Urban Land Use Changes Simulation with CA-ANN Model: A Case Study of Mae Sot District, Tak Province, Thailand

Klanreungsang, B.[1*] and Nilsonthi, P.[2]
Geography and Geoinformatics, Faculty of Humanities and Social Sciences, Chiang Mai Rajabhat University, Thailand, E-mail: baromasak_kla@g.cmru.ac.th,[1*] piyawadee_nil@cmru.ac.th[2]
Corresponding Author

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Abstract
To comprehend environmental changes and develop sustainable land management plans, it is crucial to thoroughly understand the complexities involved in land use change. This study investigated land use changes in Mae Sot district, Tak province, Thailand, in the years 2003, 2013, and 2023 using pixel-based supervised classification employing the Random Forest (RF) algorithm. The findings revealed that a substantial portion of the area is dedicated to agricultural purposes, accompanied by a decrease in forest areas and an increase in urban development. Furthermore, five spatial factors—elevation, slope, distance from the city center, distance from the main road, and population—were integrated as explanatory variables in training the cellular automata-artificial neuron network (CA-ANN) model to construct a land use change simulation for 2023. A comparison of the projected and actual land use maps for 2023 demonstrated a high level of agreement, with a kappa coefficient of 0.81, confirming the reliability of the model's predictions. Subsequently, the CA-ANN model was used to forecast future land use for the year 2033. The projection suggested a significant expansion of built-up areas, primarily originating from the core of Mae Sot sub-district and spreading towards Tha Sai Luat, Mae Pa, and Mae Tao, and potentially extending northward along the national highway to Mae Kasa sub-district. Additionally, forested areas are anticipated to diminish, transitioning into agricultural zones, while certain existing agricultural regions are expected to be converted into urban spaces. These findings underscore the imminent expansion of urban areas within Mae Sot, emphasizing the necessity for well-thought-out planning to ensure long-term development.

Keywords: CA-ANN, Land use change, Land use prediction, Random Forest, Urban expansion

1. Introduction

Mae Sot, positioned as a border town in the western district of Thailand, plays a pivotal role in connecting with the neighboring Myanmar town of Myawaddy. At the heart of its significance is the thriving border trade between Thailand and Myanmar, representing a substantial 45% of the entire Thai-Myanmar trade value [1]. This underscores the city's integral role in facilitating cross-border commerce. Mae Sot is experiencing steady and rapid economic growth, with its economy expanding at an impressive annual average of 20 percent [2]. This attests to the profound significance of border trade in propelling economic development within the region. Another noteworthy fact of Mae Sot is that it serves as a key outpost on the East-West Economic Corridor (EWEC) within the Greater Mekong Sub-region (GMS).

This corridor links the South China Sea to the Andaman Sea via various waypoints including Mawlamyine – Myawaddy (Myanmar) – Mae Sot – Mukdahan (Thailand) – Savannakhet – Dan Savannah (Laos) – Lao Bao – Danang (Vietnam), and it holds immense sway over regional transportation networks. Therefore, focused endeavors have been made to officially designate Mae Sot and its neighboring areas as a Special Border Economic Zone, with the objective of promoting and revitalizing trade and investments. Moreover, there is a coordinated effort to establish Mae Sot as an independent Thai local government body, enhancing its ability to function as a commercial gateway to neighboring countries. Because of its special status, Mae Sot draws attention from both domestic and foreign traders who are willing to co-finance or participate in large-scale projects in collaboration with the Thai government.

Furthermore, Mae Sot has witnessed exceptional population growth, with numbers rising from 105,747 in 2012 to 196,158 in 2022–a growth rate of 8.5 percent annually [3]. There has also been an influx of 183,642 undocumented individuals or migrant workers, almost exactly equal to the population of the city [4]. Mae Sot is grappling with initial challenges arising from unchecked urban expansion, land management, and inadequate access to public amenities and utilities [5]. As urban development progresses, the surge in human activities will intensify the demand for land resources. However, the relatively fixed availability of land will inevitably lead to heightened competition for land use. The seriousness of this situation will escalate due to a lack of awareness regarding the responsible utilization of environmental resources and uncontrolled resource usage without accounting for future risks. Thus, there is a need for a spatial planning study to provide the city with tools it needs to navigate its rapid development and anticipate future expansion in a sustainable and informed manner.

In the era of satellite technology, the proliferation of large amounts of data, and a growing inclination towards information accessibility, there is a concerted effort to utilize models for studying future land use changes and urban development. Prominent among these models are the SLEUTH model [6][7] and [8], CA-Markov [9][10] and [11], agent-based model (ABM) [12] and [13], and CLUE model [14][15] and [16]. Each of these models possesses distinct attributes and ranges of applicability. For example, while the SLEUTH model excels in urban growth simulation and long-term forecasting, its simulation process is constrained by fixed factors that cannot be altered [17]. CA-Markov can elucidate the probability of land use transitions over time but does not fully consider the impact of socio-economic and natural factors [18]. On the other hand, although an agent-based model can simulate human decision-making processes and offer insights into land use changes, its generalizability to different conditions is limited [19]. The CLUE model is capable of providing a thorough simulation of land use change; however, its adaptability is restricted as it relies solely on regression for its model construction [20].

Recent research has successfully merged cellular automata (CA) with an artificial neural network (ANN) to forecast future land use patterns [21][22] [23] and [24]. The hybrid CA-ANN model offers several benefits, such as its capability to discern intricate interdependencies among the influencing factors, its ability to train multiple algorithms, its efficient management of large datasets, and its improved reliability in prediction [25][26] and [27]. Consequently, the CA-ANN model served as the primary tool in this work to address the research inquiries:

1. What is the trajectory of land use transformation in Mae Sot district?
2. Which specific regions within Mae Sot district would undergo expansion?

