**MORPHOLOGY OF STREET NETWORKS IN URBAN NEIGHBORHOODS IN GHANA**

**CHAPTER THREE**

**RESEARCH METHODOLOGY AND PROFILE OF STUDY AREA**

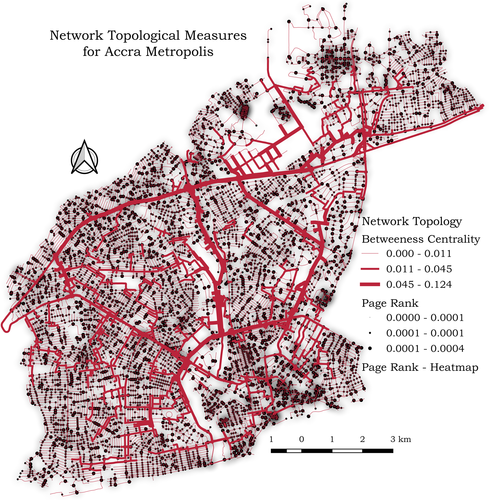
**3.1 Introduction**

This chapter presents the modern analytical and open-science methods, tools, and resources used during the research. It continues to emphasize the importance of supporting and doing open and collaborative research using modern computational tools at our disposal as researchers and policymakers. The overarching aim of this study is to show how these tools make it easier to understand the intricate structure of street networks, making the argument that the only way to make things better especially in developing countries is by joining forces and doing mutually beneficial work that can be built upon by both policy and pedagogy. It also stresses that this study seeks to build upon work done by Dumedah & Garsonu (Dumedah & Garsonu, 2021b) to advance and popularize the use of the modern open-science and computational urban informatics field and its importance in transportation planning, settlement design, and other fields involved geospatial analytics.

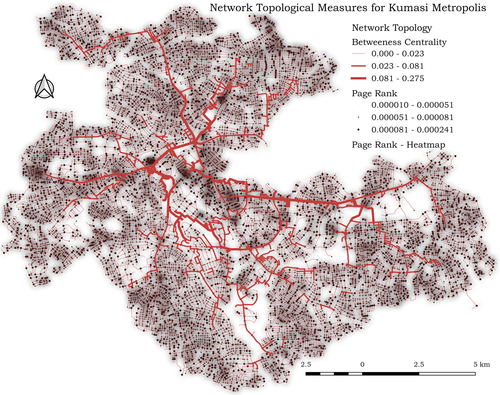
**3.2 Study Area and Data Sources**

The study area for this research encompasses six neighborhoods from two of the most populated districts in Ghana which comprise regional capitals in their respective regions, Accra and Kumasi. Accra (*Fig 1*) the national capital of Ghana is by far the most populated and in a close second is, Kumasi (*Fig 2*), which is the regional capital of the Ashanti Region. According to the provisional report from the population and housing census of Ghana conducted in 2021, one-third of persons living in Ghana live in either the Greater Accra Region with its capital Accra or Ashanti Region with its capital Kumasi.

All street network data is downloaded from OpenStreetMap, a collaborative open mapping project that provides spatial datasets covering every place on earth. As of 2016 it was reported to be 83% complete worldwide and of high spatial resolution (Boeing, 2020b; Haklay, 2010; Neis et al., 2011). Accessing the databases of OSM is free of any charges which is a huge motivator, especially for students wanting to conduct geospatial research. Also, for a country like Ghana where it is hard to obtain accurate and valuable geospatial datasets from any local agencies (Dumedah & Garsonu, 2021b), OSM is the best bet for obtaining data for any kind of geospatial analysis. However, it should be noted that, though the data from OSM is almost complete and of high quality, further preprocessing is needed to qualify the data for the kind of street network analysis described in this research.



*Fig 1: Graph theoretic model of Accra metropolis showing different topological and geometric features of the street network (Adapted from* (Dumedah & Garsonu, 2021b)*)*



*Fig 2: Graph theoretic model of Kumasi metropolis showing different topological and geometric features of the street network (Adapted from* (Dumedah & Garsonu, 2021b)*)*

**3.3 Opensource Analytical Framework**

Following the approach to produce research that qualifies to be described as open in its entirety, all tools, methodologies, and resources used to create the analysis framework are open collaborative projects and resources gathered from the internet. OSM data is obtained and preprocessed primarily with the OSMnx tool. This tool allowed us to acquire political boundaries and building footprints, and download, and construct street networks into multigraphs for further analysis. In the spirit of automating and documenting the workflow involved in carrying out the analysis, a separate python module, [autogis](https://github.com/Joe-Degs/AutoGIS/tree/master/test-thesis/autogis), was constructed from scratch to automate the processes involved in acquiring, visualizing, and obtaining topological and geometric measures from the data. This effort was done in direct response to the paper by Boeing (2020b) urging researchers to engage some of their efforts in building new tools and documenting existing ones to make the analytical landscape a more approachable one for the younglings in the field.

