INTEGRATING REMOTE SENSING AND GIS IN DETECTING DEFORESTATION IN KOTA KINABALU, SABAH

by

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A final year project report submitted in fulfillment of the requirements for the degree of Bachelor of Applied Science (Natural Resources Science) with Honours

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DECLARATION

I declare that this thesis entitled "Integrating Remote Sensing and GIS in Detecting Deforestation in Kota Kinabalu, Sabah" is the result of my own research except as cited in the references. The thesis has not been accepted for any degree and is not concurrently submitted in candidature of any other degree.

Signature :

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Date : 11 AUGUST 2024

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Integrating Remote Sensing and GIS in Detecting Deforestation In Kota Kinabalu, Sabah

ABSTRACT

Deforestation poses a significant threat to biodiversity and environmental stability in Kota Kinabalu, Sabah. Traditional forest monitoring methods are often inadequate due to their time-consuming, expensive, and limited nature. Therefore, this study was conducted to classify the land use and land cover changes in Kota Kinabalu and analyse a 10-years deforestation trends from 2014 to 2024. Two satellite images of the study area were processed and analysed using geospatial analysis. The land use and land cover changes were analysed using supervised classification technique following Maximum Likelihood algorithm in ArcGIS v10.8 and produces six LULC classes. From year 2014 to 2024, the forest area decreased at 10.53km^2. It was defined by the expansion of urbanization area where it show an increase of 16.9% or 62.14km^2 in ten year time. The increment is attributed to population growth and development, such as establishment of new settlements. The results of this study highlight the importance of utilizing geospatial technology in environmental monitoring and it could contribute to the development of effective forest management strategies in Sabah.

Pengintegrasian Penderiaan Jauh dan GIS dalam Mengesan Penyahhutanan di Kota Kinabalu, Sabah

ABSTRAK

Penyahhutanan menimbulkan ancaman besar kepada biodiversiti dan kestabilan alam sekitar di Kota Kinabalu, Sabah. Kaedah pemantauan hutan tradisional selalunya tidak memadai kerana sifatnya yang memakan masa, mahal dan terhad. Oleh itu, kajian ini dijalankan untuk mengklasifikasikan penggunaan tanah dan perubahan litupan tanah di Kota Kinabalu dan menganalisis trend penyahhutanan dalam masa 10 tahun dari 2014 hingga 2024. Dua imej satelit kawasan kajian telah diproses dan dianalisis menggunakan analisis geospatial. Penggunaan tanah dan perubahan litupan tanah dianalisis menggunakan teknik pengelasan yang diselia mengikut algoritma *Maximum Likelihood* dalam perisian ArcGIS v10.8 dan telah menghasilkan enam kelas guna tanah. Ia boleh dijelaskan dengan perluasan kawasan pembandaran yang mana telah menunjukkan peningkatan sebanyak 16.9% atau 62.14km^2 dalam tempoh sepuluh tahun. Kenaikan ini dikaitkan dengan pembangunan bandar dan pertumbuhan penduduk, seperti penubuhan penempatan baharu. Hasil kajian ini menekankan kepentingan penggunaan teknologi geospatial dalam pemantauan alam sekitar dan ia boleh menyumbang kepada pembangunan dan strategi pengurusan hutan yang berkekalan di Sabah.

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LIST OF ABBREVIATIONS

ArcGIS	Aeronautical Reconnaissance Coverage Geographic Information System
DIVA-GIS	Data-Interpolating Variational Analysis Geographic Information System
E	East
EROS	Earth Resources Science & Observation
GIS	Geographic Information System
LULC	Land Use Land Cover
MLC	Maximum Likelihood Classification
MODIS	Moderate Resolution Imaging Spectroradiometer
N	North
NDVI	Normal Difference Vegetation Index
NIR	Near Infrared
NIR	Near Infrared
OA	Overall Accuracy
OLI	Operational Land Imager
PA	Produces Accuracy
RS	Remote Sensing
TIRS	Thermal Infrared Sensors
UA	User Accuracy
USGS	United States Geological Survey

LIST OF SYMBOLS

ha	Hectares
kha	Kilo Hectares
K_{hat}	Kappa Hat
Km^2	Kilometre Square
m	Meter
%	Percentage

CHAPTER 1

INTRODUCTION

1.1 Background of Study

The changes of forest cover are a broad, fast-moving process primarily caused by anthropogenic activities and natural events, which in turn cause changes that would affect the environment in nature. Effective forest management and better decision-making require an understanding of forest patterns, changes, and the interplay between human activity and natural phenomena (Abyot Yismaw, 2014). When it comes to how humans use the land, land-use change is a historical occurrence. Water, soil, and vegetation are among the resources whose availability is changed (Dires Tewabe et al., 2020). The LULC has drastically altered as a result of urbanization, industrialization, and population increase (Prabuddh Kumar Mishra, 2020). Land cover alternate entails knowledge and tracking modifications in land use and coverage, in addition to their causes, significance, path and magnitude. The use of remote sensing and GIS technology has been proven to science-primarily based totally consequences and coverage recommendations. This has helped planners and decision-makers sell sustainable development, especially in city regions which can be experiencing fast urbanization. Additionally, the spatiotemporal and spectral elements of land use and land cover modifications at nearby and worldwide scales, far off sensing and GIS have become widely used techniques (Sonam Wangyel Wang et al., 2020).

Nowadays, satellite data is very suitable and useful for studying and detecting changes in forest cover. Accurate comprehension of the services provided by forests can be achieved by identifying their conditions and keeping an eye on changes in a range of structural and biophysical characteristics. The main application of remote sensing in change detection is to monitor changes in forest cover. Observing an object or event at several intervals allows one to notice changes in its status. This method is known as change detection. Based on remote sensing, change detection uses a particular change detection technique to compare a set of temporal photographs covering a time period of interest. With the advancement of technology, this problem may now be practically solved in a wide range of application areas with the use of data from earth observation satellites and decision support tools like Geographic Information Systems (Abyot Yismaw, 2014).

Deforestation in Malaysia has been a hot topic since the 1970s. During that time, large amounts of forest were cleared, mainly for rubber and oil palm plantations (Repetto, 1988). These estimations are necessary for understanding the ecology of deforestation as well as the cycles of phosphorus, nitrogen, carbon, and many other elements. In areas of severe deforestation, the spectral characteristics of land use and land cover as captured by Landsat 8 and Landsat 9 are described in this paper, which may be useful for automatic detection.

1.2 Problem Statement

Kota Kinabalu is known for the broad coverage of forests that covered the majority of the area. There is many development that occurred in Kota Kinabalu which is development such as settlement, urbanization and facilities were expanded from the past few years. Due to urbanization, the eradication of forest will affect the flora and fauna habitat, conflict between human-wildlife will arise and changes the ecosystem. Since 2002, Kota Kinabalu, Sabah lost 595 ha of humid primary forest, making up 15% of its total tree cover loss in the same time period. The problem statement of this study is a lack of studies on deforestation in Kota Kinabalu, Sabah spanning the period from 2014 to 2024.

1.4 Objective

The objective of this study is to detect deforestation by estimating land use and land cover changes over a decade in Kota Kinabalu Sabah (2014-2024) using integration of remote sensing and GIS technique.

