Modelling Past and Future Land Use Changes and Potential Conflicts from Mining, Agriculture, and Industry in the Rapidly Developing Region of Kuantan, Malaysia

Supervisors:
Dr. Alex M. Lechner (UNM)
Dr. Tapan Kumar Nath (UNM)

Student: Sharun Bt Beream Nasir
Student ID: 18817027

MRes in School of Environmental and Geographical Sciences, Faculty of Science and Engineering, University of Nottingham Malaysia (UNM)

Thesis submitted to the University of Nottingham for the degree of Master of Research
August 2021

Abstract

Kuantan is emerging as a dynamically developing region supported by the mega-economic development projects such as the East Coast Economic Development Plan in conjunction with the extension of China-Malaysia bilateral industrial parks and establishment of East Coast Rail Link (ECRL), a part of the great Belt and Road Initiative (BRI). Such a rapidly developing region requires a robust spatial analysis to understand the changing landscape pattern and its socio-environmental impacts to guide sustainable development. Addressing the lack of research focused on this key economic development region, this study aims to characterise and evaluate the historic and future projection of land use land cover (LULC) change patterns to understand the dynamics of the regional development process and to identify potential future land use conflicts. The methodology for this research includes construction of coarse-scale land cover classes by using Landsat 5 TM and Landsat 8 OLI data based on a combination of Random Forest classifier on Google Earth Engine (GEE) platform and manual refinement to construct fine-scale LULC maps by using auxiliary reference data. The produced timeseries imageries' overall accuracy assessment scored at an average of 83%. Subsequently, to further assess and model the future LULC change pattern, the Land Change Modeler (LCM) in TerrSet was utilized by training the multilayer perceptron (MLP) neural network and using the Markov chain analysis.

The study shows that the region's land cover will be largely altered by human intervention driven by urbanisation and the region's evolving economic vision. Overall, the LULC timeseries for the years 2010 to 2020 revealed a prominent increase in oil palm plantation, followed by mining, residential, and industrial site expansion, with a consequent decline in forest and disturbed vegetation cover. The future land use projection for the year 2030 also revealed similar land use development patterns. Both the historical remote sensing data and future projections showed that industry, mining, and residential are clustered and growing in close proximity while expanding extensively, which may likely be a cause of future land use conflict. Although modelled future projections may contain many uncertainties, having the ability to envision future possible scenarios provide key insights into the current and evolving future patterns of land use changes and predicting their impacts on people and the environment. This will assist government bodies, stakeholders, and policy makers by providing information essential for future planning and sustainable development decisions.

Acknowledgement

We would like to thank Professor John Owen and the Centre for Social Responsibility in Mining (CSRM) at the Sustainable Minerals Institute for providing funds for this research as a part of an MRes study. We are also extremely thankful to the supervisors, both Dr. Alex Mark Lechner and Dr. Tapan Kumar Nath for their constant support and guidance throughout this research. We would also like to thank Michelle Li Ern Ang, one of our research associate in the Landscape Ecology and Conservation (LEC) lab for her endless guidance and contribution to this thesis. Also, we wish to acknowledge Dr. Angela Tritto from the Institute of Emerging Market Studies of The Hong Kong University of Science and Technology, Hong Kong for sharing insightful information regarding the Belt and Road Initiative (BRI) project. Finally, we wish to thank the members of the Landscape Ecology and Conservation (LEC) lab team for data provision and their constructive ideas and feedbacks towards this research. Last but utmost the author expresses her gratitude to God for making this research successful with the help of great individuals both from her working space and family members and also by the funding bodies.

Table of Contents

List of Figures

List of Tables

Chapter 1: Introduction

1.1. Problem Statement and Scope of Research

To centralise and enhance the development in the East Coast Economic Region (ECER), Kuantan city and its surrounding region have been made a focus for development, known as the East Coast Economic Region Special Economic Zone (ECER-SEZ) (*ECER Master Plan 2.0*, 2019). Kuantan is acknowledged as the Port City and gateway to the Asia-Pacific markets that bring in various investment and trade opportunities with advancing high-profile manufacturing sectors and lead bilateral trade relation ventures between Malaysia and China (Nur Fatin, 2016; The Report Malaysia, 2012). In addition, to the thriving industrial and also logistic sector developments such as the construction of East Coast Rail Link (ECRL) track in Kuantan, the region is also known for its abundant natural resources, namely for its agricultural produce and bauxite resources which are locally processed and exported (Naz Karim & Shah, 2016). Hence, Kuantan is playing a vital role in the ECER-SEZ and aspires to become a central location for development in South East Asia; offering various opportunities, to transform the region into a vibrant trading centre, a potential resource and manufacturing base, an export platform equipped with great infrastructure and logistics hub, and also as a major local tourism destination for its cultural and natural attraction (ECERDC, 2010). The implementation of these high-impact development plans and continuous exploitation of natural resources in Kuantan have resulted in major land cover changes over the past decades, as such rapid economic growth is often interconnected with a record of increased land use changes (Chen et al., 2020). Overtime, the various growing land use profiles in that development concentrated region have also led to land use conflicts, mainly affecting on the surrounding environment and people's livelihood (Aw & Awale, 2015).

In order to support spatial planning in dynamic regions such as Kuantan, an important first step is characterising historical land use change using remote sensing to understand the past and present physical properties of landscapes (Lechner, Foody & Boyd, 2020; Ngo et al., 2020). The Landsat satellite series has one of the longest timeseries of historical imagery and along with supervised classification methods and its medium resolution data, it represents as one of the most established methods to accurately map and monitor the dynamic changes in LULC distribution (e.g., Coppin et al., 2004; Lu et al., 2004; Lu & Weng, 2007; Singh, 1989; Tso & Mather, 2009). Such mapping can provide details on the intensification, conversion, and abandonment of specific regions, and the socio-environmental impacts of these transformations (Ang et al., 2021; Gyawali et al., 2004; Lechner et al., 2019; Yiran et al., 2012). Hence, in this study, Landsat satellite imagery was used accompanied with the Random Forest classification method in the Google Earth Engine (GEE) and ArcGIS software to analyse and characterise the historical land use change activities. Additionally, multiple sources of ancillary data were also used for land use detection and interpretation due to constraint of using Landsat sourced 30m resolution data.

Using historical maps of LULC change, it is possible to model future LULC changes based on historical patterns of change to support spatial land use planning. Future LULC modelling can predict key LULC change patterns by discerning the potential socioeconomic and biophysical forces that influence the rate and spatial patterns of LULC change and urbanisation processes (Aburas et al., 2018; Al-sharif & Pradhan, 2014; Shivamurthy et al., 2013; Yang et al., 2012). Common methods of land change modelling include: (1) machine learning, (2) cellular-based, (3) spatial modelling, (4) agent-based approaches (Han et al., 2015; Yang et al., 2012), and (5) hybrid approaches (Wang & Maduko, 2018). One common approach to modelling land change is using the Land Change modelling system, part of the TerrSet software, which integrates a multilayer perceptron (MLP); a feed-forward neural network that calculates the weights/influence of input variables and Markov Chain (MC) modelling (Hasan et al., 2020). It is an extensively used modelling procedure to forecast future LULC change based on the transition probabilities of historic land use change activities (Hasan et al., 2020). These methods have been applied to analyse the spatio-temporal patterns and predict the LULC change and urban growth (Han et al., 2015; Mas et al., 2014; Ozturk, 2015; Sundara Kumar et al., 2015; Wang & Maduako, 2018). Therefore, this method is replicated in this study too for the similar purposes; analysing both the historical and future spatio-temporal patterns and determining possible factors to land use conflicts due to coexisting different land use profiles.

1.2. Aim and Objectives of Research

This research aims to characterise spatio-temporal land use land cover (LULC) changes over the rapidly developing region of Kuantan using remote sensing and land change modelling methods. The main objectives of this research are to (1) map the patterns of LULC change over the past two decades using Landsat satellite imagery, (2) identify the land use classes which significantly changed in the region and are likely to have significant socio-environmental impacts, and to (3) model the possible future land use change of the study area. These objectives will be achieved by creating a timeseries LULC maps, analysing the land use change activities, and modelling the future LULC change patterns. The results are used to understand the dynamics of the urbanisation process and to identify potential land use conflicts to assist the land use planners make an informed decision, regulate strategic land use development spatial planning, support sustainable development in Kuantan, and ultimately to understand the types of development challenges for fast-growing developing regions in Southeast Asia.

Chapter 2: Literature review

2.1. Land Use Land Cover (LULC) Change in Malaysia

Urban land expansion is one of the most visible, irreversible, and rapid type of LULC change process in human history, largely driven by urbanisation, both directly through the transformation of existing land cover to settlements and indirectly through the consumption of resources (Gao & O'Neill, 2020; Nuissl & Siedentop, 2021). This large-scale global environmental change is led by the exponential growth in population, demographic changes, and socio-economic development activities (Spyra et al., 2021). Currently, developing countries are experiencing a considerably faster rate of urbanisation than the developed ones (Carneiro Freire et al., 2019) resulting in extensive LULC change patterns (Yao et al., 2015). Large developing countries with emerging market economies like China and India have experienced rapid land use changes from being an agricultural based-country to an industrialized country (Rathee, 2014; Shi et al., 2018). Similarly among the East Asia region, Malaysia is exemplified as one of the fastest urbanising developing countries and is emerging as a new industrialized country while expanding its market economy in service, manufacturing, mining, and agricultural sectors (Abu Dardak, 2015; Samat et al., 2020).

A key dimension of the Malaysian government's economic strategy focuses on balancing the uneven regional development throughout the country by creating new development centres in resource frontier regions. Development in these regions is based on utilizing local natural resources of the less-developed states in support of the national economic development, while strengthening rural agricultural and industrial sectors (Ngah, 2011b). Hence, the Malaysian government is particularly focused on addressing the disparity in economic development between the west and east coast of Peninsular Malaysia, through the establishment of an economic corridor in the east coast known as the East Coast Economic Region (ECER) (Huam et al., 2018). Over the past 2 decades, such economic corridors are recognized as a vehicle for sub-regional economic development advancement and in promoting equitable regional growth by providing economic connectivity between major metropolitan centres (Athukorala & Narayanan, 2018; Yeo & Rimmer, 2015). Realizing the importance of providing an efficient and effective logistics system to expand the economic connectivity between these different regions and Southeast Asia, the Malaysian government along with international financiers is developing the 620km long East Coast Rail Link (ECRL) project (Huam et al., 2018). The ECRL project is a part of China's Belt and Road Initiative (BRI) that will act as a major land bridge in connecting the ECER region to the rest of the country, whilst boosting the local tourism sector (ECER Master Plan 2.0, 2019), but potentially having negative environmental and social impacts (Lechner et al., 2019; Ng et al., 2020; Teo et al., 2019).

In recent decades, researchers have made substantial progress in empirically addressing the various forms of land use changes to determine the major land-use conversion and occurring land use conflicts (Elias et al., 2012; Nuissl & Siedentop, 2021; Winkler et al., 2021), as LULC change have a significant impact on the environment and society (Gao & O'Neill, 2020). To promote long-term sustainable regional development, better knowledge of how development alters the local environment is required (Kivinen et al., 2018a) and this is especially important for rapidly changing regions like Kuantan and other locations across rapidly developing South East Asia. With the lack of study encompassing the spatial changes of this rapidly developing region of Kuantan, this research's aim and objectives are envisioned to deliver more knowledge on the extent and rate of land use changes, and in understanding the land use dynamic and arising land use conflict between different land use profiles. Characterising spatio-temporal LULC patterns will assist policy and decision-makers in analysing the causes and consequences of land use dynamics and in supporting the implementation of strategic land use spatial planning (Verburg et al., 2004). Strategic land use spatial planning can contribute to meeting the current and future societal needs while addressing land use conflict (Brown & Raymond, 2014; Lechner et al., 2020).

2.2. Kuantan

Kuantan is located in the eastern part of Peninsular Malaysia at the latitude of 3° 48' 27.72" N and longitude of 103° 19' 33.60" E and is the capital city of Pahang with a population approaching half a million people (DOSM, 2021). The topography of Kuantan mainly consists of lowlands and the city extends along the coast. The city is rich with local culture, known for its natural and heritage tourism attractions, and also for the abundant natural resources. These attributes have shaped the various livelihood opportunities for the people of Kuantan. The early economy for many Kuantan locals was dependent on agricultural activities (comprised of oil palm plantation, rubber plantation, orchards), marine and freshwater fisheries sectors, small businesses such as craft production, small-scale manufacturing, and also local tourism activities (ECER, 2016).

Kuantan is a fast-growing region that is an integral part of the East Coast Economic Region's development plan (ECERDC, 2010). Its strategic geographic location of facing the South China Sea and being in one of the world's main shipping lanes and trading routes was a significant factor for the city being chosen as the focal point in the ECER-SEZ development project (Huam et al., 2018; Nur Fatin, 2016). The five key economic drivers focused in the ECER master plan for this region are namely tourism, oil and gas, petrochemical, manufacturing; agriculture and agro-based industry, and human capital development (ECERDC, 2010). These key economic drivers are expected to create economic growth in the region, raise the knowledge capacity of the population, and generate 200,000 jobs (*ECER Master Plan 2.0*, 2019). The recent discovery of Kuantan land being rich in gibbsite minerals has also led to the acceleration of mining activities fulfilling China's growing demand for bauxite resources (Lines, 2015). The extent of the study area (Figure 1) chosen for this research includes these thriving development activities within the region. The key drivers to the rapid development within the study area are the growing industrial sectors, vast agricultural activities, bauxite mining excavation, and also encompassing the future ECRL track.

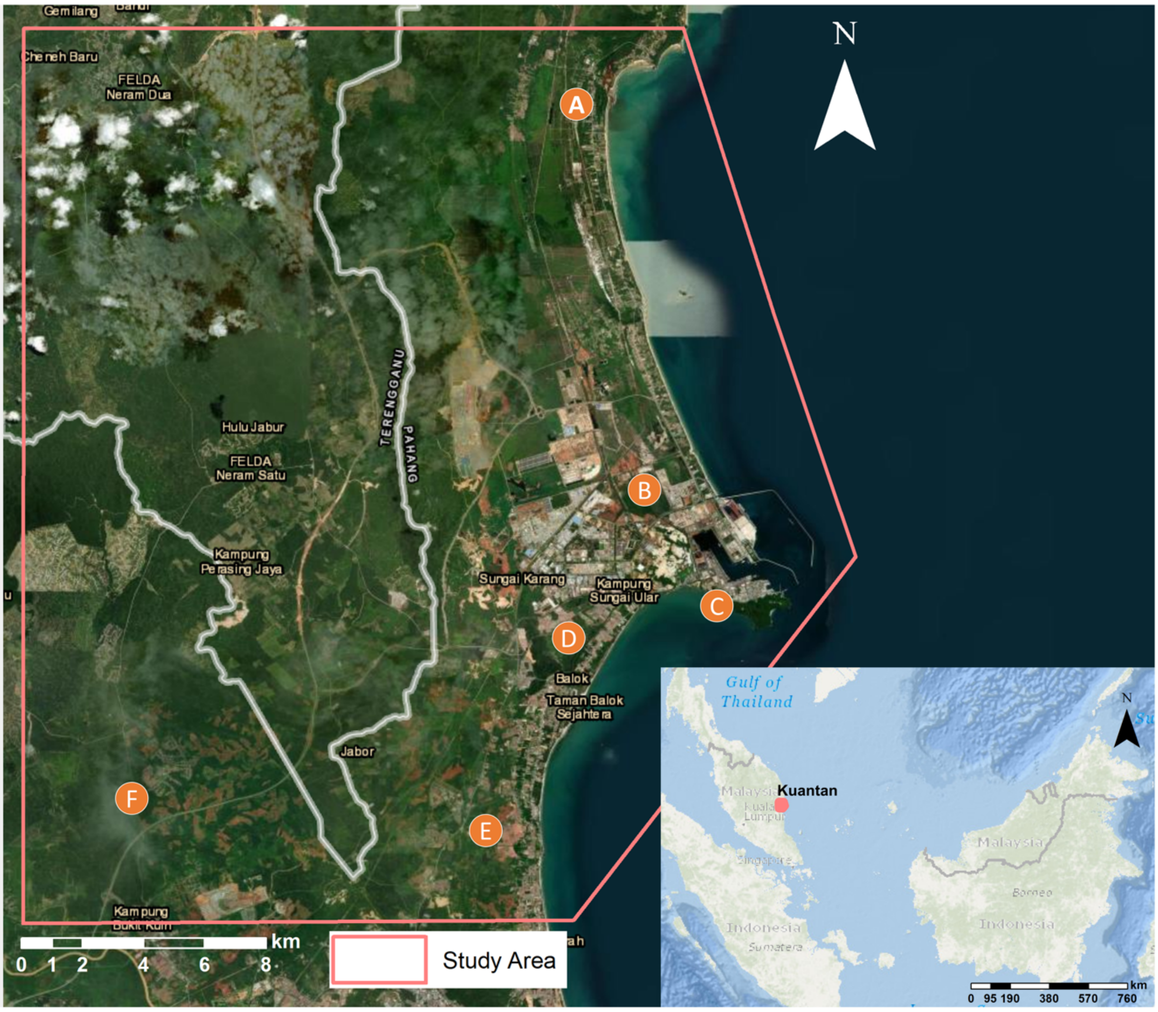

Figure 1. Map of Kuantan city in Peninsular Malaysia (on the bottom right corner) and the research's study area in Kuantan. The labelled locations within the study area indicate some of the important economical and urbanisation nodes; A: Cherating, B: Gebeng, C: Kuantan Port, D: Balok, E: Beserah, F: Bukit Goh.

