Predicting Land Use and Land Cover Changes in Pathumthani, Thailand: A Comprehensive Analysis from 2013 to 2023 Using Landsat Satellite Imagery and CA-ANN Algorithm, with Projections for 2028 and 2038

Thammaboribal, P.* and Tripathi, N. K.
Remote Sensing and Geographic Information Systems FoS., Asian Institute of Technology, Pathumthani, Thailand, E-mail: prapasgnss@gmail.com
Corresponding Author

DOI: https://doi.org/10.52939/ijg.v20i5.3225

Abstract
This article presents the findings from a study on Land Use and Land Cover (LULC) predictions for Pathumthani province in 2028 and 2038. Utilizing Landsat satellite imagery data from 2013, 2018, and 2023, and employing the Cellular Authomata – Artificial Neural Network (CA-ANN) algorithm in MOLUSCE plugin in QGIS, the study simulated future LULC trends. The predictor variables used in the analysis are distance from main roads, distance sky train stations, distance from universities, and distance from markets. The overall accuracy and kappa coefficient of the prediction model validate its reliability for forecasting LULC changes. The results illustrate evolving urban landscapes and environmental dynamics, with vegetation predominating in the eastern and western regions of Pathumthani in 2028, while built-up areas concentrate along major transportation routes. By 2038, these trends persist, with notable expansion of built-up areas, particularly in Muang Pathumthani, Khlong Luang, and Lam Luk Ka districts. Significant urbanization is observed in Muang Pathumthani along the Chao Phraya River, driven by proximity to Nonthaburi. Lam Luk Ka experiences substantial development, supported by infrastructure and connectivity to Bangkok, while Thanyaburi sees urbanization along the Rangsit-Nakornnayok road. Khlong Luang emerges as an urban expansion hub, influenced by Highway No.1 and industrial estates. The study underscores the complex interplay of infrastructure, demographics, and environmental factors, emphasizing the need for sustainable planning to address future challenges.

Keywords: CA-ANN, Landsat, LULC, MOLUSCE, Pathumthani, Prediction

1. Introduction

Land use and land cover (LULC) dynamics are critical components of environmental management and sustainable development, especially in rapidly urbanizing regions [1]. The Pathumthani province of Thailand has undergone significant transformations in its landscape over the past few decades due to urbanization, agricultural expansion, and other human activities. Understanding these changes is essential for effective land-use planning, resource management, and environmental conservation.

This research aims to investigate LULC changes in Pathumthani province from 2013 to 2023, as well as simulate LULC of the study area in 2028 and 2038 employing Cellular Automata (CA) and Artificial Neural Network (ANN) modeling techniques. These computational approaches offer powerful tools for simulating and predicting land cover changes, providing valuable insights into future landscape scenarios [2] and [3]. The choice of Pathumthani province for conducting research on LULC prediction using CA-ANN modeling is strategically driven by several factors:

1.) Rapid Urbanization and Development: Urbanization is characterized by the proliferation of cities, marked by heightened population densities, leading to the transformation of land to facilitate residential, commercial, and industrial growth [4]. Pathumthani has been experiencing significant urbanization and development over the past few decades. As one of the central provinces near Bangkok, it has become a focal point for economic activities, infrastructure development, and population growth [5]. The accelerated urbanization makes it an ideal case study to understand the dynamics of land use changes in response to urban expansion.

2.) Ecological Diversity: Pathumthani is characterized by a mix of urban, suburban, and rural landscapes, including agricultural areas and natural ecosystems. This diversity allows researchers to examine a wide range of land use and land cover types, providing a holistic view of the factors influencing changes in the region.

3.) Proximity to Bangkok: Being in close proximity to the capital city, Bangkok, Pathumthani is influenced by the urban sprawl and development emanating from the metropolitan area [5]. This proximity adds complexity to the land use dynamics, with potential impacts on commuting patterns, infrastructure development, and the transformation of rural areas into urban spaces.

4.) Policy Implications: Pathumthani is subject to various policies and planning initiatives aimed at managing urban growth and preserving natural resources [6]. Studying LULC changes in this province can contribute valuable insights for policymakers, enabling them to make informed decisions about land use planning, zoning regulations, and sustainable development practices.

5.) Socioeconomic Factors: The province's socioeconomic dynamics, including population growth, industrialization, and agricultural practices, play a crucial role in shaping land use patterns [7]. By focusing on Pathumthani, researchers can investigate the interconnectedness of these factors and their influence on LULC changes.

6.) Model Validation and Accuracy: To develop reliable predictive models like CA-Markov, it is essential to have accurate and comprehensive historical data. Pathumthani's well-documented land use history, along with the availability of satellite imagery and other relevant data, makes it an ideal location for model validation and calibration.

In summary, conducting research in Pathumthani provides a microcosm of the broader challenges and opportunities associated with urbanization and land use changes in rapidly developing regions. The insights gained from this study can contribute not only to the local context but also to the development of more generalized models and strategies for sustainable land use planning in similar regions worldwide.

This study holds particular significance for the sustainable development of Pathumthani, as it provides a comprehensive understanding of the evolving land use dynamics. The results can inform policymakers, urban planners, and environmental managers about the potential impacts of current trends on the region's ecological balance, biodiversity, and overall landscape health. As we delve into the intricacies of LULC prediction, our research also contributes to the broader field of geospatial science and land change modeling. The findings are expected to enhance our ability to develop robust models for land use planning and management, which can be applicable to similar regions facing rapid urbanization and environmental changes. Through this research, we aim to foster a more informed and sustainable approach to land use decision-making in Pathumthani province and beyond.

2. Study Area

Pathum Thani, situated in the central region of Thailand, emerges as a compelling focal point for investigating LULC change in this study. Positioned just north of Bangkok, this region bears notable economic and cultural importance, significantly influencing the nation's overall dynamism. Its geographical makeup encompasses a diverse blend of urban and rural landscapes, encompassing zones of industrial development, residential areas, and expansive agricultural regions [8].

The province is situated on the low alluvial plains of the Chao Phraya River between the latitude of 13° 55′N to 14° 18′N, and the longitude of 100° 20′E to 100° 57′E as illustrates in Figure 1. Numerous canals (khlongs) intersect the region, providing irrigation to large rice paddies within the area. The province consists of 7 districts namely: Mueang Pathum Thani, Lat Lum Kaew, Sam Khok, Khlong Luang, Nong Suea, and Lam Luk Ka. Pathum Thani province is traversed by the prominent "Paholyothin Highway" (Highway no. 1), a major thoroughfare linking the province to Bangkok, as well as the northern and northeastern regions of Thailand. Furthermore, the significance of the Rangsit-Nakornnayok road in the province's transportation network also contributes to a notable concentration of activities along these key roadways [9]. A provincial comprehensive plan is a strategic and detailed framework designed to guide the long-term development and growth of a province. This comprehensive plan typically encompasses various aspects of land use, transportation, infrastructure, economic development, environmental conservation, and social services. It serves as a blueprint for sustainable and coordinated development within the province, taking into account demographic trends, economic priorities, and environmental considerations.

