Impact of spatial planning and policies application on land transformation under the National Physical Plan regional policies in Selangor State between 2005 and 2020: a satellite based analysis

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The National Physical Plan (NPP) of Malaysia is a pivotal framework that helps to translate national spatial policies into actionable strategies at various planning levels. The first NPP (NPP1) in 2005 substantially emphasised land-use policies, which prompted the need to assess their impact on land use and land-cover (LULC) dynamics. This study focuses on LULC changes in Selangor, Malaysia, spanning from 1990 (pre-NPP1) to 2020 (post-NPP3). Leveraging remote sensing data collected from satellites such as Landsat 5 and 8, both single and multiple regression analyses were conducted to elucidate the primary drivers behind these transformations. Single regression analysis revealed that LULC in 2015 emerged as a robust predictor in LULC in 2020, explaining nearly 60% of the variation in LULC of that year. Conversely, multiple regression analysis revealed that all four predictors (LULC in 2005, 2010, 2015 and 2020) had statistically substantial regression coefficients, thus contributing to explaining the variations in LULC observed in 1990. These findings offer invaluable insights into the multifaceted factors influencing LULC changes in Selangor. They serve as a foundational resource for crafting evidence-based policies and strategies aimed at effectively managing and regulating LULC transitions within the region.

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Introduction

The existing literature offers a plethora of methods and approaches to evaluate the implementation of various plans and policies. Among these, the most notable research endeavours are those that rely on 'rich data sources' and are based on collecting time-series data with high precision (Cronin et al. 2011, Chauhan et al. 2022). However, a crucial aspect frequently remains underemphasised, unnoticed or even absent. This aspect pertains to the theory of change, an approach and tool sourced from the realm of programme evaluation (Wathern 2013, Sovacool et al. 2021). Environmental issues are characterised by several fundamental traits, such as their intricate nature, time-delayed effects and the often uneven distribution of consequences among different geographical areas. These characteristics shape the formulation of environmental policy strategies, which include a diverse array of measures aimed at various hierarchical levels and targeting distinct factors or triggers (Weber et al. 2014). Policy processes can be comprehensively evaluated by considering their outputs, outcomes and impacts. Outputs are the concrete results generated by a policy, often taking the form of actionable programmes or well-defined plans (Pulighe–Pirelli 2023). Outcomes, in the research correspond to the reaction showed by the specified recipient groups in response to the outputs. Notably, an ideal outcome aligns with the primary policy objectives (Moosavian et al. 2022). Finally, impacts refer to discernible and measurable physical alterations in the environment. For instance, this could encompass a visible reduction in environmental pollution levels. As an example, such principles can be applied to LULC changes, where these evaluation perspectives could shed light on the transformations occurring in a particular area (Zarandian et al. 2022, Mirchooli et al. 2023).

Both single and multiple regression analyses utilize statistical methods to uncover significant correlations between independent and dependent variables while accounting for other factors that may influence these correlations (Lee 2022). These approaches help identify the key drivers of land change and their interactions, providing valuable insights for land-use planning and policy decisions (Dadashpoor et al. 2019, Boroughani et al. 2022). However, regression analysis has its limitations. It assumes a linear relationship between independent and dependent variables, which may not always hold true in complex land change processes. Additionally, regression analysis may not capture non-linear relationships and feedback loops that are important in studying land change (Busico et al. 2020, Zeraatpisheh et al. 2019). Therefore, it is important to complement regression analysis with other techniques and methodologies, such as remote sensing, spatial analysis, and scenario modeling, to gain a more comprehensive understanding of land change processes (Goswami et al. 2022, Naikoo et al. 2022).

Land-change analysis uses multiple and single regression approaches to investigate the link between land use and land-cover (LULC) changes and the causes of these changes (Potapov et al. 2020, Chen et al. 2019). Single regression analysis is used to investigate the link between independent and dependent variables. In the context of land-change analysis, the independent variable may be a driver of LULC change, such as population increase, economic development or policy interventions, whereas the dependent variable could be a LULC type, such as forest cover, urbanisation or agriculture (Pravitasari et al. 2021, Etminani-Ghasrodashti–Hamidi 2019, Ghalehteimouri et al. 2023). Multiple regression analysis investigates the relationship between several independent factors and a single dependent variable. This strategy enables a more in-depth knowledge of the causes of land change and how they interact with one another. Multiple regression analysis, for example, may be used to determine the relative contributions of population increase, economic development and land-use policy to urbanisation (Allahviranloo–Aissaoui 2019, Sikos–Szendi 2022).

Changes in planning and policies are widespread in today's world due to the dynamic environment and population, influenced by socioeconomic factors. Evaluating and emphasizing various environmental resources like land, soil, water, and green ecosystems has led to the development of new alternative planning strategies and methods (Nijkamp et al. 2013, Ghalehteimouri et al. 2023). Land-use models are advantageous as they can capture the complex relationships between land use, socioeconomic factors, and environmental conditions. These models help assess the effectiveness of different approaches in achieving planning objectives at various levels of the planning system. For example, land-use models can be used to evaluate the impacts of policies on urban sprawl, transportation infrastructure, environmental conservation, and climate change adaptation (Koomen et al. 2011, Csizovszky–Buzási 2023). Changes in land use, such as urbanization and industrialization, often lead to natural habitat degradation, environmental degradation, and alterations in the hydrological cycle. Infrastructure development like roads can fragment habitats, contribute to air and noise pollution, and increase greenhouse gas emissions (Agudelo-Vera et al. 2011, Grießinger et al. 2022). Promoting sustainable land-use practices that balance economic growth with environmental conservation is essential to mitigate the negative impacts of human activities on the environment. This may involve supporting green infrastructure, reducing greenhouse gas emissions, and preserving biodiversity and natural ecosystems (Ghalehteimouri et al. 2024). Recognizing that the natural environment is a finite resource that must be managed responsibly to ensure its sustainability for future generations is crucial (Ersoy Mirici 2022, Kireyeva et al. 2023).

Because planning academics and scientists have different viewpoints and methodologies, understanding the role of planning in influencing land transformation is difficult. Planning academics understand that space is a social construct and that context and social variables influence land-use decisions are made. In contrast, land-change scientists look for causal connections between factors and consequences and tend to consider space as an objective entity that can be quantified and studied (Kim et al. 2020, Tellman et al. 2020). Addressing uncertainties is another area in which opinions diverge. Although land-use planners quantify and identify sources of uncertainty in land-cover estimates, planning experts recognise the inherent uncertainty in land-use decisions and expect future development to be open-ended (Hersperger et al. 2018, Ghalehteimouri et al. 2022). Because there is a lack of research bridging the two paradigms, planning and quantitative analyses of land change have not been integrated. This makes it more difficult to create planning techniques that can effectively direct land-use decisions towards sustainable outcomes (Mousavi et al. 2023). Therefore, a long-term evaluation based on comparison, made feasible by regression methodologies and approaches, is required to identify the weaknesses and strengths of land-use planning under various planning and policy frameworks in a country.

Selangor (regionalism) in the National Physical Planning context

Vision 2020 is a long-term national development strategy introduced by the Malaysian government in 1991 to transform Malaysia into a fully developed country by the year 2020. This strategy outlines the country's aspirations in various sectors, including economic development, social development, political development and environmental sustainability. The National Physical Plan (NPP) is a key component of Malaysia's development strategy, providing a framework for physical development and land-use management. The NPP aims to guide physical development and land-use management in Malaysia to ensure sustainability and balance. The NPP is directly linked to Vision 2020, as it provides a means to physically implement the goals of the development strategy. The NPP aims to support Vision 2020 by promoting sustainable development practices, enhancing the quality of life for Malaysians and promoting balanced regional development (Ghalehteimouri–Ros 2020, myplan 2023, Ministry of Housing and Local Government 2005).

