Wetland Degradation

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Wetland degradation monitoring using multi-temporal remote sensing data and watershed land degradation index

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ABSTRACT

BACKGROUND AND OBJECTIVES: The condition of the Watershed area in particularly in Tabunio Watershed as a watershed with priority treatment is due to the condition of critical land included in the qualification for very high recovery with an area of critical land of 19,109.89 ha. The condition of diminishing water absorption also results in flooding in the rainy season and drought in the dry season. Environmental damage in the Tabunio watershed is exacerbated by the existence of traditional gold mining and has become a concern for many parties. The perceived increase in natural disasters, such as floods, landslides and droughts from year to year, requires an evaluation of land degradation in the Tabunio watershed.

METHODS: The objective of this study was to monitor and simulate the spatial and temporal aspects of land degradation in the Tabunio watershed. It was suggested that a complete land degradation index be developed in order to capture the spatiotemporal aspects of land degradation between the years 2005 and 2020. This index integrates land use land cover, vegetation coverage, soil erosion and soil moisture content.

FINDINGS: The proposed comprehensive Land Degradation Index in this study approach demonstrated that: (a) Land Degradation Index, which successfully monitored the spatiotemporal characteristics of land degradation (Kappa Coefficient > 0.73 and Overall Accuracy > 86%), is regarded as having high accuracy; (b) When compared with individual indices, the Land Degradation Index is able to reveal land degradation in a more comprehensive manner (c) Land Degradation Index is readily transferable and applicable to other study areas due to the fact that all of its land degradation indices can be quickly extracted from remotely sensed imagery (d) Land Degradation Index can be used in a wide variety of contexts, and it made quantitative predictions regarding the possibility of land degradation (e) The rate of land degradation will generally increase from 2005 to 2020, with 2010 being the most extreme year;

CONCLUSION: In this study, the proposed comprehensive Land Degradation Index method is able to describe the spatiotemporal aspect of land degradation from 2005 to 2020 in the watershed area in particularly Tabunio Watershed. The proposed approach shows that the level of land degradation from 2005 to 2020 generally increases and the extreme years of land degradation was 2010 and most years, the amount of land degradation was moderate, and only a few years had severe or extreme degradation. As a consequence of this, some land degradation management measures ought to be created in advance in order to guarantee the protection of this vital region that is a source of freshwater.

KEYWORDS: *Land degradation index; land use/land cover (LULC); Soil erosion; Soil moisture content; Vegetation coverage.*

