Developing a Decision Framework Driven by Land Use Simulation to Evaluate Sri Lanka's National Physical Policies: A Case Study of the National Physical Plan (2023-2048)

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***Abstract**: The National Physical Plan (NPP) of Sri Lanka, prepared by the National Physical Planning Department (NPPD), is a strategic framework aimed at guiding the country's physical and spatial development, particularly over a long-term time horizon. The main objective of the plan is to provide a broad national framework for planning and executing development activities, impacting Sri Lanka's physical environment and infrastructure. To achieve this objective, it is necessary to assess development scenarios based on land use changes to determine whether the proposed policy framework can be envisioned. Hence, this study aims at developing a land use simulation-based decision framework using QGIS MOLUSCE plugin, for predicting land use change in accordance with proposed projects outlined in the National Physical Plan 2023 – 2048. Previous studies utilizing MOLUSCE predominantly focused on small-scale predictions, encountering limitations due to edge effects in contexts where simulation model results are influenced by adjacent countries. However, since Sri Lanka is an island nation, simulations can be conducted without external interferences, thereby eliminating edge effects and yielding more realistic predictions. The methodology of this study involves digitizing proposed infrastructure projects, particularly railway and expressway projects, and creating predictive maps for 2028, 2035, and 2050 to demonstrate short-term, medium-term, and long-term scenarios, respectively. Distance to water bodies, railway stations, main towns, highway interchanges, slope, and population are the main factors considered in developing the land use change model. Overall, this research addresses the critical need to assess the effectiveness, and implications of proposed projects outlined in the NPP, providing insights into future land use patterns, and supporting evidence-based policies for sustainable development in Sri Lanka.*

Keywords: Land Use Simulation, National Physical Plan, QGIS MOLUSCE Plugin

Introduction

The planning process in developing countries is predominately bounded by arbitrary and subjective decisions, instead of predicted and validated futuristic decisions, due to lack of technical know-how and the non - availability of effective tools (Wickramasuriya, 2007), (Jayasinghe, Sano, Abenayake, & Mahanama, 2019). In Sri Lanka, the National Physical Plan serves as a blueprint for future land use. It can identify three main Planning categories in National Physical plan: short term, medium-term and long-term. Each policy outlines goals and objectives aligned with its time frame. The challenge is the National Physical Plan's dynamic nature, which is subject to revision without a concurrent assessment of whether the current land use is consistent with the plan's proposed outcomes. In the last decade, many land use models have evolved into tools that can be used to study land use change processes, conduct scenario studies or perform policy analyses for real world cases (Aljoufie et al., 2013; Hellmann and Verburg, 2011; Stanilov and Batty, 2011). The integration of land use simulation models into national physical planning frameworks has emerged as a promising approach to forecast future land use patterns and assess the impacts of policy interventions (Bacau et al., 2018). Models provide an opportunity to explore possible future pathways for development in different locations, at different scales, and under different conditions (Osman et al., 2018). In Simulation models, the edge effect which is impacted by nearby nations becomes a constraint. But because of Sri Lanka is an island nation, it is possible to run the simulation without interference from outside sources, removing the edge effect while providing a more realistic prediction. Another advantage is this simulation provides macro-level land use predictions to overcome the edge effect. This study aims to answer questions, about how proposed projects can achieve sustainable development goals, how resilient land use plans are in the face of socio-economic uncertainties and how environmental integrity can be preserved during rapid urbanization. By combining insights from Molusce based simulations with existing knowledge this research hopes to provide information for decision making and contribute to the creation of evidence-based policies for sustainable land use management in Sri Lanka.

Literature Review

This literature review centers on two primary objectives. To identify the diverse mode of land use simulations and the relevance of that simulation to the Sri Lakan context. further that can deploy to assess Sri Lankas National Physical Plan to identify the driving factors for the land use changes in the Macro level land use planning.

- **Models of land use Simulations**

A simulation is a model that mimics the functioning of an existing or suggested system and can test various scenarios or adjustments to the process to provide evidence for decision-making. Spatial simulation is a geo-statistical technique, which has great potential as a tool for dealing with various problems associated with spatial uncertainty (Al-Darwish et al., 2018). It provides methods and tools as spatial decision support systems (SDSS), to assess different policy implications and to maximize comprehensiveness of policy decisions. SDSS provides computerized support for decision-making, when there is a geographic or spatial component to the decision. Spatial simulation synonyms with urban simulation - thus, urban simulation models initially predicated on forecasting development at a cross section in time, were the first to adjust in dealing with such dynamics (Batty, 2011); (Moghadam, 2019). Below are some land use simulation models identified through literature reviews.

- **Cellular Automata**

Cellular Automata is a system of cells in an n-dimensional network in which n>1 are discrete in terms of time and space. A cell represents a discrete moment and changes its state using a set of rules, mainly determining the local transfer function depending on the current state of the adjacent cells (Feng & Liu, 2013). It is updated individually based on the number of adjacent cells at the previous moment (the state at tC1 is determined by the state at t, but not the other way around) (Noszczyk, 2019). The major principle in CA is that LULC can be explained by the current state of a cell and the change in the state of its adjacent cells based on the principle of continuity of historical development and the result of its surrounding influence (Lantman, et al., 2011). The advantage of CA is that it is one of the simplest spatial modeling methods for LULC (Noszczyk, 2019).

- **Markov chain model**

The Markov chain (MC) analysis is a stochastic modeling approach that has been used widely in urban growth modeling (Halmy et al., 2015). It works under the physics assumption that future state depends only on the current state (Bell and Hinojosa, 1977). The MC method monitors the temporal change in land-use type depending on transition matrices (Guan et al., 2011). In land-use, the Markov chain uses matrices to represent changes between land-use categories, and its history dates to Burnham's 1973 study (Lantman, et al., 2011). This is a model of trend forecasting, as if current artificial factors continue, the results would gradually change along a certain trend, tend to stabilize over a long time and finally reach a balanced state (Kumar, Radhakrishnan, & Mathew, 2014). The Markov chain model describes land-use changes from one period to another and uses it to predict future changes (Noszczyk, 2019). For ecological modelling, monitoring changes and trends, and projecting future scenarios at different spatial scales, the Markov model is well-known and reliable. Using transition potential matrices for each LULC class, it predicts possible changes in Land Use and Land Cover (LULC) from one time cycle ($t = 1$) to the next ($t + 1$). Within the model, these modifications are considered stochastic processes. The incapacity of this model to offer the spatial distribution of LULC change activities, however, is a serious drawback. Using the below-mentioned equation, future simulation of LULC changes can be calculated:

$$S(t+1) = p_{ij} * S(t)$$

$$(p_{ij}) = \begin{pmatrix} P_{11} & P_{12} & P_{1n} \\ P_{21} & P_{22} & P_{2n} \\ P_{n1} & P_{n2} & P_{nn} \end{pmatrix}$$

$$0 \leq \ p_{ij} < 1 \ and \sum_{j=0}^{n} p_{ij} = 1, (i, j = 1,2, \dots . n)$$

In this equation, S(t) represents the state of the system at time t, while S(t + 1) represents the state of the system at the next time step (t + 1). The transition probability matrix from the current state i to the next time state j is denoted as Pij. Numerous research studies have utilized the Markov chain model to evaluate future Land Use and Land Cover (LULC) scenarios.

This is one of the most effective methods for estimating any land-use transfer due to its efficient algorithm which uses transition stochastic matrix changes (Kumar, Radhakrishnan, & Mathew, 2014). The Markov process assumes that a future state can be emulated based on a previous one. The major drawback of this technique is the neglect of the spatial aspect (Noszczyk, 2019). Markov models may be combined with CA for LUCC modeling, as evidenced by joint CA Markov models (Li and Reynolds 1997; Balzter, Braun, and Kohler 1998).

- **PLUS Model**

PLUS model mainly contains two major functions: land expansion analysis strategy (LEAS) and the CA based on multiple random seeds (Zhang et al., 2022). Multiple objective programming (MOP) was used to determine the optimal land use structures under different scenarios. For example, previous land resource planning studies, including those of Gibert et al. (1985), Diamond and Wright (1989), Chang et al. (1995), Seppelt and Voinov (2003), and Stewart et al. (2004), used mathematical programming to analyze the connection between objectives and find the optimal solution based on the given conditions as well as decision makers' requirements. The PLUS (Pattern, Land Use, and Simultaneity) Model is a simulation model used in urban planning and land-use management to forecast future land-use changes based on current patterns and trends. Developed by Paul Waddell and his colleagues, the PLUS Model integrates various factors such as demographic shifts, economic development, transportation networks, and environmental considerations to simulate the dynamics of land-use changes over time. Research by Waddell (2002) introduced the PLUS Model as a comprehensive framework for understanding and predicting urban growth patterns. The model incorporates spatially explicit data and employs sophisticated algorithms to simulate the complex interactions between different land-use categories and socio-economic factors. By capturing the simultaneous effects of multiple variables, the PLUS Model offers valuable insights into the potential impacts of different policy interventions and urban development scenarios. According to Waddell et al. (2003), the PLUS Model represents a significant advancement in land-use modeling, allowing planners and policymakers to assess the long-term consequences of their decisions and identify strategies for sustainable development. The model's ability to incorporate feedback loops and account for spatial dependencies makes it a valuable tool for urban planners seeking to optimize land-use allocation and mitigate adverse environmental impacts. Additionally, research by Khan et al. (2018) highlights the versatility of the PLUS Model in addressing diverse urban planning challenges, ranging from transportation planning to environmental management. By integrating data-driven analysis with scenario-based simulations, the model facilitates informed decision-making and promotes collaboration among stakeholders in the planning process. The PLUS Model, as described by Waddell (2002) and Waddell et al. (2003), stands as a sophisticated simulation tool that enables planners and policymakers to anticipate and respond to the dynamic nature of urban growth and land-use change. Its holistic approach to modeling and simulation offers valuable insights into the complex interactions shaping urban landscapes, thereby supporting more informed and sustainable development strategies.

- **CA ANN model**

Artificial Neural Network (ANN) is one of the most powerful models that depend on artificial intelligence. It can be defined simply as nodes or neurons that are managed in multiple layers (Mohammady et al., 2014). ANN can capture the non-linear relationships between factors and deal with complex patterns such as urban growth and changes in land-use with great efficiency. Moreover, its provision of non-linearities and its ability to deal with missing or fuzzy data as well (Aburas et al., 2019). For simulation purposes, ANN model identifies changes in land-use and other patterns using data that illustrate the behavioral dynamics of land-use phenomenon (Mohammady et al., 2014). Therefore, it can detect potential interdependencies through implied driving forces (Shafizadeh-

Moghadam et al., 2017a). Moreover, the significance of using ANN model is that the model illustrates the effects of each driving factor used in the simulation operation and specifies which factors affect the land change more to give a clear understanding of the land change process (Park et al., 2011).

Identification of influence factors for land use changes

The literature reviews have identified several key factors influencing land use change, categorized into three main spatial influencing categories as physical factors, transportation infrastructure, and socioeconomic factors.

Table 1 Literature review Spatial Influencing Factors.

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Spatial Influencing Categories	Spatial Influencing Factors	Reference
Physical Factors	Distance from Water Bodies	Wang et al. (2001) Integrating water-quality management and land-use planning in a watershed context. Journal of Environmental Management, 61(1), 25-36.
	Slope	Becker et al. (2007) Ecological and land use studies along elevational gradients. Mountain Research and Development, 27(1), 58-65.
Transportation Infrastructure	Distance from Highway Interchanges	Moon Jr et al. (1988) Modelling land use changes around non-urban interstate highway interchanges. Land Use Policy, 5(4), 394-407.
	Distance from Railway Stations	Badoe et al. (2000) Transportation–land-use interaction: empirical findings in North America, and their implications for modeling. Transportation Research Part D: Transport and Environment, 5(4), 235-263.
Socioeconomic Factors	Population	Meyer et al. (1992) Human population growth and global land-use/cover change. Annual Review of Ecology and Systematics, 23(1), 39-61.
	Distance from Main Towns	Surya et al. (2020) Land use change, spatial interaction, and sustainable development in the metropolitan urban areas, South Sulawesi Province, Indonesia. Land, 9(3), 95.

Methodology

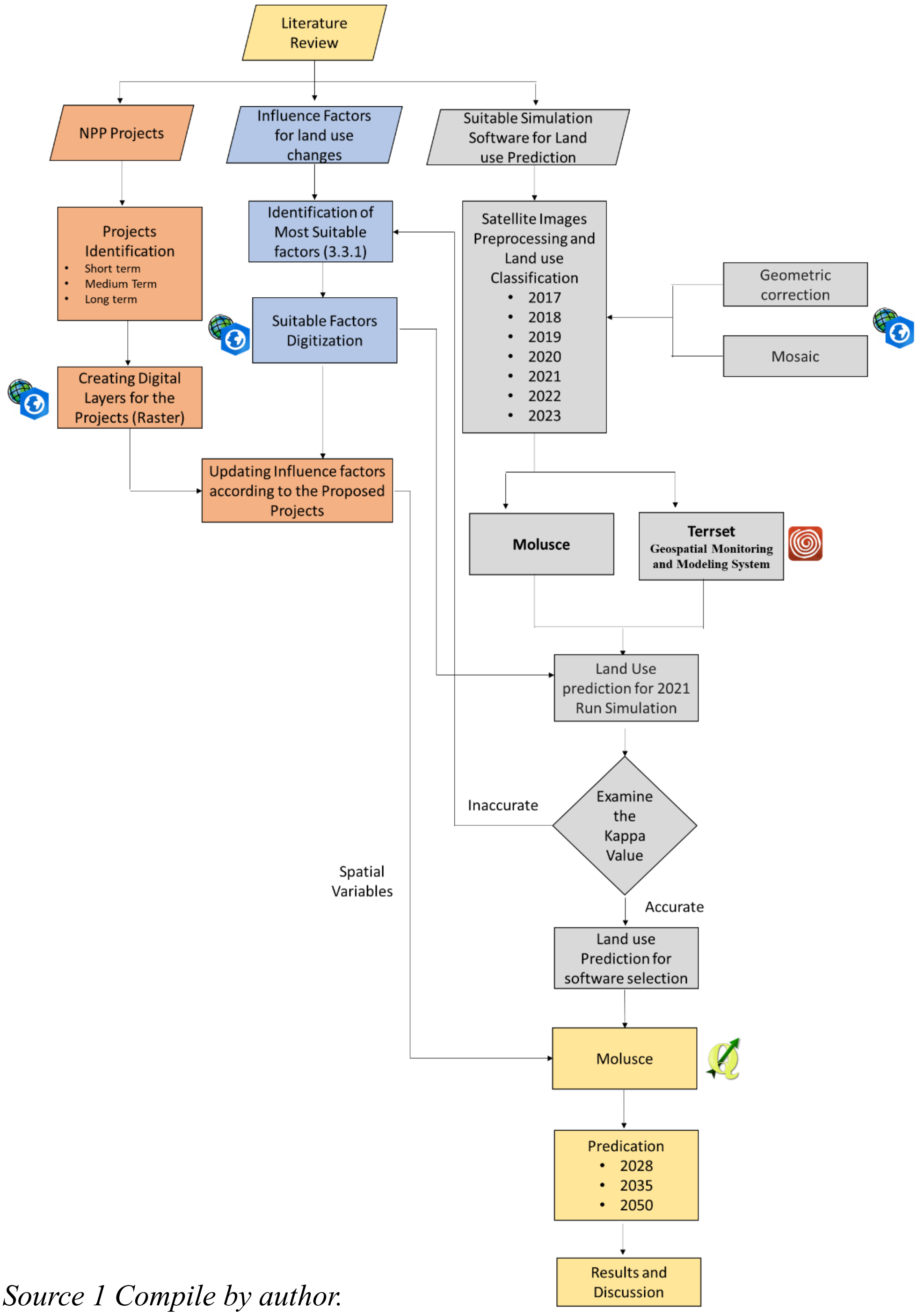

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Figure 1 Methodology.

In this study, accurate monitoring and modeling of land use dynamics are essential for informed decision-making in land management and environmental planning. The validation process for land use predictions for the year 2021 in Sri Lanka was conducted using two prominent software programs: Terrset Geospatial Monitoring and Modeling Software, and the QGIS Molusce plugin.

