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Assessing of driving factors and change detection of mangrove forest in Kubu Raya District, Indonesia

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Land cover change information is needed to support decision-making in land-based natural resource management, especially in coastal areas and mangrove ecosystems. This study aims to assess the drivers and detect mangrove forest cover change over the last 30 years in Kubu Raya District, Indonesia, using satellite imagery data from the United States Geological Survey (USGS) Earth Explorer. Maximum Likelihood Classification was used to analyze satellite images from four different recording years digitally: 1993 (Landsat 5), 2003 (Landsat 7), 2013 and 2023 (Landsat 8). Getis-Ord Gi* analysis was also used to observe fragmentation distribution patterns to determine areas with hot spots or cold spots with the Reticular Fragmentation Index (RFI) value as a consideration. Binary Logistic Regression (BLR) analysis was used to assess the drivers of social and natural variables, including population density, education, accessibility, soil type, rainfall, temperature, slope, and elevation. The results showed a significant decrease in mangrove forest cover, from 1,011.37 km^2 in 1993–964.37 km^2 in 2023, with an average loss of mangrove forest cover of 3.25 km^2 per year, including mangroves, open areas, ponds, water bodies, agricultural areas, and settlements. The fragmentation pattern that occurs is that in some areas in the northern part, there are insignificant points in 1993 and then turn into hot spots in 2023. Meanwhile, from 1993 to 2023, there were cold spots that shifted and spread in the central part of the study area. In addition, social and natural variables provide values that are directly and inversely proportional to the driving factors. Social factors, especially population density, education, and land access, have a relationship with land change. Regulations made by the government and the presence of an educated community are the main points for mangrove ecosystem conservation; existing land access is not used as exploitation access but only for daily activities. Natural factors, such as alluvial soil types, have a high concentration of nutrients, making them ideal for sustainable agriculture and ponds.

Rainfall intensity contributes to higher agricultural production and stable pond water. Conservation efforts must consider these changes and spatial dynamics to effectively protect mangrove ecosystems in the future.

KEYWORDS

driving factor, changes detection, fragmentation pattern, mangrove forest, Kubu Raya District, Indonesia

1 Introduction

Globally, mangrove forests are found in approximately 120 countries (Gandhi and Jones, 2019; Menéndez et al., 2020). Indonesia is an archipelago that has the largest mangrove forest area in the world, and Indonesian mangroves can be found around the tropical line with more than 17,504 islands (Das et al., 2022; Giri, 2023; Sumarga et al., 2023). Mangrove forests are unique in their constituent plants, which are a combination of characteristics of plants that live inland and coastal (Lai et al., 2022; Rodda et al., 2022; Wiarta et al., 2019; Worthington et al., 2020). Mangrove forests can protect coastal areas from erosion and flooding caused by storms and tides (Menéndez et al., 2020; Trégarot et al., 2021; Wu, 2021). Indonesia now has 33,640.8 km^2 of mangrove forests, accounting for 20% of the world's total (Sidik et al., 2023), but in the last seventeen years, mangrove forest area has declined in some areas, even at an alarming rate of forest cover change (Bhowmik et al., 2022; Kaskoyo et al., 2023). The continuous increase in human population has converted large areas of mangrove forests into agriculture, aquaculture and plantations, compromising coastal areas' environmental protection and balance functions (Newton et al., 2020; Sahavacharin et al., 2022).

Land use and land cover (LULC) is an increase in land use from one side to the other, followed by a decrease in the other over time (Montalván-Burbano et al., 2021; Twisa and Buchroithner, 2019). LULC is the result of various interactions between people and their environment, thus reflecting the impact of human activities on nature (Duan et al., 2023; Fang et al., 2022; Liu et al., 2022; Liu et al., 2020). This phenomenon also affects surrounding mangrove ecosystems and occurs in developing countries (Hasan et al., 2023; Hoque et al., 2022; Mishra et al., 2021). Land cover change can affect the magnitude of peak discharge and trigger flooding in forest areas (Aghsaei et al., 2020; Li and Bortolot, 2022; Sugianto et al., 2022), physical and biological soil processes at the earth's surface (Chaemiso et al., 2021; Kidane et al., 2019; Ozsahin et al., 2018), as well as landscape change, plant and animal extinction, and other environmental consequences (Olorunfemi et al., 2020; Roy et al., 2022). Landscape loss can affect biodiversity stability and connectivity and is one of the consequences of fragmentation and deforestation (Mansori et al., 2023). Forest fragmentation can affect biodiversity through four main mechanisms: (1) sampling effects (representativeness); (2) area size (area effects); (3) isolation (isolation effects); and (4) edge effects (Jacobson et al., 2019; Palmeirim et al., 2021). These effects can also impact population and ecosystem distribution levels (Hending et al., 2023; Hussain et al., 2024; Liu et al., 2019). In the vegetation health perspective, fragmentation can lead to ecosystem degradation due to increased edge effects, resulting in higher environmental stress on smaller, more isolated mangrove patches (Jaramillo et al., 2023), increased exposure to wind, solar radiation and salinity, which contributes to the physiological deterioration of mangrove trees and accelerates the process of structural degradation of the ecosystem (Noor et al., 2020). In the ecosystem services, habitat fragmentation decreases carbon storage capacity, reduces mangroves' function as a coastal bulwark against abrasion and storms, and reduces fisheries productivity due to loss of spawning habitat for fish and other marine life (Ding et al., 2020; Li et al., 2022). Fragmentation can also increase the vulnerability of mangroves to land conversion as smaller fragments tend to be more susceptible to anthropogenic pressures, such as agricultural expansion, urbanization, and conversion to ponds (Ferreira et al., 2022; Ward et al., 2016). Biodiversity declines can be halted by lowering fragmentation rates and increasing connectivity (Anderson et al., 2023). Understanding the drivers of LULC change is a prerequisite for mitigating and managing the impacts and consequences of LULC (Arficho and Thiel, 2020; Benavidez-Silva et al., 2021). Analysis of the drivers of LULC change became a popular topic in the 1990s, mainly addressing how human and biophysical forces influence land use change (Wu et al., 2021; Zhai et al., 2020). Recent studies in many countries have shown that human activities are the main factor causing LULC change (Bhowmik et al., 2022; Duan et al., 2023; Liu et al., 2020; Newton et al., 2020; Olorunfemi et al., 2020; Zhai et al., 2020). To understand future land use conditions and to develop management plans, preliminary information on the drivers that cause LULC is needed (Benavidez-Silva et al., 2021; Hailu et al., 2020; Wu et al., 2021; Zhai et al., 2020).