The aim of this study is to examine the alterations in land utilization within Mae Sot district from 2003 to 2023, and to forecast the growth of urban areas by the year 2033. The findings of this research could provide a basis for informed decision making regarding sustainable urban development, resource management, and spatial layout optimization within Mae Sot district.

2. Study Area

This research was carried out specifically in Mae Sot district, situated within the Tak Special Economic Development Zone in western Thailand (Figure 1). This area spans latitudes 16°32′10″ to 16°59′10″ north and longitudes 98°27′43″ to 98°46′48″ east, encompassing a total land area of 788.24 km^2. This district comprises eight subdistricts: Mae Kasa (MK), Tha Sai Luat (TS), Mae Pa (MP), Mae Sot (MS), Mae Tao (MT), Phra That Pha Daeng (PT), Mae Ku (MU), and Mahawan (MH). Mae Sot is situated within a basin, flanked by the Thanon Thong Chai Mountain range in Thailand and the Dawna Range in Myanmar. It shares its border with the city of Myawaddy in Myanmar, with the Moei River serving as the natural boundary, positioning Mae Sot as a crucial trading hub at the border.

3. Material and Methods

3.1 Data Acquisition

3.1.1 Satellite data

In this study, Landsat multispectral images from the years 2003, 2013, and 2023 were utilized. These images were captured by Landsat 5 Thematic Mapper (TM), Landsat 8 Operational Land Imager (OLI), and Landsat 9 Operational Land Imager 2 (OLI-2) sensors via the US Geological Survey (USGS). Access was facilitated through Google Earth Engine (GEE), a cloud-based geospatial analytics platform. The acquired images had a spatial resolution of 30 meters in the World Geodetic System (WGS84). Standard image pre-processing, including cloud filtering, geometric corrections, image enhancement, and layer stacking was performed. Composite images for each selected year were generated using the yearly median value, offering a representative snapshot of land use dynamics over time.

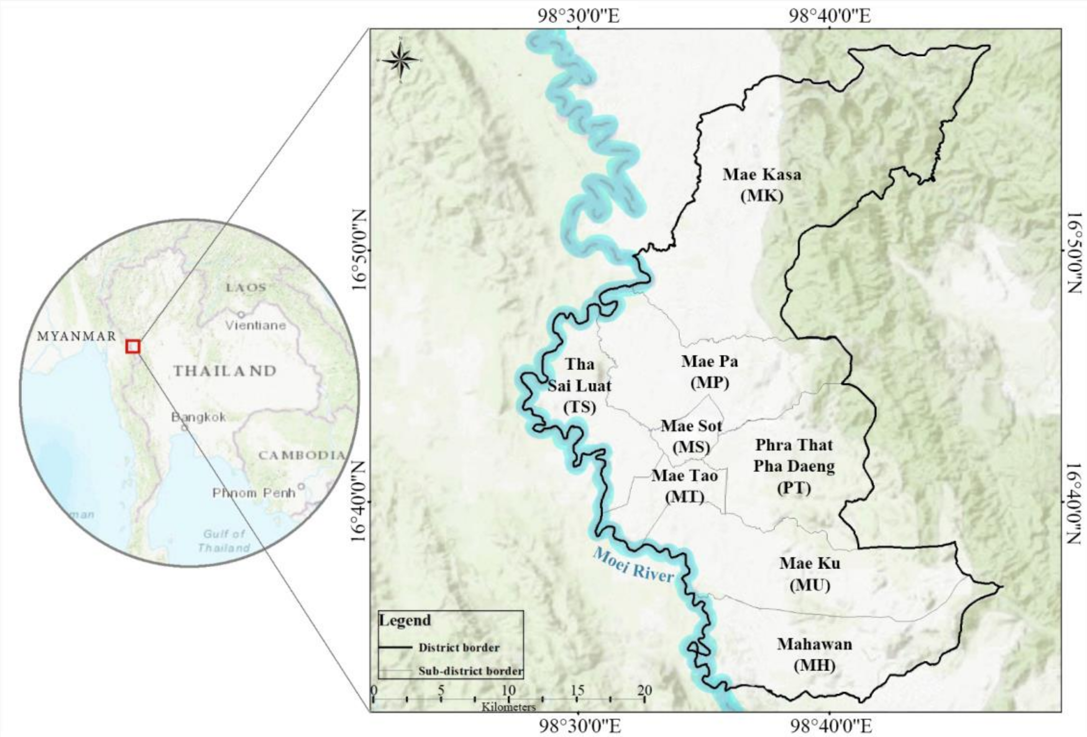

Figure 1: Mae Sot district, Tak province, Thailand

Table 1: Description of land use classes

Land use	Description
Built-up area	Land covered by buildings and other man-made structures. Residential, commercial, industrial, and other urban land services
Agriculture	Land covered with temporary crops followed by harvest period. Crop fields and pasture, paddy fields, orchards, and perennial plants
Forest	Land dominated by trees with a percentage cover of >60% and height exceeding 2 meters. Deciduous forest land and evergreen forest land
Water body	Streams, canals, ponds, and reservoirs

3.1.2 Classification training and testing data

The study focused on four primary land use categories: (1) Built-up area (2) Agriculture (3) Forest and (4) Water body, as detailed in Table 1. Representative samples for each land use category were identified through onscreen digitization, a method widely recognized for its reliability and precision, to construct classification datasets [28] and [29]. These samples were sourced from high-resolution Google Earth imagery, historical land use maps, and supplemented with data like normalized difference built-up index (NDBI) and normalized difference vegetation index (NDVI), thereby augmenting the precision of land use classification [30] and [31]. A total of 800 samples were selected at the pixel level, and they were stratified for each class, subsequently being randomly divided into 70% for training data and 30% for testing data.

