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Land Cover Changes from Forest Fires Using CA-Markov in Pelalawan, Indonesia

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Abstract: Forest and land fires pose significant risks to ecosystems, particularly in Pelalawan Regency, Indonesia, where slash-and-burn practices during the dry season exacerbate peatland degradation. This study integrates Cellular Automata (CA) and Markov-chain analysis to model and predict land cover changes and carbon stock dynamics over the next 20 years. The model projects spatial patterns of land cover changes from 2002-2033 by analyzing historical forest fire intensity and land use data. The study incorporates three key variables: CA simulation results, landscape carbon assessment, and forest fire vulnerability to develop spatial planning scenarios aimed at mitigating fire risks and supporting sustainable development. The results show a substantial decline in forest cover (from 92% in 2002 to an estimated 22% by 2033), alongside an increase in non-forest land use. Carbon stock analysis highlights a significant release of 18 million tons of carbon dioxide due to forest degradation. This research provides actionable insights for policymakers in spatial planning and fire risk management to balance ecological preservation with development demands.

Keywords: Forest Fire, Cellular Automata (CA), Landscape Carbon, Spatial Planning Scenario

Introduction

The major driver of rising land demand for human activity that affects Land Use and Land Change (LULC) is the fast rise of the population and urban activities (Koko *et al*., 2020; Santillan and Heipke, 2024; Sarayrah *et al*., 2024). Forest fires are one of the increased human and urban activities generating negative environmental impacts (Kolanek *et al*., 2021; Singh, 2022). Forest fires represent a significant environmental challenge due to their economic and ecological consequences (Kalogiannidis *et al*., 2023; Jesús, 2024). Indonesia, particularly the Pelalawan Regency, is very susceptible to land and forest fires due to its peat soil topography, which becomes flammable throughout the summer season (Fulazzaky *et al*., 2022; Tata *et al*., 2018). These fires are not only localized environmental disasters but also contributors to broader issues such as transboundary haze pollution and climate change. One of the most concerning effects of forest fires and LULC changes is the release of large amounts of carbon dioxide into the atmosphere. This increase in carbon emissions exacerbates global warming and disrupts climate stability (Datta and Krishnamoorti, 2022; Mansoor *et al*., 2022; Sannigrahi *et al*., 2020; Singh, 2022).

In light of these issues, proficient management of land cover alterations and carbon sequestration is crucial for alleviating environmental repercussions and promoting sustainable development. Policies and tactics that forecast and regulate future land use alterations are essential for attaining this objective, and one approach used to anticipate land cover changes is Cellular Automata-Markov Chain analysis (Abdelkarim, 2023; Khan and Sudheer, 2022). This methodology incorporates geographical and temporal aspects, allowing researchers and policymakers to predict changes and formulate educated solutions to tackle the issues presented by forest fires and land use/land cover alterations.

Literature Review

The Cellular Automata model is a stochastic approach for analyzing land change dynamics at various scale periods (William, 1989; Maria de Almeida *et al*., 2003; Ding *et al*., 2013; Muller and Middleton, 1994; Singh *et al*., 2015). Cellular automata and Markov chains are commonly employed to predict infrastructure development and future regional expansion (Theres *et al*., 2023; Xu *et al*., 2019; Yeh *et al*., 2021). The influence of the cell and grid systems on work areas is the basic principle of cellular automata analysis (Clarke and Gaydos, 1998; Mishra and Rai, 2016).

The value of the Cell and Grid produced in these models represents the impact of historical land use data on past and current land transformation (Eastman, 2009; Halmy *et al*., 2015; Pijanowski *et al*., 2002). According to Yan (2008), cellular automata models comprise five fundamental components: The cell, the state, the neighborhood, the transition rule, and the time. In order to plan effectively, manage natural resources, and achieve sustainable development, monitoring spatio-temporal LULC changes offers critical decision-making information (Aburas *et al*., 2019; Koko *et al*., 2020; Kulithalai Shiyam Sundar and Deka, 2022).

Recent research has used the CA-Markov model to recreate LULC changes in various parts of the world, such as identifying and allocating the drivers of land use change using a regional stochastic model application (Clarke and Gaydos, 1998; Kafy *et al*., 2021; Mohamed and Worku, 2020; Tong and Feng, 2020; Xu *et al*., 2023), pollution of the environment (Guariso and Maniezzo, 1992; Sarkar *et al*., 2024; Wang *et al*., 2023), urban heat island effect (Garzón *et al*., 2021; Meng *et al*., 2021; Amir Siddique *et al*., 2021), climate change (Collados-Lara *et al*., 2021; Roy and Rahman, 2023; Roger *et al*., 2000).

In order to prevent and manage forest fires, this study uses Cellular Automata Markov-chain analysis to forecast changes in the land cover of peatland forests and to calculate carbon stock (Hernández Encinas *et al*., 2007; Mutthulakshmi *et al*., 2020; Purnomo *et al*., 2021; Sun *et al*., 2024; Tobore and Bamidele, 2022). One of the issues highlighted by this study is the ineffectiveness of spatial planning regulations in preventing land use changes that contribute to forest fires. The conclusions of the research will primarily focus on problem-solving and their implications for spatial planning regulations. Cellular Automata Markov-chain analysis will be employed to predict alterations in the land cover of peatland and forest within the Regency of Pelalawan from 2002-2033. Identification of land cover with Landsat data TM (Alawamy *et al*., 2020; Kumar *et al*., 2020; Potapov *et al*., 2020; Seto *et al*., 2002), identification and determination of variables impacting land cover changes, model calibration, and simulation of the land cover change are the phases for the study that will be investigated using the Cellular Automata Markov-chain method. According to Adrianto *et al*. (2020); and Miettinen and Soo Chin (2003), due to almost 90% of Riau extensively scorched primary vegetation seeing alterations in land cover from 1998-2002, the authors selected Pelalawan, Riau, as a case study for this research.

Three variables: CA results, landscape carbon calculation analysis, and forest fire-prone analysis, are integrated to develop a spatial pattern scenario encompassing protected regions, buffered areas, and cultivated zones. Notably, the Cellular Automata (CA) results provide a basis for projections for land cover changes over the next 20 years. In addition, the government will generally employ the spatial pattern scenario to manage and prevent the peatland forest in Pelalawan, Indonesia. Then, the research provides suggestions and instructions for spatial rules to manage and mitigate forest fires in Pelalawan Regency, Indonesia.

Materials and Methods

Study Area

As seen in Fig. (1), the study area is Pelalawan (regency), Riau Province, Indonesia, located on Sumatra Island's eastern coast. Pelalawan covers an area of 13,408.72 square kilometers and is made up of lands, rivers, lakes, and peatlands (Kabupaten Pelalawan Dalam Angka, 2023; Tata *et al*., 2018). In 2019, there were 1,691 forest fires in Pelalawan Regency, consuming 10,729 hectares of land (Syaufina and Abi Hamzah, 2021; Tata *et al*., 2018). The flames forced thousands of people to flee their homes and significantly damaged the environment and the economy (Wasis *et al*., 2019).

Materials

Landsat TM +7 Image (path/row 126/60) (U.S. Geological Survey [USGS], 2002-2014), which was obtained over three various time scales (2002, 2013, and 2014), was utilized in the study of Cellular automata Markov-chain model. In addition, data on land use, road infrastructure, waterways, and slope areas are employed as supporting data in this research. Primary and secondary data are the two types of data collected, with primary data looking at field surveys of areas affected by forest fires and secondary data looking for journal resources, institutions, and scientific publications. Table (1) contains all the information utilized.

Both primary and secondary data were used in this case study. Spatial analysis is the approach employed, and tools for spatial analysis, such as ArcGIS, Idrisi Selva 17.0, ER Mapper, and remote sensing technology tools, are used.