Kubu Raya District is one of the areas in West Kalimantan Province that has experienced significant changes in forest cover (Sugiardi, 2020; Suratiningsih, 2023). Mangrove forests, which are high-value wetland forests, dominate Kubu Raya District in this province. Mangrove ecosystems in this area have been severely degraded and are declining, resulting in reduced ecological functions due to various factors. However, it has not been clearly recorded how mangrove forest changes occur, the current condition of the land cover, the pattern of fragmentation, and what are the driving factors that cause LULC changes. One of the first steps to investigate and provide a credible database on LULC change is to use multi-year classified image analysis. For this reason, this study was conducted to provide three comprehensive understandings of mangrove forest change. Specifically, this study aims to (1) evaluate LULC changes over a periodic period (10-year interval) from 1993 to 2023, (2) analyze fragmentation patterns, and (3) analyze drivers of mangrove forest change in Kubu Raya District, Indonesia.

2 Materials and methods

2.1 Study area

According to Central Statistics of Kubu Raya District (2022), Kubu Raya is the newest district in West Kalimantan Province and has been definitive since 2007. Kubu Raya District is geographically (Figure 1) located between 109° 03′ 11.48″ to 109° 58′ 23.50″ east longitude and 0° 13′ 47.16″ north latitude to 1°00′ 51.38″ south latitude. North latitude to 1°00′ 51.38″ South latitude. Kubu Raya District is bordered to the west by the Natuna Sea, Pontianak City and Mempawah to the north, Sanggau and Ketapang to the east, and North Kayong to the south. Amounting 609,392 people live in an area of 6,985.20 square kilometers, consisting of 4,785 square kilometers of land and 2,197 square kilometers of water, 39 small islands, and 149 square kilometers of coastline. The area is generally flat and has an average elevation of 84 m above sea level, with a percentage of 0–100 m by 20.2%, 101–500 m by 27.2%, 501–1,000 m by 26.7%, and 1,001 m and above by 25.9%. The Sub-districts of Sungai Kakap, Teluk Pakedai, Kubu, and Batu Ampar own mangrove forests in Kubu Raya District. In the study area, mangrove forests surround several rivers, tides, small channels, and small bays (Romañach et al., 2018; Sumani et al., 2021). In addition, many man-made waterways may cross mangrove forests (Krishnan and Ramasamy, 2022; Narmada and Annaidasan, 2019).

2.2 Satellite image data processing and classification

In this study, Landsat image data covering the last 30 years (10-year interval) from 1993 to 2023 was downloaded from the Earth Explorer of the United States Geological Survey (USGS) (Table 1) and used to analyze changes in mangrove forest cover in the study area. In addition, the base map for the analysis was obtained from the Rupa Bumi Indonesia map.

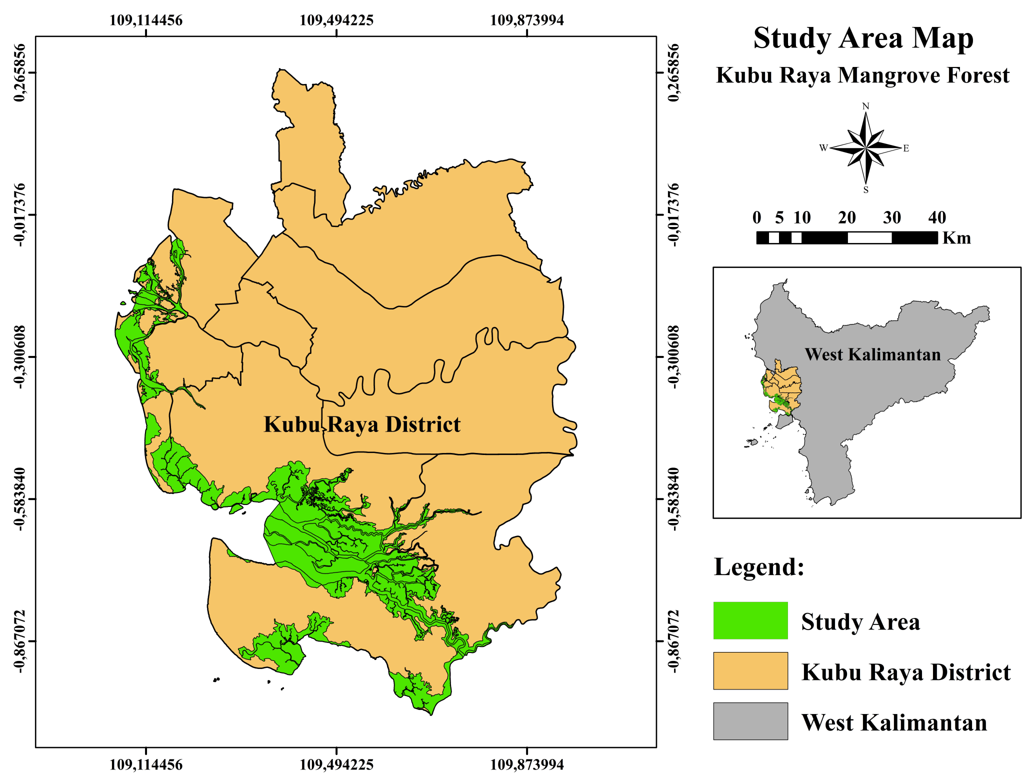

FIGURE 1
Study area.

TABLE 1 Characteristics of satellite imagery.

Datasets	Acquisition date	Path/row	Spatial resolution (m)	Swath (km)
Landsat 5 (TM)	August, 27th 1993	121/061	30 m	180 × 180
Landsat 7 (ETM +)	February, 20th 2003	121/161	30 m	180 × 180
Landsat 8 (TIRS)	September, 19th 2013	121/161	30 m	180 × 180
Landsat 8 (TIRS)	May, 10th 2023	121/161	30 m	180 × 180

Digital image processing for each image was completed by creating composite photos, creating mosaic images, and performing classification to obtain land cover classes (Filippi et al., 2022; Saleem et al., 2021) at each year interval using ArcGIS 10.8 software (1993, 2003, 2013, and 2023). A guided classification method with a maximum likelihood classifier was used to determine the land classification (Chowdhury, 2024; Ganesh et al., 2023; Polat and Kaya, 2021). To improve classification accuracy, training samples are selected with sufficient homogeneity to be spectrally and spatially representative of each LULC class (Table 2). The training samples will determine the final LULC map and overall classification accuracy, which is the most important part of supervised classification (Amini et al., 2022; Ganesh et al., 2023).

2.3 Accuracy assessment

Accuracy refers to how well the map is created and conforms to the classification. A good approach to assessing accuracy and analyzing changes in forest areas is essential to ensure the veracity of land use change information (Galiatsatos et al., 2020; Hussain et al., 2024; Stehman and Foody, 2019). Accuracy assessment is conducted to improve classification accuracy to obtain maximum results (Badshah et al., 2024; Chakma et al., 2023). In this study, 150 samples were distributed each period across mangroves, water bodies, open areas, settlements, ponds, and agricultural land in the study area to evaluate the accuracy (Table 3). Google Earth Pro was used to assess accuracy for the period 1993–2013, with ground-truth verification conducted for 2023.