3.1.3 Spatial variable data

To simulate future land use, it is advisable to take into account several key predictor variables that have a substantial impact on these changes [32][33][34] and [35]. After conducting a comprehensive analysis of spatial variables across multiple literature sources, five specific factors were chosen and compiled from various references. Two natural variables, specifically elevation and slope, were extracted from the Advanced Land Observing Satellite Digital Surface Model (ALOS DSM) provided by the Japanese Aerospace Exploration Agency (JAXA). Additionally, two urban infrastructure variables, namely the distance from the city center and the main road, were obtained from the GIS database of the Department of Public Works and Town & Country Planning.

Besides, the analysis utilized the official demographic numbers obtained from the Department of Provincial Administration for the years 2013 and 2023. All data for driving factors were standardized to a resolution of 30 x 30 meters and the WGS 84 coordinate system, as depicted in Figure 2.

3.2 Methodology

The conceptual framework for this study is depicted in Figure 3, comprising three primary components: image classification, land use prediction, and future land use prediction. Image classification was performed using GEE, while the succeeding stages were implemented using the Python programming language. Each of these components will be elaborated upon in detail in the following sections to provide a comprehensive understanding of the workflow outlined in the flowchart.

3.2.1 Image classification

In order to categorize land use types within the study area, supervised machine learning was employed to train datasets using satellite images from 2003, 2013 and 2023. The Random Forest (RF) algorithm was opted for its consistent and robust classification accuracy which outperformed alternative algorithms [36] and [37]. RF serves as a classifier comprising numerous decision trees applied to different subsets of the dataset. Unlike relying on a single decision tree, RF uses a series of decision trees to select the best classification for all pixels within the imagery to ensure precise classification by aggregating majority votes from the entire forest of trees.

Land use classification accuracy was determined by calculating the overall accuracy value, which involved comparing the classification land use map with testing data on a cell-by-cell basis. This value was computed by adding the number of correctly classified values and dividing them by the total number of values. According to [38] and [39], it is imperative that the minimum level of interpretation accuracy for identifying land use categories from remote sensor data is at least 85%.

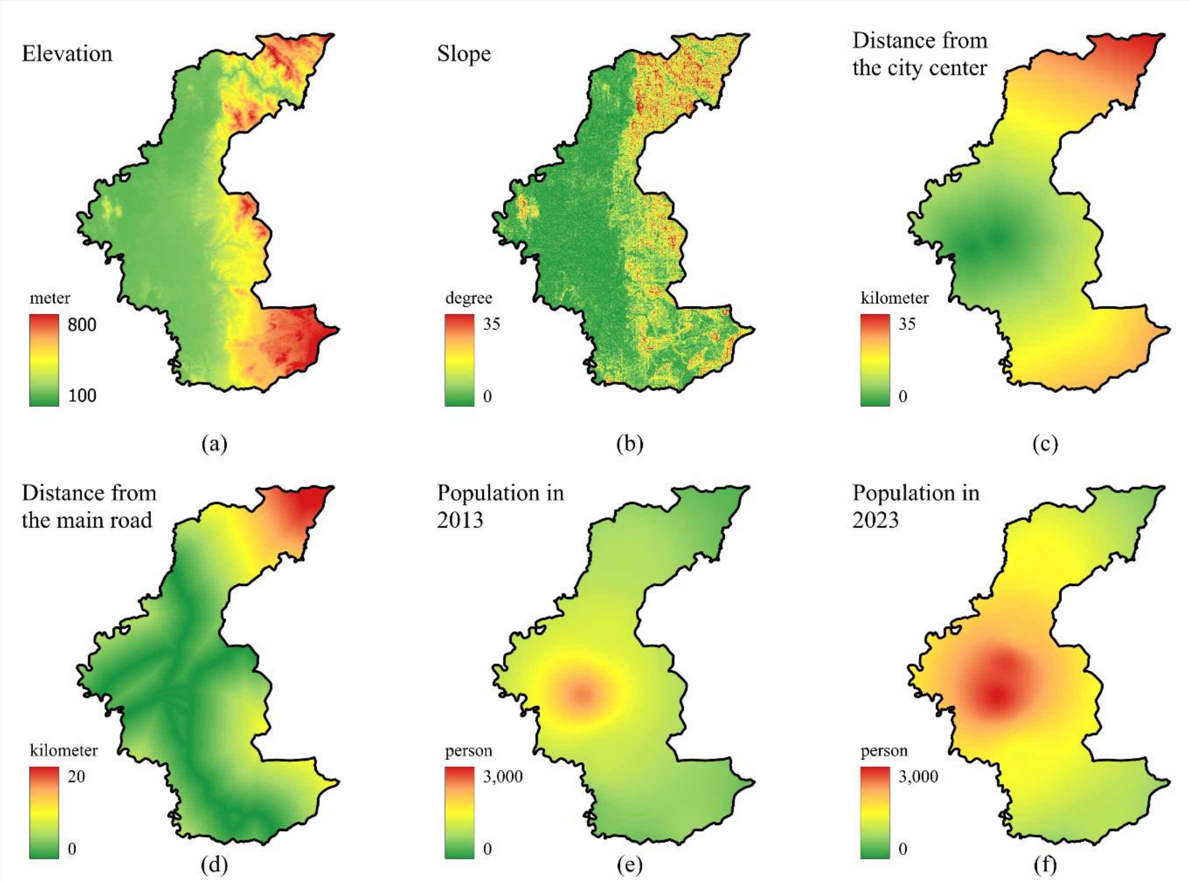

Figure 2: Spatial variables used for land use prediction:
(a) elevation, (b) slope, (c) distance from the city center, (d) distance from the main road,
(e) population in 2013 and (f) population in 2023

