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C O N T E N T S

Hybrid Modelling Approach for Land Use Change Prediction and Land Management in the Coronie District of Suriname

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Abstract
Monitoring and predicting changes in land use play a crucial role in addressing environmental challenges and ensuring effective land use management. Reliable models aid in planning sustainable development, safeguarding biodiversity, and efficiently managing natural resources. This study aims to identify land use changes in the Coronie district of Suriname from 2016 to 2024 and predict changes for 2034 and 2044. Sentinel-2 images were used to analyze land use change patterns and predict future trends. The Random Forest algorithm was employed to classify the various land use classes with high accuracy and reliability. A hybrid approach, combining Markov chain analysis with cellular automata, multilayer perceptron, support vector machines, and logistic regression, was used to predict future land use dynamics for 2034 and 2044. The support vector machine-Markov chain hybrid predictive model, incorporating an agricultural land expansion transition sub-model, demonstrated an impressive accuracy of 96.05%, outperforming the rest of hybrid models. This model is recommended for generating land use change prediction maps, which can serve as a crucial baseline for sustainable land use management.

Keywords – Land Cover, Dynamics, Prediction, Hybrid Models, Land Use Management.

Introduction

Land use change as a critical driver of environmental and socio- economic transformations, has significant impacts on the both ecosystems and human livelihoods. Analyzing spatiotemporal trends in land use and land cover (LULC) change is pivotal for gaining deep insights that are vital to effective and sustainable land management and environmental conservation (van Ommeren-Myslyva et al., 2024; Devi & Shimrah, 2023; Girma et al., 2022). The Surinamese district of Coronie due to its location, in the North- west of Suriname, plays a crucial role in the future developments of the country, especially with the expecting economic developments and faces increasing pressure on its land due to various factors such as agricultural expansion, infrastructure development, and natural circumstances like a dynamic coast and climate change. Thus, understanding these changes is crucial for the region's sustainable development and environmental conservation. Regardless of the evident occurrence of land use changes in Commewijne, a notable gap exists in studies specifically addressing the detection of current trends and the prediction of future dynamics in regional land use and land cover. This research is part of a project on LULC change modelling for the next 20 years, conducted by the Ministry of Spatial Planning and the Environment of Suriname (ROM) for all 10 districts in the country, with the Commewijne district already completed (van Ommeren et al., 2024). The outcomes of the project will contribute to the ROM's initiative to establish a Geospatial Intelligence Hub (GIH) in Suriname, aimed at storing and making geo- data accessible to the general public. The data provided by the GIH will support sustainable spatial planning, effective natural resource management, environmental protection, and climate change mitigation efforts.

Literature Review

LULC change modelling plays an essential role in understanding and managing environmental dynamics, natural resources, and land assets. It is crucial for environmental monitoring, as it helps detect changes in ecosystems and biodiversity (Kafy et al., 2020; Belgiu & Csillik, 2018). Predictive models are indispensable for evaluating the impacts of urbanization, deforestation, and agricultural expansion on natural habitats (Song et al., 2020; Phiri & Morgenroth, 2017). Effective management of natural resources – including forests, wetlands, and other vital ecosystems – also relies on accurate LULC models to predict changes and guide conservation efforts (Tehrany et al., 2020; Xie et al., 2019). Additionally, LULC change models are critical for planning sustainable agricultural practices, urban development, and infrastructure projects (Adhikari & Southworth, 2018; Roy et al., 2018). These models offer valuable insights into land suitability for various uses, helping to prevent land degradation and ensure optimal use of resources (Lambin & Meyfroidt, 2019; Aloqaili et al., 2021). Furthermore, LULC modelling plays an important role in climate change mitigation by enhancing our understanding of the carbon sequestration potential of different land covers (Deng et al., 2020; Luo et al., 2021). Remote sensing (RS) has become a crucial tool for monitoring changes in land use and land cover by utilizing high-resolution satellite imagery, enabling precise mapping and assessment of LULC transformations (Abbas et al., 2023; Abdullahi & Pradhan, 2016). Numerous studies have explored LULC changes using various satellite datasets, including Landsat (El Ghoul et al., 2023; Hussain et al., 2022), MODIS (Al-Hamdan et al., 2017), RapidEye (Kafy et al., 2021), Sentinel (Guzder-Williams et al., 2023; Sánchez-Espinosa & Schröder, 2019), and SPOT (McCarthy et al., 2018). The integration of RS with GIS technologies provides a robust platform for analyzing LULC changes (Dey et al., 2021). Researchers worldwide have employed various methods to predict future land use and land cover changes (Abbas et al., 2023). LULC change prediction methods involve advanced techniques to forecast future land cover and use based on historical data and trends (van Ommeren-Myslyva et al., 2024). Frequently employed models for predicting land use changes include statistical models (Yeh & Liaw, 2021), Cellular Automata (CA) models (Muhammad et al., 2021), Markov Chain (MC) models (Mohamed & Worku, 2020), hybrid models (Asif et al., 2023), and multi-agent-based models (Robinson et al., 2021). Among these, hybrid models, which combine different predictive methods to leverage the strengths of each approach, produce more precise projections of future changes. The MC model is widely used for LULC prediction due to its ability to quantify land use transition probabilities (Day et al., 2021). However, its primary limitation is its inability to incorporate spatial heterogeneity, making it less effective in indicating the direction of LULC changes (Wang et al., 2021). The integration of MC with CA improves spatial dynamics by considering neighborhood effects in land use transitions (Hamidi et al., 2022). Studies show that combining MC and CA can effectively simulate realistic patterns of urban expansion and deforestation (Zhao et al., 2021). Another successful hybrid approach involves combining Markov Chain analysis with machine learning techniques, such as Artificial Neural Networks (ANN) and Support Vector Machines (SVM), to complement the Markov model (Girma et al., 2022; Gharaibeh et al., 2020). This integration enhances the model's ability to capture complex relationships and non-linear patterns in land use change, leading to more accurate predictions of future scenarios (Wang et al., 2021). Logistic Regression (LR) is also commonly used in LULC modelling due to its simplicity and interpretability. When combined with CA and MC, LR adds probabilistic reasoning to LULC change predictions (Hashemzadeh et al., 2021). Despite its linear nature, LR as part of hybrid models can efficiently predict binary land use transitions, such as forest-to-urban conversions, with satisfactory accuracy (Wang et al., 2023).

This study seeks to develop predictive models capable of forecasting future land use scenarios in the Coronie district over the upcoming 20-year period. Such models not only offer insights into current trends but also provide a basis for assessing the potential impacts of alternative land management strategies. Taking into account the aforementioned, this study pursues a threefold objective: (1) to collect and process initial geospatial data on land use and land cover; (2) to evaluate the accuracy and reliability of hybrid predictive models based on joint application Markov chains with CA, MLP, SVM and LR in predicting future land use changes within Coronie district of Suriname; and (3) to develop a robust hybrid simulation model for predicting LULC change over the upcoming 10-year period, aiming to provide valuable insights for strategic planning and decision-making in the context both Coronie (locally) and Suriname's (nationally) sustainable development.

Methodology

Study area

The area of interest is Coronie, a district of Suriname covering a total area of 3902 km^2, situated in the northern part of the country. Geographically, Coronie is located to the north between 5.29° and 5.90° N and to the west between 55,87° and 56,60° W within the Young and Old Coastal Plains, ranging from 15 below to 43 m above mean sea level. The district is divided into three administrative districts, namely Welgelegen, Totness and Johanna Maria. Fig. 1 depicts the research area's location. The climate of the study area is tropical- equatorial (Af) according to the Köppen-Geiger climate classification. The soil cover of the study area is represented by Umbric Gleysols and Fibric Histosols according to the international soil classification system (WRB, 2014).

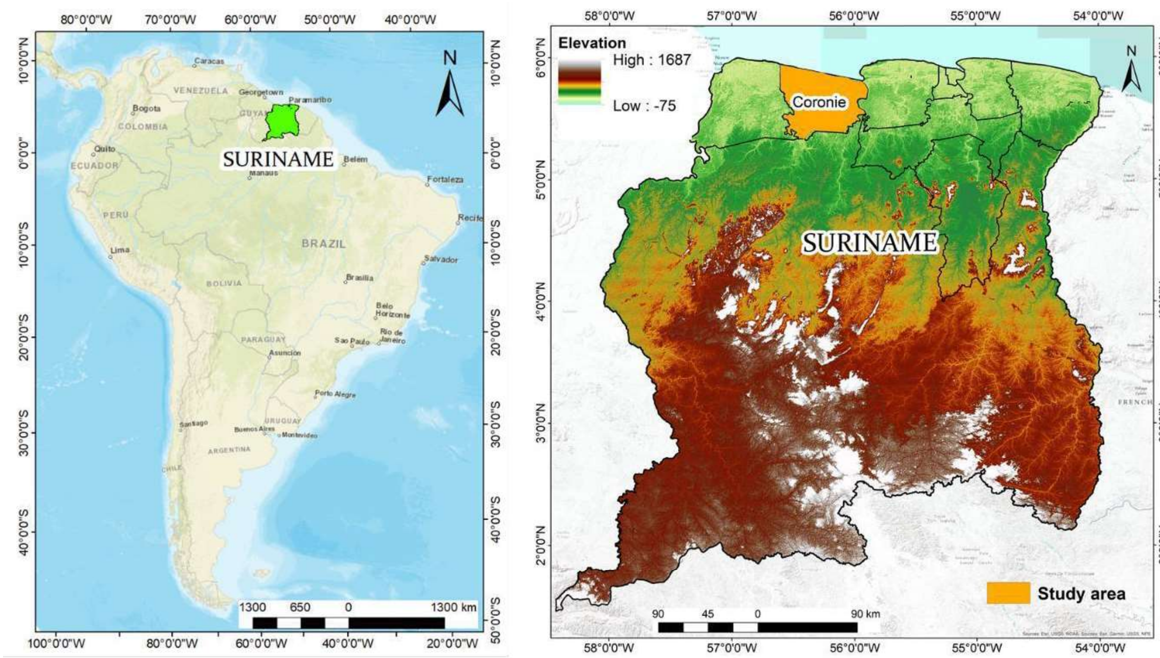


Figure 1: Location of the study area (developed by the authors)

Data collection

This study employed three remotely sensed satellite images to analyze LULC change dynamics and develop the predictive model (Table 1).

