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APPLICATION OF A HYBRID CELLULAR AUTOMATON-MARKOV MODEL IN LAND USE CHANGE DETECTION AND PREDICTION IN FLOOD-PRONE AREA, JOHOR, MALAYSIA

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Abstract

Changes in land use can significantly impact natural resource sustainability, socioeconomic activities, and flood risks. Cellular Automata-Markov model (CA-Markov) is utilized in this study to predict land use changes by modeling the spatial dynamics and transitions of land use categories over time in one of the flood-prone area in Segamat district, Johor. Satellite images obtained from Landsat 5 Thematic Mapper and Satellite Pour I'Observation de la Terre (SPOT) 5, 6, and 7 for years 2006, 2011, and 2016 were utilized to assess the magnitude of the land use change via unsupervised and supervised classification. Additionally, ancillary data such as residential, road, water bodies, and slopes were used as input to forecast future land use. The findings revealed that between 2006 to 2026, there was an increase in built-up areas and mixed agriculture up to 26%. The expansion of built-up areas and mixed agricultures involves the removal of forests, further exacerbating flood risks. This fundamental research can provide valuable insights for effective land management and urban planning.

***Keywords**:* Markov chain model; Change simulation; Urban Development; Image classification; Environmental Planning

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INTRODUCTION

Assessing spatial-temporal land use has become a prime concern in determining how human activities interact with the environment. Land use changes are triggered by a variety of factors, such as urbanisation, industrialization, deforestation, land modification, agricultural intensification, and the introduction of artificial forests (Islam et al., 2018; Zhao et al., 2018). All of these result in forest fragmentation, habitat degradation, biodiversity loss, diminished ecosystem service function, altered soil quality and loss of soil resources, as well as global and regional climate change, which ultimately influence natural resource sustainability and socioeconomic activities (Islam et al., 2018; Zhao et al., 2018; Hu & Zhang, 2020). Aside from that, changes in land use also have a serious impact on floods and become one of the main drivers of flooding in urban areas (Muhamed Noordin et al., 2007; Rogger et al., 2017). Abdulkareem et al. (2018) posit that changes in land use can impose a negative impact on infiltration, surface runoff, flood peaks, rate of evaporation, rate of sediment transport, soil moisture, streamflow, and groundwater flow. Additionally, land use changes such as the removal of natural buffer zones like forests and wetlands have severely harmed watershed areas' ability to mitigate floodwaters (Ponting et al., 2021).

Malaysia has not been exempted from land use changes caused by population and economic growth. For instance, the country has experienced deforestation and the conversion of land to oil palm plantations following its status as the largest exporter of oil palm (Omran & Schwarz-Herion, 2020). Additionally, Malaysia is expected to have a population of 33.8 million in 2040, signifying an increase in built-up areas as 85% of the population will live in urban areas (Samat et al., 2020). In particular, the Segamat district in Johor was recognized as a flood-prone area. The district is a rural area which is not exempted from land use changes, particularly deforestation and conversion to oil palm and rubber plantations that are planted on estates as well as the FELCRA and FELDA land programmes (Johor Land and Mines Office, 2022). Although the local development seemed slow between 2007 to 2017 (Segamat District Council, 2022), it is still worrisome because both small and large scale floods have been an annual occurrence in Segamat, with the flooding events that happened in 2006, 2011, and 2017 having the most devastating hit towards the district (Reza et al., 2017; Sach et al., 2018). Floods pose a threat not only to society and infrastructure but also to the agricultural sector that may result in monetary losses, damage to existing drainage systems, and equipment and machinery disruption (Muhadi et al., 2017; Muhammad et al., 2018).

A spatial-temporal analysis is required to understand the characteristics of past and future landscape changes, and dynamic change information is necessary for experts to estimate the potential environmental impact of changes (Wan Ibrahim & Muhamad Ludin, 2016). As a result, scientists from various disciplines are interested in using modelling to study the environmental impacts of land changes (Abba Umar et al., 2021; Azari et al., 2022). Cellular Automata-Markov (CA-Markov) is a robust model that has outperformed other techniques and is capable to simulate long-term predictions of any intricate pattern's spatial variations (Mathanraj et al., 2021; Wang et al., 2021). The aims of the study are to employ remote sensing and GIS technology to assess the spatial-temporal of land use change from 2006 to 2016 and predict future changes using a hybrid CA-Markov model in Segamat district, Malaysia.

