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Research Article

Urbanization Dynamics and 2050 Land Use Simulation in Ao Nang, Krabi: A CA-Markov Approach

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Abstract

Ao Nang, a coastal tourist city in Krabi Province, has been developing its area to support both Thai and foreign tourists since 1983. This research selected Landsat 1 satellite imagery from 1973, which was before tourism development, to conduct this research. The objective of this research is to analyze the changes in land use patterns between 1973 and 2025, and to model future land use using the CA-Markov model in Ao Nang. The results found that in 1973, the city, town, and commercial areas covered an area of 9.38 km^2 (7.82% of the total area), and in 2025, the area increased to 21.95 km^2 (18.31% of the total area). Urban expansion has affected other types of land use, such as evergreen forest and various agricultural areas, such as para rubber and mixed orchard. During 1973–2025, urbanization has occurred in important beach areas, such as Nopparat Thara Beach, Ao Nang Beach, Railay Beach, Tubkaek Beach, and Khlong Muang Beach; and important highways along the line, such as 4201, 4203, 4034, and 6024. The results of the Cellular Automata Markov Model (CA-Markov Model) show the simulation of future land use, which occurs in 2050. The CA-Markov model predicts that urban and built-up areas will expand significantly to 40.32 km^2 by 2050, representing an 83.7% increase from the baseline. Conversely, forest cover and agricultural land are projected to decline by 18.78% and 12.72%, respectively. The results show that in the next 25 years, the city, town, and commercial areas will expand the most, followed by shrimp farms. If land use changes occur without control, it may affect the use of such land to increase rapidly. However, the research results this time have shown land use data in spatial form that is useful for planning land use development in the coastal tourist city of Ao Nang effectively. Furthermore, this information will support decision-making in preparing for spatial development for sustainable tourism.

Keywords: Ao Nang, CA-Markov model, coastal tourist city, future land use change, urbanization

1. INTRODUCTION

In recent decades, the growth of the tourism industry has become one of the key factors driving rapid urbanization, especially in economically and culturally important tourist cities [1]-[3]. The expansion of economic activities and tourism-related infrastructure has led to rapid land use changes, such as the conversion of agricultural, forestry, or wetland areas into hotels, resorts, roads, and other facilities that accommodate a large number of tourists [4]-[5]. Cities with coastal areas often have tourism potential. These cities often experience infrastructure construction that changes land use from agricultural or natural areas to commercial uses and tourism services [6]-[7]. Such changes have environmental impacts, local ecosystems, and the long-term sustainability of land resources [8]-[9]. This creates the need to understand the nature and extent of land use changes in tourism cities, especially coastal tourism cities, to use as information for sustainable spatial planning.

The rapid expansion of coastal tourism cities necessitates systematic spatial analysis to ensure sustainable planning. Remote sensing (RS) and geographic information systems (GIS), integrated with high-resolution satellite imagery such as Landsat and Sentinel-2, have emerged as primary tools for monitoring and forecasting land use and land cover (LULC) changes [10]-[12]. Previous studies, such as those conducted in Hangzhou [13] and the coastal city of Antalya, Turkey [14], highlight that economic and tourism factors act as catalysts for construction and shape urban growth patterns. Furthermore, research in South Asia [15] confirms that urban sprawl contributes directly to the depletion of agricultural land and forest cover, underscoring the vital role of satellite data in formulating effective future management strategies. The integration of Sentinel-2 and Landsat data within a GIS framework has proven highly effective for detailed monitoring of urban dynamics,

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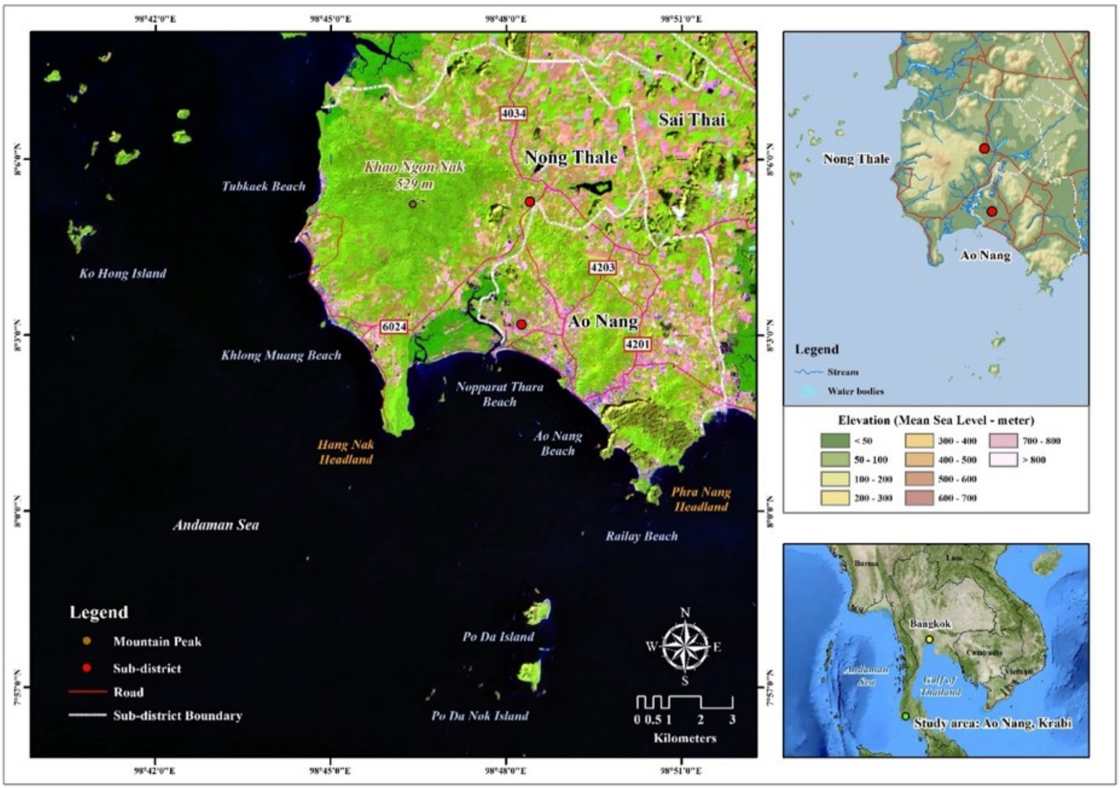

Figure 1. Location of Ao Nang and Nong Thale Sub-district, Krabi Province, Thailand.

particularly in Mediterranean coastal tourism zones [16]. In these regions, the proliferation of hotels and infrastructure often leads to the loss of natural habitats and the degradation of coastal ecosystems. This aligns with findings from a study of 53 Chinese coastal cities [17], which noted that spatiotemporal changes result in biodiversity loss and increased pollution. Additionally, Dahy et al. [18] pointed out the cumulative environmental impacts observed in the Persian Gulf region over the past 50 years. Consequently, systematic analysis of land-use change serves as a crucial instrument for sustainable planning, striking a balance between tourism-driven urban development and the effective conservation of natural resources and the environment.

Rapid land use changes in coastal tourist cities require systematic analysis and monitoring for sustainable planning. The RS and GIS technologies, using Landsat and Sentinel satellite data, are important tools to monitor and understand urban expansion and other land use changes. Research indicates that this expansion often leads to loss of natural areas, ecosystem destruction, and increased pollution. Therefore, modeling future land use using historical and current land use data is essential to maintain a balance between development and environmental conservation, leading to sustainable urban development in the future. World-renowned researchers have presented research on future land use modeling, such as the work of Saadani et al. [19] who modeled the spatial and temporal urban growth of El Jadida city, Morocco. The results show that the city is likely to experience significant urban expansion. In particular, the built-up areas tend to increase rapidly, which affects agricultural areas, forest areas, and natural areas.

The applied CA–Markov model demonstrates its high capability and accuracy in modeling and forecasting urban growth in spatial and temporal dimensions. In contrast, Zhu et al. [20] integrated the CA-Markov and InVEST models to study the dynamics of land use change and assess the changes in ecosystem carbon stock in coastal China from 1980 to 2050. The results predict that China's coastal areas will experience significant land use changes. As a result, the ecosystem carbon stock will continue to decline until 2050, especially in urban and industrial areas. Lu et al. [21] used the CA-Markov model to analyze and forecast the future land use changes in the coastal metropolis of Tianjin. The results show that the developed model can effectively identify urban sprawl and estimate future land use demand. It enables optimal planning of green space allocation and reduces the environmental degradation rate by 12% over a five-year period. And Dumdumaya & Cabrera [22] researched on the future land use change prediction using artificial neural network (ANN) of Davao City, Philippines. The results show that Davao City is likely to have a significant increase in built-up area in the future, which will result in a decrease in agricultural and forest areas. Research on future land use prediction is very useful for research by helping researchers to understand and model the dynamics of urban land-scape changes in space and time systematically, to assess sustainable development options, and as important information for policymakers in planning and managing future cities.

Despite the widespread application of the CA-Markov model in predicting coastal urban dynamics internationally, a significant research gap persists regarding Ao Nang, Krabi—a world-class tourism destination characterized by its unique topography. Existing literature often lacks in-depth spatial projections that account for the intricate interplay between rapid tourism expansion and stringent legal conservation boundaries. Furthermore, prior studies have predominantly focused on the quantitative expansion of built-up areas, often failing to reflect the impact on Ao Nang's 'spatial identity,' such as the encroachment into green spaces on limestone foothills—a vital natural aset for the tourism industry. This research aims to bridge these gaps by developing an integrated CA-Markov model that incorporates localized driving factors. The findings are intended to serve as a strategic tool for urban planning in Ao Nang, facilitating a balance between economic growth and long-term environmental sustainability.

