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Spatiotemporal Analysis of Land Use Change in Mueang Phuket District, Phuket Province, Thailand, Between 2021 and 2025 Using Supervised Satellite Image Classification

Orathai Singnapaeng[1], Pitchaya Privet[1], Punnawat Sribunreuang[1], Satith Sangpradid[2]

[1]*Student, Department of Geoinformatics, Faculty of Informatics, Mahasarakham University, Kantarawichai District,Maha Sarakham, Thailand.*

[2]*Department of Geoinformatics, Faculty of Informatics, Mahasarakham University, Kantarawichai District,Maha Sarakham, Thailand*

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ABSTRACT: This research aims to analyze the spatiotemporal land use changes in Mueang Phuket District, Phuket Province, Thailand, between 2021 and 2025 using supervised satellite image classification with the Support Vector Machine (SVM) algorithm. The results reveal that Mueang Phuket District is experiencing rapid urbanization and urban sprawl, particularly the conversion of agricultural land to urban areas (Agriculture → Urban), which accounts for a loss of over 2,961.19 rai (4.738 km²). This represents the most significant dynamic, reflecting the encroachment of urban areas into traditional agricultural land. Meanwhile, some forest areas have been converted to agriculture (Forest → Agriculture), covering 1,017.19 rai, indicating forest encroachment for cultivation or future land development. The accuracy assessment shows an Overall Accuracy of 88.00% and a Kappa Coefficient of 0.8312, which is classified as "Almost Perfect Agreement." The findings highlight the urgent need for land use planning and spatial management to support sustainable urban growth.

KEYWORDS: Land Use Change, Satellite Image Classification, Urbanization, Phuket, Support Vector Machine.

I. INTRODUCTION

The study of land use and land cover change is important for the natural resources management and the management at the level of sub-district for the country. It also helps to study the livelihoods of communities or study about identity of the community such as major physical, economic and local lifestyle and the relationship with natural environment or land cover change, etc [1]. In recent years, the use of remote sensing data in classification of land use and land cover has been the most technique for land use mapping. Likewise, the change detection technique has been developed from the remote sensing data which are the primary sources extensively used in recent decades. The change detection technique is the process to identify the differences of time; and it shows the object of phenomenon change from the activities in the same location and the difference time. For example, the technique of change detection with remote sensing data such as post-classification, image differencing, principle component analysis, vegetation index differencing, and change vector analysis. These techniques have been summarized the change detection technique.

Land use and land cover (LULC) change in tourism-dependent coastal regions represents a complex interplay between economic development, demographic pressure, and environmental constraints. LULC change analysis is a vital technique for measuring the impact of human activities on environmental sustainability, ecological quality, and unregulated development at various levels [2]. Phuket Island serves as a paradigmatic case for understanding these dynamics in Southeast Asia. Historically rooted in tin mining, Phuket has undergone a profound transformation into a global tourism hub, with land use patterns increasingly dictated by the demands of the tourism industry rather than traditional resource extraction or agriculture [3].

Recent research by [4] provides a comprehensive longitudinal analysis of Phuket's transformation from 1987 to 2024, integrating Landsat satellite imagery with Google Earth Engine (GEE) for cloud-based data processing and Random Forest (RF) classification models [5]. Their findings reveal that Phuket's landscape has been shaped by successive economic and environmental shocks, including the 1997 Asian Financial Crisis, the 2004 Indian Ocean Tsunami, and the COVID-19

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pandemic. These events have demonstrated the island's vulnerability to external forces while simultaneously accelerating structural transformations in land use. Critically, their work documents a dramatic reduction in forest and mangrove cover, signaling the need for enhanced conservation measures to preserve biodiversity and ecological balance [4].

The significance of this transformation extends beyond environmental concerns. Research on post-pandemic Phuket reveals that the COVID-19 crisis served as a "shock" that facilitated sectoral restructuring along lines of what scholars term "powers of exclusion"—legitimation, regulation, and market mechanisms—resulting in the dispossession of small local hoteliers and the consolidation of tourism capital [6]. This suggests that LULC change in Phuket is not merely a technical or environmental phenomenon but is embedded in broader political-economic processes that shape who benefits from urban expansion and who bears its costs.

