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ASSESSING SPATIAL SUSCEPTIBILITY OF LAND USE CHANGE AROUND SUKHOTHAI HISTORICAL PARK AREA, MUEANG SUKHOTHAI DISTRICT, SUKHOTHAI PROVINCE, THAILAND

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ABSTRACT

Sukhothai Historical Park is considered one of the most important ancient sites in Thailand. It was registered as an ancient site of Sukhothai Old City in 1935. It has been continuously restored and renovated until 1991 when it was registered as a World Heritage Site under the list number 574. Currently, it is affected by the encroaching constructions near Sukhothai Historical Park. Therefore, it is necessary to use geographic information technology to inspect the surrounding area. The purpose of this study is to assess the sensitivity to land use changes in the area surrounding Sukhothai Historical Park, Mueang Sukhothai District, Sukhothai Province during 2007-2021 using the statistical principle of logistic regression in ArcMap 10.8 software. The research results found that the area with high sensitivity to land use change covered the highest area of 244.022 km^2 (43.77% of the total area). The area is mostly located in the central part of the study area, covering a 5km buffer zone of Sukhothai Historical Park. The results of the logistic regression analysis can identify important variables affecting land use changes in sensitive areas, including distance to road, distance to commercial and services area, distance to villages, and distance to recreation area. The preparation of spatial susceptibility of land use change Map in Mueang Sukhothai is a highlight of this research, which shows the level of sensitivity to land use change in the study area as a spatial pattern for systematic land use planning management, to support the sustainable change of the area surrounding Sukhothai Historical Park in the future.

KEYWORDS: Spatial Susceptibility, Land Use, Land Use Change, Sukhothai Historical Park Area, Sukhothai Province

1. INTRODUCTION

Sukhothai is a city with great historical, cultural and economic significance in Thailand (Kanchanakunjara et al. 2014; Prakitnonthakan 2019; Singtuen et al. 2024). In terms of cultural history, Sukhothai Province has been prosperous and has been the center of government, religion and economy for more than 700 years (Bishop et al. 1996; Kasetsiri 2019; Patnukao et al. 2024). With its long history, it has been declared by UNESCO as Sukhothai Historical Park. With its historical and cultural value such as the palace, religious sites and ancient sites, Sukhothai has become a famous cultural tourist attraction (Srisamoot 2024; Esichaikul and Chansawang 2022). With Sukhothai Historical Park as the center and the satellite cities of Kamphaeng Phet and Si Satchanalai, it has also been established by UNESCO. This led to the city becoming Kamphaeng Phet Historical Park and Si Satchanalai Historical Park. At present, the area surrounding the historical park has undergone land use changes, which has had a significant impact on the ancient site. Therefore, there is an idea to study the land use patterns surrounding Sukhothai Historical Park.

Land use change is a human activity that has a major impact on the Earth's surface (Zhai et al. 2021; Elfadaly et al. 2022). It is a change in the landscape pattern that is consistent with the changing time period and is related to economic and social development (Liu et al. 2024). Land use is an indicator of human activities and the use of resources and the environment in that area (Biłozor et al. 2024; Safo et al. 2024), which is caused by economic and social development as a factor driving such changes. In Thailand, land use changes are caused by important factors such as population growth, urban expansion, growth in the agricultural sector, industrial sector, tourism and service sector, etc. (Kombate et al.2022; Kumar and Agrawal 2023). As a result, the demand for land use has increased accordingly. Currently, the rapid expansion of urban areas has resulted in changes in land use and land cover in large cities (Haq et al. 2021; Waiyasusri and Tananonchai 2022). The important policies that attempt to push Thailand to have economic expansion are the spatial development plan according to the national strategy (2017-2036) and the National Economic and Social Development Plan No.12 (2017-2021) (Office of the National Economic and Social Development Board, Office of the Prime Minister, Bangkok, Thailand 2016). There is a concept for the development approach as "stability, prosperity, sustainability through development according to the philosophy of sufficiency economy" which In line with the United Nations' Sustainable Development Goals (SDGs) Goal 11 (Yamasaki and Yamada 2022). The goal aims to make cities and human settlements inclusive, safe, resilient and sustainable (Xiao et al. 2018; Velentza 2023). This has led to the development of both the city's engineering infrastructure and buildings to support the tourism industry, resulting in a significant urban expansion.

There are many researches on the application of Geo-informatics technology in land use change prospection. For example, the research of Xiao et al. (2006) applied the technology to evaluate urban expansion and land use change in Shijiazhuang, analyzed by remote sensing during 1987-2001. It showed empirical data that there was a rapid urban growth to accommodate the increasing population. The expansion of transportation and industrial development affected the area changes near the historical site. Region of India were also affected by land use changes. This is shown in the research of Banerjee and Srivastava (2013) applied remote sensing and GIS data, especially data from Landsat imagery satellite, in this research. The results of the study enable the assessment. of the archaeological site area to be clearly identified, and the area can be managed under the conservation and development of the cultural heritage of India. The problem of land use change near the UNESCO World Heritage Site area is also evident in Kaziranga Eco-Sensitive Zone, India. As Nath et al. (2023) used Landsat imagery satellite data to study the area from 1990 to 2020. The study found that forest and water areas were replaced by urban and built-up areas. The outcome of this study is expected to be useful for the long-term management of the Kaziranga Eco-Sensitive Zone. Currently, the United Nations has been trying to push the SDGs to support and promote better living conditions for the population. Development in various areas cannot escape the change of land conditions in each region around the world. As Kalfas et al. (2023) studied urbanization and land use planning for achieving the SDGs in Greece. The study found that indicators of sustainable urbanization are not just the conversion of agricultural areas or forest areas, but also the development of urban or community areas to make the most of the land, by showing the participation of people in the community and government agencies (such as local municipalities) to cooperate in creating and developing areas for economic, social, and cultural sustainability. The important thing about this research is that such areas should have systematic urban planning for future sustainability. In addition, new technologies such as the development of artificial intelligence (AI) and language models are becoming popular. The research of Agapiou and Lysandrou (2023) has collected such technologies to apply in earth observation and remote sensing in archaeology. The ChatGPT language model is becoming an interesting option for exploring archaeological and historical sites. From all the research mentioned above, it is realized that Geo-informatics technology is very helpful for studying archaeological sites. If such technology is applied to land use planning, it can help develop the area effectively.

This research aims to assess the sensitivity to land use changes in the area surrounding Sukhothai Historical Park, Mueang Sukhothai District, Sukhothai Province, between 2007-2021 using geo-informatic technology. In addition, the novelty of this research is the application of logistic regression statistics principles together with geo-informatics technology to analyze the factors that influence the change of land use in the area, in order to propose an appropriate land use guideline for the World Heritage Ancient City. The goal is to create understanding among communities surrounding Sukhothai Historical Park about the relationship between geographic location, culture and natural environment. This is essential basic information for planning spatial management, especially the ancient city of Sukhothai, a world cultural heritage site, to lead to both physical and policy recommendations for appropriate land use guidelines, allowing communities to coexist with sustainable development.

