A SPATIAL SCENARIO MODEL FOR SUSTAINABLE VILLAGE FOREST MANAGEMENT IN THE PELANGAI WATERSHED, PESISIR SELATAN REGENCY, WEST SUMATRA, INDONESIA

Ikhwan IKHWAN [1], ***Triyatno TRIYATNO*** [2], ***Febriandi FEBRIANDI*** [2] & ***Dian Adhetya ARIF*** [3]

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ABSTRACT

Village forest management requires spatially explicit information on where forest change may occur and how strongly individual villages may be affected. This study develops a spatial scenario framework for the Pelangai Watershed, West Sumatra, with three objectives, namely 1) to model the 2024 Land-Use and Land-Cover (LULC) baseline and the 2034 and 2044 scenarios using the Cellular Automata-Markov Chain model; 2) to quantify the magnitude and spatial distribution of projected LULC and village-forest change; and 3) to identify spatial priorities for monitoring and sustainable village-forest management. Landsat 8 imagery from 2015 and 2020, terrain, accessibility variables, and village boundaries were integrated in the spatial analysis. The scenarios indicate declines in primary, secondary, and village forest, accompanied by expansion of mixed-fruit orchards and oil-palm plantations. The largest projected village-forest losses occur in Pelangai Kaciak and Pelangai Gadang, especially during 2024-2034. Area Under the Curve values of 0.7369-0.7438 indicate moderate internal discrimination. Because independent future reference maps were unavailable, the 2034 and 2044 outputs are interpreted as comparative planning scenarios rather than validated forecasts. The findings support targeted monitoring of forest-agriculture interfaces and protection of remaining forest in the most affected villages.

Keywords*: Spatial scenarios; LULC; CA-Markov; Village Forest; Sustainable Forest Management.*

1. INTRODUCTION

Village forests in tropical regions are under increasing pressure from human activities that threaten their ecological integrity and long-term sustainability. Community-driven land-use changes, including agricultural and residential expansion and natural resource extraction, have contributed to forest loss across Southeast Asia and other tropical regions (Andrew et al., 2023; López-Carr, 2021). In Indonesia, the village forest program was established to strengthen community participation in forest governance. However, the delegation of management authority does not automatically reduce forest cover loss when local economic needs remain closely linked to forest conversion (Rochmayanto et al., 2023). Reliance on fuelwood, timber, and non-timber forest products can place additional pressure on forest resources and complicate sustainability goals (Acheampong et al., 2022). The Pelangai Watershed is located within the Batang Pelangai River system in Ranah Pesisir Sub-district, Pesisir Selatan Regency, West Sumatra Province, Indonesia. This area exemplifies the challenges of village forest management because local land-use decisions must balance ecological protection with the livelihood needs of surrounding communities.

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[1]*Department of Sociology, Universitas Negeri Padang, Padang, Indonesia, ikhwan@fis.unp.ac.id*
[2]*Department of Geography, Universitas Negeri Padang, Padang, Indonesia.*
[*]*Corresponding author triyatno@fis.unp.ac.id; andi_geografi@fis.unp.ac.id*
[3]*Vocational School of Remote Sensing Technology, Universitas Negeri Padang, Padang, Indonesia, dianadhetyaarif@fis.unp.ac.id*

Many studies have examined Land-Use and Land-Cover (LULC) change using spatial modeling methods. Markov Chain and Cellular Automata (CA) models are widely used to analyze and project LULC transitions (Tariq & Mumtaz, 2023). However, many models rely primarily on biophysical and accessibility variables, such as elevation and distance to roads, while incorporating socioeconomic conditions only indirectly (Leta et al., 2021). Consequently, these models may identify where LULC changes occur without fully explaining the social and institutional conditions associated with land conversion (Supiyandi & Mailok, 2025).

