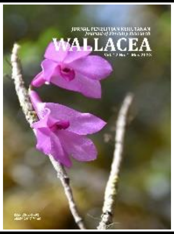

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Article

The spatial patterns of deforestation in the Ko'mara forest area

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Abstract

Land-use changes result from changes in the human population, their activities, and social and environmental activities, which occur in a complex and dynamic manner. The change of forested areas to non-forested areas, also known as deforestation, is a land-use change. Deforestation influences land cover by creating a specific distribution pattern (fragmentation). Almost the entire forest has been fragmented into smaller areas, but the pattern of each of these forest areas is uncertain. As a consequence, it would be more challenging to control potential deforestation. Using the spatial metrics of Clumpiness index, Contiguity index, and Patch density, deforestation in one of the forest areas, namely the Ko'mara forest area, was carried out. This research was analyzed using GIS and Fragstat software in raster data format. The analysis results show that the spatial pattern of deforestation in this area has a clumped distribution, with a high level of patch contiguity and a low to medium level of fragmentation. This pattern represents the form of deforestation in the Ko'mara forest area in 2005-2010 and 2010-2015 was classified as Low Deforestation with a deforestation rate of <1%, but was classified as Moderate Deforestation in 2015-2019 because the value obtained was 1.1%.

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INTRODUCTION

Land-use change is a sequence of events that occur in certain types of land use, resulting in the creation of new types of land use (Kastanya & Kastanya, 2006). Complex and dynamic changes connect to nature and humans, where increasing human population growth, activities, social and environmental activities can result in changes in land cover and land use (Altaweel et al., 2010; Tampubolon & Yanti, 2015). Humans' need for land is driven by their desire to increase their welfare continuously. As a result, land management is carried out without regard for environmental conservation-based management principles (Fajarini et al., 2015). The change of forested to non-forested areas, also known as deforestation, is a common type of land-use change.

Deforestation events in Indonesia have been measured to be about 1.6 million ha per year over the last ten years (1990-2000) (Suhendang, 2002). According to Tacconi (2012), the average rate of deforestation at the national level between 2000 and 2002 was calculated to be about 1.8 million ha per year (1.7% per year), which is significantly higher than the rate of deforestation that occurred between 1985 and 2000, which was about 1 million ha per year (0.93% per year). Continuous deforestation can create a distribution pattern that changes the macroclimate, resulting in hydrometeorological disasters that, if not addressed, will have a significant impact on the country's economy, community welfare, and ecosystem (Rijal et al., 2016).

Knowing the spatial patterns will provide information about land-use change processes and drivers of deforestation. Geographic information system technology and remote sensing can be used to conduct spatial analysis of deforestation events. Since spatial patterns of forest change, such as fragmentation patterns, are useful for early detection of areas vulnerable to land conversion, future deforestation events can be predicted by creating spatial models (Kurniawan et al., 2018). Almost every forest area in Indonesia has been fragmented. Fragmentation of forests occurs when extensive, intact forests are divided into smaller areas due to road construction, agriculture, urbanization, or other development. Fragmentation impairs the forest's ability to function as a habitat for biodiversity (Gunawan et al., 2010).

The Ko'mara forest area is a complex ecosystem comprised of several area functions, including conservation forest in the form of wildlife reserve, which covers an area of 2,838.27 hectares, hunting park, which covers an area of 4,126.07 hectares, and production forest, which covers an area of 2,804.67 hectares. This forest area is divided into 3 (three) regencies: Gowa, Takalar, and Jeneponto in South Sulawesi. The area covered by this forest group represents two conservative forest functions and one that enables production activities to support the development movement. The conservative forest provides a wildlife reserve and hunting park, which is dedicated to habitat management for deer (Cervus timorensis) and other protected species such as black monkeys (Macaca maura), hornbills (Rhyticeros cassidix), wild boar (Sus vitatus), weasels (Felisbengalensis), and kuskus (Phalangerursinus). For approximately two decades, the wildlife reserve ecosystem quality has deteriorated, as has the production forest's function as a buffer zone.

As a forest area adjacent to community-owned land, it is a prime location for the emergence of factors driving change in the Ko'mara forest area. This change results from a variety of factors, including illegal logging, encroachment, land grabs, and forest fires (Sahruddin et al., 2019). Therefore, the spatial pattern of land-use change, mainly deforestation, in the Ko'mara forest area should be analyzed to determine the fragmentation of deforestation events. This information on forest fragmentation could be necessary to measure deforestation events in the Ko'mara forest area. Furthermore, considering the state of the Ko'mara forest area, which occurs widely in land use and cover, restoration of the ecosystem is necessary for the future.