1.5 Scope of Study

The research on changes in deforestation in Kota Kinabalu, Sabah, takes an integrated approach, taking into account social, environmental, and economic factors. The study attempts thoroughly assess the effects of deforestation on the biodiversity, ecosystems, and natural resources of the area. It can facilitate understanding of the spatial pattern of deforestation, this study investigates the use of sophisticated remote sensing and a geographic information system "GIS" technique for measuring and evaluating various changes in land cover over a period of time. The inquiry also looks into the causes of deforestation, including logging, increased agricultural production, and infrastructure development.

1.6 Significant of Study

The important research on differences in deforestation in Kota Kinabalu, Sabah is extremely important because it can provide valuable insights into the complicated nature of environmental, social, and economic changes. Kota Kinabalu is an important case study with a broader impact since it is a sample of the opportunities and problems related to deforestation. This study is to understanding of the rate and trends of deforestation could provide important data for environmental impact assessments, guiding the development of conservation strategies for preventing ecosystem degradation and biodiversity loss. Determining the causes of deforestation whether they are caused by logging operations or changes in land use helps to provide a more complex picture of the human elements affecting these changes.

CHAPTER 2

LITERATURE REVIEW

2.1 Remote Sensing

Remote sensing (RS) satellite images provide a source of up-to-date land cover data, which can track ecosystem changes over time. The study of identifying features on the surface of the earth and estimating their geo-biophysical characteristics by interacting with electromagnetic radiation is known as remote sensing process. Major features of the sensor/target that help in target discrimination are spectral, spatial, temporal, and polarization signatures. Spectral information is extracted after radiometric and geometric correcting of earth surface data was observed by the sensors at various wavelengths (reflected, scattered, or emitted). When comparing RS data to traditional approaches, it is preferable because it offers a synoptic perspective, repeating coverage with calibrated sensors to detect changes, and observations at multiple resolutions (Ranganath et al., 2007).

RS has been useful in tracking climate change outcomes, including the importance of land use change, which is one of the main drivers of change. It can support dynamic change of land use and land cover (LULC) of an area. However, there are several disadvantages to using RS methods. One of them is the definition of forest land as the lowest land surface, being the smallest spatial surface varying from very high to high altitude, hence the high resolution data are costly (Susana Martínez, 2012).

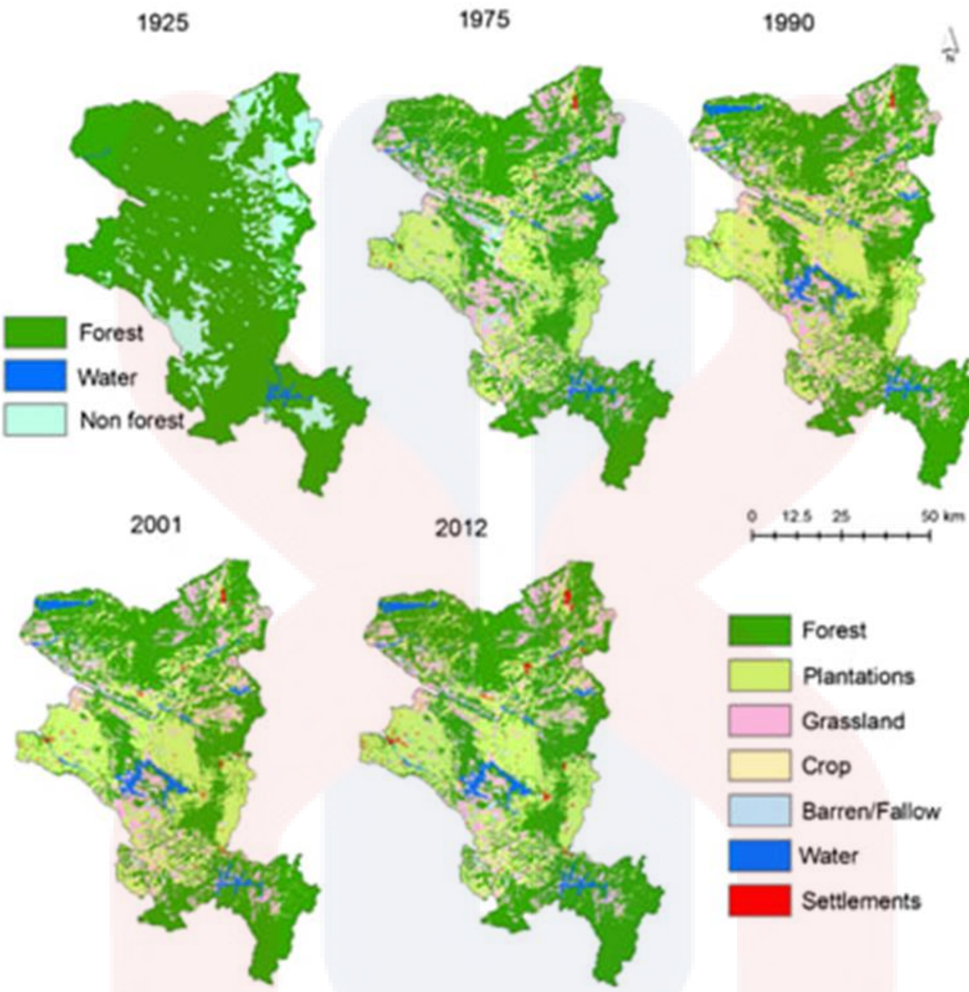
2.2 Landsat Data and Application

The historical record of global surface observations provided by the Landsat satellite, a legacy following the successful launch of Landsat-8 in 2013, includes the Thermal Infrared Sensor (TIRS) and ground control image creator (OLI) (Roy et al., 2015). The Landsat 9 was launched on 27 September 2021. The Landsat 8 project managed to extend the said record to more than 42 years, and this record is still growing. Therefore, the Landsat archive has proved itself as the most longest and uninterrupted collection of Earth's surface imagery captured from a satellite's orbital perspective. Approximately 70,000 detectors are part of the technology utilized by L8 OLI, which is a significant improvement over previous Landsat that used for imagers and had much fewer detectors (≤136) (Nischal et al., 2016). The new Landsat 8 features are numerous Radiometric resolution increased from 8 to 12 bits; Two sensors, OLI and TIRS; two energy bands including coastal aerosols and cirrus bands; Ten groups are divided into two groups; It improved the coverage of specific bands and improved the spectral response in channels such as near infrared (NIR) and panchromatic bands (Kun Jia et al., 2014). Landsat-8 provide more precise geometry, better resolution and signal-to-noise characteristics, and narrower spectral bands (Roy et al., 2016).

2.3 Land Use and Land Cover

Land use and land cover (LULC) changes are important for understanding local, regional and global environmental changes. The land cover is describes the types of land and water that cover the Earth and its surfaces, including forests, wetlands, agricultural land, and dry lands. It is describe how people use the environment for development, conservation, etc. Residential, wildlife, agricultural and built-up land are all examples of land uses (Vivekananda et al., 2021). Land utilization and land cover play an essential role in the management of ecosystem services and ecosystem conservation to avoid environmental degradation (Paula et. al, 2012).

The social, material, cultural, and spiritual needs of humans have been met by LULC and its resources, but in the process, humans have caused about major changes. Many essential resources, such as water, soil, and vegetation, have decreased as a result of the LULC's rapid changes, especially in developing nations (Sekela et al., 2019).



