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Monitoring Agricultural Land Loss by Analyzing Changes in Land Use and Land Cover

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Abstract

The agricultural sector's output holds paramount significance for the global population, serving as an indispensable resource for survival and consumption. Consequently, alterations in agricultural landscapes bear substantial implications for the world's food supply. The objectives of this research are to investigate the depletion of agricultural land, with a specific focus on Samut Songkhram Province—an agriculturally prominent region in Thailand renowned for supplying seafood and fruits to Bangkok. By employing advanced remote sensing and change detection methods and incorporating indices like NDVI, NDWI, and NDBI, the study meticulously analyzed land-use changes. The outcomes were rigorously scrutinized through supervised classification, validated by on-site inspections, and corroborated with data from pertinent agencies. Findings revealed that Samut Songkhram had sustained its prominence in agricultural land, constituting around 70% of the province's total area over the past two decades. However, this expanse has undergone persistent transformation during the last 20 years. Notably, the most substantial surge was observed in the conversion of agricultural land to urban and developed areas, particularly in the urban zones of Amphawa District, followed by Mueang Samut Songkhram and Bang Khonthi districts. This investigation illuminates a consistent downward trend in agricultural land, a vital source of sustenance for Thailand's population and the global community.

Keywords:

Agricultural Land;
Change Detection;
LU/LC;
Image Classification;
Samut Songkram, Thailand.

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1- Introduction

Currently, agriculture serves as a primary food source for the global population and constitutes one of the four fundamental factors of human needs. Ongoing demographic shifts and urban expansion, coupled with changing global climate conditions, have led to significant transformations in the world's agricultural landscape. This phenomenon is particularly pronounced in the densely cultivated agricultural regions of Southeast Asia, including countries like Vietnam, Indonesia, and Thailand.

On the East Coast of Southeast Asia, a group of nations demonstrates substantial agricultural production as major export commodities due to the presence of vast, fertile river valleys, such as the Mekong and Chao Phraya River Basins.

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Despite this, statistical data from the Food and Agriculture Organization (FAO) indicates that countries in this region require an increasing demand for food, not only within Southeast Asia but globally as well [1]. Grace et al. (2014) argued that, currently, the global population is confronting a critical issue, namely, food insecurity, closely linked to economic activities in agriculture, particularly in developing countries [2]. Therefore, they estimated agricultural production in border and food-insecure areas of Kenya using high-resolution satellite imagery. Similarly, Becker-Reshef et al. (2020) conducted a study on the decision to support agriculture in countries at risk of food insecurity using the GEOGLAM Crop Monitor for Early Warning. The aforementioned issues have led to a subsequent trend in health problems, such as malnutrition and depression, even resulting in suicide [3–5]. All of the above shows that agricultural areas play a crucial role in the current global population's well-being [6, 7].

Samut Songkhram Province is located near Bangkok, the capital city of Thailand. Most of the land in this province is predominantly agricultural, with significant potential in this field [8]. Farmers in Samut Songkhram specialize in cultivating a variety of crops, including Samut Songkhram Kom Lychee (or Fragrant Longan Lychee) and a large white pomelo variety called Samut Songkhram Khaoyai Pomelo. These crops have been registered as geographical indicators with the Department of Intellectual Property of Thailand, indicating the unique origin of the produce from this area [9]. Additionally, coconut cultivation is prevalent, covering over 30% of the province's land area.

In recent times, the study of land use through remote sensing has become highly popular, particularly for monitoring changes in cultivated areas [10]. Specifically, the utilization of Change Detection techniques [11–13] has gained prominence in tracking land use changes using satellite imagery. Additionally, a study conducted by Narayani and Nagalakshmi (2023) explored changes in land use to monitor the expansion of urban areas and construction activities [14]. Their findings revealed that land cover with vegetation tended to reappear in areas undergoing recent development, but simultaneously, urban areas and construction increased from vacant land. Their study employed validation methods such as the Confusion Matrix and Kappa coefficient. Likewise, Alam and Ahamed (2022) conducted a study to assess changes in land use for predicting agricultural areas in Bangladesh using remote sensing with Google Earth Engine [15]. The study concluded that there was a significant reduction in land use for agriculture, emphasizing the acceptance and application of such tools for monitoring changes in land use. The problem of land use change is becoming more serious, especially regarding the expansion of urban and built-up areas. As a result of this problem, agricultural land is continuously decreasing, causing farmers to expand their cultivation areas, which results in encroachment problems in conservation areas such as forests, mangroves, and grasslands [16]. Furthermore, there are also studies of geographically diverse agricultural land use changes, such as agricultural changes in mountainous areas, and tropical areas [17, 18]. However, there has been no study of changes in agricultural areas in river basins, especially along river mouths. For example, the study area of Samut Songkhram Province, which includes the mouth of the Mae Klong River, is also an important wetland area for Thailand.

This study therefore aims to monitor the loss of agricultural land in Samut Songkhram Province. It uses remote sensing analysis to detect changes in land use and land cover. This discovery is expected to help understand and realize future trends in agricultural production, which is the main economic income of the people in the area, and realize its importance as a source of food for the world's population as well.

2- Material and Methods

2-1- Study area

Samut Songkhram Province is one of the central provinces of Thailand, situated approximately 64 kilometers west of Bangkok along Highway 35 (Thonburi–Pak Tho). It covers an area of approximately 413.8 square kilometers and is situated on the Gulf of Thailand coast, its latitude and longitude coordinates are 13.446 and 100.032, respectively. The topography of the province is characterized by flat plains, with the Mae Klong River flowing through the area and forming an estuary at the Gulf of Thailand. There is a notable wetland area in this region known as Don Hoi Lot, encompassing three districts: Mueang Samut Songkhram, Bang Khonthi, and Amphawa. In addition to its geographical features, Samut Songkhram Province is distinguished by its three types of water: fresh water from the Mae Klong River, brackish water from the Gulf of Thailand, and brackish water in the estuary of the Mae Klong River. The province's fertile soil, especially in the triangular delta at the mouth of the river, makes it suitable for cultivation, particularly fruit orchards. Samut Songkhram is renowned for its diverse agriculture, including fruit cultivation, and is also engaged in both freshwater and saltwater fishing. The province's unique combination of water types and fertile soil contributes to its agricultural richness, as illustrated in Figure 1.

