A network centrality-based simulation approach to model traffic volume

(ネットワークトポロジーを考慮した交通需要モデル）

Amila Buddhika Jayasinghe

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A dissertation submitted in partial fulfillment of the requirements for the degree of
Doctor of Engineering

By

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Abstract

This study is placed in a milieu where existing methods on modeling vehicular traffic volume are hampered by data, cost and technical know-how constraints, especially in developing countries. To overcome those constraints, this study has developed an alternative approach to model vehicular traffic volume on road segments by a network centrality-based simulation.

The study proposes that trip makers' movements are guided by 'road network centrality.' Thus, a given trip originates at a road segment, pass-by through several segments and ends at another segment within the same road network. The road segments that are highly close to each other generate more 'origin-destination' (O-D) trips whereas the road segments that are highly intermediate among the others attract more pass-by trips. Hence, the proposed approach utilizes betweenness centrality and closeness centrality to capture 'pass-by' and 'O-D' trips respectively. The study introduces 'path-distance' to capture topological and mobility characteristics of roads; 'trip length-based moving-boundary' to capture trip catchment area; a 'vehicle growth' to capture temporal socio-economic changes; 'aggregated-zonal-level-centrality,' to capture trip generation; and 'relative-closeness-centrality,' to capture the trip distribution.

At first, the study conducted two pilot studies to examine the importance of travel time relative to topological distance; and to examine whether the relationship between traffic volume and centrality changes over the method of computing centrality. Next, the approach has been validated internally and externally, in three Sri Lankan case cities. Finally, the study examined the applicability of the proposed approach as a strategic planning and investment tool. The study compared and contrasted the advantages and disadvantages of the proposed approach in comparison to the existing methods. Furthermore, the study developed 'centrality-spectrums' and 'tailor-made guidance' which describes application options of the proposed approach per the data availability.

The results revealed that centrality values computed based on the proposed path distance recorded higher R^2 value compare to the centrality values computed based only on the topology of the road network. The model is on a par with the international standards (R^2>0.85, MdAPE<30%, RMSE<30%) and able to predict future traffic volume as accurate as the multi-step demand modeling. The model can be calibrated by using a little amount of actual observation points (N<40). Further, the findings revealed the ability to model the volume of trip generation by utilizing 'aggregated-zonal-closeness-centrality'(R^2>0.85, MAPE<25%); and the trip distribution between trip destination and trip origin zone by utilizing 'relative-closeness-centrality' (r>0.65, p<0.01). Furthermore, findings indicated that the approach is a capable to predict traffic volume based on various road network scenarios and to examine the structural coherence of road networks.

The proposed approach requires only road network data and able to implement by using publicly available network analysis software. Further, the proposed approach bypasses all four stages of the multi-step demand modeling. Accordingly, the applicability of the proposed approach is prominent in data scarce and cost-constraint situations. The research contributes to the transport engineering and planning fields by developing an accurate, cost-effective and technically efficient approach that can utilize as a decision-making tool to model traffic volume in planning road networks.

List of Publications

Peer reviewed publications

1. **Amila Jayasinghe,** Kazushi Sano, Hiroaki Nishiuchi, "Explaining Traffic Flow Patterns using Centrality Measures", **International Journal for Traffic and Transport Engineering** (IJTTE), vol. 5, no. 2, pp. 134-149, 2015.
2. Amila Jayasinghe, Kazushi SANO, Hiroaki NISHIUCHI, "Network Centrality Assessment (NCA) as an alternative approach to predict vehicular traffic volume: A case of Colombo, Sri Lanka", **Journal of the Eastern Asia Society for Transportation Studies**, vol. 11, pp. 834-853, 2015.
3. **Amila Jayasinghe,** Kazushi Sano, Rattanaporn Kasemsri, Hiroaki Nishiuchi, "Travelers' Route Choice: Comparing Relative Importance of Metric, Topological and Geometric Distance", **Procedia Engineering- Journal**, vol. 142, pp. 18-25, 2016.
4. **Amila Jayasinghe,** Kazushi Sano, "Estimation of Annual Average Daily Traffic on Road Segments: Network Centrality Based Method for Metropolitan Areas", **Compendium of Transportation Research Board (TRB)** 96th Annual Meeting. Transportation Research Board of the National Academies, No.17-03141, pp. 1-18, 2017.
5. **Amila Jayasinghe,** Kazushi Sano, Rattanaporn Kasemsri, "Application for developing countries: Estimating trip attraction in urban zones based on centrality", **Journal of Traffic and Transportation Engineering**, (in press). ID No: JTTE_2016_215

Conferences presentations

1. 11th International Conference of Eastern Asia Society for Transportation Studies (**EASTS**) held on 11th-14th September 2015 at Radisson Blu Hotel Cebu, Cebu, **The Philippines**. "Network Centrality Assessment (NCA) as an alternative approach to predict vehicular traffic volume: A case of Colombo, Sri Lanka". A. Jayasinghe, K. Sano and H. Nishiuchi. (Published in the Journal of the Eastern Asia Society for Transportation Studies)
2. 52nd Japan Society of Civil Engineers (**JSCE)** Infrastructure and Planning Conference held on 21st-23rd November 2015 at Akita University, Akita, **Japan**. "The Role of Centrality Characteristics of Road Network in Travelers' Route Choice: A case of Colombo, Sri

Lanka". A. Jayasinghe, K. Sano, R. Kasemsri and H. Nishiuchi. (Included in the conference proceedings)

3. International Conference on Sustainable Development of Civil, Urban and Transportation Engineering–**CUTE** 2016 held on 11th-14th April 2016 at Ton Duc Thang University, Hochiminh City, **Vietnam**. "Travelers' Route Choice: Comparing Relative Importance of Metric, Topological and Geometric Distance", A. Jayasinghe, K. Sano, R. Kasemsri and H. Nishiuchi. (Published in the Procedia Engineering-Journal)
4. Research for Transport & Logistics Industry (**R4TLI**) held on 3rd-4th June 2016 at Hotel Galadari, Colombo, **Sri Lanka**. "A Network Centrality Application: Examination of Structural Coherence of Colombo Road Network". A. Jayasinghe, C. de Silva and K. Sano. (Included in the conference proceedings)
5. 54th Japan Society of Civil Engineers (**JSCE)** Infrastructure and Planning Conference held on 4th–6th November 2016 at Nagasaki University, Nagasaki, **Japan**. "Network Centrality Assessment (NCA) to Simulate Traffic Volume: A Strategic Planning and Investment Tool for Developing Countries". A. Jayasinghe, R. Kasemsri, D. Bandara and K. Sano. (Included in the conference proceedings)
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Chapter – 1
Introduction

1.1. Background

The movements of people are one of the most important factors for the quality of human life and development of the society. Accordingly, various transport infrastructure has been introduced to facilitate human movements, and the provision of the transport infrastructure has become a common tool used for development (Rodrigue, 2017). "Along with the need for development, rapid urban growth unconscionable pressure on the traffic infrastructure" (Gehl, 2013). With rapid urbanization and motorization, it has become a challenge to meet the need of transport infrastructure facilities. The most of intensive urbanization takes place in developing countries, and it has caused an extreme pressures on transport infrastructure in mega cities as well as small and medium townships in those countries (Kumar, et al., 2011), (Bliss & Breen, 2012), (Pojani & Stead, 2015), (United Nations, 2016), (Rodrigue, 2017). Accordingly, the rapid urbanization in cities in developing countries have led to a sudden jump in traffic volume and caused several problems such as traffic congestion, road accidents, and air pollution (Pucher, et al., 2007), (Roy, 2009). Solving those problems, which has become a strong challenge for governments and government-related institutions, not only constrained by high investment costs but also due to the limited-availability of accurate and up-to-date data on traffic volume difficulties in the prediction of the future scenarios, etc. This demands a strategic, quick and cost-effective solutions to identify the existing traffic volumes and model the trajectories of future scenarios especially in developing countries (Hassan & Hoque, 2008), (Walker, et al., 2010), (Fujiwara & Zhang, 2013), (Zhang, et al., 2013), (Verma & Ramanayya, 2014). Therefore, practitioners and researchers who work in the domain of transport engineering and planning in developing countries have paid meticulous attention to develop new approaches to model the existing traffic situations and to predict future scenarios.

1.1.1. Applicability of existing traffic volume estimation and travel demand prediction methods in the context of developing countries

Different methods to model traffic volume can be broadly distinguished into three approaches as ‘coverage count’, ‘direct demand modeling’ and ‘multi-step travel demand modeling’ (Lowry, 2014), (McDaniel, et al., 2014). A continuous record of the collected traffic volume data throughout the year is the most reliable input for obtaining Annual Average Daily Traffic (AADT) volume. However, it is not economically feasible to install Automatic Traffic Recorders (ATRs) for extensive road networks in developing countries. As an alternative, coverage count method (also called as traditional factor approach) is widely used in estimating AADT (Zhao & Chung, 2001), (Transport, 2014) and recommended by the guidelines of AASHTO (1992). In the standard coverage count approach, study region (city or region) is divided into a set of zones and carry out at least a 24-hour coverage count survey in each zone, and adjust based on daily and seasonal variations using an expansion factor (Stokes & Banks, 2004). However, it is still not economical enough for all road segments in a network (Zhao & Chung, 2001), (Lowry, 2014). Particularly in the context of developing countries, it requires a considerable amount of labor and technical equipment for collecting traffic counts. Unavailability of accurately localized adjustment factors and guidelines further constrains the accuracy of results in developing countries (Samuel, et al., 2012). Moreover, coverage count is only suitable to estimate existing traffic volume and not able to employ for predicting future scenarios.

Accordingly, many researchers have attempted to develop alternative methods to estimate traffic volume without using extensive traffic count data, and those methods predominately belong to ‘direct demand modeling’. Direct demand models (also called as regression modeling) estimate traffic volume based on a set of explanatory variables including roadway characteristics, land use characteristics and socioeconomic factors. Socio-economic characteristics, vehicle registrations, and gasoline prices were used in Shon (1989) with an application of multiple regression model to estimate AADT. Cheng (1992) introduced a regression model-based application utilizing population by geographical areas, road functional classification, road width and roadway surface type. Mohamad, et al.,’s (1998) model comprised with four variables as type of location (rural or urban), accessibility, population and road mileage. Zhao and Chung (2001) also have developed a set of regression models for estimating traffic volumes by road functional classification, the number of lanes, access to expressways, accessibility to regional employment locations, population and employment.

Pans' (2008) developed a model including a GIS-based socio-economic and roadway characteristics data for a period of 10 years and calibrated. Lowry (2012) used the number of lanes and speed limit to predict traffic volume. Doustmohammadi and Anderson (2016) introduced a regression model including number of lanes on the roadway, roadway functional classification, population and retail employment. However, applicability of the above-mentioned method were questioned in the context of developing countries as well as small and medium-size cities due to the unavailability of continuous, short-interval, micro-data for significant predictors such as long-term socio-economic conditions (Zhong & Hanson, 2009), (Wang, et al., 2013), (Keehan, et al., 2017). Further, direct demand models have mostly considered the localized characteristics of roadways (i.e. functional category, roadway surface, access locations to highways) and unable to conceptualize road network as a system; and ignore the mutual interactions between land use and transport system.

Methods that have been developed based on multi-step travel demand modeling approach are considered as the most advanced application in traffic volume estimation and travel demand modeling. The most popular multi-step travel demand modeling approach is the 'four-step land use transport model'. The model comprised of four uni-directional steps as trip generation, trip distribution, modal split and trip assignment (AASHTO, 1998). The very first versions of four-step models represent a recursive system and unable to capture the influence of land uses. (Bureau of Transport Economics, 1998). Next generation of this modeling approach is 'integrated urban land use transport models'. This modeling approach represents the complex connections between transport system and land use system (Webster, et al., 1988). Integrated urban land use transport models have developed based on a random utility theory, welfare economics theory, microeconomics theory, gravity interaction and mathematical programming (Southworth, 1995), (Bureau of Transport Economics, 1998). Conventional four-step models and integrated urban land use transport models are considered as an aggregated trip-based models due to the capability to account travel as a function of the size of a zone and travel demand as a function of trips than of activities. Recent studies emphasized that, though "aggregated trip-based models have been applied extensively over past 40 years" (Castiglione, et al., 2015), many limitations including being ignore the organization and relationship between trips, spatial and temporal aggregation errors and lack of behavioral realism are still exists (Hunt, et al., 2005), (Sivakumar, 2007), (Bradley, et al., 2010), (Pel, et al., 2012), (Heppenstall, et al., 2012). Further, aggregated trip-based models treat land-use as merely an input variable for travel demand estimation at the trip generation stage and fail to acknowledge the dynamic intricate connection between land use and transport systems (Torrens & O'Sullivan, 2001), (Wegener, 2004), (Shivakumar, 2007), (Putman, 2012), hence, unable to reasonably represent the effects of dynamic land use changes, strategic transportation policies (Castiglione, et al., 2015).

Accordingly, multi-step travel demand modeling has been shifting towards disaggregated trip-based models, tour-based models, and activity-based models. Activity-based models consider “travel needs of the human are determined by their need to participate in activities spread out over time and space” (Shivakumar, 2007). Activity-based models are able to consider the individual level and household level travel choices, and predict travel demand for long-term and short-term. As a result, recently, activity-based models have become a popular application in transport engineering and planning (Shivakumar, 2007), (Lawe, et al., 2011), (Castiglione, et al., 2015). When it comes to the applicability of multi-step travel demand modelling approach, many researchers (Hamad & Faghri, 2003), (Pucher, et al., 2005), (Paul, 2009), (TRL report cited in Cairns, 2011), (Hamad, et al., 2015), (Castiglione, et al., 2015), (Sperry, et al., 2016) and government policy documents in developing countries (Gov. of India: (HPEC (High Powered Expert Committee), 2011)), (Gov. of Sri Lanka: (RDA, 2007)), (Gov. of Bangladesh; (Smith, 2009)) have highlighted key difficulties of adopting multi-step modeling in the context of developing countries due to following reasons.

- Inadequate up-to-date land-use and O-D trip data
- Lack of financial resources for data collection and for purchasing sophisticated software applications
- Inadequate technical expertise in local level agencies

Castiglione, et al. (2015) with reference to the context in USA, have highlighted that the limited number of activity-based modelling examples is likely a result due to the “costs and development schedule, data requirements, institutional issues, and software and hardware requirements” This situation is more likely in resource-constraint developing countries.

Other methods utilize to estimate traffic volume are based on, image-based data such as high-resolution satellite images and aerial photographs (McCord, et al., 2003), (Jiang, et al., 2006); machine learning algorithms such as Artificial Neural Network (ANN) (Lam & Xu, 2000), (Sharma, et al., 2001), (Shamo, et al., 2015), and location-based social network data such as social media, GPS, Bluetooth data (Wolf, et al., 2001), (Caceres, et al., 2007), (Friedrich, et al., 2010). Howevere application of those methods are limited due to, cost constraint to purchase and process image data (Pan, 2008), (Wang, et al., 2013); required extensive baseline data and more complex statistical procedures that demand high technical competence for calibration of machine learning algorithms (Wang, et al., 2013), (Staats, 2016); and lack of big data and limited online users makes the sample size too small for application of location-based social network data (McCord, et al., 2003), (Luna, 2014), (Orcutt, 2016).

1.2. Research need

There is a need to develop an alternative method to identify existing traffic situation and predict future travel demand scenarios, which can efficiently work under above-mentioned data, cost and technical know-how constraint situations, particularly in developing countries. In catering to the above need, this study focused on a set of research literature related to network centrality measures. “Centrality measures, which have been evolved from graph theory, were initially a popular concept in the fields of social network analysis and computer engineering; and applied to the field of spatial planning; to explain matters related to accessibility” (Jayasinghe & Munshi, 2004) and it is less cost intensive and required less data (Paul, 2015). ‘Space Syntax’ is one of those recently popularized network centrality methods. Space Syntax is a theory on space and human behavior. It consists of tools to analyze human interactions in the built environment and impacts of accessibility in spatial layouts on behavior (Hillier 1999). It maps centrality as a property of the topology of a given network mainly based on an index of ‘integration’ or ‘closeness’ (Hillier & Iida, 2005). Recently, network centrality has been applied to explain traffic flow. Existing applications have employed two centrality measures to explain traffic flow, namely, integration [closeness centrality] (Hillier et al. 1993, Hillier 1999, Hillier and Iida 2005) and betweenness centrality (Turner 2007; Jiang and Liu 2009).

The results previous works (Hillier et al. 1993, Penn et al. 1998, Raford and Ragland 2004, Hillier and Iida 2005, Chiaradia 2007, Turner 2007, McCahil and Garrick 2008, Jiang et al. 2008, Jiang and Jia 2011, Lowry 2014, Galafassi and Bazzan 2014, Jayasinghe et al. 2015) have repeatedly claimed that the centrality is capable of explaining pedestrian and vehicular flows (refer Table 1.1). Many of these studies have explained pedestrian movements and vehicular traffic flow of specific mode in micro scale, especially in urban blocks and cities. Jiang et al. (2008) and Lowry (2014) have attempted to explain the relationship between AADT and centrality of a road network. Jiang et al. (2008) have “investigated the the join principles and deflection angle threshold with respect to the formation of natural roads, and their correlation to AADT" by using both national wide and urban road networks in Sweden. Lowry (2014) has attempted to estimate AADT of the urban road network in Moscow, Idaho, USA based on 'origin-destination centrality'.

Even though the results of the previous studies have provided a green light (refer Table 1.1), many challenges are yet to overcome when employing centrality measures to simulate vehicular traffic volume particularly at the macro scale and in developing countries. There are case studies where the correlation between centrality and traffic volumes are not satisfactory (Peponis, et al., 1997), (Paul, 2009), (Xia, 2013). In the existing studies, link costs of explanatory variables were primarily referred to the cognitive behavior of human movements (i.e., topological shortest path, least angular turns) and the influence of the roadway characteristics such as mobility, traffic congestion, and network uniqueness have not considered. Paul's (2013) works on the limitations of space syntax in modeling the distribution of vehicular movements has highlighted the importance of an impedance factor for account mobility characteristics of roadway units such as land use access opportunities, traffic congestion, travel time. Previous studies related to vehicular traffic volume and centrality have only concerned flow of through trip-distribution (i.e. pass-by trips) and have not exploded land use generated trips [to-and-from] in relation to centrality (Paul, 2013), (Papa, et al., 2014), (Lerman, et al., 2015), (Paul, 2015) (Barros, et al., 2016). Lowry's works on AADT estimation by employing 'origin-destination centrality' also could not solely rely on centrality measures as relative 'trip production/attraction potential' values were derived from land use data. Utilizing land use data in developing countries is difficult due to lack of availability and resource consuming nature of collection. Moreover, all of these studies have so far, attempted only on explaining the relationship between centrality and traffic volume and yet to work on model traffic volume. Therefore, there is a need to further look at the applicability of network centrality to model traffic volume, particularly to develop a set of models to estimate vehicular traffic volumes and predict future scenarios while overcoming the limitation highlighted above.

Table 1-1: Summary of previous studies on traffic volume and network centrality

No	Source	Study area	Traffic	Relationship
1.	Hillier et al., 1987	London, UK	Pedestrian	r^2=0.56
2.	Hillier et al., 1987	London suburban, UK	Pedestrian	r^2=0.65
3.	Hillier et al., 1987	Bransbury, UK	Pedestrian	r^2=0.64
4.	Hillier et al., 1987	Islington, UK	Pedestrian	r^2=0.54
5.	Peponis et al., 1997	Six Greek towns, Greece	Pedestrian	r^2=0.49
6.	Peponis et al., 1997	Downtown Atlanta, USA	Vehicular	r^2=0.34
7.	Peponis et al., 1997	Buckhead, USA	Vehicular	r^2=0.29
8.	Hillier, 1998	Baltic House, UK	Pedestrian	r^2=0.77
9.	Penn et al, 1998	London, UK	Pedestrian	r^2=0.68
10.	Hillier, 1998	London, UK	Pedestrian	r^2=0.84
11.	Hillier, 1998	Santiago, UK	Pedestrian	r^2=0.54
12.	Caria et al., 2003	Avenidas Novas, Portugal	Pedestrian	r^2=0.61
13.	Karimi et al., 2003	City Isfahan, Iran	Vehicular	r^2=0.61
14.	Dawson, 2003	Arviat communities, Canada	Vehicular	r^2=0.55
15.	Eisenberg, 2005	Hamburg, German	Pedestrian	r^2=0.52
16.	Hillier et al., 2005	London, UK	Vehicular	r^2=0.72
17.	Raford et al., 2007	London, UK	Cyclist	r^2=0.90
18.	Turner, 2007	London, UK	Motorcycle	r^2=0.66
19.	Porta et al., 2007	Melbourne, Australia	PT	r^2=0.80
20.	Jun et al., 2007	Seoul, S. Korea	PT	r^2=0.70
21.	Weiland, 2007	Worldwide 19 case studies	Subway	r^2<0.80
22.	Kishimoto, 2007	Tokyo railway station, Japan	Pedestrian	r^2<0.60
23.	Jiang, 2009	London, UK	Pedestrian	r^2=0.89
24.	Paul, 2009	City of Lubbock, USA	Vehicular	r^2=0.18
25.	Paul, 2009	Lubbock, USA	Vehicular	r^2=0.18
26.	Jian et al., 2009	London, UK	Vehicular	r^2=0.70
27.	Altshuler, 2011	Israel	Vehicular	r^2=0.67
28.	Gao et al., 2012	Qingdao, China	Vehicular	r^2=0.62
29.	Galafassi et al., 2013	Porto Alegre, Brazil	Vehicular	r^2<0.70
30.	Rami, et al, 2013	Israel	Vehicular	r^2<0.70
31.	Xia, 2013	London, UK Paris, France	Vehicular Vehicular	r^2=0.55 r^2=0.43
32.	Jayasinghe et al., 2014	Ahmedabad, India	BRT	r^2=0.79
33.	Lowry, 2014	Moscow, USA	Vehicular	r^2=0.90
34.	Omer & Jiang, 2015	Barnsbury & Kensington, UK	Vehicular	r^2<0.75
35.	Liu et al, (2015)	Kitakyushu, Japan	Pedestrian	-
36.	Monokrousou & Giannopoulou, 2016	Athens, Greece	Pedestrian	r^2<0.90
37.	Abhijit, 2016	Lubbock, USA	Vehicular	r^2<0.65
38.	Ye et al., 2016	San Francisco, USA and Nanjing, China	Taxi	r^2<0.70
39.	Cooper, 2017	Cardiff, UK	Cyclist	r^2=0.70
40.	Zhao et al., 2017	Wuhan, China	Vehicular	r^2<0.70

Note: Constructed by author based on literature

1.3. Objective

The main objective of this research is to develop an approach to model traffic volume by a network centrality-based simulation.

In this study traffic volume has been defined as the number of vehicles passing a point on a road segment during a day. The research output anticipates a pragmatic approach to transportation planning and engineering which can efficiently work under data, cost and technical know-how constraint situations, particularly in developing countries.

1.4. Sub-objectives and specific research questions

The set of sub-objectives along with the specific research questions are listed as follows.

1. To theoretically validate the relationship between traffic volume and network centrality.

    1.1. What is the theoretical relationship between traffic volume and network centrality?

    1.2. Is it possible to explain the notion of traffic movement from the notion of centrality? If so, How?

2. To formulate and validate a set of models based on network centrality to model traffic volume

    2.1. What are the appropriate centrality measures to capture traffic volume, particularly accounting pass-by trips and to-and-from trips?

    2.2. Should mobility characteristics be incorporated into network centrality measures? If yes, How to compute?

    2.3. How to identify the suitable boundary of the road network when computing network centrality?

    2.4. In the classical four-step, traffic volume has been derived from trip generation and trip distribution of Traffic Analysis Zones (TAZs). Is network centrality able to capture trip generation and trip destruction as well? If yes, How to compute?

3. To assess the applicability of the proposed network centrality-based approach as a strategic planning and investment tool

    3.1. What are the possible applications that can utilize developed approach in transport engineering and planning; and urban and regional planning processes?

    3.2. What are the advantages and disadvantages of the developed approach in the context of traffic volume modeling?

1.5. Scope of the study

Traffic volume can be measured either as the number of vehicles or the number passengers and this study has opted for the 'number of vehicles'. As the vehicles per road segment per day is the unit of observation, motorized trips are the primary consideration in this study. Hence, traffic on transport networks other than road networks such as railways, water-based or air-based transport routes were not included in the research design.

In transportation planning, the widespread use of travel modeling is on the regional scale. Therefore, this study also focused primarily on the macro (metropolitan-region, sub-regional) scale despites two case studies at the local (township) scale. However, the applicability at the block level or the neighborhood scale has not been aimed to test.

The data availability in case study areas has made the validation limited to average daily traffic volume without being more specific to peak and off-peak variations and seasonal variations. The outcome of this research is anticipated to be an approach, which can efficiently work under data, cost and technical know-how-constraint situations in developing countries. Sri Lanka being a developing country is a versatile-enough selection as a case study. However, if applying this model elsewhere it is better to recalibrate the parameters, but the model structure and method of computing centrality should generalize without modification.

1.6. Research design

The research design consists of five key stages as illustrated in figure 1.1.

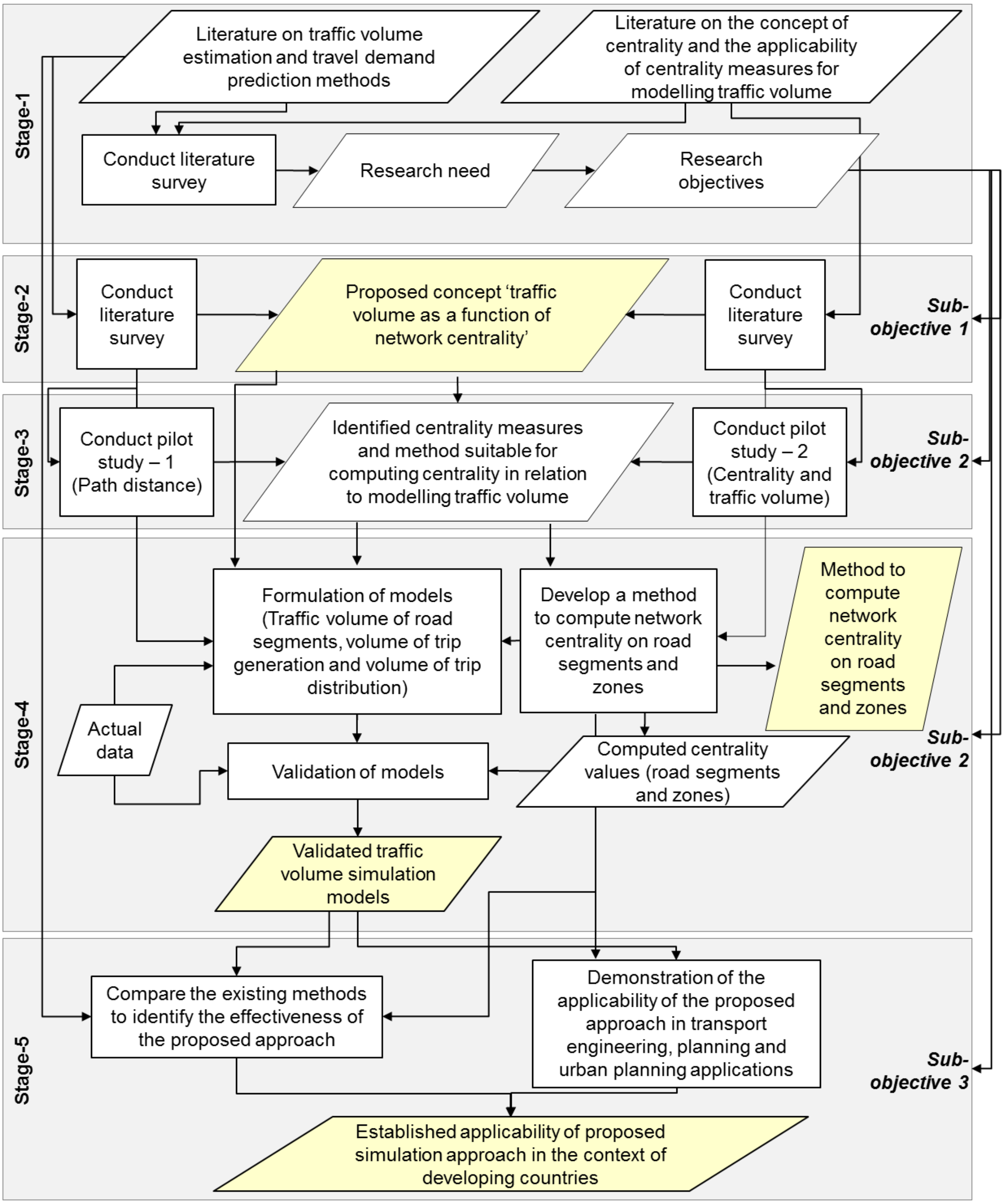


Figure 1-1: Research design
Note: Key outputs of the study are illustrated in yellow colored parallelograms

Stage 1

The first stage consists of a literature-based preliminary survey which has precedent to the research objectives. The study reviewed traffic volume estimation and travel demand prediction methods with reference to 48 studies which has been conducted during last three decades. Investigation of the applicability of those methods in the context of developing countries was also been supported by policy literature in the context of developing countries including India, Sri Lanka, Bangladesh, and international reviews from TRL (Transport Research Lab, UK)and TRB (Transport Research Board, USA). Accordingly, the study could establish the research need based on the identified theoretical and practical limitations of the existing modeling methods. Further, the study has reviewed another set of 40 research publications on the concept of network centrality and its possibility to apply as an alternative method to model vehicular traffic volume. As the primary outcome of this stage, the study has established the research need and formulated the research objectives along with specific research questions.

Stage 2

The second stage aims to theoretically validate the relationship between traffic volume and network centrality. A literature survey will be carried out to develop a theoretically-conceptualised, logically-structured relationship between modeling traffic volume and network centrality measures. The theoretical conceptualization has been designed to be based on two theories - notion of land-use transport interaction and the notion of the theory of movement economies- as explained in recent literature on four-step transport modeling process and network centrality. A set of theorized statements are going to be conceptualized and utilized as the premises of logically-structured arguments in order to validate propositions. The theoretical validation aims to prove the feasibility of modeling traffic volume as a function of network centrality.

Stage 3

As inferred from the findings of the first stage, a certain technical and practical limitations emphasized in existing studies are required to be overcome prior to developing the intended network centrality-based model. The key limitations need to be addressed; selecting the most suitable centrality measure/s and road network graph to represent traffic volume; and overcoming the theoretical challenges in integrating mobility characteristics to the path distance variable, and reducing the edge effect. In the third stage, two pilot studies have been designed to overcome these limitations. The first one is aiming to examine the importance of travel time relative to topological distance and the second one aims to examine the strength of relationship between network centrality and traffic volume and to identify whether the relationship changes over the measures and methods (i.e. preparation of graph, shortest path, boundary of the road network) of computing network centrality values as well as over the type of vehicles. The first pilot study utilizes primary data on trip-makers' actual movements. The second pilot study uses data on total vehicular traffic volume and traffic volume by type of vehicles. The analysis will be carried out at two different level. The first tier of analysis is undertaken to identify the relationship between network centrality values and traffic volumes and the second tier is to investigate the relationship changes over the method of computing network centrality values and type of vehicles.

Two pilot studies are conducted in Colombo metropolitan region (Area= 995.54 sqkm, Number of road segments=34,861). GIS shape files of the road network was obtained from the Survey Department of Sri Lanka. Vehicular traffic counts for 266 location and number of vehicles by type for 56 locations have been obtained from Road Development Authority, Sri Lanka and JICA, Tokyo. The pilot study on path distance utilizes primary data on trip-makers' (N=250) actual movements (3,091 tracks, 31 O-D Paris, 410 routes). Trip-makers' movements were traced by an open-source mobile GIS application embedded to cell-phone. Socio-economic characteristics and travel preference data of trip makers were collected by a semi-structured questionnaire survey. Network analysis tool in GIS, 'Axwoman' extension in GIS, sDNA tool, and UCL Depth Map software were employed in geospatial network analysis. Statistical analysis including distribution tests (Histogram and percentile, Power law distribution), spatial correlation analysis, and multiple linear regression analysis will be utilized for inferences.

Stage 4

The fourth stage is aiming to formulate and validate a set of models based on network centrality for modeling traffic volume. In the first stage of the study surveys literature on traffic volume estimation and travel demand prediction methods. In the second stage, the study theoretically validates the concept of 'traffic volume as a function of network centrality'. In the third stage, the study proposes improvements to overcome some of the known technical and conceptual limitations of applying network centrality measures to model traffic volume. In the fourth stage, the proposed method to model traffic volume will be built upon these three inferences. AADT values (N=1927) of Colombo Metropolitan Area, Sri Lanka for the year 2013 have been collected for the formulation of the model. Five validation approaches are decided to be followed to test the power of the proposed model. The first approach is an internal cross-validation that the study randomly selects 90% of the AADT values for calibration (i.e., a random subset of calibration data) and 10% to validation. The second approach is to externally validate the proposed model by using AADT values (N=29) of the same area (CMA) for the year 2004. This tests the proposed model's sensitivity to temporal variation. The third approach attempts to test the proposed model's competence in comparison to the AADT values estimated for Colombo by multistep demand modeling. Multistep demand modeling is the most widespread technique in modeling traffic volume. This test has been designed to compare the traffic volumes computed by the proposed model with the modeled traffic volumes of ComTrans project for 2035 (N=2064). The fourth validation approach also concerns the multi-step demand modeling. In multistep demand modeling, traffic volume is the primary output, and trip distribution and trip generation are the correspondent inputs. If the proposed model can explain the traffic volume, it is logical to have a certain capability of explaining its inputs. With this proposition, the fourth approach of validation tests the power of the model to estimate trip distribution (O-D pairs = 612) and trip generation (TAZs = 340). All four of the above-mentioned validation tests refers to the same case study area (i.e., CMA) that will be utilized for model formulation. The fifth validation approach tests the validity of the proposed model with the actual AADT values of two alternative case study areas, i.e., Galle Municipal-council Area (16.52 sqkm); (N= 23) and Kandy Municipal-council Area (28.53 sqkm); (N= 25).

For computing utility score as per road type, the study will conduct a questionnaire survey (n=100) employing the standard procedure of Analytical Hierarchical Process (AHP) technique. GIS shape files of Road network for Colombo, Kandy, and Galle were obtained from the Survey Department, Sri Lanka and for proposed road network in Colombo (2035) was collected from JICA, Tokyo. The study obtained traffic volume data from secondary sources including JICA and RDA. Traffic volume has been reported as Annual Average Daily Traffic (AADT), converted to Passenger Car Unit (PCU) per day using the recommended AASHTO (American Association of State Highway and Transportation Official) PCU factors. Trip attraction data, trip production data, trip length, number of vehicles, land use data and population data for CMA area have also been obtained from JICA. Trip length CMA 2013 (JICA). Demographic data for KMA and GMA was obtained from Census and Statistics Department, Sri Lanka. However, the absence of location-specific O-D dataset constrained the validation of trip distribution.

GIS and sDNA tool will be utilized for spatial data analysis. The study employs Ordinary Least Squares Regression (OLS), Robust Regression (RR) and Poisson Regression (PR) when formulating the model and non-linear regression for the fourth approach of validation (i.e., Trip distribution model formulation). Variance inflation factors and R-squared values are utilized to derive inferences during model formulation. The accuracy of the model shall be compared with the international standards such as goodness of fit test including R-squared values, median absolute percent error (MdAPE) and root-mean-square error (RMSE).

Stage 5

The fifth stage aims to assess the applicability of the proposed network-centrality-based approach as a strategic planning and investment tool with reference to three demonstrations. The first demonstration examines the applicability of the proposed approach as a tool to analyze the impact of new road proposals on the existing road network with reference to the two highway development projects -Colombo–Katunayake Expressway (KE) and Outer-circular Expressway (OCH)-. The second demonstration is to identify the impact of the proposed urban development projects on traffic volumes of the existing road network with reference to a township development project in Colombo. The third demonstration is to examine the structural coherence of the road network. Further, the fifth stage compares and contrasts the advantages and disadvantages of proposed approach with comparison to the existing methods. Comparison considers the set of multi-step travel demand modeling and direct demand modeling approaches including ‘conventional four stage travel demand modeling process’, ‘activity and tour-based modeling system’, ‘direct demand modeling based on roadway characteristics and socioeconomic factors’, ‘modeling based on image-based data’ and ‘modeling based on location-based social network data’.

The spatial data has been obtained from JICA for two expressways and from Urban Development Authority, Sri Lanka for the township development project. The comparison is designed to perform based on 26 attributes correspondent to four criteria. Selection of criteria, as well as the review, was supported by the set of literature on traffic volume estimation and travel demand prediction methods which has been collected during the first stage of the study.

Figure 1-2: Case study areas
Source: Extracted from (www.mapsofworld.com, 2016)
Note: Refer annexures for structure plan, land use plan and population distribution in case study areas. CMA: annexure 7-13, GMA annexure 14-15, and KMA annexure 16-17

1.7. Structure of the dissertation

This thesis comprises of nine chapters as briefly introduce below.

Chapter 1: Introduction

The introduction chapter presents the research background along with a comprehensive review of the applicability of existing traffic volume modeling method in the context of developing countries, and research need including an extensive review of the applicability of network centrality about traffic volume modeling and critically analyzes their advantages and disadvantages related to traffic volume modeling. Further, the chapter presents the research objective, specific research questions, and the research design.

Chapter 2: Theoretically Validation: Relationship between Traffic Volume and Network Centrality

The chapter two aims to theoretically validate the relationship between traffic volume and network centrality. The chapter reviews the modeling process of traffic volume has been described by the conventional four-step transport model and the network centrality concept in relation to graph theory and space syntax. This review examines the relationship between the notion of land-use transport interaction and the notion of the theory of movement economies. The chapter presents a set of theorized statements indicating the relationship between network centrality and traffic volume. This chapter concludes by introducing a concept of ‘traffic volume as a function of network centrality.'

Chapter 3: Pilot Study-1: Examine the Importance of Travel Time Relative to Topological Distance

This chapter presents the first pilot study. The objective of this pilot study is to examine the importance of travel time relative to topological distance. Accordingly, the chapter gives a brief review of factors influence on trip-makers route choice; the method uses to capture trip-makers’ actual movements traces and results of the analysis. The findings suggest that it is more appropriate to consider geometric distance (angular changes) compare to travel time when considering the shortest path in computing centrality.

Chapter 4: Pilot Study-2: Investigation of Relationship between Network Centrality Values and Traffic Volume

Chapter four presents the second pilot study. The objective of the second pilot study is to examine the strength of relationship between network centrality and traffic volume, and to identify whether the relationship changes over the centrality measures and methods (i.e. preparation of graph, shortest path, boundary of the road network) of computing network centrality values as well as over the type of vehicles. The findings suggest that it is possible to explain traffic volume based on network centrality and it is more appropriate to consider both closeness and betweenness centrality measures, and use road segment graph and select a suitable radius of road network boundary when computing network centrality.

Chapter 5: A Network Centrality-based Simulation of Traffic Volume by Road Segments

The sub-objective aimed to achieve from the study explains in this chapter is to develop a set of models to estimate AADT and predict vehicular traffic volume of road segments based on the road network centrality values. First, this chapter describes the proposed concept that is 'traffic volume of road segment as a function of betweenness and closeness centralities'. Next section of the chapter provides a description of the method of computing centrality of road segments and dataset used in the study. Then, the study explains the model formulation and validation. The chapter performs a comprehensive evaluation of the statistical results of the main case study carried out in Colombo Metropolitan Area, Sri Lanka and the validation results of two other urban areas in Sri Lanka. The chapter introduces set of models to simulate traffic volume and steps to follow when computing network centrality on road segments. The findings point out that network centrality-based models able to estimate and predicate traffic volume of road segments with an accepted level of predictability and accuracy.

Chapter 6: Network Centrality-based Simulation of Trip Generation Volume in Traffic Zones

This chapter aimed to validate the relationship between traffic volume and network centrality in relation to the trip generation. The chapter describes the developed models to estimate trip attraction and trip production using aggregated-zonal-closeness-centrality values as an endogenous variable. Further, the chapter introduces a method to compute aggregated-zonal-closeness-centrality of a zone.

Chapter 7: Network Centrality-based Simulation of Trip Distribution

This chapter aimed to validate the relationship between traffic volume and network centrality in relation to the trip distribution. This chapter introduces a network centrality-based aggregated model to estimate trip distribution, and the chapter expresses 'inter-zonal trip attractiveness' as a function of relative closeness centrality between trip destination zone and trip origin zone.

Chapter 8: Applicability of the Proposed Network Centrality-based Approach to Model Traffic Volume: As a Strategic Planning and Investment Tool

Chapter 8 assess the applicability of the proposed network centrality-based approach as a strategic planning and investment tool. Accordingly, the chapter discusses possible applications that can use developed models in transport engineering and planning; and urban and regional planning process with three examples as

1. To analyze the impact of new road proposals on the existing road network
2. To identify the impact of the proposed urban development projects on traffic volumes of the existing road network
3. To examine the structural coherence of the road network

Further, the chapter discusses the advantages and disadvantages of proposed approach in comparison to the current traffic volume modeling methods. Furthermore, the study developed 'centrality spectrums' and 'tailor-made guidance' which describes application options of the proposed approach per the data availability.

Chapter 9: Conclusions and Recommendations

Chapter 9 summarizes the method adopted, key findings and contribution to the current state of knowledge and practice, from this dissertation.

Chapter – 2
Theoretically Validation: Relationship between Traffic Volume and Network Centrality

2.1. Introduction

The first sub-objective of this study is to theoretically validate the relationship between traffic volume and network centrality. Accordingly, this chapter reviews the theoretical relationship between traffic volume and network centrality. Modeling process of traffic volume has been described by the conventional four-step transport model. A brief introduction to the evolution and application of network centrality concept has been provided with reference to the graph theory and space syntax. The relationship between traffic volume and network centrality has been explained based on two notions; the notion of land-use transport interaction and the notion of the theory of movement economies. This review examines the relationship between the notion of traffic movement and the notion of centrality, and possibilities of explaining the notion of traffic movement from the notion of centrality.

2.2. Modeling traffic volume

Traffic volume is "the number of persons or vehicles passing a point on a lane, roadway or another traffic way during some time interval" (AASHTO, 2009). Traffic flow is defined as "the number of vehicles passing a point on a highway in a unit of time" (AASHTO, 2009). The primary interest in this study is vehicular traffic volume in a road segment, which is the number of vehicles passing a point on a road segment during a day. In transport planning and engineering applications, traffic volume of a road segment is referred in related to Average Annual Daily Traffic (AADT) (Jessberger, et al., 2016). Annual Average Daily Traffic (AADT) volume -the average 24-hour total volume of vehicles on both directions of a roadway segment over an entire year (AASHTO, 2009). In travel modeling, which is a key component of regional transport planning and engineering, traffic volume is derived as one of the final outputs (Shivakumar, 2007).

2.2.1. Four-step transport model

The earliest travel demand models (i.e. classical four-step models), where the traffic volume is computed based on aggregate level zonal trip volumes were aggregated level trip-based models (Bureau of Transport Economics, 1998). Advances in modeling techniques resulted in a shift away from these aggregated models and led to the development of disaggregated trip-based models, tour-based models and activity-based models. Amongst classical four-step models is the most applied tools in modeling travel demand (Shivakumar, 2007). The four-step model comprised of four phases (refer figure 2.1): i. Trip generation, ii. Trip distribution, iii. Modal split, and iv. Traffic assignment (route choice).

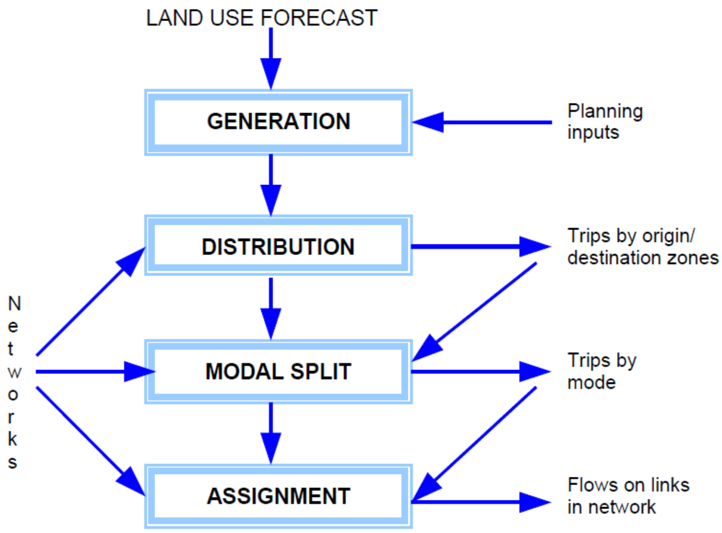


Figure 2-1: Conventional four-step transport model

Source: (Button, 1977)

The trip generation includes trip production and trip attraction. It is usually assumed that the trip generation is determined primarily by socio-economic and land use factors (Bureau of Transport Economics, 1998), (Institute of Transportation Engineers, 2010). Accordingly, traffic generated by zone i can be expressed as equation 2.1.

$$T_i \ = f(E_i.LU_i\,) \tag{2.1}$$

Where;

$T_i \quad = Traffic\ generated\ by\ zone\ i,$

$E_i \quad = Socio - economic\ characteristics\ of\ zones\ i,$

$LU_i\ = Land\ use\ characteristics\ of\ zones\ i,$

Trip distribution is the second component which models the number of trips that occur between each of the origin and destination zones. The general form of trip distribution model can be expressed as equation 2.2 (Bureau of Transport Economics, 1998).

$$T_{ij} = f\left(T_i, T_j, F_{ij}\right) \tag{2.2}$$

Where;

T_{ij} $= Traffic\ flow\ between\ zone\ i\ and\ j,$

T_i $= Amount\ of\ traffic\ in\ zone\ i,$

T_j $= Amount\ of\ traffic\ in\ zone\ j,$

F_{ij} $= Impedance\ to\ travel\ between\ i\ and\ j.$

The most commonly gravity model is utilized to explain the trip distribution among a pair of Traffic Analysis Zones (TAZs) (refer equation 2.3.). Accordingly, "the amount of traffic flow between zone 'i' and zone 'j' is positively related to the product of the amount of traffic in zone 'i' and zone 'j' and inversely related to the impedance of getting from zone 'i' to zone 'j'" (Bureau of Transport Economics, 1998).

$$T_{ij} = \frac{kT_iT_j}{(F_{ij})^n} \tag{2.3}$$

Where;

k,n = *constants (1<n<2),*

T_{ij} $= Traffic\ flow\ between\ zone\ i\ and\ j,$

T_i $= Amount\ of\ traffic\ in\ zone\ i,$

T_j $= Amount\ of\ traffic\ in\ zone\ j,$

F_{ij} $= Impedance\ to\ travel\ between\ i\ and\ j.$

In modal split computes the proportion of trips between each origin zone and destination zone according to the various modes of transport available (Bureau of Transport Economics, 1998). The modal split model comprised of traffic volume between an origin and a destination (O-D), and operational characteristics of the competing transport modes (refer equation 2.4).

$$T_{ijm} = f\left(I_{ij1}, \dots, I_{ijm}, T_{ij}\right) \tag{2.4}$$

Where;

T_{ijm} $= Traffic\ flow\ between\ zone\ i\ and\ j\ by\ mode\ m,$

T_{ij} $= Traffic\ flow\ between\ zone\ i\ and\ j,$

I_{ijm} $= Operational\ characteristics\ of\ the\ competing\ transport\ modes.$

Route assignment concerns the selection of routes between an origin and a destination from alternative paths available. Therefore, route assignment is related to O-D traffic volume and roadway characteristics of various paths (refer equation 2.5).

$$T_{ijmp} = f(I_{ijm1}, \ldots, I_{ijmp}, T_{ijm}) \quad (2.5)$$

Where;

T_{ijmp} $= Traffic\ flow\ using\ route\ p\ when\ travelling\ by\ mode\ m\ between\ i\ and\ j,$

T_{ijm} $= Traffic\ flow\ between\ zone\ i\ and\ j\ when\ travelling\ by\ mode\ m,$

I_{ijmp} $= Roadway\ characteristics\ of\ various\ paths.$

2.2.2. The land-use transport interaction

The interaction between land use and transportation has been widely recognized in the fields of land use planning and transport studies (Acheampong & Silva, 2015). Accordingly, Wegener and Furst (1999); Geurs and Ritsema van Eck (2001); and Acheampong & Silva (2015) with reference to the interaction between land use and transport systems, introduced three conceptual frameworks as illustrated in figure 2.2, 2.3 and 2.4. Wegener and Furst (1999) introduced the concept of 'land-use transport feedback cycle', which explains co-determines of trip and location decisions as follows.

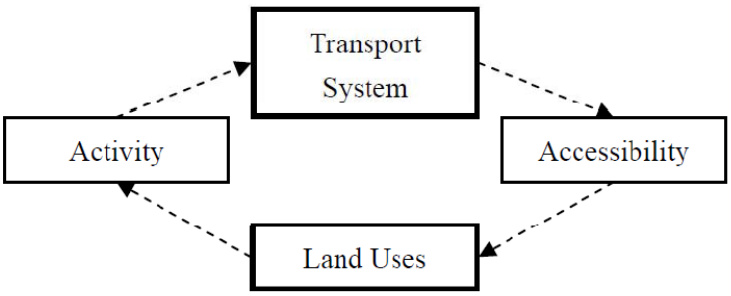


Figure 2-2: Land-use feedback cycle

Source: (Wegener & Fürst, 1999)

- The distribution of land uses (LU) determines the locations of human activities (HA)

$$HA \propto LU \quad (2.6)$$

- The distribution of human activities determines the trips (T) in the transport system

  $$T \propto HA \qquad (2.7)$$

- The distribution of infrastructure in the transport system creates travel opportunities (i.e., accessibility - A)

  $$A \propto T \qquad (2.8)$$

- The distribution of accessibility determines the changes of the land-use

  $$LU \propto A \qquad (2.9)$$

  $$\therefore LU \propto A \propto T \propto HA \propto LU \qquad (2.10)$$

Geurs & Ritsema van Eck (2001) introduced the concept of 'land-use transport system', which explain the relationship between the components of land use and transport. They also recognized co-determinacy between land uses and activities as well as transport supply and travel opportunities (as equation 2.10).

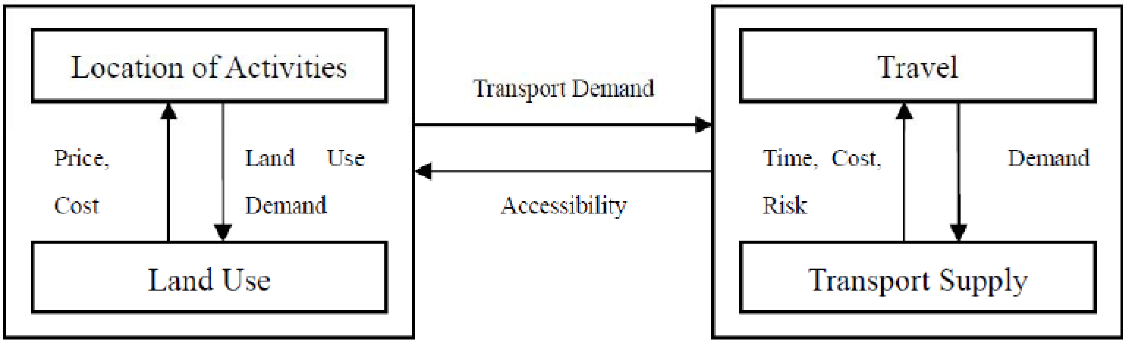


Figure 2-3: Land-use transport system
Source: (Geurs & Ritsema van Eck, 2001)

Conceptual framework introduced by Acheampong & Silva (2015) comprised of a set of land use components such as residential, employment and ancillary activities and; specified transport components including travel demand characteristics and urban spatial structure. Accordingly, they have emphasized that all land use activity locations (LU) be interdependent and directly influenced by accessibility (A) (refer equation 2.11). Further, travel demand (T) is influenced by land uses (LU) and socio-economic characteristics of individuals (E) (refer equation 2.12).

$$LU = f(A) \qquad (2.11)$$

$$T \;\; = f(LU.E) \tag{2.12}$$

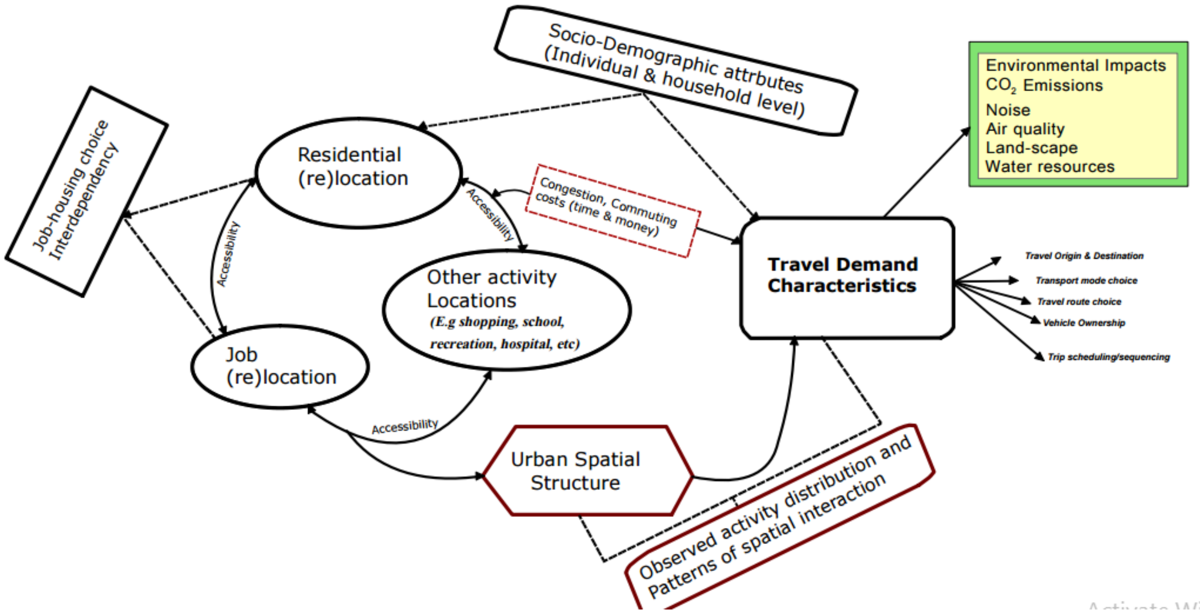


Figure 2-4: A conceptual model showing the components of land-use-transport system
Source: (Acheampong & Silva, 2015)

2.3. Network centrality

The consept of centrality is used in graph theory and network analysis to identify the importance of nodes and link within a graph. Erdos and Renyi (1959) defined the network centrality measures as analytical methods developed based on ‘Graph Theory’ which quantify the relative importance of vertex [node] or edge [link] in a graph. Network centrality concepts were initially developed in social network analysis (Newman, 2010) and later applied in the fields of urban geography, spatial planning; to model, forecast, and explain the matters related to accessibility (Jayasinghe & Munshi, 2014), (Batty, 2017). Accordingly, Bavelas (1948 cited in (Fiksel, 1980)) employed the concept of network centrality to identify the level of prominence of individuals in social networks. Losch, 1952; Isard, 1956; Alonso, 1964; Herbert and Stevens, 1960 (as cited in (Cutini, 2001) employed the concept to define the attractiveness of urban place. Hiller (1999) introduced the concept of ‘centrality as a process’ which accounting for attraction inequalities in deformed grids [street network]. Freeman (Freeman, 1977) proposed three measures to capture the properties of networks centrality. These are Degree centrality, Closeness centrality, and Betweenness centrality. Hiller introduced another set of centrality measures, i.e., Connectivity, Integration and Choice, which computes the centrality in terms of the topology of the network. According to these interpretations, centrality can be defined as 'an analytical method which has been developed based on the Graph Theory, and applicable in computing the level of centrality in a network by a set of measures'.

2.3.1. The notion of centrality in theory of 'movement economies'

The theory of movement economies, suggests that urban spaces "first generates the distribution pattern of busier and quieter movement pattern flows, which then influence land use choices, and these in turn generate multiplier effects on movement with further feedback on land use choices and the local grid [local street network] as it adapts itself to more intensive development" (Hillier, 1999). Accordingly, the theory proposed reciprocal effects of urban grid structure [i.e., spatial structure] (S) and movements [i.e., accessibility potential] (A) on each other and the multiplier effects on both (refer figure 2.5 and equation 2.13). Further, the theory has suggested that there is a multiplicity of inter-relationships between spatial structure, land uses, densities, and even socio-economic characteristics (E) of society (refer equation 2.14).

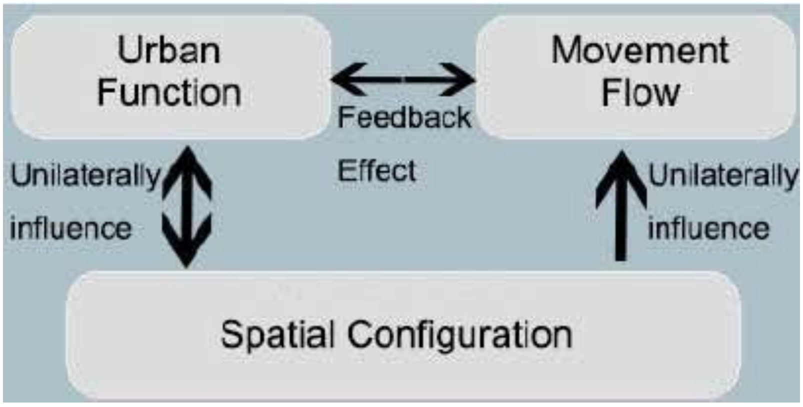


Figure 2-5 Relationship between urban function and movement flow; urban function and spatial configuration
Source: (Hillier, 1999)

$$S \leftrightarrow A \tag{2.13}$$

$$S \leftrightarrow LU \leftrightarrow E \leftrightarrow S \tag{2.14}$$

The theory of movement economies argues that "every trip in an urban system has three elements: an origin, a destination, and series of space that passed through" and their locations are determined by the structure of the grid [spatial structure] (Hillier, 1999). Hillier and colleagues at the Bartlett, University College London have introduced 'space syntax' including a set of theories and techniques to analyze this relationship (Hillier, 1999). The fundamental proposition in space syntax is that the configuration of the urban street network is in itself a major determinant of movement flows (refer figure 2.4). In space syntax, the urban grid structure is represented as a street network and bifurcate into nodes and links, then analyzed the configuration of those nodes and links in terms of topological centrality (C).

$$S \quad = f(C) \tag{2.15}$$

A series of empirical research studies dealing with space syntax have found that, there is a strong relationship between configuration [street centrality] with the parameters as population density (Rosenbloom, 1996), employment density (Cervero, 1996), (Jang & Kang, 2016), (Xiao, 2017) building density (Peponis et al., 2007), (Batty, 2017), (Caruso, et al., 2017) distribution of land uses (Min et al., 2006), (Cervero, 1996), (Munasinghe, 2007), distribution of activities in urban areas (Hillier, 1998), (Hillier and Iida, 2005), (Sarma, 2006), (Vaughan and Hillier, 2007)¸ (Abubakar and Aina, 2008), (Sohn, 2016), (Izanloo, et al., 2016), (Omer & Goldblatt, 2016), (Lee & Choi, 2017). These relationships can be summarized as equations given below.

$$J \ = f(C) \tag{2.16a}$$
$$LU = f(C) \tag{2.16b}$$
$$HA = f(C) \tag{2.16c}$$
$$P \ = f(C) \tag{2.16d}$$
$$B \ = f(C) \tag{2.16e}$$

Where;

$P \quad = Density\ of\ Popoluation$

$J \quad = Density\ of\ \ Jobs$

$B \quad = Density\ of\ Buildings$

$LU \ = Distribution\ of\ land\ uses$

$HA \ = Distribtuion\ of\ human\ activities$

2.4. Proposed concept: Traffic volume as a function of network centrality

Considering the above-mentioned relationships (section 2.2 and 2.3), this study hypothesizes that traffic volume can explain as a function of network centrality particularly based on following logics.