Ao Nang is a coastal tourist city with tourism potential in Thailand. It is a city that could attract a large number of tourists with its beautiful scenery, diverse water activities, and is a gateway to other marine tourist attractions [23]-[24]. Ao Nang has important tourist attractions such as Ao Nang Beach, Nopparat Thara Beach, Railay Beach, Thale Waek (Separate Sea) in Ko Thap Island, Ko Hong Lagoon, Khao Ngon Nak Trail, and so on. There are important tourist activities such as boat trips to Phi

Table 1. Satellite Image data over the Ao Nang area, Krabi Province.

Database	Red:Green:Blue (R:G:B)	Path/Row	Resolution (m)	Acquisition date	Format
Landsat 1 MSS [1]	7:5:4	139/54	60	2 Mar 1973	Image file
Landsat 5TM [1]	5:4:3	129/55	30	12 Feb 2000	Image file
Landsat 8 OLI [1]	6:5:4	129/55	30	31 Jan 2025	Image file
Sentinel 2A [2]	11:8:4	N0511/R061	20	30 Jan 2025	Image file

[1] Derived from https://earthexplorer.usgs.gov/; [2] Derived from https://dataspace.copernicus.eu/

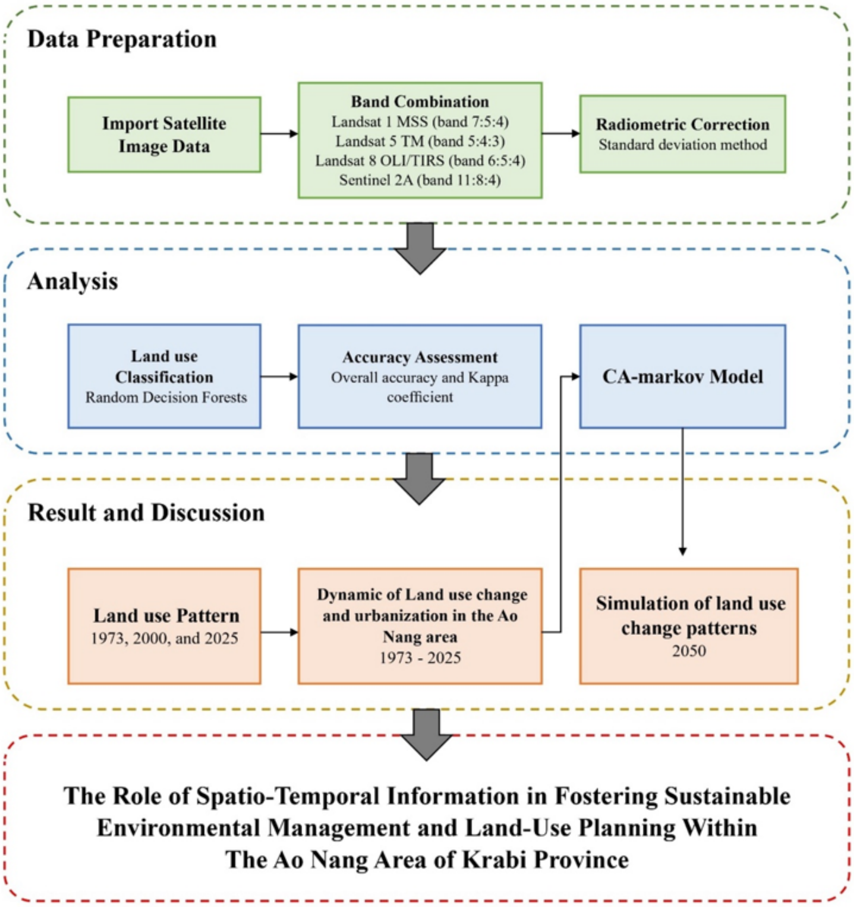

Figure 2. Flow chart of the research methodology in this work.

Phi Islands, Ko Hong Islands, or Poda Island, rock climbing activities at Railay Beach, snorkeling, kayaking, shopping at the night market, Thai massage, and hiking in Khao Ngon Nak Trail. This growth in tourism has resulted in significant changes in land use in Ao Nang. Agricultural areas and natural areas have become commercial areas such as hotels, resorts, restaurants, and shops. This has affected the coastal ecosystem, natural resources, and the way of life of local communities.

Research on land use planning in Ao Nang is therefore very important. It focuses on the efficient and sustainable allocation and management of land resources to reduce negative impacts and promote balanced development. This is in line with the Sustainable Development Goals (SDGs), especially SDG 11: Sustainable Cities and Communities in participatory and sustainable planning and management of urban and community development [25]-[26]. As well as SDG 15: Life on Land in terms of conservation, restoration and promotion of sustainable use of terrestrial ecosystems, sustainable forest management, halting and reversing land degradation and halting biodiversity loss [27]-[28]. Research on land use change in Ao Nang is therefore essential, as the area is experiencing rapid land use changes from the expansion of tourism, which has a direct impact on coastal ecosystems, natural resources and the livelihoods of local communities.

The objective of this research is to quantify the spatio-temporal dynamics of land use changes in Ao Nang, Krabi, and forecast future scenarios using a CA-Markov model. Specifically, the study integrates RS and GIS to analyze historical land use transitions between 1973 and 2025. These data are then applied to the CA-Markov model to simulate land use patterns for the next 25 years. By evaluating these transitions, the research provides a predictive framework to support sustainable land use policy-making, ensuring a strategic balance between economic expansion, environmental preservation, and the enhancement of local quality of life.

2. MATERIALS AND METHODS

2.1. Study Area

The research area in this study is the coastal tourist city of Ao Nang, which covers Ao Nang and Nong Thale sub-districts, Krabi province, Thailand. The study area has an area of 119.88 km^2. It is located at latitudes 7°54' N to 8°9' N and longitudes 98°39' E to 98°52' E (Figure 1). It is located in the southern part of the western seaboard of Thailand, adjacent to the Andaman Sea. The topography of the study area shows the coastal plain alternating with the Clastic Sedimentary Rock and Limestone Mountain ranges. The important mountain ranges in this study area include Khao Ngon Nak mountain range, a Clastic Sedimentary Rock Mountain range with an elevation of 529 m, located in the northwest of the study area. This area is an important rainforest in the southern part of Thailand, rich in biodiversity, and is also a famous tourist attraction for trekking in Krabi. In the Ao Nang area, there are two mountain ranges: in the central part of Ao Nang, there is an unnamed Clastic Sedimentary Rock Mountain range. And, in the southeast, there is a limestone mountain or Karst topography called Khao Ao Nang, continuing to Phra Nang Headland, which is an important landmark of this tourist attraction. The lime-stone mountain range is steep and runs along the beach. There are tourist attractions such as caves, stalactites and stalagmites in the area. It is also an important source of Ao Nang Mountain climbing activities. The mountain range is the dividing point between the plain and the beach in Ao Nang, resulting in beautiful beaches on the western side of the study area, namely Tubkaek Beach and Khlong Muang Beach. Both beach areas are separated by Hang Nak Headland, which is a sedimentary hill that extends into the sea. The central part of Ao Nang has a coastal plain and beautiful beaches, namely Nopparat Thara Beach, Ao Nang Beach, Railay Beach, etc. The area is located between Hang Nak Headland and Phra Nang Headland. The northern part is a rippled plain with an important wetland, Nong Thale, which is an important freshwater source in this area. And to the east, there is a limestone mountain range alternating with a plain.

2.2. Data Preparation

In this research, satellite imagery recorded by Landsat 1MSS, Landsat 5TM, and Landsat 8OLI/ TIRS in 1973, 2000, and 2025 (Table 1) was used. These satellite images were accessed from the U.S. Geological Survey. Band combination was used to obtain easily interpretable land cover and land use patterns to monitor land use change over a period of time. The Landsat 1MSS imagery was composited using the R:G:B band of 754, which is a combination of the Landsat 5TM satellite imagery has been blended with the R:G:B band of 543, which is a blend of short-wave infrared, near-infrared, and red bands [29]-[30]. The Landsat 8OLI/TIRS satellite imagery has been blended with the R:G:B band of 654, which is a blend of short-wave infrared, near-infrared, and red bands [31]. After obtaining the satellite images of the three time periods, the radio-metric correction using the Standard deviation method was performed to obtain sharp satellite imagery before interpreting the land cover [32]-[33]. This process was performed using the Erdas Imagine 8.7 program.

2.3. Methodology

The research process includes the RS and GIS process and the CA-markov model, as shown in Figure 2. Details of each step are briefly explained as below.

