Airport Development and Farmland Conversion: Spatial Land Use Dynamics in Majalengka Regency, Indonesia

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Abstract.
Introduction: Infrastructure development, particularly airports, enhances regional connectivity and investment but also triggers farmland conversion. Majalengka, a traditionally agrarian region with agriculture as a key contributor to GRDP, faces mounting pressure from the construction of Kertajati International Airport (BIJB). Remote sensing analyses indicate a decline in vegetated land and expansion of built-up areas, threatening local food production and farming livelihoods. This dual impact highlights the need for continuous spatial monitoring and integrated planning strategies that balance economic growth objectives with agricultural sustainability in rapidly transforming peri-urban landscapes.

Material and Method: This research examines land use changes in Majalengka Regency using Sentinel-2A imagery from 2015, 2020, and 2025, processed through Google Earth Engine. Median composites were generated from image mosaics and classified with the Smile-Random Forest algorithm, supported by IBI and MNDWI indices to enhance accuracy. Field validation was conducted using stratified random sampling, yielding an overall accuracy of 98.81% and a Kappa coefficient of 95.9%. The classification results were mapped in ArcGIS to analyze spatial patterns, land conversion dynamics, and land demand projections through 2035.

Results and Discussion: The findings indicate a significant decline in agricultural land in Majalengka, particularly rice fields, dry fields, and mixed gardens, with a total conversion exceeding 6,000 ha between 2015 and 2025. The period 2020–2025 represents a critical phase, marked by a reduction of 1,560 ha of rice fields and an expansion of settlements by up to 4,879 ha. The growth of industrial zones and the West Java International Airport (BIJB) were the main drivers of this change. Spatial analysis highlights a concentrated conversion pattern in the northern corridor, posing a serious threat to food production and local food security, thereby underscoring the need to strengthen spatial planning policies and protect agricultural land.

Conclution: The development of Kertajati International Airport (BIJB) has accelerated the conversion of agricultural land in Majalengka, particularly rice fields, into settlements, industrial areas, and infrastructure. Sentinel-2 imagery analysis using the Random Forest algorithm proved effective in accurately monitoring these changes. Strengthening spatial planning enforcement and protecting irrigated farmland are essential to maintaining a balance between development and food security.

Keywords: Airport, Agricultural, Google Earth Engine, Land Use Changes, Paddy Field, Sentinel 2, Spatial Pattern

تأثیر ساخت فرودگاه بر الگوی فضایی کاربری زمین در مناطق کشاورزی: مطالعه موردی شهرستان ماجالنگکا، اندونزی

مقدمه: توسعه زیرساخت‌ها، به‌ویژه فرودگاه‌ها، موجب افزایش اتصال منطقه‌ای و جذب سرمایه‌گذاری می‌شود، اما در عین حال روند تغییر کاربری زمین‌های کشاورزی را نیز تسریع می‌کند .شهرستان ماجالنگکا که به‌طور سنتی منطقه‌ای کشاورزی بوده و دارد، با فشار فزاینده ناشی از ساخت فرودگاه بین‌المللی (GRDP) بخش کشاورزی سهم مهمی در تولید ناخالص داخلی منطقه‌ای مواجه است .تحلیل‌های سنجش‌ازدور کاهش زمین‌های پوشیده از پوشش گیاهی و گسترش مناطق ساخته‌شده را (BIJB) کرجاتی نشان می‌دهد که تهدیدی برای تولید غذای محلی و معیشت کشاورزان محسوب می‌شود .این تأثیر دوگانه ضرورت پایش فضایی مستمر و تدوین راهبردهای برنامه‌ریزی یکپارچه را برجسته می‌سازد تا میان اهداف رشد اقتصادی و پایداری کشاورزی در چشم‌اندازهای پیرامونی شهری که به‌سرعت در حال تحول هستند، تعادل برقرار شود.

مواد و روش‌ها: برای تحلیل A و ۲ C در سطح‌های ۱ (MSI) در این مطالعه از تصاویر ماهواره‌ای سنتینل-۲ با حسگر چندطیفی -Sentinel کاربری و پوشش زمین استفاده شد .این پژوهش تغییرات کاربری زمین در شهرستان ماجالنگکا را با استفاده از تصاویر پردازش شدند، مورد تحلیل قرار می‌دهد .داده‌های Google Earth Engine سال‌های ۲۰۱۵، ۲۰۲۰ و ۲۰۲۵ که در بستر 2A طبقه‌بندی شدند .همچنین برای افزایش دقت از Random Forest موزاییکی تصاویر به صورت میانه ترکیب و سپس با الگوریتم استفاده شد .اعتبارسنجی نتایج با بهره‌گیری از پیمایش میدانی و روش نمونه‌گیری تصادفی MNDWI و IBI ،NDWI شاخص‌های طبقه‌بندی‌شده انجام گرفت که منجر به دقت کلی ۹۸/۸۱٪ و مقدار کاپا ۹۵/۹٪ شد .علاوه بر این، برآورد نیاز و پیش‌بینی تغییرات کاربری زمین محاسبه گردید .در ادامه، الگوهای فضایی، پویایی تغییر کاربری زمین و نیز پیش‌بینی نیاز کاربری زمین تا سال ۲۰۳۵ مورد تجزیه و تحلیل قرار گرفت.

نتایج و بحث: نتایج پژوهش نشان‌دهنده کاهش قابل‌توجه زمین‌های کشاورزی در ماجالنگکا است، به‌ویژه شالیزارها، زمین‌های دیم و باغ‌های مختلط، با مجموع تغییر کاربری بیش از ۶۰۰۰ هکتار در دوره ۲۰۱۵ تا ۲۰۲۵ .دوره ۲۰۲۰ تا ۲۰۲۵ به‌عنوان مرحله بحرانی مشخص شد، به‌طوری‌که کاهش شالیزارها به ۱۵۶۰ هکتار و افزایش مناطق مسکونی به ۴۸۷۹ هکتار رسید .گسترش مهم‌ترین عوامل محرک این تغییرات بودند .تحلیل فضایی تأیید می‌کند (BIJB) نواحی صنعتی و فرودگاه بین‌المللی جاوای غربی که الگوی تغییر کاربری در کریدور شمالی متمرکز شده و تهدیدی جدی برای تولید غذا و امنیت غذایی محلی ایجاد می‌کند .از این رو، تقویت سیاست‌های برنامه‌ریزی فضایی و حفاظت از زمین‌های کشاورزی ضروری به نظر می‌رسد.

نتیجه‌گیری: ،روند تغییر کاربری زمین‌های کشاورزی در ماجالنگکا، به‌ویژه شالیزارها (BIJB) ساخت فرودگاه بین‌المللی کرجاتی Random) با الگوریتم جنگل تصادفی Sentinel-2 را به سمت سکونتگاه‌ها، صنعت و زیرساخت تسریع کرده است .تحلیل تصاویر دقت بالای خود را در پایش این تغییرات نشان داده است .اجرای قاطع سیاست‌های کاربری زمین و حفاظت از اراضی (Forest آبیاری‌شده برای حفظ تعادل میان توسعه و امنیت غذایی ضروری است.

کلمات کلیدی: تغییرات کاربری زمین، شالیزار، سنتینل- ،(Google Earth Engine) فرودگاه، کشاورزی، موتور زمین گوگل الگوی فضایی ،۲

INTRODUCTION

Infrastructure expansion is widely acknowledged as a key force shaping both spatial structures and economic trajectories at regional and national levels. Major transport projects, including highways and airports, simultaneously enhance mobility and accessibility while fostering deeper regional market integration and attracting external investment flows (Wang et al., 2023; Xu et al., 2023). From a development perspective, infrastructure functions as a trigger for modernization and economic expansion. Yet, these benefits often come with sustainability trade-offs such as ecological degradation, declining biodiversity, and the loss of productive farmland (Kusuma & Purnama, 2023; Sari & Kushardono, 2019).

Evidence from multiple regions further illustrates this dual role. In India, improving road quality has been shown to substantially strengthen regional output and market connectivity, while mere expansion in network density without quality upgrading tends to generate diminishing marginal benefits (Nugraha et al., 2020). Comparative cross-country analyses also affirm the long-term contribution of physical infrastructure to productivity growth and trade integration (Timilsina et al., 2024). Within Indonesia, recent studies reveal a synergy between transport infrastructure and local fiscal capacity in boosting regional economic performance (Ibrahimov et al., 2023). However, the growth of transport networks frequently coincides with deforestation, ecological decline, and rapid land-use change, particularly around strategic hubs such as airports (Lu et al., 2022).