2. MATERIALS AND METHODS

2.1 Study area

Sukhothai City District is the administrative center of Sukhothai Province, located in the central region of Thailand. Phuket is located between latitudes 16°50' N to 17°10' N and longitudes 99°30' E to 100°0' E, with a total area of 557.534 km^2 (Fig. 1). The topography of the eastern part of the study area is characterized by a basin and a floodplain. The Yom River flows through this area, making it the commercial and administrative center of Sukhothai Province (Singtuen et al. 2024). In addition, the suburbs are also an important rice-growing area of Sukhothai Province. The western part of the study area is characterized by a range of mountains and colluvial deposits. The range is called Khao Luang Range, with the highest point being Phu Kha, 1244 msl. high. To the east of the range is an important historical site of Thailand, Sukhothai Historical Park. The area used to be the administrative center of the ancient Thai kingdom, the Sukhothai Kingdom, during the 13th and 14th centuries. Sukhothai Historical Park was first declared protected by the Royal Gazette, Volume 92, Part 112, dated August 2, 1961. Later in 1976, the park's restoration project was approved and officially opened in July 1988. On December 12, 1991, UNESCO announced this park as a World Heritage Site together with the historical parks in Kamphaeng Phet and Si Satchanalai under the name "Historic City of Sukhothai and Associated Towns".

2.2 Data Preparation

The data for this research were collected from both Landsat satellite imagery systems: Landsat 5 TM Image and Landsat 8 OLI/TIRS Image in 2007, 2013, and 2021 for the analysis of land use patterns and land use changes around Sukhothai Historical Park during that period. In addition, data on factors affecting land use changes were collected, including slope, distance to national park, distance to stream, distance to road, distance to commercial land and services area, distance to villages, distance to industrial area, and distance to recreation area. Such spatial data are considered important variables used in the analysis of variables affecting land use changes. All data will be generated to create a raster database with a grid cell size of 30x30 m, as shown in Table 1.

Table 1. Spatial data layers used in this research.

Spatial Database	Date	Format	Sources
Landsat 5 TM Path/Row 130/48	21 Jan 2007	TIFF	US. Geological Survey (USGS)
Landsat 8 OLI/TIRS Path/Row 130/48	6 April 2013	TIFF	US. Geological Survey (USGS)
Landsat 8 OLI/TIRS Path/Row 130/48	28 February 2021	TIFF	US. Geological Survey (USGS)
Digital Elevation Model (DEM)	2021	GRID	Royal Thai Survey Department
Slope	2021	GRID	Derived from the DEM
Distance to national park	2021	GRID	Department of National Parks, Wildlife and Plant Conservation
Distance to stream	2021	GRID	Department of Water Resource
Distance to road	2021	GRID	Land Development Department
Distance to commercial land and services area	2021	GRID	Land Development Department
Distance to villages	2021	GRID	Land Development Department
Distance to industrial area	2021	GRID	Land Development Department
Distance to recreation area	2021	GRID	Land Development Department

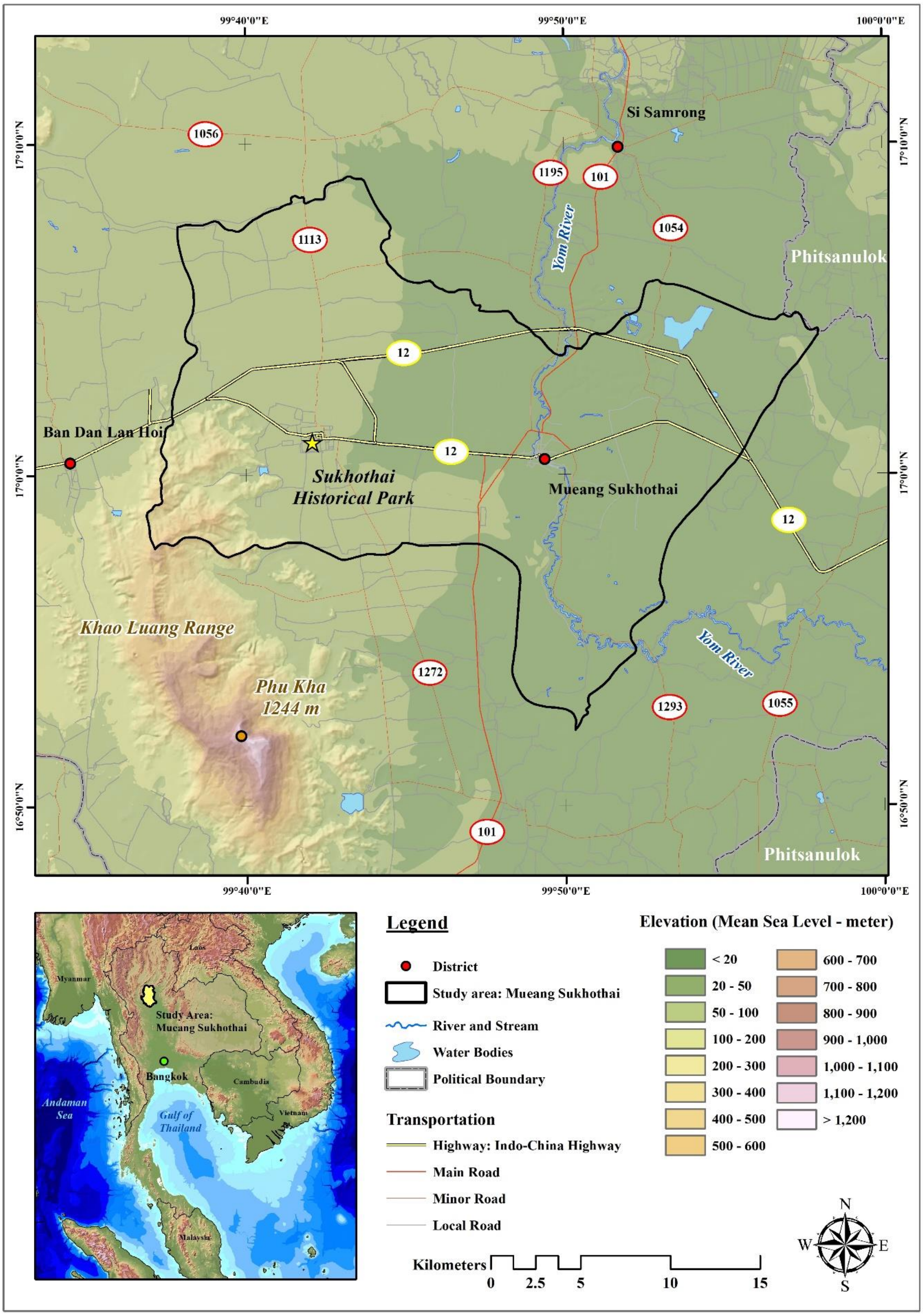

Figure 1. Location maps of the study area.

2.3 Methodology

The research process in this study consisted of the following steps: (1) Geo-informatic approach and (2) Statistical approach. The details of each step are briefly explained below (Fig. 2).

2.3.1 Geo-informatic approach

From the collection of Landsat satellite image data in three time periods. This research used the Erdas Imagine Version 8.5 satellite image processing program to mix satellite image bands (band combination) by selecting bands 5 (short-wavelength infrared), 4 (near-infrared), and 3 (red) for Landsat TM system. For Landsat OLI/TIRS system, bands 6 (short-wavelength infrared), 5 (near-infrared), and 4 (red) were used. These three bands were entered into the band combination method. After mixing, it can be used to detect urban areas and buildings clearly. These bands can distinguish urban areas from areas covered by vegetation very well (Oon et al. 2019; Waiyasusri 2021; Huang et al. 2023).

