Modeling Degraded Land Area in Province of Bangka Belitung Islands Based on Remote Sensing and Ecosystem Service to Support Sustainable Tourism

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ABSTRACT
The Province of the Bangka Belitung Islands (Babel) has a unique natural beauty that supports sustainable tourism. Sustainable tourism is highly dependent on terrestrial ecosystems. Due to mining activities, the terrestrial ecosystem inBangka Belitung can experience land degradation which is characterized by reduced land productivity, reduced land cover, and reduced soil carbon. Therefore, degraded terrestrial ecosystems need to be modelled to gain knowledge to support wisdom for sustainable tourism. This study aims to model degraded land by integrating remote sensing and ecosystem services based on the DIKW paradigm. Remote sensing data used are NDVI (MOD13Q1-coll6), land cover (ESA CCI), soil moisture (MERRA 2), rainfall (CHRIPS), evapotranspiration (MOD16A2), soil taxonomic unit (SoilGrids-USDA). Ecosystem services used are ecosystem services that regulate land productivity, provide forest and land cover, and provide soil carbon. These parameters will be synthesized for obtaining the proportion of degraded land to the total land of the study area based on Trends.Earth-Google Earth Engine. The results of the study will be evaluated using remote sensing data such as night-time lights, forest, and oil palm cover. This research is useful to support tourism in Babel Province which pays attention to sustainable life on land SDGs 15.3 Indonesia.

Keywords: *Modeling, land degradation, Bangka Belitung, sustainable tourism, remote sensing, ecosystem services.*

1. INTRODUCTION

Sustainable tourism development is not only supported by economic and social parameters but also must be supported by the environment. Known as a system dynamic of sustainable tourism, these three parameters must run in balance to realize sustainable tourism. Sustainable tourism is tourism that is environmentally sound can improve the social life of tourist areas and is able to support the economic improvement of the community. Bangka Belitung, which is developing its tourism sector, must be able to maintain economic, social, and environmental balance (Figure 1).

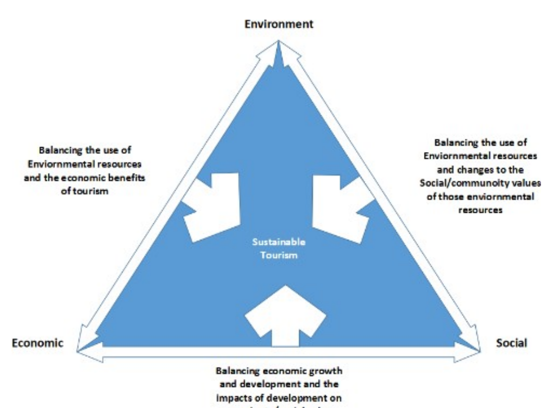

Figure 1 System Dynamic of Sustainable tourism
Source: www.sustainabletourismonline [1].

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As one of the new tourist destinations in Indonesia, mainland Bangka Belitung has ecosystem services that are very important for sustainable tourism. Some of the ecosystem services that support sustainable tourism are as a source of land productivity, a provider of forest and land cover, and as a provider of soil carbon. However, several land areas in the Bangka Belitung Islands Province are at risk from climate change and natural disasters due to the phenomenon of land degradation [2]. If the land area is degraded, it can disrupt the beauty of the terrestrial ecosystem. Disturbed terrestrial ecosystems can affect sustainable tourism in Bangka Belitung. Geospatial information (GI) to determine the condition of degraded land in Bangka Belitung is very important so that policy makers can manage land to support sustainable tourism.

The proposed method in this study is ecosystem services integration with remote sensing. Ecosystem services are benefits obtained by humans either directly or indirectly from ecosystem functions. The three main pillars of ecosystem services are vegetation structure, air use strategy, and efficient use of carbon [3]. The types of ecosystem services consist of four types of services, namely provider services, regulatory services, cultural services, and supporting services. Support services are the main services because they are required for the production of all other ecosystem services. Provider services are the benefits of ecosystems in providing food, clean water, carbon fuel, fiber, biochemical, and genetic resources. Services are ecosystem benefits in climate, disease, water, purification, and pollination. Cultural services are non-material benefits derived from ecosystems such as religion and spirituality, recreation and ecotourism, aesthetics, inspiration, education, sense of place, and cultural heritage. Supporting services are services needed to produce all other ecosystem services such as soil formation, nutrient cycling, and primary production [4].