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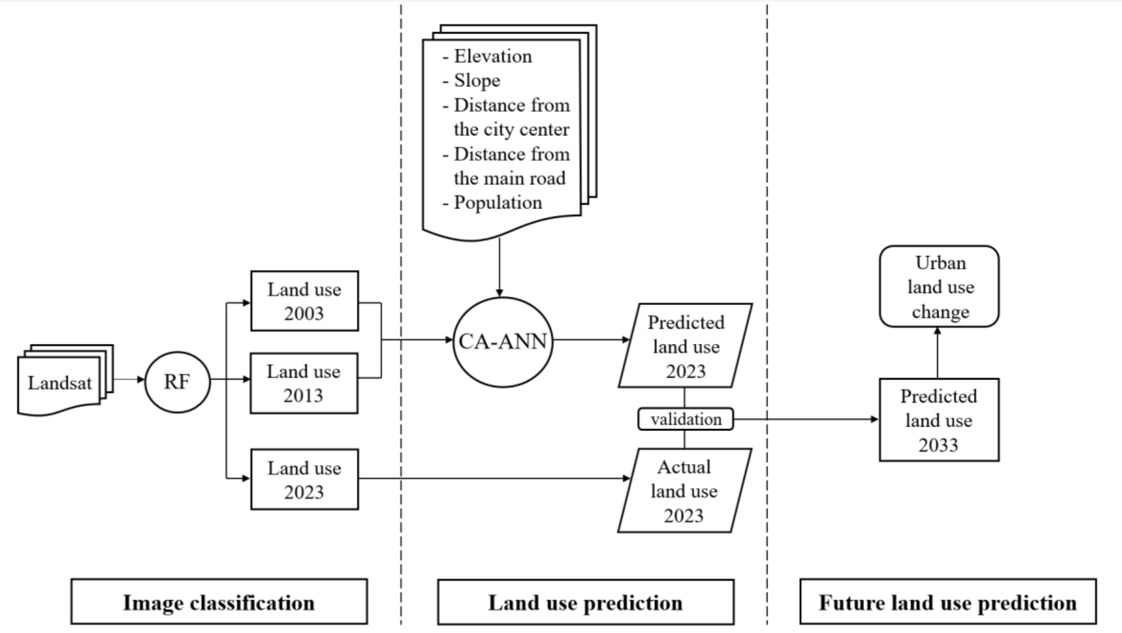

Figure 3: Flowchart of methodology

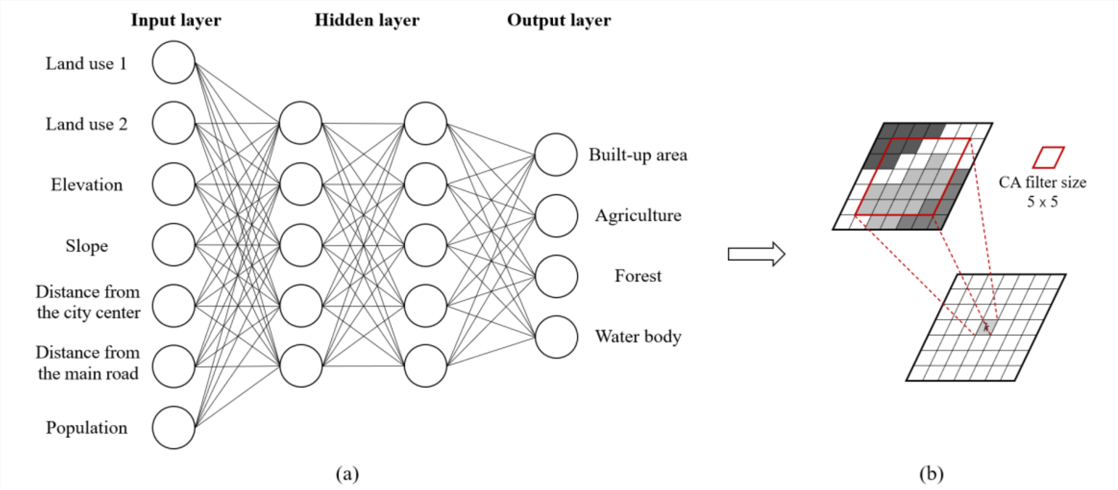

Figure 4: CA-ANN model for land use prediction

3.2.2 Land use prediction

The CA-ANN model was employed as a study tool to predict the use of land in this research. This approach is a hybrid, combining two separate models. The ANN, shown in Figure 4(a), was used to forecast the likelihood of land use transitions. It was designed with layers and neurons that mimic the organization of the human brain to facilitate learning and recall. The system is composed of three distinct layers: input, hidden, and output. The input layer incorporates data from different land use maps and related parameters to model urban expansion, while the hidden layer analyzes this information to compute transition probabilities.

The probability of land use change is determined by comparing the output layer of transition values provided by neurons, with the class shifting to the category with the highest probability. In this study, a backward propagation algorithm refined transition probability calculations by iteratively sending values from the output layer back to the preceding layers. This refinement occurred across a framework comprising 10 hidden layers and 1,000 iterations. Nevertheless, relying solely on ANN modeling overlooks the spatial distribution of land use categories because of the model's independence from neighboring cell states.

