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Mapping Potential Land Agriculture Paddy Sustainable Use Google Earth Engine in Bekasi Regency

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Abstract
This study aims to map and analyze the suitability of sustainable rice paddy land in Bekasi Regency, West Java, an area experiencing rapid urbanization. The research employed a quantitative spatial approach using multi-temporal satellite imagery from the last five years processed through Google Earth Engine (GEE) and ArcGIS 10.3. Land suitability evaluation was conducted by integrating the Analytical Hierarchy Process (AHP) and the Matching Evaluation Approach (MEA) to determine parameter weights and classify land suitability levels. The parameters analyzed included rainfall, temperature, slope, soil type, soil pH, erosion, groundwater recharge, and land use. Land suitability was classified into four categories: very suitable (S1), moderately suitable (S2), marginally suitable (S3), and not suitable (N). The results indicate that marginally suitable land (S3) dominates the study area, accounting for 42.21%, followed by moderately suitable land (S2) at 30.44%. Very suitable land (S1) covers only 1.80% of the area, while more than 23% falls into unsuitable categories (N1–N2), mainly in northern coastal areas affected by salinity and drainage constraints. These findings highlight the importance of water availability and soil conditions as dominant factors in rice land suitability. The study provides essential spatial information to support sustainable agricultural planning and land conservation strategies in Bekasi Regency.
Key words : *Land Mapping, Google Earth Engine, Remote sensing*

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Introduction

Rice (Oryza sativa L.) is one of the most essential staple crops in the world and plays a critical role in global food security, especially in Asian countries. In Indonesia, rice is the primary food source for the majority of the population, making sustainable paddy production a national priority. However, rapid urban expansion, land conversion, environmental degradation, and climate variability increasingly threaten the availability and sustainability of agricultural land. Consequently, accurate identification and mapping of potential agricultural land for sustainable paddy cultivation have become fundamental for regional planning and food security strategies.

Bekasi Regency, located in West Java Province, Indonesia, is one of the regions experiencing rapid industrialization and urban growth. As part of the Jakarta Metropolitan Area (Jabodetabek), Bekasi has undergone significant land use transformation over the past decades. Agricultural lands, particularly paddy fields, are increasingly under pressure due to infrastructure expansion, industrial estates, and residential development. This phenomenon reflects broader land conversion trends observed in many developing regions where urban expansion contributes to agricultural land fragmentation and loss (Zhou et al., 2017). Therefore, systematic mapping of potential paddy land and monitoring of land use change are necessary to support sustainable land management policies.

Advances in remote sensing (RS) and Geographic Information Systems (GIS) have revolutionized agricultural monitoring and land suitability assessment. Traditional land evaluation approaches relied heavily on field surveys and manual mapping, which are time-consuming and costly. Contemporary methods integrate satellite imagery, spatial modeling, and multi-criteria evaluation techniques to provide efficient and scalable solutions. Agricultural land suitability evaluation commonly combines remote sensing data, analytical hierarchy process (AHP), and multi-criteria evaluation analysis (MEA), as demonstrated by Han et al. (2021), who assessed agricultural land suitability in Jilin Province, China. Their study emphasized the integration of biophysical and environmental parameters such as soil characteristics, topography, and vegetation indices in producing reliable suitability classifications.

Similarly, Mostafiz et al. (2021) highlighted the importance of integrating soil-vegetation indices derived from remote sensing data for agricultural land suitability assessment. Their findings indicate that spectral indices such as NDVI, SAVI, and other vegetation metrics are powerful indicators for determining agricultural productivity potential. These approaches align with the land evaluation principles proposed by Hardjowigeno and Widiatmaka (2020), who emphasized that land suitability evaluation must consider physical land characteristics, climate, and socio-economic aspects to ensure sustainable land use planning.

In the context of paddy cultivation, remote sensing has proven highly effective in identifying rice fields and analyzing cropping intensity. Early works by Xiao et al. (2005, 2006) demonstrated the use of MODIS time-series imagery to map paddy rice agriculture across South and Southeast Asia. Their phenology-based approach leveraged temporal changes in vegetation indices and flooding signals during the transplanting stage to distinguish paddy fields from other land cover types. These pioneering studies laid the foundation for modern rice mapping methodologies.

