Date of publication SEP-30, 2024, date of current version JUL-09, 2024.
www.computingonline.net / computing@computingonline.net

Print ISSN 1727-6209
Online ISSN 2312-5381
DOI 10.47839/ijc.19.3.XX

Analysis of the Severity of Heterogeneity Protection Forest based on SVM and PCA

FERZHA PUTRA UTAMA[1], ARIE VATRESIA[1], NANANG SUGIANTO[2], ULFAH NUR AZIZAH[1]
[1]Faculty of Engineering, University of Bengkulu, Bengkulu, Indonesia
[2]Faculty of Mathematics and Natural Sciences, University of Bengkulu, Bengkulu, Indonesia

Corresponding author: Ferzha Putra Utama (e-mail: fputama@unib.ac.id).

This work was fund by Bengkulu University Research and Community Service through a fundamental research scheme with contract number 2008/UN30.15/PP/2022.

ABSTRACT Forest heterogeneity indicates the forest condition on producing more carbon into environment. Semidang Bukit Kabu Hunting Park Forest is a nature reserve lies over two districts of Central Bengkulu and Seluma, Bengkulu Province, which should have a heterogeneous forest to protect its natural resources. However, the data showed that the condition of it does not appear to have dense forest heterogeneity anymore, and its rate still remain unknown. Remote sensing as one of tools to help the remote monitoring was believed to be helpful to this question. This study showed changes in the heterogeneity from 2016 to 2021. Sentinel-2 imageries were occupied to help the process of classification of forest and non-forest areas. Support Vector Machine, as one of powerful machine learning tools, was also help the process with the integrating of Principal Component Analysis to optimize forest characteristics. This study indicates that there are significant reductions of forest heterogeneity over the area. The number of forest (heterogeny areas) continues to decline from 8122 ha in 2016 to 4339 ha in 2021. Furthermore, this study had proven that the algorithm of support vector machines showed significant performance to build the model towards the data with overall accuracy rate of 0.9434 and a kappa index of 0.9833.

KEYWORDS heterogeneity; forest; Semidang Bukit Kabu; support vector machine; principal component analysis; Bengkulu; Indonesia.

I. INTRODUCTION

FOREST are an ecosystem that is important for the sustainability of life on Earth. One of the main roles of forests is as a provider of oxygen for life. Forests have a very large number of plants, so they can produce a large enough amount of oxygen. In other functions, forests are also capable of greatly absorbing carbon emissions [1, 2]. In addition, forests also have the ability to absorb carbon dioxide from the air, thereby reducing the concentration of greenhouse gases. Forests are one of the most life-rich ecosystems on Earth. As an ecosystem, forests are habitats for various types of plants and animals [3]. The forest boasts a considerable level of biodiversity. Indonesia's tropical forest ecosystem is widely regarded as one of the most affluent and intricate ecosystems globally [4–7]. Tropical forests, which are found in areas with a hot and humid climate all year, are home to a diverse range of plants and animals [8, 9].

In Indonesia, there are several types of forests that are distinguished by their function, including production forests, conservation forests, protected forests, and hunting forests. A hunting forest, also known as a hunting park, is a type of conservation forest that allows for hunting tours [10]. Hunting activities are not only intended for tourism, but also to control certain animal populations. Hunting activities in the hunting park are strictly regulated for hunting time, types of animals that can be hunted, and weapons used for hunting. As an ecosystem for living things, forests should ideally consist of heterogeneous plants. Forest heterogeneity is the key to the existence of healthy ecosystems [11, 12]. The distribution of biodiversity is largely determined by the heterogeneity of forests [3, 13]. Many factors affect forest heterogeneity, such as topography, light, tree regeneration patterns, and climate [14, 15].

The forests in Indonesia continue to be impacted by deforestation. Changes in land use by humans are contributing to this ongoing issue [16]. Deforestation primarily results from the conversion of forested areas into plantations, logging for timber, and mining activities. This phenomenon also affects protected forests, despite efforts by the Ministry of Environment and Forestry to conserve these areas for their role as a water supply [17, 18]. Many factors, either directly or indirectly, influence forest land use [19, 20]. The transformation of the forests on the island of Sumatra was mainly driven by the encroachment of plantations, particularly those cultivating oil palm, rubber trees, and coffee. In addition to plantation activity, forest fires and natural disasters such as landslides have also played a role in altering the vegetation [21, 22]. Currently, deforestation is a concern for many parties, including governments and environmentalists. Semidang Bukit Kabu Hunting Park (SBK) is a lowland, wet tropical forest with a reasonably low topography. It is located at 0-8 meters above sea level and is geographically located at 3.778242-3.982736 S and 102°47'41"-102°60'10" E. Figure 1 illustrates the location of SBK in the Seluma and Bengkulu Tengah districts, within the Bengkulu Province of Indonesia. SBK is under the management of the Natural Resources Conservation Centre (BKSDA) of Bengkulu Province, a government organization entrusted with the oversight and protection of all flora and fauna in the region.