2.3.1. Remote Sensing and GIS Process

The process of RS and GIS was applied in this research by applying such technology to classify land use and land cover classification. In this step, satellite images from three time periods: 1973, 2000, and 2025 were imported into ArcGIS 10.8 software to analyze land use classification using the principle of machine learning. For the image classification process, the Random Forest classifier was optimized using specific false-color composites to enhance feature extraction; these included bands 7-5-4 for Landsat 1 MSS, 5-4-3 for Landsat 5 TM, and 6-5-4 for Landsat 8 OLI/TIRS. The classification scheme comprised 15 distinct land use classes, defined in accordance with the standard criteria established by the Land Development Department (LDD) of Thailand. To support the RF model, 30 training samples were systematically allocated to each class. Finally, to ensure the

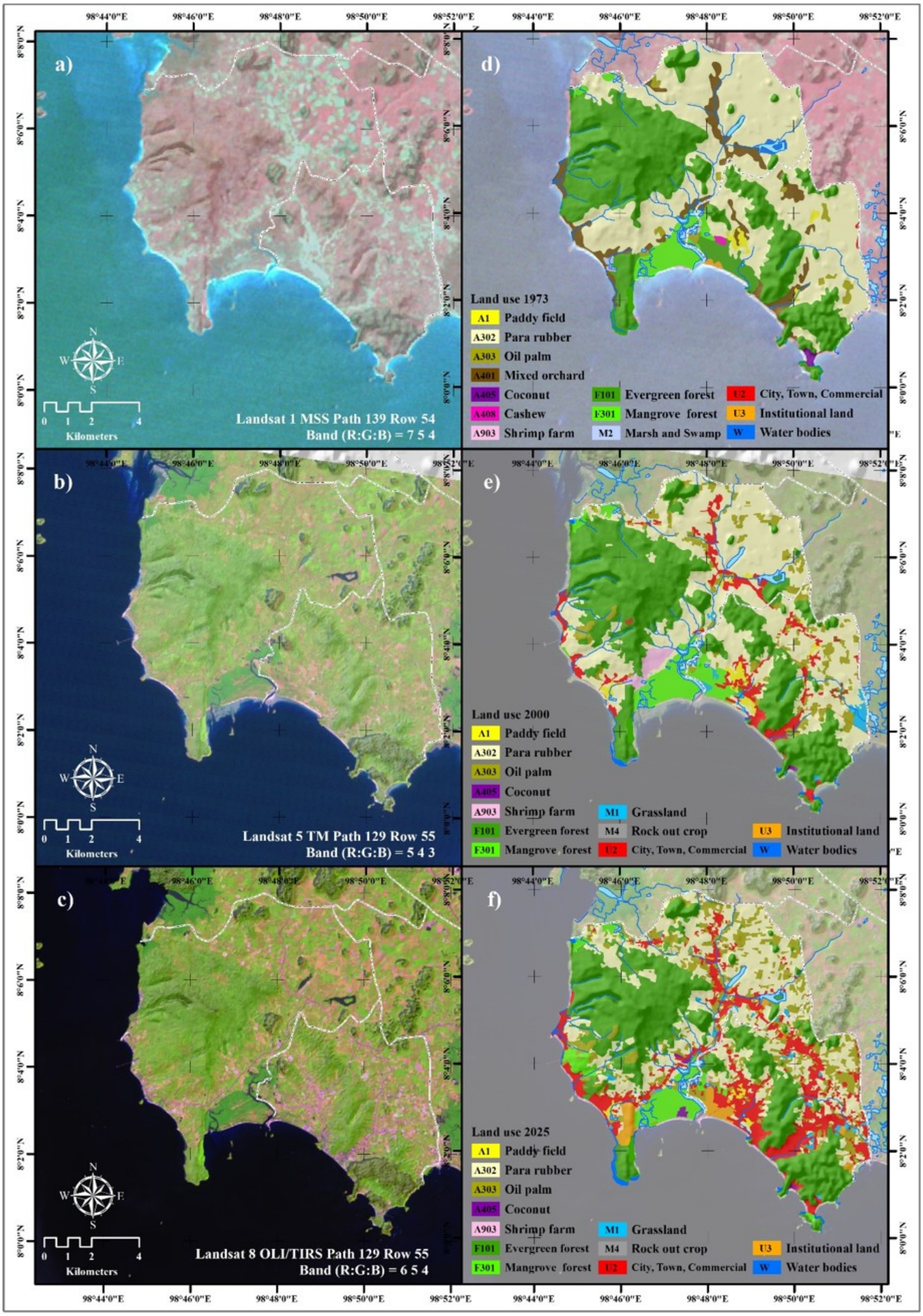

Figure 3. Landsat satellite imagery and land use pattern of Ao Nang area in 1973, 2000, and 2025.

reliability of the thematic maps produced, the classification results were rigorously validated through Overall Accuracy and Kappa Coefficient (KHAT) analyses.

The principle used deep learning classification techniques in the part of random decision forests (or random forest) is an ensemble learning method for land use and land cover classification. The random decision forests method is a popular process for interpreting land use effectively [34]. Random forest is a classification algorithm that ex-tends the decision tree method by combining the outputs of multiple weak learners—individual decision trees—to produce more accurate predictions. Unlike a single decision tree, a random forest typically yields higher accuracy by aggregating the predictions of all trees in the ensemble, most often through majority voting [35]-[36]. Training a random forest involves building decision trees iteratively, each trained on a different subset of the data. For each tree, performance is assessed using out-of-bag (OOB) samples—data points not included in the training subset for that tree. These OOB samples are passed through the forest, and their predicted classes are determined by majority vote across the trees [37]. Feature importance within the random forest is then calculated for each tree using the method outlined in Equation (1):

$$fi_i = \frac{\sum_{j:node\ j\ splits\ on\ feature\ i} ni_j}{\sum_{k \in all\ nodes} ni_j} \quad (1)$$

Where fi_i is the importance of feature I; ni_i is the importance of node j. These can then be normalized to a value between 0 and 1 by dividing by the sum of all feature importance values (Equation (2)):

$$normfi_i = \frac{fi_i}{\sum_{j \in all\ features} fi_i} \quad (2)$$

The final feature importance, at the random forest level, it is average over all the trees. The sum of the feature's importance value on each tree is calculated and divided by the total number of trees (Equation (3)):

$$RFfi_i = \frac{\sum_{j \in all\ trees} normfi_{ij}}{T} \quad (3)$$

Where $RFfi_i$_i is the importance of feature i calculated from all trees in the random forest model; $normfi_{ij}$ is the normalized feature importance for i in tree j; and T is total number of trees.

The results of the land use pattern interpretation are presented as the overall accuracy and KHAT to assess the accuracy of the classification of various data appearing on satellite imagery [38]-[39]. The sampling points in the study area were determined based on data from the LDD, Thailand. Validation was performed to compare with the data obtained from the classification. The classification criteria are as follows: < 0, means unacceptable classification data; 0.01–0.40 , means fair classification data; 0.41–0.60, means moderate classification data; 0.61–0.80, means good classification data; and 0.81–1.00, means very good classification data.

After the validation of the data obtained from the land use pattern interpretation was completed, the data that passed the overall accuracy and KHAT check criteria were analyzed for land use changes using the change detection method in the tabulate area analysis function in ArcGIS 10.8 software. The change detection analysis can be calculated as Equation (4) [40]:

$$\Delta = [(A_2 - A_1) / A_1 \times 100] / (T_2 - T_1) \quad (4)$$

where, Δ is the proportion of land use pattern that has changed (percent), A_1 is the type of land use at time one (T_1), and A_2 is the type of land use at time two (T_2). The results are displayed as a proportion of each land use type on the map in a transition matrix format, which shows the land use change pattern from 1973 to 2025. It can also display the urbanization area in Ao Nang area in a spatial format.

2.3.2. CA-markov Model

The CA-Markov model is a dynamic, multi-scale, spatially explicit, and raster-based approach used to predict areas with a high likelihood of future land use change [41]-[43]. Within this framework, the Markov chain component functions as the non-spatial demand module, estimating land use transitions at an aggregate level over multiple time steps.

In the model calibration phase for generating the land use simulation map, the CA-Markov model was configured with a cell size of 30 m, consistent

Table 2. Land use pattern statistics in Ao Nang area in 1973, 2000, and 2025 (km^2).

Land Use Pattern		1973		2000		2025		Area Change (km^2)		
		km^2	%	km^2	%	km^2	%	1973 to 2000	2000 to 2025	1973 to 2025
A1	Paddy field	0.69	0.58	0.51	0.43	0.45	0.38	-0.18	-0.06	-0.24
A302	Para rubber	50.83	42.40	42.82	35.72	31.22	26.04	-8.01	-11.6	-19.61
A303	Oil palm	1.36	1.13	7.58	6.32	14.59	12.17	6.22	7.01	13.23
A401	Mixed orchard	7.35	6.13	0	0.00	0	0.00	-7.35	0	-7.35
A405	Coconut	0.26	0.22	0.84	0.70	1.35	1.13	0.58	0.51	1.09
A408	Cashew	0.15	0.13	0	0.00	0	0.00	-0.15	0	-0.15
A903	Shrimp farm	0.52	0.43	1.72	1.43	0.59	0.49	1.20	-1.13	0.07
F101	Evergreen forest	43.99	36.70	42.6	35.54	37.72	31.46	-1.39	-4.88	-6.27
F301	Mangrove forest	4.29	3.58	6	5.01	4.98	4.15	1.71	-1.02	0.69
M1	Grassland	0.00	0.00	1.2	1.00	1.05	0.88	1.20	-0.15	1.05
M2	Marsh and swamp	0.11	0.09	0	0.00	0	0.00	-0.11	0	-0.11
M4	Rock out crop	0.00	0.00	0.4	0.33	0.13	0.11	0.40	-0.27	0.13
U2	City, Town, Commercial	9.38	7.82	11.28	9.41	21.95	18.31	1.90	10.67	12.57
U3	Institutional land	0.14	0.12	4.03	3.36	4.34	3.62	3.89	0.31	4.20
W	Water bodies	0.81	0.68	0.9	0.75	1.51	1.26	0.09	0.61	0.70
Total		119.88	100.00	119.88	100.00	119.88	100.00			
Overall Accuracy (%)		77.30		84.70		88.10				
Kappa Coefficient		0.73		0.80		0.86				

with the spatial resolution of the Landsat imagery. A 5×5 neighborhood rule was applied to account for the spatial influence of adjacent land uses, ensuring appropriate spatial aggregation in the simulated output. Regarding the establishment of transition rules, a Transition Probability Matrix was derived from the land use data of 1973 and 2000 to project change trajectories toward 2025. This process identified areas highly susceptible to transition, particularly those in proximity to existing road networks and urban centers, based on both transition probabilities and the spatial context of the base maps. Finally, the simulated 2025 map was validated against actual 2025 land use data. The validation yielded an overall accuracy of 82.6% and a Kappa coefficient of 0.80, indicating a high level of agreement and model reliability.