TABLE -1: Characteristics of Data Collected

Data	Source	Acquisition year	Scale/ Resolution
Multispectral satellite imagery	Esri Land Cover: https://livingatlas.arcgis.com/landcover/	2020	10 m
	Google Earth Engine Data Catalogue: https://developers.google.com/earth-engine/datasets/catalog	2016 2024	
Digital Elevation Model (DEM)	30-Meter SRTM Tile Downloader: https://dwtkns.com/srtm30m/	2018	1-arcsecond (3601x3601 pixels)

Note: Developed by T. van Ommeren-Myslyva

Slope, distance from water bodies, distance from roads, distance from deforestation areas, and distance from Totness airstrip datasets were developed individually in 2024 with a resolution of 10 m. These datasets underwent processing in QGIS 3.34 and ArcGIS 10.8 packages. The Euclidean distance function was employed to generate distance maps from roads, water bodies, deforestation areas, and airstrip using vector data of the features (Kafy et al., 2021; Gharaibeh et al., 2020).

Image classification

The bands 4–3–2 combination (true colour combination) and bands 8–4–3 combination (false colour combination) was utilized to perform Sentinel-2 image classification. A hybrid classification (unsupervised and supervised classification) approach was applied. Image pixel clustering (unsupervised classification) with similar spectral characteristics was performed using Iso Cluster Unsupervised Classification tools. This measure afforded to set the appropriate number of LULC classes for further detection. Based on our experience/knowledge of the area and Google Earth observation, the clusters were differentiated into seven thematic classes (Table 2).

The classified land use/land cover maps of 2016, 2020, and 2024 were generated using the supervised random forest classification. Image classification performance was evaluated using the accuracy assessment tools in the Segmentation and Classification toolbox of ArcGIS 10.8. Overall accuracy (OA), user accuracy (UA), producer accuracy (PA), and kappa coefficient (Kappa) were calculated. The overall accuracies and kappa coefficients for all the classified LULC maps of 2016, 2020, and 2024 were above 84% and 92%. This indicates a reliable and accurate classification of images for analyzing land use/land cover change.

Table-2: Major Land Use Land Cover Types Used and their Descriptions

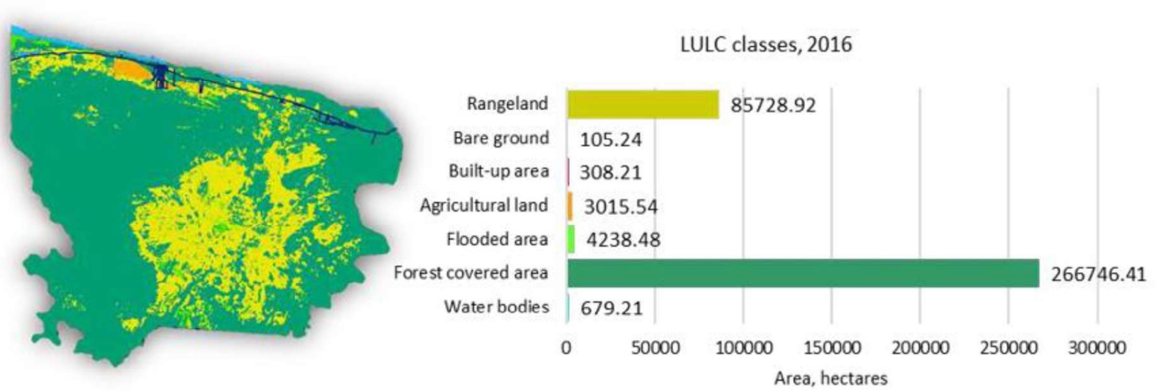
LULC class	Class description
Water bodies	Areas covered by rivers, streams, canals and reservoirs
Forest covered area	Landcover with primary trees, palm, and bamboo with a minimum crown tree cover of 30% with the potential to reach a canopy height of a minimum of 5 m and a minimum area of 1.0 hectares
Flooded area	Areas of any type of vegetation with obvious intermixing of water throughout a majority of the year; seasonally flooded area that is a mix of grass/shrub/trees/bare ground
Agricultural land	Includes areas used for perennial and annual crop production, irrigated areas, commercial farms
Bare ground	Includes land areas of exposed soil, bare soil, and open areas consisting of sand, rocks, and loam
Built-up area	Includes commercial areas, urban, residential, and rural settlements, industrial areas
Rangeland	Open areas covered in homogenous grasses with little to no taller vegetation; wild grasses with no obvious human plotting (i.e., not a plotted field)

Retrieved from https://www.arcgis.com/

Fig. 2 shows the spatial and statistical distribution of LULC classes for 2016, 2020, and 2024.

Driving variables

- Driving variables or driving factors or drivers, have a significant influence on the modelling of land use and land cover changes. These variables depict the different biophysical, socioeconomic, and infrastructural factors that impact how land is used and how it changes over time.
- Natural factors, known as biophysical drivers, play a significant role in shaping land use and land cover changes. These drivers include climate elements such as temperature, precipitation, and seasonal variations, which can affect farming practices, vegetation patterns, and the distribution of natural ecosystems. Topography also plays a role, with factors like slope, elevation, and aspects influencing the suitability of land for agriculture, construction, and other uses. Additionally, soil characteristics, including soil type, fertility, and drainage capacity, dictate the types of crops that can thrive and impact decisions regarding land use for agricultural or developmental purposes.
- Human factors, known as socioeconomic drivers, significantly influence LULC changes. These drivers encompass population trends, such as population growth, migration, and urbanization, which increase the demand for land to support housing, infrastructure, and public services.



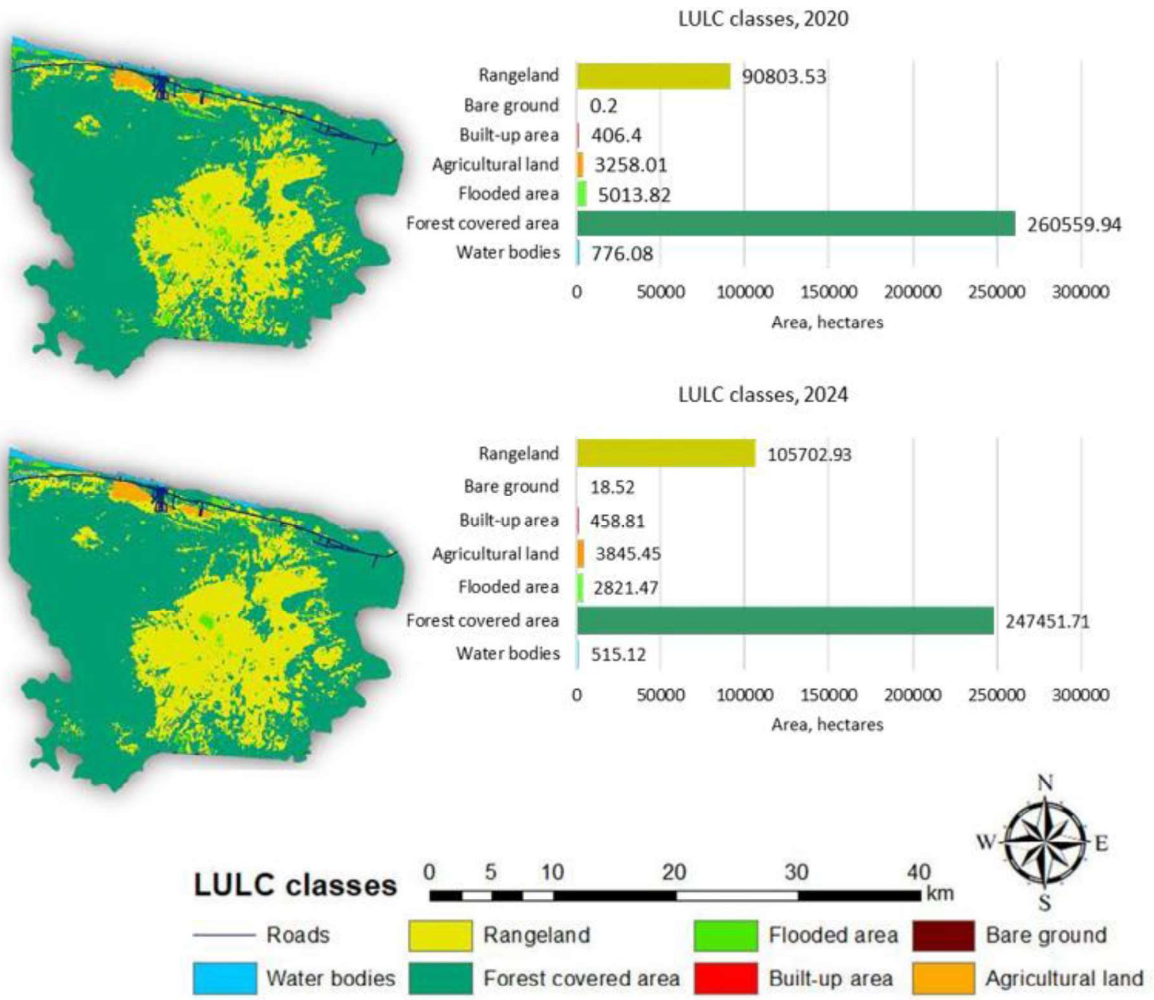


Figure 2: LULC maps of Coronie district for the years (a) 2016, (b) 2020, and (c) 2024 (developed by T. van Ommeren-Myslyva)

- Economic activities, including the expansion of agriculture, industrial development, and tourism, also contribute to land use changes as they respond to the need for economic growth. Additionally, government policies, zoning regulations, and conservation initiatives shape how land is utilized and affect patterns of land cover transformation.