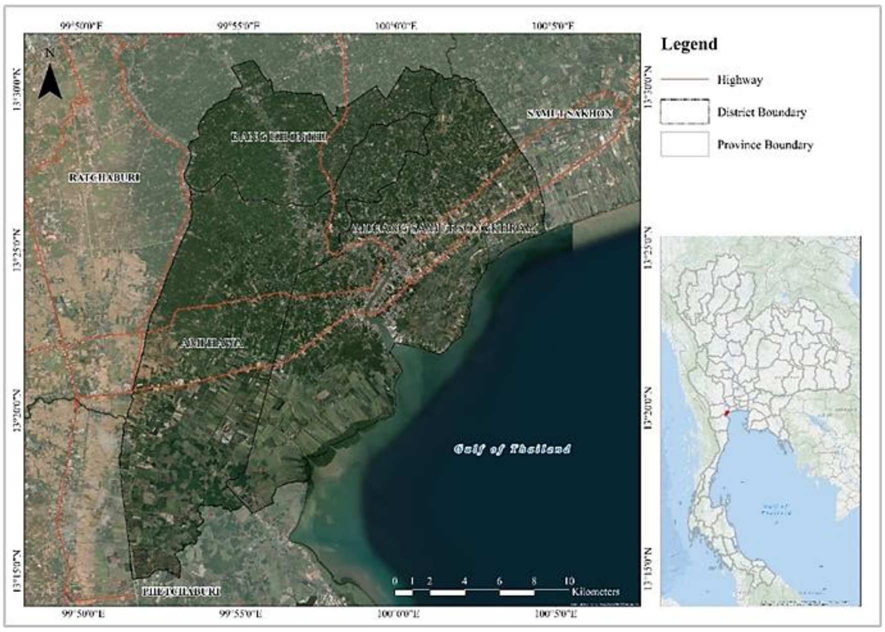


Figure 1. **Samut Songkram, Thailand Map**

2-2- Data Collection

The data used in this study consists of satellite images from Landsat 5 in fiscal year 2003, Landsat 8 from fiscal year 2013, and Landsat 9 from fiscal year 2023. These images were employed to analyze land use characteristics using the Supervised Classification method through the Google Earth Engine program. Subsequently, accuracy was verified by randomly selecting sample locations based on land use characteristics from data provided by the Department of Land Development, Ministry of Agriculture, and Cooperatives, along with on-site surveys. The details are presented in Table 1.

Table 1. **Data Compilation for the Study**

Satellite Data	Path and Row	Format	Acquisition Date	Sources
Landsat٥ TM satellite images	129, 51	Image file	19 November 2003	the U.S. Geological Survey (USGS)
Landsat 8 OLI/TIRS satellite images	129, 51	Image file	20 April 2013	the U.S. Geological Survey (USGS)
Landsat 9 OLI/TIRS satellite images	129, 51	Image file	23 March 2023	the U.S. Geological Survey (USGS)
Land Use Data (Fiscal Year 2003)	-	Vector data	2003	Land Development Department, Thailand
Land Use Data (Fiscal Year٢٠١٣)	-	Vector data	2013	Land Development Department, Thailand
On-Site Survey (Fiscal Year٢٠٢٣)	-		2023	Land Development Department, Thailand

2-3- Methods

Analysis of satellite imagery from Landsat 5, Landsat 8, and Landsat 9 was conducted over three time periods using the Supervised Classification method. The analysis employed the normalized difference vegetation index (NDVI), the normalized difference water index (NDWI), and the normalized difference built-up index (NDBI), as described in Equations 1 to 3. Accuracy of the data was verified using statistical methods, including Overall Accuracy and Kappa coefficient, as expressed in Equations 4 and 5. These measures were used to validate the field survey data and cross-verify with historical data from the Department of Land Development, Ministry of Agriculture and Cooperatives. In addition, results of the analysis from satellite images were processed using the change detection method and then used to further examine the areas of gain and loss among agricultural land. Details are presented in Figure 2.

NDVI, a widely-used index for vegetation analysis, reflects the density and vitality of vegetation in an area [19, 20]. It utilizes near-infrared and red wavelengths, and produces results ranging from -1 to 1. Values close to -1 indicate non-vegetated areas, while values approaching 1 signify vegetated areas. In this study, NDVI was applied to analyze agricultural areas in Samut Songkhram Province, as illustrated in Equation 1.

$$NDVI = \frac{NIR-Red}{NIR+Red} \tag{1}$$

where NDVI is Normalized Difference Vegetation Index, NIR is Near Infrared Reflectance, and Red is Red Reflectance.