When entering the process of interpreting satellite imagery for land use and land cover classification in 2007, 2013 and 2021, ArcGIS 10.8 software was used based on the principles of Machine learning. The principles were applied to deep learning classification in this study, namely the Random Decision Forests method. Random Decision Forests (or Random Forest) is an ensemble learning method for land use and land cover classification. The Random Decision Forests method is a popular process for interpreting land use effectively (Phinzi et al. 2023). The random forest is a classification algorithm based on decision tree method. The random forest almost always has higher accuracy than the decision tree since the random forest algorithm incorporate many weak decision trees. Here, the final decision is the combined decision from all the incorporated decision trees in which the majority vote is often employed (Rodriguez-Galiano et al. 2012; Avci et al. 2023). The training process of random forest is iterative where each iteration a new decision tree is added into the forest. After creating a decision tree, the next step is to determine the overall performance of the random Forest. The out-of-bag samples are submitted into the forest where the final decisions of each sample are made. Here the majority rule is employed (Jamali et al. 2024). The importance for each feature on a decision tree is then calculated as Equation 1:

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

Where fi_i is the importance of feature i ;ni_j is the importance of node j

These can then be normalized to a value between 0 and 1 by dividing by the sum of all feature importance values (Equation 2):

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

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

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

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

The results of the land use pattern interpretation are presented as the overall accuracy and the Kappa coefficient (KHAT) to assess the accuracy of the classification of various data types that appear on satellite imagery (Congalton 1988; Ababneh et al. 2019). By defining the sampling points in the study area based on data from the Land Development Department (LDD), Thailand, the validation was performed and compared with the data obtained from the classification. The classification criteria are as follows:

< 0 means unacceptable classification data.
0.01 – 0.40 means fair classification data.
0.41 – 0.60 means moderate classification data.
0.61 – 0.80 means good classification data.
0.81 – 1.00 means very good classification data.

After the validation of the data obtained from the land use pattern interpretation is completed, the data that passed the criteria of Overall Accuracy and KHAT, such data will be analyzed for land use changes using the Change Detection method in the Tabulate area analysis function in ArcGIS 10.8 software. The change detection analysis can be calculated as Equation 4 (Jia et al. 2014; Waiyasusri 2021):

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

WhereΔ is the proportion of land use pattern that has changed (percent)

A1 is the type of land use at time one (T_1)

A2 is the type of land use at time two (T_2)

The results are displayed as a proportion of land use of each type on the map in a transition matrix format, which shows the land use change pattern from 2007 to 2021. It can also display the urbanization area around Sukhothai Historical Park in a spatial format.

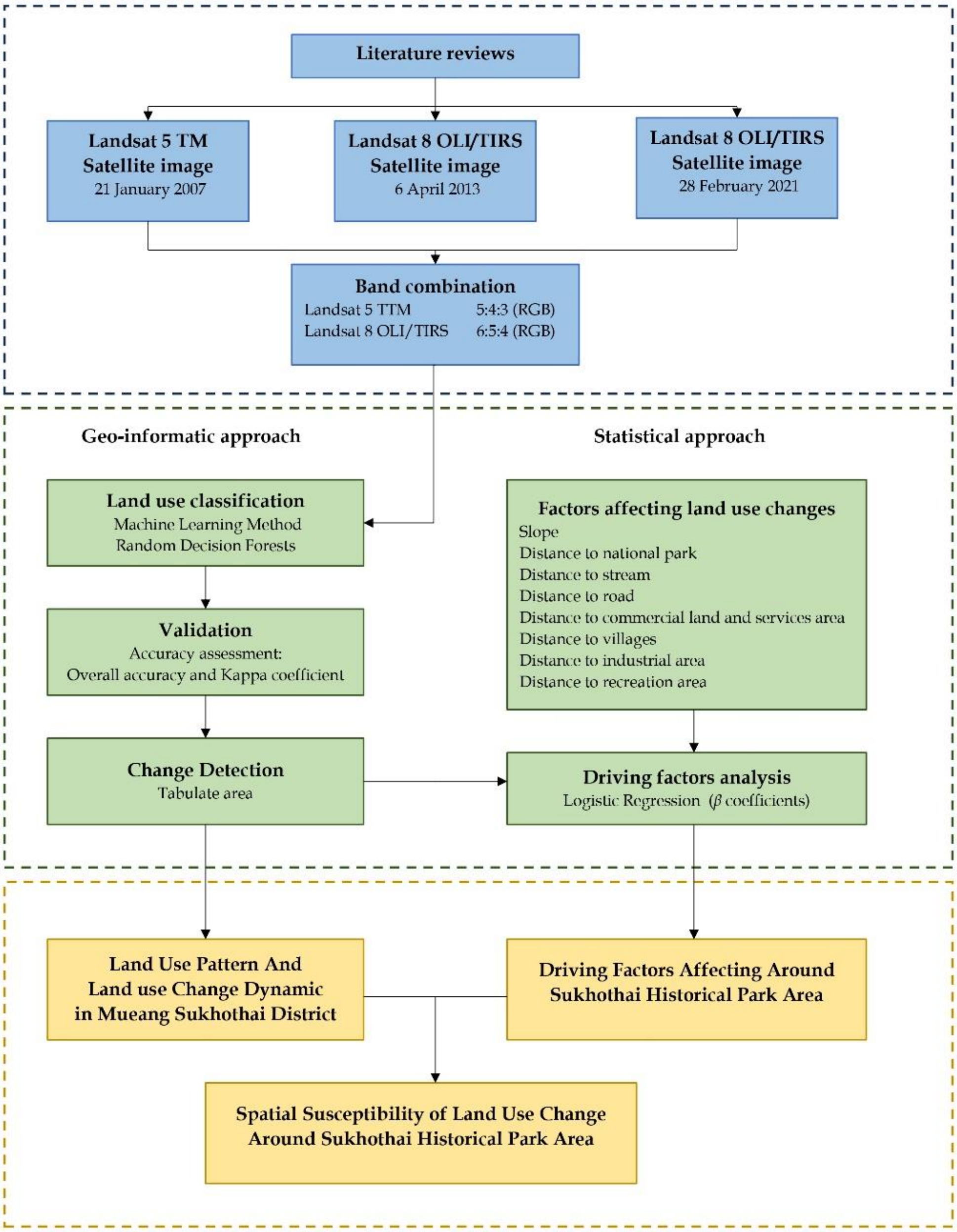

Figure 2. Flow chart of methodology.

2.3.2 Statistical approach

In this research, the factors affecting the change of land use in the area surrounding Sukhothai Historical Park were selected. The variables used in this research were slope, distance to national park, distance to stream, distance to road, distance to commercial land and services area, distance to villages, distance to industrial area, and distance to recreation area (Fig. 3).

The first important spatial data for the researchers in this study is the Elevation (digital elevation model-DEM) data obtained from the Royal Thai Survey Department (RTSD) in shapefile format, including elevation point data, contour line data, and water source and water route data. The data will be analyzed spatially using the topo to raster in technique in ArcGIS 10.4 software. The result is a DEM data with a size of 30x30 m grid cellsize. This data can be used to analyze slope variables (Fig. 3a).

