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Monitoring Vegetation Changes and Disturbances in Gunung Merbabu National Park Using Landtrendr Algorithm and Landsat Images

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ABSTRACT

Conservation areas protect biodiversity and ecosystems from human activities and climate change threats. Understanding disturbances that can damage conservation areas drives the need for effective mapping and monitoring. One of the primary disturbances is land cover change caused by forest fires, illegal logging, and other human activities. In this context, remote sensing algorithms such as LandTrendr offer an efficient approach to monitoring vegetation changes and disturbances in conservation areas. This study aims to monitor vegetation changes and disturbances in Gunung Merbabu National Park using the LandTrendr algorithm. Landsat image data from 1994 to 2023 was analyzed using Google Earth Engine. The results showed that the LandTrendr algorithm effectively identified vegetation changes, with forest fires being the primary disturbance. During 1994–2022, total vegetation loss and gain were detected at 933.57 ha and 2279.52 ha, respectively. The results highlight significant changes in the core zone of Gunung Merbabu National Park, mainly due to fires and logging activities. These findings provide a better understanding of the dynamics of vegetation change in Gunung Merbabu National Park and provide relevant insights for conservation area managers to implement appropriate mitigation measures. This research contributes to the literature on monitoring vegetation changes in conservation areas and provides a basis for more effective conservation efforts in Gunung Merbabu National Park and similar areas.

Keywords: Landtrendr algorithm, vegetation monitoring, conservation area, disturbance, Gunung Merbabu National Park.

INTRODUCTION

As the front line in maintaining biodiversity and ecosystems, conservation areas face severe threats due to human activities and climate change. They are considering the importance of this conservation area, understanding, and comprehending the various forms of disturbance that can damage this conservation area. Disturbances are sudden events that can drastically change ecosystem characteristics [Begon et al., 1986]. Disturbances to changes in land cover need to be identified through the dynamics of land cover so that managers can get input in managing the area sustainably [Turner and Simard, 2017; Ansari and Golabi, 2019]. Mapping forest disturbance and spatial patterns is essential in sustainable forest management and in implementing climate policy initiatives, such as the Reducing Emissions from Deforestation and Forest Degradation program [Coops et al., 2007; Hirschmugl et al., 2020]. This disturbance strongly influences the sensitivity of land cover changes. Fires, climbing, pests and diseases, illegal logging, tornadoes, and encroachment can cause changes in land cover. These factors indicate the level of sensitivity to changes in land cover.

To visualize disturbances in land cover changes, remote sensing images are used such as Landsat [Kennedy et al., 2010; Quintero et al., 2019; Nguyen et al., 2018] and SAR imagery [Hirschmugl et al., 2020]. The development of remote sensing algorithms is progressing significantly, including algorithmic approaches in mapping land cover, and detecting forest disturbance factors. Algorithmic approaches such as Breaks for Additive Seasonal and Trend (BFAST) [Verbesselt et al., 2010], Landsat-based detection of trends in disturbance and recovery (LandTrendr) [Kennedy et al., 2010, 2018; Cohen et al., 2018], and continuous change detection and classification (CCDC) [Zhu and Woodcock, 2014] has been widely used and applied in various studies and areas. In this research, we use the LandTrendr algorithm because it can provide information about the timing and magnitude of disturbance and recovery in land cover changes in an area [Liu et al., 2022]. The use of the LandTrendr algorithm has been widely used in various studies related to changes in forest areas [Banskota et al., 2014; Ding and Li, 2023; Li et al., 2023], mining areas [Liu et al., 2022; Xiao et al., 2020], and mangroves [Chen et al., 2022]. The LandTrendr algorithm is also used in research in conservation areas, which monitors changes in forest land cover in conservation areas and detects disturbances that cause changes [Komba et al., 2021; Zhang et al., 2023; Toker et al., 2021]. Monitoring disturbance factors that cause changes in land cover and prioritizing an area at multiple levels is needed [Smith et al., 2019], especially in areas with intensive management. In Indonesia, monitoring disturbance and recovery factors has received little attention; for this reason, the aim of this research is to detect monitoring vegetation change and disturbance in the Gunung Merbabu National Park area.

One of the most essential disturbances in land cover change is fire. Fires occur in the Gunung Merbabu National Park area almost yearly, especially during the dry season [BTNGMb, 2019a]. Trends in land cover changes, primarily due to fire, are essential to know because of how big the response is to changes in burned land cover [Soulard et al., 2016]. Climbing activity increases from year to year [BTNGMb, 2019b] and can also cause changes in the landscape structure of the Gunung Merbabu National Park area, although not too extensive. The large number of climbers causes the need for land for walking/climbing, camping, or other activities to become greater so that plants become reduced. Restoration/rehabilitation activities are also carried out annually, both in the form of Gunung Merbabu National Park office activities and by the community in the form of mass planting. This activity is directed at restoring the function of the area in the rehabilitation zone, which covers an area of around 1,298.98 ha [BTNGMb, 2018]. In forest ecosystems, disturbance is inevitable, and maintaining spatial heterogeneity in cover types, different stages of succession, and different biogeochemical states can increase resilience and biodiversity [Liang et al., 2016; Kulakowski et al., 2019].

