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CASE STUDY

Spatiotemporal analysis of oil palm land clearing

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ABSTRACT

BACKGROUND AND OBJECTIVES: Oil palm is an agricultural crop essential to Indonesia's economy. Therefore, the number of oil palm plantations has increased, leading to widespread deforestation in Indonesia, including Jambi Province. In this investigation, remote sensing with a geographic information system approach is used to evaluate deforestation and the land changes caused by oil palm expansion conducted by smallholders that eventually influence environmental change. This study conducts a spatiotemporal (spatial and temporal) analysis of oil palm land clearing in Jambi Province that results in land changes and environmental impacts.
METHODS: This research used data from Landsat 8 satellite imagery. The land cover classification was conducted using the Maximum Likelihood approach, whereas the overlay method was used for land change analysis. The accuracy assessment of classification results used a confusion matrix by considering the overall accuracy and Kappa Coefficient. Within the field observation, the validation class was the oil palm class, and documentation and plotting using the global positioning system were conducted. Other classes were validated using the region of interest collected through Google Earth. This research used the Aviation Reconnaissance Coverage Geographic Information System 10.1 software to transform the categorization results into vector data.
FINDINGS: This study shows that the land cover classification results have high accuracy and that the area of oil palm land from 2015 to 2019 has increased along with a decrease in land used, such as forests and others. The area of oil palm land in 2014 was 2,071,345 hectares, whereas that in 2019 was 2,110,545 hectares. In particular, the land cover area increased by 39.2 thousand hectares because of land clearing and deforestation. Moreover, the built-up area has increased in the last five years by 165,358 hectares. The number of oil palm plantations in relatively plain areas tends to be greater than that in areas with relatively high altitudes and steep slopes. Small farmers' area of oil palm land has increased by 1,000 hectares from 2014 to 2018. The most remarkable increase of approximately 38,889 hectares has occurred from 2016 to 2017.
CONCLUSION: This study demonstrates that using Landsat 8 imagery with Geographic Information System approaches provides the optimal method for an in-depth analysis of land cover changes related to oil palm expansion and land clearing that occur on a broad spatial and temporal scale in Jambi Province. This study shows that smallholder oil palm plantations in the Jambi region play an important role in increasing deforestation not only in Jambi Province but also throughout Indonesia. This study is expected to serve as a valuable resource for informing policy decisions aimed at addressing the issue of deforestation resulting from the prospective increase in oil palm crops in the forthcoming period.

NUMBER OF REFERENCES	NUMBER OF FIGURES	NUMBER OF TABLES
52	3	6

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INTRODUCTION

Oil palm is an agricultural crop essential for the Indonesian economy. Oil palm's versatile uses as an essential ingredient for food, cosmetics, and renewable energy have increased the demand for oil palm (Purnomo *et al.,* 2020). Indonesian oil palm production is estimated to have increased by an average of 450,000 hectares (ha) per year from 1995 to 2015 (Ven *et al.*, 2018). Nevertheless, a consistent annual increase of approximately 1 million hectares (Mha) in the quantity of oil palm plantations in Indonesia occurred in 2015 until 2018 (Kementerian Pertanian RI., 2020). Indonesian plantations reached a critical point in 2006 because of the increased productivity fulfillment to meet oil palm needs through expansion driven by local factors, economic profitability, market preferences, and foreign factors (Varkkey *et al.*, 2018). Furthermore, economic and political incentives for oil palm cultivation ultimately drive forest loss and land conversion or changes in land utilization, mainly concentrated in lowland areas, fertile wetlands, and areas of relatively minor forest density (Cisneros *et al.*, 2021). In Indonesia, deforestation is mainly driven by plantation extensification factors. The largest plantation extensification is caused by the extensification of oil palm plantations (Austin *et al.*, 2019). Various policies and regulations have been implemented to raise commitment to deforestation prevention. Nevertheless, in Indonesia, deforestation continues despite regulations and policies, such as nonstate market-driven (NSMD) regulations for agricultural commodities (for example, eco-labels and certification systems) and government policies (Heilmayr *et al.*, 2020). A total of 91 square kilometers (km^2) of forest, 24 km^2 of peat forest, and 23 km^2 of primary forest were lost in certified plantation areas after the certification process started. Indonesia's annual deforestation rate is one of the highest. The yearly deforestation rate for 2000–2015, encompassing all oil palm plantations, was 3.3 percent (%) per annum. Similar temporal dynamics also occur for peat and primary forest deforestation (Carlson *et al.*, 2018). Productivity per hectare on mature, productive land cannot increase through intensification. In this case, an additional 6 million hectares (Mha) of oil palm plantation land is the estimated area needed to meet crude palm oil (CPO) demand in 2025 (Khatiwada *et al.*, 2018). High deforestation rates and the need for land to meet this demand ultimately affect ecosystem services, such as loss of utilization for wood production, habitat loss for endemic species, risen carbon dioxide (CO_2) emissions, and reduced biodiversity (Sharma *et al*., 2019). High deforestation can also result in indigenous and forest-dependent communities losing access to forest resources and reducing ethnic heterogeneity because of fragmentation from deforestation (Alesina *et al.*, 2019). Rising oil palm production results in intense pressure on land without substantially increasing CPO yields and land protection effectiveness (Schebek *et al*., 2018). Jambi Province is one of the provinces in western Indonesia with a fast deforestation rate. Approximately 44.6% of land utilized outside forest areas in Jambi Province is abandoned or unproductive. Approximately 96% or more of protected areas (834,800 ha) are maintained according to their function (Rustiadi *et al.,* 2018). Oil palm plantations' rapid expansion will increase oil palm plantations' area by 20% between 2014 and 2040 if companies are committed to meeting the current needs and rising productivity (Afriyanti *et al*., 2016). Land changes in Jambi Province are also affected by the transmigration program integrated into oil palm plantation development through a partnership program (Yanita *et al*., 2019). Land acquisition in Jambi generally occurs through forest land utilization and market transactions (Krishna *et al*., 2017). Land changes occurring in Jambi have resulted in a rise in the earth's surface temperature, flooding frequency in Jambi, and wildlife habitat fragmentation (Sabajo *et al*., 2017). Remote sensing is an efficient and economical method that offers valuable ecological data to characterize land ecosystems and monitor changes in land cover (Austin *et al*., 2019). Remote sensing data are useful for land mapping. Spatial features can add spectral information, thereby contributing to mapping complex land cover success (Mahdianpari *et al*., 2018). Land cover mapping using remote sensing techniques often involves the utilization of image classification methods, which may include object-based image analysis to achieve accurate results. Objects are frequently formed through image segmentation, which involves separating an image into clusters of pixels. The objects are subsequently utilized as a fundamental unit for spatial analysis. A method for accuracy assessment by determining accuracy with objects that have been separated before conducting classification can be utilized (Costa *et al.*, 2018). Parameters can be categorized into pixel-based type, object-based type (such as image segmentation obtained from spatial high-resolution images), and subpixel-based type (fractional images) (Li *et al*., 2019). This study utilizes remote sensing that can see land changes over time by using a Landsat sensor. Landsat 8 is a remote sensing satellite sensor tool that provides images with relatively good spatial but coarse temporal resolution, with medium resolution (Ling *et al*., 2016). Previous studies generally used GIS and remote sensing in oil palm plantation mapping (Rosyidy *et al.,* 2023), land cover change that impacts the increase in the surface temperature in urban areas (Suharyanto *et al*., 2023), zoning of malaria distribution related to landcover changes (Payus and Sentian, 2022), zoning of polluted and unpolluted areas (Adimalla and Taloor, 2020), forest expansion (Hashemi, 2018), determining the land change status in a region (Asen *et al*., 2018), and understanding patterns and risks of natural disasters (Matin *et al.,* 2017). In previous research, a gap exists regarding efforts to determine land changes based on data comparison over a certain period accompanied by the oil palm land distribution mapping. Thus, the advantages of remote sensing and GIS are also used in the present research to determine the land changes that occurred in 2014–2019 and map the distribution of private and private oil palm lands. The visualization results in the space and time dimensions, and the digital maps help understand the problems of land changes and oil palm development by small farmers. Moreover, these results are visualized in graphical form. In this research, the samples of land change and oil palm development in Jambi Province are used to evaluate deforestation and land changes caused by oil palm expansion carried out by small farmers that eventually influence environmental change. This study was conducted in Jambi, Indonesia, in 2023.