Chapter 3: Methods

3.1. Methods Overview

The methodology for this research includes the use of remote sensing data to produce a historic timeseries LULC map for the years 2010, 2015, and 2020 through a process of image pre-processing and Random Forest classification using the Google Earth Engine (GEE) and ArcGIS. The classified LULC maps are refined further with finer land use categories by manual digitization using various sources of auxiliary reference data for interpretation (Lechner et al., 2019). The following timeseries classification methodologies is specifically delineated in Section 3.2 and 3.3 ahead. Moving on to Section 3.4, it will cover the methodology to land use change analysis and future land use modelling using the Land Change Modeler (LCM) modelling system in the TerrSet software by training the multilayer perceptron (MLP) neural network and using a stochastic modelling method, Markov chain. Accuracy assessment and validation process are carried out to determine the reliability of the classified historical LULC maps and the simulated future LULC maps.

3.2. Remote Sensing Data

The satellite imagery for this study was derived from the GEE platform. The GEE application is a web-based remote sensing platform commonly used for the provision and analysis of data. In this project, GEE was used to carry out spatial and temporal assembling of satellite imagery collections (Sidhu et al., 2018). Its advanced analyses and cloud computing capabilities are particularly well-suited to perform the time-series analysis in this study (Gorelick et al., 2017; Mutanga & Kumar, 2019). The satellite imagery dataset of the study area was sourced from both USGS Landsat 8 OLI (for 2015 and 2020) and Landsat 5 TM sensor (for 2010) (Table 1a).

Using GEE, a multi-temporal mosaic dataset was created based on specific annual date ranges within the study area extent. One of the essential criteria of the years chosen for each timestep was to provide fair coverage over key periods for the development of each sector (i.e. plantation, industrial, and bauxite mining sectors) in the study area. The choice of years was also influenced by the availability of the least cloudy scenes (with a maximum of 5% cloud cover) for better visualisation and classification process. The multitemporal mosaic was composed of the median pixel value from atmospherically corrected and cloud masked Landsat satellite surface reflectance data for the chosen 2010, 2015, and 2020 timesteps (Ang et al., 2021) (Table 1b).

Table 1. Landsat sensor and bands used, and image dates for classification of timeseries and the auxiliary reference data used as ground truth and to support the classification of specific land cover classes.

a) Landsat Satellite Data

Landsat	Bands	Wavelength range (µm)	Imagery Dates (Month/ Date)
LS 8 OLI	Coastal	0.43–0.45	2019 (10/01) - 2020 (04/10)
	Blue	0.45–0.51	2014 (01/01) - 2015 (12/31)
	Green	0.53–0.59	
	Red	0.64–0.67	
	NIR	0.85–0.88	
	SWIR1	1.57–1.65	
	SWIR2	2.11–2.29	
LS 5 TM	Green	0.5–0.6	2009 (01/01) - 2010 (12/30)
	Red	0.6–0.7	
	NIR 1	0.7–0.8	
	NIR	0.8–1.1	

b) Auxiliary Reference Data

Name	Sensor	Data type	Pixel size	Date	Source
Satellite Imagery	Landsat 4,5,7 & 8	Raster	30m	2020,2015, 2010	USGS
Basemap	Worldview 2	True Colour	0.5m	2020	ArcGIS
Basemap	Worldview 2	True Colour	0.5m	2020, 2015, 2010	Google Earth Pro
Global Forest Change	Landsat 4,5,7 & 8	Raster	100m	2020, 2015, 2010	Hansen et al., 2013
Annual Oil Palm Plantation Maps in Malaysia and Indonesia from 2001 to 2016	ALOS PALSAR, ALOS-2 PALSAR-2 & MODIS NDVI	Raster	100m	2020, 2015, 2010	Xu et al., 2020

3.3. Classification of the Historic LULC Timeseries

A multi-step land cover classification was carried out to characterize the LULC classes related to key existing and emerging land use development activities based on two major steps: (1) a supervised classification to identify the coarse-scale land covers and (2) manual digitization using auxiliary reference data to facilitate the identification of fine-scale LULC which are significant drivers of land cover change in this study (Figure 2). The first step involves the categorization of coarse-scale land covers that could be distinguished through supervised classification such as bareland, waterbody, built-up, mining sites, forest, and secondary vegetation. Carrying out the supervised classification with Landsat data had some limitations, as it could not precisely distinguish fine-scale classes that share similar spectral properties. For example, in distinguishing different vegetation types such as oil palm agricultural land with other disturbed vegetation, and also in differentiating different built-up types (i.e. residential area with industrial sites). Hence, a second step was required, where some of the broad-scale classes were divided into fine-scale classes through manual attribution with the aid of auxiliary data (Table 1b).

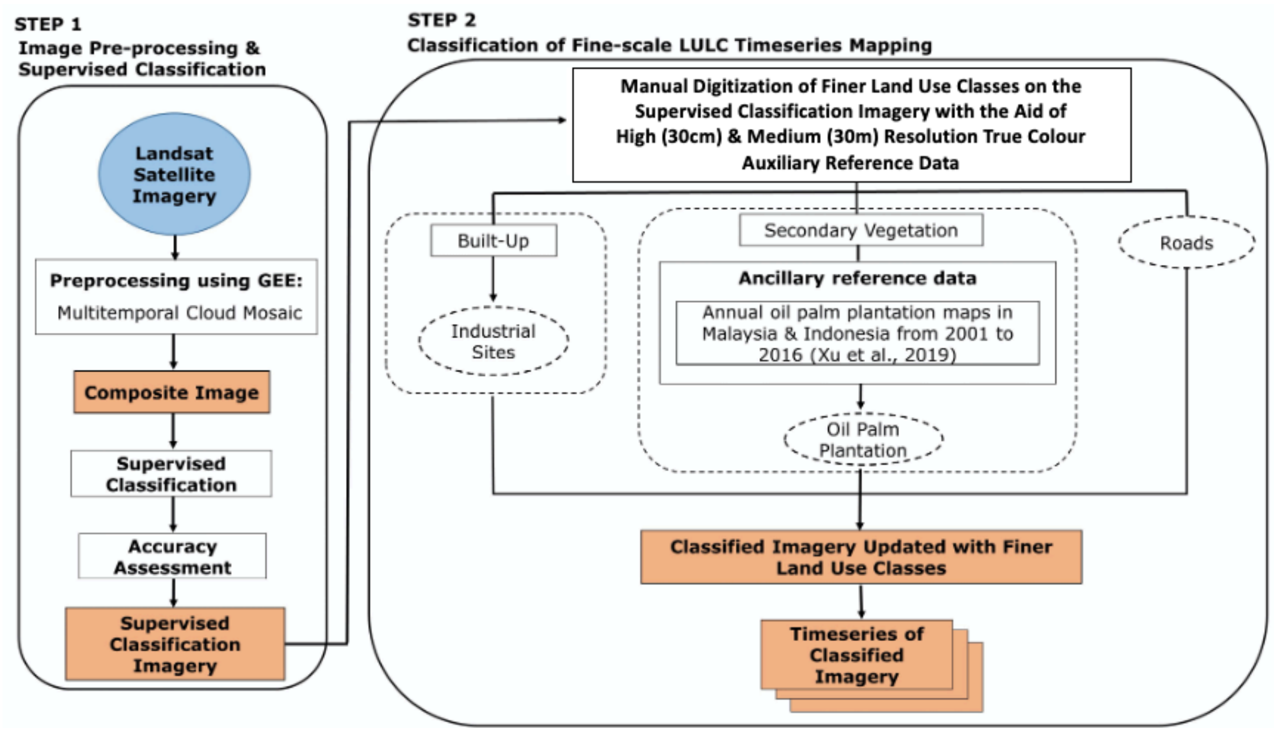

Figure 2. The land use classification methodology to produce the timeseries maps.

3.3.1. Step 1 Image Pre-processing, Supervised Classification, and Accuracy Assessment

The Random Forest classifier is a machine learning algorithm used to enhance the classification accuracy for land cover classification based on user-defined parameters, thus, this classifier was used to carry out the supervised classification process in GEE using the pre-processed multi-temporal mosaic imagery to distinguish the coarse-scale LULC classes that frame the dominant land covers in the study area (Table 2). These coarse-scale classes were identified as the land covers, which represent the direct observation of the physical material at the surface of the earth (Fisher & Unwin, 2005). This first step is essential to record and categorize the pixels with homogenous characteristics that depict the spectrally distinct land cover types. The auxiliary data from Table 1b were used as ground-truth for classifying these land covers; a commonly practiced validation method (Foody, 2002; Liu et al., 2002; Plourde & Congalton, 2003). The 0.5m to 30m resolution auxiliary reference data such as Google Earth Pro was predominantly used for ground truth, while the extent of primary forest cover was particularly identified using Global Forest Change 2000 – 2014 data by referring to Hansen et al. (2013). Additionally, the ArcGIS base map with a higher resolution at 0.5m was also used specifically for the classification of year 2020 map. Using these datasets a minimum of at least 130 training points for each of the six coarse-scale land cover classes were identified.

Table 2. Description of the coarse-scale land cover classes identified for the first classification step and fine land use classes that were manually digitized in the second classification step.

Coarse-scale land cover classes	Description	Fine-scale land use classes	Description
Bareland	Exposed-ground areas in a barren state with little to no vegetation cover, not including mining surfaces	-	
Mining Sites	Bauxite mining sites with largely exposed red dust ground	-	
Built-up	Residential/settlements, industrial, commercials, urban, and related infrastructure.	**Residential**	Residential/settlements and other public amenities (i.e. Schools, hospitals, shops, etc.)
		Industrial Sites	Industrial factories and large commercial infrastructures, including the industrial park and Kuantan port
		Roads	Highways and main roads from OpenStreetMap (OSM) data
Forest	Primary forest and Permanent Forest Reserves	-	
Other Vegetation	All vegetation covers, not including primary forest and permanent forest reserves	**Oil Palm Plantation**	Oil palm plantation of big and smallholders
		Disturbed Vegetation	Sparse natural vegetation, scrublands, emerging secondary vegetation, and small unidentified croplands
Waterbody	Sea, rivers, lakes, and reservoirs	-	

A key challenge for classifying historical data was to adequately classify historic land covers for training and validation. The quality of resolution for historical auxiliary data reduces as it goes further back in time and for the earlier years, Landsat data had to be used for ground truth as the high resolution auxiliary data were not always available, especially at years matching the mapping dates. Hence, to interpret these imageries, different band combinations were used to support the visual assessment (Appendix A.). For Landsat 8 satellite imagery particularly, the band combination of 4, 3, and 2 (true colour) and also 7, 6, and 4 (short-wave infrared) distinguished the different classes well. While, short-wave infrared composites using SWIR-2 (7), SWIR-1 (6), and red (4) display denser vegetation and sparse vegetation as darker and lighter shades of green respectively, the urban areas are displayed as blue and different types of soils with various shades of brown. As for Landsat 5 satellite imagery, the band combination 3, 5, and 7 and also 7, 5, and 3 worked the best. This specified band combination provides an image with a "natural-like" appearance, clearly distinguishing between vegetation, urban features, different top soils, and waterbody (Quinn, 2001).

The training points assigned for the coarse-scale classes were divided into a ratio of 70:30 where 70% of the training points were assigned for the Random Forest classification, while the remaining 30% were reserved for accuracy assessment as field data used in training Landsat imagery, shouldn't be combined in the method validation (Figure 3). There was a total of 546 training points and 234 accuracy assessment points. The training points assignment and supervised classification steps were refined iteratively until a satisfactory accuracy level was obtained. The output generated for accuracy assessment was interpreted as the overall accuracy, producer's accuracy, and user's accuracy. The produced classified imagery was then exported from GEE to ArcGIS for manual alteration and refinement with the aid of auxiliary reference data in the next step (Table 1b).

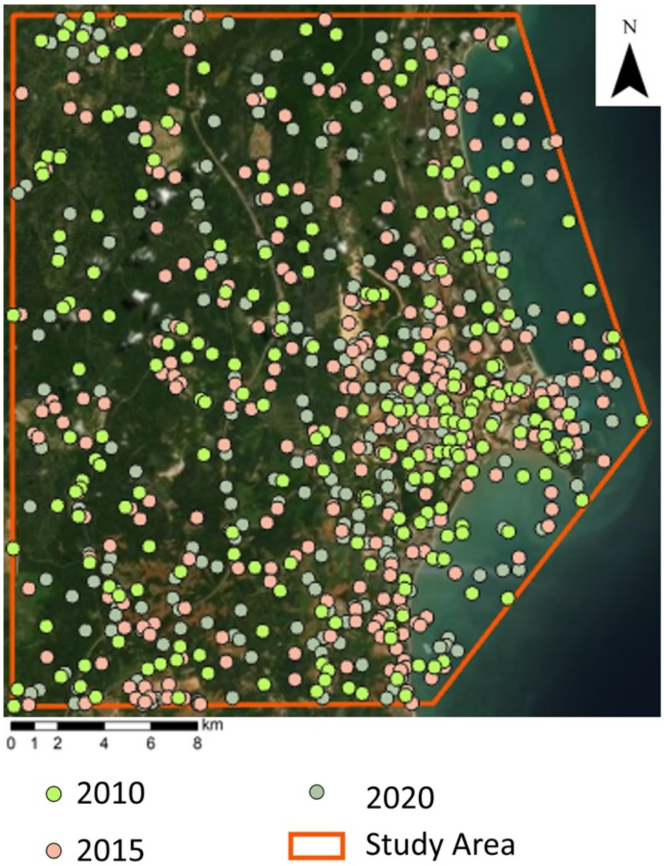

Figure 3. Allocated training points for supervised classification and validation process for each timestep.

3.3.2. Step 2 Classification of Fine-scale LULC Timeseries Mapping

The second step involves a post-classification process (Figure 2), where we manually refined and updated the produced LULC classification map with fine-scaled classes through manual digitization. At this stage, some of the coarse-scale classes were further classified into multiple fine-scale land use types as shown in Table 2. This post-classification process is necessary as certain fine-scale land uses share similar spectral properties and can hardly be distinguished through the supervised classification methods alone (i.e. residential with industrial sites and among different vegetation types). Hence, it is highly essential to have additional ancillary data and the aid of auxiliary reference data (Table 1b) in this step to identify the spectrally similar fine-scale land use classes. Throughout this post-classification process, a grid was overlaid on the maps to work as a guide and ensure that digitization efforts were distributed equally across and systematically over the large study area extent.

The post-supervised classification process for the vegetation covers and roads required additional steps. Manual interpretation using the high to medium resolution auxiliary reference data alone to classify the oil palm plantation cover was insufficient to differentiate between the different tree covers. Hence, additional ancillary reference data from the Annual oil palm plantation maps in Malaysia and Indonesia from 2001 to 2016 by Xu et al. (2020) was utilized as a reference to digitize the oil palm plantation cover within the study area. The dataset provided a good reference point despite its lower resolution at 100m, and with the additional reference using Google Earth Pro, it was effective in determining the extent of oil palm plantation cover. While to improve the accuracy of the roads, vectors from Open Street Map (OSM) were used to identify highways and main roads.

The updated land use classes layers from step 2 were mosaicked with the initial land cover classified imagery from step 1 to create the LULC classification maps. Starting with the 2020 LULC classification imagery, these two classification steps (Figure 2) were repeated, by consecutively taking into account the previously classified imagery to replicate the classification process for the remaining timesteps. This procedure was essential to ensure cohesion between the time series imagery (Ang et al., 2021). The final product was a timeseries of 3 classified images which was used in the next processing stage.

3.4. Analysing Land Use Changes and Future Land Use Projection using TerrSet

TerrSet (formerly known as IDRISI) is a geospatial software system widely used for monitoring and modelling the Earth system (*TerrSet Geospatial Monitoring and Modeling Software*, 2021). In this study, we used one of TerrSet's embedded modelling system called the Land Change Modeler (LCM), which is an integrated application for analysing the past land cover change, modelling potential future land use change, and evaluating planning interventions for maintaining ecological sustainability (Eastman, 2016). In this study, we used the LCM modelling system that utilizes a combination of MLP neural network and Markov chain analysis modelling techniques to model the land use change transition probabilities and produce future LULC change projections. To further assess the trend of land use change and predict future land use change activities of the study area, the following 3 steps were carried out in such order: (1) change analysis, (2) model validation, and (3) change prediction as shown in Figure 4.

3.4.1. Land Use Change Analysis

In step 1, the historical LULC maps were analysed as pairs (i.e. 2010 with 2015; 2015 with 2020) to obtain the transition area matrix to highlight the dominant land use transition between each class across the timeseries (Figure 4); by providing a quantitative assessment of land use change in terms of gains and losses or net change of each LULC class (Megahed et al., 2015). Based on this analysis, the model produced a series of transition potentials maps. Transition potential expresses the relative potential of a pixel to transition from one class to another in the form of a continuous value from 0-1. In this step basic quantitative information about the total areas of different classes changing between dates was described.

3.4.2. Modelling Land Use Projection for Validation and Future Scenario

In step 2 the quality of the future LULC modelling was assessed by comparing a predicted map against a reference map. In another word, simulating a 2020 LULC projection using the 2010 and 2015 land cover maps and comparing this to the classified 2020 LULC map (Figure 4). Firstly, the drivers of the transition potential produced from step 1 were estimated using a MLP neural network for a range of explanatory variables (Eastman, 2006), to describe the estimated probability of each pixel's persistence or conversion to another land cover (Dzieszko, 2014). These explanatory variables were selected based on their potential influence on the development activities such as industrial site expansion, mining, and urban sprawl (Figure 5 and Table 3).