MATERIAL AND METHODS

Study area

This study was conducted in the Gunung Merbabu National Park area, which has an area of around 5,820 ha. Gunung Merbabu National Park covers three districts in Central Java Province, Indonesia, namely Semarang, Magelang and Boyolali Districts, which are geographically located at coordinates 110°26’22”E and 7°27’13”S. Before its designation as a conservation area, Gunung Merbabu National Park served as a production forest and protected forest area under the management of Perhutani. Since 2007, Gunung Merbabu National Park Office has managed the Gunung Merbabu National Park area [BTNGMb, 2014]. This area is located in the middle of Java Island and directly borders 37 buffer villages. There are 135 types of flora identified in the Gunung Merbabu National Park area with priority types, namely *Castanopsis argantea, Anaphalis javanica, Paraserianthes lophantha,* and *Engelhardia serrata* [Hardian et al., 2020]. Land cover in Gunung Merbabu National Park consists of forests covering an area of 3689,575 Ha in 2020 [Ardiaristo et al., 2022]. In its management, Gunung Merbabu National Park is managed based on zoning, which consists of 7 zones, namely core zone, wilderness zone, rehabilitation zone, utilization zone, special zone, religious, cultural and historical zone, and traditional zone [BTNGMb, 2020] (Fig. 1).

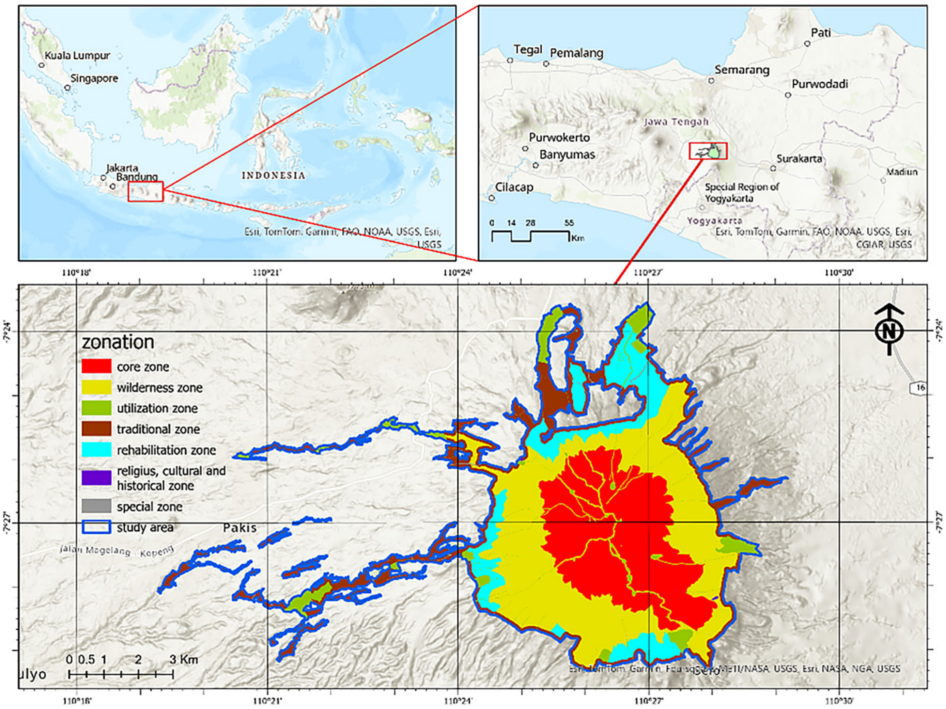

Figure 1. Map of study area

Method

This study uses various Landsat satellites, including Landsat 5 TM, Landsat 7 ETM+, and Landsat 8 and 9 OLI, from 1994 to 2023. Landsat image archive data can be accessed publicly using Google Earth Engine (GEE). The data acquisition, preprocessing, and Landtrendr processes are also carried out with GEE [Kennedy et al., 2018]. Images were only selected from July to October to reduce the influence of seasonal vegetation variations and cloud abundance. The images were extensively preprocessed, involving adjustment of surface reflectance using the LEDAPS technique for Landsat 5–7 and the LaSRC algorithm for Landsat 8–9. Sensor-to-sensor harmonization is implemented using equations to maintain uniformity across multiple sensors [Roy et al., 2016]. A medoid filtering technique selects the most representative pixels for each year by selecting pixel values closest to the median across all bands. This choice is essential for creating precise time series observations at the pixel level. This study concentrates on the Normalized Burn Ratio (NBR), a ratio statistic responsive to forest disturbance, to identify changes in forest cover. NBR is calculated using a unique formula that utilizes the near-infrared and shortwave bands, known for their efficacy in detecting forest disturbances. This study uses the LandTrendr algorithm, a multi-stage method specifically created to detect and measure vegetation changes, especially forest loss and increase. The approach consists of six main stages: removing spikes caused by noise, identifying possible nodes through regression analysis, fitting trajectories, simplifying the model, selecting the optimal model based on the p-value of the F-statistic, and assessing the segmentation results. In this study, the selected parameters were determined. Namely, Max Segment was 6, spike Threshold was 0.9, Vertex Count Overshoot was 3, prevent one-year recovery was True, recovery threshold was 0.25, pvalThreshold was 0.05, min observations needed was 6 [Wang et al., 2023]. The method is rigorous, and every step is essential for the results. This study concentrates on determining the most prominent changes in forest cover by using a magnitude filter to consider changes in NBR values that exceed 0.1. The investigation examined variations over a minimum area of 0.54 hectares, roughly equivalent to six pixels of a Landsat image. The comprehensive procedure yielded specific results regarding the length, extent, and timing of vegetation decline and recovery, as seen in the research visuals. A decrease in spectral values characterizes forest loss, while an increase in subsequent years characterizes an increase. To validate the resulting loss and gain data, an accuracy assessment was conducted using 200 sample points selected in a stratified random manner, with 100 sample points each for forest loss and 100 for forest gain. An accuracy assessment using confision matrix was carried out with R software [Umarhadi et al., 2023].

