Celebes Agricultural 4(2): 79 - 87 February (2024)

Research Article

Monitoring and Visualizing the Impact of the Lapindo Mudflow Disaster Using Earth Engine Apps Platform based on Cloud Computing

Monitoring dan Visualisasi Dampak Bencana Lumpur Lapindo Menggunakan Platform Earth Engine Apps Berbasis Cloud Computing

Ali Dzulfigar [1,2]*, Muhammad Ikhwan Ramadhan [1,3], Azzahra Pascawisudawati [1,3], Rahmat Asy'ari [1,4], Yudi Setiawan [5,6], Rahmat Pramulya[7]

[1] IPB Sustainable Science Research Student Association, IPB University, Bogor Regency 16680, Indonesia
[2] Department of Silviculture, Faculty of Forestry and Environment IPB University, IPB Dramaga Campus, Bogor Regency 16680, Indonesia
[3] Department of Geophysics and Meteorology, Faculty of Mathematics and Science, IPB University, IPB Dramaga Campus, Bogor Regency 16680, Indonesia
[4] Department of Forest Management, Faculty of Forestry and Environment IPB University, IPB Dramaga Campus, Bogor Regency 16680, Indonesia
[5] Department of Forest Resources Conservation and Ecotourism, Faculty of Forestry and Environment IPB University, IPB Dramaga Campus, Bogor Regency 16680, Indonesia
[6] Center of Environmental Science, Lembaga Penelitian dan Pemberdayaan Masyarakat IPB, IPB University, Bogor Regency 16680, Indonesia
[7] Center for Low Carbon Development, University of Teuku Umar, Aceh, Indonesia

*email: adzulfigar@gmail.com

Abstract: The Lapindo mudflow disaster at the PT Lapindo Brantas drilling site in Ronokenongo Village, Porong District, Sidoarjo Regency, East Java caused the loss of agricultural and residential areas. The research aimed to detect the areas that are affected by Lapindo mudflow 2006-2022 using Landsat 7 ETM and Landsat 8 OLI-TIRS imageries, as well as visualize their impact using the cloud computing-based Google Earth Engine/GEE platform. Spatiotemporal data analysis was performed on the GEE platform using random forest machine learning as algorithm for supervised land use classification, while visualization was carried out through Earth Engine Apps. The results showed an increase in the mudflow-affected area from 2006 (204.57 ha) to 2012 (542.32 ha) with northeast direction, whereas the increase was insignificant at the following years. Within the detection period, agricultural land was the most affected area, followed by residential areas and bare land. The area ordering was similar during all detected years. The increasing size of the affected area can potentially have both direct and indirect impacts on the surrounding area. Therefore, special action is needed for the surrounding area, such as relocating settlements to safer areas against the Lapindo mudflow disaster.

Keywords: Disaster, Landsat, Remote Sensing

Abstrak: Bencana semburan lumpur Lapindo di lokasi pengeboran PT Lapindo Brantas di Desa Ronokenongo, Kecamatan Porong, Kabupaten Sidoarjo, Jawa Timur menyebabkan hilangnya lahan pertanian dan pemukiman. Penelitian ini bertujuan untuk mendeteksi wilayah yang terkena dampak semburan lumpur Lapindo 2006-2022 menggunakan citra Landsat 7 ETM dan Landsat 8 OLI-TIRS, serta memvisualisasikannya melalui platform Google Earth Engine/GEE berbasis komputasi awan. Analisis data spatiotemporal dilakukan pada platform GEE menggunakan pembelajaran mesin random forest sebagai algoritma untuk klasifikasi penggunaan lahan terawasi, sedangkan visualisasinya dilakukan melalui Earth Engine Apps. Hasil penelitian menunjukkan terjadi peningkatan luas wilayah terdampak semburan lumpur dari tahun 2006 (204,57 ha) hingga tahun 2012 (542,32 ha) dengan arah timur laut dari lokasi awal semburan, sedangkan peningkatannya tidak signifikan pada tahun-tahun berikutnya. Lahan pertanian merupakan lahan yang paling terkena dampak, disusul pemukiman dan lahan kosong dalam kurun waktu deteksi. Urutan wilayah yang terdampak serupa sepanjang tahun deteksi. Meningkatnya luas wilayah yang terkena dampak berpotensi menimbulkan dampak langsung dan tidak langsung terhadap wilayah sekitarnya. Oleh karena itu, diperlukan tindakan khusus terhadap wilayah sekitar, seperti merelokasi permukiman ke wilayah yang lebih aman terhadap bencana lumpur Lapindo.

