019-00170-2

[39] Mobini, S., Nilsson, E., Persson, A., Becker, P., Larsson, R.: Analysis of pluvial

flood damage costs in residential buildings – A case study in Malmö. International Journal of Disaster Risk Reduction **62**, 102407 (2021) https://doi.org/10.1016/j.ijdrr.2021.102407

[40] Mobini, S., Pirzamanbein, B., Berndtsson, R., Larsson, R.: Urban flood damage claim analyses for improved flood damage assessment. International Journal of Disaster Risk Reduction **77**, 103099 (2022) https://doi.org/10.1016/j.ijdrr.2022.103099

[41] Hansson, A., Mäcks, M., Lindgren, M., Gyllenram, W.: Modellering av skyfall och extremt vattenstånd i Malmö i ett framtida klimat. Simulering av åtta delområden och tre scenarier i ett framtida klimat (år 2125): Extrem nederbörd, extrem vattennivå och medelhögvatten/ettårsregn. Technical Report 205102, AFRY, Malmö (May 2022)

[42] Cortinovis, C., Olsson, P., Boke-Olén, N., Hedlund, K.: Assessing Potential for and Benefits of Scaling up Nature Based Solutions in Malmö. In: La Rosa, D., Privitera, R. (eds.) Innovation in Urban and Regional Planning vol. 242, pp. 3–11. Springer, Cham (2022). https://doi.org/10.1007/978-3-030-96985-1_1

[43] Sharp, R., Douglass, J., Wolny, S., Arkema, K., Bernhardt, J., Bierbower, W., Chaumont, N., Denu, D., Fisher, D., Glowinski, K., et al.: InVEST 3.8. 7. user's guide. The Natural Capital Project (2020)

[44] Hamel, P., Guerry, A.D., Polasky, S., Han, B., Douglass, J.A., Hamann, M., Janke, B., Kuiper, J.J., Levrel, H., Liu, H., Lonsdorf, E., McDonald, R.I., Nootenboom, C., Ouyang, Z., Remme, R.P., Sharp, R.P., Tardieu, L., Viguié, V., Xu, D., Zheng, H., Daily, G.C.: Mapping the benefits of nature in cities with the InVEST software. npj Urban Sustainability **1**(1), 25 (2021) https://doi.org/10.1038/s42949-021-00027-9

[45] Persson, E., Granberg, M.: Implementation through collaborative crisis management and contingency planning: The case of dam failure in Sweden. Journal of Risk Research **24**(10), 1335–1348 (2021) https://doi.org/10.1080/13669877.2020.1863845

[46] Barquet, K., Englund, M., Inga, K., André, K., Segnestam, L.: Conceptualising multiple hazards and cascading effects on critical infrastructures. Disasters **48**(1), 12591 (2024) https://doi.org/10.1111/disa.12591

[47] Rodríguez-Espíndola, O., Albores, P., Brewster, C.: Disaster preparedness in humanitarian logistics: A collaborative approach for resource management in floods. European Journal of Operational Research **264**(3), 978–993 (2018) https://doi.org/10.1016/j.ejor.2017.01.021

[48] Do. Bagus, M.R., Hanaoka, S.: Interdependency patterns of potential seaport risk factors in relation to supply chain disruption in Indonesia. Journal of Shipping and Trade **8**(1), 6 (2023) https://doi.org/10.1186/s41072-023-00137-w

[49] Verschuur, J., Pant, R., Koks, E., Hall, J.: A systemic risk framework to improve the resilience of port and supply-chain networks to natural hazards. Maritime Economics & Logistics **24**(3), 489–506 (2022) https://doi.org/10.1057/s41278-021-00204-8

[50] Tsoulfas, G.T.: Port resilience: A systematic literature review. Maritime Economics & Logistics (2025) https://doi.org/10.1057/s41278-025-00326-3

[51] Francis, R., Bekera, B.: A metric and frameworks for resilience analysis of engineered and infrastructure systems. Reliability Engineering & System Safety **121**, 90–103 (2014) https://doi.org/10.1016/j.ress.2013.07.004

[52] McPhearson, T., Frantzeskaki, N., Ossola, A., Diep, L., Anderson, P.M.L., Blatch,

T., Collier, M.J., Cook, E.M., Culwick Fatti, C., Grabowski, Z.J., Grimm, N.B., Haase, D., Herreros-Cantis, P., Kavonic, J., Lin, B.B., Lopez Meneses, D.H., Matsler, A.M., Moglia, M., Morató, J., O'Farrell, P., Roy, P., Singh, C., Wang, J., Zhou, W.: Global synthesis and regional insights for mainstreaming urban nature-based solutions. Proceedings of the National Academy of Sciences **122**(29), 2315910121 (2025) https://doi.org/10.1073/pnas.2315910121

