Media Konservasi, 30 (2) 250-261

RESEARCH ARTICLE

MEDIA KONSERVASI
SCIENTIFIC JOURNAL IN CONSERVATION OF NATURAL RESOURCES AND ENVIRONMENT

Detection of Tree Cover Dynamic on Belitung Island using Random Forest Regression

Najla Natasya Aurellia[a], Tubagus Nur Rahmat Putra[a] , Qashdina Saimima Wakano[a], Ananta Fikri Ramadya[a], Rania Alifa Desenaldo[b] and Irwan Ary Dharmawan[a]

[a]Department of Geophysics, University of Padjadjaran

[b]Department of Civil Engineering, Geo and Environmental Sciences, Karlsruhe Institute of Technology

Article Info:
Received 19 May 2024
Revised 3 February 2025
Accepted 24 February 2025

Corresponding Author:
Najla Natasya Aurellia
Department of Geophysics, University of Padjadjaran, Indonesia
E-mail:
iad@geophys.unpad.ac.id

Abstract

Belitung Island faces a series of interconnected environmental problems, particularly in forest conservation. Protected forest areas play a crucial role in supporting life but their sustainability is threatened by human activities such as mining exploitation and forest conversion for plantations. Therefore, protecting and restoring protected forest areas are priorities for maintaining the ecosystem's sustainability on Belitung Island. An evaluation was conducted to assess the ecological conditions of conservation areas on Belitung Island by visualizing changes in protected land cover to assist conservation efforts. In this study, the evaluation system for vegetation cover conditions on Belitung Island and Lalang Mountain Grand Forest Park used random forest (RF) regression algorithms and remote sensing data. Satellite image data were used to determine the extent of vegetation cover on Belitung Island, utilizing combinations of bands from Landsat Satellites and MODIS Percent Tree Cover. Satellite images from 2013 to 2023 were used for comparison. This evaluation revealed several class changes in vegetation cover on Belitung Island based on percent tree cover classification over the years serving as an evaluation of land use in the areas under review. The R-squared value of 0.73 indicated that the samples used to predict land cover demonstrated a relatively high level of accuracy. This study could serve as an effective means of predicting and estimating large-scale vegetation changes, as well as a monitoring tool for conservation areas on Belitung Island.

Keywords: Forest Conservation, Random Forest, Remote Sensing, Tree-Cover Dynamics

1. Introduction

Conservation forests are areas with specific characteristics, primarily functioning to preserve the plant and wildlife diversity as well as their ecosystems [1]. Belitung Island, a natural destination in the middle of the Indian Ocean, possesses valuable assets in the form of vast nature and rich biodiversity. The Lalang Mountain conservation forest is an area on Belitung Island that needs to be preserved. However, the island has recently come under the spotlight due to extensive tin mining land clearance, with tin mining reported to have occurred since 1852, according to the Regional Development Planning Agency (Bappeda) of Bangka Belitung Province [2]. This has sparked intense debate over environmental protection versus economic interests. Moreover, the forests on Belitung Island are home to many unique plant and animal species holding significant value locally and globally as part of a fragile ecosystem. Additionally, these forests serve as important carbon sinks, helping mitigate climate change impacts [3].

However, the abundant mineral wealth on Belitung Island offers substantial economic opportunities. Still, mining activities' major impact is landscape alteration [4], often associated with negative environmental impacts. Mining encompasses various stages of activities, from initial research and management to exploitation and marketing of minerals [5]. These stages include general investigation, exploitation, feasibility assessment, infrastructure development, mining operations, processing and refining, transportation and product marketing, and various post-mining activities [6]. Consequently, it is important to assess the impact of land clearing for mining on Belitung Island with the escalating conflict between conservation efforts and industrial development.

Remote sensing methods can provide robust analysis perspectives and methods for evaluating conservation effectiveness [7]. Moreover, remote sensing has been widely used for multi-scale and long-term monitoring of ecological environments and natural resources [8]. Landsat 7 and 8 are used in remote sensing data processing supported by the random forest method, which can process large amounts of data. However, there may be difficulty in interpretation and the need for proper model tuning [9]. Previous studies have reported that the land use conditions in the Belitung Regency have already been influenced by tin mining, which has increased land use for exploitation [10]; land cover classification results based on Landsat-8 OLI imagery using the random forest method [11], a spatial approach represented by visual media in the form of maps and calculations of the percentage of land cover area geometry in Sijunjung Regency ; the application of automated supervised machine learning methods for monitoring land cover changes in Tirtomoyo District [12]; water quality classification using the random forest algorithm [4]. Therefore, combining remote sensing and random forest methods is ideal for obtaining the required data.

This paper aims to analyze the environmental and natural changes on Belitung Island to provide evaluations to maintain the balance between nature conservation and development. Quantitative and qualitative approaches were used to model and interpret the satellite imagery for Belitung Island. Mining Business Permit (IUP) areas were included to help analyze the causes of vegetation changes, along with the classification of tree cover percentage on Belitung Island and Lalang Mountain. A deeper understanding of these dynamics is hoped to help formulate appropriate policies to support sustainable development on Belitung Island.

2. Materials and Methods

2.1. Study Area

Belitung is an island located in the Bangka Belitung Province, situated between 107°31.5' - 108°18' East Longitude and 2°31.5'-3°6.5' South Latitude, with an approximate area of 4,800 km² [13]. Belitung Island is 500 meters above sea level, with its highest peak in Gunung Tajam, and has a production forest area of ~9,432.53 hectares. While there have been no changes to the conservation forest area, the protected forest area has slightly increased by 643,30 hectares or 0.23% [11]. Lalang Mountain Conservation Forest is a conservation area spanning three locations from Perawas village, Buluhtumbang village to Air Seruk village [2]. Lalang Mountain must preserve its flora, fauna, and ecosystem biodiversity to ensure expected production without diminishing or damaging its forest functions. The study area is shown in Figure 1.

