Developing a Context-based Bounded Centrality Approach of Street Patterns in Flooding: A Case Study of London

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Abstract. Floods affect an average of 21 million people worldwide each year, and their frequency is expected to increase due to climate warming, population growth, and rapid urbanisation. Previous research on the robustness of transport networks during floods has mainly used percolation theory. However, giant component size of disrupted networks cannot capture the entire network's information and, more importantly, does not reflect the local reality. To address this issue, this study introduces a novel approach to bounded context-based centrality to extract the local impact of disruption. In particular, we propose embedding travel behaviour into the road network to calculate bounded centrality and develop new measures characterising the size of connected components during flooding. Our analysis can identify critical road segments during floods by comparing the decreasing trend and dispersibility of component sizes on road networks. To demonstrate the feasibility of these approaches, a case study of London's transport infrastructure that integrates road networks with relevant urban contexts was developed. This approach is beneficial for practical risk management, helping decision-makers allocate resources efficiently in space and time.

1. Introduction

Floods have become increasingly catastrophic in recent decades, causing widespread losses worldwide. Climate change, extreme rainfall, and sea level rise are significant factors contributing to the frequency and severity of flood hazards (Dong et al., 2020). Due to the rapid development of economic assets and urbanization in flood-prone areas, global exposure to floods is expected to triple by 2050 (Aerts et al., 2018). This growing flood risk poses significant threats to infrastructure networks critical to community well-being. Among these infrastructure networks, roads are critical for transporting people and goods, evacuating individuals from affected areas, and providing access to resources and services for affected populations (Tachaudomdach et al., 2018). Road traffic disruptions can lead to more isolated communities, making emergency management more challenging due to limited access. To better understand the increasing risks and proactively mitigate impacts on communities, a quantitative flood risk assessment is needed to systematically estimate the local importance of roads and the robustness of road networks (Jongman et al., 2015). Such an assessment can inform risk mitigation, investment decisions, and the prioritization of improvement projects.

Road network robustness refers to the network's ability to access various destinations despite disruptions such as flooding (Snelder, van Zuylen and Immers, 2012). Percolation theory is often used to analyse network robustness under link and node disruption, with network robustness measured by topological connectivity based on the size of the largest connected component (Wang et al., 2019). While various studies have used percolation theory to examine roadway robustness, these approaches do not fully capture the impact of local disruptions on the network during a flood event (Loreti et al., 2022). They focus only on the overall size of the largest connected component in the network without considering the specific locations and characteristics of disrupted nodes and links. This incomplete understanding of network vulnerability and resilience can hinder efforts to mitigate the potential impact of disruptions on specific communities and areas (Berezin et al., 2015). To address these limitations, a few research studies have proposed new models to assess the local impact of disruption. However, these studies focused primarily on the accessibility of critical infrastructure such as hospitals or stations during flooding (Dong et al., 2019, 2020; Ouyang et al., 2019), rather than the impact of local disruptions on global road networks.

This study presents a novel approach to assessing the impact of local disruption on road networks by proposing a context-based boundary centrality indicator. The purpose of this paper is twofold. Firstly, a boundary centrality indicator based on traveller behaviour is used to capture the impact of local disruption on road networks. Secondly, a new approach to evaluating network robustness based on component size is introduced. To demonstrate the feasibility of these approaches, a case study of London's transport infrastructure that integrates road networks with relevant urban contexts was developed. The results of this case study highlight the effectiveness of the proposed approaches in assessing the impact of local disruption on road networks and provide valuable insights into the destructiveness and dispersiveness of the underlying mechanisms that affect network robustness.

This paper is structured as follows: Section 2 provides a comprehensive review of previous research and practice relevant to the topic of this study. Section 3 presents the research framework, which consists of three modules, and provides detailed descriptions of each module. Section 4 presents a case study based on the London transport network, demonstrating the effectiveness of the proposed framework. Finally, the conclusions of this study are presented in Section 5.