This study will assess pixel by pixel ecosystem services that are used as parameters in this study in relation to land degradation in the study area. Areas experiencing land degradation are areas that have the potential for disaster risk. Parameters of ecosystem services that can be obtained from mountainous areas such as supporting land productivity, providing land cover, and providing soil carbon [5]. Land productivity pixels are obtained from trajectory productivity, performance, and state. These three parameters were then synthesized to obtain the GI of degraded land in the study area using the data, information, knowledge, and wisdom (DIKW) paradigm approach [6].

2. MATERIALS AND METHOD

2.1 Materials

The data used in this study were obtained from Google Earth Engine (GEE) which can be further analyzed using QGIS and ArcGIS Pro software. These data are sourced from official institutions and have been used by many validated researchers, so the data is assumed to be valid for use in this study. The representative data set can be seen in Table 1.

Table 1. Data set for the study

Variabel	Sensor/Dataset	Temporal	Spasial	Extent	Unit/Description
NDVI	MOD13Q1-coll6	2001-2016	250 m	Global	Average annual NDVI*10000
Land cover	ESA CCI	1992-2015	300 m	Global	Land cover class
Soil moisture	MERRA 2	1980-2016	0,5"x 0,625"	Global	Water root zone m^3m^3*10000
Precipitation	CHIRPS	1981-2016	5 km	50N-5OS	mm/year
Evapotranspiration (ET)	MOD16A2	2000-2014	1 km	Global	Annual ET km/m^2*10
Soil taxonomy unit	Soil Grids-USDA	2000-2014	250 m	Global	Soil unit

2.2. Method

The methodological concept used in this research is to follow the DIKW paradigm. The data was obtained by the cloud computing method from Trend.Earth-Google Earth Engine (GEE) [7]. The data is then analysed geospatially using appropriate software such as QGIS 3.16.3, ArcGIS 10.8.1, and ArcGIS Pro 2.7.2 [8]. Remote sensing data used in this study is classified on a global scale with different levels of GI detail. However, various spatial resolutions do not reduce the detail of GI because the data used has been resampled before becoming output data **[9]**. The output of this research is raster data with a resolution of 250 m which can be adapted to province scale RTRW map, 250m. The lowest resolution of data set is precipitation data (5km). It can be adjusted for scale adjustment the resolution 250m using resampling techniques.

Remote sensing and ecosystem services are integrated based on Trends.Earth and Google Earth Engine **[10]**. GI for degraded areas is obtained from geospatial data from three sub-indicators, namely: dynamic land productivit land cover, and soil organic carbon. Based on time series concept, the period used is the initial period 2001-2009 and the comparison period 2010-2020.

2.2.1. Dynamic Land Productivity

Productive land is a good place to grow crops. Land productivity is the biological ability of land to produce resources such as food, vegetation, fiber, and fuel that are needed by humans. On the other hand, unproductive land is an indication that the land is being degraded. Plants obtain and store solar energy during the process of photosynthesis. Land productivity is highly dependent on net primary productivity (NPP). NPP is the net amount of carbon stored and released after photosynthesis and autotrophic respiration over a certain period of time [11]. One way to determine NPP is to use the Normalized Differential Vegetation Index (NDVI) of the red and near infrared electromagnetic spectrum. In Trends.Earth, the biweekly product of the 2000-2018 temporal MODIS (MOD13Q1-coll6) data with a spatial resolution of 250 m was used to calculate the annual integral of NDVI times 10,000. Land productivity obtained by Trends.Earth is assessed using three productivity indicators derived from the NDVI time series (2001-2020), namely trajectory, performance, and state.

