BIO Web of Conferences **136**, 03002 (2024) https://doi.org/10.1051/bioconf/202413603002
ISFM XIII 2024

Integration of generative artificial intelligence and Google Earth Engine for mangrove land cover mapping

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Abstract. Mangrove ecosystems, crucial for coastal sustainability, are threatened by human activities, underscoring the need for accurate mapping for effective conservation. This research explores the novel integration of generative artificial intelligence, specifically Microsoft Copilot, with Google Earth Engine (GEE) for mapping mangrove land cover in Kembung River, Bengkalis Island, Indonesia. The methodology leverages Copilot's natural language processing capabilities to generate GEE JavaScript code, streamlining the process of Sentinel-2 imagery processing and land cover classification using the Random Forest algorithm. Copilot assists in automating complex coding tasks, reducing development time and potential human errors. However, challenges emerge in hyperparameter tuning within GEE's computational constraints. The results demonstrate an overall accuracy of 84.4% (Kappa = 0.794) in identifying nine land cover classes, with mangroves covering 46.6% of the study area. This innovative approach enhances mangrove mapping efficiency and accuracy, paving the way for improved monitoring and conservation. The study also highlights the potential of AI in environmental science applications, particularly in conservation. Future research should optimize Copilot's performance for advanced geospatial tasks, address spectral variability challenges, and explore its applicability across diverse ecosystems. This study contributes to

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mangrove conservation efforts and demonstrates the potential of AI-assisted coding in environmental science applications.

1 Introduction

Mangrove ecosystems are crucial in coastal sustainability, offering multifaceted benefits, including disaster mitigation, carbon sequestration, and support for local economies [1, 2, 3]. However, human activities increasingly threaten these vital ecosystems, underscoring the urgent need for accurate mapping to inform effective conservation strategies [4, 5, 6]. Advancements in earth observation technologies, particularly the availability of remote-sensing data, have created new opportunities for more precise and efficient monitoring, analysis, and mapping of mangrove ecosystems [7]. These technologies provide valuable insights into mangrove distribution and health status, supporting improved decision-making and conservation planning [8].

Generative AI, a cutting-edge technology excelling in processing new data frameworks, holds significant promise for environmental mapping tasks. This technology learns patterns or distributions within extensive datasets and generates original outputs distinct and reminiscent of previous examples [9]. This capability makes generative AI particularly suitable for environmental mapping tasks, where complex patterns and high variability in data prevail. In the context of mangrove mapping, generative AI offers several advantages over traditional approaches. It quickly adapts to different types of satellite imagery and spectral signatures, which is crucial given the variability in mangrove ecosystems across different regions. Generative AI excels at recognizing complex patterns in data, which is essential for distinguishing mangroves from other vegetation types in mixed coastal landscapes. Generative AI significantly reduces the time and effort required for data processing and analysis by automating much of the code generation process.

The Google Earth Engine (GEE) has emerged as a powerful global tool for measuring, monitoring, and analyzing environmental changes on Earth. GEE aggregates satellite data from various sources spanning decades, providing easy access to historical and real-time data, including maps, statistics, satellite images, and climate data [10]. Integrating state-of-the-art generative AI with GEE substantially benefits mangrove ecosystem mapping [11]. This integration enhances the potential to derive accurate data and simulations from land-based observational data, enabling in-depth analysis of environmental conditions and changes [12]. Researchers can create detailed maps of mangrove distribution and predict ecological changes over time, such as those resulting from climate change and rising sea levels.

Microsoft Copilot is an ideal choice among the various generative AI tools for integrating with GEE. Copilot specializes in code generation, making it ideal for producing the complex JavaScript code required for GEE operations. Its ability to understand context and intent allows it to generate more relevant and accurate code for specific mapping tasks. Copilot's model undergoes regular updates, ensuring access to the latest coding practices and GEE functionalities. Furthermore, Copilot's design allows seamless integration with various development environments, facilitating its use with GEE's code editor.

