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AI-Assisted NDVI Monitoring of Vegetation Change in Merapi National Park Using Google Earth Engine

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Abstract

Vegetation mapping is essential for monitoring conservation efforts in national parks and can be performed remotely using remote sensing and GIS technologies. However, the process is often complex and requires technical expertise. This study explores the use of AI, specifically ChatGPT, to simplify and support vegetation mapping workflows. We monitored monthly vegetation changes in Merapi Mountain National Park (TNGM) from 2017 to 2023 using the Normalized Difference Vegetation Index (NDVI) derived from Sentinel-2 satellite data. The workflow combined Google Earth Engine (GEE) for satellite image processing and Python in Jupyter Notebook for time series analysis, with ChatGPT assisting in code editing. Our results show NDVI patterns are significantly influenced by volcanic activity, particularly eruptions and pyroclastic clouds, and about one-third of images were affected by cloud cover, especially during the rainy season. ChatGPT performed well in non-coding queries with a 79% satisfaction rate, but only 53% of generated code prompts were correct without modification. We conclude that while AI tools like ChatGPT have strong potential to enhance accessibility and efficiency in remote vegetation mapping, human oversight and foundational knowledge in geospatial analysis remain essential for accurate results.

Keywords: AI in conservation, GIS, remote sensing, Taman Nasional Gunung Merapi, vegetation mapping

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Introductions

Google Earth Engine (GEE) has significantly transformed large-scale geospatial analysis by providing free satellite data and cloud computing services, reducing processing time compared to local computer processors (Gorelick et al., 2017). Despite its advantages, using GEE requires proficiency in JavaScript or Python, creating a barrier for non-programmers in ecology and conservation science. As remote sensing applications become increasingly valuable for environmental monitoring, simplifying access to these tools is essential for researchers and practitioners without formal coding training. To address this challenge, we propose integrating ChatGPT for code editing and generation, making GEE more accessible for ecological research.

While ChatGPT's role in scientific work raises concerns about ethics and plagiarism, it has demonstrated significant utility in translation, editing, and code transformation tasks (Foroumandi et al., 2023; Liang et al., 2024). Many ecologists lack formal training in programming, and remote sensing analysis often demands proficiency in multiple languages, including JavaScript for GEE and

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Python or R for statistical analysis (Lai et al., 2019; Rajamani & Iyer, 2023). AI-driven tools like ChatGPT can bridge this skill gap by assisting users in generating, understanding, translating, and troubleshooting code, thus lowering technical barriers (H. Zhang et al., 2023; W. Zhang et al., 2024). By integrating ChatGPT with GEE, researchers can enhance their efficiency in vegetation monitoring, making remote sensing data more accessible to broader audiences.

Monitoring vegetation dynamics is critical for conservation, particularly in dynamic volcanic landscapes like Merapi National Park, where regrowth patterns post-eruption provide key insights into ecosystem resilience (Yuniasih, 2017). The Normalized Difference Vegetation Index (NDVI) is one of the most widely used indicators for vegetation health assessment, calculated from multispectral satellite imagery by measuring the contrast between near-infrared (NIR) and red light reflectance (Carlson & Ripley, 1997; Hartoyo et al., 2025; Ichii et al., 2002; Rahmat et al., 2018). NDVI values has range from -1 (indicating water or barren land) to +1 (indicating healthy, dense vegetation). Sentinel-2, part of the European Space Agency's Copernicus program, provides high-resolution multispectral data with enhanced spatial and temporal resolution, making it particularly well-suited for vegetation analysis in comparison to Landsat data (Phiri et al., 2020; Spoto et al., 2012). Utilizing Sentinel-2 data within GEE enables efficient monitoring of vegetation changes in Merapi National Park and other similar environments.

GEE facilitates large-scale analysis by providing pre-processed satellite imagery and powerful cloud computing capabilities. Previous studies have successfully leveraged GEE for applications such as vegetation mapping, land cover classification, and climate impact assessments (Brown et al., 2022a; Lasaponara et al., 2021). However, its JavaScript-based interface limits accessibility for ecologists and conservationists who lack programming expertise. ChatGPT presents an opportunity to bridge this gap by assisting users with JavaScript scripting, enabling broader adoption of GEE for environmental research and decision-making (Foroumandi et al., 2023; Liang et al., 2024). ChatGPT can help automate workflows, allowing researchers to focus on ecological interpretation rather than coding challenges.

