

Coupling Natural Hazard Estimates with Road Network Analysis to Assess Vulnerability and Risk: Case Study of Freetown, Building Disruption Simulations in Hydrometeorological Risk Areas in Data-Scarce Sierra Leone

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Abstract

Many of the world's most disaster-prone cities are also the most difficult to model and plan. Their high vulnerability to natural hazards is often defined by low levels of economic resources, data scarcity, and limited professional expertise. As the frequency and severity of natural disasters threaten to increase with climate change, and as cities sprawl and densify in hazardous areas, better decision-making tools are needed to mitigate the effects of near- and long-term extreme events. We use mostly public data from landslide and flooding events in 2017 in Freetown, Sierra Leone to simulate the events' impact on transportation infrastructure and continue to simulate alternative high-risk disasters. From this, we propose a replicable framework that combines natural hazard estimates with road network vulnerability analysis for data-scarce environments. Freetown's most central road intersections and transects are identified, particularly those that are both prone to serviceability loss due to natural hazard and whose disruption would cause the most severe immediate consequences on the entire road supply in terms of connectivity. Variations in possible road use are also tested in areas with potential road improvements, pointing to opportunities to harden infrastructure or reinforce redundancy in strategic transects of the road network. This method furthers network science's contributions to transportation resilience under hydrometeorological hazard and climate change threats with the goal of informing investments and improving decision-making on transportation infrastructure in data-scarce environments.

Prioritizing transportation investments and optimizing transportation planning decision-making pose important challenges. On top of this, a proliferation of natural disasters, human-caused disruptions, increasing investments in adaptation, and growing anxiety over climate change have brought urban resilience and vulnerability to the forefront of conversations on city and transportation planning. Vulnerability to disasters poses enormous challenges. Environmental anomalies in cities with the highest poverty rates and lowest investment levels in resilience are particularly prone to severe disasters. Serious data scarcity and a lack of capacity to generate high-quality data, combined with broader resource constraints, restrain resilience improvement in the most vulnerable cities.

Freetown, with a population of just over 1 million, is the capital of Sierra Leone in West Africa. It stands out

both for a recent high-impact disaster and low levels of development. With a life expectancy of 51 years and an average of three years' schooling, Sierra Leone ranks 179th out of the 188 countries assessed in the Human

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Development Index (1). Freetown does not have a clear hierarchy of roads or pedestrian facilities in most high pedestrian traffic areas. The city uses a single set of traffic signals, with other critical intersections controlled by traffic police. Without any rail lines, all formal and informal inland modes travel on the road network (Figure 1).

In August 2017, a high-magnitude landslide struck the Freetown Peninsula. This was followed by mudslides and flooding. The events impacted 6000 people, with 1100 declared dead or missing. Direct impacts to the transportation infrastructure amounted to losses of US\$1 million, including the destruction of eight pedestrian bridges, two road bridges and 5.5 kilometers of roadways (2). The economic and human impact from this connectivity loss easily exceed initial loss estimates (2, 3).

As reconstruction efforts and recovery build momentum, local urban transportation integration projects seek to review and improve strategic investments for fixing infrastructure shortfalls while mitigating future disasters. Post-disaster recovery provides opportunity to improve resilience (4). Our framework contributes to this by presenting a road vulnerability assessment method that incorporates network science metrics to assess road network vulnerability to disruption.

We develop a replicable method to assess vulnerability and model the performance of the entire road network supply through simulated disruptions in high-risk areas. Using limited data sources, we pilot this method to enhance transportation infrastructure planning in data-scarce environments. Finally, we discuss the remaining limitations of the approach and potential improvements.

We first build a topological model of the road network in the Freetown Peninsula where 13,624 nodes represent road intersections and 16,279 links represent road transects that run between the nodes (5, 6). The network's structure under typical conditions is then assessed to gain an overview of the system's operational capacity. Network centrality metrics are used to identify critical nodes for Freetown's road network connectivity, then estimate serviceability and calculate vulnerability to disruption. Using Geographical Information System (GIS) mapping technology, we define high-hazard areas to estimate disruption risk and subsequent road supply consequences. High-risk nodes are then removed from the road network to simulate disruption where, for example, landslides compromised a series of intersections and rendered them impassible, and network centrality is recalculated under the disrupted conditions to project changes in the network's serviceability. Based on local government's urban transportation plans, we identified sites in need of greater redundancy or hardening, allowing for reconstruction efforts to be focused on reducing the risk of natural hazard disruption to the road network supply.

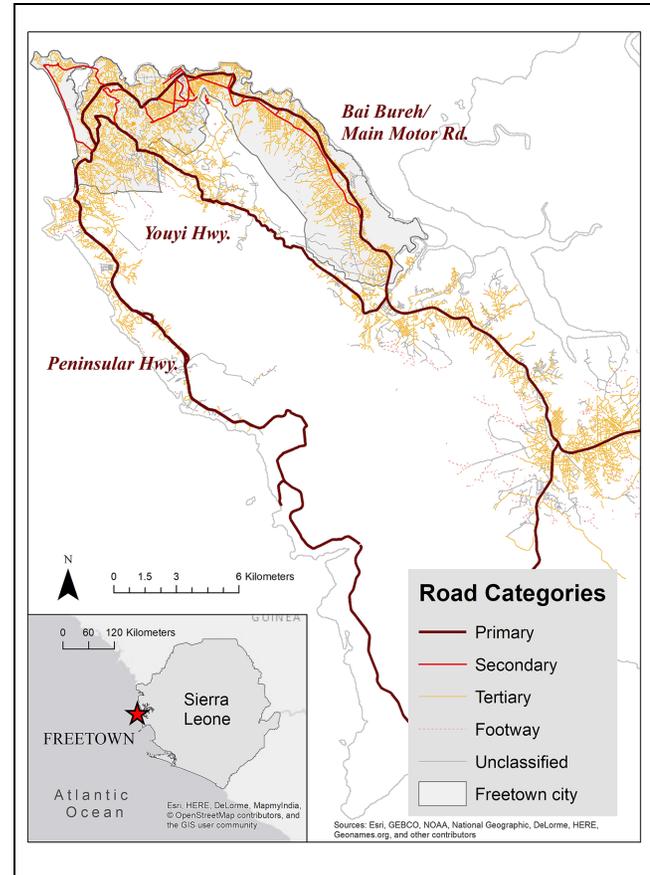


Figure 1. Study location and road network overview.

Related work on maintaining control in case of failure and establishing methods for preferential repair strategies have been subject of several studies (7).