MATERIALS AND METHODS

Study area

Segamat is a district in Johor, Malaysia, located in the northern part of the state, bordering the Pahang state in the northeastern and Negeri Sembilan in the west (Figure 1). The Segamat district occupied approximately an area of 2866.56 square kilometres (km^2) with 11 sub-districts (Gemas, Sermin, Buloh Kasap, Jabi, Sungai Segamat, Pogoh, Gemereh, Jementah, Labis, Chaah, and Bekok). Geographically, this district is a flat area with slightly undulating slopes and hills in the Segamat river basin (Reza et al., 2017). The economy of Segamat is driven by agricultural activities like oil palm and rubber, followed by the industrial and tourism industries. The population of this district was estimated at 210,000 persons in 2016 (Department of Statistics Malaysia, 2017).

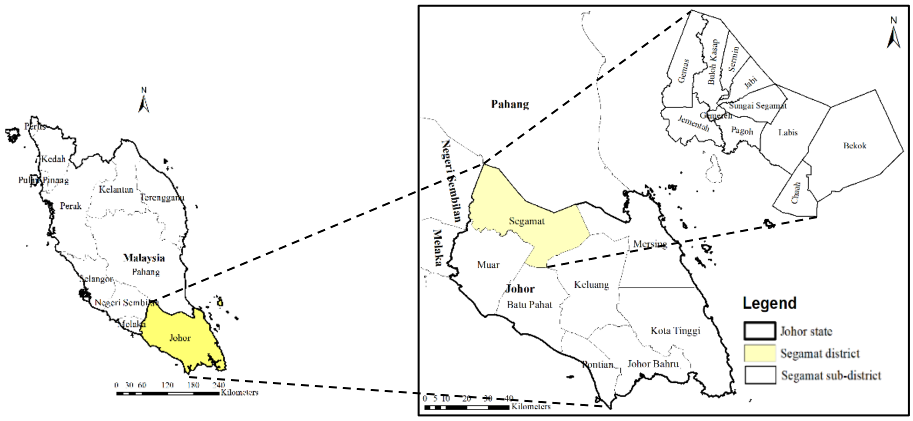

Figure 1: Geographical location of the Segamat district in Malaysia

Data and classification method

This study used Landsat and Satellite Pour I'Observation de la Terre (SPOT) satellite imagery as well as other geospatial data from the Department of Surveying and Mapping Malaysia (JUPEM) (Table 1). The Landsat imageries were downloaded from the United States Geological Survey (USGS) (https://earthexplorer.usgs.gov/) and the SPOT imageries were obtained from the Agency of Remote Sensing Malaysia (ARSM). Owing to the unavailability of SPOT imagery for 2006, different satellite imagery was used as in a previous study by Hassan et al. (2016). Thus, a comparison between Landsat and SPOT imageries for 2011 was performed to ensure that the results produced were acceptable. The selection of imageries was screened as clear and of good quality.

Table 1: List of datasets of the study

Data	Criteria	Year	source	Data format
Satellite imagery	Landsat 5 TM (30m resolution)	2006	USGS	Raster
	Landsat 5 TM (30m resolution)	2011	USGS	Raster
	SPOT 5 (10m resolution)	2011	ARSM	Raster
	SPOT 6 & 7 (6m resolution)	2016	ARSM	Raster
DEM	Slope	2014	USGS	Raster
Topographic map	Distance from residential areas, road networks and water bodies	2015	JUPEM	Vector