Source: Previous study of spatial maps of Land use and land cover of Idukki District from years 1925, 1975, 1990, 2001 and 2012. (Reshma et al., 2016)

Class	1925		1975		1990		2001		2012	
	Area	%	Area	%	Area	%	Area	%	Area	%
Forest	4675.7	93.2	2707.6	53.9	2619.6	52.2	2617.1	52.1	2613.4	52.1
Plantations*	0	0	1236.2	24.6	1322.4	26.3	1313.5	26.2	1317.3	26.2
Grassland*	0	0	818.8	16.3	777.6	15.5	774.6	15.4	772.6	15.4
Crop*	0	0	111.1	2.2	101	2.0	99.6	2.0	86.3	1.7
Water	33.3	0.7	61	1.2	149.4	3.0	155.5	3.1	155.4	3.1
Barren/Fallow*	310.0	6.1	76.4	1.5	37.4	0.7	34.9	0.7	34.9	0.7
Settlements*	0	0	8.1	0.2	11.8	0.2	24	0.5	39.3	0.8
Total	5019	100	5019	100	5019	100	5019	100	5019	100

*Included in Barren/Fallow category. In topographical maps of 1925 non forest categories i.e. plantations, grasslands, crop, barren/fallow, settlements are not distinguishable properly and hence included in Barren/Fallow

Source: Previous study (Distribution of land use and land cover in Idukki district from 1952 to 2012 (Area in km2) (Reshma M. Ramachandran., 2016)

2.4 Satellite Image Classification

Satellite images provide quantitative and qualitative data, simplifying field operations and also reducing survey time. Remote sensing systems collect information and images periodically (Sunitha Abburu et al., 2015). The main purpose of image classification methods is to automatically classify each pixel into a subject or class related to land cover. An each pixel's spectral signature is defined by the relative reflectance across several wavelength ranges. Through analyzing these spectral signatures and classifying the pixels according to similar signatures, multi-spectral classification is an information extraction method (Jayaraman, 2007).

The main reason for using feature classification, either by supervised or unsupervised methods, is to automatically identify pixels with similar reflectance values to land use and cover (LULC) categories. Supervised classification, which uses training points as reference points for the classification process, is a user-guided method (Akhtar Alam, 2019).

2.5 Classification Accuracy and Assessment

The processing of data from remote sensing is classification accuracy or known as validation. It determines how much information a user will find useful in the generated data. By comparing each pixel and its classification with specific land cover conditions obtained from real data, the accuracy of the classified image is determined (Sophia et al., 2017). The assessment of site-specific accuracy through the use of a statistical method aimed at assessing the Kappa test statistic and inter classifier agreement (Fitzgerald, 1994). Classification techniques can be classified as either object-oriented base classifiers or pixel-based classifiers. The Maximum Likelihood Classification approach (MLC), which is frequently used for LULC extraction, generates decisions about the covariance and mean of each individual class on a surface (Zahraa Abbas et al., 2020).

CHAPTER 3

MATERIAL AND METHOD

3.1 Study Area

The study area is located in Kota Kinabalu, Sabah, Malaysia. It is situated at approximately 5.9844° N latitude and 116.0773° E longitude (Figure 3.1). Total population in Kota Kinabalu, Sabah in 2023 is 525,300. Kota Kinabalu area is 351 square kilometres in area. Kota Kinabalu is the capital city of Sabah. It has an intriguing research field with a distinctive fusion of ecological, cultural, and economic components. Sabah is rich in biodiversity it includes vast tropical rainforests, mangrove swamps, and diverse ecosystems. The area is home to unique flora and fauna, including endangered species such as Orang-Utans, Pygmy Elephants and Proboscis Monkeys. Through this focused study, Kota Kinabalu emerges not only as a geographic location of significance but also as a key player in the global discourse on sustainable land management and conservation practices.

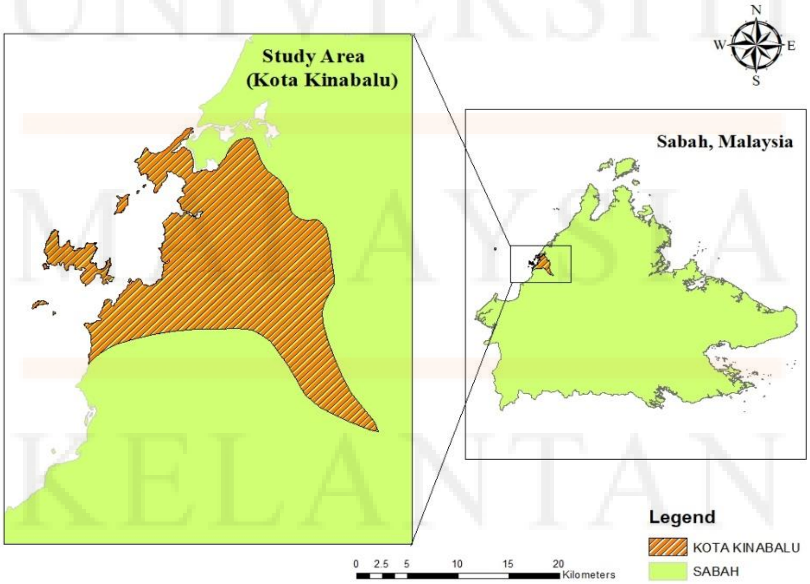


Figure 3.1: Map of Study Area in Kota Kinabalu, Sabah

3.2 Material and Methods

3.2.1 Materials

In this study two multispectral satellite images of Landsat 8 and 9 were use to assess the LULC changes of the study area. It was downloaded from United States Geological Survey (USGS) Earth Explorer. The USGS Centre for Earth Resources Science and Observation (EROS) can be accessed at http. //glovis.usgs.gov/.

USGS Earth Explorer is a website that has function to search for datasets of satellite and aerial imagery depending on specific variables like location, time frame, cloud cover, and type of sensor. It provides access to a wide variety of Earth observation datasets, such as MODIS, Sentinel, Landsat, and more. USGS Earth Explorer are used to download the aerial image to create the map.

Downloaded satellite images were then analysed using ArcGIS v10.8. ArcGIS is used for geographical analysis, mapping, and organising geographic data. In deforestation studies, ArcGIS is applied to analyse and identifying area from satellite information, construct maps show deforestation trends, and perform spatial analysis to determine the amount and impact of deforestation. Multiple spectrum images are obtained by Landsat satellites. The historical images from these satellites could be used to examine long-term changes in land cover, including deforestation.

Table 3.2.1: Details of the image used in the study

Image	Path/Row	Acquisition Date
Landsat 8	118/56	17/09/2014
Landsat 9	118/56	12/03/2024

3.2.2 Methods

3.2.1 Data Acquisition

Data acquisition is the process of digitizing information from the outside world so that a computer can display, examine, and store it. To study the dynamic change of land cover in Kota Kinabalu Sabah, two multispectral satellite images of 2014 and 2024 were acquired for the comparison process. Landsat 8 and Landsat 9 satellite images of study area were downloaded from the USGS website for the specific year chosen. The date of acquired satellite image with cloud cover <5% were selected and downloaded from United States Geological Survey (USGS) (http://glovis.usgs.gov) website. Moreover, the shape file of State boundary was also downloaded from DIVA GIS for the extraction of AOI.