RUNNING TITLE: Wetland degradation monitoring

INTRODUCTION

The resources provided by the land constitute an essential component of the material basis for human existence and advancement. However, in recent years, the irresponsible use of land resources, combined with poor management of those resources, as well as the growth of the world's population, has led to severe land degradation across the globe (Ahmad and Pandey, 2018). Land degradation is characterized as a deterioration in a land's biological or economic productive capacity induced by human activities, aggravated by natural processes, and frequently exacerbated by the consequences of climate change and biodiversity loss. (Zhu *et al*., 2022). The degradation of land can have a wide range of negative effects on the surrounding environment, including the amplification of soil loss, a decline in biodiversity, a deterioration in ecosystem services, and a loss in land's capacity to be used for other purposes (Dubovyk, 2017; Faisal *et al*., 2019). Since addressing land degradation effectively is crucial, in 2015 the United Nations General Assembly applied the 'Sustainable Development Goals', One of these consists of combating and restoring degraded land. (Dubovyk, 2017; Moonrut *et al*., 2021). This goal aims to achieve land degradation neutrality by the year 2030. The mitigation of climate change and the conservation of biodiversity, as well as the improvement of food security and the upkeep of sustainable livelihoods, all benefit from the management of land degradation. (Tolche *et al*., 2022). The use of remote sensing techniques has become increasingly common in the field of land degradation research due to the fact that these techniques have many benefits, including the ability to detect land degradation of varying degrees (Ejegu *et al*., 2022; Kumsa and Assen, 2022; Shange, 2020); as well as the capability of locating and mapping land degradation At the moment, there are four of them major steps in the process of using remote sensing techniques to evaluate land degradation (Gashaw *et al*., 2014; Hu *et al*., 2020). Despite the fact that remote sensing technologies and geographic information systems (GIS) have generated satisfactory results in studies of land degradation (Auliana *et al*., 2018; Kadir and Farma, 2017), commonly used land degradation indices are inadequate because they do not accurately capture the full range of land degradation's severity and temporal and spatial dimensions (Zhu *et al*., 2022). Despite the success of remote sensing technologies in studying land deterioration, this remains the case. Numerous studies use a combination of indices to indicate land degradation, for example, the normalized difference vegetation index (NDVI), soil erosion (SE) (Ghobadi *et al*., 2012; Kumsa and Assen, 2022), land use/cover change (Gashaw *et al*., 2014; Moonrut *et al*., 2021; Van Lynden and Mantel, 2001), and land desertification (Ibrahim *et al*., 2015), In addition to this, the accuracy of the monitoring cannot be verified in a satisfactory manner. As a result, improving the precision of land degradation monitoring and creating a comprehensive index of land degradation are both urgent requirements. The ability to simulate and predict the degradation of land can provide important information that can help guide decision-making. System dynamics model (SD), Markov model, GeoMod, universal soil loss equation (USLE), modified universal soil loss equation (MUSLE), and multi-agent model are some examples of the simulation and prediction models that are are widely employed in research on land degradation. (MUSLE), as well as an erosion and sedimentation prediction tool called EROSET (Borrelli *et al*., 2021; Karydas *et al*., 2014; Ly *et al*., 2019; Wiratmoko and Gunawan, 2019). However, none of these models are foolproof, and the majority of them concentrate on simulating changes in land use or land cover, or on simulating individual indicators of land degradation. Only a few of these models are used to simulate land degradation in its entirety (Borrelli *et al*., 2021; Febrianti *et al*., 2018; Karaburun, 2010; Karydas *et al*., 2014). Quantitatively predicting a dynamic change in landscape characteristic is within the capabilities of Markov models, but these models are unable to resolve the spatial characteristic of landscape change (García *et al.*, 2019; Liping *et al.*, 2018; MohanRajan and Loganathan, 2021; Oguz and Zengin, 2011). On the other hand, the CA model is able to forecast the spatial distribution of the landscape pattern, but it is unable to forecast the temporal change (Liping *et al.*, 2018; MohanRajan and Loganathan, 2021; Oguz and Zengin, 2011). The methods of simulating water loss and soil erosion known as USLE, MUSLE, and EROSET do not have the capability to simulate other indices of land degradation. In light of these considerations, it is essential to integrate a variety of modeling approaches in order to successfully simulate the spatiotemporal characteristics of land degradation. For instance, the CA-Markov model, which combines CA with Markov, has the ability to simulate the spatio-temporal dynamics of land degradation and has numerous applications in a variety of scientific communities (Mariye *et al.*, 2022; Tadese *et al.*, 2020; Zhu *et al.*, 2022. It is necessary to have an integrated remote sensing index that can track the spatial and temporal features of land degradation in order to provide coverage for the aforementioned indices. Tabunio Watershed is one of the most important sources of fresh water in the Tanah Laut regency. However, the land degradation, such as soil erosion, the loss of quality farmland, and the fall of plant coverage, is affecting the water quality. Although Tabunio watershed is one of the most important supply in Tanah Laut regency, its water quality is being negatively impacted. It is imperative that departments of land management and local government do the following: to gain an understanding of the spatial and temporal characteristics of land degradation as well as the factors that cause it, with the goal of improving environmental protection. The findings of this study can provide baseline information that can be used for the purpose of preserving the environmentally sound growth of this watershed ecosystem. The purpose of this research is to create an extensive land degradation index (LDI) by integrating indices from multiple remote sensing sources in order to monitor the spatial and temporal aspects of land degradation. This study has been carried out in Tabunio Watershed from 2005 to 2020.