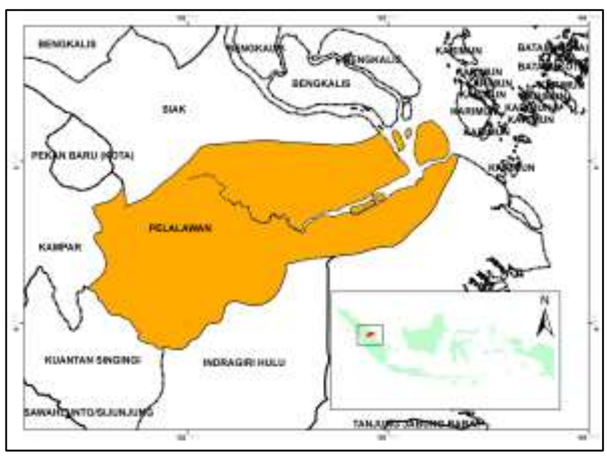

Fig. 1: Map of Pelalawan Regency, Riau, Indonesia

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Table 1: Data used for the study

No.	Name of data	Type of data	Year	Source
1.	The map of Pelalawan administration	Spatial vector (map)	Latest	Planning agency of Pelalawan, Riau
2.	Landsat TM +7 image of Pelalawan in 2002, 2013, 2014	Spatial raster (map)	Time series 2002-2014	United State Geological Survei (USGS)
3.	The topography/ slope area map and the base map of road River and the plantation area	Spatial raster (map)	Latest	Planning agency of Pelalawan, Riau
4.	Data of road distance, river distance, plantation area distance and slope distance	Special raster (map)	Latest	Planning agency of Pelalawan, Riau

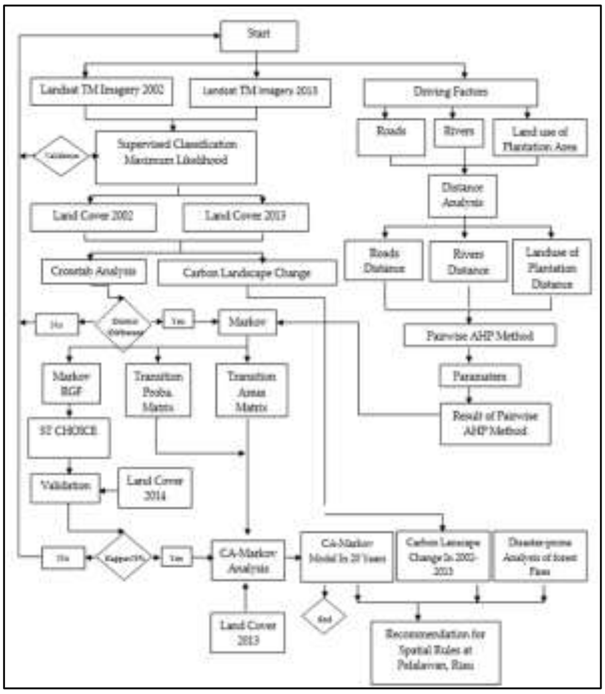

Fig. 2: Diagram of the research process

Methods

This study comprises four primary analyses: One on land transformation (2002-2013), one utilizing cellular automata Markov chains, one assessing land usage and carbon calculations, and another focused on disaster-prone forest fires. Figure (2) illustrates the execution of the analytical method.

Analysis of Peatland Forest Land Cover Change from 2002-2013

Landsat ETM +7 data from various time scales (2002, 2013, and 2014) were employed in this analysis. Remote sensing tools such as ER Mapper, ArcGIS, and Global Mapper were also used. Remote sensing uses a human interpretation process before being divided into different land cover groups. As a result, the training site area was used as a pixel digital sample for the classification in this study, which makes use of supervised classification. Because this research focuses solely on the dynamics of land cover in peatland forests, the classification method used is the Maximum Likelihood standard. The types of land cover classes only include three classes: Forest area, non-forest area, and water-body.

The forest area class includes all forest types, while the non-forest area class includes urban and built-up areas, plantation areas, and open spaces. The 2002, 2013, and 2014 Landsat TM +7 imagery comes from *earthexplorer.usgs.gov* (U.S. Geological Survey [USGS], 2002-2014).

Analysis of Carbon Landscape Reserve for the Years 2002-2013

Based on the Indonesian Forest Agency (SNI) landscape carbon standard of land cover, the Carbon Landscape Reserve analysis uses four categorization levels. The methodology uses a carbon calculator and the Ditjen Plan's standard (Indonesia) for carbon landscape reserves in land cover as of December 2012.

Cellular Automata-Markov Chain Analysis

The data used for CA-Markov are raster data with the same X-Y coordinate as ASCII data, and Idrisi Selva 17 is one of the tools for the Cellular Automata Markov-chain. The variables for the CA-Markov analysis are included as driving factors, and the data utilized in this study contains land cover/land use for three separate timeframes (2002, 2013, and 2014). The Cellular Automata Markov Chain procedure includes cross-tabulation analysis (finding the correlation), matrix of transition probability, weight-AHP analysis, Cellular Automata model constructor, and validation (Halmy *et al*., 2015).

Analysis of Forest Fires Prone Areas

This analysis employs ArcGIS software to analyze areas prone to forest fires using an overlay function method. The analysis integrates multiple variables based on previous research and builds upon findings from the 2007 forest fire-prone map. The formula used for this analysis, as shown in Eq. (1), combines key variables with assigned weights to determine the relative susceptibility of different regions:

$$Prone\ map\ of\ forest\ fires = [40\% \times (Landcover/Landuse)] + [30\% \times Peatland\ Depth] + [30\% \times (Topography/\ slope\ area)] \quad (1)$$

Results

The study will examine the findings of all analyses, which include analyses of land cover change, carbon landscape reserves, Cellular Automata Markov-chains, disaster-prone analyses of forest fires, and spatial pattern scenarios.

Analysis of Peatland Forest Land Cover Change in Pelalawan between 2002 and 2013

Figure (3) depicts the Pelalawan land cover in 2022, and Fig. (4) illustrates the map land cover change from 2000-2013 after image classification post-processing in GIS and Remote Sensing.

Land cover in 2022 Fig. (3), according to image processing and supervised classification using remote sensing technology, it was obvious that 12,126 Km^2 (92%) of the entire area of Pelalawan Regency, or the land cover of Pelalawan, was still covered in forest in 2002. On the other hand, roughly 870 km^2 (6%) of non-forest land was used. As a result, it might be concluded that the land cover from 2002 still predominates over forest land cover.

The map displayed in Fig. (4) shows the change in land cover from 2002-2013. Based on visual interpretation, the data indicated that the change in land forest classes was greater than in non-forest classes. Forest land cover classes declined while non-forest land cover classes increased.

The graph in Fig. (5) presents a comparison of the land cover change in Pelalawan between 2002 and 2013.

It is important to compare the forest classes with non-forest classes from 2002-2013. In comparison to 2002 in Table (2), land cover changes in the forest classes declined by about 55% (-7,217 Km^2), whereas those in the non-forest classes grew by around 50% (7,176 Km^2). The significant alterations to the land cover were caused by the implementation of spatial regulations in Pelalawan, Indonesia, which resulted in the extensive conversion of peatland forests. Typically, the conversion of recently built-up, plantation land, and commercial activity many the forest classes.

Table 2: Area (Km^2) of land cover change in Pelalawan, Indonesia from 2002-2013

No.	Type of Land Cover	Area (Km^2)
1.	Forest	(-) 7,217
2.	Non-Forest	7,176
3.	Water-body	41
	Total Area	13,085

The results of the investigation of how the land cover of peatland forests has changed were followed by test validation in the field. A validation test seeks to gauge the reliability of the data utilized. Table (3) shows the supervised classification validation test results from 2002-2013.

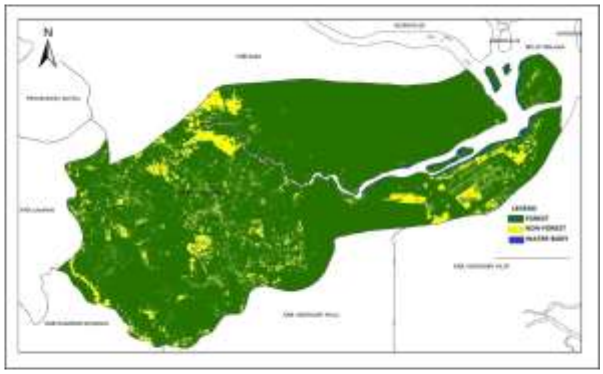

Fig. 3: Map of land cover in Pelalawan, 2002

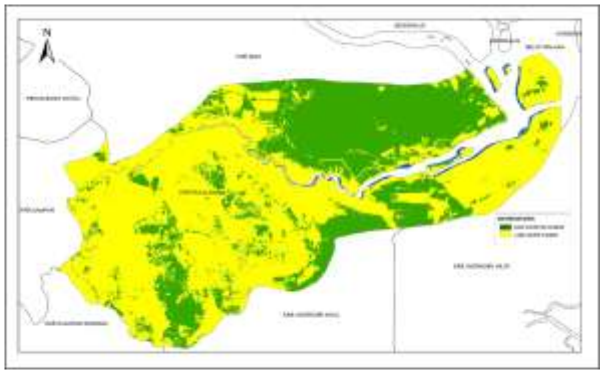

Fig. 4: Map of land cover change in Pelalawan from 2002-2013

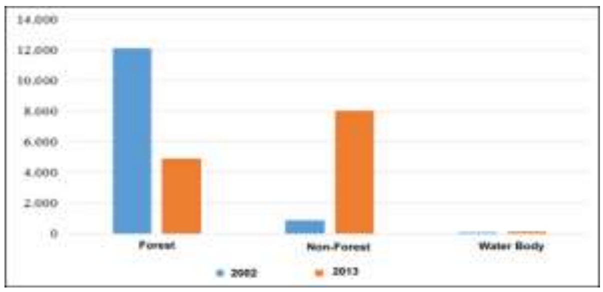

Fig. 5: The comparison of land cover change in Pelalawan from 2002-2013 (Km^2)

