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Government Policy Influence on Land Use and Land Cover Changes: A 30-Year Analysis

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Abstract

This study investigated land use and land cover (LULC) patterns and changes in the Bandon Bay area of Thailand from 1991 to 2021 using satellite imagery, the first comprehensive effort to assess historical LULC trends over the past 30 years and forecast future LULC scenarios using the CA-Markov model for 2031, 2041, and 2051. Results showed the predominant LULC during 1991-2001 was the abandoned paddy fields, and during 2006-2021 was the oil palm plantations. During 1991-2001, the abandoned paddy fields changed significantly, with a net gain of 59.28 km^2. From 2001-2011 and 2011-2021, the oil palm plantations experienced the most crucial change, with a net gain of 292.94 km^2 and 70.06 km^2. In 2031, 2041, and 2051, the LULC was predicted to be oil palms, shrimp farms, mangroves, and urban and built-up lands. The LULC changes were consistent with the government policies implemented and indicated government policy as a driving force in LULC dynamics on Bandon Bay area forestry, aquaculture, and agriculture, particularly on oil palm cultivation. Government management and regulation on land use is crucial for reducing the expansion of agricultural areas, especially oil palm plantations and aquaculture areas, to mitigate negative impacts on the Bandon Bay ecosystem.

Keywords:

LULC Change;

Bandon Bay;

Remote Sensing;

Geographic Information System.

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1- Introduction

Land use and land-over land (LULC) classification is a dynamic and multifaceted process driven by a complex interplay of natural and anthropogenic factors. Socioeconomic forces like population increase, urban sprawl, and industrial growth fuel land-use intensification, potentially leading to accelerated LULC changes and subsequent ecological repercussions such as habitat fragmentation and ecosystem service decline [1]. Land use transition results from complicated interactions among regional conditions, economic and social development, and government policies [2]. Various public policies have contributed to the change in LULC classes [3]. Social and economic development conditions are intricately linked with land use policies, which manifest through human activities such as deforestation [4, 5], plantation [6, 7], duration [8], etc. Transitions in LULC classes have been demonstrably linked to environmental degradation, such as biodiversity decline [9], diminished air quality [10], altered water quality [11], habitat loss for terrestrial and aquatic species [12], human settlement, and other factors.

A recent approach to track LULC classes is through the use of satellite imagery. Satellites could document images, provide comprehensive coverage, and display multiband and multi-resolution images so that the data covers the past and

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present. Spatiotemporal analysis of LULC changes using historical data is crucial for developing informed and sustainable LULC management plans for the future. LULC change analysis provides a robust methodology for quantifying human influence on land use practices' magnitude, spatial patterns and ecosystem dynamics. In recent years, the assessment and modeling of LULC change have been critical key aspects as LULC change influences socio-economic and environmental structures [13]. Monitoring changes in LULC is crucial in supporting efficient LULC decision-making in LULC management [14, 15].

Bandon Bay is a critical coastal embayment in Surat Thani Province, Thailand. The bay's extensive coastline stretches approximately 120 km, encompassing 695.32 km^2 [16]. Notably, the bay exhibits shallow bathymetry, with depths ranging from one to five meters [17]. The Tapi River serves as the primary freshwater source for the bay, with a network of smaller canals further enriching the aquatic ecosystem. Bandon Bay plays a vital ecological role as a fishery, spawning ground, and nursery for various marine life [18]. The bay's economic significance stems from its abundance of commercially valuable shellfish species, including blood cockles, mussels, and oysters. Surat Thani Province, with Bandon Bay as a critical contributor, represents Thailand's second-largest producer of shellfish farming, with an annual yield of 11,381.18 tons in 2021, valued at 1.08 billion Baht [19]. Furthermore, Bandon Bay is recognized as a significant source of blue swimming crabs in Thailand. According to the Fisheries Development Policy and Planning Division [20], the bay's blue swimming crab fishery yielded an estimated 703 tons in 2021, with an economic value of 130.19 billion Baht.

A time series analysis of ecological and environmental changes in Bandon Bay was conducted, dividing the study period into three intervals: pre-development (before 1961), development (1961-2001), and the contemporary period (2002-present) [21]. During the pre-development phase, the community structure exhibited autonomous ecological system characteristics by the villagers practicing a subsistence livelihood strategy, relying on agricultural production, small-scale horticulture, and nearshore fisheries to meet their basic needs. After the pre-development period, government policy shifts were observed. During the 1961-2001 intervals, private entities were granted concessions to harvest timber from mangrove ecosystems restricted to designated zones [21]. However, anthropogenic pressure intensified as these concessions triggered incursions into adjacent mangrove stands for shrimp aquaculture establishments. Driven by the high profitability of shrimp aquaculture, a rapid expansion was observed during this period. This intensification coincided with a 1987 governmental policy shift promoting shrimp farming for export. This policy change resulted in expanding shrimp farming areas into mangrove forests. Subsequently, shrimp farming production witnessed a significant increase from 1997-2002 [21]. Economic considerations, including declining shrimp market prices and escalating aquaculture input costs, resulted in the cessation of shrimp farming activities by smaller-scale operations during the contemporary period (2002-present) [21]. These economic pressures led to financial losses and debt accumulation, rendering shrimp farming unsustainable for these entities. Conversely, large, privately owned shrimp aquaculture enterprises possessed the financial resources to navigate these economic challenges and continue production.

The Ocean Food Bank Project was implemented in 2002 following this economic shift. This initiative aimed to promote the cultivation of cockles as an alternative aquaculture practice with the potential for increased financial and ecological sustainability. As a result, Bandon Bay has been occupied for raising cockles since then [21]. Concurrently, additional governmental policies have demonstrably influenced LULC changes within the Bandon Bay region. Notably, the strategic framework implemented by the oil palm industry from 2004 to 2029 underscores a focus on transitioning towards a global export-oriented production model, emphasizing supplying Malaysia and Indonesia. Additionally, this strategy emphasizes the development of the industry as a sustainable source of domestic energy [22, 23]. In late 2005, Thailand established a national strategy to promote and develop palm biodiesel as a biofuel alternative [22, 23]. The policy prioritized advancements in rural agriculture, potentially expanding the nation's agricultural exports [24-26].

