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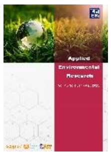

Research Article

Assessing Forest Fragmentation and its Impact on Ecosystem Service Value in Relation to Land Cover Change, Nan Province, Thailand

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Abstract

The increasing pressure from land use change and agricultural expansion in Nan Province, northern Thai-land, accelerated forest fragmentation and reduced the ecosystem service value (ESV) of the landscape. This study aims to assess land use and forestland fragmentation changes in Nan Province between 2014 and 2022 and evaluate the impact of land use change on ESV. Landsat 8 OLI satellite imagery from 2014 and 2022 was used to classify land cover into five types: forestland, agriculture, developed-up areas, water bodies, and bare land. Forest fragmentation was evaluated using landscape metrics such as the number of patches, mean patch size, edge length, and core area. The ESV was calculated using the benefit transfer method based on standardized coefficients for each land use class. The results indicate a net loss of forest area of approximately 62,000 ha, primarily due to the expansion of agriculture over 8 years. The forest patches became increasingly fragmented, with a 13.23% increase in the number of patches and a 17.81% decrease in the mean patch size. The total forest edge area increased by 4.6%, while the core forest area decreased by more than 75,000 ha. These changes correspond to a 4.85% decline in total ESV, which is equivalent to a reduction of USD 0.14 million per year. Forest ecosystems remained the greatest contributor to the ESV, but their loss significantly reduced the provision of regulating and supporting services. Future land use planning in Nan Province should prioritize forest restoration and the protection of remaining core areas to maintain eco-system functions and enhance landscape resilience.

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Introduction

Forest fragmentation, the division of large, continuous forestland areas into smaller, isolated patches, is a widespread consequence of land use change. Globally, approximately 70% of the remaining forests are located within one kilometer of an edge, making them highly vulnerable to ecological disruptions associated with edge effects (Haddad et al., 2015). Fragmentation contributes to biodiversity loss and impairs ecosystem functioning, particularly in small and disconnected patches where species face increased extinction risks and altered ecological processes over time (Haddad et al., 2015; Laurance et al., 2011). These impacts raise concerns about the long-term viability of forest eco-systems and their ability to provide critical services such as carbon storage and climate regulation (Brinck et al., 2017).

Southeast Asia is among the most affected regions, containing approximately 15% of the world's tropical forests and experiencing some of the highest deforestation rates globally. The region has lost an estimated 1.2% of its forestland area each year (Achard et al., 2014). From 2001 to 2019, more than 610,000 km^2 of forest cover were lost, which is an area larger than

Thailand itself (Curtis et al., 2018). Much of this loss has occurred in upland and mountainous areas, where forestland has been cleared for agricultural use. The expansion of crops such as oil palm in the lowlands and maize in the highlands has led to highly fragmented and degraded forest landscapes (Wilcove et al., 2010). This widespread clearing has fuelled a regional biodiversity crisis and contributes approximately 10% of global greenhouse gas emissions through the release of stored carbon (Baccini et al., 2017). Forest loss on steep terrain also intensifies problems such as soil erosion, landslides, and downstream flooding (Ziegler et al., 2009).

In Thailand, forest cover declined dramatically during the twentieth century because of widespread logging and agricultural conversion. Although national policies and reforestation programs have helped slow forest loss in recent decades (Trisurat et al., 2019). deforestation remains a serious issue in several provinces. Nan Province in northern Thailand is one such example. Once extensively forested and mountainous, Nan has undergone significant land use change since the early 2000s. Between 2001 and 2016, the province lost approximately 66,000 ha of forestland, which was equivalent to approximately 9% of its forestland area in 2000. Nearly all of the deforested land was converted to maize cultivation (Trisurat et al., 2018). This conversion has been driven by favorable market prices and government-supported contract farming initiatives (Trisurat et al., 2019). Forest loss often occurs in small, scattered plots across steep terrain, further isolating remaining forest patches and disrupting ecological continuity (Fischer and Lindenmayer, 2007). These changes threaten local biodiversity, weaken ecosystem services, and reduce the ability of the landscape to regulate water and store carbon (Brinck et al., 2013; Haddad et al., 2015). In recognition of these threats, the Thai government has identified Nan as a key area for reforestation and sustainable land use under the Nan Model program (Office of Natural Resources and Environmental Policy and Planning, 2020).