This study analyze Merapi's vegetation cover from 2017 to 2023 using Sentinel-2 NDVI data processed within GEE. We standardize NDVI visualization across different years and generate statistical summaries of vegetation trends, providing insights into ecosystem recovery patterns post-eruption. ChatGPT facilitates JavaScript and Python coding, improving data accessibility and workflow efficiency. Our framework demonstrates that integrating AI-assisted coding with remote sensing technology can empower non-programmers, including researchers, policymakers, and forest managers, to leverage satellite data for ecological monitoring. By lowering technical barriers, this approach enhances the usability of geospatial analysis tools, fostering more inclusive and data-driven conservation practices.

Methods

Study Area

Merapi National Park is a dynamic and ecologically significant area located on the slopes of Mount Merapi, one of Indonesia's most active volcanoes The park experiences frequent volcanic eruptions—roughly once every decade—that cause disturbances and reshape the landscape (Newhall et al., 2000). Since 2017, Mount Merapi has experienced multiple eruptions, including significant activity in 2018 and 2020. These disturbances have substantial ecological impacts, altering vegetation patterns and affecting habitats and species within the park (Afrianto et al., 2020; Suryanto et al., 2010). Monitoring vegetation is crucial for managing and conserving the biodiversity and ecosystem health of this dynamic environment.

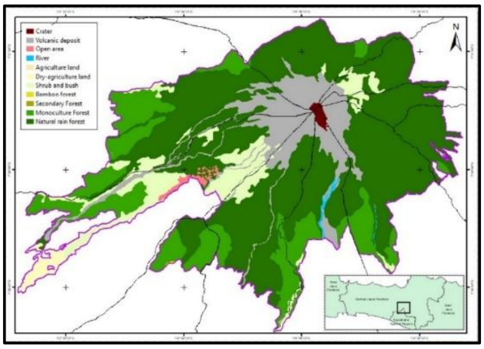

Figure 1. Map of Merapi National Park and its ecosystem types

Data Processing

The first step involves uploading the shapefile (.shp) of Merapi National Park (provided by Balai Taman Nasional Gunung Merapi, TNGM) to Google Earth Engine (GEE). This file delineates the national park's border, which is essential for focusing the NDVI analysis specifically on the target area. We manually imported the shapefile via the 'Assets' section, allowing for efficient data management and facilitating further processing.

After delineating the national park area, the next step was to compute the NDVI based on Sentinel-2 imagery (Amiri & Pourghasemi, 2022). We used a base script provided on the GEE website and inputted it into ChatGPT, instructing it to modify the code according to our needs. Specifically, we prompted it to apply the national park boundary file and calculate NDVI within that area. We encountered several errors during the process, particularly with images not displaying correctly. After multiple iterations of checking and debugging the code, we discovered that Sentinel-2 data for the Merapi region is only available from May 2017 onward, even though Sentinel-2 began operating in 2015.

Once we successfully processed NDVI for May 2017, we instructed ChatGPT to generate monthly NDVI images for the entire year. However, since the script automatically applies a cloud mask, data for certain months—especially during the rainy season—was unavailable. Additionally, images could not be generated during volcanic eruptions due to excessive cloud coverage. After successfully generating NDVI images for 2017, we prompted ChatGPT to modify the script for batch processing, enabling the automatic generation of NDVI images for each month from 2018 to 2023. The resulting NDVI images are then exported to Google Drive and downloaded into local storage. Finally, we also prompted ChatGPT to generate a script to calculate the mean and median NDVI for each month and export the results as a CSV file. We repeated these processess several times to ensure repeatbility.

Data Analysis and Visualization

We conducted data visualization using Python in the Jupyter Notebook interface. All files were placed in the Jupyter Notebook working directory, and we prompted ChatGPT to create a visualization of one NDVI map. After successfully generating a single map, we asked ChatGPT to create a script for a collage of 12 monthly images, allowing for year-long comparisons. Some challenges arose during this process. By default, ChatGPT normalized the NDVI scale for each image using min-max scaling to enhance contrast. However, this approach resulted in inconsistent NDVI color scales, making comparisons difficult. It took several prompts to ensure a consistent NDVI color scale across all images.