Kata kunci: Bencana, Landsat, Penginderaan Jauh

Citation:
Dzulfigar A, Ramadhan MI, Pascawisudawati A, Asy'ari R, Setiawan Y, Pramulya R. 2024, Monitoring and Visualizing the Impact of the Lapindo Mudflow Disaster Using Earth Engine Apps Platform based on Cloud Computing. *Celebes Agricultural*. 4(2): 79-87. doi: 10.52045/jca.v4i2.703

Recived: August 2024
Accepted: October 2024
Published: December 2024

p-ISSN: 2723-7974
e-ISSN: 2723-7966
doi: 10.52045/jca.v4i2.703

Website:
https://ojs.untika.ac.id/index.php/faperta

INTRODUCTION

Remote sensing allows collecting data without direct contact with objects in time series to monitor land cover dynamics (Zhou et al. 2016; Asy'Ari et al. 2023; Rivai et al. 2023). The obtained data can provide specific information for monitoring land cover on the earth's surface using classification techniques (Rembold et al. 2015). The spectral characteristics of satellite image data that are acquired within a certain time span can be clustered using supervised or unsupervised classification to obtain spatiotemporal trend data on land cover changes (Gomez et al. 2016). Analyses on satellite imagery can spatiotemporally detect land changes including changes in spectral value thresholds, changes in index thresholds, image segmentation, image classification, and statistical analysis of spatial data (Zhu 2017).

The rapid development of remote sensing has encouraged the innovations to accelerate the retrieval and analysis of satellite image data. Currently, the development of cloud-based mapping platforms (cloud computing) is considered matured that capable to process large data (Mutanga and Kumar 2019). Google Earth Engine (GEE) is a cloud computing-based geospatial processing platform for monitoring and analyzing large-scale spatial data. The GEE platform can be used for educational and research purposes, allowing users to do scripting, discover, analyze/process and visualize large amounts of georeferenced data (Kumar and Mutanga 2018).

The capability to analyze time-series remote sensing data using cloud computing technology provide easy access to spatial information for monitoring purposes, specifically for disaster monitoring. Through satellite imagery analysis, spatial modelling capable to predict vulnerability, severity, and the intensity of disasters (Klemas 2015). Monitoring natural disasters can also be carried out using spatial indices as an indication of the drought disaster occurrences with differences in certain threshold values (Wang et al. 2022). The Lapindo mudflow disaster seriously impacted the social and economic aspects of society, which can result in conflict (Intakhiya et al. 2021). This disaster submerged agricultural, residential and industrial areas into a vast sea of mud (Dewantara 2013). Therefore, it is necessary to carry out spatiotemporal monitoring of the areas affected by the Lapindo mud flow as a consideration to prevent and handle this disaster.

MATERIALS AND METHODS

Research Location

The study location is in Sidoarjo Regency, East Java, especially at the Lapindo mudflow location. The location of the Lapindo mudflow is in three sub-districts, namely Porong, Tanggulangin, and Jabon. The location of the Lapindo mudflow is near the Porong River and the pond area to the east. A map of the research location is shown in Figure 1.

