# EXPLORING LAND USE DYNAMICS AND IMPACT OF PLANNING SCENARIOS WITH LAND USE SIMULATION MODELS: A CASE STUDY OF THE MOLUSCE LAND USE MODEL TO TRINCOMALEE, SRI LANKA

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**Abstract:** Land use simulation models are increasingly utilized to explore various land use planning scenarios. However, in Sri Lanka, the setup and calibration of such models are often challenged by limited data availability and the complexities of the calibration process. This study presents a practical application of the MOLUSCE land use simulation model, focusing on Trincomalee as the case study region. The model incorporates four primary land use types and nine spatial variables as key determinants in shaping land use patterns. The initial calibration of the model achieved a satisfactory kappa statistic, indicating its adequacy for scenario testing. This research offers a comprehensive overview of anticipated land use changes under different planning scenarios, providing valuable insights for effective land use management in the region.

**Keywords:** *Land use, simulation, planning, scenarios,* MOLUSCE

## 1. Introduction

Over the years urban simulation models have been developed using many approaches, to explore the mentioned complexities associated with land uses. Models are simplifications of reality – theoretical abstractions that represent systems in such a way that essential features crucial to the theory and its application are identified and highlighted. Land use simulation models are considered important tools for urban and regional planning with its ability to forecast the outcomes of different planning scenarios and support informed decision-making. Such models provide urban planners the opportunity to evaluate multiple scenarios, such as zoning changes and infrastructure developments, by integrating diverse data sources, including demographic, economic, and environmental information (Batty et al., 2012). Additionally, simulation models aid in risk assessment by evaluating potential hazards and vulnerabilities associated with various land use scenarios. By supporting long-term planning and policy evaluation, these models contribute to insightful decision-making.

This paper presents the findings of the application of a land use summation model tailored to a Trincomalee in Sri Lanka. The ability to integrate various development scenarios and uncertainties considered as is important and is increasingly receiving academic attention (Polasky et al., 2011). Further, Zheng, Xu, Zhang, & Liu (2012) emphasize the usefulness of simulating, evaluating, and predicting intensive land use has significance for the future planning and management of land utility. In predicting land use, most studies focused on model-building methods by integrating geographic information systems and remote sensing to explore current patterns of land use and then simulate the future of land use (Wu & Zhang, 2012). Liu et al (2009), emphasized the need to integrate policy decisions in representing the human factor. Integrating policies for land use simulations is recognized as under-studied (Lloyd & Peel, 2007). This is particularly important for Trincomalee considering its current geopolitical interests and policy considerations. SIMULACRA: Fast Land-Use—Transportation Models for the Rapid Assessment of Urban Futures, is one such model developed for large metropolitan areas that will enable decision makers to rapidly test many different development scenarios pertaining to both short-term and long-term urban futures (Batty et al., 2013). Yet the scale and data requirements of such models make them less effective for contexts like Trincomalee considering the scale and data availability.

The study involves setting up and calibrating this model to accurately reflect the unique socio-economic and environmental conditions of the selected urban area. The data fusion is used for preparing the data for the model. This was crucial in overcoming incompatibility issues.

Through a rigorous calibration process, the model was validated with a recent level of accuracy to align with local data and conditions. The model is then used to test three distinct planning scenarios that are unique to Trincomalee. Further,

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the research will extend beyond mere model calibration by testing its efficacy under various development scenarios. This approach will provide insights into how different developmental strategies impact land use patterns and facilitate better decision-making. The study aims to illustrate the model's utility in forecasting and evaluating the outcomes of diverse planning alternatives. Li et al (2018) highlight that, while many models are effective at broader scales, there is often a lack of applicability to local contexts and smaller geographic areas. Further, the corresponding authors highlight the need to develop models that can be tailored to specific local conditions and variations while maintaining general applicability.

The paper provides comprehensive practical guidance on land use model calibration and scenario testing while highlighting its potential as a decision-support tool for urban planners and policymakers in Sri Lanka and similar settings.

The second section of the paper outlines the methodology adopted in the paper and model calibration is explicitly presented in the third part of the paper. The results of the simulation exercise for various planning scenarios are presented in the fourth section.

## 2. Methodology

2.1. TRINCOMALEE: AS THE CASE STUDY AREA

The study focuses on the Trincomalee Town and Gravets Divisional Secretariat Division (Figure 1), located in the Eastern Province of Sri Lanka. Trincomalee, serving as the capital of the Eastern Province, holds strategic significance due to its prominent port and rich historical heritage.

The division area spans an area of 148 square kilometers. Trincomalee Town and Gravets experience a tropical climate with distinct dry and wet seasons. According to the 2012 census, the population of Trincomalee Town and Gravets was recorded at 97,487 population. The economy of Trincomalee Town and Gravets is multifaceted, encompassing fisheries, agriculture, tourism, and trade. The Trincomalee Harbor, renowned as one of the world's finest natural harbors, plays a pivotal role in the local economy by serving as a critical hub for maritime trade and transportation.

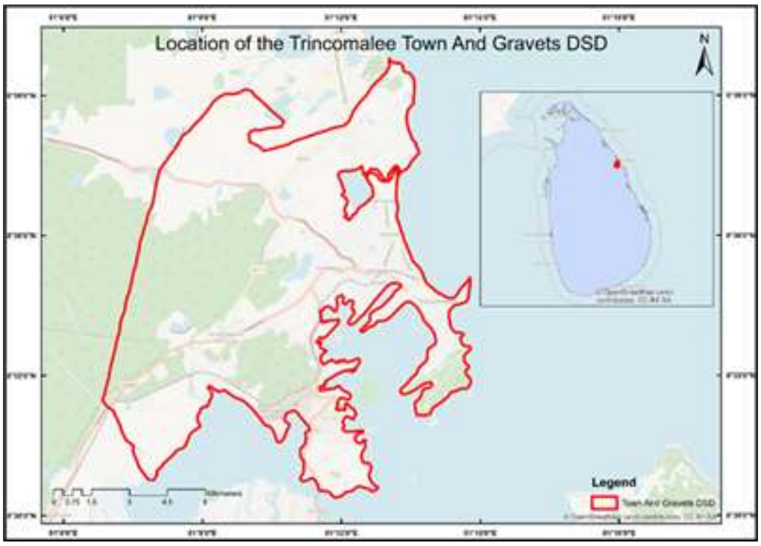


Figure 1, Study area – Trincomalee Town and Gravest

2.2. DATA SOURCES

The research adopts a data fusion approach in setting up the model. Table 1 provides a comprehensive overview of the data and sources used for the model.

