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# Forest quality decline and restoration priorities in Indonesia's New Capital Region

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**Abstract.** *Irfaddien R, Kiswanto, Herlambang H, Anwar S, Farahdita WL. 2026. Forest quality decline and restoration priorities in Indonesia's New Capital Region. Asian J For 10 (1): r100108. https://doi.org/10.13057/asianjfor/r100108.* Rapid development in the Capital City of Nusantara (IKN), East Kalimantan, Indonesia, is occurring within a landscape that still contains extensive humid tropical forest. This study quantifies spatiotemporal Land Cover change (2016-2025) and evaluates landscape-scale ecosystem condition using a Land Cover Quality Index (LCQI) derived from Sentinel-2 imagery, complemented by a DPSIR (Driving force–Pressure–State–Impact–Response) synthesis to frame restoration and management priorities. Land cover was mapped into 10 classes using a Random Forest classifier, achieving an overall accuracy of 85.2% (κ=0.82). Total forest cover decreased from 181,656 ha (70.8%) in 2016 to 138,700 ha (54.1%) in 2025 (-43,000 ha), including primary forest loss of 36,500 ha (-3,650 ha yr$^{-1}$) and a marked increase in degraded forest (256 to 20,600 ha). Shrubland expanded by 32,600 ha, while built-up area increased from 8,400 to 27,200 ha. Consistent with these transitions, LCQI declined from 71.3 to 54.8, falling below the degradation threshold (≤65), a commonly used screening benchmark in environmental quality assessments. Hotspot analysis identified concentrated forest loss along infrastructure corridors in the northern and eastern parts of IKN, as well as near mining and river-valley conversion fronts. Insights from key-informant interviews (n=25) suggest that capital relocation, associated population growth, and investment flows are prominent drivers associated with land-conversion pressures. We do not directly measure biodiversity responses in the field; therefore, biodiversity implications are inferred from established relationships between forest loss/fragmentation and species viability. The driver–pressure linkages framed in the DPSIR framework should be interpreted as a structured synthesis of evidence and stakeholder perspectives rather than experimentally demonstrated causation. Accordingly, results are presented as spatial risk indicators to support restoration prioritization rather than as observed biological outcomes. Spatially explicit priorities include protecting remaining primary-forest blocks, rehabilitating degraded forest and shrubland-transition areas, and institutionalizing periodic LCQI-based monitoring to support the Forest City vision.

**Keywords:** DPSIR, ecosystem restoration, forest habitat, Land Cover Quality Index, Nusantara Capital City

**Abbreviations:** DPSIR: Driving force-Pressure-State-Impact-Response, EQI: Environmental Quality Index, GIS: Geographic Information Systems, IKN: *Ibu Kota Nusantara* (Capital City of Nusantara), LCQI: Land Cover Quality Index, NDVI: Normalized Difference Vegetation Index, RTH: *Ruang Terbuka Hijau* (Green Open Space)

## INTRODUCTION

The relocation of Indonesia's capital from Jakarta to the Capital City of Nusantara (IKN) in East Kalimantan Province represents a transformative national initiative with profound implications for tropical forest ecosystems, landscape connectivity, and regional biodiversity (Government of Indonesia 2022a, b). While official IKN planning documents emphasize a Forest City approach that integrates forest protection with urban development, rapid infrastructure expansion still poses substantial risks to forest habitats, carbon storage, and hydrological regulation that are critical for ecological resilience and long-term urban sustainability.

Beyond area loss, rapid development can intensify forest degradation through fragmentation and edge effects, reducing habitat quality and the functional integrity of remaining forest blocks. Consequently, monitoring frameworks that capture forest condition/quality, not only forest extent, are required to inform restoration prioritization and adaptive planning in emerging urban–forest mosaics.

Monitoring Land Cover dynamics using satellite-based geospatial analysis is essential for understanding environmental change processes and designing effective restoration strategies (Wang et al. 2020; Hadi et al. 2022).

Multitemporal satellite imagery enables detection of deforestation, forest degradation, and land-use conversion across large areas (Reiche et al. 2016; Höhl et al. 2020). However, traditional binary forest/non-forest classifications fail to capture declines in ecosystem condition, a critical gap in rapid-development contexts. Land cover quality indicators and related remote-sensing ecological indices synthesize ecosystem composition and functional capacity to provide standardized metrics for monitoring condition and restoration effectiveness (Roy et al. 2022; Lu et al. 2023; Wang et al. 2024).

Integrating spatiotemporal Land Cover analysis with the Driving force-Pressure-State-Impact-Response framework provides a structured basis for policy-relevant environmental assessment (Rahmawaty et al. 2022; Yousafzai et al. 2022; Yao et al. 2024). Here, the framework is used as an interpretive synthesis rather than experimental attribution. It helps organize evidence on plausible drivers (e.g., national capital relocation, population migration) and pressures (e.g., mining, land conversion) and link them to observed spatial patterns to inform management responses (Quevedo et al. 2023; Flick et al. 2025).