METHODS

Research Time and Location

Field activities in the Ko'mara forest area were conducted in three regencies in South Sulawesi, namely Gowa, Takalar, and Jeneponto, from February to April 2021, as shown in Figure 1. The komara forest area studied includes the ecosystem unit of the komara forest group as stipulated by Act of the Ministry of Forestry Number 237 in 1997 including hunting park areas, wildlife reserves and production forests. Meanwhile, data analysis was carried out at the Laboratory of Forestry Planning and Information System, Faculty of Forestry.

Tools and Materials

The research uses both field survey and data analysis tools. Roll meter, compass, GPS, and camera are used as field survey tools. While the data analysis tool of choice is a personal computer (PC)/laptop provided with GIS software for image data processing and Fragstat software for spatial model analysis. The study uses administrative spatial data, spatial data on forest areas in South Sulawesi Province (SK. 362 / MENLHK / SETJEN / PLA.0 / 5/2019), and Landsat 7 TM+ Path Row 114/64 imagery acquired on September 9, 2005, and September 2 2010, as well as Landsat 8 OLI / TIRS Path Row 114/64 imagery acquired on August 8, 2015, and August 2 2019.

Procedures and Analysis of Research

The research procedure is divided into several stages, including an interpretation of land cover, an analysis of land cover change, an analysis of deforestation rates, and an analysis of fragmentation levels.

Interpretation of land covers

Land cover interpretation in the Ko'mara Forest Group area, including image correction, stacking of layers, cropping, image interpretation, ground check, and accuracy testing. Prior to further processing Landsat 7 TM + imagery from 2005 and 2010 and Landsat 8 OLI / TIRS imagery from 2015 and 2019, corrections are made to ensure that clear objects are visible in the image. Corrective measures are taken in the form of radiometric and geometric corrections. To assist in identifying the land cover in the study area, a band is combined (layer stacking) utilizes the red, green, and blue bands (Natural Color). The combined band's result is then used to interpret the image. Cropping the image to be interpreted in accordance with the research area's boundaries enables more efficient image data processing at the research location.

The image is interpreted using a combination of unsupervised and visual classification methods with layer delineation (on-screen digitizing). This method begins with an unsupervised classification procedure that determines the number of classes (clusters) to create. After obtaining the results, the analysis assigns the object classes to the computer-generated spectral classes. Multiple generated cluster classes can be combined into a single class that contains the same information (Rahmawan et al., 2020). To elaborate on the results of unsupervised classification, an improvement process using on-screen digitizing was used, specifically to separate, combine, or add classes that could not be accomplished through unsupervised classification, such as the presence

