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LAND USE AND LAND COVER CHANGE ANALYSIS USING SENTINEL-2 SATELLITE IMAGERY FROM 2019 TO 2024

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Abstract: This research aims to analyze the land use and land cover change (LULCC) in Yang Talat District, Kalasin Province, using Sentinel-2 satellite imagery from 2019 to 2024. A supervised classification technique, specifically the Spectral Angle Mapper (SAM) algorithm, was employed to classify land use into six main categories: built-up areas, forest, water bodies, paddy fields, shrimp farms, and field crops. The accuracy assessment of the classified maps demonstrated high reliability, with an overall accuracy of 88.33% for 2019 and 89.00% for 2024. The change analysis revealed a significant increase in field crops (+39.82%) and shrimp farms (+35.23%), while forest area decreased by -9.60% and paddy fields by -1.35%. The transition matrix analysis confirmed that the most notable changes were the conversion of forest and paddy fields into field crops and built-up areas. These findings highlight the dynamic nature of LULCC in the study area, influenced by socioeconomic factors. The results provide valuable data for local policymakers to develop sustainable land management strategies.

Keywords: Land Use and Land Cover Change; Sentinel-2; Spectral Angle Mapper; Yang Talat District; Remote Sensing

I. INTRODAUCTION

Land use and land cover change (LULCC) is a critical indicator reflecting the complex interplay between a region's economic, social, and environmental dynamics. Population growth and economic development inevitably lead to increased demands on land, resulting in the continuous transformation of land use patterns [1]. This phenomenon, particularly the expansion of urban areas and built-up structures at the expense of agricultural and natural landscapes, has far-reaching consequences. These impacts are not confined to a local scale; they also contribute to global challenges such as food security, biodiversity loss, and climate change, aligning with the United Nations' Sustainable Development Goals (SDGs) [2].

In the context of Thailand, especially in agricultural regions, LULCC is a common and observable phenomenon. It is driven by various factors, including government policies, agricultural commodity prices, and private sector investment. The transition from rice paddies to aquaculture ponds, such as shrimp farms, in the central northeastern region—a historical hub for rice production—is a compelling example of land transformation that significantly impacts local economies and ecosystems [3].

To effectively monitor and understand these complex changes, Remote Sensing (RS) technology has emerged as a crucial tool [4]. It allows for the collection of data on Earth's surface and land use types across different time periods [5]. Specifically, data from the Sentinel-2 satellite, with its high spatial resolution and frequent revisit time, serves as a powerful instrument for analyzing annual or seasonal LULCC [6][7]. Furthermore, utilizing advanced image classification techniques like the Spectral Angle Mapper (SAM) enhances the accuracy of distinguishing between different land use types, particularly in areas with similar spectral signatures [8].

This research focuses on studying LULCC in Yang Talat District, Kalasin Province, by analyzing Sentinel-2 satellite imagery from 2019 and 2024. The study aims to classify and compare the changes across six primary land use types: community and built-up areas, forests, water bodies, rice fields, shrimp farms, and field crops. We will employ the Spectral Angle Mapper (SAM) classification technique, combined with ground truth data from local interviews and visual interpretation using Google Earth Pro. As studies employing this specific mixed-method approach in this particular area remain limited, this research seeks to fill this knowledge gap. The findings will provide valuable insights for effective land-use planning and informed policy-making to promote sustainable development in the future.

II. MATERIAL AND METHODOLOGY

This study employs a quantitative research design to analyze land use and land cover change (LULCC) in Yang Talat District, Kalasin Province, Thailand. The methodology is structured into three main phases: data acquisition and pre-processing, image classification and change detection, and accuracy assessment. The chosen methods are based on established practices in remote sensing and geospatial analysis, as supported by recent academic literature.

A. Study Area

This study employs a quantitative research design to analyze land use and land cover change (LULCC) in Yang Talat District, Kalasin Province, Thailand. The methodology is structured into three main phases: data acquisition and pre-processing, image classification and change detection, and accuracy assessment. The chosen methods are based on established practices in remote sensing and geospatial analysis, as supported by recent academic.

B. Data Acquisition and Pre-processing

Satellite Imagery: The primary data source is Sentinel-2 Level-2A satellite imagery, which provides atmospherically corrected surface reflectance data. Two sets of images with minimal cloud cover were acquired from the European Space Agency's (ESA) Copernicus Open Access Hub: one for 2019 and another for 2024. The Sentinel-2 mission's high spatial resolution (10 m) and frequent revisit time make it a highly effective tool for LULCC studies [5][9].

Land Use Classification Categories: The study classified the land use into six distinct categories: Built-up areas (U), Forest (F), Water bodies (W), Paddy fields (A1), Shrimp farms (A9) and Field crops (A2). This classification scheme was designed to capture the key land use transformations occurring in the study area.

