Graph-based Framework for Road Network Performance and Flood Risk Assessment

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ABSTRACT: The road network provides a connecting infrastructure that facilitates countless daily pursuits, supporting communication and economic activity. Flooding hazard often threaten the road network with physical damage and service interruption. Traffic disruptions are reflected in increased travel distance, increased travel time, and even inability to travel at all. This paper proposes a framework combining flooding scenarios and road network topological features to assess road network performance and risk. A graph-based model is introduced to assess the global network performance in terms of connectivity and accessibility. This model also allows to identify the critical components in the road network. The flood hazard is then presented in terms of flood depth and velocity for multiple return periods. Flood intensity maps are used to assess the vehicle risk of degraded driving performance on the entire network. The methodology is applied for the road network of Bristol, UK. Flood scenarios with 10-year and 200-year return periods are considered. The results presented herein may be used to support the development of mitigation strategies to improve the resilience of road networks.

1. INTRODUCTION

Transportation networks play an important role in supporting social and economic activities. In the road network system, roads and bridges are vulnerable to flood hazards (Somy et al., 2021). The increasing frequency of extreme weather due to climate change has spawned catastrophic natural disasters, rendering road networks non-functional, and threatening human life of the users (e.g., Zhang & Alipour, 2019, Wardhana & Hadipriono, 2003).

Several indicators quantifying infrastructure loss of functionality have been proposed in the literature. For general infrastructures, Bruneau et al. (2003) defined resilience as the ability to resist a damage and maintain the functionality during and after a disaster. For road network performance, Zhang (2019) identified two indicators: average node degree and average shortest path (see Sec. 2.1). Cimellaro et al. (2010) quantified road network resilience through an image-based methodology, where resilience is represented as area under the continuous curve composited by the relationship between road network functionality and flood extension. Henry et al. (2021) evaluated the importance of each link via betweenness centrality (BC) (see Sec. 2.1).

Shahdani et al. (2022) researched the varied maximum vehicle velocity due to different flood depths. Wang et al. (2021) considered flood velocity as the parameter affecting the sliding of different vehicle typologies. Alabbad et al. (2021) assessed the road network accessibility for different flood return periods and identified dysfunctional bridges. Although the above studies investigated the impact of flooding on road network resilience for different goals, limitations still exist. Specifically, there remains a need for optimizing the assessment of the road performance combining a graph-based analysis aimed at the identification of the road risk, and a functionality analysis aimed at checking the vulnerability of vehicles for the most vulnerable links. To this aim, an integrated graph-based method is developed and combined with the assessment of car stability during flooding. This method is applied to Bristol's road network performance. Bristol is a flood-prone area in Southwest England, UK. The results presented here may be used to support the development of mitigation strategies to improve the resilience of road networks.

2. METHODOLOGY

Fig. 1 shows the methodology underpinning this study, which includes nine steps.

1. Construction of the road network graph using nodes and links as per Gauthier et al. (2018).
2. Definition of the indicators quantifying the global road network performance.
3. Stress tests of the network to assess the network functionality.
4. Identification of the critical links based on betweenness centrality.
5. Assignation the elevation of each link using the Digital Surface Model (DSM).
6. Extraction of flooding intensities including depth and velocity from the flood maps.
7. Computation of critical flood velocity to evaluate risk level of vehicle due to flood velocity.
8. Identification of risk level of vehicle due to flood depth.
9. Classification of link risk.