Trajectory productivity measures the rate of change in primary productivity over time (2001-2020). The Mann- Kendall non-paremetric significance test was used to determine the significant change indicating the probability value (p). The p value < 0.05 means the land is degraded, the p value = 0.05 means the land is stable, and the p value > 0.05 means the land is improved. Productivity performance is an indicator used to measure local productivity relative to other similar vegetation in the same land cover type or bioclimatic area throughout the study area. Productivity performance using a combination of soil units (soil taxonomic units using the USDA system provided by soil grids with a spatial resolution of 250m and temporal 2000-2014) and land cover (37 full land cover classes provided by ESA CCI with a spatial resolution of 300m and temporal 1992-2015) to define the area of analysis. The NDVI series was averaged with the 90th percentile and the land cover and soil classes were intersected. The average observation value is compared with productivity to obtain performance productivity. If performance < 0.5, then the area is potentially degraded. State productivity allows detection of the 2010-2020 target NDVI time series compared to the 2001-2010 baseline NDVI time series. The target/comparison NDVI average that has been subtracted from the baseline NDVI average will get three classes of change. The three classes of change are improvement (≥+2), stable (-1 to 1), and potentially degraded (≤-2). The three indicators are combined to obtain GI on six classes of land productivity in the study area, namely no data, declining, early signs of decline, stable but stressed, stable, and increasing.

2.2.2 Land Degradation Map

Dynamic land productivity is then combined with land cover and soil organic carbon. Land cover for the baseline period (2001) and the target period (2020) was reclassified into seven classes, namely forest, grassland, agricultural land, swamp, artificial land, vacant land, and water. Land cover is analyzed to obtain a transition map and combined with the transition criteria. There are three classes of transition criteria, namely degradation, stability, and improvement.

The result is four classes, namely no data, degraded, stable, and improvement. Information on degraded land in the study area that is adapted to the context of sustainable tourism is knowledge in Spatial Planning and other sciences such as Geodesy, Geomatics, Environment, and Forestry [12]. The contextual knowledge is based on measurable data and information which is wisdom that can be used to support the decision to replan the land ecosystem of the study area (Figure 2).

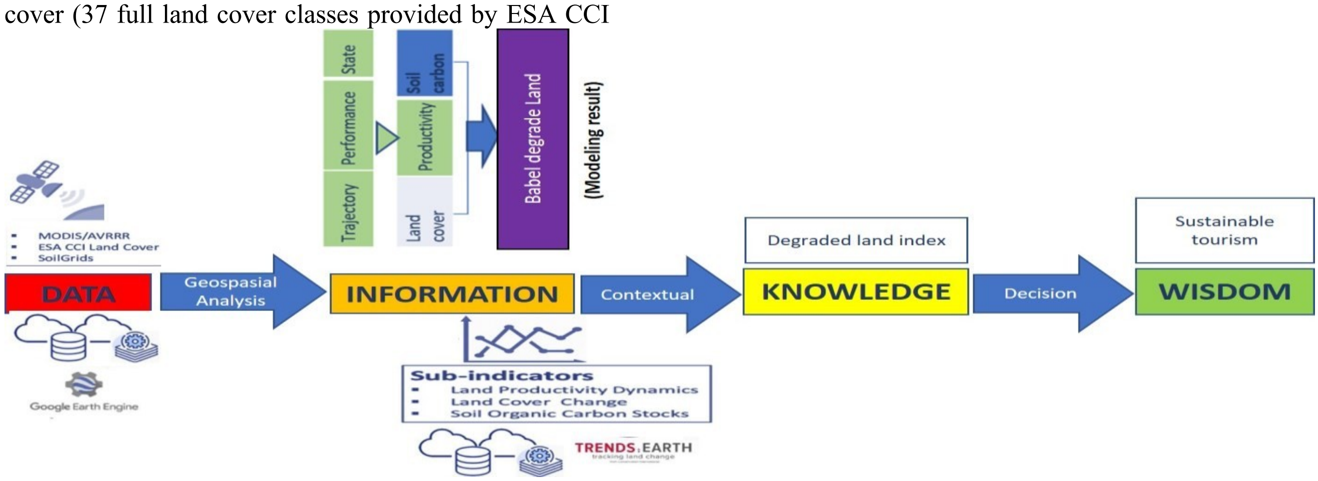

Figure 2 Research methodology.

