CLASSIFICATION OF GRANULAR FEATURES IN URBAN BUILT LAND USING MACHINE LEARNING TECHNIQUES IN GOOGLE EARTH ENGINE PLATFORM

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DEDICATION

This thesis is dedicated to my family, who taught me that perseverance is the key to success and that family is always there to support you.

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ABSTRACT

Rapid urbanisation has resulted in uncontrollable growth in developing cities, thus threatening the environment's stability and quality of life. While expanding infrastructure development is intended to benefit city dwellers, rising traffic, health, and environmental problems are causes for concern. To mitigate the negative effects of increasing urbanisation, urban planning is critical in improving city planning and advancing the goal of sustainable urban development. The urban planning sector uses land use land cover (LULC) change as a primary reference point for monitoring, where it is now primarily used to monitor environmental conditions with little emphasis on defining infrastructure in developed areas. A more accurate representation of urban development properties for a densely populated area allows urban planners to make better decisions about future development, hence mitigating the effects of uncontrollable growth caused by rapid urbanisation. As a consequence, this research aims to enhance urban planners' visualisation of urban development by developing an urban built land classification model using Google Earth Engine (GEE) and satellite data. The research was conducted in three phases: first, a literature review was conducted; second, the classification model was developed using satellite imaging data; and third, the classification model's performance was evaluated using designated assessment metrics. The first step in developing this model was to investigate the machine learning techniques and features used in existing LULC models, focusing on those built using the GEE platform. Random Forest was chosen to develop the urban built model in this study due to its resilience and performance in creating classification models on the GEE platform. In addition, the features analysis resulted in the emergence of a new set of granular features for the classification of urban developed land, namely the automobile, construction land, transport lane, building, vegetation, and water bodies. In the LULC class system, these characteristics represent a finer scale for urban or built-up land and come closest to defining an area's urban development properties. The urban built land classification model was developed on GEE using Landsat 7 and Landsat 8 imagery from the Google Earth Engine Data Catalog for Selangor from 2015 to 2020. The model was created using Random Forest with the optimal number of trees and the feature set of automobile, construction land, transport lane, building, vegetation, and water bodies after the hyperparameters were tuned. Each feature's classification result was displayed on the map, clearly illustrating the distribution of pixels for each detected feature using a defined colour code to provide an accurate representation of the feature's concentration. The accuracy of the urban built land classification model was then determined using the Overall Accuracy (OA), Kappa coefficient, Producer Accuracy, and User Accuracy, yielding 88% to 92%, 0.69 to 0.79, 53% to 98%, and 53% to 96%, respectively. The high overall accuracy showed that the urban built land classification model had successfully classified finer scale details such as automobile, construction land, transport lane, and building spread, thereby improving existing LULC models and providing a more complete picture of development. In conclusion, the findings of this study will help urban planners make informed decisions about highly urbanised cities, thereby achieving a safe, resilient, and sustainable city whilst limiting unsustainable development.