The recommended accuracy to be used in the analysis is kappa accuracy, as it is considered the most relevant measure, and kappa accuracy considers all elements in the error matrix (Amini et al., 2022; Ganesh et al., 2023; Satapathy et al., 2024). Accuracy can be determined mathematically using Equations 1–4.

$$\text{User's Accuracy}: \frac{Xii}{X+1} \times 100\% \quad (1)$$

$$\text{Producer's Accuracy}: \frac{Xii}{X+i} \times 100\% \quad (2)$$

TABLE 2 Land classification categories.

No.	LULC classes	Code	Description
1	Mangrove	Ma	Area covered with mangrove vegetation.
2	Water bodies	Wb	The area covered by rivers and canals.
3	Open area	Oa	The areas were described with non-forest cover and bare land.
4	Settlements	Set	Areas covered with community houses and small fisher houses.
5	Ponds	Po	Areas covered by fish ponds, shrimp ponds or crab ponds.
6	Agriculture	Agri	Areas covered by rice land, coconut farm, vegetable farm, and palm oil plantation area.

$$\text{Overall Accuracy}: \frac{\sum_{i=1}^{r} Xii}{N} \times 100\% \quad (3)$$

$$\text{Kappa Accuracy}: \frac{N\sum_{i=1}^{r} Xii - \sum_{i=1}^{r} Xii\, Xi_{+}X_{+i}}{N^2 - \sum Xi{+}X_{+i}} \times 100\% \quad (4)$$

Where:
N = Number of pixels used
r = Number of rows or columns in the error matrix (number of classes)
Xi+ = Number of pixels in row i
X+i = Number of pixels in column i
Xii = Diagonal value of the ith row and ith column contingency matrix

2.4 LULCC detection 1993–2023

The analysis process was carried out using overlay techniques. The overlay technique used was the 1993, 2003, 2013, and 2023 mangrove forest land cover maps with the Kubu Raya Regency administrative boundary map, which resulted in a land cover map of the study area for each period. Then calculate the area per land cover per year and compare at each point of the observation year. The formula used to detect LULC is as follows (Equation 5) (Li S. et al., 2023; Yagoub et al., 2017):

$$\text{LULC} = \frac{\text{LULCb} - \text{LULCa}}{\text{LULCa}} \times \frac{1}{\text{T}} \times 100\% \quad (5)$$

2.5 Fragmentation pattern

Getis-Ord Gi* analysis was used to observe the fragmentation distribution pattern in order to determine which areas have hot spots or cold spots in the study area by considering the Reticular Fragmentation Index (RFI) values. Z-scores and P-values indicate significant differences in RFI values between the ranges considered high and low, with statistical significance at the 5% level ($P \leq 0.05$). Z-scores above 1.96 are categorized as hot spots, while Z-scores below −1.96 are categorized as low spots. Z-scores between −1.96 and 1.96 are considered insignificant ($P > 0.05$), indicating the presence of random spatial processes (Jaramillo et al., 2023; Rivas et al., 2021). Getis-Ord Gi* analysis is a statistical method used to identify statistically significant spatial clusters with high values (hot spots) and low values (cold spots) in a geographic data set (Tola et al., 2021).

2.6 Driving factor analysis

The Binary Logistic Regression (BLR) analysis method was used to find the elements that influence land use change. BLR is a method to identify the relationship between categorical dependent variables and independent variables (Bera et al., 2020; Getu and Gangadhara Bhat, 2024; Pasaribu et al., 2020; Wang et al., 2020). The dependent variable in this study is based on the status of land use change (Y), with $y = 0$ indicating land change and $y = 1$ indicating no land change. At the same time the independent variables use variables

TABLE 3 Sampling distribution through classes.

Years	Classified/sampling						
	Ma	Wb	Oa	Set	Po	Agri	Total
1993	70	40	25	15	0	0	150
2003	50	30	30	20	20	0	150
2013	50	30	20	15	15	20	150
2023	50	30	20	15	15	20	150

X1: population density (people/km^2), X2: education level (from low to high education), X3: river access, X4: land access [distance between the study area and the road), X5: soil (soil type), X6: rainfall (average/year (30 years)], X7: temperature [average/year (30 years)], X8: slope (flat to very steep), and X9: elevation (low to high). These variables were used to identify the drivers of land change in mangrove forests in the study area. ArcGIS 10.8 was used to combine variables assumed to be drivers of land use change with data on land use change. Each independent variable data uses a scoring system, and the matrix formula (Equation 6):

$$Log[\frac{P}{1-p}] = a + \beta 1X1 + \beta 2X2 + ... + \beta nXn \qquad (6)$$

Where:

Log: the natural logarithm; P: the success probability on the binary dependent variable.

a: constant (intercept); βn: independent variable regression coefficient estimator (Xi)

Xn: a dependent variable whose influence will be studied

3 Results

3.1 Accuracy assessment

The land cover classification successfully categorized the study area into six classes: mangrove, water body, open area, residential, pond, and agriculture. The classification results demonstrated a high level of accuracy. The producer accuracy (PA) and user accuracy (UA) values ranged from 80 to 99%, indicating a strong agreement between classified outputs and reference data. The overall accuracy (OA) reached an average of 94.6%, and the kappa coefficient (KA) values were close to 1, confirming a substantial level of agreement beyond chance (Table 4).

3.2 LULC changes detection from 1993 to 2023

3.2.1 Land cover 1993–2023

The land cover analysis used 1993, 2003, 2013, and 2023 imagery. Land cover is classified into six categories: mangrove, water body, open area, residential, pond, and agriculture (Figure 2). The land cover classification result is displayed in square kilometers (Figure 3). Mangrove forests still dominated in 1993, 2003, 2013, and 2023, with an area of 1011.37, 1011.85, 960.20, and 964.36 km^2, respectively. The area of mangrove forest cover decreased from 1,011.37 km^2 (1993) to 960.20 km^2 (2013) and a slight increase of 964.36 km^2 in 2023. The total land area that changed was 97.68 km^2, with an average annual change of 3.25 km^2 during the monitoring period.

TABLE 4 Confusing matrix image 1993–2023.

Years	PA (%)	UA (%)	OA (%)	KA
1993	98.6	94.6	97.3	0.97
2003	96.6	94.0	95.3	0.95
2013	95.1	93.2	94	0.93
2023	95.7	88.6	92	0.92

3.2.2 Change detection 1993–2023

3.2.2.1 1993–2003

During the LULC identification process, five land cover classes occurred between 1993 and 2003 (Table 5). During this period, significant changes occurred in each class. Mangrove forests changed into open areas by 8.18 km^2, mangrove forests into settlements by 0.31 km^2, and mangrove forests into ponds by 2.89 km^2. In contrast, settlement areas turned into aquaculture and into mangrove forests, totaling 0.016 and 10.90 km^2, respectively. In addition, water bodies turned into settlement areas by 0.06 km^2 (Figure 4a).