In this study, land use change and forest fragmentation in Nan Province were investigated for the period from 2014 to 2022, with particular attention given to edge dynamics. Using Landsat 8 satellite imagery and spatial landscape analysis, we classified land cover and calculated a series of landscape metrics to assess changes in patch size, edge length, and core forestland area. In addition, we estimated changes in ecosystem service value (ESV) using the benefit transfer method to link land use transitions to ecological function. This analysis provides insight into how forest fragmentation has progressed and how it affects the structure, function, and economic value of the landscape in Nan Province.

Materials and methods

1) Study area and data acquisition

This study focused on Nan Province, which is located in northern Thailand (Figure 1) and has undergone extensive forest-to-agriculture conversion in recent decades. To assess land cover change and forest fragmentation, satellite imagery from the Landsat 8 Operational Land Imager (OLI) was used for the years 2014 and 2022. Four cloud-free scenes were selected to cover the province, with two images per year (Path/Row: 130/047 and 129/047), captured during the dry season between January and March. This time window was chosen to minimize errors due to vegetation phenologyy and seasonal agricultural activity. All scenes were downloaded from the USGS Earth Explorer platform and processed from Landsat Collection 1 Level-1 data at 30-meter resolution (Table 1).

2) Image processing

The satellite images from the same year were combined and clipped to the boundary of the Nan Province. Preprocessing was conducted in QGIS version 3.22 (QGIS Development Team, 2022) using the semiautomatic classification plugin (SCP, version 7.0.0) (Congedo, 2021), including the conversion of digital numbers to radiance and reflectance and atmospheric correction using the dark object subtraction (DOS) method (Zhang et al., 2010). The Landsat image acquired on 15 January 2014 was obtained as a Level-1 image and exhibited thin clouds and haze, which caused uneven illumination and reduced radiometric contrast. For this scene, histogram equalization was applied as a preprocessing step to normalize brightness values and improve spectral separability prior to supervised classification. All remaining scenes were obtained as Level-2 surface reflectance products and were used directly without additional radiometric enhancement.

Table 1 Details of Landsat 8 OLI satellite images acquired for Nan Province in 2014 and 2022.

No.	Path/Row (WRS-2)	Acquisition date	Spatial resolution (m)
1	130/047	15 January 2014	30
2	129/047	25 January 2014	30
3	130/047	08 February 2022	30
4	129/047	30 March 2022	30