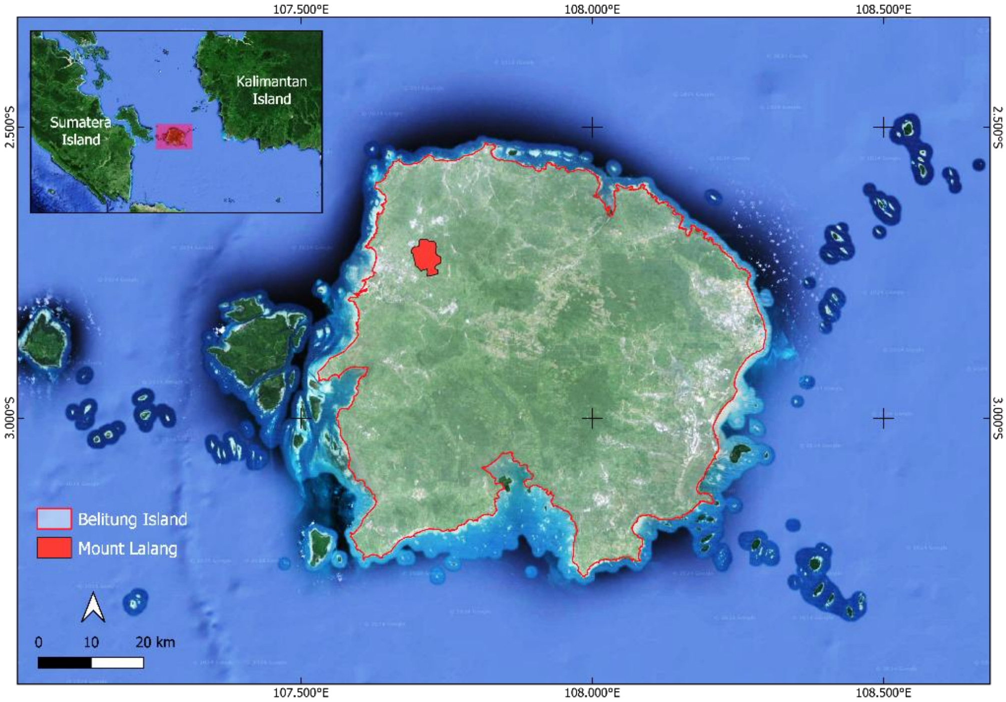

Figure 1. The study area location of Belitung Island and Gunung Lalang, Indonesia.

2.2. Data and Materials

The Google Earth Engine (GEE) was utilized for satellite image acquisition, processing, and analysis. GEE is a platform that offers image processing algorithms and computations using various application programming interfaces [12], providing a range of classification algorithms, such as random forest [14]. In this paper, all satellite images were obtained from GEE's database.

Landsat 7 and 8 satellite images served as independent data sources, both of which have eight multispectral bands, each with a spatial resolution of 30 meters and a panchromatic band with a resolution of 15 meters [4] Integrating multi-source data is crucial to complement each other and provide data with minimal noise. Terra MODIS Vegetation Continuous Fields imagery was used as dependent data. It utilizes the percent tree cover band, which measures the percentage area covered by the tree canopy within one satellite image pixel. This value ranges from 0% to 100%, where 0% indicates no tree cover and 100% indicates full coverage by tree canopy. Details of the satellites are provided in Table 1.

Table 1. Satellite platforms used for this study.

Year	Satellite	Resolution
1999 – 2024	USGS Landsat 7 Level 2, Collection 2, Tier 1	30 m
2013 - 2024	USGS Landsat 8 Level 2, Collection 2, Tier 1	30 m
2000 - 2020	MOD44B.006 Terra Vegetation Continuous Fields Yearly Global 250m	250 m

Landsat 7 and 8 images were first combined into a single image collection using the merge function in GEE. Then, the bitmask-based cloud masking function was applied to remove cloud cover and shadows. This technique uses bit information within the QA_PIXEL to determine pixel quality, including the presence of clouds or cloud shadows, and it is an efficient and commonly used method with Landsat datasets, although it may have limitations in detecting thin clouds or misidentifying shadows. Following this, time and area filtering was performed on all the Landsat 7, Landsat 8, and MODIS data for the selected periods, 2013, 2015, 2017, 2019, 2021, and 2023. Scale resampling of the data resolutions by 250 pixels was performed to simplify the processing between bands.

2.3. Remote Sensing Indices

Two primary remote sensing indices were used: the normalized difference vegetation index (NDVI) to compare the greenness of vegetation based on the spectral values of the near-infrared (NIR) and red (RED) channels [4][15]:

$$\mathrm{NDVI} = \frac{\mathrm{NIR} - \mathrm{RED}}{\mathrm{NIR} + \mathrm{RED}} \tag{1}$$

The NIR channel captures the reflectance values in the near-infrared spectrum, which vegetation strongly reflects, while the RED channel captures the reflectance values in the red spectrum. The NDVI can be used to quantify the density and health of vegetation cover in a given area with higher NDVI values typically indicating denser and healthier vegetation. In comparison, lower values suggest sparse or stressed vegetation cover.

The enhanced vegetation index (EVI) was also utilized to minimize errors and ambiguity, which can be significant due to varying atmospheric background conditions and canopy [15][16]:

$$EVI = \mathrm{G}\ \frac{\mathrm{NIR} - \mathrm{RED}}{(\mathrm{NIR} + \mathrm{C1} \times \mathrm{RED} - \mathrm{C2} \times \mathrm{BLUE} + \mathrm{L})} \tag{2}$$

Equation 2 incorporates reflectance values from multiple spectral bands and accounts for factors such as aerosol scattering and canopy background, enhancing its sensitivity to vegetation changes compared to traditional indices like NDVI. The term G serves as a scale factor adjusting the overall magnitude of the index and NIR, RED, and BLUE represent the reflectance values in their respective spectral channels. Additionally, the weighting factors C1 and C2 are applied to correct for aerosol influences, while the parameter L accounts for canopy and soil background effects. EVI provides a more robust measure of vegetation health and density, particularly in areas with varying atmospheric conditions or surface characteristics.