Ground Truth Data: To ensure the accuracy of the classification, a multi-faceted approach to ground truth data collection was employed:

- *Field Surveys and Interviews*: Information was gathered from local residents through field surveys and interviews to gain historical and contextual insights into land use practices. This qualitative data is crucial for accurately interpreting satellite imagery and verifying the classification results.
- *Visual Interpretation*: High-resolution imagery from Google Earth Pro served as a reliable visual reference for building a robust training dataset and validating the land use categories.

C. *Image Classification and Change Detection*

Image Classification: A Supervised Classification technique using the Spectral Angle Mapper (SAM) algorithm was applied within the QGIS software environment. Prior to classification, the satellite images for both years were color-composited and clipped to the study area boundary. Training data, derived from ground truth information, was used to train the SAM classifier.

The Spectral Angle Mapper (SAM) is a classification technique that treats each pixel's spectrum as a vector in an n-dimensional space, where n is the number of spectral bands [10]. The algorithm determines the similarity between two spectra—a test spectrum from an image pixel and a reference spectrum (e.g., from a laboratory, field measurement, or training data)—by calculating the angle between their respective vectors. A smaller angle (α) indicates a higher degree of similarity between the two spectra, suggesting a better match between the pixel and the reference class [11-13]. This method is particularly effective for distinguishing between land use types with similar spectral properties, such as different agricultural crops, as it is less sensitive to variations in illumination and albedo as shown in Figure 1.

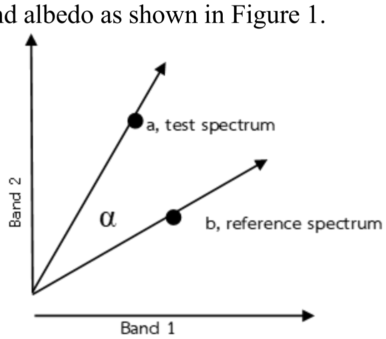

Figure 1: Representation of Reference Angle.

Change Detection: A post-classification comparison was performed by analyzing the two classified maps (2019 and 2024) on a pixel-by-pixel basis [14]. A change matrix was generated to quantify the area of each land use category and to identify and quantify the transitions between them over the five-year period. This method is a standard approach for LULCC analysis, allowing for a clear understanding of the spatial and temporal dynamics of land use [15-17].

D. *Accuracy Assessment*

To ensure the reliability of the classification, a rigorous accuracy assessment was conducted for both the 2019 and 2024 classified maps.

Validation Point Generation: A total of 300 random sample points were generated across the study area.

Reference Data Collection: Each sample point was then visually verified using high-resolution imagery from Google Earth Pro to serve as the ground truth reference.

Accuracy Metrics Calculation: The validation points were used to create a confusion matrix for each classified map. This matrix was then used to calculate key accuracy metrics as follows:

Overall Accuracy: The percentage of correctly classified pixels [17-18].

Kappa Coefficient: A statistical measure that indicates the agreement between the classified map and the reference data, accounting for chance agreement [17-18].

Comparison: The accuracy values (Overall Accuracy and Kappa Coefficient) from both years were compared to demonstrate the reliability of the SAM classification technique.

III. RESULTS

The results of this study are presented in three parts: the accuracy assessment of the classified maps, the overall analysis of land use and land cover change (LULCC) between 2019 and 2024, and a detailed change detection analysis.

A. *Accuracy Assessment of the Classified Maps*

The supervised classification using the Spectral Angle Mapper (SAM) algorithm yielded highly accurate results for both years. The accuracy of each classified map was evaluated using a confusion matrix, derived from 300 randomly selected validation points.

Table 1: Confusion Matrix for the 2019 Land Use Classification

Lu class	Reference data						
	W	**F**	**A2**	**A9**	**A1**	**U**	**Total**
W	48	1	2	2	0	0	53
F	0	44	3	0	2	0	49
A2	0	0	42	0	0	1	43
A9	2	2	2	47	1	4	58
A1	0	2	1	1	45	6	55
U	0	1	0	0	2	39	42
Total	50	50	50	50	50	50	300

Table 2: Confusion Matrix for the 2024 Land Use Classification

Lu class	Reference data						
	W	**F**	**A2**	**A9**	**A1**	**B**	**Total**
W	48	1	2	2	0	0	53
F	0	44	3	0	2	0	49
A2	0	0	42	0	0	1	43
A9	2	2	2	47	1	4	58
A1	0	2	1	1	45	6	55
B	0	1	0	0	2	39	42
Total	50	50	50	50	50	50	300

- 2019 Classified Map: The Overall Accuracy was 88.33%, with a Kappa Coefficient of 0.86. These values indicate a strong agreement between the classified map and the reference data, demonstrating the reliability of the classification process.