MATERIALS AND METHODS

Jambi Province is situated on the island of Sumatra. The province possesses a total land area of 53,435 km^2. Jambi Province is located between 0 degrees (°) 45 minutes (′) South (S) to 20°45′ S and 101°10′ East (E) to 104°55′ E. The northern boundaries of Jambi Province are shared with Riau Province and Riau Islands. The eastern boundary of the region is next to the South China Sea. The southern boundaries of Jambi Province are shared with the Provinces of South Sumatera, West Sumatera, and Bengkulu. The province comprises 11 districts, including the Districts of Kerinci, Merangin, Sarolangun, and Batanghari, Sungai Penuh City, East Tanjung Jabung, West Tanjung Jabung, Tebo District, Bungo District, Jambi City, and Muaro Jambi (Fig. 1). In 2021, the observation station of the meteorology, climatology, and geophysics agency/Badan Meteorologi, Klimatologi, dan Geofisika (BMKG) Muaro Jambi indicated that the average air temperature in Jambi Province was 27.2 Degrees Celsius (°C), with a minimum temperature of 21.6 °C. The maximum temperature in Jambi Province was close to 34 °C. In Jambi Province, the dry season is short and hot, and the rainy season is usually short and warm. The weather is generally hot, rainy, and cloudy all year round. Jambi Province displays a varied topographical landscape, with altitudes ranging from 0 meters (m) above sea level in the east to over 1,000 m above sea level. As one progresses toward the west, the terrain becomes increasingly elevated, eventually giving way to the hilly and mountainous expanse of the Bukit Barisan Range, which borders the Bengkulu and West Sumatra Provinces.

Data collection

The data utilized in this investigation comprised a satellite image obtained from the Landsat 8 Enhanced Thematic Mapper (ETM) instrument, with an ensured cloud coverage of less than 10%. Landsat 8, launched in 2013, represents the latest advancement in the series of LANDSAT satellite projects. The instrument is outfitted with two sensors: the operational land imager (OLI) and the thermal infrared sensor (TIRS). The OLI sensor is equipped with nine bands. Each band possesses a spatial resolution of 30 meters. The channels under consideration encompass coastal or aerosol, blue, green, red, near-infrared (NIR), short-wave infrared one (SWIR1), short-wave infrared two (SWIR-2), and Cirrus. The only exception is the panchromatic band, which has a high spatial resolution of 15 meters. The comparison of the two sensors shows that Thermal Infrared (TIR) possesses two bands: Thermal Infrared one (TIR1) and Thermal Infrared two (TIR2). Both bands exhibit a spatial resolution of 100 meters (Shidiq and Ismail, 2016). Landsat 8 orbits the Earth at an average altitude of 705 kilometers (km), with an inclination angle of 98.2°. Citra Landsat 8 also supports monitoring research because it is free and has time series data. Table 1 shows the acquisition of imagery data utilized.