- Infrastructural drivers refer to human-made structures and their effects on land use. These include proximity to transportation networks, as access to roads plays a role in the development of urban areas, agricultural zones, and industrial sites. The distance to markets and essential services like schools, hospitals, and other facilities also influences land use choices, with areas closer to these services being more attractive for residential or commercial development. Infrastructure expansion further affects how land is used and developed.

- The proximity to water bodies, including the distance from rivers and creeks, plays a key role in land use decisions. Locations near water sources are often preferred for agriculture, industry, and residential development because of the easy access to water resources.

- Environmental drivers, on the other hand, relate to ecological factors that impact land use. These include biodiversity and ecosystem services, where regions with high biodiversity or essential ecosystem functions may be prioritized for conservation, thereby influencing how the land is utilized.

- Recognizing the need to incorporate the potential influence of independent variables in simulating LULC changes (Gharaibeh et al., 2020), this study considered seven key driver variables. These variables include population, distances from water bodies, roads, airstrip and regions with deforestation, as well as terrain relief and slope represented by the digital elevation model (Fig. 3).

LULC change detection and simulation

The Land Change Modeler (LCM) in the TerrSet software was employed to detect and simulate future LULC changes within the study area. This stepwise, empirically driven process involves change analysis, transition potential modelling, and change prediction based on historical changes from 2016 to 2020. The Markov probability matrix was utilized to determine the likelihood of converting from one LULC class to another in the next period. Transition potentials, indicating the probability of land transitioning from one class to another, were assessed using a multi-layer perceptron neural network (MLP), support vector machine algorithm (SVM), and logistic regression (LR).

Finally, validation was conducted to compare actual and simulated land use/land cover maps of 2024, ensuring the reliability of different models in predicting future scenarios for 2034 and 2044 (Fig. 4).

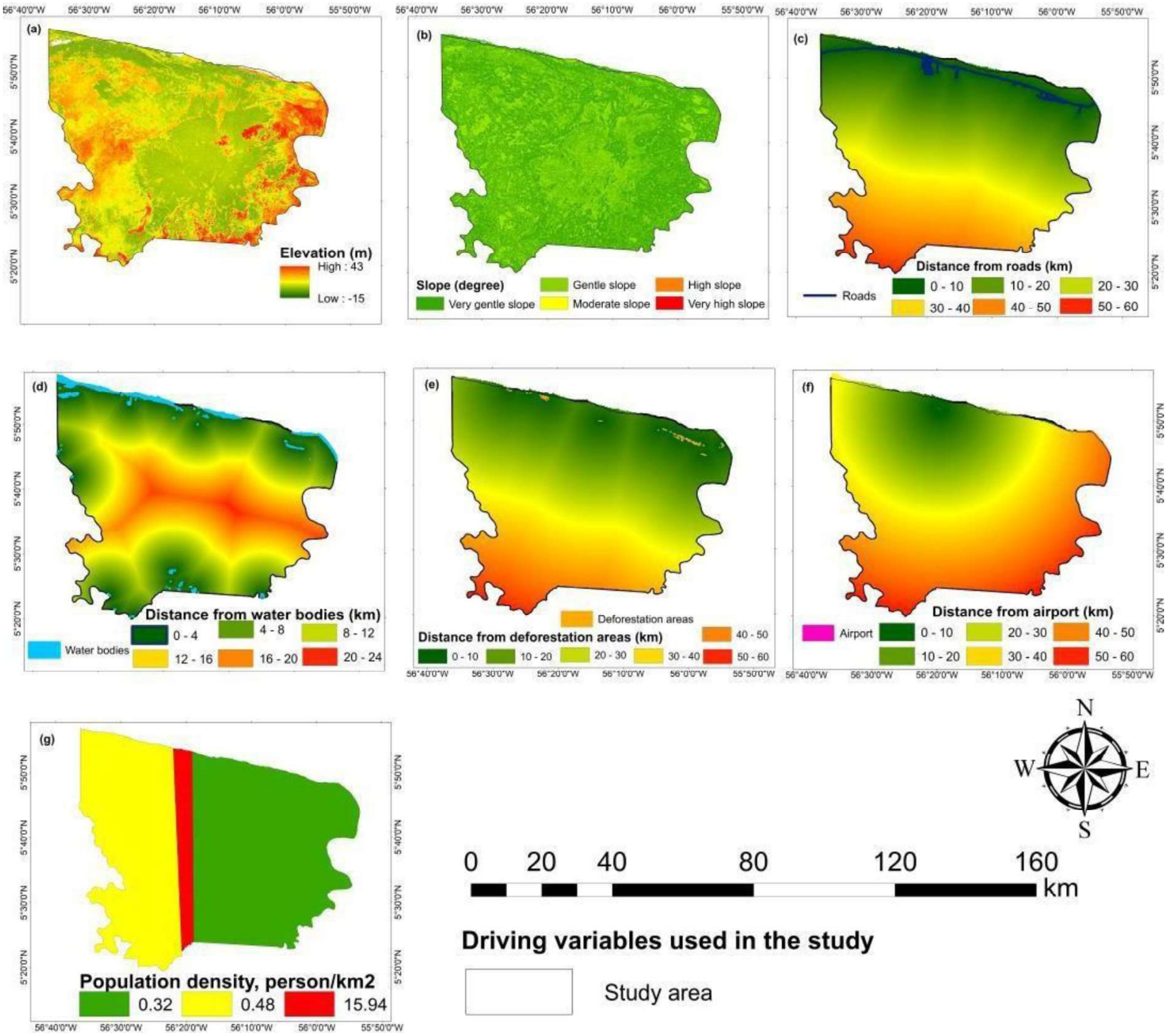


Figure 3: Driving variables used in the study: (a) elevation, (b) slope, (c) distance from main roads, (d) distance from water bodies, (e) distance from deforestation areas, (f) distance from airstrip, (g) population (developed by the authors)

Validation of the Model's Outputs

The validation process was conducted to assess the agreement and disagreement between the actual and simulated LULC maps of 2024, ensuring the reliability and acceptance of different hybrid model approaches in predicting the future scenario in 2034 and 2044 (Kafy et al., 2021; Dey et al., 2021). Validation was carried out using the Validate module in TerrSet software. This module computed kappa index statistics using the hard prediction as a comparison map, including kappa for no information (Kno), kappa for grid cell level location (Klocation), kappa for stratum-level location (KlocationStrata), and kappa standard (Kstandard) (Girma et al., 2022; Mishra et al., 2018). A strong and acceptable Kappa value is typically associated with values around 80% and above (Girma et al., 2022; Gharaibeh etal., 2020). For future prediction, the images of 2016 and 2020 were taken as the dependent variable to simulate the LULC map of 2034 and 2044.

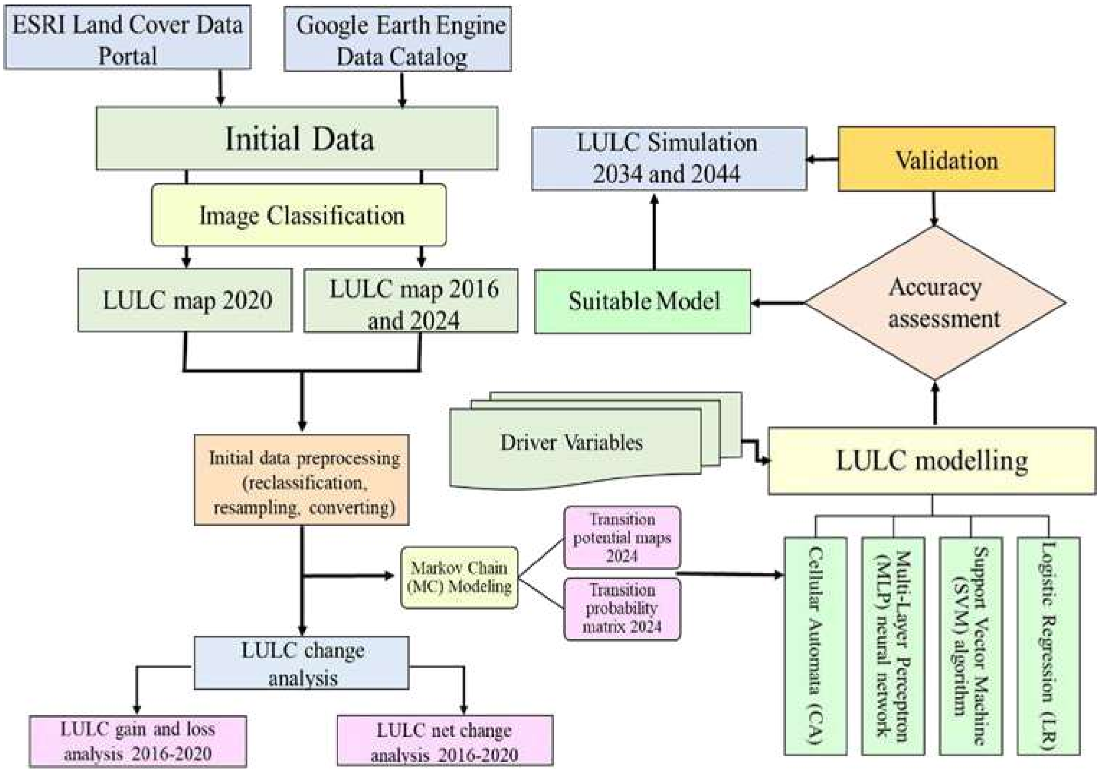


Figure 4: Research design flowchart (developed by T. van Ommeren-Myslyva)