Overview of Network Disaster Resilience, Vulnerability, and Risk

Hazards assessment, vulnerability diagnostics, and infrastructure investments aim to improve urban and transportation system resilience. The concept of resilience has gained traction through diverse fields, and with special applications to multiple modes in transportation (8, 9). It centers on how systems perform and recover after disasters or stress (10, 11).

The United Nations Office for Disaster Reduction presents a broader definition of resilience as “the ability of a system, community or society exposed to hazards to resist, absorb, accommodate, adapt to, transform and recover from the effects of a hazard in a timely and efficient manner, including through the preservation and restoration of its essential basic structures and functions through risk management” (12). We view resilience as the flipside of vulnerability, which aligns with climate-change

scholarship (13). Increased resilience diminishes vulnerability and therefore risk, with risk as the product of hazard likelihood, magnitude, and consequence. (14–17).

Network science is the “study of the collection, management, analysis, interpretation, and presentation of relational data [that] allows us to address deep questions about human, biological, economic, and other systems that exhibit interdependent organization” (18). As it builds from graph theory and mathematics, it focuses less on geography and more on relational connectivity. Nodes connect to each other through links, and the network’s arrangement of component nodes connected through links is defined as its topology. To incorporate the crucial role of physical space, we set nodes as physical intersections of streets, and links as the street transects that run between the nodes to construct a topological model of transportation street network (6).

Network science has been recognized for its applications to the study of human mobility for nearly two decades, and subsequently used to identify vulnerabilities to random and targeted attacks or disruption to transportation infrastructure in myriad studies (19–21). Some examples are: the critical elements of the Australian National Highway system (22), the Swiss road transportation network vulnerability (23), seismic vulnerability of rural roads in Italy (24), differentiated network vulnerability effect of the Swedish national road system (25), city road network vulnerability in France (26), critical links in Florida’s transport network (27), the structural impact in the 2010 earthquake aftermath in Haiti (28), the Madrid metro circular system vulnerability in Spain (29), and the public network vulnerability index of York, England (30). In that same period, network science was reinforced through a review as a revealing vulnerability analysis method with important implications for policy development and infrastructure planning (31). In addition, piloting studies have specifically identified the potential for transportation networks to significantly improve disaster resilience through topological models based on their ability to describe systemic performance (32).

This paper builds upon traditional concepts of risk and network science as pillars to study road network vulnerability. For the purposes of this study, analysis of resilience is focused on network performance amidst disruptions in data-scarce environments, whereas applications to long-term recovery and resilience to natural hazards are discussed but are otherwise reserved for future study. Additionally, we focus on hydrometeorological hazards, or natural hazards that originate from atmospheric, hydrological or oceanographic processes (12) which have become central to climate-change resilience research, (16) such as river and coastal flooding (sea level rise and storm surge), landslides and mudslides. It innovates by using centrality metrics to study the different roadway nodes and

links importance to the overall network performance in data-scarce environments. It thus presents new replicable methodology to measure vulnerability within natural hazard and risk theory by identifying “where failure of some part of the transport infrastructure would have the most serious effects on access to specific locations and on overall system performance” (22).

Methodology

Identifying High-Centrality Intersections

Topological centrality is used to identify the most important road intersections and transects (33), serving as a proxy to road network supply or serviceability (34). Centrality metrics rely upon calculation of the shortest path, here defined as the shortest possible route between an origin and a destination. The key metric of betweenness centrality (BC) quantifies the number of times a node lies on any shortest paths in the graph, including every possible pair of origin and destination points. Its calculation is given by:

$$BC(v) = \sum_{i \neq v \neq j} \frac{\sigma_{ij}(v)}{\sigma_{ij}} \quad (1)$$

where v is any node, σ_{ij} is the total number of shortest paths between unordered node pairs i and j , and $\sigma_{ij}(v)$ is the number of those shortest paths which pass through v (35). It thus represents the percent of total shortest paths that pass through any given node, ranging from 0 to 1 in value. BC serves as a strong measure of how important each node is for all origin–destination node pairs within the transportation network, especially established for identifying critical transportation junctures which lie on many shortest paths and have low redundancy in nearby links (19).

In order to calculate the BC metrics for all nodes in the Freetown road network, we used GIS data of Freetown Peninsula’s street features provided by the World Bank (Sierra Leone 1968 UTM Zone 28N projection). The Shapely package in Python was used to generate a list of 13,624 uniquely enumerated and geocoded nodes, 16,279 edges, and various attributes including the physical distance measures calculated in GIS software.

Given the lack of data related to traffic counts, trips, needed destinations, and other demand information, we used the Dijkstra algorithm in Python’s NetworkX package to determine shortest paths by distance weights. The NetworkX package also served to assess the road network centrality in a base case and under disruption simulations. ArcGIS served to assess environmental variables that identified natural hazard areas and geocoded nodes with these areas.

Identifying High-Hazard Areas with Mainstream Environmental GIS Data

In order to determine those areas where natural disaster occurrence was likely, we used open-sourced environmental GIS data such as the United States Geological Survey's coarse-grain (30-meter resolution) Digital Elevation Model (DEM) and Freetown's hydrographic information provided by the World Bank to build our hazard models. The World Bank has been active in the region collecting environmental data sets through partnerships with government agencies and local university institutions with the aim to foster technical assistance and capacity building, and collaborates with international universities to develop research in pressing areas such as disaster risk reduction. These inputs helped us develop five hazard layers commonly considered: river flooding, landslides, mudslides, low sea level rise plus storm surge, and high sea level rise plus storm surge.

We recognize that in data-poor environments, hydro-meteorological risk maps may not be available. Therefore, we additionally utilized ESRI Mapping software's recommendation of using geographic buffers around medium- to high-slope areas and river polylines to estimate areas at risk of riverine flooding, landslide, and mudslide in Colorado (36), and applied these methods to Freetown to gain an approximation of the extent of high riverine hazard areas. These methods returned almost identical results to the local samples of hydrographic information, flooding and landslide hazard maps while only relying on DEM and polyline river shapefiles.

With the DEM, low and high sea level rise plus storm surge hazard areas are proposed based on average vertical predictions of sea level rise and extreme sea level events caused by storm surges and high tides for Sierra Leone. Global predictions indicate that by 2100 there is high confidence that the lowest sea level rise will be of 0.2 m (0.65 ft.) and the highest sea level rise will be of 2 m (6.56 ft.) above current mean sea level (37). According to global hydrodynamic models, the 100-year return period storm surge event estimates for the Sierra Leone coast vary from 2 to 2.5 m (6.56 to 8.2 ft.) (38). Overlapping these five hazard layers allowed us to build a multi-hazard constraint map for Freetown's peninsula.