Pre-processing of satellite imagery should be performed before classification to reduce or minimize distortions due to the sensor, atmospheric and topographic effects during acquisitions, and to improve image quality and interpretability (Dangulla et al., 2020). Therefore, the imageries were subjected to geometric correction, mosaic, and image sub-setting using the ArcGIS 10.4 software. The imageries were co-registered to Malaysia's common local geographical coordinate system - Rectified Skew Othomorphic (RSO) projection. Four classes were identified in this paper: (1) built-up areas, comprising residential, commercial and services, and industrial and road; (2) mixed agriculture, comprising oil palm, rubber, orchards, and mixed vegetation; (3) forest, comprising all types of forest (evergreen); and (4) water bodies, comprising lakes, ponds, rivers, and reservoirs. These classes were identified based on the visual interpretation of satellite imageries and verified by field observation. After pre-processing, both unsupervised (Iterative Self-Organizing Data Analysis or ISODATA) and supervised (Maximum likelihood classification or MLC) classification techniques were performed via the ENVI 5.1 software. The MLC technique is one of the most frequently used since it is deemed reliable and accurate (Khan et al., 2016).

Accuracy assessment

The accuracy of land use classification maps is crucial, and Dangulla et al. (2020) suggested the maps must have an accuracy of at least 85%. Assessing the accuracy of land use map can be done using indicators such as producer's accuracy (PA), user's accuracy (UA), overall accuracy (OA), and Kappa coefficient (KC), as shown in Eqs. 1–4 (Ren et al., 2018). The 100 points were selected randomly and reference data, such as a land-use map from the Department of Agriculture Malaysia as well as Google Earth Pro, were used to assess the accuracy of land use maps extracted from satellite images.

$$\mathrm{OA} = \frac{\sum_{i=1}^{r} n_{ii}}{N} \tag{1}$$

$$\mathrm{PA_i} = \frac{n_{ii}}{n_{+i}} \tag{2}$$

$$\mathrm{UA_i} = \frac{n_{ii}}{n_{i+}} \tag{3}$$

$$\mathrm{KC} = \frac{N\sum_{i=1}^{r} n_{ii} - \sum_{i=1}^{r}(n_{i+}n_{+i})}{N^2 - \sum_{i=1}^{r}(n_{i+}n_{+i})} \tag{4}$$

Where, N is the total number of pixels, n_{ii} is the number of pixels that are correctly classified, n_{i+} is the number of pixels in land use map, n_{+i} is the number of pixels in a reference data, r is the number of the classes, and i is the i^{th} class.

CA-Markov model

In many land use change studies, the Markov Chain (MC) model has been successful in simulating land use change status (Khwarahm et al., 2020). Nevertheless, one of the disadvantages of the MC model is its inability to provide the occurrences of spatial distribution in each land use class, instead providing only an estimate of land use change magnitude, as well as the lack of a spatial dimension (Khwarahm et al., 2020; Matlhodi et al., 2021). Since the MC model provides no information about any land use class's spatial distribution, integration with the Cellular Automata (CA) model is necessary because the CA model is closely linked to the spatial variables (Azizi et al., 2016; Liping et al., 2018). The integration of CA and MC models (CA-Markov) is deemed to be advantageous for forecasting land use changes due to its ability to accurately simulate spatial forecasts (Hua, 2017; Liping et al., 2018). The MC (Eqs. 5-7) and CA (Eq. 8) models are expressed as follows (Liping et al., 2018):

$$\mathrm{P}_{ij} = \begin{bmatrix} \mathrm{P}_{11} & \cdots & \mathrm{P}_{1n} \\ \vdots & \vdots & \vdots \\ \mathrm{P}_{n1} & \cdots & \mathrm{P}_{nn} \end{bmatrix} \tag{5}$$

$$0 \leq \mathrm{P}_{ij} < 1 \; and \; \sum_{j=1}^{n} \mathrm{P}_{ij} = 1, i, j = 1, 2, \cdots, n \tag{6}$$

$$S_{t+1} = \mathrm{P}_{ij} \times S_t \tag{7}$$

Where, S is the status of land use, n is the number of land use types, P_{ij} is the probability matrix of state transitions, and t; t+1 is the time point.

$$S_{t+1} = f(S_t, N) \tag{8}$$

The set of states of the finite cells is denoted by S. t and $t + 1$ are different moments; N is the cell neighbourhood; and f is the local space transformation rule.

To derive the transition probability matrix for each land use class, calibration data between 2006-2011 and 2006-2016P were calculated to simulate and predict land use in 2016 and 2026. As per Table 2, the trend to remain in the same land use class is higher for all periods. In order to develop the criteria for MCE, factors such as slope and distance from residential areas, roads, and water bodies were used (Table 3) following previous studies by Keshtkar and Voigt (2016) and Camara et al. (2020).

