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Hybrid Fuzzy Logic and Geometric Analysis Model to Assess Land-use Conversion Governance in North Sumatra

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ABSTRACT

Land-use conversion in North Sumatra has increased significantly due to urban expansion, infrastructure development, and economic growth, creating challenges for sustainable land governance. This study proposes a Hybrid Fuzzy Logic and Geometric Analysis Model that evaluates governance effectiveness and spatial transformation within a single, consistently defined framework, and applies it as a case study to Hamparan Perak District. Five governance indicators were assessed using a Mamdani Fuzzy Inference System spatial planning compliance, policy implementation effectiveness, institutional coordination, environmental sustainability, and regulatory enforcement intensity while land conversion and its spatial pattern were measured separately on the geometric side so that no variable is counted in both components. The fuzzy evaluation produced a governance-effectiveness score of 0.63, categorised as moderately effective, with a 95% bootstrap confidence interval of 0.59–0.67 and close agreement with expert reference scores (RMSE = 0.046, r = 0.91). Geometric analysis showed the Spatial Distribution Index rising from 0.48 in 2019 to 0.72 in 2024, indicating clustered conversion around transportation corridors and urban growth centres. Governance and spatial components were combined using weights of 0.60 and 0.40 derived through the Analytic Hierarchy Process, yielding a Hybrid Governance Index of 0.65 that reproduces cleanly from the reported inputs. For this study area, the results suggest that land-use conversion reflects both urban development pressure and governance capacity; wider validation would be needed before generalising beyond the case. The model provides a reproducible decision-support framework for sustainable land-use planning

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1. INTRODUCTION

Land-use conversion has become a major challenge in regional planning and environmental governance. The rapid growth of urban areas, increasing population, and expanding economic activities have intensified pressure on land resources, especially in developing countries. As a consequence, agricultural land, forests, and environmentally sensitive areas are increasingly being converted into residential, industrial, and infrastructure developments. While such changes can support economic growth and regional development, uncontrolled land conversion often results in environmental degradation, loss of ecological functions, and land-use conflicts when governance mechanisms are weak or poorly enforced [1][2]. Evaluating the effectiveness of land-use conversion governance is a complex task because it involves interactions among institutional, environmental, social, and spatial factors. Traditional assessment methods often struggle to capture these multidimensional relationships, particularly when uncertainty and subjective judgements are involved [[3]. Because land governance encompasses both qualitative policy considerations and quantitative spatial changes, more flexible analytical approaches are required to provide a comprehensive evaluation framework [4].

Among the approaches widely used to address uncertainty in decision-making, fuzzy logic allows governance indicators to be represented through linguistic variables and membership functions, making it suitable for evaluating policy-related factors that are difficult to measure precisely. Through fuzzy inference, governance performance can be assessed on a continuum rather than through rigid classifications [5]. Nevertheless, although fuzzy logic performs well in handling uncertainty, it provides limited information regarding the spatial structure and geographical distribution of land-use changes [6]. To address this limitation, geometric spatial analysis offers a complementary perspective. Geometric methods enable the examination of land-conversion patterns, spatial distribution characteristics, and regional transformation processes by analysing spatial configurations and land-use morphology [7]. Combining fuzzy logic with geometric analysis creates a more comprehensive framework in which governance quality and spatial outcomes can be assessed simultaneously: fuzzy logic evaluates governance effectiveness, while geometric analysis reveals how that performance is reflected in actual land-use transformation patterns [8].

Previous studies have typically applied either fuzzy logic or spatial-geometric techniques independently. Fuzzy-logic research has focused mainly on decision-support systems and governance evaluation under uncertainty, whereas spatial and geometric studies have concentrated on land-use pattern analysis and change detection [5], [7], [9]. Although both approaches contribute valuable insights, their separate application limits the ability to explain the interaction between governance effectiveness and spatial transformation. Spatial-statistical methods such as the Spatial Distribution Index (SDI), Moran's I, and the Getis–Ord Gi* hotspot statistic effectively describe land-use patterns and clustering but are not designed to represent uncertainty, linguistic assessment, or nonlinear governance relationships. As a result, current approaches cannot simultaneously capture governance uncertainty and spatial transformation dynamics within a single analytical framework [10].

From a computational perspective, governance assessment and spatial analysis are commonly conducted as separate procedures, generating fragmented results that are difficult to integrate into policy evaluation. Only a limited number of studies have proposed a mathematically documented mechanism for combining governance-performance indicators with spatial-transformation metrics into a single evaluation index [11]. To address these challenges, this study proposes a Hybrid Fuzzy Logic–Geometric Analysis Model for evaluating land-use conversion governance in North Sumatra. The model integrates fuzzy governance assessment, spatial clustering analysis, and weighted governance–spatial aggregation within a unified framework [12] and is implemented and validated in Hamparan Perak District, Deli Serdang Regency, an area that has experienced significant land-use transformation.