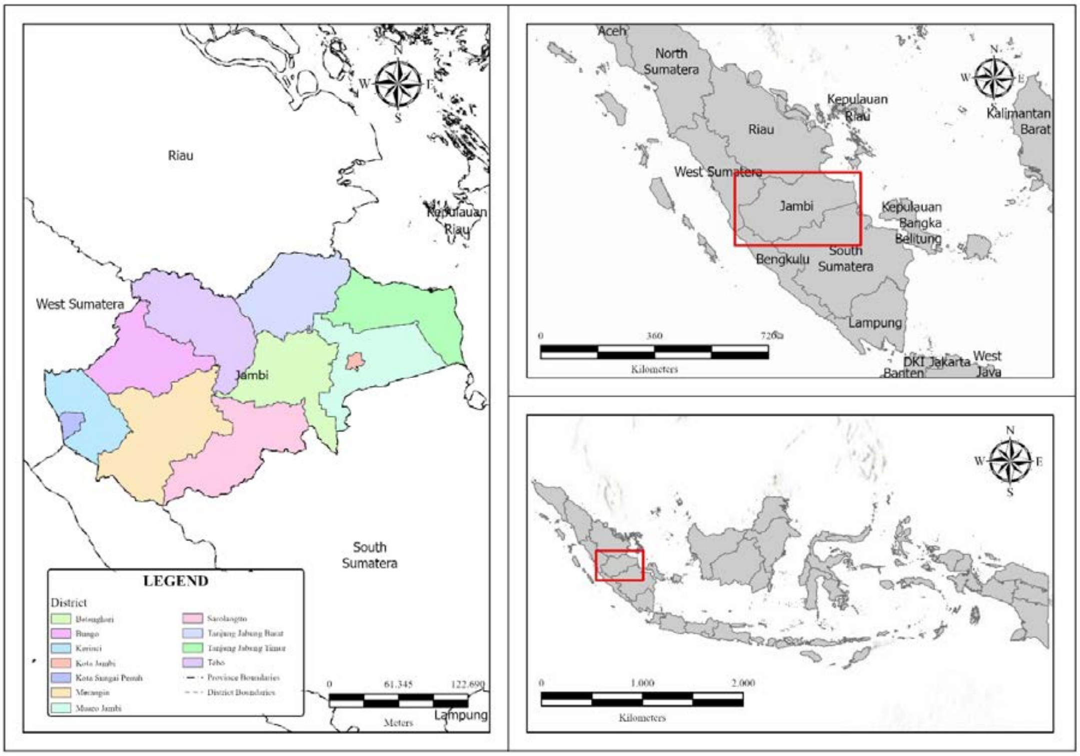


Fig. 1: Geographic location of the study area in Jambi, Indonesia

Table 1: Imagery data utilized in the current study

Path dan row	Acquisition 2014	Acquisition 2019–2020
Path 125, Row 062	2014/07/16	02/05/2019
Path 126, Row 062	2014/06/21	02/05/2019
Path 126, Row 061	2014/06/21	02/05/2019
Path 125, Row 061	2014/09/02	15/08/2019
Path 124, Row 061	2014/07/25	20/04/2020

Land cover mapping

Land cover mapping has three phases. The first stage is preprocessing imagery data. This stage involves merging multispectral (layer stacking) canals, image cropping, radiometric correction, and radiometric calibration. This stage is accomplished to overcome the inaccuracy of remote sensing and error in measuring devices (Ramana and Rajesh, 2018). At this stage, the digital number (DN) value is changed to reflect the value shape and facilitate Eq. 1 to obtain the Reflektan value (USGS, 2019).

$$\rho\lambda' = M\rho \; x \; Qcal + A\rho, \quad (1)$$

Where;

$M\rho$: The band-specific multiplicative rescaling factor

$A\rho$: Band-specifik additive rescaling factor

$\rho\lambda'$: The uncorrected top-of-atmosphere (TOA) reflectance angle of the sun

Qcal : Pixel value (DN)

The following stages are the makers of the region of interest (ROI) and spectral signature. ROI serves as a sampling area in classification and guidance in assessing classification accuracy level. Furthermore, ROI serves as a sample in extracting spectral signature values, which are further utilized in maximum likelihood method preparation. ROI is derived from Google Earth data, which present Earth images with high accuracy of spatial and temporal resolutions. The subsequent phase involves land cover classification. The classification approach employed in this study is the maximum likelihood classification method. It was implemented using ENVI 5.1 software. This method was also utilized by Hossain *et al*. (2016), who classified land cover with agricultural land, built-up land classes, plantations, open land, and forests. Furthermore, this approach was employed by Butt et al. (2015) to separate agricultural land, settlements, empty land, vegetation, and water bodies. This method also separates oil palm land from other land covers. Maximum likelihood classification is derived from the assumption that the pixel value distribution sampled from each class obeys the Bayesian Decision Rule, where each class probability is the same for normally distributed pixel values. This method's advantage is that data processing does not take long. After obtaining classification results, the researchers utilized GIS software to calculate the area of each land cover, particularly oil palm land area, in 2014 and 2019. The aeronautical reconnaissance coverage geographic information system (ArcGIS) 10.1 software was employed in the present study to transform the categorization outcomes into vector data.

