

# HOW TOPOLOGY CHANGES UNDER DISRUPTIVE CONDITIONS AFFECT TRANSPORTATION SYSTEM RESILIENCE A CASE STUDY OF COLOMBO

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The transportation system is often considered the most critical infrastructure since the failure of its components makes a substantial impact on the economy and social activities. Hence, numerous studies evaluate the resilience of transportation systems when they are subjected to disruptions from various disturbances and how these systems return to their previous equilibrium state. However, it remains a difficult task due to several major limitations; First, current studies primarily used a deterministic approach, using pre-hazard events that are unlikely to happen with similar potential in the future and do not represent all possible hazardous events. Second, although these studies claimed the topological parameters cause significant changes in transportation network behavior, in-depth statistical studies at both macro and micro scales to assess transportation network resilience are limited. Third, the majority of these studies focused on developed cities, while the majority of Asian cities, which are still underdeveloped and prone to numerous disruptions, received limited attention. To tackle the abovementioned limitations, this study incorporates critical-link attacks that disrupt the transportation segments. This helps to capture the network resilience precisely when it disrupts all the potential road segments and incorporates all the possible network disruptions regardless of their pre-occurrences. This study employs in-depth statistical and spatial analysis to assess transportation network resilience in both macro and micro events by utilizing topological parameters and assessing the functionality changes under various disruptive levels. The study considered the Colombo Metropolitan Area in Sri Lanka as the study area. Therefore, the findings of this study would be beneficial for most of the cities in Asia to assess the transportation network resilience since this area is similar to urban development and socio-economic patterns in Asia. The findings apply to studying transportation network resilience in all the possible disruptive events, which is important for evaluating network performance and disaster-risk reduction.

**Key Words :** *Transportation Resilience; Road Network Topology; Complex Networks; Network Science; Graph Theory; Disruption Analysis*

## 1. INTRODUCTION

The transportation system is often considered the most critical infrastructure since the failure of its components can have a substantial impact on the

economy and social well-being of a country (Taylor and D'Este 2007). Since of this critical importance in our daily lives, transportation has evolved into a complex and interdependent system over time, making it vulnerable to disruptions and difficult to recover

from. This causes unexpected failures of these systems serviceability, and their burdens are dramatic in their financial and social aspects (Zhou, Wang and Yang 2019). For instance, earthquakes, landslides, flashfloods, and hurricanes cause severe disruption of the transportation network in certain segments, rendering those road segments or the entire road network inaccessible in an unexpected manner (Pregolato, et al. 2017); (Lu, Peng and Zhang 2015); (Wang, et al. 2019); (Wisetjindawat, Kermanshah, et al. 2017). Such a way, these events caused to disrupt the transportation network's equilibrium state, resulting in unexpected traffic flow distribution, increasing traffic congestion, and eventually draining the entire transportation network's serviceability to a catastrophic level (Wan, et al. 2018); (Kim and Yeo 2017); (Bell, et al. 2008). In such a way, many concepts have been utilized to study the resilience of transportation systems when they are exposed to such disruptions from various disturbances, ranging from frequent road network failures resulting in roadblocks to rare natural disasters and to study their network vulnerability and reliability to maintain the optimal serviceability of the transportation system under future disruption occurrences events (Wan, et al. 2018); (Zhou, Wang and Yang 2019). These efforts caused the study of transportation resilience studies to emerge as one of the major streams of transportation-related research during recent years and it is an important area of research in the global effort to adapt to climate change and one of the critical measure in Sustainable Development Goals 2035 (Derrible 2017).

In transportation study domains, the resilience is defined as a measure of the maximum agitation a system can take in before getting displaced from one state to another (Bhavathrathan and Patil 2015). In other words, resilience is simply defined as the ability of a system to withstand or respond to changes that assess the system's ability to provide and maintain an acceptable level of service when normal operations are challenged (Croope and McNeil 2011). In such a context, as a result of the unprecedented increase in environmental and social instability, most transportation networks are vulnerable to a wide range of natural and manmade hazards, significantly disrupting the accessibility and serviceability of urban transportation systems due to road segment failures and loss of network functionality (Hellervik, Nilsson, and Andersson 2019). Such events significantly impacts to the traffic flow distribution of the transportation system and resulting impact iterating throughout the entire network due to the relative impacts caused by the network effect (Arasan and Arkatkar 2010). These incidents caused to generate unprecedented traffic congestions due to the unexpected traffic flow generation in certain areas and create traffic bottlenecks where

the road capacity is insufficient for the increasing demand. In such a way, transportation resilience studies, study the vulnerability and reliability of the transportation system when it was exposed to a disruption event, which helps to enhance the redundancy and robustness of the transportation system against disruptions and to enhance the coping capacity of the system against future disaster occurrences, which is the most significant connotation of transportation resilience studies.

In such a way, in the transportation engineering domain of study, several methodological approaches have been utilized to evaluate the resilience of the transportation system. However, although many efforts have been made to assess the transportation system's resilience, it is still difficult task to assess transportation system resilience due to several technical, theoretical, and practical limitations that need to be addressed in the immediate efforts for a successful transportation resilience assessment. In such a context, the present study attempts to make a significant contribution to the following key limitations noted in emerging researches in the domain of transportation system resilience studies.

- (a) First, majority of resilience studies have only considered the deterministic approach by considering pre-hazard events to assess the transportation system's resilience. These events are unlikely to happen with similar potential in the future and do not represent all possible hazardous events. As a result, such studies did not consider unexpected or unprecedented disruption occurrences as threats to the road network's vulnerability and resilience assessments.
- (b) Second, despite the fact that numerous studies claim that topology and its morphological parameters cause significant changes in transportation behavior, in-depth statistical studies at both macro and micro scales to assess transportation network resilience under topological perspectives are limited.
- (c) Third, present resilience studies, give intensive attention to the assessment of the transportation system resilience under the vulnerability aspects. Thus, limited attention has been paid to assessing the transportation system's performance under disruptive events.
- (d) Forth, the majority of resilience studies focused on developed cities, while the majority of Asian cities, which are still underdeveloped and prone to numerous disruptions, received limited attention.

Considering the above identified limitations of the existing transportation resilience studies, it identified excessive demand for the novel framework to assess

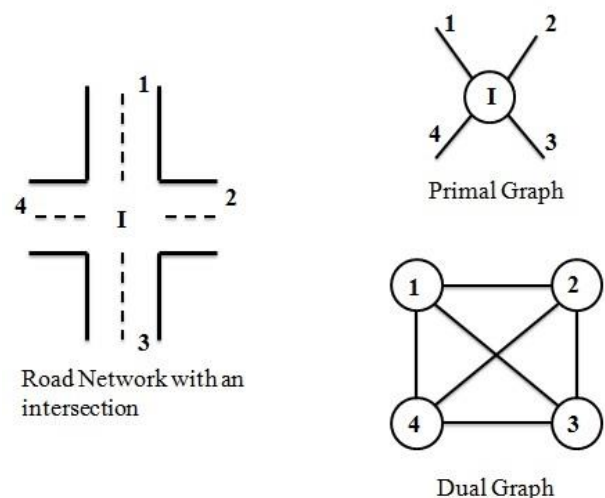
the transportation system resilience. In such a context, to mitigate the above mentioned limitations, this study utilised critical-link attacks to disrupt the transportation network segments. This helps to capture the network resilience precisely when it disrupts all the potential road segments and incorporates all the possible network disruptions regardless of their pre-occurrences. In addition, this study utilized transportation network topology as proxy to assess the transportation network resilience under disruptive conditions by employs in-depth statistical and spatial analysis in both macro and micro events by utilizing topological parameters. It utilizing the structural and network properties of the road network morphology as the attributes of measures. It is distinguished that, although many studies claim the relationship between the topological features and traffic flow distribution, limited studies have been conducted to assess the transportation system's performance and vulnerability when the topology changes under the disruptive condition, which is predominantly assessed in this study. The study considered Colombo metropolitan area in Sri Lanka as its study area due to its regional importance as a susceptible area to many environmental and manmade disruptions and also the data availability. Therefore, the findings of this study would be beneficial for most of the cities in Asia to assess the transportation network resilience since this area is similar to urban development and socio-economic patterns in Asia. In order to calculate the topological properties and transportation network resilience, the study utilized the Networkx Library under the Python Environment. The study also utilized GIS Software Package to data pre-process, preparing maps and visualize the findings where it can deliver more sophisticated understanding of the study findings. The findings of the study can be applicable for studying the transportation network resilience and traffic flow distribution in any given disastrous event as it can incorporate the critical link attacks to disrupt the transportation segments. In addition, it is also capable of studying transportation network resilience in unexpected situations, which is important for disaster risk reduction and preparation of evacuation plans and evaluating transportation network performance.

Following this introduction, Section 2 presents the conceptual framework of the study, where it discusses the study's utilised topological transformation method, topological parameters, and the network disruptive methods, which are utilised to attack the critical links of the network. The study area, data description, methodology, and analytical framework are presented in Section 3. Section 4 presents the analysis of the study. Discussion and conclusion are summarized in Section 5. Finally, section 6 presents the limitations and future.