3. RESULTS AND DISCUSSION

The land productivity of the study area is a combination of trajectory productivity, performance, and state. There are four bands obtained from land productivity, namely the black band (no data), the purple band (degradation), the yellow band (stable), and the green band (improvement). Dynamic land productivity is a combination of the three sub-indicators announced that the improved land is 4,717.9 km2 (28.50%), stable land is 7,568.2 km2 (45.72%), degraded land is 4,009.9 km2 (24.22%), and no data or surface water area is 258.9 km2 (1.56%) of the total land area of Babel (16,554.8 km2) (Figure 3).

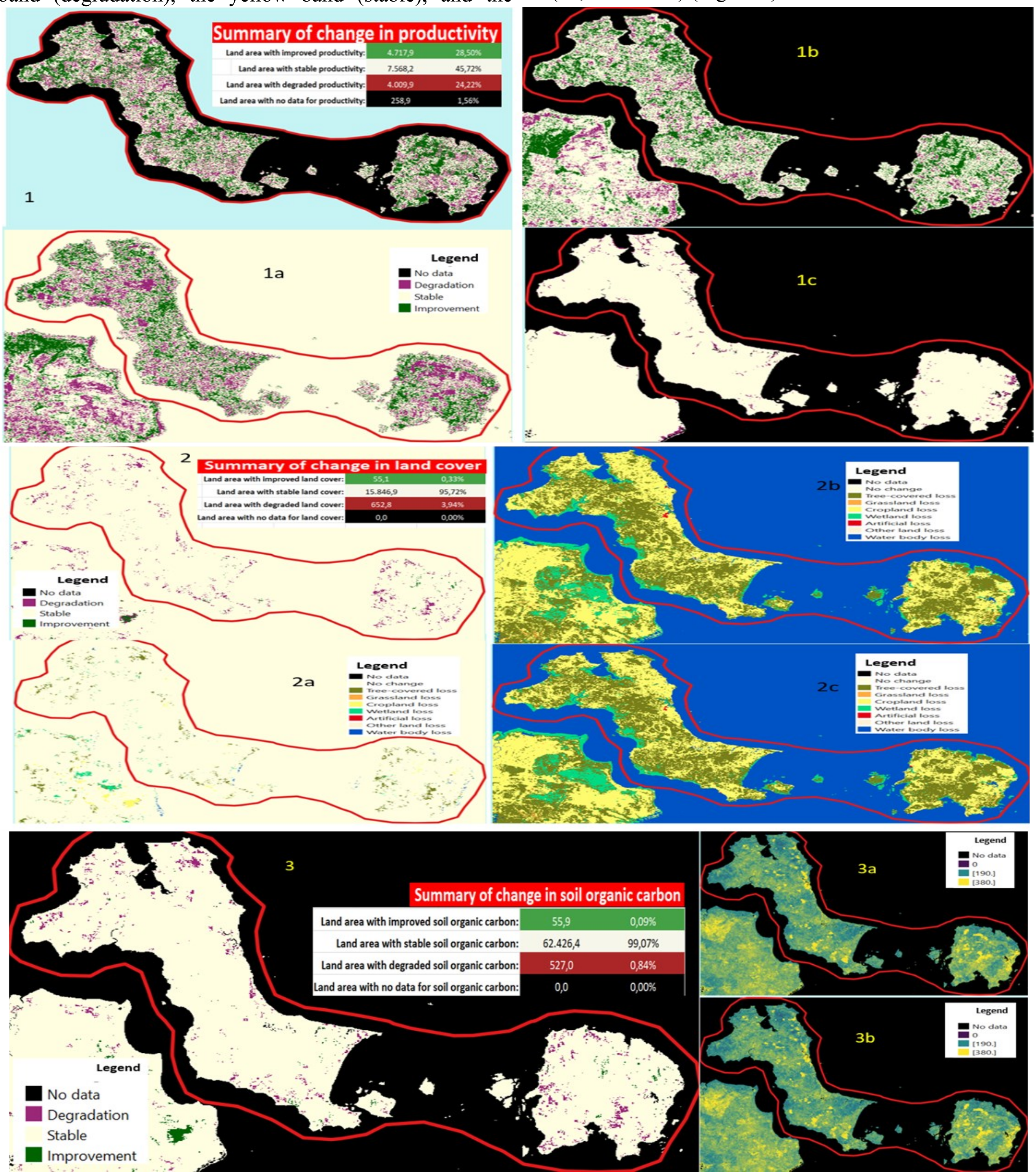

Figure 3 1. Land productivity, 1a. Productivity state degradation, 1b. Productivity trajectory degradation, 1c. Productivity performance degradation; 2. Land cover degradation 2010-2020, 2a. Land cover transition 2010-2020, 2b. Land cover 2020, 2c. Land cover 2010; 3. Soil organic carbon degradation, 3a. soil organic carbon 2020, 3b. soil organic carbon degradation 2010.

3.1. Land Degradation Map

The combination of three ecosystem services parameters in this study, namely land productivity, land cover, and soil organic carbon, obtains information on land degradation to the total area of interest (AOI). The synthesis of these three parameters resulted in improved land information of 4,573.7 km2 (27.63%), stable land 7,201.5 km2 (43.50%), degraded land 4,508.8 km2 (27.24%), and no data or surface water 270.8 km2 (1.64%). Degraded land in mainland Babel can lead to deforestation and land degradation due to reduced soil fertility. Land degradation determined by the three parameters mentioned above. Land productivity parameter very clearly inform that the study area is experiencing degradation. The soil organic carbo informs that the study area is most stable, while the land cover parameter informs that the study area is the same as the state of the soil organic carbon, which is stable. In this study, land productivity parameters determine the occurrence of land degradation in the study area (Figure 4). This study assumes that these indicators are decision support for the consideration of replanning degraded land areas. Degraded land areas are particularly vulnerable to disaster risk compared to plain areas. Following the Minister of ATR/BPN Number 11 of 2021, reducing disaster risk aspects can be used as one of the considerations for conducting a spatial review in an area. A general knowledge that Babel is one of the provinces with potential disasters such as hurricanes, floods, landslides, and abrasion. Many public and social facilities in the area suffered severe damage due to being affected by floods. One of the causes of flooding is that the existing vegetation structure is insufficient to withstand the run-off of very heavy rainwater. The tree-dominated vegetation structure has been deforested in the period 2000-2019 based on monitoring with Hanson forest based on Land.Trend-Google Earth Engine (Fahrudin et al., 2020).

3.2. Evaluation of Degraded Land Area

Spatial planning and other scientific disciplines are used as knowledge to create wisdom. Wisdom to support.

