UNIVERSITY
OF TECHNOLOGY
SYDNEY

2D, 3D NOISE MODELLING ON MOBILE GIS APPLICATION THROUGH MACHINE LEARNING BASED MODELS

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Thesis submitted in fulfilment of the requirements for the degree of

Doctor of Philosophy

under the supervision of Professor Biswajeet Pradhan and Dr. Osama Sohaib

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May 2023

Certificate of Original Authorship

I, Ahmed Abdulkareem Ahmed Aldulaimi, declare that this thesis, is submitted in fulfilment of the requirements for the award of Doctor of Philosophy in Faculty of Engineering and Information Technology at the University of Technology Sydney.

This thesis is wholly my own work unless otherwise referenced or acknowledged. In addition, I certify that all information sources and literature used are indicated in the thesis. This document has not been submitted for qualifications at any other academic institution. This research is supported by the Australian Government Research Training Program.

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ACKNOWLEDGEMENTS

"In the name of Allah, the most beneficent and the most merciful"

I praise ALLAH for his magnificent loving generosity, that has brought all of us to encourage and tell each other and who has pulled us from the darkness to the light. All respect for our holy prophet (Peace be upon him), who guided us to identify our creator. I also thank all my brothers and sister who answered ALLAH's call and have made their choice to be in the straight path of ALLAH.

As always it is impossible to mention everybody who had an impact to this work, however, there are those whose spiritual support is, even more, important. I sense a deep emotion of gratefulness for my father and mother, who taught me good things and established part of my vision that truly affair in life. Their effective support and love have constantly been my strength. Their sacrifice and patience will stay my revelation throughout my life. I am also very much grateful to all my family members for their constant inspiration and encouragement.

My heartfelt thanks to my wife for her moral support. She always helped me out when I got any difficulties regarding all the aspect of life. Again, I thank her for standing by my side.

I also take this occasion to express my deep acknowledgement and profound regards to my guide Prof Dr. Biswajeet Pradhan for his ideal guidance, monitoring and continuous motivation during the course of this thesis. The help, blessing and guidance offered by him from time to time will support me a long way in the life journey on which I am about to embark. He formed an atmosphere that motivated innovation and shared his remarkable experiences throughout the work. Without his unflinching encouragement, it would have been impossible for me to finish this research.

Lastly, I would be remiss in not mentioning my friends who are Professor Odey Z. Jasim, Haider Ali (Chief Executive Officer of In2Networks), Mohammed Alshakly (Chief Executive Officer of Allware Technology) and Doctor Omer Saud Azeez. Their belief in me has kept my spirits and motivation high during this process.

List Of Publications

Published journal papers:

1. Ahmed, A. A., & Pradhan, B. (2019). Vehicular traffic noise prediction and propagation modelling using neural networks and geospatial information system. Environmental monitoring and assessment, 191(3), 1-17. https://link.springer.com/article/10.1007/s10661-019-7333-3

2. Pradhan, B., Ahmed, A. A., Chakraborty, S., Alamri, A., & Lee, C. W. (2021). Orthorectification of WorldView-3 Satellite Image Using Airborne Laser Scanning Data. Journal of Sensors, 2021. https://www.hindawi.com/journals/js/2021/5273549/

3. Adulaimi, A. A. A., Pradhan, B., Chakraborty, S., & Alamri, A. (2021). Traffic Noise Modelling Using Land Use Regression Model Based on Machine Learning, Statistical Regression and GIS. Energies, 14(16), 5095. https://www.mdpi.com/1996-1073/14/16/5095

4. Ahmed, A. A., Pradhan, B., Chakraborty, S., Alamri, A., & Lee, C. W. (2021). An Optimized Deep Neural Network Approach for Vehicular Traffic Noise Trend Modeling. IEEE Access, 9, 107375-107386. https://ieeexplore.ieee.org/abstract/document/9500224/

5. Ahmed, A. A., Pradhan, B., Chakraborty, S., & Alamri, A. (2021). Developing vehicular traffic noise prediction model through ensemble machine learning algorithms with GIS. Arabian Journal of Geosciences, 14(16), 1-14. https://link.springer.com/article/10.1007/s12517-021-08114-y

Papers under review:

1. Machine Learning Based GIS Model for 2D and 3D Noise Modelling.

2. Ensemble Multi-Level Machine Learning and Propagation Mathematical Models For 2D Traffic Noise Prediction and 3D Propagation Maps.

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List of Symbols and Acronyms

$\bar{a}$	Average of All Observed Values
a_i	Actual Parameter's Value
ANN	Artificial Neural Network
ASJ RTN	Road Traffic Noise Prediction Model of Japan
$\bar{b}$	Average of All Predicted Values
BE	Baghdad Erbil Expressway
BGIS 2000	Aerospace's Global Imaging System 2000
b_i	Predicted Value
BIM	Building Information Modelling
BSTN	Basic Statistical Traffic Noise Model
C.N.R	Contrast Noise Ratio Model
C_{air}	Air Interaction Coefficient
C_{air}	Weather Coefficient
C_b	Barrier Coefficient
C_d	Distance Coefficient
CFS	Correlation-Based Feature Selection Model
CoRTN	Comparison of Road Traffic Noise Prediction Models
CPCB	Central Pollution Control Board
C_{rg}	Road Geometry Coefficient
dB	Decibel
DEM	Digital Elevation Model
DNN	Deep Neural Network
DOE	Department of Environment's
DSM	Digital Surface Model
DT	Decision Tree
EIA	Environmental Impact Assessment
FHWA	Federal Highway Administration
GIS	Geographic Information System
GPS	Global Position System
GPS 60	Garmin Global Positioning System
HJ2.4-2009	Technical Guidelines For Noise Impact Assessment

h_w	Height of The Calculation Point In Reference To The Ground Level At The Calculation Point Also In Meters.
h_{weg}	Height of The Road In Reference To The Ground Level Next To The Road
IDW	Inverse Distance Weighting
JTG B03-2006	Environmental Impact Assessment of Highways
KIDEX	Kinrara–Damansara Expressway
$L_{(eq,15)}$	Equivalent Continuous Noise Level Per 15 Minutes
LAeq	Sound Level Equation
L_{den} (morning, evening and night	Sound Level Equation At Morning, Evening And Night
$L_{eq,20}$	Continuous Sound Pressure Level Per 20 Minutes
L_{eq24h}	Sound Level Equation In 24 Hours
L_{Final}	Final Output Sound Level In Decibels
Lidar	Light Detection And Ranging
L_{lc}	Sound Level Raster After Adjusting For Landcover
L_{night}	Sound Level Equation At Night
L_p	Sound Level Raster Based Solely On Distance And Elevation
LR	Linear Regression
LUR	Landuse Regression
MAD	Mean Absolute Deviation
MAE	Mean Absolute Error
MCC	Multi-Scale Curvature Classification
MCS	Mobile Crowd Sensing Method
ML	Machine Learning
MLP	Multilayer Perceptron Model
NDVI	Normalized Difference Vegetation Index
NKVE	New Klang Valley Expressway
NMPB	National Medicinal Plants Board Model
NMPB	French Road Noise Prediction Method
NSW	New South Wales

ORNAMENT	Ontario Ministry of Transport Road Traffic Noise Model
R	Coefficient of Correlation
r	Shortest Distance Between The Road And The Calculation Point
R^2	Correlation Coefficient
RBF	Radial Basis Function Model
RF	Random Forest
RLS 90	The National German Standard For The Prediction of Road And Parking Lot Noise
RMSE	Root Mean Square Error
RPC	Rational Polynomial Coefficients
SVR	Support Vector Regression
TES 52A	Equipment of Sound Level Meter
UAE	United Arab Emirates
WHO	World Health Organization Standards
WS	Wind Speed
μ Pa	Pascal
7th EAP	Seventh Environment Action Programme

Abstract

Vehicular traffic is one of the most significant engines for economic growth, therefore, its importance cannot be over emphasised. This noise causes a serious negative impact on the people living around the environment. Road traffic is known to be the major source of noise which often causes annoyance and interference. The aim of this research is to produce 2D and 3D noise maps for the study area and generate noise maps with the aid of mobile application through building two models (2D and 3D noise models) would be developed using machine learning algorithms, ArcGIS software, noise level, LiDAR data and road geometry and surrounding environments. So, the specific objectives and contributions of this research are developing noise sampling methods and generating observation points for modelling, model traffic noise in 2D and 3D using landuse regression (LUR) and machine learning methods, improve efficiency and scalability of noise models through integration and optimisation and develop noise visualisation tool for mobile application based on the models developed in this research. In this research was built two models: 2D noise model for roads and 3D noise model for buildings by using fewer noise samples. The 2D and 3D noise models were combined to produce 3D noise map for the study area. Also, the proposed models based on machine learning such as artificial neural network model (ANN), random forest (RF) and support vector machine (SVM), and the performance of three models were ascertained by calculating three performance measures: correlation (R), correlation coefficient (R2) and root mean square error (RMSE). The result of training and testing indicated ANN as the best model. The random forest (RF) has proven to be better than the support vector machine (SVM); the RMSE of the RF is less than RMSE of SVM. The RMSE of RF model showed (1.82, 6.00) and (9.83, 4.50) for training and testing 2D and 3D model respectively. While RMSE of SVM model was recorded to be (3.60, 6.16) and (10.34, 4.75) for training and testing 2D and 3D model, respectively. The main contributions of this study were the development of the noise prediction and propagation modelling methods. Both noise prediction and propagation models are valuable tools for traffic noise assessment during the highway design stage and to evaluate the impacts of traffic noise emitted from a vehicle on highways on the population.

Keywords: traffic noise; noise prediction; noise propagation, machines learning, artificial neural networks, mathematical models; 2D noise model; 3D noise model.

Chapter One
INTRODUCTION

1.1 Introduction

Noise pollution, air pollution, and water pollution have always been universal anxiety, which affects the public's health and the earth's brittle ecosystems (Sonaviya and Tandel, 2019; Sonaviya and Tandel, 2021; Mishra et al. 2021). Among all the pollution, one of the grave and major issues of the environment is noise pollution. It is a growing problem for communities in large urban areas (Maiti and Agrawal, 2005). Studies on noise pollution show that more than twenty percent of the globe population exists under deniable noise levels and about 60% of the European population is exposed to serious noise levels during a daytime (Rivas et al. 2003). Health-related issues like physiological disorders, psychological disorders, hypertension, and ischemic heart diseases are seen nowadays (Canter, 1996). There are various harmful sources of ambient noise on public places like industrial activity, construction activity, huge machine sets, loudspeakers, music systems, vehicular horns, and other mechanical devices, which affect the human being health, and the psychology of human (Gupta et al. 2018; Bala and Verma, 2020; Singh, 2016; Jindal et al. 2018).

A skill of measuring traffic noise level and signify them on a geographical information system map can provide a powerful set of tools for recognized noise sources, its rising influence, management and take judgments relating to its control measurements (Oliveira et al. 1999). The major source of environmental pollution is a road traffic noise in urban areas. Several nations have proposed limits for vehicular noise and allotted guidelines to control road traffic noise (Abbaspour et al. 2006). For a developing nation like Malaysia, where the growth of urbanization is quite high, vehicular noise is a significant source of environmental noise pollution (Alam, 2011). In the face of sudden traffic route, traffic is increased, and it results in increase noise level (Dursun et al. 2006).

The geographical information system can give a strong set of tools for collecting, recovering, converting and picturing spatial data from the real world for suitable purposes (Burrough et al. 2015; Jovanović, 2016; Longley et al. 2005). In GIS, cataloguing and meta-data organization systems are used to trace data handling at every step of the process. These systems contain variations in input data, interpretation of the data, interpolation techniques, calculation methods and its settings, which can affect the precision of the output results. Therefore, the geographical information system is an important tool which aids in the study of noise pollution (Jovanović, 2016).

The geographical information system can provide the graphical visualization of the impact of noise and an additional tool that is used for analysing the outcomes (Karthik et al. 2018). Noise mapping can be done using appropriate GIS software for better graphic of representation of the noise impact and its daily variations (Debnath and Singh, 2018). Interpolation techniques can be used to develop contour maps that show the noise level variations and so it is an effective technique for the intention of noise mapping (Harman et al. 2016; Mendez et al. 2013). The interpolation technique can be used to evaluate the acoustic behaviour of the topographical region. The integration of GIS with noise prediction models and a GIS-based approach to noise mapping can provide a precise and fast assessment of the noise impact on the environment (Buckley, 1990). GIS can give better graphical acquaintance of the areas with maximum noise levels, traffic accumulations and classifies the most exposed areas under the noise pollution peril. As well as this research focus on the prediction of 2D and 3D noise maps generated from vehicular traffic noise and that impact negatively on the surrounding environment such as urban areas by using several machine learning methods.

1.2 Research Background

In this section, the summary of the traditional noise map methods, GIS and remote sensing, as well as Light Detection and Ranging (LiDAR) in noise modelling are explicitly explained and presented.

Firstly, the traditional method of noise prediction depends on interpolation methods in predicting noise around a developed environmental (Law et al. 2011). However, this approach is not usually accurate, because of the human bias nature and skills involved. Different studies have specific determinants which are different from one another. Hence, the use of traditional noise mapping is limited to the biggest problem of noise in a particular region (Eason 2013; Stoter et al. 2008; Kurakula, 2007).

Figure 1.1 shows the traditional method of calculating sound levels of noise and interpolation of the noise data through the use of devices. The data is subsequently converted to noise measurement with the aid of software in the form of digital data such as points (Geo-referencing) to make it editable at their precise locations. Firstly, linear interpolation is applied to produce the model and algorithms. The results are represented in the form of contour lines as a map of noise measurements (Wedge and Rutledge 1992).

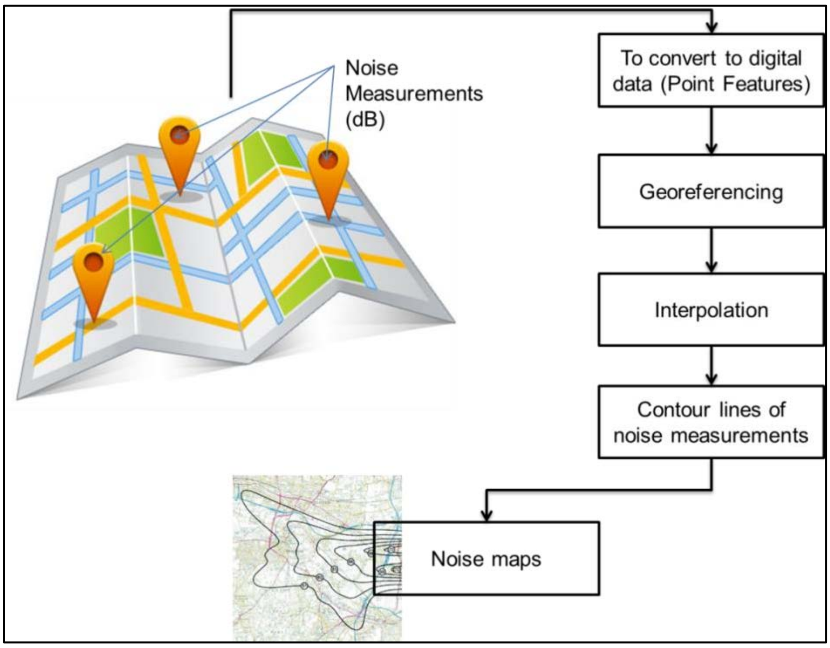

Figure 1.1 Diagram showing traditional interpolation of noise samples.

Secondly, GIS and remote sensing are powerful tools used for noise modelling and mapping with satellite images as input (Ayalew and Yamagishi, 2005). For example, QuickBird imagery is used for high-resolution aerial photography. It has been deployed in Japan for landcover uses in GIS digitised maps and other thematic layers through image processing to acquire more accurate noise models (Arroyo et al., 2010; Hilbert and Schmullius, 2012; Zhou and Qiu, 2015). Several commercial models have been used for noise prediction, which could be quite expensive due to the variability in the noise determinant across various countries (Asensio et al., 2009; Merchan and Diaz-Balteiro, 2013; Ozkurt et al., 2014). Many models were later developed which were appropriate for every region to estimate the noise level and compare the results to different kinds of literature with similar indicators. According to Kurakula et al. (2007), the application of remote sensing with GIS provides a visual representation of noise pollution in the form of an active area-wide traffic noise contour. Also, a Geographic Information System

(GIS) has the capacity to process a huge quantity of complex geographical data such as road gradient, surface nature, and configuration. The traffic noise based on the GIS model exhibits high spatial resolution close to the individual buildings on both sides of the road, which makes it viable to support spatial analysis of traffic noise in densely populated cities with complex traffic situations (Li et al., 2002; Zhao and Qin, 2014).

Finally, Light Detection and Ranging (LiDAR) has been used to produce 3D noise maps of cities for noise modelling. LiDAR unlike aerial photography, acquisition takes place below cloud cover and could be used to develop high-resolution maps applicable in archaeology (Corns et al., 2009), geodesy (Akel et al., 2004), geology (Buckley et al., 2013), geography (Johansen et al., 2011), geomatics (Zazo et al., 2015), seismology (Rovithis et al., 2016), atmospheric physics (Ware et al., 2016), geomorphology (Orem et al., 2015), forestry (Asner et al., 2014), transportation (Williams et al., 2013) and wind farm optimization (Seong et al., 2011; Zhou and Qiu, 2015). LiDAR uses visible, infrared or ultraviolet light to produce an object image over a wide range of materials such as rocks, clouds, rain, aerosols, chemical compounds, single molecules, etc. It also provides point cloud with 3D (x, y, z) positions that is a high accuracy contour line with day or night task except when coupled with digital cameras (Bastián-Monarca et al., 2016; Ragettli et al., 2016a; Ragettli et al., 2016b; Ryu et al., 2017; Steele, 2001). Furthermore, LiDAR offers high precision digital surface and elevation models that could be beneficial for any 3D analysis (Hu, 2004; Lefsky et al., 2002). It provides geospatial solutions for the development of simple to complex models with detailed information on the attributes of build-ups and landscapes. The attributes such as height, building footprints, transportation, trees and other utilities can be extracted from the model. This information on the attribute would assist in developing more detailed noise models and produce 3D noise maps for city centres (Gulliver et al., 2015; Monazzam et al., 2015; Zhou and Qiu, 2015).

1.3 Problem Statement

Traffic is known to be the major source of noise pollution in urban environments that subsequently affect human physical/ mental health and labour productivity. Therefore, this call for the need to model noise produced by vehicles under different scenarios (Nedic et al., 2014). However, the need to use a suitable predictive model cannot be over emphasized. Literature has shown that several models used for traffic noise prediction from 1950s to 2010s were designed and developed based on various parameters such as traffic volume, speed with zero acceleration, ground attenuation and gradient. These models are federal highway administration (FHWA), comparison of road traffic noise prediction models (CoRTN), road traffic noise prediction model of Japan (ASJ RTN), national medicinal plants board model (NMPB), the national German standard for the prediction of road and parking lot noise (RLS 90), contrast noise ratio model (C.N.R) and French road noise prediction method (NMPB). Most of these models are used to predict and propagate traffic noise in the USA, England and Australia, Japan and Europe, respectively. However, the models might be suitable for road traffic conditions and urban environments in the individual countries due to the individual local conditions that affects road traffic noise differs (Hamad et al., 2017). As well as, the prediction and propagation techniques differ and also are distinct from one method to the other. Furthermore, noise propagation using the aforementioned models are considered complex. Therefore, the need to develop individual model that can perform effectively in traffic noise prediction with different their peculiar traffic parameters of road traffic conditions has become highly imperative (Kim et al., 2019).

Conversely, 2D noise maps are developed with information on noise levels for a particular height. But, in reality, noise is transmitted in all directions and the impact of the noise is in all directions. Hence, information from a noise source at one particular height is not enough to reduce or control noise pollution. In a busy urban environment, many people live in high-rise buildings. The inhabitants living in the high-rise building are also severely affected by traffic noise. The actual number of people annoyed by noise cannot be accurately calculated using 2D noise maps. The location of hotspots of high noise levels and noisiest roadways is difficult to identify with 2D noise maps. This is because; the variations in noise levels cannot be properly visualised in 2D noise maps. Noise levels vary with the gradient of road. Places where cars are engaged on hills make more noise than when they travel down the other side. Also, the effect of gradient on noise levels cannot be shown accurately in 2D noise maps. The 2D noise maps do not provide enough information on noise levels for analysis and are likely to be underestimated due to exposure. With 2D noise maps, it is difficult to predict the actual reason for sudden changes in noise levels. This is because, 2D noise maps provide information only on noise, but not the 3D information of other features (buildings, roads, trees) which account for the increase or decrease in noise levels. The noise due to interference with buildings and other structures cannot be visualised on 2D noise maps. 2D noise maps do not provide enough information for calculating the efficiency of noise mitigation measures such as barrier effect and building insulation material. In order to have a better solution for these problems, it is necessary to have a noise map that can provide complete information of noise effect in all directions. This would be possible with 3D noise models. The 3D models have a data structure that reference locations in real 3D space (x,y,z). This means that they can provide volumetric information in 3D models with attribute data presented in voxels or 3D grids.

Subsequently, 3D noise maps are required to enable estimation of noise on building façades with different heights and determine complete noise levels at observer points. In 3D noise model, more input data are required such as observation point, noise samples and 3D building which lead to a problem in ArcGIS called "Big Data". In addition, several authors applied 3D noise maps based on the commercial model and complex software.

Finally, machine learning (ML) and ArcGIS software are entirely separate platforms, thus require integration. Thus, it is necessity to develop a method based on the ML with GIS to overcome these challenges that can be used at the early stages of highway construction and design. This approach is crucial and depends on the requirement of Environmental Impact Assessment (EIA). Therefore, this study will determine a suitable 2D and 3D noise models based on ML with GIS that can be able to produce noise maps with the aid of mobile apps.

1.4 Research Objectives and Scope

The aim of this research is to produce 2D and 3D noise maps for the study area and generate noise maps with the aid of mobile application. In this research, two models (2D and 3D noise models) would be developed using machine learning algorithms, ArcGIS software, noise level, Lidar data and road geometry and surrounding environments.

The specific objectives and contributions of this research are:

1. To develop noise sampling methods and generating observation points for modelling.
2. To model traffic noise in 2D and 3D using landuse regression (LUR) and machine learning methods.
3. To improve efficiency and scalability of noise models through integration and optimisation.
4. To develop noise visualisation tool for mobile application based on the models developed in this research.

This study is limited to the evaluation of noise pollution around the Expressway, major and second roads of Kirkuk in Iraq and Shah Alam located in Malaysia. The proposed model is inexpensive and easy-to-use engineering methods for noise impact assessment. Also, 2D and 3D noise maps generated by ML with GIS can be available for residents to check the situations before and after the construction of such expressways via modelling and simulations.

This research covers noise pollution around residential, commercial, industrial, public, educational, and other parts of the environment in the study area. High-resolution image is used to build the geodatabase and LiDAR data (cloud points) to acquire valuable information for the proposed model.

Machine learning (ML) and several statistical such as Chi-square statistical analysis, feature selection method and others are used for the proposed prediction model. The parameters such traffic noise, traffic volume, speed vehicles, traffic light, type of roads, landuse area, bus stop, bus line, railway station, railway line, gas station, digital surface model (DSM), digital elevation model (DEM), temperature and wind speed are employed in the proposed model.

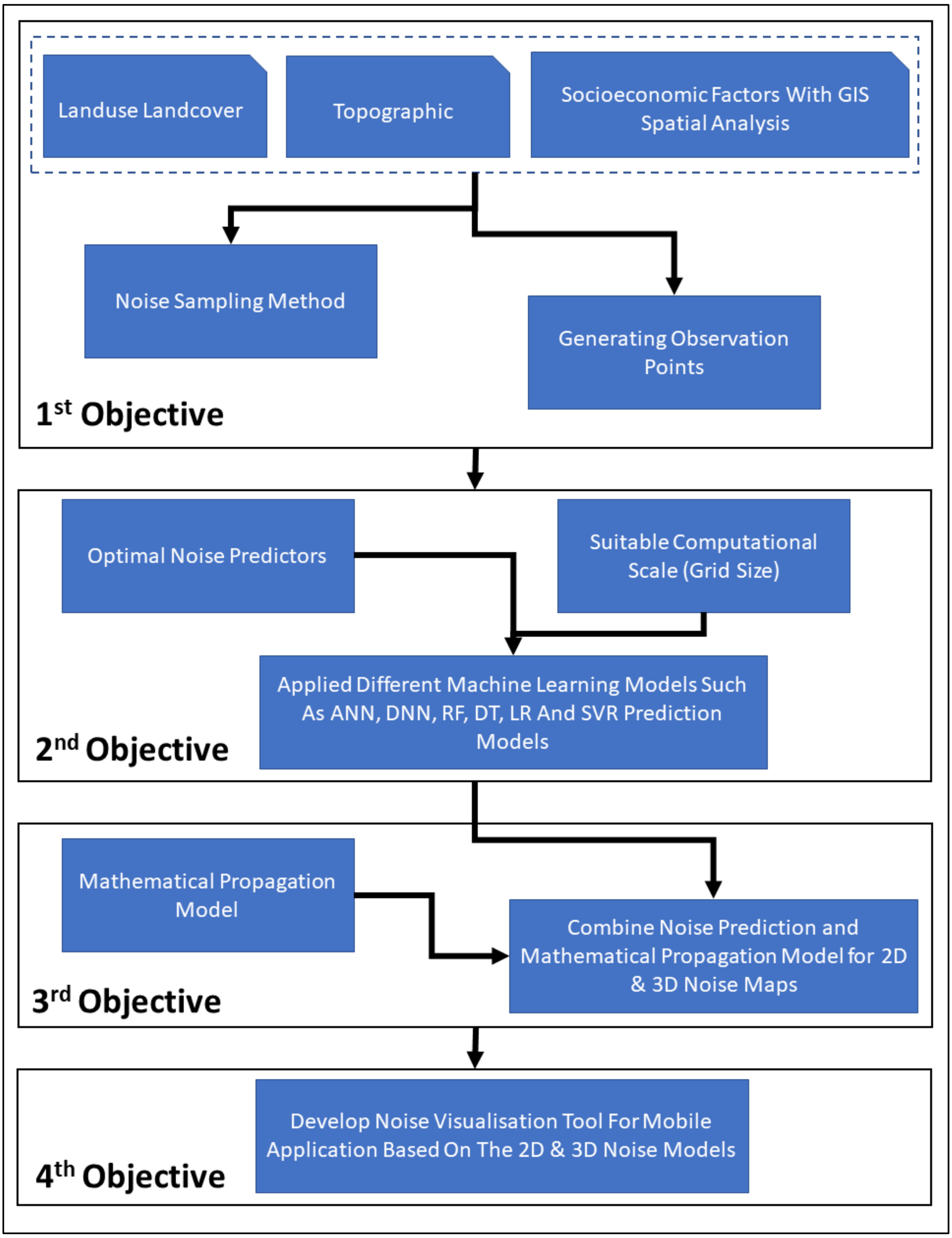

Figure 1.2 Shows conceptual framework of the study.

1.5 Research Questions

The following are pertinent questions that address the identified problems toward achievement of the research objectives:

For objective 1:

1- How to generate noise samples considering topographic, landuse landcover and socioeconomic factors with GIS spatial analysis?
2- How to generate 3D observation points for 3D noise modelling?

For objective 2:

1. What the noise predictors are optimal for noise modelling with the landuse regression method?
2. What is the optimal or suitable computational scale (grid size) in landuse regression based on noise modelling?
3. How different machine learning models such as ANN, DNN, RF, DT, LR and SVR models perform for noise modelling?

For objective 3:

1. What integration farm work should be used to combine noise prediction, propagation model and standard noise map of landuse landcover in the study area?
2. What are the factors affecting efficiency and scalability of noise modelling?

For objective 4:

1- What are the platform features necessary to deploy the developed model to mobile application?

1.6 Significance of the Study

The noise models provide quantitative relationships between noise measurement, traffic flow, and the surrounding environment, which considered those noise predictors important for the study area by making good predictions of the noise of the road and surrounding environment. This model will help the government establishments and the planner's decision-making for suitable environmental areas, as well as to assess the Environmental Impact Assessment (EIA) of noise pollution. EIA is considered one of the compulsory requirements for all new infrastructure projects. Moreover, the assessment of noise pollution by the consultancy agencies is more costly due to high demands for experts, complex models, and costly devices of noise measurement systems. So, our model is inexpensive and can be used by governments because it depends on the GIS, which can reduce EIA projects' budgets. In addition, the noise modelling is changing based on the local conditions affecting traffic noise standards and increasing city development. In addition, this model can help to develop the transportation systems through visualisation of noise pollution (noise mapping) in the landscape of the study area.

On the other hand, several concerns about traffic noise from residents in urban areas have been reported in newspapers, magazines and other mediums, especially for newly planned expressways such as the Kinrara–Damansara Expressway (KIDEX) in Malaysia. So, the noise maps of the study area will be published online to help the residents check the situations by themselves before and after the construction of expressways.

1.7 Scope of the Study

This study is limited to evaluation of noise pollution around tolls in Shah Alam Seksyen 13, Kuala Lumpur, Malaysia for smart roads and the capital city of Kirkuk, Iraq to efficient traffic noise control for future traffic design and planning. The proposed model is inexpensive and easy-to-use engineering methods for traffic noise impact assessment. Also, the noise maps generated by GIS can be available by which residents can check the situations before and after the construction of such expressways via modelling and simulations.

The research covers noise pollution around the residential, commercial, industrial, public, educational, religious, and other parts of the environment in capital city of Kirkuk, Iraq and Shah Alam Seksyen 13, Shah Alam Seksyen 7 and Subang Jaya (60 cm) panchromatic resolution and (60 cm) multispectral resolution image satellite QuickBird and (31 cm) panchromatic resolution and (1.24 m) multispectral resolution image satellite worldview-3 were used to build Geodatabase and cloud points (LiDAR data) to acquire valuable information for the proposed model.

Furthermore, the research was carried out in the capital of Kirkuk, Iraq. This study area was chosen due to its features, such as industrial and residential buildings, characterised by low/high-density population, making it suitable for noise-related investigations. Moreover, according to the Iraq Ministry of Planning, Kirkuk is the capital of Iraqi culture, characterised by high traffic flow. In addition, it embodied different types of road networks, such as the Baghdad Erbil expressway (BE) and primary and secondary roads in the city. These diversities make the site suitable for traffic noise studies.

Artificial Neural Network (ANN) and Chi-square statistical analysis were utilized for the proposed predicted model and propagation model, respectively. The noise parameters inputted into 2D and 3D noise models such as number of cars, number of heavy vehicles, number of motorbikes, sum of vehicles, car ratio, heavy vehicle ratio, motorbike ratio, highway density, a Digital Surface Model (DSM), and wind speed (WS) was employed in ANN model. While in the 3D noise model, the noise parameters considered are the distance from high light vehicle, medium light vehicle, low light vehicle, high truck, medium truck, low truck, high motorbike, medium motorbike, low motorbike, high semitrailer, medium semitrailer, low semitrailer, high bus, medium bus, low bus, medium average speed, low average speed, high maximum speed, medium maximum speed, low maximum speed, high average speed and DSM. Also, factors such as wind direction and speed, barriers such as tall buildings, and the interaction of air particles with the noise waves are employed in the noise propagation model.

1.8 Thesis Organization

This section presents the layout of the thesis and the content of each chapter as follows:

Chapter one presents the introduction and research background to the need for the environmental noise assessment of highway traffic on settlements Kirkuk city and Shah Alam Seksyen 13 and also the aim and objective of the study. The problem statement and scope of the research work are also presented.

Chapter two presents the literature review on some aspects concerning noise and its effects on inhabitants. Also, research works conducted on prediction and propagation models used in the literature is reported in this chapter.

Chapter three present the research methodology employed in these experiments. The procedure used, data pre-processing and preparation, model of prediction and the propagation models used, and the features considered in the experiment to obtain an accurate result are discussed in detail.

Chapter four describes the result obtained from the experiments carried out on the prediction and the propagation of noise generated from vehicular traffic along the study area. Various analytical tools used were discussed and compared for optimum result.

Chapter five presents the conclusions and recommendations based on the data obtained and the result of the analysis carried out for further investigation or action.

Chapter Two

LITERATURE REVIEW

2.1 Introduction

Increase in global population and rural-urban migration are the major causes of increased vehicular traffic across cities around the world (Cai et al. 2015). The increase in the number of vehicular traffic has led to a corresponding increase in environmental noise pollution which is becoming a global challenge especially in city areas (Bastián-Monarca et al. 2016; Halonen et al. 2012; Paviotti and Vogiatzis 2012; Paunović et al. 2009; Belojevic et al. 2008). Apart from its contribution to greenhouse emissions, this effect results in a noisy environment as reported in many studies (Vogiatzis 2013; Can et al. 2011; Foraster et al. 2011).

Vehicular traffic and industrial noise have serious consequences and direct effects on human health and the environment (Gislason et al. 2016). It is among the major environmental pollutants that cause sleep disturbances (Gislason et al. 2016; Can et al. 2011). Road traffic noise around residential areas adjoining the road has a significant adverse effect on the quality of life. These effects could be psychological disorders, hypertensions and heart diseases. Therefore, traffic noise is considered as a major environmental issue that needs to be addressed in urban areas.

Therefore, noise control and management are highly imperative and should be given careful consideration in modern cities towards a better quality of lives. This could be achieved through noise modelling and mapping by using effective geospatial tools that provide solutions for environmental noise control and subsequently noise reduction. A noise map is a graphical representation of sound levels in an area within a specific period (Yilmaz and Hocanli 2006).

The main applications of noise maps are in the assessment of sound levels and the pre-evaluation of action plans and noise control measures, or the estimation of people's exposure to noise. It is a useful tool for acoustic urban planning in landuse studies and environmental impact assessment of any activity before to its implementation.

Therefore, this research focus on prediction of 2D and 3D noise maps generated from vehicular traffic noise and other noise predictors that impact negatively on the surrounding environment such as urban areas by using several machine learning methods.

2.2 Geographic Information System (GIS)

A geographic information system (GIS) is a system designed to capture, store, retrieve, analyse, manage, and visualize spatial data in the form of maps and other graphic displays (Goodchild, 1992). The features of GIS stored data are typically classified as points, lines, or areas, and raster images. According to Parish and Müller (2001), data could be stored as points, road, lines, and boundaries of areas, while aerial photos could be stored as raster images in city maps. Also, GIS is a spatial index that makes it possible to identify features located in any region on a map. For example, GIS can quickly detect and map all the locations within a specific area or point that run through a territory (Law et al., 2011; Tsai et al., 2009). In most geospatial applications, several GIS layers are usually combined to provide a suitability map for effective decision making as shown in (Figure 2.1).

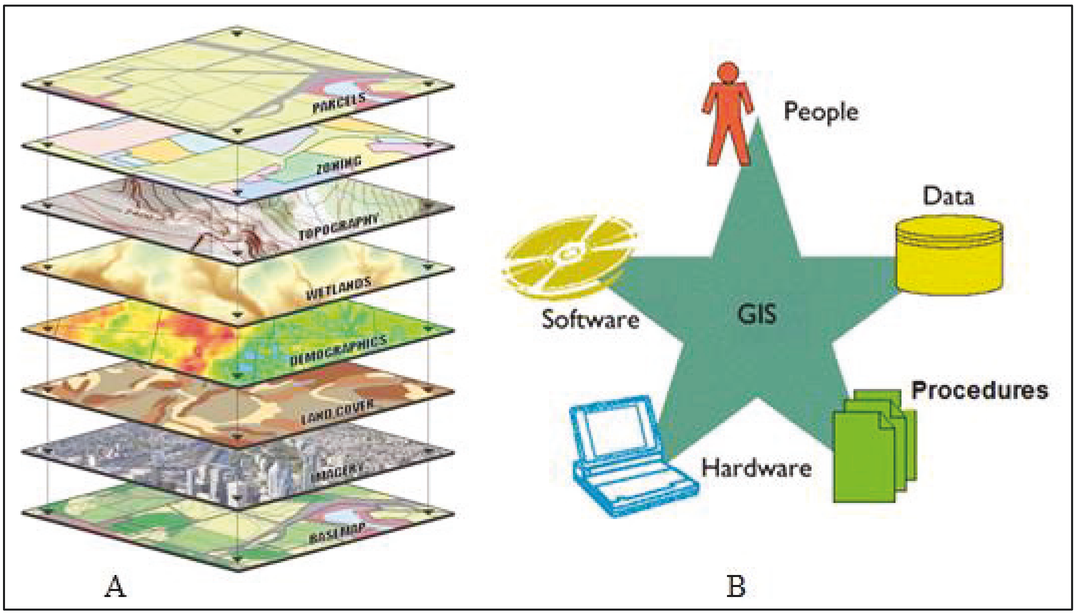

Figure 2.1 Elements of GIS: (A) GIS data layers, and (B) GIS system. (Chang et al., 2006).

Statistical and spatial analysis of GIS has been used to predict noise levels in urban and rural areas which have proven to be a useful tool for traffic noise studies (Li et al., 2002;

Makarewicz and Gałuszka, 2011; Zhao and Qin, 2014). More so, GIS enables mapping of air quality, traffic emissions, and human exposure at workplaces, homes, and on the streets (Gualtieri and Tartaglia, 1998; Pamanikabud and Tansatcha, 2010). GIS improves the quality of the noise modelling and prediction as well as decreases the cost of data collection. Furthermore, GIS makes it possible to integrate both the geographic features of the surroundings and the noise prediction models. This integration (relation) generates noise models automatically based on the available geographical data, design information and noise sources. It also calculates the impact of noise on the environment and human that supports decision-making processes in infrastructural planning (Lohmann and McMurran, 2009; Wawa and Mulaku, 2015).

2.3 Applications of Remote Sensing and GIS in Noise Modeling

Geographic information system (GIS) is a powerful tool for mapping that uses satellite images as input for noise modelling (Ayalew and Yamagishi, 2005). QuickBird, a is high resolution image aerial photography which have been employed in Japan to make landcover uses GIS digitize maps, and other thematic layers through image processing which are used to acquire more accuracy in the noise modelling (Arroyo et al., 2010; Hilbert and Schmullius, 2012; Zhou and Qiu, 2015).

Several commercial models have been used for noise prediction which could be quite expensive due to the variability in the noise determinant across various countries (Merchan and Diaz-Balteiro, 2013; Ozkurt et al., 2014; Asensio et al., 2009). Many authors begin to develop models appropriate for every region to estimate the noise level and compare the results to different kinds of literature with similar indicators. According to Kurakula et al. (2007), the application of remote sensing with GIS provides a visual representation of noise pollution in the form of active area-wide traffic noise contour. Figure 2.2 shows the traffic noise map for Guangzhou, China, whereas the red colour display on the map indicates areas of traffic noise.

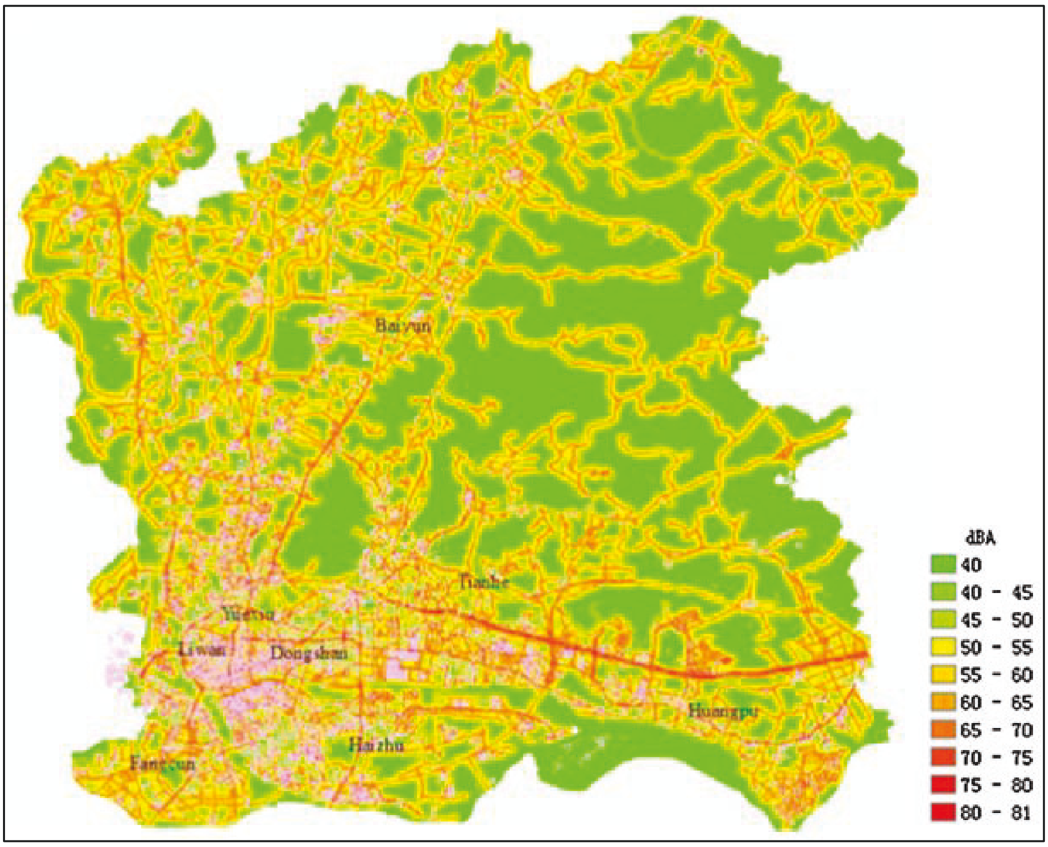

Figure 2.2 Map showing areas of traffic noise (Cai et al., 2015).

Geographic Information System (GIS) processes a huge quantity of complex geographical data like road gradient, surface nature, and configuration. The traffic noise based on the GIS model exhibits high spatial resolution close to the individual buildings on both sides of road which makes it viable to support spatial analysis of traffic noise in a densely populated cities with complex traffic situations (Farcaş and Sivertunb, 2010; Li et al., 2002; Zhao and Qin, 2014).

2.4 LiDAR Technology for Noise Mapping

Light Detection and Ranging (LiDAR) is a method used to measure the distance between the sensor and a target surface, which is obtained by computing the elapsed time between the emission and the return signal of a short duration laser pulse at the sensor's receiver ends (Hu, 2004; Lefsky et al., 2002). So, the time interval between the to and fro trip multiplied by the speed of light results gives the round-trip distance travelled which is divided by two to yield the measured distance between the sensor and the target.

LiDAR unlike aerial photography, acquisition takes place below cloud cover and could be used to develop high-resolution maps applicable in archaeology (Corns et al., 2009), geodesy (Akel et al., 2004), geology (Buckley et al., 2013), geography (Johansen et al., 2011), geomatics (Zazo et al., 2015), seismology (Rovithis et al., 2016), atmospheric physics (Ware et al., 2016), geomorphology (Orem et al., 2015), forestry (Asner et al., 2014), transportation (Williams et al., 2013) and wind farm optimization (Seong et al., 2011; Zhou and Qiu, 2015). LiDAR uses visible, infrared or ultraviolet light to image objects over a wide range of materials such as rocks, clouds, rain, aerosols, chemical compounds, single molecules, etc. It also provides point cloud with 3D (x, y, z) positions that is a high accuracy contour line as well day or night task except when coupled with digital cameras (Bastián-Monarca et al., 2016; Ragettli et al., 2016b; Ryu et al., 2017; Steele, 2001).

Furthermore, LiDAR offers high precision digital surface and elevation models that could be very beneficial for any 3D analysis. It provides geospatial solutions for developing simple to complex models with detailed information on the attributes of build-ups and landscapes. The attributes such as height, building footprints, transportation, trees, and other utilities can be extracted from the model. This information on the attribute would assist in developing more detailed noise models and produce 3D noise maps for city centres (Gulliver et al., 2015; Monazzam et al., 2015; Zhou and Qiu, 2015).

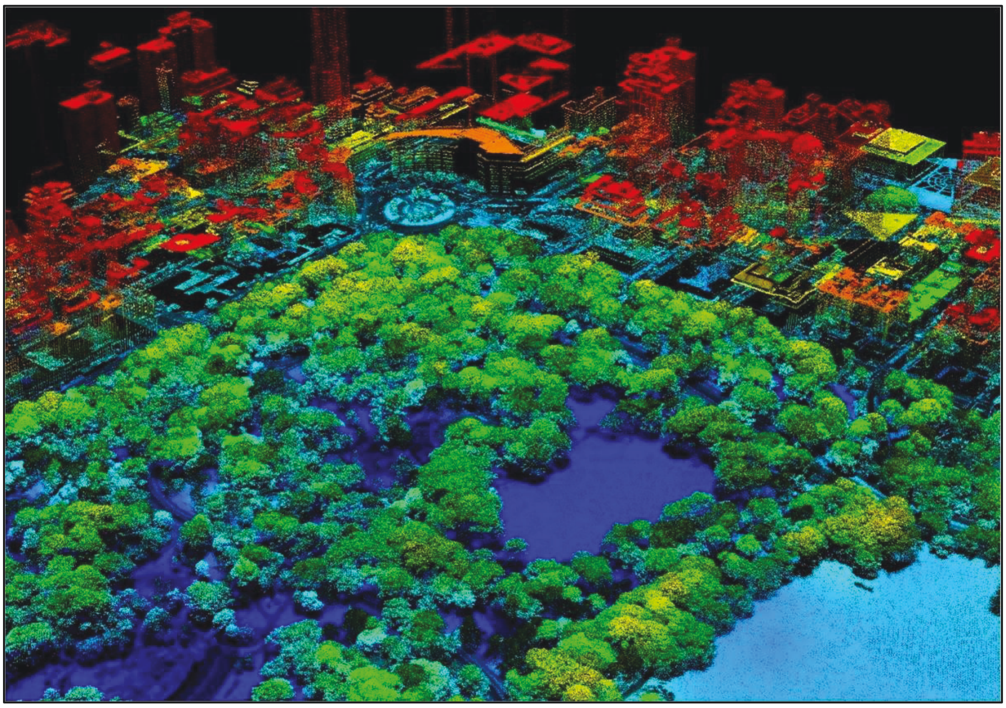

Figure 2.3 Cloud Point (LiDAR) (Google Images)

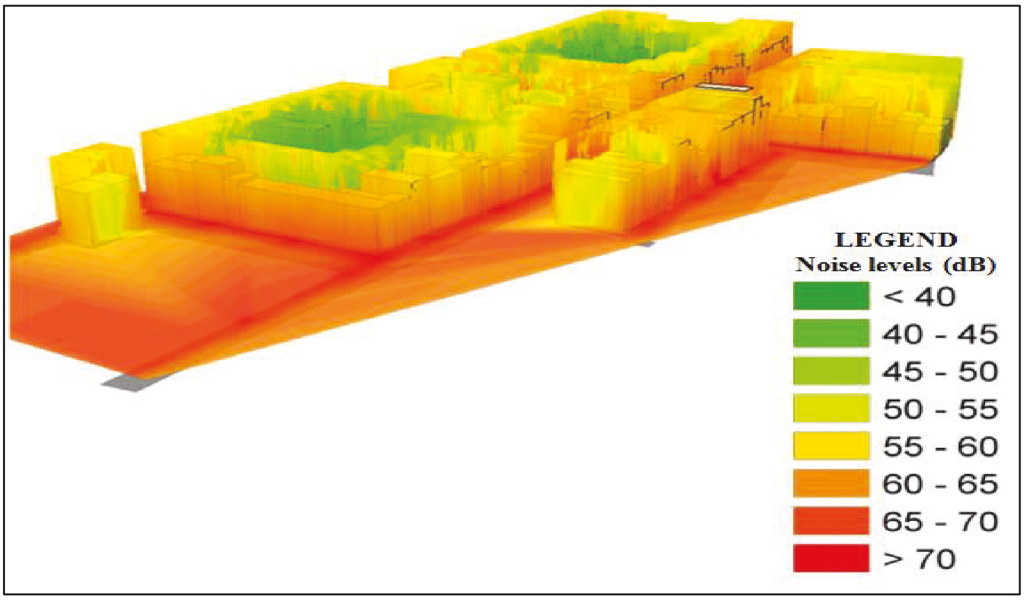

Figure 2.4 Cloud Point (LiDAR) for noise (Google Images)

2.5 Noise Pollution

Any unwanted sounds such as environmental noise, encompassing noise, sounds generated from human exercises or unsafe open-air sounds and noise emitted through traffic activities like street traffic, air traffic are referred to as ‘Noise’.

2.5.1 Measurement of Noise

Human ear responds to sounds or noise in a logarithmic manner rather than linear. Ear responds depends on sound intensity measured in Pascal (μ Pa) unit. According to Bruel and Kjaer (2002), sound intensity of 20 μ Pa is equivalent to a typical individual's hearing threshold, hence, it is regarded as hearing threshold. A 100Pa of sound pressure is loud enough to cause pain, thus is regarded as a threshold of pain. The ratio between the two aforementioned extreme sound levels is greater than 1000000:1 (Bruel and Kjaer, 2002). The direct use of linear scales for sound pressure measurement would lead to huge number. Thus, it would make more sense to evaluate sound in a logarithmic balance format called decibel or dB.

The sensitivity of human ear varies depending on the frequency; the sensitivity is higher at higher frequency and lower at lower frequency and has a short frequency range. Adjustment of sound intensity level is required to achieve a reasonably better weight to frequency that can be detected easily by human ear (Environment Agency, 2002). As a result, many weighting systems are proposed, however, the weighting option 'A' is most predominantly used for all noise levels. The measurement of noise using 'A' scale of weight is designated by dBA. In 'A' weighting scale, double of sound frequency is similar to increased sound level by 10 dBA. A sample of some commonly used sound levels on the dBA scale. In the linear scale, the large numbers in the 'A' weighted scale is converted to a manageable Zero (0) dB to 130 dB scale which is from threshold of hearing (20 μ Pa) to threshold of pain (~ 100 Pa) respectively (Bruel and Kjaer, 2002).

Noise level has been prescribed by various government agencies across the world. In Dutch, the maximum noise level for air, rail and road traffic has been imposed to be 50 dBA at the property located within a specific distance from the highway and railway. However, under certain circumstances, the noise level can be between 55- 70 dBA. Even though 70 dBA is relatively loud, which is comparable to traffic noise generated by freeways as shown in table 1 (Theebe 2004).

Table 2.1 Classification of noise level (Theebe, 2004).

Data Class	dB	Indication	Example
1	≤ 40	≤ Quiet	< Quiet street noises
2	41 - 45	Quiet	
3	46 - 50	Quiet	Light traffic
4	51 - 55	Quiet	
5	56 - 60	Moderately loud	Noise in average restaurant
6	61 - 65	Moderately loud	
7	66 - 70	Moderately loud	Normal city/freeway traffic
8	71 - 75	Moderately loud	
9	76 - 80	Loud	Heavy traffic
10	≥ 81	≥ Very loud	≥ Motorcycles at 25 feet

2.5.2 Road Traffic Noise

Highway traffic is the most commonly known sources of noise in most part of the world and often causes interference and anger (Bruel and Kjaer, 2002). Highway traffic noise usually spawned from vehicle mechanical parts and wheels due to the frictional resistance between the engine parts and vehicle with the ground respectively (WHO, 1999). Vehicular traffic volume, speed, quantity of heavy-duty vehicles and texture of road surface determine the level of noise generated. The level of road traffic noise is determined by the average individual vehicular noise which represents the unit for source of highway traffic noise. Every vehicle makes different tones of noise from its sources like road and tyre contact, engine, fan, exhaust and air intake.

Fuel combustion and mechanical parts interactions are the principal sources of engine noise. Transmission noise emanates from drive shafts, gearboxes and rear axles which are within the range of 68 to 78 dBA (ABOU EL SEOUD, 1994). When the exhaust valve is open, gas is suddenly released into the exhaust system which produces exhaust noise. Furthermore, the noise produced by frictional resistance between the road surface and the tyres exhibits considerable effect on the total level of noise generated from vehicles in motion. According to Harland (1974), when vehicular speed exceeds 100km/h, road- tyre surface becomes the major source of noise from traffic. Even though, substantial achievement has been observed toward reduction of noise generation from individual vehicles, noise pollution is still persisting which could have a significant effect on quality of human life.

2.5.3 Effects of Noise on Human

2.5.3.1 Physical Effects of Noise

High-intensity noise volume could result in permanent or temporary hearing damage. The science behind these hearing defects is well known. High noise volume or sound could cause noise-induced hearing problems that are experienced in many circumstances. Bearing in mind the substantial variations in sensitivity of human ear to noisy environment, it can result to hearing challenges. The harmful effect of noisy environment is regarded as “damage risk”. However, when the equivalent sound level is below 75 dBA, the risk is considered negligible especially when the exposure period is not more than 8 hours.

2.5.3.2 Physiological Effects of Noise

Noise could lead to temporary stress reactions such as high blood pressure and heartbeat rate which would tell negatively on our respiratory and coordination systems. Noise could result to persistent rise in blood pressure after exposure to noise for a long time. Some reviews were carried out on the general population by systematic comparison of the physiological behaviour between those living in quiet areas to those in noisy areas. The result indicated an increased blood pressure in those living in noisy environments.

2.6 Comprehensive Literature Review of Noise Models for Study Area

2.6.1 Traffic Noise in Malaysia

Several investigations have been carried out on traffic noise mapping in Malaysia and its impacts on health and environments. Abdullah et al. (2009) conducted a study on traffic noise levels in Putrajaya, Malaysia. In this study, the authors analysed the traffic noise data by special software and compared the results with World Health Organization standards (WHO). Their results revealed that there is a positive relationship between urban noise, and traffic volume. The result showed that the distance between the noise source and the incident location influences the noise level and 30% of the measurements carried out in the study area were higher than 75 dBA which is exceeded the limit recommended by WHO. This level of noise is detrimental to health and can lead to hearing loss.

Yusoff and Ishak (2005) presented an evaluation of urban highway environmental noise pollution in Malaysia (Bandar Sunway, Kelana Jaya and Taman Megah., Petaling Jaya.) was carried out. Traffic volume along the road was recorded and categorized into six major classes of vehicles. The study revealed that the noise level exposure experienced by the residents exceeds the Department of Environment's (DOE) guidelines on a daily basis while the measures taken were inadequate to curb the noise menace emitted from the nearby urban highway.

Jahandar et al. (2012) studied traffic noise under Stop and Go conditions at road intersections in Johor, Malaysia. The results suggested that the vehicles produce more sound at start up (initial move) than when they travel at a constant speed. Therefore, the study recommended that special considerations and priority of allocating funds should be given to these critical spots.

Aziz et al. (2012) presented an assessment of traffic noise pollution in Bukit Mertajam, Malaysia. This study showed that the noise level in Leq for the studied locations varied between 74 and 76 dBA, while the average background noise level was between 60 and 65 dBA, which exceeds the Malaysian Department of Environment (DOE) guidelines. Based on these results, it was suggested that noise level could be reduced by designing vehicle enclosures for engines and produce better-designed mufflers. It was also recommended that the speed limit could be used to reduce traffic noise because noticeable decreases were observed at reduced vehicle speeds.

Nadya et al. (2010) discussed the occupational noise exposure among toll tellers at Toll Plaza in Malaysia. The method combined survey questionnaire and field noise measurements. Noise dosimeter microphone was located at the hearing zone of the Toll Teller working inside the tollbooth, and full-period measurements were collected for each work shift. The results indicated that an occupational noise exposure among Toll tellers for L_{eq}, L_{max} and, L_{peak} were 79.2 ± 1.4 dBA, 107.8 ± 3.6 dBA, and 136.6 ± 9.9 dBA respectively. The research findings showed that the primary risk exposure to Toll Tellers comes from the noise emitted from heavy vehicles. Most of the Toll Tellers show symptoms of noise-induced hearing loss and are annoyed by the sources of noise at the Toll Plaza.

In another work, Daruis et al. (2014) studied the effects of night-time road traffic noise on a discomfort-A case study in Dungun, Terengganu, Malaysia. Data of the noise level produced at night in the residential area were taken at three different locations using the soundtrack LxT sound level meter. Data were recorded to produce L_{Aeq}, L_{max}, L_{10}, and L_{90}. The noise levels inside and outside of the residences exceeded the noise level permitted by DOE and WHO. The noise level in residence was 66.4 dBA which is much higher than the level proposed by DOE. While the highest L_{Aeq} of the traffic noise measured inside the residence was 57.5 dBA which is also considered high. Moreover, the maximum noise level inside the residences could reach up to 85.3 dBA at night during the weekends. This study also showed that from 114 respondents who were selected randomly, 61% felt that their residential area is noisy at night. The noise produced by the traffic at Paka Road, Dungun at night is considerably high and affects the residents' quality of life.

2.6.2 Traffic Noise in Iraq

Several researchers have conducted noise maps in Iraq to assess environment noise levels. Aziz et al. (2012) studied environmental noise pollution in Erbil City, Iraq: monitoring and solutions. The researcher examined the noise pollution level in this city and noises generated from outdoor, indoor, and road traffic sound sources, such as aircraft, road traffic, inside residential buildings, libraries, restaurants, classrooms, administration offices, construction equipment, and electrical generator. This research used a mathematical model to calculate the sound pressure level from 177 sites.

Chaichan et al. (2018) attempted to explore and establish a relationship between the volume of activity and the movement of motor vehicles of various compounds and contaminants resulting from their exhaust pipes, such as sulphur dioxide and particulate matter oxides of nitrogen, VOCs, and unburned hydrocarbons. The study focused on and around Mohammad Al-Qasim highway adjacent to the University of Technology, Baghdad. The results showed the need for urgent treatments addressed by the environmental authorities in the city. The study results demonstrated that these contaminants are increased during periods of the beginning and end of working hours for government departments. The Iraqi government should make greater efforts to protect the environment and humans in this country from the transportation pollution risks. At the same time, Qzar et al. (2020) studied to determine noise levels (LAeq) indoors and outside classrooms in different schools depending on the stage, gender, and course time. The researchers took 135 noise measurements in and near selected classrooms at 12 schools (primary and intermediate) in Basra City, Iraq. Noise parameters analysed were LAeq (including maximum and minimum); noise pressure levels higher than 10%, 50%, and 90% of the total measurement time; and noise pollution. The researcher discovered that the average equivalent LAeq inside classrooms, in school corridors, and outdoors alongside streets during active teaching were 72.41 dBA, 75.50 dBA, and 63.33 dBA, respectively. This research found that the indoor LAeq and background LAeq, when not in active-teaching mode (> 34.2 dBA), demonstrate that outdoor noise sources do not significantly influence indoor LAeq.

Selman (2018) studied noise pollution in urban environments in Al-Samawah City, Al-Muthanna, Iraq. The noise pollution level was measured in 20 locations around the city using a GM1351 digital sound level meter with a range of 30-130 dB. Day-time urban noise quality assessment was studied in Al-Samawah city for six critical zones: industrial, commercial, residential, recreational, silence zone, and traffic areas. The Excel computer programme was used to fit model equations to the experimental data. Results indicated that the highest Leq of 72.5 dB in the industrial zone, followed by 70.0 dB in traffic areas, 68.1 dB was observed in the commercial zone, 65.2 dB in the residential zone, 63.5 dB in the silent zone, and 62.4 dB in the recreational zone. As excessive noise affects people's health deleteriously, establishing an agency under the name of the Iraqi Environmental Protection Agency (IEPA) is essential for controlling this and similar hazards.

Finally, Ali et al. (2017) studied traffic noise pollution levels in Kirkuk City, Iraq, using the ArcGIS application. This study will help the planners for high-interest points of future Kirkuk city, especially urban planning and economic issues of the city. Also, this paper can help planners solve the problem of traffic jams in this area. The researcher found the main source of traffic noise pollution in this area is the transportation and the horn of vehicles such as heavy and medium trucks, buses, and automobiles. The study was on six roads: the Governorate region, Baghdad roads, Alwasti, Alaskary, Alnasir, and North garage. All those six regions were surveyed, and the noise at intersection of the roads was measured. The noise measurements were captured at the interestion points on three different days: Sunday, Monday, and Tuesday (3–5 January 2016). The results showed a high level of noise pollution and surpassed, on many occasions, the prescribed levels by the Central Pollution Control Board (CPCB). For example, the maximum level of noise pollution was 94.6 dB(A) in the Alwasti region near the road that leads to Kirkuk university. In comparison, the minimum level of noise pollution was 48 dB(A) in the Alnasir region. So, this paper prepared a noise mass for Kirkuk city for three days at peak hours.

2.7 Comprehensive Literature Review of Noise Models for the Objectives

2.7.1 First Objective of this Research

2.7.1.1 Noise Data Equation and Sampling

Traffic noise has a significant impact on human life and urban environments, as well as other noise predictors that may increase the effects of traffic noise on the population. So, a detailed study on traffic noise should properly plan for noise and traffic data collection. In addition, the study should set up the field measurement, noise sampling methods, generating observation points, and noise predictors. Therefore, this section presents all the above details and how the authors have applied them in different cities.