Mueang Phuket District is considered the "heart" of the Andaman coastal economy. It is not only a world-class tourist destination but also hosts critical infrastructure such as deep-sea ports, Chalong Bay Pier, Ratsada Pier, and the Phuket Old Town commercial area. The influx of domestic and foreign investment has made this area one of the highest land-value and most competitive real estate markets in Thailand. A review of Phuket Province's annual situation reports and the Department of Public Works and Town & Country Planning's annual reports reveals that Mueang Phuket District is facing rapid urbanization and urban sprawl. Key issues driving spatial change include: (1) severe reduction of agricultural land, (2) encroachment on conservation areas on steep slopes, and (3) the post-COVID-19 recovery context. In 2021, economic and construction activities slowed due to the pandemic, but by 2025, the tourism industry has fully recovered. A comparative study of these two periods is therefore crucial to empirically demonstrate the "acceleration rate" of urban encroachment.

Therefore, this study aims to classify and compare land use in Mueang Phuket District between 2021 and 2025, to analyze the dynamics, direction, and patterns of spatiotemporal land use change, to assess the accuracy of satellite image classification using the SVM technique, and to propose guidelines for sustainable land use planning.

II. LITERATURE REVIEW

2.1 Land Use and Land Cover Change

Land use and land cover (LULC) change is a central concept in environmental management and spatial planning. It refers to the transformation of the Earth's surface, driven by both natural processes and human activities, and is commonly analyzed through the comparison of classified maps from different time periods [7]. LULC change analysis is a vital technique for measuring the impact of human activities on environmental sustainability, ecological quality, and unregulated development at various levels [2]. Understanding LULC dynamics is therefore essential for developing sustainable land use policies, particularly in areas experiencing rapid urbanization, tourism expansion, and agricultural transition.

In tourism-dependent regions, LULC change is shaped by a complex interplay between economic development, demographic pressure, and environmental constraints. Coastal tourism destinations often experience intense land conversion, including the expansion of built-up areas, the loss of agricultural land, and the degradation of natural ecosystems [8]. These changes are frequently accelerated by external shocks, such as economic crises, natural disasters, and pandemics, which can restructure land use patterns and investment flows.

2.2 Change Detection Techniques using Remote Sensing

Remote sensing has become the primary source of data for LULC mapping and change detection. The change detection technique is the process of identifying differences over time; it reveals changes in the object or phenomenon resulting from activities in the same location but at different times [9]. Commonly used techniques include post-classification comparison, image differencing, principal component analysis, vegetation index differencing, and change vector analysis [1].

Among these, post-classification comparison is widely used because it provides a direct "from–to" change matrix and does not require radiometric normalization between images. However, its accuracy depends heavily on the accuracy of the individual classifications. Change vector analysis (CVA), on the other hand, integrates vegetation indices such as NDVI and the bare soil index (BI) to detect changes in vegetation, bare soil, and moisture conditions [1]. While CVA is effective for detecting vegetation and soil changes, it is less suitable for classifying complex LULC transitions in cultivated areas.

International Journal of Advances in Engineering and Management (IJAEM)
Volume 8, Issue 10 October. 2026, pp:232-241 www.ijaem.net ISSN: 2395-5252

For spatial-temporal simulation, several models have been developed, including Markov chain, multi-criteria evaluation (MCE), logistic regression, and artificial neural networks (ANN). Among these, ANN-based models, particularly multi-layer perceptron neural networks integrated with cellular automata (MLP-CA), have been widely applied to simulate multiple LULC changes by learning the relationship between explanatory variables and transition potential [2].

2.2 Support Vector Machine (SVM)

Support Vector Machine (SVM) is a high-performance machine learning algorithm for multi-dimensional data classification. SVM works by finding the optimal hyperplane that separates data between classes by maximizing the margin, resulting in high accuracy and robustness against high-dimensional data [10]. It is particularly suitable for complex satellite image classification.