Sustainability concerns are particularly urgent in agrarian regions where farmland underpins food production and rural livelihoods. While land resources are increasingly allocated to housing, industry, mining, and transportation, farmland remains strategically vital as the backbone of food security in the context of rapid demographic growt (Adrian et al., 2022; Mulyani et al., 2023). Recognizing this, the Indonesian government enacted Law No. 41 of 2009 on the Protection of Sustainable Agricultural Land (LP2B), which underscores that farmland conversion directly undermines national food sovereignty. In Majalengka Regency, West Java, agriculture has historically been the leading sector in terms of welfare and economic contribution, accounting for the highest share of the Gross Regional Domestic Product (GRDP) between 2015 and 2025 (BPS, 2025).

The development of Kertajati International Airport provides a clear example of the tension between economic growth and sustainability. Conceived as a national strategic project to enhance connectivity and attract new investment, the airport has simultaneously induced significant spatial transformation in its surrounding areas. Remote sensing analyses indicate a decline in vegetated land and a rise in non-vegetated surfaces, pointing to accelerated conversion from agriculture to non-agriculture. This process not only reduces the capacity for local food production but also directly threatens the livelihoods of farming households that depend on agricultural activity (Adrian et al., 2024; Sari et al., 2022).

Remote sensing technologies play a crucial role in monitoring such land transformations. Applications of Sentinel-2 and Landsat-8 imagery have consistently demonstrated high accuracy in detecting farmland conversion related to infrastructure development (Hermanto, 2021; Huber & Rinner, 2020). Advances in deep-learning-based land-cover classification applied to these datasets allow for detailed mapping of agricultural areas and provide robust insights into land-use dynamics. In Majalengka, Sentinel-2 imagery documented a decline in vegetation quality between 2016 and 2020, directly associated with the construction of Kertajati Airport and nearby toll roads (Papadopoulou et al., 2023). These findings underscore not only the transformative role of airports in regional connectivity but also their tangible consequences for farmland conversion, reinforcing the importance of satellite-based monitoring to inform mitigation strategies that balance economic expansion with food sustainability (Alem & Kumar, 2022). However, few studies have quantified the spatial dynamics of farmland conversion triggered by BIJB, combining remote sensing with land demand projection models. This study addresses that gap.

Against this backdrop, the present study investigates the spatial impacts of airport development on agricultural land-use patterns. Specifically, it aims to: (1) analyze the extent and dynamics of land-use change before and after the construction of Kertajati International Airport; (2) identify spatial patterns of farmland conversion in the surrounding area; and (3) evaluate the implications of these changes for sustainable agriculture and spatial planning. By pursuing these objectives, the study contributes to advancing knowledge at the intersection of infrastructure development, spatial transformation, and agricultural sustainability, while providing empirical evidence to support more effective land governance in Indonesia.

MATERIALS AND METHODS

Case Study

This study was carried out in Majalengka Regency, located in West Java Province. The Regency consists of 26 Districts and is geographically situated between 108°03' and 108°25' East Longitude and 6°36' and 6°58' South Latitude. Furthermore, it shares borders with Indramayu Regency to the north, Garut, Tasikmalaya, and Ciamis Regencies to the south, Sumedang Regencies to the west, and Cirebon and Kuningan Regencies to the east. The study area can be seen in **Figure 1**

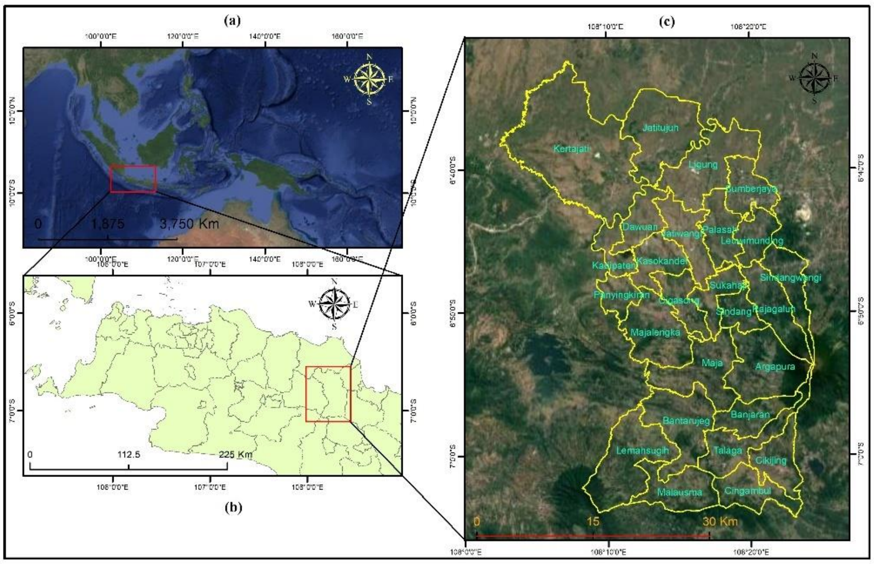

Figure 1. Map of the Study Area of Majalengka Regency.

The research Variables

Primary and secondary data were employed in this study. The primary data used were survey findings obtained through image interpretation in the field. Meanwhile, the secondary data include land use maps from 2015, as well as administrative and rice field standard maps. Satellite imagery was also utilized and processed using Google Earth Engine (https://code.earthengine.google.com) to develop a land use map (GEE) application software and ArcMap 10.8. The maps contain land use information for the years 2015, 2020, and 2025. The information was then cross-checked with regional planning data and the Majalengka Regency Spatial Planning for 2015-2031, can be seen in Table 1:

Table 1. Generated map and sources of original data

Data Name	**Data Type**	**Data Source**	**Data Description**
LU/LC 2015, 2020 and 2025	Raster	Processing using (GEE) scripts	
Regional Spatial Plan Map	Vector	Regency Spatial Planning Office, 2025	
Detailed Spatial Plan Map	Vector	Regency Spatial Planning Office, 2025	
Agricultural Protection Areas	Raster	(Adrian et al., 2024)	Journal
land suitability for paddy map in Majalengka Regency	Vector	(Adrian et al., 2022)	Journal
Administrative Map of Majalengka Regency	Vector	Regency Spatial Planning Office, 2025	

Point of Interest	Vector	Google (Scrap Data PoI)	
Statistical data from Statistics Indonesia (BPS) for Majalengka Regency	Tabular	Statistics Indonesia (BPS)	

Procedures and data analysis

The study focused on altering the utilization of paddy fields in Majalengka Regency. The stages of land use/cover analysis carried out are as follows; (1) Creation of a mosaic Sentinel-2A MSI (Multi-Spectral-Instrument) Level-1C and Level-2A image data. This involves combining numerous scenes using an analysis tool to filter dates within one year and include the Sentinel Level-2A collection property, orthorectified atmospherically adjusted surface reflectance. (2) Taking the average (median) value of the image mosaic in that period. (3) Processing and cutting image mosaics using the administrative boundary polygons of the study area. (4) Displaying image visualization. (5) Determining land use/cover sampling (6) Conducting supervised classification analysis using the Smile-Random Forest machine learning approach. (7) Testing and calculating Overall Accuracy (OA) and Kappa Accuracy. (8) Adding NDBI and NDWI analysis to increase accuracy (9) downloading analysis results (10) processing land cover/use maps in ArcGIS to calculate spatial patterns of land change. The land use classification flowchart is presented in Figure 2 below.