Table 2: Markov transition probabilities matrix of 2006-2011 and 2006- 2016P

Periods	**Land use**	**Mixed agriculture**	**Forest**	**Built-up areas**	**Water bodies**
2006-2011	Mixed agriculture	0.9601	0.0229	0.0107	0.0062
	Forest	0.0756	0.9203	0.0000	0.0040
	Built-up areas	0.2124	0.0000	0.7826	0.0049
	Water bodies	0.5159	0.0411	0.0212	0.4218
2006-2016P	Mixed agriculture	0.9624	0.0160	0.0151	0.0065
	Forest	0.0888	0.9064	0.0000	0.0048
	Built-up areas	0.1564	0.0000	0.8404	0.0033
	Water bodies	0.5030	0.0358	0.0282	0.4329

Table 3: Extracted weights based on AHP and Fuzzy model standardization for built-up areas

Factors	**Fuzzy membership functions type**	**Control point**	**Weight**
Distance from residential areas	Linear	0–100m highest suitability 100-5000m decreasing suitability >5000m no suitability	0.38
Distance from road	J-Shaped	0–50m highest suitability 50-1500m decreasing suitability >1500m no suitability	0.28
Distance from water bodies	Linear	0–100m no suitability 100-7500m increasing suitability >7500m highest suitability	0.15
Slope	Sigmoidal	0% highest suitability 0-15% decreasing suitability >15% no suitability	0.19

The VALIDATE module was used in this study to compare the predicted and observed land use in 2016. The results revealed kappa statistics above 0.8, such as Kstandard (0.9640), Kno (0.9735), and Klocation (0.9681), subsequently indicating that the model performed well and was credible in modelling future land use patterns. Models with accuracies greater than 80% indicate a degree of confidence in the simulation (Keshtkar & Voigt, 2016). The simulation was conducted using ArcGIS 10.4 and IDRISI Selva 17.0.

RESULTS AND DISCUSSION

Spatial-temporal of land use changes

In the study area, bare land and mixed agriculture were classified as one class since bare land was seen as agricultural land without crops at the time, notably in oil palm plantations. The overall accuracy of all four land use classification maps was 86% and above, with kappa statistics considerably over 0.80. The land use classification was deemed satisfactory as per the accuracy assessment result because it exceeded the recommended level (85%). Considering most of the classes have user and producer accuracy of 70% or above (Table 4), it can be inferred that the classified image and the ground reality it represents are in acceptable agreement (Yesuph & Dagnew, 2019). Meanwhile, the overall accuracy and kappa coefficient of the SPOT imagery were 91% and 0.87, respectively, compared to the of the Landsat imagery, which was 89% and 0.85, respectively. A similar result by Mosime and Tesfamichael (2017) revealed that SPOT imagery outperformed Landsat imagery with an overall accuracy of 71% and 53% using unsupervised classification (ISODATA). This is owing to SPOT performing better due to its higher spatial resolution—10 m as instead of 30 m for Landsat. The accuracy, cost, and effectiveness of data analysis are all influenced by the spatial resolution of satellite imagery; as a result, the use of high spatial resolution data typically results in more precise estimates because it allowed for the capture and detect of detailed landscape characteristics as well as specific small land use changes that have possibly been missed with coarse satellite, notably Landsat (Fisher et al., 2018).

Figures 2a-2d summarise the changes in land use between 2006 and 2016. The continuing expansion of built-up areas accounted for around 2.44% of the total land area in 2016, up from 1.76% in 2006. Meanwhile, forest and water bodies have continued to decrease, with forests covering 31.63% of the total land area in 2006 and 30.10% in 2016, and water bodies covering 0.74% of the total land area in 2006 and 0.45% in 2016. For mixed agriculture, Landsat imageries (2006 and 2011) and SPOT imagery (2016) showed continued expansion, accounting for around 65.87% of the total land area in 2006, up to 66.76% in 2011 and 67.01% in 2016. Conversely, an "increase-decrease" was seen in mixed agriculture for Landsat imagery (2006) and SPOT imageries (2011 and 2016), which accounted for around 65.87% of total land area in 2006, up to 67.48% in 2011 and decreased to 67.01% in 2016.