2.1. Road network topology analysis

In graph-based methods, a road network consists of links (e.g. roads) and nodes (e.g. origins/terminals and junctions). Zhang (2019) proposed two important indicators, the average node degree (d_{ave}) and average shortest path (P_{ave}), shown in Eq. 1 and Eq. 2, respectively. Definitions of these two variables are identified in the Table 1.

$$d_{ave} = \frac{1}{N}\sum_{i=1}^{N}(d_i^{In} + d_i^{Out}) \qquad (1)$$

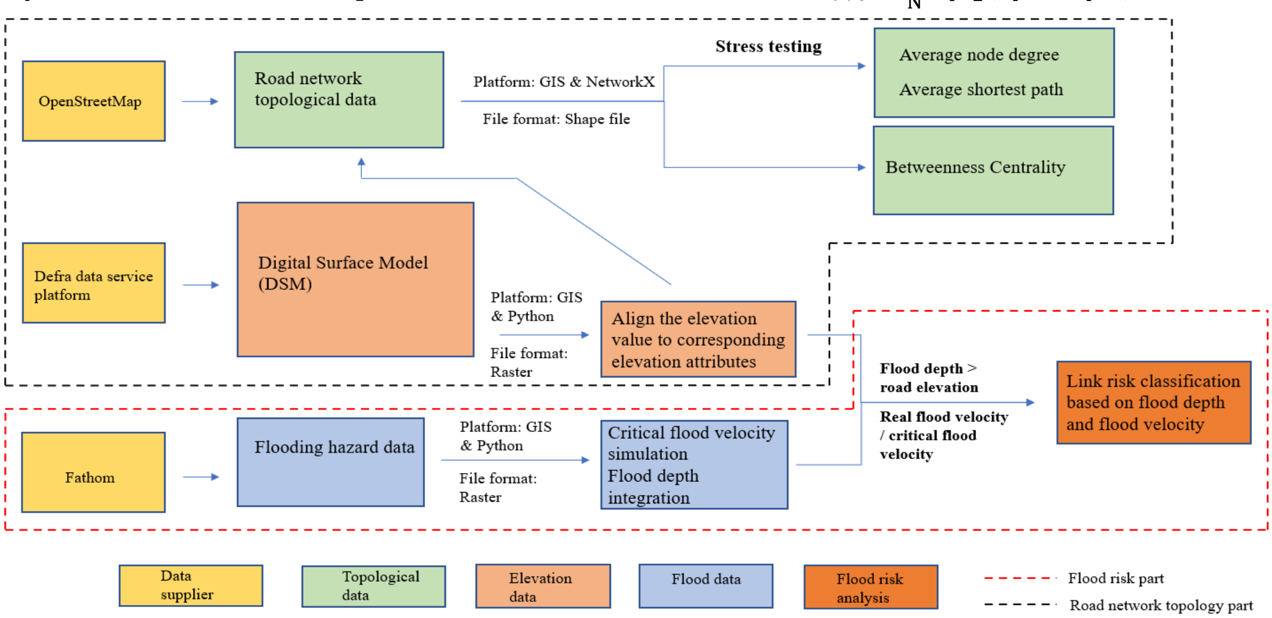


Figure 1: Methodological flowchart underpinning this study.

$$P_{ave} = \frac{1}{N(N-1)} \sum_{i=1, i \neq j}^{N} \sum_{j=1, j \neq i}^{N} SP_{ij} \qquad (2)$$

where N is the node number in the road network while i and j are indices of origin node and destination node. Furthermore, d_i^{In} and d_i^{Out} are the sum of number of incoming links to node i and the sum of number of outcoming links to node i, respectively. SP_{ij} is the shortest travel path between i and j.

Table 1: Indicators and definitions of road network performance quantification

Indicators	Definition
Average node degree	The average of the sum of the number of links connected to all nodes in the road network. This parameter represents the connectivity of the road network.
Average shortest path	The average of the sum of the shortest traversable distances between any two nodes. This parameter represents the accessibility of the road network.

Betweenness Centrality (BC) is also a vital variable to evaluate the link importance. The definition of BC is "the frequency with which a point falls between pairs of other points on the shortest paths connecting them" (Freeman, 1978: p221). The definition of BC is also applicable to the evaluation of link criticality. The higher the value of BC, the more critical the link is to the performance of the global road network.
The expression of the BC is:

$$BC(l) = \sum_{i \neq l \neq j} \frac{\sigma_{ij}(l)}{\sigma_{ij}} \qquad (3)$$

where $\sigma_{ij}(l)$ is the number of shortest paths that pass through the link l from node i to node j, while the σ_{ij} is the number of all available paths that traverse from these two nodes in the road network.
Elevation is a significant attribute of a link. By calculating the difference between the flood depth and the elevation of the corresponding link, the inundation depth of the link by the flood can be derived. The road network elevation can be obtained from a Digital Surface Model (DSM).