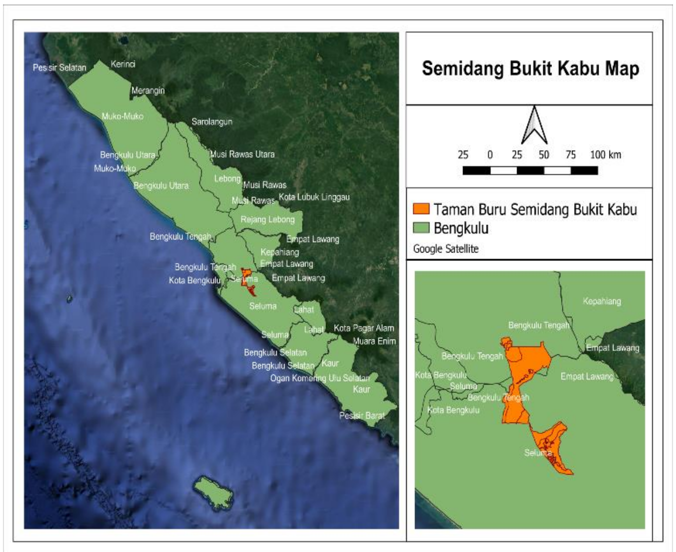


Figure 1. The SBK map

The primary function of the SBK forest is to protect the living natural resources and ecosystems in its area. However, this forest is also used for hunting activities, tourism purposes, and pest control. There are still many protected endangered species in this area, such as the Sumatran tiger, deer, wild boar, and other protected species. Nevertheless, the reality of the 2021 SBK forest does not look like a heterogeneous forest with a high density. The heterogeneity of SBK forests as conservation forests decreases from year to year. This is likely to change the land use of SBK forests into plantations or residential areas. This condition is very worrying and threatens the survival of animals and ecosystems in the SBK forest. Serious efforts are needed from the government and communities to maintain the health of Indonesia's forests. SBK has undergone a succession process of ecosystem changes toward a more orderly and stable environment. Succession is an anti-deforestation effort by the government to restore forest heterogeneity. However, the succession by the relevant government has not been optimal. As mentioned earlier, there has been a lot of deforestation in SBK forests. Various problems are faced in managing the SBK area, such as encroachment, illegal logging, and poaching. It was recorded that 120 squatters cleared forest areas by turning the forest into plantation land, taking forest wood, and hunting Sumatran tigers. The arrival of forest encroachers from outside Seluma Regency blindly cleared the forest for oil palm plantations, coffee, and rubber. The latest condition is that the vegetation in SBK consists of logged-over areas, young and old shrubs, and several plantations. This causes an increase in the homogeneity of vegetation in forest conservation areas.

We have undertaken a comprehensive analysis of forest and non-forest density through remote sensing imagery to better comprehend the pattern of vegetation change in the SBK area [23, 24]. Research [25, 26] shows the trend of cover changes and land changes through satellite image processing. The SVM method, according to [27–30], is numerous and accurate in the classification process of remote sensing image data, particularly forest images. The classification of forest objects based on remote sensing data entails the deployment of machine learning models. These models systematically analyze the features and attributes of objects to discern and categorize them. Notably, the scrutiny of pixel-based point patterns enables the identification of various object classes, particularly land cover, through remote sensing technology [31, 32]. The data series used for analysis in this research are Landsat images from 2016 to 2021. It is critical to understand the current SBK forest area and how it has changed over time [10]. This study categorizes land cover into two classes: forest and non-forest. Vegetation is classified as forest if it comprises diverse plant species, whereas bare land and homogeneous vegetation are categorized as non-forest. The PCA (Principal Component Analysis) model is employed to differentiate between the forest and non-forest classes [33–35]. PCA is a technique used to simplify data with linear transformations that form a new coordinate system with maximum variance [36]. Through PCA, it can be seen what factors play the most role in explaining phenomena in the dataset while maintaining the characteristics of the data (maximum variance). Hence, our research leverages PCA to improve SVM's ability to differentiate between forest and non-forest areas with greater accuracy. To date, there has been no research addressing changes in forest areas within SBK. This study seeks to analyze the distribution pattern of land density (forest and non-forest) to enhance the conservation of natural resources and ecosystems. This includes the preservation of plant and animal species diversity and their ecosystems, which are vital for supporting life.

II. METHOD

This research constitutes a quantitative study that seeks to ascertain the extent of changes in the SBK forest land area. The analysis of forest area changes is based on the delineation of forest and non-forest parameters. The study indicates a significant level of deforestation in the SBK region from 2016 to 2021. Achieving accurate land cover classification in the SBK area is essential, which is why we utilized remote sensing data from the Sentinel-2 satellite through the USGS Earth Explorer. Sentinel-2 imagery is known for its high accuracy in classifying objects, particularly in wetland areas [37, 38]. We believe these images will be suitable for classifying forest and non-forest land in the SBK area. When performing remote sensing-based object classification, various methods such as Random Forest (RF), Naïve Bayes (NB), and Stochastic Gradient Descent (SGD) have been commonly utilized [39–41]. In this research, SVM was selected due to its superior classification results in comparison to other methods when applied to low-resolution remote sensing images using QGIS-based tools. In the research [42, 43], RF, NB, and SGD demonstrated better performance than SVM. However, SVM outperformed in classifying two object classes (forest and non-forest) with limited data. Moreover, research [44, 45] show the SVM method remains highly effective for classifying vegetation, land cover, including forests, compared to other methods.

The research method presented in Figure 2 outlines the stages involved in the land classification process. The research commences with the analysis of satellite imagery of the SBK area from 2016 to 2021. This data is utilized to forecast changes in the protected forests over time [30]. Geometric and radiometric corrections are provided to make the image more representative and avoid distortion [46–48]. Geometric and radiometric corrections were performed using the Semi-Automatic Classification (SCP) plugin in QGIS [49, 50]. A composite band or band combination involves combining bands in image data. This process entails entering the selected channel into the three primary colors (RGB) to create a composite image. The aim of using color composites is to obtain better visual information than using only a single band. The process is typically carried out using the Semi-Automatic Classification (SCP) plugin.