2. Literature Review

Investigating robustness in disrupted networks typically involves measuring vulnerability and reliability (Sullivan, Aultman-Hall and Novak, 2009). Vulnerability refers to the extent to which a system cannot function following a disruption. Reliability can be defined as the probability that a system can maintain satisfactory operation over a significant time frame (Mattsson and Jenelius, 2015). Reliability analysis is divided into three categories: connectivity reliability, travel time reliability, and capacity reliability (Murray and Grubesic, 2007). These classifications are based on determining the probability that a node will remain connected, a trip between nodes can be completed within a specified time interval, and a network can accommodate a specific level of travel demand, respectively. Reliability studies in this context require knowledge of travel demand from a designated origin-destination pair (Dong et al., 2019). However, the collection of actual post-disaster demand data is limited, making it impractical to apply such analyses in real-world studies.

The idea of network robustness is based on evaluating how well a system can sustain its performance in response to unforeseen internal or external events or alterations (Albert and Barabási, 2002). Regarding the evaluation of real-world network robustness, some research presents several common features (LaRocca et al., 2015). 1) Researchers typically generate empirical data or simulate a network through random graph generation or mapping real network data. 2) Measuring structural features of the network under investigation. 3) Implementing a random failure or targeted attack on networks. 4) Evaluating the performance of the network, both for static and dynamic cases. In the field of road networks, this analysis involves viewing road infrastructure as a system of nodes (intersections) and links (roads) to examine the impact of network disruption on society as a whole. As a result of this research, various network robustness measures have emerged in recent years.

The measurement of giant connected components (GCC) based on percolation theory is a well-established framework used in network science to assess the robustness of disrupted networks (Albert and Barabási, 2002; Newman, 2003). Researchers have applied percolation theory to study the disruptive effects of earthquakes, traffic congestion, and flooding events on road networks (Loreti et al., 2022). Abdulla et al. (2020) presented a flood diffusion model to investigate the effects of flood diffusion on road network connectivity. By measuring the size of the giant components for each fraction of the removed nodes, they found that the connectivity of road networks was particularly vulnerable to flood propagation that started from nodes with high values of betweenness. Based on this study, Farahmand et al. (2020) proposed a probabilistic approach to examine the failure of road networks, which was assessed by calculating the giant component size of the network. The node removal process resulted in significant drops in network connectivity, as indicated by the size of the giant component. This indicates the existence of critical roads in the network. Dong et al. (2019) proposed a probabilistic link removal to mimic earthquake-induced failures and addressed the effects on the Portland Road network. They claimed that measures of network's robustness should consider critical infrastructures rather than giant components size based on global networks. Similarly, Loreti et al (2022) propose partitioning the Voronoi Cell-based road network of critical infrastructure and defining new measures that characterize the impact of the flood event. However, in urban environments, the coverage range and spatial distribution of infrastructures with different hierarchical levels is often not spatially uniform, which can be observed in the different coverage ranges of national and regional infrastructures. In addition, when a network is split into smaller sub-networks, nodes located at the boundary of these sub-networks lose neighbouring properties because these nodes are no longer considered part of the larger network.

In most of these previous studies related to the application of percolation-based flood modelling on the road system, the network's functionality was expressed through the size of the GCC and its evolution when roads are removed. However, GCC is an aggregated quantity that does not capture the entire network's information and, more importantly, does not reflect the local reality. Therefore, more precise information is necessary, particularly on a local scale, for a realistic evaluation of the disruption's effects.

3. Research Framework

A research framework for this study is proposed to assess the robustness of road networks under flooding by exploring local impacts of disruption. The research framework consists of three modules, as illustrated in Fig. 1. Module 1 involves collecting relevant datasets, such as road networks, commuter behaviour, and road hierarchy, for calculating the bounded centrality of nodes in Module 2. Module 1 includes the creation of a flood map of road networks based on flood simulation software.

Module 2 proposes a centrality map that integrates the bounded centrality and exposure of road networks and establishes a framework for extracting the local importance of nodes from road networks. The centrality map consists of three steps: 1) Calculating bounded centrality based on commuter behaviours to capture the local impact of nodes. 2) Extracting the exposure rate of network segments from the flood map. 3) Devising an integrated centrality map that combines different levels of bounded centrality and exposure rate to create a context-based road centrality map for assessing road network robustness in Module 3.