2.4. Random Forest Regression

Random forest (RF) is a popular machine learning algorithm, particularly for classification and regression tasks, which operates by constructing multiple decision trees. In each tree, training is performed on data samples independently and then combined into a single model [17]. It utilizes bagging (bootstrap aggregating) to train individual models with random subsets of data in parallel to create aggregate predictors, with 70% of the data used for training, while the remaining 30% is used for testing [18].

The parameters for RF regression to model the prediction of percent tree cover are as follows:

1. 10,014 points were sampled and distributed randomly in the area of interest, Belitung Island. The values were extracted from each band for every point encompassing several spectral bands and vegetation indices, including red, green, blue, NIR, shortwave infrared (SWIR), NDVI, EVI, and percent tree cover.
2. The data were divided into training (70%) and validation (30%) samples with 6972 training samples and 3042 validation samples extracted randomly. The training samples were used to build the prediction model, while the validation samples were used to test the constructed prediction model.
3. The number of trees (Ntree) was 500 to create a model with 500 decision trees which is commonly used because it exhibits stable error rates before reaching the number of classification trees [19].

The percent tree cover band from MODIS was the dependent variable, while the Landsat bands, such as Red, Green, Blue, NIR, SWIR, NDVI, and EVI, served as independent variables. Each spectral band provided different information about the characteristics of the Earth's surface. Therefore, a model was constructed to accurately predict tree cover in Belitung Island using a combination of data from Landsat bands as independent variables and percent tree cover from MODIS as the dependent variable. This model utilized the RF regression algorithm to combine information from various spectral bands and generate accurate predictions.

The r^2 or coefficient of determination was used as a benchmark to assess the model accuracy. Generally, a higher r^2 value indicates that the model has better precision and accuracy in predicting the percent tree cover. In the context of using Landsat 7 and Landsat 8 satellite imagery and MODIS data for predicting tree cover, a high r^2 value indicates that the model can effectively capture patterns and relationships in the data. The categories of r^2 values are shown in Table 2.

Table 2. R-Square Categories [20]

r^2	Category
$r^2 \geq 0.67$	Strong
$0.33 \leq r^2 < 0.67$	Moderate
$0.19 \leq r^2 < 0.33$	Weak

2.5. Analysis

The percentage of tree cover was classified into four categories based on its density to identify and understand the tree cover distribution and monitor changes over time. Class 1 0-25% represents areas with very low or almost no tree vegetation; Class 2 25-50% indicates areas with moderate tree vegetation; Class 3 50-75% has dense tree vegetation; Class 4 75-100% indicates areas with very dense and thick tree vegetation. Then, the vegetation type was estimated based on the vegetation density and the original bands of the satellite image to classify the vegetation and land use (Table 3).

Table 3. Classification Table Based on Vegetation Density Analysis.

Category	Percentage range (%)	Density	Vegetation
Class 1	$0 < x \leq 25$	Zero to low	Water bodies, settlements, mines
Class 2	$25 < x \leq 50$	Low to moderate	Shrubs, grassland, agriculture area
Class 3	$50 < x \leq 75$	Moderate to fairly high	Agriculture, oil palm cultivation
Class 4	$75 < x \leq 100$	Fairly high to high	Forest, mangroves

The dynamics of changes in the area of each class were evaluated from 2013 to 2023 to understand how tree cover has changed over a decade, providing insights into trends of deforestation or reforestation. Important information can be obtained regarding changes in local ecosystems by analyzing changes in the area of each class.

3. Results and Discussion

3.1. Results

3.1.1. Model Performance

The coefficient of determination obtained from the scatterplot was 0.7455. This showed that the evaluation of the model performance confirmed the developed model has a high predictive strength and can be used to predict outcomes in other years with good accuracy (Figure 2). Thus, the evaluation model can predict trends or outcomes in subsequent years.

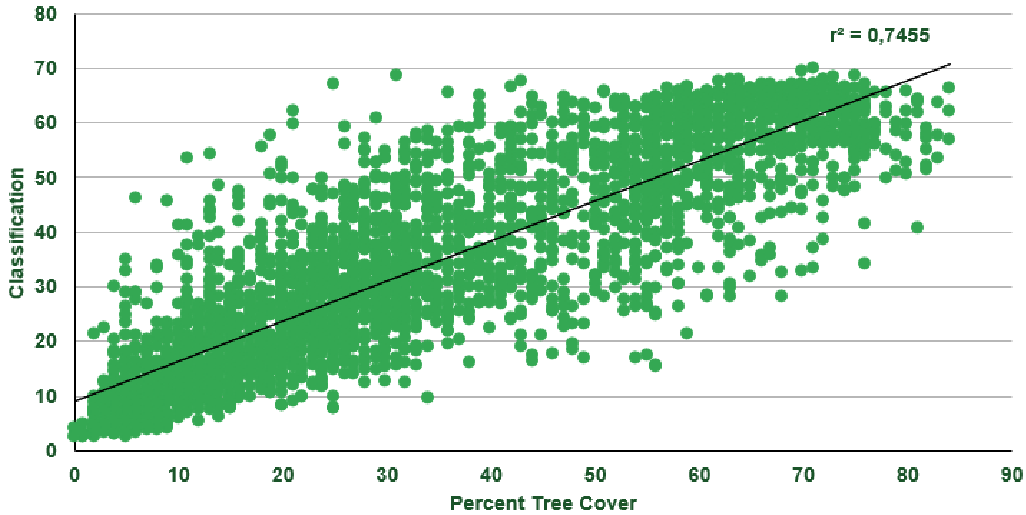

Figure 2. Scatterplot of validation results versus training results showing that the model performs well across various levels of tree cover but with some predictions being less accurate than others.