Markov chain analysis is a stochastic method that simulates the progression of land use states using geospatial data. It utilizes land use distributions at the beginning and end of a specified time interval, along with a transition matrix that captures the probabilities of changes between land use categories during that period. This matrix is generated through the classification of three multi-spectral Landsat images, applying the maximum likelihood algorithm, and expresses the proportion of each land use class [44]. The resulting matrix forms an essential component of the Markov chain model and is represented mathematically in Equation (5);

$$P_{i,j} \times i_t = i_{t+1},$$

$$\begin{bmatrix} P_{uu} & P_{ua} & P_{uw} \\ P_{au} & P_{aa} & P_{aw} \\ P_{wu} & P_{wa} & P_{ww} \end{bmatrix} \begin{bmatrix} U_t \\ A_t \\ W_t \end{bmatrix} = \begin{bmatrix} U_{t+1} \\ A_{t+1} \\ W_{t+1} \end{bmatrix} \quad (5)$$

where t is the time (year), $P_{i,j}$ is the transition probability matrix of the land use class I change to class j. I and j are the land use classes in the first year and the second years, respectively.

The CA-markov analysis was used to determine the demand for the probability of each land use pattern, where the probability of transition ($P_{i,j}$) is given for every ordered set of conditions. In a CA-markov with a limited number of conditions, such as j, a new transition probability matrix is bounded, as in Equation (6) [45]:

$$V_j \times P_{jk} = [V_1, V_2, V_3, \dots, V_n] \begin{bmatrix} P_{11} & P_{12} & \cdots & P_{1m} \\ P_{21} & P_{22} & \cdots & P_{2m} \\ P_{31} & P_{32} & \cdots & P_{3m} \\ \vdots & \vdots & & \vdots \\ P_{n1} & P_{n2} & \cdots & P_{nm} \end{bmatrix} \quad (6)$$

where $Vj \times Pjk$ is the proportion of land use in the second year. P_{jk} is the land use activity (f) derived from the transition probability matrix, V_j is the proportion of land use in the first year, j is the type of land use in first year, and k is the type of land use in the second year. The CA-markov model, an efficiently rapid analyzing tool, uses land use ratios for the reference year to determine the potential distribution of the land use types. The results of the model will provide future land use data in 2050 in spatial format. This data will be used for urban development planning to prepare for future spatial changes in Ao Nang area.

3. RESULTS AND DISCUSSIONS

3.1. Detection of Land use in the Ao Nang Area

Land use patterns were interpreted from Landsat satellite images from three time periods: 1973, 2000, and 2025 using the random forest classification method. The results of this study revealed that there were 15 land use patterns in Ao Nang: paddy field, para rubber, oil palm, mixed orchard, coconut, cashew, shrimp farm, evergreen forest, mangrove forest, marsh and swamp, grassland, rock outcrop, city and commercial (city, town, commercial), institutional land, and water bodies (Figure 3). The overall accuracy assessment was 88.1%, 84.7%, and 77.3% in 2025, 2000, and 1973, respectively, with a Kappa coefficient of 0.86, 0.80, and 0.73, respectively. The classification results were at the good to very good level.

The classification accuracy for 1973 an overall accuracy of 77.3% and a Kappa coefficient of 0.73. The primary constraint in the 1973 land use classification stems from the technical specifications of the Landsat 1 MSS sensor, which possesses a spatial resolution of approximately 60 m. This coarser resolution leads to a higher prevalence of mixed pixels compared to modern 30 m sensors. Furthermore, limitations in spectral and radiometric resolutions hinder the ability to distinguish between land covers with similar spectral signatures, such as agricultural land versus rangeland, or fragmented urban settlements

Table 3. Matrix of Land use change in Ao Nang area during 1973 to 2025 (km^2).

Land use change		2025													Changing Area	
		A1	A302	A303	A405	A903	F101	F301	M1	M4	U2	U3	W	Total	km^2	%
	A1	0.15	0.02	0.07	0.00	0.00	0.00	0.00	0.00	0.00	0.46	0.00	0.00	0.69	-0.24	-34.78
	A302	0.05	25.74	11.01	0.06	0.05	4.16	0.50	0.84	0.04	8.10	0.28	0.00	50.83	-19.61	-38.58
	A303	0.00	0.17	0.81	0.00	0.02	0.03	0.06	0.03	0.00	0.23	0.01	0.00	1.36	13.23	972.79
	A401	0.09	0.66	0.86	0.13	0.02	0.35	0.19	0.11	0.00	4.70	0.15	0.10	7.34	0.00	0.00
	A405	0.00	0.00	0.00	0.00	0.00	0.04	0.04	0.00	0.00	0.18	0.00	0.00	0.26	1.09	419.23
	A408	0.00	0.01	0.00	0.00	0.00	0.00	0.09	0.00	0.00	0.05	0.00	0.00	0.15	0.00	0.00
1973	A903	0.00	0.00	0.07	0.00	0.28	0.03	0.12	0.00	0.00	0.00	0.00	0.01	0.51	0.07	13.46
	F101	0.08	4.48	1.50	0.01	0.04	32.85	0.90	0.03	0.02	1.93	1.56	0.61	43.99	-6.27	-14.25
	F301	0.00	0.05	0.20	0.14	0.14	0.14	3.08	0.01	0.06	0.07	0.06	0.33	4.29	0.69	16.08
	M2	0.09	0.01	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.11	-0.11	-100.00
	U2	0.00	0.01	0.01	1.02	0.00	0.00	0.00	0.00	0.00	6.17	2.00	0.17	9.38	12.57	134.01
	U3	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.13	0.00	0.13	4.20	3000.00
	W	0.00	0.08	0.07	0.00	0.03	0.12	0.00	0.03	0.00	0.05	0.14	0.30	0.81	0.70	86.42
	Total	0.45	31.22	14.59	1.35	0.59	37.72	4.98	1.05	0.13	21.95	4.34	1.51	119.88		

interspersed with vacant land—a common landscape characteristic of Ao Nang in 1973. Such spectral confusion complicates image interpretation and contributes to accumulated errors, directly impacting the accuracy and Kappa values of the baseline map. Additionally, validating the 1973 dataset is challenging due to the scarcity of historical ground truth data contemporary to the satellite overpass. Unlike modern assessments that utilize high-resolution imagery from Google Earth, historical validation often faces geometric errors during overlay analysis. The limited and uneven distribution of reference points serves as a systemic factor resulting in relatively lower statistical accuracy. These findings align with Mohajane et al. [46], who noted that early Landsat MSS classifications frequently encounter spectral confusion due to a limited number of bands and coarse spatial resolution (60 m). Notably, their study reported an overall accuracy of 66.8% and a Kappa of 0.413, suggesting that the accuracy levels achieved in this research remain robust within the context of historical sensor limitations.

In 1973, Ao Nang was primarily covered by para rubber land use, reaching 50.83 km^2 (42.4% of the total area), gradually decreasing to 42.82 km^2 (35.72% of the total area) by 2000 and 31.22 km^2 (26.04% of the total area) by 2025, respectively. This land use extends widely from the north to the southeast. Meanwhile, evergreen forest land use covered 43.99 km^2 (36.70% of the total area) in 1973, gradually decreasing to 42.6 km^2 (35.54% of the total area) by 2000 and 37.72 km^2 (31.46% of the total area) by 2025, respectively. The area encompasses Khao Ngon Nak, Hang Nak Headland, and Khao Ao Nang, extending to Phra Nang Headland. These are the major mountain ranges in the central and eastern part of Ao Nang. The city, Town, and Commercial areas covered 9.38 km^2 (7.82% of the total area) in 1973, gradually expanding to 11.28 km^2 (9.41% of the total area) in 2000 and 21.95 km^2 (18.31% of the total area) in 2025, respectively. Land use has expanded along Highways 4201, 4203, 4034, and 6024. In 2000 and 2025, City, Town, and Commercial areas appeared along Ao Nang beach, Nopparat Thara beach, Klong Muang beach, and Tubkaek beach. The most notable land use area seen to expand is oil palm. Between 1973 and 2025, the area expanded by a whopping 12 times, as it is an economically important oil crop, replacing rubber and coconut trees. Institutional land also experienced a three-fold expansion during this period, as Krabi Province shifted its administrative system from central to local. To facilitate management, government buildings were constructed along Nopparat Thara Beach and Klong Muang Beach. The remaining land uses that did not appear in 2025 were mixed orchard, cashew, and marsh and swamp. These land use patterns were affected by urbanization due to economic and tourism expansion in Ao Nang. The details of the proportions of different land use types are shown in Table 2.

3.2. Dynamic of Land use Change and Urbanization in the Ao Nang Area

The land use change over the past 52 years (1973 to 2025) in the Ao Nang area shows changes in both the expansion and transformation of agricultural land use, deforestation, and urbanization (Table 3). This research study reveals that between 1973 and 2025, agricultural land in the Ao Nang area experienced significant expansion. This change indicates that land use category A303 (Oil palm) expanded by as much as 972.79%, followed by A405 (Coconut) at 419.23%, and A903 (Shrimp farm) at only 13.46%. Conversely, areas A1 (Paddy field) and A302 (Para rubber) decreased by -34.78% and -38.58%, respectively. Agri-cultural land use has significantly transformed into oil palm plantations, with the A302 (para rubber) becoming the A303 (oil palm) the largest, stretching 11.01 km^2. This land use change extends from the northern part of the Ao Nang area to the southeast, and east along Road 6024. The A401 (mixed orchard) and A408 (cashew) areas are virtually absent from 2025. Most of this land use has been transformed into U2 (city, town, commercial) areas, stretching 4.7 km^2. These land use changes are found along Road 4201, 4203, and 4034.