The approval timeline for Malaysia's NPPs is as follows: NPP1 gained approval in 2005, followed by NPP2 in 2010 and NPP3 in 2015. These comprehensive plans extend their coverage across Malaysia, encompassing Peninsular Malaysia, Sabah, Sarawak and the Federal Territory of Labuan. Their planning horizon extends up to the year 2020. The NPPs serve as holistic frameworks that address various facets of physical development and land-use management. They encompass crucial areas such as land-use policies, regional planning and policies, transportation infrastructure, environmental preservation and fostering public participation. Notably, these plans prioritise sustainable development and the equitable growth of regions, aligning seamlessly with the core objectives of Vision 2020. The NPPs play a pivotal role in translating Vision 2020 into tangible physical outcomes. They are instrumental in ensuring that Malaysia's development remains sustainable, well-balanced and accessible to all Malaysians (myplan, 2023, Ministry of Housing and Local Government 2005, MOH 2023).

The first NPP (NPP1)

NPP in Malaysia was approved by the Cabinet and National Physical Planning Council (NPPC) in April 2005. It covers the entire country, including Peninsular Malaysia, Sabah and Sarawak, and its planning period is until 2020, with an implementation period of 2005–2020. The NPP provides a framework for physical development and land-use management in Malaysia to achieve sustainable development (myplan 2023, Ministry of Housing and Local Government 2005, MOH 2023). NPP concepts include promoting balanced regional development, optimising land use, promoting sustainable development practices and enhancing environmental quality. Its goals include ensuring social equity, economic growth and environmental sustainability. The NPP has several land use and regional planning policies, including the identification of growth centres, the establishment of development corridors and the protection of environmentally sensitive areas. The NPP also emphasises the importance of public participation and collaboration among government agencies and stakeholders in its implementation. In general, the NPP serves as a guide for physical development and land-use management in Malaysia to achieve sustainable development and improve the quality of life for Malaysians (myplan 2023, Ministry of Housing and Local Government 2005, MOH 2023).

NPP2

In Malaysia, the NPP series is integral to guiding the nation's physical development and land-use management. The most recent instalment, NPP3, builds upon its predecessor, NPP2, which received approval from both the Cabinet and the NPPC in August 2010. NPP3 covers Peninsular Malaysia, encompassing the planning horizon until 2020, with an active implementation period spanning from 2011 to 2015. NPP2 serves as a logical progression from NPP1, with a strong emphasis on fostering sustainable development, achieving balanced regional growth and enhancing the overall quality of life for Malaysians. The key principles of NPP2 include the promotion of sustainable development practices, the enhancement of transportation infrastructure and the judicious utilisation of land resources (myplan 2023, Ministry of Housing and Local Government 2010, MOH 2023).

The primary objectives of NPP2 are to drive economic growth, promote social equity and ensure environmental sustainability. These objectives are underpinned by a suite of land-use policies that involve the identification of development corridors and growth centres, optimisation of land and resource utilisation and safeguarding of environmentally fragile areas. NPP2 also places substantial emphasis on public participation and collaborative efforts between governmental bodies and stakeholders throughout its execution, underscoring its commitment to inclusivity and cooperative governance. NPP2 serves as a robust framework for steering physical development and land-use management in Malaysia. Its primary goal is to ensure that future development adheres to principles of sustainability and balance, making it a comprehensive blueprint for shaping Malaysia's physical development and land use, focusing on sustainable growth, regional equilibrium and enhancing the well-being of Malaysians (Ministry of Housing and Local Government 2010, MOH 2023).

NPP3

The Malaysian government approved NPP3 in 2015, with its jurisdiction spanning the entirety of the nation (Peninsular Malaysia, Sabah, Sarawak and the Federal Territory of Labuan). It extends its planning horizon until the year 2020, with an active implementation phase from 2016 to 2020. The core objectives of NPP3 revolve around realising long-term national aspirations and addressing forthcoming challenges, which include the pursuit of sustainable development, the promotion of balanced regional growth and the enhancement of Malaysians' quality of life. These objectives are underscored by principles such as promoting sustainable development practices, enhancing transportation infrastructure and optimising land use (myplan, 2023, Ministry of Housing and Local Government 2015, MOH 2023).

NPP3 has set forth a multifaceted approach to achieve its goals of stimulating economic growth, ensuring social equity and bolstering environmental sustainability. Its land-use policies involve the identification of development corridors, growth centres and the protection of designated areas. Notably, the plan emphasises the pivotal role of public participation and collaborative efforts among government entities and stakeholders during its execution. Furthermore, NPP3 introduces innovative strategies such as the National Key Economic Areas and the Economic Transformation Programme (ETP 2010) to propel Malaysia's economic growth and competitiveness. It also aligns with the sustainable development goals established by the United Nations in 2015. NPP3 represents a comprehensive framework for steering physical development and land-use management in Malaysia, with a central focus on sustainability, regional equilibrium and the improvement of Malaysians' quality of life (Samsi et al. 2020, Abd Rashid et al. 2020, Ministry of Housing and Local Government 2010).

In this study, we focused on Selangor State, a prominent region within Malaysia where the sprawling Kuala Lumpur metropolitan area is located, housing the largest forest reserve in the region. The urgency of preserving this delicate environment becomes apparent, particularly considering the substantial urbanisation witnessed in recent decades. Human activities, such as agricultural expansion, oil palm plantations and oil palm industries, have exerted substantial pressures on the local environment. Despite the implementation of various policies and initiatives, the depletion of vital natural resources, notably forest trees, continues unabated. In this regard, the NPP emerges as an effective and commendable framework for land-use management and the preservation of natural resources, particularly the conservation of forest trees, because of its robust emphasis on spatial planning. A simulation map for LULC in 2020 was generated in this study, and a comprehensive assessment was conducted, comparing shifts in each land-use category. The primary objectives include evaluating the impact of human activities, notably agricultural development, oil palm plantations and oil palm industries, on the environment of Selangor State, Malaysia, with a specific focus on the conservation of forest trees. Furthermore, the study aims to assess the effectiveness of the NPP as a strategic framework for land-use management and the conservation of natural resources, with a strong emphasis on spatial planning. In addition, ecosystem service values from 1990 to 2020 were quantified using satellite data, providing invaluable insights into the dynamics of the region's environment (Samsi et al. 2020, Abd Rashid et al. 2020, Ministry of Housing and Local Government 2010).

Methods and materials

Study area

Selangor is a state located on the west coast of Peninsular Malaysia. It is the most developed and populous state in Malaysia, with a total area of approximately 8,000 square kilometres and a population of over 6 million people. Selangor is known for its urban centres, including the capital city of Shah Alam and the major metropolitan area of Klang Valley, which includes the cities of Kuala Lumpur and Petaling Jaya. Selangor is also home to several important industrial and commercial centres, including Port Klang, the largest port in Malaysia and the Multimedia Super Corridor, a government-led initiative to promote the growth of technology-based industries. In addition to its urban and industrial areas, Selangor also has a substantial amount of natural resources, including forests, rivers and coastal areas, which are important for biodiversity conservation, water management and recreation. Given its diverse landscape and important economic and ecological roles, Selangor is a critical area for research and study in various fields, including urban planning and environmental and social sciences. Research in Selangor may focus on issues such as urbanisation, land-use change, water management and conservation, among others (see in Appendix, Figure A1). (Selangor State Government 2023, Environmental Quality Report 2019).