After completing the yearly NDVI maps, we generated maps for multiple years. We encountered a similar issue, ChatGPT applied min-max scaling based on each year's average NDVI, leading to inconsistencies across years. Finally, we prompted ChatGPT to use an absolute NDVI scale for all years, ensuring a consistent and comparable color scale. We also instructed ChatGPT to retain months without available images, displaying them as empty maps with only the park boundary. Once the composite images for each year were generated, we loaded the CSV table containing mean and median NDVI values from GEE. We asked ChatGPT to create a Python script for visualize these values across the months from 2017 to 2023. Some initial errors occurred when the axis labels were too crowded, but ChatGPT successfully generated suitable graphs after some troubleshooting.

We analyzed the capability of ChatGPT by counting the number of prompts that resulted in satisfactory code versus those that produced errors. We also categorize the chat into coding and non coding chat. Since ChatGPT is not a perfect tool and operates based on prompts, it sometimes generates answera or code that contains errors.

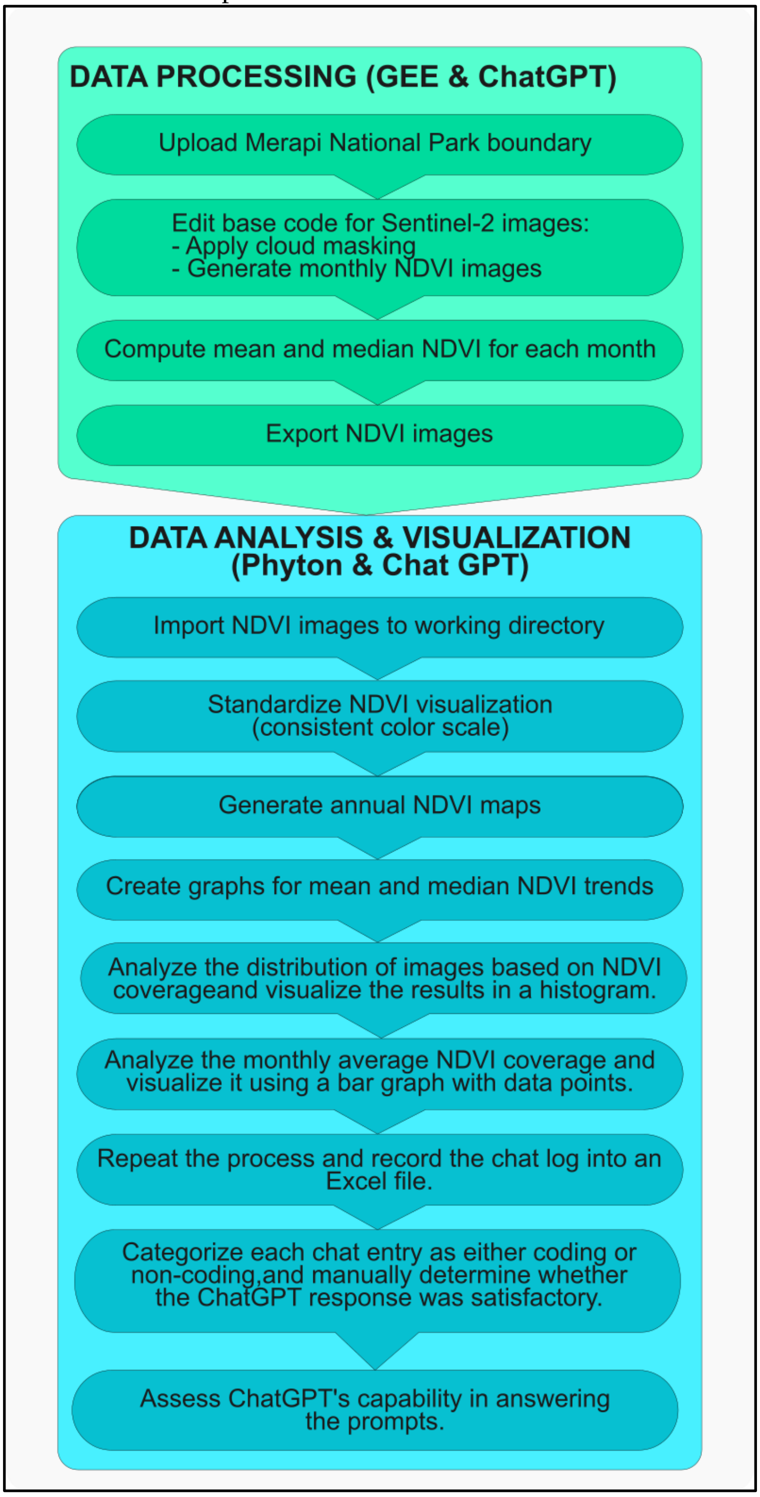

Figure 2. Schematic overview of NDVI data processing, analysis, and visualization steps applied to Merapi National Park, supported by Google Earth Engine, Python, and ChatGPT.

