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An Integrative Quantitative Approach to Assess the Impact of Mega Infrastructure on Agricultural Land Conversion and Fragmentation in Sumedang Regency

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Abstract: Mega-infrastructure development is a major driver of agricultural landscape transformation in Indonesia. This study quantitatively assesses the impacts of strategic projects—the Cisumdawu Toll Road and three major reservoirs—on agricultural land dynamics in Sumedang Regency. The methodology integrates multi-temporal Landsat imagery (2013-2024) with MLPNN-Markov-based predictive modeling to project land use/land cover to 2038. The predictive model was validated with a high degree of accuracy (kappa = 0.82). Spatial fragmentation was evaluated using landscape metrics synthesized via Principal Component Analysis (PCA). Results show a significant decline in agricultural land, primarily converted to built-up areas and water bodies, alongside intensified landscape fragmentation around infrastructure corridors. Projections indicate these trends will continue, revealing two distinct impact mechanisms: a rapid "pulse" impact from reservoirs and a sustained "press" impact from the toll road. These findings underscore the urgent need for integrated spatial planning and agricultural land protection policies in future infrastructure strategies.

Keywords: Fragmentation; Land use; Mega infrastructure; Predictive modeling

Introduction

Mega infrastructure development has emerged as a major driver of landscape transformation in developing countries (Xiong et al., 2018). This phenomenon is reflected in Indonesia, one example being in Sumedang Regency, West Java (Wardana et al., 2023). Various national strategic projects, such as the Tol Cileunyi–Sumedang–Dawuan (Cisumdawu) Toll Road and the Jatigede Reservoir, have triggered rapid and extensive land use changes within their development area (Makbul et al., 2024), making Sumedang a suitable area to be used as a 'laboratory' for regional development. Flyvbjerg (2014) defines mega infrastructure as projects with broad and complex social, economic, and environmental impacts, serving as key catalysts for land use transformation in affected regions.

The most apparent primary impact of mega infrastructure development is the conversion of agricultural land, driven by the land demands of construction projects with most common form of conversion involves the transformation of agricultural land into non-agricultural uses, primarily due to development pressures and urbanization (Lambin & Meyfroidt, 2011). This phenomenon is closely linked to the process of deagrarianization, a long-term transformation in which rural populations gradually abandon agricultural activities through changes in occupation, income orientation, social identity, and spatial relocation (Makwana & Elizabeth, 2024). Consequently, the large-scale conversion of rice fields in key regions such as West Java, has contributed to a significant decline in agricultural land area and fluctuations in rice production (Panuju et al., 2013).

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Empirical studies have demonstrated that such land conversion directly reduces food production, decreases the availability of cultivable land, and increases the vulnerability of regional food security (Fitri et al., 2022; Govindaprasad & Manikandan, 2016). Infrastructure development, such as roads and new transportation networks, not only facilitates urban expansion but also directly alters land use patterns, highlighting the critical role of infrastructure in shaping land dynamics and reinforcing local spatial dependencies in land cover transformation (Pravitasari et al., 2015, 2024; Savitri et al., 2023). Furthermore, several recent analyses in East Java, Ciamis Regency, and Serang Regency indicate a recurring mismatch between actual land cover transformation and designated spatial plans (RTRW), particularly in rapidly urbanizing and infrastructure-affected regions (Nurfaizah et al., 2023; Pravitasari et al., 2021), highlighting a gap in similar analyses for regions like Sumedang, which are currently at the epicenter of national strategic project development.

Equally significant yet often overlooked impact is the fragmentation of agricultural land (Marealle et al., 2016). Land fragmentation occurs when agricultural holdings are subdivided into spatially scattered small plots, reducing the economic viability of individual land management, giving an impact of increases production costs, impedes agricultural mechanization, and leads to tenure insecurity, which in turn contributes to land degradation (Sklenicka, 2016). Furthermore, fragmentation poses a threat to ecosystem integrity and ecological connectivity, ultimately diminishing the land's capacity to support sustainable agricultural practices (Mitchell et al., 2015; Pravitasari et al., 2018).

The relationship between infrastructure development and agricultural land fragmentation manifests through two primary mechanisms. First, the construction of linear infrastructure such as toll roads directly disrupts agricultural landscapes, leading to physical fragmentation and altering the surrounding environmental quality (Latruffe & Piet, 2014). Second, infrastructure enhances regional accessibility, attracts further investments in residential, industrial, and other economic developments, thereby causing indirect fragmentation that is spatially complex and difficult to manage (van Noorloos & Kloosterboer, 2018).

The implications of fragmentation on agricultural productivity include increased transportation costs, challenges in managing scattered land parcels, land losses for access roads and boundaries, and inefficiencies in the use of agricultural inputs. Globally, agricultural land fragmentation recognized as a major constraint to agricultural modernization, production efficiency, and food security efforts (Mayele et al., 2024).

While numerous studies have addressed the issues of land conversion and fragmentation due to infrastructure development, there remains a significant gap in research that explicitly integrates three key aspects—land conversion, fragmentation, and land use change prediction—within a single analytical framework (Alaei et al., 2022; Jaya et al., 2021). Such integration is crucial for a holistic understanding of landscape dynamics, while in turn enables the formulation of more effective and evidence-based policy recommendations for spatial planning and agricultural land protection (Más-López et al., 2023). This need is particularly pronounced in Indonesia, where land use change studies have largely focused on agricultural land conversion into non-agricultural uses (Ivanka et al., 2024), such as settlements, urban areas, or monoculture plantat, while comprehensive assessments that explicitly incorporate land fragmentation in response to and mega infrastructure development remain limited. Therefore, this study aims to address the identified gap. This research provides an integrated analysis of agricultural land conversion, spatial-temporal fragmentation patterns, and land use change prediction in a region undergoing rapid transformation.