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Thus, the CA component is integrated to address this limitation by creating a spatial and temporal framework for land use change simulation. The CA model posits that both its own changes and those of neighboring cells influence a grid cell's land use. By incorporating transition probabilities from the ANN and employing a contiguity filter, the CA algorithm assesses land use alterations, considering both the current state and changes in neighboring cells. The study defined neighborhood relationships using a standard 5x5 contiguity filter, as shown in Figure 4(b). This iterative technique forecasts land use changes over a specified time frame.

This study utilized land use maps from 2003 and 2013, alongside selected spatial variables such as elevation, slope, distance from the city center, distance from the main road, and the population in the year 2013, as inputs for ANN learning. This allowed the calculation of the probability of each satellite data pixel transitioning to different types of land use. These probabilities were then fed into CA to generate a land use forecast map for 2023. The CA-ANN model's accuracy assessment of predicted land use was evaluated using the kappa coefficient, which measures the agreement between the predicted land use map and actual observations. The value of kappa was calculated using equation 1:

$$k = \frac{P_0 - P_e}{1 - P_e}$$

Equation 1

where:

P_0 = the proportion of observed agreements

P_e = the proportion of agreements expected by chance

The interpretation of kappa coefficient suggested by McHugh [40] can be simplified as in Table 2.

3.2.3 Future land use prediction

If the accuracy of the CA-ANN model in forecasting land use during the previous stage is sufficient, it is possible to create forecasts for future land use. Given this situation, the CA-ANN model's settings and parameters can precisely determine the amount and location of land use changes [23] and [41]. In this study, land use projection for the year 2033 was computed utilizing land use maps from both 2013 and 2023, along with identical spatial variables, with the exception of population data, which was replaced with information from 2023. Following this, the growth of urban areas could be extracted.

4. Results

4.1 Land Use Classification

The land use classification of satellite data using the RF supervised technique demonstrated an overall classification accuracy of 91%, 93%, and 92% for the years 2003, 2013, and 2023, respectively. Each year's accuracy exceeded 85%, suggesting an acceptable classification outcome and indicating that the procedure effectively mitigated errors by more than 90%. The land use classification results for each year are presented in Table 3.

Table 2: Kappa coefficient values and agreement degrees

Kappa coefficient value	Agreement degree
<0.21	No agreement
0.21–0.39	Minimal agreement
0.41–0.59	Weak agreement
0.61–0.79	Moderate agreement
0.80–0.90	Strong agreement
>0.90	Almost perfect agreement

Table 3: Land use classes areas for the years 2003, 2013, and 2023

Land Use	2003		2013		2023	
	Area (km^2)	%	Area (km^2)	%	Area (km^2)	%
Built-up area	30.44	3.86	52.23	6.62	77.83	9.87
Agriculture	460.17	58.38	471.18	59.78	466.46	59.18
Forest	293.34	37.22	260.41	33.04	239.62	30.40
Water body	4.29	0.54	4.42	0.56	4.33	0.55
Total	788.24	100.00	788.24	100.00	788.24	100.00

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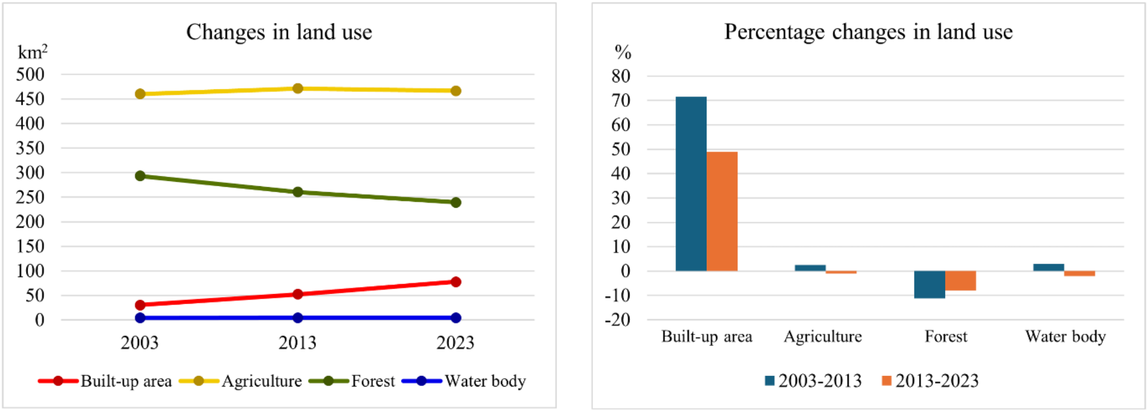

(a) (b)

Figure 5: Relative changes in land use over different time intervals

Table 4: Comparison of actual and predicted land use in 2023

Land Use	Actual land use 2023 (km^2)	Predicted land use 2023 (km^2)	Differences between actual and predicted land use	
			Area (km^2)	%
Built-up area	77.83	87.82	9.99	12.83
Agriculture	466.46	469.88	3.42	0.73
Forest	239.62	226.61	-13.01	-5.42
Water body	4.33	3.93	-0.40	-9.23

It was found that agriculture predominated among all classes within Mae Sot district, consistently occupying more than half of the total area throughout the study period. Additionally, approximately one-third of the entire area was covered by forest. Built-up areas accounted for 30.44 km^2 (3.86%) in 2003, 52.23 km^2 (6.62%) in 2013, and 77.83 km^2 (9.87%) in 2023. In the meantime, water bodies were observed in small quantities, with areas varying slightly between 0.54% and 0.56% of the total area.