Habitat loss and fragmentation are well-documented drivers of declines in tropical forest biodiversity (Haddad et al. 2015; Laurance et al. 2018; Hending et al. 2023). The documented Land Cover changes in IKN are projected to reduce habitat for forest-dependent species through increased edge effects, microclimatic stress, and human-wildlife interactions. We do not directly measure biodiversity responses in the field; therefore, biodiversity implications discussed in this paper are inferred from established relationships between forest loss/fragmentation and species viability and should be interpreted as risk indicators rather than observed biological outcomes.

Despite extensive planning documentation for IKN, a comprehensive decade-scale assessment that combines a satellite-derived Land Cover Quality Index with a Driving force–Pressure–State–Impact–Response synthesis to produce spatially explicit restoration priorities remains limited. This study addresses that gap by (i) mapping annual land cover (2016-2025) from Sentinel-2 imagery, (ii) quantifying landscape-scale condition using a Land Cover Quality Index, and (iii) integrating hotspot patterns with a structured driver–pressure interpretation to support restoration and adaptive planning aligned with the Forest City vision.

Rapid infrastructure expansion in tropical forest frontiers often reduces effective interior-forest area through fragmentation and edge exposure, with consequences for ecological functioning that may persist even when some tree cover remains (Haddad et al. 2015; Laurance et al. 2018). Importantly, forest landscapes commonly follow a degradation–recovery continuum in which canopy opening, biomass loss, and regrowth trajectories vary across management contexts; therefore, restoration prioritization benefits from metrics that capture quality change rather than binary forest/non-forest extent alone (Ghazoul and Chazdon 2017). In the context of IKN, integrating spatiotemporal Land Cover transitions with a quality index provides an operational basis for distinguishing areas where strict protection, assisted natural regeneration, or active rehabilitation is most defensible.

Recent IKN-focused studies reinforce the importance of combining ecological monitoring with governance analysis. For example, household surveys in six villages around IKN documented strong local social capital but also showed that community influence over forest-related decision-making remains constrained by institutional arrangements and overlapping authority (Anwar et al. 2025a, b). In parallel, spatial suitability modelling for future built-up expansion around the new capital shows that development pathways differ markedly depending on how ecosystem sensitivity, accessibility, and socioeconomic factors are integrated, underscoring the need to embed ecological safeguards in land-allocation decisions from the outset (Virtriana et al. 2025).

This study addresses three research questions: (i) How have Land Cover composition and ecosystem condition in IKN evolved during 2016-2025 based on satellite analysis, and what are the spatial patterns of change? (ii) What are the primary drivers of observed Land Cover change, and how do they relate to declines in Land cover quality within a Driving force–Pressure–State–Impact–Response framing? (iii) What spatially explicit restoration strategies are most appropriate for improving Land cover quality and supporting the Forest City concept?

## MATERIALS AND METHODS

### Study area

The study encompassed the entire formally designated IKN area (256,142.74 ha, with core area 56,180.87 ha) located between 0°59'-0°56' S and 116°38'-116°44' E (Figure 1). The region spans portions of Kutai Kartanegara and Penajam Paser Utara regencies in East Kalimantan, Indonesia. The landscape is characterized by a humid tropical climate (2,500-3,500 mm annual precipitation), diverse topography (0-200 m elevation), and a lowland dipterocarp forest as the dominant natural vegetation.

The Mahakam River system traverses the area, serving as the region's primary transportation corridor. Forest-designation layers indicate that the landscape spans statutory management contexts (e.g., protection-oriented, production-oriented, and conversion/non-forest allocations). These designations are reported here to provide a forestry-management context for interpreting Land Cover transitions and restoration priorities across governance zones.