Table 3: Confusion matriks of land cover classification (supervised classification) from 2002-2013

No.	Land cover	Class			Total of row	Pixel commission	Users
		1	2	3			
1	Forest	95	3	0	98	3.06	96.93
2	Non-forest	3	233	0	236	1.27	98.72
3	Waterbody	0	0	132	132	0	100
Total/ KH		98	236	137	466		
Pixel commission		3.06	1.27	0			
Producers		96.93	98.72	100			
Overall accuracy		98.71					
Kappa		0.97					

The categorization of Landsat images in 2013 was validated using supervised classification (maximum likelihood), and the resulting data had a kappa accuracy of 0.97 (97%). As a result, the supervised classification error was 0.03 (or 3%). Due to the data being utilized meeting the norms of validation results of categorization by 85%, the validation result is 97%, indicating that the data is reliable or accurate (Liao *et al*., 2022-2023; Shao *et al*., 2019).

Carbon Landscape Reserve Analysis in Pelalawan from 2002-2013

The Agency of the Forestry Ministry, Indonesia, conducted an analysis of carbon landscape changes using a standard in 2012. The reserve for carbon landscape in Pelalawan will subsequently be determined based on classes of land cover categorization and the standard for carbon landscape. The four classes that make up the supervised categorization are peatland or swamp forest, open land, palm oil plantations, and water bodies. Tables (4-5) show estimates of the carbon landscape reserve in Pelalawan from 2002-2013.

According to the land cover maps in Figs. (6-7), there were 165 million tons of carbon landscape in 2002. This map will serve as a foundation for estimating future general carbon landscape releases or losses and will be compared to the overall carbon landscape from the 2013 land cover map.

In 2013, there were estimated to be 151.811.908 tons of carbon landscape reserve on land cover. The peatland and swamp forests have a total carbon landscape reserve of 79.981.435, 80 tons. There were 46.631.253,64 tons of carbon landscape reserves in the palm oil plantation class.

According to estimations of the quantity of carbon landscape reserves, key types of forests release carbon landscapes owing to changes in the forest land. Table (6) shows the changes in land cover in Pelalawan from 2002-2013 and the release of Carbon Landscape.

Table 4: Estimates of the amount of carbon landscape reserve in Pelalawan in 2002

No.	Type of land cover	Area (Ha)	Carbon standard (C_tot/ Ha)	Total of carbon landscape (Tons)
1.	Peatland of swamp forest	500,812.27	196.00	98,159,204.92
2.	Palm oil plantation	551,942.64	68.00	37,532,099.52
3	Open land of forest fires	240,067.95	126.01	30,250,962.38
4.	Waterbody	15,677.14	0.00	0.00
Total		1,308,500.00	390.01	165,942,266.82

Table 5: Estimates of the amount of carbon landscape reserve in Pelalawan in 2013

No.	Type of land cover	Area (Ha)	Carbon standard (C_tot/ Ha)	Total of carbon landscape (Tons)
1.	Peatland of swamp forest	408,068.55	196.00	79,981,435.80
2.	Palm oil plantation	685,753.73	68.00	46,631,253.64
3.	Open land of forest fires	199,977.93	126.01	25,199,218.96
4.	Waterbody	14,699.79	0.00	0.00
Total		1,308,500.00	390.01	151,811,908.40

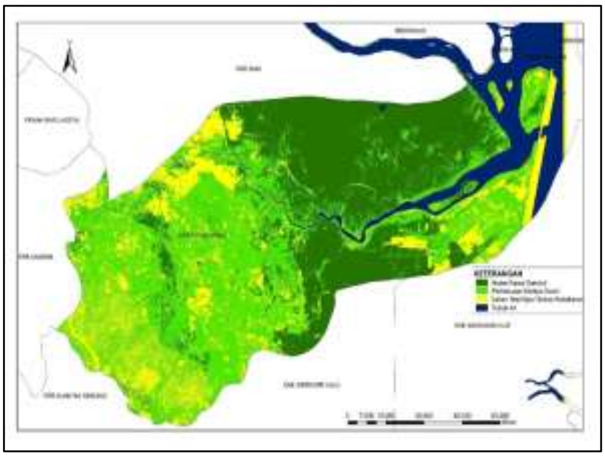

Fig. 6: Map of land cover data for carbon calculation in 2022 (dark green = peatland forest, green = palm oil plantation, yellow = non-forest, blue = water body)

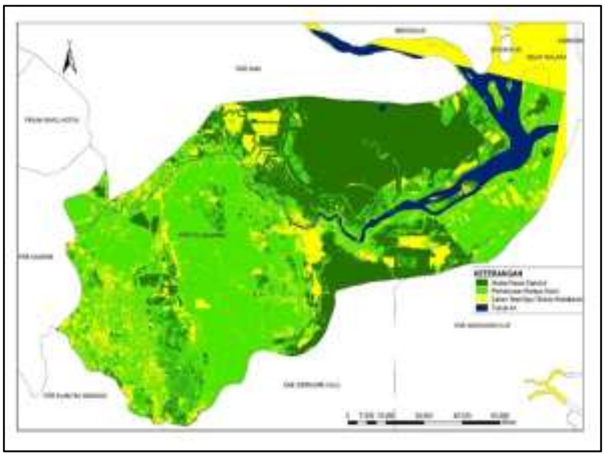

Fig. 7: Map of land cover data for carbon calculation in 2013 (dark green = peatland forest, green = palm oil plantation, yellow = non-forest, blue = water body)

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Table 6: Estimates of carbon landscape changes in Pelalawan from 2002-2013

No.	Types of land cover	Δ Carbon landscape (Tons)
1.	Peatland of swamp forest	-18,177,769.12
2.	Palm oil plantation	9,099,154.12
3.	Open land of forest fires	-5,051,743.42
4.	Water-body	0.00

Peatland landscape changes due to carbon have a greater impact on environmental problems, such as the rising levels of carbon dioxide in the atmosphere. According to a study, the peatland forest class released about 18 million tons of carbon dioxide into the atmosphere between 2002 and 2013. This indicates that the effects of land use changes and the worsening of the air pollution caused by the burning method result in around 5 million tons of carbon emissions. There may be a rise in climate change.

The chart in Fig. (8). titled Carbon Landscape Changes in Pelalawan from 2002-2013 (tons), shows that the most notable characteristic is the significant reduction of carbon storage in peatland and woodland regions.

Conversely, there has been a noteworthy augmentation in carbon sequestration inside palm oil plants. This suggests that these plantations have been proliferating, possibly to the detriment of natural ecosystems. The carbon storage in aquatic environments and open land seems to have stayed largely steady, indicating little changes in these land cover categories.

Cellular Automata Markov-Chain Analysis of Forest Land Cover Year of 2002-2013

In Pelalawan, land cover change modeling lasts 20 years. It uses Markov-chain, a statistical stochastic tool for examining the dynamics of land changes.

Cross-Classification Analysis

Image categories from 2000 and 2013 were compared, as seen in Figs. (9-10), and a table showing the number of cells in each combination was created. The Crosstab module of IDRISI was used to accomplish cross-categorization. It compares photographs using categorical variables of two types, known as complicated classification, where every pixel in the maps is fully classified into a single category.