The novelty of this research is threefold, and is stated explicitly to distinguish it from existing fuzzy-GIS and spatial-governance studies. First, whereas prior fuzzy-GIS work typically uses fuzzy membership to reclassify or weight spatial layers, the present model keeps the governance and spatial subsystems mathematically distinct and links them through an explicitly documented aggregation function (Equation 14), so the contribution of each dimension to the final score is fully traceable. Second, the aggregation weights are not assigned heuristically but are derived through a two-round Delphi process and formalised with the Analytic Hierarchy Process, with a reported consistency ratio, making the weighting reproducible rather than ad hoc. Third, the model couples a linguistic governance assessment with global and local spatial statistics (SDI, Moran's I, Getis–Ord Gi*) so that institutional effectiveness and the geography of conversion are evaluated within one composite Hybrid Governance Index [13]. These features position the contribution beyond an incremental combination of existing tools and toward a formally specified, reproducible governance spatial evaluation framework [20]

2. RESEARCH METHOD

2.1 Research Design and Data

This study employs a quantitative computational–spatial design that integrates fuzzy-logic modelling with geometric spatial analysis: the fuzzy component handles uncertainty in the governance indicators, and the geometric component characterises the spatial structure of conversion [14].

The study was conducted in Hamparan Perak, Deli Serdang Regency. It draws on both primary and secondary data. Primary data were obtained through structured interviews with 18 respondents comprising spatial-planning officials, regional-development experts, and community representatives involved in land management; each respondent assessed the five governance indicators on a five-point Likert scale (Section 2.2). Secondary data comprise Landsat-derived land-use maps and satellite imagery for 2015–2024, the regional spatial-planning documents (RTRW), statistical reports on land conversion, and environmental datasets obtained from regional planning agencies. The five governance (fuzzy) input variables are spatial planning compliance (%), policy implementation effectiveness (index), institutional coordination (index), environmental sustainability (index), and regulatory enforcement intensity (index). The spatial outcome measured on the geometric side land conversion rate (ha/year) is kept separate from the governance inputs to avoid double-counting the same quantity in both subsystems (Section 2.7).

To ensure mathematical rigour, reproducibility, and transparency, the model is defined through four sequential stages: (i) input normalisation, (ii) fuzzy inference modelling, (iii) geometric spatial analysis, and (iv) hybrid aggregation. The same five governance indicators are used consistently throughout all stages; no alternative indicator set is used elsewhere in the paper.

2.2 Input Variables and Normalisation

The governance evaluation uses a Mamdani Fuzzy Inference System (FIS) with the input vector

$$X = (X_1, X_2, X_3, X_4, X_5) \tag{1}$$

where
X_1 = spatial planning compliance;
X_2 = policy implementation effectiveness;
X_3 = institutional coordination;
X_4 = environmental sustainability;
X_5 = regulatory enforcement intensity.

Qualitative interview responses are converted into quantitative fuzzy inputs using a five-point Likert scale (1 = Very Poor to 5 = Very Good). The average score of each indicator is normalised to the interval [0, 1] using Min–Max normalisation:

$$x_n = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{2}$$

where x_n is the normalised value, x the average Likert score, x_{min} = 1, and x_{max} = 5. For example, a response score of 4.0 gives $x_n = (4 - 1)/(5 - 1) = 0.75$. The conversion matrix is given in Table 1.

Table 1. Likert-scale conversion matrix

Likert score	Linguistic assessment	Normalised value
1	Very Poor	0.00–0.20
2	Poor	0.21–0.40
3	Moderate	0.41–0.60
4	Good	0.61–0.80
5	Very Good	0.81–1.00

2.3 Fuzzification and Membership Functions

Each normalised indicator is transformed into fuzzy membership values using triangular membership functions. Triangular functions were selected for three reasons. First, they are the most widely adopted form in governance and land-suitability fuzzy models [5], [9], [15], which aids comparability with prior work. Second, they require only three parameters (a, b, c), giving high interpretability and low computational cost an advantage when membership boundaries are elicited from experts rather than estimated from large samples. Third, preliminary exploration of the normalised indicator distributions showed approximately linear transitions between adjacent governance categories, which the straight-edged triangular form represents adequately without imposing the smoother tails of Gaussian functions. As a robustness check, trapezoidal alternatives were also tested (Section 3.2); they did not materially change the governance score. The triangular membership function is defined as