2.7.1.2 Noise Sampling Methods

Based on several studies available regarding methods of noise data collection from the site, the most important aspect is the distribution of noise samples and their quality (Stoter et al., 2008; Ranjbar et al., 2012). The distribution of noise samples is significantly affected by interpolation of results which subsequently lowers the accuracy of predicted noise at un-sampled locations. The observation points should be located on the highest surface of the terrain since the interpolated noise surface will be draped over the 3D city model, while point density should be high enough to attain an accuracy of the interpolated results. Conversely, it is absolutely necessary to avoid too many points to reduce the computation time of the noise software. It is highly imperative to adjust the density of the noise samples by considering noise propagation characteristics (Stoter et al., 2008). Moreover, the study a traffic noise measurement based on a GIS model for random generation of locations, that showed the approach was developed for data collection of traffic noise and accounting for spatial balancing. The method generates noise samples with optimal density by considering adequate numbers in the study area. Although this method has advantages over other techniques due to its ability to be deployed for 2D noise modelling, it neglects the height parameters which is one of the most important factors consider in 3D noise modelling. And the parameters used as input to this model are just three layers of land use types namely residential, commercial, and industrial layers (Ragettli et al. 2016).

2.7.1.3 Generating Observation Points

The most important operation in 3D noise modelling is the generations of observation points. The observation points are the location of virtual microphones within the jurisdiction where noise levels are to be determined. It is indeed difficult to determine the spacing between observation points, because there is no existing standard for the determination of observation point spacing. However, based on the rule of thumb, larger number location of points can yield better results. Therefore, some studies estimate observation points based on interviews with acoustic, consultant, scale or density of landuse in the study area. For instance, the research a performance evaluation of IDW, kriging and multiquadric interpolation methods in producing noise mapping: A case study at the city of Isparta, Turkey, the result indicated better outcome with the used of grid resolution set at 50*50 m^2 compared with others such as 100*100 m^2 and 200*200 m^2 (Harman et al,2016). While the result indicated better with grid size of 100 × 100 m^2 cells in two major cities in Israel: Tel- Aviv and Beer Sheva. The results of RMSE in Tel- Aviv which recorded 2.67 dB (A) which is less than 4.33 dB (A) for Beer Sheva. However, Tel- Aviv study area covers 51 km2 while Beer Sheva covered 39 km^2 (Harouvi et al., 2018). Moreover, the research a GIS-based approach for 3D noise modelling using 3D city models, carried out the observation points by using 2*2*2 m^3 which was designed based on interview with Mr. Henk de Kluijver, an acoustic consultant form dB vision office, Utrecht. So, it was observed that scale and density of observation points are generated based on the size of the study area which should be sufficient to achieve adequate accuracy in the results by (Kurakula, 2007). So, we found the scale of the city is important and is directly proportional to the grid resolution.

2.7.1.4 Noise predictors and Time Measuring of Noise Levels

The main objective of the noise prediction model is to accurately estimate noise level at any given location based on noise predictors within a period of time. According to the literature, there are some parameters of noise modelling that are deemed important and yield more accurate noise maps at any given time. These noise descriptors include number of cars, number of heavy vehicles, number of motorbikes, sum of vehicles, car ratio, heavy vehicle ratio, motorbike ratio, highway density, digital surface model (DSM), digital elevation model (DEM.), and wind speed. Furthermore, there are some other noise predictors in noise models that yield better accuracy: these are road, rail, buildings, land use, vegetation and population. Some road furniture also contributes to the accuracy of results such as: bus stop, traffic lights and industrial area. On other hand, the time of noise level measurement also contributes to better outcomes to achieve the main goals of noise prediction map. An LUR noise estimation model based on a different period of time were carried out by Harouvi et al. 2018. The noise levels were measured at rush hour and off-peak times of 20 min short term. Also, some studies used measured noise sampling using noise levels within two (2) min and 20 min periods (Ragettli et al., 2016). In addition, short-term measurements of road traffic noise was taken at 20 min in non-rush hours by Aguilera et al. (2015). These investigations showed that time duration and off or peak periods play significant roles in determining the accurate results.

In addition, some authors used noise predictors as input in their noise models within certain period of time and observed the influence of the time on the accuracy of the noise modelling. For example, the research an application of land use regression modelling to assess the spatial distribution of road traffic noise in three European cities, it was used landuse regression (LUR) model to examine traffic noise in three different cities in Europe (Aguilera et al. 2015). The model was based on local government data generated previously for epidemiological studies. The input variables for the LUR model include roads, land use (industrial, residential), agricultural, forest, semi-natural, and population. The developed LUR model is based on linear regression and follows the ESCAPE project in a large number of European study areas. The study suggested that LUR modelling with accurate GIS source data can be a promising tool for noise in epidemiological study. More so, the increase in R^2 values is observed in the "Best" models through the use of GIS variables such as roads, land use (industrial, residential) and agricultural. Furthermore, the study a statistical modelling of the spatial variability of environmental noise levels, used the LUR modelling approach with long-term noise measurements and land use characteristics to examine ambient levels of noise in Montreal, Canada (Ragettli et al., 2016). The study developed its LUR models based on various transportation noise sources such as air, rail and road in other to predict the equivalent continuous sound pressure levels L_{eq24h}, L_{night} and L_{den} (morning, evening and night). The noise predictor variables of all the three transportation sources were included in the model. The road transport was observed to be the most relevant noise source described with GIS variables such as distance to highways, length of major roads, traffic counts, and number of intersections. While the most important single variable in all the three noise models was the NDVI, which was negatively associated with environmental noise levels.

Whilst this research a Land use regression modelling of outdoor noise exposure in informal settlements in Western Cape, South Africa, was employed LUR modelling to assess the outdoor noise variability for adults living in informal settlements. The exercise involved constant monitoring of outside noise levels during the week. Data recorded related to about 134 homes from four different areas were taken. The LUR model was developed for the study based on noise sources such as transportation networks (air, rail, and road), local buildings, land use and community in order to obtain the daytime, evening and night-time values for the equivalent sound level. The results showed that the final LUR model developed by a total of five relevant variables—two variables related to road traffic, one to the household density, and two to the land use (commercial and industrial) (Sieber et al., 2017). More recently, in the research noise estimation model development using high-resolution transportation and land use regression, was conducted research work by utilizing LUR development with high-resolution transportation to estimate noise during two periods of the day (rush hour and off-peak) in two cities of Israel (Harouvi et al, 2018). It was discovered that using LUR supported by GIS approach showed good performance in terms of estimation of noise pollution map for environmental noise assessment. It was observed that the spatial variables of noise predictors were generated using GIS such as distances from bus stop, road, rail line, bus line, and traffic light, as well as traffic volume, length of roads, length of bus lines, build area coverage, and land use coverage.

2.7.2 Second Objective of this Research

Several investigations have been conducted to determine the influence of traffic noise on human health and the environment. In general, the literature contains noise modelling based on Geographic Information System (GIS), Global Position System (GPS), Machine learning (ML), landuse regression (LUR) and noise propagation. This section presents an overview of some recent and important works carried out on noise modelling using the methods discussed above.

2.7.2.1 GIS Method

GIS is usually served as a tool for data analysis and noise maps development. Several thematic maps and noise equations are combined to model a traffic noise distribution in a region and produce informative maps that can aid in taking effective decisions. For example, a regression model of traffic noise intensity in metropolitan city using artificial neural networks, this study developed a mathematical model for predicting noise level in, Delhi. The parameters used in the model include vehicle volume/hr, average vehicle speed and percentage of heavy-duty vehicles. It was reported that traffic noise in Delhi reached high levels above the Central Pollution Control Board (CPCB) limits. The author suggested that an effective measure is required to control noise levels by applying noise barriers or by finding means of reducing the noise from the source. The limitation of this study is that it requires experienced users in mathematics and software modelling to convert the data into maps. Furthermore, the maps generated using this method are not always accurate. Because it depends on parameters of traffic flow and speed to produce the noise maps (Kumar and Kumar, 2017).

The study shows a performance evaluation of IDW, Kriging and multiquadric interpolation methods in producing noise mapping: A case study at the city of Isparta, Turkey. This research was applied three methods in GIS such as inverse distance weighting (IDW), kriging and multiquadric interpolation methods. And it was observed that measurements of noise at certain locations and with the suitable mathematical model are absolutely necessary for an accurate noise map of a city to be produced. Also, a homogeneous distribution of the noise point's measurement and calculation of the noise values are fundamental factors in the production of noise maps. Although the authors succeed to create the distribution of the noise measurements for the study area, but this method was used based on a just distribution of locations. If this method of noise measurements distribution takes the type of land use and land cover as input into the model in addition to the type of roads for the production of the noise map, it would lead to a better result and more accurate noise maps (Harman et al, 2016).

The study developed a road traffic noise prediction model for different categories of roads in Vadodara city, India. was presented a model developed for road traffic noise for use in Indian environmental condition. Their predicting model was based on weighted equivalent noise levels to determine the road traffic noise. It was observed that noise dominate the spectrum of environmental which could lead to an induced hearing loss. The authors concluded that sources of noise pollution differ from one place to another. Sound level was observed to be above 110 dBA during the peak hours which becomes physically painful. The authors applied hypothesis which is difficult to implement in traditional GIS software and requires professional programmers to implement. Therefore, the noise maps were not validated (Tandel et al., 2016).

A GIS based simplistic noise prediction model for urban areas, this research presented a GIS-based simple noise prediction model for urban areas of Chandigarh, India. The investigation took into the traffic roads in cities leading to increasing the noise pollution was carried out. The investigation takes into consideration the road planners decision making for suitable environmental areas. In this study, the data of noise collected two cases. Stationary and mobile sources of noise and the mobile sources were considered as equivalent multi-point stationary sources. The data collected was inputted in the GIS software which is considered suitable and most reliable for large spatial data. The results were used to produce the trends in noise variations around the city in the form of noise maps. Although the authors applied IDW-GIS algorithms to produce accurate noise maps. But the method is considered expensive and time consuming due to the collection of extra noise (94 noise measurement locations) by using mobile sources. As well as the study area considered in this regard used just 7 roads, stationary noise sources (167) and the study area was used on a small scale so no need to extra noise measurement (Tahlyan et al., 2015).

In this research, a comparison of ANN and analytical models in traffic noise modelling and predictions, was presented a model to predict the equivalent continuous sound level generated due to traffic noise for various locations in Delhi, India. The model demonstrated the capability of producing accurate results of hourly traffic noise levels. The proposed prediction model may serve as a tool for predicting and regression of traffic noise for appropriate measures to be undertaken in Delhi city. The limitation of this study is the development of the model using ANN based backpropagation network. This model uses only one hidden layer in the network. More so, they found that there are some disadvantages in the proposed model which is time consuming and depends on the size of training data and network structure (Garg et al, 2015).

Whereas, the research proposed a highway traffic noise prediction based on GIS (Zhao and Qin, 2014), was predicted the traffic noise generated from vehicle noise. In their approach, the traditional methods of traffic noise prediction which is based on certain locations were avoided due to its time-consuming and costly nature. Therefore, different models' specifications for Environmental Impact Assessment of Highways (JTG B03-2006) model and the Technical Guidelines for Noise Impact Assessment (HJ2.4-2009) model were combined to predict the traffic noise which depends on the circumstances. The noise predicted values at each point were generated as contours of noise. The thematic maps were developed by overlaying the village data on the noise contours. The authors reported that the use of GIS in this prediction model could greatly assist decision-makers due to its spatial analysis function and visualization capabilities. Although, authors usually combined the commercial models, but the output of this model is in the form of a contour line that cannot be easily understood. Also, there are so many regions where the ground is not sufficiently flat, but the model neglected the terrain factor. However, the limitation of these models depends on the CAD data of the highway for predicting the traffic noise.

And the study a strategic noise mapping with GIS for the Universitat Jaume was proposed a noise prediction model which incorporated several features that could improve the existing models. The features incorporated include spatial and temporal data such as buildings, trees, street furniture, and other barriers including their sound absorbent information. Also, reflective surfaces, atmospheric conditions such as (wind direction and speed), humidity and ground temperature. And also, different traffic and road information such as start and stop conditions, traffic density at various times of day and week and road surface conditions were considered. Although, the author successfully applied sound attenuation equations to create a multiple noise source propagation and combination interpolation toolset in ArcGIS. But there are limitations that the authors took the noise measurements by using professional equipment and expensive wireless devices. So, this has made both methods too expensive due to the manpower or equipment requirements (Eason, 2013).

The research presented a noise impact assessment by utilizing noise map and GIS, was carried out an assessment of noise impact using noise map and GIS in Chungju, Korea (Ko et al, 2011). A model was developed for the noise impact assessment map. A 3-D terrain model was produced using the available data from the prepared draft and digital maps. A map for sources of noise was generated for each road for the development of the noise evaluation model. The level of noise was taken at 25 positions near the roads and compared with the expected levels of noise for verification purposes. It was observed that the model yields an accurate estimate of the exposed area and population. In the same year, Law et al. (2011) presented an advanced method of predicting noise map in Hong Kong. The experiment was conducted in a complex environment close to skyscrapers and GIS was used to calculate the sound levels of the noise which was analysed and produced as a noise map. Also, GIS software was deployed to generate the noise map in form 2-D and 3-D maps. Authors are expected to compare the final road-traffic noise map with those of the noise-standard map. Because these are different standards employed such as German standard models of RLS90 as compared with Korea which have different local condition of roads and environment. Although, visualization of the level of road-traffic noise along roads with the aid of mapping tools aid to understand the relationship between noise levels and traffic flow. It is also imperative to find the risk maps for the locations of exposed citizens to high traffic noise. Conclusively, the authors inferred that noise mappings around skyscrapers do not reveal the accurate result of noise display in environment.

The study performed a noise mapping in urban environments and studied the influence of spatial features of urban area noise to predict noise level maps in Tainan, Taiwan. In their investigations, 345 noise monitoring stations were identified at varying intervals and data were taken during the morning, afternoon, and evening in two seasons of summer and winter. The spatial distributions of noise levels were analysed and visualized using GIS software. The results showed 69.6 dBA and 59.3 dBA as the highest and lowest average noise levels during summer mornings and winter evenings, respectively. This result is not in conformity with the provision of the regulatory standards on noise. Therefore, based on the provisions of the US Department of Housing and Urban Development, the results indicated that over 90% of the Tainan City population is exposed to the unacceptable noise level. Noise maps were developed using GIS to integrate the monitored data of noise measurement with spatial information on the type of landuse. But this model neglected the important parameters such as roadway and buildings. The model is based on the traditional algorithm of Kriging-GIS and the final maps are expected to compare with other algorithms such as IDW, Spline and Natural neighbour available in GIS platform (Tsai et al, 2009).

The research presented a geoinformatics prediction of motorway noise on buildings in 3D GIS, was proposed motorway noise prediction model on the buildings in Thailand as a case study (amanikabud and Tansatcha, 2009). GIS was used to predict the noise map based on the impacts of road traffic noise on surrounding buildings. The impact of the noise on the buildings was investigated considering different incident angles from the noise source, and the results were produced in the form of 2D and 3D maps. Clear visual display of the results of the impact of noise level from the roadway on building blocks was produced in 2D and 3D (dimensional) forms which make it easier for planners to understand. Script programming written in Visual Basic Application was used to input the previously built motorway traffic noise model in ArcGIS program. The methods are in two forms: physical and regression models which are considered difficult to convert to digital maps except aided by professional programmers. In addition, this model has been tested on a single building. So, it has not been ascertained if the model would be successful when applied on more than one building or on medium scale. Li et al. (2002) presented a road traffic noise prediction model based on GIS and it was concluded that the model is appropriate for use in China. Some of the factors considered in the model were local environmental standards, traffic conditions, and vehicle types. The proposed model was observed to have an accuracy of about ~0.8 dBA and 2.1 dBA at open space and in a house respectively. An integrated GIS system was introduced to serve as general functions for modelling and design of noise. This model offers better efficiency and accuracy in traffic noise design and assessment. But the accuracy decreases gradually after 70 m away from roadway until 100 m when the model fails.

The research noise mapping and GIS: optimising quality and efficiency of noise effect studies, was presented a noise mapping method based on GIS which is aimed at optimizing the quality and efficiency of effect noise (de Kluijver and Stoter, 2003). It was reported that industry and infrastructure are major causes of noise in cities, and these could lead to undesirable effects on people and the environment. The authors in this research suggested that developing models that take into consideration similar indicators for noise exposure and assessment methods is necessary. Therefore, it is highly imperative to develop standardised methods for noise mapping and consequently clarify the summary used to standardize the noise mapping tools for appropriate noise control around the world. The GIS model of this research was succeeded when used on larger data collection of noise measurements. So, results will longer vary with the used methods that was mentioned from the authors in this paper. In conclusion, the influence of noise samples on this model is becoming significantly important (de Kluijver and Stoter, 2003).

The research integration of a road traffic noise model (ASJ) and traffic simulation (AVENUE) for a built-up area, was introduced road traffic noise model (ASJ) and traffic simulation (AVENUE) integration approach for built-up areas in Japan (Bhaskar et al, 2004). The researcher created a model to measure the noise from road traffic. Therefore, the model was integrated with simulator for road traffic to cushion the noise on road traffic. It was observed that GIS-based integrated tool helped to improve to predict noise interval in built-up area. In addition, the relationship with GIS gives the buffers of noise to look like the form of active city-wide traffic noise contour maps. The models are regarded as a commercial application which require physical parameters such as dynamic traffic flow, traffic speed, strip connecting lane segment and reception point distribution for different classes of vehicles, power level of vehicle noise, vehicle type and running condition (for each vehicle class). All these model requirements are difficult to collect from the field. Pamanikabud and Vivitjinda (2002) proposed a highway traffic noise model that relies on type of vehicles. The traffic data such as traffic noise levels, vehicle type, vehicles spot speed, traffic volumes based on vehicle classification, highway sections dimension obtained from local highways in Thailand with free-flow traffic conditions. Level of noise for each vehicle type is developed on the direct basis measurement of $L_{eq\ (10\ s)}$ from the running situation of the types of vehicles. The final model was proposed based on $L_{eq\ (10\ s)}$ of the new six groups of vehicles; heavy truck, medium truck, light truck, full trailer and semi-trailer, bus and motorcycles. The success of this model depends on how straight the section of the highway is designed without any noise barriers. In this model, the surrounding environment is excluded from the highway design. Therefore, this model would be more useful before building infrastructures in a city.

So, the advantages of GIS methods are:

- Excellent capabilities in the spatial analysis which greatly support noise modelling and noise map production.
- It is capable of automatic modelling and data processing which results in time and cost savings.
- It supports statistical analysis and geodatabases, which help to predict noise levels and produce summary tables for each noise sample.

While, the disadvantages of GIS methods are:

- The accuracy of noise maps depends on the accuracy of each data source and the algorithm of GIS tools.
- The 3D spatial analysis is not effective as 2D analysis tools which limit the 3D noise modelling and mapping.
- Top decision makers have some reservation on the acceptability of noise maps produced by automated method in GIS.

2.7.2.2 GPS Method

Aside from GIS approaches, several works have been reported in the literature using GPS technology. The GPS technique is used to measure the speed of cars, collect positional data, and support noise data collections. For example, the study a noise mapping using measured noise and GPS data, was used GPS, sound level meter and database program for analysing the data measured. The noise map was developed with the aid of the computer model of the area under consideration. Therefore, GPS was used to capture the location data and the sound meter was used to measure the noise level in such locations which are interfaced together to produce and store the noise level. The selected results measured are exported to the noise map in the form of noise contour line that can easily be opened in SHP and DXF file formats for further processing in GIS software (Cho et al., 2007).

Asensio et al, 2009 proposed a GPS-based method for speed data collection for a GPS-based speed collection method for road traffic noise mapping in the city of Alcobendas, Madrid, Spain. In this research, the approach was considered due to the difficulty and high nature of the conventional approach. Therefore, the global positioning systems (GPS) method was used at point locations to calculate the acoustic levels of noise. It was observed that the results acquired using these approaches are reliable and profitable. All measurements were taken at intervals of less than 20 m between noise samples in one street section and at intersections on streets. However, this method is considered the most difficult and expensive in noise pollution maps development especially when used on a large scale. So, authors should use the necessary spatial location to estimate noise samples with good results. Street axes and measurement of locations should match to achieve high accuracy without exaggeration in measurements of noise at 20 m between noise samples (Asensio et al, 2009).

Finally, Cai et al., 2015 presented road traffic noise mapping in Guangzhou using GIS and GPS. They developed several day and night traffic noise maps for the study area. Global positioning system (GPS) was used to estimate the average speed of vehicles, roads, and buildings were extracted from the GIS data. A regional traffic noise calculation model was developed, and the results indicated mean error between the predicted and measured figures which are below two (2.0) dBA. The major benefits of the new proposed model are suitable for rapid noise mapping in the GIS environment. Also, the algorithm combines the emission model of vehicle noise with the noise propagation model which exhibits accurate noise mapping in study area. GPS data was used collected from various sources with over 17,000 floating cars in the database. Although, the model used environment parameters, but the noise maps are based on only the roadway. It was observed that the algorithm works best in cities than in the rural areas and may require calibrations (Cai et al., 2015).

So, the advantages of GPS methods are:

- Accurate estimation of vehicle speeds, traffic volumes which can improve accuracy and reliability of noise model studies.
- Provides efficient ways for real time noise mapping and monitoring.
- GPS systems are available in markets of different types and costs which can support different projects of various scales.

While, the disadvantages are:

- GPS data is discrete, and its accuracy is affected by several factors including weather, sky view and skills of GPS operator.
- The transformation from one coordinate system to another could reduce the accuracy of the data.
- GPS data collection for large areas is time-consuming and costly.

2.7.2.3 ML Method

This section explains some research which used an artificial neural network-based approach. For examples, vehicular traffic noise modelling using artificial neural network was studied by Kumar et al., 2014. Their study was necessitated due to rapid growth in the number of vehicles on Indian roads causing crowding and noise pollution. The ANN model was used to predict 10 percentile that surpassed sound level (L_{10}) and equivalent continuous sound level (L_{eq}) in dBA. The data chosen for this model are total vehicle volume/hour, average vehicle speed and percentage of heavy vehicles. The comparison between the predicted highway noise using ANN, regression and the field measurement indicated that with ANN approach, a lower percentage difference could be achieved compared with the regression method. Furthermore, the goodness-of-fit of the models against field data was checked using statistical t-test at five (5%) significance level. The result proved that the Artificial Neural Network (ANN) approach is a powerful approach for traffic noise modelling. ANN model could be sensitive, and the accuracy changes based on hypermeters used. But, in this study, ANN model based on multilayer feed forward back-propagation (BP) neural network approach was used for the road traffic noise prediction. The authors did not compare the proposed model with the most commonly used traffic noise prediction models like CORTN, FHWA and ASJ. Because of the input parameters and the noise measurements are the same in the models. Nedic et al. (2014) presented comparison between predicted traffic noise using ANN and classical statistical methods in Serbian. The parameters chosen for those models are the number of light motor vehicles, medium trucks, heavy trucks, buses and the average speed for traffic flow. Whereas the results of the ANN approach were found to be superior to the other statistical method in traffic noise level prediction. Out of this study, the authors proved that the ANNs can be a useful method for the noise prediction with sufficient accuracy. Although the ANN model yielded better result that the statistical method, but it is based on traffic flow as input to the model. The authors should use important parameters like road width and slop of roads and compared with other statistical methods that use similar parameters as input to their models.

While, a modeling of road-traffic noise with the use of genetic algorithm, was proposed a genetic algorithm-based model for prediction and assessment of road traffic noise pollution in Mashhad City of Iran. The model applied traffic speed and volume composition as parameters in the model. The predicted model was validated which shows that the proposed model is in agreement with field measurement data obtained for the noise levels. The model recorded an accuracy of ±1% which could be good for low road noise prediction. Although, the proposed models are simple to use and can be utilized with the aid of hand calculators. Whereas the mathematical models have been proposed using genetic algorithms which can be used for calculating traffic noise Leq. But both mathematical models are based on three variables, namely: traffic flow, composition, and speed without those three variables in the proposed model that leads to failure (Rahmani et al, 2011).

Moreovers, a vehicular traffic noise prediction using soft computing approach, was proposed using four soft computing techniques like Decision Trees, Generalized Linear Model, Neural Networks and Random Forests. These methods were used to predict hourly equivalent continuous sound pressure level (Leq), in Patiala city of India. Traffic volume per hour, average speed of vehicles and heavy vehicles percentage were the major parameters used in the experiment. Performance based comparison was carried out between the four models using mean square error, coefficient of determination and accuracy. The stability was checked with 10-fold cross validation using random forest model which yield the best performance. Also, a t-test was carried out to ascertain the fitness of the model to the acquired field data. The limitation of this work, the authors are expected to compare the best model with the most commonly used traffic noise prediction models such as FHWA, CoRTN and RLS-90. Because the input parameters and noise measurements are the same in the models. Furthermore, soft computing techniques like neural networks were used as the default hypermeters without optimisation of hypermeters in the architectural network (Singh et al, 2016).

More recently, in 2017, a modelling roadway traffic noise in a hot climate of Sharjah City of United Arab Emirates (UAE) using ANN was deployed for traffic noise model using data obtained from three different sites (field). The model was developed based on average speed, traffic volume and roadway temperature taken hourly during 420 measurements. The ANN model with 16 feed-forward back-propagation coupled with one and two hidden layers was used. The best model based on output was observed and compared with two other conventional models: (i) The Basic Statistical Traffic Noise Model (BSTN) and (ii) the Ontario Ministry of Transport Road Traffic Noise Model (ORNAMENT). The ANN models indicated better result than the other two conventional models. Furthermore, both the traditional and ANN road noise models were further remodelled to include pavement temperature. Therefore, ANN model was observed to be able to categorise the relationship as projected. The critical analysis carried out indicated that distance from the side of the road was observed to be the most significant factor while heavy-duty vehicles volume was found to record the least. Although the authors succeeded through the use of ANN approach which indicated superiority to other conventional models. However, this model can be applied for prediction of roadway traffic noise in hot-climate region (Hamad et al, 2017).

From the previous studies for producing the traffic noise maps by using ML method, this method has some advantages and disadvantages.

So, the advantages of ML methods are:

- Adaptive learning: An ability to learn how to do tasks based on the data given for training or initial experience.
- Self-Organisation: can create its organisation or representation of the information it receives during learning time.
- Real time operation and fault tolerance via redundant information coding.

While the disadvantages of noise Machine learning (ML) methods are its significant limitation to their computational complexity and drawback of overlearning.

2.7.2.4 Landuse Regression (LUR)

Various models for predicting traffic noise in cities have been used by previous research studies; however, this section discusses a land use regression model (LUR). The LUR model based on the linear regression has been previously used for assessing and predicting such as traffic noise, air pollution, health and epidemiological studies. This section focusses on LUR modelling used for the traffic noise study. Such as, an application of LUR modelling to assess the spatial distribution of road traffic noise in three European cities, a statistical modelling of the spatial variability of environmental noise levels in Montreal, Canada, using noise measurements and land use characteristics, and land use regression modelling of outdoor noise exposure in informal settlements in Western Cape, South Africa.

Aguilera et al, 2015 employed the LUR model as a first study for monitoring levels of traffic noise over a short and long term. The data was recorded in 20-minutes non-peak traffic period (taken during non-rush hours). The input variables for the LUR model include roads, land use (industrial, residential), agricultural, forest, semi-natural, and population. The developed LUR model is based on linear regression and following the ESCAPE project in large number of European study areas. The study suggested that LUR modelling with accurate GIS source data can be a promising tool for noise in epidemiological study (Aguilera et al, 2015). While the second study was conducted by

Ragettli et al, 2016 in which they used LUR modelling with long-term noise measurements and land use characteristics to examine ambient levels of noise in Montreal, in Canada. The study developed LUR models based on various transportation noise sources such as air, rail and road, in order to predict the equivalent continuous sound pressure levels L_{eq24h}, L_{night} and L_{den} (morning, evening and night) which was improved upon previous research conducted in the area (Ragettli et al, 2016). In another work, Sieber et al, 2017 employed LUR model to assess the outdoor noise variability for adults living in informal settlements in Western Cape of South Africa. The exercise involved constant monitoring of outside noise levels during the week and recorded data related to 134 homes in four different areas. The LUR model was developed for the study considered noise sources such as transportation networks (air, rail, and road), local buildings, land use and community in order to derive the daytime, evening and night-time values for the equivalent sound level (Sieber et al, 2017).

Although, the previous researchers produced the final noise maps, but there is limitation in the methods which depends on its selected buffer size for each source data and apply linear regression method. The final noise maps are not clear and most of them were produce with grey colour. This has led to difficultly in identifying the error and specific locations of high and low noise levels, especially the medium noise level's locations.

On the other hand, this method has some points as the advantage of LUR is that it is applicable in many areas such as traffic noise, air pollution, health and epidemiological studies for assessment and prediction. Furthermore, LUR modelling can be scaled depending on the size of the city being examined. It has a high degree of accuracy and capacity to manage complex variables and computationally expensive. Furthermore, LUR has been used successfully in North America, Africa, Asia and Europe for modelling traffic noise. While the disadvantage of LUR model is the accuracy of the model output maps based on the accuracy of data source and the algorithm used.

2.7.2.5 2D Noise Modelling

Several researchers applied 2D noise maps and in this section reviews the most of studied were taken is about 2D noise modelling used in those studies. In this section, we explained the noise maps and the methods used to produce these maps such as, Yang et al, 2020 evaluated the traffic noise pollution based on noise maps for urban area. Twenty-four-hour noise maps of the Chancheng District in Foshan, China were developed for this study, and the results were analysed. The study area is divided into four types, based on the land use requirements for the acoustic environment, and the calculated noise value is compared to the noise limits of each class of the area. The results showed that the noise level of the city is higher during off-peak hours than during rush hours, probably due to the faster speed and larger traffic volume during the off-peak hours. In 2020, Lan et al developed the dynamic noise map or the noise spatiotemporal distribution which was used for noise management and acoustical planning in urban areas. In this study, a method about urban road traffic noise spatiotemporal distribution mapping is proposed to obtain the representative road traffic noise maps of different periods. This method relies on the proposed noise spatiotemporal distribution model with two time-dependent variables - traffic density and traffic speed, and the spatiotemporal characteristics derived from multisource data. The results showed that can save 90% above of the computing time. In a separate study by Lokhande et al. 2021, performed a GIS-based mapping and assessment of noise pollution in Turkey, to determine and map the noise pollution levels in Safranbolu District Centre, especially in the regions where motor vehicle and/or pedestrian traffic is intense. Measurements were conducted at morning (8:00 a.m.–10:00 a.m.), lunchtime (12:00 p.m.–2:00 p.m.) and evening (6:00 p.m.–8:00 p.m.) hours of weekdays and weekends throughout the seasons of summer 2017 and winter 2018 through 47 measurement points. The result showed that the level of summer season weekday and weekend noise pollution in the morning, noon and evening is close to each other. And also, the level of winter season weekdays and weekend noise pollution in the noon is generally higher than morning and evening. As well as the results of a survey conducted as a part of this study were given, and possible measures and suggestions to reduce these noise levels in the district down to the desired limit values were discussed.

More recently, Lee et al. (2022) constructed an urban traffic noise map (including road and railway traffic noises) of the Panyu District in Guangzhou City by combining field measurement and numerical modelling methods (Lee et al, 2022). This noise map was then used to identify the area covered by different noise quality levels and the compliance rate of traffic noise in various acoustic environment functional areas throughout the day, night and day–night. The results showed that traffic noise pollution along the traffic arteries was severe. The area with heavy noise pollution was as large as 157.5 km2

(29.72%) and 146.2 km2 (27.59%) in the day and night, respectively. Finally, Gheibi ta l, 2022 was evaluated traffic noise pollution using geographic information system and descriptive statistical method in Mashhad, Iran. All measurements and records were done during the peak of morning crowd (10–12 AM) and evening crowd (4–6 PM) on both sidewalks of each street around the Holy Shrine. This study showed that the pollution in the evening time span (4–6 PM) has the maximum level of noise. And also showed the pollution wave has a direct relationship with the number of crossroads and the number of traffic lights and the main factor that intensifies this pollution is the wearing out of the brake pads of personal and public vehicles.

2.7.2.6 3D Noise Modelling

In reality, noise travels in all directions, and residents living in high-rise buildings are also severely affected by traffic noise. It is therefore important to develop 3D noise maps that can show the influence of noise in all directions because 2D noise maps are built with the noise levels of one particular height. So, in this section, we talk about how 3D city models can be used to build 3D noise maps.

In this research, Deng et al. (2016) built information modelling (BIM) and 3D GIS to combine traffic noise evaluation in outdoor and indoor environments in a single platform. In our developed BIM–GIS integration platform, the built environment is represented in a 3D GIS model that contains information at a high level of detail from BIM. With the integration with BIM, the 3D GIS model now has access to detailed indoor features such as interior walls and interior rooms. Furthermore, the 3D GIS model is connected with detailed BIM to reflect any changes in the indoor and outdoor features. This paper presents the details of the development of the noise-mapping BIM–GIS platform based on ArcGIS and shows the process of both urban planning and interior design.

Alam et al. (2020) tried to determine the effects of traffic-induced noise on nearby residential buildings through 3D noise mapping with and without noise barriers in Delhi, India. 3D noise mapping has been done using hourly average noise levels for the locations exposed to maximum noise. The developed 3D noise map shows the variation of noise levels along X, Y, and Z directions for all selected locations before and after the installation of noise barriers. Moreover, the result also shows that an exact assessment of noise impact is possible through 3D noise mapping when a multi-story building close to the source of noise is taken into consideration. This paper also elaborates on the adequate height, distance, and NRC value of noise barriers to reduce the effect of road traffic noise on nearby high-rise buildings. This type of study could support decision-makers during the adaptation of suitable remedial measures.

Cai et al, 2018 produced an urban traffic noise maps under 3D complex building environments on a supercomputer using parallel algorithm focusing on controlling the compute nodes of the supercomputer. Moreover, a rendering method is provided to visualize the noise map. In addition, a strategy for obtaining a real-time dynamic noise map is elaborated. Finally, two efficiency experiments are implemented. One experiment involves comparing the expansibility of the parallel algorithm with various numbers of compute nodes and various computing scales to determine the expansibility. With an increase in the number of compute nodes, the computing time increases linearly, and an increased computing scale increases computing efficiency. The other experiment compares the computing speed between a supercomputer and a normal computer; the computing node of Tianhe-2 is found to be six times faster than that of a normal computer (Cai et al, 2018).

Zamingard and Vafaeinejad, (2020) produced 3D traffic noise map in urban area by using GIS and CORTN model, in which the amount of noise pollution caused by traffic on the surfaces of buildings is specified in the form of colour maps with noise scales. Each of the CORTN, FHWA, CNR, RLS90, and SCM1 models has unique calculating relations and characteristics. After analysing these models from the calculation and structural aspects, we found the CORTN model, its simplicity and calculability of all of its parameters, and its ability to calculate the noise scales in different heights for predicting the noise. Finally, after calculating and predicting the noise in all sample areas, the Kriging interpolation model was used to create interpolation maps of areas in the ArcGIS software. Lastly, sketch UP software merged these maps with the buildings' surfaces. The results of this study show the distribution of noise pollution on different surfaces and can help planners in better planning for choosing the kind of usage of different floors in a building (Zamingard and Vafaeinejad, 2020).

In a study by Krikun (2020), the authors calculated 3D-modeling of traffic noise in Magadan, Russian Federation, using the acoustic 3D automated workstation. The results of traffic noise modelling using the Acoustic 3D automated workstation programme are presented; field surveys of urban areas have been carried out, calculations have been made in the software package, and traffic noise maps have been built. The disadvantages of the noise calculation methodology implemented in the automated workstation programme have been distinguished. They included typical coefficients, the use of which leads to an increase in the error of transport noise calculations. The author predicted indicators of traffic noise for various classes of highways using the one-factor model.

2.7.3 Third Objective of this Research

Many features affect spatial patterns of noise propagation in natural environment. Without any interference, sound levels decrease geometrically at a point square of the distance from the source of spread of the sound waves. Sound energy absorption in the atmosphere depends on certain features such as air temperature, elevation and humidity. The wind and temperature gradients cause refraction of the sound waves which change the spatial pattern of propagation (Fang and Ling, 2003). Geography of location and atmospheric condition determines the relative importance of noise propagation. Usually, traffic noise will drop by three (3) dBA at twice the distance.

Noise analysis, design and modelling can reduce the high cost associated with inappropriate or inadequate traffic noise control after completion of road projects. Ideally, the difference in characteristics and nature causes noise effect from a stop and go in traffic around an urban area which requires different approaches to modelling noise propagation toward achieving accurate result (Pamanikabud and Tansatcha 2003; Pamanikabud and Vivitjinda 2002).

Various propagation models have been carried out by several research, and in every case, different parameters are considered. Çolakkadıoğlu and Yücel (2017) modelled highway-induced noise pollution of Tarsus-Adana-Gaziantep in the Adana city, Turkey. Features such as elevation, green-field site, open-space area, hospital, school, and residential buildings are captured in ‘‘SoundPLAN 7.3” software. It was inferred that the noise distribution received higher values during the summer compared with the winter period throughout the time-zones. It was observed that 63% of the research area exceeds the threshold of 68 dBA during daytimes in summer period. Close to 5% of the population in city centre under consideration are exposed to higher noise levels of about 68 dBA. At night, about 12.5% of the people are exposed to 58 dBA. This indicated that the noise level in this city is greater than the acceptable noise specified in standards. Reed et al. (2012) proposed a GIS tool for modelling noise propagation in the natural environment. The SPreAD-GIS is integrated with commonly available datasets on topography, landcover, and weather conditions to estimate noise propagation configurations and excess noise beyond ambient level for one-third octave frequency bands around one or multiple sound sources (Çolakkadıoğlu and Yücel, 2017). Similarly, Pijanowski et al. (2011), carried out spatial patterns and temporal dynamics modelling of noise disturbances. The author reported that the results would help planners to understand and predict how noise affects the environment and its inhabitants. Noise modelling of vehicular traffic roadway was carried out based on perpendicular propagation analysis. The parameters considered in this model are traffic volume and vehicle type and their average spot speed and the physical features of the pavement such as lane width, the number of lanes, the width of shoulder, and width of the median. The noise levels in the roadway model were modified by the sufficient ground along the propagation path (Tansatcha et al. 2005). Authors mentioned that, a large number of input variables such as number of vehicles, speed of vehicle, road type, elevation, green-field site, open-space area, residential buildings and others are required to produce a noise map depending on the software used. There are many software available like STAMSON, STAMINA, TNM, LimA, CadnA,and SoundPlan with basic mapping support. Also, the most common way to map is by tracing polygon on the map. This task is suitable for smaller areas. If be applied on a bulky scale, it be time-consuming. The development of noise propagation maps is based on measurements and requires large number of data, data sources and software.

As well as there some disadvantages point of the propagation method such as: i) difficult to implement in traditional GIS software, ii) it is difficult to convert into digital maps unless professional software and programmers are available, iii) it is not effective for large areas as the modelling and simulation take very long time, and iv) it requires experienced users in mathematics and software modelling.

2.7.4 Fourth Objective of this Research

2.7.4.1 Application Users

The application of noise modelling helps organisations monitor and manage their environmental impact. The flexible solutions enable the decision-makers to optimise operations, efficiently comply with regulations, and communicate more effectively with internal and external stakeholders. There are several utilities of application noise modelling, such as experience in delivering monitoring, modelling, and environmental noise assessment for industrial, road, and railways, energy, and oil and gas sources.

In 2010, the city planners elected competent officials, scholars, and residents and gave them access to comprehensive aircraft and road noise inventory data, to help them design infrastructure, create policy, and conduct research, such as the national transportation noise map, a project from the US Department of Transportation. Also, the objective of the World Health Organisation (WHO) is that noise pollution in the EU should be decreased significantly by 2020, which was included in the Seventh Environment Action Programme (7th EAP). According to the Department of Environment, Road and Climate Change, and Water of NSW in Australia, the traffic noise pollution contributes to reducing the economic and social wellbeing of the people of NSW. At the same time, road traffic noise can significantly impact the community. Therefore, those departments need a balance between providing efficient road transport infrastructure and minimising the adverse environmental effects of road use. So, the department of environment and conservation commissioned a community survey of neighbourhood noise issues in NSW. Road traffic noise was considered the main issue affecting neighbourhood amenities. Moreover, the traffic noise project in NSW aims to identify the strategies that address the issue of road traffic noise through existing roads, new road projects, road redevelopment projects, and new traffic-generating developments.

2.7.4.2 Noise Visualization in Mobile Application

In 2010, Kanjo (2010) conducted a on noiseSpy: A real-time mobile phone platform for urban noise monitoring and mapping, was presented a design, implementation, evaluation, and user experiences of the NoiseSpy application (Kanjo, 2010). It is a sound sensing system that turns a mobile phone into a low-cost data logger for monitoring environmental noise. It enables users to explore any city area while collaboratively visualising noise levels in real-time. Although the authors succeeded, the software combines the sound levels with GPS data to generate maps of sound levels recorded during a journey. But the noise map is in point form and shows all the noise measurements without prediction on un-sampling. This indicates that the method requires an additional algorithm for un-sampling prediction. As well as, in the study a mobile crowd sensing accuracy for noise mapping in smart cities, was studied traffic noise problems in urban areas in terms of noise mapping. The mobile crowd sensing (MCS) method was expatriated in detail. Furthermore, the results were compared from the standard method that uses a sound level metre. It is worth noting that the accuracy and precision of measurements achieved by using calibrated smartphones are acceptable. Although the successes recorded are laudable compared to the accuracy of the traditional methods, minor differences were observed between the methods. But generally, the method used to predict the map is weak because it is generated on the road network. Finally, this research has shown that it is possible to obtain a final noise map by calibrating measured smartphone values. In the near future, works will focus on upgrading smartphone applications for data collection (Grubeša et al, 2018).

Kumar (2017) used a novel approach that involves the smartphone user community to monitor noise prevalence in the study a traffic noise mapping of Indian roads through smartphone user community participation. The system involves a client application on smartphones that visualises noise levels on Google Maps. The authors used the fuzzy logic method and classification of noise maps to the fourth type of noise which is significant, very significant, and extremely significant. But the noise maps were produced for the road network on a small study area which included two roads. So, the novelty of this study is the methods used and the output of the model, a published noise map on Google Maps (Kumar et al, 2017). In a separate work, Jotanovic et al. (2018) propsoed a mobile application for recording road traffic noise. Their app measured noise level on the main road near the hospital complex in the city of Doboj based on noise measurements performed by a mobile application. The relationship between the level of traffic noise and the traffic flow frequency was analysed. So, the mobile application was used to record traffic noise, representing a fast and efficient way to record noise without presenting the noise maps for the study area (Jotanovic et al, 2018).

All previous authors succeeded with the mobile application through recorded traffic noise, obtained the average traffic noise efficiently, and published noise maps. But, until now, no publication is available on any client application on smartphones that record noise, publish, share and present the information of the noise map for roads network with environments and buildings as 2D and 3D noise map. With this application, these geo-located indicators are then stored in a database to develop noise maps that reflect reality as closely as possible, with extremely dense connections. These noise maps are obtained via smartphone data. Local governments can use them to implement more targeted plans of action for preserving or improving the quality of road networks and environments.

2.8 Summary

In this chapter, various methods and practices of noise mapping were studied. In addition, data acquisition, method used, quantity and quality of results are also thoroughly investigated. It was observed that assessment of noise with the current 2D and 3D noise maps methods prove to be a difficult task due to its numerous limitations. Therefore, the need for 2D and 3D noise models has become highly imperative due to its ability to overcome the limitations of the current methods. It would also ensure more flexible and practical resolutions for noise level challenges. Furthermore, noise intensity can be estimated with the aid of the established noise estimation model which can be integrated with GIS to develop a noise map. LiDAR data can serve to build 3D building models for cities with high level of accuracy that could be deployed for noise simulation.

From the above literature reviews, we found some limitations, challenges and research gaps as mentioned below.

1) For 2D noise mapping:

- Noise map data for 2D models are only available at one fixed height which is not sufficient to provide solution needed for noise pollution. Noise transmissions are exhibited in all directions and its impact is also in all directions. Hence, it is highly imperative to identify the influence of noise at different elevations.
- The total number of individuals affected by the effect of noise cannot easily be ascertained using the 2D noise maps due to its one height noise information.

- The 2D noise maps does not have sufficient information required for decision making and noise mitigation implementation and measures due to the fact that noise is transmitted in multi-directions with effects felt equally in all directions.
- Also, gradient effects may not be easily seen in 2D noise maps.

2) For 3D noise mapping:

- Noise map data for 3D are generally expensive and always require commercial model to succeed.
- Noise sample measurements are also expensive and time consuming. Because noise level of each floor of a building needs to be calculated.
- Most 3D noise maps come in small-scale map due to the large-scale map needs more input data required for modelling such as observation point, noise samples and 3D building accuracy which led to the problem of big data in ArcGIS.
- It requires expensive and complex software to produce 3D noise maps.

3) For noise model of large scale:

- Field survey is time-consuming, expensive, and not safe.
- Commercial traffic noise modelling tools are costly.
- Process is long-drawn-out of and not effective for large areas and 3D noise model.
- Requires experienced users in mathematics and software modelling.
- There are no specific tools in ArcGIS software for 2D and 3D noise mapping.
- Noise models for prediction and propagation techniques are separate.
- Accurate 3D noise model requires detailed information about 3D building structures which cannot be collected from the field within a short time and with an acceptable accuracy.

Chapter Three
MATERIAL AND METHODOLOGY

3.1 Introduction

This chapter describes the location of the study area, data collection and noise predictor variables, data pre-processing and preparation such as LiDAR data, Worldview-3 image, Worldview-3 orthorectification, Quickbird image, landuse mapping and method of measurement noise and traffic data collection, as well as landuse prediction regression and noise propagation modelling. Finally, model evaluation and summary of this chapter are presented.

3.2 Overall Methodology

The overall methodology proposed for the traffic noise modelling and evaluation in GIS uses machine learning-based prediction and mathematical simulation of noise propagation. Figure 12 presents the methodology adopted in this proposed model combined 2D and 3D models of traffic noise based on machine learning (ML). Meanwhile, the predicted traffic noise maps for the study area are based on GIS modelling. This study used remote sensing digital surface model raster and Quickbird image. The data were collected using field surveys (capital of Kirkuk) such as traffic volume and traffic noise. The dataset was prepared and managed in a GIS database, and the predicted traffic noise maps were achieved using GIS. The multi-level prediction models have been developed using three machine learning methods: artificial neural network (ANN), random forests (RF), and support vector machine (SVM). The input parameters for the 2D noise model are light vehicle, truck, motorbike, semitrailer, bus, digital surface model (DSM), average speed, and maximum speed. In the 3D noise model, the noise parameters included distance from high light vehicle, distance from medium light vehicle, distance from low light vehicle, distance from high truck, distance from medium truck, distance from low truck, distance from high motorbike, distance from medium motorbike, distance from low motorbike, distance from high semitrailer, distance from medium semitrailer, distance from low semitrailer, distance from high bus, distance from medium bus, distance from low bus, distance from high average speed, distance from medium average speed, distance from low average speed, distance from high maximum speed, distance from medium maximum speed, distance from low maximum speed and DSM, and location of noise samples the output or dependent parameter is the equivalent continuous sound pressure level per 20 minutes (L(eq,20) dB(A)) for rush hours of morning and afternoon at weekday.

Furthermore, the results of the proposed model and other models were validated based on correlation (R), correlation coefficient (R2), and root mean square error (RMSE) algorithms. Finally, the prediction of 2D and 3D noise maps for the study area based on the best model achieves less RMSE. While the mathematical simulation of noise propagation through using equation which calculate the noise level from the main sources of noise considered are the vehicles (cars, heavy vehicles, and motorbikes). The traffic noise emitted from vehicles can propagate from the point of origin to other surrounded areas called calculation points. Several factors affect reducing, increasing, and redirecting the noise levels and paths generated by vehicles, such as wind direction and speed, barriers such as tall buildings, and the interaction of air particles with the noise waves.

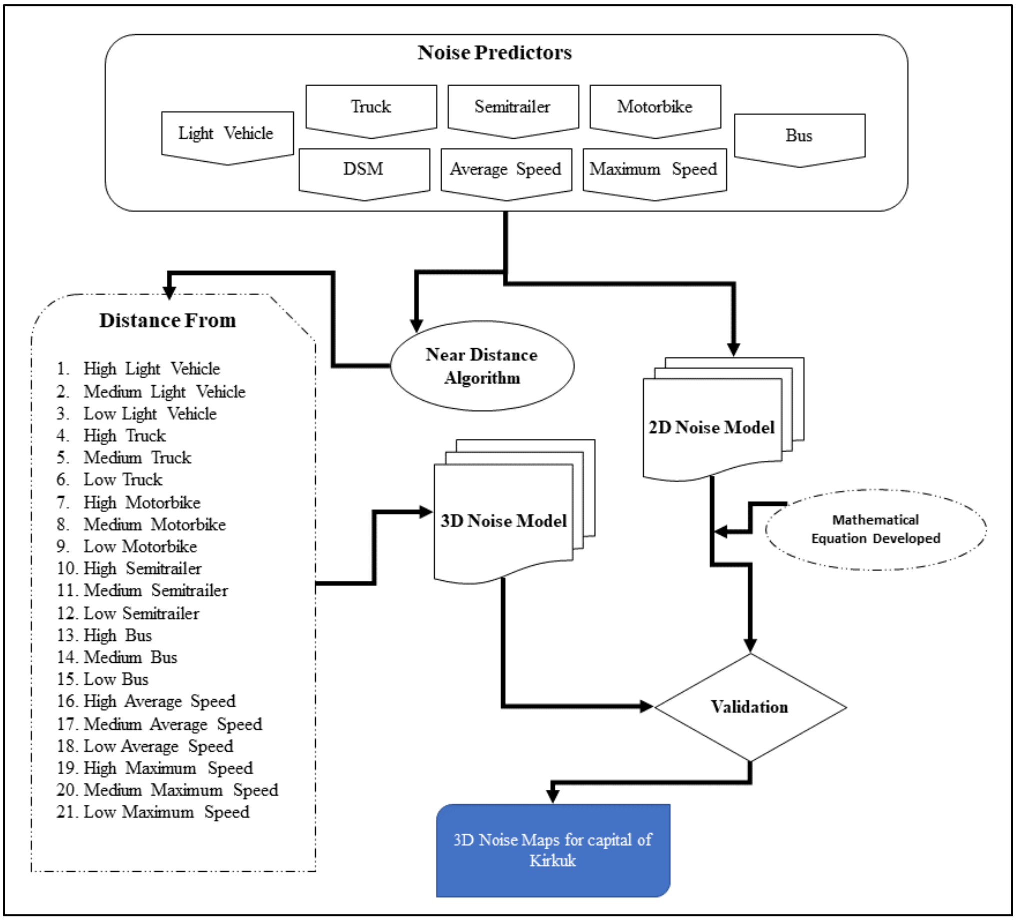

Figure 3.1 Shows the overall methodology.

3.3 Description of the Study Area

The study was carried out in two different sites i); in the capital city of Kirkuk, Iraq and ii); in the New Klang Valley Expressway (NKVE) located in Selangor, Malaysia. The reason to select these sites contain residential, industrial, and residential low/high density population areas which make it suitable for landuse noise related investigations. According to the information available in (Iraq ministry of planning) Kirkuk is the capital of Iraqi culture and always has high traffic flow. Additional reason includes different types of road networks such as Baghdad Erbil (BE) expressway, primary, and secondary roads located in the city. These diversities make the site suitable for studying the traffic noise for various conditions. Figure (3.2) shows the capital of Kirkuk, Iraq. While, figure (3.3) shows NEW Klang Valley Expressway (NKVE) located in Selangor, Malaysia. Whereas the NKVE is a 35-kilometre expressway which is located between Kuala Lumpur (Jalan Duta) and the New Klang industrial and urban area (Bukit Raja). According to the information available in (PLUS Official Website), the NKVE is a bustling route for residents in Kuala Lumpur, Shah Alam, Petaling Jaya, Subang, Damansara, Sungai Buloh, and Klang. The speed limit stipulated for the expressway is 110 km/h (68 mph) on Bukit Raja-Bukit Lanjan stretch and 90 km/h (55 mph) for Bukit Lanjan-Jalan Duta route. This site of study area criteria contains; high expressway which indicates the vehicles, residential, industrial and commercial areas which makes it suitable for traffic, and noise related investigations. Moreover, it’s considered as critical area in term of heavy traffic.

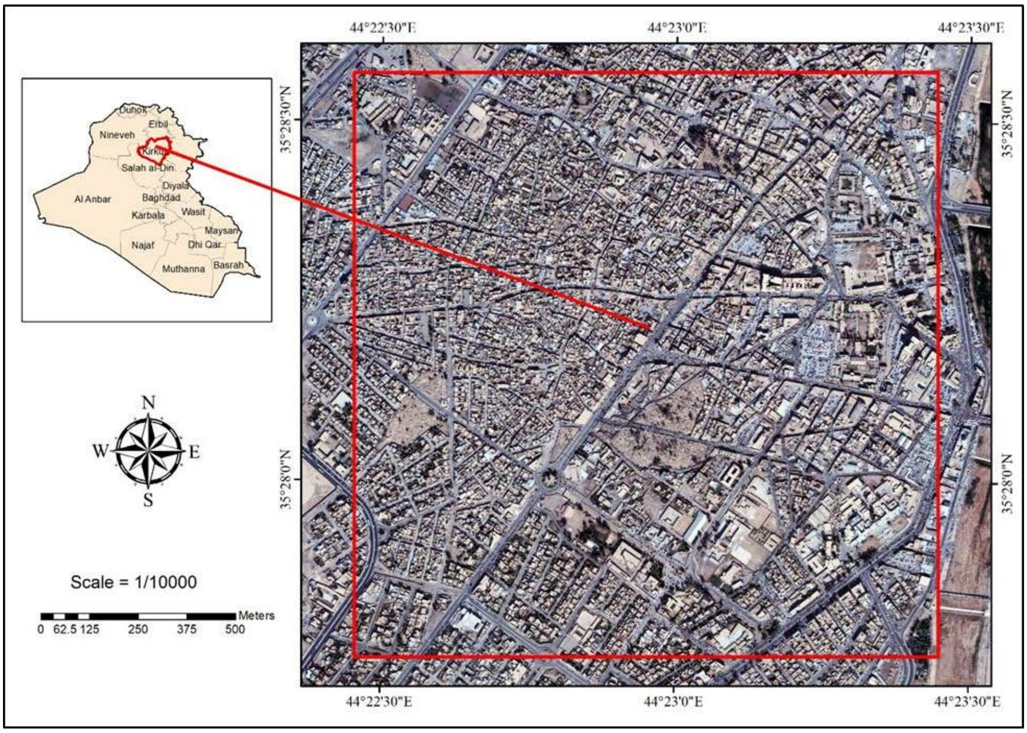

Figure 3.2 Shows the capital of Kirkuk, Iraq (study area1).

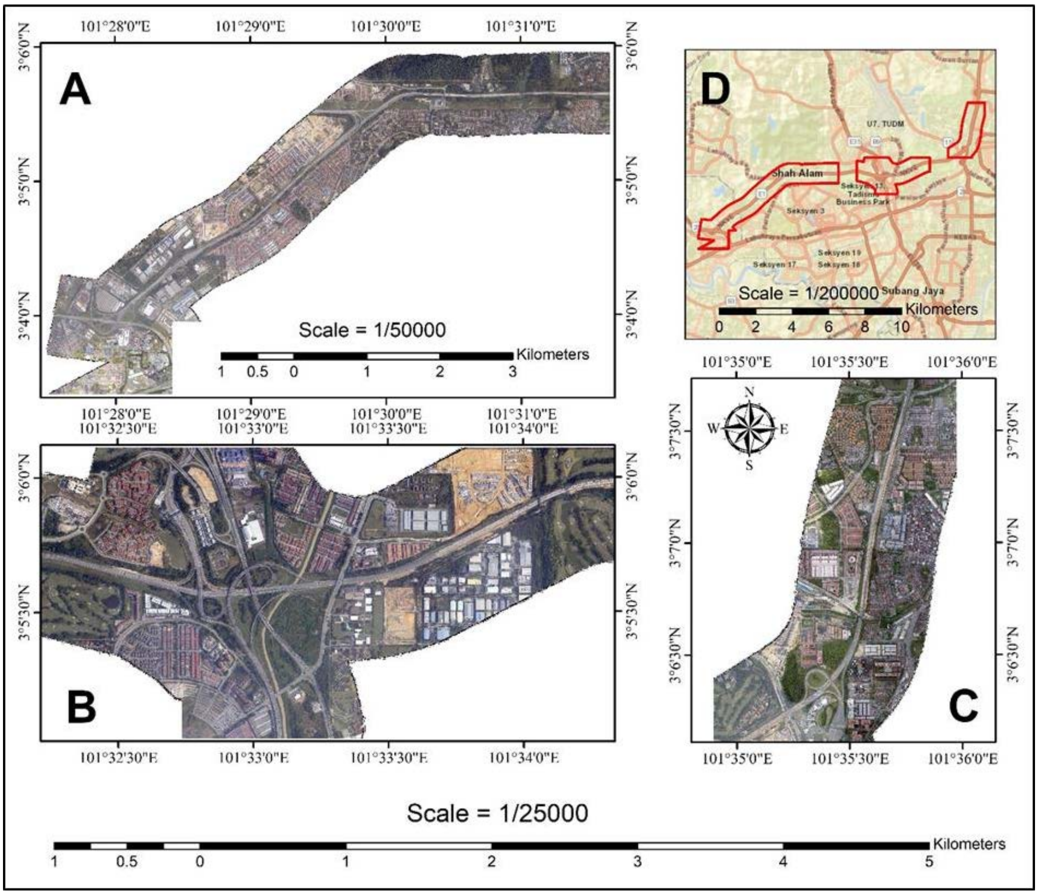

Figure 3.3 Shows NEW Klang Valley Expressway (NKVE) located in Selangor, Malaysia (study area2).

3.4 Data Collection and Noise Predictor Variables

In Kirkuk, Iraq (study area 1), the dependent variable of the model is noise levels (time averaged sound pressure level). It is the equivalent steady level over a given period of time that contains the same amount of noise energy as the actual fluctuating level. Measurements of noise were taken at random sites (selected randomly with the use of the ArcGIS Sampling Design Tools) across city. The measurements were performed using a CESVA SC102 sound level meter (class 2 ± 0.7 dB). We measured the noise level (dB (A)—Decibel A-weighted) at each site at 20-min measurement intervals, and 1.5 m above ground. Measurements were conducted in summer season during 12-15 of March 2018. The measurements at sites were taken during rush hours morning (7:00 –9:00) and afternoon (12:00–2:00). The measurements were taken at various sites during rush hour: some on and near a highway and major streets, and on Background Street (a side street with low levels of noise) and another in a background open space site as well as on different floor of buildings. Measurements were made during one 20 min period at sites. Additional data were collected from traffic flow. A total of 26 measurements as shown in figure (3.4), were taken 26 noise samples for 3D noise model, which were divided into 18 for training and 8 for testing and 9 noise samples for 2D noise model, which were divided into 6 for training and 3 for testing.

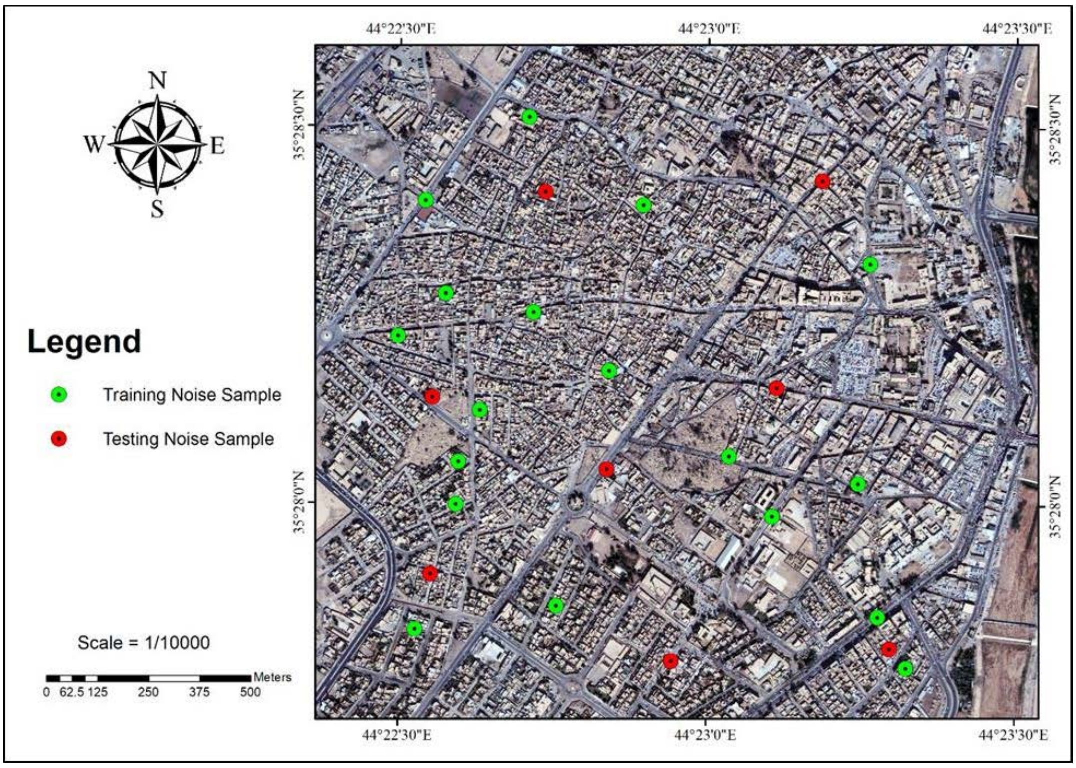

Figure 3.4 Shows training and testing noise samples in the study area1 (Kirkuk, Iraq).