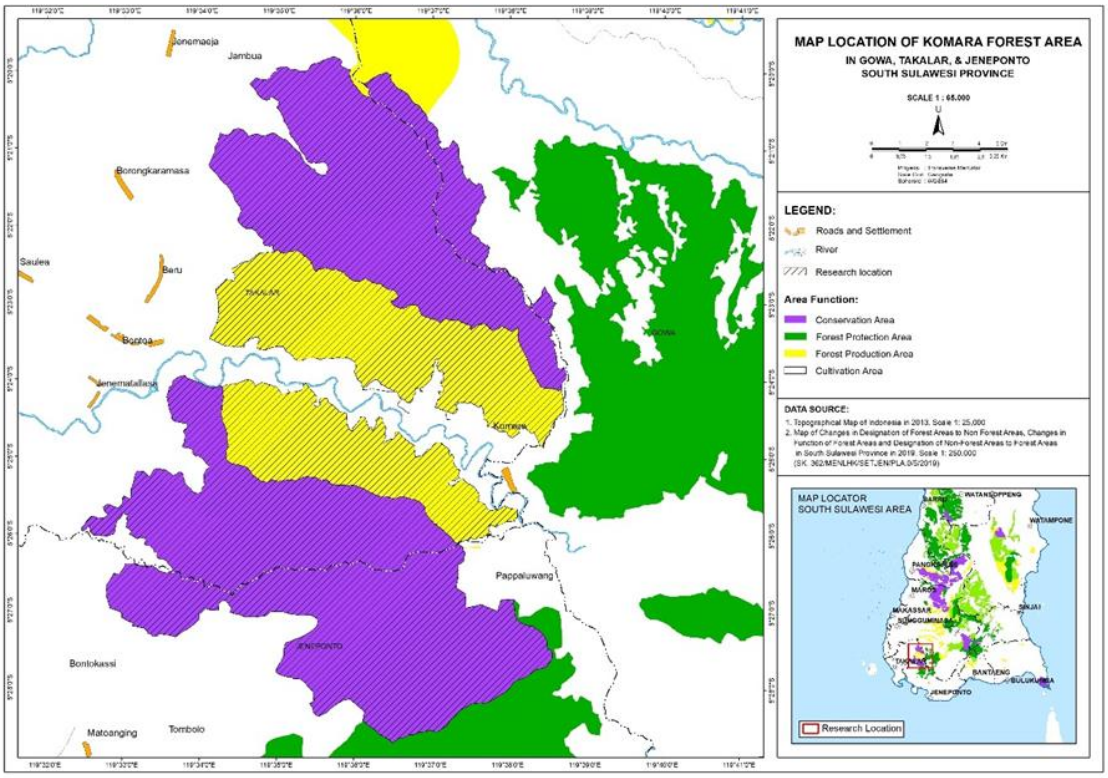

Figure 1. Map of research location

of cloud-covered land. The land cover class used in Landsat image interpretation is based on the Indonesian National Standardization Agency (BSNI) Number 7645 in 2010.

The reliability of the interpretation results is evaluated and validated through reference data (ground truth) and field checks (ground check). The verification of reference data is carried out by assessing the interpretation results and comparing them to official maps (for land cover interpretation in 2005, 2010, and 2015). The results of land cover interpretation in 2019 are verified in the field by establishing observation points. Using color differences to determine observation points for land cover classes identified in the field. Purposive sampling was used to determine the observation points. Each point was visited, and data collection, observation, and recording of important information were conducted. The data collected is the GPS coordinates of the field observation points. The state of the land cover around the field points illustrated with photographs and the results of community interviews (Munir et al., 2017).

The accuracy of the results of field checks is then validated using the kappa accuracy test, as defined by the formula:

$$Kappa\ Accurac = \frac{\sum_{i=1}^{r} x_{ii} - \sum_{i=1}^{r} \ (xi \ \times \ x + i)}{N^2 - \sum_{i=1}^{r} (xi \ \times \ x + i)}$$

Information:

r : The row number in the matrix

xii : the number of correct cell numbers in the class

xi : the total for row i

x+I : the total for column i

N : the total number of cells in the error matrix

Kappa accuracy testing is performed using a confusion matrix, which illustrates the relationship between classification results based on interpretation and data samples collected under field conditions (Lillesand et al., 2005). The acceptable level of image interpretation accuracy is 85% (Lillesand et al., 2005). This means that at least 85 of every 100 sample points must be consistent with field conditions.

Analyses of land cover change

Land cover change analysis is performed by overlaying two land cover maps using GIS software over a predetermined period. The analysis period is divided as follows:

1) The initial period, from 2005 to 2010. This period refers to the time before the forest areas were designated in accordance with SK. 434/Menhut-II/2009.
2) The middle period, from 2010 to 2015. This period refers to the time since the forest area was designated in accordance with SK. 434/Menhut-II/2009, as well as a transitional period to allow for the revision of the provincial spatial plan.
3) The final period, from 2015 to 2019. This period represents the time during which the provincial spatial plan was revised and until the latest forest area designation, SK. 362/MENLHK/SETJEN/PLA.0/5/2019, is issued.

The overlay will generate a matrix of land-use change for each of the three analysis periods. These changes affect the extent and shape of land cover classes ranging from forest functions to other land uses.

Analyses of spatial deforestation patterns

Spatial patterns of deforestation were analyzed to obtain information about the distribution and pattern of deforestation, which was then correlated with the rate of deforestation. Spatial pattern analysis using the Fragstat software. Fragstat is a program for analyzing spatial patterns that generate metrics for forest landscapes (McGarigal & Marks, 1995; Morrison et al., 1999). Aggregation Metrics, Shape Metrics, and Subdivision Metrics are the three types of forest landscape metrics used.