ABSTRAK

Perbandaran yang pesat membawa kepada pertumbuhan bandar yang tidak terkawal dan boleh mengancam kestabilan alam sekitar dan kualiti hidup. Walaupun pembangunan infrastruktur memberi manfaat kepada penduduk bandar, peningkatan lalu lintas, kesihatan dan kebimbangan alam sekitar adalah punca kebimbangan. Untuk mengurangkan kesan negatif peningkatan urbanisasi, perancangan bandar memainkan peranan penting dalam mencapai matlamat pembangunan bandar yang mampan. Sektor perancangan bandar menggunakan perubahan guna tanah litupan tanah (LULC) sebagai titik rujukan utama untuk pemantauan, di mana ia sekarang digunakan terutamanya untuk memantau keadaan persekitaran dengan sedikit penekanan pada penentuan infrastruktur di kawasan maju. Ciri-ciri pembangunan bandar yang lebih tepat untuk kawasan berpenduduk padat membolehkan perancang bandar membuat keputusan yang lebih baik tentang pembangunan akan datang, mengurangkan kesan pertumbuhan yang tidak terkawal yang disebabkan oleh urbanisasi pesat.Tujuan penyelidikan ini adalah untuk meningkatkan visualisasi perancang bandar dalam pembangunan bandar dengan membangunkan model klasifikasi tanah binaan bandar menggunakan Google Earth Engine (GEE) dan data satelit. Penyelidikan dijalankan dalam tiga fasa: pertama, tinjauan literatur; kedua, pembangunan model klasifikasi menggunakan data pengimejan satelit; dan ketiga, penilaian prestasi model klasifikasi menggunakan metrik penilaian yang ditetapkan. Langkah pertama dalam pembangunan model ini adalah untuk menyiasat teknik dan ciri pembelajaran mesin yang digunakan dalam model LULC sedia ada, terutamanya yang dibina menggunakan platform GEE Mesin pembelajaran Random Forest dipilih untuk membangunkan model binaan bandar dalam kajian ini kerana ketahanan dan prestasinya dalam menghasilkan model klasifikasi di platform GEE. Selain itu, kajian ini menggunakan satu set fitur baharu dalam klasifikasi pembangunan tanah bandar, iaitu kenderaan, tanah pembinaan, lorong pengangkutan, bangunan, tumbuh-tumbuhan, dan kawasan berair. Dalam sistem kelas LULC, fitur ini mewakili skala yang lebih halus untuk kawasan bandar atau tanah binaan dan lebih sesuai dalam menentukan sifat pembangunan sesuatu kawasan. Model klasifikasi tanah binaan bandar di platform GEE menggunakan imej Landsat 7 dan Landsat 8 daripada Katalog Data GEE untuk Selangor dari tahun 2015 hingga 2020. Model ini dibuat menggunakan Random Forest dengan bilangan pokok yang optimum setelah hiperparameter ditala dan set fitur kenderaan, tanah pembinaan, lorong pengangkutan, bangunan, tumbuh-tumbuhan, dan kawasan berair. Hasil klasifikasi setiap fitur dipaparkan pada peta dengan jelas menggambarkan penyebaran piksel untuk setiap fitur yang dikesan menggunakan kod warna yang ditentukan, memberikan gambaran yang tepat mengenai tumpuan fitur tersebut. Ketepatan model klasifikasi tanah binaan bandar kemudian ditentukan dengan menggunakan Keseluruhan Ketepatan (OA), pekali Kappa, Ketepatan Pengeluar, dan Ketepatan Pengguna, masing-masing menghasilkan 88% hingga 92%, 0.69 hingga 0.79, 53% hingga 98%, dan 53% hingga 96%. Ketepatan keseluruhan yang tinggi menunjukkan bahawa model klasifikasi tanah binaan bandar berjaya mengklasifikasikan perincian skala yang lebih halus seperti kenderaan, tanah pembinaan, lorong pengangkutan, dan penyebaran bangunan. Dengan itu model cadangan kajian ini menambah baik model LULC sedia ada dan berupaya memberikan gambaran pembangunan yang lebih lengkap. Kesimpulannya, dapatan kajian ini akan membantu perancang bandar membuat keputusan yang tepat mengenai bandar-bandar yang sangat pesat pembangunannya, dan juga dapat menghadkan pembangunan yang tidak mampan dalam usaha untuk mencapai bandar yang selamat, berdaya tahan, dan mampan.

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LIST OF ABBREVIATIONS

ABM	-	Agent Based Model
ANN	-	Artificial Neural Network
API	-	Application Programming Interface
CA	-	Cellular Automata
CART	-	Classification And Regression Trees
CE	-	Commission Error
CNN	-	Convolutional Neural Network
DCNN	-	Deep Convolutional Neural Network
DL	-	Deep Learning
DNN	-	Deep Neural Network
DT	-	Decision Tree
ERT	-	Extremely Random Tree
ETM	-	Enhanced Thematic Mapper
FPR	-	False Positive Rate
GBDT	-	Gradient Boosting Decision Trees
GEDC	-	Google Earth Data Catalog
GEE	-	Google Earth Engine
LR	-	Linear Regression
LULC	-	Land Use Land Cover
MD	-	Mahalanobis Distance
ML	-	Machine Learning
MLC	-	Maximum Likelihood Classifier
MP	-	Multilayer Perception
NASA	-	National Aeronautics and Space Administration
NB	-	Naive Bayes
NDVI	-	Normalised Difference Vegetation Index
OA	-	Overall Accuracy
OE	-	Omission Error
OLI	-	Operational Land Imager
PA	-	Producer Accuracy