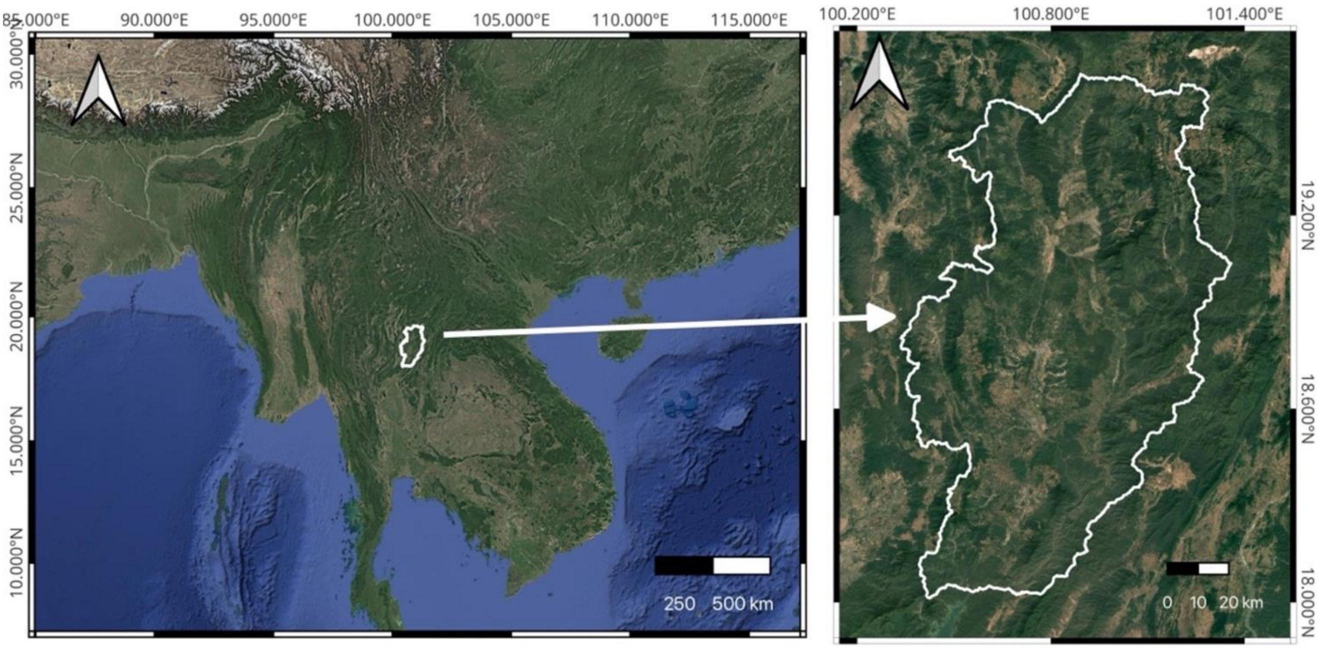

Figure 1 Location of the study area in Nan Province, northern Thailand. The left panel shows the regional context, and the right panel shows the study area boundary over satellite imagery.

3) Image classification

The satellite imagery was classified into land cover classes on the basis of the spectral signatures of Landsat Bands 2–7. We classified two satellite images (after being merged and trimmed) for two distinct years (2014 and 2022) that indicated the exact position of the study area using the supervised classification method (maximum likelihood classifier: MLC) from the semiautomatic classification plugin (SCP, version 7.0.0) (Congedo, 2021) into five classes: forestland, agriculture, developed-up area, water body, and bare land (Table 2). The training sites for classification were collected from both field surveys (100 points in Wiang SA and Nan Districts during February–March 2022, which is 20 for each class) and visual interpretation (300 random points from overall Nan Province) of Google Earth imagery for 2021 (1 January 2021).

Because forest fragmentation was the primary focus of this study, most analyses emphasized the forestland class rather than other land cover categories. The classification process was designed to capture temporal dynamics and to better understand how different land cover types have developed and transformed over time.

4) Accuracy assessment

The classification accuracy was assessed by comparing the classified land cover maps with the ESA Climate Change Initiative (ESA CCI) land cover datasets for 2014 and 2022 (ESA Climate Change Initiative, 2017), which were used as independent reference data. The ESA CCI land cover dataset provides global annual land cover maps at a spatial resolution of 300 m and is based on the United Nations Land Cover Classification System (UN-LCCS). It includes 22 thematic land cover classes that describe major land cover types (ESA Climate Change Initiative, 2017).

A total of 500 reference points were generated for each year using stratified random sampling with proportional allocation across land cover classes. To ensure consistency between datasets, the original ESA CCI land-cover classes were reclassified to match the land-cover categories used in this study (Table 3), resulting in five aggregated classes: forestland, agricultural land, developed-up area, water body, and exposed soil. The classification accuracy was evaluated using confusion matrices to determine the producer's accuracy, the user's accuracy, the overall accuracy, and the kappa coefficient (Jiang et al., 2012).

Table 2 Definitions of land cover classes used in this study

Land cover class	Definition
Forest	Areas dominated by closed or semiclosed tree canopy, including natural forest (deciduous forest and evergreen forest) and dense secondary forest, and could be forest plantation
Agriculture	Areas used for crop cultivation, including paddy field, maize, and recent sapling plantations
Built-up area	Urban and rural settlements, roads, and other impervious surfaces.
Water body	Rivers, reservoirs, ponds, and other permanent water features.
Bare land	Areas of bare or sparsely vegetated ground, including fallow fields, construction sites, and eroded land

Table 3 Reclassification of ESA CCI land-cover classes for comparison with this study

ESA CCI original class	Description	Reclassified class in this study
Closed to open (>15%) forest; Closed forest (>40%); Tree cover, broadleaved, evergreen; Tree cover, broadleaved, deciduous; Mixed tree cover	Natural and managed forest	Forest
Cropland, rainfed; Cropland, irrigated; Mosaic cropland; Mosaic natural vegetation	Agricultural areas and Mixed agricultural landscapes	Agricultural land
Urban areas	Built-up surfaces	Built-up area
Water bodies	Rivers, lakes, reservoirs	Water body
Bare areas	Exposed soil, sparsely vegetated land	Bare land

5) Analysis of forest fragmentation and edge danymics

Change detection between 2014 and 2022 was assessed using landscape patch metrics derived from classified land cover maps. Vector forest layers were converted to raster format using the v.to.rast tool in GRASS GIS (GRASS Development Team, 2024), after which class-level metrics were calculated with the Land-scape Ecology Statistics (LecoS) plugin (Jung, 2013). Five metrics were selected to quantify fragmen-tation and edge dynamics: class area, number of patches, edge length, edge area, and core forest area. These metrics collectively describe not only changes in total forest extent but also the spatial reorganization of forest patches and the intensity of edge effects. The definition and ecological meaning of each metric are summarized in Table 4.