3.2.2.2 2003–2013

Between 2003 and 2013, six land cover classes were identified (Table 5). All classes changed during this period; specifically, mangrove forests changed to open areas by 31.35 km^2, to settlements by 0.62 km^2, to agricultural areas by 10.70 km^2, and to aquaculture areas by 19.67 km^2. Conversely, open area changed to mangrove forest by 8.77 km^2, settlement area to mangrove area by 0.30 km^2, and pond to mangrove forest by 0.45 km^2 (Figure 4b).

3.2.2.3 2013–2023

From 2013 to 2023, the mangrove forest changed to open area by 16.22 km^2, to settlement area by 0.11 km^2, to water body by 0.33 km^2, to agricultural area by 6.94 km^2, and to pond area by 4.97 km^2. In addition, open area changed to mangrove forest by 31.06 km^2, and pond area changed to mangrove forest by 0.71 km^2 (Table 4 and Figure 4c).

3.2.2.5 Overview 1993–2023

Over the 30 years (1993–2023), each class experienced significant changes, such as mangrove forests turning into agricultural land, open areas, settlements, pond areas, and water

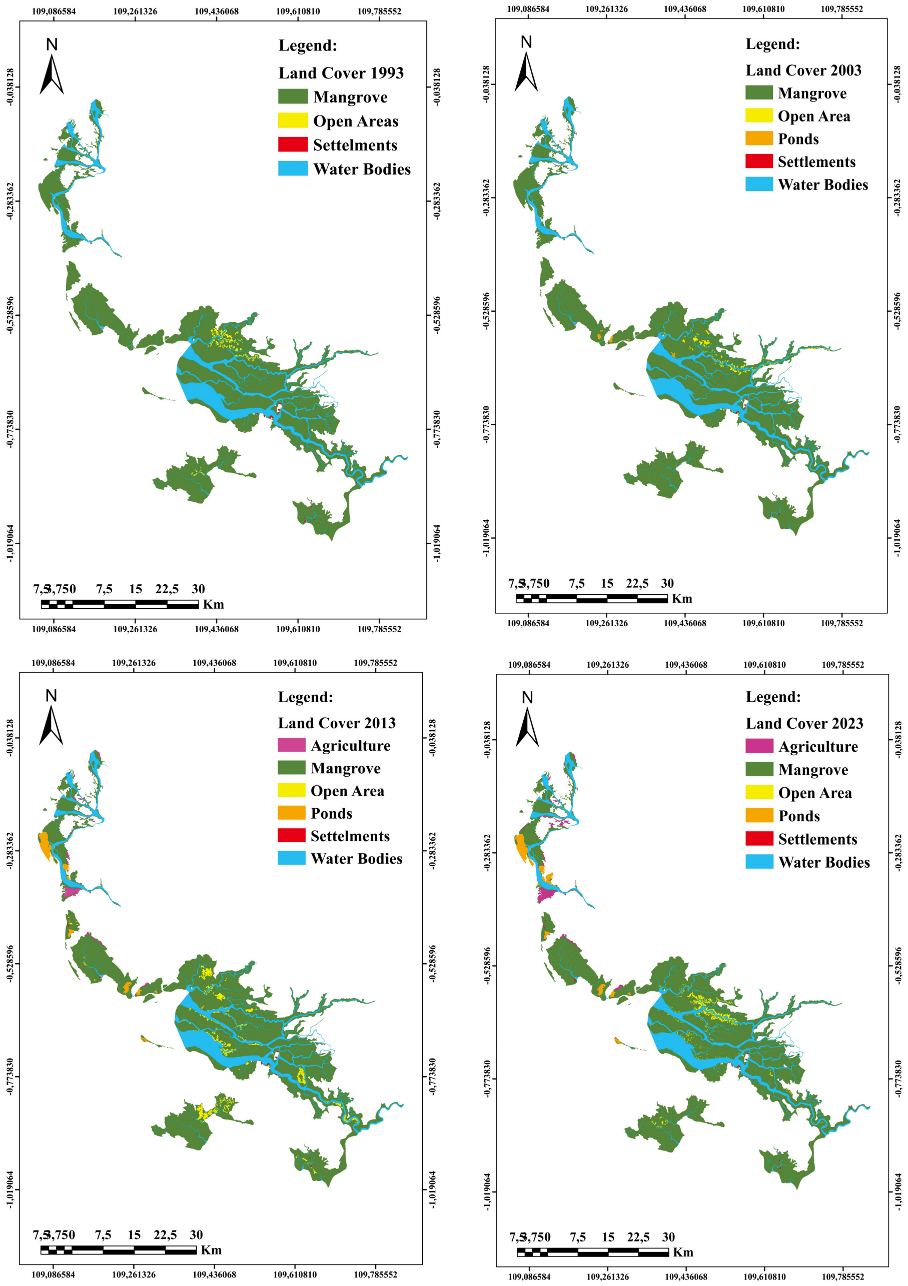

FIGURE 2
Kubu Raya mangrove forest covers 1993–2023.

bodies. In addition, there was a shift from open area to mangrove forest, settlement area to mangrove forests, and water body to settlement area (Table 5 and Figure 4d).

3.3 Fragmentation pattern

Our results show two distinct patterns of fragmentation distribution, particularly in the northern and central parts of the study area. Some places in the north that previously had insignificant spots (1993) turned into areas with hot spots (2023), indicating a big expansion in the area of hot spots. Our data also shows that from 1993 to 2023, cold spots changed and spread in the center part of the study area, indicating that areas with low of fragmentation are increased, while area with a high fragmentation are decreased.

3.4 Driving factor

The significance level of the independent variables on the dependent variable is 95%. The BLR analysis revealed that social and natural factors have a relationship with land change in the study area, including the variables of population density, education level,