PCM	-	Percent Correct Match
PCPC	-	Percentage of Correctly Predicted Cells
PCPUC	-	Percentage of Correctly Predicted Cells Unchanged
PRISMA		Preferred Reporting Items for Systematic Reviews and Meta–Analyses
QA	-	Quality Assessment
RBF	-	Radial Basis Function
RF	-	Random Forest
RNN	-	Recurrent Neural Network
ROC	-	Relative Operating Characteristic
RS	-	Remote Sensing
RT	-	Real Time
SAM	-	Spectral Angle Mapper
SD	-	Sustainable Development
SDG	-	Sustainable Development Goal
SLC	-	Scan Line Corrector
SR	-	Surface Reflectance
SVM	-	Support Vector Machine
TF	-	True Negative Rate
TFR	-	Fall-Out -False Positive Rate
T1	-	Tier 1
TIRS	-	Thermal Infrared Sensor
TPR	-	True Positive Rate
UA	-	User Accuracy
UN	-	United Nation
USGS	-	United States Geological Survey

LIST OF SYMBOLS

$\hat{C}_b(x)$	-	class prediction of the bth random-forest
K	-	Kappa
Po	-	overall accuracy of the model
Pe	-	measure of the agreement between the model predictions and the actual class values due by chance

CHAPTER 1

INTRODUCTION

1.1 Overview

Rapid urbanisation refers to the movement of a large population from villages or rural settlements to an urban area. According to the United nation, Africa and Asia are the two continents to witness rapid urbanisation soon as they would see a 90% increase in urban population by 2050. Going further, the Southeast Asia region population will reach 740 million by 2035, and Malaysia is a country to be categorised as a highly urbanised country (Samat et al., 2019). According to Farrell (2017), urban growth refers to the increase of people in urban areas. Urbanisation refers to the rise in the proportion of urban versus rural areas (Gomes, 2020). While both terms are used, the focus of this research is on urbanisation.

Urbanisation is a positive indicator of any country because it correlates with economic growth (Evans Mwamba, 2021; Riffat et al., 2016; D. o. E. a. S. A. United Nations, Population Division 2019). Job opportunities, technology advancement, and economic growth are the pull factors for rural to city migration. Undoubtedly, urbanisation offers economic advantages, but it has projected significant disadvantages to the environmental stability and quality of life (Riffat et al., 2016). In specific, rapid urbanisation poses a high risk for infrastructure, disease, and climate management, making city management a daunting task.

Many literature highlights the negative impacts of accelerated urbanisation (Gomes, 2020; Riffat et al., 2016). An increase of 83% in urbanisation, in Bhubaneswar, a city in India, had a significant alteration in land use land cover (LULC), causing an accumulation of heat and a drastic drop in vegetation area, impacting long term sustainability (Swain et al., 2017). Megacities in China faced extreme urban rainfall, leading to unpredicted climate issues due to rapid urbanisation (D.-L. Zhang, 2020). Another research in Egypt highlighted significant urban and built-up areas since the 1990s that have caused air temperature to increase, causing discomfort to the people in Cairo (Mahmoud and Gan, 2018). More recent research in Bangladesh described how rapid urbanisation had increased the burden in managing infectious diseases like Covid 19, causing a dip of 40% income for the urban dwellers (Mohiuddin, 2020). These are some examples of environmental disruptions, directly or indirectly impacting the quality of life and sustainability.

Rapid urbanisation is a primary contributor to uncontrollable development, which goes against the notion of sustainable development goals (SDG) prescribed by the United Nations (UN) (D. o. E. a. S. A. United Nations, Population Division 2019). SDG, in particular, SDG 11 “Making cities and human settlements inclusive, safe, resilient and sustainable”, targets have adequate, safe infrastructure and facilities for urban dwellers to have a quality life (Krellenberg et al., 2019). A recent article by the UN further highlighted 90% of Covid-19 cases hit the highly dense cities (D. o. E. a. S. A. United Nations, Population Division, 2020). The same report (D. o. E. a. S. A. United Nations, Population Division, 2020) highlighted approximately 75% of carbon emissions in the cities expose the condensed urban areas to drastic climate change and natural disasters. Sustainable urban planning is key to stabilising the effects of rapid urbanisation and developing a safe, resilient, and sustainable city (Moroke et al., 2019).