2.2. Flood intensity measure and risk analysis
The impact of floods on the road network is mainly determined by two factors, the flood depth and the flood velocity. The flood depth refers to the inundation depth of the link by the floodwater. Shahdani (2022) proposed a relationship between the maximum vehicles speed and inundation depth (Table 2).

Table 2: Effect of flood level on link maximum vehicle speed (from Shahdani et al., 2022)

Flood Depth (m)	Max Vehicle Speed (km/h)
Depth < 0.1	Road Speed unlimited
0.1 ≤ Depth < 0.3	20
0.3 < Depth	0 (Link Closed)

According to these three categories, as the flood depth increases, the max speed of vehicle on roads decreases and the risk to the road posed by floods becomes higher.
Flood velocity is another factor affecting link performance, causing vehicle instability during flood events. The flood depth derives the critical flood velocity, determining the maximum flood velocity that vehicle can withstand (Wang 2021). Herein, the critical flood velocity in two directions is considered: the flow parallel and perpendicular to the vehicle (Eq. 4 and Eq. 5).

For 0° and 180°:

$$U_c = \alpha(h_f/h_c)^{\beta} \sqrt{2gl_c[\frac{\rho_c h_c}{\rho_f h_f} - R_f]} \qquad (4)$$

For 90°:

$$U_c = \alpha(h_f/h_c)^{\beta} \sqrt{2gb_c[\frac{\rho_c h_c}{\rho_f h_f} - R_f]} \qquad (5)$$

where U_c is the critical flood velocity of the incoming flow to cause the vehicle instability; α and β are parameters associated to the vehicle physical features and vehicle-road connection condition, such as vehicle appearance, type of tyre and roughness of vehicle-road connection surface. h_f and h_c are flood depth and vehicle height respectively, g is the acceleration of gravity (9.8 m/s^2), ρ_c and ρ_f are densities of vehicles and incoming water, R_f is a parameter that controls

Table 3: Parameters for calculating critical flood velocity of SUVs and Car (from Wang et al., 2021).

Vehicle	Parameters								
	α	β	h_c (m)	g (m*s^-2)	l_c (m)	b_c (m)	ρ_c (kg*m^-3)	ρ_f (kg*m^-3)	R_f
SUV	0.367	-0.451	1.737	9.8	5.089	1.983	203	1000	0.551
car	0.492	1.48	-0.344	9.8	4.945	1.845	170.44	1000	0.65

whether the vehicle floats or not. In Eq. 4 and Eq. 5, only two parameters are different (l_c and b_c), which represent the length and width of the vehicle suffering incoming flood. According to Wang (2021), the most unfavourable condition is due to incoming flood perpendicular to vehicle; therefore, the Eq. 5 is adopted to derive the critical incoming flood velocity. Values of all parameters in Eq. 5 for critical velocity calculation are shown in Table 3.

Wang (2012) determined the risk to vehicles due to flood velocity by calculating the ratio of the actual flood velocity and the critical flood velocity (Eq. 6).

$$\text{Risk} = U_f/U_c \tag{6}$$

Due to the different weights of different vehicles, the ability to resist the impact of floods is also different. For each return period, two different types of vehicles (SUV and car) are analysed separately (Wang et al., 2021). Eventually, the risk level of the road network is visualized at network level through maps.