Table 1; The data and sources used for the model

| Data | Criteria | LULC Simulation | Year | Description | Source | Data format |
|---|---|---|---|---|---|---|
| LULC map | Land Use & Land Cover | Input maps | 2010 & 2020 | Satellite images from Landsat | USGS Earth Explorer: https://earthexplorer.usgs.gov/ | .tif |
| Distance to CBD map | Distance from CBD | Special variable map | 2020 | Map of areas based on the proximity to the central business district of the study area. | Created by Author | .shp |

| | | | | | | |
|---|---|---|---|---|---|---|
| Distance to nearest service centers map | Distance from service centers | Special variable map | 2020 | Map of areas based on the proximity to the nearest service centers of the study area. | Geofabrik GmbH. Point of Interest (POI) data for Sri Lanka: https://download.geofabrik.de/asia/sri-lanka.html | .shp |
| Distance to highly connected nodes map | Distance from highly connected nodes | Special variable map | 2020 | Map of areas based on the proximity to the highly connected nodes of Trincomalee Town & Gravets DSD. | Created by Author | .shp |
| Distance to public facilities map | Distance from public facilities | Special variable map | 2020 | Map of areas based on the proximity to the public facilities of the study area. | Geofabrik GmbH. Point of Interest (POI) data for Sri Lanka: https://download.geofabrik.de/asia/sri-lanka.html. | .shp |
| Distance to defense activities map | Distance from defense activities | Special variable map | 2020 | Map of areas based on the proximity to the defense activities of the study area. | UDA data | .shp |
| Distance to the road map | Distance from roads | Special variable map | 2020 | Map of areas based on the proximity to the roads of the study area. | Geofabrik GmbH. Point of Interest (POI) data for Sri Lanka: https://download.geofabrik.de/asia/sri-lanka.html. | .shp |
| Distance to flood-prone areas map | Distance from flood-prone areas | Special variable map | 2020 | Map of areas based on the proximity to the flood-prone areas. | UDA data | .shp |
| Distance to water-bodies map | Distance from water-bodies | Special variable map | 2020 | Map of areas based on the proximity to the water bodies. | UDA data | .shp |
| Population Density map | Population density in each GND | Special variable map | 2020 | Map of distribution of population across each GND. | UDA data | .shp |

## 2.3. CELLULAR AUTOMATA (CA) AND MOLUSCE

Cellular Automata (CA) was employed in this study to model and predict land use changes in Trincomalee Town and Gravets Divisional Secretariat Division (DSD). CA, a computational modeling framework that simulates the evolution of spatial systems through local interactions, was chosen for its ability to capture the complex dynamics of urban growth and environmental change. The basic unit of the CA model is the cell, representing a specific geographical area within the study region.

For this simulation, the cell sizes were set as 30 by 30 and that results in a total of row and column values are 486, 576 for the entire study area. The cell states are assigned as built-up, vegetation, agricultural, or inland water bodies.

The transition of cells from one state to another is influenced by the neighbouring effect, where the state of a cell is affected by the states of its adjacent cells. This effect captures the spatial dependencies and interactions among different land uses. The neighbourhood for this modeling activity is set as 15m.

Transition rules, which govern these state changes, were defined based on historical land use changes and expert judgments. For instance, a cell might transition from agricultural to built-up use if a certain percentage of its neighbouring cells are already built-up, and if other conditions such as proximity to roads and population density thresholds are met. The details of the land use classification are provided in section 3.1. of the paper. The parameter values for these rules are calibrated during the modeling process. These are the elements of cellular automata,

1. Cell - Cells are the basic units that form the grid in a cellular automaton. Each cell occupies a specific location in the grid and can be in one of a finite number of states.
2. States - The state of a cell represents its current condition or configuration. It could be binary (0 or 1), multi-state (e.g., different colors), or more complex depending on the application.
3. Neighbouring Rules - Neighboring rules define which cells influence the state of a given cell. The neighborhood is a set of adjacent cells surrounding the cell of interest.
4. Transition Rules - Transition rules specify how the state of a cell changes over time based on the states of its neighbors.

MOLUSCE, a QGIS Python Plugins Repository is used for setting up the model. MOLUSCE adapts the cellular automata concept and provides a set of algorithms for land use change simulations.

The initial year for the simulation was set as 2010 and the final year was set as 2020, the model was calibrated using the land use data sets prepared for 2010 and 2020. The selection of years is constrained by the availability of credible data for the above years.

## 3. Model calibration

3.1. LAND USE CLASSIFICATION
Satellite imagery from the Landsat 5 and Landsat 8 satellites was utilized, with Landsat 5 data from 2010 and Landsat 8 satellite data from 2020 sourced from the USGS Earth Explorer portal. Supervised classification was performed using ArcMap 10.7.1, where training samples were established to represent four main land use categories: vegetation, inland water bodies, built-up areas, and agricultural lands. Vegetation includes natural green cover such as forests, grasslands, shrublands, and wetlands. Inland Water Bodies consist of lakes, rivers, streams, and marshes. Built-up areas feature residential zones, commercial areas, industrial zones, and transportation infrastructure. Agricultural Areas encompass land used for crop fields, plantations, paddy fields, and livestock farms. Subsequent to classification, post-processing procedures were executed to refine the maps, enhancing their precision. The final classified land use maps for 2010 (Figure 2) and 2020 (Figure 3) were then integrated into QGIS using the Molusce plugin, enabling detailed simulation and analysis of land use changes within the study area.