Additionally, we analyzed the resulting NDVI images and evaluated their usefulness (Poldrack et al., 2023). This assessment was based on the number of successfully generated monthly NDVI images that were fully covered by cloud, partially covered by cloud, and not covered by clouds and how interpretable the images were. We also examined the correlation between the images and real-world events, such as climate conditions and volcanic eruptions, that may have influenced the results (Pettorelli et al., 2005). Finally, we provided suggestions for improving the accuracy and interpretability of the NDVI analysis.

Total 80 monthly NDVI images were generated from May 2017 to December 2023 (Figure 3). Temporal analysis of NDVI values (Figure 4) indicates relatively stable vegetation conditions between 2017 and 2021, with mean NDVI values ranging from 0.5 to 0.6. However, from 2022 onward, a decline is observed, with values dropping between 0.3 and 0.4. This reduction may be linked to increased volcanic activity at Mount Merapi. Notably, significant eruptions occurred in 2022 and 2023, including major events in March and May 2023, which released volcanic ash and pyroclastic flows, potentially impacting vegetation cover.

Results and Discussion

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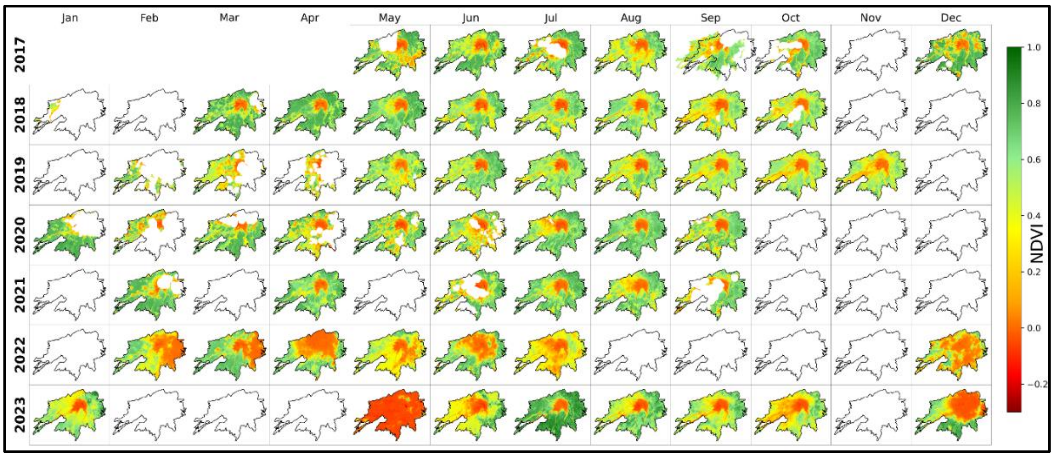

Figure 3. Monthly NDVI maps of Merapi National Park for 2017 and 2023. Sentinel-2 satellite data is not available for this area before May 2017. Empty maps indicate that high cloud coverage prevented the automatic generation of NDVI images by Google Earth Engine.