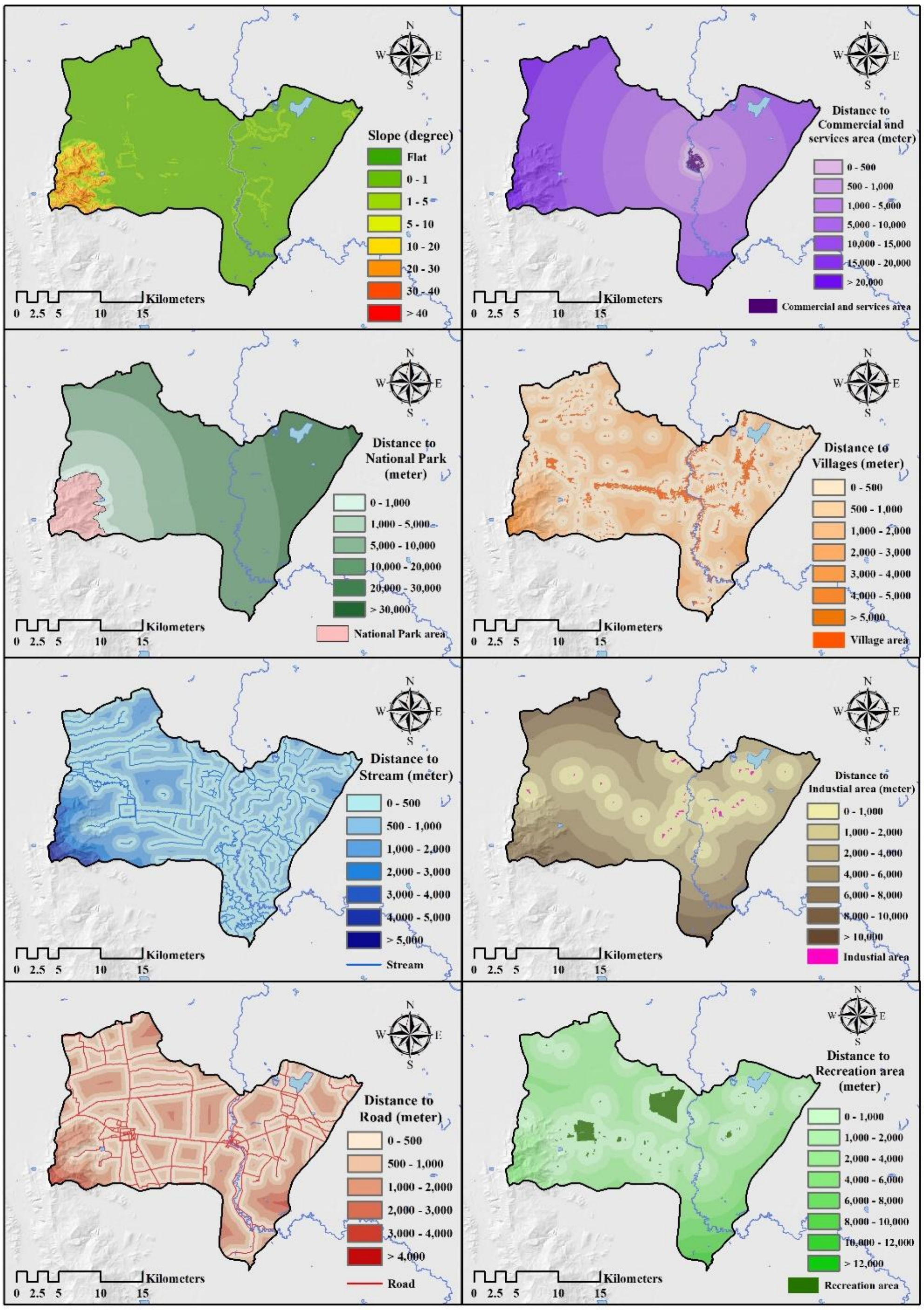

Figure 3. Spatial database of factor affecting land use change in Around Sukhothai Historical Park Area. a) slope, b) distance to national park, c) distance to stream, d) distance to road, e) distance to commercial land and services area, f) distance to villages, g) distance to industrial area, and h) distance to recreation area.

The socio-economic factor data that affect land use changes are: distance to national park (Fig. 3b), distance to stream (Fig. 3c), distance to road (Fig. 3d), distance to commercial land and services area (Fig. 3e), distance to villages (Fig. 3f), distance to industrial area (Fig. 3g), and distance to recreation area (Fig. 3h). The data will be converted to raster data format. Then, it will be analyzed using Euclidean distance technique in spatial analysis tools. Euclidean distance is measured from the center of the source cell to the center of each neighboring cell (Zeferino et al. 2020; Ye et al. 2024). The true Euclidean distance is computed by each distance tool. The method works by calculating the distance from a target cell to each source cell, using the hypotenuse of a right triangle, with the x_max and y_max values as the other two sides. This technique provides the true Euclidean distance, as opposed to the simpler cell-to-cell distance (Navin and Agilandeeswari 2020; Choudhury et al. 2023). The shortest distance to a source is identified, and if it is within the specified maximum distance, the corresponding value is assigned to the cell in the output raster. The Euclidean distance can be calculated as Equation 5.

$$D = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2} \quad (5)$$

where D is the Euclidean distance, and are the Cartesian coordinates of the two points. The squares and the square root in the formula take care of distance being a scalar quantity (squares and square roots cannot be negative), so absolute value bars are not needed in the two-dimensional formula.

When the data on factors affecting land use change in raster format is complete, it is then analyzed using the statistical method logistic regression analysis. Logistic Regression is a technique for discovering the empirical relationships between a binary dependent and several independent categorical and continuous variables (Ozdemir 2016; Kim et al. 2020; Cao et al. 2020). Logistic regression analysis is calculated using the following Equation 6.

$$\text{Log}\left(\frac{P_i}{1-P_i}\right) = \beta_0 + \beta_1 x_{1,i} + \beta_2 x_{2,i} + \ldots + \beta_n x_{n,i} \quad (6)$$

where P is the flood prone area, xi are independent variables and β is the coefficient value. This statistical method was used to provide the variables that were analyzed to determine which variables had an influence on land use changes in the study area. The statistical principles considered the independent and dependent variables in every grid cell in the study area. In summary, the results of the analysis can be used to analyze areas that are sensitive to land use changes (Spatial susceptibility of land use change) by classifying the method into 5 classes: very high, high, moderate, low, and very low. It is displayed as Spatial susceptibility of land use change mapping. This is to obtain results for managing areas that are sensitive to land use changes that may occur in the future.

3. RESULT

3.1 Land Use Pattern in Mueang Sukhothai District

In the study area, it was visually classified into 13 land-use classes: Paddy field (A1), Field crops (A2), Perennial crops (A3), Orchards (A4), Pasture (A7), Fishery (A9), Forest land (F), Urban and built-up land (U), Water bodies (W), Grass land (M1), Wetland (M2), Mineral (M3), and Landfill (M4) (Fig. 4). The results of the interpretation of land-use patterns using the Random Decision Forests method will be adjusted for accuracy (Post classification and reclassification). The overall accuracy assessment was 84.2, 85.8 and 91.3 % for 2007, 2013 and 2021, respectively, with a kappa coefficient (k^) of 0.81, 0.83 and 0.87, respectively. It can be seen that the Increased classification accuracy has a higher level of accuracy than in the past years, because the current Landsat satellites have improved the radiometric accuracy in the Landsat image. The data after land use classification shows the overall accuracy and kappa coefficient at 0.80-1.00, which indicates that the interpretation of the land use pattern this time is at the very good classification data level.

The research results show that the land use conditions of Mueang Sukhothai District are mostly used as paddy fields. Throughout the past 14 years, it can be seen that the rice planting area tends to increase every year. This can be seen from the proportion of land use as paddy fields, which covers an area of 280.129 km^2 (50.24%), 385.950 km^2 (69.22%), and 380.330 km^2 (68.22%), in the years 2007, 2013, and 2021, respectively.