MATERIAL AND METHODS

Study area

Tabunio watershed (3°37'2.72"-3°51' 51.43" SL and 114°36' 12.02"114°57'47.62" EL) is located in Tanah Laut regency. It has an area of approximately 62,558.56 ha, and dominated lowest elevations. Tabunio Watershed is (Fig. 1). The watershed is not only an essential resource for the economic and social growth of Tanah Laut regency in a sustainable manner, but it is also a source of water resources for the Riam Kanan dam. The land resources in the Tabunio watershed are rapidly deteriorating as a result of both natural and human-caused changes in the surrounding environment, which is drawing an increasing amount of attention to the need for mitigation.

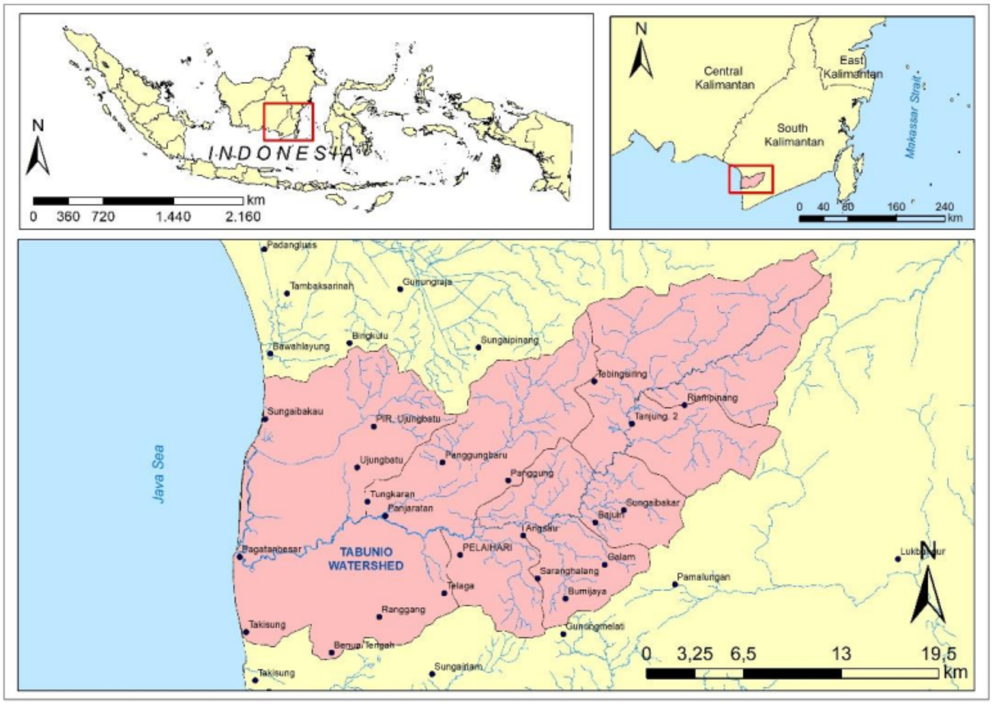

Fig. 1: Geographical location of the study area in Tabunio Watershed, South Kalimantan, Indonesia

Data source

The multispectral image of the research region that was taken on January 20 and did not contain any clouds was retrieved from the USGS Global Visualization Viewer. These data were captured by LANDSAT 7 ETM+ (2005 and 2010), and LANDSAT 8 OLI (2015 and 2020). These images have a spatial resolution of 30 meters, six or eight spectral bands at visible and shortwave wavelengths, and one panchromatic band with a resolution of 15 meters (for ETM+ and OLI). ETM+ images have eight spectral bands, while the OLI image only has one. The historic rainfall, relative humidity, and temperature data for January 20 were downloaded from the Center of Hidrometeorology and Remote Sensing (CHRS). The years 2005, 2010, 2015 and 2020 were used for the study. The digital vector data can be found at the following location: Tabnio Watershed administration provided us with a soil type map, a scale of 1:125.000, and data on land use planning for the Tabunio Watershed.