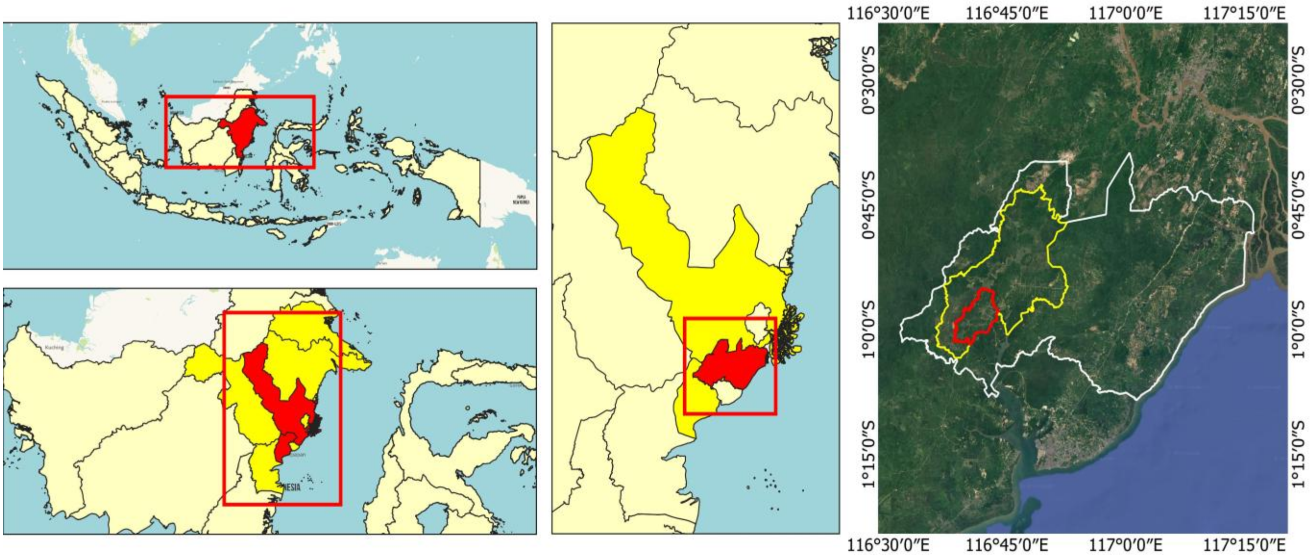


**Figure 1.** Location of study

## Geospatial data and satellite imagery

Multitemporal Sentinel-2 images (10-20 m spatial resolution, 12 spectral bands) were acquired for the dry seasons (August-September) of 2016-2025 to minimize phenological variation and enhance spectral separability across Land Cover classes. Dry-season imagery provides: (i) maximum vegetation–water contrast for improved forest/water boundary discrimination; (ii) reduced atmospheric haze and cloud obstruction, critical for accurate multispectral classification in tropical regions; and (iii) stable spectral indices (NDVI, NDWI, NDBI) enabling consistent year-to-year comparison in time-series analysis. All images had ≤5% cloud cover to ensure adequate spatial coverage. Data were obtained from the Copernicus Open Access Hub. Supplementary datasets included forest-function/designation layers from KLHK (e.g., protection-oriented forests, production forests, and non-forest/conversion allocations), which were used to contextualize observed Land Cover transitions and restoration priorities.

## Land cover classification and accuracy assessment

Sentinel-2 images underwent standard preprocessing: atmospheric correction using the FLAASH algorithm, spectral index calculation (NDVI, NDWI, NDBI), and image mosaicking. Supervised classification was conducted using a Random Forest classifier (500 trees) implemented in Google Earth Engine and validated against multisource reference data.

## Training data and validation

Training data were acquired from high-resolution reference imagery (Copernicus Sentinel Hub) and field observations conducted during both dry season (August-September 2024) and wet season (February-March 2024) to capture phenological variation across Land Cover classes. For each of 10 Land Cover classes, stratified random sampling generated at least 120 sample points per class (n = 1,200 total), distributed across the study area to ensure representative geographic coverage. Field validation employed GPS-enabled visual assessment with at least two validation visits per class and season to ensure temporal and spatial consistency. Classification accuracy was assessed using an error matrix with 30% of the validation data withheld, stratified by Land Cover class.

Ten Land Cover classes were defined: (1) primary dense forest, (2) secondary forest, (3) degraded forest, (4) shrubland, (5) grassland, (6) agricultural land, (7) water bodies, (8) built-up areas, (9) bare soil, and (10) green open space (RTH). Overall classification accuracy was 85.2%, and the Kappa coefficient was 0.82, exceeding the 70% threshold.

## Land cover dynamics analysis

Annual land cover maps were generated for 2016-2025. Cross-tabulation transition matrices were constructed to quantify conversions between land cover classes. Rates of change (ha/year and % change) were calculated for key classes. Spatial hotspots of intensive change were identified using Local Moran's I statistic for spatial autocorrelation.

## Land Cover Quality Index (LCQI)

LCQI was calculated as a weighted index to represent relative ecosystem condition based on Land Cover composition:

$$LCQI = (\Sigma (A_i \times W_i) / A_{total}) \times 100$$

Where, $A_i$ is the area (ha) of Land Cover class i, $W_i$ is its ecological weight (0-1), and $A_{total}$ is the total study-area extent. Weights were assigned to reflect relative ecosystem service provision and habitat-support potential (Table 1).

Following common screening practices for environmental quality indices, an LCQI <65 was interpreted as a degraded landscape condition. LCQI is used here as a comparative metric to support trend interpretation; it does not directly measure biodiversity or ecosystem processes. Weights were standardized through author consensus and cross-checked against published evidence on relative carbon storage and habitat-support values for tropical Land Cover classes. Weight factors reflect ecosystem service provision capacity and carbon storage potential based on published tropical forest assessments (Table 1).

