EVALUATION OF MOBILE LIDAR TECHNOLOGY IN ROAD ASSET MANAGEMENT: CASE OF KeNHA HIGHWAYS IN NAIROBI CITY METROPOLIS

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Evaluation of Mobile Lidar Technology in Road Asset Management: Case of KeNHA Highways in Nairobi City Metropolis

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DECLARATION

This thesis is my original work and has not been presented for a degree in any other university

Signature……………………………………………Date………………………….

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This thesis has been submitted for examination with our approval as the University Supervisors

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DEDICATION

I dedicate this thesis to my family whose love and support has been unparalleled.

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ACRONYMS AND ABBREVIATIONS

ARICS	Annual Road Inventory and Condition Survey
ESRI	Environmental Systems Research Institute
GIS	Geographic Information System
GNSS	Global Navigation Satellite System
IRI	International Roughness Index
KeNHA	Kenya National Highways Authority
KeRRA	Kenya Rural Roads Authority
Km	Kilometers
KURA	Kenya Urban Roads Authority
LIDAR	Light Detection and Ranging
NCHRP	National Cooperative Highway Research Program
OECD	Organization for Economic Co-operation and Development
RAM	Road Asset Management

DEFINITION OF OPERATIONAL TERMS

Cloud Point:	Point cloud is a discrete set of data points in space created using a 3D scanner, lidar, or photogrammetry software.
Mobile Lidar:	Is a remote sensing & surveying technology that measures distance by illuminating a target with a pulsed laser light.
Road Asset Management (RAM):	Refers to a strategic and systematic process of operating, maintaining, and improving physical assets, with a focus on both engineering and economic analysis

ABSTRACT

Vandalism of road furniture in Kenya roads has been alarming over the years. For instance, KeNHA reported that 150 out of 200 (75%) road signages placed in the period between July to September 2022 had been vandalized posing danger to motorists who ply along the Nairobi –Narok busy highway. Despite its usefulness, there has been a challenge on how this data is collected and analyzed to give a clear picture of the road assets management. The manual methods of road assets data collection do not guarantee accuracy, are time consuming and output requires manipulation to achieve recording quality. The manipulations of data collected using manual methods does not give a fair value of road assets hence poor budgeting practices by the road agencies. Therefore, the main objective of the study was to evaluate mobile LiDAR technology use in road assets management with a case study of KeNHA highways in Nairobi City Metropolis Road network. Specifically, the study sought to assess mobile LiDAR technology use in the management of road surface pavement condition of KeNHA highways within Nairobi City Metropolis, to evaluate mobile LiDAR technology use in the management of road furniture inventory along KeNHA highways within Nairobi City Metropolis and to assess the effectiveness of Road Inventory and Condition Survey (RICS) data quality in Road Asset Management (RAM) of KeNHA Highways within the Metropolis. The research covered nine (9) dualled KeNHA highways spanning a total of approximately 277 Km, out of which a distance of 253 Km (91%) with assorted road surface conditions and furniture was sampled. The study adopted a correlational survey design. Data for this study was obtained through site visits through which spatial and non-spatial data was captured, and processed using a set of Mobile LIDAR technology gadgets. The cloud points in the sensor's coordinate system were advanced to Universal Transverse Mercator (UTM) which presents measurements in meters. Descriptive statistics was used to explain the features of data collected. According to the findings detected across the sampled roads the average length, width and depth of potholes was 14.1cm, 8.7cm and average 3.8cm respectively. The pothole dimensions were significant in that they were easily detected. Some of the cracks and rusting were severe with an average length of 1-4meters and average width of 20cm. However, for the cracks and ruttings, the depth was not significant and hence detected but not applied as the units of measure were very minimal. The findings revealed that the accuracy level of data collection using mobile LiDAR was high at 86.6 % accuracy rate. The false hit and false miss percentages were 7.8 % and 5.6 % respectively. The interpretation of the high level of hits was that KeNHA had reasonably ensured maintenance of road assets on various highways in Nairobi City Metropolis despite the cited cases of vandalism. Pavement Surface Evaluation and Rating (PASER) findings revealed that most of the roads in the study area are in Good or Fair condition. However, some areas had poor score with visible slippage, cracks and potholes. The study concluded that automation of road asset management practices using the Mobile LiDAR technology presents an opportunity to improve the reliability, validity and timeliness of inventory data for effective decision-making, budgeting and planning purposes. Based on the findings, the study recommends that road agencies in Kenya make routine use of mobile LiDAR to collect accurate data on various road conditions as this will aid in corrective planning and accuracy in budgeting.

CHAPTER ONE

INTRODUCTION

1.1 Background of the Study

Infrastructure projects among them roads have a crucial role within societies in converging the economic development need and most importantly changing the citizens' quality of life (Matu et al., 2020). The central role of public infrastructural projects in sustaining development is acknowledged in Chapter 27 of the 21st agenda of the United Nations (UN Charter 1945). Likewise, the Kenya Vision 2030 recognizes infrastructure as an enabler for sustained development under the economic pillar.

Rapidly increasing population and urbanization in large cities have directed the attention of researchers to the importance of traffic services including timely road asset maintenance, updated road information, road safety, and comprehensive management (Riveiro *et al*, 2015). These services highlight the need for a variety of specialized software for road design, expansion, and asset inventory to achieve accurate, comprehensive, and systematic road management and efficient road maintenance (Wang *et al.,* 2017*)*. Roads are essential national assets that steer economic growth in a country. Mutai and Obura, (2018) advanced that efficient and effective road transport is central to the economic growth and development of developing countries and particularly this mode of transport accounts for eighty to ninety per cent of the continent's total trade in goods and services. Developing countries are therefore in need of adequate road infrastructure management policies, strategies and institutions to manage this crucial asset optimally.

According to Organization for Economic Co-operation and Development (OECD, 2001), road network constitutes one of the largest community assets and is predominately government owned. The Kenya Roads Board (KRB) reports that the road network in Kenya is approximately over 160,000 kilometres and is valued at Ksh 3.5 trillion (Annual Public Roads Programme 2020-2021). This therefore constitutes one of the country's largest public investments bringing forth the need for the road networks to be constantly developed and maintained prudently and cost-effectively.

Civil Engineering infrastructure projects undergo three main phases during their lifetime—planning and design, construction and maintenance. The use and maintenance phase has the longest duration and involves most of the project cost. Different construction engineering projects, such as the development of roads and bridges usually have design life and are expected to be usable for several years. However, damage and deterioration are unavoidable. The amount of money spent on the repair or replacement of the assets is also very high. To make the process of maintenance and improvements more manageable, it is necessary to document the assets and inventories in an appropriate format. The recent advancements in digital maps and GIS (Geographic Information System) technology have improved the efficiency of asset and inventory management. GPS (Global Positioning System) is an instrument that is widely used to locate and map the positions of assets. The most important task in the development of an asset management system is the collection of accurate spatial data and its related attributes. Manual data collection using field data loggers with GPS and traditional survey methods is commonly seen for asset inventory data collection. Though this methodology provides accurate results, it involves more time and manpower. Several remote sensing products, such as aerial imageries, terrestrial photographs and laser point clouds with high accuracies also contribute to the development of an asset inventory database.

Remote-sensing technologies for road information inventory are undergoing rapid developments. The possibility of acquiring three-dimensional (3D) information of large-area roadways with survey-grade accuracy at traffic speeds is opening up new and efficient ways for road information inventory. Recent advances in sensor electronics and data treatment make these technologies affordable. The two major remote-sensing technologies that are popularly used in road information inventory are image-based and laser-based mobile mapping systems (Toth, 2009).

Mobile LiDAR, a widely used technology since the year 2003 when the first mobile LiDAR system emerged (Glennie, 2009), has attracted much attention for mainly transportation-related applications along various corridors because of the extreme ease in capturing comprehensive high resolution 3D topographic data at highway speed (Yadav et al., 2013).

1.1.1 Road Asset Management

Road Asset Management (RAM) also known as infrastructure asset management is a strategic and systematic process of operating, maintaining, and improving physical assets, with a focus on both engineering and economic analysis based upon quality information, to identify a structured sequence of maintenance, preservation, repair, rehabilitation, and replacement actions that will achieve and sustain a desired state of good repair over the lifecycle of the road assets at minimum practicable costs (Greenwood et al., 2012).

Road assets that include traffic signs and signals, light poles, guardrails, and culverts, are essential components of transportation networks. They guide, warn, and protect drivers and regulate traffic. Road inventory plays a critical role in highway maintenance and asset management (Song, He & Liu, 2018). State Departments of Transportation (DOTs) and local transportation agencies always need up-to-date inventory data to establish the condition of the road networks within their jurisdictions, prioritize reconstruction and repair work and value their highway assets.

Road asset management represents a systematic process of maintaining, upgrading and operating assets, combining engineering principles with sound business practice and economic rationale, and providing tools to facilitate a more organized and flexible approach to making the decisions necessary to achieve the public's expectations (OECD, 2001). Road asset management is consequently about managing road agency resources more like a business. There is therefore need for road agency managers to develop a common language with budget holders, hence giving them the critical ability to demonstrate the implications of investment options (Mutai & Obura, 2018). This business-like approach of road asset management requires an estimation of the value of infrastructure assets, as this value is a significant factor in determining priorities for future investment in road assets. The valuation process, with its emphasis on economics or finance, represents a shift in thinking from the traditional engineering approach to transport program development.

According to Mutai and Obura (2018), road assets management as a practice in road maintenance has a significant contribution to the performance of road agencies in Kenya. The Road Agencies in Kenya which include Kenya National Highways Authority (KeNHA), Kenya Rural Roads Authority (KeRRA) and Kenya Urban Roads Authority (KURA) are undertaking Annual Road Inventory and Condition Surveys (ARICS) on the existing road network as a way of obtaining data to be used for informed decision making on the appropriate maintenance interventions to be undertaken. The objective of the survey is to record the condition of a road as is and assess the interventions (maintenance or improvement) required to keep the road in a good state or in its original design standard.

Developing or updating a road inventory is time-consuming and laborious. Apart from the tedious data collection work, separating and extracting useful information from an abundance of raw data also requires a lot of work (Brown et al., 2022). Therefore, automatic detection methods or even semi-automatic detection methods would be helpful. The study thus assesses the use of mobile LiDAR in Road Asset Management in Kenya.

1.1.2 Mobile LiDAR Technology

The use and adoption of technology advancement is increasingly gaining acceptance across the globe. Recognizing the potential value of this emerging and transformative technology to Road Agencies such as remote sensing and mobile LiDAR can be a breakthrough to increase efficiency and improve the performance of the agencies by eliminating obsolete processes and advocating for continuous improvement through adopting new technology.

Mobile LiDAR is an important technology that has major implications for how geospatial data is collected, exploited, managed and maintained by transportation agencies (Guideline for the use of Mobile LiDAR in Transportation Application). Mobile LiDAR system (MLS) is gaining popularity in three-dimensional (3D) mapping applications along various road corridors (Yadav et al., 2013), because of the extreme ease it provides in capturing comprehensive high-resolution 3D topographic data at highway speed (Yadav et al., 2016). As road agencies transition from 2D workflows to 3D model-based design and asset management, the ability to make efficient use of mobile LiDAR will only increase. With a mobile LiDAR system, mapping engineers can drive on a highway, rural road and railroad, or along the shoreline of a river or lake as the system captures trees, bridges, streetlights, buildings, power lines and other street-scene small objects (e.g. cracks, road markings, etc.) in the form of 3D point clouds. In addition, the acquired 3D point clouds provide accurate

3D geospatial information of roadways. The collected data are a immersive 3D view of the objects and surroundings (Rybka, 2011).

Compared with other remote sensing technologies, LiDAR is more automatic, efficient, and accurate. Furthermore, it can work both during the daytime and at night because laser scanning is relatively independent of sunlight (Moselhi et. al., 2020). Since its introduction, LiDAR has been used for a wide range of applications, including high-resolution topographic mapping, 3D surface-modelling, infrastructure and biomass studies, archaeological site detection, remote monitoring and object detection. LiDAR technologies have become well-established surveying techniques for acquiring geospatial information because Global Navigation Satellite System (GNSS) technologies have been widely commercially used since the early 1990s (Beraldin et al., 2010). Closely followed by airborne LiDAR, terrestrial LiDAR (that is, the laser scanner is mounted on a tripod) and mobile LiDAR technologies have been rapidly developed. Figure 1.1 shows a schematic representation of a mobile LiDAR system with various components.

Figure 1.1: Schematic Diagram of Mobile LiDAR

Source: (www.gim-international.com)

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1.1.3 Kenya National Highways Authority

Kenya National Highways Authority (KeNHA) a Road Agencies in Kenya is responsible for the development, rehabilitation, management and maintenance of all National Trunk Roads comprising Classes S, A and B roads, totaling to approximately 21,553 Km. According to the Kenyan Constitution of 2010, the National Government (through the Ministry of Transport, Infrastructure, Housing, Urban Development, and Public Works) is responsible for the provision of a functional and efficient road network in Kenya. Policy and regulatory frameworks, liaison, oversight, oversight, liaison with other state organs, and any other services required for the efficient operation of the sub-sectors are all responsibilities of the Ministry (Kursai, 2018). Road projects in Kenya, like those in many other African countries, have faced several obstacles, including completion delays, abandoned construction projects, as well as poor management (Maina, 2018)

Ravi and Habib (2020) advanced that with an ever-increasing network of thousands of kilometres of pavement laid out over highways and road networks, their continuous monitoring is a task of utmost importance to public road agencies responsible for their maintenance. The existing approaches of Annual Road Inventory Condition Survey (ARICS) mostly rely on a manual detection of pavement distress based on acquired observatory data – an approach that is time-consuming, costly, and whose results are subjective to the nominated rater. This necessitates the need for development and adoption of a system that is capable of quick data acquisition along with an efficient algorithm for the detection and quantification of road asset based on the acquired data. This research proposes an evaluation of mobile LiDAR technology in road asset management so as to establish its effectiveness and guide in decision making for appropriate maintenance interventions.

1.2 Statement of the Problem

Road infrastructure accounts for the biggest capital asset that any country's public sector holds. Consequently, in order to properly manage the public asset in a businesslike and systematic way, proper records and road inventory data should be easily and readily available as well as be up to date. However, this is not the case especially in most developing countries as they tent to use manual methods which is an ongoing challenge. Until now, collecting this type of data has been done by field crews, using tripod-mounted survey equipment albeit with inaccuracies and inconsistencies. The current method of undertaking the ARICS exercise is considered largely outdated, time-consuming, costly, and unreliable. Not only is this method slow, but it also exposes surveying personnel to potential safety hazards and causes a disruption to the operation of the roads resulting into inconveniences and loss of income.

According to the Japan International Cooperation Agency (JICA) annual report (2020) on the Data Collection Survey on Road Asset Management Platform Technical Support, it was noted that the challenge facing road asset management in various developing countries is a lack of proper data collection techniques. According to the report where Kenya was among the countries surveyed, the manual methods of road assets data collection used do not guarantee the accuracy, are time-consuming and output require manipulation to achieve recording quality. Besides this being a time-consuming and costly task, the final results are influenced by the subjectivity and the experience of the raters (Bianchini et al, 2010). The manipulations of data collected using manual methods do not give a fair value of road assets hence poor budgeting practices by the road agencies. This may cause over budgeting leading to waste of public resources or under budgeting which does not solve the problem and risk at hand.

Vandalism of road inventory assets in Kenya roads has been alarming over the past few years. For instance, KeNHA reported that 150 out of 200 signage placed in the last three months had been vandalized posing danger to the motorists who ply along the Nairobi –Narok busy highway. According to the Auditor General report (2020) on performance audit on the installation and maintenance of road furniture in Kenya, inspection of road furniture on the sampled roads revealed that various warning signs for bumps, bends and pedestrian crossings were missing at crucial locations. The report further recorded that, there were 50 vandalized road signs, 40 vandalized guardrails and 14 vandalized bridge rails on the 22 KeNHA roads inspected. According to KeNHA annual report (2020-2021), the Authority continues to face challenges from vandalism of road furniture, delays in relocating utilities and encroachment on road reserves. Road asset vandalism puts road users at risk due to misinformation leading to accidents and loss of lives.

Despite the well-known challenges facing road asset management, the road agencies do not have robust and consistent information about the true cost of holding and maintaining the assets, or the size of maintenance and investment backlogs. They also lack the detailed information required to derive down the cost bases and improve service delivery.

1.3 Objectives the Study

This study was guided by the general and specific objectives as follows:

1.3.1 General Objective

The main objective of the study was to evaluate the application of Mobile LiDAR technology in Road Assets management using the case of KeNHA highways within Nairobi City Metropolis.

1.3.2 Specific Objectives

i. To assess the effectiveness of Mobile LiDAR technology use in monitoring and managing the condition of road surface pavements on KeNHA highways within Nairobi City Metropolis.
ii. To evaluate the effectiveness of Mobile LiDAR technology use in the management of road furniture inventory along KeNHA highways within Nairobi City Metropolis.
iii. To analyze the quality and reliability of data captured through Mobile LiDAR technology for Road Inventory and Condition Survey (RICS) - on KeNHA Highways within Nairobi City Metropolis.

1.4 Research Questions

i. What is the effectiveness of mobile LiDAR technology in monitoring and managing the condition of road surface pavements on KeNHA highways within Nairobi City Metropolis?
ii. What is the effectiveness of mobile LiDAR technology use in the management of road furniture inventory along KeNHA highways within Nairobi City Metropolis?

iii. What is the extent of quality and reliability of data captured through Mobile LiDAR technology for Road Condition and Surveys (RICS) - on KeNHA highways within Nairobi City Metropolis?

1.5 Justification of the Study

The use of mobile terrestrial LiDAR mapping arguably provides a faster, and safer alternative to surveying that uses ground-based and tripod-mounted equipment. Mobile LiDAR systems equipped with side-looking 3D laser scanners and cameras acquire dense point data from the ground.

The benefits of the use of mobile LiDAR in transport applications have been found to increase the efficiency and performance of the Road Agencies involved in the maintenance of road assets. With the ever-increasing expansion and upgrading of the road to bitumen standards, the manual observatory approach will become obsolete and not practical to undertake. Further, the rapid road infrastructure expansion in Kenya calls for protection of the road assets through proper maintenance interventions. To ascertain the appropriate maintenance intervention to be undertaken on a particular road, a road asset inventory and condition survey is required.

The study findings will provide more data to the various road infrastructure agencies in Kenya for informed decision-making and guide policy development for the use of mobile LiDAR technology in transport applications.

1.6 Scope of the Study

The study mainly focused on collecting road assets and condition data by use of Mobile LiDAR in comparison to the manual site observatory approach method to get the distinction in terms of efficiency.

The study covered major roads under KeNHA management and maintenance within the Nairobi City Metropolis area. According to the KeNHA report (2022) and KURA report to the media, Nairobi and Mombasa Counties lead on road furniture vandalism hence the selection of the study area. The demands for scrap metal in the cities as well as poor usage of roads by motorists in the cities have contributed to the rise of vandalism and consequently increase in road accidents (KURA Annual report, 2021). The study reviewed literature anchored to stakeholders' theory and technology adoption life cycle theory. Data was captured from all nine (9) KeNHA highways serving the Nairobi City Metropolis. This being academic research, it was time bound hence conducted for twelve (12) months.