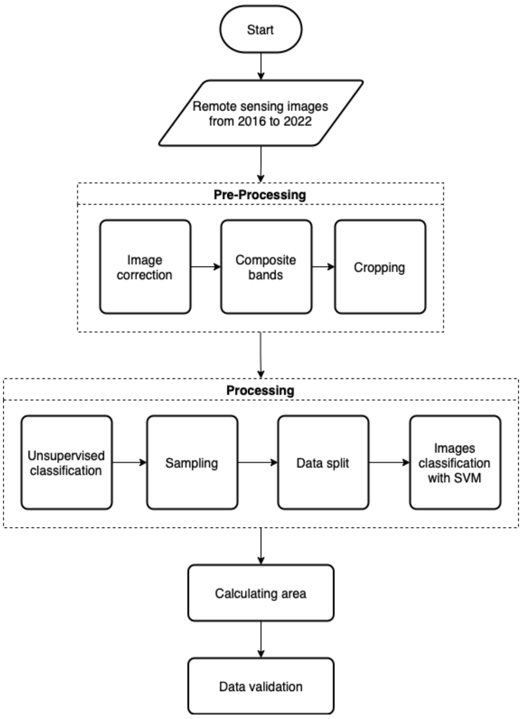


Figure 2. Research method

In addition, the correction is also intended so that the image can represent the shape in actual conditions with the appropriate coordinates. The following process is to crop the image according to the administrative boundary as an Area of Interest (AOI). The processing stage, which follows the preprocessing phase, consists of five distinct steps. Due to the extensive range of color values in remote sensing images, the utilization of unsupervised clustering becomes imperative, as these images cannot be effectively classified during the initial stages of processing [51]. The clustering process is automatically done by using the K-Means method [52, 53]. Unsupervised clustering is the process of grouping image pixels into several classes using cluster analysis [54, 55]. The clustering stage yields ten distinct classes in the AOI image, each characterized by a specific range of values depicted in Figure 3. The subsequent step involves using PCA to discern whether the area pertains to the forest or non-forest class. Typically, PCA is utilized for feature extraction to differentiate between forest and non-forest areas [56].

```
Clustering

Class   Signature        Distance
C_ID_1  0.04438446922715493,0.04981656165367O155,
C_ID_2  0.03310740485808588,0.03992562653499511,0
C_ID_3  0.040252975804751435,0.05130117160859277,
C_ID_4  0.031203873532587554,0.04059751157933389,
C_ID_5  0.031666046341340265,0.0434278259502492,0
C_ID_6  0.03257916598960026,0.047114201919257574,
C_ID_7  0.03359354627229862,0.05214295764060371,0
C_ID_8  0.033412497490644455,0.04776249825954437,
C_ID_9  8.057549418342138e-08,8.926629697568514e-
C_ID_10 0.04395144032304848,0.045300000495557796,
C_ID_11 0,0,0,0,0,0,0,0,0,0,0,0,0       0.0
```
Figure 3. Clustering range value

To ensure accurate classification, it is imperative to verify that the area is assigned to one of the classes by conducting the K-Means clustering iteration in the third stage. This involves the utilization of stratified random sampling, which facilitates the automatic selection of 200 points from the image for each class. The sampling process is executed utilizing the AcATAMa plugin, which effectively streamlines the selection of representative points for classification purposes [49, 57]. Automating the process of classifying forest and non-forest objects involves determining sample points, which are then used to partition the data into training and test sets. The training data is crucial for model development, while the test data is essential for model evaluation. In this study, 70% of the data is designated for training and 30% for testing to ensure that the differences in land cover distribution, as revealed by the confusion matrix, are clearly visible. The subsequent step entails employing SVM to classify the training data. To ensure precision and minimize errors, the classification process utilizes skit-learn within the OseGEO Shell toolkits on QGIS, as illustrated in Figure 4 [58, 59]. The process of determining the area of the classification results involves converting the image format from raster to vector and subsequently utilizing the calculator feature within QGIS for computation. Following this, the data is subjected to validation to verify the correspondence of the SVM classification results with each class. This validation procedure encompasses the application of a confusion matrix to 120 samples from both classes.

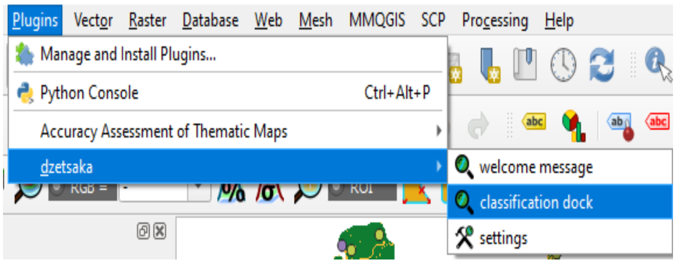


Figure 4. Classification using SVM

III. RESULTS AND DISCUSSION

Table 1 presents data from an image classification study using a 200 x 200 pixel dataset for forest and non-forest classes. The PCA model suggests that utilizing SVM for classification would be more effective, as the classification parameters based on class have been revealed through PCA. The input image used in the study depicts multiple plots for PCA, summarizing numerous independent variables (X) that are found to be correlated or influencing each other, consolidating them into one or more new variables containing a blend of the original independent variables. The data in Table 1 also includes a contour plot of the PCA model, which visually represents the data by displaying images with colors based on variations in one of the main components. There are discernible differences in pixel colors in forest and non-forest models. In essence, PCA can highlight distinct parameters in the forest and non-forest classification processes.

Table 1. PCA model

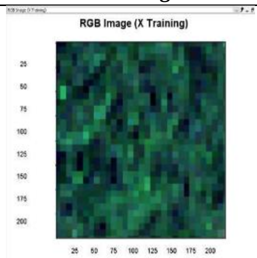
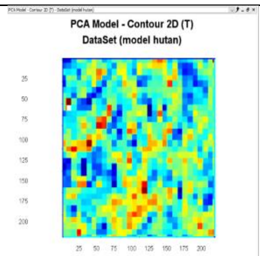
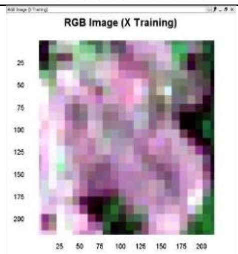
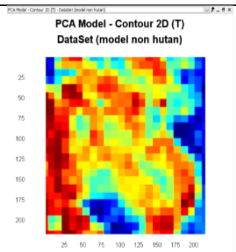
Class	RGB images	PCA model contour 2D
Forest		
Non-forest		