## 2. CONCEPTUAL FRAMEWORK

### (1) Topological Transformation of Geometrical Networks into Topological Networks

In simply, any spatial representation of geographic network consist of two major elements; known as nodes, (i.e., intersections) and segments, (i.e., line intermediate by two intersections) which are distinguished the zero dimensional graph entities and one dimensional graph entities, respectively in a Euclidean Space (Newman 2010); (Bondy and Murty 1976). Such a way, direct representation of geographic network into spatial form known as the “primal graph” networks in the graph theory due to the higher coherence between the dimension of geographic and graph entities (Lin and Ban 2013); (Porta, Crucitti and Latora 2006). Meanwhile, graph representation of nodes turns into segments and segments turns into nodes are known as the “indirect” or “dual graph” representation in the graph theory which represent more advanced and abstract graphical representation of the graph such as in Space Syntax Analysis (Lin and Ban 2013); (Porta, Crucitti and Latora 2006). However, under the topological transformation of this geometrical networks, both primal and dual graph representations are distinguished in a more abstract form, which is far less characterized by geometric and spatial characteristics and rich in topological aspects (Ma, et al. 2019); (Jiang & Claramunt, 2004). In such a way, in the topological study domain, both primal and dual graph representation are built upon a variety of topological considerations, (i.e., Axial Line Graph - lines of sights (Hillier and Hanson 1989), Street Based Topological Representations – Natural Street (Liu and Jiang 2012); (Jiang, Zhao and Yin 2008) and Named Streets (Jiang and Liu 2009); (Ma, et al. 2019).



**Fig.1** Primal and Dual graph representation for an arbitrary road network (Oberoi, et al. 2017).

In such a context, this study utilised a street-based

topological transformation approach to convert the geometric transportation network into a topological network. In recent transportation studies, (Ma, et al. 2019); (Jiang and Liu 2009) claims that traffic flow and human activities can be well distinguished (i.e., predicted) by the street-based topological representations, which have been proposed as an alternative to the axial line representation. These street-based representations are mainly distinguished by the two kinds of topological representations, namely: I. Named-Street Topological Representation and II. Natural-Street Topological Representation (Thomson 2004); (Jiang and Claramunt 2004). In terms of Named-Streets Topologies, streets are merged with the street segments which are belonging to the same street name (Jiang & Claramunt, 2004) while, Natural-Streets Topologies are generated by considering the good continuity of the street segments by considering the angle change of the two intermediate road segments (Thomson 2004). In such a context, (Ma, et al. 2019) distinguished that the street based Natural-Street topological representations are excellent proxies to capture the human activities or traffic flow none other than any topological representation that utilized in the recent studies.

Considering the above mentioned characteristics of the street-based topological representations, this study follows the street-based topological representation to study the transportation network resilience followed by the natural-street topological transformation aspects, as it can precisely capture the transportation network resilience under the transportation network disruptive events due to its higher capability to capture the traffic flow and human activities in the urban environment. Furthermore, in order to prepare graph representation, the study utilized the primal graph approach as it can be easily constructed in the GIS environment with limited complexity to interpretations for the diversified audience. In such a context, the primal graph topological representation can be represented as graph ( $G$ ) which consists of a finite set of vertices (i.e., nodes) ( $V$ ) and edges (i.e., segments) ( $E$ ). Thus, the graph is derived as  $G(V, E)$ , where  $V$  is the set of vertices, (i.e.,  $V = \{v_1, v_2, \dots, v_n\}$ , where the number of nodes depicts the  $N$ ), and  $E$  distinguished the set of edges, is a subset of the cartesian product  $V \times V$ . For computational purposes we represent a connected, undirected, and unweighted (that is, all links with a unit distance) graph by an adjacency matrix  $R(G)$ . In such a way, a graph can be represented as an adjacency matrix  $R(G)$  whose  $r_{ij}$  value is [1] if the segments are intersected and [0] when they are not. This phenomenon is formally distinguished as follows:

$$R(G) = [r_{ij}]_{n \times n}$$

Where,

$$R_{ij} = \begin{cases} 1 & \text{Intersected, if } v_i v_j \in E, \\ 0 & \text{Not Intersected} \end{cases} \quad (1)$$

The above form of adjacency matrix representation is symmetric, (i.e.,  $\forall r_{ij} \rightarrow r_{ij} = r_{ji}$ ). Thus, all diagonal elements of  $R(G)$  are equal to zero. Then the lower or upper triangular matrix of  $R(G)$  is sufficient for a complete description of the graph  $G$

## (2) Topological Measures and their Characteristics

There have been a variety of topological measures in the recent transportation study domain that are capable of capturing the diverse network characteristics in a complex urban environment (Barabási, 2013). In this study, we utilized these topological measures under the two major subsectors: I. Topological measures to capture the structural properties of the network disruption II. Topological measures to capture the network characteristics of the network disruption. In crude manner structural measures are utilized to distinguish the inherent, hidden, and complex characteristics of the network, such as small-world network, scale-free property and traffic flow pattern (Watts and Strogatz 1998); (Derrible and Kennedy 2011). Meanwhile, network centrality characteristics are mostly utilized to capture specific network property in their local and global aspects, (i.e., accessibility, origin-destination trips distribution, critical paths, etc.) (Tsiotas and Polyzos 2017); (Lin and Ban 2013). In such a way, this study is able to capture the transportation system's resilience as the implications of both structural and network characteristics change under the critical segments gets attacked in the transportation network. The detailed description of each structural and network measure and their applicability to assess the transportation network resilience depicts as follows;

### a) Structural Measures and their Characteristics

This study considered a range of topological measures, including **street connectivity**, **average path-length**, and **clustering coefficient**, which are significantly utilized to capture the structural properties of the topological networks. It is claimed that these measures are well suited to capturing the traffic flow pattern, human activities, small-world and scaling properties of the street network which are critical for understanding human activities and transportation flow distribution in the urban transportation network as a whole, complex system, but not individual perceptions (Buhl, et al. 2006); (Boeing 2022); (Lämmer, Gehlsen and Helbing 2006); (Jiang, Zhao and Yin 2008); (Barabási 2003). For instance, (Ma, et al. 2019) discovered that the topological representation

of natural streets accurately depicts strict power-law distribution and scale-free property in street connectivity. In such a way, the study claims that this underlying scaling structure makes human activities predictable, even though in the sense of collective rather than individual human movement behavior. A similar study was also carried out by Jiang and Liu (2009) to predict the traffic flow pattern of an urban transportation network by utilizing the same structural measures of the transportation network. The findings of the study derived that street-based topological representations (i.e., more precisely, natural streets) and analyses are superior to predicting traffic flow as it depicts excellent correlation (i.e.,  $r > 0.82$ ,  $p < 0.01$ ) with the Hong Kong Annual Average Daily Traffic (AADT) datasets utilized in the particular study. The study further claims that street-based topological representation is an excellent proxy to capture the small world properties through the structural measures utilised in the study.

Such a way, it can depicts that, these structural properties of the transportation network are excellent proxy to identify the diverse of underneath characteristics of the transportation network. Such a way, this study utilized these properties to identify the transportation system's resilience when the critical link of the network attacked by the each disruptive events. Each specific structural measure, their formula and characteristics are depicts as follows;

**Street Connectivity:** Street connectivity refers to a fundamental structural property of transportation networks known as scale-free property, which explains why street connectivity of the transportation network follows the power-law distribution as the majority of segments represent the small street connectivity while only a few segments represent the greater connectivity (Barabasi and Albert 1999); (Jiang and Claramunt 2004); (Ma, et al. 2019); (Jiang, Yin and Zhao 2009).

$$R(v_i) = \sum_{j=1}^n R_{ij}$$

Where;

$R(v_i)$  :Steet Connectivity of  $v_i$

$R_{ij}$  :Intersected Nodes of the Adjacency Matrix,  $[v_i v_j \in E]$

$n$  :Number of Intersected Nodes of  $v_i$

**Path-Length:** Path-length is utilised to capture the small-world property of the real world networks, which distinguished the separation between any two randomly selected segments is very short in the urban street network as the small-world networks are well connected with the surrounding segments in the network (Barabasi and Albert 1999); (Jiang and Claramunt 2004); (Ma, et al. 2019); (Porta, Crucitti and

Latora 2006).

$$L(v_i) = \sum_{j=1}^n d_{min}(i, j)$$

Where;

$L(v_i)$  :Path Length of  $v_i$

$d_{min}(i, j)$  :Minimum Distance between the Two Vertices  $i$  and  $j$

$n$  :Total Number of Nodes of the Network

**Clustering Coefficient:** The clustering coefficient is used to measure the clustering degree of a particular segment, which is calculated by measuring to what extent the neighboring segments of a particular segment are also linked with each other. It is utilised as an important determinant to distinguish the small-world property of the real world network (Barabasi and Albert 1999); (Jiang & Claramunt, 2004); (Ma, et al. 2019); (Porta, Crucitti and Latora 2006).

$$C(v_i) = \frac{2l_i}{m_i(m_i - 1)}$$

Where;

$C(v_i)$  :Clustering Coefficient of  $v_i$

$l_i$  :Number of Actual Edges Among the Immediate Neighbors of  $v_i$

$n$  :Number of Possible Edges Among the Immediate Neighbors of  $v_i$

## b) Network Centrality Measures and their Characteristics

This study considered betweenness centrality, closeness centrality, and eigenvector centrality, to assess the transportation network resilience under the network centrality perspective. It is depicts that in the recent transportation study domain, these measures have been widely utilised to predict diverse network characteristics, such as traffic-flow pattern, accessibility, origin-destination trip distribution, and urban development pattern, by utilising the topological representation of the transportation network (Tsiotas and Polyzos 2017); (Derrible and Kennedy 2011); (Chen, et al. 2021); (Porta, Crucitti and Latora 2006); (Turner 2007). For instance, Jayasinghe et al. (2015) utilised the centrality parameters (i.e., degree, closeness centrality, and betweenness centrality) to explain and predict traffic-flow patterns by vehicular type by utilising the topological representation of the transportation network. The findings of the study depicts that, human cognition of the space mostly the topological and their dynamic consequences on space such as traffic-flow can well be distinguished by these network centrality measures. Subsequently, (Jiang, Yin and Zhao 2009); (Jiang, Zhao and Yin 2008) investigate the relationship between both AADT and GPS data with the network centrality

measures under the topological representation of the transportation network. The findings of the study demonstrate a significant correlation with the study's utilized centrality measures and AADT and GPS data. In addition, findings further constitute the emergent properties of the self-organized nature of the natural roads, which would be excellent crucibles for predicting traffic flow and understanding the dynamics of road networks and their traffic from the perspective of complex networks (Samaniego and Moses 2008); (Lämmer, Gehlsen and Helbing 2006). It also found that these centrality measures are significantly correlated to human movement rates, thus which can utilized for predicting human movement.