Satellite data analysis

The data collected for this study spans various periods and originates from different satellites, each equipped with distinct bands. Comprehensive correction processes, including atmospheric and geometric corrections, were applied to ensure data accuracy. Subsequent accuracy assessments were conducted before using the data. Landsat time series, comprising images from 1990, 2005, 2010, 2015 and 2020, are important for monitoring long-term changes in land cover and environmental variables, enabling the detection of shifts in land use, vegetation, water resources and natural factors, offering insights into the impacts of human activity, natural disasters and climate change. Image processing techniques, including data pre-processing, image classification and change detection analysis, along with statistical models and algorithms, facilitate the identification and quantification of land-cover changes over time. In summary, the Landsat time series serves as an indispensable tool for tracking environmental changes, supporting environmental management, land-use planning and the conservation of natural resources.

Supervised vector machine

In remote sensing applications, supervised vector machine (SVM) is a machine learning method that may be used for image categorisation and is a supervised learning method used for classification tasks. SVM has been used to classify different classes of land cover, map different types of forests, identify urban areas and identify crops using remote sensing data (Sheykhmousa et al. 2020).

The SVM method finds the optimum hyperplane in the feature space that divides the various classes and selects it to increase the margin between these classes. Preprocessing the satellite image data is the initial step in using SVM for satellite image classification. Methods for image improvement, radiometric correction and atmospheric correction may all be used. The last step is to choose a set of training samples that correspond to various types of land cover in the image. The appropriate land-cover class is marked on these samples (Oommen et al. 2008).

Regression

Single regression

This study uses both single and multiple linear regression models in conjunction with remote sensing and geograpical information systems (GIS) techniques to detect LULC changes within a specified geographical area over a 30-year timeframe (Potapov et al. 2020). Single and multiple regression analyses are valuable tools for assessing the significance of LULC changes. Unlike simple trend lines or tabular descriptions, they provide precise quantitative relationships, handling multiple variables and complex interactions. These analyses offer statistical significance assessments, enable prediction of future LULC changes and allow control for confounding factors. Multiple regression further aids in identifying the most influential predictors. Overall, they provide a more comprehensive, precise and statistically robust understanding of the factors driving LULC changes (Tran et al. 2017, Darvishi et al. 2020).

Change detection objective: The primary objective of this change detection process is to gain comprehensive insights into alterations within various land-use categories spanning three decades. This involves identifying instances of both increased and decreased land-use types, as well as transformations from one land-use type to another (MohanRajan et al. 2020).

Significance of change detection: Change detection is a powerful tool for revealing the pace and magnitude of transformations occurring within the study area. It provides valuable insights into LULC dynamics, highlighting regions that have experienced substantial changes, whether positive or negative, in terms of land-use patterns.

Simple linear regression: The formula for simple linear regression is expressed as follows:

$$Y = \beta 0 + \beta 1 \times X + \varepsilon \quad (1)$$

where: Y is the dependent variable; X is the independent variable or predictor variable; β0 is the intercept; β1 is the coefficient or slope associated with the predictor variable; ε is the error term or residual.

This formula represents a linear relationship between the dependent variable Y and a single predictor variable X. Simple regression estimates the values of coefficients β0 and β1 that minimise the sum of squared errors between predicted and actual values of Y (Cohen et al. 2003, Foody 2003). It assumes a constant linear effect of X on Y for all X values. Simple regression is commonly used to model and understand the relationship between two variables, enabling predictions and pattern identification (Overmars–Verburg 2006).

Multiple linear regression: The formula for multiple regression involving p predictor variables, is expressed as follows:

$$Y = \beta 0 + \beta 1X1 + \beta 2X2 + ... + \beta p \times Xp + \varepsilon \quad (2)$$

where: Y is the dependent variable; X1, X2,..., Xp are the predictor variables; β0 is the intercept; β1, β2,..., βp are the coefficients or slopes associated with each predictor variable; ε is the error term or residual (Rasskazova–Sinits 2019 Dunn–Smyth 2018).

This formula depicts a linear relationship between the dependent variable Y and multiple predictor variables X1, X2,..., Xp. Multiple regression estimates coefficients β0, β1, β2,..., βp that minimise the sum of squared errors between predicted and actual values of Y (Apat et al. 2022, Movaghar 2022). The application of these regression models, in conjunction with remote sensing and GIS, facilitates a comprehensive analysis of LULC changes, aiding in our understanding of the complex dynamics within the study area.

Results and analysis

Single regression

LULC between 1990 and (2005, 2010, 2015 and 2020)

Regression analysis revealed that the period with the most substantial LULC transformations in Selangor is from 1990 to 2020. The regression equations underscore a positive relationship between LULC in 1990 and that of the subsequent years in Selangor, as evidenced by the positive slope coefficients. Furthermore, the coefficient of determination (r-squared) demonstrates a moderate to strong positive correlation between LULC in 1990 and LULC in Selangor in the years that followed, ranging from 0.618 to 0.698.

Nonetheless, it is important to note that the r-squared value varies between 38.24% and 48.69%, indicating that the LULC changes cannot be solely attributed to the conditions in 1990. Other influential factors such as population growth, economic development and urbanisation may also have played pivotal roles in shaping these LULC changes. Notably, the most pronounced and noteworthy LULC shifts are observed during the timeframe 1990–2020 (see in Appendix, Figure A2).

LULC between 2005 and (2010, 2015 and 2020)

The regression equations underscore a positive association between LULC in 2005 and that of the subsequent years (2010, 2015 and 2020) in Selangor. This is evident through the presence of positive slope coefficients in the equations. Furthermore, when examining the r-squared, we observe a noteworthy moderate to strong positive correlation between LULC in 2005 and LULC patterns in Selangor during subsequent years (range: 0.694–0.730). However, it is crucial to recognise that the r-squared fluctuates between 48.14% and 53.26%. This variability indicates that changes in LULC cannot be solely attributed to changes in LULC during 2005. Other influential factors, such as population growth, economic development and urbanisation, may also have played pivotal roles in driving these LULC changes. For a visual representation of these findings, please refer to Figure A3 (see in Appendix).

LULC single regression between 2010 and (2015 and 2020)

In both single regression models, we observe a positive correlation between LULC changes in Selangor over time. This implies that higher values of LULC change correspond to higher values of Y, representing LULC changes in 2015 or 2020. The r-squared for both models falls within the moderate range, indicating that approximately 50%–53% of the variability in land use and land-cover changes in Selangor can be accounted for by the predictor variable, specifically LULC changes in 2010.

The standard error of estimate (SEE) values for both models are quite similar, with slightly elevated values for the 2010–2020 model. This suggests that the model's predictions may carry an approximate margin of error of +/−1.2–1.3 units. Consequently, both models exhibit analogous trends and associations, with the 2010–2020 model marginally explaining a greater portion of the variation in LULC changes in Selangor than the 2010–2015 model. Nevertheless, the disparities between the two models remain relatively minor. As a result, both models offer valuable insights into understanding the intricate relationship between LULC changes in Selangor across different time frames (refer to Figure A4, see in Appendix).