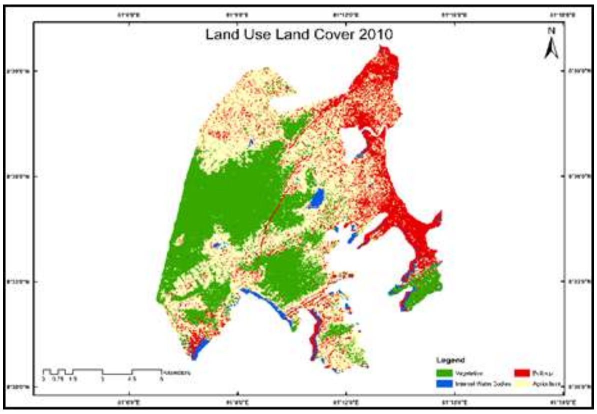


Figure 2, Land use map of 2010

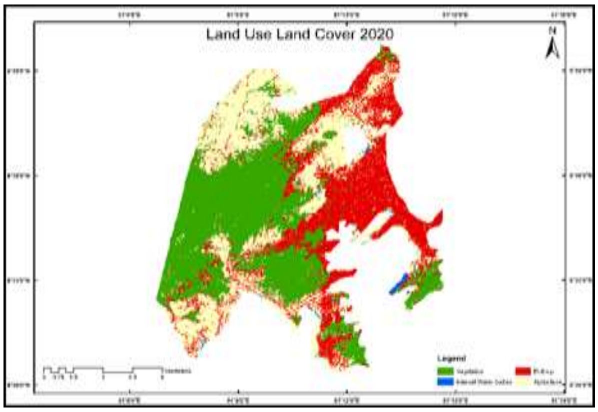


Figure 3, Land use map of 2020

3.2. THE SPATIAL VARIABLES
Nine significant spatial variables were chosen for the land use simulation based on their significant impact on land use patterns, as identified by ground surveys and interviews with locals. These variables have considerably impacted land-use activities throughout the last two decades in the study area.

I. **Connectivity**: connectivity is an important aspect in determining accessibility and movement. Because of the ease with which services, goods, and individuals may move, areas with more connectivity are predicted to experience urban expansion. Because nodes with extremely high connectivity are not in the DSD, nodes with weights of more than 1.04 in the area are considered highly connected from the natural breaks of the connectivity dataset, and the Euclidean distance between those nodes is determined.

ii. **Distance to central business district (CBD)**: one of the most important variables influencing the intensity of land use is the proximity to CBD. A greater level of both commercial and residential growth is typically correlated with closer proximity to the CBD, indicating the CBD's significance in social and economic activity. For Trincomalee, the area with the highest concentration of commercial activities is taken as the CBD area.

III. **Flood-prone areas**: planning for sustainable land use requires the identification of flood-prone areas. As one increases more distance from flood-prone locations, urban expansion usually gets higher.

IV. **Distance to roads**: changes in land use are greatly impacted by proximity to major roads. Major roads make an area more accessible, which makes it more desirable for growth. This component aids in locating possible areas for urban growth.

V. **Distance to nearest service centers**: patterns of land use are greatly influenced by the accessibility of service centers (towns), which include markets, retail stores, and educational facilities. Because these centers are convenient and offer inhabitants needed services, the development of areas surrounding them is more likely.

VI. **Distance to public facilities**: the presence and accessibility of public facilities, such as those for administration, entertainment, education, religion, health care, and other facilities, improve the standard of living and make a location more desirable for residential and commercial development. As one gets farther from public facilities, urban expansion slows down.

VII. **Distance to defense activities**: This is a unique variable to Trincomalee with the location of defense-related land uses in the study area with possible security concerns, land uses are restricted in areas close to defense activities. This component aids in ensuring that land use patterns adhere to security laws and urban growth increases as the distance from defense activities increases.

VIII. **Population density**: one of the main variables of urbanization is population density. Major modifications to land use are more likely to occur in places with high population densities. This variable sheds light on the population's spatial distribution and how it affects the dynamics of land use.

IX. **Distance to water bodies**: a key determinant of land use patterns is proximity to water bodies. Although residential, commercial, and recreational areas close to sources of water are frequently desirable, careful planning is needed to avoid environmental deterioration.

These variables were carefully chosen to offer a thorough framework for the Trincomalee Gravets DSD for land use simulation. Every component contributes uniquely to the study, thus guaranteeing a comprehensive and strong grasp of the dynamics of land use in this area.

## 3.3. SETTING UP THE MODEL

As the first step in analysing land cover change, it is essential to ensure that all raster layers are in the same projected coordinate system of WGS 84, with a resolution pixel size of 30 meters. Using the QGIS MOLUSCE plugin, the process begins with 2010 Land Use Land Cover (LULC) data as the initial dataset and 2020 LULC data as the final dataset. Key spatial variable factors incorporated into the analysis include Connectivity, Distance to Central Business District (CBD), Flood Prone Areas, Distance to Roads, Distance to Nearest Towns, Distance to Public Facilities, Distance to Defense Activities, Population Density, and Distance to Water Bodies. By integrating these layers, the plugin generates a comprehensive analysis of land cover change from 2010 to 2020, evaluating the correlation between the mentioned factors and calculating the percentage of area change within the given period. It also produces a transition matrix that illustrates the proportion of pixels shifting from one land use cover to another. Based on the initial and final data, along with the spatial factors, the plugin can generate predictive land cover maps for 2030 and 2040, providing valuable insights into future land use changes.