Table 2. Spectral and PCA model overview

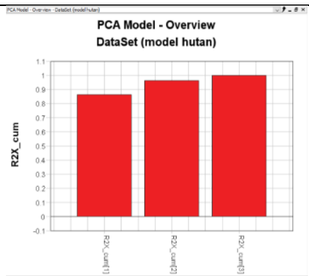
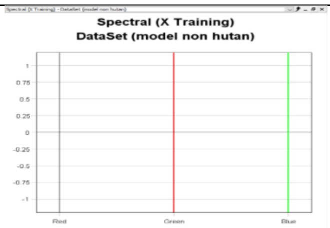
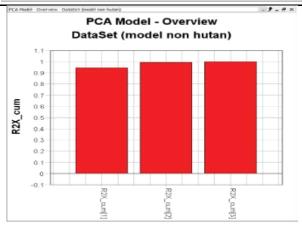
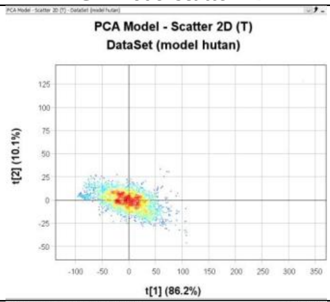
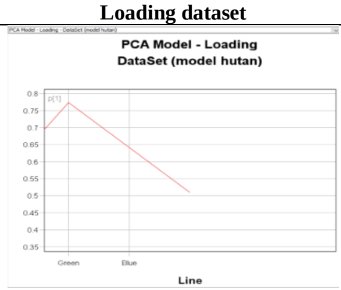
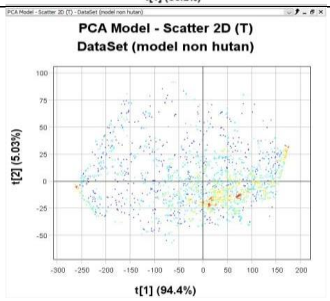
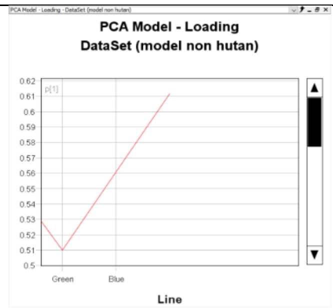
Class	Spectral	PCA model
Forest		
Non-forest		

Table 3. PCA model scatter 2D and loading dataset

Class	PCA model scatter 2D	Loading dataset
Forest		
Non-forest		

PCA aims to explain the structure of variance-covariance through a linear combination of variables. Table 2 shows the percentage of variation explained by the PCA model. The forest model has three main components that describe RGB values of 0.88 for red, 1.0 for green, and 0.98 for blue. In comparison, the non-forest model has an RGB value of 0.97 for red, 1.0 for green, and 1.0 for blue. Based on the plot, it is known that the non-forest model has a more stable RGB level compared to the forest model.

The scatter plot in Table 3 shows the differences in the model with several groupings of pixels of different types. Based on the dataset processed through the Evince application, an overview is shown according to each model.

The analysis of both models confirms their ability to accurately predict data for each class. The forest model achieves an accuracy rate of 86.2%, while the non-forest model achieves an accuracy rate of 94.4%. The visualization in Table 3 illustrates that nearly all sample datasets are correctly categorized. Each model's graph displays an inverse relationship with the PCA model loading graph. In the forest model, the graph decreases, whereas in the non-forest model, it increases with varying accuracy values. This disparity is attributed to the confusion matrix, revealing that in the forest model, five sample points are misclassified as non-forest, resulting in a lower accuracy compared to the non-forest model.

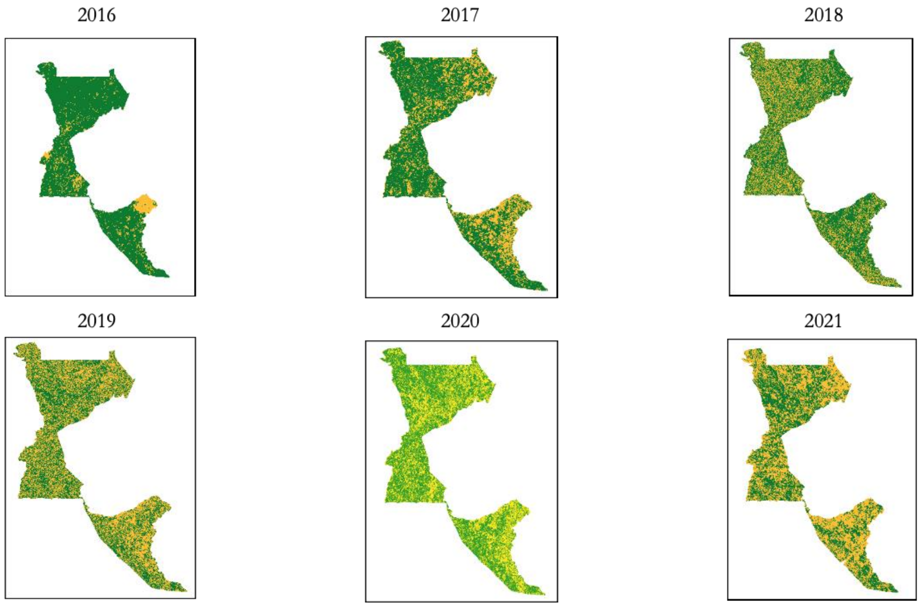


Figure 5. SVM classification results

The six maps in Figure 5 represent heterogeneity changes that occurred in SBK. The green color represents the forest area, while the yellow color represents the non-forest area. We can see significant deforestation from 2016 to 2021, spread evenly within the protected forest area. In other words, the area included in the non-forest class is expanding.

Table 4. Classification result area

Classification	Area in years (ha)					
	2016	2017	2018	2019	2020	2021
Forest	8122	6458	5967	5814	5621	4339
Non-forest	1102	2766	3258	3411	3604	4978

The data in Table 4 also supports map data that shows deforestation in yearly numbers. Meanwhile, the area defined as the non-forest area in the SBK area is increasing. Indeed, further research is needed to determine what happened in the conversion of this forest area, which is now defined as non-forest. Sentinel-2 image processing data classified as SVM is validated using a truncated Sentinel-2 image. The accuracy test can be calculated by using a confusion matrix. The results of the SVM accuracy test can be found in Table 5.

This study utilized six remote sensing images, one captured each year. We applied a 10% cloud cover threshold to the Sentinel-2 image and selected the clearest one to optimize identification results. After testing with 120 forest and non-forest sample points, we found the lowest accuracy to be 0.84 on January 26, 2019, and the highest accuracy to be 1.00 on March 12, 2017, and March 11, 2020, resulting in an average overall accuracy of 0.94. These accuracy values demonstrate that the results of the SVM classification of the Sentinel-2 image are reliable for identifying forest and non-forest areas. Additionally, the user accuracy provides the average probability (%) of a pixel from the classified image representing these classes in the field. If a class has a user accuracy value of 100%, it indicates that these classes have not been misclassified by not taking pixels from other classes. The accuracy test results are shown in Table 6.