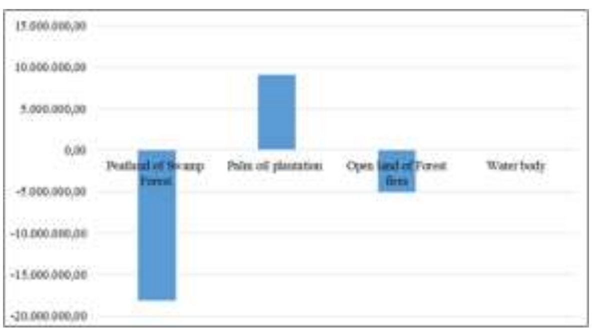


Fig. 8: Chart of carbon landscape changes in Pelalawan from 2002-2013 (tons)

Fig. 9: Land cover data used in Idrisi Selva 17.0 for 2002 (0 = background, 1 = forest, 2 = non-forest, 3 = water-body)

Fig. 10: Land cover data used in Idrisi Selva 17.0 for 2013 (0 = background; 1 = forest; 2 = non-forest; 3 = water-body)

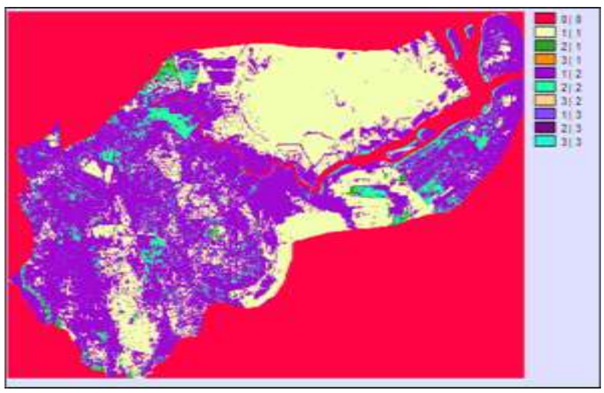


Fig. 11: The comparison of land cover change in Pelalawan from 2002-2013 (Km^2) (0 = background, 1 = forest, 2 = non-forest, 3 = water body)

Figure (11) shows the raster data used in Cellular Automata analysis of land cover changes in Pelalawan from 2002-2013, categorized into three primary types: Forest, non-forest, and water bodies.

Using Crosstab, a cross-classification picture and table are produced. The cross-tabulation result is a tabular matrix that displays how many pixels in each of the two pictures under comparison belong to each combination of categories.

Crosstab expresses the tabular matrix as a percentage of the total number of pixels. Summary data are provided by Crosstab, including Cramer's V and Kappa (Gbadegesin *et al*., 2020).

The cross-tabulation result shows that the Cramer's V is 0.728 and the Chi-square is 43493820.00000. It suggests that the change in land cover between 2000 and 2013 is perfectly correlated with a Cramer's V near 1 (Miguel *et al*., 2017).

The Kappa score is 0.5494, which indicates that the result is accepted because it is more than 0.05, close to 1 (Sánchez-Reyes, 2017).

Figure (12) reveals that class 1/cl.1 (forest) and class 3/cl.3 (water body) have the largest probability changes to class 2/cl.2 (non-forest), 0.8352 (83%), and 0.8138 (81%), respectively, while the class 2/Cl.2 (non-forest) has a low probability (0.2730 (27%) to shift to cl.1 (forest). According to it, there is a chance that the land cover may change in the following 20 years.

Weight-AHP Analysis

According to the result in Fig. (13), the distance of streets, rivers, and palm plantations are also factors that affect the land cover through the burning of the land system. The authors employ AHP analysis and assign a score ranging from moderate to strong, and the weight consistency analysis is acceptable (0.05).

Prediction of LULC Based on Cellular Automata Markov Chain Model

According to the estimated model, there is a 30% chance that non-forest land cover will change and an 80% chance that forest land will alter its cover. Additionally, this study is based on variables with a 79% kappa validation. In Pelalawan, land cover changes are analyzed over a 20-year period. Every five years during the 20 years, the author also offers a comparison, making the modeling results cover the periods of five, ten, and twenty years beginning in 2013 and ending in 2033.

```
Given :     Probability of changing to :

            cl. 1  cl. 2  cl. 3

Class 1   : 0.1412 0.8352 0.0236
Class 2   : 0.2730 0.6893 0.0377
Class 3   : 0.1667 0.8138 0.0195
```

Fig. 12: Probability matrix of land cover change in 20 years

```
The eigenvector of weights is :

   G:\TUGAS AKHIR\UII COBA\Driving Factor\JALAN.rst : 0.2660 (distance to roads)
   G:\TUGAS AKHIR\UII COBA\Driving Factor\PERKEBUNAN.rst : 0.6334 (distance to location of palm plantation)
   G:\TUGAS AKHIR\UII COBA\Driving Factor\SUNGAI1.rst : 0.1006 (distance to rivers)

Consistency ratio =   0.05
Consistency is acceptable.
```

Fig. 13: Consistency ratio of AHP analysis

Fig. 14: Results of modeling projection for 5 years (0/black = background, 1/red = forest, 2/yellow = non-forest, 3/green = water body)

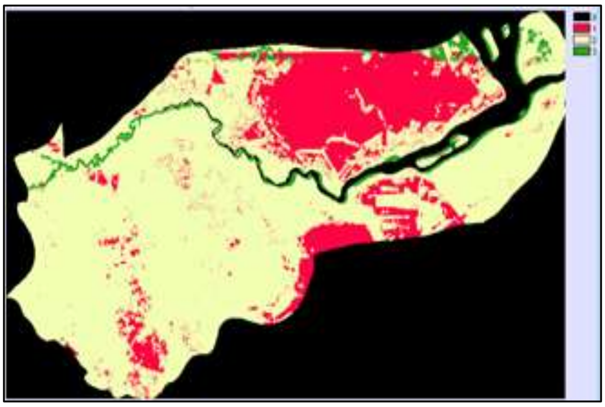


Fig. 15: Results of modeling projection for 10 years (0/black = background, 1/red = forest, 2/yellow = non-forest, 3/green = water body)

Due to data constraints and limited variables that influence forest land cover changes, the results of modeling projections for the next 20 years do not provide highly significant changes to forest land. In addition, the level of validation achieved is 79%, with a standard of 75% characterizing the expected outcome, which is not particularly significant. In Figs. (14-15), it is evident in the analysis of cellular automata Markov-chain modeling of forest land cover variations occurring every five years.

As seen in Fig. (16), the changes in forest land cover over the next 20 years appear quite significant. Class 1 forest land cover changes (Forest) are declining between 2013 and 2033, while class 2 non-forest land cover (non-forest) is increasing. This is owing to the enlargement of class 3 river water bodies since 2013. The extent of the changes is depicted in Table (7) and Fig. (17), which provides additional information about the scale of the changes.

Based on the total area, the analysis results indicate that Pelalawan's model of land cover change over the next 20 years will face a significant change. It is anticipated that 22% of forest land cover classes will convert to non-forest land, while non-forest land cover classes will increase to 75%. In addition, the extent of river water bodies has increased by 3 percent since 2013.

For reference, Fig. (18) shows the visually changed land cover since the year 2013. As a result of the remaining 22% of land being converted, forest land cover classes continue to drop. While the percentage of non-forest land cover classes has dramatically expanded from 60-75% in 2013. The government must adopt layout regulations that will serve as legally binding guidelines and fines. Forest land cover changes severely impact ecosystems, worsened by land-clearing practices like burning.

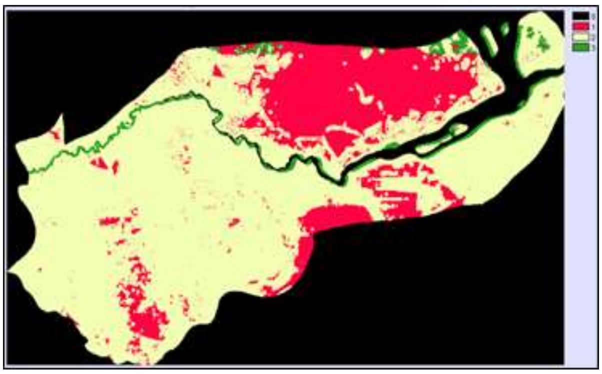


Fig. 16: Results of modeling projection for 20 years (0/black = background, 1/red = forest, 2/yellow = non-forest, 3/green = water body)

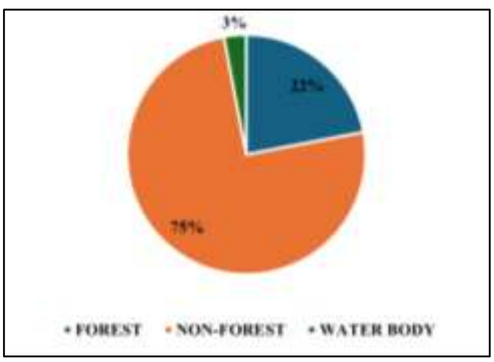


Fig. 17: Pie chart showing the projected forest cover for the next 20 Years

Table 7: The prediction of the total area of land cover in Pelalawan in 2033

No.	Type of land cover	Size (Km^2)	Percentage (%)
1.	Forest	2,912.14	22.25
2.	Non-forest	9,751.06	74.52
3.	Waterbody	421.61	3.22
Total		13,085	100.00