## 3.4. MODEL CALIBRATION

The evaluation of correlation is a fundamental component in the analysis of spatial variables and their influence on land cover changes. By employing Pearson correlation coefficients, the strength and direction of linear relationships among critical factors such as Connectivity, Distance to CBD, Flood Prone Areas, Distance to Roads, Distance to Nearest Towns, Distance to Public Facilities, Distance to Defense Activities, Population Density, and Distance to Water Bodies can be rigorously quantified (Figure 4). This statistical measure facilitates the identification of variables that significantly impact land use transitions. The derived correlation matrix offers a detailed understanding of the interdependencies among these variables, thereby enhancing the accuracy of predictive models and supporting evidence-based urban planning decisions.

| | Reclass_Pop_new | Reclass_CBD | Reclass_Connectivity | Reclass_defense | Reclass_Rds | Reclass_PublicF | Reclass_NearTowns | Reclass_EucD_water1 | Reclass_EucD_flod1 |
|---|---|---|---|---|---|---|---|---|---|
| Reclass_Pop_new | -- | -0.703277452383 | -0.26444068302 | -0.346347168615 | -0.385703008735 | -0.443446257203 | -0.428414719637 | 0.351034274761 | -0.112609221477 |
| Reclass_CBD | | -- | 0.383885355068 | 0.40927878245 | 0.53030905503 | 0.506456082136 | 0.467131491879 | -0.238077102704 | 0.30768195778 |
| Reclass_Connectivity | | | -- | -0.123415336424 | 0.330779513573 | 0.392715829151 | 0.379223100755 | 0.11496002681 | 0.112452610415 |
| Reclass_defense | | | | -- | 0.406390151011 | 0.403648985523 | 0.225433460914 | -0.246380825948 | 0.100430390789 |
| Reclass_Rds | | | | | -- | 0.779288646611 | 0.672906989572 | 0.165148998863 | 0.597188870919 |
| Reclass_PublicF | | | | | | -- | 0.718704351783 | 0.0686524850011 | 0.428270408884 |
| Reclass_NearTowns | | | | | | | -- | 0.230490471029 | 0.423734735939 |
| Reclass_EucD_water1 | | | | | | | | -- | 0.42065422595 |
| Reclass_EucD_flod1 | | | | | | | | | -- |

Figure 4, Pearson correlation coefficients of factors

### *3.4.1 Area Change*

Analysing the area change between 2010 and 2020 is fundamental to understanding land cover dynamics. By comparing land use land cover (LULC) maps from these two years, we can quantify the shifts in land use categories. This involves calculating the total area of each land cover type for both years and determining the net changes. The analysis reveals significant trends such as urban expansion, deforestation, and agricultural transformation, providing insights into the underlying drivers of these changes.

### *3.4.2 Transition Potential Model*

Transition Potential Modelling involves predicting land cover changes by evaluating the likelihood of land transitioning from one use or cover type to another. In this study, the QGIS MOLUSCE plugin was employed to model these transitions using historical Land Use Land Cover (LULC) data from 2010 and 2020. The methodology incorporated Artificial Neural Networks (ANN) to handle complex and uncertain data, utilizing various spatial variables. The ANN, enhanced with fuzzy logic, generated a continuous transition potential index ranging from 0 to 1, indicating the likelihood of land use changes. This index facilitated the prediction of future land cover scenarios for 2030 and 2040, providing valuable insights for planning and resource management.

*3.4.3 Neural Networking Learning Curve*

In this study, the neural networking learning curve, illustrated in Figure 5, provides a detailed representation of the ANN model's performance during training. The x-axis of the curve represents the number of training epochs, while the y-axis displays the loss/error values. The curve is split into two distinct lines: red and green.

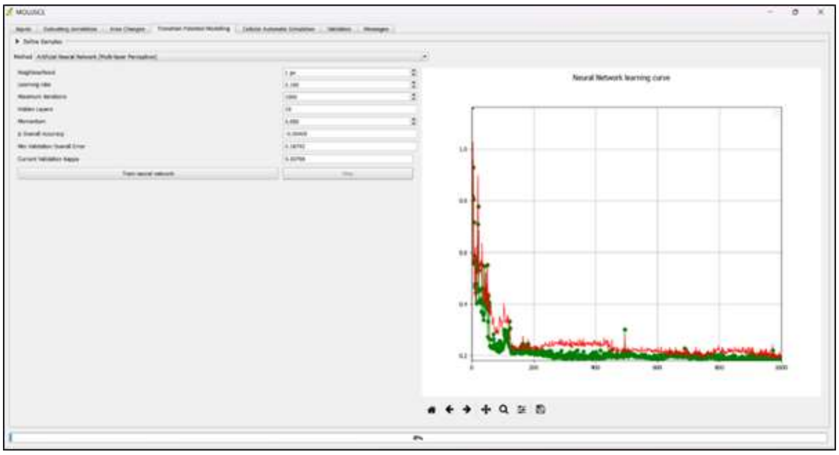

Figure 5, Neural Networking Learning Curve

*3.4.4 Validation*

The accuracy of Land Use and Land Cover (LULC) predictions was assessed using the kappa coefficient, calculated through the 'Validation' option in the Molusce plugin in QGIS. Validation was performed between the predicted and real LULC maps of 2020 by calculating both the overall kappa value and the histogram kappa statistic.

The area covered by vegetation in the classified 2020 layer was 51.95 square kilometers, accounting for 39.65% of the total land area, while the predicted 2020 layer indicated a reduced coverage of 42.86 square kilometers, representing 32.71% of the total area. Water bodies showed an increase from 0.92 square kilometers (0.70%) in the classified 2020 layer to 2.95 square kilometers (2.26%) in the predicted 2020 layer. In the classified 2020 layer, built-up areas covered 37.19 square kilometers (28.39%), whereas the predicted 2020 layer showed a reduced coverage of 26.29 square kilometers (20.07%). The classified layer identified 40.95 square kilometers (31.26%) of agricultural land, while the predicted layer revealed an expanded area of 58.90 square kilometers (44.96%).