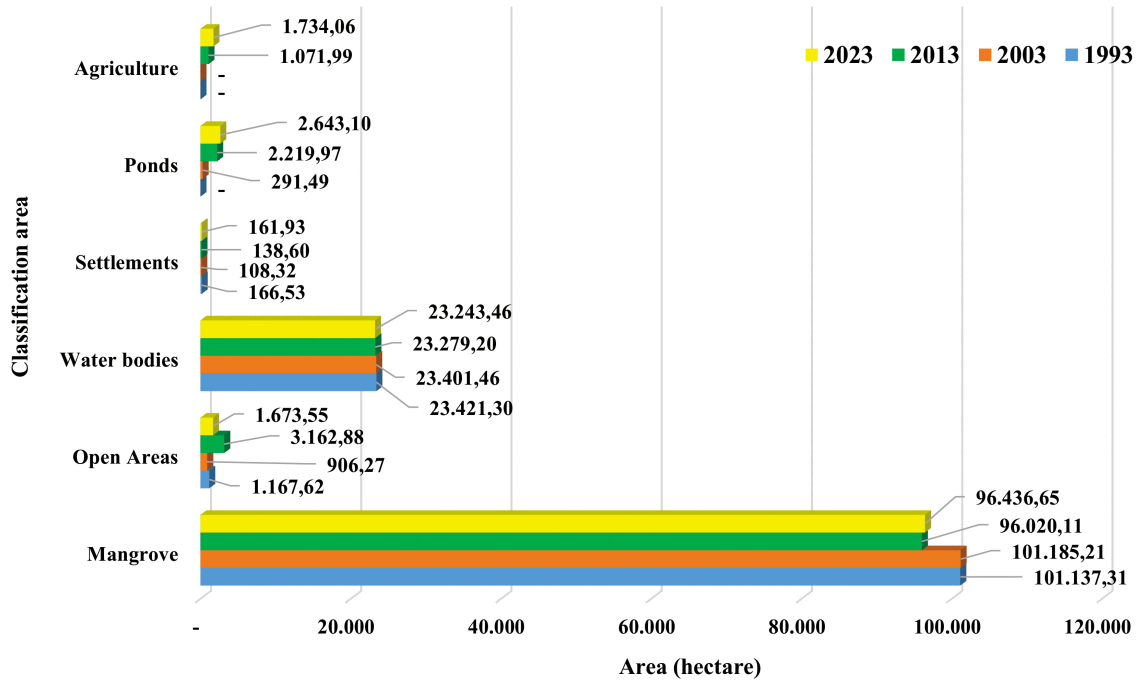

FIGURE 3
Mangrove forest area in 1993–2023.

land access, soil type, and rainfall. Then, based on the table, the final logit model of land use change is formed as: logit (change) = −2.152 population −0.695 education −0.756 land access + 0.583 soil + 0.665 rainfall. Positive variable values indicate that land change occurs more frequently, while negative variable values indicate that land change occurs less frequently or does not occur at all. The results of the binary logistic regression analysis and the map of driving factors are presented in Table 6 and Figure 5.

4 Discussion

4.1 Accuracy assessment

The kappa statistic takes into account all members of the error matrix other than the diagonal elements and is used to estimate classification accuracy (Foody, 2020; Hassan et al., 2022). The results of the accuracy calculation with guided classification noted that the highest record was in 1993 (97%) and the lowest record was in 2023 (92%) during four different eras (Table 2). This result is in line with several studies that have found more than 85% accuracy in all accuracy classifications (Ebrahimy and Zhang, 2023; Weitkamp and Karimi, 2023; Wu et al., 2023). The Kappa coefficient was higher than 0.9% in each of the four time periods (1993, 2003, 2013, and 2023). In this study, the kappa coefficient was higher than 0.9% in each of the four time periods (1993, 2003, 2013, and 2023). The results of the kappa accuracy test show that the resulting land use map has a high level of accuracy, earning it the title of very good (Near Perfect Agreement). These results are also very similar to several previous studies that assessed the Kappa coefficient of all forest classes to be more than 0.8% (Foody, 2020; Hussain et al., 2024; Selmy et al., 2023; Weitkamp and Karimi, 2023).

4.2 LULC changes detection from 1993 to 2023

The LULC identification process for the period 1993–2023 identified six land cover classes (Table 2). The largest land cover change occurred from mangrove forests to ponds, agriculture, and open areas. From 1993 to 2003, there was also a significant shift in land cover from mangrove forests to open areas and ponds. According to Karstens and Lukas (2014) in the early 1990s, there were several small ponds in Kubu Raya District, and these were first created by transmigrants from Java, and by the end of 2000, larger ponds appeared in Sepuk Laut (Sungai Kakap sub district) and Selat Remis (Teluk Pakedai sub district). Natural mangrove regeneration is well underway, covering open land and settlement areas. Such natural regeneration improves ecological function and structural diversity (Azman et al., 2021; Ferreira et al., 2023; Hanggara et al., 2021). From 2003 to 2013, there was a vast land conversion from mangroves to open area, agriculture, and ponds. These changes have adverse impacts on mangrove ecology and ecosystems, such as loss of animal habitat, reduced biodiversity, and loss of carbon stocks (Goldberg et al., 2020; Saragi-Sasmito et al., 2019). According to Central Statistics of Kubu Raya District (2022), the agriculture, forestry, and fisheries sector contributes 21.08% per year to West Kalimantan's GDP. For example, charcoal production has become an economic activity with an increase in charcoal-making units by local communities, and this increased use of charcoal raw materials has threatened

TABLE 5 Land cover changes from 1993 to 2023.

Years	Land cover	2003					
		Ma	Oa	Set	Wb	Po	Agri
1993	Ma	999.97	8.18	0.31	–	2.89	–
	Oa	10.90	0.76	–	–	–	–
	Set	0.95	–	0.69	–	0.01	–
	Wb	–	–	0.06	234.14	–	–
	Po	–	–	–	–	–	–
	Agri	–	–	–	–	–	–
				2013			
2003	Ma	949.48	31.35	0.62	–	19.67	10.70
	Oa	8.77	0.18	–	–	–	–
	Set	0.30	–	0.76	0.01	–	–
	Wb	–	–	–	234.12	–	–
	Po	0.45	–	–	–	2.45	–
	Agri	–	–	–	–	–	–
				2023			
2013	Ma	931.27	16.22	0.11	0.33	4.97	6.94
	Oa	31.06	0.51	–	–	–	–
	Set	–	–	1.49	–	–	–
	Wb	–	–	–	233.40	–	–
	Po	0.71	–	–	–	21.45	–
	Agri	–	–	–	–	–	10.40
				2023			
1993	Ma	952.21	15.02	0.86	0.33	26.43	17.34
	Oa	9.90	1.71	–	–	–	–
	Set	0.94	–	0.74	–	–	–
	Wb	–	–	–	233.40	–	–
	Po	–	–	–	–	–	–
	Agri	–	–	–	–	–	–

the ecosystem (Ajibola et al., 2020; Harfadli and Ulimaz, 2021; Ng and Ong, 2022; Nyangoko et al., 2022; Onyena and Sam, 2020). Finally, from 2013 to 2023, mangrove land cover continued to decrease across all land cover classes, but not as much as in the previous period. The most significant change is from open areas to mangrove forests. This change is due to replanting initiatives on open area by the government and businesses and the transition of production forests to ecosystem recovery areas, thus increasing conservation efforts (Ferreira et al., 2023). Mangrove regeneration provides positive support for the future environment (Akram et al., 2023; Numbere, 2021; Sasmito et al., 2023; Yu et al., 2023).