6) Ecosystem service value

To assess the ecological cost of land cover change, we estimated the total ESV in 2014 and 2022 using the benefit transfer method of Xie et al. (2010) and Li et al. (2010) (Table 5). Each land cover class was assigned a standardized ESV coefficient (USD/ha/year). The total ESV was calculated by multiplying the area of each land cover class by its corresponding coefficient and summing across all classes. The ESVs estimated in this study were derived using a benefit-based valuation approach based on coefficients from the literature. These values represented the relative magnitude of ecosystem service provision rather than actual market prices or realized economic outputs (Niu et al., 2022).

Table 4 Description of the landscape matrix

Metric	Formula	Description	Ecological meaning
Class area	pixels × pixel area	Calculated as the total number of raster pixels belonging to a given class multiplied by the pixel area (resolution × resolution). This represents the total area occupied by all patches of the same class within the landscape or buffer zone, expressed in the map unit.	Indicates overall forest loss or gain; declining area reflects habitat reduction, a primary driver of fragmentation.
Number of patches		Defined as the total count of discrete patches of a given class within the landscape. This metric reflects the degree of fragmentation; higher values typically indicate increasing subdivision of habitat into smaller, isolated units, often resulting from edge expansion and the emergence of new fragmented patches around forest cores.	Higher values indicate increasing subdivision of continuous forest into smaller fragments, reflecting advanced fragmentation (Liu et al., 2015).
Edge length	$\text{Shape Index (SI)} = \frac{P}{2\sqrt{\pi A}}$ where P is the perimeter A is the patch area	Edge length was defined as the total perimeter of forest patches, expressed in meters. In addition, patch shape complexity was quantified using Patton's Shape Index (Patton, 1975). This index compares the patch shape to a circle, which has the minimum perimeter-to-area ratio; higher values indicate more complex patch shapes, associated with greater edge effects.	Longer total edge reflects increased exposure to edge effects such as microclimatic stress, invasion, and disturbance (Liu et al., 2015).

Table 4 Description of the landscape matrix *(Continued)*

Metric	Formula	Description	Ecological meaning
Edge area	Edge area=Edge width (60 m)×perimeter pixels	Edge area was defined as the portion of forest within 60 m of the forest boundary, following Brinck et al. (2017), who identified 60 m as an ecologically meaningful edge depth in tropical forests. For Landsat imagery with a 30 m pixel size, this corresponds to a two-pixel buffer along the patch boundary.	Represents the portion of forest influenced by edge effects; increasing values indicate expansion of edge-dominated habitat (Liu et al., 2015).
Core forest area	Core forest area = Class area−Edge area	Core forest area was calculated as the difference between the total forest class area and the edge area. This represents the interior portion of forest patches that remains unaffected by edge influence.	Reflects availability of stable habitat for edge-sensitive species; declining core area signals ecological degradation despite remaining forest cover (Liu et al., 2015).

Table 5 Coefficient values of different LULC types for ESV evaluation (modifiled from Xie et al. (2010) and Li et al. (2010))

Ecosystem service category	Ecosystem service function	Coefficient values of different LULC types (USD per ha per year)					Total
		Forest	Cropland	Build up area	Water body	Bare land	
1. Regulating services	1.1 Gas regulation	0.500	0.071	0.000	0.000	0.000	0.571
	1.2 Climate regulation	0.386	0.127	0.000	0.066	0.000	0.579
	1.3 Waste treatment	0.457	0.086	0.000	2.911	0.004	3.459
2. Supporting services	2.1 Soil formation	0.557	0.209	0.000	0.001	0.003	0.770
	2.2 Biodiversity protection	0.187	0.234	0.000	2.597	0.001	3.020
3. Provision services	3.1 Water supply	0.466	0.101	0.000	0.356	0.049	0.971
	3.2 Food production	0.014	0.143	0.000	0.014	0.001	0.173
	3.3 Raw materials	0.371	0.014	0.000	0.001	0.000	0.387
4. Cultural services	4.1 Recreation and culture	0.183	0.001	0.000	0.620	0.001	0.806
	Total	3.121	0.987	0.000	6.567	0.060	10.736