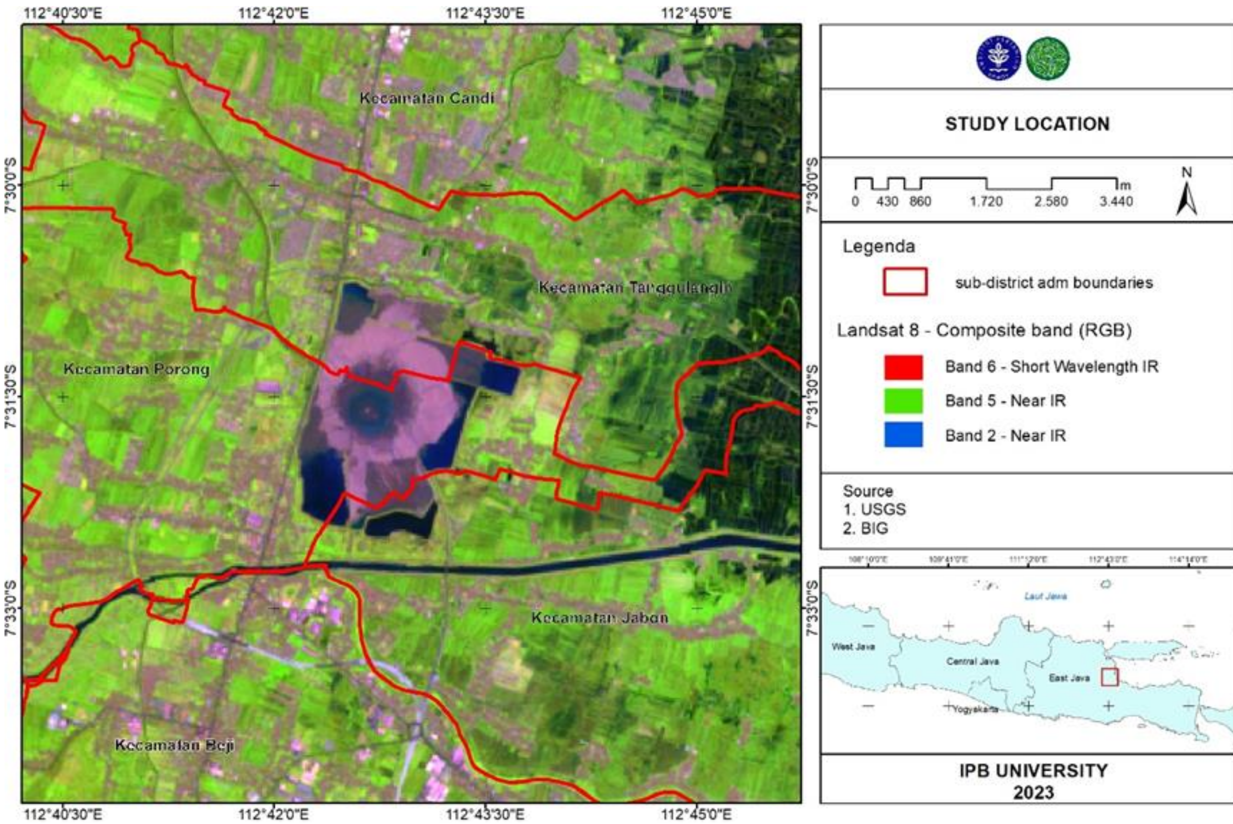

Figure 1. Map of research location

Data Processing

This research used secondary data in the form of Landsat-7 ETM+ satellite images for images in 2004, 2006, 2008, 2010, and 2012, as well as Landsat-8 OLI-TIRS for images in 2014, 2016, 2018, 2020, and 2022. Landsat-7 ETM+ is the second generation launched by NASA in 1998. Landsat-8 OLI-TIRS launched in 2013 is the generation after Landsat 7. Landsat 8 carries two sensors, namely Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS) (Adiri et al. 2020). Furthermore, other spatial data were obtained from the Indonesian Topographic Map (Peta Rupabumi Indonesia/RBI) including administrative boundaries of Sidoarjo Regency.

Data processing was conducted using the cloud computing-based GEE platform. This study classified the land cover using supervised classification to detect areas affected by the Lapindo mudflow (Figure 1) from 2004 to 2022. Random forest algorithm trained by 3380, 1018, 163, 561, and 4536 pixels of agricultural land, residential areas, bare land, water bodies, and mud, respectively. A total of 250 validation points (50 points per land uses) were created to assess the detection accuracy. Moreover, visualization of the affected areas was also carried out using the Earth Engine Apps platform (EE apps) with the SWIR-NIR-RED composite band. This research workflow is shown in Figure 2.