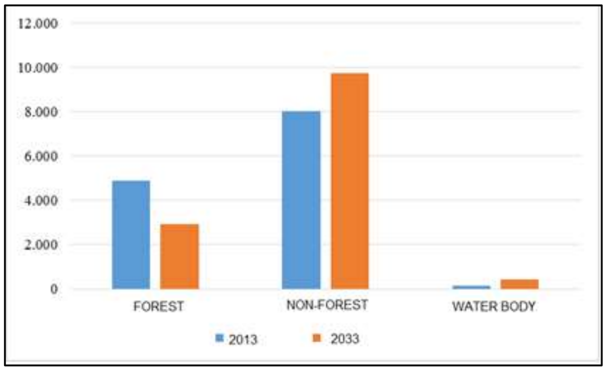
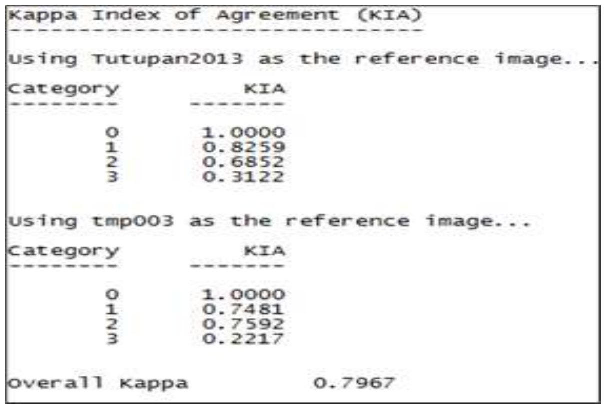


Fig. 18: Chart of the comparison of LULC for 20 years from 2013-2033 (Km^2)



```
Kappa Index of Agreement (KIA)
------------------------------
Using Tutupan2013 as the reference image...
Category        KIA
--------      -------
   0          1.0000
   1          0.8259
   2          0.6852
   3          0.3122

Using tmp003 as the reference image...
Category        KIA
--------      -------
   0          1.0000
   1          0.7481
   2          0.7592
   3          0.2217

Overall Kappa          0.7967
```

Fig. 19: The value of kappa model cellular automata markov-chain

Validation of Model Cellular Automata Markov Chain

To assess the consistency of the simulation process in terms of quantity and location, validation of the model is important (Engelen and White, 2008; Yeh *et al*., 2021). The model's overall performance was assessed using the kappa, and its ability to correctly identify locations was assessed using the kappa location (Zomlot *et al*., 2017). These numbers are crucial for assessing the simulation model's overall correctness. A kappa statistic of 0% indicates that there is no correlation between land cover maps and their probability, while a value of 100% indicates a perfect correlation (Koko *et al*., 2020; van Vliet *et al*., 2011).

Figure (19) shows that the validation result indicates an overall kappa of 0.7967 (79%), signifying appropriate kappa index values that validate the efficacy of the model for future land cover simulations (Zhang *et al*., 2011).

Analysis of Land Cover Vulnerability to Forest Fire

The result of the Pelalawan forest fire vulnerability map is depicted in Fig. (20) below.

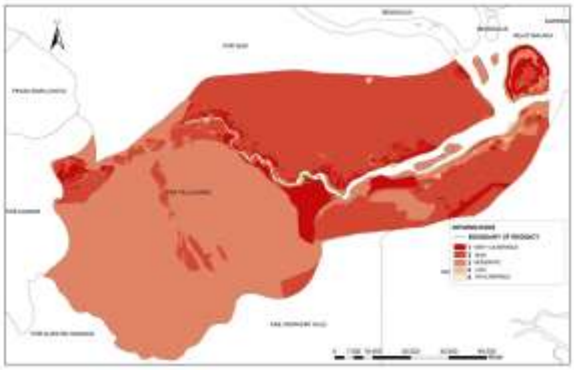


Fig. 20: Map of the vulnerability of forest fires in Pelalawan

According to the results of the above map, the general average of peat wetland forest in Pelalawan is high to moderate in forest fire-prone areas. According to the above hazard map results, nearly 80 percent of the forest is flammable. Based on the results of the hazard mentioned above map Fig. (20), the Forest Fire Hazard Map in Pelalawan is validated to determine the accuracy of the generated data. The validation is performed using a remote sensing application and confusion matrix validation (error matrix).

The results in Table (8) of the validation of the fire hazard map using the confusion matrix technique yield a data confidence level (Kappa Accuracy) of 0.79 (79%). Based on the matrix error value in Table (8), the author's interpretation is 21% off. The validation result of 79% indicates that the data used can be relied upon with a moderate degree of accuracy, as it meets the validation standards of 75%.

Table 8: Validation of forest fire vulnerability map in Pelalawan

No.	Reference data	Class					Total of rows	Pixel commission	Users
		1	2	3	4	5			
1	Very vulnerable	20	0	0	0	0	20	0	100
2	High	0	28	0	0	0	28	0	100
3	Moderate	1	0	2	0	0	3	33.37	66.66
4	Low	0	1	9	0	0	10	100	0
5	Invulnerable	0	0	0	0	12	12	0	100
Total/ KH		21	29	11	0	12	73		
Pixel Commission		4.76	3.44	81.81	0	0			
Producers		95.23	96.55	18.18	0	100			
Overall Accuracy		84.93							
Kappa		0.79							

Table 9: Scenario score of spatial pattern in Pelalawan

No.	20 years of Land Cover Modeling	Spatial pattern score (30%)	No.	Carbon Landscape Mapping in Pelalawan	Spatial pattern score (35%)	No.	Fire Hazard Map	Spatial pattern score (35%)
1.	Forest	Protected area (1)	1.	Peat Swamp Forest	Protected area (1)	1.	Very vulnerable	Protected area (1)
2.	Non-forest	Cultivation area (2)	2.	Oil palm plantation	Conditional protected area (3)	2.	High	Protected area (1)
3.	Water-body	Protected area (1)	3.	Open land/Used Fires	Cultivation area (2)	3.	Moderate	Conditional protected area (3)
			4.	Water-body	Protected area (1)	4.	Low	Cultivation area (2)
						5.	Invulnerable	Cultivation area (2)

Scenarios of Spatial Planning Pattern in Pelalawan

The constructed scenario overlays Cellular Automata analysis, Landscape Carbon Calculation Analysis, Vulnerability Analysis, and Pelalawan Forest Fire analysis. Table (9) provides details on the integrity of each variable.

Based on these variables, a scenario map of Pelalawan's spatial patterns from 2016-2033 is generated. The Pelalawan administration can utilize this scenario as a recommendation for preparing district spatial planning (RTRW). The built scenario of the spatial pattern endeavors to provide recommendations for environmentally and ecologically sustainable development. The Pelalawan spatial pattern map scenario for 2016-2033 is depicted in Fig. (21).

Four categories comprise the scenario of the generated spatial pattern map: Protected area, conditional protected area, conditional cultivation area, and cultivation area. These groups preserve biological processes based on the carbon landscapes in all land use types. Additionally, it preserves the regions vulnerable to forest fires and changes in land usage. The study's designation of the region as a protected area means that its peat swamp forest ecosystem services should be preserved. The protected region is susceptible to forest fires and has a high carbon standard of 196 C_tot/ha.

The term "conditional protected area" refers to an area that is both maintained as a protected area and is permitted to be utilized for agriculture with care on the methods of land clearing (do not burn) and preservation of the area's carbon landscape. The land that falls under the category of conditional cultivation may be utilized for plantation agriculture, settlements, and other activities, as well as a protected area or buffer. The region that is appropriate for converting to aquaculture has a low carbon landscape and is resistant to forest fires, falls under the category of cultivated area.

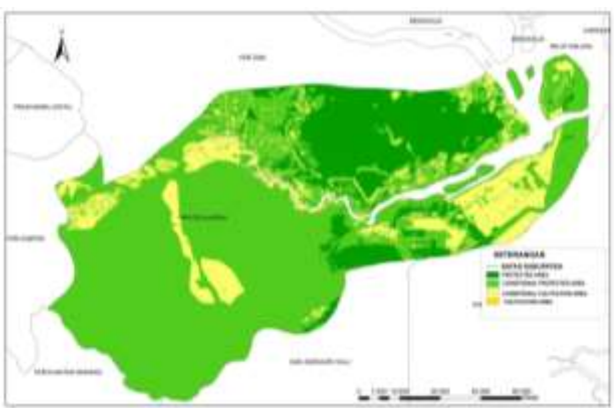


Fig. 21: The Pelalawan spatial pattern scenario map for the years 2016-2033

Discussion

According to the examination of land cover changes in Pelalawan between 2002 and 2013, a considerable shift in the forest land cover has occurred. It may be observed in a decline in the percentage of land covered by forests, which fell from 98% in 2002 to 38% in 2013. Due to the rising demand for oil palm plantations, the amount of forest land has substantially decreased, allowing the public and private sectors to access the forest area. The data from a crosstab statistical spatial analysis used to generate the association between the change in land use from 2002-2013 amounted to Crimer's V = 0.72 and kappa >0.5, supporting the changes in forest land cover between 2002 and 2013.