Studies of forest-dependent communities have identified demographic conditions, livelihood strategies, and institutional arrangements as important factors associated with forest-use decisions. Household characteristics, including education, land ownership, income sources, and household size, are associated with decisions concerning forest use and land clearing (Ameneshewa et al., 2024; Habtie et al., 2024). Poverty, population growth, and market access can also influence forest loss at the community level (Bekere et al., 2023; Ellis et al., 2021). Therefore, understanding human-forest relationships is crucial for developing forest governance approaches that are responsive to local contexts (Oldekop et al., 2020). However, social analyses are not always integrated with spatially explicit LULC models that can inform zoning, land-use planning, and targeted management interventions. Although CA-Markov models are widely used for LULC scenarios, fewer studies distinguish clearly between modeled baselines and observed validation maps, quantify village-level forest-change hotspots, and translate watershed-scale scenarios into spatial monitoring priorities (Rahnama, 2020; Hussain et al., 2025). To address this gap, the study develops a spatial scenario framework for sustainable village-forest management in the Pelangai Watershed. Its objectives are 1) to model the 2024 LULC baseline and the 2034 and 2044 scenarios using CA-Markov; 2) to quantify the magnitude and spatial distribution of projected LULC and village-forest change; and 3) to identify spatial priorities for monitoring and sustainable village-forest management. The contribution is a village-sensitive spatial assessment that treats future maps as comparative scenarios rather than deterministic forecasts.

2. STUDY AREA

The study was conducted in the Pelangai Watershed. The watershed lies on the western coast of Sumatra, approximately 110 km south of Padang City.

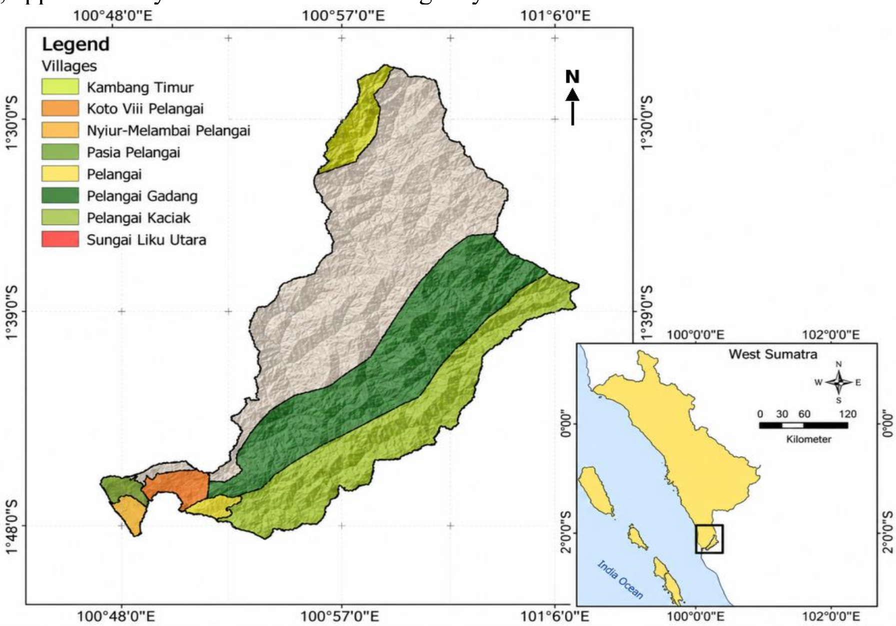

Fig. 1. Location of the Pelangai Watershed and its associated villages in Pesisir Selatan Regency, West Sumatra Province, Indonesia.

Based on the coordinate grid in **Fig. 1**, the mapped area extends approximately from 100°48′00″ E to 101°06′00″ E and from 1°30′00″ S to 1°48′00″ S. The watershed originates in the upland area around Mount Mande Rabiah, near Kerinci Seblat National Park, and drains westward toward the Indian Ocean. It includes several nagari, or villages, such as Pelangai Gadang, Koto VIII Pelangai, Pelangai Kaciak, Pasia Pelangai, Nyiur-Melambai Pelangai, Kambang Timur, and Sungai Liku Utara. Several communities directly manage village forest areas according to local social institutions, livelihood practices, and cultural norms. The Pelangai Watershed supports domestic water use, agriculture, and local livelihoods. However, the area is vulnerable to hydrometeorological hazards, particularly flash floods during periods of intense rainfall. These physical characteristics make the watershed an appropriate site for evaluating spatial LULC and village-forest change and for identifying monitoring priorities.

3. DATA AND METHODS

3.1. Data Sources

The spatial analysis used Landsat 8 imagery from 2015 and 2020 obtained from the United States Geological Survey (USGS). Slope, roads, educational facilities, economic centers, health facilities, watershed boundaries, and village boundaries were used as terrain, accessibility, and reporting layers. The 2015 and 2020 classifications provided the transition information used to generate the modeled 2024 baseline and the 2034 and 2044 scenarios.