LULC single regression between 2015 and 2020

The single regression model, represented by the equation $Y = 0.333085 + 0.797933X$, exhibits a moderate positive correlation between LULC changes in Selangor from 2015 to 2020. This correlation is substantiated by an r-squared value of 59.98%, signifying that approximately 59.98% of variations in the Y variable (pertaining to LULC changes in Selangor in 2020) can be elucidated by variations in the X variable (pertaining to LULC changes in Selangor in 2015). In this context, it is noteworthy that the standard deviation of X is 1.744148, whereas that of Y is 1.797064. The SEE, serving as an approximation of the typical deviation between the observed Y values and their predicted counterparts, is calculated to be 1.136913. In addition, the standard error of the Beta coefficient is 0.000145.

Further emphasising the statistical significance of these findings, the t-value for the Beta coefficient is notably high at 5,518.7335576, indicating its robust statistical significance. Moreover, the t-value for Beta, which is not equal to 1, stands at −1,397.550411, underscoring the substantial disparity between the Beta coefficient and 1. With a substantial sample size (n) of 20,325,144 and apparent degrees of freedom (df) equal to 20,325,142; this regression model suggests a discernible positive relationship between LULC changes in Selangor from 2015 to 2020. However, additional factors may also influence this relationship. For a visual representation of these findings, please refer to Figure A5 (see in Appendix).

Based on the data analysis, it becomes evident that the period spanning from 1990 to 2020 stands out as the epoch exhibiting the most substantial LULC changes in Selangor. The regression equations and correlation coefficients portray a prevailing positive trend in LULC, implying an increase in land utilisation for diverse purposes over time. However, delving deeper into the underlying factors driving these LULC changes and their repercussions on both the environment and society warrants further scrutiny.

The regression analysis underscores that the period from 1990 to 2020 holds particular significance, with a coefficient of 0.703349 and an r-squared of 48.69%. This indicates that the interplay between LULC changes in Selangor during this timeframe exerts a more pronounced influence compared with the other analysed periods. Notably, the correlation coefficient (r) exhibits an ascending trend, progressing from 2010–2015 to 2010–2020, signalling an increasingly robust relationship between LULC changes in Selangor over time. Moreover, the r-squared in single regression demonstrates a corresponding ascent from 2010–2015 to 2010–2020, suggesting that the regression model can elucidate a larger proportion of the variance in LULC changes in the latter period.

When considering the single regression analysis results for the three distinct periods, a consistent positive correlation between LULC changes in Selangor over time emerges. The r increases from 0.715336 in 2010–2015 to 0.726239 in 2010–2020 and further surges to 0.799767 in 2015–2020. This steady progression indicates a strengthening linear relationship between these two variables, particularly in the later period. Concurrently, the r-squared follows suit, amplifying from 51.17% in 2010–2015 to 52.74% in 2010–2020 and surging to 59.98% in 2015–2020. This signifies that the variance in LULC changes in Selangor can be expounded by the linear relationship between these variables to a greater extent in the later period. Although the standard deviation of X (pertaining to LULC changes in the initial year) remains constant across all periods, reflecting comparable variability in LULC changes in 2010, the standard deviation of Y (related to LULC changes in the subsequent year) escalates from 1.744148 in 2010–2015 to 1.797064 in both 2010–2020 and 2015–2020. This elevation underscores an amplified variability in LULC changes in Selangor over time.

Furthermore, the SEE displays a pattern of increase from 1.218777 in 2010–2015 to 1.235378 in 2010–2020, followed by a decrease to 1.136913 in 2015–2020. This suggests an enhanced fit of the regression line to the data in the latter period, indicating a more precise predictive capability. Thus, the findings strongly indicate a positive and progressively strengthening linear relationship between LULC changes in Selangor over time. This evolving relationship has become more robust and predictable in the later period of the analysis.

Multiple regression results

Multiple regression analysis yields compelling insights into the relationship between LULC changes in Selangor from 1990 to 2020. The regression equation affirms a statistically substantial and positive linear connection between these variables during this timeframe. Notably, the adjusted r-squared value of 0.554965 indicates that the model effectively accounts for 55.5% of the variance observed in the dataset. The ANOVA regression table corroborates the significance of the regression model, with an F-statistic of 6,336,445.500000 and a p-value lower than 0.05. This outcome signifies that at least one of the independent variables considerably predicts the dependent variable, strengthening the model's credibility.

Examining the individual regression coefficients, it is evident that all independent variables serve as substantial predictors of the dependent variable. The coefficient values further reveal a consistent upwards trend in LULC changes in Selangor over time, with the most pronounced shift occurring between 2020 and earlier years. In short, the multiple regression analysis results strongly support the existence of a positive and substantial trend in LULC changes in Selangor from 1990 to 2020. However, it is essential to exercise caution when interpreting these results, considering the assumptions and limitations inherent in both the model and the data employed.

Regression equation: LULCselangor_1990_new = 0.095332 + 0.194411 × LULCselangor_2005_new + 0.086588 × LULCselangor_2010_new + 0.202385 × LULCselangor_2015_new + 0.291003 × LULCselangor_2020_new

Regression statistics:

- Apparent R = 0.744960
- Apparent R squared = 0.554965
- Adjusted R = 0.744960
- Adjusted R squared = 0.554965
- F (420,325,139) = 6,336,445.500000

Table 1

ANOVA regression table

Source	Apparent degrees of freedom	Sum of squares	Mean square
Regression	4	31,283,123.52	7,820,781
Residual	20,325,139	25,086,377.94	1.23
Total	20,325,143	56,369,501.45	

Table 2

Individual regression coefficients

	Coefficient	t_test (20,325,139)
Intercept	0.095332	302.864502
LULCselangor_2005_new	0.194411	853.824646
LULCselangor_2010_new	0.086588	406.817719
LULCselangor_2015_new	0.202385	817.564453
LULCselangor_2020_new	0.291003	1,183.012085

The regression equation serves as a vital tool for illustrating the connection between the 1990 LULC (the dependent variable) and the 2005, 2010, 2015 and 2020 LULC (the independent variables) in Selangor. In this equation, the coefficients assigned to each independent variable elucidate the strength and direction of their respective relationships with the dependent variable. Notably, the adjusted r-squared value of 0.554965 signifies that the independent variables collectively account for 55.5% of the variability observed in the 1990 LULC in Selangor. The F-statistic, standing at 6,336,445.500000, accompanied by its associated p-value, affirms the overall statistical significance of the model.

The ANOVA regression table helps to break down the contributions of the regression model and the residuals to the total variance in the dependent variable. In this context, the regression sum of squares (31,283,123.52) indicates the extent to which the model explains the variability in the 1990 LULC in Selangor, whereas the residual sum of squares (25,086,377.94) represents the portion of variability that remains unexplained by the model. Examining the individual regression coefficients further reveals the strength and direction of the relationship between each independent and dependent variable. It is important to note that all coefficients are statistically substantial, which means that each independent variable makes a substantial contribution to the model. Finally, the intercept (0.095332) represents the expected 1990 LULC value in Selangor when all independent variables have a value of zero.