3.1.2. Percent Tree Cover Dynamics

Figure 3 shows a noticeable change in the percentage of tree cover from 2013 to 2023, with the color gradation indicating the degree of tree cover from less (yellow) to more (dark green) tree cover.

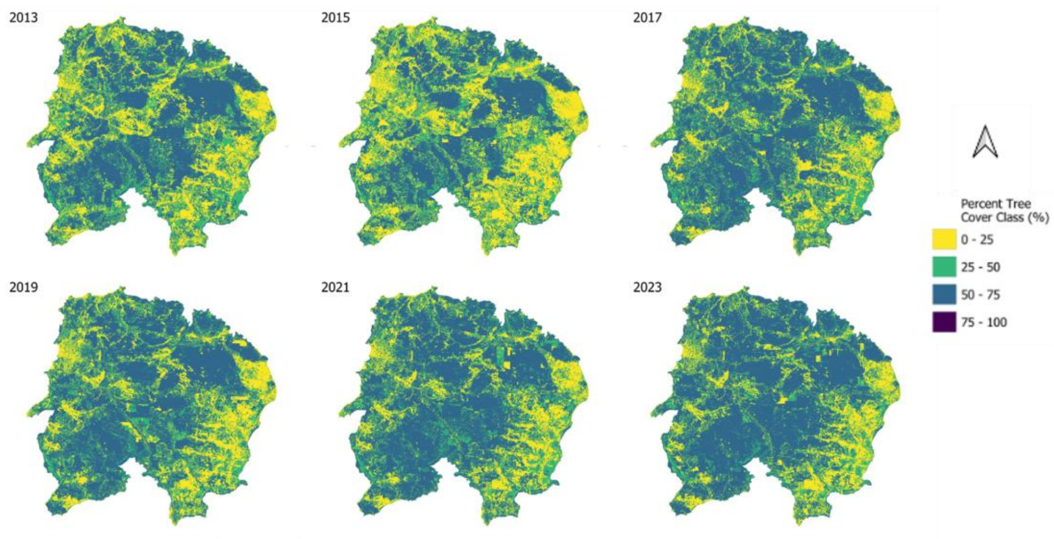

Figure 3. Percentage of tree cover on Belitung Island. A decrease in vegetation density occurred in 2015, after which there was an increase in the percentage of tree cover, and the classification of class 1 (areas with very minimal vegetation) gradually decreased.

There was a slight decrease in tree cover in certain regions in 2015 compared to 2013, possibly due to deforestation. Then, the tree cover remained relatively stable between 2015 and 2017, with some areas experiencing slight increases or decreases in coverage. The tree cover loss until 2019 suggests deforestation or degradation of forested areas. There appears to be a further decline in tree cover in some areas from 2019 to 2021, suggesting the continuing trend of deforestation or land-use change affecting tree cover. By 2023, the maps show some areas potentially recovering tree cover (evidenced by more dark green patches), while others show signs of significant deforestation.

The area of each class was counted and visualized in Figure 4, showing that there was a significant increase from 2013 to 2015 for Class 1 (0–25%), after which this area decreased until 2023, indicating a decline in tree cover in areas that are very sparsely wooded or have been degraded. There was a continuous annual decline in Class 2 (25–50%), indicating a reduction in the areas with moderate tree cover. The Class 3 (50–75%) areas fluctuated, generally significantly increasing from 2015 to 2023, indicating that higher tree cover areas have increased, possibly due to rehabilitation efforts or good forest management.

The predicted tree cover percentage map was compared to satellite RGB maps to understand activities potentially influencing vegetation changes in the study area. Additionally, Mining Business Permits (IUP) areas were incorporated to assess the potential impact of mining activities (Figure 5), showing that there was a loss of vegetation or tree cover from 2013 to 2015, characterized by an increase in Class 1 with a noticeable escalation in land clearings on the satellite RGB maps. However, some of these areas fall outside the designated IUP zones. Notably, by 2017, areas previously identified as cleared (depicted in white-yellowish tones) began to display signs of regeneration, transitioning to green with similar trends persisting in subsequent years.