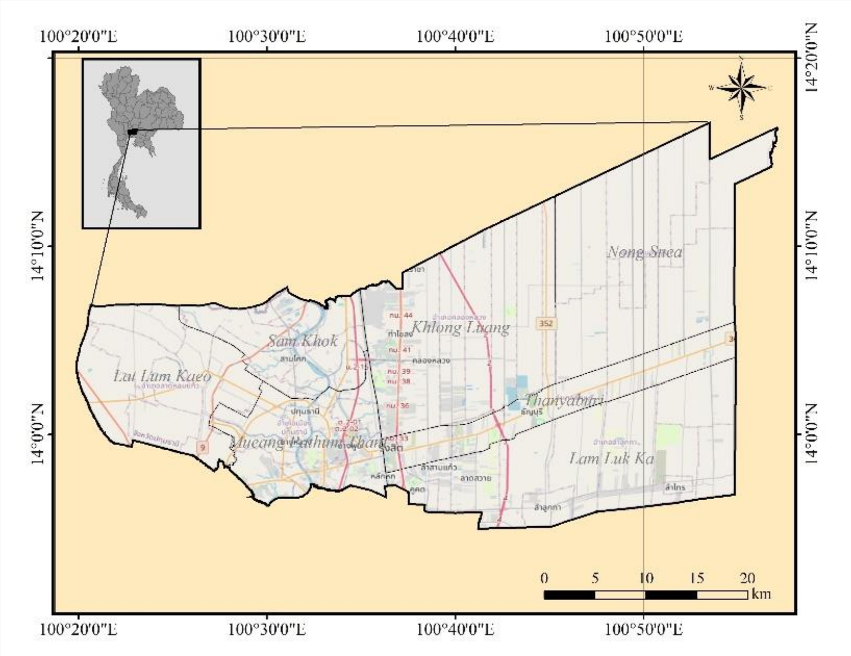

Figure 1: Pathumthani province of Thailand

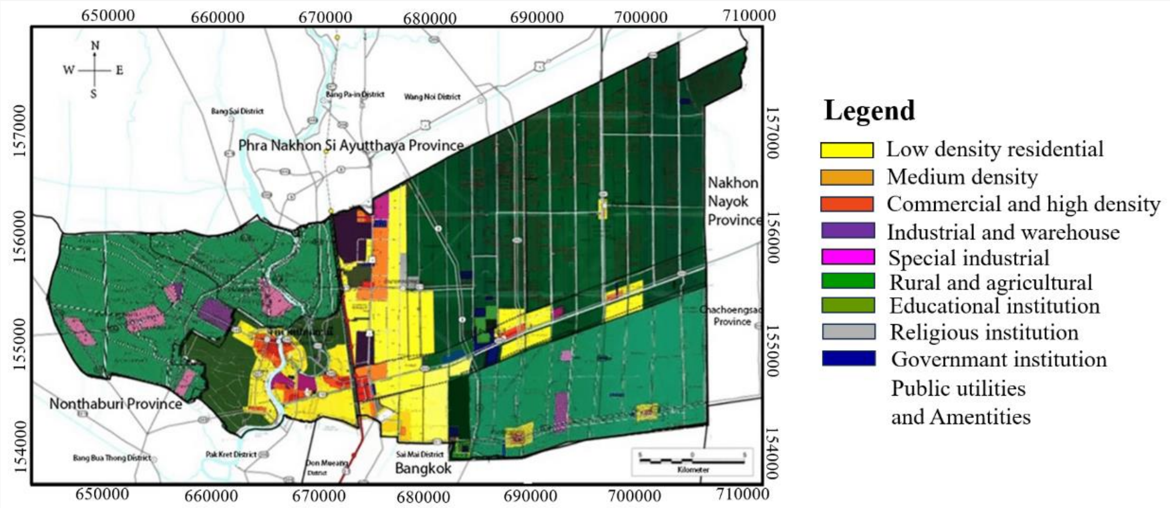

Figure 2: Pathumthani comprehensive plan iof 2015 [8] (Modifed by author)

The plan often involves extensive consultation with stakeholders, including local communities, businesses, and government agencies. Through a thoughtful and inclusive process, a provincial comprehensive plan aims to promote effective land management, improve infrastructure, address social and economic inequalities, and create a vision for the overall well-being and prosperity of the province and its residents. The most recent comprehensive plan for Pathumthani, updated in 2015, is illustrated in Figure 2.

3. Data Used and Methodology

3.1 Data Collection

This study is dedicated to predicting Land Use and Land Cover (LULC) changes in Pathumthani province, Thailand, through the analysis of LULC data from 2013 and 2023 using the CV Markov model. Landsat 5 and 8 image data were acquired for the specified years, and the LULC was categorized into four groups: (1) built-up areas; (2) vegetation areas; (3) water bodies; and (4) bareland.

Table 1: Data acquisition dates

Year	Acquisition dates	Landsat series
2013	14 May 2013	Landsat 5 TM
2018	18 April 2018	Landsat 8 OLI/TIRS
2023	18 May 2023	Landsat 8 OLI/TIRS

The classification process utilized a supervised technique known as "maximum likelihood," incorporating both visible bands (R-G-B) and near-infrared (NIR) bands. The satellite imagery was obtained from USGS EarthExplorer, accessible at https://earthexplorer.usgs.gov/. The data acquisition dates are outlined in Table 1. The images were acquired with minimal cloud cover, constituting less than 10%.

3.2 Land Use Land Cover Classification

Land use classification is a process that furnishes details on both land cover and the specific human activities associated with land use [10]. This classification method encompasses two approaches: supervised and unsupervised classification. In this study, a supervised classification method was employed. Supervised classification involves utilizing samples of known characteristics to categorize pixels of unknown identity. This methodology results in a map wherein each pixel is assigned to a class based on its multispectral composition. Land Use and Land Cover (LULC) classification using satellite imagery involves categorizing different Earth surface types based on their spectral characteristics captured by remote sensing satellites [11]. This process is pivotal for monitoring and comprehending landscape changes over time. Initially, satellite imagery is acquired and preprocessed to correct for atmospheric effects and geometric distortions. Subsequently, representative areas, known as Regions of Interest (ROIs), are selected, and spectral information is extracted to form a training dataset for the classification algorithm [12].