Results and Discussions

For reliable forecasting of future trends in LULC change over the next two decades, detecting and understanding historical trends in land use and land cover dynamics is essential (Myslyva et al., 2024; Girma et al., 2022; Regasa et al., 2021). The study area experienced significant landscape transformations and various land use changes from 2016 to 2020, as depicted in Fig. 5.

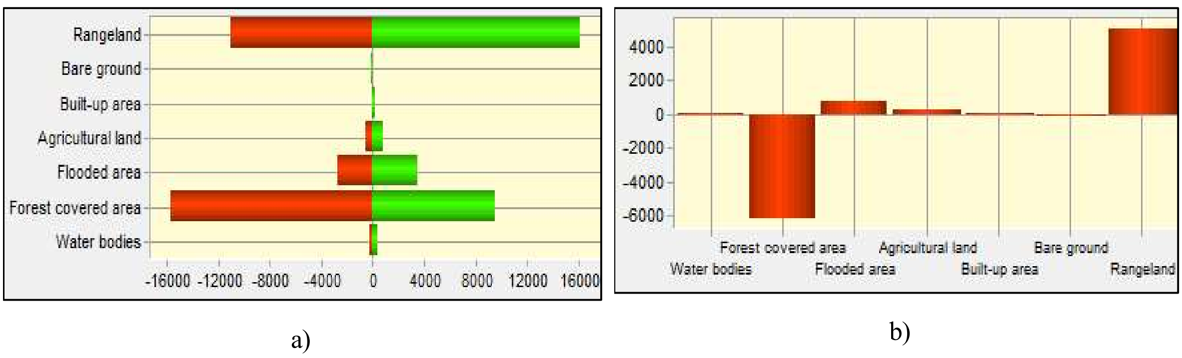


Figure 5: Gains and losses (a) and net change (b) in LULC within the limits of Coronie district between 2016 and 2020, hectares (developed by T. van Ommeren-Myslyva)

The data indicates a dynamic land-use environment, with large portions of the land remaining stable but also significant transitions between natural and human-modified landscapes. Urbanization and land management practices such as afforestation or deforestation appear to play a central role in shaping the future landscape. Additionally, water-related transitions suggest environmental factors like flooding are critical to understanding LULC changes in the study region.

The main contributions to the net changes in various land use and land cover categories are as follows (Fig. 6). The net change in water bodies is primarily influenced by changes in flooded areas.

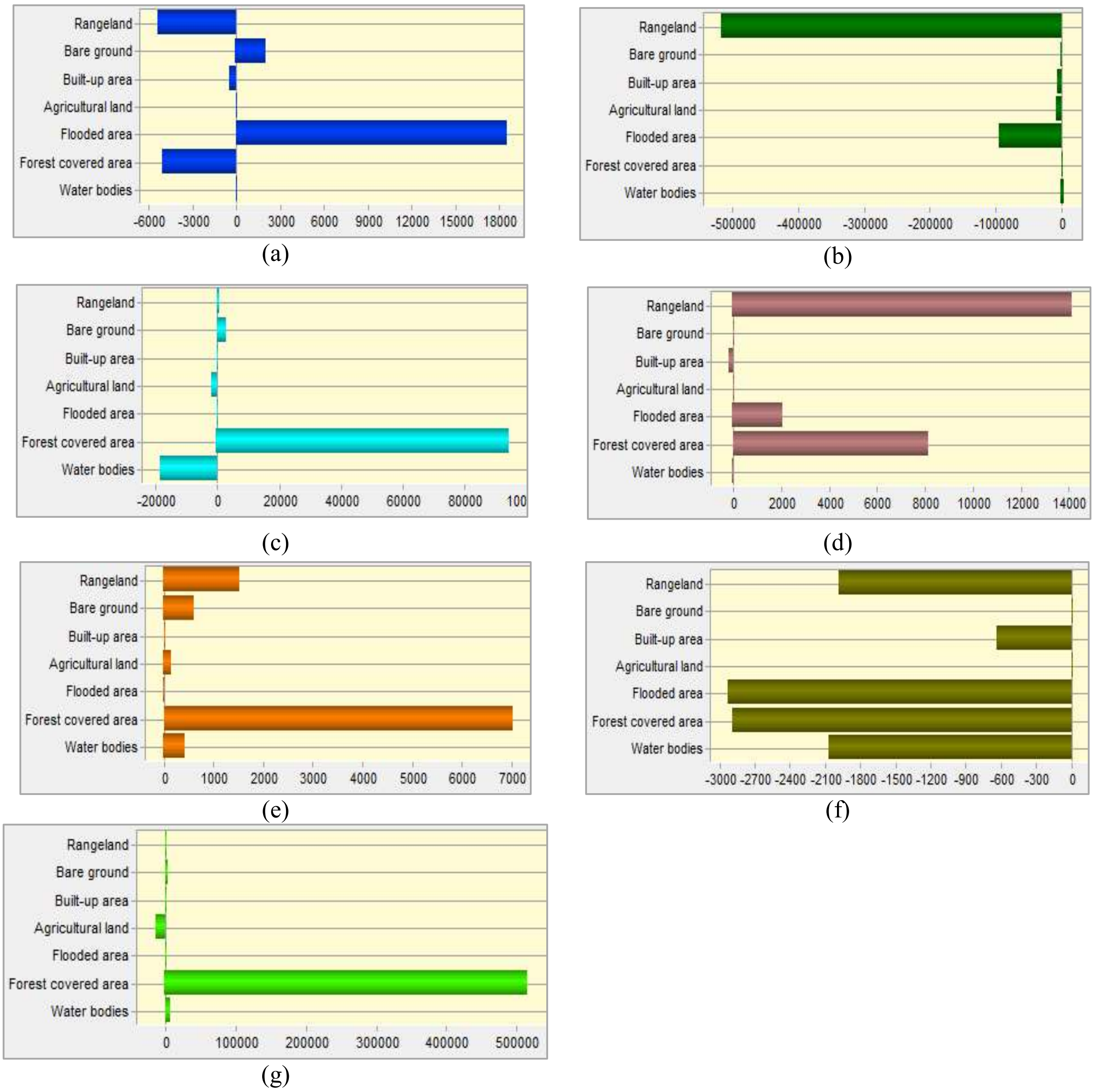


Figure 6: Contributions to the net change in different LULC classes within the limits of Coronie between 2016 and 2020, hectares (a – water bodies; b – forest cover; c – flooded area; d – agricultural land; e – built-up area; f – bare ground; g – rangeland) (developed by T. van Ommeren-Myslyva)

The net change in forest cover is significantly impacted by the conversion of rangeland. The net change in flooded areas is driven by both forest cover and water bodies dynamics. The expansion of agricultural land is largely due to the conversion of forest covered area and rangeland. The net increase in built-up areas is influenced by changes in forest cover, rangeland and bare ground. The net decrease in bare ground is largely attributed to increases in flooded areas, forest covered areas, rangelands, water bodies and built-up areas. The net decrease in rangeland is primarily driven by the expansion of forest cover.

Fig. 7 illustrates the combined LULC change map from 2016-2020 and Fig. 8 presents the gains and losses in different LULC classes during the 2016-2020 timeframe. The main trend observed during the period from 2016 to 2024 is the mutual transition between forest- covered areas (13,716.88 ha) and rangelands (8,548.97 ha), suggesting both natural forest regrowth and deforestation or land degradation in certain areas. This highlights the importance of incorporating the distance from deforested areas as a key driving variable in the LULC change predictive model.