Accuracy assessment

The accuracy assessment for this study used a confusion matrix by considering the overall accuracy and Kappa Coefficient. This accuracy assessment was utilized for similar research (de Almeida *et al.*, 2020). Confusion matrix is an effective method for explaining the overall accuracy of each classification category and fault classification. In this study, a sample point for accuracy assessment was obtained from Google Earth imagery and field observation interpretation. Within the field observation, the validation class was the oil palm class, and documentation and plotting utilizing the global positioning system (GPS) were conducted. Thirty sample points in the oil palm were collected to validate the oil palm area. However, other classes were validated using the ROI collected through Google Earth.

Land cover change analysis

The GIS overlay method can identify the threaded land between two temporal resolutions. The overlay analysis was performed using the spatial analysis toolbox in ArcGIS 10.1 software. Various data processing methods, including intersection, union, erase, identity, spatial join, symmetrical difference, and update, are available within this toolbox. In this study, the union method was employed. This technique facilitates the overlay of two or more sets of vector or polygon data at the same location, allowing for a comprehensive overview of different features within a single area. Consequently, the results provide detailed insights into the changes in land cover within the same locations by overlaying the land cover data of Jambi Province for 2014 and 2019. As stated by Butt *et al.* (2015), this method can describe land types that change in the research area. These land types are displayed with the two-way cross-matrix. This method can also calculate the changing land area of the two data in two temporal resolutions.

RESULTS AND DISCUSSION

Classification results indicate that the land images obtained by Landsat 8 imagery are bare land, water bodies, built-up areas, and forests. Oil palm plantations, other vegetation, and other land covers are also included. Determining a land cover type is based on the visual interpretation of the medium resolution of Landsat 8 imagery combined with high-resolution imagery from Google Earth. This study emphasizes the land cover of oil palm plantations and uses of other land cover types to analyze land conversion in the study area. The interpretation results of the land cover in Jambi Province are shown in Table 2.

The application of the maximum likelihood method in classification demonstrates a high level of accuracy, as indicated by an overall accuracy rate of 96.61% and a kappa coefficient of 0.94 for land cover in 2014. The results of the land cover categorization conducted in 2019 demonstrate an overall accuracy rate of 89% and a kappa coefficient of 0.7. The aforementioned accuracy metric demonstrates the potential utility of land cover classification outcomes for subsequent research. The disparity in precision rates between 2014 and 2019 can be attributed to variations in the duration of data acquisition for individual Landsat 8 image scenes and various atmospheric interferences, including cloud cover and smoke emanating from forest fires. The comparison of the confusion matrices for 2014 and 2019 is shown in Tables 3 and 4, respectively.

Table 2: Landsat 8 and Google Earth images interpretation derived from each land cover class

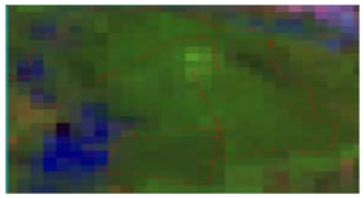
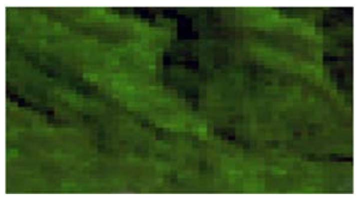
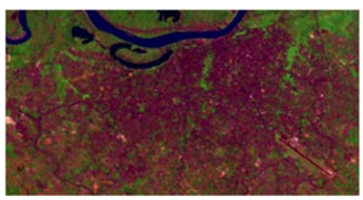
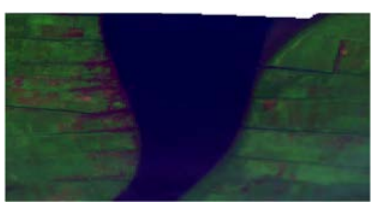
Classification	Landsat 8 imagery (false color composite 6,5,3)	Googel Earth imagery
Privately owned oil palm plantations		
Oil palm plantation land owned by small farmers		
Other vegetation		
Bareland		
Built-up area		
Water body		
Other (cloud and shadow)		

Table 3: Confusion matrix for land cover classification in 2014

Class	Oil palm	Other vegetation	Built-up	Bare land	Water body	Cloud	Shadow	Total
Oil palm	331165	42636	447	2521	11	1015	31	377826
Other vegetation	32553	1733371	48	206	9	0	6	1766193
Built-up	4606	2490	15210	3694	32	426	10	26468
Bare land	982	1735	904	113275	15	138	3	117052
Water	0	79	0	2	72350	0	0	72431
Cloud	3664	1286	104	2691	1017	719857	0	728619
Shadow	110	1436	0	3	2	0	2657	4208
Total	373080	1783033	16713	122392	73436	721436	2707	3092797

Table 4: Confusion matrix for land cover classification in 2019

Class	Oil palm	Other vegetation	Built-up	Bare land	Water body	Cloud	Shadow	Total
Oil palm	236597	225001	52	105	16	24	235	462030
Other vegetation	15560	2145158	0	40	1	546	80	15002
Built-up	3542	1299	9225	206	104	546	80	15002
Bare land	1326	15572	242	25696	665	740	253	44494
Water	0	18	0	0	67791	0	5	67814
Cloud	1064	2793	83	238	3	104498	66	108745
Shadow	184	49076	0	34	0	39	16385	65718
Total	258273	2438917	9602	26319	68580	105854	18063	2925608