1.7 Limitations of the Study

Kenya has not developed Guidelines for the use of Mobile LiDAR in Transport applications; thus, this study relied more on secondary information from other developed nations such as the United States of America NCHRP Report 748, 2013.

This being academic research, it was subject to a particular time and scope hence limited. Thus, the study did not cover detailed condition surveys for major structures such as bridges that ideally require longer time and more resources.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

This chapter presents relevant literature to the study**,** and this includes the concepts related to this study and similar and related studies that help establish the rationale of this research which is the gap that, is intended to be filled by conducting this study.

2.2 Theoretical Framework

The study is anchored on the stakeholder theory in road asset management and technology adoption life cycle theory.

2.2.1 Stakeholder Theory in Road Asset Management

The Stakeholders theory was advanced by Freeman (1999). The theory postulated that a road infrastructure project consists of many complex activities which the project teams have to manage. Stakeholder theory is a theory of organizational management and ethics (Phillips, Freeman & Wicks, 2003). It opposes the free market norm of shareholder capitalization and promotes stakeholder maximization. One of the activities consists of managing the project stakeholders who have a certain interest and power in the project in which they are involved (Hartmann et al., 2012).

Effectively managing and controlling these stakeholders and their expectations has become intrinsic to project success (Parnell et al., 2011). The tool in doing so is also considered to be extremely important for achieving project success. Stakeholder is a concept that refers to the necessity for an organization to manage the relationships with its specific stakeholder groups in an action-oriented way. (Freeman, 1999).

Attention to stakeholders is important throughout the planning process of road maintenance projects because the project's success is defined by the stakeholders depending on their evaluation of the infrastructure (Bryson, 2004). However, public agencies responsible for managing infrastructure assets routinely fail to consider the relationship between the road assets and those people and organizations being influenced by the performance of those road assets.

Sutterfield et al. (2006) argue that to achieve a successful road project outcome, road project managers must adapt to managing the interest of stakeholders throughout the project management process. A good project stakeholder management enhances the possibility of a good project result. To manage the road network, road managers and operators have to consider existing policies, such as the requirement to keep the network in good condition, and to deliver this condition at a minimum whole-life cost. However, the condition should also meet the expectations of stakeholders. The management process has to optimise the total costs for society, whilst minimizing the effects of given condition levels on safety, reliability, environmental impact, economics and sustainability (Edvardsson et al, 2013).

2.2.2 The Technology Adoption Life Cycle Theory

The theory was developed by Moore (1999) and split the technology implementation lifecycle into groups of five final users' traits as well as motivations. The theory postulates that the circulation of new technologies across the groups of final users is assumed to trail on a normally distributed bell curve prototype (Coughlan, Dew & Gates, 2008). The lifecycle is an expected blueprint pursued by technical modernism beginning from the setting up and project growth to market dissemination and into market subrogation (Ahmad, 2011).

The theory defines five classes of persons: the innovators, early adopters, the early majority, the late majority, and the laggards. The innovators seek new technologies insistently (Ahmad, 2011) while early adopters acquire new invention ideas very early in their lifecycles and unlike the modernizers, they are not technicians (Coughlan, Dew & Gates, 2008). The early majorities contribute to being part of the early adopters' capacity to relate to technologies, except eventually, they are motivated by sharp realism senses (Vasseur, 2012). The late majority waits in anticipation of a thing to be established in levels for their adoption to the technology and finally, the laggards; those who do not want everything dealing with new technologies because of dissimilar motives that may be economic or individual (Tangkar & Arditi, 2004). Technology adoption life cycle theory is heterogeneous and is founded on different advancements. The theory analyses three unique life cycles: invention, industry and technology secondly, this literature is on the rise due to assistance from various studies like business plans, economics, and promotional and sociological studies (Vasseur, 2012). The theory is relevant to this study as it explains the stages of adoption of technology which gives a justification for level of adoption of mobile LiDAR by KeNHA.

2.3 Empirical Literature Review

2.3.1 Road Assets Management

Arif and Bayraktar (2012) did a theoretical framework for transportation infrastructure asset management based on review of best practices. The study provided a review of the best practices adopted by different transportation infrastructure agencies internationally and in the United States. The review showed that the front-runners in the asset management system internationally are Australia while Michigan takes the lead in US. Finally, based on the review of best practices, a theoretical framework for transportation infrastructure asset management was proposed. The framework focused on six important aspects of an asset management system i.e. asset management organization and concept, planning, contractual arrangement and mechanisms, monitoring and performance measurement, information systems and decision-making.

Byaruhanga and Basheka (2017) conducted a study on contractor monitoring and performance of road infrastructure projects in Uganda and developed a management model. The objectives of the study were to assess the relationship between contractors monitoring and performance of national road infrastructure projects in Uganda. Purposive sampling was employed in selecting the procurement professionals, and engineers and simple random sampling was adopted in selecting private consultants, members of parliament and respondents from the civil society organizations. The findings revealed that weak procurement rules lead to awarding road projects to incompetent contractors; contractor monitoring being handled by unqualified, incompetent and inexperienced professionals; lack of contractors and contract supervisor’s appraisal system; delay of contractors’ payments which affects timelines in services delivery; lack of a strong internal project monitoring and evaluation mechanism at the Uganda National Roads Agency (UNRA).

Geddes et al. (2016) reviewed economic growth through effective road asset management. The main purpose of the project was to review literature and report on existing and recent road management and maintenance programs and identify ‘what works’ and ‘what doesn’t work’ in the type of environment likely to be encountered in the project area. The approach to the project was intended to foster self-reliance in road agencies in the project areas and encourage greater accountability to road users and other sector stakeholders.

Sodikov and Jamshid (2015) conducted a study on road asset management systems in developing countries with specific reference to Uzbekistan. The study explored the key issues on how to manage existing assets in a way that delivers maximum benefit to the public taking into account limited financial resources. The road asset management system was reviewed from the perspective of four major components such as goals, budget, assets and performance. The study established that there are several issues at the policy level of analysis such as setting up long-term goals, expansion of road network, traffic safety action plans, environmental impact analysis, economic development and others; at the budget level to plan year and multiyear financing plan, budget breakdown and cost estimation; at data management level inventory and condition data collection, database management, traffic data and other; at performance modelling level to predict the future condition, network level analysis and other; at programmed optimization level to perform economic, environmental and risk analysis, multi-criteria analysis and other; implementation programme to carry out construction, maintenance and operation of road assets.

2.3.2 Determining Condition of the Road Pavement

Shtayat et al., (2020) did a review of monitoring systems of pavement condition in paved and unpaved roads. The review indicated that the rising number of vehicles on roadways expedites the urge to increase efforts in implementing monitoring systems that look after road pavement conditions. This rise in the number of vehicles on roadways also causes more damage and distress on road pavement. Road pavement conditions should be accurately evaluated to identify the severity of pavement damages and types of pavement distress. Therefore, monitoring systems are considered a significant step in maintenance processes. Paved roads and unpaved roads require regular maintenance to provide for and preserve users' usability, accessibility, and safety. Transport agents and researchers would spend a lot of time and money inspecting some sections of the roadway surface; that inspection would then be followed by results recording and data analysis to diagnose the type of treatment required. These monitoring systems have been developed using various methods that include smart technologies and prepared equipment. Many related studies evaluate road pavement degradation and distress, while others focus on identifying the best maintenance monitoring approach in terms of time and cost. This paper set out to explore different monitoring techniques used to evaluate road pavement surface conditions. Also, the study introduces dynamic and static monitoring systems used in both paved and unpaved roads to identify the severity of pavement degradation.

In a study by Ragnoli, et al., (2018) on pavement distress detection methods, it was found that road pavement conditions affect safety and comfort, traffic and travel times, vehicle operating costs, and emission levels. To optimize road pavement management and guarantee satisfactory mobility conditions for all road users, the Pavement Management System (PMS) is an effective tool for the road manager. An effective PMS requires the availability of pavement distress data, and the possibility of data maintenance and updating, to evaluate the best maintenance program. In the last decade, many researchers have focused on pavement distress detection, using a huge variety of technological solutions for both data collection and information extraction and qualification. This paper presents a literature review of data collection systems and processing approaches aimed at pavement condition evaluation. Both commercial solutions and research approaches have been included. The main goal is to draw a framework of the actual existing solutions, considering them from a different point of view to identify the most suitable for further research and technical improvement, while also considering the automated and semi-automated emerging technologies. An important attempt is to evaluate the aptness of the data collection and extraction to the type of distress, considering the distress detection, classification, and quantification phases of the procedure.

Andrei, et al., (2010) assessed road pavement conditions, based on the combined concept of chance, change and entropy. The assessment of road pavement condition was based on three powerful concepts, aimed to accommodate the uncertainty caused by the complex interrelationships, material defects, structural deficiencies, human errors, and ambient fluctuations characterizing the pavement systems. These very useful concepts, selected with the aim, of approaching, in a new comprehensive manner, the difficult task of assessment of road pavement condition are as follows: the concept of chance, expressed in terms of probabilities and reliability; the concept of change, expressed in terms of dynamics, e.g. of change of the pavement condition in time; the concept of entropy, expressed in terms of differences in pavement system's entropy, occurred in time, as an appropriate quantitative parameter, measuring the degree of uncertainty of pavement to meet its specific structural, surface and traffic safety requirements.

Attoh-Okine and Adarkwa (2013) did a study on pavement condition surveys overview of current practices of the Delaware Center for Transportation, University of Delaware. Pavement Condition Surveys refer to activities performed to indicate the serviceability and physical conditions of road pavements. These activities have three main aspects namely data collection, condition rating and quality management. In recent times, most state agencies have been inclined towards automated and semi-automated means of collecting pavement data. Condition rating involves quantifying the condition of pavement assets based on a chosen scale or index. The rating index selected by an agency depends on the agency's available resources and its ability to address pavement issues prevalent in the area. There are two main groups of condition indexes; estimated and measured condition indexes. Estimated condition ratings are based on observed physical conditions of the pavements while the measured condition rating systems are not only based on observations by trained raters but are also backed by physical measurements such as roughness and mathematical expressions. Quality management is done to ensure that the data collected meets the needs of the pavement management process. It involves activities such as specification of data collection protocols, quality criteria, responsibilities of personnel, quality control, quality acceptance, corrective action and quality management documentation. There is room for improvement in all aspects of the pavement management process. Quality criteria need to be updated periodically using basic statistical tools. All quality management procedures must be well documented to help improve future data quality control and assurance procedures. With quality and reliable data, pavement management will be improved and this will ultimately lead to efficient use of pavement assets.

2.4 Assessment of Road Furniture

Li et al. (2019) did a semantic segmentation of road furniture in mobile laser scanning data. In the framework, they first detect road furniture from unorganized mobile laser scanning point clouds. Then detected road furniture is decomposed into poles and attachments (traffic signs). In the interpretation stage, they extract a set of features to classify the attachments by utilizing a knowledge-driven method and four representative types of machine learning classifiers, which are random forest, support vector machine, Gaussian mixture model and naïve Bayes, to explore the optimal method. The designed features are the unary features of attachments and the spatial relations between poles and their attachments. Two experimental test sites in the Enschede dataset and Saunalahti dataset were applied where the Saunalahti dataset was collected in two different epochs. In the experimental results, the random forest classifier outperforms the other methods, and the overall accuracy acquired is higher than 80% in the Enschede test site and higher than 90% in both Saunalahti epochs. The designed features play an important role in the interpretation of road furniture. The results of two epochs in the same area prove the high reliability of our framework and demonstrate that the method achieves good transferability with an accuracy of over 90% by employing the training data of one epoch to test the data in another epoch.

Gonzalez-Gomez et al. (2021) did an assessment of intersection conflicts between riders and pedestrians using a GIS-based framework and portable LiDAR. An algorithm for the automatic detection of zebra crossings from mobile LiDAR data was developed and tested to be applied for road management purposes. The algorithm consists of several subsequent processes starting with road segmentation by performing a curvature analysis for each laser cycle. Then, intensity images are created from the point cloud using rasterization techniques, to detect zebra crossing using the Standard Hough Transform and logical constraints. To optimize the results, image processing algorithms are applied to the intensity images from the point cloud. These algorithms include binarization to separate the painting area from the rest of the pavement, median filtering to avoid noisy points, and mathematical morphology to fill the gaps between the pixels in the border of white marks. Once the road marking is detected, its position is calculated. This information is valuable for inventorying purposes of road managers that use Geographic Information Systems. The performance of the algorithm was evaluated over several mobile LiDAR strips accounting for a total of 30 zebra crossings. That test showed a completeness of 83%. Non-detected marks mainly come from painting deterioration of the zebra crossing or by occlusions in the point cloud produced by other vehicles on the road.

Yadav et al. (2017) did an extraction of road surfaces from mobile LiDAR data of complex road environments. The proposed method was constructed using unstructured MLS data as input and does not require any other additional data. The method was divided into three major steps, that is, MLS data structuring and ground filtering, road surface point extraction, and road boundary refinement. The first step filters ground points from input MLS data, while the second step identifies road surface points from among the ground points. The second step was designed using specific characteristics of a road, that is, topology, surface roughness, and variation of point density. The third step refines road boundaries. Three test sites, quite complex with heterogeneous characteristics, were used for demonstration of the proposed method. Road surfaces of these three roadways were accurately extracted without being affected by on-road objects and the absence of a raised curb. Average accuracy measures like completeness, correctness, and quality were found to be 93.8%, 98.3%, and 92.3%, respectively, in three test sites. Further, road boundaries of extracted road surfaces of these three test sites were refined at average completeness, correctness, and quality of 95.6%, 97.9%, and 93.7%, respectively. The proposed method has shown satisfactory performance for complex roadways having road sections with and without raised curbs and has the potential to be employed for such road environments, which are not uncommon. The proposed method was implemented on a GPU-based parallel computing framework, which significantly saved the run time in the processing of MLS data of three test sites.

Li et al. (2018) performed a pole-like road furniture detection in sparse and unevenly distributed mobile laser scanning data. They used a framework to detect pole-like road furniture from sparse mobile laser scanning data. The framework was carried out in four steps. The unorganized point cloud is first partitioned. Then above ground points are clustered and roughly classified after removing ground points. A slicing check in combination with cylinder masking is proposed to extract pole-like road furniture candidates. Pole-like road furniture is obtained after occlusion analysis in the last stage. The average completeness and correctness of pole-like road furniture in sparse and unevenly distributed mobile laser scanning data was above 0.83. It is comparable to the state of the art in the field of pole-like road furniture detection in mobile laser scanning data of good quality and is potentially of practical use in the processing of point clouds collected by autonomous driving platforms.

2.5 Quality and Reliability of Road Asset Inventory Survey Data

Early work on road asset inventory has focused on quantifying the capabilities of several learning machine-learning techniques in predicting maintenance interventions using a reduced set of historical records (Morales et al., 2017). A lateral study was conducted to define the relevant information that needs to be recorded during maintenance works, regarding the asset’s condition just before and after being maintained, to provide self-learning capabilities to facilitate maintenance predictions (Morales et al., 2017).

Morales et al. (2021) performed a study on machine learning methodology to predict alerts and maintenance interventions in roads. This contribution is about predicting maintenance alerts on roads and selecting the most appropriate type of interventions recommended for preventing the occurrence of future failures. The objective was aligned with that covered by pavement maintenance decision support systems (PMDSS), though the methodology presented can be applied to other non-pavement road linear assets. The purpose was to summarize the main findings in the development of an approach based on testing the four most extended machine learning techniques (ML). The machine learning techniques include Decision Trees (DT), K-Nearest Neighborhood (KNN), Support Vector Machines (SVM) and Artificial Neural Networks (ANN), using data from the historical inventory of inspections and maintenance interventions. The correlation process embodies supervised and unsupervised training of models. The maintenance predictions are presented and compared over various segments corresponding to the real maintenance interventions conducted on an existing road network of a geographical zone.

Li, et al. (2020) did a study on Automatic Road surveys by using vehicle-mounted laser for road asset management. In most countries, local roads (i.e., urban and rural) form over 80% of the entire road network and constitute the country's largest asset value. For local roads to remain fit for purpose and maintain their value, they require periodic maintenance. To make the best use of scarce maintenance resources, road maintenance needs to be preventative which requires the condition of the road to be assessed periodically. Traditional road surveys suffer from the lack of repeatability and reproducibility and are high-cost and time-consuming. This work proposes a vehicle-mounted point laser system for the automated, rapid and inexpensive measurement of a major mode of local road deterioration, namely fretting. Compared to other technologies such as Ground Penetrating Radar (GPR), visual sensors and the Mobile Laser Scanning (MLS) system, the point laser requires less computational power, is less sensitive to the surrounding environment and is of comparatively low cost. A robust approach is proposed which consists of several pre-processing algorithms to deal with noise and the effects of the vehicle's dynamic motion, and a signal processing algorithm which analyses histograms of the distance from the road surface measured by the laser to account for changes in road texture. Road fretting measured by the proposed system on a variety of roads is compared with fretting determined using a standard visual assessment process. The results indicate that the proposed system can measure road fretting to the levels of detail which are suitable for planning, programming and preparation of road management functions.

Soilan et al., (2019) did a review of laser scanning technologies and their applications for road and railway infrastructure monitoring. Improving the resilience of infrastructures is key to reducing their risk vulnerability and mitigating the impact of hazards at different levels (from increasing extreme events, driven by climate change); or from human-made events such as accidents, vandalism or terrorist actions. One of the most relevant aspects of resilience is preparation. This is directly related to (i) the risk prediction capability; (ii) the infrastructure monitoring; and (iii) the systems contributing to anticipate, prevent and prepare the infrastructure for potential damage. This work focuses on those methods and technologies that contribute to more efficient and automated infrastructure monitoring. Therefore, a review that summarizes the state of the art of LiDAR (Light Detection and Ranging)-based data processing is presented, giving a special emphasis to road and railway infrastructure. The most relevant applications related to monitoring and inventory transport infrastructures are discussed. Furthermore, different commercial LiDAR-based terrestrial systems are described and compared to offer a broad scope of the available sensors and tools for remote monitoring infrastructures based on terrestrial systems.

2.6 Geographic Information System (GIS)

Almost everything that happens, happens somewhere. Knowing where something happens can be critically important (Goodchild et al., 2005). GIS is an organized collection of computer hardware, software, geographic data and personnel designed to efficiently capture, store, update, manipulate analyze and display all forms of geographically referenced information (ESRI, 2021). GIS is an effective tool for different types of data integration particularly locational attributes and spatial relations which enables the analysis function to help decision makers. Typical components of a GIS include data, hardware, software, users and procedures. To make sense of massive geospatial data such as data generated from LiDAR systems, Geographic information software systems are used for data capture and update, storage and management, analysis and simulation and visualization of geospatial data.