This research explores the feasibility and effectiveness of integrating Microsoft Copilot with GEE to enhance mangrove ecosystem mapping efficiency. The study addresses a significant gap in current research: the need for more exploration into how AI-assisted coding can streamline and improve the accuracy of environmental mapping processes, particularly for complex ecosystems like mangroves. The approach seeks to identify innovative methods for monitoring and analyzing this sensitive and critical ecosystem, leveraging extensive volumes of earth observation data and conducting advanced analytics. The study aims to develop more precise predictive models for the dynamism inherent in mangrove ecosystems, supporting theoretical mapping advancements and offering practical pathways for integrating these technologies into global conservation and management programs.

2 Materials and methods

2.1 Location and time of research

The mangrove ecosystem along the Kembung River on Bengkalis Island in Riau Province, Indonesia, served as the research site (see Figure 1). Field observations were conducted in June 2024. The study area is located at a longitude range of 102°21'47.96" to 102°29'47.69" E, and a latitude range of 1°31'25.34" to 1°26'28.18" N. Mangroves thrive along the Kembung River and its tributaries, extending from the upper reaches to the lower reaches, where the river drains into the Malacca Strait. Coastal areas directly facing the Malacca Strait have been impacted by erosion, particularly affecting fringing mangroves, including Avicennia alba and Sonneratia alba. These mangroves are vital for the livelihoods of several communities along the coast of the Kembung River, providing marine products and timber. The Akit people, an indigenous community residing in the mangrove forests, rely on mangrove-related activities for their sustenance.

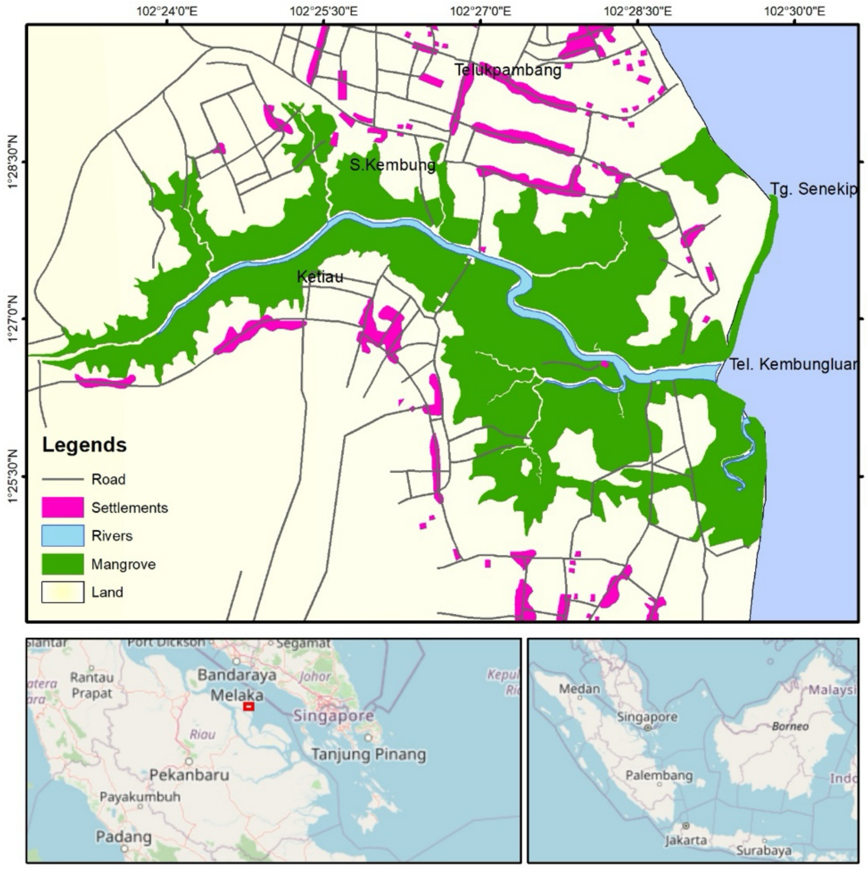

Fig 1. Maps illustrate the position (marked by a red square) of the Kembung River, which is the focus of this research