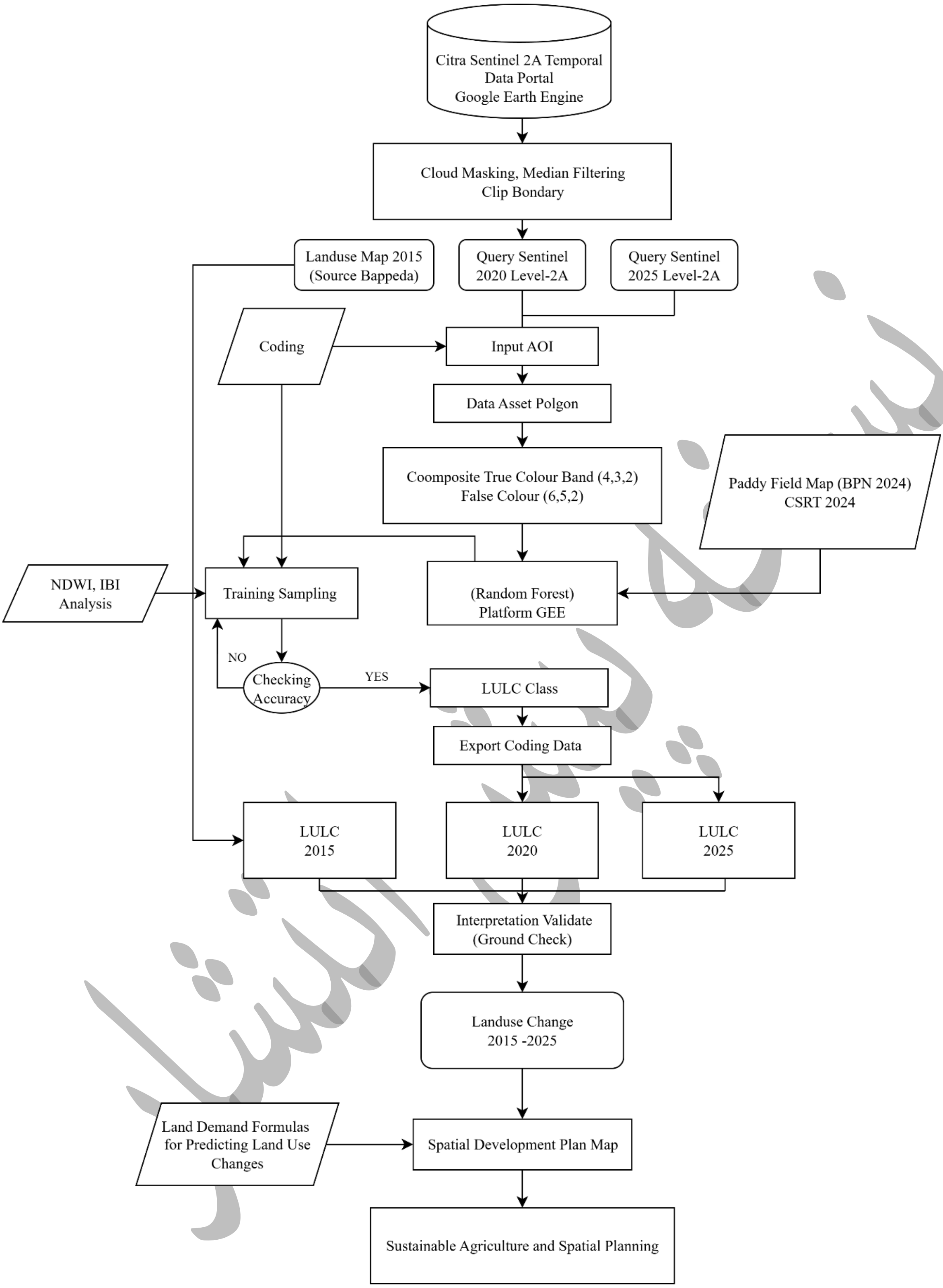

Figure 2. **Research Flow Spatial Pattern of Paddy Field Conversion**

The mapping procedure

The land use/land cover classification in this study was based on the norms specified in SNI 7645-2014 for land cover and land use classification. This classification yielded a total of nine land use types. The validation test for the 2025 land use/land cover utilized the stratified random sampling estimation method as part of the remote sensing procedure (Ghodsi et al., 2020). The approach of stratified random sampling distribution generated 400 test sites for accessing the accuracy of the land use/land cover classification in 2025. As shown in the table above, the Slovin formula approach was employed to determine the sample points based on the number of pixels obtained through classification. The Google Earth Engine script was used to analyze the annual land use/cover changes between 2020 and 2025.

a. LULC Classification Methods

Breiman proposed the Random Forest machine learning method (Daryaei et al., 2021; la Cecilia et al., 2023),which is a classifier based on decision trees. Each tree contributes one vote, and the final classification or prediction results are determined by voting (Amani et al., 2020; Piao et al., 2021). The GEE platform was used to implement the RF classification method. The RF classifier was trained using training data, and the classification error was assessed using verification data. While using the RF models in GEE, two parameters needed to be specified: the number of decision trees to create for each class (number of trees) and the minimum size of a terminal (min leaf). During the LULC classification, multiple values of the number of trees and min-leaves were tested. The best parameters were selected based on total classification precision. Google Earth Engine (GEE) script used to analyze annual changes in land cover/land use, as well as to compute the Index-Based Built-up Index (IBI) and Modified Normalized Difference Built-up Index (MNDBI) between 2020 and 2025, is presented in Figure 3. The complete code is accessible via the following link: (https://code.earthengine.google.com/84f71973c7ce2af2071351041393e75f).

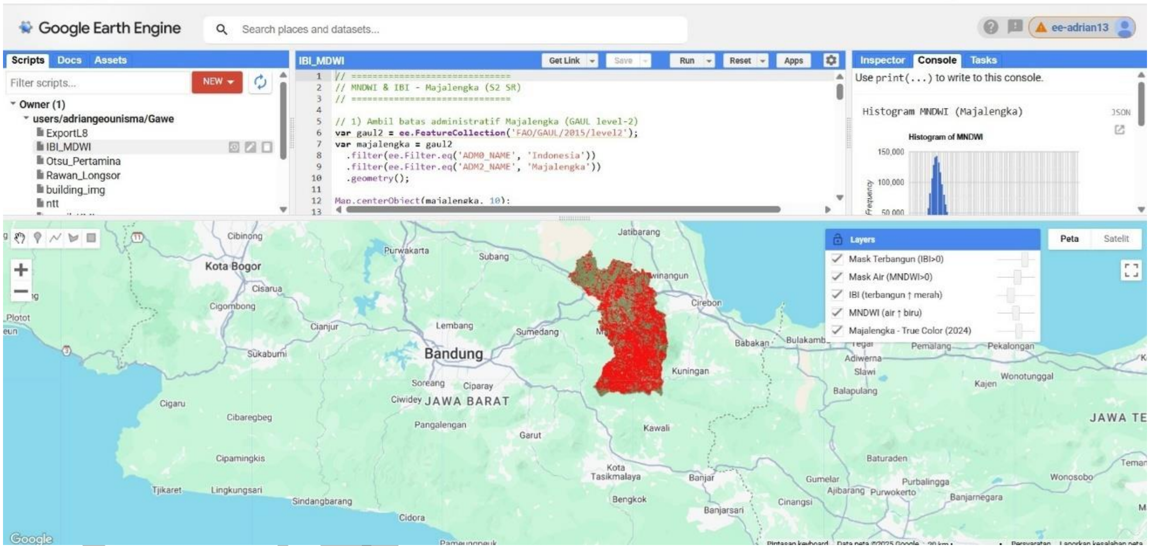

Figure 3. **Random Forest, IBI and MNDWI Script Google Earth Engine**

b. Algorithm Of IBI

The Index Based Built-up Index (IBI) is an algorithmic method used to estimate the density of built-up areas (Airiken et al., 2022). The underlying concept of this algorithm is to enhance architectural objects by calculating the ratio of midi-infrared (MIR) to near-infrared (NIR) bands. Objects in urban environments tend to have higher reflectance in the MIR band compared to the NIR band, which allows for differentiation. However, in certain scenarios, dry terrain and built-up areas exhibit similar patterns, with MIR reflectance values significantly higher than NIR waves (Trinh et al., 2021). Table 2 displays the formula for computing NDBI, the commonly used index for detecting built-up regions in remote sensing imagery. This approach has been widely employed in mapping analysis to enhance the accuracy of identifying residential land cover in built-up areas. The Index-based Built-up Index (IBI) offers several advantages over the traditional Normalized Difference Built-up Index (NDBI). While NDBI often misclassifies bare soil and dry land as built-up areas due to their similar spectral characteristics, IBI integrates NDBI with the Normalized Difference Vegetation Index (NDVI) and the Modified Normalized Difference Water Index (MNDWI). This integration effectively reduces confusion with vegetation and water bodies, resulting in more accurate delineation of urban areas. Moreover, IBI provides a clearer representation of urban spatial patterns and performs more reliably in complex tropical environments where mixed land covers are common. As a result, IBI is considered a more robust and precise tool for monitoring urbanization and mapping built-up areas, particularly in densely populated and heterogeneous city landscapes (Li et al., 2021).

c. Algorithm of MNDWI

The Modified Normalized Difference Water Index (MNDWI) is a method used to determine the presence of water bodies. This technique utilizes the green and infrared bands (RED) as water bodies exhibit high reflectance in the green spectrum (GREEN) and high absorption in the near-infrared spectrum (Motwake et al., 2024). By comparing the values of these two bands, the radiometric value of objects containing water is higher compared to other objects (Bandak et al., 2023). However, when NDWI is applied to extract water bodies within built-up areas such as cities, the extracted information may significantly deviate from the actual water body information. Incorporating this algorithm can enhance the accuracy of land cover classification for water bodies and agricultural land. The formula for calculating MNDWI can be found in Table 2, while the process of integrating the IBI and MNDWI platforms with land cover/use classification is illustrated in Figure 4.