4.3 Fragmentation pattern

Based on Figure 6, the Getis-Ord Gi* analysis identified crucial locations with the highest (hotspots) and lowest (cold spots) levels of fragmentation. In 1993, mangrove forest fragmentation hotspots already existed, but their distribution was relatively limited. Hotspots expanded in 2023, especially in the northern part of the study area. This means the region's fragmentation intensity has increased dramatically over the past 30 years. Meanwhile, in 1993, areas with shallow fragmentation (cold spots) were more visible in the central part, meaning that there were still areas that were intact or less affected by fragmentation. Where's in 2023, low fragmentation (cold spots) still presents in some areas; however, the cold spot areas have shifted or shrunk. Meanwhile, in 1993 and 2023, statistically insignificant areas were scattered between hotspots and cold spots. These areas may have experienced inconsistent or fluctuating changes in fragmentation over the period.

Forest or habitat fragmentation is a serious problem worldwide; fragmentation usually results from habitat loss due to land conversion that disrupts mangrove functions (Jaramillo et al., 2023; Ma et al., 2023). However, habitat change is inevitable as no habitat or landscape is permanent (Pu et al., 2024; Zhang and Chen, 2022). Declining habitat quality has a detrimental influence on ecological services, such as the ability

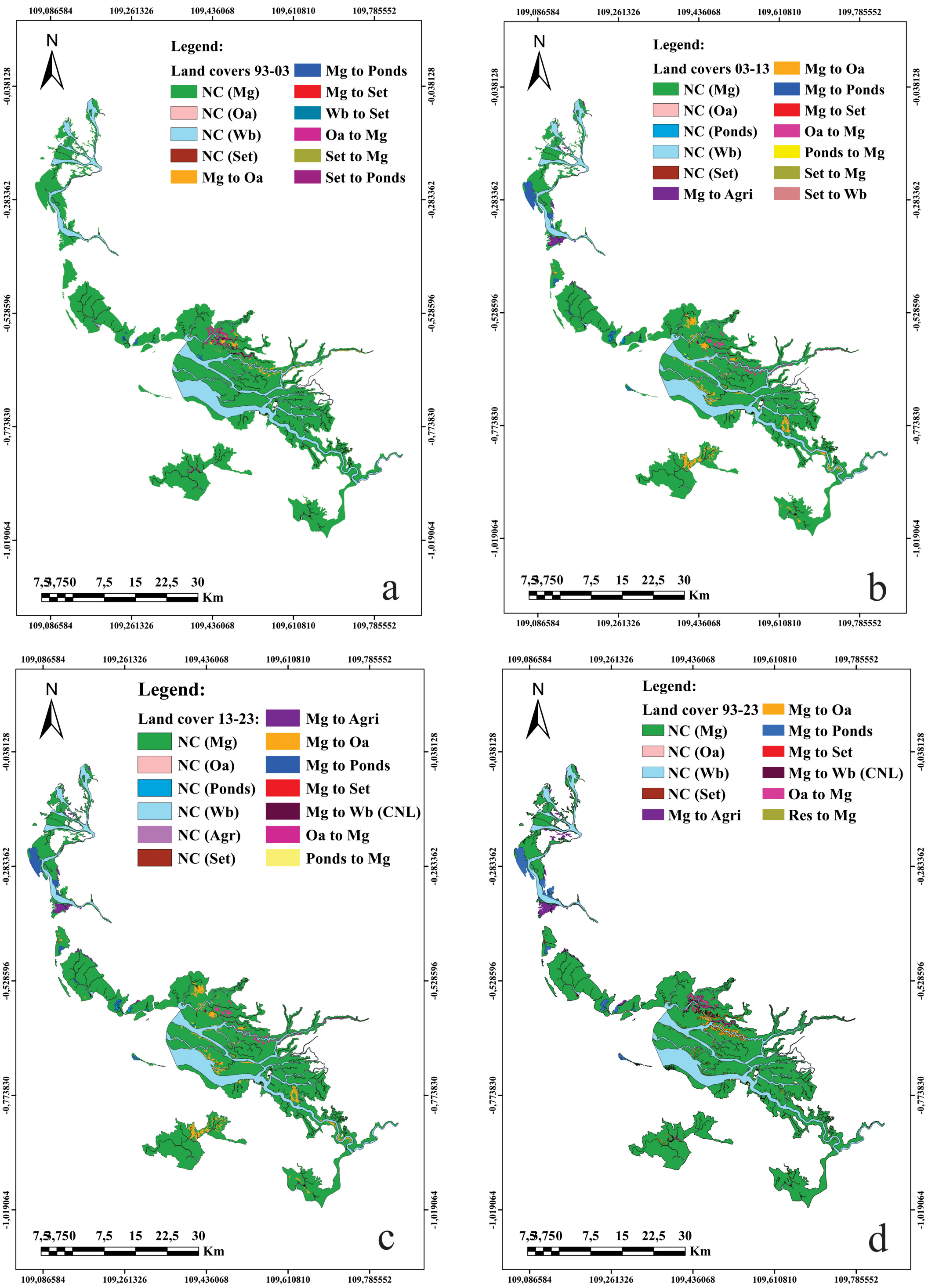

FIGURE 4
LULCC maps: **(a)** 1993–2003, **(b)** 2003–2013, **(c)** 2013–2023, **(d)** 1993–2023.

of ecosystems to maintain biodiversity (Bai et al., 2019; Onyena and Sam, 2020; Rumondang et al., 2024). Mangrove ecological services can be recognized by physical, chemical, and biological elements, such as ecosystem balancing, aberration control, and habitat for biodiversity (Barletta and Lima, 2019; Islam et al., 2024). As a result, fragmentation that leads to deforestation in mangrove ecosystems reduces their function as nursery, foraging, and nesting grounds for various aquatic biota (Barletta and Lima, 2019). According to Bunting et al. (2022), the expansion of forest edge boundaries affects changes in biodiversity habitat, which in turn affects changes in forest resources. Human disturbance leads to habitat disruption, and human activities contribute to forest fragmentation (Hussain et al., 2024; Kong et al., 2021).

TABLE 6 Result of binary logistic regression analysis.

Variable		B	S.E.	Df	Sig
Social factor	Population	−2.152	0.597	1	0.000*
	Education	−0.695	0.184	1	0.000*
	Land access	−0.756	0.318	1	0.017*
	River access	−0.012	0.174	1	0.947
Natural factor	Soil	0.583	0.208	1	0.005*
	Rainfall	0.665	0.160	1	0.000*
	Temperature	−0.258	0.260	1	0.322
	Slope	−0.214	0.302	1	0.478
	Elevation	−0.006	0.279	1	0.983
	Constant	−0.664	1.324	1	0.616

*Significant.