The explanatory variables mainly consist of topographic and proximity factors. Topographic factors such as the digital elevation model (DEM), slope, and landform dataset acquired from Farr et al. (2007) and Theobald et al. (2015) for this study, are generally considered as one of the most significant factors affecting urban sprawl, influencing city size and spatial distribution (Hasan et al., 2020). The population density dataset from Gaughan et al. (2013), was also included as it drives urbanisation growth. These datasets were downloaded from the GEE platform using respective sources. Additional explanatory variables including soil and lithology datasets sourced from Law (1968) and, Hartmann and Moosdorf (2012) are important determinants of potential mining and agricultural land areas. Whereas, proximity factors are also drivers for urban sprawling due to the likelihood of having neighbourhood effects where non-built up areas are transformed to build up areas through the introduction of convenience and access towards resources and everyday needs (Hasan et al., 2020). By training the MLP neural network with these explanatory variables, the model produces the LULC transition probabilities included with information regarding the relative power of the explanatory variables through LCM's backward stepwise analysis by consecutively eliminating the weakest explanatory variable one by one. This analysis assesses the best combinations of explanatory variables that influence the modelling sensitivity in projecting the transition probability of each LULC class.

Having the transition probability as a foundation (Dzieszko, 2014), LCM uses the Markov chain analysis, to model the expected quantity of change using a competitive land allocation model to determine scenarios for the year 2020. At this stage, two versions of predictions are made by the model: (1) hard prediction and (2) soft prediction. The hard prediction map projects the land cover map with each class representing their most likely probability of land cover class in 2020 (Ayele et al., 2019; De Alba, 2011; Megahed et al., 2015). Whereas, the soft prediction projects a vulnerability map, determining the probability of the pixels changing to another land category (Adepoju et al., 2006; Ayele et al., 2019; De Alba, 2011).

In order to validate the accuracy of the model, differences between the simulated and the actual map of the year 2020 was assessed using the Kappa Index Agreement (KIA) approach, which is extensively used in LULC change prediction measure agreement (Kitada & Fukuyama, 2012; Parsa et al., 2016; Mishra & Rai, 2016; Subedi et al., 2013). This KIA validation assessment is done by measuring the accuracy and skill of the modelling system that accounts for all the transitions and persistence of the pixels during the MLP training process (Eastman & Toledano, 2018). The steps 1 and 2 discussed above were replicated in the final step 3 but with the 2015 and 2020 LULC maps instead without including the model validation processes to project the LULC map for the year 2030 (Figure 4).

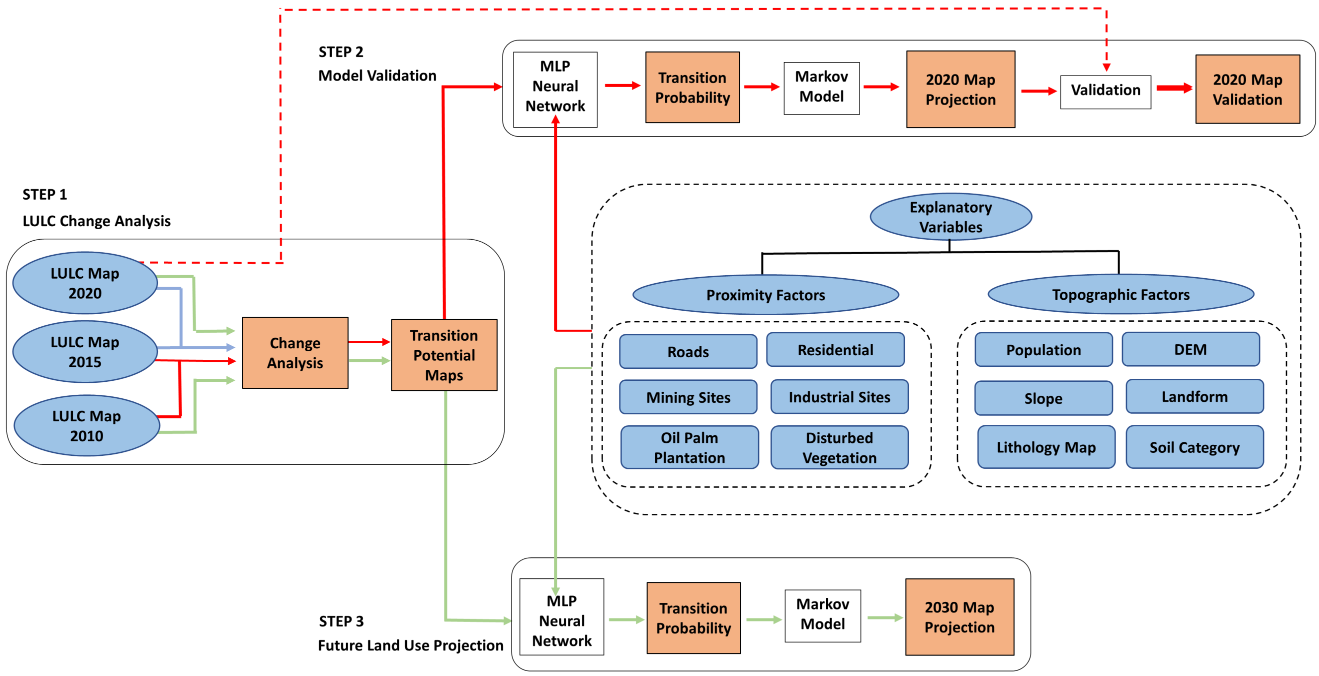

Figure 4. Land use change assessment and future land cover projection using the TerrSet software.

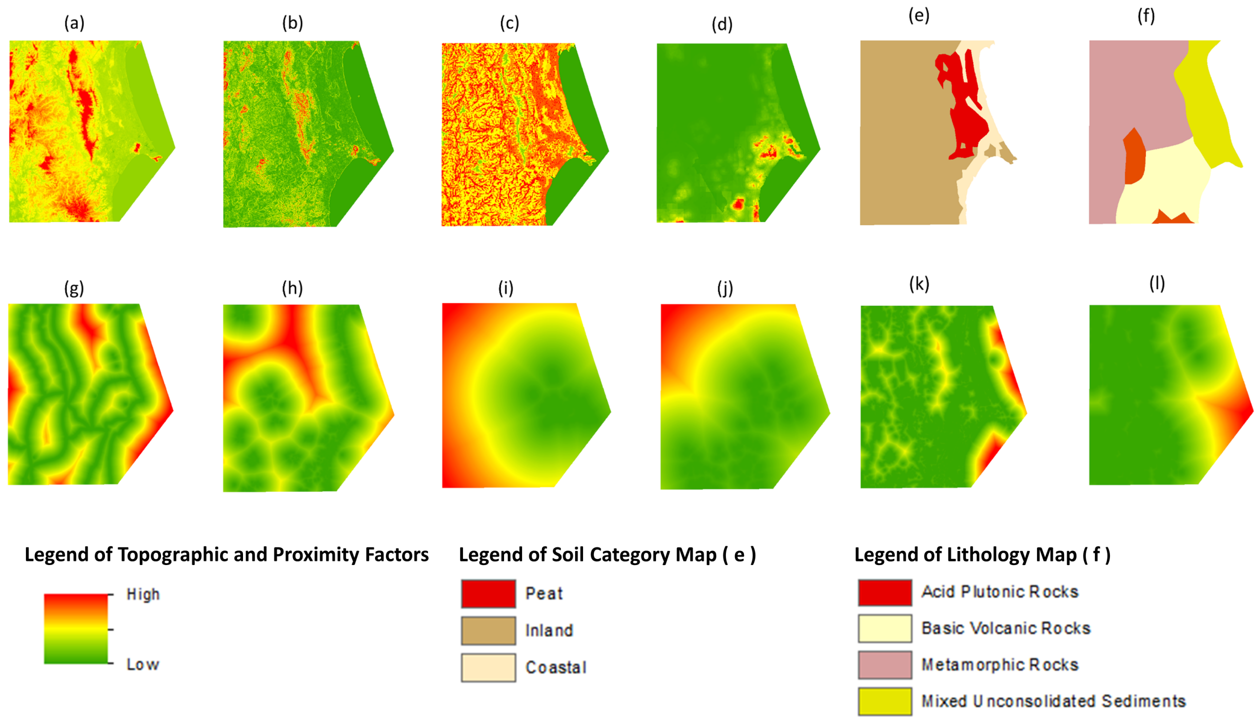

Figure 5. Explanatory variable maps layers that were inserted in the land change modeler (LCM). The type of map layers presented in this figure are described in Table 3.

Table 3. The explanatory variables inserted in the land change modeler (LCM).

a) Topographic Factors Data

Data Type	Dataset Description	Resolution	Source
(a) Digital Elevation Model (DEM)	A high resolution digital topographic database capturing the Digital Terrain Elevation Data (DTED) through the Shuttle Radar Topography Mission (SRTM)	30m	Farr et al., 2007
(b) Slope	Dataset of digital elevation data obtained through the Shuttle Radar Topography Mission (SRTM)	30m	Farr et al., 2007
(c) Landform	Dataset of landform classes created by combining Continuous Heat-Insolation Load Index and the multi-scale Topographic Position Index datasets	30m	Theobald et al., 2015
(d) Population	Census-based population counts matched to a range of geospatial covariate layers depicting the estimated population density in each grid cell	100m (resampled at 30m using the Nearest Neighbour method)	Gaughan et al., 2013
(e) Soil Category	A reconnaissance soil map of Peninsular Malaysia Series L40A gathered under the European Digital Archive of Soil Maps (EuDASM)	Resampled at 30m using the Nearest Neighbour method	Law, 1968
(f) Global Lithology Map (GLiM)	A high resolution global lithology map representing rock types of the Earth surface by assembling lithological information translated from existing regional geological maps and literature	Resampled at 30m using the Nearest Neighbour method	Hartmann & Moosdorf, 2012

b) Proximity Factors Data

Data Type	Data Description
(g) Distance to Roads	Dataset was produced by using the Euclidean Distance tool in ArcGIS
(h) Distance to Residential	
(i) Distance to Industrial Sites	
(j) Distance to Mining Sites	
(k) Distance to Disturbed Vegetation	
(l) Distance to Oil Palm Plantation	

Chapter 4: Results

4.1. Timeseries of Classification Map and Accuracy Assessment

The classified LULC maps for the years 2010, 2015, and 2020 are shown in Figure 6, while Figure 7 delineates the area (km^2) of the LULC classes for each timestep. The spatial distribution of the LULC in the study area changed continuously throughout the time series, with the largest LULC extents made up of oil palm plantation, forest cover, disturbed vegetation, and waterbody which includes the ocean and standing freshwater bodies. These classes are also the LULC that have experienced the most land use change activities over time (Figure 7). Towards the southeast region of the study area, the minor LULC classes (Figure 6) such as industrial sites, residential, and mining sites are clustered together within a highly developing and dynamic region. The constant expansion among these minor LULC classes has increased the proximity to each other. Other LULC such as waterbody and roads did not exhibit significant changes in their total area.

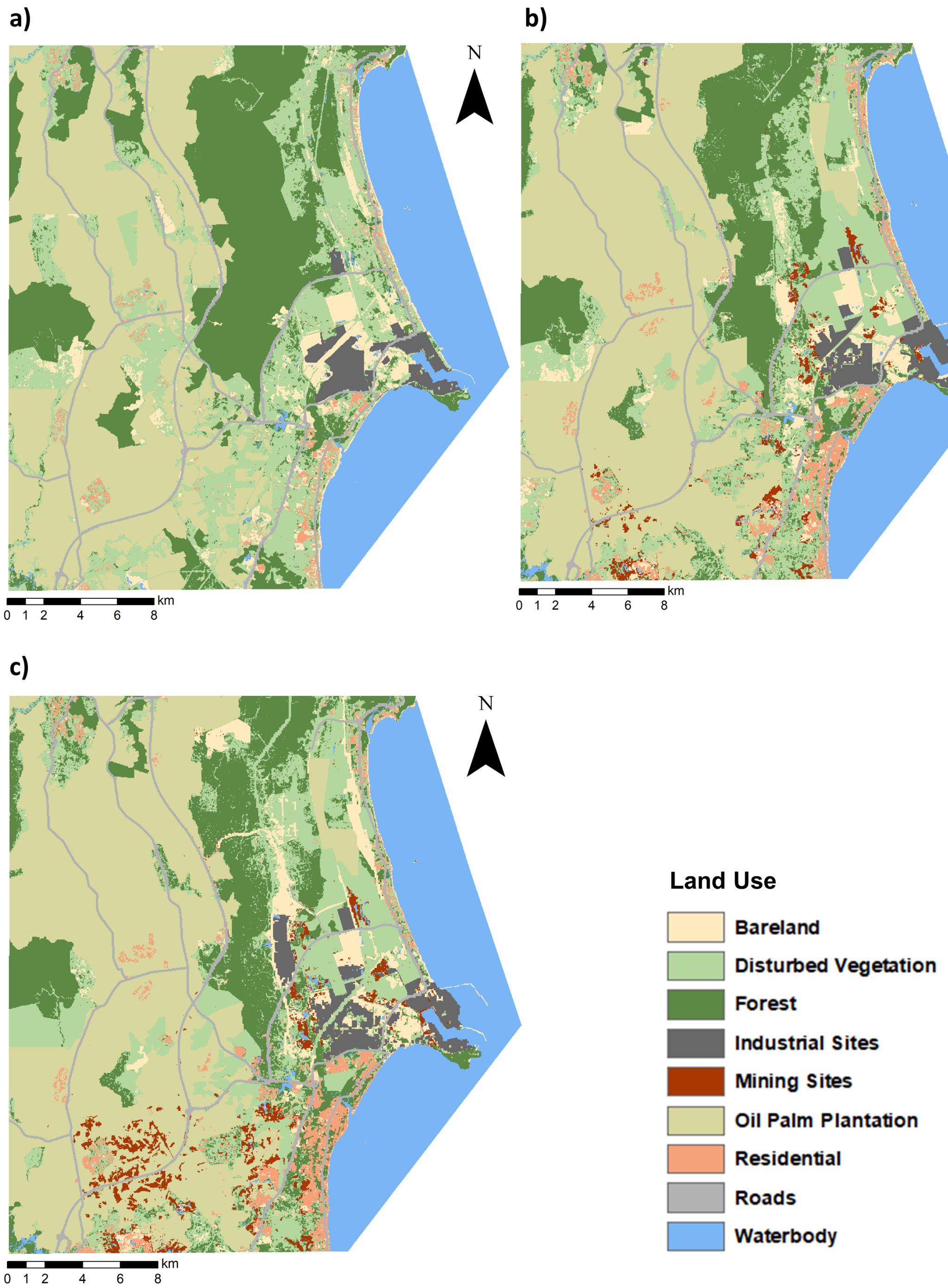

Figure 6. The classified remote sensing LULC maps for (a) 2010, (b) 2015, and (c) 2020 timesteps.

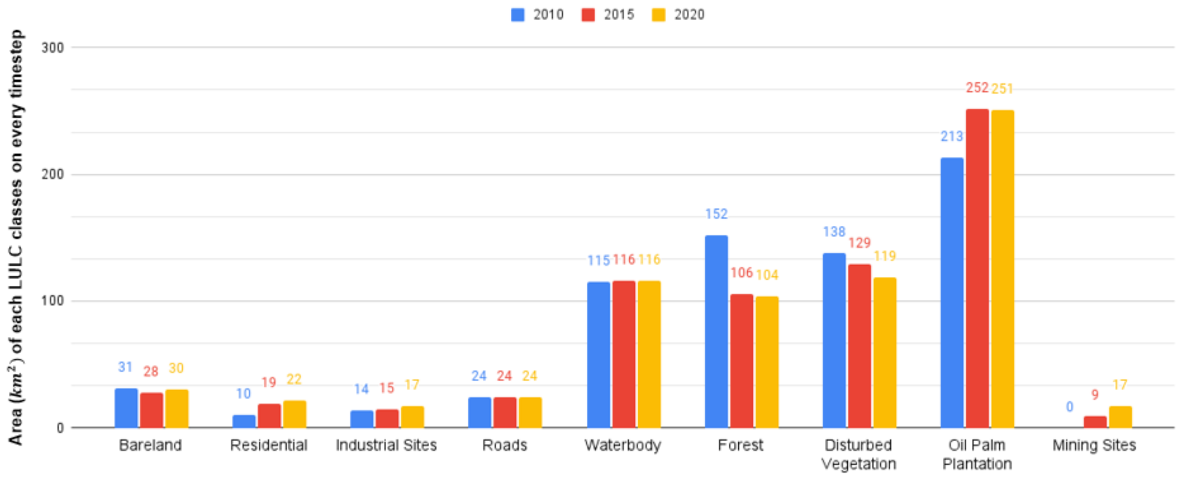

Figure 7. The graph indicates the area (km^2) of each LULC class for each remotely sensed mapped timestep.

The accuracy assessment for the timeseries takes into account the coarse scaled land cover classes, namely, built-up, bareland, waterbody, forest cover, and disturbed vegetation. The calculated accuracy score indicates a reasonable level of overall accuracy at an average of 83%. In some cases, the accuracies were as low as 60% for bareland in the year 2020, and 66% for built-up in the year 2010 (Table 4). This may be due to inaccurate classification and the comparatively coarse resolution of auxiliary data used as a reference. Due to Landsat's 30m-by-30m resolution, LULC classes smaller than the satellite's sensor's pixel will be difficult to be detected and distinguished. The complete accuracy assessment matrix is presented in Table 4 for further reference.