Table2. Spectral Index Formula

No.	Indeks	Formula
1	IBI	IBI = NDBI−(NDVI+MNDWI) /
2	MNDWI	MDWI = (NIR - SWIR) / (NIR + SWIR1)

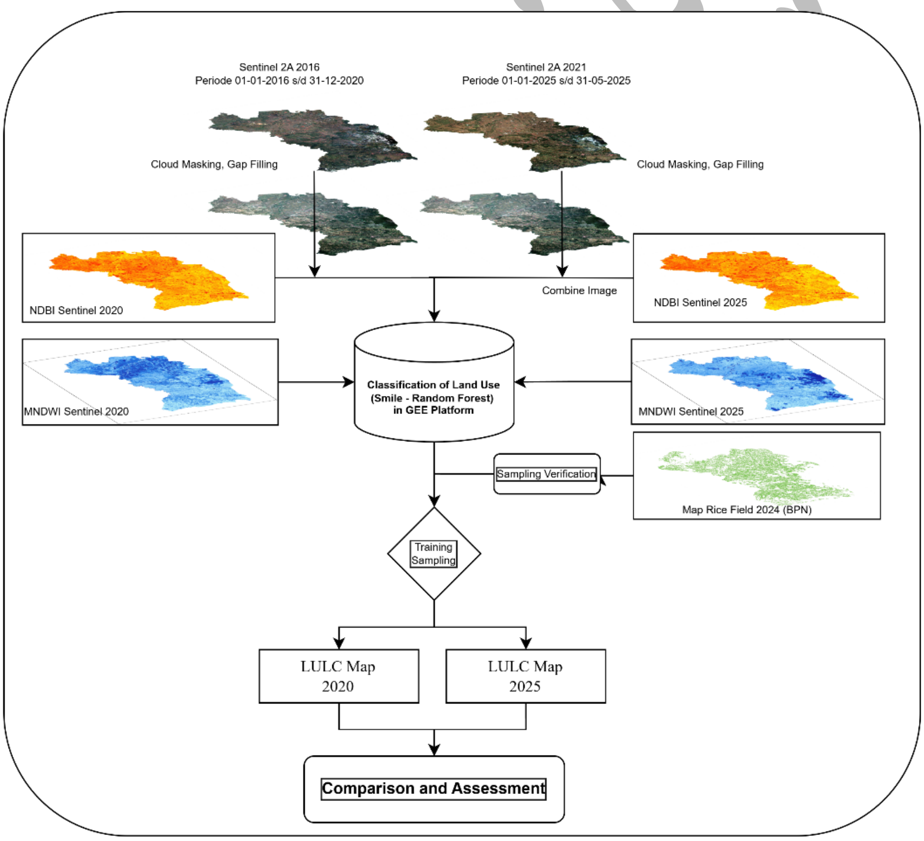

Figure 4. Combining NDBI, NDWI Methods with Land Cover Analysis

c. Interpretation and Calculation of Maping Procedure

The validation employed in this study involved field data verification and sample point tests conducted at the locations. To access the accuracy of this step, the approach and assessment method of stratified random sampling for remote sensing (Shetty et al., 2021) are followed as outlined below:

1. Field inspection were carried out at selected sampling points for each land use type, with a more thorough inspection conducted for paddy fields. The number of sampling areas was determined based on the homogeneity of the sampling points associated with each land cover/use type.
2. The degree of alignment between the results of image classification analysis and the actual field conditions was examined.
3. The confusion matrix, which is a matrix used to evaluate the accuracy of land cover/use types, was calculated based on the analysis of digital image data. The Slovin formula was used to determine the locations of the sampling points (Mishra et al., 2021).

$$D = \frac{s}{s} a^2$$

Where :
D = sample;
s = population;
a = 90% precision value or sig. = 0.1

d. Primary survey or site verification

To ensure the accuracy of land cover and land use data in relation to current field conditions, the 2025 land use dataset was validated through a field survey approach. The primary survey, or site verification, consisted of direct observations within the study area and documentation of land use characteristics. This procedure was undertaken both to confirm the reliability of the existing land use classification and to determine representative sample sizes for each land use category, as presented in Table 3.

Table3. Validation of Land Use / Land Cover Samples (Ground Truth)

Land use / Land cover (SNI 7645-2014)	Cell count (10x10) m	Number of Samples
1. Paddy field	4826671	145
2. Field	3140747	94
3. Mixed Crop	3023493	91
4. Scrub	28748	1
5. Forest	365871	11
6. Settlement	1689374	51
7. Water body	144720	4
8. Industrial Area	33457	1
9. Airport	71652	2
Total	13324733	400

e. Estimation of needs and prediction of land changes

This study estimates non-agricultural land demand in Majalengka Regency through 2045 using a stock-and-flow framework that links multi-temporal LULC dynamics (2015–2025) and a 2025 baseline inventory with policy targets in the revised RTRW (2025–2035) and relevant RDTRs. Equations (1)–(5) derive net land needs by category—residential, industrial-logistics, and services/commercial—adjusted for floor area ratio (FAR), net-to-gross allowances, and densification effects, and then add infrastructure and rights-of-way as a proportion of those totals. Industrial demand is parameterized by job density and, under an airport/SEZ pathway, a logistics component keyed to cargo volume. All outputs are reported in hectares at the sub-district level for 2035 and 2045 and are evaluated against protected irrigated paddy constraints. Three scenarios are assessed—Business-as-Usual, Aerocity/SEZ-accelerated, and Conservation/Densification—together with ±10% sensitivity tests on key parameters (FAR, net-to-gross, densification, job density, logistics coefficient) to gauge robustness and policy relevance.

1) Residential Land: $L\,res.t = \frac{P^t}{HHS^t}\ \ x\,A_{plot}\ X\ \frac{1}{FAR^t}\ X\ (1+\alpha\text{N2G})x(1-\delta dens)$
2) Industrial–logistics land: $L\,ind.t = \frac{Eind^t}{Njobs} + \gamma logQt.cargo$
3) Services/commercial land: $Lsvc.t = \frac{AGFApcPt}{FAR^t}\ \ x\ \times \kappa \times (1+\alpha N2G)$
4) Infrastructure & rights-of-way (ROW): $Linfra.t = \beta ROW(Lres.t + Lind.t + Lsvc.t)$
5) Total land need & protection constraint: $Ltotal.t = Lres.t + Lind.t + Lsvc.t + Linfra.t\ .subject\ toLpaddy.t \geq Lmin - protect$

Variable definitions (all land outputs in hectares):

P^t : projected population in year t
HHS_t : average household size in year t (persons/household)
A_{plot} : standard plot size per dwelling (ha/dwelling)
FAR_t : floor area ratio in year t (dimensionless)
αN2G : net-to-gross uplift for internal roads/open space
δdens : densification/infill reduction factor (0–0.30; higher = less greenfield land)
$Eind.t$: projected industrial employment (jobs)
$Njobs$: industrial job density (jobs/ha)
γlog : logistics land coefficient (ha per unit cargo
$Qt.cargo$: cargo volume
$AGFApcPt$: required gross floor area per capita for services (m² per person)
κ : conversion from m² to ha
βROW : share for external ROW
$Lpaddy.t$: safeguarded irrigated paddy land in year t (ha)
$Lmin - protect$: minimum protected paddy land (ha)

RESULTS

Land use/land cover classification

The accuracy of the land cover/land use classification was assessed using a confusion matrix. From this matrix, three key indicators were derived: user's accuracy, producer's accuracy, and overall accuracy, as presented in Table 4. Overall accuracy represents the proportion of pixels correctly classified into their respective land use categories. Producer's accuracy reflects the degree to which pixels of a given category are correctly identified, while user's accuracy indicates the reliability of the classification, showing the likelihood that a pixel classified into a specific category actually corresponds to that category in the field.