Sumedang Regency, West Java, was selected as the study site due to its high relevance in illustrating the tangible impacts of multiple national strategic infrastructure projects (Akhyadi et al., 2016) and its strategic position within the regional development structure of West Java (Noviyanti et al., 2020). Geographically (Figure 1), the regency covers approximately 155,871.98 hectares with a diverse topography, and its location within three major watersheds (Cimanuk, Citarum, and Cipunegara) supports extensive agricultural systems that are particularly sensitive to large-scale land transformation.

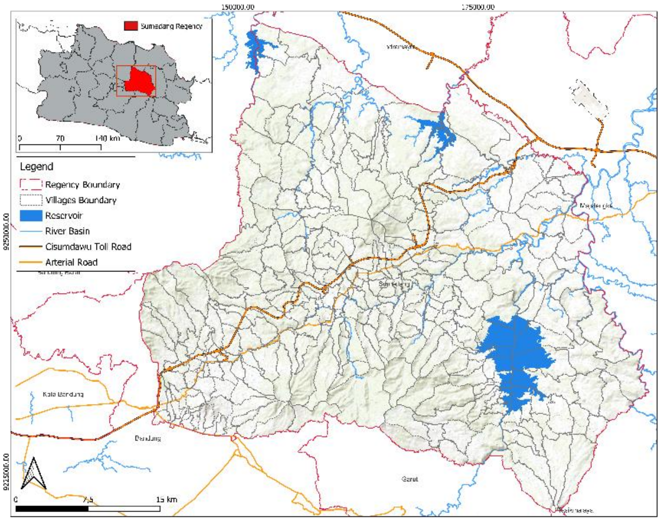

Figure 1. Map of research location

This vulnerability is being tested by recent projects, which include the ±59-kilometer Cisumdawu Toll Road, fully operational operate since June 2023; the Jatigede Dam, operation operate since 2017 with an inundation area of approximately ±4,980 hectares; and the Cipanas and Sadawarna Reservoirs, both completed in 2024 (Perda Kabupaten Sumedang No. 4 Tahun 2018). The presence of these infrastructures has intensified development and urbanization pressures, contributing to increased land conversion and spatial fragmentation of rice fields (Pravitasari et al., 2019). This situation presents an urgent challenge, as Sumedang's economy is reliant on its agricultural sector, with approximately 27,552 hectares of productive rice fields, the area is under substantial conversion pressure, reflected in the declining trend of rice field area and fluctuating rice production (BPS, 2025.) These conditions underscore the importance of this research to provides in-depth insights into the impacts of mega infrastructure development on agricultural landscapes, particularly within rapidly urbanizing corridors like the Jakarta–Bandung mega urban region (Pravitasari et al., 2022).

By employing a spatial analysis approach using proven landscape metrics land (Che Man & Salihin, 2018; Mitchell et al., 2015), this study is expected to contribute both theoretically and practically to regional planning. The findings are not be locally relevant for addressing sustainable development challenges in Sumedang but will also applicable to other regions across Indonesia that facing similar pressures from mega infrastructure expansion.

Method

This study utilizes secondary data obtained from ESRI World Imagery Wayback, and Landsat 8 OLI Level -2 satellite imagery from 2013, 2018, and 2024, sourced from the United States Geological Survey (USGS) via the Earth Explorer website, and topographic base maps (Rupa Bumi Indonesia/RBI). The analytical tools used include QGIS 3.34, ArcGIS 10.8, TerrSet, and R Studio. This quantitative analysis is contextualized and supported by a review of relevant scientific literature and policy documents.