Table 4. A compilation of accuracy assessment results for all three LULC timesteps from the classification process using the Google Earth Engine (GEE) platform.

Year		**2010**	**2015**	**2020**
Kappa Coefficient		**87%**	**84%**	**79%**
Overall Accuracy		**92%**	**89%**	**83%**
Producer Accuracy	Build Up	66%	99%	88%
	Bareland	84%	79%	60%
	Mining Sites	-	73%	92%
	Waterbody	97%	93%	100%
	Primary Vegetation	99%	80%	78%
	Secondary Vegetation	93%	87%	86%
User Accuracy	Build Up	73%	94%	86%
	Bareland	77%	94%	78%
	Mining Sites	-	92%	92%
	Waterbody	98%	90%	97%
	Primary Vegetation	92%	90%	81%
	Secondary Vegetation	97%	78%	80%

4.2. Land Use Land Cover Change Analysis

4.2.1. Land Use Change Analysis Involving the Gain and Losses of LULC

The trend of land use changes from 2010 to 2020 is shown in Figure 8 and Table 5. From 2010 to 2015, the forest cover had the largest net reduction in area by 46.00 km^2. The disturbed vegetation and bareland classes also experienced a decrease, but at a relatively lower rate. In contrast, oil palm plantations had an exponential growth with a net increase of 39.13 km^2, occupying a large extent of the study area, especially towards the west region, where the region is less developed. Other minor LULC classes such as the residential and mining sites also expanded with a net increase of 9.08 km^2 and 8.91 km^2 respectively, followed by the industry which recorded only a gradual increase. The expansion of these minor LULC classes was mainly concentrated near the coastal region where it is more populated and focused on infrastructure development.

The overall land use change in the following years of 2015 to 2020 exhibited a moderate trend in change. The net change in disturbed vegetation was recorded as the highest among the classes for this change period, with a net decline of about 9.44 km^2. The decreasing trend in land use area is followed by the forest cover and oil palm plantation but at a lower rate. Mining sites on the other hand continued to expand further by 8.00 km^2, followed by a gradual net increase in residential, industrial site, and bareland classes. Waterbody and roads LULC classes had no significant changes throughout the three timesteps. This is because the waterbody largely represented the ocean, coastline, and other standing freshwater bodies which did not change. Whereas for the roads, no major additional highways and main roads development took place.

In summary, the dominant LULC changes for the whole study period between 2010 to 2020 include a reduction in forest cover and disturbed vegetation, and increases in oil palm plantation, mining, and residential areas. Hence, the region's natural land cover is largely altered by the increase in land use development with different development types growing in proximity to each other (Figure 6). Such a trend of different land uses clustering together increases the likelihood of causing land use conflicts due to various socioeconomic incompatibility and potential environmental degradation, i.e. residential areas near industry.

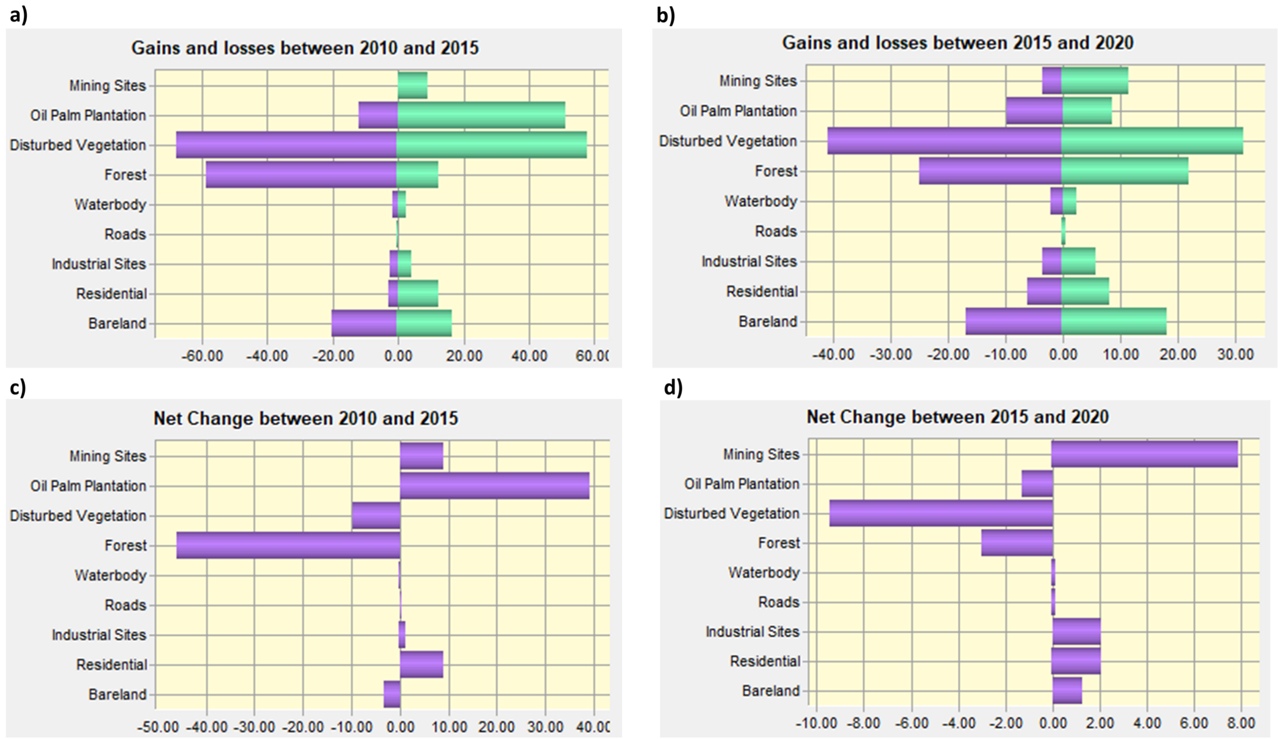

Figure 8. Gain and losses of LULC (on the upper row) depict the expansion and reduction rate of land use area while the net changes of LULC (on the lower row) depict the dominant trend that trades off from the interchange between the gain and losses of each land use classes, all in km^2. (a) and (c) represent years 2010-2015 and figures (b) and (d) represent years 2015-2020.

Table 5. The total area of net change, and gains and losses of each LULC class in km^2. The shaded boxes indicate a declining trend in the net changes.

	2010-2015			2015-2020		
	Gain	**Loss**	**Net Change**	**Gain**	**Loss**	**Net Change**
Bareland	16.98	-20.21	-3.23	18.25	-16.99	1.26
Residential	12.22	-3.14	9.08	8.37	-6.25	2.12
Industrial Sites	3.99	-2.44	1.55	5.82	-3.74	2.08
Roads	0.07	-	0.07	0.20	-	0.20
Waterbody	2.18	-1.89	0.29	2.35	-2.18	0.17
Forest	12.90	-58.90	-46	21.97	-24.98	-3.01
Disturbed Vegetation	58.07	-67.75	-9.68	31.53	-40.97	-9.44
Oil Palm Plantation	51.06	-11.93	39.13	8.47	-9.76	-1.29
Mining Sites	8.91	-	8.91	11.65	-3.73	7.92

4.2.2. LULC Transition Assessment

The transitions among different LULC classes for this study are delineated in Figure 9, presenting the different LULC being converted to one another over time. Based on Figure 9, forest cover, disturbed vegetation, and bareland experienced the highest land use conversion from the year 2010 to 2015. About 40.60 km^2 of forest cover was degraded and converted to disturbed vegetation due to forest clearing and encroachment. Such high trend of forest cover loss can be observed at the largest patch of forest in the study area (Figure 6). Subsequently, a smaller but notable amount of forest was converted to oil palm plantation (9.10 km^2) and bareland (6.04 km^2). Disturbed vegetation transitioned into a range of land use classes including 37.67 km^2 of oil palm plantations and it also significantly contributed to the increase in bareland by 7.51 km^2, residential by 5.87 km^2, and mining sites by 3.63 km^2. Bareland also contributed to the increase of disturbed vegetation, residential and oil palm plantation areas, but at a relatively lower rate.

The land use change activities in 2015 to 2020 were more dynamic with increased area of land use transition for each class. Among all the LULC classes, disturbed vegetation continued to be the land use with the greatest amount of change, contributing to an increase in 19.76 km^2 of forest cover, indicating secondary forest regrowth, 9.23 km^2 bareland, 4.30 km^2 of oil palm plantation, and a range of other LULC classes such as residential and mining sites, but at a minor scale. Whereas, the extent of forest cover conversion was lower compared to the year 2010 to 2015, only transitioning 17.44 km^2 of forest cover to disturbed vegetation and 4.90 km^2 to bareland. Bareland had noticeably experienced a large amount of change to disturbed vegetation by 6.70 km^2, and industrial sites and residentials by 3.37 km^2 and 3.10 km^2 respectively. Meanwhile, oil palm plantation was converted to mining sites by 6.41 km^2.

Overall, the greatest amount of land use transition was from or to forest, disturbed vegetation, and bareland (Figure 9). The conversion of forest and disturbed vegetation to other land uses shows a decline in the natural green spaces and an increase in other developing land use classes. Although the land use conversion for the rest of the LULC classes were rather minor, they generally represented an increasing trend to an increase in land use area, except for oil palm plantation which exhibited a large decrease in the year 2015 to 2020 (Figure 9b). Finally, the very small changes in land use for waterbody and roads are mainly due to small differences associated with misclassification.

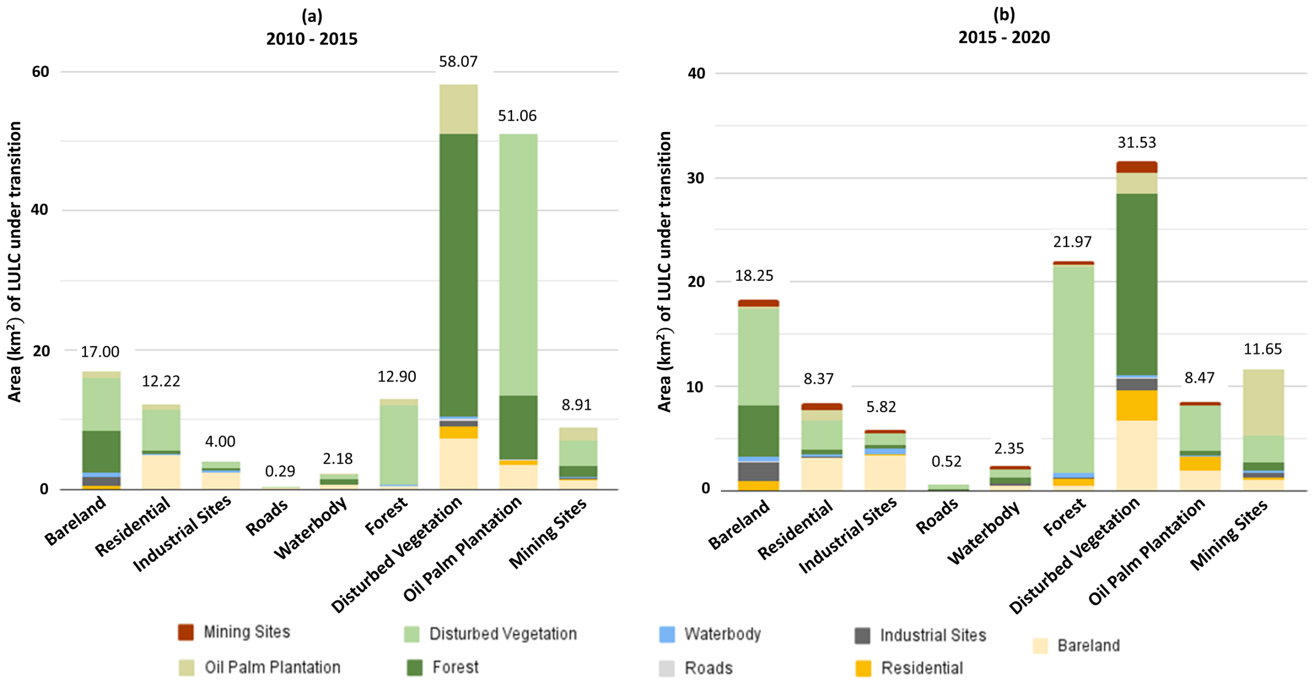

Figure 9. Transition matrix of LULC area (km^2) for (a) 2010 - 2015 and (b) 2015 - 2020. The cumulative bar chart shows the various LULC in the former year (ie: 2010/2015) being converted into the respective LULC on the x-axis in the latter year (ie: 2015/2020). The value on top of each bar refers to the overall area (km^2) involved in the LULC conversion.

4.3. Future LULC Change Projection

4.3.1. Transition Probability Modelling and Model Sensitivity Analysis

The modelling sensitivity can be understood through the backward stepwise analysis that eliminates the weakest explanatory variables one by one to test the influence of the explanatory variables on the skill measure and accuracy of the modelling system to predict class transitions and persistence. The result in Table 6 shows that the model with all 12 explanatory variables is the best model combination that results in 58.19% of accuracy rate and 0.5471 of skill measure. Hence, all 12 layers were shown to significantly contribute to train the MLP neural network in producing the transition probability maps.

Table 6. The result of MLP with backward stepwise constant forcing together with the description for each explanatory variable.

Explanatory Variables	Map Description
var.[1]	Landform
var.[2]	DEM
var.[3]	Slope
var.[4]	Study Area Population
var.[5]	Soil Category
var.[6]	Lithology
var.[7]	Distance to Disturbed Vegetation
var.[8]	Distance to Roads
var.[9]	Distance to Residential
var.[10]	Distance to Oil Palm Plantation
var.[11]	Distance to Mining Sites
var.[12]	Distance to Industrial Sites

Model	Variables included	Accuracy (%)	Skill measure
With all variables	All variables	58.19	0.5471
Step 1: var.[1] constant	[2,3,4,5,6,7,8,9,10,11,12]	58.07	0.5457
Step 2: var.[1,3] constant	[2,4,5,6,7,8,9,10,11,12]	57.86	0.5435
Step 3: var.[1,3,4] constant	[2,5,6,7,8,9,10,11,12]	57.20	0.5363
Step 4: var.[1,3,4,5] constant	[2,6,7,8,9,10,11,12]	55.39	0.5167
Step 5: var.[1,3,4,5,2] constant	[6,7,8,9,10,11,12]	51.32	0.4726
Step 6: var.[1,3,4,5,2,8] constant	[6,7,9,10,11,12]	46.94	0.4252
Step 7: var.[1,3,4,5,2,8,6] constant	[7,9,10,11,12]	44.61	0.4000
Step 8: var.[1,3,4,5,2,8,6,12] constant	[7,9,10,11]	40.67	0.3573
Step 9: var.[1,3,4,5,2,8,6,12,9] constant	[7,10,11]	33.50	0.2796
Step 10: var.[1,3,4,5,2,8,6,12,9,11] constant	[7,10]	26.97	0.2088
Step 11: var.[1,3,4,5,2,8,6,12,9,11,7] constant	[10]	15.91	0.0890

4.3.2. Model Validation

Model validation was conducted to determine the quality of the 2030 simulated map by first evaluating the difference between the simulated and actual LULC map in the year 2020. The visual comparison between the classified and simulated LULC maps for the year 2020 is shown in Figure 10 and the area statistics of both the maps are presented in Figure 11. Based on Figure 11, most of the LULC classes share a similar trend in land use area statistically, except for the forest cover and oil palm plantation. The simulated model overestimated the forest cover loss and oil palm plantation expansion in contrast to the classified 2020 LULC map. The incoherency between the simulated and classified LULC maps is assumed to be due to the abrupt changes experienced by these two classes in terms of their land use change activity in the years 2010 to 2015 compared to 2015 to 2020. Forest and oil palm plantation classes were among the ones that had the most dynamic land use change activity in 2010 to 2015, followed by a lower rate of land use change in the later years of 2015 to 2020 (Figure 7). The simulated map also failed to estimate the extent of mining sites as per the 2020 classified LULC map and projected more mining sites to grow near the industrial region (Figure 10), although statistically the differences in land use area between the simulated and classified LULC maps was low (Figure 11).

To further verify the simulated map, a more detailed quantitative analysis is accomplished using the Kappa index assessment (KIA). The KIA for both actual and simulated map of the year 2020 in this study resulted in the following; K_{no}= 0.7886, $K_{location}$= 0.802, $K_{standard}$= 0.7658. Here, K_{no} indicates the overall agreement of the simulation run, whereas, $K_{location}$ indicates the extent to which the two maps agree in terms of the location of each category, and $K_{standard}$ indicates the proportion of simulation assigned correctly *versus* the proportion that is correct by chance. Hence, with the K values scoring an average of 0.7896, the model is considered to have a reasonable level of agreement between the actual and simulated maps. Despite overestimating land use changes and failure to estimate the extent of future land use changes spatially as in Figure 10, the K value of the model suggests that the simulation was able to capture the expected magnitude of land use change activities.