The subsequent steps involve the utilization of the maximum likelihood algorithm, a widely employed technique for LULC classification [13]. This algorithm computes the probability of a pixel belonging to a specific land cover class by assuming that the spectral values for each class follow a normal distribution. The pixel is then assigned to the class with the highest probability, facilitating the creation of a classified image [14]. Feature selection is crucial for choosing the most relevant spectral bands for input to the algorithm, maximizing the separability of different land cover classes. The Maximum Likelihood (ML) classifier is a widely used statistical method in remote sensing and image processing for classifying pixels within satellite or aerial imagery into different land cover classes. It is a supervised classification algorithm [15] and [16], meaning that it requires training samples of known classes to learn the statistical characteristics of each class. The fundamental principle behind the Maximum Likelihood classifier is to assign a pixel to the class that has the highest likelihood of generating the observed spectral values for that pixel. It assumes that the spectral values for each class follow a multivariate normal distribution, and it calculates the probability that a particular pixel's observed spectral values belong to each class. The following step is used when ML is implemented in the LULC classification.

1. Training Phase: Representative samples from each class, known as training samples, are used to estimate the mean and covariance of the spectral values for each class.
2. Probability Calculation: For a given pixel, the algorithm calculates the probability of it belonging to each class based on the estimated mean and covariance of that class.
3. Classification: The pixel is assigned to the class with the highest probability.

The ML classifier is effective when the assumptions of normality and equal covariance matrices hold for the spectral signatures of the classes. It is known for its simplicity, efficiency, and robustness, making it a popular choice in various remote sensing applications for land cover classification. The effectiveness of the maximum likelihood algorithm hinges on adhering to the assumptions of normality and equal covariance matrices for spectral signatures and requires a supervised approach with training samples for each land cover class [17][18] and [19]. In this study, LULC was categorized into four classes, namely built-up area, vegetation area, waterbody, and bareland.

3.3 Accuracy Assessment

Field data is utilized in the accuracy assessment process for the classification results of Landsat satellite imagery for the year 2023. A total of 100 random points were employed for validating and assessing the accuracy of the classification outcomes.

The selection of these random points is carried out to characterize areas representing each desired land cover class and to establish a numerical description of the spectral properties associated with each land cover type. The identification of random points is based on field data, and the analysis provides statistical information on various land use types.

Users of LULC maps require knowledge of the map's accuracy level for more efficient and correct utilization. The accuracy of interpreting land use and land cover change should not fall below 80% [20]. The widely advocated method for presenting classification accuracy is through an error matrix, which facilitates the derivation of a series of descriptive and analytical statistics [21]. The accuracy assessment can be determined from LULC confusion matrix [22] which used to compare the relationship between the real LULC and classified LULC. Equations 1 to 3 are commonly used in LULC accuracy assessment.

$$UA = \frac{CP_R}{TP_R} \times 100$$

Equation 1

where:

- UA is user’s accuracy (indicates the likelihood that the prediction accurately represents reality.)
- CP_R is number of pixels in each LULC type that correctly classified
- TP_R is total number of pixels in each LULC type (total in the row)

$$PA = \frac{CP_P}{TP_P} \times 100$$

Equation 2

where:

- PA is producer’s accuracy (reflects the quality of the classification for pixels in the training set)
- CP_P is number of pixels in each LULC type that correctly classified
- TP_P is total number of pixels in each LULC type (total in the column)

$$OA = \frac{CP_D}{TP} \times 100$$

Equation 3

where:

- OA is overall accuracy (reflects the accuracy or quality of the map classification)
- CP_D is sum of diagonal elements of confusion matrix (diagonal sum)
- TP is total number of pixels

Omission errors (OE) pertain to the reference pixels that were excluded or omitted from the accurate class in the classified map. While commission errors (CE) are characterized by the misclassification of pixels belonging to a particular class in the map, representing a counterpart to user accuracy. The OE and CE are determined from Equations 4 and 5, respectively.

$$OE = 100\% - PA$$

Equation 4

$$CE = 100\% - UA$$

Equation 5

Another frequently employed accuracy metric is the kappa coefficient (*K*), assessing the classification's performance relative to randomness. The kappa coefficient's value spans from -1 to 1: a negative value signifies that the classification is inferior to a random assignment of categories, 0 indicates no discernible improvement over randomness, and a positive value signifies an enhanced classification compared to random assignment [23]. Kappa coefficient is determined from Equation 6.

$$K = \frac{N \cdot CP_D - \sum_{i=1}^{k} X_{Ri} X_{Ci}}{N^2 - \sum_{i=1}^{k} X_{Ri} X_{Ci}}$$

Equation 6

where:

- N is total number of pixels (equivalent to *TP*)
- k is number of LULC classes
- X_{Ri} is total number of pixels in row *i*
- X_{Ci} is total number of pixels in column *i*

The interpretation of kappa agreement is expressed in Table 2.

Table 2: Kappa coefficient agreement [24]

Kappa coefficient value(K)	Rating criteria
0.81 – 1.00	Almost perfect agreement
0.61 – 0.80	Substantial agreement
0.41 – 0.60	Moderate agreement
0.21 – 0.40	Fair agreement
0.00 – 0.20	Slight agreement
< 0.00	Disagreement

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3.4 MOLUSCE

Methods of Land Use Change Evaluation (MOLUSCE) is a QGIS plugin which designed for land use change evaluation [25] and [26], the plugin facilitates the following process:

1. Data Input: Raster data representing land use categories for two distinct time period: A (past) and B (present) and raster files that contain explanatory variables or factors.
2. Model Training: Trains a predictive model capable of forecasting land use changes from the past to the present.
3. Prediction of Future Changes: Applies the trained model to predict future land use changes based on the current state of land use and relevant factors.

This comprehensive approach empowers users to train the model with input and factor rasters to generate an output state raster, offering a nuanced understanding of land use changes over time.

The MOLUSCE plugin (available at https://plugins.qgis.org/plugins/molusce/), an open-source model compatible with QGIS 2.0 and above, has been developed by Asia Air Survey for the analysis, modeling, and simulation of LULC changes. It incorporates a Cellular Automaton (CA) model along with a transition probability matrix. It is widely adopted by researchers [27][28][29][30] and [31], this plugin employs four prominent algorithmic models: Artificial Neural Networks (ANN), Logistic Regression (LR), Multi-criteria Evaluation (MCE), and Weights of Evidence (WoE) [24][32] and [33]. The CA-ANN model within MOLUSCE stands out as a reliable tool for predicting future LULC, offering valuable applications in land use planning and management. This approach proves effective for forecasting spatial LULC shifts, leveraging assessments of a pixel's current condition based on its initial state, neighboring conditions, and governing changeover laws.