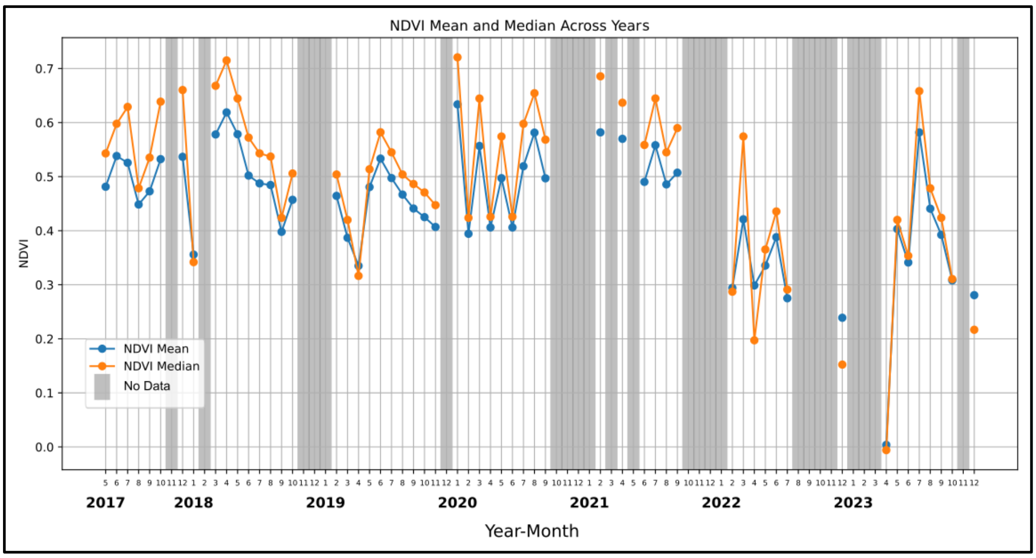

Figure 4. Monthly mean and median NDVI values of Merapi National Park from May 2017 to December 2023. Gray bars indicate months with no available data due to cloud coverage or missing imagery.

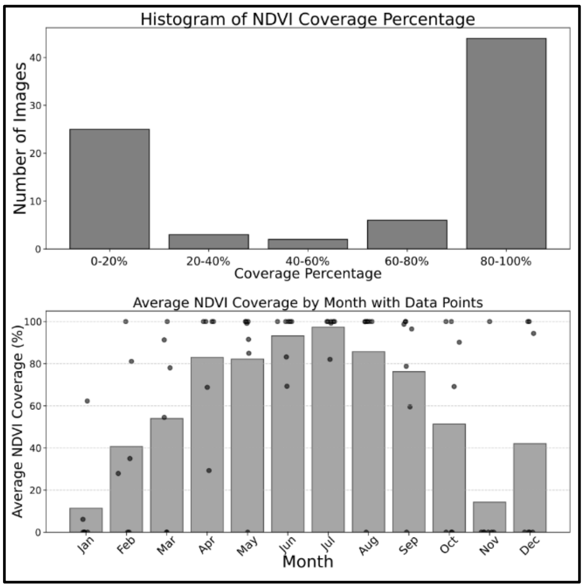

Figure 5. Distribution of the images based on percent NDVI coverage (above) and average NDVI coverage based on months (below).The data points represent same months from different year of 2015-2023.

Figure 5A presents a histogram of NDVI image coverage after cloud masking. The distribution follows a near-bimodal pattern, where 44 images (55%) exhibit 80–100% cloud-free NDVI coverage, while 24 images (30%) have only 0–20% clear NDVI coverage. The remaining images are distributed more evenly across intermediate bins, including 20–40%, 40–60%, and 60–80% coverage. Seasonal analysis of NDVI image coverage (Figure 5B) shows a clear trend, where dry season months (April–September) consistently achieve higher coverage, often exceeding 80%. This is expected, as reduced cloud cover during the dry season improves satellite image clarity. Previous studies have shown that cloud cover significantly affects the quality of remote sensing data, particularly in tropical regions, where persistent cloudiness can obstruct observations (Nazarova et al., 2020; Rodríguez-Puerta et al., 2024; Ruwaimana et al., 2019).

Table 1 summarizes ChatGPT's performances in assisting with coding and non-coding tasks. A total of 207 interactions were analyzed across eight sessions, with seven being non-informative (e.g., greetings). Of the remaining 200 prompts, 171 (85.5%) were related to coding, with ChatGPT providing satisfactory responses in 84 cases (49.1%) and unsatisfactory responses in 87 cases (50.9%). Common errors in unsatisfactory responses included incomplete code, incorrect outputs, and mistakes in remote sensing visualizations, such as incorrect NDVI color scaling. For non-coding queries, which accounted for 29 interactions (14.5%), ChatGPT performed notably better, delivering satisfactory responses in 23 cases (79.3%) and unsatisfactory responses in only six cases (20.7%).