With the emergence of cloud computing platforms, agricultural mapping has become more efficient and scalable. Google Earth Engine (GEE) is a cloud-based geospatial processing platform that provides access to petabytes of satellite imagery and computational resources. It enables large-scale land cover classification, time-series analysis, and machine learning applications without requiring high-end local computing infrastructure.

Recent studies have demonstrated the effectiveness of GEE in paddy rice mapping. Nagendram (2023) applied machine learning algorithms within GEE to map paddy cropland in Guntur District, achieving high classification accuracy. Similarly, Fan et al. (2025) proposed a rice-mapping method integrating automatic training sample generation and Random Forest classification within GEE. Their approach significantly reduced manual intervention while improving classification performance.

Fatchurrachman et al. (2022) conducted high-resolution mapping of paddy rice extent and phenology using GEE, highlighting the capability of Sentinel-2 time-series imagery for detecting growth stages. Meng et al. (2024) further advanced large-scale and high-resolution paddy rice intensity mapping using GEE, demonstrating that cloud-based platforms can efficiently process multi-year datasets across extensive geographic areas.

The phenology-based delineation of irrigated and rain-fed paddy fields has also been explored using GEE (dela Torre et al., 2021). By analyzing temporal patterns of vegetation and surface water indices, the study distinguished between irrigation regimes, which is crucial for sustainable agricultural planning. Chen et al. (2020) integrated multi-temporal SAR and optical data to enhance paddy mapping accuracy, emphasizing the importance of combining radar and optical sensors to overcome cloud cover limitations in tropical regions.

In Indonesia, several studies have utilized GEE for land cover classification and agricultural monitoring. Juan Vincent Elfonda et al. (2024) applied GEE for land cover classification in Trenggalek Regency, demonstrating its reliability for regional-scale mapping. Karina and Kurniawan (2021) used Landsat 8 imagery through GEE to identify land use patterns, while Mulyaqin et al. (2022) employed Sentinel-2 and GEE to detect paddy field conversion in Serang City. These studies confirm the applicability of GEE in Indonesian contexts.

Rizaldi et al. (2023) also emphasized the potential of GEE in monitoring agroforestry land, further reinforcing its versatility in agricultural landscapes. Moreover, Sultan et al. (2025) compared machine learning algorithms within GEE for land use classification, highlighting the importance of algorithm selection for optimal mapping accuracy.

Land use and land cover (LULC) change analysis is critical in understanding agricultural sustainability. Urban expansion significantly contributes to agricultural land loss and fragmentation (Zhou et al., 2017). In rapidly developing regions such as Bekasi Regency, conversion of paddy fields into industrial and residential land threatens local food production capacity.

Time-series remote sensing analysis plays a crucial role in detecting LULC changes. Weng (1999–2022) emphasized the importance of temporal evaluation in understanding urban growth and land transformation patterns. Similarly, the "Status and Prospects of Google Earth Engine in Agricultural Research" (2024) highlighted the role of GEE in facilitating long-term monitoring and trend analysis.

Fernando et al. (2024) developed a two-decadal time record of rice field maps using GEE, demonstrating the platform's capacity for historical analysis. Such temporal mapping approaches are essential for identifying areas that remain suitable for sustainable paddy cultivation and those that have undergone irreversible conversion.

Sustainable paddy cultivation requires not only identification of existing rice fields but also evaluation of land suitability for future cultivation. Land suitability assessment integrates multiple criteria, including soil properties, slope, drainage, rainfall, and temperature. Han et al. (2021) integrated RS, AHP, and MEA to assess agricultural land suitability, demonstrating a structured approach to multi-criteria evaluation.

Mostafiz et al. (2021) emphasized the use of remote sensing-derived soil and vegetation indices for suitability analysis, while Ningsih et al. (2024) applied GIS-based evaluation for rice suitability in Sinjai Regency, Indonesia. Their results underscore the importance of spatial modeling in identifying highly suitable land categories.

Hardjowigeno and Widiatmaka (2020) argued that land suitability evaluation must align with land use planning policies to ensure long-term sustainability. In rapidly urbanizing regions such as Bekasi, integrating suitability maps with spatial planning frameworks can support evidence-based decision-making.

Although numerous studies have applied GEE for rice mapping and land use classification, limited research specifically integrates paddy mapping with land suitability assessment for sustainable agricultural planning in Bekasi Regency. Most Indonesian studies focus either on land cover classification (Juan Vincent Elfonda et al., 2024) or detection of land conversion (Mulyaqin et al., 2022), without combining these outputs with structured suitability analysis.