2.2 Data analysis

2.2.1. Microsoft Copilot

Microsoft Copilot is an evolution of the language model ChatGPT developed by the technology giant Microsoft [13]. Copilot uses large-scale machine-learning techniques and artificial neural networks to understand users' natural language input and generate relevant textual responses [14]. Compared to its previous version, ChatGPT 3.5, Copilot has higher accuracy since it uses a much more extensive training dataset reaching billions of byte-pair-encoded (BPE) tokens, improved machine learning algorithms, and reinforcement learning with human feedback [15]. Copilot, launched in 2021, has gained widespread use among research communities across various scientific fields [16-18]. However, systematic studies exploring Copilot's applications, specifically in remote sensing and satellite image classification, remain limited [19, 20]. Copilot offers the potential for automating satellite image processing and analysis through pre-prepared textual prompts. Using standardized prompts can save researchers time and prevent incorrect Copilot model training. Copilot enhances the research process in several ways:

- Rapid code generation: Copilot can quickly produce complex JavaScript code for GEE operations, reducing development time from hours to minutes.
- Error reduction: By generating syntactically correct code, Copilot minimizes human errors in coding.
- Adaptability: Copilot can quickly adjust to different GEE tasks, from image filtering to classification algorithm implementation.

2.2.2. Google Earth Engine

Google Earth Engine (GEE) is a free, open-source platform for geospatial data analysis that offers high-performance computing capabilities and access to a vast repository of satellite imagery and geospatial datasets spanning over 40 years. These datasets include images from satellites like MODIS, ALOS, Landsat, and Sentinel and supplementary data such as Digital Elevation Models, shapefiles, meteorological data, and land cover information. GEE's ability to process large-scale data efficiently makes it essential for remote sensing and big data analysis. Its web-based interactive interface facilitates easy access and manipulation of these datasets, leading to a significant increase in scientific publications utilizing GEE across various disciplines, including vegetation studies, land use analysis, hydrology, climate analysis, and heritage conservation. In this research, Microsoft Copilot was employed to generate relevant JavaScript programming code, streamlining data processing in GEE and addressing challenges associated with local satellite data computation and manual coding. The focus was remote sensing land cover mapping in mangrove areas using Microsoft Copilot. Data for this research were sourced from the European Space Agency's Sentinel-2 series, selected for optimal spatial, spectral, and temporal resolutions among open data within GEE suitable for mangrove mapping applications. Specifically, images from the 'COPERNICUS/S2_SR_HARMONIZED' collection with temporal coverage from January to December 2023 were utilized.

2.2.3. Copilot Approach and Its Limitations

Using Copilot is a collaborative process where user input is essential. It starts with the user asking a question or requesting in natural language. Copilot then processes this input, leveraging its internal knowledge and current information from web searches to generate a relevant and accurate response. The interaction can continue with further questions, requests, or feedback, allowing Copilot to adapt and improve its response quality and relevance. In the context of GEE and mangrove mapping, Copilot's assistance can be requested in various tasks, from writing code for satellite data analysis to interpreting results and drawing conclusions. For example, a request might be made for Copilot to generate a JavaScript code snippet that filters the Sentinel-2 image collection for images taken in 2023 with less than 10% cloud cover from 'COPERNICUS/S2_SR_HARMONIZED', selects the first image that meets these criteria, and clips the selected image to a specified boundary (Figure 2).

JavaScript

```javascript
// Filter the Sentinel-2 image collection for images in 2023 with less than 10% cloud cover
var filteredImages = ee.ImageCollection('COPERNICUS/S2_SR_HARMONIZED')
    .filterBounds(boundary)
    .filterDate('2023-01-01', '2023-12-31')
    .filter(ee.Filter.lt('CLOUDY_PIXEL_PERCENTAGE', 10));
// Select the first image that meets the criteria
var image = filteredImages.first();
// Clip the image to the boundary
var clippedImage = image.clip(boundary);
```

AI-generated code. Review and use carefully. More info on FAQ.