3.2.2 Data Pre-processing

Pre-processing included geometric rectification, also known as image registration, radiometric calibration, atmospheric correction, topography correction, and the detection and repair of problematic lines. A specific goal of satellite image processing prior to detection modification is to create a direct relationship between the data and biological features (Coppin et al., 2004). Classification methods that combine multiple data sources require accurate geometric correction or image registration of remote sensing data (Mahendra et al., 2015).

The correction of spatially variable atmospheric or noise caused by haze and smoke has been implemented in this study following Carlos et al., (2013). The cause for this is because atmospheric correction of a date image usually involves deleting values from satellite image spectral band imagery pixels (Zahraa Abbas et al., 2020). The pre-processing of satellite imagery is crucial for reducing potential data changing or distortion, and for establishing a logical connection between the data and biophysical processes.

Radiometric and atmospheric correction was done in this study to fix any errors in the satellite images caused by the sensor itself or the way the images were taken. It will produces the colours and brightness that truly represent the ground truth. The atmospheric correction was done aimed to remove the effects of the atmosphere like clouds, dust, and gases from the satellite images so that the images are accurately reflect the Earth's surface.

3.2.3 Data Analysis

After data pre-processing, Landsat images of 2014 and 2024 is ready for classification and comparison process. Both Landsat images of the study area were imported to ArcGIS v10.8 application for classification analysis.

Image classification was done using supervised classification technique which employed a maximum likelihood algorithm (MLC). Supervised classification is used to recognise and label different aspects in satellite photos. This includes selecting certain regions, referred to as training sites which is represent various cover types, such as water bodies, forest, agriculture area, urban area and others. By these training sites, an interpretation key a guide containing numerical explanations of the colours and patterns connected to each feature can be constructed. Each pixel in the real data set is compared numerically to the categories in the interpretation key during analysis. The name of the category that the pixel most closely matches is then labelled on it. By analysing their spectral separability, the supervised technique determines the kinds of features forests, for example and evaluates how separate they seem in the photos.

Additionally, NDVI (Normalized Difference Vegetation Index) analysis was done to evaluate or detect the forest health and the coverage. The higher NDVI value indicates that the vegetation of the area is denser and healthier. Moderate NDVI levels (between 0.2 and 0.5) can be translated as sparse vegetation, such as bushes, and grasslands. Dense vegetation is translated as high NDVI values of 0.6 to 0.9 (Jesslyn Brown, 2018). The main objective to use NDVI in this study is to differentiate the vegetation or forest area with the non-vegetated area of the study site. The NDVI is calculated using the followings:

NDVI = (Band 5 – Band 4) / (Band 5 + Band 4)

NDVI = (NIR - RED) / (NIR + RED)

Where:

NIR is the near-infrared band reflectance

RED is the red band reflectance

Finally, both image classification results were compared to calculate the changes of the area within a 10 years period. The percentage of area changes of both map 2014 and 2024 have been tabulated in Microsoft Excel for the comparison process.

3.2.4 Accuracy Assessment

Accuracy assessment provides the necessary information to estimate the uncertainty of map classes and to construct confidence intervals (Owojori, 2005). Accuracy assessments involve comparing the classified image to another data source considered to be accurate, often ground truth data. For the 2021 image, the accuracy assessment was performed to verify the correctness of the classified map. In this study, Google Earth was used as the reference data. Eight to ten points for each class were selected to evaluate the accuracy of the classified images. User and producer accuracy were calculated, and the overall accuracy (including both user and producer accuracy) was determined using the kappa coefficient formula as shown below:

Overall accuracy =

Number of correct pixels/ Total number of pixels x 100

User accuracy =

Correctly classified pixels/ Classified total pixels x 100

Producer accuracy =

Correctly classified pixels/ Reference total pixels x 100

Kappa Coefficient =

$$\frac{(TS \times TCS) - \text{Total (Column total x Row Total)} \times 100}{TS2 - \text{Total (Column total – Row Total)}}$$

Where;

TS -total sample

TCS – total correct sample

The Kappa statistic is used to assess the degree of agreement between two dataset classification sets. It's used for assessing how well prediction models agree with a collection of field surveyed sample points in order to determine how accurate the models are. The flow chart of the study is shown in Figure 3.1.2.

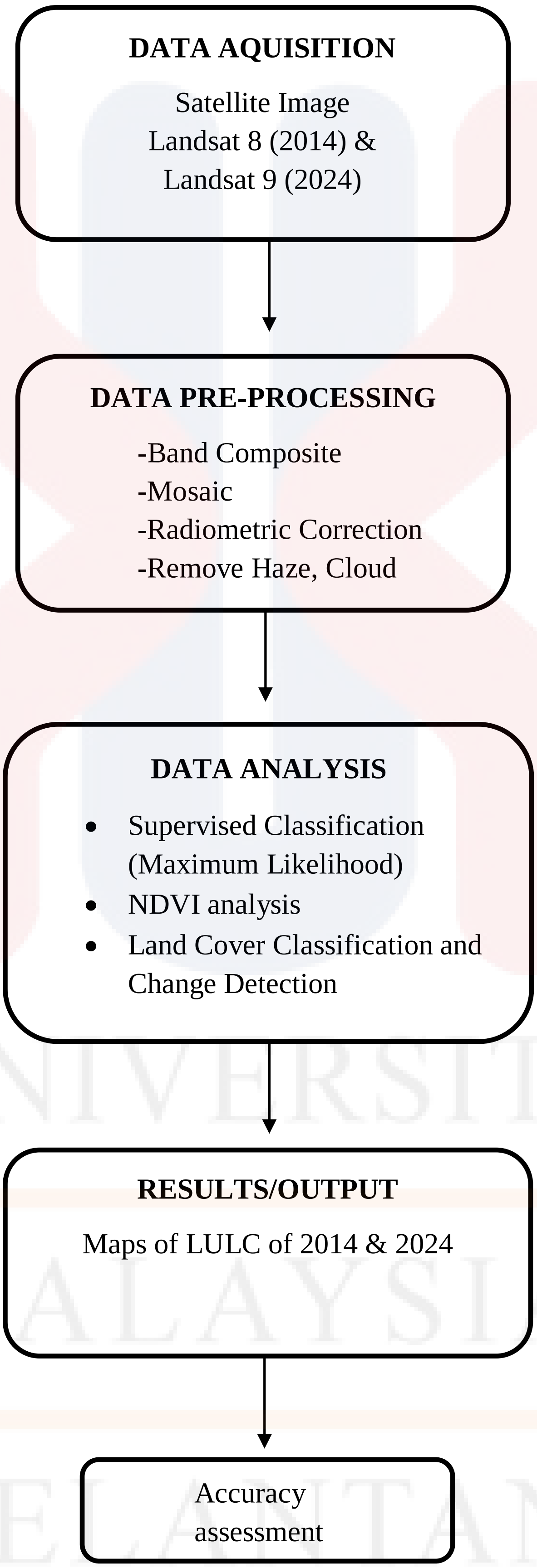


Figure 3.2: The flowchart of the study

CHAPTER 4

RESULT AND DISCUSSION

4.1 Image Pre-processing

The satellite imagery of Kota Kinabalu, Sabah in year 2014 to 2024 undergoes the radiometric and atmospheric correction to improve the quality of the image during pre-processing. It is important to ensure the accuracy and reliability of data collected from satellite and airborne sensors and improves visual quality. Corrected images can improve contrast and clarity, making it easier to visually interpret and analyse features. Figure 4.1.1 and Figure 4.1.2 show the corrected images of 2014 and 2024.