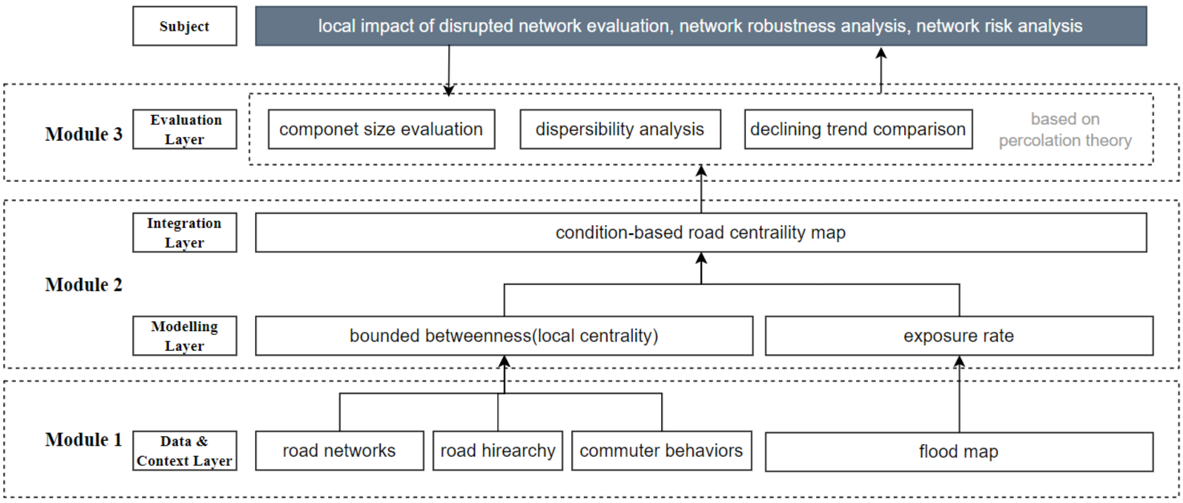

Figure 1 Framework of Exploring the Impact of Road Disruption under Flood.

In Module 3, a new method for evaluating network robustness is presented, which is based on the component size list. The method involves removing nodes of high local importance at multiple levels, in order to investigate the impact on the speed of network collapse and dispersion.

3.1 Module 1: Data & context Layers

Challenges in integrating contextual information with road segments involve (i) no explicit local community representation as the boundary for road networks, as local node impacts on networks often rely on explicit topology information (Hillier and Hanson, 1984); (ii) no uniform framework for integrating road networks with various levels of local impact during flooding events, which require flood map information (Wang et al., 2019). Responding to the above challenges, this module is designed to collect relevant datasets to support further calculations.

In order to establish the boundary for road segments, first of all, the coverage range of a single road network refers to the road segments that people commonly use within a certain distance. As described in Figure 2, different levels of roads have different coverage ranges. For example, 2-5 km for primary roads and 1-2 km for secondary and tertiary roads. However, because coverage also depends on surrounding information, such as population density and location, this study applied different radii to road segments, such as 500m, 1000m and 2000m, to capture their local centrality on various scales. Based on this method, the surrounding relationships of the selected road segments can be calculated in Module 2.

Secondly, in order to obtain the flood map based on road networks, we simulate the flood using the High Performance Integrated Hydrodynamic Modelling System (HiPIMS) (Liang and Smith, 2015) for runoffs with flood distribution and obtain the direct failures of a road network measured by flooded intersections. HiPIMs treated the whole catchment as the computational domain and will be discretised using a uniform grid at a hyper-resolution of 5~10 m (Xia, Liang and Ming, 2019). High-quality DEM integrated with terrain and building height information could provide background information on HiPIMs. In addition, land cover data provided information on Manning coefficient-based related friction. Using rainfall as input directly, HiPIMS predicts the dynamics of surface water moving between grid cells based on this input data.