GIS-based systems bring unique power due to the following capabilities:

i. Analysis- spatial is the crux of GIS since it includes all transformations, manipulations and methods applied to geospatial data to add value, support decisions and reveal patterns.
ii. Integration- GIS can seamlessly handle spatial and non-spatial data, perform analysis and disseminate to concurrent users with different backgrounds.
iii. Data Management- GIS databases can manage data in various forms such as vector and raster with their respective spatial information.
iv. Visualization- with the exponential democratization of GIS, communication with the audience or users is no longer a challenge. 3D geo-visualization which entails visualizing geographic information in any of the steps of spatial analysis including the time component makes GIS-based systems easily understandable to users.

2.7 LiDAR Technology

LiDAR stands for Light Detection and Ranging, it is a remote sensing measuring technique that uses light in the form of a pulsed laser to measure ranges to the Earth. The information obtained therein forms 3-dimensional information about the earth's surface and its characteristics, often referred to as point clouds. Modern LiDAR systems are fully integrated sensor platforms, typically comprising one or more laser scanners, digital cameras of different spectral ranges, and inertial measurement units coupled with global navigation satellite system receivers (Peter & Andreas, 2021). There are four popular platforms for producing point clouds which include the following (Nathan et al., 2021).

i. Aircraft and unmanned aerial vehicles (UAVs)
ii. Mobile LiDAR mounted on moving vehicles including road, rail and water
iii. Terrestrial LiDAR normally mounted on a tripod
iv. Handheld, short-range LiDAR using SLAM (Simultaneous Localization and Mapping) technology- suitable for capturing data within indoor spaces.

2.7.1 Airborne LiDAR

Airborne LiDAR consists of an onboard navigation unit for continuous measurement of the platform's position and the attitude of the sensor. The position measured shows the direction of the laser beam and the distance between the target and the sensor. Distance is obtained by measuring the time the pulse takes to reach the target and back. Advancements in laser technology have led to the removal of noise in the measurements by analyzing overlapping laser footprints in post-processing which are obtained by having redundant echoes (Gottfried, 2019). The cost-effectiveness of using UAVs as opposed to aircraft as platforms have seen miniaturization of the LiDAR systems and increased adoption. The amount of data generated on these platforms has been a challenge especially due to the sizes involved running to hundreds of GBs, however, the increased use of cloud processing has enabled timely processing of data which could also be done onboard the platform.

2.7.2 Terrestrial LiDAR

The principle of operation involves the emission of a laser beam which is deflected by a mirror and automatically scans the scene. Each emitted beam allows measurement of distance and therefore creates 3D cloud points characterized by 3D coordinates and a reflectance value (Mathieu et al., 2011). Multiple scans are possible by measuring similar objects at each instance which are then used to merge the datasets of the various stations. Improvements in technology have led to real-time appreciation of the data being collected by viewing in a tablet.

2.7.3 Handheld LiDAR

This system enables the LiDAR system to position itself in GNSS-denied locations (Nathan et al., 2021). Improvements in algorithms that enable precise location determination have enabled this technology to become an alternative technology to the terrestrial LiDAR. This LiDAR system would be very useful in the collection of data in enclosed spaces such as roads passing through tunnels.

2.7.4 Mobile LiDAR

Vehicle-mounted systems have proven to be effective in measuring road and city environments (Antero et al., 2019). Mobile LiDAR systems have transformed complex systems to plug-and-play systems which can be operated with relative ease. There has been increased use of two scanners in a dual-head system which has led to an increase in the level of details captured which consequently has led to less time spent collecting the data and also better representation of objects due to different angles from which they are measured. Precisely placed survey control points are needed to verify the accuracy of the mobile LiDAR cloud point data.

The incorporation of cameras which are accurately aligned has led to the integration of high-resolution imagery to the point cloud data. This highly detailed and aligned imagery enables high-quality RGB (Red Green Blue) colorized point clouds for improved visualization and analysis (Nathan et al., 2021). The Ultimate surveying of the Great Ocean Road in Victoria

Australia, represented as Figure 2.1, is a good example illustrating the vehicle-mounted systems for Mobile LiDAR.

Figure 2.1: Mobile LiDAR System

Source: (www. gim-international.com)

The advent of autonomous vehicles provides an opportunity for more geospatial data to be collected. In this case, the vehicles are fitted with the LiDAR system which would then collect data and beam the data to a server in real time and this shorten the processing time. More capabilities such as cameras onboard the vehicles will provide additional datasets to be used together with the LiDAR data. The point cloud must be 'precisely fit' so that they can be overlaid with the colors from the photographs.

2.8 Summary of Literature and Research Gaps

The existing literature reviewed has indicated a mix reaction on the application of Mobile LiDAR in various aspect. However, it is not clear on how Mobile LiDAR technology has help to improve management of road asset. The studies previously have failed to justify the accuracy of this technology as opposed to the other methods of data collection. From the locally reviewed research, there is lack of a comprehensive study in Kenya on use of Mobile

LiDAR technology to assist in solving the recurring problem associated with insufficient data collection techniques for road asset management in Kenyan roads.

The various research gaps from the existing literature are summarized in table 2.1.

Table 2.1: Summary of Literature Review and Research Gap

Author	Study Title	Main Findings	Research Gaps
Arif & Bayraktar (2012)	Theoretical framework for transportation infrastructure asset management based on review of best practices	The review showed that the front-runners in the asset management system internationally are Australia while Michigan takes the lead in US. Finally, based on the review of best practices, a theoretical framework for transportation infrastructure asset management was proposed.	The study framework focused on six important aspects of an asset management system i.e. asset management organization and concept, planning, contractual arrangement and mechanisms, monitoring and performance measurement, information systems and decision making. The study was limited to geographical location and did not focus on modern construction technologies for road asset management. The current study will address the gap by establishing the use of mobile LIDAR as a modern construction technology for road asset management
Byaruhanga & Basheka (2017)	Contractor Monitoring and Performance of Road Infrastructure Projects in Uganda	Purposive sampling was employed in selecting the procurement professionals, engineers and simple random sampling was adopted in selecting private consultants, members of parliament and respondents from the civil society organizations The findings revealed that weak procurement rules which lead to awarding road projects to incompetent contractors	Even though the study focused on performance of road infrastructure, it failed to evaluate the new technology of collecting road assets data and focused on the traditional method of road asset management. The study did not have a specific objective to consider how monitoring is conducted. The current study will have comparative analysis between data that will be conducted using mobile Lidar and the existing data collected using manual methods.
Geddes, Gongera & Solutions (2016)	Economic growth through effective road asset management	the project was intended to foster self-reliance in road agencies in the project areas and encourage greater accountability to road users and other sector stakeholders	The study was done in central Europe hence creating a contextual gap. The current research is being conducted in Kenya which is a developing nation with depressed economy compared to Europe countries. Further, the study focuses on issues of economic growth and did not target the methods of collecting data on road assets management

Author	Study Title	Main Findings	Research Gaps
Shtayat et al., (2020)	monitoring systems of pavement condition in paved and unpaved roads	The review indicated that the rising number of vehicles on roadways expedites the urge to increase efforts in implementing monitoring systems that look after road pavement conditions. This rising in number of vehicles on roadways also cause more damages and distresses on road pavement	Study introduces dynamic and static monitoring systems used in both paved and unpaved roads to identify the severity of pavement degradations. There is need to consider current technology for roads monitoring system. Moreover, the study focused only on the issues of pavement leaving all other road assets. The current study will consider other road assets such as sign boards, bridges, pot holes, caravans among others
Morales et al., (2021)	machine learning methodology to predict alerts and maintenance interventions in roads	The purpose was to summarize the main findings in the development of an approach based on testing the four most extended machine learning techniques (ML). The machine learning techniques include; Decision Trees (DT), K-Nearest Neighborhood (KNN), Support Vector Machines (SVM) and Artificial Neural Networks (ANN), using data from the historical inventory of inspections and maintenance interventions. The correlation process embodies supervised and unsupervised training of models. The maintenance predictions are presented and compared over various segments corresponding to the real maintenance interventions conducted on an existing road network of a geographical zone	The study did not focus on issues of technology as a solution to address the problem of road asset inventory management. More specific the study did not focus on mobile LiDAR technology which is the main subject of the current research.
Yadav, Singh & Lohani (2017)	Road Surface Detection From Mobile LiDAR Data	The proposed method has shown satisfactory performance for complex roadways having road section with and without raised curb, and has potential to be employed for such road environments, which are not uncommon. Proposed method was implemented on GPU-based parallel computing framework, which significantly saved the run time in processing of MLS data of three test sites	The study was conducted in India hence creating a contextual gap. Moreover, the parameters of measure in the current research will be different. The study did not have specific objects and the results of the finding were generalized. The current study sets to address the issues at hand in Kenya and will be precise as stipulated by the specific objectives to address every issue separately.

Author	Study Title	Main Findings	Research Gaps
Yadav & Signh (2018)	Rural Road Surface Extraction Using Mobile LiDAR Point Cloud Data	The study found that the quantitative assessment of the proposed method was performed in terms of correctness, completeness and quality, which were 96.3, 94.2, and 90.9%, respectively	The study was conducted in India hence creating a contextual gap. The study had only one objective which was to examine road surface extraction and tested the parameters of correctness, completeness and quality. The current study will focus on three key specific objectives as outlined and each has various parameters of measure
Aljohani et al., (2017)	Investigated material management	Established that material management as one of the major causes of cost overrun	Did not consider management of roads assets which the current study extends to incorporating additional variables. The study is different from the current study in that material management is very different from road asset management.

2.9 Conceptual Framework

The conceptual framework portrays the independent variables and the dependent variable. For this study, the conceptual framework shows the relationship between the quality of data in the determination of road pavement and infrastructure using the Mobile LiDAR on road asset inventory. The road pavement data to be collected include road pavement condition relating to cracks, potholes and rutting while for road furniture includes data on road marking, guard rails, signage and drainage. The quality of data will be assessed either to be accurate, quantifiable and giving a forecast.

The data collected from road pavement and road furniture which are the independent variables were subjected to scrutiny for quality and in terms of accuracy of capture. Further the data will be discussed on how it can aid in decision making for road assets management practices such as road condition assessment, Asset inventory control, decision making on Road safety, road maintenance planning, performance monitoring as well as budgeting finances for road repairs and maintenance which are the dependent variable indicators.

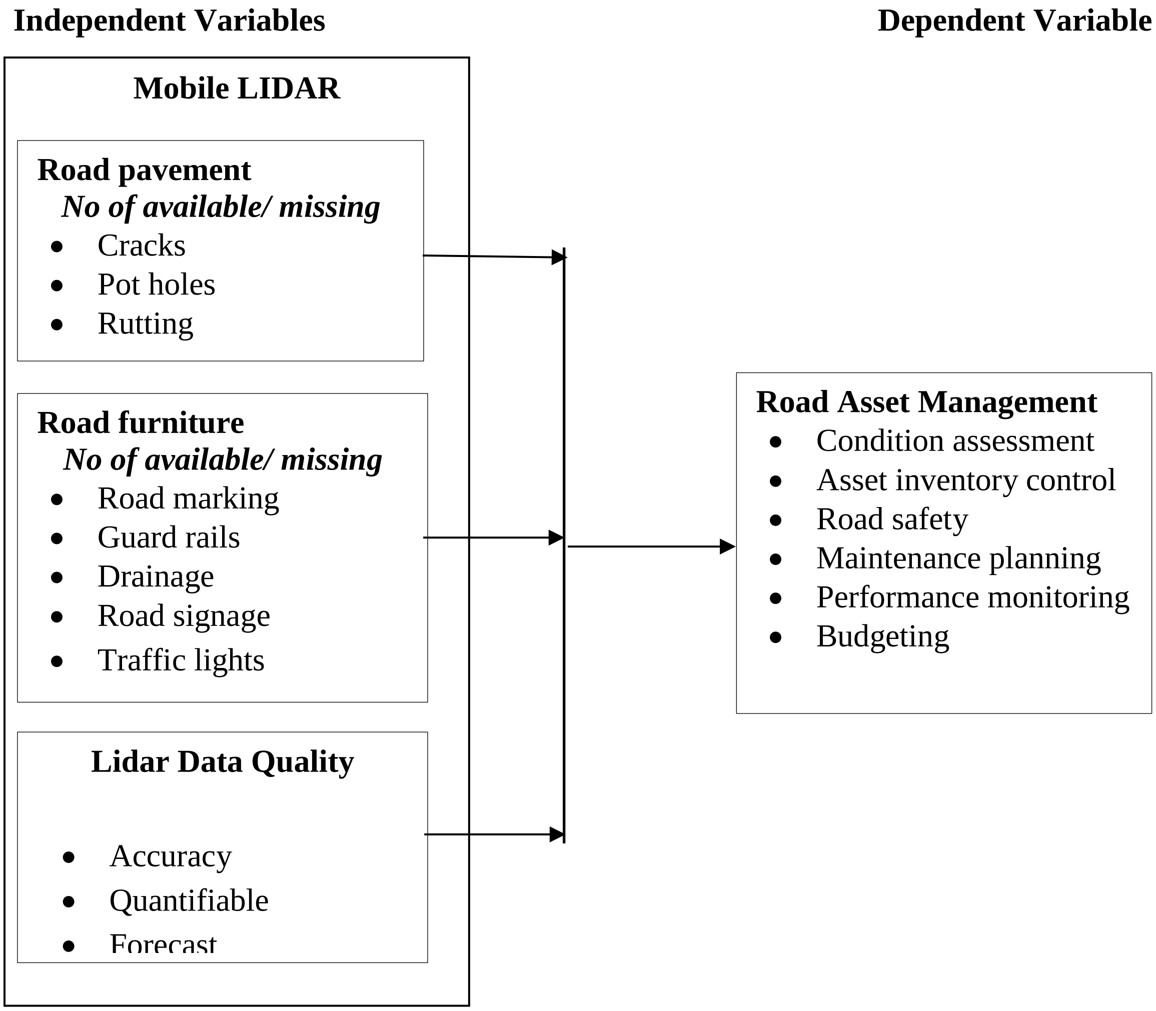


Figure 2.2: Conceptual Framework

Source: Author (2024)

CHAPTER THREE

RESEARCH METHODOLOGY

3.1 Introduction

This chapter outlines the methodology used in the research, detailing how data was collected, sampled and analyzed. It describes the research location area, design, target population, sampling techniques, data collection, analysis and presentation.

3.2 Location of Research Area

The study was conducted within the Nairobi City Metropolis Road network, which serves as a central hub for highways in Kenya. Due to high traffic volumes and a growing population, these major roads require frequent maintenance hence receive significant budget allocations from the Authorities. According to recent annual reports from KeNHA, instances of vandalism have been on the rise necessitating closer monitoring. Figure 3.1 presents a pictorial location map of the study area.

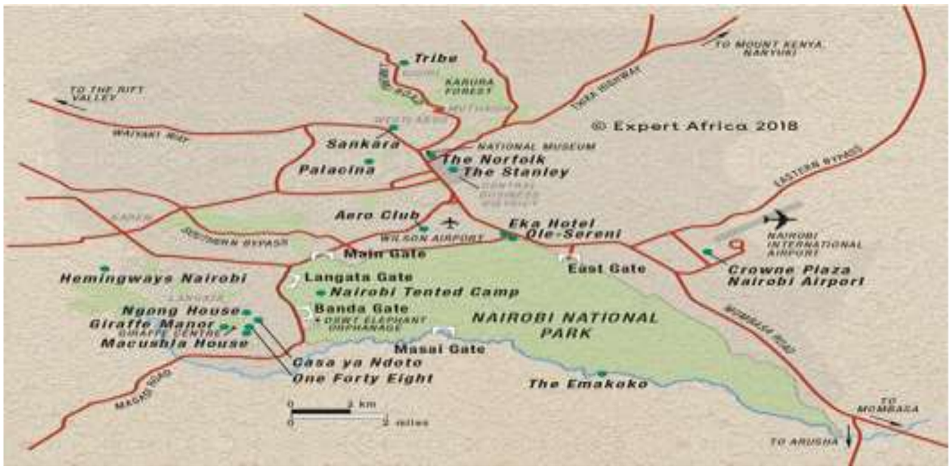


Figure 3.1: KeNHA roads in Nairobi (Not To Scale)

Source: KeNHA (2023)

3.3 Research Design

The study adopted a correlational survey design. According to Cooper and Schindler (2014), this design measures multiple variables simultaneously, enabling analysis of their relationships through regression techniques. A mobile LiDAR system was set up to capture road pavement, road furniture and other roadside asset data concurrently.

3.4 Summary of Methodology

Figure 3.2 contains a research methodology workflow diagram which guided the implementation of the data collection, processing and analysis.

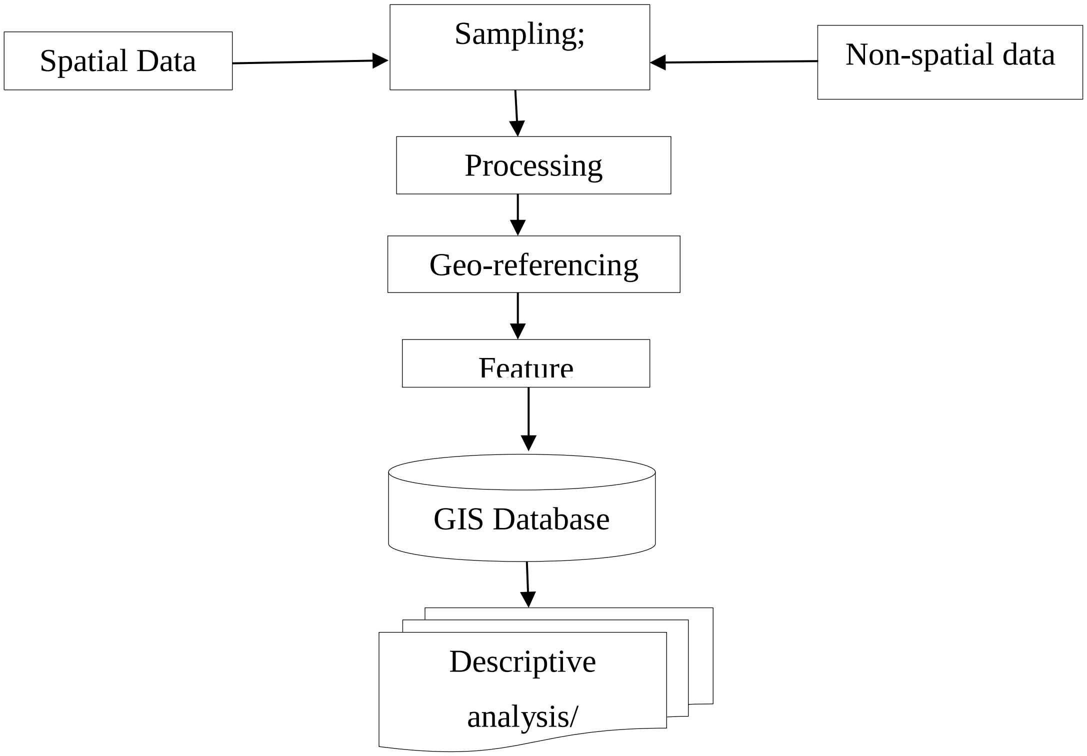


Figure 3.2: Summary Methodology

3.5 Population and Sample Size

The unit of analysis was nine (9) dualled highways owned and managed by KeNHA within the Nairobi City Metropolis Road network, spanning a total of approximately 277 Kilometers (Km) in length. Purposive sampling technique was applied to ensure each highway's uniqueness and location diversity aspects are considered for better generalization of findings. Guided by the Krejcie & Morgan (1970) sample size table, data collection targeted road pavement condition and furniture inventory installed over a total distance of 253 out of 277 Km (91%) across all the target highways. Table 3.1 presents a profile of the roads and sample size.