Primary dense forest (W=1.0) represents a baseline intact forest with maximum ecosystem service delivery and carbon stock. Secondary forests (W=0.8) retain substantial but reduced service capacity due to the need for structural recovery. Water bodies (W=0.7) and green open space/urban forest (W=0.9) provide critical hydrological and microclimate regulation in urban contexts (Han et al. 2021; Roy et al. 2022). A degraded forest (W=0.5) indicates structural degradation with substantially reduced capacity (Lu et al. 2023). Shrubland (W=0.3) represents secondary succession with minimal ecosystem service capacity. Anthropogenic/ built-up classes (W=0.1) provide negligible ecosystem services and carbon storage. LCQI values range from 0 (completely degraded) to 100 (pristine forest). Following precedent in tropical environmental management (Han et al. 2021; Roy et al. 2022), LCQI≤65 indicates degraded ecosystem status with reduced capacity to support biodiversity and provide ecosystem services. This threshold is applied as a general screening benchmark adopted from Environmental Quality Index literature, not as a site-specific ecological limit.

### DPSIR framework integration

The Driving force–Pressure–State–Impact–Response (DPSIR) framework was used to contextualize quantitative Land Cover and LCQI results within socioeconomic and governance processes. We conducted semi-structured key-informant interviews (n=25) with national and regional authorities, local communities, planners, academics, and private-sector actors. Participation was voluntary and obtained through informed verbal consent, in accordance with institutional ethical guidelines for social research. Interview responses were thematically coded to identify dominant driving forces, pressures, and perceived impacts. These themes were used for qualitative triangulation to interpret the spatial 'State' indicators (Land Cover transitions, hotspots, and LCQI trends) and to compile candidate policy and management responses. DPSIR is presented as a structured synthesis of evidence and stakeholder perspectives rather than as experimental attribution.

### Statistical analysis

Linear regression was used to test for significant temporal trends in forest loss and LCQI decline ($\alpha$=0.05). Regression assumptions were assessed: normality of residuals via the Shapiro-Wilk test (all $p>0.05$); independence via the Durbin-Watson statistic (DW=1.8-2.2, acceptable for time series); and homogeneity of variance via Levene's test (all $p>0.05$). These results confirm that linear models are appropriate for testing decade-long trends. Limitations include the inability to account for potential nonlinear acceleration or lagged effects in rapid development contexts.

## RESULTS AND DISCUSSION

### Land cover composition and temporal trends

Total forest cover (primary, secondary, and degraded classes combined) declined from 181,656 ha (70.8%) in 2016 to 138,700 ha (54.1%) in 2025, a net loss of 43,000 ha representing 16.7% of baseline cover (Figure 2). Within this aggregate decline, three distinct processes are evident:

*Primary forest decline*

The observed reduction in primary forest extent, equivalent to approximately 3,650 ha·year$^{-1}$ based on end-point comparison, coupled with the proliferation of fragmentation hotspots, indicates elevated biodiversity risk.

*Secondary forest decline*

Secondary forest declined at 1,410 ha·year$^{-1}$, representing slower but persistent loss. Secondary forest loss is consistent with marginal land utilization, where less economically valuable forest is preferentially converted to agricultural use.

*Degraded forest proliferation*

The distinct surge in degraded forest (0.1% to 8.0%) signals that ecosystem quality decline is driven not just by deforestation, but by cryptic degradation processes. This 80-fold increase reflects pervasive fragmentation and edge effects penetrating the remaining forest blocks (Mansourian and Vallauri 2014), a nuance often missed in binary forest/non-forest assessments.

**Table 1.** LCQI weight factors and justification

| Land cover class | Weight ($W_i$) | Justification |
|---|---|---|
| Primary Dense Forest | 1.0 | Maximum ecosystem services (carbon, water, biodiversity) |
| Secondary Forest | 0.8 | Recovering structure; reduced but substantial services |
| Water Bodies | 0.7 | Hydrology; aquatic ecosystem support |
| Green Open Space / Urban Forest | 0.9 | Urban microclimate, flood regulation, and recreation |
| Degraded Forest | 0.5 | Reduced structure; impaired services (Han et al. 2021) |
| Shrubland | 0.3 | Low diversity; minimal carbon and biodiversity value |
| Built-up / Anthropogenic | 0.1 | Negligible ecosystem services or carbon (Roy et al. 2022) |