3.2. Analytical Framework

The analysis comprised three linked spatial stages. First, the 2015 and 2020 LULC maps were used to estimate transition probabilities and calibrate the CA-Markov model. Second, the calibrated model generated the modeled 2024 baseline and comparative scenarios for 2034 and 2044, from which class-level and village-level forest changes were quantified. Third, ROC/AUC statistics were used to assess internal model discrimination. Because independent future reference maps do not exist, all future outputs were interpreted as planning scenarios rather than validated forecasts.

3.2.1. LULC Analysis Using the CA-Markov Model

Landsat 8 imagery from 2015 and 2020 was classified into the LULC classes reported in the Results. Slope and distances to roads, educational facilities, economic centers, and health facilities were included as spatial driving variables because terrain and accessibility can influence land-conversion patterns (Tahir et al., 2025). The CA-Markov approach combines temporal transition probabilities from a Markov Chain with neighborhood-based spatial allocation rules from CA (Koko et al., 2020; Tariq et al., 2022). The Markov component estimated the probability that one LULC class would change to another during a specified interval:

$$S_{t+1} = S_t P \tag{1}$$

where S_t and S_{t+1} are the LULC state vectors at times t and t+1, respectively, and P is the transition-probability matrix (Acheampong et al., 2022).

The CA component allocated the projected transitions spatially according to the preceding land-cover state, neighborhood configuration, spatial driving variables, and transition probabilities:

$$L_{i,t+1} = f\left(L_{i,t}, N_{i,t}, D_i, P\right) \tag{2}$$

where $L_{i,t+1}$ is the simulated LULC class of cell i at time $t + 1$, $L_{i,t}$ is its preceding class, $N_{i,t}$ is the neighborhood configuration, D_i is the vector of spatial driving variables, P is the Markov transition matrix, and f is the transition rule (Leta et al., 2021).

The 2015 and 2020 LULC maps were used to estimate transition probabilities and calibrate the CA-Markov model. The calibrated model generated the modeled 2024 baseline, which served as the starting condition for the 2034 and 2044 scenarios. Because the 2024 layer was modeled rather than derived from independent reference imagery, it was treated as a modeled baseline and not as an independently observed validation map. Model discrimination was assessed using Receiver Operating Characteristic curves and the Area Under the Curve. AUC values closer to 1.00 indicate stronger discrimination, whereas 0.50 indicates random discrimination. Because independent future reference maps were unavailable, the 2034 and 2044 AUC values were interpreted as measures of internal discrimination rather than independent validation (Rahnama, 2020; Hussain et al., 2025).

4. RESULTS

4.1. LULC SCENARIOS

The modelled 2024 LULC baseline and the 2034 and 2044 scenarios show spatially uneven change across the Pelangai Watershed. The main changes are concentrated in the lower and middle watershed, particularly where forest, settlement, and cultivated land meet. The spatial distribution is presented in **Fig. 2**.

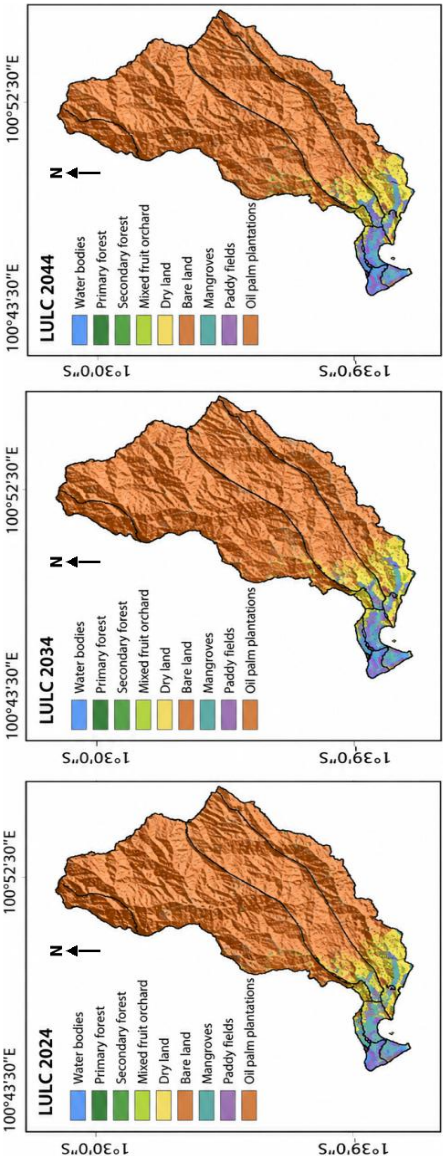

Fig. 2. Modelled LULC in 2024 and projected LULC scenarios for 2034 and 2044.