Deforestation in Ao Nang area: The study found that it occurred in the areas surrounding Khao Ngon Nak, Hang Nak Headland, and Khao Ao Nang. The study found that areas in the western, eastern, and northern parts of Khao Ngon Nak were transformed from F101 (Evergreen Forest) into A302 (Para rubber) and A303 (oil palm) areas scattered throughout. The deforestation area was found to be

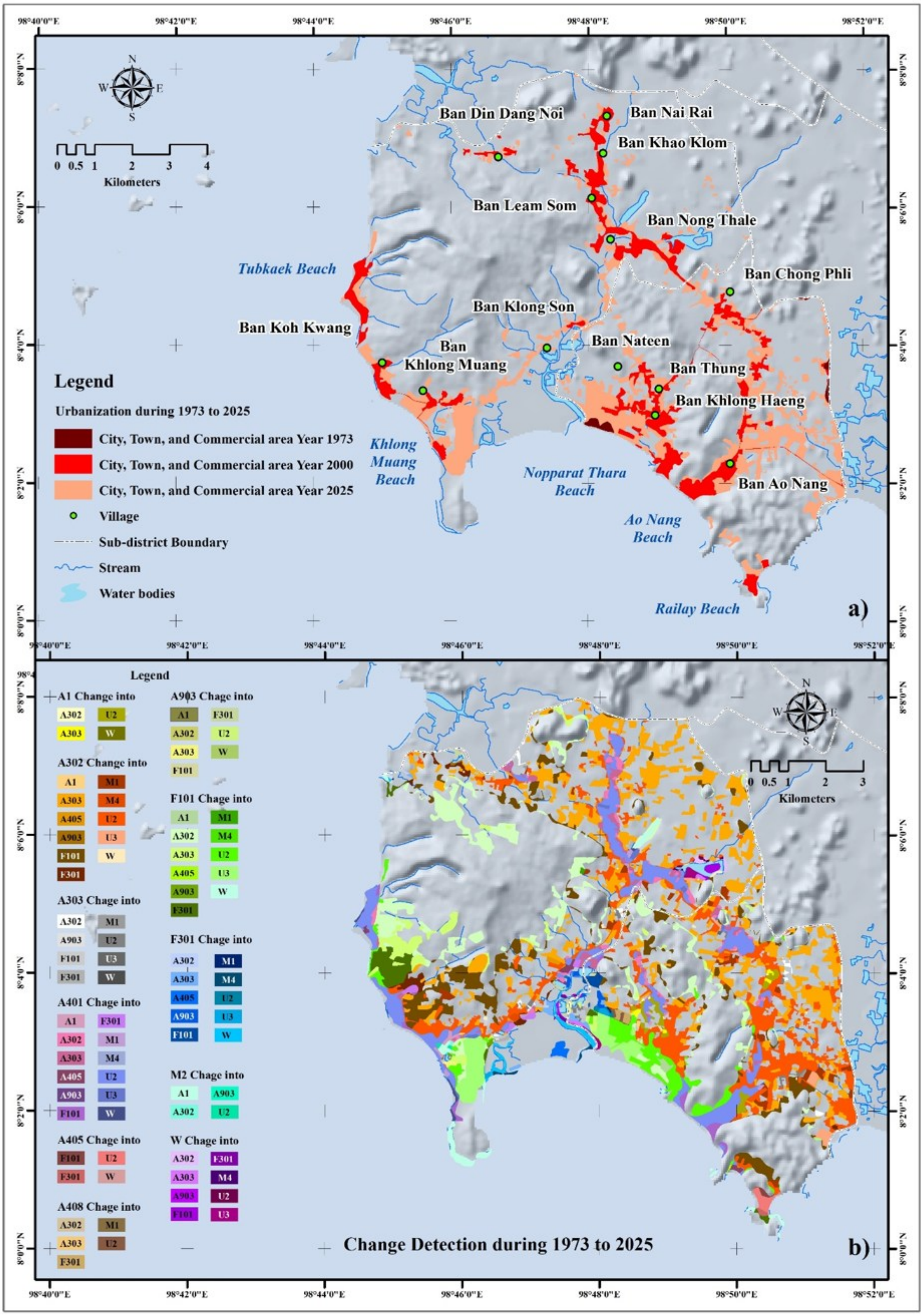

Figure 4. (a) Urbanization and (b) land use change dynamic map during 1973 to 2025 in Ao Nang area, Krabi Province.

4.48 km^2 and 1.50 km^2, respectively. In the areas of Nopparat Thara Beach and Ao Nang Beach, the Evergreen Forest area was transformed into U2 (City, Town, Commercial) areas. As for urbanization in Ao Nang area, the study found that there were the most changes. The areas of U2 City, Town, Commercial, and U3 Institutional land have expanded as high as 134.01% and 3000%, respectively. It was found that the land use areas that were converted to U2 (City, Town, Commercial) were A302 (para rubber), A401 (Mixed orchard), and F101 (Evergreen Forest), with the areas changing as much as 8.10 km^2, 4.70 km^2, and 1.93 km^2, respectively. Additionally, the land use areas that were converted to U3 (Institutional land) were U2 (City, Town, Commercial), F101 (Evergreen Forest), and A302 (para rubber), with the areas changing as much as 2.00 km^2, 1.56 km^2, and 0.28 km^2, respectively. Changes from various land use patterns U2 and U3 areas are mostly found along important beaches, including Nopparat Thara Beach, Ao Nang Beach, Railay Beach, Tubkaek Beach, and Khlong Muang Beach. U2 expansion areas are also found along important highways, including 4201, 4203, 4034, and 6024. The changes in land use and urbanization in the Ao Nang area over the past 52 years are shown in spatial data in Figure 4.

3.3. Simulation of Land use Change Patterns with the CA-markov Model in the Ao Nang Area

Research results from simulating future land use to the year 2050. The CA-Markov model simulates future land use as empirical spatial database and pro -vides a clear perspective. The results of this research show that the change in land use in the next 25 years, the area U2 (City, Town, Commercial) has expanded the most, from the original area of 21.95 km^2 in 2025 to 40.32 km^2 in 2050, accounting for 83.67%. Next is A903 (Shrimp farm), which has increased by 80.08%. The land use area that decreased the most is M4 (Rock out crop), which decreased by as much as -107.69%, followed by A405 (Coconut), which decreased by -82.96%. Details of the change in the proportion of land use between 2025 and 2050 are shown in Table 4.

The results of the CA-markov model show that urbanization is inevitable in the Ao Nang area. It can be seen that the type of land use that was converted to U2 area the most was F101 (6.11 km^2), followed by U3 (3.88 km^2), and the different types of land use were A302 (3.19 km^2), F301 (1.69 km^2), A303 (1.25 km^2), A405 (1.05 km^2), W (1.00 km^2), M1 (0.68 km^2), A1 (0.43 km^2), M4 (0.13 km^2), and A903 (0.05 km^2), respectively. The areas that were converted to U2 area were along Highway No. 4201, 4203, 4034, and 6024. There was also a change in land use pattern from A303, A405, M1, U3, F101, and F301, which occurred in the northern part of Ao Nang, around Ban Din Dang Doi Village, Ban Nai Rai Village, Ban Khao Klom Village, Ban Leam Som Village, Ban Nong Thale Village, Ban Chong Phli Village, BanAo Nang Village, Ban Thung Village, Ban Koh Kwang, and Ban Khlong Muang. These villages are located along major roads and have unique local topography and culture, leading to a shift in land use patterns towards U2 (City, Town, Commercial). The results of the research on future land use patterns from CA-markov model simulations and future land use patterns between 2025 and 2050 in the Ao Nang area are shown in Figure 5.

In this study, uncertainty in future projections reveal that urban and built-up expansion patterns in Ao Nang are significantly correlated with specific spatial drivers. Simulations using various neighborhood definitions indicate that areas proximal to coastlines, primary road networks, and central business districts exhibit the highest sensitivity. Urban growth follows a linear trajectory along transportation corridors and clusters within high-value economic zones. This aligns with Zhang et al. [47], who argued that in coastal tourism destinations, proximity to the shore and accessibility serve as primary determinants of land-use change, outweighing short-term demographic factors. Multiple model iterations to test spatial uncertainty confirm that even with minor weight adjustments, these strategic areas maintain a high transition probability, reflecting the robustness of the projections in these locales.

Furthermore, transition rules conducted through the integration of physical constraints—specifically preserving the high-slope limestone karsts—was a critical step in mitigating model bias. Without slope constraints, the CA-Markov model tends to overestimate urban encroachment into ecologically

Table 4. Matrix of Land use change in Ao Nang area during 2025 to 2050 (data in km^2).