Other tools integral to the development include; 1. NetworkX, a python language package for exploration and analysis of networks and network algorithms, (Hagberg et al., 2008) was fundamental to a lot of the street network analysis that was undertaken. 2. Geopandas and Pandas, open source data analytics tools for fast and programmatic manipulation of data both geospatial or otherwise (Jordahl et al., 2019). 3. Jupyter notebook, another open source tool that provides a fully hosted in-browser python execution environment that facilitates the sharing of code snippets, workflows, data, and visualizations detailing the research process. It features a virtual lab environment for computational analysis and a community that actively develops, documents, and updates it to what is considered standard in the data analytics landscape (Boeing, 2019b; Randles et al., n.d.). 4. Matplotlib, a portable 2D plotting and imaging python package aimed primarily at the visualization of data (Barrett et al., 2005). At the heart of all these opensource tools is Python, a Turing Complete, general purpose, dynamically typed, interpreted, high-level programming language that for its expressiveness—due to its lux type system—is useful in the modern data analytics framework (Ayer et al., 2014; Van Rossum & Drake Jr, 1995).

For downloading and pre-processing of geospatial data, the autogis tool is responsible for taking coordinates or place names of the study area (mostly embedded in a CSV file) it geocodes the place names to coordinates or reverse-geocodes the coordinates to get the place names and then proceeds to use OSMnx to download and construct the street network graph of the specified areas. With the use of the Matplotlib tool, autogis is capable of both interactive and static plotting of geocoordinates in any CRS (Coordinate Referencing System). OSMnx uses the NetworkX tool to correct most of the anomalies that appear in representing geospatial data as multigraphs, it does these corrections by removing points along curves that separate single streets into multiple edges (Boeing, 2017a). All these are done under the hood and the process is not visible to the third-party user. Consequently, the output of all this work produces a graph-theoretic representation of the street network of the study areas, that we derive meaningful insights. All the processes, data, tools, and processes are completely documented, reproducible and open to the general public in the public repository [here](https://github.com/Joe-Degs/AutoGIS/tree/master/test-thesis).

**3.4 Measures of Network Topology and Geometry**

The morphological and design properties coupled with the network's topology and its design have a great effect on the functioning of the network and how efficient the network is in its performance. And since street networks are the backbone of things flowing through space, the entire urban infrastructure is affected if the street network is affected. It is, therefore, necessary that the topological configuration, connectedness, robustness of the network, and its geometry—which is a concern of its design and placement in space—are measured and insights drawn from such measurements to guide the continuous development of the entire urban infrastructure (Boeing, 2018; Sharifi, 2019).

From the literature, the basic topological measures include the measures of density, connectedness, length, degrees of nodes, and edges in the graph-theoretic representation of the street network (Barthélemy, 2011a; Boeing, 2019c, 2020a). We measure for each network that we have, the total number of nodes and edges connecting those nodes or themselves—in the case of self-loops. The average of the node degree is calculated and indicates the connectedness of the network, higher values are indicative of a more connected graph with lots of options for turns (Yen et al., 2021). The optimal functioning of street networks hinges on the number and connectedness of nodes and edges (whether they are fine-grained or coarse-grained), their capacity, and how they are connected as Sharifi argues (2019).

When talking about the topology of a network, centrality, and connectivity are major interwoven measures that are important to understanding how the network functions (or at the very least speculating it). Centrality is important because not all nodes or edges in a graph are the same, therefore there is the need to compute the importance of each node and edge to the overall functioning of the network. A node’s degree is the number of edges incident to it (Boeing, 2017a). Therefore, the degree of centrality of a node is the number of nodes connected to it by edges. The more connected a node is to other nodes in the network, the higher its degree of centrality in the network. Other measures of centrality include betweenness centrality, closeness centrality, information centrality, and straightness centrality (Boeing, 2017a; Sharifi, 2019). The closeness centrality of a node is indicative of the time and distance required to reach other nodes (destinations) in the network assuming it is the source. It is essential to consider closeness centrality when making decisions about the location and accessibility of amenities and services (Sharifi, 2019). Betweenness centrality, on the other hand, is an indication of how many shortest paths pass through a certain node, this measure is particularly indicative of how central the nodes are in the network. The higher the betweenness centrality of a node, the higher the number of shortest paths passing through it, which implies how central it is to commute behaviors as most rational commuters will pick routes that get them to their destinations in less time. An unevenly distributed betweenness centrality is indicative of a fragile network, one that when node(s) with high betweenness centrality fail (or are removed), the network breaks, and things come to a halt in the system (Boeing, 2020a; Sharifi, 2019).

Connectivity measures are used to examine the functionality of the street network under normal and/or in emergencies (Sharifi, 2019). The node connectivity of the network is indicative of how resilient the network is, especially concerning the minimum number of nodes to remove from the network to disconnect the network (Boeing, 2017a) and the same goes for the edge connectivity, it is the minimum number of edges to remove from the network to disconnect it and render it useless. A well-connected street network is expected to facilitate smooth origin-destination flow, reduce travel distance, and improve access to services, employment, and utilities; people often have a perception of certain trip length thresholds when making decisions to walk, bike, or drive (Sharifi, 2019). Consequently, having redundant connections (alternative routes) is helpful to maintain the state of the network in the case of emergencies. Other measures of connectivity include intersection density—the number of nodes per unit area, the average distance between intersections, and characteristic path lengths. It is to be noted that, street patterns have a significant bearing on how connected the network is (Barthélemy & Flammini, 2008; Boeing, n.d.; Sharifi, 2019).