Methods

The following methodological framework was developed in this study for the purpose of tracking and predicting the degradation of land. It includes the creation of a Land Degradation Index (LDI), the evaluation of the risks associated with land degradation, as well as observing and simulating accuracy assessments. Waste and quality loss of cultivated land from irrational land use (such as logging, impervious surface development, and mineral exploitation), water loss and soil erosion from natural disasters and anthropogenic harm, decline of vegetation coverage from overgrazing and logging, and drought from climate change and soil moisture loess are the most common types of land degradation (Loukrakpam and Oinam, 2021). These types of land degradation are primarily responsible for Therefore, four indicators that describe land degradation were choosen according to actual conditions observed in the field in Tabunio Watershed. These indicators are land use/land cover (LULC), vegetation coverage (VC), soil erosion (SE), and soil moisture content (SMC). Because changes in LULC are one of the most significant factors contributing to land degradation in Tabunio Watershed, LULC was chosen to be one of the indices used to describe land degradation. For the preprocessing of the LANDSAT TM/ETM+/OLI images that were downloaded, the ENVI 5.3 software. The band combined, FLAASH atmospheric adjustment, combining images, and image selection were all accomplished through the use of this software. This technique has the potential to improve the spatial accuracy of a multispectral bands while maintaining the accuracy of the spectral information included in the source data. Each image was initially categorized into one of ten different LULC types. These LULC types were then arranged in descending order of the likelihood of land degradation, starting from the least likely to the most likely scenario. When looking at the LULC types, a higher ranking indicates that there is a greater likelihood of land degradation. The order of the ranking is as follows: water body, forest, settlement, plantation, agriculture, bare land, swamp, shrubs and mining.

Vegetation coverage

There is a one-to-one correlation between the state of the vegetation cover and the level of land degradation (Aires *et al.*, 2020; Fang *et al.*, 2021; Sun *et al.*, 2020). The composite vegetation index (CVI), an important metric of vegetation coverage, was determined in this study using the forest canopy density mapping approach (FCD) proposed by the International Tropical Timber Organization. The model is dependent on vegetation indices, and the indices that are generally used to generate the canopy cover index (CVI) are the normalized difference vegetation index (NDVI), the shadow index (SI), and the bare soil index (BI), using Eqs. 1, 2 and 3 (Godinho *et al.*, 2016; Loi *et al.*, 2017; Su Mon *et al.*, 2012).

$$CVI = (NDVI + nBI) * SI \tag{1}$$

$$VC = \frac{(CVI - CVI_{soil})}{(CVI_{veg} - CVI_{soil})} \tag{2}$$

Where, CVI_{veg} and CVI_{soil} represent CVI values of vegetation cover and bare soil cover, respectively using Eqs. 3, 4 and 5 (Godinho *et al.*, 2016; Loi *et al.*, 2017).

$$NDVI = \frac{\rho NIR - \rho RED}{\rho NIR + \rho RED} NDVI = \frac{\rho NIR - \rho RED}{\rho NIR + \rho RED} \tag{3}$$

$$SI = [(256 - \rho_{BLUE})(256 - \rho_{GREEN})(256 - \rho_{red})]^{1/3} \tag{4}$$

$$BI = \frac{\rho_{swir} + \rho RED - \rho NIR - \rho BLUE}{\rho_{swir} + \rho RED + \rho NIR + \rho BLUE} \tag{5}$$

Where, BLUE, GREEN, RED, NIR, and SWIR each stand for the reflectance of LANDSAT images in the blue band, the green band, the red band, the near-infrared band, and the first shortwave infrared band, respectively.

According to the FCD model, the percentage of land covered in vegetation has a positive correlation with SI and NDVI but a negative correlation with BI. Consequently, a combination of NDVI, BI, and SI can be used to calculate CVI (Equation 4), which can reduce the effect of shadow and soil background. BI stands for brightness index, and SI stands for spectral intensity.