Land use change		2050													Changing Area	
		A1	A302	A303	A405	A903	F101	F301	M1	M4	U2	U3	W	Total	km^2	%
2025	A1	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.43	0.00	0.00	0.45	-0.30	-65.56
	A302	0.04	24.90	1.94	0.00	0.44	0.10	0.19	0.42	0.00	3.19	0.01	0.01	31.22	-0.96	-3.07
	A303	0.11	4.20	8.35	0.00	0.23	0.27	0.15	0.04	0.00	1.25	0.00	0.00	14.59	-4.23	-28.99
	A405	0.00	0.04	0.00	0.21	0.00	0.06	0.00	0.00	0.00	1.05	0.00	0.00	1.35	-1.12	-82.96
	A903	0.01	0.12	0.06	0.00	0.35	0.00	0.01	0.01	0.00	0.05	0.00	0.00	0.59	0.47	80.08
	F101	0.00	0.66	0.00	0.00	0.00	30.71	0.03	0.01	0.00	6.11	0.20	0.00	37.72	-6.59	-17.46
	F301	0.00	0.00	0.00	0.02	0.05	0.00	3.18	0.00	0.00	1.69	0.04	0.01	4.98	-1.43	-28.71
	M1	0.00	0.33	0.00	0.00	0.00	0.00	0.00	0.02	0.00	0.68	0.01	0.00	1.05	-0.56	-53.10
	M4	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.13	0.00	0.00	0.13	-0.14	-107.69
	U2	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	20.86	1.08	0.01	21.95	18.37	83.67
	U3	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	3.88	0.46	0.00	4.34	-2.54	-58.53
	W	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	1.00	0.00	0.50	1.51	-1.00	-65.89
	Total	0.16	30.26	10.36	0.23	1.06	31.13	3.55	0.49	0.01	40.32	1.80	0.52	119.88		

vulnerable zones. By incorporating these transition rules, the future scenarios attain higher realism, consistent with the unique topography of Ao Nang. This approach is supported by Qian et al. [48], who emphasized that explicit spatial constraints effectively reduce both quantity and location disagreements. Our findings suggest that future growth in Ao Nang will be characterized by compact expansion within the confined plains between valleys and the coast. This inevitable increase in building density underscores the urgent need for stakeholders to implement spatial management strategies to mitigate forthcoming environmental impacts.

3.4. Discussion

This research revealed that over the past 52 years, Ao Nang has experienced al-most every type of land use change, due to its status as a major coastal tourist destination in Thailand. Land use patterns with a relatively high annual increase from 1973 to 2025, representing a relatively high percentage, are U3 (3000%), A303 (972.79%), A405 (419.23%), and U2 (134.01%). This is due to Krabi province's tourism development since 1983, the year the Hat Noppharat Thara–Mu Ko Phi Phi National Park was established. The establishment of this national park has played a crucial role in pre-serving the area's natural beauty and attracting more tourists ever since. Krabi's tour-ism has continued to grow, with infrastructure developed to accommodate a diverse range of travelers, from luxury seekers to ecotourists and adventurers. Krabi's popularity reflects the province's evolving tastes and preferences, which place a growing emphasis on sustainability and cultural authenticity.

Ao Nang, Krabi Province, has been significantly impacted by tourism development over the past several decades. Significant land use has been transformed, with areas previously agricultural and residential, transforming into commercial and tourist accommodation, including hotels, resorts, guesthouses, restaurants, bars, and other establishments, concentrated along the beach and surrounding areas. This expansion has also led to the development of infrastructure and utilities, such as roads, water supply, electricity, and waste management, to accommodate the growing tourist and population growth. Studies have shown that evergreen forests, mangrove forests, grasslands, marshes, and swamps will all significantly decrease in land use by 2025 due to the impact of this development.

The CA-Markov model clearly shows the future land use outcomes in 2050. It shows an increase in U2 (City, Town, Commercial) areas along major beaches, including Nopparat Thara Beach, Ao Nang Beach, Rai Lay Beach, Tubkaek Beach, and Khlong Muang Beach. This land use expansion also occurs inland along major highways, including Highways 4201, 4203, 4034, and 6024. The CA-Markov model results are consistent with the research of Zhang et al. [48] in Guangxi Province, which found that urban expansion and the rapid development of tourism impact wetlands. In Ao Nang, at Ban Koh Kwang Village to the east and Ban Din Dang Doi Village to the north of Ao Nang, wetlands such as mangrove forests were transformed into urban areas by 2050. However, these changes have put pressure on natural resources and the environment, including encroachment on protected forests and national parks, as well as water pollution and waste from tourism activities. This has led the government to implement measures to regulate and control land use, through the issuance of ministerial regulations and local ordinances, to prevent and control the impacts of uncontrolled development.

In addition to the CA-Markov model results showing the proportion and area of future land use in Ao Nang, this research investigated future land use changes using the Change Detection method in the Tabulate area analysis function in the GIS. This differs from the research by Matlhodi et al. [49], Fu et al. [50], and Atef et al. [51], which did not utilize the Change Detection technique to compare current and future land use in the form of a transition matrix and land use change maps. This research approach reflects the impact of future land use changes by presenting the data as a spatial database for planning responses to the affected area if it is sensitive to change. This model is useful for sustainable land use planning. The CA-Markov simulation results indicate a drastic surge in urban and built-up areas in Ao Nang, projected to increase by 83.7% (40.32 km^2) by 2050, while forest and agricultural lands face significant depletion. This trend reflects a spatial dynamic far more complex than simple tourism growth. While the tourism

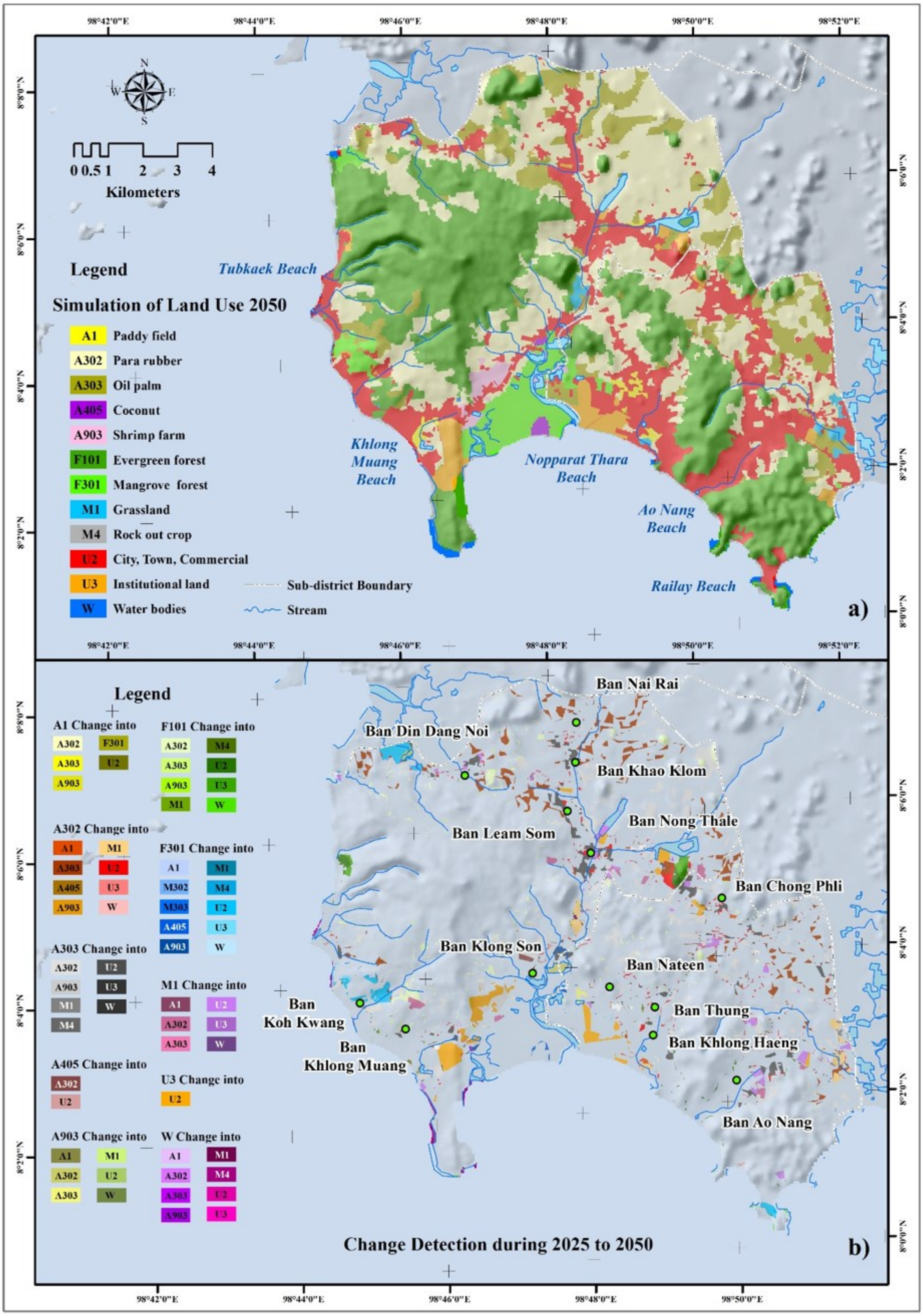

Figure 5. Land use simulation maps in 2050 from (a) CA-markov model simulation and (b) land use change dynamic map during 2025 to 2050 in Ao Nang area, Krabi Province.

industry remains the primary driver for investment in hospitality services, the expansion is accelerated by infrastructure development under Krabi Province's connectivity policies. Improvements in transportation networks linking the city center and the airport to Ao Nang have enhanced the economic potential of formerly remote areas [52]. This has catalyzed land conversion from the low-yield agricultural sector, particularly as volatile prices for rubber and oil palm render local agricultural policies less effective against the high-return allure of real estate development [53]. Furthermore, the influx of non-registered populations and service-sector laborers has intensified the demand for housing and public utilities.

From a land use policy perspective, these projections highlight critical challenges for future urban planning and building control enforcement. Without stringent regulatory measures, the projected 18.78% loss in forest cover may trigger a negative feedback loop, degrading the natural capital that sustains the tourism industry itself. The findings suggest that urban expansion in Ao Nang is the result of a 'synergy' between tourism-driven economic opportunities, provincial strategic development, and the household-level transition from agriculture to services. Consequently, future planning should not merely focus on limiting tourism growth but must prioritize sustainable infrastructure management and the clear demarcation of conservation boundaries. Such measures are essential to balance urban development with the preservation of Krabi's vital natural resource base.