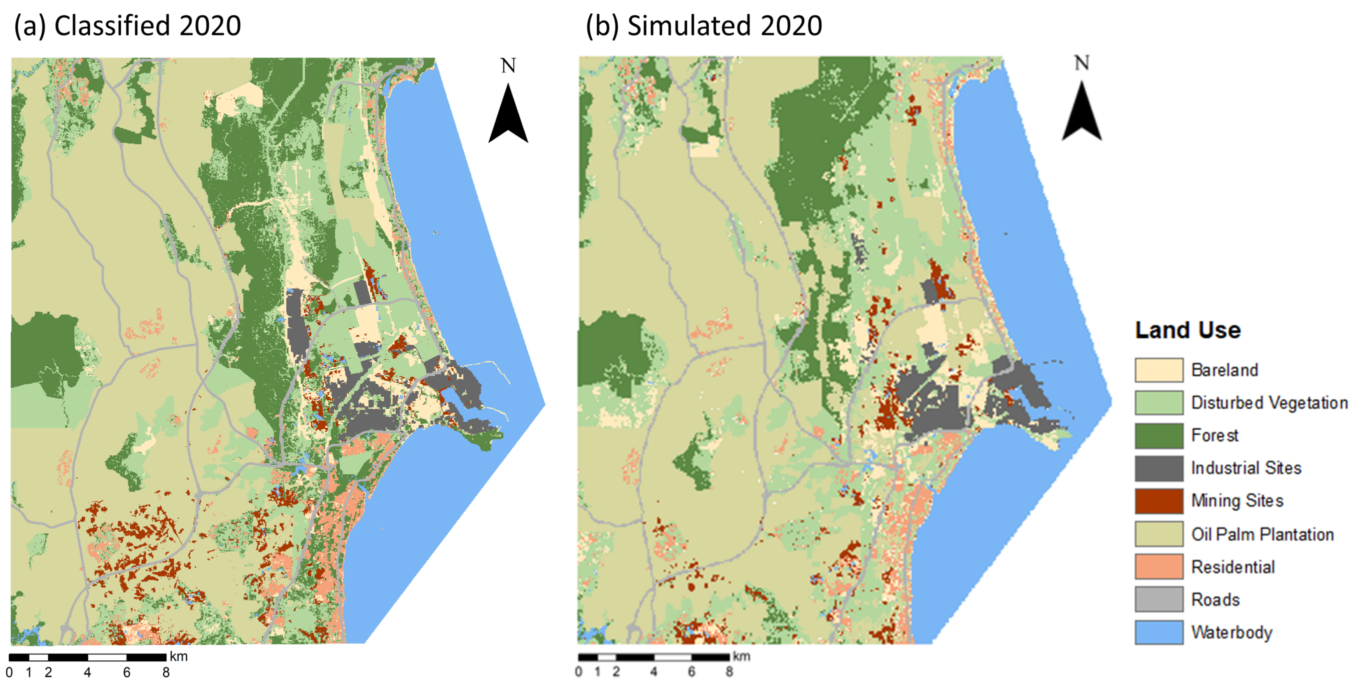

Figure 10. Classified (a) and simulated (b) LULC map for the year 2020.

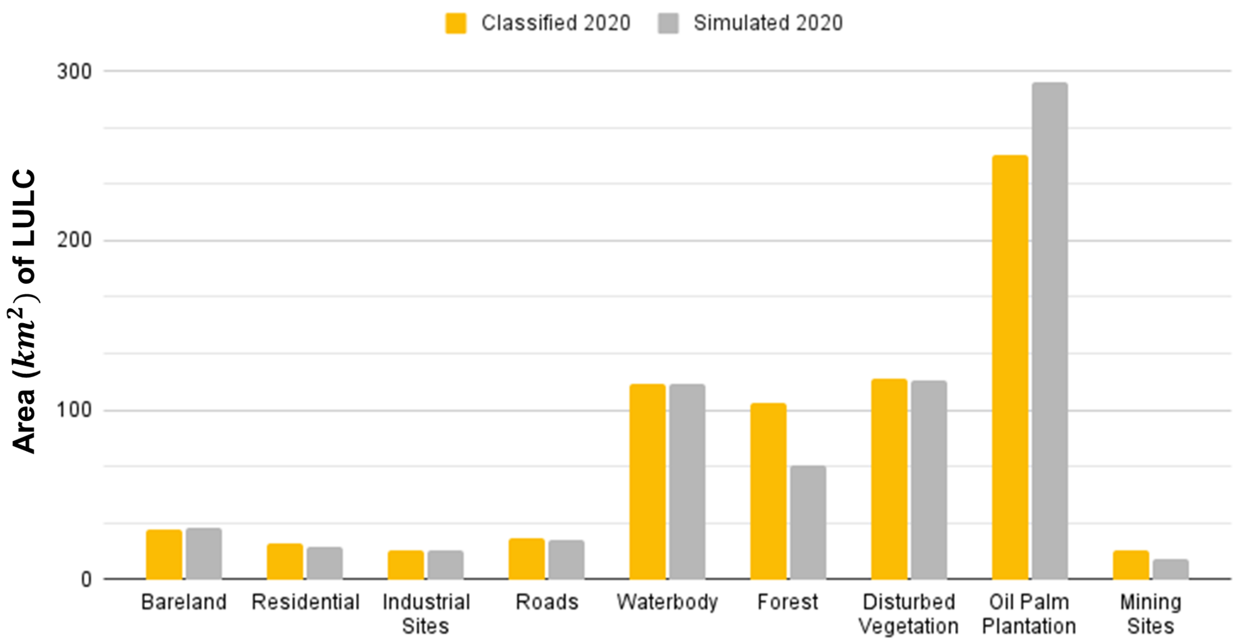

Figure 11. Area (km^2) of the actual and simulated LULC maps for 2020.

4.3.3. Projection of Future Land Use Map

The projected future LULC map for the year 2030 is shown in Figure 12 in two forms; hard and soft projection. Here, the hard projection illustrates the potential land use scenario based on the most likely future land use change activities, while the soft projection shows a continuous map of vulnerability of an area to change based on the degree to which a pixel belongs to each of the land use class (Eastman, 2016). Additionally, the statistical record of the projected 2030 LULC map in comparison to the earlier timestep years (2010, 2015, and 2020) is shown in Figure 13. Overall, the model predicts an increase among all the LULC classes except for the forest cover and disturbed vegetation. These two classes were simulated to decrease following a similar trend to the earlier years, however, at a slower rate. Some of the distinct changes found in the year 2030 compared to the observed trends in previous years are the large increase in mining sites and oil palm plantation, by 30.41 km^2 and 283.61 km^2 respectively. These two classes are projected to expand further towards the east of the study area and further encroach the residential area and industrial sites (Figure 12). As the 2030 projections in Figure 12 indicate, the southeast region of the study area is more vulnerable to land use change activities; mainly involving the rapid expansion of mining sites, oil palm plantation, and reduction in forest cover.

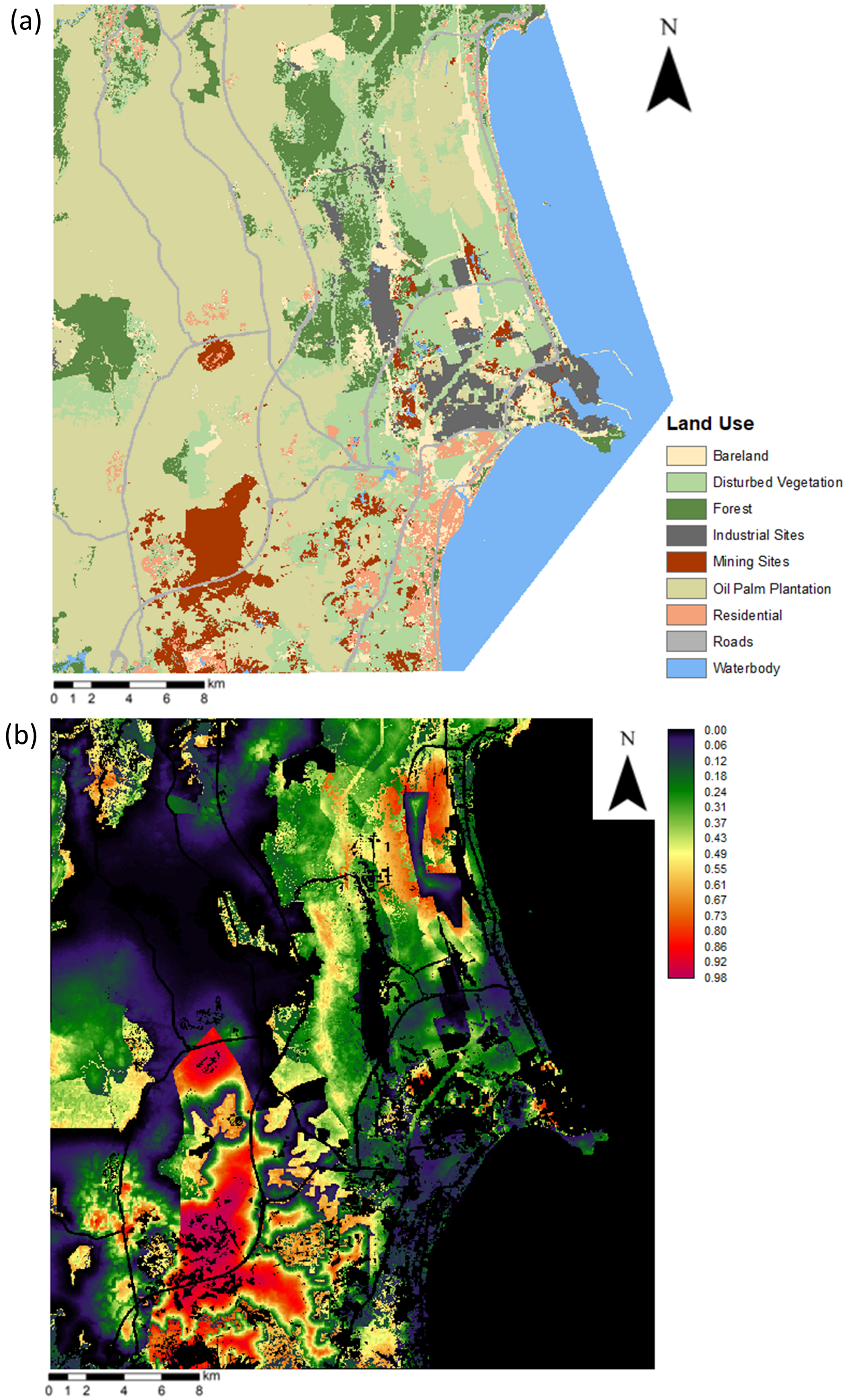

Figure 12. Simulated LULC map in 2030 as (a) hard projection and (b) soft projection. The hard projection in (a) shows the projected 2030 land use scenario while in (b) it illustrates the vulnerability of an area to land use change; the range provided on the upper right corner of (b) indicates the probability of the pixels changing to another land use category where 0 to 1 represent a lower to higher rate of pixel changing probability respectively.

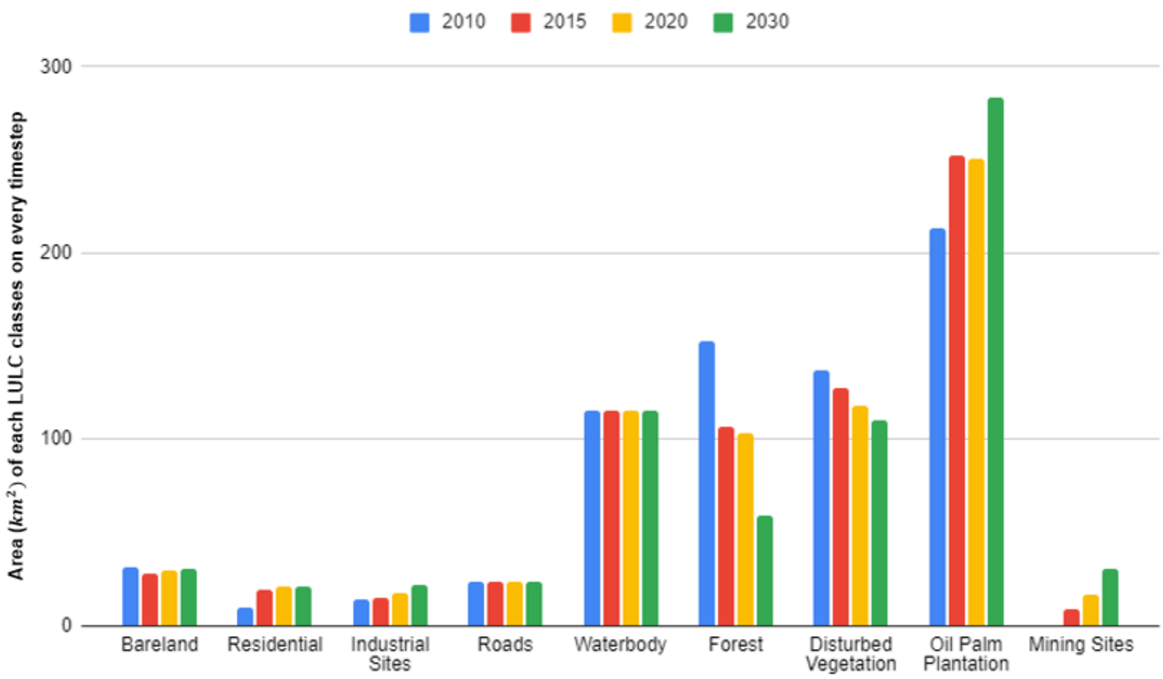

Figure 13. Area (km^2) of each LULC class for every timestep derived with remote sensing (2010, 2015, and 2020) and the land use simulation (2030).

Chapter 5: Discussion

5.1. Historic and Future Trends in LULC Change

Our analysis showed great spatial and temporal changes throughout the timeseries among the LULC classes especially for the forest cover, oil palm plantation, and disturbed vegetation as these three classes were observed to constantly experience trade-offs between them. As shown in Figure 6 and Figure 7, oil palm plantation has had the largest land use area increase over the years through conversions of other LULC classes; mainly from disturbed vegetation, forest cover, and bareland (Figure 8). Oil palm plantations are biophysically highly suitable to be established in coastal and lowland areas. Hence, with the nearby palm oil processing and exporting facilities at Kuantan Port, it makes Kuantan a well-suited location for the mass plantation (Shevade & Loboda, 2019). The large extent of oil palm plantation found in the study area also resonates with the fact that oil palm is one of the most important agricultural crops in Malaysia and the conversion of natural forests to oil palm is one of the key drivers of biodiversity loss (Shevade & Loboda, 2019; Wilcove & Koh, 2010).

The next largest land cover in the region is forest and disturbed vegetation that occupied 35% of the study area throughout the year 2010 till 2020. Both these classes experienced a constant reduction and were cleared for oil palm plantation, bareland, and other LULC classes; disturbed vegetation and bareland represent as transitional land cover classes to other land use developments. Major deforestation was observed at the existing largest patch of forest in Figure 6Figure 12 which contains protected areas such as the Balok and Beserah forest reserves. The consistent and significantly diminishing vegetation cover in the study area will likely persist into the future based on the timeseries analysis and future projection. This is concerning as the land use changes are causing forest fragmentation and reduction in natural green spaces. Forest fragmentations will be a threat to the natural biodiversity and existing wildlife as it leads to a reduction in viable habitat areas and increased human disturbance due to edge effects from the surrounding land use development activities that gradually expand surrounding the remnant forest cover (Figure 6) (Sodhi et al., 2010; Tee et al., 2018).

A dynamic trend of different LULC classes' expansion was found mainly in the southeast of the study area (Figure 6Figure 12) involving residential, mining, and industrial sites growing in closer proximity to each other. The increasing trend among these land use classes indicates the growing urbanisation and industrialisation activities of the Kuantan region, which if not sustainably managed, may negatively affect the urban ecosystem services and potentially exacerbate pollution while inducing land use conflicts among the locals (Lechner et al., 2020; Lourdes et al., 2021).

Figure 12 portrays how the historical land use changes likely lead to the future LULC pattern of the region in 2030. Based on the statistical analysis of the year 2030 projection in Figure 13, oil palm plantation is projected to dominate about 41% or equivalent to 283.61 km^2 of the study area. While other leading expanding LULC classes are projected to keep growing into closer proximity to each other, i.e. the mining sites with industrial sites and residential. The simulated locations for the expansion of mining sites overlapped with the lithology map in Figure 5 and project that mining sites will be found from Bukit Goh to the coastal area due to the underlying basic volcanic rocks which are dominated by basalt (Hartmann & Moosdorf, 2012), the parent rock to the mineral composition of bauxite resources found in Kuantan (Najwa et al., 2019). Residential areas are also projected to increase to keep up with the population growth as the area develops (*ECER Master Plan 2.0*, 2019). Whereas, the projection for the industrial sites shows a minimal increase due to the slower rate of expansion recorded in the historic LULC maps. Overall, the projection suggests that the expanding development activities may engulf a large part of the forest cover and other natural green areas. Finally, land use conflicts are more likely to occur in areas of LULC with very different development profiles (i.e. mining versus residential).

5.2. Extent of ECER Development

The study region of this research falls in one of the important Key Development Areas (KDAs) or Nodes called the ECER Special Economic Zone (ECER-SEZ). The Malaysian government established the nodes to accelerate the region's development through the rural-urban integration strategy by focusing on the region's economic strength and rich resources (*ECER Master Plan 2.0*, 2019). This is in line with the strategies adopted by the Malaysian government to correct the uneven regional development through "in-situ" rural development by the dispersal of industrialization and commercialization to the less developed region and the creation of townships such as the Federal Land Development Authority (FELDA) which supports large-scale agriculture development (Alden & Awang, 1985; Ngah, 2011a). Additionally, the ECRL track will also be introduced to run along the ECER region connecting to the west coast of Peninsular Malaysia and other main trade routes (Tat, Chin & Chew, 2018). These complexities can be observed in the land change modelling in terms of increased urbanisation, conversion of natural areas to oil palm, and even more intensive land uses like mining and industrialisation. In a way, the Kuantan region represents a microcosm of some of the main land use challenges occurring in Malaysia and other developing regions in Southeast Asia.