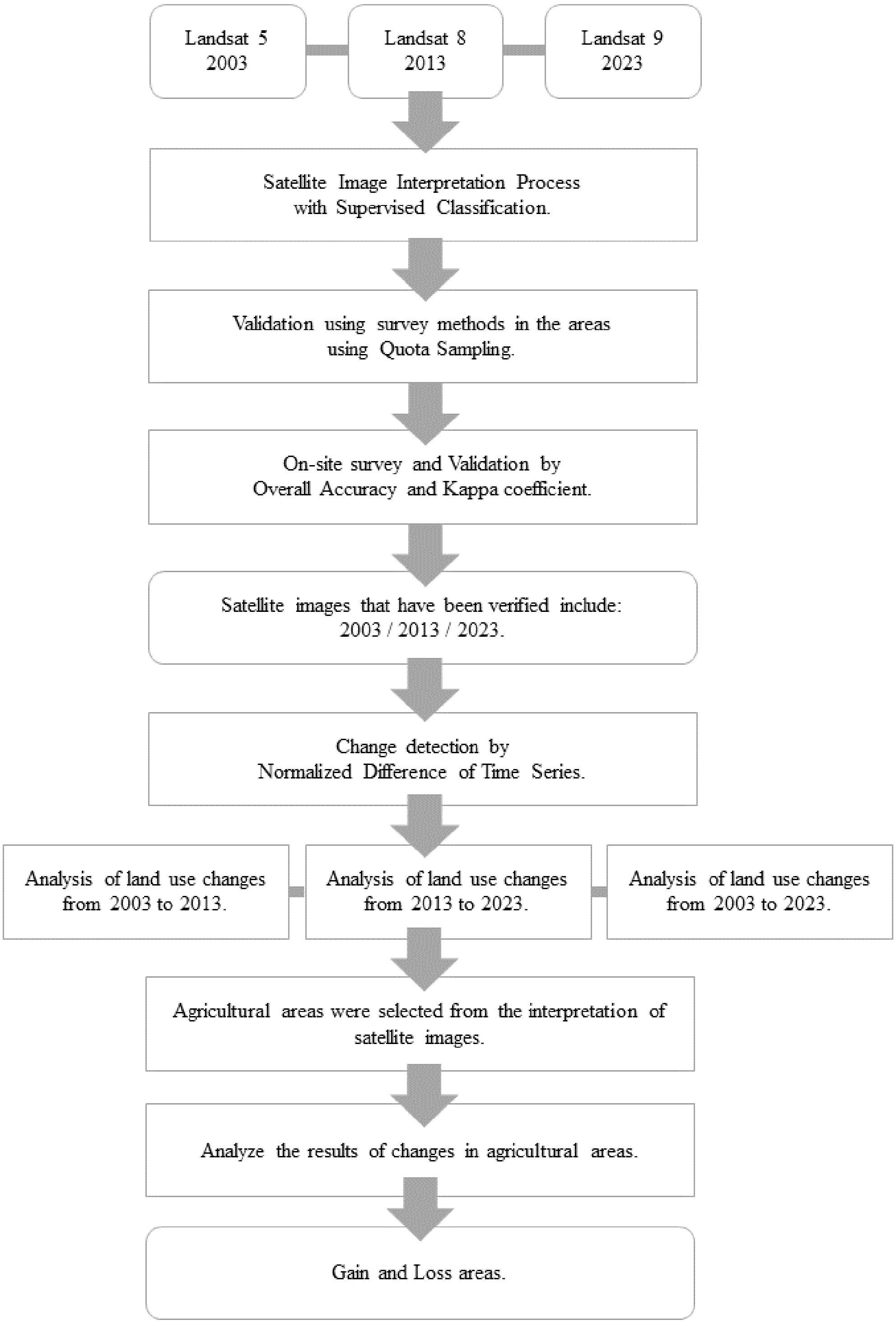


Figure 2. The conception framework

The normalized difference water index (NDWI) is a commonly used index in Remote Sensing methods for analyzing moisture and water areas [21, 22]. This index relies on the principle of analysis using near-infrared and green wavelengths, with results ranging from -1 to 1. If the value is less than 0.3, it indicates a dry or non-water area. Conversely, if it is greater than 0.3, it signifies a water area, as shown in Equation 2.

$$NDWI = \frac{Green - NIR}{Green + NIR} \quad (2)$$

where NDWI is Normalized Difference Water Index, NIR is Near Infrared Reflectance, and Green is Green Reflectance.

The normalized difference built-up index (NDBI) is an index used to analyze and classify built-up areas. This analysis is based on near-infrared and shortwave infrared wavelengths [23, 24]. The results range from -1 to 1. If the value approaches -1, it indicates a non-built-up area. Conversely, if it approaches 1, it signifies a built-up area, as illustrated in Equation 3.

$$NDBI = \frac{SWIR-NIR}{SWIR+NIR} \tag{3}$$

where NDBI is Normalized Difference Built-up Index, NIR is Near Infrared Reflectance, SWIR is Shortwave Infrared Reflectance.

Based on the aforementioned process, the interpreted satellite image results were then validated for accuracy using statistical methods, employing the Overall Accuracy method as per Equation 4 and the Kappa coefficient as per Equation 5 [25], respectively.

$$Overall\ Accuracy = \frac{\sum_{i=1}^{c} n_{ii}}{n} \tag{4}$$

$$Kappa\ coefficient = \frac{\sum_{i=1}^{c} n_{ii} - \sum_{i}^{c} n_i + n - 1}{n^2 - \sum_{i=1}^{c} n_i + n + i} \tag{5}$$

where n is The pixels' total number, n_{ij} is Total number of the classified pixels, and n_i is The instances number, and the label (i) of classified into the label (j).

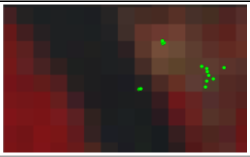
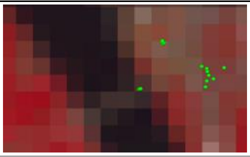
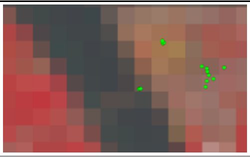
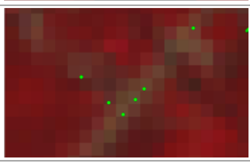
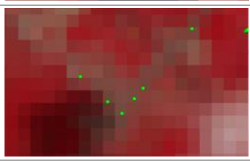
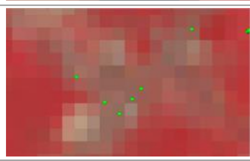
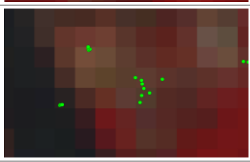
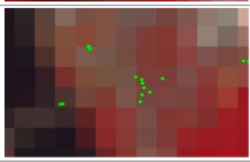
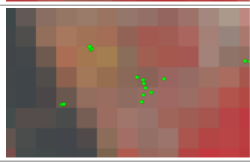
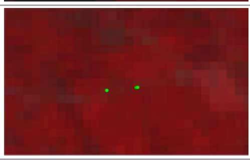
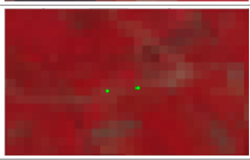
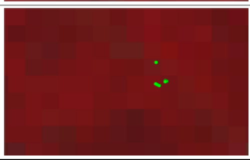
Subsequently, a comprehensive examination was conducted to assess the evolution of land-use patterns in Samut Songkhram Province across three distinct periods—each spanning a decade. The intervals considered were 2003–2013 and 2013–2023. Following this, a meticulous analysis was performed to scrutinize the alterations in land-use dynamics within Samut Songkhram Province over a two-decade span, ranging from 2003 to 2023. This investigation employed the NDTS (Normalized Difference of Time Series) methodology [26], as shown in Equation 6.