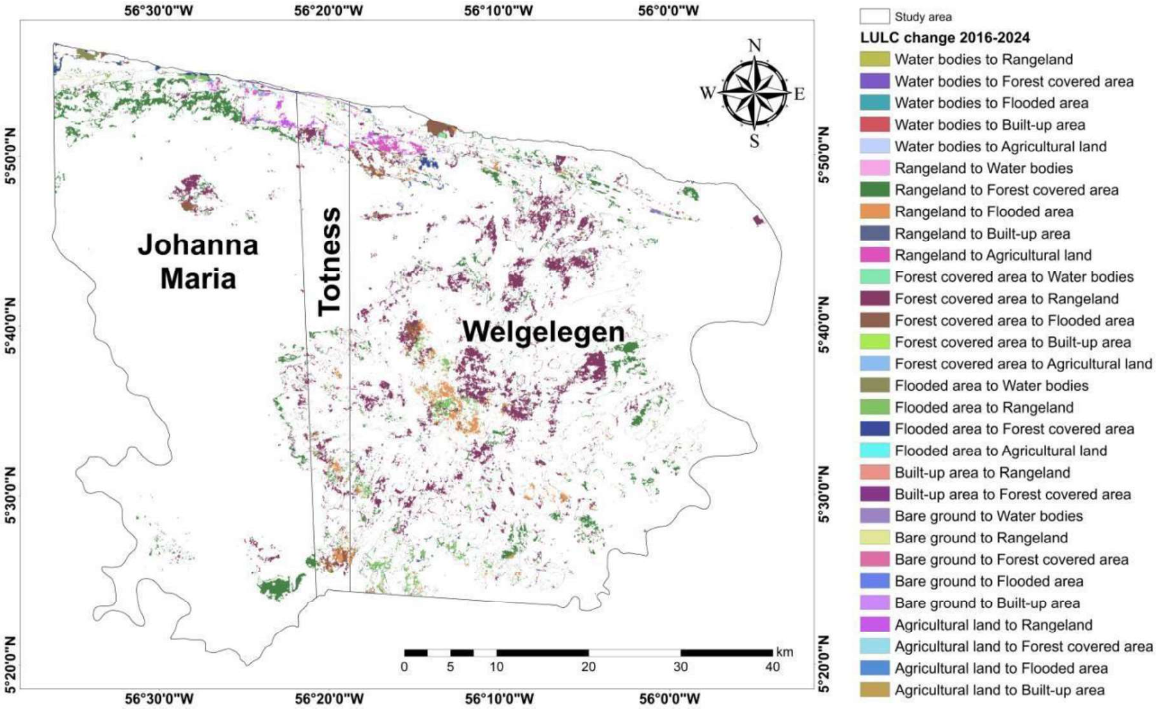


Figure 7: Combined LULC change map during the 2016-2024 timeframe (developed by T. van Ommeren-Myslyva)

Additionally, significant transitions are observed from forest-covered areas to flooded areas (1,647.55 ha) and from rangelands to flooded areas (1,787.56 ha), indicating water-related environmental changes, either seasonal or due to extreme weather events.

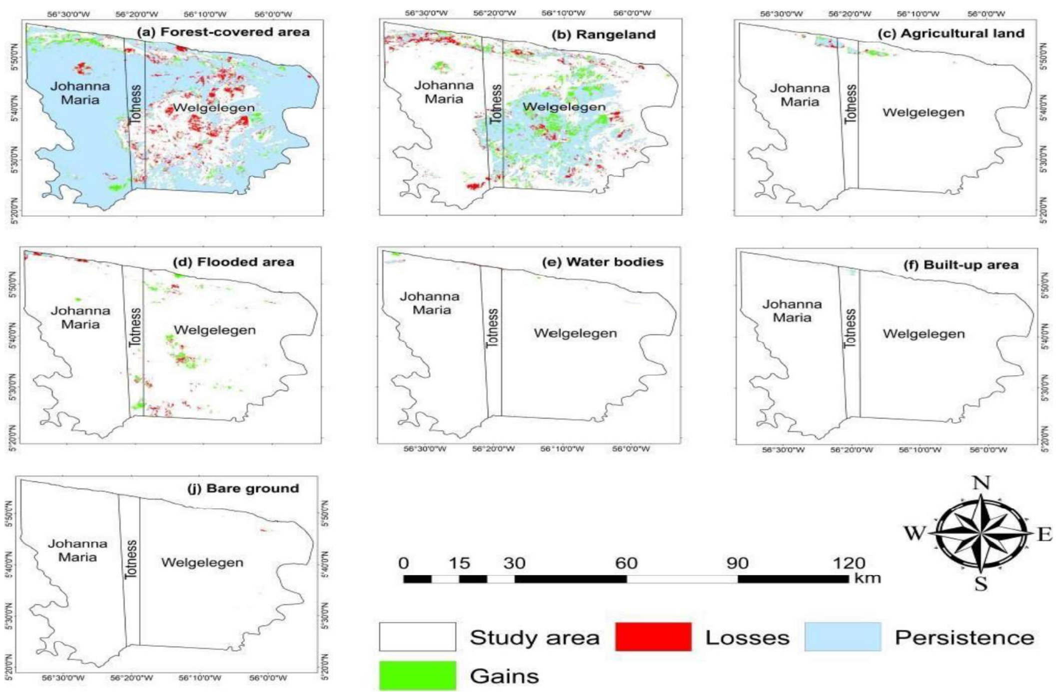


Figure 8: Gains and losses in different LULC classes during the 2016-2024 timeframe (developed by T. van Ommeren-Myslyva)

The conversion of 84.38 ha of forest into water bodies also suggests water expansion into forested areas, driven by flooding or water management issues. The main drains between the East-West Connection Road and the Atlantic Ocean are heavily silted and no longer function effectively, leading to increased water retention and flooding in the surrounding forest areas. This siltation, combined with poor maintenance and inadequate drainage infrastructure, exacerbates waterlogging and accelerates the conversion of forested land into water bodies. Furthermore, rising sea levels and increased rainfall intensity, driven by climate change, are likely contributing to the encroachment of water bodies into forested areas. These factors underscore the urgent need for improved water management practices. Consequently, the inclusion of the distance from water bodies as a driving variable in the LULC change predictive model is crucial. Agricultural land remains relatively stable (2,484.72 ha), but moderate transitions to rangeland (481.07 ha) and forest-covered areas (125.23 ha) suggest potential reforestation or land abandonment. Given this trend, agricultural land transitions could be selected as one of the sub-models for future LULC change prediction. The built-up area is expanding primarily through conversions from forest-covered areas (79.47 ha), rangelands (17.31 ha), and other categories, indicating urbanization or infrastructure development. This highlights the necessity of including the distance from roads and airstrip as the driving variables in the LULC change predictive model.

The results of the LULC change analysis form the basis for developing transition sub- models, the best of which will be incorporated into the final predictive model. These findings have identified four sub-transition models, focusing on the most significant gains and losses for each land use class (Table 3).

Table - III: Transition Sub-Models and their Descriptors

Transition sub-model	Description	Land cover transition	Explanation
Forest covered areas losses (FLO)	Forest-covered areas are converted to other land-use classes	Forest-covered areas to rangeland Forest-covered areas to flooded area Forest-covered areas to agricultural land Forest-covered areas to built-up area	This transition sub-models are strongly interlinked, with forests being the primary land type converted for agricultural use, underscoring deforestation as a key issue
Agricultural expansion (AEX)	Other land classes are converted to agricultural land	Forest-covered areas to agricultural land Flooded areas to agricultural land Rangeland to agricultural land	
Flooded areas transformation (FAT)	Other land classes are converted to flooded areas and flooded areas are converted to other land classes	Forest-covered areas to flooded areas Flooded areas to water bodies	This transition sub-model highlights the importance of water-related environmental changes, potentially driven by poor drainage or extreme weather events
Rangeland transformation (RAT)	Other land classes are converted to rangeland and rangeland are converted to other land classes	Forest-covered areas to rangeland Water bodies to rangeland	This transition sub-model reflects environmental degradation processes, where ecosystems are becoming less productive and more prone to desertification

Note: Developed by T. van Ommeren-Myslyva

The FLO sub-model captures the conversion of forest-covered areas to other land-use classes and highlights deforestation trends, driven by agriculture expansion, urbanization, and environmental factors like flooding. The choice of this transition sub-model is because significant loss of forest cover is critical to understanding land degradation, biodiversity loss, and climate change impacts. The AEX sub-model describes the expansion of agricultural land by converting other land-use types into farmland. Because agricultural expansion often occurs at the expense of natural ecosystems such as forests and rangelands, this may indicate growing pressures on land resources for food production, which could lead to habitat loss and reduced ecosystem services if not managed sustainably. The FAT sub-model represents the conversion of other land classes into flooded areas, as well as the conversion of flooded areas into other land classes and suggests changes in hydrological patterns, potentially driven by rapid climate change, poor water management and seasonal fluctuations. Conversions from forest to flooded areas linked to deforestation, which reduces water retention, while flooded areas converting to water bodies represent permanent water expansion. The RAT sub-model tracks the conversion of other land-use types into rangeland and vice versa and reflects the degradation of forest and wetland ecosystems into more arid rangelands, due to deforestation, climate change or unsustainable water assets use.

The factors influencing land use changes are identified through spatial analysis and included in the model as static or dynamic components to enhance its precision (Leta et al., 2021). In this study, topographical and proximity driving variables were utilized to forecast LULC changes. Prior to incorporating these factors into the predictive model, the chosen variables underwent testing to determine their explanatory significance. The strength of the association was measured using Cramer's V, and p-values were employed to assess statistical significance (Table 4).