Argument 1: On the basis of relationships 2.1 and 2.16b, trip generation can be explained as a function of centrality (C) and socio-economic characteristics.

$$\begin{aligned} &Premise\ 1\ :\ T_i\ = f(E_i.LU_i\ ) \\ &Premise\ 2\ :\ LU = f(C) \\ &Conclusion:\ T_i\ = f(E_i.C_i\ ) \end{aligned} \tag{2.17}$$

Argument 2: On the basis of relationships 2.2 and 2.17, trip distribution can be explained as a function of centrality (C), socio-economic characteristics (E) and impedance to travel between two locations (F).

$$\begin{aligned} &Premise\ 1\ :\ T_{ij}\ = f\left(T_i, T_j, F_{ij}\right) \\ &Premise\ 2\ :\ T_i\ = f(E_i.C_i) \\ &Premise\ 3\ :\ T_j\ = f\left(E_j.C_j\right) \\ &Conclusion:\ T_{ij}\ = f\left(E_i.C_i, E_j.C_j, F_{ij}\right) \end{aligned} \tag{2.18}$$

Argument 3: On the basis of relationships 2.4 and 2.18, modal split can be explained as a function of centrality (C), socio-economic characteristics (E), impedance to travel between two locations and operational characteristics of the competing transport modes (I_m)

$$\begin{aligned} &Premise\ 1\ :\ T_{ijm}\ = f\left(I_{ij1}, \dots, I_{ijm}, T_{ij}\right) \\ &Premise\ 2\ :\ T_{ij}\ = f\left(E_i.C_i, E_j.C_j, F_{ij}\right) \\ &Conclusion:\ T_{ijm}\ = f\left(I_{ij1}, \dots, I_{ijm}, E_i.C_i, E_j.C_j, F_{ij}\right) \end{aligned} \tag{2.19}$$

Argument 4: On the basis of relationships 2.5 and 2.19, route choice can be explained as a function of centrality (C), socio-economic characteristics (E) impedance to travel between two locations and roadway characteristics of various paths (I_p).

$$\begin{aligned} &Premise\ 1\ :\ T_{ijp}\ = f\left(I_{ij1}, \dots, I_{ijp}, T_{ijm}\right) \\ &Premise\ 2\ :\ T_{ijm}\ = f\left(I_{ij1}, \dots, I_{ijm}, E_i.C_i, E_j.C_j, F_{ij}\right) \\ &Conclusion:\ T_{ijp}\ = f\left(I_{ij1}, \dots, I_{ijp}, I_{ij1}, \dots, I_{ijm}, E_i.C_i, E_j.C_j, F_{ij}\right) \end{aligned} \tag{2.20}$$

Argument 5: With regards to relationship 2.12 and 2.16b, traffic volume can be explained as a function of centrality (C) and socio-economic characteristics (E)

$$Premise\ 1\ :\ T\ = f(LU.E)$$

$$Premise\ 2\ :\ LU = f(C)$$

$$Conclusion:\ T \quad = f(C.E) \tag{2.21}$$

2.4.1. Definition of the proposed concept

A fundamental argument of the proposed concept is that traffic volume derives from trip maker's movements which is guided by the centrality of the transport network. Therefore the proposed concept assume that transport opportunities offered by the network centrality are efficiently exploited through a land use-transport accessibility feedback cycle. This concept is based on 'movement economic theory' and 'cognitive behavioral theory' about how people make decisions about their movements. The proposed concept represents the interaction between transport system and land uses, and human activities and accessibility based on the centrality of the transport network (refer figure 2.6). Accordingly, the concept argues that there is a reciprocal relationship between traffic volume generated by land uses and supply from transport system; and human activity movement needs and accessibility opportunities. This concept recognizes that activities, land use, transport networks and trip makers' movements are interrelated, and there are reciprocal relationships; between transport networks and trip makers' movements; between transport network and land uses, and between transport networks and activities. The proposed concept treats a given trip maker's movement originates at a component of the transport network (i.e. road segments, intersection) pass-by through one or several components and ends at another component of the same network (refer figure 2.7). The components highly close to each other (i.e. closeness centrality) attract more movements as well as produce more movements. The components located with high intermediacy among the components (i.e., Betweenness centrality) attract more pass-by movements. Accordingly, the highly attractive components accumulate more activities and produce agglomeration of activities (refer figure 2.8). As a response, the agglomeration of activities, such locations attract and produce more movements (refer figure 2.9). This makes reciprocal relationships; between transport system and land uses (supply and demand), and between accessibility and activities (opportunities and needs). For instance, construction of a roadway increases the network centrality and increase the supply of commercial land uses, which will generate additional transport demand. Further, increased centrality provides more opportunities for activities due to the increase of accessibility. This reciprocal relationship can be measured by the centrality of the transport network.

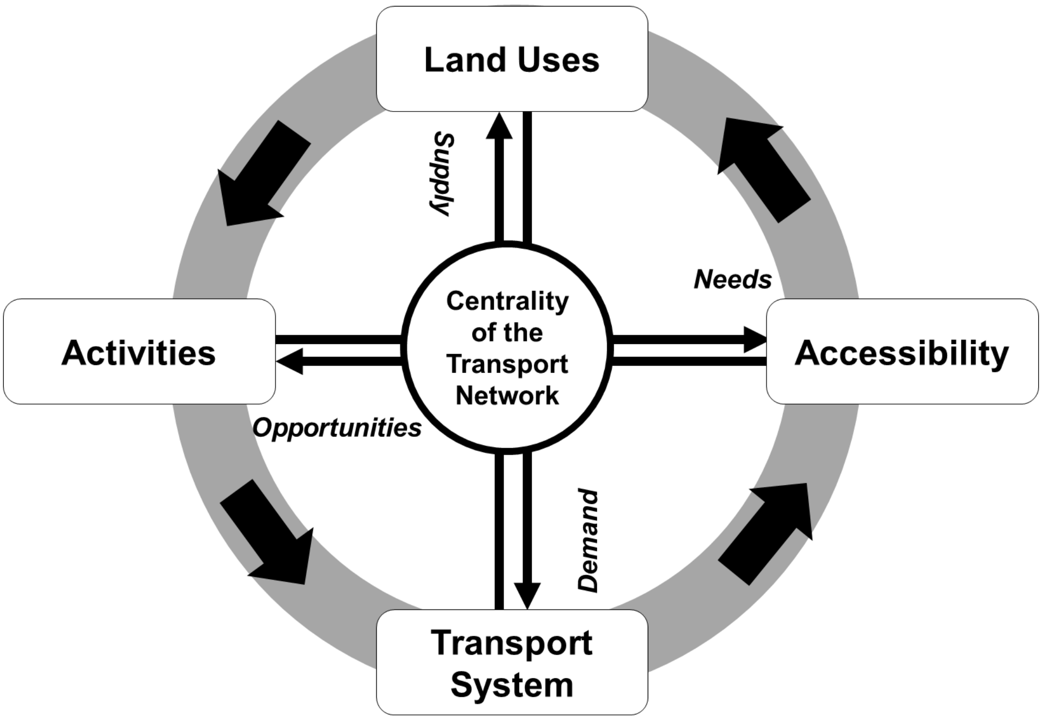


Figure 2-6: The proposed concept-Traffic volume as a function of network centrality

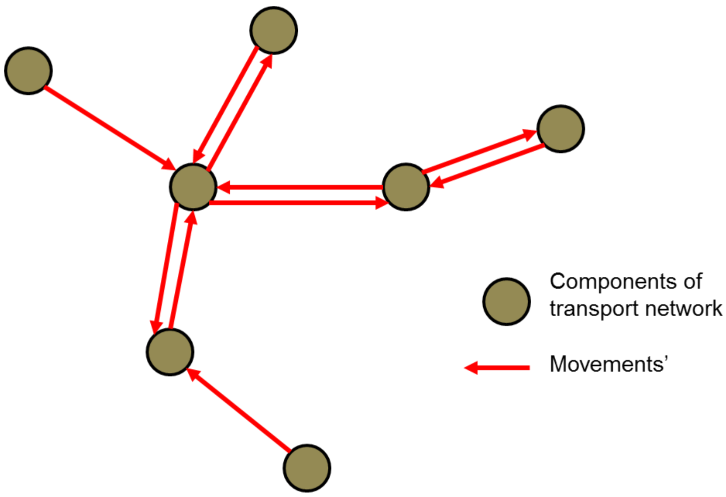


Figure 2-7: Trip makers' movements in a given transport network

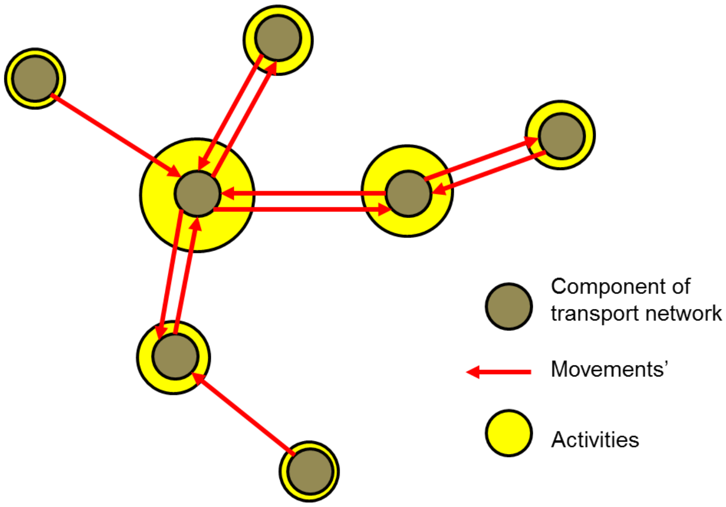


Figure 2-8: Agglomeration of activities

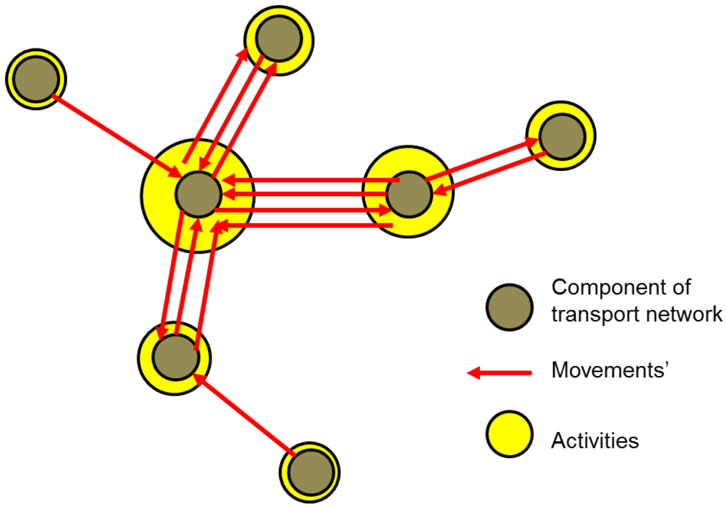


Figure 2-9: Agglomeration of activities attracts more traffic

2.5. Conclusion

The first sub-objective of this study is to theoretically validate the relationship between traffic volume and network centrality. This chapter reviewed the theoretical relationship between traffic volume and network centrality. The review has identified the relationship between traffic volume and network centrality and complementary to each other. Accordingly, the study proposed a concept namely traffic volume as a function of network centrality.

Chapter – 3
Pilot Study-1: Examine the Importance of Travel Time Relative to Topological Distance

3.1. Introduction

The main objective of this research is to develop an approach to model traffic volume by a network centrality-based simulation. Accordingly, traffic volume represents as a function of network centrality which computes base on centrality measures. To compute centrality of road segments, identification of shortest path between road segments is one of key requirement. Usually, the centrality of network computes based on unit distance (i.e. topological distance) in the space syntax approach (Paul, 2013). It has been argued in the space syntax approach referring to the notion of 'movement economies,' which has been explained in 'cities as movement economies,' people move in lines and tend to approximate lines in more complex routes (Hillier, 1999). Accordingly, space syntax suggested that the metric distance assumption is might not suitable, "not perhaps because trip makers' do not seek to minimize travel distance, but because trip makers' notions of distance are compromised by the visual, geometrical and topological properties of networks" (Hillier, 1999). Further, cognitive behavioral theories of human-way-finding, which is explained in neuroscience, have highlighted the role of 'hippocampi' in this regard. Hippocampus is a part of the brain that involved in body functions such as spatial orientation, navigation, and memorization. It conveys information about places based on the landmark, unit distance and directional changes (Gooledge, 1999). Accordingly, unit distance and directional changes considered as playing the key role in the route choice of humans than metric distance. Hochmair and Frank (2002); Dalton (2003) and Duckham and Kulik (2003) also have proposed that the directional change might be useful to direct trip-makers' to their destination more simply in comparison to the metric distance. Further, Hillier and Iida (2005) have argued that "topological and geometric complexities are critically involved in how people navigate urban grids [road network]".

However, in the fields of traffic and transport planning and engineering, it has been recognized that individual trip-maker select the best route that maximizes their utility, which is predominately consider based on the notion of travel time (Juan de Dios Ortúzar & Willumsen, 1990), (Hanson & Giuliano, 2004). ‘All-or-nothing’ and ‘equilibrium analysis are two contemporary methods use for determining route choice (Patriksson, 2015). All-or-nothing approach considers only free-flow time whereas, in an equilibrium analysis, the delay due to traffic congestion is also considered along with free flow travel time (Fricker & Whitford, 2004). Free-flow travel time is a function of the trip distance and speed. Further many automobile navigation systems are developed based on ‘Dijkstra’ algorithm, which identifies the shortest path in terms of metric distance (Nakajima, et al., 2012). Metric distance is a simple measure that is used in most of the navigation systems to identify the best path (Blue, et al., 1997). However, Tversky (1992), Jan, Horowitz and Peng (2000) Turner and Dalton (2005), and Zhang (2011) have highlighted that the “utility function which, has been developed based on length, congestion, travel time are far away from the actual situation and have been overlooked the trip-makers’ own perceptual and cognitive understanding of the road network.” Further, Jiang et al. (2014) have highlighted that “drivers evaluate the alternative routes by individual experience, cognition, and attitudes which are not considered in the Expected Utility Theory (EUT) or Random Utility Theory (RUT) models” and Witlox argue that travellers’ reported distance estimates may cause a serious bias on maximize their overall utility (Witlox, 2007). According to the Witlox (2007) “The notion of distance that people carry around in their heads, i.e., the so-called cognitive, estimated or subjective distance, is very different from the objective, real world distance... Human beings seem to incorporate a far more complex unity of (not always logical) criteria for path selection (i.e. least effort, shortest path, shortest time path, etc) which cannot be modeled in one simple algorithm”.

In such background, the objective of this pilot study is to examine the importance of travel time relative to topological distance in determining the route choice behavior of trip-makers. The pilot study used data on trip-makers’ actual movements which has traced by using mobile GIS application and analyzed the relative importance of travel time relative to topological distance in determining the route choice of trip-makers’ by mode of travel.

3.2. Method of study

3.2.1. Dataset - trip-makers' route choice behavior

The pilot study was conducted in Colombo Municipal Area (CMA). This study employed open source mobile GIS application embedded to cell-phone in tracing trip-makers' movements. The sample included the movements of 250 trip-makers which have been traced within first four months of 2015. Trip-makers were asked to switch on the mobile tracking application which was installed on their cell phones, on all the journeys they took for their day to day activities. Each participant responded to a survey with questions about socio-economic characteristics (refer Table 3.1), the importance of various factors in choosing a given route and frequency of traveling on the route.

Table 3-1: The characteristics of trip-makers who participated in the survey

Socio-economic characteristics	No of participants	% of participants
Sex		
Male	155	62%
Female	95	38%
Mode		
Car	67	27%
Motorcycle (MC)	58	23%
Taxi (Tuk-tuk)	64	26%
Bus	61	24%
Income level (SLR)		
<10,000	39	16%
10,000-25,000	116	46%
25,000-50,000	86	34%
>50,000	9	4%
Age		
<20	19	8%
20-30	64	26%
30-40	95	38%
40-50	46	18%
50-60	18	7%
>60	8	3%

(Note: Total number of participants 250)

At the end of the period, the GPS-based movements tracks were collected. The movement tracks were downloaded and geographically adjusted to road network by using GIS application. The tracks were undergone accuracy checking considering the continuity and geographical overlapping referring to the actual road network. 22% of tracks were removed due to lack of precision and 3,091 tracks were selected for further analysis (refer figure. 3.1). Then these tracks were assigned to road segments of the study area (refer figure. 3.2) and categorized into 31 O-D pairs. O-D locations were selected based on the level of concentration of tracks at the points of start and end respectively. The considered O-D points were adjusted to the nearest well-known node (i.e. small town, popular intersection). Referring to these 31 O-D pairs, 410 routes were identified considering the routes which have been selected by at least one trip-maker.

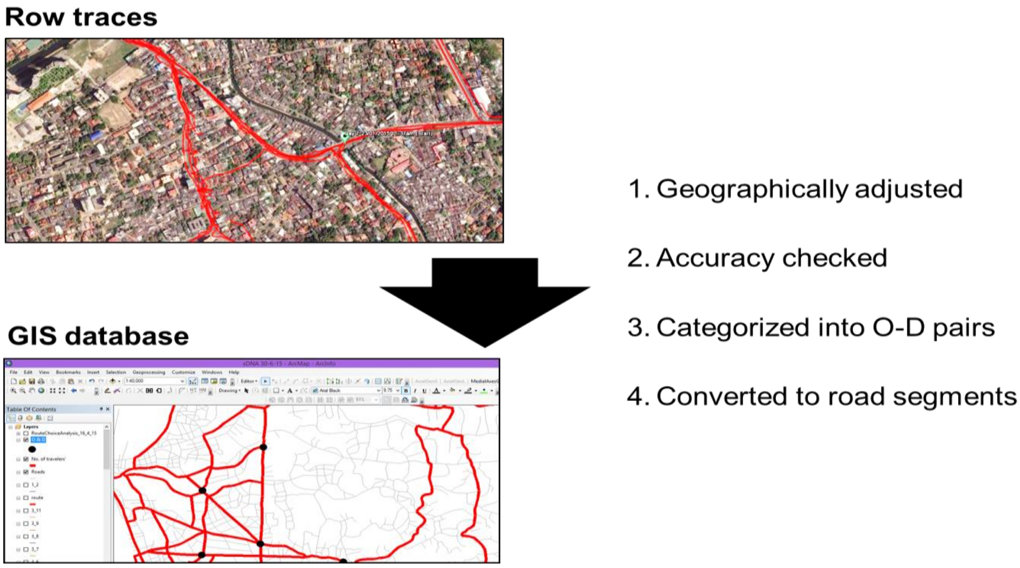


Figure 3-1: Preparation of GIS database of trip-makers' movements tracks

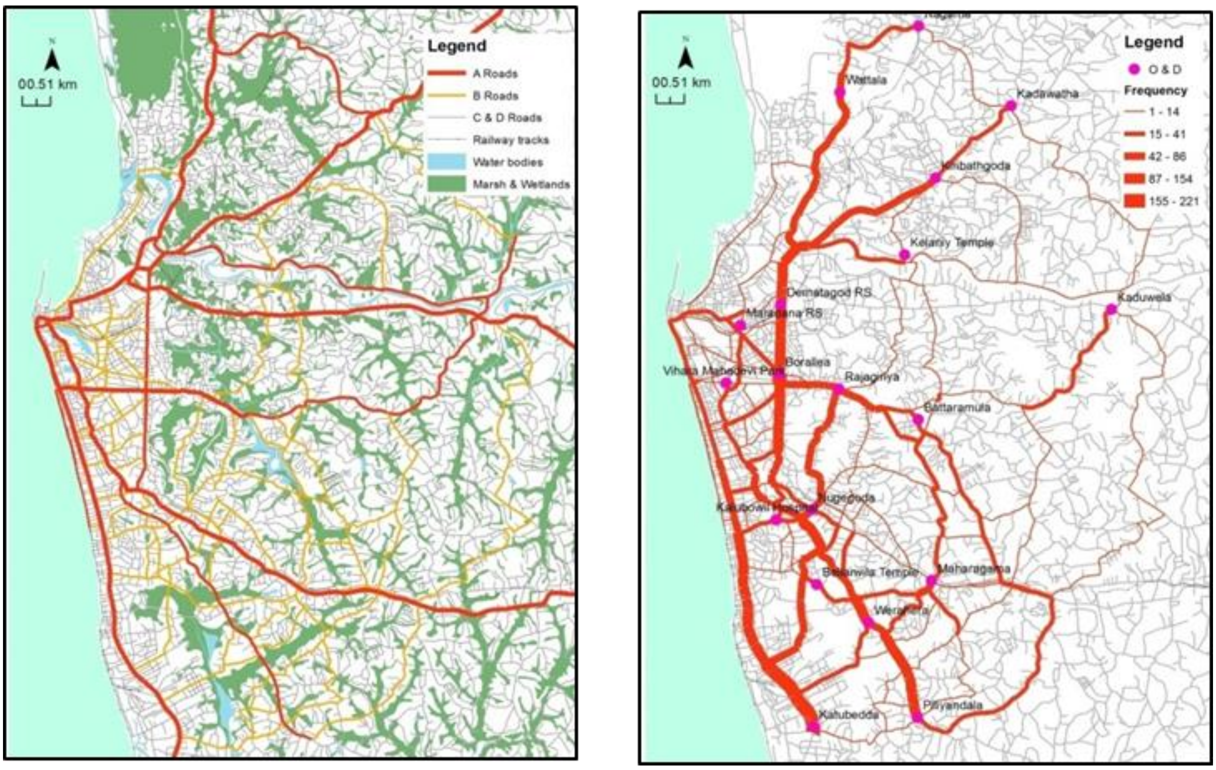
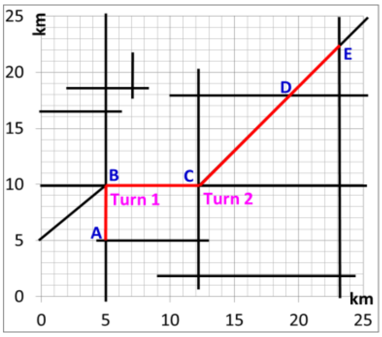
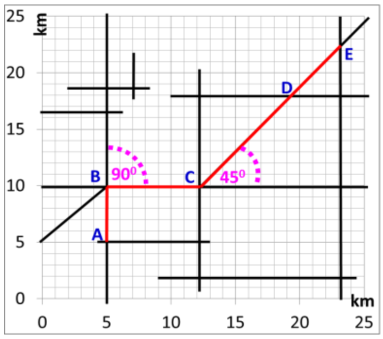
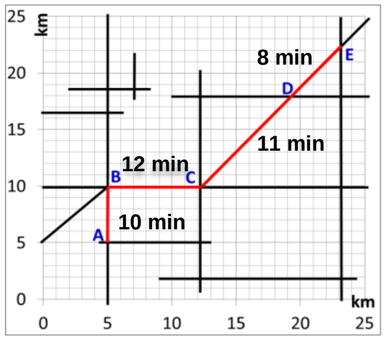


Figure 3-2: Road network of the study area and trip-makers' movement tracks

Topological distance (TD) and angular change [geo-metrical distance] (GMD) were calculated as per the method introduced by Hillier & Iida (2005) by a space syntax tool embedded to GIS application (refer Table 3.2). The travel time (Tt) of each route is calculated based on average travel time taken to travel long each road segment. For this purpose study used recorded travel time of each GPS based movements track and obtained the average travel time on each road segment.

Table 3-2: Methods of calculating the topological distance and travel time

Topological (TD)	**Geo-metric (GMD) - Angular**	**Travel time (Tt)**
		
TD is the cumulative number of ‘turns’ between two points. Ex. TD_{AE} = Turn at B + Turn at C = 2 turns	GMD is the cumulative ‘angle change’ between two points. Ex. GMD_{AE} $= 90/180\times2 + 45/180\times2$ = 1.5	Tt is the cumulative travel time between two points Ex. Tt_{AE} = 10 + 12 + 11 + 8 = 41 min

3.2.2. Ranking of routes based on distance

All routes between each O-D pair were ranked based on TD, GMD and Tt respectively. For instance, trip-makers who travel from ‘Katubedda’ to ‘Nugegoda’ (refer figure 3.3, i.e. O-D pair ID 10) have used three alternative routes (i.e. route-1 in red, route-2 in purple and route-3 in blue in figure 3.3). Table 3.3 shows how these three routes are ranked by TD, GMD and Tt values.

It indicates that the route ranks are different when organized the data by TD, GMD and Tt respectively. For instance, the first rank was obtained by route-1 by Tt, route-2 by GMD and route-3 by TD. To identify the measure which best represents the route choice, route ranks of three methods were compared with the actual number of trip-makers who have chosen the given route. Where there is the strongest inverse relationship between Route rank and the number of trip-makers can be considered as the best measure (i.e. out of TD, GMD and Tt) in explaining the route choice of trip-makers. For this purpose, this study has compared the movement tracks obtained by 250 trip-makers with the TD, GMD and Tt values.

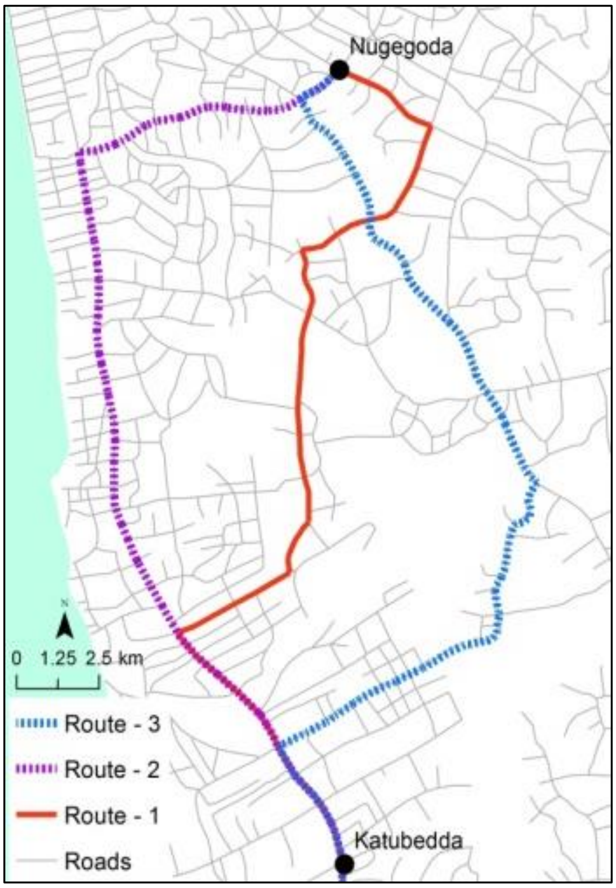


Figure 3-3: an example of ranking routes between a selected O-D pair

Table 3-3: An example of ranking routes between a selected O-D pair

O-D pair ID	Route ID	TD (no. of links)	Rank-TD	GMD (angular change)	Rank-GMD	Travel time (min)	Rank-Tt
10	1	48	2	401.77	2	15.12	1
	2	77	3	243.23	1	24.42	2
	3	46	1	767.59	3	18.24	3

3.3. Analysis and discussion

The first level of comparison was undertaken without considering the mode of travel, second level with considering the mode of travel and third level with considering both mode of travel and journey length. The findings of the study at each level discuss how TD, GMD and Tt are capable of representing the trip makers' route choice. Histograms below (refer figure. 3.4) indicate the number of trip-makers' who selected each route by route rank which has been computed by TD, GMD and Tt respectively. In all three graphs, number of trip-makers shows an inverse relationship to route rank.

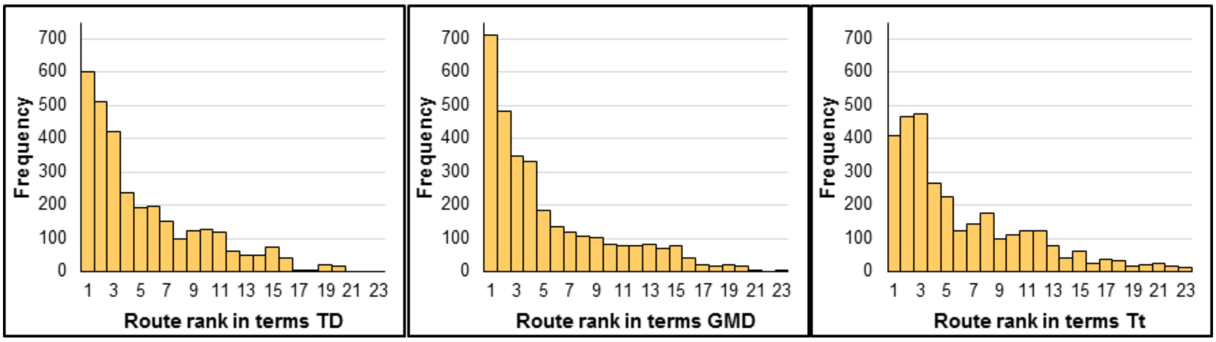


Figure 3-4: The number of trip-makers' (frequency) route choice based on route rank in terms of (a) TD, (b) GMD and (c) Tt

Table 3-4: Correlation between route ranks

	Rank_TD	**Rank_GMD**	**Rank_Tt**
Rank_TD	**1**	**.446****	**.232****
Rank_GMD		**1**	**.346****
Rank_Tt			**1**

Note: **Correlation significant at 0.01 and *Correlation significant at 0.05

The capability of TD, GMD and Tt in explaining the route choice was assessed comparing the cumulative percentage distribution of number of trip-makers who have chosen each route by route rank derived by TD, GMD and Tt respectively (refer Table 3.5). When referring to rank-1, 23% of trip-makers' has traveled on the route which was selected as rank-1 according to the GMD whereas only 13% has traveled on the route which was selected as rank-1 according to the Tt. Though this shows GMD better represent the trip makers' route choice compare to Tt, this requires further investigation.

The next sections investigated this further concerning the mode of travel and journey length. For that, the number of passengers was categorize based on mode of travel. Figure 3.5 illustrated the percentile distribution of trip-makers' route choice based on route rank by mode. When referring the results about car or MC users, recorded 50th percentile rank values in terms of GMD are close to 1. In contrast, recorded 50th percentile rank values in terms of Tt are 5 and

4 for car and MC riders receptively. However, recorded 50th percentile rank values in terms of Tt is lower than TD and GMD for both bus and tuk-tuk.

Table 3-5: The cumulative percentage distribution of trip-makers' route choice based on route rank in terms of TD, GMD and Tt

Rank	TD		GMD		Tt	
	Cum. no. trip-makers	Cum. % trip-makers	Cum. no. trip-makers	Cum. % trip-makers	Cum. no. trip-makers	Cum. % trip-makers
1	601	19%	713	23%	411	13%
2	1113	36%	1194	38%	879	28%
3	1534	49%	1542	49%	1355	43%
4	1770	57%	1875	60%	1620	52%
5	1964	63%	2060	66%	1846	59%
6	2163	69%	2194	70%	1969	63%
7	2317	74%	2312	74%	2111	68%
8	2414	77%	2419	78%	2289	73%
9	2538	81%	2521	81%	2387	77%
10	2667	86%	2605	84%	2499	80%

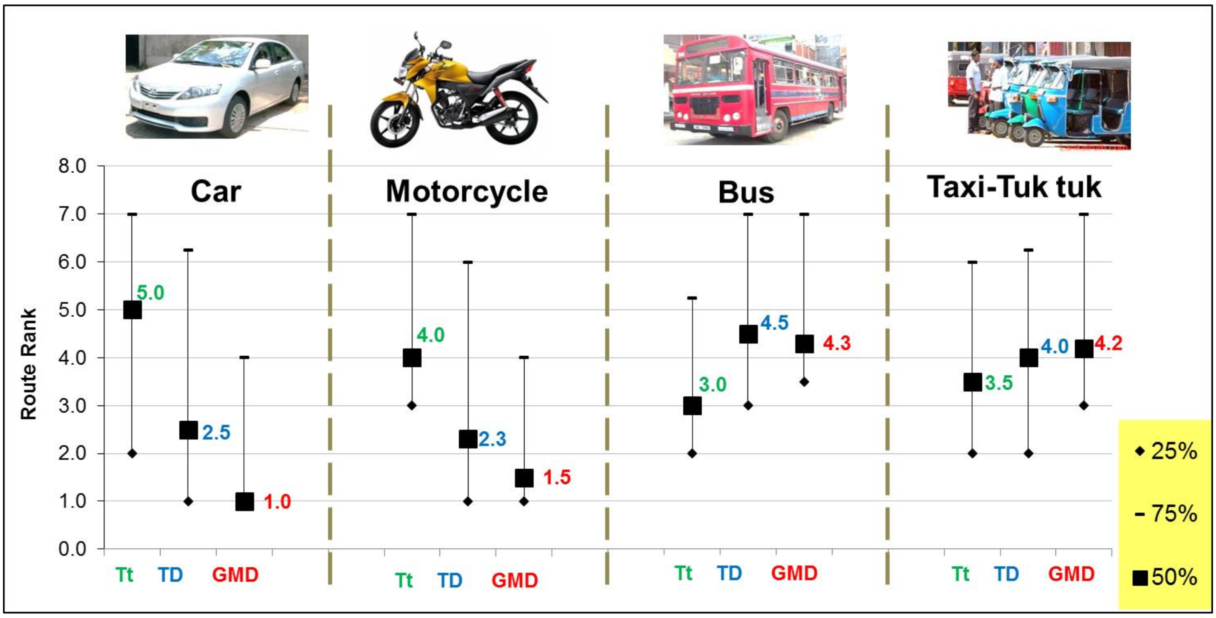


Figure 3-5: Percentile distribution of trip-makers' route choice based on route rank by modes

Then the study investigates this further concerning mode of travel and journey length. Then the number of passengers were categorize based on mode of travel and journey length. Figure 3.6 and Table 3.6 summarized the result of that.

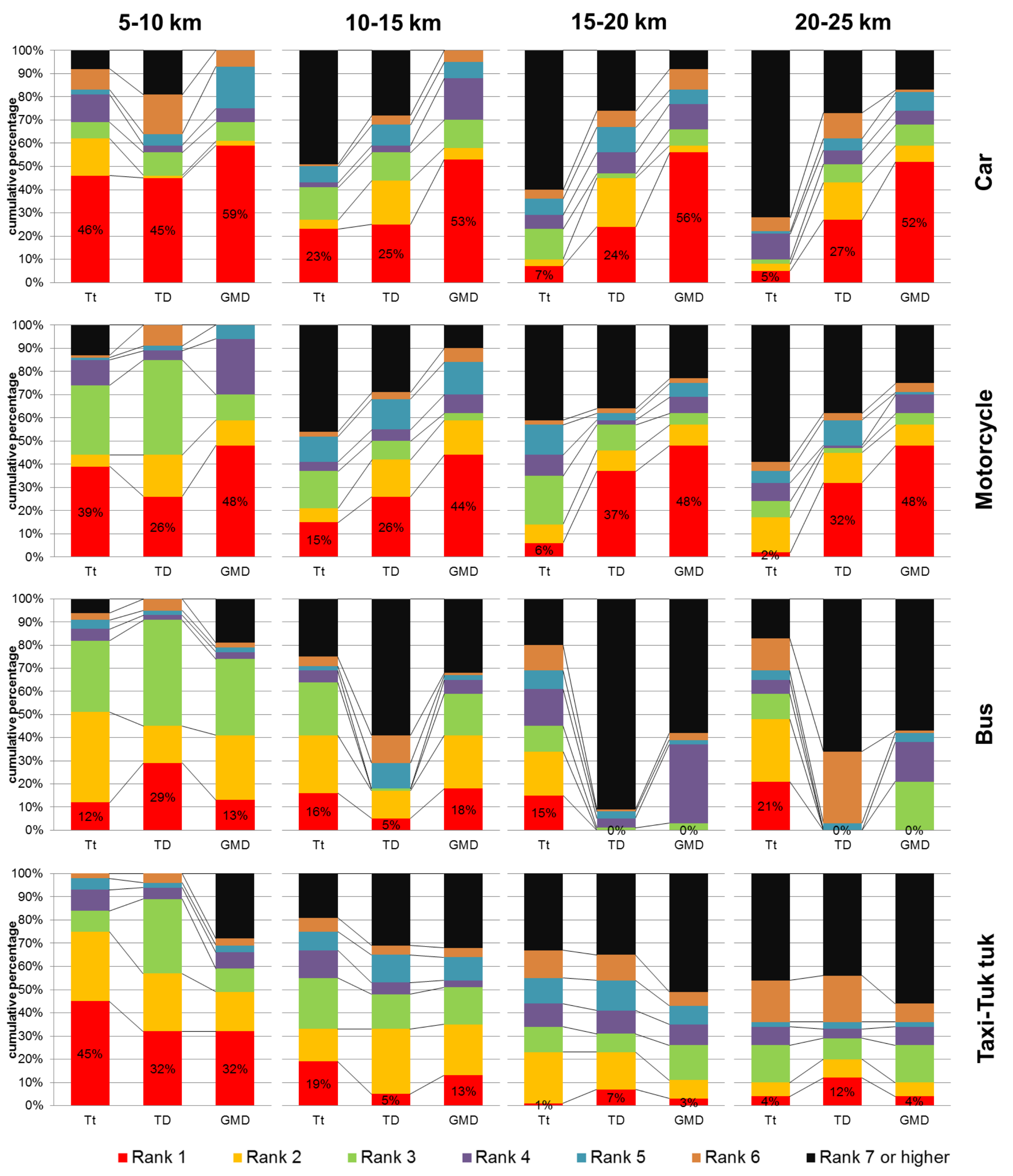


Figure 3-6: The cumulative frequency distribution of trip-makers' route choice based on route rank and by mode and journey length

Table 3-6: Distribution of trip-makers' route choice based on route rank and by mode and journey length

		Journey Length											
		5-10km			10-15km			15-20km			20-25km		
Mode	**Rank**	**Tt**	**TD**	**GMD**	**Tt**	**TD**	**GMD**	**Tt**	**TD**	**GMD**	**Tt**	**TD**	**GMD**
Car	1	1435	1404	1840	717	780	1653	218	749	1747	156	842	1622
	2	499	31	62	125	593	156	94	655	94	94	499	218
	3	218	312	250	437	374	374	405	62	218	62	250	281
	4	374	94	187	62	94	561	187	281	343	343	187	187
	5	62	156	561	218	281	218	218	343	187	31	156	250
	6	281	530	218	31	125	156	125	218	281	187	343	31
	>6	330	673	80	1608	953	80	1951	891	330	2326	922	610
MC	1	1216	811	1497	468	811	1372	187	1154	1497	62	998	1497
	2	156	561	343	187	499	468	250	281	281	468	405	281
	3	936	1279	343	499	250	94	655	343	156	218	62	156
	4	343	125	749	125	156	250	281	62	218	250	31	250
	5	31	62	187	343	405	437	405	94	187	156	343	31
	6	31	281	0	62	94	187	62	62	62	125	94	125
	>6	485	80	80	1515	985	392	1359	1203	797	1920	1265	860
Taxi – Tuk tuk	1	374	905	405	499	156	561	468	0	0	655	0	0
	2	1216	499	873	780	374	717	593	0	0	842	0	0
	3	967	1435	1029	717	31	561	343	31	94	343	0	655
	4	156	62	94	156	0	187	499	125	1060	187	0	530
	5	125	62	62	62	343	62	250	94	62	125	94	125
	6	94	156	62	125	374	31	343	31	94	437	967	31
	>6	374	905	405	499	156	561	468	0	0	655	0	0
Bus	1	1404	998	998	593	156	405	31	218	94	125	374	125
	2	936	780	530	437	873	686	686	499	250	187	250	187
	3	281	998	312	686	468	499	343	250	468	499	281	499
	4	281	156	218	374	156	94	312	312	281	250	125	250
	5	156	62	94	250	374	312	343	405	250	62	94	62
	6	62	125	94	187	125	125	374	343	187	561	624	250
	>6	80	80	953	673	1047	1078	1109	1172	1671	1515	1452	1827

When refer the results pertaining to car or MC users, it indicated that high percentage of trip-makers (i.e. 59%, 53%, 56% and 52% of car riders who travelled within the range of 5-10km, 10-15km, 15-20km, 20-25km respectively and 48%, 44%, 48% and 48% of motorcyclists who travelled within the range of 5-10km, 10-15km, 15-20km, 20-25km respectively) who travels along the routes which was recorded as rank-1 according to the GMD. In contrast, the percentage of trip-makers who travels along the route, which was recorded as rank-1 according to the Tt is low (i.e. In the case of cars; for 5-10km it is 46%, 10-15km it is 23%, 15-20km it is 7% and 20-25km it is 5% and in the case of motorcyclists; for 5-10km it is 39%, 10-15km it is 15%, 15-20km it is 6% and 20-25km it is 2%). In other words, the percentage gap between the number of trip-makers' (who used Car or MC) who select the top ranked routes (i.e., 1st, 2nd) by GMD and number of trip-makers' who selected top-ranked routes by Tt is increased with the journey length. This finding can be substantiated by the claim of Hiller et al. (2010) that is "urban space is locally [shorter journey length] metric and global [longer journey length] topo-geometric." Results about bus or taxi users indicated that high percentage (>50%) of trip-makers travels along the routes which were recorded as rank-1 and rank-2 according to the either Tt or GMD for journey length less than 15km. However, that percentage is very low for longer journeys.

While the study explains the trip-makers' route choice based on TD, GMD and Tt, how trip-makers explain the reasons for their route choice? This was questioned during the survey of 250 respondents and reasons mentioned were travel time, cost, road condition, convenience, and familiarity. The study attempt to interpret the route choices derived from computing TD, GMD and Tt with the trip-makers responses (see Table 3.7).

Table 3-7: Percentage distribution of trip-makers' responded as per key reasons to select a route by mode of travel

1st key reason to select route	% of trip-makers' by Car	% of trip-makers' by MC	% of trip-makers' by Taxi	% of trip-makers' by PT
Travel time	13.6%	13.9%	38.5%	25.5%
Travel cost	13.2%	11.8%	24.6%	49.3%
Road condition	10.9%	06.6%	18.9%	04.3%
Convenience	42.1%	44.6%	09.7%	07.6%
Familiar road	20.2%	23.1%	08.3%	13.3%

Travel cost and the travel time as mentioned as the 1st key determinant of the route choice predominantly by taxi and PT users. Convenient and familiarity are mentioned as the key determinant of the route choice predominantly by car and MC users. It is explained in the literature that convenience and familiarity related with cognitive behavior (i.e. which has a direct relationship with GMD and TD than Tt) of human wayfinding (Lotan, 1997), (Hensher, et al., 2004), (Hölscher, et al., 2011).

3.4. Conclusion

The objective of this pilot study was to examine the importance of travel time relative to topological distance in determining the route choice behavior of trip-makers. Results revealed from this study can be summarized in four points as follows. First, the results indicated that 23% of trip-makers' has traveled on the route which was selected as rank-1 according to the GMD whereas only 13% has traveled on the route which was selected as rank-1 according to the Tt. Second, the results about car or motorcycle users clearly indicated that high percentage of trip-makers who travels along the routes which were recorded as rank-1 according to the GMD. In contrast, the proportion of trip-makers who travels along the route which was recorded as rank-1 according to the Tt is low. Third, the results about bus or taxi users high percentage of trip-makers travel along the routes which were recorded as rank-1 and rank-2 according to the Tt and GMD for journey length less than 15km. Fourthly, convenience and familiar road play a significant role in trip-makers' route choice compare to travel time. Familiarity and convenience are a behavioral determinant associated with d trip-makers' network knowledge and more related to a cognitive understanding on the network than precious travel time or cost (Hensher, et al., 2004). Further, the notion of 'movement economies,' cognitive behavioral theories of human-way-finding and recent works of Hochmair and Frank (2002); Dalton (2003); Duckham and Kulik (2003); Hillier and Iida (2005) also have proposed that the geometric distance is useful to direct trip-makers to their destination. Further to this, researchers' argued that past memories, travel experiences (Golledge & Stimson, 1987); structure and functional relationship of the city (Walmsley, 1988), (Hillier, 1999) can be explained by geometric distance. Hence, it can be concluded that it is more appropriate to consider geometric distance (GMD) compare to travel time (Tt) when considering the shortest path in computing centrality.

Chapter – 4
Pilot Study-2: Investigation of Relationship between Network Centrality Values and Traffic Volume

4.1. Introduction

The objective of this pilot study is to examine the strength of relationship between network centrality and traffic volume, and to identify whether the relationship changes over the centrality measures and methods (i.e. preparation of graph, shortest path, boundary of the road network) of computing network centrality values as well as over the type of vehicles.

4.2. Method of study

4.2.1. Study area and description of data

The pilot study conducted in Colombo Metropolitan Area (CMA) which is the main urban agglomeration area in Sri Lanka. The per capita trip rate is 1.87 per person and the number of trips per day is around 700,000 in CMA (JICA, 2014). Table 4.1 gives a brief description of the traffic and transport characteristics of CMA area.

Table 4-1: Traffic and transport characteristics of CMA area

Mode	Share of Vehicle Ownership	Modal Share	Average Trip Length (km)
NMT (Non-Motorized Modes)	-	21.5%	2.2
Railway	-	2.7%	25.0
Bus	1%	37.7%	9.2
Three Wheeler	23%	12.9%	4.1
Motorcycle	49%	14.1%	6.7
Car	23%	11.1%	7.6
Heavy vehicle	4%	-	-

Source: (JICA, 2014)

Seven national roads are radiated from the center (i.e. Colombo Fort Area) and connect major towns of the CMA as well as other main cities and towns in the country. Further, Baseline road connect north and south of the Colombo Municipal Council (CMC) area (refer figure 4.1)

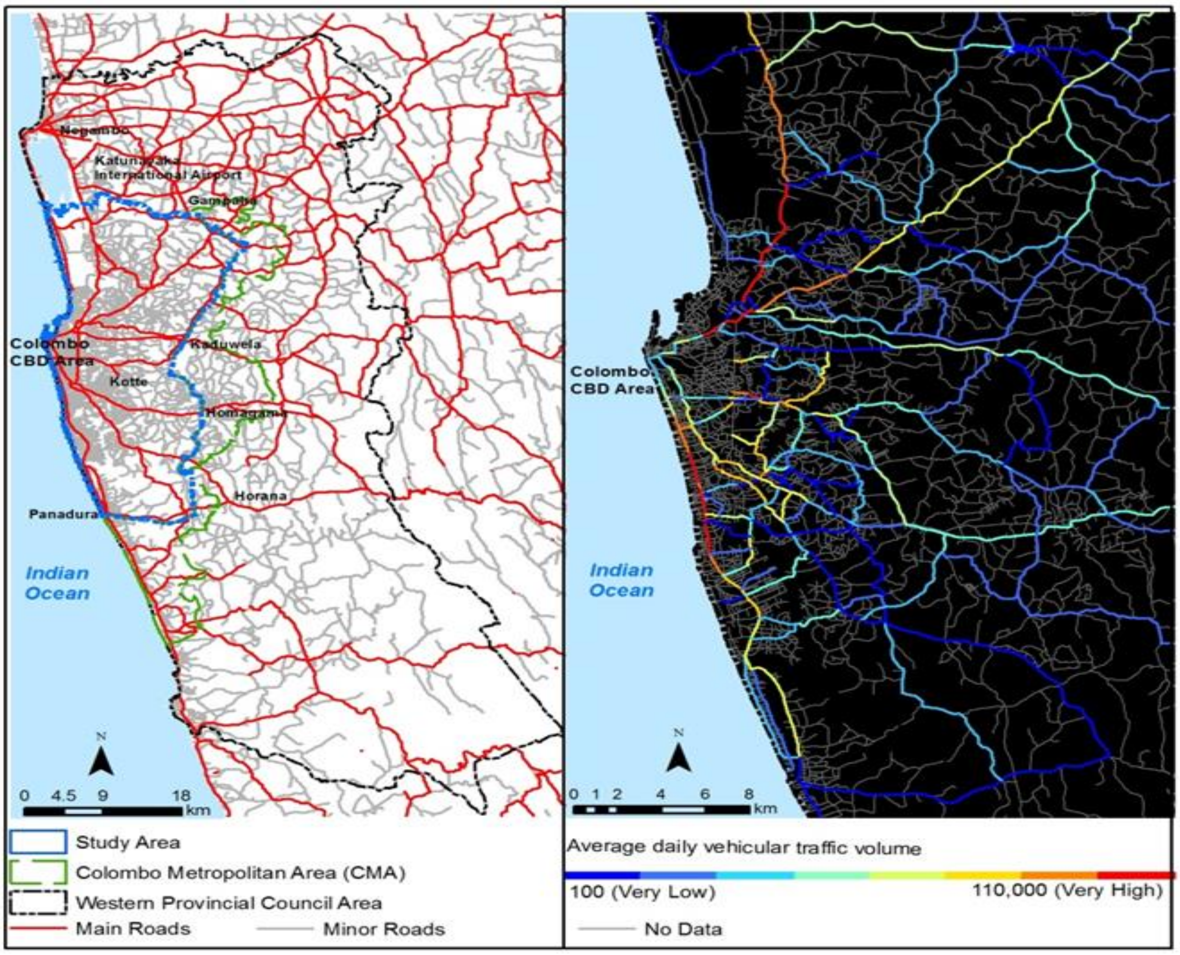


Figure 4-1: Study area and CMA and Distribution of average daily vehicular traffic volume

Data related to average daily vehicular traffic volume and road network were collected from secondary sources (refer table 4.2)

Table 4-2: Description of Data

Data Type	**Source**	**Remarks**
Average daily vehicular traffic volume	Road Development Authority (RDA), Sri Lanka	▪ Total number of vehicles, 266 data records, year 2007
	JICA	▪ Number of vehicles by modes, 56 data records, year 2013
Road network	Survey Department, Sri Lanka	▪ Included information related to road name, road type and year of construction ▪ Polygon GIS layer : Road polygon ▪ Line GIS layer: Road centerline

4.2.2. Computation of 'Network Centrality'

This pilot study used three types of graphs; 'axial lines,' 'natural roads' and 'road segments' to represent road networks. Topological, metric and angular (geo-metrical) analysis techniques are employed to compute network centrality based on connectivity, closeness and betweenness centrality (refer figure 4.2). Steps of computing network centrality values are introduced along with basic principle and some the basic concepts in following subsections.

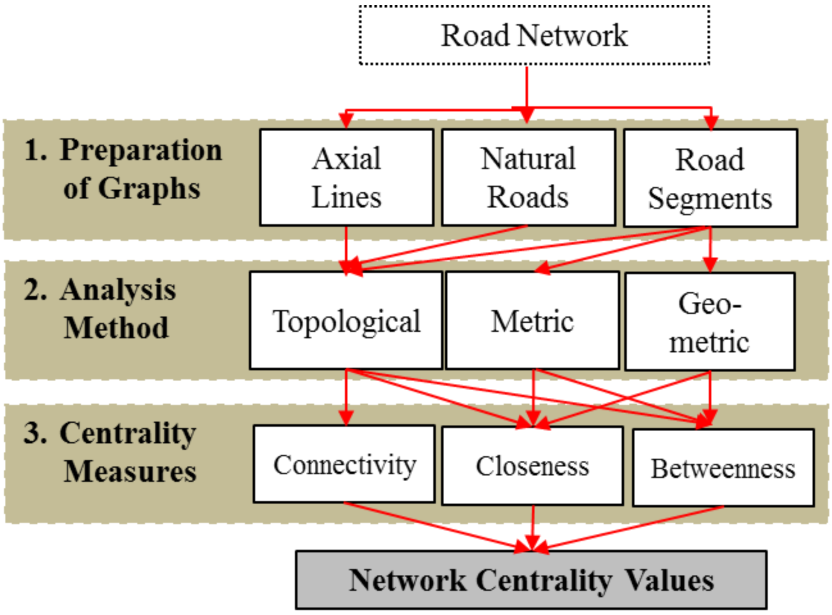


Figure 4-2: Computation of network centrality values

4.2.2.1. Preparation of graphs

This study used three kinds of graphs which are 'Axial Lines,' 'Road Segments' and 'Natural Roads' to represent road network. Figure 4.3 depicts a sample extracted from study area which represents a total number of links by three types of graphs.

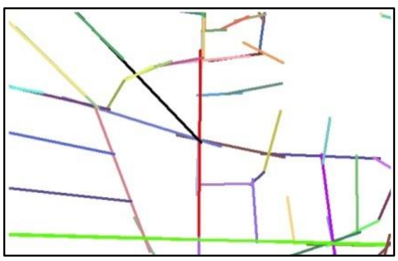
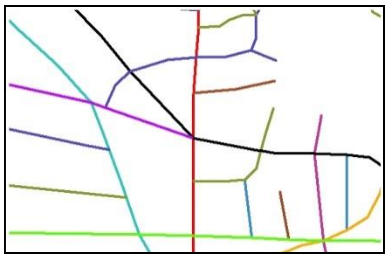
Axial Lines	Road Segments	Natural Roads
		
No. of Link =11,286	No. of Link =34,861	No. of Link =2,323

Figure 4-3: Three kinds of graphs

Hillier and Hanson (1984) have introduced the axial line-based representation, and it represents the longest visibility lines over the space or along the road. This study has used a GIS data layer of road polygons and converted it into axial lines by using UCL Depth Map 10 software application (refer figure 4.4). Accordingly, this graph represents the unobstructed line of movement along the road (Hillier & Hanson, 1984).

Road polygons	Axial Lines generated by using UCL Depth Map	Graph: Axial Lines

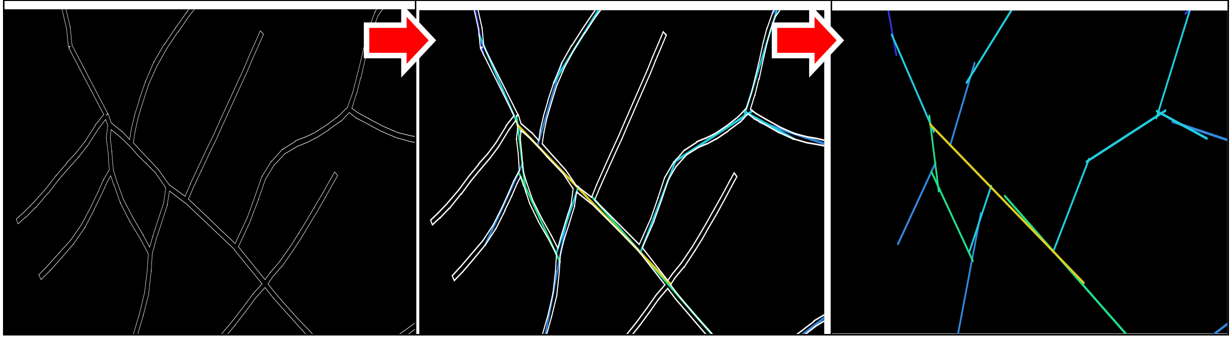


Figure 4-4: Preparation of Axial Lines based graph
Note: Unique color has been given to symbolized the each link

Segments based graph representation has been introduced by Turner (2001) and Dalton (2003). This graph facilitates the metric and angular (Geo-metric) analysis of the road network by considering the effect of metric distance and turn angles at road intersections. Road segment graph is formed by chopping the original road center lines at each junction into smaller individual parts (refer figure 4.5).

Road centerlines	Chopping centerlines at intersection by using GIS	Graph: Road Segments

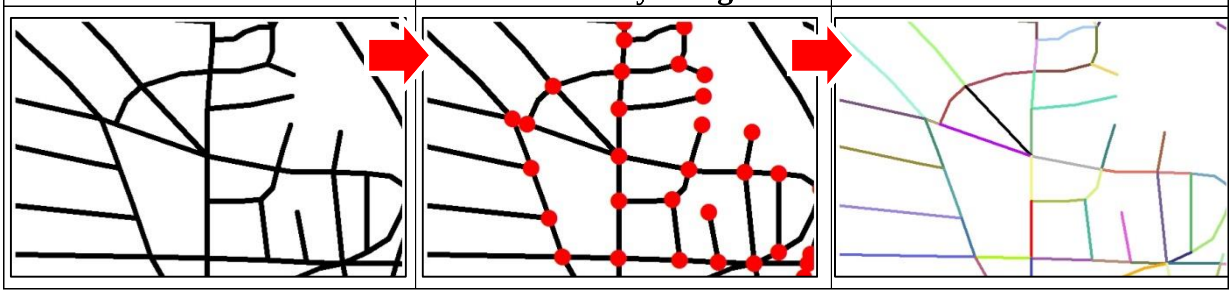


Figure 4-5: Preparation of Road Segments based graph

Note: Unique color has been given to symbolized the each link

Next graph is the natural road, and it represents roads which are naturally merged with good continuity (Liu & Jiang, 2011). This study has used road segments graph prepared in the previous step to create natural road graph. ‘Axwoman’ extension in GIS software has been used to automatically generate natural road graph by tracking the road segments within a 45-degree value of angle change limitation (refer figure 4.6).

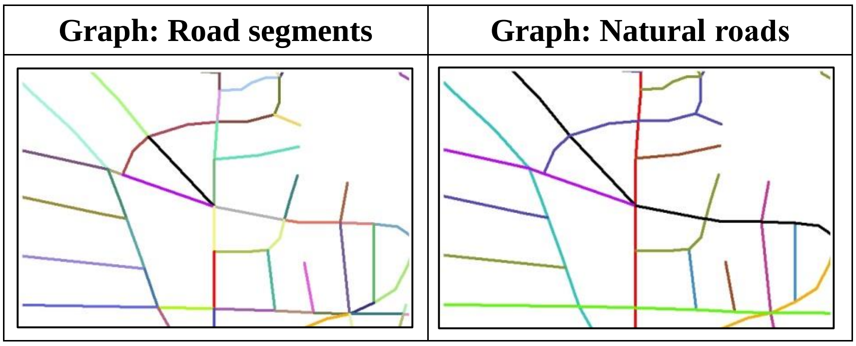


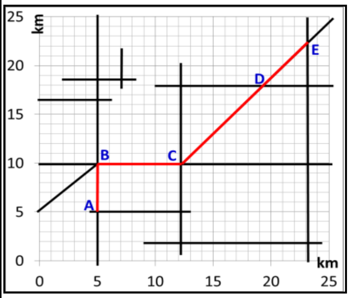
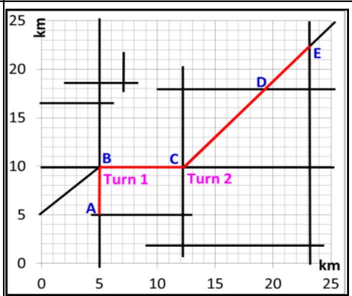
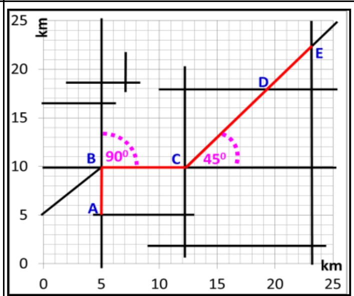
Figure 4-6: Preparation of Natural roads based graph

Note: Unique color has been given to symbolized the each link

4.2.2.2. Analysis methods (Path distance)

This study used three kinds of analysis methods which are metric, topological and geo-metric (angular) and Table 4.3 summarizes key features of those methods. The basic difference among the three analysis methods is the way of calculating the shortest path.