According to Figure 5, the forest area showed a consistent pattern of decline, with a reduction of 32.93 km^2 from 2003 to 2013, followed by an additional 20.79 km^2 from 2013 to 2023. This represents a percentage loss of -7.98% and -11.23%, respectively. The built-up area, in contrast, has been steadily increasing, expanding by 12.21 km^2 from 2003 to 2013 and further by 26.95 km^2 from 2013 to 2023, with percentage changes of 71.58% and 49.01%, respectively. Meanwhile, agricultural land experienced marginal fluctuations, expanding by 11 km^2 (2.39%) between 2003 and 2013, followed by a contraction of 4.72 km^2 (-1.00%) between 2013 and 2023. The land use maps for the years 2003, 2013, and 2023 are presented in Figures 6(a), 6(b), and 6(c), respectively.

4.2 Land Use Prediction

The CA-ANN model was initially used to predict the land use for the year 2023 in order to ensure the accuracy of the prediction results using land use data for the years 2003 and 2013 obtained from the previous classification step together with the spatial variables which included elevation, slope, distance from the city center, distance from the main road, and the population in the year 2013 as input data. The results of the 2023 land use forecast are shown in Figure 6(d).

The agreement between the predicted land use for the year 2023 and the actual land use for the same year was evaluated using the kappa index value. The study showed a high level of agreement, with a kappa index value of 0.81, indicating significant agreement between both maps. Table 4 illustrates the disparities between the actual and predicted land use for 2023.

4.3 Future Land Use Prediction

After assessing the precision of the utilized model and achieving satisfactory levels of dependability, the CA-ANN model was employed to project the land use for the year 2033. As indicated in Table 5, from 2023 to 2033, the built-up area is anticipated to expand by 22.46%, equating to 95.31 km^2 by 2033.

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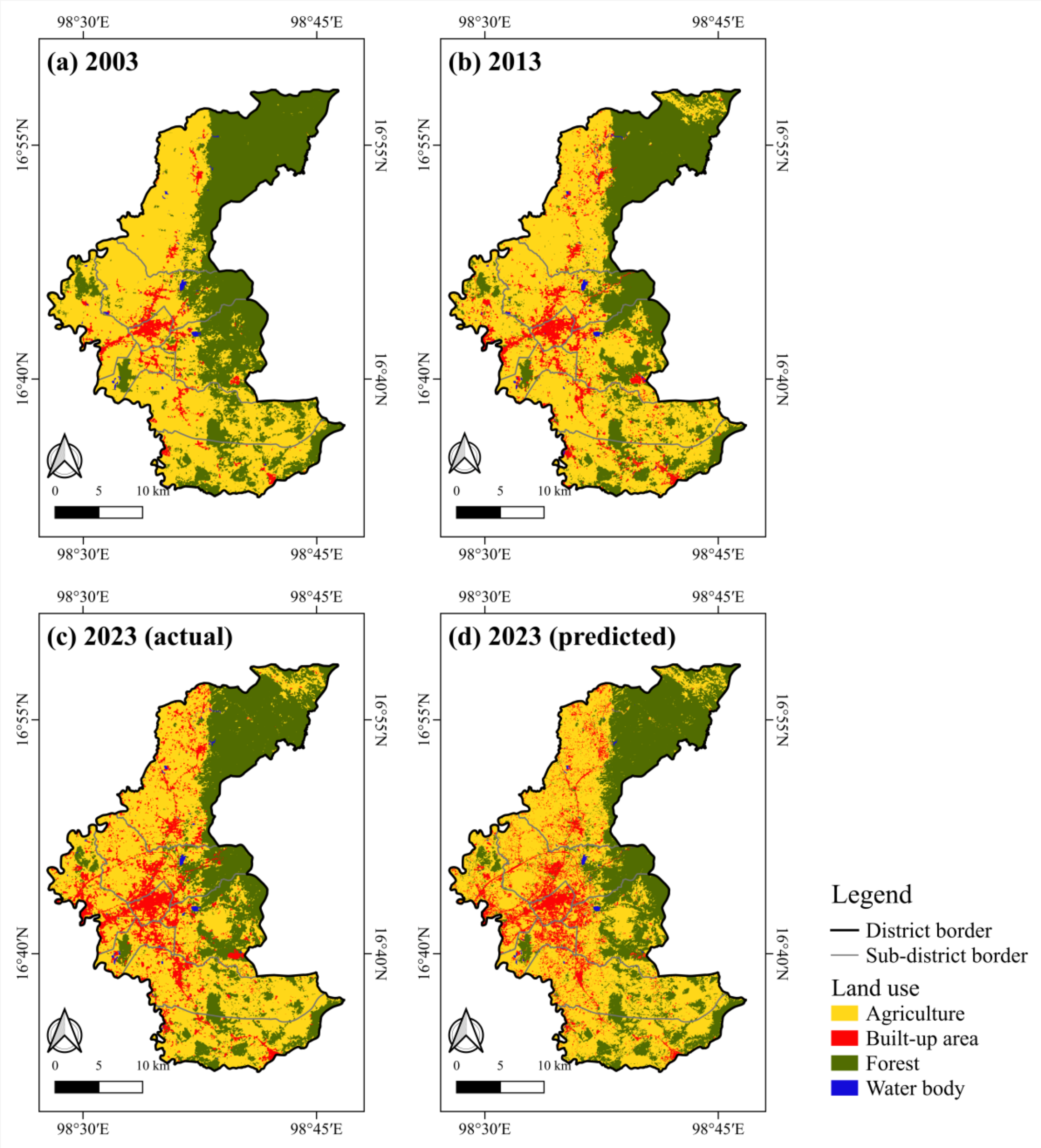