4. CONCLUSIONS

This study successfully achieved its primary objective of projecting land-use changes in Ao Nang over the next 25 years (up to 2050) using the CA-Markov model. The findings highlight a significant trend of urbanization, particularly along key coastlines and primary transportation corridors. The simulation results indicate a drastic expansion of urban and built-up areas, projected to surge by 83.7% (40.32 km^2) by 2050. Conversely, forest cover and agricultural land are expected to decrease steadily by 18.78% and 12.72%, respectively. These spatial insights underscore the urgent need for proactive management of coastal tourism growth. Practically, this research provides crucial evidence for driving Ao Nang's development in alignment with the United Nations SDGs, specifically Goal 11 (Sustainable Cities and Communities) and Goal 15 (Life on Land). The spatial projections serve as a strategic roadmap for stakeholders to plan infrastructure and public utilities in advance, preventing disordered urban sprawl. Furthermore, the quantified forest loss offers empirical support for establishing buffer zones or stringent conservation areas to protect the natural capital essential to Krabi's tourism identity. Integrating these findings into updated urban master plans and land-use policies will be a vital mechanism for balancing economic growth with environmental preservation. Despite its contributions, this study has several limitations that should be considered. First, the use of historical Landsat MSS (1973) imagery, with its coarser spatial resolution, may have introduced minor classification errors in early baseline maps. Second, while the CA-Markov model effectively captures spatial trends based on historical patterns, it does not directly integrate socio-economic drivers, such as population growth rates, Provincial Gross Domestic Product (GDP), or fluctuating tourism statistics. Furthermore, long-term 25-year projections entail inherent uncertainties from external factors, including sudden shifts in urban planning policies, climate change impacts, or global economic crises. Therefore, future research should incorporate multi-dimensional variables that encompass socio-economic and environmental dimensions. Enhancing data resolution and adopting hybrid modeling approaches will further improve predictive accuracy, providing a more robust evidence-based tool for sustainable policy-making in Ao Nang and similar coastal tourism regions.

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Conflicts of Interest

The authors declare no conflict of interest.

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DECLARATION OF GENERATIVE AI

Not applicable .

REFERENCES

[1] Y. Yu, Y. Shen, J. Wang, Y. Wei, L. Nong, and H. Deng. (2021). "Assessing the Response of Vegetation Change to Drought During 2009-2018 in Yunnan Province, China". *Environmental Science and Pollution Research*. **28** : 47066-47082. 10.1007/s11356-021-13835-4.

[2] J. Ma, J. Wang, S. He, J. Zhang, L. Liu, and X. Zhong. (2024). "Direct and Indirect Effects of Urbanization on Vegetation: A Survey of Yunnan Central Urban Economic Circle, China". *Ecological Indicators*. **166** : 112536. 10.1016/j.ecolind.2024.112536.

[3] Y. Liu, Y. Xue, H. Zhao, H. Yao, X. Zhan, S. Suk, L. Wang, and Y. Yuan. (2025). "Coupling Coordination and Spatiotemporal Dynamic Evolution Between Culture and Tourism Industry in Japan". *Scientific Reports*. **15** (1): 7777. 10.1038/s41598-025-88515-1.

[4] A. Ansari and M. H. Golabi. (2019). "Prediction of Spatial Land Use Changes Based on LCM in a GIS Environment for Desert Wetlands: A Case Study of Meighan Wetland, Iran". *International Soil and Water Conservation Research*. **7** (1): 64-70. 10.1016/j.iswcr.2018.10.001.

[5] B. S. Wiwoho, N. McIntyre, and S. Phinn. (2024). "Assessing Future Land Uses Under Planning Scenarios: A Case Study of the Brantas River Basin, Indonesia". *Environmental Challenges*. **15** : 100873. 10.1016/j.envc.2024.100873.

[6] D. Mustelier and C. Henríquez. (2024). "Modeling Land Use Change of Mid-Sized Cities in the Process of Metropolization: Case Study La Serena-Coquimbo Conurbation, Chile". *Geography, Environment, Sustainability*. **17** (2): 106-118. 10.24057/2071-9388-2024-2984.

[7] Y. Huang and Q. Xue. (2024). "Spatio-Temporal Distribution Characteristics and Driving Factors of Traditional Villages in the Yellow River Basin". *PLOS ONE*. **19** (5): e0303396. 10.1371/journal.pone.0303396.

[8] K. Waiyasusri, R. Vangpaisal, and S. Chotpantarat. (2024). "Climate and Land Use Change Impacts on Groundwater Recharge in Prachinburi-Sakaeo Groundwater Basin by Integrating the CA-Markov Model with the WetSpass Model". *Earth Systems and Environment*. **8** (4): 1179-1206. 10.1007/s41748-024-00436-7.

[9] N. A. Veridiano-de Castro, K. J. Almadrones -Reyes, J. C. Redeña-Santos, J. E. Limbo-Dizon, and N. H. A. Dagamac. (2024). "Applying Geomatic Analyses Using Landsat Imagery: Implications for Ecosystem Management in Occidental Mindoro, Philippines". *GeoJournal*. **89** (5): 229. 10.1007/s10708-024-11215-2.

[10] N. Z. Zhensikbayeva, G. Abiyeva, B. T.

Sabyrbayeva, G. A. Avgusthanova, N. K. Kabdrakhmanova, and N. Amangeldy. (2024). "Studying the Development Potential of Tourism Industries in the South Altai by Hydrological, Climatic, Geomorphological Way and Visualization Using GIS". *GeoJournal of Tourism and Geosites.* **53** (2): 528-537. 10.30892/gtg.53216-1228.

[11] H. Nguyen-Quoc, H. H. Thi-Viet, and P. Phan-Van. (2025). "Monitoring Forest Changes in Lowland Hilly Terrain of the Central Highlands of Vietnam Using Landsat Satellite Imagery: A Case Study in Dak Nong Province". *Ecological Engineering and Environmental Technology.* **26** (4). 10.12912/27197050/201330.

[12] B. B. Thien, V. T. Phuong, and A. R. Ioshpa. (2025). "Assessing the Environmental Destruction in Forest Cover Using Landscape Metrics and Spatial Analysis in Quang Nam Province, Vietnam". *Environmental Earth Sciences.* **84** (13): 1-22. 10.1007/s12665-025-12377-z.

[13] Y. An, J. Y. Tsou, K. Wong, Y. Zhang, D. Liu, and Y. Li. (2018). "Detecting Land Use Changes in a Rapidly Developing City During 1990-2017 Using Satellite Imagery: A Case Study in Hangzhou Urban Area, China". *Sustainability.* **10** (9): 3303. 10.3390/su10093303.

[14] M. Yılmaz and F. Terzi. (2020). "Characteristics of Spatio-Temporal Urban Growth Patterns Due to the Driving Forces of Urbanization: The Coastal City of Antalya, Turkey". *International Review for Spatial Planning and Sustainable Development.* **8** (3): 16-33. 10.14246/irspsd.8.3_16.

[15] M. Ranagalage, T. Morimoto, M. Simwanda, and Y. Murayama. (2021). "Spatial Analysis of Urbanization Patterns in Four Rapidly Growing South Asian Cities Using Sentinel-2 Data". *Remote Sensing.* **13** (8): 1531. 10.3390/rs13081531.

[16] A. Lagarias and A. Stratigea. (2023). "Coastalization Patterns in the Mediterranean: A Spatiotemporal Analysis of Coastal Urban Sprawl in Tourism Destination Areas". *GeoJournal.* **88** (3): 2529-2552. 10.1007/s10708-022-10756-8.

[17] Y. Huang, T. Chen, D. Hu, T. Lin, W. Zhu, G. Zhang, and X. Xue. (2023). "Spatiotemporal Patterns and Influencing Factors of Urban Ecological Space Availability in Coastal Cities of China During Rapid Urbanization". *Ecological Indicators.* **154** : 110757. 10.1016/j.ecolind.2023.110757.

[18] B. Dahy, M. Al-Memari, A. Al-Gergawi, and J. A. Burt. (2024). "Remote Sensing of 50 Years of Coastal Urbanization and Environmental Change in the Arabian Gulf: A Systematic Review". *Frontiers in Remote Sensing.* **5** : 1422910. 10.3389/frsen.2024.1422910.

[19] S. Saadani, R. Laajaj, M. Maanan, H. Rhinane, and A. Aaroud. (2020). "Simulating Spatial-Temporal Urban Growth of a Moroccan Metropolitan Using CA-Markov Model". *Spatial Information Research.* **28** : 609-621. 10.1007/s41324-020-00322-0.

[20] L. Zhu, R. Song, S. Sun, Y. Li, and K. Hu. (2022). "Land Use/Land Cover Change and Its Impact on Ecosystem Carbon Storage in Coastal Areas of China from 1980 to 2050". *Ecological Indicators.* **142** : 109178. 10.1016/j.ecolind.2022.109178.

[21] L. Lu, S. Qureshi, Q. Li, F. Chen, and L. Shu. (2022). "Monitoring and Projecting Sustainable Transitions in Urban Land Use Using Remote Sensing and Scenario-Based Modelling in a Coastal Megacity". *Ocean and Coastal Management.* **224** : 106201. 10.1016/j.ocecoaman.2022.106201.

[22] C. E. Dumdumaya and J. S. Cabrera. (2023). "Determination of Future Land Use Changes Using Remote Sensing Imagery and Artificial Neural Network Algorithm: A Case Study of Davao City, Philippines". *Artificial Intelligence in Geosciences.* **4** : 111-118. 10.1016/j.aiig.2023.08.002.

[23] P. Pongsakornrungsilp and S. Pongsakornrungsilp. (2023). "Mindful Tourism: Nothing Left Behind-Creating a Circular Economy Society for the Tourism Industry of Krabi, Thailand". *Journal of Tourism Futures.* **9** (3): 366-380. 10.1108/JTF-01-2021-0001.

[24] P. Pongsakornrungsilp, S.