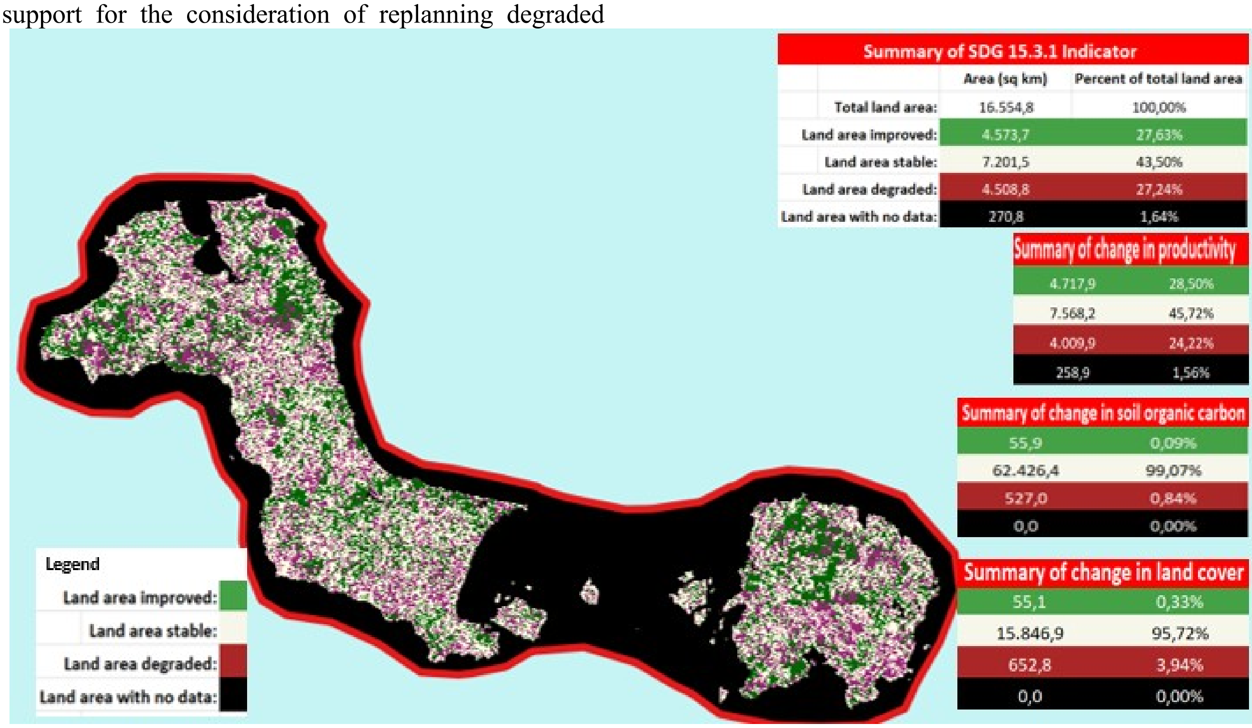

Figure 4 Degraded land of Bangka Belitung Archipelago Province as SDGs 15.31 indicator, proportion of land that is degraded over total land area.

Most of the causes of land degradation in the study area are due to community socio-economic activities such as mining, community mining, and company-scale mining. Mining has had social, economic, and ecosystem impacts on the environment around the Babel area, but these impacts are not investigated further in this study. However, this does not mean that mining is not good, but that it is necessary to rearrange the degraded land area of Babel concerning sustainable tourism. The total degraded land area to the total land area is 15.3.1 SDGs indicator replanning is based on the aspect of reducing the impact of disaster risk. The study area can be rearranged by looking at the principles of the benefits of sustainable tourism in other aspects that support replanning without reducing the socio-economic activities of the community through comprehensive and strategic plans. Replanning is mainly focused on the degraded land spatial pattern, while the other degraded AOI spatial pattern areas are adjusted. A comprehensive plan or master plan is a spatial management plan that uses community input and historical context to shape development goals, forest andoil palm land management, transportation, and parks and recreation for some time to come. A strategic plan has a similar function to a comprehensive plan but operates over a shorter time span. The plan outlines the policies, actions and partnerships needed to achieve the re-spatial goals that can help address the threat posed by disaster risks from land degradation.

Revision of the spatial layout can be done by converting the area which was previously a mining designation area into another designation area that does not have the potential to damage the ecosystem in the mainland area of Babel. In addition to this study, other studies need to be carried out to support spatial planning, for example a study of the social, economic, and ecosystem impacts of the Babel mainland with the spatial pattern of the mining allotment area compared to other designation areas.