Soil erosion (SE)

SE is a complicated physical process that is affected by a wide range of variables. Some of these variables include precipitation, soil erodibility, topography, vertical continuity, and soil conservation efforts (Yang *et al.*, 2020). In this study, rainfall data, VC, slope, and LULC types were extracted from remote sensing data and DEM. In addition, soil types, a spatial distribution map of rainfall, and a universal soil loss equation (USLE) were used to extract SE values, using Eq. 6 (Borrelli and Schütt, 2014; Mariye *et al.*, 2022; Nurlina *et al.*, 2022).

$$SE = (R \times K \times L \times S \times C \times P) \times f \quad (6)$$

Where, SE is the unit of average soil loss (t/ha/yr), R refers to rainfall erosivity factor (MJ mm/ha/hr/yr), K represents a soil erodibility factor (t hr/MJ/mm), L and S are slope length and slope steepness factors, respectively (no unit), C is vegetation cover factor, P means a dimensionless erosion control practice factor and f is correction factor.

Soil moisture content (SMC)

The soil moisture content, is a direct indicator of drought intensity; increasing SMC can help reduce the severity of land degradation (Peng *et al.*, 2020; Perdana *et al.*, 2020; Tajudin *et al.*, 2021). NDVI was integrated with historical temperature data by utilizing an algorithm called a mono-window algorithm. This was done in order to identify the land surface temperature (LST) of the area that was being researched. (El Garouani *et al.*, 2021; Fashae *et al.*, 2020; Guha and Govil, 2021; Nurlina *et al.*, 2023). SMC was calculated using the temperature-vegetation drought index (TVDI) (Equations 7–9) in this study. This index is based on the TS-NDVI principle, using Eqs. 7, 8 and 9 (Peng *et al.*, 2020; Wang *et al.*, 2020; Younis and Iqbal, 2015).

$$SMC \approx TVDI = \frac{Ts - Ts_{min}}{Ts_{maks} - Ts_{min}} \quad (7)$$

$$Ts_{maks} = a_1 + b_1 * NDVI \quad (8)$$

$$Ts_{min} = a_2 + b_2 * NDVI \quad (9)$$

Where T_S, T_{Smin}, and T_{Smax} each represent the temperature of the land surface of a single pixel in Kelvin (K), the highest and lowest surface temperatures that correspond to NDVI (K), respectively. The coefficients for the dry edge equation and the wet edge equation are a_1, b_1, a_2, and b_2, respectively.

Land degradation risk assessment

In this research, the relative importance of each of the indices that have been previously mentioned was determined by comparison, in accordance with the AHP principle, and the scores of all indices in the land degradation evaluation matrix were calculated from expert scoring (Anh *et al.*, 2014; Ardali, 2016; Kang *et al.*, 2016; Sar *et al.*, 2015; Vaishali and Patil, 2015. The weights of LULC, VC, SE, and SMC were computed with AHP Software, using Eqs. 10 and 11.

$$IDL = w_1 LULC + w_2 VC + w_3 SE + w_4 SMC \quad (10)$$

$$W = (w_{TL}, w_{TV}, w_{ET}, w_{KT})^T = (0.3361, 0.2802, 0.2869, 0.0968)^T \quad (11)$$

Where, w_1, w_2, w_3, and w_4, each stand for the respective weights of LULC, VC, SE, and SMC. As a result of the assessment matrix having a consistency of CR = 0.0121 0.1, the requirements for this study were successfully met.
Following are some of the findings that emerged from our investigation of several indices: (a) the level of land degradation increase when the values of LULC and SE increased; (b) the level of land degradation decreased when the rates of VC and SMC increased Because of this, in order to simplify the calculations, the amounts of VC and SMC were standardized using Eq. 12, while the values of LULC and SE were normalized using Eq. 12. (Yang *et al*., 2020)

$$X = \frac{x_i - x_{min}}{x_{max} - x_{min}} \; ; \; X = \frac{x_{max} - x_i}{x_{max} - x_{min}} \quad (12)$$

where X is the normalized value of x_i, x_{min} and x_{max} are the minimum and maximum value of the indices, respectively, and X is the value that has been normalized.