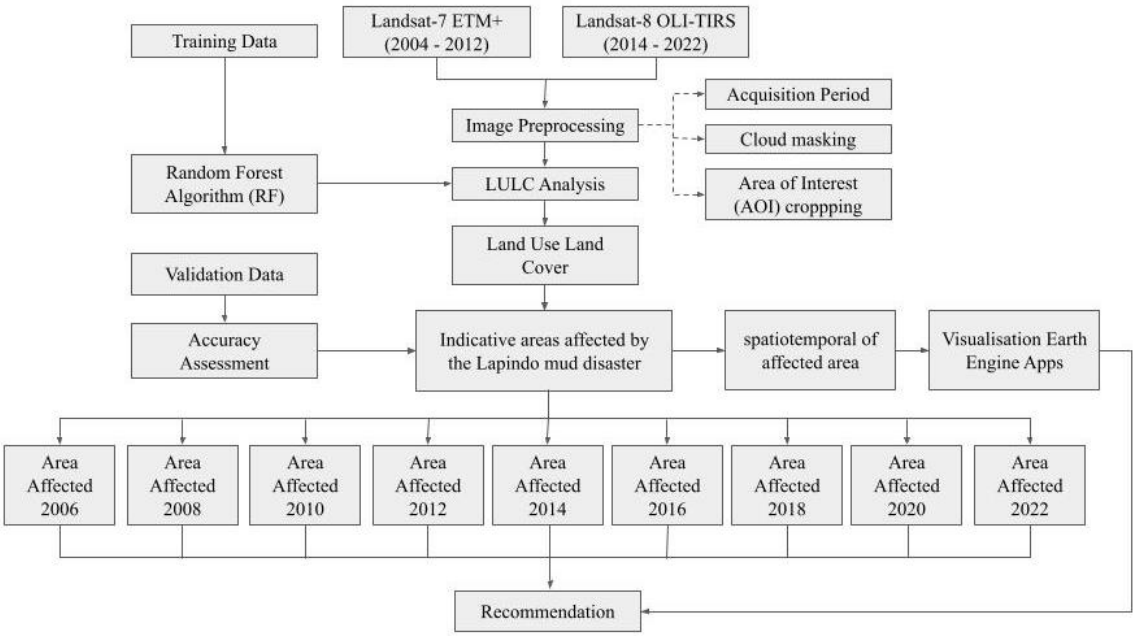

Figure 2. Map of research location

RESULTS

Detection of Areas Affected by The Lapindo Mudflow

The detection results presented in Figures 3 and 4 revealed that the mud affected areas increased dramatically from 2006 to 2012, encroaching northeastern areas since its inception. However, the slope showed an incremental pattern at the following years until the end of detection period. The most affected area submerged by the mudflow disaster was agricultural land, totalling around from 183.56 ha at the first detection year to 387.67 ha at the end of detection. Residential areas were the second most affected by mudflow disaster, constituted less than 5% of total mud-submerged areas. Its percentages were then significantly increased to one third of the total affected areas until 2012, which then remained steady until 2022. The least affected land use was bare land, which was detected less than 1% in 2006. Its contribution was increased to around 4% at the end of detection year. The land use ordering of mudflow-affected areas was similar in all detected years.