Table 5. Land cover area of Jambi Province in 2014 and 2019

Land cover classes	Width of the area (ha)	
	2014	2019
Oil palm	2071345	2110545
Other vegetation	1692777	1071001
Water body	30427	33736
Bare land	336059	660121
Built-up area	43845	209203
Shadow	30390	217766
Cloud	426723	629181
Total	4631566	4931554

GIS technology is utilized to calculate area. The findings of the categorization analysis show that the predominant land cover in the Jambi Province region mostly comprises oil palm plantations. These plantations encompass privately held land dedicated to oil palm cultivation and smallholder plantations. In 2014, the proportion of land dedicated to oil palm cultivation in Jambi Province accounted for approximately 45% of the overall land area. This amount is equal to a total land area of 2,071,344.5 ha. In 2019, the area of oil palm land reached approximately 43% of the total area of Jambi Province. However, bare land increased by 324,063 ha in 5 years. The built-up land area increased by 165,358 ha. The bare land/ land area increases because of land clearing and deforestation, making way for private oil palm plantations and community gardens. Other vegetation in this study includes forest and grass areas. The area of this vegetation decreased. The land area for each classification result is shown in Table 5.

This study used the most popular conventional classification method, namely, the maximum likelihood classifier, for mapping and analyzing the spatial patterns of land cover change in Jambi Province. This method still has limitations due to the amount of training sample, and these limitations affect the classification accuracy (Rosyidy *et al.*, 2023). The maximum likelihood classifier cannot handle complex images, resulting in the incorrect classification of many pixels (Deilmai *et al.*, 2014). Some studies introduced novel machine learning approaches for land cover mapping, demonstrating increased classification accuracy and significantly reduced time consumption. Nasiri *et al.* (2022) employed a machine learning approach, particularly the random forest classifier, for mapping and classifying land cover using Landsat 8 and Sentinel 2 imagery. Other researchers also utilized machine learning approaches with cloud computing tools (Google Earth Engine), such as support vector machine (SVM), classification and regression trees (CART), and artificial neural network (ANN) (Samimi and Mohadesi, 2023); thus, a significant rule is provided for developing and improving land cover mapping and change analysis, particularly in detecting spatial patterns of oil palm plantations (Li *et al.*, 2020). However, the integration of advancements in information technology in the remote sensing and GIS applications for land cover mapping must be incorporated to result in comprehensive and accurate research outcomes.

Spatial and temporal patterns of oil palm plantation

Jambi Province has a plain topography in the east and tends to have a mountainous and hilly landscape in the west. Oil palm plantations are frequently located in topographically plain or gently sloping regions. Oil palm plantations in hilly regions characterized by high altitudes and steep slopes are generally less prevalent than those in comparatively level locations in terms of geographic distribution and time. The results of this study align with those of previous research in Malaysia, indicating that oil palm plantations are found in areas previously forested with lowland topography (Williamson *et al.,* 2020). Research in Myanmar also indicated something similar; in particular, oil palm plantations are concentrated in coastal or lowland areas with plain topography (Poortinga *et al.,* 2019). In 2014, Tebo District had the largest expanse of oil palm plantations, with a total area of 369,403.4 ha. Conversely, Jambi City had the smallest area of oil palm plantations, amounting to only 2,612.5 ha. In 2019, the Serolangun Regency exhibited the highest extent of oil palm plantations, encompassing a total land area of 1,434,556.3 ha. Conversely, the Sungai Banyak City possessed the largest oil palm plantation area, spanning a total of 1,037.6 ha. An observable increase in the total land area dedicated to oil palm crops was found between 2014 and 2019. The expansion of oil palm plantations was observed in the Districts of Bungo, Merangin, West Tanjung Jabung, and Kerinci. By contrast, other districts experienced a decrease in the total area of land designated for oil palm plantations. The observed phenomena can be attributed to the deforestation of oil palm trees, which is undertaken to allow the development of new oil palm seedlings. Consequently, a significant portion of the area transformed into uninhabited terrain. Sarolangun District experienced the most significant increase in oil palm land area, with a substantial surge of 1,265,155 ha. The second district is West Tanjung Jabung, encompassing an area of 91,237.15 ha. The graph depicting the fluctuations in oil palm cultivation across various districts is presented in Fig. 2. Increasing the area of oil palm plantations is intended to increase palm oil productivity even though it hurts environmental aspects, such as encouraging carbon emissions and biodiversity loss. However, increasing palm oil productivity can be accomplished through environmentally friendly methods. Previous research indicated that increasing palm oil productivity can be realized by replanting oil palms without opening new lands. Replanting oil palm at 4% every year, accompanied by enhanced management practices or improved cultivars, can optimize the increase in palm oil production (Zhao *et al*., 2023).

Land utilization and land cover change

The analysis showed the land utilization and land cover changes in the Jambi area over the last 5 years. Table 6 shows that significant changes in land utilization and land cover were found between 2014 and 2019. Remote sensing with Google Earth and Landsat can contribute to mapping land utilization and land cover in the Jambi area. This condition proves that remote sensing contributes to the success of mapping complex land cover (Mahdianpari *et al*., 2018). Parameters for land change are shown in Table 6. Pixel parameters were used to calculate land areas.