Results and discussion

1) Land cover classification and accuracy assessment

Our results revealed that in 2014, forestland was the dominant land cover class, covering 831,246.0 ha (67.34% of the study area). Agricultural land was the second most extensive class (280,684.4 ha, 22.74%), followed by developed-up areas (58,792.7 ha, 4.76%), bare land (55,381.1 ha, 4.49%), and water bodies (8,020.2 ha, 0.65%). In 2022, forestland remained the dominant land cover class, occupying 769,235.1 ha (62.32% of the study area). Agricultural land covered 331,684.7 ha (26.87%), while developed-up area and bare land accounted for 62,902.3 ha (5.09%) and 62,138.6 ha (5.03%), respectively. Water bodies represented the smallest class, covering 8,163.7 ha (0.66%). Overall, forestland and agricultural land constituted the greatest proportions of the landscape in both years, whereas developed-up areas, bare land, and water bodies occupied relatively smaller fractions of the total area of Nan Province (Table 6).

The accuracy of the land cover classification for 2014 and 2022 was assessed using overall accuracy, producer accuracy, user accuracy, and the kappa coefficient (Table 7). For 2014, the overall accuracy was 82.00%, with a kappa coefficient of 0.716, whereas for 2022, it slightly increased to 83.20%, with a kappa coefficient of 0.731, indicating substantial agreement in both years. User accuracy was highest for water bodies (100.00%) and lowest for bare land (38.30% in 2014 and 36.54% in 2022), whereas producer accuracy ranged from 72.00% to 88.00% in 2014 and from 73.33% to 88.80% in 2022. Overall, the accuracy statistics indicate that the classification performance was robust and suitable for land cover analysis.

2) Land cover changes from 2014 to 2022

The forest area decreased from 831,246.0 ha in 2014 to 769,235.1 ha in 2022, corresponding to a net loss of 62,010.95 ha (-7.46%). In contrast, agricultural land expanded from 280,684.4 ha to 331,684.7 ha, representing an increase of 51,000.35 ha (+18.17%). The built-up area increased by 4,109.61 ha (+6.99%), while bare land expanded by 6,757.53 ha (+12.20%). Water bodies slightly increased by 143.56 ha (+1.79%). Overall, these results indicate a clear shift from forestland to agricultural and developed-up land, reflecting the ongoing land use transformation in Nan Province from 2014–2022.

Table 6 Land cover changes between 2014 and 2022 (area in ha)

Class	2014	2022	Area change	% change (relative to year 2014)
Forest	831,246.0	769,235.1	-62,010.95	-7.46
Agriculture	280,684.4	331,684.7	51,000.35	18.17
Build-up area	58,792.7	62,902.3	4,109.61	6.99
Water body	8,020.2	8,163.7	143.56	1.79
Bare land	55,381.1	62,138.60	6,757.53	12.20
Total	1,234,124.3	1,234,124.3		

Table 7 Error matrix comparing the accuracies of producers' and users' land cover classification for 2014 and 2022

Class	2014		2022	
	User accuracy	Producer accuracy	User accuracy	Producer accuracy
Forest	98.04%	83.33%	98.23%	87.00%
Agriculture	57.59%	80.00%	58.51%	73.33%
Build-up area	83.33%	80.00%	89.39%	78.67%
Water body	100.00%	88.00%	100.00%	88.80%
Bare land	38.30%	72.00%	36.54%	76.00%
Overall classification accuracy	82.00%		83.20%	
Kappa statistics	0.716		0.731	