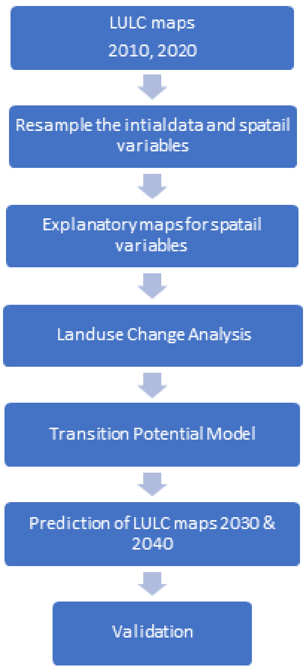


Figure 6, Methodologi-cal Flow Chart

The overall prediction accuracy was 60.56%, indicating that approximately 60.56% of the land use changes were correctly predicted by the model. The overall kappa value of 0.41364 indicates a "moderate" level of agreement between the predicted and actual LULC maps. According to established kappa interpretation guidelines, values between 0.41 and 0.60 indicate a moderate level of agreement, suggesting that the model captured changes reasonably well but with room for improvement. In contrast, the histogram kappa statistic of 0.77307 demonstrates a "substantial" level of agreement, indicating that the model's predictions more accurately captured the distribution of individual LULC classes. This higher histogram kappa value supports the reliability of the model in replicating class proportions within the study area.

## 4. Land Use Simulations and Scenario Analysis

This section presents the results of the validated model and how the model is used to test three planning scenarios derived for the region. The scenarios are derived from field observations and stakeholder discussions[1]

4.1. LAND USE SIMULATION: BUSINESS AS USUAL SCENARIO

The temporal area shifts for each LULC category in land use and land cover as a percentage of the entire land area are displayed in Figures 11, 12, and 13. This demonstrates the overall pattern of LULC change from 2010 to 2040 for built-up, vegetation, and agricultural lands. There is no significant shift in waterbodies.

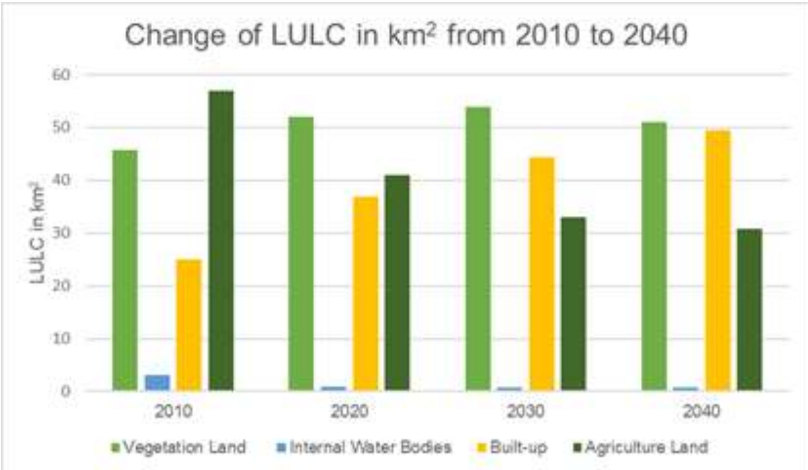


Figure 7, Change of land uses from 2010 to 2040 (simulated with business-as-usual scenario)

The maps of the projected LULC for 2030 and 2040 are shown in Figure 14 and Figure 15. Figure 7 illustrates the area-level land use and land cover changes for different categories during a ten-year interval from 2010 to 2040.

***Land Use Changes from 2010 to 2020***

The land use analysis from 2010 to 2020 shows notable changes in several land use categories. The built-up area expanded from 19.18% to 28.24%, indicating an urbanization encouraged by economic growth and population growth. Conversely, agricultural lands decreased from 43.45% to 31.35%, showing a decrease in agricultural activities, maybe due to the expansion of built-up areas, there is identified conversion of agricultural land into built-up areas. There was an increase in the percentage of vegetation areas, from 34.9% to 39.69%, indicating that there were conservation efforts in forested areas. Internal water bodies decreased from 1.76% of the total area with a very slight change, suggesting stable hydrological conditions over this time.

***Land Use Changes from 2020 to 2030***

Predictions relating to the period from 2020 to 2030 suggest that urban areas will continue to expand, with built-up areas predicted to expand from 28.24% to 33.6%. The continued urbanization trends and the need for residential and commercial space are highlighted by this expansion. The estimated 1.31% increase in vegetation areas points to the possibility of either natural regrowth or reforestation activities. It is projected that there will be a notable decline in agricultural areas, from 31.35% to 24.97%, due to the encroachment of urban areas into agricultural areas. The projections for internal water bodies show a slight drop of 0.09%, suggesting that changes in land use will have only a minimal effect on aquatic habitats.

***Land Use Changes from 2030 to 2040***

Predictions related to the period from 2030 to 2040 indicate a sustained yet decelerated level of urban expansion, with built-up areas predicted to rise from 3.83%. This slower growth rate could indicate saturated prime development areas and more

[1] These field observations and stakeholder discussions were carried out during the field visit to Trincomalee from 22nd to 26th January 2025.

sensible land use regulations. The expected decline in vegetation areas is 2.22 %; this could be attributed to pressures from land development and increased urban growth. It is anticipated that agricultural areas will decrease by 1.59%, maintaining the downward trend in available agricultural land. With a small decrease of 0.003%, internal water bodies are expected to be comparatively steady, indicating no change in water resources.

### 4.2. LAND USE SIMULATION: FORMULATED THREE PLANNING SCENARIOS

Scenario analysis is an essential technique in urban planning for exploring future land use and land cover changes. This study uses scenario analysis to examine the impacts of three different planning scenarios on land use dynamics from 2020 to 2040. Three different planning scenarios are formulated with the stakeholder views expressed during the consultations (Note: Not all views are considered as scenarios here for this paper)

- Scenario 01: Construction of a new road from 4th Mile Post Junction to Kanniya (connecting two transportation nodes)
- Scenario 02: Removal of military land uses and release of the land development
- Scenario 03: Combined scenario (scenarios 01 and 02)

By simulating these three scenarios, it was expected to understand how various decisions might change the land use pattern of the study area, providing valuable insights for policymakers and planners to guide informed decision-making and land management strategies.