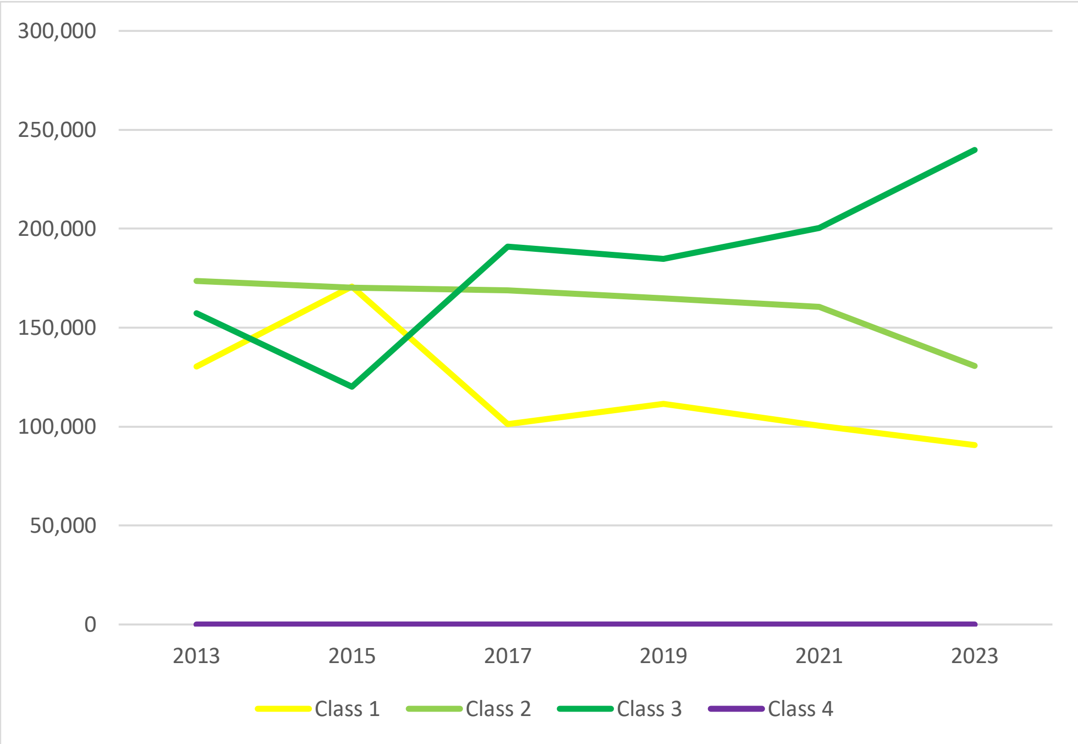

Figure 4. Area (Ha) per year of each tree cover percentage classification in Belitung Island.

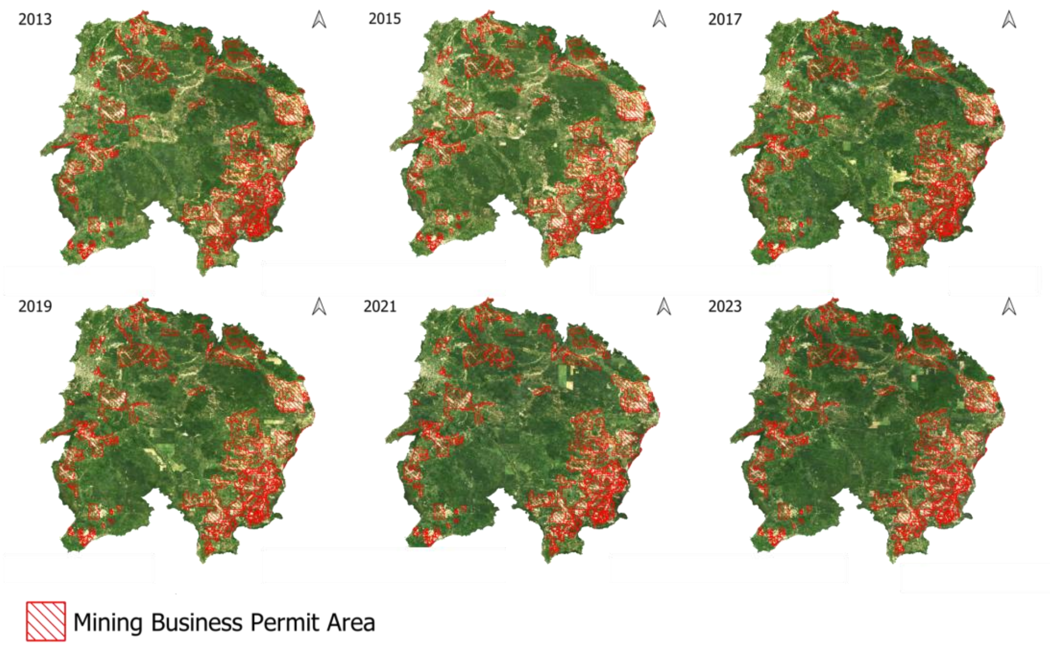

Figure 5. Natural Color (RGB) image of Belitung Island, including mining business permit (IUP) areas.

The predicted percent tree cover map from 2013 to 2023 for Lalang Mountain, a conservation area on Belitung Island, is shown in Figure 6. In 2015, there was a 14.1% increase in Class 1 (0–25%), covering 790,02 hectares, and a 21% decrease in Class 3 (50–75%), equivalent to 535,3 hectares. In 2017, there was a 16.6% decrease in Class 1 and an 11.9% increase in Class 3. Until 2023, Class 3 continued to increase, reaching 76.2%, or 1945.8 hectares of land, indicating a revitalization of vegetation becoming quite dense.

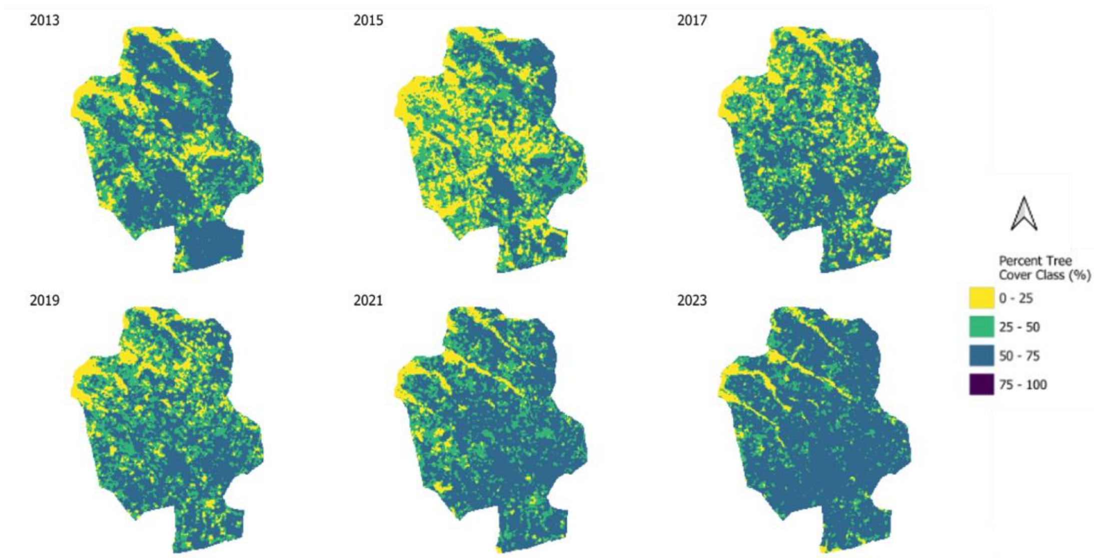

Figure 6. Percentage of tree cover in Lalang Mountain conservation area. Consistent with the Belitung Island area findings, Lalang Mountain also experienced a decrease in vegetation density in 2015. There was an increase in Class 3 by 2023, indicating that Lalang Mountain has undergone forest recovery.