The noise parameters were pre-determined and selected based on reviews which consider traffic and weather characteristics of the area under consideration. The noise parameters inputted into 2D noise model are light vehicle, truck, motorbike, semitrailer, bus, digital surface model (DSM), average speed and maximum speed. While 3D noise model, the noise parameters inputted are distance from high light vehicle, distance from medium light vehicle, distance from low light vehicle, distance from high truck, distance from medium truck, distance from low truck, distance from high motorbike, distance from medium motorbike, distance from low motorbike, distance from high semitrailer, distance from medium semitrailer, distance from low semitrailer, distance from high bus, distance from medium bus, distance from low bus, distance from high average speed, distance from medium average speed, distance from low average speed, distance from high maximum speed, distance from medium maximum speed, distance from low maximum speed and DSM. The parameters of 2D and 3D noise models are summarized based on statistics as shown in table 3.1. Figure (3.5) shows type of road networks parameter, figure (3.6) shows low, medium, and high of light vehicle parameter, figure (3.7) shows low, medium, and high of truck parameter, figure (3.8) shows low, medium, and high of motorbike parameter, figure (3.9) shows low, medium, and high of semitrailer parameter, figure (3.10) shows low, medium, and high of bus parameter, figure (3.11) shows low, medium, and high of average speed parameter, figure (3.12) shows low, medium, and high of maximum speed parameter, figure (3.13) shows the digital surface model (DSM) for the study area1.

Table 3.1 Statistical summary of noise predictors of 2D and 3D noise models in the study area1.

Parameter	Minimum	Maximum	Mean	Deviation
Average Noise	28.21	83.28	47.71	20.14
Light Vehicle	0.00	354.00	20.15	70.01
Truck	0.00	92.00	8.69	22.76
Motorbike	0.00	29.00	2.00	5.87
Semitrailer	0.00	108.00	5.53	21.39
Bus	0.00	129.00	9.69	26.92
DSM	2.47	29.2	13.73	15.66
Average Speed	0.00	49.64	11.65	17.02

Maximum Speed	0.00	66.00	13.69	21.57
Distance from High Light Vehicle	0.00	1079.08	432.70	261.98
Distance from Medium Light Vehicle	0.00	1002.72	252.37	239.22
Distance from Low Light Vehicle	0.00	539.36	58.45	103.52
Distance from High Truck	0.00	628.94	220.19	164.74
Distance from Medium Truck	0.00	594.40	119.59	129.21
Distance from Low Truck	0.00	738.88	120.67	161.98
Distance from High Motorbike	0.00	1157.50	468.80	268.63
Distance from Medium Motorbike	0.00	926.08	243.85	233.62
Distance from Low Motorbike	0.00	569.75	65.09	114.28
Distance from High Semitrailer	0.00	1549.70	636.87	378.83
Distance from Medium Semitrailer	0.00	849.06	250.78	191.34
Distance from Low Semitrailer	0.00	379.29	25.43	47.44
Distance from High Bus	0.00	910.39	158.78	208.53
Distance from Medium Bus	0.00	445.29	84.82	88.49
Distance from Low Bus	0.00	1059.13	295.93	272.59

Distance from High Average Speed	0.00	666.25	141.29	137.27
Distance from Medium Average Speed	0.00	406.50	78.55	81.38
Distance from Low Average Speed	0.00	652.80	117.52	129.15
Distance from High Maximum Speed	0.00	722.50	170.70	178.77
Distance from Medium Maximum Speed	0.00	442.07	75.57	84.09
Distance from Low Maximum Speed	0.00	829.62	179.87	195.56

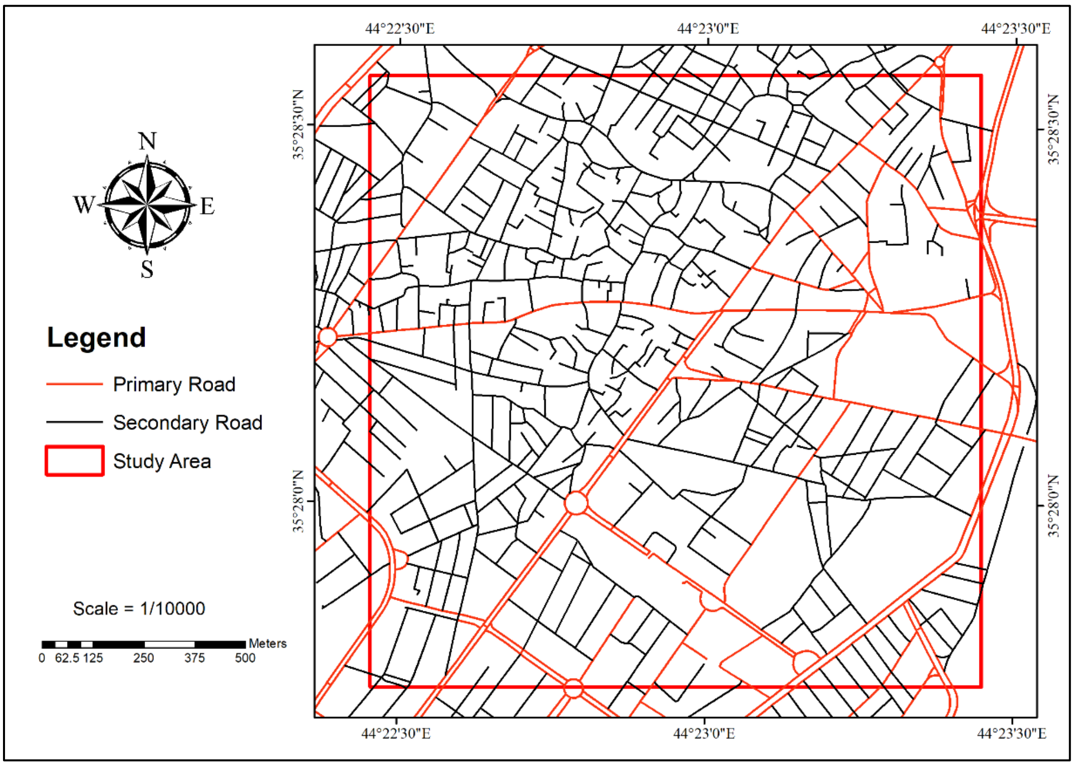

Figure 3.5 Shows type of road networks parameter in the study area1.

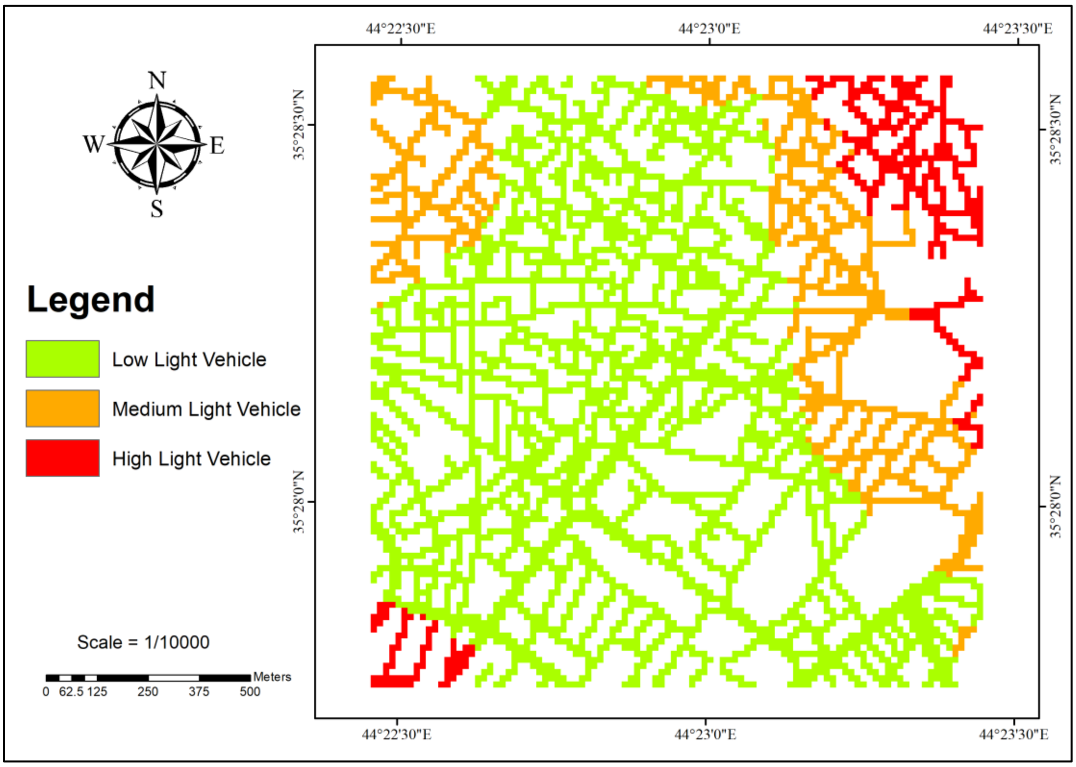

Figure 3.6 Shows low, medium, and high of light vehicle parameter in the study area1.

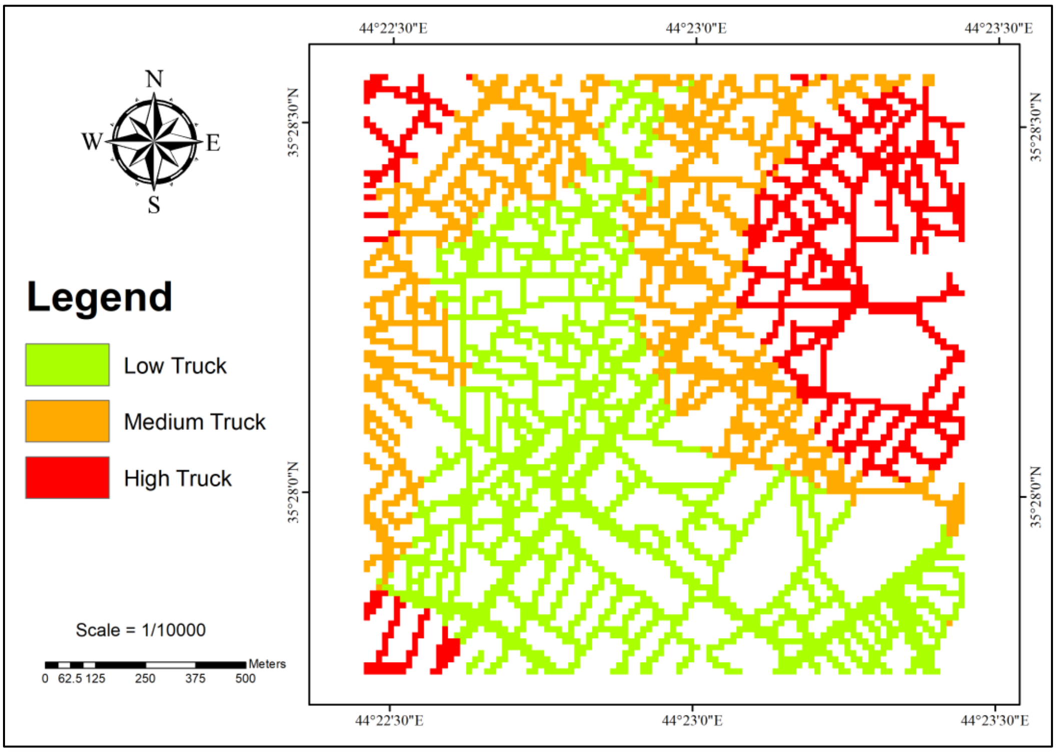

Figure 3.7 Shows low, medium, and high of truck parameter in the study area1.

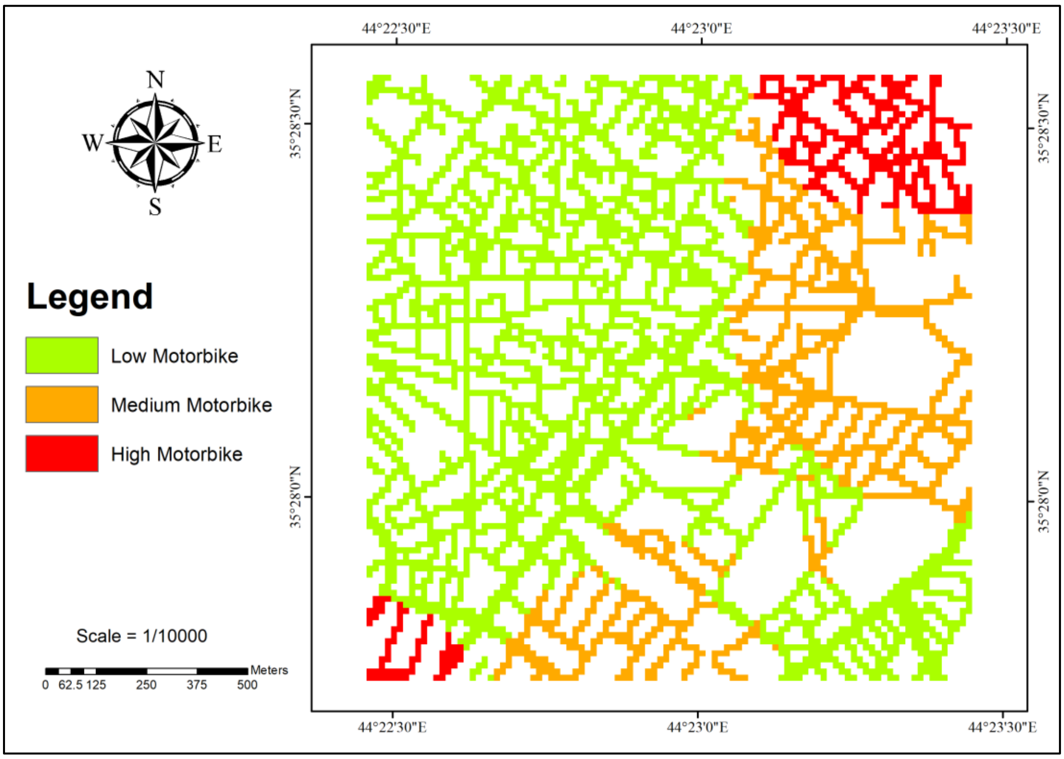

Figure 3.8 Shows low, medium, and high of motorbike parameter in the study area1.

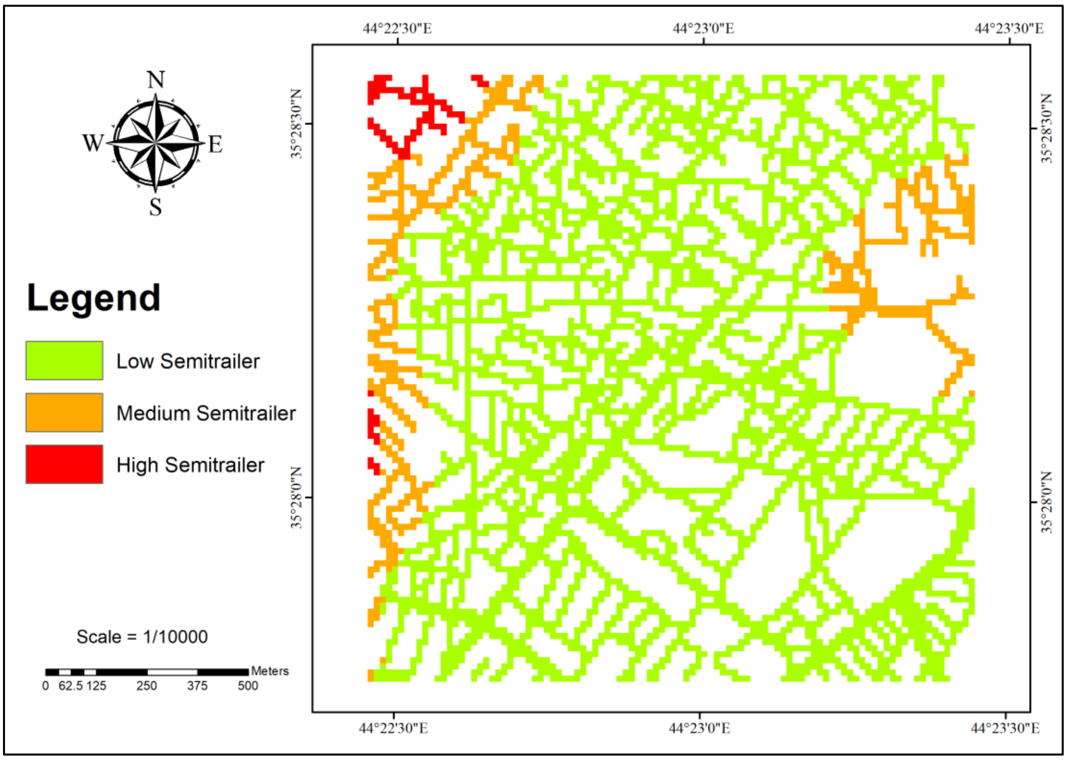

Figure 3.9 Shows low, medium, and high of semitrailer parameter in the study area1.

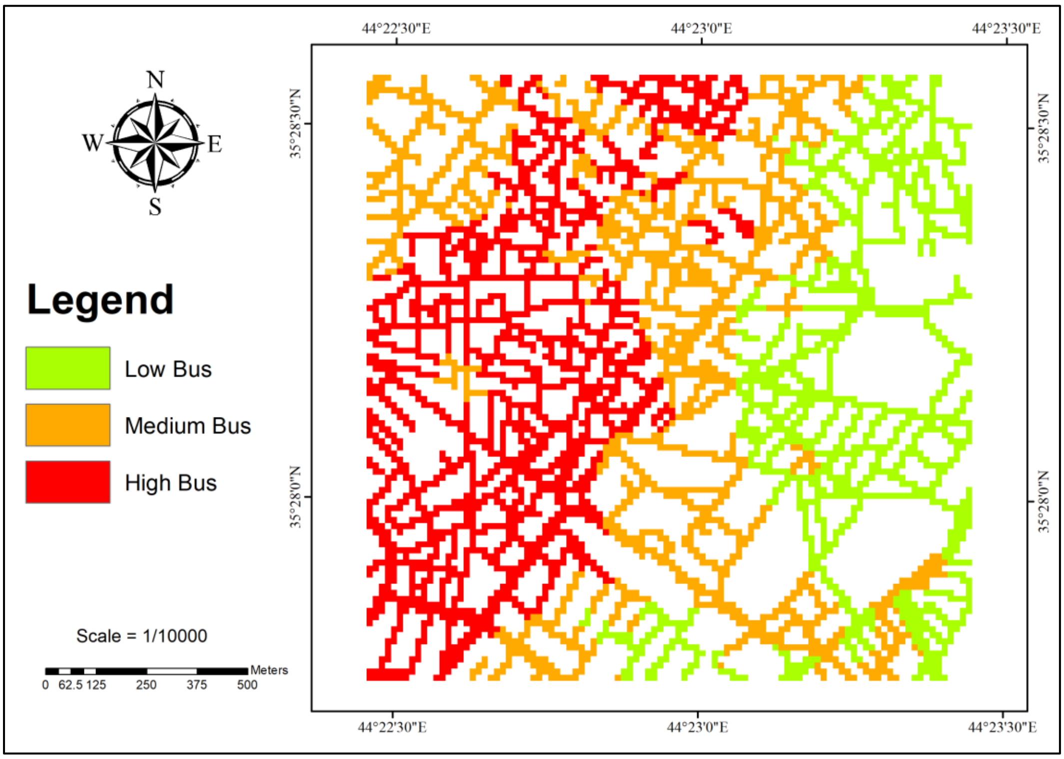

Figure 3.10 Shows low, medium, and high of bus parameter in the study area1.

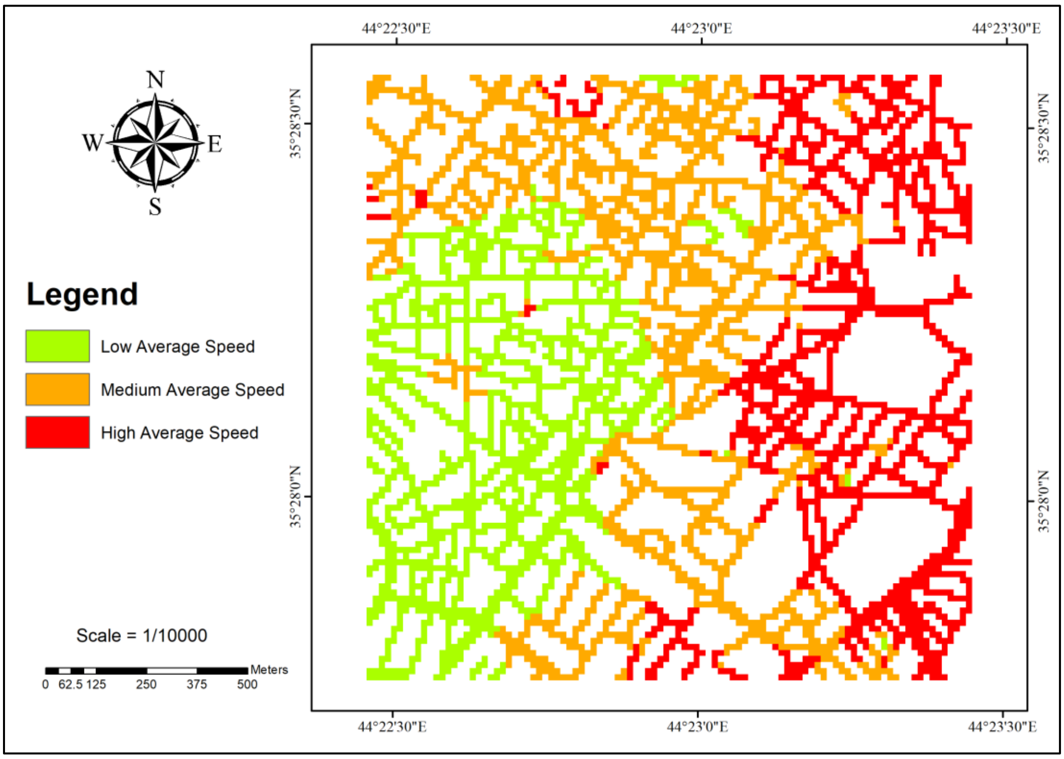

Figure 3.11 Shows low, medium, and high of average speed parameter in the study area1.

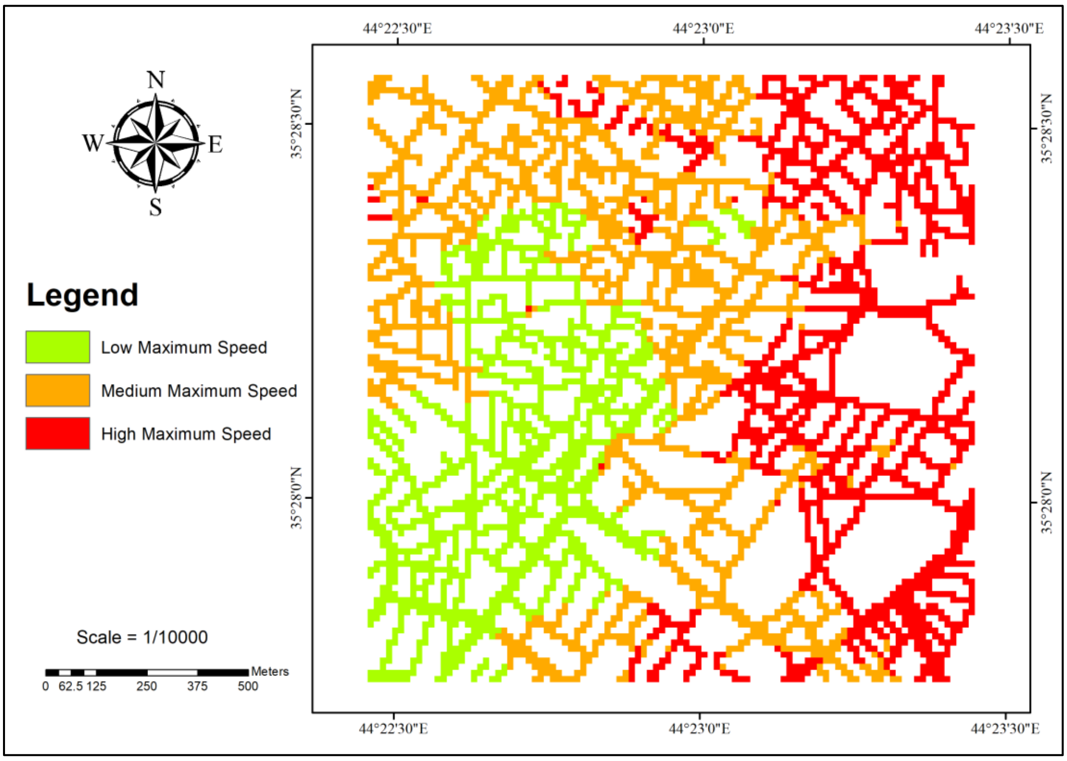

Figure 3.12 Shows low, medium, and high of maximum speed parameter in the study area1.

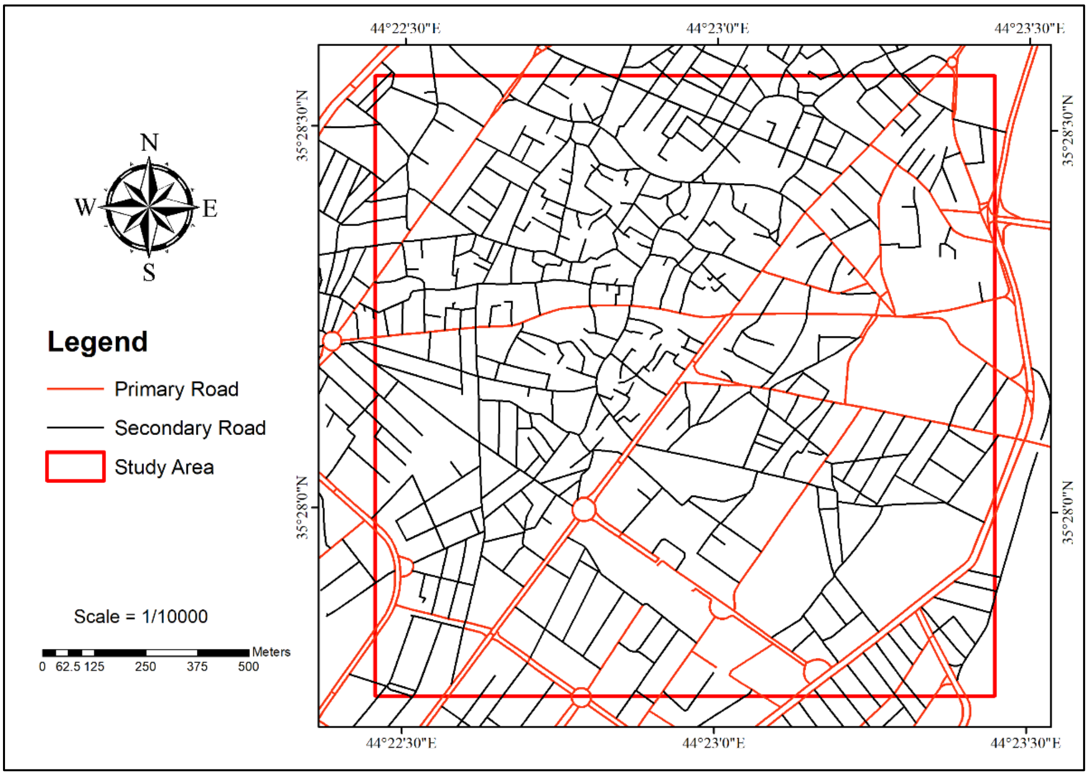

Figure 3.13 Shows the digital surface model (DSM) in the study area1.

While, in the NEW Klang Valley Expressway (NKVE), Selangor, Malaysia (study area2), the first area (A), the noise levels of traffic flow on Shah Alam roads were evaluated with three equipment of sound level meter (TES 52A). Additional data was collected from a wind speed meter and a traffic tally for reading wind speed and number of vehicles, respectively. The traffic noise measurements were generated randomly for various sites by using the ArcGIS sampling design tools across the city area [28-29]. On 11–12 February 2017, field data was collected at every 20 minutes at a height of 1.5 meters during rush hours (6:30 - 8:00; 10:00 - 12:00; 18:00 - 20:00; 23:00 - 00:00). A total of 95 measurements resulted which was divided into 67 for training and 28 for testing as shown in figure 3.14. The data used by the landuse regression model (LUR) to determine the traffic noise, these data are area of residential low/high density, type of network road (expressway, primary and secondary), land use (residential, industrial and tree), digital surface model (DSM), wind speed (WS), and traffic noise average (Leq). Additional information on traffic jams, road intersections, traffic lights, road toll gate, public transport (bus stop and bus line) and gas stations were also used. These details are summarised in tables 1.2 and 1.3. As well as the predictor variables shown in the figures (3.15) the DSM raster; (3.16) the area of residential high density, area of residential low density, industrial area and trees area; (3.17) the type of road network such as expressway, primary and secondary roads; (3.18) the population raster; (3.19) the road toll gate, gas station, traffic light, intersect, bus stop and bus line, and (3.20) wind speed.

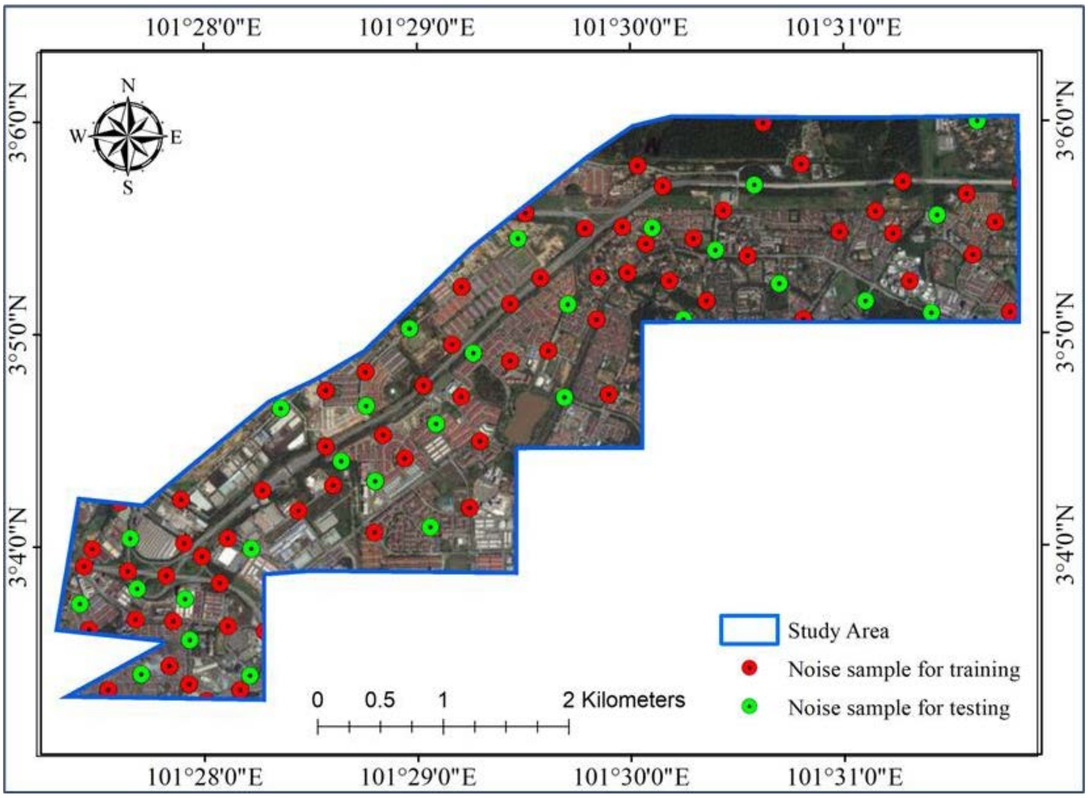

Figure 3.14 Shows the study area2 (A).

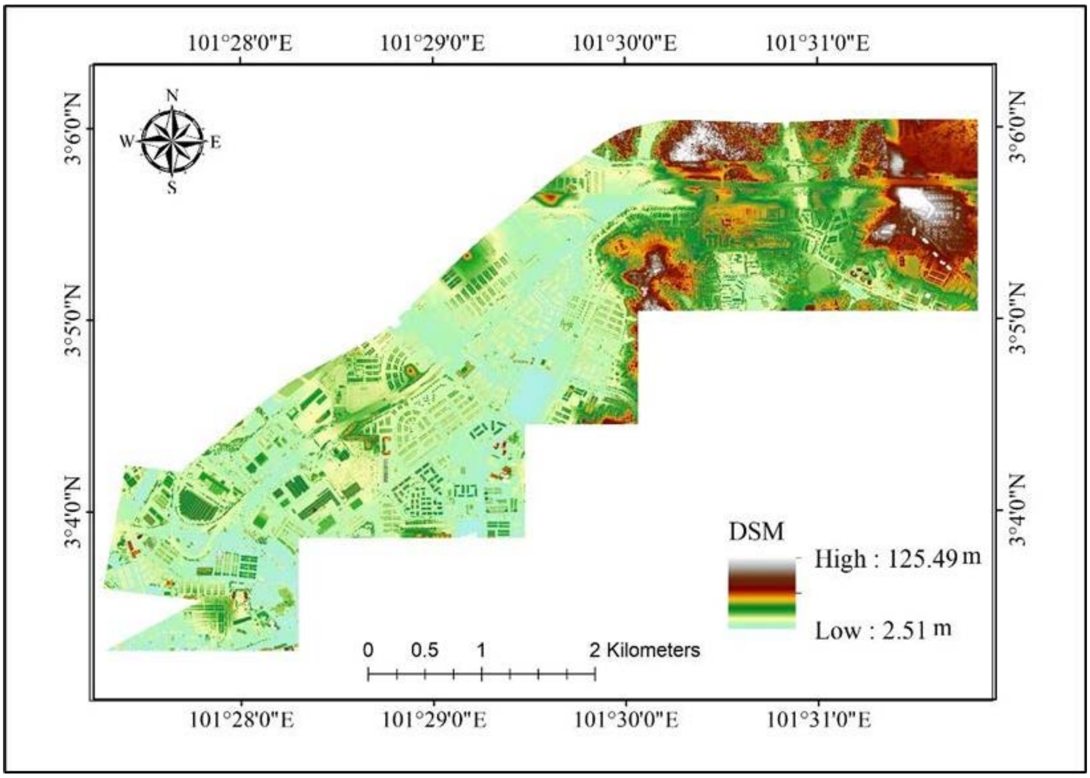

Figure 3.15 Shows the digital surface raster (DSM) in the study area2 (A).

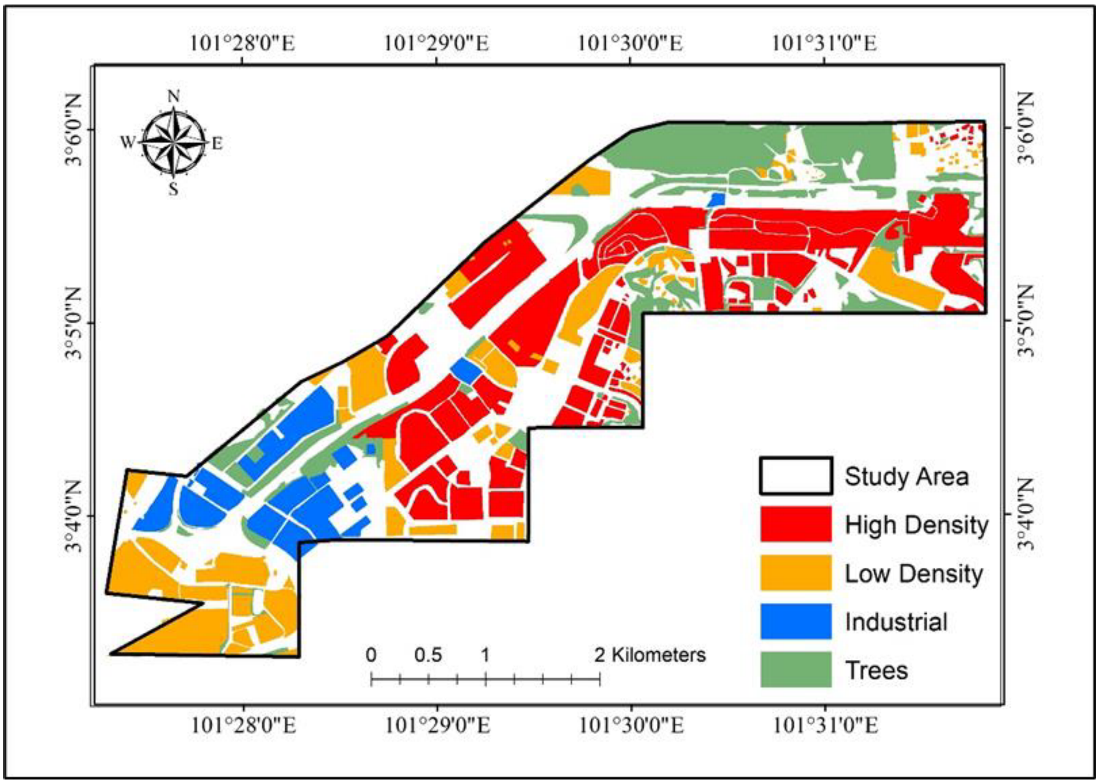

Figure 3.16 Shows the area of residential high density, area of residential low density, industrial area and trees area in the study area2 (A).

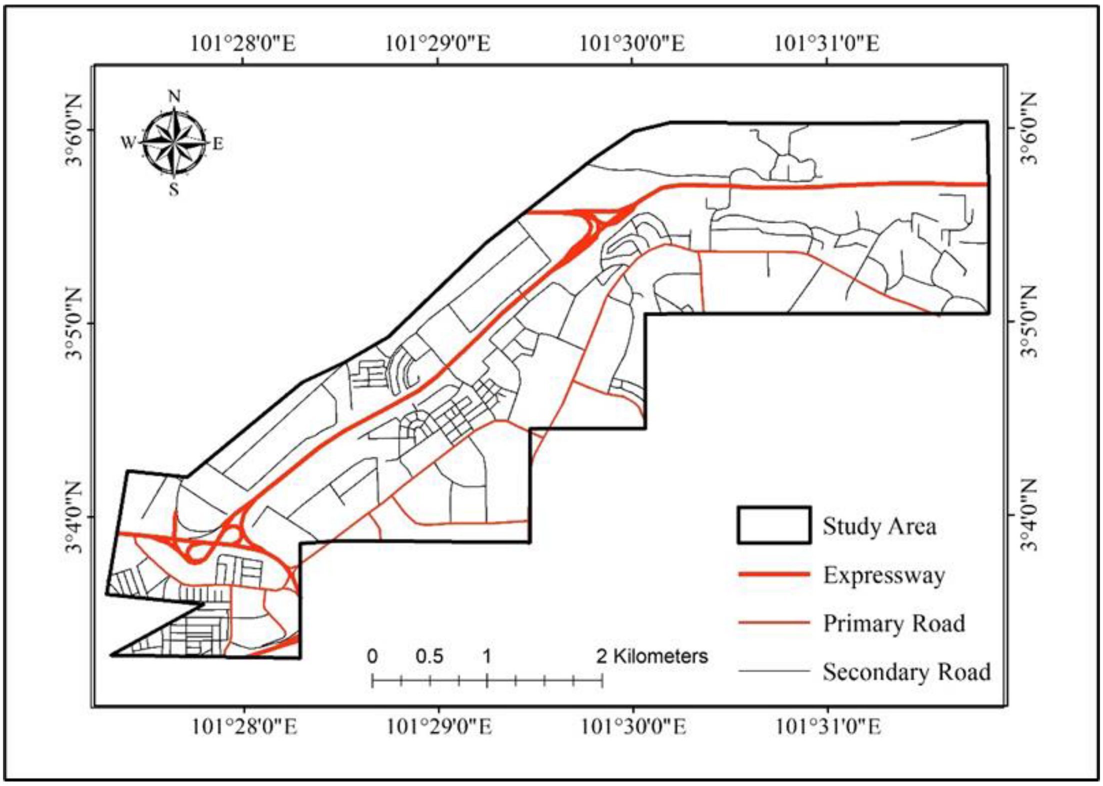

Figure 3.17 Shows the type of road network such as expressway, primary and secondary roads in the study area2 (A).

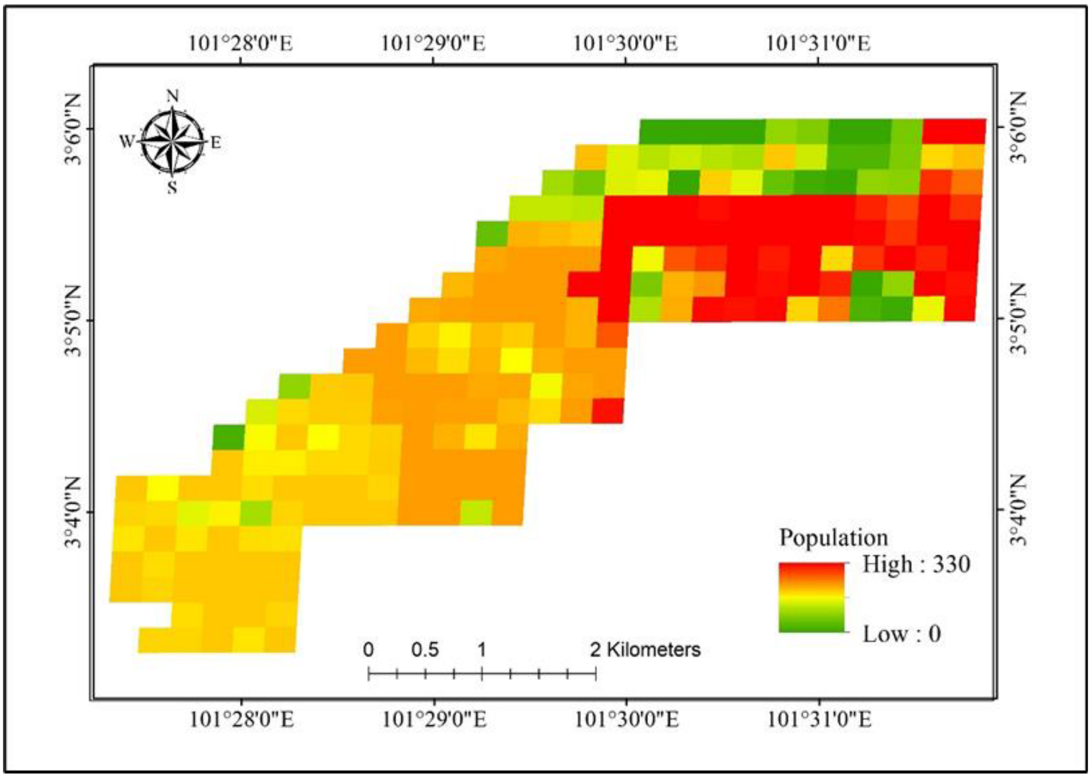

Figure 3.18 Shows the population raster in the study area2 (A).

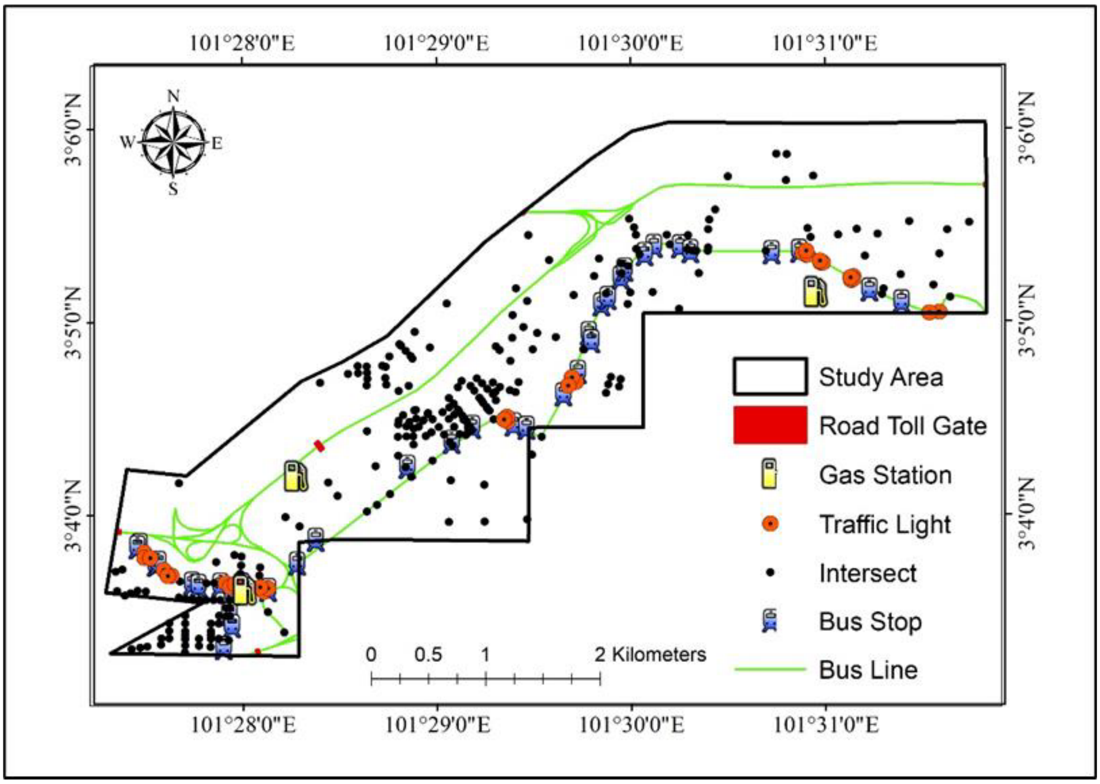

Figure 3.19 Shows the road toll gate, gas station, traffic light, intersect, bus stop and bus line in the study area2 (A).

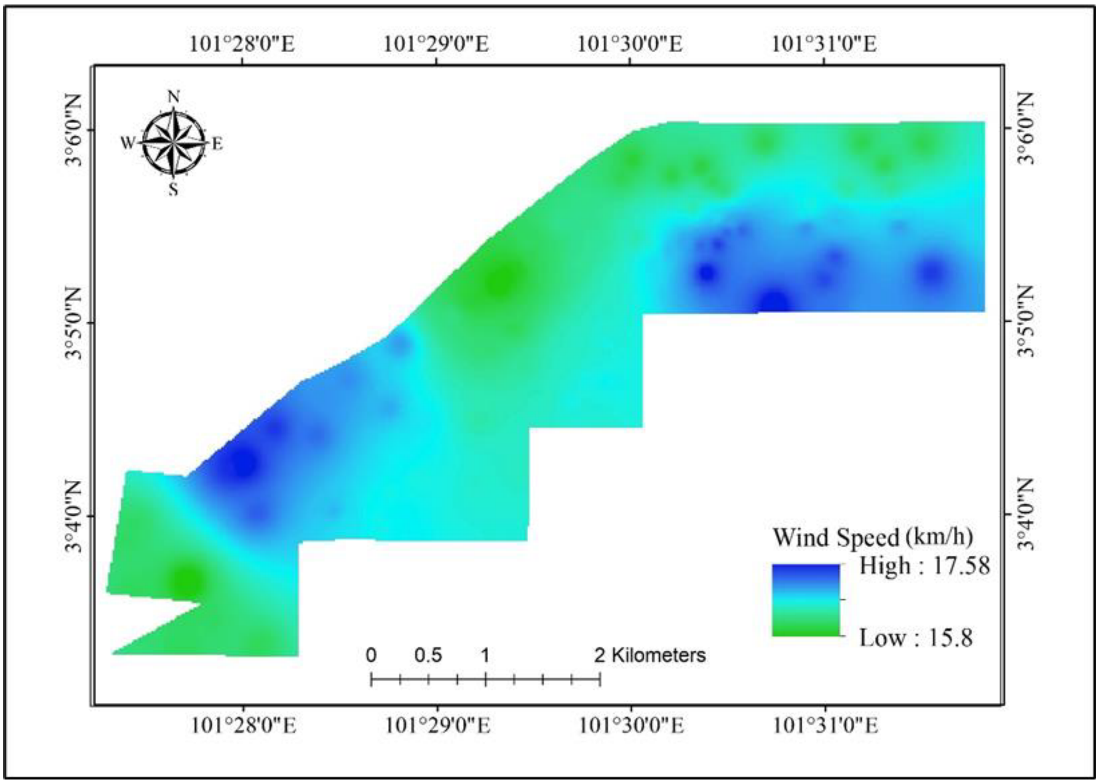

Figure 3.20 Shows the wind speed in the study area2 (A).

Table 3.2 Noise samples data in the study area2 (A).

No.	Data	No.	Data	No.	Data	No.	Data	No.	Data
1	67.57	20	80.39	39	64.32	58	62.82	77	83.54
2	62.89	21	68.36	40	63.49	59	67.33	78	60.5
3	67.03	22	62.64	41	86.92	60	63.86	79	66.34
4	67.28	23	61.3	42	67.19	61	59.15	80	75.12
5	71.63	24	88.48	43	68.85	62	89.04	81	80.16
6	67.38	25	65.39	44	71.48	63	58.6	82	68.98
7	67.37	26	78.24	45	67.02	64	59.63	83	59.8
8	68.13	27	70.99	46	56.09	65	78.91	84	61.98
9	86.11	28	67.83	47	64.07	66	86.88	85	68.24
10	83.45	29	56.02	48	68.38	67	64.08	86	62.57
11	87.03	30	52.91	49	66.34	68	73.68	87	57.68
12	80.08	31	71.77	50	69.69	69	51.23	88	54.62
13	60.05	32	54.56	51	83.51	70	53.37	89	60.24
14	58.68	33	78.64	52	63.28	71	55.08	90	63.58

15	59.31	34	68.39	53	71.29	72	76.58	91	60.91
16	65.37	35	87.02	54	61.73	73	80.22	92	60.87
17	67.86	36	63.85	55	61.37	74	81.82	93	68.59
18	57.17	37	86.89	56	60.25	75	68.14	94	67.64
19	68.09	38	81.51	57	70.38	76	85.65	95	69.37

Table 3.3 Summary statistics of noise predictors in the study area2 (A).

Parameter (noise predictors)	**Unit**	**Mean**	**Min**	**Max**	**Std. Dev.**
Traffic volume (per 15 minutes)	Veh/hour	122	9	810	183.66
Distance from all type of roads	Meters	67.37	2.11×10^{-5}	465.12	65.31
Distance from expressway	Meters	426.66	1.74×10^{-4}	1638.76	334.54
Distance from primary road	Meters	468.26	1.83×10^{-3}	1732.76	366.96
Distance from secondary road	Meters	97.90	2.11×10^{-5}	483.40	88.58
Distance from area of residential high density	Meters	402.66	0	2826.72	615.76
Distance from area of residential low density	Meters	190.79	0	855.10	175.38
Distance from residential Area	Meters	94.60	0	855.10	159.93
Distance from industrial Area	Meters	705.13	0	2470.92	568.72
Distance from trees Area	Meters	157.48	0	947.91	168.87
DSM	Meters	19.25	2.51	125.49	16.27

WS	km/h	16.62	15.8	17.58	0.53
Distance from gas station	Meters	1183.00	0	2726.06	651.41
Distance from traffic lights	Meters	780.87	0.58	1975.83	432.05
Distance from intersect	Meters	203.25	0.14	909.12	159.71
Distance from road toll gate	Meters	1010.38	0	2239.69	513.18
Distance from bus stop	Meters	528.22	0.083	1736.24	334.74
Distance from bus line	Meters	214.94	1.86×10^{-4}	946.33	161.00

For rhe second area (B), noise levels were measured with Sound Level Meter TES-52 in terms of minimum, maximum, and averages continuously at 15-min intervals using type A filter (dB (A), 0.1 dB resolution). The installation of the noise meters was carried out at 10 cm from signs or poles which is separated from noise barriers by at least two (2) m allowance. Garmin Global Positioning System (GPS 60) was used to acquire the geographic coordinates of each sampling location. The noise level measurement was taken four times every day during weekdays. This comprise of morning hours (6.30am-8.30am), afternoon (11.30am-1.30pm), afternoon (6.30pm – 8.30pm), and night (11pm-12midnight) each day. The traffic volume data were segregated to mainly five classes light vehicle, heavy vehicle, motorbike, truck with lorry and bus. The traffic noise information was collected to produce traffic noise distribution maps. The main purpose of this model is to estimate the traffic noise level at a particular location and period of time. In this study, the dependent parameter, that is the highway noise descriptor is the equivalent continuous noise level per 15 minutes ($L_{(eq,15)}$) for the morning, afternoon, evening and the night. The noise parameters were pre-determined and selected based on reviews which consider traffic and weather characteristics of the area under consideration. The noise parameters inputted into the model are light vehicle, heavy vehicle, motorbike, truck and lorry, bus, digital surface elevation (DSM), time (i.e., morning, afternoon, evening and night), gradient, density of road, temperature, humidity. Whilst, the maximum, minimum and average traffic noise as output to the model. These parameters are summarized based on statistics as shown in table 3.4.

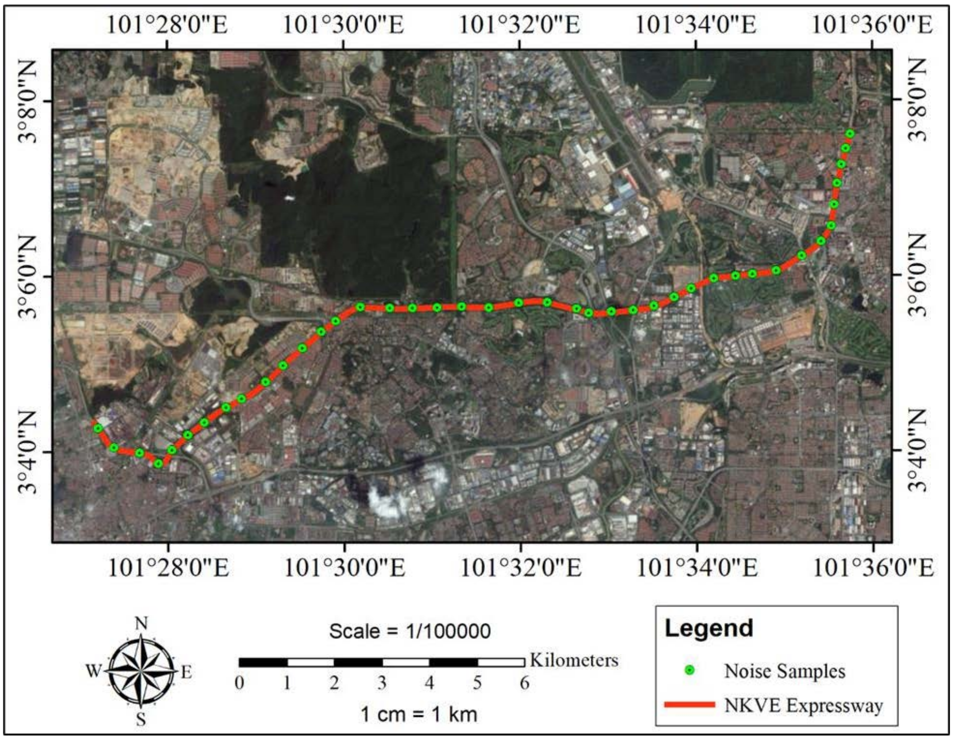

Figure 3.21 Shows the study area2 (B).

Table 3.4 Statistical summary of noise predictors in the study area2 (B).

Parameter	Minimum	Maximum	Mean	Deviation
Maximum Noise	77.10	116.20	106.96	6.86
Minimum Noise	63.40	94.80	80.05	5.98
Average Noise	71.55	113.35	91.52	6.84
Light Vehicle	7.00	2820.00	782.97	719.17
Heavy Vehicle	3.00	618.00	93.22	102.67
Motorbike	2.00	605.00	92.29	115.78
Truck and Lorry	2.00	443.00	63.09	71.18
Bus	1.00	175.00	30.13	31.94
DSM	3.74	41.61	17.27	11.16
Time	Morning, Afternoon, Evening and Night			
Gradient	0.40	203.85	12.81	33.55

Density of Road	0.03	0.05	0.05	0.00
Temperature	19.80	31.60	25.72	3.94
Humidity	42.70	79.60	65.75	9.38

3.5 Data Preprocessing and Preparation

The data processing of various remote sensing data such as LiDAR, Worldview-3 image, Worldview-3 orthorectification, landuse mapping, method of measurement noise and traffic data collection, and field survey were prepared for proposed modelling.

3.5.1 LiDAR Data Processing

LiDAR data often come as point clouds which are points with 3D coordinates (X, Y, and Z) and the intensity of the laser pulse. Sometimes, the LiDAR point clouds have several returns. However, in this case, the LiDAR data contained only one return. The main purpose of using LiDAR data in this project was to derive the accurate Digital Surface Model (DSM), Digital Elevation Model (DEM), and ground object heights which are necessary for noise modelling. Figure 3.22 shows the LiDAR point clouds for the study area.

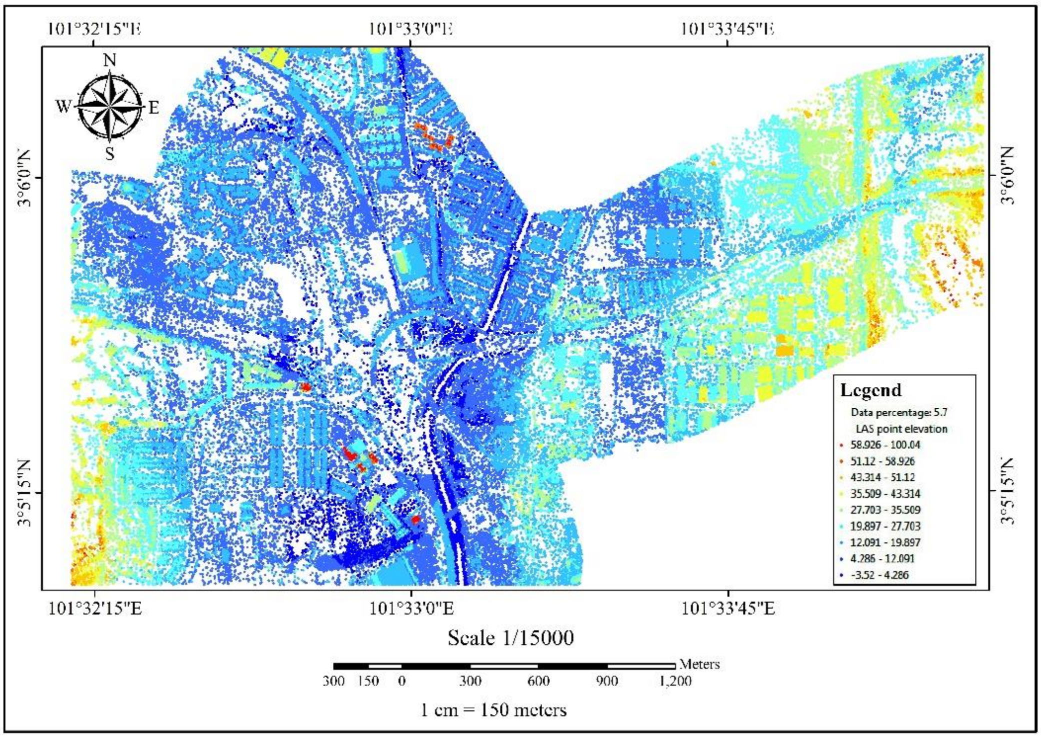

Figure 3.22 LiDAR point clouds in study area2 (Shah Alam-Seksyen 13).

The LiDAR DSM was created by interpolating the first return LiDAR point clouds using Inverse Distance Weighted (IDW) method. The DSM was generated at 0.3 m spatial resolution to extract the buildings and the roads in the study area. The higher spatial resolutions (<0.3 m) added more noise to the output and therefore, the extraction of building, road, and land use features were much difficult. While the DSM with the less spatial resolution (> = 0.3 m) resulted less noise in pixelated boundaries for the building and road features. On the other hand, also the DSM was used to accurately account for road geometry and vehicle acceleration effects on the generated noise level. Figure 3.23 shows the DSM created for the study area.

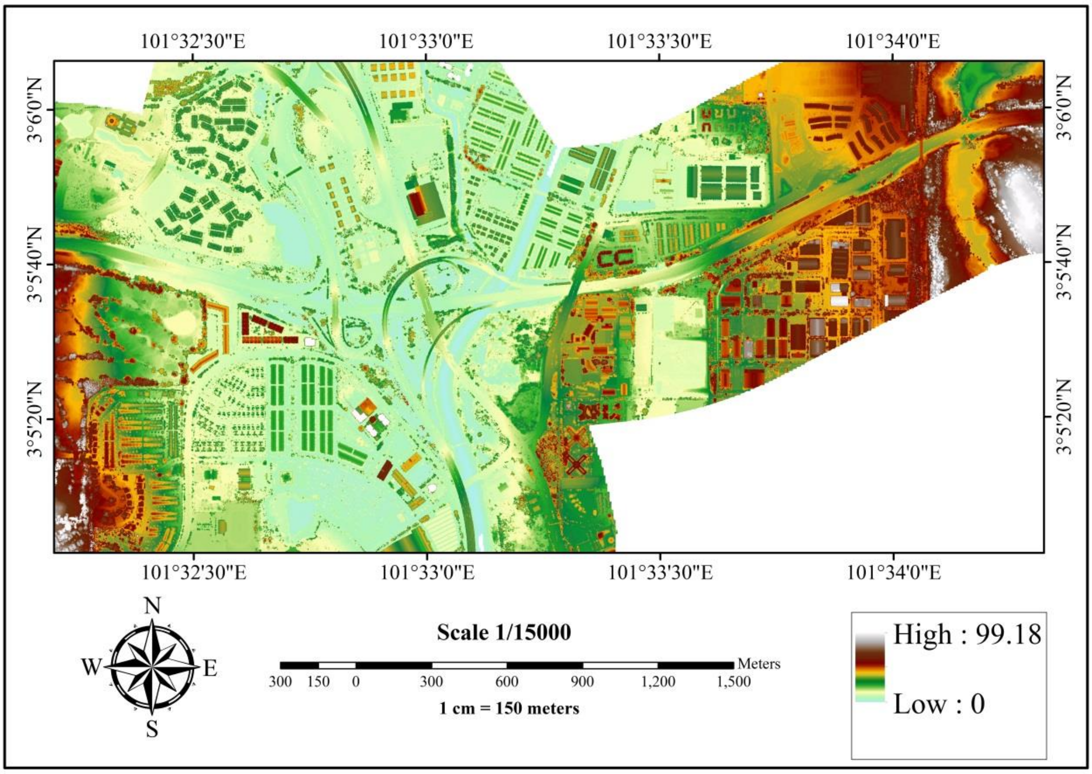

Figure 3.23 LiDAR-derived DSM at 0.3 m spatial resolution.