After images were pre-processed, the band composite of false colour image was setup for both satellite image of 2014 and 2024. Band composite is necessary in this step to improve multispectral data analysis and visualization. Figures 4.1.3 and 4.1.4 show false colour band combination of land/water which is band 5 for Red, Band 6 for Green and Band 4 for Blue. This band combination had increased the contrast between different features that are difficult to distinguish in a true colour band composite image. This composite band can make it easier to analyse the image better.

Figure 4.1.1: Satellite Image after Radiometric and Atmospheric correction for 2014

Figure 4.1.2: Satellite Image after Radiometric and Atmospheric correction for 2024

Figure 4.1.3: Band Composite (False Colour Image) of Landsat 8 in 2014

Figure 4.1.4: Band Composite (False Colour Image) of Landsat 9 for 2024

4.2 Normalized Difference Vegetation Indices (NDVI)

The NDVI value calculated from Landsat satellite image of the year 2014 and 2024 were ranges from -0.74 to 0.85 and -0.88 to 0.88, respectively. The NDVI value range of non-vegetation include water bodies, open area and settlement or urbanization is <0.3 following Ravi (2016). The decrease of forest areas in 10 years indicates that the change in land use of the study area mainly due to the loss of forest area due to human encroachment

Table 4.2.1 shows the area (km^2) and the percentage for the two classes, namely vegetation and non-vegetation classes. In 2014, the area of non-vegetation area is 86.60 km^2 or 24% from the total area, while in 2024 it decrease to 36% (133.66 km^2). The difference between these two years clearly shows a significant change of LULC in the study area.

Vegetation area in 2014 and 2024 show a significant decreased with 12%. From this study, although the non-vegetation area was increased, it does not affect the health of the vegetation in Kota Kinabalu, Sabah where the maximum NDVI value of 2024 was calculated at 0.88. This shows that development in the Kota Kinabalu, Sabah area was still under control, well planned and sustainable where vegetation can grow healthy and accordingly. The visual map of vegetated and non-vegetated area in study site for both years are as shown in Figure 4.2.1 and 4.2.2.

Table 4.2.1: NDVI area for Kota Kinabalu, Sabah in 2014 and 2024

Class	**2014**		**2024**	
	Area (km^2)	**%**	**Area (km^2)**	**%**
Non -vegetation	86.60	24%	133.66	36%
Vegetation	281.33	76%	234.27	64%
Total	367.94	100%	367.94	100%

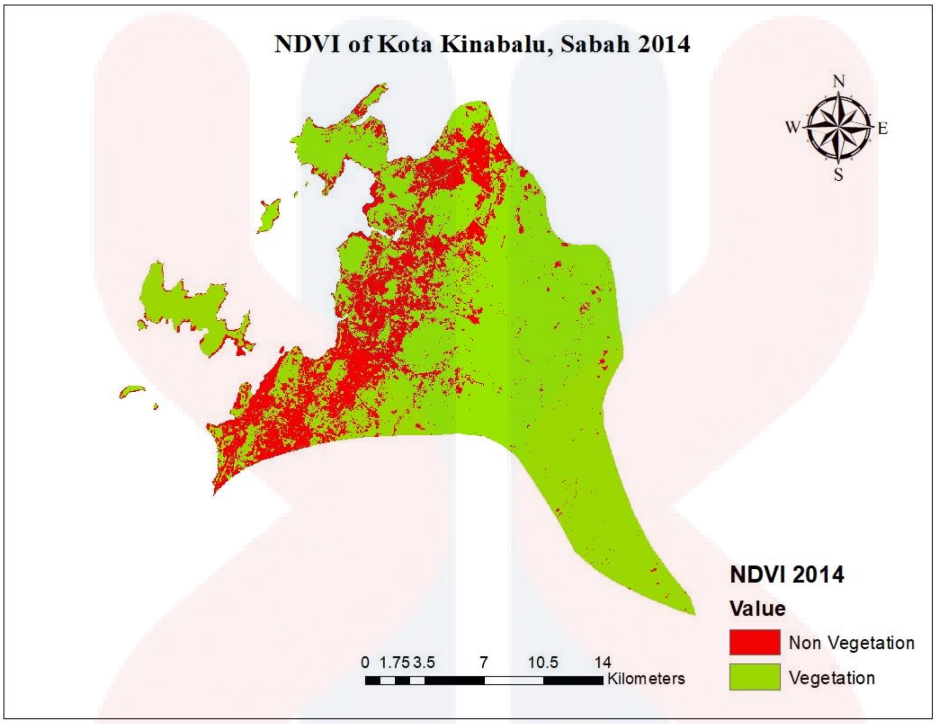


Figure 4.2.1: NDVI Map of Kota Kinabalu, Sabah in 2014

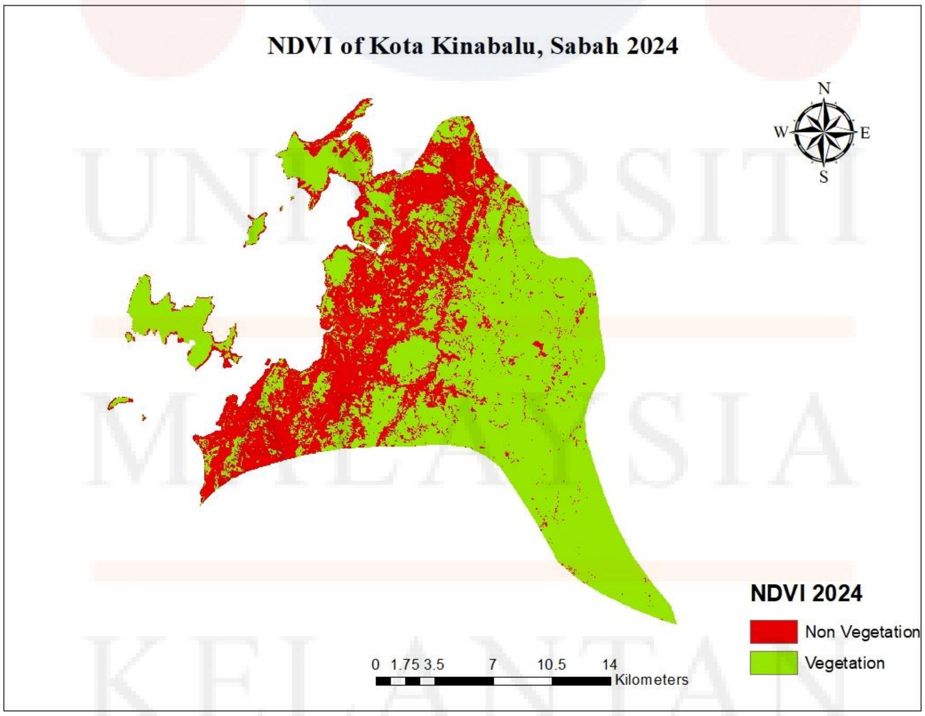


Figure 4.2.2: NDVI Map of Kota Kinabalu, Sabah in 2024

4.3 Image Classification

The supervised image classification using Maximum Likelihood is carried out where pixels in the image were categorized into predefined classes. Image classify was determined manually based on the classification and training area. In this study 6 classes were setup namely forests, water bodies, water body, agricultural land and urban areas. According to Jensen (2005), it extracts the training sites' spectral properties, or features. These characteristics show the reflectance values for each class over several spectral bands.