Based on the analysis presented in Table 4, the highest user's accuracy was recorded in 2020 and 2025 for the land cover classes of shrubs, forest, settlement, water bodies, industry, and airport, each achieving 100%. In contrast, the lowest user's accuracy in 2016 was observed for dryland agriculture (90.32%), while in 2021 it improved to 93.62%. For paddy fields, the accuracy in 2016 was 96.55%, increasing to 97.24% in 2021 when combined with field survey validation. The relatively lower accuracy for dryland agriculture is primarily attributed to its frequent conversion into paddy fields due to crop rotation practices among farmers in the study area. With such a relatively small classification error, the overall accuracy values—ranging from 97.81% to 98.81% for the 2016 and 2021 maps—indicate that the Random Forest (RF) algorithm implemented on the GEE platform provides a robust model for land use/land cover mapping. Considering that the minimum accuracy threshold for land cover/land use maps is 85%, the results of this study can be regarded as sufficiently reliable to serve as input for further spatial analysis.

The results indicate that the application of the Random Forest (RF) algorithm on the Google Earth Engine (GEE) platform can produce land use maps with high accuracy, achieving an overall accuracy (OA) of 92.6%. These findings are consistent with previous studies, which demonstrated that the integration of spectral imagery and combined indices generally yields higher classification accuracy compared to the use of single classifiers. In this study, the integration of the Index-Based Built-up Index (IBI) and the Modified Normalized Difference Water Index (MNDWI) within the GEE platform significantly improved the accuracy of land cover classification. Furthermore, the correction of paddy field boundaries using reference data from the Indonesian National Land Agency (BPN) enhanced the precision of agricultural land mapping, particularly for paddy field use. The processed outputs and the resulting land use maps are presented in Figure 5.

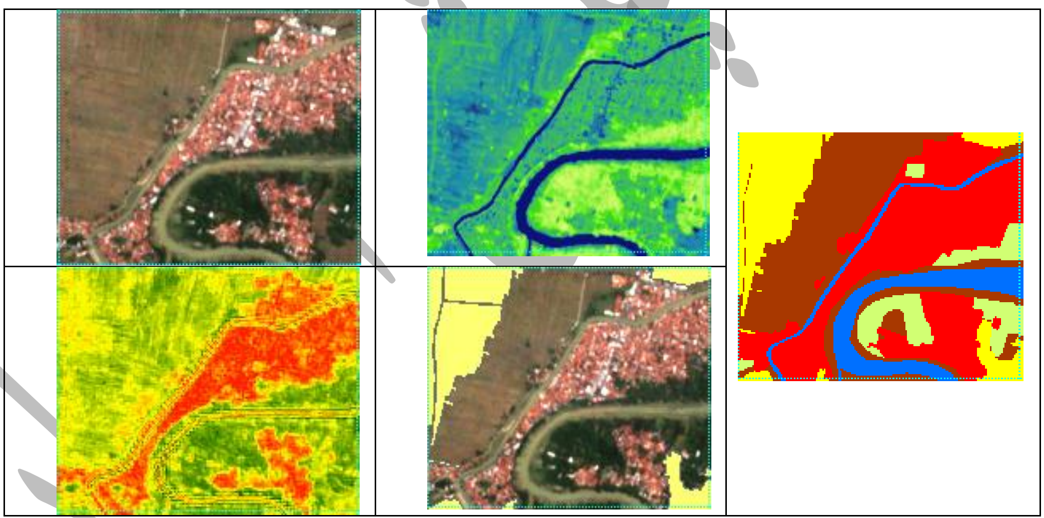

Figure 5. Comparison of predictor variables (Sentinel imagery, MNDWI, IBI, and paddy field maps) and land use/land cover classification results for the periods 2015–2020 and 2020–2025.

One of the most challenging aspects of this research was the classification of paddy fields. This difficulty is mainly due to their highly dynamic nature and the alternating land use practices observed in time-series imagery, where paddy fields are often interspersed with seasonal crops such as maize, soybeans, and other secondary crops. Predicting land cover and land use changes requires accurate representation of current field conditions. To address this, validation was conducted using existing 2025 land use samples derived from SPOT imagery (2024) combined with field surveys carried out in 2025. The sampling population was calculated based on the number of training sampling cells for the 2025 land use classification (as presented in Table 4). Sampling precision was set at 98%, determined in consideration of the available time, resources, and spatial extent of the study area. Furthermore, the official paddy field map provided by the Indonesian Ministry of Agriculture was used as an independent variable. The vector data were converted into raster format with a 10 m spatial resolution, consistent with Sentinel-2A imagery. Classification accuracy was then assessed by comparing the agreement between classified samples and ground-truth samples obtained during field verification.

Table 4. Land use accuracy results

		Field survey Validation											
		1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**Total**	**Not Suitable**	**Suitable**
LU/LC Classification	**1**	142	3								145	3	97,93%
	2		90	2	2						94	4	95,74%
	3	1	3	87							91	4	95,60%
	4				1						1	-	100,00%
	5					11					11	-	100,00%
	6						51				51	-	100,00%
	7							4			4	-	100,00%
	8								1		1	-	100,00%
	9									**2**	2	-	100,00%
Total											**400**	**11**	**98,81%**

LU/LC	1. Paddy field	4. Scrub	7. Water body
Code	2. Field	5. Forest	8. Industry
	3. Mixed Crop	6. Settlement	9. Airport

Land use during the periods 2015–2020 and 2020–2025

The validated land use/land cover (LULC) maps of Majalengka Regency for 2015, 2020, and 2025 were subsequently quantified by calculating the areal extent of each land cover/use class, followed by an overlay analysis. The overlay of maps was conducted using ArcGIS to detect and measure changes in land use over time. Statistical analysis of the LULC transitions revealed both the dynamics and processes of land use conversion within the study area. The change detection was based on two independent classification results derived from Sentinel-2A imagery for the years 2020 and 2025. The analysis focused on land use/cover categories from 2015, 2020, and 2025, with particular emphasis on industrial zones, settlements, and the extent of paddy fields. Through this spatial analysis, the distribution and magnitude of land use change across these categories were identified. The results highlight the extent and percentage of land use transitions across the three time periods, providing insights into the scale and direction of land cover dynamics. The detailed area and percentage changes for each category are presented in Table 5.

Table 5. Comparison of Land Use Area in years (2015, 2020, and 2025)

Land Use	2015 (Ha)	%	2020 (Ha)	%	L 2025 (Ha)	%
1. Paddy field	59.899,62	33,23	59.450,63	32,98	58.339,46	32,36
2. Field	46.993,92	26,07	46.527,01	25,81	44.096,72	24,46
3. Mixed Crop	45.104,24	25,02	44.957,62	24,94	43.183,78	23,95
4. Scrub	1.537,67	0,85	1.537,67	0,85	1.537,67	0,85
5. Fores	8.917,99	4,95	8.917,99	4,95	8.917,96	4,95
6. Settlement	13.561,73	7,52	14.072,77	7,81	18.951,46	10,51
7. Water body	2.247,76	1,25	2.247,45	1,25	2.182,44	1,21
8. Industrial Area	9,66	0,01	82,07	0,05	346,60	0,19
9. Airport	-	-	479,39	0,27	716,49	0,40
Total	178.272,60	100	178.272,60	100	178.272,60	100

The analysis indicates that land use in Majalengka Regency remains predominantly agricultural, particularly paddy fields; however, significant changes occurred during the 2015–2025 period. The years 2020–2025 represent the most critical phase, with a sharp decline in paddy fields (−1,560.17 ha), dryland agriculture (−2,897.19 ha), and mixed gardens (−1,920.47 ha). These reductions highlight the rapid and large-scale conversion of agricultural land within a relatively short timeframe.