Table 4-3: Methods of analysis

Analysis	**Metric**	**Topological**	**Geo-metric (Angular)**
Diagram			
Way of calculating the shortest path and distance	▪ Based on ‘shortest metric’ distance between two points ▪ $Distance_{AE} = Length_{AB} + Length_{BC}$ ….. ▪ Ex: Distance = 5+7+10.6+5.7 = 28.3km	▪ Based on ‘fewest turns’ between two points ▪ Distance = Total number of turns ▪ Ex: Distance = 2	▪ Based on ‘least angle change’ between two points ▪ Distance = 90/180 ×2 + 45/180 ×2 ▪ Ex: Distance = 1.5

4.2.2.3. Centrality measures

The study computed network centrality based on connectivity, closeness and betweenness centrality. Connectivity centrality (Cn) compute the number of links directly connected to the particular link in a graph. The study utilized Hillie & Iida's (2005) formula to compute Cn of links (refer equation 4.1).

$$Cn_i = k \tag{4-1}$$

Where,

Cn_i = *Connectivity centrality of link 'i',*

k = *Number of links directly connected the link 'i'*

Closeness Centrality (CC) measures how close the location [link] to all others along the shortest path (Porta, et al., 2012). The study utilized Sabidussi's (1966) formula to compute CC of links (refer equation 4.2).

$$\mathrm{CC}_{i[r]} = \frac{(N-1)}{\sum_{j\in N, j\neq i} d_{ij}} \tag{4-2}$$

Where,

CC_i = *Closeness centrality of link 'i'*

N = *Total number of links in a network*

d_{ij} = *Distance between links 'i' and 'j' along the shortest path*

r = *Radiuses of influence system considered*

Betweenness Centrality (BC) is referred to the extent a given link belongs to the shortest-path between any pairs of two in a graph (Porta, et al., 2012). The study utilized Freeman's (1977) formula to compute BC of links (refer equation 4.3).

$$\mathrm{BC}_{i[r]} = \frac{1}{(N-1)(N-2)} \sum_{j,k\in N; j\neq k; k\neq i} \frac{p_{jk_{(i)}}}{p_{jk}} \tag{4-3}$$

Where,

BC_i = *Betweenness centrality of link 'i'*

N = *Total number of links in a network*

p_{jk} = *Number of geodesics between link 'j' and 'k'*

$p_{jk_{(i)}}$ = *Number of geodesics between link 'j' and 'k' that passing through link 'i'*

r = *Radiuses of influence system considered*

The study computed the centrality of each link based on the above-mentioned centrality parameters by using prepared graphs. Accordingly, computation produced 13 types of centrality values for each link based on centrality measure, graph and analysis method used (refer Table 4.4).

Table 4-4: Combinations calculated

Type of graph	**Centrality measure**	**Method of analysis**		
		Metric (MD)	**Topological (TD)**	**Geo-metric (GMD)**
Axial lines (AL)	Connectivity (Cn)	-	✓	-
	Closeness (CC)	-	✓	-
	Betweenness (BC)	-	✓	-
Road segments (RS)	Connectivity (Cn)	-	✓	-
	Closeness (CC)	✓	✓	✓
	Betweenness (BC)	✓	✓	✓
Natural roads (NR)	Connectivity (Cn)	-	✓	-
	Closeness (CC)	-	✓	-
	Betweenness (BC)	-	✓	-

Note: ✓ Computed

4.3. Analysis and discussion

The first level of analysis is undertaken to identify the relationship between network centrality values and traffic volumes and the second tier investigates the relationship changes over method of computing network centrality values and type of vehicles

4.3.1. Relationship between network carnality values and traffic volumes

Figures 4.7 demonstrate power law distribution of network centrality values. To examine power law distribution, the study plots the log-log plots where the x-axis represents log centrality values, and the y-axis represents cumulative log probability in terms of road length. Betweenness (BC) and closeness (CC) centrality values exhibit a very close relationship to the power law distribution than connectivity (Cn). This finding indicates that BC and CC values follow the small world and scale-free properties and suitable to represent centrality of the road network.

Figure 4.8, Figure 4.9 and Figure 4.10 indicates the spatial distribution of network centrality values**.** The highest values are indicated in red color, and the lowest values are indicated in blue color. Maps are visualizing the betweenness and closeness centrality the spatial distribution patterns according to the three analysis methods in figure 4.8. Figure 4.9 indicates maps visualizing the connectivity, betweenness and closeness centrality values based on types of graphs**.** Figure 4.10 shows the spatial distribution of centrality values based on analysis methods. Visual comparison of those maps indicates that spatial distribution pattern of each centrality parameter based on different types of analysis methods and graphs are unique and have a significant variation with each other.

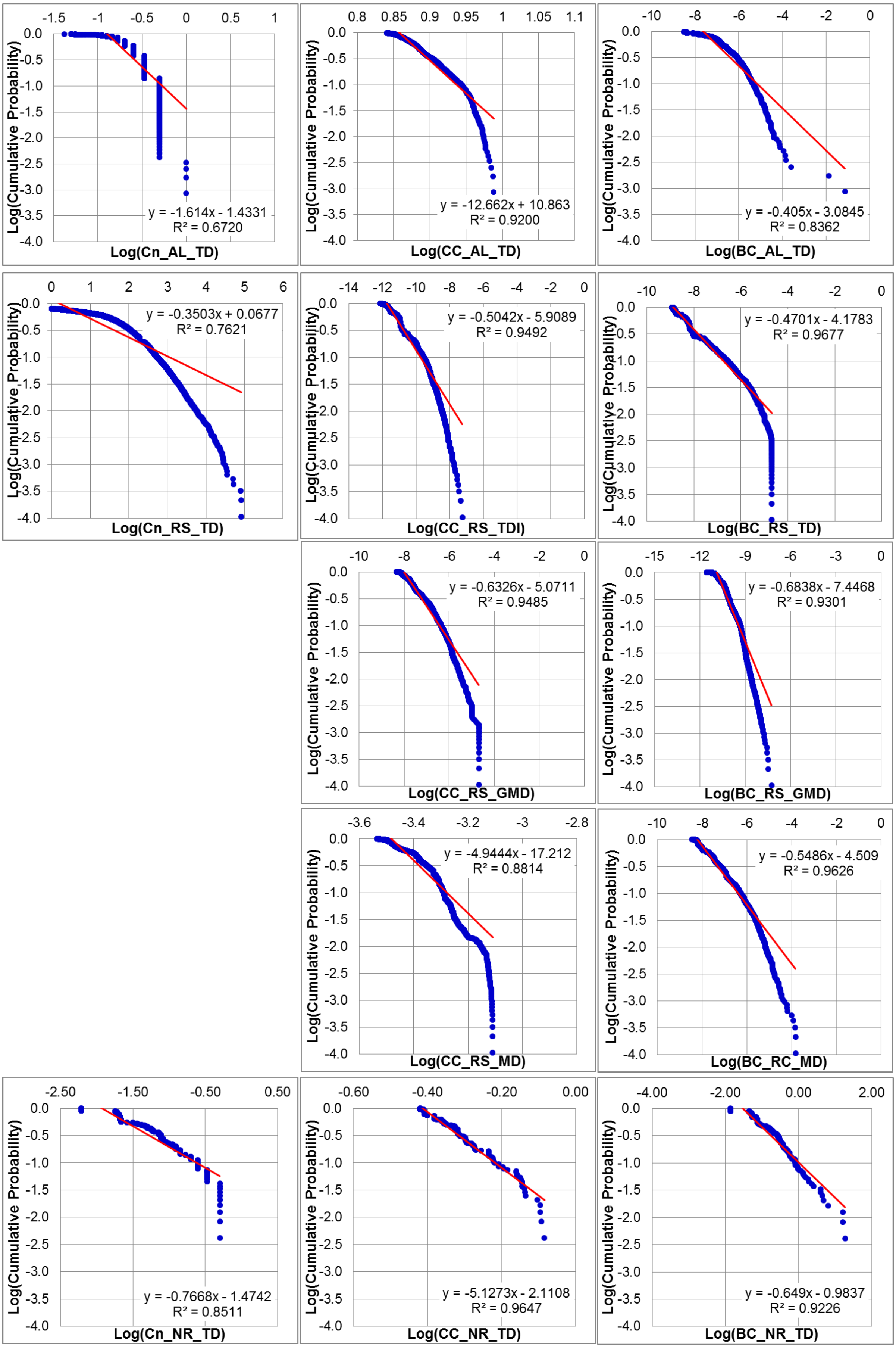


Figure 4-7: Power law distribution – Network centrality values

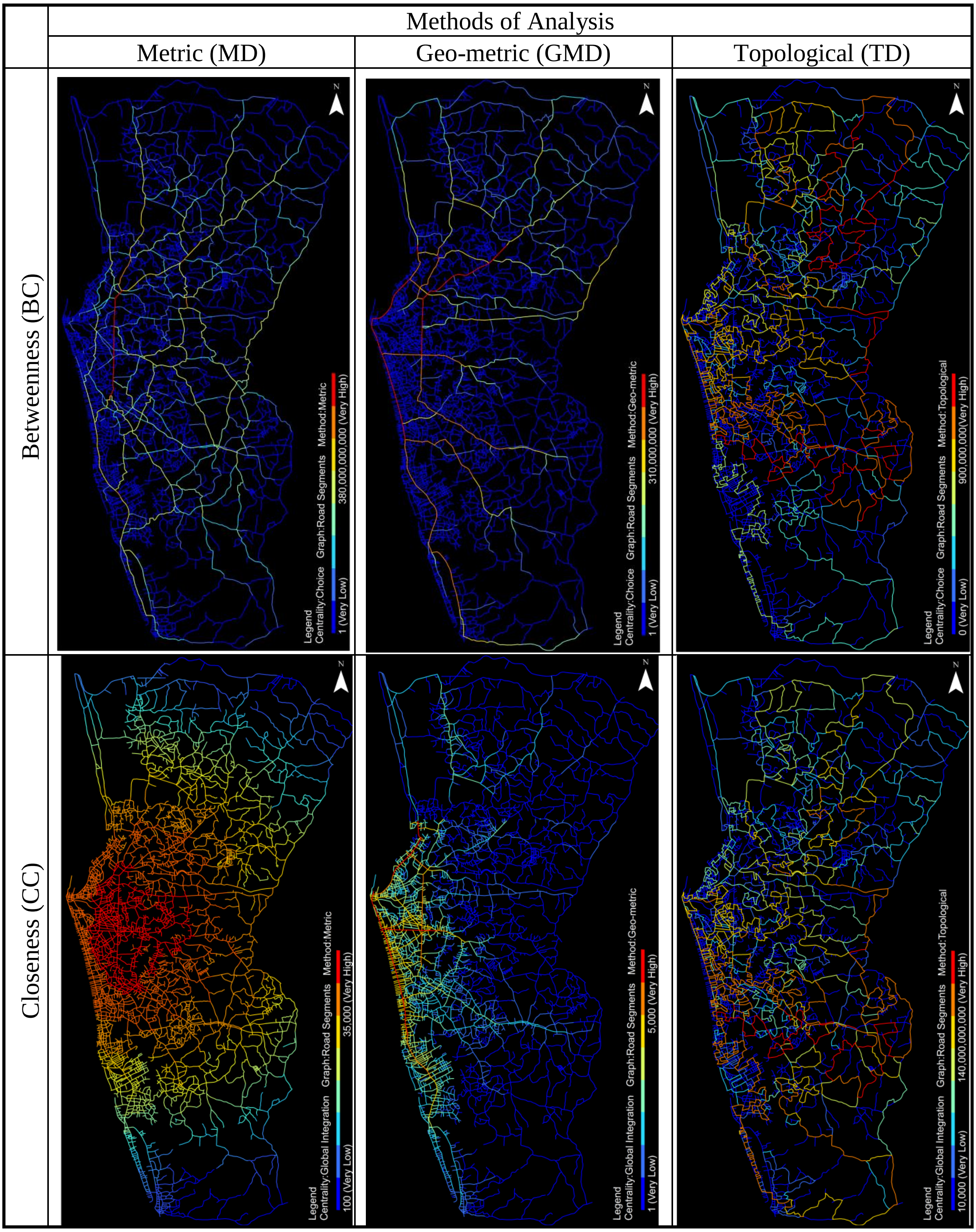


Figure 4-8: Spatial distribution of betweenness and closeness centrality values based on methods of analysis

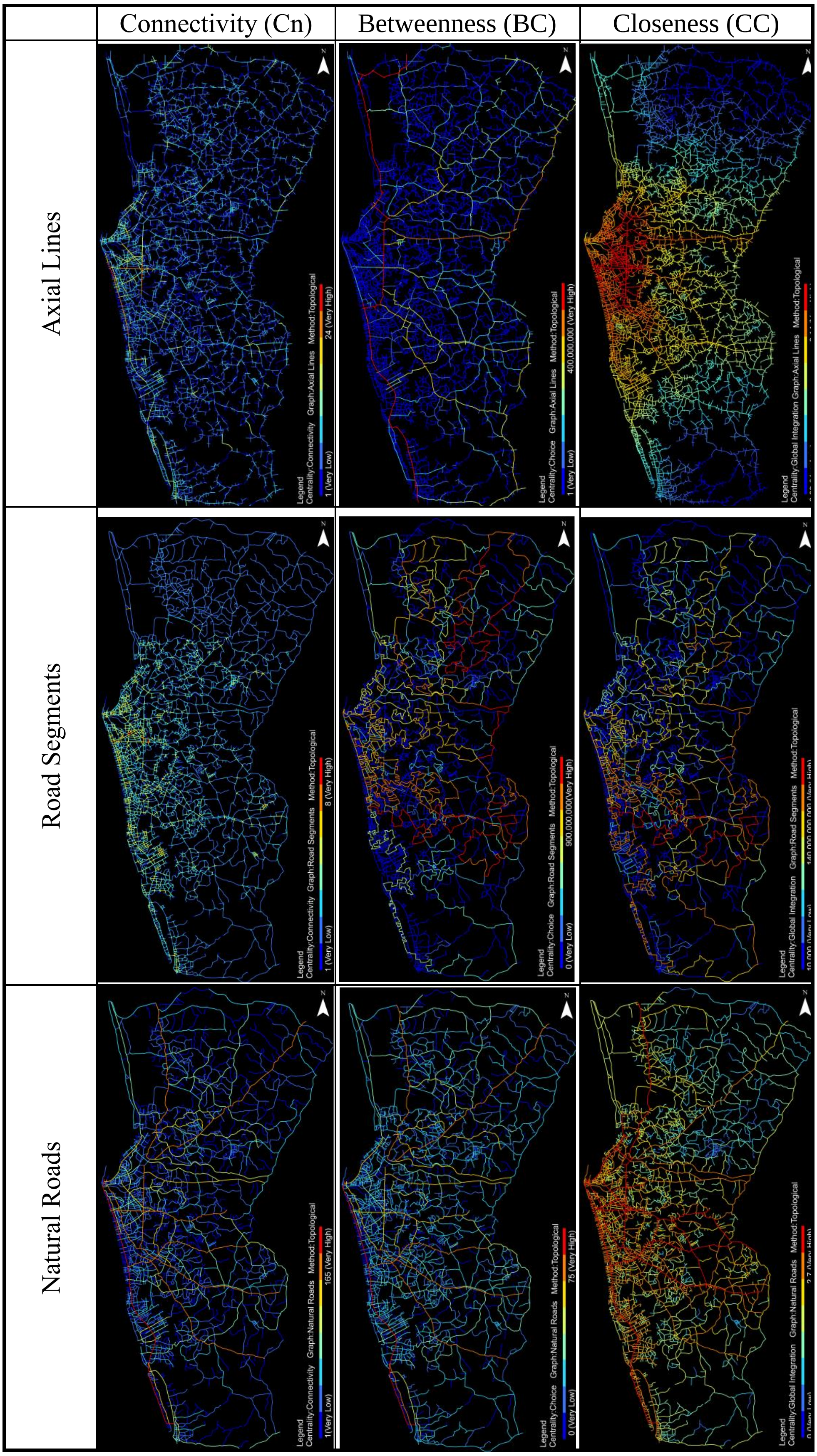


Figure 4-9: Spatial distribution of centrality values based on types of graphs

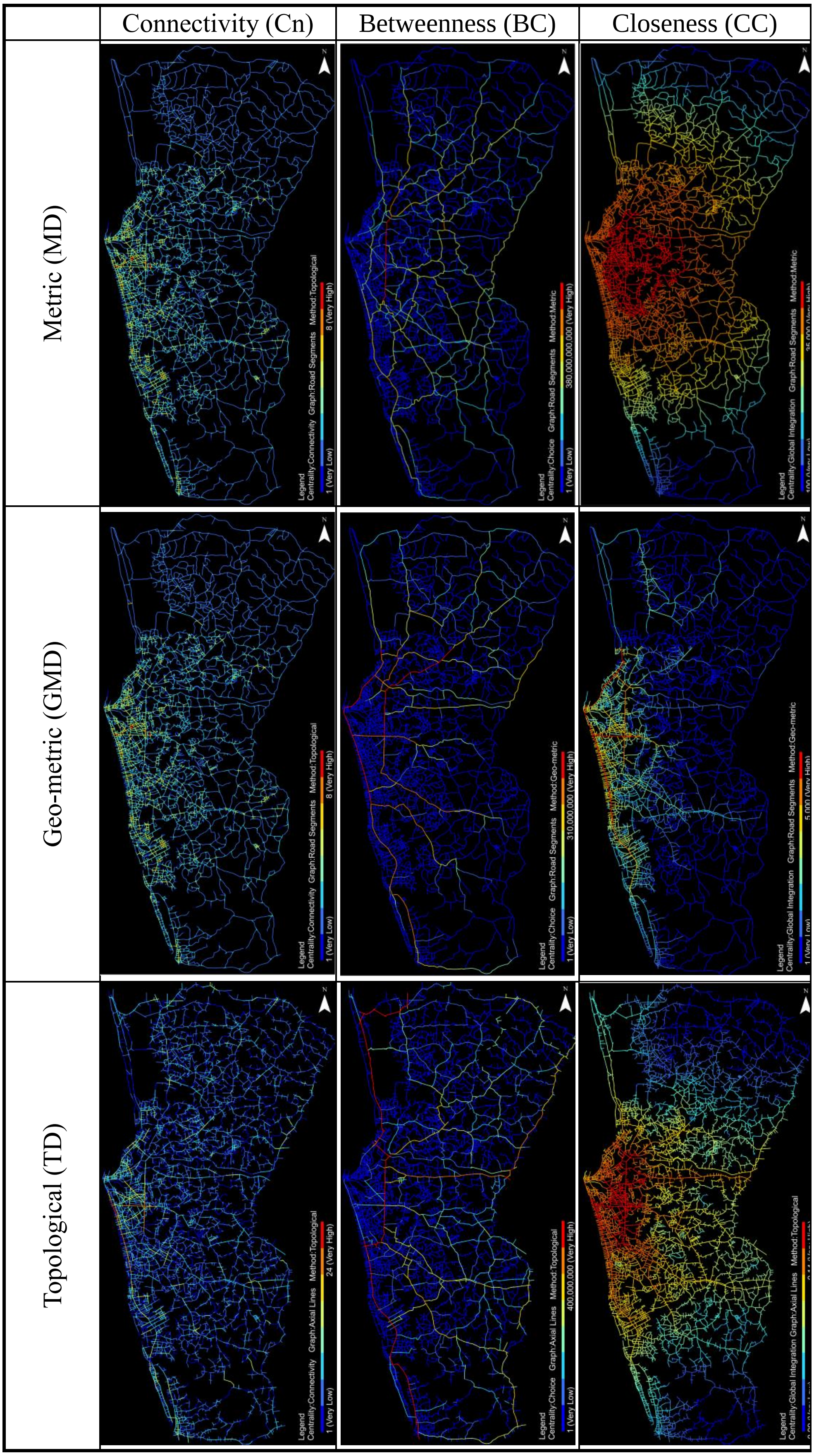


Figure 4-10: Spatial distribution of centrality values based on methods of analysis

Spearman correlation coefficient test was employed to find out the nature and the strength of the relationship between traffic volume and network centrality. Table 4.5 illustrates the summary result of correlation analysis.

Table 4-5: Correlation between centrality values and traffic volume

Centrality measure	**Type of graph**	**Method of analysis**	**r-value (Correlation coefficient)**	**Rank according to the r-value**
Connectivity (Cn)	Axial Lines	Topological	.227*	7
	Road Segments	Metric	.147*	
		Geo-metric		10
		Topological		
	Natural Roads	Topological	.399**	3
Betweenness (BC)	Axial Lines	Topological	.216*	9
	Road Segments	Metric	.338**	5
		Geo-metric	.727**	1
		Topological	-.181	11
	Natural Roads	Topological	.388**	4
Closeness (CC)	Axial Lines	Topological	.234**	6
	Road Segments	Metric	.216*	9
		Geo-metric	.592**	2
		Topological	-.088	12
	Natural Roads	Topological	.225**	8

Note: **Correlation significant at 0.01 and *Correlation significant at 0.05, N=266

In this inquiry, significant positive correlation between traffic volume and network centrality values were identified. That indicates there is a relationship between traffic volume and network centrality. However, the level of coefficient of correlation is different by centrality parameters, type of graph as well as methods of analysis. In summary;

1. Road segment graph revealed a relatively higher value than those for the other two types. It can be concluded that road segment is the best type of graph followed by natural road and axial line graphs.

2. Geo-metric methods revealed a relatively higher value than those for other two methods. Accordingly, geo-metric analysis method is the best method followed by topological and metric.

3. It could also be seen that betweenness centrality seems to have the highest correlation with the correspondent traffic volume, followed by the closeness centrality.

4.3.2. Relationship changes over method of computing network centrality values and type of vehicles

Usually, network centrality of any given link or node is computer by considering the influence of all links and nodes in the entire network. However, it can be computed based on different impact area, i.e., radiuses influence boundary of the road network. When all links and nodes are taken into the computation, it called as global level analysis. If it is set to a specific radius (e.g.: radius =3km), network within the area of 3km radius take into account and termed as 'local level centrality.' Most of the studies on the centrality and urban space (related to predestine movements) have selected the entire city as the global area and 500-800m radius as the local area. Porta et al. (2009) stated that "local measures are useful to overcome the edge effect, i.e. the distortion that lowers the centrality values near the edge of a network and it very significant for the closeness index when calculated on highly fragmented networks". Literature has further emphasized that the global centrality measures not reveal network properties on a local scale instead local measures capture properties of space at the neighborhood. Hillier (1996) suggested that "in fact, it is slightly more subtle and depends on the typical length of journeys. Pedestrian densities on lines in local areas can usually be best predicted by calculating centrality for the system of lines up to three lines (radius- 500m) away from each line while, cars on larger-scale routes depend on higher radius centrality (though not in local areas, where radius-3 is the not the best predictor) because car journeys are on the whole longer and motorists therefore read the possible routes according to larger-scale logic than pedestrians". Krafta et al. (2011); Herrera-Yagüe et al. (2015) and Zhong et al., (2015) pointed out that there are different functional levels of locations in urban structure and centrality of them changes over the urban space. In other words, some locations obtain higher centrality values at the neighborhood level and act as local centers while some other locations obtain higher centrality values at the district level and act as district hubs. When it comes to the road network, road obtains higher centrality values at the regional level serve as a trunk road and attract regional traffic while some other road obtains higher centrality at the neighborhood level and attract more local traffic. Above discussed literature suggested calculating centrality of links in different levels to capture the centrality of links at various influence area of the network.

Accordingly, the study computed centrality for a set of radiuses of influence boundary of the road network as 500m, 1.5km, 3km, 5km, 7.5km, 10km, 15km, 20km, and 25km. Then investigated the relationship between those centrality values and traffic volumes. Further, the study investigated the relationship between traffic volume by type of vehicles as car, motorcycles (MC), tuk-tuk, bus and heavy vehicles (HV). Figure 4.11, 4.12 and Table 4.6 summarizes the coefficient of correlation between centrality values and traffic volumes at different radiuses and by type of vehicles.

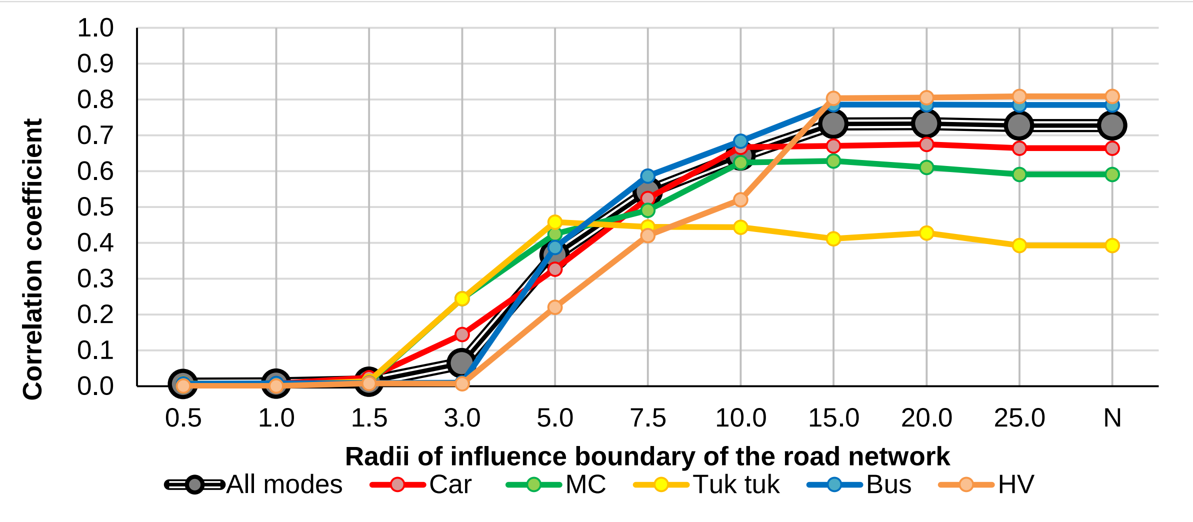


Figure 4-11: Comparison of fluctuation of coefficient of correlation values at different radiuses and by type of vehicles for betweenness centrality

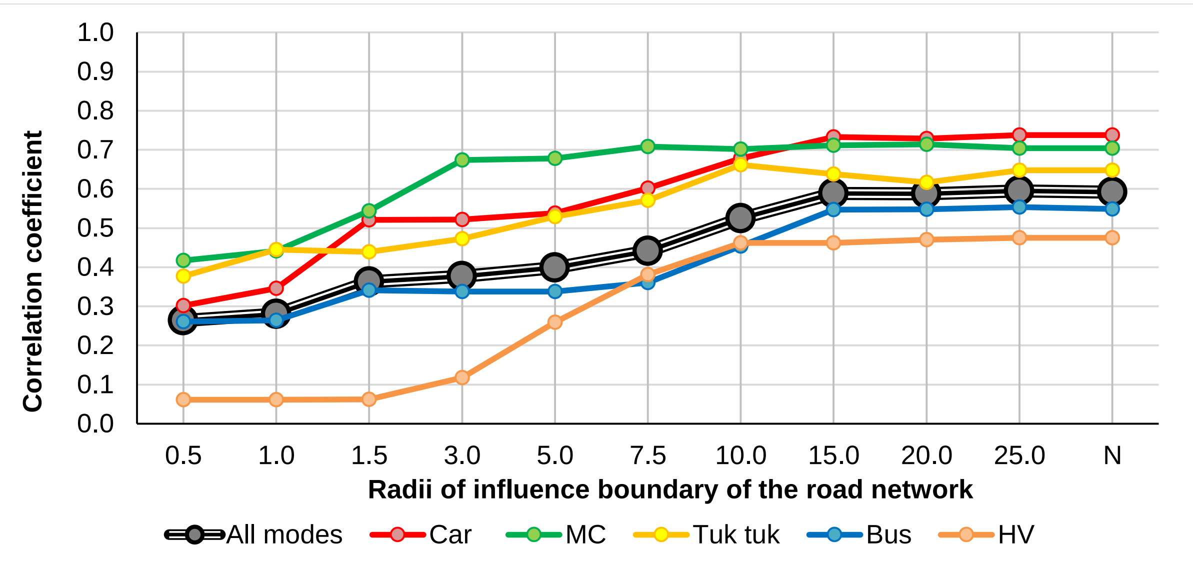


Figure 4-12: Comparison of fluctuation of coefficient of correlation values at different radiuses and by type of vehicles for closeness centrality

Table 4-6: Summary results of correlation analysis between centrality values at different radiuses and traffic volume by type of vehicles

Centrality measure	Radius of influence boundary	Correlation coefficient between centrality values and traffic volume					
		All	Car	Motorcycles (MC)	Tuk-tuk	Bus	Heavy vehicles
Betweenness (BC)	0.5	0.006	0.005	0.001	0.008	0.007	0.001
	1.0	0.007	0.007	0.004	0.004	0.008	0.001
	1.5	0.012	0.024	0.012	0.014	0.009	0.008
	3.0	0.064	0.145*	0.245*	0.245*	0.010	0.007
	5.0	0.366**	0.327**	0.425**	0.458**	0.388**	0.221*
	7.5	0.543**	0.524**	0.491**	0.445**	0.587**	0.421**
	10.0	0.644**	0.667**	0.624**	0.444**	0.684**	0.521**
	15.0	0.732**	0.671**	0.629**	0.412**	0.786**	0.804**
	20.0	0.733**	0.675**	0.611**	0.428**	0.786**	0.806**
	25.0	0.727**	0.665**	0.591**	0.393**	0.785**	0.809**
	N	0.727**	0.665**	0.591**	0.393**	0.785**	0.809**
Closeness (CC)	0.5	0.264*	0.302**	0.417**	0.377**	0.261*	0.061
	1.0	0.280*	0.346**	0.442**	0.445**	0.264*	0.061
	1.5	0.363**	0.521**	0.544**	0.439**	0.341**	0.062
	3.0	0.377**	0.522**	0.674**	0.473**	0.338**	0.118*
	5.0	0.399**	0.538**	0.678**	0.529**	0.338**	0.259*
	7.5	0.441**	0.602**	0.708**	0.571**	0.361**	0.381**
	10.0	0.525**	0.678**	0.702**	0.662**	0.454**	0.463**
	15.0	0.588**	0.733**	0.712**	0.638**	0.547**	0.462**
	20.0	0.587**	0.729**	0.714**	0.617**	0.548**	0.470**
	25.0	0.595**	0.738**	0.704**	0.648**	0.554**	0.475**
	N	0.592**	0.738**	0.704**	0.648**	0.549**	0.475**

Note: ****Correlation significant at 0.01 and *Correlation significant at 0.05. N=56

Correlation results indicated that;

1. BC and CC computed at 15 km radius or more recorded a higher correlation with total traffic volume as well as traffic volume by different type of vehicles, than those computed at 10km radiuses or less.
2. Bus and HV recorded a higher correlation with BC values than total traffic volume, car, MC and tuk-tuk. However, bus and HV recorded a lower correlation with CC values, than total traffic volume, car, MC and tuk-tuk.

4.4. Conclusion

The objective of this pilot study was to examine the strength of the relationship between network centrality and traffic volume and to identify whether the relationship changes over the measures and methods (i.e. preparation of graph, shortest path, the boundary of the road network) of computing network centrality values as well as over the type of vehicles. Results revealed from the pilot study can be summarized into three points as follows. First, road segments graph based on geo-metric analysis method has been far better in explaining the vehicular traffic volume in comparison to the other combinations. Second, as many other authors (Puzis, et al., 2013); (Galafassi & Bazzan, 2014) agreed, betweenness which is computed based on geo-metric analysis method has significantly influenced in predicting traffic volume. However, findings of this pilot study stress that, the closeness centrality computed based on geo-metric analysis method also have a significant relationship with traffic volume. Father, the level of relationship of each centrality measures varies depending on the type of vehicles. Hence, this study concluded that it is more appropriate to consider the multiple influences from multiple centrality measures in modeling vehicle volumes rather than strict into the single best centrality measure. Thirdly, results revealed that radius of boundary of the road network has a significant impact on the relationship between network centrality values and traffic volume. Accordingly, it can be concluded that it is possible to explain traffic volume based on network centrality and it is more appropriate to consider both closeness and betweenness centrality measures, and use road segment graph and a suitable radius for the road network boundary when computing network centrality.

Chapter – 5
A Network Centrality-based Simulation of Traffic Volume by Road Segments

5.1. Introduction

The sub-objective aimed to achieve from the study explains in this chapter is to develop a set of models to estimate AADT and predict vehicular traffic volume of road segments based on the road network centrality values. First, this chapter describes the proposed concept that is traffic volume as a function of network centrality along with appropriate centrality measures to capture traffic volume, particularly accounting pass-by trips and to-and-from trips. Next section provides a description of the method and data. Then, the study explains the model formulation and validation.

5.2. The proposed concept: Traffic volume as a function of network centrality

In the proposed concept betweenness (BC) and closeness (CC) centrality are the output of traffic volume model which simulates origin-destination trips and pass-by trips respectively, subject to a maximum trip distance. Thus it replaces all four stages of the traditional transport model trip generation, trip distribution, mode choice and route choice. Following sections explain how the study derive the concept and the details of the concept.

Traffic volume of a road segment is equal to the sum of the volume of to-and-from trips (either origin or destination) and the pass-by trips within the given road segment (refer equation 5.1). Pass-by trips and to-and-from trips can be explained by the illustration provided in Figure 5.1. Accordingly, locations A, B, C, D, E, F, G, H and X are considered as either origin (O) or destination (D). When considering traffic volume of road segment X, trip makers traveling from A to X, B to X, E to X, X to F, X to C make to-and-from trips whereas trip makers traveling from A to E via X, A to G via X, B to D via X, B to H via X make pass-by trips.

$$\begin{aligned}\textit{Traffic volume of road segment } i = \; & \textit{Volume of to-and-from trips of road segment } i \\ & + \textit{Volume of pass-by trips of road segment } i \end{aligned} \qquad (5\text{-}1)$$

Figure 5-1: To-and-from trips and pass-by trips

In this study, closeness centrality (CC) was utilized to capture the volume of to-and-from trips of a given road segment (refer equation 5.2). Closeness centrality explains "the notion of accessibility of a location [road segment] and measures how close the location [road segment] to all others along the shortest path" (Porta, et al., 2012). The research has already validated the applicability of CC to measure the flows works in the domain of information flow analysis (Borgatti, 2005). In an information flow context, CC use to measure the flow of information and find a direct relationship between CC and flow of information (Borgatti, 2005). This study utilized Chiaradia, et al's (2013) formula to compute CC of links (refer equation 5.3).

$$Volume\ of\ to-and-from\ trips\ of\ road\ segment\ _i = CC_i \tag{5-2}$$

$$CC_i = \sum_{j \in N, j \neq i} \frac{1}{d_{ij}} \tag{5-3}$$

Where,

CC_i = Closeness centrality of road segment 'i'

d_{ij} = Distance between road segment 'i' and 'j' along the shortest path

N = Total number of road segment in a network

Betweenness centrality (BC) was utilized to capture the volume of pass-by trips of a given road segment (refer equation 5.4). BC captures "a special property in a particular location [road segment] that does not act as either origin or destination but as a pass-by location" (Porta, et al., 2012). The study utilized Chiaradia, et al's (2013) formula to compute BC of road segments (refer equation 5.5).

$$Volume\ of\ pass - by\ trips\ \ of\ road\ segment_i =\ BC_i \tag{5-4}$$

$$BC_i = \sum_{j,k \in N; j \neq k; k \neq i} \frac{p_{jk_{(i)}}}{p_{jk}} \tag{5-5}$$

Where,

BC_i = Betweenness centrality of road segment 'i'

N = Total number of road segment in a network

p_{jk} = Number of geodesics between road segments 'j' and 'k'

$p_{jk_{(i)}}$ = Number of geodesics between road segments 'j' and 'k' that passing through road segment 'i'

Figure 5.2 has illustrated the distribution of computed closeness centrality and betweenness centrality values of a given road network. Road segments X, Y and Z obtain higher CC values followed by road segments W and V. Accordingly, road segments X, Y and Z receive more traffic due to to-and-from trips compare to the road segments W and V. In relation to BC, road segment X obtains higher BC value while road segments V,W and Z obtain lower BC value. It indicates that the road segment X receives more traffic from pass-by trips compare to road segments V, W and Z. In comparison to CC and BC road segments, X obtain cumulative centrality value higher than the same of road segment Y. Accordingly, road segment X receives more traffic (cumulative volume; to-and-from trips and pass-by trips) than road segment Y. Road segment Y obtains higher cumulative centrality value compare to road segment W and road segment Y receives more traffic (cumulative volume; to-and-from trips and pass-by trips) than road segment W. Accordingly, road segment X receives the highest centrality and the highest traffic volume followed by road segments Y, Z, W, V.

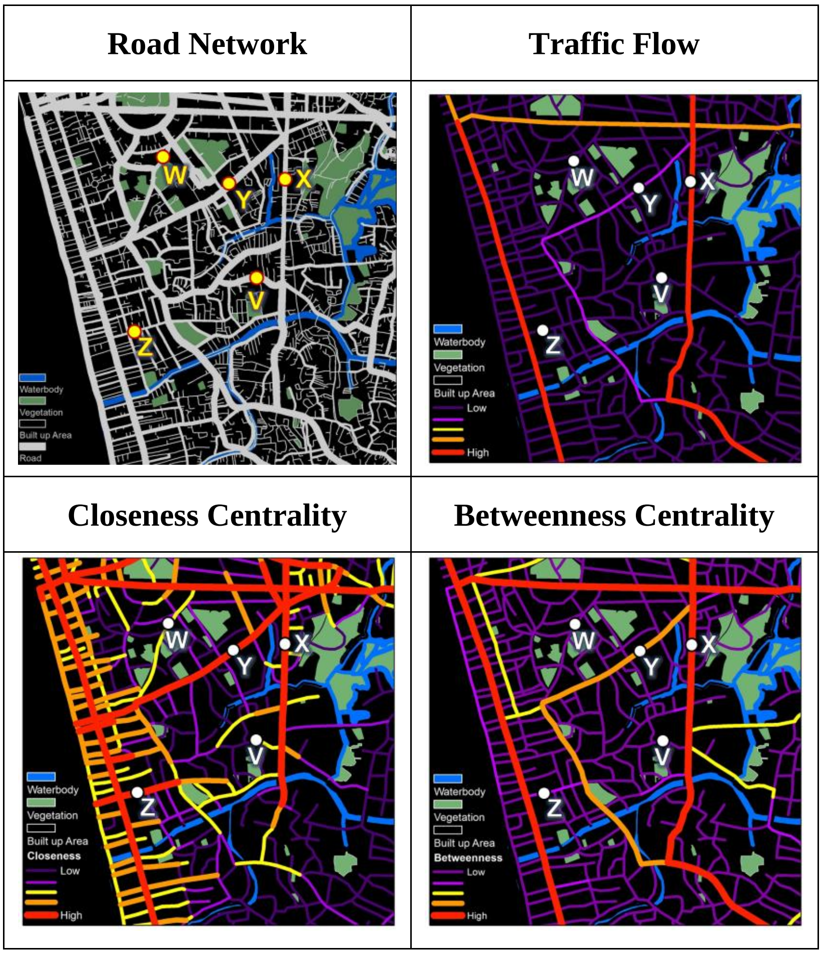


Figure 5-2: Distribution of traffic, closeness centrality and betweenness centrality values of a road network

Note: In the gradient legend highest values are indicated in red color and the lowest values are indicated in dark purple color

Accordingly, segments with high BC value are located central/in-between to the shortest path, which links trip origins (O) and trip destinations (D) therefore, attract more pass-by traffic. Road segments with high closeness values are recorded the least sum of the distance from all other road segments, hence, act as popular trip destinations or origin. As a result, road segments have high BC and CC able to receive a high volume of vehicular traffic than the others. According to the relationships illustrated in equation 5.1, 5.2 and 5.4, traffic volume of a road segment can be explained as a function of network centrality values. Equation 5.6 indicates this relationship between traffic volume and network centrality.

$$Traffic\ volume\ of\ road\ segemnt_i = f\ (CC_i\ .\ BC_i\ ) \tag{5-6}$$

5.2.1. Conceptualizing the shortest path

The previous section has elaborated the traffic volume of a road segment as a function of closeness and betweenness centrality. As indicated in equations 5.3 and 5.5, ‘shortest paths’ is a significant factor in computing the network centrality.

Space syntax utilize topologically shortest paths when computing centrality and the integration [closeness] computed based on topological distance, recorded high correlation (R^2 >0.5) with pedestrian and cyclist traffic (Hillie, et al., 1981), (Penn, et al., 1998), (Hillier, 1999), (Desyllas, et al., 2003), (Raford & Ragland, 2004), (Raford, et al., 2007), (McCahill & Garrick, 2008), (Jiang, 2009), (Jiang & Liu, 2009). However, when it come to the vehicular traffic the correlations recorded by previous studies are quite low (r-squared <0.5) (Peponis, et al., 1997), (Dawson, 2003), (Hillier, et al., 2010), (Gao, et al., 2013), (Paul, 2013). Paul’s (2013) recommendations regarding to overcome the limitations of space syntax when modeling the distribution of vehicular movements have highlighted the importance of incorporating an impedance factor which can account mobility into the topological distance. Further, the notion of ‘movement economies’, cognitive behavioral theories of human-way-finding and the recent works of Hochmair and Frank (2002), Dalton (2003), Duckham and Kulik (2003), Hillier and Iida (2005), (Dabaghian, et al., 2014) and (Javadi, et al., 2017) argue that the behavioral implications of the travelers’ knowledge on road network are more related to visual and topological properties of the network than mere travel time. The pilot studies (Jayasinghe, et al., 2015)**,** (Jayasinghe, et al., 2016) which have been explained in chapter 3 and 4, have also revealed that when computing centrality, it is more appropriate to consider the shortest path in terms of geometric distance (i.e. topological anguler change).

In the fields of traffic and transport planning and engineering, link cost in route choice modeling is often expressed by a travel time (Juan de Dios Ortúzar & Willumsen, 1990), (Hanson & Giuliano, 2004). Table 5.1 has summarized the often considered methods of computing link cost in transport modeling. Primarily, three kinds of methods are employed in estimating travel time for route choice modeling, i.e., free flow travel time, congested travel time and time-dependent travel time.

Table 5-1: Methods of computing link cost in route choice modeling.

Method	**Description**	**Link cost**	**Required data to compute link cost**
All-or-nothing analysis	Assumes that trip-makers minimize a single variable such as distance or travel time	A ratio of metric length and free-flow travel time	▪ Metric length ▪ Free flow speed
Deterministic user equilibrium analysis - Congested time	Assumes that individuals minimize travel time themselves	A congested travel time; which is a function of the volume of trip-makers using a link and the design capacity of the link	▪ Metric length ▪ Free flow speed ▪ Designed road capacity
Deterministic user equilibrium analysis - Dynamic traffic assignment	Considers the variability (dynamic nature) of travel time by time-varying link flow rates and a network performance	A dynamic travel time; which is influenced by variability in travel demand and link flow, and capacity of the road	▪ Metric length ▪ Free flow speed ▪ Dynamic travel demand ▪ Dynamic link flow ▪ Designed road capacity
Stochastic user equilibrium	Travelers select feasible paths based on utility	Trip-makers' anticipated travel costs	▪ Metric length ▪ Number of turns ▪ Travel time ▪ Road condition ▪ Environmental condition

Studies on route choice behavioral mechanisms argue that trip-makers do not selected the optimal solution due to several reasons. Firstly, rationality of individuals is limited by imperfect knowledge on precise travel time (i.e., Bounded rationality) (Gigerenzer & Goldstein, 1996). Secondly, individuals seek for a satisfactory solution than optimal travel time (i.e., Satisficing) (Simon, 1972). Thirdly, perception errors on travel time (Mis-perception) (Vreeswijk, et al., 2013) can exist. Fourthly, individuals tend to travel on paths that one knows to perform reasonably well rather trying to find the best travel option for each new trip (i.e. Inertia) (Chorus, 2012). Fifthly, each individual has their own specific threshold limits (i.e. Indifference band) (Vreeswijk, et al., 2014). Considering the above points, recent studies have suggested to incorporate the traveller's perception of travel time instead of purely depending on real travel time (Sumalee, et al., 2009), (Parthasarathi, et al., 2013), (Varotto, et al., 2014), (Tawfik & Rakha, 2014). Further, the selection of route choice approaches need to be logical or realistic with reasonable computational time, and ease of use (Telgen, 2010), (Duivenbooden, 2012), (Vreeswijk, et al., 2014).

While taking into account the above-mentioned research findings and arguments, this study conceptualize the path distance (PD) as a functional hierarchy of road, i.e. road type (Ty), angular changes (GMD), and metric distance (MD) (equation 5.7). Accordingly, the combined effect of MD and Ty can account the mobility characteristics whereas the GMD can account the topological characteristics.

$$PD_{ij} = f\left(GMD_{ij}.MD_{ij}.Ty_{ij}\right) \qquad (5-7)$$

Where,
PD_{ij} = Path distance between links 'i' and 'j'

GMD = Geometric distance (angular change, $(\theta * 2/180)$)

MD = Metric distance (in meters)

Ty = A score, which is given based on the road type and derives by trip-makers' preference respect to travel time. Trip-makers' preference is represented as 'PRSP - Percent Ratio Scale of Priority' (i.e. Ty = 1/ PRSP and 0<PRSP <1)

Figure 5.3 provides an example to explain the relationship of GMD, MD, Ty to PD. A trip-maker starts from location A to location E travels MD_1 distance along the road segment A-B by type Ty_1 road, MD_2 distance along the road segment B-C by type Ty_2, and MD_3 distance along the road segment C-E by type Ty_3 road. Further, the trip-maker makes two turns at intersection B and C. Turning angle at intersection B is θ_1 and intersection C is θ_2. Those intersections are the decision points, where the trip-maker decides which segment to choose when traveling towards the destination. Accordingly, PD between A and E depends on the GMD, MD, and Ty.

GMD and MD are continuous variables. Therefore, MD measures by the length of the road segment (m) and GMD measures by the angular change at intersections $(\theta * 2/180)$. The study proposes to assign a utility score to capture the effect of road type (Ty).

Accordingly, PD from A to E can be calculated as follows (Equation 5.8).

$$PD_{AE} = (MD_1.Ty_1 + MD_2.Ty_2 + MD_3.Ty_3).(\theta_1 * \frac{2}{180} + \theta_2 * \frac{2}{180}) \qquad (5-8)$$

The above-mentioned example elaborated how the proposed path distance is able to capture both topological characteristics and mobility characteristics. Accordingly, PD logically represents the trip-makers' notion of time and the notion of congested travel time. Further, PD can be computed by simple calculating procedures utilizing commonly available data and applicable for any geographical area.

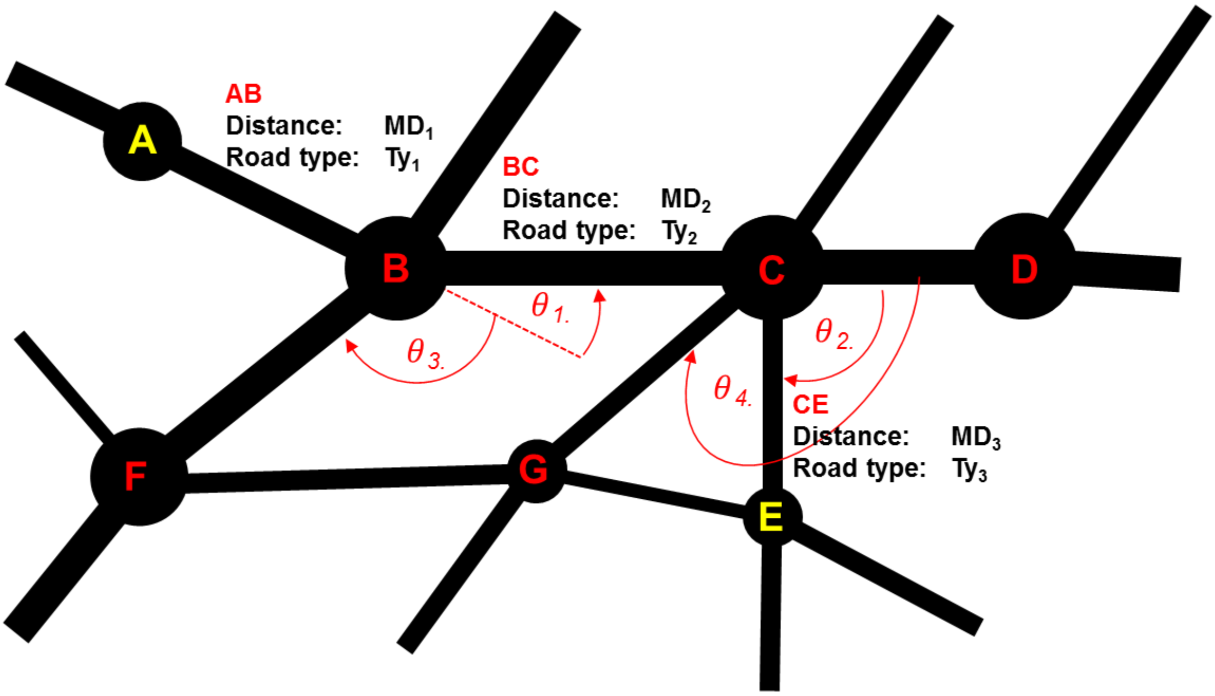


Figure 5-3: Example illustrating the method of computing path distance (PD)

5.2.2. Conceptualizing the boundaries of the road network

The network centrality of a road segment is computed relative to a given road network as indicated in the equation 5.3 and 5.5. The results of the pilot study-2 (section 4.3.2) reported that the network centrality values of road segments are very based on the boundaries of the study area. In other words, road networks continuously spread connecting the areas larger as countries or even continents. In such circumstances, shall the study areas expand all over or shall a boundary be hypothetically determined? In practical terms, it is difficult to compute the relative influence of large networks and it may not be always useful to consider national or continental road networks when studying traffic volume in regional-scale analysis. Therefore, it is important to appropriately delineate the boundaries of the study area. Mostly the project areas of transportation plans are correspondent to administrative boundaries, yet in many instances, there are provisions to delineate study area boundaries. In the figure 5.4 left, project boundary of CMA is indicated in red color and boundaries of provincial councils (regional administrative areas) indicated in orange color. In figure 5.4 right, three selected road segments (i.e. A, B and C) are indicated in purple color and 5km buffer area from those selected road segments are indicated in green color.

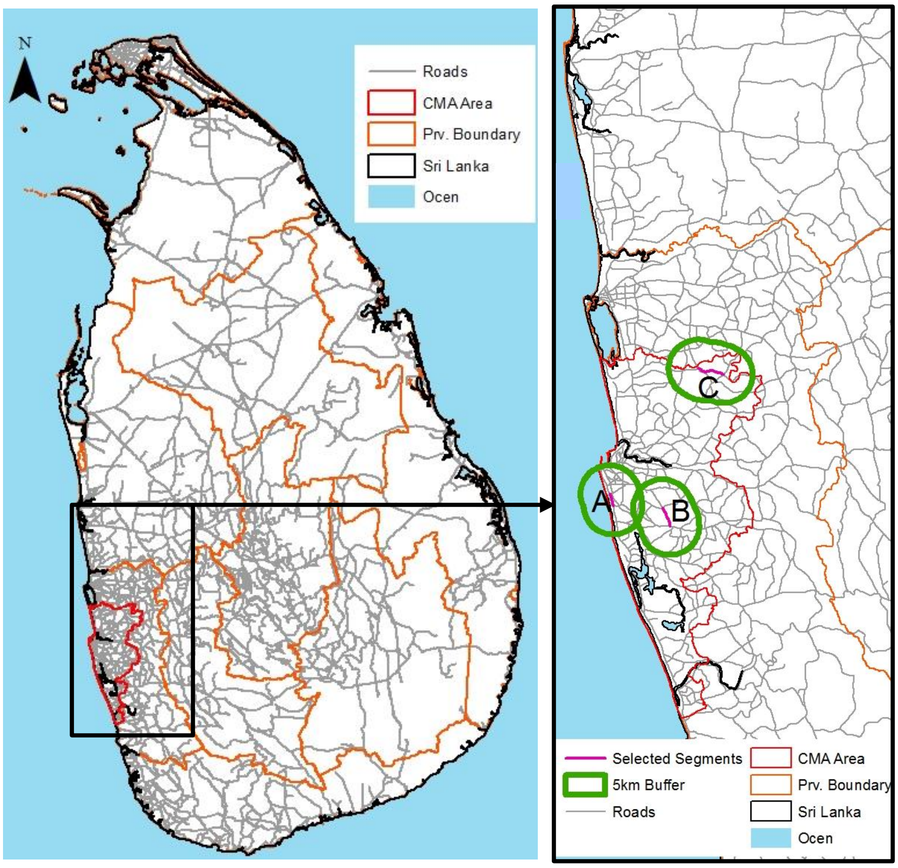


Figure 5-4: Example illustrating the "edge effect"

If assume a scenario of computing the network centrality of road segments within the road network of CMA area, centrality values of the road segments located at the edge of the boundary (e.g. C) it might not represent the actual centrality. Because ideally it should consider all of the surrounding road segments, but in the given circumstances, the road segments which are located outside the CMA boundary are disproportionately segregated from the analysis. Therefore, it affects the results by losing the relative influence of some road segments. This problem is technically termed as the ‘edge effect’ and it is recognized as a prime concern in the fields dealing with spatial network analysis (Peponis, et al., 2008), (Okabe & Sugihara, 2012), (Gil, 2015). One of the earliest solutions provided to overcome this problem is ‘catchment area of the catchment area’ method (Hillier, et al., 1993). This approach considers a catchment larger than the project area and computes the centrality of road segments including the influence of the catchment. In this approach usually, the catchment area is selected by considering the functional catchment of the project area (Oliveira, 2016). For instance, as illustrated in Figure 5.5, the catchment areas of CMA can be considered as the western province boundaries. Accordingly, the network centrality of the road segments of CMA area can be computed by considering the road network within the western province.

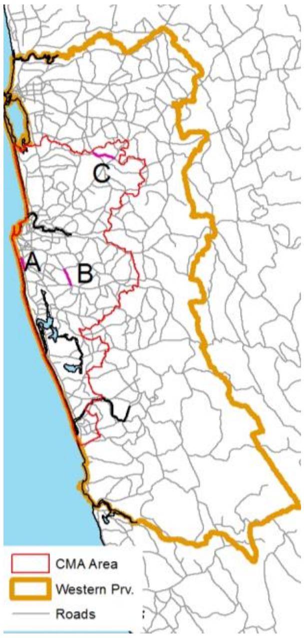


Figure 5-5: An example illustrating the application of catchment area method to CMA

This approach is able to overcome the edge effect to a certain extent. However, it still provides larger catchment to the centroid whereas smaller catchments to the edges. For instance, network centrality of road segment A in figure 5.5 is computed by considering a larger area compare to the road segment C. So, this approach cannot be considered as an effective enough method in the context of traffic volume simulation. In recent researches, ‘moving boundary’ approach has been proposed (Hillier, 1999), (Hillier & Penn, Rejoinder to Carlo Ratt, 2004). To overcome this issue, Hillier et al. (1996); (Hillier, 1999); (Hillier & Penn, Rejoinder to Carlo Ratt, 2004) proposed a moving boundary method, where the centrality of each road segment is computed by using a radius of analysis working as a moving boundary (Gil, 2015). Accordingly, this method is able to compute centrality by considering the same size of influence area for each road segment. However, application of this method so far is limited pedestrian analysis and consider a radius of 500m influence area (Gil, 2015). Gil’s works which claimed “first empirical and quantitative approach to understanding the “edge effect” of the spatial network model boundary on the closeness and betweenness centrality analysis results of urban networks”, has further emphasized that “the moving boundary method prove adequate to eliminate the edge effect, however selecting of impact radius need to identify by considering the purpose of study and centrality measure going to use (2015).

Accordingly, this study proposed to implement moving boundary method and the suitable radius for this study has been determined as per the purpose of the study and centrality measure going to use. One of the sub-objectives of this overall study is to develop a set of models based on network centrality to model traffic volume. In order to achieve this sub-objective, this study has conceptualized that the road segments located in-between to the trip makers shortest path, attracts more pass-by traffic (BC) and road segments located closer to the trip makers destination and origin generates/attracts more to-and-from traffic (CC). Accordingly, the study has hypothesized that the traffic volume can be simulated as a function of BC and CC. BC and CC are directly influenced by the origin, destination and trip length. To account the influence of trip length on trip-maker' movement, the study proposed to select trip length as the impact radius of moving boundary.

5.2.3. Summary of proposed approach: Simulation of traffic volume of road segments

One of the sub-objectives of this overall study is to develop a set of models based on network centrality to model traffic volume. Accordingly, betweenness centrality (BC) and closeness centrality (CC) measures are proposed to capture the traffic volume of a road segment including pass-by-trip, and to-and-from-trips respectively. Further, the study proposed to modify the conventional method of computing centrality by introducing two elements. Firstly, introduced the concept of path distance (PD) incorporating mobility characteristics into topological distance variable. Secondly, proposed the trip length as an appropriate variable to decide the radius when applying moving-boundary method in conceptualizing the boundary of road network.

5.3. Method of study

5.3.1. Study framework

The sub-objective aimed to achieve from the study explains in this chapter is to develop a set of models based on network centrality to model traffic volume. For that purpose, the study developed a set of models to estimate AADT and predict traffic volume based on network centrality values. The study framework is composed of two key stages as illustrated in figure 5.6. The first stage is Network Centrality Assessment (NCA) and the second stage is model formulation and validation.