Fig 2. A snippet of JavaScript code filters through Earth's imagery for clear, insightful observations created by Copilot

Despite the advantages of using Copilot for code generation in GEE, specific limitations were encountered, particularly in the hyperparameter tuning of machine learning algorithms. Copilot often suggested default hyperparameters or generic values that were not optimal for the dataset and the specific nuances of mangrove land cover classification. For instance, default numbers were recommended for the number of trees or maximum depth in the Random Forest classifier without considering the balance between computational efficiency and classification accuracy. These limitations necessitated manual adjustments and domain expertise to fine-tune the hyperparameters effectively. The AI could not dynamically adapt hyperparameters based on dataset characteristics, such as class imbalance or the spectral variability inherent in mangrove ecosystems. Future AI tools could improve by incorporating adaptive learning mechanisms considering dataset-specific features and historical tuning outcomes to suggest more precise hyperparameters. Additionally, integrating a user feedback loop where adjustments are learned and considered in subsequent suggestions would enhance the utility of AI assistants like Copilot.

2.2.4. Classification Algorithm Selection

The Random Forest algorithm was selected for the classification task due to its robustness against overfitting, efficiency in handling high-dimensional data, and ability to provide variable importance metrics, which are valuable for understanding the factors influencing classification. While algorithms like Support Vector Machines (SVMs) and deep learning models (e.g., Convolutional Neural Networks) are also applicable in remote sensing, they present challenges such as higher computational requirements and the need for extensive parameter tuning or large labeled datasets. SVMs, for instance, can be computationally intensive with large datasets typical of remote sensing imagery and require careful kernel selection. Deep learning models demand substantial computational resources and large labeled datasets, which may not be feasible for all studies.

2.2.5. Methodological Framework

The advanced approach by Abate *et al.* [18] involves more complex technical processes, such as selecting and filtering datasets, creating vegetation indices, choosing areas for analysis, performing spectral and statistical assessments, calculating environmental statistics for images, and producing supervised classifications. Users can seek assistance from Copilot to implement this advanced mangrove mapping method. This study's methodological framework builds upon the approach developed by Jhonnerie *et al.*[21]. The process includes several key steps:

- Asset path definition establishes paths to assets stored on GEE, including training area, testing area, and study area boundary.
- Asset loading: loads defined assets as ee.FeatureCollection objects for further processing.
- Sentinel-2 image filtering: select Sentinel-2 Level 2A images from 2023 within the specified boundary with less than 10% cloud cover.
- Image clipping to boundary: Trims selected Sentinel-2 image to fit the study area's boundary for focused analysis.
- Band selection for classification: chooses specific bands from Sentinel-2 images pertinent to mangrove land cover classification.
- Training and testing dataset preparation: generates datasets by sampling selected bands within respective areas and tagging them with class numbers.
- Classifier optimization through hyperparameter tuning: Configure the Random Forest classifier using the best hyperparameters from previous tuning exercises. Despite Copilot's assistance, manual tuning was necessary to optimize parameters such as the number of trees and maximum depth, highlighting the limitations of AI tools in hyperparameter tuning.
- Clipped image classification: applies trained classifier to the clipped image to categorize each pixel into a land cover class.
- Accuracy assessment: evaluates classification accuracy using an error matrix, calculating overall accuracy, kappa statistics, producer's, and user's accuracy.
- Land cover area calculation: determines the area covered by each land cover class within the study boundary.
- Variable importance analysis: analyzes the importance of each spectral band in the classification process and displays information graphically.
- Results display and export: visualizes RGB composite and classified image on GEE map interface and exports classified image to Google Drive for further use.

2.2.6. Integration of Copilot with GEE

The integration of Copilot with GEE follows a structured approach:

- Task Definition: The specific GEE task is defined in natural language.
- Code Generation: Copilot processes the task description and generates relevant JavaScript code.

- Code Review and Modification: The generated code is reviewed, and adjustments are made if necessary, particularly in hyperparameter tuning, where Copilot may provide generic suggestions.
- Execution in GEE: The final code is executed in the GEE environment.