$$NDTS = \frac{I_{t2} - I_{t1}}{I_{t2} + I_{t1}} \tag{6}$$

where I_{t2} is Data in the Landsat image during the second time period, and I_{t1} is Data in the Landsat image during the first time period.

Finally, the land use was compared using Geographic Information System (GIS) tools for all three periods, namely 2003, 2013, and 2023. The analysis results are presented in Table 2.

Table 2. Examples of Satellite Image Analysis Displays

Coordinates (X,Y)	Land Use Type	Landsat 5 Satellite Images (2003)	Landsat 8 Satellite Images (2013)	Landsat 9 Satellite Images (2023)	Actual Land Conditions (2023)
602112 1489484	Water Areas				
601075 1490199	Water Areas				
604887 1490568	Urban Areas				
602294 1488390	Urban Areas				
610204 1491371	Agricultural Land				
606387 1491607	Agricultural Land				

3- Results

3-1- Land Use Classification of Samut Songkhram Province Using Satellite Imagery (2003-2023)

In 2003, land use in Samut Songkhram Province was analyzed using Landsat 5 TM satellite imagery. The province's total area was found to be 408.98 square kilometers or 255,617.95 rai. When categorizing land use into five types, it was observed that in 2003, agricultural land covered an area of 311.21 square kilometers or 194,506.51 rai, accounting for 76.09% of the province's total area. Urban and built-up areas occupied 37.24 square kilometers or 23,276.85 rai, representing 9.1% of the province's total area. Forest land comprised 31.93 square kilometers or 19,957.27 rai, making up 7.80% of the province's total area. Miscellaneous areas accounted for 15.52 square kilometers or 9,701.36 rai, constituting 3.79% of the province's total area. Water bodies covered an area of 13.08 square kilometers or 8,175.97 rai, making up 3.19% of the province's total area. Upon statistical verification, the study exhibited a high level of accuracy, with an overall accuracy of 84% and a Kappa statistic (KHAT) of 81%. These results are detailed in Table 3.

Table 3. Land Use Classification of Samut Songkhram Province, 2003

Type of Land Use	Square Kilometers	Rai	Percentage
Water Areas	13.08	8,174.97	3.19
Urban Areas	37.24	23,274.65	9.10
Forests	31.93	19,953.27	7.80
Agricultural Land	311.21	194,505.51	76.09
Miscellaneous Areas	15.52	9,700.36	3.79
Total	408.98	255,609.75	100.00

For year 2013, the analysis of land use in Samut Songkhram Province using satellite imagery from Landsat 8 OLI/TIRS revealed that the province had an area of 408.98 square kilometers or 255,617.95 rai. When categorizing land use into five types, it was found that in 2013, agricultural land covered an area of 300.69 square kilometers or 187,935.81 rai, accounting for 73.52% of the province's total area. Urban and built-up areas occupied 48.65 square kilometers or 30,411.69 rai, representing 11.89% of the province's total area. Forest land covered 31.12 square kilometers or 19,454.54 rai, making up 7.61% of the province's total area. Miscellaneous areas comprised 15.51 square kilometers or 9,699.20 rai, accounting for 3.79%, and water bodies encompassed 12.97 square kilometers or 8,108.52 rai, making up 3.17% of the province's total area. Statistical verification indicated high accuracy, with an overall accuracy level of 84% and a Kappa statistic (KHAT) of 81%. Details are presented in Table 4.

Table 4. Land Use Classification of Samut Songkhram Province, 2013

Type of Land Use	Square Kilometers	Rai	Percentage
Water Areas	12.97	8,108.52	3.17
Urban Areas	48.65	30,411.69	11.89
Forests	31.12	19,454.54	7.61
Agricultural Land	300.69	187,935.81	73.52
Miscellaneous Areas	15.51	9,699.20	3.79
Total	408.98	255,609.75	100.00

In 2023, the analysis of land use in Samut Songkhram Province using satellite imagery from Landsat 9 OLI/TIRS revealed that the province covered an area of 408.98 square kilometers or 255,617.95 rai. When categorizing land use into five types, it was found that in 2023, agricultural land accounted for 280.23 square kilometers or 175,144.17 rai, constituting 68.51% of the province's total area. Urban and built-up areas covered 59.24 square kilometers or 37,025.61 rai, representing 14.48% of the provincial area. Forest land comprised 30.82 square kilometers or 19,263.46 rai, making up 7.53% of the total area. Miscellaneous areas accounted for 25.55 square kilometers or 15,969.47 rai, constituting 6.24%. Water bodies covered 13.17 square kilometers or 8,231.48 rai, making up 3.22% of the provincial area. Statistical verification indicated a high level of accuracy, with an overall accuracy of 88% and a Kappa Statistic (KHAT) of 85%, as shown in Table 5 and in Figure 3.