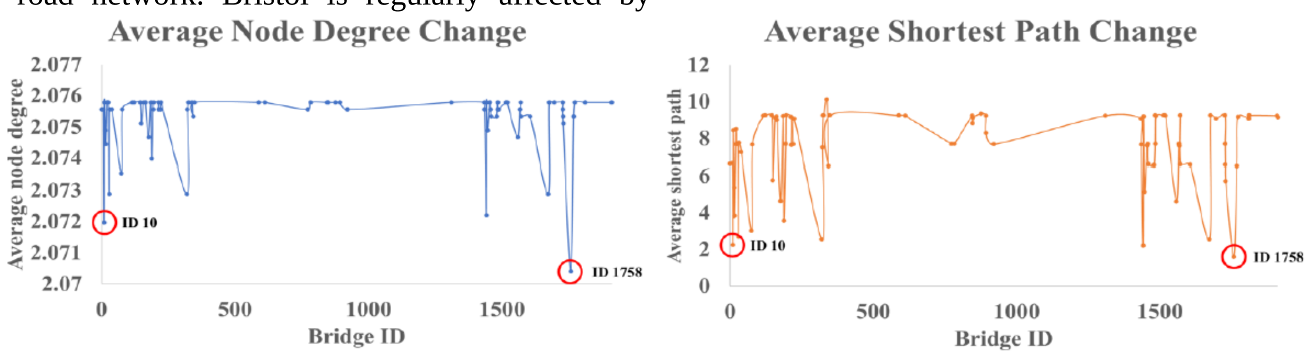
2.3. The case study

Bristol is a middle-size city in the southwest of England, cut across by the Avon River. There are many bridges located in Bristol, connecting the road network. Bristol is regularly affected by flooding hazards, resulting in damaged bridges and a less functional road network (ARUP, 2020). Road network data were collected from OpenStreetMap (OSM), an open-source database that synthesizes all geospatial features (Costa Fonte et al., 2017). NetworkX is used to construct the digital road network components and analyse the topological performance of the road network; it is a Python module that can support user to create, manipulate and analyse the structure and physical features of road network (NetworkX, 2022). Moreover, BC can be calculated directly in NetworkX.

The DSM was obtained from the UK's Department for Environment Food & Rural Affairs (DEFRA) data service platform (2021). It should be noted that DSM data is applied instead of Digital Elevation Model (DEM) because DSM contains the elevation of all environmental and artificial features, while DEM is the elevation of the bare surface of the earth.

Flood data for the different return periods is provided by Fathom who is a company leading in flood and climate risk (Fathom, 2023); 10-year and 200-year return periods are used for the road network risk analysis.

In a preliminary application, two main road classes (motorway and trunk) are obtained from OSM and imported into GIS. The road network



(a) (b)

Figure 2: Average node degree (a) and average shortest path (b) variations based on bridge closed.

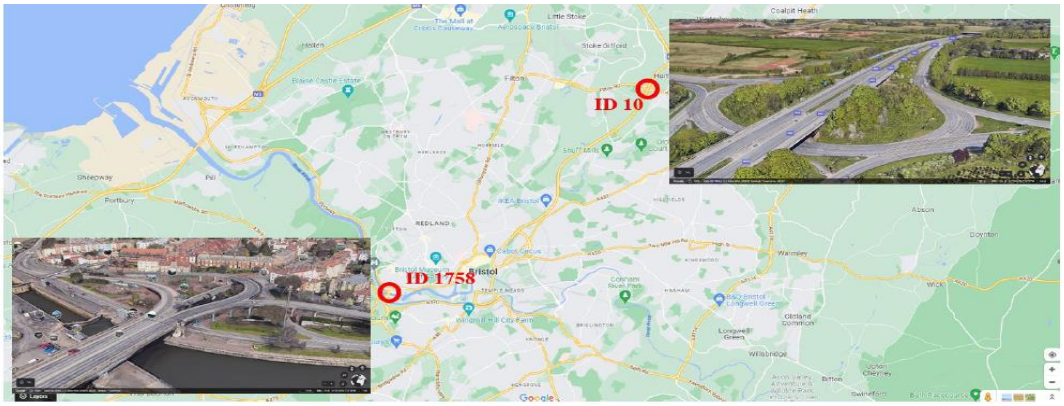


Figure 3: Locations and photos of bridges with ID 1758 (left) and 10 (right).

extends from Kingswood to the east, Avonmouth to the west, Hartcliffe to the south, and Severn beach to the north. The network is composed of 8920 nodes and 1944 links, including 89 bridges and 1855 roads.