Transformation of LULC at Selangor (regional scale) under the NPP implementation

After conducting an in-depth analysis of satellite data and comprehensive mapping, a clear narrative of Selangor's evolution emerged. In 1990, Selangor experienced gradual growth, mainly within the Klang Valley. This expansion was primarily due to the strategic significance of Port Klang and Kuala Lumpur as the capital city. The population grew rapidly to 2,431,200 during this period. However, a series of changes in socioeconomic policies and rapid industrialisation led to a substantial transformation in Selangor's population. By 2005, the population had grown to 4,849,600. During this period, there was a noticeable shift towards urban industrialisation in the Klang Valley and Kuala Lumpur. Agricultural development also saw substantial growth across the central, northern and southern regions of Selangor, driven by international demand for palm oil and rubber. The growth was further amplified by the emergence of new urban and town areas, such as Putra Jaya and Cyber Jaya.

By 2010, Selangor's population had surged to 5,502,100; prompting the implementation of NPP2. This strategic move aimed to mitigate urbanisation in the middle regions of Selangor, where agricultural lands, rubber estates and oil palm plantations faced increasing pressure. However, in 2015, the initiation of NPP3 coincided with the finalisation of Vision 2020 in Malaysia. Unfortunately, despite its ambitious goals, this plan grappled with environmental, political and social challenges. The population continued to grow, reaching 6,178,000; with discernible repercussions on the landscape and ecosystem of Selangor (Department of Statistics 2023), (refer to Figure A6 [see in Appendix] for visual representation).

Despite the pervasive influence of political factors in shaping Malaysia's plans and policies, the NPP's implementation stood out for its unwavering commitment to spatial planning, which played a crucial role in controlling widespread environmental degradation. A detailed analysis of the results from both single and multiple regression analyses provides valuable insights. It is discerned that the correlation between 1990 and the period preceding NPP1's inception in 2005 exhibited a relatively weaker connection than the correlation observed between NPP1 in 2005 and NPP2 in 2010. This shift highlights the effectiveness of NPP in influencing LULC dynamics. Similarly, the correlation between NPP3 in 2015 and the culmination of NPP3 in 2020 emerged as notably stronger than the correlation before the advent of NPP1. This trend reaffirms the transformative impact of NPP in managing and regulating the expansion of Malaysia, particularly in Selangor. Importantly, NPP3 particularly emphasised environmental concerns, despite encountering certain adverse effects stemming from LULC changes due to national and international policies. This strategic focus culminated in the highest correlation between the initiation and conclusion of NPP3, registering an impressive 59.98%. This robust correlation underscores the influence of NPP3 in shaping Selangor's approach to growth and development, demonstrating its ability to navigate challenges more effectively. It is worth noting that while these policies proved effective in controlling growth, they were less successful in mitigating adverse environmental consequences. This is substantiated by the positive yet relatively modest correlations observed between NPP1 and NPP2 and between NPP2 and NPP3. Attention to environmental concerns within the framework of NPP3 likely played a role in overcoming these challenges, ultimately yielding a more robust association between its initiation and conclusion (refer to Figure A7 [see in Appendix] for visual representation).

Henceforth, the implementation of the NPP has emerged as an indispensable instrument in orchestrating and regulating Malaysia's growth and development. Notably, the pronounced focus of NPP3 on environmental concerns has considerably augmented the relationship between the inception and culmination of this policy. Despite these strides, there exists room for further enhancement in managing the adverse repercussions of rapid growth and development. Future policy endeavours should sustain an unwavering commitment to fostering sustainable development.

The NPP of Malaysia has traversed a journey marked by successive revisions, each iteration building upon its predecessor while seamlessly incorporating novel developments and confronting contemporary challenges. Key differentiators between NPP1 and NPP3, contributing to a tempered pace of development, include the following:

1. **Coverage expansion:** NPP1's purview was confined to Peninsular Malaysia, whereas NPP3 boldly extended its ambit to encompass Sabah and the Federal Territory of Labuan.

2. **Climate change integration:** NPP3 embodies a heightened emphasis on climate change, necessitating proactive measures to mitigate its impacts. This inclusive approach encompasses strategies for addressing concerns such as rising sea levels, escalating temperatures and the intensification of extreme weather events.
3. **Sustainable development emphasis:** NPP3 accentuates the imperative of sustainable development, deftly balancing economic growth with the imperatives of environmental preservation and social equity. It ardently advocates the promotion of green infrastructure, adoption of renewable energy sources and embrace of eco-conscious building practices.
4. **Connectivity amplification:** Recognising the importance of connectivity, NPP3 accentuates the imperative of bolstering transport infrastructure and connectivity, both intra-regional and inter-regional. This vision champions the development of integrated transport systems and the harnessing of technology to fortify connectivity.
5. **Cross-border engagement:** NPP3 takes an overt stance on cross-border issues, highlighting the necessity for heightened cooperation and coordination between Malaysia and its neighbouring nations.
6. **Disaster preparedness:** The policy framework of NPP3 incorporates provisions to elevate disaster management and preparedness, including the establishment of early warning systems and active emergency response mechanisms.

These elucidate only a fraction of the pivotal distinctions between NPP1 and NPP3. In summary, NPP3 embodies a holistic and integrative approach to physical development and land-use management, deftly attuned to the evolving needs and challenges that Malaysia grapples with in the 21st century.

Discussion

In the realm of studies on LULC change, numerous investigations have been conducted to understand the dynamics of these transformations over time (Memarian et al. 2012, Nourqolipour et al. 2015, Muhammed et al. 2022). However, what sets this study apart is its unique focus on assessing LULC changes concerning the NPP in Malaysia. Although previous research has delved into various aspects of LULC, the influence of critical policy frameworks such as the NPP has seldom been rigorously evaluated. The NPP is a pivotal national-level planning tool, and this study provides a comparative analysis of its application, shedding light on its successes and areas where it falls short in shaping LULC changes. This approach adds a novel dimension to the existing body of research, offering valuable insights into the effectiveness of the NPP in managing land use and preserving natural resources.

One noteworthy aspect of this study is the use of both single and multiple regression analyses to dissect the relationship between LULC changes and the implementation of the NPP. This methodological choice enables a nuanced exploration of the factors driving LULC changes over time. Although trend analyses and tabular descriptions can certainly highlight substantial shifts in land use, regression models provide a deeper understanding of the underlying drivers and the extent to which various predictors contribute to these changes. By applying these statistical techniques, this study reveals the intricate dynamics of LULC changes in Selangor, offering policymakers and land-use planners a valuable toolkit for informed decision-making.

Furthermore, this research contributes to the broader discourse on sustainable land-use management. By evaluating the impact of the NPP, which places strong emphasis on spatial planning, it offers a framework for policymakers to assess and enhance the effectiveness of such planning tools in achieving sustainable development goals. In an era marked by increasing urbanisation, environmental challenges and the need for responsible land use, the findings of this study underscore the importance of robust policies and their successful implementation. Ultimately, this research bridges the gap between policy and practice, paving the way for more informed, effective and sustainable land-use planning and management strategies.

Conclusion

In pursuit of the research objectives, we initially leveraged pre-NPP installation data to underscore the substantial impact of human activities on land use and land-cover changes in Selangor. Subsequently, we segmented the data into distinct periods, including the NPP1 implementation phase (2005–2010), the NPP2 implementation phase (2010–2015) and the year 2020, coinciding with the Vision 2020 target. This study unveiled a marked decline in ecosystem services within Selangor, attributable to urbanisation, population expansion and industrialisation in the region. These findings emphasise the crucial role of effective planning and policy implementation in safeguarding the region's precious natural resources. In comparing the two analytical models used in this study, the multiple regression model offers a more comprehensive understanding of the intricate relationship underpinning LULC changes in Selangor over time. This model encompasses multiple predictors, each potentially influencing the dependent variable. Conversely, the single regression model, characterised by its simplicity and interpretability, relies on a single predictor. Notably, both models converge in revealing a positive correlation between LULC changes in Selangor over time, thereby providing invaluable insights into the contributing factors. Nevertheless, a substantial distinction emerges in terms of the temporal correlations.