Table 5. Results of SVM Classification Confusion Matrix

Date	Overall accuracy
April 9, 2016	0.90
March 12, 2017	1.00
April 11, 2018	0.94
January 26, 2019	0.84
March 11, 2020	1.00
July 29, 2021	0.99

The next step is the Kappa accuracy test to determine whether one error matrix is significantly different from another. The final step is to determine the overall accuracy, which is the ratio of the total number of areas (pixels) correctly classified to the entire area (pixels) of observations. The test results could reveal the truth about the classified image. The results of the overall accuracy calculation for both forest and non-forest classes are 0.9434, while the kappa index is 0.9833.

Table 6. Performance Model

Classification data	Reference data				
	Forest	Non-forest	Row total (x)	xy	User accuracy (%)
Forest	59	1	60	3540	98.336
Non-forest	0	60	60	3660	100
Column total (y)	59	61	120	7200	

The classification of forest and non-forest areas in SBK to determine the rate of heterogeneity change shows outstanding results using the SVM method. This study used the appropriate data to produce a classification. This is indicated by the high accuracy of classification [60]. Studies [61–64] have also shown very high accuracy, above 90%, for image classification. Optimization of feature recognition in remote sensing image classification using PCA is more effective in obtaining high accuracy than other methods [65, 66].

IV. CONCLUSIONS

The primary purpose of using PCA in this study is to differentiate between two specific classes. However, further research is necessary to broaden the scope of object classifications. The classification results indicate deforestation in SBK from 2016 to 2021. Nevertheless, additional investigations are required to identify the underlying causes of deforestation and assess the sustainability of the forest succession program in the SBK area. The area of Semidang Bukit Kabu Hunting Park Forest decreased from 8122 ha in 2016 to 4339 ha in 2021, indicating a continued decline in forest area. The most significant deforestation occurred from 2016 to 2017, with a total extent of 1664 ha. The application of SVM and PCA methods to classify forest and non-forest areas in remote sensing images yields high overall accuracy of 0.9434 and a Kappa index of 0.9833.

References

[1] Y. Han, S. Gao, and C. Liu, “Evaluation and analysis of forest carbon sequestration and oxygen release value under cloud computing framework,” *Procedia Comput. Sci.*, vol. 228, pp. 519–525, 2023, https://doi.org/10.1016/j.procs.2023.11.059.

[2] M. Almaraz *et al.*, “Dinitrogen emissions dominate nitrogen gas emissions from soils with low oxygen availability in a moist tropical forest,” *J. Geophys. Res. Biogeosciences*, vol. 128, no. 1, p. e2022JG007210, 2023, https://doi.org/10.1029/2022JG007210.

[3] J. C. Habel, M. Teucher, P. Gros, V. Gfrerer, and J. Eberle, “The importance of dynamic open-canopy woodlands for the conservation of a specialist butterfly species,” *Landsc. Ecol.*, vol. 37, no. 8, pp. 2121–2129, 2022, https://doi.org/10.1007/s10980-022-01472-2.

[4] H. Y. S. H. Nugroho *et al.*, “Mainstreaming ecosystem services from Indonesia’s remaining forests,” *Sustain.*, vol. 14, no. 19, p. 12124, 2022, https://doi.org/10.3390/su141912124.

[5] N. E. Lelana *et al.*, “Bagworms in Indonesian plantation forests: Species composition, pest status, and factors that contribute to outbreaks,” *Diversity*, vol. 14, no. 6, p. 471, 2022, https://doi.org/10.3390/d14060471.

[6] I. W. S. Dharmawan, N. M. Heriyanto, R. Garsetiasih, R. T. Kwatrina, and R. Sawitri, “The dynamics of vegetation structure, composition and carbon stock in peatland ecosystem of old secondary forest in Riau and South Sumatra provinces,” *Land*, vol. 13, no. 5, p. 663, 2024, https://doi.org/10.3390/land13050663.

[7] S. Rahayu *et al.*, “Functional trait profiles and diversity of trees regenerating in disturbed tropical forests and agroforests in Indonesia,” *For. Ecosyst.*, vol. 9, p. 100030, 2022, https://doi.org/10.1016/j.fecs.2022.100030.

[8] S. D. Hayati, I. Qayim, R. Raffiudin, N. S. Ariyanti, W. Priawandiputra, and M. Miftahudin, “Traditional knowledge of plants for Sunggau Rafters on three forest types for conservation of Apis dorsata in Indonesia,” *Forests*, vol. 15, no. 4, p. 657, 2024, https://doi.org/10.3390/f15040657.

[9] A. B. Suwardi, Z. I. Navia, A. Mubarak, and M. Mardudi, “Diversity of home garden plants and their contribution to promoting sustainable livelihoods for local communities living near Serbajadi protected forest in Aceh Timur region, Indonesia,” *Biol. Agric. Hortic.*, vol. 39, no. 3, pp. 170–182, 2023, https://doi.org/10.1080/01448765.2023.2182233.

[10] S. Withaningsih, Parikesit, and R. Fadilah, “Diversity of bird species in Pangheotan grassland and Mount Masigit Kareumbi hunting park, West Java, Indonesia,” *Biodiversitas*, vol. 23, no. 6, pp. 2790–2798, 2022, https://doi.org/10.13057/biodiv/d230602.

[11] Y. Nugroho *et al.*, “Vegetation diversity, structure and composition of three forest ecosystems in Angsana coastal area, South Kalimantan, Indonesia,” *Biodiversitas*, vol. 23, no. 5, pp. 2640–2647, 2022, https://doi.org/10.13057/biodiv/d230547.