The reason why the rice planting area has increased is because the government has continuous measures to help rice farmers and the price of paddy rice that farmers can sell tends to increase. Therefore, farmers have returned to rice farming in the fields that were previously vacant. This has affected the change in the pattern of wetland land use. In 2007, wetlands (the second largest area after paddy field) covered 129.482 km^2 (23.22%), but in 2013 and 2021, the area covered only 10.748 km^2 (1.93%) and 10.041 km^2 (1.80%), respectively. It can be seen that wetlands have a clear tendency to decrease in area, which is a result of the expansion of agricultural areas, especially areas for agriculture such as rice fields, orchards, animal husbandry, and local fisheries. The urban and built-up land area was identified as 48.789 km^2 (8.75%), 63.364 km^2 (11.37%), and 67.466 km^2 (12.10%) in the years 2007, 2013, and 2021, respectively. The land use has also expanded. The proportion of land-use area in Mueang Sukhothai District as shown in Table 2.

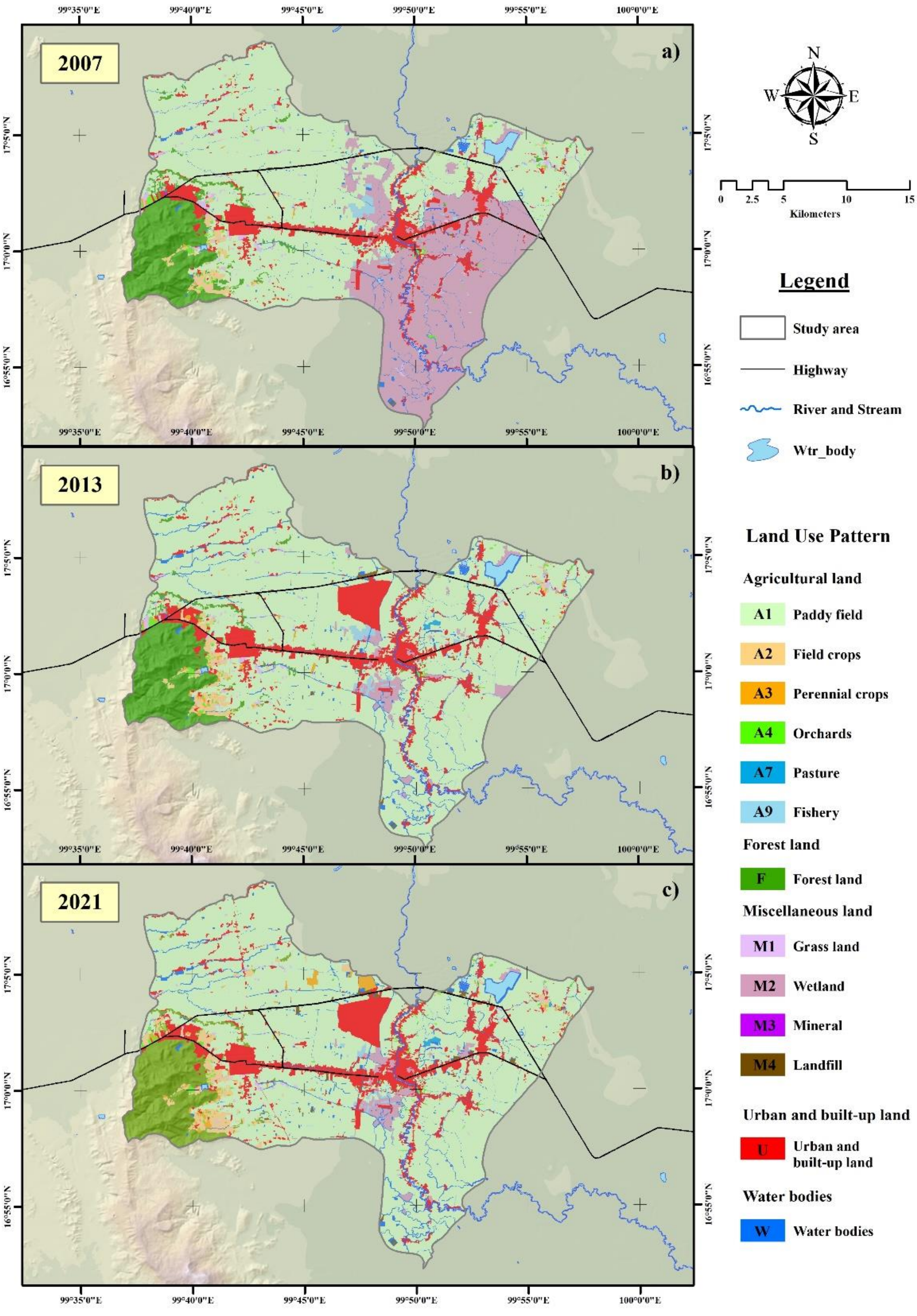

Figure 4. Land-use pattern in Mueang Sukhothai District during 2007, 2013, and 2021.

Table 2. Land-use area statistics in Mueang Sukhothai District for the years 2007, 2013, and 2021 (km^2).

Land use pattern	2007 km²	2007 %	2013 km²	2013 %	2021 km²	2021 %
Agricultural land						
A1 Paddy field	280.129	50.24	385.950	69.22	380.330	68.22
A2 Field crops	5.707	1.02	8.917	1.60	13.387	2.40
A3 Perennial crops	1.563	0.28	2.722	0.49	4.961	0.89
A4 Orchards	2.948	0.53	2.595	0.47	3.042	0.55
A7 Pasture	7.863	1.41	0.623	0.11	0.683	0.12
A9 Fishery	3.376	0.61	3.437	0.62	1.929	0.35
Forest land	48.778	8.75	46.028	8.26	45.344	8.13
Urban and built-up land	48.789	8.75	63.364	11.37	67.466	12.10
Water bodies	14.892	2.67	21.171	3.80	24.366	4.37
Miscellaneous land						
M1 Grass land	7.955	1.43	5.670	1.02	3.470	0.62
M2 Wetland	129.482	23.22	10.748	1.93	10.041	1.80
M3 Mineral	5.521	0.99	4.853	0.87	0	0.00
M4 Landfill	0.531	0.10	1.456	0.26	2.515	0.45
Total	557.534	100.00	557.534	100.00	557.534	100.00
Overall Accuracy (%)	84.2		85.8		91.3	
Kappa coefficient (*KHAT*)	0.81		0.83		0.87	

3.2 Land Use Change Dynamic Around Sukhothai Historical Park Area

Once the results of the Land Use Pattern were obtained, this research organized the land use data using the GIS analysis tool, which is dissolve analysis. The land use pattern will be categorized into only 5 groups: Agricultural land, Forest land, Urban and built-up land, Waterbodies, and Miscellaneous land. This is to reduce redundancy of land use data and to analyze Land Use Change Dynamic to find the appropriate proportion of land use change. The results of the Land Use Change Dynamic Around Sukhothai Historical Park Area research are shown in Table 3. The results of this research found that during 2007-2021, the type of land use that tended to decrease the most was Miscellaneous land, with an area decreasing by -127.463 km² (-88.831%), followed by Forest land, with an area decreasing by -3.434 km² (-7.040%). The Miscellaneous land that tended to decrease the most was because the wetland area was transformed into rice fields due to economic policies. The type of land use with the highest tendency is Waterbodies, with an increase of 9.474 km² (63.618%), followed by Urban and built-up land, with an increase of 18.677 km² (38.281%), and Agricultural land, with an increase of 104.193 km2 (34.939%). However, when examining the changes in each type of land use during 2007-2021, it was found that Agricultural land was transformed into Forest land and Urban and built-up land the most, at 43.15 km² and 32.45 km², respectively. Forest land changed the least, but some areas were transformed into Agricultural land and Urban and built-up land the most, at 7.80 km² and 6.30 km², respectively. Miscellaneous land was transformed into Urban and built-up land the most, at 10.98 km². Urban and built-up land and Waterbodies changed little. With a change area not exceeding 5 km².