For the river flooding hazard levels, the hydrographic GIS data was used and Euclidean buffered zones of 100 and 200 m (328 and 656 ft.) around the river polylines were defined as higher and lower likelihood, respectively, of flooding. For the landslide hazard levels, we calculated Euclidean buffered zones of 100 and 200 m around slope polygons with degrees varying between 20–40 (39) giving us higher and lower likelihood, respectively, of landslide events. To define the mudslide hazard levels, we first identified intersections of river flooding and landslide hazard to determine mudslide initiation zones.

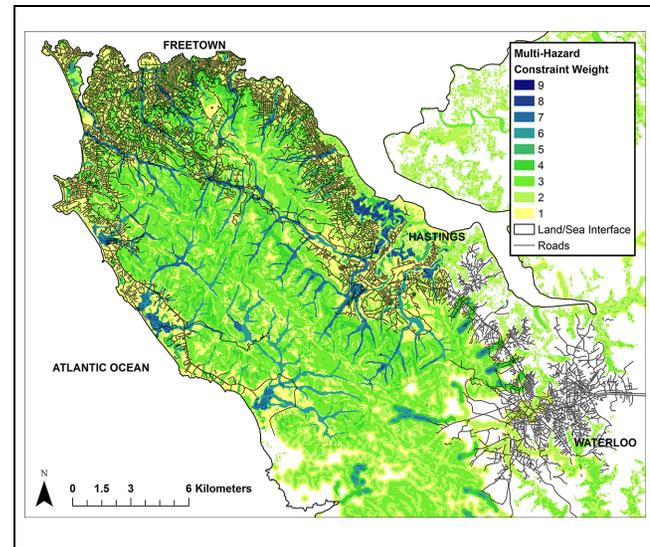


Figure 2. Multi-hazard constraint map for Freetown's peninsula illustrating the convergence of the ratings for river flooding, landslides, mudslides, sea level rise, and storm surge likelihood and extent.

Secondly, we applied 100-meter buffers for higher likelihood (328 ft.) and 200-meter buffers for lower likelihood (656 ft.) around river polylines extending up to 1 km downstream from mudslide initiation zones. For the identification of low and high sea level rise plus storm surge hazard areas, inland surfaces adjacent to the coastline equal or inferior to 2 and 5 m (6.56 and 16.4 ft.), respectively were assessed as low flooding hazard likelihood. Finally, we combined the different hazard likelihood weights into one multi-hazard constraint layer that resulted in nine levels of hazard likelihood (depicted in Figure 2).

This constraint layer summarizes the general likelihood of any given area to suffer disruption from a weather-related hazard or coastal flooding. This method derives from McHarg's concept of "Suitability Analysis" (40) that investigates best, and in this case, worst environmental conditions for human habitation with the use of transparent map overlay techniques to identify these conditions in space. These constraint layers only aim to project areas that are more at risk in general in the long term, for example for river and coastal flooding, and do not consider that all these hazards have the possibility of converging in time for a specific disaster event. For multi-hazard disaster events, it is important to consider hazard combinations with similar triggering factors such as rainfall for river flooding, landslides, and mudslides.

Previous hazard assessments done in Freetown allowed us to validate the quality of our constraint layers and hazard estimations. Additionally, our models coincided with the impacted areas of the 2017 mudslide, which supports our method's approximate accuracy (2).

With the highest centrality intersections defined in the street network, we aimed to identify subsets of nodes with high natural disaster risk. This allowed us to formulate a risk assessment.

Measuring Risk through the Interaction of Topological Centrality and Multi-Hazard Constraint Layers

Disaster risk assessment is commonly done by identifying hazards, exposed elements, and their intrinsic characteristics (12). This is also referred to as the crossing of likelihood and consequence. Hazards can be characterized by their location, probability, frequency, and intensity; whereas the exposed elements can be described by their vulnerability through their various properties, such as physical, social, environmental, etc. In this project, hydrometeorological hazards such as riverine floods, landslides, mudslides, and coastal flooding are characterized by their approximate area of extent and their likelihood of occurrence and causing road disruption $I(D)$. Our subject of study, or exposed element, is the road network in the Freetown Peninsula. The road intersection and transects BC quantifies the node or link's importance to the network's overall connectivity. The network element's vulnerability or BC relates to the consequences of disruption $c(D)$ in case of a hazard occurrence.

Considering the above, disaster risk R is here represented by the conceptual formula:

$$R = I(D) * c(D) \tag{2}$$

Our risk matrix design was inspired by Cox's theory (41) for building semi-quantitative screening tools for risk assessment, based on the principle of weak consistency between the categorization and ranking of risk. Thus, the idea that any given ranking of high risk needs to be separated by at least one other class from low risk, which assumes the minimum need for three risk classes (depicted in Figure 3).

Considering that we are looking at the potential for loss from disruption or damage to the road infrastructure, the novelty here is using network centrality metrics to assess vulnerability, gauging systemic consequences or loss. Network science allows for measuring significance of individual elements in terms of connectivity within the overall network. Therefore, our risk calculations assess how the disruption or damage of a street crossing might impact the street supply system in the overall network developed to serve the Freetown Peninsula. The risk classification thresholds are based on quartiles for BC and for hazard ratings. As our BC values for the Freetown Peninsula road network nodes range from 0 to 0.4, Low