[12] Y. Yang, J. Ma, H. Liu, L. Song, W. Cao, and Y. Ren, “Spatial heterogeneity analysis of urban forest ecosystem services in Zhengzhou

City," *PLoS One*, vol. 18, no. 6 June, pp. 1–27, 2023, https://doi.org/10.1371/journal.pone.0286800.
[13] Q. Zaldo-Aubanell *et al*., "Environmental heterogeneity in human health studies. A compositional methodology for land use and land cover data," *Sci. Total Environ.*, vol. 806, 2022, https://doi.org/10.1016/j.scitotenv.2021.150308.
[14] T. Merrick *et al.*, "Unveiling spatial and temporal heterogeneity of a tropical forest canopy using high-resolution NIRv, FCVI, and NIRvrad from UAS observations," *Biogeosciences*, vol. 18, no. 22, pp. 6077–6091, 2021, https://doi.org/10.5194/bg-18-6077-2021.
[15] J. R. Matangaran, I. N. Anissa, Q. Adlan, and M. Mujahid, "Changes in floristic diversity and stand damage of tropical forests caused by logging operations in North Kalimantan, Indonesia," *Biodiversitas*, vol. 23, no. 12, pp. 6358–6365, 2022, https://doi.org/10.13057/biodiv/d231233.
[16] M. Dede, C. Asdak, and I. Setiawan, "Spatial dynamics model of land use and land cover changes: A comparison of CA, ANN, and ANN-CA," *Regist. J. Ilm. Teknol. Sist. Inf.*, vol. 8, no. 1, pp. 38–49, 2022, https://doi.org/10.26594/register.v8i1.2339.
[17] H. Y. S. H. Nugroho *et al.*, "Toward Water, energy, and food security in rural Indonesia: A review," *Water (Switzerland)*, vol. 14, no. 10, pp. 1–25, 2022, https://doi.org/10.3390/w14101645.
[18] A. Umami, H. Sukmana, E. A. Wikurendra, and E. Paulik, "A review on water management issues: potential and challenges in Indonesia," *Sustain. Water Resour. Manag.*, vol. 8, no. 3, p. 63, 2022, https://doi.org/10.1007/s40899-022-00648-7.
[19] A. Fosch *et al.*, "Replanting unproductive palm oil with smallholder plantations can help achieve sustainable development goals in Sumatra, Indonesia," *Commun. Earth Environ.*, vol. 4, no. 1, pp. 1–12, 2023, https://doi.org/10.1038/s43247-023-01037-4.
[20] H. Purnomo *et al.*, "Public and private sector zero-deforestation commitments and their impacts: A case study from South Sumatra province, Indonesia," *Land use policy*, vol. 134, no. July, p. 106818, 2023, https://doi.org/10.1016/j.landusepol.2023.106818.
[21] N. Adani, Y. Subiakto, and S. Pranoto, "Structural mitigation of rob flood disaster through mangrove forest conservation in Indonesia coastal areas," *IOP Conf. Ser. Earth Environ. Sci.*, vol. 1173, no. 1, 2023, https://doi.org/10.1088/1755-1315/1173/1/012066.
[22] P. Agarwal, D. Sahoo, Y. Parida, K. Ranjan Paltasingh, and J. Roy Chowdhury, "Land use changes and natural disaster fatalities: Empirical analysis for India," *Ecol. Indic.*, vol. 154, no. June, p. 110525, 2023, https://doi.org/10.1016/j.ecolind.2023.110525.
[23] D. Rosalina *et al.*, "Application of remote sensing and GIS for mapping changes in land area and mangrove density in the Kuri Caddi Mangrove tourism, South Sulawesi Province, Indonesia," *Biodiversitas*, vol. 24, no. 2, pp. 1049–1056, 2023, doi: 10.13057/biodiv/d240246.
[24] E. P. Yankovich, K. S. Yankovich, and N. V. Baranovskiy, "Dynamics of Forest Vegetation in an Urban Agglomeration Based on Landsat Remote Sensing Data for the Period 1990–2022: A Case Study," *Remote Sens.*, vol. 15, no. 7, 2023, https://doi.org/10.3390/rs15071935.
[25] Md. O. Sarif and R. D. Gupta, "Spatiotemporal mapping of land use/land cover dynamics using remote sensing and GIS approach: a case study of Prayagraj City, India (1988–2018), *Environ Dev Sustain*, vol. 24, pp. 888–920, 2022. https://doi.org/10.1007/s10668-021-01475-0.
[26] Purwanto, S. Latifah, Yonariza, F. Akhsani, E. I. Sofiana, and M. R. Ferdiansah, "Land cover change assessment using random forest and CA markov from remote sensing images in the protected forest of South Malang, Indonesia," *Remote Sens. Appl. Soc. Environ.*, vol. 32, p. 101061, 2023, https://doi.org/10.1016/j.rsase.2023.101061.
[27] Z. Zafar, M. Zubair, Y. Zha, S. Fahd, and A. Ahmad Nadeem, "Performance assessment of machine learning algorithms for mapping of land use/land cover using remote sensing data," *Egypt. J. Remote Sens. Sp. Sci.*, vol. 27, no. 2, pp. 216–226, 2024, https://doi.org/10.1016/j.ejrs.2024.03.003.
[28] R. Thakur and P. Panse, "Classification performance of land use from multispectral remote sensing images using decision tree, k-nearest neighbor, random forest and support vector machine using EuroSAT data," *Int. J. Intell. Syst. Appl. Eng.*, vol. 10, no. 1s, pp. 67–77, 2022.
[29] M. P. Singh, V. Gayathri, and D. Chaudhuri, "A simple data preprocessing and postprocessing techniques for SVM classifier of remote sensing multispectral image classification," *IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens.*, vol. 15, pp. 7248–7262, 2022, https://doi.org/10.1109/JSTARS.2022.3201273.
[30] Z. A. Kakarash, H. S. Ezat, S. A. Omar, and N. F. Ahmed, "Time series forecasting based on support vector machine using particle swarm optimization," *Int. J. Comput.*, vol. 21, no. 1, pp. 76–88, 2022, https://doi.org/10.47839/ijc.21.1.2520.