Furthermore, while international studies demonstrate advanced phenology-based and machine learning methods (Fan et al., 2025; Meng et al., 2024), localized applications considering regional characteristics, climate, and policy context remain limited. Therefore, there is a need to integrate remote sensing-based paddy mapping, multi-criteria land suitability evaluation, and sustainability analysis within a unified GEE framework tailored to Bekasi Regency.

Based on the identified gaps, this study aims to:

1. Map existing paddy fields in Bekasi Regency using multi-temporal satellite imagery within Google Earth Engine.
2. Analyze land use and land cover changes affecting agricultural land.
3. Evaluate land suitability for sustainable paddy cultivation using multi-criteria analysis integrating biophysical parameters.
4. Identify potential agricultural land zones suitable for long-term sustainable use.

This research contributes theoretically and practically. Theoretically, it integrates phenology-based rice mapping (Xiao et al., 2005; dela Torre et al., 2021), machine learning classification in GEE (Nagendram, 2023; Fan et al., 2025), and land suitability evaluation frameworks (Han et al., 2021; Mostafiz et al., 2021). Practically, it provides spatial decision-support information for policymakers in Bekasi Regency to protect and optimize sustainable paddy land.

The use of Google Earth Engine ensures scalability, reproducibility, and cost-effectiveness, making the methodology adaptable for other regions experiencing similar land conversion pressures.

Method Study

Study This use approach quantitative with analysis spatial based image satellites and systems information geographic (GIS). Design study nature descriptive-analytical with utilise combination Analytical Hierarchy Process (AHP) and Matching Evaluation Approach (MEA) methods for analyze suitability land agriculture rice in Bekasi Regency . Research implemented for 6 (six) months , namely from February until July 2025, which includes stage studies literature and preparation (February – March 2025), secondary and primary data collection (March –April 2025), acquisition and processing imagery (April–May 2025), data analysis and mapping (May– June 2025), and validation results and writing report (June – July 2025)

Location study located in Bekasi Regency , Province West Java which has area of 127,388 ha, with 35,341.52 ha in the form of land rice fields . Population study is all over land agriculture rice fields in Bekasi Regency , while sample study in the form of point observations (ROI/Region of Interest) taken purposively based on distribution spatial land rice fields and image data availability satellite .

For support analysis suitability land , research This utilise various data type with different characteristics in accordance need research . The data used includes tabular data (number population and area land agriculture ricefield 2021–2024 from BPS Bekasi Regency), spatial data (boundary maps administration , network road , use land , distribution land , topology , type land , slope surface , soil pH , and water absorption from INA Geospatial /BIG), image data satellite (rainfall Rain from CHIRPS and temperature from Sentinel-2 via Google Earth Engine 2020–2024), as well as derived data results GIS overlay analysis (erosion map) soil and water absorption). For data consisting of from secondary and primary obtained through studies documentation , downloads from a trusted agency digital platform , and processing advanced use device GIS software .

besides data, research this also requires a number of tools and devices soft For supports processing , analysis and mapping processes .

1. Google Earth Engine (GEE) **:** image data processing satellite .
2. ArcGIS 10.3 **:** analysis spatial and mapping .
3. Laptop with specification i5 processor /16GB RAM **.**

Data analysis was performed through a number of stages systematically . First , the image data satellite processed use Google Earth Engine (GEE) For extract biophysical parameters like temperature surface and rainfall rain . Second , spatial data integrated and analyzed use ArcGIS 10.3 through overlay technique for generate derivative maps like erosion soil and water absorption .

Third , the method Analytical Hierarchy Process (AHP) implemented For give weight on each suitability parameter land based on level importance . Parameter weights refer to research Wahyunto et al. (2016) who emphasized importance factor rainfall rain , slope , type soil , and soil pH in determine suitability land rice , as shown in Table 1

Table 1 Parameter weighting for suitability land agriculture paddy
Source : (Wahyunto et al., 2016)

NO	Parameter	Weight
1	Slope	5
2	Rainfall	6
3	Soil Type	5
4	Erosion	4
NO	Parameter	Weight
5	Groundwater Infiltration	4
6	Soil pH	3
7	Temperature	4
8	Use Land	3