3. RESULTS

In this section, the indicators presented in Sec. 2 are applied to understand the road network performance for 10-year and 200-year return periods. The analysis of the results is divided into the global performance of the road network, the criticality assessment of the links and the risk assessment of the links during floods.

3.1. Global road network performance analysis

Fig. 2 shows the average node degree and the average shortest path considering the closure of different bridges. Critical bridges which, if removed (i.e. rendered inaccessible to traffic) give rise to the lowest indicators or performance. Fig. 2 also shows that the change trends of the average node degree and of the average shortest path are coherent when bridges are consequentially closed. It is worth noting that in Fig. 2(a) and Fig. 2(b) the minimum values of these two indicators are reached when bridges with ID 10 and ID 1758 are closed. Therefore, it can be inferred that these two bridges are critically significant for the topological capacity of the global road network. Fig. 3 shows the location of these two bridges in Google Maps, and photos in Google Earth.

ID 10 bridge is a viaduct at the intersection between Bristol and the main highway M32 in the UK. So, the viaduct significantly impacts traffic entering and leaving Bristol. ID 1758 bridge (Cabot Way) is a riverine bridge within the main arterial road in the centre of Bristol. When this bridge is closed, connectivity and accessibility between the sides is significantly reduced. Therefore, the bridge plays an important role in the road network.

3.2. Criticality of link analysis

According to Sec. 2.1, Eq. 4 is used to calculate the criticality of links in the road network. To express the criticality of links in the road network, the BC values of all links in Bristol are mapped in the graph according to five categories of BC, which represent low criticality (green), medium-low criticality (cyan), medium criticality (yellow), medium-high criticality (orange), and high criticality (red). Fig. 4 shows the classification and mapping of link criticality in the road network in Bristol. The majority links in North of Bristol are in the high criticality and medium-high criticality classifications, and links in the South are generally in the low criticality classification.

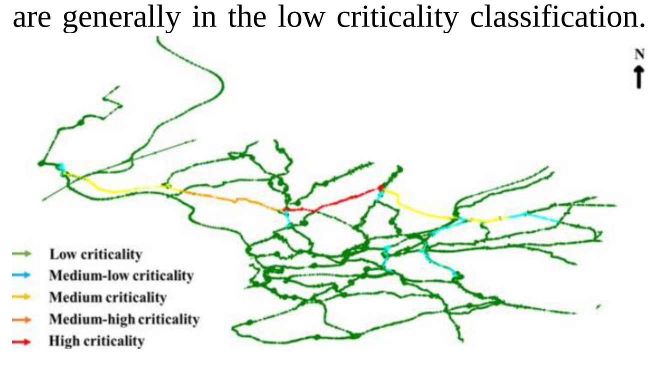


Figure 4: Link criticality classification and mapping in Bristol.

This result shows that the links in the North are more critical than those in the South. From the geographical distribution of Bristol's road network, the road network in the North of Bristol is sparser than that in the South. It shows that the redundancy of the northern road network is relatively low. Compared with the southern road network, the available routes in the northern road network are more limited. In addition, for vehicles in the East-West direction, the high criticality and medium-high criticality paths do not need to detour, and the driving distance is shorter than the low criticality path. Hence, in the East-West