[31] R. Kosarevych, O. Lutsyk, B. Rusyn, O. Alokhina, T. Maksymyuk, and J. Gazda, "Spatial point patterns generation on remote sensing data using convolutional neural networks with further statistical analysis," *Sci. Rep.*, vol. 12, no. 1, pp. 1–9, 2022, https://doi.org/10.1038/s41598-022-18599-6.
[32] A. Vatresia, F. Utama, N. Sugianto, A. Widyastiti, R. Rais, and R. Ismanto, "Automatic image segmentation model for indirect land use change with deep convolutional neural network," *Spat. Inf. Res.*, no. 0123456789, 2023, https://doi.org/10.1007/s41324-023-00560-y.
[33] I. Ali, Z. Mushtaq, S. Arif, A. D. Algarni, N. F. Soliman, and W. El-Shafai, "Hyperspectral images-based crop classification scheme for agricultural remote sensing," *Comput. Syst. Sci. Eng.*, vol. 46, no. 1, pp. 303–319, 2023, https://doi.org/10.32604/csse.2023.034374.
[34] R. Sugumar and D. Suganya, "A multi-spectral image-based high-level classification based on a modified SVM with enhanced PCA and hybrid metaheuristic algorithm," *Remote Sens. Appl. Soc. Environ.*, vol. 31, p. 100984, 2023, https://doi.org/10.1016/j.rsase.2023.100984.
[35] K. F. Reich, M. Kunz, A. W. Bitter, and G. Von Oheimb, "Do different indices of forest structural heterogeneity yield consistent results?," *IForest*, vol. 15, no. 5, pp. 424–432, 2022, https://doi.org/10.3832/ifor4096-015.
[36] M. Greenacre, P. J. F. Groenen, T. Hastie, A. I. D'Enza, A. Markos, and E. Tuzhilina, "Principal component analysis," *Nat. Rev. Methods Prim.*, vol. 2, no. 1, p. 100, 2022, https://doi.org/10.1038/s43586-022-00184-w.
[37] A. M. Simón Sánchez, J. González-Piqueras, L. de la Ossa, and A. Calera, "Convolutional Neural Networks for Agricultural Land Use Classification from Sentinel-2 Image Time Series," *Remote Sens.*, vol. 14, no. 21, 2022, https://doi.org/10.3390/rs14215373.
[38] S. Yousefi *et al.*, "Image classification and land cover mapping using Sentinel-2 imagery: Optimization of SVM parameters," *Land*, vol. 11, no. 7, 2022, https://doi.org/10.3390/land11070993.
[39] N. Baccari, "Evaluation of SVM and RF Machine Learning Algorithms in Land Use / Land Cover Change Assessment : Tessa Watershed Case Study (Northwest of Tunisia)," *Appl. Geomatics*, 2024, https://doi.org/10.21203/rs.3.rs-4359112/v1.
[40] S. Basheer *et al.*, "Comparison of land use land cover classifiers using different satellite imagery and machine learning techniques," *Remote Sens.*, vol. 14, no. 19, pp. 1–18, 2022, https://doi.org/10.3390/rs14194978.
[41] E. Piaser and P. Villa, "Comparing machine learning techniques for aquatic vegetation classification using Sentinel-2 data," *Proceedings of the 2022 IEEE 21st Mediterranean Electrotechnical Conference (MELECON)*, 2022, pp. 465–470, https://doi.org/10.1109/MELECON53508.2022.9843103.
[42] C. Matyukira and P. Mhangara, "Land cover and landscape structural changes using extreme gradient boosting random forest and fragmentation analysis," *Remote Sens.*, vol. 15, no. 23, 2023, https://doi.org/10.3390/rs15235520.
[43] A. Rash, Y. Mustafa, and R. Hamad, "Quantitative assessment of land use/land cover changes in a developing region using machine learning algorithms: A case study in the Kurdistan Region, Iraq," *Heliyon*, vol. 9, no. 11, p. e21253, 2023, https://doi.org/10.1016/j.heliyon.2023.e21253.
[44] A. Azedou, A. Amine, I. Kisekka, S. Lahssini, Y. Bouziani, and S. Moukrim, "Enhancing land cover/land use (LCLU) classification through a comparative analysis of hyperparameters optimization approaches for deep neural network (DNN)," *Ecol. Inform.*, vol. 78, no. April, p. 102333, 2023, https://doi.org/10.1016/j.ecoinf.2023.102333.
[45] Y. Ouma *et al.*, "Comparison of machine learning classifiers for multitemporal and multisensor mapping of urban Lulc features," *Int. Arch. Photogramm. Remote Sens. Spat. Inf. Sci. - ISPRS Arch.*, vol. 43, no. B3-2022, pp. 681–689, 2022, https://doi.org/10.5194/isprs-archives-XLIII-B3-2022-681-2022.
[46] G. Doxani *et al.*, "Atmospheric correction inter-comparison eXercise, ACIX-II Land: An assessment of atmospheric correction processors for Landsat 8 and Sentinel-2 over land," *Remote Sens. Environ.*, vol. 285, no. October 2022, 2023, https://doi.org/10.1016/j.rse.2022.113412.
[47] P. Azinwi Tamfuh *et al.*, "Mapping land use/land cover changes caused by mining activities from 2018 to 2022 using Sentinel-2 imagery in Bétaré-Oya (East-Cameroon)," *J. Geosci. Geomatics*, vol. 12, no. 1, pp. 12–23, 2024, https://doi.org/10.12691/jgg-12-1-3.
[48] J. E. Ayala Izurieta *et al.*, "Improving the remote estimation of soil organic carbon in complex ecosystems with Sentinel-2 and GIS using Gaussian processes regression," *Plant Soil*, vol. 479, no. 1–2, pp. 159–183, 2022, https://doi.org/10.1007/s11104-022-05506-1.
[49] A. Galodha1, N. T. Ngoc, D. Raniwala, and S. Mundia, "Impact of coal mining, thermal plants, anthropogenic activities on wildlife corridors for national parks and wildlife sanctuaries in the state of Madhya Pradesh, India," *Int. Arch. Photogramm. Remote Sens. Spat. Inf. Sci. - ISPRS Arch.*, vol. 46, no. M-2–2022, pp. 233–239, 2022, https://doi.org/10.5194/isprs-archives-XLVI-M-2-2022-233-2022.