Past studies have shown problems with community wastewater and shrimp farming in the Bandon Bay area [18, 27]. These problems are due to poor seawater quality, microplastic spread in surface seawater [28], and heavy metal contamination in marine sediment [29]. These issues impact aquatic animals, as shown by the contamination of heavy metal and fecal coliform bacteria found in cockles and oysters [30, 31]. To ensure sustainable development, we need to analyze the past, current, and predicted changes in LULC driven by economic and social forces. Existing research on LULC changes in Bandon Bay and surrounding areas needs to be revised and updated. Previous studies have investigated LULC changes across the following years: 1990, 1993, 1996, and 1999 [32]; 1994, 2001, 2005, and 2017 [33]; 2007 [34]; 2000, 2009, and 2012 [25]; 2000, 2009, and 2016 [26]; and 2001, 2007, and 2011 [35]. This research is the first comprehensive effort to assess historical Land Use/Land Cover (LULC) trends over the past 30 years and forecast future LULC scenarios in Bandon Bay. Understanding these trends would inform the development of a sustainable management plan for Bandon Bay, mitigating negative environmental consequences. The study objectives are (i) to investigate the LULC classes in 1991, 1996, 2001, 2006, 2011, 2016, and 2021; (ii) to study the change in LULC in 1991-2001, 2001-2011, and 2011-2021; and (iii) to forecast LULC classes for 2031, 2041, and 2051 by using the CA-Markov model. The research methodology schema is outlined in Figure 1.

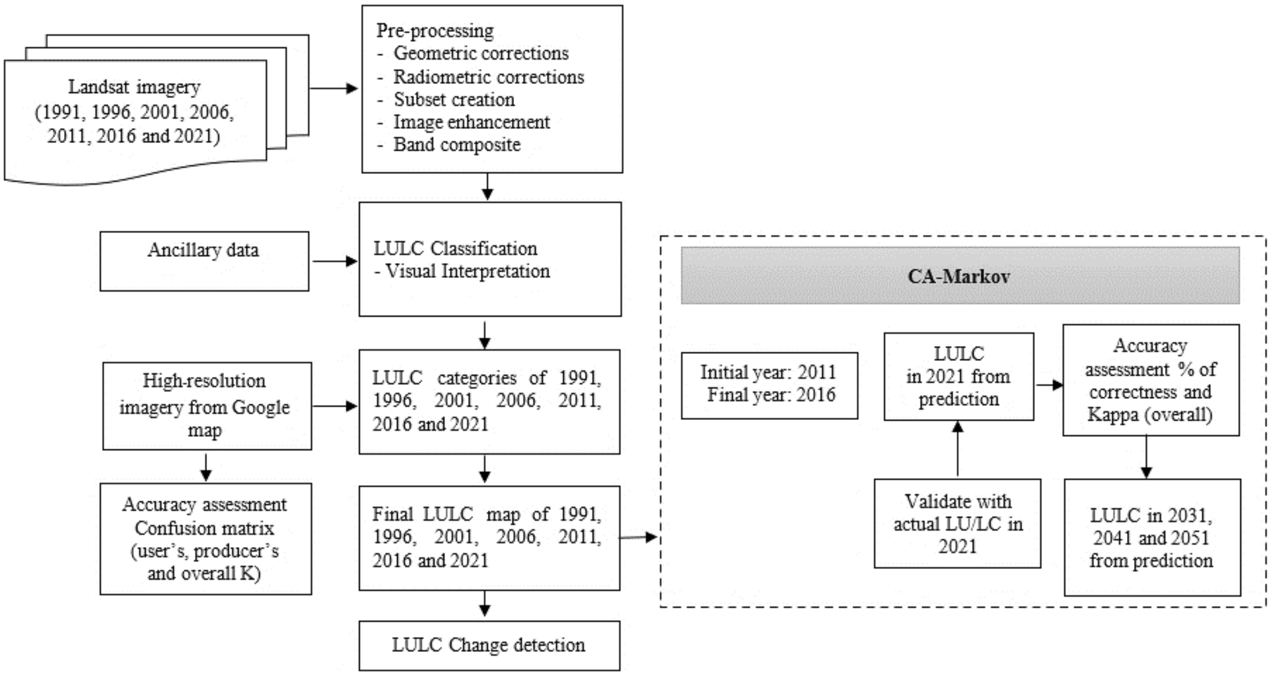
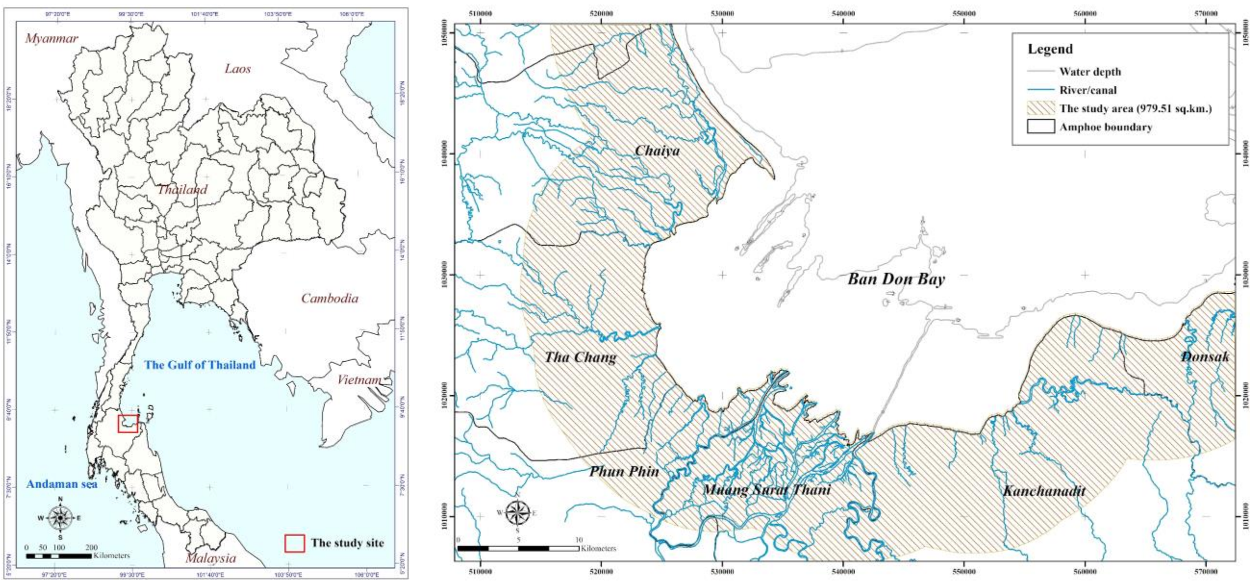


Figure 1. **Research methodology schema**

2- Material and Methods

2-1- Study Area

This study was conducted within a 10-km coastal buffer zone surrounding Bandon Bay, Surat Thani, Thailand (Figure 2A, B). The study area is situated along the Gulf of Thailand coastline (latitude 9°06′–9°30′ N; longitude 99°05′- 99°39′ E). This region comprises six districts: Chaiya, Tha Chang, Phun Phin, Muang Surat Thani, Kanchanadit, and Don Sak. The total area encompassed by the study site measures 979.51 km^2. Bandon Bay experiences a tropical monsoon climate regime characterized by alternating wet and dry seasons driven by the interplay of the southwest and northeast monsoon winds. The southwest monsoon, originating from the Indian Ocean, delivers moisture-laden air masses to the region, resulting in widespread precipitation events between mid-May and mid-October. Conversely, the northeast monsoon, dominant over Thailand from mid-October to mid-February, brings cooler temperatures to the Bandon Bay area. However, precipitation persists during this period, with November experiencing the highest rainfall. The annual temperature in Bandon Bay exhibits a range of 23.2-32.9°C, with a mean annual temperature of 27.1°C. Yearly precipitation averages 1,669.8 mm [36].