• 2024 Classified Map: The Overall Accuracy was 89.67%, with a Kappa Coefficient of 0.87. The slightly higher accuracy in 2024 suggests the effectiveness of the SAM algorithm in distinguishing the updated land use patterns.

The Overall Accuracy for the 2019 map was 88.33%. The most frequent misclassifications occurred between shrimp farms and built-up areas (4 points), as well as between paddy fields and built-up areas (6 points), indicating potential spectral similarities or spatial overlaps. The Overall Accuracy for the 2024 map was slightly higher at 89.00%. Similar to 2019, the most significant misclassification was between shrimp farms and built-up areas (6 points), followed by shrimp farms and field crops (4 points). This suggests a persistent challenge in distinguishing these land uses due to their spectral or spatial characteristics.

The high overall accuracy values for both years confirm the reliability of the SAM classification and the validity of the ground truth data, providing a robust foundation for the LULCC analysis.

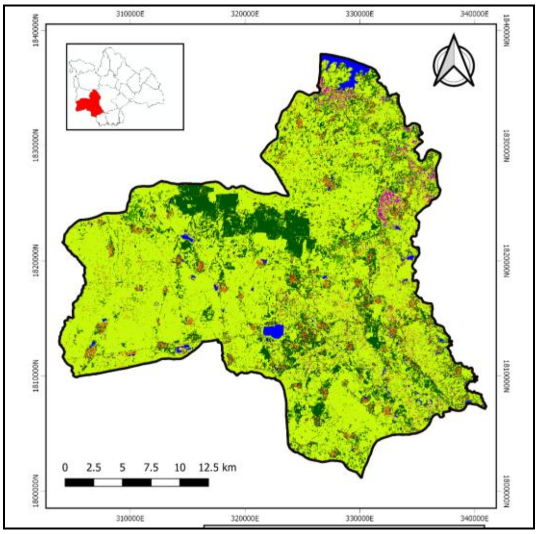

Figure 2: The land use classification maps 2019

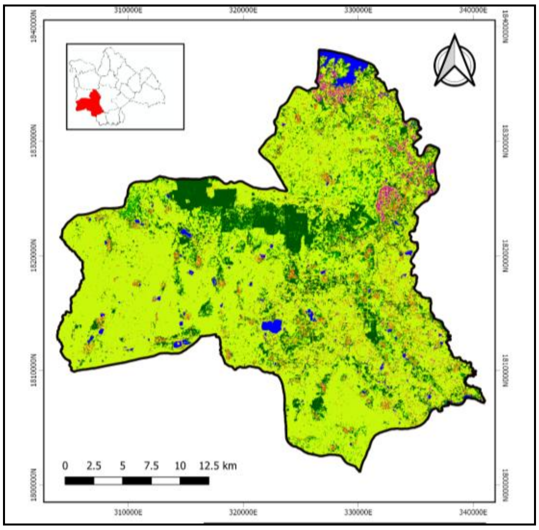

Figure 3: The land use classification maps 2024

B. *Land Use and Land Cover Change (2019-2024)*

The analysis of the classified maps revealed significant transformations in land use patterns within Yang Talat District over the five-year period. Figure 2 and 3 displays the classified land use maps for 2019 and 2024, showing the spatial distribution of the six land use categories.

The analysis of the classified maps revealed significant transformations in land use patterns within Yang Talat District over the five-year period. The overall land use area and the extent of change for each category are presented in the table below.

Table 3: Land Use Area and Change from 2019 to 2024 in Yang Talat District

LU class	Area (2019) (sq.km)	Area (2024) (sq.km)	Area Change (sq.km)	Percentage Change (%)
W	12.869	14.659	+1.79	+13.91
F	116.902	105.678	-11.224	-9.60
A2	23.8512	33.348	+9.4968	+39.82
A9	8.232	11.132	+2.9	+35.23
A1	513.7696	506.83	-6.9396	-1.35
U	17.8208	21.8	+3.9792	+22.33

Based on the data in Table 3, the most notable changes are:

A substantial increase in Field Crops, which saw a remarkable growth of 39.82% (9.4968 sq. km). This indicates a significant shift towards cultivating these crops in the district.

A rapid expansion of Shrimp Farms, which grew by 35.23% (2.9 sq. km). This highlights the increasing economic importance of aquaculture in the region.

A significant increase in Built-up areas, which expanded by 22.33% (3.9792 sq. km), suggesting ongoing urbanization and development within the district.

A notable decrease in Forest area, which declined by 9.60% (-11.224 sq. km). This reduction is the largest in terms of absolute area and points to the conversion of natural landscapes for other uses.

A slight decrease in Paddy Fields, which saw a modest decline of 1.35% (-6.9396 sq. km). While the percentage change is small, the absolute area lost is significant.