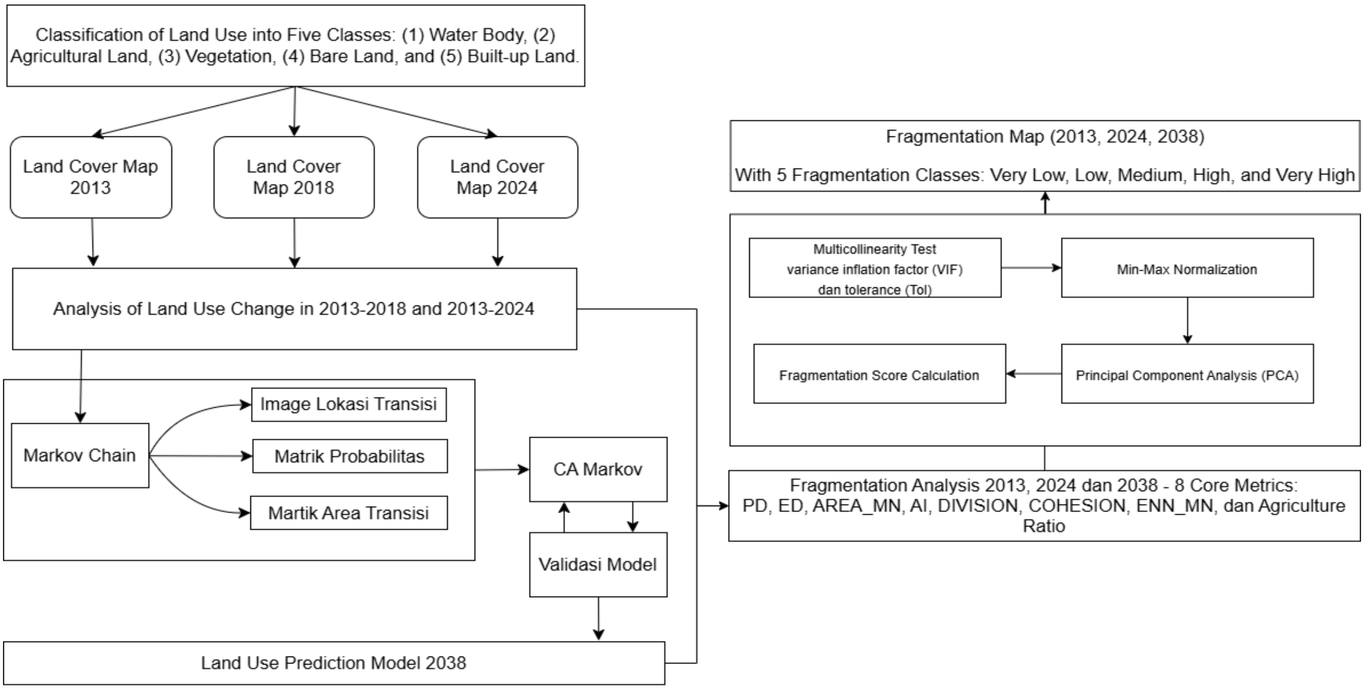

Figure 2. Research flow chart

This research is structured around an integrative analytical framework, as illustrated in figure 2, designed to provide a comprehensive understanding of the impacts of mega infrastructure development in Sumedang Regency. The framework consists of three interrelated methodological phases: an analysis of historical Land Use/Land Cover (LULC) change, a prediction of future LULC transformation, and a spatial-temporal evaluation of agricultural land fragmentation. Each phase is not isolated; instead, the output of one stage serves as the primary input for the next, forming a coherent and mutually reinforcing chain of analysis.

Historical LULC Change Analysis

LULC classification was conducted on Landsat 8 for the years 2013, 2018, and 2024. The classification method employed was supervised classification using the Maximum Likelihood algorithm, implemented through the Semi-Automatic Classification Plugin (SCP) in QGIS software. This classification process resulted in five primary LULC classes: water bodies, agricultural land, mixed forest/plantation, bare land, and built-up areas. The selection of these five classes was adapted from the socio-economic function dimension as described by Danoedoro (2008).

The distinction between agricultural land and mixed forest/plantation during the training set collection was performed visually based on spatial pattern interpretation; agricultural land is characterized by regular geometric patches and a homogenous texture (anthropogenic), mixed forest/plantation exhibits irregular patterns and a coarser texture (organic). The mixed forest/plantation class is a composite category, representing perennial tree-vegetated areas that are spectrally and texturally difficult to distinguish in medium-resolution satellite imagery. This class includes natural forest areas, agroforestry systems such as mixed gardens, plantations, and fallow land that has undergone secondary vegetation succession.

Classification accuracy validation was conducted using the AcATaMa plugin in QGIS, with reference data sourced from ESRI World Imagery Wayback. This service provides high-resolution satellite imagery with detailed acquisition date metadata, enabling precise validation for specific time periods directly within the QGIS environment. This approach aligns with the recommendations of Olofsson et al. (2014), which emphasize probability-based sampling and the use of a confusion matrix. The Process employed a stratified random sampling approach based on the proportional area of each class, with sampling performed with a standard error of 0.01, a minimum of 50 samples per class, and a minimum spatial separation of 150 meters between samples. The AcATaMa plugin calculated metrics from the confusion matrix, including producer's accuracy, user's accuracy, and overall accuracy, which reflects the proportion of correctly classified points. The total number of validation points collected was 516 (2013), 502 (2018), and 496 (2024), resulting in overall accuracy rates of 89.7% (2013), 91.25% (2018), and 91.39% (2024), respectively.

Predictive Modeling of LULC Change

Future LULC prediction analysis was conducted by developing two models within a systematic CA-Markov validation framework (Surabuddin et al., 2019). Model 1 was constructed to simulate the 2024 LULC using historical data from 2013 and 2018, while Model 2 projected the 2038 LULC based on data from 2018 and 2024 (Memarian et al., 2012) The core principle of the CA-Markov method lies in calculating transition probabilities, represented by a probability matrix that indicates the likelihood of each pixel changing from one land use/cover type to another between two time points (Hamad et al., 2018). This method was selected for its ability to probabilistically model future LULC dynamics based on the temporal trends observed in the past (Li & Yeh, 2002).

LULC prediction was carried out using the Land Change Modeler (LCM) approach within the TerrSet software. This approach consists of three main stages: historical change analysis (Change Analysis), modeling of transition potential (Transition Potential), and future LULC prediction (Change Prediction). The historical change analysis stage utilized the 2013–2018 transition matrix as the basis for identifying LULC dynamics. Transition categories accounting for less than 0.1% of the total area were excluded from the modeling process to ensure that the model focused on significant changes.

In the transition potential modeling stage, a Multilayer Perceptron Neural Network (MLPNN) was applied to capture the non-linear relationships between LULC change drivers and actual LULC transitions. The driving variables included several spatial and demographic factors, namely distance to reservoirs, distance to toll roads, population density, distance to primary roads, and slope gradient. The statistical relevance of these variables was tested using Cramer’s V, and only variables with values greater than 0.1 were included in the model.

Validation of the LULC prediction performed by comparing the predicted 2024 LULC map (Model 1) with the actual 2024 LULC map. The validation results yielded a kappa coefficient of 0.82, indicating high prediction accuracy and thus confirming the model’s reliability (Surabuddin et al., 2019). Thus, Model 2, aims to predict LULC change for the year 2038. In this study, the Business as Usual (BAU) scenario was chosen, which assumes no significant policy intervention in land change patterns, so that the projection results reflect the natural trend of change.