Table 5. Land Use Classification of Samut Songkhram Province, 2023

Type of Land Use	Square Kilometers	Rai	Percentage
Water Areas	13.17	8,231.48	3.22
Urban Areas	59.24	37,025.61	14.48
Forests	30.82	19,263.46	7.53
Agricultural Land	280.23	175,144.17	68.51
Miscellaneous Areas	25.55	15,969.47	6.24
Total	408.98	255,609.75	100.00

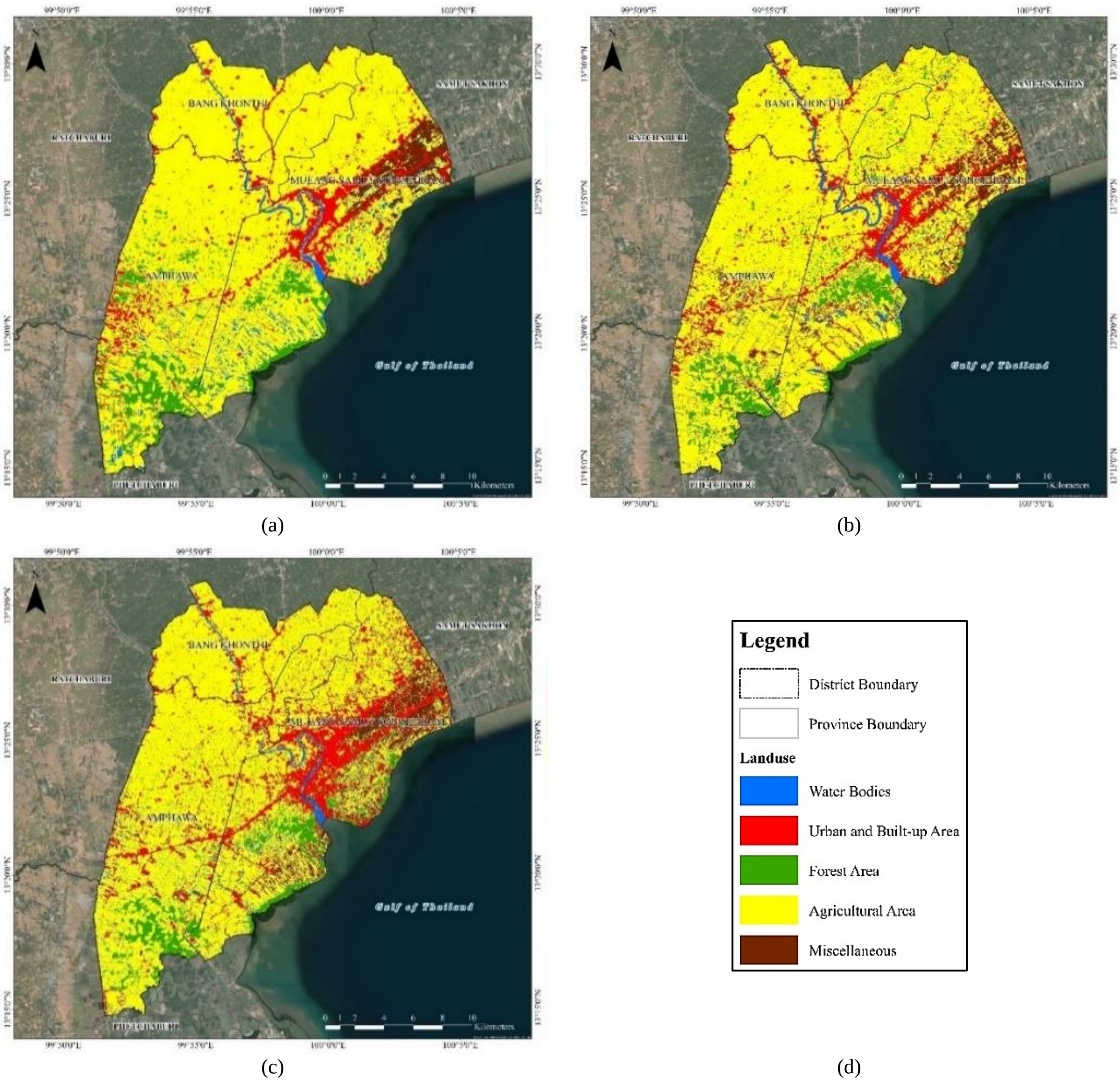


Figure 3. **Land Use Map of Samut Songkhram Province, (a) 2003 (b) 2013 and (c) 2023 (d) legend of the map**

3-2- Analysis of Agricultural Land Loss in Samut Songkhram Province between 2003-2023

To monitor changes in land use in Samut Songkhram Province from 2003 to 2023, the data was analyzed in two 10-year intervals (2003-2013 and 2013-2023) and one 20-year interval (2003-2023). This approach aimed to highlight changes in various land use types clearly. In the period between 2003 and 2013, it was observed that urban and built-up areas increased by 11.415 square kilometers (7,134.84 rai), representing a 2.791% increase in the province's total area. Conversely, agricultural land in Samut Songkhram Province decreased by 10.513 square kilometers (6,570.70 rai), accounting for a 2.570% reduction in the provincial area. Forest land experienced a decrease of 0.804 square kilometers (502.73 rai), equivalent to 0.196% of the provincial area, during the same period. Water bodies saw a reduction of 0.107 square kilometers (67.45 rai), representing a 0.206% decrease in the provincial area. Notably, the land use type with the smallest change was miscellaneous areas, which decreased by 0.003 square kilometers (2.16 rai), making up 0.0008% of the provincial area. The details are presented in Table 6 and Figure 4.