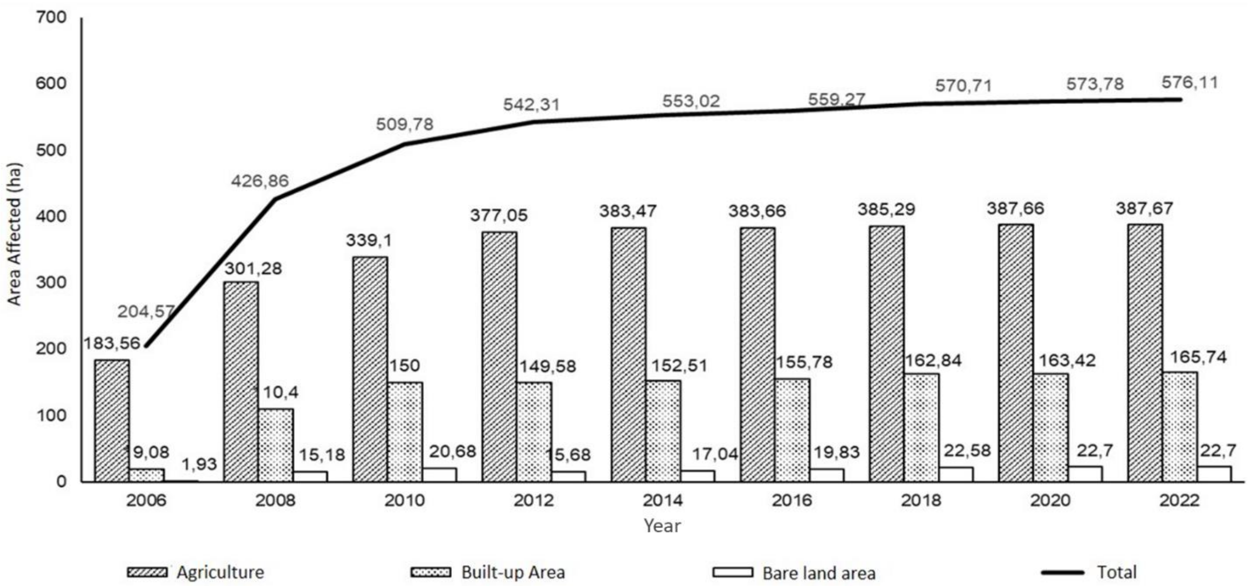

Figure 3. Graph of the area affected by the Lapindo mudflow

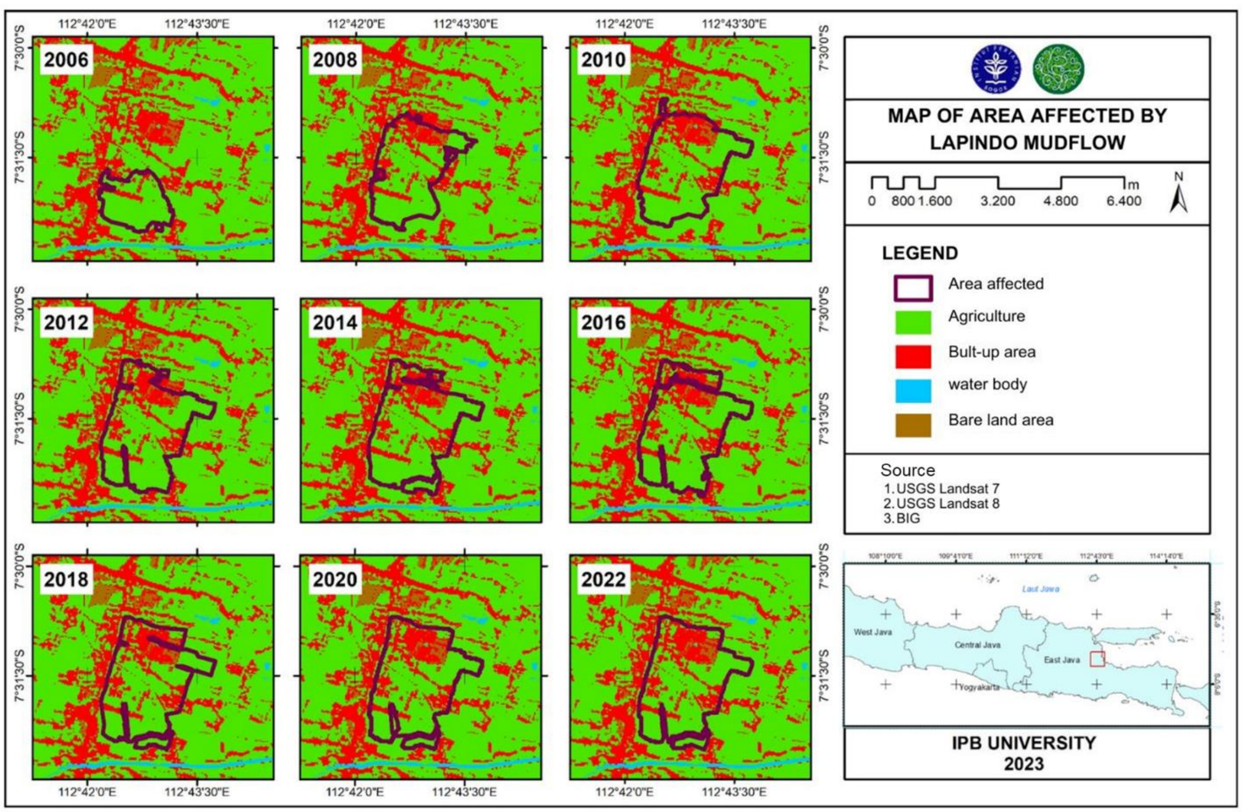

Figure 4. Spatiotemporal map of the area affected by the Lapindo mudflow

Earth Engine Apps Platform

The visualization results are displayed in the webGIS platform (Figure 5) with the SWIR-NIR-RED composite band. This platform can be accessed by the public via the EE Apps website (https://datastat-ssrs.users.earthengine.app/view/volume-08). The webGIS platform has an important role in providing interactive information and representing simple conditions. This webGIS platform was developed through GEE and is featured in the EE Apps feature.