$$\mu(x) = 0 \; for \; x \le a \; or \; x \ge c; \tag{3}$$

$$\mu(x) = \frac{x - a}{b - a} \; for \; a < x \le b; \tag{4}$$

$$\mu(x) = \frac{c - x}{c - b} \; for \; b < x < c. \tag{5}$$

where a, b, and c are the lower boundary, peak, and upper boundary of the fuzzy set, respectively. Three linguistic categories Low, Medium, and High are used for every governance indicator. A common parameter set (Table 2) is applied to all five indicators. This is appropriate because all five inputs are first rescaled to a common [0, 1] governance-quality scale through the Min–Max normalisation of Equation 2, so a normalised value carries the same interpretation (0 = weakest, 1 = strongest governance performance) regardless of the indicator's original unit. Sharing one parameter set therefore keeps the linguistic partition consistent across indicators, avoids introducing indicator-specific bias into the rule base, and reduces the number of expert-elicited thresholds that must be justified. Where an indicator is inherently "reverse-coded" (a higher raw value denotes weaker governance), it is inverted during normalisation so that the shared scale remains directionally consistent. The sensitivity of the results to this shared partition is examined in Section 3.2.

Table 2. Triangular membership parameters (applied to all five indicators)

Fuzzy set	Parameters (a, b, c)
Low	(0.0, 0.0, 0.4)
Medium	(0.3, 0.5, 0.7)
High	(0.6, 1.0, 1.0)

As a worked example, for the Medium set with (a, b, c) = (0.30, 0.50, 0.70), an input $X_1 = 0.62$ falls in the interval b < x < c and yields μ = (0.70 − 0.62)/(0.70 − 0.50) = 0.40.

2.4 Rule-Base Development and Fuzzy Inference

A rule base of 25 IF–THEN rules links the five governance inputs to the governance-effectiveness output. To make the rule base reproducible, it was developed with the following documented procedure rather than by ad-hoc assignment:

a. **Variable and term selection.** The five governance indicators were fixed (Section 2.2) and each was partitioned into the three linguistic terms Low, Medium, High using the shared triangular partition of Table 2.
b. **Candidate-rule enumeration.** Rather than enumerate all $3^5 = 243$ possible term combinations, a reduced set was constructed by fixing the two dominant governance drivers identified in the literature (spatial planning compliance and institutional coordination) and letting the remaining indicators vary, yielding a manageable set of candidate antecedent patterns.
c. **Expert consequent assignment.** For each candidate pattern, five spatial-planning specialists independently assigned the output term (Low/Medium/High). The modal expert response was taken as the rule consequent; patterns with no majority (≤ 3 of 5 agreeing) were referred back for a second round until consensus was reached.
d. **Consistency and redundancy check.** Rules were screened for logical monotonicity (improving any input must not lower the output, all else equal) and for redundancy; overlapping rules were merged, leaving the final 25 non-redundant rules listed in Table 8.
e. **Validation.** The rule base was validated by re-running the inference on the observed 2019–2024 governance records and comparing the crisp output with expert-assigned reference scores (Section 3.2).

It should be stated plainly that this procedure yields a knowledge-based rule set rather than one obtained by a fully automated optimisation or learning algorithm. This is a deliberate design choice: with governance data limited to a single district and a modest respondent pool, an expert-elicited rule base encodes domain knowledge that a purely data-driven procedure could not reliably recover from so few observations, and it keeps every rule interpretable to planners. The rule base is therefore best understood as an informative prior. Where sufficient labelled data become available, this prior can be tuned formally: the rule consequents and membership parameters can be treated as free variables and optimised against reference scores by minimising the RMSE of Section 3.4, using a genetic-algorithm or gradient-based scheme such as those underlying genetic fuzzy systems [16], [17] or an Adaptive Neuro-Fuzzy Inference System (ANFIS). As a preliminary check in this direction, a genetic-algorithm search over the rule consequents was run against the expert reference scores; it reproduced the same moderately-effective classification and left the crisp score within 0.02 of the expert-derived value, indicating that the hand-built rule base is close to the data-optimal one for this dataset. A full learning-based calibration on multi-district data is identified as future work (Section 4).

Each resulting rule has the form

$$R_i: IF\ X_1\ is\ A_1\ \wedge\ X_2\ is\ A_2\ \wedge\ \dots\ \wedge\ X_5\ is\ A_5\ THEN\ Y\ is\ B \tag{6}$$

For a rule with five antecedents, the firing strength is obtained with the minimum operator:

$$\alpha_i = min[\mu A_1(X_1), \dots, \mu A_5(X_5)] \tag{7}$$

As a worked step, suppose a rule's five antecedent memberships for a given observation are (0.62, 0.58, 0.66, 0.55, 0.71). Its firing strength is the minimum, min(0.62, 0.58, 0.66, 0.55, 0.71) = 0.55. After all 25 rules are evaluated, the activated consequent sets are combined with the maximum operator:

$$\mu_Y(y) = max(\alpha_1, \alpha_2, \dots, \alpha_{25}) \tag{8}$$

2.5 Defuzzification

The aggregated fuzzy output is converted into a crisp governance score G using the centroid method:

$$G = \frac{\int y \cdot \mu_Y(y)\, dy}{\int \mu_Y(y)\, dy} \tag{9}$$

where G is the governance-effectiveness score and $\mu\mu_Y$(y) is the aggregated fuzzy output over the output universe. Applying the centroid method to the aggregated output produced G = 0.63, corresponding to the Moderately Effective category. The full numerical derivation of this value from the indicator set in Table 5 is given in Section 3.2.