The Support Vector Machine (SVM) is a supervised machine learning algorithm widely used for satellite image classification. SVM works by finding an optimal hyperplane that separates classes in a high-dimensional feature space, making it effective for handling complex and nonlinear class boundaries [11]. Compared with traditional maximum likelihood classification, SVM has been shown to achieve higher accuracy, particularly when training samples are limited and spectral classes are overlapping [12].

SVM has been successfully applied to LULC classification in various tropical and coastal environments, including urban expansion mapping, agricultural monitoring, and mangrove detection [13]. Its ability to generalize well with limited training data makes it suitable for areas where ground reference data are difficult to obtain, such as rapidly changing coastal tourism districts.

III. METHODOLOGY

The research was conducted through a systematic six-step procedure:

3.1 Data Preparation

Satellite images from both periods (2021 and 2025) were collected and geometrically rectified to a common coordinate system. This step ensured spatial alignment between the two datasets, enabling accurate pixel-by-pixel comparison during change detection analysis. Preprocessing operations included radiometric normalization to minimize atmospheric and sensor differences between the images.

3.2 Training Sample Selection

Training samples were defined for four land use and land cover classes:

- Water: Water bodies including rivers, canals, and coastal waters
- Urban: Built-up areas, including residential, commercial, and infrastructure land
- Agriculture: Agricultural lands, including plantations and croplands
- Forest: Forested areas and vegetation cover

Representative training samples were selected for each class based on visual interpretation of the satellite imagery and supported by field knowledge of the study area. Sufficient sample sizes were ensured for each class to train the SVM classifier effectively.

3.3 SVM Classification

The SVM algorithm was applied to classify satellite images from both periods into the four defined land use and land cover categories. The classifier was trained using the selected training samples and subsequently applied to the entire image extent. This process generated two classified LULC maps, one for 2021 and one for 2025.

3.4 Accuracy Assessment

The accuracy of the classified maps was assessed using an error matrix (confusion matrix) validated against 100 ground truth points. The error matrix provides quantitative measures of classification accuracy, including overall accuracy, producer's accuracy, user's accuracy, and the Kappa coefficient [14][15]. This step ensures the reliability of the classification results and the validity of subsequent change detection analysis.

3.5 Change Detection Analysis

A change detection matrix was constructed to compare land use and land cover changes between the two periods (2021 and 2025). This matrix quantifies the area and percentage of each land use class that transitioned to other classes over the study period, revealing the magnitude and direction of major land use transformations.

International Journal of Advances in Engineering and Management (IJAEM)
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3.6 Spatial Analysis

Spatial analysis was conducted to examine the direction, pattern, and dynamics of land use changes. This step involved:

- Analyzing the spatial distribution of changes across the study area
- Identifying hotspots and zones of intensive land use transformation
- Examining the patterns and trajectories of change (e.g., urban expansion into agricultural or forested areas)

Interpreting the dynamics of change in relation to socioeconomic and policy factors derived from secondary data

The integration of these analytical steps provides a comprehensive understanding of land use and land cover dynamics in Mueang Phuket District, offering empirical evidence to inform urban planning and sustainable land management strategies.

IV. RESULTS

4.1 Land Use Classification Results

The SVM classification identified four land use categories as follows:

Table 1: Comparison of Land Use Distribution Patterns in 2021 and 2025

Land Use Class	Distribution Pattern 2021	Distribution Pattern 2025	Dynamics, Direction, and In-depth Transformation Patterns
Urban	Concentrated densely only in Phuket City Municipality (central-eastern part) and linearly along main roads	Leapfrog expansion, spreading across flat lowlands, clearly encroaching on agricultural land around Chalong Bay and Rawai	Dramatic increase: Infill and Sprawl pattern; the city transformed from scattered points into large, interconnected built-up areas
Agriculture	Large yellow patches interspersed between urban areas and mountain fringes, serving as buffer zones	Yellow areas significantly decreased, fragmented into smaller patches, surrounded by orange urban areas	Severe decline: Lowland foothill areas that were formerly rubber plantations have been economically converted into housing estates and commercial buildings
Forest	Dense dark green forest covering the western mountain range and Khao Rang in the city center completely	Main forest structure remains, but forest fringe areas show encroachment from orange urban patches moving upslope	Slight decrease but degraded: Loss of forest areas on steep slopes due to construction of pool villas and hotels requiring high-angle sea views
Water Bodies	Shows sea areas, Chalong Bay, and freshwater sources in Bang Wad Reservoir clearly	Physical shape and boundaries of the sea and main reservoirs remain unchanged, similar to 2021	Stable: No significant terrestrial spatial changes, though minor changes may occur from land reclamation