The LiDAR DEM was created using Multi-scale Curvature Classification (MCC) algorithm using the same software. According to (Evans and Hudak, 2007) MCC is an iterative multi-scale algorithm for classifying LiDAR returns as ground and non-ground. The algorithm incorporates curvature filtering with a scale component and variable curvature tolerance. The surface is interpolated at different resolutions using the thin-plate spline method (Lim and Yang, 2005) and points are classified based on the curvature threshold parameter. The curvature tolerance parameter increases as the resolution coarsen compensate for slope effect, and the data are generalized. (Figure 3.24) shows the created DEM for the study area.

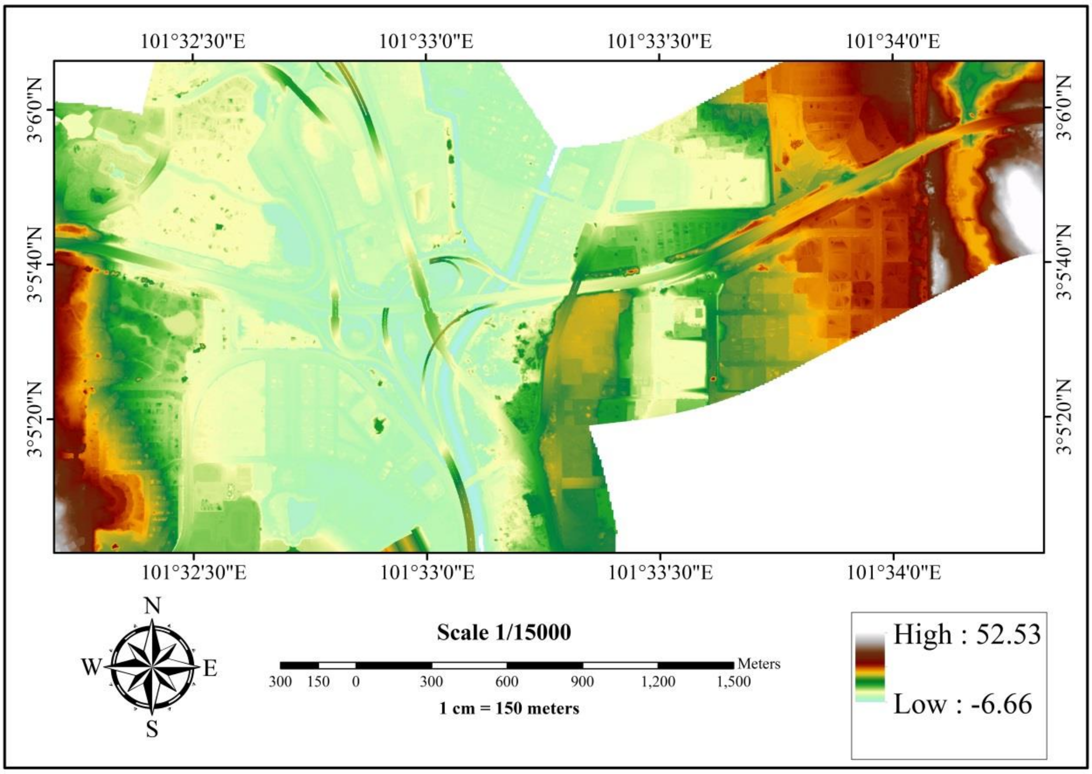

Figure 3.24 LiDAR derived DEM at 0.3 m spatial resolution.

Noise modelling requires information about transportation and building. The main source of traffic noise is the transportation (vehicles) while the buildings are the noise barriers and are included in noise modeling. In this research, a workflow was designed to extract such information from LiDAR point clouds as shown in (Figure.3.25). Initially, the LiDAR point clouds were interpolated to create the Digital Surface Model (DSM). The DSM data was pre-processed by correcting the geometric errors and the gaps in the data were filled by using the global mapper software. Subsequently, the data were segmented and prepared for analysis. The ENVI software was used to automatically extract the buildings shown in (Figure 3.26) and the roads shown in (Figure 3.27) in the study area. These data were organized and linked into the GIS database to be used for noise modelling.

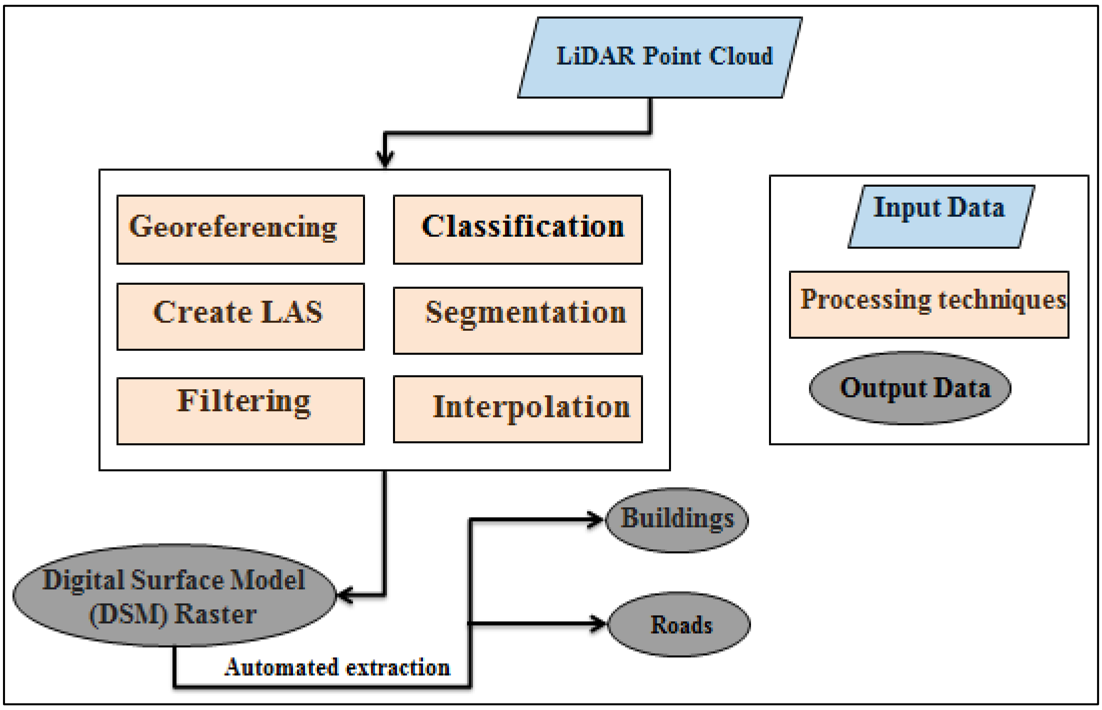

Figure 3.25 Workflow of extracting building and roads features from LiDAR data.

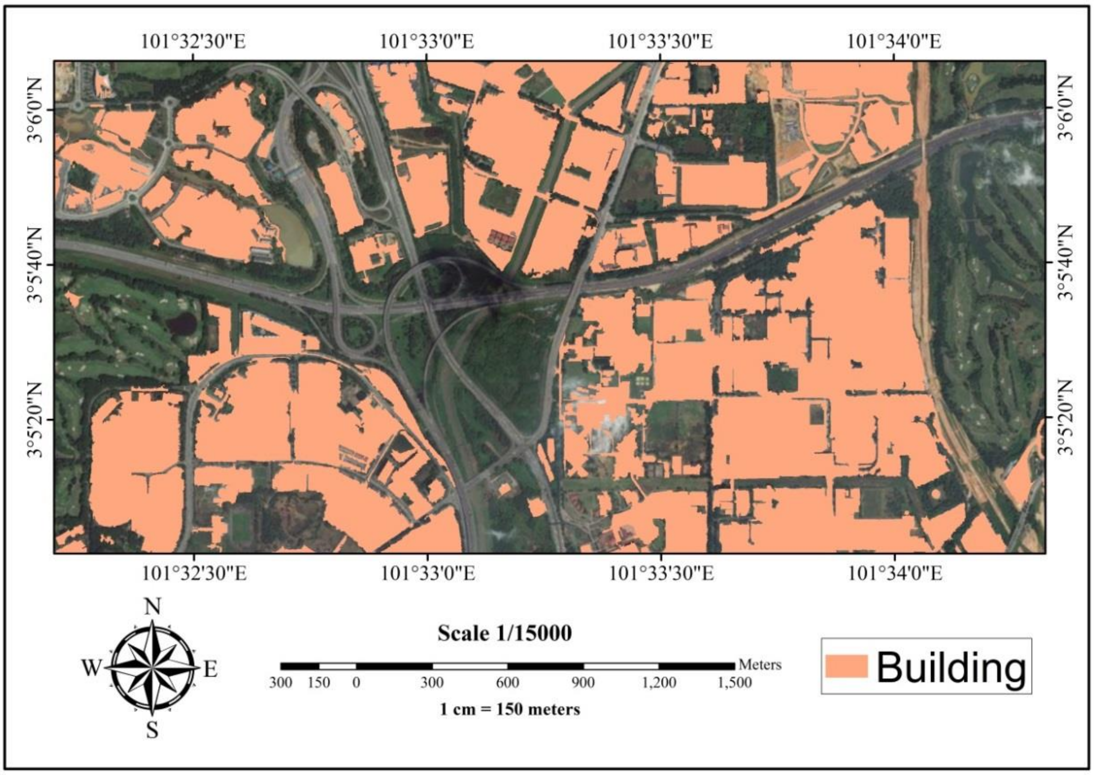

Figure 3.26 Buildings in the Shah Alam-Seksyen 13 delineated from LiDAR data and updated based on the Worldview-3 image.

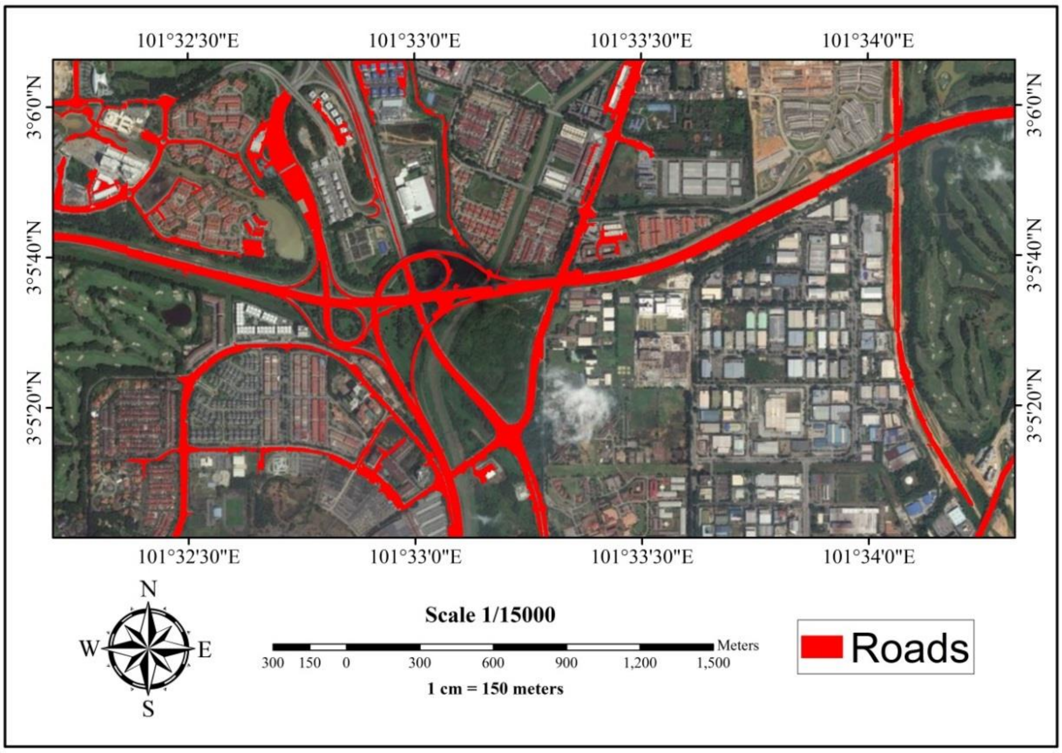

Figure 3.27 Roads in the Shah Alam-Seksyen 13 delineated from LiDAR data and updated based on the Worldview-3 image.

3.5.2 Processing of Worldview-3 Image

The Worldview-3 image has eight spectral bands with 1 m spatial resolution which covered visible to near-infrared (Rana et al.,2015) spectral regions (400 to 1040 nm), and one panchromatic band with a spatial resolution of 0.3 m. The image is georeferenced to follow the LiDAR data and the Universal Transverse Mercator projection and the world geodetic system 1984 datum. In addition, the radiometric correction was performed using the QUACK atmospheric correction module available in ENVI software (Boulder, Colorado) to retrieve spectral reflectance from multispectral radiance images. After applying radiometric correction, multispectral band pansharpening was performed using the PANSHARP algorithm which improved the visualization of urban features (Hamedianfar et al., 2014). Figure 3.28 shows the Worldview-3 image of the area after preprocessing.

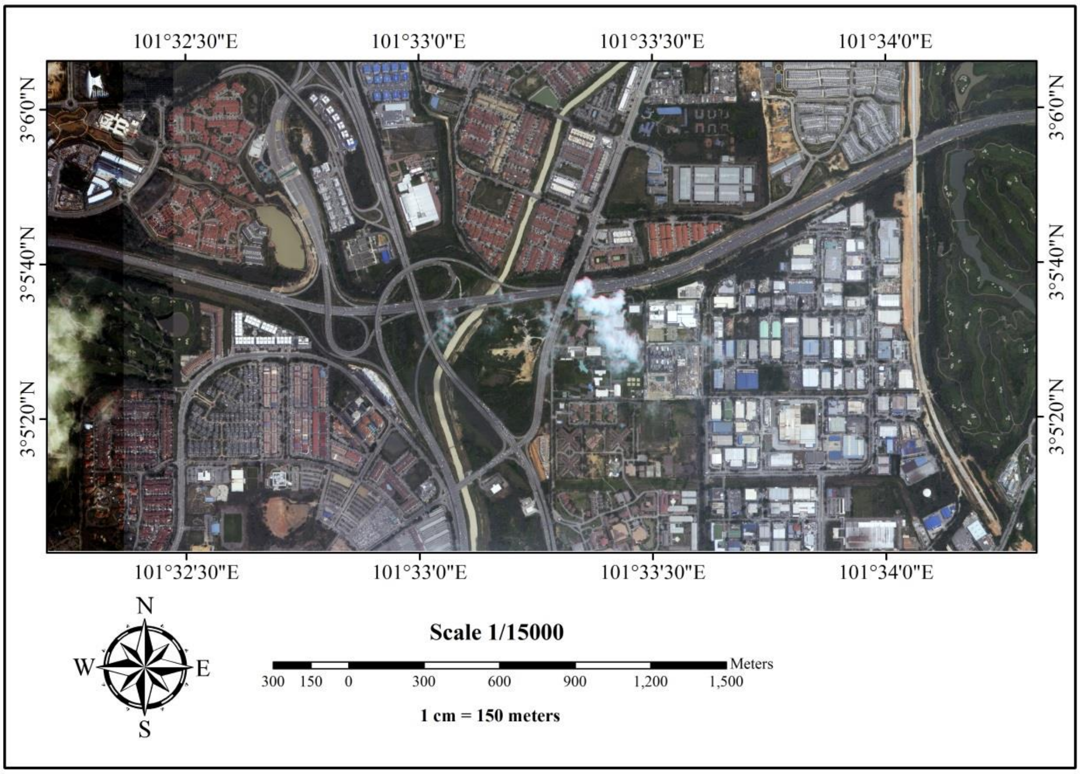

Figure 3.28 Worldview-3 image of the Shah Alam-Seksyen 13 after preprocessing.

3.5.3 Worldview-3 Orthorectification

Increasing number of commercial high resolution satellite images has led to more applications of remote sensing which are applied to develop and serve many industrial, governmental, and educational institutions. High resolution satellite images provide a wealth of information about our planet and ground objects which are the basic elements to study the physical phenomenon of nature. Remote sensing applications include environment, climate change, land use mapping and monitoring, glacier mapping, urban planning, agriculture, transportation, natural hazards, and civil engineering. To maximize the information extraction from high resolution satellite images, sophisticated data pre-processing algorithms and feature extraction methods are necessary. One of the biggest problems with high resolution satellite images is the dense urban areas and tall buildings which are oblique especially in off-nadir regions. Figure 3.29 shows three parts (A, B and C) where (A) is the error points (Oblique buildings which are in off-nadir) of Worldview-3 image, (B) is the correct points of DEM (0.3 m) and (C) is the error points of image and the correct points of DEM. These challenges cause reduced dimensions of the pixels and the off-nadir viewing. Therefore, it is not practicable to use remotely sensed images directly in geographic information system (GIS) and other applications due to the problems above. In other to practically use them, corrections must be made to the geometric deformations introduced during the acquisition.

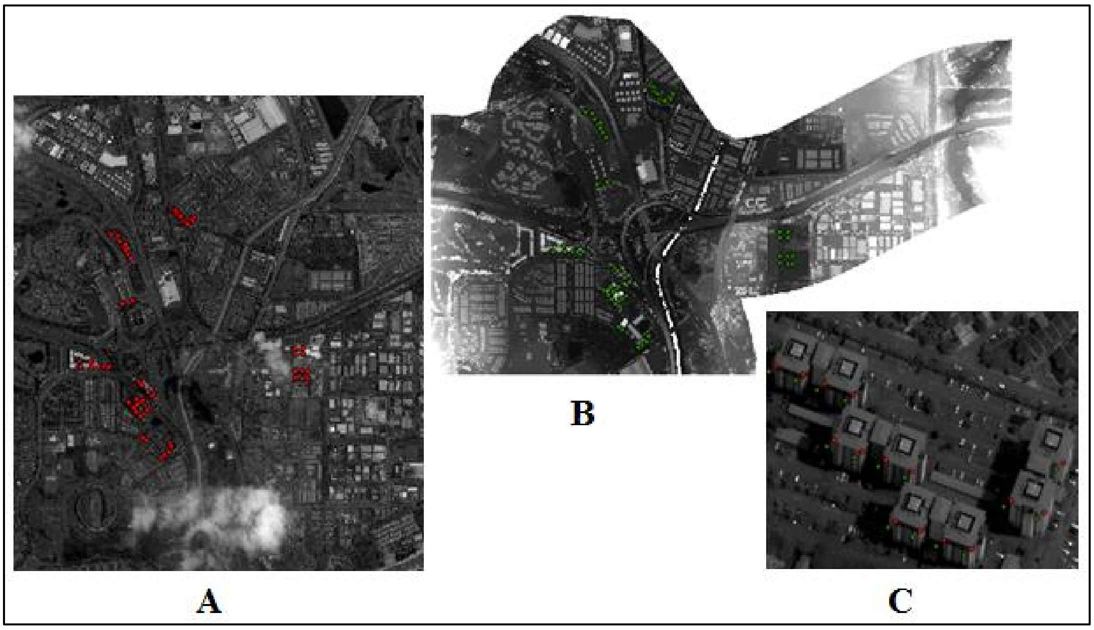

Figure 3.29 Oblique buildings which are in off-nadir for study area.

In addition, very high spatial resolution satellite imageries such as Worldview-3 and Worldview-2 play a major role in urban mapping (Fratarcangeli et al., 2016) and noise modelling (Çolakkadıoğlu et al., 2017). The incorporating spatial and spectral information into feature extraction processes permits accurate and detailed mapping for practical applications. However, images acquired by satellites are affected by the systematic sensor and platform-induced geometry errors, which introduce terrain distortions when the sensor is not pointing directly at the nadir location of the sensor. The topographical variations in the surface of the earth and the tilt of the satellite or aerial sensor affect the distance with which features on the satellite or aerial image are displayed. The more topographically diverse the landscape is, the more distortion inherent in the image. With the current advances in laser scanning technologies, terrain distorted satellite images can be corrected.

Hence, to extract landuse features from the Worldview-3 image, the distortion of Worldview-3 image must be corrected by orthorectified tool using LiDAR-derived digital elevation model (DEM) and digital surface model (DSM). After pre-processing and preparing the Worldview-3 image and LiDAR (DEM, DSM), the orthorectification model was applied in three stages which include a selection of orthorectified model, conversion model, and orthorectification process itself. The optimized technique was obtained by simulating spatial resolutions of DSM (0.3 m), rational polynomial coefficients (RPC) which used spatial resolution of DEM (0.3 m), and orthorectification model. Finally, the proposed technique (the excellent orthorectified Worldview-3 image) in addition to the urban planning served various applications such as land cover feature extraction, map updating, and environmental studies. Therefore, it is a useful and cost-effective solution to be deployed by governmental, industrial and educational agencies.

The overall workflow of the proposed orthorectification process is presented in Figure 3.30. Four inputs including Worldview-3 image, LiDAR point clouds, rational polynomial coefficients (RPC), and GCPs. The Worldview-3 image is radiometrically calibrated in the process of converting image digital numbers into reflectance values using the QUACK method which requires no spectral information from the field. The ground points were filtered from LiDAR point clouds using ArcGIS Software which produced different spatial resolutions of DSM (0.3, 0.5, 1, 2, 3, 5, 10, 15, 20 m) and spatial resolution of DEM (0.3 m), and free data of digital elevation model (DEM = 29 m) to evaluate the effect of the spatial resolution and to find the best the spatial resolution for using in orthorectification model. The spatial resolution of the Worldview-3 image was enhanced by a pan-sharpening process using the panchromatic image with 0.3 m spatial resolution. The enhanced Worldview-3 image is orthorectified using three process procedures: selection of the orthorectified model, conversion model, and orthorectification process. Once the Worldview-3 image was orthorectified, it was validated by the evaluation of positional accuracy compared with GCPs which was extracted from LiDAR-derived DEM. If the produced corrected image meets the requirements, the process is stopped, and the output is delivered, otherwise different resolution of DSM is utilized. This process was iterated until all the available resolutions of DSM and free DEM were evaluated. Finally, the excellent orthorectified Worldview-3 image was used for various applications such as land cover feature extraction.

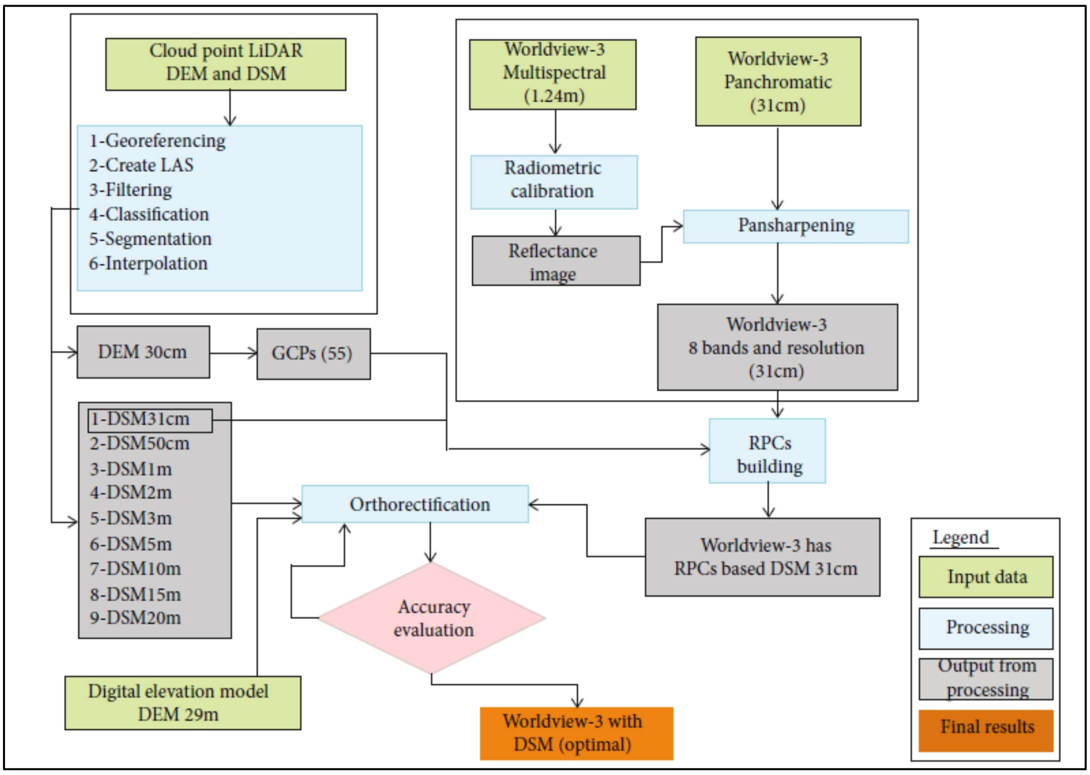

Figure 3.30 Overall workflow of the proposed orthorectification process.

3.5.4 QuickBird Image

QuickBird was a high-resolution commercial earth observation satellite, owned by Digital Globe launched in 2001 and decayed in 2015. It was the first satellite in a constellation of three scheduled to be in orbit by 2008. QuickBird used Ball Aerospace's Global Imaging System 2000 (BGIS 2000). The satellite collected panchromatic (black and white) imagery at 61-centimetre resolution and multispectral imagery at 2.44- (at 450 km) to 1.63-meter (at 300 km) resolution, as orbit altitude is lowered during the end of mission life.

At this resolution, detailed features such as buildings and other infrastructure are easily visible. However, this resolution is insufficient for working with smaller objects such as a license plate on a car. The imagery can be imported into remote sensing image processing software, as well as into GIS packages for analysis. The imagery can also be used as a backdrop for mapping applications, such as Google Earth and Google Maps.

Table 3.5 Characteristics of QuickBird sensors

Band	Wavelength (μm)	Resolution (at nadir)	Radiometric Resolution
1 (blue)	0.45 - 0.52	2.5 m	11 bit
2 (green)	0.52 - 0.60	2.5 m	11 bit
3 (red)	0.63 - 0.69	2.5 m	11 bit
4 (NIR)	0.76 - 0.89	2.5 m	11 bit
Panchromatic	0.45 - 0.90	0.61 m	11 bit

3.5.5 Landuse Mapping

Landuse is another critical data required to develop the traffic noise maps in the study area. Landuse indicate the human activities in the study area and therefore, are necessary to evaluate the effects of high noise levels based on the landuse information. Landuse map was created using the LiDAR data and Worldview-3 image. The LiDAR data including the DSM and DEM were utilized to extract the nDSM which indicate the height of objects. The height raster (0.3 m) was segmented using the multiresolution segmentation algorithm. The parameters of the segmentation algorithm were selected through trial-and-error method. After segmentation, several features were extracted from LiDAR data and Worldview-3 image. These features include spectral bands of the Worldview-3 image, DSM, DEM, height, textual features, and spatial features such as shape index, rectangular fit, and length/width. The objects were classified into five classes such as buildings, roads, grasses, trees, and water bodies using the Support Vector Machine methods (SVM) (Melgani et al., 2004). This algorithm required several parameters such as the kernel function and the penalty parameter to optimize. These parameters were then selected by grid search over specific search domain. The analysis showed that the best combinations of segmentation parameters are as follows: scale= 25, shape = 0.3, and compactness = 0.8. The best SVM parameters were found to be rbf and c = 100.

The results of image classification were evaluated by calculating the confusion matrix. This matrix was then used to calculate the overall accuracy, kappa index, user, and producer accuracy. The table 3.6 shows the confusion matrix along the estimated accuracies, overall accuracy and kappa index which the overall accuracy and the kappa index were 92.5%, 0.90, respectively. On the other hand, the highest and lowest user accuracy were one (1) (road, water) and 0.828 (tree), respectively. Figure 3.31 shows the landuse map of the study area.

Table 3.6 The confusion matrix and accuracy indicators that were calculated to evaluate the proposed classification framework.

User Class/ sample	**Building**	**Road**	**Grass**	**Tree**	**Water**	**Sum**
Confusion Matrix						
Building	67	3	1	0	0	71
Road	0	42	0	0	0	42
Grass	2	0	35	4	0	41
Tree	2	0	2	24	1	29
Water	0	0	0	0	16	16
Sum	71	45	38	28	17	
Accuracy						
Producer	0.944	0.933	0.921	0.857	0.941	
User	0.944	1	0.854	0.828	1	
Overall Accuracy	0.925					
KIA	0.901					

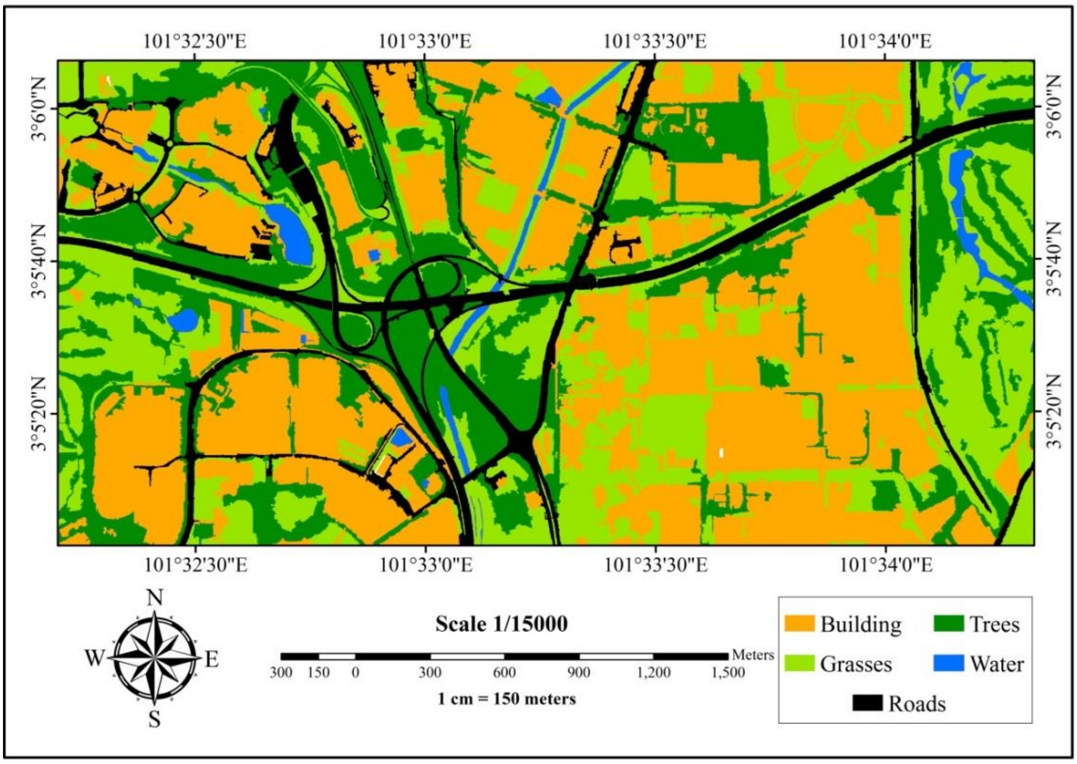

Figure 3.31 Landuse map of the Shah Alam-Seksyen 13.

3.5.6 Method of Measurement Noise and Traffic Data Collection

Proper planning for noise and traffic data collection is highly imperative for comprehensive traffic noise assessments. The distribution of noise samples and quality within the selected site are the most important aspect of noise data collection (Ranjbar et al., 2012; Stoter et al., 2008). The distribution of noise samples is significantly affected by the interpolation of results and subsequently affects the accuracy of predicted noise at un-sampled locations. It was ensured that point density is sufficiently high in other to reach an adequate accuracy of interpolation results. Too many points were avoided in other to reduce the computation time of the software. Specifically, the density of noise samples was adjusted due to the characteristics of noise propagation. In this study, the noise data were collected by the procedure outlined by Ragettli et al., (2016a). The method was based on a GIS spatial analysis for randomly generated traffic noise measurement locations which was developed for noise data collection for spatial balancing. The model generates an adequate number of noise samples locations and optimal density sufficient for the study area.

Initially, three layers of landuse types (residential, commercial, industrial) were extracted. These layers were converted into points with a spatial constraint to force them to be generated inside the landuse polygons. The density of points was then estimated using 150 m search radius and the resolution of output density raster was set to 25 m. After that, the three-density raster were combined using different weights of 3, 2, and 1 for residential, commercial, and industrial respectively. A combined density raster that covers the study area was generated. The combined density raster was rescaled using the linear method from 0 to 1. This produced the inclusion probability raster to be used for selection of noise samples in the study area. Then, the spatially balanced points were generated within the survey area by utilizing the inclusion probability raster. The numbers of points generated in the survey area depends on the total length of road networks, the cost of the project and the noise instruments used in the data collection. The generated points are distributed within the boundary of the study area. Therefore, additional processing steps are required to refine the generated points to select the final noise samples based on the transportation features. Tessellated grids size of 25 was generated to cover the study area and the grids that intersect with the generated points and transportation features were selected while the remaining tessellated grids were removed. Finally, the noise samples were chosen within the remaining tessellated grids and transportation features. Figure 3.32 shows the noise samples in the study area which was developed by the GIS model.

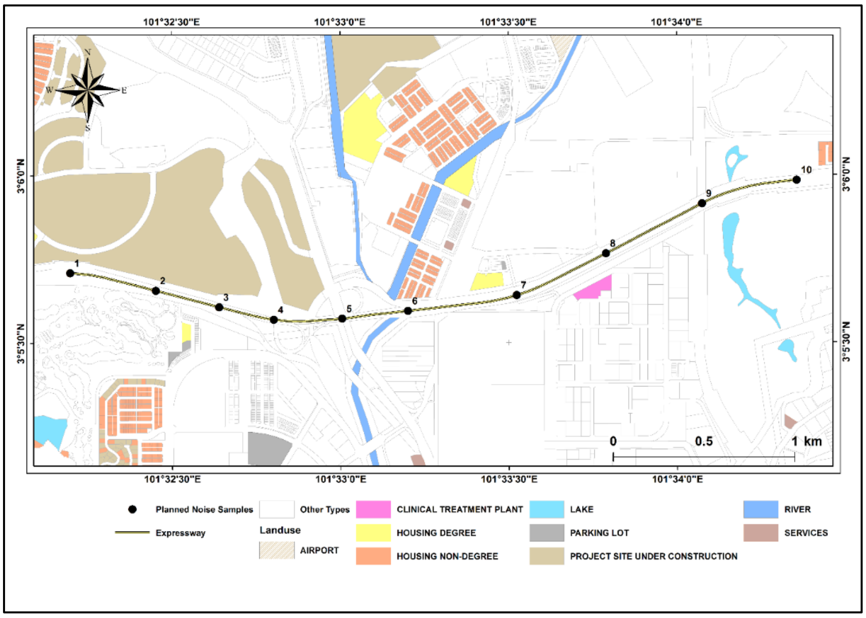

Figure 3.32 The surveying map planned (the noise samples) to collect noise and traffic data in the study area.

3.6 Modeling

3.6.1 Land Use Prediction Regression Models

3.6.1.1 Machine Learning Models

Machine Learning (ML) is a field of inquiry devoted to understanding and building methods that 'learn', that is, methods that leverage data to improve performance on some set of tasks. It is seen as a part of artificial intelligence. Machine learning algorithms build a model based on sample data, known as training data, in order to make predictions or decisions without being explicitly programmed to do so. Machine learning algorithms are used in a wide variety of applications, such as in medicine, email filtering, speech recognition, and computer vision, where it is difficult or unfeasible to develop conventional algorithms to perform the needed tasks. In this research we are taken three models of machine learning such as artificial neural network (ANN), random forest (RF) and support vector machine (SVM).

3.6.1.1.1 Artificial Neural Network (ANN)

ANN is a machine learning technique that uses biological and statistical learning models. ANN is used to create models of a system state using nonlinear combinations of the input variables (Recknagel, 2001; Cruz and Wishart, 2006; Goyal et al, 2014; Patel et al, 2015; Witten, 2016; Wang and Srinivasan, 2017; Chen et al, 2017; Charte et al, 2018, Goldstein et al, 2019). The ANN employed in this study is a back-propagation network with sigmoid activation functions in the hidden layers and a linear activation function in the output node. Since according to Bishop's (1995) study more than one hidden layer is often not necessary, our architectures have only one hidden layer. The ANN is trained using a back-propagation algorithm with gradient descent and momentum terms.

The ANN requires that the learning rate, number of nodes in a single hidden layer, and maximum number of training epochs are specified (Hill and Minsker, 2010). In this study, we used the optimal number error approach. The number of the hidden layer was varied between three (3) and 30, and the learning rate was varied from 0.01 to 0.8 in increments of 0.05. The table 3.7 shows the hyperparameters of ANN model for traffic noise prediction through use the search space. For each configuration, the RMSE and R^2 between the model output and the measured data were calculated. ANN algorithm is based on the principle of error minimization using iterative gradient designed as shown in Eq. (1). As a model, ANN has recorded tremendous success in remote sensing applications; however, the high computational complexity posed a remarkable limitation of the model and a drawback of overlearning (Baczyński and Parol, 2004).

$$E = \frac{1}{2}\sum_{i=1}^{L}\left(d_j - o_j^M\right)^2 \qquad (1)$$

where, d_j and o_j^M represent the desired output and current response of node ‘‘j’’ in the output layer, respectively, and ‘‘L’’ is the number of nodes in the output layer. In an iterative method, corrections to weight parameters are calculated and added to the previous values, shown as follows:

$$\begin{cases} \Delta w_{i,j} = -\mu \dfrac{\partial E}{\partial w_{i,j}} \\ \Delta w_{i,j}(t+1) = \Delta w_{i,j} + \alpha \Delta w_{i,j}(t) \end{cases} \qquad (2)$$

Where, $w_{i,j}$ is the weight parameter between nodes i and j, Δ is a positive constant that controls the amount of adjustment and is called learning rate; α is a momentum factor that can take on values between 0 and 1 and ‘‘t’’ denotes the iteration number. Parameter α smooths the rapid changes between the weights; as such, it is called smoothing or stabilising factor (Yang, 1995).

Table 3.7 Hyperparameters of the proposed model for noise prediction and their search space used for fine-tuning.

Hyperparameters	Search Domain
Type of Network	{MLP}
Number of Hidden Units	(3–30)
Training Algorithm	{BFGS, RBFT}
Hidden and Output Activation	{Identity, Logistic, Tanh, Exponential, Gaussian}
Learning Rate	(0.01–0.9) by step of 0.05
Momentum	(0.1–0.9) by step of 0.1

3.6.1.1.2 Random Forest Model (RF)

RF algorithm is a supervised classification algorithm (Xu et al. 2012; Caruana and Niculescu-Mizil, 2012; Osisanwoet et al. 2007). We can see it from its name, which is to create a forest by some way and make it random. There is a direct relationship between the number of trees in the forest and the results it can get: the larger the number of trees, the more accurate the result (Caruana and Niculescu-Mizil, 2012). But one thing to note is that creating the forest is not the same as constructing the decision with information gain or gain index approach.

RF can be used for both classification and regression tasks. Overfitting is one critical problem that may make the results worse, but for Random Forest algorithm, if there are enough trees in the forest, the classifier won't over fit the model. The third advantage is the classifier of Random Forest can handle missing values (Zhao et al. 2012), and the last advantage is that the Random Forest classifier can be modelled for categorical values (Mendez et al. 2008).

RF algorithm works in two stages, one is random forest creation, the other is to make a prediction from the random forest classifier created in the first stage.

1. Randomly select "K" features from total "m" features where k << m.
2. Among the "K" features, calculate the node "d" using the best split point.
3. Split the node into daughter nodes using the best split.
4. Repeat the a to c steps until "l" number of nodes has been reached.
5. Build forest by repeating steps a to d for "n" number times to create "n" number of trees.

In the next stage, with the random forest classifier created, we will make the prediction. The random forest prediction pseudocode is shown below:

1. Takes the test features and use the rules of each randomly created decision tree to predict the outcome and stores the predicted outcome (target).
2. Calculate the votes for each predicted target.
3. Consider the high voted predicted target as the final prediction from the random forest algorithm.

3.6.1.1.3 Support Vector Machine Model (SVM)

SVR is a machine learning algorithm used for nonlinear regression issues and can be used as universal approximates of multivariate task at any level of accuracy (Miao and Wang, 2002; Deng et al. 2005; Lima et al. 2013). SVR model is applied to predict dependent variable ‘y’ depending on group of independent variables ‘x’, as presented in Eq. 3:

$$y = (w^T . \emptyset \text{ (X)} + \text{b}) + \text{noise} \tag{3}$$

Where, the noise of the model is represented by the tolerance of error (ε). w represents the vector of coefficient, whereas b represents a constant value. The kernel function is represented by Φ and used to convert the data values to high-dimensional feature space to make them more separable than the original space. The task is to find a functional form for $w^T . \emptyset$ (X) + b. This form can be obtained by tuning the model. Then, the error function reduction is used to derive w and busing Eqs. 4, 5 and 6:

$$\frac{1}{2} w^T . \text{w} + \text{C} \sum_{i=1}^{N} \varepsilon_i + \text{C} \sum_{i=1}^{N} \varepsilon . \text{i} \tag{4}$$

$$w^T . \emptyset \text{ (X)} + \text{b} - \text{y}_{\text{i}} \leq \varepsilon + \varepsilon . \text{i} \tag{5}$$

$$\varepsilon . \text{i}, \varepsilon . \text{i} \geq 0, \text{i} = 1, \ldots, \text{N} \tag{6}$$

Where, C indicates a positive constant that determines the degree of penalized loss as calibration error occurs; N is the sample size; and ε.i and $\varepsilon.i$ are slack variables specifying the upper and lower calibration errors subject to ε, respectively.

3.6.1.2 2D Noise Models

This model is just about all types of roads, initially, three layers of landuse types (residential, commercial, industrial) were extracted. These layers were converted into points with a spatial constraint to force them to be generated inside the landuse polygons. The density of points was then estimated using 100 m search radius and the resolution of output density raster was set to nine (9) m. After that, the three-density raster were combined using different weights of three (3), two (2), and one (1) for residential, commercial, and industrial, respectively. A combined density raster that covers the study area was generated. The combined density raster was rescaled using the linear method from zero (0) to one (1). This produced the inclusion probability raster to be used for selection of noise samples in the study area. Then, the spatially balanced points were generated within the survey area by utilizing the inclusion probability raster. The numbers of points generated in the survey area depends on the total length of road networks. The generated points are distributed within the boundary of the study area. Therefore, additional processing steps are required to refine the generated points to select the final noise samples based on the transportation features. Tessellated grids size of nine (9) was generated to cover the study area and the grids that intersect with the generated points and transportation features were selected while the remaining tessellated grids were removed. Then, the noise samples were chosen within the remaining tessellated grids and transportation features. Then, they have been ready to predict traffic noise on the whole points were generated on type of roads through using several models such as ANN, RF and SVM algorithms and evaluate models to select the best prediction model through using correlation (R), correlation coefficient (R^2), and root mean square error (RMSE). The noise parameters inputted into model are light vehicle, truck, motorbike, semitrailer, bus, DSM, average speed and maximum speed. Finally, the GIS model was spatially designed to represent the traffic noise prediction level generated from vehicular traffic on the expressway. The designed is based on the final implementation of the proposed model (best model). The parameters of the model were converted to geodatabase through sample connection of the attributes with their various positions obtained with the aid of GPS. Further conversion of the parameters was done to aster form using geostatistical interpolation (IDW interpolation) for proper information on noise prediction. The IDW method was chosen due to its ability to provide highly correlated result than Spline and Kriging methods. On the other hand, higher distortion of the interpolated result was observed in the Spline and Kriging results compared with the IDW. The model's parameters were combined in GIS background based on the overlying inquiries of the proposed model. It was applied on a grid at high-resolution of 3*3 m in other to predict road traffic noise for the un-sampled areas. Each grid exhibit values based on the intersected values that represent the disparity in traffic noise values and distribution of traffic noise level in the results.

3.6.1.3 3D Noise Models

While 3D model of the noise was achieved by dividing the study area by 3*3*3 m^3 to generate observation point as 3D and apply similar procedure as in the 2D model (Adulaimi et al, 2021). First, 3D building model was prepared based on DSM raster. The 3D noise modelling was applied on building. The noise predicting variables in the model were based on GIS data which included road networks, traffic flow, traffic speed and land use coverage and DSM collected from both publicly available and government data. So, the spatial noise predictors parameters inputted into model are distance from high light vehicle, distance from medium light vehicle, distance from low light vehicle, distance from high truck, distance from medium truck, distance from low truck, distance from high motorbike, distance from medium motorbike, distance from low motorbike, distance from high semitrailer, distance from medium semitrailer, distance from low semitrailer, distance from high bus, distance from medium bus, distance from low bus, distance from high average speed, distance from medium average speed, distance from low average speed, distance from high maximum speed, distance from medium maximum speed, distance from low maximum speed and DSM. We calculated the spatial noise predictors through using the nearest algorithm is available on GIS which is working to calculate the distance from the nearest any noise predictors (of any type) to the centroid in the grid in meters. And we intersected the building data with the grid cell, and then calculated the total area of building coverage in each cell and divided it by the grid cell area to get the percentage of the building coverage in each grid cell. Then, data preparation for use as input in the machine learning models (ANN, RF and SVM), the R, R^2, and RMSE for all models calculated of machine learning. The best model is then chosen based on the evaluated algorithms. The proposed model is then linked and integrated to GIS. Finally, conversion algorithm is used to convert these data to feature and combining with 2D prediction noise map for subsequent production of 3D noise map.

3.6.2 Noise Propagation Model

This section describes the developed noise propagation model by collecting traffic noise data especially on high-speed highways which could be dangerous and expensive. Therefore, predicting noise levels on highways help to generate noise data that can be used for further studies. In this study, the measured and predicted noise levels are used for propagation simulation of the noise emissions in the study areas. The benefits of this step are to assess the impact of noise levels on people and environments due to the effect of traffic flow and heavy vehicles.

Figure 3.33 shows an illustration of traffic noise propagation from a single source to a receiver and the potential factors that influence the propagation way of the traffic noise. The main sources of noise considered are the vehicles (cars, heavy vehicles, and motorbikes). The traffic noise emitted from vehicles can propagate from the point of origin to other surrounded areas called calculation points. Several factors have effects on reducing, increasing, and redirecting the noise levels and paths generated by vehicles such as wind direction and speed, barriers such as tall buildings, and the interaction of air particles with the noise waves.

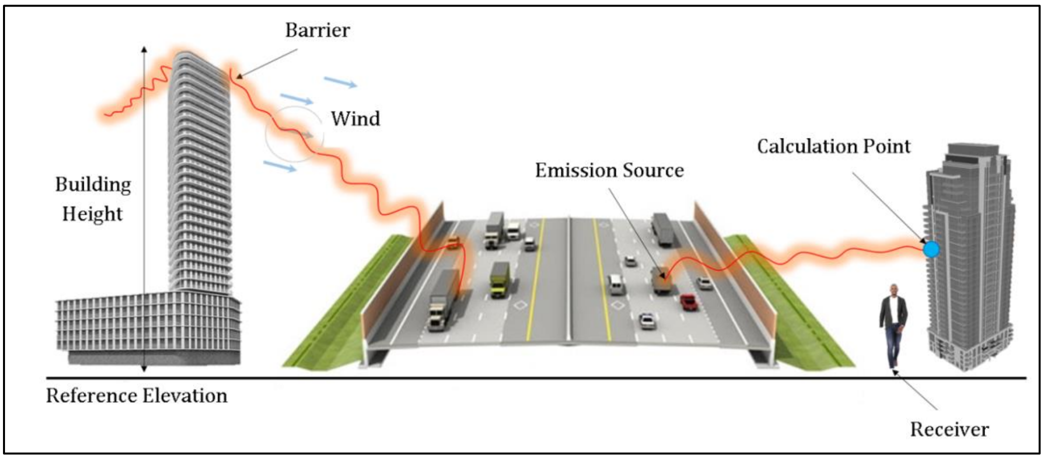

Figure 3.33 Traffic noise propagation from a source point to a calculation point.

In many countries, local conditions such as vehicle types and weather conditions cause a difference in traffic noise levels generated by vehicles. Therefore, it is suggested that for each region, a specific noise propagation model is developed. By considering the natural, physical, and traffic characteristics of the chosen site and reviewing the previous models and having interviews with experts in the areas of traffic noise, the following model was developed.

$$L_{Aeq} = E + C_{rg} - C_b - C_d - C_{air} - C_w$$

Where, L_{Aeq} is the average equivalent noise at calculation point, E is the noise emission of vehicles calculated for a specific time, C_{rg} is the road geometry coefficient (road gradient), C_b is the barrier coefficient, C_d is the distance coefficient, $C_{a\,i\,r}$ is the air interaction coefficient, and C_w is the weather coefficient.

The road geometry coefficient accounts for road design elements, which have effects on the noise level emitted from vehicles due to acceleration and breaking due to different road geometry. The DSM derived from laser scanning data allowed modeling road geometry with centimetre precisions. The information extracted from the road geometric model is used to estimate the road geometry factor. In addition, the barrier coefficient is essential for correcting the noise levels due to effects of barriers such as tall buildings. This coefficient is estimated in GIS using the spatial analysis tools, which compare the noise source, the roadway and the neighbour buildings with their heights calculated from laser scanning data. The concept of GIS spatial analysis for calculating the road geometry and barrier coefficients are illustrated in (Figure 3.34).

Initially, the study area is divided into regular grids of size 3 m × 3 m× 3 m. Then, the centroid of the generated grid polygons is compared with the noise samples and the roadway using near distance function of GIS. This feature calculates the nearest distance between the centroid of grid polygons and other features and links the attributes of the features in a single table. This information is then utilized to calculate the road geometry and barrier coefficients, which is based on the distance and the elevation information for the road geometry coefficient and building height for the fence factor.

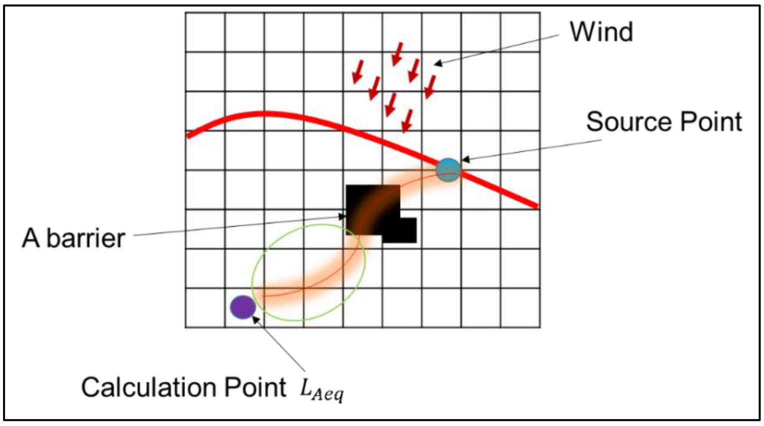

Figure 3.34 The core concept of GIS analysis for calculating the road geometry and barrier coefficients.

The distance coefficient is due to the reduction of the noise depending on distance and is calculated using the following formula (Ranjbar et al., 2012):

$$C_d = 10\log(r) \tag{8}$$

Where, r is the shortest distance between the road and the calculation point (in meters).

The air coefficient (C_{ai}) accounts for the reduction of noise due to absorption in the air calculated as follows:

$$C_{air} = 0.01 \times r^{0.9} \tag{9}$$

Then, the noise propagation model accounts for weather effects such as wind direction using the weather coefficient (C_w) which is calculated using the following expression:

$$C_w = 3.5 - 3.5e^{\frac{-0.04\,r}{(h_{weg} + h_w + 0.75)}} \tag{10}$$

Where, h_{weg} is the height of the road in reference to the ground level next to the road (in meters) and h_w is the height of the calculation point in reference to the ground level at the calculation point also in meters.

Finally, elevation is the last factor used to predict traffic noise levels. In many sound models used in mountainous regions, the actual elevation has an effect on how the sound is propagated. In the same way that the landcover data was used to modify the sound levels based on distance from the source, the DEM modified the previously calculated sound levels. In order to do this, the DEM was reclassified to a -10 to 10 scale, with the lowest elevation having a 10 value and the highest elevation having a -10 value (Reed et al, 2010). These values were used as percentage gain or percentage loss based on whether or not the location had a high elevation, which would tend to reduce the amount of sound carried from the Interstate, or a low elevation, which would tend to pool the sound. The reclassified DEM was used to predict how the sound moves over higher elevations and through lower elevations. Using the sound level raster developed and the initial sound level raster based solely on distance from the source, the new sound level was calculated using the percentage gained and lost using the following formula:

$$LFinal = Llc + (Lp * (Elevation\ Value / 100)) \tag{11}$$

Where, $LFinal$ is the models final output sound level in decibels, Llc is the sound level raster after adjusting for landcover, Lp is the sound level raster based solely on distance and Elevation value is the adjusted elevation raster with values from -10 to 10.

3.7 Model Evaluation

The performance of the three models was ascertained by calculating three performance measures: correlation (R), correlation coefficient (R2) and root mean square error (RMSE), in the knowledge that this would give estimates of Leq. To evaluate the predictive performance of the models, four performance measures were used. These performance measures indicate the accuracy of model's predictions by comparing the actual parameter's value (a_i), predicted value (b_i) and number of sample data points (n) and others such as average of all observed values ($\bar{a}$) and average of all predicted values ($\bar{b}$) which could be useful when comparing different models.

First, equation (12) describes the correlation between the two data sets used to calculate linear relationship. The value of R lies between -1 and +1. Second, equation (13) was used to calculate the coefficient of determination and the result value of R^2 lies between -1 and +1. Finally, the equation (14) used to calculate the RMSE to evaluate the average performance of the model across different testing samples.

$$R = \frac{\sum_{i=1}^{n}(a_i - \bar{a})(b_i - \bar{b})}{\sqrt{\sum_{i=1}^{n}(a_i - \bar{a})^2 \sum_{i=1}^{n}(b_i - \bar{b})^2}} \tag{12}$$

$$R^2 = (R)^2 \tag{13}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(|b\,i - a\,i|)^2}{n}} \tag{14}$$

3.8 Mobile Application

In this study, ArcGIS online platform service would be used for this application. This approach would enable map service to be easily made available on website using ArcGIS.

The map was developed in ArcMap and was published on ArcGIS Server site. Internet or intranet users can easily use the map service in web applications, ArcGIS for Desktop, ArcGIS Online, and other client applications. Furthermore, a map service makes maps, features and attribute data available in many types of client applications. A common example is the use of map service to show data on top of base map tiles from ArcGIS Online, Bing Maps or Google Maps. In addition, there are many benefits of using map services such as dynamic maps, dynamic layers, cached maps, features, and network analysis functions, maps through KML and maps for mobile devices.

As well as we used android studio to publish the application on the Google play as the figure 3.35 which shows the android studio software was used to build the application 2D & 3D Noise Maps of ArcGIS. Android Studio is the official integrated development environment for Google's Android operating system, built on JetBrains' IntelliJ IDEA software and designed specifically for Android development. Whereas android Studio provides a unified environment where you can build apps for Android phones, tablets, Android Wear, Android TV, and Android Auto. Structured code modules allow you to divide your project into units of functionality that one can independently build, test, and debug.

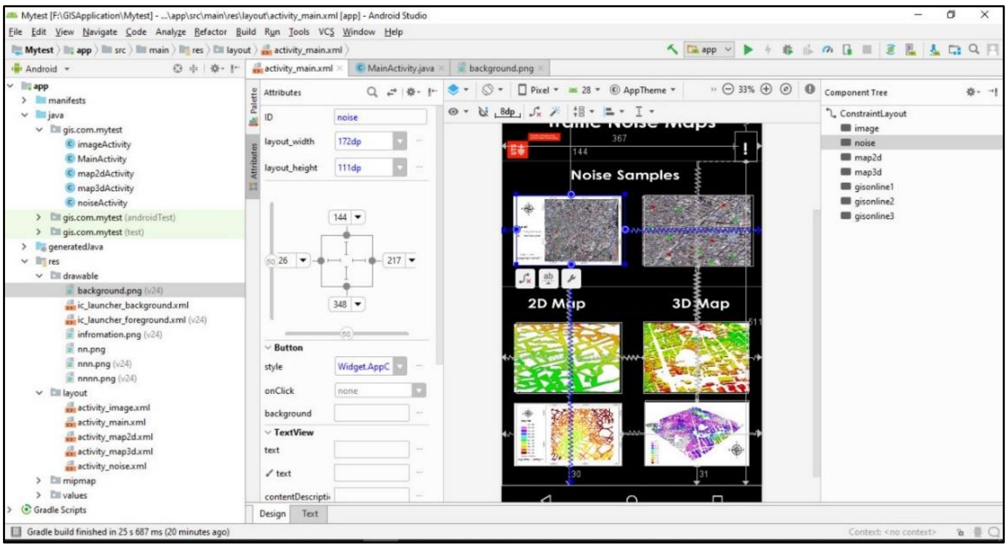

Figure 3.35 Shows the android studio software which was used to build the application 2D & 3D noise maps of ArcGIS.

3.9 Summary

This chapter describes the study area which was carried out in Kirkuk city, Iraq and New Klang Valley Expressway (NKVE) located in Selangor, Malaysia. Also, describes the data collection for traffic noise calculation and modelling through three types (traffic noise, traffic flow and information regarding the road and surrounding buildings) of basic data required.

Various pre-processing steps and data preparation are used to improve the prediction and propagation models are LiDAR data, Worldview-3 image, QuickBird image, landuse mapping, Worldview-3 orthorectification, method of measurement of the noise and traffic data collection and field survey. Land use regression prediction model was carried out based on machine learning such as ANN, RF and SVM. The proposed model is combined 2D and 3D noise models to produce 3D noise map for the capital of the study area which is considered this is the novelty of this research. As well as this research used mathematical model based on the 2d model to produce 3D noise maps for the city. The main goal of a noise prediction model is to estimate the noise level at a given location and within a period of time and the landuse parameters was used in this step to develop this model. Secondly, the proposed network architecture for traffic noise prediction was designed based on the results of network structure and hyperparameter optimization. Four, optimization procedure was used to explained the structures and hyperparameters which are evaluated in the current study and their search space domain. The developed noise propagation model was carried out by collecting traffic noise data especially on high-speed highways and calculate the noise level on each point of area, then we used the developed equation to produce 3d noise map for the area based on the noise level on from road traffic noise.

Chapter Four
RESULTS AND DISCUSSION

4.1 Introduction

This chapter presents the results obtained in this research which includes results of Worldview-3 image orthorectification, result of 2D and 3D in Kirkuk city, result of 2D land use regression model, result of optimized deep neural network algorithm for vehicular traffic, result of noise propagation and prediction in Malaysia, result of mobile application and summary. The result is carefully evaluated and discussed appropriately in each sub-heading as follows:

4.2 Results Worldview-3 Image Orthorectification

4.2.1 Worldview-3 Image Orthorectification Based GCPs and DSM

Using the above-referenced method and most of them based on Grodecki et al 2001; Hu et al, 2002; Nichol et al, 207. Worldview-3 image was orthorectified to the final orthoimage. The results are presented as nine results with different accuracies based on DSM resolution and GCPs as shown in figure 4.1.

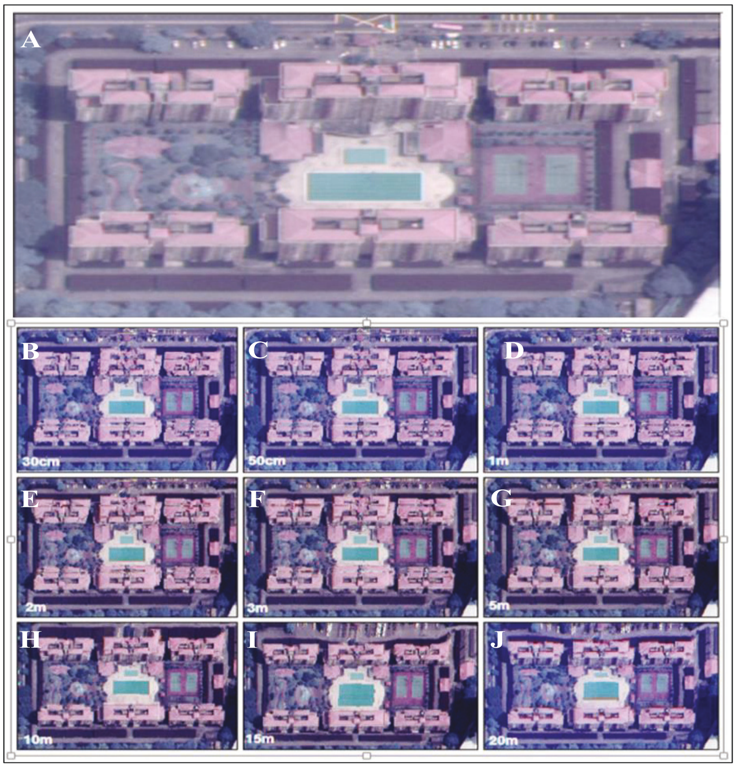

Figure 4.1 (A) Shows the image before orthorectification and (B- J) shows the image after orthorectification process whereas the results based on different spatial resolution DSM.