Such a way, it can depicts that, network centrality measures in the transportation study domain are excellent proxies to identify the diverse, complex, dynamic characteristics of the urban transportation network. Such a way, this study utilized these properties to assess the transportation system's resilience when the critical link of the network gets attacked by disruptive events. Each network centrality measure, its formula, and characteristics are depicted below;

**Betweenness Centrality:** The betweenness centrality depicts the importance of segments within a network by measuring to what extent a particular segment is between the other segments in the network, which reflects the intermediary location of a segment. It captures the pass-by segments of the origin or destination trip distribution which is excellent proxy for predicting traffic and human activity in urban areas (Porta, et al., 2012); (Freeman 1978); (Turner 2007); (Lin and Ban 2013).

$$BTW_i = \sum_{j=1}^n \sum_{k=1}^{j-1} \frac{P_{ikj}}{P_{ij}}$$

Where;

$BTW_i$  :Betweenness Centrality of Segment or Node  $i$

$P_{ij}$  :Number of shortest paths from  $i$  to  $j$

$P_{ikj}$  :Number of shortest paths from  $i$  to  $j$  that pass through  $k$

$n$  :Number of Segments of the Network

**Closeness Centrality:** Closeness centrality measures the shortest distance from a given node to all other nodes of the network which depicts the distance, (i.e., or how far) of a particular node or segment related to the other nodes or segment in the network. It captures the notion of accessibility of a segment which is an excellent proxy to predict the accessibility of the network (Porta, et al., 2012); (Freeman 1978); (Lin and Ban 2013); (Turner 2007).

$$CLS_i = \frac{n-1}{\sum_{k=1}^n d(i,j)}$$

Where;

$CLS_i$  :Betweenness Centrality of Segment or Node  $i$

$d(i,j)$  :Shortest Distance between Node  $i$  and  $j$

$n$  :Number of Segments or nodes of the Network

**Eigenvector Centrality:** Eigenvector centrality assesses the connectivity of a particular segment to the other surrounding segments on the network in their local and global group. It captures the importance of a connected segment as it captures the direct influence and influence over the segment in global terms by considering the entire topological network (Bonacich and Lloyd 2001), (Presto, Belden, & Lavarato, 2019).

$$EGN_i = \frac{1}{\lambda} \sum_{j=1}^n A_{ij} EGN_j$$

Where,

$EGN_j$  : Eigenvector value of Node  $j$

$A_{ij}$  : Intersected Nodes of the Adjacency Matrix,  $[v_i v_j \in E]$

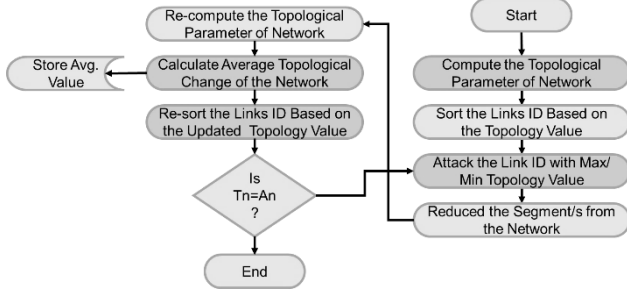
$\lambda$  : The Constance, (i.e., the largest eigenvalue of the adjacency matrix)

$n$  : Number of Nodes in the Network

### (3) Network Disruptive Methodology

In recent studies, there have been utilized wide variety of network disruption methods to assess the network functionality under the disruptive conditions which are mainly consist of two categories; I. Critical Links Failures (CLF) and II. Random Link Failures (RLF) (Gauthier, Furno and El Faouzi 2018); (Wisetjindawat, Kermanshah, et al. 2017). In terms of critical links failure method it intentionally select the highly significant road segment and assess the transportation network resilience when the particular road segments are not in the function (Hosseini Nourzad and Pradhan 2016). Such a way, CLF method mostly followed the deterministic or stochastic probability approach to determine the critical road segments to assess the transportation system resilience (Postance, et al. 2017); (Jenelius and Mattsson 2012). Other way, random link failure method it randomly select the potential segments from the road network and assess the transportation network resilience when the those road segments are not in the function (Abdulla and Birgisson 2021). Such a way, RLF method mostly followed the network characteristics to determine the potential road segments to assess the transportation system resilience (Wisetjindawat, Wilson,

et al. 2019); (García-Alviz, et al. 2021).



**Fig.2** The Analytical Framework of the Critical-Link Failure Method

In such a context, considering both above mentioned network disruption methods, this study utilized the critical link failure method to assess the transportation network resilience. This helps to capture the transportation network resilience precisely when it disrupts all the potential road segments. In addition, since the current studies used a deterministic approach with pre-hazard events that are unlikely to occur with similar potential in the future and do not represent all possible hazardous events that are potentials to occur proposed approach is capable of incorporating all possible network disruption events regardless of their pre-occurrences and assessing network resilience in all possible disruptive events. The analytical framework of the study utilized critical link failure method depicts in the Figure 2.

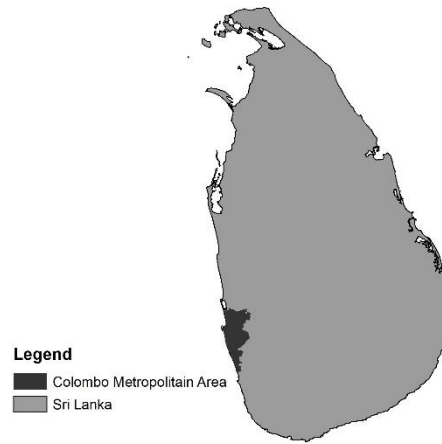
As depicted in Figure 2, the study utilized CLF method calculates the critical segment at each iteration and attacks the critical link segments from highest critical to least critical order. In this way, the proposed method can identify the critical segments specifically at each iteration and assess the transportation network resilience when the particular segment gets attacked at each iteration. In such a way, since the disruption of all the road segments does not have a similar impact on the functionality and serviceability of the transportation network, the proposed approach can accurately study the transportation system's resilience when the network loses its critical road segments, which has a significant impact under the disruption situations in any given situation in future scenarios. It is important to mention that, in this study, critical segments are defined as the significant values of each topological parameter, which are calculated repeatedly at each network iteration to capture the critical segments of the network until all the road segments get attacked.

### 3. MATERIALS AND METHOD

#### (1) Characteristics of the Study Area

The Colombo Metropolitan Area (CMA) in Sri

Lanka (i.e., 6°56'04"N 79°50'34"E) was chosen as the study area due to its regional importance as a developing commercial capital in a South Asian context and its vulnerability to numerous natural and man-made disruptions (i.e., flashfloods, cyclones, road renovations, and traffic-barricades). In addition, according to the JICA Study (2014), total person trip production in the CMA would increase to nearly 12.2-million-person trips per day by 2035, which is 1.75 times the current person trip demand of 6.9-million-person trips per day. In such a way, the findings of the study would be extremely beneficial in assessing the resilience of the transportation system for future possible disruption occurrences. Figure 3 depicts the spatial composition of the study area.



**Fig.3** The Spatial Composition of the Study Area

The basic socio-demographic and economic characteristics of the study area are depicts in the Table 1 as follows;

**Table 1** The Socio-Demographic and Economic Characteristics of the Study Area

Characteristics of Colombo Metropolitan Area	
Land Area	3,593 km <sup>2</sup>
Population	5,851,130
Urbanization Rate	38.8%
Number of Employment	1,835,000
GRDP (USD)	27, 720 (Mn.)
Total Length of Roads	3,664 km (Road Development Authority Roads)
Total length of Railway – CMR	210 km

#### (2) Data Description and Sources

The entire study is based on secondary data sources that are freely available and openly accessible for reproduction. The geographical road network of CMA was used as the primary dataset of the study, which was transformed into the topological network to assess the transportation network resilience. The

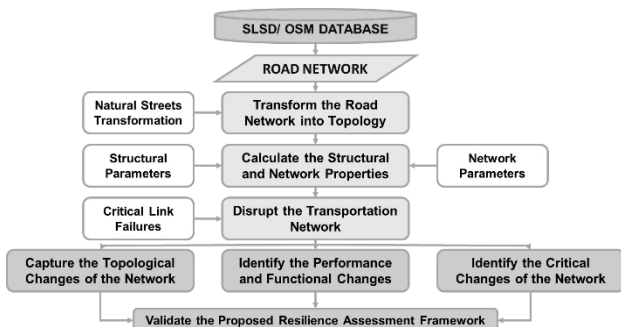
data used for the study is presented in Table 2.