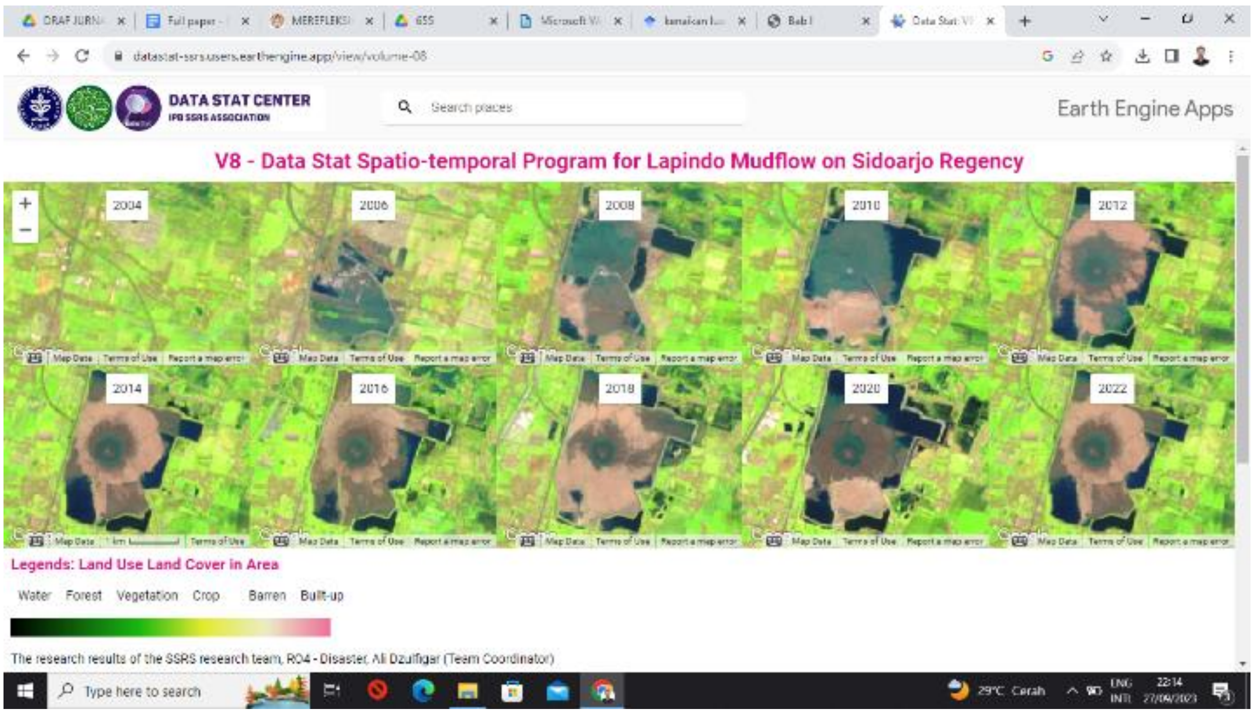

Figure 5. View of the Lapindo mud disaster monitoring webGIS platform

DISCUSSION

The Lapindo mudflow damaged the infrastructures around the affected area, such as subside the land elevation, bend the railway tracks, rupture the PDAM pipes, and collapse the mud retaining embankments (Ekawati 2018). The increase of the affected area by the Lapindo mudflow disaster is visually presented in a spatiotemporal map (Figure 4). The results of detecting areas affected by the Lapindo mudflow show an annual increase in the area. First, the area affected by the Lapindo mudflow started in 2006 was 204.57 ha and continued to increase rapidly to 542.32 ha in 2012. The type of land use most affected by the Lapindo mudflow disaster is agricultural land. The area of agricultural land lost due to the Lapindo mudflow disaster in 2022 is 387.67 ha or around 67% of the total area affected, while the residential area in 2022 is 165.74 ha. Conversely, the increase in Lapindo mudflow area from 2012 to 2022 was found to be insignificant (Figure 3). An area expansion was detected towards the north with the beginning of the mudflow in the rice fields (Figure 4). The first burst occurred in Siring Village, Porong District, Sidoarjo Regency, on 29th May 2006 due to a petroleum drilling error carried out by company of PT. Lapindo Brantas

(Suryaningsih and Handayani 2017). The increase of the affected areas was controlled by huge volume of released mud, which estimated to be around 5,000 to 50,000 m^3/day (Dewantara 2013).

The accuracy assessment resulted in total accuracy value of 93.2% with kappa value of 0.91. Our result was similar to Rivai et al (2023) who reported above 90% accuracy of the random forest algorithm in classifying land. Meanwhile, Madinu et al (2024), also reported that the random forest algorithm capable to differentiate land and sea with an accuracy of above 97%. Using 50 validation data, the algorithm correctly detected mud land cover with 100% accuracy. The increasing size of the affected area can potentially have both direct and indirect impacts on the surrounding area. Therefore, special action is needed for the surrounding area, such as relocating settlements to safer areas against the Lapindo mudflow disaster.