Table 3.1: Population and Sample Size

No.	Name of KeNHA Highway	Road Code/ Class	Estimated Length (Km)	Sampled Distance (Km)	Sample Size (Percent)
1	Nairobi-Mombasa Road	A8	26	25	96%
2	Thika Superhighway	S1	84	70	84%
3	Waiyaki Way	A8	25	24	96%
4	Uhuru Highway	A8	3	3	100%
5	Nairobi Expressway	S3	32	30	94%
6	Nairobi Southern Bypass	S2	37	34	92%
7	Nairobi Northern Bypass	B115	21	20	96%
8	Nairobi Eastern Bypass	B115	32	30	94%
9	Nairobi Western Bypass	B115	17	17	100%
	Total		**277**	**253**	**91%**

Source: KeNHA (2022)

3.6 Data Sources and Tools

Both spatial and non-spatial data was obtained from the scheduled site visits, processed and presented from the set Mobile LiDAR in various categories and formats as shown in Table 3.2. The key road assets which were of interest for this research included sidewalks, medians, guardrails, fencing, concrete structures, lighting, landscape areas, striping, crosswalks, raised pavement markers and the condition of the carriageway pavement. Additionally, the features for these assets were also populated. The typical database structure for such an inventory as used in this study included qualities such as condition and dimensions.

Table 3.2: Data Sources and Tools

S/No.	Category	Data	Format
1.	Spatial	Inventory data	Cloud points
2	Non-spatial	Road marking Guard rails Drainage structures Road signs Road reserves marker post	Tabular data

The tools used to store and analyze the data were two, namely: Hardware (HP Laptop with Core i7, 2TB storage, and 8GB RAM); and Software (ArcGIS 10.8 (ESRI), Hexagon geospatial ERDAS Imagine).

3.7 Data Collection Procedure

The data was collected using by a mobile LiDAR scanner. Data was collected from a scanner mounted on a moving vehicle. As the vehicle moves, sensors onboard collect 3D point data and 2D images as well as position and attitude of the sensor. An onboard GPS unit and an Inertial Measurement Unit (IMU) recorded the position of the points about the ground. The position information enables reference to the different datasets collected and different epochs tied to the same coordinate system. This made overlay operation of datasets possible and thus performed analysis. The data included geometric properties and attributes. Geometric properties depicted the length, width, lane, direction, surface and road objects such as traffic lights. Attribute property included a description of the road for example road material, road type, and road status.

The mobile LiDAR point clouds used in this study contain both road surfaces and roadside features. Inventory mapping of road surfaces only focuses on road surface point clouds. To reduce the amount of data being processed and the time complexity of the proposed strategy, the researcher segment road surfaces from the entire point clouds rapidly and accurately.

The study aimed at collecting data on road surface pavement conditions which included ruttings, potholes and cracks. The information collected was then grouped into Spatial and non-spatial data. For the first objective the research adopted a data collection category (DCC) approach as provided in the Guidelines for the Use of Mobile LIDAR in Transportation Applications (NCHRP report 748, 2013). The approach enabled the identification of the general accuracy and density requirements for the point cloud for each application. The classification system established in this study focused on extracting data on pavement and then grading it to slight pavement distresses and severe pavement distresses.

The algorithm used to road assets data collection in this study was developed in previous research by Gargoum et al. (2017). The procedure included a multistep process which involved (i) intensity-based filtering of the point cloud, (ii) density-based clustering of the filtered points, (iii) buffer-zone definition and filtering, and (iv) geometric filtering. In addition to coordinate information, LiDAR scanning also collected information about the amount of energy in the reflected light beam measured as an intensity reading. For objects with a high retro-reflectivity such as traffic signs, intensity readings were significantly higher than the remainder of the point cloud. Therefore, filtering the point cloud based on intensity reading helped narrow down the data to highly reflective objects only.

3.8 Data Processing and Geo-Referencing

The cloud points in the sensor’s coordinate system were converted to a global coordinate system preferably UTM (Universal Transverse Mercator) which presented measurements in meters in the cartesian plane and divided the earth into 60 zones each 6 degrees. Specifying a location meant specifying the zone and the x, y coordinate plane. The projection from a spheroid to a UTM zone was some parameterization of the cylindrical transverse Mercator projection. These parameters vary by nation, region or mapping system. Each zone is divided into horizontal bands 8 degrees of latitude wide. The 20 bands are labelled with letters, beginning with C and ending with X from south to north as shown in Figure 3.2. Letters I and O are omitted to prevent confusion with numbers one and zero. Note that N designates the first latitude band above the equator so any letter of the alphabet after N refers to a band in the Northern hemisphere and any letter below the N band refers to a band in the Southern hemisphere. To specify a UTM grid zone, the zone number (column) is given before the zone letter (row) such as zone 37M. To give the coordinate for instance Nairobi is UTM Arc 1960 37S (meaning Nairobi is 37 south of the equator).

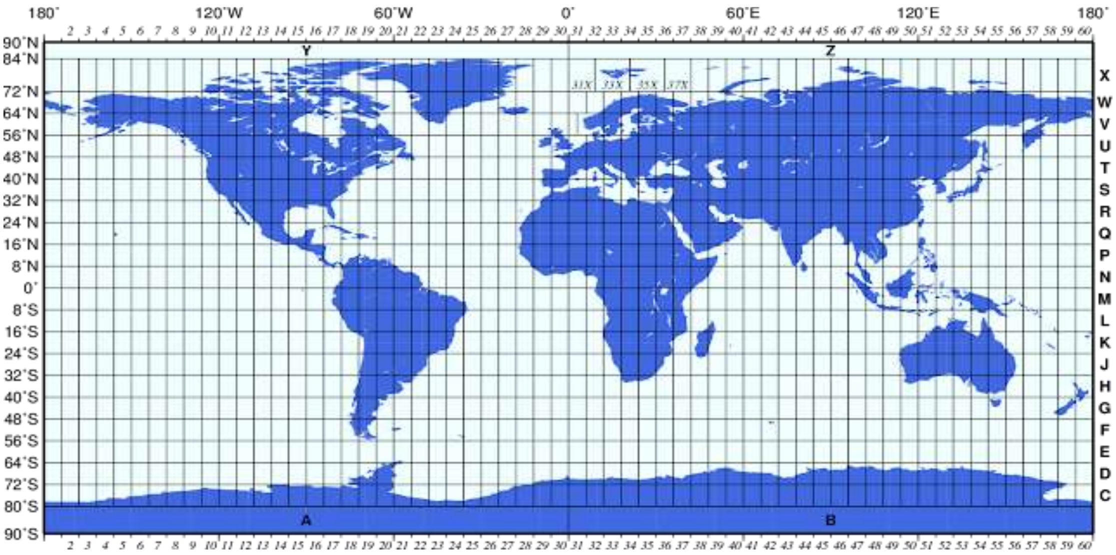


Figure 3.3: UTM zones of the world

Ground control points were used to check the quality of point clouds. Points well defined on ground and point clouds were used as GCPs (Ground Control Points). Measurements on the ground-based system was done by GNSS (Global Navigation Satellite System) receiver and total stations.

3.9 Feature Extraction

Automatic and semi-automatic methods of feature extraction were used to extract the information from the datasets. For instance, using height and dimension constraints, points that do not belong to road signs were eliminated. It is important to know the symbol of the sign for attribute information, this is done through the use of geo-referenced images which help identify from the points clouds. Other assets are extracted through the modelling of the point clouds. Geo-referenced data provided a three-dimensional model of the entire roads. Road surface conditions were identified based on intensity differences. Geo-referencing involves assigning a ground coordinate system to datasets so that they can be placed in the real world.

3.10 Database Design and Implementation

The information extracted from the datasets was imported into the Geographic Information System environment for overlay and analysis. The data was entered into a spatial database commonly referred to as Geo-database, to facilitate carry out of operations such as containment, adjacency and derive relationships.

3.11 Descriptive Analysis Visualization and Rendering

Data was subjected to descriptive statistical analysis (mean, mode, standard deviation, variance) for road furniture attributes. International rating standards were applied to evaluate the data, with regularity analysis conducted by computing International Roughness Index (IRI) values for various road segments.

3.12 Logical Framework

The logical framework outlined the expected outcomes for each research objective, specifying required inputs, activities, and anticipated outputs as provided in Table 3.3.

Table 3.3: Logical Framework

Objective	Input	Activities	Output
To assess the effectiveness of Mobile LiDAR technology use in monitoring and managing the condition of road surface pavements on KeNHA highways within Nairobi City Metropolis.	Mobile platform Laser scanners. Optics system. Satellite, Camera. Computer and Data storage ArcGIS & ERDAS Imagine	• Mapping • Positioning and navigation • Sensing • Data communication • Transmitting • Photogrammetry	Spatial and non-spatial data on the number and width of cracks, number and size of potholes, depth and number of road rutting. Publication of a research paper on the assessment of mobile LiDAR technology use in the management of road surface pavement condition of KeNHA roads within Nairobi City Metropolis
To evaluate the effectiveness of Mobile LiDAR technology use in management of road furniture inventory along KeNHA highways within Nairobi City Metropolis	Mobile platform Laser scanners. Optics system. Satellite, Camera. Computer and Data storage ArcGIS & ERDAS Imagine	• Mapping Positioning and navigation and Sensing • Data communication • Transmitting • Photogrammetry	Spatial and non-spatial data on Road marking guard rails, road signs and drainage. Availability of the asset, number of those assists missing. Publication of a journal on evaluation of mobile LiDAR technology use in the management of road furniture inventory along KENHA roads within Nairobi City Metropolis.

Objective	**Input**	**Activities**	**Output**
To analyze the quality and reliability of data captured through Mobile LiDAR technology for Road Inventory and Condition Survey (RICS) onn KeNHA Highways within Nairobi City Metropolis	Mobile platform Laser scanners. Optics system. Satellite, Camera. Computer and Data storage ArcGIS & ERDAS Imagine	• Data processing and analysis. • Visualization and rendering • Data storage • Data retrieval	• Accurate and quantifiable three-dimensional measurements and models. • Give a clear condition of road assets. • Asset inventory control and a Maintenance plan • Publication of a research paper with the title; assessment mobile LiDAR technology use in management of road asset data quality of KeNHA roads within Nairobi City Metropolis

CHAPTER FOUR

RESULTS AND DISCUSSIONS

4.1 Introduction

In this chapter the qualitative results were presented using tables and figures. Descriptive statistics was used to analyze qualitative data and inferential statistics was used to present quantitative results. The data was subjected to preliminary scrutiny before further analysis. The findings are presented as per each of the study variable.

4.2 LiDAR Technology Use in Management of Road Surface Pavement Condition

The first objective of the study was to assess mobile LiDAR technology use in management of road surface pavement condition of KeNHA highways within Nairobi City Metropolis. The data in Table 4.1 presents a comprehensive analysis of road distress types based on LiDAR detection, categorizing distress into distinct types, potholes, cracks and rutting each further evaluated by specific indicators and assigned a grade. The table underscores two principal grades, "Slight" and "Severe," determined by the depth of each distress type. Depth serves as a primary indicator, with a threshold of 15 mm distinguishing slight from severe conditions across all types of distress.

For potholes, slight grades correspond to shallow depressions less than 15 mm deep and smaller than 0.1 square meters in area, indicating minimal impact on road quality. Severe potholes, conversely, are characterized by deeper cavities exceeding 15 mm and covering a larger surface area, suggesting substantial degradation likely to impact vehicle stability and user comfort. This classification helps prioritize repair interventions, with severe potholes requiring more immediate attention due to their potential safety hazards.

Cracks are similarly divided into slight and severe grades based on branching complexity and depth. Slight cracks exhibit fewer branches and remain within the 15 mm depth limit, implying lower risks to structural integrity. In contrast, severe cracks display more extensive branching and deeper fissures, increasing vulnerability to water infiltration and subsequent road base erosion. Addressing severe cracks is essential to prevent further road degradation and maintain infrastructure durability.

The rutting category provides additional insight into the quality of road surfaces as experienced by drivers. Slight rutting, with a depth of 15 mm or less, does not produce notable driving discomfort, indicating manageable wear. However, rutting classified as severe, where depressions exceed the 15 mm threshold, leads to a visibly uneven and bumpy driving experience. Severe rutting signifies that the road surface has undergone substantial deformation, likely affecting both vehicle handling and passenger comfort, necessitating targeted maintenance.

Overall, the table provides a structured framework to assess road conditions using LiDAR data, where depth metrics serve as consistent indicators across distress types, aiding in uniform evaluation. By employing these depth-based grades, transportation authorities can systematically identify and prioritize road maintenance needs, optimizing resource allocation and ensuring safer, smoother roads for users. This data-driven approach not only enhances maintenance efficiency but also extends road longevity by addressing severe distresses promptly.

Table 4.1: Road Distress LiDAR Data

Types of Distress	Description	Indicator	Grade
Pothole	Shallow hole, small area ($<0.1m^2$)	depth ≤ 15 mm	Slight
	Deep hole, large area ($>0.1\ m^2$)	depth > 15 mm	Severe
Cracks	Fewer branches	depth ≤ 15 mm	Slight
	More branches	depth > 15 mm	Severe
Rutting	Shallow, no obvious discomfort in driving	depth ≤ 15 mm	Slight
	Deep, clearly bumpy in driving	depth > 15 mm	Severe

Figure 4.1 provides a comparative visual analysis of two stages in LiDAR point cloud processing for road surface assessment.

Part (a) shows the original point cloud, which captures a dense, detailed representation of the road and its surrounding features. This raw data contains a vast amount of information, not only from the road surface but also from adjacent objects like vegetation, infrastructure, and vehicles. The diversity of elements in this initial data highlights the extensive capability of LiDAR sensors to capture complex environments, making it a valuable tool for comprehensive mapping and data collection. However, the inclusion of irrelevant information can hinder effective analysis focused on road conditions. Thus, the raw point cloud requires substantial processing to extract useful data specific to the road surface.

Part (b) of the figure illustrates the result after filtering, isolating only the road surface points and removing all non-road elements. This filtered point cloud presents a clean, streamlined dataset that focuses exclusively on the road surface, which is crucial for accurately identifying and assessing road distress features. By removing noise, such as the data points associated with roadside elements, the filtered dataset improves the clarity and usability of the point cloud for specific analysis objectives, like evaluating surface damage. The filtering process thereby eliminates potential interference and enhances the accuracy of distress detection, especially for indicators such as potholes, cracks, and rutting, which rely on precise depth measurements.

This progression from the original to the filtered point cloud underscores the importance of preprocessing in LiDAR-based road assessment methodologies. The filtering step not only refines the dataset but also significantly reduces the computational complexity of subsequent analyses by limiting the dataset to relevant points. This, in turn, accelerates processing times and enhances the efficiency of automated algorithms used to classify and grade road distresses. Additionally, the cleaner dataset allows for more reliable grading based on standardized depth thresholds, as any extraneous data that could skew depth measurements has been removed. This refinement ensures that road maintenance prioritization can be effectively based on objective, accurate, and interference-free LiDAR measurements, ultimately leading to better-targeted interventions and optimized resource allocation in road maintenance practices.

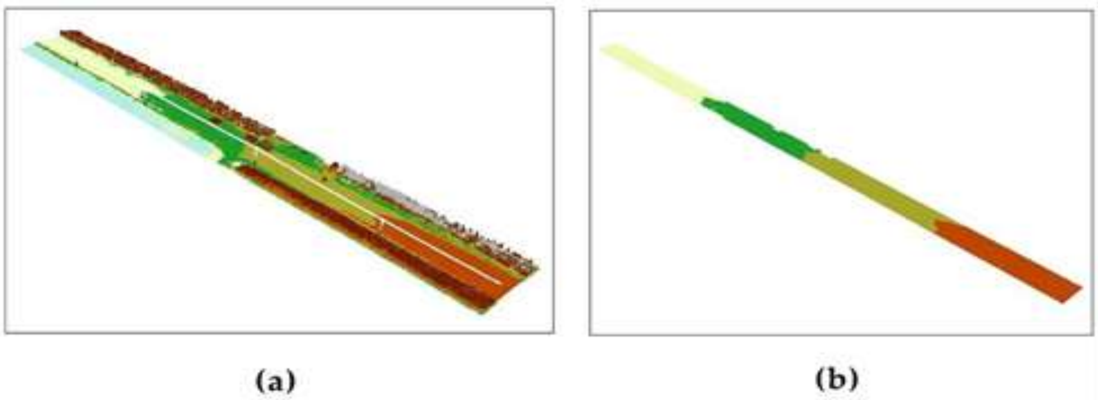

(a) (b)

Figure 4.1: (a) The original Point Cloud; and, (b) The Filtered Road Surface Point Cloud

Figure 4.2 presents a Triangulated Irregular Network (TIN) model illustrating various forms of pavement distress across a road surface, captured through a high-resolution mapping technique. The TIN model provides a detailed, topographic representation of the road, enabling precise identification of specific distress types, including potholes, rutting, subsidence, and cracks. Each type of distress is visually marked and enlarged in separate boxes, showcasing the TIN model's ability to render nuanced variations in surface texture and depth, which are critical for categorizing the severity and type of road distress.

The highlighted potholes, as depicted in the insets, show depressions with varying depths and shapes, indicative of surface wear and material loss. These potholes, depending on their depth and size, can impact vehicle handling and comfort, making their accurate detection essential for timely road repairs. The TIN model effectively captures the geometry of these potholes, providing a basis for depth measurement, which aids in classifying them as either slight or severe, as outlined in the depth-based grading criteria.

Rutting, another form of distress shown in the model, is represented by elongated, shallow depressions that follow the direction of traffic. These ruts are indicative of structural deformation in the pavement layers, often resulting from repeated vehicle loading. The TIN model's high-resolution capabilities allow for the assessment of rut depth and width, factors that influence driving comfort and safety. Through precise measurements, this model supports a more reliable evaluation of rutting severity and the prioritization of maintenance actions to restore evenness in the road surface.

Subsidence, a less common but significant type of distress, is also depicted in the model. Subsidence refers to localized depressions due to underlying soil displacement or material compaction. Unlike rutting, subsidence affects larger areas and can destabilize surrounding pavement sections. The TIN model’s accuracy in capturing subtle surface changes aids in early detection, which is vital for preventing larger structural failures.