**Table 2.** Land cover dynamics in the Capital City of Nusantara, Indonesia (2016-2025)

| Year | Primary forest (Ha) | Secondary forest (Ha) | Degraded forest (Ha) | Total forest (Ha) | Forest % | Built-up (Ha) | Agricultural (Ha) | Land Cover Quality Index |
|---|---|---|---|---|---|---|---|---|
| 2016 | 108,400 | 73,000 | 256 | 181,656 | 70.8 | 8,400 | 45,200 | 71.3 |
| 2017 | 101,800 | 69,200 | 3,600 | 174,600 | 68.1 | 11,200 | 52,400 | 69.1 |
| 2018 | 97,600 | 66,800 | 5,200 | 169,600 | 66.2 | 13,100 | 56,800 | 67.3 |
| 2019 | 92,400 | 63,200 | 7,600 | 163,200 | 63.7 | 15,600 | 61,200 | 65.8 |
| 2020 | 87,200 | 60,100 | 9,800 | 157,100 | 61.3 | 17,800 | 66,000 | 64.1 |
| 2021 | 81,400 | 56,200 | 12,400 | 150,000 | 58.6 | 20,400 | 71,200 | 60.9 |
| 2022 | 77,800 | 52,900 | 14,600 | 145,300 | 56.8 | 22,600 | 75,100 | 59.3 |
| 2023 | 74,600 | 49,800 | 17,200 | 141,600 | 55.3 | 24,800 | 78,900 | 57.4 |
| 2024 | 72,200 | 47,100 | 19,800 | 139,100 | 54.3 | 26,500 | 82,400 | 55.2 |
| 2025 | 71,900 | 46,200 | 20,600 | 138,700 | 54.1 | 27,200 | 84,100 | 54.8 |

Note: Data compiled from Sentinel-2 multitemporal classification

**Land Cover Quality Index (LCQI) dynamics**

*Land Cover Quality Index decline*

The LCQI declined from 71.3 (2016) to 54.8 (2025), a 16.5-point decrease indicating a transition from moderate to degraded ecosystem status. By 2020 the index had already fallen below the screening threshold of 65, and the decline persisted thereafter. This trajectory is numerically documented in Table 2 and formally tested in Table 3.

Primary forest declined by 36,500 ha over 2016-2025, equivalent to an average net loss of approximately 3,650 ha·year$^{-1}$ based on end-point comparison. Linear regression indicates a fitted temporal decline of -4,244 ha·year$^{-1}$ ($R^2$ = 0.969, $p < 0.001$; Table 3).

Trend significance (linear regression). Linear regression confirmed a strongly and significantly negative temporal trend in LCQI during 2016-2025, with a decline of -1.93 index points·year$^{-1}$ ($R^2$ = 0.992, $p < 0.001$; Table 3). Over the same period, primary forest area declined at -4,244 ha·year$^{-1}$ ($R^2$ = 0.969, $p < 0.001$; Table 3), indicating that interannual variability occurred around a consistent long-term downward trajectory rather than random fluctuation. Accordingly, Table 3 reports the regression parameters used to support the temporal interpretation of ecosystem-quality decline in IKN.

A Land Cover Quality Index below 65 is associated in the literature with a substantive reduction in the capacity to provide ecosystem services (Lu et al. 2023). Specific mechanisms include: (i) reduced carbon sequestration potential due to primary forest loss and forest degradation (forest degradation increased from 0.1% to 8% of IKN area, indicating substantial carbon-stock vulnerability); (ii) altered hydrological regulation through forest fragmentation, reducing water-retention capacity and increasing flood-drought volatility; and (iii) reduced forest-interior microhabitats for biodiversity due to edge-effect proliferation, which can reduce interior-forest microhabitats and alter microclimatic conditions (Haddad et al. 2015; Laurance et al. 2018). However, this assessment does not quantify carbon stocks, hydrological parameters, or species-level responses empirically in this study. The decline in the Land Cover Quality Index is a composite indicator signaling ecosystem stress; field-based carbon accounting, hydrological monitoring, and biodiversity surveys would be necessary to quantify specific service losses.

Comparable long-term monitoring in other rapidly urbanizing capital regions has shown that sustained settlement expansion is commonly accompanied by forest fragmentation and declining core-forest area, supporting the use of periodic LCQI updates as an early-warning tool for IKN rather than relying only on end-point Land Cover statistics (Gilani et al. 2020).

**Land cover transition pathways and spatial distribution**

Cross-tabulation analysis revealed specific conversion pathways. Primary forest was predominantly converted to: (1) built-up areas (48.2% of primary forest loss); (2) agricultural land (28.9%); (3) shrubland/secondary succession (15.4%); and (4) bare soil/mining (7.5%). Secondary forest showed similar patterns but with higher agricultural conversion (42.1%) and secondary succession (31.2%).

Spatial hotspot analysis using Local Moran's I identified statistically significant clusters of forest loss ($p<0.05$, clustering detected at a 2-3 km spatial scale). Hotspots are concentrated in:

**Northern Zone:** Road corridors linking Penajam and Samboja districts, associated with agricultural expansion (oil palm) and extractive activities (mining concessions IUP active 2016-2020).

**Eastern Zone:** Infrastructure development corridors (airport access, administrative center roads, utility right-of-ways) within Sepaku and Penajam Paser Utara, showing rapid built-up expansion (224% increase in built-up area from 8,400 ha in 2016 to 27,200 ha in 2025, Table 2).