5.2.1. Projection of the 2030 LULC Map in Comparison to the Envisioned Future of Kuantan as the ECER-SEZ

The agricultural sector is recognised as a major economic sector in the ECER region that has and will contribute to a significant proportion of GDP growth through current productivity and the development of new areas (ECERDC, 2010). This can be seen in the mapping of oil palm plantations, as the largest and highest expanding land use in the study area region (Figure 13). However, the region's development vision has shifted its focus more towards the industrialization and commercialization sectors, mainly involving the industrial and mining activities, which have been predicted to accelerate rapidly in the future (*ECER Master Plan 2.0*, 2019; Lines, 2015). Although these classes only exhibit a gradual expansion in the projected 2030 LULC map comparing to the other larger LULC classes, they are envisioned to bring in more dynamic and intense development in the neighbouring areas.

The projected LULC map for the year 2030 in Figure 12 accounted for the land use change patterns that occurred for the past decade of 2010 to 2020. Hence, on this basis, the validation process for the projection resulted in a reasonable level of modelling predictability. However, the simulated 2030 LULC map will likely differ from what is expected to be seen in the actual year 2030, especially for the projected three main dynamically changing economic activities framed in the study area: oil palm plantation, industrial, and mining sites. This is due to external factors and policies that were not recorded in the past land use changes trend and future land use planning that may take place but were not accounted for in our modelling. For example, oil palm plantation expansion is likely to reduce in Kuantan following the government's planning to cap the extent of Malaysian's palm oil estate at 6 million hectares (Butler, 2019). Hence, although the oil palm plantation's expansion rate in the study area region from the year 2015 to 2020 had a decreasing trend, the simulated projection for year 2030 rather showed an overestimation in the expansion rate (Figure 13).

In contrast to older less profitable and more traditional industries which provide a small number of jobs (i.e. small-scaled business and agricultural activities, and fisheries sector), mining and industrial sites can be expected to expand exponentially with the future development project plans and promising job opportunities (*ECER Master Plan 2.0*, 2019), although the simulated 2030 map did not highlight a major increase for the industrial sites (Figure 13). According to the Hong Kong Trade Development Council (2017) and the local district plan draft of the Kuantan Municipal Council (2015), the industrial park in Gebeng will expand to over 3,500 acres to establish MCKIP 2 and MCKIP 3, making way for more high-end technology development, petrochemical and chemical manufacturing companies, and multi-purpose development including light industry, commercial property, residential areas, and tourism parks. Such high-impact projects will spur more future industrial activities to take place, leading to the expansion of Kuantan Port into a deepwater port - the New Deep Water Terminal (NDWT) project. The NDWT project will fulfill the demand for doubling the capacity of the port by 52 million freight weight tonnes (FWT) and to allow more industries and enable larger ships to berth (Foon, 2017).

As for the mining industry in Kuantan, the industrial experts suggest that mining is expected to thrive as new sources of bauxite are required to fulfill China's and other industries' growing demand for bauxite resources and aluminum production (Lines, 2015; Tan, 2016). Kuantan is rich in gibbsite minerals (required for bauxite) which are mainly located near Batu Goh towards the coast of Kuantan where basalt, the parent rock of bauxite is found (Najwa et al., 2019; Ismail et al., 2018; Jusopp, 2016). The rest of this region can be expected to be further exploited with the increased demand and interest in this lucrative business, likely causing oil palm and fruit orchard owners to sell off their lands to mining companies (Alagesh, 2019).

Kuantan is also home to the game-changing ECRL project which will run along the ECER region connecting the west coast of Peninsular Malaysia and other main trade routes (Huam et al., 2018). The planned 620 km ECRL route is expected to catalyze the local and national economy by improving the logistical issues between the Klang and Kuantan ports, reducing the shipping time, and enhancing connectivity between Malaysia and China (Lopez, 2016). The ECRL track within the study area will contain 3 stations planned to be situated at Cherating; a major tourism spot, and 2 more stations near the Kuantan Port which is projected to primarily benefit mass freight weight transportation (i.e. mineral and agricultural commodities such as bauxite and palm oil products, and also manufacturing and chemical liquid goods, and marine produce), as it is expected to accommodate 70% of cargo and 30% of passengers (Malaysia Rail Link, 2019; Zainuddin, 2019). Additionally, the proposed route may also boost the tourism sector by significantly reducing the traveling time within the Peninsular (Loke, 2019). While the footprint of the train route is relatively small as they promised to significantly reduce traffic congestion around the busy ports and in reducing carbon emissions (Malaysia Rail Link, 2019), the future track is likely to be a key driver of land use change in the surrounding area by accelerating the industrial activities and bauxite excavation. The ECRL track will also have potential negative impacts on the natural environment and wildlife and lead to habitat loss and fragmentation in some of the Peninsular's central forests (Mayberry, 2017).

5.3. Arising Land Use Conflicts and Spill-over Effect from the Industrial Sites and Bauxite Mining Activities

The study area is an evolving dynamic arena with these various development occurring in parallel. However, the expansion of these developing regions may lead to the rise in land use conflicts. Land use conflicts occur when there is an incompatible interest among the land use stakeholders as a result of land use development that has conflicting negative effects on the surrounding environment and society (Von Der Dunk et al., 2011). Land use conflicts in coastal regions like Kuantan are likely to be greater as the implementation of mega infrastructural projects will compete with coast-dependent economic activities like fisheries, tourism, and residential development as well as environmental and agricultural interests (Susman et al., 2021). The current coexistence of industrial and mining sites with the other LULC has already spurred land use conflicts and disputes among the locals due to the growing proximity and extensive negative spill-over impacts from the developing sites. Degraded environments and pollution from existing industrial and mining activities deteriorate environmental conditions and impose negative effects on the locals especially affecting the livelihood of fishermen and the surrounding tourism sectors (Aw & Awale, 2015; Sobahan et al., 2013). Such contrasting land uses are key challenges for land-use planning and decision making globally (Everingham et al., 2018; Hilson, 2002; Ocelík et al., 2019).

The spill-over environmental effects from developing industrial sites have been shown to cause deterioration in the surrounding environment including within existing residential areas, affecting people's health both directly and indirectly (Hossain et al., 2012). This issue has been raised in various case studies in the region, news reports, and research (had all the citations below here as well). According to one recent study by Hossain et al. (2012), the water bodies near the operating industrial areas in Gebeng, namely at Pengorak, Tunggak, and Balok rivers, and Pengorak beach, experienced an abnormal level of heavy metal and aluminium concentrations with traces of radioactive materials suspected to originate from the nearby industrial and bauxite mining sites (Hossain et al., 2012). Other similar studies have also found that the rivers located in the vicinity of industrial sites contained higher contaminants mainly from industrial pollutants and the rivers were degraded due to geomorphology and anthropogenic factors such as urbanisation and industrialisation (Ata et al., 2018; Yaakub et al., 2018; Sobahan et al., 2013). Local residents also have mixed feelings towards the operating industries such as the rare earth processing plant known as Lynas Advanced Material Plant (LAMP) at Gebeng (Ali, 2014; Baharom, 2018; Bodetti, 2019; Golingai, 2018; Ibrahim, 2017; Lipson & Hemingway, 2019; Megahed et al., 2015; Samsudin, 2019). Despite the LYNAS's claim of being hazardous-free, environmentalists and some local residents are worried about the fate of the generated waste products that contain low-level radioactive materials on the health of 700,000 people living within a 30 km radius of the LAMP plant and its potential to contaminate the surrounding natural environment especially the groundwater through the leakage of heavy metals from Lynas' onsite waste storing (Bodetti, 2019; New Straits Times, 2019; Raman & Abdul Kader, 2019).

Bauxite mining has resulted in many land areas being turned into large red wastelands. Several cases have been identified where bauxite runoffs caused by heavy downpour and "bauxite washing" processes have generated effluents with traces of heavy metals such as arsenic, mercury, and aluminium, especially in the water samples taken near Bukit Goh and Kuantan (Abdullah et al., 2016; Academy of Sciences Malaysia, 2017). Analysis of these effluents indicated that they've breached the recommended guidelines and are likely to be hazardous to the aquatic ecosystem and human health (Mohd Kusin et al., 2016). A group of scientists also reported that a fish sampled in the Pengorak river had high levels of arsenic ranging from 70.8 to 104.5g/kg, exceeding the permissible level which is by 1mg/g (Naz Karim & Shah, 2016). During the peak of bauxite mining activities in 2015, an incident headlined as the "red sea" phenomenon in local newspapers, happened along the shores of Balok and Batu Hitam beach, where the seawater turned red due to bauxite residues allegedly being swept from nearby bauxite stockpiles at Kuantan Port into nearby rivers and eventually flowed into the sea (Alagesh, 2015). Similarly in that year, the main source of domestic water supply in Kuantan was disrupted at the Sungai Kuantan basin due to increased sediment load from the surrounding unregulated mining activities (Academy of Sciences Malaysia, 2017).

The red dust from bauxite is also another environmental problem caused by the improper management of mining activities. According to a report, the level of air pollution from the bauxite dust recorded by monitoring the 24-hour PM10 levels in Bukit Goh, Beserah (just outside residents' homes), and the Gebeng Industrial Estate, exceeded the standard levels of 150 $\mu g/m^3$, under the 24-hour Malaysian Ambient Air Quality Standard for PM10, by a record of 222.13 $\mu g/m^3$ (Bukit Goh), 164.05 $\mu g/m^3$ (Beserah) and 276.79 $\mu g/m^3$ (Gebeng) (Naz Karim & Shah, 2016). Lorries transporting bauxite ores release suspended red dust in the air, which covers the surrounding residential areas, roads, and plantations. This led to some of the locals suffering from frequent respiratory and skin rash problems due to their daily exposure to the bauxite dust (Abdullah et al., 2016; Academy of Sciences Malaysia, 2017). Some of the oil palm plantation and fruit orchard owners also are concerned as their lands turned infertile due to the nearby ongoing mining activities (Alagesh, 2019). The discussed land use conflicts from the spill over effects of the industrial and bauxite mining activities are expected to increase as non-complementary land uses expand within closer proximity to each other.

5.4. Limitations and Future Study Recommendations

The mapping of LULC changes and findings from this study provides an insight into how land use development has altered and will likely continue to alter the region's vulnerable environment. However, remote sensing by nature is limited to only providing spatial information up to a given level of resolution. In addition, there is potential for the remote sensing classification error to propagate and impact on the land use change projections. However, the findings from the literature review was also able to support the mapping and modelling results in the study, but it had limited information concerning the scale and consequences of certain land use development processes. In order to improve the spatial analysis and to obtain more detailed information on the current land use development progress and further insight on the occurring land use conflict, the public participation geographic information (PPGIS) method can be incorporated as a further step to this research.

PPGIS is a crowdsourcing and spatially explicit method where GIS and digital communication technologies are used to engage the public and local stakeholders through a collaborative effort to acquire local knowledge and perspective of specific locations (Fagerholm et al., 2011). PPGIS has been proven to significantly contribute to understanding how local people perceive and experience the landscape, as they are regarded as the true experts of their environment and they could provide knowledge that may not be able to be derived from the process of mapping, modelling, and literature reviews alone (Costanza et al., 1997; Fagerholm et al., 2011; Kivinen et al., 2018b; Nedkov & Burkhard, 2012; Stephenson, 2008; Willemen et al., 2008). Hence, to understand the implications of the land use development activities and arising land use conflicts, a combination of the mapping, modelling, and PPGIS methods could serve as a great tool in framing the land use patterns and determining the land use conflicts and impacts of land use change activities from a local' 'in-situ' perspective whilst allowing them to be engaged in future land use planning decision making.

Chapter 6: Conclusion

This research represents one of the few studies in Malaysia on regional mapping of LULC changes using remote sensing and future land change modelling to assess and quantify the spatio-temporal pattern and draw links to socio-environmental impacts from the LULC changes. A high-accuracy time series of the region in Kuantan between 2010 to 2020 was successfully characterized using the Landsat satellite imagery with a combination of Random Forest classification in GEE and manual digitization. With the aid of multiple ancillary data, key fine thematic resolution land uses were extracted from the coarse land use satellite imagery of the study region. Using LCM the dynamic changes in land use were modelled for 2030, highlighting significant temporal trends in LULC change activities.

The study showed that by 2020 the region had experienced major land use changes following 2010, mainly from the expansion of oil palm plantation, mining, industry, and residential at the expense of declining natural green spaces with an increase in forest and disturbed vegetation clearing. According to the 2030 projection, forest cover and disturbed vegetation will continue to decline tremendously as oil palm plantation and mining sites continue to expand widely. However, future land use policies of reducing oil palm plantation expansion and mega project development planning encouraging rapid urbanisation and industrialisation process may change these projected futures. Both historical remote sensing data and future projections show that industry, mining, and residential are clustered and growing into closer proximity while expanding extensively, which may likely be a cause of future land use conflict. In conclusion, the study shows that the region’s land cover will be largely altered by human intervention driven by the interest in urbanisation and the region’s evolving economic vision. Although the future projection may contain many uncertainties, having the ability to envision future possible scenarios granted key insights in understanding the current and evolving future patterns of land use changes and predicting their impacts on people and the environment. This will assist government bodies, stakeholders, and policy makers by providing information essential for future planning and sustainable development decisions.

Appendix

Appendix A.

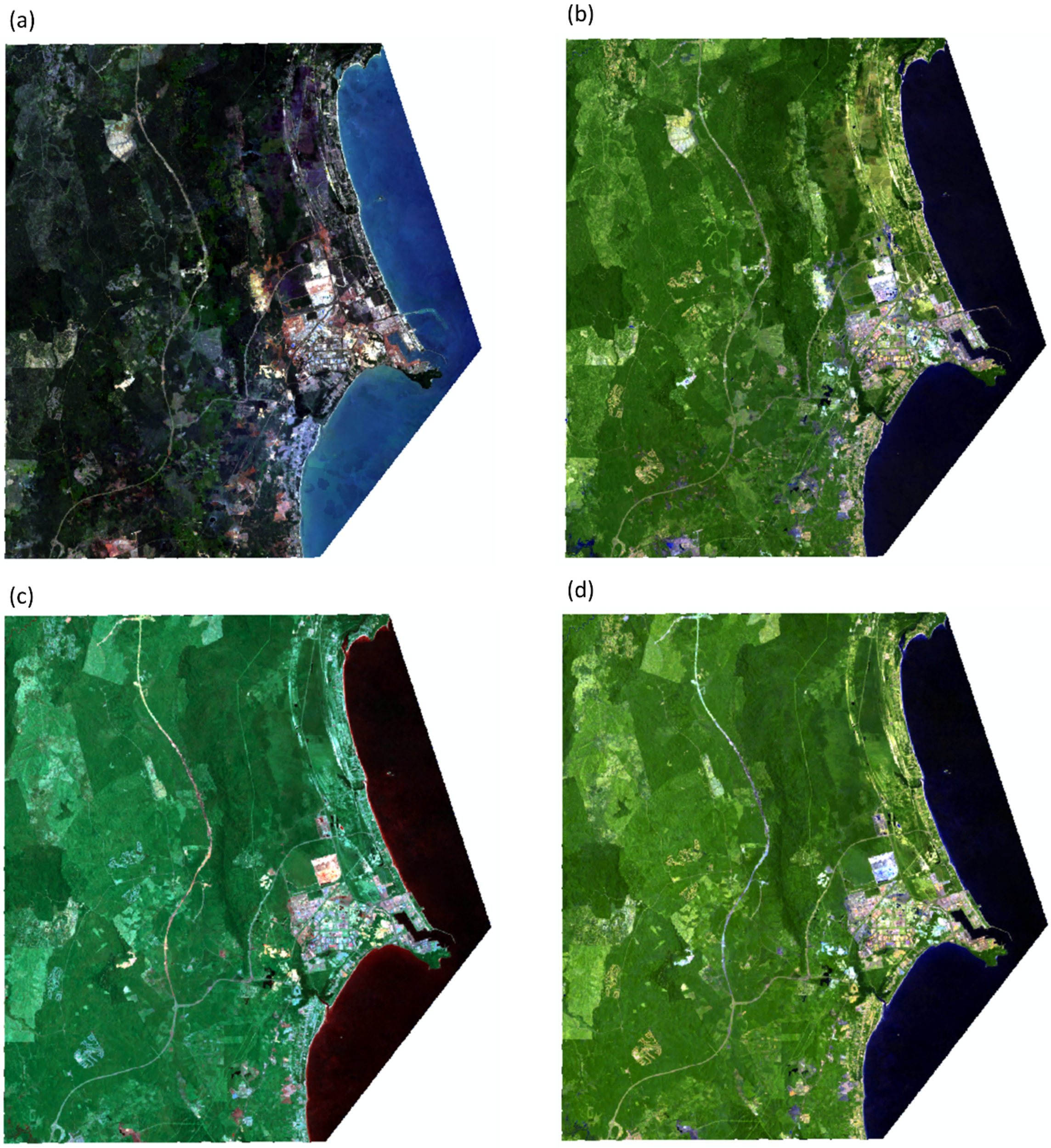

Figure A.1. Landsat satellite imageries with different band combinations used to support the visual assessment; (a) and (b) refers to Landsat 8 satellite imageries with the band combination 4,3,2 and 7,6,4 respectively, while (c) and (d) refers to Landsat 5 satellite imageries with the band combination 3,5,7 and 7,5,3 respectively.

References

Abdullah, N. H., Mohamed, N., Sulaiman, L. H., Zakaria, T. A., & Abdul Rahim, D. (2016). Potential health impacts of bauxite mining in Kuantan. In *Malaysian Journal of Medical Sciences* (Vol. 23, Issue 3, pp. 1–8). Penerbit Universiti Sains Malaysia.