4.4 Driving factor

Binary logistic regression analysis shows that social and natural variables provide directly proportional and inversely proportional values to the driving factors of mangrove forest change that occur in Kubu Raya District, West Kalimantan (Table 6). With every unit increase in population, the log odds of mangrove forest cover change will decrease by 2.152. This means that as the population increases around the mangrove forest, the level of mangrove forest damage in the study area can be reduced. The existence of regulations made by the government to maintain and protect mangrove forest areas has been responded to by the surrounding community and implemented. The involvement of national governments and international organizations can increase the effectiveness of mangrove conservation initiatives (Kairu et al., 2024; Mohamed et al., 2023). The existence of mangrove awareness groups around the study area also supports increased community awareness of coastal environmental issues and provides a strong incentive to protect mangrove forests. Furthermore, the granting of concession licenses by the government to companies or investor groups in the study area restricts the community from directly exploiting the forest because of the rules set by the government and concession managers; only fishermen use mangrove forest areas in the study area to catch fish. This finding is in starkly contrast to previous similar studies, particularly in Asia and Africa, where millions of people depend on mangrove ecosystem services for food, income, and overall well-being. Anthropologic factors are key indicators of forest degradation and major contributors to global mangrove degradation, such as urbanization, population density, logging, and infrastructure development (Akram et al., 2023; Ferreira et al., 2022; Giri, 2023; Goldberg et al., 2020; Newton et al., 2020; Sharma et al., 2022). Some studies show that increasing population pressure in coastal areas has historically led to massive conversion of mangrove forests to other uses. However, this trend is not universal and may have changed in recent years, especially in our study area.

Education level: For every unit increase in education level, the log odds of mangrove forest cover change decreased by 0.695. This means that the higher the education level, the lower the chance of mangrove deforestation. According to Central Statistics of Kubu Raya District (2022), the number of people who continue their education to a higher level is increasing yearly, especially in the four sub-districts in the research area. This has a positive impact on the existence of mangrove forests in the study area. With higher levels of education and knowledge, communities around the study area increasingly understand the importance of maintaining mangrove forests and environmental issues and tend not to depend directly on mangrove forests for resources, potentially reducing exploitation. They understand the value and benefits of mangrove forests so that they can make the right decisions in forest management. This is under several studies state that people with higher education levels are more aware of the importance of forest mitigation and protection and are aware of the negative impacts of land use change on ecosystems, and vice versa (Esengulova et al., 2024; Jadin and Rousseau, 2022; Mallick et al., 2021; Nguyen et al., 2023; Opelele Omeno et al., 2024).

Land access: for every unit increase in land access, the logarithmic probability of change in mangrove forest cover decreases by 0.756. As land access increases, the probability of change in mangrove forest cover decreases. In the study area, the current access road is exclusively used for daily activities by the community, not for mangrove exploitation, and has not changed over time. The concession owner has provided information on clear boundaries to communities living around the mangrove forest so that communities understand the limits of activities carried out around the mangrove forest and they do not interfere with concession activities. Local policies or good management by concessionaires play an important role in maintaining mangrove forests, despite increased accessibility. This contradicts the findings of several studies that state that the proximity of road access to forest areas affects land conversion in the forest area itself, making it easier for local people to convert mangrove forests into non-mangrove forest areas (Gizachew et al., 2024; Salomon et al., 2022; Vu and Shen, 2021; Yu and Liu, 2024).

Soil type: for every unit increase in soil type, the log odds of mangrove forest cover change will increase by 0.583. This means that the more soil types, the greater possibility of mangrove forest cover change. In the study area, there are four soil types, namely alluvial, alluvial (Gley humus), organosol, and podzolic (kambiosol). Most LULC in the study area is agricultural land and ponds, both of which are found in areas with alluvial soil types. In coastal areas, this type of alluvial soil is ideal for agricultural land and fish farming (AbdelRahman and Arafat, 2020; Akram et al., 2023; Akter et al., 2023). Alluvial soil types that are rich in nutrients are very supportive of mangrove growth and the continuity of agriculture and pond (Halder et al., 2024; Mama et al., 2024; Rizki and Leilani, 2020; Sabriyati et al., 2023; Sumani et al., 2021). The conversion of mangrove areas to ponds and agriculture has significant impacts on coastal lands, altering sediment size and quality (Phan and Stive, 2022; Ramos et al., 2023; Solihuddin et al., 2024; Tarunamulia et al., 2024).

Rainfall: For every unit increase in rainfall, the logarithmic probability of mangrove forest cover change increases by 0.665. This means that rainfall patterns can increase the possibility of mangrove forest cover change. Rainfall intensity can lead