Spatio-Temporal Analysis of Landscape Fragmentation

The analysis of agricultural land fragmentation aims to evaluate the impact of infrastructure development at the village scale in Sumedang Regency. The analysis conducted on LULC data from 2013, 2024, and predicted LULC data from 2038, using village administrative boundaries as the unit of analysis.

Eight indicators of farmland fragmentation were selected (Che Man & Salihin, 2018; Mitchell et al., 2015; Peng et al., 2010) namely patch density (PD), mean patch area (AMN), edge density (ED), area-weighted mean fractal dimension indeks (FMN), division index (DI), aggregation index (AI), and mean Euclidean nearest neighbour distance (ENN). An explanation of each indicator can be seen in the following Table 1.

Table 1. Indicator of Farmland Fragmentation in Use

Indicator	Description	Unit
PD	Number of agricultural patches per 100 hectares	Patch/100 ha
AMN	Average area of each agricultural patch	Hectar
ED	Total edge length of patches per unit area of the village	m/ha
FMN	Mean patch shape complexity	1-2
DI	Patch isolation level in the landscape; a higher value indicates greater fragmentation	0–1
AI	Patch aggregation level; a higher value indicates patches are more clustered	%
ENN	Average distance between the closest patches	meter

Indicator normalization was performed using the min-max scaling method before PCA to equalize the scale of the fragmentation metric data, as the indicators have different units and scales. This normalization ensures that fragmentation indicators contribute proportionally to PCA without bias due to differences in data scale. The normalization formula used is as follows:

$$X_{norm} = \begin{cases} \frac{X - X_{min}}{X_{max} - X_{\min}} \ ; \ for\ positive\ indicator \\ \frac{X_{max} - X}{X_{max} - X_{\min}} \ ; \ for\ negative\ indicator \end{cases} \quad (1)$$

where *Xnorm* is the indicator value after normalization, *X* is the indicator value before normalization, and *Xmin* and *Xmax* are the minimum and maximum values of the indicator, respectively.

The weighting of fragmentation indicators was done through Principal Component Analysis (PCA), due to its ability to reduce the dimensions of highly correlated fragmentation indicators into fewer independent components but still retain most of the information (variance) of the original indicators (Jollife & Cadima, 2016). PCA is also useful for simplifying the interpretation of spatial patterns of fragmentation in an effective and transparent manner.

Before PCA is performed, the data is tested for feasibility using the Kaiser-Meyer-Olkin (KMO) test to ensure sample adequacy and data suitability. The KMO test results show a value of 0.64 with the MSA value of each indicator in the range of 0.50-0.84. KMO value >0.60 indicates that the data is good enough for PCA. In addition, Bartlett's Test produces a chi-square value of 2101.329 with a p-value <0.01, indicating a significant correlation between indicators, so PCA is feasible.

After PCA was performed, the weight value (loading factor) for each indicator was obtained. Furthermore, the level of agricultural land fragmentation was calculated through the agricultural fragmentation score (SFP). The SFP value is obtained by multiplying the normalized indicator value (X_{Norm}) with the PCA loading weight (W_i), then summing the results into a total fragmentation score for each village. The formula is as follows:

$$SFP = \sum_{i=0}^{n} (X_{Norm} \times W_i) \quad (2)$$

After obtaining th agricultural fragmentation score (*SFP*) for each observation period, the annual average change in *SFP* was calculated to determine the pattern of agricultural land fragmentation dynamics. The calculation is done by using the SFP value at the beginning of the period SFP_b and the end of the period SFP_e, then calculating the annual average change over a period of T years. The formula for the annual average change in *SFP* (*R*) is as follows:

$$R = \frac{SFP_e - SFP_b}{SFP_b} \times \frac{1}{T} \times 100\% \quad (3)$$

The R value indicates whether the level of fragmentation of agricultural land has increased or decreased each year on average. Positive values indicate an increase in fragmentation, while negative values indicate a decrease in fragmentation.

Result and Discussion

The Impact of Mega Infrastructure on Agricultural Land Conversion

Analysis of LULC change in Sumedang Regency between 2013-2024 reveals significant dynamics as a direct result of the mega infrastructure development projects in the region. Table 2 reflects a consistent decline in agricultural land, which falls from 59,982.16 ha in 2013 to 53,718.66 ha in 2024, equivalent to a reduction of approximately 10.4%. Mixed forest/plantation is also under similar pressure, with a decrease in area from 84,099.26 ha (2013) to 80,905.07 ha (2024).

Meanwhile, the built-up land increase 46.8%, rising from 9,259.24 ha to 13,591.05 ha. This is closely related to the construction of the 59km Cisumdawu Toll Road, which began construction in early 2014 and fully operational in June 2023. The construction of this toll road led to considerable conversion into built-up areas and encouraged the expansion of urban areas. In addition, the high increase around water bodies that reached 292.7%, from 1,494.26 ha to 5,868.15 ha, was due to the full operation of Jatigede Dam since 2017, with an inundation area of approximately 4,980 ha, as well as the construction of Cipanas Reservoir and Sadawarna Reservoir, each of which was completed in 2024.

Table 2. LULC Conversion to Built-up Land

LULC	LULC Area (Ha)			Difference in Area 2013-2024	
	2013	2018	2024	Ha	%
Water Body	1494.26	4780.86	5868.15	4373.89	292.71
Agriculture	59982.16	55694.52	53718.66	-6263.50	-10.44
mixed forest /plantation	84099.26	81382.72	80905.07	-3194.19	-3.80
Bare Land	2091.23	2682.44	2843.21	751.99	35.96
Built up	9259.24	12385.60	13591.05	4331.81	46.78
Total	156926.14	156926.14	156926.14		

Bare land also increased, although at a smaller scale, from 2,091.23 hectares in 2013 to a significant 2,682.44 hectares in 2018, and further to 2,843.21 hectares in 2024. This increase was largely the result of land clearing activities during infrastructure development, particularly in 2018 when construction was at its peak.