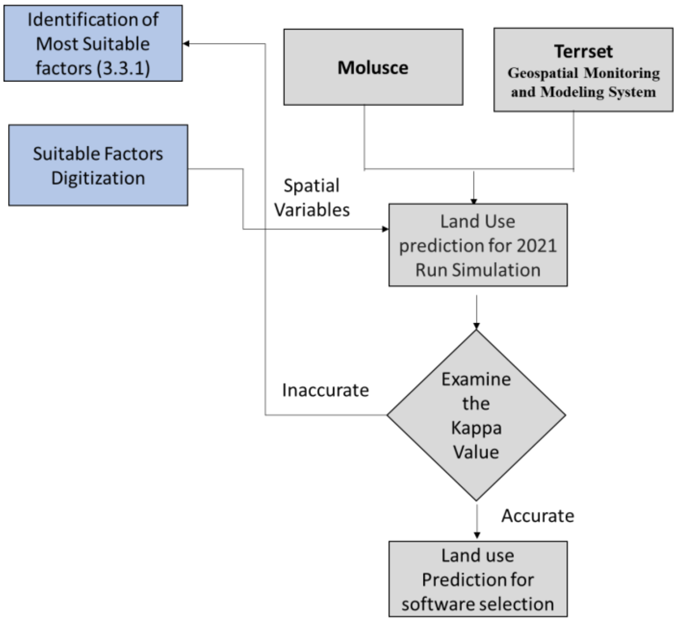

Figure 2 Software Selection

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To validate the accuracy of the results, the original 2021 land use layer of Sri Lanka was utilized. This validation process involved the use of two software programs: Terrset Geospatial Monitoring and Modeling Software and the QGIS Molusce plugin. Initially, the 2017 land use raster file was used as the starting point, with the 2019 layer serving as the current data in both software platforms. These layers were then utilized to predict the land use for the year 2021. It's important to note that the land use images were sourced from ESA Sentinel-2 imagery at 10m resolution. Subsequently, the predicted 2021 land use results from each software were compared with the original 2021 land use layer.

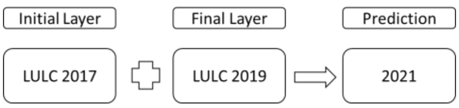

Figure 2 2021 Modeling Process

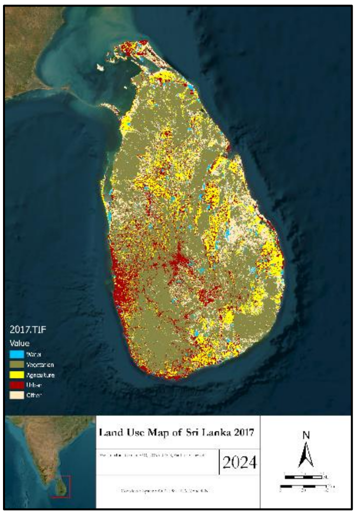

Figure 3 Land use map of Sri Lanka 2017

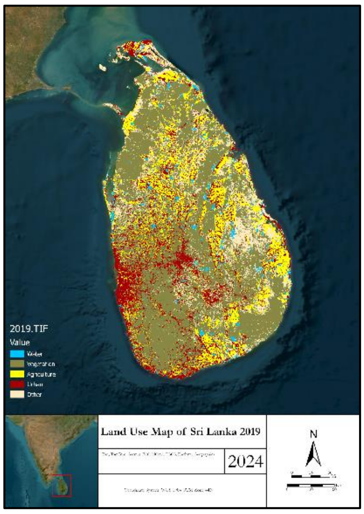

Figure 4 Land use Map of Sri Lanka 2019

This comparison was crucial for evaluating the accuracy of the predictions against the actual data. Through this comprehensive validation process, the performance of the models in both Terrset and QGIS Molusce was assessed, ensuring the reliability of the findings for further analysis and interpretation in the research.

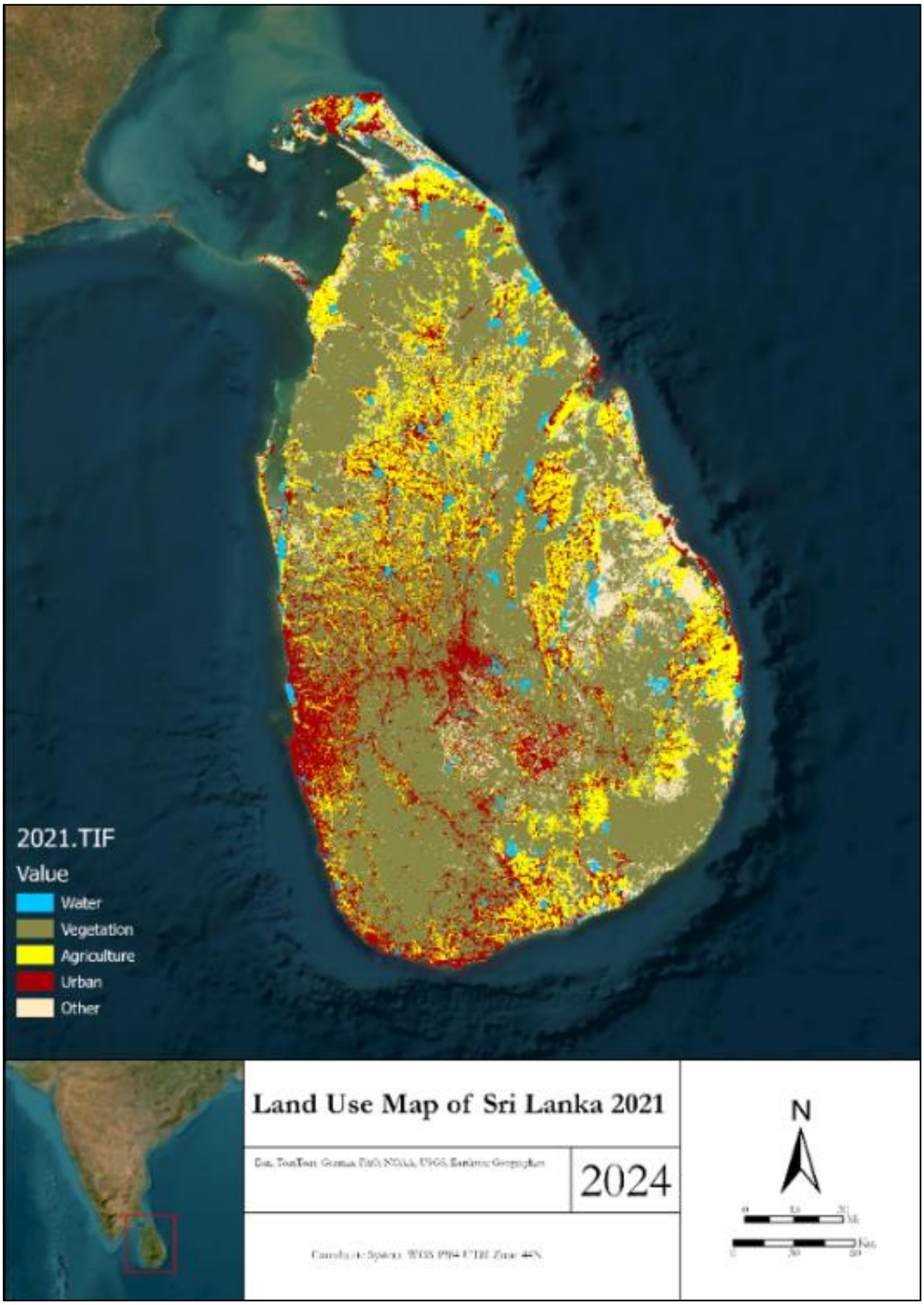

Figure 5 Land use Map of Sri Lanka 2021

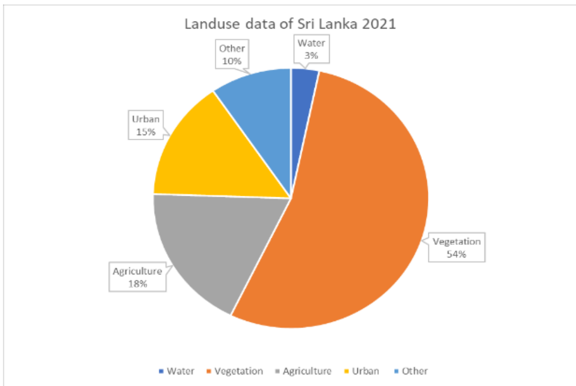

Figure 6 Land use data of Sri Lanka 2021

Terrset Geospatial Monitoring and Modeling System for LULC 2021.

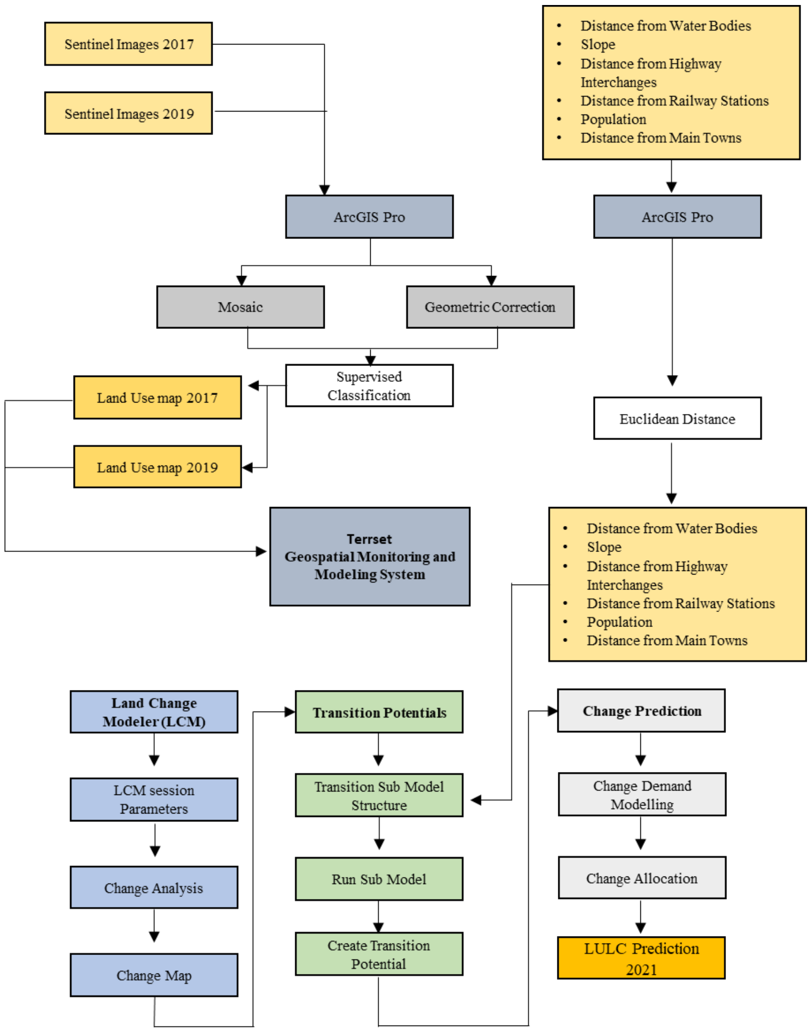

Figure 7 Process of Terrset Geospatial Monitoring and Modeling System for 2021 LULC Prediction

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QGIS Molusce Plugin land use prediction System for LULC 2021

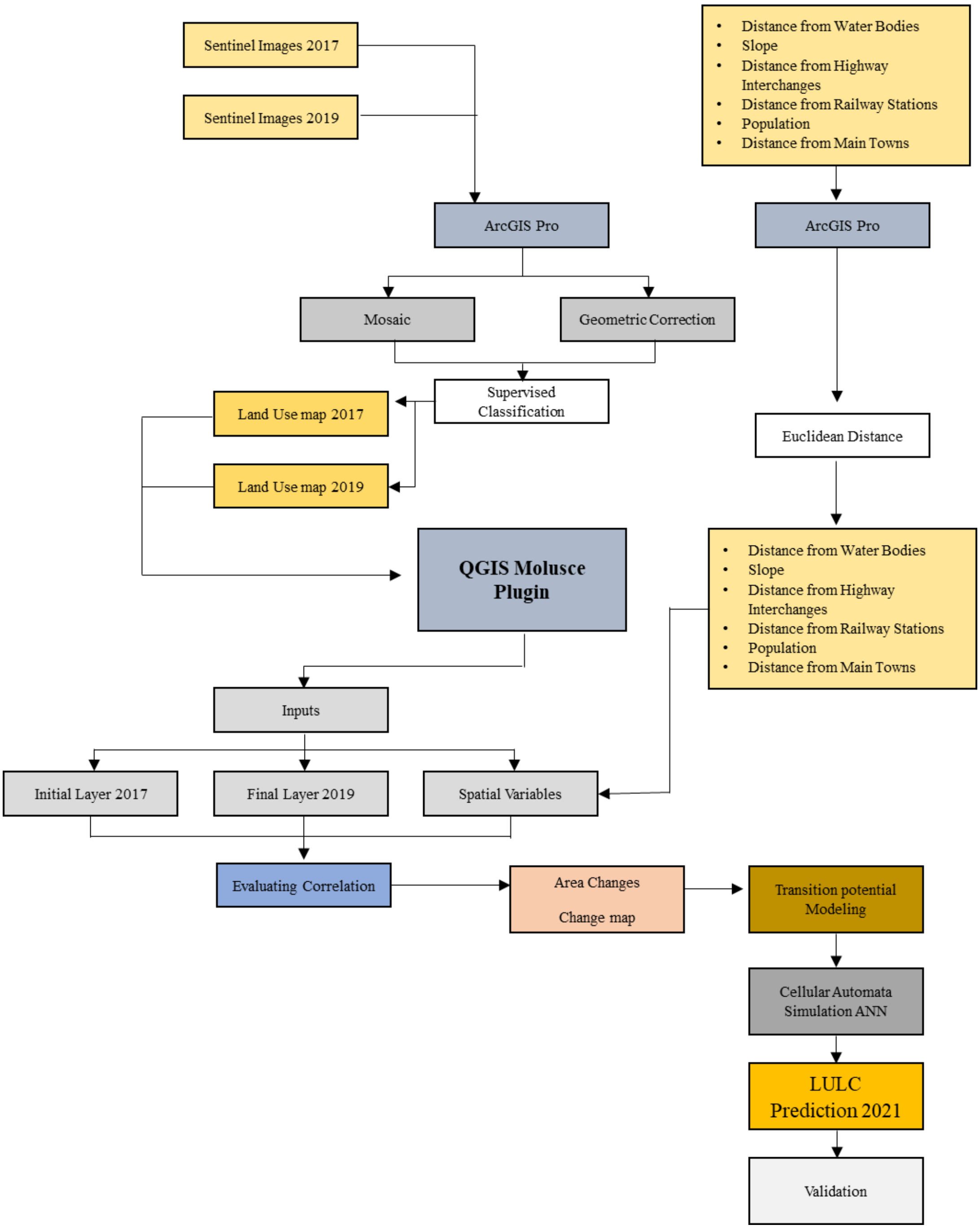

Figure 8 Process of QGIS Molusce Plugin land use prediction System for LULC 2021.

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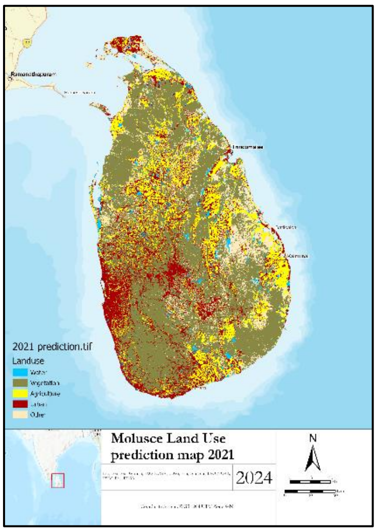

Figure 9 Molusce land use prediction map of Sri Lanka 2021

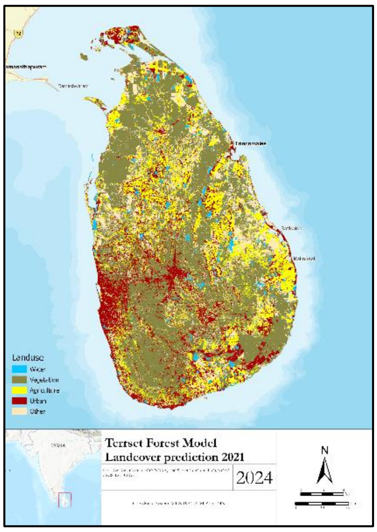

Figure 10 Forest Model 2021.

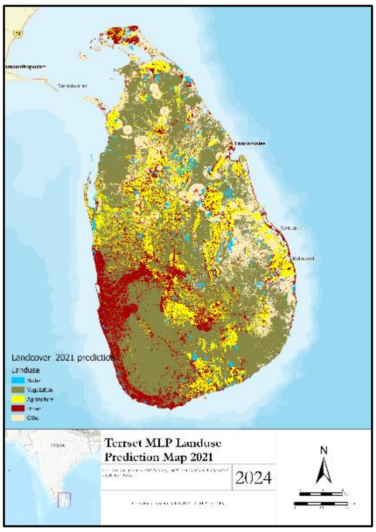

Figure 11 Terrset MLP model 2021.