RESULT AND DISCUSSION

Accuracy assessment

The Landtrendr algorithm is a tool that can be used to monitor changes temporally [Tao et al., 2023]. Reference data is needed to obtain validation results with high accuracy in addition to applying the suitable parameters and stages when validating samples. In addition to using Google Earth images and Landsat imagery, this research also uses information about events that can influence change, such as fires or logging [Komba et al., 2021]. For example, according to Figure 2a, a sample was collected from Google Earth in both 2014 and 2021, showing the occurrence of loss in that area. Additionally, Timesync visualization is also used to see the development of a temporal observation plot [Cohen et al., 2010]. As can be seen in Figure 2b, changes in vegetation cover lost due to logging are visualized from Timesync. In 1996, logging was carried out at this location because the location was a patch of pine production forest previously managed by Perhutani (BTNGMb 2014). Accuracy assessment of forest loss and gain from 1994 until 2022 obtained by the Landtrendr algorithm resulted in forest loss of 80.42% and forest gain of 87.76%. These results show that the results of the Landtrendr algorithm in this study are strong.

Vegetation change

One of the Landtrendr algorithm results is a vegetation change map containing duration, magnitude, and year of change [Kennedy et al., 2010]. In this study, changes in vegetation were chosen as loss and gain to describe the sensitivity of disturbances to vegetation, presented in Figure 3. This figure shows that the total gain is greater than the total loss during 1994–2021. Specifically, there is a total gain of 2279.52 hectares and a total loss of 933.57 hectares. Based on Figure 3 and Table 1, the average total gain magnitude during the research period was 323, and the average total loss magnitude was 335. The average duration of gain and loss was one year, which illustrates the reasonably rapid changes in vegetation within one year [Umarhadi et al., 2023].

Table 1 shows that there were no loss and gain values from vegetation in some years. Specifically, there were no losses in 2004, 2010, 2013, and 2014, and no gains in 2004, 2006, 2015, and 2018. There are several possibilities for this to happen. Another effect is a bad image due to the influence of clouds at the research location [Shen et al., 2022] or no significant changes within a certain period.

According to Figure 3 and Table 1 show that the largest area of vegetation loss occurred in 2018, with an area of 121.95 ha. If examined further, in 2018, there was a reasonably large

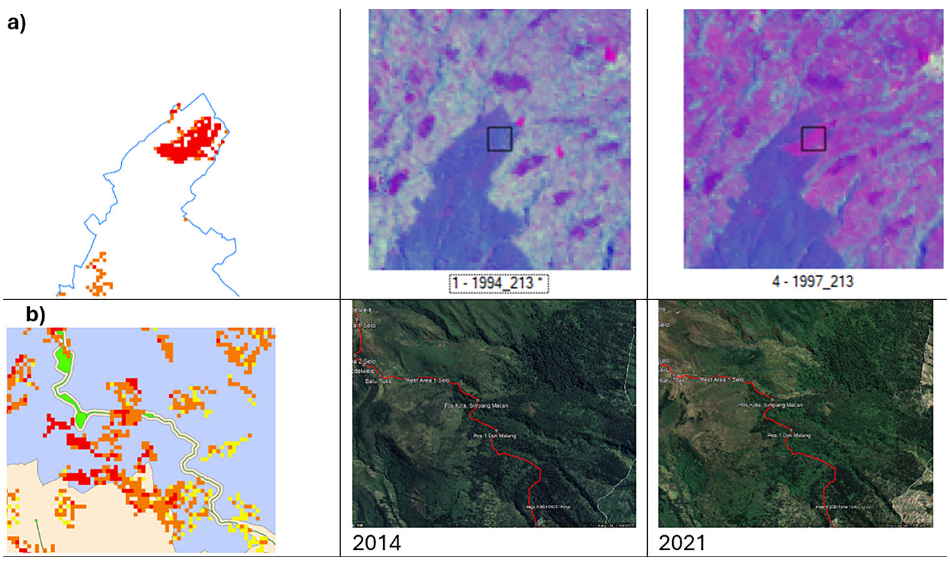

Figure 2. Example of forest loss for sample points from (a) Timesync and (b) Google Earth image