In parallel, expansion was observed in non-agricultural land uses, including settlements (increasing from 14,072 ha to 18,951 ha), industrial areas (from 82 ha to 346 ha), and the West Java International Airport (BIJB) area (from 479 ha to 716 ha). This pattern underscores that strategic infrastructure development and the expansion of residential–industrial zones constitute the main drivers behind the loss of productive farmland. Such findings demonstrate that agricultural land decline is not merely a spatial fluctuation but reflects systematic conversion towards non-agricultural uses. This process carries serious implications for local food sustainability. Consequently, the land use dynamics in Majalengka highlight the growing pressure of development on agricultural resources, with the potential to undermine regional food security in the future, The spatial distribution of land use in 2015, 2020, and 2025 is illustrated in Figure 6

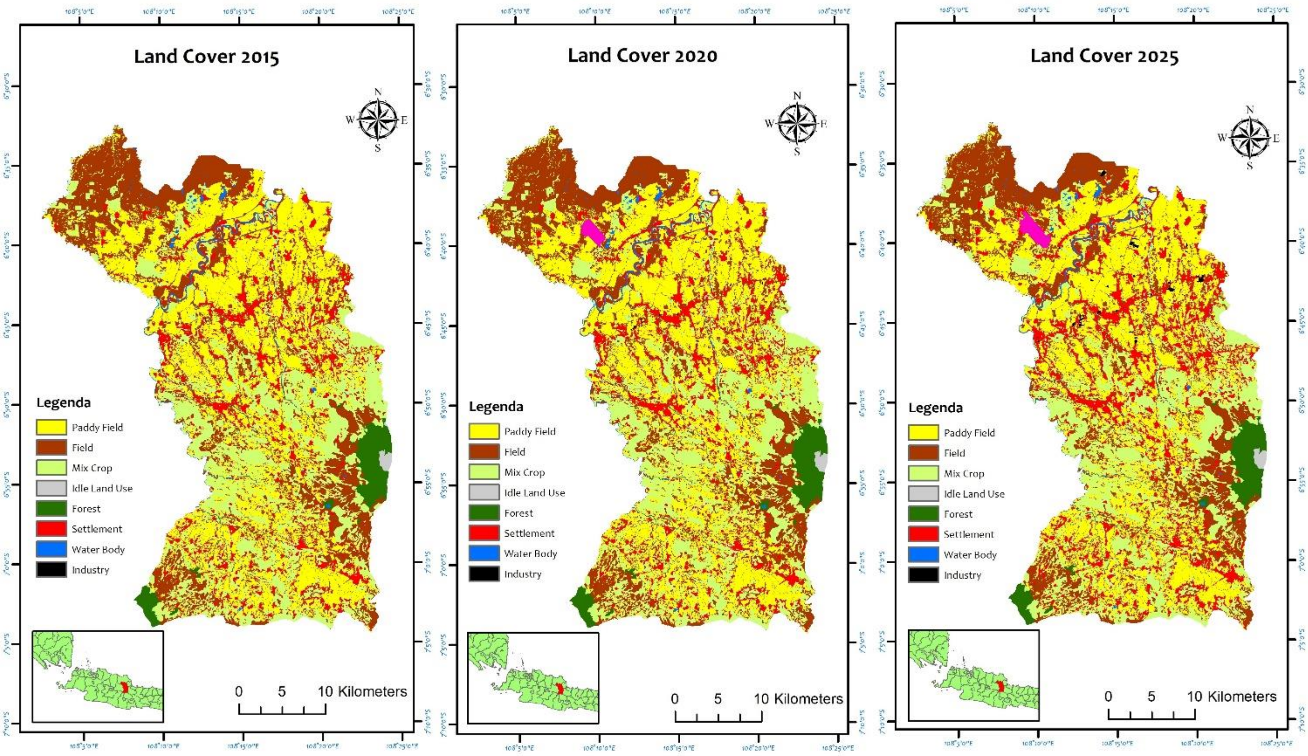

Figure 6. Land use/land cover changes in Majalengka Regency for the period 2015–2025.

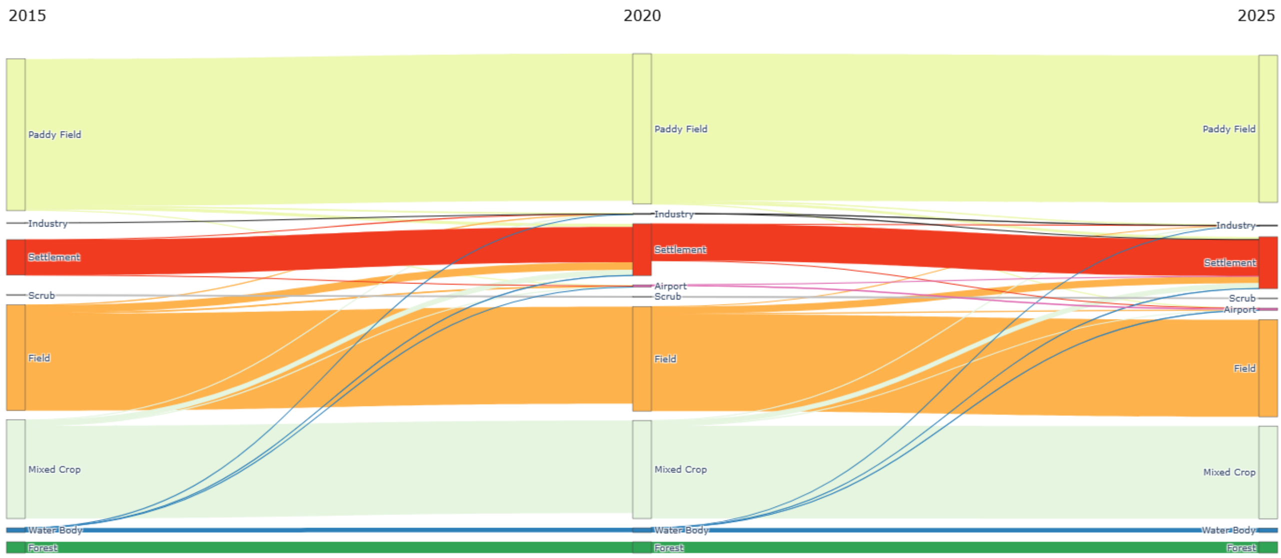

Figure 7. Land use/land cover change matrix of Majalengka Regency, 2015–2025.

Based on the analysis of land use/land cover (LULC) changes presented and visualized through the Conversion Matrix in Figure 7, it is evident that land conversion is a continuous phenomenon accompanying population growth and regional development. Such patterns are commonly observed in both urban and rural areas, with a general tendency for agricultural land to be converted into uses with higher economic value, including settlements, industrial zones, commercial centers, and major infrastructure. In Majalengka Regency, the most prominent agricultural land conversion occurred in the northern region, particularly in Kertajati, Dawuan, Jatitujuh, and Jatiwangi sub-districts. The results indicate that paddy fields in these areas have been converted into airport facilities, residential areas, and industrial estates. The relatively flat to gently sloping topography, combined with proximity to the road network, has accelerated this conversion process.

These findings are consistent with previous studies, which emphasize that the development of industrial growth centers tends to accelerate farmland conversion, especially in developing countries where economic development policies strongly encourage industrial expansion and intensify rural land transformation. In the case of Majalengka, the construction of the West Java International Airport (BIJB) has acted as a major driver, converting productive farmland into airport areas and associated infrastructure. This conversion has directly reduced the extent of agricultural land and poses a potential threat to agricultural productivity in the region, The spatial distribution of land use change, validated with field data, is presented in Figure 8.