Additionally, alterations in forest land cover in Pelalawan are made worse by the destructive slash-and-burn forest burning practices, which harm ecosystems both locally and worldwide. A study was conducted to anticipate the availability of carbon landscape stocks and carbon changes/releases between 2002 and 2013. It gives projections of carbon release owing to changes in forest land by type of land cover based on the analysis of changes in the carbon landscape. 18,177,769.12 C_ton is the maximum quantity of carbon released and it happens under peat swamp forest cover. It gives information on how peat swamp forest land degradation affects climate change, which is a result of the highest global carbon emissions (Kolanek *et al*., 2021; Swails *et al*., 2024).

Results from 20 years of Cellular Automata Markov Chain modeling, with a 79% validity rate, yield a remarkable finding. According to the findings of the changes in forest land cover in 2033, the quantity of forest cover in 2013 decreased by 16%, leaving just 22% of its original amount in the forest. The extent of non-forest land cover climbed to 75% as a result of the decline in forest area, which was accompanied by a 15% increase in non-forest land cover. The outcomes of the cell-based modeling of the changing forest land cover may be used to further explore the spatial pattern scenario in relation to other environmental factors. The author also analyzes a forest fire hazard map in addition to cellular automata. One of the factors in the spatial pattern scenario is this analysis. Five categories are used to group the findings of a hazard map analysis: Highly susceptible, high, moderate, low, and invulnerable. The average region in the "very vulnerable" group has thin peat, a gentle slope, and forest land cover. Average vulnerability is found in non-forest areas with a kind of deep peat and a steep, upward slope.

Conclusion

This study employed a Cellular Automata Markov-chain model to analyze and predict land cover changes in Pelalawan Regency, focusing on the impacts of forest fires, peatland degradation, and carbon stock dynamics. The findings revealed a significant reduction in forest cover, from 92% in 2002 to a projected 22% by 2033, accompanied by an increase in non-forest land use due to urbanization and agricultural expansion. The carbon stock analysis highlighted the release of approximately 18 million tons of carbon dioxide during the study period, emphasizing the critical link between land cover changes and climate change.

The results of the research underscore the pressing need for sustainable land use policies and proactive spatial planning strategies to mitigate the adverse effects of land degradation. By integrating spatial modeling with forest fire hazard analysis and carbon assessment, this research provides a robust framework for policymakers to balance ecological conservation with development needs. The proposed spatial pattern scenarios offer actionable insights into protecting vulnerable peatland ecosystems while promoting sustainable economic activities.

Future research should focus on enhancing the predictive accuracy of land cover models by incorporating additional socio-economic and environmental variables. Further, exploring the integration of machine learning techniques with Cellular Automata could refine the simulation of complex land cover dynamics. These advancements will be crucial in addressing the dual challenges of environmental degradation and climate change while supporting sustainable development goals.

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Author's Contributions

Apri Zulmi Hardi: Conceptualization, methodology, software, validation, formal analysis, investigation, resources, data curation, writing-original draft preparation, writing-review and editing, visualization.

Abdulkader Ali Murad: Conceptualization, methodology, software, validation, formal analysis, investigation, resources, data curation, writing-original draft preparation, writing-review and editing, visualization.

Ethics

The writers confirm that the work in this publication is original and unpublished. There are no ethical concerns because the paper has been read and authorized by all authors.

References

Abdelkarim, A. (2023). Monitoring and Forecasting of Land Use/Land Cover (LULC) in Al-Hassa Oasis, Saudi Arabia Based on the Integration of the Cellular Automata (CA) and the Cellular Automata-Markov Model (CA-Markov). *Geology, Ecology and Landscapes*, 1–32. https://doi.org/10.1080/24749508.2022.2163741

Aburas, M. M., Ahamad, M. S. S., & Omar, N. Q. (2019). Spatio-Temporal Simulation and Prediction of Land-Use Change Using Conventional and Machine Learning Models: A Review. *Environmental Monitoring and Assessment*, *191*(4), 205. https://doi.org/10.1007/s10661-019-7330-6

Adrianto, H. A., Spracklen, D. V., Arnold, S. R., Sitanggang, I. S., & Syaufina, L. (2020). Forest and Land Fires Are Mainly Associated with Deforestation in Riau Province, Indonesia. *Remote Sensing*, *12*(1), 3. https://doi.org/10.3390/rs12010003

Alawamy, J. S., Balasundram, S. K., Mohd. Hanif, A. H., & Boon Sung, C. T. (2020). Detecting and Analyzing Land Use and Land Cover Changes in the Region of Al-Jabal Al-Akhdar, Libya Using Time-Series Landsat Data from 1985 to 2017. *Sustainability*, *12*(11), 4490. https://doi.org/10.3390/su12114490

Amir Siddique, M., Wang, Y., Xu, N., Ullah, N., & Zeng, P. (2021). The Spatiotemporal Implications of Urbanization for Urban Heat Islands in Beijing: A Predictive Approach Based on CA–Markov Modeling (2004–2050). *Remote Sensing*, *13*(22), 4697. https://doi.org/10.3390/rs13224697

Clarke, K. C., & Gaydos, L. J. (1998). Loose-Coupling a Cellular Automaton Model and GIS: Long-Term Urban Growth Prediction for San Francisco and Washington/Baltimore. *International Journal of Geographical Information Science*, *12*(7), 699–714. https://doi.org/10.1080/136588198241617

Collados-Lara, A.-J., Pardo-Igúzquiza, E., & Pulido-Velazquez, D. (2021). Assessing the Impact of Climate Change – and its Uncertainty – on Snow Cover Areas by Using Cellular Automata Models and Stochastic Weather Generators. *Science of The Total Environment*, *788*, 147776. https://doi.org/10.1016/j.scitotenv.2021.147776

Datta, A., & Krishnamoorti, R. (2022). Understanding the Greenhouse Gas Impact of Deforestation Fires in Indonesia and Brazil in 2019 and 2020. *Frontiers in Climate*, *4*, 799632. https://doi.org/10.3389/fclim.2022.799632

Ding, W.-J., Wang, R.-Q., Wu, D.-Q., & Liu, J. (2013). Cellular Automata Model as an Intuitive Approach to Simulate Complex Land-Use Changes: An Evaluation of Two Multi-State Land-use Models in the Yellow River Delta. *Stochastic Environmental Research and Risk Assessment*, *27*(4), 899–907. https://doi.org/10.1007/s00477-012-0624-7

Eastman, J. R. (2009). *IDRISI Taiga Guide to GIS and Image Processing*. Worcester: Clark Labs, IDRISI Productions.

Engelen, G., & White, R. (2008). Validating and Calibrating Integrated Cellular Automata Based Models of Land Use Change. In S. Albeverio, D. Andrey, P. Giordano, & A. Vancheri (Eds.), *Validating and Calibrating Integrated Cellular Automata Based Models of Land Use Change* (pp. 185–211). Physica-Verlag HD. https://doi.org/10.1007/978-3-7908-1937-3_10

Fulazzaky, M. A., Ismail, I., Harlen, H., Sukendi, S., Roestamy, M., & Siregar, Y. I. (2022). Evaluation of Change in the Peat Soil Properties Affected by Different Fire Severities. *Environmental Monitoring and Assessment*, *194*(10), 783. https://doi.org/10.1007/s10661-022-10430-z

Garzón, J., Molina, I., Velasco, J., & Calabia, A. (2021). A Remote Sensing Approach for Surface Urban Heat Island Modeling in a Tropical Colombian City Using Regression Analysis and Machine Learning Algorithms. *Remote Sensing*, *13*(21), 4256. https://doi.org/10.3390/rs13214256

Gbadegesin, A. S., Bello, H. O., & Ojo, O. I. (2020). *The Hydraulically Assisted Bathymetry Modeling of Effect of Weather on Reservoir Water Level* [Faculty of Engineering Hunedoara]. https://doi.org/10.13140/RG.2.2.14813.64487

Guariso, G., & Maniezzo, V. (1992). Air Quality Simulation Through Cellular Automata. *Environmental Software*, *7*(3), 131–141. https://doi.org/10.1016/0266-9838(92)90010-2