#### *4.2.1 Scenario 1: Construct a New Road from 4th Mile Post Junction to Kanniya*

This scenario focuses on the construction of a new road connecting the 4th Mile Post Junction to Kanniya (Figure 8) between 2025-2028. Distance to roads and distance to high connectivity nodes input layers were changed according to the new road construction. Based on that road layer and connectivity enhancement, this analysis evaluates the influence on land use change.

The temporal area shifts for each LULC category and their corresponding percentage changes relative to the total land area are indicated in Figures 11,12 and 13. The maps of the projected LULC for scenario 1 in 2030 and 2040 are shown in Figure 16 and Figure 17.

***Land Use Changes from 2020 to 2030***

Scenario predictions relating to the period from 2020 to 2030 emphasize that vegetation land decreased by 0.4 $km^2$ (0.3%) and internal water bodies by 0.17 $km^2$ (0.13%), indicating less vegetation clearing and slight impacts on waterbodies. Due to increased accessibility and economic opportunities, urban expansion along the road resulted in a significant increase of 7.3 km2 (5.52%) in built-up land. This expansion caused agricultural land to decrease by 6.73 $km^2$ (5.09%), marking a shift from agricultural to urban land use.

***Land Use Changes from 2030 to 2040***

According to the scenario prediction, vegetable land dropped by 0.24 $km^2$ (0.19%) between 2030 and 2040, suggesting a slower rate of deforestation. Internal water bodies had no further impact, remaining constant with a slight change of 0 $km^2$ (-0.002%). Built-up land modestly increased by 0.5 $km^2$ (0.38%), reflecting slower urban growth while agricultural land slightly decreased by 0.26 $km^2$ (0.19%) indicating that the majority of land conversions to urban areas.

#### 4.2.2. *Scenario 2: Remove All Military Bases*

This scenario examines the impact of removing all military bases (Figure 8) between 2025 -2028 on land use and land cover from 2020 to 2040. Figures 11,12 and 13 show the temporal changes in area and percentage for each LULC category. Although we anticipated that the removal of military bases would result in a scattered distribution of built-up areas all over the DSD, however, the MOLUSCE model predicts built-up areas in a concentration pattern. The maps of the projected LULC for scenario 2 in 2030 and 2040 are shown in Figure 18 and Figure 19.

***Land Use Changes from 2020 to 2030***

From 2020 to 2030, the removal of military bases led to notable land use changes. Built-up land increased significantly by 7.36 $km^2$ (5.58%), while agricultural land decreased by 6.44 $km^2$ (4.87%) highlighting a shift from agriculture to urban development. The removal of military bases resulted in a 0.81 $km^2$ (0.62%) decline in vegetated land and a 0.11 $km^2$ (0.087%) slight reduction in internal water bodies during this period.

***Land Use Changes from 2030 to 2040***

There was a notable slowdown in land use changes between 2030 and 2040. A slight decline of 0.18 $km^2$ (0.137%) in vegetation land and internal water bodies remained unchanged, showing no additional impact. While agricultural land significantly decreased by 0.06 km2 (0.046%), built-up land expanded slightly by 0.24 km2 (0.18%), reflecting a slowdown in urban expansion.

*4.2.3. Scenario 3: Construct a New Road and Remove Military Bases (Combination)*

This combined scenario (Figure 9) assesses the impacts of both constructing a new road (scenario 1) and removing military bases (scenario 2). Figures 11,12 and 13 show the temporal changes in area and percentage for each LULC category. The maps of the projected LULC for scenario 3 in 2030 and 2040 are shown in Figure 20 and Figure 21.

***Land Use Changes from 2020 to 2030***

From 2020 to 2030, the removal of military bases and road construction resulted in a slight decrease in vegetation land by 0.34 $km^2$ (0.26%) and internal water bodies decreased by 0.17 $km^2$ (0.13%), showing slight effects from land reclamation. The built-up area increased by 8.73 $km^2$ (6.61%) primarily due to the urbanization of former military zones. Agricultural land decreased by 8.9 $km^2$ (6.74%), indicating a significant shift from agriculture to urban usage.

**Land Use Changes from 2030 to 2040**

Vegetable land declined by 0.66 $km^2$ (0.5%) between 2030 and 2040, indicating ongoing but reduced impacts on natural habitats. Internal water bodies indicate a negligible decrease of 0.01 $km^2$ (0.009%). The area covered by built-up land rose by 1.28 $km^2$ (0.97%), indicating continued, though slowed, urban expansion. The amount of land used for agriculture decreased by 0.06 km2 (0.46%), indicating that the majority of the transition from agriculture to urban use had already occurred.

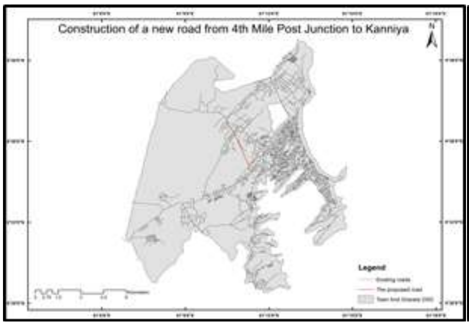


Figure 8, Scenario 1


Figure 9, Scenario 2

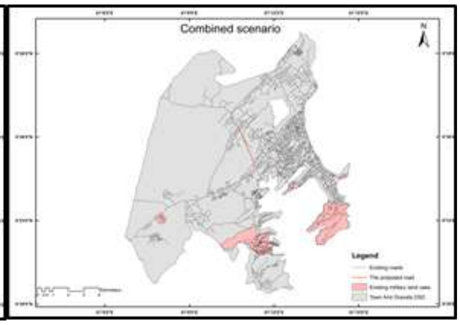


Figure 10, Scenario 3

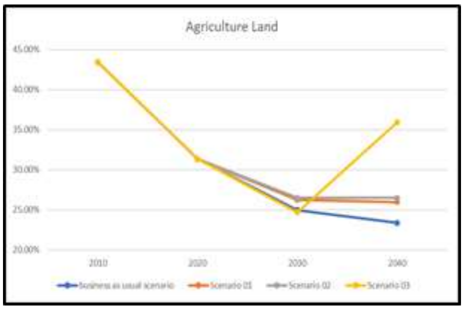


Figure 11, Comparison of actual and simulated land use changes of Agriculture lands (from 2010 to 2040 with four scenarios)