Abu Dardak, R. (2015). *Transformation of Agricultural Sector in Malaysia Through Agricultural Policy | FFTC Agricultural Policy Platform (FFTC-AP)*. https://ap.fftc.org.tw/article/818

Aburas, M. M., Abdullah, S. H., Ramli, M. F., Ash'Aari, Z. H., & Ahamad, M. S. S. (2018). Simulating and monitoring future land-use trends using CA-Markov and LCM models. *IOP Conference Series: Earth and Environmental Science*, *169*(1), 12050. https://doi.org/10.1088/1755-1315/169/1/012050

Academy of Sciences Malaysia. (2017). *Sustainable Mining: Case Study for Bauxite Mining in Pahang by Academy of Sciences Malaysia*. https://issuu.com/asmpub/docs/sustainable_mining_bauxite

Adepoju, M. O., Millington, A. C., & Tansey, K. T. (2006). *LAND USE/LAND COVER CHANGE DETECTION IN METROPOLITAN LAGOS (NIGERIA): 1984-2002*.

Al-sharif, A. A. A., & Pradhan, B. (2014). Monitoring and predicting land use change in Tripoli Metropolitan City using an integrated Markov chain and cellular automata models in GIS. *Arabian Journal of Geosciences*, *7*(10), 4291–4301. https://doi.org/10.1007/s12517-013-1119-7

Alden, J. D., & Awang, A. H. (1985). Regional Development Planning in Malaysia. *Regional Studies*, *19*(6), 495–508. https://doi.org/10.1080/09595238500185491

Ali, S. H. (2014). Social and Environmental Impact of the Rare Earth Industries. *Resources 2014, Vol. 3, Pages 123-134*, *3*(1), 123–134. https://doi.org/10.3390/RESOURCES3010123

Ang, M. L. E., Arts, D., Crawford, D., Labatos, B. V., Ngo, K. D., Owen, J. R., Gibbins, C., & Lechner, A. M. (2021). Socio-environmental land cover time-series analysis of mining landscapes using Google Earth Engine and web-based mapping. *Remote Sensing Applications: Society and Environment*, *21*(July 2020), 100458. https://doi.org/10.1016/j.rsase.2020.100458

Any Lynas benefit not worth the risk. (2019). *New Straits Times*. https://www.nst.com.my/opinion/letters/2019/04/479491/any-lynas-benefit-not-worth-risk

Ata, F. M., Kamarudin, M. K. A., Yaakub, N., Abd. Wahab, N., Toriman, M. E., Juahir, H., Gasim, M. B., Sunardi, Halim, A. A. A., Abd Raoff, M. N. A., & Haris, M. N. (2018). Impact of hydrological study to water quality status in Kuantan River, Pahang, Malaysia. *International Journal of Engineering and Technology(UAE)*, *7*(3.14 Special Issue 14), 35–43. https://doi.org/10.14419/ijet.v7i3.14.16859

Athukorala, P. chandra, & Narayanan, S. (2018). Economic corridors and regional development: The Malaysian experience. *World Development*, *106*, 1–14.

https://doi.org/10.1016/j.worlddev.2018.01.009

Aw, N., & Awale, S. (2015). *How the bauxite rush is taking a toll on Kuantan's future*. Malaysiakini. https://www.malaysiakini.com/news/324788

Ayele, G., Hayicho, H., & Alemu, M. (2019). Land Use Land Cover Change Detection and Deforestation Modeling: In Delomena District of Bale Zone, Ethiopia. *Journal of Environmental Protection*, *10*(04), 532–561. https://doi.org/10.4236/jep.2019.104031

Baharom, H. (2018). *What exactly do we want from Lynas?* https://www.malaysiakini.com/letters/447712

Bodetti, A. (2019, January 10). *Malaysia's Rare Earth Debate – The Diplomat*. https://thediplomat.com/2019/01/malaysias-rare-earth-debate/

Brown, G., & Raymond, C. M. (2014). Methods for identifying land use conflict potential using participatory mapping. *Landscape and Urban Planning*, *122*, 196–208. https://doi.org/10.1016/j.landurbplan.2013.11.007

Butler, R. (2019). *Malaysia to ban oil palm expansion?* https://news.mongabay.com/2019/03/malaysia-to-ban-oil-palm-expansion/

Carneiro Freire, S., Corban, C., Ehrlich, D., Florczyk, A., Kemper, T., Maffenini, L., Melchiorri, M., Pesaresi, M., Schiavina, M., & Tommasi, P. (2019). JRC Publications Repository - Atlas of the Human Planet 2019. *Publications Office of the European Union*. https://doi.org/10.2760/014159

Chen, C., He, X., Liu, Z., Sun, W., Dong, H., & Chu, Y. (2020). Analysis of regional economic development based on land use and land cover change information derived from Landsat imagery. *Scientific Reports 2020 10:1*, *10*(1), 1–16. https://doi.org/10.1038/s41598-020-69716-2

Coppin, P., Jonckheere, I., Nackaerts, K., Muys, B., & Lambin, E. (2004). Digital change detection methods in ecosystem monitoring: A review. *International Journal of Remote Sensing*, *25*(9), 1565–1596. https://doi.org/10.1080/0143116031000101675

Costanza, R., d'Arge, R., de Groot, R., Farber, S., Grasso, M., Hannon, B., Limburg, K., Naeem, S., O'Neill, R. V., Paruelo, J., Raskin, R. G., Sutton, P., & van den Belt, M. (1997). The value of the world's ecosystem services and natural capital. *Nature 1997 387:6630*, *387*(6630), 253–260. https://doi.org/10.1038/387253a0

De Alba, H. (2011). *Deforestation in the Kayabi Indigenous Territory: Simulating and Predicting Land Use and Land Cover Change in the Brazilian Amazon*.

DOSM. (2021). *Department of Statistics Malaysia Official Portal*. Department of Statistics Malaysia. https://www.dosm.gov.my/v1/index.php?r=column/cone&menu_id=b2lJM0IwRGdGSjVnV1dOZktWVGYzdz09

Dzieszko, P. (2014). Land-cover modelling using corine land cover data and multi-layer perceptron. In *Quaestiones Geographicae* (Vol. 33, Issue 1, pp. 5–22). Adam Mickiewicz University Press. https://doi.org/10.2478/quageo-2014-0004

Eastman, J. R. (2016). *TerrSet Tutorial*. Clark University. www.clarklabs.orgclarklabs@clarku.edu

Eastman, J. R., & Toledano, J. (2018). *A Short Presentation of the Land Change Modeler (LCM)* (pp. 499–505). https://doi.org/10.1007/978-3-319-60801-3_36

Eastman, J Ronald. (2006). *IDRISI Andes Tutorial*.

ECER. (2016). *INTRODUCTION OF EAST COAST ECONOMIC REGION DEVELOPMENT COUNCIL (ECERDC), MALAYSIA "DEEPENING AND STRENGTHENING THE ECONOMIC COLLABORATION BETWEEN MALAYSIA & JAPAN."*

ECER Master Plan 2.0. (2019). East Coast Economic Region Development Council (ECERDC) & UKM Pakarunding. https://www.ecerdc.com.my/wp-content/uploads/2020/03/Master-Plan-2.0_BI_rev046-low-res.pdf

ECERDC. (2010). *Transforming the East Coast*.

Elias, P., Dekolo, S. O., & Babatola, O. (2012). *Land Use Change Modelling In Developing Countries : Issues And Prospects*. https://www.researchgate.net/publication/265476803_LAND_USE_CHANGE_MODELLING_IN_DEVELOPING_COUNTRIES_ISSUES_AND_PROSPECTS

Everingham, J. A., Rolfe, J., Lechner, A. M., Kinnear, S., & Akbar, D. (2018). A proposal for engaging a stakeholder panel in planning post-mining land uses in Australia's coal-rich tropical savannahs. *Land Use Policy*, *79*, 397–406. https://doi.org/10.1016/j.landusepol.2018.08.038

Fagerholm, N., Käyhkö, N., Ndumbaro, F., & Khamis, M. (2011). Community stakeholders' knowledge in landscape assessments - Mapping indicators for landscape services. *Ecological Indicators*, *18*, 421–433. https://doi.org/10.1016/j.ecolind.2011.12.004

Farr, T. G., Rosen, P. A., Caro, E., Crippen, R., Duren, R., Hensley, S., Kobrick, M., Paller, M., Rodriguez, E., Roth, L., Seal, D., Shaffer, S., Shimada, J., Umland, J., Werner, M., Oskin, M., Burbank, D., & Alsdorf, D. E. (2007). *NASA SRTM Digital Elevation 30m | Earth Engine Data Catalog*. The Shuttle Radar Topography Mission. https://developers.google.com/earth-engine/datasets/catalog/USGS_SRTMGL1_003#citations

Fisher, P., & Unwin, D. (2005). Land Use and land cover: Contradiction or Complement. *Re-Presenting GIS*, *January*, 85–98.

Foody, G. M. (2002). Status of land cover classification accuracy assessment. *Remote Sensing of Environment*, *80*(1), 185–201. https://doi.org/10.1016/S0034-4257(01)00295-4

Foon, H. W. (2017). *Kuantan Port set to spur economy | The Star Online*. The Star Online. https://www.thestar.com.my/business/business-news/2017/11/20/kuantan-port-set-to-spur-economy

Gao, J., & O'Neill, B. C. (2020). Mapping global urban land for the 21st century with data-driven simulations and Shared Socioeconomic Pathways. *Nature Communications 2020 11:1*, *11*(1), 1–12. https://doi.org/10.1038/s41467-020-15788-7

Gaughan, A. E., Stevens, F. R., Linard, C., Jia, P., & Tatem, A. J. (2013). *WorldPop Global Project Population Data: Estimated Residential Population per 100x100m Grid Square*. High Resolution Population Distribution Maps for Southeast Asia in 2010 and 2015.

https://developers.google.com/earth-engine/datasets/catalog/WorldPop_GP_100m_pop#citations

Golingai, P. (2018). *No more dramatic comedy in Kuantan | The Star*. https://www.thestar.com.my/opinion/columnists/on-the-political-ground/2018/04/29/no-more-dramatic-comedy-in-kuantan-it-could-be-a-stale-soap-opera-in-the-pahang-capital-city-now-tha

Gorelick, N., Hancher, M., Dixon, M., Ilyushchenko, S., Thau, D., & Moore, R. (2017). Google Earth Engine: Planetary-scale geospatial analysis for everyone. *Remote Sensing of Environment*, *202*, 18–27. https://doi.org/10.1016/j.rse.2017.06.031

Gyawali, B., Fraser, R., Wang, Y., & Bukenya, J. (2004). *Land Cover and Socio-economic Characteristics in the Eight Counties of Alabama: A Spatial Analysis*. https://www.researchgate.net/publication/23505598_Land_Cover_and_Socio-economic_Characteristics_in_the_Eight_Counties_of_Alabama_A_Spatial_Analysis

Han, H., Yang, C., & Song, J. (2015). Scenario simulation and the prediction of land use and land cover change in Beijing, China. *Sustainability (Switzerland)*, *7*(4), 4260–4279. https://doi.org/10.3390/su7044260

Hansen, M. C., Potapov, P. V., Moore, R., Hancher, M., Turubanova, S. A., Tyukavina, A., Thau, D., Stehman, S. V., Goetz, S. J., Loveland, T. R., Kommareddy, A., Egorov, A., Chini, L., Justice, C. O., & Townshend, J. R. G. (2013). *High-Resolution Global Maps of 21st-Century Forest Cover Change*. https://earthenginepartners.appspot.com/science-2013-global-forest/download_v1.2.html

Hartmann, J., & Moosdorf, N. (2012). The new global lithological map database GLiM: A representation of rock properties at the Earth surface. *Geochemistry, Geophysics, Geosystems*, *13*(12), 12004. https://doi.org/10.1029/2012GC004370

Hasan, S., Shi, W., Zhu, X., Abbas, S., & Khan, H. U. A. (2020). Future simulation of land use changes in rapidly urbanizing South China based on land change modeler and remote sensing data. *Sustainability (Switzerland)*, *12*(11), 4350. https://doi.org/10.3390/su12114350

Hilson, G. (2002). An overview of land use conflicts in mining communities. *Land Use Policy*, *19*(1), 65–73. https://doi.org/10.1016/S0264-8377(01)00043-6

Hossain, M. A., Nasly, M., Islam Mir, S., Ab Wahid, Z., & A.Aziz, E. (2012). *Assessment of Spatial Variation of Water Quality of Tunggak River Adjacent to Gebeng Industrial Estate, Malaysia*. https://www.researchgate.net/publication/233080715_Assessment_of_Spatial_Variation_of_Water_Quality_of_Tunggak_River_Adjacent_to_Gebeng_Industrial_Estate_Malaysia

Huam, H. T., Thoo, A. C., & Dan, J. C. (2018). Does The Belt and Road Initiative in the East Coast of Peninsular Malaysia Create Win-win Partnership with China? *Journal of Arts & Social Sciences*, *1*, 98–105.

Ibrahim, A. (2017). *Lessons from the lynas episode*. New Straits Times. https://www.nst.com.my/opinion/letters/2017/09/279593/lessons-lynas-episode

Iqhlima Najwa, I. N., Haryati, A., Ramadhansyah, P. J., & Idris, A. M. (2019). A comparative study of Kuantan bauxite mineralogy as potential material in civil engineering. *IOP Conference Series: Earth and Environmental Science*, *244*(1), 012002. https://doi.org/10.1088/1755-1315/244/1/012002

Ismail, S. N. S., Abidin, E. Z., Praveena, S. M., Rasdi, I., Mohamad, S., & Ismail, W. M. I. W. (2018). Heavy metals in soil of the tropical climate bauxite mining area in Malaysia. *Journal of Physical Science*, *29*, 7–14. https://doi.org/10.21315/JPS2018.29.S3.2

Kitada, K., & Fukuyama, K. (2012). Land-use and land-cover mapping using a gradable classification method. *Remote Sensing*, *4*(6), 1544–1558. https://doi.org/10.3390/rs4061544

Kivinen, S., Vartiainen, K., & Kumpula, T. (2018a). People and post-mining environments: PPGIS mapping of landscape values, knowledge needs, and future perspectives in Northern Finland. *Land*, *7*(4), 151. https://doi.org/10.3390/land7040151

Kivinen, S., Vartiainen, K., & Kumpula, T. (2018b). People and post-mining environments: PPGIS mapping of landscape values, knowledge needs, and future perspectives in Northern Finland. *Land*, *7*(4). https://doi.org/10.3390/LAND7040151

Kuantan Municipal Council. (2015). *Local Plan Draft of Kuantan District 2035*. http://epublisiti.townplan.gov.my/turun/kuantan2035/ringkasan.pdf

Law, W. . (1968). *Reconnaissance Soil Map of Peninsular Malaysia. Sheet 1. Series L 40A. - ESDAC - European Commission*. Director of National Mapping, Malaysia. https://esdac.jrc.ec.europa.eu/content/reconnaissance-soil-map-peninsular-malaysia-sheet-1-series-l-40a

Lechner, A. M., Foody, G. M., & Boyd, D. S. (2020). Applications in Remote Sensing to Forest Ecology and Management. *One Earth*, *2*(5), 405–412. https://doi.org/10.1016/J.ONEEAR.2020.05.001

Lechner, A. M., Gomes, R. L., Rodrigues, L., Ashfold, M. J., Selvam, S. B., Wong, E. P., Raymond, C. M., Zieritz, A., Sing, K. W., Moug, P., Billa, L., Sagala, S., Cheshmehzangi, A., Lourdes, K., Azhar, B., Sanusi, R., Ives, C. D., Tang, Y.-T., Tan, D. T., … Gibbins, C. (2020). Challenges and considerations of applying nature-based solutions in low- and middle-income countries in Southeast and East Asia. *Blue-Green Systems*, *2*(1), 331–351. https://doi.org/10.2166/BGS.2020.014

Lechner, A. M., Meng Tan, C., Tritto, A., Horstmann, A., Chen Teo, H., Owen, J. R., Campos-arceiz, A., & Mui Keng Terrace, H. (2019). *Trends in Southeast Asia: The Belt And Road Initiative: Environmental Impacts In Southeast Asia*. http://bookshop.iseas.edu.sgtrs18/19s

Lechner, A. M., Owen, J., Ang, M. L. E., Edraki, M., Che Awang, N. A., & Kemp, D. (2019). Historical socio-environmental assessment of resource development footprints using remote sensing. *Remote Sensing Applications: Society and Environment*, *15*. https://doi.org/10.1016/j.rsase.2019.100236

Lechner, A. M., Verbrugge, L. N. H., Chelliah, A., Ang, M. L. E., & Raymond, C. M. (2020). Rethinking tourism conflict potential within and between groups using participatory mapping. *Landscape and Urban Planning*, *203*, 103902. https://doi.org/10.1016/J.LANDURBPLAN.2020.103902

Lines, M. (2015). *Bauxite Developments Vietnam & Malaysia*.