Projected change is concentrated in the lower and middle watershed, particularly at interfaces among forest, settlement, and cultivated land. The principal modeled transition is from forest classes toward mixed-fruit orchards and oil-palm plantations (**Figs. 2 and 3**).

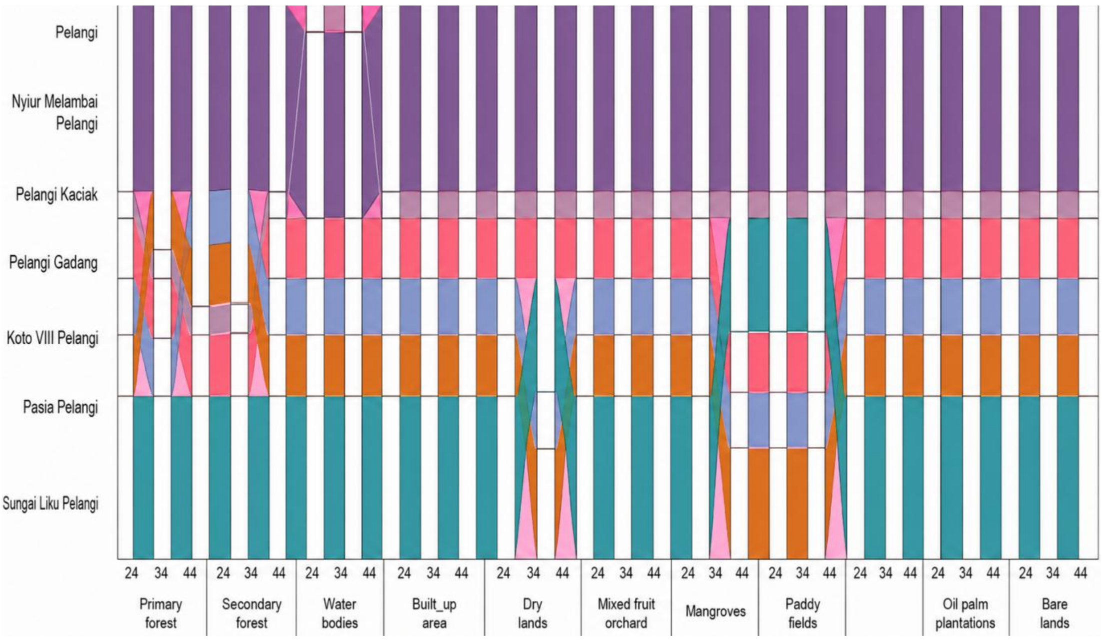

Fig. 3. Projected LULC changes from 2024 to 2044.

Primary and secondary forest areas decline across the scenarios, while mixed-fruit orchards and oil-palm plantations expand. Pelangai Kaciak shows primary-forest losses of 109.82 ha during 2024-2034 and 57.41 ha during 2034-2044, together with the largest modeled increase in mixed-fruit orchards. Pelangai Gadang and Sungai Liku Pelangai show comparable forest-to-cultivation transitions, although their magnitudes differ.

4.2. Projected Village-Forest Change

Village-forest area declines from 2024 to 2044, with substantial differences among villages.