In addition, quarrying activities in the southern area of Mount Tampomas—serving as a source of construction materials—have also contributed to the ongoing expansion of bare land. Overall, land change in Sumedang is heavily influenced by mega infrastructure developments that not only change the ecological structure of the region but also put serious pressure on the agricultural and mixed forest /plantation sectors.

Specifically, the land use transition matrix for the period 2013–2024, as presented in Table 2 reveals notable patterns of change. Agricultural land underwent large-scale conversion into several other LULC classes, with the majority transforming into mixed forest /plantation (4,975.92 hectares), water bodies (2,952.63 hectares), and built-up areas (3,166.56 hectares). These conversions reflect the direct impact of the construction of the Jatigede Dam, as well as the Cipanas and Sadawarna reservoirs, which transformed productive agricultural areas into inundated zones (Figure 3).

Mixed forest/plantation, also experienced conversion pressure, with 1,849.95 hectares transformed into built-up areas and 1,630.98 hectares into water bodies. Development expansion was not limited to agricultural land but also significantly affected vegetated areas. The bare land formed during this period was caused by two main activities: land clearing for the Cisumdawu Toll Road project site and the expansion of the quarry area. A quarry is a surface mining location to extract rock and sand materials used as raw materials for construction.

Table 3. Matrix of LULC Change in Sumedang Regency 2013-2024

LULC		2024					
		Water Body	Agricultural Land	mixed forest /plantation	Bare Land	Built up Land	Total
2013	Water Body	1431.35	28.35	9.99	6.21	18.36	1494.26
	Agricultural Land	2048.56	49972.94	3875.92	918.18	3166.56	59982.16
	Mixed forest /plantation	2180.38	3579.36	76924.48	422.64	992.40	84099.26
	Bare Land	40.33	77.35	65.25	1438.50	469.80	2091.23
	Built up Land	167.53	60.66	29.43	57.69	8943.93	9259.24
Total		5868.15	53718.66	80905.07	2843.21	13591.05	156926.14
Difference Area		4373.89	-6263.50	-3194.19	751.99	4331.81	

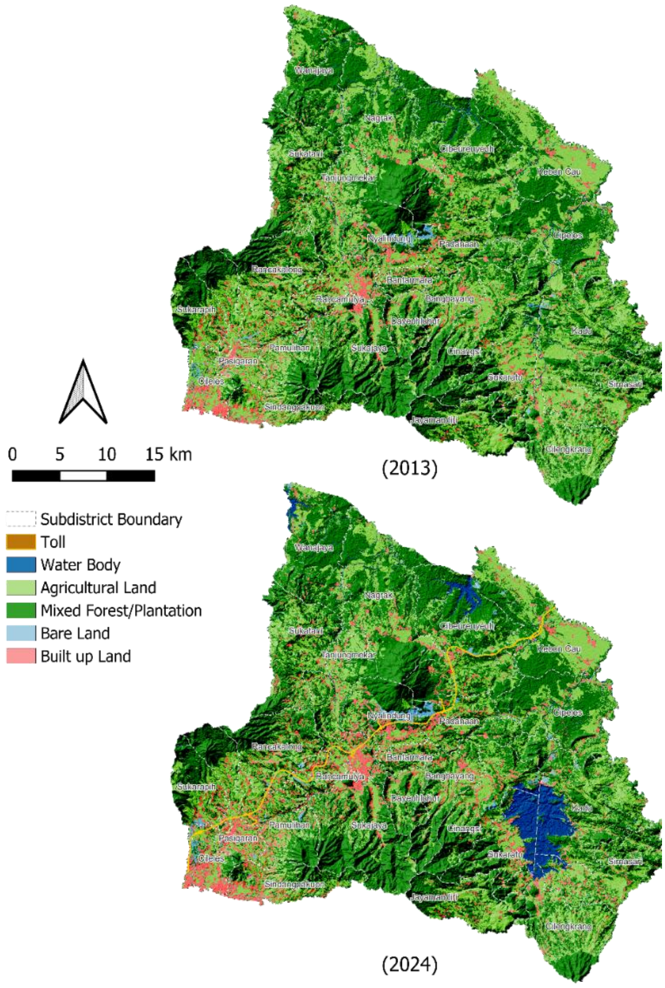

Figure 3. LULC map of Sumedang regency

Theoretically, in land systems, conversion to built-up land is considered to have a high degree of irreversibility due to large capital investments (Meyfroidt et al., 2022). However, the finding of reverse conversion from built-up land to other LULC classes in the transition matrix is not a classification error but rather an empirical manifestation of an uncommon dynamic, triggered by mega-infrastructure intervention during the 2013-2024 period.

This process is driven by two primary mechanisms. First, the conversion of built-up land into water bodies (an area of 167.53 ha) is a direct consequence of large-scale inundation by reservoirs. This data represents built assets such as settlements and local infrastructure networks that were permanently submerged. Second, the conversion of built-up land into bare land, mixed forest/plantation, and even agricultural land was predominantly identified along the Cisumdawu Toll Road construction corridor. Existing low-density built-up areas in this corridor, such as scattered rural settlements, underwent demolition and land reclamation to meet the project's right-of-way requirements. This land was then temporarily repurposed as construction support areas (bare land) or revegetated as part of infrastructure slope stabilization efforts (mixed forest/plantation). Thus, this seemingly anomalous transition is a significant finding that reflects the magnitude of mega-infrastructure intervention, which is capable of fundamentally re-engineering the existing landscape structure.