Figure 5 showed the appearance of the EE apps application. This platform allows users to access land cover changes resulting from the Lapindo mud disaster without having special skills in the field of GIS. Further development of this platform can be used to monitor land cover dynamics spatially and temporally. Apart from monitoring land cover, with certain modelling using satellite imageries, GIS analyst can use this platform to display evapotranspiration (Mhawej and Faour 2020), disaster impacts (Scheip and Wegman 2021), and water quality monitoring (Singh et al. 2021). This is an advantage of the Google Earth engine which is able to provide informative and open-source data based on cloud computing. As reported by Zhang et al (2020), Google Earth Engine can host and process satellite data into a cloud computing-based platform, providing information on changes in agricultural land cover. Furthermore, Allen et al (2015) developed an Earth Engine Apps-based platform using Google Earth Engine data.

CONCLUSIONS

The results of data analysis show that the area affected by the Lapindo mudflow has increased quite rapidly from 2006 (204.57) to 2012 (542.31 ha). In 2022, the affected area will be 576.11 ha. The type of land use most affected by the Lapindo mud disaster is agricultural land. The area of agricultural land lost due to the Lapindo mudflow disaster in 2022 is 387.67 ha or around 67% of the total affected area. Meanwhile, the residential area affected in 2022 is 165.74 ha or around 28.77% of the total affected area. The spatiotemporal map of the area affected by the Lapindo mudflow disaster is visualized on the EE Apps platform so that users can easily access spatial information related to the area affected by the Lapindo mudflow disaster.

ACKNOWLEDGMENT

The author would like to thank the head of IPB SSRS Association who has provided guidance and research facilities so that this paper can be completed.

REFERENCES

Adiri Z, Lhissou R, El Harti A, Jellouli A & Chakouri M. 2020. Recent advances in the use of public domain satellite imagery for mineral exploration: A review of Landsat-8 and Sentinel-2 applications. *Ore Geology Reviews*. 117: 103-332. https://doi.org/10.1016/j.oregeorev.2020.103332

Allen RG, Morton C, Kamble B, Kilic A, Huntington J, Thau D & Robison C. 2015. EEFlux: A Landsat-based evapotranspiration mapping tool on the Google Earth Engine. In 2015 ASABE/IA Irrigation Symposium: Emerging Technologies for Sustainable Irrigation-A Tribute to the Career of Terry Howell, Sr.). *American Society of Agricultural and Biological Engineers*. 1: 1-11. https://doi.org/10.13031/irrig.20152143511

Asy'Ari R, Ranti A, Rahmawati AD, Zulfajrin M, Nurazizah LL, Putra MCA, Sudrajat A. 2023. High Heterogeneity LULC Classification in Ujung Kulon National Park, Indonesia: A Study Testing 11 Indices, Random Forest, Sentinel-2 MSI, and GEE-based Cloud Computing. *Celebes Agricultural*. 3(2): 82–99. https://doi.org/10.52045/jca.v3i2.381

Dewantara AW. 2013. Merefleksikan hubungan antara etika Aristotelian dan bisnis dengan studi kasus lumpur lapindo. *Arete*, 2(1):23-40. https://doi.org/10.33508/arete.v2i1.663

Ekawati, J. 2018. Kebertahanan Kultural dan Religi di Area Permukiman Terdampak Bencana Lumpur Lapindo Sidoarjo, Jawa Timur. Sabda: *Jurnal Kajian Kebudayaan*. 13(2):122-134. https://doi.org/10.14710/sabda.13.2.122-134

Gómez C, White JC & Wulder MA. 2016. Optical remotely sensed time series data for land cover classification: A review. *ISPRS Journal of photogrammetry and Remote Sensing*. 116:55-72. https://doi.org/10.1016/j.isprsjprs.2016.03.008

Gorelick N, Hancher M, Dixon M, Ilyushchenko S, Thau D & Moore R. 2017. Google Earth Engine: Planetary-scale geospatial analysis for everyone. *Remote Sensing of Environment*. 202:18–27. https://doi.org/10.1016/j.rse.2017.06.031

Intakhiya DM, Santoso UP & Mutiarin D. 2021. Strategi dalam penanganan kasus lumpur lapindo pada masyarakat terdampak lumpur lapindo Porong-Sidoarjo, Jawa Timur. *Jurnal Ilmiah Ilmu Pemerintahan*. 7(3):565-585.