Each of the indices that were derived from this process has a value that rises as the amount of land that is degraded rises. As a result, the Land Degradation Index (LDI) was devised; this index evaluates the contributions to land degradation made by water, wind, gravity, freeze–thaw cycles, and engineering in the study area. It is intended to reflect the level of land degradation (Equation 11). Equation 12 was used to normalize the LDI value so that it falls within the range [0, 1], and a higher LDI value indicates a more severe level of land degradation. LDI values were used to categorize the level of land degradation into five distinct levels, and equal intervals were used for each category. This was done so that it would be easier to compare different years (Table 1 and Fig. 2).

Table 1. Land Degradation Index Value
(Tolche *et al*., 2022)

Land Degradation Index Value	Class Degradation	Description
0 – 0,4	No Degradation	No degradation which includes water, areas of complete vegetative cover, building areas and arable land with high fertility.
0,2 – 0,4	Mild Degradation	The mild degradation is one in which agricultural output has dropped but ecosystem services have not been compromised.
0,4 – 0,6	Moderate Degradation	There has been a moderate decline in land production and some harm to ecosystem function in a region classified as moderately degraded.
0,6 – 0,8	Severe Degradation	The severe degradation category refers to a region that has suffered significant losses in terms of both land production and ecosystem function.
0,8 – 1	Extreme Degradation	The extreme type of degradation is an area where land productivity and ecosystem function are completely lost

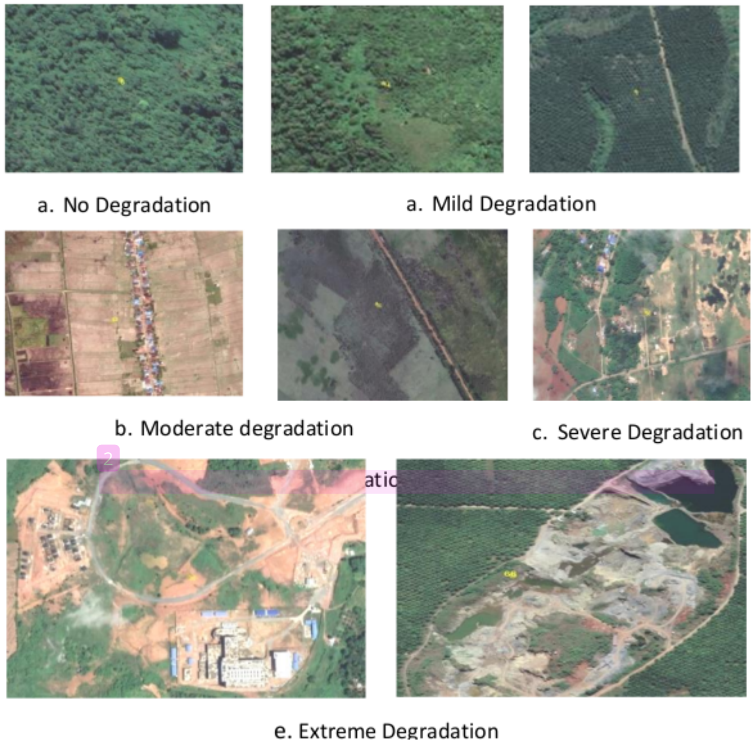

Fig. 2: The characteristics of land degradation validation samples

Monitoring and evaluation of land degrading conditions

Figure 3 shows how the rates of land decline in the Tabunio watershed changed over time, from 2005 to 2020. It is split into 5 levels: areas with no degradation, mild degradation, moderate degradation, serious degradation, and extreme degradation. The degree of land degradation was determined by the area and percentage of land degradation in each class.