CA-ANN merge the principles of Cellular Automata (CA) and Artificial Neural Networks (ANN) to predict LULC changes. CA models simulate spatial dynamics by updating the states of cells based on neighboring cell states and predefined rules. ANN, on the other hand, learn patterns from input-output pairs to make predictions. In CA-ANN the CA component initializes the system and evolves it over time, while the ANN component refines predictions based on learned patterns. This hybrid approach aims to capture both spatial dynamics and complex patterns in LULC data, offering a comprehensive tool for LULC prediction.

One advantage of CA-ANN is their ability to simulate spatial processes while considering temporal changes. The CA component allows for the simulation of local interactions and emergent phenomena, such as urban growth or deforestation, which are crucial in LULC prediction. The ANN component enhances prediction accuracy by learning from historical data or other sources, enabling the model to capture complex patterns that may not be explicitly encoded in the CA rules. Additionally, CA-ANN can incorporate various data sources and factors, such as socioeconomic variables or environmental drivers, making them adaptable to different contexts and applications.

3.5 Methodology

The methodology of this study is illustrated in Figure 3. The land use and land cover (LULC) for 2013 and 2018 were classified using the maximum likelihood classifier. LULC change detection was then performed to investigate the transition between 2013 and 2018. Subsequently, the LULC prediction for 2023 was carried out using the MOLUSCE plugin in QGIS 2.14.0. The accuracy of the 2023 LULC prediction map was validated against the 2023 LULC map derived from Landsat 8 OLI, achieving an overall accuracy and kappa coefficient greater than 80%. Finally, the LULC prediction maps for 2030 and 2040 were generated using the MOLUSCE plugin.

3.6 Spatial Predictor Variables

To forecast LULC using the CA-ANN algorithm, predictor variables significantly influence the predicted LULC output. In this study, four predictor variables namely distance from major roads (MR), distance from sky train (ST), distance from markets (MK), and distance from universities (UV) were incorporated in the LULC prediction.

3.6.1 Distance from major roads (MR)

The distance from major roads exerts a notable influence on land use and land cover (LULC) prediction. Proximity to major roads often correlates with specific land uses or covers due to accessibility, infrastructure development, and human activities. Areas closer to major roads commonly exhibit higher levels of urbanization, commercial activities, and transportation-related land uses such as roadsides, commercial zones, and residential areas. Conversely, areas farther from major roads may display characteristics associated with rural or natural land covers, such as agricultural fields, forests, or open spaces.

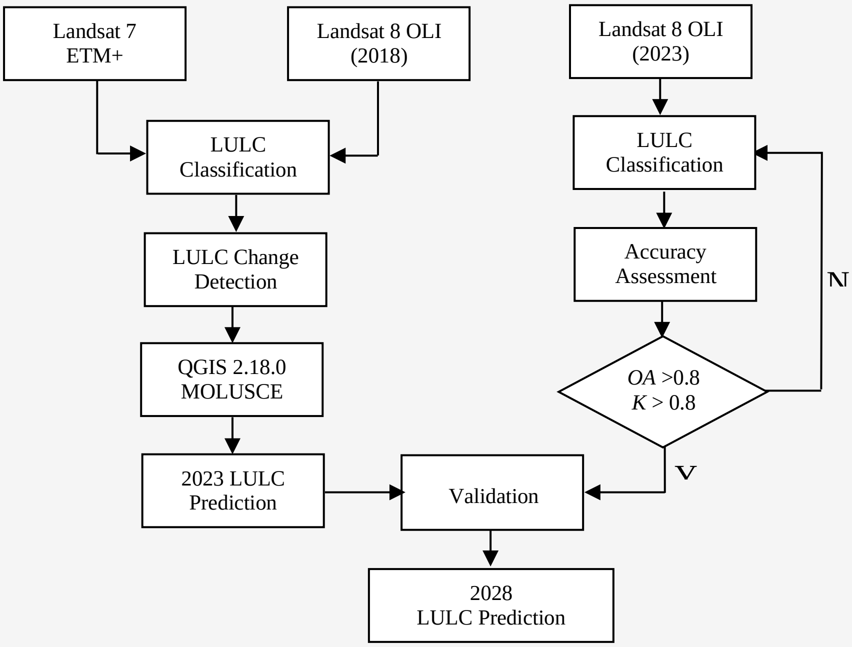

Figure 3: Study workflow

Additionally, the distance from major roads can serve as a proxy for factors like noise pollution, air quality, and land value, which further shape land use patterns. Consequently, integrating distance from major roads as a predictor variable in LULC prediction models allows for more accurate assessments of urban expansion, land use planning, and environmental management initiatives.

3.6.2 Distance from sky train stations (ST)

The distance from mass transit transportation stations, particularly train stations, holds significant influence on land use and land cover (LULC) prediction. Proximity to train stations often reflects patterns of urban development, transportation infrastructure, and accessibility to public transit services. Areas in close proximity to train stations typically exhibit higher levels of urbanization and mixed-use development, including residential, commercial, and institutional land uses. These areas often experience increased population density, economic activity, and pedestrian-oriented environments due to the convenience of public transportation. Conversely, areas farther away from train stations may show characteristics associated with lower-density development, such as suburban residential neighborhoods, industrial zones, or undeveloped land. Moreover, the presence of train stations can stimulate transit-oriented development initiatives, influencing land use policies and urban growth patterns. Incorporating distance from train stations as a predictor variable in LULC prediction models enables better understanding of urban dynamics, transportation planning, and sustainable development strategies.

3.6.3 Distance from markets (MK)

The distance from markets significantly influences land use and land cover (LULC) prediction, reflecting patterns of economic activity, urban development, and community services. Proximity to markets often correlates with mixed-use areas characterized by commercial, residential, and recreational land uses. Areas in close proximity to markets tend to experience higher levels of commercial and retail activity, as well as increased population density due to the concentration of amenities and services. These areas may also feature vibrant street life, pedestrian-oriented environments, and cultural attractions, fostering a sense of community and social interaction. Conversely, areas farther from markets may exhibit characteristics associated with residential or industrial land uses, with lower levels of commercial activity and public amenities. Moreover, the presence of markets can influence property values, neighborhood attractiveness, and urban growth patterns. Integrating distance from markets as a predictor variable in LULC prediction models enhances understanding of local economic dynamics, spatial planning, and community development strategies.

3.6.4 Distance from universities (UV)

The distance from universities plays a significant role in land use and land cover (LULC) prediction, reflecting educational, research, and knowledge-intensive activities within urban areas. Proximity to universities often correlates with patterns of mixed-use development, innovation hubs, and cultural amenities. Areas in close proximity to universities tend to exhibit higher levels of academic and research-related land uses, such as university campuses, research facilities, and student housing. These areas may also feature a vibrant intellectual environment, with cultural events, recreational spaces, and knowledge-based industries clustering nearby. Additionally, the presence of universities can stimulate economic growth, attract skilled labor, and foster partnerships between academia, industry, and government. Conversely, areas farther from universities may show characteristics associated with residential neighborhoods, industrial zones, or undeveloped land. Integrating distance from universities as a predictor variable in LULC prediction models enhances understanding of knowledge economy dynamics, urban planning strategies, and innovation ecosystem development.