(A) (B)

Figure 2. **Location of the study site within Thailand. (A) Map of Thailand highlighting Bandon Bay (red) and (B) An enlarged view of Bandon Bay encompasses the six administrative districts: Chaiya, Tha Chang, Phun Phin, Mueang Surat Thani, Kanchanadit, and Donsak.**

2-2- Satellite Data and Criteria

This study leveraged multispectral imagery acquired by Landsat satellites for LULC classification. This analysis utilized bands 3, 4, and 5 from the Landsat 5 Thematic Mapper (TM) sensor and bands 4, 5, and 6 of the Landsat 8 Operational Land Imager (OLI) sensor. Landsat imagery was acquired from the USGS Earth Explorer data portal (https://earthexplorer.usgs.gov/) for 1991, 1996, 2001, 2006, 2011, 2016, and 2021. Landsat 5 TM and Landsat 8 OLI sensors have a spatial resolution of 30 m. Following the acquisition, all Landsat scenes for path/row 129/054 were subjected to a rigorous geometric correction process to ensure spatial accuracy. The data underwent re-projection to the Universal Transverse Mercator (UTM) coordinate system; precisely, Zone 47 North referenced the WGS-84 datum. To improve classification accuracy and aid in visual interpretation, high-resolution imagery from Google Earth, existing land-use data, and topographical maps were utilized as ancillary data sources.

2-3- Data Processing and Analysis

2.3.1. Data Collection

Landsat images for 1991, 1996, 2001, 2006, 2011, 2016, and 2021 were used to classify the LULC classes and create LULC maps. Before image classification, pre-processing steps were implemented, including geometric and radiometric corrections, image sub-setting, and potential image enhancement techniques [37]. Bandon Bay is mainly covered with evergreen forests, mangroves, rubber trees, and oil palms. Based on the pre-processed imagery, false-color composite images were generated using specific band combinations: band combination RGB (4, 5, 3) for Landsat 5 TM and band combination RGB (5, 6, 4) for Landsat 8 OLI. These band combinations were chosen to enhance the visual discrimination of LULC classes [38].

2.3.2. LULC Classification and Accuracy Assessment

The visual interpretation was used to classify satellite images. Like aerial photography, satellite image interpretation leverages fundamental visual interpretation elements for feature recognition: shape, size, spatial pattern, spectral response (color/ton), texture, shadows, geospatial context, and spatial association. It is based on training, field experience, geographical knowledge, observation, and the interpreter's patience. While acknowledged as a time-intensive methodology, visual interpretation offers distinct advantages. It is a flexible approach that excels at extracting spatial information from imagery and has been demonstrated to achieve high classification accuracy [39]. Following a LULC classification scheme established by the Land Development Department of Thailand, the study categorized the imagery into 14 distinct classes as follows: (1) Urban and built-up lands (U), (2) Abandoned paddy fields (A100), (3) Active paddy fields (A101), (4) Perennial crop (A3), (5) Para rubber (A302), (6) Oil palms (A303), (7) Orchards (A4), (8) Abandoned aqua-cultural lands (A900), (9) Shrimp farms (A903), (10) Evergreen forests (F1), (11) Mangrove forests (F3), (12) Swamp forests (F4), (13) Water bodies (W), and (14) Miscellaneous lands (M). Evaluating classification accuracy is a critical step to ensure the reliability of LULC maps. The last step in the classification process was to assess accuracy. The current method compares random points with the Google Earth engine [40, 41]. For accuracy assessment, a reference dataset of ground-truth points was acquired from Google Earth to evaluate the number of correctly classified land-cover pixels [42]. Agreement between the classified map and reference data was quantified using accuracy assessment metrics derived from a random point-based error matrix. Overall accuracy, producer's accuracy, user's accuracy, and Kappa coefficient were calculated [43]. The Kappa coefficient indicated a high level of agreement between the classified map and reference data, exceeding 0.81 [44].

2.3.3. LULC Change Analysis

LULC change dynamics were quantified by calculating area gains, net changes, and losses for various categories using a simple overlay technique of ArcGIS 9.2. The overlay technique, which combines multiple layers into a single map, can also detect changes in LULC between two specific years [45]. This study classified maps in 1991, 2001, 2011 and 2021 enabled spatiotemporal analysis of LULC change patterns across three decades (1991-2001, 2001-2011, 2011-2021) [46] and provided an overview of changes spanning 30 years (1991-2021).

2.3.4. LULC Prediction

The CA-Markov model has emerged as a powerful tool for analyzing and predicting LULC dynamics [47], including agriculture [48] and urban expansion [49]. CA-Markov models offer several advantages when studying LULC changes such as integration of spatial and temporal dynamics, long term predictions, ease of use, scenario analysis and flexibility. CA-Markov models have two key limitations: reliance on past trends and data dependence. The Markov chain model has been established as a valuable quantitative tool for predicting LULC change trajectories

[40]. The CA-Markov model leverages the strengths of both CA and Markov chains to spatially simulate and predict LULC class transitions and their characteristics over time [50]. Predicting future LULC changes using historical data (e.g., CA-Markov) informs policy and planning [44]. The CA-Markov module in the Quantum GIS software (Version 2.18.23) was used to predict LULC for 2031, 2041, and 2051. This study selected the 2031, 2041, and 2051 projections to intentionally be consistent with Surat Thani's 20-year Provincial Development Plan (2017-2036). It had to be validated before the model could project LULC classes for 2031, 2041, and 2051. This study used LULC maps in 2011 as the baseline and LULC maps in 2016 as the final year to project LULC classes in 2021. Model validation was achieved by comparing the interpreted 2021 LULC map derived from reference data with the corresponding LULC map predicted by the model for 2021. Kappa validation (≥ 0.81 suggests near-perfect agreement) [44] supports the model's use for future LULC projections.