**Table 2** The Data description

Data Type	Area	Year	Source	Description
Road Network	Colombo Metropolitan Area	2012	Survey Department Of Sri Lanka	GIS Files (Polyline)
Annual Average Daily Traffic	Colombo Metropolitan Area	2012	CoMTrans Urban Transport Master Plan	GIS Files (Polyline)
Passenger Car Volume	Colombo Metropolitan Area	2012	CoMTrans Urban Transport Master Plan	GIS Files (Polyline)

### 3) Analytical Framework of Study

The analytical framework of the study can be divided into three main stages known as: I. The Data Processing Stage; II. The Analyzing Stage; and III. The Evaluation and Validation Stage. In terms of the data processing stage, which includes the topological transformation of the transportation network, calculation of topological parameters, and implementation of the desired network disruption method. Analytical stage includes evaluating the characteristics of the transportation system's resilience by utilising statistical techniques. Finally, the evaluation and validation stages discuss the applicability of the proposed



framework to assess the transportation network resilience. Figure 4 depicts analytical framework of the study.

**Fig.4** Analytical Framework of the Study

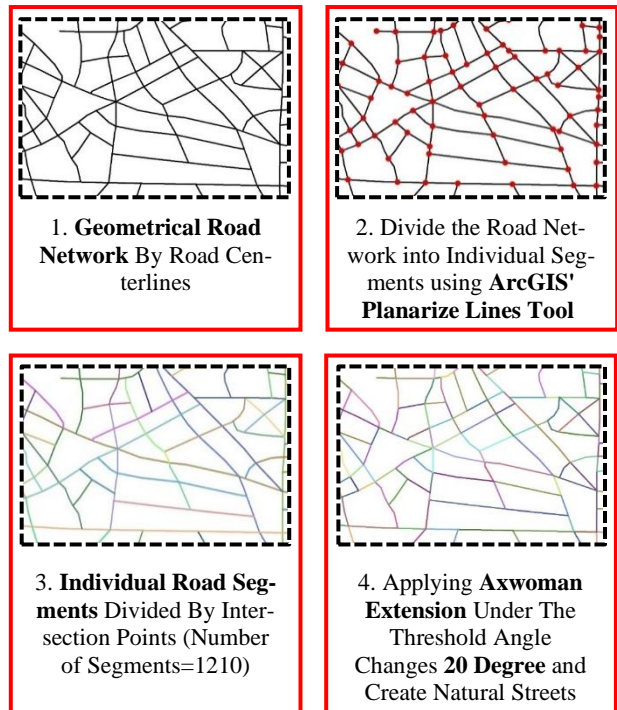
#### a) The Data Processing Stage

The data processing stage mainly consists of three main stages: I. The topological transformation of the geometric network. II. Calculation of topological parameters and III. Implementation of the network disruption method. The detailed descriptions of each

step are presented in the following sections.

#### *The Topological Transformation of the Geometric Network*

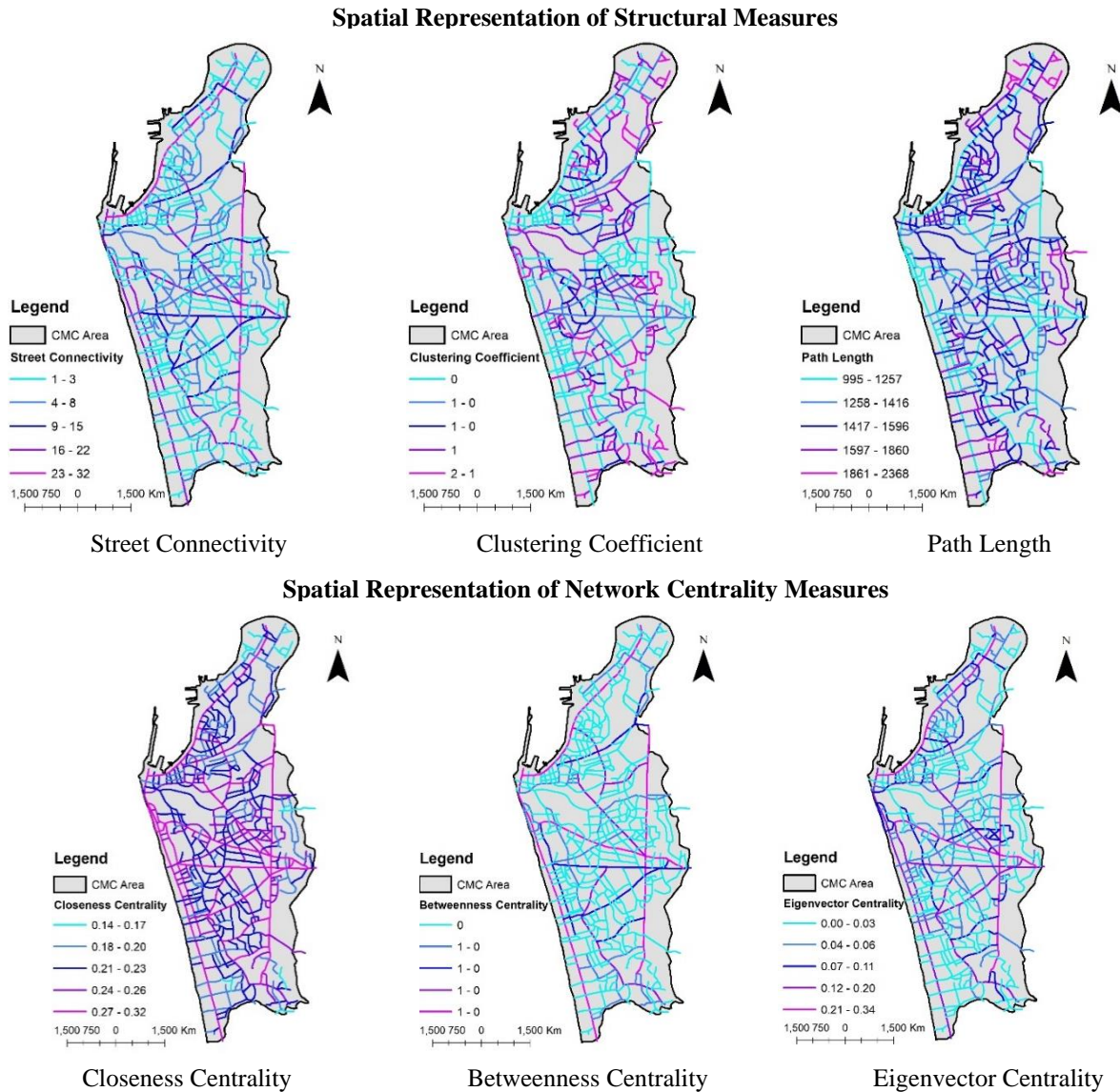
In order to transform the geometric road network into the natural-street topological representation, first it split the geometrical road network into individual road segments by their each individual road intersection points as it can easily measure the angle change of the each individual road segments when preparing the natural streets. Then it measure the each and every intermediate road segments and create the natural streets by considering the given threshold angle change to the natural street preparation. This study followed the method introduced by the Jiang and Liu (2009) known as the Axwoman extension in ArcGIS to easiest the topological transformation (Jiang and Claramunt 2002). In Axwoman, it creates the natural roads by tracking the angle change of each individual road segment. In this study, it utilised 20 degrees as the angle change threshold by considering the road geometrical structure of the study area. The detailed graphical explanation of the topological transformation of the geometric network is depicted in Figure 5. The geometrical road network of the study area consists of 1210 individual road segments. Finally, after applying the threshold angle change of 20 degrees, the natural street network consists of 323 street segments, which is utilised in the transportation network resilience assessment.



**Fig.5** The Graphical Explanation Of The Topological Transformation Of The Geometric Network.

#### *Calculation of Topological Parameters*

This study utilised the NetworkX Library under the



**Fig.6** Spatial Representation of Structural and Network Centrality Measures

Python Environment to calculate the topological parameters of both structural and network centrality measures under the normal condition where all the road segments are functioning without any disruptions. Afterwards, the calculated results of each topological parameter spatial Join their corresponding road segment IDs to distinguish the spatial representation of each topological parameter. The spatial representation of each topological parameter is depicted in Figure 6.

**Implementation of the Network Disruption Method**

As mentioned in the above, this study utilised the critical-link failure method to disrupt the topological network. In terms of that, it calculates the critical-link segment at each iteration and attacks it at each iteration sequence until all the road segments are disrupted. The study utilised the Python environment to implement the desired network disruption method, which also records each topological parameter value

change related to the consecutive critical-link attack, which is essential for the in-depth analysis.

**4. ANALYSIS**

As we mentioned in the analytical framework of the study, in-depth analysis related to the transportation system resilience is carried out under the three major aspects, known as: I. Capturing the topological changes of the network; II. Identifying the network performance and functional changes; and III. Identifying the critical changes of the network. The detailed discussion of each analytical aspect would be presented as follows;

**(1) Assess the Topological Changes of the Network under the Disruptive Condition**

The study utilised descriptive statistics to assess

**Table 3** Topological Changes of the Network under the Disruptive Condition

Parameter	Assessment Stage	Impacted Nodes	Increase	Decrease	No Change
<b>Degree</b>	10% Stage	32	0 (0%)	263 (81%)	60 (19%)
	20% Stage	64	0 (0%)	298 (92%)	25 (8%)
	30% Stage	96	0 (0%)	315 (98%)	8 (2%)
<b>Clustering Coefficient</b>	10% Stage	32	74 (23%)	56 (17%)	193 (60%)
	20% Stage	64	57 (18%)	124 (38%)	142 (44%)
	30% Stage	96	13 (4%)	198 (61%)	112 (35%)
<b>Path Length</b>	10% Stage	32	0 (0%)	323 (100%)	0 (0%)
	20% Stage	64	0 (0%)	323 (100%)	0 (0%)
	30% Stage	96	0 (0%)	323 (100%)	0(0%)
<b>Closeness Centrality</b>	10% Stage	32	0 (0%)	323 (100%)	0 (0%)
	20% Stage	64	0 (0%)	323 (100%)	0 (0%)
	30% Stage	96	0 (0%)	323 (100%)	0 (0%)
<b>Eigenvector Centrality</b>	10% Stage	32	106 (33%)	180 (56%)	37 (11%)
	20% Stage	64	93 (29%)	192 (59%)	38 (12%)
	30% Stage	96	48 (15%)	234 (72%)	41 (13%)
<b>Betweenness Centrality</b>	10% Stage	32	80 (25%)	71 (22%)	172 (53%)
	20% Stage	64	32 (10%)	90 (28%)	201 (62%)
	30% Stage	96	6 (2%)	104 (32%)	213 (66%)

the topological changes of the transportation network in three selected disruptive situations for each structural and network parameter. Since the significant functional changes of each parameter are depicted in the critical-link attacks of the first 10%, 20%, and 30% of situations, those events are selected to assess the topological changes of the network. Table 3 depicts the topological changes of both structural and network centrality measures related to the three selected disruptive conditions.