In 2021, land use in Sri Lanka exhibited a diverse distribution, with water bodies comprising 3% of the total land area, while vegetation covered the majority at 54%. Agriculture accounted for 18% of land use, reflecting the country's significant reliance on farming practices. Urban areas constituted 15% of the landscape, highlighting ongoing urbanization trends. The remaining 10% was categorized as 'Other,' encompassing various land uses such as barren land or infrastructure. This breakdown provides valuable insights into the spatial distribution of land utilization across different sectors in Sri Lanka.

Table 2 Comparison of Land Use Classification Results by Molusce, ANN and Forest Models for 2021.

	Original 2021(%)	**Mistake**			**Mistake (%)**		
		Molusce	**terrset**		**Molusce**	**terrset**	
		2021(%)	**2021(%)**		**2021(%)**	**2021(%)**	
			ANN	**Forest Model**		**ANN**	**Forest Model**
Water	**3.30**	-1.00	-0.22	-0.64	-30.23	-6.75	-19.25
Vegetation	53.91	-2.96	-6.04	-5.84	-5.49	-11.21	-10.84
Agriculture	18.32	-2.54	-1.20	-1.26	-13.87	-6.54	-6.86
Urban	14.92	2.25	2.72	2.72	15.09	18.23	18.25
Other	9.55	4.24	4.74	5.01	44.43	49.66	52.48
	100.00						
				Mistake %	9.93	43.39	33.78
				Accuracy%	90.07	56.61	66.22
				Kappa Value	0.90	0.57	0.66

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Table 3 (Zach, 2021)

Kappa Value	Interpretation
0	No agreement
0.10 – 0.20	Slight agreement
0.21 – 0.40	Fair agreement
0.41 – 0.60	Moderate agreement
0.61 – 0.80	Substantial agreement
1	Perfect agreement

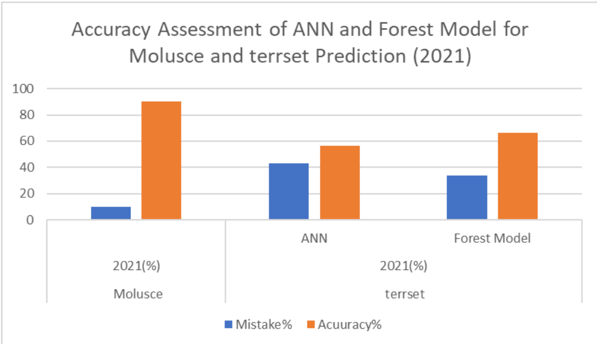

Figure 3 Accuracy Assessment of ANN and Forest Model for Molusce and terrset

Kappa (Overall) >=0.6 is considered as the satisfactory result and acceptable (Saputra & lee, 2019).Based on the provided data, Molusce outperforms Terrset in terms of accuracy, with an accuracy percentage of 90.07% (figure 13) compared to Terrset's 56.61%. Additionally, Molusce achieves a higher kappa value of 0.90, indicating substantial agreement beyond chance, whereas Terrset lags behind with a kappa value of 0.57. When examining the mistakes made by each model, Molusce demonstrates a lower mistake percentage of 9.93% compared to Terrset's 43.39%. These findings suggest that Molusce is the most accurate simulation model among the two, providing more reliable and consistent results for the given dataset. Therefore, it is decided to continue the study using Molusce Plugin in QGIS.

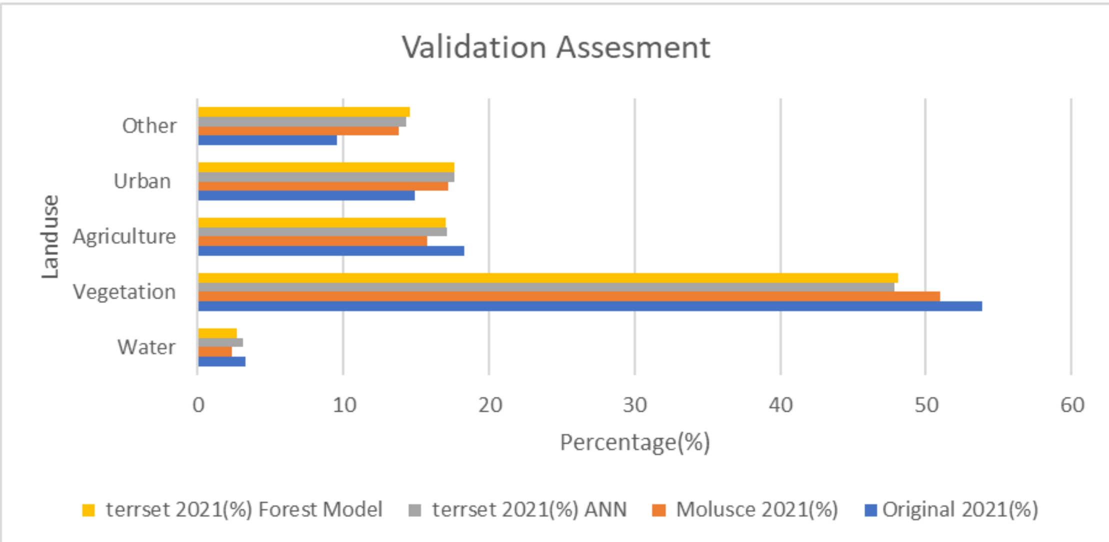

Figure 12 Model Validation

Analysis and Interpretation

Model Simulation

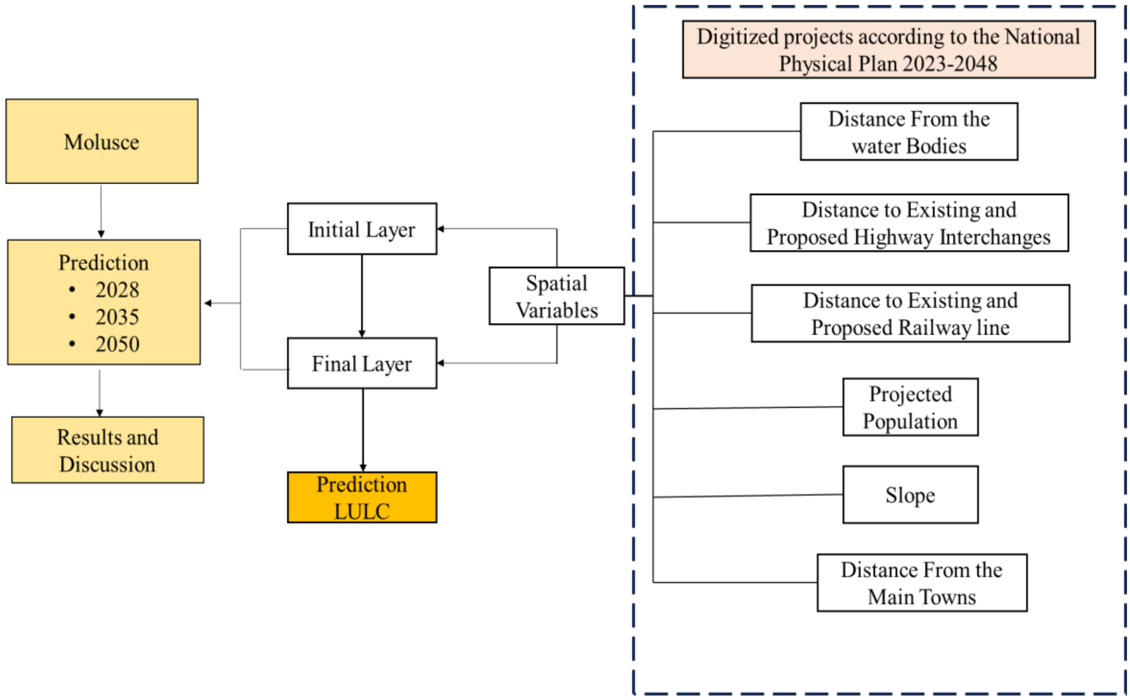

Figure 13 Model Simulation Process

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After the selection of the appropriate software, the QGIS Molusce Plugin, the proposed road and infrastructure projects were digitized for simulation. The simulation spans three years: 2028, 2035, and 2050, with distinct sets of digitized projects for each year. This approach allows for the assessment of land use dynamics over time, considering the evolving infrastructure landscape and its potential impact on urban development.

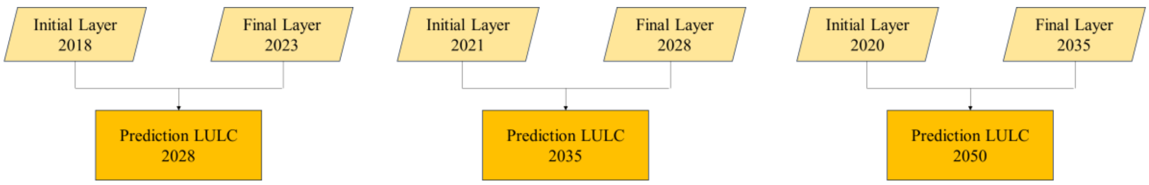

Figure 14 Prediction Process

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a) Model Structure for Year 2028

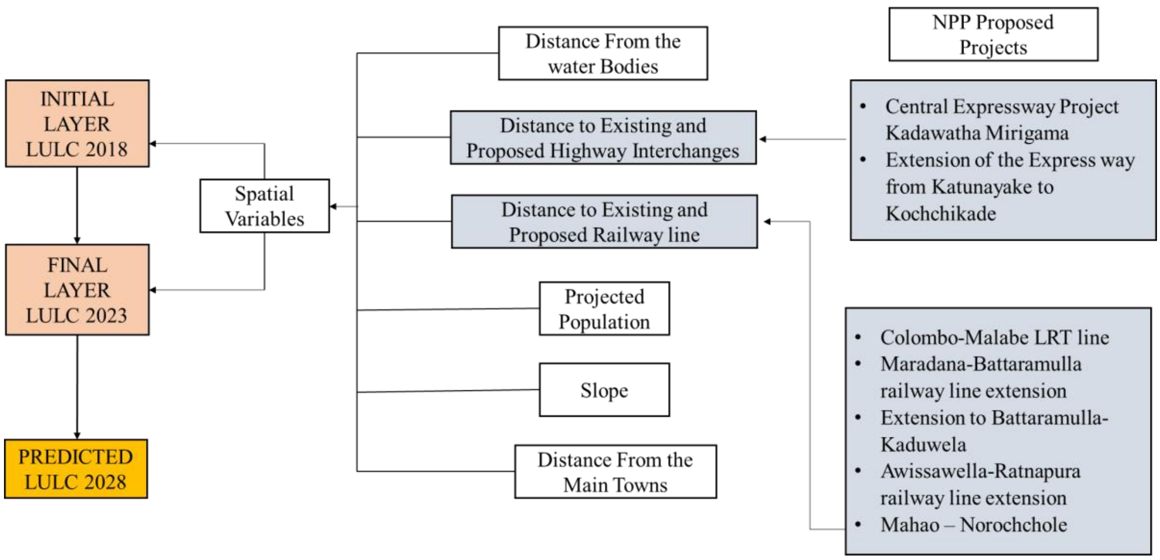

Figure 15 Model Structure for 2028

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In this phase of the research, ongoing and proposed projects falling within the timeframe of 2023 to 2028 are being digitized and incorporated into the simulation model. By digitizing these projects, including infrastructure initiatives and urban development projects, their spatial representation n is accurately captured. Subsequently, through simulation, the anticipated impacts of these projects on land use and transportation dynamics are assessed. The focus is on generating a predictive map for the year 2028, reflecting the cumulative effects of these initiatives on the urban landscape.

Table 4 Proposed NPP projects for 2028.

Type of Infrastructure	2028 Projects (Short Term)
Railway Projects	Colombo-Malabe LRT line
	Maradana-Battaramulla railway line extension
	Extension to Battaramulla-Kaduwela
	Awissawella-Ratnapura railway line extension
	Mahao – Norochchole
Road Infrastructure Projects	Central Expressway Project Kadawatha Mirigama
	Extension of the Express way from Katunayake to Kochchikade

The map displays (Figure 16) the digitized representation of proposed projects, along with the reclassified railway line map, intended for integration into the Molusce software as spatial variables. The proposed projects, encompassing developments outlined in the National Physical Plan (NPP), have been delineated and overlaid onto the railway infrastructure map, which has been reclassified to facilitate its utilization as a spatial variable within the Molusce simulation framework. This combined dataset serves as a foundational component for conducting land use change simulations, enabling the assessment of potential impacts and interactions between proposed projects and existing spatial features such as railway lines.

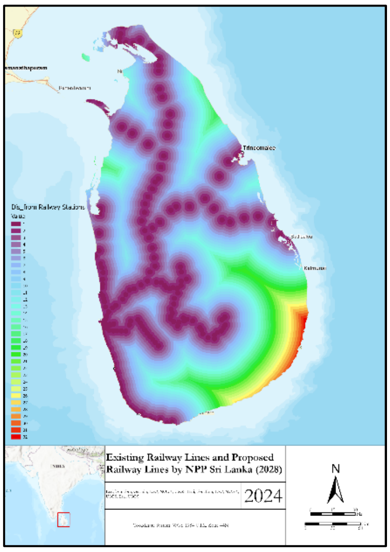

Figure 16 Existing Railway Lines and Proposed railway lines by NPP 2028

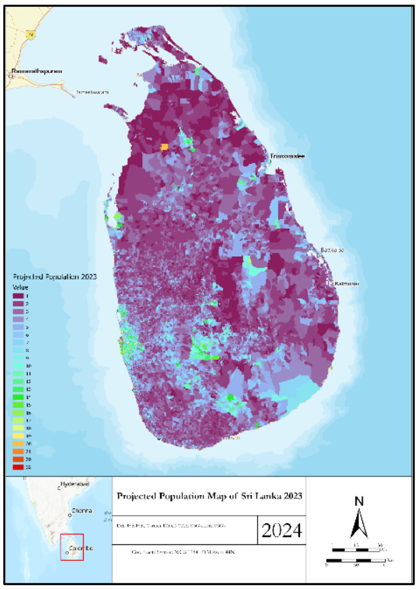

Figure 17 Projected Population Map of Sri Lanka 2023

In addition to the digitized proposed projects and reclassified railway line map, projected population data for the year 2023 has been incorporated as a spatial variable within the Molusce simulation framework. This projected population dataset serves as a crucial input for the simulation model, providing insights into anticipated population distribution and density across the study area.

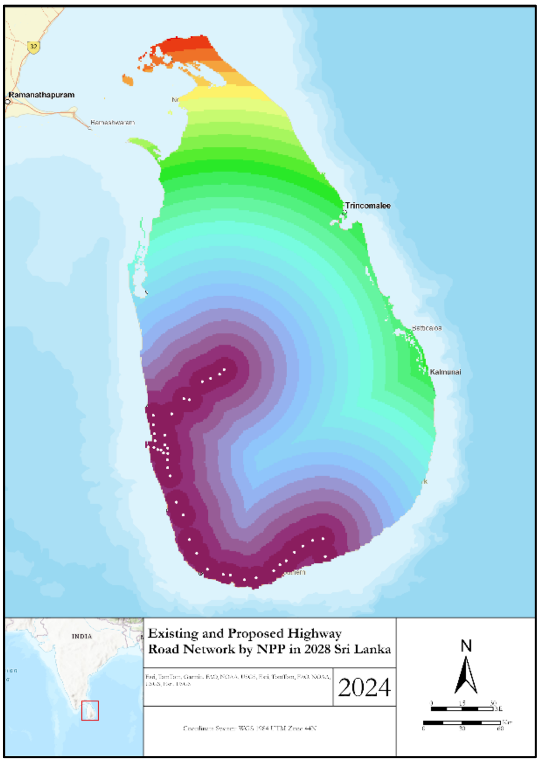

Figure 18 Existing and Proposed Highway Network by NPP 2028

Combined with the digitized proposed road projects for the year 2028, a reclassified raster representing these road developments has been generated to incorporate into the spatial variables utilized within the Molusce simulation framework. By integrating this reclassified raster dataset into the Molusce model, it becomes possible to assess the potential impacts of proposed road infrastructure expansions on land use patterns and transportation networks. The inclusion of road projects as a spatial variable enables the simulation of various scenarios, allowing researchers and policymakers to evaluate the consequences of different development pathways on urban growth, accessibility, and environmental sustainability. This approach enhances the comprehensiveness of the simulation analysis.

The digitized proposed projects outlined in the 2023 National Physical Plan (NPP) have been integrated into the spatial variables utilized within the Molusce simulation framework. These projects, slated for completion by 2028, encompass a range of infrastructural developments, including road expansions, railway line extensions, and urban amenities. By incorporating these proposed projects into the spatial variables, the Molusce model can account for their potential impacts on land use dynamics and transportation networks.