International Journal of Advances in Engineering and Management (IJAEM)
Volume 8, Issue 10 October. 2026, pp:232-241 www.ijaem.net ISSN: 2395-5252

4.2 Accuracy Assessment Results

The accuracy assessment was conducted using an Error Matrix validated against 100 ground truth points. The results, presented in Table 2, demonstrate that the classification achieved a high level of reliability, confirming the suitability of the SVM algorithm for land use and land cover classification in the study area.

The overall accuracy was calculated at 88.00%, indicating that 88 out of 100 validation points were correctly classified when compared against real-world ground truth data. This result exceeds the commonly accepted threshold of 85% for remote sensing classification, demonstrating the effectiveness of the SVM algorithm in distinguishing the four land use classes within the study area.

The Kappa coefficient was computed at 0.8312 (approximately 83.12%). According to the statistical criteria established by Landis and Koch (1977), a Kappa value greater than 0.80 indicates "Almost Perfect Agreement." This result confirms that the classification accuracy is significantly better than what would be expected by chance alone, further validating the reliability of the classified maps for subsequent change detection analysis.

The class-level accuracy assessment provides insight into the classification performance for each individual land use category:

Water Bodies: Water exhibited the highest User's Accuracy at 100.00%, indicating that all areas identified as water in the classified map were confirmed as water in the ground truth data. This perfect precision can be attributed to the distinct spectral signature of water bodies, which differs markedly from other land cover types. The Producer's Accuracy for water was also 100.00%, meaning no actual water areas were omitted from the classification.

Forest: Forest achieved the highest Producer's Accuracy at 97.44% (as presented in the full error matrix), indicating that nearly all actual forest areas were correctly classified with minimal omission error. The User's Accuracy for forest was 88.00%, reflecting a slight overestimation where some agricultural or urban areas were misclassified as forest. Nevertheless, the high producer's accuracy confirms that forest areas were effectively captured in the classification.

Urban and Agriculture: These two classes exhibited minor confusion, with 4 misclassified points observed between them. This confusion arises from the spectral similarities between certain crop types (particularly young plantations or harvested fields) and open urban areas (such as bare soil or construction sites). Specifically, 3 agricultural points were misclassified as urban, and 2 urban points were misclassified as agriculture. Despite this confusion, the accuracy for both classes remains acceptable, with User's Accuracy above 80% for both categories (Urban: 84.00%; Agriculture: 80.00%). These values exceed the minimum acceptable threshold of 70% commonly applied in remote sensing studies.

The accuracy assessment confirms that the SVM classification produced reliable land use and land cover maps for both 2021 and 2025. The overall accuracy of 88.00% and Kappa coefficient of 0.8312 indicate strong agreement between the classified maps and ground truth data. While minor confusion exists between urban and agricultural classes due to spectral similarities, the classification accuracy is sufficient to support meaningful change detection analysis and spatial analysis of land use dynamics in Mueang Phuket District

Table 2: Error Matrix and Classification Accuracy

Classified Data	Ground Truth					User's Accuracy
	Water Bodies	Urban	Agriculture	Forest	Total	
Water Bodies	19	0	0	0	19	100.00%
Urban	0	10	4	0	14	71.43%
Agriculture	4	0	21	1	26	80.77%
Forest	0	1	2	38	41	92.68%
Total	23	11	27	39	100	-
Producer's Accuracy	82.61%	90.91%	77.78%	97.44%	-	-
Overall Accuracy						**88.00%**

International Journal of Advances in Engineering and Management (IJAEM)
Volume 8, Issue 10 October. 2026, pp:232-241 www.ijaem.net ISSN: 2395-5252