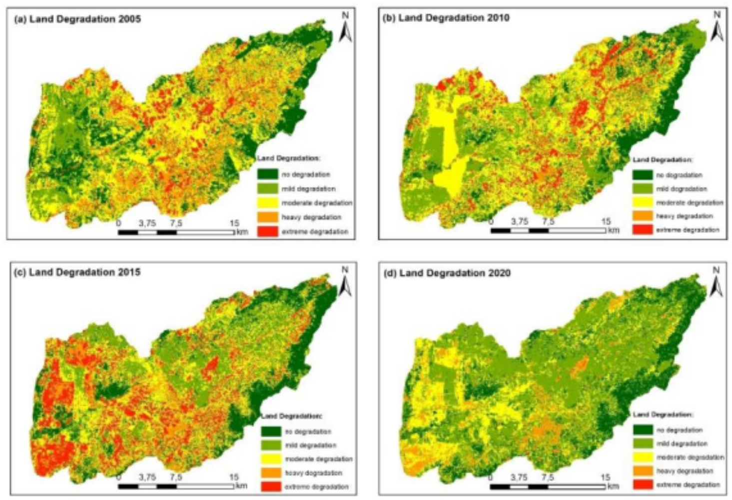

Fig. 3: The spatiotemporal distribution of regions with no, mild, moderate, severe and extreme land degradation is depicted

From the perspective of spatial distribution, non-degraded areas are found in land cover water bodies and forests, while degraded areas are evenly distributed in mining areas, open land, agricultural land and plantations with steep and gentle slopes around the Tabunio watershed. In 2015, most of the areas with severe and extreme land degradation were in the south and west, and most of the areas with light and moderate land degradation were in the hilly and plantation zones around the upstream watershed. In terms of the patterns and measurements of land degradation in the Tabunio watershed, it usually worsened from 2005 to 2020, however the amount of land that was degraded reduced steadily from 2015 to 2020, with the exception of the years 2005 and 2010. Between the years 2005 and 2015, there was a significant increase in the amount of land that was degraded, which was greater than 50,000 hectares (ha) and 53 percent. Land degradation degree underwent drastic changes in 2015-2020; and specifically, the area undegraded increased from 12% in 2010 to 17% in 2015, with an increase in area of 3,271 ha (Table 2); moderate and extreme degradation decreased from 24,352 ha (38.93%) and 11,810 ha (18.88%) respectively in 2015 to 14,416 ha (23%) and 226.2 (0.36%) in 2020. From 2005 to 2020, the total area of degraded land remains at or below 50,000 ha. In terms of the degree of land degradation, mild to severe land degradation was observed almost throughout the year, while the proportion of areas with extreme degradation was relatively small. In addition, the rate of land degradation will have dropped by a sizeable amount by the year 2020, and the percentage of land that will be severely and extremely degraded will drop to 9% and 1%, respectively Table 2. Area and proportion of land degradation in the Tabunio watershed from 2005 to 2020.

Table 2: Proportion of land degradation in the Tabunio watershed from 2005 to 2020

Degradation Class	2005		2010		2015		2020	
	Area (ha)	Proportion (%)	Area (ha)	Proportion (%)	Area (ha)	Proportion (%)	Area (ha)	Proportion (%)
No degradation	11.266,05	18,01	7.689,62	12,29	10.960,44	17,52	12.282,15	19,63
Mild degradation	15.177,40	24,26	20.638,21	32,99	16.024,79	25,62	30.273,44	48,39
Moderate degradation	21.318,96	34,08	24.352,41	38,93	18.092,33	28,92	14.416,51	23,04
Severe Degradation	8.905,55	14,24	2.908,26	4,65	5.670,68	9,06	5.360,24	8,57
Extreme Degradation	5.890,61	9,42	6.970,05	11,14	11.810,33	18,88	226,22	0,36