4. Results and Discussion

4.1 LULC in 2013 and 2018

M The Maximum Likelihood classifier was employed for LULC classifications. The LULC categories were divided into four groups: water bodies, built-up areas, vegetation areas, and bareland, as illustrated in Figure 4. Figure 4(a) indicates that the majority of the area, particularly in the eastern part of Pathumthani, is dominated by vegetation, while bareland is frequently observed throughout the province in 1998. The Chaophraya River runs through the area. Rama 9, a substantial water reservoir constructed in 1995 serves the purpose of supplying water to support off-season rice farming and agricultural activities during the dry season. In times of flooding, the reservoir stores water to mitigate flooding issues in lower-lying areas. Additionally, it plays a role in addressing water pollution problems in canals and communities by releasing water from the storage pond to cleanse and dilute contaminants, facilitating the drainage of wastewater. The reservoir covers an area of 4.128 sq.km. situated in Khlong Luang district.

Figure 4(b) illustrates the transformation of Pathumthani in 2018, indicating that the region was predominantly characterized by vegetation as in 2013. Notably, a substantial portion of bareland underwent a transition to vegetation and built-up areas. The discernible surge in built-up areas over the two decades is evident, with urban expansion occurring both north and south along the Paholyothin highway, as well as eastward along the Rangsit-Nakhon Nayok road. Water bodies were prevalent in the agricultural zones, and the configuration and dimensions of the Rama 9 reservoir remained unchanged.

4.2 Accuracy Assessment

According to the accuracy assessment results presented in Table 3, regarding User Accuracy (UA), water bodies exhibited the lowest accuracy, while vegetation had the highest accuracy in the years 2013, 2018, and 2023. Conversely, Producer Accuracy (PA) for water bodies across all three years demonstrated the highest accuracy of 1.00. Both UA and PA for each LULC class in 2013, 2018, and 2023 were higher than 0.8, with overall accuracies (OA) of 0.90, 0.90, and 0.91, along with Kappa (K) values of 0.83, 0.87, and 0.88 in 2013, 2018, and 2023, respectively.

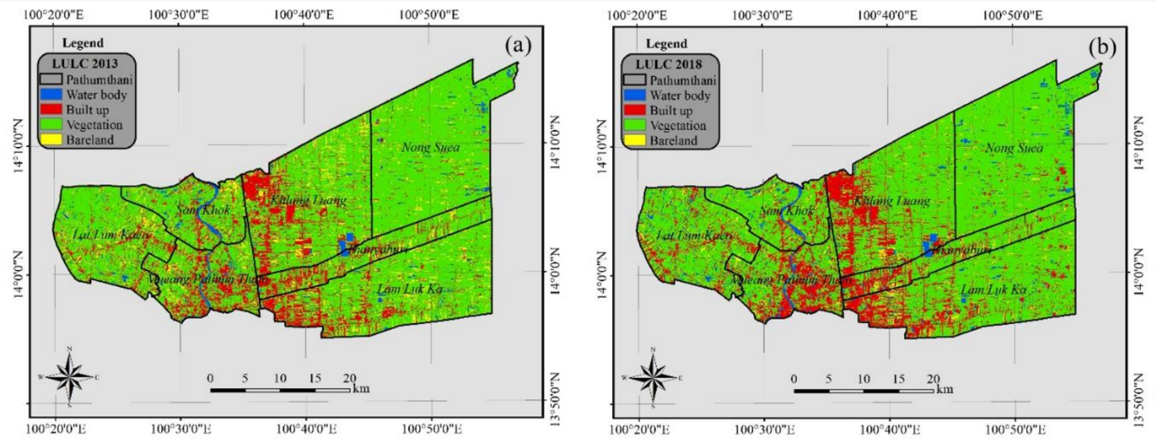

Figure 4: LULC of Pathumthani (a) 2013 (b) 2018

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Table 3: Accuracy assessment of LULC classifications

LULC classes	2013		2018		2023	
	UA (%)	PA (%)	UA (%)	PA (%)	UA (%)	PA (%)
Water body	0.80	1.00	0.84	1.00	0.88	1.00
Built up	0.85	0.92	0.92	0.88	0.92	0.82
Vegetation	0.92	0.95	0.92	1.00	0.96	0.89
Bareland	0.91	0.75	0.92	0.77	0.88	0.96
OA (%)	0.90		0.90		0.91	
Kappa	0.83		0.87		0.88	