Specifically, the correlation between 1990 and 2005, marking the onset of NPP1, is notably weaker than that observed between the start of NPP3 in 2015 and the subsequent five-year period leading to 2020. The multiple regression analysis results affirm the statistical significance of all predictors (LULC Selangor in 2005, 2010, 2015 and 2020) through their respective regression coefficients, signifying their contribution to elucidating the LULC variations in 1990. Furthermore, the adjusted r-squared value, 0.554965, signifies the model's competence in elucidating 55.5% of the variations observed in LULC in 1990. This underscores the model's robustness in predicting LULC in 1990 based on LULC data from the years 2005, 2010, 2015 and 2020. Conversely, the single regression analysis underscores a compelling positive relationship between LULC in 2015 and LULC in 2020. The impressive r-squared value of 59.98% attests to the single predictor's capability to elucidate nearly 60% of the variations witnessed in LULC in 2020. This finding emphasises the efficacy of LULC data from 2015 as a potent predictor of LULC in 2020, rendering it a valuable tool for forecasting future LULC changes. In summary, the outcomes derived from both the multiple and single regression analyses offer profound insights into the intricate relationship governing LULC at different periods. The multiple regression model emerges as a robust tool for predicting LULC in 1990 based on LULC data from 2005, 2010, 2015 and 2020. Moreover, the single regression analysis shows that LULC data from 2015 is a potent predictor of LULC in 2020. These findings will guide land-use planning and management endeavours in Selangor, Malaysia towards a more sustainable future.

Appendix

Figure A1

Study area

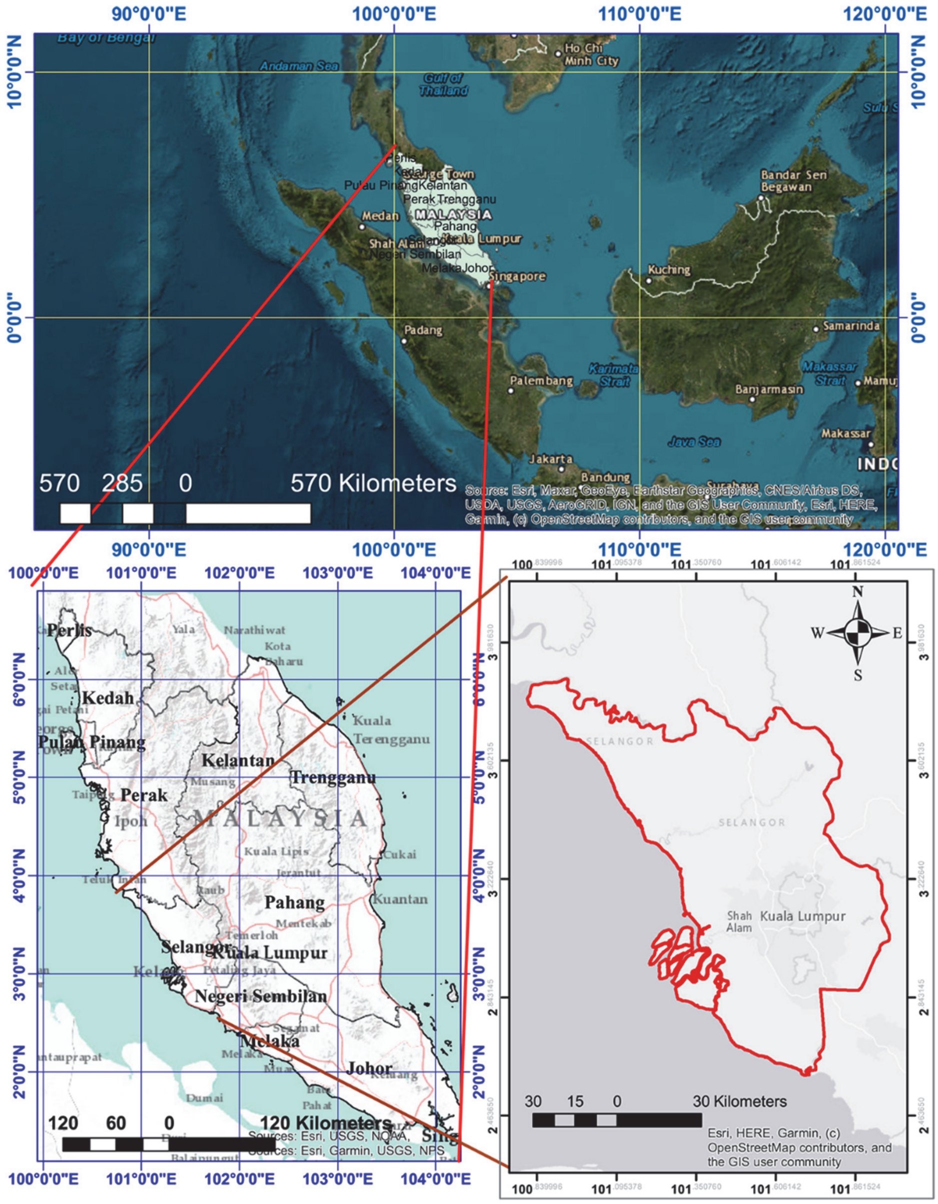
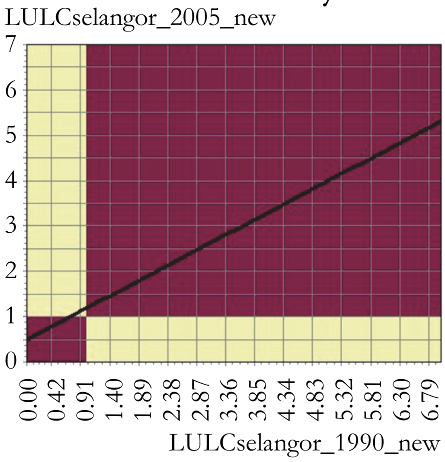


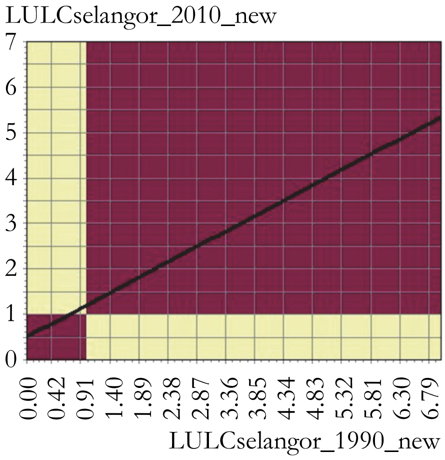
Figure A2

LULC analysis based on the 1990 data collection



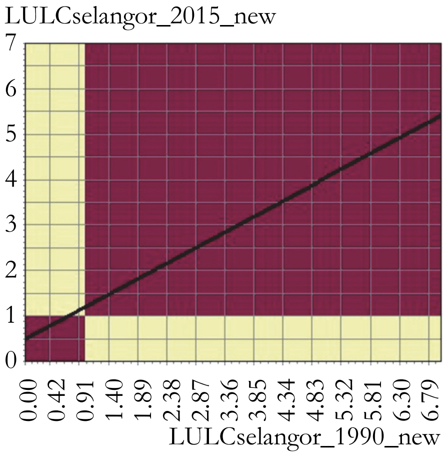
Y = 0.493220 + 0.687667X r = 0.653413

Coefficient of determination = 42.69%
Standard deviation of X = 1.665349
Standard deviation of Y = 1.752650
Standard error of estimate = 1.326759
Standard error of Beta = 0.000177
t-statistics for r or Beta = 3,891.419567
t-statistics for Beta <> 1 = –1,767.455958
Sample size (n) = 20,325,144
Apparent df = 20,325,142