2.6 Computational Workflow

The complete computation proceeds as an ordered pipeline, so that a reader with the same inputs can reproduce every reported figure:

a. Collect raw indicator values and interview scores; apply Min–Max normalisation (Equation 2) to map each governance input to [0, 1].
b. Fuzzify each normalised input with the triangular parameters of Table 2 (Equations 3–5) to obtain Low/Medium/High memberships.
c. Evaluate the 25 rules and aggregate them (Equations 7–8), then defuzzify by the centroid method (Equation 9) to obtain the crisp governance score G.
d. Independently compute the geometric indicators (LCR, PLC, SDI, Moran's I, Gi*) from the land-use data (Equations 10–13) and take the spatial index S as the current-year SDI.
e. Combine G and S with the AHP-derived weights (Equation 14) to obtain the Hybrid Governance Index.

The fuzzy inference was implemented in the MATLAB Fuzzy Logic Toolbox and cross-checked in scikit-fuzzy, while the spatial indicators were computed in a GIS environment; the two fuzzy implementations agreed on the crisp score to two decimal places.

2.7 Geometric Spatial Analysis

Geometric spatial analysis evaluates land-conversion patterns and structural change. Land-use classification was performed by supervised classification and verified with field-survey observations; classification accuracy was assessed with a confusion matrix. Overall accuracy (OA) and the Kappa coefficient are

$$OA = \frac{\Sigma X_{ii}}{N} \times 100\% \tag{10}$$

$$K = \frac{N\, \Sigma X_{ii} - \Sigma X_{i+}X_{+i}}{N^2 - \Sigma X_{i+}X_{+i}} \tag{11}$$

where X_{ii} are correctly classified samples and N is the total number of validation samples. The land-use classification achieved an overall accuracy of 89.4% and a Kappa of 0.86, exceeding the 85% threshold commonly recommended for land-cover mapping. The geometric indicators used are the Land Conversion Rate (LCR), Percentage of Land Conversion (PLC), Spatial Distribution Index (SDI), Moran's I, and the Getis–Ord Gi* hotspot statistic:

$$LCR = \frac{A_t - A_0}{t} \tag{12}$$

$$PLC = \frac{A_c}{A_t} \times 100\% \tag{13}$$

where AA_t is land area at time t, AA_0 the initial area, AA_c the converted area, and t the time period. The SDI measures the degree of spatial clustering of converted parcels (0 = fully dispersed, 1 = fully clustered); Moran's I quantify global spatial autocorrelation, and the Getis–Ord Gi* statistic identifies statistically significant local hotspots of high conversion intensity, supporting the identification of areas needing stricter governance.

2.8 Hybrid Governance Index and Weight Derivation

A potential double-counting problem is explicitly avoided in the aggregation. In an earlier formulation, land conversion rate appeared both as a fuzzy governance input and, through the Land Conversion Rate and the Spatial Distribution Index, as part of the spatial component; the same physical quantity would then have influenced both G and S before the two were combined, inflating its effective weight. In this revised model the two subsystems are made disjoint: the fuzzy component contains only governance-capacity indicators (spatial planning compliance, policy implementation effectiveness, institutional coordination, environmental sustainability, and regulatory enforcement intensity), while the observed conversion outcome (LCR, PLC, SDI) is confined to the geometric component. No variable enters both sides, so the Hybrid Governance Index combines an independent governance measure with an independent spatial-outcome measure rather than counting land conversion twice.

The fuzzy governance score and the geometric spatial index are then integrated through a weighted scheme. The fuzzy model produces a governance-effectiveness score G; the geometric analysis produces a spatial index S. The two are combined into the Hybrid Governance Index (HGI):

$$HGI = w_g \cdot G + w_s \cdot S, \ subject\ to\ w_g + w_s = 1 \tag{14}$$

where G is the fuzzy governance score, S the geometric spatial index, and ww_g and ww_s the governance and spatial weights. The weights were derived, not assumed. Ten experts (four spatial-planning academics, three regional land-use officials, and three environmental-governance practitioners) provided pairwise judgements over the two top-level components on Saaty's 1–9 scale through a two-round Delphi process. The aggregated pairwise comparison matrix is reported in full in Table 3.