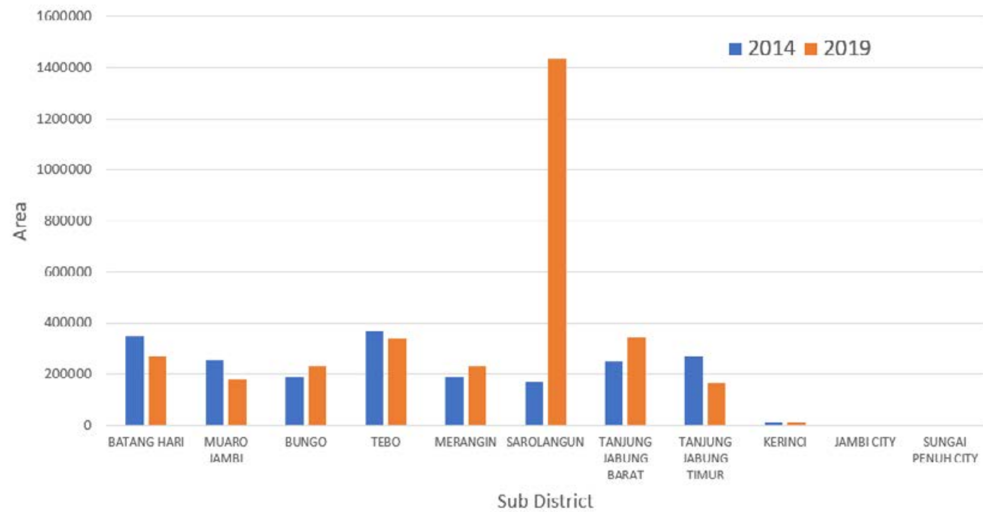


Fig. 2: Changes in the oil palm plantation areas across various districts during 2014–2019

Table 6: ROI collection within this study

ROI	ROI (Broad category)	2014		2019		Source
		Pixel	Area (ha)	Pixel	Area (ha)	
Oil palm	Forest	373,080	33,577.20	25,273	23,244.57	Google Earth
Other vegetation		1,783,033	160,472.97	2,438,917	219,502.53	Google Earth
Water body	Water Body	73,436	6,609.24	6,858	6,172.20	Google Earth
Bare land	Bare land	122,392	11,015.28	26,319	2,368.71	Google Earth
Built-up area	Built-up area	16,713	1,504.17	9,602	864.18	Google Earth
Shadow	Other land cover	2,707	243.63	1,063	1,625.67	Landsat 8
Cloud		721,436	64,929.24	105,854	9,526.86	Landsat 8

The parameters in sensing mapping can be derived from objects, pixels, or subpixels (fractional images) (Li *et al*., 2019). Table 6 shows that some areas are covered by shadow and cloud. This result is the same as that stated by former literature explaining that Indonesia, a tropical region, has a significant obstacle in the form of persistent cloud cover; thus, remote sensing opportunities are limited (Van der Laan *et al*., 2018).

Table 6 shows the increase in oil palm land area. The use and change of land in Jambi Province to oil palm land can be caused by increasing productivity to meet the need for oil palm through expansion driven by local factors, economic profitability, market preferences, and foreign factors (Varkkey *et al*., 2018). Moreover, the changes in land use and cover in Table 6 can be caused by economic and political incentives for oil palm cultivation, which ultimately encourages land conversion or changes in land use (Cisneros *et al*., 2021). If corporations remain dedicated to fulfilling existing demands and enhancing productivity, the oil palm industry is projected to gain a 20% growth in plantation areas from 2014 to 2040. This growth can be attributed to the swift expansion of oil palm plantations (Afriyanti *et al*., 2016). Generated land used as a building area can be affected by changing forest land or other vegetation into oil palm plantations. This condition can be caused by the distance from roads, distance from oil palm plantations, slope, distance from rivers and settlements, and altitude (Nurwanda *et al*., 2016). In Jambi Province, changes in land use and cover can also be caused by the development of the transmigration program in the Jambi region (Yanita *et al*., 2019). The preparation of oil palm plantation areas or oil palm rejuvenation areas can increase bare land. This area can be the remains of a forest burning area prepared for developing other land or an oil palm plantation area (Prasetyo *et al*., 2016).

Smallholders and deforestation

Jambi is one of the provinces on Sumatra Island experiencing rapid deforestation (Rustiadi *et al*., 2018). Fig. 2 shows that the land structures in Jambi are generally other vegetation areas (plantations or agriculture) and forests. The existing development area is still limited even though it is spread across every district in Jambi. Deforestation in Jambi generally intends to change the land from forest to other vegetation areas or from one vegetation to another vegetation. Plantation and agricultural areas in Jambi are dominated by rubber and oil palm plantations. Changes in land cover due to land clearing and oil palm plantations occur, with an increase in oil palm plantations reaching approximately 120 thousand ha in 2014. This scenario decreased the forest land amount in Jambi Province (Nurwanda *et al*., 2016). The robust growth of the export industry, which is supported by legal ambiguity and strong internal security measures for acquired land (Krishna *et al*., 2017), drives land change and further deforestation in Jambi. These land changes increase CO_2 emissions in the atmosphere. The extent of CO_2 emissions arising from land-use change scenarios is impacted by modifications in the policy scenarios that control them. Enhanced policy enforcement can have a significant mitigation effect in terms of land utilization change, as it can reduce deforestation by 50%–53%. The total area of private and community oil palm plantations in 2020 was 827,969.54 ha, with the total area of community plantations being twice the private plantations area (Fig. 3). Land changes in Jambi Province are dominated by smallholder plantations because of changes in Jambi land; these plantations are affected by transmigration program, which is integrated into oil palm plantations development through partnership programs (Yanita *et al*., 2019). Additionally, land acquisition in Jambi is generally accomplished through forest land utilization and market transactions. Partnership-based transmigration programs have been developing in Indonesia since 1980. This partnership program allows small farmers to receive financial and technical assistance for oil palm plantation management and distribution of the harvest obtained (Krishna *et al*., 2017). This program was carried out to encourage the development of people's plantations to grow. The area of oil palm land owned by farmers increased by approximately 1,000 ha from 2015 to 2018, and a significant increase of approximately 38,899 ha occurred in 2016–2017. Overall, the land area for oil palm (private and community oil palm plantations) can still increase if oil palm productivity in Indonesia is increased to emphasize that the extensification process and market influence factors are vital (Van der Laan *et al*., 2018). This opportunity arises because of the motivation to fulfill domestic and international demands. Indonesia is expected to produce 51 million tons of CPO by 2025, with an additional requirement of 6 million ha of land productivity remaining as it is today (Khatiwada *et al*., 2018).