This image classification for both images were based on Base Map and Google Earth Pro (Figure 4.3.1). Base map used as a reference to validate the classification results. It can compare the classification results with the information on the base map to assess the accuracy of the classification. This helps in better visualization and interpretation of classification results.

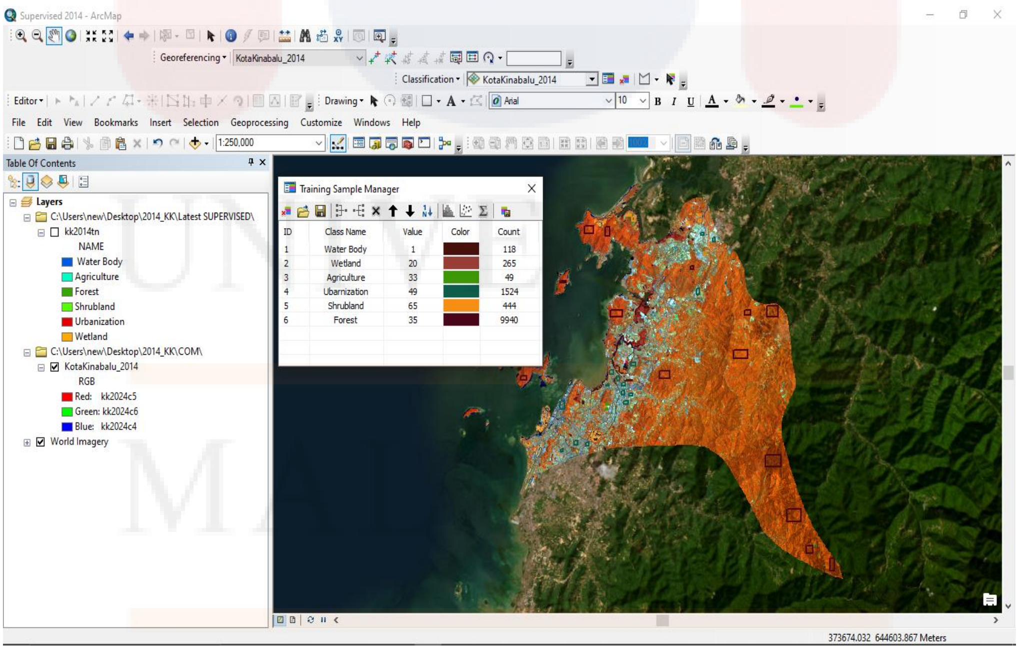


Figure 4.3.1: Supervised Image classification using ArcMap with GoogleEarth as base map

The accuracy was assessed by validating the 50 random sample points. Validation of classified map for 2024 was done based on pixel and visual assessment of satellite images with the aid of Google Earth Pro Map. The overall accuracy and Kappa coefficient (K_{Hat}) of the image classification was at 88% and 0.81 respectively (Table 4.5.1). $K_{Hat\ of}$ 0.81 represent a strong agreement and good accuracy following Zahraa Abbas (2020).

Table 4.5.1: Overall Accuracy and Kappa Statistic value

Satellite Image/Year	Landsat 9 (2024)
Overall Accuracy (%)	88%
Kappa Statistic	0.81

4.4 Land Use and Land Cover Change for 2014 and 2024

MLC classification produced maps of LULC for both years. Six classes were setup as Forest, Wetland, Water Body, Urbanization, Shrub land and Agriculture and pixels consists at each classes were calculated and compared.

The land use and land cover maps of Kota Kinabalu, Sabah for 2014 and 2024 were presented in Figure 4.4.1 and 4.4.2 respectively. The statistics show that in 2014 about 200.27 km^2 (54%) of the land covered by forest. Meanwhile, it was found decreased with an area of 189.75 km^2 (52%) in 2024. In a decade, forest in Kota Kinabalu had decreased with 2.9% that equal to 10.52 km^2. Based on Global Forest Watch (2023), Kota Kinabalu had 24.4k ha of natural forest in 2010, extending over 68% of its land area. However, in 2023, it lost 181 ha of natural forest. The deforestation in Kota Kinabalu, Sabah occurred for several reasons. In 2024, the agriculture land was decreased. It was due to urbanization such as development of settlements due to population increased and infrastructure development.

A slight changes happen in wetland area where during 2014 the area was 2.39 km^2 and it was decreased to 1.68 km^2 in 2024. The changes of wetland area from 2014 to 2024 was about 0.71 km^2.

A total of agriculture land in the study area was 45.22 km^2 had also recorded a reduction trend. The agriculture land changes was 37.79 km^2 (10.3%). It might due to several factors. As cities expand and industrial activities increase, agricultural land is often converted into urban or industrial areas. This leads to a direct reduction in the amount of land available for farming. Hence, it relates to factor of increasing population which demands more housing and services, which often leads to the conversion of agricultural land into residential and commercial areas. Shrub land of the study area was 29.60 km^2 (8%) in 2014. It decreased to 15.07 km^2 in 2024. The changes is about 4%.

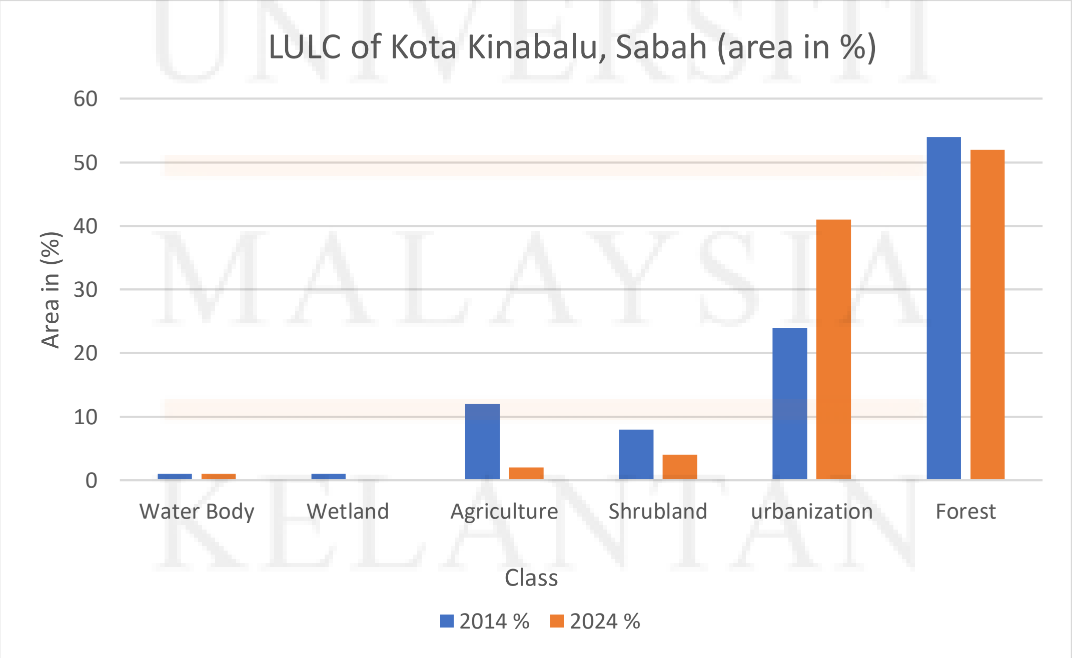
The increasing trend of LULC area were on water body and urban class types. The water body expended 0.4% which was calculated at 1.41 km^2 in a decade. In 2014, it was 2.65 km^2 and increased to 4.06 km^2.