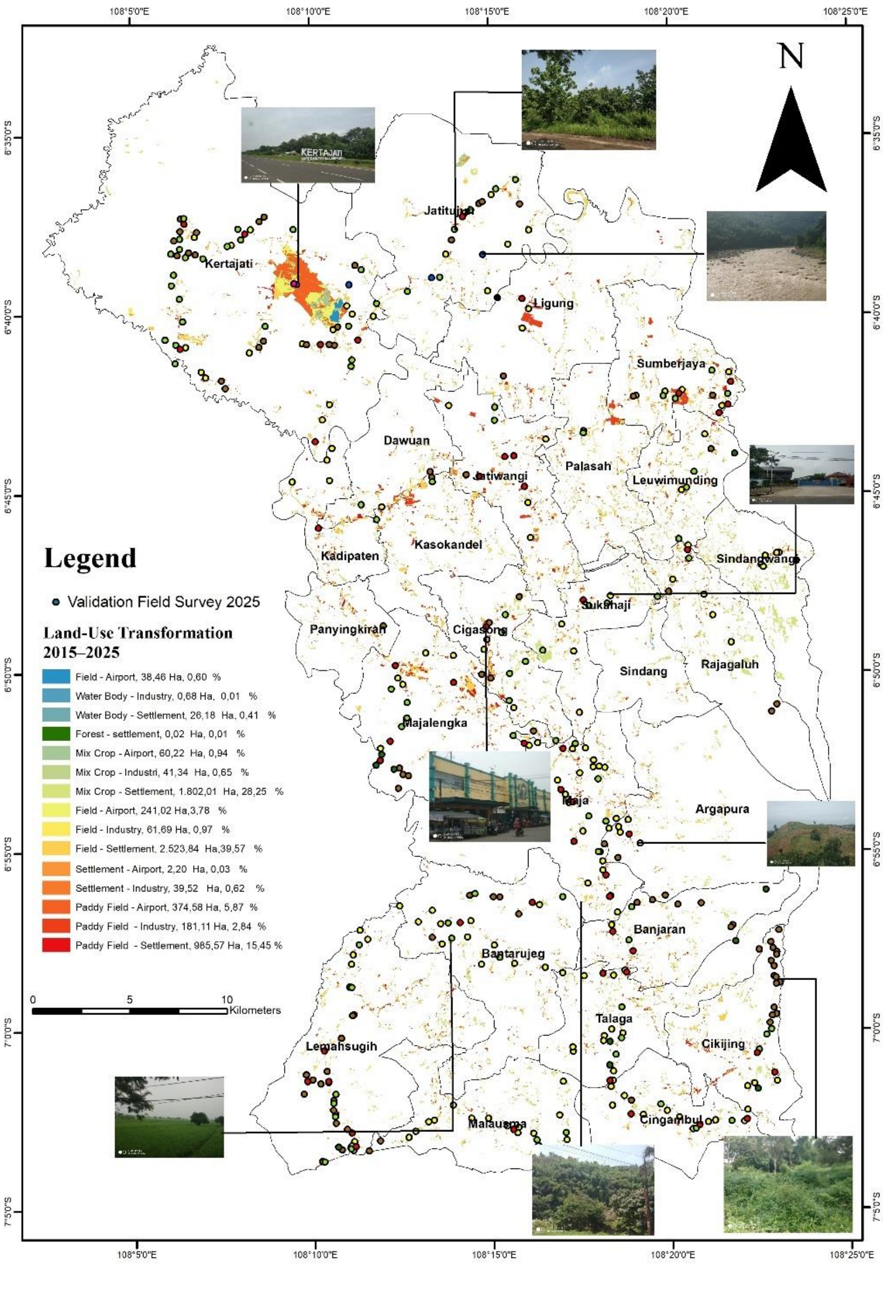

Figure 8. **Map of Spatial Pattern Changes (Field Validation)**

Land conversion is a dynamic process that continues alongside population growth and regional development. Among agricultural land types, paddy fields are particularly vulnerable because they are often located in strategically accessible areas. As shown in Table 6, agricultural land conversion in Majalengka Regency is predominantly characterized by the transformation of paddy fields, dryland agriculture, and mixed gardens into settlements, industrial zones, and airport infrastructure. Spatially, the largest conversion of paddy fields into settlements occurred in Majalengka Sub-district (83 ha) as the administrative center, followed by Kertajati (62 ha), influenced by airport development, and Sumberjaya (144 ha), which is evolving into an industrial hub.

The most significant conversion of dryland agriculture into settlements was recorded in Kertajati (248 ha) and Sumberjaya (144 ha). Industrial expansion has progressed in parallel with rising housing demand, particularly after the establishment of the Rebana Special Economic Zone (SEZ). Conversion into industrial land has also increased sharply, involving 181 ha of paddy fields, 61 ha of dryland agriculture, and 41 ha of mixed gardens, mainly concentrated in the northern and central areas. Field observations confirm that the development of the West Java International Airport (BIJB) in Kertajati has acted as a primary driver, resulting in the conversion of 374 ha of paddy fields, 241 ha of dryland agriculture, and 60 ha of mixed gardens, largely to accommodate runways and supporting facilities.

The implications of this conversion are substantial, including reduced food production—particularly rice as the primary staple crop—loss of farming employment opportunities, and a decline in the agricultural sector's contribution to Majalengka's Gross Regional Domestic Product (GRDP). Therefore, farmland conversion driven by airport and industrial development not only reshapes the spatial pattern of land use but also poses critical challenges to food security and the socio-economic structure of the region.

Land Cover Prediction

This analysis estimates the total land requirements for future development in Majalengka Regency. In line with the Regency Spatial Plan (RTRW), growth in residential and industrial areas will drive land demand; accordingly, we provide estimates of minimum residential land needs in accordance with applicable planning standards. The projection horizon extends to 2035, reflecting the typical ten-year evaluation cycle stipulated in the RTRW and the Detailed Spatial Plan. This section estimates land demand in Majalengka Regency for 2021–2045 using a baseline inventory of built-up areas (2021/2025), multi-temporal LULC dynamics (2015–2025), and policy targets from the revised RTRW (2024; horizon 2025–2035) and relevant RDTRs. Residential, industrial–logistics, and service/commercial needs are projected under three scenarios—Business-as-Usual (BAU), Aerocity/SEZ-accelerated, and Conservation-led—accounting for population and employment projections, urban densification (FAR), net-to-gross land adjustments, and infrastructure rights-of-way. Outputs are expressed as net land requirements (ha) by sub-district for 2035 and 2045, with agricultural protection constraints applied to irrigated paddy areas and critical ecosystems. Results highlight increasing non-agricultural land demand concentrated in the northern corridor (Kertajati–Sumberjaya), reflecting airport-driven development and associated industrial–residential expansion, while densification policies moderate greenfield conversion under the conservation-led scenario. The calculation results regarding projected land requirements are presented in Table 6.

Table 6. Projected Land Demand by Scenario

Scenario	$L\,res.t$ (ha/yr)	$L\,ind.t$ (ha/yr)	$L\,svc.t$ (ha/yr)	$L\,infra.t$ (ha/yr)	$L\,Total.t$ (ha, in year 2035)
BaU	975.74	52.91	251.87	239.5	17.866
Moderate	829.38	52.91	251.87	239.5	16,216
Optimistic	829.38	52.91	188.81	197.37	10,104

The analysis shows that Majalengka's total area remained constant at ~178,273 ha in 2015, 2020, and 2025, indicating that observed changes reflect redistribution among land-use functions rather than overall expansion or loss. Agricultural land (paddy fields, dryland farming, and mixed gardens) declined by 6,378 ha (from 85.26% to 81.68%), with the largest reduction in dryland farming (−2,897 ha), followed by mixed gardens (−1,920 ha) and paddy fields (−1,560 ha). In contrast, non-agricultural uses increased, particularly settlements (+5,390 ha), airports (+716 ha), and industrial areas (+337 ha), while forest cover (~8,918 ha) remained stable and water bodies slightly decreased (−65 ha).

Conversion accelerated after 2020. During 2015–2020, land-use change was moderate, with settlements expanding by +511 ha and paddy fields declining by −449 ha. In 2020–2025, the process intensified, as settlements surged by +4,879 ha (~976 ha/year) while paddy fields fell by −1,111 ha (~222 ha/year). A considerable share of agricultural land loss is spatially associated with the development of the new airport and its surrounding aerocity zone, which triggered rapid conversion in peri-urban areas. These dynamics illustrate a spatial shift from agrarian to non-agricultural functions, especially housing and infrastructure, while stable forest areas suggest effective protection. Without stronger policy interventions, however, the trajectory could weaken local food production and escalate infrastructure costs.