3- Results

3-1- Image Classification and Analysis

The accuracy assessment generated a confusion/error matrix for each LULC class. High-resolution satellite imagery from Google Earth Pro, acquired in 2006, 2011, 2016, and 2021, was used to collect ground truth data for map generation. The analysis revealed that the total accuracy ranged from 89.32-95.74%, and the Kappa coefficient (K) ranged from 0.87-0.95. Our results (Table 1, Figure 3 and 4) showed that between 1991 and 2001, most of the LULC classes in the Bandon Bay area were abandoned paddy fields, and there was an increasing trend over time. Abandoned paddy fields covered 214.52 km^2 in 1991, 229.70 km^2 in 1996, and 273.8 km^2 in 2001. From 2006 to 2021, most LULCs in the Bandon Bay area were oil palm plantations. It covered an area of approximately 323.20 km^2 in 2006, 329.6 km^2 in 2011, 345.9 km^2 in 2016, and 400.31 km^2 in 2021. Abandoned paddy fields significantly decreased area coverage, declining from 47.31 km^2 to 18.9 km^2 between 2006 and 2021. The abandoned paddy fields increased between 1996 and 2001 from 214.52 km^2 to 273.80 km^2. Since 2006, the area of abandoned rice fields has been decreasing dramatically. The area of active paddy fields has declined steadily since 1996-2021, from 142.92 km^2 to 8.23 km^2. Mangroves decreased between 1991 and 2011 from 106.03 km^2 to 79.52 km^2; between 2016 and 2021, the mangrove area increased from 89.88 km^2 to 94.91 km^2. As for the shrimp farming area, they increased from 1991 to 2001 (104.98 km^2 to 144.40 km^2). After that, in 2006-2021, the trend decreased from 104.72 km^2 to 96.83 km^2. 1991-2011, the Para rubber area increased from 104.02 km^2 to 151.94 km^2. After that, between 2016 and 2021, the area decreased from 148.12 km^2 to 140.46 km^2.

Table 1. Total area cover and the percentage of LULC classes in Bandon Bay, Thailand, from 1991 to 2021

LULC classes	1991		1996		2001		2006		2011		2016		2021	
	Area (km^2)	%	Area (km^2)	%	Area (km^2)	%	Area (km^2)	%	Area (km^2)	%	Area (km^2)	%	Area (km^2)	%
Urban and built-up land (U)	39.48	4.03	50.23	5.13	50.89	5.20	75.09	7.67	79.54	8.12	83.97	8.57	86.35	8.82
Abandoned paddy field (A100)	214.52	21.90	229.7	23.45	273.80	27.95	47.31	4.83	37.70	3.85	27.12	2.77	18.9	1.93
Active paddy field (A101)	142.92	14.59	76.48	7.81	23.60	2.41	20.89	2.13	11.94	1.22	12.17	1.24	8.23	0.84
Perennial crop (A3)	0.93	0.09	0.81	0.08	0.82	0.08	8.92	0.91	8.43	0.86	8.14	0.83	5.94	0.61
Para rubber (A302)	104.02	10.62	125.81	12.84	125.98	12.86	150.35	15.35	151.94	15.51	148.12	15.12	140.46	14.34
Oil palm (A303)	25.54	2.61	36.79	3.76	37.16	3.79	323.20	33.00	330.10	33.70	345.90	35.31	400.16	40.85
Orchard (A4)	96.21	9.82	95.57	9.76	92.10	9.40	52.81	5.39	57.85	5.91	52.49	5.36	40.72	4.16
Abandoned aquaculture land (A900)	2.17	0.22	10.59	1.08	9.45	0.97	21.16	2.16	24.52	2.50	20.41	2.08	10.33	1.05
Shrimp farm (A903)	104.98	10.72	132.97	13.58	144.40	14.74	104.72	10.69	106.39	10.86	101.60	10.37	96.83	9.89
Evergreen forest (F1)	9.72	0.99	9.27	0.95	9.41	0.96	7.39	0.75	8.65	0.88	7.38	0.75	8.62	0.88
Mangrove forest (F3)	106.03	10.83	94.91	9.69	95.12	9.71	88.95	9.08	79.52	8.12	89.88	9.18	94.91	9.69
Swamp forest (F4)	5.27	0.54	4.59	0.47	4.85	0.50	1.10	0.11	0.86	0.09	1.17	0.12	0.86	0.09
Water body (W)	27.94	2.85	27.84	2.84	27.86	2.84	30.49	3.11	27.82	2.84	30.54	3.12	27.8	2.84
Miscellaneous land (M)	99.78	10.19	83.95	8.57	84.07	8.58	47.13	4.81	54.25	5.54	50.60	5.17	39.4	4.02
Total	979.51	100	979.51	100	979.51	100	979.51	100	979.51	100	979.51	100	979.51	100