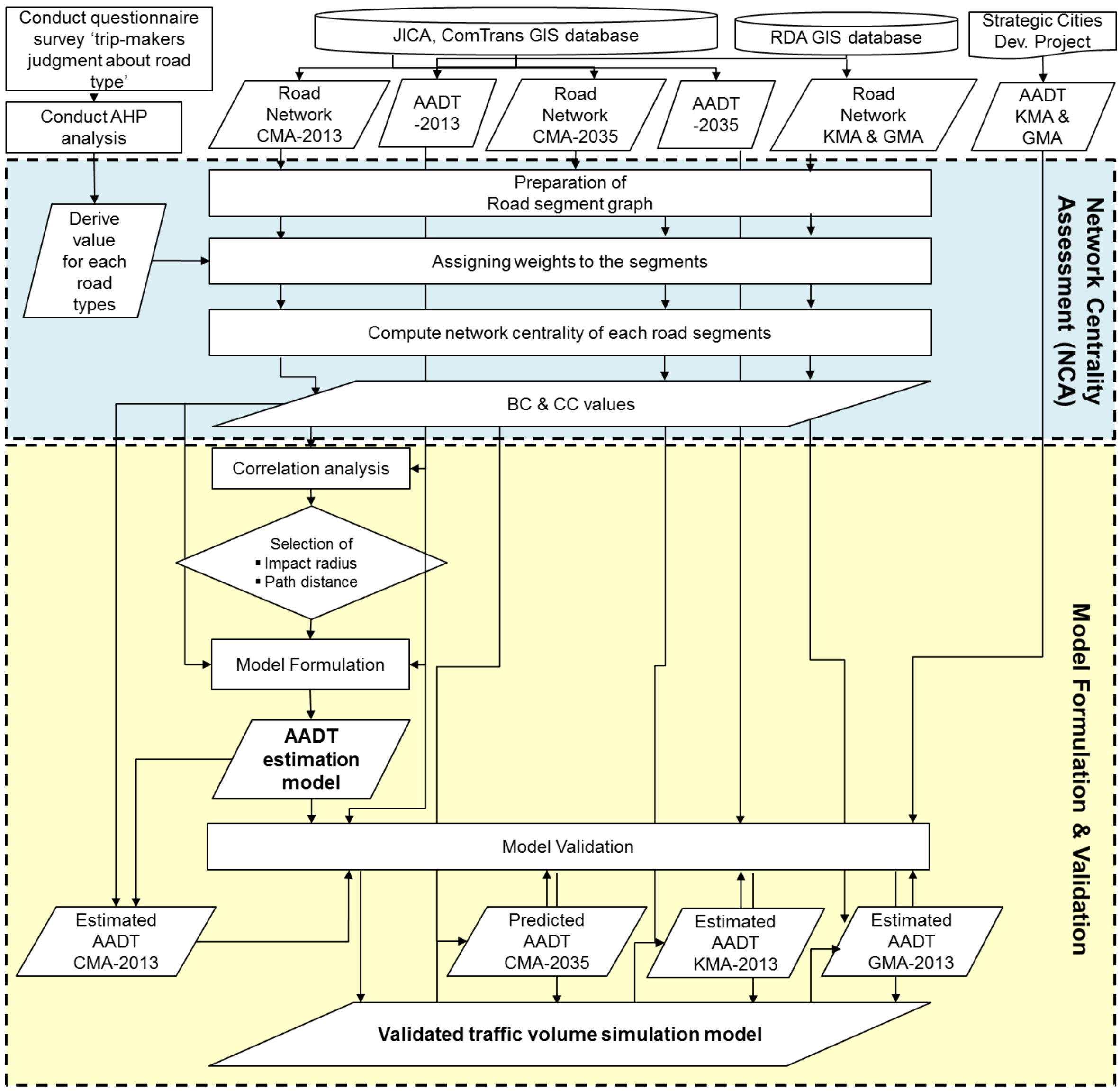


Figure 5-6: Method of 'traffic volume simulation model' formulation and validation

5.3.2. Study areas and description of data

The initial model development was built upon a case study in Colombo Metropolitan Area (CMA), Sri Lanka. Next, the study validated the proposed method with two other urban areas in Sri Lanka, namely Kandy Municipal-council Area (KMA) and Galle Municipal-council Area (GMA) (Table-5.2). CMA is the largest urban agglomeration in the country that contribute to nearly a half of the national Gross Domestic Product (GDP). KMA and GMA are the second most growing urban localities of the country following Colombo.

Table 5-2: Study areas

Study area	Extent (sqkm)	Population (`000)
1. Colombo Metropolitan Area (CMA)*	995.54	3700
2. Kandy Municipal-council Area (KMA)**	28.53	125
3. Galle Municipal-council Area(GMA)**	16.52	99

(Source: * JICA, 2014 and ** Department of Census and Statistics, Sri Lanka, 2011)

Traffic volume is the response variable in the proposed model. The study obtained traffic volume data from secondary sources. Traffic volume has been reported as Annual Average Daily Traffic (AADT), converted to Passenger Car Unit (PCU) per day using the recommended AASHTO (American Association of State Highway and Transportation Official) PCU factors. Table 5.3 provides a brief description of the dataset.

Table 5-3: Description data and sources

Data Type	Area	Year	Source	Description
Actual AADT	CMA	2004	Road Development Authority (RDA), Sri Lanka	N=26
Actual AADT	CMA	2013	JICA, 2014	N=56
Estimated AADT	CMA	2013	JICA, 2014	N=1927 Estimated by using the 'CoMTrans' multi-step land use-travel demand model
Predicted AADT	CMA	2035	JICA, 2014	N=2064 Predicted by using the 'CoMTrans' multi-step land use-travel demand model
Actual AADT	KMA	2013	Strategic Cities Dev. Project, Urban Development Authority (UDA), Sri Lanka	N=25
Actual AADT	GMA	2013	Strategic Cities Dev. Project, Urban Development Authority (UDA), Sri Lanka	N=23
Road network	CMA	2004	Survey Department, Sri Lanka	GIS data: Road centerlines as polylines Attributes: Road type
Road network	CMA	2013	JICA, 2014	GIS data: Road centrelines as polylines Attributes: Road type/ Road capacity/ Speed/ LOS
Road network	CMA	2035	JICA, 2014	GIS data: Road centrelines as polylines Attributes: Road type/ Road capacity/ Speed/ LOS
Road network	KMA	2013	Survey Department, Sri Lanka	GIS data: Road centerlines as polylines Attributes: Road type
Road network	GMA	2013	Survey Department, Sri Lanka	GIS data: Road centerlines as polylines Attributes: Road type

5.3.3. Network Centrality Assessment (NCA)

Network centrality assessment is aiming to compute the centrality values of each road segments. NCA consists of three steps, (1) preparation of a graph, (2) assigning weights to the segments, and (3) computing network centrality value of road segment by using centrality measure.

5.3.3.1. Preparation of a graph

Firstly, the actual road network was converted into a graph that consists of nodes and links. This study utilizes 'road-segments' graph method (Turner, 2001) to compute centrality of road segments. In this graph, the links represent the road segments, and the nodes represent the intersections. For preparing road segments graph the study utilized 'road centerlines,' i.e., vector line data that represent the geographic center of the road rights-of-way on road networks (refer figure 5.7). In road segments graph, segments represent physical locations of trip origins and destinations. Each road segment is connected to the whole road network. How much central a given road segment in the entire network is correspondent to the share of trips takes place within the road segment out of the total trips of the whole road network.

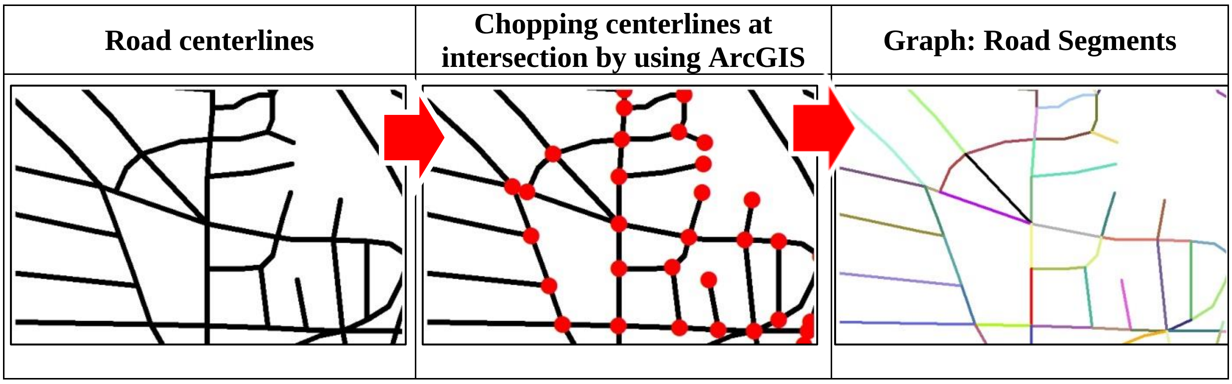


Figure 5-7: Preparation of road segments graph
Note: Unique color has been given to symbolize each link

5.3.3.2. Assigning weights to the segments

The second step is to assign weights by road segment. This study proposed to utilize path distance (PD) which accounts topological characteristics and mobility characteristics as explain in section 5.2.1 and comprised of three factors as geometric distance, metric distance and road type (refer equation 5.7). The study proposed to assign a utility score to capture the effect of road type (Ty).

The study area is comprised of five types of roads such as Expressways, A-class, B-class, C-class and D-class (refer Table 5.4). When computing utility score as per road type, the study needed to assign a value to each road type. For this purpose, the study conducted an online questionnaire survey (n=100, refer appendix -1) and asked trip-makers to evaluate each road type (pairwise comparison) with respect to travel time. The selection of participants was random based on family and friends network. Accordingly, the value of each road type is derived from trip-makers' preference processed through Analytical Hierarchy Process (AHP). Participants' were instructed to give pairwise comparison values on the scale from 1-9 for road types where one refers to the similar level of importance, and nine relates to the highest level of relative importance of the particular road type compare to another road type. The study employed the standard procedure of Analytical Hierarchical Process (AHP) technique (Saaty, 2008) and computed the 'Percent Ratio Scale of Priority' (PRSP, 0<PRSP<1) by road type. The level of consistency of AHP is <9%. The inverse of PRSP value has been utilized as the utility score of each road type (Ty=1/PRSP) (refer Table 5.4).

Table 5-4: Road types and Ty values

Road type	**Description***	**Avg. Speed (km/h)***	**Road capacity (PCUs per Hour)***	**PRSP****	**Ty value**
Expressways (High-speed arteries)	Expressways (toll roads and controlled-access highways that connect the national capital to provincial capitals	80-100	>3600	0.471	1/0.471
A-class (Major arteries)	Connects two or more provincial capitals	50-70	1500-2500	0.271	1/0.271
B-class (Minor arteries)	Connects the medium and small towns within a province	30-40	1200-1500	0.152	1/0.152
C-class (Collectors)	Connects local areas to a medium or small town	20-30	500-750	0.072	1/0.072
D-class (Local roads)	Connects neighbourhood residential areas to C-class roads	<15	<100	0.035	1/0.035

(Note: * (JICA, 2014); ** PRSP values derived from AHP by considering the trip-makers' preference according to the travel time of various type of roads)

Nevertheless, study plan to compare the accuracy of proposed path distance (PD) with geometric distance (GMD) and travel time (TT). Therefore, the study utilized secondary data on 'travel speed by road sections' (Source: JICA, 2014; Method used: floating vehicle method; Duration: 8 months) to compute travel time and compute centrality based on travel time.

5.3.3.3. <u>Computing network centrality</u>

The third step is computing network centrality of each road segment as BC and CC respectively. The study employed 'network analysis' tool in GIS environment to compute BC and CC. The network analysis tool requires road segment graph and two input variables as 'link cost' and 'influence area .'Utility score by road type' (Ty), 'geometric distance' (GMD) and 'travel time' (TT) were entered alternatively as the input variables of the 'link-cost. As mentioned in section 5.2.2., the study proposed to use moving boundary method considering trip length as the impact radius. Figure 5.8 illustrates the distribution of travel distance in CMA by purpose, mode and income group. Accordingly, it is difficult to determine which trip length would be the most suitable distance to be selected as the impact radius. Therefore, the study proposed to compute centrality based on multiple impact radii and find out the most appropriate one. Impact radii were given as 0.5km, 1km, 2.5km, 5km, 7.5km, 10km, 12.5km, 15km, 20km and 25km

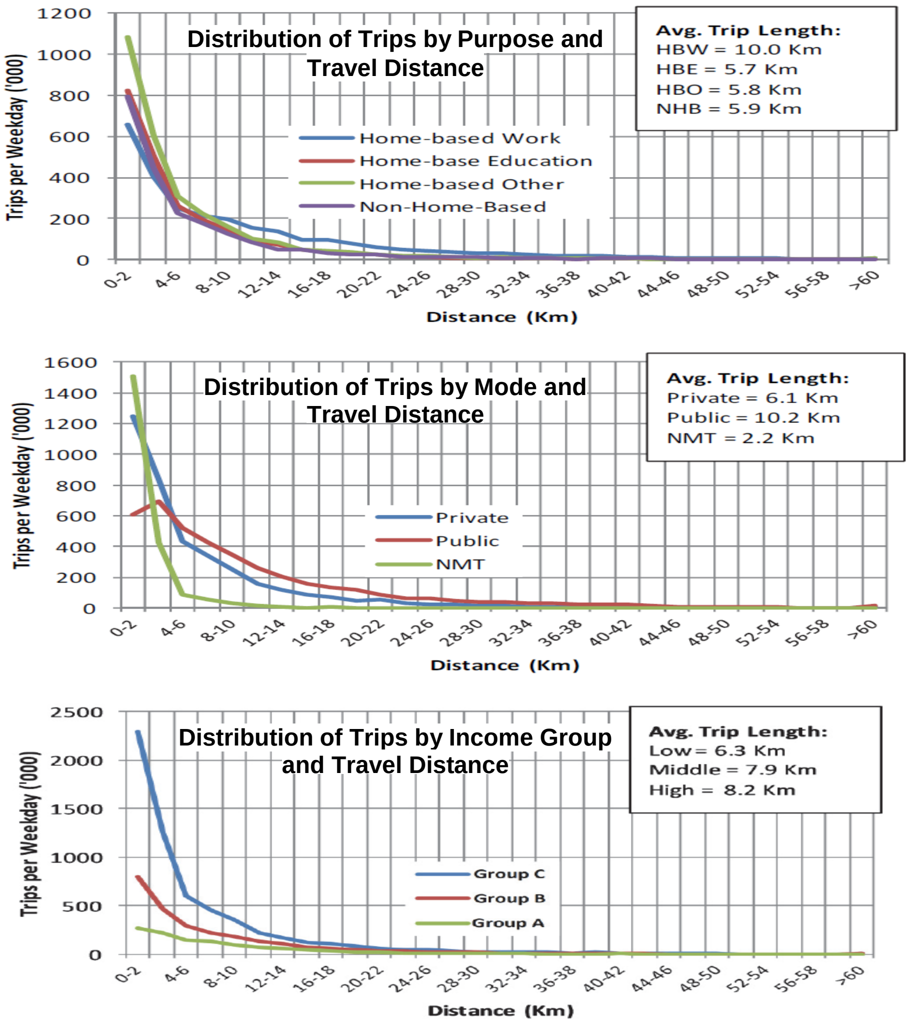


Figure 5-8: Distribution of travel distance in CMA
Source: (JICA, 2014)
Note: Income per month SLR Group A: >80,000, B:80,000-40,000 and C: <40,000

Accordingly, the study computed network centrality values of each road segment and generated 30 output files for BC and CC respectively. As there were three combinations of link-cost, ten influence areas, and two centrality measures, 60 network centrality values were computed for each road segment. Accordingly, 60 output files were generated for all road segments.

5.4. Model formulation and validation

5.4.1. Correlation between traffic volume and centrality values

This study employed the spatial correlation analysis to identify the nature and the strength of the relationship between traffic volume and network centrality values referring CMA as the first case study. Table 5.5 and figure 5.9 provides the summary of the spatial correlation analysis along with correlation coefficient (r) values (Spearman correlation).

Table 5-5: Summary results of correlation analysis between centrality values at different radiuses and AADT values

Centrality measure	Influence radius areas	Segments weighted by		
		PD	GMD	TT
CC	0.5	0.12*	0.10*	0.00
	1.0	0.12*	0.10*	0.01
	1.5	0.18*	0.11*	0.01
	3.0	0.28**	0.12*	0.01
	5.0	0.29**	0.15*	0.00
	7.5	0.34**	0.16*	0.02
	10.0	0.41**	0.28**	0.05
	15.0	0.57**	0.28**	0.00
	20.0	0.58**	0.28**	0.02
	25.0	0.57**	0.28**	0.00
BC	0.5	0.03	0.00	0.00
	1.0	0.00	0.01	0.00
	1.5	0.04	0.00	0.00
	3.0	0.10*	0.11*	0.04
	5.0	0.41**	0.41**	0.25**
	7.5	0.58**	0.50**	0.35**
	10.0	0.74**	0.57**	0.58**
	15.0	0.83**	0.57**	0.58**
	20.0	0.82**	0.58**	0.59**
	25.0	0.81**	0.57**	0.58**

Note: N=1927, **Correlation significant at 0.01 and *Correlation significant at 0.05

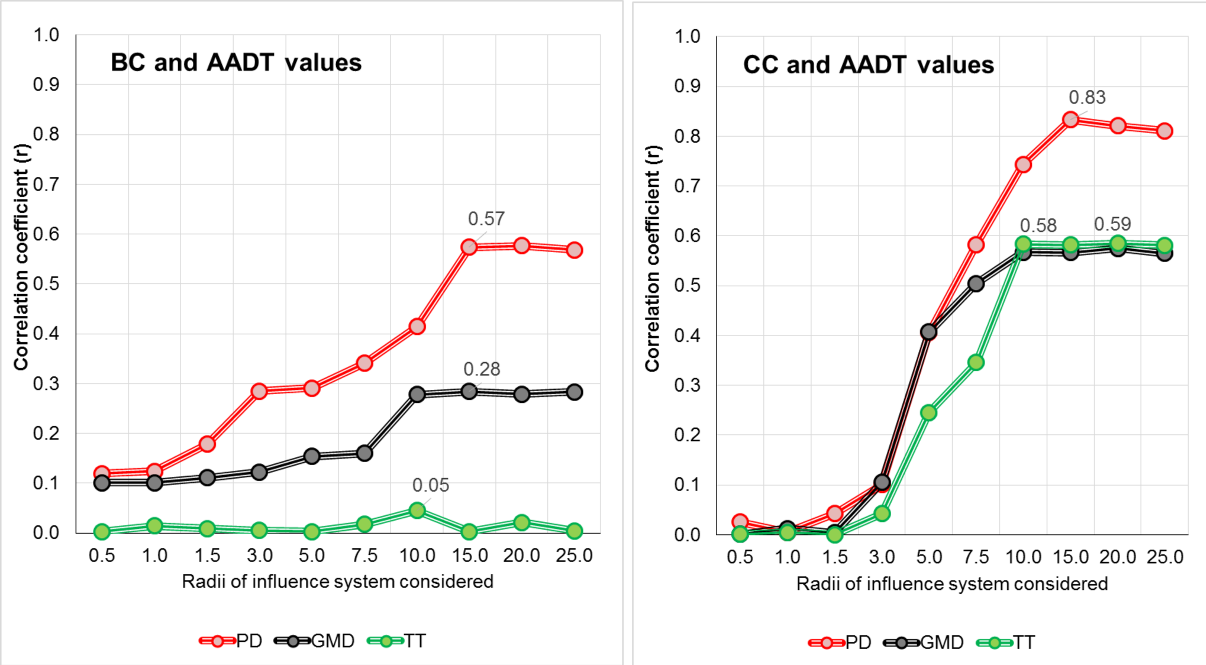


Figure 5-9: Correlation between centrality values at different radii and AADT values

BC has recorded higher correlation coefficient with AADT than CC. According to the link-weight options, PD recorded higher correlation coefficient with AADT followed by GMD with both BC and CC, whereas travel time (TT) recorded very low correlation coefficient with AADT. Therefore, the study concludes that the proposed path distance (PD) is a better option than solely depending on the cognitive distance (GMD: i.e. angular change). The proposed path distance (PD) is computed by considering the influence of both angular change at intersection and mobility characteristics (trip-maker general notion of travel time). Regarding network boundary areas, BC and CC computed at 10-15km radius recorded the highest correlation with AADT values compare to other options.

5.4.2. Model formulation and validation: AADT estimation

To this point, AADT and network centrality values showed a strong and significant correlation particularly compute by using the proposed path distance (PD), distance at 15km radius. The results indicated a strong possibility of utilizing network centrality values to estimate AADT. Hence the next step is to develop a workable model to estimate AADT. For this purposes, the study employed regression analysis and utilized Ordinary Least Squares Regression (OLS), Robust Regression (RR) and Poisson Regression (PR) statistical techniques. After checking the multicollinearity among explanatory variables, the study utilized R^2 (refer equation 5.8) and Median Absolute Percent Error (i.e., MdAPE) (refer equation 5.9) to test the goodness-of-fit when selecting the most suitable model. R^2 and MdAPE together provide a sound understanding about the predictability of the model (Lowry, 2014).

$$R^2 = 1 - \frac{\sum(y_n - \hat{y}_n)^2}{\sum(y_n - \bar{y})^2} \qquad (5-8)$$

Where;

R^2 = Coefficient of determination

y_n = Actual AADT

$\hat{y}_n$ = Estimated AADT

$\bar{y}$ = Mean of actual AADT

$$\text{MdAPE} = \text{Median}\left(\frac{|y_n - \hat{y}_n|}{y_n}\right) * 100 \qquad (5-9)$$

Where;

MdAPE = Median Absolute Percent Error

y_n = Actual AADT

$\hat{y}_n$ = Estimated AADT

N = Total number of data points

The study has utilized 60 combinations (i.e., three link-cost, ten influence areas and two centrality measures), and their natural logarithm (ln) values as explanatory variables when developing regression models. Even though it was possible to include additional explanatory variables, this study only utilized network centrality values. Because the purpose of the study is to identify the capability of network centrality in explaining AADT values. First, the study randomly selected 90% of the data for calibration (i.e., a random subset of calibration data) and 10% to validation. Table 5.6 illustrates the statistics and specifications of the best model out of the once have been developed to estimate AADT. In the model, BC and CC were computed based on the proposed path distance (PD) at 15km radius. The R^2 values of the model were 0.87 and 0.90 for calibration and validation respectively, and there was no multicollinearity (Tolerance = 0.78 and VIF = 1.28) among variables. Further, MdAPE values of the model were 29% and 30% for calibration and validation respectively. Validation results according to different random subsets also recorded similar R^2 values and MdAPE values (refer Appendix -3). This R^2 and MdAPE values are on a par with the results of previous works on estimating

AADT using multi-step travel demand modeling (Zhao & Chung, 2001), (Lowry, 2014), (Staats 2016) and RMSE values are in line with international standards (i.e FHWA, (FHWA, 1997)). Hence, this result is versatile enough to recommend the developed model in estimating AADT. Equation-5.10a indicates the best model obtained from regression analysis and the equation-5.10b express the corresponding AADT estimation formula. Equation-5.10b captures the traffic volume of a road segment including both 'to-and-from-trip' volumes (i.e., CC) and 'pass-by-trip' volumes (i.e., BC). Hence, the proposed model is capable of explaining both land uses-generated movements ('to-and-from-trip') and non-land uses-generated movements ('pass-by-trip') by CC and BC variables respectively. Further, the proposed path distance (PD) can capture trip makers' route-choice rationales that are influenced not only by topological characteristics of road network but also by roadway mobility characteristics.

Table 5-6: Statistics and specifications of the model

Specifications		**Coefficient value**	**Value**	**t-value**	**p-value**
Variables [a]	Constant	3.865		38.704	<.0001
	$\ln BC_{(PD\_15km)}$	0.591	.792 [b]	80.519	<.0001
	$\ln CC_{(PD\_15km)}$	2.031	.246 [b]	24.959	<.0001
F Value			5731.78 (<0.0001)		
Presence of multicollinearity					
Tolerance			0.783		
VIF			1.277		
Goodness-of-fit					
Calibration [c]	R^2		0.869		
	Adjusted R^2		0.869		
	MdAPE		28.98%		
Validation [d]	R^2		0.900		
	MdAPE		29.88%		

Note : a: Response variable lnAADT; b: Beta value, i.e., standardized coefficients value
c : random 90% of the sample (n = 1730), d : random 10% of the sample (n = 197)
(Refer appendix -3 for validation results according to different random subsets)

Table 5-7: MdAPE and RMSE for estimated AADT volumes of road segments by AADT categories

AADT	RMSE as per FHWA standards*	RMSE in the study area	MdAPE in the study area	Number of road segments
> 50,000	10	9.3%	9.9%	105
25,000 – 50,000	15	13.0%	20.7%	241
10,000 – 25,000	20	24.9%	24.0%	538
5,000 – 10,000	25	16.4%	23.8%	311
2,500 – 5,000	50	22.6%	30.0%	202
1,000 – 2,500	100	27.7%	37.1%	274
< 1,000	200	193.1%	126.0%	256
Average	30	22.1%	28.2%	1927

Note: *Federal Highway Administration, Source for FHWA (FHWA, 1997)

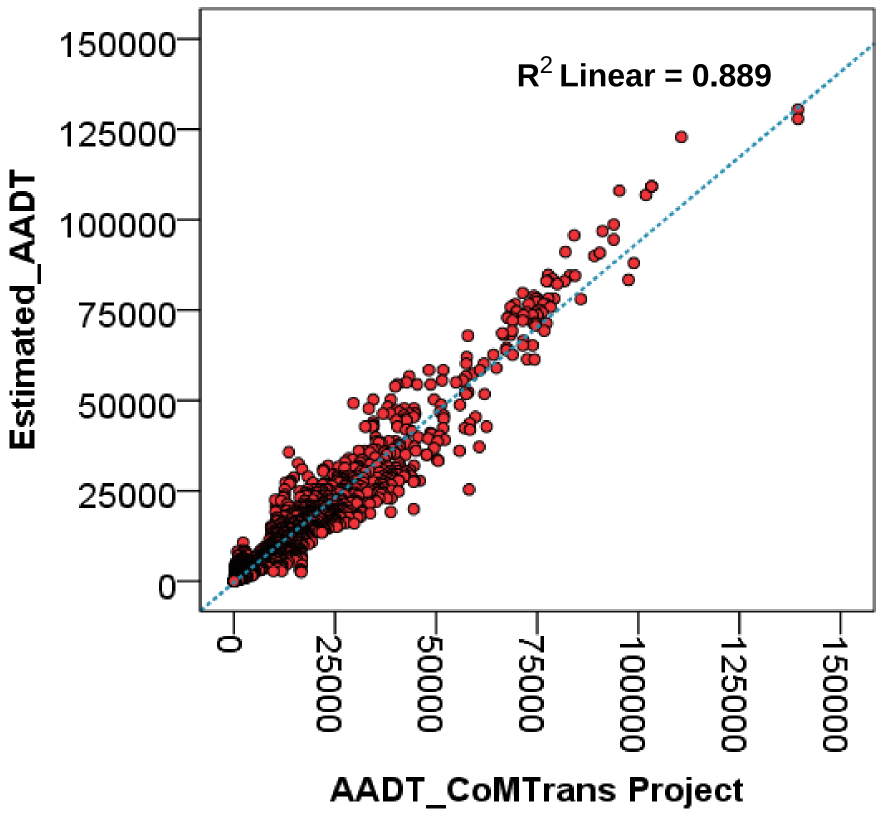


Figure 5-10: The relationship between the AADT_CoMTrans Project (estimated by multi-step demand model) and estimated by Eq-5.10a for CMA area, years 2013

Note: Refer appendix -2 for histogram distribution of AADT values

$$lnAADT_i = 3.865 + 0.591 * lnBC_{(PD,15km)i} + 2.031 * lnCC_{(PD,15km)i} \qquad (5-10a)$$

$$AADT_i = a. BC_{(PD,15km)i}{}^{b}. CC_{(PD,15km)i}{}^{c} \qquad (5-10b)$$

Figure 5.12 illustrates the spatial and cumulative probability distribution of explanatory variables in the model. Figure 5.13 depicts the spatial distribution of actual and estimated AADT values of CMA.

In order to validate further, the study compared the estimated AADT values (using Equation 5.10a) with actual AADT values of 56 locations. Figure 5.11 illustrates the relationship between actual values and estimated AADT values. Results indicated a significant accuracy (R^2=0.95, MdAPE=17.81% and RMSE=23.76%) and it further indicates the validity of proposed model.

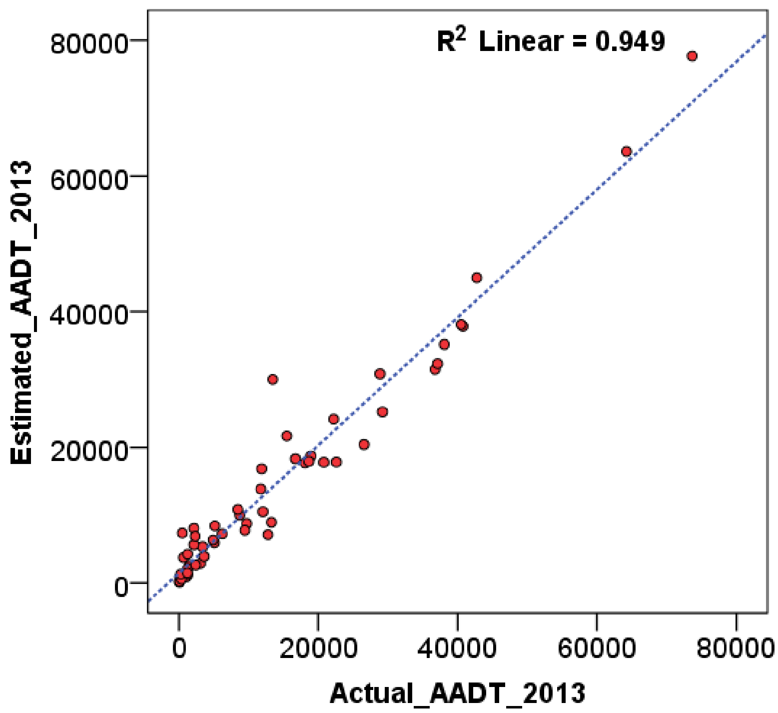


Figure 5-11: The relationship between the actual AADT and estimated by Eq-5.10a for CMA area, years 2013

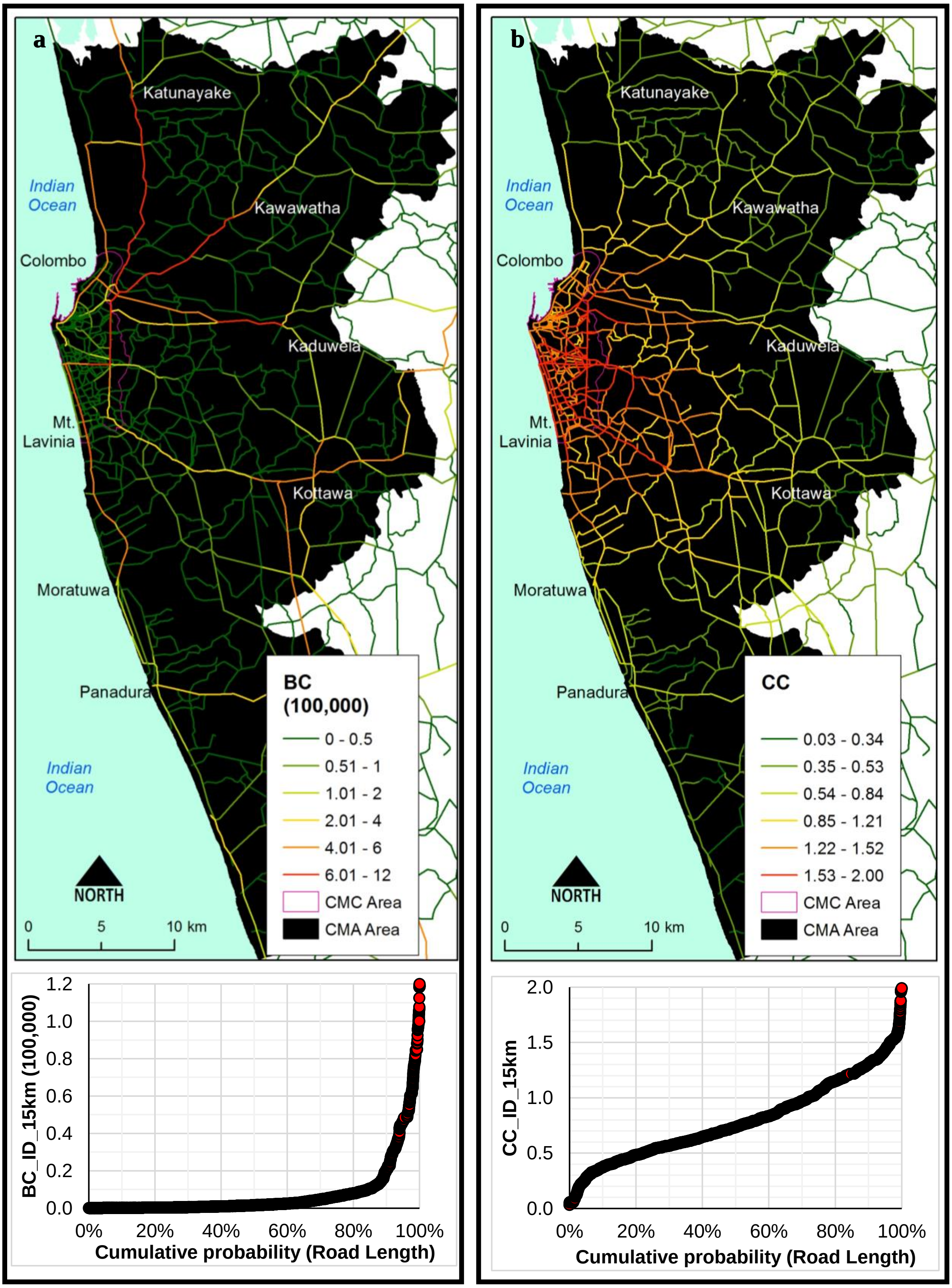


Figure 5-12: Spatial and cumulative probability distribution of two variables in the model (a) $BC_{(PD,\ 15km)}$ and (b) $CC_{(PD,\ 15km)}$

Refer appendix -4 for spatial distribution of $BC_{(GMD,\ 15km)}$ and $CC_{(GMD,\ 15km)}$

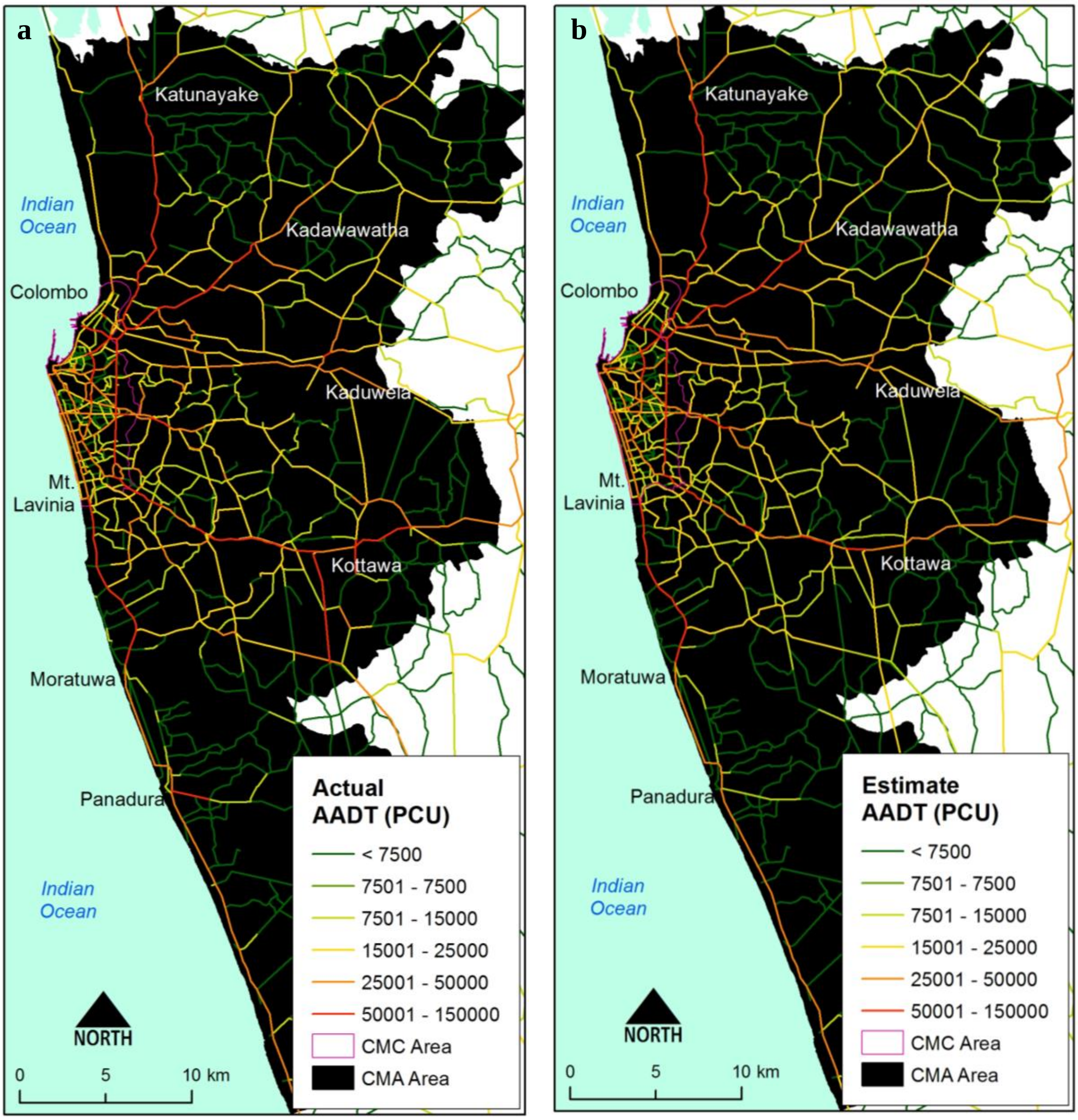


Figure 5-13: Spatial distribution of a.) JICA study AADT and b.) estimated AADT based on the Eq.-5.10a

5.4.3. Prediction of traffic volume

As of now, the results have proved the ability of network centrality values to estimate AADT with reference to the road network of CMA. Nevertheless, roads are dynamic networks that evolve temporally. Hence, this section examines the capability of the proposed model to predict AADT with an account of the dynamic nature of road networks. The study utilized two different road network scenarios of CMA, i.e., the actual road network in 2004 and the proposed road network for 2035 (refer Table 5.8) and estimated the AADT values by employing formula-5.10a.

Table 5-8: Scenarios utilized for prediction

Scenario	Year	Road network	Available AADT values	VPP
A	2004	Actual road network in the year 2004 Length: 3174.24 km	▪ Actual AADT values of 2004 ▪ Method: Coverage counts ▪ Source: Road Development Authority, Sri Lanka ▪ N=29	▪ Total number of vehicle registered in the year 2004 in CMA ▪ Total population in the year 2004 in CMA ▪ Source: (JICA, 2014)
B	2035	The proposed road network from CoMTrans project for 2035 Case A1 Highway intensive scenario Length: 3553.89 km	▪ Estimated AADT for 2035 ▪ Method: Land use transport travel demand model ▪ Source: CoMTrans project (JICA, 2014) ▪ N=2276	▪ The projected annual addition of vehicles for the year 2035 in CMA ▪ The projected population for the year 2035 in CMA ▪ Source: (JICA, 2014)

(Note: The length of CMA road network is 3226.85 km in the year 2013)

AADT values derived from formula-5.10a were compared with the actual AADT values of the year 2004 and estimated AADT values for the year 2035 respectively (refer Table 5.9 for details). AADT values that estimated based on formula-5.10a revealed significant R^2 values with the two sets of available AADT values (refer Table 5.9). However, MdAPE and RMSE values were quite high. Estimated AADT values are comparatively higher for the year 2004 whereas lower for the year 2035. This might be because the developed network centrality values-based model does not account the long-run elasticity of road traffic demand such as population growth, income growth, and price change. Hence, the study modified the formula-5.10a by introducing a factor, i.e. VPP (Vehicles Per Person) (refer equation 5.11). This factor aims to capture the temporal and spatial influences of demographic and economic conditions of road traffic demand. Many studies have indicated that car ownership has a strong and positive effect on the income elasticity of road traffic demand (Walker, et al., 2010); (Transport, 2014), (Graham & Glaister, 2004). Accordingly, the proposed formula can capture the influence of road network centrality on traffic volume as well as demographic and economic factors on road traffic demand.

$$AADT_i = (a.BC_{(PD,15km)i}{}^{b}.CC_{(PD,15km)i}{}^{c}) * VPP_{i(AX)} \quad (5-11)$$

Where,

$$VPP_{i(A,X)} = \frac{VPP_{A,X}}{VPP_{CMA,2013}}$$

$$\mathrm{VPP}_{A,X} = \frac{Total\ Number\ of\ vehicles\ registered\ in\ Area\ A\ in\ Year\ X}{Population\ above\ 18\ year\ in\ Area\ A\ in\ Year\ X}$$

Table 5-9: MdAPE values according to two situations

Goodness-of-fit	Scenario - A		Scenario - B	
	Without growth factor (Eq 5-10a)	**With growth factor (Eq 5.11)**	**Without growth factor (Eq 5-10a)**	**With growth factor (Eq 5.11)**
N	26	26	2276	2276
R^2	0.99	0.99	0.88	0.88
MdAPE	61.6%	6.1%	27.9%	18.0%
RMSE	57.6%	4.7%	41.8%	27.2%

The study re-calculated the AADT values incorporating the growth factor (VPP, Eq.-5.11) and tested the relationship between AADT values of 2004 and 2035 respectively (refer table 5.9 and figure 5.14 for details). AADT values that estimated based on formula-5.11 recorded an acceptable level of R^2 (>0.85) values as well as MdAPE and RMSE (close to 30%) values with the two sets of available AADT values respectively.

Scatterplots in figure 5.14a shows the relationship between actual AADT values of the year 2004 and the AADT values predicted by equation-5.10a and equation-5.11 respectively for the same year. Accordingly, equation-5.11 is better in explaining the relationship. Similarly, among scatterplots figure 5.14b that represent the relationship between AADT values of the year 2035 -predicted by CoMTrans model (multi-step demand model) and the AADT values derived from network centrality values, equation-5.11 illustrates a strong relationship.

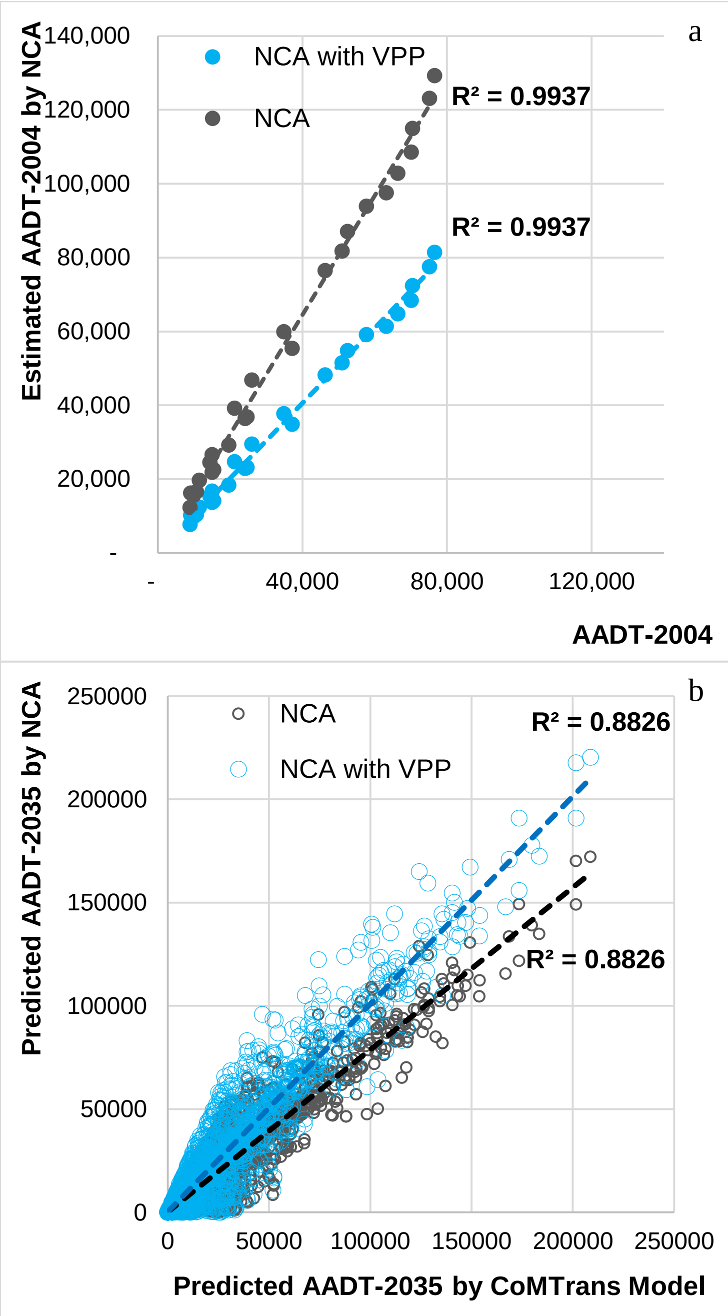


Figure 5-14: The relationship with the AADT predicted by 5.10a (without VVP) and 5.11 (with VVP) with available AADT of CMA for years 2004 (Actual) and 2035 (Modeled by CoMTrans)

Accordingly, the study concluded that the proposed model is not only appropriate for estimating AADT of the existing road network. It has even confirmed that results compare well with the AADT values predicted by standard models, in this case, predicted AADT values for 2035 in CoMTrans project by using multi-step travel demand modeling.

5.4.4. Validation of the proposed model in KMA and GMA areas

So far, the study could validate the proposed model for estimation and prediction of traffic volume with a case study in CMA. Nevertheless, the traffic volume is sensitive to the morphological variations of different geographic contexts. Hence, the next attempt of this study was focused on validating the proposed model with two case applications in KMA and GMA. Accordingly, the study computed the BC and CC values and estimated the AADT values using Eq.-5.10a and Eq.-5.11, for KMA and GMA and compared with the actual AADT values (Table 5.10). The AADT estimated based on Eq.-5.11revealed a strong relationship with actual AADT values with an acceptable level of R^2, MdAPE, and RMSE values (refer Table 5.10) for both geographical areas.

Table 5-10: R^2 and MdAPE values in two geographical areas

Goodness-of-fit	Galle Municipal Council (GMA)		Kandy Municipal Council (KMA)	
	Without growth factor (Eq 5.10a)	With growth factor (Eq 5.11)	Without growth factor (Eq 5.10a)	With growth factor (Eq 5.11)
N	23	23	25	25
R^2	0.98	0.98	0.95	0.95
MdAPE	71.4%	9.4%	73.7%	18.4%
RMSE	105.7%	9.8%	92.6%	21.7%

Note: Refer Appendix 4 and 5 for the spatial distribution of $BC_{(PD,\ 15km)}$ and $CC_{(PD,\ 15km)}$ Galle and Kandy Area. Refer appendix 6 for scatterplots

In summary, the developed model can credibly employ in predicting traffic volume when making future modifications to the road network in CMA. Based on the positive results revealed model could be able to simulate traffic volume of any given geographical area.

5.4.5. Minimum AADT values required for calibrations of the model

The model (Eq 5.10a) developed in this study was based on AADT values of 1730 locations (refer Table 5.6). Is it necessary to have so many actual observation? To calibrate the model. To answer this question, the study performed a 'repeated random sub-sampling validation' (Maimon & Rokach, 2010). The MdAPE for sample size is illustrated in the table 5.11. The results suggest that, after about 40 observations, MdAPE achieved the acceptable level (MdAPE<30%). It indicated that model can be calibrated by very little observation points and able to overcome time-consuming and expensive data collection constraints.

Table 5-11: MdAPE and sample size from repeated random sub-sampling

No. observation for calibration	% of observation	Calibration MdAPE	Validation MdAPE
19	1	22%	43%
39	2	23%	33%
58	3	22%	27%
96	5	26%	27%
193	10	29%	28%
385	20	27%	28%
578	30	29%	28%
771	40	29%	28%
964	50	28%	28%
1156	60	28%	29%
1349	70	28%	29%
1542	80	28%	27%
1734	90	29%	30%
1927	100	28%	28%

(Refer appendix -3 for validation results according to different random subsets)

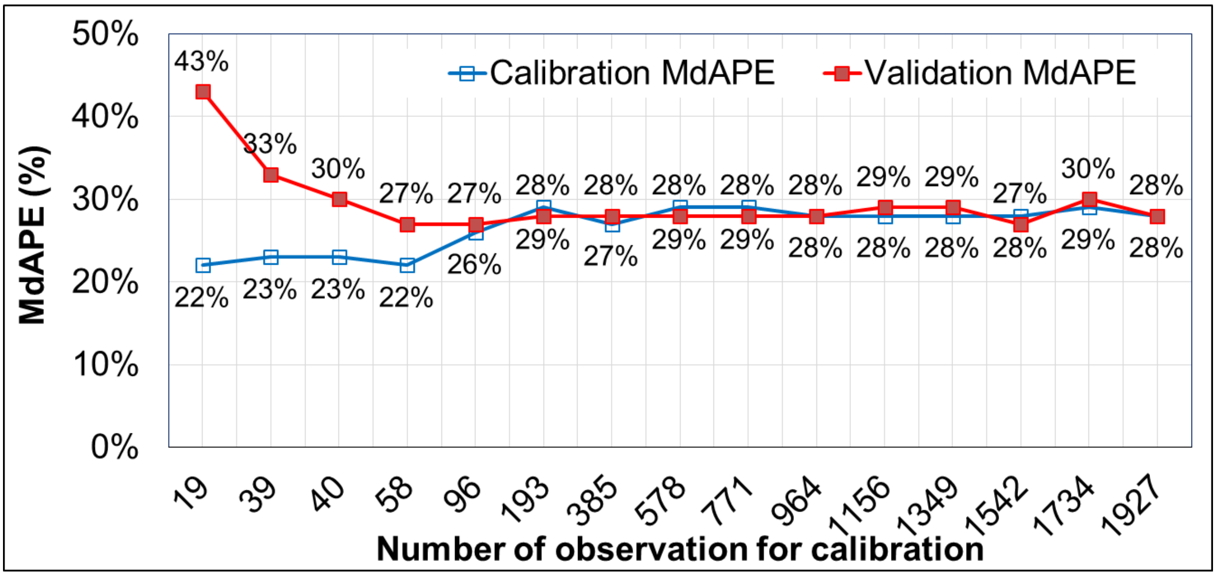


Figure 5-15: Recorded MdAPE according to the number of observation used for model calibration

5.5. Conclusion

The sub-objective aimed to achieve from the study explains in this chapter was to develop a set of models to estimate AADT and predict vehicular traffic volume of road segments based on the road network centrality values. Accordingly, this study, introduced key steps to follow when computing network centrality of road segments; and proposed a model to simulate traffic volume of road segment by using network centrality values as endogenous variables, with an accepted level of predictability and accuracy (R^2> 0.85, MdAPE <30% and RMSE<30%).

The proposed models has four key features as follows.

1. Two centrality measures (Betweenness centrality and Closeness centrality) that capture traffic generated due to both ‘to-and-from-trips’ and ‘pass-by-trips.'
2. Path distance (PD) that captures trip makers’ route-choice notions that are influenced by topological characteristics of road network and roadway mobility characteristics.
3. Trip length-based moving boundary that eliminates edge effect and accounts the influence of trip length.
4. Growth factor (VPP) that captures the influence of demographic and economic status on road traffic demand. This feature has made the model more dynamic and responsive to the changes in the road network and socio-economic conditions.
5. The mode can calibrate by using a little amount of actual observation points (N<40).

Chapter – 6
Network Centrality-based Simulation of Trip Generation Volume in Traffic Zones

6.1. Introduction

Trip generation is the first step of the traditional four-step travel demand modeling process (Ortúzar & Willumsen, 2011) and it aims to estimate the total number of trips generated from zones and attracted to zones within a given area. Accordingly, trip attraction identifies the number of trips attracted by urban activities in a traffic analysis zone (TAZ) and trip production identifies the number of trips produced by household in a TAZ (Stover & Koepke, 1988). In practice, trip generation is estimated based on land use characteristics and socio-economic characteristics of individuals or households (McNally, 2007), (Ortúzar & Willumsen, 2011). However, previous studies have recognized trip generation modeling is practically constrained due to inadequate up-to-date land use data and household travel information (James, et al., 2009), (George, et al., 2013), (Bwambale, et al., 2017). Further, researchers argue that most of the 'trip production models are expressed in terms of socio-economic and land use variable, and unable to account the impact of transport supply (i.e., accessibility) on trip attraction and production (Hansen, 2007), (Leake & Huzayyin, 2007), (McNally & Rindt, 2008).

In this background, the sub-objective aimed to achieve from the study explains in this chapter is to develop a method to the model volume of trip generation based on road network centrality values while overcoming issues highlighted above. First, this chapter proposed trip generation as a function of network centrality and introduced the method to compute centrality of TAZs. Next section provides a description of the method and data. Then, the study explains the model formulation and validation.

6.2. The proposed concept: Trip generation as function of network centrality

Trip generation model is used to predict the number of trips originated within each traffic zone and the number of trips attracted to each traffic zone in a given area. Many studies on travel demand has found that trip attraction has strong co-relation with the land use types and its' activities such as land use distribution (Escamilla, et al., 2016); floor area, number of employee and number of shop (Sasidhar, et al., 2016); number of employee (Parikh & Varia, 2016); number of employee, number of schools and school enrolment (JICA, 2014); number of employee in a commercial node, number of offices in a commercial node (George, et al., 2013); number of employment opportunities, Percent land use distribution as commercial, industrial, institutional, public semi–public land (CEPT University, 2013); gross floor area, number of stores in a shopping centers (Uddin, et al., 2012); numbers of employee, number of schools and volume of retail sales (Al-Taei & Taher, 2006); floor area (Fillone & Tecson, 2003); numbers of employee, number of parking lots, number of stores (Innes, et al., 1990). In trip production models, household size and household income (Gonzales-Ayala, 1999), (CEPT University, 2013), (JICA, 2014); population and number of apartments (Zenina & Borisov, 2013); household income, dwelling type (Panackel & Padmini, 2013); ownership of houses and rent (Asad, 2016) have been used as independent variables. The above-mentioned relationships can be illustrated as figure 6.1 and figure 6.2.

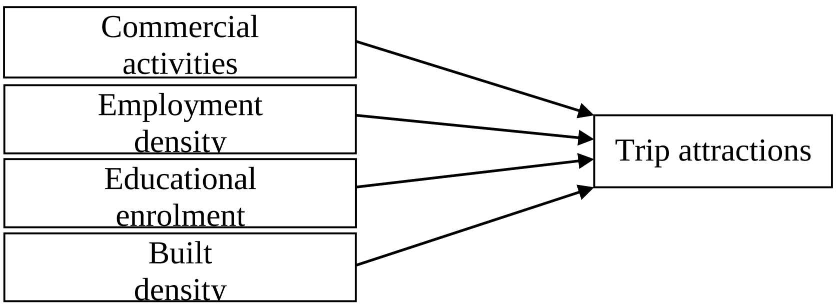


Figure 6-1: Relationship between urban land uses and the volume of trip attractions

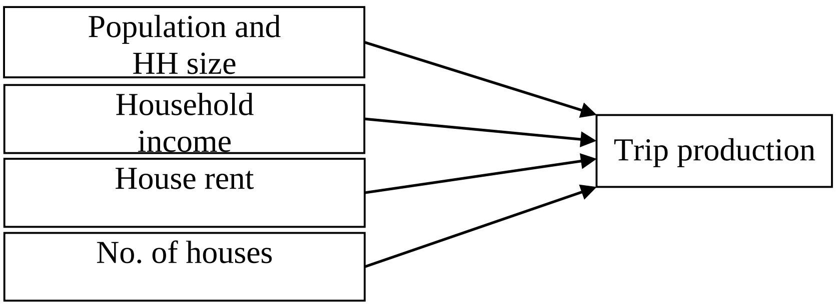


Figure 6-2: Relationship between socio-economic status of households and the volume of trip production

Empirical research studies related to the centrality and built-environment have revealed strong correlations between street centrality and characteristics of built environment such as density of commercial land uses in urban areas (Whitehand, 2001), (Mora, 2003), (Min, et al., 2006), (Bandara & Munasinghe, 2007); distribution of land values (Min, et al., 2006), (Shi & Huang, 2012), (Yaolin, et al., 2015); house rent (Chiaradia , et al., 2009), (Xiao & Webster, 2017); location of residential areas and socio-economic characteristics of dwellers (Law, et al., 2013), (Xiao & Webster, 2017); distribution of employment density (Kim & Sohn, 2004); distribution of built density (Peponis & Allen, 2006); urban morphology (Hillie & Iida, 2005), (Hillier & Vaughan, 2007), (Marcus, 2010). This relationship has been summarized in figure 6.3.

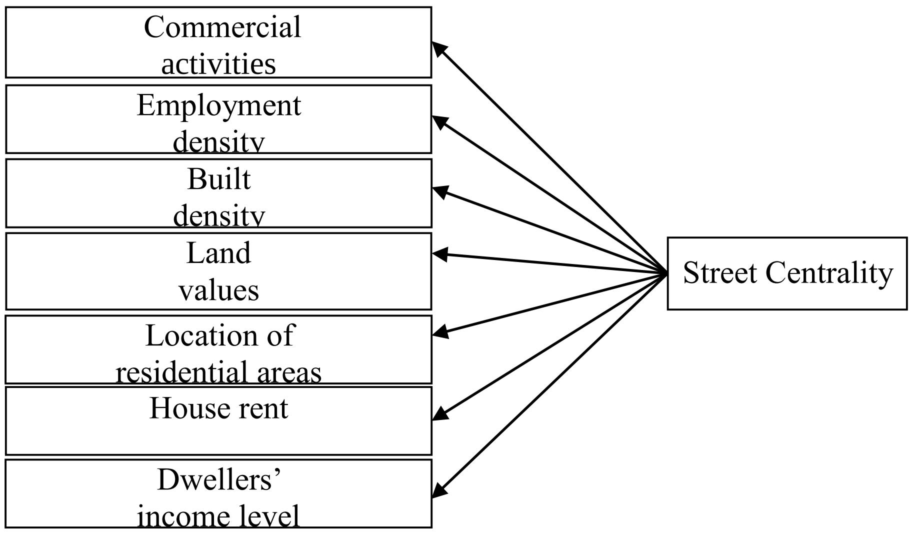


Figure 6-3: Relationship between the characteristics of built environment and street centrality

Figure 6.1 illustrated a relationship of trip attractions to a set of attributes are commercial land use, built density and employment density. Figure 6.3 illustrated a relationship of these three attributes to street centrality. On that basis, it can be hypothesized that trip attractions are related to street centrality. This transitive relationship has been illustrated in figure 6.4.

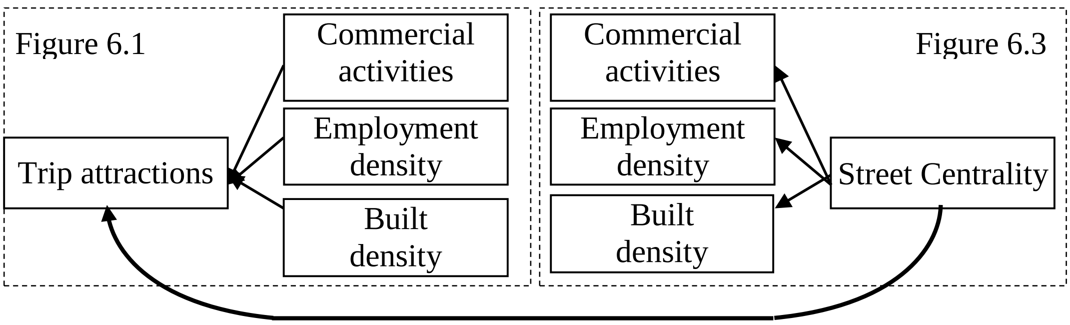


Figure 6-4: Transitive relationship between trip attraction and street centrality

Figure 6.2 illustrated a relationship of trip production with household income and rent. Figure 6.3 illustrated a relationship of those two attributes to street centrality. On that basis, it can be hypothesized that trip productions are related to street centrality. This transitive relationship has been illustrated in figure 6.5.