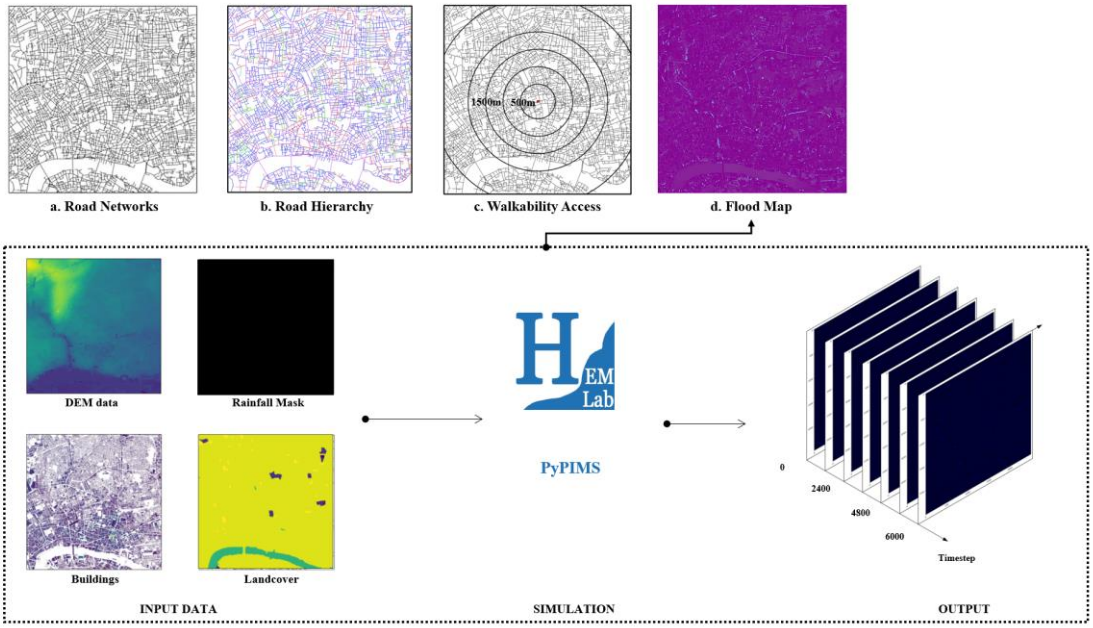

Figure 2 Framework of Module 1

3.2 Module 2: Modelling Layer

Challenges in extracting the local importance of road segments (i) Most existing methods have difficulties in capturing precise local information (Loreti et al., 2022); (ii) Although some methods attempt to capture local value, they focus on critical infrastructure rather than pedestrian travel behaviour (Dong et al., 2019). This approach would overlook some urban areas with fewer critical infrastructures, such as commercial areas.

The second module proposes a centrality calculation approach to integrate urban context information to extract the local importance of road segments in the network. The shortest path betweenness centrality measures a node's importance in a network based on its ability to connect different parts of the network (Freeman 1977). The betweenness $C_B(v)$ of a vertex v ∈ V is defined to be

$$C_B(v) = \sum_{s,t \in V} \frac{\sigma(s,t|v)}{\sigma(s,t)} \tag{1}$$

s, t stands for the head and tail of the shortest path, denote by $\sigma(s,t)$ the number of shortest (s,t)-paths and let $\sigma(s,t|v)$ be the number of shortest (s,t)-paths passing through some vertex v other than s, t. In the context of road networks, traditional network graph treated intersection as ‘node’, and road segment as ‘link’. To explore the impact of local network segments, this study constructed a network graph by treating roads as nodes and their connection as links. A road segment with high betweenness centrality indicates an important link between different network parts. Therefore, if this road segment is disrupted or damaged, it may significantly impact the overall network's functionality and connectivity. By using betweenness centrality in road robustness assessment, transportation planners and decision-makers can identify critical road segments that, if disrupted, could have severe consequences on the network's performance. This information can help prioritise investments in road maintenance, improve emergency response planning, and inform decisions about infrastructure investments.