This approach streamlines the coding process and highlights areas where AI assistance currently falls short, such as hyperparameter tuning, necessitating human expertise for optimal results. Future improvements in AI tools could focus on enhancing capabilities in these areas, potentially through adaptive learning and user feedback mechanisms.

3 Result and discussion

The classification of mangrove land cover in the study area of Kembung River, Bengkalis Island, Riau Province, Indonesia, reveals a complex and dynamic coastal landscape. Sentinel-2 image analysis using Google Earth Engine and Microsoft Copilot identified nine land cover classes (Figure 3). Mangrove ecosystems dominate the study area, covering 3,350.52 hectares (46.6%), demonstrating their ecological significance in this region. This substantial mangrove presence is crucial in coastal protection, carbon sequestration, and habitat provision for various species [22]. However, the landscape exhibits various other land cover types, reflecting complex interactions between natural ecosystems and human activities. Coconut trees (14.8%) and rubber trees (7.5%) indicate significant agricultural activities, highlighting economic pressures on the coastal ecosystem [23]. These plantations posed classification challenges due to spectral similarities with mangroves, especially in mixed-pixel scenarios. Built-up areas (7.6%) and open land (0.9%) further emphasize anthropogenic influences on this landscape. Built-up areas, often comprising a mix of structures and vegetation, were prone to misclassification with bare soil or degraded vegetation areas. Water bodies covering 11.0% of the area may include rivers, streams, and ponds, often associated with mangrove conversion. Transitional vegetation (8.2%) and shrubs (2.3%) may indicate areas undergoing succession or regeneration, potentially suitable for mangrove restoration. Although only 1.0%, Sago palm trees demonstrate this species' economic and cultural importance to local communities. This land cover distribution provides insights into the ecological and socio-economic complexities of the coastal region, emphasizing the importance of an integrated management approach that considers both mangrove ecosystem conservation and local community needs [24].

The confusion matrix heatmap (Figure 4) generated from the classification results demonstrates the model's performance in identifying each land cover class. The primary diagonal displaying high numbers indicates the count of correctly classified pixels for each class. For example, the mangrove class shows a value of 237 on its diagonal, signifying the model's high accuracy in classifying mangrove pixels. However, classification errors appear in the off-diagonal numbers, such as the coconut tree class having several pixels misclassified as transitional vegetation and mangrove. While built-up areas showed significant misclassification, transitional vegetation also exhibited lower accuracies (UA: 41.7%, PA: 26.3%), indicating confusion with mangrove and non-mangrove classes. The water body class, though well-classified overall, showed some confusion with mangroves in areas of narrow creeks or overhanging canopies. The confusion matrix results indicate that while the model achieves good overall accuracy, with a value of 0.844 and a kappa statistic of 0.794, there remains room for improvement in reducing misclassification between similar classes. This study's accuracy test demonstrates better results than the previous research by Jhonnerie et al. [21], which achieved an overall accuracy of 0.811 and a kappa statistic of 0.71. Although Jhonnerie et al. [25] improved accuracy in their follow-up study, their results still need to catch up to the achievement of this research, which attained an overall accuracy of 0.836 with a kappa statistic of 0.790, potentially reshaping the landscape of this field.