**Table 3.** Linear regression results for LCQI and primary forest trends in IKN, Indonesia (2016-2025)

| Response variable | Slope (Annual trend) | R2 | p-value | n |
|---|---|---|---|---|
| LCQI | -1.93 points·yr$^{-1}$ | 0.992 | <0.001 | 10 |
| Primary Forest Area | -4,244 ha·yr$^{-1}$ | 0.969 | <0.001 | 10 |

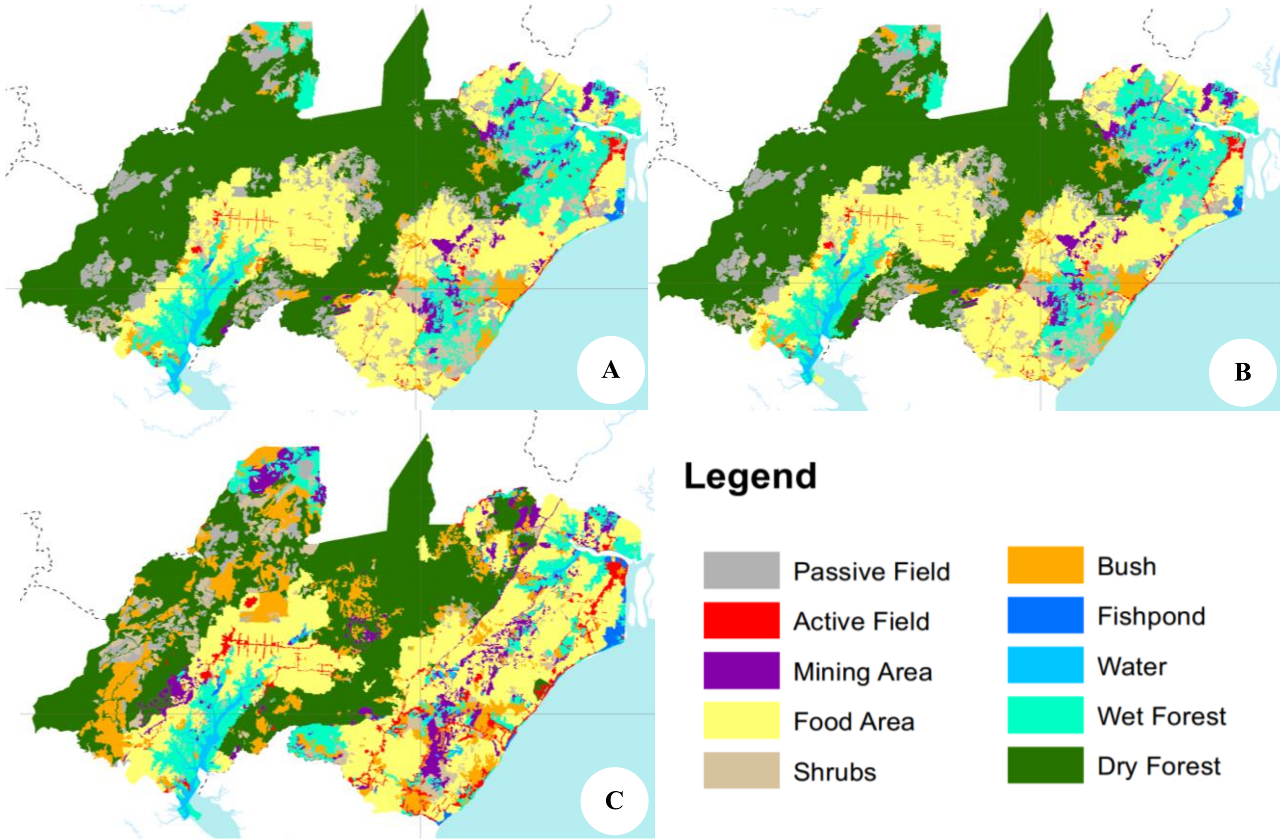


**Figure 2.** Spatial distribution of land cover types in the Capital City of Nusantara (IKN), Indonesia, showing: A. 2016 baseline with dominant forest cover, B. 2020 intermediate conditions with increased fragmentation, and C. 2025 current state showing expansion of built-up areas (red) and shrubland (orange) at the expense of primary forest (dark green) in northern and eastern IKN regions

**River Valleys:** Mahakam and tributary corridors showing secondary forest conversion (1,410 ha·year$^{-1}$) driven by agricultural and aquaculture activities. Notably, hotspot zones align with IKN planning boundaries (go/no-go areas; Peraturan Presiden (Perpres) No. 64 Tahun 2022 (2022), suggesting that even within designated protected areas (no-go zones), monitoring enforcement gaps permit unauthorized conversion. This spatial alignment is detailed in the Driving force–Pressure–State–Impact–Response analysis.