Table 6. **Changes in Land Use in Samut Songkhram Province between 2003-2013. (Square kilometers)**

2023 / 2003	Water Areas	Urban and Built-up Areas	Forests	Agricultural Land	Miscellaneous Areas	Total
Water Areas	4.524	0.163	0.053	7.406	0.928	13.074
Urban and Built-up Areas	0.345	22.368	0.538	12.953	1.020	37.217
Forests	0.374	1.513	14.827	14.999	0.185	31.897
Agricultural Land	7.332	22.782	15.594	259.599	5.968	311.276
Miscellaneous Areas	0.385	1.796	0.097	5.830	7.410	15.519
Total	**12.96**	**48.62**	**31.11**	**300.79**	**15.51**	**408.99**

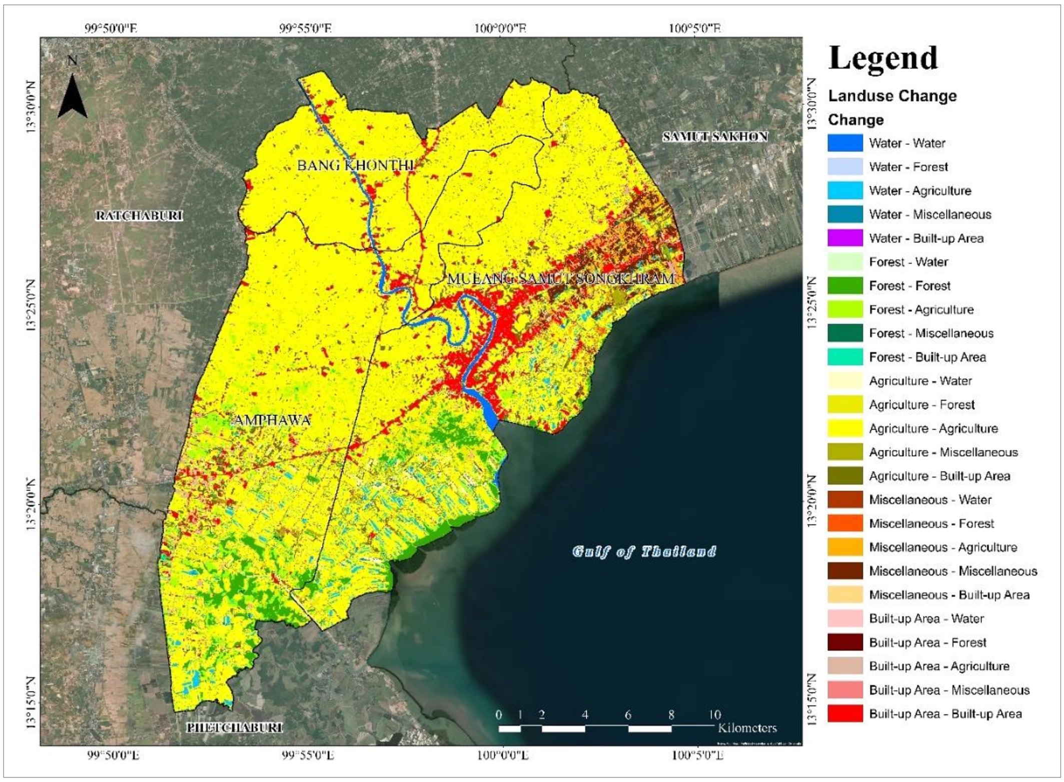


Figure 4. Map of Changes in Land Use in Samut Songkhram Province, 2003-2013

From the study of changes in land use during the period 2013-2023, it was found that land use in Samut Songkhram Province in 2023 saw an increase in urban and built-up areas by 10.582 square kilometers (6,613.92 rai), representing an increase of 2.587 percent of the province's total area. Additionally, there was an expansion of water areas by 0.196 square kilometers (122.96 rai), accounting for 0.048 percent of the province's total area. There was also an increase in miscellaneous areas by 10.032 square kilometers (6,270.27 rai), taking up 2.452 percent of the province's total area. However, agricultural land in Samut Songkhram Province decreased by 20.466 square kilometers (12,791.64 rai), constituting a reduction of 5.004 percent of the province's total area. Furthermore, there was a decrease in forest land, with an area reduction of 0.305 square kilometers (191.08 rai), equivalent to 0.074 percent of the province's total area. These findings are summarized in Table 7 and illustrated in Figure 5.

Table 7. Changes in Land Use in Samut Songkhram Province between 2003-2013. (Square kilometers)

2013 \ 2023	Water Areas	Urban Areas and Buildings	Forests	Agricultural Land	Miscellaneous Areas	Total
Water Areas	3.795	0.532	0.292	6.965	1.514	13.098
Urban Areas and Buildings	1.407	27.072	1.380	16.744	2.098	48.702
Forests	0.516	0.717	13.725	15.624	0.486	31.068
Agricultural Land	6.750	28.288	15.140	235.901	14.550	300.629
Miscellaneous Areas	0.818	2.708	0.219	4.904	6.842	15.491
Total	**13.29**	**59.32**	**30.76**	**280.14**	**25.49**	**408.99**

From the study of changes in land use between 2003 and 2023, it was found that in 2023, land use in Samut Songkhram Province experienced an increase in urban and built-up areas by 21.998 square kilometers (13,748.76 rai), accounting for 5.378% of the province's total area. Additionally, there was an increase in water areas by 0.888 square kilometers (55.51 rai), representing 0.021% of the province's total area. Furthermore, miscellaneous areas increased by 10.028 square kilometers (6,268.11 rai), accounting for 2.452% of the province's total area. However, agricultural areas in Samut Songkhram Province decreased by 30.979 square kilometers (19,362.34 rai), constituting a reduction of 7.574% of the province's total area. As for forest areas, there was a decrease with 1.110 square kilometers (693.81 rai), representing 0.271% of the province's total area. These findings are summarized in Table 8 and illustrated in Figure 6.