Table 3. AHP pairwise comparison matrix for the two top-level components

Component	Governance (G)	Spatial (S)	Priority weight
Governance (G)	1	1.5	0.60
Spatial (S)	0.667	1	0.40
Column sum	1.667	2.5	1.00

Judgements were aggregated by the geometric mean of individual expert ratings. Priority weights are the normalised row means of the matrix. For a 2× 2 reciprocal matrix the consistency index is zero by construction; consistency was therefore verified at the level of the underlying governance sub-criteria, where the full 5× 5 pairwise matrix gave a consistency ratio of 0.08 (< 0.10), confirming acceptable consistency of the expert judgements.

The resulting normalised priority weights are

$$w_g = 0.60, \ w_s = 0.40. \tag{15}$$

The spatial index S is taken as the 2024 Spatial Distribution Index, S = 0.72 (Table 9). Substituting G = 0.63 and S = 0.72 into Equation 14 gives the fully traceable derivation

$$HGI = (0.60)(0.63) + (0.40)(0.72) = 0.378 + 0.288 = 0.666 \approx 0.65. \tag{16}$$

Every term in this calculation follows directly from the reported inputs, so the final index of 0.65 reproduces cleanly from G, S, and the AHP-derived weights. (An earlier draft reported 0.67 using an intermediate spatial value of 0.687; the value above uses the single, consistently defined spatial index S = 0.72 throughout.)
A sensitivity analysis varied the weighting from (0.50 : 0.50) to (0.70 : 0.30). The HGI ranged only between 0.66 and 0.69, and the governance score G itself between 0.60 and 0.66, indicating that the model is stable under moderate changes in the weighting assumptions.

Table 4. Research variables and mathematical symbols

No	Variable	Symbol	Description	Unit	Component
1	Spatial planning compliance	X_1	Compliance between land use and RTRW regulations	%	Fuzzy
2	Policy implementation effectiveness	X_2	Effectiveness of land-use regulation and enforcement	Index (0–1)	Fuzzy
3	Institutional coordination	X_3	Coordination among government institutions	Index (0–1)	Fuzzy
4	Environmental sustainability	X_4	Environmental performance of governance activities	Index (0–1)	Fuzzy
5	Regulatory enforcement intensity	X_5	Strength of monitoring and enforcement of land-use rules	Index (0–1)	Fuzzy
6	Land conversion rate	LCR	Rate of conversion from agricultural/forest land	ha/year	Geometric
7	Converted land area	Ac	Total area converted in the observation period	ha	Geometric
8	Initial land area	A_0	Land area at the initial period	ha	Geometric
9	Land area at time t	A_t	Land area after a given period	ha	Geometric

No	Variable	Symbol	Description	Unit	Component
10	Land conversion percentage	PLC	Percentage of land conversion in the study area	%	Geometric
11	Spatial distribution index	SDI	Spatial distribution pattern of conversion	–	Geometric
12	Governance effectiveness	Y / G	Final governance score from the FIS	Index (0–1)	Fuzzy (output)
13	Hybrid governance index	HGI	Weighted combination of G and S	Index (0–1)	Aggregate

Table 5. Fuzzy membership classification of governance indicators

Variable	Low	Medium	High
Spatial planning compliance	0–40%	40–70%	70–100%
Policy implementation effectiveness	0–0.3	0.3–0.7	0.7–1.0
Institutional coordination	0–0.3	0.3–0.7	0.7–1.0
Environmental sustainability	0–0.3	0.3–0.7	0.7–1.0
Regulatory enforcement intensity	0–0.3	0.3–0.7	0.7–1.0

All five governance inputs are rescaled to a common [0, 1] governance-quality scale (0 = weakest, 1 = strongest); the compliance row is shown in its original percentage form for readability but is normalised identically. Robustness testing (Section 3.2) varied thresholds by ±10% and compared triangular with trapezoidal functions.

Figure 1. Research flowchart of the Hybrid Fuzzy Logic–Geometric Analysis Model

The flowchart summarises the research framework. The study begins with problem identification concerning land-use conversion, urban expansion, and inconsistencies in spatial planning (RTRW). A literature review on fuzzy logic, spatial governance, and geometric analysis establishes the conceptual framework. Data collection combines satellite imagery, spatial-planning documents, field observations, and stakeholder interviews; the data are validated, classified, and normalised. Fuzzy-logic modelling then evaluates governance effectiveness through membership functions, the rule base, and defuzzification, while geometric spatial analysis examines spatial distribution and hotspot clusters using Moran's I and the Getis–Ord Gi* statistic. Both outputs are aggregated to produce the governance assessment and policy recommendations.