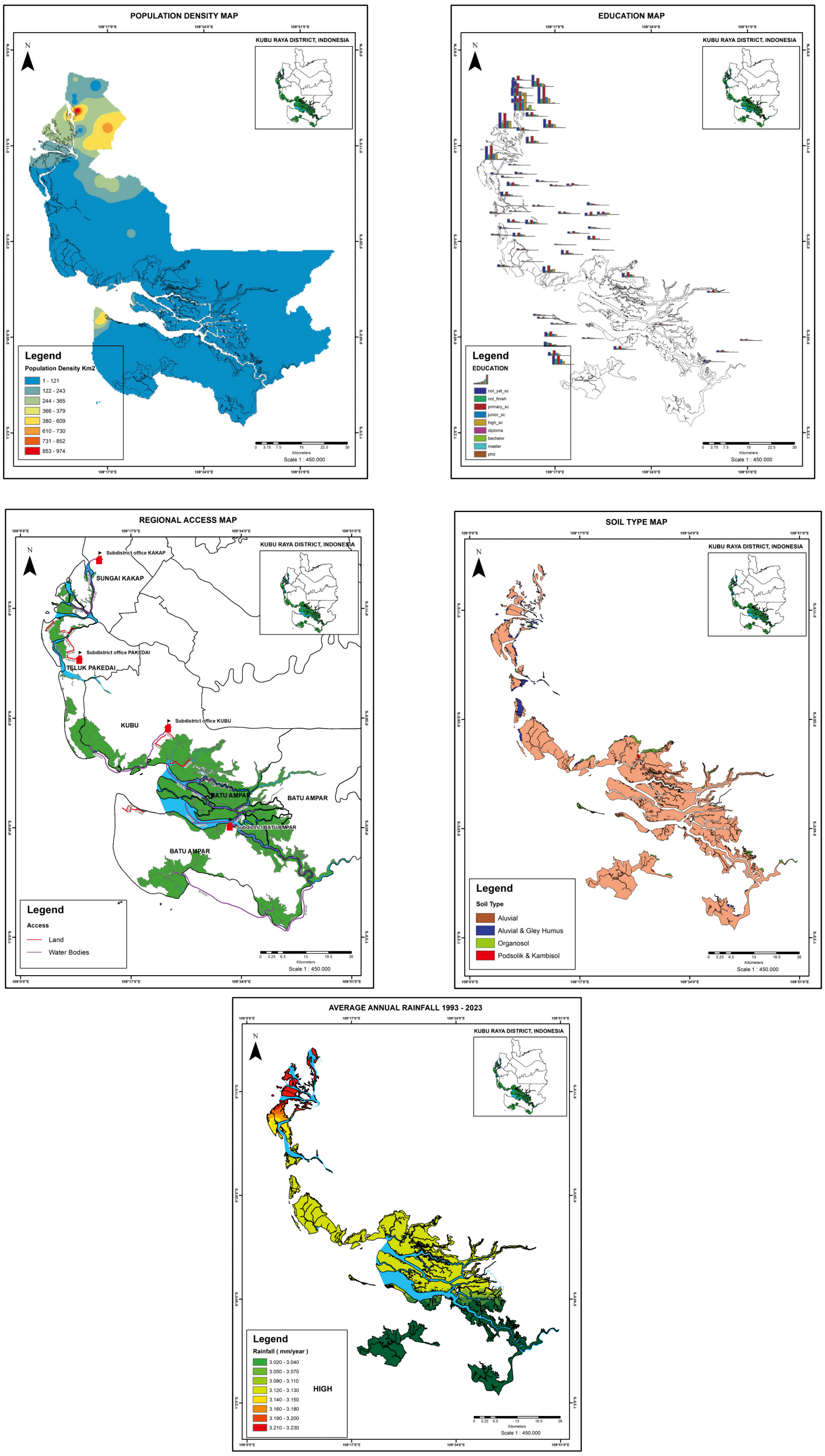

FIGURE 5
Driving factors maps population density, education level, accessibility, soil type, and average annual rainfall.

to changes in land use, such as conversion of mangrove land to agricultural land or ponds (Hasan et al., 2023; Li C. et al., 2023; Nong et al., 2021). Changes in rainfall patterns affect soil moisture levels, salinity, and general ecosystem health, and can lead to the shift of natural ecosystems such as mangrove forests to agricultural or pond environments (Safitri et al., 2022; te Wierik et al., 2021; Wang et al., 2021).

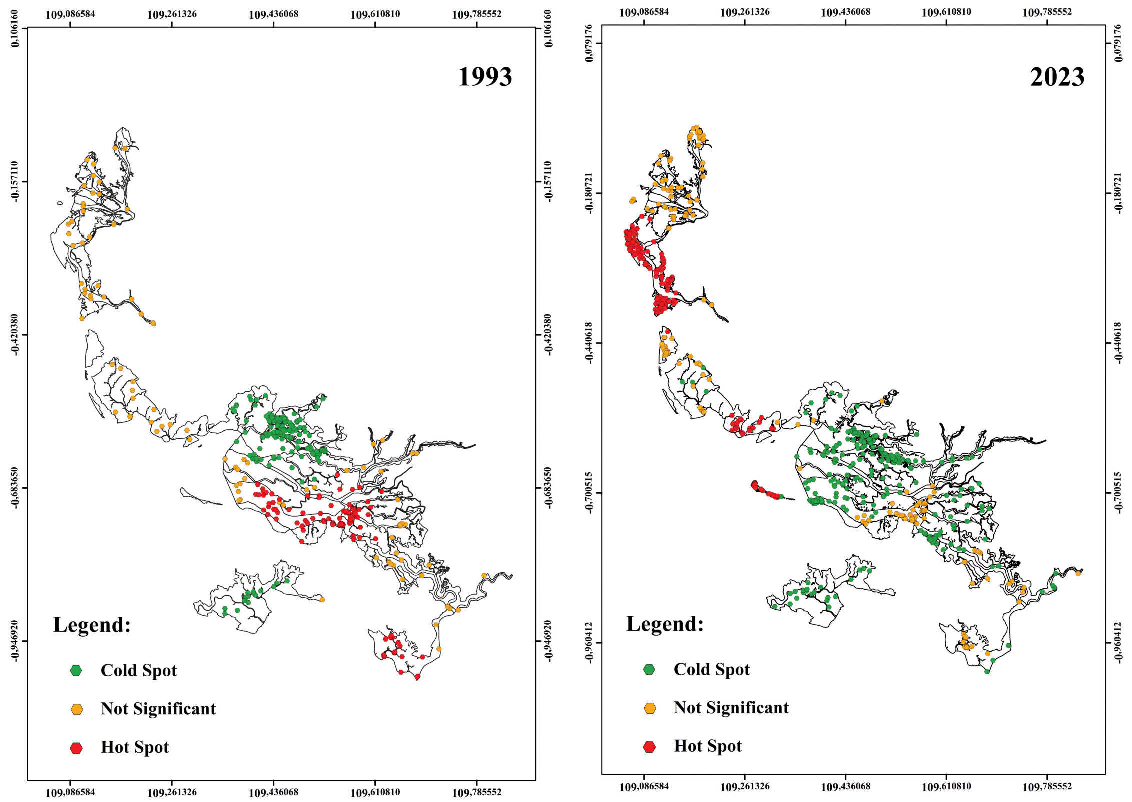

FIGURE 6
Fragmentation pattern 1993–2023.

5 Conclusion

Land cover classification results in 1993, 2003, 2013, and 2023 were mangroves, water bodies, open land, settlements, ponds, and agricultural areas. The study results show that the area of mangrove forest cover has decreased along with the growth of open space and other land uses, including ponds and agricultural land. Mangrove forest land cover decreased from 1,011.37 square kilometers (1993) to 963.06 square kilometers (2023). The total area of change was 97.68 square kilometers over three decades, or equivalent to 3.25 km^2 per year. The fragmentation pattern is that some areas in the north were insignificant hotspots in 1993, then turned into hotspots in 2023. Meanwhile, in 1993 and 2023, there were cold spots that shifted and also spread in the central part of the study area. This study proves that there has been considerable fragmentation in the study area. Social factors are related to land change in the study area: population density, education level, and accessibility. Reasonable regulations made by the government and highly educated people are a source of concern for preserving mangrove ecosystems. Coupled with the existing land, access is not used as access to exploit mangrove forests but only for daily activities. In addition, natural factors such as soil type and rainfall also have a mutually beneficial relationship for agriculture and aquaculture, especially alluvial soils. Alluvial soils have a high concentration of nutrients, making them ideal for the sustainability of agriculture and ponds. While rainfall intensity contributes to higher agricultural production and stable pond water. The final logit model of land use change is: 2.152 population, −0.695 education, −0.756 land access, +0.583 soil, and +0.665 rainfall. Based on these finding, we recommend to the local government to enforce spatial planning regulations that strictly limit the conversion of mangrove areas, particularly in areas identified as fragmentation hotspots. We also encourage to regularly monitor fragmentation hotspot and mangrove cover changes in the Kubu Raya District using remote sensing technology, ensuring early detection of land conversion activities and supporting data-driven decision-making processes.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

RW: Writing – original draft, Writing – review & editing, Conceptualization, Data curation, Formal Analysis, Investigation, Methodology, Resources. RF: Writing – original draft, Conceptualization, Data curation, Formal Analysis, Investigation, Resources, Writing – review & editing. MI: Writing – review & editing, Data curation, Conceptualization.

MB: Writing – review & editing, Data curation, Resources. UH: Writing – review & editing, Formal Analysis, Investigation. JM: Data curation, Methodology, Supervision, Writing – review & editing, Conceptualization, Funding acquisition, Writing – original draft.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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