Projections for 2038 and the Evolution of the Impact of Mega Infrastructure

The LULC change prediction for the 2024–2038 period was conducted under a Business as Usual (BAU) scenario. As shown in Figure 4, this expansion is projected to creep along the perimeter of the Jatigede Reservoir and follow the access corridors leading to the Cisumdawu Toll Road. This projection assumes that no policy interventions are designed to address the development impacts that emerged in the previous period, thus allowing the historical trends of change to continue. The modeling results show that pressure on agricultural land and mixed forest/plantation areas will remain high, concurrent with the increasingly massive expansion of built-up land.

The LULC transformation between 2013 (pre-development) and 2024 (post-development) reveals not only significant aggregate landscape changes but also spatially heterogeneous impacts driven by different types of infrastructure. An analysis of agricultural land conversion density based on distance from infrastructure confirms that each project possesses a distinct impact character.

During the pre-development period, the reservoirs demonstrated a localized "epicenter" impact. As seen in Table 4, the nearest zone (0-2 km) experienced an agricultural land conversion density of 72.00%, visually identifiable as a dense, concentrated cluster of conversion around the reservoir's perimeter. This high number is attributed to a combination of direct physical impacts (inundation) and speculative development along the new waterfront (e.g., tourism and settlements). This influence decreases drastically with distance. In contrast, the Cisumdawu Toll Road exhibited a more diffuse "corridor" impact. While the conversion density in its nearest zone (12.88%) was significant, its influence extended further, reflecting the toll road's role as a trigger for linear urbanization by improving accessibility along its route. Interestingly, in the furthest zone (>10 km), the conversion density slightly increased again for both the reservoir (7.23%) and the toll road (8.69%), confirming a hypothesis of interacting and overlapping influences. This indicates that Sumedang's agricultural landscape is under dual pressure from multiple simultaneous infrastructure projects.

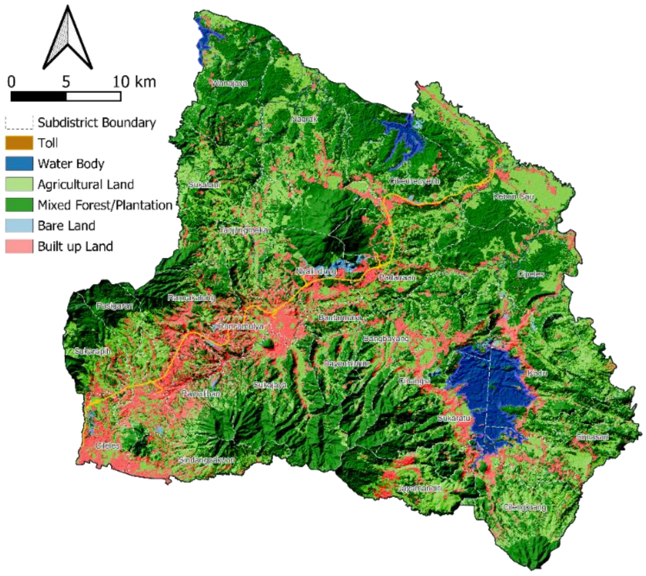

Figure 4. Sumedang regency LULC prediction map on 2038

Looking toward the future, the predictive model indicates a shift in these dynamics. The impact of the reservoir is predicted to evolve, confirming a spatial saturation phenomenon. While the conversion density in its nearest zone remains high at 65.17%, the slight decrease from the historical period suggests the area is entering a consolidation phase as the most vulnerable land has already been converted. This pattern is characteristic of a pulse impact—a massive, high-acceleration shock in the initial phase that later reaches saturation.

Table 4. Comparison of Agricultural LULC Conversion Density Based on Distance from Reservoirs and Highways

Distance Zone (km)	Conversion Density from Reservoirs (%)		Conversion Density from Toll Roads (%)	
	2013-2024	2024-2038	2013-2024	2024-2038
0-2	65.17	72.00	12.27	12.88
2-5	26.51	42.86	3.34	6.25
5-10	1.85	4.03	2.24	4.15
>10	7.18	7.23	3.38	8.69

Conversely, the toll road is predicted to continue functioning as a persistent driver of corridor urbanization, following a press impact pattern sustained, incremental pressure that slowly transforms the landscape, similar to the results of research by Zhao et al. (2021) and Zhixue et al. (2021). The projected conversion density of 12.27% in its nearest zone indicates that the accessibility it provides will continue to trigger the conversion of agricultural land. This finding is crucial as it signifies a shift in primary driving factors. While the physical-destructive impact of reservoir construction was dominant historically (2013-2024), the functional-accessibility impact from the toll road's operation is predicted to play a relatively larger role in shaping Sumedang's landscape in the future (post-2024).

Although this analysis is limited to a Business as Usual (BAU) scenario, it is precisely this projection that underscores the urgency for policy intervention. These findings provide a scientific basis for recommending targeted spatial planning: consolidation and rehabilitation policies around the saturated reservoir areas, and strict development control policies along the still-expanding toll road corridor.

Fragmentation of Agricultural Land in Sumedang Regency

The results from the Principal Component Analysis (PCA) were used to construct a composite fragmentation index, in which the weight and direction of each indicator's relationship were determined by the most significant principal component. Table 9 presents the decomposition of this index, where the indicators with the largest positive weights are Patch Density (PD) at 0.55 and Edge Density (ED) at 0.54. This logically indicates that a higher number and density of patches, along with a greater total length of edges between them, corresponds to a higher degree of fragmentation.