Drastic change was found in urbanization class when 62.14 km^2 or 16.9% of study area was expended for this purpose. The increasing trend of urbanization area is an indication of the ongoing trends towards the population increase in the Kota Kinabalu, Sabah. Our findings is in line with study by Ricky and Oliver (2020) where their analysis results discovered that the land cover changes for a built-up area increase 5.1% from 1991 to 2018, decrease the water and vegetation land cover with 1.4% and 4.33% in the similar location of Kota Kinabalu. The migration of residents from rural villages to urban areas has also driven urban expansion and led to a significant shift from vegetated land cover to human-made structures in recent decades (United Nations, 2018). Table 4.4.1 show the details of area changes of the study area based on LULC's classes while below the table show the summarization of the analysis data by bar graph.

Table 4.4.1: Changes in LULC Area of the Kota Kinabalu, Sabah

LULC Class	**2014**		**2024**		**Changes**	
	Area (km^2)	%	Area (km^2)	%	Area (km^2)	%
Water Body	2.65	1%	4.06	1%	1.41	0.4
Wetland	2.39	1%	1.68	0%	0.71	(0.2)*
Agriculture	45.22	12%	7.43	2%	37.79	(10.3)*
Shrub land	29.60	8%	15.07	4%	14.53	(4.0)*
Urbanization	87.69	24%	149.83	41%	62.14	16.9
Forest	200.27	54%	189.75	52%	10.52	(2.9)*
Total	367.82	100%	367.82	100%		

*(% decrease)



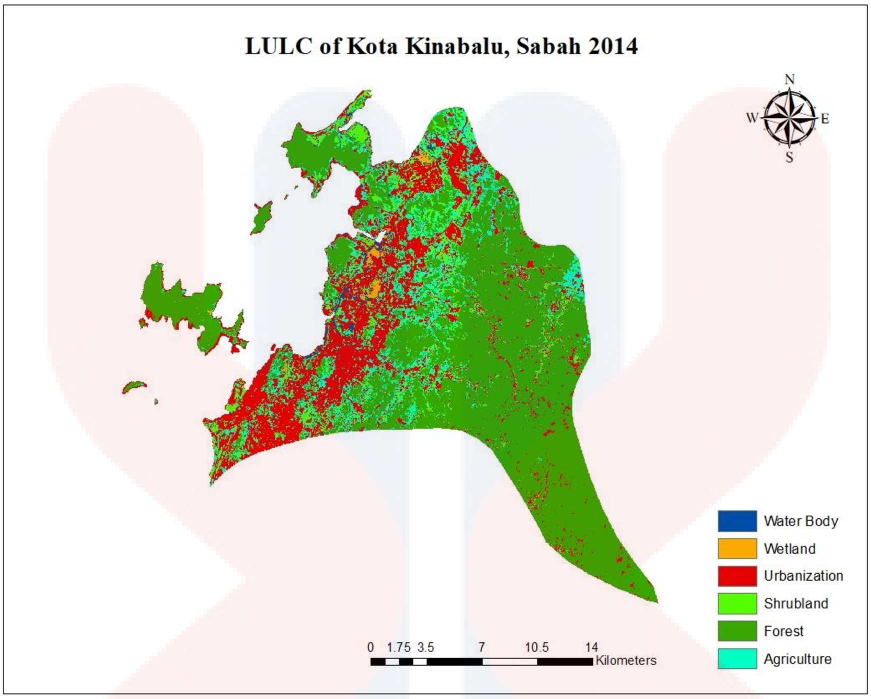


Figure 4.4.1: LULC Map of Kota Kinabalu, Sabah for 2014

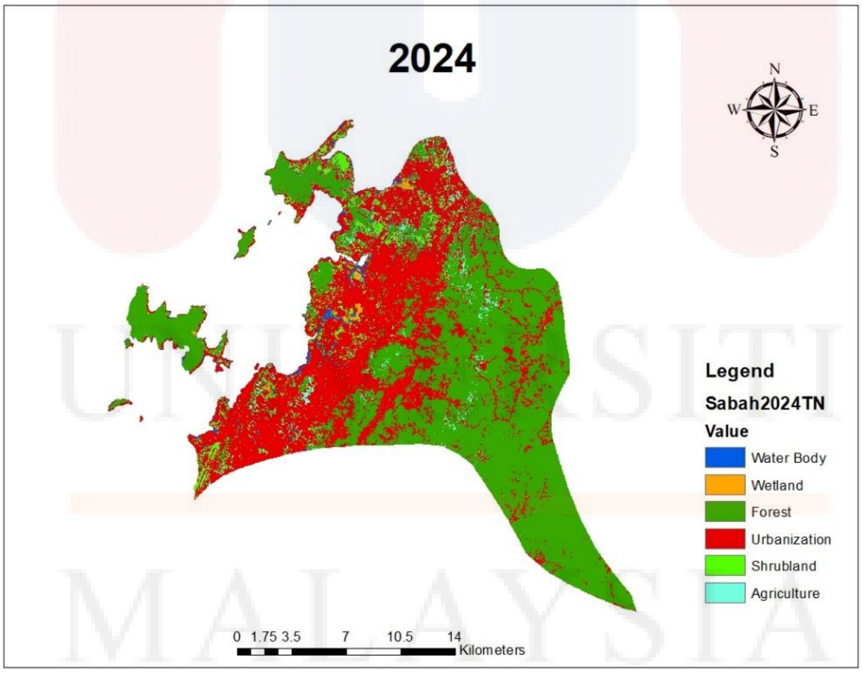


Figure 4.4.2: LULC Map of Kota Kinabalu, Sabah for 2024

4.5 Accuracy Assessment

The accuracy was validated independently of the mapping. The random point was 50 ground random sample points have been selected for assessing the classification accuracy. Validation of classified map for 2024 was done based on visual assessment of satellite images which was using software such as Google Earth Pro. The overall accuracy and Kappa coefficient (K_{Hat}) for the year 2024 are 88% and 0.81 respectively (Table 4.5.1). Kappa coefficient 0.81 represent a strong agreement and good accuracy.

Table 4.5.1: Overall Accuracy and Kappa Statistic

Satellite Image/Year	**Landsat 9 (2024)**
Overall Accuracy (%)	88%
Kappa Statistic	0.81

CHAPTER 5

CONCLUSION AND RECOMMENDATIONS

5.1 Conclusion

LULC change of Kota Kinabalu, Sabah between 2014 and 2024 have been classified and identified into six classes named Agriculture, Wetland, Forest, Urbanization, Water body and Shrub land. From all classes, only water body and urbanization showed an increasing trend over time. The remaining classes was found decrease and it has significant influence on urbanization factors.

From year 2014 to 2024, the forest area of study area decreased at 10.53km^2. It was defined by the expansion of urbanization area where it show an increase of 16.9% from the total area in Kota Kinabalu, Sabah. Increase in population and development are the main cause of this event. The results from this study is important for many stakeholders such as decision makers, forest manager and town planners to organize and designed a sustainable urban planning of a development area. Effective and sustainable urban planning can help to initiate a realistic solution towards land use and the effect especially to sustain the natural resources of the study area.