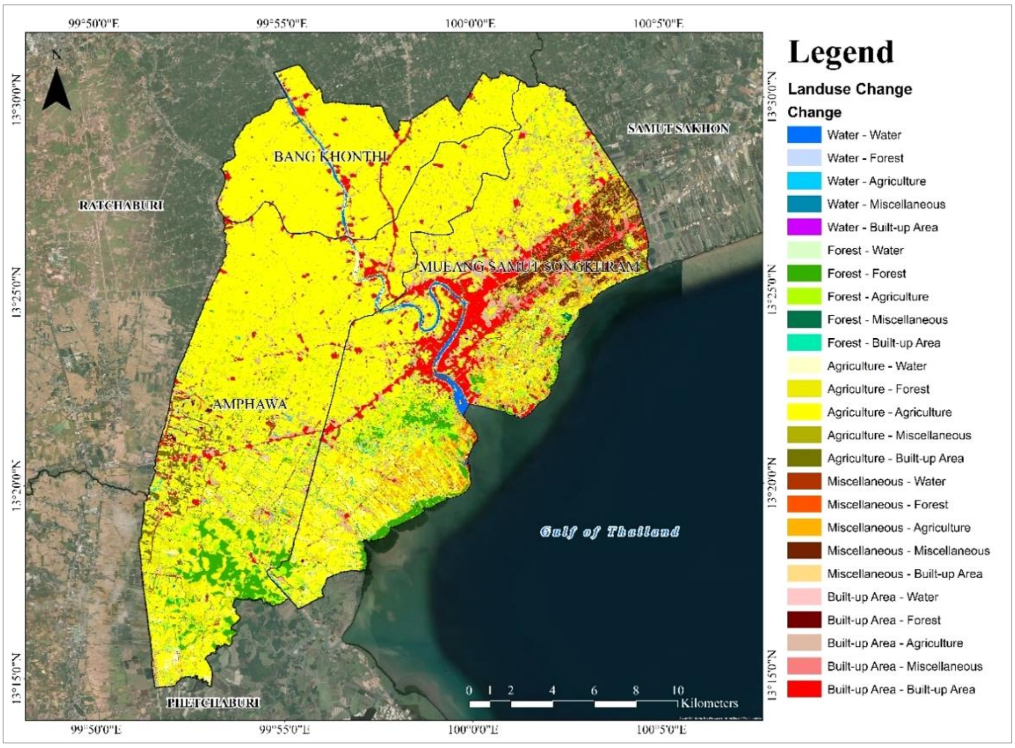


Figure 5. Map of Changes in Land Use in Samut Songkhram Province, 2013-2023

Table 8. Changes in Land Use in Samut Songkhram Province between 2003-2013

2013 \ 2023	Water Areas	Urban Areas and Buildings	Forests	Agricultural Land	Miscellaneous Areas	Total
Water Areas	3.176	0.913	0.947	7.509	0.583	13.128
Urban Areas and Buildings	0.344	22.386	1.058	32.227	3.362	59.378
Forests	0.175	0.875	13.393	15.876	0.443	30.761
Agricultural Land	7.201	11.713	15.482	242.107	3.651	280.154
Miscellaneous Areas	2.162	1.287	0.967	13.534	7.618	25.568
Total	**13.06**	**37.17**	**31.85**	**311.25**	**15.66**	**408.99**

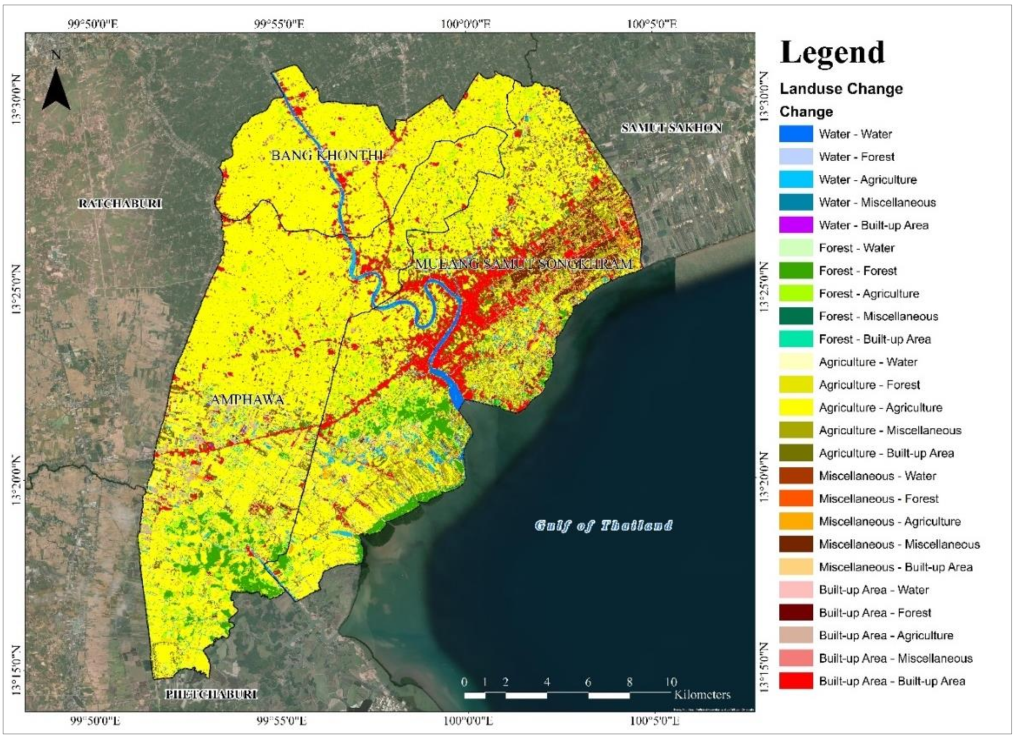


Figure 6. Map of Changes in Land Use in Samut Songkhram Province, 2003-2023

By analyzing the loss of agricultural land over the past 20 years, from 2003 to 2023, it was found that Samut Songkhram Province has lost an agricultural area totaling 31.099 square kilometers (19,437.43 rai). This was particularly pronounced in the Amphawa District of Samut Songkhram Province, which experienced the highest agricultural land loss. Due to development into a cultural tourism area, the Amphawa District area has changed into more urban and built-up areas, especially after 2003, when the area was developed into hotels and more buildings. This has caused a clear impact on agricultural land use. The analysis can be illustrated in Figure 7.