Table 5. Direction and Weight Fragmentation Indicator

Indicator	Direction	Weight
Patch Density (PD)	+	0.55
Edge Density (ED)	+	0.54
Division Index (DI)	+	0.37
Mean ENN Distance (ENN)	+	0.15
Fractal Index (FMN)	+	0.05
Mean Patch Area (AMN)	-	0.37
Aggregation Index (AI)	-	0.30

Conversely, the indicators with a significant negative relationship and weight are Mean Patch Area (AMN) at -0.37 and Aggregation Index (AI) at -0.30. This means that landscapes dominated by agricultural patches that are, on average, larger and tend to be more clustered or adjacent (aggregated) will be assessed as having a lower fragmentation score. In essence, the index quantitatively describes the process of fragmentation: a condition where the landscape is broken down into smaller, and more isolated units.

To facilitate interpretation, the fragmentation index values were classified into five classes using the Natural Breaks (Jenks) method. This classification depicts the landscape condition continuum, starting from a Very Low level, representing a whole and unified agricultural expanse; progressing to a Low level, where the expanse begins to be slightly dissected by other elements like roads or small settlements; and then to a Medium level, which shows a balanced mixed pattern of agricultural and non-agricultural land, causing efficiency to decline. At the High level, agricultural land is already fractured into many small, separated patches, culminating in the Very High level, where only remnants of agricultural land are visible, appearing as small 'islands' in a sea of built-up areas.

These fragmentation levels represent the indirect impacts of infrastructure development. Beyond the direct impact of physical land splitting by the toll road alignment, the more extensive and sustained impact comes from increased regional accessibility. This new accessibility acts as a magnet, attracting additional investment in the form of residential, industrial, and other economic activities, which often drives sporadic and piecemeal land changes. It is this process that gradually transforms a village from a unified landscape (Very Low or Low category) to a mixed pattern (Medium), and, if it continues uncontrolled, will push it towards a fragmented state (High) until only remnants of farmland remain (Very High).

The overall analysis reveals a significant and consistent trend of increasing agricultural land fragmentation in Sumedang Regency from 2013 through the 2038 projection. Based on the proportion of villages (Table 10), the percentage of villages falling into the "Very High" fragmentation category steadily increases from 10.11% in 2013 to 12.27% in 2024 and projected to reach 15.88% by 2038.

Table 6. Percentage Proportion of Number of Villages by Fragmentation Class Level in Sumedang Regency

Year	Very Low (%)	Low (%)	Medium (%)	High (%)	Very High (%)
2013	9.03	19.49	29.96	31.41	10.11
2024	8.66	18.77	31.41	28.88	12.27
2038	3.61	22.74	29.96	27.80	15.88

This trend did not occur randomly but instead exhibited a clear spatial pattern, as visualized in Figure 5. In 2013, high fragmentation clusters (dark green) were already identified in the southwestern region. However, by 2024, these clusters appeared more intensive and had expanded along the now-operational Cisumdawu Toll Road corridor. Simultaneously, significant new fragmentation clusters emerged around the Jatigede Reservoir area in the southeast, as well as the Sadawarna and Cipanas Reservoirs in the north.

The pattern of high fragmentation around the Cisumdawu Toll Road indicates that this linear infrastructure plays a crucial role in accelerating radial fragmentation, similar to the findings of Yokohari et al. (2000), who demonstrated that transportation infrastructure often triggers the fragmentation of agricultural land. From both economic and ecological perspectives, this high degree of fragmentation has serious implications for agricultural land management, particularly by increasing production costs due to the difficulty of applying mechanization to small, isolated plots. Ecologically, this condition also risks disrupting the connectivity between agricultural and natural mixed forest/plantation patches, which could decrease long-term agricultural productivity and affect biodiversity.

This fragmentation pattern is projected to intensify through 2038, with highly fragmented areas increasingly dominating the landscape around these infrastructure nodes. This indicates that mega-infrastructure not only has a localized impact but also functions as a nucleus, propagating fragmentation pressure into surrounding regions over time. To understand the underlying mechanisms, we analyzed the spatial correlation of this trend with two distinct infrastructure types: concentric reservoirs (hydrological) and linear toll roads (connectivity). The comparison between the historical (2013-2024) and projected (2024-2038) periods reveals two fundamentally different processual impacts.

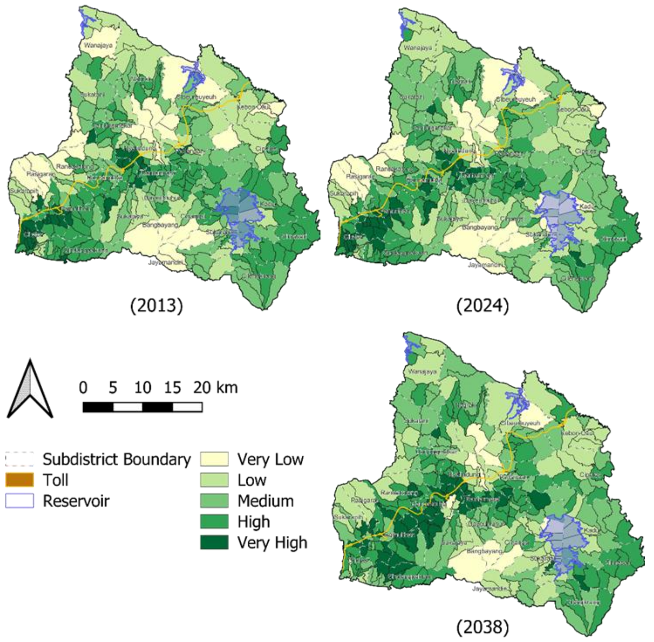

Figure 5. Spatial distribution of fragmentation in Sumedang Regency

The dynamics around the reservoirs reveal an unusual process. During the 2013-2024 construction period, the nearest zone (0–2 km) exhibited a highly negative rate of fragmentation change (down to -0.97) (Figure 6). This phenomenon confirms a mechanism of "landscape removal," where the total loss of agrarian function—caused by the disappearance of thousands of small rice paddies—statistically increases the average size of the remaining patches. This creates a landscape that appears simpler but is, in fact, severely degraded (Seto et al., 2011). However, in the projected 2024-2038 period, this pattern is expected to shift. The rate of change in the same zone becomes highly positive (up to 0.39), indicating a transition to secondary fragmentation, where the remaining agricultural lands begin to fragment due to new development around the reservoirs after the initial removal is complete.