A significant increase in the land owned by smallholders in 2016–2017 could indicate large-scale land clearing in the former year. In 2015, Indonesia experienced the worst fires since 1998. The fires led to the dispersion of smoke haze to neighboring countries of Indonesia. For land preparation purposes, this situation was also utilized by many organizations, including oil palm plantations and forestry firms. During the 2001–2015 period in Jambi, 20.67% of the fire incident area was converted into forest plantations, and 27.06% was converted into oil palm plantations. Moreover, 52.27% of the remaining land in Jambi was owned by small planters/communities; the initial vegetation of the land change was scrub and disturbed secondary forest (Prasetyo *et al*., 2016). Hence, in the year before 2016, smallholders dominated land clearing to fulfill the economic and social activities. Furthermore, the high quantity of land conversion to oil palm land caused by smallholders shows that smallholders play an essential role in preventing further deforestation not only in Jambi but also throughout Indonesia. The agricultural land expansion process is affected by the activities of large-scale companies, local elites, and smallholders (Barbier, 2020). The data from BPS RI Provinsi Jambi (2023b) show that Jambi Province had 187,756 oil palm farmers in 2013. The number of oil palm farmers increases yearly. In 2018, Jambi Province had 221,711 palm oil farmers. In particular, the number of oil palm farmers increased by 33,955 in 5 years. Farmers tend to expand oil palm plantations in the forest. In Indonesia, 68% of smallholder oil palm plantations are illegally located in forest areas (Nurfatriani *et al*., 2019). The Indonesian government has ratified Keputusan Presiden Republik

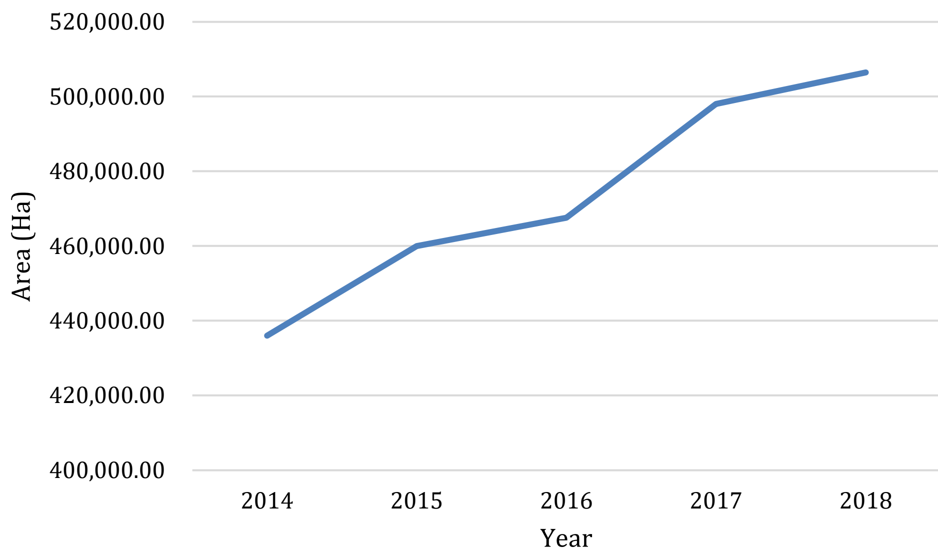


Fig. 3: Graph of the increase in smallholder oil palm land area in 2014–2018 (BPS RI Provinsi Jambi, 2023a)