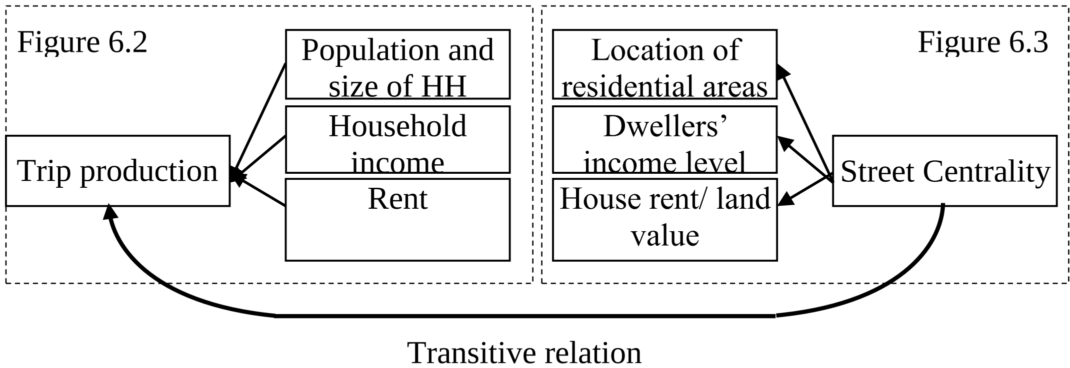


Figure 6-5: Transitive relationship between trip production and street centrality

Further to this, some of the studies on the relationship between street centrality and the characteristics of built-environment have found that street integration [closeness] has a high correlation with land values, rent, building density, employment density and intensity of commercial uses (Hillier, 1999), (Chiaradia , et al., 2009), (Shi & Huang, 2012), (Yaolin, et al., 2015), (Kahraman & Kubat, 2015), (Xiao & Webster, 2017). Accordingly, this study hypothesize that trip attraction and trip production can be estimated based on road network centrality and introduces trip attraction and trip production as a function of the closeness of road network (refer equation 6.1 and 6.2).

$$TA_i = f(CC_i \,.\, S_i) \tag{6-1}$$

$$TP_i = f(CC_i \,.\, S_i) \tag{6-2}$$

Where;

$TA_i = Volume\ of\ trip\ attraction\ in\ zone\ i,$

$TP_i = Volume\ of\ trip\ production\ in\ zone\ i,$

$CC_i = Closeness\ centality\ of\ zone\ i,$

$S_i \quad = Size\ of\ zone\ i$

6.2.1. Computing of network centrality of traffic zone in an area

Section 5.3.3 in the previous chapter has explained the method to compute centrality of road segments in a road network. Trip generation model (both trip attraction and production) expresses the trip volume of a geographical area as Traffic Analysis Zone (TAZ), urban block and not as a volume of a road segment. The conceptual proposal of this chapter attempt to model trip attraction and trip production as a function of closeness centrality. Therefore, it is necessary to compute centrality of traffic zones than road segments. However, there are very limited studies have attempted to compute centrality of zones (Zhao, et al., 2017). Some researchers have used dual graph approach where zones considered as nodes and interaction between them as links (refer figure 6.6).

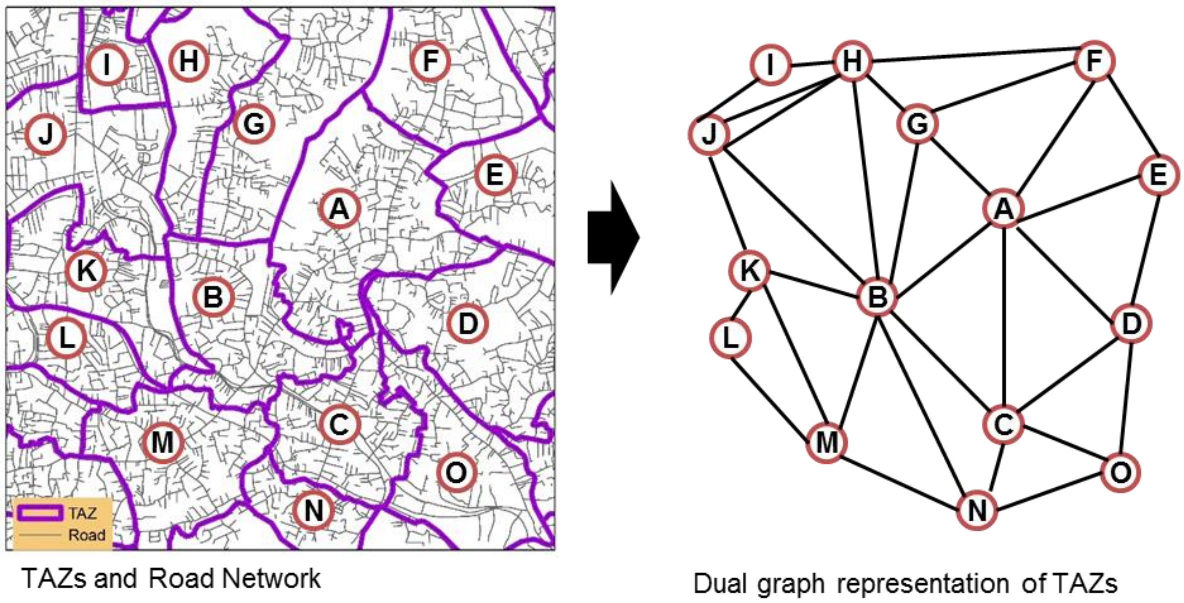


Figure 6-6: Example of dual graph representation of TAZs

This study has noted two limitations in the application of dual graph approach in the context of trip generation. First, dual graph approach is unable to capture centrality of road segments which are located inside the zones. Second, it unable to capture the magnitude of the interaction between two zones. Accordingly, the study recognized this method is not adequate enough to employ in trip generation modeling.

Thus, the study alternatively proposed to use a value that represents total CC (TCC) of a zone, and average CC (ACC) of a zone which is derived from the centrality of road segments located within the zone (refer equation 6.3 And 6.4).

$$TCC_X = \sum CC_i \tag{6-3}$$

$$ACC_X = {\sum CC_i . l_i}\Big/{\sum l_i} \tag{6-4}$$

Where;

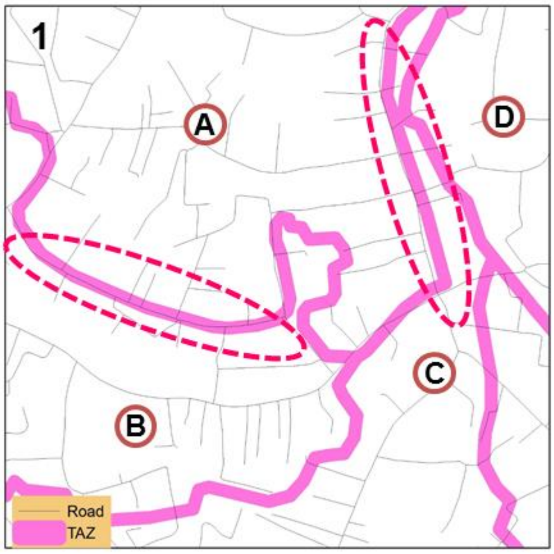
$TCC_X = Total\ closeness\ centrality\ of\ zone\ X,$

$ACC_X = Average\ closeness\ centrality\ of\ zone\ X,$

$CC_i\ \ = Closeness\ centrality\ \ of\ road\ segment\ i\ which\ is\ located\ within\ the\ zones\ X,$

$l_i\ \ \ \ \ = Lenght\ \ of\ road\ segment\ i$

The proposed TCC represents the cumulative sum of closeness centrality of all road segments within the zone whereas ACC represents the average of closeness centrality of all road segments within the zone. The closeness centrality of each road segment is computed based on the method proposed in section 5.3.3. Accordingly, the proposed $TCC\ and\ ACC$ values are able to capture closeness centrality of road segments which are located in each zone (intra-zonal) and closeness centrality of those segments in relation to the entire road network (inter-zonal). However, when geographically aggregating CC values of road segments in to TAZs some problems can interfere (figure 6.7). In the left illustration of figure 6.7, road segments which are indicated by red dotted-lined-circular patches are overlapping the boundaries of two or more zones. In the right illustration of figure 6.7, road segments which are indicated by red dotted-lined-circular patches do not reach zone L but located very closer to its boundary. This problem technically termed as the 'boundary problem', a phenomenon create due to the arrangement of boundaries and it is a common problem interferes with aggregating line data into polygon in geography and spatial analysis (Barber, 1988), (Getis, 2005).



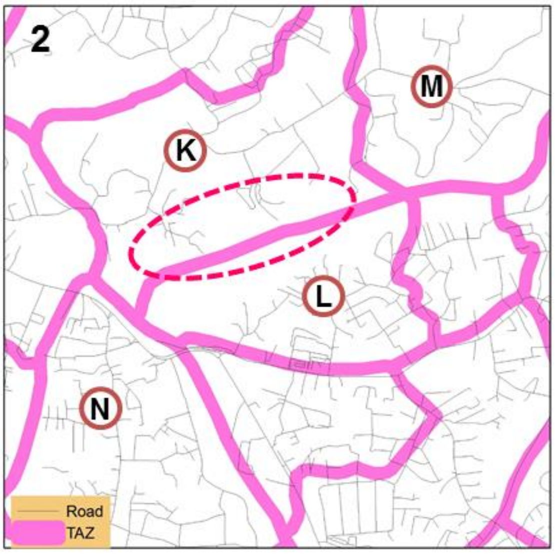


Figure 6-7: Boundary problem in relation computation of TCC and ACC

'Kernel Density Estimation' (KDE) in GIS is one of the methods employs to minimize the boundary problem (Carlos, et al., 2010) (Porta, et al., 2012) Therefore, this study employed the Kernel Density Estimation (KDE) method when computing TCC and ACC.

6.3. Method of study

6.3.1. Study framework

The sub-objective aimed to achieve from the study explains in this chapter is to develop a method to the model volume of trip generation based on road network centrality values. For this purpose, firstly, the study attempts to compute the centrality of traffic zones based on the method explained in section 5.2.2 and then analyses the relationship with real trip attraction and production values. In the model formulation and validation stage, the study aims to propose a trip attraction model and a trip production model based on closeness centrality (figure 6.8).

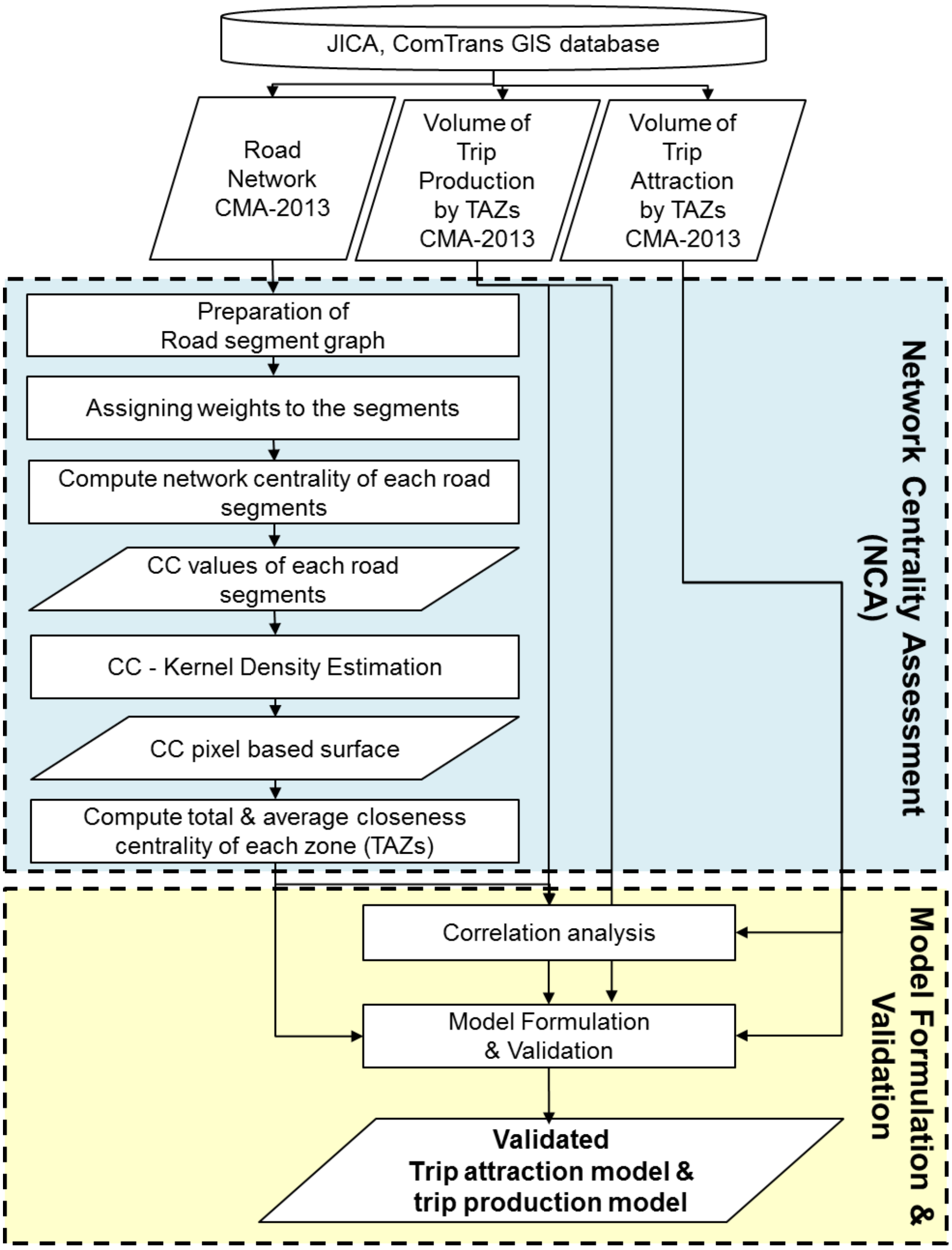


Figure 6-8: Method of formulating trip attraction and trip production models and validation

6.3.2. Study area and description of data

The model development was built upon a case study in Colombo Metropolitan Area (CMA), Sri Lanka. CMA is the main urban agglomeration in Sri Lanka and one of the medium-scale cities with 5.8 million residential population. Large agglomeration of trip can be observed inside the Colombo municipal council (CMC) area, and the number of trips for commuting to work in CMC is around 400,000 trips per day (JICA, 2014). Trip attraction (TA) is varied in the range of 1,325 trips to 109,698 and trip production (TP) is varied in the range from 1,747 trips to 99,331 (refer figure 6.9). The recorded highest trip attraction density (TAD) is 281,983 trips per sqkm and the highest trip attraction density (TPD) is 244,398 trips per sqkm (refer figure 7.10). TAD and TPD values have skewed right. The spatial distribution of trip volumes and their densities are illustrated in figure 6.11 and 6.12.

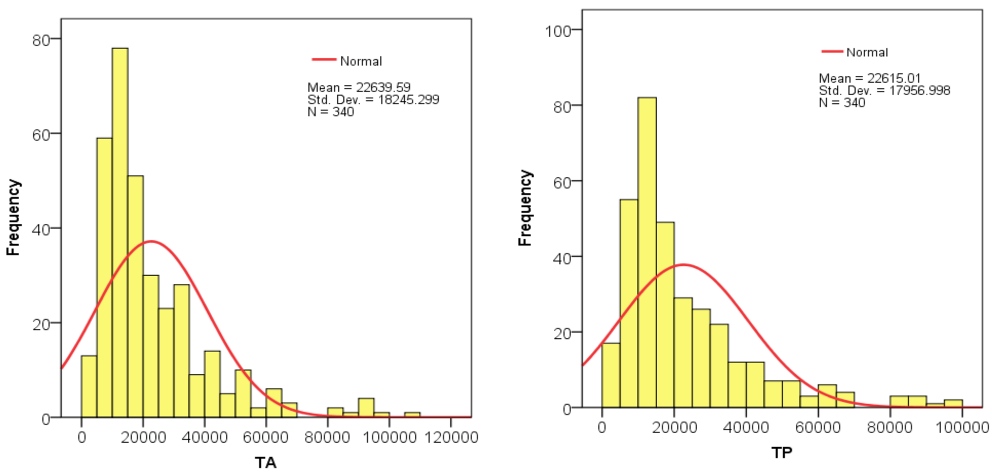


Figure 6-10: Distribution of trip attraction and trip production in CMA

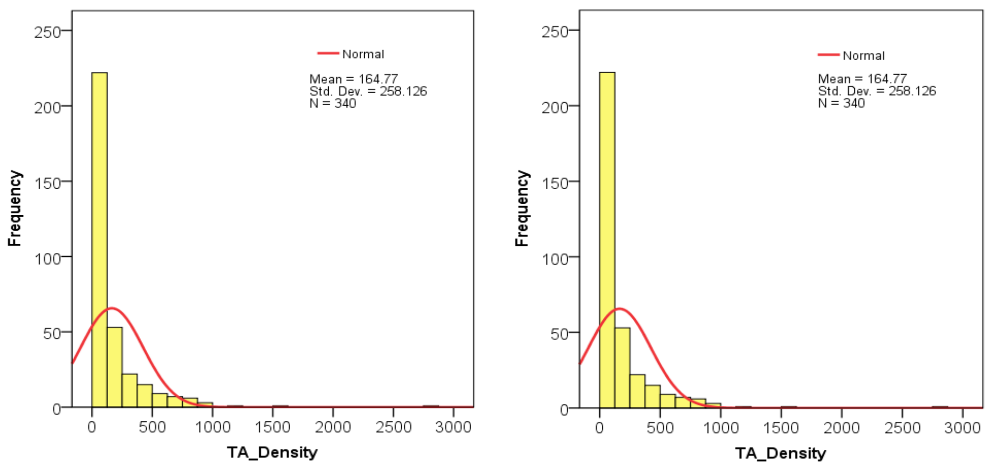
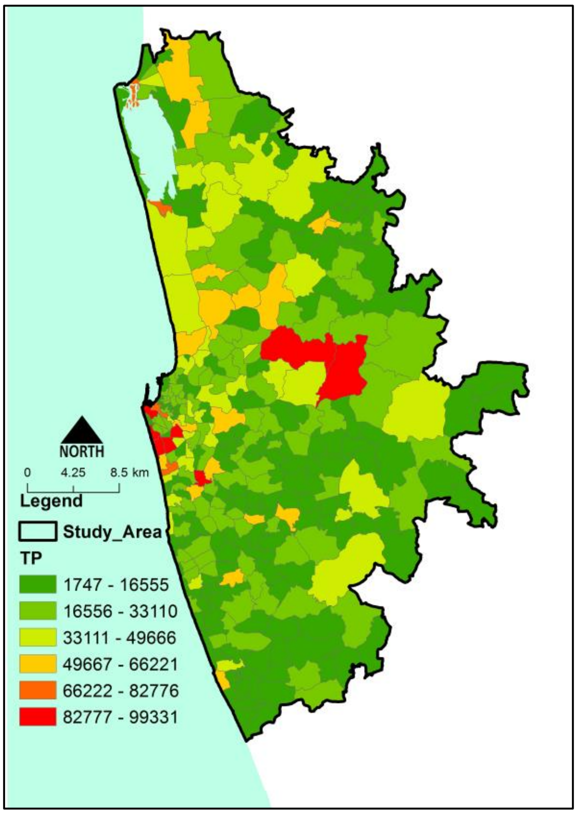


Figure 6-9: Distribution of trip attraction densities and trip production densities in CMA



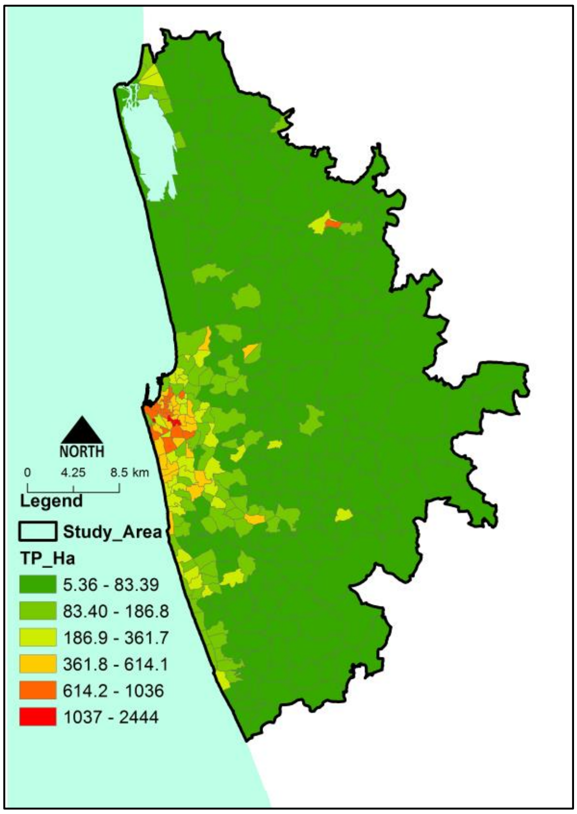
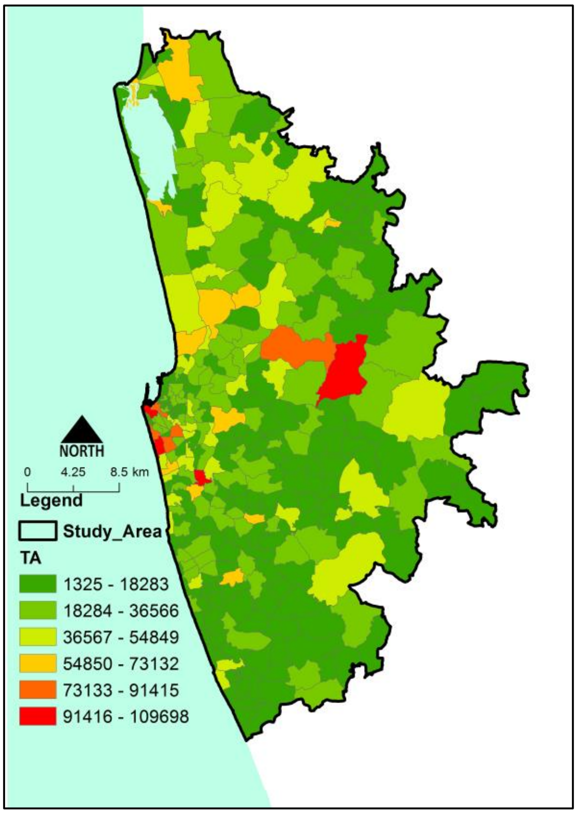


Figure 6-12: Spatial distribution of trip production and trip production density in CMA



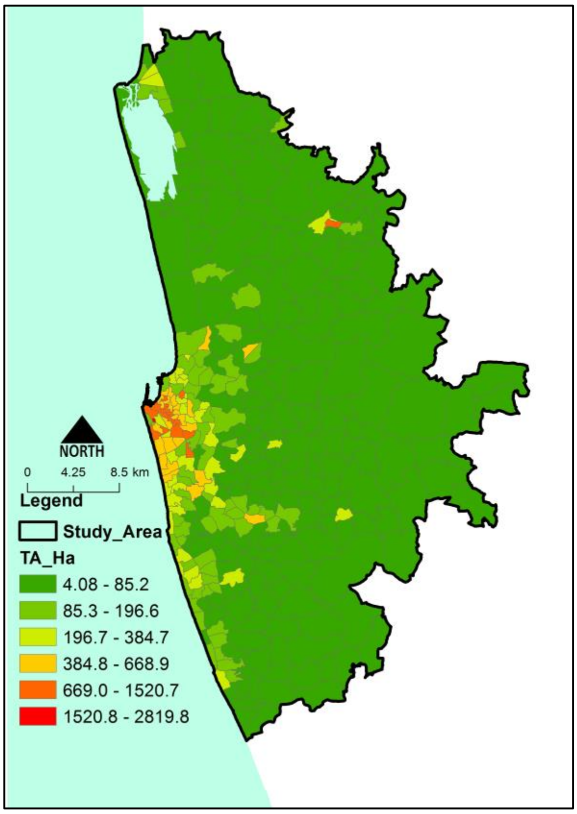


Figure 6-11: Spatial distribution of trip attraction and trip attraction density in CMA

Trip attraction and production volumes are the response variables in the proposed models. The study obtained trip attraction and production data from JICA-CoMTrans GIS Database for the year 2014. Table 6.1 provides a brief description of data obtained for this study.

Table 6-1: Description data and sources

Data Type	**Year**	**Source**	**Description**
Trip attraction volume	2013	JICA, 2014	N=340 Zones Estimated value
Trip production volume	2013	JICA, 2014	N=340 Zones Estimated value
Land use	2013	JICA, 2014	Updated in the year 2012
Population	2013	JICA, 2014	N=340 Zones National population censuses - 2012
Road network	2013	JICA, 2014	GIS data: Road centre line as polyline

6.3.3. Computation of centrality of traffic zones

The study utilized the computed CC values of road segments that has been explained in the previous chapter (Section 5.3.3 in Chapter 5) for computing closeness centrality of TAZs. As described in section 6.2.2, the study proposed to use total CC values (TCC) of a TAZ and average CC value (ACC) of a TAZ as the network centrality values of the given TAZ. In this implementation, the study employed the Kernel Density Estimation (KDE) method to compute TCC and ACC. To do that, the study created a raster dataset of CC by applying KDE to the CC values of road segments (refer figure 6.13). The cells size was set at 10 meters by 10 meters. Based on the prepared raster dataset, the study calculated TCC and ACC values by TAZ using raster calculation methods in GIS. Accordingly, the dataset of CC values and trip attraction and trip production were converted into same resolution and thus permits to perform the relationship analysis.

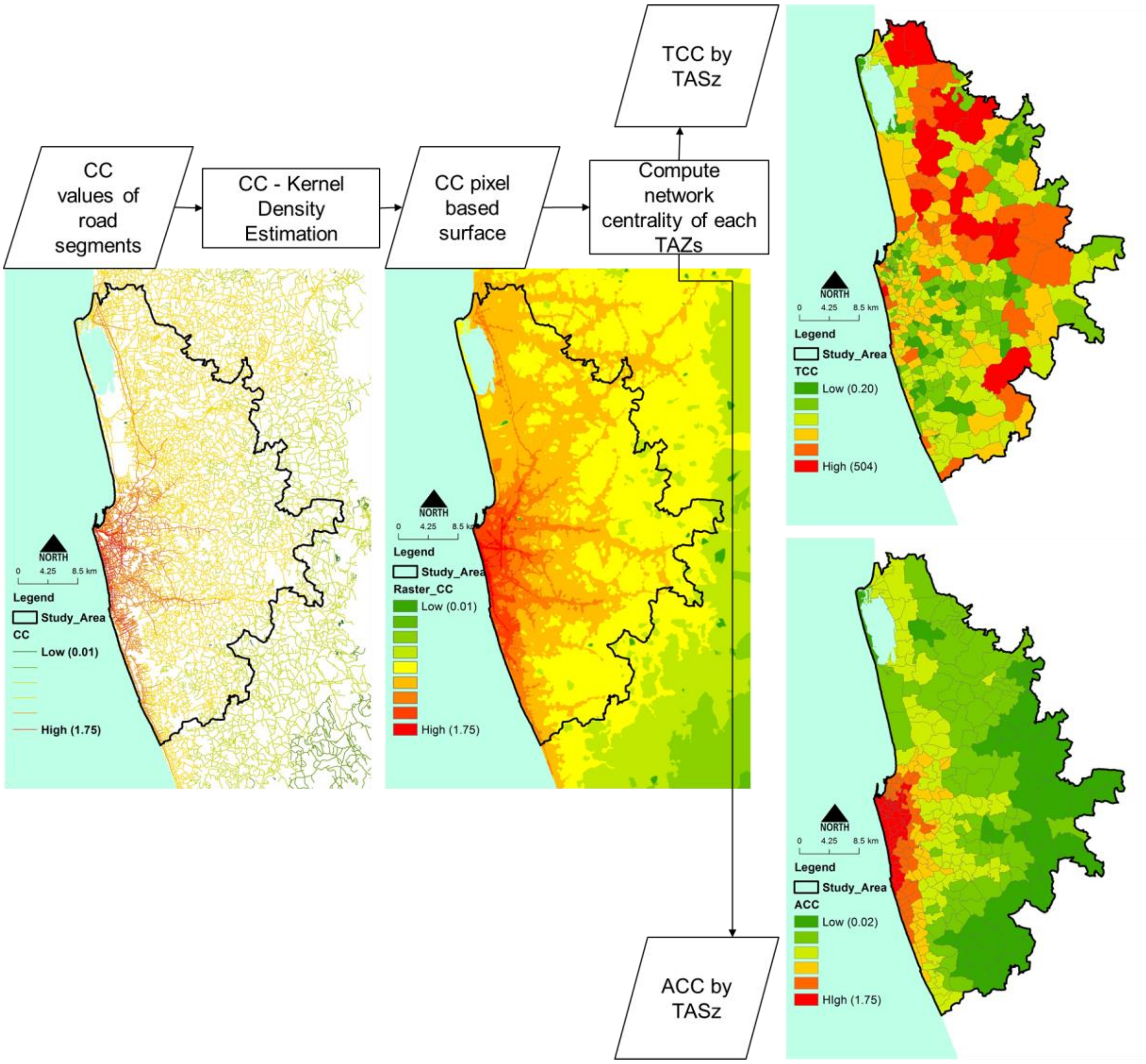


Figure 6-13: Computation of TCC and ACC of TAZs

6.4. Trip attraction and trip production models formulation and validation

6.4.1. The relationship between volume of trip generation and the closeness centrality

This section examines the relationship between centrality values and trip volumes. First, the study investigated the relationship between TCC and ACC. Figure 6.14 illustrates the distribution of TCC and ACC values by TAZs and figure 6.15 illustrates the relationship between TCC and ACC values. A strong, significant correlation has been revealed between TCC and ACC (r=0.920, p<0.01)

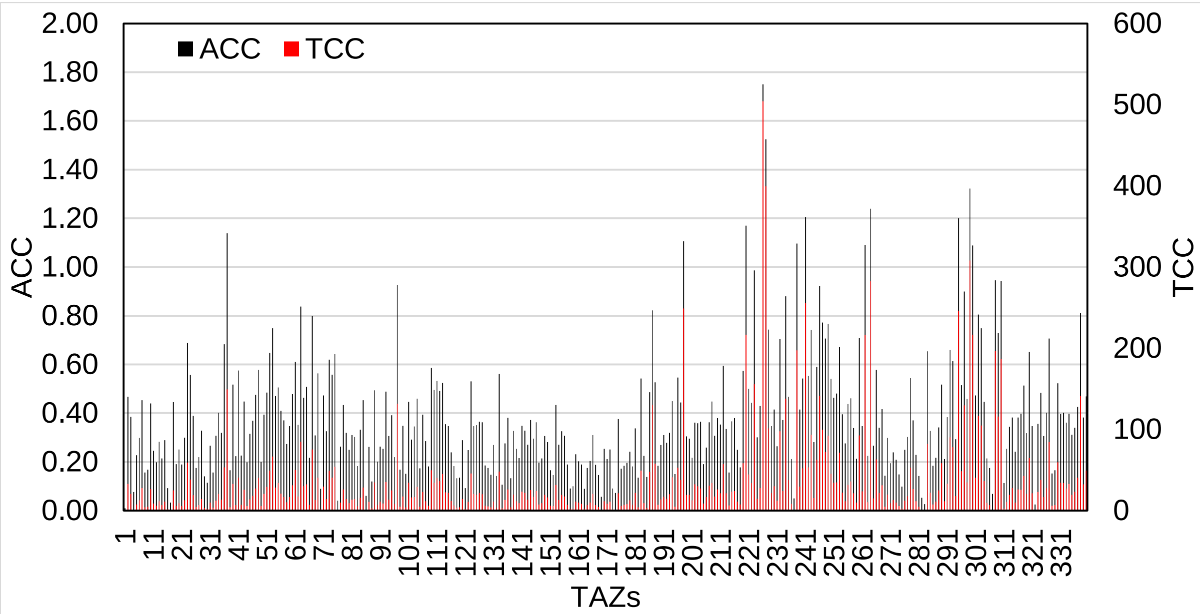


Figure 6-14: Distribution of TCC and ACC values

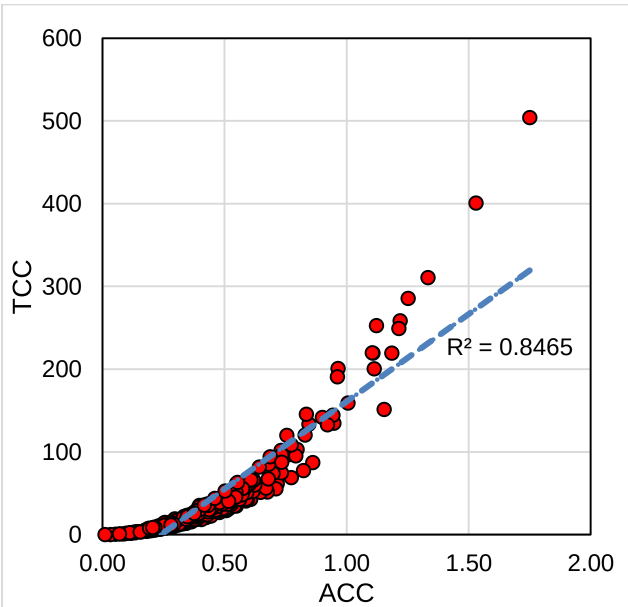


Figure 6-15: Scatterplot illustrating the relationship between TCC and ACC

Then study examined the relationship of centrality values with trip attractions (TA) and trip production (TP) respectively. Table 6.2 and 6.3 shows the results of Pearson and Spearman's rho correlation analysis. Trip attraction and production values exhibited significant, moderately strong correlation coefficient values with both TCC and ACC.

Table 6-2: Pearson correlation coefficient

Correlations				
	TP	**TA**	**ACC**	**TCC**
TP	1	.921**	.594**	.463**
TA		1	.602**	.470**
ACC			1	.920**
TCC				1

Note: N=340, **Correlation significant at 0.01 and *Correlation significant at 0.05

Table 6-3: Spearman's rank order correlation coefficient

Correlations				
	TP	**TA**	**ACC**	**TCC**
TP	1	.994**	.652*	.595**
TA		1	.654**	.599**
ACC			1	.984**
TCC				1

Note: N=340, **Correlation significant at 0.01 and *Correlation significant at 0.05

6.4.2. Model formulation and validation: Trip attraction and trip production

The study proposed volume of trip attraction as a function of closeness centrality and size of TAZs (refer equation 6.1 and 6.2). The study utilized land extent (LE) and total residential population (Pop) to represent the size of TAZs' for TA model and TP model respectively. Then, the study employed ordinary least squares regression analysis for the purpose of model formulation. In this purpose, the study utilized both actual values and their natural logarithm (ln) values. Table 6.4 summarized the regression results. For trip attraction, model-4 recorded the highest R^2 values (R^2=0.487) and lnACC variable is significant ($p<0.0001$) in the model. However, it cannot be considered as the best model to estimate trip attraction because the predictability of the model is less than the standard, acceptable level i.e. $R^2 > 0.85$ (Institute of Transportation Engineers, 2012). For trip production, model-8 recorded the highest R^2 values (R^2=0.876). However, lnACC is insignificant ($p>0.05$) in the model. So it is indicated that both proposed trip attraction and trip production model are not credible for practice.

Table 6-4: Statistics and specifications of the trip attraction and production models

Specifications		Adjusted R Square	F	B[a]	Beta[b]	t-value	p-value	VIF
Model - 1		.247	57.047				<.0001	
TA	Constant			1099.763		16.827	<.0001	
	TCC			20.069	.630	9.932	<.0001	1.82
	LE			2.44E-04	.238	3.758	<.0001	1.82
Model - 2		.394	111.852				<.0001	
TA	Constant			1491.122		2.473	<.0001	
	ACC			3714.693	.731	14.301	<.0001	1.47
	LE			1.97E-04	.229	4.473	<.0001	1.47
Model - 3		.456	142.865				<.0001	
lnTA	Constant			12.014		25.877	<.0001	
	lnTCC			.547	.831	16.645	<.0001	1.55
	lnLE			.267	.378	7.566	<.0001	1.55
Model - 4		.487	159.93				<.0001	
lnTA	Constant			13.523		27.434	<.0001	
	lnACC			1.043	.786	5.873	<.0001	1.31
	lnLE			.185	.262	17.627	<.0001	1.31
Model - 5		.815	754.096				<.0001	
TP	Constant			701.919		1.141	.255	
	TCC			8.798	.017	.629	.530	1.38
	Pop			.052	.913	33.355	<.0001	1.38
Model - 6		.818	769.401				<.0001	
TP	Constant			824.075		.464	.643	
	ACC			2169.399	.875	29.310	.118	1.67
	Pop			.056	.047	1.569	<.0001	1.67
Model - 7		.875	1185.336				<.0001	
lnTP	Constant			.693		3.211	.001	
	lnTCC			.028	.042	1.716	.087	1.63
	lnPop			.975	.909	37.11	<.0001	1.63
Model - 8		.876	1190.081					
lnTP	Constant			.942		3.342	.001	
	lnACC			.070	.053	2.033	.043	1.83
	lnPop			.964	.900	34.637	<.0001	1.83

Note: N=340, a: Unstandardized coefficients; b: Standardized coefficients

6.4.3. Modified model formulation and validation: Trip attraction and trip production

To this point, results of the analysis indicated that, though network centrality values (i.e. TCC and ACC) and trip volume (TA and TP) showed a significant correlation among them, however, the proposed models are not optimal for estimating trip production and trip attraction. Therefore, the study carried out an investigation and diagnosed the possible reasons for that.

1. Explanatory variables in the proposed model are not able to capture trip attraction and trip distribution volume and need to incorporate some additional variables.
2. The Modified area unit problem (MAUP), might have caused due to aggregating two different areal units. In the process of model formulation and validation, the study has utilized zone based trip volumes. Explanatory variables (i.e. closeness values) are derived from road segments and converted into zones. Accordingly, scales at which the study have chosen to formulate the model are on two different levels, and it causes an error (i.e. scale MAUP). Further, zoning schemes use to represent trip attraction, and production volume may not be able to represent the actual locations (i.e. Zone MAUP).

Figure 6.16 illustrates the issues related to analyzing zone-based trip volume data with road segment-based network centrality values. In the figure, land uses which attract trips (i.e. commercial area, industrial areas, education institutions etc.) are indicated in black color while land uses which produce trips (i.e. residential areas, apartments etc.) are indicated in yellow color and natural environmental features (i.e. water bodies, marsh, forest etc.) are indicated in green color. When considering the zone-A, trip attraction land uses are mostly concentrated into the area encircled by the balck colored patch/es which is about 20% of the total land area of the zone. As the network centrality values have been computed for the entire zone, it is logically plausible to reduce the strength of the relationship. In order to have better results, it is required to relate the locations of trip attractions with the network centrality. Similar phenomena can be seen in zone-B related to trip production land uses.

To overcome this problem, the study modified the method of computing the aggregate closeness centrality of a zone as indicated in equation 6.5a and 6.6a (refer figure 6.17 for illustrations of the modified method).

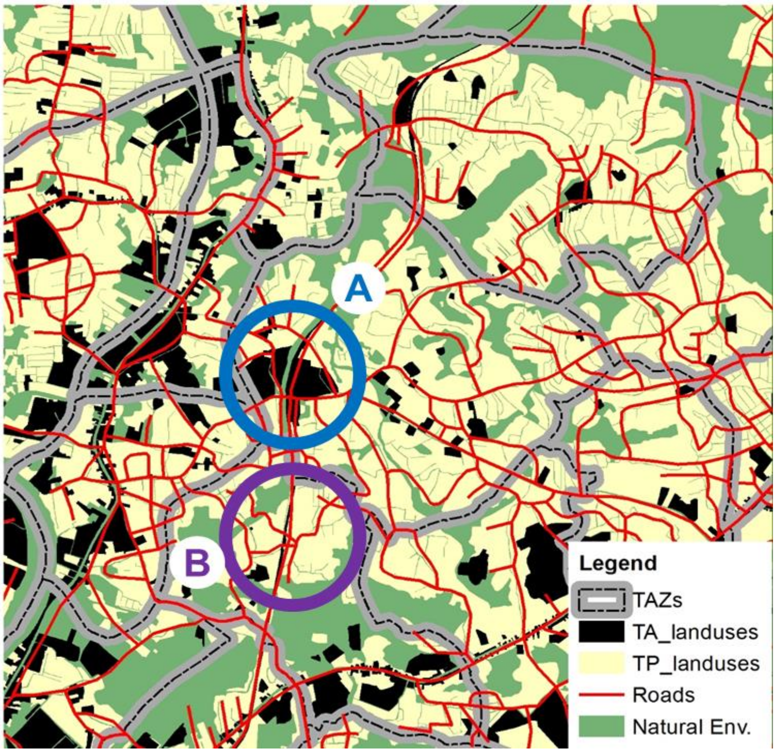


Figure 6-16: MAUP in relation to computing zone level centrality values

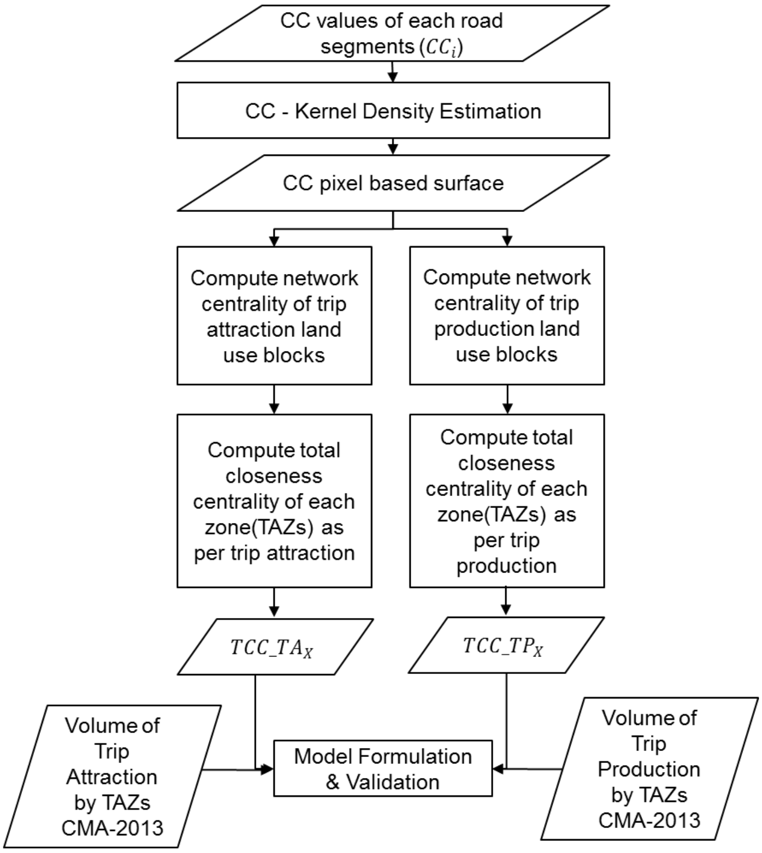


Figure 6-17: Modified method – Trip attraction and trip production models formulation and validation

Accordingly, for accounting the trip attraction, the modified aggregate closeness centrality of a zone is proposed to be computed as the aggregate closeness centrality value of all trip-attraction-land-use blocks ('trip attraction land use block' + 500m buffer area) in the given zone. Similarly, for accounting the trip production, the modified aggregate closeness centrality of a zone is proposed to be computed as the aggregate closeness centrality value of all trip-production-land-use blocks ('trip production land use block' + 500m buffer area) in the given zone.

$$TCC\_TA_X = \sum TCC\_TA_{mX} \tag{6-5a}$$

$$TCC\_TA_{mX} = \sum CC_{imX} \tag{6-5b}$$

Where;

$TCC\_TA_X = Total\ closeness\ centrality\ of\ trip - attraction - land - use\ in\ zone\ X,$

TCC_TA_{mX} = *Total closeness centrality within the trip-attraction-land-use block m and 500m buffer zone from m, in zone X*

CC_{imX} = *Closeness centrality of road segment i where i is located within the-trip-attraction-land use block m and 500m buffer from m, in zone X*

Note: Trip-attraction-land-uses: Airport, Education Institutions, Administrative Institutions, Financial Institutions, Health Institutions, Industries, Service for manufacturing centers, Commercial Activities, Hotels and Restaurants, Logistics and Transport centers, Parks and Playgrounds, and Recreational activities

$$TCC\_TP_X = \sum TCC\_TP_{kX} \tag{6-6a}$$

$$TCC\_TP_{kX} = \sum CC_{ikX} \tag{6-6b}$$

Where;

$TCC\_TP_X = Total\ closeness\ centrality\ of\ trip - production - land - uses\ in\ zone\ X,$

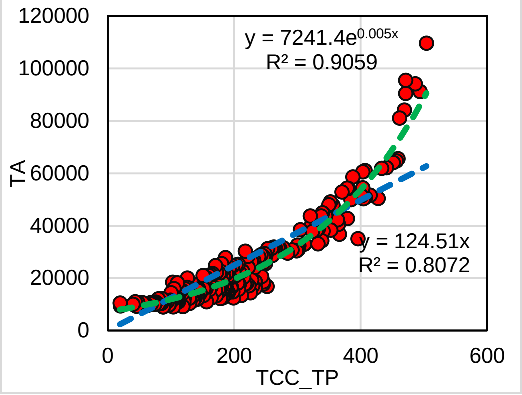
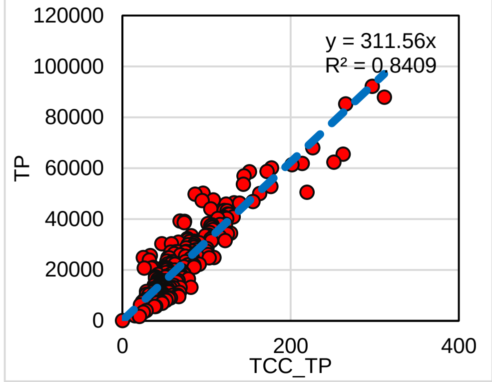
$TCC_{TP_{kX}}$ = *Total closeness centrality of trip-production-land-use block k and 500m buffer zone are in zone X,*

CC_{ikX} = *Closeness centrality of road segment i which is locate within the trip production land use block k and 500m buffer zone are in zone X,*

Note: Trip-production-land-uses: Condominium scheme, Housing schemes, Individual housing areas, Hostels

The study remodeled the centrality values according to the equation 6.5a and 6.6a. Table 6.5 summarized the specifications of the formulated trip attraction model and production model.

Table 6-5: The formulated trip attraction model and trip production model

	Trip attraction model		**Trip production model**	
				
Model	$TA^{a} = 7241.4*e^{0.005TCC\_TA}$ $TA^{c} = 124.51*TCC\_TA$	(6.7a) (6.7c)	TP = 311.56*TCC_TP	(6.7b)
R^2	$^{a}0.906$ / $^{c}0.8072$		0.840	
MAPE	$^{a}14.17\%$ / $^{c}34.51\%$		23.19%	

Both models recorded an acceptable level of accuracy. Accordingly, the study concludes that the proposed network centrality-based models are able to estimate trip attraction and trip production.

Further, the study analyzed the relationship between network centrality values and actual trip attraction volumes of 30 locations. JICA (2014) provides a published dataset of a trip generation survey at 30 locations within the study area. Table 6.6 shows the recorded trip attraction volumes of 30 locations and the computed TCC_TA values. Figure 6.18 illustrated the distribution of those actual trip attraction volumes and computed TCC_TA (N=30). There is a strong relationship between TCC_TA values and total trips (R^2=0.85). The results further validate the applicability of network centrality for modeling trip generation (trip attraction and production) volumes.

Table 6-6: Actual trip attraction volumes of 30 locations and computed TCC_TA values

Type	No	Name of Facility	Total Land Area (km)**	Average Number of Visitors*	Number of Employees*	Total Trip Attractions*	TCC_TA **
Government Office Building	1	Ministry of Transport	2,820	50	242	292	0.76
	2	Ceylon Petroleum Corporation	502,200	200	1,205	1,450	5.13
	3	Immigration & Emigration	2,610	2,500	500	3,000	13.04
	4	National Development Bank Building	4,710	60	523	583	1.72
	5	Suwasiripaya	9,060	150	1,500	1,650	9.59
	6	Colombo Municipal Council	16,570	1,000	1,000	2,000	14.00
	7	Department of Motor Traffic	5,700	2,000	132	2,132	13.98
	8	Department of Registration of Persons	3,210	2,000	499	2,499	12.96
	9	Sethsiripaya	34,760	5,000	4,700	9,700	17.02
	10	Foreign Employment Bureau	4,200	2,500	820	3,320	14.55
Private Office Building	1	Ceylon Tobacco Company	30,670	50	410	460	0.42
	2	Unilever	35,290	50	450	500	1.10
	3	Orion City IT Park	51,830	125	2,250	2,375	7.61
	4	Coca Cola Beverages	59,320	200	610	810	5.81
	5	John Keels Head Office	20,620	150	440	590	4.83
	6	Dialog Axiata	7,940	600	30	630	6.15
	7	Nestlé Lanka	6,050	30	407	437	0.64
	8	Sampath Bank Head Office	3,820	1,600	885	2,485	12.88
	9	Access Tower	4,460	300	626	926	7.19
	10	Aitken Spence Tower	6,180	300	976	1,276	6.85
Shopping Malls, Supermarkets and Traditional Market	1	Cool Planet	450	1,200	55	1,255	12.24
	2	Crescat Boulevard	5,490	2,500	430	2,930	14.40
	3	People's Park	9,280	3,000	985	3,985	14.68
	4	Arpico Super Centre	17,250	3,500	194	3,697	15.54
	5	Odel	9,670	1,500	416	1,916	13.34
	6	Colpity Central Market	4,600	1,000	141	1,141	11.62
	7	Liberty Plaza	6,280	3,000	545	3,545	15.70
	8	Majestic City	7,430	5,000	750	5,750	16.75
	9	Unity Plaza	,800	6,000	150	6,150	17.34
	10	Lady J Family Supermarket	480	6,000	150	6,150	16.89

Note: *Source JICA, 2014; **computed by this study

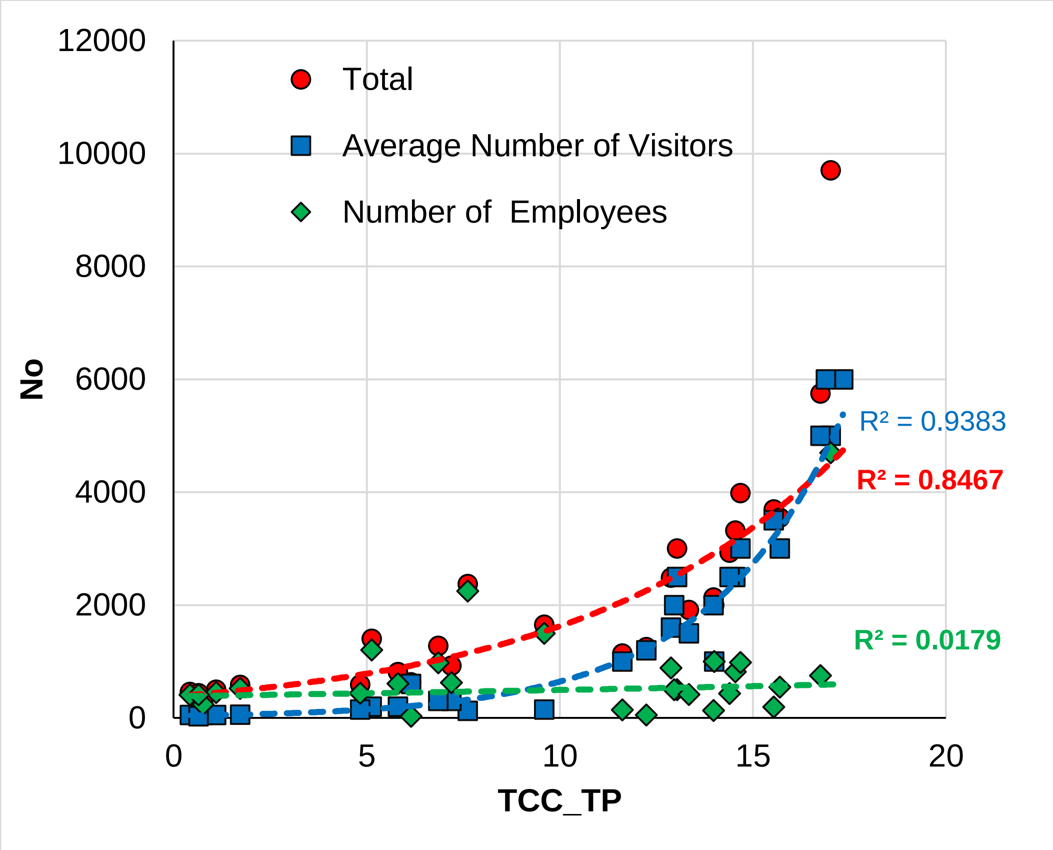


Figure 6-18: Relationship between actual trip attraction volumes and TCC_TA

6.5. Conclusion

The sub-objective aimed to achieve from the study explains in this chapter was to develop a method to the model volume of trip generation based on road network centrality values while overcoming issues highlighted in recent studies. Accordingly, the study proposed a method to model trip attraction and trip production volumes by using aggregated-zonal-closeness-centrality values as an endogenous variable. First, the study analyzed the relationship between trip attraction and trip production volumes with the aggregated TAZs level closeness centrality values and the result revealed a significant correlation among them but with moderate strength. Therefore, the study realized that the proposed aggregated TAZs level closeness centrality value is not confident-enough to estimate trip production and trip attraction, especially due to MAUP error. To overcome this technical problem, the study modified the method of computing aggregate closeness centrality of a zone and able to develop a trip attraction model and a production model with acceptable accuracy (R^2 > 0.85, MAPE<25%).

Chapter – 7
Network Centrality-based Simulation of Trip Distribution

7.1. Introduction

Trip distribution is the second stage in the traditional four-step travel demand modeling process, and it models the number of trips that takes place between originating zone and destination zone (Meyer, 1992). Models that are predominately employed for estimating trip distribution are developed based on the gravity function of Newton's fundamental law of attraction (Ortúzar & Willumsen, 2011). The gravity based trip distribution models assume that the interaction between two zones is positively correlated with a number of activities at each zone and it declines as per the travel cost between two zones (Ortúzar & Willumsen, 2011). However, many of the recent studies have highlighted that the trip distribution is the weakest step in the four-step travel demand modeling process and this weakness is mainly due to the inadequacy of attractiveness attributes of the model. (Cascetta & Papola, 2008), (Veenstra, et al., 2010), (Yang, et al., 2013). Further, those studies have emphasized that the limited land use data constrains the estimation of attractiveness based on land uses and traditional trip distribution models are unable to capture the attractiveness generate due to the accessibility (Cascetta & Papola, 2008), (Veenstra, et al., 2010), (Yang, et al., 2013).

In such background, this chapter introduces a network centrality-based aggregated model to model trip distribution. In the proposed model, attractiveness has expressed based on the relative closeness centrality between trip destination zone and trip origin zone. First, this chapter proposed trip distribution as a function of network centrality. Next section provides a description of the method and data. Then, the study explains the model formulation and validation.

7.1.1. The proposed Concept: Trip distribution as function of network centrality

The general form of the double-constraint trip distribution model can be expressed as follows.

$$\mathrm{T_{ij}} = \frac{\alpha \mathrm{P_i^{\gamma}} \beta \mathrm{A_j^{\tau}}}{\mathrm{D_{ij}^{\rho}}} \qquad (7-1)$$

Where "T_{ij} is the interaction between two locations (or zones), P_i is the production of trips from zone i, A_j is the attractiveness of zone j, D_{ij} is the distance between zones i and j, ρ is the exponent of P_i, τ is the exponent of A_j, D is the exponent of distance, and α is a constant. Where α is a constant for the productions, P_i^{γ}, but β is a constant for the attractions, A_j^{τ}" (Ortúzar & Willumsen, 2011). This model assumes that trip makers travel more to highly attractive zones than to less attractive zones. Further, the level of attractiveness of the model is derived from the volume of trip attractive-land use activities. In chapter 6, the study has established that the volume of trip attraction in a zone is a function of the aggregated closeness centrality of the particular zone. Further in chapter 5 the study has established that road segments with high closeness values recorded the least sum of distance from the all other road segments, hence, act as popular trip destinations [i.e. the most attractive locations]. Accordingly, this study hypothesized that attractiveness of destination zone can be explain as a function of the aggregated closeness centrality of the given zone. Further, the study conceptualized that attractiveness is a relative phenomenon, hence, needs to express in relative terms as relative closeness. Because, trip makers intend to travel to higher-opportunity-destinations relatively to the origin (Erlander & Stewart, 1990), (Kockelman, 1991), (Peyerson, 2007). Consequently, the study expresses the attractiveness of the destination zone as function of relative aggregated closeness centrality of the destination zone compare to the zone of origin (refer equation 7.2).

$$A_{ji} \propto \left(\frac{ACC_j}{ACC_i}\right) \qquad (7-2)$$

Where;

A_{ji} = *Relative attractiveness of zone j compare to zone i,*

ACC_i = *Aggregated closeness centrality of TAZ_i*

ACC_j = *Aggregated closeness centrality of TAZ_j*

Accordingly, the volume of trip distribution between two zones can be expressed as follows,

$$T_{ij} \propto {A_{ji}.P_i} \Big/ {D_{ij}} \qquad (7-3)$$

Where;

T_{ij} = *Volume of trips distribute from zone i to j*

A_{ji} = *Relative attractiveness of zone j compare to zone i,*

P_i = *population of the zone i,*

Dij = *Distance between zones i and j*

7.2. Method of study

In this chapter, the study introduced a formula (equation 7.3), which has been derived from the aggregated closeness centrality value, in order to explain the trip distribution. The analysis of this chapter is aimed to achieve the sub-objectives, to investigate the possibility to model volume of trip distribution between TAZs. For that purpose, the study obtained O-D trip distribution data from CoMTrans GIS database (JICA, 2014). The database provided trip distribution data for 612 O-D combinations. The aggregate closeness centrality of TAZi is a key variable in the proposed model, and the study utilized the previously computed TCC_TA_X values (section 6.4.3). The overall method of this study has been illustrated in figure 7.1.