1) The group of aggregation metrics makes use of the Clumpiness Index (CI). CI is used to characterize the temporal, spatial pattern of deforestation distribution. The CI indicates a range of values from -1 to 1. Closer to -1 suggests that the patch is uniformly distributed, closer to 0 indicates that the patch is randomly distributed, and 1 indicates that the patch is clumped distributed (Morrison et al., 1999). The Clumpiness Index is determined by the following equation:

$$Given\ Gi = \left[\frac{Gii}{\left(\sum_{k=1}^{m} gik\right) - min\ ei}\right]$$

$$Clump = \left[\begin{Bmatrix} \dfrac{gi-pi}{1-pi} for\ Gi \geq pi \\ \dfrac{gi-pi}{1-pi} for\ Gi < pi; pi \geq 5 \\ \dfrac{gi-pi}{-pi} for\ Gi < pi; pi < 5 \end{Bmatrix}\right]$$

Information:

Gii : the number of adjoining class i patch pixels, and corresponding based on a double count

gik : the number of patch pixels of class i bordering class i, and k based on double-counting

min ei : the minimum perimeter (across a number of cell surfaces) of the patch type (class) i, for the maximal class that is clumped

pi : the proportion of landscapes occupied by patches in class i

2) The shape metrics group use the Contiguity Mean Index (CONTIG_MN) to characterize the form in which patches are connected (low, medium and high). CONTIG_MN is a shape metric that is used to describe the spatial relationship or contact between cells in individual patches (connectedness and contiguity). The CONTIG_MN index value indicates the strength of the connection (Morrison et al., 1999) and vice versa. The Contiguity Mean Index is determined by the following equation:

$$CONTIG_{MN} = \left[\frac{\sum_{j=1}^{n} Xij}{ni}\right]$$

Information:

Contig_MN : the mean value of the same patch connectedness

Xij : the metric value on patch -ij as appropriate

ni : the number of patches of the same type

3) The subdivision metrics group uses Patch Density (PD) to characterize the level of fragmentation. The PD metric is part of the field, density, and edge metrics (McGarigal & Marks, 1995; Rijal et al., 2016). The number of patches per 100 ha of landscape units is defined as PD. Land cover classes are becoming rapidly scattered or fragmented, according to high-scoring PD. The equation is used to calculate the Patch Density value:

$$PD = \frac{N}{A} x10000x100$$

Information:

PD : the number of forest patches per 100 ha
N : the number of forest patches
A : the forest area

By combining the three spatial metric values, the temporal spatial pattern of deforestation is constructed. The combination of three spatial metrics, namely the Clumpiness index (Uniform, Random, Clumped), the Contiguity index (low contiguity, medium contiguity, and high contiguity), and the Patch density (unfragmented and fragmented), enables the creation of various spatial patterns of deforestation. The spatial metrics obtained are then correlated with the rate of deforestation. The following equation is used to determine the rate of deforestation:

$$r = (\frac{1}{t2 - t1}) \ln (\frac{A2}{A1})$$

Information:

r : The deforestation rate (% per year)
A1 : The initial cover area
A2 : The final cover area
t1 : The initial period
t2 : The final period

Low deforestation is defined as a deforestation rate (r) of less than 1%, r values of 1% to 2% are considered moderate deforestation. while r values greater than 2% are classified as high deforestation (Rijal et al., 2016).

RESULTS AND DISCUSSION

Classification of Landcover

The interpretation of Landsat images in the Ko'mara forest area resulted in a classification of land cover for each period with a different area. The classification of land cover resulted in the identification of five classes of land cover types: secondary dryland forest, shrub, dryland agriculture, mix dryland agriculture, and rice fields. Figure 2 and Table 1 below illustrate the distribution.

On the basis of Landsat satellite imagery classification results in the Ko'mara forest area, 120 land cover polygons were created and classified into 5 (five) cover classes. To estimate the population proportionately by land cover type, assuming a 95% reliability level or a 0.05 estimator error (Setiawan, 2007), validation tests were conducted in the field at 94 observation points. The number of observation points is calculated using the Slovin formula. The results of field sampling yielded a kappa analysis value of 91% accuracy.

Table 1. Area distribution of land cover classification in the Ko'mara forest area

No	Land Cover	2005		2010		2015		2019	
		(Ha)	(%)	(Ha)	(%)	(Ha)	(%)	(Ha)	(%)
1	Secondary dryland forest	7,296.50	74.69	7,132.16	73.01	6,494	66.48	6,213.84	63.61
2	Dryland Agriculture	114.10	1.17	149.40	1.53	265.65	2.72	361.40	3.7
3	Mix Dryland Agriculture	707.88	7.25	765.29	7.83	801.05	8.2	1,106.60	11.33
4	Rice Field	240.55	2.46	319.51	3.27	432.48	4.43	467.89	4.79
5	Shrub	1,409.98	14.43	1,402.65	14.36	1,775.83	18.18	1,619.28	16.58
	Total	9,769.01	100	9,769.01	100	9,769.01	100	9,769.01	100