[50] K. Tempa and K. R. Aryal, "Semi-automatic classification for rapid delineation of the geohazard-prone areas using Sentinel-2 satellite imagery," *SN Appl. Sci.*, vol. 4, no. 5, 2022, https://doi.org/10.1007/s42452-022-05028-6.

[51] F. Uhl, T. G. Rasmussen, and N. Oppelt, "Classification ensembles for beach cast and drifting vegetation mapping with Sentinel-2 and PlanetScope," *Geosci.*, vol. 12, no. 1, pp. 1–18, 2022, https://doi.org/10.3390/geosciences12010015.

[52] G. S. Geethika, V. S. Sreeja, T. Tharuni, and V. Radhesyam, "Vegetation change detection of multispectral satellite images using remote sensing BT - High performance computing, smart devices and networks," *Proceedings of the Conference on Performance Computing, Smart Devices and Networks*, 2024, pp. 337–349. https://doi.org/10.1007/978-981-99-6690-5_25.

[53] A. Mullapudi, A. D. Vibhute, S. Mali, and C. H. Patil, "Spatial and seasonal change detection in vegetation cover using time-series landsat satellite images and machine learning methods," *SN Comput. Sci.*, vol. 4, no. 3, p. 254, 2023, https://doi.org/10.1007/s42979-023-01710-7.

[54] K. He, "Pharmacological affinity fingerprints derived from bioactivity data for the identification of designer drugs," *J. Cheminform.*, vol. 14, no. 1, pp. 1–19, 2022, https://doi.org/10.1186/s13321-022-00607-6.

[55] M. J. van Strien and A. Grêt-Regamey, "Unsupervised deep learning of landscape typologies from remote sensing images and other continuous spatial data," *Environ. Model. Softw.*, vol. 155, no. April 2021, 2022, https://doi.org/10.1016/j.envsoft.2022.105462.

[56] E. M. Ordway *et al.*, "Mapping tropical forest functional variation at satellite remote sensing resolutions depends on key traits," *Commun. Earth Environ.*, vol. 3, no. 1, pp. 1–11, 2022, https://doi.org/10.1038/s43247-022-00564-w.

[57] X. Peng *et al.*, "A Comparison of random forest algorithm-based forest extraction with GF-1 WFV, Landsat 8 and Sentinel-2 images," *Remote Sens.*, vol. 14, no. 21, p. 5296, 2022, https://doi.org/10.3390/rs14215296.

[58] A. N. Rasyidah, I. S. Astuti, and I. Carolita, "Analysis of deforestation as impact of changes on oil palm land use in Tanah Bumbu Regency, South Kalimantan using satellite remote sensing data," *IOP Conf. Ser. Earth Environ. Sci.*, vol. 1066, no. 1, p. 012005, 2022, https://doi.org/10.1088/1755-1315/1066/1/012005.

[59] M. Zickel, M. Gröbner, A. Röpke, and M. Kehl, "MiGIS: micromorphological soil and sediment thin section analysis using an open-source GIS and machine learning approach," *E G Quat. Sci. J.*, vol. 73, no. 1, pp. 69–93, 2024, https://doi.org/10.5194/egqsj-73-69-2024.

[60] Y. Xi, A. M. Mohamed Taha, A. Hu, and X. Liu, "Accuracy comparison of various remote sensing data in lithological classification based on random forest algorithm," *Geocarto Int.*, vol. 37, no. 26, pp. 14451–14479, 2022, https://doi.org/10.1080/10106049.2022.2088859.

[61] Z. Zhao *et al.*, "The PCA-NDWI urban water extraction model based on hyperspectral remote sensing," *Water (Switzerland)*, vol. 16, no. 7, 2024, https://doi.org/10.3390/w16070963.

[62] M. Mehmood, A. Shahzad, B. Zafar, A. Shabbir, and N. Ali, "Remote sensing image classification: A comprehensive review and applications," *Math. Probl. Eng.*, vol. 2022, 2022, https://doi.org/10.1155/2022/5880959.

[63] G. Liu, L. Wang, D. Liu, L. Fei, and J. Yang, "Hyperspectral image classification based on non-parallel support vector machine," *Remote Sens.*, vol. 14, no. 10, pp. 1–22, 2022, https://doi.org/10.3390/rs14102447.

[64] Y. Shang, X. Zheng, J. Li, D. Liu, and P. Wang, "A comparative analysis of swarm intelligence and evolutionary algorithms for feature selection in SVM-based hyperspectral image classification," *Remote Sens.*, vol. 14, no. 13, 2022, https://doi.org/10.3390/rs14133019.

[65] A. Singleton, D. Arribas-Bel, J. Murray, and M. Fleischmann, "Estimating generalized measures of local neighbourhood context from multispectral satellite images using a convolutional neural network," *Comput. Environ. Urban Syst.*, vol. 95, no. April, p. 101802, 2022, https://doi.org/10.1016/j.compenvurbsys.2022.101802.

[66] Z. Bao *et al.*, "Remote sensing-based assessment of ecosystem health by optimizing vigor-organization-resilience model: A case study in Fuzhou City, China," *Ecol. Inform.*, vol. 72, p. 101889, 2022, https://doi.org/10.1016/j.ecoinf.2022.101889.

FERZHA PUTRA UTAMA obtained his B.Eng. in informatics from the University of Bengkulu and his M.Eng. in information technology from the University of Gadjah Mada. He has worked as a lecturer in the Information Systems Department at the University of Bengkulu from 2015 to the present. His area of interest includes the modeling of geographic information systems, information technology, artificial intelligence, and system security.

ARIE VATRESIA *received her master's* in information technology from the University of Indonesia and her PhD in computer science from the University of Birmingham. She also an visiting researcher in National Research and Innovation Agency, Indonesia. Her area of interest includes spatial mining and artificial intelligence.

NANANG SUGIANTO received his master's degree in geophysics from the University of Gadjah Mada and is currently pursuing his PhD at the same institution. He is a lecturer in the Department of Geophysics at the University of Bengkulu. His area of interest includes geoscience, disaster mitigation, and seismology.

ULFAH NUR AZIZZAH was a fresh graduate in informatics. She gets a B.Eng. from the University of Bengkulu. Now she is a research assistant in the artificial intelligence laboratory at the University of Bengkulu. She is interested in spatial mining, information systems, and artificial intelligence.

• • •