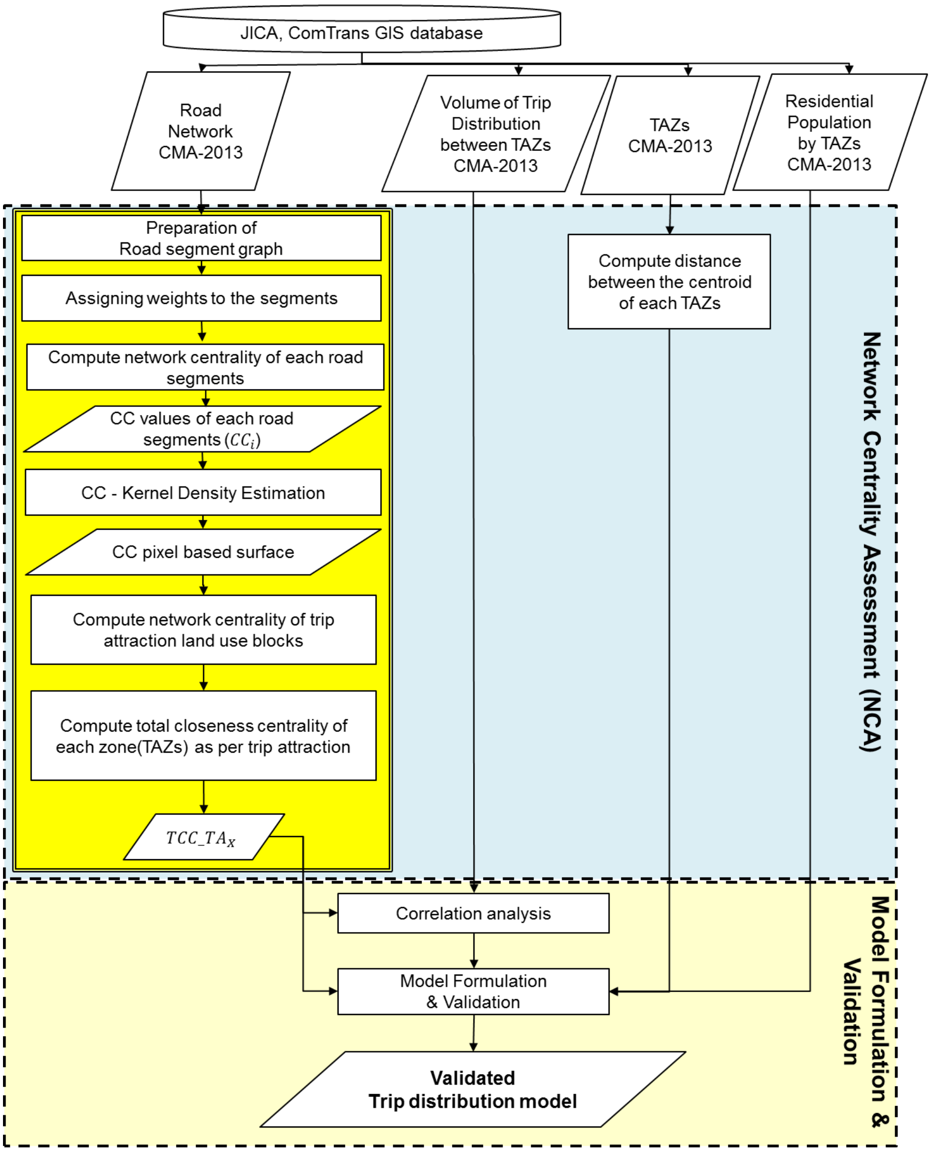


Figure 7-1: Method of trip attraction and trip production models formulation and validation
Note: Steps indicated by yellow color box have been explained in section 6.4.3

7.3. Model formulation and validation

7.3.1. The relationship between trip distribution and aggregated closeness centrality

Trip distribution volume (TD) is varied in the range from 2,722 trips to 412. The average TD is 304, and the distribution is skewed right (refer figure 7.2).

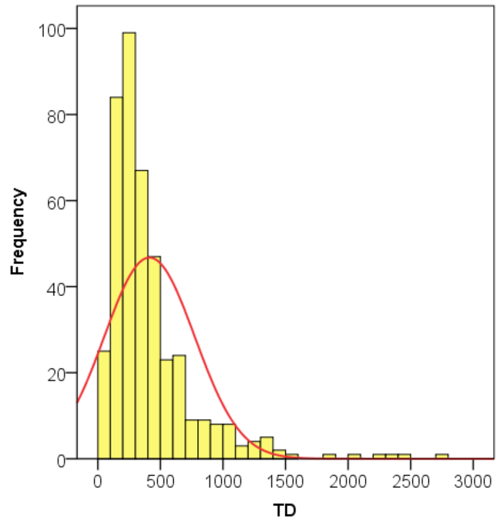


Figure 7-2: Distribution of TD values

This section examines the relationship between 'relative attractiveness of zone 'j' compare to zone 'i' [$A_{ji} \propto \left(\frac{\mathrm{ACC_j}}{\mathrm{ACC_i}}\right)$] and the 'volume of trips distribute from zone i to j' [T_{ij}]. A_{ji} recorded a moderately strong, significant relationship with T_{ij} (r Pearson =0.674, p<0.01, r Spearman =0.501, p<0.01 and R^2=0.45) (refer figure 7.3)

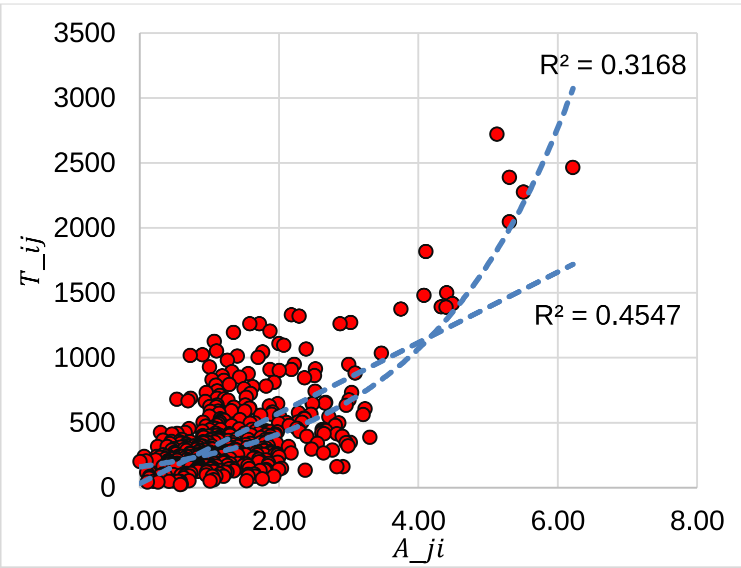


Figure 7-3: Relationship between A_{ji} and T_{ij}

7.3.2. Model formulation and validation: Trip distribution

The study utilized nonlinear regression analysis technique to formulate the trip distribution model. In this process, the study randomly selected 90% of the data for calibration (i.e., a random subset of calibration data) and 10% to validation. Table 7.1 illustrates the statistics and specifications of the best model out of the once have been developed to estimate TD.

The model recorded R^2 values of 0.753 and 0.741 for calibration and validation respectively. Further, model recorded MdAPE values of 26.61 and 21.70, and recorded MAPE values of 27.97 and 24.69 for calibration and validation respectively (refer Table 7.2). Accordingly, the models is little far from the acceptable level of goodness-of-fit ($R^2 > 0.85$, MAPE < 25).

The primary technical limitation caused this results can be the modifiable areal unit problem (MAUP), which occurs during the computation of aggregate centrality values when converting road segment values into TAZs (Refer section 6.4.3. for details). In the trip generation model which has been discussed in chapter 7, the same technical problem had occurred but could successfully overcome by adjusting centrality values more especially to trip-production and trip-attraction land use types. However, such adjustments are constrained in this situation due to the absence of location-specific O-D dataset. The available data set is zone-based and not place-based. Nevertheless, future studies to formulate and validate adjusted centrality values are essential to make this relationship established though it can be a highly resource-consuming assignment.

Table 7-1: Statistics and specifications of the model

MODEL PROGRAM a=0 b=0 c=0 d=-5

COMPUTE PRED_=a*[(A_{ji}** b)*(P_i ** c)*(D_{ij} ** d)]

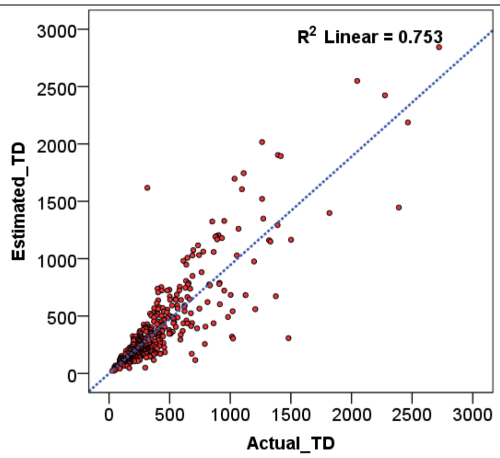
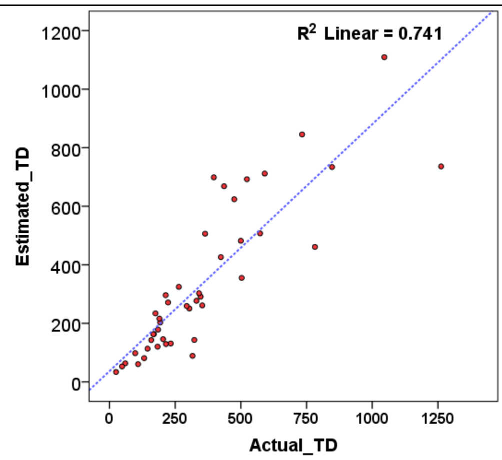
COMPUTE Estimation= 0.186*[A_{ji} **.951]*[(P_i** .817)*(D_{ij}**-0.403)]

Parameter Estimates				
Parameter	**Estimate**	**Std. Error**	**95% Confidence Interval**	
			Lower Bound	**Upper Bound**
a	.186	.042	.138	.205
b	.951	.022	.908	.994
c	.817	.040	.737	.896
d	-.403	.035	-.473	-.334

Correlation				
	T_{ij}	A_{ji}	D_{ij}	P_i
T_{ij}	1	.674**	-.093*	.162**
A_{ji}		1	-.153**	.237**
D_{ij}			1	-.185**
P_i				1

ANOVA[a]			
Source	**Sum of Squares**	**df**	**Mean Squares**
Regression	116327985.413	5	23265597.083
Residual	11196967.587	419	26723.073
Uncorrected Total	127524953.000	424	
Corrected Total	45334971.375	423	
Dependent variable: TD[a]			
a. R squared = 1 - (Residual Sum of Squares) / (Corrected Sum of Squares) = .753			

Table 7-2: Accuracy of the model

	Calibration[a]	**Validation**[b]
R^2	0.753	0.741
		
MAPE	27.97%	24.69%

Note: a: random 90% of the sample (n = 423), b: random 10% of the sample (n = 45)

7.4. Conclusion

In this chapter, the study attempted to introduce a network centrality-based aggregated model to model the trip distribution. In the proposed model, attractiveness has been expressed based on the relative centrality between trip destination zone and trip origin zone. Results revealed a moderately strong, significant relationship of 'relative centrality between trip destination zone and trip origin zone' with 'volume of trip distribution between trip origin zone and trip destination zone' ($r=0.674$, $p<0.01$ and $R^2=0.45$). The study developed a model to estimate trip distribution volume, and it recorded R^2 values of 0.753 and MAPE values of 27.97. However, the study suggest further studies to validate the accuracy of the model, primary technical limitation caused by the modifiable areal unit problem (MAUP). Nevertheless the proposed model provides two main advantages as follows.

- higly efficient because demands neither extensive O-D trip data nor trip attraction data when estimating trip distribution.
- able to capture the attractiveness generate not only due to the land use activities but also due to the accessibility. Further, the proposed model to captures both inter-zone and intra-zone accessibility.

Chapter – 8
Applicability of the Proposed Network Centrality-based Approach to Model Traffic Volume: As a Strategic Planning and Investment Tool

8.1. Introduction

The sub-objective aimed to achieve from the study explains in this chapter is to assess the applicability of the proposed network centrality-based approach as a strategic planning and investment tool. Accordingly, the chapter introduces proposed 'approach to model traffic volume by a network centrality-based simulation' as a tool for transport engineering and urban planning applications. Further, the chapter discusses the advantages and the disadvantages of the developed approach with a comparison to the existing methods.

8.2. As a tool for transport engineering and urban planning applications

8.2.1. To analyze the impact of new road proposals on the existing road network

The proposed 'approach to model traffic volume by a network centrality-based simulation' can employ in identifying the impact of new road proposals on the existing road network. To elaborate the application, this study analyzed the impact of newly introduced expressways on the existing road network. Accordingly, the study considers newly introduced two expressways as Colombo–Katunayake Expressway (KE) and Outer-circular Expressway (OCH) in CMA area (refer table 8.1 and figure 8.1). KE and OCH expressways have already constructed and opened to the public recently, so this brings up an excellent case study to compare modeled situation with empirical evidence. Frist, the study computed network centrality values of the new road network and then estimated the AADT values of road segments by using the previously developed model (refer formula 5.10a in section 5.4.2). The method of analyzing the impact of new road proposals on the existing road network using the proposed network centrality-based approach is illustrated in figure 8.2.

Table 8-1: Characteristics of newly introduced expressways

Name	No	Length (Km)	Opened
Colombo–Katunayake Expressway (KE)	E03	25.8	2013
Outer-circular Expressway (OCH)	E02	29.2	2014

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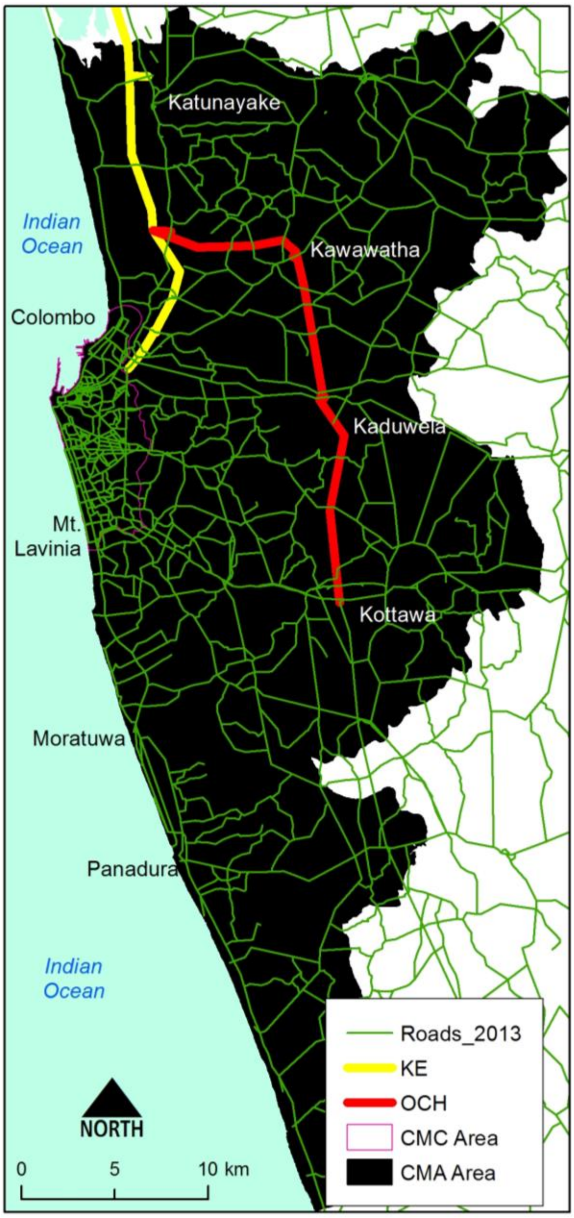


Figure 8-1: Newly introduced expressways

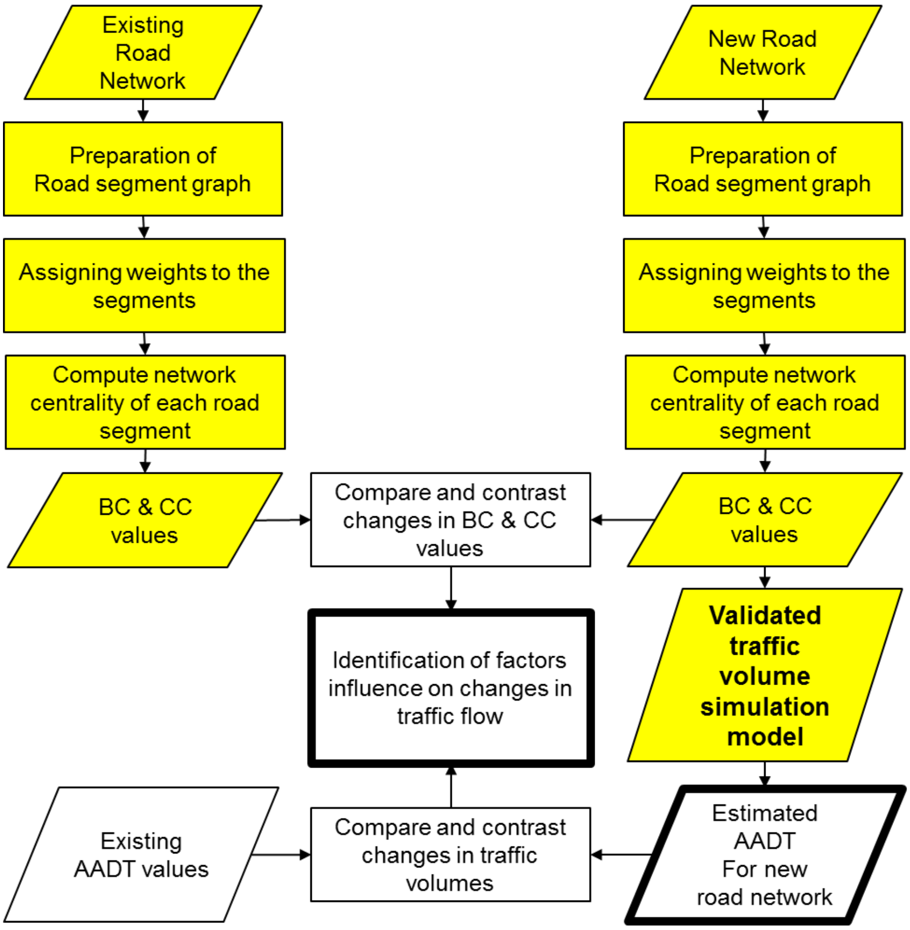


Figure 8-2: Method of analyzing the impact of new road proposals on the existing road network using the proposed network centrality-based approach
Note: Steps of proposed network centrality-based approach indicates in yellow

The existing road network has been changed with the introduction of expressways. Accordingly, the network centrality values (BC and CC) of existing road segments have subjected to a significant change. The following figures (8.3 and 8.4) depict those changes. Newly introduced expressways (KE and OCH) able to obtained very high BC values (BC > 600,000). Galle road (<70%), Negambo road (<80%), Kandy road (<55%), Biyagama road (<60%) and B596 road (<50%) recorded high percentage decrease in BC values whereas Ratnapura road (<50%), Dehiwela road (<80%), High level road (<20%) and Kotte road (<100%) recorded large percentage increase in BC values with new highways (refer figure 8.3). However, recorded change in CC values of those roads are very minimum (refer figure 8.4). Figures 8.5 depicts spatial distribution of AADT values of the existing road network and estimated AADT values for road network with newly introduced expressways. Figures 8.5 and Table 8.3 indicates that recorded changes of AADT values follow the pattern of BC values. In chapter 5 (section 5.2), the study has explained that BC values capture the pass-by trips whereas

CC values capture the to-and-from trips. So it indicated that proposed expressway attracted more pass-by trips and resulted in high traffic volume. Further, it indicated that reduction of pass-by trips drove the decrease of traffic volume in Galle road, Negambo road, Kandy road, Biyagama road and B596 road. It indicated that the proposed network centrality-based approach could employ not only in estimating traffic volume but also in analyzing the impact of new road proposals on the existing road network.

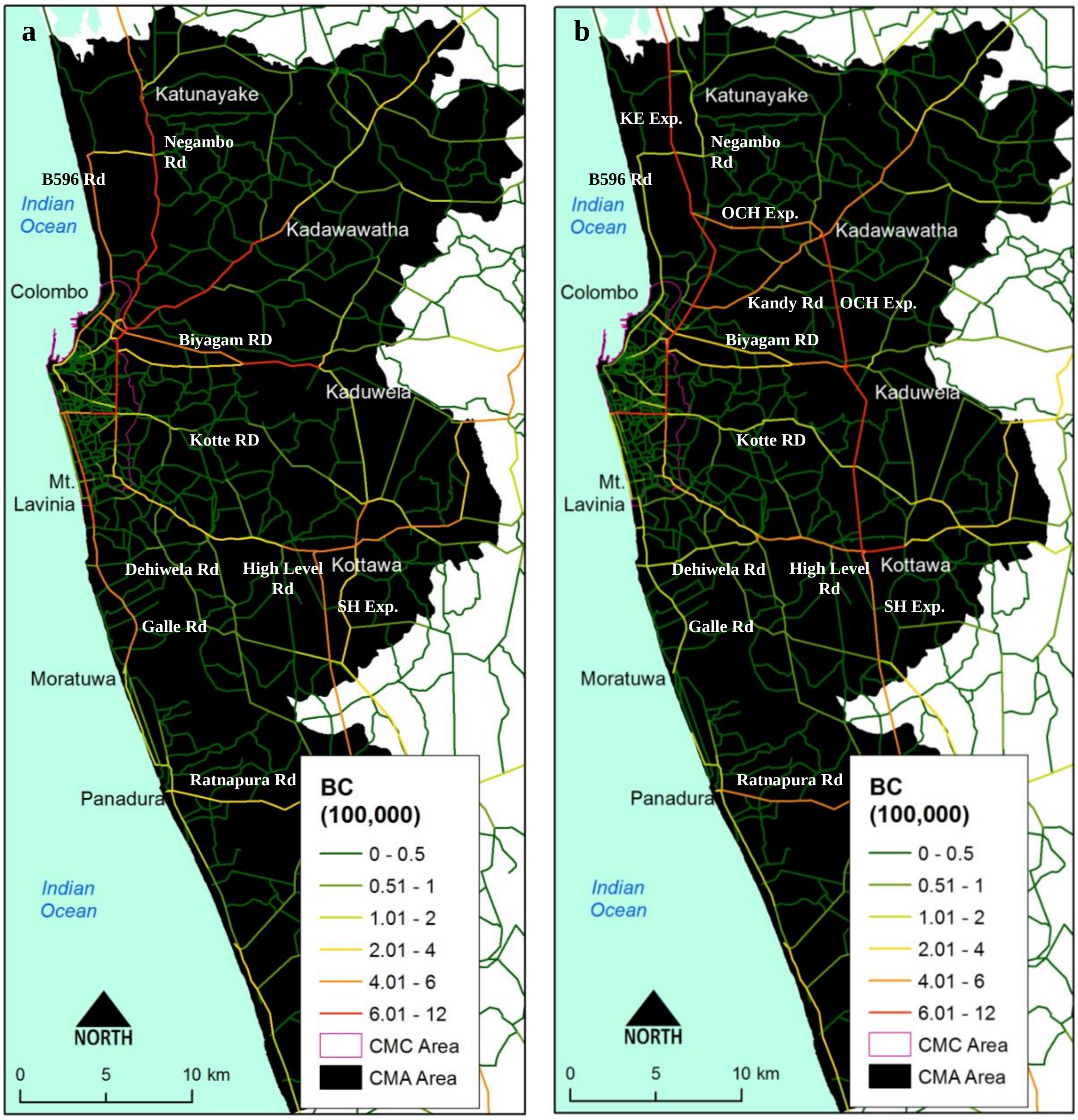


Figure 8-3: BC value of road segments a. Road network-year 2013 and b. Road network with newly introduced expressways

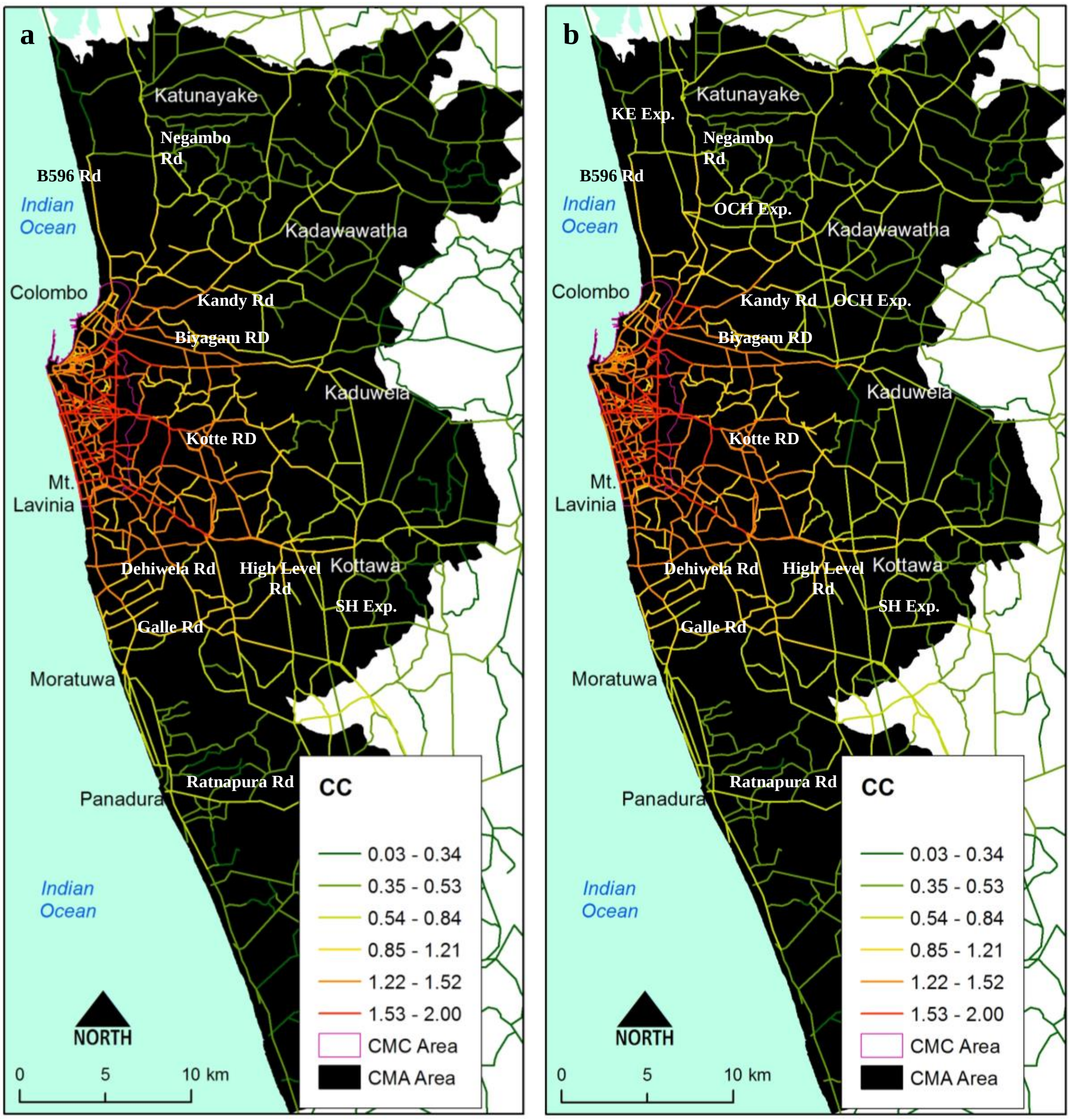


Figure 8-4: CC value of road segments a. Road network-year 2013 and b. Road network with newly introduced expressways

Table 8-2: Recorded significant changes of BC, CC and AADT

Name	**BC Change**	**CC Change**	**Traffic Volume Change**
Negambo Rd	-80%	+5%	-75%
Galle Rd	-70%	-1%	-65%
Biyagama Rd	-60%	+5%	-50%
Kandy Rd	-55%	+1%	-50%
B596	-50%	+1%	-50%
Ratnapura Rd	+50%	+1%	+50%
Dehiwela Rd	+80%	+1%	+75%
Kotte Rd	+100%	+5%	+80%

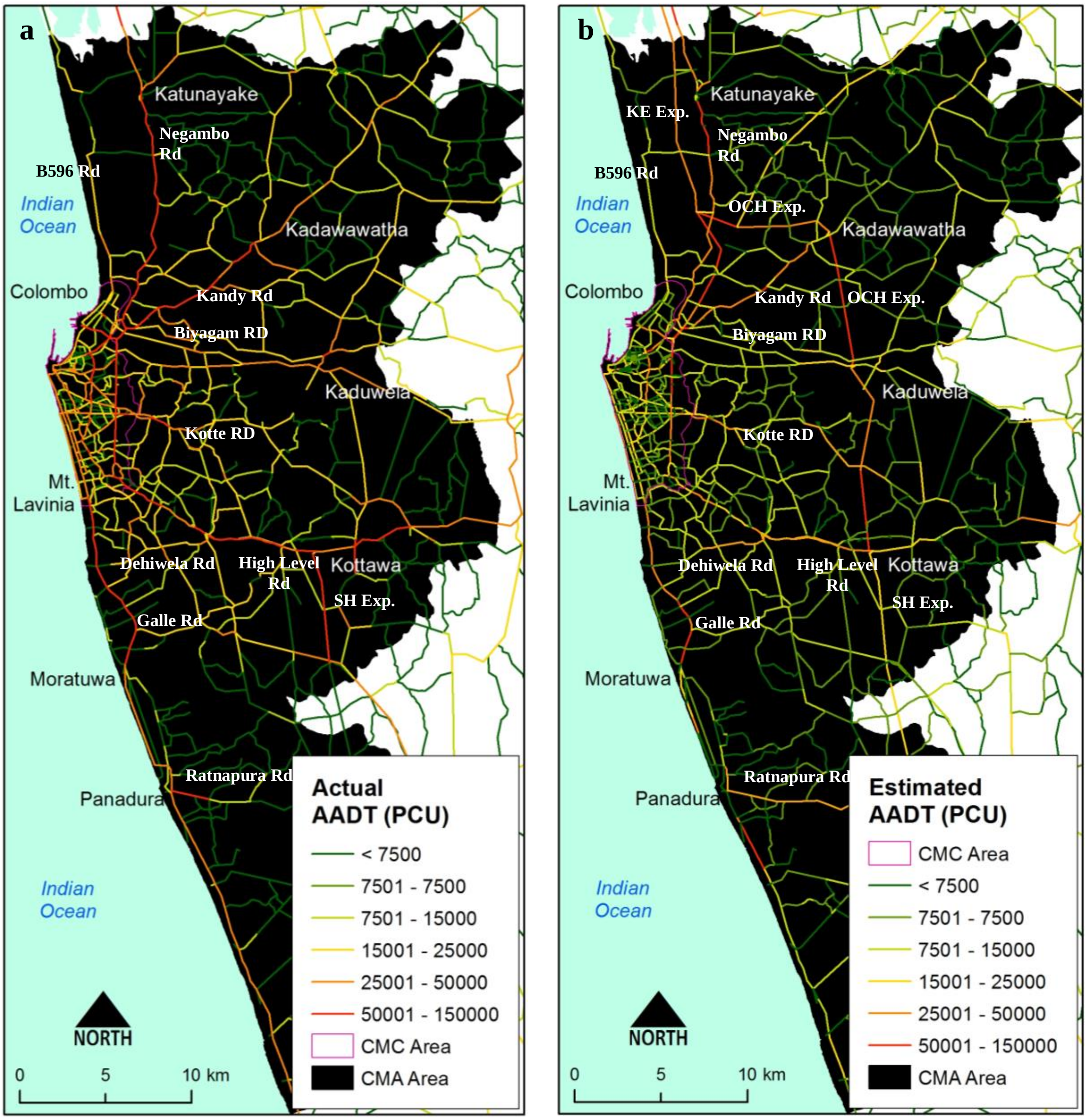


Figure 8-5: AADT value of road segments a. road network-year 2013 and b. road network with newly introduced expressways

Therefore, the study suggested that the proposed 'approach to model traffic volume by a network centrality-based simulation' can be very useful to transport engineers and planners,

- to estimate new traffic volume based on the new road network,
- to identify the changes in traffic flow due to new roads and how it impact to existing roads and
- to identify the influence of to-and-from (CC) trips and/or pass-by trips (BC) on traffic volume changes.

8.2.2. To identify the impact of the proposed urban development projects on traffic volumes of the existing road network

Emerging metropolitan area like Colombo, continuously attract investment (township or industrial) and thereby result in a series of rapid and frequent land use changes. In that case, there is a possibility to occur correspondent rapid and frequent changes traffic volumes of the existing road network. In this regard, planners need to made importance and quick decisions on the capacity of roads, traffic congestion, etc. However, it is difficult to implement four-stage travel demand model and identify those changes quickly and cost effectively. Accordingly, the chapter explains the applicability of the 'proposed network centrality-based approach' as a tool to determine the impacts of land use changes on traffic volume using a case of 'Gothamipura', Colombo township development project. 'Gothamipura township development project' is recently proposed by the urban development authority, Sri Lanka. It is a residential development project spreads over 1.8 sq km of land extent and 7500 of anticipated residential population. Figure 8.6 depicts the study area and the proposed subdivision plan.

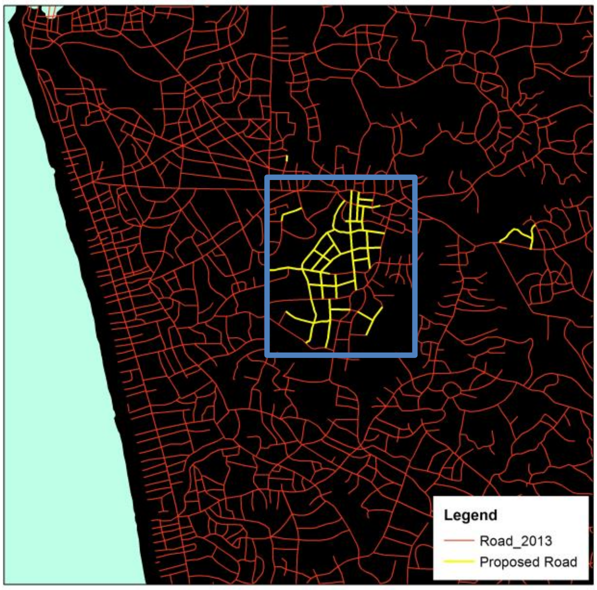


Figure 8-6: Township development project area

In this case study, existing road network has been modified including the proposed roads by the project (refer figure 8.7). Then centrality values were calculated for the modified road network and estimated the AADT values using the validated traffic simulation model (refer formula 5.10a in section 5.4.2).

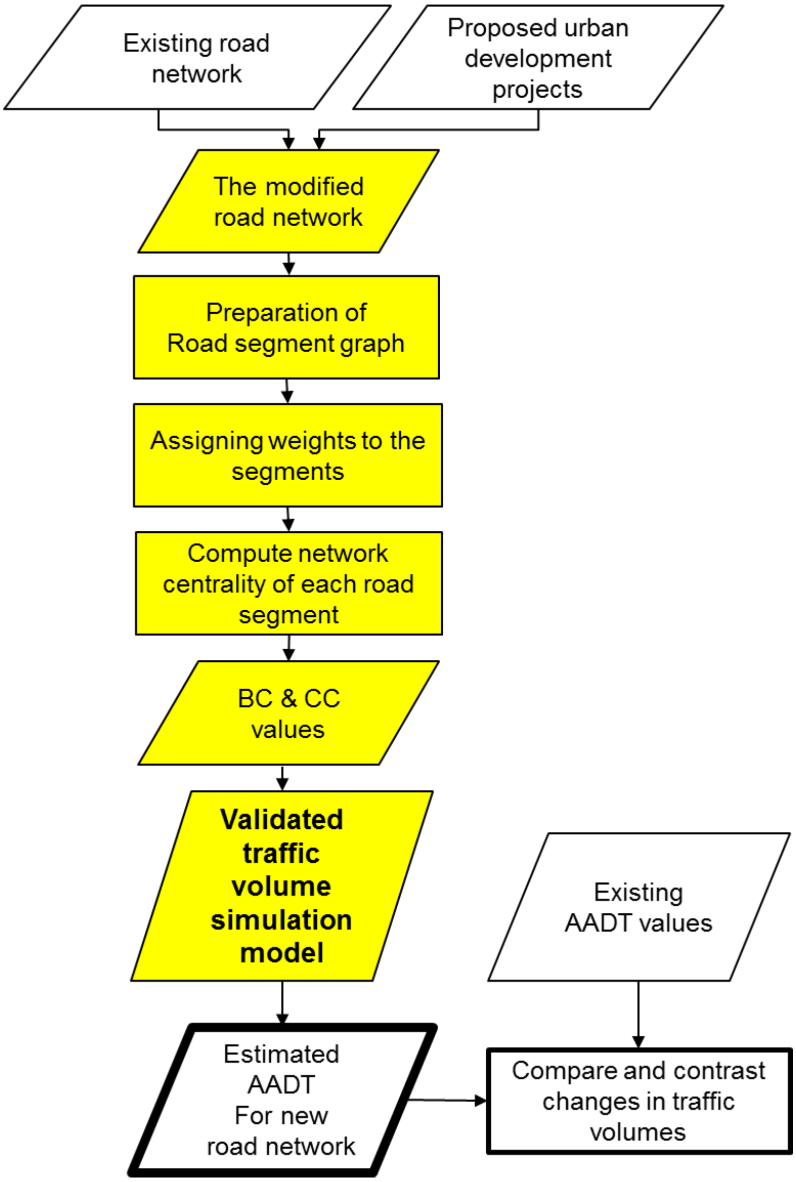


Figure 8-7: Method of identifying the impact of the proposed urban development projects on traffic volumes of the existing road network using the proposed network centrality-based approach

Note: Steps of proposed network centrality-based approach indicates in yellow

The existing road network has been changed with the proposed township development project. Accordingly, the network centrality values (BC and CC) of existing road segments have subjected to change. Figures 8.8 depicts those changes. CC values recorded major change with project compare to the current situation while BC recorded minor modification (refer Table 8.3). So it indicated that proposed township development project generate more to-and-from trips (i.e. CC) while does not attract more pass-by trips (i.e. BC). Accordingly, it resulted an increased in traffic volume at intersection B, C, I and J, and along B-K-J, C-D, D-E, D-F and H-M roadways (refer Table 8.3).

Table 8-3: Changes in network centrality values and AADT values with proposed development project

Name	CC change	BC change	AADT change	AADT with project
B	50%	1%	9%	51,000
C	42%	6%	8%	52,000
I	28%	1%	4%	51,000
J	32%	1%	5%	51,500
B-K-J	56%	10%	94%	16,500
C-D	14%	0%	10%	16,500
D-E	7%	0%	11%	19,500
D-F	10%	0%	14%	16,500
H-M	9%	0%	15%	16,500
C-H	32%	9%	8%	53,000
H-G	8%	1%	5%	83,000

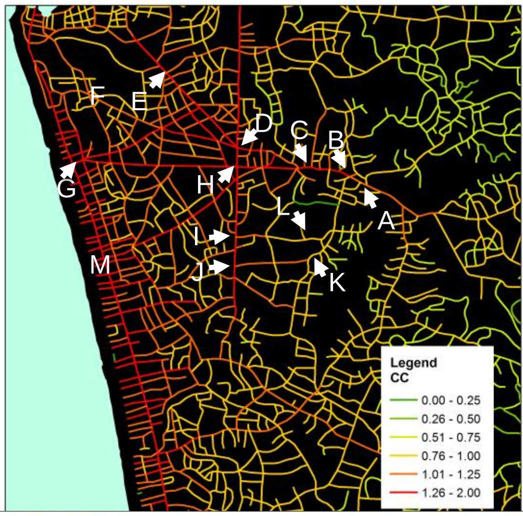
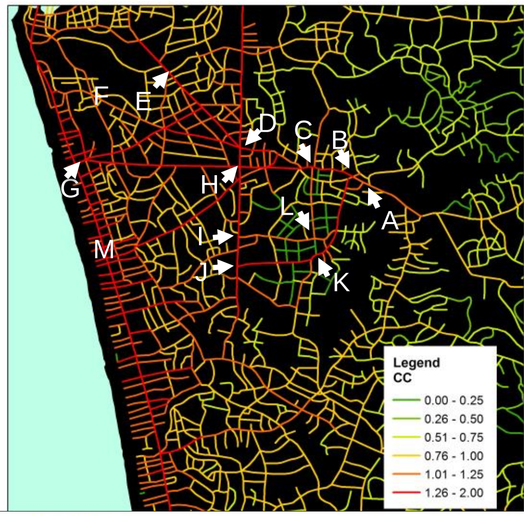
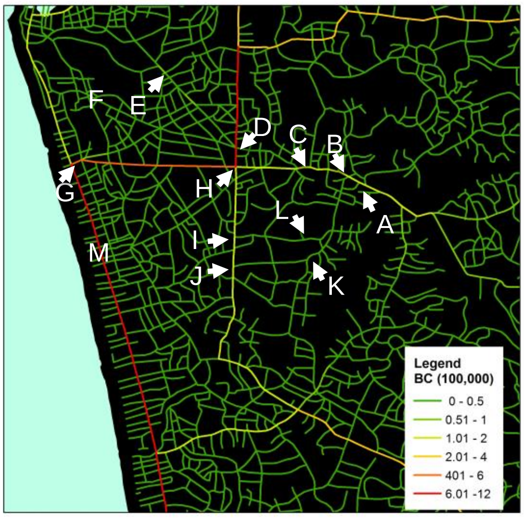
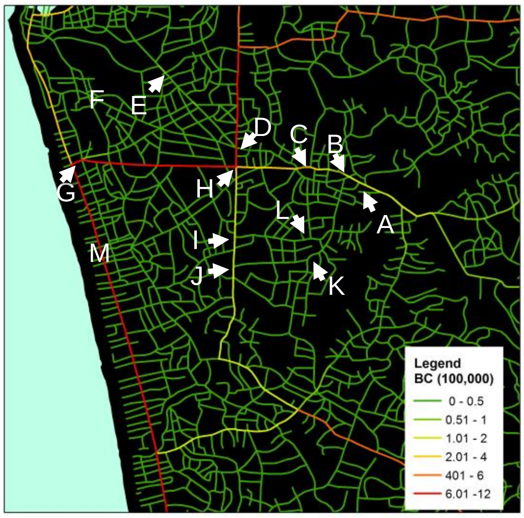
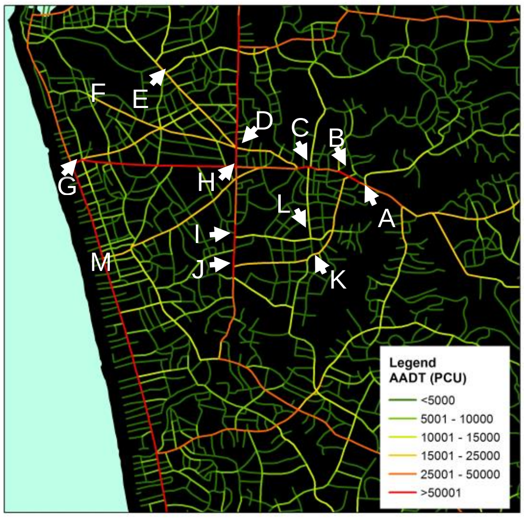
	Existing situation	With proposed development
CC		
BC		
AADT		

Figure 8-8: Compression of CC, BC and AADT value of road segments between existing road network and road network with township development project

Further, the study estimated the future trip production volume and trip attraction volume of the proposed site using models proposed in section 6.4.3. For that study used the aggregate closeness centrality values of the proposed development project site. The result indicated that proposed site would generate 8,500 trips (refer Table 8.4).

Table 8-4: Estimation of trip generation

	Model*	**TCC**	**No. Trips**
TA	TA = 124.51*TCC_TA	3.2562	405
TP	TP = 311.56*TCC_TP	26.049	8116
Trip Generation			8521

Note: *Refer section 8.4.3 for TA and TP models

Accordingly, these findings indicates that proposed the 'approach to model traffic volume by a network centrality-based simulation' can be very useful to transport engineers and planners,

- to identify the changes in traffic flow due to the proposed urban development project,
- to identify how it impact to 'to-and-from trips' (CC) and/or 'pass-by trips' (BC) volume changes and
- to estimate new traffic volume and trip generation volume based on proposed development plans or projects.

8.2.3. To examine the structural coherence of the road network

Urban streets demonstrate a hierarchical structure in the sense that a majority is trivial, while a minority is vital (Jiang, 2009). Jiang claimed that "coherent urban streets demonstrate a scaling law and characterized by the 80/20 road hierarchy principle, i.e. 80% of streets are less central (below the average), while 20% of streets are more central (above the average); out of the 20%, there is 1% of streets that are extremely well central" (2009). Recent works on structural analysis of urban street networks in terms of topological centrality in European and USA cities done by Yang et al. (2011), Hillier et al. (2005), Huang et al. (2015), Levinson (2012), Wang et al. (2012), Gao et al. (2013) have also supported the above claim. Accordingly, this study introduced the proposed 'approach to model traffic volume by a network centrality-based simulation' can use as a tool to identify the structural coherence of transport networks. As an example, the study compares and contrasts the structural coherence between existing CMA road network (2013) and road network with newly introduced two expressways (i.e., KE and

OCH). In this case, the study used computed network centrality values of road segments and analysis the cumulative percentage distribution of road length with cumulative percentage distribution of BC for the year 2013 and with KE and OCH expressways.

Figures 8.9 depicts the cumulative percentage distribution of road length according to the network centrality values. The distribution of BC values of both road networks are highly right-skewed. Further, the study noted in terms of BC, the percentage of more central (above the average) streets is less than 20% (for 2013 road network, it is 2.86%, and for road network with KE and OCH expressways, it is 3.79% refer Table 8.5) of the length of the total road network. It indicated that the centrality of the road network of the CMC is far below the 80% rule regarding BC values, for the existing situation as well as with proposed expressways. It indicated that the road network of CMA lacks structural coherence which causes inefficiency and capacity problems. “The urban web self-organizes itself as a hierarchical and it reinforce the heterogeneity and diversity that characterize living cities, ….therefore multiplicity rule that can be applied to urban planning and design” (Jiang, 2009).

Table 8-5: The percentage distribution road length by hierarchy of BC values

Hierarchy levels	% of road length (L)	
	Road network-2013	Road network with two expressways
Top 1%	0.05%	0.08%
Top 20%	0.53%	0.98%
Above the average	2.86%	3.79%
Below the average	97.14%	96.21%
Bottom 20%	86.56%	72.59%
Bottom 1%	43.54%	45.87%

Accordingly, the study recommends transport engineers and planners to make attention on this issue and develop suitable road network while overcoming the problems associated with the structural coherence of road network. Further, these findings indicated that the proposed ‘approach to model traffic volume by a network centrality-based simulation’ could be very useful to transport engineers and planners simulate not only traffic volume but also analysis the structural coherence of road network.

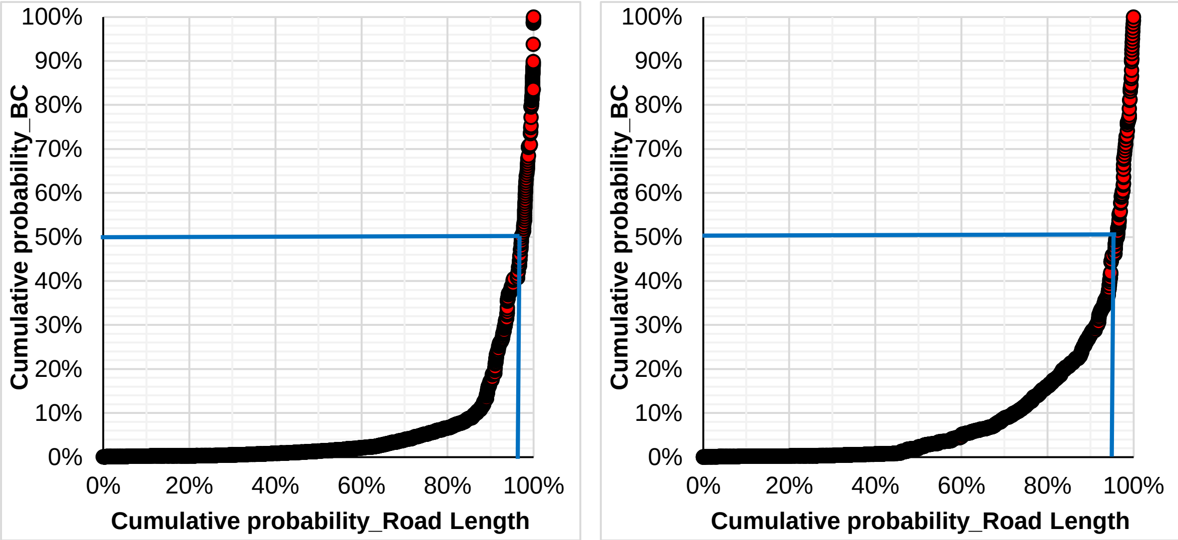


Figure 8-9: Cumulative percentage distribution of road length with BC values a. Road network-2013 and b. Road network with two expressways

8.3. Advantages and the disadvantages of developed approach with comparison to the existing methods

As mentioned in the research need section, this study aim to develop approach to overcome the barriers in estimating and predicting traffic volume such as lack of updated land use data, implementing cost and technical know-how (Hamad & Faghri, 2003), (Pucher, et al., 2005), (Paul, 2009), (TRL report cited in Cairns, 2011), (Jayasinghe & Munshi, 2014), (Hamad, et al., 2015). Findings of this study indicated that proposed 'approach to model traffic volume by a network centrality-based simulation' as a capable tool to estimate traffic volume and predict traffic volume of road segments based on new scenarios in the road network and land use changes. Table 8.5 assesses the advantages and the disadvantages of the proposed 'approach to model traffic volume by a network centrality-based simulation' with conventional four stage travel demand modeling process and activity and tour-based modeling system under four criteria' i.e. computational capabilities, simulation capabilities, suitability of policy analysis and operational requirements. Conventional four stage travel demand modeling process and 'activity and tour-based modeling system' often largely land use and O-D data dependent and required higher level computation capabilities while the proposed approach required only transport network data and able to implement in publicly available GIS software. Accordingly, the proposed approach has fewer development, application, and maintenance time and costs. Further, the proposed approach also able to simulate long term traffic volume changes. Conventional four stage process is based on zone data and hampered by the lack of dynamic interaction with transport network and land use system (Bureau of Transport Economics, 1998), (Shivakumar, 2007). The proposed approach is developed based on wider theoretical base as integrating between transport network and land use systems, the city as movement economics, human cognitive behavior; therefore it can produce long-term prediction while capturing essential urban dynamics. Further, the proposed approach is useful for scenario generation from transport network aspect as well as land use aspect. However, the proposed approach has moderate level policy sensitivities, although it is sensitive to the land uses, transport and urban design regulations it is less sensitive to transport mode pricing policies. Further, the proposed approach is incapable of explaining the competition between different types of transport modes. Therefore, the approach is insensitive to mode choice. The proposed approach can implement at the strategic zonal level (i.e. TAZs as well as block level) and transport network level, which is vital for evaluation investment decisions. This analysis indicated that the proposed approach is a desire to analyze many scenarios quickly and less expensive to implement and apply.

Table 8.7 assesses the advantages and the disadvantages of the proposed approach with direct demand modeling based on roadway characteristics and socioeconomic factors, modeling based on image-based data and modeling based on location-based social network data. Better predictability (traffic volume), incorporated land use transport interaction and consider route choice behavior are key advantages of proposed method compared to the other modeling approaches. In terms of operational requirements, proposed approach recorded advantage position compare to image-based data method and location-based social network method use to less data input and able to implement in basic GIS software and hardware tools.

By considering all advantages and the disadvantages, it can be concluded that the proposed 'approach to model traffic volume by a network centrality-based simulation' as a strategic, cost effective and technically efficient approach compare to the existing methods.

Table 8-6: Comparison of proposed 'approach to model traffic volume by a network centrality-based simulation' with conventional four stage travel demand modeling process and activity and tour-based modeling system

Criteria's		**Conventional four stage travel demand modeling process ***	**Activity and tour-based modeling system****	**Proposed 'network centrality-based' approach**
Computational capabilities	Geographical area	Moderate (City to regional)	Moderate (City to regional)	Moderate (City to regional)
	Network analysis	High (Link and nodes)	High (Link and nodes)	High (Link and nodes)
	Zone-based analysis	High	High	High
	Block level analysis	No	Moderate	High
	Person/ HH details	Moderate	High	No
	Time periods analysis	Moderate (Ave. day, peak and off-peak time)	High (Hourly)	Low (Average day)
	System optimization	Moderate	High	Moderate
	Stochastic effects	Low	Moderate	High
Simulation capabilities	Traffic volume estimation	High	High	High
	Long term traffic prediction	Low	High	High
	Land use transport interaction	Low	High	High
	Trip generation	Moderate	High	High
	Trip distribution	Low	High	Moderate
	Route choice	Low	High	High
	Mode choice	Low	High	Low
Suitability of policy analysis	Transport regulations	Moderate	High	Moderate
	Land use regulations	Moderate	Moderate	High
	Urban design regulations	Low	Moderate	Moderate
	Pricing policies	Moderate	High	Low
	Investment policies	Moderate	High	High
	Welfare implications	Low	High	Moderate
Operation requirements	Easy of runtime	Moderate	Low	High
	Computational machinery	Moderate	High	Low
	Software	Moderate	High	Low
	Data	Moderate	High	Low
	Cost	Moderate	High	Low

Source: * (Bureau of Transport Economics, 1998), ** (Castiglione, et al., 2015)

Table 8-7: Comparison of proposed 'approach to model traffic volume by a network centrality-based simulation' with direct demand modeling approaches

Criteria's		Roadway characteristics and socioeconomic factors*	Image-based data*	Location-based social network*	Proposed 'network centrality-based' approach
Computational capabilities	Geographical area	Moderate (City to regional)	Moderate (City to regional)	High (Local to regional)	Moderate (City to regional
	Network analysis	High	Moderate	Low	High
	Zone-based analysis	Low	Moderate	High	High
	Block level analysis	Low	Moderate	High	High
	Person/ HH details	Moderate	Low	Moderate	No
	Time periods analysis	Low (Ave. day)	Low (Ave. day)	High (Hourly)	Low (Ave. day)
	System optimization	Moderate	Low	Low	Moderate
	Stochastic effects	Low	Low	High	High
Simulation capabilities	Traffic volume estimation	Moderate	Moderate	Moderate	High
	Long term traffic prediction	Moderate	Low	Low	High
	Land use transport interaction	Moderate	Low	Low	High
	Trip generation	Moderate	Moderate	High	High
	Trip distribution	Low	Low	High	Moderate
	Route choice	Moderate	Low	Moderate	High
	Mode choice	Moderate	Low	Moderate	Low
Suitability of policy analysis	Transport regulations	Moderate	Low	Low	Moderate
	Land use regulations	Low	Moderate	Low	High
	Urban design regulations	Low	Moderate	Low	Moderate
	Pricing policies	Moderate	Low	Low	Low
	Investment policies	Moderate	Low	Moderate	High
	Welfare implications	Moderate	Low	Low	Moderate
Operation requirements	Easy of runtime	High	Low	Moderate	High
	Computational machinery	Low	High	High	Low
	Software	Low	High	Moderate	Low
	Data	Moderate	High	High	Low
	Cost	Low	High	Moderate	Low

Source: *Based on literature which has been discussed in the section 1.1. Chapter 1

Table 8-8: Comparison of the proposed approach with the existing works based on network centrality and traffic volume

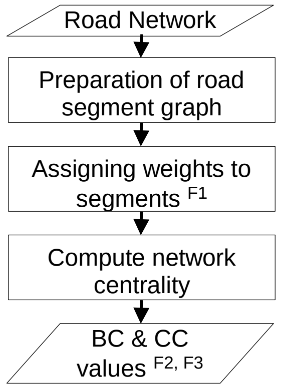
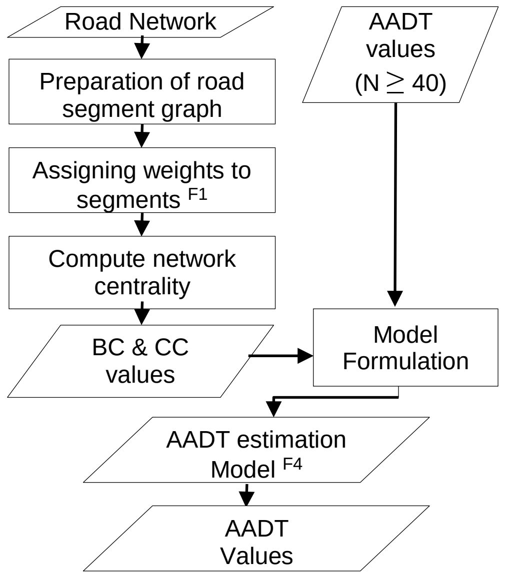
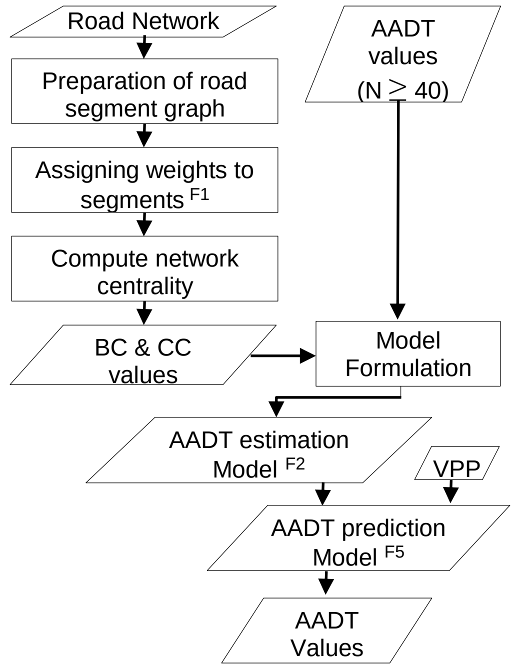
Criteria's	Previous centrality-based methods*	Proposed 'network centrality-based' approach
Traffic volume on road segments	Consider predominately flow of through trips (i.e. pass-by trips)	Considered both flow of through trips (i.e. pass-by trips) and land use generated trips (i.e. from-to trips)
Trip generation at zones	-	Model based on aggregate zonal level closeness centrality variable
Trip distribution among zones	-	Model based on relative aggregated closeness centrality variable
Route-choice	Consider influence of topological characteristics of road network	Considered influence of both topological characteristics and mobility characteristics of road network
Long-run elasticity of road traffic demand	Not considered	Included a factor, i.e., Vehicles Per Persons per year ▪ This factor captures the temporal and spatial influences of demographic and economic conditions of road traffic demand.
Relationship analysis between traffic flow	Only correlation and regression analysis to explain traffic flow	Developed models (model formulation and validation) ▪ Internal validation with random subsets ▪ External validation with actual AADT values in three case studies

Note: *Based on the literature which has been discussed in the section 1.2 in chapter 1)

8.4. How to use proposed 'approach to model traffic volume by a network centrality-based simulation' in planning and engineering practice.

The study developed a 'tailor-made guidance' and a 'centrality spectrum' based on the findings of the study. The tailor-made guidance describes three application options for using the proposed network centrality-based simulation approach with varying levels of data availability (refer section 8.4.1). The proposed centrality spectrum illustrates a hierarchal of traffic volume and road types with different levels of centrality values.