Graphical representations of the total area of each classification in Lalang Mountain were created to track the progress of each class per year (Figure 7), showing that in 2015, there was an increase in the area of Class 1 vegetation, followed by an increase in the area of Class 3 vegetation in the following years.

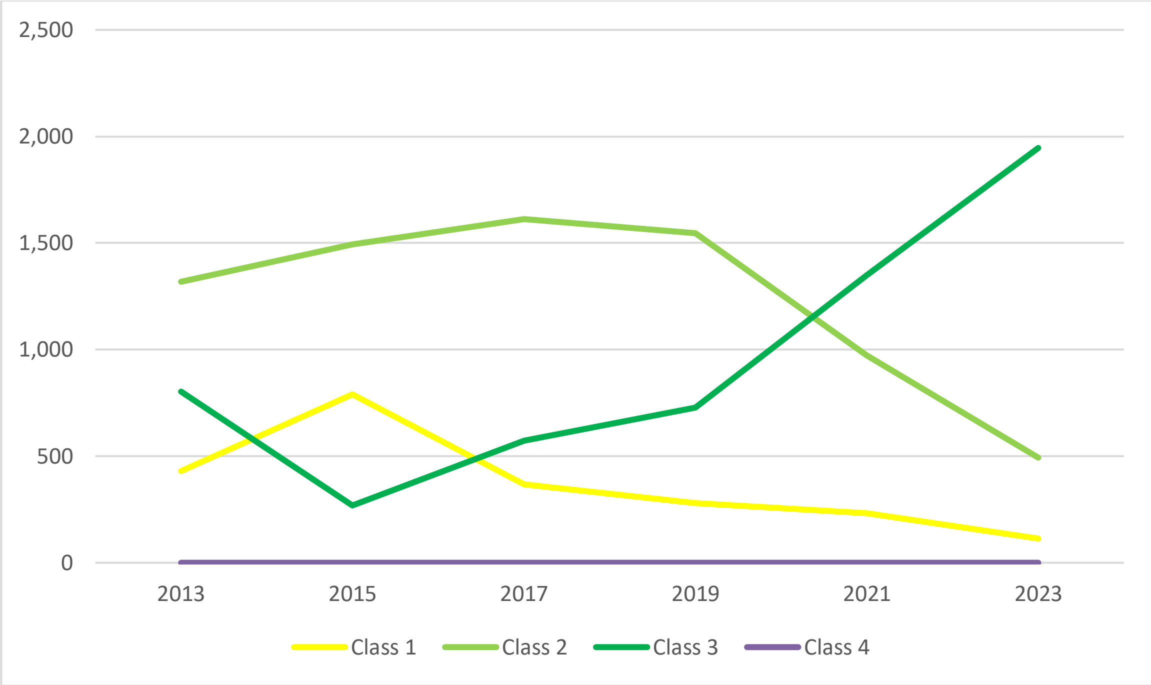

Figure 7. Area (Ha) per year for each tree cover percentage classification in Lalang Mountain.

The predicted tree cover percentage map was compared to the RGB image maps for Lalang Mountain (Figure 8). There are no IUP zones in Lalang Mountain, but there are noticeable changes in the vegetation dynamics.

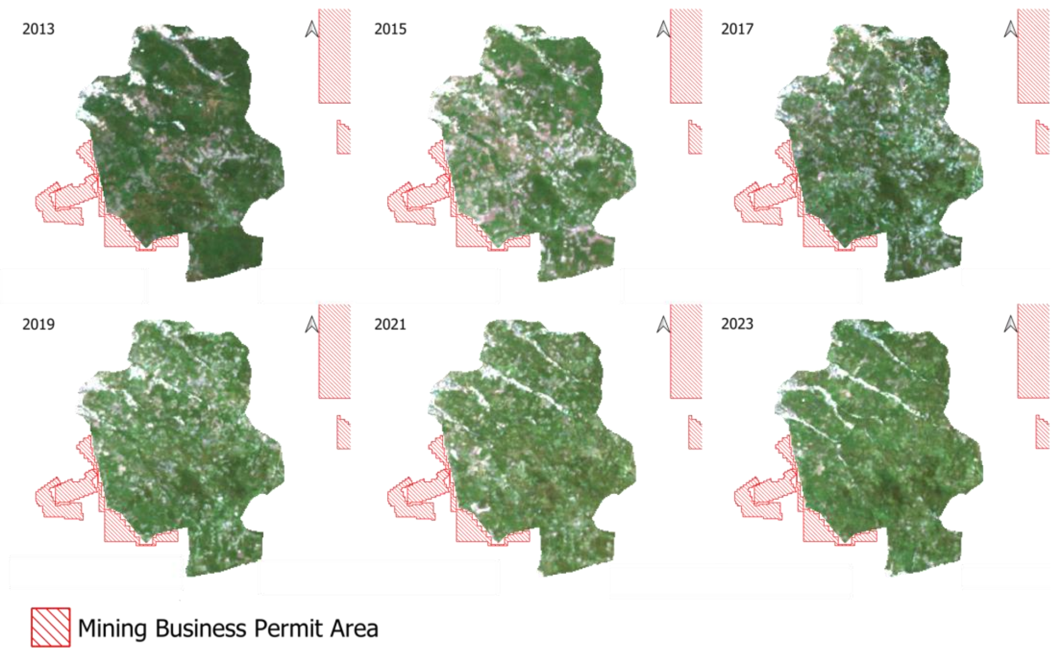

Figure 8. Natural Color (RGB) Image of Belitung Island, including Lalang Mountain Nature Reserve and the mining business permit (IUP) areas.