Y = 0.504290 + 0.690890X r = 0.618379

Coefficient of determination = 38.24%
Standard deviation of X = 1.665349
Standard deviation of Y = 1.860628
Standard error of estimate = 1.462231
Standard error of Beta = 0.000195
t-statistics for r or Beta = 3,547.440838
t-statistics for Beta <> 1 = –1,587.153374
Sample size (n) = 20,325,144
Apparent df = 20,325,142

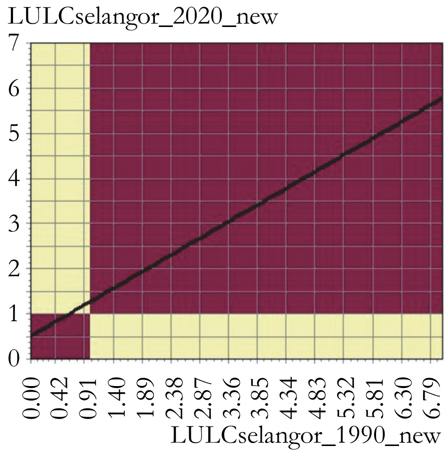


Y = 0.481637 + 0.703349X r = 0.671572

Coefficient of determination = 45.10%
Standard deviation of X = 1.665349
Standard deviation of Y = 1.744148
Standard error of estimate = 1.292308
Standard error of Beta = 0.000172
t-statistics for r or Beta = 4,086.266854
t-statistics for Beta <> 1 = –1,723.464207
Sample size (n) = 20,325,144
Apparent df = 20,325,142

(Figure continued on the next page.)

(Continued.)

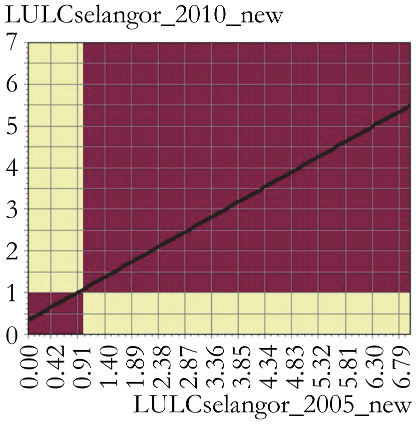


$Y = 0.510264 + 0.752933X$ $r = 0.697747$

Coefficient of determination = 48.69%
Standard deviation of X = 1.665349
Standard deviation of Y = 1.797064
Standard error of estimate = 1.287317
Standard error of Beta = 0.000171
t-statistics for r or Beta = 4,391.294161
t-statistics for Beta <> 1 = –1,440.960037
Sample size (n) = 20,325,144
Apparent df = 20,325,142

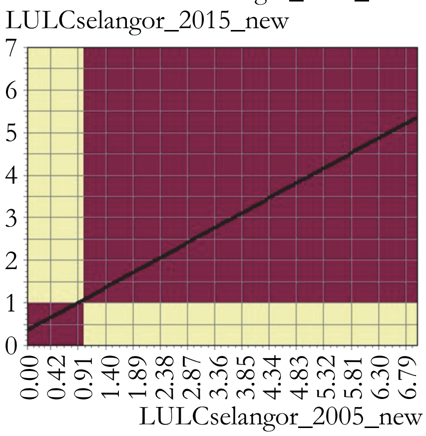
Figure A3

LULC analysis based on the 2005 (NPP1) data collection



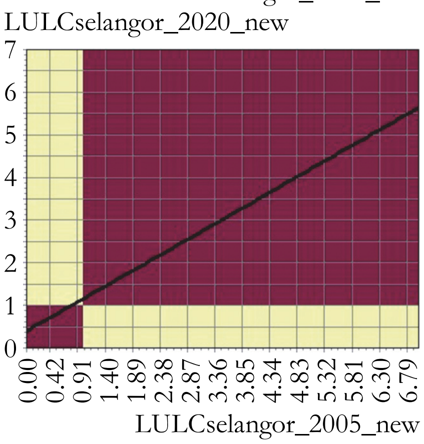
Y = 0.340191 + 0.736588X r = 0.693841

Coefficient of determination	= 48.14%
Standard deviation of X	= 1.752650
Standard deviation of Y	= 1.860628
Standard error of estimate	= 1.339891
Standard error of Beta	= 0.000170
t-statistics for r or Beta	= 4,343.773273
t-statistics for Beta <> 1	= –1,553.383454
Sample size (n)	= 20,325,144
Apparent df	= 20,325,142



Y = 0.356384 + 0.716053X r = 0.719544

Coefficient of determination	= 51.77%
Standard deviation of X	= 1.752650
Standard deviation of Y	= 1.744148
Standard error of estimate	= 1.211219
Standard error of Beta	= 0.000153
t-statistics for r or Beta	= 4,671.266658
t-statistics for Beta <> 1	= –1,852.364246
Sample size (n)	= 20,325,144
Apparent df	= 20,325,142

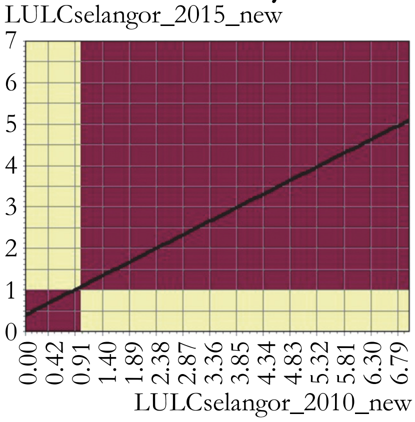


Y = 0.398722 + 0.748299X r = 0.729805

Coefficient of determination	= 53.26%
Standard deviation of X	= 1.752650
Standard deviation of Y	= 1.797064
Standard error of estimate	= 1.228572
Standard error of Beta	= 0.000155
t-statistics for r or Beta	= 4,812.675749
t-statistics for Beta <> 1	= –1,618.809980
Sample size (n)	= 20,325,144
Apparent df	= 20,325,142

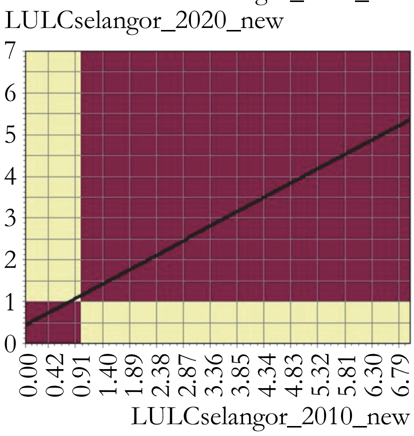
Figure A4

LULC analysis based on the 2010 (NPP2) data collection



Y = 0.402872 + 0.670554X r = 0.715336

Coefficient of determination	= 51.17%
Standard deviation of X	= 1.860628
Standard deviation of Y	= 1.744148
Standard error of estimate	= 1.218777
Standard error of Beta	= 0.000145
t-statistics for r or Beta	= 4,615.151853
t-statistics for Beta <> 1	= –2,267.442346
Sample size (n)	= 20,325,144
Apparent df	= 20,325,142