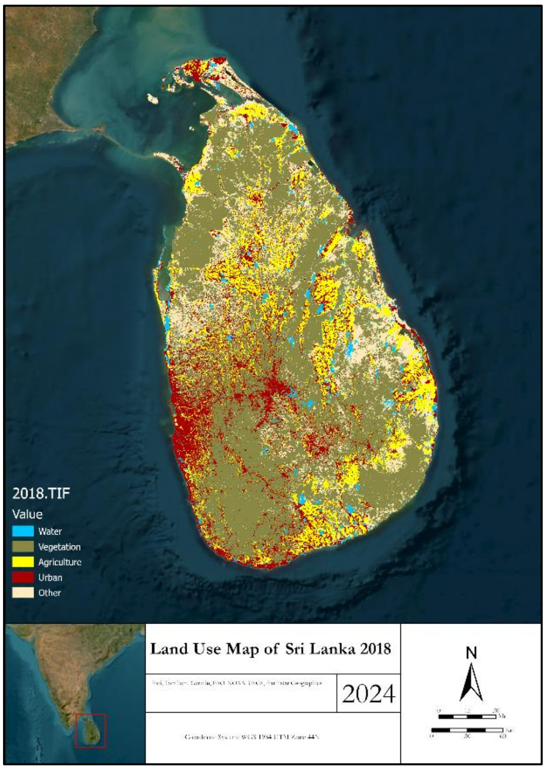

Figure 19 land use map of Sri Lanka 2018.

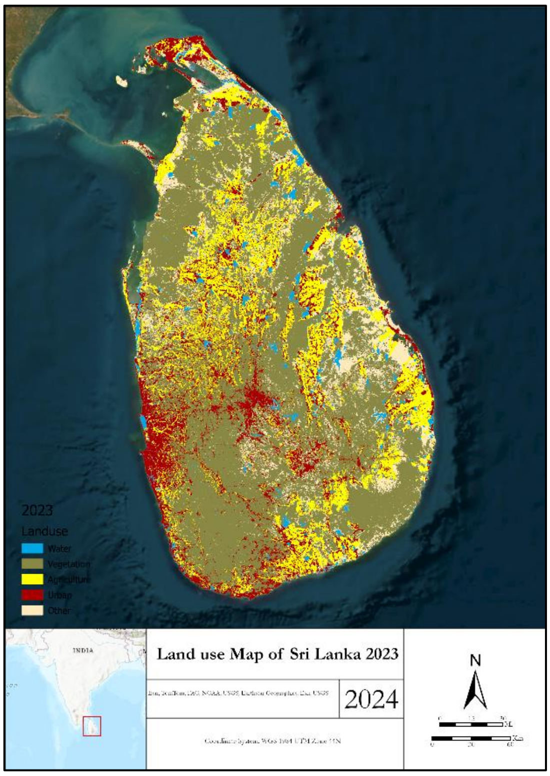

Figure 20 land use map of Sri Lanka 2023.

Furthermore, spatial variables such as distance from water bodies, existing and proposed highway interchanges, railway lines, slope, proximity to main towns, and projected population have been utilized to enhance the accuracy and comprehensiveness of the simulation analysis. The 2018 layer serves as the initial layer in Molusce, while the 2023 layer and the final layer represent the conditions in 2023 and the predicted outcomes for 2028, respectively. This approach enables researchers to simulate various scenarios and assess the implications of proposed developments on urban growth, accessibility, and environmental sustainability.

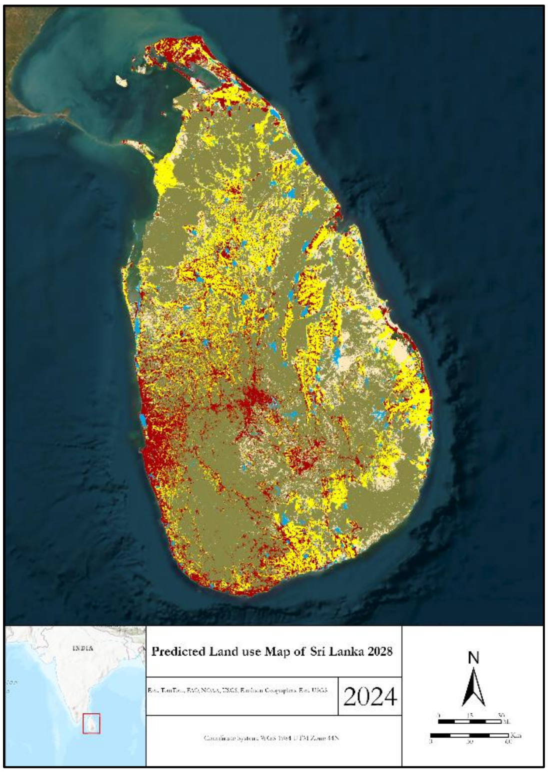

Figure 21 land use Prediction map of Sri Lanka 2028

Table 5 Landuse data 2018,2023 and predicted 2028

Land Use Type	**Original 2021**	**Original 2018**	**Predicted 2028**	**2018(%)**	**2023(%)**	**2028(%)**
Water	2179	1567	1871.52	2	3	3
Vegetation	35599	35062	35139.73	53	53	53
Agriculture	12097	9666	12126.51	15	17	18
Urban	9853	9071	10520.31	14	15	16
Other	6309	10392	6404.12	16	11	10

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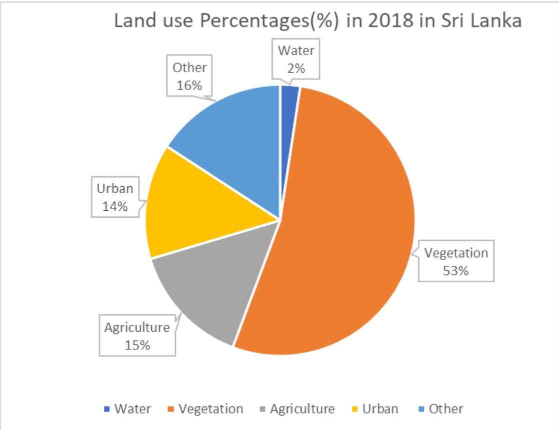


Figure 22 Land use Percentages (%) in 2018 in Sri Lanka

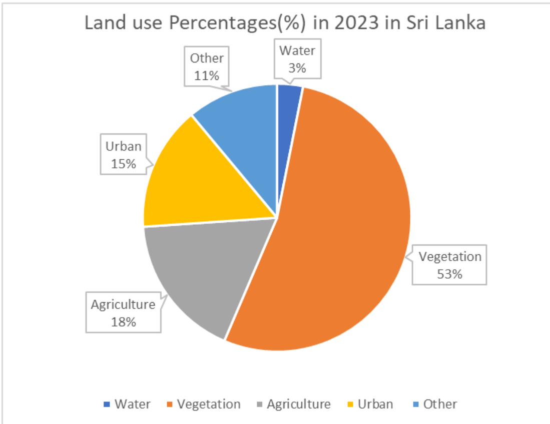


Figure 23 Land use Percentages (%) in 2023 in Sri Lanka

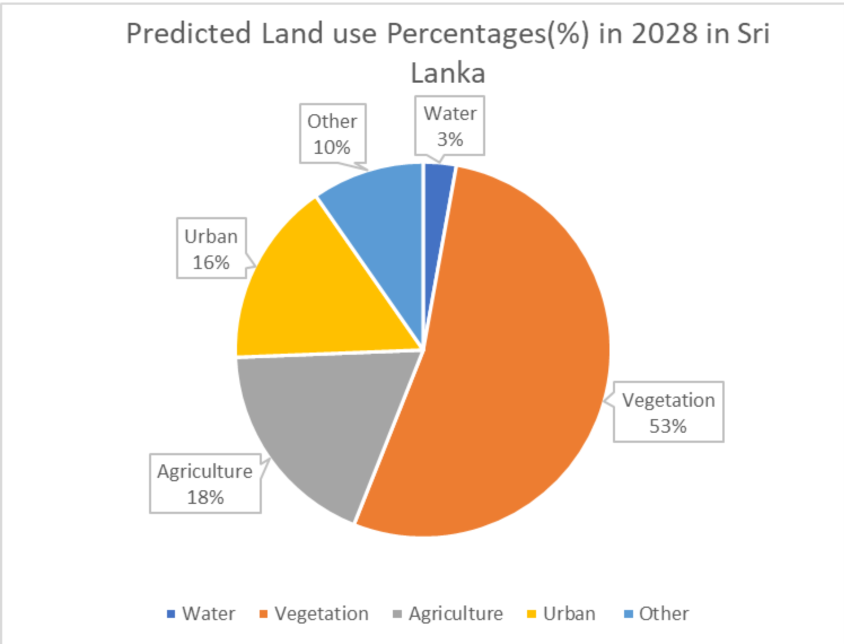


Figure 24 Predicted land use percentage (%) in 2028 in Sri Lanka

b) Model Structure for Year 2035

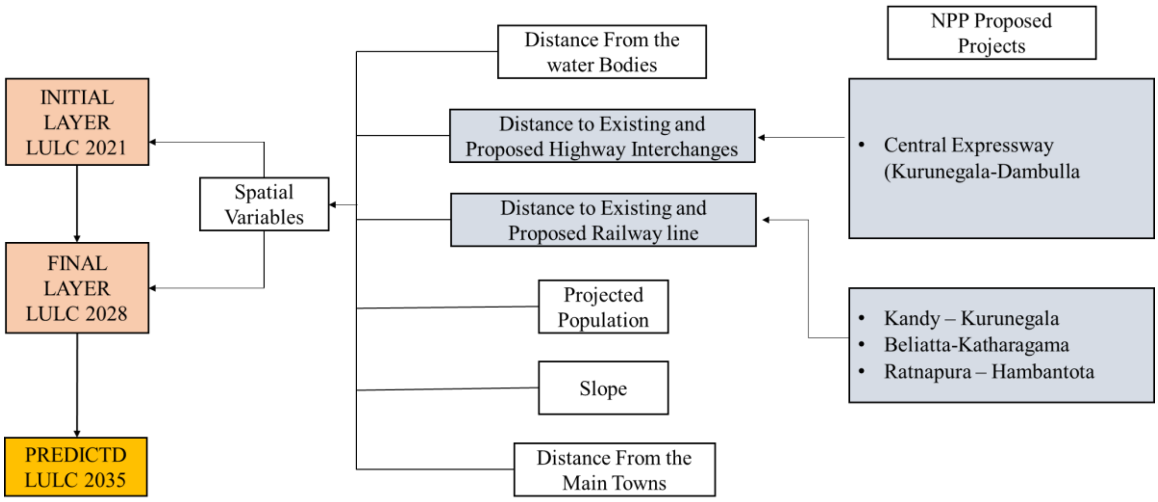


Figure 25 Model Structure for 2035

Source 11 Compile by author.

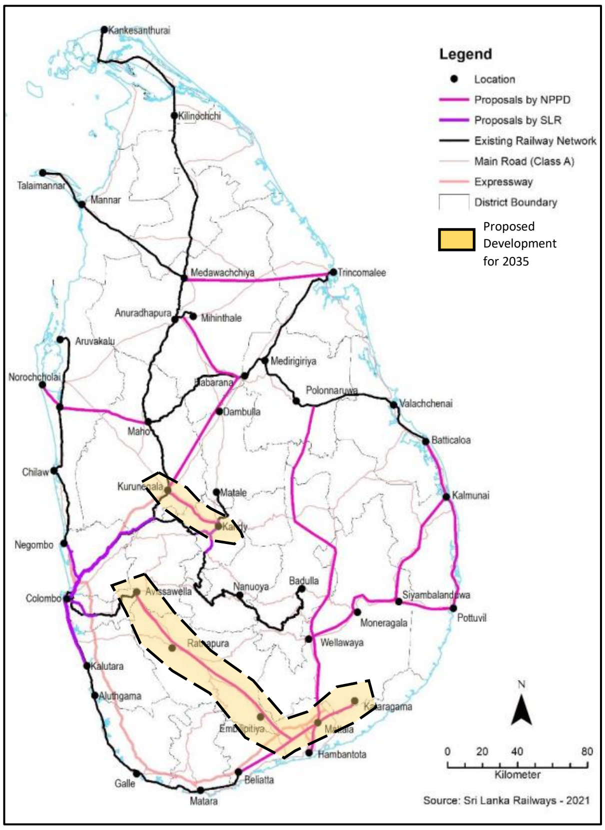
During this phase of the research, ongoing and proposed projects within the timeframe of 2023 to 2028 are meticulously digitized and integrated into the simulation model. This encompasses various infrastructure initiatives and urban development projects, ensuring their spatial representation is accurately captured. Through simulation, the anticipated impacts of these projects on land use and transportation dynamics are thoroughly assessed. The primary objective is to generate a predictive map for the year 2028, reflecting the cumulative effects of these initiatives on the urban landscape.

In the subsequent phase, the simulation progresses to the year 2035, utilizing the initial layer from 2021 and the final layer derived from the 2028 simulated outcomes. This iterative approach allows for a comprehensive evaluation of land use changes and transportation patterns, providing valuable insights into the long-term implications of the proposed projects.

Table 6 Proposed NPP projects for 2035.

Type of Infrrastructure	2035 Projects
Railway Projects	Kandy – Kurunegala
	Beliatta-Katharagama
	Ratnapura – Hambantota
Road Infrastructure Projects	Central Expressway (Kurunegala-Dambulla)

In this phase of the research, ongoing and proposed projects from 2023 to 2028 are being carefully integrated into the simulation model. These projects include infrastructure developments like roads and railways. Their spatial locations are accurately depicted on the map to assess their potential impacts on land use and transportation in the future. The goal is to predict how these projects might shape the urban landscape by 2028. Next, the simulation progresses to 2035 using data from 2021 as a starting point and insights gained from the 2028 simulation. This iterative approach helps understand the long-term implications of these proposed projects.The proposed projects have been visually represented on a map, and a reclassified map with digitized proposed projects has been created.



Source 12 National Physical Plan Sri Lanka

Figure 26 Completed Railway project in 2035.

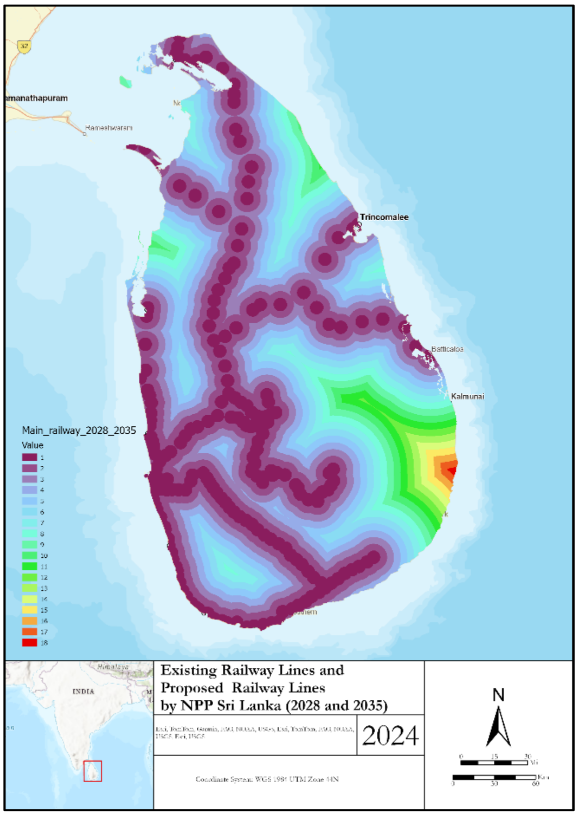


Figure 27 Existing Railway Lines and Proposed Railway Lines by NPP Sri Lanka (2028 and 2035)

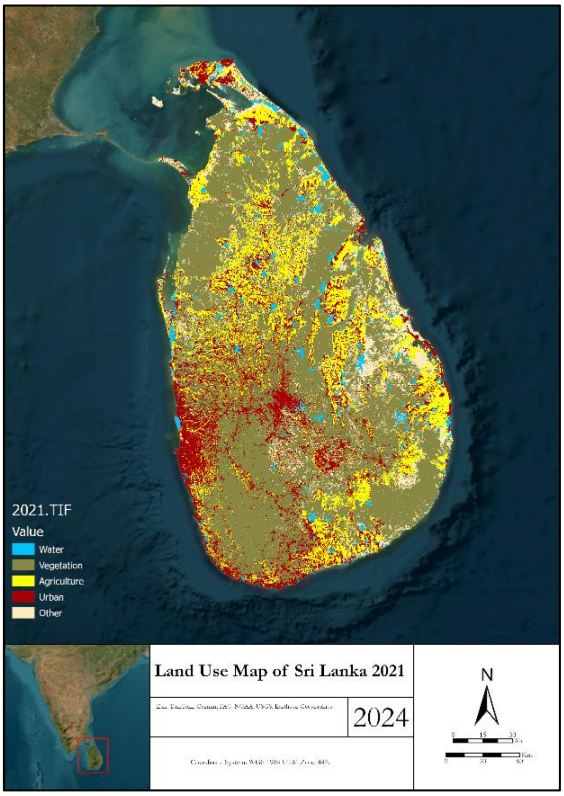


Figure 28 land use map of Sri Lanka 2021

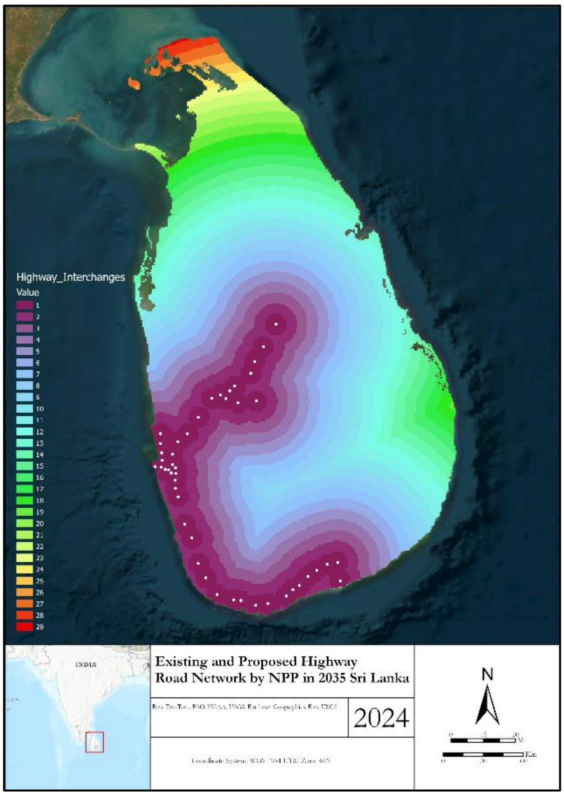


Figure 29 Existing and Proposed Highway Network by NPP 2035

Integrated with the digitized proposed road projects for the year 2035, a reclassified raster has been generated to represent these road developments. This raster dataset is incorporated into the Molusce simulation framework, enabling the assessment of potential impacts on land use patterns and transportation networks.