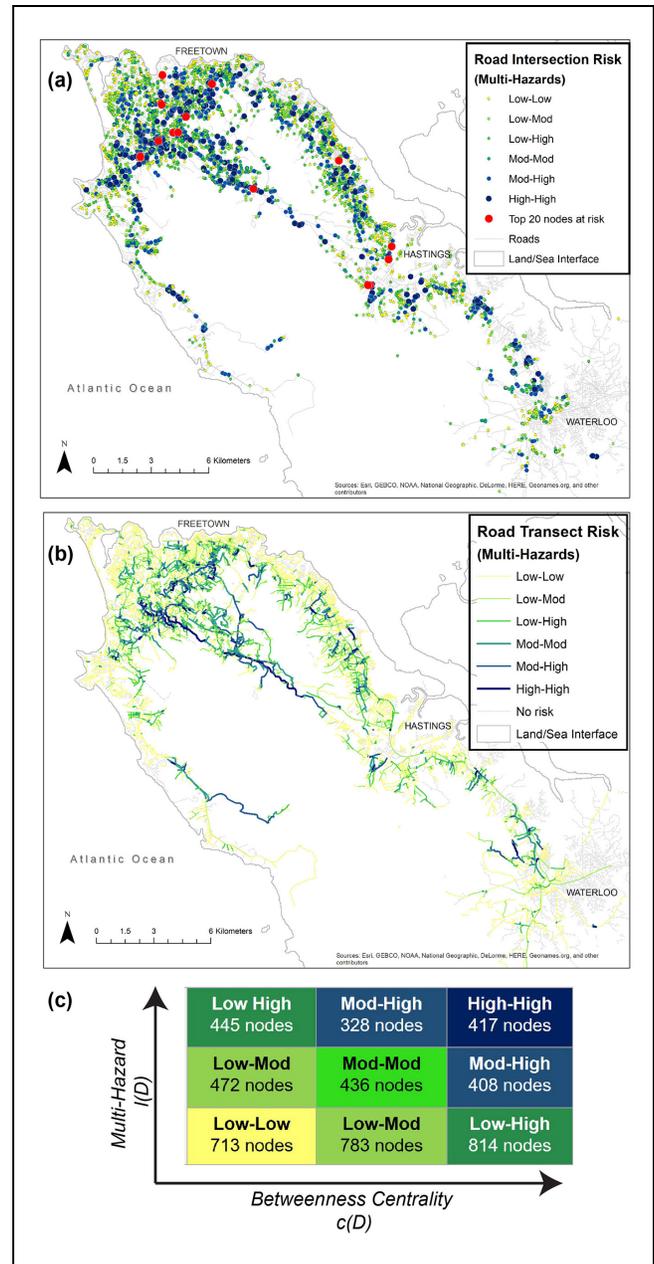


Figure 3. Showing risk categories for (a) road intersections, and (b) road transects, based on (c) multi-hazard risk matrix.

$c(D)$ class correspond to 0.000180–0.001424; Moderate $c(D)$ class correspond to 0.001425–0.007268; and High $c(D)$ class correspond to 0.007269–0.400221 values. Our multi-hazard classes constraint weights range from 1 to 9, where Low $I(D)$ corresponds to areas with 1–3 hazard constraint weights; Moderate $I(D)$ corresponds to areas with 4–6 hazard constraint weights and High $I(D)$ class corresponds to areas with 7–9 hazard constraint weights.

Findings

Road Disruption Risk Matrix

The road intersections (nodes) in the Freetown Peninsula network were categorized as a function of their risk to all hazards studied in this project (Figure 3a). The node risk level at the end and beginning of each street transect was averaged to obtain the risk for the network links or transects (Figure 3b). We can identify a total of 412 nodes and 26.7 km of links that present high *BC* and high exposure to natural hazards corresponding to high-high risk network components. In Figure 3a and b, results identify specific road nodes and links that are highly exposed to natural hazards and if disrupted will most likely cause the most severe consequences to the Freetown Peninsula's road supply network. The high-high risk nodes serve important roles in the everyday connectivity of the network and are at high risk of failure due to natural hazards. Figure 3c illustrates the risk matrix built for the multi-hazards constraint with the number of nodes under each risk class.

Road Disruption Simulations in High Risk Areas and Consequential Changes in Centrality

High-high risk nodes were removed to simulate where specific natural hazard types have the highest likelihood of disabling a road intersection with the highest impact on the overall connectivity. Figure 4 identifies five simulations of high-high risk node elimination. The simulation areas were chosen from the top twenty highest risk nodes to represent different parts of the city and a diverse array of natural hazards. Simulations 1 and 3 show road disruption scenarios in high-hazard mudslide areas overlapping the arterial Bai Bureh Road in Hastings coastal town and in Wellington suburb, respectively; Simulation 2 shows a disruption in high-hazard landslide area crossing the inland arterial highway of Youyi, between Regent and Bathurst villages; Simulation 4 tests the road network cut off due to both river and sea level rise flooding hazards in Freetown's central business district (CBD) near Bambara Spring and Nicol Brook River; finally, Simulation 5 eliminates road intersections surrounding the Peninsular Highway in high-hazard mudslide areas in the Lumley suburb, mimicking the 2017 disaster impact to the road network in that region (2).

Although single nodes that coincide with those identified in the risk matrices are readily identifiable, eliminating only one key node has a relatively small effect on a system. To account for this and model the likely extent of a hazard-specific road disruption, neighboring nodes classified as high-high risk from the same hazard typology were eliminated as a group. Centrality for all nodes was then recalculated following each of the simulations

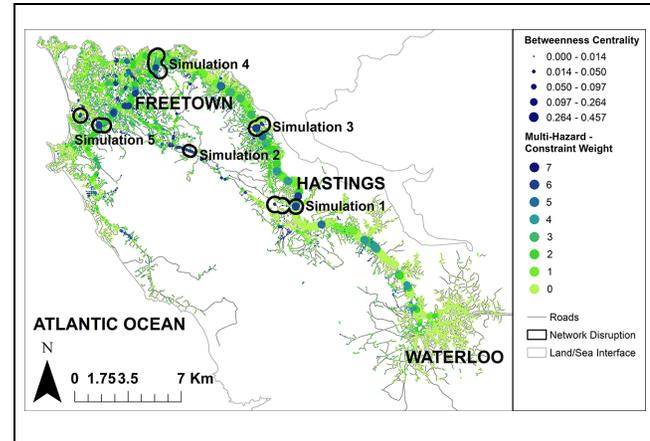


Figure 4. Road disruption simulation locations based on high-high risk node eliminations.

to project areas where there is gain and loss in *BC*. Deltas for each node were calculated by subtracting the *BC* after simulation from the base *BC*, with resultant values ranging from possible extremes of -1 to 1 , and 0 representing no change (Figures 5 and 6).

A summary of the impact to road network serviceability in Freetown from each of the five disruption simulations in high-hazard areas are presented below:

- Simulation 1: The disruption simulation at the mudslide high-high risk area in Hastings would disable Bai Bureh Road, the arterial highway of the peninsula, leading to a large redirection of centrality from the southeastern coastal road to the inland Youyi Highway. This translates to a detour of up to 25 km over roads with greatly decreased capacity to access the same nodes in the network. Important to note is that in this scenario, the nodes which become more central to the network also have high risk weights for rainfall triggering hazards and are therefore not reliable as an alternate route in the case of landslide and flooding weather conditions. In this respect, one policy implication may be the necessity to harden bridges against riverine hazards.
- Simulation 2: The inland landslide moderate-high risk area simulation disables intersections in a high landslide hazard but moderate to low centrality area in Youyi Highway. The result is low and diffuse gains in centrality throughout the system, with changes in centrality at approximately 10% the magnitude of other scenarios.
- Simulation 3: The coastal arterial mudslide high-high risk area cutoff at Wellington causes very similar results to Simulation 1, with a large redistribution of centrality towards the inland Youyi