Finally, cracks are represented as linear fractures in the pavement, with branching patterns captured in the model. The model distinguishes between minor and severe cracks based on depth and branching, which can influence water infiltration and further deterioration. By visualizing these cracks in detail, the TIN model facilitates targeted interventions to seal or repair the cracks, preventing moisture intrusion that could lead to more extensive damage.

Overall, the TIN model shown in Figure 4.2 provides a robust tool for analyzing road surface distress with a high degree of spatial accuracy. The model enables transportation authorities to systematically evaluate the condition of road surfaces, prioritize repairs based on distress severity, and optimize maintenance resources. This approach not only enhances road safety and durability but also minimizes long-term repair costs by addressing issues promptly through detailed, data-driven assessments.

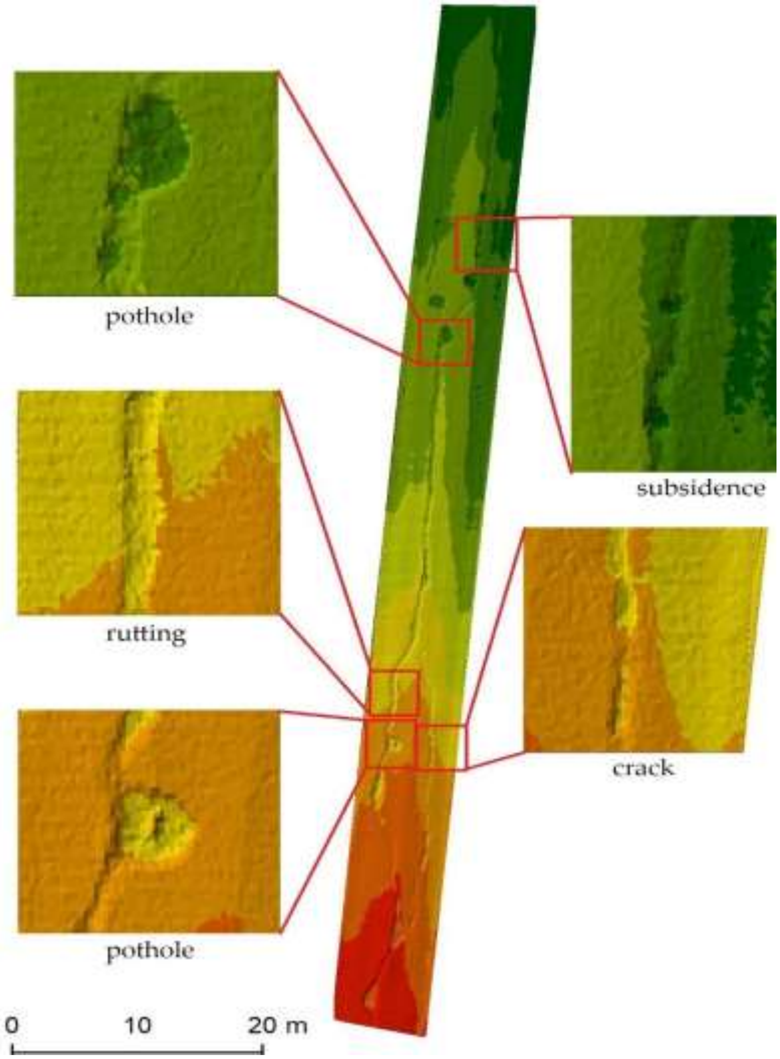


Figure 4.2: Triangulated Irregular Network (TIN) Model of Road Surface Showing Pavement Distress in Various Forms

4.2.1 Spatial and Non-Spatial Data

The data in Table 4.2 represents an analysis of road distress along major highways in Nairobi, categorizing the type and dimensions of visible distresses. The table systematically details spatial (length, width, and depth) and non-spatial aspects of road distresses, including potholes, cracks, and rutting across several critical routes. The information presented provides insights into the severity and nature of wear on these roads, offering an evidence-based basis for assessing the durability and maintenance needs of Nairobi's road infrastructure.

On the Nairobi-Mombasa Road, a prominent inter-regional connector, distress types vary significantly in size and form. Potholes are recorded with a length of 24 cm, a width of 15 cm, and a depth of 5 cm, reflecting notable surface degradation. This road also exhibits extensive cracking, with lengths between 1 and 3 meters and widths up to 5 cm. Cracks of such dimensions indicate structural fatigue likely exacerbated by heavy traffic and environmental factors. Additionally, rutting a form of surface depression caused by repeated traffic load is observed in lengths from 10 to 15 meters and a width of 24 cm, highlighting significant subsurface instability that demands maintenance to prevent further structural compromise.

Thika Road, another essential route, shows relatively minor potholes at 10 cm in length and 2 cm in depth, suggesting a less severe wear profile. Interestingly, cracks and rutting on this road are relatively minimal, with rutting extending only 1-2 meters, possibly indicating less intense vehicular load or more frequent maintenance compared to the Nairobi-Mombasa Road. However, this does not discount potential deterioration risks, as even small potholes can escalate rapidly if left unattended.

Waiyaki Way, Uhuru Highway, and Nairobi Eastern Bypass Highway all exhibit a combination of potholes, cracks, and rutting, albeit with varying spatial dimensions. Waiyaki Way, for instance, has potholes measuring 20 cm in length, 10 cm in width, and 5 cm in depth, aligning with other high-traffic roads. The presence of cracks, stretching between 1 and 5 meters, indicates prolonged exposure to traffic and environmental elements, possibly reflective of patchwork repairs that have not mitigated foundational weaknesses. Similarly, Uhuru Highway and the Eastern Bypass show similar distress patterns, with pothole depths of up to 5 cm and rutting widths of 24 cm, illustrating the high degree of wear that these highways experience.

The Nairobi Expressway, notably newer and possibly built to higher engineering standards, shows only minimal pothole damage, with dimensions as small as 2 cm in both length and depth. The lack of observed cracks or rutting implies that this road benefits from modern construction materials and methods, enabling it to withstand traffic demands better than older infrastructures. This contrasts sharply with the other roads analyzed, underlining the impact of recent advancements in road engineering and materials on longevity and resilience.

In comparison, the Northern, Southern, and Western Bypass Highways—bypasses intended to alleviate traffic from the central business district—show varying levels of deterioration, which may be influenced by both traffic volumes and construction quality. For instance, the Northern Bypass exhibits potholes of 11 cm in length and rutting up to 24 cm wide, while the Southern and Western Bypasses show rutting less consistently, with potholes generally less severe. The distress patterns here suggest moderate traffic load and possibly more frequent maintenance or less impactful environmental wear, aligning with their roles as peripheral routes.

In conclusion, the distress analysis in Table 4.2 reveals notable differences in the spatial and non-spatial attributes of road degradation across Nairobi’s highways. The severity and frequency of distress types are linked to both the age and usage intensity of these roads, as well as potential variances in construction standards and maintenance practices. High-traffic routes like the Nairobi-Mombasa Road exhibit significant structural issues across all distress types, while newer or less trafficked routes show more limited distress, emphasizing the need for targeted maintenance and future planning that accounts for both current and projected traffic demands.

Yadav et al. (2016) noted that Mobile LiDAR system (MLS) provided an extreme ease in capturing comprehensive high resolution 3D topographic data at highway speed. Some of the cracks and rutting were severe with an average length of 1-4meters and average width of 20cm. However, for the cracks and ruttings the depth was not significant hence detected but was not application as the units of measure were very minimal.

The finding of this study were supported by the findings of Li *et al.,* (2019) who conducted a semantic segmentation of road furniture in mobile laser scanning data. In the framework, they first detect road furniture from unorganized mobile laser scanning point clouds. Then detected road furniture is decomposed into poles and attachments (traffic signs).

Yadav et el. (2017) did an extraction of road surface from mobile LiDAR data of complex road environment. The proposed method was constructed using unstructured MLS data as input and does not require any other additional data. The method was divided into three major steps, that is, MLS data structuring and ground filtering, road surface point extraction, and road boundary refinement where the three roadways were accurately extracted without being affected by on-road objects and absence of raised curb. The Average accuracy measures like completeness, correctness, and quality were found to be above 90.0 in three test sites. The method has shown satisfactory performance for complex roadways having road section with and without raised curb and has potential to be employed for such road environments, which are not uncommon.

Table 4.2: Spatial and Non-Spatial Data

Road	distress	Length	width	depth
Nairobi-Mombasa Road	pothole	24cm	15cm	5cm
	Cracks	1-3 m	1-5cm	-
	Rutting	10-15m	24cm	-
Thika road.	pothole	10cm	5	2cm
	Cracks	-	-	-
	Rutting	1-2m	24cm	-
Waiyaki Way	pothole	20cm	10cm	5cm
	Cracks	1-5m	1-2cm	-
	Rutting	1-2m	24cm	-
Uhuru Highway	pothole	15cm	10cm	5cm
	Cracks	1-5m	1-2cm	-
	Rutting	1-5m	24cm	-
Nairobi Express way	pothole	2cm	2cm	2cm
	Cracks	-	-	-
	Rutting	-	-	-
Nairobi Northern Bypass Highway	pothole	11cm	7cm	3cm
	Cracks	1-5m	1-2cm	-
	Rutting	1-5m	24cm	-
Nairobi Eastern Bypass Highway	pothole	20cm	15cm	5cm
	Cracks	1-10m	1-5cm	-
	Rutting	1-10m	24cm	-
Nairobi Southern Bypass Highway	pothole	15cm	10cm	5cm
	Cracks	1-5m	1-2cm	-
	Rutting	-	-	-
Nairobi Western Bypass Highway	pothole	10cm	5cm	5cm
	Cracks	1-5m	1-2cm	-
	Rutting	-	-	-

4.2.2 Sample of Images Captured

The Mobile mapping system includes the following; One or more Cameras with a 360 degree view such as GV360 images was used to assess the condition of roads and determine roads that need repair due to potholes. Road improvement can also be determined using GV360, such as addition of road shoulders, pedestrian walks and cycle lanes depending on availability of space.

Figure 4.3 illustrates the road surface condition along Mombasa Road, emphasizing the presence and distribution of potholes. The top image, an aerial view, reveals a series of vehicles navigating a visibly deteriorated road, marked by multiple potholes represented by icons along the roadway. These icons highlight the prevalence and regular spacing of surface distress across both lanes, suggesting widespread degradation likely caused by high traffic volumes and the cumulative effects of weathering and load-induced stress. The image shows a marked section where these potholes appear frequently, aligning with previously discussed data in Table 4.2 that indicates potholes of substantial depth and width on this route. Such surface distress disrupts traffic flow, as vehicles must slow down or swerve to avoid these hazards, potentially leading to increased congestion and elevated risk of accidents. In the bottom half of the figure, a closer view provides additional context to the physical state of the road, depicting a rough, uneven surface with signs of erosion at the road edges, possibly due to poor drainage or subpar materials used in construction. The road edges appear worn and eroded, contributing further to the hazardous conditions, especially for smaller vehicles and motorcycles. This visual evidence highlights the urgent need for maintenance interventions to address these deteriorations, as the current state not only affects road safety and comfort but also accelerates further road wear, ultimately increasing long-term repair costs.

Figure 4.3: Road Surface Condition Highlighting Potholes along Mombasa Road

Figure 4.4 depicts a section of Mombasa Road showcasing evident rutting along the road surface. Rutting is visible as longitudinal depressions or grooves that have formed within the wheel paths, indicative of significant wear resulting from repeated vehicular loads. This condition likely stems from a combination of high traffic volumes, especially of heavy vehicles, and potentially insufficient pavement thickness or substandard materials that fail to support prolonged loads effectively. The image demonstrates how the rutting is concentrated along specific paths, corresponding to the wheels' travel lines, suggesting that the road may be subject to frequent and concentrated traffic flow.

The rutting observed is concerning as it affects the structural integrity and safety of the roadway. Over time, such depressions can retain water, especially in rainy conditions, leading to a greater risk of hydroplaning for vehicles. Additionally, rutting disrupts the smoothness of the road surface, forcing vehicles to adjust their path within lanes, which can contribute to unsafe driving behaviours and potentially increase the likelihood of accidents. Rutting also exacerbates wear on vehicle suspension systems and tires, raising maintenance costs for road users. This type of degradation underscores the urgent need for pavement rehabilitation on Mombasa Road, emphasizing the necessity of engineering interventions that could include overlaying with more durable materials or enhancing the base structure to improve load-bearing capacity. As rutting continues to deepen and expand without timely repairs, it risks compounding the deterioration rate, ultimately leading to more extensive and costly repairs.

Figure 4.4: Rutting in Mombasa Road

Figure 4.5 illustrates a segment of Mombasa Road showing the presence of both potholes and interconnected cracks, a common sign of pavement distress in heavily trafficked areas. The image reveals a pothole of moderate size, surrounded by a network of radial and intersecting cracks, suggesting that the surface layer of the road has undergone significant fatigue. These cracks, often referred to as alligator or fatigue cracks, typically emerge from repeated stress cycles induced by constant vehicular loading and environmental factors, such as temperature fluctuations and moisture infiltration. The proximity of the cracks to the pothole indicates that the underlying layers of the road may have lost cohesion and support, allowing water ingress and accelerating the degradation process.

This distress pattern is concerning, as it highlights structural weaknesses that can rapidly worsen without intervention. Potholes such as the one depicted in the image not only pose direct hazards to road users, potentially leading to tire blowouts and suspension damage, but also amplify the cracking in surrounding areas. As vehicles traverse over these distressed zones, they exert additional force on the compromised sections, which can cause existing cracks to widen and deepen, eventually forming more potholes. This cycle of deterioration suggests that Mombasa Road may require comprehensive resurfacing or reconstruction, particularly if underlying foundational issues are found to be contributing to the rapid wear. In the long term, without timely repairs, these surface and sub-surface weaknesses will lead to escalating repair costs, reduced road safety, and greater inconvenience for road users. Effective intervention would likely involve sealing the cracks, filling the pothole, and possibly reinforcing the subgrade to mitigate further structural damage and extend the pavement’s service life.

Figure 4.5: Potholes and Cracks along Mombasa Road

Figure 4.6 shows rutting and cracking on the Eastern Bypass, highlighting significant surface deformation that suggests both structural and material deficiencies in the road. The rutting, visible as pronounced depressions along the wheel paths, is indicative of excessive load impacts that have caused the pavement to sink and form grooves. This deformation is likely a result of repeated traffic loads, especially from heavy vehicles, which exert substantial pressure on the road surface, leading to the compaction and displacement of pavement layers over time. The rutting is not isolated but rather continuous along the wheel paths, suggesting that this segment of the Eastern Bypass has been subjected to persistent stress without adequate maintenance interventions.

The cracks in the image further emphasize the road’s deteriorating condition. These cracks run parallel and intersect the rutted areas, indicating that the surface layer has lost its flexibility and strength, which may be due to aging, environmental exposure, or subpar materials used during construction. Cracks allow water to penetrate beneath the surface, which weakens the subgrade and exacerbates the rutting effect, as the softened base layer provides insufficient support for the pavement above. Over time, this combination of rutting and cracking can create hazardous driving conditions, as vehicles are forced to navigate uneven surfaces, increasing the risk of accidents and damage to vehicle suspensions and tires.

The condition seen in Figure 4.6 underscores the need for structural improvements on the Eastern Bypass. Addressing the rutting and cracking would require not only surface repairs, such as crack sealing and patching but potentially deeper rehabilitation to strengthen the base layer and improve load distribution. Figure 4.6 reveals that, without timely and appropriate repairs, these distresses will likely propagate, leading to further pavement failure, increased repair costs, and reduced road safety and functionality for all users.

Figure 4.6: Ruttings and Cracks in Eastern Bypass

4.3 Mobile LiDAR Technology Use in the Management of Road Furniture Inventory

The second objective of the study was to evaluate mobile LiDAR technology use in management of road furniture inventory. Table 4.3 presents an analysis of sign detection and localization using LiDAR point cloud data, with key metrics including hits, false hits, and misses, along with their respective percentages. This analysis offers insights into the effectiveness and accuracy of LiDAR technology for detecting and localizing signs within an environment.

The *hits* metric represents the number of correctly identified signs within the point cloud data, with 2,145 hits accounting for a substantial 86.6% of the total detections. This high percentage indicates that the LiDAR system is proficient in identifying and accurately localizing the majority of signs in its scanning area. This level of accuracy is critical in applications where reliable sign detection is essential, such as in autonomous vehicle navigation, infrastructure monitoring, and urban mapping.

The *false hits* metric, which comprises 193 instances or 7.8% of detections, reflects cases where the LiDAR system erroneously identifies objects as signs. While the false hit rate is relatively low, reducing it further would enhance the system's precision, ensuring that unnecessary or misleading information does not interfere with data processing. False hits can be attributed to various factors, including noise in the point cloud, objects with similar shapes or reflective properties as signs, or limitations in the LiDAR sensor’s resolution.

The *misses* metric, recorded at 138 cases or 5.6%, indicates instances where the system failed to detect signs present in the environment. Although this percentage is relatively low, reducing misses is crucial for applications where full detection coverage is required for safety and operational efficiency. Misses may arise from occlusions, where objects block the LiDAR sensor’s view of signs, or from the sensor’s inability to capture fine details at greater distances.

In summary, the LiDAR point cloud data demonstrates strong performance in sign detection and localization, with an 86.6% hit rate indicating high reliability. However, the presence of false hits (7.8%) and misses (5.6%) points to areas for improvement in the system’s algorithm and hardware. Enhancing the filtering techniques, refining detection algorithms, or incorporating additional data sources could further improve the accuracy and robustness of the sign detection system, making it more effective for real-world applications requiring precise environmental mapping and object detection.

The findings of this study are supported by Guan et al. (2014) who used the LiDAR technology to locate and extract manhole covers by applying distance-dependent thresh-holding, multi-scale tensor voting and morphological operations to the interpolated feature images. Likewise, Landa and Prochazka (2014) applied the same technology to trace road signs where 86 signs were inside a tested area; 80 signs were detected correctly representing 93% success rate 6 (7%) misses were reported. Out of the 6 misses, 3 were caused by low point density; a larger distance of the sign from the sensor or by the degradation of the paint; and the other 3 misses were bus stop signs that were near the sensor.

The imagery findings were in support of the study, Nautiyal and Sharma (2021) discovered that GIS may be used to gather both spatial and non-spatial data, as GIS is a multi-criteria decision-making technique that can be used in pavement repair and maintenance operations. Furthermore, Duffell and Rudrum (2005) discuss inventory mapping as a secondary benefit that can be utilized from a point cloud. Inventory mapping can include any structure, pavement, signage and traffic signalling devices that can be extracted from a point cloud. In addition to feature extraction, they also demonstrate the ability of software to automatically detect road signs and classify them by shape as defined by the Manual on Uniform Traffic Control Devices (MUTCD).