Table 4: Classification accuracy assessments of Segamat district from 2006 to 2016 using error matrix

Land use	Landsat				Spot			
Class	2006		2011		2011		2016	
	UA	PA	UA	PA	UA	PA	UA	PA
Built-up areas	90.00	90.00	85.00	94.44	85.00	100	70.00	100
Forest	100	76.92	100	90.91	100	82.33	100	86.96
Mixed agriculture	87.50	85.37	92.50	82.22	82.50	88.10	97.50	78.00
Water bodies	65.00	100	75.00	100	85.00	100	65.00	100
OA	86 %		89 %		91 %		86 %	
KC	0.81		0.85		0.87		0.80	

Note: the abbreviations UA, PA, OA, and KC represent user's accuracy, producer's accuracy, overall accuracy, and Kappa coefficient, respectively

A comparison of observed and predicted land use for 2016 was conducted to determine the similarity of land use classes (Figures 2d-2e). The results indicated that all classifications revealed contrasting areas. In the predicted map, built-up areas and forest showed a slightly lower percentage of 2.24% and 29.78%, respectively, as opposed to 2.44% and 30.10% in the observed map. Meanwhile, mixed agricultural and water bodies accounted for 67.23% and 0.75% of the total area, respectively, in the projected map, as opposed to 67.01% and 0.45% in the observed map. Figure 2f reveals the predicted land use using the CA-Markov model for 2026. The results showed that the built-up area, forest, mixed agriculture, and water bodies accounted for approximately 2.92%, 28.21%, 68.15%, and 0.72% of the total land area, respectively. Furthermore, land use changes across the study period of 2006-2016 and 2006-2026 revealed that built-up areas and mixed agriculture continued to expand while forest and water bodies continued to decrease. The expansion of built-up areas was spurred by the concentration of settlements, particularly around Segamat town (Figure 3), which serves as the district's municipal and administrative centre (Liew et al., 2021).