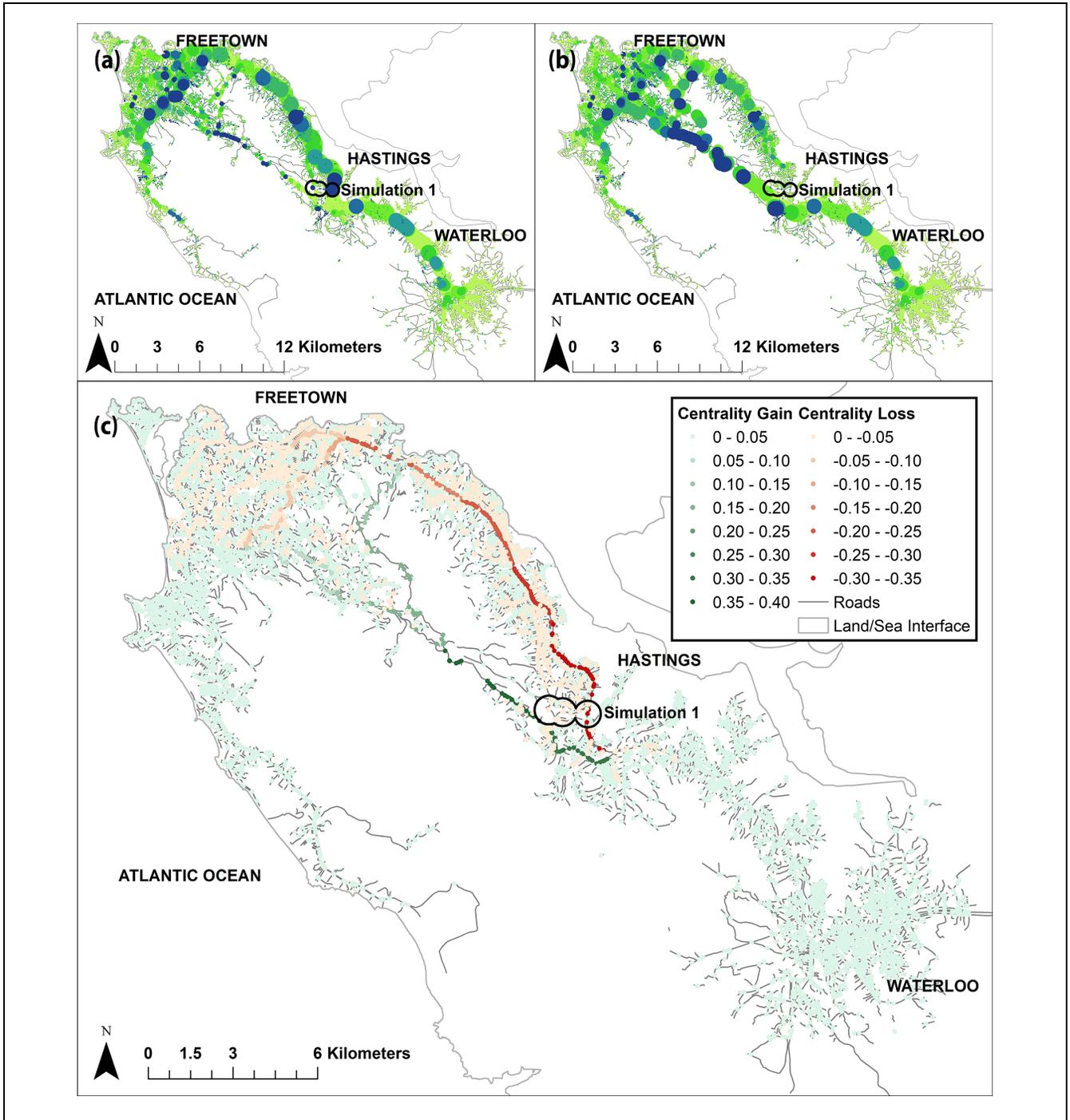


Figure 5. Simulation I: Southeastern mudslide, Hastings town BC in: (a) baseline scenario; (b) after simulation; (c) change in betweenness centrality.

Highway. However, here the disruption is projected at the midpoint of the Bai Bureh Road segment, rather than the far southeastern corner, causing the remaining arterial highway's centrality to decrease more significantly in comparison with Simulation 1. In Simulation 1, people directly north of the

disaster would still have to travel reasonably far north along Bai Bureh Road to reach any given destination, whereas they would have less distance to travel along this route in Simulation 3.

- Simulation 4: Freetown's CBD river and coastal flooding high-high risk area road disruption may