Table-IV: Cramer's V and P-Value for Each of the Explanatory Variables

Driver variables	Cramer's V	p-value
Elevation	0.4456	0.0000
Slope	0.2548	0.0000
Distance from water bodies	0.3945	0.0000
Distance from roads	0.3841	0.0000
Distance from airstrip	0.3721	0.0000
Distance from deforestation areas	0.3899	0.0000
Population density	0.5706	0.0000

Note: Developed by T. van Ommeren-Myslyva

According to Eastman (2016), Cramer's V values of 0.15 or higher are considered "useful," while values of 0.4 or higher are deemed "good" for prediction usage. All the driving variables included in the predictive models are considered useful for forecasting land classes transitions. All the variables are statistically significant predictors of LULC change (p-value = 0.0000), with population density and elevation showing the strongest associations, while slope has the weakest impact. This analysis highlights the importance of both human and natural factors in driving changes in land use and land cover within Coronie district.

To select the most appropriate transition sub-model, accuracy rates for each hybrid model with their corresponding transition sub-models, were calculated. For assessing the accuracy of the LR-MC hybrid model, the Relative Operating Characteristic (ROC) method was employed. This approach compares a suitability image, representing the likelihood of the class occurring (i.e., the input image), with a Boolean image, which shows the actual presence of the class (i.e., the reference image) (Eastman, 2016). The summarized results of the accuracy assessment for different sub-models are presented in Table 5.

Table-V: Hybrid Modelling Approaches and their Accuracy

Transition sub-model	Modelling approach accuracy rate (%)		
	MLP-MC	SVM-MC	LR-MC
FLO	83.98	86.57	87.67
AEX	80.28	98.70	88.35
FAT	85.39	94.76	87.03
RAT	87.72	93.43	88.60

Note: Developed by T. van Ommeren-Myslyva

The suitability of different transition sub-models was not assessed for the CA-MC predictive model, as this model used a transition areas file from a Markov Chain analysis (transitioning from all to all). However, due to the limited availability of historical data (considering the period from 2016 to 2020), this model was still selected for predicting LULC changes.

The acceptable range for model accuracy should be 80% or higher to validate the training results (Gharaibeh et al., 2020; Silva et al., 2020). Therefore, all hybrid models in this study are suitable for LULC change prediction. Accuracy rates for the MLP-MC and LR- MC models ranged from 80.28% to 85.39% and 87.03% to 88.60%, respectively, while SVM- MC showed superior performance, with values ranging from 86.57% to 98.70%. Notably, SVM-MC consistently outperformed both MLP-MC and LR-MC across all transition sub- models, especially for AEX and FAT transitions. Although previous studies (Girma et al., 2022; Leta et al., 2021; Gharaibeh et al., 2020) have documented higher accuracy rates for the multi-layer perceptron (MLP), the support vector machine (SVM) demonstrated better predictive capabilities in the current study. The observed higher accuracy of SVM may be due to its robustness when working with smaller datasets (Myslyva et al., 2024), such as the limited five-year dataset used in this study.

Further, the MLP-MC and LR-MC hybrid models with the RAT transition sub-model, the SVM-MC hybrid model with the AEX transition sub-model, and the CA-MC hybrid model were selected to create simulated LULC maps for 2024. To validate the model's predictive accuracy, the Kappa statistic (k-index) for quantity and location was computed by comparing the hard simulation with the reference map for 2024. The statistics reveal that all Kappa index values surpass the satisfactory range (≥80%) (Table 6).

Table-VI: The k-Index Values of the Simulated Lulc Map of 2024

Hybrid model	Index				Overall agreement, %
	Kno	Klocation	KlocationStrata	Kstandard	
CA-MC	0.9168	0.9382	0.9613	0.9613	94.59
MLP-MC	0.9307	0.9496	0.9669	0.9669	95.59
SVM-MC-	0.9378	0.9548	0.9827	0.9827	96.05
LR-MC	0.9366	0.9539	0.9815	0.9815	95.97

Note: Developed by T. van Ommeren-Myslyva

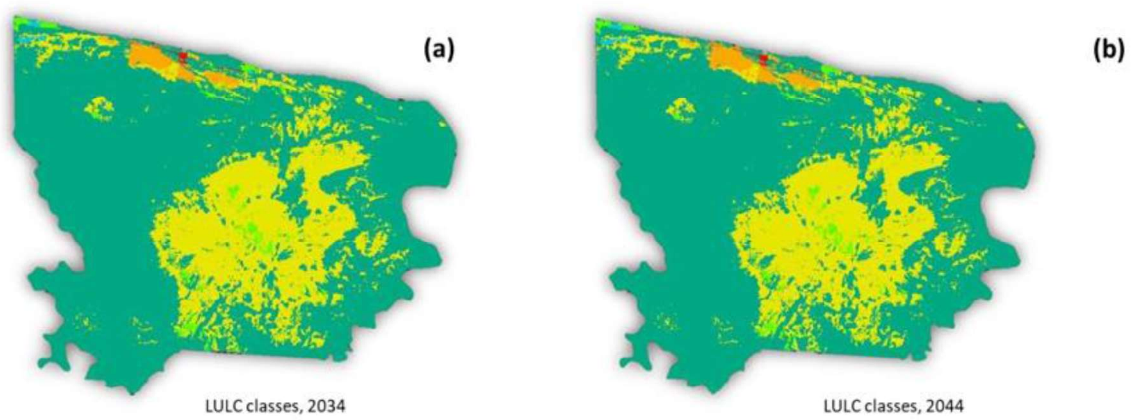
Despite the presence of quantity errors, the overall agreement between the actual and simulated maps is high, ranging from 94.59% to 96.05%. Clearly, in scenarios involving small datasets, the SVM-MC model proves more effective than the MLP-MC, LR-MC, or CA-MC hybrid models. This observation aligns with both our previous research on LULC change prediction in the Commewijne district, where SVM also demonstrated superior accuracy (van Ommeren-Myslyva et al., 2024), and with the results obtained by other authors (Liu & Li, 2021; Zhou & Liu, 2022). The model with the highest accuracy is detailed with parameters outlined in Table 7.

Table-VII: Predictive Hybrid Model Parameters and Accuracy

Parameter	Value
Modelling approach	SVM learning algorithm + Markov Chain analysis
Transition sub-model	Flood intensification
Kernel type	Radial Basis Function
Epsilon (ε)	0.0100
Class number	6
Total cross-validation number	282
Total sample number	7050
Overall cross-validation accuracy	0.9870
Overall out-of-sample accuracy	0.9864
Overall skill measure	0.9727

Note: Developed by T. van Ommeren-Myslyva

The developed model was then used to predict future land use and land cover changes for the years 2034 and 2044. Fig. 9 illustrates the LULC predictive maps for the years 2034 and 2044 and Table 8 depicts the area and net change of existing and predictive LULC classes.



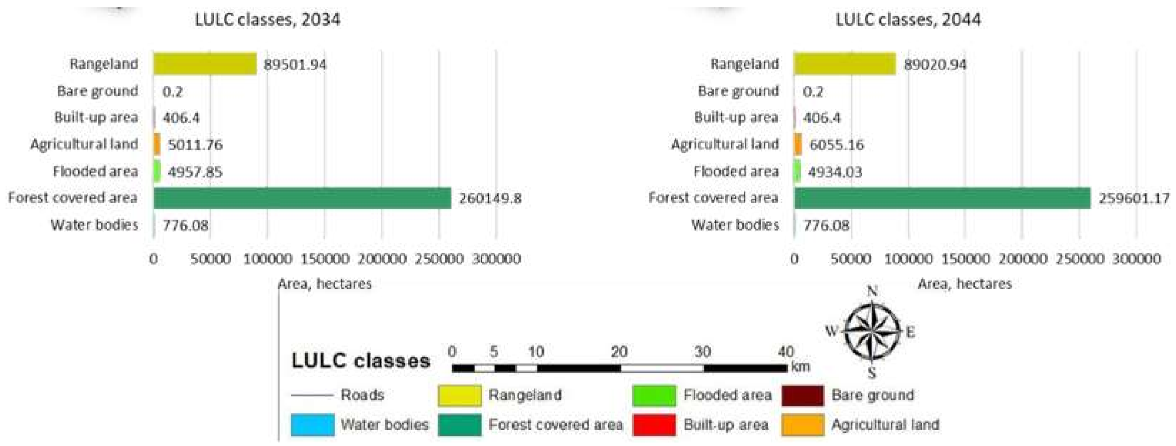


Figure 9 : Projected LULC maps for the territory of the Coronie district for 2034 (a) and 2044 (b) (developed by T. van Ommeren-Myslyva)

The projected LULC change dynamics for the periods 2024-2034, 2024-2044, and 2034- 2044 reveal significant trends in the Coronie district. Water bodies show no changes during the period 2034-2044, maintaining stability, although the prior decade (2024-2034) indicates a notable expansion of over 50%. Forest covered area shows a consistent decrease between 2034 and 2044, with a slight negative change (-0.21%). This contrasts the positive change observed between 2024-2034 and 2024-2044, suggesting deforestation pressures could ease by 2044. Flooded areas exhibit a minimal decline (-0.48%) during the 2034-2044 period, reversing the rapid expansion observed in previous decades (e.g., 75.73% in 2024- 2034). Agricultural land demonstrates a significant expansion, with an increase of 104.34 ha/year (20.8%) between 2034 and 2044, continuing the strong growth observed from 2024- 2044 (73.49%). This suggests that agricultural activities will expand at an accelerated rate.