Halmy, M. W. A., Gessler, P. E., Hicke, J. A., & Salem, B. B. (2015). Land Use/Land Cover Change Detection and Prediction in the North-Western Coastal Desert of Egypt Using Markov-CA. *Applied Geography*, *63*, 101–112. https://doi.org/10.1016/j.apgeog.2015.06.015

Hernández Encinas, A., Hernández Encinas, L., Hoya White, S., Martín del Rey, A., & Rodríguez Sánchez, G. (2007). Simulation of Forest Fire Fronts Using Cellular Automata. *Advances in Engineering Software*, *38*(6), 372–378. https://doi.org/10.1016/j.advengsoft.2006.09.002

Jesús, R.-C., & Luca, S. (Eds.). (2024). *Fire Hazards: Socio-Economic and Regional Issues* (1st ed.). Springer. https://doi.org/10.1007/978-3-031-50446-4

Kabupaten Pelalawan dalam Angka. (2023). https://pelalawankab.bps.go.id/publication.html

Kafy, A.-A., Naim, Md. N. H., Subramanyam, G., Faisal, A.-A.-, Ahmed, N. U., Rakib, A. A., Kona, M. A., & Sattar, G. S. (2021). Cellular Automata Approach in Dynamic Modelling of Land Cover Changes using RapidEye Images in Dhaka, Bangladesh. *Environmental Challenges*, *4*, 100084. https://doi.org/10.1016/j.envc.2021.100084

Kalogiannidis, S., Chatzitheodoridis, F., Kalfas, D., Patitsa, C., & Papagrigoriou, A. (2023). Socio-Psychological, Economic and Environmental Effects of Forest Fires. *Fire*, *6*(7), 280. https://doi.org/10.3390/fire6070280

Khan, A., & Sudheer, M. (2022). Machine Learning-Based Monitoring and Modeling for Spatio-Temporal Urban Growth of Islamabad. *The Egyptian Journal of Remote Sensing and Space Science*, *25*(2), 541–550. https://doi.org/10.1016/j.ejrs.2022.03.012

Koko, A. F., Yue, W., Abubakar, G. A., Hamed, R., & Alabsi, A. A. N. (2020). Monitoring and Predicting Spatio-Temporal Land Use/Land Cover Changes in Zaria City, Nigeria, Through an Integrated Cellular Automata and Markov Chain Model (CA-Markov). *Sustainability*, *12*(24), 10452. https://doi.org/10.3390/su122410452

Kolanek, A., Szymanowski, M., & Raczyk, A. (2021). Human Activity Affects Forest Fires: The Impact of Anthropogenic Factors on the Density of Forest Fires in Poland. *Forests*, *12*(6), 728. https://doi.org/10.3390/f12060728

Kulithalai Shiyam Sundar, P., & Deka, P. C. (2022). Spatio-Temporal Classification and Prediction of Land Use and Land Cover Change for the Vembanad Lake System, Kerala: A Machine Learning Approach. *Environmental Science and Pollution Research*, *29*(57), 86220–86236. https://doi.org/10.1007/s11356-021-17257-0

Kumar, S., Shwetank, & Jain, K. (2020). A Multi-Temporal Landsat Data Analysis for Land-Use/Land-Cover Change in Haridwar Region using Remote Sensing Techniques. *Procedia Computer Science*, *171*, 1184–1193. https://doi.org/10.1016/j.procs.2020.04.127

U.S. Geological Survey [USGS]. (2002-2014). *Landsat TM 7 Data.* Accessed September 2023 at https://earthexplorer.usgs.gov/

Liao, J., Tang, L., & Shao, G. (2022). Multi-Scenario Simulation to Predict Ecological Risk Posed by Urban Sprawl with Spontaneous Growth: A Case Study of Quanzhou. *International Journal of Environmental Research and Public Health*, *19*(22), 15358. https://doi.org/10.3390/ijerph192215358

Liao, J., Tang, L., & Shao, G. (2023). Coupling Random Forest, Allometric Scaling and Cellular Automata to Predict the Evolution of LULC Under Various Shared Socioeconomic Pathways. *Remote Sensing*, *15*(8), 2142. https://doi.org/10.3390/rs15082142

Mohamed, A., & Worku, H. (2020). Simulating Urban Land Use and Cover Dynamics Using Cellular Automata and Markov Chain Approach in Addis Ababa and the Surrounding. *Urban Climate*, *31*, 100545. https://doi.org/10.1016/j.uclim.2019.100545

Muller, M. R., & Middleton, J. (1994). A Markov Model of Land-Use Change Dynamics in the Niagara Region, Ontario, Canada. *Landscape Ecology*, *9*(2), 151–157. https://doi.org/10.1007/bf00124382

Mansoor, S., Farooq, I., Kachroo, M. M., Mahmoud, A. E. D., Fawzy, M., Popescu, S. M., Alyemeni, M. N., Sonne, C., Rinklebe, J., & Ahmad, P. (2022). Elevation in Wildfire Frequencies with Respect to the Climate Change. *Journal of Environmental Management*, *301*, 113769. https://doi.org/10.1016/j.jenvman.2021.113769

Maria de Almeida, C., Batty, M., Vieira Monteiro, A. M., Câmara, G., Soares-Filho, B. S., Cerqueira, G. C., & Pennachin, C. L. (2003). Stochastic Cellular Automata Modeling of Urban Land use Dynamics: Empirical Development and Estimation. *Computers, Environment and Urban Systems*, *27*(5), 481–509. https://doi.org/10.1016/s0198-9715(02)00042-x

Meng, X., Meng, F., Zhao, Z., & Yin, C. (2021). Prediction of Urban Heat Island Effect over Jinan City Using the Markov-Cellular Automata Model Combined with Urban Biophysical Descriptors. *Journal of the Indian Society of Remote Sensing*, *49*(4), 997–1009. https://doi.org/10.1007/s12524-020-01274-6

Miettinen, J., & Soo Chin, L. (2003). Connection Between Fire and Land Cover Change in Riau Province, Sumatra from 1998 to 2002. *IGARSS 2003. 2003 IEEE International Geoscience and Remote Sensing Symposium. Proceedings (IEEE Cat. No.03CH37477)*, 2496–2498. https://doi.org/10.1109/igarss.2003.1294487

Miguel Á., P.-D. la C., Adalberto, G.-A., Miguel J., E.-M., Silvia del C., R.-A., Alberto J., S.-M., & Eunice, P.-S. (2017). Analysis of Land Use Change in an Urban Ecosystem in the Drainage Area of the Grijalva River, Mexico. *Revista Chapingo Series Forest and Environmental Sciences*, *23*(1), 105–120. https://doi.org/10.5154/r.rchscfa.2016.03.018

Mishra, V. N., & Rai, P. K. (2016). A Remote Sensing Aided Multi-Layer Perceptron-Markov Chain Analysis for Land Use and Land Cover Change Prediction in Patna District (Bihar), India. *Arabian Journal of Geosciences*, *9*(4), 249. https://doi.org/10.1007/s12517-015-2138-3

Mutthulakshmi, K., Wee, M. R. E., Wong, Y. C. K., Lai, J. W., Koh, J. M., Acharya, U. R., & Cheong, K. H. (2020). Simulating Forest Fire Spread and Fire-Fighting Using Cellular Automata. *Chinese Journal of Physics*, *65*, 642–650. https://doi.org/10.1016/j.cjph.2020.04.001

Pijanowski, B. C., Brown, D. G., Shellito, B. A., & Manik, G. A. (2002). Using Neural Networks and GIS to Forecast Land Use Changes: A Land Transformation Model. *Computers, Environment and Urban Systems*, *26*(6), 553–575. https://doi.org/10.1016/s0198-9715(01)00015-1

Potapov, P., Hansen, M. C., Kommareddy, I., Kommareddy, A., Turubanova, S., Pickens, A., Adusei, B., Tyukavina, A., & Ying, Q. (2020). Landsat Analysis Ready Data for Global Land Cover and Land Cover Change Mapping. *Remote Sensing*, *12*(3), 426. https://doi.org/10.3390/rs12030426

Purnomo, D. M. J., Bonner, M., Moafi, S., & Rein, G. (2021). Using Cellular Automata to Simulate Field-Scale Flaming and Smouldering Wildfires in Tropical Peatlands. *Proceedings of the Combustion Institute*, *38*(3), 5119–5127. https://doi.org/10.1016/j.proci.2020.08.052

Roger, W., Guy, E., & Inge, U. (2000). Modelling Land Use Change with Linked Cellular Automata and Socio-Economic Models: A Tool for Exploring the Impact of Climate Change on the Island of St Lucia 1S9 Introduction. In J. Hill Michael & J. A. Richard (Eds.), *Spatial Information for Land Use Management* (1st ed., pp. 245–260). CRC Press. https://doi.org/10.1201/9781482283129-29