The documented primary-forest loss rate in IKN was approximately 3,650 ha·year$^{-1}$, calculated from the multitemporal Land Cover results presented in Table 2. Figure 3 does not present raw deforestation data; rather, it provides a conceptual DPSIR synthesis of the relationships among drivers, pressures, state changes, impacts, and responses. Therefore, the empirical basis for the forest-loss estimate is Table 2, while Figure 3 serves as an interpretive framework.

Remote sensing-based detection of forest degradation offers substantial methodological advances over traditional approaches that focus solely on binary forest/non-forest classification. This study's detection of degradation processes reveals the true scope of ecosystem quality loss, extending beyond simple deforestation accounting (Reiche et al. 2016; Hadi et al. 2022).

Comparison with other tropical urbanizing/frontier regions suggests that the magnitude and pattern of change observed in IKN are consistent with broader evidence that infrastructure-led development accelerates fragmentation and degrades the quality of remaining forest. For example, studies from Amazonian forest frontiers and Southeast Asian land-conversion landscapes report that road expansion and settlement growth can reduce interior-forest habitat disproportionately relative to the area cleared, amplifying edge effects and long-term ecological impacts (Haddad et al. 2015; Laurance et al. 2018). In this context, the LCQI trajectory in IKN provides a comparable landscape-scale indicator for tracking the degradation–recovery continuum and evaluating whether development pathways align with restoration objectives (Ghazoul and Chazdon 2017).

### Driving force-Pressure-State-Impact-Response framework: Linking drivers to observed Land Cover change

Driving force-Pressure-State-Impact-Response is presented as a structured synthesis of evidence and stakeholder perspectives rather than as experimental attribution. Figure 3 is a schematic diagram of Driving force-Pressure-State-Impact-Response chain for the IKN landscape, linking capital-relocation drivers and development pressures to mapped Land Cover/LCQI state indicators and proposed management responses.

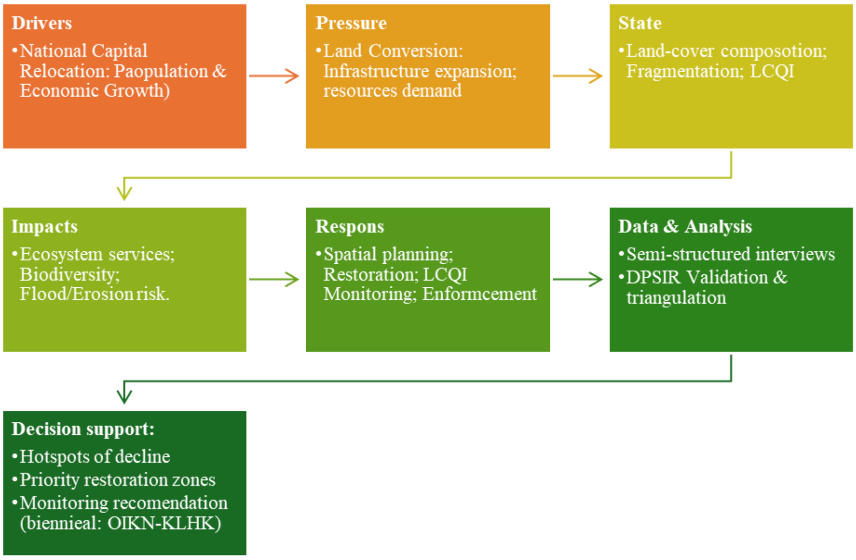


**Figure 3.** DPSIR framework (Drivers–Pressures–State–Impacts–Responses) used to structure the analysis and triangulate remote-sensing indicators (LCQI, fragmentation) with stakeholder interviews for policy-relevant response options in Nusantara, Indonesia

Specific example of the DPSIR chain: national capital relocation (driver; formalized through Government of Indonesia 2022a and subsequent spatial planning in Government of Indonesia 2022b) -> infrastructure-development pressure (roads, facilities, and utility rights-of-way; built-up area increased from 8,400 ha in 2016 to 27,200 ha in 2025) -> mapped state change in the form of built-up expansion concentrated in northern and eastern zones (Figure 2) -> accelerated primary-forest decline of approximately 3,650 ha year-1 calculated from Table 2. Thus, Figure 3 should be interpreted as a conceptual pathway diagram, whereas the supporting numerical evidence is provided in Tables 2 and 3.

Pressure-State indicator mapping: overlay interpretation indicates that several secondary-forest loss hotspots in the northern zone are adjacent to mining-concession areas. In this manuscript, that spatial coincidence is used qualitatively to support the pressure narrative, but it is not presented as a formal causal attribution or as a percentage estimate attributable solely to mining. This clarification is consistent with the study's stated interpretation boundary for DPSIR.