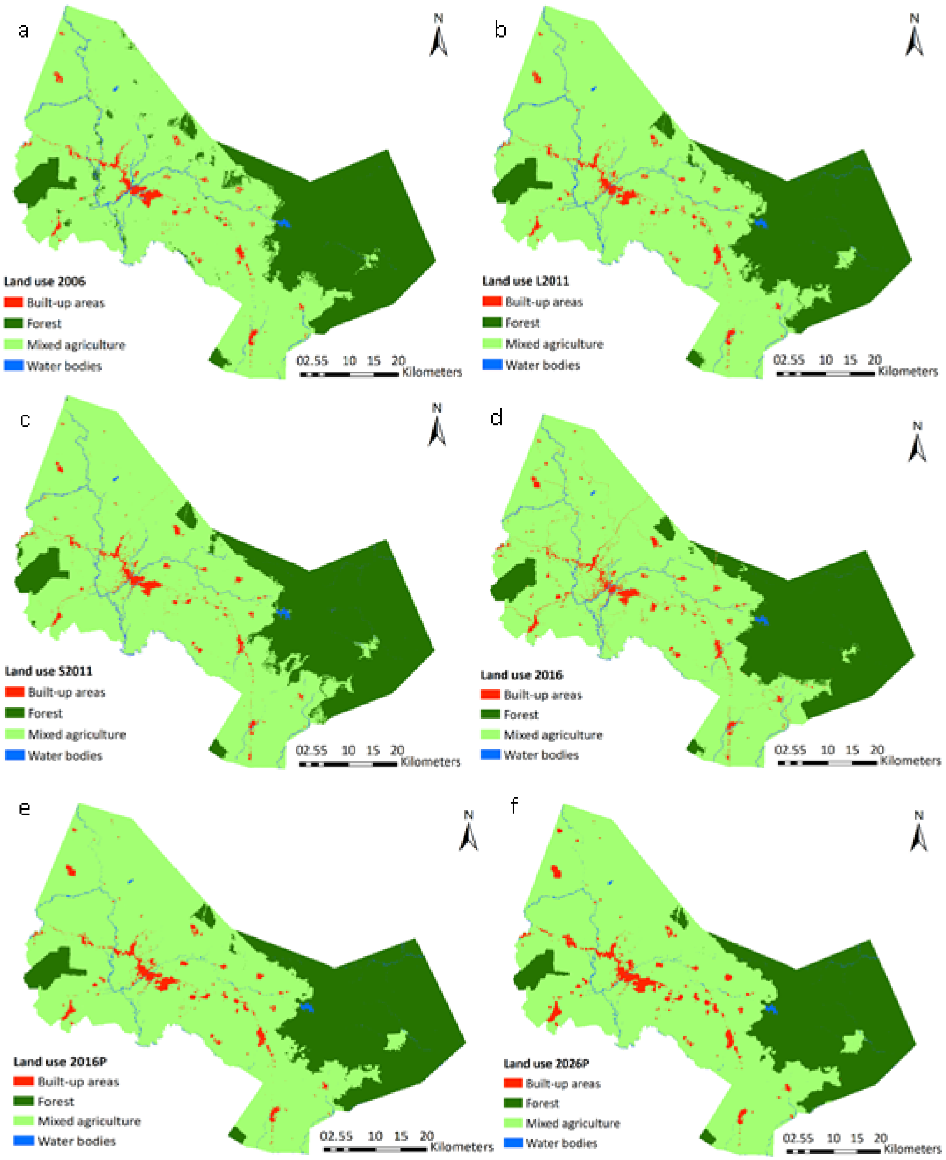

Figure 2: Spatial patterns of land use in Segamat district from 2006 to 2016, land use for the year 2006 (Landsat imagery) (a), 2011 (Landsat imagery) (b), 2011 (SPOT imagery) (c), 2016 (SPOT imagery) (d), 2016 (Predicted) (e), and 2026 (Predicted) (f)

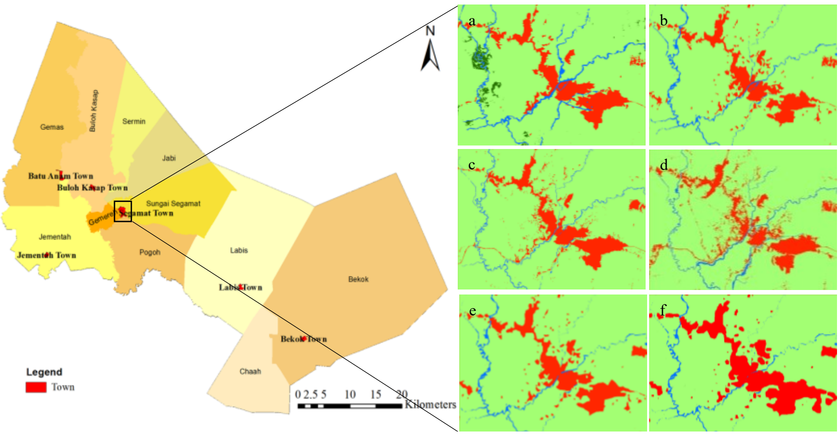

Figure 3: Spatial patterns of land use in Segamat town from 2006 to 2016; land use for the year 2006 (Landsat imagery) (a), 2011 (Landsat imagery) (b), 2011 (SPOT imagery) (c), 2016 (SPOT imagery) (d), 2016 (Predicted) (e), and 2026 (Predicted) (f)

Conversion of Land Use Types

Figure 4 and Table 5 summarise the land use type conversion from 2006 to 2026. Approximately 80 km^2 of the forest was cleared between 2006 and 2016, with 95% of the land converted to mixed agricultural and 5% of the total area converted to built-up areas and water bodies. Approximately 50 km^2 of mixed agriculture has been converted into built-up areas and forest, accounting for 40% and 43% of the total loss, respectively. Within 20 years (2006-2026), around 110 km^2 of the forest will be cleared with roughly 97% being converted to mixed agriculture. Meanwhile, roughly 50 km^2 of mixed agriculture has been converted into built-up areas, forests, and water bodies, with 65%, 20%, and 14%, respectively.