Fourth, the Matching Evaluation Approach (MEA **) method** is used to match actual land characteristics with rice field suitability criteria. These suitability criteria are based on the FAO classification guidelines. (Food and Agriculture Organization of the United Nations (FAO), 1967) and research by Han et al. (2021) which classifies land into classes S1 (very suitable), S2 (fairly suitable), S3 (marginally suitable), and N (not suitable) , as shown in Table 2

Tab el 2 Classification level suitability plant paddy
Source : (Han et al., 2021)

Characteristic Classification	**Feature Category**	**Suitability Class**			
		S1	**S2**	**S3**	**N**
	Rating scale	100 – 85	85 – 60	60 – 40	40 – 0
Topography (T)					
Slope (%)	Paddy	≤ 3	3 - 8	8 – 15	≥ 15

Physical soil characteristics (S)					
Texture	Paddy	SC,C ,SiC,CL	L,SiL	SL,LS	S
Water infiltration	Paddy	Well	Imperfect	Poor	-
Erosion	Paddy	Very light , light	Currently	Heavy	Very heavy
Soil fertility characteristics (F)					
pH (soil)	Paddy	5.5 - 8.2	5.0 – 5.5, 8.2 – 8.5	4.5 – 5.0, 8.5 – 9.0	≤ 4.5, > 9.0

Characteristic Classification	**Feature Category**	**Suitability Class**			
		S1	**S2**	**S3**	**N**
	Rating scale	100 – 85	85 – 60	60 – 40	40 – 0
Climate characteristics (C)					
Mean annual temperature (◦C) [2]	Paddy	24 – 30	22 – 25, 30 - 32	18 – 22, 32 - 35	≤ 18, > 35
Mean annual rainfall (mm/year) [2]	Paddy	2500 – 3000, ≥ 3000	1500 – 2500	1000 – 1500	≤ 1250

The final result is a map of rice farming land suitability with classifications S1, S2, S3, and N. Validation of the results is carried out through field checks on selected sample locations and analysis of map accuracy using a confusion matrix.

Results and Discussion

The results of spatial analysis using a combination of AHP (Analytical Hierarchy Process) and MEA (Matching Evaluation Approach) show that the suitability of rice farming land in Bekasi Regency varies from class S1 (very suitable) to N2 (permanently unsuitable). Overall, the S3 category (marginally suitable) is the most widespread (42.21%), followed by the S2 category (quite suitable) at 30.44%. Only a small portion of the area (1.80%) is included in the S1 category (very suitable), while the unsuitable category (N1–N2) reaches more than 23% of the area. These findings indicate that although Bekasi Regency has quite extensive rice fields, most of the land still requires technical intervention for optimal rice productivity.

The spatial distribution of rice field suitability in Bekasi Regency can be seen in Figure 2. The map shows that the southern and central regions are dominated by classes S1–S2, while the northern region tends to fall into the N1–N2 category. Most of the land in the central–eastern region falls into the S3 category, which can still be optimized through technical intervention.