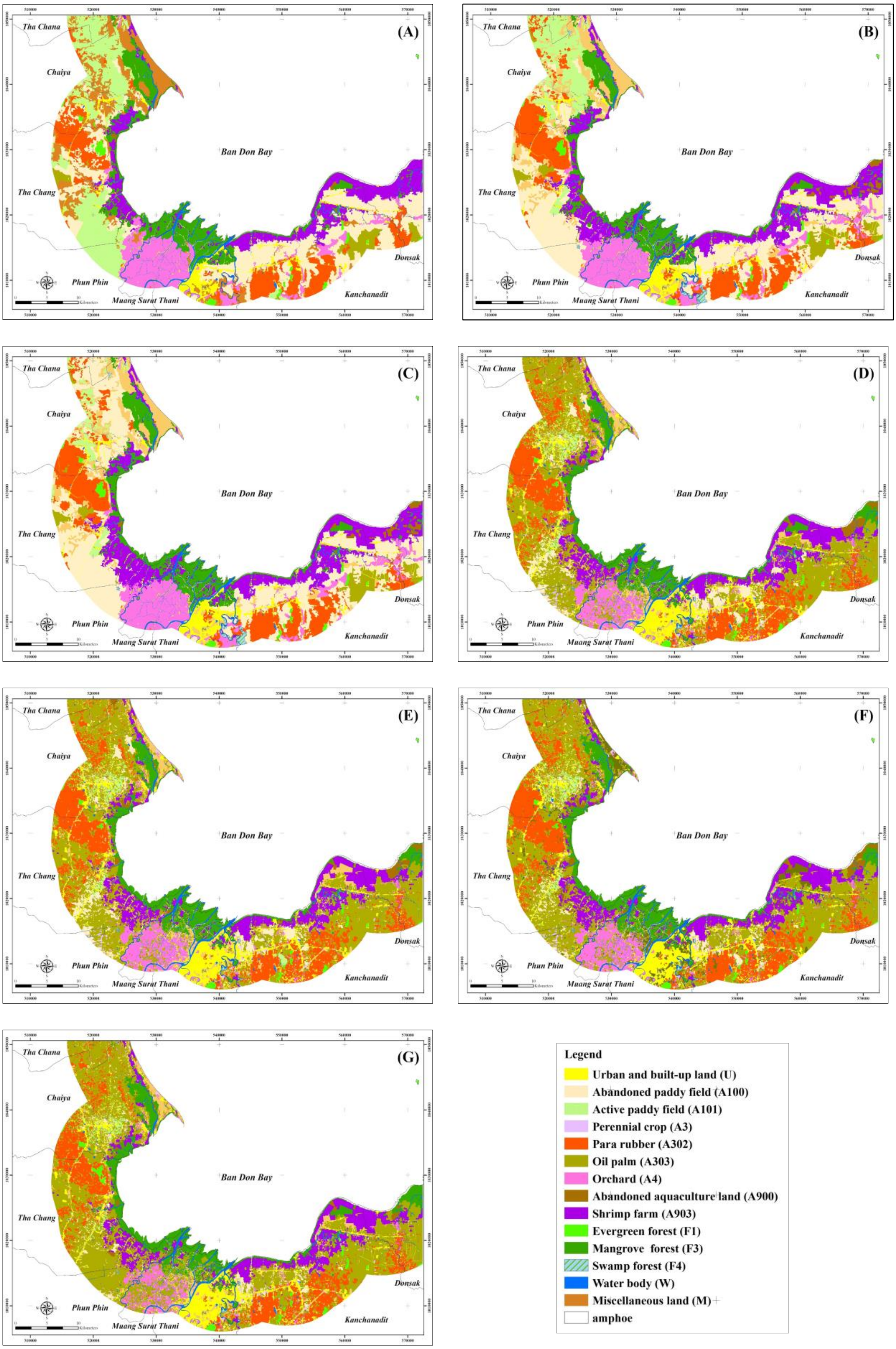


Figure 3. LULC classes in Bandon Bay, Thailand (A: 1991, B: 1996, C: 2001, D: 2006, E: 2011, F: 2016, and G: 2021)

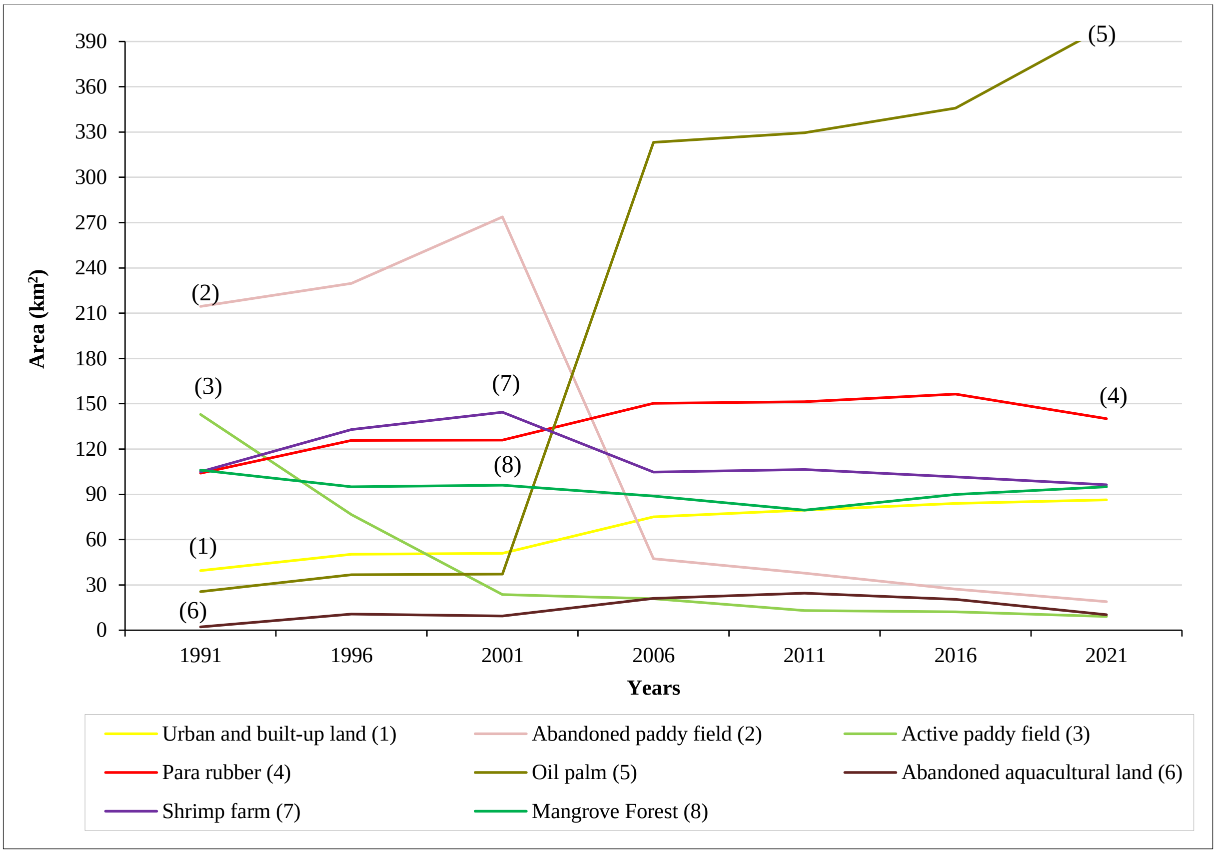


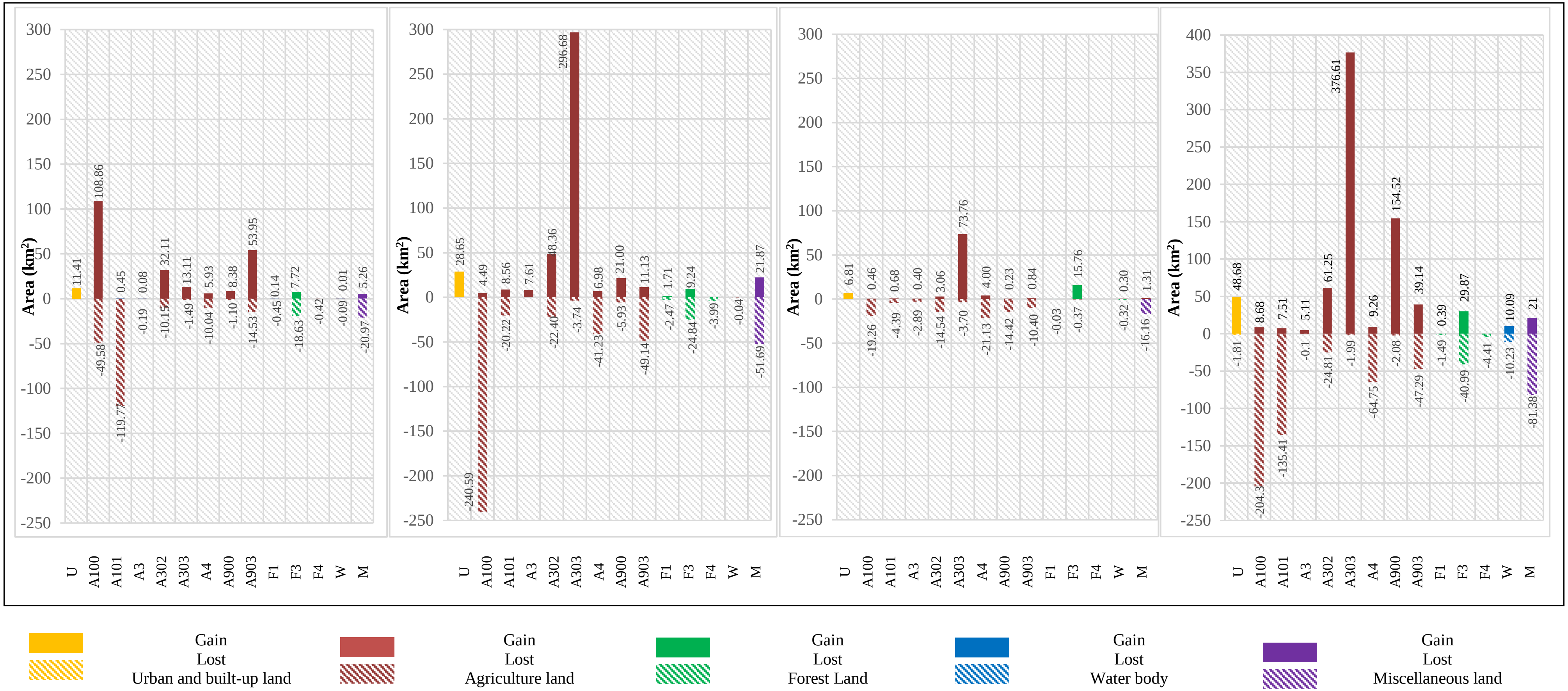
Figure 4. **Trends in LULC classes in the Bandon Bay area, Thailand, from 1991 to 2021**