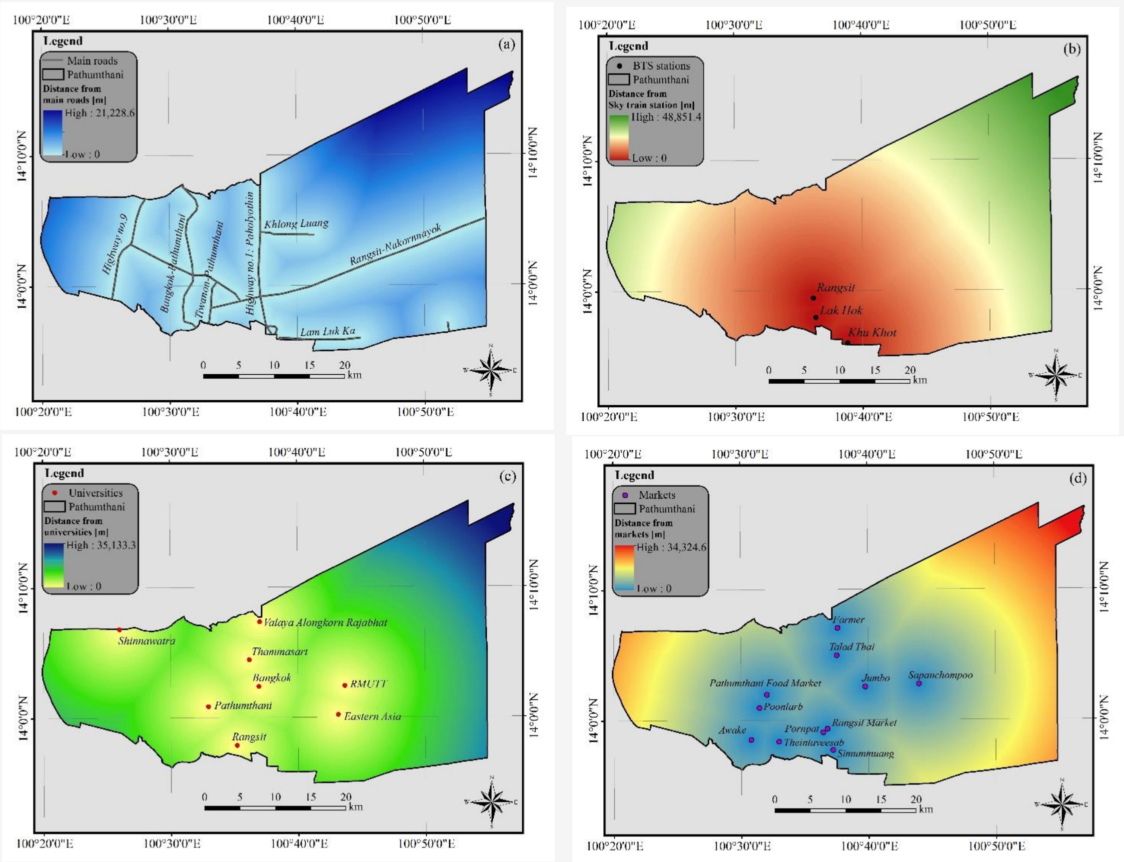

Figure 5: Distances from predictor variables (a) main roads (b) sky train stations (c) universities (d) markets

As both OA and K surpassed 0.8, these outcomes indicate that the classified LULC maps closely align with real-world LULC. Consequently, the classified LULC maps are deemed reliable for use in LULC prediction.

4.3 Predictor Variables Illustration

The location of each predictor variable was acquired from Google map (https://www.google.co.th/maps). The distances from the particular points were created from "Euclidean Distance" tool in ArcMap software. The distances from the predictor variable presents in Figure 5. All these four variables were used in MOLUSCE plugin in QGIS software to predict future Pathumthani LULC in 2028 and 2038.

4.4 Validation of LULC Prediction Model

The land use and land cover (LULC) for the year 2023 was determined using Landsat 7 ETM+ imagery, while the predicted LULC for the same year was simulated using the MOLUSCE plugin in QGIS. Figure 6 illustrates the visual comparison between the actual and predicted LULC. According to Table 3, the overall accuracy of 0.91, along with a kappa coefficient of 0.88, demonstrates a strong alignment between the classified 2023 LULC and the actual LULC on the earth's surface. Consequently, the classified LULC for 2023 served as the benchmark for assessing the accuracy of LULC predictions derived from the CA-ANN algorithm.

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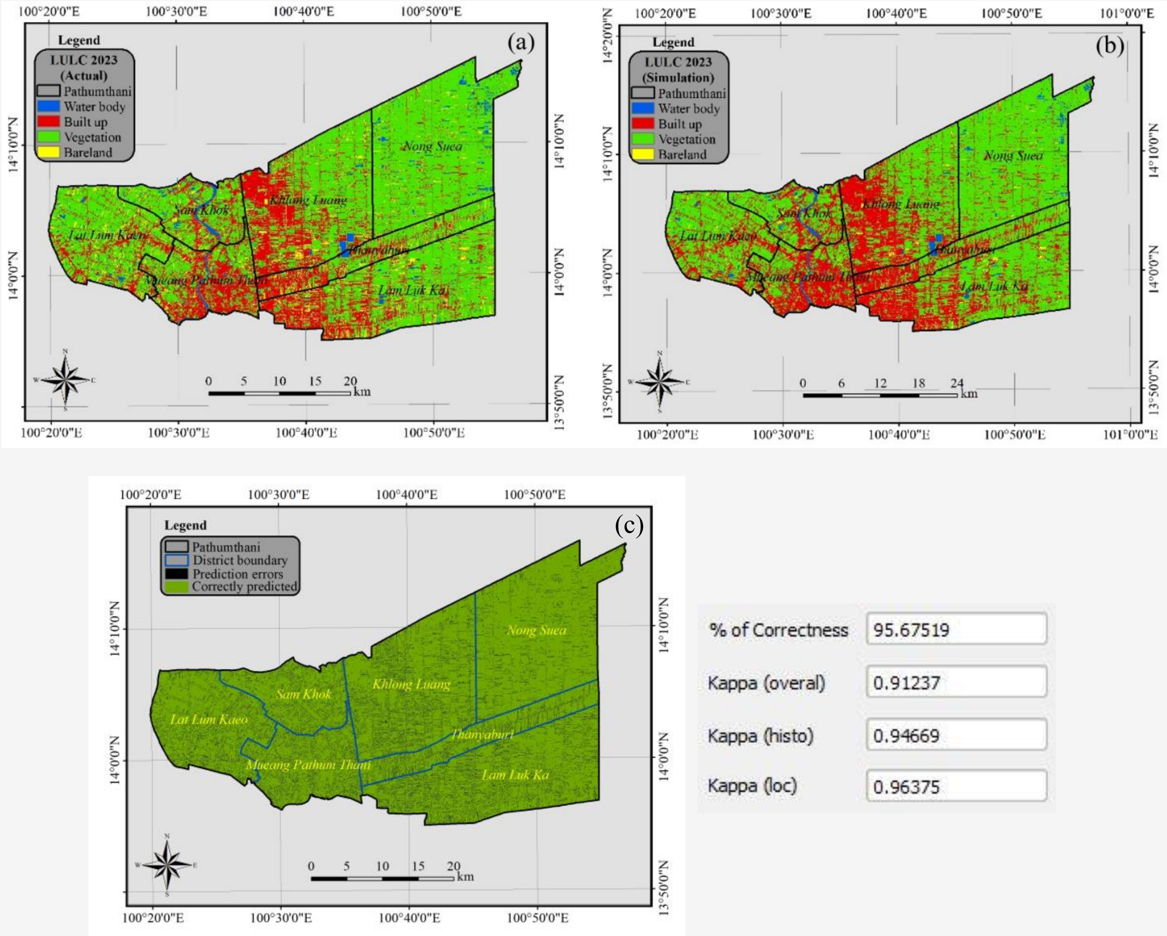

Figure 6: Comparison of LULC in 2023 (a) actual LULC (b) predicted LULC (c) difference between actual and predicted LULC

The overall kappa coefficient of 0.822 and correctness percentage of 90.98 indicate an exceptionally high level of agreement between the predicted and actual LULC for the year 2023. This suggests that the prediction model, derived from data of the year 2013 and 2018, is well-suited for forecasting future LULC changes. Figure 6(c) visually contrasts the actual and predicted LULC, highlighting any disparities. While some prediction errors are observable across the study area, they appear randomly distributed rather than concentrated in specific regions. These errors manifest as pixel discrepancies. Thus, it can be affirmed that the prediction model is robust and applicable for future LULC projections.