State → Impact → Response chain: The Land Cover Quality Index decline (71.3 → 54.8), together with quantified forest loss (43,000 ha; 16.7% of baseline cover), indicates a documented state shift that warrants management response. Interview-derived recommendations (n=25 key informants) align with the Driving force–Pressure–State–Impact–Response logic by emphasizing (i) strict protection of remaining primary forest to reduce conversion risk associated with capital-expansion-related development, (ii) rehabilitation of degraded zones to improve forest quality and ecosystem condition, and (iii) strengthened enforcement in mining zones to reduce extraction-related pressures.

## Policy and management implications

These findings suggest that restoration and forest-protection strategies in IKN should combine ecological prioritization with governance strengthening. In particular, remaining primary-forest blocks and highly connected secondary-forest corridors should be treated as priority conservation zones, while degraded areas adjacent to infrastructure corridors should be prioritized for restoration and monitoring. A co-governance approach that aligns formal planning instruments with local institutional capacity may improve the effectiveness of implementation under the Forest City agenda.

Evidence-based priorities for the Forest City roadmap include: (i) reinforcing protection status for the remaining primary-forest blocks identified as high-risk hotspots; (ii) targeting rehabilitation specifically in the 20,600 ha of degraded forest to prevent transition to shrubland; and (iii) institutionalizing LCQI monitoring to provide a scalable, quantitative metric for evaluating restoration performance over time (Wang et al. 2024; Yao et al. 2024).

To institutionalize LCQI monitoring, we recommend a biennial (every 2 years) update using standardized Sentinel-2 processing workflows, led by the IKN Authority (OIKN) in coordination with KLHK and provincial agencies. A fixed monitoring calendar (e.g., dry-season acquisition window) and an open metadata/reporting protocol would allow consistent comparison across cycles and provide an actionable trigger for targeted enforcement and restoration investments in identified hotspots.

The policy response should also address the social-institutional dimensions of forest governance in IKN. Recent studies from the same landscape show that communities retain strong bonding and bridging social capital, yet their effective role in forest governance is weakened by limited procedural influence and fragmented institutional authority (Anwar et al. 2025a, b). At the same time, scenario-based modelling of suitable future built-up areas indicates that urban expansion can be directed toward locations with relatively lower ecological risk when ecosystem-service constraints are evaluated together with access and socioeconomic variables (Virtriana et al. 2025). Taken together, these findings suggest that restoration and protection strategies in IKN should combine biophysical prioritization with co-governance mechanisms that recognize local institutions and steer development away from ecologically sensitive forest blocks.

**Limitations and interpretation boundaries**

Several limitations should be considered when interpreting these results. First, LCQI estimates inherit classification uncertainty (approximately 15% error rate), which may propagate to index values and produce a confidence interval of roughly +/-2-3 points. Second, the index relies on expert-assigned weights. A sensitivity analysis (varying primary- and secondary-forest weights by +/-10%) indicated that while absolute values shifted, the decadal degradation trend (declining from >70 to <55) remained consistent across all scenarios, confirming the robustness of the trajectory. Third, DPSIR linkages integrate stakeholder perspectives and documentary evidence; they provide a structured interpretation of plausible pathways but do not constitute experimental attribution of observed changes to specific drivers. Fourth, hotspot delineation should be interpreted at the corridor or landscape scale rather than as precise parcel boundaries, because classification error and spatial autocorrelation settings can shift cluster edges and transition proportions. Finally, biodiversity implications are interpreted as risk indicators inferred from established relationships between forest loss/fragmentation and species viability rather than as directly observed biological outcomes. Additional sensitivity tests varying degraded-forest and shrubland weights by +/-10% produced the same qualitative conclusion of persistent decadal decline.

In conclusion, this decade-long assessment documents substantial and accelerating forest cover loss in IKN (43,000 ha over 10 years, 3,650 ha·year$^{-1}$ for primary forest) alongside ecosystem quality degradation (Land Cover Quality Index decline from 71.3 to 54.8). Spatial analysis shows that forest loss is concentrated along infrastructure corridors and mining zones, a pattern consistent with capital-relocation–associated development pressures. The Driving force–Pressure–State–Impact–Response synthesis maps plausible linkages consistent with the observed spatiotemporal patterns: capital relocation (driving force) → infrastructure expansion (pressure) → forest-loss hotspots (state) → reduced ecosystem service capacity and habitat integrity (impact). These linkages should be interpreted as structured inference rather than experimental attribution. The Land Cover Quality Index framework provides a practical tool for integrating ecosystem-quality monitoring into development planning. Remote sensing-based Land Cover Quality Index assessment, updated at multi-year intervals and linked to management response protocols, enables adaptive management in rapid-change contexts. Adoption of periodic Land Cover Quality Index monitoring and spatial prioritization (e.g., protecting remaining primary forest blocks identified in hotspot analysis) could help balance development and conservation objectives.

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