3-2- LULC Change Detection

In 1991-2001, one of the significant LULC classes in Bandon Bay was the abandoned paddy fields, which substantially increased over this decade. The area of abandoned paddy fields had lost 49.58 km^2 and gained 108.86 km^2, with a net gain of 59.28 km^2 (Figure 5). Active paddy fields had significantly lost 119.77 km^2 and gained 0.45 km^2, with a net loss of 119.32 km^2. About 108.86 km^2 of the active paddy area was converted into abandoned rice fields. At the same time, approximately 18.35 km^2 of abandoned paddy fields, 17.2 km^2 of mangrove forests, and 10.37 km^2 of miscellaneous lands have been converted into shrimp farms. A significant change in the LULC classes in 2001-2011 was the oil palm plantations, which had gained 296.8 km^2 and lost 3.74 km^2, with a net gain of 292.94 km^2, while the abandoned paddy fields lost 240.59 km^2 and gained 4.49 km^2, with a net loss of 236.10 km^2. Approximately 174.27 km^2 of abandoned paddy fields were turned into oil palm plantations. Similarly, in 2011-2021, the oil palm plantations had gained 73.76 km^2 and lost 3.70 km^2, with a net gain of 70.06 km^2 (Figure 5). The increase of 70.06 km^2 in the oil palm area was mainly converted from 19.0 km^2 of orchards, 17.14 km^2 of abandoned paddy fields, and 12.91 km^2 of Para rubber area. The most significant changes in LULC patterns from 1991 to 2021 were found in the area of oil palm plantations, with an increase of up to 370.70 km^2. Most of this change was attributed to the conversion of abandoned paddy fields, accounting for 124.85 km^2, and active paddy fields, accounting for 111.70 km^2.

3-3- Future LULC Prediction

The predicted LULC changes generated by the CA-Markov model are presented in Table 2 and Figure 6. Overall, the land use forecast results for 2031, 2041, and 2051 showed that the predominant LULC will be covered with oil palms. A continued expansion is predicted in the oil palm area, which increased from 407.00 km^2 in 2031 to 408.96 km^2 in 2041 and then to 409.62 km^2 in 2051. The Para rubber cover is predicted to experience a decline from 140.06 km^2 in 2031 to 128.48 km^2 in 2051. The shrimp farm cover is predicted to maintain its increasing trend between 2031 and 2051 as the total area cover increased from 96.47 km^2 to 97.63 km^2, respectively. Similarly, the urban and built-up land cover area is predicted to increase from 87.95 km^2 in 2031 to 88.89 km^2 in 2051, whereas mangrove forests were reduced from the predicted 93.77 km^2 (9.57%) in 2031 to 92.99 km^2 (9.49%) in 2051. The other eight LULC classes in Table 2 had minimal changes during the study period. The CA-Markov to predict LULC changes has been validated, resulting in a Kappa coefficient of 0.89.



Urban and built-up land (U)

Agriculture land (Abandoned paddy field: A100, Active paddy field: A101, Perennial crop: A3, Para rubber, A302, Oil palm: A303, Orchard: A4, Abandoned aquaculture land: A900, Shrimp farm: A903

Forest Land (Evergreen forest: F1, Mangrove forest: F3, Swamp forest: F4)

Water body (W)

Miscellaneous land (M)

Figure 5. LULC gains and losses (km^2) by categories during (A) 1991-2001, (B) 2001-2010, (C) 2010-2021, and (D) 1991 - 2021

Table 2. Comparison of the LULC class areas and the percentage in 2021, and the predicted LULC class areas and the percentages for 2031, 2041, and 2051, in Bandon Bay, Thailand

LULC classes	2021		2031		2041		2051	
	Area (km^2)	%	Area (km^2)	%	Area (km^2)	%	Area (km^2)	%
Urban and built-up land (U)	86.24	8.80	87.95	8.98	88.62	9.05	88.89	9.07
Abandoned paddy field (A100)	18.90	1.93	18.86	1.93	18.87	1.93	18.89	1.93
Active paddy field (A101)	9.08	0.93	8.88	0.91	8.01	0.82	7.98	0.81
Perennial crop (A3)	5.94	0.61	5.76	0.59	5.74	0.59	5.72	0.58
Para rubber (A302)	140.06	14.30	130.96	13.37	129.06	13.18	128.48	13.12
Oil palm (A303)	400.31	40.87	407.00	41.55	408.96	41.75	409.62	41.82
Orchard (A4)	40.73	4.16	39.35	4.02	39.21	4.00	39.19	4.00
Abandoned aquaculture land (A900)	10.33	1.05	12.55	1.28	12.94	1.32	12.96	1.32
Shrimp farm (A903)	96.33	9.83	96.47	9.85	97.21	9.92	97.63	9.97
Evergreen forest (F1)	8.62	0.88	8.52	0.87	8.51	0.87	8.49	0.87
Mangrove forest (F3)	94.91	9.69	93.77	9.57	93.31	9.53	92.99	9.49
Swamp forest (F4)	0.86	0.09	0.84	0.09	0.82	0.08	0.81	0.08
Water body (W)	27.80	2.84	29.89	3.05	29.90	3.05	29.93	3.06
Miscellaneous land (M)	39.40	4.02	38.71	3.95	38.35	3.92	37.93	3.87
Total	979.51	100	979.51	100	979.51	100	979.51	100