Based on the 2024 revision of the Majalengka Regency Spatial Plan (RTRW), projections for the next decade use 2025 as the baseline year. The estimated demand for built-up land is derived by integrating a 2015–2025 time-series analysis with the targets of the 2025–2035 RTRW. Detailed figures are reported in Table 6 below. This study estimates residential land requirements in Majalengka Regency by projecting demand to 2035 , based on minimum spatial standards and aligned with the Regional Spatial Plan (RTRW) and Detailed Spatial Plan (RDTRK), which adopt a ten-year evaluation framework.

he policy strategy was evaluated through three scenarios: (i) a Business as Usual (BAU) scenario, which follows existing development trends without additional interventions; (ii) a Moderate scenario, which assumes consistent enforcement of the Regional Spatial Plan (RTRW) by incorporating spatial planning constraints into the land-use change simulation; and (iii) an Optimistic scenario, which not only enforces the RTRW consistently but also integrates the priority of sustainable rice field protection (Objective 4) while complying with national regulatory standards, including Ministry of Industry Regulation No. 30/2020, Ministry of Public Works and Housing Regulation No. 12/2021, and SNI 03-1733-2004 on urban housing planning, The policy analysis, structured into three models, is presented in Table 7.

Table 7. Spatial Model Simulation Scenarios of Land-Use Change up to 2035

Strategic Policy	Predicted Scenario for 2035		
	Model 1 BaU	Model 2 Moderate	Model 3 Optimistic
Spatial Planning Quality (Food Crop Area)	Consistency of Projections with Regional Spatial Planning (82 %)	Consistency of Projections with Regional Spatial Planning (85 %)	Consistency of Projections with Regional Spatial Planning (83 %)
Enforcement of Protected Agricultural Land Regulations	Maintaining the agricultural land area of 40,473 ha of rice fields and 28,692 ha of dry fields	Maintaining the agricultural land area of 42,123 ha of rice fields and 28,621 ha of dry fields	Maintaining the agricultural land area of 40,235 ha of rice fields and 31,229 ha of dry fields
Reduction in Rice Field Area	17,886 ha	16,216 ha	10,104 ha

A spatial analysis using the master plan of the West Java International Airport (BIJB) Kertajati aerocity development, overlaid with high-resolution imagery, reveals that the area surrounding the airport is designated for the establishment of an aerocity. This planned airport city is expected to stimulate economic activities in Kertajati and, more broadly, across Majalengka Regency. According to the master plan, future development of BIJB Kertajati and its vicinity will be concentrated in the northern section of the Cipali toll road. This northern corridor is currently dominated by agricultural land, which carries substantial potential for conversion into built-up areas as the city expands. The findings align with previous studies on urban growth dynamics, which consistently show that agricultural land adjacent to major infrastructure is highly vulnerable to conversion pressures. Details of the planned expansion of the BIJB Kertajati Aerocity are presented in Figure 8.

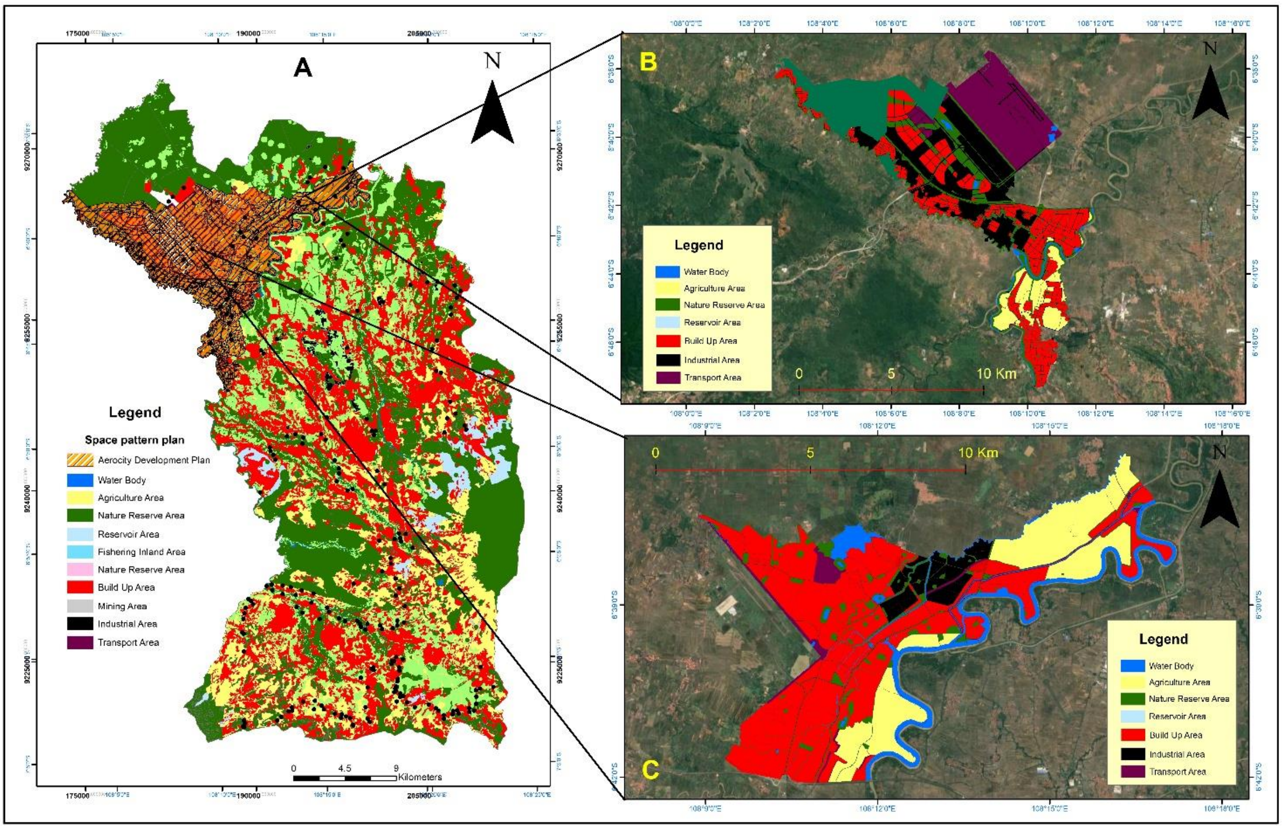

Figure 9. (A) Spatial Planning Map, (B) Western BIJB Kertajati Detailed Spatial Plan, C Eastern BIJB Kertajati Detailed Spatial Plan

The decline of agricultural land surrounding BIJB Kertajati reflects overlapping pressures from aerotropolis (Aerocity) development and the conversion of irrigated rice fields into residential, industrial, and airport-supporting infrastructure. An overlay analysis with development and expansion plans for the Aerocity, combined with related regulatory frameworks, demonstrates an integrated development orientation that spatially encroaches upon agricultural land in the northern Kertajati corridor, particularly in areas north of the Cipali toll road.

DISCUSSION

The results demonstrate that land use in Majalengka Regency has undergone rapid transformation following the development of Kertajati International Airport (BIJB) and the establishment of the Rebana SEZ. Agricultural land, particularly paddy fields, dryland farming, and mixed gardens, declined by more than 6,000 ha between 2015 and 2025, while settlements, industrial estates, and airport facilities expanded significantly. These findings align with previous studies in Indonesia and other developing regions, which consistently show that large-scale infrastructure projects accelerate farmland conversion in peri-urban landscapes.

The spatial concentration of conversion in the northern corridor highlights the vulnerability of fertile irrigated farmland adjacent to transport hubs. This pattern is comparable to the conversion processes observed around Yogyakarta International Airport, where agricultural decline directly affected local food systems and rural employment. The expansion of built-up areas in Majalengka similarly threatens food security, reduces agricultural employment opportunities, and undermines the sector’s contribution to regional GRDP. While remote sensing techniques proved highly effective for monitoring these changes, the broader challenge lies in governance: without consistent enforcement of farmland protection and spatial planning regulations, Majalengka risks long-term food insecurity and unsustainable development. Integrating conservation scenarios, densification strategies, and adaptive land governance will therefore be critical for balancing economic growth with agricultural sustainability.

CONCLUSION

The results of this study confirms that agricultural land in Majalengka Regency has declined sharply—over 6,000 ha between 2015 and 2025—primarily driven by the construction of BIJB Kertajati and industrial–residential expansion. The integration of Sentinel-2 imagery, Random Forest classification, and spectral indices achieved high accuracy (>98%), enabling robust monitoring of land use change. Projections to 2035 and 2045 indicate further pressure on farmland, especially in the northern corridor. To mitigate risks, local government must strengthen farmland protection, enforce spatial planning, and prioritize conservation-led development scenarios. These findings provide empirical evidence for policymakers to balance infrastructure-driven growth with long-term food security and sustainable land governance.

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