Considering the topological changes of both structural and network centrality measures related to the three selected disruptive conditions; it's very clear that even though the direct impact is caused by very limited number of nodes in the network, their impact to the entire network is very significant. For instance, in path-length and closeness centrality, 10% of disruption causes disruption to the entire network functionality. This clearly distinguished the network effect of the transportation network disruption. In addition, the level of the disruption and decrease of the each considered parameter depicts very homogeneous relationship as it decrease the parameter value when it increase the significance of the attack of the network. However, the impact of removing the highly critical 10% segments from the network is extremely high when compared to the next two disruptive conditions (i.e., 20% & 30%), as their contributions to network disruption are significantly lower when compared to the impact of removing the first 10% segments from the network. This well demonstrates that the first 10% of segments are extremely critical for the network when compared to the other 90% of segments of the network, as their impact on

the disruption of the network is negligible to the network. This clearly distinguishes the scale nature of the transportation network.

Apart from that, it also identified that, the disruption of critical road segments caused to the increase of centrality value of certain road segments, (i.e., eigenvector centrality and betweenness centrality). This is mainly caused by the increase in network importance of certain road segments after the disruption of critical road segments and network flow change after the disruption. For instance, eigenvector centrality depicts the important road segments in the network, as it captures the direct influence and influence over the other segments in global terms by considering the entire topological network. Thus, it caused the remaining segments to increase in importance when it disrupted the critical segments of the network. In another way, betweenness centrality depicts the highly intervened road segments of the network and is a proxy for the traffic-flow distribution of the network. Such a way, when it disrupting the highly between road segments from the network, the traffic flow transfer to the remaining road segments which caused to increase the betweenness value of the certain road segments. However, it is clear that this trend tends to decrease as when the percentage of network disruption getting increased as it loss the network connectivity of the transportation network as most of the road segments are becoming isolated when in removing the critical road segments from the network.

In addition, the study assessed the change of the average structural parameters from normal condition to disruptive condition to study the structural changes of the network under the disruptive condition. Table

**Table 4** Average Structural and Network Centrality Value Change at each Disruptive Condition

Assessment Stage	Node Count	Degree Connectivity	Clustering Coefficient	Path Length	Closeness Centrality	Eigenvector Centrality	Betweenness Centrality
<b>Normal Condition</b>	323	3.80	0.33	4.67	0.21	0.03	0.01
<b>10% Stage</b>	291	1.78 (53%)	0.23 (28%)	4.36 (7%)	0.01 (95%)	0.03 (19%)	0.00 (99%)
<b>20% Stage</b>	259	1.11 (71%)	0.11 (65%)	4.16 (11%)	0.00 (97%)	0.03 (12%)	0.00 (100%)
<b>30% Stage</b>	227	0.634 (83%)	0.030 (91%)	3.99 (14%)	0.00 (99%)	0.03 (23%)	0.00 (100%)

4 depicts the average structural and network centrality value change from the normal condition to each disruptive condition.

As depicted in Table 4, the results are very clear that the disruptions are significantly affected by the decrease in both structural and network centrality parameters from their baseline conditions. In such a context, when considering the structural properties, the impact of each disruption stage has a significant impact on the transportation network's scale-free property and small-world network property.

In terms of scale-free property, the natural-street representation of the topological network distinguishes the scale-free property of the transportation network under the undisrupted condition as it follows the power-law distribution (i.e.,  $f(x) = cx^\alpha$ , where  $c$  is a constant and  $\alpha$  depicts the parameter of the distribution) as the log-log plot at the undisruptive condition is pretty close to a straight line with an exponent of around 2.0, which is a clear indication of scale-free property. However, the average street connectivity decreased significantly as it lost network connectivity due to network disruptions at each disruptive level (i.e., 10%-53%, 20%-71%, and 20%-83%). This significantly impacts the scale-free property of the transportation network as most of the attacked segments in each iteration are highly critical segments to the network in each iteration as they are high in their degree of connectivity. In this manner, it clearly demonstrates that after the disruption of 30% of critical segments, the network almost (i.e., 83%) loses its street connectivity and scale-free property, despite the fact that 227 segments continue to function in the network with a low degree of connectivity. This is clearly distinguished by the power-law distribution of the street connectivity at each disruptive level, which significantly drains from their baseline condition to each impacted level, and the power-law relation does not further exist after each (i.e., from 10% attack onwards) disruptive condition. Figure 7 depicts the log-log plot of the power law distribution at each disruptive condition, where the x-axis and y-axis represent the logarithms of street connectivity and cumulative probability, respectively.

In another way, the natural-street representation of topological networks distinguished the small-world network characteristics in the undisrupted condition, which are distinguished by their clustering coefficient and path length. Such a way, clustering coefficient depicts the higher connectedness with their neighboring segments of the network, (i.e., 0.33 of clustering coefficient) and path-length depicts the very short average separation between the segments of the network, (i.e., 4.67 steps). Such a way, both measures claims that, the natural street network under the undisrupted condition distinguished the small-world network characteristics in their topological representation. However, clustering coefficient and path-length are distinguished contrast reaction to the small-world property under the disruption situation. For instance clustering coefficient parameter clearly depicts the decrease of average clustering coefficient related to the significance of the disruption situation as it drains the ability of segments to be linked due to the segments are getting attacked at each iteration, (i.e., 10%-28%, 20%-65%, and 20%-91%).

Other way in contrast to the clustering coefficient, path length depicts an excessive decrease of the path-length related to each disruption situation, which causes one to misinterpret the significant increase of small-world property under the disruptive situation. However, this mainly caused the isolated clusters and segments under the disruptive situations, which shows the path-length of the network is significantly decreasing with the increasing attack level. In such a way, it is identified that the network separation under the disruptive situation is very short, although the network as a whole becomes chaotic and isolated. In such a context, by comparing the two properties of the small-world network (i.e., clustering coefficient and path length), it can distinguish significant decrease of small world property under the disruptive situation (i.e., it may not exist during the disruptive situations).

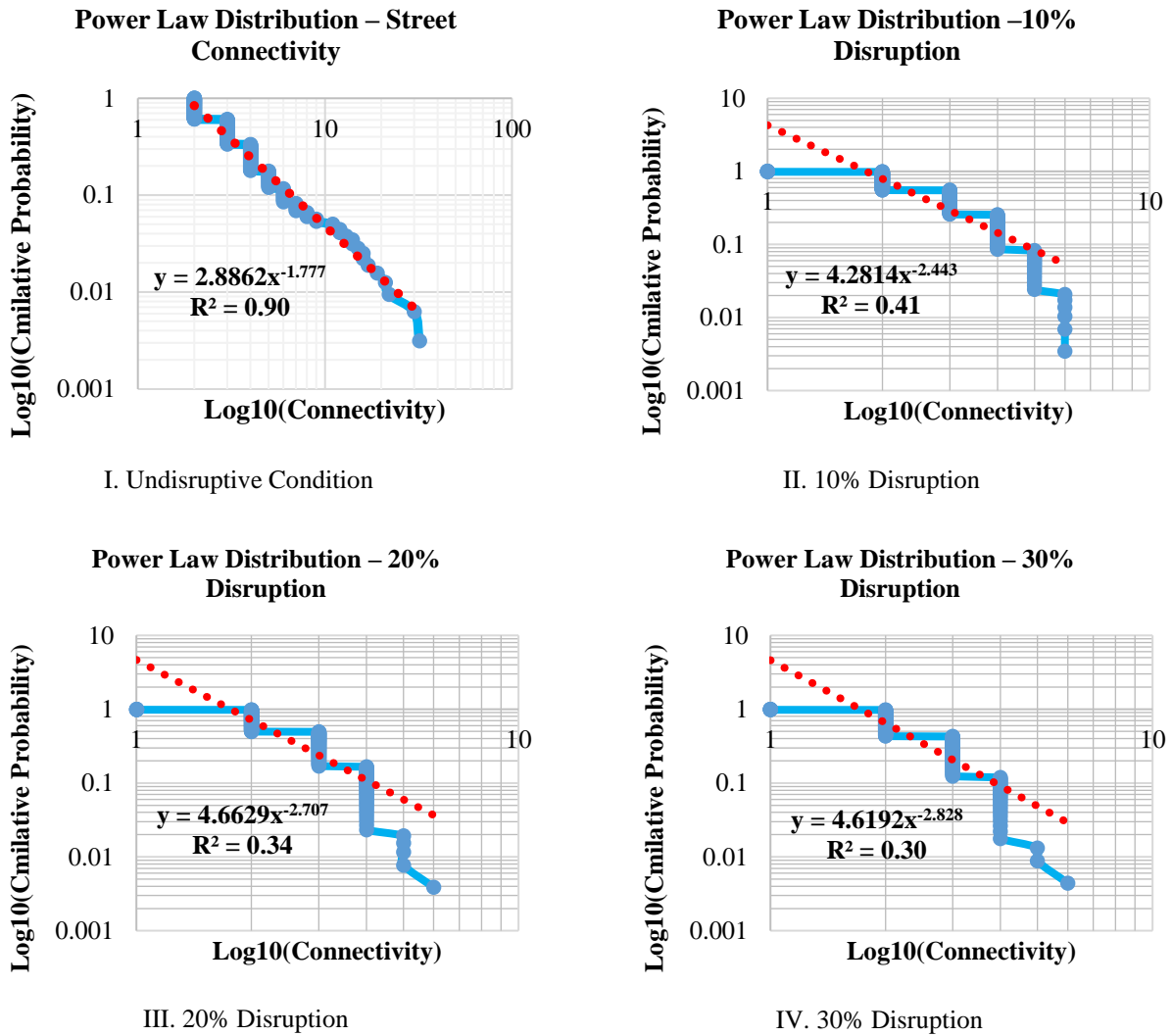


Fig.7 The Power-Law Distribution of the Street Connectivity under Disruptive Condition