Sustainable urban planning or development is related to the physical and spatial planning to optimise the distribution of land allocation to support human activities (Geneletti et al., 2017). In an urban context, this implies creating efficient resource systems and good, engaging urban design for attractive cities with good quality of life (Haaland and van den Bosch, 2015)). A perfect urban design and planning start with a good analysis of the LULC. LULC provides an insight into the ground attributes and its change over time, helping urban planners plan development better

Rapid urbanisation and recent advancements in remote sensing technologies have invited increasing research interest on LULC dynamics in urban planning. Urban planning involves making alterations to the LULC, thus using tools and technologies is important to gain accurate information. However, with many variations in land use patterns , obtaining the correct information to understand the current situation and plan development for the future is a tedious and expensive process. Advancement in remote sensing technologies coupled with big data has provided an avenue for detailed research on LULC with mass amounts of heterogeneous spatial data from different sources. Urban planners using the standalone automation tools have also shifted to leverage the big data technologies and cloud platforms to better understand the city structure and further aid them in predicting and classifying geospatial data (Ilin et al., 2018). However, with such advancement, there is a gap in planning LULC either locally or regionally leading to uncontrollable development (Aboelnour and Engel, 2018).

LULC classification gives an insight into urban built, vegetation, and water bodies, useful for urban planners to understand what changed the land cover properties. However, these classification models cannot classify the granular attributes like automobiles, construction sites, transportation lines, and buildings because obtaining huge amounts of high resolution data and processing objects is resource-intensive. Having insights into detailed information on urban built areas will help urban planners control unplanned development.

With the debut of Google Earth Engine as a geospatial data analytics cloud platform, LULC classification study has acquired academic interest and improvements in recent years (L. Lin et al., 2020). Google Earth Engine (GEE), a free cloud development platform with petabytes of geospatial data and the capacity to execute geospatial research on a high-end Google infrastructure, has shown enormous potential in the urban planning area. GEE's imagery classification capabilities, which include filtering image collection, image visualisation, Landsat simple composite, and generating statistics on image region, considerably assist the urban planning sector in efficiently classifying LULC properties without the requirement for a high-end infrastructure hosted locally (Tamiminia et al., 2020).

To date, there is little evidence on the further classification of urban or built-up land attributes. This research aims to study the existing LULC classification models used in urban planning and further enhance the classification model with additional urban-built features using open source geospatial data on a cloud platform. The improved classification model would help urban planners better understand the granular features in a developed area and then use it for better planning in a highly urbanised area. In the problem background, the problems with urban planning, their relationship to sustainability, and the deficiencies in LULC categorization that contribute to rapid urbanisation are discussed further.

1.2 Problem Background

Increasing traffic, unpredicted climate, spreading infectious disease are common phenomena in highly urbanised countries(Sharifi and Khavarian-Garmsir, 2020). Urbanites in smaller and dense cities spend most of their time in traffic, face health issues, and have unpredictable geohazards such as flash floods. These scenarios are a result of uncontrollable development caused by rapid urbanisation.

Increased traffic, unpredictable weather patterns, and the spread of infectious diseases are all common occurrences in highly urbanised countries. Urbanites in smaller, more densely populated cities spend the majority of their time stuck in traffic, face health problems, and face unforeseen geohazards such as flash floods. These scenarios are the result of uncontrolled urbanisation. Urban design and planning departments carry the burden to ensure development plans create a sustainable city for a better future. The recent paradigm shift on urbanisation has also awakened the need for sustainable urban planning to support sustainability goals. Sustainable urban planning is related to the physical and spatial planning to optimise the distribution of land allocation to support human activities (Geneletti et al., 2017). Land development along with land transactions in the cities is a forced change by urbanisation.

Nevertheless, when global migration to major cities happens rapidly, this change is viewed as a positive relationship between land development and land-based revenue growth (W. Chen et al., 2018). Due to this, policymakers and urban planners are often bound by the economic growth indicator to decide further development. The development of residential, commercial, and other amenities has continuously increased as city dwellers' need increases. As a result, the infrastructure ecosystem becomes unstable, causing traffic congestion, climate change, urban crimes, and many other adverse effects.