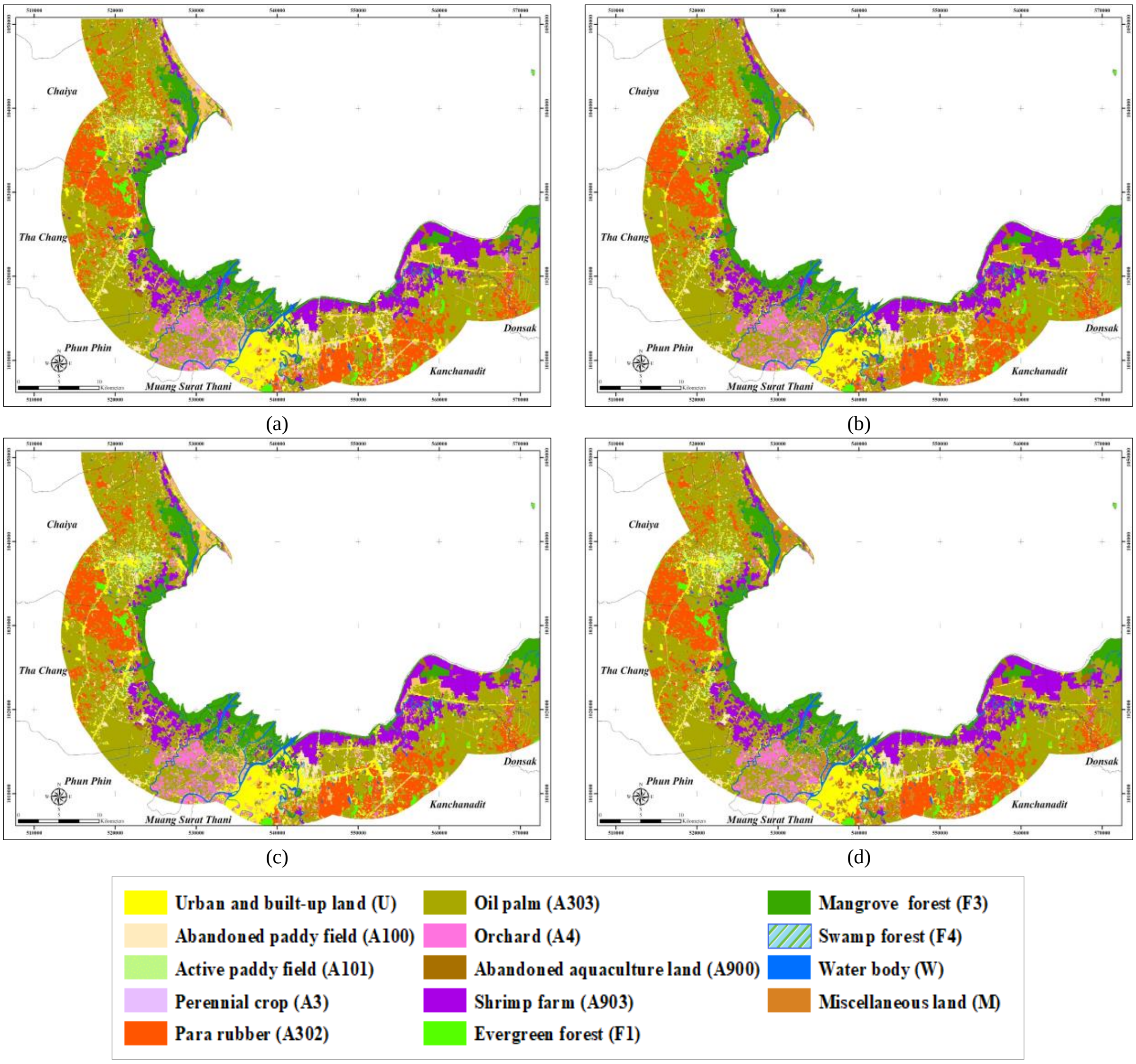


Figure 6. LULC classes in Bandon Bay, Thailand: (a) 2021, (b) 2031, (c) 2041, and (d) 2051

4- Discussion

4-1- Image Classification and Change Detection

Our results showed that between 2006 and 2021, the area covered by oil palm plantations increased significantly. This expansion came primarily at the expense of abandoned land and paddy fields. Our findings align with Saswattecha et al. [25], who documented a rising trend of oil palm cultivation in Thailand's southern Tapi River basin between 2000 and 2012. This study extends their analysis by examining oil palm expansion specifically in the Bandon Bay area up to 2021. Oil palm's footprint in the region surged from just 7% in 2000 to 16% by 2016, fueled by the conversion of paddy fields, fallow paddies, orchards, and previously unused land. Our observations mirror those of Srisunthon & Chawchai [26], who reported a similar surge in oil palm cultivation across Southern Thailand between 2000 and 2016. This expansion coincided with a consistent decline in paddy field area during the same period.

An important turning point began in 1999 when the Thai government encouraged oil palm plantations to expand. The cultivation of good oil palms was being promoted as a replacement for palms older than 20 years [23], particularly the oil palm industry's 2004-2029 [22, 23] strategy and the strategies for developing and promoting biodiesel from palm 2005. This indicated that, consistent with the study results from 2001 to 2006, the number of oil palm areas increased significantly from 37.16 km^2 to 323.20 km^2. Since the early 2000s, Thai government policy has consistently favored the expansion of oil palm plantations. This support stems from three main factors: biofuel alternatives, investment incentives, and potential for economic growth. First, biofuel alternative: in 2006, the government specifically promoted oil palm cultivation as a source of biodiesel (2006-2009). This aimed to reduce reliance on imported fossil fuels and enhance energy security. Secondly, investment incentives: The government provided financial aid programs to encourage farmers to switch to oil palm. These subsidies helped offset the initial costs of establishing new plantations. Finally, potential for economic growth: Oil palm cultivation was viewed as a driver of economic development in rural areas. The crop offered farmers a potentially lucrative income source and created jobs within the palm oil industry.

The 2007 oil palm industry development plan incorporated a project targeting land reform areas. This project, running from 2008 to 2012, aimed to unlock the potential of oil palm cultivation for these communities by providing resources, training, or infrastructure support to help farmers benefit from oil palm production in land reform areas. The Thai government significantly bolstered oil palm cultivation between 2008 and 2012. This initiative included two key measures: ambitious area expansion and Land use conversion incentives. For ambitious area expansion, in 2008, the government set a target for farmers to increase oil palm cultivation by a substantial 500,000 rai annually for the following four years (2008-2012). For land use conversion incentives, the following year (2009), a specific policy was introduced to promote oil palm as a replacement crop for aging fruit orchards and abandoned paddy fields. This policy likely offered incentives, such as subsidies or tax breaks, to promote the conversion of existing land uses to oil palm plantations. Between 2014 and 2016, a government initiative provided high-quality oil palm seeds to farmers, to replace their aging trees. This program aimed to support plantation renewal and boost yields. However, it is essential to note that widespread replacement of older palms could raise concerns about deforestation, especially if it incentivized farmers to clear additional land for new plantings. In line with the 2017-2036 oil palm and palm oil reform strategy [51], 2016 saw the promotion of large-scale oil palm cultivation projects. These projects aimed to leverage conversion systems to enhance production efficiency and reduce farmers' costs. However, it is crucial to acknowledge that large-scale land conversion can raise environmental concerns, so sustainable practices and economic benefits must be a key consideration. Surat Thani's development plans (2005-2017 [52] and 2018-2022 [53]) likely played a role in boosting domestic crude palm oil demand [54]. This surge in demand is suspected to be a significant factor behind the dominance of oil palm expansion in the region.