4.5 Changing of LULC

Figure 7 and Table 4 provide insights into the LULC dynamics across 2013, 2018, and 2023. Notably, there is minimal variation in the water body area, which consistently ranges from 2.40% to 3.44% of the study area from 2013 to 2023. Conversely, the bareland area witnessed a substantial decrease from 7.75% in 2018 to 3.94%, followed by a rise to 6.39% by 2023. This fluctuation can be attributed to the timing of satellite data collection, occurring in April for 2018 and May for both 2013 and 2023. During April, vegetation tends to be less abundant than in May, potentially leading to misclassification of vegetation as bareland. In contrast, the vegetation area remains consistent between 2013 and 2018, as depicted in Figure 6, but experiences a notable decline by 2023. This phenomenon underscores the likelihood of misclassification of vegetation and bareland if satellite data were collected at different times of the year. The changing of built up and vegetation areas from 2013 to 2023 provide evidence of the increasing trend in built-up areas from 2013 to 2023, with a gain of 143.9 sq.km. over the decade. Conversely, vegetation tends to decrease, attributed to urban sprawl in Pathumthani.

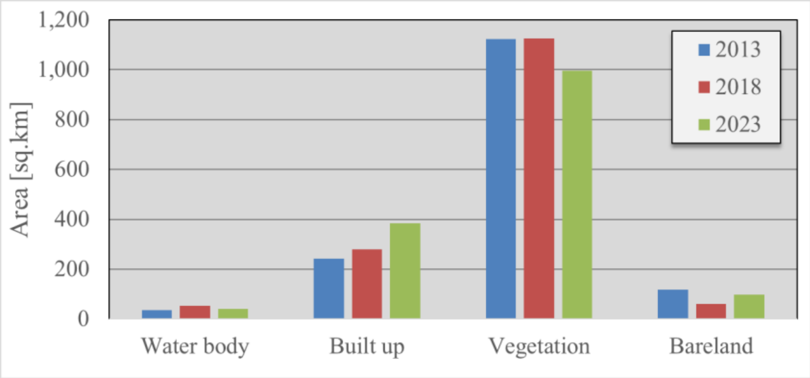

Figure 7: Areas of LULC in 2013, 2018, and 2023

Table 4: Areas and percentage of LULC in 2013, 2018, and 2023

LULC classes	Area in sq.km [%] 2013	2018	2023	LULC change in sq.km. 2012-2018	2018-2023
Water body	36.46 [2.40]	52.14 [3.44]	40.3 [2.66]	15.68	-11.84
Built up	240.84 [15.87]	279.81 [18.44]	384.74 [25.36]	38.97	104.93
Vegetation	1,122.43 [73.97]	1,125.67 [74.18]	995.37 [65.60]	3.24	-130.30
Bareland	117.65 [7.75]	59.77 [3.94]	96.99 [6.39]	-57.88	37.22

4.7 Prediction of LULC in 2028 and 2038

LULC predictions for 2028 and 2038 were generated using the MOLUSCE plugin within QGIS software, based on data from 2013 (initial map) and 2018 (final map). To simulate LULC changes, the plugin requires the specification of the "Number of simulation iterations." In this study, each interval of 5 years corresponded to 1 iteration. Thus, for the prediction of LULC in 2028 and 2038, the "Number of simulation iterations" was set to 1 and 3, respectively.

Figure 8 depicts the projected Land Use and Land Cover (LULC) for the year 2028. The illustration reveals that vegetation predominates in the eastern sector of Pathumthani, specifically in Nong Suea and parts of Lam Luk Ka districts. Additionally, vegetative areas extend to the western region of Pathumthani, encompassing the Lat Lum Kaew district. Built-up zones are concentrated predominantly along major thoroughfares, notably Paholyothin Road and Rangsit-Nakornnayok Road [9]. Notably, the southern perimeter of Pathumthani, bordering Bangkok, the capital of Thailand, features an international airport (Don Muang) situated at the administrative boundary between these two provinces. Moreover, within this vicinity, two sky train stations (BTS) are strategically positioned, fostering urban expansion towards the western precincts of Lam Luk Ka district. Substantial alterations in built-up areas within Muang Pathumthani are not anticipated due to its high population density and predominant classification as a built-up area. However, considerable urban sprawl is forecasted in Khlong Luang and Thanyaburi districts, primarily along major transportation arteries. Urban development is anticipated along canals numbered 4 and 5. Notably, the western expanse of Khlong Luang district is poised for urban governance, facilitated by the passage of Paholyothin Road, serving as a conduit to the northern and northeastern regions of Thailand.

Figure 9 depicts the projected Land Use and Land Cover (LULC) for the year 2038. Vegetation predominates in Nong Suea district, with some extending into Lam Luk Ka districts, and also in some part of Sam Khok and Lad Lum Kaew districts. These areas exhibit low population densities (137 – 603 people per square kilometer) and lack major roads passing through, therefore urban expansion is not predicted in these regions. In Muang Pathumthani district, most of the area will turn into urban area expands from the both sides of the Chao Phraya River. The southern part of this district is adjacent to Nonthaburi province that contains high population density, so that the urban area in Nonthaburi province is likely to sprawl to Muang Pathumthani district. Therefore, the LULC of this district is predicted to be dominated by built up areas. In the western part of Lam Luk Ka district, a significant portion of the area is projected to be designated as built-up due to the robust infrastructure development. This region boasts a network of highways, sky train stations, and proximity to Don Muang International Airport.

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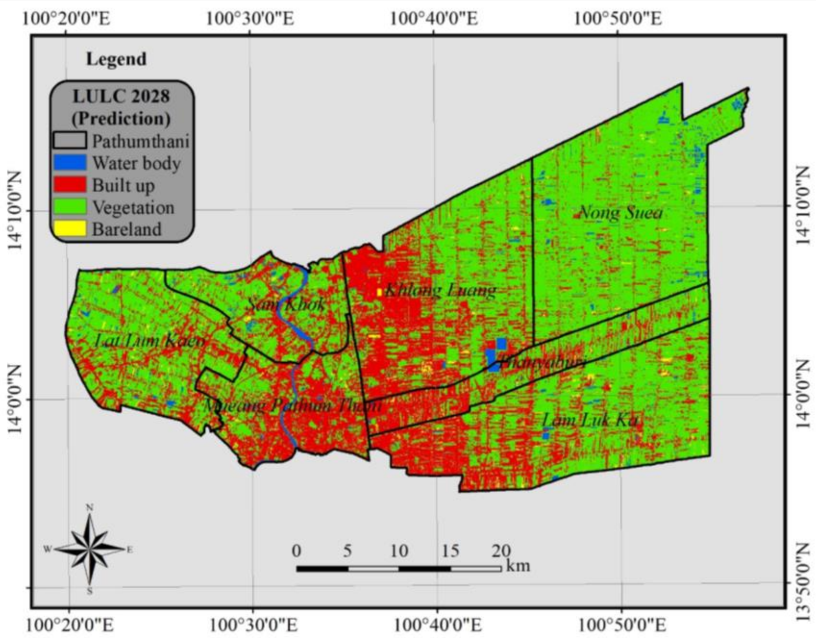