Lipson, D., & Hemingway, P. (2019, September 12). *Australian mining company Lynas gets permission to dispose of radioactive waste in Malaysia, dividing locals - ABC News*. https://www.abc.net.au/news/2019-08-22/malaysians-divided-on-radioactive-waste-from-aussie-miner-lynas/11434122

Liu, X. H., Skidmore, A. K., & Van Oosten, H. (2002). Integration of classification methods for improvement of land-cover map accuracy. *ISPRS Journal of Photogrammetry and Remote Sensing*, *56*(4), 257–268. https://doi.org/10.1016/S0924-2716(02)00061-8

Loke, A. S. F. (2019). *Renegotiated ECRL brings more benefits, economic spin-offs*. https://www.thesundaily.my/local/renegotiated-ecrl-brings-more-benefits-economic-spin-offs-NF1153168

Lopez, L. (2016). *Malaysia's East Coast Rail Line touted as a game changer, SE Asia News & Top Stories - The Straits Times*. The Straits Times. https://www.straitstimes.com/asia/se-asia/malaysias-east-coast-rail-line-touted-as-a-game-changer

Lourdes, K. T., Gibbins, C. N., Hamel, P., Sanusi, R., Azhar, B., & Lechner, A. M. (2021). A Review of Urban Ecosystem Services Research in Southeast Asia. *Land 2021, Vol. 10, Page 40*, *10*(1), 40. https://doi.org/10.3390/LAND10010040

Lu, D., Mausel, P., Brondízio, E., & Moran, E. (2004). Change detection techniques. *International Journal of Remote Sensing*, *25*(12), 2365–2401. https://doi.org/10.1080/0143116031000139863

Lu, D., & Weng, Q. (2007). A survey of image classification methods and techniques for improving classification performance. In *International Journal of Remote Sensing* (Vol. 28, Issue 5, pp. 823–870). Taylor and Francis Ltd. https://doi.org/10.1080/01431160600746456

M. A. Sobahan, Islam Mir, S., Zakaria, I., & M. A. Hossain. (2013). *Surface Water Contamination Due to Industrial Activities in Gebeng Area, Kuantan, Malaysia*.

Malaysia Rail Link. (2019). *The Development of East Coast Rail Link Project (ECRL)*. https://www.cmpa.asia/index.php/zh/event/edocument/category/29-4th-cmpa-annual-meeting-2019-and-forum?download=146:9-paper-ix-mrl-cmpa-19-aug-2019

Mas, J. F., Kolb, M., Paegelow, M., Camacho Olmedo, M. T., & Houet, T. (2014). Inductive pattern-based land use/cover change models: A comparison of four software packages. *Environmental Modelling and Software*, *51*, 94–111. https://doi.org/10.1016/j.envsoft.2013.09.010

Mayberry, K. (2017). *Malaysia's East Coast Rail Link a double-edged sword for environment, wildlife*. Mongabay. https://news.mongabay.com/2017/08/malaysias-east-coast-rail-link-a-double-edged-sword-for-environment-wildlife/

Megahed, Y., Cabral, P., Silva, J., & Caetano, M. (2015). Land cover mapping analysis and urban growth modelling using remote sensing techniques in greater Cairo region-Egypt.

ISPRS International Journal of Geo-Information, *4*(3), 1750–1769. https://doi.org/10.3390/ijgi4031750

Mishra, V. N., & Rai, P. K. (2016). A remote sensing aided multi-layer perceptron-Markov chain analysis for land use and land cover change prediction in Patna district (Bihar), India. *Arabian Journal of Geosciences*, *9*(4), 1–18. https://doi.org/10.1007/s12517-015-2138-3

Mohd Kusin, F., Abd Rahman, M. S., Madzin, Z., Jusop, S., Mohamat-Yusuff, F., Ariffin, M., & Md Z, M. S. (2016). The occurrence and potential ecological risk assessment of bauxite mine-impacted water and sediments in Kuantan, Pahang, Malaysia. *Environmental Science and Pollution Research*. https://doi.org/10.1007/s11356-016-7814-7

Mutanga, O., & Kumar, L. (2019). Google earth engine applications. *Remote Sensing*, *11*(5), 591. https://doi.org/10.3390/rs11050591

Naz Karim, F., & Shah, A. (2016). Kuantan facing severe danger. *New Straits Times*. https://www.nst.com.my/news/2016/01/120276/kuantan-facing-severe-danger

Nedkov, S., & Burkhard, B. (2012). Flood regulating ecosystem services—Mapping supply and demand, in the Etropole municipality, Bulgaria. *Ecological Indicators*, *21*, 67–79. https://doi.org/10.1016/J.ECOLIND.2011.06.022

Ng, L. S., Campos-Arceiz, A., Sloan, S., Hughes, A. C., Tiang, D. C. F., Li, B. V., & Lechner, A. M. (2020). The scale of biodiversity impacts of the Belt and Road Initiative in Southeast Asia. *Biological Conservation*, *248*, 108691. https://doi.org/10.1016/J.BIOCON.2020.108691

Ngah, I. (2011a). Challenges of Regional Development in Malaysia in the Globalization Context. *ResearchGate*. https://www.researchgate.net/publication/283078879_Challenges_of_Regional_Development_in_Malaysia_in_the_Globalization_Context

Ngah, I. (2011b). *Overview of Regional Development in Malaysia*.

Ngo, K. D., Lechner, A. M., & Vu, T. T. (2020). Land cover mapping of the Mekong Delta to support natural resource management with multi-temporal Sentinel-1A synthetic aperture radar imagery. *Remote Sensing Applications: Society and Environment*, *17*, 100272. https://doi.org/10.1016/J.RSASE.2019.100272

Nuissl, H., & Siedentop, S. (2021). *Urbanisation and Land Use Change* (pp. 75–99). https://doi.org/10.1007/978-3-030-50841-8_5

Nur Fatin. (2016). *KUANTAN IDENTIFIED AS PORT CITY DUE TO ITS STRATEGIC LOCATION | Kuantan Port*. Kuantan Port Consortium. http://www.kuantanport.com.my/en_GB/kuantan-identified-as-port-city-due-to-its-strategic-location/

Ocelík, P., Svobodová, K., Hendrychová, M., Lehotský, L., Everingham, J. A., Ali, S., Badera, J., & Lechner, A. (2019). A contested transition toward a coal-free future: Advocacy coalitions and coal policy in the Czech Republic. *Energy Research and Social Science*, *58*. https://doi.org/10.1016/J.ERSS.2019.101283

Ozturk, D. (2015). Urban growth simulation of Atakum (Samsun, Turkey) using cellular automata-Markov chain and Multi-layer Perceptron-Markov chain models. *Remote Sensing*, *7*(5), 5918–5950. https://doi.org/10.3390/rs70505918

Parsa, V. A., Yavari, A., & Nejadi, A. (2016). Spatio-temporal analysis of land use/land cover pattern changes in Arasbaran Biosphere Reserve: Iran. *Modeling Earth Systems and Environment*, *2*(4), 1–13. https://doi.org/10.1007/s40808-016-0227-2

Plourde, L., & Congalton, R. G. (2003). Sampling method and sample placement: How do they affect the accuracy of remotely sensed maps? *Photogrammetric Engineering and Remote Sensing*, *69*(3), 289–297. https://doi.org/10.14358/PERS.69.3.289

Prospects for the Malaysia-China Kuantan Industrial Park and Kuantan Port | HKTDC Belt and Road Portal. (2017). https://beltandroad.hktdc.com/en/insights/prospects-malaysia-china-kuantan-industrial-park-and-kuantan-port

Quinn, J. W. (2001). *Band Combinations*. http://web.pdx.edu/~nauna/resources/10_BandCombinations.htm

Raman, M., & Abdul Kader, M. (2019). Lynas must remove its radioactive wastes from Malaysia. *Malaysia Kini*. https://www.malaysiakini.com/letters/479589

Rathee, G. (2014). Trends of land-use change in India. *Urbanization in Asia: Governance, Infrastructure and The Environment*, 215–238. https://doi.org/10.1007/978-81-322-1638-4_13

Samat, N., Mahamud, M. A., Tan, M. L., Tilaki, M. J. M., & Tew, Y. L. (2020). Modelling land cover changes in peri-urban areas: A case study of george town conurbation, malaysia. *Land*, *9*(10), 1–16. https://doi.org/10.3390/land9100373

Samsudin, S. (2019). *Isu Lynas: Wong Tack, Tan, Fuziah tak wakili kami, kata penduduk*. https://www.malaysiakini.com/news/487397

Shevade, V. S., & Loboda, T. V. (2019). Oil palm plantations in Peninsular Malaysia: Determinants and constraints on expansion. *PLoS ONE*, *14*(2). https://doi.org/10.1371/journal.pone.0210628

Shi, G., Jiang, N., & Yao, L. (2018). Land use and cover change during the rapid economic growth period from 1990 to 2010: A case study of Shanghai. *Sustainability (Switzerland)*, *10*(2). https://doi.org/10.3390/SU10020426

Shivamurthy, V. ., Ramachandra, T. V. ., Aithal, B. H., Kumar, U., Joshi, N. V., & Rao, V. (2013). *Modelling Urban Revolution in Greater Bangalore, India*. https://www.researchgate.net/publication/258316417_Modelling_Urban_Revolution_in_Greater_Bangalore_India

Sidhu, N., Pebesma, E., & Câmara, G. (2018). Using Google Earth Engine to detect land cover change: Singapore as a use case. *European Journal of Remote Sensing*, *51*(1), 486–500. https://doi.org/10.1080/22797254.2018.1451782

Singh, A. (1989). Review Articlel: Digital change detection techniques using remotely-sensed data. *International Journal of Remote Sensing*, *10*(6), 989–1003. https://doi.org/10.1080/01431168908903939

Sobahan, M. A., Sujaul Islam Mir, Zakaria, I., & Hossain, M. A. (2013). Surface Water Contamination Due to Industrial Activities in Gebeng Area, Kuantan, Malaysia.

International Conference on Civil and Architecture Engineering. https://core.ac.uk/download/pdf/159186352.pdf

Sodhi, N. S., Koh, L. P., Clements, R., Wanger, T. C., Hill, J. K., Hamer, K. C., Clough, Y., Tscharntke, T., Rose, M., Posa, C., & Lee, T. M. (2010). Conserving Southeast Asian forest biodiversity in human-modified landscapes. *Biological Conservation*, *143*, 2375–2384. https://doi.org/10.1016/j.biocon.2009.12.029

Spyra, M., Kleemann, J., Calò, N. C., Schürmann, A., & Fürst, C. (2021). Protection of peri-urban open spaces at the level of regional policy-making: Examples from six European regions. *Land Use Policy*, *107*, 105480. https://doi.org/10.1016/J.LANDUSEPOL.2021.105480

Stephenson, J. (2008). The Cultural Values Model: An integrated approach to values in landscapes. *Landscape and Urban Planning*, *84*(2), 127–139. https://doi.org/10.1016/J.LANDURBPLAN.2007.07.003

Subedi, P., Subedi, K., & Thapa, B. (2013). Application of a Hybrid Cellular Automaton – Markov (CA-Markov) Model in Land-Use Change Prediction: A Case Study of Saddle Creek Drainage Basin, Florida. *Applied Ecology and Environmental Sciences*, *1*(6), 126–132. https://doi.org/10.12691/aees-1-6-5

Sundara Kumar, K., Udaya Bhaskar, P., & Padmakumari, K. (2015). *APPLICATION OF LAND CHANGE MODELER FOR PREDICTION OF FUTURE LAND USE LAND COVER A CASE STUDY OF VIJAYAWADA CITY*.

Susman, R., Gütte, A. M., & Weith, T. (2021). Drivers of Land Use Conflicts in Infrastructural Mega Projects in Coastal Areas: A Case Study of Patimban Seaport, Indonesia. *Land 2021, Vol. 10, Page 615*, *10*(6), 615. https://doi.org/10.3390/LAND10060615

T.N., A. (2015). Environment Dept begins probe on Balok red sea. *New Straits Times*. https://www.nst.com.my/news/2015/12/119689/environment-dept-begins-probe-balok-red-sea-video

T.N., A. (2019). The bauxite boom and bust. *New Straits Times*. https://www.nst.com.my/news/nation/2019/02/463154/bauxite-boom-and-bust

Tan, S. L. (2016). The lucrative business of bauxite trade | Astro Awani. *Astro Awani*. https://www.astroawani.com/berita-malaysia/the-lucrative-business-of-bauxite-trade-88548

Tee, S. L., Samantha, L. D., Kamarudin, N., Akbar, Z., Lechner, A. M., Ashton-Butt, A., & Azhar, B. (2018). Urban forest fragmentation impoverishes native mammalian biodiversity in the tropics. *Ecology and Evolution*, *8*(24), 12506–12521. https://doi.org/10.1002/ece3.4632

Teo, H. C., Lechner, A. M., Walton, G. W., Chan, F. K. S., Cheshmehzangi, A., Tan-Mullins, M., Chan, H. K., Sternberg, T., & Campos-Arceiz, A. (2019). Environmental Impacts of Infrastructure Development under the Belt and Road Initiative. *Environments 2019, Vol. 6, Page 72*, *6*(6), 72. https://doi.org/10.3390/ENVIRONMENTS6060072

TerrSet Geospatial Monitoring and Modeling Software. (2021). Clark Labs. https://clarklabs.org/terrset/

The Report Malaysia. (2012). *A big push: Several sectors will support growth in the East Coast Economic Region | Malaysia 2012 | Oxford Business Group*. Oxford Business Group Malaysia. https://oxfordbusinessgroup.com/analysis/big-push-several-sectors-will-support-growth-east-coast-economic-region

Theobald, D. M., Harrison-Atlas, D., Monahan, W. B., & Albano, C. M. (2015). *Global SRTM Landforms | Earth Engine Data Catalog | Google Developers*. Ecologically-Relevant Maps of Landforms and Physiographic Diversity for Climate Adaptation Planning. https://developers.google.com/earth-engine/datasets/catalog/CSP_ERGo_1_0_Global_SRTM_landforms?hl=en

Tso, B., & Mather, P. (2009). *Classification Methods for Remotely Sensed Data -Second Edition*. https://books.google.com.my/books?hl=en&lr=&id=oXpzROm11QMC&oi=fnd&pg=PP1&ots=AWuPOW9R-v&sig=9k9DDbBSzobEZLA33ubCqdDQlDg&redir_esc=y#v=onepage&q&f=false

Verburg, P. H., Schot, P. P., Dijst, M. J., & Veldkamp, A. (2004). Land use change modelling: Current practice and research priorities. *GeoJournal*, *61*(4), 309–324. https://doi.org/10.1007/s10708-004-4946-y

Von Der Dunk, A., Grêt-Regamey, A., Dalang, T., & Hersperger, A. M. (2011). Defining a typology of peri-urban land-use conflicts – A case study from Switzerland. *Landscape and Urban Planning*, *101*(2), 149–156. https://doi.org/10.1016/J.LANDURBPLAN.2011.02.007

Wang, J., & Maduako, I. N. (2018). Spatio-temporal urban growth dynamics of Lagos Metropolitan Region of Nigeria based on Hybrid methods for LULC modeling and prediction. *European Journal of Remote Sensing*, *51*(1), 251–265. https://doi.org/10.1080/22797254.2017.1419831

Wilcove, D. S., & Koh, L. P. (2010). Addressing the threats to biodiversity from oil-palm agriculture. *Biodiversity and Conservation*, *19*(4), 999–1007. https://doi.org/10.1007/S10531-009-9760-X

Willemen, L., Verburg, P. H., Hein, L. G., & Mensvoort, M. E. F. van. (2008). Spatial characterization of landscape functions. *Landscape and Urban Planning*, *88*(1), 34–43. https://doi.org/10.1016/J.LANDURBPLAN.2008.08.004

Winkler, K., Fuchs, R., Rounsevell, M., & Herold, M. (2021). Global land use changes are four times greater than previously estimated. *Nature Communications 2021 12:1*, *12*(1), 1–10. https://doi.org/10.1038/s41467-021-22702-2

Xu, Y., Yu, L., Li, W., Ciais, P., Cheng, Y., & Gong, P. (2020). Annual oil palm plantation maps in Malaysia and Indonesia from 2001 to 2016. *Earth Syst. Sci. Data*, *12*, 847–867. https://doi.org/10.5194/essd-12-847-2020

Yaakub, N., Raoff, M. N. A., Haris, M. N., Halim, A. A. A., & Kamarudin, M. K. A. (2018). Water quality index assesment around industrial area in Kuantan, Pahang. *Journal of Fundamental and Applied Sciences*, *9*(2S), 731. https://doi.org/10.4314/JFAS.V9I2S.45

Yang, X., Zheng, X. Q., & Lv, L. N. (2012). A spatiotemporal model of land use change based on ant colony optimization, Markov chain and cellular automata. *Ecological Modelling*, *233*, 11–19. https://doi.org/10.1016/j.ecolmodel.2012.03.011

Yao, X., Wang, Z., & Wang, H. (2015). Impact of Urbanization and Land-Use Change on Surface Climate in Middle and Lower Reaches of the Yangtze River, 1988-2008. *Advances in Meteorology*, *2015*. https://doi.org/10.1155/2015/395094

Yeo, G.-T., & Rimmer, P. J. (2015). Asian-Pacific Rim Logistics: Global Context and Local Policies. *The Asian Journal of Shipping and Logistics*, *31*(1), 187–189. https://doi.org/10.1016/j.ajsl.2015.03.008

Yiran, G. A. B., Kusimi, J. M., & Kufogbe, S. K. (2012). A synthesis of remote sensing and local knowledge approaches in land degradation assessment in the Bawku East District, Ghana. *International Journal of Applied Earth Observation and Geoinformation*, *14*(1), 204–213. https://doi.org/10.1016/j.jag.2011.09.016

Zainuddin, D. (2019). *70% of ECRL revenue will come from cargo load: Daim*. The Sun Daily. https://www.thesundaily.my/local/70-of-ecrl-revenue-will-come-from-cargo-load-daim-BI802614