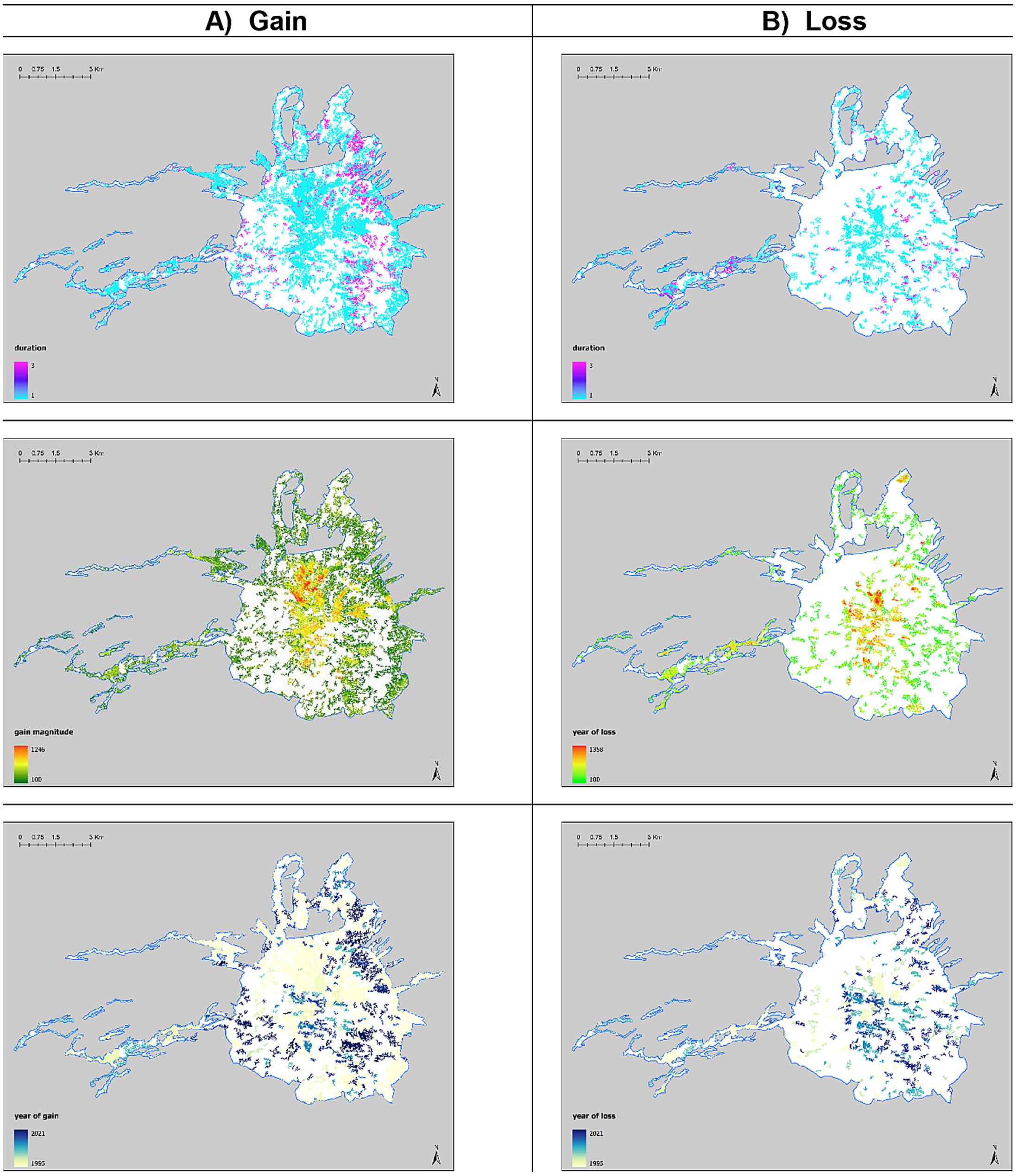

Figure 3. The output map of the Landtrendr algorithm is a map of the duration, magnitude and year of changes in vegetation gain (a) and vegetation loss (b)

fire in the Gunung Merbabu National Park area of up to 457 ha [BTNGMb, 2019a]. Likewise, in 1997, there was a vegetation loss of 101.07 ha, one of the areas of which was Perhutani plots where logging was carried out. This can be seen from this example, which can be seen in Figure 4, where at the point of vegetation loss, value of NDVI spectral value, we can see fluctuations in the spectral value; where when vegetation loss occurs, the NDVI value suddenly drops, and the following year it rises.

The most significant vegetation gain in 1994 was 1294.38 ha, which covered 56% of the total vegetation gain in 1994–2021. There needs to be more information about what happened in 1995 because Perhutani still carried out management, but if we look at the location and Landsat images from 1995, it is possible because vegetation recovered from a relatively large fire incident in 1994 and recovered again in 1995. As shown in Figure 5, the NBR spectral value in 1994 was -260; in 1995, it increased to 329. A low or negative NBR value can indicate that the area has experienced a fire, with high reflectance in the short-wave infrared band. Due to carbon and other burning materials [Li et al., 2021].