Table 4.3: LiDAR Point Cloud Sign Detection and Localization

Measure factor	LiDAR point cloud	Percentage
Hits	2,145	86.6
False hits	193	7.8
Misses	138	5.6

Figure 4.7 provides a comprehensive view of the Langata Interchange, illustrating key roadway features such as signage, lane markings, curbs, and streetlights. In the top section of the figure, an aerial view offers a structural perspective of the interchange layout, showcasing multiple lanes that curve and loop to accommodate the complex traffic flow between intersecting highways. This design likely serves to streamline vehicle movement, reduce congestion, and enhance safety by minimizing abrupt turns and ensuring a smooth transition between connecting roads. The organized pattern of lane markings visible in this aerial view delineates traffic directions and guides drivers through the interchange, which is essential in such a multi-lane, multi-directional setting. These markings, along with other visual cues, are instrumental in managing traffic flow and reducing the likelihood of collisions, particularly at merging and diverging points.

In the lower images, close-up views of the interchange highlight the presence of road signage and streetlights, both critical for driver information and safety. The road signage, prominently displayed on an overpass, provides directional information for approaching drivers, making navigation intuitive and reducing the chances of last-minute lane changes. The size, visibility, and placement of these signs suggest they are strategically designed to ensure readability from a distance, a necessity in high-speed or high-traffic areas. The streetlights visible along the roadway further enhance safety, especially at night, by improving visibility for drivers and ensuring that key elements like signage, lane markings, and curbs remain visible under low-light conditions. Proper lighting is particularly important at an interchange, where complex lane shifts require clear visibility to prevent driver confusion and improve reaction time.

The curbs, visible along the edges of the roadway, serve not only as physical barriers that define the driving lanes but also as structural components that protect pedestrians and prevent vehicles from veering off the road. These curbs may also aid in drainage management by directing water away from the driving lanes, which is crucial for maintaining road integrity and preventing hydroplaning hazards during rain. The overall design, including the arrangement of signage, markings, and other infrastructural elements, indicates a well-planned approach to traffic management and safety at the Langata Interchange.

In summary, Figure 4.7 highlights how an integrated combination of signage, lane markings, street lighting, and curbs contributes to the operational efficiency and safety of the Langata Interchange. The aerial and ground-level perspectives together illustrate the functional design of this interchange, which prioritizes clarity in navigation and safety for all road users. This layout not only accommodates heavy traffic volumes but also provides a secure and organized environment for maneuvering, making the interchange a critical element of Nairobi's transport infrastructure.

Figure 4.7: At Langata Interchange Showing Road Signage, Markings, Kerb and Streetlights

Figure 4.8 provides an in-depth look at the Mombasa Road Interchange, showcasing essential elements such as road markings, curbs, barriers, and bridge columns that collectively enhance the safety, organization, and structural integrity of the interchange. The top aerial view reveals a complex network of intersecting lanes designed to facilitate smooth transitions for high volumes of traffic moving in multiple directions. Road markings are clearly visible, delineating lanes and guiding drivers through this intricate layout, thereby reducing the likelihood of confusion and collisions in areas where vehicles merge, diverge, or change direction. These markings are crucial for maintaining order, especially in high-speed environments where sudden lane changes can pose significant risks.

The ground-level image in the lower half of Figure 4.8 offers a close-up view of the underpass, highlighting the robust bridge columns that support the elevated lanes above. These columns are not only structural necessities, bearing the weight of the bridge and accommodating the movement of vehicles on the upper level, but they also demonstrate thoughtful design placement, allowing for sufficient clearance beneath to ensure unobstructed passage of traffic below. This clearance is particularly important for facilitating continuous traffic flow on the lower level without creating visual or physical obstacles for drivers.

Additionally, the presence of a barrier along the edge of the roadway enhances safety by acting as a containment measure, especially valuable in an interchange setting where high speeds and frequent lane changes can increase accident risks. This barrier serves as both a physical boundary to prevent vehicles from veering off the roadway and as a psychological guide for drivers, reinforcing lane discipline. The curb visible along the edge further defines the boundary of the driving lane, helping to prevent vehicles from straying onto pedestrian or shoulder areas. The combination of barriers and curbs is critical in maintaining a controlled driving environment within the interchange, ensuring that vehicles stay within designated lanes, thereby improving both safety and traffic flow.

Overall, Figure 4.8 illustrates the functional and structural components that make the Mombasa Road Interchange a well-organized and secure infrastructure system. The road markings, barriers, curbs, and bridge columns are not merely individual elements but integral parts of a coordinated design that prioritizes safety, efficiency, and durability. Together, these features support the interchange’s role as a major traffic hub, enabling it to handle the demands of heavy, multi-directional traffic while ensuring that vehicles can navigate the interchange safely and effectively.

Figure 4.8: Mombasa road Interchange Showing the Road Markings, Kerb, Barrier as Well as Bridge Columns

Figure 4.9 provides a detailed view of Thika Road, highlighting key infrastructural elements such as road markings, signage, guard rails, streetlights, and curbs, all of which contribute to the road’s functionality, safety, and navigability. In the aerial view at the top, the broad multi-lane configuration of Thika Road is evident, designed to accommodate a high volume of traffic with a clear separation of lanes, allowing for efficient flow and reduced congestion. The road markings are distinctly visible, helping guide vehicles and enforce lane discipline, which is crucial for managing traffic on this major artery. These markings ensure that vehicles remain within designated lanes, minimizing erratic movements that could lead to accidents, especially on a busy road where speeds are often high.

The ground-level image provides a close-up perspective on the signage, which spans across the entire width of the road and is prominently positioned above each lane. The signage clearly demarcates lane-specific destinations, guiding drivers towards exits and different routes, such as Exit 6, the GSU, and major destinations like Nairobi and Garissa. The structured organization of this signage into individual lanes reduces the likelihood of last-minute lane changes, enhancing safety by giving drivers ample information to make informed navigation choices well in advance. Additionally, the signs are large and legible, designed for visibility from a distance, which is crucial for fast-moving vehicles on this expansive roadway.

The presence of guard rails along the road’s edges provides an added layer of safety, acting as a physical barrier to prevent vehicles from leaving the roadway, especially in the event of a collision or loss of control. These guard rails are strategically positioned to separate traffic from pedestrian areas or surrounding infrastructure, thereby reducing the risk of more severe accidents. They serve as both a protective measure and a visual boundary that reinforces lane adherence, contributing to an organized and safer driving environment.

Streetlights are also visible along the road, ensuring that Thika Road remains well-illuminated during nighttime, enhancing visibility for drivers and allowing them to spot potential hazards or road conditions more easily. Adequate lighting is particularly important for maintaining safety on such a high-speed and high-traffic road, as it reduces the risks associated with low visibility and ensures that key elements like signage, markings, and the road layout are discernible at all times. The inclusion of curbs further delineates the boundary between the road and surrounding areas, adding structure to the roadway and preventing vehicles from encroaching onto non-traffic spaces.

Overall, Figure 4.9 illustrates a comprehensive approach to road design on Thika Road, integrating road markings, clear signage, guard rails, streetlights, and curbs to create a secure, organized, and efficient transportation environment. Each of these elements serves a specific function that contributes to the overall infrastructure's ability to handle high traffic volumes while maintaining safety and navigation ease for drivers. This thorough design facilitates smoother traffic flow, reduces accident risks, and enhances the usability of Thika Road as a vital route within the region’s transportation network.

Figure 4.9: Thika Road showing the Road Markings, Signage, Guard Rails, Street Lights, Kerb

Figure 4.10 shows a section of Mombasa Road where a section of 1 kilometre was captured. Findings show that all the hits captured were visible. However, some high-raised signs were missed in some data sets sections of the camera. Nevertheless, this can be avoided by titling the camera angle of elevation.

The LiDAR datasets as well as the imagery obtained are combined to create an environment that allows easy and efficient digitizing of the features of interest. The assets of interest for road furniture inventory include sidewalks, medians, guardrails, fencing, concrete structures, lighting, landscape areas, delineators, striping, symbols and messages, crosswalks, stop bars, raised pavement markers, attenuators and highway signs. In addition to the spatial component, the attributes for these assets are also populated. The typical database structure for such an inventory as used in this study included attributes such as condition and dimensions. The different road signs were also tagged with the symbol represented by the signage. The spatial component of the assets may be points, lines or polygons depending on their geometry and may also require some customized attributes. Hence, each asset is stored in an individual table with attributes as shown in table 4.4. The Asset ID is unique for every asset. In addition to the process of manual digitization of assets, automatic and semi-automatic methods of feature extraction were also utilized. Road Furniture attributes are stored in a GIS database.

Figure 4.10: Mombasa Road Showing Signage, Utilities

The table presents a structured format for recording various attributes of urban road assets, detailing the specific characteristics and data types required to capture the essential aspects of each asset. For sidewalks, attributes include width, curb height, segment length, ramp availability, condition (on a scale of 1 to 10), comments, and geometric data represented as polygons. This combination of measurements and qualitative information allows for a comprehensive assessment of sidewalk quality and accessibility, particularly relevant for urban planning focused on pedestrian-friendly design. Similarly, medians are characterized by width, height, segment length, condition, and comments, also represented as polygons. The inclusion of both structural dimensions and condition ratings ensures that the median's effectiveness in traffic separation and aesthetic appeal is adequately documented.

Guard rails and fencing share similar attributes, including height, segment length, condition ratings, and textual comments, with geometry captured as lines. These attributes facilitate the assessment of physical barriers, ensuring they meet safety standards and contribute effectively to road boundary definitions. The table also includes lighting assets, defined by height, type, condition, and additional comments, with each unit represented as a point geometry. This setup allows for precise mapping and assessment of lighting quality across road networks, which is critical for nighttime visibility and safety. The condition rating on a standardized scale enables easy comparison across multiple units, while comments provide room for detailed observations, such as repair needs or operational status.

Other key elements include landscape areas, delineators, lanes, road markings, and road signs or boards. Landscape areas are measured by area and condition, emphasizing maintenance needs and the spatial extent of greenery within urban areas. Delineators and road signs, recorded with attributes like height, type, and condition, also utilize point geometry for precise spatial mapping, supporting traffic guidance and safety functions. Lanes and road markings are categorized by striping type and condition, essential for traffic organization and driver guidance, with line geometry aiding in mapping their exact positions on the road. The comprehensive structure of this table, integrating both quantitative and qualitative data across various geometry types, provides an effective framework for managing urban road infrastructure, enabling thorough asset management and supporting decision-making processes aimed at maintaining and enhancing road safety, functionality, and aesthetics.

Table 4.4: Attributes of Road Furniture

Asset	Attributes (Format/Type)
Sidewalk	Width (Double) Curb Height (Double) Length of the segment (Double) Availability of ramp (Boolean—true/false) Condition (Integer; range—1–10) Comments (Text) Geometry (Polygon)
Median	Width (Double) Height (Double) Length of the segment (Double) Condition (Integer; range: 1–10) Comments (Text) Geometry (Polygon)
Guard Rail	Height (Double) Length of the segment (Double) Condition (Integer; range: 1–10) Comments (Text) Geometry (Line)
Fencing	Height (Double) Length of the segment (Double) Condition (Integer; range: 1–10) Comments (Text) Geometry (Line)
Lighting	Height (Double) Type (Text) Condition (Integer; range: 1–10) Comments (Text) Geometry (Point)
Landscape Areas	Area of landscaping (Double) Condition (Integer; range: 1–10) Comments (Text) Geometry (Polygon)
Delineators	Height (Double) Type of Delineator (Text) Condition (Integer; range: 1–10) Comments (Text) Geometry (Point)
Lanes	Type of striping (Text) Condition (Integer; range: 1–10) Comments (Text) Geometry (Line)

Asset	Attributes (Format/Type)
Road Markings	Type of striping (Text) Condition (Integer; range: 1–10) Comments (Text) Geometry (Line)
Road Signs/Boards	Message (Text) Type of sign (Text) Condition (Integer; range: 1–10) Comments (Text) Geometry (Point)

The major advantage of a mobile mapping system with multiple sensors onboard is that the data from each sensor complements the other and helps extract maximum information about the scene. Implementing a combination of image processing and geometry algorithms on images and point cloud data helps in detecting the road markings with almost nil manual intervention. The edges of the sidewalk detected from the images are used to define the boundary of the road and the bare-earth LiDAR points within the boundary are considered as road points. To ensure clear visibility for the drivers, road lane markings have a much higher reflectance when compared to the road surface. The boundaries of the road markings can be extracted from the images as well as by classifying the LiDAR point cloud based on the intensity of the return pulse. Road marking extraction is illustrated in figure 4.11;

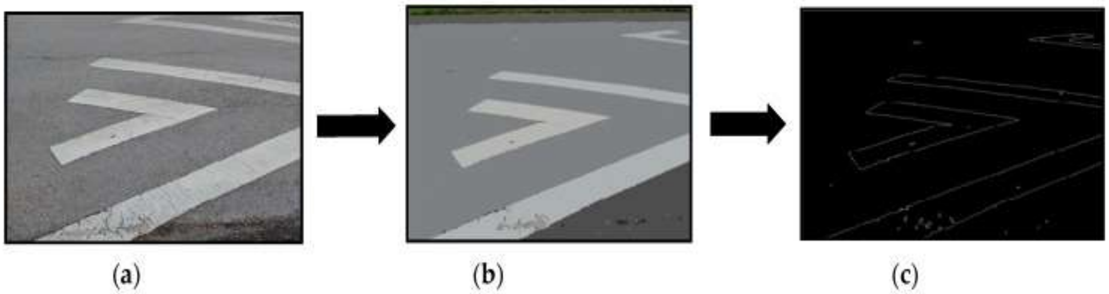


Figure 4.11: Extraction of Road Markings

where (a) Localization of road marking; (b) Segmented image; and (c) Edges were extracted from a segmented image showing boundaries of road markings

Road signs are non-ground points and do not lie on a definite plane. They are made up of aluminum which is highly reflective and also distinguishable on the point cloud. The shape of the signboard is determined from the boundary of clusters of high-intensity point cloud returns. Hence, by using the height and dimension constraints, points that do not belong to road signs can be eliminated and the precise shape of the signboard can be established as captured in figure 4.12 and figure 4.13. It was also important to know the symbol on the road sign to add attribute information to the extracted spatial data. Since the content on the signboard cannot be well identified from the point cloud, geo-referenced images were used for this purpose. The location of the signboard can be determined on the set of referenced images by using the coordinate corresponding to the centroid of the signboard extracted from the point cloud.

Figure 4.12: Extraction of Road Signs from Lidar Point Clouds and Images

Figure 4.13 illustrates a point cloud representation of a roadway, effectively capturing essential features such as the road surface, lane markings, and signage. The image employs a color gradient to differentiate various elements, with shades transitioning from green to blue, which likely correspond to height variations or intensity levels within the point cloud data. This gradient enhances the clarity of each feature, allowing for easy identification of road attributes. Lane markings are distinctly visible, running parallel along the roadway and providing structure and guidance for traffic flow. The precision of these markings within the point cloud data is crucial for applications such as autonomous vehicle navigation, where accurate lane positioning is essential for safe and efficient movement.

The signage along the roadway is also clearly captured, identifiable by its distinct shapes and positioning near the road edges. The ability of the point cloud to accurately represent signs and their relative positions is vital for road safety, as these signs convey critical information to drivers. By preserving the spatial location and orientation of signs, this point cloud data enables effective mapping and analysis, supporting functions such as traffic management, navigation assistance, and infrastructure assessment. The high-resolution data offers detailed insights into the positioning and visibility of these signs, which are integral to guiding drivers and ensuring compliance with traffic rules.

Additionally, the surface quality of the roadway can be inferred from the point cloud, as variations in height or texture may indicate irregularities, wear, or potential hazards on the road. This type of surface detail is valuable for maintenance planning, allowing infrastructure managers to identify areas requiring repairs or resurfacing. Overall, Figure 4.13 demonstrates the utility of point cloud data in capturing a comprehensive view of road infrastructure, from surface quality to essential road markings and signage. This level of detail supports a range of applications, from automated systems and urban planning to ongoing maintenance, making point cloud data an invaluable resource in modern road asset management and safety analysis.

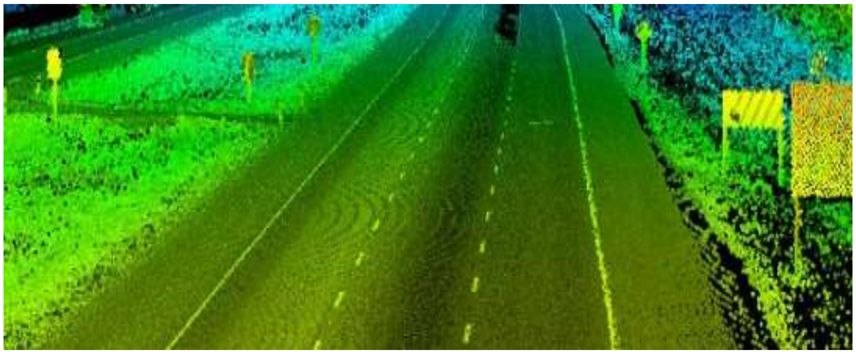


Figure 4.13: Point Cloud Showing Road Surface, Markings, Signage

4.3 Road Inventory and Condition Survey (RICS) LiDAR data quality

The third objective of the study was to assess effects of Road Inventory and Condition Survey (RICS) data quality in Road Asset management. This analysis was conducted through a comparison of the current study findings in objective one and two and the KeNHA RICS. Table 4.5 provides an in-depth assessment of road conditions across major highways in Nairobi based on RICS LiDAR data, focusing on road width, Paser score, and grading. The Paser (Pavement Surface Evaluation and Rating) system categorizes pavement conditions on a scale from 1 (very poor) to 10 (excellent), while grading terms like "poor," "fair," and "good" qualitatively describe the roads' current usability. These data points offer a nuanced understanding of the condition and functionality of key roads in the Nairobi area.

On the Nairobi-Mombasa Road, two sections are assessed: Belleview and GM. Both sections exhibit narrow road widths of 0.7m and 1.2m, respectively, with a Paser score of 3, which is classified as "poor." This low rating indicates significant surface degradation, likely due to high traffic volumes and heavy vehicle loads that exceed the structural capacity of these segments. The poor grading suggests the need for substantial rehabilitation to improve the road's functionality and safety, particularly given that Nairobi-Mombasa Road is a major transit route critical to regional trade and logistics.

In contrast, Thika Road, specifically in the Pangani and Githurai areas, shows a notable difference in condition. Pangani area has a width of 1.5m and a high Paser score of 7, graded as "good," reflecting recent upgrades or better maintenance practices. This section appears capable of handling traffic demands with minimal distress. Githurai area, also 1.5m wide, has a slightly lower Paser score of 5, marked as "fair," suggesting moderate wear that may benefit from routine maintenance but does not require immediate repair. This contrast along Thika Road may reflect varied traffic densities or maintenance schedules, highlighting the importance of targeted maintenance strategies based on specific location demands.