4.2.2 Accuracy assessment

Table 4.1 presents the reports of minimum, maximum and the root mean square error of orthorectified images based on different DSM resolution with respect to the GCPs. The horizontal accuracy of the orthorectified images are evaluated based on RMSE error value obtained from computing changes in coordinates object at very-high resolution DEM 31 cm to the coordinates object in the orthoimage result. Equations 15 [13] are used to determine the RMSE for X and Y coordinates and RMSE horizontal (X, Y) respectively.

$$RMSE=\sqrt{\frac{\sum_{i=1}^{n}(|\text{x inpu t} - \text{x cont rol}|)^2 + (|\text{y inpu t} - \text{y cont rol}|)^2}{n}} \quad (15)$$

X, Y input represents the coordinate of the ortho-image worldview-3 and X control, Y control are the coordinates of the intensity of the DEM 31cm reference points. The parameters n and i represent the checkpoints tested for an integer between (1 to n) respectively. Based on the results shown in table 4.1, the RMSE was observed to be 0.638 at DSM value of 31 cm, this value increased to 0.764 When the DSM resolution increased to 50 cm. Also, a consistent increase in RMSE values was observed between DSM 1 to 20 m resolution yielding RMSE values from 1.302 to 7.175. It was observed that experimental results consistently yield the most accurate values for validation of the GCPs of the orthoimage based on 30 cm DSM in orthoimages. This result proved that the accuracy of the orthoimages has been improved significantly based on the DSM data.

Table 4.1 Summary of residual errors of GCPs for orthoimages (unit: meter)

Warp image and DSM	Orthorectified image	RMSE
Worldview-3 and DSM 31cm	a1	0.638
Worldview-3 and DSM 50cm	a2	0.764

Worldview-3 and DSM 1m	a3	1.302
Worldview-3 and DSM 2m	a4	1.718
Worldview-3 and DSM 3m	a5	2.106
Worldview-3 and DSM 5m	a6	3.26
Worldview-3 and DSM 10m	a7	5.529
Worldview-3 and DSM 15m	a8	6.501
Worldview-3 and DSM 20m	a9	7.175
Worldview-3 and free DEM 30m	a10	7.947

The RPCs orthorectification model was applied on the Worldview-3 image based on the free source DEM 30 m (SRTM). The result obtained indicated the highest RMSE value of 7.947 compared to the orthoimage, which was obtained from high-resolution (DSM) 31 cm. The comparison indicates that significant difference between the DSM (31) cm and the DEM (SRTM) 30 m results indicating a unique relationship between the DEM or DSM accuracy and the orthorectification accuracy as shown in table 4.2.

Table 4.2 Summary of residual errors of GCPs for orthoimages based DEM 30m

Warp image and DSM	**Orthorectified image**	**RMSE**
Worldview-3 and DSM 31cm	a1	0.638
Worldview-3 and free DEM 30m	a10	7.947

4.2.3 Discussion

According to the results obtained, the final optimal DSM of the orthorectification process was 31 cm resolution which showed the least RMSE value. The high-resolution DSM and GCPs derived from high resolution DEM were combined together in the proposed model (RPCs orthorectification model) to reduce the root-mean-square-error of the orthorectification of the final result to 0.638 m compared with the 1.07 m achieved by Zhang et al. (2011) who developed a model based on a combination of Rational Polynomial Coefficients (RPCs) with Spline Function Model and using DEM SRTM 30 m. The orthorectification model was applied different times to produce various orthoimages. Each orthoimage has different horizontal distortion and buildings lean effects. So, increasing the DSM resolution result to increase in the accuracy level of the orthoimages result while the distortion and buildings lean effects were decreased as shown in figure 4.2.

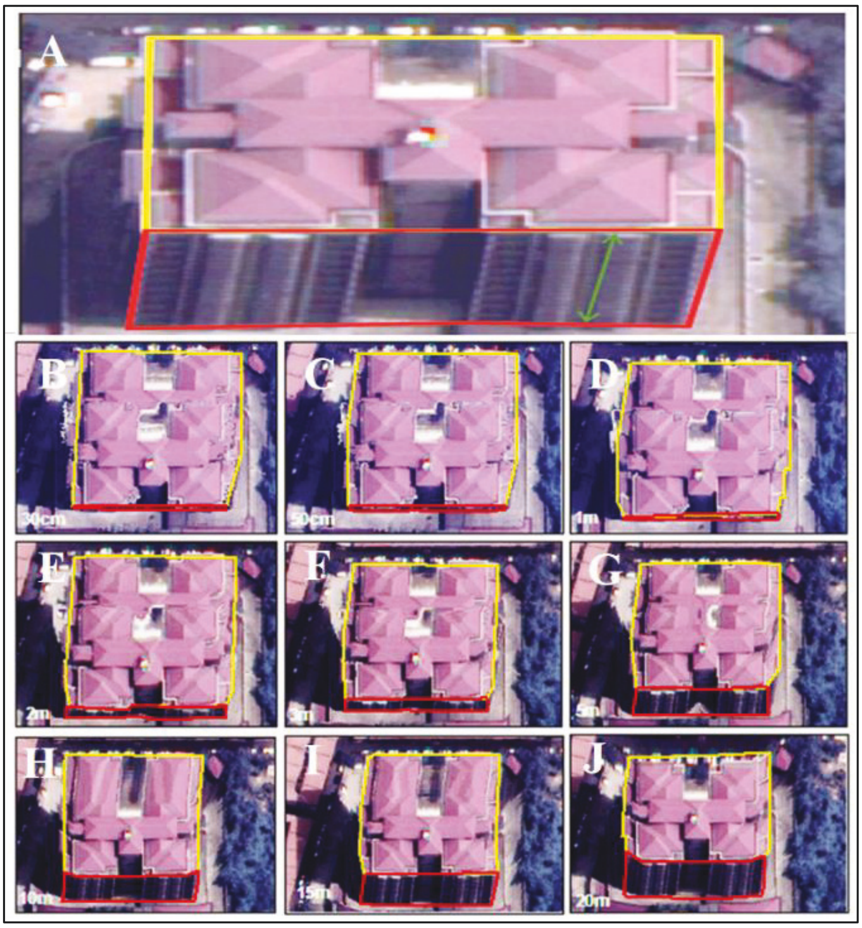

Figure 4.2 (A) Shows the image before orthorectification and (B- J) shows the image after orthorectification process whereas the results based on different spatial resolution DSM.

According to the final results, a significant relationship is observed between buildings lean and the accuracy of the DSM. The original building lean was 13.65 which was decreased to 11.46 after applying the orthorectification to the building at DSM 20 m. figure 4.3 shows the details of the results obtained after the orthorectification.

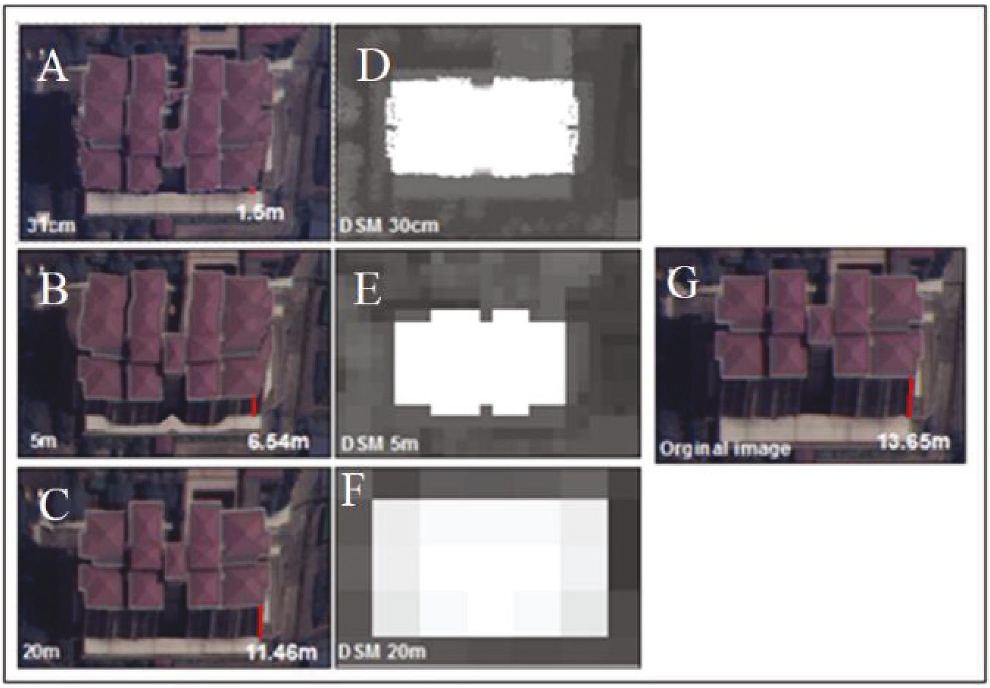

Figure 4.3 (A-F) Shows the relation between DSM resolution and leaning of building and (G) shows the image before orthorectification process.

Therefore, it is absolutely necessary to develop an approach for presenting table-based ranking comparing with the accuracy obtained from the orthorectification process for the same image and GCP with different DSM resolution. This approach would make available clearer Information for future analysis and development. In this study, LiDAR point clouds with very high spatial resolution were used to produce a very high-resolution DEM. Till date, no available criterion have been provided on the best DEM data to be employed in this regard. A better result for image orthorectification could be achieved if DEM data of high spatial resolution are available for orthorectifying images. Increase in the DSM resolution indicated decrease error of horizontal distortion of high buildings (>30m). For instance, when the building height is (100m - 120m), the horizontal distortion is measured and are shown in table 4.3.

Table 4.3 Sample of horizontal distortion in buildings with height between (91m-120m).

Type of DSM	Horizontal distortion
The original image before	13.5 - 14.5

orthorectification	
DSM 30cm	1.31 - 1.4
DSM 50cm	1.41 - 1.6
DSM 1m	2.51 - 3.00
DSM 2m	3.51 - 4.00
DSM 3m	5.01 - 5.8
DSM 5m	8.01 - 10.00
DSM 10m	9.41 - 11.30
DSM 15m	10.61 - 12.20
DSM 20m	10.81 - 12.40

4.2.4 Summary

In this study, LiDAR-derived GCPs and different resolution DSM (31 cm, 50 cm, 1m, 2m, 3m, 5 m, 10 m, 15 m, 20 m) is proposed for image orthorectification. LiDAR data are used to obtain high ability GCPs and DSM at a higher level of accuracy required for photogrammetric and orthorectification. The final image demonstrated the advantage of using LiDAR-based GCPs with high-resolution DSM to produce high-quality ortho-images with an accuracy of 0.638 m. The accuracy of the orthorectified image was improved by increasing GCPs more than the usual number. The comparison between final results indicates that the optimal orthoimage is selected based on the best accuracy in the final results which depends on the optimal images. Also, it was observed that the optimal DSM used in orthorectification process with WV-3 image was DSM resolution (31) cm. on the other hand, the orthorectification applied on WV-three (3) multispectral image resolution one (1) m, the optimal DSM was one (1) m. Furthermore, the correlation between the horizontal distortion and the resolution of DSM was identified. It was observed that an increase in accuracy leads to a decrease in the horizontal distortion. The development of advanced remote sensing data makes it possible to generate GCPs and would be useful in the event of limited access to field survey. The orthorectified images increase the quality of land use and land cover used in many fields. Therefore, it is hoped that the proposed methodology would go a long way in providing a very useful tool to aid decision makers in selecting the best LiDAR for orthorectification.

4.3 Results of 2D and 3D Noise Models in the Kirkuk City

4.3.1 The Proposed Artificial Neural Network Architecture (ANN)

Figures 4.4 and 4.5 show the proposed network architecture designed for 2D and 3D noise prediction, receptively with about 500 networks training of different combination and parameters (Ahmed et al, 2021). The output of the ANNs models is defined by average equivalent continuous noise level (dB) L_{eq20}. These designed is based on the results of network structure and optimized hyperparameters presented in chapter three. According to the result of 2D noise prediction, the best validation was achieved by a network of eight (8) input parameters and 18 hidden layers. Also, the best trained of network was with BFGS algorithms, while the best hidden and output activation was used Identity. Furthermore, the best gradient momentum and learning rate obtained are 0.3. All the hyperparameters of the ANN model were used for the traffic noise prediction together with their search space for fine-tuning. The ANN training model was achieved at 0.003 for root mean square error (RMSE) and 1.00 for correlation (R), correlation coefficient (R2). While ANN testing model, 7.14, 0.87 and 0.75 were recorded for RMSE, R and R2 of the traffic noise prediction respectively in the study area. On the other hand, the result of 3D noise prediction of 22 input parameters and 11 hidden layers was the best validation. While the best trained of network and the best hidden and output activation were RBFT algorithms and logistic respectively. And also, the best gradient momentum and learning rate are 0.3. This network of 3D noise perfection models was achieved at 0.058 for root mean square error (RMSE) and 1.00 for correlation (R), correlation coefficient (R2), while testing model were recorded 4.46, 0.82 and 0.68 for RMSE, R and R2 of the traffic noise prediction respectively.

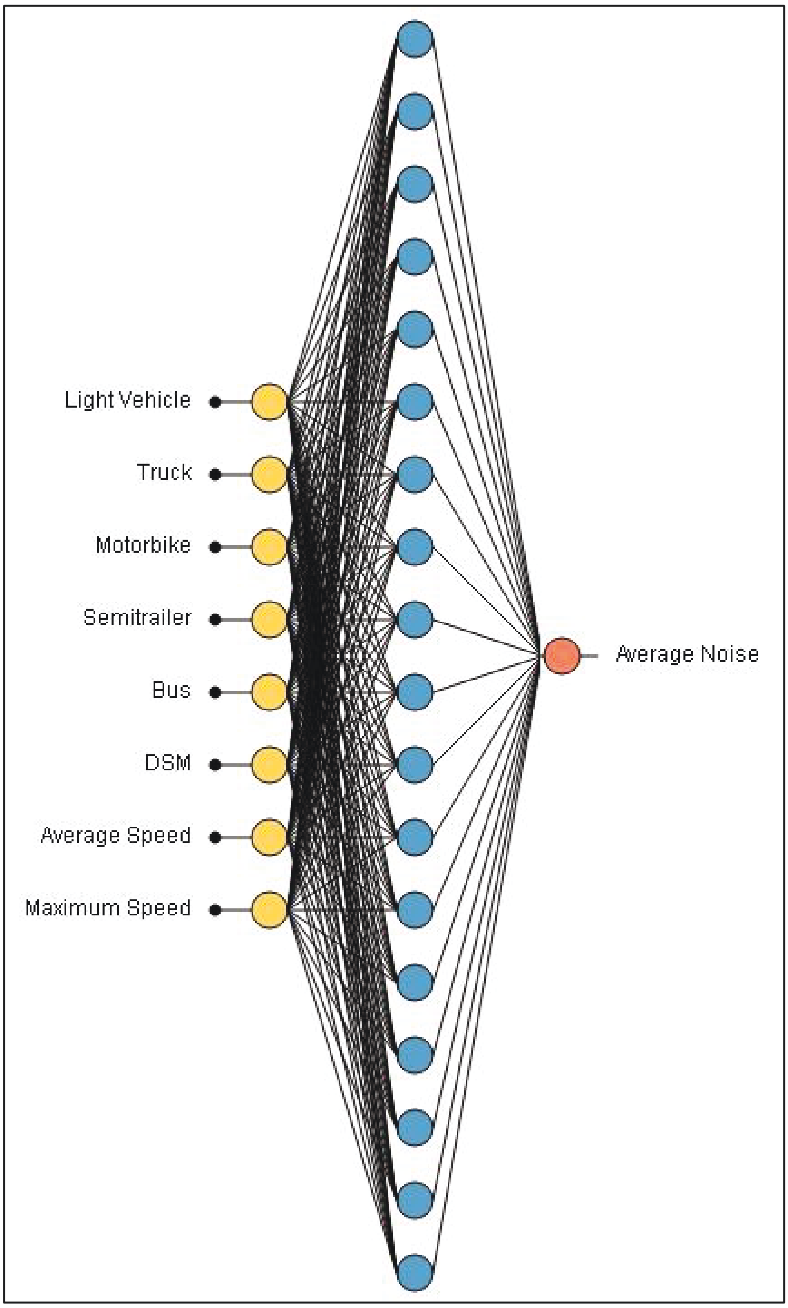

Figure 4.4 Shows the architecture of artificial neural network of 2D traffic noise prediction (8-18-1).

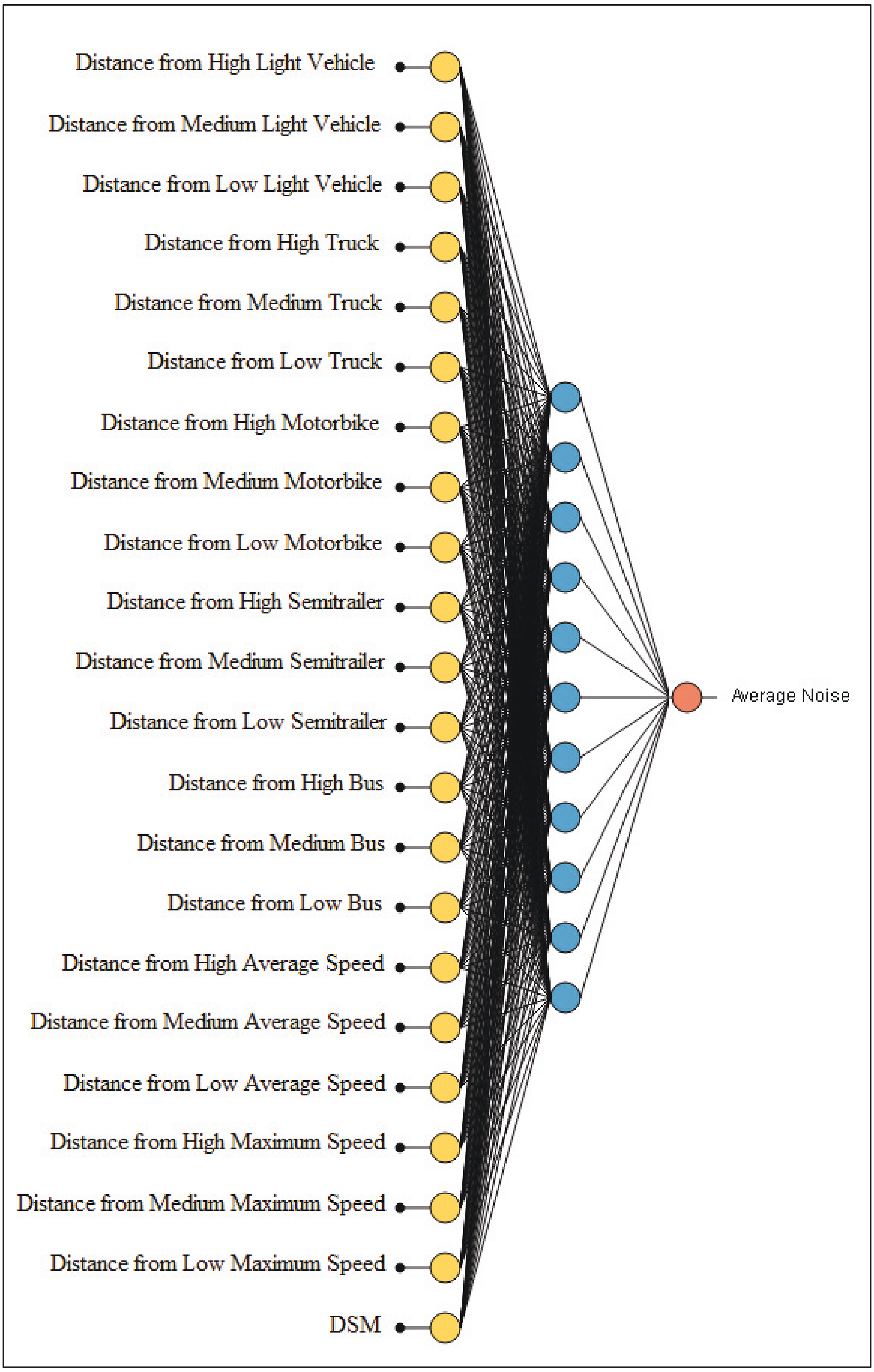

Figure 4.5 Architecture of artificial neural network of 3D traffic noise prediction (22-11-1).

4.3.2 Sensitivity Analysis

There are several parameters, which affect the accuracy of the proposed ANNs models for 2D and 3D traffic noise prediction. Those parameters include some hidden units in the hidden layer, learning rate, gradient momentum, and activation function of the hidden and the output layers. First, figure 4.6 shows the number of hidden units with root mean square error (RMSE) for 2D and 3D traffic noise prediction. This figure shows that the best number of hidden units is 18 with RMSE = 0.003 for 2D noise model and shows the best hidden unit is 11 with RMSE = 0.058 for 3D noise model. This figure was observed that RMSE is increasing gradually after hidden units 18 with increase in hidden number units in 2D noise model, while the RMSE at 3D model was higher when the hidden units is less 11 and bigger 22.

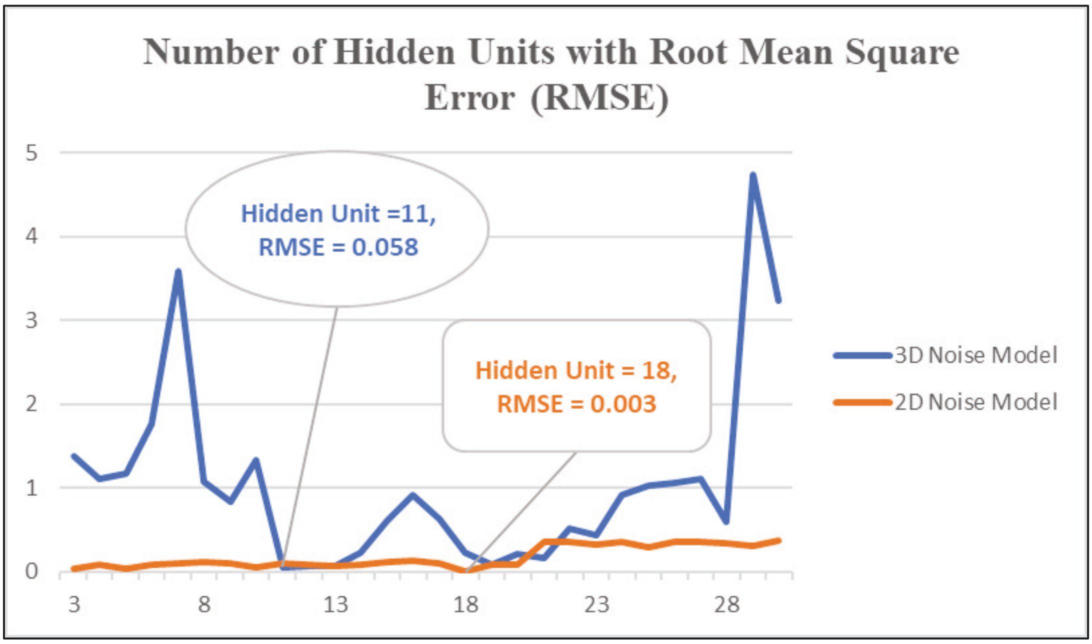

Figure 4.6 Shows the number of hidden units with RMSE for 2D and 3D noise model prediction.

According to the table 4.4, the hidden and output activation of ANN model training is observed the identity algorithm with RMSE of 0.003 for 2D noise model and RMSE of 3D noise model was 0.058 with logistic algorithm.

Table 4.4 Show the hidden and output activation hyperparameters of the proposed model for 2D and 3D noise model.

Model	Hyperparameter	Identity	Logistic	Tanh	Exponential	Gaussian
2D Noise Model	Hidden and Output Activation	0.003	0.0248	0.1892	2.0043	0.2373
3D Noise Model		0.0805	0.058	0.3584	1.2066	0.1166

While training algorithm of 2D and 3D noise models were observed BFGS and RBFT algorithm for 2D and 3D noise model, respectively. Whereas RMSE of BFGS algorithm was observed (0.003 and 2.6287) for 2D and 3D noise model, respectively, while RBFT algorithm was observed (0.058 and 0.1746) for 2D and 3D noise model, respectively. So, BFGS algorithm is better than RBFT at 2D noise model, while was opposite RBFT algorithm is better than BFGS algorithm for at 3D noise model.

On other hand, the effects of the learning rate and the gradient momentum of the optimization algorithm on the performance of ANN models were also investigated (figures 4.7), which is showing the learning rate and the gradient momentum with root mean square error (RMSE). This figure shows the best learning rate and gradient momentum were 0.3 in 2D and 3D noise models, whereas RMSE was 0.003 and 0.058 for 2d and 3D noise model respectively. RMSE were significantly decreased at the learning rate between 0.01 – 0.5. While RMSE was gradually decreased with increase the gradient momentum and learning rate. Gradient momentum is vital if local minima stuck is to be avoided. In general, large values of momentum enable fast convergence, while small values cannot reliably avoid local minima which slow down training of a system.

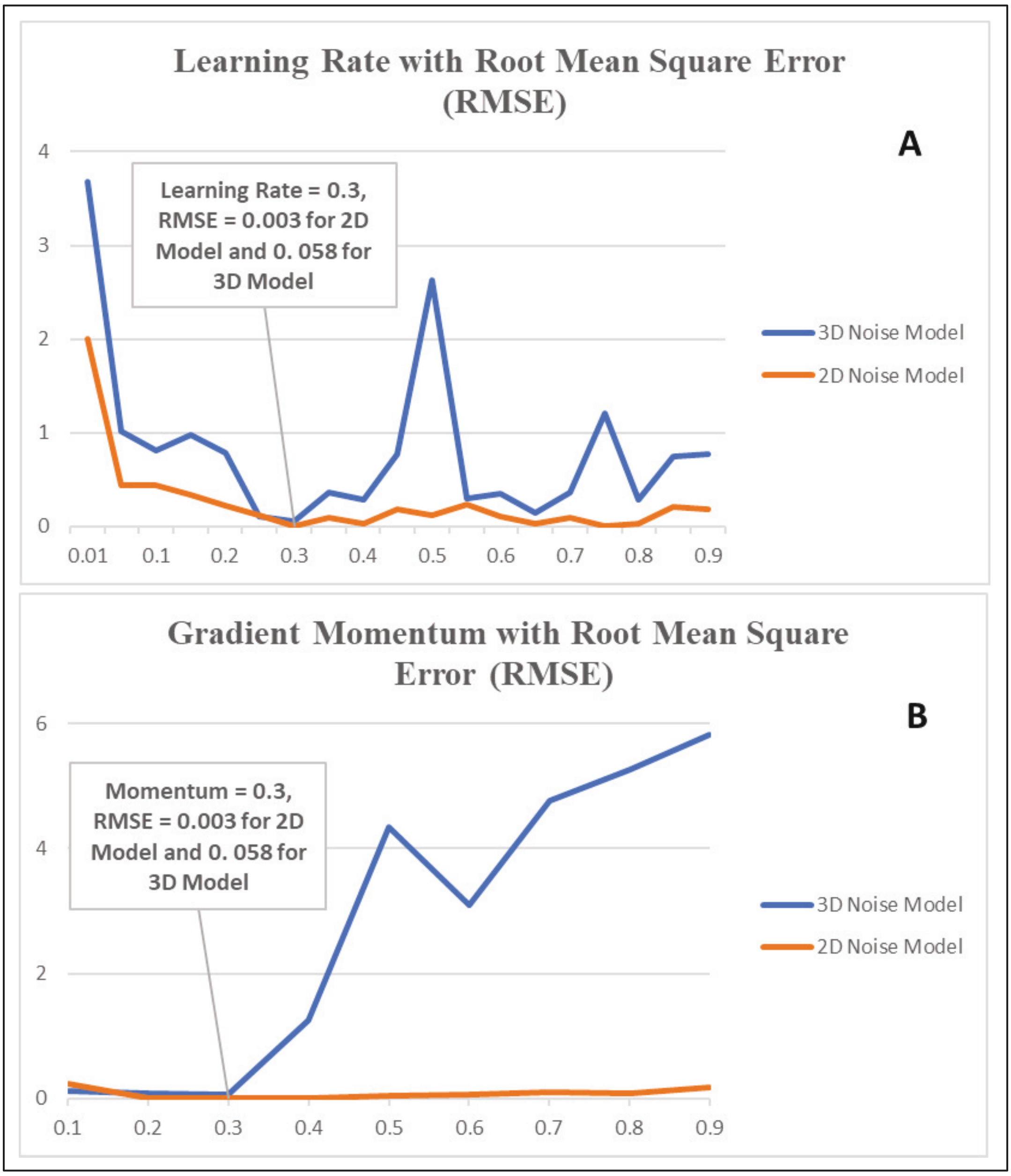

Figure 4.7 Shows the learning rate and the gradient momentum with RMSE for 2D and 3D noise model prediction.

4.3.3 Comparison ANN Proposed Model with other Models

The proposed model (ANN) was compared with other popular models such as random forest (RF) and support vector machine (SVM). The ANN supersede the performance of the other models through as shown in table 4.5. This can be seen in R, R^2 and RMSE in the training and testing data. Also, figures 4.8 and 4.9 were shown the correlation between observed and predicted traffic noise of ANN, RF and SVM models for training and testing for 2D and 3D noise model.

Statistically, for 2D noise model, the correlation (R) and the correlation coefficient (R^2) of 1.00 were achieved, the RMSE (0.003) for training, while for the testing, R, R^2 and RMSE were 0.87, 0.75 and 7.14, respectively for ANN model. While the lower model is SVM model, which was achieved R (0.85), R^2 (0.72) and RMSE (3.6) for training model, while testing model was achieved R (0.81), R2 (0.65) and RMSE (10.34). Finally, RF model was achieved R (0.98), R2 (0.97) and RMSE (1.82) and R (0.82), R2 (0.68) and RMSE (9.83) for training and testing model, respectively.

For 3D noise model, the correlation (R) and the correlation coefficient (R2) of 1.00 were achieved, the RMSE (0.058) for training, while for the testing, R, R2 and RMSE were 0.82, 0.68 and 4.46, respectively for ANN model. Also, the lower model is SVM model which was achieved R (0.98), R2 (0.96) and RMSE (6.16) for training model, while testing model was achieved R (0.77), R2 (0.60) and RMSE (4.75). Finally, RF model was achieved R (0.98), R2 (0.96) and RMSE (6.00) and R (0.80), R2 (0.64) and RMSE (4.50) for training and testing model, respectively. So, from 2D and 3D noise model were found the best model is ANN, and RF is better than SVM.

Table 4.5 Shows the performance of models such as ANN, SVM and RF for 2D and 3D noise models.

Model	Type of Model	Training (R)	Testing (R)	Training (R^2)	Testing (R^2)	Training (RMSE)	Testing (RMSE)
2D Noise Model	ANN	1.00	0.87	1.00	0.75	0.003	7.14
	SVM	0.85	0.81	0.72	0.65	3.60	10.34
	RF	0.98	0.82	0.97	0.68	1.82	9.83
3D Noise Model	ANN	1.00	0.82	1.00	0.68	0.058	4.46
	SVM	0.98	0.77	0.96	0.60	6.16	4.75
	RF	0.98	0.80	0.96	0.64	6.00	4.50

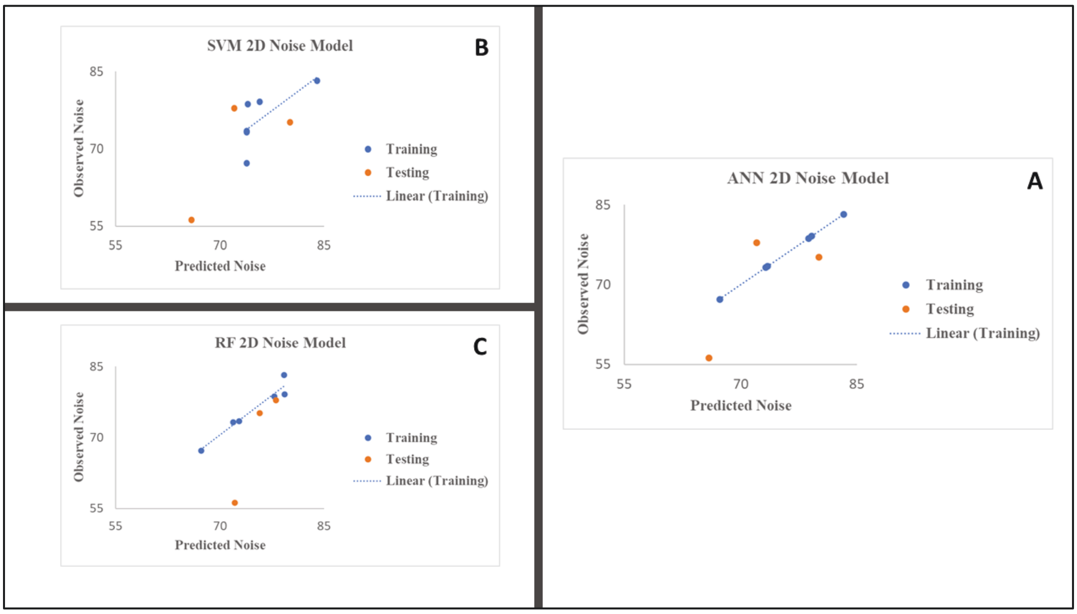

Figure 4.8 Shows correlation between observed and predicted traffic noise of 2D noise models (ANN, SVM and RF) prediction for training and testing.

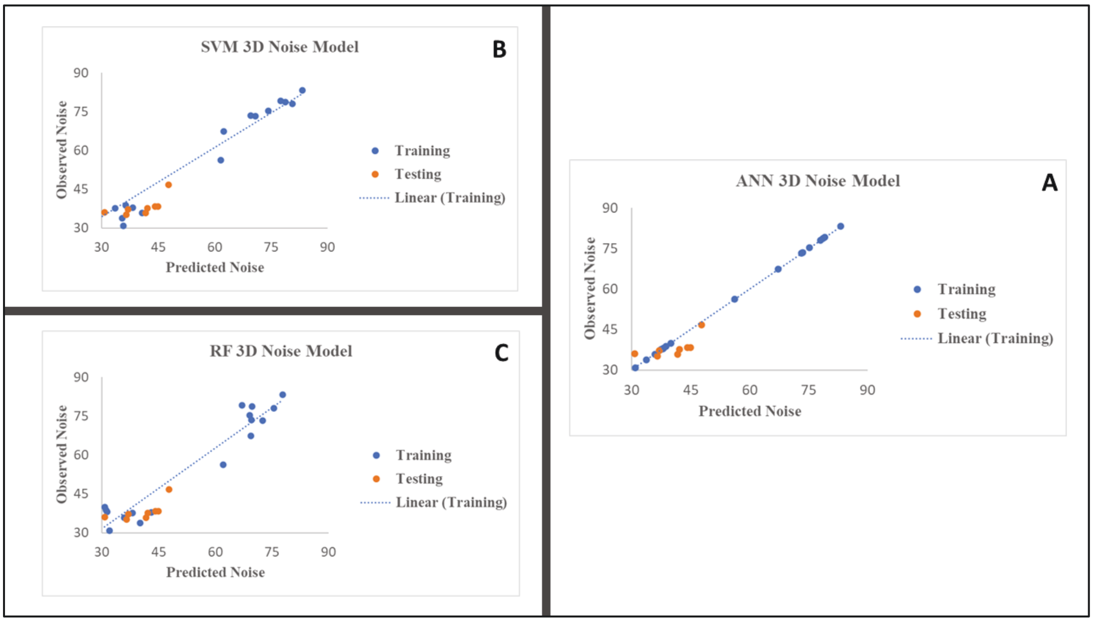

Figure 4.9 Shows correlation between observed and predicted traffic noise of 3D noise models (ANN, SVM and RF) prediction for training and testing.

4.3.4 2D and 3D Traffic Noise Prediction Maps

Noise distribution maps for the study area were generated using the proposed noise model in GIS. The output of the model is a continuous noise level accounting for the field conditions and other factors such as topography. In this research, the noise and traffic volume were measured at different periods time, morning, afternoon, of weekdays. Figures 4.10 shows 2D noise prediction for roads at the study area, while figures 4.11 and 4.12 shows 3D noise prediction for building at the study area. While the figure 4.13 shows noise prediction for whole the study area through combined the noise 2D noise maps with 3D noise map. However, this section presents only the recommended maps for planning purposes. It was discovered that the road is characterized by high traffic noise level in the morning, afternoon hours. The following figures show the proposed noise distribution maps (average traffic noise level) of the study area for weekday in the morning, afternoon.

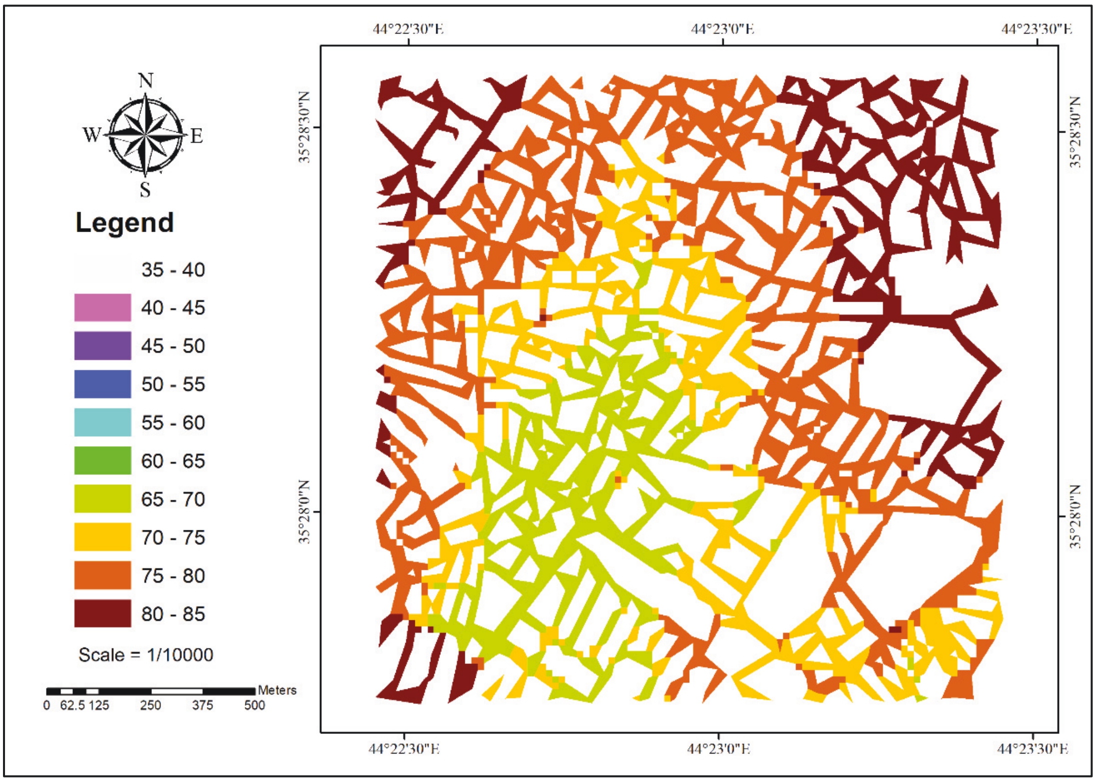

Figure 4.10 Shows 2D average noise prediction map for roads at the study area from 2D ANN noise model.

Figure 4.11 Shows 3D average noise prediction map for building at the study area from the 3D noise model.

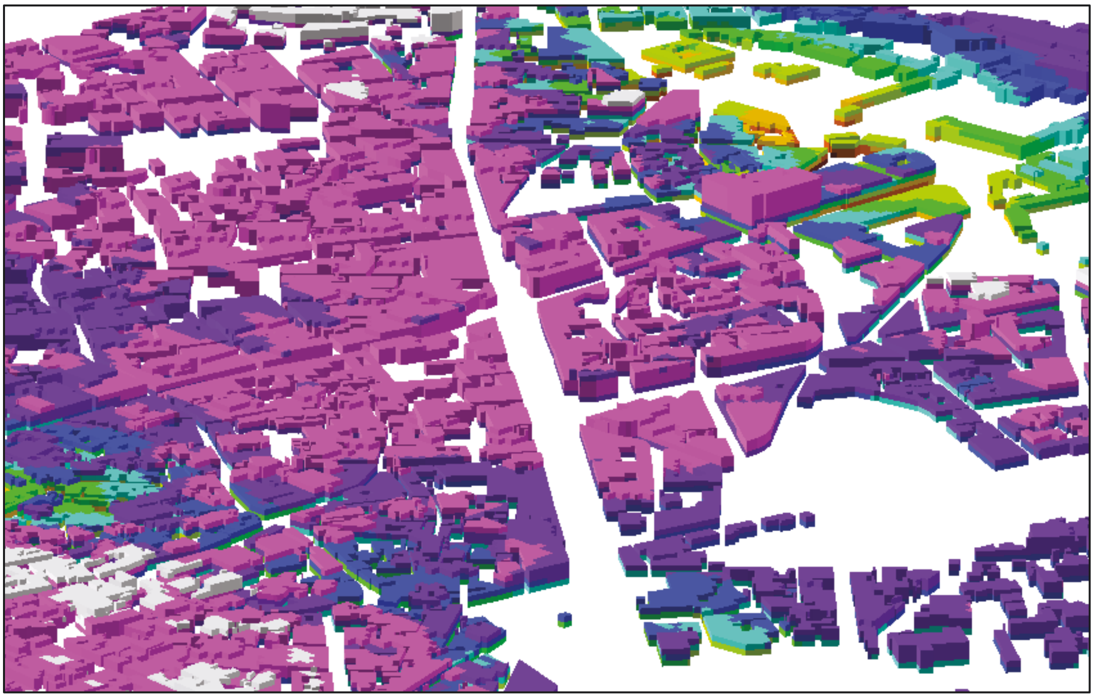

Figure 4.12 Shows average noise prediction map for building at the study area from the 3D noise model for part of study area.

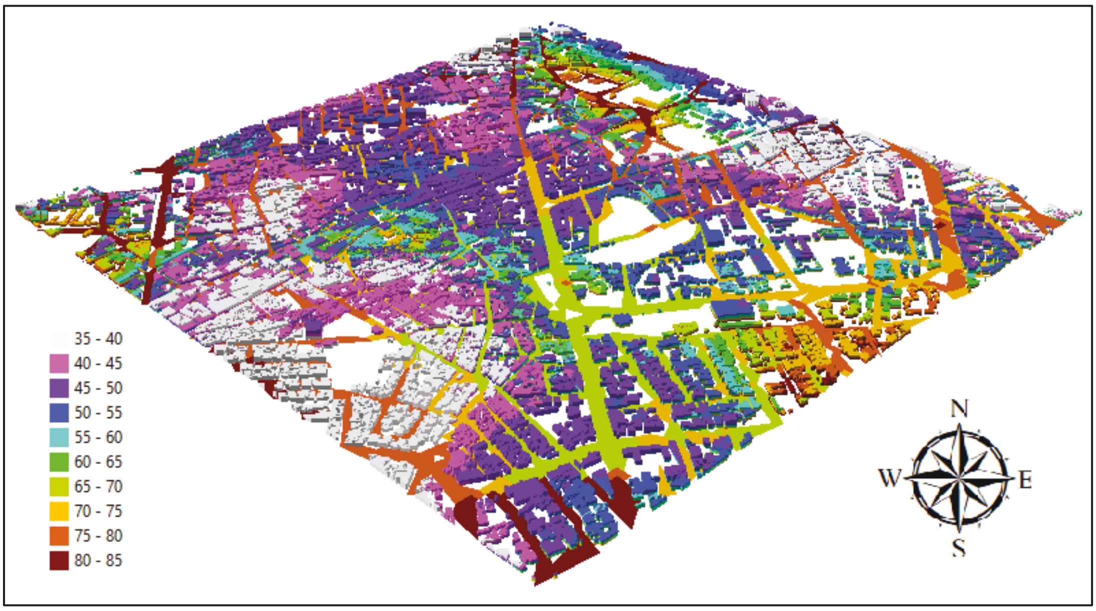

Figure 4.13 Shows average noise prediction map for roads and building at the study area through combined 2D and 3D model maps.

4.3.5 Summary

Vehicular emissions such as traffic noise are one of the major sources of environmental pollution in urban areas (Law et al, 2011; Kurakula et al, 2008; Duan et al, 2016), where road networks, and traffic flow are present. Traffic noise prediction models and spatial models are used to assess the impacts of vehicular emissions from different types of vehicles on human health and the environment (Alam et al, 2020; Zhao et al, 2017). In this study, was presented how noise impact studies and improving visualization of noise impact through using basic 2D and 3D GIS functionalities and to increase accuracy of noise impact assessment studies through build two models 2D noise model for roads and 3D noise model for buildings through using less noise samples. And then, combined 2D and 3D noise models to produce 3D noise map for the capital of the study area which is considered this is the novelty of this research. The prosed 2D model noise prediction was achieved 0.003 for root mean square error (RMSE) and 1.00 for correlation (R), correlation coefficient (R2), while testing model, 7.14, 0.87 and 0.75 were recorded for RMSE, R and R2 of the traffic noise prediction respectively in the study area. Either in the prosed model 3D noise prediction was achieved 0.058 for root mean square error (RMSE) and 1.00 for correlation (R), correlation coefficient (R2), while testing model were recorded 4.46, 0.82 and 0.68 for RMSE, R and R2 of the traffic noise prediction respectively. And the best architecture of 2D artificial neural network noise prediction model was achieved by a network of eight (8) input parameters, 18 hidden layers, BFGS algorithm of trained of network, identity algorithm of hidden and output activation, and 0.3 of gradient momentum and learning rate. While the best architecture of 3D artificial neural network noise prediction model was achieved by a network of 22 input parameters, 11 hidden layers, RBFT algorithm of trained of network, logistic algorithm of hidden and output activation, and 0.3 of gradient momentum and learning rate. Moreover, we found the best model is ANN, and random forest (RF) is better than support vector machine (SVM) though RMSE of RF is less than RMSE of SVM, whereas RMSE of RF model was (1.82, 6.00) and (9.83, 4.50) for training and testing 2D and 3D model, respectively, while RMSE of SVM model was (3.60, 6.16) and (10.34, 4.75) for training and testing 2D and 3D model respectively. The GIS modelling was applied to improve visualization of 2D, and 3D noise maps and these maps were the average traffic noise level of the study area for weekday in the morning and afternoon.

4.4 Result of 2D Land Use Regression Model

4.4.1 Contribution of Noise Predictors

One of the findings of the study was that the traffic noise predictors actually contribute to the noise values gathered. To explain, by using the Chi-square method as part of our statistical analysis, we found that the multicollinearity of primary road and bus stop parameters amounted to 9.15 and 8.96. The reason, these noise predictors (primary road and bus stop) were important and crucial for prediction noise map. The findings also showed how the traffic volume, road types (expressway, primary and secondary), public transport, land use (industrial, residential and tree), DSM and WS all had a significant impact on prediction noise levels. Table 4.6 describes this further.

Table 4.6 Results of assessing the contribution of noise predictors using the Chi-square method.

Noise Predictor	Multiple R-Square	VIF
Traffic volume	0.64	2.78
All type of roads	0.25	1.33
Expressway	0.82	5.64
Primary road	0.89	9.15
Secondary road	0.37	1.59

Area of residential high density	0.82	5.49
Area of residential low density	0.63	2.71
Residential area	0.71	3.45
Industrial area	0.70	3.28
Trees area	0.49	1.96
DSM	0.53	2.14
WS	0.74	3.87
Gas station	0.75	4.06
Traffic lights	0.71	3.47
Intersect	0.61	2.56
Tool road	0.65	2.82
Bus stop	0.89	8.96
Bus line	0.72	3.52

4.4.2 Noise Prediction

The study used four models: two of machine learning and two of statistical regression. The data were trained and tested by using these models, the number of data sub-sets totalled 95. This was divided into 67 for training and 28 for testing. Table 4.7 (above) shows the 18 parameters used to predict traffic noise (L_{eq}). The first model, the LR algorithm.

The LR model fit for Shah Alam was:

(0.0204) × Traffic volume (per 15 minutes) – (0.7139) × All type of roads – (0.0085) × Expressway – (0.0054) × Primary road + (0.0067) × Secondary road – (0.0005) × Area of residential high density + (0.006) × Area of residential low density – (0.0135) × Residential Area – (0.0023) × Industrial Area – (0.0041) × Trees Area + (0.0008) × DSM + (4.8595) × Wind speed + (0.0007) × Gas station – (0.0035) × Traffic lights + (0.0106) × Intersect – (0.0028) × Tool road + (0.0108) × Bus stop – (0.0164) × Bus line + 45.5861 ……………………………………………………………...(17)

The second model was trained with the same parameters based on DT with the hypermeters such as min split = 20, max depth = 30 and min Bucket = 7.

The same hyperparameters were applied when using eleven parameters for training and testing. While DT, the hypermeters are min split = 20; max depth = 30; min bucket = 7.

The third model is RF method to training and testing. In this case, the hypermeters were: n estimators = 150; mtry = 500; min split = 20; max depth = 30.

Finally, the fourth model also known as the SVR model was trained and tested with the hypermeters: kernel = rbf; gamma= sigmoid; tol = 3; decision function shape = ovo.

The SVR model fit for Shah Alam was:

(0.519) × Traffic volume (per 15 minutes) - (0.0805) × All type of roads - (0.1612) × Expressway – (0.0571) × Primary road + (0.0256) × Secondary road – (0.0763) × Area of residential high density + (0.1465) × Area of residential low density – (0.2626) × Residential Area – (0.1618) × Industrial Area – (0.1304) × Trees Area – (0.0713) × DSM + (0.1042) × Wind speed + (0.0738) × Gas station – (0.2101) × Traffic lights + (0.2613) × Intersect – (0.1905) × Tool road + (0.2157) × Bus stop – (0.1546) × Bus line + 0.6028 ……………………………………………………………………((18)

The findings for all four models showed that the difference between the predicted values was low (meaning the prediction errors for all models was small). From this, we concluded that the RF algorithm was the most effective and successful. As shown below, the R value of RF model was a higher (0.95) when used for training than for testing (0.93). Furthermore, for RMSE, training was 4.18 and testing 5.22. For MAE, training was 3.30 and 4.46. Table 4.7 describes this in more detail for all models.

Table 4.7 Results of predictions with LR, DT, RF and SVM models with all parameters.

Method / Evaluation	LR		DT		RF		SVM	
	Training	**Testing**	**Training**	**Testing**	**Training**	**Testing**	**Training**	**Testing**
R	0.93	0.91	0.92	0.91	0.95	0.93	0.94	0.92
R2	0.864	0.83	0.84	0.82	0.90	0.866	0.88	0.85
MAE	3.88	4.49	4.04	4.62	3.30	4.46	3.81	4.80
MSE	23.12	32.73	26.82	29.13	17.48	27.26	20.93	28.76
RMSE	4.81	5.72	5.18	5.40	4.18	5.22	4.58	5.36
MAPE	5.72	7.26	6.15	7.11	4.86	7.06	5.55	7.43

On the other hand, the model was trained and tested by the same models but the combination with the correlation-based feature selection model (CFS) and the eleven parameters that had been identified by this model. These parameters are the primary road, the bus stop, traffic volume, all type of roads, expressway, bus line, area of residential high density, industrial area, trees area, DSM and WS. In order to make the optimized prediction process, the CFS algorithm was used to identify the highly correlated parameters, and to show which of the parameters was most effective when used to predict traffic noise for the study area.

From the CFS, it was found eleven parameters were most effective for predicting traffic noise which was then trained and tested by above four models. In the case of all four models, the hypermeters were the same. However, the new equation regression of both

the LR and SVR models (both using eleven parameters) registered a difference in the instances where eighteen parameters was used for the Shah Alam area.
The LR model for Shah Alam (trained and tested using eleven parameters) recorded the following results:

(0.0229) × Traffic volume (per 15 minutes) – (8.5402) × All type of roads – (0.0092) × Expressway + (0.0026) × Primary Road + (0.0013) × Area of residential high density + (0.0011) × Industrial Area – (0.0027) × Trees Area - 0.0037 × DSM + (3.9434) × Wind speed + (0.0007) × Bus stop – (0.0164) × Bus line + 46.4032… (19)

In turn, the SVR model (trained and tested using eleven parameters relevant to Shah Alam) recorded the following results:

(0.4495) × Traffic volume (per 15 minutes) – (0.1553) × All type of roads – (0.3021) × Expressway + (0.0955) × Primary Road – (0.0021) × Area of residential high density + (0.1113) × Industrial Area – (0.11) × Trees Area – (0.1202) × DSM + (0.1767) × Wind speed – (0.0137) × Bus stop - (0.2569) × Bus line + 0.45………………… (20)

Table 4.8 shows the four model's results when filtered and reduced from eighteen parameters to eleven parameters based on the CFS method which finds features that have higher correlation with the class but are uncorrelated with each other. Therefore, the highest correlated parameters were used for the prediction analysis, which resulted in improving the prediction accuracy. This is described in more detail in Table 5.

In this case, the results of all four models improved the prediction accuracy as evidenced from the MSE and RMSE values, respectively. According to the results, it appeared the RF model was the most successful of the four models, even when the parameters were reduced from eighteen to eleven. By evaluating it in comparison to the other three models, the RF model repeatedly seemed to offer the most accurate and effective way of predicting noise for the Shah Alam area under consideration. Figure 4.14 is traffic noise prediction map for Shah Alam created using the RF model with eleven parameters.

Table 4.8 Results of predictions with LR, DT, RF and SVM models with eleven parameters.

Method / Evaluation	LR		DT		RF		SVM	
	Training	**Testing**	**Training**	**Testing**	**Training**	**Testing**	**Training**	**Testing**
R	0.94	0.94	0.95	0.94	0.96	0.95	0.94	0.94
R2	0.88	0.88	0.90	0.88	0.92	0.90	0.89	0.88
MAE	3.66	4.46	3.36	4.26	2.99	3.86	3.64	4.30
MSE	20.25	22.91	17.99	23.35	13.99	19.96	19.10	23.95
RMSE	4.50	4.79	4.24	4.83	3.47	4.47	4.37	4.89
MAPE	5.45	6.28	5.05	6.42	4.37	5.94	5.35	6.65

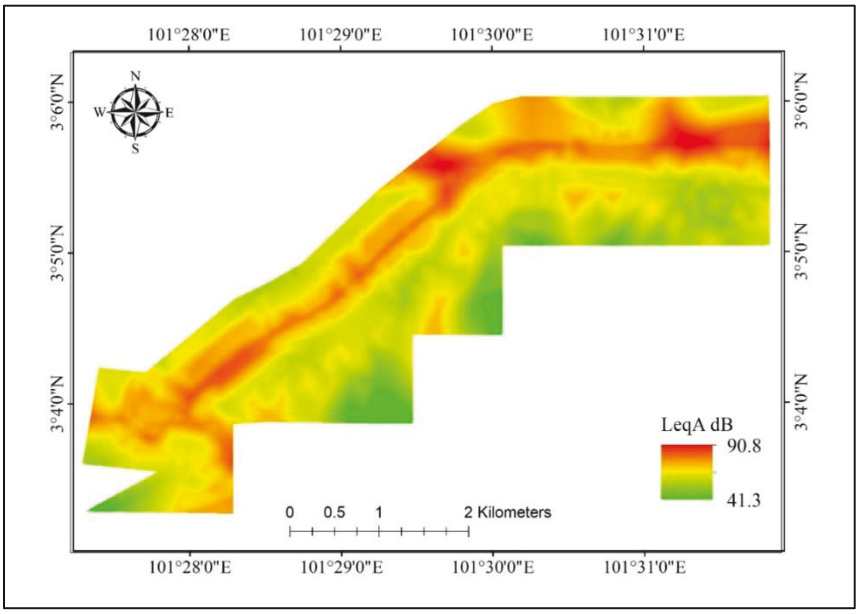

Figure 4.14 Shows the prediction noise map (Leq) on Shah Alam of Malaysia based on RF model with eleven parameters.

4.4.3 Validation of Noise Prediction Maps

The machine learning and statistical regression models are validated by using the criteria of R, R2, MAE, MSE, RMSE, and MAPE between the measured and predicted. Table 4.9 and Table 4.10 above show the result of six criteria for each model.

The comparative results of four models (LR, DT, RF and SVR) from Table 4.9 and Table 4.10 above for training and testing make the RF model the best algorithm and overcome other models.

The RF model's ability to record better results even when the number of parameters is reduced from 18 to 11 can be seen when considering, for example, the comparative RMSE values. When the parameters were set at 18, the RMSE for training was 4.18, while the RMSE for testing was 5.22. Changed to 11 parameters, the RMSE for training was 3.47 and for testing was 4.47. This identifiable trend continued when the MSE values decreased with 11 noise predictors.

To further clarify how and why the RF model is the preferred algorithm, it is worth considering a few other attributes and potential applications for it. To start with, the RF model is demonstrably faster when used to process data sets of a large size, including multiple variables. Was noted that it was quicker at producing usable results than the other models, but its advantages do not end there. The RF model is also capable of functioning and producing reliable results even when some input values are missing. This is because it is an ensemble method. In turn, this makes the model able to create real-time predictions. Moreover, taken outside the research environment, the model would prove attractive to institutions requiring accurate predictive data for environmental reasons.

The success of the RF model at effectively and accurately predicting noise levels (L_{eq} dB) is described in figure 4.15. These scatter plot graphs depict an imagined but plausible scenario that could occur based on the variables of: the primary road, the bus stop, traffic volume, all type of roads, expressway, bus line, area of residential high density, industrial area, trees area, DSM and WS. Predictions of the type shown would be of use to the environmental and town planning industries. For example, it could help predict the impact new infrastructure will have on the environment, or it could aide in designing and implementing programmes of traffic control, including the re-routing of vehicles and the creation of new roads.

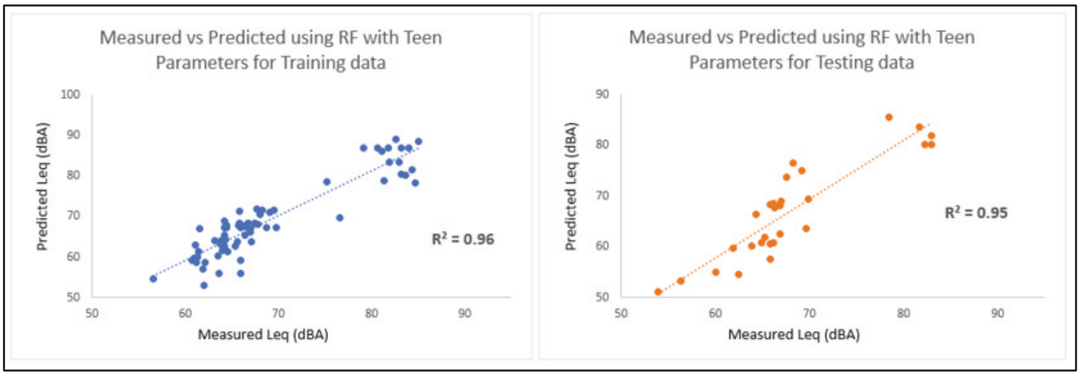

Figure 4.15 Scatter plot of Leq (measured vs predicted) using random forest for training and testing dataset with eleven parameters.

In addition to this, Figure 4.16 shows the data results when ten-fold cross-validation was performed on the RF model to see if it maintained its status as the best model for predicting noise levels. Not only did the RF model stay performing well under the scrutiny of cross-validation, it also proved itself to be stable. This is shown by how the six performance criteria stay regular across the six different iterations. Similarly, the observed and predicted L_{eq} figures for the testing data set were close in value. Figure 4.16 showed the values of L_{eq} predicted using RF fit well with the field data.