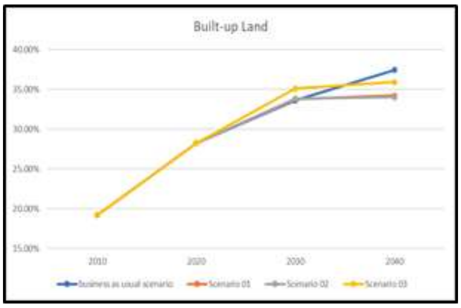


Figure 12, Comparison of actual and simulated land use changes of built-up lands (from 2010 to 2040 with four scenarios)

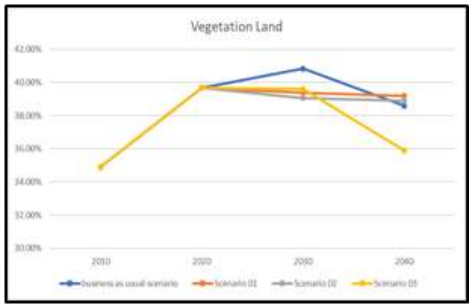


Figure 13, Comparison of actual and simulated land use changes of Vegetation lands (from 2010 to 2040

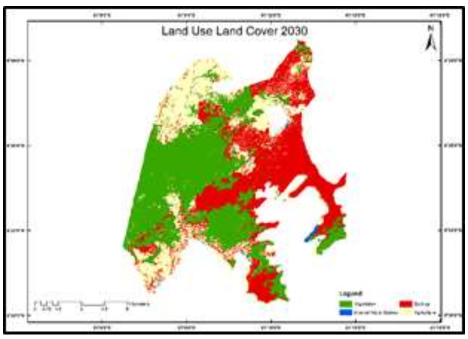


Figure 14, Land use for 2030 (simulated with business-as-usual

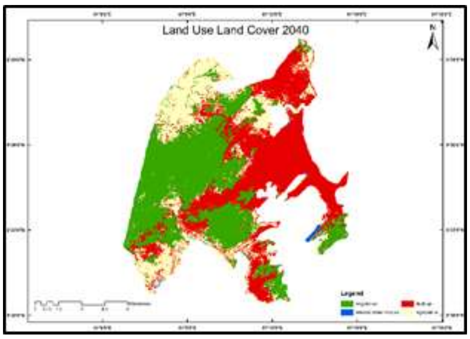


Figure 15, Land use for 2040 (simulated with business-as-usual

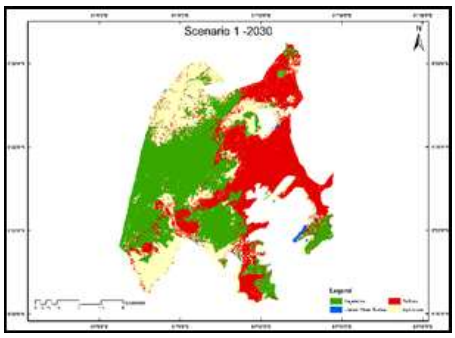


Figure16, Land use for 2030 (Simulated for Scenario 01)

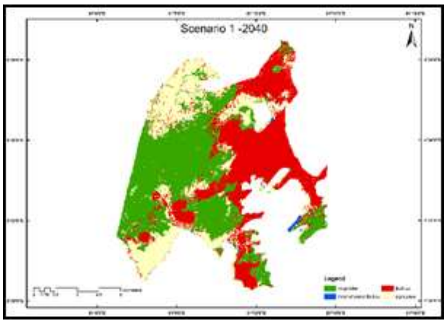


Figure 17, Land use for 2040 (Simulated for Scenario 01)

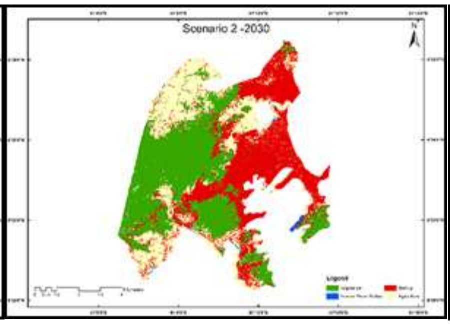


Figure 18, Land use for 2030 (Simulated for Scenario 02)

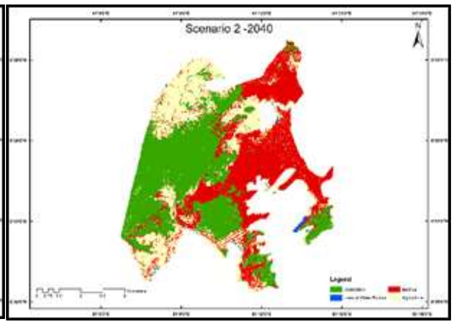


Figure 19, Land use for 2040 (Simulated for Scenario 02)

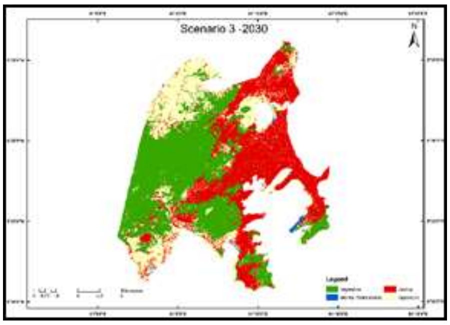


Figure 20, Land use for 2030 (Simulated for Scenario 03)