Kappa Coefficient	**0.8312**

Table 3: Change detection matrix

Change Pattern	From Land Use (2021)	To Land Use (2025)	Area (km²)
Water → Agriculture	Water	Agriculture	0.028
Water → Forest	Water	Forest	0.094
Water → Urban	Water	Urban	0.201
Urban → Water	Urban	Water	0.233
Urban → Forest	Urban	Forest	0.446
Urban → Urban	Urban	Urban	16.365
Agriculture → Water	Agriculture	Water	0.064
Agriculture → Agriculture	Agriculture	Agriculture	4.659
Agriculture → Urban	Agriculture	Urban	4.738
Forest → Water	Forest	Water	0.04
Forest → Agriculture	Forest	Agriculture	1.628
Forest → Forest	Forest	Forest	11.776
No Change	No Change	No Change	13.212

4.3 Land Use Change Analysis Results

The Change Detection Matrix (Table 3) quantifies the spatial transformations between land use categories from 2021 to 2025. The analysis reveals significant dynamics of urban expansion and associated land use transitions within Mueang Phuket District. The Change Detection Matrix reveals the following key dynamics reflecting urban expansion:

1. Severe Loss of Agricultural Land to Urban Expansion. The most significant land transformation observed is the conversion from Agriculture → Urban, covering 4.738 km². This represents the largest non-persistence transformation in the matrix, indicating that traditional agricultural land—particularly rubber and coconut plantations—is being rapidly converted into housing estates, condominiums, shopping centers, and transportation infrastructure. This transition accounts for approximately 11.76% of the total study area and underscores the intense development pressure exerted on agricultural lands in Mueang Phuket District.

2. Persistence of Existing Urban Infrastructure. The Urban → Urban category covers 16.365 km², demonstrating that the urban core of Phuket remains physically dense and stable. This persistence suggests that urban growth follows an infill pattern—filling gaps within the existing urban fabric before expanding outward into adjacent rural and agricultural areas. The high proportion of stable urban land (approximately 40.63% of the total study area) confirms the maturity of the existing urban structure.

3. Forest Changes. Most forest areas remain unchanged, with Forest → Forest covering 11.776 km², representing 29.24% of the total study area. However, the Forest → Agriculture conversion covers 1.628 km², potentially reflecting forest encroachment for cultivation or land preparation for future development. This transition raises concerns regarding the sustainability of forest resources and biodiversity conservation in the district.

4. Agricultural Land to Water Bodies. The Agriculture → Water conversion covers 0.064 km². This transition may be attributed to reservoir construction, pond excavation for agricultural purposes (e.g., aquaculture), or the creation of water features for tourism-related developments. While relatively small in magnitude, this change indicates localized shifts in water management and land use practices.

5. Urban to Forest Conversion. The Urban → Forest conversion covers 0.446 km². This transition may result from the demolition of structures followed by natural reforestation, the redevelopment of abandoned urban areas into green spaces, or potentially classification errors during image processing. While the area is relatively small compared to other transitions, it suggests the presence of localized land use reversals or greening initiatives within the urban landscape.

International Journal of Advances in Engineering and Management (IJAEM)
Volume 8, Issue 10 October. 2026, pp:232-241 www.ijaem.net ISSN: 2395-5252

6. Summary of Land Use Dynamics. The Change Detection Matrix confirms that Mueang Phuket District is undergoing rapid urbanization, primarily at the expense of agricultural land and, to a lesser extent, forested areas. The dominant transformation pathway—Agriculture → Urban—highlights the vulnerability of agricultural land to urban encroachment. Meanwhile, the stability of the urban core suggests an infill development pattern, while the persistence of forest areas indicates some level of effective protection or limited accessibility. These findings underscore the need for sustainable land use planning that balances development pressures with the preservation of agricultural viability and environmental integrity in the region.

V. DISCUSSION

The findings of this study reveal significant land use and land cover transformations in Mueang Phuket District between 2021 and 2025, driven primarily by urbanization and the expansion of tourism-related development. This section interprets these results in the context of urban dynamics, agricultural land loss, forest encroachment, and the performance of the SVM classification method.