It can be seen that the land use changes that occurred in the area in Mueang Sukhothai District during 2007-2021 occurred around the Sukhothai Historical Park Area. From Fig.5 shows the expansion of the Urban and built-up land area. Such changes have led to the urbanization process, especially the area along both sides of Highway No. 12, which is an important road in Thailand. It is also known as Indochina Road and is an important economic route in the central region of Thailand. Fig.5a shows the urban expansion in 2007, 2013, and 2021 along the highway and along both sides of the Yom River, which was originally a waterway since the Sukhothai period. The central part of Mueang Sukhothai District is an important commercial and residential area. However, at present, the city has begun to expand to the northeast and the west of the study area. In particular, the expansion that occurred to the west has now expanded to the Sukhothai Historical Park area, which has clearly affected the spatial changes around Sukhothai Historical Park. In the expansion of the urban area in the past, it was used as other types of land use. It shows the original area before changing into urban and built-up land area as shown in Fig.5b. It clearly shows that the central part of the study area has changed the most along Highway No. 12 and along the Yom River. Before becoming an urban area, most of the area used to be a wetland.

Table 3. Matrix of land use change in Mueang Sukhothai District during 2007-2021 (km^2)

		2021					Changing area	
	Land use change	Agricultural land	Forest land	Miscellaneous land	Urban and built-up land	Waterbodies	km^2	%
2007	Agricultural land	142.58	43.15	13.28	32.45	1.10	104.193	34.939
	Forest land	7.80	103.85	2.01	6.30	1.12	-3.434	-7.040
	Miscellaneous land	3.57	3.79	13.50	10.98	3.35	-127.463	-88.831
	Urban and built-up land	2.97	4.12	4.72	115.11	1.67	18.677	38.281
	Waterbodies	0.14	0.55	0.11	0.82	5.57	9.474	63.618

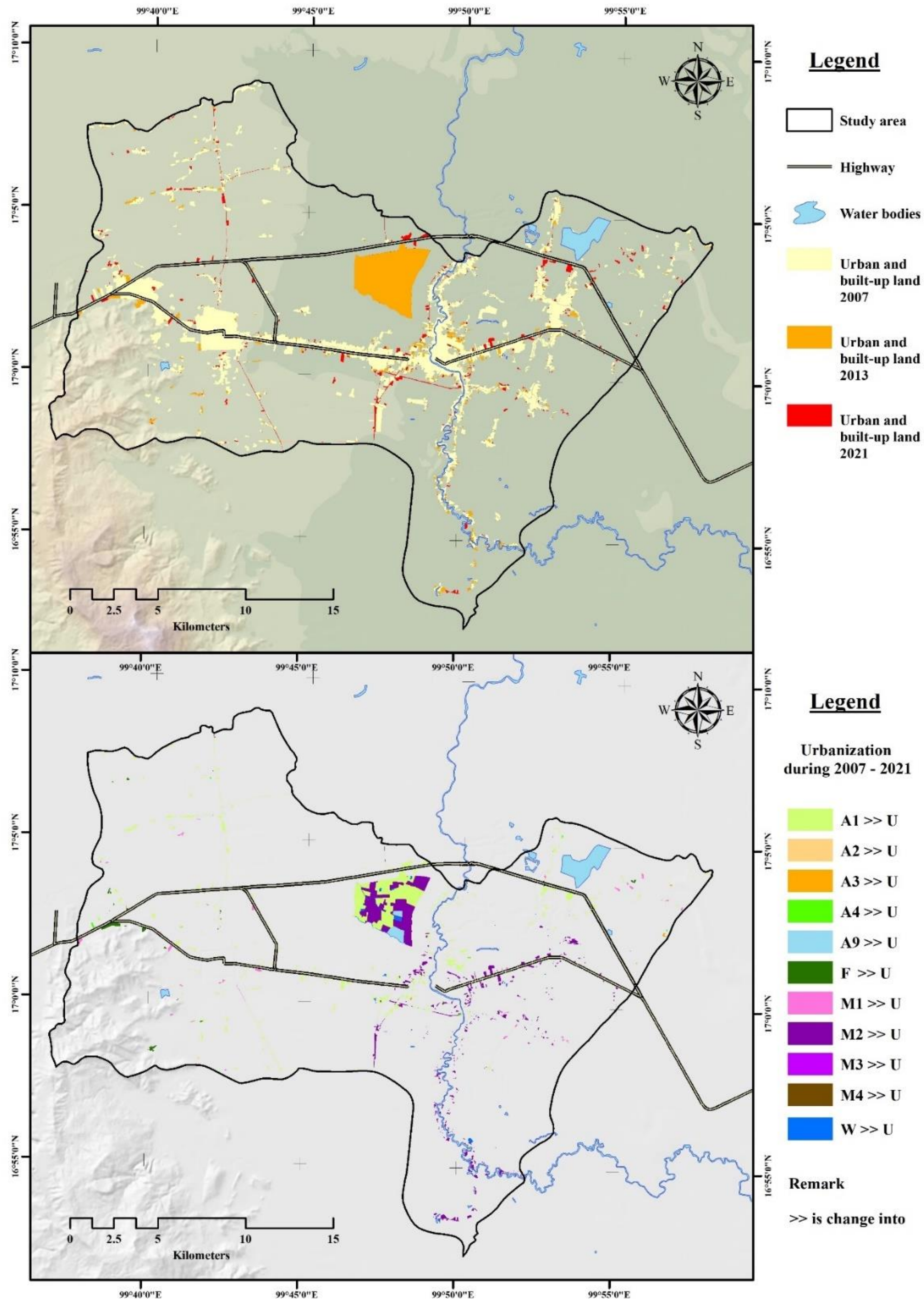

Figure 5. Urban and built-up land area in 2007, 2013, and 2013 (a), and Urbanization during 2007-2021 in Mueang Sukhothai District (b).

3.3 Driving Factors Affecting Around Sukhothai Historical Park Area

Negative and positive β coefficients obtained in logistic regression analysis indicated the positive and negative relationship between various land use change with the driving variables (Table 4). The results of the research found that there were 4 driving factors affecting the change in agricultural land area: slope (β = -0.030), distance to road (β = 0.005), distance to commercial and services area (β = 0.012), and distance to industrial area (β = 0.003), respectively. It can be seen that most of the variables are positive β coefficients, indicating that the greater the distance from road, commercial and services area, and industrial area, the greater the sensitivity to change to agricultural land. On the other hand, if the factor affecting the change in agricultural land type is negative β coefficients, which is the slope variable, it shows that the area with a relatively low slope or a flat area is found. This can easily affect the sensitivity to change to Agricultural land. The driving factors that affect the change in Forest land area are 7 variables: slope (β = 0.032), Distance to National Park (β = -0.050), Distance to Road (β = 0.080), Distance to Commercial and services area (β = 0.006), Distance to Villages (β = 0.100), Distance to Industrial area (β = 0.001), and Distance to Recreation area (β = 0.001), respectively. It can be seen that most of the variables are positive β coefficients, meaning that if the area has a high slope and is far from the road, commercial area, village, industrial area, and tourist attractions, it can easily affect the sensitivity to change to forest land.

The main point of this research is to examine the current urban and built-up land areas that have impacted Around Sukhothai Historical Park Area. It can be seen that the driving factors that affect the change in urban and built-up land areas are 6 variables: Distance to National Park (β = 0.001), Distance to Road (β = -0.064), Distance to Commercial and services area (β = -0.051), Distance to Villages (β = -0.023), Distance to Industrial area (β = -0.001), and Distance to Recreation area (β = -0.003), respectively. It can be seen that most of the variables are negative β coefficients, indicating that areas near roads, commercial areas, villages, industrial areas, and tourist attractions are more susceptible to changes to urban and built-up land use. In particular, the variables Distance to Road, Distance to Commercial and services area, and Distance to Villages show strong negative β coefficients.