Table 1. Average value of magnitude and area during 1995–2021

Year	Loss		Gain	
	Average magnitude (NBRx1000)	Area (ha)	Average magnitude (NBRx1000)	Area (ha)
1995	293	109.98	328	1294.38
1996	396	90.72	442	21.51
1997	365	101.07	568	27.45
1998	302	12.69	338	159.57
1999	313	16.02	291	9.54
2000	337	13.77	209	7.38
2001	264	24.66	286	9.9
2002	383	33.03	237	5.76
2003	341	12.06	411	5.67
2004	0	0	0	0
2005	242	15.84	314	5.49
2006	343	104.4	0	0
2007	278	26.28	304	83.61
2008	385	12.87	272	15.03
2009	232	15.3	419	2.16
2010	0	0	298	19.35
2011	547	49.05	195	3.42
2012	177	11.88	516	40.77
2013	0	0	264	27.27
2014	0	0	336	2.25
2015	484	74.88	0	0
2016	298	24.84	441	110.16
2017	287	43.2	268	3.51
2018	213	121.95	0	0
2019	232	7.65	153	0.18
2020	275	10.17	236	369.27
2021	224	1.26	315	55.89

Figure 6 shows that the most significant changes in vegetation, both loss, and gain, occurred in the core zone with quite large magnitudes. The area of vegetation loss during the 1994–2022 period was 373.68 ha with an average magnitude of 411, while the area of vegetation gain was 722.01 Ha with an average magnitude of 437. Magnitude illustrates the significant changes and disturbance levels occurring in this core zone. The location of the core zone, most of which is at an altitude of more than 2400 meters above sea level and vegetation cover apart from savanna, also protects the habitat of the Rek-rekan (*Presbytis commata Frederica*). Fires caused disturbances in the core zone during the long dry season. Although vegetation recovery is taking place quite quickly, fire disturbances must be anticipated, whether caused by human or natural influences.

Using the Landtrendr algorithm to monitor vegetation changes in studies is very useful for knowing how disturbances to vegetation occur in specific periods. The study of conservation areas requires accurate data and information regarding vegetation cover within them and disturbances that influence vegetation changes. The application of the Landtrendr algorithm can be seen because this algorithm analyzes the history of the spectral value of each pixel in the image for a certain period [Komba et al., 2021]. Using the Landtrendr algorithm can also be done quickly and does not require significant resources because the processing is done via Google Earth Engine or could computing [Kennedy et al., 2018; He et al., 2023]. However, there are also limitations in applying the Landtrendr algorithm in this study, namely information about disturbances that

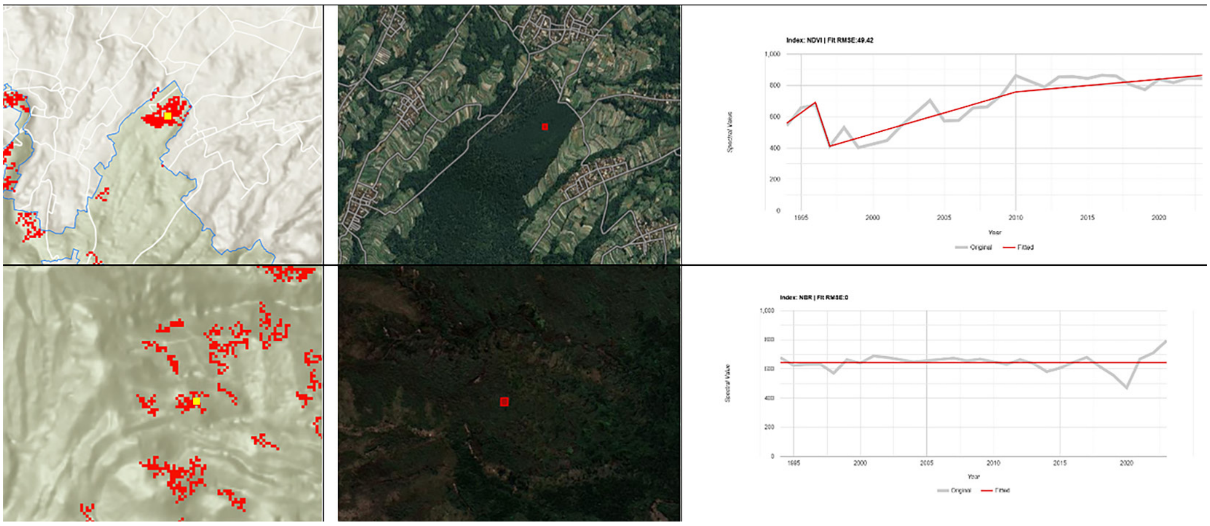

Figure 4. Sampling plot of vegetation loss and LandTrendr fitted disturbance trajectories based on NBR and NDVI