Overall, ChatGPT demonstrated a 53.5% satisfaction rate across all interactions. These findings suggest that while ChatGPT can be useful for coding assistance, its effectiveness is limited by its tendency to generate incomplete or incorrect scripts. ChatGPT is primarily designed for natural language processing, so it performs better in non-coding tasks, such as explanations or general conceptual discussions (Sun et al., 2024). Users should, therefore, possess foundational programming and remote sensing knowledge to effectively utilize ChatGPT-generated code.

Table 1. Valuation of ChatGPT's performance in responding to prompts. The table shows the number and percentage of prompts classified as coding or non-coding, along with whether the responses were judged satisfactory (Y) or unsatisfactory (N). Human judgment was used to determine the quality of each response. The complete chat log is available in the supplementary document.

		Satisfactory		
		Y	**N**	**Total**
Chat Category	**Coding**	84 (49.1%)	87 (50.9%)	171
	Non-coding	23 (79.3%)	6 (20.7%)	29
	Total	107 (53.5%)	93 (46.5%)	200

Utilization of ChatGPT to use Google Earth Engine (GEE) presents an accessible approach to democratizing remote sensing analysis, particularly in the ecological and environmental sciences (Foroumandi et al., 2023; W. Zhang et al., 2024). This study demonstrates how ChatGPT can facilitate code generation, troubleshooting, and script optimization, significantly reducing the technical barriers for researchers with limited programming experience. One key advantage observed in this integration is the acceleration of data processing workflows. Traditional remote sensing analysis in GEE requires proficiency in JavaScript or Python, which can be a bottleneck for many researchers. ChatGPT mitigates this challenge by providing contextual assistance, suggesting syntax corrections, and even generating entire scripts based on user queries while refining the scripts based on further prompts. This not only improves productivity but also enables a broader audience to utilize GEE for environmental monitoring, conservation efforts, and land-use studies (Foroumandi et al., 2023; Zhu et al., 2023).

Despite these benefits, there are certain limitations to be addressed. ChatGPT's responses depend on the clarity of user queries, and its generated code may occasionally contain errors or inefficiencies that require human verification (Poldrack et al., 2023; Zhu et al., 2023). example, GPT does not recognize that Sentinel data for early 2017 does not exist, and it tends to normalize the scale, making composite maps incomparable across years. Thus, users have to debug and find mistakes by themselves. Based on our data, GPT tends to make mistakes in more than half of the scripts it generates. However, it should also be noted that we used the free version of ChatGPT, while the paid version might potentially yield better results (Jo, 2025). Nevertheless, as the primary of this research is to make this process accessible to everyone, we did not use the paid version. We also have not yet tested other AI models, and comparing different AI tools could be an area for future exploration (Chowdhury et al., 2025). Additionally, as a disclaimer, at the time of this experiment, we had significant experience in GIS but little to no understanding of JavaScript or Python coding, and the entire code was generated by GPT AI based on our prompts.

At the current stage of GPT AI, with nearly half of the generated code containing errors, this technique cannot yet be implemented by anyone wishing to create maps. A basic understanding of data sources and a general grasp of GIS processes are still necessary to craft effective prompts for ChatGPT and verify whether GPT has made mistakes. A sanity check is crucial, as GPT repeatedly makes errors, such as miscalculating NDVI color scaling. Future improvements in AI-driven code assistance could address these limitations by incorporating more domain-specific training (Espinel et al., 2024; Hendler, 2023).

Our resulting NDVI maps derived from Sentinel data face a major challenge: cloud cover. This is a significant issue in remote sensing, particularly in tropical regions such as Merapi National Park, where persistent cloudiness can obscure satellite observations. Cloud cover further complicates NDVI analysis by limiting the availability of clear-sky images. Of the 80 images analyzed, only 55% (44 images) exhibit 80–100% cloud-free NDVI coverage, while 30% (24 images) have only 0–20% clear NDVI coverage. Seasonal trends show that dry-season months (April–September) achieve higher cloud-free coverage, often exceeding 80%, while wet-season months experience substantial cloud obstruction. In the case of Merapi, an active volcano, pyroclastic clouds are also frequently released, further obscuring the images. Therefore, though the codes used in this research already utilize image compositing by combining images from multiple dates within a monthly time window, cloud cover remains a significant challenge.