Landcover Change

During the observation period, the land cover in the area of the Ko'mara forest group changed in size and shape. The most widespread distribution and the land cover type is secondary dryland forest cover, which covered 7,296.50 ha or 74.69% of the Ko'mara Forest Group's total area in 2005 and decreased 6,213.84 ha or 63.61% in 2019. According to field observations, changes in forest land are more pronounced in areas with road access, as the community requires access to

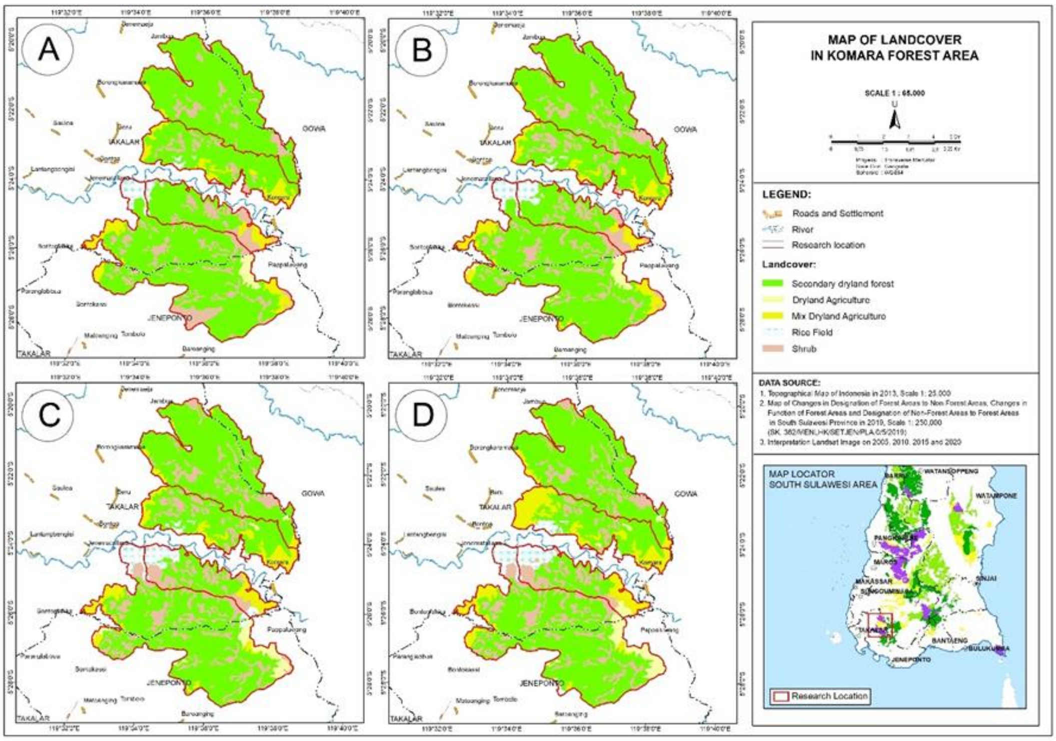

Figure 2. Map of land cover for 2005 (A), 2010 (B), 2015 (C) and 2019 (D) in the Ko'mara forest area