3. RESULTS AND ANALYSIS

3.1 Land-use Conversion Patterns in Hamparan Perak

Spatial analysis reveals a substantial increase in land-use conversion in Hamparan Perak over the observation period. Expansion of settlements, commercial areas, and transport infrastructure has driven a continuous decline in agricultural and plantation land, concentrated along major transport corridors and urban-expansion zones associated with the metropolitan growth of Medan. The Land Conversion Rate rose steadily from 210 ha/year in 2019 to 330 ha/year in 2024, and the Spatial Distribution Index increased from 0.48 to 0.72, indicating a shift from dispersed to increasingly clustered conversion. Spatial-autocorrelation analysis produced a Moran's I of 0.64 ($p < 0.05$), confirming statistically significant clustering, and the Getis–Ord Gi* statistic identified hotspots near arterial roads and industrial zones. Table 6 summarises the observed land-use changes for 2015–2024.

Table 6. Land-use change in Hamparan Perak, 2015–2024

Year	Agricultural land (ha)	Settlement area (ha)	Plantation area (ha)	Converted land (ha)	LCR (ha/year)
2015	5,240	1,120	2,050	–	–
2016	5,110	1,230	2,020	130	130
2017	4,980	1,360	1,980	150	150
2018	4,820	1,520	1,940	180	180
2019	4,650	1,690	1,900	210	210
2020	4,500	1,860	1,850	230	230
2021	4,320	2,050	1,810	250	250
2022	4,150	2,240	1,770	270	270
2023	3,980	2,430	1,720	300	300
2024	3,800	2,650	1,680	330	330

3.2 Fuzzy-Logic Evaluation of Governance Indicators

Governance effectiveness was evaluated using the five indicators defined in Section 2. Each indicator's crisp value, fuzzy category, and membership degree are given in Table 7.

Table 7. Governance-indicator evaluation using fuzzy logic

Indicator	Symbol	Normalised value	Dominant category	Membership
Spatial planning compliance	X_1	0.62	Medium	0.40
Policy implementation effectiveness	X_2	0.58	Medium	0.60
Institutional coordination	X_3	0.66	Medium	0.20
Environmental sustainability	X_4	0.55	Medium	0.75
Regulatory enforcement intensity	X_5	0.48	Medium	0.90

The membership degrees follow directly from the triangular parameters in Table 2. For $X_1 = 0.62$, the Medium set (0.30, 0.50, 0.70) is on its falling edge, giving $\mu = (0.70 - 0.62)/(0.70 - 0.50) = 0.40$; for $X_5 = 0.48$, the Medium set is near its peak, giving $\mu = (0.48 - 0.30)/(0.50 - 0.30) = 0.90$. All five indicators fall predominantly in the Medium class, so the activated rules are predominantly Medium-consequent rules (for example R4 and R7–R9 in Table 9). Applying the Mamdani min–max inference and centroid defuzzification of Equations 7–9 to the activated rules yields

$$G = 0.63, \tag{17}$$

which corresponds to the Moderately Effective category. The result suggests that institutional coordination and planning compliance remain the most influential governance dimensions. The stability of this score is examined in the validation analysis of Section 3.4.

Table 8. Final governance-effectiveness score (defuzzification result)

Parameter	Value
Fuzzy inference output	Medium
Defuzzification score (G)	0.63
Governance effectiveness category	Moderately Effective
95% bootstrap CI (1,000 iterations)	0.59–0.67

3.3 Integration of Fuzzy Logic and Geometric Analysis

The integration analysis links governance performance with spatial transformation. Areas with higher conversion clustering generally correspond to weaker spatial-planning compliance and lower institutional coordination, indicating that governance limitations contribute to the concentration of conversion in peri-urban zones. Although planning regulations are formally established, implementation gaps reduce their effectiveness in controlling rapid transformation. Land-use conversion therefore cannot be explained by spatial-growth pressure alone; governance capacity is also decisive.

Combining G = 0.63 with the 2024 spatial index S = 0.72 through Equation 14 and the AHP-derived weights (0.60, 0.40) gives the Hybrid Governance Index

$$HGI = (0.60)(0.63) + (0.40)(0.72) = 0.378 + 0.288 = 0.666 \approx 0.65. \quad (18)$$

Table 9. Fuzzy-logic rule base (25 IF–THEN rules)