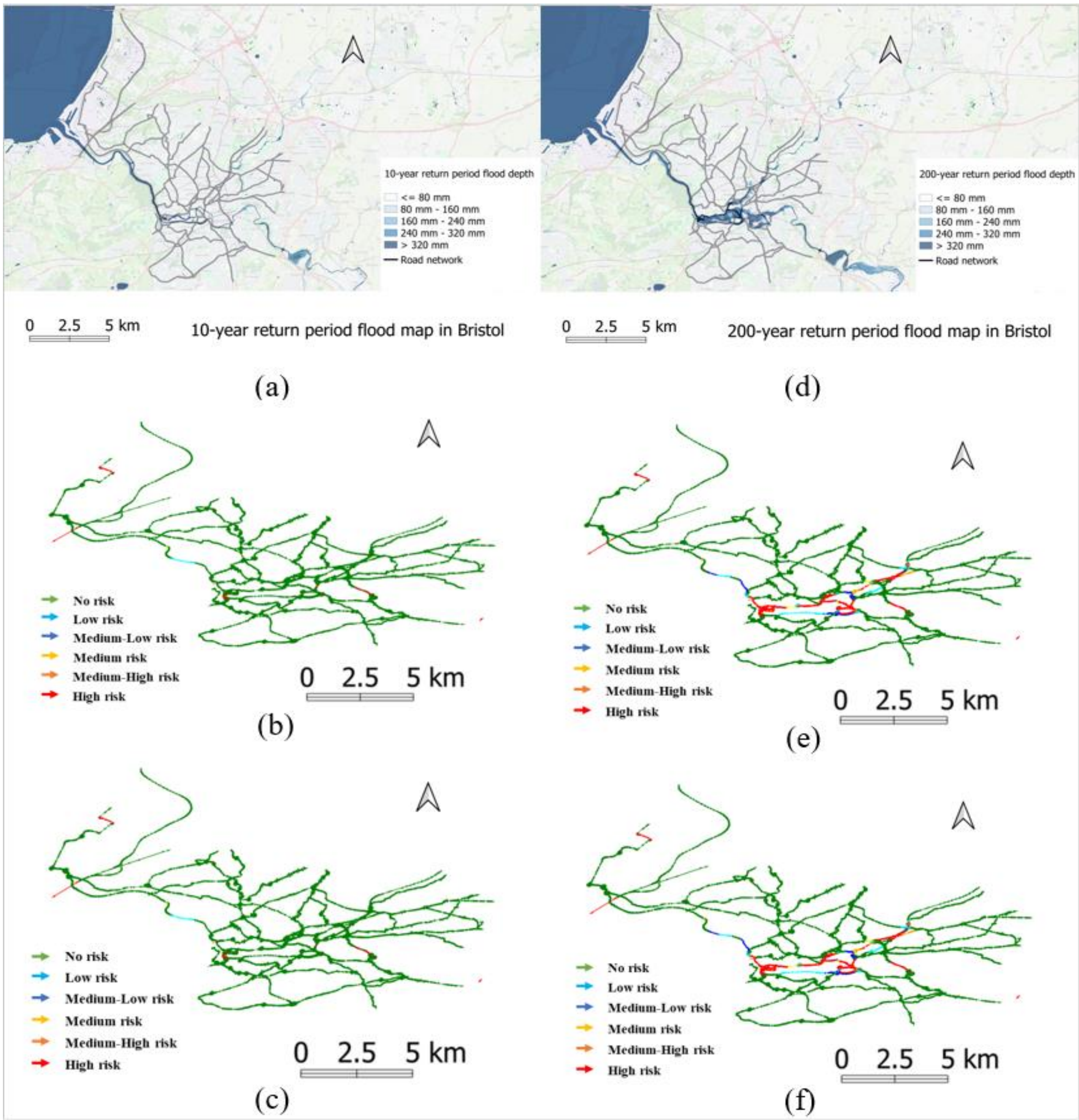


Figure 5: Link risk classification; a) 10-year return period flood extent; b) risk classification for SUVs in 10-year; c) risk classification for cars in 10-year; d) 200-year return period flood extent; e) risk classification of SUVs in 200-year; f) risk classification of cars in 200-year.

direction, more shortest paths pass through the high criticality and medium-high criticality links. Therefore, Fig. 4 shows high and medium-high criticality of the road network in the North of Bristol, while low criticality characterizes the South.