Figure 6: Land use map (a) 2003, (b) 2013, (c) 2023, and (d) predicted land use map in 2023

Table 5: Predicted land use classes in 2033

Land Use	Predicted 2033		Change from 2023 to 2033	
	Area (km^2)	%	Area (km^2)	%
Built-up area	95.31	12.09	17.48	22.46
Agriculture	471.71	59.84	5.25	1.13
Forest	217.48	27.59	-22.14	-9.24
Water body	3.74	0.48	-0.59	-13.63

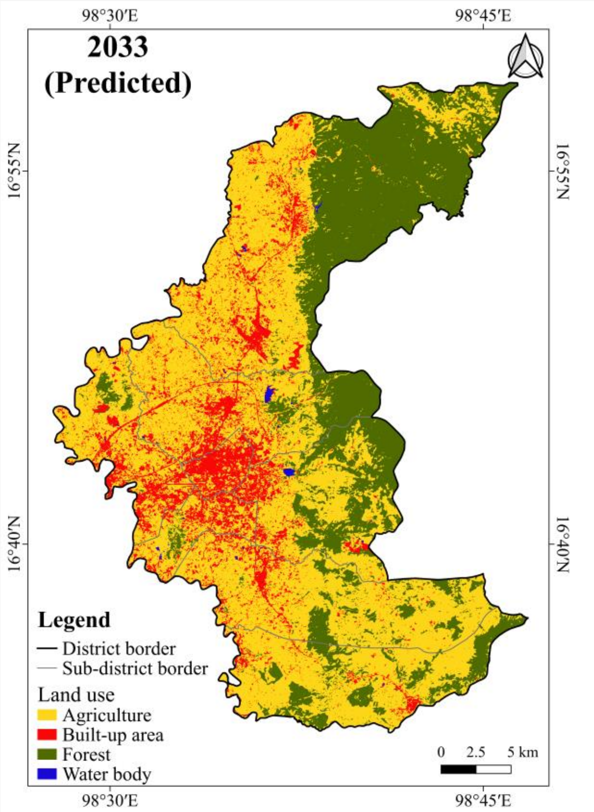

Figure 7: Predicted land use map for the year 2033

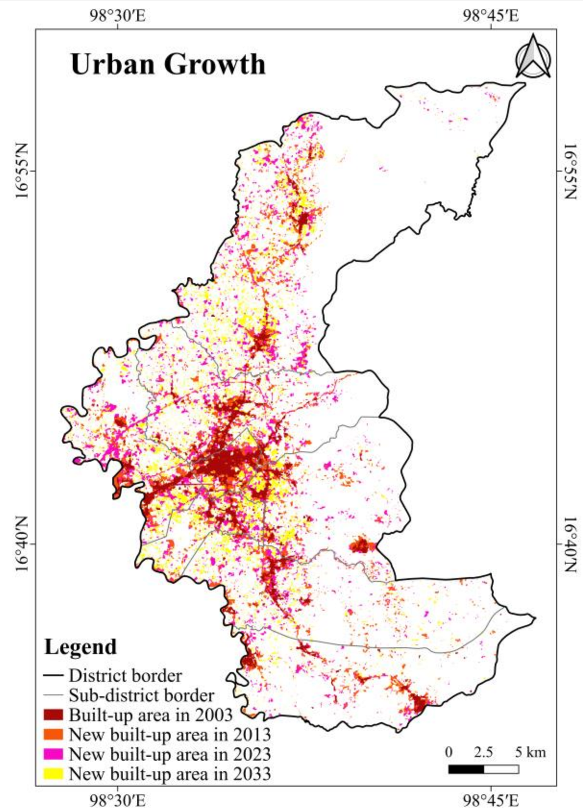

Figure 8: Urban growth in Mae Sot district

Table 6: Land use transition from 2023 to 2033

Class		Predicted land use in 2033 (km²)				
		Built-up area	Agriculture	Forest	Water body	Total
Actual land use 2023 (km²)	Built-up area	74.91	2.17	0.75	0.00	77.83
	Agriculture	20.12	443.07	2.58	0.69	446.46
	Forest	0.18	25.71	213.69	0.04	239.62
	Water body	0.10	0.76	0.46	3.01	4.33
	Total	95.31	471.71	217.48	3.74	788.24

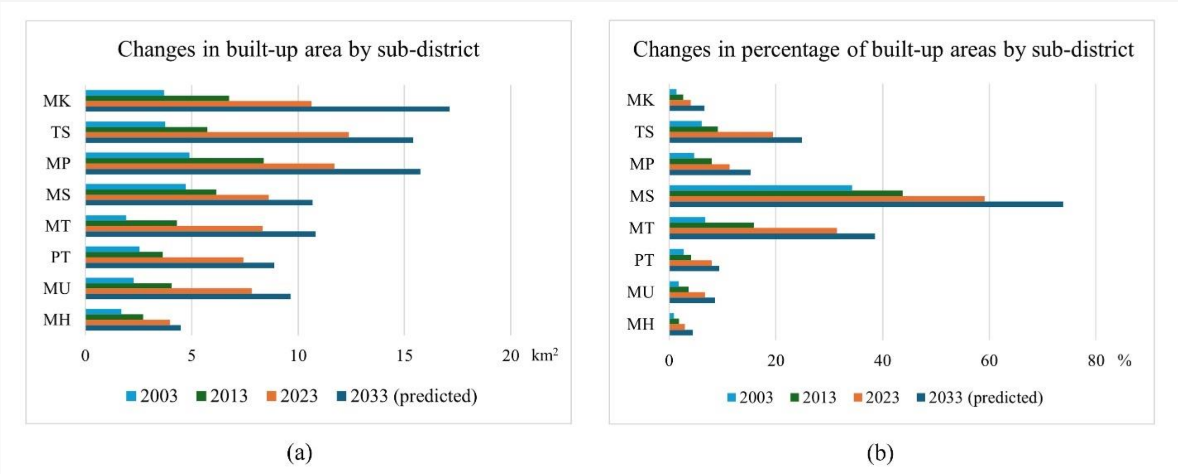

Figure 9: Expansion of built-up areas from 2003 to 2033 by sub-district
(a) area of change (b) percentage of change