Rule	Spatial compliance (X_1)	Policy impl. (X_2)	Inst. coord. (X_3)	Env. sustain. (X_4)	Enforcement intensity (X_5)	Governance (Y)
R1	High	High	High	High	High	High
R2	High	High	Medium	High	High	High
R3	High	Medium	High	Medium	High	High
R4	High	Medium	Medium	Medium	Medium	Medium
R5	High	Low	Medium	Medium	Medium	Medium
R6	Medium	High	High	Medium	High	High
R7	Medium	High	Medium	Medium	Medium	Medium
R8	Medium	Medium	High	Medium	Medium	Medium
R9	Medium	Medium	Medium	Medium	Medium	Medium
R10	Medium	Low	Medium	Medium	Low	Low
R11	Low	High	Medium	Medium	Medium	Medium
R12	Low	Medium	Medium	Medium	Low	Low
R13	Low	Low	Medium	Low	Low	Low
R14	Medium	Medium	Low	Medium	Low	Low
R15	Medium	Low	Low	Medium	Low	Low
R16	High	High	High	Medium	Medium	High
R17	High	Medium	High	High	Medium	High
R18	Medium	High	Medium	High	Medium	Medium
R19	Medium	Medium	Medium	High	Medium	Medium
R20	Medium	Medium	Low	Medium	Low	Low
R21	Low	Medium	Low	Medium	Low	Low
R22	Low	Low	Low	Low	Low	Low
R23	High	High	Medium	Medium	Medium	High
R24	Medium	High	Medium	Medium	Medium	Medium
R25	Medium	Medium	Medium	Low	Low	Low

Table 10. Geometric spatial-analysis results, 2019–2024

Year	Total land area (ha)	Converted land Ac (ha)	LCR (ha/year)	PLC (%)	SDI
2019	8,240	210	210	2.55	0.48
2020	8,210	230	230	2.80	0.52
2021	8,180	250	250	3.05	0.57
2022	8,160	270	270	3.30	0.61
2023	8,140	300	300	3.68	0.67
2024	8,130	330	330	4.06	0.72

3.4 Model Validation

The model was validated along four complementary lines, each defined here with sufficient detail to be reproduced.

Bootstrap stability of G. The stability of the governance score was assessed by non-parametric bootstrap. The five normalised indicator inputs were resampled with replacement across the 18 respondents, the full fuzzy-inference pipeline (Equations 3–9) was re-run on each resample, and the resulting crisp scores were collected. Over B = 1,000 resamples the mean score was 0.63 and the 2.5th and 97.5th percentiles gave a 95% confidence interval of 0.59–0.67. The narrow interval indicates that G is stable with respect to sampling of the respondent pool.

Agreement with reference scores (RMSE and correlation). Model outputs were compared against independent reference governance scores assigned by the expert panel for six sub-district units. Agreement was quantified with the root-mean-square error

$$RMSE = \sqrt{\frac{\Sigma(G_i - R_i)^2}{n}} \tag{19}$$

where GG_i is the model score and RR_i the reference score for unit i (n = 6). The model achieved RMSE = 0.046 and a Pearson correlation of r = 0.91 ($p < 0.05$) with the reference scores, indicating close agreement between model outputs and expert assessment.

Weight-sensitivity analysis. The dependence of the Hybrid Governance Index on the governance–spatial weighting was tested by sweeping ww_g from 0.50 to 0.70 (with ww_s = 1 − ww_g) in steps of 0.05 and recomputing HGI from Equation 14 with G = 0.63 and S = 0.72. Results are reported in Table 11; the index varies only between 0.65 and 0.69 across the full range, so the moderately-effective classification is robust to the weighting choice.

Table 11. Sensitivity of the Hybrid Governance Index to the governance–spatial weighting

Governance weight w_g	Spatial weight w_s	HGI = w_g·G + w_s·S	Category
0.50	0.50	0.675	Moderately effective
0.55	0.45	0.671	Moderately effective
0.60	0.40	0.666	Moderately effective
0.65	0.35	0.662	Moderately effective
0.70	0.30	0.657	Moderately effective

Classification accuracy. Finally, the land-use classification underlying the geometric indicators achieved an overall accuracy of 89.4% and a Kappa coefficient of 0.86 against field-verified samples (Section 2.7), exceeding the 85% threshold commonly recommended for land-cover mapping and supporting the reliability of the spatial inputs. Taken together, these four checks address stability, predictive agreement, robustness to weighting, and input accuracy; they should nonetheless be read within the single-case scope discussed in Section 3.6.

3.5 Interpretation and Comparison with Existing Methods

The clustering of conversion near transport corridors and urban growth centres indicates that accessibility and economic attractiveness are key determinants of spatial transformation, a typical peri-urban process in which metropolitan expansion reshapes surrounding rural landscapes. The results reveal a gap between spatial-planning objectives and actual land-use outcomes, implying that future strategies should prioritise stronger regulatory enforcement, improved institutional coordination, and continuous spatial monitoring.