One potential solution is using of cloud-penetrating sensors such as Synthetic Aperture Radar (SAR) data from Sentinel-1 to monitor vegetation, which is unaffected by cloud cover and can provide complementary vegetation and land cover information (Francis & Rothery, 2000).However, this technique has limitations, especially in highly variable terrain like mountain slopes, where the digital surface model created by SAR Sentinel-1 is less accurate. This challenge is further compounded by volcanic eruptions, which cause extreme changes in ground cover. A possible approach is to combine multiple satellite platforms or focus on analyzing dry-season images to reduce uncertainty caused by cloud cover (Xu et al., 2022). However, this method would sacrifice data from the rainy season, which is equally or even more critical in ecological and phenology studies, as it is when plant growth is at its peak.

Another viable solution is the utilization of drone camera, as drones fly below the cloud cover and are thus unaffected by it (Ruwaimana et al., 2019; Tang & Shao, 2015). Current drone technology, such as fixed-wing drones, can already cover hectares of land, and attaching multispectral cameras makes vegetation analysis possible. However, compared to satellite data, drone surveys are quite costly. For example, a recent Merapi National Park commission for drone-based imaging cost several hundred millions of rupiah to capture an area of several hectares, whereas Sentinel satellite images are freely available. Ultimately, the choice of data source and analysis method depends on the user, the availability of resources, and the trade-offs between the pros and cons of each approach (Kenyeres et al., 2023; Ruwaimana et al., 2018). Users must weigh factors such as accuracy, cost, temporal coverage, and accessibility when deciding how to conduct their analyses.

Conclusions and Suggestions

The findings of this study highlight the potential and limitations of using ChatGPT to assist in remote sensing analysis with Google Earth Engine (GEE). While ChatGPT effectively streamlines coding tasks by providing syntax corrections and script generation, its accuracy remains a significant concern. More than half of the generated scripts contained errors, requiring human verification and debugging. This limitation suggests that ChatGPT, in its current form, is best suited as a supplementary tool rather than a standalone solution for remote sensing applications. Foundational knowledge in GIS and programming remains essential for users to effectively utilize AI-generated scripts while ensuring data integrity and analysis accuracy.

Cloud cover emerged as a significant challenge in NDVI analysis, particularly in tropical environments like Merapi National Park, where persistent cloudiness significantly obstructs remote sensing observations (Xu et al., 2022). Despite compositing techniques to mitigate this issue, nearly half of the analyzed images had low clear-sky coverage, impacting the reliability of long-term vegetation monitoring. Seasonal trends revealed that the dry season provided better image clarity, but volcanic activity further complicated NDVI analysis due to pyroclastic cloud interference. Future studies could explore alternative data sources, such as Synthetic Aperture Radar (SAR) from Sentinel-1, which penetrates cloud cover, although terrain distortion in mountainous regions remains a concern.

A combination of approaches should be considered to improve remote sensing analysis in challenging environments. While SAR data offers an alternative to optical imagery, drone-based surveys provide higher-resolution vegetation analysis at a higher cost. The trade-offs between accuracy, accessibility, and financial constraints must be carefully evaluated depending on research objectives.

This study also has several limitations. The analysis was restricted to free AI tools, and it is possible that paid AI services or AI models specifically designed for coding tasks—such as GitHub Copilot or DeepCode—may perform better than ChatGPT in generating reliable scripts (W. Zhang et al., 2024). Furthermore, the quality of prompts plays a critical role in determining the usefulness of AI-generated outputs. Although all participants had at least a basic understanding of GIS and mapping, variability in how prompts were formulated influenced the clarity and accuracy of ChatGPT's responses. This highlights the importance of both user expertise and prompt design in maximizing the benefits of AI-assisted coding.

Future research could expand in several directions. First, systematic studies on prompt design are needed to better understand how wording, structure, and context affect AI-generated code quality and accuracy. Second, comparative evaluations of different AI models, both free and paid, as well as those purpose-built for coding, would provide a clearer picture of their strengths and weaknesses in geospatial applications (Poldrack et al., 2023; H. Zhang et al., 2023; W. Zhang et al., 2024; Zhu et al., 2023). Third, future coding experiments should extend beyond Sentinel-2 imagery to incorporate a broader range of satellite datasets, including Landsat, MODIS, and commercial high-resolution imagery, which may improve vegetation monitoring and ecological assessments (Brown et al., 2022b; Phiri et al., 2020). By combining these approaches, researchers can develop more robust frameworks for integrating AI into remote sensing workflows, enhancing both accessibility and reliability for ecological monitoring and conservation efforts

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