Table 7 Land Use change 2035.

Land Use Type	2021(sq.km)	2028(sq.km)	2035(sq.km)	2021(%)	2028(%)	2035(%)
Water	2179.34	1871.52	2156.68	3.30	2.83	3.27
Vegetation	35599.20	35139.73	34645.32	53.91	53.19	52.59
Agriculture	12096.54	12126.51	13277.03	18.32	18.36	20.15
Urban	9852.75	10520.31	10784.81	14.92	15.92	16.37
Other	6308.60	6404.12	5012.57	9.55	9.69	7.61

Source 13 Compile by author.

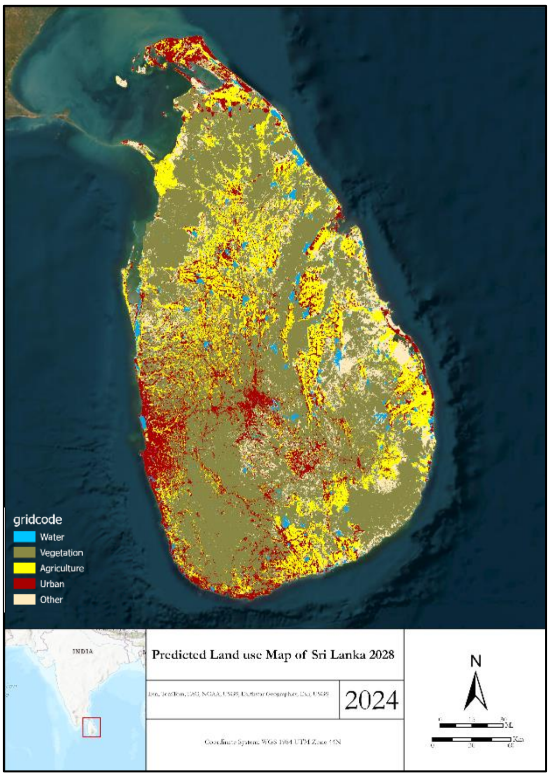


Figure 30 land use map of Sri Lanka 2028

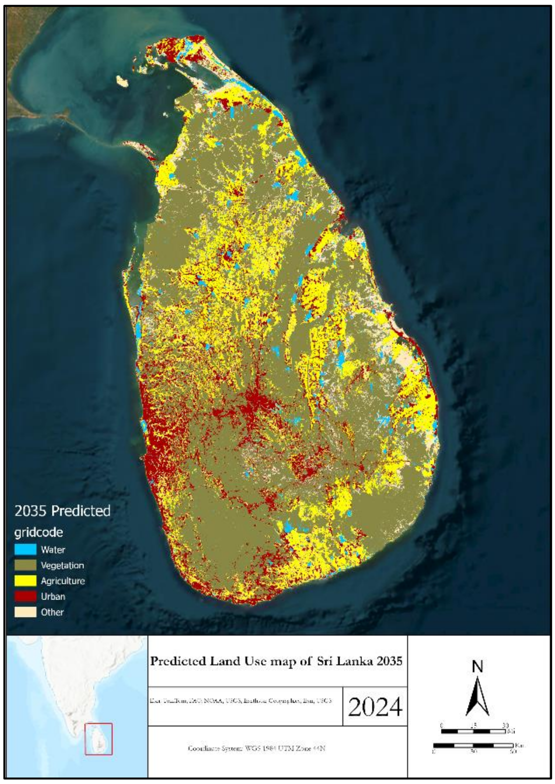


Figure 31 land use map of Sri Lanka 2028

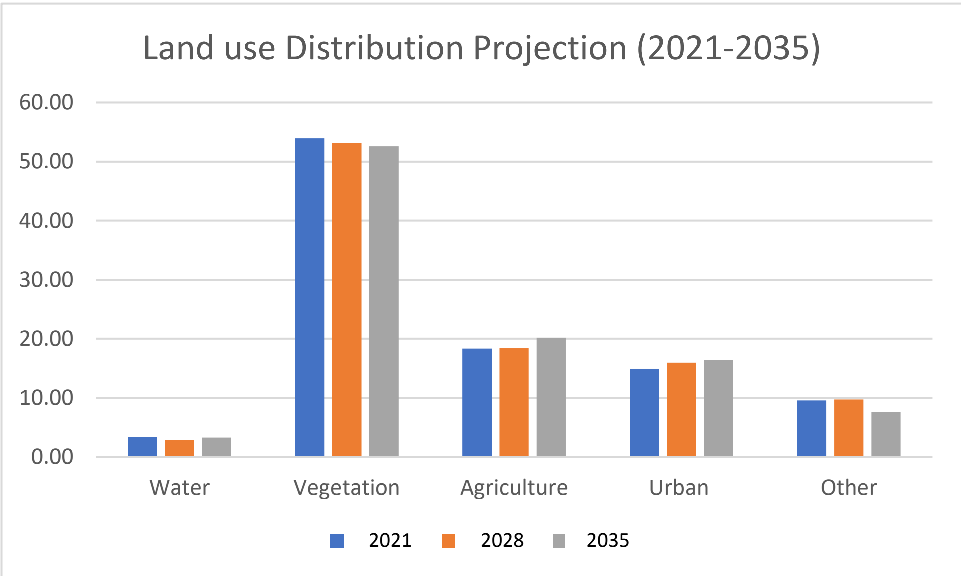


Figure 32 Land use Distribution Projection (2021-2035)

c) Model Structure for Year 2050

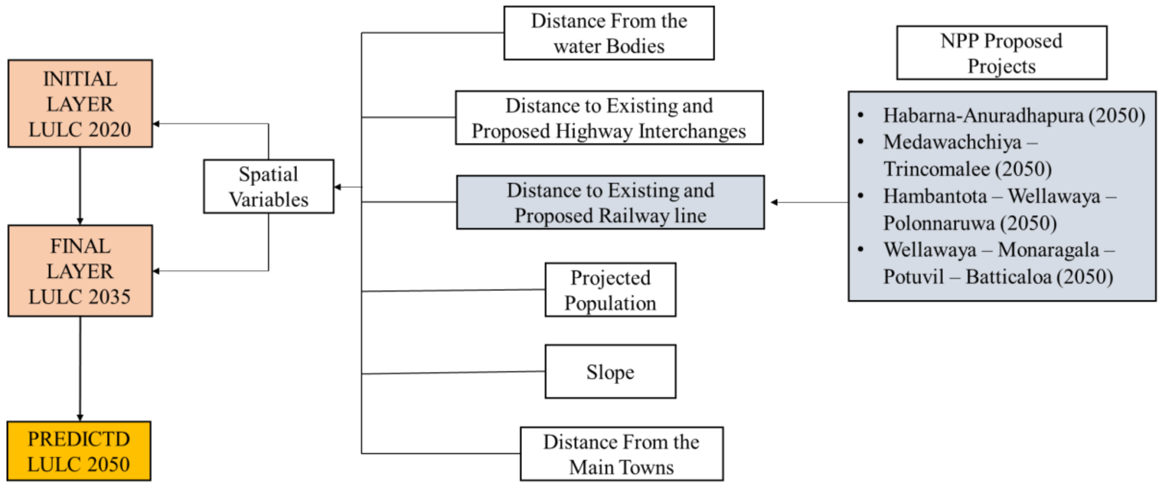


Figure 33 Model Structure for 2050

Source 14 Compile by author.

During this phase of the research, ongoing and proposed projects from 2023 to 2028 are being digitized and integrated into the simulation model. This includes various infrastructure projects. Through simulation, assessing the expected impacts of these projects on land use and transportation dynamics, with the primary goal of generating a predictive map for the year 2028 that reflects the cumulative effects of these initiatives on the urban landscape. Subsequently, the simulation progresses to the year 2035, utilizing the initial layer from 2020 and the final layer derived from the 2028 simulated outcomes. This iterative approach enables a comprehensive evaluation of land use changes and transportation patterns, providing valuable insights into the long-term implications of the proposed projects. The digitized projects for 2035 include railway expansions such as the Habarna-Anuradhapura line, the Medawachchiya-Trincomalee line, the Hambantota-Wellawaya-Polonnaruwa line, and the Wellawaya-Monaragala-Potuvil-Batticaloa line, which are projected to be completed by 2050. These projects will be integrated into the simulation model to forecast land use dynamics and transportation networks up to the year 2050.

Table 8 Proposed NPP projects for 2035.

Type of Infrastructure	2035 Projects
Railway Projects	Habarna-Anuradhapura (2050)
	Medawachchiya – Trincomalee (2050)
	Hambantota – Wellawaya – Polonnaruwa (2050)
	Wellawaya – Monaragala – Potuvil – Batticaloa (2050)

Source 15 Compile by author.

.In this phase, I've digitized and reclassified several railway projects planned for completion by 2050. These include the Habarna-Anuradhapura line, the Medawachchiya-Trincomalee line, the Hambantota-Wellawaya-Polonnaruwa line, and the Wellawaya-Monaragala-Potuvil-Batticaloa line. By adding these digitized projects into the QGIS Molusce plugin, we aim to assess their potential impacts on land use and transportation dynamics. This integration allows us to simulate various scenarios and evaluate how these railway expansions might shape urban development and accessibility in the future. It's a crucial step in understanding the long-term implications of these infrastructure projects.

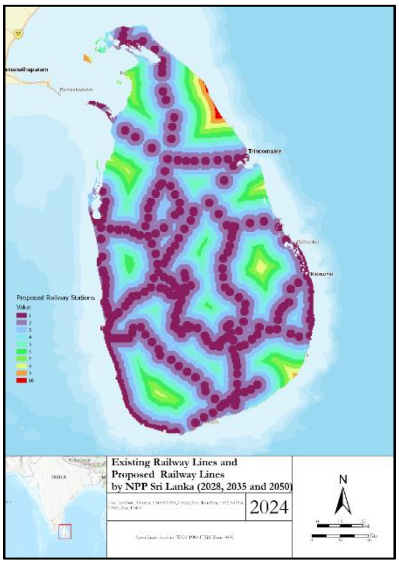


Figure 34 Existing Railway Lines and Proposed Railway Lines by NPP Sri Lanka (2028, 2035 and 2050)

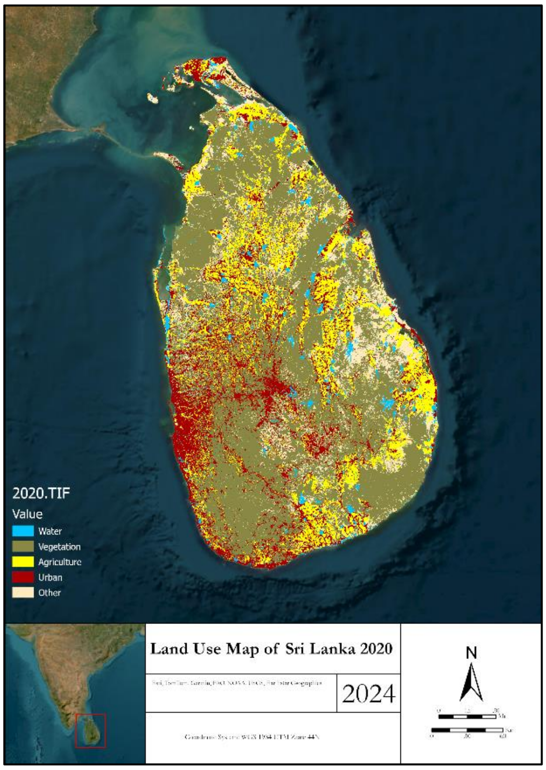


Figure 35 land use map of Sri Lanka 2020

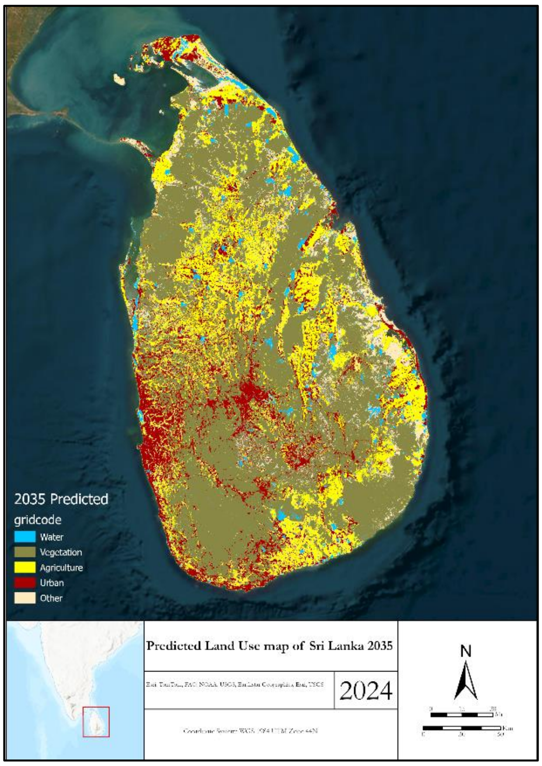


Figure 36 Predicted land use map of Sri Lanka 2035

Table 9 Land Use change 2050.

Landuse Type	2020(sq.km)	2035(sq.km)	2050(sq.km)	2020(%)	2035(%)	2050(%)
Water	1886.58	2156.68	1752.117	2.87	3.27	2.66
Vegetation	34108.52	34645.32	31599.8	51.87	52.59	48.06
Agriculture	11267.48	13277.03	11217.51	17.13	20.15	17.06
Urban	10157.62	10784.81	11599.18	15.45	16.37	17.64
Other	8339.27	5012.57	9576.911	12.68	7.61	14.57

Source 16 Compile by author.