In contrast, the toll road corridor exhibits a more conventional "landscape splitting" dynamic, which evolves significantly between its construction and operational phases. During construction (2013-2024), a high positive rate of change (up to 0.43) reflects the infrastructure's active role as a physical dividing agent. This dynamic is projected to shift during the operational period (2024-2038), revealing a "leapfrog" phenomenon where the fragmentation rate in the nearest zone (0-2 km) decelerates. This suggests the formation of a "shadow corridor," where physical proximity to the toll road no longer correlates with development utility due to negative externalities (e.g., noise and air pollution). These factors collectively reduce the zone's attractiveness for residential and commercial development, the primary drivers of fragmentation.

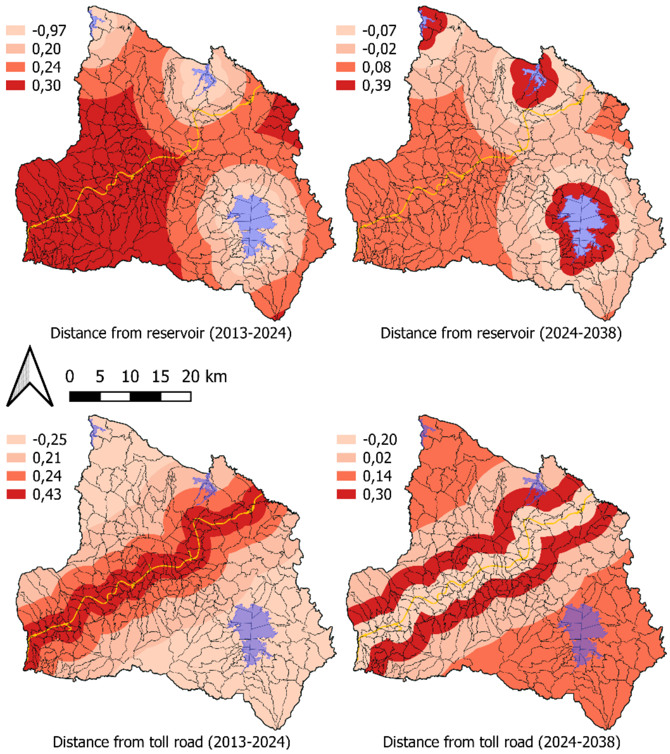

Figure 6. Average annual fragmentation change rate based on distance zone

Consequently, the functional benefits of the toll road are optimally realized in the next zone (2-5 km). Its location—far enough to avoid direct negative externalities, yet close enough to leverage full regional accessibility—makes it the prime location for new settlement and economic expansion. The combination of high accessibility and initially more affordable land prices logically establishes this zone as the new epicenter for agricultural land conversion and fragmentation in the predicted period.

This comparative analysis clarifies two distinct processual impacts from each infrastructure type. Hydrological infrastructure like reservoirs tends to deliver a large but short-lived impact; an initial phase of massive landscape removal, reflected by extreme negative values in fragmentation change, is followed by a more moderate, positive rate of secondary fragmentation during the operational phase. Conversely, connectivity infrastructure like toll roads produces a more gradual and sustained impact. The strongest effect occurs from construction to early operation, marked by significant fragmentation from landscape splitting, but the rate of change naturally decelerates as the corridor stabilizes.

Conclusion

By employing an integrative quantitative approach, this study successfully assessed the multifaceted impacts of mega infrastructure on agricultural land in Sumedang Regency. A key contribution of this approach was the ability to distinguish two fundamentally different impact pathways based on infrastructure typology. The analysis quantitatively confirmed that reservoirs induce "landscape removal" through massive, concentrated conversion, while the toll road triggers incremental "landscape splitting" along its corridor. Future projections reveal an evolution of these dynamics; the reservoirs' "pulse impact" leads to spatial saturation, whereas the toll road's sustained "press impact" establishes it as the dominant driver of future change. This predictive analysis also uncovered a "leapfrog" phenomenon in fragmentation patterns along the toll road, where negative externalities create a "shadow corridor" immediately adjacent to the road, shifting the new epicenter of development further away. Therefore, this research provides two primary contributions: empirically, it clarifies the distinct, long-term landscape consequences of different infrastructure types, and methodologically, it demonstrates a robust framework for evidence-based spatial planning applicable to other rapidly urbanizing regions.

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Conceptualization, M.S.I.N. and A.E.P. and D.R.P.; methodology, M.S.I.N.; validation, M.S.I.N., A.E.P., and D.R.P.; formal analysis, M.S.I.N.; investigation, M.S.I.N.; resources, M.S.I.N.; data curation, M.S.I.N.; writing—original draft preparation, M.S.I.N.; writing—review and editing, M.S.I.N., A.E.P., and D.R.P.; visualization, M.S.I.N.; supervision, A.E.P. and D.R.P.; project administration, M.S.I.N.

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The authors declare no conflicts of interest. This research was conducted independently, and all decisions were made with scientific integrity, free from any influence of personal or financial relationships.

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