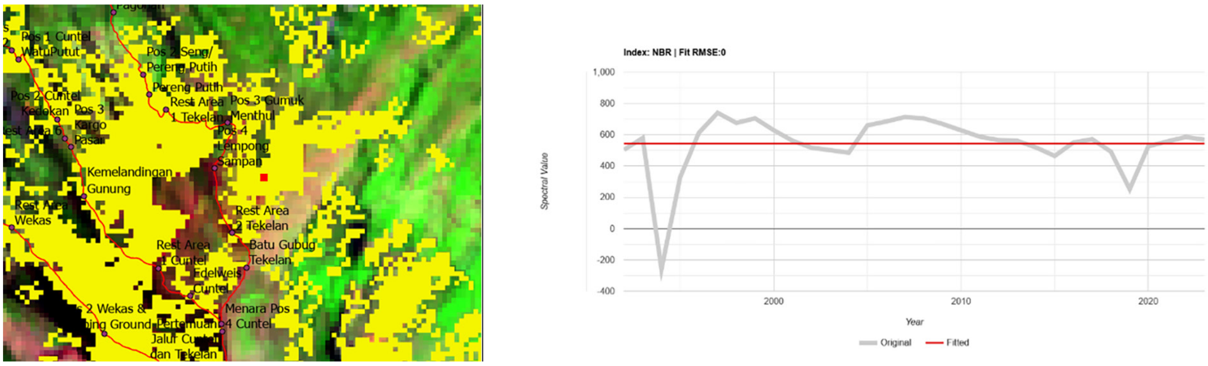

Figure 5. Sampling plot of vegetation gain and LandTrendr fitted disturbance trajectories based on NBR

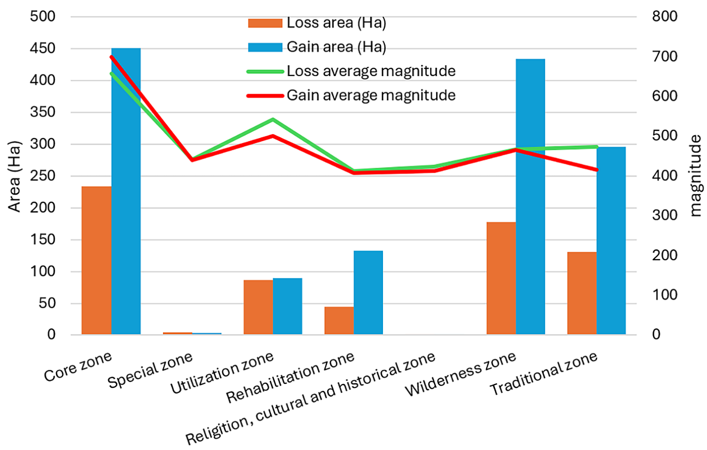

Figure 6. Graph of the area and the average magnitude of vegetation loss and gain

occurred in the past, mainly before area management was carried out by the Gunung Merbabu National Park Office, which can cause some information about disturbances to be missed. In addition, using Landsat imagery with medium spatial resolution causes the detection of changes in vegetation to be missed [Fu et al., 2022]. Application of imagery with higher resolution in the future, such as Sentinel 2 or lidar, was needed [Li et al., 2023]. If we look at the management of the Gunung Merbabu area, where in 2007 the area was carried out by the Gunung Merbabu National Park Office, the vegetation loss from 2007 to 2021 was 399.33 Ha and the vegetation gain was 732.87 Ha. Management of conservation areas that focus on protecting flora and fauna habitats and water catchment areas requires managers to maintain the existence of vegetation. Management of the Gunung Merbabu area differs from when the area was managed by Perhutani, where logging was still permitted for thinning or plant replacement. The most significant vegetation gain in the 2007–2021 period in 2020 was 369.27 Ha. This vegetation gain location is spread to the east of the Gunung Merbabu National Park area, which is a rehabilitation zone [BTNGMb, 2018] where ecosystem restoration activities were carried out from 2015 to 2019 and has now been removed from the rehabilitation zone to become wilderness zone [BTNGMb, 2020]. Vegetation loss in 2018, when overlaid with the climbing route, shows vegetation loss adjacent to the Selo climbing route before Post 3 Watu Tulis. If we examine further, this location was the site of fires in 2018 and 2019, and many Albizia lophanta died because fire and disease.

CONCLUSIONS

This study utilizes the Landtrendr algorithm to monitor vegetation changes and disturbances in Gunung Merbabu National Park located in Central Java Province, Indonesia. This algorithm leverages Google Earth images, Landsat imagery, and event information such as fires or logging to produce high-accuracy vegetation change maps. The research findings indicate that the Landtrendr algorithm effectively identifies vegetation changes, with vegetation gain exceeding loss from 1994–2021. However, there are several years with no loss or gain values, potentially due to poor image conditions or the absence of significant changes. So, it underscores the importance of validating results with reference data and understanding factors influencing vegetation change.

Applying the Landtrendr algorithm in this study provides in-depth insights into the dynamics of vegetation change in Gunung Merbabu National Park. The analysis reveals significant changes in the core zone of the area, primarily due to fires and logging activities. Nevertheless, the management of the area by the Gunung Merbabu National Park since 2007 demonstrates successful efforts in minimizing vegetation loss and increasing vegetation gain. This research enhances our understanding of temporal vegetation changes. It offers pertinent insights for conservation area managers to undertake appropriate mitigation measures to sustain ecosystem integrity and flora and fauna habitats in Gunung Merbabu National Park.