Pongsakornrungsilp, A. Jansom, and S. Chinchanachokchai. (2022). "Rethinking Sustainable Tourism Management: Learning from the COVID-19 Pandemic to Co-Create the Future of Krabi Tourism, Thailand". *Sustainability.* **14** (18): 11375. 10.3390/su141811375.

[25] F. Koch and K. Krellenberg. (2018). "How to Contextualize SDG 11? Looking at Indicators for Sustainable Urban Development in Germany". *ISPRS International Journal of Geo-Information.* **7** (12): 464. 10.3390/ijgi7120464.

[26] M. Al-Raeei. (2024). "Artificial Intelligence for Climate Resilience: Advancing Sustainable Goals in SDGs 11 and 13 and Its Relationship to Pandemics". *Discover Sustainability.* **5** (1): 513. 10.1007/s43621-024-00775-5.

[27] S. Liu, J. Bai, and J. Chen. (2019). "Measuring SDG 15 at the County Scale: Localization and Practice of SDGs Indicators Based on Geospatial Information". *ISPRS International Journal of Geo-Information.* **8** (11): 515. 10.3390/ijgi8110515.

[28] K. Peng, W. Jiang, Z. Ling, P. Hou, and Y. Deng. (2021). "Evaluating the Potential Impacts of Land Use Changes on Ecosystem Service Value Under Multiple Scenarios in Support of SDG Reporting: A Case Study of the Wuhan Urban Agglomeration". *Journal of Cleaner Production.* **307** : 127321. 10.1016/j.jclepro.2021.127321.

[29] G. Zhang, T. Yao, H. Xie, K. Zhang, and F. Zhu. (2014). "Lakes' State and Abundance Across the Tibetan Plateau". *Chinese Science Bulletin.* **59** : 3010-3021. 10.1007/s11434-014-0258-x.

[30] T. D. H. Le and L. T. Vinh. (2025). "Applying Random Forest and Support Vector Machine for Land-Use Classification in Phu Giao District, Vietnam". *Applied Environmental Research.* **47** (2): 016. 10.35762/AER.2025016.

[31] V. F. Sales, D. C. Zanotta, A. Marques Jr, G. Racolte, M. Muller, C. L. Cazarin, D. Ibanez, L. Gonzaga Jr, and M. R. Veronez. (2023). "An Adaptive Spectral Index for Carbonate Rocks Using OLI Landsat-8 Imagery". *Geocarto International.* **38** (1): 2179671. 10.1080/10106049.2023.2179671.

[32] Y. Du, P. M. Teillet, and J. Cihlar. (2002). "Radiometric Normalization of Multitemporal High-Resolution Satellite Images with Quality Control for Land Cover Change Detection". *Remote Sensing of Environment.* **82** (1): 123-134. 10.1016/S0034-4257(02)00029-9.

[33] S. Hantson and E. Chuvieco. (2011). "Evaluation of Different Topographic Correction Methods for Landsat Imagery". *International Journal of Applied Earth Observation and Geoinformation.* **13** (5): 691-700. 10.1016/j.jag.2011.05.001.

[34] K. Phinzi, N. S. Ngetar, Q. B. Pham, G. G. Chakilu, and S. Szabó. (2023). "Understanding the Role of Training Sample Size in the Uncertainty of High-Resolution LULC Mapping Using Random Forest". *Earth Science Informatics.* **16** (4): 3667-3677. 10.1007/s12145-023-01117-1.

[35] V. F. Rodriguez-Galiano, B. Ghimire, J. Rogan, M. Chica-Olmo, and J. P. Rigol-Sanchez. (2012). "An Assessment of the Effectiveness of a Random Forest Classifier for Land-Cover Classification". *ISPRS Journal of Photogrammetry and Remote Sensing.* **67** : 93-104. 10.1016/j.isprsjprs.2011.11.002.

[36] C. Avci, M. Budak, N. Yağmur, and F. Balçık. (2023). "Comparison Between Random Forest and Support Vector Machine Algorithms for LULC Classification". *International Journal of Engineering and Geosciences.* **8** (1): 1-10. 10.26833/ijeg.987605.

[37] A. A. Jamali, A. Behnam, S. A. Almodaresi, S. He, and A. Jaafari. (2024). "Exploring Factors Influencing Urban Sprawl and Land-Use Changes Analysis Using Systematic Points and Random Forest Classification". *Environment, Development and Sustainability.* **26** (5): 13557-13576. 10.1007/s10668-023-03633-y.

[38] G. M. Foody. (2020). "Explaining the Unsuitability of the Kappa Coefficient in the Assessment and Comparison of the Accuracy of Thematic Maps Obtained by Image

Classification". *Remote Sensing of Environment.* **239** : 111630. 10.1016/j.rse.2019.111630.

[39] F. Chaaban, J. El Khattabi, and H. Darwishe. (2022). "Accuracy Assessment of ESA WorldCover 2020 and ESRI 2020 Land Cover Maps for a Region in Syria". *Journal of Geovisualization and Spatial Analysis.* **6** (2): 31. 10.1007/s41651-022-00126-w.

[40] K. Jia, S. Liang, L. Zhang, X. Wei, Y. Yao, and X. Xie. (2014). "Forest Cover Classification Using Landsat ETM+ Data and Time Series MODIS NDVI Data". *International Journal of Applied Earth Observation and Geoinformation.* **33** : 32-38. 10.1016/j.jag.2014.04.015.

[41] D. Guan, H. Li, T. Inohae, W. Su, T. Nagaie, and K. Hokao. (2011). "Modeling Urban Land Use Change by the Integration of Cellular Automaton and Markov Model". *Ecological Modelling.* **222** (20-22): 3761-3772. 10.1016/j.ecolmodel.2011.09.009.

[42] M. Jafari, H. Majedi, S. M. Monavari, A. A. Alesheikh, and M. K. Zarkesh. (2016). "Dynamic Simulation of Urban Expansion Through a CA-Markov Model: Case Study of the Hyrcanian Region, Gilan, Iran". *European Journal of Remote Sensing.* **49** (1): 513-529. 10.5721/EuJRS20164927.

[43] C. Xu, X. Hu, Z. Liu, X. Wang, J. Tian, and Z. Zhao. (2023). "Predicting the Evolution Trend of Water and Land Resource Carrying Capacity Based on CA-Markov Model in an Arid Region of Northwest China". *Sustainability.* **15** (2): 1269. 10.3390/su15021269.

[44] S. Adhikari and J. Southworth. (2012). "Simulating Forest Cover Changes of Bannerghatta National Park Based on a CA-Markov Model: A Remote Sensing Approach". *Remote Sensing.* **4** (10): 3215-3243. 10.3390/rs4103215.

[45] A. Butt, R. Shabbir, S. S. Ahmad, and N. Aziz. (2015). "Land Use Change Mapping and Analysis Using Remote Sensing and GIS: A Case Study of Simly Watershed, Islamabad, Pakistan". *The Egyptian Journal of Remote Sensing and Space Science.* **18** (2): 251-259. 10.1016/j.ejrs.2015.07.003.

[46] M. Mohajane, A. Essahlaoui, F. Oudija, E. Hafyani, A. Hmaidi, E. A. Ouali, G. Randazzo, and A. C. Teodoro. (2018). "Land Use/Land Cover (LULC) Using Landsat Data Series (MSS, TM, ETM+, and OLI) in Azrou Forest, in the Central Middle Atlas of Morocco". *Environments.* **5** (12): 131. 10.3390/environments5120131.

[47] C. Qian, H. Qiang, C. Qin, Z. Wang, and M. Li. (2022). "Spatiotemporal Evolution Analysis and Future Scenario Prediction of Rocky Desertification in a Subtropical Karst Region". *Remote Sensing.* **14** (2): 292. 10.3390/rs14020292.

[48] Z. Zhang, B. Hu, W. Jiang, and H. Qiu. (2021). "Identification and Scenario Prediction of Degree of Wetland Damage in Guangxi Based on the CA-Markov Model". *Ecological Indicators.* **127** : 107764. 10.1016/j.ecolind.2021.107764.

[49] B. Matlhodi, P. K. Kenabatho, B. P. Parida, and J. G. Maphanyane. (2021). "Analysis of Future Land Use Land Cover Changes in the Gaborone Dam Catchment Using CA-Markov Model: Implications on Water Resources". *Remote Sensing.* **13** (13): 2427. 10.3390/rs13132427.

[50] F. Fu, S. Deng, D. Wu, W. Liu, and Z. Bai. (2022). "Research on the Spatiotemporal Evolution of Land Use Landscape Pattern in a County Area Based on CA-Markov Model". *Sustainable Cities and Society.* **80** : 103760. 10.1016/j.scs.2022.103760.

[51] I. Atef, W. Ahmed, and R. H. Abdel-Maguid. (2024). "Future Land Use Land Cover Changes in El-Fayoum Governorate: A Simulation Study Using Satellite Data and CA-Markov Model". *Stochastic Environmental Research and Risk Assessment.* **38** (2): 651-664. 10.1007/s00477-023-02592-0.

[52] Y. Cui, R. Zhao, L. Jiang, X. Duan, M. Xiao, Z. Liu, L. Wang, X. Duan, and S. Teerarojanarat. (2025). "What Drives Nighttime Tourism Intensity in Thailand? Evidence from Thai Attractions Based on Satellite Observations". *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing.* **18** : 6086-

6095. 10.1109/JSTARS.2025.3535790.

[53] N. Kaswiset, P. Panklang, P. Thaler, G. Le Maire, and A. Thoumazeau. (2026). "Oil Palm Spreads, but Rubber Still There—Mapping the Continuous but Slow Changes of Plantation Areas in Southern Thailand". *Regional Environmental Change.* **26** : 24. 10.1007/s10113-026-02524-y.