3.2. Discussion

The objective of this study was to develop an accurate and robust model Random Forest (RF) machine learning algorithm to accurately estimate the vegetation cover, which will help us to determine if Belitung Island faced by things potentially harmful to environment, whether its naturally occurred or because of human acitivities. This lead us on how to evaluate the remaining and later condition of the Island. Thus, from this algorithm a model was developed using remote sensing data and a random forest regression algorithm to predict the percent tree cover in Belitung Island and the Gunung Lalang Nature Reserve. We used two locations to determine the possible factor of the change. The percent tree cover density was classified into four classes: Class 1 with very minimal vegetation; Class 2 with low to moderate vegetation; Class 3 with moderate to fairly high vegetation; Class 4 with fairly high to high vegetation.

The model showed that there was a significant increase in Class 1 indicating damage to conservation areas, possibly caused by human activities such as land clearing or natural disasters. Most IUP areas tended to have Class 1 percent tree cover, validating that there was a potential for working or abandoned mining zones. The satellite RGB maps revealed surface changes (from green to yellow) indicating vegetation loss. Since it was outside the IUP area, there are possibilities such as land change to less vegetation cover (savannas or shrubland), agriculture potential, residental area, or even illegal mining areas. After a sharp decline from 2013 to 2015, Class 3 saw a very significant increase while Class 2 remained relatively stable, suggesting a noticeable recovery in tree cover reflecting a consistent regeneration of vegetation in the area. This is a good sign of reforestation in Belitung Island and Gunung Lalang. There was no significant area with 75–100% tree cover throughout the period indicating the absence of areas with dense forest cover or degradation led to the loss of high vegetation cover. Overall, these positive changes suggest forest or land recovery but these results highlight vegetation degradation that requires further attention for forest conservation in Belitung Island and the Gunung Lalang Nature Reserve.

The most recognizeable change that is shown from the result is on the year of 2015. As we can see from Figure 3, there was a decrease in tree cover in certain regions in 2015 compared to 2013, possibly due to deforestation. This indicate that there was a harmful activity towards the vegetations. If we look at the RGB Image (Figure 4), some of them were mining zone. If we consider Gunung Lalang from Figure 6, the tree cover percentage was also decreased significantly. Since Gunung Lalang is a conservation area thus there must not any mining activities, it is possible that the vegetations decreased because of El Nino that happened in 2015-2016 [21]. It is reported that in 2015, El Nino phenomenon occurred alongside the Equator and almost every dominating vegetations (including Oil Palm Trees and Forest) were affected [22].

The loss of tree cover until 2019 suggests deforestation or degradation of forested areas, which potentially caused by conversion of the forest to cropland. There appears to be a further decline in tree cover in some areas from 2019 to 2021, suggesting the continuing trend of deforestation or land-use change that affects tree cover. Previous study using Land Use Land Cover (LULC) method suggest that until 2020, there were many substantial parts of Belitung Island Forest that decreased or even entirely lost like the dryland forest [23]. In 2021 and 2023, we can see that the tree cover is getting higher which indicate possible reforestation of Belitung Island.

Though there were some declines, the tree covers overall made an increasing number based on Figure 4. This indicates that the forest of Belitung Island is increasing by 2023.

This study demonstrates that changes in vegetation over large areas can be more easily detected using satellite imagery and it is possible to evaluate how the surface conditions of the study area have evolved by understanding these vegetation changes. The results revealed significant dynamics in vegetation density, indicating damage to conservation areas and emphasizing the importance of regular vegetation monitoring and the use of remote sensing technology for effective forest conservation, like in Belitung Island.

Future studies should consider using higher-resolution data to improve accuracy. Additionally, in-depth studies of human activities such as agriculture activities, building, or even illegal mining potential in conservation areas can provide more precise insights into the causes of vegetation damage or tree cover loss. Future studies could also explore the use of other algorithms or a combination of algorithms to enhance the accuracy of vegetation cover predictions.

4. Conclusions

An accurate predictive model was developed to predict the percent tree cover on Belitung Island, including Lalang Mountain Forest Park, and it showed signs of vegetation regeneration in some areas. These findings provide valuable insights for policy development to support sustainable development on Belitung Island, considering the need for environmental conservation and resource management.

Author Contributions

NNA: Conceptualization, Analysis/Interpretation of Data, Writing - Review & Editing; **TNR**: Software, Acquisition of Data, Critical review/Supervising; **QSW**: Methodology, Writing - Review & Editing, **AFR**: Resource, Writing - Review & Editing; **RAD**: Critical review/Supervising; **IAD**: Critical review/Supervising.

Conflicts of interest

The authors declare that they have no conflict of interest regarding the publication of this paper. We have no financial or personal relationships with other people or organizations related to our study that could inappropriately influence any work.

Acknowledgment

The authors thank the Geophysics Department of Universitas Padjadjaran for fully supporting this research.