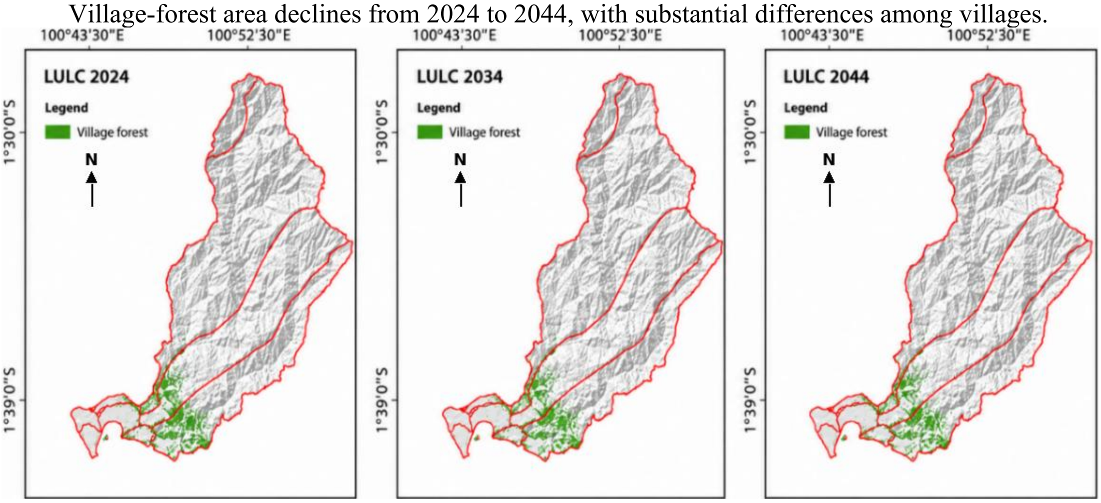

Fig. 4. Modelled village-forest distribution in 2024 and projected distributions for 2034 and 2044.

The modeled spatial distribution is presented in **Fig. 4**, and the magnitude of change by village is summarized in **Fig. 5**.

The scenarios show progressive contraction of village forest, particularly in Pelangai Kaciak and Pelangai Gadang. Villages with smaller initial village-forest areas show more limited absolute change (**Figs. 4 and 5**).

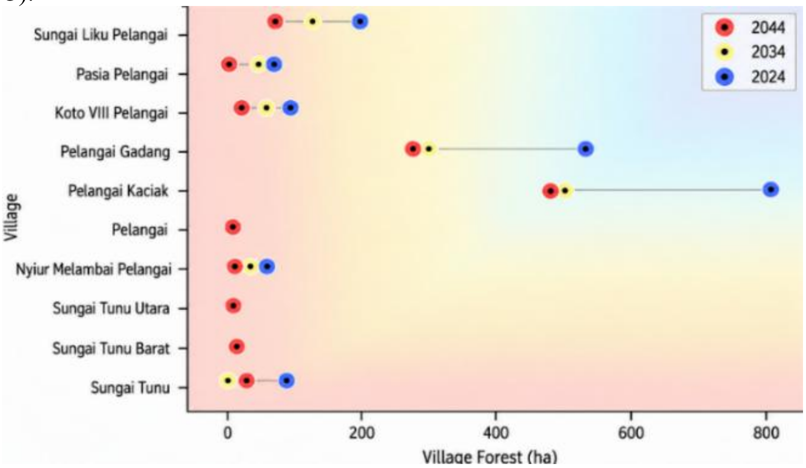

Fig. 5. Projected changes in village-forest area during 2024-2034 and 2034-2044.

Pelangai Kaciak is projected to lose 288.00 ha of village forest during 2024-2034 and a further 6.27 ha during 2034-2044. Pelangai Gadang is projected to lose 214.10 ha and 10.35 ha during the same periods. These two villages therefore form the principal spatial priorities for monitoring and field verification (**Fig. 5**).

Table 1

Internal ROC/AUC discrimination statistics for the modelled 2024 baseline and the 2034 and 2044 scenarios.

Year	AUC	Standard error	Asymptotic *p*-value	95% LCL	95% UCL
2024	0.7388	0.0871	0.0033	0.5681	0.9096
2034	0.7438	0.0758	0.0008	0.5952	0.8923
2044	0.7369	0.0712	0.0006	0.5972	0.8765

AUC values of 0.7388, 0.7438, and 0.7369 indicate moderate internal discrimination for 2024, 2034, and 2044, respectively (**Table 1**).