Roy, B., & Rahman, M. Z. (2023). Spatio-Temporal Analysis and Cellular Automata-Based Simulations of Biophysical Indicators Under the Scenario of Climate Change and Urbanization Using Artificial Neural Network. *Remote Sensing Applications: Society and Environment*, *31*, 100992. https://doi.org/10.1016/j.rsase.2023.100992

Sánchez-Reyes, U. J., Niño-Maldonado, S., Barrientos-Lozano, L., & Treviño-Carreón, J. (2017). Assessment of Land Use-Cover Changes and Successional Stages of Vegetation in the Natural Protected Area Altas Cumbres, Northeastern Mexico, Using Landsat Satellite Imagery. *Remote Sensing*, *9*(7), 712. https://doi.org/10.3390/rs9070712

Sannigrahi, S., Pilla, F., Basu, B., Basu, A. S., Sarkar, K., Chakraborti, S., Joshi, P. K., Zhang, Q., Wang, Y., Bhatt, S., Bhatt, A., Jha, S., Keesstra, S., & Roy, P. S. (2020). Examining the Effects of Forest Fire on Terrestrial Carbon Emission and Ecosystem Production in India Using Remote Sensing Approaches. *Science of The Total Environment*, *725*, 138331. https://doi.org/10.1016/j.scitotenv.2020.138331

Shao, G., Tang, L., & Liao, J. (2019). Overselling Overall Map Accuracy Misinforms About Research Reliability. *Landscape Ecology*, *34*(11), 2487–2492. https://doi.org/10.1007/s10980-019-00916-6

Santillan, J. R., & Heipke, C. (2024). Assessing Patterns and Trends in Urbanization and Land Use Efficiency Across the Philippines: A Comprehensive Analysis Using Global Earth Observation Data and SDG 11.3.1 Indicators. *PFG – Journal of Photogrammetry, Remote Sensing and Geoinformation Science*, *92*(5), 569–592. https://doi.org/10.1007/s41064-024-00305-y

Sarayrah, H., Hayek, W., Thneibat, A., & Ibrahim, M. (2024). Mapping of Population Growth Influence on Land Use Transformation from 1994 to 2015 in Madaba Governorate, Jordan. *Environmental Monitoring and Assessment*, *196*(3), 250. https://doi.org/10.1007/s10661-024-12436-1

Sarkar, S., Chatterjee, M., Saha, S., & Chakraborty, S. (2024). Wolfram'S Cellular Automata Model for Unhealthy Gas Leakage Detection. *International Journal of Information Technology*, *16*(7), 4127–4135. https://doi.org/10.1007/s41870-024-01904-z

Seto, K. C., Woodcock, C. E., Song, C., Huang, X., Lu, J., & Kaufmann, R. K. (2002). Monitoring Land-Use Change in the Pearl River Delta Using Landsat Tm. *International Journal of Remote Sensing*, *23*(10), 1985–2004. https://doi.org/10.1080/01431160110075532

Singh, S. (2022). Forest Fire Emissions: A Contribution to Global Climate Change. *Frontiers in Forests and Global Change*, *5*, 925480. https://doi.org/10.3389/ffgc.2022.925480

Singh, S. K., Mustak, SK., Srivastava, P. K., Szabó, S., & Islam, T. (2015). Predicting Spatial and Decadal LULC Changes Through Cellular Automata Markov Chain Models Using Earth Observation Datasets and Geo-information. *Environmental Processes*, *2*(1), 61–78. https://doi.org/10.1007/s40710-015-0062-x

Sun, X., Li, N., Chen, D., Chen, G., Sun, C., Shi, M., Gao, X., Wang, K., & Hezam, I. M. (2024). A Forest Fire Prediction Model Based on Cellular Automata and Machine Learning. *IEEE Access*, *12*, 55389–55403. https://doi.org/10.1109/access.2024.3389035

Swails, E., Frolking, S., Deng, J., & Hergoualc'h, K. (2024). Degradation Increases Peat Greenhouse Gas Emissions in Undrained Tropical Peat Swamp Forests. *Biogeochemistry*, *167*(1), 59–74. https://doi.org/10.1007/s10533-023-01110-2

Syaufina, L., & Abi Hamzah, A. (2021). Changes of Tree Species Diversity in Peatland Impacted by Moderate Fire Severity at Teluk Meranti, Pelalawan, Riau Province, Indonesia. *Biodiversitas Journal of Biological Diversity*, *22*(5), 2899–2908. https://doi.org/10.13057/biodiv/d220555

Tong, X., & Feng, Y. (2020). A Review of Assessment Methods for Cellular Automata Models of Land-Use Change and Urban Growth. *International Journal of Geographical Information Science*, *34*(5), 866–898. https://doi.org/10.1080/13658816.2019.1684499

Tata, H. L., Narendra, B. H., & Mawazin, M. (2018). Forest and Land Fires in Pelalawan District, Riau, Indonesia: Drivers, Pressures, Impacts and Responses. *Biodiversitas Journal of Biological Diversity*, *19*(2), 544–551. https://doi.org/10.13057/biodiv/d190224

Theres, L., Radhakrishnan, S., & Rahman, A. (2023). Simulating Urban Growth Using the Cellular Automata Markov Chain Model in the Context of Spatiotemporal Influences for Salem and Its Peripherals, India. *Earth*, *4*(2), 296–314. https://doi.org/10.3390/earth4020016

Tobore, A., & Bamidele, S. (2022). Wetland Change Prediction of Ogun-River Basin, Nigeria: Application of Cellular Automata Markov and Remote Sensing Techniques. *Watershed Ecology and the Environment*, *4*, 158–168. https://doi.org/10.1016/j.wsee.2022.11.001

van Vliet, J., Bregt, A. K., & Hagen-Zanker, A. (2011). Revisiting Kappa to Account for Change in the Accuracy Assessment of Land-Use Change Models. *Ecological Modelling*, *222*(8), 1367–1375. https://doi.org/10.1016/j.ecolmodel.2011.01.017

Wang, W., Ji, C., Li, C., Wu, W., & Gisen, J. I. A. (2023). Source Identification in River Pollution Incidents Using a Cellular Automata Model and Bayesian Markov Chain Monte Carlo Method. *Environmental Science and Pollution Research*, 1. https://doi.org/10.1007/s11356-023-27988-x

Wasis, B., Saharjo, B. H., & Putra, E. I. (2019). Impacts of Peat Fire on Soil Flora and Fauna, Soil Properties and Environmental Damage in Riau Province, Indonesia. *Biodiversitas Journal of Biological Diversity*, *20*(6), 1770–1775. https://doi.org/10.13057/biodiv/d200639

William, L. B. (1989). A Review of Models of Landscape Change. *Landscape Ecology*, *2*(2), 111–133. https://doi.org/10.1007/BF00137155

Xu, Q., Zhu, A.-X., & Liu, J. (2023). Land-Use Change Modeling with Cellular Automata Using Land Natural Evolution Unit. *CATENA*, *224*, 106998. https://doi.org/10.1016/j.catena.2023.106998

Xu, T., Gao, J., & Coco, G. (2019). Simulation of Urban Expansion Via Integrating Artificial Neural Network with Markov Chain – Cellular Automata. *International Journal of Geographical Information Science*, *33*(10), 1960–1983. https://doi.org/10.1080/13658816.2019.1600701

Yan, L. (2008). *Modelling Urban Development with Geographical Information Systems and Cellular Automata* (1st ed., pp. 25–52). CRC Press Taylor and Francis Group. https://doi.org/10.1201/9781420059908.ch2

Yeh, A. G. O., Li, X., & Xia, C. (2021). Cellular Automata Modeling for Urban and Regional Planning. In W. Shi, M. F. Goodchild, M. Batty, M.-P. Kwan, & A. Zhang (Eds.), *Urban Informatics* (pp. 865–883). Springer Singapore. https://doi.org/10.1007/978-981-15-8983-6_45

Zhang, Q., Ban, Y., Liu, J., & Hu, Y. (2011). Simulation and Analysis of Urban Growth Scenarios for the Greater Shanghai Area, China. *Computers, Environment and Urban Systems*, *35*(2), 126–139. https://doi.org/10.1016/j.compenvurbsys.2010.12.002

Zomlot, Z., Verbeiren, B., Huysmans, M., & Batelaan, O. (2017). Trajectory Analysis of Land Use and Land Cover Maps to Improve Spatial–Temporal Patterns and Impact Assessment on Groundwater Recharge. *Journal of Hydrology*, *554*, 558–569. https://doi.org/10.1016/j.jhydrol.2017.09.032