Consequently, it distinguished that topological changes in both structural and network centrality measures caused by disruptive conditions have a significant impact on transportation network functionality as a whole, even though the direct impact is caused by the small number of nodes, which ultimately drains the transportation network's reliance to a catastrophic level.

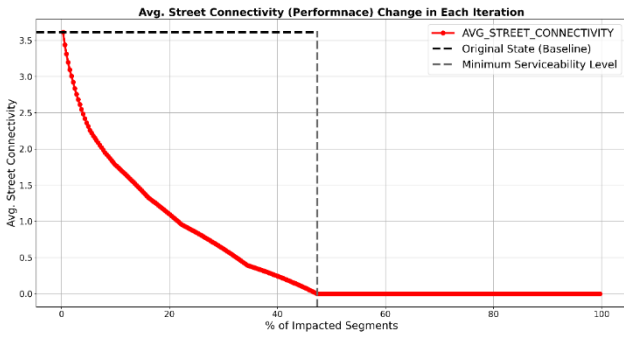
**(2) Identifying the Network Performance and Functional Changes under the Disruptive Condition**

**a) Network Performance Change under the Disruptive Condition**

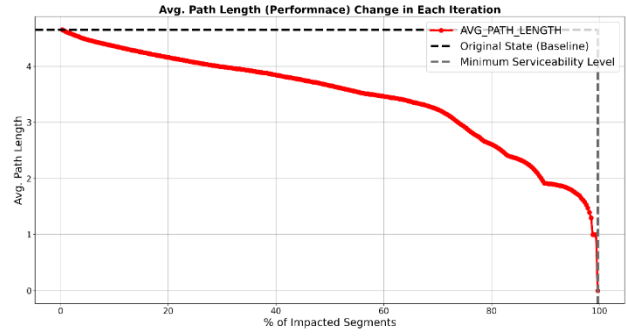
In this study, network performance change under the disruptive condition was assessed as the reduction of the baseline condition of each topological parameter under the disruptive conditions as it changes the parameter value when the segment gets attacked at each iteration. The study utilised the average parameter value as the indicator to measure the performance change of each parameter. Figure 8 depicts the

change of the average topological value of each parameter in relation to their successive critical-link attacks.

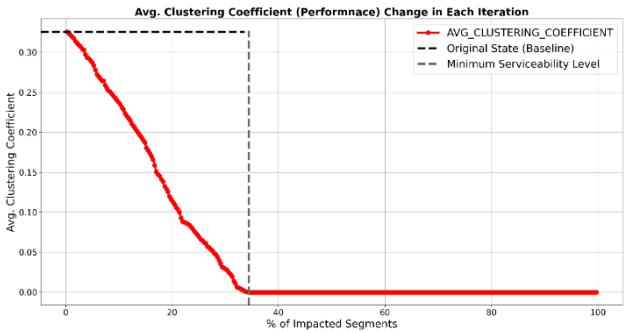
As depicted in Figure 9, critical-link attacks on each topological parameter distinguished significant fluctuations in the baseline performance level of each structural and network centrality parameter. It distinguished that all of the parameters identified critical fluctuations in network performance and damage to the overall network's functionality during their initial critical-link attacks, as the network lost highly important road segments during the early iterations. However, after a certain level, the impact of the critical-link attacks on the network performance decreases as most of the important road segments are lost during their initial attacks on the network, which causes the remaining road segments to be broken into isolated clusters and the network performance to be permanently terminated. As a result, network performance for all parameters reaches its minimum serviceability level before the entire critical-link road segment is attacked, while the majority of the road



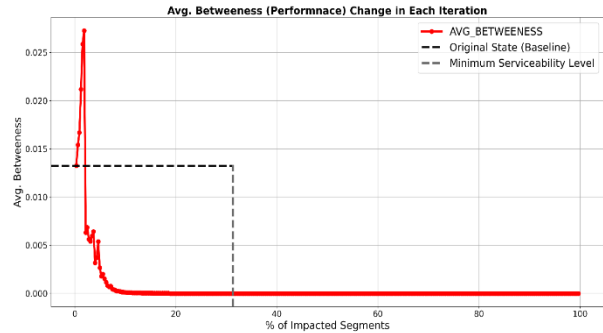
Change in Average Street Connectivity



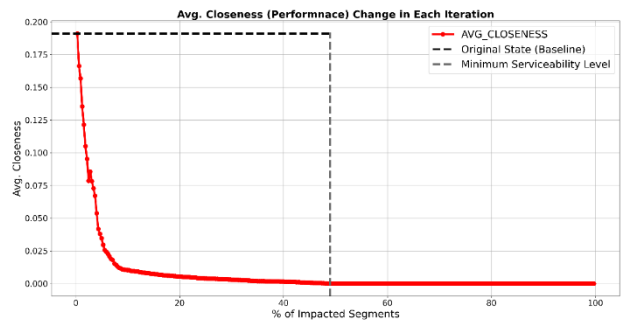
Change in Average Path Length



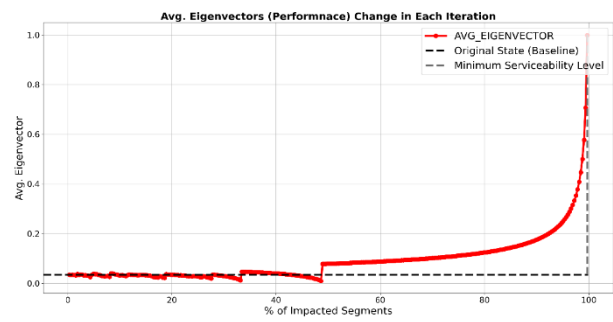
Change in Average Clustering Coefficient



Change in Average Betweenness Centrality



Change in Average Closeness Centrality



Change in Average Eigenvector Centrality

**Fig.8** Changes in the Average Topological value of each Parameter

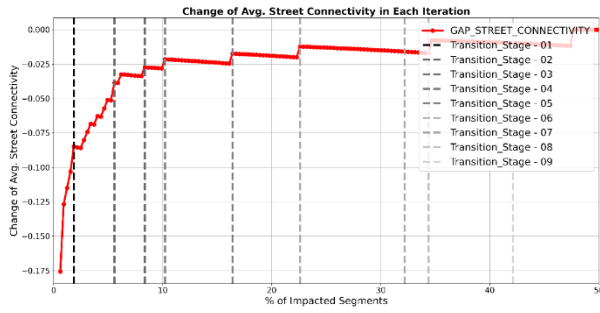
segments remain in the network.

In addition, it has been noted that critical-link attacks on certain topological parameters cause them to increase their performance levels temporally, such as betweenness and closeness centrality. This mainly caused the loss of a certain road segment, which may increase the performance of another road segment due to the network functionality changes after the disruptions. Last but not least, it has been noted that the eigenvector centrality tends to increase its performance level with critical-link attacks. This is due to the network importance of the segments, which tends to increase when the network size is dwindling due to critical-link attacks. In such a way, the higher the network attacks, the importance of the remaining road segments is increased, which is falsely portrayed as the performance increase of the transportation network.

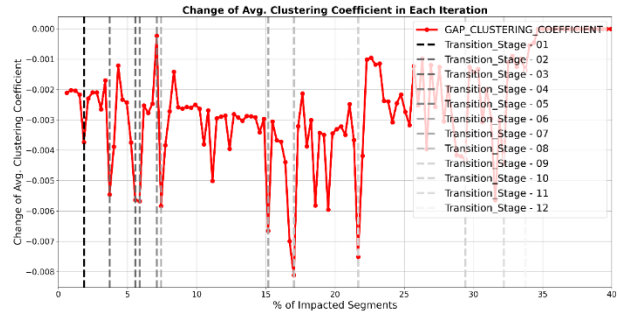
In such a context, the study identified that the disruption of the network topology and the transportation network performance have a very sensitive relationship. Therefore, the proposed method can be utilised to identify the critical-link segments specifically at each iteration and assess the transportation network's resilience when the particular segment gets attacked.