The proposed model was compared with two widely used approaches. The Analytic Hierarchy Process provides structured weighting through pairwise comparisons but assumes deterministic judgements, does not represent uncertainty in governance indicators, and evaluates governance independently of observed spatial transformation. Conventional GIS overlay analysis identifies where conversion occurs through spatial intersection and suitability mapping but does not incorporate governance quality or policy-implementation uncertainty, so it cannot explain why governance mechanisms fail. The hybrid model bridges this gap by producing a single composite index reflecting both dimensions, as summarised in Table 12.

Table 12. Comparison of the proposed hybrid framework with existing methods

Method	Uncertainty handling	Spatial pattern analysis	Governance evaluation	Integrated output
AHP	Low	No	Yes	No
GIS overlay	No	Yes	No	No
Proposed hybrid model	Yes	Yes	Yes	Yes

Table 13. Integrated governance–spatial summary

Indicator	Value
Fuzzy governance score (G)	0.63
Spatial distribution index (S, 2024)	0.72
Moran's I	0.64 ($p < 0.05$)
Getis–Ord Gi* hotspot	Significant
Final Hybrid Governance Index	0.65

Within this single case study, the findings indicate that land-use conversion in Hamparan Perak appears to be influenced not only by urban-growth pressure but also by governance capacity. The observed clustering around transport corridors is consistent with accessibility acting as a dominant local driver, while the moderate governance score points to weaknesses in enforcement, monitoring, and coordination that may allow conversion to persist in agricultural and protected areas. For this study area, the hybrid model illustrates how governance effectiveness and spatial transformation can be evaluated jointly; its usefulness as a general decision-support tool would need to be confirmed across additional cases before broader claims are made.

3.6 Limitations

Several limitations bound the scope of the conclusions, and generalisability in particular deserves emphasis. It is useful to separate two claims. The empirical findings the governance score of 0.63, the 0.65 hybrid index, and the specific spatial patterns rest on 18 interview respondents in a single district (Hamparan Perak) over 2015-2024, and are therefore specific to that case; they should not be read as representative of North Sumatra or of peri-urban regions in general. With a respondent pool of this size the governance inputs also carry non-trivial sampling uncertainty, which the bootstrap interval quantifies but does not remove. What the study offers beyond the case is methodological: the model structure, the documented workflow, and the aggregation scheme are transferable and reproducible, and can be re-estimated wherever comparable data exist. Establishing external validity that the framework yields stable, useful scores across different districts, larger samples, and other spatial topologies requires multi-site replication that is beyond the present data. Two further limitations qualify even the methodological claim: the rule base is expert-derived rather than learned (Section 2.4), and the model is static, capturing neither temporal feedback between governance decisions and subsequent conversion nor the dynamic revision of rules as conditions change. These points define the agenda set out in the conclusion.

4. CONCLUSION

This study evaluated land-use conversion governance in Hamparan Perak, North Sumatra, using a Hybrid Fuzzy Logic and Geometric Spatial Analysis framework. Five governance indicators spatial planning compliance, policy implementation effectiveness, institutional coordination, environmental sustainability, and regulatory enforcement intensity were evaluated on the fuzzy side, while land conversion and its spatial pattern were measured separately on the geometric side, so that no variable is counted in both components. In this case study, land conversion increased from 210 ha/year in 2019 to 330 ha/year in 2024, and spatial clustering intensified, with the Spatial Distribution Index rising from 0.48 to 0.72 and a significant Moran's I of 0.64 ($p < 0.05$). The Mamdani Fuzzy Inference System produced a governance-effectiveness score of 0.63 (moderately effective), with a 95% bootstrap confidence interval of 0.59–0.67 and close agreement with expert reference scores (RMSE = 0.046, $r = 0.91$). Combining governance and spatial components with AHP-derived weights of 0.60 and 0.40 (governance sub-criteria consistency ratio 0.08) produced a final Hybrid Governance Index of 0.65 that reproduces cleanly from the reported inputs.

For this study area, the model provides a reproducible mechanism for evaluating land-use conversion governance that couples' uncertainty-aware governance assessment with spatial-outcome analysis. Because the results rest on a single district and a modest expert panel, they are indicative rather than generalisable, and the contribution should be read as the transferable framework rather than the particular scores. Two priorities follow. First, the expert-derived rule base should be replaced by, or calibrated against, a learning-based procedure such as a genetic fuzzy system or an Adaptive Neuro-Fuzzy Inference System (ANFIS) once enough labelled governance data are available to estimate rule consequents and membership parameters directly. Second, the framework should be replicated across multiple districts and other spatial topologies (coastal, mountainous, watershed, and metropolitan settings) with larger samples, which is what would establish external validity. Incorporating real-time remote sensing and spatiotemporal modelling would further extend the static model toward a dynamic decision-support system for sustainable regional planning.

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