Waiyaki Way, a prominent thoroughfare, is assessed at two locations: James Gichuru Junction and ABC Place. The widths range from 1.5m to 1.7m, with Paser scores of 4 and 5, graded as "fair." These scores indicate that Waiyaki Way is experiencing moderate wear, possibly from heavy urban traffic and environmental factors, which is consistent with its use as a key urban route. Although the "fair" grading does not suggest an immediate need for major repairs, it highlights a potential area for proactive maintenance to prevent further deterioration.

Uhuru Highway, assessed along Nyayo Stadium and Uhuru Park, shows variability in width and condition. The Nyayo Stadium section, with a width of 0.8m and a Paser score of 5, is graded "fair," indicating adequate but not optimal conditions. Conversely, the section near Uhuru Park is slightly wider at 1.0m with a Paser score of 6, graded as "good," possibly reflecting more recent maintenance or lower traffic loads in this section. The good grading near Uhuru Park is significant, as this area is central and experiences high visibility, where maintaining road quality could contribute to improved urban aesthetics and functionality.

The Nairobi Expressway sections, particularly between Cabanas and SGR, and near Nextgen Mall, exhibit a high standard of road conditions, with both segments receiving a Paser score of 7 and graded as "good." The widths vary from 0.4m to 1.5m, yet the consistent high scores suggest that the Nairobi Expressway, being a newly constructed roadway, was built to withstand current and anticipated traffic demands effectively. This level of quality underscores the benefits of recent advancements in road engineering, materials, and construction methods, particularly for newly developed infrastructure.

The Nairobi Northern Bypass Highway demonstrates mixed conditions across different areas. Kahawa West has a width of 1.0m with a Paser score of 5, graded as "fair," while Mirema, slightly wider at 1.2m, has a score of 6 and a "good" grading. The disparity in condition suggests varied maintenance practices or environmental impacts on different sections of the Northern Bypass. The "fair" grading in Kahawa West implies the need for routine maintenance to prevent further degradation, while the "good" grading in Mirema highlights sections that are better maintained or less impacted by heavy traffic.

Nairobi Eastern Bypass Highway shows contrasting conditions between Utawala and Embakasi. Utawala, with a width of 1.5m, scores poorly with a Paser of 3, indicating substantial wear and a "poor" grading, which points to structural weaknesses or inadequate maintenance. Embakasi, on the other hand, despite having a narrower width of 0.7m, scores a 4 on the Paser scale and is graded as "good." This discrepancy may reflect differences in traffic volume or maintenance frequency, suggesting that Utawala requires urgent intervention to improve safety and usability, while Embakasi is relatively better maintained.

The Nairobi Southern Bypass Highway also varies, with sections near Ngong Road Junction and Langata scoring Paser ratings of 5 and 4, respectively, both graded as "fair." The width of these sections ranges from 0.9m to 1.1m. The fair grading indicates moderate wear but suggests the road is serviceable, potentially due to regular maintenance that keeps it in usable condition. However, with further usage and environmental exposure, these sections may require more focused upkeep to prevent slipping into poorer grades.

Finally, the Nairobi Western Bypass Highway, at Gitaru and Lower Kabete, demonstrates relatively high-quality road conditions, with both sections having a width of around 1.0-1.1m, a Paser score of 6, and a "good" grading. This reflects adequate structural integrity and possibly less intensive traffic or effective maintenance strategies. The good grading in these sections suggests that the Western Bypass is well-maintained and can accommodate current traffic levels without major concerns.

In conclusion, the RICS LiDAR data in Table 4.5 reveals significant variability in road conditions across Nairobi’s major highways, influenced by location-specific factors such as traffic volume, maintenance practices, and possibly environmental exposure. Roads like Nairobi-Mombasa Road and sections of the Eastern Bypass require urgent attention due to poor conditions, while newer or less trafficked roads, such as the Nairobi Expressway and portions of the Western Bypass, exhibit strong structural integrity and usability. This analysis underscores the importance of targeted, location-specific maintenance interventions to optimize road infrastructure and ensure safe, efficient travel across Nairobi's expanding network of urban and interurban highways.

Table 4.5: RICS Lidar Data

Road	Location	Width	Paser	Grading
Nairobi-Mombasa Road	Belleview	0.7m	3	poor
	GM	1.2m	3	poor
Thika road.	Pangani area	1.5m	7	good
	Githurai area	1.5m	5	fair

Road	Location	Width	Paser	Grading
Waiyaki Way	James gichuru junction	1.7m	4	fair
	ABC place	1.5m	5	fair
Uhuru Highway	Along Nyayo stadium	0.8m	5	fair
	Along Uhuru park	1.0m	6	good
Nairobi Express way	Cabanas-SGR	0.4m	7	good
	Nextgen mall	1.5m	7	good
Nairobi Northern Bypass Highway	Kahawa west	1.0m	5	fair
	Mirema	1.2m	6	good
Nairobi Eastern Bypass Highway	Utawala	1.5m	3	Poor
	Embakasi	0.7m	4	good
Nairobi Southern Bypass Highway	Ngong road junction	1.1m	5	fair
	Langata	0.9m	4	fair
Nairobi Western Bypass Highway	Gitaru	1.1m	6	good
	Lower kabete	1.0m	6	good

In comparison with previous survey, The Authority undertook ARICS (Annual Road Inventory and Condition Surveys) to update the inventory of road assets, assess the condition of the road network, and the degree of change in such conditions over the last year. Table 4.6 presents an analysis of the International Roughness Index (IRI) for different pavement types (paved and unpaved) over two fiscal years, FY 2019/2020 and FY 2020/2021. The data categorizes pavement conditions into three distinct ratings—"Good," "Fair," and "Poor"—for both paved and unpaved surfaces, providing a comprehensive perspective on the state of road infrastructure and highlighting areas where surface conditions have either improved, deteriorated, or remained stable.

For paved roads, the distribution of IRI ratings remains consistent across the two fiscal years. In both FY 2019/2020 and FY 2020/2021, 70% of paved roads are classified as "Good," 24% as "Fair," and 6% as "Poor." This stability indicates that the condition of paved roads has been relatively well-maintained, possibly due to effective maintenance programs, regular assessments, and sufficient budget allocations focused on preserving road quality. The high percentage of paved roads rated as "Good" reflects an infrastructure strategy that prioritizes the upkeep of high-traffic, high-importance roadways, likely considering that paved roads are integral to economic and social mobility, handling a significant share of both urban and interurban traffic.

The static 6% of paved roads classified as "Poor" suggests that while most of the paved infrastructure is in favorable condition, a small segment remains neglected or requires substantial rehabilitation efforts. These "Poor" segments, though a minor percentage, could indicate specific problem areas with underlying structural issues that periodic maintenance alone cannot address. Over time, such segments may risk further degradation, increasing the costs of repair if not addressed promptly. Given that these values did not change between fiscal years, it may suggest either a lack of targeted intervention for the poorest sections or that deterioration is counteracted by regular repairs that maintain these segments at the threshold of "Poor" rather than allowing further decline.

For unpaved roads, there is notable variation between the two fiscal years, indicating a dynamic shift in their condition. In FY 2019/2020, 18% of unpaved roads were rated as "Good," 53% as "Fair," and 26% as "Poor." By FY 2020/2021, these ratings had shifted, with "Good" condition roads increasing to 27%, while "Fair" roads decreased to 42%, and "Poor" condition roads rose slightly to 31%. This shift suggests a significant reallocation of unpaved road conditions over the fiscal year. The increase in "Good" roads by 9% implies that certain segments received improvements or more intensive maintenance, possibly involving grading or resurfacing to temporarily improve surface smoothness and accessibility.

The decrease in "Fair" condition roads from 53% to 42% and the corresponding increase in "Poor" roads from 26% to 31% reflect a dual trend: while some unpaved roads have been upgraded, a considerable portion has continued to deteriorate. This suggests that maintenance efforts on unpaved roads may be sporadic or reactive rather than preventive. The high susceptibility of unpaved roads to rapid deterioration, driven by factors such as weather conditions, heavy vehicular loads, and natural erosion, highlights the need for more strategic maintenance approaches. Seasonal weather changes, particularly rainfall, can exacerbate the degradation of unpaved roads, rapidly shifting them from "Fair" to "Poor" conditions if not maintained consistently.

The high percentage of unpaved roads classified as "Fair" or "Poor" in both fiscal years underscores a fundamental challenge in managing unpaved infrastructure. Unpaved roads, often located in rural or less-developed areas, may not receive the same level of financial investment as paved roads due to lower traffic volumes and budget prioritization. However, these roads are crucial for local communities, particularly for agricultural and resource-dependent regions where they facilitate access to markets and essential services. The gradual increase in "Poor" ratings suggests that without an adaptive maintenance strategy that includes more frequent grading, stabilization, or surface treatment, these roads are likely to continue deteriorating, potentially increasing isolation and transport costs for communities relying on them.

In summary, Table 4.6 illustrates a consistent quality in the paved road network, indicative of effective maintenance practices that ensure a majority "Good" rating across fiscal years. Conversely, the unpaved network reflects instability, with a noticeable shift in road conditions from "Fair" to both "Good" and "Poor" categories. This variability in unpaved road quality emphasizes the need for more robust and proactive maintenance frameworks tailored to unpaved surfaces, which are more susceptible to environmental impacts and usage-related wear. Addressing the maintenance requirements of unpaved roads could enhance connectivity, reduce transportation costs, and promote economic resilience, particularly in rural areas where unpaved roads are often the primary mode of access. Overall, this data underscores the need for a differentiated approach to pavement management, aligning maintenance investments with the specific demands and challenges of paved and unpaved road networks.

Table 4.6: International Roughness Index

Pavement Type	**FY 2019/2020**				**FY 2020/2021**			
	Good	**Fair**	**Poor**	**Total**	**Good**	**Fair**	**Poor**	**Total**
Paved	70%	24%	6%	100%	70%	24%	6%	100%
Unpaved	18%	53%	26%	100%	27%	42%	31%	100%

Figure 4.14 illustrates the International Roughness Index (IRI) differences along the right and left wheel tracks, offering insights into the variability in road surface roughness between the two sides of the road. IRI is a standard measure used globally to assess pavement smoothness, with higher values indicating a rougher surface that may impact vehicle stability, ride quality, and road safety. This plot examines the disparities between the right and left

wheel tracks, a factor that can signal differential wear, uneven surface degradation, or possible structural issues in the road foundation.

The data points in the plot are marked with small circles, representing mean IRI values for each wheel track category. Each mean value is accompanied by error bars that extend to the upper and lower bounds of the IRI range, signifying the variability in roughness across different sections of the track. Observing these bars, it is evident that while both wheel tracks have roughly comparable mean IRI values, there is variability, particularly in the left wheel track, where the error bars are longer, indicating greater inconsistency in surface roughness. This variability suggests that the left track may have sustained more irregular wear, potentially due to factors such as water drainage patterns, localized material degradation, or uneven loading from vehicle traffic.

The right wheel track, with relatively shorter error bars, indicates a more consistent surface condition, implying that it may be subjected to uniform traffic and environmental factors. Such uniformity might also reflect a more stable substructure or effective drainage that prevents localized damage. In contrast, the larger variability in the left wheel track points to a need for closer inspection and possibly targeted maintenance to address specific areas of roughness, which may affect vehicle handling and cause uneven tire wear.

The importance of monitoring IRI differences between wheel tracks lies in its implications for maintenance strategies and road safety. Uneven wear across the wheel tracks can contribute to alignment issues for vehicles, create hazardous conditions during wet weather, and signal underlying structural vulnerabilities in the pavement. Therefore, this analysis underscores the need for road maintenance programs to consider not only the average roughness across both wheel tracks but also the individual conditions of each track. Addressing these differences can help improve the durability of the pavement, ensure a smoother ride for road users, and ultimately enhance the safety and longevity of the roadway infrastructure.

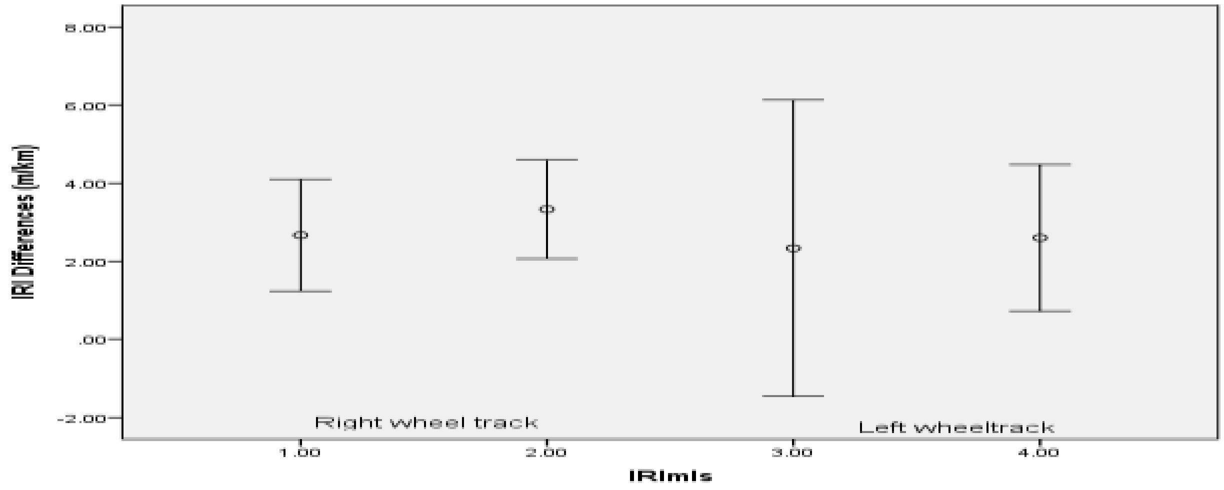


Figure 4.14: IRI Different Plot Graph

In Table 4.7, the standard deviation values 1.23669 for IRIPROF and 1.12132 for IRIMLS highlight significant variability in pavement roughness across the sampled sections. The relatively high standard deviations suggest that roughness levels fluctuate considerably, indicating inconsistent surface quality. For IRIPROF, the slightly higher standard deviation implies greater sensitivity to surface irregularities, potentially capturing more extreme roughness variations. This variation may reflect differences in road wear or maintenance effectiveness, emphasizing the need for targeted interventions to address rougher segments. High variability in both measures suggests that uniformity in road conditions is lacking, potentially impacting ride comfort and vehicle wear across the network.

Table 4.7: IRIMLS and IRIPROF Correlation

Descriptive Statistics					
	N	**Minimum**	**Maximum**	**Mean**	**Std. Deviation**
IRIprof	17	1.00	4.00	2.8235	1.23669
IRImls	17	1.00	4.00	2.5882	1.12132
Valid N (listwise)	17				

The two scatter plots display the relationship between IRIPROF and IRIMLS values for both the left and right wheel tracks, with correlation coefficients reflected by the R^2 value, which measure the strength and fit of the linear regression between these variables. For the left wheel track, the scatter plot shows an R^2 value of 0.8549, indicating a strong positive correlation between IRIPROF and IRIMLS. This high R^2value suggests that as IRIPROF (likely a roughness measurement derived from profiling) increases, IRIMLS (a comparable roughness measure) also tends to increase in a relatively predictable manner for the left wheel track. The data points generally align along the regression line, with only slight deviations, indicating a consistent relationship between these two indices on this track. This strong correlation implies that for the left wheel track, both IRIPROF and IRIMLS capture similar aspects of pavement roughness. Therefore, they could be used interchangeably for assessing roughness on this side, or together, to corroborate pavement conditions reliably.

For the right wheel track, the scatter plot yields an R^2 value of 0.816, slightly lower than the left track but still indicating a strong positive correlation. Similar to the left wheel track, this correlation suggests that increases in IRIPROF are associated with increases in IRIMLS, though the relationship appears slightly less consistent than on the left track. Some data points deviate more noticeably from the regression line, which might indicate slight inconsistencies in how roughness is captured between IRIPROF and IRIMLS on the right side. Despite this minor variability, the strong R^2 value suggests that the two indices still generally align well on the right wheel track and could serve as complementary or interchangeable measures of roughness.

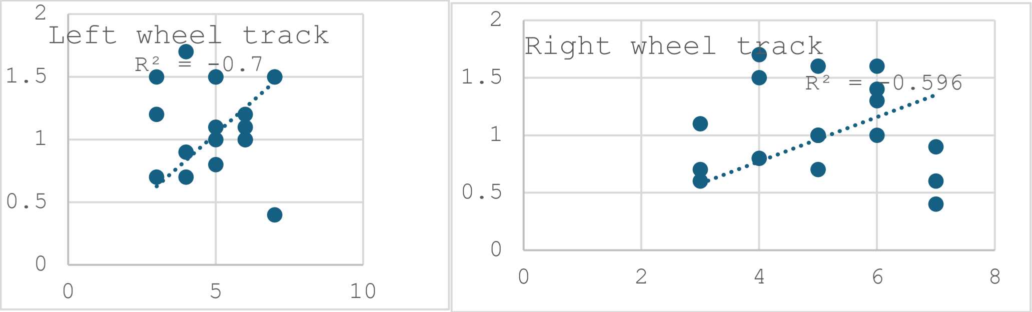
The comparison of the R^2 values—0.8549 for the left wheel track and 0.816 for the right—reveals slightly better alignment between IRIPROF and IRIMLS on the left side. This could indicate a more uniform surface condition on the left track or suggest that the left wheel track experiences less disturbance that affects roughness measurements. The slight reduction in correlation strength on the right wheel track might stem from factors such as uneven wear, differences in vehicle load distribution, or environmental factors impacting the right side differently.

In practical terms, the high correlation in both wheel tracks demonstrates that IRIPROF and IRIMLS are reliable metrics for evaluating roughness and can be confidently used in tandem or separately to assess pavement conditions. The minor differences between the two-wheel tracks might inform maintenance priorities, suggesting that the right track could benefit from more detailed inspection or targeted maintenance if the inconsistency reflects underlying structural issues. Overall, these correlations provide valuable insights for pavement management, allowing for more efficient assessment and prioritization of road segments based on their roughness characteristics.

The scatter plots presented show the correlation between IRIPROF and σLSM for the left and right wheel tracks, with respective R^2 values of 0.9149 and 0.8065. These R^2 values offer a quantifiable measure of the linear relationship between the two variables, providing insight into the consistency of roughness variability in relation to IRIPROF for each wheel track. For the left wheel track, the R^2 value of 0.9149 suggests a very strong positive correlation between IRIPROF and σLSM, indicating that as the IRIPROF value (representing average roughness) increases, there is a predictable and proportionate increase in the standard deviation of roughness (σLSM). This strong correlation implies that rougher sections on the left wheel track are also characterized by higher roughness variability, suggesting inconsistencies in the pavement surface that may be caused by patchy repairs, differential wear, or structural weaknesses within the roadway foundation. Such variability is of practical concern as it affects vehicle stability and ride comfort, which may necessitate a more targeted maintenance approach on the left wheel track to address these fluctuations in roughness.