Due to the standard measure of betweenness considering shortest paths regardless of their length, very long distances may not be realistic for network relationships (Brandes, 2008). Thus, it would not be sufficient to capture the importance of road segments among networks, if only considering the global betweenness of roads, as other factors such as the road's importance to local communities would also be relevant. Therefore, the inclusion of contextual information is essential and necessary, and it can be crucial for a more comprehensive assessment of importance, which was not included in previous research studies. Borgatti and Everett (2006) define the k-betweenness of a vertex as the sum of the dependencies of pairs at most k apart, i.e., only contributions from shortest paths bounded by a constant k are included. Let

$$C_{B(k)}(v) = \sum_{s,t \in V:dist(s,t) \leq k} \frac{\sigma(s,t|v)}{\sigma(s,t)} \tag{2}$$

If paths longer than a certain distance (k) are to be excluded, the breadth-first search algorithm can be stopped when a vertex that is k distances from the starting vertex. Thus, in this paper, based on the distance set by the coverage range of road segments in Module 1, the community local spatial scale has been embedded into graph calculation via setting k as 500m, 1000m, 2000m, 3000m and global to capture node's neighbourhood relationship on networks.

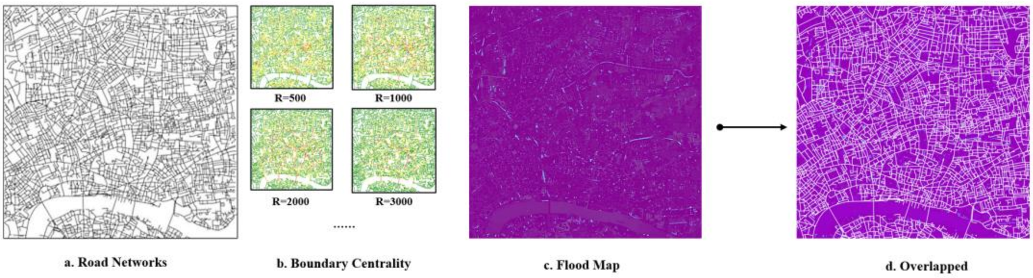

Figure 3 Framework of Module 2

3.3 Module 3: Evaluation Layer

Based on percolation theory, the challenges faced by the indicators to evaluate network robustness include: (1) Existing methods focus only on the giant connected component, ignoring the connectivity of the entire network and thus failing to evaluate the overall performance of the networks (Loreti et al., 2022).

Module 3 aims to assess the effectiveness of the network at different spatial scales by analysing component sizes. This module also seeks to validate the feasibility of context-based bounded centrality methods in identifying critical road networks during flooding. In network theory, a component is a subset of nodes that are connected to each other but not to any nodes outside that subset. It refers to a group of nodes that are "reachable" from each other, but not from any other nodes outside that group (Albert and Barabási, 2002). Understanding component sizes in networks is critical to understanding network structure and behaviour (Newman, 2010). There are various types of components in a network, including the giant component, which is the largest connected component containing a significant proportion of nodes in the network. Networks with a larger giant component are generally more robust and less vulnerable to disruption than networks with a smaller giant component. It is worth noting that smaller components in the network, although they may consist of only a few nodes, can also reflect the type of network interruption that can quickly reduce urban connectivity (Wang et al., 2019). Ignoring these small, connected components can make emergency management difficult due to limited access. Evaluating the number and size of these smaller connected components can provide valuable insights into the localised road disruption that can lead to rapid reductions in urban connectivity.

In this paper, a novel approach is proposed to measure the size of components in disrupted networks. Since the centrality map built in Module 2 is an undirected graph, a breadth-first search algorithm (Goerdt, 1997) is utilised to calculate the connected components in the graph. Unlike previous approaches that rely only on the size of the giant component, our approach preserves the size of all components. As shown in Figure 4(c), this list of component sizes allows us to compare the dispersal of the network after disruption by component quantity, average value, and standard deviation of component size. In addition, the Augmented Dickey-Fuller (ADF) test (Dickey and Fuller, 1979) is used to evaluate the stability of the component size list. Our approach offers three benefits. Firstly, the changing trend in component size and count is demonstrated by plotting component size, amount, and removal probability on a Cartesian coordinate system, as shown in Figure 4(d). Secondly, data from the component size list are analysed to determine whether roads with high local betweenness centrality are more detrimental than those with high global value. Thirdly, the dispersal of the connected components is calculated to assess the local disruption's ability to fragment into multiple disconnected components at spatial scales. This approach is valuable in studying network resilience and can help design more robust network systems.