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Agricultural land is estimated to increase by 5.25 km^2, or 1.13%, of its initial extent. Conversely, projections indicate a decrease of 9.24% and 13.63% in forest and water bodies, respectively. Despite these changes, agriculture remains the predominant land use in Mae Sot district, occupying 471.71 km^2 (59.84% of its total land use). According to Table 6, there will be a conversion of 25.71 km^2 of forest into agriculture between 2023 and 2033. Furthermore, a considerable expanse of land devoted to agriculture will be transformed into built-up areas by 20.12 km^2.

The projection for land use in 2033 is depicted in Figure 7, while the expansion of the Mae Sot city area is illustrated in Figure 8. It is notable that, on average, built-up areas are anticipated to increase by around 1.68 km^2 annually, with further expansion occurring around the initial urban boundaries. Upon closer examination by sub-district, as depicted in Figure 9, it becomes apparent that each sub-district will experience increased urbanization, with Mae Kasa and Mae Pa being the most impacted, despite the fact that the percentage of built-up area remained marginally low between 2003 and 2033. On the other hand, Mae Sot sub-district will maintain its position as the area with the highest proportion of developed land, comprising 73.84% of its total area in 2033. Following this, Mae Tao and Tha Sai Luat will be developed, culminating in a continuous urban area in the middle of the study area with western connections to the Myanmar border crossing.

5. Discussion

The study outcomes indicate that the CA-ANN model effectively identified both the extent and spatial distribution of land use changes, supported by a kappa coefficient exceeding 0.80. This means that the predicted land use map and actual observations agreed very well. This verifies the model's capability to simulate future land use with similar precision, consistent with prior research [42] and [43].

The results provide insights into the land use characteristics of Mae Sot district, which primarily consists of agricultural zones. Urbanization is concentrated centrally, particularly within Mae Sot sub-district, expanding outward from the historic city center to encompass nearly the entire sub-district. Additionally, development extends into the urban area of Tha Sai Luat sub-district, aligning with governmental plans to consolidate these areas under an independent local government body named "Nakhon Mae Sot" [5]. Minor growth was also observed around the original cores of other sub-districts situated along national highway No. 105, enhancing interconnectivity among urban centers.

The model indicated that while the built-up area in Mae Sot district would expand over the next decade, most of the land would remain agricultural. This finding is consistent with observations made in Chiang Khong District, Chiang Rai Province, a Thai-Myanmar border city in northern Thailand [44], and Khlong Lan District, Kamphaeng Phet Province, in central Thailand [45].

The observed changes in land use types align closely with findings from multiple studies [46] [47] and [48]. Forest areas exhibited a notable propensity to convert into agricultural areas, prompting concerns regarding conservation efforts aimed at mitigating environmental impacts. Simultaneously, agricultural areas demonstrated a tendency to transition into built-up areas at a rate of 1.68 km^2/year, posing challenges for infrastructure development and sustainability.

It is important to acknowledge that a limitation of the CA-ANN model for predicting land use is its sensitivity to initial conditions and parameter settings. Minor adjustments in input data or model parameters can result in significant variations in predicted outcomes. Another limitation is the dependence on past data and assumptions about future trends, which may overlook unforeseen events or abrupt changes in land use patterns. For instance, political instability in Myawaddy could potentially impede the anticipated growth of Mae Sot. Nevertheless, despite these challenges, the study's findings significantly enhance our understanding of land use dynamics.

6. Conclusion

Mae Sot, a frontier town, plays an important role in production and border trade. While agriculture prevailed as the primary land use during the study period, there was a noticeable increase in urban development. The successful implementation of the CA-ANN model, leveraging historical land use data and spatial variables, establishes a robust framework for future projections. Looking forward to 2033, anticipated shifts in land use indicate a dynamic transformation of the landscape. Forested areas are expected to give way to expanded agricultural zones, facilitating increased crop cultivation. Additionally, the ongoing trend of urbanization is set to convert existing agricultural areas into built-up spaces, underscoring the imperative for strategic planning to address urban challenges effectively. The projected growth of Mae Sot is envisioned to radiate outward from its original center in Mae Sot sub-district, encompassing areas such as Tha Sai Luat, Mae Pa, and Mae Tao, with potential northward expansion along the national highway towards Mae Kasa sub-district.

7. Recommendations

While the CA-ANN model has demonstrated effectiveness in predicting future land use dynamics, its accuracy hinges significantly on the quality and resolution of the training data. This dataset includes land use interpretations derived from satellite imagery and selected spatial variables. To enhance the robustness of future studies, it is imperative to improve the resolution of land use maps and incorporate additional factors such as flood-prone areas, migration rates, and governmental policies. These factors could provide deeper insights into the underlying drivers of land use changes. Conducting sensitivity analyses that explore different parameter values, such as the number of hidden layers, iterations, and the size of CA filters, can also refine the prediction capabilities of the CA-ANN model.

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