In contrast, the right wheel track, with an R^2 value of 0.8065, displays a strong but slightly lower correlation between IRIPROF and σLSM. While this relationship remains positive and indicative of a proportional increase in variability with roughness, the lower R^2 suggests that the roughness on the right track is less consistently associated with high variability compared to the left track. This lower correlation may reflect more uniform wear patterns or a more homogenous pavement condition on the right wheel track. It could also indicate fewer localized roughness spikes or less uneven degradation on this side, potentially due to differences in traffic distribution or environmental exposure. However, even with this slight reduction in correlation strength, the relationship remains robust, underscoring that the right track, like the left, experiences increased roughness variability in proportion to higher roughness values.

The comparison between the two-wheel tracks highlights an important aspect of pavement assessment. The higher correlation on the left wheel track suggests it may have more areas of concentrated damage or wear, which could be a result of design factors, load distribution, or directional biases in road usage patterns. The right wheel track, with a slightly weaker but still strong correlation, suggests comparatively uniform roughness increases, though variability in roughness remains a concern. Understanding these correlations aids in identifying segments where variability could exacerbate surface roughness issues, pointing to the need for differentiated maintenance strategies for each wheel track. By addressing not only the roughness but also the associated variability, maintenance efforts can improve the driving experience, enhance road safety, and reduce vehicle wear across both tracks.



IRI$_{PROF}$ vs σ_{LSM}

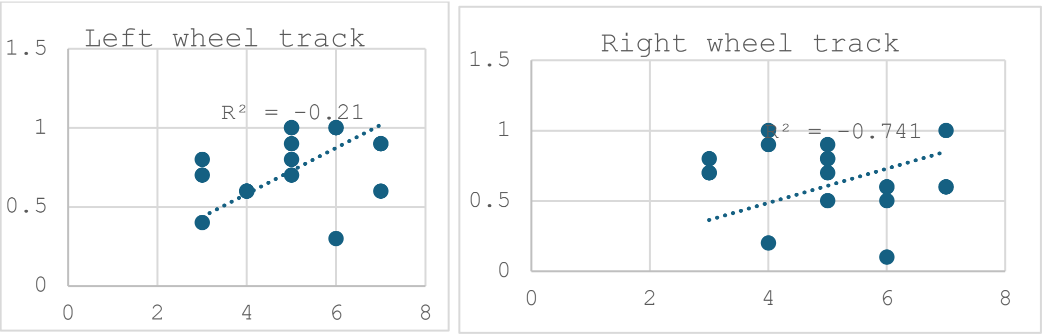


Figure 4.15: 3-D Surface Roughness Indices

Figure 4.15 presents a 3-D surface plot comparing roughness indices across different road sections, providing a visual representation of roughness variability along the measured segments. The plot displays color-coded roughness ranges, with indices segmented as 0-0.5 (dark blue), 0.5-1 (orange), 1-1.5 (green), and 1.5-2 (lighter blue), representing varying degrees of surface irregularity.

The color gradations indicate the intensity of roughness across different segments, with lower roughness (dark blue and orange) generally dominating the baseline levels and suggesting smoother areas of the pavement. In contrast, higher roughness values, represented by green and light blue, appear as peaks in the 3-D landscape, illustrating sections where roughness exceeds typical levels. The distribution of these peaks suggests non-uniform roughness across the observed segments, with some areas showing significantly higher indices than others, likely due to localized pavement wear or structural inconsistencies.

This uneven distribution highlights potential problem areas requiring targeted maintenance. The prevalence of moderate roughness values (0.5-1 and 1-1.5) across multiple segments suggests widespread minor degradation, which, if left unchecked, could evolve into more severe surface issues. Peaks in the 1.5-2 range indicate sections where surface quality has deteriorated more substantially, posing potential impacts on vehicle stability and comfort. Such areas may necessitate immediate intervention, as higher roughness indices correlate with increased vehicle wear and reduced driving comfort.

Overall, the 3-D roughness index comparison provides valuable insights into the spatial variability of pavement conditions, emphasizing the need for differentiated maintenance based on roughness intensity. By identifying segments with higher roughness peaks, infrastructure managers can prioritize repairs to improve surface quality, enhance safety, and extend the longevity of the pavement. The 3-D plot serves as an effective tool for visualizing and understanding the distribution of roughness across the network, facilitating strategic, data-driven maintenance planning.

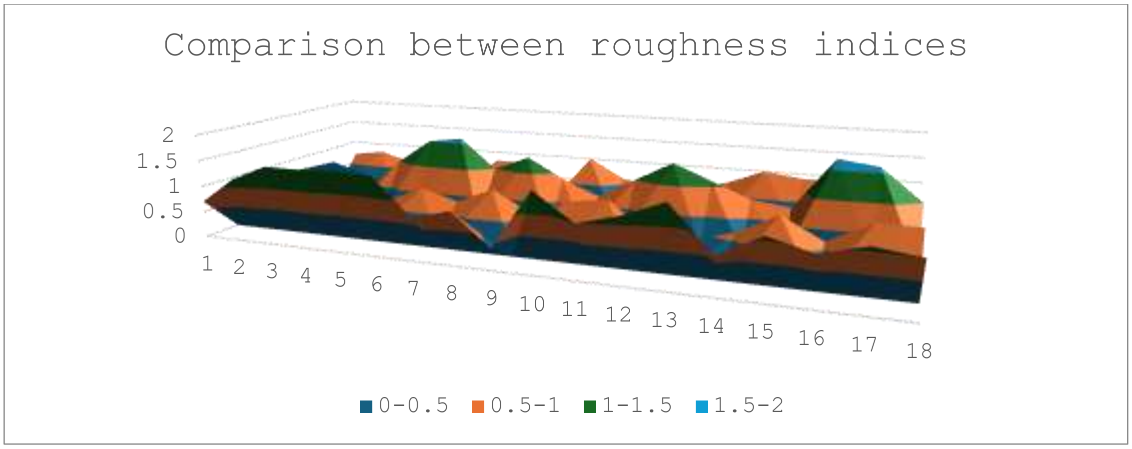


Figure 4.16: Wireframe Contours

Figure 4.16 showcases a wireframe contour plot comparing roughness indices across various road segments, offering a detailed visual of surface roughness patterns and their spatial distribution. The color-coded contour levels, corresponding to different roughness ranges (0-0.5 in light blue, 0.5-1 in orange, 1-1.5 in green, and 1.5-2 in darker blue), provide a layered representation that highlights areas of varying pavement conditions.

The extensive presence of contours in the 0.5-1 range (orange) across multiple sections suggests a widespread, moderate level of roughness that may not yet impact safety severely but could reduce comfort and increase wear on vehicles over time. The smooth transition from lower to higher roughness indices in some areas indicates gradual degradation, possibly from consistent vehicular loads, whereas abrupt changes between contours in other areas could signal isolated defects or areas of concentrated wear. Such distinctions are crucial for maintenance planning, as gradual wear can often be managed with regular maintenance, while abrupt roughness variations may call for more immediate and specific interventions.

The wireframe contours in Figure 4.17 serve as an effective tool for visualizing spatial roughness patterns, helping infrastructure managers to prioritize maintenance based on both the intensity and extent of roughness variations. By focusing on the zones with higher roughness indices, particularly those with contours in the 1-1.5 and 1.5-2 ranges, maintenance teams can address sections most likely to impact vehicle stability and driver comfort. This contour plot, by combining colour and spatial structure, facilitates a holistic assessment of pavement conditions across the road network, aiding in data-driven, efficient maintenance strategies.

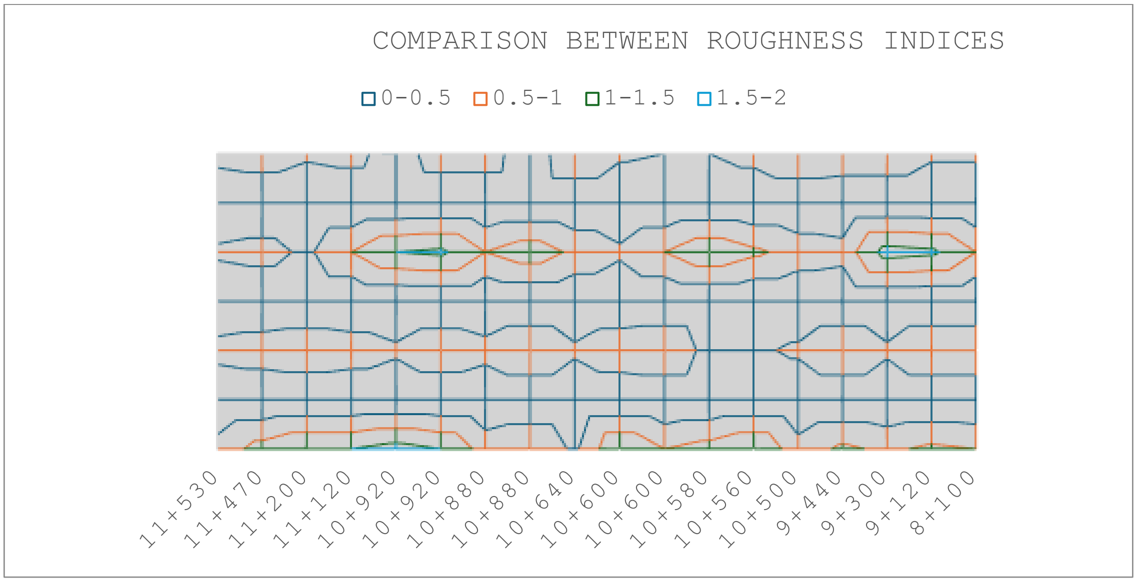


Figure 4.17: Wireframe Contours

Figure 4.18 presents a percentage-based visualization of surface roughness indices across various segments, highlighting the proportion of road sections that fall within certain roughness categories along the measured route. The plot provides a clear indication of roughness distribution as a percentage of the total roadway, offering insights into the prevalence of different roughness levels at each segment.

The x-axis represents the road segment identifiers, such as "11+530" and "10+920," denoting specific kilometer points or locations along the roadway. The y-axis shows the percentage scale, ranging from 0% to 100%, allowing for a quick assessment of how much of each segment exhibits specific roughness characteristics. This format effectively illustrates the extent of roughness across the route, aiding in understanding where high roughness indices dominate and where smoother sections prevail.

The variations in roughness percentages across segments indicate substantial changes in surface quality. Peaks in the graph, where the roughness percentage reaches 60-80%, suggest segments with a high prevalence of roughness, potentially signifying sections that have experienced extensive wear or structural weaknesses. Such peaks could correlate with areas of heavy traffic or segments that have undergone less frequent maintenance, resulting in higher surface roughness. These peaks mark priority areas for maintenance intervention, as a high percentage of roughness in these zones likely affects a substantial portion of the roadway, impacting overall driving quality and vehicle stability.

The valleys, or dips, in the plot, where roughness percentages fall below 50%, indicate segments with comparatively smoother surfaces. These lower roughness percentages may reflect sections that have either been recently maintained, experienced lighter traffic loads, or are structurally sound and resilient to wear. This variability in roughness percentage suggests an uneven distribution of road quality, which could be due to differences in maintenance schedules, construction quality, or environmental exposure across different segments.

By illustrating the distribution of roughness as a percentage, Figure 4.18 aids infrastructure managers in quickly identifying areas where roughness is particularly pronounced. Such visualizations help prioritize maintenance based on surface quality distribution, enabling resources to be allocated effectively to sections where roughness is most concentrated. This data-driven approach can enhance pavement longevity, improve ride comfort, and support efficient roadway management.

The distress of the road surface can be of a functional or structural type (Muniz, 2009). Distress is classified as functional if the superstructure is still efficient but has critical issues in terms of regularity and adherence, which can make the drive uncomfortable and unsafe, producing significant damage in the long term. Distress is classified as structural if the pavement is broken due to cyclical loads, i.e., due to ageing, or due to poor design or maintenance. From the analysis, the study findings revealed a structural type of distress. This was due to the various cyclical loads that were captured due to aging of the road as well as lack of maintenance. This type of distress includes localized distress, which significantly reduces the safety of users (Bella et al, 2011). The detection of pavement distress, which until now had been based mainly on manual inspections, has recently been based on the analysis of digital images or on-point clouds from LiDAR (Light Detection and Ranging) surveys;

this is mainly because the data acquired with manual techniques were often incomplete, risky to acquire and insufficient for the assessment of road conditions. One of the strong points of LiDAR data is that they are much denser than those measured with manual techniques and also more accurate (Kremen, Stroner & Trasak, 2014).

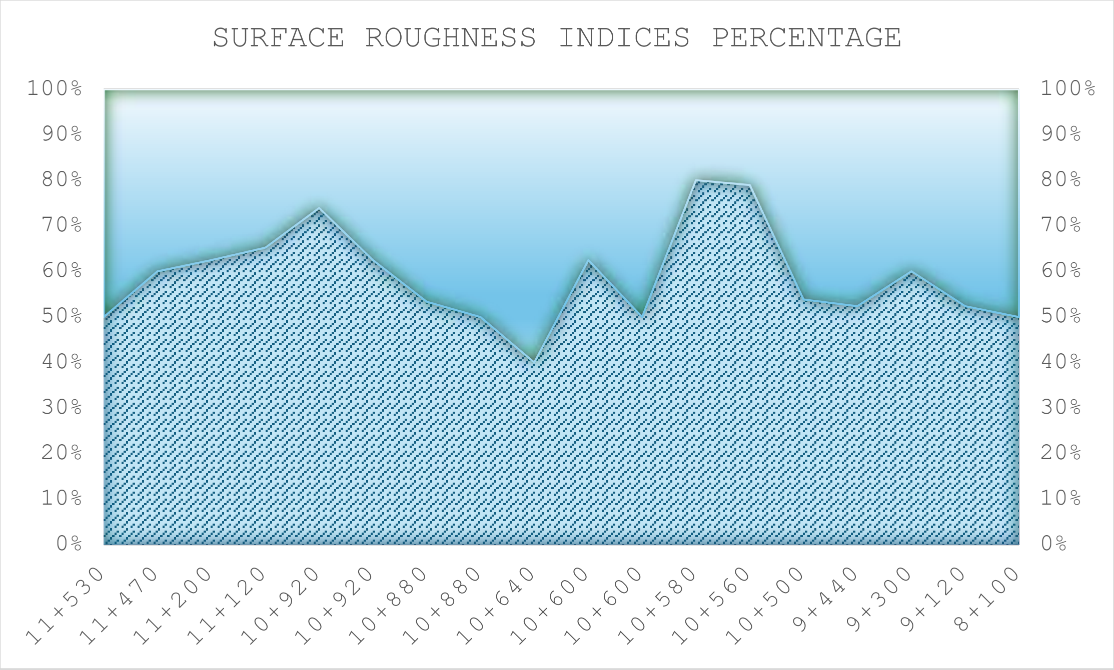


Figure 4.18: Surface Roughness Indices Percentage

CHAPTER FIVE

CONCLUSION AND RECOMMENDATIONS

5.1 Introduction

This chapter presents summary of the findings, conclusion and recommendation on the effectiveness of mobile LIDAR technology use in road assets management in Kenya with a case study of KENHA highways in Nairobi City Metropolis.

5.2 Conclusion

The study established that Mobile LiDAR technology is highly effective in monitoring and managing road surface pavement conditions on KeNHA highways within Nairobi City Metropolis. This technology captures detailed, accurate data on pavement conditions, detecting distresses such as potholes, cracks, and rutting with an accuracy rate of 86.6%. Compared to traditional, manual methods of road survey, Mobile LiDAR offers higher resolution and faster data acquisition, enabling road agencies to collect extensive data in a shorter time frame. This rapid and precise data collection is particularly beneficial for high-traffic areas, where frequent and detailed monitoring can help to address deteriorating conditions proactively. Through Mobile LiDAR, road agencies can improve maintenance schedules, reduce operational disruptions, and extend the lifespan of the road surface, effectively safeguarding the infrastructure and enhancing safety for road users.

Regarding road furniture inventory management, Mobile LiDAR technology demonstrates significant potential by enabling the precise capture of data on a wide array of road furniture, including signs, guardrails, lighting, and road markings. This high level of detail is critical in ensuring that all road furniture assets are cataloged accurately, thereby facilitating effective maintenance and inventory control. Traditional methods of monitoring these assets often result in missed details due to factors like traffic density or the small size of certain assets. By contrast, Mobile LiDAR technology provides a comprehensive view of these assets, helping road agencies to maintain the functional integrity of essential road furniture, which directly influences road user safety and efficient traffic management.

In analyzing the quality and reliability of data captured through Mobile LiDAR for Road Inventory and Condition Survey (RICS), the study found that the technology yields data of high quality, supporting robust and data-driven asset management practices. The false hit and false miss rates, 7.8% and 5.6% respectively, indicate that Mobile LiDAR's accuracy is superior to manual methods, where subjective assessment often impacts data reliability. This precision enables road agencies to make more informed decisions regarding budgeting, resource allocation, and prioritization of maintenance interventions. Moreover, Mobile LiDAR enhances the credibility of road inventory data, making it a reliable tool for both immediate and long-term planning. By integrating this technology into RICS processes, road agencies can better allocate funds, streamline project execution, and effectively manage the upkeep of critical road infrastructure.

5.3 Recommendations

Given the study's findings, it is recommended that road agencies adopt Mobile LiDAR technology as a routine tool for road surface pavement monitoring. Regular use of this technology will allow for a proactive approach to pavement maintenance, where early detection of distresses such as cracks and potholes enables swift intervention. This routine monitoring will not only help maintain road quality but will also optimize resource allocation, particularly on high-traffic roads like the Nairobi-Mombasa Road, where maintaining good pavement condition is essential to ensure traffic flow and reduce accident risks associated with poor road conditions.

For road furniture inventory management, further development and refinement of Mobile LiDAR’s detection algorithms are recommended to enhance the accuracy of asset recognition, particularly in areas with dense or complex road furniture configurations. Regular monitoring of road furniture using Mobile LiDAR can provide an up-to-date and comprehensive inventory, allowing agencies to address issues like vandalized or missing signs promptly. This practice will directly contribute to the safety and functionality of the road network, as well-maintained road furniture is crucial for effective road use and traffic management.

To maximize the benefits of Mobile LiDAR in enhancing road asset management through RICS, it is advised that road agencies invest in high-resolution sensors and provide thorough training for personnel on data collection and interpretation using this technology. Such investment will improve data precision and reliability, helping to minimize the already low rates of false hits and misses. Additionally, there is a need for informed policy development to support the integration of Mobile LiDAR technology in national and regional road management practices. Developing guidelines for the use of Mobile LiDAR, coupled with policy-driven budget allocations, will ensure that resources are directed toward areas where they can have the most impact. In particular, budget allocations should focus on high-quality data-driven planning and maintenance, with a special emphasis on accurately assessing and maintaining the most vulnerable or heavily trafficked road segments.

5.4 Areas for Further Studies

The current research was limited to KeNHA roads and only in Nairobi Metropolis. Future researchers should explore replica studies in other sections of the roads especially outside the city and urban areas to assess whether the conditions of the road is the same and whether the accuracy of the LiDAR technology would be maintained.

Future researchers may also consider other independent variables not considered in this study so as to expand the scope of investigation and build upon already available empirical research related to this field of research.

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