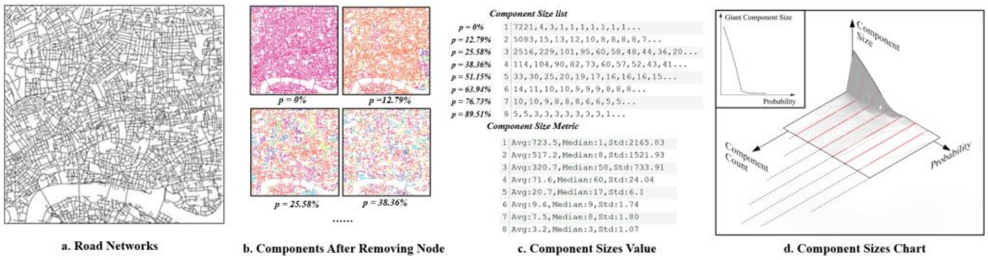

Figure 4 Framework of Module 3

4. Case Analysis

To test our approach and our new indicator, a portion of the Central London Road network (OS MasterMap Highways Network, 2022) was selected as a test area, covering 29.5km2 (edge length: 5500m), as shown in Fig. 5(b). Firstly, to simulate the flood map of the selected area, HiPIMs was used to simulate 2 hours of surface runoffs after 1.2 hours of rain based on DEM (Lidar Composite Digital Terrain Model England 2m resolution, 2020), land cover data (Land Cover Map of Great Britain, 2021) and rainfall mask data (Met Office, 2023). The results can be seen in Figure 5(c). Secondly, graphs are constructed by adding different levels of radius (radius: 500m, 1000m, 2000m, 3000m, global) to incorporate travel behaviours and calculate the boundary betweenness centrality. The resulting graphs have a node count of 7250. Thirdly, combine flood exposure rates with their local importance to create a context-based bounded centrality map, as shown in Fig 6(c). Fourthly, the performance of the network was observed by removing roads based on the ranking of the importance of road segments. In this calculation, the component size list was used to evaluate the decreasing trend and dispersibility of networks based on their giant component size, average size, amount, standard deviation, and ADF test.

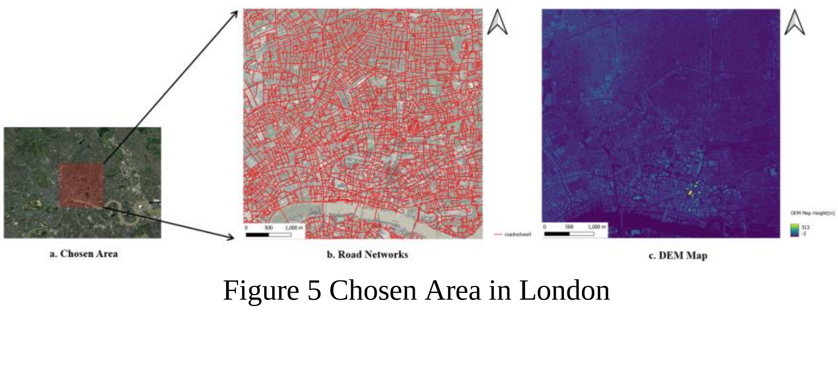

Figure 5 Chosen Area in London

From Fig7(a), it can be observed that removing those nodes with high local betweenness centrality results in greater damage to the giant connected component in initial disruption, which is highlighted in the red rectangle box. For example, compared to nodes with high global centrality values (decreasing from 7100 to 5040), removing nodes with high local betweenness values in R=1000m, 2000m, and 3000m reduces the giant component size from 7100 to about 2880. However, after removing 25% of nodes, R=Global has the greater power to reduce the size of giant connection components compared to others.