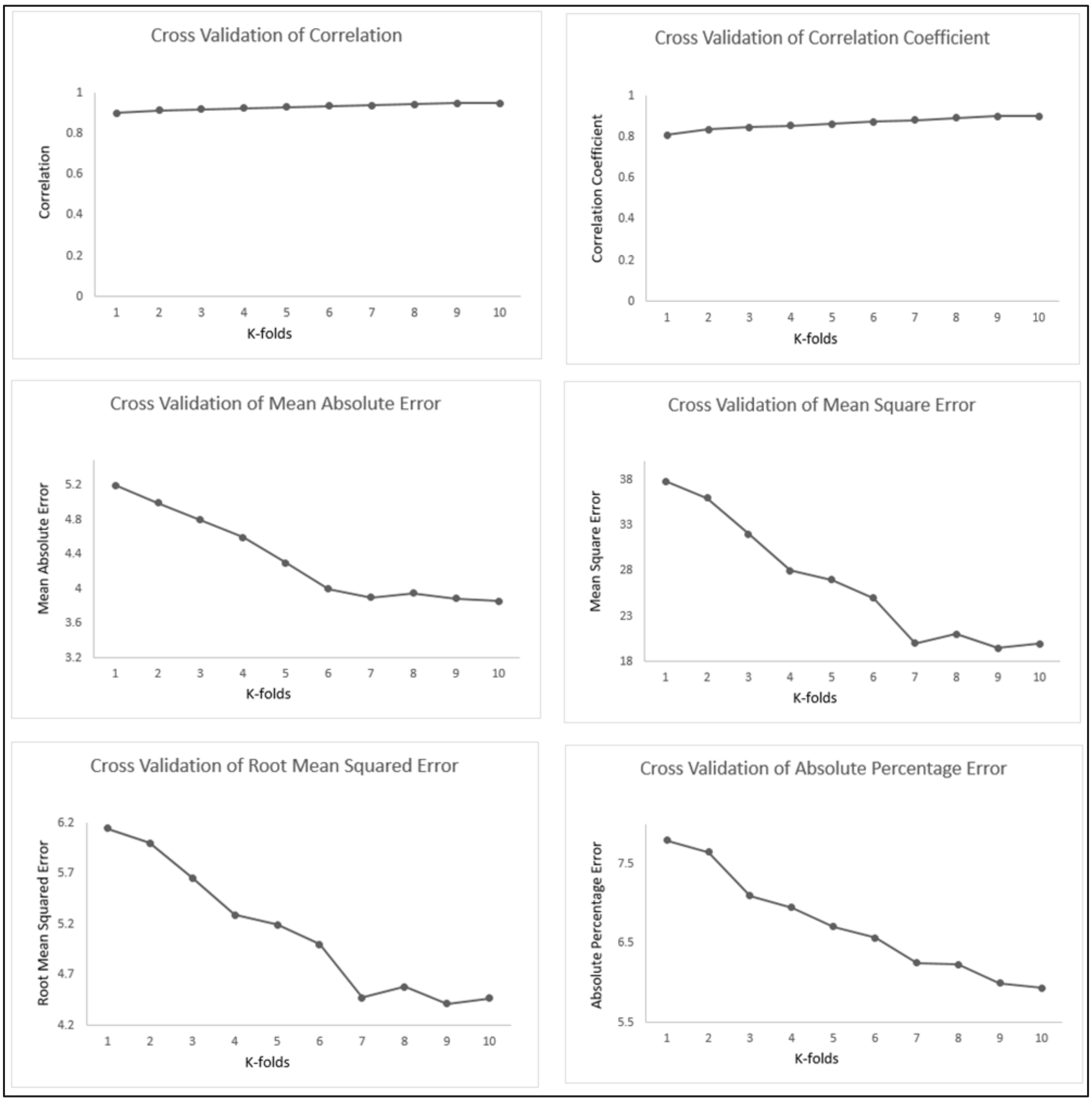

Figure 4.16 Shows 10-fold cross-validation of R, R2, MAE, MSE, RMSE and MAPE in predicting Leq using the testing dataset by RF method.

4.4.4 Summary

In summary, this chapter has evaluated the merits of four different soft computing models (machine learning and statistical regression) used to predict traffic noise levels in Shah Alam, Malaysia. Several traffic noise prediction models for cities have been proposed by previous studies based on the land use regression model (LUR) such as Aguilera et al. (2015) applied the LUR model to examine traffic noise in three different cities in Europe, Ragettli et al. 2016 used LUR modelling with long-term noise measurements and land use characteristics to examine ambient levels of noise in Montreal, in Canada, Sieber et al. 2017 employed LUR modelling to assess the outdoor noise variability for adults living in informal settlements in South Africa, and More recently Harouvi et al. (2018) utilized

the LUR model with high-resolution transportation to estimate the noise in two periods of the day (rush hour and off-peak) at two cities in Israel. Moreover, this study used six evaluation criteria to check the performance of the model. The successive stages of the research including studying and changing the parameters have been described in detail, along with information on the four different models and the research findings. Throughout the research, the noise prediction models are developed, with L_{eq} as the output (dependent variable) and the noise variables: the primary road, the bus stop, traffic volume, all type of roads, expressway, bus line, industrial area, trees area, DSM and WS, as the independent variables. According to the performance criteria of R, R2, MAE, MSE, RMSE, and MAPE, the results showed that the RF model was the most effective and reliable at predicting traffic noise levels. K-fold cross-validation further proved the stability of the RF model in making predictions.
The results of the study show that the RF model has both a high rate of prediction and a high rate of stability. However, through the methodology this study was presented can be extended and utilized to a greater number of variables to improve the prediction traffic noise map. For future work, diverse traffic conditions with the inclusion of time as a variable can be explored by LUR based on artificial neural network and deep neural network models. Probably that lead to increase the accuracy of prediction models like the ones discussed in this study.

For urban areas like Shah Alam, the number of vehicles on city streets is the cause of high levels of pollution. In order to propose a useful model, this study combined the CFS, RF, and GIS models. The results of RF model then demonstrated the lowest RMSE 4.37 ppm for testing data and when was used all 18 parameters, the RMSE of testing was 5.22 ppm. The models were applied based on the most of parameters derived from LiDAR data, and GIS layers were extracted to produce prediction map. According to the prediction map, where the highest values (high noise) were concentrated near highly expressway, whilst the lowest values (low noise) were distributed far away from expressway and primary road.

However, Both LUR statistical modelling and GIS techniques are important tools for planning and prediction maps. Ultimately, this study was proved that the machine learning overcome the regression method. In conclusion, we have suggested an affordable and easy-to-use method of helping to monitor noise levels that could be useful for governmental and urban planning projects.

4.5 Result of Optimized Deep Neural Network Algorithm

4.5.1 The Proposed Deep Neural Network Architecture

4.5.1.1 DNN Model Based on the Optimization Algorithms

Figure 4.17 shows the proposed network architecture designed for traffic noise prediction with about 500 networks training of different combination and parameters (Ahmed et al, 2021). This designed is based on the results of network structure and optimized hyperparameters. According to the result, the best validation was achieved by a network of 11 input parameters and 23-7 hidden layers. Also, it shows that the network is best trained with Levenberge-Marquardt algorithm, while identity algorithm indicated the best output for hidden and output activation. Furthermore, the best gradient momentum and learning rate obtained are 0.9 and 0.5, respectively. All the hyperparameters of the DNN model were used for the traffic noise prediction together with their search space for fine-tuning. The DNN training model was achieved at 3.4 and 5.2 for MAD and RMSE, respectively. While, the DNN testing model, 3.61 and 5.57 was recorded for MAD and RMSE of the traffic noise prediction respectively in the study area. The output of the DNN model is defined by maximum, minimum and average equivalent continuous noise level (dB) $L_{eq,15}$. The Figure 4.18 shows the number of hidden units with mean absolute deviation (MAD) and root mean square error (RMSE). It shows that the best number of hidden units is 23-7 through the MAD = 3.4 and RMSE = 5.2. Also, in the figure 4.20, it was observed that RMSE with MAD is increasing gradually with increase in hidden number units.

According to the DNN model training shown in Figure 4.19, there are four successful algorithms for training. However, the best algorithm observed is Levenberge-Marquardt for training which recorded 3.4 and 5.2 for MAD and RMSE, respectively. However, the best hidden and output activation is observed to be Identity algorithm with MAD of 3.4 and RMSE of 5.2.

On other hand, the effects of the learning rate and the gradient momentum of the optimization algorithm on the performance of the DNN model were also investigated

(Figure 4.20). This figure shows the gradient momentum and the learning rate with mean absolute deviation (MAD) and root mean square error (RMSE). The figure shows the best gradient momentum and learning rate to be 0.9 and 0.5, respectively with MAD of 3.4 and RMSE of 5.2.

Regarding the learning rate, the best value was found to be 0.5, while the small values of learning rate is higher both RMSE and MAD. This means that the model will witness increase RMSE and MAD gradually. The MAD and RMSE were significantly decreased at the learning rate between 0.1 – 0.5. On the other hand, it was observed that increase in momentum of the optimization algorithm improve the MAD and RMSE of noise prediction. The DNN model has been enhanced from momentum value 0.6 to 0.9. Momentum is vital if local minima stuck is to be avoided. In general, large values of momentum enable fast convergence, while small values cannot reliably avoid local minima which slow down training of a system. Figure 4.21 shows the best gradient momentum with learning rate of 0.9 and 0.5, respectively with MAD of 3.4 and RMSE of 5.2.

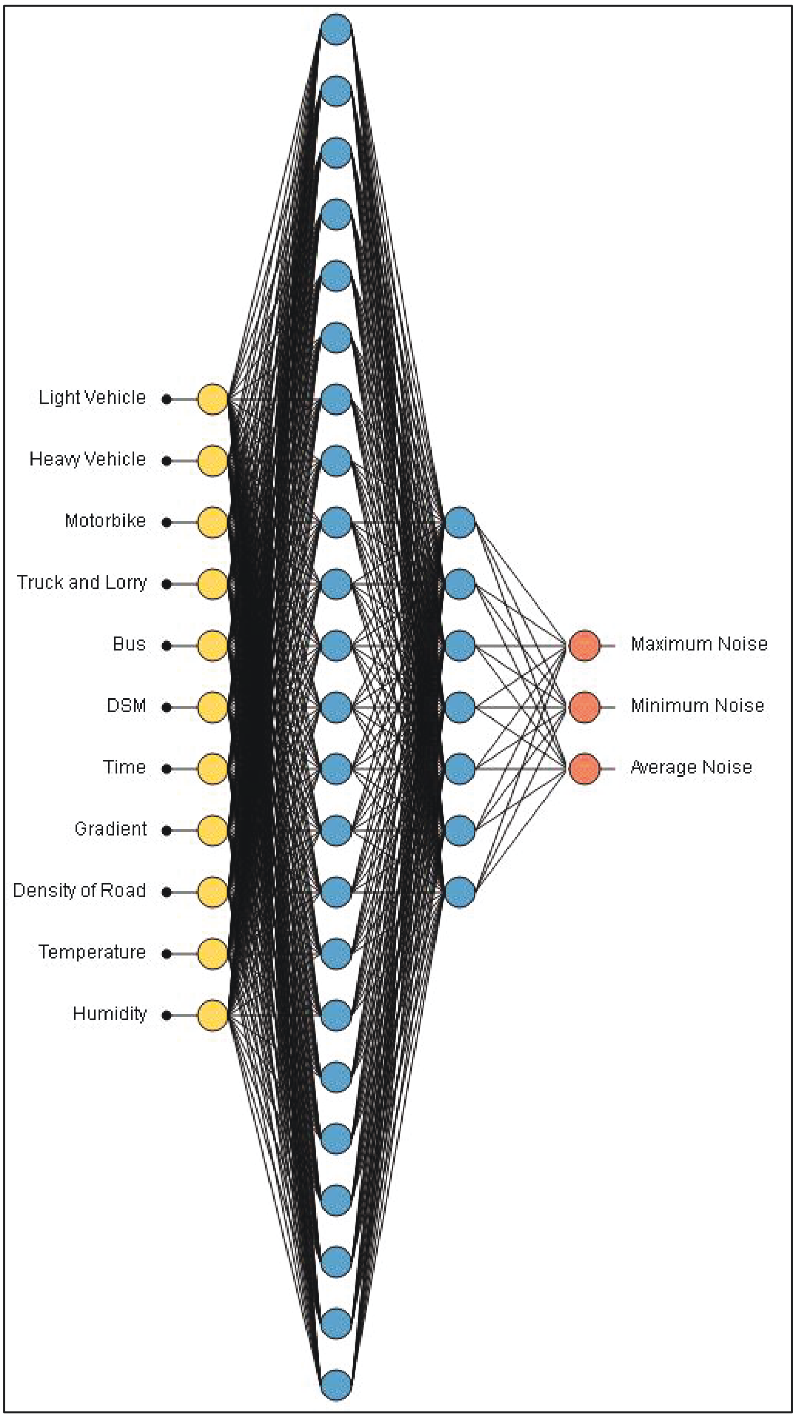

Figure 4.17 Architecture of the deep neural network for vehicular traffic noise prediction (11-23-17-3).

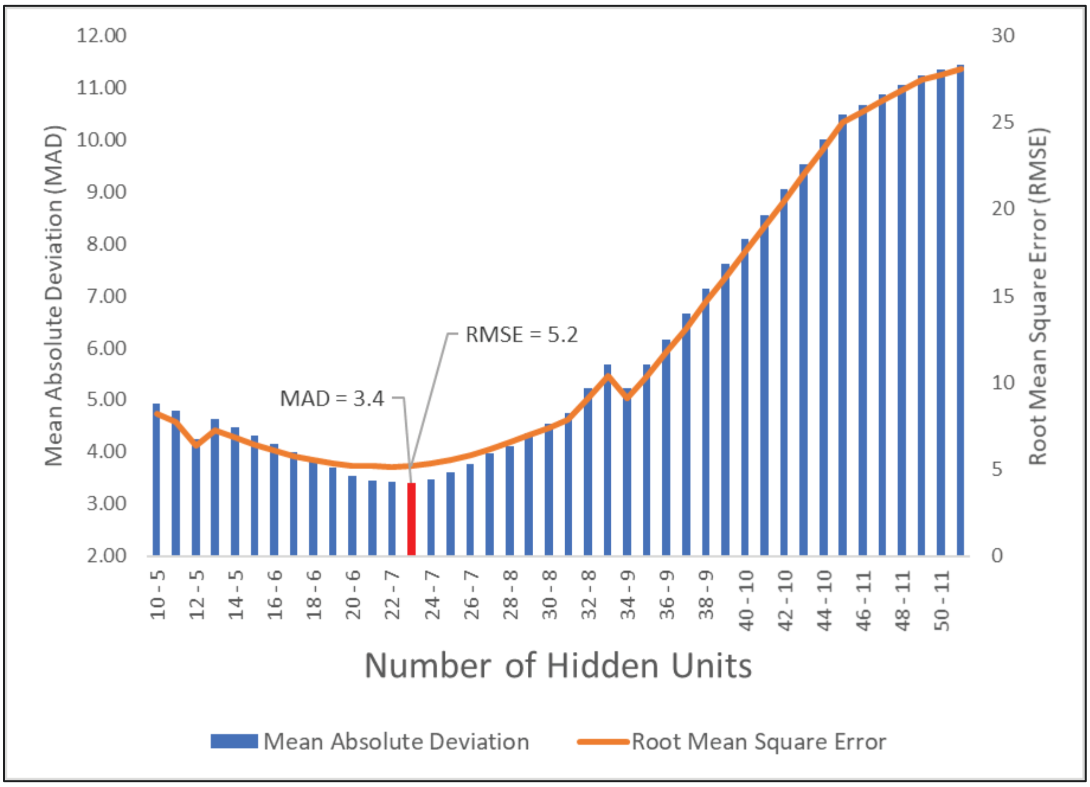

Figure 4.18 The number of hidden units with mean absolute deviation (MAD) and root mean square error (RMSE).

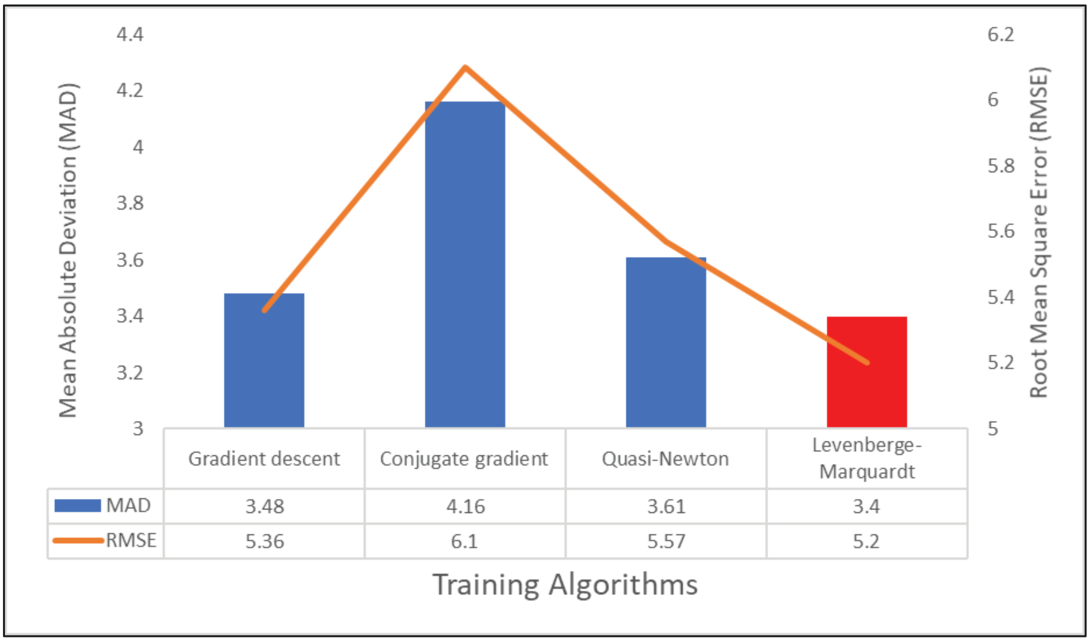

Figure 4.19 The training algorithms with mean absolute deviation (MAD) and root mean square error (RMSE).

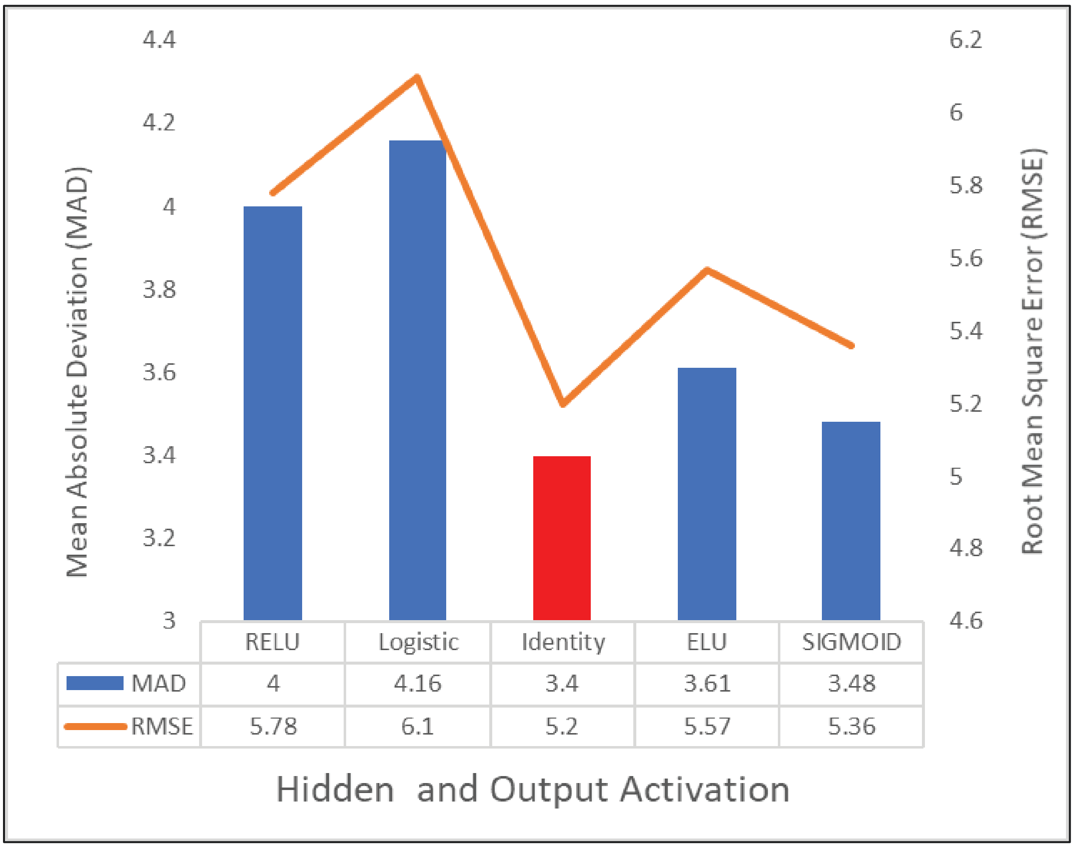

Figure 4.20 The hidden and output activation with mean absolute deviation (MAD) and root mean square error (RMSE).

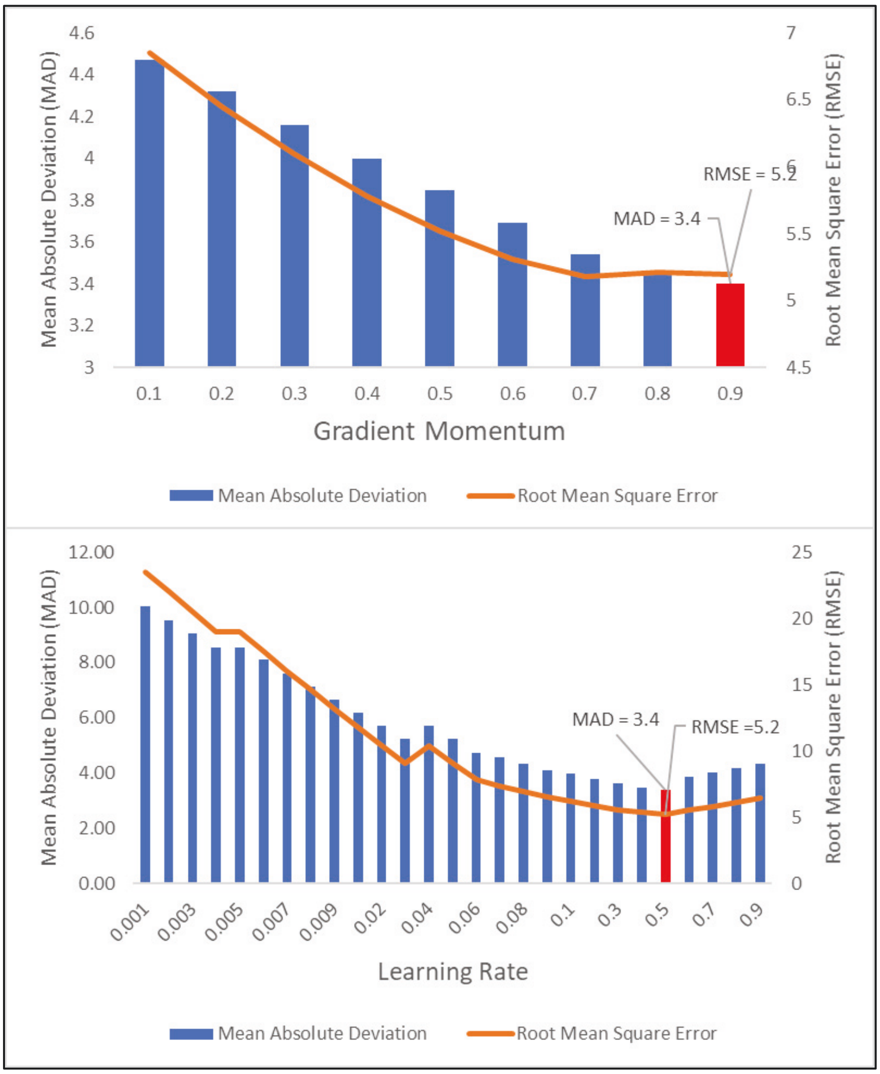

Figure 4.21 The gradient momentum and the learning rate with mean absolute deviation (MAD) and root mean square error (RMSE).

4.5.1.2 Integration Feature Selection (CFS And WFS) with DNN Model

Based on the results presented in table 4.9, noise predictors have different contribution levels when used in each feature selection methods (CFS and WFS) for prediction of maximum, minimum and average traffic noise level in the study area. When, CFS method was used, it was found that the noise predictors such as motorbike, bus and humidity are significant at 100% confidence level which is imperative to use in DNN model prediction. In addition, there are other noise predictors that can yield good prediction such as heavy vehicle, DSM and temperature parameters. While the noise predictors such as light vehicle, truck and lorry, time, gradient and density of road are not important and used in the model. The CFS method was excluded from the DNN model due to its less correlation with traffic noise predictors which makes its insignificant for DNN prediction model.

Based on WFS method, it was found that the noise predictors such as time and humidity are significant at 100% confidence level with substantial use in the DNN model. Also, there are other important parameters used in the DNN model prediction such as light vehicle, heavy vehicle, motorbike, truck and lorry, bus, DSM and gradient. While the noise predictors were not significant for DNN prediction model such as density of road and temperature.

The statistical result indicates that the CFS method was able to establish that the parameters such as light vehicle, truck and lorry, time and gradient are not significant for DNN prediction model. On the other side, the WFS method found those parameters significant especially the time, truck and lorry parameters for DNN model.

Table 4.9 Results of assessing the contribution of noise predictors using CFS and WFS methods.

Parameter	**CFS method**		**WFS method**	
Maximum Noise	**Importance**	**Used**	**Importance**	**Used**
Light Vehicle	20		70	✓
Heavy Vehicle	50	✓	60	✓
Motorbike	100	✓	80	✓
Truck and Lorry	40		90	✓
Bus	100	✓	70	✓
DSM	60	✓	70	✓
Time	0		100	✓
Gradient	20		60	✓
Density of Road	0		20	
Temperature	80	✓	40	
Humidity	100	✓	100	✓

Finally, feature selection methods (CFS and WFS) were integrated with DNN model and the training DNN model. It was found that the training and testing of wrapper-DNN model has the least MAD with RMSE which is considered in the proposed model in this study.

Figure 4.22 shows the proposed deep neural network architecture and the table 4.10 describe the hyperparameters of each model which consist of input, number of hidden layer and the output of the model. The training and testing model abased on the MAD and RMSE, the training and the hidden and output activation of model based on algorithms, the learning rate and the momentum.

Table 4.10 Results of DNN, CFS-DNN and WFS-DNN models noise prediction.

Hyperparameter	**DNN**	**CFS-DNN**	**WFS-DNN**
Architecture (input – (number of hidden layer) – output)	11 - (23-7) - 3	6 – (10 – 6) - 3	9 – (15 - 5)- 3
Training Model MAD – RMSE	3.4 - 5.2	3.05 - 4.27	2.23 – 2.85
Test Model (MAD – RMSE)	3.29 - 5.56	3.14 – 5.33	2.28- 3.97
Training Algorithm	Levenberge-Marquardt		
Hidden and Output Activation	Identity		
Learning Rate	0.5	0.3	
Momentum	0.9		

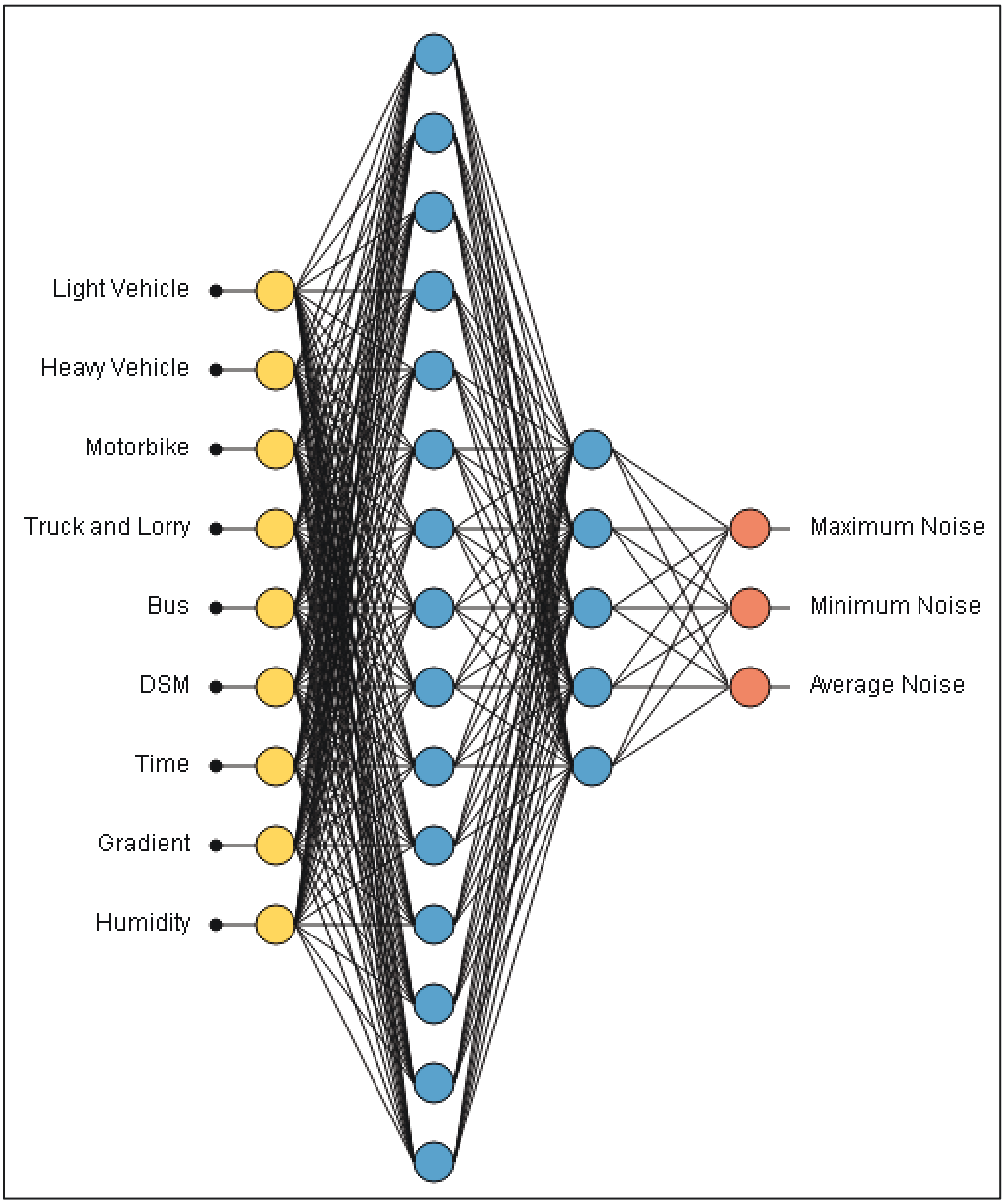

Figure 4.22 The proposed deep neural network architecture

4.5.2 Comparison WFS-DNN Model with other Models

The proposed model was compared with other popular models such as the artificial neural network (ANN), Multilayer Perceptron (ANN MLP) and ANN radial basis function (ANN RBF) models. The WFS-DNN supersede the performance of the other models through as shown in table 4.11. This can be seen in both the MAD and RMSE in the training and testing data. Also, Figure 4.23 shows the correlation between observed and predicted vehicular traffic noise of WFS-DNN, ANN MLP and ANN RBF models for training and testing.

Statistically, the correlation coefficient (R2) of 0.95 was achieved, the mean absolute error (MAD) (2.23) and RMSE (2.85) for training, while for the testing, R2 of 0.94, MAD is 2.28 and RMSE is 3.97 in WFS-DNN model. Lower R2 (0.90, 0.87), MAD and RMSE are recorded for ANN RBF for training and testing of model. However, the ANN MLP model shows the best performance compared with ANN RBF model. Because MAD and RMSE of ANN MLP indicated lower values than the ANN RBF. Conclusive, it can be inferred that the best model is the WFS-DNN model even though it has the least MAD and RMSE of training and testing than the other two models (ANN MLP and ANN RBF).

Table 4.11 Results of WFS-DNN, ANN MLP and ANN RBF models noise prediction.

Type of Models	Training MAD	Testing MAD	Training RMSE	Testing RMSE
WFS-DNN	2.23	2.28	2.85	3.97
ANN MLP	3.69	3.85	5.31	5.52
ANN RBF	4.16	4.32	6.10	6.45

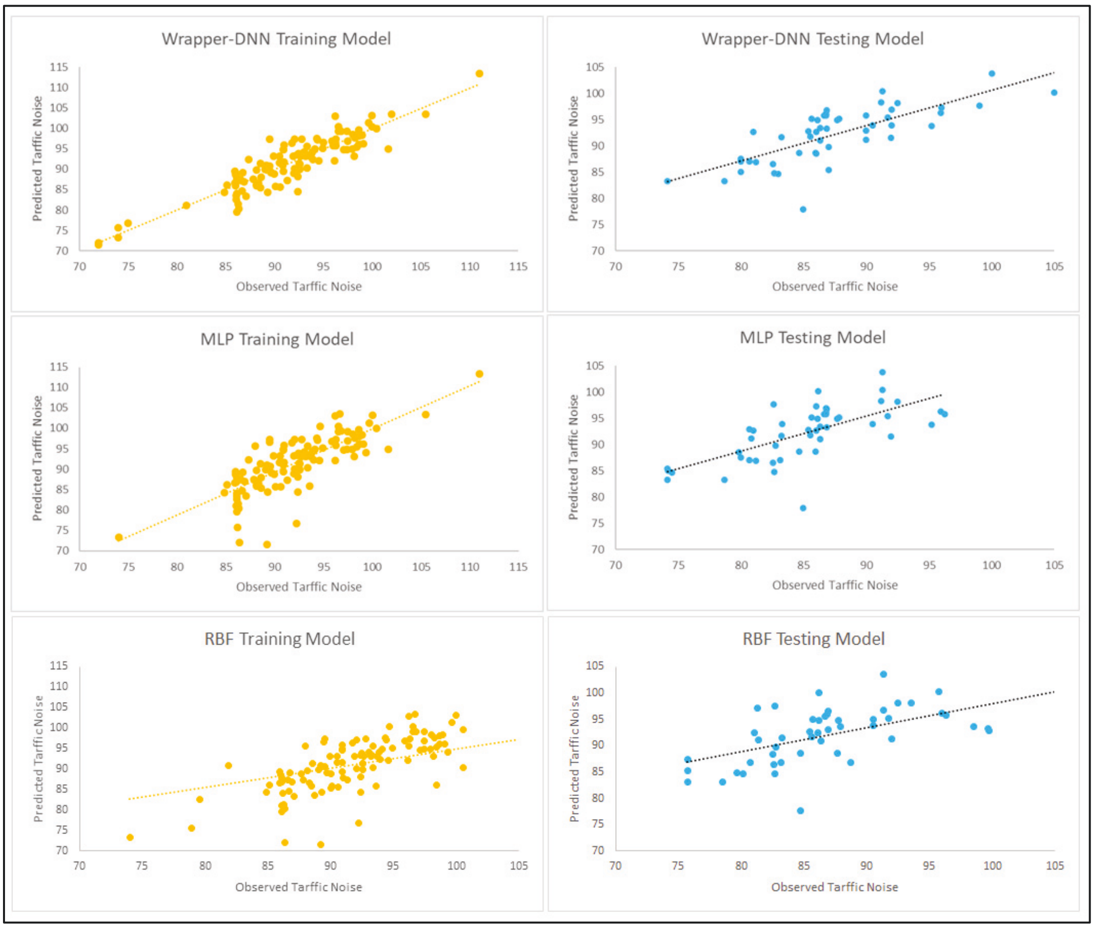

Figure 4.23 Correlation between observed and predicted vehicular traffic noise of WFS-DNN, ANN MLP and ANN RBF models for training and testing.

4.5.3 Vehicular Traffic Noise Prediction Maps

Noise distribution maps for the study area were generated using the proposed noise model in GIS. The output of the model is a continuous noise level accounting for the field conditions and other factors such as topography, weather and other noise predictors. In this research, the noise and traffic volume were measured at different periods, morning, afternoon, evening and night of weekdays. Figures 4.24, Figures 4.25 and Figures 4.26 show the maps of each period. However, this section presents only the recommended maps for planning purposes. It was discovered that the road is characterized by high traffic noise level in the morning, afternoon and night hours. The following figures show the proposed noise distribution maps (maximum, minimum and average traffic noise level) of the study area for weekday in the morning, afternoon, evening and night.

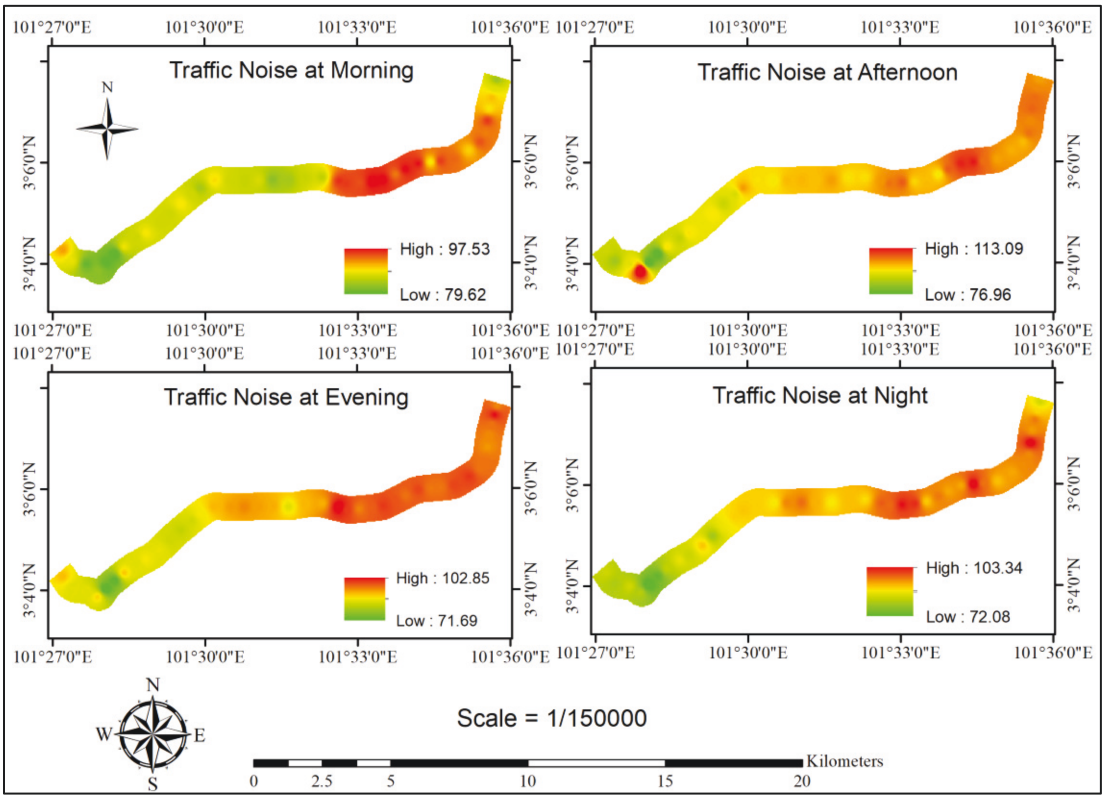

Figure 4.24 Average traffic noise map.

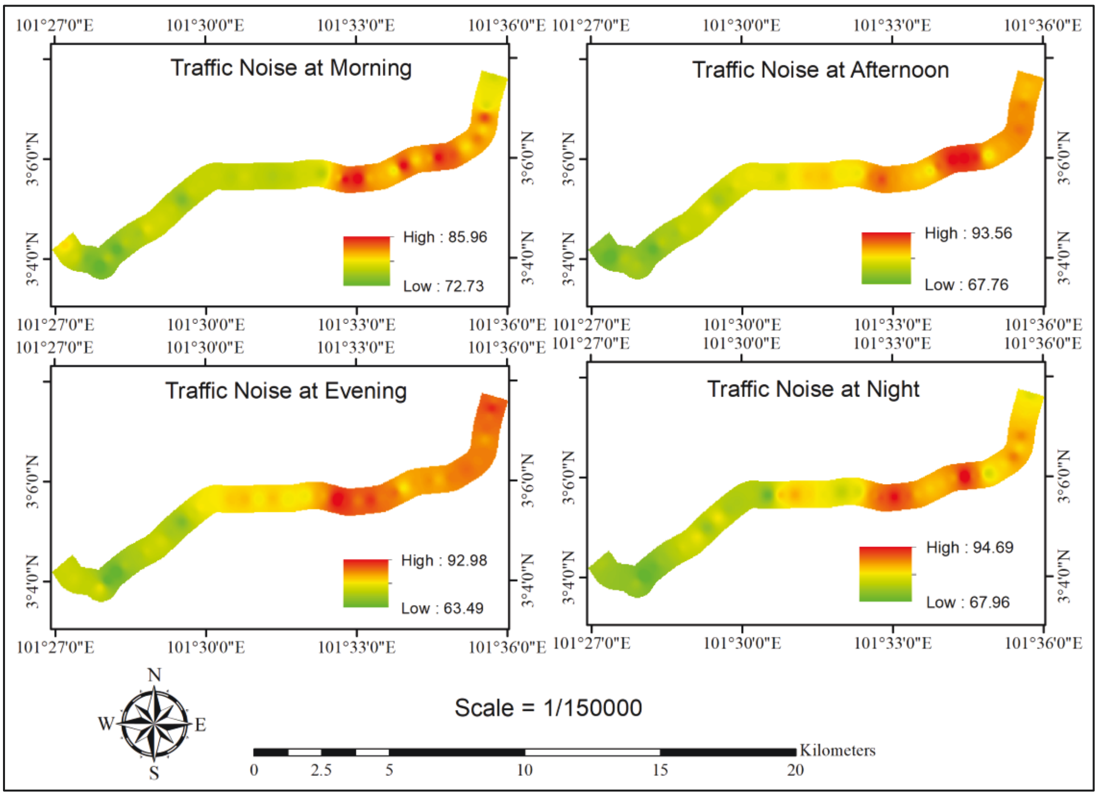

Figure 4.25 The minimum traffic noise map.

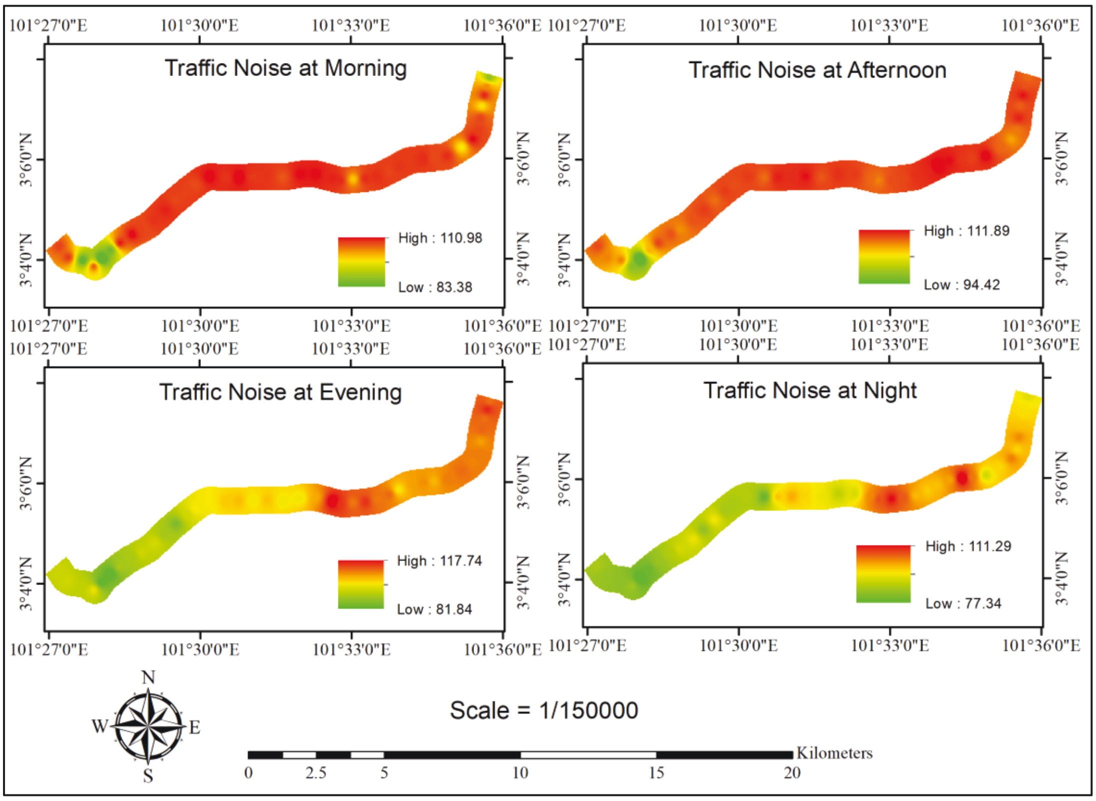

Figure 4.26 The maximum traffic noise map.

4.5.4. Summary

Vehicular emissions such as traffic noise are one of the major sources of environmental pollution in urban areas, where road networks, intersections and tolls are present. Vehicular traffic noise prediction models and spatial models are used to assess the impacts of vehicular emissions from different types of vehicles on human health and the environment. In this study, a proposed model was developed based on the integration of the deep neural network with features section methods (WFS) in GIS. The prosed model accurately predicted the vehicular noise with 2.23, 2.28 and 2.85, 3.97 for training and testing model. The default model parameters were 11 parameters, after the implementation of the CFS and WFS models, the input parameters were reduced to six (6) and nine (9) parameters each for the CFS-DNN and WSF-DNN models receptively. The WSF-DNN model was observed to be the best model and outperformed the other models such as DNN without integration with features section methods, CFS-DNN and the ANN networks (MLP and RBF). Moreover, the model found that the noise predictors such as the time and humidity are significant at 100% confidence level with important to the use of DNN model. Furthermore, there are other important parameters used in the DNN model prediction such as light vehicle, heavy vehicle, motorbike, truck and lorry, bus, DSM and gradient. The GIS modelling was applied based on the parameters derived from LiDAR data. The GIS layers were extracted from interpolation techniques to produce the prediction maps for different times per day for the weekdays along the route at the study area. According to the noise prediction maps, it was observed that the high traffic noise level in the morning, afternoon and night hours. The proposed noise distribution maps were the maximum, the minimum and the average traffic noise level of the study area for weekday in the morning, afternoon, evening and night.

4.6 Result of Noise Propagation and Prediction

4.6.1 Noise Distribution in the Selected Study Areas

4.6.1.1 Overview of Noise Distribution in the Selected Areas

Noise maps were created for the selected study areas using the proposed methods (in chapter three Section 3.6.2) and for a different period, including day-night, weekdays and weekends. Table 4.12 shows the summary of the field measurements regarding noise level and traffic volume for the selected study areas on weekends (Sunday). The measurements show that for the Shah Alam Seksyen 7, the minimum noise level was recorded at 70.6 dB on morning and afternoon. The maximum noise level was found to be 114 dB recorded at mid-night. The average noise level in this study area was measured to be 88.95 dB, 90.67 dB, 75.21 dB, and 75.02 dB, for the morning, afternoon, evening, and midnight, respectively. On the other hand, the traffic volume measurements showed that the maximum cars (385) passes during evening time and lowest cars (137) were passed during morning time. The heavy vehicles including trucks and buses were recorded at a maximum of 16 during the afternoon, and at midnight the number was very low five (5). Regarding the average number of motorcycles passes in this study area measured for 15 minutes showed that the maximum number is (28) during the evening time and the lowest (10) at midnight.

Table 4.12 Summary of noise and traffic flow information recorded in the selected study areas on Sunday.

Study Area	Time	Average Noise Level (per 15 min)-dB			Average Traffic Volume (per 15 min)		
		Min	Max	Mean	Cars	Trucks	Motorcycles
Shah Alam (Seksyen 7)	Morning	70.6	112	88.95	137	10	23
	Afternoon	70.6	112	90.67	325	16	17
	Evening	74.22	110.9	75.21	385	13	28
	Night	74.1	114	75.02	140	5	10
Shah Alam (Seksyen 13)	Morning	78	111.7	92	442	34	66
	Afternoon	**80**	114.3	**94.71**	1039	54	41
	Evening	76.8	113.4	91.87	1154	37	58
	Night	75.5	112.8	90.9	388	21	26
Subang Jaya	Morning	74.3	110.4	87.85	648	34	**105**
	Afternoon	75	110	91.75	**1767**	**58**	75
	Evening	77.5	111.5	90.91	1755	40	96
	Night	78.1	**121**	91.46	530	31	33

In addition, the noise measurements in the Shah Alam-Seksyen 13 showed slightly higher noise levels compared with the Shah Alam-Seksyen 7. The minimum noise level was recorded during mid-nighttime, and it reached 75.5 dB. The maximum noise level was 114.30 dB during afternoon hours. On the other hand, the average noise level in this area was found to be 92 dB, 94.71 dB, 91.87 dB, and 90.90 dB, on the morning, afternoon, evening, and midnight, respectively. Besides, the information of traffic flow shows that the highest number of cars were passed during the evening and it was counted as 1154 cars. The maximum number of heavy vehicles and motorcycles were counted to be 54 (afternoon) and 66 (morning), respectively.

In Subang Jaya, the minimum (74.3 dB) and maximum (121 dB) noise levels were measured on morning and midnight, respectively. The average noise level was 87.85 dB on the morning, above 90 dB on afternoon, evening, and midnight. Alternatively, the traffic flow data indicate that the highest number of cars (1767), heavy vehicles (58), and motorcycles (105) were passed during the afternoon, afternoon, and morning, respectively.

On the other hand, table 4.13 shows the summary of noise measurements and traffic flow information in the selected study areas on weekdays (Monday). The data indicates that the minimum noise level in the Shah Alam-Seksyen 7 is 63.4 dB which was measured during evening time. The average maximum noise of 115.3 dB was recorded during evening time. In addition, the average noise level in the Shah Alam- Seksyen 7 was found to be 86.22 dB, 91.99 dB, 87.25 dB, and 87.14 dB, during the morning, afternoon, evening, and midnight. In contrast, the traffic volume data indicate that the highest and lowest number of cars were 471 and 78 during evening and midnight time, respectively. The largest number of heavy vehicles (97) were recorded during the afternoon, and the highest motorcycles (82) were recorded during the evening.

Table 4.13 Summary of noise and traffic flow information recorded in the selected study areas on Monday.

Study Area	Time	Average Noise Level (per 15 min)-dB			Average Traffic Volume (per 15 min)		
		Min	Max	Mean	Cars	Trucks	Motorcycles
Shah Alam (Seksyen 7)	Morning	72.7	111	86.22	444	28	60
	Afternoon	67.7	111.5	91.99	297	97	23
	Evening	63.4	115.3	87.25	471	49	82
	Night	67.9	111.3	87.14	78	9	10
Shah Alam (Seksyen 13)	Morning	79	109.9	95.43	**2190**	61	**373**
	Afternoon	80.1	111.9	99	1078	263	67
	Evening	78.4	111.4	96.88	1774	140	195
	Night	82.5	111	96.82	271	40	23
Subang Jaya	Morning	78	110.8	91.28	2057	**410**	48
	Afternoon	80.4	111.9	**97.81**	1538	112	329
	Evening	**83**	**117.8**	95.79	1757	215	130
	Night	78	111.2	93.65	446	40	53

The data of the Shah Alam-Seksyen 13 suggest that the minimum noise level in the area can be recorded during the evening which measured to be 78.4 dB. However, the maximum noise level in this area can reach at 111.9 dB during the afternoon. The average noise level was found to be 95.43 dB, 99 dB, 96.88 dB, and 96.82 dB, during the morning, afternoon, evening, and midnight, respectively. Regarding the traffic volume in this area, the highest number of cars were 2190 during morning time, the lowest number of cars were found to be 271 during mid-nighttime. Furthermore, the maximum number of heavy vehicles and motorcycles were found to be 263 (afternoon) and 373 (morning), respectively. During midnight, the number of heavy vehicles and motorcycles were the lowest. Moreover, in the Subang Jaya, the data shows that the minimum noise level (78 dB) were recorded during morning and midnight time. The maximum noise level was measured on the evening, and it was around 117 dB. The average noise level in this area was at 91 dB all the time. In this area, the highest number of cars were passed during the morning and counted to be 2057. The maximum number of heavy vehicles and motorcycles were during morning and afternoon, respectively. On the other hand, during mid-night, the number of cars and heavy vehicles were the lowest, and the lowest number of motorcycles were recorded during morning time.

4.6.1.2 Noise Distribution Maps

Noise distribution maps for the selected study areas were generated by the proposed 3D noise model in GIS through applied the developed equation. The output of the model is a continuous noise level accounting for field conditions and other factors such as topography, weather, and land use. In this project, the noise and traffic volume were measured at different period, day and night, weekdays and weekends. However; this section only presents the recommended maps for planning purposes. In this section was proposed morning time for daytime (Monday) for three study area. The reason for this time is because, during these time periods, the noise level is at its highest level. The following figures show the proposed noise distribution maps for the selected study areas for the weekday times (Monday). As well as, in this section took the sound level average at morning time.

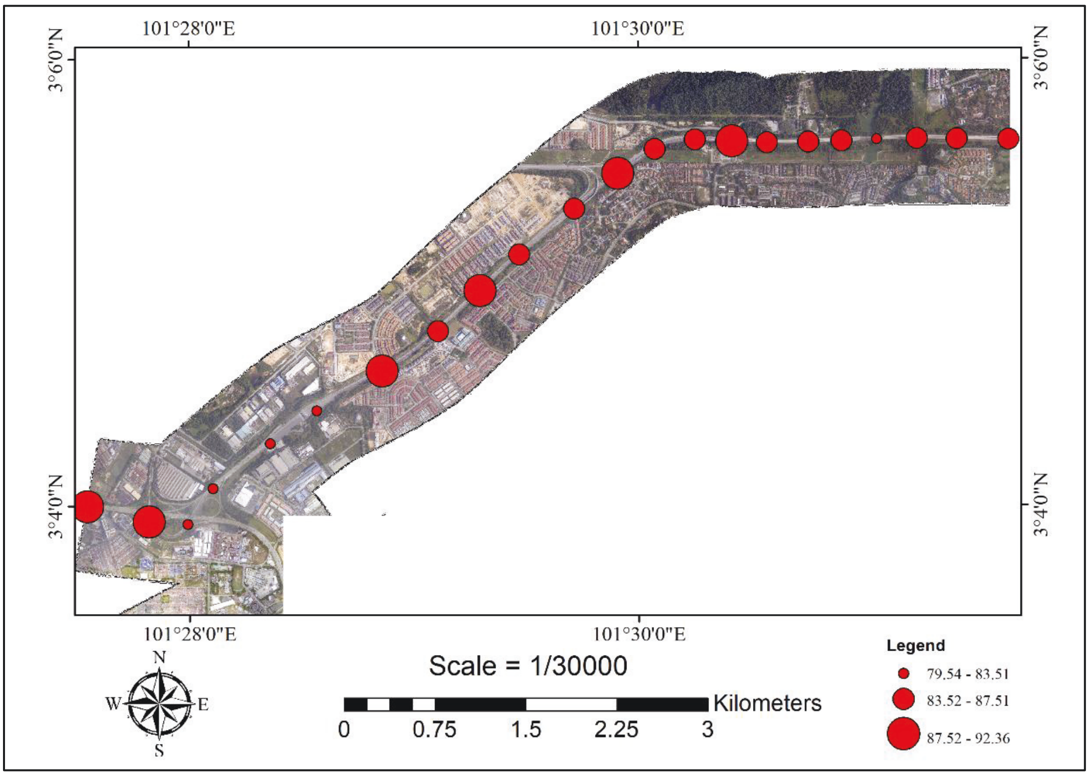

Figure 4.27 Shows noise samples of Shah Alam - Seksyen 7 (Morning time, Monday).

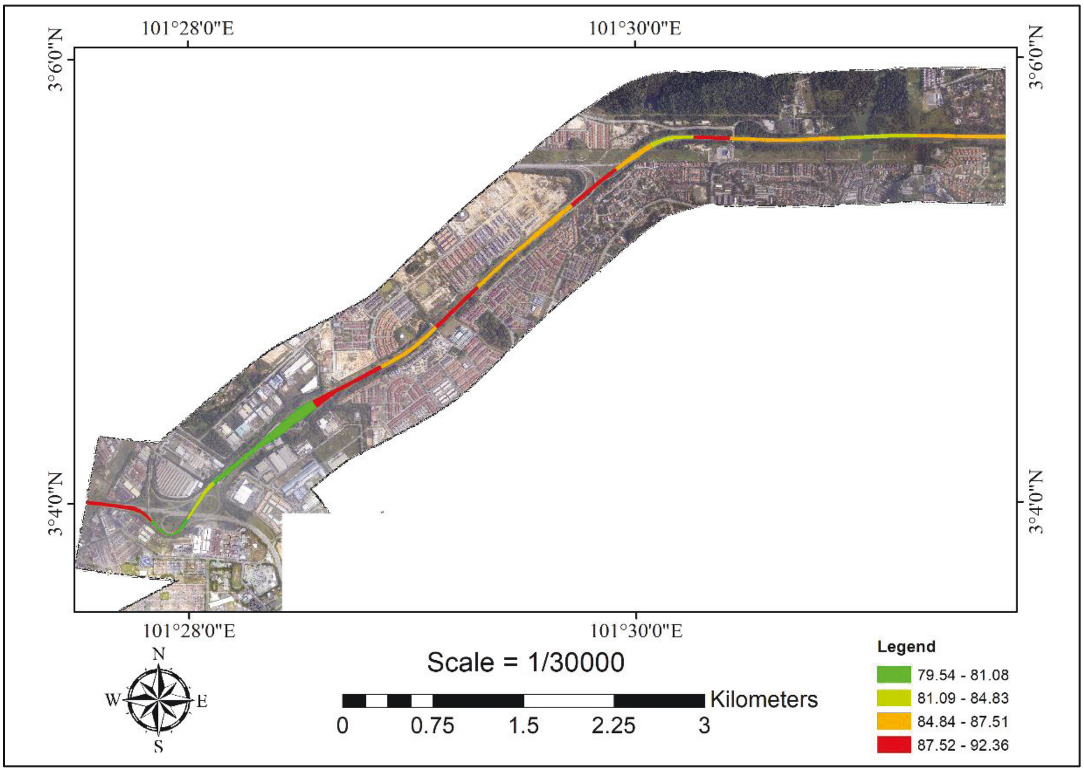

Figure 4.28 Shows 2D road noise prediction of Shah Alam - Seksyen 7 (Morning time, Sunday).

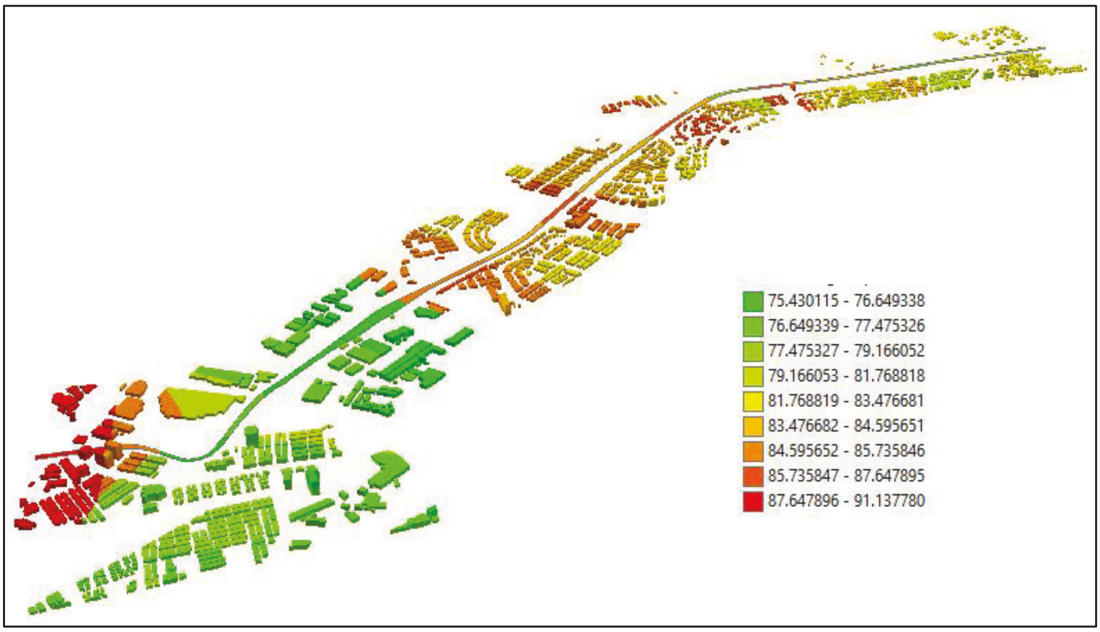

Figure 4.29 Shows 3D noise propagation of Shah Alam - Seksyen 7 (Morning time, Sunday).

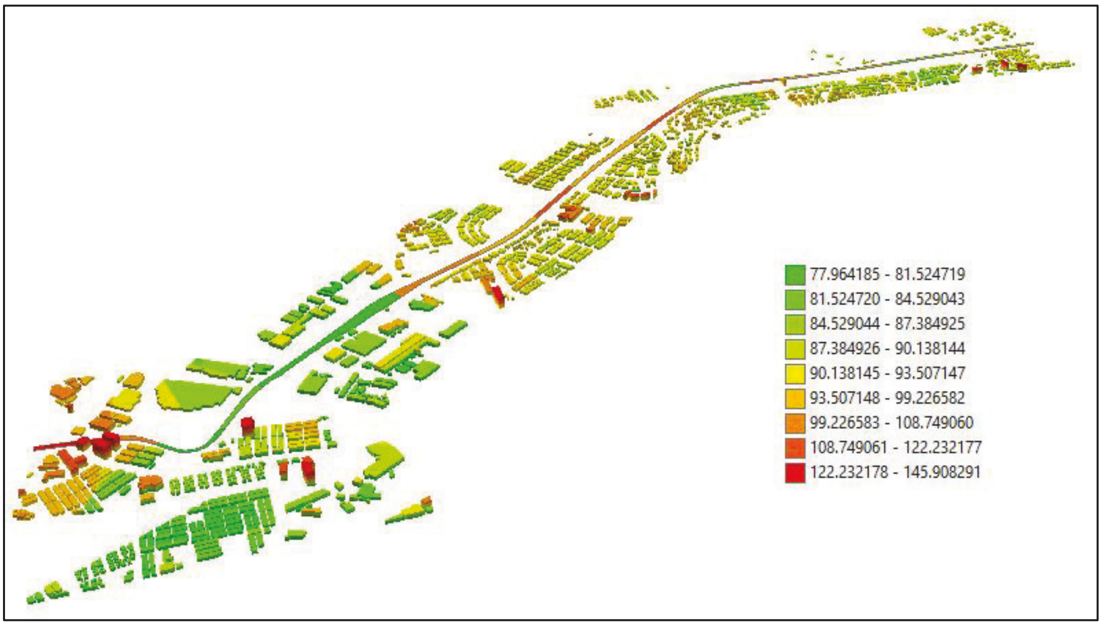

Figure 4.30 Shows 3D noise perdition of Shah Alam - Seksyen 7 (Morning time, Sunday).