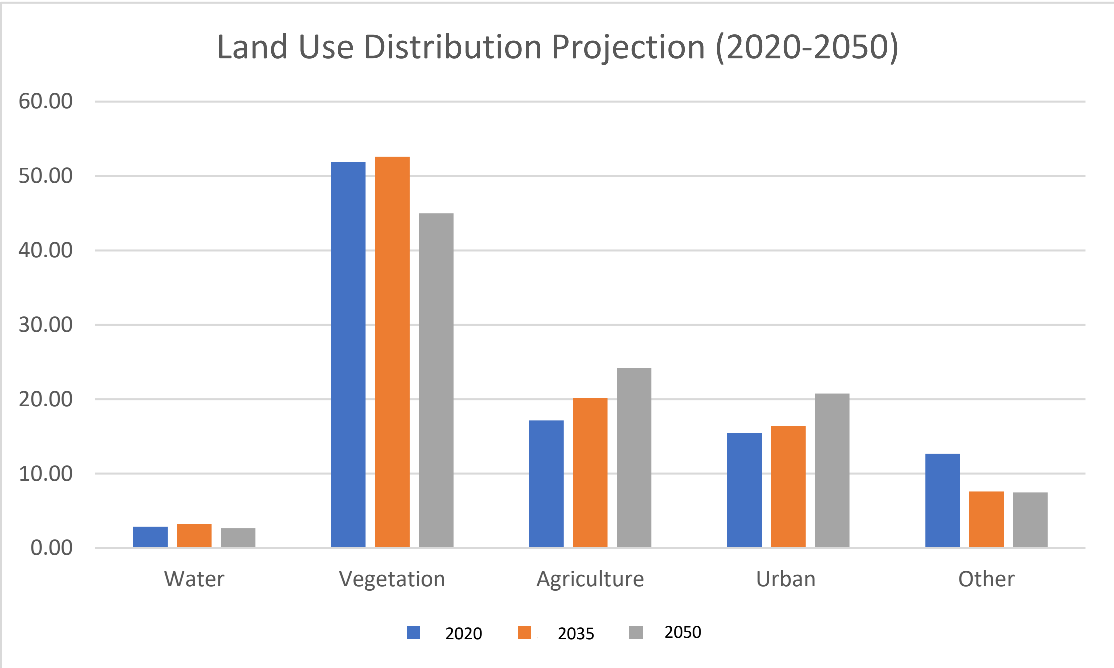


Figure 37 Land Use Distribution Projection (2020-2050)

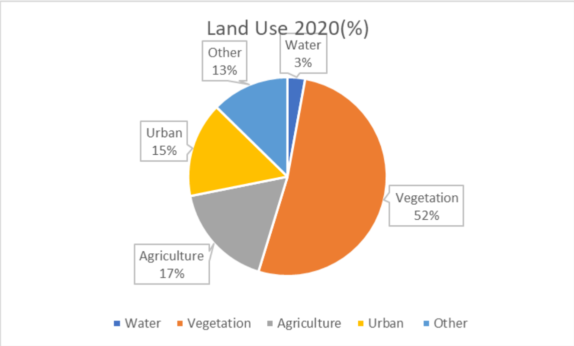


Figure 38 Land Use 2020(%)

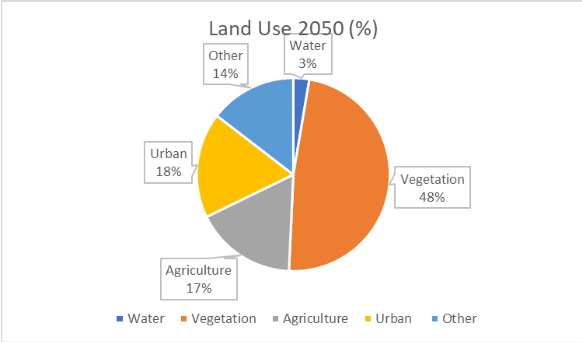


Figure 39 Land Use 2050(%)

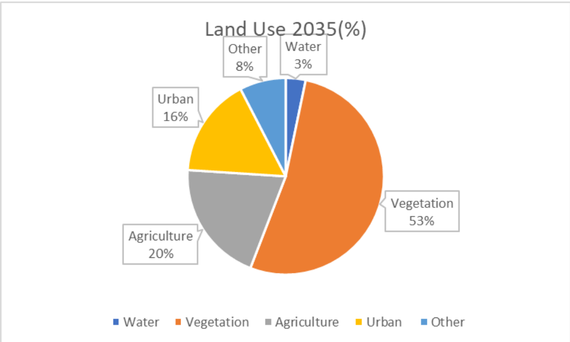


Figure 40 Land Use 2035(%)

The digitized projects for 2035 include railway expansions such as the Habarna-Anuradhapura line, the Medawachchiya-Trincomalee line, the Hambantota-Wellawaya-Polonnaruwa line, and the Wellawaya-Monaragala-Potuvil-Batticaloa line, which are projected to be completed by 2050. These projects will be integrated into the simulation model to forecast land use dynamics and transportation networks up to the year 2050. Finally, the simulation will show the 2050 simulated map, providing insights into the anticipated land use patterns. (Figure 51).

Results and Discussion

- **Impact of Proposed Railway Projects.**

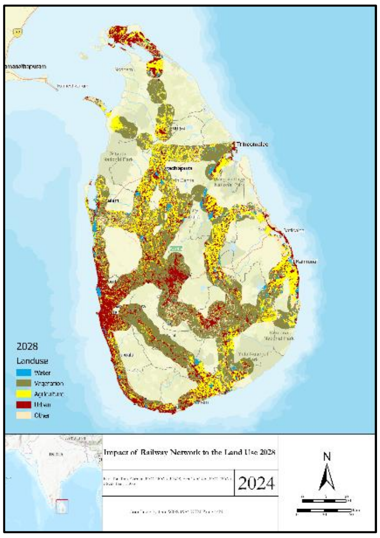


Figure 41 Impact of Railway Network to the Land Use 2028

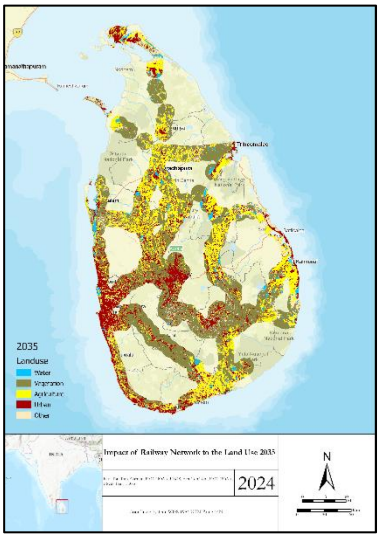


Figure 42 Impact of Railway Network to the Land Use 2035

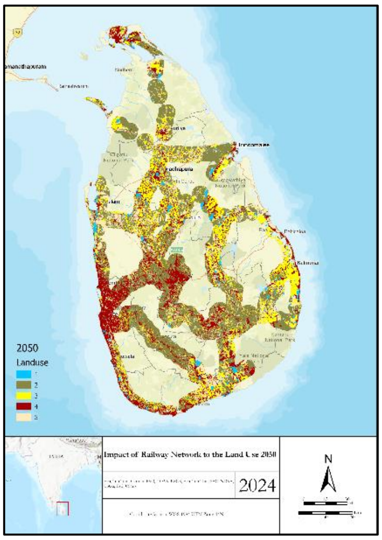


Figure 43 Impact of Railway Network to the Land Use 2050

Table 10 Impact of Railway Network to the Land Use 2028, 2035 and 2050

Land Use Type	Area			Percentage%		
	2028	**2035**	**2050**	**2028**	**2035**	**2050**
Water	1002.40	1124.33	964.18	3.16	3.56	3.05
Vegetation	13445.12	12800.71	12284.53	42.40	40.53	38.90
Agriculture	7227.52	7740.59	6055.46	22.79	24.51	19.18
Urban	7315.03	7478.16	7577.02	23.07	23.68	24.00
Other	2721.87	2437.74	4695.14	8.58	7.72	14.87

Source 17 Compile by author.

Above data presents the land use type distribution for the years 2028, 2035, and 2050, with a focus on the impact of the railway network on land use dynamics. Let's analyze the changes observed over these time periods:

The area occupied by water bodies experiences slight fluctuations over time, with a decrease from 2028 to 2050. This suggests minimal impact from the railway network on water bodies.

The area covered by vegetation shows a declining trend from 2028 to 2050. This could indicate land conversion for urban or agricultural purposes, possibly influenced by the proximity to railway stations and associated development.

Agricultural land area decreases gradually over the simulation period. This decline might be attributed to urban expansion and infrastructure development, including the railway network, which could lead to land conversion for residential or industrial purposes.

Urban areas witness steady growth throughout the simulation period. This expansion could be linked to increased accessibility facilitated by the railway network, attracting population influx, and driving urban development.

In this research, predictive simulations were conducted for the years 2028, 2035, and 2050 to analyze land use changes, utilizing six influential factors identified from the study: Distance from Water Bodies, Slope, Distance from Highway Interchanges, Distance from Railway Stations, Population, and Distance from Main Towns. Additionally, proposed infrastructure projects outlined in the National Physical Plan (NPP) for the years 2023-2048 were considered, focusing on spatially representable projects such as road and railway developments. To assess the impact of railway stations on land use, existing and proposed stations were identified from the NPP, and a buffer zone of 10 kilometers around these stations was delineated. This buffer zone served as the area of interest for evaluating the influence of railway stations on land use dynamics.

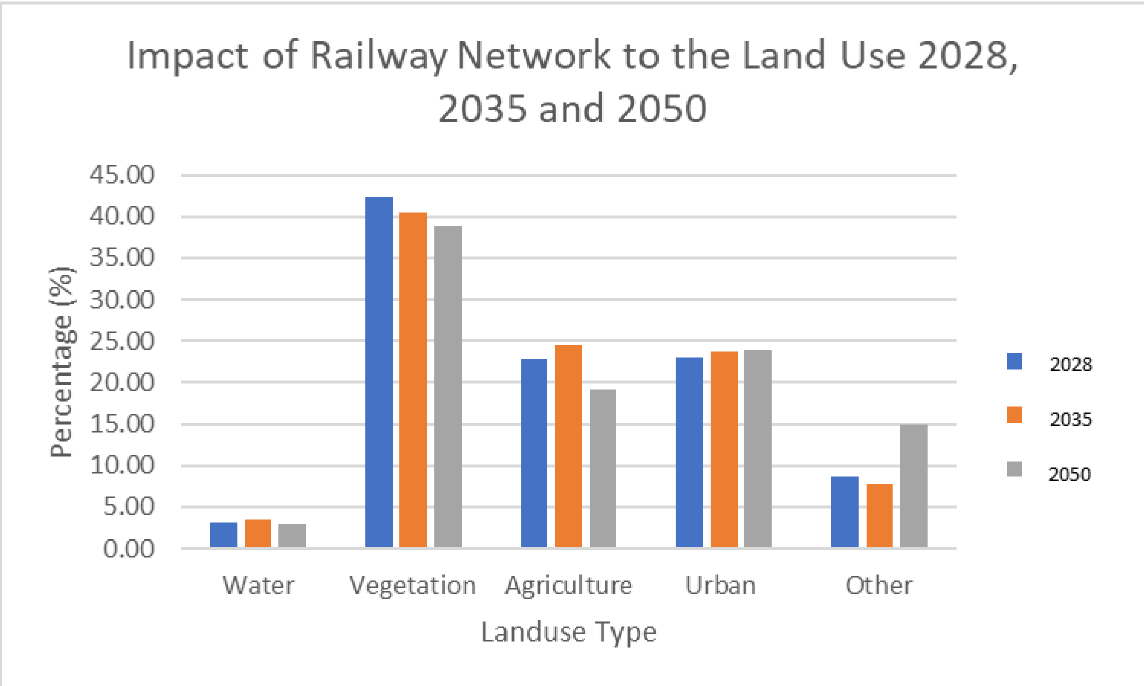


Figure 44 Impact of Railway Network to the Land Use 2028, 2035 and 2050

- **Impact of Proposed Expressway (Highway Interchanges) Projects.**

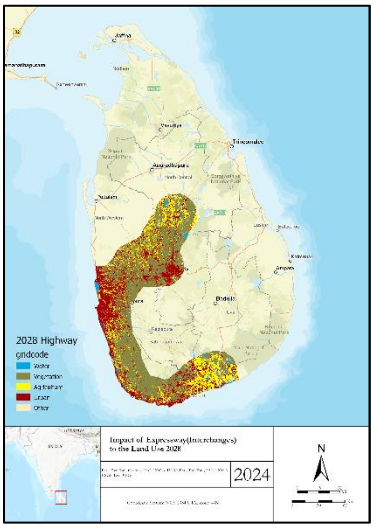


Figure 45 Impact of Expressway (Interchanges) to the Land Use 2028

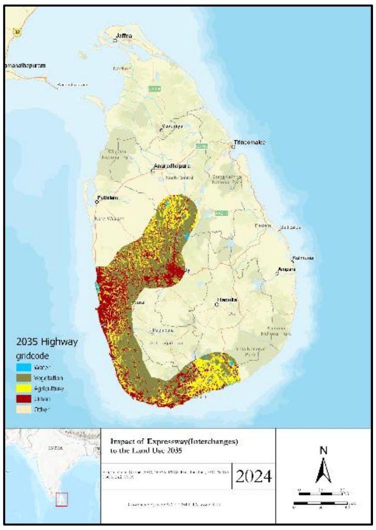


Figure 46 Impact of Expressway (Interchanges) to the Land Use 2035

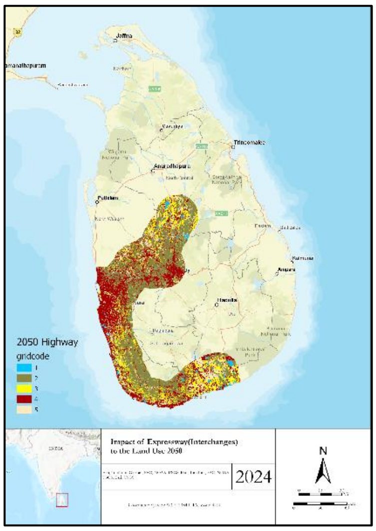


Figure 47 Impact of Expressway (Interchanges) to the Land Use 2050

Table 11 Impact of Expressway network to the Land Use 2028, 2035 and 2050

Land Use Type	**Area**			**Percentage%**		
	2028	**2035**	**2050**	**2028**	**2035**	**2050**
Water	309.91	260.10	317.64	2.06	1.73	2.12
Vegetation	7319.68	6586.63	5997.03	48.66	43.79	39.97
Agriculture	2459.50	3010.89	2221.00	16.35	20.02	14.80
Urban	4524.98	4563.74	4977.76	30.08	30.34	33.17
Other	428.14	619.80	1491.21	2.85	4.12	9.94

Source 18 Compile by author.

Similarly, the impact of highway interchanges on land use was examined by identifying existing and proposed interchanges from the National Physical Plan. A buffer zone with a radius of 15 kilometers around these interchanges was delineated. This buffer zone served as the spatial boundary for analyzing the effect of highway interchanges on land use transformations.

By employing this systematic approach, the research aimed to provide insights into how proposed infrastructure development, particularly railway stations and highway interchanges, could shape land use patterns over time. This methodological framework allowed for a comprehensive analysis of the spatial relationships between infrastructure development and land use changes. Analyzing the impact of highway interchanges on land use dynamics across the simulated years of 2028, 2035, and 2050 reveals notable shifts in land use patterns. Here's a detailed analysis based on the provided data:

The area of water bodies shows a slight increase from 2028 to 2050, suggesting minimal impact from highway interchanges. Despite fluctuations, the percentage of area occupied by water remains relatively stable over the study period.

There is a consistent decline in vegetation areas from 2028 to 2050, indicating a gradual conversion of vegetated areas to other land use types. The percentage of land covered by vegetation decreases significantly, indicating substantial changes in ecosystem composition possibly due to urbanization or agricultural expansion facilitated by highway interchanges.

Agricultural land area experiences fluctuations throughout the study period, with a notable decrease from 2028 to 2050. The percentage of land allocated for agriculture follows a similar trend, suggesting a shift away from agricultural activities possibly due to urbanization or land use conversion for other purposes facilitated by highway interchanges.

Urban areas witness a steady increase in both areas and percentage coverage from 2028 to 2050. This trend reflects the expansion of urban infrastructure facilitated by the presence of highway interchanges, leading to increased urbanization and development.