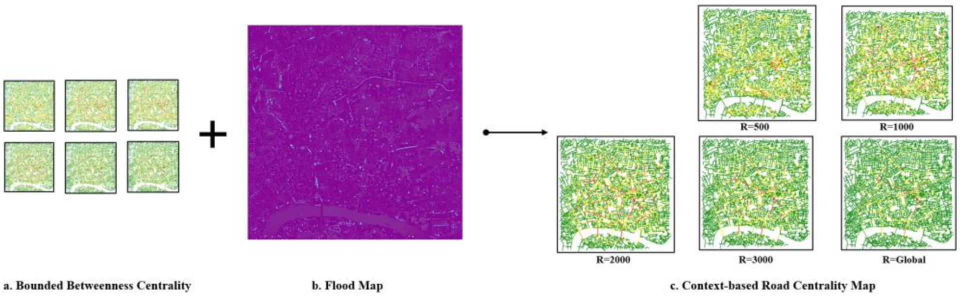

Figure 6 Context-based Bounded Centrality Map

Fig 7(b,c) provides a lesson that in the first and second stages, networks of high local importance, particularly R=1000m, 2000m, and 3000m, have a higher component quantity and smaller average component size than networks of high global value. In addition, in comparison to the removal of the high global centrality road network and the random removal of nodes, the removal of the high local road network results in a significant difference in the size of the network components, with relatively large fluctuations at different stages (Fig.7(d, e)). Thus, removing the high local centrality road network can quickly divide the network into smaller components in the short term. At the same time, from the perspective of view of network division, removing the road network with high local attributes also makes the network size more unbalanced and dispersed. Therefore, understanding the importance of these nodes at different levels can help identify and mitigate the impact of disruptions, which is particularly important for ensuring the resilience of local communities.

This paper presents three potential contributions. Firstly, a novel approach is proposed to capture node local centrality, demonstrating that removing nodes with high local centrality could cause more significant network damage than traditional methods. Secondly, a new evaluation method is introduced to evaluate network performance during node disruption, focusing on the destructiveness and dispersibility of components. However, the presented approach has some limitations, 1) the absence of transportation simulation after node removal and 2) the need to rebuild the network and recalculate the component size after each node removal. Future research could explore 1) the effect of removing roads with different levels of local centrality on network robustness and travel time for commuters and 2) the development of an algorithm that can speed up component size calculations based on previous steps.

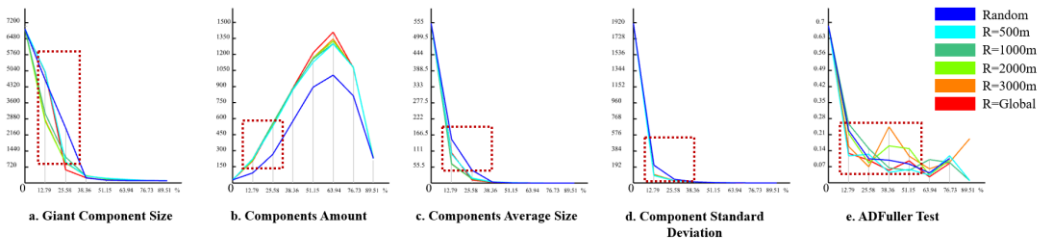

Figure 7 Indicators of Component Size List

5. Conclusion

In conclusion, floods pose a serious threat to transport networks, and with climate change, population growth and rapid urbanisation, the frequency and severity of floods are likely to increase. To understand the effects of flooding on road systems, experts use a variety of methodologies, including percolation theory, to measure network robustness. However, considering the robustness of the network based solely on the giant connected component, it may not accurately represent the impact of flooding on local communities. This paper proposes a context-based boundary centrality approach for calculating the impact of local communities on each segment of the road network and a novel approach for evaluating network robustness based on the size of network components. The case study on the London transport network validates the feasibility of these approaches. By considering the impact of local disruptions, our proposed approach provides a more comprehensive and accurate assessment of network robustness and can assist in urban disaster management.

Acknowledgement

This research is funded by the 2023 WTW Research Network.

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