8.4.1. Tailor made guidance: Options for network centrality-based simulation approach to model traffic volume

Options	**1. Pattern analysis**	**2. Traffic volume estimation**	**3. Traffic volume prediction**
Required data	▪ Road network	▪ Road network ▪ Actual traffic counts (AADT volume) (N ≥ 40)	▪ Road network ▪ Actual traffic counts (AADT volume) (N ≥ 40)) ▪ Vehicle growth rate (VPP)
Method			
Formulae	F1: $PD_{ij} = f(GMD_{ij}.MD_{ij}.Ty_{ij})$ F2: Pass-by trips = $f(BC_i)$ F3: To-and-From(O-D) trips = $f(CC_i)$	F1: $PD_{ij} = f(GMD_{ij}.MD_{ij}.Ty_{ij})$ F4: $T_i = f(CC_i . BC_i)$ Where, $CC_i = \sum_{j\in N, j\neq i} \frac{1}{d_{ij}}$ $BC_i = \sum_{j,k\in N; j\neq k; k\neq i} \frac{p_{jk(i)}}{p_{jk}}$	F1: $PD_{ij} = f(GMD_{ij}.MD_{ij}.Ty_{ij})$ F2: $T_i = f(CC_i . BC_i)$ F5: $T_i = f((CC_I . BC_I) * VPP)$ Where, $VPP = VPP_{A(t+n)}/VPP_{At}$
Outputs	⇨ BC & CC values of each road segments	▪ Traffic estimation model ⇨ AADT values of road segments	▪ Traffic volume prediction model ⇨ AADT values of road segments
Applications	▪ Analysis of urban morphology (i.e study of the form of human settlements and the process of their formation and transformation) ▪ Analysis of structural coherence of the road network	▪ Preparation of Road Improvements Plans ▪ Preparation of Traffic Management Plans	▪ Preparation of Road Network Plans and Transport Plans ▪ Preparation of Regional Structure Plan, Sub- Regional Structure Plan and for Land Use Planning

PD_{ij} = Path distance between links 'i' and 'j' , GMD = Geometric distance , MD= Metric distance , Ty = A utility score, which was given based on the road type , CC_i = Closeness centrality of road segment 'i' , BC_i= Betweenness centrality of road segment 'i' , d_{ij}= Distance between road segment 'i' and 'j' along the shortest path (i.e. PD_{ij}), N = Total number of road segment in a network , p_{jk}= Number of geodesics between road segments 'j' and 'k', $p_{jk(i)}$ = Number of geodesics between road segments 'j' and 'k' that passing through road segment 'i' , VPP_{At} = Total Number of vehicles registered in Area 'A' in Year 't'/ Population above 18 year in Area 'A' in Year 't'.

8.4.2. Centrality spectrum

The study developed two centrality spectrums to illustrate a hierarchal level of traffic volume and road types with varying levels of centrality values. The first spectrum illustrates the hierarchal level of traffic volume with different levels of centrality values (refer figure 8.10). This spectrum was developed based on the findings of Colombo (CMA) case study. The AADT hierarchy spectrum illustrates the variation of AADT values according to the betweenness and closeness centrality values. This will helpful for practitioners to quickly estimate the AADT values of road segments based on network centrality values without performing modeling.

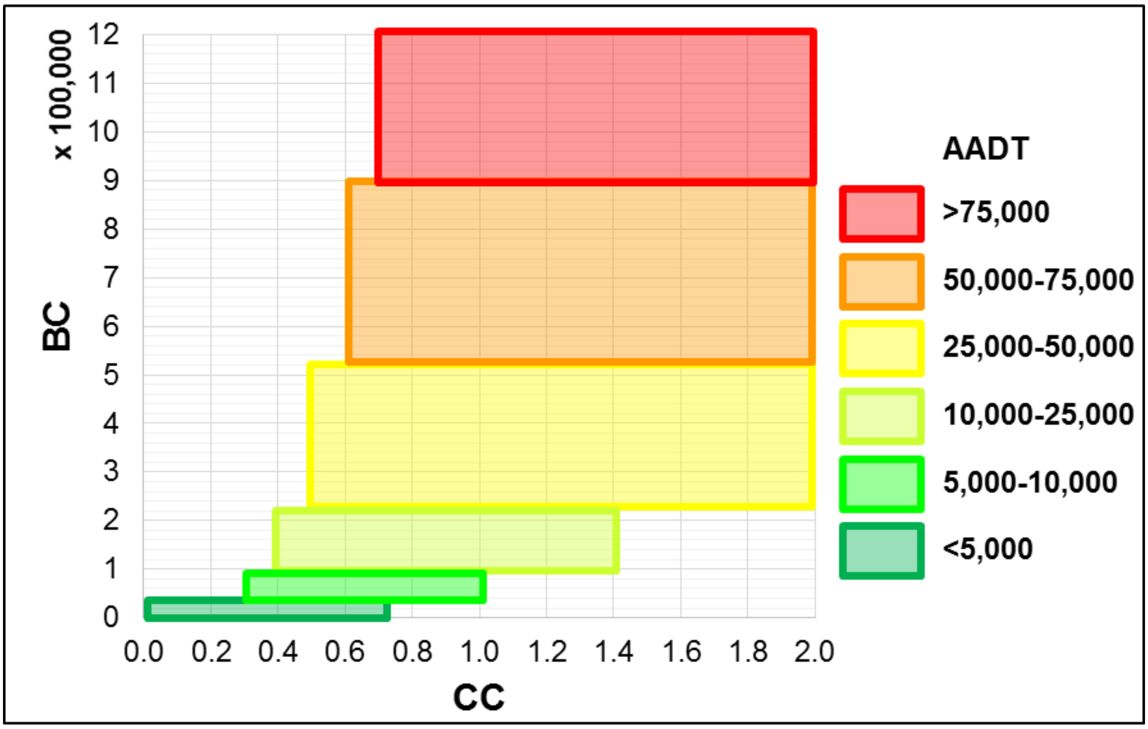


Figure 8-10: Centrality spectrum for traffic volume hierarchy

Table 8-9: Hierarchal level of traffic volume with varying levels of centrality values

AADT levels	Betweenness (BC) values in 100,000			Closeness (CC) values		
	Avg	Min	Max	Avg	Min	Max
<5,000	0.1	0.0	0.2	0.4	0.0	0.7
5,000-10,000	0.3	0.2	0.1	0.7	0.3	1.0
10,000-25,000	1.9	1.0	2.2	0.9	0.4	1.4
25,000-50,000	3.1	2.2	5.2	1.3	0.5	2.0
50,000-75,000	6.9	5.2	9.0	1.0	0.6	2.0
>75,000	10.4	9.0	11.7	1.1	0.7	2.0

Note: Avg – Average, Min – Minimum, Max – Maximum, SD - Standard Deviation

The second spectrum illustrates the road type's hierarchy with varying levels of centrality values. This spectrum was also developed based on the findings of Colombo (CMA) case study. The spectrum illustrates the centrality values of according to the hierarchy of road refer to figure 8.11. This will helpful for practitioners to identify the appropriate centrality values ranges need to achieve when designing a road network.

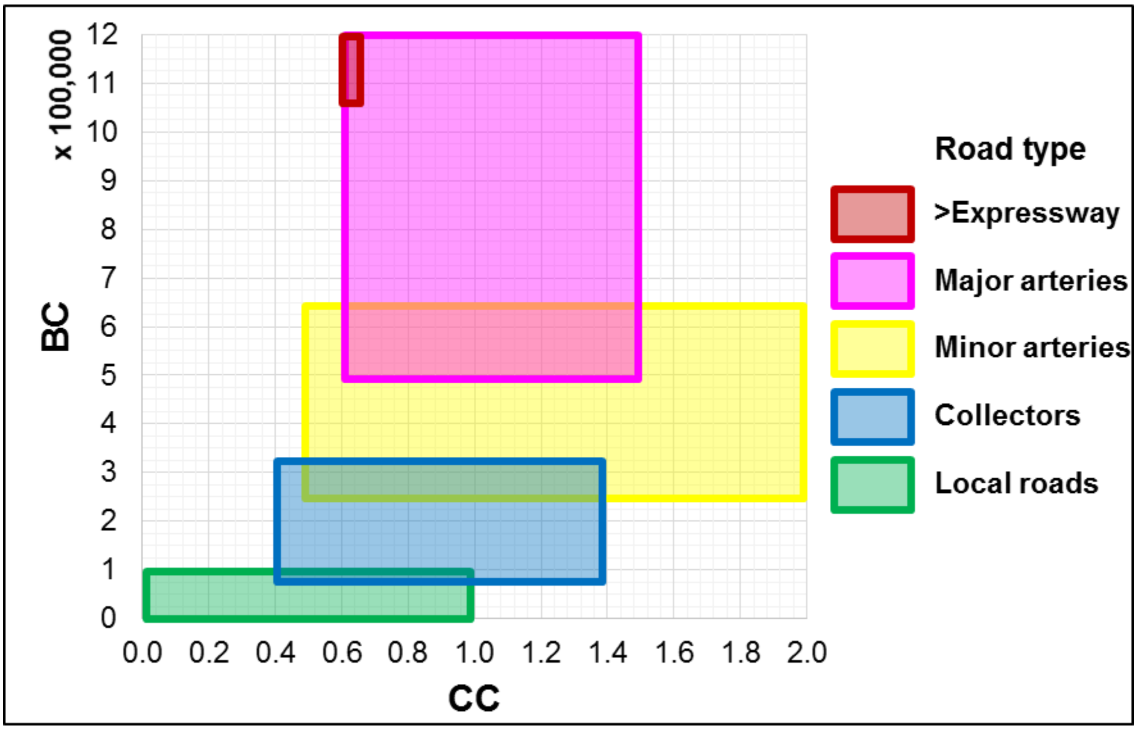


Figure 8-11: Centrality spectrum for road type's hierarchy

Table 8-10: Hierarchal level of traffic volume with varying levels of centrality values

Road types	**Betweenness (BC) values in 100,000**			**Closeness (CC) values**		
	Avg	**Min**	**Max**	**Avg**	**Min**	**Max**
Local roads	0.3	0.0	1.0	0.5	0.0	1.0
Collectors	1.7	0.9	3.2	0.9	0.4	1.4
Minor arteries	4.8	2.4	6.4	1.3	0.5	2.0
Major arteries	8.4	5.0	11.7	1.0	0.6	1.5
Expressway	10.9	10.6	11.2	0.63	0.6	0.65

Note: Avg – Average, Min – Minimum, Max – Maximum, SD - Standard Deviation

8.5. Conclusion

This chapter presented a series of examples to demonstrate the applicability of research findings. This included three important applications as

1. To analyze the impact of new road proposals on the existing road network
2. To identify the impact of the proposed urban development projects on traffic volumes of the existing road network
3. To examine the structural coherence of the road network

Findings of this chapter indicated that proposed 'approach to model traffic volume by a network centrality-based simulation' can be very useful to transport engineers and planners to

- estimate traffic volume based on new road projects,
- estimate traffic volume and trip generation volume based on proposed urban development plans or projects.
- identify the changes in traffic flow due to new roads and how it impact to existing roads,
- determine the changes in traffic flow due to the proposed urban development project and
- identify how new roads and urban development projects (land use changes) impact to to-and-from (CC) trips and/or pass-by trips (BC) volume changes
- examine the structural coherence of the road network

Accordingly, the proposed network centrality-based approach can be considered as a not only a modeling tool but also as a tool for planning and designing road network. The second part of this chapter discussed advantages and the disadvantages of developed approach, with a comparison to the existing methods. Further, the chapter introduced developed 'centrality spectrums' and 'tailor-made guidance'. The chapter concluded that the proposed 'approach to model traffic volume by a network centrality-based simulation' as a strategic, cost effective and technically efficient approach compare to the existing methods.

Chapter – 9
Conclusions and Recommendations

9.1. Approach in brief

This research has been placed in a milieu where existing methods on identification of existing vehicular traffic volumes and prediction of future traffic scenarios of road network were hampered by data, cost and technical know-how constraints. To overcome those constraints, this study has developed an approach to model traffic volume by a network centrality-based simulation. Centrality measures were initially a popular concept in the fields of social network analysis and computer engineering and applied to the field of spatial planning to explain matters related to the accessibility. Several studies have already claimed network centrality as an alternative approach to model pedestrian and vehicle traffic flows. Some of the case studies have revealed a significant correlation between topological network centrality and traffic volumes. The next step of this line of research was to develop a method to model vehicular traffic volume on roads following the recommended standards in the fields of traffic and transport planning and engineering. Further, the proposed method needed to be capable of overcoming the limitations of previous studies. Two of such key limitations addressed in this study were on how to incorporate roadway mobility characteristics into the topological distance and, how to improve centrality measures to capture both traffic volume generated due to the 'pass-by' trips and 'O-D' trips.

The primary objective of the study was to develop an approach to model traffic volume by a network centrality-based simulation. In order to achieve the objective, the study was built on five stages. In the first stage of the study surveyed literature on traffic volume estimation and travel demand prediction methods, the concept of network centrality and its possibility to apply as an alternative method to model vehicular traffic volume. In the second stage, the study theoretically validated the concept of 'traffic volume as a function of network centrality'. In the third stage, the study carried out two pilot studies and examined the importance of travel time relative to topological distance, the strength of the relationship between network centrality and traffic volume, whether the relationship changes over the measures and methods of computing network centrality values as well as over the type of vehicles. In the fourth stage, the study formulated a set of models and proposed a method to model traffic volume based on network centrality. The validity of the proposed model has been tested by five independent validation approaches. The first approach was an internal cross-validation that the study randomly selected 90% of the AADT values for calibration and 10% to validation of CMA area for year 2013. The second approach was to externally validate the proposed model by using AADT values of the same area (CMA) for year 2004. The third approach tested the proposed model's competence in comparison to the AADT values estimated for CMA for year 2035 by multistep demand modeling. The fourth approach of validation tested the power of the model to estimate trip distribution and trip generation. The fifth validation approach tested the validity of the proposed model with the actual AADT values of two alternative case study areas in Sri Lanka i.e., Galle Municipal-council Area and Kandy Municipal-council Area. In the fifth stage, the study assessed the applicability of the proposed network-centrality-based approach as a strategic planning and investment tool with reference to three demonstrations and compared and contrasted the advantages and disadvantages of the proposed approach with comparison to the existing methods.

9.2. Key findings

Key findings of this study which has been derived from the theoretical validation, pilot studies, model formulation and validation and assessment of applicability can be summarized as follows.

Based on the theoretically validation;

1. Trip generation, trip distribution and trip volume on a given road segment can be explained as a function of centrality.

2. Activities, land uses, transport networks and trip makers' movements are interrelated, and there are reciprocal relationships; between transport networks and trip makers' movements; between transport network and land uses, and between transport networks and activities. This reciprocal relationship can be measured by the centrality of the transport network.

Based on pilot studies;

3. It is more appropriate to consider geometric distance (i.e. angular change) compare to real travel time when considering the path distance in computing centrality.

4. It is possible to explain traffic volume based on network centrality, and it is more appropriate to consider both closeness and betweenness centrality measures, and use road segment graph and a suitable radius for the road network boundary when computing network centrality.

Based on the model formulation and validation;

5. The proposed models for simulating traffic volume of road segments by utilizing network centrality values as endogenous variables recorded an accepted level of predictability and accuracy (R^2> 0.85, MdAPE <30% and RMSE<30%). Refer figure 9.1 for more details.

   5.1. Centrality values computed based on the proposed path distance (i.e. PD), which captures angular changes, metric distance and mobility by road type, recorded higher R^2 value (i.e., R^2 of CC_PD=0.32 and R^2 of BC_PD=0.69) compare to the centrality values computed based only on topology (i.e. angular change) of the road network. (i.e., R^2 of CC_GMD=0.08 and R^2 of BC_GMD=0.34).

   5.2. The proposed model (R^2>0.85), that captures traffic volume on road segments using both betweenness centrality and closeness centrality values as endogenous variables recorded a very high level of accuracy compare to the previous centrality based studies (refer Table 1.1 in chapter 1) on vehicular traffic volume ($0.25<R^2<0.75$) as well as travel demand modeling studies ($0.65<R^2<0.95$).

   5.3. The proposed model is on a par with the international standards, particularly FHWA (R^2> 0.88)

   5.4. The mode can calibrate by using a little amount of actual observation points (N<40).

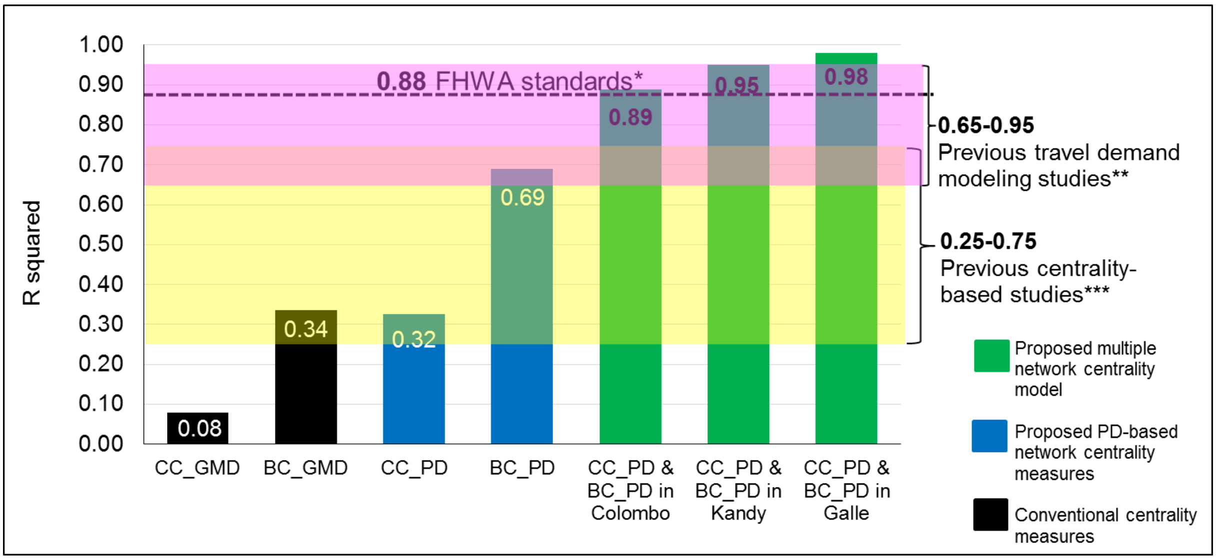


Figure 9-1: Comparison of accuracy of the proposed approach

Note: * (FHWA, 1997), **based on (Mohamad, et al., 1998), (Zhao & Chung, 2001), (Pan, 2008), (Lowry & Dixon, 2012), (Zhong & Hanson, 2009), (Wang, et al., 2013), (Keehan, et al., 2017) ***refer Table 1.1 in chapter 1
CC_GMD: Closeness centrality computed based on geometric distance (angular changes)
BC_GMD: Betweenness centrality computed based on geometric distance (angular changes)
CC_PD: Closeness centrality computed based on proposed path distance (angular changes, metric distance, and road type)
BC_PD: Betweenness centrality computed based on proposed path distance (angular changes, metric distance, and road type)
Colombo N=1927, Kandy N=25, Galle N=23

5.5. The introduced growth factor (i.e. Vehicles per Person) made the model more dynamic and able to predict future traffic volume road segments (R^2>0.88) as accurate as the multi-step demand modeling.

5.6. Volume of trip attraction and volume of trip production at an aggregate zonal level able to be modeled by utilizing aggregated-zonal-closeness-centrality values as endogenous variables with an acceptable accuracy (R^2 > 0.85, MAPE<25%).

5.7. Trip distribution between zones was able to be explained by the 'relative centrality between trip destination zone and trip origin zone' (r=0.674, p<0.01).

Based on the assessment of applicability;

6. The proposed network centrality-based approach can be utilized as a planning and decision-making tool to model traffic volume when planning road networks.

7. The proposed ‘approach to model traffic volume by a network centrality-based simulation’ is a strategic, cost effective and technically efficient approach compared to the existing traffic volume modeling methods. Hence its applicability is prominent in the limited data available situations, cost-constraint, particularly, in the developing countries.

9.3. Contributions to the current state of knowledge and practice

1. Proposed an accurate, less data consuming, technically simpler, and financially affordable approach to model vehicular traffic volume on road segments in a road network, which is especially beneficial for limited data available situations and sophisticated multi-step demand models generally cannot afford. In the proposed concept betweenness and closeness centrality are the output of traffic volume model which simulates origin to destination trips and pass-by trips respectively, subject to a maximum trip distance. Thus it replaces all four stages of the traditional transport model.

2. Conceptualized traffic volume as a function of network centrality.

3. Demonstrated steps to follow when computing network centrality of road segments, and developed a set of models to simulate traffic volume of road segment by using network centrality values as endogenous variables.

4. Introduced multiple centrality measures which captures both pass-by trips (i.e. through-trips) and to-and-from trips (i.e. land-use-generated trips).

5. Introduced path distance variable that captures trip makers’ route-choice notions that are influenced by topological characteristics of road network and roadway mobility characteristics.

6. Introduced trip length-based moving boundary that eliminates edge effect and accounts the effect of trip length.

7. Demonstrated steps to follow when computing network centrality of zones; and developed a set of models to estimate trip attraction, trip production, and trip

generation volumes by using aggregate zone closeness centrality values as endogenous variables.

8. Introduced aggregated-zonal-level centrality variable, to capture inter-zonal and intra-zonal closeness.
9. Introduced relative-aggregated-closeness centrality variable, to capture the attractiveness of the destination zone compare to the zone of origin.
10. Demonstrated applicability of the proposed network centrality-based approach as a strategic planning and investment tool.

9.4. Recommendations`

The study has contributed with a strategic, cost effective and technically efficient approach to model traffic volume by a network centrality-based simulation. Transport planners and engineers can employ the proposed network centrality-based approach to estimate AADT values, in evaluating the condition of road networks such as safety level and the level of service and to predict traffic volume in different road network scenarios. Further, this can be utilized as a strategic planning and investment tool for evaluating cost-benefits of transport infrastructure investments, scenario building, and impact analysis of future development projects. This method is highly recommended for assignments carry out in data, time and cost constraint situations due to the following key merits.

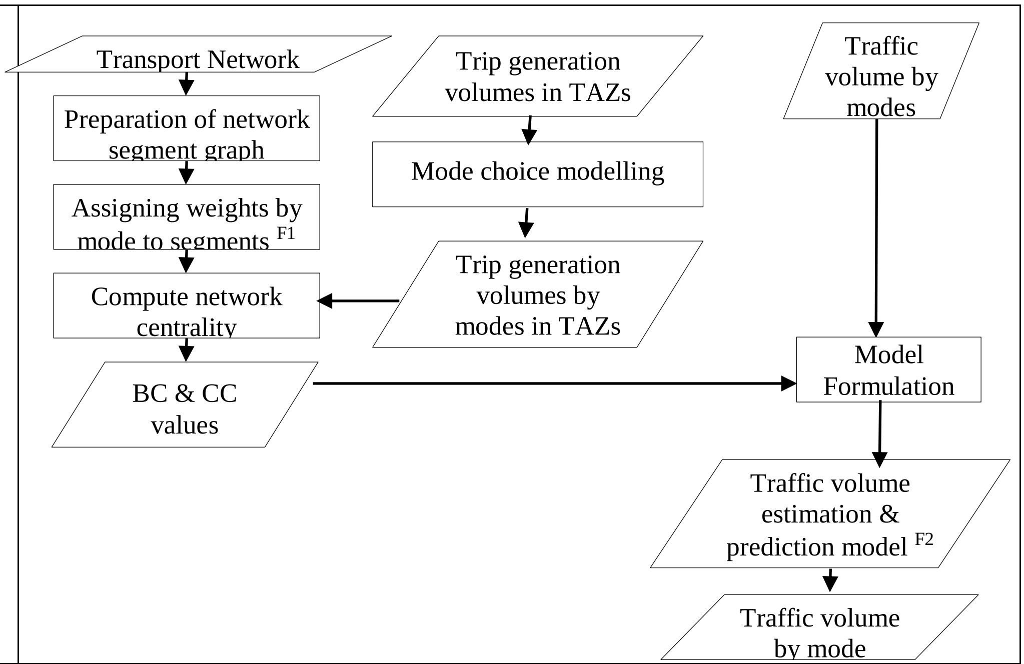
- Derived intrinsically from network centrality parameters. Hence, does not demand an extensive land use and O-D trip data
- Computed by using publicly available network analysis software. Hence, technically simple and financially affordable to execute
- Able to be completed within a short period and requires few number of coverage counts for calibration purpose. Hence, technically feasible and financially affordable
- Exhibits strong predictability at road segment levels in all type of roads. Hence, provides an opportunity to estimate AADT values in detail in regional and local scales.

The study has established an adequate means of simulating traffic volume based on a road network centrality-based approach, particularly for developing countries. However, not only in developing countries but also in any area, where collecting traffic volume counts is not affordable, or updated data is limited, and sophisticated multi-step demand modeling cannot afford, can ideally opt for this method. Validation with further case studies can increase the credibility of the model enabling to apply in a range of 'traffic volume simulation' applications in future. The study proposed an improved network centrality approach that can simultaneously account pass-by trips and from-to trips, topological characteristics and mobility characteristics of a road network. Further, the proposed approach eliminates the edge effect, accounts the influence of trip length, and captures network centrality at zonal level. Hence, this study can be considered as a constructive contribution to the emerging literature on application of network centrality analysis.

Though this study has been completed by successfully achieving the desired objectives, it opens a path for further studies on applying network centrality transport modeling. Few of the future research areas may include, but not limited to the followings.

- Model temporal changes (Peak and Off-peak, Time intervals in a day) in vehicular traffic volume based on network centrality
- Model vehicular traffic volume by type of vehicles. Refer table 9.1 for proposed method to model vehicular traffic volume by type of vehicles based on network centrality. However, this method has been left for future testing with real traffic and trip generation volumes
- Model trip volumes in a multi-modal transport system based on network centrality
- Model intra-zonal trip distribution based on network centrality

Table 9-1: Possible method to model vehicular traffic volume by type of vehicles based on network centrality*

<table>
<tr><td>Method</td><td>
</td></tr>
<tr><td>Formulae</td><td>

F1: $\mathrm{PD_{mij}} = \mathrm{f}(\mathrm{GMD_{ij}}.\ \mathrm{MD_{ij}}.\ \mathrm{Ty_{mij}})$

F2: $\mathrm{T_{mi}} = \mathrm{f}\,(\mathrm{CC_{mi}}\,.\,\mathrm{BC_{mi}})$

Where,

$$\mathrm{CC_{mi}} = \sum_{j \in N, j \neq i} \frac{\mathrm{TG_{mi}} * \mathrm{TG_{mj}}}{\mathrm{d_{mij}}}$$

$$\mathrm{BC_{mi}} = \sum_{j,k \in N; j \neq k; k \neq i} \frac{\mathrm{p}_{mjk_{(i)}}\,(\mathrm{TG_{mj}} * \mathrm{TG_{mk}})}{\mathrm{p_{mjk}}}$$

$\mathrm{PD_{mij}}$= Path distance between links ‘i’ and ‘j’ by mode ‘m’ , GMD = Geometric distance , MD= Metric distance , Tym = A utility score, which was given based on the road type related to the mode ‘m’, $\mathrm{CC_{mi}}$ = Closeness centrality of road segment ‘i’ by mode ‘m’, $\mathrm{BC_{mi}}$= Betweenness centrality of road segment ‘i by mode ‘m’’, $\mathrm{d_{mij}}$= Distance between road segment ‘i’ and ‘j’ along the shortest path (i.e. $\mathrm{PD_{ijm}}$) by mode ‘m’, $\mathrm{p_{mjk}}$= Number of geodesics between road segments ‘j’ and ‘k’ by mode ‘m’, $\mathrm{p}_{mjk_{(i)}}$= Number of geodesics between road segments ‘j’ and ‘k’ that passing through road segment ‘i’ by mode ‘m’, $\mathrm{TG_{mi}}$ = Volume of trip generated in road segment ‘i for mode ‘m’

</td></tr>
<tr><td>Required data</td><td>

- Transport network
- Actual traffic counts by modes (N ≥ 40)
- Trip generation volumes in TAZs or Trip generation volumes by modes in TAZs if not Land use data

</td></tr>
<tr><td>Outputs</td><td>

- Traffic volume by mode prediction model
- Traffic volume of road segments by mode

</td></tr>
<tr><td>Applications</td><td>

- Preparation of Comprehensive Transport Plans
- Preparation of Regional Structure Plan, Sub- Regional Structure Plan and for Land Use Planning

</td></tr>
<tr><td colspan="2">* Note: This method has been left for future testing with real traffic and trip generation volumes</td></tr>
</table>

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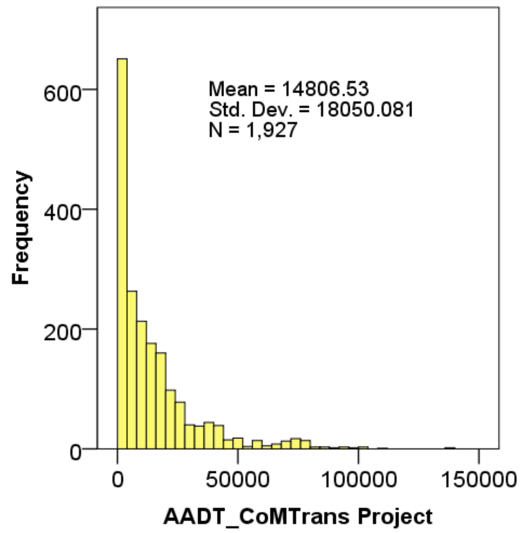
Appendices

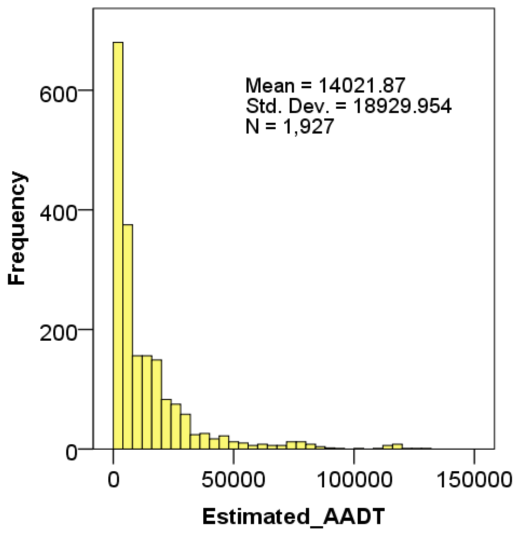
1. The characteristics of trip-makers who participated in the online questionnaire survey (Road type - AHP Analysis)

Characteristics	**% of participants**
Sex	
Male	55%
Female	45%
Predominantly use mode	
Car	40%
Motorcycle (MC)	30%
Bus	30%
Age	
20-30	20%
30-40	40%
40-50	25%
50-60	15%

N= 100

2. Distribution of a.) AADT_CoMTrans Project and b.) estimated AADT based on the Eq.-5.10a





3. Validation results according to different random subsets Colombo MA (CMA) Area – Year 2013

a.) Random subsets 90:10

Specifications		**Coefficient value**	**Value**	**t-value**	**p-value**
Variables [a]	Constant	3.865		38.704	<.0001
	$lnBC_{(PD\_15km)}$	0.591	.792 [b]	80.519	<.0001
	$lnCC_{(PD\_15km)}$	2.031	.246 [b]	24.959	<.0001
F Value			5731.78 (<0.0001)		
Presence of multicollinearity					
Tolerance			0.783		
VIF			1.277		
Goodness-of-fit					
Calibration [c]	R^2		0.869		
	Adjusted R^2		0.869		
	MdAPE		28.98%		
Validation [d]	R^2		0.900		
	MdAPE		29.88%		

Note : a: Response variable lnAADT; b: Beta value, i.e., standardized coefficients value
c : random 90% of the sample, N=1927

b.) Random subsets 80:20

Specifications		**Coefficient value**	**Value**	**t-value**	**p-value**
Variables [a]	Constant	3.837		35.651	<.0001
	$lnBC_{(PD\_15km)}$	0.594	.791 [b]	75.185	<.0001
	$lnCC_{(PD\_15km)}$	2.002	.242 [b]	23.000	<.0001
F Value			5093.36 (<0.0001)		
Presence of multicollinearity					
Tolerance			0.770		
VIF			1.299		
Goodness-of-fit					
Calibration [c]	R^2		0.868		
	Adjusted R^2		0.868		
	MdAPE		27.99%		
Validation [d]	R^2		0.885		
	MdAPE		27.15%		

Note : a: Response variable lnAADT; b: Beta value, i.e., standardized coefficients value
c : random 80% of the sample, N=1927

c.) Random subsets 70:30

Specifications		Coefficient value	Value	t-value	p-value
Variables [a]	Constant	3.812		34.149	<.0001
	$lnBC_{(PD\_15km)}$	0.596	.795 [b]	72.361	<.0001
	$lnCC_{(PD\_15km)}$	1.982	.242 [b]	22.045	<.0001
F Value			4616.982 (<0.0001)		
Presence of multicollinearity					
Tolerance			0.781		
VIF			1.280		
Goodness-of-fit					
Calibration [c]	R^2		0.871		
	Adjusted R^2		0.870		
	MdAPE		27.81%		
Validation [d]	R^2		0.865		
	MdAPE		28.61%		

Note : a: Response variable lnAADT; b: Beta value, i.e., standardized coefficients value
c : random 70% of the sample, N=1927

d.) Random subsets 60:40

Specifications		Coefficient value	Value	t-value	p-value
Variables [a]	Constant	3.994		34.221	<.0001
	$lnBC_{(PD\_15km)}$	0.588	.786 [b]	68.412	<.0001
	$lnCC_{(PD\_15km)}$	2.215	.269 [b]	23.375	<.0001
F Value			4167.087 (<0.0001)		
Presence of multicollinearity					
Tolerance			0.799		
VIF			1.251		
Goodness-of-fit					
Calibration [c]	R^2		0.879		
	Adjusted R^2		0.879		
	MdAPE		27.79%		
Validation [d]	R^2		0.861		
	MdAPE		29.07%		

Note : a: Response variable lnAADT; b: Beta value, i.e., standardized coefficients value
c : random 40% of the sample, N=1927

e.) Random subsets 50:50

Specifications		**Coefficient value**	**Value**	**t-value**	**p-value**
Variables [a]	Constant	3.861		30.576	<.0001
	$lnBC_{(PD\_15km)}$	0.593	.791 [b]	62.069	<.0001
	$lnCC_{(PD\_15km)}$	2.030	.256 [b]	20.058	<.0001
F Value			3321.297 (<0.0001)		
Presence of multicollinearity					
Tolerance			0.806		
VIF			1.241		
Goodness-of-fit					
Calibration [c]	R^2		0.870		
	Adjusted R^2		0.869		
	MdAPE		27.93%		
Validation [d]	R^2		0.865		
	MdAPE		28.08%		

Note : a: Response variable lnAADT; b: Beta value, i.e., standardized coefficients value
c : random 50% of the sample, N=1927

f.) Random subsets 5:95

Specifications		**Coefficient value**	**Value**	**t-value**	**p-value**
Variables [a]	Constant	3.739		8.248	<.0001
	$lnBC_{(PD\_15km)}$	0.580	.842 [b]	19.565	<.0001
	$lnCC_{(PD\_15km)}$	1.455	.163 [b]	3.785	<.0001
F Value			408.640 (<0.0001)		
Presence of multicollinearity					
Tolerance			0.600		
VIF			1.665		
Goodness-of-fit					
Calibration [c]	R^2		0.909		
	Adjusted R^2		0.907		
	MdAPE		26.00%		
Validation [d]	R^2		0.891		
	MdAPE		27.00%		

Note : a: Response variable lnAADT; b: Beta value, i.e., standardized coefficients value
c : random 5% of the sample, N=1927

g.) Random subsets 3:95

Specifications		Coefficient value	Value	t-value	p-value
Variables [a]	Constant	3.643		8.913	<.0001
	$lnBC_{(PD\_15km)}$	0.611	.809 [b]	19.557	<.0001
	$lnCC_{(PD\_15km)}$	1.860	.268 [b]	6.486	<.0001
F Value			312.622 (<0.0001)		
Presence of multicollinearity					
Tolerance			0.841		
VIF			1.189		
Goodness-of-fit					
Calibration [c]	R^2		0.949		
	Adjusted R^2		0.901		
	MdAPE		22.00%		
Validation [d]	R^2		0.844		
	MdAPE		27.00%		

Note : a: Response variable lnAADT; b: Beta value, i.e., standardized coefficients value
c : random 3% of the sample, N=1927

h.) Random subsets 2:98

Specifications		Coefficient value	Value	t-value	p-value
Variables [a]	Constant	4.775		6.831	<.0001
	$lnBC_{(PD\_15km)}$	0.515	.733 [b]	10.155	<.0001
	$lnCC_{(PD\_15km)}$	2.269	.317 [b]	4.392	<.0001
F Value			129.446 (<0.0001)		
Presence of multicollinearity					
Tolerance			0.671		
VIF			1.491		
Goodness-of-fit					
Calibration [c]	R^2		0.906		
	Adjusted R^2		0.899		
	MdAPE		23.00%		
Validation [d]	R^2		0.803		
	MdAPE		33.00%		

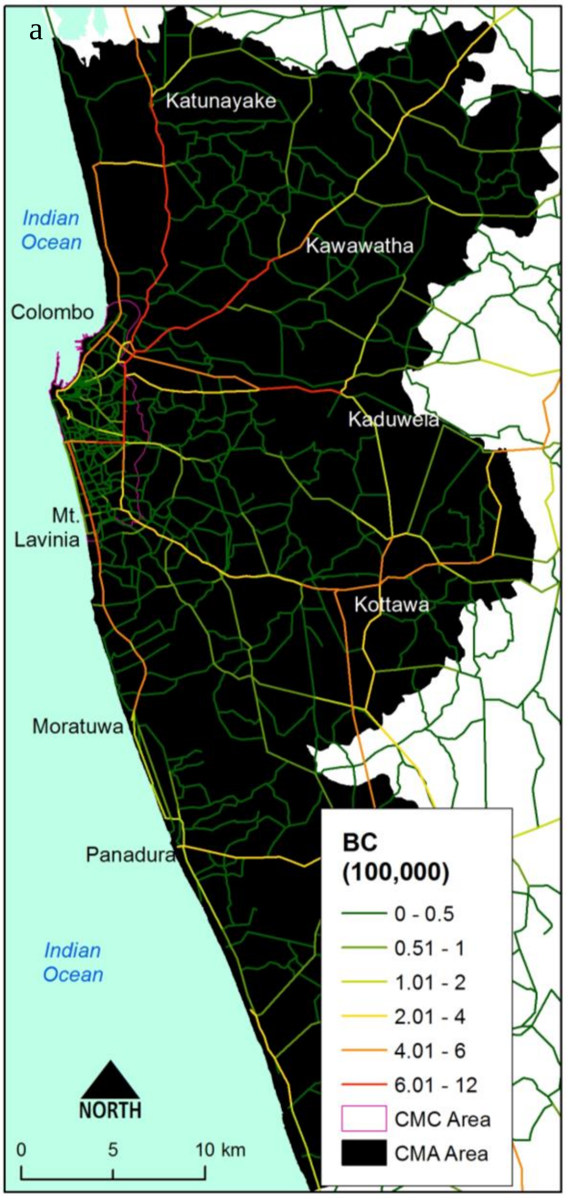
Note : a: Response variable lnAADT; b: Beta value, i.e., standardized coefficients value
c : random 2% of the sample, N=1927

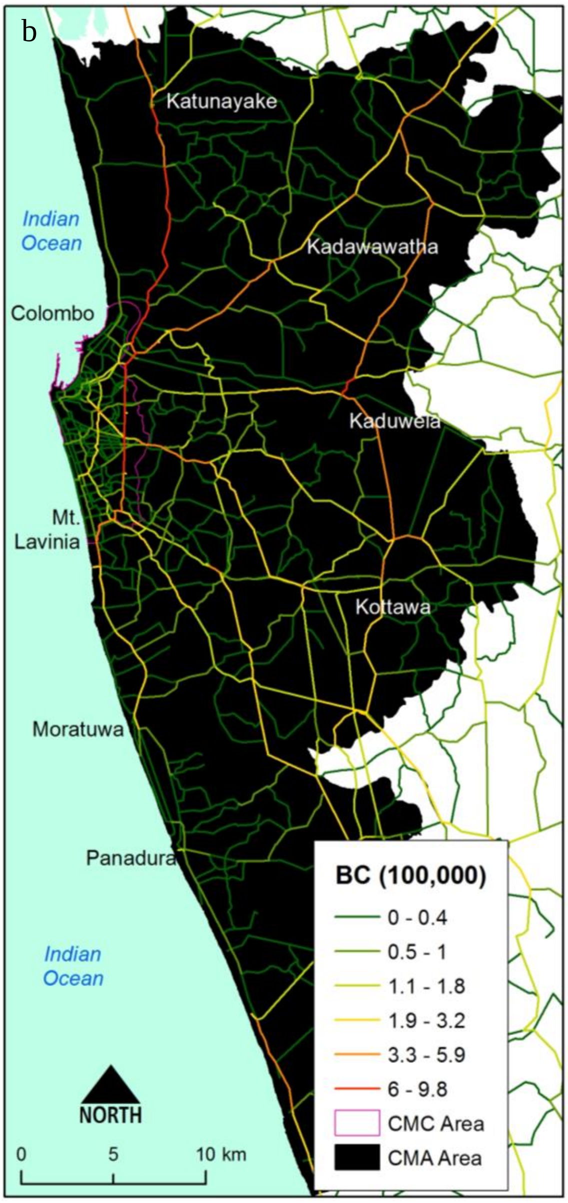
i.) Random subsets 1:99

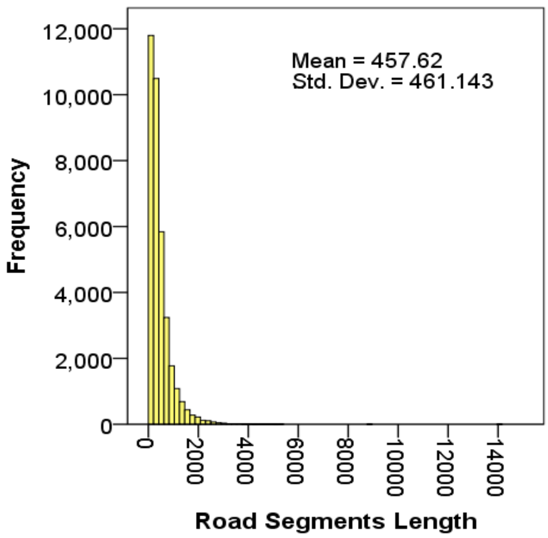
Specifications		Coefficient value	Value	t-value	p-value
Variables [a]	Constant	4.031		5.681	<.0001
	$lnBC_{(PD\_15km)}$	0.573	.817 [b]	10.373	<.0001
	$lnCC_{(PD\_15km)}$	1.946	.269 [b]	3.410	<.0001
F Value			96.202 (<0.0001)		
Presence of multicollinearity					
Tolerance			0.789		
VIF			1.268		
Goodness-of-fit					
Calibration [c]	R^2		0.941		
	Adjusted R^2		0.932		
	MdAPE		22.00%		
Validation [d]	R^2		0.803		
	MdAPE		42.67%		

Note : a: Response variable lnAADT; b: Beta value, i.e., standardized coefficients value
c : random 1% of the sample, N=1927

2. **Spatial distribution of (a) $BC_{(PD, 15km)}$ and (b) $BC_{(GMD, 15km)}$ in CMA area - 2013**

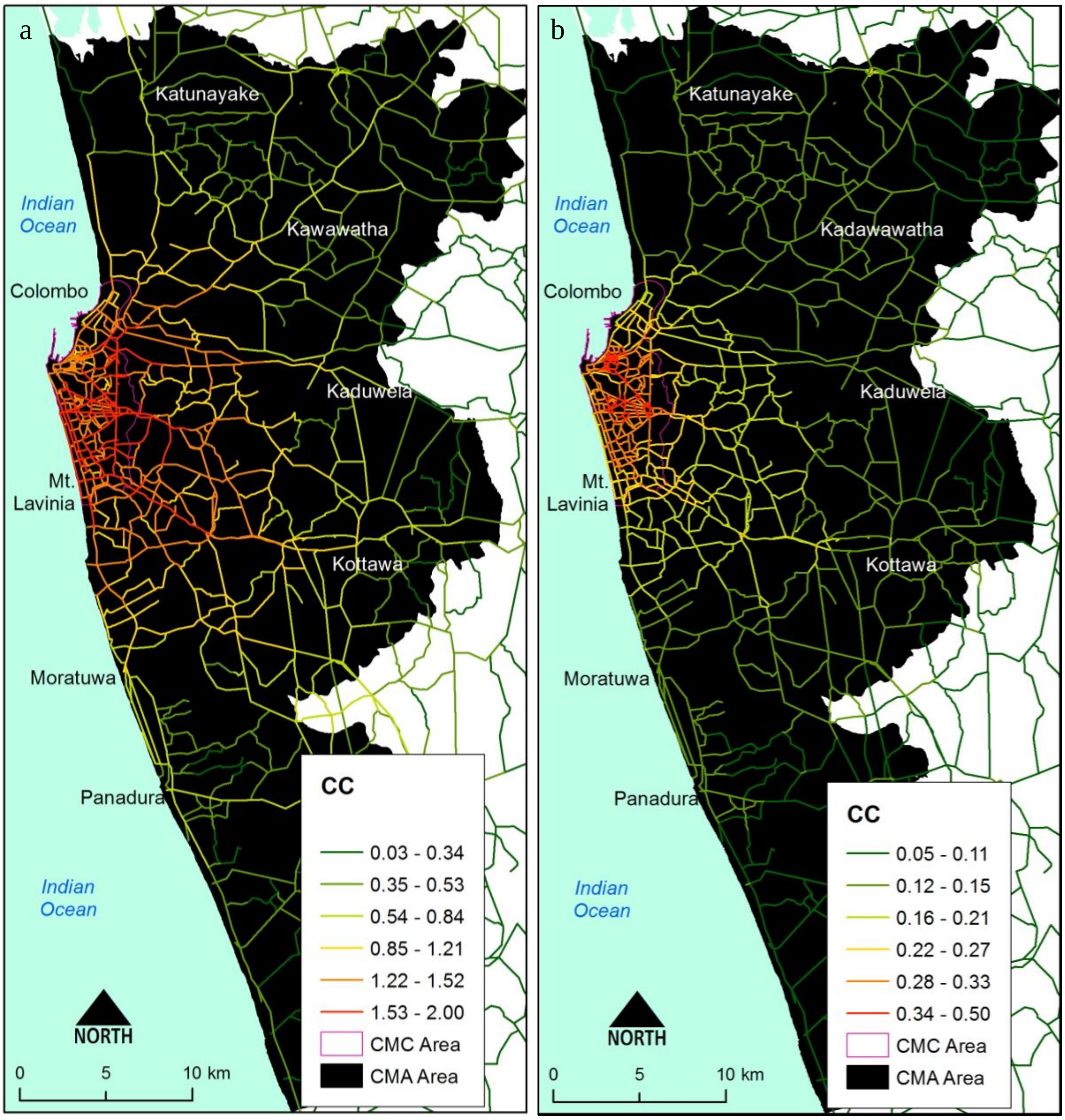






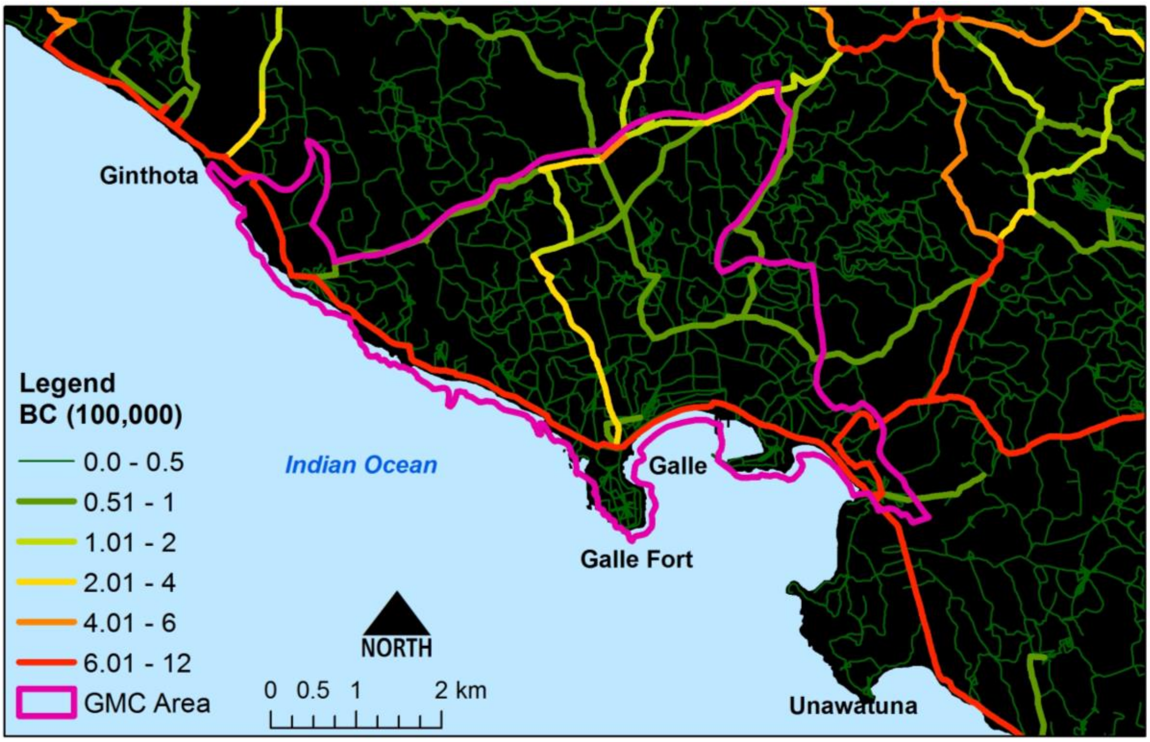
Distribution of road segments length in Colombo MA area year -2013

3. Spatial distribution of (a) $CC_{(PD,\ 15km)}$ and (b) $CC_{(GMD,\ 15km)}$ in CMA area - 2013

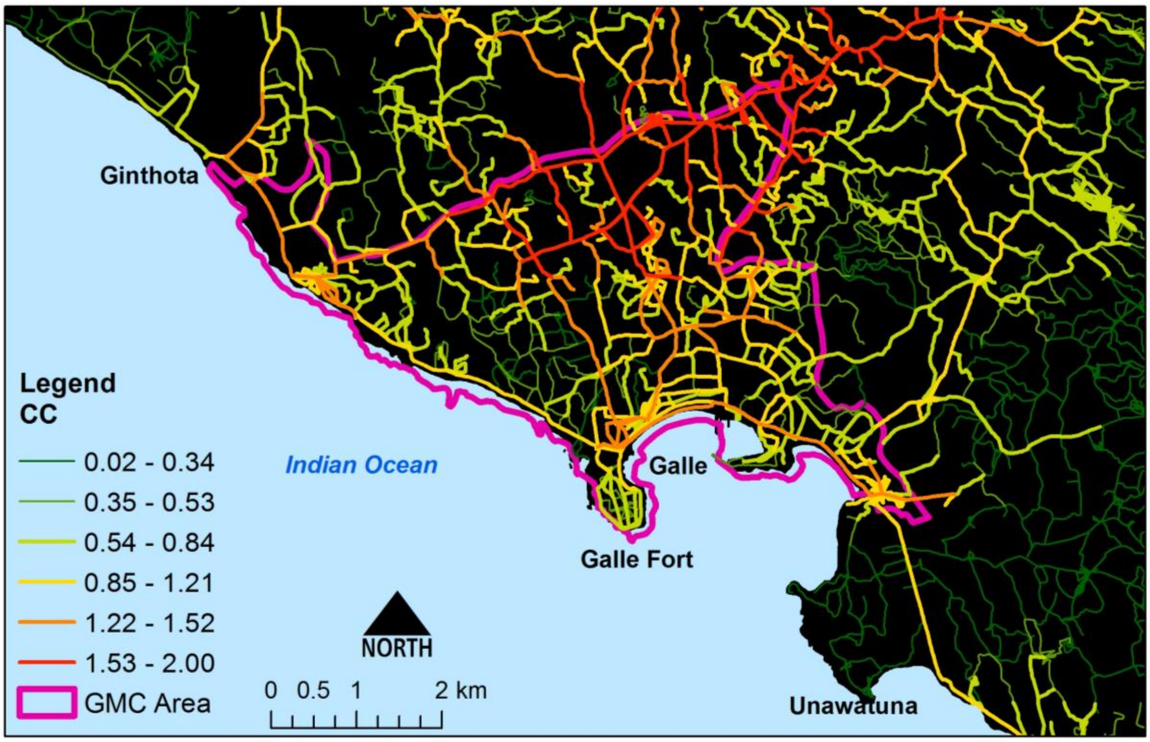


4. Spatial distribution of a.) $BC_{(PD,\ 15km)}$ and b.) $CC_{(PD,\ 15km)}$ in Galle MC area

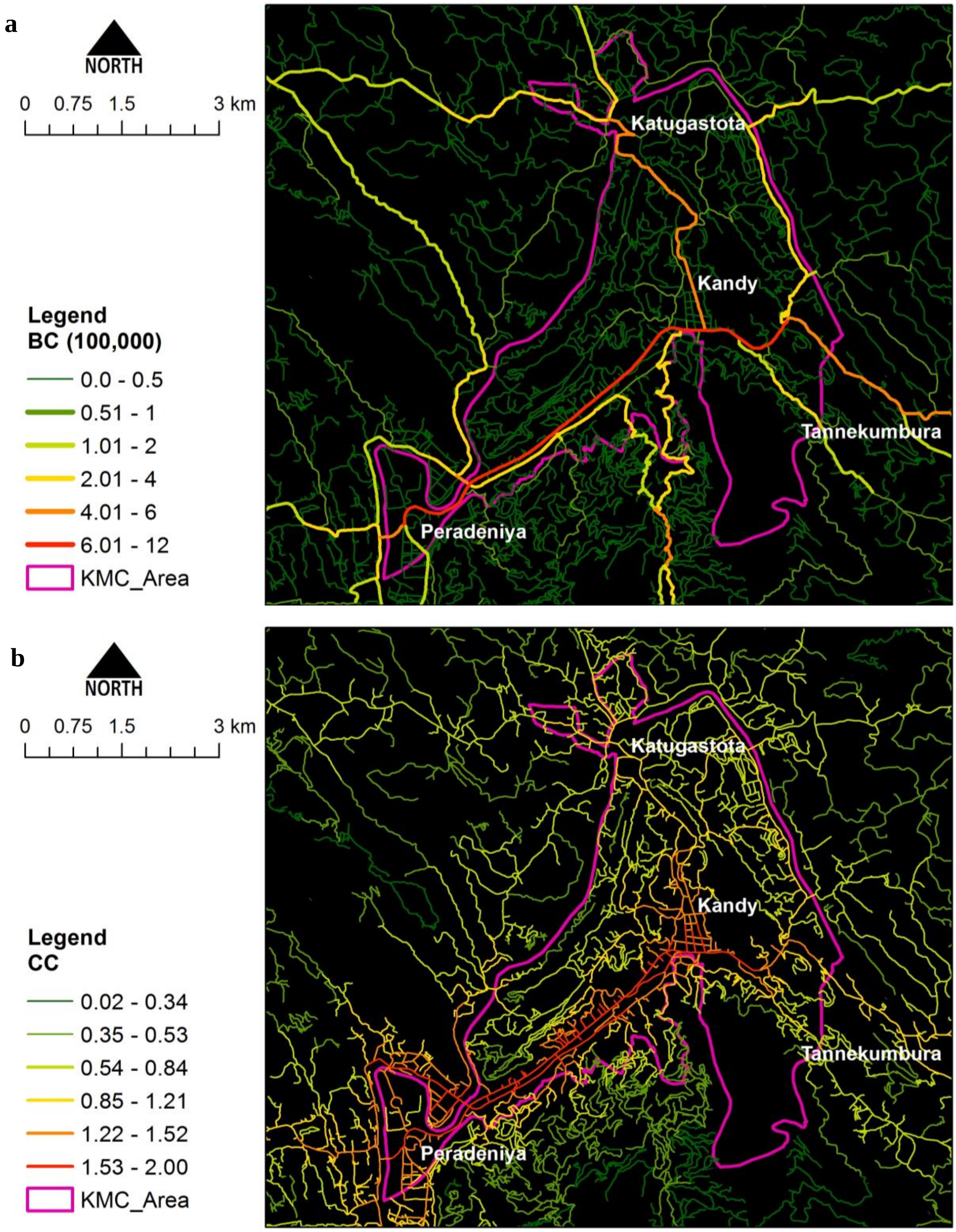
a



b

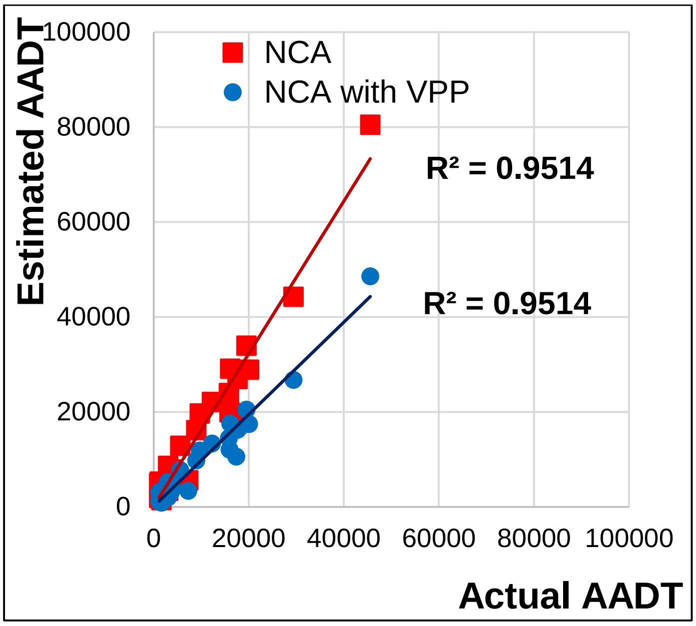


5. **Spatial distribution of a.) $BC_{(PD,\ 15km)}$ and b.) $CC_{(PD,\ 15km)}$ in Kandy MC area**

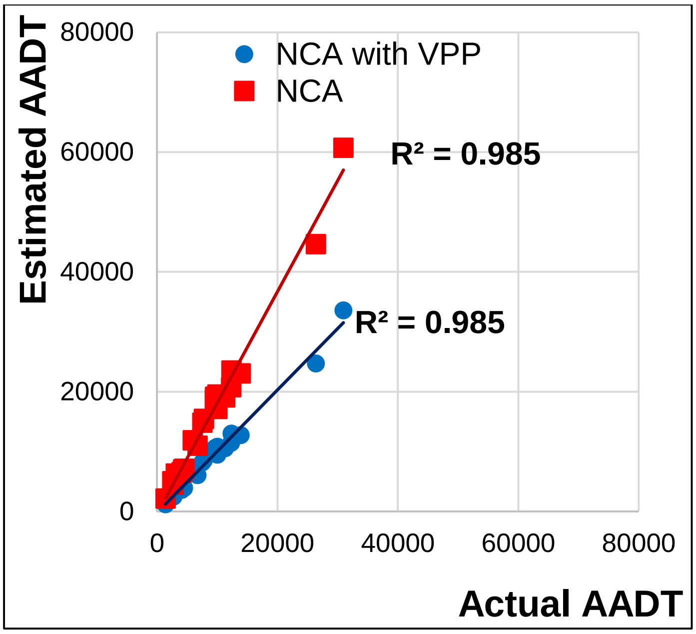


6. The relationship with the AADT estimated by 5.10a (without VVP) and 5.11 (with VVP) with actual AADT of Kandy and Galle Area