The extensive LDI that was proposed in this research proved to be effective in monitoring the spatial and temporal aspects of land degradation. (KC > 0.73 and OA > 86%), which is significant when taking into account that a Kappa coefficient that falls within the range of 0.70–0.85 is regarded as having "high accuracy" (Chikhaoui *et al*., 2005; Ibrahim *et al*., 2015; Tolche *et al*., 2022). When compared with individual indices, the LDI is able to reveal land degradation in a more comprehensive manner. LDI is easily transferable and relevant to various research areas because all of its land degradation indices may be produced quickly from remotely sensed data. As a result, LDI can be used in a wide variety of contexts, and it made quantitative predictions regarding the possibility of land degradation. In this study, the procedure for deriving the LDI land degradation evaluation matrix was exhaustive, and the assessment matrix was consistent (CR = 0.0121). This is significant when taking into consideration that a CR of less than 0.1 is considered to be qualified (Atmaja *et al*., 2019; Solangi *et al*., 2019). This study area experienced an acceleration in the loss of biodiversity, destruction of vegetation, and loss of water and soil due to the development of tourism and expansion of oil palm plantation. This resulted in land degradation, with significant areas and a percentage of land degraded between 2005 and 2020. It is important to note the dramatic shift that occurred in the land degradation classes between the years 2005 and 2005. The local government began implementing the Grain for Green Programme policy at the beginning of 2015. The goal of this policy was to assist in converting bare land and mining back into forest or plantation. This policy reduced the degree to which land was degraded, which may explain why areas with no degradation increased while areas with severe degradation decreased during the period of 2005–2020. The Tabunio Watershed Management Department engaged in a number of protective efforts, such as delimiting development zones, restricting population expansion, and greening scenic regions. Among these tasks was the delineation of prohibited development zones. It was anticipated which includes retiring field, urban region, reservoir construction, and human activities, would lead to a decrease in cultivated land, building region, roads, structure. These policies and measures resulted in a gradually reduce in the rate of land degradation. It is interesting that the amount of rain in the Tabunio Watershed affects the level of SE and that the level of SE goes up in years when there is a lot of rain. The SE is a significant indicator of land degradation; consequently, changes in the SE reflect land degradation to a significant degree. During the years 2005–2020, the annual precipitation in the Tabunio Watershed showed a very slight downward trend. However, beginning in the year 2015, this precipitation began a significant downward trend (Nurlina *et al*., 2022). As a result, the disparity between the amount of precipitation and the amount of water lost to evaporation was a driving force behind the reduction of SE in the Tabunio

Watershed from 2005 to 2020, which indicated that land degradation was present a trend toward improvement, particularly after the year 2010. The proposed comprehensive LDI approach shows that the land degradation classes of the Tabunio Watershed under went rapid change during the period of 2005–2022, and the vast majority of the effects of these shifts, in terms of slowing down or even reversing land degradation, were beneficial. Some examples of these positive consequences include the expansion of areas with no degradation and the reduction of areas with severe degradation. However, the control measures for bettering the management of land degradation still need to be worked on. In light of the findings of an investigation into the causes and effects of land degradation, in conjunction with an examination of the characteristics of Tabunio Watershed, the following proposals for preventative and corrective actions could be made: (a) Using fewer pesticides and chemical fertilizers, or switching to organic; (b) recommending the employing of biological or engineering construction methods for severely degraded areas, like better slope surface management, terraces water storage to reduce water loss and soil erosion, and increased plant life, increases the effectiveness of the rehabilitation program. (Akumu et al., 2018; Khawaldah et al., 2020).

CONCLUSION

In this study, the proposed comprehensive LDI method is able to describe the spatiotemporal characteristics of land degradation from 2005 to 2020 in the watershed area in particularly Tabunio Watershed were described using LDI. The degree to which land was degraded from 2005 to 2020 was, on average, lower than it had been during that time period. Furthermore, the increase in areas with no degradation, as well as the decrease in areas with light and severe degradation, were both positive for the mitigation of land degradation. In comparison to the state of the land in 2005, it was anticipated that the degradation of the land would remain relatively increased in 2005 until 2015. Both natural and anthropogenic factors were responsible for the land degradation that took place in this watershed. Control methods for land degradation should be created based on the results of monitoring and forecasting for the Tabunio Watershed. The suggested approach demonstrates that the degree of land degradation increased generally from 2005 to 2020, with the extreme year of land degradation being 2010, and the level of land degradation in different years being mostly moderate, with few cases of severe or extreme degradation. Therefore, some land degradation control measures ought to be established in advance in order to ensure the protection of this essential source region for freshwater.

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