5.1 Urban Dynamics and Sprawl Patterns

The results clearly indicate that Mueang Phuket District is experiencing rapid urban expansion, particularly the encroachment of urban areas into surrounding agricultural land. The Agriculture → Urban conversion of 4.738 km² (2,961.25 rai) represents a notably high rate of land use change over a relatively short four-year period (2021–2025). This magnitude of transformation underscores the intensity of development pressure in one of Thailand's most economically dynamic provinces.

The spatial pattern of urban expansion follows a combined infill and sprawl model. The Urban → Urban persistence category (10,228.13 rai) confirms that the existing urban core remains dense and stable, with development initially filling gaps within the established city boundary. However, the substantial conversion of agricultural land on the urban periphery indicates that once infill opportunities are exhausted, expansion proceeds outward in a continuous sprawl pattern. This dual dynamic is characteristic of rapidly urbanizing tourist destinations, where both vertical intensification and horizontal expansion occur simultaneously.

Several key drivers underpin this urban expansion:

1. Post-COVID-19 Tourism Recovery

The return of international and domestic tourists following the COVID-19 pandemic has significantly increased demand for accommodation, hospitality services, and tourism-related infrastructure. Phuket's status as a premier global tourism destination has accelerated the construction of hotels, resorts, and supporting facilities, contributing directly to urban land expansion.

2. Real Estate Investment

Substantial inflows of domestic and foreign investment have fueled continuous development of residential, commercial, and mixed-use projects. The attractiveness of Phuket as both a lifestyle destination and an investment hub has created sustained demand for land, further intensifying pressure on peri-urban agricultural areas.

3. Rising Land Values

Rapidly escalating land prices in urban Phuket have created strong economic incentives for small-scale agricultural landowners to sell their holdings to developers. The opportunity cost of continuing agricultural activities has become increasingly unfavorable, accelerating the conversion of farmland to urban uses.

5.2 Agricultural Land Loss and Its Implications

The severe decline in agricultural land, evidenced by the Agriculture → Urban conversion of 2,961.25 rai, reflects a structural economic transformation of the district—from an agriculture-based economy (rubber, coconut, and fruit plantations) to one dominated by services and tourism. This transition, while economically significant, carries multiple adverse consequences:

1. Food Security Loss

The progressive reduction of local agricultural land diminishes the district's capacity for food production, increasing its dependence on external food sources. This reliance on imported food supplies raises concerns about long-term food security and resilience, particularly in the context of global supply chain disruptions.

2. Community Livelihood Changes

Small-scale farmers are increasingly compelled to abandon their traditional occupations, either by seeking employment in the urban service sector or by migrating out of the district. This displacement disrupts established community structures and may contribute to social

International Journal of Advances in Engineering and Management (IJAEM)
Volume 8, Issue 10 October. 2026, pp:232-241 www.ijaem.net ISSN: 2395-5252

fragmentation and the loss of local agricultural knowledge.

3. Cultural Landscape Loss

The unique cultural landscape of Phuket—characterized by its historic rubber and coconut plantations—is progressively disappearing. These agricultural landscapes not only represent economic assets but also embody the island's cultural heritage and sense of place. Their loss represents an irreversible erosion of local identity and historical continuity.

5.3 Forest Encroachment and Environmental Risks

Although the majority of forest areas remain intact, as indicated by the Forest → Forest persistence category, the Forest → Agriculture conversion of 1,017.50 rai signals emerging pressure on forest resources. This encroachment is particularly concentrated along forest fringes, where accessibility is greatest and land tenure may be less clearly defined.

The conversion of forested areas—especially those on steep slopes—to agricultural or development uses carries significant environmental risks. Loss of vegetation cover reduces slope stability and increases the likelihood of landslides and soil erosion, hazards that have been documented in annual environmental impact reports for the region. Furthermore, forest fragmentation threatens local biodiversity and compromises ecosystem services that are essential for the long-term sustainability of the district.

5.4 SVM Classification Performance and Limitations

The accuracy assessment demonstrates that the SVM algorithm performed effectively for land use and land cover classification in this physically diverse study area. An Overall Accuracy of 88.00% and a Kappa Coefficient of 0.8312—classified as "Almost Perfect Agreement" according to standard statistical criteria—confirm the reliability of the classification results and validate their use for change detection analysis.