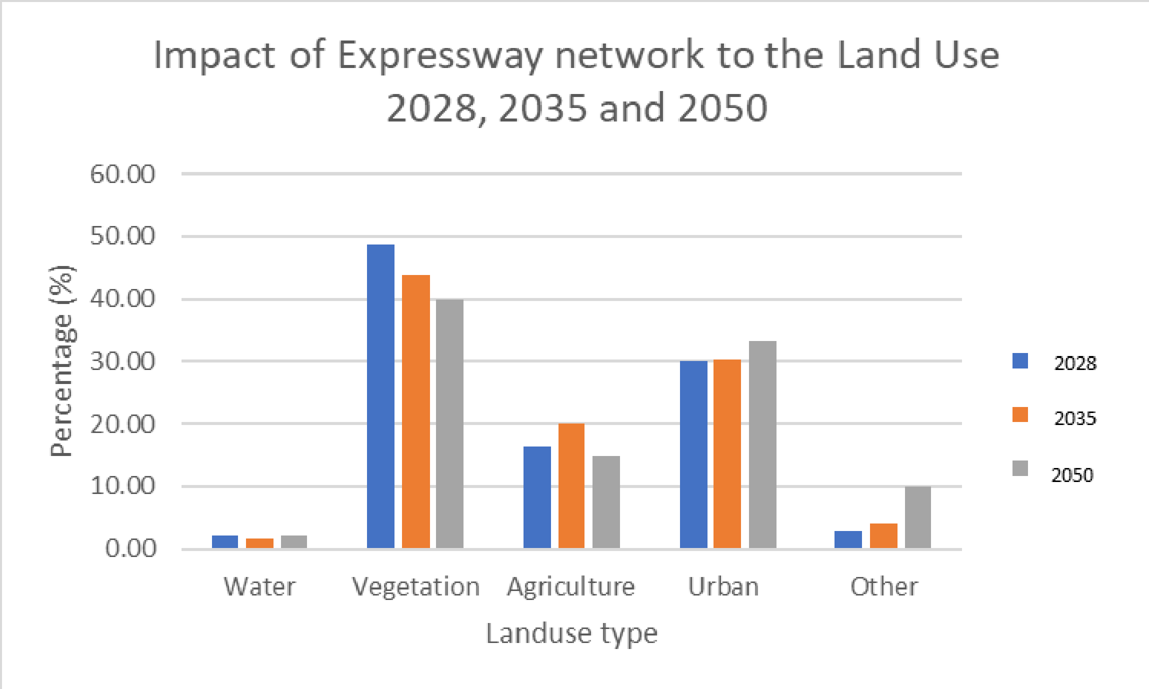
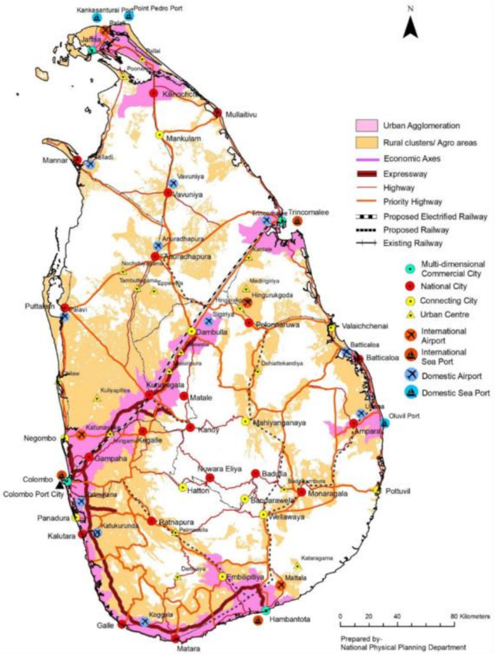


Figure 48 Impact of Expressway network to the Land Use 2028, 2035 and 2050

- **Impact for Proposed Urban Settlement Hierarchy**

The "Impact of Proposed Urban Settlement Hierarchy" refers to the assessment and analysis of the designated areas outlined in the National Physical Plan 2023-2048, which delineates zones for urban agglomeration and rural clusters/agro areas. This zoning map, termed the Urban Settlement Hierarchy, serves as a strategic blueprint for guiding development and land use decisions within the specified timeframe. Based on the data provided, it is evident that the area allocated to agriculture (Agro areas) is decreasing over time due to the implementation of proposed projects. Here's a breakdown of the findings. As observed, the area designated for agriculture decreases from 7883.45 Sq. Km in 2028 to 6942.29 Sq. Km in 2050, representing a decline in percentage from 27.34% to 24.21%. This reduction suggests a gradual conversion of agricultural land to other land uses, likely driven by urbanization and infrastructure development projects outlined in the National Physical Plan. Consequently, the diminishing area allocated to agriculture may have implications for food security, rural livelihoods, and environmental sustainability, necessitating careful consideration and strategic planning to mitigate adverse impacts.



Source 19 National Physical Plan 2023-2048

Figure 49 Proposed Urban Settlement Hierarchy

Table 12 Impact of Proposed Urban Settlement Hierarchy

Land Use Type	Area (Sq. Km)			Percentage%		
	2028	2035	2050	2028	2035	2050
Water	711.819	802.879	632.542	2.468877	2.79726	2.20604
Vegetation	11007.1	10459.1	9964.75	38.17709	36.43989	34.75286
Agriculture	7883.45	8375.06	6942.29	27.34301	29.17901	24.21179
Urban	6552.58	6604.02	6626.81	22.72701	23.00865	23.11153
Other	2676.74	2461.28	4506.79	9.284021	8.57519	15.71779

Source 20 Compile by author.

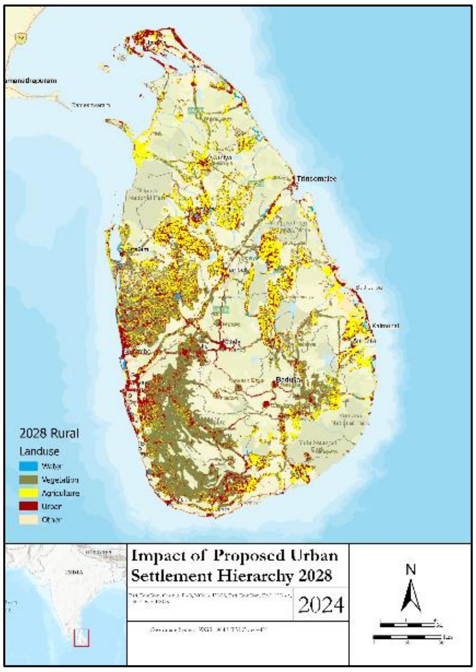


Figure 50 Impact of Proposed Urban Settlement Hierarchy 2028

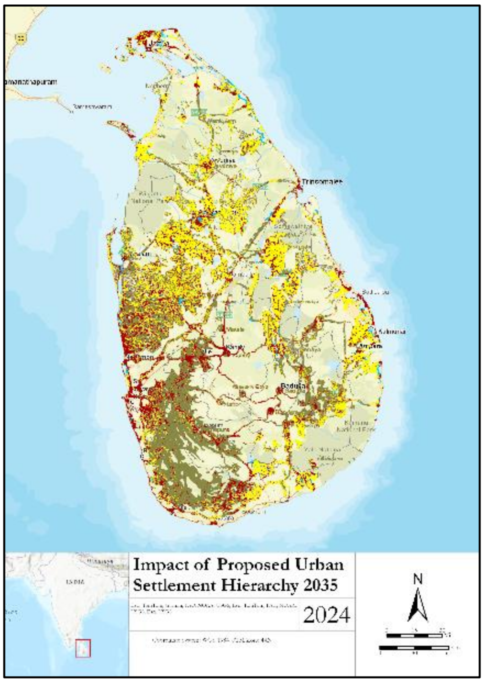


Figure 51 Impact of Proposed Urban Settlement Hierarchy 2035

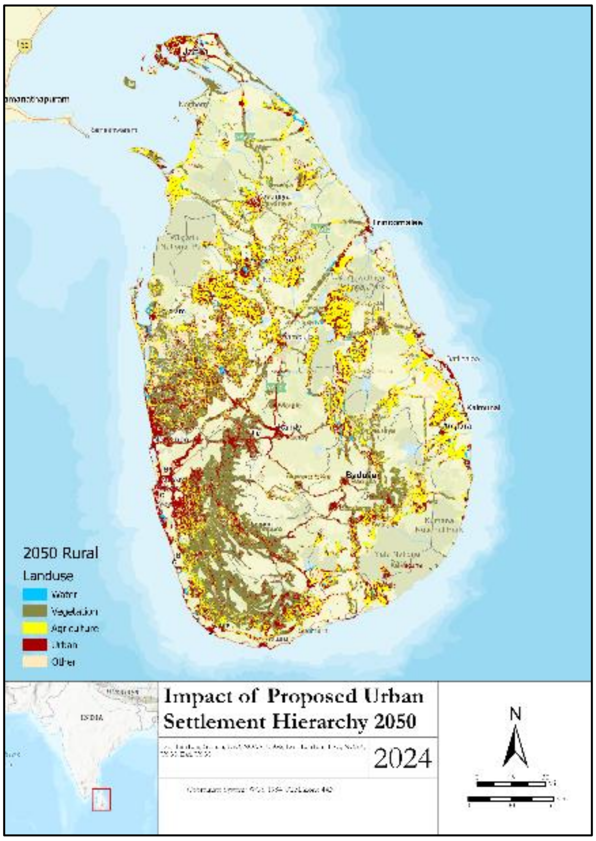
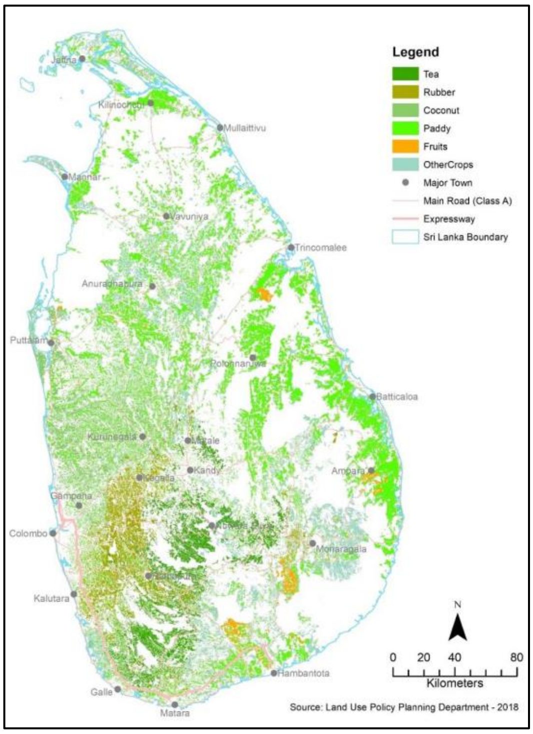


Figure 52 Impact of Proposed Urban Settlement Hierarchy 2050

- **Impact for Agro Conservation zone**

The table indicates a concerning trend of diminishing agricultural and vegetation areas over time in Sri Lanka. Specifically, the data shows a reduction in agricultural land from 11718.76 sq.km in 2028 to 10347.55 sq.km in 2050, representing a decrease in the percentage of agricultural land from 24.23% to 21.56% over the same period. Similarly, there is a decline in vegetation area from 20379.89 sq.km in 2028 to 18585.28 sq.km in 2050, with the percentage of vegetation decreasing from 42.14% to 38.72% over the respective years. This notable loss of agricultural and vegetation lands signifies a significant threat to agro conservation zones and underscores the urgency of balancing development initiatives with the preservation of vital agricultural resources for sustainable land use practices and food security.



Source 21 National Physical Plan 2023-2048 Agro Conservation area.

Figure 53 Agro conservation Area NPP 2023-2048

Table 13 Impact for Agro Conservation zone

Land Use Type	Area(Sq.Km)			Percentage%		
	2028	2035	2050	2028	2035	2050
Water	1304.62	1514.09	1107.77	2.70	3.14	2.31
Vegetation	20379.89	19687.65	18585.28	42.14	40.85	38.72
Agriculture	11718.76	12642.43	10347.55	24.23	26.23	21.56
Urban	9961.75	10151.46	10313.88	20.60	21.06	21.49
Other	4994.90	4199.08	7648.25	10.33	8.71	15.93

Source 22 Compile by author.

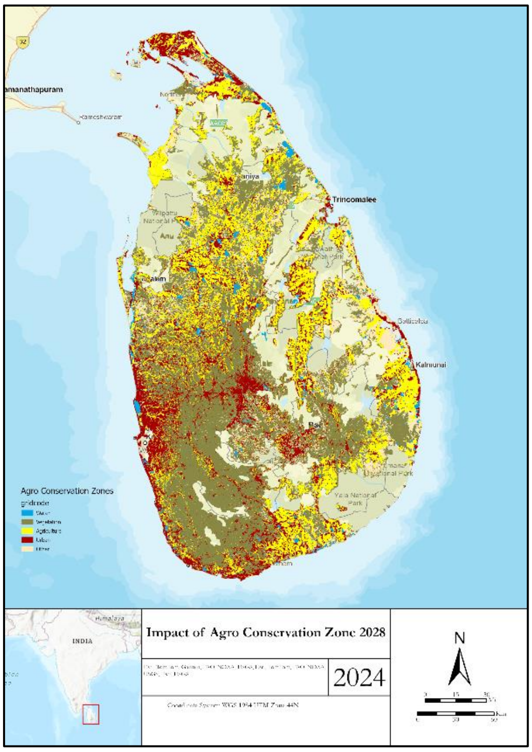


Figure 54 Impact of Agro Conservation Zone 2028

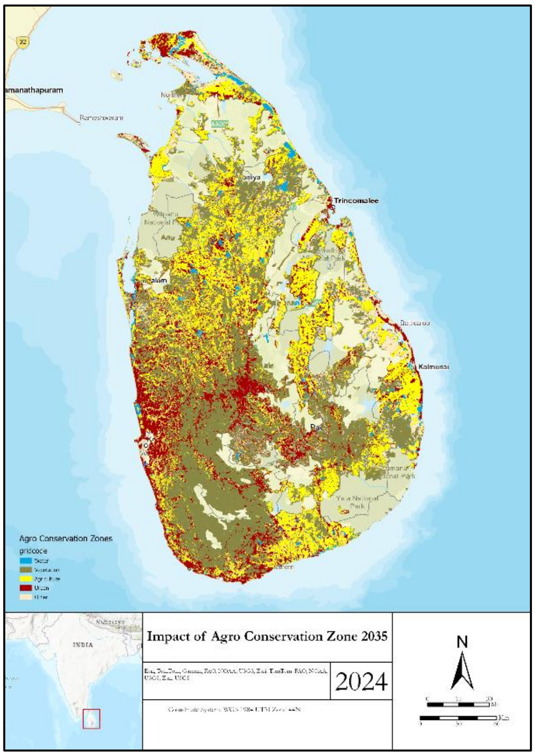


Figure 55 Impact of Agro Conservation Zone 2035

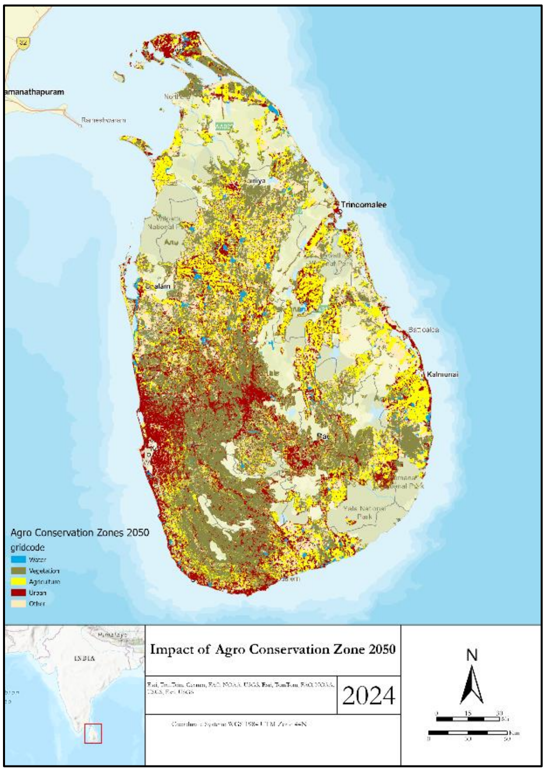


Figure 56 Impact of Agro Conservation Zone 2050

Conclusion

In conclusion, this research demonstrates the profound impact of infrastructure projects outlined in Sri Lanka's National Physical Plan (NPP) on land use dynamics from 2023 to 2050. Using the QGIS MOLUSCE Plugin for predictive simulations, the study reveals significant shifts in land use patterns, such as a decline in agricultural and vegetative areas alongside urban expansion, driven by the proposed railway, expressway, and urban settlement developments. The findings highlight the complex interplay between infrastructure development, urbanization, and land conservation, emphasizing the need for integrated and sustainable planning approaches. To further enhance understanding, it is suggested to expand the analysis by simulating land use changes based solely on influencing factors, offering clearer insights into the distinct impact of infrastructure projects on future land development.