3.3. *Risk analysis of link by integrating flood depth and velocity*

In this study, the flood data of 10-year and 200-year return periods are used to analyse the risk level of the road network in low-intensity and high-intensity flood hazards, respectively. As mentioned in Sec. 2.2, flood depth and flood velocity are two factors that affect the link risk level. For the assessment of the flood velocity on the risk level of the road network, the unfavorable principal proposed by Wang (2021) was used, and the critical flood velocity of the two vehicles was calculated by Eq. 5. Then, the risk level of the vehicle caused by the flood velocity is derived by Eq. 6. For the assessment of the flood depth on the risk level of the road network, the criterion of the impact of the flood depth on the vehicle speed in Table 2 is used. To integrate flood velocity and flood depth into a comprehensive assessment of vehicle risk, Table 4 presents a classification matrix for vehicle risk based on these two factors. Classification is divided into 6 categories as no risk (green), low risk (cyan), medium-low risk (blue), medium risk (yellow), medium-high risk (orange), and high risk (red). Fig. 5 shows the risk range of the road network in the flood of 10-year and 200-year return periods, as well as the classification of the risk level of SUVs and cars.

Table 4: Link risk classification

The ratio of actual flood velocity to critical flood velocity (Uf/Uc) \ Flood depth (m)	[0, 0.1)	[0.1, 0.15)	[0.15, 0.2)	[0.2, 0.0.25)	[0.25, 0.3)	[0.3, +∞]
[0.000, 0.005)	No risk	Low risk	Medium-Low risk	Medium risk	Medium-high risk	High risk
[0.005, 0.25)	Low risk	Low risk	Medium-Low risk	Medium risk	Medium-high risk	High risk
[0.25, 0.5)	Medium-Low risk	Medium-Low risk	Medium-Low risk	Medium risk	Medium-high risk	High risk
[0.5, 0.75)	Medium risk	Medium risk	Medium risk	Medium risk	Medium-high risk	High risk
[0.75, 1)	Medium-high risk	Medium-high risk	Medium-high risk	Medium-high risk	Medium-high risk	High risk
[1, +∞]	High risk	High risk	High risk	High risk	High risk	High risk

As expected, the risk level of SUVs and cars in the 200-year return period flood is higher than that in the 10-year return period flood. Therefore, high-intensity flood events have a more profound impact on the road network. However, in both 10-year and 200-year flood return periods, the risk level and distribution of SUVs and cars are the same.

4. DISCUSSIONS

This graph-based model quantified the global road network performance in terms of average node degree and average shortest path. Furthermore, through stress testing, the importance of bridges who have significant contribution to global road network performance were assessed based on average node degree and average shortest path changes. Road criticalities were evaluated through betweenness centrality to show the critical roads within road network. Moreover, for road network risk analysis, this model adopted 10-year (low-intensity flood) and 200-year (high-intensity flood) flood return periods to assess the vehicle risks both for SUVs and cars. Results showed that high-intensity flood resulted in higher vehicle risk.

However, in this study, the two features of road network performance and flood hazard are unintegrated. In future work, links defined as high risk in risk classification cloud be use for stress testing to derive the changes in average node degree and average shortest path to reflect the performance degradation of the road network and the redistribution of link criticality in actual flood event.

5. CONCLUSIONS

This article introduced a graph-based integrated framework to study the road network topological performance and risk in flooding events. This framework consists of two features: the road network topology feature and the flood intensity feature. For the topology module, the performance of the road network in Bristol was quantified by average node degree and average shortest path, reflecting the connectivity and accessibility of road network. By using the stress testing on all bridges in Bristol, two critical bridges identified. Combined with Google Maps and Google Earth, the reasons why these two bridges are critical were analysed from the perspective of geographical location and type. Furthermore, the criticality of links is evaluated by betweenness centrality. This study showed that the criticality of paths with low redundancy and short length is relatively high in the whole road network. For the risk assessment of the road network in flood events, low-intensity floods and high-intensity floods were used to evaluate the risk levels of SUVs and cars, respectively. Results showed that high-intensity flooding increases the risk to the road network, although this study showed no difference in the risk level of SUVs and cars during the same flood scenario.

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