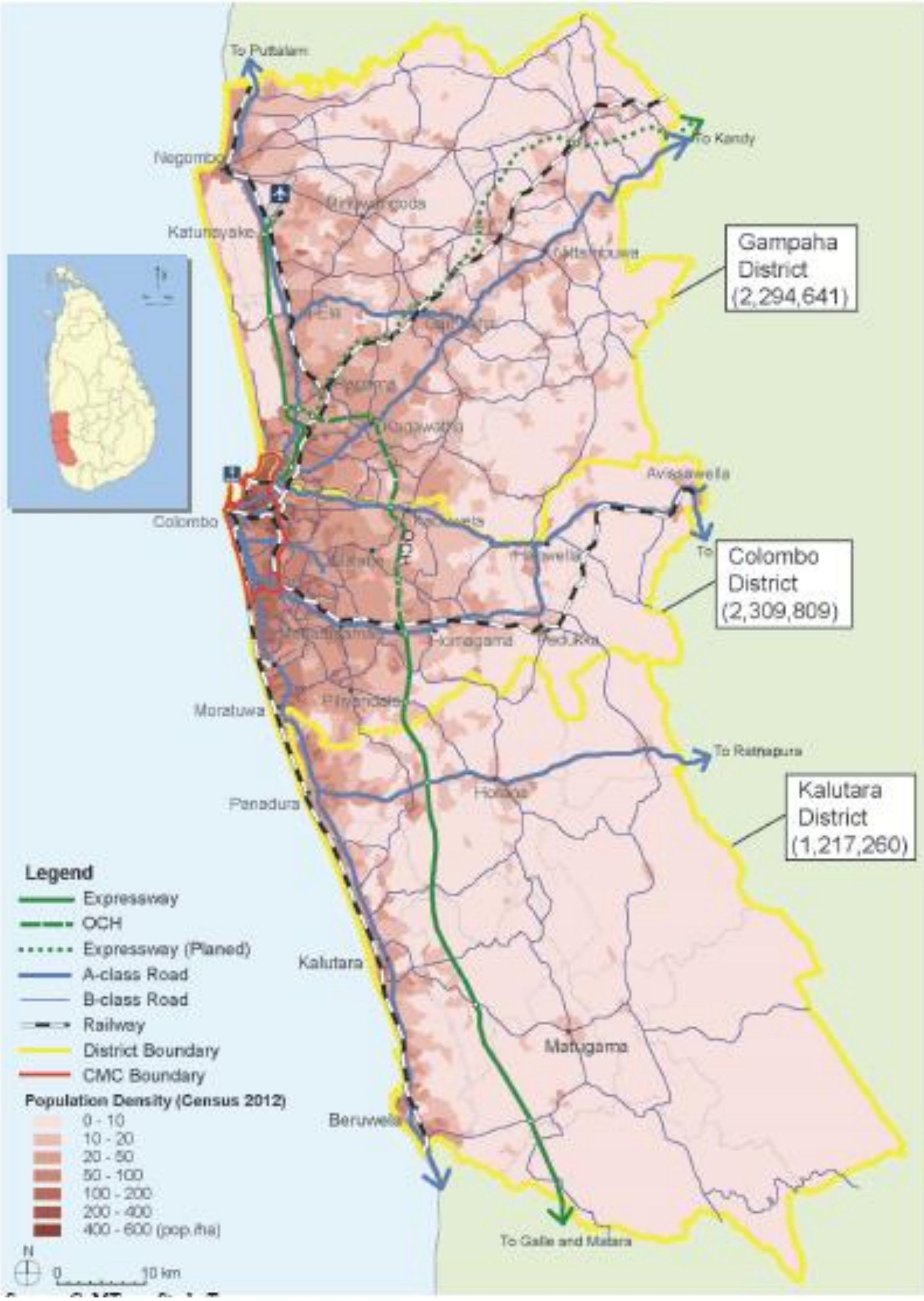
a.) Kandy MC Area



b.) Galle MC Area

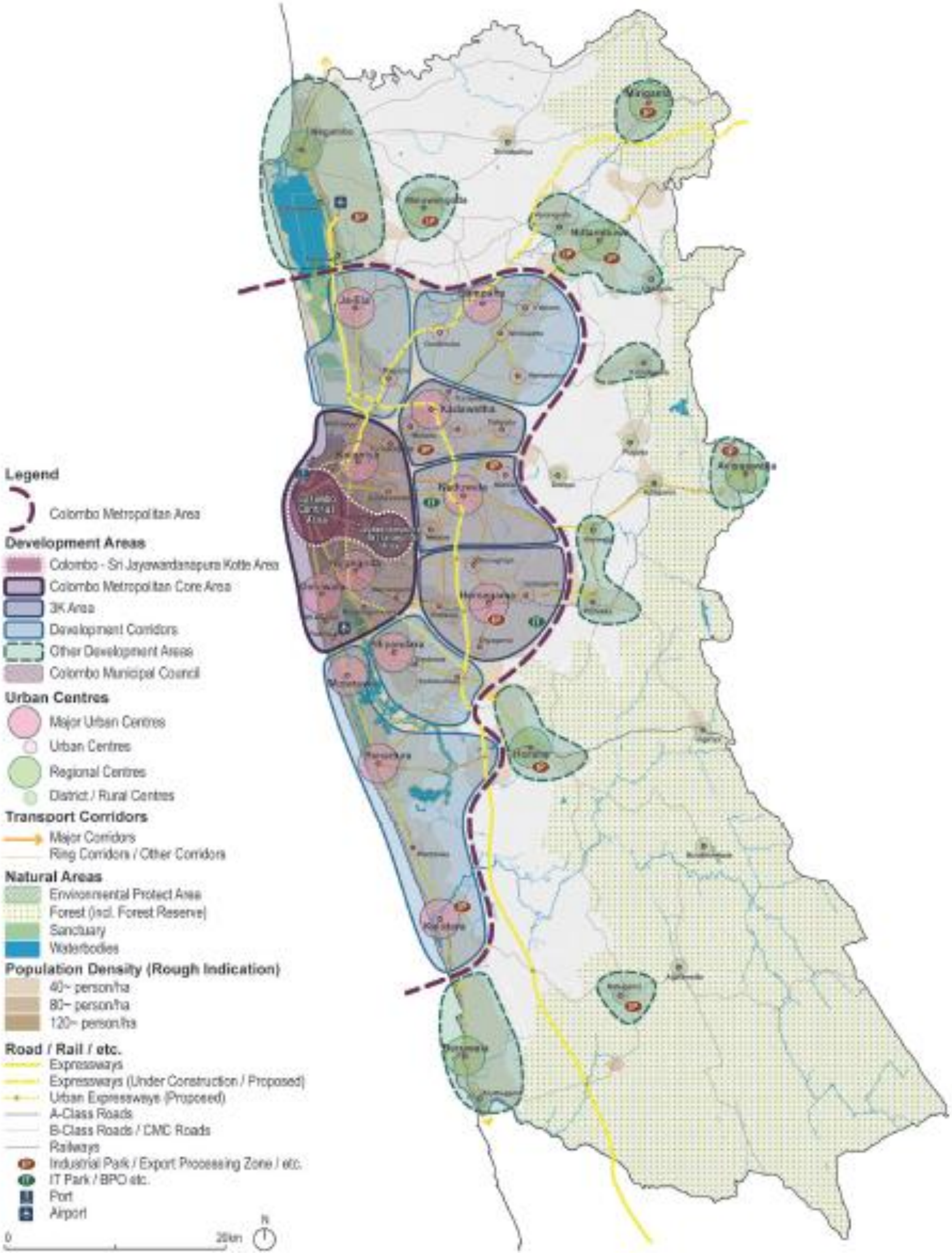


7. Colombo metropolitan (CMA) Area



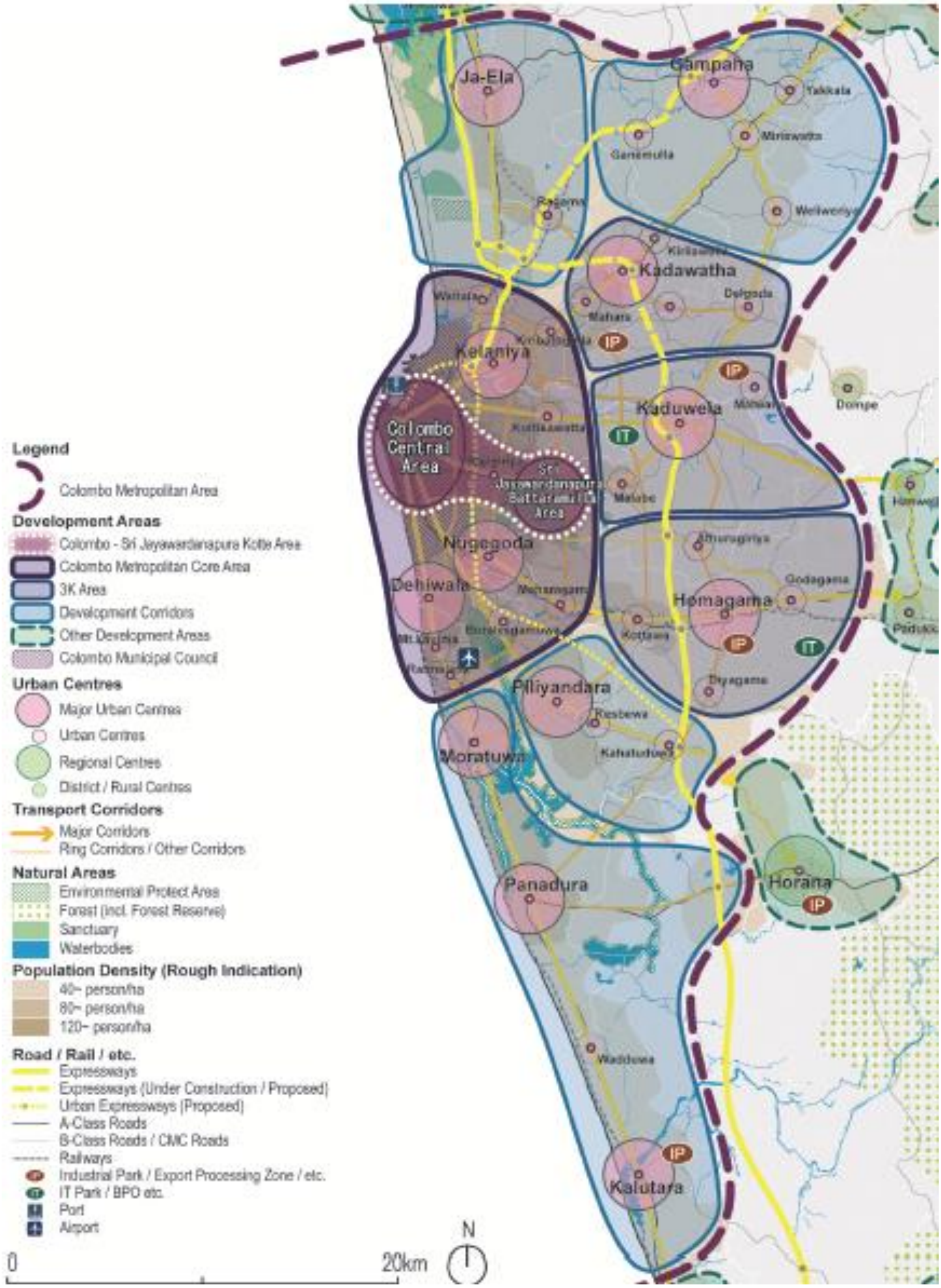
Source: (JICA, 2014)

8. a.) Urban Structure Plan – CMA



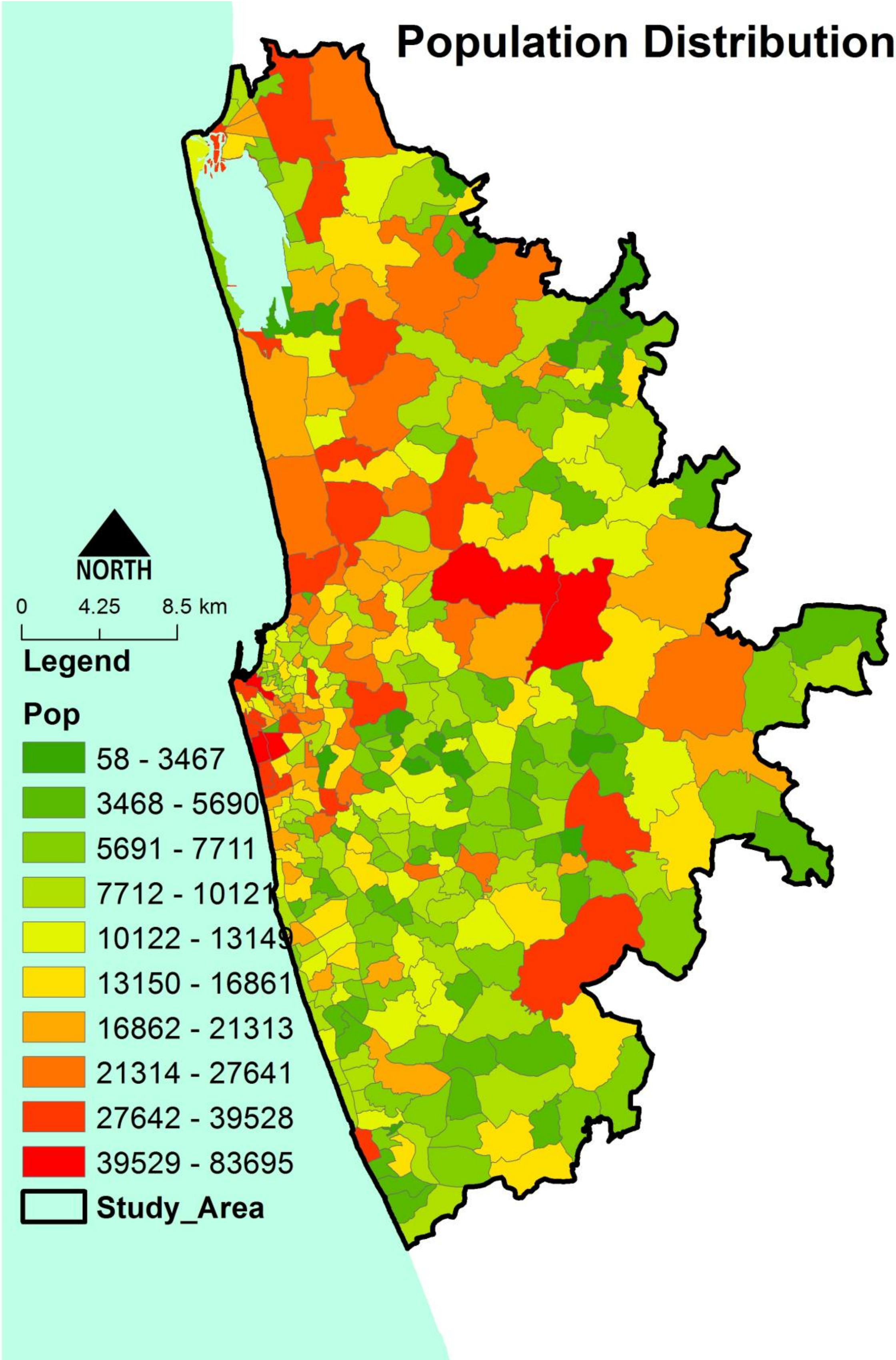
Source: (JICA, 2014)

b.) Urban Structure Plan – CMA



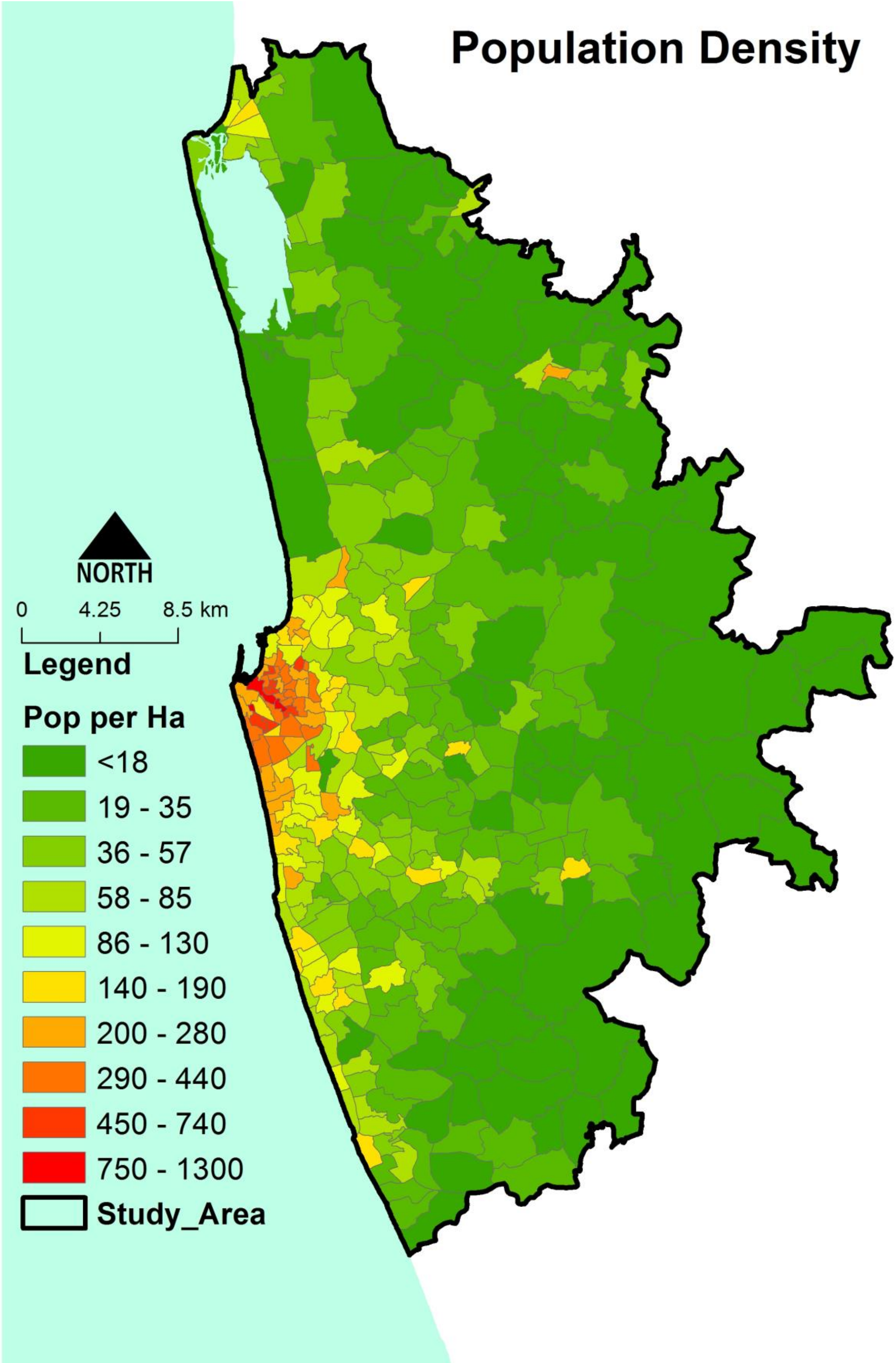
Source: (JICA, 2014)

9. Distribution of Population by TAZs- CMA



Source: Constructed based on JICA,2014 data

10. Population Density by TAZs - CMA



Source: Constructed based on JICA,2014 data

11. Population and average annual growth rates in CMA

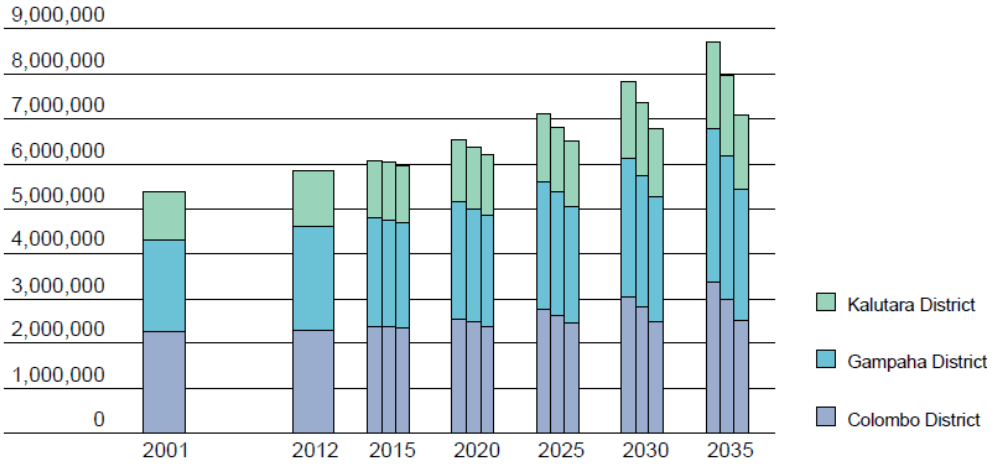
Census Population	1953	1963	1971	1981	2001	2012
Sri Lanka	**8,097,800**	**10,582,100**	**12,689,897**	**14,846,750**	**18,797,257**	**20,263,723**
Western Province	**2,232,276**	**2,838,877**	**3,401,779**	**3,919,807**	**5,381,197**	**5,821,710**
Colombo District	1,708,726	2,207,420	1,498,393	1,699,241	2,251,274	2,309,809
Gampaha District*			1,173,872	1,390,862	2,063,684	2,294,641
Kalutara District	523,550	631,457	729,514	829,704	1,066,239	1,217,260
Average Annual Growth Rate		**'53-'63**	**'63-71**	**'71-'81**	**'81-'01**	**'01-'12**
Sri Lanka		**2.71%**	**2.30%**	**1.58%**	**1.19%**	**0.69%**
Western Province		**2.43%**	**2.29%**	**1.43%**	**1.60%**	**0.72%**
Colombo District		2.59%	2.42%	1.27%	1.42%	0.23%
Gampaha District*				1.71%	1.99%	0.97%
Kalutara District		1.89%	1.45%	1.30%	1.26%	1.21%

Source: (JICA, 2014), Western Province: CMA Area

Scenario 1 High	**2001**	**2012**	**2015**	**2020**	**2025**	**2030**	**2035**
Colombo District	2,251,274	2,309,809	2,382,600	2,555,700	2,774,400	3,045,800	3,368,800
Gampaha District	2,063,684	2,294,641	2,393,200	2,586,000	2,821,400	3,101,800	3,435,900
Kalutara District	1,066,239	1,217,260	1,277,500	1,396,500	1,537,300	1,704,300	1,903,100
Western Province	5,381,197	5,821,710	6,053,300	6,538,200	7,133,100	7,851,900	8,707,800
AAGR		**'01-'12**	**'12-'15**	**'15-'20**	**'20-'25**	**'25-'30**	**'30-'35**
Colombo District		0.23%	1.04%	1.41%	1.66%	1.88%	2.04%
Gampaha District		0.97%	1.41%	1.56%	1.76%	1.91%	2.07%
Kalutara District		1.21%	1.62%	1.80%	1.94%	2.08%	2.23%
Western Province		0.72%	1.31%	1.55%	1.76%	1.94%	2.09%
Scenario 2 Mid	**2001**	**2012**	**2015**	**2020**	**2025**	**2030**	**2035**
Colombo District	2,251,274	2,309,809	2,359,400	2,476,100	2,624,400	2,795,900	2,979,700
Gampaha District	2,063,684	2,294,641	2,377,900	2,536,700	2,725,700	2,943,500	3,178,500
Kalutara District	1,066,239	1,217,260	1,270,200	1,373,200	1,492,100	1,629,700	1,782,000
Western Province	5,381,197	5,821,710	6,007,500	6,386,000	6,842,200	7,369,100	7,940,200
AAGR		**'01-'12**	**'12-'15**	**'15-'20**	**'20-'25**	**'25-'30**	**'30-'35**
Colombo District		0.23%	0.71%	0.97%	1.17%	1.27%	1.28%
Gampaha District		0.97%	1.20%	1.30%	1.45%	1.55%	1.55%
Kalutara District		1.21%	1.43%	1.57%	1.67%	1.78%	1.80%
Western Province		0.72%	1.05%	1.23%	1.39%	1.50%	1.50%
Scenario 3 Low	**2001**	**2012**	**2015**	**2020**	**2025**	**2030**	**2035**
Colombo District	2,251,274	2,309,809	2,332,500	2,379,500	2,428,700	2,480,200	2,534,100
Gampaha District	2,063,684	2,294,641	2,364,200	2,485,300	2,618,000	2,757,200	2,903,000
Kalutara District	1,066,239	1,217,260	1,262,800	1,346,700	1,437,000	1,534,600	1,640,600
Western Province	5,381,197	5,821,710	5,959,500	6,211,500	6,483,700	6,772,000	7,077,700
AAGR		**'01-'12**	**'12-'15**	**'15-'20**	**'20-'25**	**'25-'30**	**'30-'35**
Colombo District		0.23%	0.33%	0.40%	0.41%	0.42%	0.43%
Gampaha District		0.97%	1.00%	1.00%	1.05%	1.04%	1.04%
Kalutara District		1.21%	1.23%	1.29%	1.31%	1.32%	1.34%
Western Province		0.72%	0.78%	0.83%	0.86%	0.87%	0.89%

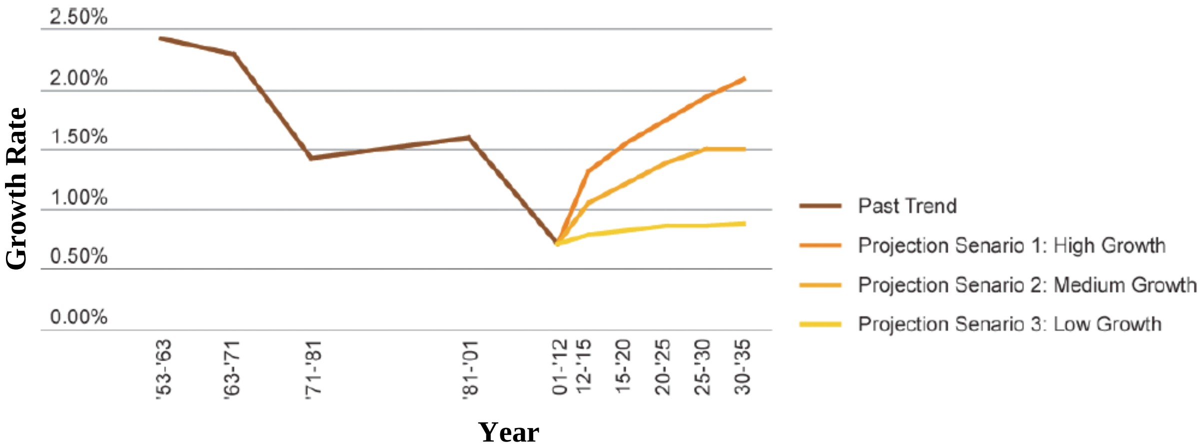
Source: (JICA, 2014)

Population Projection - CMA



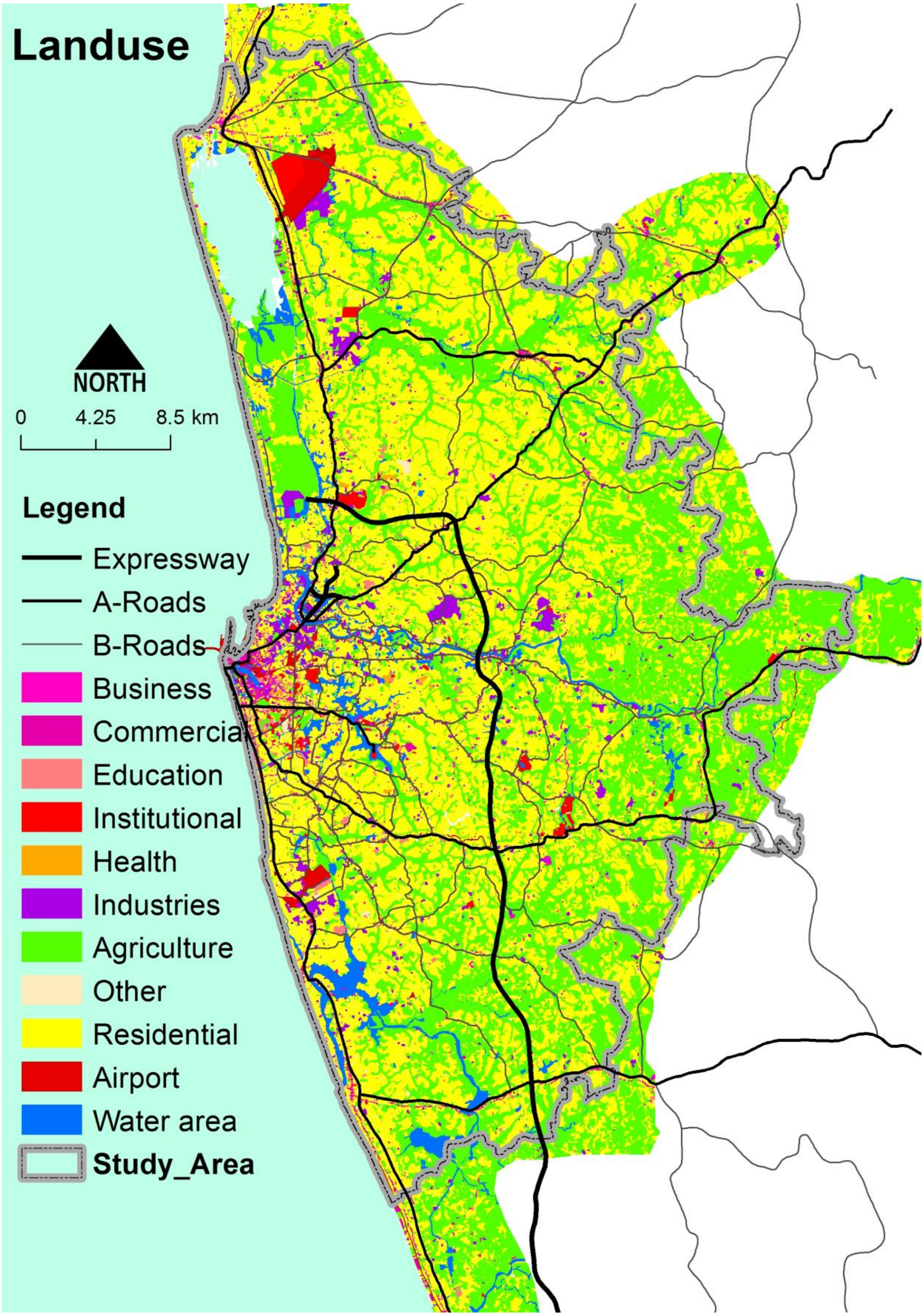
Note: After 2015, the projected populations are shown in the High, Medium, and Low growth scenarios.
Source: CoMTrans Study Team

Source: (JICA, 2014)



Source: (JICA, 2014)

12. Land Use - CMA

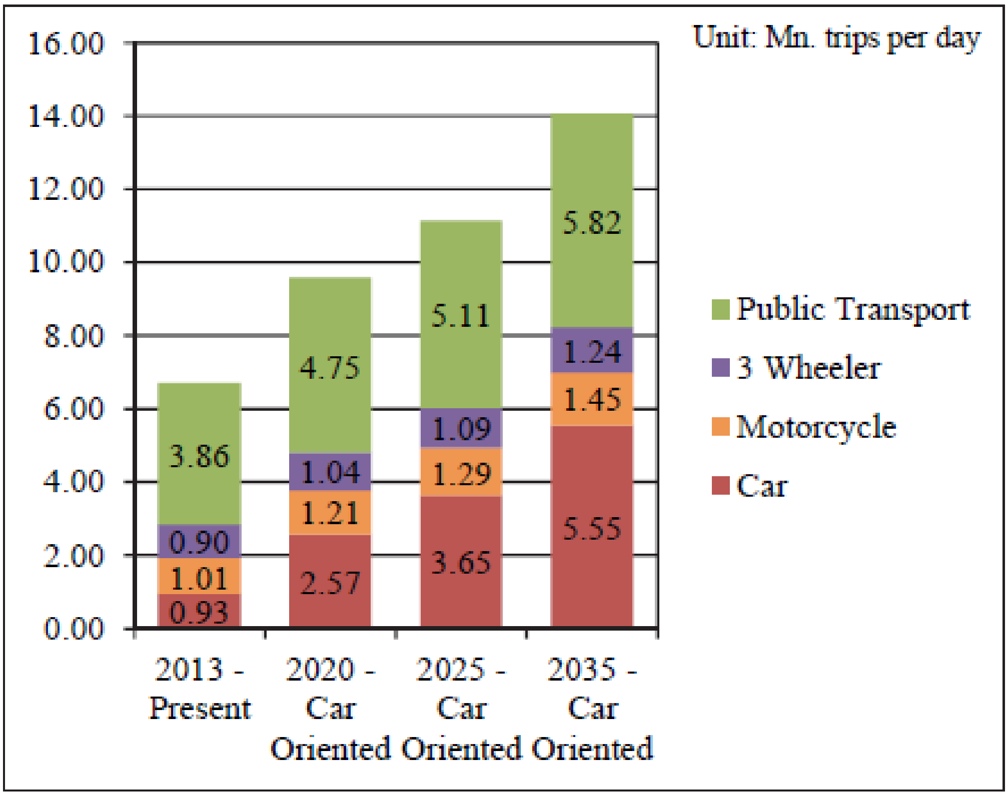


Source: Constructed based on JICA, 2014 data

Land Use Classes	Colombo District (km^2)	Gampaha District (km^2)	Kalutara District (km^2)	Total (km^2)	Share of the Survey Area
11- Commercial	3.3	2.0	1.7	7.0	0.4%
12 - Residential	294.4	462.3	165.7	922.4	53.2%
13 - Business	5.6	4.9	1.8	12.3	0.7%
14 - Health	1.4	0.7	0.2	2.3	0.1%
15 - Education	7.2	5.8	2.5	15.5	0.9%
16 - Industries / Distribution	13.6	20.5	2.7	36.8	2.1%
17 - Government / Institutions	5.8	5.3	0.7	11.8	0.7%
18 - Transport	5.8	7.6	0.7	14.1	0.8%
19 - Other Built-up Land	3.3	2.6	1.8	7.7	0.4%
21 - Open Land	181.8	260.7	150.7	593.2	34.2%
22-1 - Wet Land	7.7	8.1	2.9	18.7	1.1%
22-2 - Water Bodies	14.6	7.8	13.5	35.9	2.1%
23 - Roads	21.5	24.8	8.8	55.1	3.2%
Sub Total in the Survey Area	566.0	813.1	353.7	1,732.8	100.0%
Outside of the Survey Area	114.0	589.5	1,292.7	1,996.2	-
Total	680.0	1,402.6	1,646.4	3,729.0	-

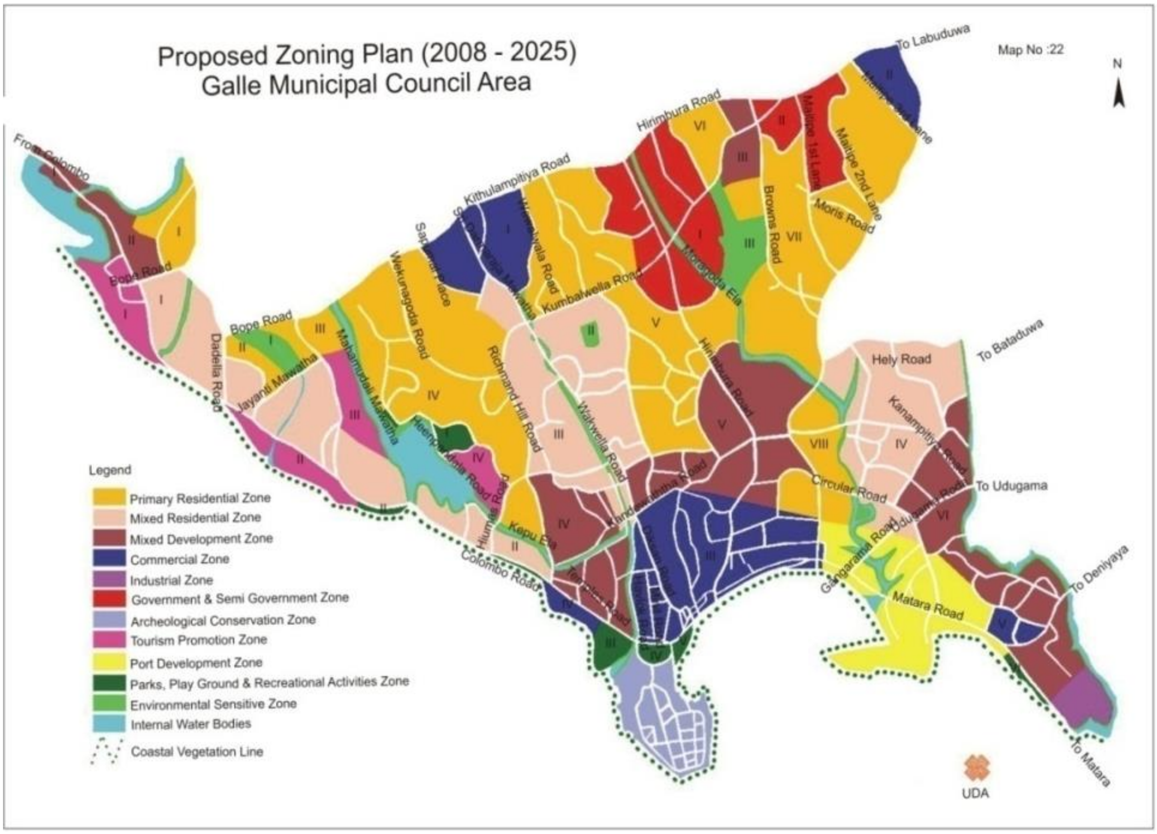
Source: (JICA, 2014)

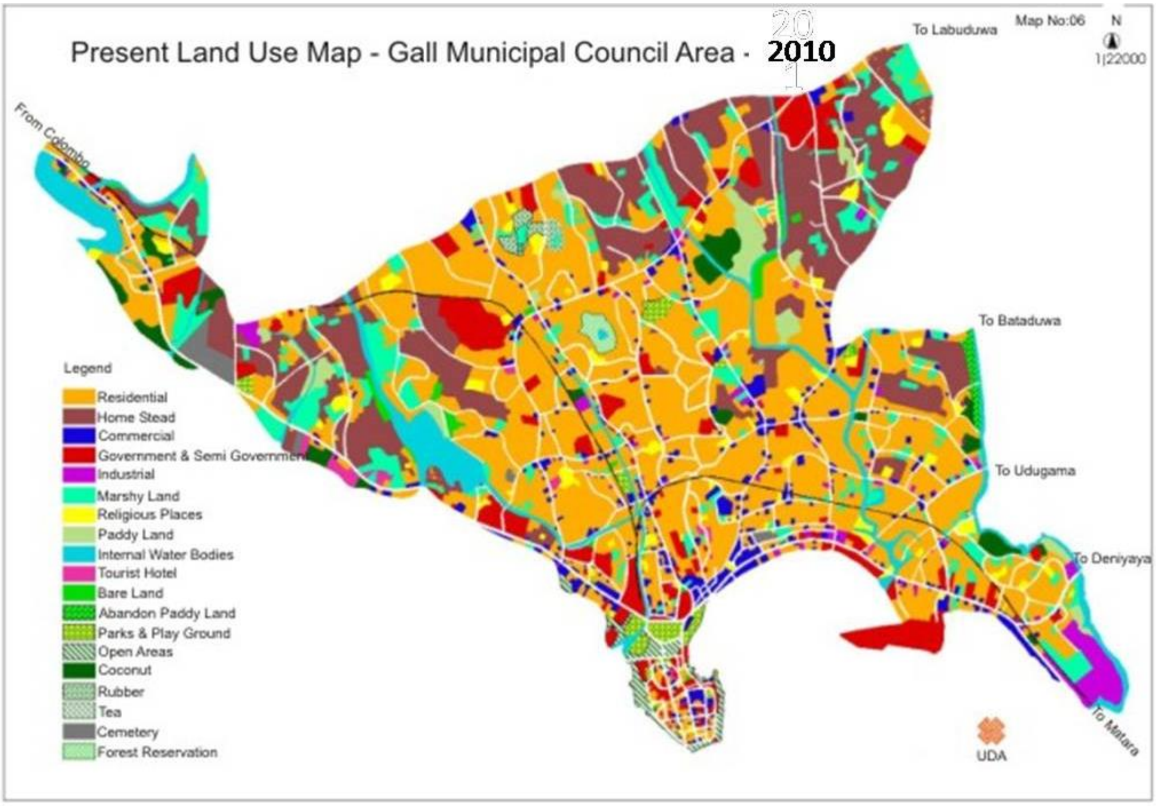
13. Trip growth - CMA



Source: CoMTrans Estimate, Car Oriented Scenario, Excluding non-motorised transport

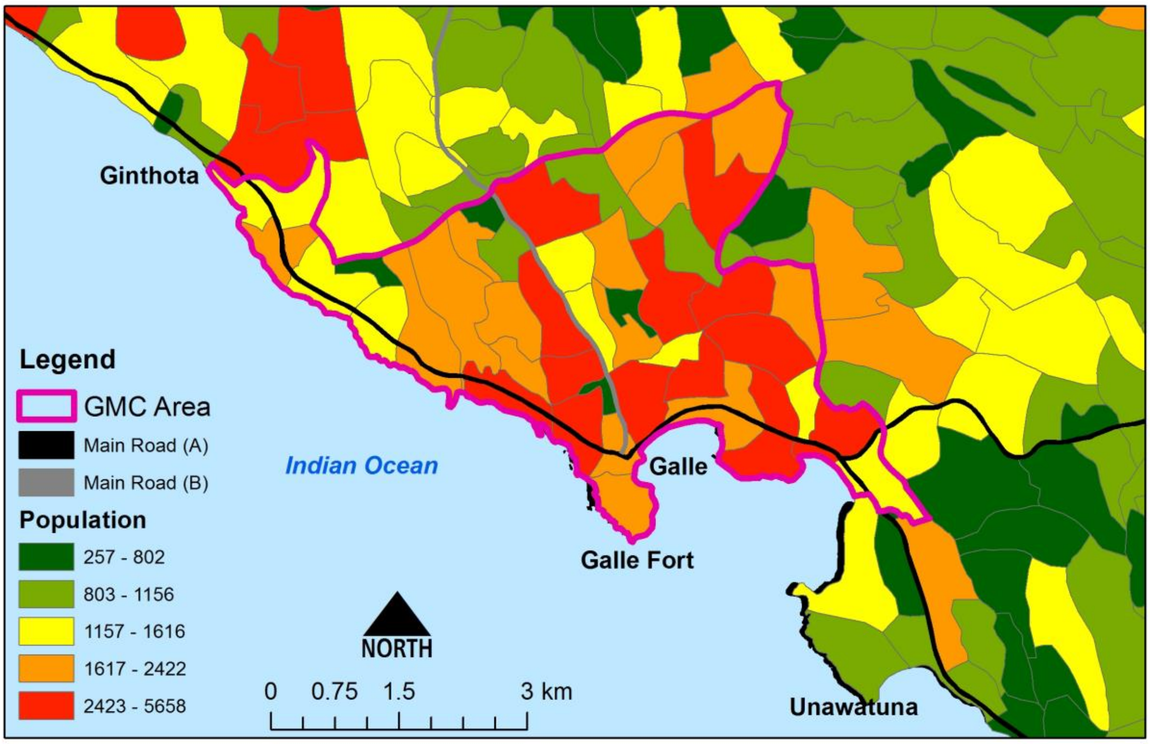
14. Zoning Plan and Land Use Map – Galle

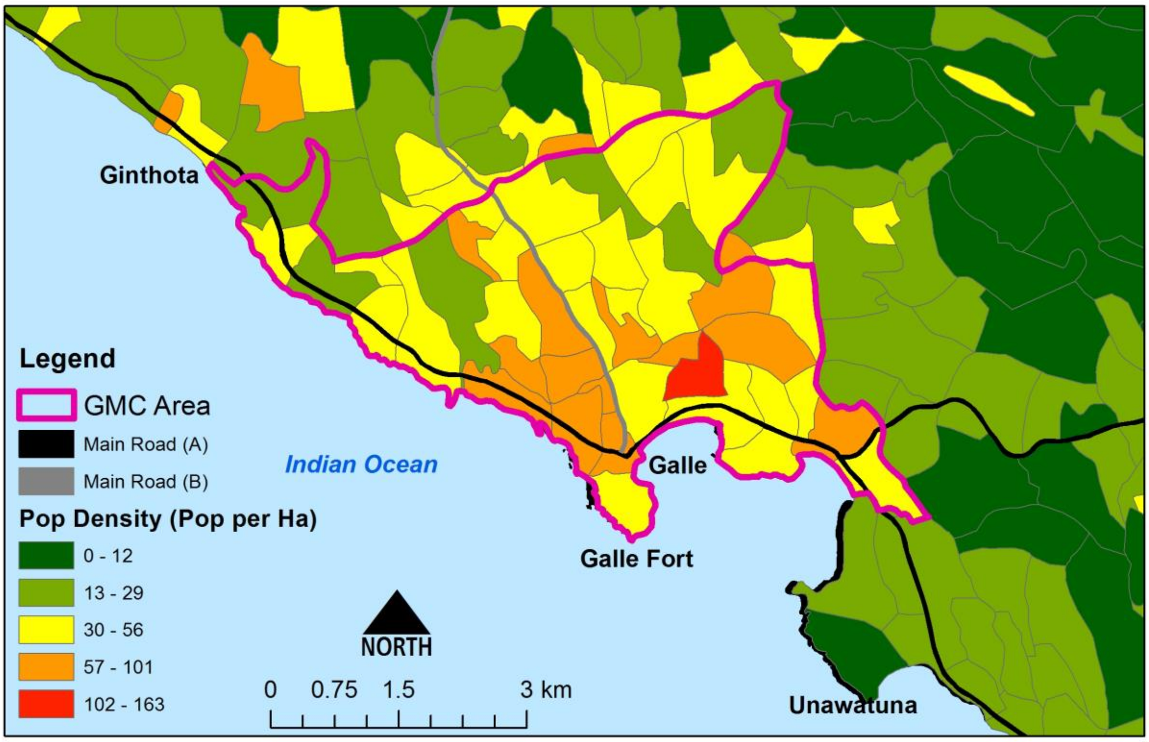




Source: Urban Development Authority, Galle

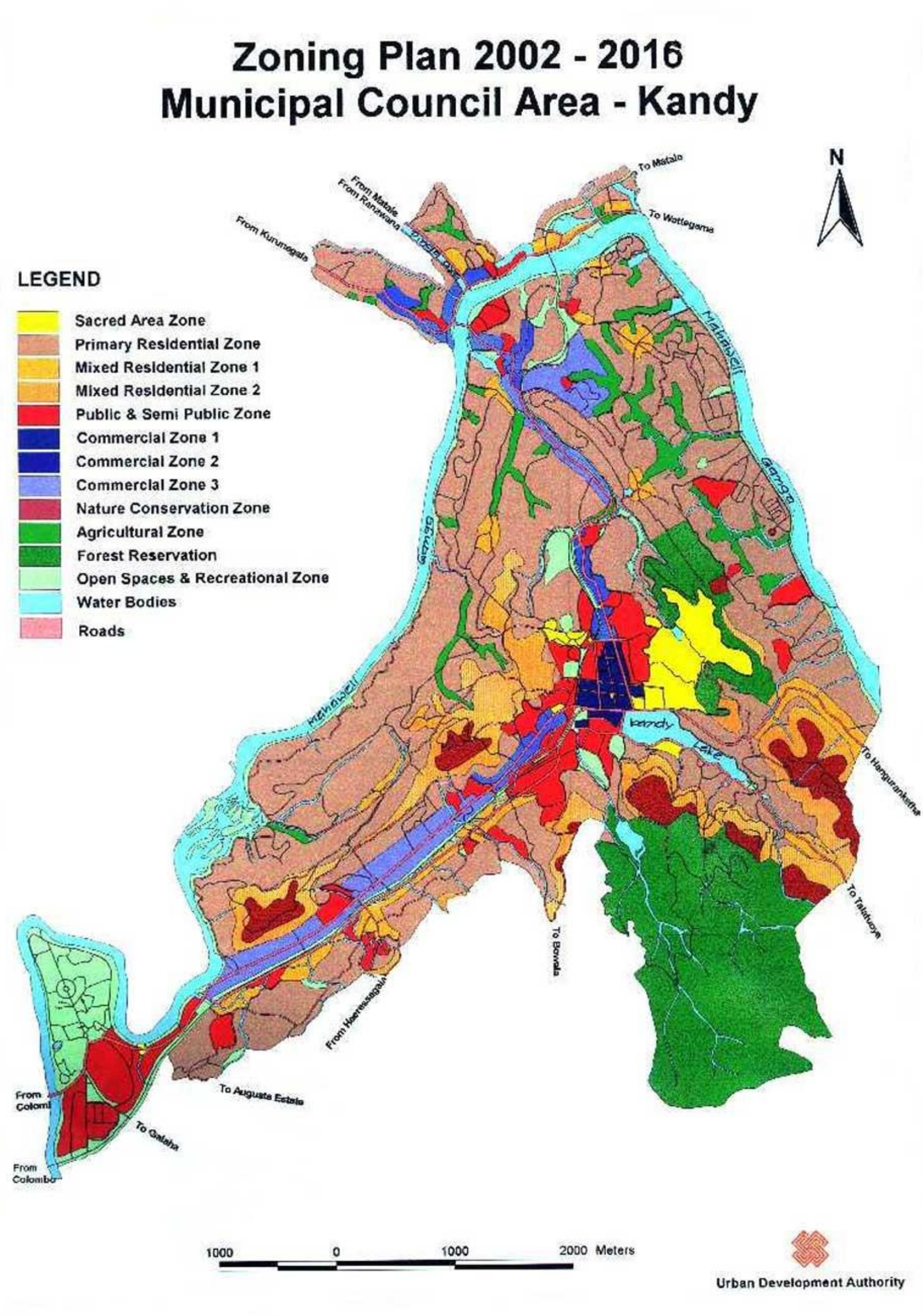
15. Distribution of Population – Galle





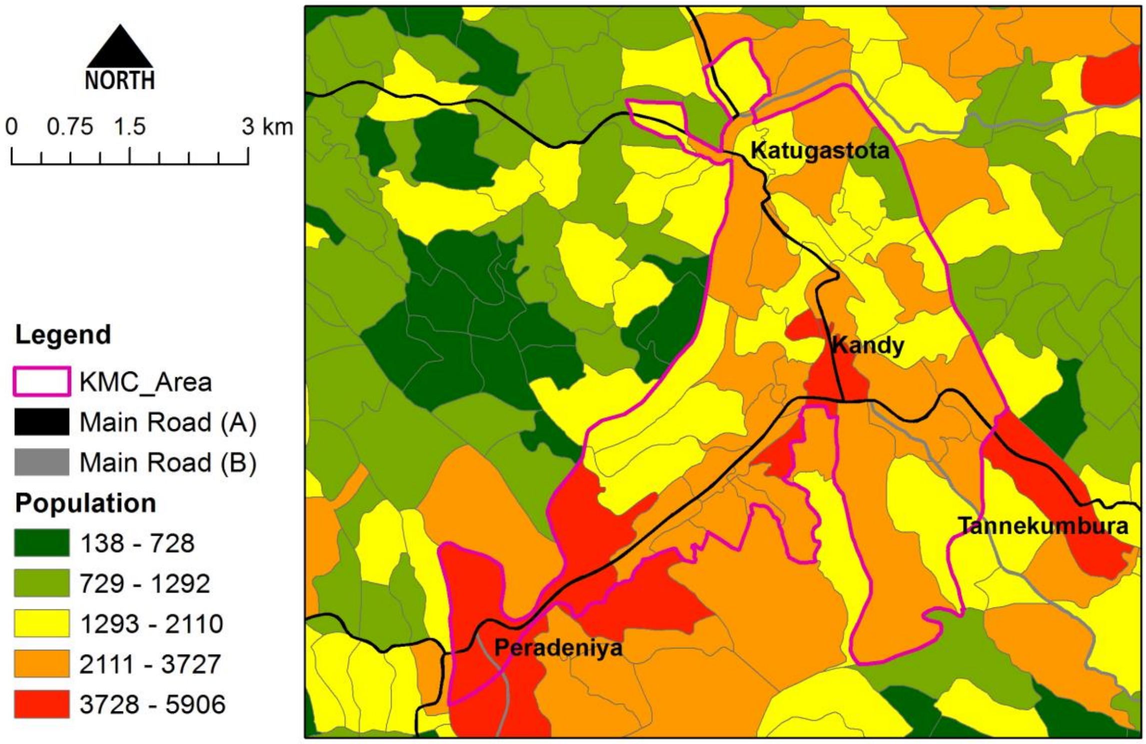
Note: Constructed based on Census and Statistic data-2012, Department of Census and Statistics, Sri Lanka.

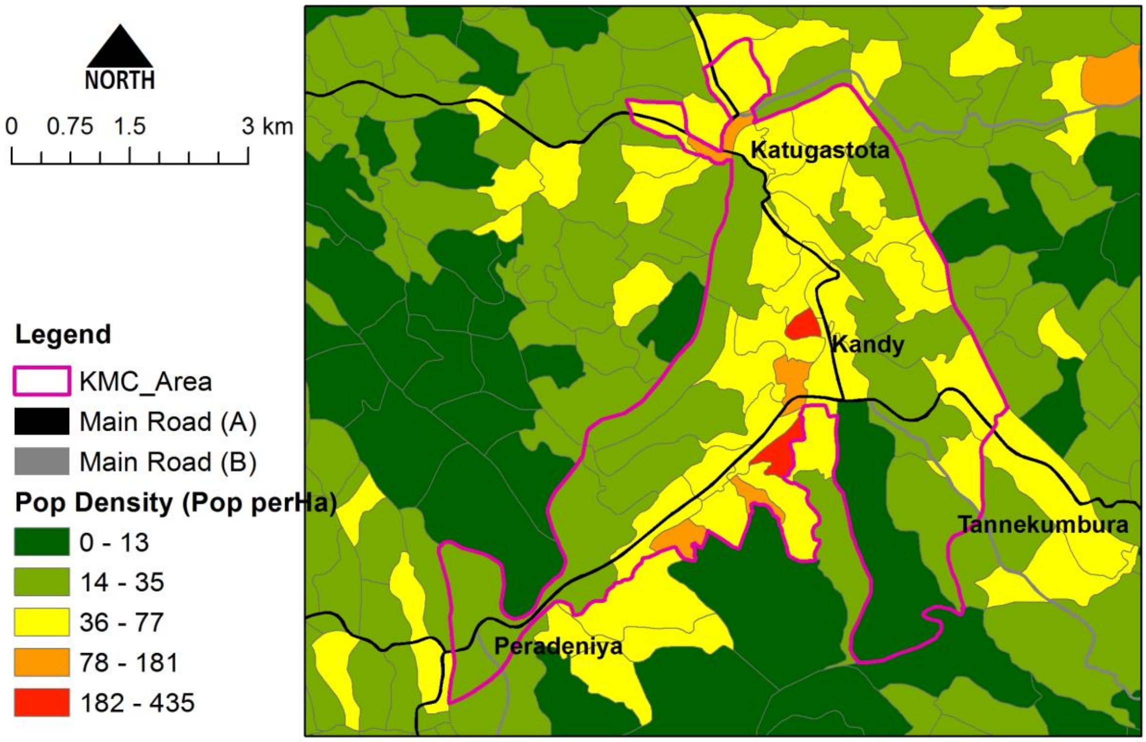
16. Zoning Plan– Kandy



Source: Urban Development Authority, Galle

17. Distribution of Population – Kandy





Note: Constructed based on Census and statistic data-2012, Department of Census and Statistics, Sri Lanka.

Glossary

Travel model: A travel model is an analysis tool that provides a systematic framework for representing how travel demand changes in response to different input assumptions. Travel models are used to provide objective assessments of the advantages and disadvantages of different alternatives (Castiglione, et al., 2015).

Traffic volume: In this study traffic volume has been defined as the number of vehicles passing a point on a road segment during a day.

Annual Average Daily Traffic (AADT) volume: The average 24-hour total volume of vehicles on both directions of a roadway segment over an entire year (AASHTO, 2009).

Passenger Car Unit (PCU): Passenger Car Unit is a measure of the impact that a mode of transport has on traffic variables compared to a single standard passenger car (Institute of Transportation Engineers, 2010).

Conventional four-step models ('four-step land use transport model'): The model comprised of four uni-directional steps as trip generation, trip distribution, modal split and trip assignment (AASHTO, 1998)

Activity-based models: Activity-based models share some similarities to traditional 4-step models: activities are generated, destinations for the activities are identified, travel modes are determined, and the specific network facilities or routes used for each trip are predicted. However, activity-based models incorporate some significant advances over 4-step trip-based models, such as the explicit representation of realistic constraints of time and space and the linkages among activities and travel for an individual person as well as across multiple persons in a household (Castiglione, et al., 2015).

Trip generation: Trip generation is the first stage of the classical first generation aggregate demand models. The trip generation aims at predicting the total number of trips produced and attracted to each zone of the study area (Institute of Transportation Engineers, 2010).

Trip distribution: Trip distribution is a model of the number of trips that occur between each origin zone and each destination zone. Trip distribution is a model of travel between zones or links (Institute of Transportation Engineers, 2010).

Modal split: Modal split models aim to determine the number of trips on different modes given the travel demand/trip volume between different pairs of nodes or zones (Bureau of Transport Economics, 1998).

Trip assignment: Trip assignment concerns the selection of routes between an origin and a destination from alternative paths available (Bureau of Transport Economics, 1998).

Traffic analysis zone (TAZ): TAZ is special geographical area delinated with in the study area for the purposed of trabulation traffic-related data. A TAZ usually consists census blocks (AASHTO, 2009).

Network centrality: The network centrality as analytical methods developed based on 'Graph Theory' which quantify the relative importance of importance of vertex [node] or edge [link] in a graph (Erdős & Rényi, 1959). This study is defined centrality as 'an analytical method which has been developed based on the Graph Theory, and apply in computing the level of centrality in a network by a set of centrality measures'

Space Syntax: Space syntax is a science-based, human-focused approach that investigates relationships between spatial layout and a range of social, economic and environmental phenomena. In space syntax the urban grid structure is represented as a street network and bifurcate into nodes and links, then analyzed the configuration of those nodes and links in terms of topological centrality (Hillier, 1999).

Connectivity: Connectivity measures the number of immediate neighbours that are directly connected to a space. This is a static local measure (Klarqvist, 2013). In this study connectivity centrality represents the links [road segment] directly connected to the particular link [road segment] in a graph [road network].

Integration: Integration measures how many turns have to be made from a street segment to reach all other street segments in the network, using shortest paths (Hillier, 1999). Theoretically, the integration measure shows the cognitive complexity of reaching a street, and is often argued to 'predict' the pedestrian use of a street: the easier it is to reach a street, the more popular it should be. This is a static global measure (Klarqvist, 2013).

Choice: Choice is a dynamic global measure of the "flow" through a space. A space has a strong choice value when many of the shortest paths, connecting all spaces to all spaces of a system, passes through it (Klarqvist, 2013).

Closeness centrality: Closeness centrality explains "the notion of accessibility of a location [road segment] and measures how close the location [road segment] to all others along the shortest path" (Porta, et al., 2012).

Betweenness centrality: Betweenness centrality captures "a special property in a particular location [road segment] that does not act as either origin or destination but as a pass-by location" (Porta, et al., 2012).

To-and-from trip [origin or destination], [O-D trips], [from-to trips]: In this study to-and-from trip has been defined as trips that either start from an origin or end from a destination location [road segment].

Pass-by trip [Flow of through trip]: In this study pass-by trip has been defined as trips that does not either start from an origin or end from a destination but as a pass-by a location [road segment].

Topological characteristic: Topological characteristic is the arrangement of road network which represents by unite distance (number of turns) and geometric distance (angular changes) (Chiaradia , et al., 2009).

Mobility characteristic: Mobility characteristic is the functional classification [road type] of roads that distinguishes the level of mobility [speed] and land access (AASHTO, 2009).