Jog S & Dixit M. 2016. Supervised classification of satellite images. *Conference on Advances in Signal Processing (CASP)*. 2016: 93-98. https://doi.org/10.1109/CASP.2016.7746144

Klemas V. 2015. Remote sensing of floods and flood-prone areas: An overview. *Journal of Coastal Research*. 31(4):1005-1013. https://doi.org/10.2112/JCOASTRES-D-14-00160.1

Kumar L & Mutanga O. 2018. Google Earth Engine applications since inception: Usage, trends, and potential. *Remote sensing*. 10(10):1-15. https://doi.org/10.3390/rs10101509

Madinu AM, Jouhary NA, Ulfa A, Rahmadhanti IN, Pudjawati NH, Asy'Ari R, Zamani NP, Pramulya R & Setiawan, Y. 2024. Monitoring of coastal dynamics at Subang Regency using Landsat Collection Data and Cloud Computing Based. *BIO Web of Conferences*. 106: 1-18, https://doi.org/10.1051/bioconf/202410604005

Mhawej M & Faour G. 2020. Open-source Google Earth Engine 30-m evapotranspiration rates retrieval: The SEBALIGEE system. *Environmental Modelling & Software*. 133: 1-9. https://doi.org/10.1016/j.envsoft.2020.104845

Mutanga O & Kumar L. 2019. Google earth engine applications. *Remote sensing*. 11(5):1-4. https://doi.org/10.3390/rs10101509

Rembold F, Meroni M, Urbano F, Royer A, Atzberger C, Lemoine G & Haesen D. 2015. Remote sensing time series analysis for crop monitoring with the SPIRITS software: new functionalities and use examples. *Frontiers in Environmental Science*. 3(46):1-11. https://doi.org/10.3389/fenvs.2015.00046

Rivai, FA, Asy'Ari R, Fadhil MH, Jouhary, NA, Saenal N, Ardan F, Pohan A, Pramulya R, & Setiawan, Y. 2023. Analysis of Land Use Land Cover Changes using Random Forest through Google Earth Engine in Depok City, Indonesia. *SSRS Journal B: Spatial Research*. 1:1-12

Rwanga SS & Ndambuki JM. 2017. Accuracy assessment of land use/land cover classification using remote sensing and GIS. *International Journal of Geosciences*. 8(04):611-622. https://doi.org/10.4236/ijg.2017.84033

Scheip CM & Wegmann KW. 2021. HazMapper: a global open-source natural hazard mapping application in Google Earth Engine. *Natural Hazards and Earth System Sciences.* 21(5), 1495-1511. https://doi.org/10.5194/nhess-21-1495-2021

Singh S, Singh H, Sharma V, Shrivastava V, Kumar P, Kanga S, Singh S K. 2021. Impact of forest fires on air quality in Wolgan Valley, New South Wales, Australia—A mapping and monitoring study using Google Earth Engine. *Forests*. 13(1): 2-17. https://doi.org/10.3390/f13010004

Suryaningsih A & Handayani BL. 2017. Bertahan Hidup Dalam Kubangan Lumpur (Studi tentang Korban Lumpur Lapindo di Desa Glagaharum Kecamatan Porong Sidoarjo). *Electronical Journal of Social and Political Sciences (E-SOSPOL)*. 4(1):6-11

Wang Q, Zhao L, Wang M, Wu J, Zhou W, Zhang Q & Deng M. 2022. A Random Forest Model for Drought: Monitoring and Validation for Grassland Drought Based on Multi-Source Remote Sensing Data. *Remote Sensing*. 14(19):1-16. https://doi.org/10.3390/rs14194981

Zhang C, Di L, Yang Z, Lin L & Hao P. 2020. AgKit4EE: A toolkit for agricultural land use modeling of the conterminous United States based on Google Earth Engine. *Environmental Modelling & Software*. 129: 1-34, https://doi.org/10.1016/j.envsoft.2020.104694

Zhou J, Jia L, Menenti M & Gorte B. 2016. On the performance of remote sensing time series reconstruction methods–A spatial comparison. *Remote Sensing of Environment.* 187:367-384. https://doi.org/10.1016/j.rse.2016.10.025

Zhu W, Jiang H, Zhou S & Addison M. 2017. The review of prospect of remote sensing image processing. *Recent Patents on Computer Science.* 10(1):53-6. https://doi.org/10.2174/2213275909666160616115416