Table 4. Logistic regression results of the spatial distribution of land use change in Mueang Sukhothai District.

Land use Variables	Agricultural land		Forest land		Urban and Built-UpLand		Water bodies		Miscellaneous land	
	β	$Exp(\beta)$	β	$Exp(\beta)$	β	$Exp(\beta)$	β	$Exp(\beta)$	β	$Exp(\beta)$
Slope	-0.030	0.971	0.032	1.033					0.028	1.028
Distance to National Park			-0.050	0.945	0.001	1.001	-0.001	0.999	0.001	1.001
Distance to Stream							-0.02	0.979	0.001	1.000
Distance to Road	0.005	1.005	0.080	1.076	-0.064	0.938				
Distance to Commercial and services area	0.012	1.009	0.006	1.005	-0.051	0.945				
Distance to Villages			0.100	1.092	-0.023	0.981				
Distance to Industrial area	0.003	1.001	0.001	1.000	-0.001	0.998	-0.001	0.998		
Distance to Recreation area			0.001	1.001	-0.003	0.995			-0.085	0.915
Constant	-0.282		-1.681		-0.804		-2.862		-2.421	
ROC value	0.750		0.810		0.86		0.72		0.77	

The relative operating characteristic (ROC) is a method to verify the effectiveness of the auto logistic regression. The results showed that the ROC values of various land-use patterns in Mueang Sukhothai District showed values greater than 0.7, which indicated that the auto logistic model was relatively high. The results were obtained ROC values of 0.75 (agricultural), 0.81 (forest), 0.86 (urban/built-up lands), 0.72 (waterbodies) and 0.77 (miscellaneous land).

3.4 Spatial Susceptibility of Land Use Change Around Sukhothai Historical Park Area

The results of the study of Spatial Susceptibility of Land Use Change Around Sukhothai Historical Park Area using the statistical analysis principle of logistic regression by using the β value to create a spatial database and display it as a map. This map shows the level of sensitivity to land use changes in urban and built-up land. This is to prepare for future land use planning that will occur in the study area. The results of the study analyzed spatial data in GIS together with statistical values from logistic regression as shown in Equation 7.

Y = -0.804 + (“Distance to road” * -0.064) + (“Distance to commercial and services area” * -0.051) + (“Distance to village” * -0.023) + (“Distance to recreation area” * -0.003) + (“Distance to industrial area” * -0.001) + (“Distance to national park” * 0.001)

Table 5. Spatial Susceptibility of Land Use Change area around Sukhothai Historical Park area (km²).

Spatial Susceptibility of Land Use Change level	Area	
	km²	%
Very Low	8.169	1.47
Low	38.940	6.98
Medium	141.675	25.41
High	244.022	43.77
Very high	124.727	22.37
Total	557.534	100.00

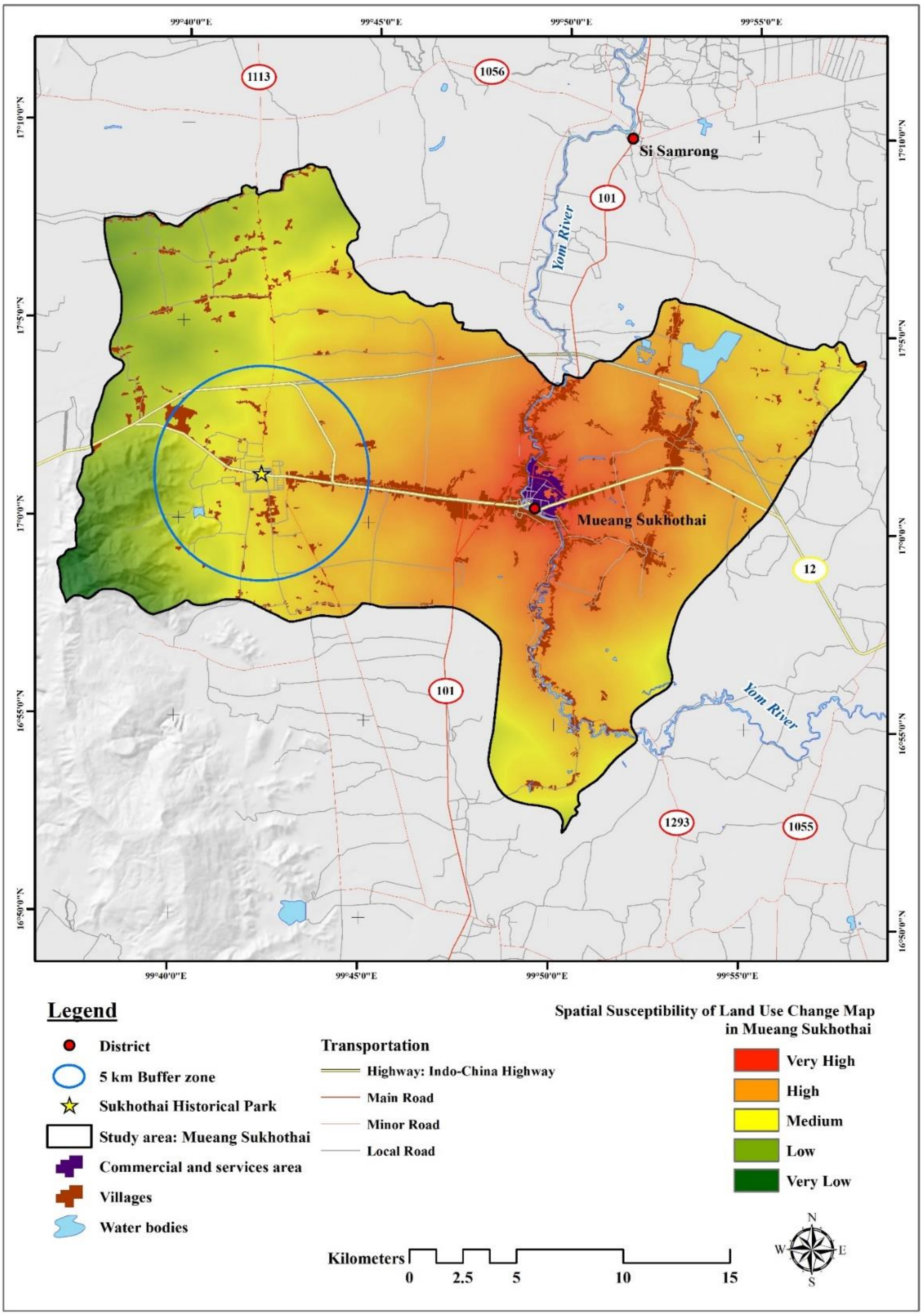

Figure 6. Spatial Susceptibility of Land Use Change Map in Mueang Sukhothai.

The results of β values of various variables make the findings highlight of this research that can show the sensitivity level of land use change as spatial data to facilitate management and planning of future land use. The results of the study of Spatial Susceptibility of Land Use Change show the sensitivity level to land use change divided into 5 levels: areas with very low sensitivity to land use change, areas with low sensitivity to land use change, areas with moderate sensitivity to land use change, areas with high sensitivity to land use change, and areas with very high sensitivity to land use change, respectively, as shown in Table 5.