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Annexes

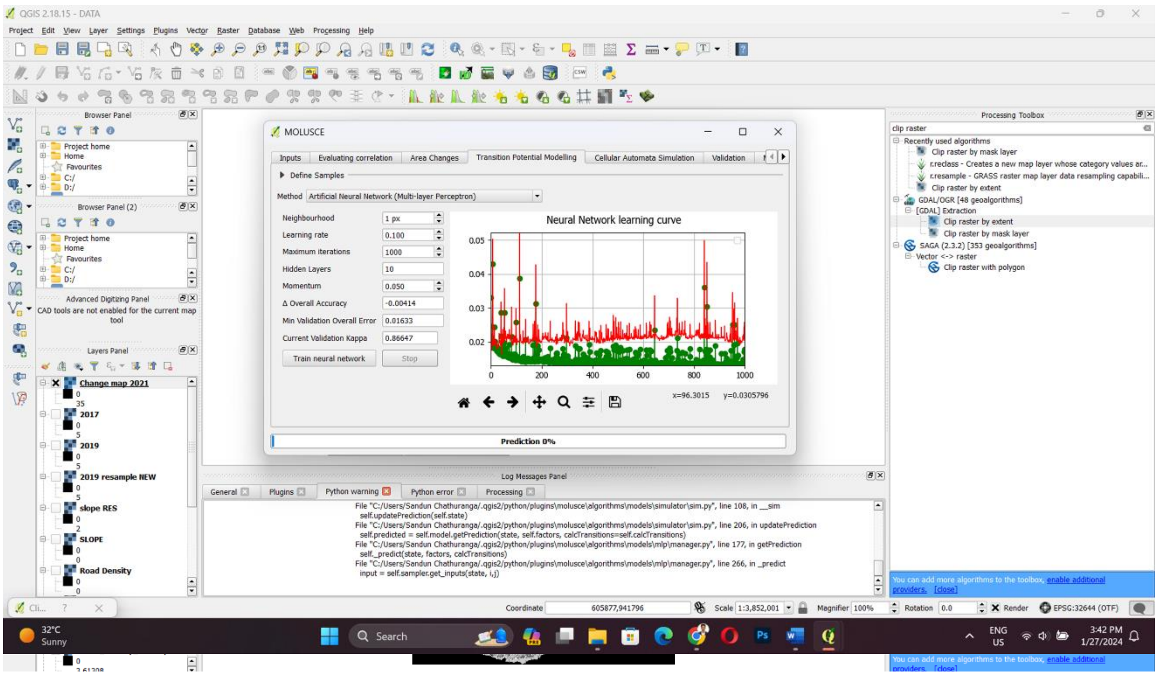

Figure 57 Molusce Simulation ANN 2021 *Compile by author.*

Figure 58 Molusce Accuracy 2021 *Compile by author.*

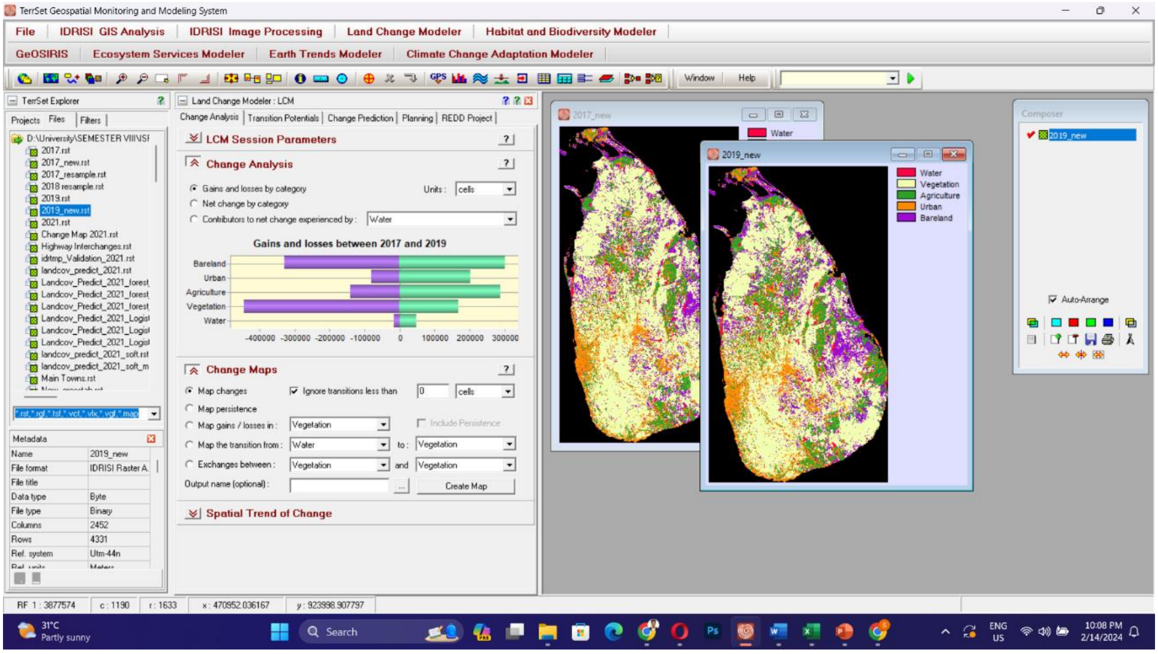

Figure 59 Terrset input years and change analysis. Compile by author.

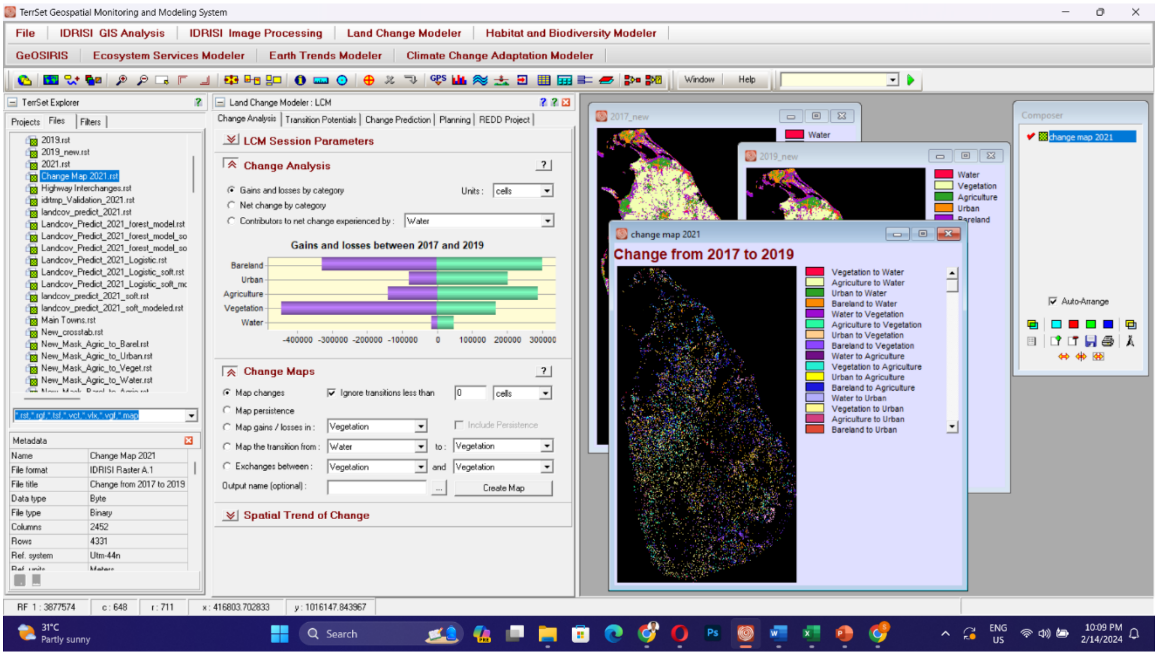

Figure 60 Terrset change map 2017, 2019. Compile by author.

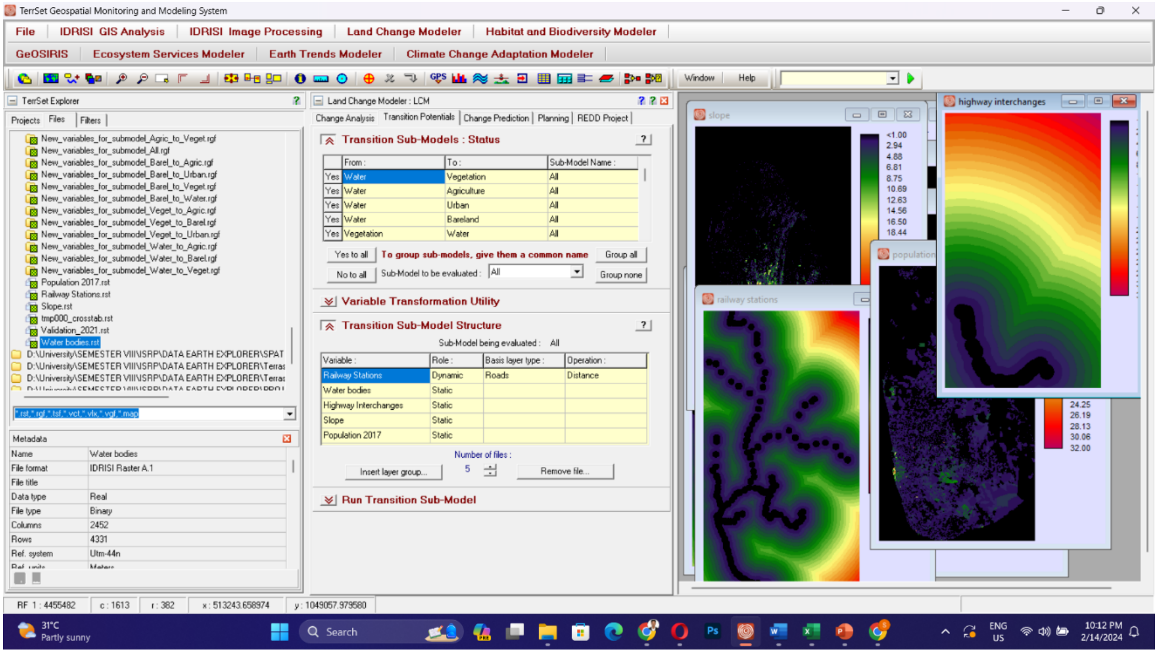

Figure 61 terrset land use influence factors. Compile by author.

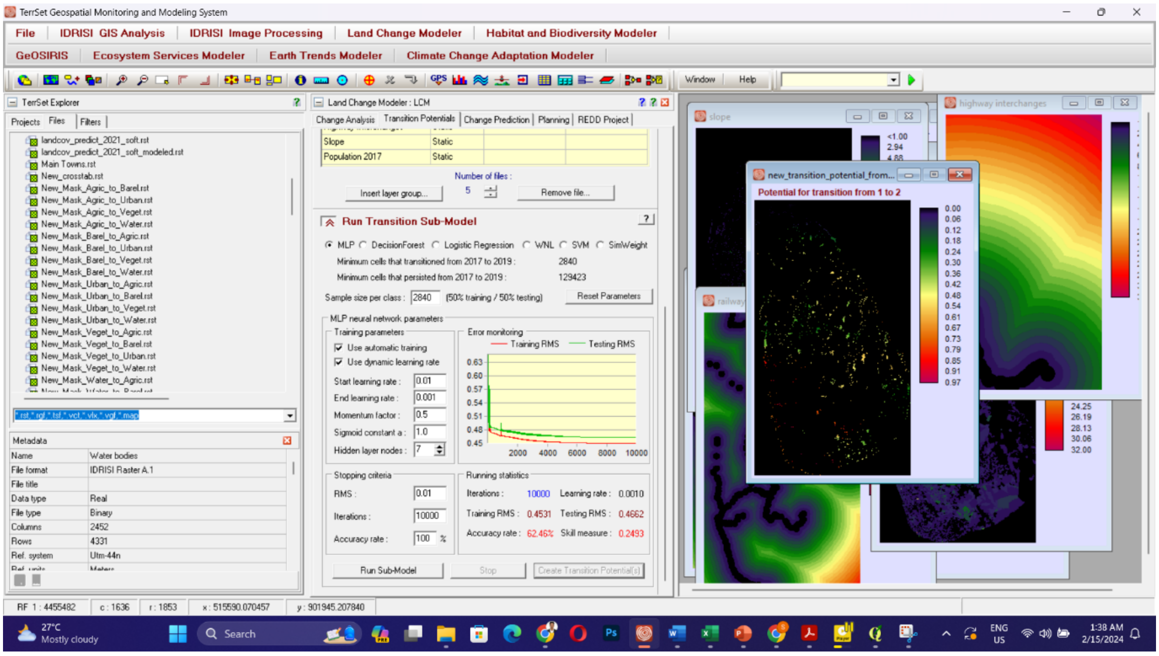

Figure 62 Terrset Transition Potential Map. Compile by author.

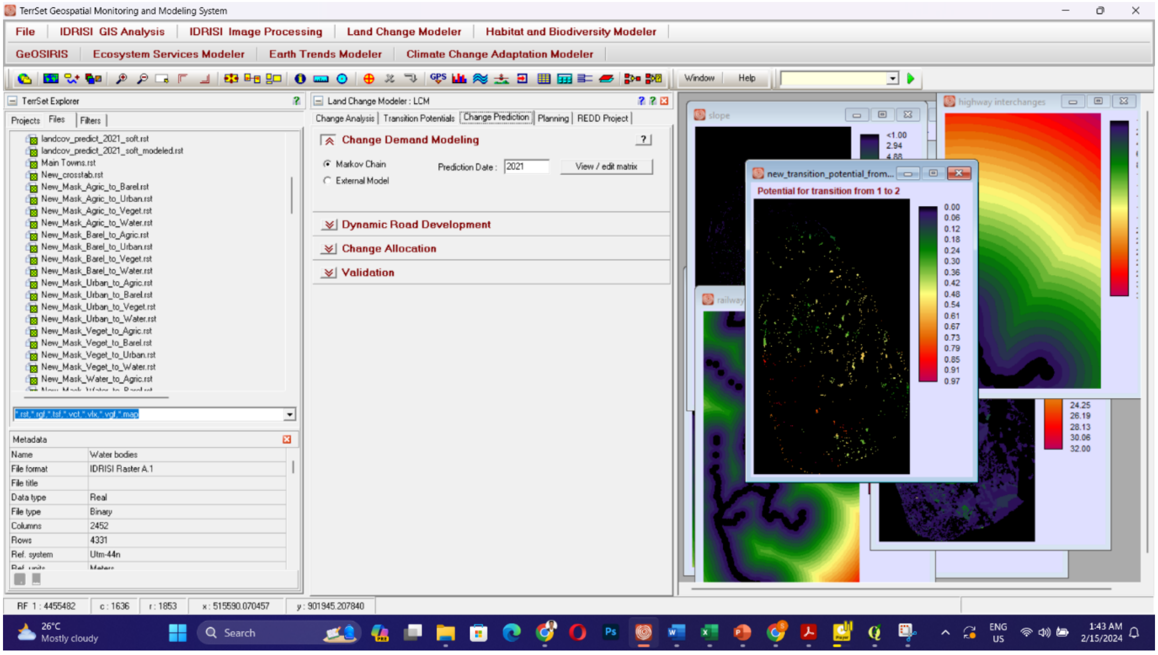

Figure 63 Terrset Model Selection Compile by author.

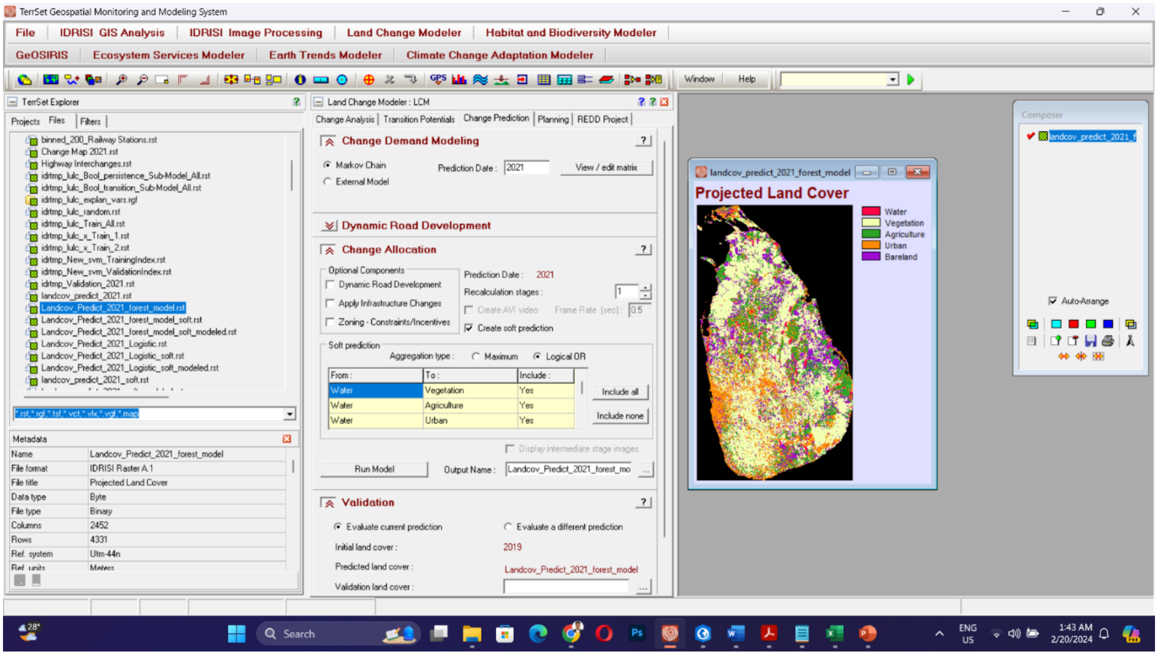

Figure 64 Terrset land cover prediction for 2021. *Compile by author.*