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REFERENCES

1. Ansari A., Golabi MH. 2019. Prediction of spatial land use changes based on LCM in a GIS environment for Desert Wetlands – A case study: Meighan Wetland, Iran. Int. Soil Water Conserv. Res. 7: 64–70.
2. Ardiaristo A., Prasetyo L.B., Syaufina L., Kosmaryandi N. 2022. The dynamics of land cover in conservation areas using cloud computing platform: Cases in Gunung Merbabu National Park. In: IOP Conference Series: Earth and Environmental Science.
3. Banskota A., Kayastha N., Falkowski M.J., Wulder M.A., Froese R.E., White J.C. 2014. Forest Monitoring Using Landsat Time Series Data: A review. Can. J. Remote Sens. 40: 362–384.
4. Begon M., Harper JL., Townsend CR. 1986. Ecology: individuals, populations and communities. Ecol. Individ. Popul. communities.
5. BTNGMb. 2019a. Laporan Kinerja 2018 Balai Taman Nasional Gunung Merbabu. Boyolali (ID): Balai Taman Nasional Gunung Merbabu.
6. BTNGMb. 2014. Rencana Pengelolaan Taman Nasional Gunung Merbabu Periode 2014-2023(review). Boyolali (ID): Balai Taman Nasional Gunung Merbabu. (in Indonesian).
7. BTNGMb. 2019b. Statistik Balai Taman Nasional Gunung Merbabu Tahun 2018. Boyolali (ID): Balai Taman Nasional Gunung Merbabu. (in Indonesian).
8. BTNGMb. 2020. Zona Pengelolaan (Revisi) Taman Nasional Gunung Merbabu Kabupaten Boyolali, Semarang dan Magelang Provinsi Jawa Tengah. Boyolali (ID): Balai Taman Nasional Gunung Merbabu. (in Indonesian).
9. BTNGMb. 2018. Zona Pengelolaan Taman Nasional Gunung Merbabu. Boyolali (ID): Balai Taman Nasional Gunung Merbabu. (in Indonesian).