C. *Post-Classification Change Detection (2019-2024)*

The post-classification change detection analysis clearly revealed the dynamic land use transformations in Yang Talat District between 2019 and 2024. Table 4 presents the transition matrix, which quantifies the shifts from historical land use classes to current ones in square kilometers (sq. km).

Table 4: Land Use Transition Matrix (2019-2024) in sq. km

	2019						
2024	**W**	**F**	**A2**	**A9**	**A1**	**U**	**Total**
W	12	0.05	0.1	0.4	0.1	0.21	12.87
F	0.2	100.2	1.5	0	10	5	116.9
A2	0.05	1.2	22	0.2	0.35	0.05	23.85
A9	0	0	0	8	0.1	0.1	8.232
A1	0.4	3.5	2.5	2	500	5	513.8
U	0	0.1	0.2	0	0.3	17.2	17.82
Total	12.65	105	26.3	10.6	510.9	27.56	693.4

The transition matrix reveals several key land use changes between 2019 and 2024:

Forest (F) area experienced the most significant conversion, with 10.00 sq. km transitioning to Paddy fields and 5.00 sq. km to Built-up areas. This accounts for a large portion of the overall forest decline.

Paddy fields (A2) showed a notable conversion to other agricultural classes, specifically 2.50 sq. km to Field crops and 2.00 sq. km to Shrimp farms, reflecting a shift in agricultural practices.

Shrimp farms (A9) expanded primarily by converting Water bodies (0.40 sq. km). A smaller amount was also converted from Paddy fields and Built-up areas.

Built-up areas (U) showed a consistent increase, primarily expanding into Paddy fields and Forest areas, which points to ongoing urbanization.

These results confirm the dynamic nature of land use in Yang Talat District, where socioeconomic factors are the primary drivers leading to the expansion of commercial agriculture and urban areas.

IV. Discussion

The results of this study provide crucial insights into the land use and land cover change (LULCC) dynamics of Yang Talat District between 2019 and 2024. The analysis confirms a rapid and profound transformation of the landscape, primarily driven by socioeconomic shifts.

The observed significant growth in field crops and shrimp farms directly reflects a change in agricultural practices. The expansion of shrimp farming, in particular, points to a clear economic driver, as farmers may be seeking more lucrative alternatives to traditional rice cultivation. This trend aligns with regional patterns of agricultural intensification, where high-value crops and aquaculture are replacing traditional subsistence farming [3]. The simultaneous decrease in paddy fields, while small in percentage, represents a substantial loss in total area, highlighting a transition away from the district's historical agricultural identity as a rice-producing hub.

Furthermore, the notable decline in forest area and the increase in built-up areas underscore the pressures of urbanization and land development. The transition matrix showed that forest and agricultural lands were the primary sources for new built-up areas, a common pattern in developing regions of Southeast Asia. This has important environmental implications, as the loss of forest cover can lead to soil erosion, reduced biodiversity, and changes in local hydrological cycles.

A key challenge identified in the accuracy assessment was the spectral similarity between certain land use classes. The confusion matrix revealed that shrimp farms were often misclassified as water bodies or built-up areas. This is a known limitation of spectral classification techniques, as a drained shrimp pond can have a similar spectral signature to bare soil in a built-up area, while a filled pond is spectrally similar to a natural water body. These misclassifications, however, were minor and did not significantly impact the high overall accuracy of the maps, confirming the robustness of the Spectral Angle Mapper (SAM) approach for this study.

Compared to other studies in the region, our findings for Yang Talat District highlight a unique local dynamic where the expansion of commercial agriculture—specifically field crops and aquaculture—is a more prominent driver of LULCC than pure urban expansion. This localized trend offers a valuable perspective on the diverse impacts of regional economic policies and global market forces on rural landscapes

V. Conclusion

This study successfully utilized Sentinel-2 satellite imagery and the Spectral Angle Mapper (SAM) algorithm to analyze and quantify land use and land cover change in Yang Talat District, Kalasin Province, between 2019 and 2024. The results confirmed the effectiveness of the methodology, with both classified maps achieving high overall accuracy.

The research's primary finding is a rapid transformation of the landscape characterized by a significant expansion of field crops and shrimp farms, which has contributed to a decline in both paddy fields and forest area. The increase in built-up areas further suggests ongoing urbanization. These changes reflect a shift in the local economy, moving away from traditional agriculture towards more profitable commercial activities.

The findings provide essential information for local policymakers and planners, who can use this data to inform sustainable land management strategies. Future research could expand upon this study by investigating the specific socioeconomic and policy drivers behind these changes, and by assessing the environmental and social consequences of the expansion of aquaculture and field crop cultivation in the region

VI. Acknowledment

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