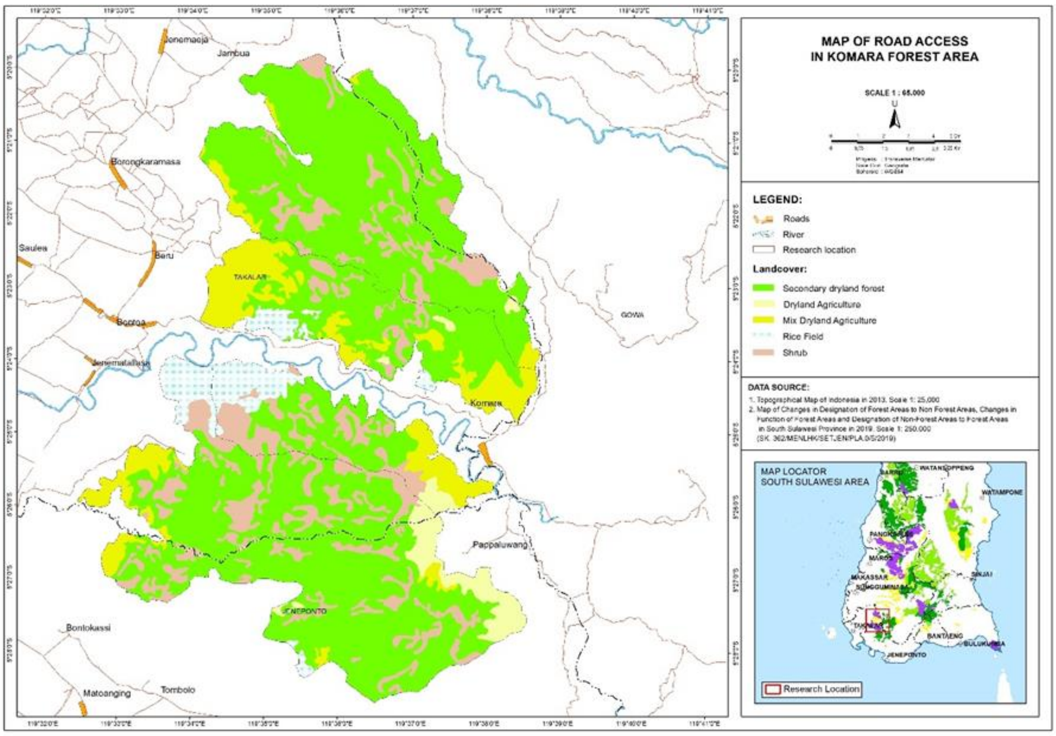

Figure 3. Map of road access around the Ko'mara forest area

to the location for honey hunting, as illustrated in Figure 3. There is an access road to the Ko'mara forest area that runs through Barugaya and Barana villages and is a path that can be accessed by two or four wheeled vehicles.

The Ko'mara forest area immediate surroundings are secondary dryland forest that has been converted to agricultural land. The settlement pattern in Komara and Kale Komara villages, located in the central of the Ko'mara forest area, allows for easy encroachment on forest areas by the surrounding community. Other forest changes have occurred due to honey search activities conducted by residents of Bissoloro

Village. They typically use ignition or fire smoke to locate beehives, resulting in forest fires. According to interviews with people in Pappaluang Village, a lack of knowledge about the area's boundaries resulted in ongoing encroachment and land claims, resulting in the conversion of forest cover to agricultural land. The slightest change in land cover in the form of forest occurs in Barana Village due to the village's limited road access, which is still in the condition of hardened roads.

Figure 4. Dryland agriculture within the Ko'mara forest area

Land cover data were obtained from image interpretation in the Ko'mara forest area and then classified as forest or non-forest. The division is based on the National Land Use Database's Land Use and Land Cover Classification 2006, which classifies shrubs into forest classes, with shrubs and secondary dryland forests included in the forest class dryland agriculture, mix dryland agriculture, and rice fields classified as non-forest classes. (Nurfatimah, 2020). Additionally, a deforestation analysis was conducted to determine the extent and distribution of deforestation in the Ko'mara forest area for each period. The analysis of land cover change in the Ko'mara forest area is presented in Table 2 and Figure 5 below.

Table 2. Deforestation data in the Ko'mara forest area

No.	Classification	Area per period (ha)			
		2005-2010	2010-2015	2015-2019	2005-2019
1	Deforestation	194,75	275,02	448,62	902,83
2	Non-Deforestation	9.574,27	9.494,00	9.320,39	8.866,18
	Total	9.769,01	9.769,01	9.769,01	9.769,01

According to Table 2, deforestation in the Ko'mara forest area increased in each period from 2005 to 2019. The period from 2015 to 2019 will have the most deforestation, covering an area of 448.62 ha, while the period from 2005 to 2010 has seen the least, covering an area of 194.75 ha. Deforestation occurred in several periods from the outer borders to the middle area.

Deforestation Spatial Patterns

A spatial metric assessment was conducted to assess the pattern of deforestation in the Ko'mara forest area. Three metrics were used in the assessment: the Clumpiness Index (CI), the Contiguity Mean Index (CONTIG_MN), and Patch Density (PD). Figure 6 illustrates the results of the spatial analysis of deforestation metrics in the Ko'mara forest area.

a) Clumpines Index

The Clumpines index for the Ko'mara forest area indicates that the distribution value of deforestation is typically close to one, namely 0.9788 (2005-2010), 0.9766 (2010-2015), and 0.9808 (2015-2020). This value indicates that the patch is clumped. However, the trend of the CI value for each period is different, decreasing from 2005 to 2010 to 2010 to 2015. The decline in the CI value results from the small remaining forest area, which increases the tendency to clear forest for other purposes. This is because forest encroachment in the area began during that period. However, between 2015 and 2019, the CI value increased, indicating that land clearing in the Ko'mara forest area occurred only in certain clumped areas during the current period.

b) Contiguity Mean Index

The Contiguity Mean Index demonstrates increased patch connectivity in the initial and middle periods (2005-2010 to 2010-2015). then continued to decrease in the final period (2015-2019). The highest level of connectivity in the second period indicates that deforestation occurred directly from the previous deforestation area to the adjacent forest area during that period. This is because the deforestation event tracks the distribution of the remaining forest. The decreased connectivity in the third period indicates that the deforested area is isolated from other patches.