5.2 Recommendation

In this study, there are few limitations that can be identified including the data error, image quality and accuracy of the findings. For future study, it is suggests to:

- Use high resolution satellite image such as IKONOS or QuickBird to get an accurate results for image classification. However, this will incurred cost since the data is expensive.
- Instead of using Google Earth as references data in supervised classification, ground thruthing is require to accurately sample the point to assess the accuracy of the image processed.
- Compare the results with town plans and strategies develop by the states. In Kota Kinabalu, Sabah, documents for sustainable planning for forest management could be borrowed to aid in interpret the findings of this study.

REFERENCES

Abyot Yismaw, B. G. (2014). Forest cover change detection using remote sensing and GIS in Banja district, Amhara region, Ethiopia. *Science Publishing Group*, 1-2.

Adel Shalaby, R. T. (2007). Remote sensing and GIS for mapping and monitoring land cover and land-use changes in the Northwestern coastal zone of Egypt, Appl. *Research Gate*, 3-8.

Akhtar Alam, .. M. (2020). Using Landsat satellite data for assessing the land use and land cover change in Kashmir valley. *GeoJournal*, 1-4.

Ali Hassan Chughtai, H. A. (2021). A review on change detection method and accuracy assessment for land use land cover. *Elsevier* , 1-4.

Ali Rahmat, M. A. (2018). Normalized Difference Vegetation Index (NDVI) In The Integration Conservation Education Forest At Wan Abdul Rachman Using Modis Data. *Research Gate*, 3.

András Gudmann, N. C. (2020). Improvement in Satellite Image-Based Land Cover Classification with Landscape Metrics. *Remote Sensing*, 1-6.

Carlos M. Souza, J. V. (2013). Ten-Year Landsat Classification of Deforestation and Forest Degradation in the Brazilian Amazon. *Remote Sensing*, 1-5.

Christoph Hütt, W. K. (2016). Best Accuracy Land Use/Land Cover (LULC) Classification to Derive Crop Types Using Multitemporal, Multisensor, and Multi-Polarization SAR Satellite Images. *Remote Sensing*, 1-7.

Dengsheng Lu, M. B. (2012). Land use/cover classification in the Brazilian Amazon using satellite images. 1-3.

Geographer), J. B. (2018, November 27). *NDVI, the Foundation for Remote Sensing Phenology*. Retrieved from NDVI, the Foundation for Remote Sensing Phenology: https://www.usgs.gov/special-topics/remote-sensing-phenology/science/ndvi-foundation-remote-sensing-phenology#:~:text=NDVI%20values%20range%20from%20%2B1.0,(approximately%200.2%20to%200.5).

Guild, W. B. (2004). Detection of deforestation and land conversion in Rondonia, Brazil using change detection techniques. *Taylor & Francis* , 5-7.

Jonh Piter G. LUBIS, N. N. (n.d.). Land Use and Land Cover Change Detection using Remote Sensing and Geographic Information System in Bodri Watershed, Central Java, Indonesia. *International Development and Cooperation* , 5-7.

Katcho, K. (2019). Assessing Forest Cover Change and Deforestation Hot-Spots in the North Kivu Province, DR-Congo Using Remote Sensing and GIS. *Research Gate*, 6-8.

Kun Jia, X. W. (2014). Land cover classification using Landsat 8 Operational Land Imager data in Beijing, China. *Research Gate*, 1-6.

Lillesand, T. K. (2015). Remote Sensing and Image Interpretation. *Wiley*, 5-6.

Matthias. (2000). Change Detection Of Natural High Forests In Ethiopia Using Remote Sensing And Gis Techniques . 1-5.

Mersha Alemu, H. H. (2019). Land Use Land Cover Change Detection and Deforestation Modeling: In Delomena District of Bale Zone, Ethiopia. *Scientific Research* , 1-4.

Nety Nurda, R. N. (2020). Change Detection and Land Suitability Analysis for Extension of Potential Forest Areas in Indonesia Using Satellite Remote Sensing and GIS. *Forest*, 2-7.

Nety Nurda, R. N. (2020). Change Detection and Land Suitability Analysis for Extension of Potential Forest Areas in Indonesia Using Satellite Remote Sensing and GIS. *MDPI*, 4-10.

Nischal Mishra, D. H. (2016). Continuous calibration improvement in solar reflective bands: Landsat 5 through Landsat 8. *Science Direct* , 1-2.

Pablo Pozzobon de Bem, O. A. (2020). Change Detection of Deforestation in the Brazilian Amazon Using Landsat Data and Convolutional Neural Networks. *MDPI*, 6-10.

Paula K. Lira, L. R. (2012). Land-use and land-cover change in Atlantic Forest landscapes. *Elsevier*, 2-3.

Roy D. P (2016). Characterization of Landsat-7 to Landsat- 8 reflective wavelength and normalized difference vegetation index continuity. *Science Direct*, 1-5.

Ranganath R. Navalgund, V. J. (2007). Remote sensing applications: An overview. 6-8.

Ravi P. S. (2016). Normalized Difference Vegetation Index (NDVI) Based Classification to Assess the Change in Land Use/Land Cover (LULC) in lower Assam, India. *Cloud Publications* , 4-8.

Reshma M Ramachandran, S. R. (2016). Monitoring of deforestation and land use changes (1925–2012) in Idukki district, Kerala, India using remote sensing and GIS. *Research Gate*, 4-7.

Ruefenacht, E. H. (2005). Cloud-Free Satellite Image Mosaics with Regression Trees and Histogram Matching. 1-6.

Sanchez-Azofeifa, G. A. (2002). Dynamics of Tropical Deforestation Around National Parks: Remote Sensing of Forest Change on the Osa Peninsula of Costa Rica. *BioOne*, 1-4.

Seong-Hyeok Lee, K.-J. H.-J.-Y.-J. (2020). Classification of Landscape Affected by Deforestation Using High-Resolution Remote Sensing Data and Deep-Learning Techniques. *MDPI*, 6-10.

Sonam Wangyel Wang, B. M.-K. (2020). Land Use and Land Cover Change Detection and Prediction in the Kathmandu District of Nepal Using Remote Sensing and GIS. *MDPI*, 1-8.

Sophia S. Rwanga, J. M. (2017). Accuracy Assessment of Land Use/Land Cover Classification Using Remote Sensing and GIS. *Scientific Research Publishing*, 1-2.

Sunitha Abburu, S. B. (2015). Satellite Image Classification Methods and Techniques: A Review. *Computer Application*, 1-3.

Susana Martínez, D. M. (2012). From Land Cover to Land Use: A Methodology to Assess Land Use from Remote Sensing Data. *Remote Sensing*, 2-4.

Vivekananda, R. S. (2020). Multi-temporal image analysis for LULC classification and change detection. *Taylor and Francis Journal*, 1-5.

Watch, G. F. (2024). *Kota Kinabalu, Sabah, Malaysia Deforestation Rates & Statistics.* Retrieved from Kota Kinabalu, Sabah, Malaysia Deforestation Rates & Statistics: https://www.globalforestwatch.org/dashboards/country/MYS/13/6/

Zahraa Abbas, D. H. (2020). Accuracy assessment of supervised classification methods for extraction land use maps using remote sensing and GIS techniques. *IOP Publishing*, 2-3.