Figure 8: Projected LULC in 2028

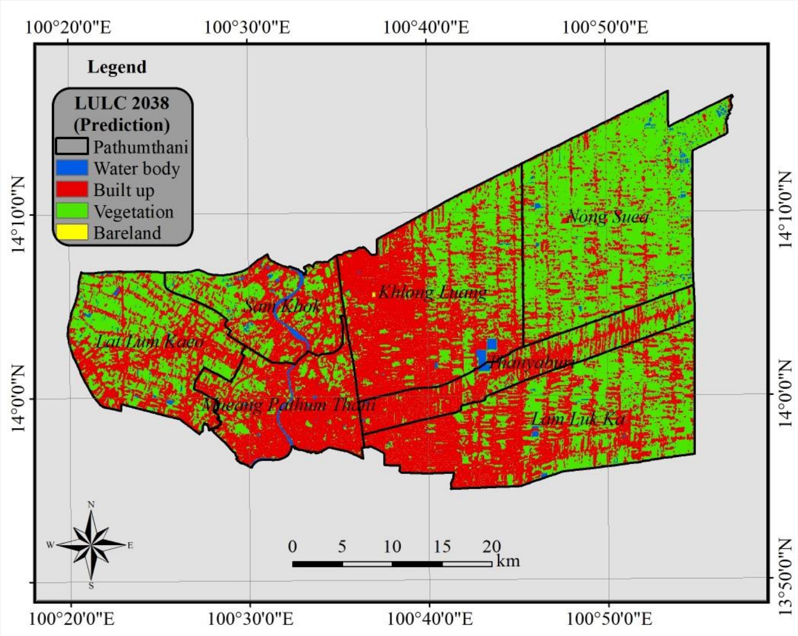

Figure 9: Projected LULC in 2038

Furthermore, its connection to Bangkok, the capital of Thailand, influences the district's Land Use and Land Cover (LULC) dynamics, facilitating urban expansion from the city. Additionally, built-up areas are anticipated along the canal within the district, as land prices are comparatively lower than those in the western part. Consequently, the transition of vegetation areas to built-up areas is predicted in the eastern part of Lam Luk Ka by 2038. Thanyaburi, established in 1901, the Rangsit Canal runs through this district in the east-west direction. This man-made waterway comprises 16 sub-canals running in a north-south direction. With a population density of 1939 people per square kilometer as of 2023, Thanyaburi boasts the highest density in the province. The prominent thoroughfare known as the "Rangsit-Nakornnayok" road runs parallel to the main canal, facilitating transportation through the district. Figure 11 illustrates the expansion of built-up areas along this major road and the sub-canals, particularly evident from Canal No. 1 to 5. Hosting three universities and numerous markets, the district is largely projected to transition to built-up areas by 2038. This shift is supported by the substantial traffic flow along the Rangsit-Nakornnayok road, which has been among the busiest in the province. Furthermore, the upcoming establishment of a new zoo within this vicinity signals a directional expansion of built-up areas within the province.

In Khlong Luang, the western portion of the district is anticipated to be primarily characterized by built-up areas due to the passage of Highway No.1, commonly referred to as the "Paholyothin Highway," through this area. This highway serves as a major artery leading to the northern and northeastern regions of Thailand, experiencing high traffic volumes. Moreover, the presence of the Navanakorn Industrial Estate, several factories, the large Talad Thai market, and esteemed universities such as Bangkok, Thammasart, and Valaiya Alongkorn along the highway further propels the expansion of built-up areas. This urban expansion is forecasted to extend along the sub-canals from sub-canal No.1 to 8 (Khlong 1 to 8), with particularly dense built-up areas predicted in canals No.1 to 3. The density of built-up areas is expected to decrease progressively with the higher canal numbers. In summary, the Land Use and Land Cover (LULC) dynamics in 2038 predominantly feature vegetation on the eastern and western fringes of Pathumthani, particularly in Nong Suea and Lam Luk Ka districts, while the central area is characterized by built-up zones, notably along major roads. The focal point of urban expansion lies at the administrative convergence of Khlong Luang, Thanyaburi, Lam Luk Ka, and Muang Pathumthani districts. Built-up areas are projected to proliferate in all directions from these convergence points, notably from Rangsit sub-district, where the prominent Future Park Rangsit shopping mall is situated.

5. Conclusion

The LULC predictions for Pathumthani province in 2028 and 2038 were generated by simulating Landsat satellite imagery data collected in 2013, 2018, and 2023, utilizing the MOLUSCE plugin in QGIS. The overall accuracy and kappa coefficient validate the reliability of the prediction model, affirming its suitability for forecasting future LULC trends. In conclusion, the simulated LULC for 2028 and 2038 in Pathumthani illustrates the overview of evolving urban landscapes and environmental dynamics. In 2028, vegetation predominates in the eastern and western extents of Pathumthani, with built-up areas concentrated along major transportation arteries. By 2038, these trends persist, with notable expansions in built-up areas, particularly in Muang Pathumthani, Khlong Luang, and Lam Luk Ka districts. Muang Pathumthani experiences significant urbanization, particularly along the Chao Phraya River, driven by its adjacency to Nonthaburi and the resultant population pressures. Lam Luk Ka's western region witnesses substantial built-up development, facilitated by robust infrastructure and connectivity to Bangkok, while Thanyaburi sees notable urbanization along the Rangsit-Nakornnayok road corridor.

Khlong Luang emerges as a focal point for urban expansion, influenced by Highway No.1 and the presence of key industrial estates, markets, and educational institutions. These developments are forecasted to radiate from central convergence points, notably Rangsit sub-district, where major commercial centers like Future Park Rangsit are situated. Overall, these projections highlight the intricate interplay between infrastructure, population dynamics, and environmental factors shaping the future landscape of Pathumthani and its neighboring districts, underlining the importance of sustainable planning and management practices to navigate future challenges and opportunities.

When using MOLUSCE in LULC prediction, CA-ANN requires careful calibration and validation to ensure accurate predictions. The model performance heavily relies on the quality of input data, the selection of appropriate CA rules, and the architecture and training of the ANN. Additionally, CA-ANN may struggle with capturing long-term trends or abrupt changes in LULC patterns, as they primarily focus on local interactions and gradual evolution. Furthermore, interpreting the results of CA-ANN can be challenging due to their inherent complexity, making it difficult to understand the underlying mechanisms driving LULC changes. Despite these challenges, CA-ANN remain a valuable tool for LULC prediction, offering insights into spatial dynamics and supporting informed decision-making in land management and planning endeavors.

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