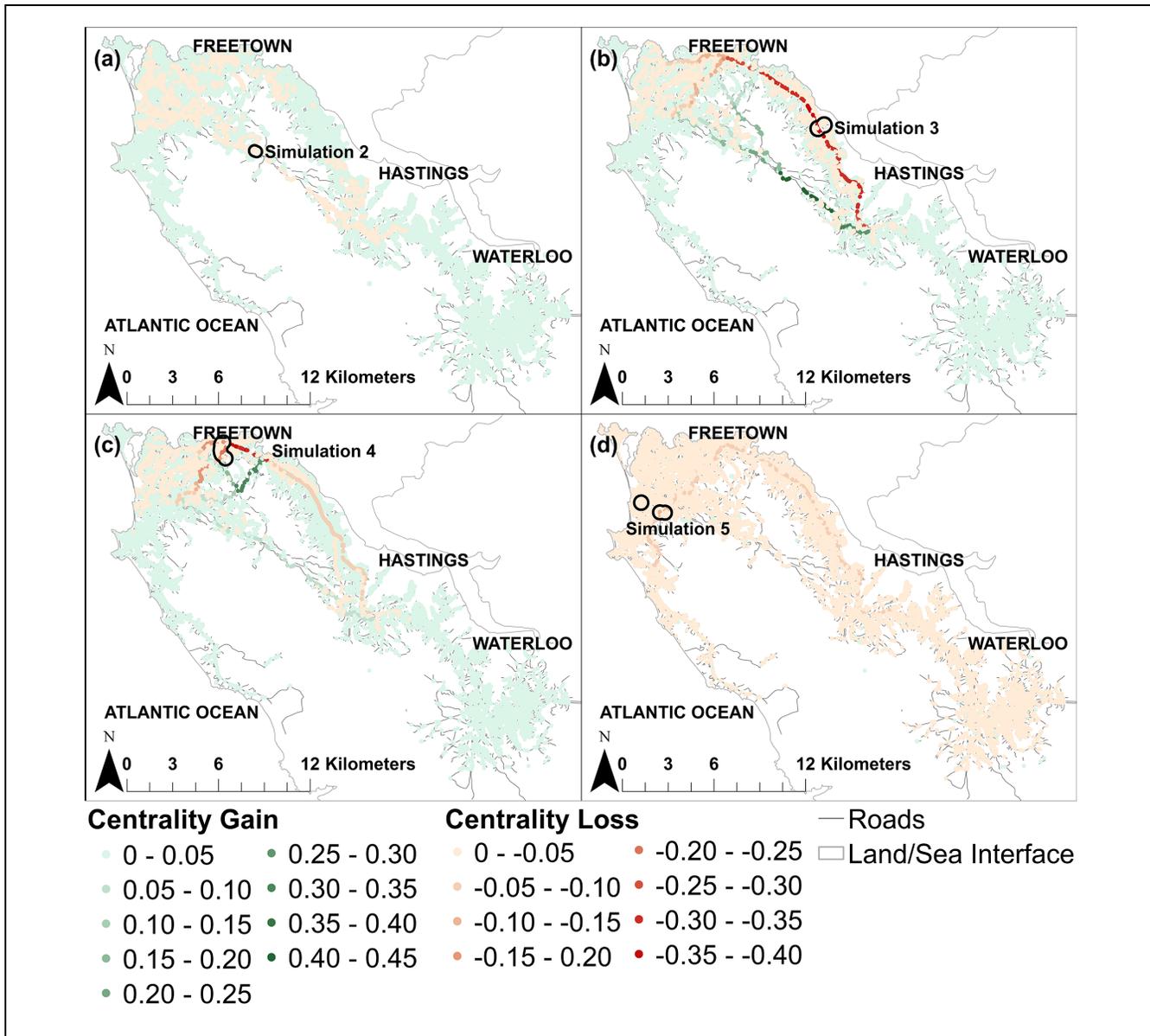


Figure 6. Change in BC in: (a) Simulation 2: Inland landslide between Regent and Bathurst villages; (b) Simulation 3: Coastal arterial mudslide, Wellington suburb; (c) Simulation 4: River and sea level rise flooding in Freetown CBD; (d) Simulation 5: 2017 mudslide impact in Lumley suburb.

have potentially devastating effects on loss of property and life, but the grid-like plan of the road network makes this zone more resilient in terms of road connectivity than all the other high-risk areas cutoff scenarios. Although the magnitude of change in centrality is similar to other simulations, fewer nodes experience significant gains and losses in centrality and the variations radiate over shorter distances.

- Simulation 5: The 2017 mudslide impact zone scenario results in an effective bifurcation of Freetown Peninsula's network creating two large

subnetworks. Since these two subnetworks are fully separated, each subnetwork has a smaller set of origin and destination nodes. Because BC represents the percent of a network's shortest paths that pass through any given node, within each subnetwork almost all nodes experience low loss in centrality. Thus, it is important to put this metric into functional perspective: the bifurcation of the network—not the changes in BC —has grave consequences for the smaller western subnetwork that becomes almost completely cut off from the capital.

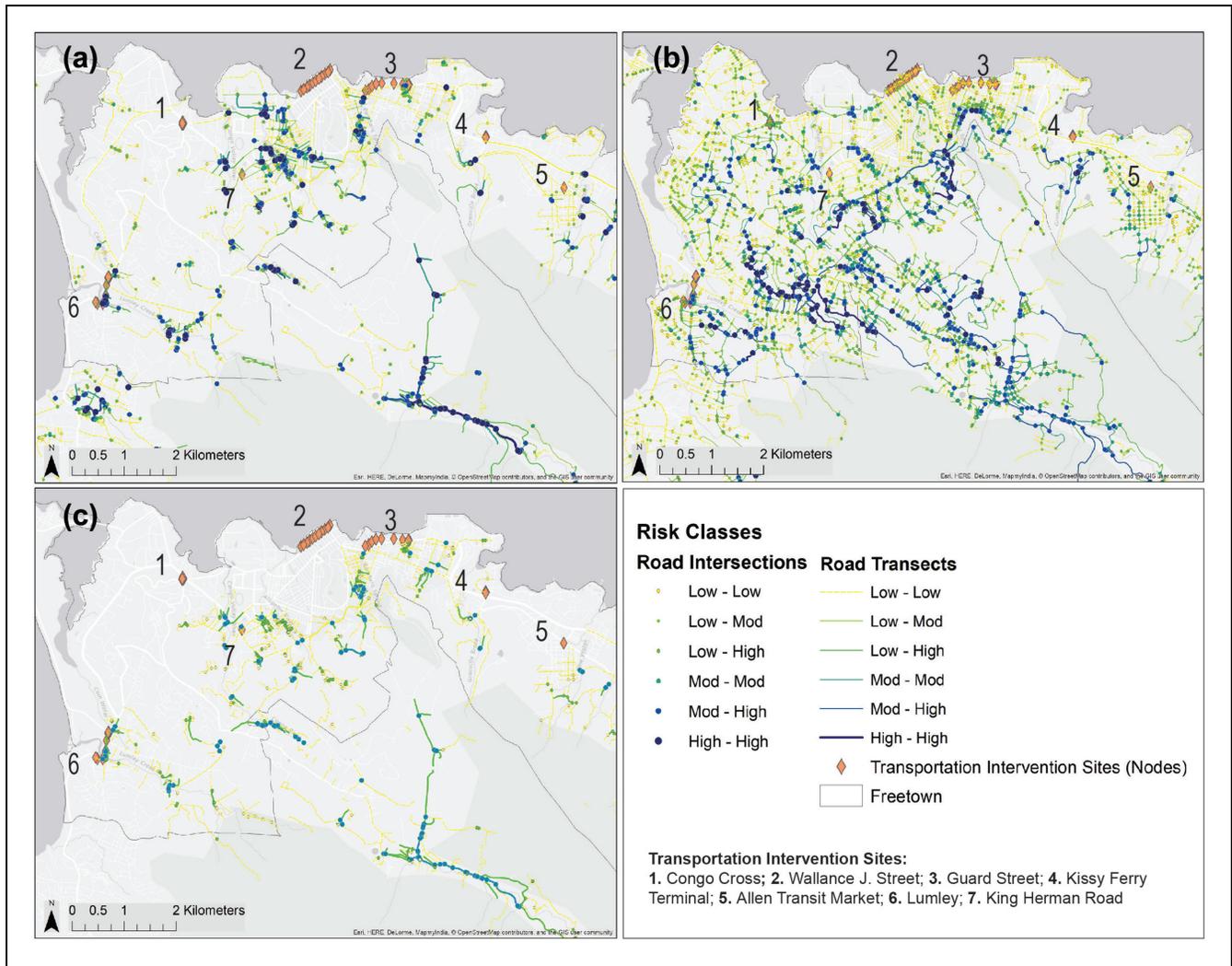


Figure 7. Target nodes under potential interventions and (a) flooding, (b) landslide, and (c) mudslide risk assessment for surrounding nodes and links.