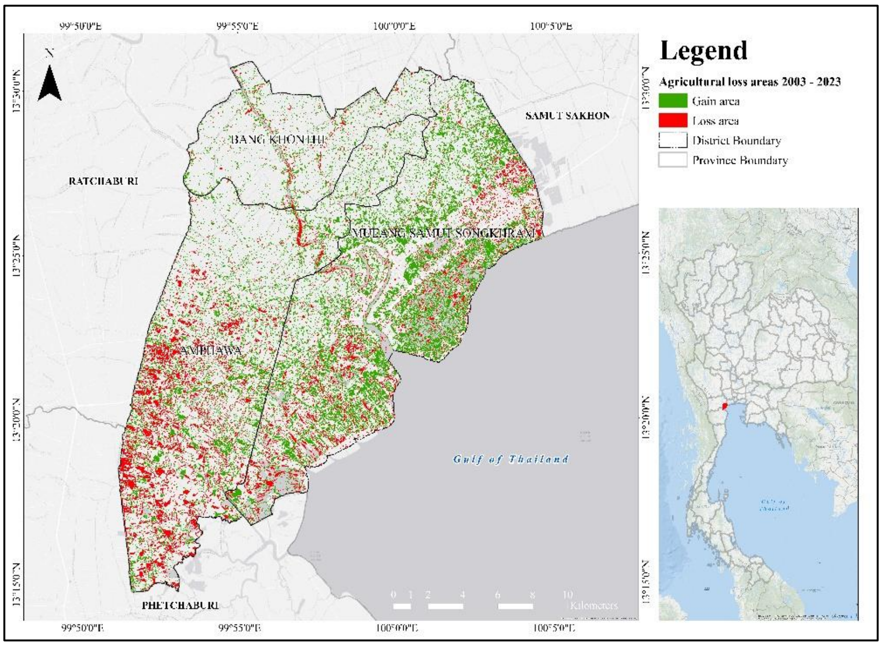


Figure 7. Map of Agricultural Land Loss in Samut Songkhram Province, 2003-2023

4- Discussion

The study of changes in land use has been widespread and beneficial for understanding the evolution of human behavior, whether it involves alterations in land use or forested areas [27, 28]. These studies examined changes in the environmental system of forests and the challenges between forested land and agricultural areas. However, for Samut Songkhram Province, a notable shift from agricultural to urban and built-up areas was observed, resulting in rapid urbanization processes. Yan et al. (2009) studied the relationships between land use when agricultural areas affected by urbanization. This corresponds with the work of Ayambire et al. (2019) and Gandharum et al. (2022) by proposing solutions for rural area transformation and agricultural land changes [29, 30]. To address land use change issues, suitable models for future studies [31, 32] could be employed. Remote sensing tools, especially Change Detection methods, are popular for monitoring increases or decreases in land areas [33–35]. The advantage of Change Detection is not only in quantifying changed areas but also in identifying the location and boundaries of these spatial changes [36]. In addition, analysis using the Supervise Classification remote sensing process found that, considering the index when selecting the study area groups, it will result in more accurate results as follows: Using the NDVI index will help in separating plant areas by species or agricultural areas very well. However, the NDBI index helps to better separate urban areas and buildings. NDWI is used to better separate water areas, whether it's rivers or areas covered by water in satellite images. However, even though remote sensing is an effective method for monitoring spatial changes, it is crucial to consider other factors influencing land use change, such as human behavioral factors, trends in agricultural commodity prices, and changes in land prices influenced by government policies. Therefore, for more comprehensive future studies, economic dimensions and human behavior aspects should also be considered.

5- Conclusion

In conclusion, this comprehensive study spanning two decades has revealed noteworthy transformations in the land use patterns of Samut Songkhram Province. The land was systematically categorized in 2003, including agricultural land, urban and built-up areas, forest land, miscellaneous areas, and water bodies. The accuracy of this classification was substantiated with an overall accuracy of 84 and a Kappa statistic of 81, attesting to its high reliability. By 2013, agricultural land constituted 73.52% of the province, with urban and built-up areas, forest land, miscellaneous areas, and water bodies following in descending order. The validation metrics for this period exhibited an overall accuracy of 84 and a Kappa statistic of 81, reinforcing the robustness of the data. The study extended to 2023, marking a reduction in agricultural land to 68.51%, while urban and built-up areas, forest land, miscellaneous areas, and water bodies experienced an expansion. The overall accuracy for this year reached 88, with a Kappa statistic of 85, affirming the reliability of the analytical findings.

Delving into the changes between 2003 and 2023, the most prominent surge occurred in urban and built-up areas, primarily fueled by the conversion of agricultural land. Over the initial decade (2003–2013), urban and built-up areas were augmented by 22.782 square kilometers (14,239.04 rai), accounting for 5.57% of the province's total area. The transition from agriculture predominantly contributed to the rise in urban and built-up areas, followed by miscellaneous areas and forest land. The trend persisted from 2013 to 2023, with urban and built-up areas continuing to escalate, predominantly originating from agricultural land of 28.287 square kilometers (17,679.92 rai, constituting 6.916% of the province's area). Subsequently, an in-depth analysis of changes in agricultural land from 2003 to 2013 pinpointed Amphawa District with the highest agricultural land, followed by Mueang Samut Songkhram District and Bang Khonthi District.

The agricultural landscape exhibited an unequivocal diminishing trajectory in the province over the two-decade span (2003–2023), with Mueang Samut Songkhram District experiencing a reduction exceeding 27.520 square kilometers (17,200.57 rai). Bang Khonthi District and Amphawa District followed suit, encountering reductions surpassing 3.214 square kilometers (2,009.24 rai) and 0.242 square kilometers (151.36 rai), respectively. The comprehensive and meticulous examination conducted in this research instills confidence in the accuracy and reliability of the findings, offering valuable insights into the dynamic shifts in land use within Samut Songkhram Province.

6- Declarations

6-1- Author Contributions

Conceptualization, M.W. and N.K.; methodology, M.W. and N.K.; software M.W. and K.T.; validation M.W., N.K., and P.H.; investigation N.K.; writing—original draft preparation N.K., M.W., K.T., and P.H.; visualization N.K. 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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6-4- Acknowledgements

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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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