Other important topological and geometric measures extracted from OSMnx using the autogis tool are presented and summarized in Table 1, which is adapted from Boeing and Dumedah & Garsonu (2017a; 2021b). Emphasis is placed on network topological measures like clustering, which measures how strongly connected a network is (Boeing, 2017a). Consequently, the averages of nodes and edge degrees, connectivity indices, intersection densities, PageRank and centrality, and measures of street design intricacies like network patterns, area of the network, and block sizes are taken into consideration in the analyses because of how important they are to understanding the street network in all of its totality (Boeing, 2017a; Sharifi, 2019). It is to be noted that all metrics and measures are extracted from a planar graph model of the street network in the selected study areas.

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| **Metrics and Measures** | **Description** |
| Area | The total area that the network covers |
| n – number of nodes | Number of nodes in the network |
| m – number of edges | Number of edges in the network |
| Proportion and count of streets per node | Number of streets incident to each node and the ratio of edges to each node |
| Average Street length | The average length of edges in the network, which is a proxy for block size |
| Intersection density | The ratio of the number of intersections to the total area of the network |
| Node/Edge densities | The ratio of total counts of nodes/edges to the area of the graph; is indicative of whether the network is fine-grained or coarse-grained |
| Average street per node | Average of the number of streets emanating from each node |
| Average circuity | The ratio of network distance to Euclidean distance (its inverse is directness); is a proxy for how long and complicated routes in the network are. |
| Self-loop proportion | The proportion of edges that have a single incident node. |
| Diameter/Radius | Maximum/minimum distance from a node to all other nodes in the network. |
| Degree Centrality | The average number of nodes that a node is connected to; is used to rank the importance of each node in the network. |
| Node/Edge connectivity | The minimum number of nodes/edges that have to be disconnected to disrupt the flow of information in the network. |
| Clustering Coefficient | The extent to which a node’s neighborhood (edges and nodes incident to it) forms a complete graph; high values are indicative of a self-sufficient and strong network structure. |
| Betweenness centrality | The proportion of shortest paths passing through the node; is indicative of node importance in the network. |
| Closeness centrality | The average distance from a node to all other nodes in the network. |
| Page rank | Ranking of nodes based on the structure of incoming edges. |

*Table 1: Descriptive statistic measures of topological and geometric network features used to evaluate street networks (Adapted from* (Boeing, 2017b, 2019a; Dumedah & Garsonu, 2021a)*)*

**3.5 Variables and Data Collection and Analysis**

The research starts out seeking to understand the current tool landscape as used in similar literature, one of its most salient objectives is to identify ways in which to secure free spatial data and tools for analytics. As put forward by Boeing (2020b), the current tool landscape for geospatial analyses is dominated by point-and-click GIS tools that do not take full advantage of the computational power that current computer systems come with, this is not to say they are not important. But they require more time to operate, are difficult to document, and lack any form of comprehensive automation capabilities. It is also a goal of the author of this work to enhance the development of the field by creating tools that can be built upon by other researchers and policymakers. Graph theory as is employed by most studies involved in acquiring a modern intuitive view of spatial networks—of which street networks are an integral part—is the backbone of the current literature (Barthélemy, 2011b; Boeing, 2017b, 2019b, 2020b, 2021; Brede, 2012; Corcoran et al., 2013; Dumedah & Garsonu, 2021b).

Constructing a graph model of street networks is no small feat and the use of tools that make it hard to automate the processes involved make it harder to interested people who are not well vested in the mathematical and computational rigor required to do such work. The criteria for selecting the tools used in this research was 1. Tools that can free and open-source 2. Tools that do not require domain specific knowledge in computer science or mathematics; because tools like this are harder to work with. 3. Tools that are programmatic and easy to automate. 4. Tools that do not require any kind of special hardware to use; there some analysis tools that require the use of GPUs (Graphic Processing Units) instead of CPUs (Central Processing Unit) to ran any kind of efficient analysis. 5 Tools are more suitable for spatio-temporal network analysis. Considering the above criteria, only QGIS (Development Team, 2009) (and its network analysis tools) and Python (Van Rossum & Drake Jr, 1995) make the cut as free and open-source tools used in geospatial network analytics landscape. Based on google search indexing, searching for the keyword “geospatial network analysis tools” almost always yields a front page result listing ArcGIS Pro, a proprietary software package for geospatial analysis and ESRI, the company that creates, documents, updates and owns the software. It is almost as if the term geospatial analysis is synonymous with ArcGIS or other GIS related tooling. But GIS tooling was disqualified based on the premise that they are harder to automate and documentation and usability does not nearly reach the level that Python tooling can boast. Because python is an open-source project it has the added benefit of people from everywhere contributing to make it better both the software package and its documentation.

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