To achieve sustainable urban planning, a good understanding of land change dynamics is essential, and for this, an accurate LULC is mandatory. The 1950's manual study of land use and land cover (LULC) has continued to the present day, but with the aid of advanced remote sensing technologies. The LULC maps servers as an important document for planning developments locally or at the national level (Hamad, 2020). The growing research interest in LULC classification techniques is driven by the continuous need for more accurate LULC maps to plan for sustainable development (Alshari and Gawali, 2021). The accuracy of LULC maps depends on the classifier and features employed in the classification model.

A literature compilation by Alshari and Gawali (2021) highlighted various research attempts on finding the right combination of machine learning techniques and features to best classify the land cover properties to the classes defined in LULC classification classes by Anderson et al. (1976). While these researches have immensely helped to understand the land cover change assessment for the broader classes in the classification system, less work is demonstrated on the further classification of Urban or Built-up Land class. One of the reasons for the lack of this research in this area could be tedious work in identifying the detailed features, requiring large and high quality geospatial data and a high-end processing platform.

Spatial data also known as geospatial data are information about features, locations and natural earth constructs represented in numerical values in system (VoPham et al., 2018). Geospatial data refers to data associated with a geographical and are used in the form of vector data, raster data and tabular data by the geospatial processing platform and geographic information systems(GIS) tools for LULC analytics. Further improvement in LULC classification algorithm accuracy necessitates large data sets of high resolution geospatial data, which have always been a challenge in LULC analytics due to their availability and processing cost. With the emergence of Google Earth Engine (GEE) and its ability to provide high resolution geospatial data or satellite imagery data, its platform provides an excellent opportunity to develop a better classification model to better classify the attributes of Urban or Built-up Land classes and improve the visualisation of urban development on a LULC map (Tamiminia et al., 2020)

The Urban or Built-up land class entails building all kinds of transportation; however, the existing LULC classification models do not classify these features individually. Uncontrollable residential and commercial development in major cities claims to support the needs of the growing population, but these developments have led to massive jams in major cities. To prohibit further development in a congested area, a good understanding of existing structures would help urban planners to assess and plan the city development better. For this, additional classification of the Urban or Build Land is necessary. With a classification of the granular features of the urban development on the LULC map, the urban planners will understand the ground properties like the sprawl of automobiles, construction sites, transport lanes, and building individually. For example, a high automobile spread on a classified LULC map would indicate that the area has high crowd mobility. Granular features in this study refer to properties on the LULC map with a low spatial resolution of less than 10m, and granular classification refers to classifying granular features of land cover using a 30 resolution satellite imagery collection, which is also known as fine scale classification. These terms are defined in greater detail in Chapter 3 along with their application to this research.

This research proposes an enhanced urban development classification model to classify urban built-land class granular features using open source geospatial data on Google Earth Engine platform. The classification map from this model would serve as an early indicator to evaluate the need for further development in a highly urbanised area. The upcoming section describes the problem statement of this research, which is thereafter used to devise the research question and objective.

1.3 Problem Statement

Currently, the LULC classification model characterises any man-made infrastructure as urban or built land, making it impossible to determine the causes of increased development in the same focus area. The classification of urban or constructed land features at a granular scale has received little attention because it is believed that classifying pixels at that low resolution is impractical and may result in a lower accuracy of classification, in contrast to vegetation features which have a wider spread of pixels over a land area, which results in higher accuracy in LULC classification models. However, in order to gain precise insights into the development of a specific area and comprehend crowd mobility, traffic, and adjacent developments, the LULC maps must also display the granular features of urban built properties for the field of urban planning. Despite the fact that big data analysis has contributed new ways of developing LULC models, such as using cloud platforms like Google Earth Engine, classification on urban development properties is still not as clear as it is for vegetation land classification.

The purpose of this thesis is to identify additional granular features for urban development classification and then to develop an urban built land classification model employing the identified granular features that is capable of detecting the urban development properties of a given geographical area using open source geospatial data on Google Earth Engine.

1.4 Research Questions

Following are the research question outlined for this study:

(a) What are the available LULC classification models for sustainable planning?