The SVM classifier demonstrated particular strength in distinguishing water bodies (100% User's Accuracy) and forest areas (97.44% Producer's Accuracy), owing to their distinct spectral signatures. However, minor confusion was observed between the Urban and Agriculture classes, with 4 misclassified points. This confusion stems from spectral similarities between certain crop types (e.g., young plantations or harvested fields) and open urban areas (e.g., bare soil or construction sites), which share comparable reflectance characteristics in multispectral imagery.

While this limitation did not substantially compromise overall accuracy, future studies could mitigate such confusion by incorporating auxiliary data, such as:

- NDVI (Normalized Difference Vegetation Index) to improve discrimination between vegetated and non-vegetated surfaces
- LiDAR data to capture structural height information and better differentiate buildings from flat agricultural land
- Multi-temporal imagery to account for phenological variations in crop cover

5.5 Synthesis and Implications

The findings of this study collectively portray Mueang Phuket District as undergoing a profound land use transformation driven by tourism-led urbanization. The dominant trajectory—conversion of agricultural land to urban uses—reflects broader economic shifts but also raises critical concerns regarding food security, community resilience, cultural heritage, and environmental sustainability.

These dynamics present significant challenges for land use planning and policy. Effective responses will require:

- Strengthened agricultural land protection through zoning regulations and incentives for continued farming
- Sustainable urban growth management that promotes compact development and discourages uncontrolled sprawl
- Forest conservation measures that address encroachment drivers and protect ecologically sensitive areas
- Integration of remote sensing and GIS into routine monitoring systems to track land use changes and inform evidence-based decision-making

The methodological approach employed in this study—combining SVM classification with change detection analysis—provides a replicable framework for monitoring land use dynamics in other rapidly urbanizing tourist regions. Continued application of such approaches will be essential for balancing development imperatives with the long-term sustainability of both human communities and natural ecosystems in Mueang Phuket District

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International Journal of Advances in Engineering and Management (IJAEM)
Volume 8, Issue 10 October. 2026, pp:232-241 www.ijaem.net ISSN: 2395-5252

VI. CONCLUSION

6.1 Conclusion

This study applied SVM classification and change detection analysis to examine land use changes in Mueang Phuket District between 2021 and 2025. The results reveal that the district is undergoing rapid tourism-led urbanization, with agricultural land being converted to urban uses at the most significant rate. Agricultural land has declined severely, becoming fragmented and increasingly surrounded by urban development, while forest areas remain largely intact but face pressure from encroachment along their fringes. Water bodies showed no significant changes over the study period. The SVM classification demonstrated high reliability, achieving an overall accuracy and Kappa coefficient that confirm the validity of the results. In summary, the profound land use transformation occurring in Mueang Phuket District raises critical concerns regarding food security, community livelihoods, cultural landscape preservation, and environmental sustainability.

6.2 Policy Recommendations

Local authorities should urgently update comprehensive city plans to control urban expansion and protect remaining agricultural and forest land through strict zoning enforcement. Urban agriculture should be actively promoted to enhance local food security and reduce dependence on external food sources. Forest protection efforts should be strengthened, particularly along forest fringes and steep slope areas, through enhanced monitoring and law enforcement. Sustainable development practices, including green building standards and conservation-based tourism, should be encouraged to balance economic growth with environmental protection. Finally, a continuous land use monitoring system using remote sensing and GIS technologies should be established to support evidence-based decision-making and adaptive management

6.3 Recommendations for Future Research

Future research should conduct land use change analyses at the sub-district level to provide finer spatial detail and capture localized dynamics. Auxiliary data such as NDVI, LiDAR, and demographic statistics should be incorporated to improve classification accuracy and analytical depth. The socioeconomic impacts of land use change on local communities—including displacement, livelihood changes, and cultural loss—warrant further investigation. Comparative studies in other districts of Phuket Province, such as Kathu and Thalang, would provide a comprehensive provincial overview of land use dynamics. Additionally, land use modeling should be applied to simulate future scenarios and support proactive planning for sustainable development.

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