10. Chen G., Zhong C., Li M., Yu Z., Liu X., Jia M. 2022. Disturbance of mangrove forests in Guangxi Beilun Estuary during 1990—2020. Natl. Remote Sens. Bull. 26: 1112 – 1120.
11. Cohen W.B., Yang Z., Healey SP., Kennedy RE., Gorelick N. 2018. A LandTrendr multispectral ensemble for forest disturbance detection. Remote Sens. Environ. 205: 131–140.
12. Cohen W.B., Yang Z., Kennedy R. 2010. Detecting trends in forest disturbance and recovery using yearly Landsat time series: 2. TimeSync — Tools for calibration and validation. Remote Sens. Environ. 114: 2911–2924.
13. Coops N., Wulder., White J. 2007. Identifying and describing forest disturbance and spatial pattern. In: Wulder MA, Franklin SE, editors. Understanding Forest Disturbance and Spatial Pattern; Remote Sensing and GIS Approaches. Florida (US): CRC Press, p 31–61.
14. Ding N., Li M. 2023. Mapping forest abrupt disturbance events in southeastern China—comparisons and tradeoffs of Landsat time series analysis algorithms. Remote Sens. 15.
15. Fu B., Lan F., Xie S., Liu M., He H., Li Y., Liu L., Huang L., Fan D., Gao E., Chen Z. 2022. Spatio-temporal coupling coordination analysis between marsh vegetation and hydrology change from 1985 to 2019 using LandTrendr algorithm and Google Earth Engine. Ecol. Indic. 137.
16. Hardian A.S., Firmansyah K.H., Aprazah AS., Pritta B.K., Ekowati Ratnaningrum E., Wahyudi J., Dewi K., Sulaksono N., Putra R., Sayudi D.S., Santoso A.B., Cholik N., Agusta R., Rusiani Hidayat S., Doludea T., Kristianto D. 2020. Mandala Merbabu, Seri Ekologi Merbabu Buku I. Harlan M, Sulaksono N, editors. Boyolali (ID): Balai Taman Nasional Gunung Merbabu. (in Indonesian).
17. He T., Guo J., Xiao W., Xu S., Chen H. 2023. A novel method for identification of disturbance from surface coal mining using all available Landsat data in the GEE platform. ISPRS J. Photogramm. Remote Sens. 205: 17 – 33.
18. Hirschmugl M., Deutscher J., Sobe C., Bouvet A., Mermoz S., Schardt M. 2020. Use of SAR and optical time series for tropical forest disturbance mapping. Remote Sens. 12.
19. Kennedy R., Yang Z., Gorelick N., Braaten J., Cavalcante L., Cohen W., Healey S. 2018. Implementation of the LandTrendr Algorithm on Google Earth Engine. Remote Sens. 10: 691.
20. Kennedy R.E., Yang Z., Cohen W.B. 2010. Detecting trends in forest disturbance and recovery using yearly Landsat time series: 1. LandTrendr - Temporal segmentation algorithms. Remote Sens. Environ. 114: 2897 – 2910.
21. Komba A.W., Watanabe T., Kaneko M., Chand M.B. 2021. Monitoring of vegetation disturbance around protected areas in central tanzania using landsat time-series data. Remote Sens. 13.
22. Kulakowski D., Buma B., Guz J., Hayes K. 2019. The Ecology of Forest Disturbances. Elsevier Inc. 1–12 p.
23. Li M., Zuo S., Su Y., Zheng X., Wang W., Chen K., Ren Y. 2023. An approach integrating multi-source data with LandTrendr Algorithm for refining forest recovery detection. Remote Sens. 15.
24. Li Y., Wu Z., Xu X, Fan H., Tong X., Liu J. 2021. Forest disturbances and the attribution derived from yearly Landsat time series over 1990–2020 in the Hengduan Mountains Region of Southwest China. For. Ecosyst. 8.
25. Liang L., Hawbaker T.J, Zhu Z, Li X, Gong P. 2016. Forest ecology and management forest disturbance interactions and successional pathways in the Southern Rocky Mountains. For. Ecol. Manage. 375: 35–45.
26. Liu Y., Xie M., Liu J., Wang H., Chen B. 2022. Vegetation disturbance and recovery dynamics of different surface mining sites via the LandTrendr Algorithm: Case study in Inner Mongolia, China. Land 11.
27. Nguyen T.H., Jones S.D., Soto-Berelov M., Haywood A., Hislop S. 2018. A spatial and temporal analysis of forest dynamics using Landsat time-series. Remote Sens. Environ. 217: 461–475.
28. Quintero N., Viedma O., Urbieta I.R., Moreno J.M. 2019. Assessing landscape fire hazard by multitemporal automatic classification of landsat time series using the Google Earth Engine in west-central Spain. Forests 10: 518.
29. Roy D.P., Kovalskyy V., Zhang HK., Vermote E.F., Yan L., Kumar S.S., Egorov A. 2016. Characterization of Landsat-7 to Landsat-8 reflective wavelength and normalized difference vegetation index continuity. Remote Sens. Environ. 185: 57–70.
30. Shen J., Chen G., Hua J., Huang S., Ma J. 2022. Contrasting forest loss and gain patterns in subtropical China detected using an integrated LandTrendr and Machine-Learning Method. Remote Sens. 14: 3238.
31. Smith V., Portillo-Quintero C., Sanchez-Azofeifa A., Hernandez-Stefanoni J.L. 2019. Assessing the accuracy of detected breaks in Landsat time series as predictors of small scale deforestation in tropical dry forests of Mexico and Costa Rica. Remote Sens. Environ. 221: 707–721.
32. Soulard C.E., Albano C.M., Villarreal M.L., Walker J.J. 2016. Continuous 1985-2012 Landsat monitoring to assess fire effects on meadows in Yosemite National Park, California. Remote Sens. 8: 1–16.
33. Tao C., Guo T., Shen M., Tang Y. 2023. Spatio-temporal dynamic of disturbances in planted and natural forests for the Saihanba Region of China. Remote Sens. 15.
34. Toker M., Çolak E., Sunar F. 2021. Spatiotemporal change analysis of the protected areas: A case study

- Ä°ä neada floodplain forests. In: International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences - ISPRS Archives. International Society for Photogrammetry and Remote Sensing, p 735–740.

35. Turner M.G., Simard M. 2017. Using spatial statistics and landscape metrics to compare disturbance mosaics. In: Gergel SE, Turner MG, editors. A Practical Guide to Concepts and Techniques. Learning Landscape Ecology. New York (US): Springer, p 175–190.
36. Umarhadi D.A., Wardhana W., Senawi Soraya E. 2023. Monitoring forest gain and loss based on LandTrendr algorithm and Landsat images in KTH Pati social forestry area, Indonesia. J. Appl. Nat. Sci. 15: 1051 – 1060.
37. Verbesselt J., Hyndman R., Newnham G., Culvenor D. 2010. Detecting trend and seasonal changes in satellite image time series. Remote Sens. Environ.
38. Wang W., Zhu L., Li L., Xue X., Feng Y., Xing H. 2023. A LandTrendr Algorithm– based study of forest disturbance from 2000 to 2020 in Jilin Province, China. Polish J. Environ. Stud. 32: 309 – 319.
39. Xiao W., Deng X., He T., Chen W. 2020. Mapping annual land disturbance and reclamation in a surface coal mining region using google earth engine and the landtrendr algorithm: A case study of the shengli coalfield in Inner Mongolia, China. Remote Sens. 12.
40. Zhang S., Yu J., Xu H., Qi S., Luo J., Huang S., Liao K., Huang M. 2023. Mapping the age of subtropical secondary forest using dense landsat time series data: An ensemble model. Remote Sens. 15.
41. Zhu Z., Woodcock C.E. 2014. Continuous change detection and classification of land cover using all available Landsat data. Remote Sens. Environ. 144: 152–171.