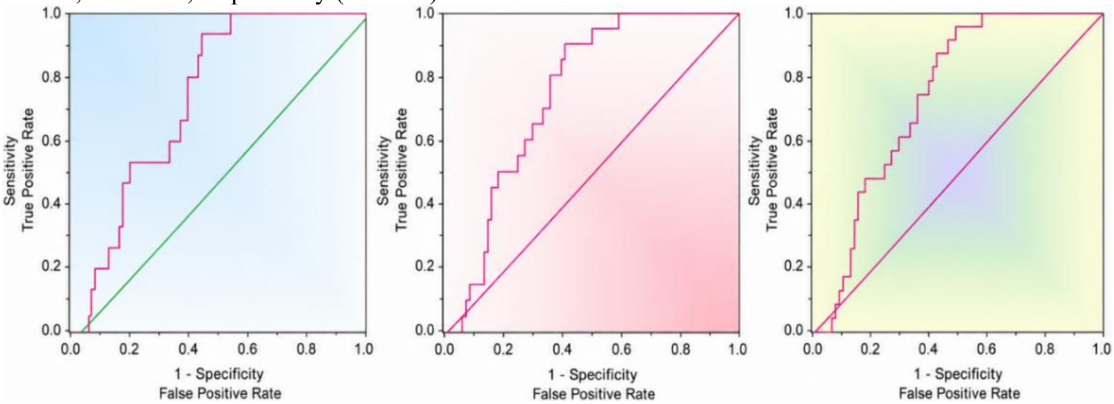

Fig. 6. ROC curves showing internal discrimination for the modeled 2024 baseline and the 2034 and 2044 scenarios.

The 2034 and 2044 statistics are measures of internal discrimination, not independent validation of future conditions. The ROC curves are consistent with the AUC values in Table 1 and indicate moderate internal discrimination across the three modeled years (**Fig. 6**).

5. DISCUSSION

The modeled scenarios indicate a persistent shift from forest classes toward mixed-fruit orchards and oil-palm plantations. This pattern is consistent with evidence that smallholder and commercial agricultural expansion can be important pathways of tropical forest conversion (López-Carr, 2021; Acheampong et al., 2022). The scenarios do not establish the household or institutional causes of conversion, but they identify where monitoring should be concentrated. Comparable forest-to-cultivation transitions have been reported elsewhere in West Sumatra (Febriandi et al., 2025; Ikhwan et al., 2025). In the Pelangai Watershed, the strongest modeled changes occur in the lower and middle watershed at forest-agriculture interfaces. These interfaces should therefore be prioritized for field verification, boundary monitoring, and periodic updating with new imagery. Projected village-forest loss is concentrated in Pelangai Kaciak and Pelangai Gadang, especially during 2024-2034. This spatial pattern requires further investigation using parcel-level tenure, accessibility, household decisions, and conversion-permit data. Until such evidence is available, the results should guide monitoring priorities rather than be interpreted as causal or deterministic predictions.

Forest decline may also weaken soil retention, water regulation, and microclimate functions (Yang et al., 2025). However, this study did not model runoff, erosion, flood discharge, or landslide probability. Management implications are therefore limited to protecting remaining forest, monitoring steep and riparian zones, and controlling expansion at mapped forest-agriculture interfaces (Haryani et al., 2025). Loss of riparian vegetation and buffer zones can also reduce infiltration, water retention, and sediment regulation, thereby increasing flood risk (Hermon et al., 2026). Comparable watershed research in Pesisir Selatan likewise prioritizes upstream forest conservation, community knowledge, institutional strengthening, and land-use control (Barlian et al., 2025). The AUC values near 0.74 indicate moderate internal discrimination. The principal limitations are the modeled 2024 baseline, the absence of independent future reference maps, and uncertainty inherent in scenario-based allocation. Consequently, the 2034 and 2044 maps are suitable for comparative planning and hotspot identification but not as independently validated forecasts (Rahnama, 2020; Hussain et al., 2025).

6. CONCLUSION

This study developed a spatial scenario framework for village-forest management in the Pelangai Watershed. The modeled 2024 baseline and the 2034 and 2044 scenarios indicate declines in primary, secondary, and village forest, accompanied by expansion of mixed-fruit orchards and oil-palm plantations. Pelangai Kaciak and Pelangai Gadang show the largest projected village-forest losses and should be prioritized for monitoring and field verification. AUC values of 0.7369-0.7438 indicate moderate internal discrimination. Therefore, future maps should be used as comparative planning scenarios rather than validated forecasts. Management should focus on remaining forest, riparian and steep-slope areas, and forest-agriculture interfaces. The scenarios should be updated when independent imagery, field observations, tenure information, and land-conversion records become available.

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