According to the agricultural statistics of Thailand, market prices of palm fruit bunches increased from 1,660 Baht/ton in 2000 to 2,300 baht/ton in 2005 and 6,500 baht/ton in 2021 [55, 56]. Rising prices drove farmers to plant oil palms instead of other crops (e.g., rice and para rubber) [57]. Following palm oil expansion and LULC change, market price has minimal influence as a driver in this region. Several factors likely influenced the observed LULC changes, including government policy support for LULC shifts, a potential diversification trend among farmers, and decreased labor requirements for oil palm cultivation compared to para rubber [25]. Since 2012, Surat Thani Province has had the largest palm plantation area in Thailand [56], whereas the rubber plantation areas have tended to decrease [56]. The reason is that farmers were cutting down old rubber trees and shifting to oil palm and fruit trees [25, 53].

This study revealed a concerning decline in mangrove cover between 1991 and 2006, coinciding with extensive forestry concessions and coastal aquaculture expansion in Thailand (1961-2002). During this time, government policy significantly impacted mangrove ecosystems in two ways: logging concessions and shrimp farming encroachment. For logging concessions, the government granted private companies rights to harvest timber from designated mangrove areas. This directly led to the destruction of these ecologically valuable forests. For shrimp farming encroachment, even mangroves outside concession zones faced threats. Shrimp aquaculture emerged as a lucrative industry, and some farmers invaded these areas to create ponds, further contributing to mangrove loss. Due to the high yield, shrimp farming expanded rapidly. Our findings align with Muttitanon & Tripathi's research [32], which documented a decline in mangrove cover and increased shrimp farm area between 1993 and 1999. This overlap strengthens the evidence that shrimp aquaculture expansion was a significant driver of mangrove loss during this period in Thailand.

In 1987, the government had a policy to promote shrimp farming for export, thus expanding shrimp farming areas to mangrove areas. Shrimp farming increased significantly in 1997-2002. Economic pressures stemming from declining shrimp prices and rising aquaculture costs since 2002 have driven small-scale shrimp farmers to abandon aquaculture due to financial losses and accumulated debt. Only large private companies could continue to produce shrimp [58, 21]. In response to the economic shift impacting shrimp farming, the Ocean Food Bank Project was initiated in 2002 [21]. This project aimed to introduce cockle cultivation as a more sustainable alternative aquaculture practice, targeting economic viability and ecological benefits.

The project's implementation has seen Bandon Bay become a center for cockle farming activity [21]. In 2014, Thailand implemented a policy framework to address deforestation, public land encroachment, and encourage sustainable natural resource management practices [59]. This framework aligned with the environmental and economic objectives outlined in the 12th National Economic and Social Development Plan [60]. Notably, the policy framework incorporated a specific directive to expand the national mangrove area. The policy framework included a particular directive to expand the national mangrove area. A study conducted between 2016 and 2021 investigated the effects of these policy measures on mangrove cover [3]. The study's findings utilizing LULC classification techniques revealed an upward trend in mangrove forest cover, suggesting a positive association between the implemented public policies and changes in LULC classes [3].

4-2- LUCC Prediction

The spatiotemporal analysis of LULC changes revealed a dominance of agricultural land uses within the Bandon Bay region, particularly on oil palm plantations, rubber plantations, and shrimp farms. This study demonstrates that agricultural land, particularly oil palm plantations, rubber plantations, and shrimp farms, comprise the dominant current and predicted LULC classes. The area of the oil palms has continued to increase over the study period, while the productivity of other food crops, such as active paddy fields and perennial crops, has decreased, leading to food insecurity [25, 26]. Agricultural activities have employed fertilizers, pesticides, and other chemicals to improve crop growth and prevent pests; however, these chemicals are a source of pollution [61, 62]. Surat Thani's plan (2017-2036) for oil palm should balance development with sustainability through controlled expansion and technological improvements. LULC management will help prevent potential future adverse impacts on the Bandon Bay ecosystem.

5- Conclusion

This study employed a spatiotemporal analysis of LULC changes in the Bandon Bay region using multi-temporal Landsat imagery acquired between 1991 and 2021. Based on the classification of LULC classes in 1991, 1996, 2001, 2006, 2011, 2016, and 2021, the land use pattern can be divided into 1991-2001 and 2006-2021. From 1991 to 2001, LULC classes mainly comprised abandoned paddy fields, shrimp farms, para rubber plantations, and mangroves. In the second period, from 2006-2021, LULC classes were dominated by oil palms, para rubber, shrimp farms, and mangroves. The detection of LULC changes was a 10-year change detection study split into three periods: 1991-2001, 2001-2011, and 2011-2021. Our analysis revealed the most significant increase in abandoned paddy fields between 1991 and 2001. This abandonment primarily occurred through converting active paddy fields to other land-use categories. Changes throughout 2001-2011 showed that abandoned paddy fields experienced the most significant decrease in area, where they were transformed into oil palm areas. During 2011-2021, the oil palm areas have increased the most, as in the past, with the transition from orchards, abandoned paddy fields, and para rubber plantations. The driving factors of LULC reform in Bandon Bay mainly came from government policies and population growth. The results of the LULC class predictions for 2031, 2041, and 2051 showed that most of the LULC classes will be oil palms, shrimp farms, mangroves, and urban and built-up lands. Based on the forecasts, most Bandon Bay areas will become agricultural. Sustainable land management practices are crucial for the future. This includes strategically limiting the expansion of farming areas, particularly oil palm plantations and aquaculture. Instead of increasing areas for oil palms, land management should focus on using technology and increasing productivity for the oil palms already planted to prevent or minimize adverse impacts on the Bandon Bay ecosystem, a source of shellfish cultivation, aquatic animal nurseries, and essential fisheries in Thailand.

6- Declarations

6-1- Author Contributions

Conceptualization, J.R., M.J., and K.J.; methodology, J.R., M.J., and K.J.; formal analysis, J.R., K.J., and M.J.; investigation, J.R., M.J., and K.J.; data curation, J.R.; writing—original draft preparation, J.R., K.J., M.J., and E.B.S.; writing—review and editing, J.R., K.J., M.J., and E.B.S. All authors have read and agreed to the published version of the manuscript.

6-2- Data Availability Statement

The data presented in this study are available on request from the corresponding author.

6-3- Funding

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6-5- Institutional Review Board Statement

Not applicable.

6-6- Informed Consent Statement

Not applicable.

6-7- Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this manuscript. In addition, the ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, and redundancies have been completely observed by the authors.

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