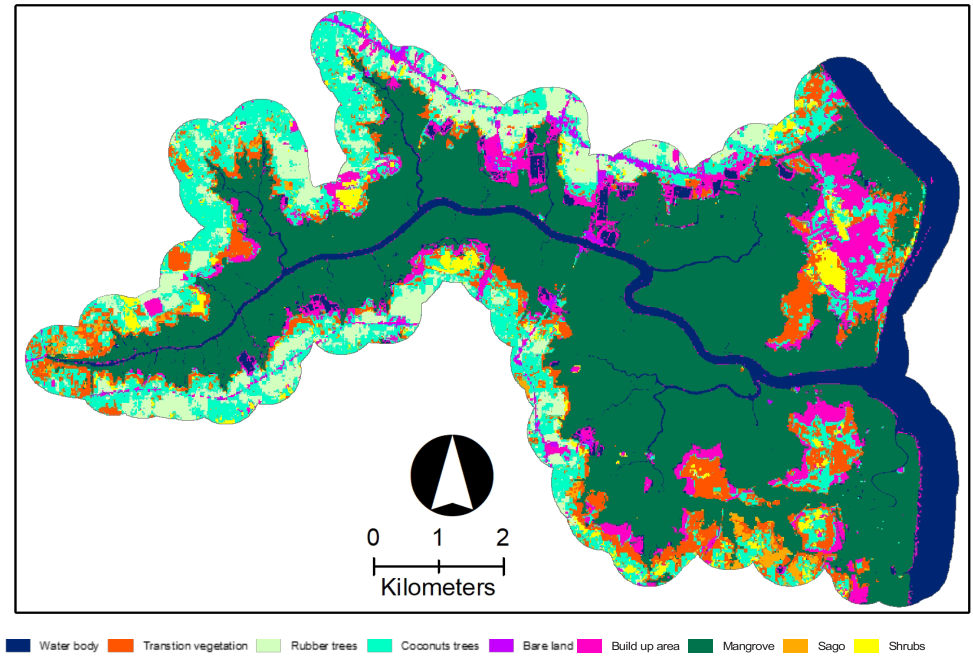

Fig 3. Land cover classification map of the study area, showing nine land cover types, using random forest algorithm

The User's Accuracy (UA) and Producer's Accuracy (PA) for each class provide further insight into the classification model's performance. The mangrove class stands out with a UA of 0.960 and PA of 0.952, indicating the model's high efficiency in correctly recognizing and classifying mangrove pixels. Conversely, the built-up area class shows a lower UA of 0.604 despite a relatively high PA of 0.829, suggesting that while the model correctly identifies many actual built-up area pixels, it also misclassifies numerous pixels into this class. This misclassification likely stems from spectral similarities between the built-up area class and other classes in satellite imagery, often causing ambiguity in the classification process. Although the model demonstrates high overall accuracy, further analysis and potential refinements in data pre-processing or classification algorithms are necessary to enhance classification precision for specific classes.

Various factors influence the accuracy of mangrove land cover classification. Atmospheric conditions, particularly in coastal areas, significantly affect satellite image quality. Asmala *et al.* [26] state that atmospheric aerosols and water vapor can reduce spectral contrast between land cover classes, especially in humid coastal environments. Image spatial resolution also plays a crucial role Wang *et al.*[27] and *Wang et al.*[28] found that increasing spatial resolution from lower to higher spatial resolution can improve mangrove classification accuracy. Spectral band selection is equally important. Additionally, the potential of object-based classification methods in improving the accuracy of mangrove mapping is exciting. Jhonnerie *et al.* [21] demonstrated that imagery with higher spectral resolution (such as Landsat 5 TM) produces better overall accuracy compared to imagery with lower spectral resolution (such as SPOT 6). More advanced algorithms, particularly machine learning-based algorithms like Random Forest, can produce more accurate classification results [29]. Similarly, object-based classification methods show improved accuracy compared to pixel-based classification in mangrove mapping [25], opening up new possibilities for further research.