References

1. THE LAW OF THE REPUBLIC OF INDONESIA NUMBER 41 YEAR 1999 CONCERNING. **1999**, *19*, 1649–1654.
2. Sandika, A.M.P.; Megantara, E.N.; Husodo, T. Analysis of Biodiversity Potency In Gunung Lalang Forest Park, Belitung Regency. *Ecodevelopment* **2018**, *1*, 18–23, doi:10.24198/ecodev.v1i1.37583.
3. Indonesian Law No. 41 Articles 6 and 7 on Concerning Forest. **1999**.
4. Muchsin, F.; Fibriawati, L.; Pradhono, K.A. Model Koreksi Atmosfer Citra Landsat-7 (Atmospheric Correction Models of Landsat-7 Imagery). *J. Penginderaan Jauh dan Pengolah. Data Citra Digit.* **2018**, *14*, doi:10.30536/j.pjpdcd.1017.v14.a2595.
5. Said, N.I. TEKNOLOGI PENGOLAHAN AIR ASAM TAMBANG BATUBARA "Alternatif Pemilihan Teknologi." *J. Air Indones.* **2018**, *7*, 119–138, doi:10.29122/jai.v7i2.2411.
6. Roy, D.P.; Kovalskyy, V.; Zhang, H.K.; Vermote, E.F.; Yan, L.; Kumar, S.S.; Egorov, A.; Space, G.; Information, T.; Branch, S. Characterization of Landsat-7 to Landsat-8 Reflective Wavelength and Normalized Difference Vegetation Index Continuity. **2020**, *185*, 57–70, doi:10.1016/j.rse.2015.12.024.Characterization.
7. Mutoffar, M.M.; Fadillah, A. Klasifikasi Kualitas Air Sumur Menggunakan Algoritma Random Forest. *Naratif J. Nas. Riset, Apl. dan Tek. Inform.* **2022**, *4*, 138–146, doi:10.53580/naratif.v4i2.160.
8. Chen, B.; Huang, B.; Xu, B. Multi-Source Remotely Sensed Data Fusion for Improving Land Cover Classification. *ISPRS J. Photogramm. Remote Sens.* **2017**, *124*, 27–39, doi:10.1016/j.isprsjprs.2016.12.008.
9. Breiman, L. Random Forest. *Int. J. Adv. Comput. Sci. Appl.* **2001**, *7*, 5–32, doi:10.14569/ijacsa.2016.070603.
10. Febriani, N.; Yunidar, S.; Hidayat, R.A.; Amor, G.; Indrayani, P. Klasifikasi Citra Satelit Dengan Metode Random Forest Untuk Observasi Dinamika Landskap Ekosistem Kabupaten Sijunjung. *El-Jughrafiyah* **2022**, *2*, 75, doi:10.24014/jej.v2i2.18730.
11. Sylva, N. (Comperison Of Forest Area Before And After The Proposed Plan Of The Provincial Spatial (Case Study At Bangka Belitung Island Province. **2015**, *15*.

12. Tamiminia, H.; Salehi, B.; Mahdianpari, M.; Quackenbush, L.; Adeli, S.; Brisco, B. Google Earth Engine for Geo-Big Data Applications: A Meta-Analysis and Systematic Review. *ISPRS J. Photogramm. Remote Sens.* **2020**, *164*, 152–170, doi:10.1016/j.isprsjprs.2020.04.001.

13. Fahrezy, N.; Hendargi, F.; Widyasamratri, H. Kajian Literatur : Arahan Pengembangan Wilayah Berbasis Struktur Geologi Kawasan Di Pulau Belitung. *UNIPLAN J. Urban Reg. Plan.* **2021**, *2*, 29, doi:10.26418/uniplan.v2i2.50028.

14. Pérez-Cutillas, P.; Pérez-Navarro, A.; Conesa-García, C.; Zema, D.A.; Amado-Álvarez, J.P. What Is Going on within Google Earth Engine? A Systematic Review and Meta-Analysis. *Remote Sens. Appl. Soc. Environ.* **2023**, *29*, 100907, doi:10.1016/j.rsase.2022.100907.

15. Mahesti, T.; Umar, E.; Ariadi, A.; Prasetyo, S.Y.J.; Fibriani, C. Identifikasi Perubahan Tutupan Vegetasi Dan Curah Hujan Kabupaten Semarang Menggunakan Citra Saltelit Lansat 8. *Indones. J. Model. Comput.* **2020**, *3*, 30–42.

16. Noviantoro Prasetyo, N.; Sasmito, B.; Prasetyo, Y. Analisis Perubahan Kerapatan Hutan Menggunakan Metode Ndvi Dan Evi Pada Citra Satelit Landsat 8 Tahun 2013 Dan 2016 (Area Studi : Kabupaten Semarang). *J. Geod. Undip Juli* **2017**, *6*, 21–27.

17. Zulfajri; Danoedoro, P.; Heru Murti, S. Klasifikasi Penutup/Penggunaan Lahan Data Landsat-8 OLI Menggunakan Metode Random Forest. *J. Penginderaan Jauh Indones.* **2021**, *03*, 1–7.

18. Dutta, R.K.; Gnananandarao, T.; Sharma, A. Application of Random Forest Regression in the Prediction of Ultimate Bearing Capacity of Strip Footing Resting on Dense Sand Overlying Loose Sand Deposit. *J. Soft Comput. Civ. Eng.* **2019**, *3*, 28–40, doi:10.22115/SCCE.2019.137910.1080.

19. Lawrence, R.L.; Wood, S.D.; Sheley, R.L. Mapping Invasive Plants Using Hyperspectral Imagery and Breiman Cutler Classifications (RandomForest). *Remote Sens. Environ.* **2006**, *100*, 356–362, doi:10.1016/j.rse.2005.10.014.

20. Chin, W.W. The Partial Least Squares Approach to Structural Equation Modelling. In Marcoulides G. A. (Ed.). *Mod. Methods Bus. Res.* **1998**, *295*, 295–336.

21. Suryani, A.S. 22. Info Singkat-VII-13-I-P3DI-Juli-2015-67. **2015**, *VII*.

22. Darlan, N.H.; Pradiko, I.; Winarna; Siregar, H.H. Effect of El Niño 2015 on Oil Palm Performance in Central and Southern. *J. Tanah dan Iklim* **2016**, *40*, 35–42.

23. Oktavia, D.; Pratiwi, S.D.; Kamaludin, N.N.; Widiawaty, M.A.; Dede, M. Dynamics of Land Use and Land Cover in the Belitung Island, Indonesia. *Heliyon* **2024**, *10*, e33291, doi:10.1016/j.heliyon.2024.e33291.