Indonesia Nomor 9 Tahun 2023 tentang Satgas Penyempurnaan Tata Kelola Industri Kelapa Sawit dan Optimalisasi Pendapatan Negara (the Presidential Decree of the Republic of Indonesia Number 9 of 2023 Concerning the Task Force for Improving Palm Oil Industry Governance and Optimizing State Revenue) (Pemerintah Indonesia, 2023a). This regulation was passed by considering the development of the palm oil commodity-based industry, which continues to increase. However, obstacles in the governance of the palm oil industry remain. These obstacles can finally result in loss of state revenue from taxes and/or nontaxes. This decision by the president of the Republic of Indonesia is a tool to suppress the growth of the illegal and poorly managed palm oil industry. Indonesia has also explained the licensing of business activities in forest areas, including palm oil businesses, in Undang-Undang RI No. 6 Tahun 2023 tentang Penetapan Peraturan Pemerintah Pengganti Undang-Undang No. 2 Tahun 2022 tentang Cipta Kerja menjadi Undang-Undang (Law of the Republic of Indonesia No. 6 of 2023 Concerning Stipulation of Government Regulations in Lieu of Law No. 2 of 2022 Concerning Job Creation becomes law) in articles 110 A and 110 B. Article 110 A states that every person who carries out business activities that have been established and has a location permit and/or business permit in the plantation sector by an authorized official before its enactment Law Number 11 of 2020 Concerning Job Creation but have not fulfilled the requirements in accordance with the provisions of laws and regulations in the forestry sector must complete the requirements no later than November 2, 2023. If the requirements are not completed within the specified time, these individuals would be subjected to administrative fines, and/or the sanction of the requested permit would be revoked. Article 110 B states that every person who carries out business activities in forest areas without a business permit before November 2, 2020, would be subjected to temporary business permit sanctions, payment of administrative fines, and/or government coercion (Pemerintah Indonesia, 2023b). Oil palm plantations provide a positive economic effect. Otherwise, the process increases the deforestation rate, resulting in ecosystem services loss. Sharma *et al.* (2019) found that when oil palm expansion is conducted utilizing a sustainable intensification scenario, a significant compromise is found between the supply of ecosystem services and oil palm yields. Therefore, a significant opportunity to reduce the deforestation rate from the smallholder land clearing process can be found by increasing smallholders' productivity. Nevertheless, the challenge is increasing smallholders' productivity by shifting the extensification process to the intensification process; the reason is that smallholders' productivity only reaches half of the company's productivity because smallholders' productivity is approximately half of that of the company (Purnomo *et al*., 2019). Furthermore, smallholders must still be involved in preventing further deforestation. Smallholder involvement in preventing further deforestation and forest degradation makes deforestation prevention projects inclusive, realistic, and long-lasting while ensuring smallholder livelihoods in the long term (Duker *et al*., 2019). Thus, oil palm cultivation can potentially support people's income, particularly small farmers. However, the increasing growth in land clearing every year shows that palm oil productivity still depends on extensification efforts. These limitations can be triggered by farmers' lack of knowledge about other efforts that can be utilized to increase palm oil productivity, such as sustainable intensification scenarios. The intensification scenario includes rejuvenating oil palm plants by replacing old plants with oil palm seeds, chopping oil palm branches and stems, planting cover crops, and soil conservation. This intensification scenario is a middle way between meeting the economic needs of the community, which supports regional economic development, and fulfilling the responsibility of preventing damage to the environment.

CONCLUSION

The present study effectively employed Landsat 8 satellite imagery to delineate spatially the extent of oil palm plantations, encompassing a land area of 2,071,345 ha in 2014 and 2,110,545 ha in 2019. A notable expansion of oil palm plantations in Jambi Province was determined between 2014 and 2019. This expansion resulted in an increase of approximately 39.2 thousand ha. This expansion can be attributed to the practices of land clearing and deforestation. Over the past 5 years, increases in bare land and built-up land in Jambi Province have been observed. This scenario results in a decrease in the amount of vegetated land. Between 2014 and 2019, a notable expansion of 324,063 ha was found in unoccupied land, accompanied by a concurrent growth of 165,358 ha in developed land. The findings of this study indicate that the presence of oil palm plantations and the topographical characteristics of the land have a positive correlation. In particular, locations with relatively plain terrain exhibit a high concentration of oil palm plantations, whereas regions with high altitudes and steep slopes tend to have a low prevalence of such plants. The oil palm land area of small-scale farmers notably increased by 1,000 ha throughout the period spanning from 2014 to 2018. The largest observed expansion of approximately 38,889 ha occurred during the 2016–2017 period. The augmentation of oil palm production yields economic advantages for society but is accompanied by potential environmental ramifications. Hence, devising interventions congruent with the economic advantages for society and promoting sustainable and ecologically sound oil palm cultivation are imperative. Moreover, the government must develop and implement many effective policies to achieve substantial mitigation outcomes in relation to alterations in land utilization. Hence, the government's involvement as a regulating body is essential in mitigating the deforestation rate while simultaneously ensuring that the local economy, particularly in relation to oil palm productivity, remains unaffected. In addition, the community responsible for oil palm management can significantly contribute toward mitigating deforestation rates by adopting sustainable intensification strategies in their practices.

AUTHOR CONTRIBUTIONS

M.K. Rosyidy participated in writing the original draft, reviewing and editing, preparing pictures and tables of study results, and drawing conclusions. E. Frimawaty was the corresponding author, supervising the study, obtaining funding, and conceptualization, participated in data analysis and interpretation.

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CONFLICT OF INTEREST

The author declares that there is no conflict of interests regarding the publication of this manuscript. In addition, the ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, and redundancy have been completely observed by the authors.

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ABBREVIATIONS

°	Degrees
′	Minutes
°C	Degrees Celsius
–	Until
%	Percent
ANN	Artificial Neural Network
ArcGIS	Aeronautical reconnaissance coverage geographic information system
BMKG	Badan Meteorologi, Klimatologi, dan Geofisika (Meteorological, Climatological and Geophysical Agencies)
BPS RI	Badan Pusat Statistik Republik Indonesia (Central Statistics Agency of the Republic of Indonesia)
CART	Classification and regression trees
CO_2	Carbon dioxide
CPO	Crude palm oil
DN	Digital number
E	East
ETM	Enhanced thematic mapper
GIS	Geographic information system
GPS	Global positioning system
Ha	Hectares
Km	Kilometers
km^2	Square kilometers
Mha	Million hectares
NIR	Near-infrared
NSMD	Nonstate market-driven
OLI	Operational Land Imager
ROI	Region of Interest
S	South
SVM	Support Vector Machine
TOA	Top-of-atmosphere
SWIR-1	short-wave infrared one
SWIR-2	Short-wave infrared two
TIR	Thermal Infrared
TIR1	Thermal Infrared one
TIR2	Thermal Infrared two
TIRS	Thermal infrared sensor

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