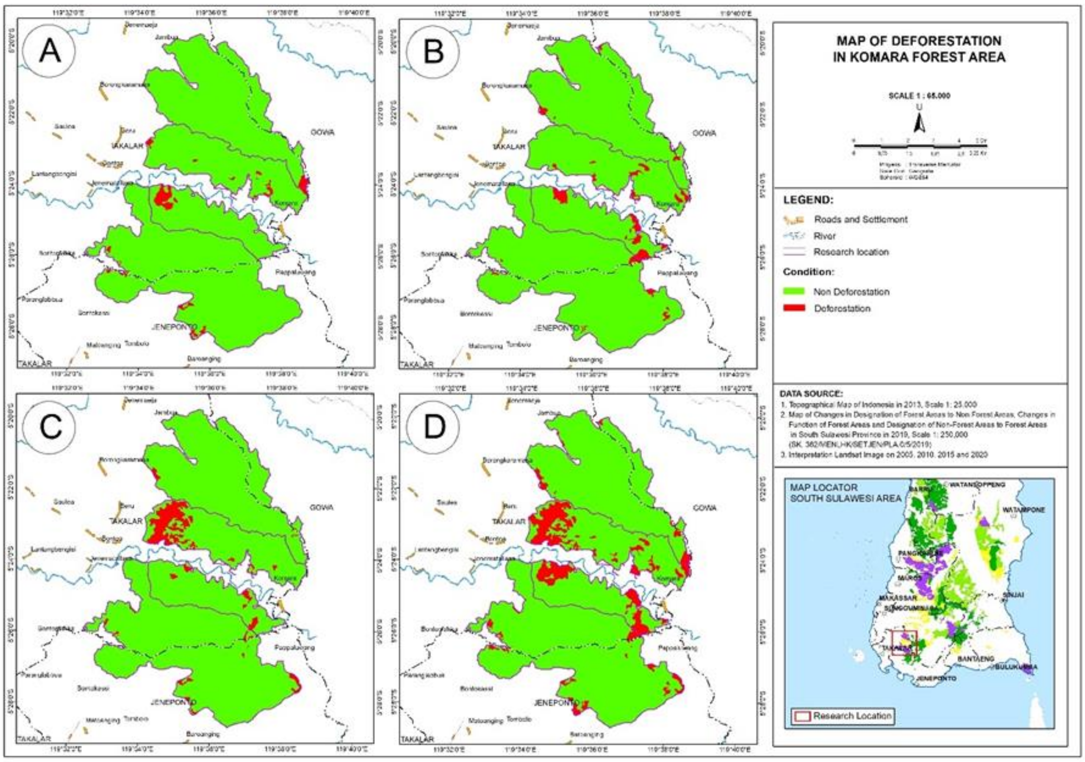

Figure 5. Map of Deforestation for 2005-2010 (A), 2010-2015 (B), 2015-2019 (C) and 2005-2019 (D)