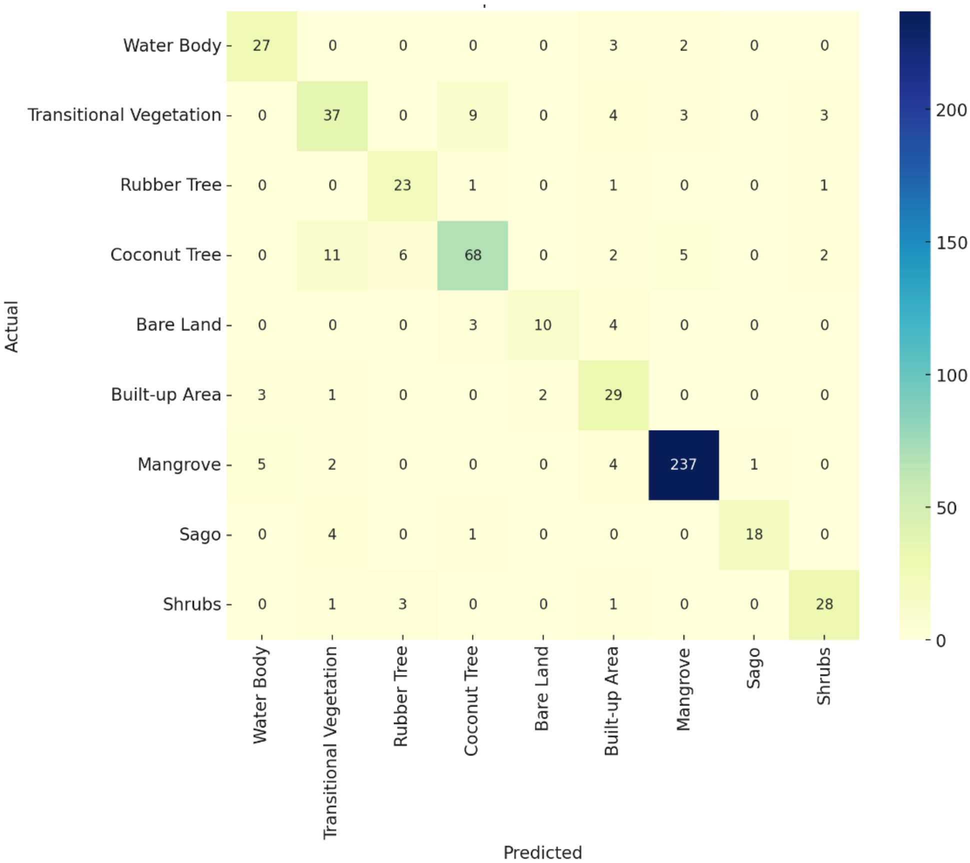

Fig 4. Confusion matrix heatmap illustrating the classification performance for various land cover classes. The matrix highlights the actual versus predicted classifications, with the mangrove class showing the highest correct classification count of 237

The variable importance analysis reveals that the most significant Sentinel-2 bands for mangrove land cover classification are B10 (SWIR Cirrus, 13.629), B1 (Coastal Aerosol, 13.374), B5 (Vegetation Red Edge, 11.292), and B11 (SWIR 1, 10.231) (Figure 5). The dominance of these bands reflects the unique characteristics of mangrove ecosystems and the challenges in their classification. SWIR Cirrus and Coastal Aerosol bands are crucial in detecting thin clouds, atmospheric water vapor, and aerosols, which are critical in humid coastal environments [30]. The sensitivity of the Vegetation Red Edge band to chlorophyll content and canopy structure enables better differentiation between various mangrove and non-mangrove vegetation types and vegetation health assessment [31]. SWIR bands contribute to distinguishing soil types, sediments, and vegetation water content, which are critical in mangrove ecosystems [32, 33]. The findings on the importance of SWIR and Red Edge bands align with previous studies (e.g., Kuenzer et al. [24], Heumann [43]), which highlighted their effectiveness in distinguishing mangroves and assessing vegetation health. The significance of the Coastal Aerosol band may relate to its ability to detect partially submerged vegetation, as noted by Wang and Sousa [44]. Visible (B2, B3, B4) and NIR (B8) bands show lower importance, possibly due to being less discriminative in the specific mangrove context than other bands, although they still contribute to the overall classification. These results affirm that using a broader spectrum, especially those capturing specific mangrove characteristics such as moisture, canopy structure, and coastal atmospheric conditions, is crucial in improving land cover classification accuracy in complex mangrove ecosystems. Although this study's findings on important parameters differ from those reported by [25], the debate surrounding the determination of variables important in the random forest algorithm remains an active topic among researchers [35, 36].