Table-VIII: Area and Net Change of Existing and Predictive Lulc Classes

LULC Class	**Time Period**	**Annual Change (ha/year)**	**Net Change (ha)**	**Percentage Change (%)**
Water bodies	2024-2034	26.10	260.96	50.68
	2024-2044	13.05	260.96	50.68
	2034-2044	–	–	–
Forest covered area	2024-2034	1269.81	12698.09	5.13
	2024-2044	607.47	12149.49	4.91
	2034-2044	-548.63	-54.86	-0.21
Flooded area	2024-2034	213.64	2136.38	75.73
	2024-2044	105.63	2112.56	74.89
	2034-2044	-23.82	-2.38	-0.48
Agricultural land	2024-2034	116.63	1166.31	30.33
	2024-2044	110.48	2209.71	73.49
	2034-2044	1043.4	104.34	20.8
Built-up area	2024-2034	-5.24	-52.41	-11.42
	2024-2044	-2.62	-52.41	-11.42
	2034-2044	-	-	-
Bare ground	2024-2034	-1.83	-18.32	-98.92
	2024-2044	-0.92	-18.32	-98.92
	2034-2044	-	-	-
Rangeland	2024-2034	-1611.10	-16111.00	-15.24
	2024-2044	-841.10	-1682.00	-1.59
	2034-2044	-480.0	-48.0	-0.54

Note: Developed by T. van Ommeren-Myslyva

Built-up areas and bare ground remain unchanged during the 2034-2044 period. However, the negative trend seen in earlier periods (e.g., -11.42% for built-up areas between 2024 and 2034) highlights the possible contraction of urban areas. Rangeland consistently declines across all periods, with a reduction of 0.54% during the 2034-2044 period. This follows a more significant loss in the 2024-2034 period (-15.24%), suggesting a shift from extensive rangelands towards other land uses, possibly agriculture or forest regeneration. The changes in these LULC classes reflect evolving land use practices, particularly the expansion of agricultural land at the expense of forest cover and rangeland, while water bodies and urban areas remain relatively stable.

Considering that Coronie district faces a significant shortage of land resources suitable for building, infrastructure development, and agricultural activity, coupled with the continued use of the most productive land parcels for building construction, there is a pressing need to implement an urgent land management plan which will help mitigate the negative consequences of irrational land use during the last decades. The description of the identified trends in LULC change and the necessary activities for mitigating their negative impacts are outlined in Table 9.

Table-IX: Descriptions and Explanations for Observed Trends in Lulc Changes in Coronie District (2024–2044 Predictions)

LULC class	**Trend**	**Trend explanation**	**Required land management activities**
1	2	3	4
Water bodies	Continuous expansion is observed during the period from 2024 to 2034, with the rate of growth slowing in the following years	The increase in water bodies area demonstrates the impact of sea-level rise and coastal erosion impact. Natural processes like sediment deposition, tidal flooding, and water could also expand water bodies over time	Sustainable water management practices are essential for supporting mangrove and wetland ecosystems, as well as for the development and maintenance of water management infrastructure (e.g., drainage canals, levees)
Forest covered area	Forest area continues recovering, though the rate of increase slows slightly after 2034	The moderate growth in forest cover between 2024 and 2034 may be driven mostly by natural regeneration. However, this growth slows between 2034 and 2044, likely due to increasing land use pressures and agricultural expansion	Sustainable forestry management practices such as selective logging, reforestation, and community- based forest management are essential to balance conservation with economic activities. Agroforestry and sustainable harvesting of non-timber forest products can provide local communities with income while preserving forest ecosystems. Additionally, initiatives like carbon sequestration projects and maintaining riparian buffer zones help protect biodiversity and support long-term forest sustainability
Rangeland	Significant reduction in rangeland area, with a substantial decrease in the rate of loss	From 2024 to 2034, rangeland decreases significantly due to intensified land conversion for agriculture. Between 2024 and 2044, the rate of decline slows as the most accessible rangeland is already converted, and ongoing conservation efforts may mitigate further loss	Effective land use planning should be implemented to protect rangeland from conversion to agriculture or urban areas. Promoting sustainable agricultural practices and enhancing conservation efforts, such as establishing protected areas and supporting reforestation, will help preserve rangeland. Additionally, engaging local communities in conservation efforts will ensure sustainable land use and recovery of degraded areas.
Bare groun d	Ongoing and rapid decline in bare ground, with a slight reduction in the rate of loss	The area of bare ground will decrease due to its transformation into other land use and land cover types	Monitoring and managing bare ground are essential for preventing soil degradation and maintaining ecosystem health

Table 9 Contd…

1	2	3	4
Flooded area	Flooded areas expand significantly from 2024 to 2034, then start to shrink slightly between 2034 and 2044	The significant expansion of flooded areas from 2024 to 2034 may be due to increased rainfall, rising sea levels, or changes in land use that enhance water accumulation. The slight shrinkage of flooded areas between 2034 and 2044 may result from natural variability in climate patterns and changes in regional weather conditions	To prevent the expansion of flooding, it is essential to develop and maintain efficient drainage systems and restore wetlands to enhance water absorption. Reforestation and improved land use planning, including floodplain management, can further mitigate flood risks by controlling runoff and preventing construction in high-risk areas. Additionally, implementing erosion control measures and increasing community education on flood risks will support long-term flood prevention and resilience
Agricultural land	Agricultural land show continuous expansion, though the rate of growth slows in later years (2034-2044)	The continuous expansion of agricultural land can be attributed to ongoing demand for food production and economic incentives for agricultural development. However, the slowing rate of growth in later years (2034-2044) may result from land constraints. Additionally, factors such as soil degradation and changing climate conditions might also impact the rate of agricultural expansion	To mitigate the negative impacts of agricultural land expansion, it is crucial to implement sustainable agricultural practices and land use planning that prevent encroachment into sensitive ecosystems. Integrating agroforestry and employing soil conservation techniques can help maintain soil health and biodiversity. Additionally, supporting sustainable agriculture through incentives and educating the community on best practices will promote long-term environmental sustainability
Built-up areas	Continued decline in built-up areas, with a slowing rate of decrease to 2044	The continued decline in built-up areas, with a slowing rate of decrease until 2044, can be attributed to factors such as limited urban development and possibly lower population growth or migration trends. However, with the planned reconstruction of an airstrip at Totness resort, which is likely to attract more residents and stimulate economic activity, the trend of decreasing built-up areas may change	To support optimal urbanization, it is crucial to implement integrated urban planning that balances growth with environmental sustainability, and invest in essential infrastructure. Involving local communities in the planning process and addressing potential challenges will ensure that urbanization is both resilient and aligned with local needs

Note: Developed by the authors

Effective management of water bodies requires sustainable water management practices, including drainage systems, levees, and support for mangrove and wetland ecosystems, to address rising sea levels and coastal erosion. For forest areas, sustainable forestry practices like selective logging, reforestation, and agroforestry balance conservation with economic needs, enhancing biodiversity and carbon sequestration while mitigating land use pressures.

To manage the expansion of flooded areas, developing efficient drainage systems, restoring wetlands, and improving land use planning are crucial to enhance water absorption and reduce flood risks. Implementing erosion control measures and community education on flood risks further supports flood prevention. In agricultural lands, adopting sustainable practices and land use planning helps prevent encroachment into sensitive ecosystems and maintains soil health. Integrated urban planning, including investment in infrastructure and community involvement, supports optimal urbanization and mitigates the decline in built-up areas. Monitoring and managing bare ground are essential for preventing soil degradation, with a focus on transforming bare areas into productive land uses. Finally, effective land use planning and conservation efforts, including promoting sustainable practices and establishing protected areas, are necessary to preserve rangeland and mitigate further loss.

Conclusion

The transformation of land use and land cover (LULC) in the Coronie district of Suriname from 2024 to 2044 was simulated using various hybrid predictive models. This study employed a combination of dependent and independent spatial datasets, and TerrSet software was used for analyzing LULC changes through both statistical and graphical methods. Four hybrid predictive models were evaluated: Markov chain analysis with cellular automata (CA-MC), multilayer perceptron (MLP-MC), support vector machines (SVM-MC), and logistic regression (LR-MC).

Accuracy assessments indicated that the SVM-based model, which integrated the AEX transition sub-model for forest, flooded areas, and rangeland conversion to agricultural land, achieved an overall accuracy of 98.70%. Although MLP models showed higher accuracy in previous studies, the SVM model proved superior in this research due to its robustness with small datasets and ability to handle high-dimensional data effectively. The reliability of the SVM model was confirmed with Kappa statistics of 96.05% for predictions in 2024.

Forecasts for 2034 and 2044 predict increased agricultural land and reduced areas of bare ground, built-up areas, and rangeland. These trends emphasize the need for effective land and water resource management strategies to mitigate negative environmental impacts and balance ecosystem services. Given the unique characteristics of individual resorts in Coronie, future studies should develop more detailed predictive models incorporating specific driving variables relevant to each area.

References

Abbas, H., Tao, W., Khan, G., Alrefaei, A. F., Iqbal, J., Albeshr, M. F., & Kulsoom, I., (2023). Multilayer perceptron and Markov Chain analysis-based hybrid-approach for predicting land use land cover change dynamics with Sentinel-2 imagery, Geocarto International, 38(1).

Abdullahi, S., & Pradhan, B., (2016). Sustainable brownfields land use change modeling using GIS-based weights-of-evidence approach, Applied Spatial Analysis and Policy, 9(1). pp. 21–38.

Adhikari, U., & Southworth, J., (2018). Land use and land cover change modelling for sustainable development, Sustainability, 10(6). pp. 1838.