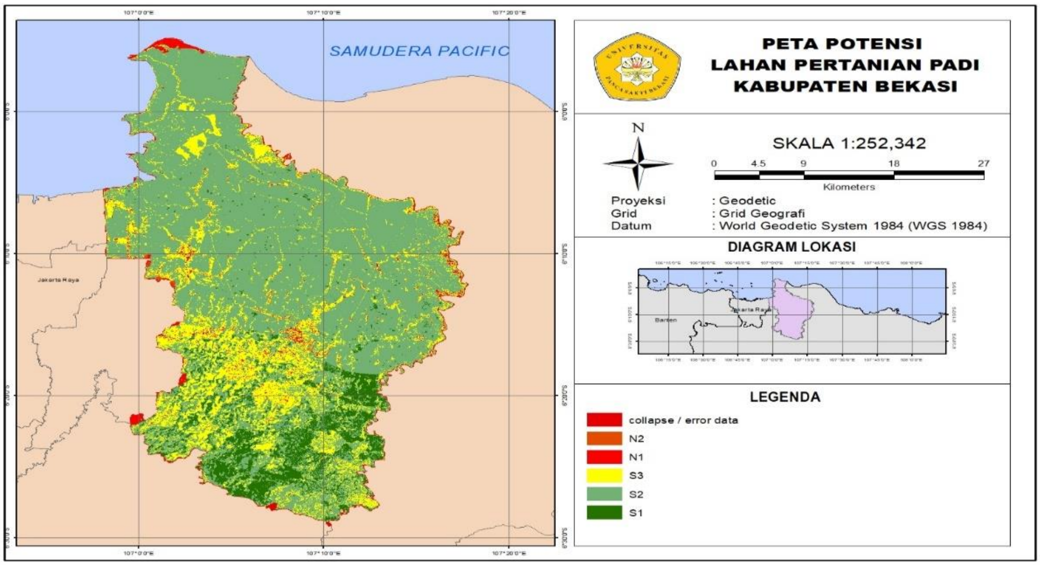

Figure 1Distribution map suitability land agriculture rice in Bekasi Regency

Spatially, land with categories S1 and S2 is mainly spread across the southern and central districts, such as Cibarusah, Central Cikarang, South Cikarang, Serang Baru, Sukatani, Sukakarya, and Tambelang. This condition is closely related to the relatively flat topography and adequate irrigation system support. This aligns with the findings of Han et al. (2021), who stated that water availability and land slope are key factors determining the suitability of irrigated rice fields.

In contrast, sub-districts in the north, such as Babelan, Cabangbungin, Pebayuran, and Muara Gembong, have a higher percentage of N1–N2 categories. This is thought to be influenced by salinity and drainage factors, given that these areas directly border the north coast of West Java. These results are consistent with research. Hardjowigeno & Widiatmaka, (2020) which confirms that coastal rice fields often experience problems with salinity and tidal flooding which reduce rice productivity.

Other findings indicate that rainfall and water availability are the most dominant parameters in determining land suitability (AHP weight = 6). Areas with permanent irrigation water availability tend to fall into categories S1–S2, while areas with limited rainfall and poor drainage are more likely to fall into categories S3–N. This finding aligns with a study (Al Farizi et al., 2024) that emphasized the importance of water balance in tropical irrigated rice paddy systems.

This study demonstrates that the land suitability for rice cultivation in Bekasi Regency varies significantly across spatial zones, ranging from class S1 (very suitable) to class N2 (not permanently suitable). The spatial analysis reveals that the southern and central regions of Bekasi Regency possess the greatest potential for sustainable rice development, as these areas are predominantly classified within S1 and S2 suitability categories. In contrast, the northern region exhibits substantial limitations due to salinity intrusion, frequent flooding, inadequate drainage conditions, and lower soil quality, resulting in a higher proportion of land categorized as N1 (currently not suitable) and N2 (permanently not suitable). These findings underline the spatial heterogeneity of agricultural potential within the regency and emphasize the importance of site-specific land management strategies.

The results confirm that water availability, rainfall distribution, soil characteristics, and drainage conditions are the dominant parameters influencing rice land suitability. This aligns with the land evaluation principles proposed by Hardjowigeno and Widiatmaka (2020), who emphasized that sustainable land use planning must integrate physical land characteristics, hydrological conditions, and climate variables. Furthermore, the findings are consistent with Han et al. (2021), who demonstrated that integrating remote sensing (RS), Analytical Hierarchy Process (AHP), and multi-criteria evaluation (MEA) provides a robust framework for agricultural land suitability assessment. The dominance of water-related parameters in this study reflects the fundamental ecological requirements of paddy rice, which depends heavily on controlled irrigation and optimal soil moisture conditions.

The higher suitability observed in the southern and central regions can be attributed to more favorable topographic conditions, better soil fertility, and more reliable water availability. These conditions support stable rice phenology and productivity, similar to findings reported in rice mapping studies that highlight the importance of hydrological and phenological indicators in identifying productive paddy systems (Xiao et al., 2005; Xiao et al., 2006). Moreover, the integration of multi-temporal satellite imagery within Google Earth Engine (GEE) allowed accurate identification of paddy distribution patterns, reinforcing the effectiveness of cloud-based remote sensing platforms for agricultural monitoring (Nagendram, 2023; Fan et al., 2025).

Conversely, the northern coastal region faces structural environmental constraints. Salinity intrusion, likely influenced by coastal processes and tidal flooding, reduces soil productivity and limits rice growth potential. Poor drainage exacerbates flood vulnerability, leading to prolonged waterlogging beyond optimal rice growth conditions. These findings are consistent with broader research on land degradation and agricultural land fragmentation caused by environmental and anthropogenic pressures (Zhou et al., 2017). Without adequate mitigation measures, continued land conversion and hydrological instability may further reduce the availability of suitable paddy land in these vulnerable zones.