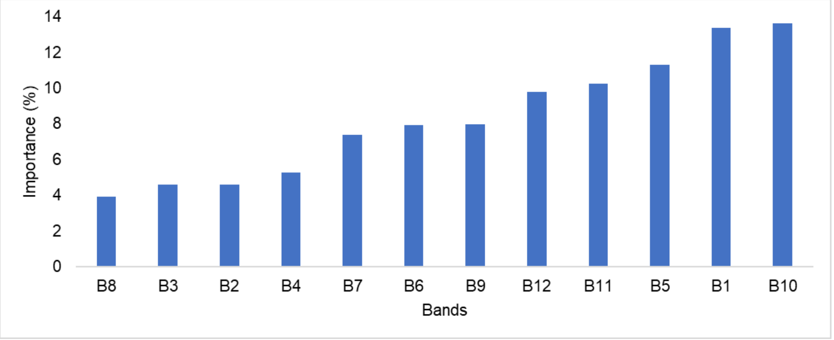

Fig 5. The bar chart shows the importance of different spectral bands in the classification process, with Band 10 and Band 1 having the highest importance at over 12% each.

Visible (B2, B3, B4) and NIR (B8) bands show lower importance, possibly due to being less discriminative in the specific mangrove context than other bands, although they still contribute to the overall classification. These findings align with previous studies emphasizing the importance of SWIR and Red Edge bands in mangrove mapping [34]. These results affirm that using a broader spectrum, especially those capturing specific mangrove characteristics such as moisture, canopy structure, and coastal atmospheric conditions, is crucial in improving land cover classification accuracy in complex mangrove ecosystems. Although this study's findings on important parameters differ from those reported by [25], the debate surrounding the determination of variables important in the random forest algorithm remains an active topic among researchers [35, 36].

The evaluation of Microsoft Copilot in mangrove mapping using GEE demonstrates significant potential for improving analysis efficiency and accuracy. Copilot showcases the ability to generate comprehensive JavaScript code covering various analysis stages, from data preparation to result evaluation. This effectiveness aligns with Smit et al. [37] findings, reporting productivity increases to a certain degree in code development using AI-assisted programming. The improved accuracy can be attributed to Google Earth Engine's efficient processing of Sentinel-2 imagery and Microsoft Copilot's AI-assisted coding, enabling the implementation of advanced classification algorithms. These technologies, combined with Sentinel-2's enhanced spectral resolution, contributed significantly to the improved results compared to previous studies. Copilot's adaptive capabilities, as highlighted in various studies [38], suggest the potential for continuous performance improvement, resembling transfer learning concepts in deep learning [45].

By leveraging AI-powered tools like Copilot, developers can benefit from automated code suggestions, defect fixes, and test writing, ultimately enhancing software systems' code quality and reliability [38]. Copilot's ability to generate solutions for fundamental algorithmic problems, although with some limitations in advanced tasks, showcases its potential for assisting developers in basic programming tasks [40]. Continuous improvement through adaptive learning aligns with transfer learning principles in deep neural networks, where prior knowledge is utilized to enhance performance across various tasks, ultimately leading to more efficient and effective problem-solving capabilities [46].

4 Conclusion

This research demonstrates the significant potential of integrating Microsoft Copilot with GEE to enhance the efficiency and accuracy of mangrove land cover mapping, achieving an overall accuracy of 84.4% (Kappa = 0.794) across nine land cover classes. The method revealed the dominance of mangrove ecosystems (46.6%) while also uncovering anthropogenic pressures. Although effective, challenges remain in complex tasks such as hyperparameter tuning and addressing spectral variability. The approach developed here has potential applications beyond mangrove ecosystems, extending to various land cover mapping and environmental monitoring tasks where spectral complexity and large dataset processing are common challenges. Future research should explore advanced machine learning techniques to address spectral variability, investigate hybrid processing approaches to overcome GEE computational constraints and integrate multi-temporal and multi-source data for improved accuracy. This study paves the way for more efficient global ecosystem monitoring and conservation approaches, offering a promising framework for enhancing our understanding and management of diverse landscapes worldwide. While further development is necessary to overcome existing limitations, the methodology presented here significantly advances the field of remote sensing-based environmental mapping.

Acknowledgment

We want to express our sincere gratitude to Universitas Riau for supporting this research through the Riset Unggulan Universitas Riau program, as detailed in the 2024 Fiscal Year Budget Implementation List under contract number 15578/UN19.5.1.3/AL.04/2024.

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