Centrality Variations from Disruption Simulations on Potential Road Interventions in Freetown

Beyond these scenarios, network science allows for another dimension of analysis on the impact of the potential road interventions (Figure 7). By representing these intervention sites as nodes within the transportation network model, we have assessed the centrality of each node in relation to the overall network serviceability both as it operates daily and as it would operate under five specific disruption simulations based on our risk assessment. Understanding which hazard types are most dominant at certain areas is the first step to investing in appropriate design and planning strategies.

In this section, we assess the relation between the level of risks and potential infrastructure projects in the region. Namely, we evaluate the exposure of the areas where potential road interventions are planned. The

considered risks are flooding, landslide, and mudslide that are evaluated separately. This is a primary result to guide specific design interventions that could be incorporated into these projects’ production plan. By hardening the infrastructure or increasing redundancy of critical nodes and links, resilience to climate-change threats can be increased at a system level. Our results show that most of the nodes and links targeted for the transportation interventions planned by the federal government do not fall directly under high-risk categories for flooding, landslides, and mudslides (Figure 8), except for the transportation projects located at the Lumley Market. The road intersections here fall under high-moderate risk of landslide and mudslide and high-high risk of river and coastal flooding. This area is one of the regions that are under reconstruction and recovery from the 2017 flooding and mudslide impacts.

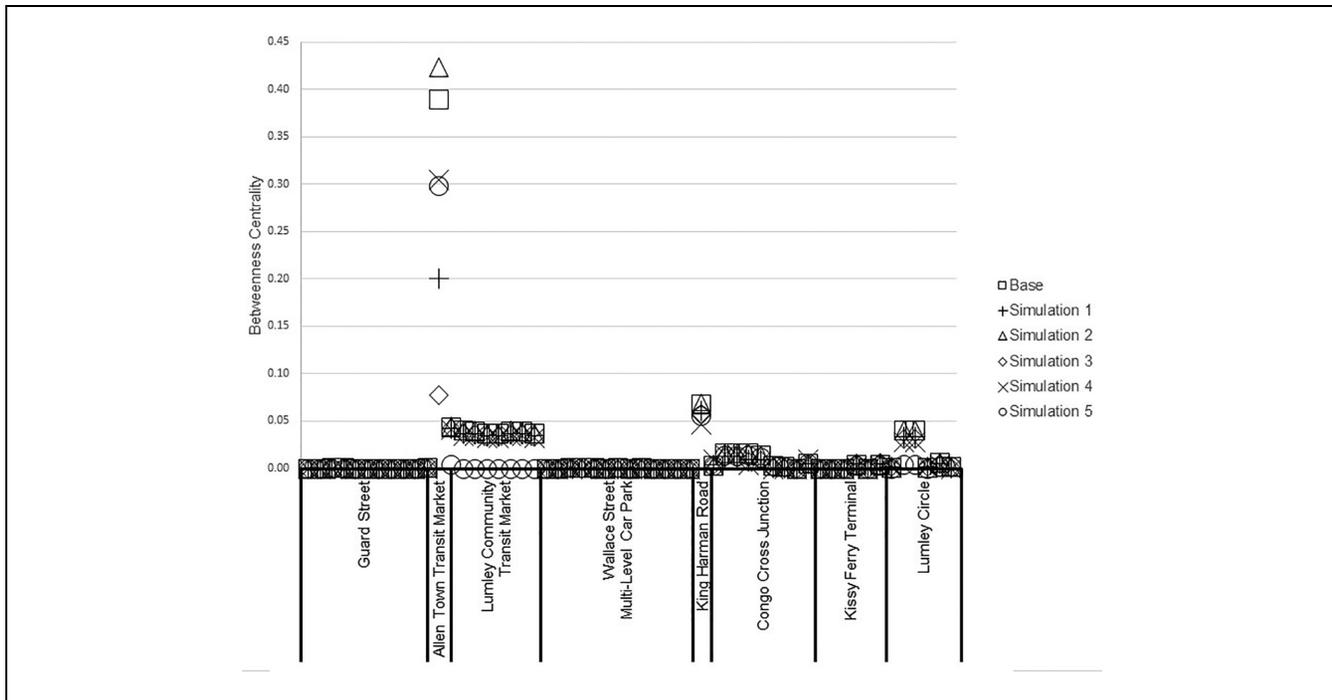


Figure 8. Centrality variations measured after high hazard, $I(D)$, disruption simulations 1–5 of road intersections targeted for transportation interventions.

Although more of the infrastructure projects were not categorized under high-high risk for flooding, landslides, or mudslides, it is important to take into consideration their connection with nodes that are under high-high risk. Figure 8 illustrates how the disruption of high-high risk nodes tested through Simulations 1 through 5 could impact the road network by changes in centrality, specifically by examining their effects on the centrality of potential intervention nodes.

The most significant changes in centrality are predicted for one specific node at Allen Town Transit Market intersection. As the Allen Town Transit Market intersection is a central node under normal circumstances, almost all disaster simulations result in centrality decrease here. The decrease ranges from approximately 0.08 to 0.31, indicating loss of connectivity importance in case of disruption from simulations 1, 3, 4, and 5. However, Simulation 2, which disables the inland Youyi Highway, results in a centrality gain of nearly 0.05, indicating an increase in importance of this intersection in case of landslide-related interruptions between Regent and Bathurst villages. Smaller centrality losses of approximately 0.04 are predicted for the road intersection improvement at Lumley in reference to Simulation 5 only. Once again, as Simulation 5 projects hazard occurrence that impacts the Lumley project intersections themselves, variations are limited. All other targeted nodes for projected urban transportation interventions exhibited negligible centrality variation to the

five simulations. This is likely due to the fact that these nodes are located at the periphery of the network and therefore already have low centrality.

Table 1 presents preliminary design suggestions to the potential transportation intervention sites. These suggestions are based on our hazard-specific risk assessments, the changes on the nodes centrality in the overall network, and changes in centrality measured specifically at the targeted intervention sites following the five disruption simulations. The suggested design incorporations derive from transportation planning literature for increasing disaster resilience and are here focused on safeguarding network connectivity in the face of near- and long-term weather hazards.