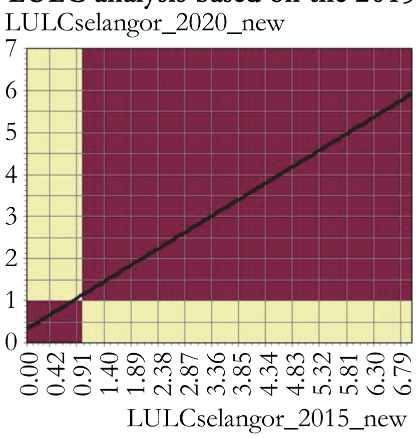


Y = 0.446456 + 0.701428X r = 0.726239

Coefficient of determination	= 52.74%
Standard deviation of X	= 1.860628
Standard deviation of Y	= 1.797064
Standard error of estimate	= 1.235378
Standard error of Beta	= 0.000147
t-statistics for r or Beta	= 4,762.772435
t-statistics for Beta <> 1	= –2,027.331659
Sample size (n)	= 20,325,144
Apparent df	= 20,325,142

Figure A5

LULC analysis based on the 2015 (NPP3) and the Vision 2020 data collection



Y = 0.333085 + 0.797933X r = 0.774438

Coefficient of determination	= 59.98%
Standard deviation of X	= 1.744148
Standard deviation of Y	= 1.797064
Standard error of estimate	= 1.136913
Standard error of Beta	= 0.000145
t-statistics for r or Beta	= 5,518.733576
t-statistics for Beta <> 1	= –1,397.550411
Sample size (n)	= 20,325,144
Apparent df	= 20,325,142

Figure A6

LULC calibration before the NPP implementation and the NPP3

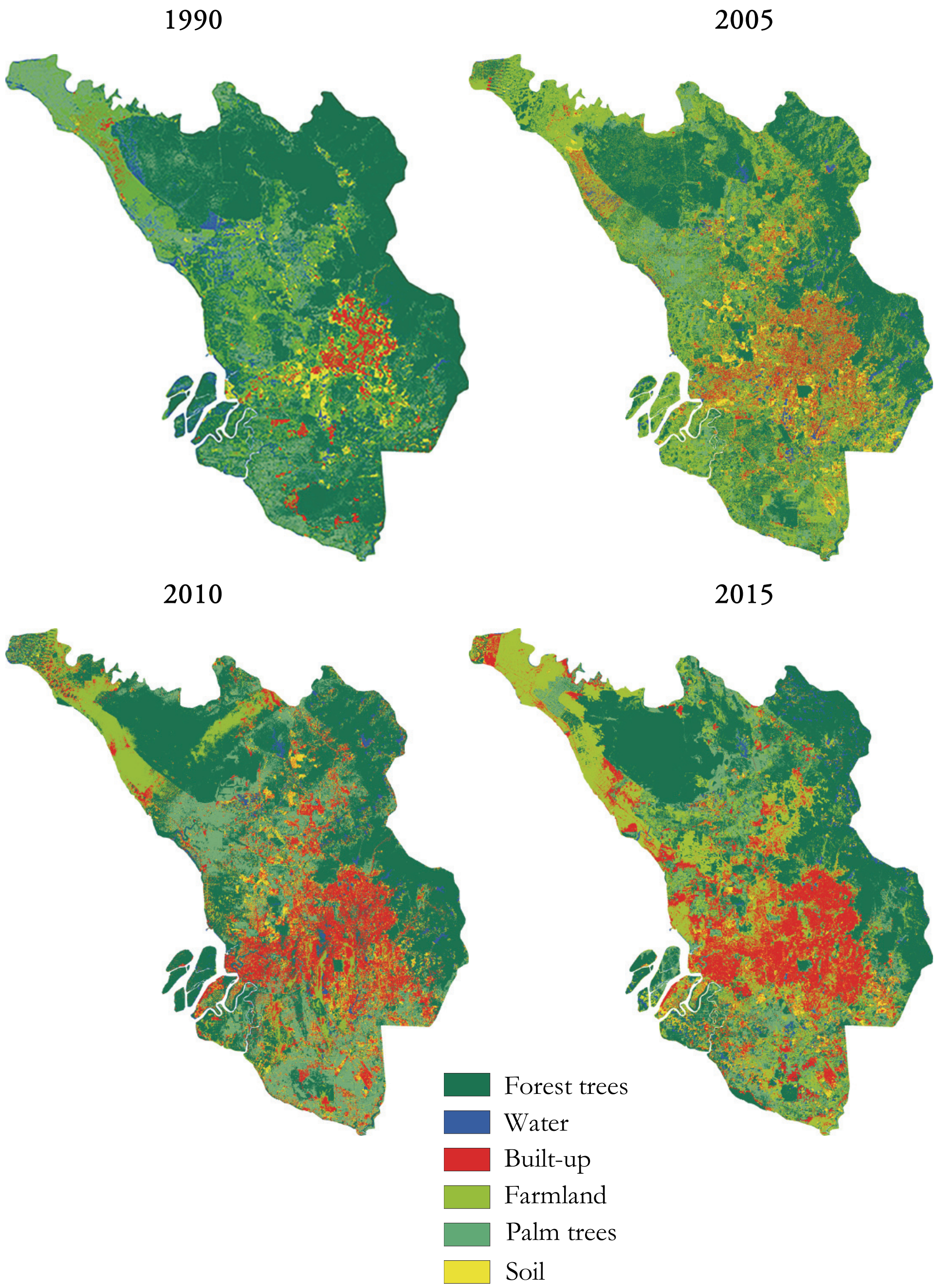
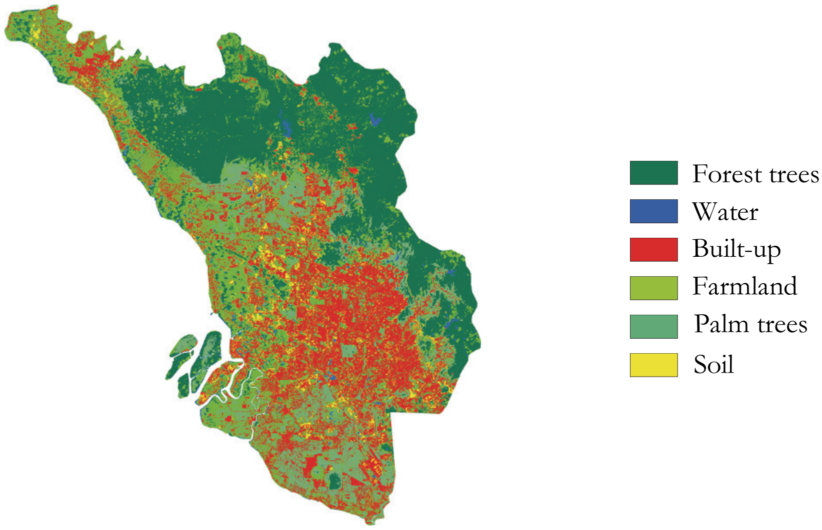


Figure A7

Vision 2020



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