**b) Functional Changes under the Disruptive Condition**

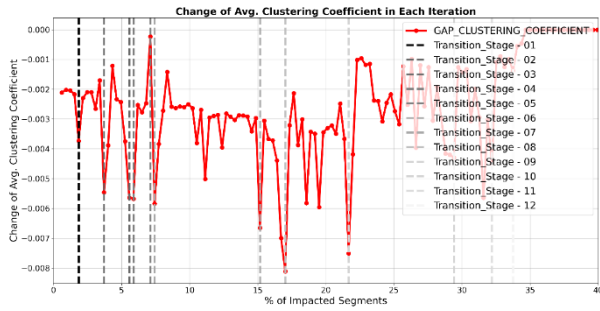
Since the network topology and the transportation network performance distinguish sensitive relationships, functional changes of the network under each respective disruption iteration were assessed to identify the transportation network resilience. In such a context, the study calculated the relative change rate of each parameter at each disruptive iteration and



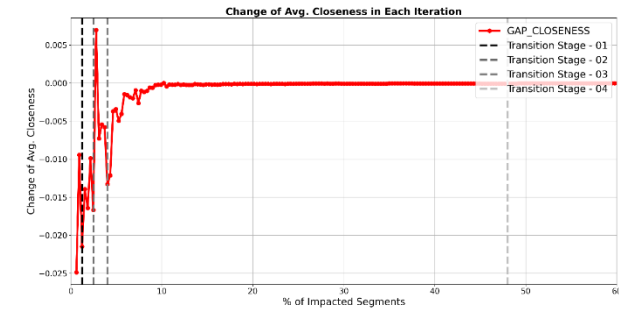
Functional Change of Average Street Connectivity



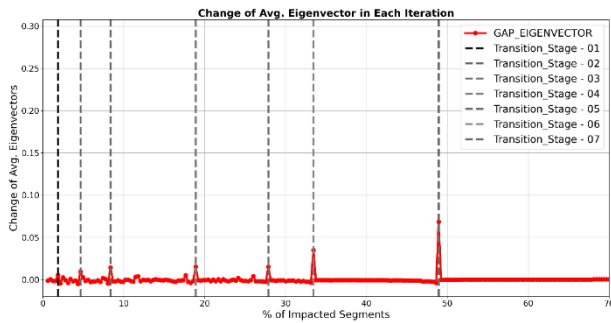
Functional Change of Average Clustering Coefficient



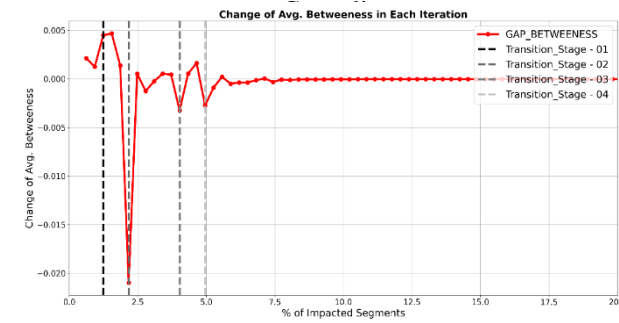
Functional Change of Average Path Length



Functional Change Stages of Average Betweenness



Functional Change of Average Closeness Centrality



Functional Change of Average Eigenvector Centrality

**Fig.9** Functional Changing Categories related to the Topological Parameters

categorized the significant functional changes of the network into specific categories by evaluating the maximum functional changes of the relative changing sequence. In such a way, it evaluates the nearest maximum value or value change of the relative changing rate sequence from rank  $K$  to the end and classifies them into categories. This process continues until all the sequences are categorized into a specific category. The formula to calculate the Relative Change Rate is shown as follows (Dong, et al. 2015).

$$R_k = \frac{S_k - S_{k+1}}{S_k} \quad (07)$$

Where;

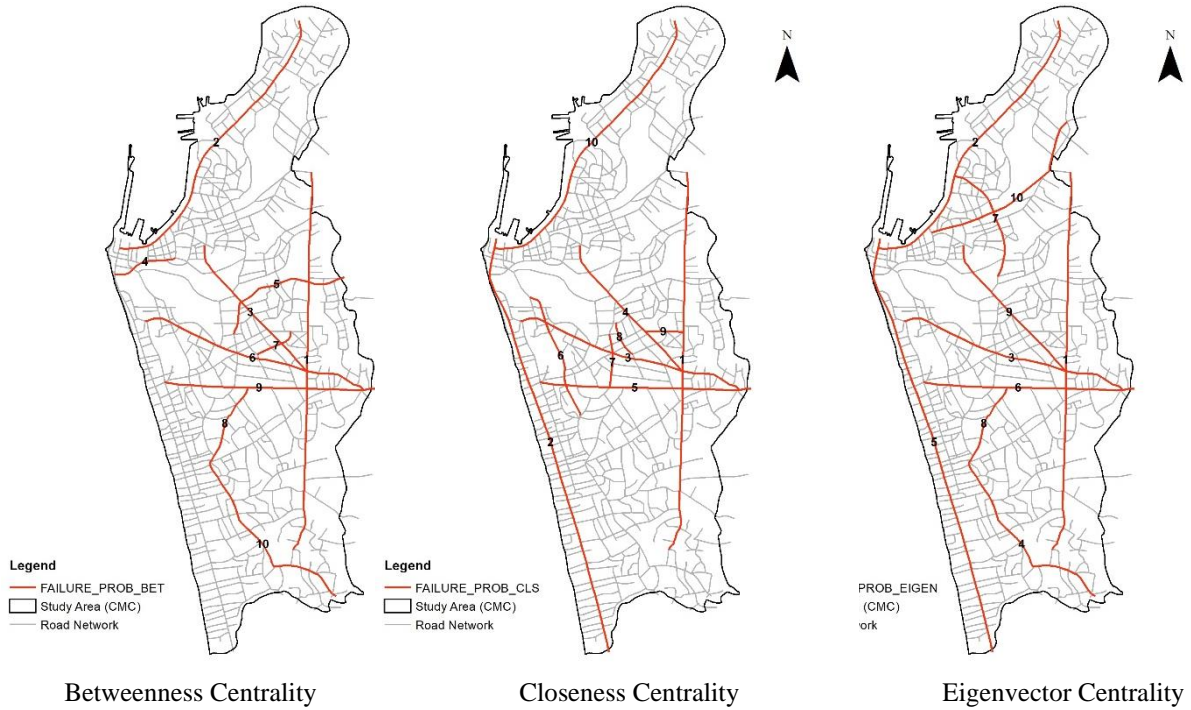
$R_k$  : Relative Change Rate

$S_{k+1}$  : Parameter  $S$  from Rank  $k$  to the  $k + 1$

It is important to mention that in this study it used the average parameter value of each parameter to measure the relative change rate and calculate the absolute relative change value to categorize the signifi-

cant functional changes. Figure 9 depicts the functional changing categories related to the topological parameters utilised in this study.

As depicted in Figure 9, there can be identified instant variation of functional changing categories of all the topological parameters in their early stages as their relative changes are extremely high in the initial network disruption iterations. This mainly caused the loss of essential critical road segments in their initial stages of the network. However, after certain stages of the network disruption, the relative changes of each parameter become stabilized as the entire network functionality becomes terminated as the performance becomes minimized due to the critical segment failure. For instance, functional changes of the structural parameters show how network structure change is related to each functional changing category. It can be clearly distinguished that the street connectivity and clustering coefficient are significantly changed in their initial disruption stages.



**Fig.10** Critical Change of the Road Segments by their Failure Probabilities

Meanwhile, the path-length of the network is distinguished by relatively minor impact in the initial stage of the disruption, as the removal of a few road segments does not have a significant impact on the average path-length in the structural perspective, although it does from the network perspective. In terms of functional changes of the network centrality parameters, the average betweenness and closeness centrality values are distinguished as significant functional changes in their initial stage as the loss of critical road segments significantly impacts the traffic-flow changes and road accessibility of the transportation network. Meanwhile, eigenvector centrality identified relatively low impact in their initial stage of network disruption because the importance of the road segments is relatively low during the initial stage because the majority of the road segments are still on the network in their global perspective.

In such a context, this study is capable of identifying the functional changing categories associated with each structural and network centrality parameter from each network disruption situation, which is critical knowledge for studying the transportation network changes in the structural perspective and helps to maintain the optimal transportation network functionality and serviceability, traffic flow distribution, and minimize disaster risk associated with each disruption stage.

### (3) Identifying the Critical Links of the Network under the Disruptive Condition

This study exploited the failure probability of road segments at each iteration to identify the critical road

segments under the disruptive condition. This helps to identify the most critical road segment in the transportation network related to each disruptive condition. It is essential knowledge for transportation planners and traffic engineers as it helps to identify the potential vulnerable road segments related to each disruptive condition and to manage the optimal transportation serviceability and traffic flow when such critical road segments get disrupted.

For instance, when certain road segments get disrupted due to man-made or natural consequences, the proposed method can identify the most critical road segments under the aspects of each topological parameter. In such a way, it can identify the most critical road segments under the O-D trip distribution, network accessibility, and important road segments under the global connectivity aspects. This knowledge is critical for maintaining optimal transportation network performance, functionality, and serviceability under disruptive conditions because it can forecast critical road segments under each aspect and organize traffic management plans accordingly. Figure 10 depicts the critical change of the road segments by their failure probabilities under each topological perspective.

## 5. DISCUSSION AND CONCLUSION

In this study, main purpose was to study the how topology changes under disruptive conditions affect transportation system resilience by utilising the transportation network topological measures as a proxy.

In such a context, this study assesses the transportation network resilience under three major aspects, known as: I. Capturing the topological changes of the network; II. Identifying the network performance and functional changes; and III. Identifying the critical changes of the network under the disruptive condition. The study utilised critical-link attacks to disrupt the transportation segments and capture the network resilience precisely by incorporating all the possible network disruptions regardless of their pre-occurrences by employing the in-depth statistical and spatial analysis in both macro and micro events through the utilization of topological parameters. This avoids the limitations of traditional transportation resilience studies, which are primarily focused on pre-hazard occurrences. The empirical analysis has been carried in the road network of CMA, Sri Lanka by utilizing the Networkx Library under the Python Environment.