The results of the study of Spatial susceptibility of land use change level are shown in Figure 6. In Mueang Sukhothai District, there is a moderate to very high level of sensitivity to land use change. As can be seen from the results of this research, it was found that the area with high sensitivity to land use change covers the highest area of 244.022 km2 (43.77% of the total area). Most of this area is located in the central part of the study area, covering a radius of 5 km buffer zone of Sukhothai Historical Park. It also appears on the east side of Mueang Sukhothai District. The area with moderate sensitivity to land use change covers the second highest area, covering an area of 141.675 km2 (25.41% of the total area). This area covers most of the western part of the study area, found around Sukhothai Historical Park, the south side, and the eastern edge of the study area. The area with very high sensitivity to land use change covers the third largest area. It covers an area of 124.727 km^2 (22.37% of the total area). The area is found in the central part of the study area, which is the area of Sukhothai New City and along the Yom River. The area is the location of Sukhothai City, which is the center of trade and economics, politics and government, and an important residential area at present.

4. DISCUSSION

Our results revealed that showed the trend of increasing land use types of waterbodies, urban and built-up land, and agricultural land respectively. The type of land use with the highest trend was waterbodies with an increase of 9.474 km^2 (63.618%), followed by urban and built-up land with an increase of 18.677 km^2 (38.281%) and agricultural land with an increase of 104.193 km^2 (34.939%). In the first 7 years (200-2013), the rate of expansion of agricultural land, especially rice fields, was clearly observed. Following the issuance of government policies of the administrative system, the national strategic guidelines were set every 5 years, the Tenth National Economic and Social Development Plan 2007-2011 was issued (Office of the National Economic and Social Development Board, Office of the Prime Minister, Bangkok, Thailand 2006). As a result, the agricultural sector plays an important role in the development of the country and the country's economy. The Thai Ministry of Agriculture and Cooperatives has therefore set an appropriate agricultural development strategy that is in line with the current situation. The agricultural development plan has given importance to the development of the agricultural sector, especially land resources. Therefore, during this period in the study area, there has been a change in the use of wetland land, with more than 90% of the wetland area becoming paddy fields. Such changes occurred in the southwest of the study area and on both sides of the Yom River because these areas are low-lying areas with standing water, making it easy to grow rice.

During 2012-2021, the 10th and 11th National Economic and Social Development Plans were covered. The period emphasized the development of people and the economy together, resulting in a great deal of infrastructure in the country. Therefore, the study area has developed roads, whether it be new roads, increasing traffic lanes, or developing public utilities, etc., which has led to a significant expansion of the urban area during this period. The process of urbanization therefore occurred in this period clearly, with Urban and built-up land being identified as 48.789 km^2 (8.75%) expanding to 67.466 km^2 (12.10%) over a period of 14 years. Such changes are often found in large cities with historical significance, as the impacts of urban expansion in the Paphos area in Cyprus, where modern constructions have been built near Monuments and archaeological sites (Agapiou et al., 2015). The technique of investigating the urbanization area in Paphos district uses Geo-informatic technology to investigate the areas of change and their impacts, which is consistent with the approach of this research. It can be seen that the areas sensitive to land use changes appear around historical sites and on the outskirts of the city. For example, Xi'an City, China, has used geo-informatics technology to measure urban expansion using nighttime light satellite images. The effectiveness of satellites has shown its potential in monitoring traffic networks and heritage sites, clearly showing the areas of change near heritage sites (Zhou et al., 2024). It can be seen that geo-informatics technology is very important for efficient land monitoring and can also be used as a database to plan for future land use changes. If there are no measures to support these changes, they may have negative impacts on historical sites.

For the factors affecting land use change, especially in areas that have become urbanized, the most important thing for land use change analysis is the variable that affects the area in that area. In this research, both physical and socio-economic factors were used, namely slope, distance to national park, distance to stream, distance to road, distance to commercial land and services area, distance to villages, distance to industrial area, and distance to recreation area. This is different from other research that chooses different sets of variables, such as the study of land use and cover change in the Lancang–Mekong River Basin, which has different variables such as population density and nighttime light (Lang et al., 2024). This research shows that most of the land use changes are caused by slope variables, which is different from our research that urban expansion is caused by the variables distance to road and distance to commercial and services area, even though they are in the same Southeast Asian region. The study of land use change in Nashe Watershed in Ethiopia identified important variables such as elevation, slope, distance from roads, distance from streams, distance from urban area, and evidence likelihood of raster. The results of the study found that the evidence likelihood is an empirical probability of change in the LULC categories between an earlier and a later map (Leta et al., 2021). The variable had the greatest impact on land use change, followed by elevation. The study of land use change and driving factors in rural China identified the following variables for analysis: elevation, slope, temperature, precipitation, GDP, and population. The results of the study showed that elevation and slope had the greatest impact on urban expansion (Zhou et al., 2020). In summary, most research studies that analyzed the factors affecting land use change showed that terrain was a significant factor in driving urbanization. This is different from the study in this case, where the study area was flat, because it had a floodplain topography, so most of the selected variables were land-use variables. socio-economic factors. However, the selection of variables to be studied must take into account the spatial context as an important factor.

In Thailand, there are often problems of urban expansion and agricultural areas encroaching on ancient sites. This often occurs in historical parks located in the old city, such as Ayutthaya Historical Park, Si Satchanalai Historical Park, Kamphaeng Phet Historical Park, Si Thep Historical Park, Phimai Historical Park, and Sukhothai Historical Park. In particular, Sukhothai Historical Park, which is the subject of this research, has analyzed the sensitivity to land use changes in the surrounding areas using Logistic regression techniques. The findings are that the area with high sensitivity to land use changes covers the highest area of 244.022 km^2 (43.77% of the total area). Most of this area is located in the central part of the study area, covering a 5 km buffer zone of Sukhothai Historical Park. It also appears on the eastern side of Sukhothai City District. However, this technique has been used in a variety of research works. Such as the application of logistic regression techniques to find settlements and distributions of archaeological sites of colony fissioning among the Hutterites of North America (Alberti, 2014). Application of logistic regression models to predict and find archaeological sites in North Israel (Wachtel et al., 2018), and in Xiangyang City, China (Li, et al. 2022). It can be seen that such techniques will be used to predict and find archaeological sites. This is different from this research that used such techniques to analyze the sensitivity to land use changes around the historical park area, which is an important archaeological site in Thailand.

It can be seen that geographic information technology can be applied to manage important historical sites in a cost-effective manner. Such data can provide important information, especially at the level of areas that are sensitive to land use changes. This is very important for planning the spatial management of Sukhothai Old City, an important cultural heritage site of the world.

5. CONCLUSION

Sukhothai Historical Park has been listed as a World Heritage Site. As a result, the surrounding area has undergone changes in land use patterns, especially the continuous expansion of urban areas and buildings. Therefore, geographic information technology has been applied to monitor land use changes in Mueang Sukhothai District. To find the sensitivity to land use change using logistic regression technique, it shows the sensitive area data divided into empirical sensitivity levels, which is the highlight of this research. This method can be applied in other areas to find the sensitivity to land use change in other international historical areas. However, the advantage of this method is that the variables can be changed to suit the conditions of international historical areas in other locations as appropriate. And, random decision forests method is also an effective way to examine land use in an area, which can effectively show actual land use. The spatial database obtained from this research study is useful for relevant government and private agencies that are looking for prevention methods. This information will help reduce the environmental impact on archaeological sites and historical parks, as well as set policy frameworks to prevent and reduce damage to areas surrounding archaeological sites. Therefore, the spatial format of the database is suitable for systematic land use planning to support sustainable changes in the future.

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