Specialist research groups on transportation policy on the adaptation of infrastructure to weather-related hazards, guidelines from the Conference of European Directors of Roads (CEDR) (42), and the International Transport Forum (ITF) (43) reiterate that current transport projects provide an unprecedented opportunity to increase resilience to near- and long-term weather hazards. Therefore, these seven transportation project areas are here considered as priority locations for flood, landslide, and mudslide hardening and/or alternative adaptation methods that would reinforce the road network supply capacity and reduce risk for users. Some examples of hardening techniques cited by CEDR and ITF include creating or improving rainfall drainage

Table 1. Potential Interventions Design Considerations for Climate Change Resilience for Freetown City's 2018 Transportation Projects

2018 transportation intervention site	Risk summary	Design suggestion
1. Congo Cross Junction intervention	Only low landslide risk. No gain in centrality after disaster simulations.	Continue as planned.
2. Wallace Street Multi-Level Car Park intervention/ City Centre – traffic management intervention	A large dense network of streets leads to high levels of redundancy and low <i>BC</i> .	Continue as planned.
3. Guard Street intervention	Near the water in a high-moderate risk area from river and sea level rise flooding.	Consider hardening against flooding.
4. Kissy Ferry Terminal Junction intervention	Along the Bai Bureh major highway. Not in a high-risk area but surrounding nodes are particularly susceptible to large decrease in <i>BC</i> given the disruptions in Simulations 3 and 5 from high mudslide risk and <i>BC</i> increase from the flooding in Simulation 4.	Consider increasing supply capacity in case of mudslides in Freetown's CBD.
5. Allen Town Transit Market intervention	Parallel to Bai Bureh major highway. Under low risk, but centrality increases in case of mudslide disruption in Wellington suburb (Simulation 3).	Consider increasing supply capacity in case of mudslides in Wellington suburbs.
6. Lumley Projects (Circle and Transit Terminal interventions)	In high-high risk areas for flooding and moderate-high risk areas for landslides and mudslides. A major terminal point for intercity buses. Because it is on the western edge of the network, elimination results in the network being fully split into two subnetworks. A major poda poda (private minibus) and taxi route terminus with adjacent market.	Consider ensuring redundant paths nearby. Consider physically hardening against landslides, mudslides, and flooding.
7. King Harman Road/Old railway line intersection intervention	Low centrality decreases in all simulations except 2. At moderate risk of mudslides.	Consider hardening against mudslides and ensuring redundant paths nearby.

infrastructure, designing stormwater infrastructure that takes into account lower frequency events in strategic areas (e.g., 10-year to 50-year rainstorm return period), increasing safety factors for slope stability and increasing concrete strength, and building strategic flood and mudslide protective walls. For alternate adaptation methods known as “soft measures,” examples include guaranteeing redundancy of high-risk transects, and incorporating maintenance and operational systems that are sensible to risk and can be used to increase awareness in the community through road signal and early warning systems.

Conclusions and Further Research

We present a method by which network science measures can be applied with disaster risk analysis to evaluate transportation network performance amidst unscheduled disruptions in a data-scarce environment. This serves as an important first step in progressing towards resilience, which in addition to disruption includes the entire recovery time and process. These methods require only limited open-source data as processed through NetworkX. The key data required are mainstream environmental GIS for

accessible hazard mapping techniques. This was also the result of a collaboration with the World Bank, that has been active in Freetown collecting environmental data sets through partnerships with government agencies and local university institutions with the aim to foster technical assistance and capacity building. As such, this work overall represents a collaborative effort between global institutions, local and regional government, and education institutions.

By innovating traditional risk formulas, we assess vulnerability of transportation networks through topological models and centrality analysis. We built a topological model of Freetown, Sierra Leone and used betweenness centrality to calculate each road intersection's importance to the network. Hydrographic information, open-source DEMs and global sea level rise and storm surge predictions were used to identify hydrometeorological hazard risk and areas prone to landslides, mudslides, river flooding, and coastal flooding (sea level rise and storm surges). By overlapping Freetown's road network with our multi-hazard constraint layer, we built a risk matrix for each hazard and for all hazards combined, reflecting likelihood of road disruption from weather events and associated consequences to the network's supply and serviceability.

These mainstream hazard assessment methods come with uncertainties from low spatial resolution and low availability of environmental GIS data. Our hazard exposure analysis presents a primary overview of likelihood and extent. More in-depth modeling is required to increase accuracy of natural hazards estimates. Risk matrices are built based on the assumption that there is a positive correlation between likelihood and consequences. Therefore, they require caution for risks that have low likelihood and high consequences, or "black swan" events, and for risks that have high likelihood and low consequences. More broadly, risk matrices' intrinsic uncertainties include the fact that the definition of the thresholds usually follows statistical classification methods that should be empirically validated to correspond to thresholds defined by observed hazard occurrences and local stakeholders.

Road network disruption simulations were tested by eliminating the nodes with the highest landslide, mudslide, river flooding, and storm surge risk categories. Each of these simulations resulted in variations of centrality throughout the network that helped us understand the effects of connectivity loss in Freetown Peninsula. Additionally, centrality gain and loss were also measured for each disaster simulation on planned urban transportation intervention sites. Road intersections that gain centrality become more important for the overall network connectivity during simulated hazard-related disruptions, inferring the higher pressure from users and the

need for hardening or reinforcing redundant paths. The results show that although certain areas, such as Allen Town Market, are under low risk, safeguarding this area's serviceability is important in reducing Freetown's road network vulnerability to the high mudslide risk identified in Wellington suburb, by reinforcing redundant low-risk paths. These highlight the importance of taking into account the system's vulnerability when assessing road infrastructure risk and not only physical and single-asset oriented assessments. Including physical properties in future research, such as road type, pavement quality, length, and number of lanes, aggregated with network connectivity factors, would improve the applied method for systemic vulnerability assessment (44). Enriching the road network data would facilitate additional study of recovery time after disruption and thus overall resilience.

This paper serves as a strong proof of concept for supply-side modeling. Given the current lack of traffic counts, transit ridership or other measures of demand, centrality to total shortest distance paths in network was used to understand vulnerability as a consequence of connectivity failure. Including other attributes in the links such as road width, surface condition, and average vehicle speed could change the centrality metrics.

Moving forward, network weights should also be modeled as a function of true demand and usage volume, where betweenness centrality reflects nodes with the most trips passing through them. These could be modeled through a stochastic subset of origin destination pairs or by using mobile phone data and emerging techniques, the centrality could be weighted by trip flows rather than random origin destinations (45). Using these demand side measures would improve the identification of critical nodes based on the number of travelers impacted and provide transportation demand data for prioritizing investment decisions.

Another possibility is using accessibility changes such as closeness to schools, jobs, and health services to measure the impacts of hazards and degradation on access to critical services, as was done by Chen et al. (46) with a road network. This information combined with population data is useful to rank zones and groups most vulnerable to loss of key services in a disaster scenario.

Finally, this paper combines network science metrics with natural hazards estimates to improve transportation infrastructure decision-making and investments. By applying this approach to Freetown, Sierra Leone, it pilots new methodology optimized for data-scarce, disaster-prone and capacity-constrained environments.

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