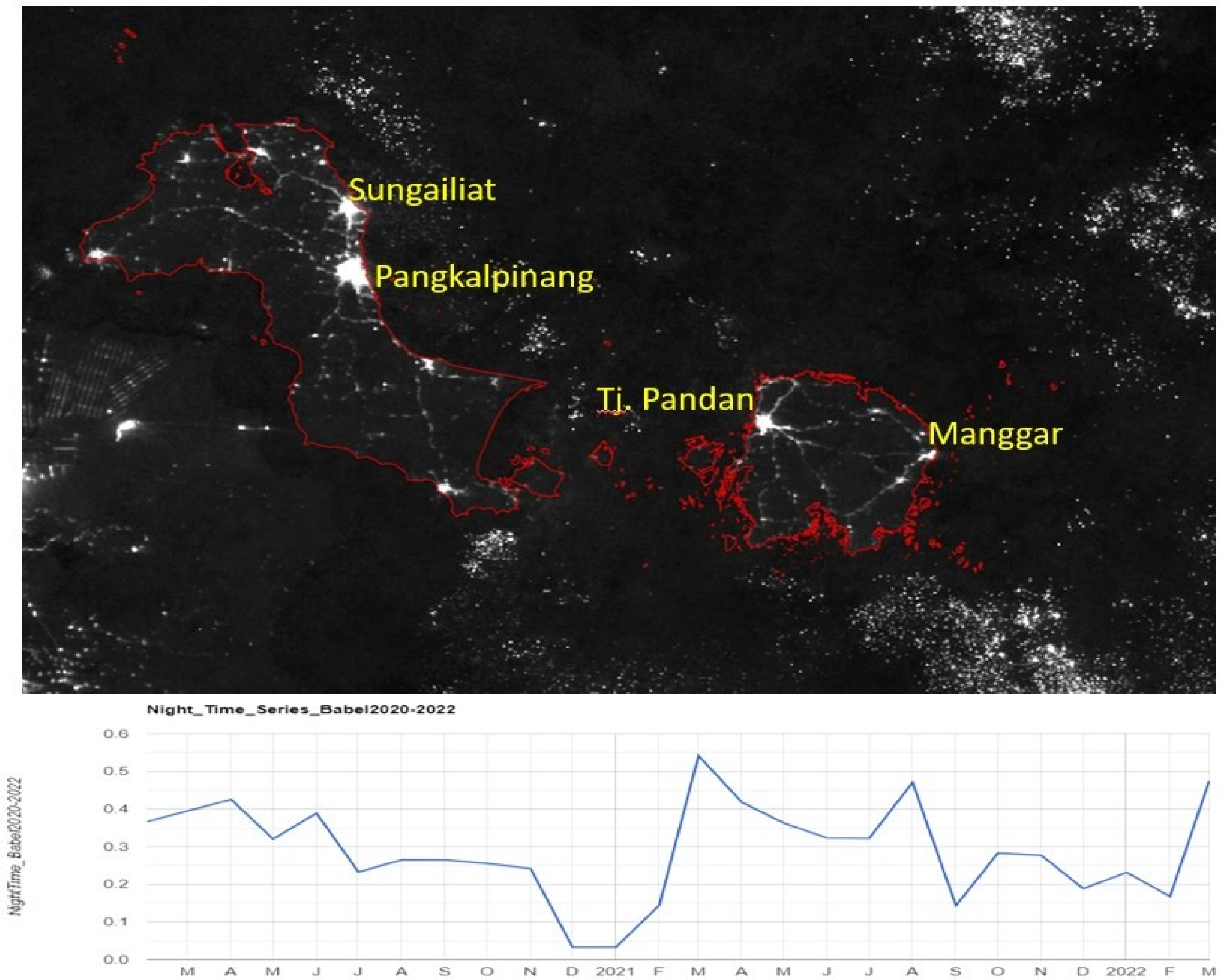

Figure 5 Nigh-time Light Babel Time Series 2020-2022.

Based on monitoring with nighttime-light time series data for the 2020-2022 period, Bangka Belitung's condition at night experienced a decrease in the intensity of electric light at night due to the impact of the Covid-19 pandemic. The decrease in night light intensity occurred in March 2020 - December 2020 and March 2021 - December 2021. The intensity of the night increased in January - March 2021 and February 2022 - March 2022. Overlay analysis of Babel nighttime data was used to evaluate the state of Babel at night during Covid-19 pandemic. Socio-economic activity at night was reduced during the pandemic, but someactivities at night in the mining area and seacontinues (Figure 5).

4. CONCLUSION

The integration of ecosystem services parameters using remote sensing technology is successful in modeling the degraded land in the study area. The total AOI of the study area is ± 16.554,8 km2. The indicator consists of land area improved ± 4.573,7 km2 (27,63%), land area stable 7.201,5 (43,50%), land area degraded 4.508,8 km^2 (27,24%), and no data 270,8 km^2 (1,64%). This model can be used as geospatial data to support sustainable tourism in Babel.

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