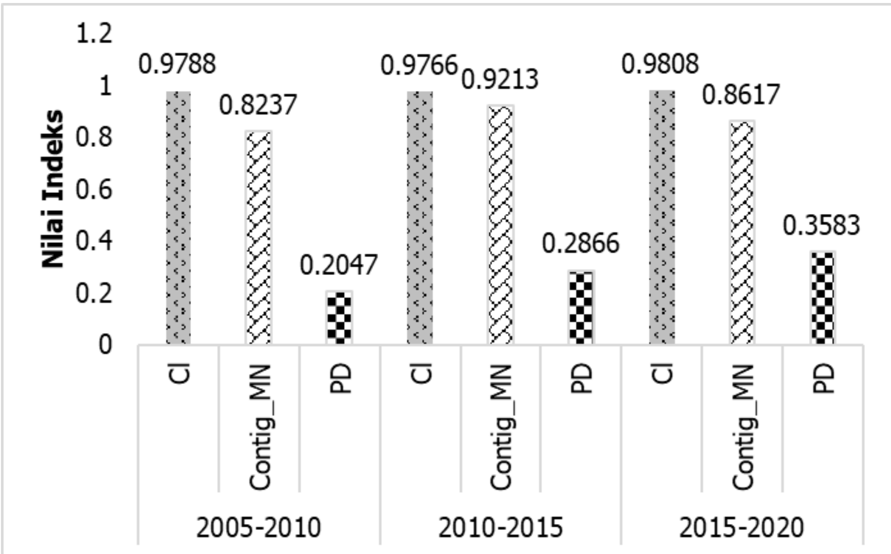

Figure 6. Metrics spatial of deforestation in the Ko'mara forest area

As a result, deforestation is rarely associated with the previous area. According to Margono's (2016) research, the spatial pattern of deforestation with a low level of connectivity is also typically driven by deforestation that occurs as a result of changes in plantation land use, an agricultural expansion for small-scale rice fields, and other factors, resulting in deforestation areas that are scattered and far apart.

c) Patch Density

The lowest level of fragmentation occurred during the initial period (2005-2010), indicating that deforestation continued to expand and spread into adjacent areas, resulting in less fragmented forests and index values increased during the middle and final periods (2010-2015 and 2015-2019), indicating that deforestation events were more widespread during those periods. This demonstrates that deforestation events in the Ko'mara forest area are becoming increasingly fragmented, with forest fragmentation defined as the process by which extensive, connected forests are divided into smaller blocks due to land conversion and road construction (Septanti, 2019). This incident is consistent with Rijal's (2016) research, which indicates that increased human activities such as shifting cultivation, a high incidence of forest fires, and settlement development contribute to the increased fragmentation.

Following that, the metric analysis is correlated with the rate of deforestation. In general, the deforestation that occurred in the Ko'mara area between 2005 and 2010 and 2010 to 2015 was classified as low deforestation. In contrast, the deforestation that occurred from 2015 to 2019 was classified as moderate deforestation, as the values obtained ranged between 1% and 2%. (Rijal et al., 2016, 2019). The assessment of the relationship between spatial metrics and deforestation rates in the Ko'mara forest area is represented in Table 3.

Table 3. Deforestation rate in the Ko'mara forest area

Period	CI		CONTIG_MN		PD		Rate of Deforestation (%)
	Index	Class	Index	Class	Index	Class	
2005-2010	0.9788	Clumped	0.8237	High contiguity	0.2047	Low fragmentation	0.4
2010-2015	0.9766	Clumped	0.9213	High contiguity	0.2866	Low fragmentation	0.6
2015-2019	0.9808	Clumped	0.8617	High contiguity	0.3583	Moderate fragmentation	1.1

The relationship between deforestation rate and clumpines index reveals two patterns in deforestation events and distribution, namely low deforestation rates with a clumped distribution and moderate deforestation rates with a clumped distribution. As shown in Table 3, deforestation occurs in groups at both low and moderate rates, implying no significant relationship between deforestation rate and deforestation distribution. According to Rijal (2016), the spatial distribution pattern of deforestation in groups typically indicates that the majority of deforestation occurs due to land conversion to the plantation, agricultural, or urban areas. Similarly, path density reveals two distinct patterns in the occurrence and distribution of deforestation: low deforestation rates with low fragmentation rates and moderate deforestation rates with moderate fragmentation levels. A low patch density indicates that the event and distribution of deforestation thus far have been dominated by large-scale conversion of forest to non-forest areas. In contrast, a high patch density shows that deforestation occurs on a small scale, resulting in smaller patches.

CONCLUSSION

The spatial pattern of deforestation in the Ko'mara forest area has revealed that the dominant type of land change occurs when forested land cover is converted to agricultural land. The spatial pattern of deforestation in this area is clustered, with a high level of patch connectivity and a low to moderate level of fragmentation. The primary factor affecting the rate of deforestation is the availability of roads to forest areas. Due to the ease of access, the surrounding community clears land and converts forest land to agricultural land.

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AUTHOR CONTRIBUTIONS

Leny Rachmawati: research conceptualization, research coordinator, data analysis, data interpretation, manuscript writing; Samuel A. Paembonan: member contributor, research implementer, manuscript writing; Syamsu Rijal: member contributor, research implementer, manuscript writing; Munajat Nursaputra: data analysis, data interpretation, member contributor, research implementer, manuscript writing; Andang Suryana Soma: member contributor, manuscript writing; Syamsuddin Millang: member contributor, manuscript writing; A. Mujetahid: member contributor, manuscript writing.

CONFLICTS OF INTEREST

The authors declare there is no conflict of interest related to financial funding and authorship order for this article.

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