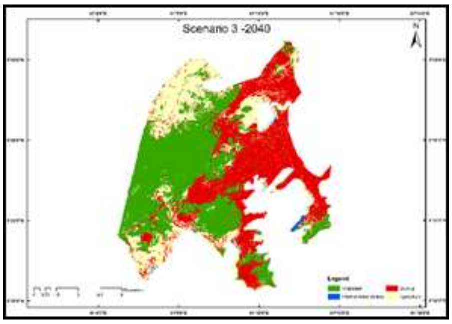


Figure 21, Land use for 2040 (Simulated for Scenario 03)

## 4.3. COMPARATIVE DISCUSSION

Significant trends and consequences for land use planning and sustainability are highlighted by the observed and predicted land use changes in the area period of 2010 to 2040.

**Urban Expansion**: The pressure of urbanization is indicated by the constant growth in built-up areas over all periods. To handle growth while protecting natural and agricultural areas, sustainable urban planning is essential, as seen by the rise from 19.18% in 2010 to 37.42% by 2040. Based on scenario testing, new road construction and other infrastructure improvements greatly improve connectivity and encourage urban growth. In Scenario 1, the new road causes urban areas to rise by 5.52% between 2020 and 2030 and by 0.38% between 2030 and 2040. The removal of military bases leads to a rise in built-up land of 5.6% between 2020 and 2040 in a concentration pattern. The necessity for strategic planning to strike a balance between development and safeguarding the environment is highlighted by Scenario 3, which indicates the greatest expansion in built-up areas. To lessen the negative effects of urban sprawl on the environment, these trends call for the adoption of comprehensive urban planning techniques.

**Vegetation Cover:** The amount of land covered with vegetation will somewhat increase around 2020 and 2030, then perhaps decline between 2030 and 2040. Both Scenarios 1 and 2 depict a reduction in vegetation as a result of expanding urbanization. The combined scenario (Scenario 3) indicates continuous but diminished impacts on natural habitats, with a decrease of 0.7% from 2020 to 2040. These patterns indicate that although efforts may be taken in the short term to preserve or enhance the diversity of vegetation, a loss may occur due to long-term pressures. To safeguard these areas, conservation tactics and ongoing observation are essential. Programs for restoration and afforestation may be crucial to maintaining the amount of vegetation cover.

**Agriculture Areas:** According to the business-as-usual scenario, a transition away from agriculture is seen in the large decline in agricultural land from 31.35% in 2020 to 23.38% by 2040, which may be caused by urbanization and shifting land use priorities. There will be a noticeable decline in agricultural land across the scenarios, especially in Scenario 3, where there is a fall of 7.2% from 2020 to 2040. Policies that strike a balance between preserving agriculture and promoting urban growth are necessary in light of this reduction's impact on food security and rural life. The primary strategies include promoting sustainable farming methods and preventing the conversion of important agricultural land

**Internal Waterbodies:** The area that is covered by water bodies varies somewhat, suggesting that this category is quite stable. However, the minor decline predicted for 2020–2040 in both business-as-usual scenario and scenario testing implies that comprehensive water management strategies are necessary to preserve these vital resources. Maintaining the availability and quality of water depends on making sure that water bodies are protected from damage and development.

Overall, the dynamics of urban growth, changing vegetation, declining agricultural productivity, and stability in water bodies are highlighted by the changes in land use in the Trincomalee Gravets DSD area between 2010 and 2040. To reconcile development needs with the preservation of the environment and agricultural sustainability, these patterns highlight the significance of comprehensive land use planning and sustainable management. The impacts of military base removal and the expansion of infrastructure on land use dynamics emphasize the necessity of strategic planning and collaboration among stakeholders for balanced and sustainable growth. Ensuring a healthy combination of urban areas, ecosystems, and agricultural lands in the area requires effective policy interventions and regular evaluation.

## 5. Conclusion

This study presents the findings of the use of land use simulation models for simulating planning scenarios. Given the analysis of combining diversified and various scenarios, the study provides vital insights for urban planners and policymakers engaged in supporting balanced and sustainable growth in Trincomalee and other similar cities. The scenarios were formulated based on stakeholder suggestions and simulated after calibrating the simulation model for the study area. Further research may consider in detailing the land use classes, particularly the built-up category to represent the residential, commercial, and industrial land uses. In addition, the range of other possible planning scenarios can be formulated and tested to the modeling implications. Overall, while acknowledging the inherent limitations of land use simulation models and contextual realities. it is important to note that as the study presents simulation models can still serve as a useful in evaluating planning decisions in the actual plan-making process.

## 6. Citations and References

### 6.1. AUTHOR CONTRIBUTIONS

The model setup, calibration, land use simulation, and scenario testing were carried out collaboratively by authors D.N. Jayaratne, W.A.M.P.D.A. Athapattu, W.R. Kavishka, T.A.C. Jayani, and N.S. Sooriyaarachchi, who also jointly wrote the manuscript. Chathura Kovida De Silva provided essential mentoring and guidance throughout this study and drafting of the paper.

### 6.2. ACKNOWLEDGMENTS

- The initial land use simulation model was set up and calibrated as a part of the Land Use Planning Studio (PL240) conducted in the Trincomalee area. The authors wish to acknowledge the contributions and support of their colleagues from the Trincomalee Land Use Planning groups.
  Dr. Rizvi Noordeen (Senior Lecturer, Department of Town and Country Planning)
  Mr. Mohamed Hasan (Former Instructor, Department of Town and Country Planning)
- We acknowledge the contribution of various stakeholders from Trincomalee who shared their ideas and suggestions during the planning studio project.
- We acknowledge the use of ChatGPT [https://chat.openai.com/] to improve the readability and language of the work.

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