(b) What are the additional granular features required for the urban built land for sustainable urban planning?

(c) How to improve the accuracy of urban built land classification using spatial data for sustainable urban planning?

(d) How accurate is the proposed urban built classification model?

1.5 Research Objectives

The objectives of the research are:

(a) To analyse LULC classification model used in urban planning supporting sustainable urban planning.

(b) To determine additional granular features required for the urban built land classification model in sustainable urban planning.

(c) To develop an enhanced urban built land classification model using spatial data for sustainable urban planning.

(d) To evaluate the accuracy of the proposed classification model.

1.6 Significance of the Study

Urban planners play an important role because they make decisions on local, state, and even national level developments. In urban planning, various automation tools use LULC modelling to understand changes in land cover over time. For these LULC models, the best feature set and classification approach for earth imaging to simulate the ground truth are still being developed.

The proposed urban built land classification model will improve upon the LULC classification models by incorporating more refined urban built features that are strongly associated with urban development. The model allows urban planners to visualise finer details of densely built-up urban land and use it as one of several indicators in deciding future development to support sustainable development.

In addition, this research aims to develop the classification model using publicly available data and open source platforms in granular object classification, classifying the urban built properties. This methodology would significantly contribute to further research in granular object LULC classification and improve LULC maps' accuracy, which is a primary reference used in urban planning to achieve sustainable urban planning.

1.7 Scope of Research

This research will use Selangor as the area of study because it satisfies the population size criteria, contains an area of concentrated development, and shows a high traffic flow in urbanised areas. Selangor is an 8000 km^2 state in the west of Malaysia and has 12 counties under its provision. The state has at least 80% of vegetation land, including farmland, forest and other types of greenery. The metropolitan areas with high development and traffic is seen in Subang Jaya, Shah Alam, Klang and Petaling Jaya.

In the last five years, active constructions have been observed in these areas, which has significantly increased the traffic flow and soon will ace the uncontrollable development phenomena. These properties make Selangor a good study area because, with a better LULC map, it could indicate the finer details of urban built, which will help urban planners and the development boards gain a better insight before approving a new development in the same area. Wahap and Shafri (2020) used GEE with multiple supervised machine learning classification algorithms to classify agricultural land, forested land, water bodies, bare land, urbanised land, and paddy field to study the LULC change in Klang Valley with

Selangor as the highest area coverage. According to Wahap and Shafri (2020) Selangor has the largest economy and the most developed state in Malaysia in terms of gross domestic product (GDP), which is also a reason for selecting Selangor as the study area in this research. Additionally, this research compares impervious land properties and finer-scale land property classification using GEE to Landsat data collections by X. Liu et al. (2018) and Ai et al. (2020), which achieved an overall accuracy of 81% to 86%. This accuracy will be used as a bench mark to evaluate the accuracy of the developed urban built land classification model in this research.

The proposed classification model in this research will be developed using the Google Earth Engine (GEE) cloud platform. Using the same platform, a publicly available satellite imagery data set from the Google Earth catalogue will be used as the base map for building the classified LULC map to show the granular features of urban built-in Selangor. Google Earth Engine is a cloud platform tool for developing and visualising classification performed on a selected spatial data set for a region and time period.

1.8 Thesis outline

The overall structure of this thesis is comprised of six chapters, including this introductory chapter. The first chapter discusses the problem's context, defines the research questions, and establishes the research objective. Additionally, this chapter defines the study area and scope of the research. The second chapter summarises the existing literature on rapid urbanisation, sustainability, the LULC model, and the LULC model's features. This chapter addresses the first two research questions and also defines the proposed urban built land model's machine learning model and features. Chapter three discusses the research's overall operational framework, data collection, sampling, and evaluation methods. Chapter four discusses the framework for designing and implementing the proposed urban built land classification model. Chapter four will detail the design framework and development phases, allowing readers to comprehend how the proposed classification model is developed. Chapter five discusses the evaluation of the classification model in terms of overall accuracy and individual class accuracy. Chapter five also discusses the factors that affect the classification model's accuracy. Chapter six is the concluding chapter, in which the researcher discusses the accomplishment of the research's objective. Additionally, this section discusses the limitations and future opportunities for expanding this research.

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