[53] Esraz-Ul-Zannat, Md., Dedekorkut-Howes, A., Morgan, E.A.: Unveiling the Barriers and Drivers of Mainstreaming Nature-Based Solutions for Urban Flood Resilience. WIREs Climate Change **16**(6), 70026 (2025) https://doi.org/10.1002/wcc.70026

[54] Frantzeskaki, N., McPhearson, T.: Mainstream Nature-Based Solutions for Urban Climate Resilience. BioScience **72**(2), 113–115 (2022) https://doi.org/10.1093/biosci/biab105

[55] Vicarelli, M., Sudmeier-Rieux, K., Alsadadi, A., Shrestha, A., Schütze, S., Kang, M.M., Leue, M., Wasielewski, D., Mysiak, J.: On the cost-effectiveness of Nature-based Solutions for reducing disaster risk. Science of The Total Environment **947**, 174524 (2024) https://doi.org/10.1016/j.scitotenv.2024.174524

[56] Espada, R., Apan, A., McDougall, K.: Vulnerability assessment of urban community and critical infrastructures for integrated flood risk management and climate adaptation strategies. International Journal of Disaster Resilience in the Built Environment **8**(4), 375–411 (2017) https://doi.org/10.1108/IJDRBE-03-2015-0010

[57] Shrestha, A., Chini, C.M.: Risk-based stormwater fragility curves for urbanized coastal flooding. Journal of Hydrology **661**, 133436 (2025) https://doi.org/10.1016/j.jhydrol.2025.133436

[58] Saha, S.S., Schweitzer, E., Scaglione, A., Johnson, N.G.: A Framework for Generating Synthetic Distribution Feeders using OpenStreetMap. In: 2019 North American Power Symposium (NAPS), pp. 1–6. IEEE, Wichita, KS, USA (2019). https://doi.org/10.1109/NAPS46351.2019.9000187

[59] Ahmad, N., Chester, M., Bondank, E., Arabi, M., Johnson, N., Ruddell, B.L.: A synthetic water distribution network model for urban resilience. Sustainable and Resilient Infrastructure **7**(5), 333–347 (2022) https://doi.org/10.1080/23789689.2020.1788230

[60] Raymond, C.M., *et al.*: Uses, opportunities and risks of artificial intelligence in participatory urban planning. Discover Cities **2**(1), 93 (2025) https://doi.org/10.1007/s44327-025-00137-4

[61] Saengtabtim, K., Leelawat, N., Aumnoysombat, R., Adelifar, M., Saengwongwattana, N., Suktavornprasit, G., Suppasri, A., Imamura, F., Tang, J.: Harnessing generative AI for enhanced disaster management: A systematic review. Big Earth Data, 1–25 (2025) https://doi.org/10.1080/20964471.2025.2521157

[62] Albahri, A.S., Khaleel, Y.L., Habeeb, M.A., Ismael, R.D., Hameed, Q.A., Deveci, M., Homod, R.Z., Albahri, O.S., Alamoodi, A.H., Alzubaidi, L.: A systematic review of trustworthy artificial intelligence applications in natural disasters. Computers and Electrical Engineering **118**, 109409 (2024) https://doi.org/10.1016/j.compeleceng.2024.109409

[63] Hachem-Vermette, C.: Enhancing Urban Climate Resistance Through the Application of Selected Strategies and Technologies. Discover Cities **1**(1), 17 (2024) https://doi.org/10.1007/s44327-024-00018-2

[64] Li, H.-M., Wang, X.-C., Zhao, X.-F., Qi, Y.: Understanding systemic risk induced

by climate change. Advances in Climate Change Research **12**(3), 384–394 (2021) https://doi.org/10.1016/j.accre.2021.05.006

## Data availability

The data and code supporting this study are not publicly available due to security risks regarding critical infrastructure vulnerabilities. To support reproducibility, a synthetic dataset and the framework's code are available from the corresponding author upon reasonable academic request, subject to institutional review and a data-sharing agreement. Baseline topological data was derived from OpenStreetMap and population data was obtained from the Copernicus Global Human Settlement Layer.

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## Author contributions

KB and ZK conceived this study. MVP developed the methodology, collected the data, used the software, and carried out the formal analysis. KB, ZK, and GD acquired the funding. KB and ZK administered the project. KB, ZK, LB, and GD carried out the supervision. All authors participated in writing this paper.

## Competing interests

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.

## Clinical trial number

Not applicable.

## Ethics, consent to participate, and consent to publish

Not applicable.

## Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- AppendixAPromptLLM.pdf
- AppendixCPort.pdf
- AppendixBMunicipality.pdf