Findings of the study depicts that, the topological changes of the CMA road network under the disruptive condition doing significant impact to both transportation network structure and functionality during the disruptive condition as the direct impact is caused to the very limited number of nodes in the network, but their impact to the entire network is very significant. This distinguished the network effect of the transportation network disruption. In addition, it also distinguished the structural and network change of the network according to the each disruption occurrences as it capable to depicts the specific segments and their corresponding impact level. This is important knowledge when studying the functional and network change of the transportation network under the disruptive condition as it can clearly distinguished the corresponding roads segments and their specific impact level according to the each disruption occurrences. For instance, structural parameters distinguished significant drain of scale-free property of the transportation network at each disruptive level from their baseline condition. Similarly, clustering coefficient and path-length are distinguished the reduction of the transportation network's small-world property according to the each disruption occurrences.

In terms of network centrality parameters, betweenness centrality distinguished a significant decrease in its value as the impact on the O-D trip distribution of the CMA road network as the majority of the critical road segments are disrupted. It clearly depicts the significant road segments, (i.e., hotpots) under each disruption condition and transferring the traffic flow from impacted road segments to the re-

maining road segments which are not significant under the baseline condition. Meanwhile, closeness centrality depicts the significant decrease in the transportation network accessibility of the CMA road network under each disruption situation as it loses network connectivity. This clearly distinguished the emerging of temporary accessibility hotpots in certain areas of the network where remaining road segments exist as it transfers the baseline accessibility condition to the remaining road segments. Similarly, eigenvector centrality distinguished the reduction of the network significance of the segments in the CMA road network in global terms due to the impact of critical road segments due to network disruptions. This clearly distinguishes the significant road segments under the disruptive conditions as it captures the direct influence and influence over the nodes in global terms by considering the entire topological network. The Figure 11 depicts the topological changes of the network centrality parameters under the disruptive condition.

The other way, considering the network performance and functional changes during the disruptive conditions, the study assessed the change of the baseline condition and the relative change rate of each parameter at each disruptive event, respectively. In terms of performance change, it distinguished that all of the parameters identified critical fluctuations at their initial disruption iterations and damage to the overall network's functionality as the network lost highly important road segments during their early iterations. This caused to drain the CMA road network performance to their minimum serviceability level as remaining road segments to be broken into isolated clusters and the network performance to be permanently terminated. This depicts important knowledge to maintain the optimum transportation serviceability under the disruption situation as it can distinguished the respective performance level of the network related to the each specific segment disruption. The minimum serviceability level of each topological parameter in CMA road network depicts in Table 5.

**Table 5** Minimum Serviceability Level

Topological Parameter	Minimum Serviceability Level (as a % of Disruption)
Street Connectivity	47.36%
Clustering Coefficient	34.36%
Path-Length	99.69%
Closeness Centrality	48.91%
Betweenness Centrality	31.26%
Eigenvector Centrality	99.69%



Fig.11 Spatial representation of Topological Changes of the Network under the Disruptive Condition

Other way, the study identified the instant variation of functional changing categories of all the topological parameters in their early stages as their relative changes are extremely high in the initial network disruption iterations due to the loss of essential road segments. This clearly distinguished network functional change related to the each segment failure which is essential knowledge for road network performance and functionality assessments and evaluate the traffic volume and accessibility variations according to the each segment disruptions and maintaining optimal transportation network functionality and serviceability.

Finally, the failure probability of the critical road segments was used to identify the critical road segments under each disruptive condition. In such a context, the study captured the critical road segments under the aspects of betweenness centrality, closeness centrality, and Eigenvector centrality, which represent the critical road segments under the aspects of traffic flow distribution, network accessibility, and significance of the segments, respectively. It is distinguished that considering all CMA road network critical road segments under three aspects is almost similar, but only the level of the significance differs. In such a context, it can provide special attention to those critical road segments under the disruption condition, which helps to maintain the optimal transportation system serviceability and functionality. In addition, the study identified critical road segments are

distinguished the arterial road segments in the geometric aspect and their AADT is comparatively high compares to the remaining road segments as an empirical evaluation. In such a way, a sensitive relationship can be identified between the critical road segments, major arterials and AADT distribution, which is essential knowledge for maintaining optimal traffic flow distribution under disruptive conditions (i.e., this relationship is expected to be further studied in future studies). The AADT and major arteries of the CMA are depicted in Figure 12.

In such a context, the proposed framework could be applicable for studying the transportation network resilience and traffic flow distribution in any given disastrous event, as it can incorporate the critical link attacks to disrupt the transportation segments. In addition, it is also capable of studying transportation network resilience in unexpected situations, which is important for disaster risk reduction and preparation of evacuation plans and evaluating transportation network performance in Asian context where such studies are essential. Last but not least, this approach helps to assess the transportation network resilience in a holistic manner, identify the critical paths and traffic bottlenecks, and prepare traffic management plans and evacuation plans in the early stages before any unexpected and unprecedented disruption gets effected.

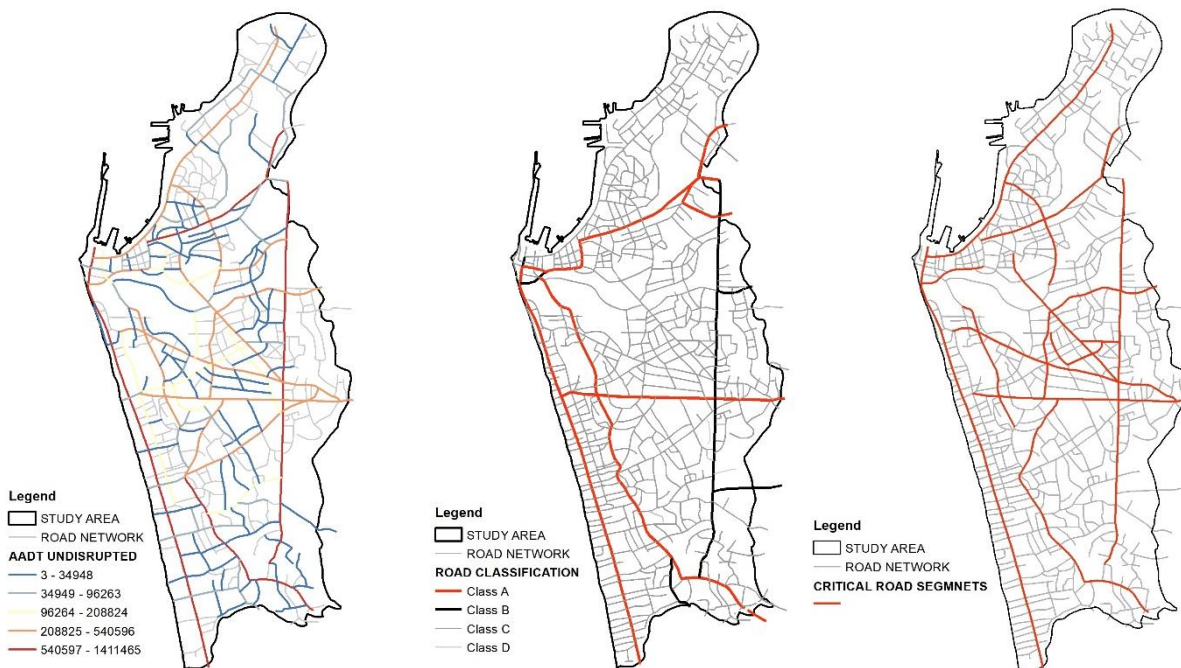


Fig.12 AADT Distribution (Left), CMA Road Network Classification (Middle) and Cumulated Critical Road Segments (Right)

## 6. LIMITATION AND FUTURE WORK

The limitation of the study depicts as follows;

- (a) This study only utilised the statistical approach to assess the transportation network resilience by utilising the topological parameters as proxies to assess the transportation network resilience. In this way, this study does not consider real world transportation behavior with empirical data.
- (b) Although the study intends to study the in-depth analysis regarding the transportation network disruption by utilising the topological parameters, many of the studies are limited due to the unavailability of transportation data related to the disruption events in the developing countries' context.
- (c) The study primarily relies on the literature to prove the applicability of topological parameters to assess the transportation network resilience. In this way, in-depth justification of each topological parameter to assess the transportation network resilience has not been carried out in this study.

In such a context, in order to mitigate the above limitations, future studies may focus on mitigating the above-identified limitations. In such a way, It can then evaluate the topological parameters in relation to the traffic flow pattern in the real-world situation and examine how each parameter is used to evaluate the influence on the traffic flow pattern during disruptive events. In addition, this study identified the homogeneous relationship between the critical segments, major arteries, and AADT, which needs further studies with more accurate data and analysis. Moreover, this study's proposed framework can be incorporated with the real-world data to identify traffic bottlenecks and traffic volume at each disruption event as it provides a more sophisticated understanding of the traffic flow and network resilience.

**ACKNOWLEDGMENT:** This study was prepared based on the current study progress of the master's study of the corresponding author, which is titled "How Topology Changes Impact on Transportation System Resilience." In addition, the authors would like to acknowledge the "Western Province Transport Demand Model (WPTDM)" of Sri Lanka for providing the AADT data of the CMA area. Last but not least, the authors are grateful to the Department of Environmental and Social Infrastructure for their kind suggestions and continuous assistance with material and data.

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