Al-Hamdan, M. Z., Oduor, P., Flores, A. I., Kotikot, S. M., Mugo, R., Ababu, J., & Farah, H., (2017). Evaluating land cover changes in Eastern and Southern Africa from 2000 to 2010 using validated Landsat and MODIS data, International Journal of Applied Earth Observation and Geoinformation, 62, pp. 8–26.

Aloqaili, H., Alomar, S., Elgazzar, R., & Mahmoud, S., (2021). Assessing land suitability and management strategies through LULC models, Journal of Land Use Science, 16(2). pp. 121–139.

Asif, M., Kazmi, J., Tariq, A., Zhao, N., Guluzade, R., Soufan, W., Almutairi, Kh., El Sabagh, A., & Aslam, M., (2023). Modelling of land use and land cover changes and prediction using CA-Markov and Random Forest, Geocarto International, 38(1).

Belgiu, M., & Csillik, O., (2018). Sentinel-2 imagery for land cover classification: A review, International Journal of Applied Earth Observation and Geoinformation, 70, pp. 1–14.

Deng, X., Liu, H., Li, W., & Zhou, X., (2020). The role of land use/land cover change in carbon sequestration, Environmental Research Letters, 15(6). p. 064010.

Devi, A. R., & Shimrah, T., (2023). Modelling LULC using Multi-Layer Perceptron Markov change (MLP-MC) and identifying local drivers of LULC in the hilly district of Manipur, India, Environmental Science and Pollution Research International, 30(26). pp. 68450–68466.

Dey, N. N., Al Rakib, A., Al Kafy, A., & Raikwar, V., (2021). Geospatial modelling of changes in land use/land cover dynamics using multi-layer perception Markov chain model in Rajshahi City, Bangladesh, Environmental Challenges, 4, p. 100148.

Eastman, J. R., (2016). TerrSet Manual, Geospatial Monitoring and Modelling System, Clark University, Worcester, USA.

El Ghoul, I., Sellami, H., Khlifi, S., & Vanclooster, M., (2023). Impact of land use land cover changes on flow uncertainty in Siliana watershed of north-western Tunisia, Catena, 220, pp. 106733.

Gharaibeh, A., Shaamala, A., Obeidat, R., & Al-Kofahi, S., (2020). Improving land-use change modelling by integrating ANN with cellular automata-Markov chain model, Heliyon, 6.

Girma, R., Fürst, C., & Moges, A., (2022). Land use land cover change modelling by integrating the artificial neural network with cellular automata-Markov chain model in Gidabo river basin, main Ethiopian rift, Environmental Challenges, 6, p. 100419.

Guzder-Williams, B., Mackres, E., Angel, S., Blei, A. M., & Lamson-Hall, P., (2023). Intra-urban land use maps for a global sample of cities from Sentinel-2 satellite imagery and computer vision, Computers, Environment and Urban Systems, 100, p. 101917.

Hamidi, S., Jafari, R., & Nouri, Z., (2022). Integration of Markov Chain and Cellular Automata to simulate urban growth: A case study of the Metropolitan City of Mashhad, Iran, Remote Sensing, 14(3). p. 762.

Hashemzadeh, A., Mohammadi, M., & Malekinejad, N., (2021). Application of hybrid logistic regression and cellular automata for modelling land use change: A case study of Tehran, Iran, Sustainable Cities and Society, 74, p. 103176.

Hussain, S., Lu, L., Mubeen, M., Nasim, W., Karuppannan, S., Fahad, S., Tariq, A., Mousa, B. G., Mumtaz, F., & Aslam, M., (2022). Spatiotemporal variation in land use land cover in the response to local climate change using multispectral remote sensing data, Land, 11(5). p. 595.

Kafy, A.-A., Naim, M. D. N. H., Subramanyam, G., Faisal, A.-A., Ahmed, N. U., Al Rakib, A., Kona, M. A., & Sattar, G. S., (2021). Cellular Automata approach in dynamic modelling of land cover changes using RapidEye images in Dhaka, Bangladesh, Environmental Challenges, 4, p. 100084.

Kafy, R., Miah, M. D., Islam, M. N., & Rahman, M. M., (2020). Impact of LULC changes on biodiversity conservation: A case study, Journal of Environmental Management, 273, p. 111118.

Lambin, E. F., & Meyfroidt, P., (2019). Global land use change, economic globalization, and the looming land scarcity, Proceedings of the National Academy of Sciences, 116(15). pp. 7350–7357.

Leta, M. K., Demissie, T. A., & Tränckner, J., (2021). Modelling and prediction of land use land cover change dynamics based on land change modeller (LCM) in Nashe watershed, upper Blue Nile basin, Ethiopia, Sustainability, 13.

Liu, X., & Li, X., (2021). Comparative analysis of SVM and MLP for land use classification using limited training samples, Journal of Applied Remote Sensing, 15(2). p. 026518.

Luo, Y., Sun, J., Li, Z., & Hu, X., (2021). Evaluating carbon sequestration potential in different land cover types, Global Change Biology, 27(8). pp. 1647–1660.

McCarthy, M. J., Radabaugh, K. R., Moyer, R. P., & Muller-Karger, F. E., (2018). Enabling efficient, large-scale high-spatial resolution wetland mapping using satellites, Remote Sensing of Environment, 208, pp. 189–201.

Mishra, V. N., Rai, P. K., Prasad, R., Punia, M., & Nistor, M.-M., (2018). Prediction of spatiotemporal land use/land cover dynamics in rapidly developing Varanasi district of Uttar Pradesh, India, using geospatial approach: A comparison of hybrid models, Applied Geomatics, 10(3). pp. 257–276.

Mohamed, A., & Worku, H., (2020). Simulating urban land use and cover dynamics using cellular automata and Markov chain approach in Addis Ababa and the surroundings, Urban Climate, 31, p. 100545.

Muhammad, R., Zhang, W., Abbas, Z., Guo, F., & Gwiazdzinski, L., (2021). Spatiotemporal change analysis and prediction of future land use and land cover changes using QGIS MOLUSCE plugin and remote sensing big data: A case study of Linyi, China, Land, 11(3). p. 419.

Myslyva, T., Dasai, M., Huisden, C. M., Nadtochiy, P., & Bilyavskyi, Y., (2024). Application of machine learning approaches for land use change modelling in Suriname, Scientific Papers. Series E. Land Reclamation, Earth Observation and Surveying, Environmental Engineering, XIII, pp. 830–840.

Phiri, D., & Morgenroth, J., (2017). Urban expansion and its effects on land cover and land use patterns, Urban Ecosystems, 20(1). pp. 101–118.

Regasa, M. S., & Loiskandl, W., (2022). Modelling land cover and climate change impacts on water resources using SWAT and future projections in Ethiopia's Rift Valley, Environmental Research, 214, p. 113900.

Robinson, D.T., (2021). Towards a spatially explicit agent-based model of land use change and ecosystem service provisioning in semi-arid rural regions. Environmental Modelling and Software, 139, p.104990.

Roy, D.P., Wulder, M.A. and White, J.C., (2018). Land cover classification with Landsat 8 OLI data. Remote Sensing of Environment, 210, pp.379–393.

Sánchez-Espinosa, A. and Schröder, C., (2019). Land use and land cover mapping in wetlands one step closer to the ground: Sentinel-2 versus Landsat 8. Journal of Environmental Management, 247, pp.484–498.

Silva, L.P., Xavier, A.P.C., da Silva, R.M. and Santos, C.A.G., (2020). Modelling land cover change based on an artificial neural network for a semiarid river basin in northeastern Brazil. Global Ecology and Conservation, 21.

Song, C., Xu, B. and Caylor, K.K., (2020). Impact of deforestation and urbanization on ecosystem services. Ecosystem Services, 42, 10114.

Tehrany, M.S., Pradhan, B. and Jebur, M.N., (2020). Spatiotemporal dynamics of land use/land cover and its effects on ecosystem services. Ecological Indicators, 117, 106643.

van Ommeren-Myslyva, T., Wesenhagen, F., Kadirbaks, R. and Abdoelrahman, F., (2024). Application of machine learning approaches for land use change modelling in Commewijne district of Suriname. Science and Innovation, 3, pp.13–29.

Wang, S.W., Munkhnasan, L. and Lee, W.-K., (2021). Land use and land cover change detection and prediction in Bhutan's high-altitude city of Thimphu, using cellular automata and Markov chain. Environmental Challenges, 2, 100017.

Wang, Y., Liu, D. and Zhang, X., (2023). An integrated Markov-Logistic Regression approach to LULC change prediction: A case study of the Yellow River Basin, China. Environmental Science and Pollution Research, 30(2). pp. 2611–2626.

Xie, Y., Zhang, L. and Chen, W., (2019). Predicting land cover changes and their impacts on the environment. Journal of Environmental Management, 245, pp.70–80.

Yeh, C.-K. and Liaw, S.-C., (2021). Applying spatial autocorrelation and logistic regression to analyze land cover change trajectory in a forested watershed. Terrestrial, Atmospheric and Oceanic Sciences, 32, pp.35– 52.

Zhao, X., Liu, Z. and Chen, Y., (2021). Markov-CA model for LULC change simulation in rapidly urbanizing regions: A case study in the Beijing-Tianjin-Hebei area. Sustainability, 13(19). p.10845.

Zhou, X. and Liu, L., (2022). Evaluating the performance of support vector machines and other classifiers for land cover classification with small sample sizes. Journal of Photogrammetry and Remote Sensing, 181, pp.174–189.