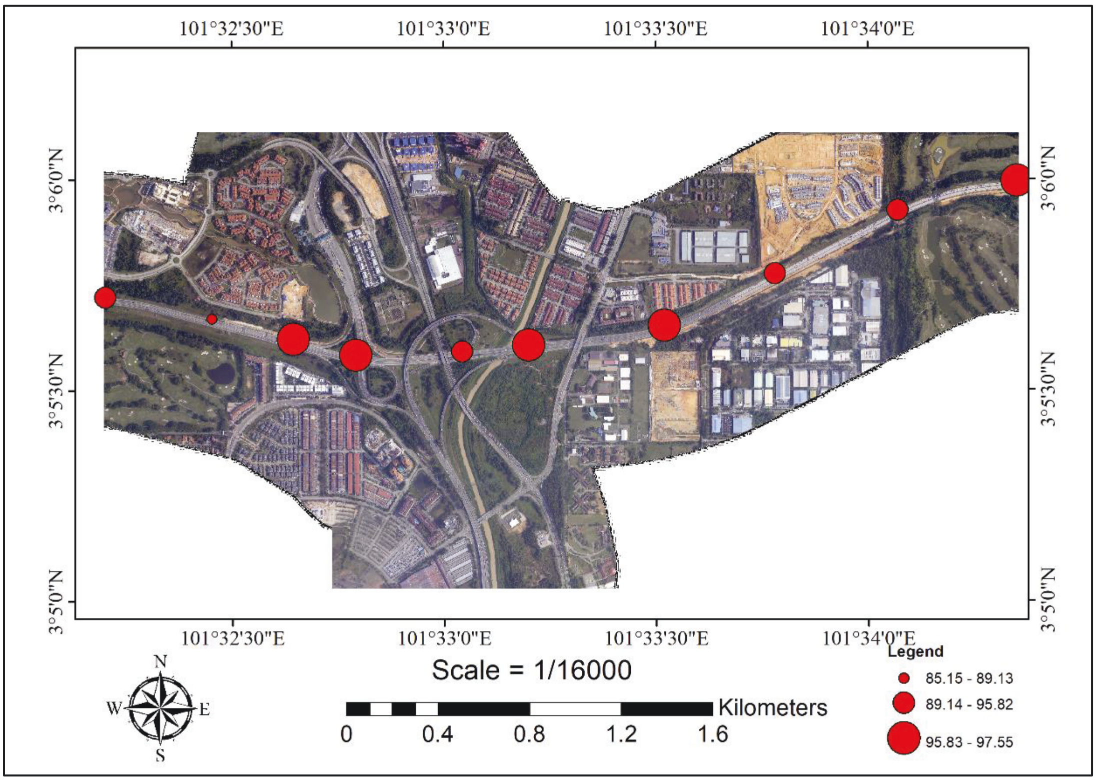

Figure 4.31 Shows noise samples of Shah Alam - Seksyen 13 (Morning time, Sunday).

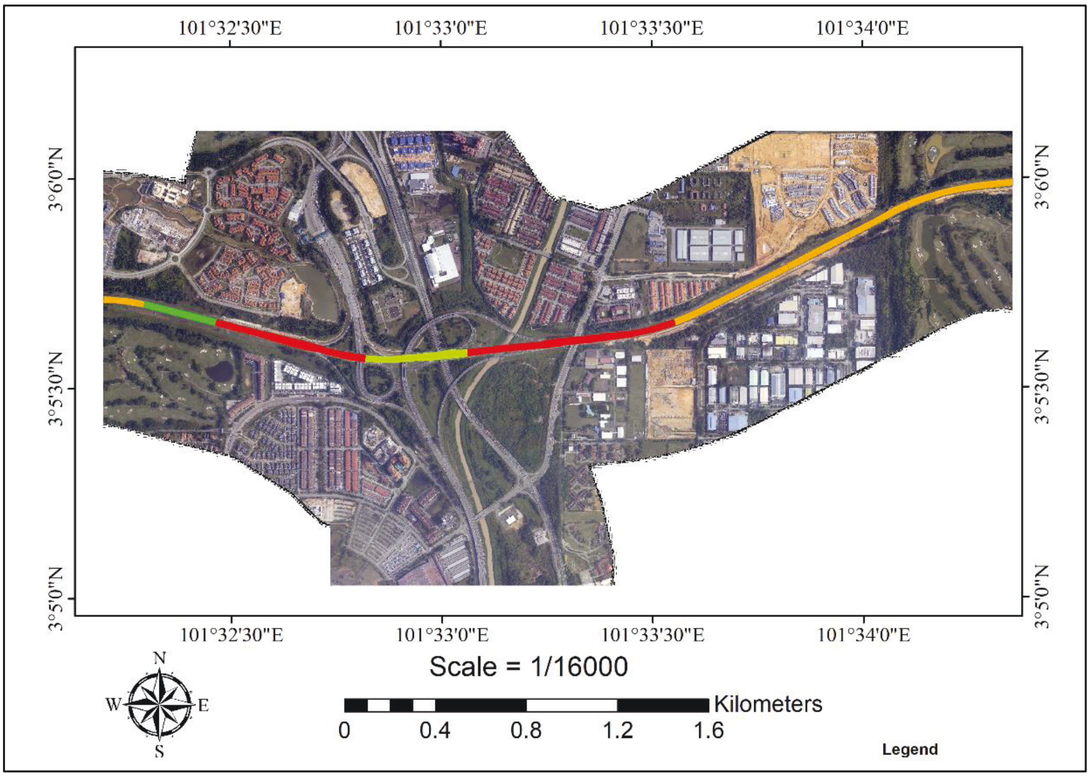

Figure 4.32 Shows 2D road noise prediction of Shah Alam - Seksyen 13 (Morning time, Sunday).

Figure 4.33 Shows 3D noise propagation of Shah Alam - Seksyen 13 (Morning time, Sunday).

Figure 4.34 Shows 3D noise perdition of Shah Alam - Seksyen 13 (Morning time, Sunday).

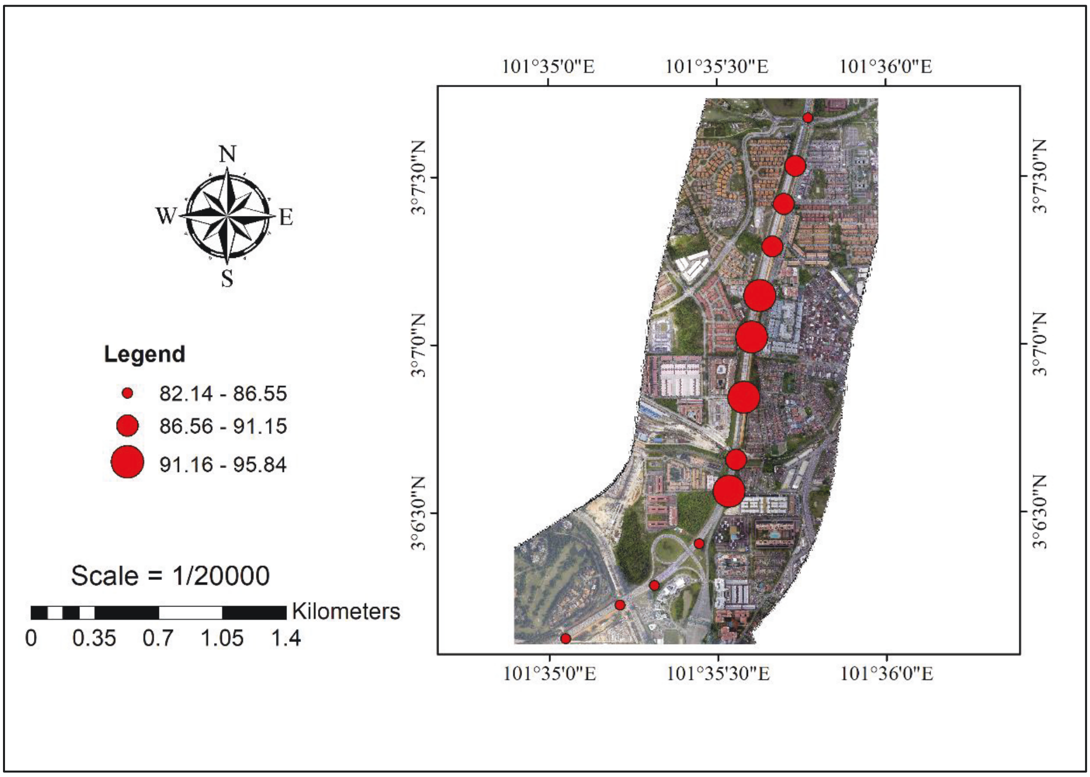

Figure 4.35 Shows noise samples of Subang Jaya (Morning time, Sunday).

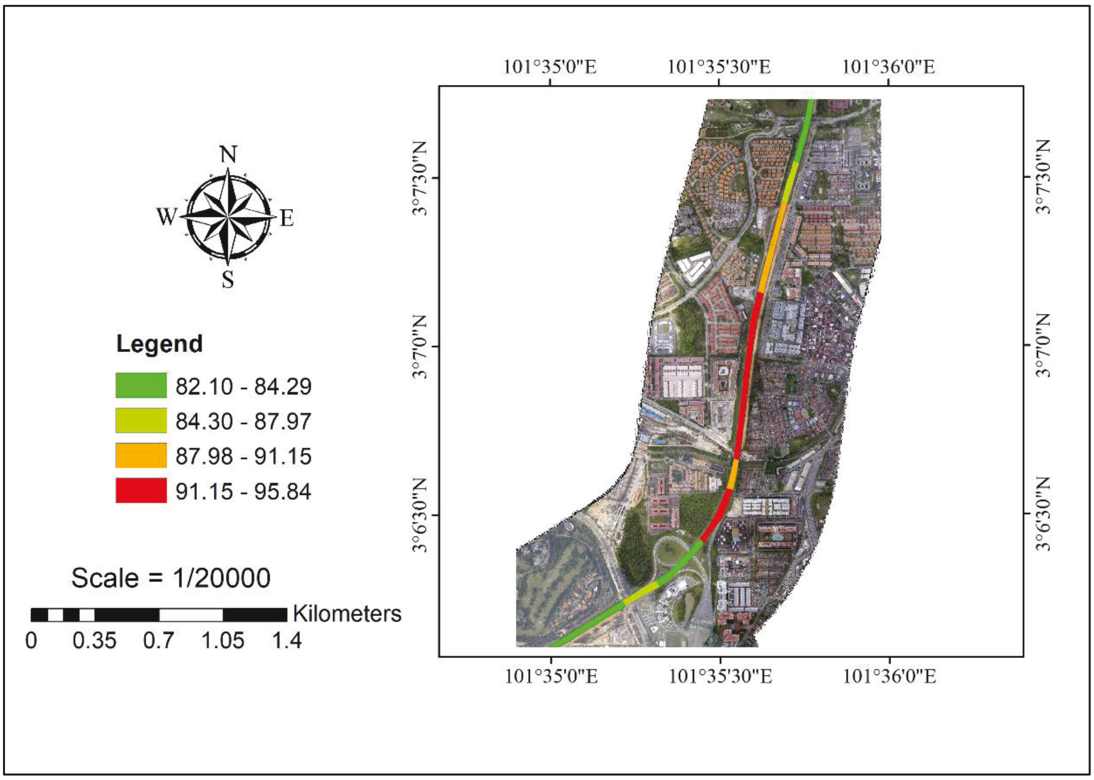

Figure 4.36 Shows 2D road noise prediction of Subang Jaya (Morning time, Sunday).

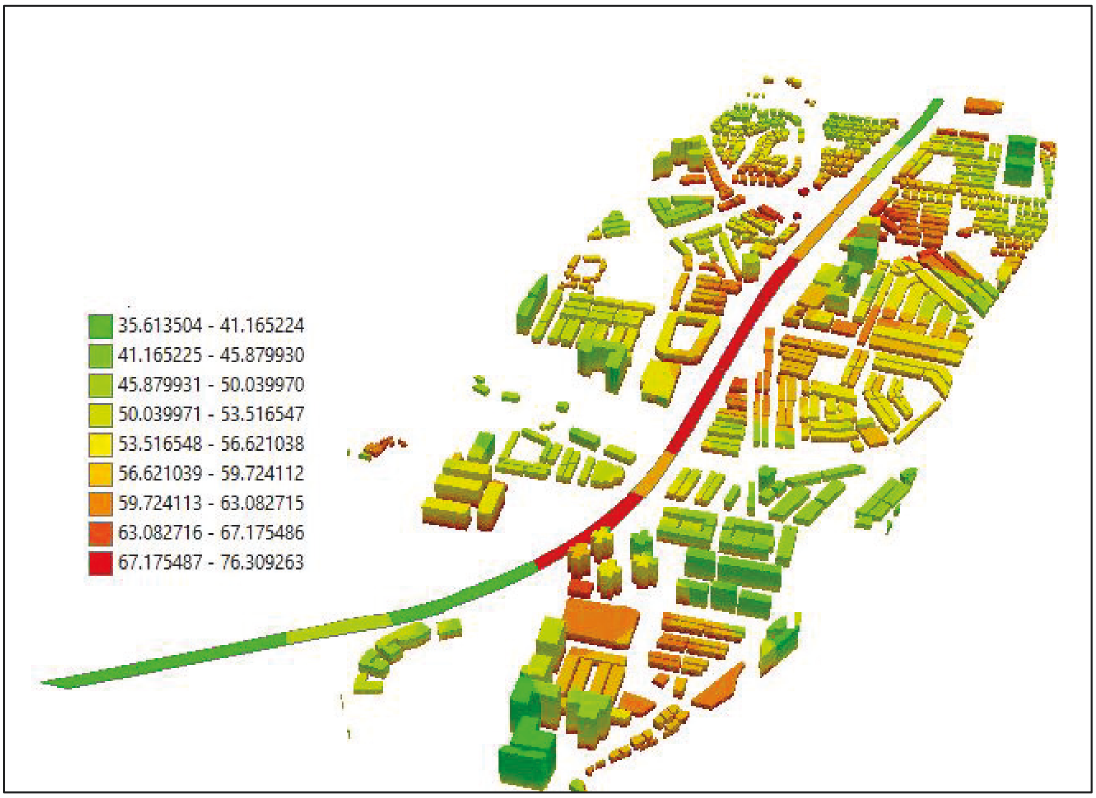

Figure 4.37 Shows 3D noise propagation of Subang Jaya (Morning time, Sunday).

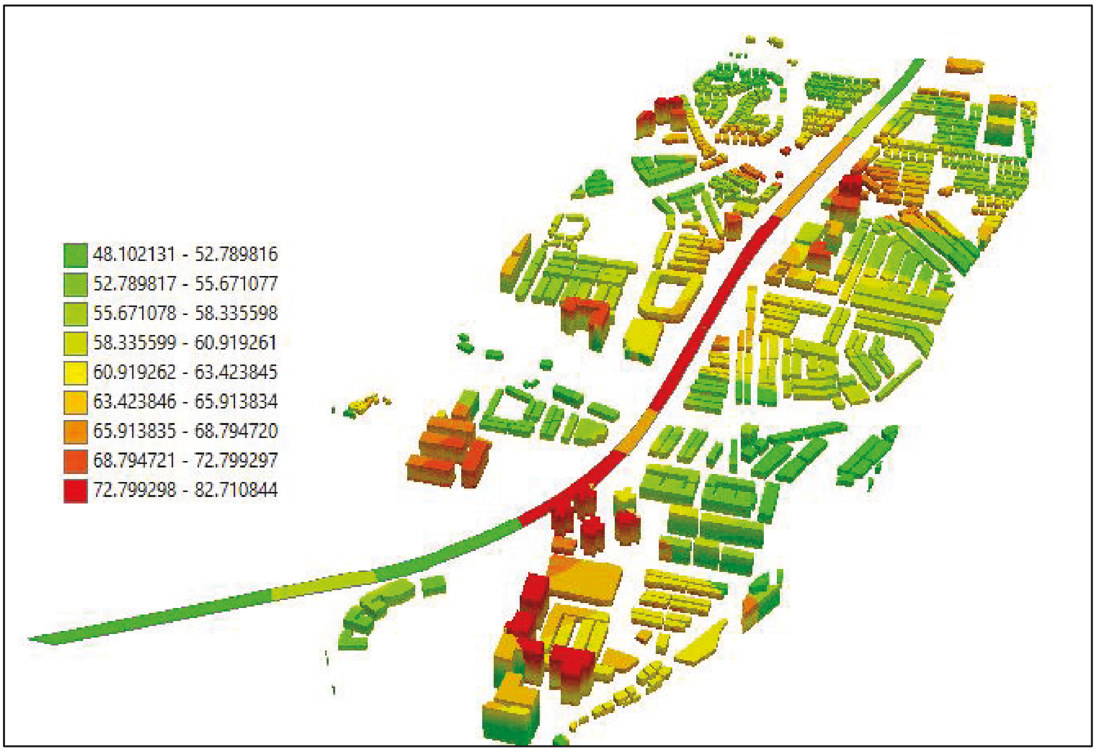

Figure 4.38 Shows 3D noise perdition of Subang Jaya (Morning time, Sunday).

4.6.2 Results of Statistical Analysis

4.6.2.1 Shah Alam – Seksyen 7

4.6.2.1.1 On Sunday

In the Shah Alam - Seksyen 7, the correlation between noise levels on different time and traffic volume has been analyzed to understand the relationship between the traffic noise and traffic volume. In the morning, the analysis showed that the highest correlation (R^2= 0.124) was between the noise level and the number of motorcycles passed during the data collection. However, the relationship between the noise level and either car or heavy vehicles were high as shown in the figure 4.39.

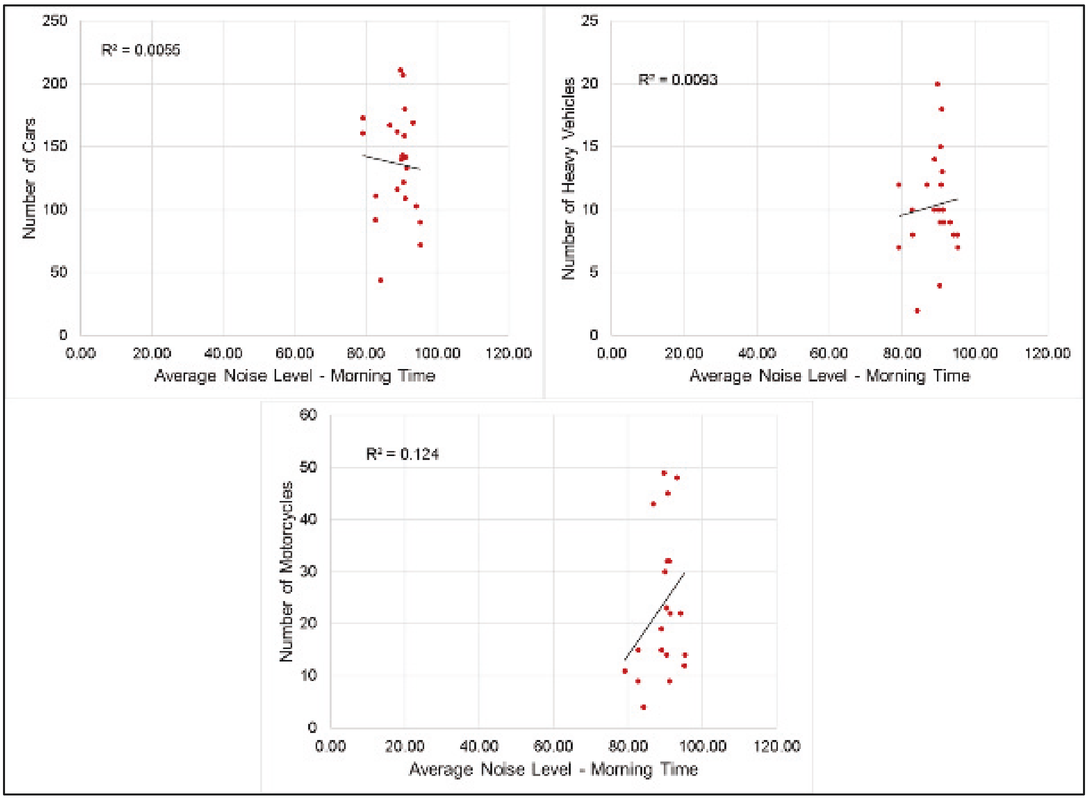

Figure 4.39 Correlation between noise level and traffic volume in the Shah Alam - Seksyen 7 – morning time - Sunday.

In the afternoon, the correlation analyses showed that the highest correlation (R^2=0.1809) was between noise level and the number of cars. On the other hand, the correlation between noise level and some heavy vehicles (R^2= 0.15) was slightly less than the correlation between noise level and the number of cars. However, the relationship between the noise level and the number of motorcycles was very low (R^2=0.028) as the figure 4.40.

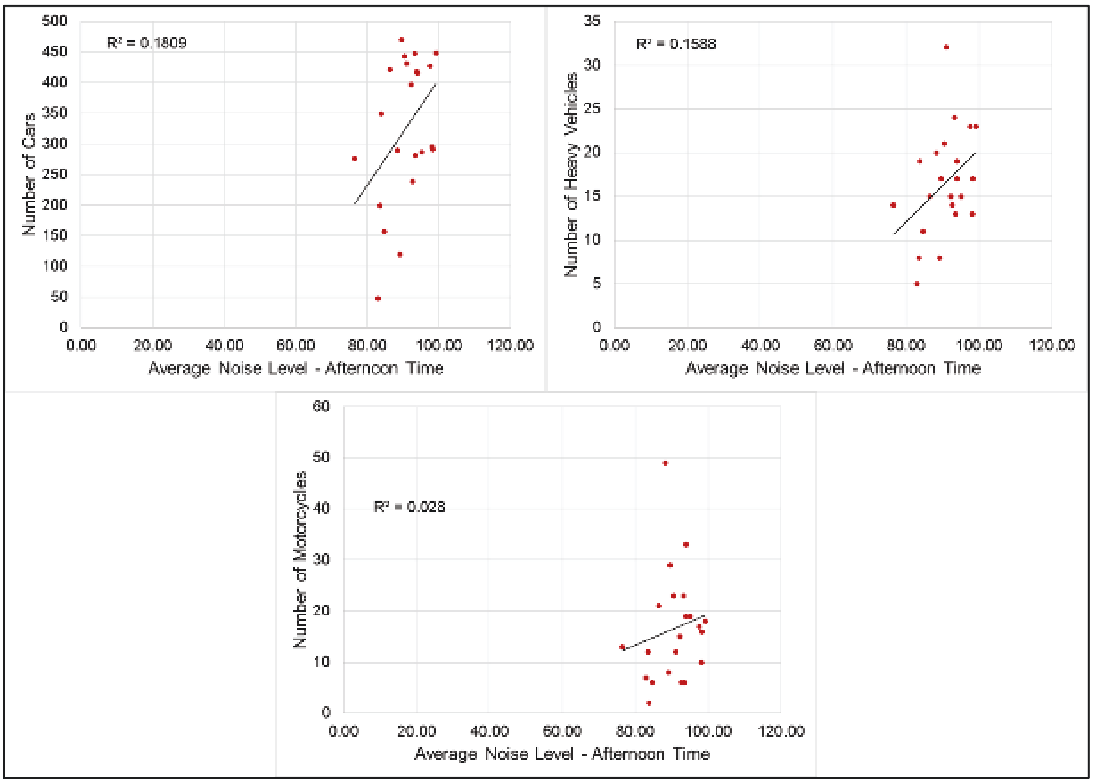

Figure 4.40 Correlation between noise level and traffic volume in the Shah Alam - Seksyen 7 – afternoon time - Sunday.

In addition, the analysis indicated that the highest correlation between the noise level and the number of heavy vehicles (R^2=0.307) during evening time. The correlation between the noise level and the number of cars (R^2=0.28) was slightly less than the correlation with the number of heavy vehicles, whereas the analysis showed relatively low correlation (R^2=0.101) between the noise level and the number of the motorcycles in the study area as the figure 4.41.

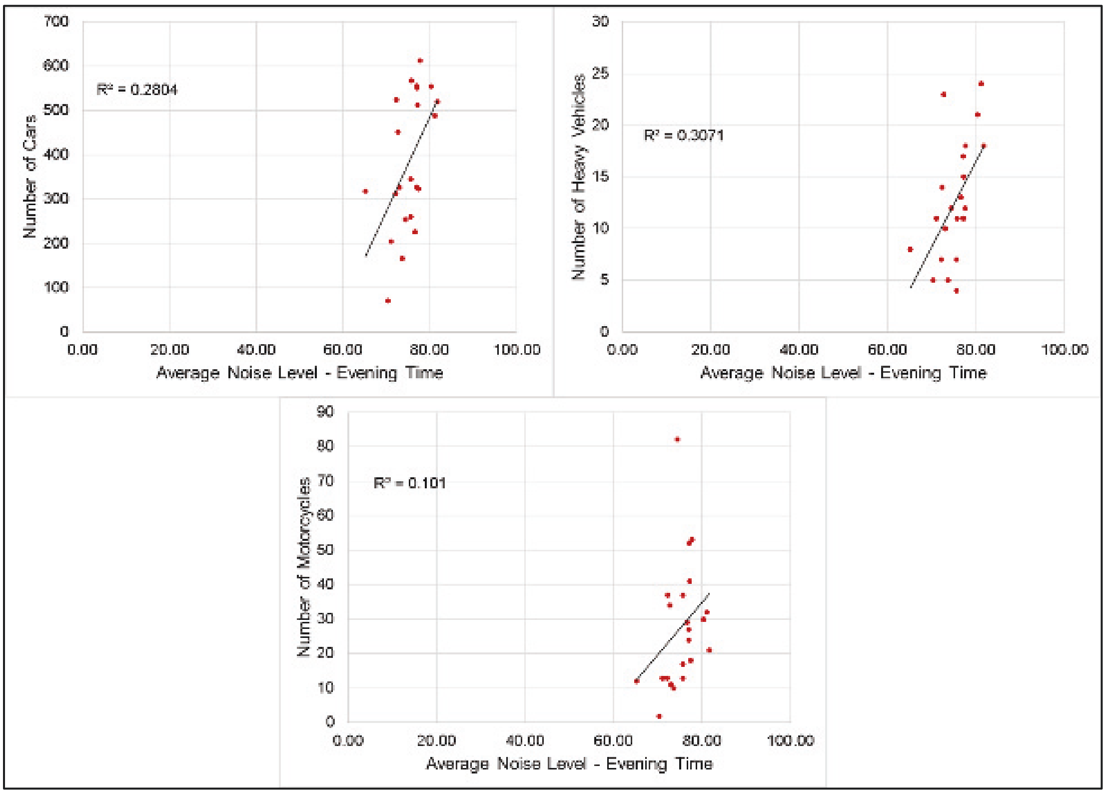

Figure 4.41 Correlation between noise level and traffic volume in the Shah Alam - Seksyen 7 – evening time - Sunday.

On the other hand, during nighttime, the highest correlation (R^2=0.659) was found between the noise level and the number of cars. Similarly, the correlation between the noise level and the number of heavy vehicles was relatively high (R^2=0.471). Alternatively, the correlation between the measured noise and the number of motorcycles passed during data collection was relatively low (R^2=0.137) as the figure 4.42.

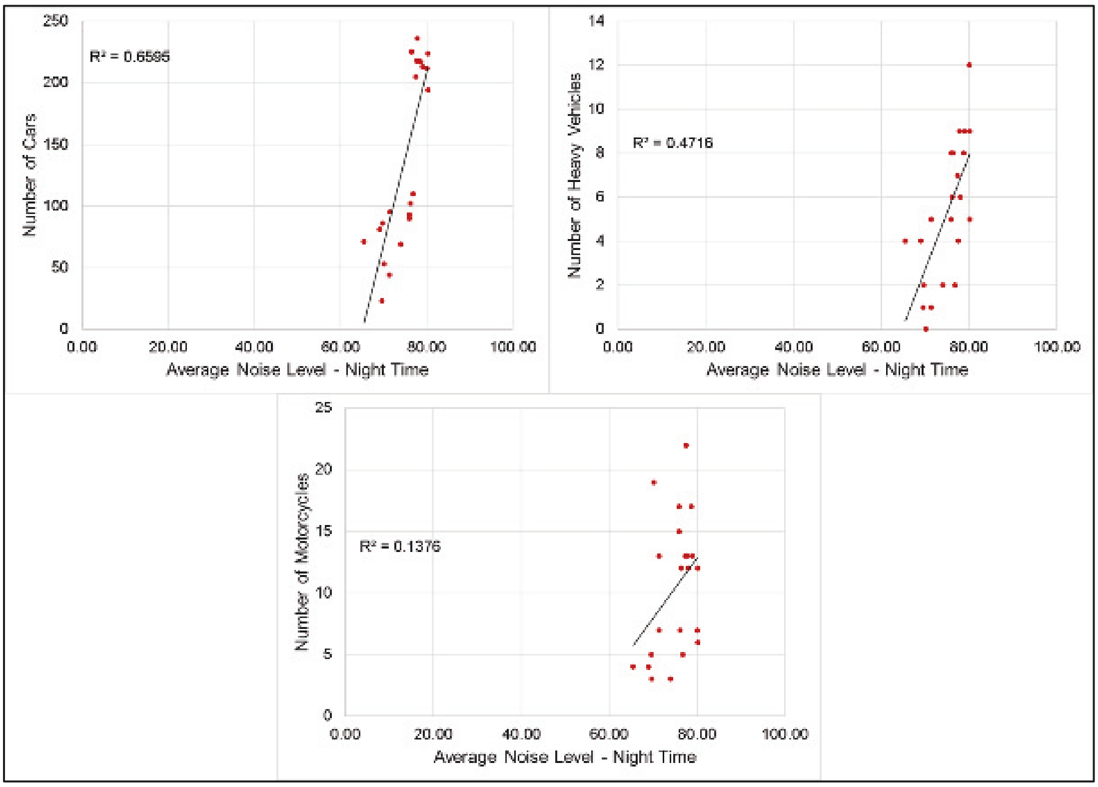

Figure 4.42 Correlation between noise level and traffic volume in the Shah Alam - Seksyen 7 – nighttime.

4.6.2.1.2 On Monday

On Monday, the statistics of the noise measurements showed that during the morning, the highest correlation (R^2=0.09) was the noise level and the number of motorcycles. The correlation between noise and the number of heavy vehicles (R^2=0.017) was higher than the correlation between the noise and the number of cars (R^2=0.0001) as the figure 4.43.

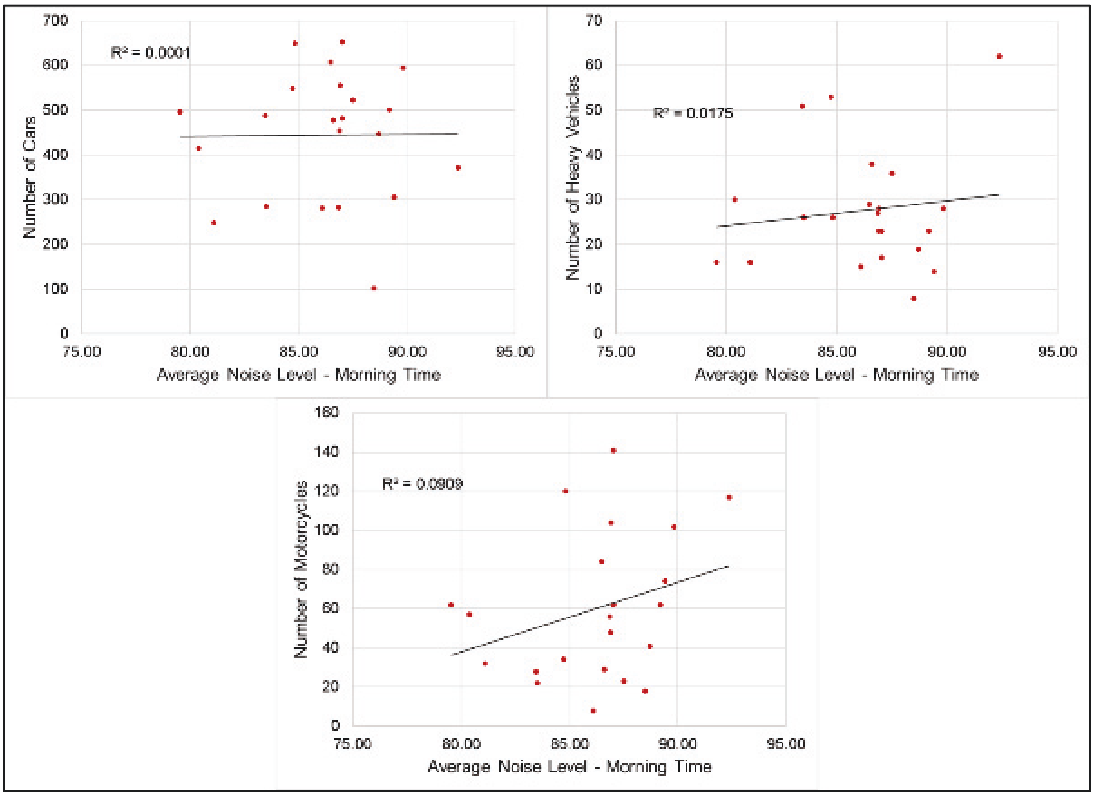

Figure 4.43 Correlation between noise level and traffic volume in the Shah Alam - Seksyen 7 – morning time- Monday.

During afternoon time, the data shows that the highest correlation (R^2=0.099) was the noise level and the number of cars. In addition, the correlation between the noise and the number of heavy vehicles (R^2=0.066) was higher than the correlation with the number of motorcycles (R^2=0.007) as the figure 4.44.

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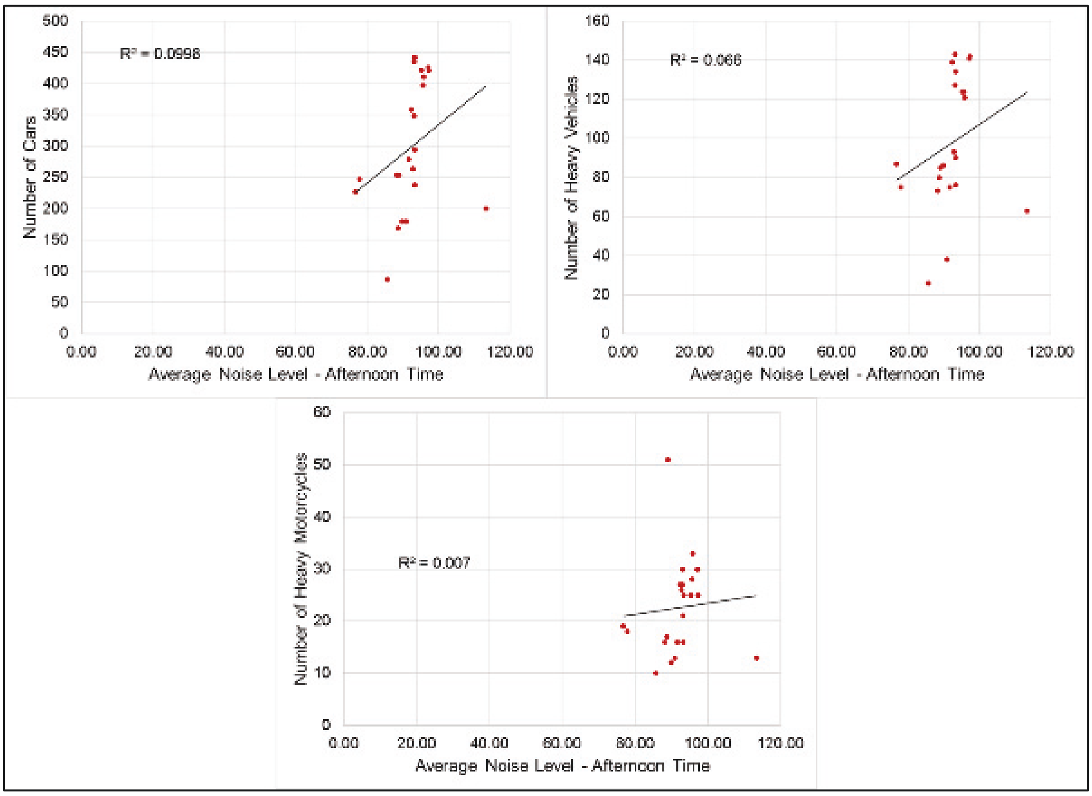

Figure 4.44 Correlation between noise level and traffic volume in the Shah Alam - Seksyen 7 – afternoon time- Monday.

In the evening, the correlation between the noise and the number of motorcycles was found the highest (R^2=0.432). The correlation between the noise and the number of cars (R^2=0.25) was greater than the correlation with the number of heavy vehicles (R^2=0.136) as the figure 4.45.

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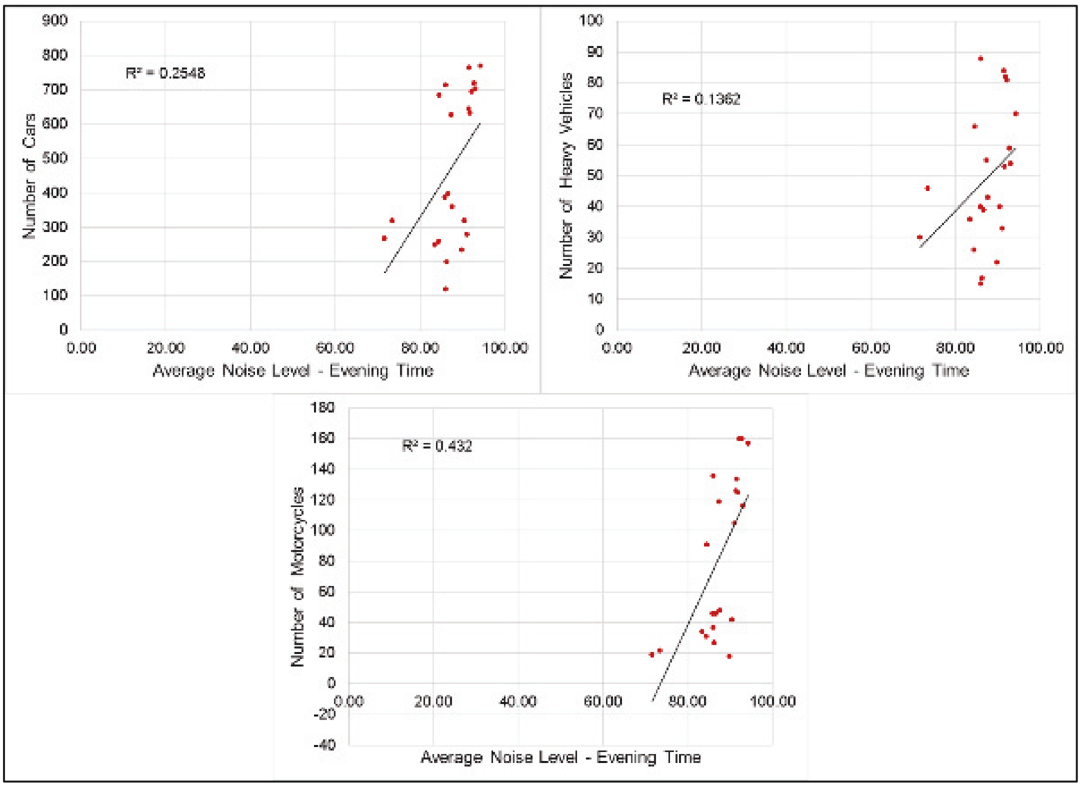

Figure 4.45 Correlation between noise level and traffic volume in the Shah Alam - Seksyen 7 – evening time- Monday.

In midnight, cars had the highest correlation with noise (R^2=0.459). In addition, the correlation between the noise level and the number of heavy vehicles was higher than the correlation with the number of motorcycles as the figure 4.46.

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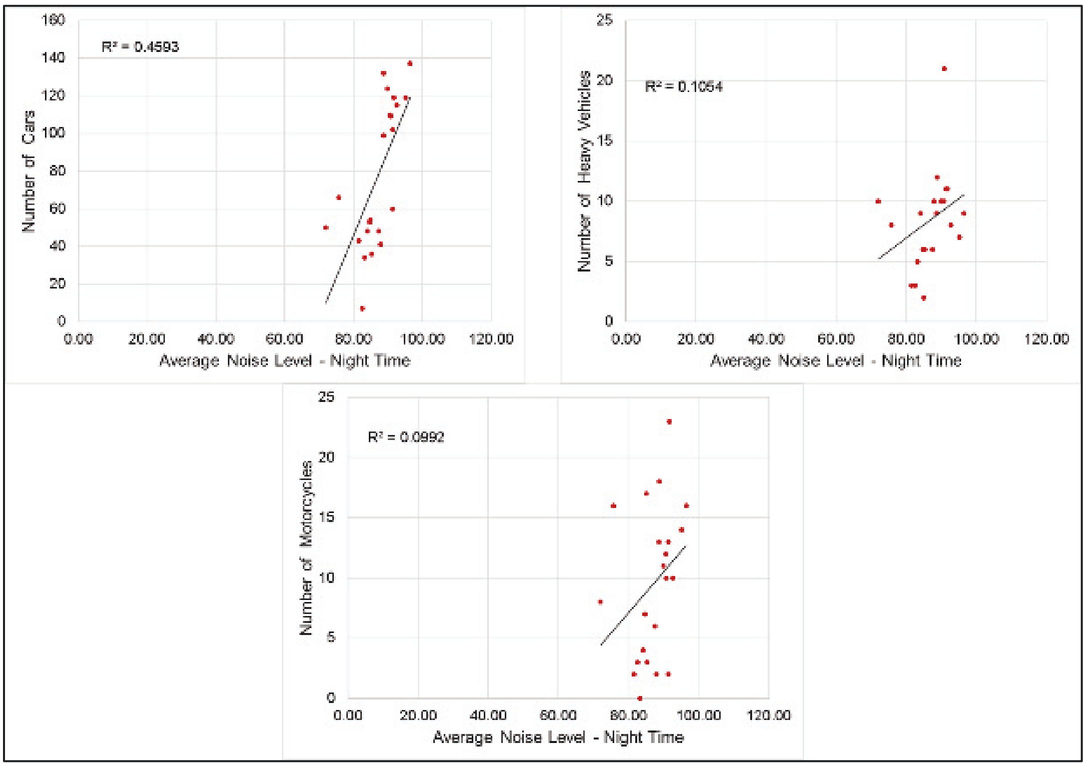

Figure 4.46 Correlation between noise level and traffic volume in the Shah Alam - Seksyen 7 – nighttime- Monday.

4.6.2.1.3 Correlation between Measured Noise on Sunday and Monday

On the other hand, the analysis showed that there is a significant difference between the noise level on Sunday and Monday. For example, the correlation between the measured noise in Sunday and Monday is 0.33. In addition, the correlation during afternoon time is lower than morning time. In the evening, the correlation is higher than the afternoon time and slightly lower than the morning time. The correlation during afternoon and evening time are 0.14 and 0.30, respectively. However, the correlation during mid-nighttime is the highest (R^2=0.66) as the figure 4.47.

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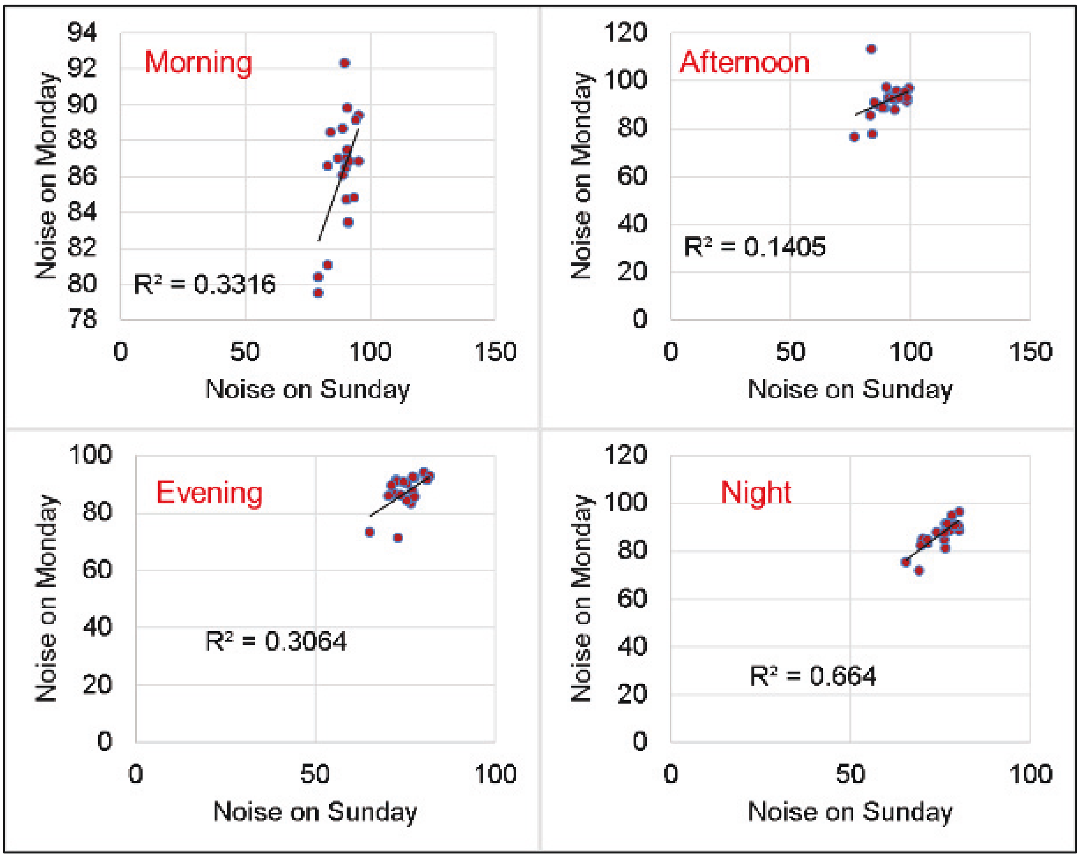

Figure 4.47 Correlation between Sunday and Monday noise levels- Shah Alam - Seksyen 7.

4.6.2.2 Shah Alam – Seksyen 13

4.6.2.2.1 On Sunday

In this study area, the highest correlation during morning time was the noise level and the number of cars (R^2=0.39). In addition, the correlation between the noise and the number of heavy vehicles was 0.075 which is slightly higher than the correlation with the number of motorcycles. On the other hand, during the afternoon time, the correlation between the noise and the number of heavy vehicles (R^2=0.28) was the highest. The correlation between noise and the number of cars or motorcycles was relatively low (R^2<0.08) as the figure 4.48 and 4.49.

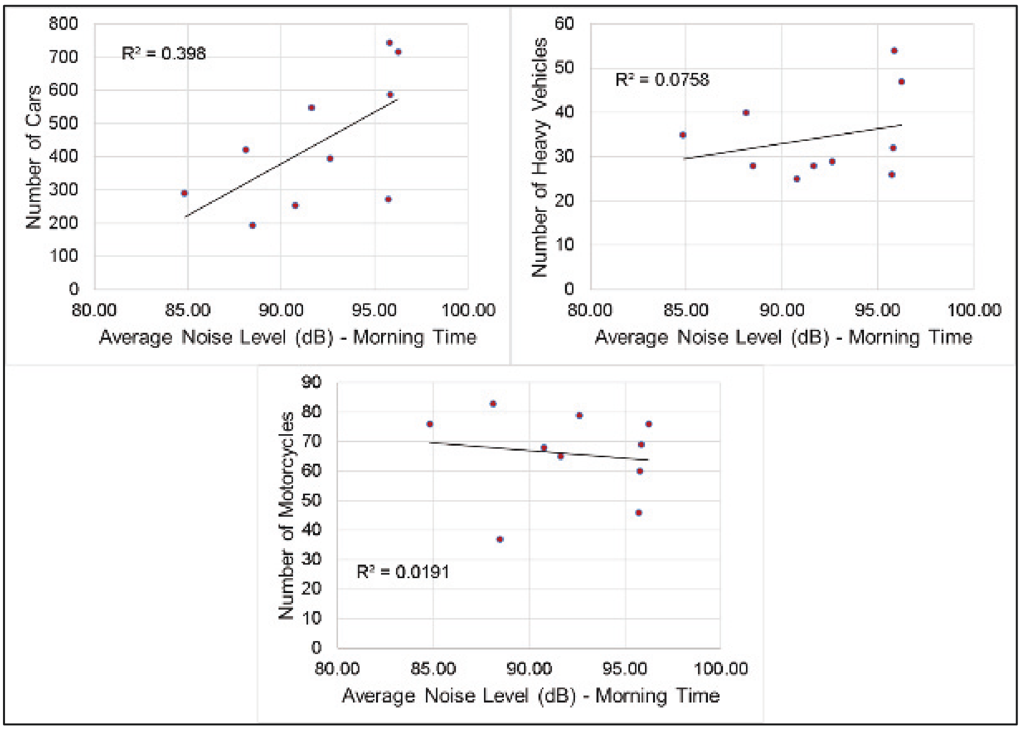

Figure 4.48 Correlation between noise level and traffic volume in the Shah Alam - Seksyen 13 – morning time- Sunday.

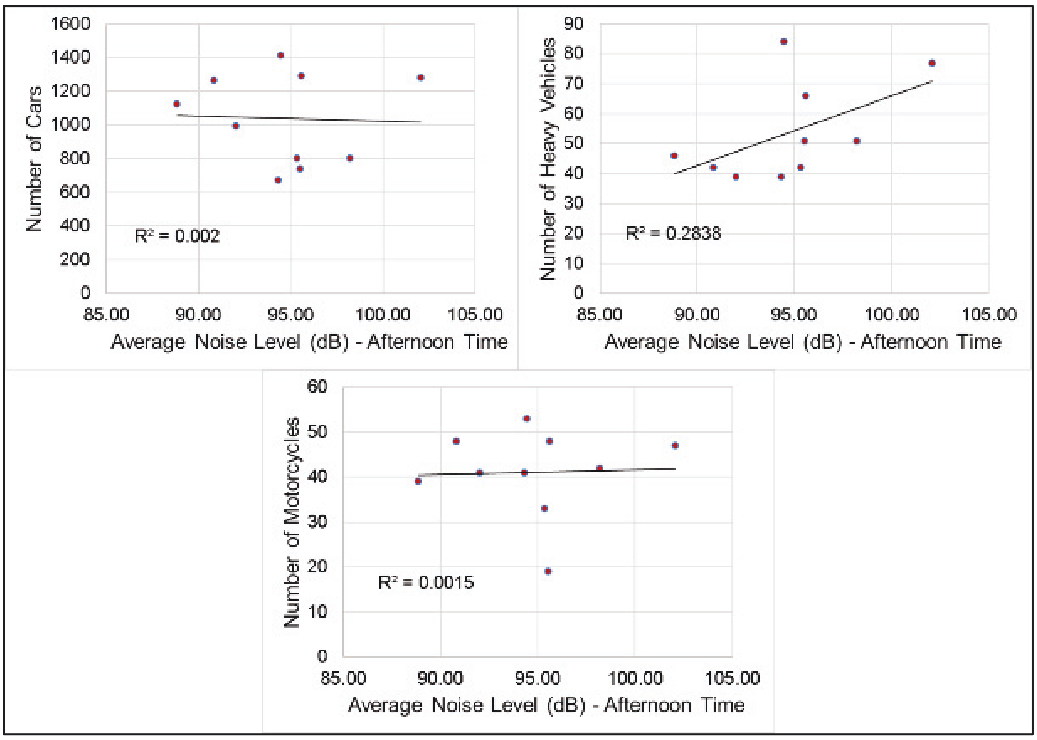

Figure 4.49 Correlation between noise level and traffic flow in the Shah Alam - Seksyen 13 – afternoon time- Sunday.

Furthermore, during evening time, the correlation between the noise level and the number of cars was the highest with an R^2 of 0.28. The correlation between noise and the number of heavy vehicles was 0.111 which was significantly greater than the correlation between the noise and the number of motorcycles. However, on mid-night, the highest correlation was found between the noise level and the number of motorcycles (R^2=152). The correlation between the noise and the number of heavy vehicles or cars was lower than 0.05 as the figure 4.50 and 4.51.

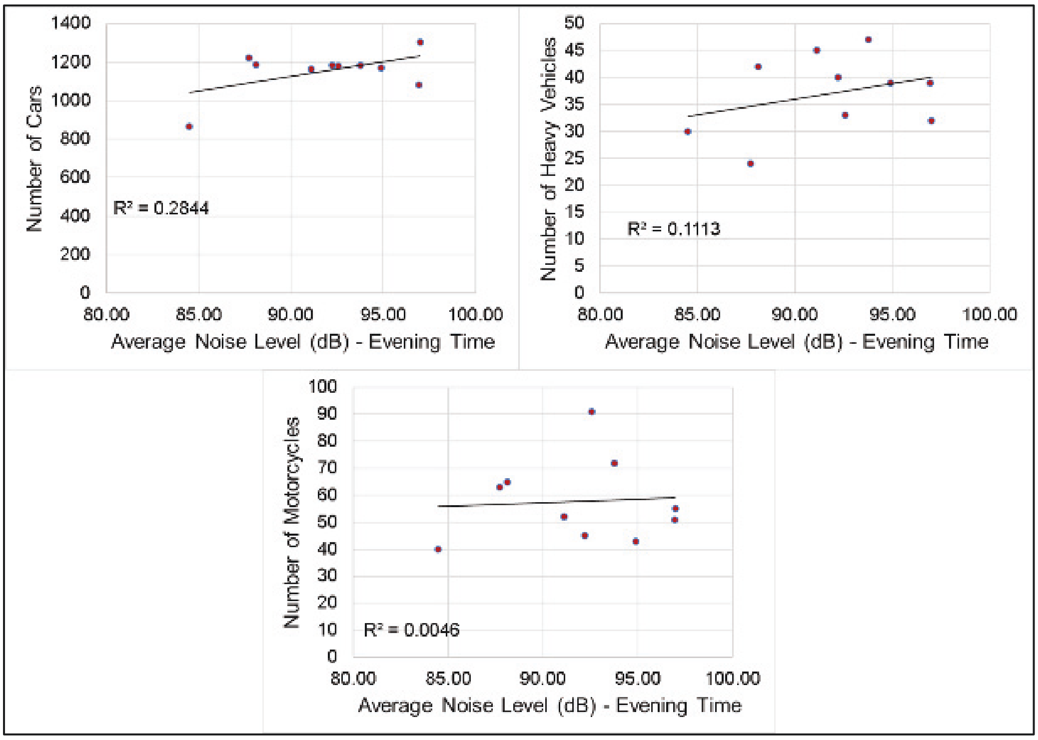

Figure 4.50 Correlation between noise level and traffic volume in the Shah Alam - Seksyen 13 – evening time- Sunday.

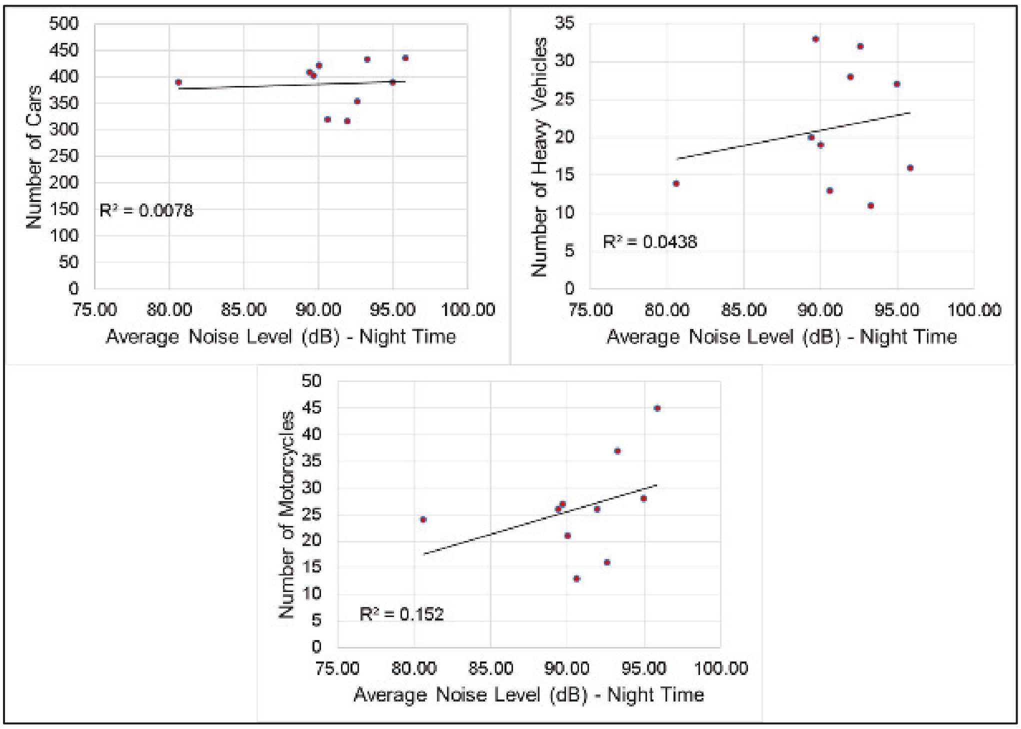

Figure 4.51 Correlation between noise level and traffic flow in the Shah Alam - Seksyen 13 – nighttime- Sunday.

4.6.2.2.2 On Monday

The correlation between noise level and the number of motorcycles was the highest during the morning and afternoon time (R^2=0.20 and R^2=0.13, respectively). During morning time, the correlation between the noise and the number of heavy vehicles was higher than the correlation between noise and the number of cars. However, during afternoon time, the correlation with some cars was greater than the correlation with heavy vehicles as the figure 4.52 and 4.53.

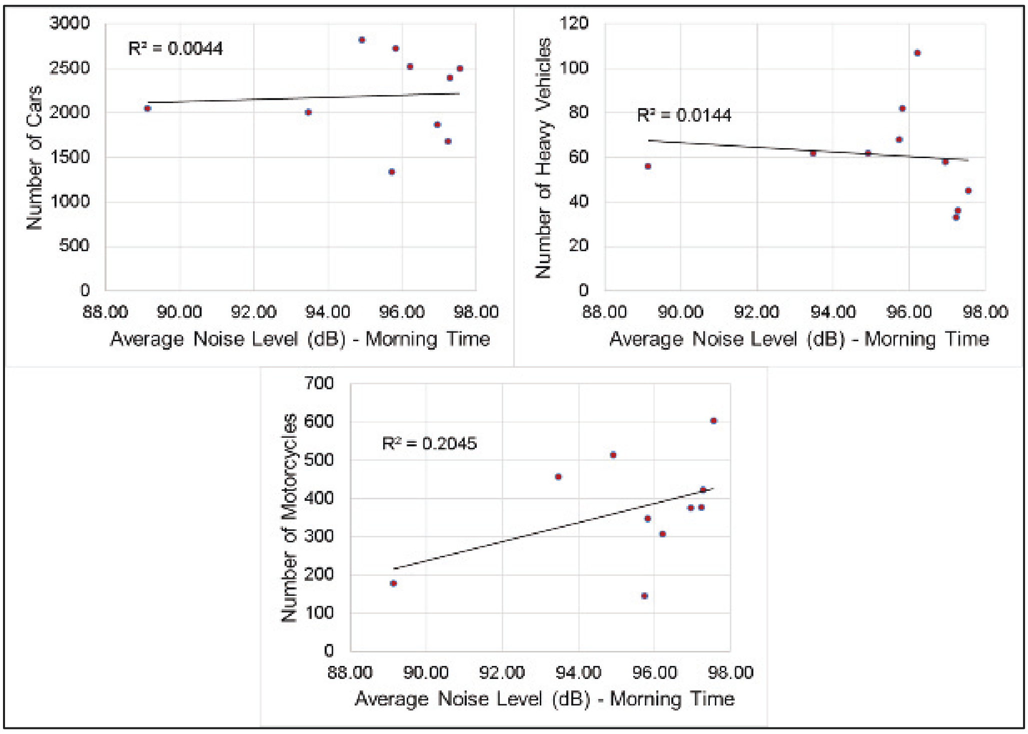

Figure 4.52 Correlation between noise level and traffic volume in the Shah Alam - Seksyen 13 – morning time- Monday.