Through land use spatial transfer characteristics over the decade, the gains in mixed agriculture and built-up areas were related to population growth and economic factor. The Segamat district was expected to have a population of 218,213 people in 2020 compared to 188,968 people in 2000, where the GDP per capita was projected to be RM 22,511 in 2020 compared to RM13,187 in 2000 (Johor State Town and Country Planning Department, 2014). As a result, the built-up areas took over mixed agricultural land especially surrounding Segamat town, as illustrated in Figure 3. Additionally, this district is located within a watershed; Camara et al. (2020) posit that watersheds are lowland areas that are highly attractive for urban development. Meanwhile, mixed agriculture has displaced forest land for oil palm plantations since Malaysia became one of the world's leading exporters of palm oil, driving forest fragmentation in the state of Johor (Omran & Schwarz-Herion, 2020; Camara et al., 2020). Despite the fact that the forest is declining, it seems quite dominant after mixed agriculture because the government gazetted the Endau-Rompin National Park as a Permanent Forest Reserve in order to protect forest resources (Johor State Forestry Department, 2006).

Table 5: Transfer matrix of land use types in Segamat district from 2006 to 2026 (km^2)

Periods	Land use	Built-up areas	Forest	Mixed agriculture	Water bodies
2006 - 2016P	Built-up areas	42.72	0.00	7.28	0.15
	Forest	0.03	828.71	71.88	3.56
	Mixed agriculture	20.78	22.36	1833.53	8.61
	Water bodies	0.57	0.67	10.36	9.01
2006 - 2026P	Built-up areas	45.41	0.00	4.69	0.04
	Forest	0.12	794.72	105.80	3.54
	Mixed agriculture	37.04	11.50	1828.56	8.13
	Water bodies	0.96	0.63	10.16	8.86

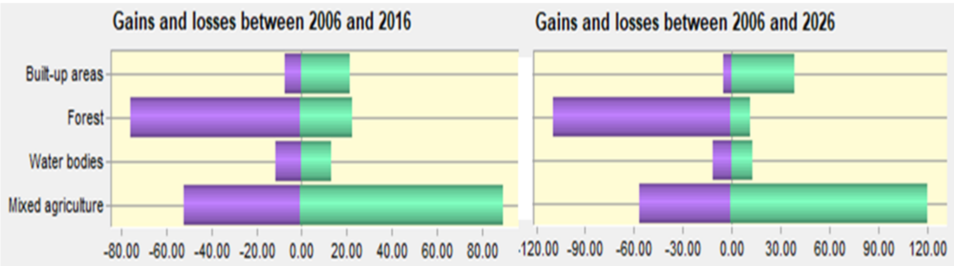

Figure 4: Gains and losses in each land-use category from 2006 to 2026 (km^2)

CONCLUSION

Assessing and understanding the spatial-temporal of land use change is necessary for protecting and managing land resources, as well as raising awareness of environmental problems. In this study, RS data and GIS technology were used to undertake a spatial-temporal research from 2006 to 2016, whereas CA-Markov was used to predict future changes. The findings showed that mixed agriculture seems to dominate the total area. This owes to the conversion of forest areas for oil palm and rubber plantations, which is the district's main economy, as well as Malaysia's economy as a major exporter of oil palm. Meanwhile, water bodies seem less dominant, accounting for less than 1% of the study area. In addition, the study found that the conversion to mixed agriculture resulted in a forest loss of roughly 95% between 2006 and 2016, and about 97% within 20 years (2006-2026). The findings also revealed that approximately 40% of mixed agricultural was lost owing to conversion to built-up areas between 2006 and 2016, and approximately 65% within 20 years (2006-2026) owing to increased population growth, causing the small town to expand by buildings and infrastructure. Generally, land use changes in the Segamat district seem to be slow; nonetheless, the study of spatial-temporal land use change is vital because this area is flooded on a small or large scale almost every year. Therefore, the expansion of built-up areas and mixed agriculture can pose significant threats to the environment that require urgent attention. Additionally, the results of this study can be potentially linked with hydrological and climatic studies to identify climate change and flood disasters. This fundamental research may help in the decision-making and policymaking of a holistic environmental management and planning strategy.

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