Importantly, this study highlights the value of integrating land suitability assessment with land use and land cover (LULC) analysis. Previous studies in Indonesia have shown that rapid urbanization and agricultural land conversion significantly threaten paddy sustainability (Mulyaqin et al., 2022; Juan Vincent Elfonda et al., 2024). In Bekasi Regency, which is part of the rapidly expanding Jakarta Metropolitan Area, similar pressures are evident. Therefore, identifying S1 and S2 zones is not only a matter of agricultural optimization but also a strategic step toward protecting high-potential agricultural land from uncontrolled urban expansion.

The application of Google Earth Engine proved instrumental in processing multi-source satellite imagery efficiently and conducting spatial modeling at regional scale. As noted in the broader literature on GEE applications in agriculture, cloud-based platforms enhance scalability, reproducibility, and long-term monitoring capacity (Meng et al., 2024; Status and Prospects of Google Earth Engine in Agricultural Research, 2024). By combining machine learning-based classification with multi-criteria land suitability evaluation, this study provides a comprehensive spatial decision-support framework for sustainable rice development.

From a policy perspective, the findings emphasize that water management and land conservation are critical priorities for sustaining rice farming in Bekasi Regency. Improving irrigation infrastructure, strengthening drainage systems in flood-prone northern areas, and implementing soil salinity mitigation measures are essential interventions. In addition, zoning regulations should prioritize the protection of S1 and S2 classified lands to ensure long-term food security. These recommendations align with sustainable land management principles, which advocate balancing agricultural productivity with environmental conservation (Mostafiz et al., 2021).

In conclusion, this research confirms that sustainable rice farming in Bekasi Regency is strongly influenced by hydrological and soil parameters, with significant spatial disparities between regions. The southern and central areas represent strategic agricultural zones with high development potential, while the northern region requires targeted environmental management interventions. By integrating remote sensing, Google Earth Engine, and multi-criteria land suitability analysis, this study contributes a scientifically grounded framework for supporting sustainable agricultural planning and protecting paddy land resources amid rapid urbanization pressures.

Conclusion

This study confirms that land suitability for rice cultivation in Bekasi Regency ranges from class S1 (very suitable) to N2 (not permanently suitable), reflecting significant spatial variability in agricultural potential. The southern and central regions show the highest potential for sustainable rice development, as they are dominated by S1 and S2 classes characterized by favorable soil conditions, adequate rainfall, reliable water availability, and better drainage systems. These findings are consistent with established land evaluation frameworks emphasizing the importance of hydrological and soil parameters in determining agricultural suitability (Hardjowigeno & Widiatmaka, 2020; Han et al., 2021). The integration of multi-temporal satellite imagery and machine learning within Google Earth Engine supports accurate identification of paddy distribution and reinforces the effectiveness of cloud-based remote sensing approaches for agricultural assessment (Nagendram, 2023; Fan et al., 2025; Meng et al., 2024).

In contrast, the northern region faces greater limitations due to salinity intrusion, flooding susceptibility, and poor drainage, resulting in a higher proportion of land categorized as N1 and N2. These environmental constraints, combined with ongoing land conversion pressures in rapidly urbanizing areas, pose challenges to long-term rice sustainability (Zhou et al., 2017; Mulyaqin et al., 2022). Therefore, strengthening irrigation management, improving drainage infrastructure, mitigating soil salinity, and protecting high-suitability (S1–S2) zones through spatial planning policies are essential strategies to ensure sustainable rice farming in Bekasi Regency. Overall, this study demonstrates that integrating land suitability analysis with Google Earth Engine-based mapping provides a reliable decision-support framework for sustainable agricultural land management.

Recommendation

This research still has several limitations, particularly the limited secondary data and the resolution of the satellite imagery used, which prevented optimal depiction of detailed spatial information at the rice field plot scale. Furthermore, limited field validation at specific points may also impact the accuracy of the land suitability classification results.

For further research, it is recommended:

1. Use image satellite with resolution more tall and climate data term long for results analysis more details.
2. Add amount point validation field use increase accuracy of the fit model land .
3. Integrate method analysis others , such as Machine learning -based GIS or crop simulation model **,** so that the results prediction productivity paddy more comprehensive .
4. Involving factor socio-economic farmers and availability infrastructure agriculture so that recommendation suitability land more applicable For policy development area .

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