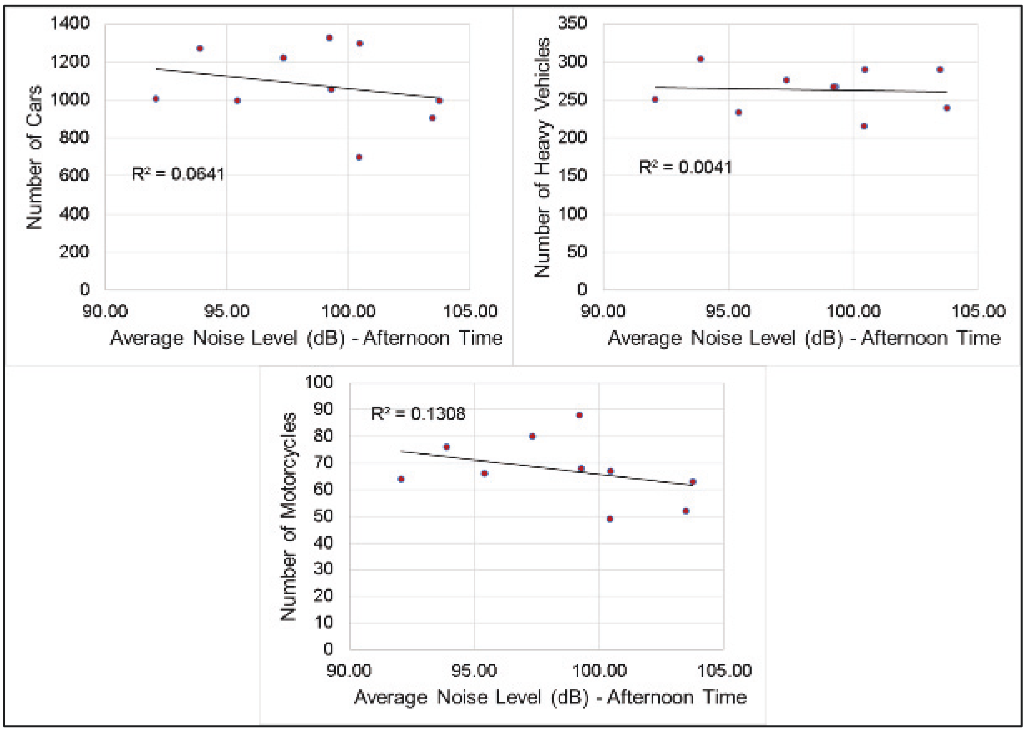

Figure 4.53 Correlation between noise level and traffic volume in the Shah Alam - Seksyen 13 – afternoon time- Monday.

In the evening, there was no high correlation between noise level and the traffic volume found. The highest correlation was 0.075 which was the noise and the number of motorcycles. During mid-nighttime, the correlation between the noise and the number of heavy vehicles (R^2=0.16) was the highest. In addition, the correlation between the noise and the number of motorcycles (R^2=0.11) was greater than the correlation with the number of cars as the figure 4.54 and 4.55.

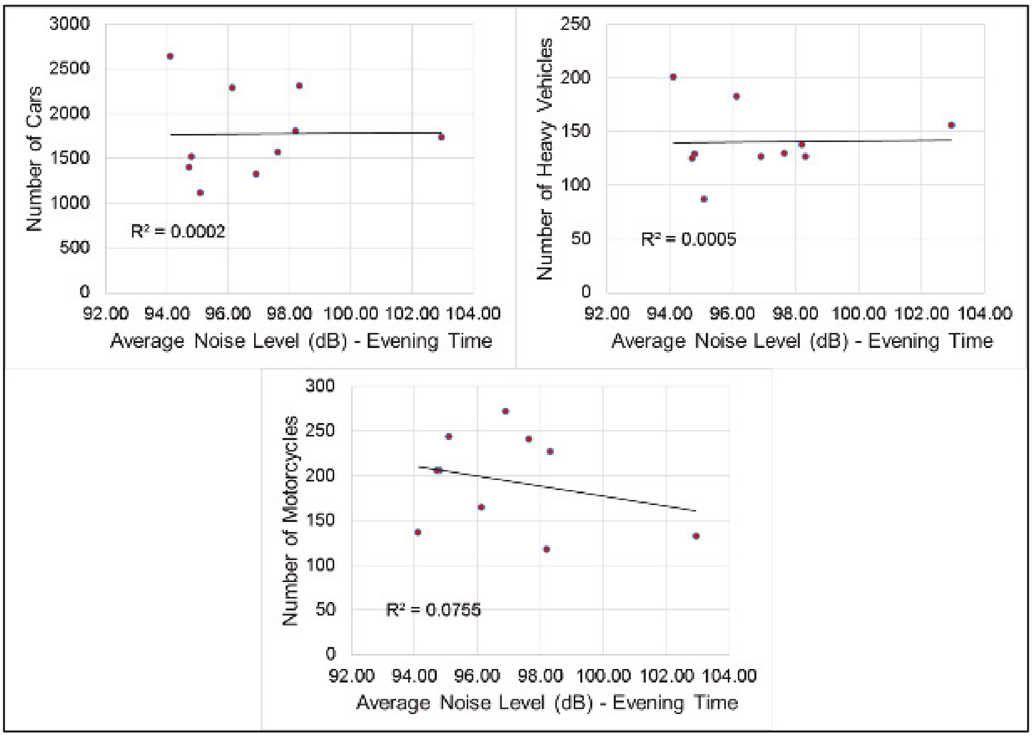

Figure 4.54 Correlation between noise level and traffic volume in the Shah Alam - Seksyen 13 – evening time - Monday.

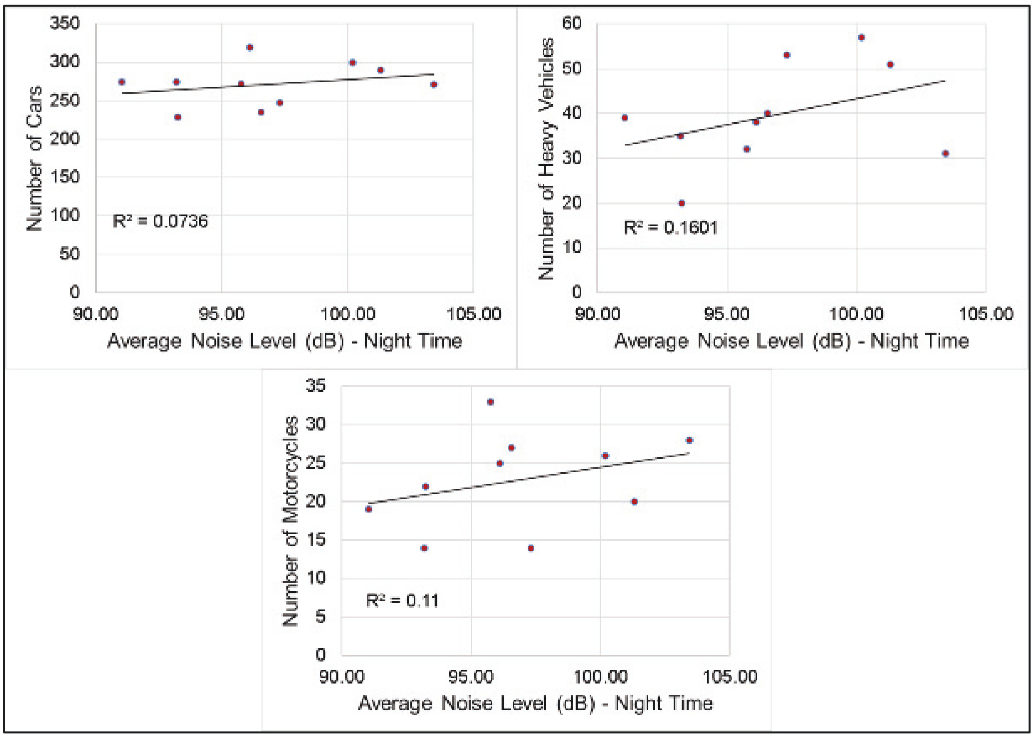

Figure 4.55 Correlation between noise level and traffic flow in the Shah Alam - Seksyen 13 – nighttime - Monday.

4.6.2.2.3 Correlation between Measured Noise on Sunday and Monday

The difference between the measured noise levels on Sunday and Monday is illustrated in Figure 66. In the morning, the correlation was low (R^2=0.021). However, the correlation was relatively high during afternoon time (R^2=0.34). During the evening, the correlation was low but higher than the morning time (R^2=0.034). In addition, in mid-night, the correlation was 0.114 which is higher than the correlation between morning and evening time as the figure 4.56.

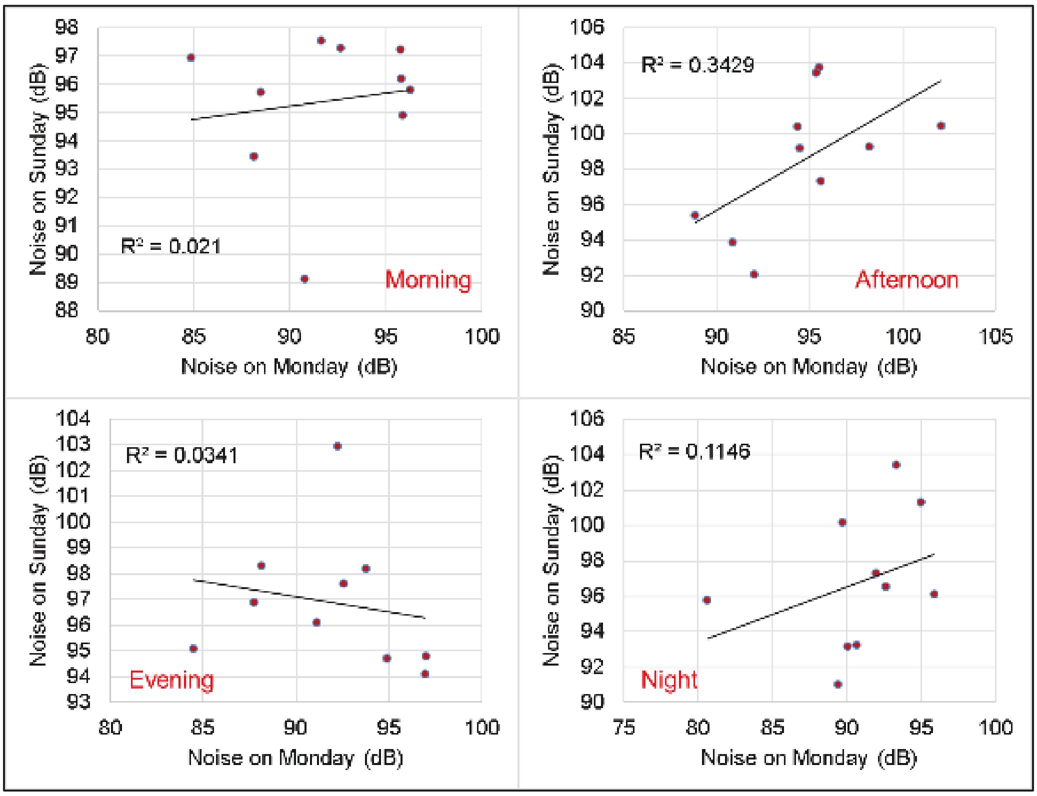

Figure 4.56 Correlation between Sunday and Monday noise levels- Shah Alam - Seksyen 13.

4.6.2.3 Subang Jaya

4.6.2.3.1 On Sunday

In the morning, the correlation between noise level and the traffic volume was relatively high with all the vehicle types. The highest correlation was with heavy vehicles (R^2=0.31). The correlation with cars and the motorcycles was 0.29 and 0.21, respectively. During afternoon time, the highest correlation was found between noise and the number of cars (R^2=0.16). The correlation between the noise and the number of heavy vehicles was 0.11 which was higher than the correlation with the number of motorcycles as the figure 4.57 and 4.58.

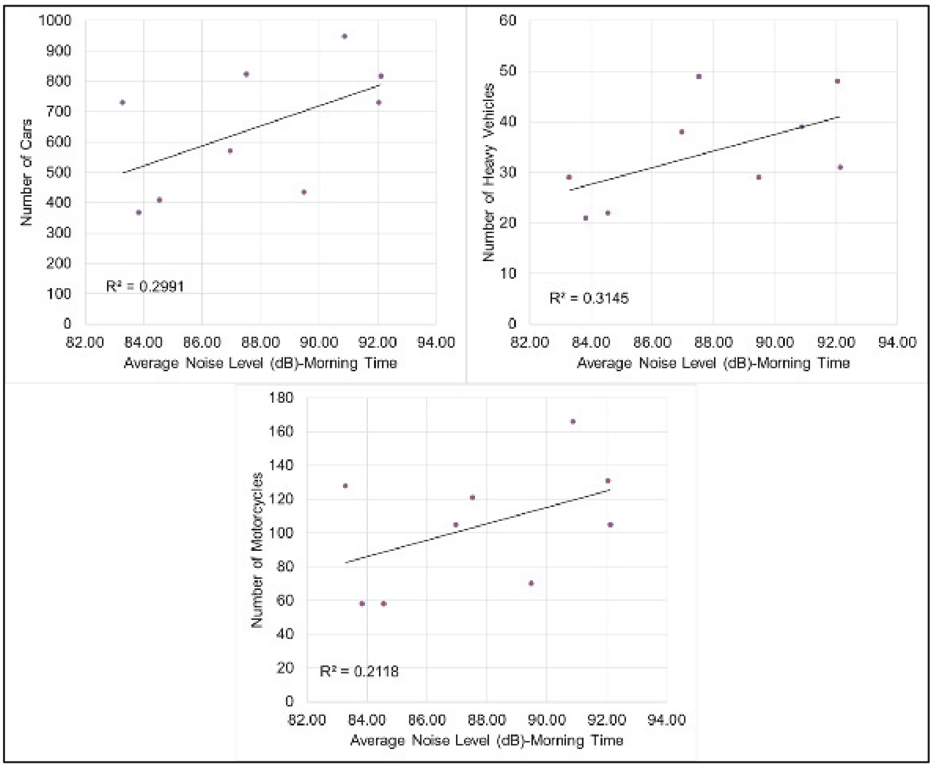

Figure 4.57 Correlation between noise level and traffic volume in the Subang Jaya – morning time - Sunday.

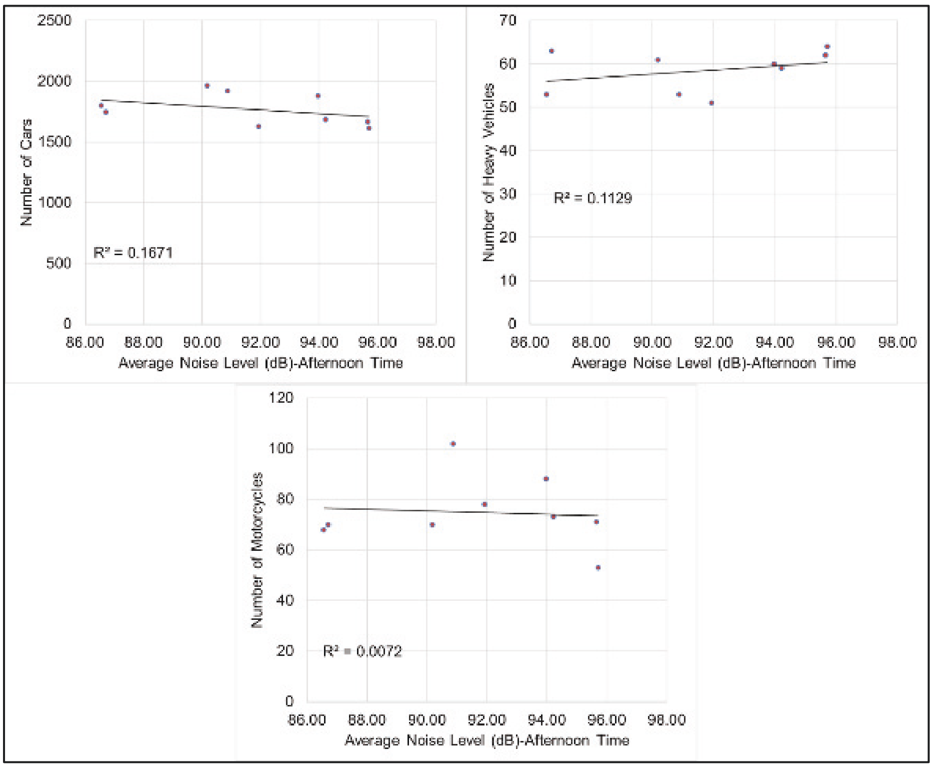

Figure 4.58 Correlation between noise level and traffic volume in the Subang Jaya – afternoon time - Sunday.

On the other hand, some motorcycles had the highest correlation (R^2=0.10) among other vehicle types with noise during evening time. In contrast, the correlation between the noise level and the other vehicle types (cars, heavy vehicles) was relatively low. The correlation of noise with cars was 0.069 but with heavy vehicles was 0.061. Furthermore, during nighttime, the highest correlation was found between noise and the number of cars (R^2=0.18). The correlation of noise and the number of heavy vehicles and the number of motorcycles were 0.043 and 0.002, respectively as the figure 4.59 and 4.60.

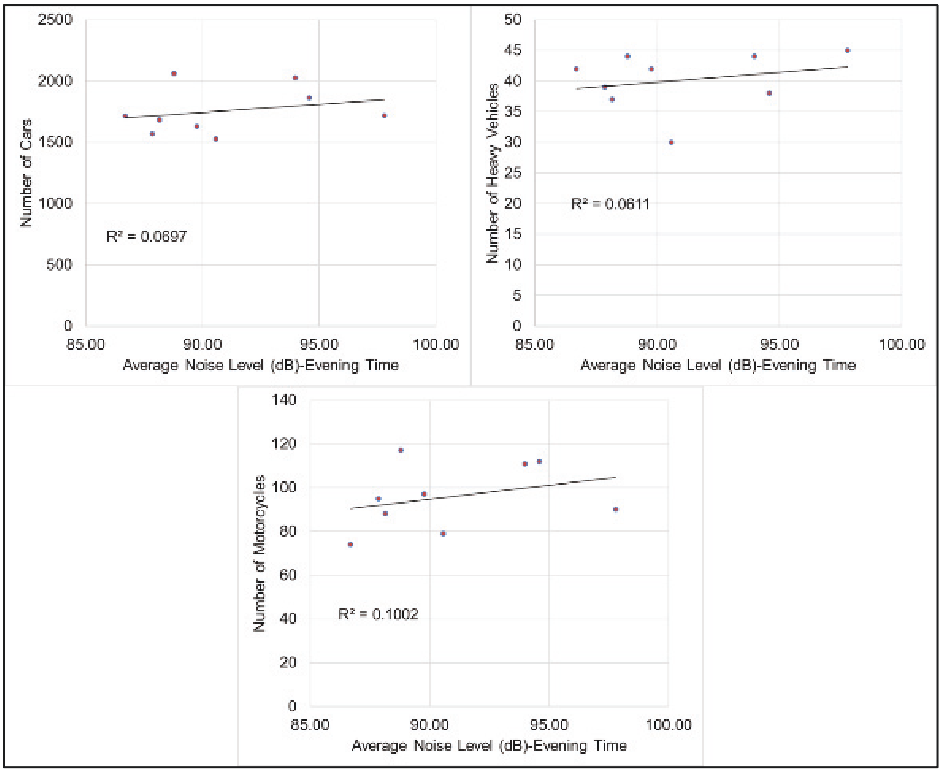

Figure 4.59 Correlation between noise level and traffic volume in the Subang Jaya – evening time - Sunday.

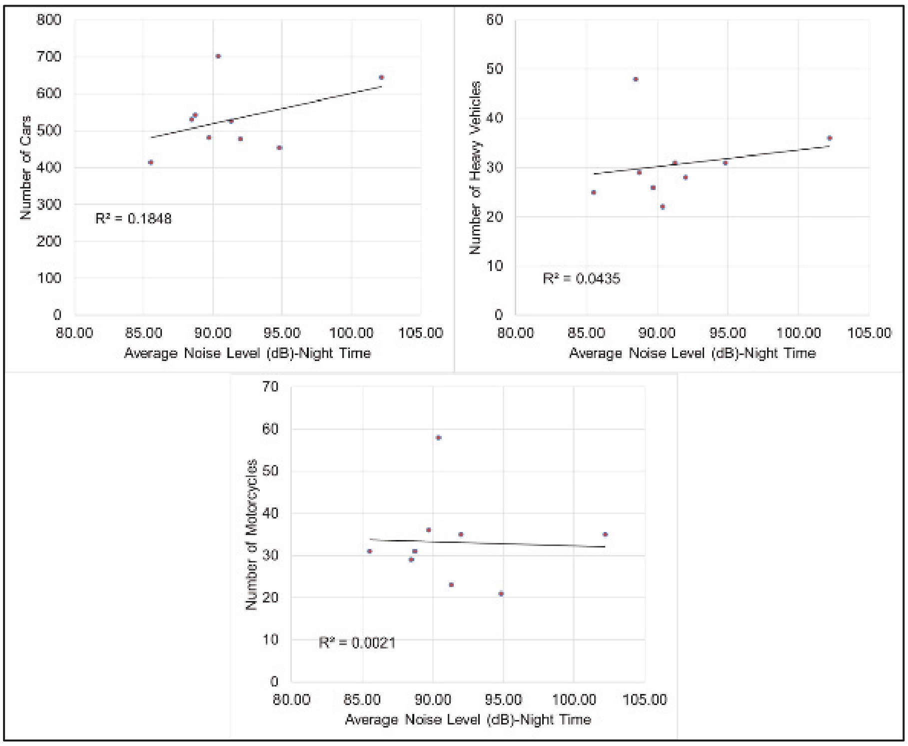

Figure 4.60 Correlation between noise level and traffic volume in the Subang Jaya – nighttime - Sunday.

4.6.2.3.2 On Monday

In this area, during morning time, the highest correlation between noise and the traffic volume was found to be 0.65 which was the noise and the number of cars. In addition, the number of heavy vehicles had the correlation of 0.48 with noise, whereas low correlation (R^2=0.04) was observed between noise and the number of motorcycles as the figure 4.61.

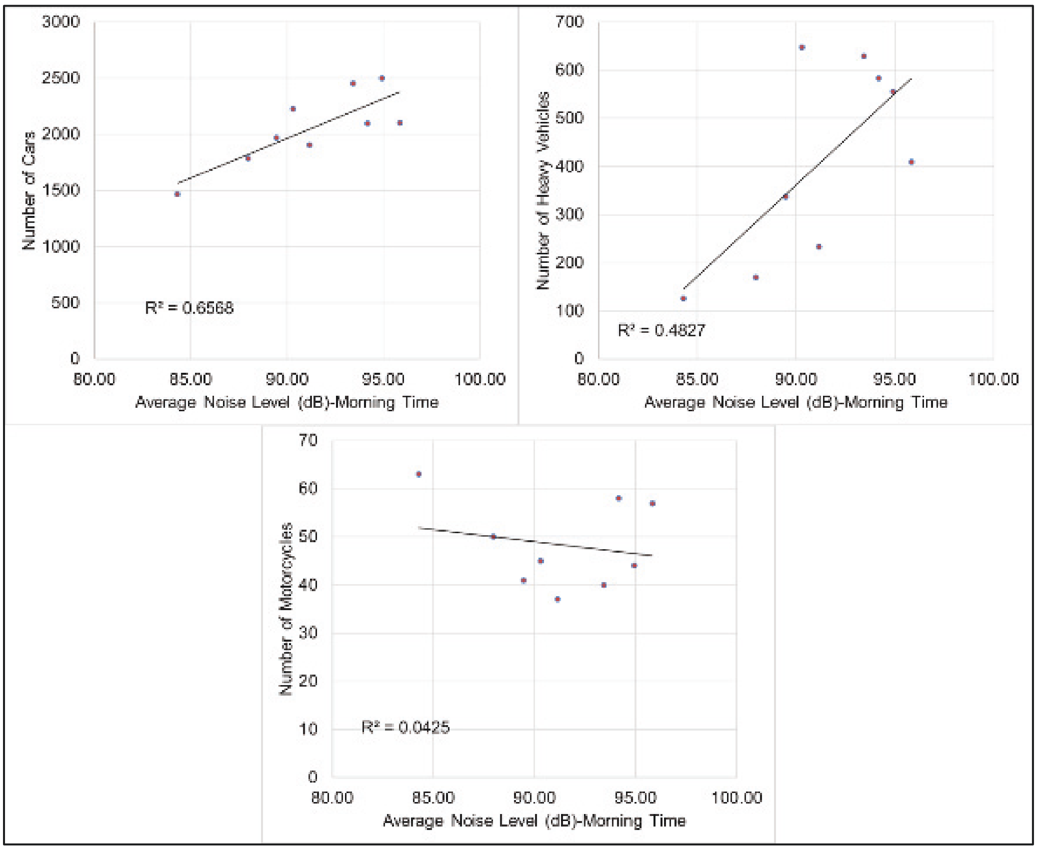

Figure 4.61 Correlation between noise level and traffic volume in the Subang Jaya – morning time - Monday.

In addition, during afternoon time, the data shows that there is a relatively high correlation between noise and the number of motorcycles (R^2=0.33) and heavy vehicles (R^2=0.24). However, a low correlation was observed between noise level and the number of cars during afternoon time. Furthermore, on the evening, the highest correlation was found between the noise and the number of motorcycles. The correlation was 0.22. In contrast, the correlation between noise and the number of cars and the number of heavy vehicles was relatively low (R^2<0.02) as the figure 4.62 and 4.63

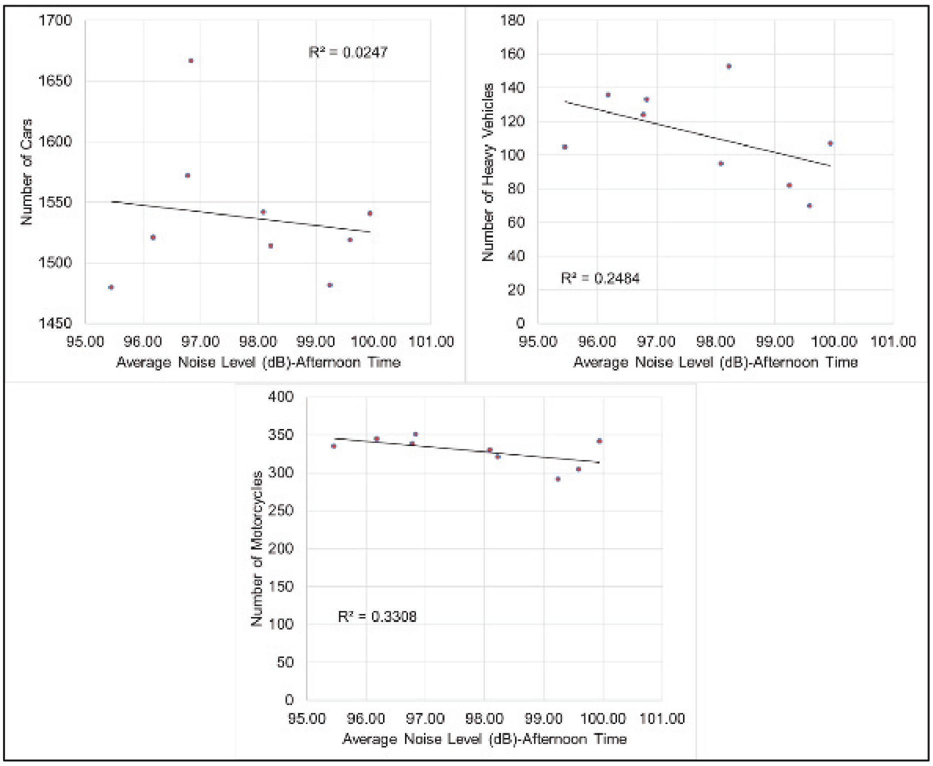

Figure 4.62 Correlation between noise level and traffic volume in the Subang Jaya – afternoon time - Monday.

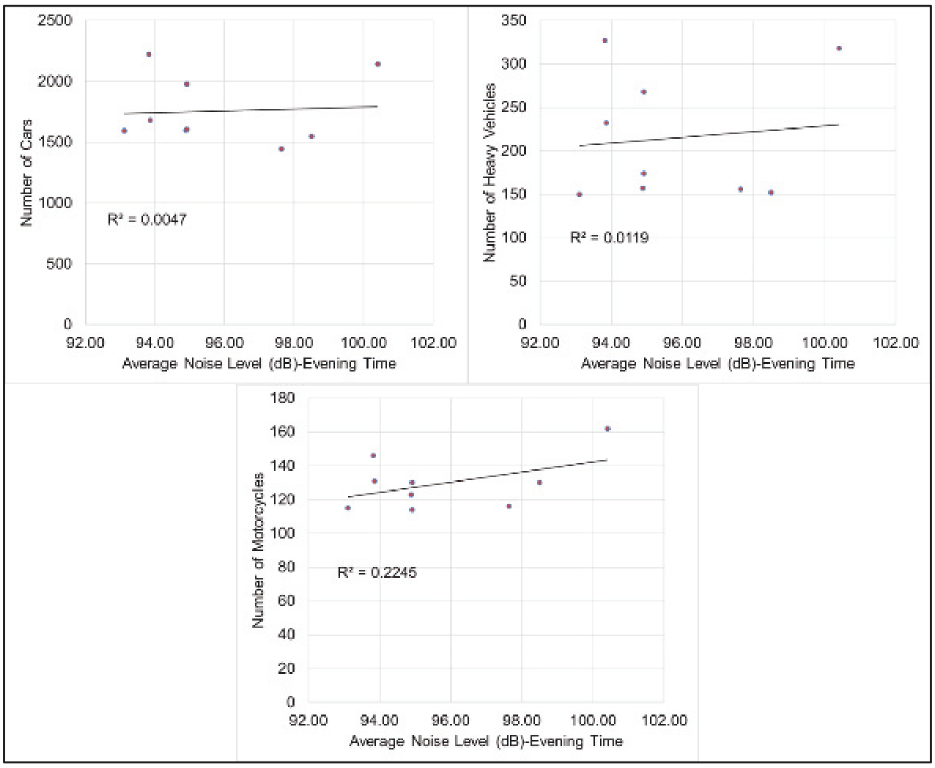

Figure 4.63 Correlation between noise level and traffic volume in the Subang Jaya – evening time - Monday.

Moreover, during nighttime, the data shows that the highest correlation (R^2=0.33) was the noise level and the number of motorcycles. Similarly, the correlation between the noise and the number of cars was relatively high (R^2=0.32). However, low correlation (R^2=0.01) was observed between noise and the number of heavy vehicles as the figure 4.64.

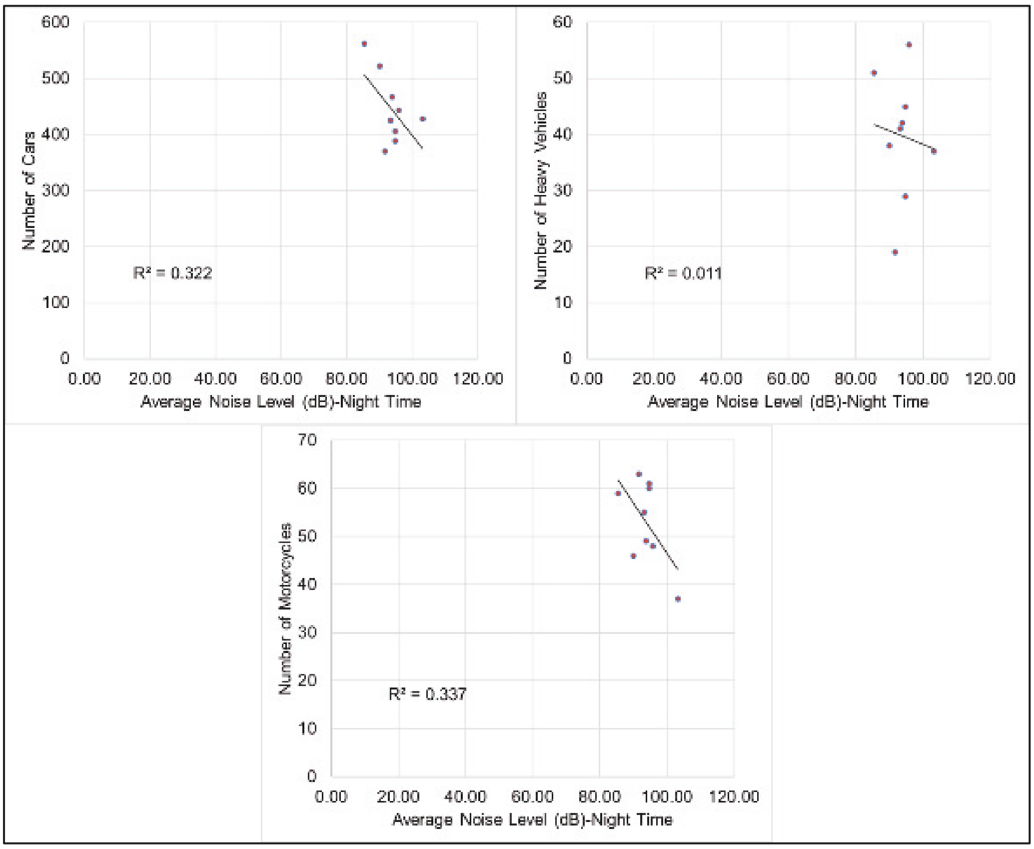

Figure 4.64 Correlation between noise level and traffic volume in the Subang Jaya – nighttime - Monday.

4.6.2.3.3 Correlation between Measured Noise on Sunday and Monday

Regarding the difference between the measured noise levels in Sunday and Monday, the data shows that during the morning the correlation is 0.28, and the highest correlation is 0.51 which was observed during afternoon time. However, the data indicates that there are not high correlations between noise measured in Sunday and Monday during evening and night time. The correlation during evening and night are 0.009 and 0.015, respectively as the figure 4.65.

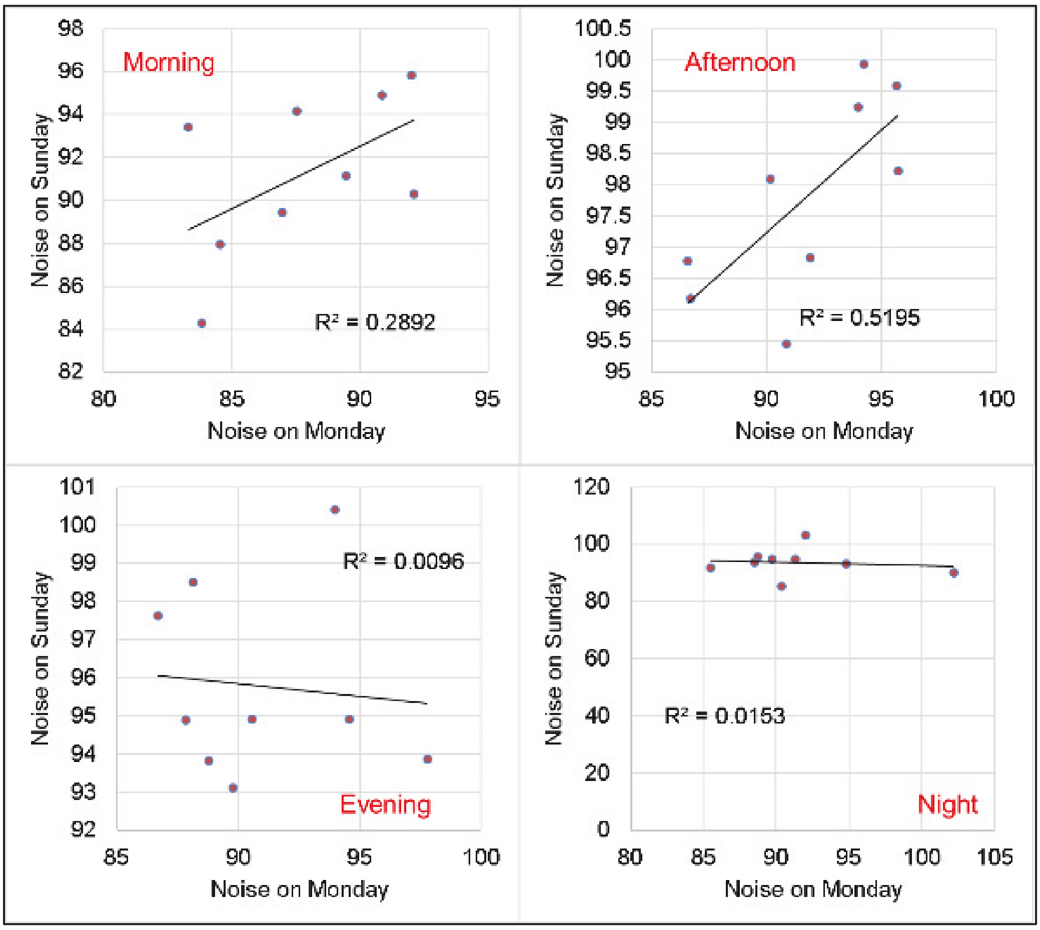

Figure 4.65 Correlation between Sunday and Monday noise levels- Subang Jaya.

4.7 Result of Mobile Application

In this study, three applications in the ArcGIS online were built: the first one about noise samples, the second application about 2D traffic noise based on roads, and the third application is about 3D noise maps based on buildings.

The first application is about noise samples. The link to this application is "https://ahmedaldulaimi86.maps.arcgis.com/apps/instant/basic/index.html?appid=a063768addc04a039bcdf4013687b80b", and figure 4.66 shows the details of noise samples in Kirkuk city. While figure 4.67 shows the 2D noise map for Kirkuk city roads, and the link of this application is " "https://ahmedaldulaimi86.maps.arcgis.com/apps/instant/basic/index.html?appid=fe791fb6f93249339fc73d1a888008fb" . Finally, the last application is about 3D noise building in Kirkuk city as the figure 4.68, and the link of this application is “https://ahmedaldulaimi86.maps.arcgis.com/apps/instant/3dviewer/index.html?appid=4539fbabd35a485aaa9314265f860ffc”.

Figure 4.66 Shows the application for the noise samples in Kirkuk city.

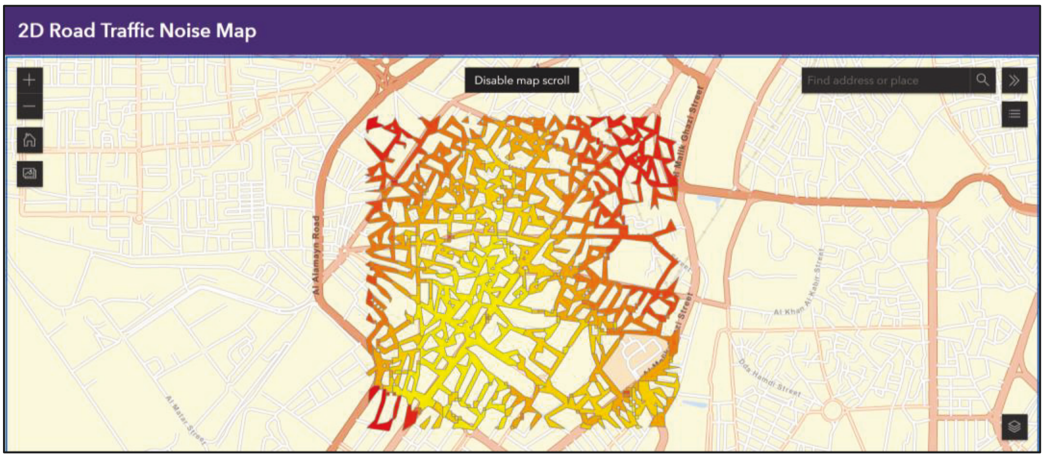

Figure 4.67 Shows the application for 2D road noise map in Kirkuk city.

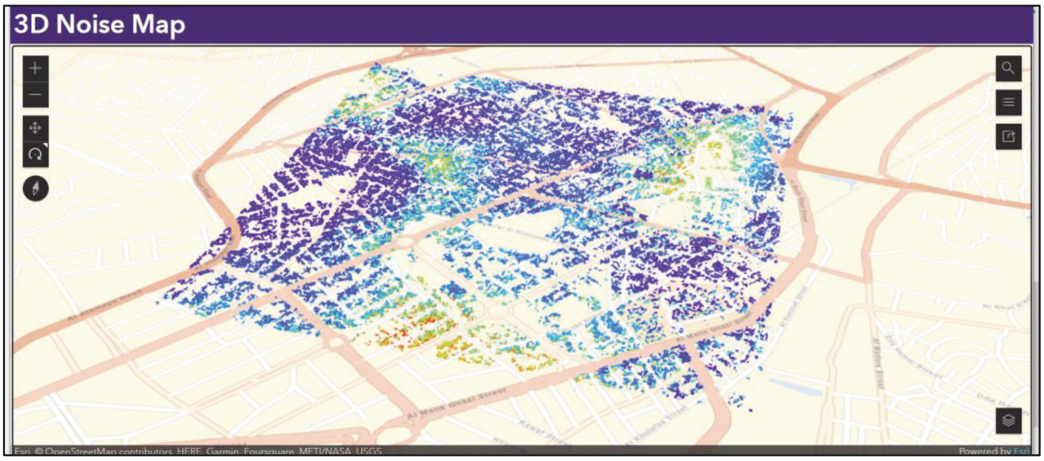

Figure 4.68 Shows the application for 3D noise map for buildings in Kirkuk city.

On the other hand, in this research, we used the android studio to publish one application online. This application has everything such as all previous applications, maps like pictures which it makes to understand their applications, policy, condition terms, and information about the authors who created this application. So, the application "2D & 3D Noise Maps of ArcGIS" is available online at Google Play. https://play.google.com/store/apps/details?id=gis.com.mytest can download and sign in with ArcGIS login. The username is "Ahmedaldulaimi86", and the password is "UTS@12345" as the figure 4.69. And this link https://pages.flycricket.io/2d-3d-noise-maps-o/privacy.html is about privacy policy, and this link https://pages.flycricket.io/2d-3d-noise-maps-o/terms.html is about terms and conditions of this application.

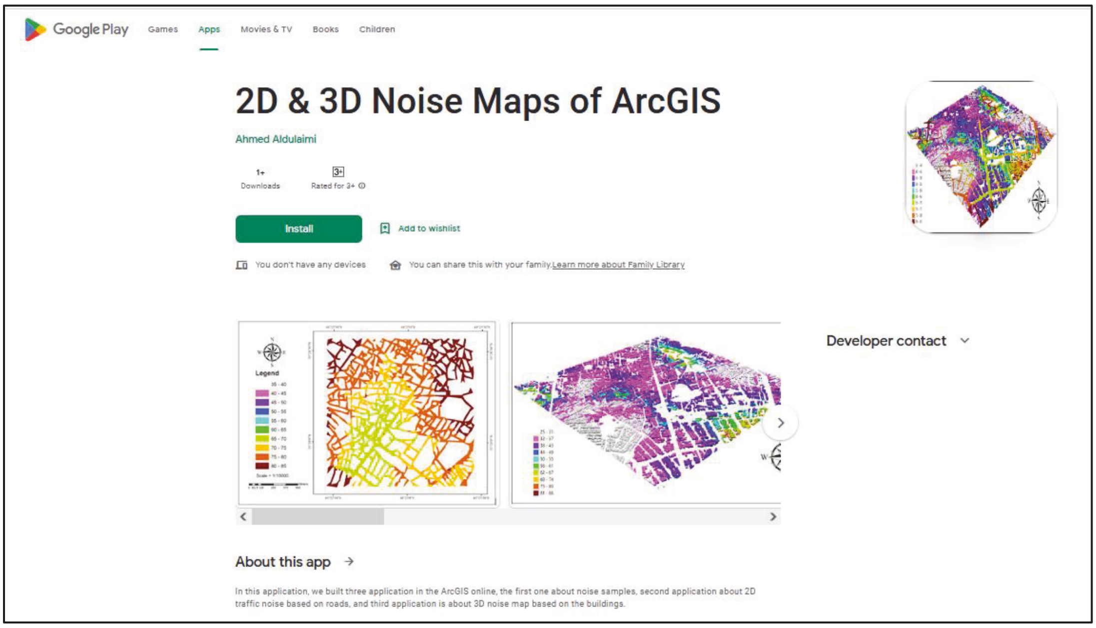

Figure 4.69 Shows the background of 2D & 3D Noise Maps of ArcGIS application.

4.8 Summary of this Chapter

This chapter describes the results of data preparation for the Worldview-3 satellite images including the orthorectification process using the LiDAR DSM data which is presented in the Worldview-3 image orthorectification section.

Further the chapter discussed the noise prediction results through contribution of noise predictors, results of optimization and results of 2D and 3D noise prediction at different daytime; whereas the contribution of noise predictors showed the result obtained from different noise predictors in the average traffic noise level in the study area (Kirkuk city). And results of optimization showed the results of the network optimization using the model of artificial neural network (ANN). Whereas the proposed network architecture designed for 2D and 3D noise prediction receptively with about 500 networks training of different combination and parameters. The output of the ANNs models is defined by average equivalent continuous noise level (dB) $L_{eq,20}$. These designed is based on the results of network structure and optimized hyperparameters presented in chapter three. According to the result of 2D noise prediction, the best validation was achieved by a network of eight (8) input parameters and 18 hidden layers. Also, the best trained of network was with BFGS algorithms, while the result of 3D noise prediction of 22 input parameters and 11 hidden layers was the best validation. And the best trained of network and the best hidden and output activation were RBFT algorithms and logistic, respectively as on the result 2D and 3D in Kirkuk city section.

The result of 2D land use regression model was evaluated the merits of four different soft computing models (machine learning and statistical regression) to predict traffic noise levels in Shah Alam, Malaysia. Throughout the research, the noise prediction models are developed, with Leq as the output (dependent variable) and the noise variables: the primary road, the bus stop, traffic volume, all type of roads, expressway, bus line, industrial area, trees area, DSM and WS, as the independent variables. According to the performance criteria of R, R2, MAE, MSE, RMSE, and MAPE, the results showed that the RF model was the most effective and reliable at predicting traffic noise levels. K-fold cross-validation further proved the stability of the RF model in making predictions. So, the RF model has both a high rate of prediction and a high rate of stability.

Moreover, the section of result of optimized deep neural network algorithm for vehicular traffic showed, the proposed model developed based on the integration of the deep neural network with features section methods (WFS) in GIS. The default model parameters were 11 parameters, after the implementation of the CFS and WFS models, the input parameters were reduced to 6 and 9 parameters each for the CFS-DNN and WSF-DNN models receptively. The WSF-DNN model was observed to be the best model and outperformed the other models such as DNN without integration with features section methods, CFS-DNN and the ANN networks (MLP and RBF). Moreover, the model found that the noise predictors such as the time and humidity are significant at 100% confidence level with important to the use of DNN model.

The section on result of noise propagation and prediction showed the noise distribution in the three study areas in Malaysia, and summary of the field measurements regarding noise level and traffic volume on different period, including day-night, weekdays and weekends. And correlation between the measured of noise on Sunday and Monday at this selected study area.

Finally, the result of mobile application section described the three applications in the ArcGIS online and the application “2D & 3D Noise Maps of ArcGIS” which collect this application. As well as all information such as username, the password, the information about the authors which were created this application and the links of privacy policy and terms and conditions of the application of 2D & 3D Noise Maps of ArcGIS which is available online google play.

Chapter Five
CONCLUSION AND RECOMMENDATION

5.1 General

Traffic noise is one of the leading causes of environmental impact faced in dense urban areas where high-speed highways pass. Noise prediction models and noise propagation simulation models are used to evaluate the impact of inappropriate noise on the population regarding health and comfort effects. Among the commonly used models is ANN, which is based on mapping a set of inputs parameters refers to as noise predictors into outputs (continuous noise equivalent) through non-linear functions. Although, these models are found to be a promising tool for traffic noise prediction, however, it requires prepared optimized and careful hyperparameter selection to uncover its black-box nature.

This study had four main objectives as following. First, to develop noise sampling methods and to generate observation points for modelling. Second, to model traffic noise in 2D and 3D using landuse regression and machine learning methods. Third, to improve the efficiency and scalability of noise models through integration and optimisation. Finally, to develop noise visualisation tool for mobile application based on the models developed in this research.

5.2 Conclusion of Objective 1

The finding of the first objective revealed the distribution of noise samples and quality within the selected site are the most important aspect of noise data collection. As well as the distribution of noise samples is significantly affected by the interpolation of results and subsequently affects the accuracy of predicted noise at un-sampled locations. So, we found the method was used on this study which was based on a GIS spatial analysis for randomly generated traffic noise measurement locations, was developed for noise data collection for spatial balancing. Whereas the model generated an adequate number of noise sample's locations and optimal density sufficient for the study area.

5.3 Conclusion of Objective 2

The findings of the second objectives suggested the LUR statistical modelling and GIS techniques are important tools for planning and prediction maps. Ultimately, this study proved that the machine learning overcome the regression method. Whereas, in this study, we used multi-models to produce 2D and 3D prediction noise maps and presented how noise impact studies and improving visualization of noise impact through using basic 2D and 3D GIS functionalities. Further, we proved thatthe accuracy of noise impact assessment was imporved through two 2D noise models for roads and 3D noise model for buildings through using less noise samples. Whereas, the proposed noise prediction model (ANN) achieved less of root-mean-square-error (RMSE), correlation (R) and correlation coefficient (R2) then others models was used in this study for 2D noise prediction as well as 3D noise prediction model. For examples, the best architecture of 2D artificial neural network noise prediction model was achieved by a network of eight (8) input parameters, 18 hidden layers, BFGS algorithm of trained of network, identity algorithm of hidden and output activation, and 0.3 of gradient momentum and learning rate. While the best architecture of 3D artificial neural network noise prediction model was achieved by a network of 22 input parameters, 11 hidden layers, RBFT algorithm of trained of network, logistic algorithm of hidden and output activation, and 0.3 of gradient momentum and learning rate. Moreover, we found the best model is ANN, and random forest (RF) is better than support vector machine (SVM) through RMSE of RF is less than RMSE of SVM, whereas RMSE of RF model was (1.82, 6.00) and (9.83, 4.50) for training and testing 2D and 3D model, respectively, while RMSE of SVM model was (3.60, 6.16) and (10.34, 4.75) for training and testing 2D and 3D model, respectively. The GIS modelling was applied to improve visualization of 2D, and 3D noise maps and these maps were the average traffic noise level of the study area for weekday in the morning and afternoon.

5.4 Conclusion of Objective 3

The findings of the third objectives improved the efficiency of 2D and 3D noise maps through combined 2D and 3D model. Whereas three models were used: one 2D prediction noise model based on the roads, and second model is 3D propagation mathematical model, and third model is mathematical models based on the elevation to predict the noise on each point or level of the building in the study area. When compared with the prediction model which was used in the objective three, no significant RMSE difference between these models were found, and hence we recommended to use this model because it needs noise samples just on the roads and no need to calculate noise sound on the different levels of buildings. In conclusion, we have suggested an affordable and easy-to-use method to monitor noise levels that could be useful for the governmental and urban planning projects. As well as this method is easy to use and cost effective which does not need more noise samples, but it needs good accurate prediction map on the roads.

5.5 Conclusion of Objective 4

The findings of the fourth objectives, suggested there are many benefits of using map services such as view maps, view layers, and view the attribute and the information for each point in the study area. Whereas ArcGIS online platform service was used for this application. This approach would enable map service to be easily made available on website using ArcGIS. The map was developed in ArcMap and published on ArcGIS Server site. Internet or intranet users can easily use the map service in web applications, ArcGIS for Desktop, ArcGIS Online, and other client applications. On the other hand, we used the android studio and linked with ArcGIS online to produce the application of traffic noise. The app was like one-stop solution wherein we put everything on this application such as the link of ArcGIS online to view the layers, the maps for noise samples and 2D and 3D noise maps. Moreover, the app is easy to use and easy to publish.

5.6 Contribution of this Research

The main contribution of the research is the production of 3D noise maps through the development of the noise prediction and propagation modelling methods. Whereas, both noise prediction and propagation models are valuable tools for traffic noise assessment during highway design stage and to evaluate the impacts of traffic noise emitted from a vehicle on highways on the population. The final maps generated by the proposed models can be used to determine the best locations of road barriers to be installed along the highway. As the noise pollution assessment by consultancy agencies is costly due to the requirements of experts and advanced noise-modelling systems. The proposed models are inexpensive and easy-to-use engineering methods for noise impact assessment with reduced costs. In addition, traffic noise standards are changing with the increase in city development around the world. This requires a periodic evaluation and development of rapid potential solutions to abate the effects of the environmental impact. Despite these advantages of the proposed models, several points need to be further analysed and improved in future works.

5.7 Recommendations

First, training models with a large amount of data in an attempt to improve the generalization capability of the models as well as developing transfer learning methods to transfer the models from one site to another. This will avoid developing models from scratch and thus reduce the costs of collecting new data from the field. Secondly, the noise propagation and prediction models need to be created one developed equation and used in different sites to ensure practicability and overall performance under various circumstances. Finally, automating the models in GIS systems can help reduce the prediction time and simulation of traffic noise which would aid non-experts to carry out traffic noise impact assessment in different agencies and organizations.

On the other hand, noise modelling is the supplement process to noise mapping for accurate and logical noise representations. Noise modelling takes some pre-estimated noise samples and other related GIS thematic layers as input data to produce accurate and logically represented noise maps for a region. It usually consists of a series of acoustic and mathematical equations to solve the noise propagation speed, distance-limit, and direction. Thus, the combination of noise modelling and mapping in GIS environments is an effective and efficient decision-making tool. It helps policy makers to make better decisions for urban developments and planning.

5.8 Summary of Main Findings of this Research

The following are the main findings of the research: -

1. The noise models can be built by integrating noise calculation software in GIS.
2. The data of DEM and DSM from LiDAR data is highly imperative in building noise models with highly improved accuracy.
3. ANN is an effective tool for building traffic noise models most especially when large parameters are involved.

4. Noise models provide quantitative relationships between traffic volumes and traffic noise and are thus, important in making predictions of noise levels on newly planned expressways.
5. Noise mapping is a very useful tool for generating information regarding environmental impacts and enables visualization of noise pollution in urban landscape. This could help to improve facilities required in advanced transportation systems such Malaysians expressways.
6. The mobile application has many benefits of using map services such as view maps, view layers and view the attribute and the information for each point in the study area.

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Appendix A (Field Survey Notebook)

Field survey notebook was used for collecting attribute and descriptive information about the locations where the noise samples were collected.

Point ID	Geographic Locations		Time/Date		Traffic		Wind Information		Weather		Distance Data		Media Tags	Road Characteristics				Topography	Remarks
	Long.	Lat.	Time	Date	Volume	Dominant Car	Wind Speed	Wind Direction	Temp.	Rain (Y/N)	Noise Meter-	Between Noise	Tag ID	Width	Type	Features	Condition	Type of	
1																			
2																			
3																			
4																			
5																			
6																			
7																			
8																			
9																			
10																			
11																			
12																			
13																			
14																			
15																			
16																			
18																			
N																			

Appendix B (Field Survey Activities)

Date	Activities	Study Area
15/01/2017	1. Noise levels will be measured continuously in 15 min intervals (recording the 15-min minimum, maximum, and averages). 2. Number of points are 10. 3. Noise levels will be measured on AM peak (6.30am-8.30am), afternoon (11.30am-1.30pm), PM peak (6.30pm – 8.30pm), and Night (11pm-12midnight).	Shah Alam/ Seksyen13
16/01/2017	1. Noise levels will be measured continuously in 15 min intervals (recording the 15-min minimum, maximum, and averages). 2. Number of points are 10. 3. Noise levels will be measured on AM peak (6.30am-8.30am), afternoon (11.30am-1.30pm), PM peak (6.30pm – 8.30pm), and Night (11pm-12midnight).	Shah Alam/ Seksyen13

Appendix C (Noise Field Measurements And The Traffic Volumes)

A) Shah Alam - Seksyen 13 (Sunday)

Sample ID	Traffic Noise (dB)- **Morning (6:30-8:30AM)**			Number of Vehicles (per 15 minutes)-**Morning (6:30-8:30AM)**		
	Maximum	Minimum	Average	Car	Truck, Lorry, and Bus	Motorbike
1	108.10	80.30	88.47	193	28	37
2	107.30	80.20	90.76	253	25	68
3	95.60	79.70	84.83	290	35	76
4	111.30	80.60	95.73	273	26	46
5	107.30	81.90	88.11	421	40	83
6	110.10	78.00	92.62	396	29	79
7	111.50	80.60	91.63	549	28	65
8	111.70	80.60	95.85	588	54	69
9	108.10	87.60	96.25	716	47	76
10	108.20	85.50	95.79	744	32	60

Sample ID	Traffic Noise (dB)- **Afternoon (11:30-1:30PM)**			Number of Vehicles (per 15 minutes)-**Afternoon (11:30-1:30PM)**		
	Maximum	Minimum	Average	Car	Truck, Lorry, and Bus	Motorbike
1	108.70	86.30	98.19	805	51	42
2	109.40	85.60	95.52	740	51	19
3	113.20	80.60	95.34	804	42	33
4	107.90	80.00	94.32	672	39	41
5	109.40	80.10	92.01	994	39	41
6	108.80	80.50	88.83	1124	46	39
7	114.30	80.40	90.82	1268	42	48
8	110.50	85.50	102.07	1283	77	47
9	110.00	83.50	94.45	1411	84	53
10	112.70	83.50	95.59	1294	66	48

Sample ID	Traffic Noise (dB)- **Evening (6:30-8:30PM)**			Number of Vehicles (per 15 minutes)-**Evening (6:30-8:30PM)**		
	Maximum	Minimum	Average	Car	Truck, Lorry, and Bus	Motorbike
1	109.20	85.30	96.99	1305	32	55
2	108.30	82.50	94.89	1169	39	43
3	108.60	79.80	92.55	1180	33	91
4	93.30	79.20	84.48	866	30	40
5	99.40	78.60	87.71	1221	24	63
6	107.00	76.80	88.11	1186	42	65
7	107.30	80.70	91.10	1162	45	52
8	113.40	85.00	96.93	1083	39	51
9	109.70	80.90	93.76	1184	47	72
10	107.70	82.50	92.21	1184	40	45

Sample ID	Traffic Noise (dB)- **Midnight (11:00-12:00AM)**			Number of Vehicles (per 15 minutes)-**Midnight (11:00-12:00AM)**		
	Maximum	Minimum	Average	Car	Truck, Lorry, and Bus	Motorbike
1	107.80	83.20	95.85	436	16	45
2	110.10	83.00	93.29	434	11	37
3	107.60	80.70	90.02	422	19	21
4	109.60	81.50	90.63	320	13	13
5	84.00	75.50	80.61	390	14	24
6	112.80	79.20	89.40	409	20	26
7	110.30	77.40	89.68	403	33	27
8	110.70	82.50	94.98	391	27	28
9	108.10	80.60	92.61	354	32	16
10	110.70	80.20	91.93	317	28	26

B) Shah Alam - Seksyen 13 (Monday)

Sample ID	Traffic Noise (dB)- **Morning (6:30-8:30AM)**			Number of Vehicles (per 15 minutes)-**Morning (6:30-8:30AM)**		
	Maximum	Minimum	Average	Car	Truck, Lorry, and Bus	Motorbike
1	107.80	85.40	95.73	1338	68	145
2	109.50	81.50	89.13	2051	56	178
3	108.80	80.20	96.95	1869	58	375
4	109.00	85.60	97.23	1678	33	378
5	108.20	79.00	93.47	2012	62	457
6	109.30	81.10	97.28	2394	36	423
7	109.50	81.30	97.55	2500	45	605
8	101.70	86.00	94.91	2820	62	515
9	109.60	85.40	95.82	2720	82	348
10	109.90	80.90	96.21	2520	107	307

Sample ID	Traffic Noise (dB)- **Afternoon (11:30-1:30PM)**			Number of Vehicles (per 15 minutes)-**Afternoon (11:30-1:30PM)**		
	Maximum	Minimum	Average	Car	Truck, Lorry, and Bus	Motorbike
1	110.30	92.40	99.30	1057	267	68
2	110.60	93.50	103.75	998	239	63
3	111.50	93.60	103.47	905	290	52
4	111.90	88.90	100.45	700	216	49
5	111.00	80.10	92.08	1005	251	64
6	110.80	82.80	95.42	996	234	66
7	110.10	84.40	93.89	1270	304	76
8	110.00	86.20	100.46	1296	290	67
9	108.40	90.10	99.22	1328	267	88
10	109.20	87.70	97.33	1223	276	80

Sample ID	Traffic Noise (dB)- **Evening (6:30-8:30PM)**			Number of Vehicles (per 15 minutes)-**Evening (6:30-8:30PM)**		
	Maximum	Minimum	Average	Car	Truck, Lorry, and Bus	Motorbike
1	108.90	81.70	94.79	1521	129	206
2	108.20	84.00	94.71	1404	125	206
3	110.10	83.00	97.63	1570	130	241
4	109.10	78.40	95.09	1114	87	244
5	107.70	86.00	96.90	1330	127	272
6	109.40	85.00	98.32	2312	127	227
7	107.50	89.00	96.12	2295	183	165
8	102.10	85.00	94.11	2645	201	137
9	111.20	88.80	98.19	1806	138	118
10	111.40	93.10	102.96	1741	156	133

Sample ID	Traffic Noise (dB)- **Midnight (11:00-12:00AM)**			Number of Vehicles (per 15 minutes)-**Midnight (11:00-12:00AM)**		
	Maximum	Minimum	Average	Car	Truck, Lorry, and Bus	Motorbike
1	108.20	86.60	96.12	319	38	25
2	111.00	94.80	103.44	271	31	28
3	108.90	84.60	93.19	274	35	14
4	107.40	83.20	93.24	229	20	22
5	108.00	82.50	95.77	272	32	33
6	107.40	83.70	91.03	274	39	19
7	108.10	88.10	100.19	300	57	26
8	110.50	91.50	101.32	290	51	20
9	109.90	88.60	96.55	235	40	27
10	109.70	86.00	97.31	247	53	14