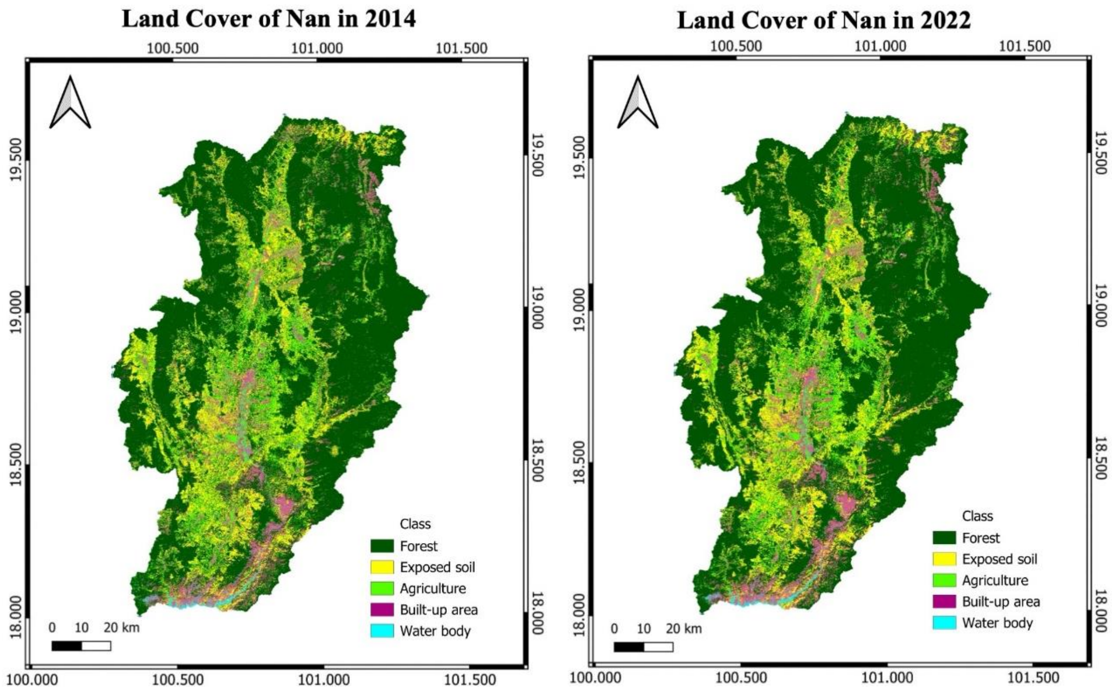

Figure 2 Land cover maps for 2014 and 2022.

The land cover transition matrix between 2014 and 2022 indicated substantial transformations across major land cover categories. A total of 34,180.44 ha of forestland were converted into agricultural land, 20,072.95 ha into developed-up areas, and 6,994.84 ha into bare land. In addition, smaller areas of forestland were reclassified into water bodies (762.73 ha). The dominant transition was the conversion of forestland into agricultural land, followed by the transformation of forestland into developed-up areas.

Agricultural land experienced considerable conversion into bare land (35,700.24 ha), while 10,302.07 ha of agricultural land was reclassified as forestland. The expansion of developed areas primarily originated from forestland (20,072.95 ha), bare land (1,426.03 ha), and agricultural land (4,737.93 ha). Similarly, the increase in bare land was attributed mainly to the conversion of agricultural land (35,700.24 ha) and forestland (6,994.84 ha).

The conversion of agricultural land (10,302.07 ha; 20.2%) and bare land (1,169.73 ha; 17.31%) into forestland between 2014 and 2022 may appear counterintuitive. These transitions may not represent spontaneous natural forest recovery but rather reflect a combination of land use dynamics, vegetation regrowth, and classification uncertainty. Portions of agricultural land converted to forestland may correspond to abandoned farmlands that underwent secondary succession, allowing woody vegetation to re-establish and develop sufficient canopy cover to be classified as forestland in the 2022 imagery. Such processes are common in the upland areas of northern Thailand, where shifting cultivation, temporary cropping, and land abandonment occur in response to economic and policy changes (Vanwambeke et al., 2007).

Moreover, transitions from bare land to forestland are consistent with postdisturbance vegetation recovery, particularly in areas affected by previous clearing, landslides, or seasonal burning. Regenerating young secondary forests may exhibit spectral characteristics similar to those of closed or semiclosed forests in imagery, leading to their classification as forests in later years (Abbas et al., 2021).

Our land cover analysis indicated a net increase of 65,218.4 ha in nonforest area over the eight-year period. The findings clearly demonstrate a continuing reduction in forest cover accompanied by the expansion of nonforestland cover. The important factors driving these changes were human settlements, agricultural land, and exposed soil. Although increases in the human population and the associated demand for housing and farmland are often major contributors to deforestation (Chakravarty et al., 2012), this explanation does not appear to apply in the present study. Thai government authorization for private settlement in Nan Province occurred primarily between 1970 and 1971, and population size has remained relatively stable over the past decade (National Statistical Office of Thailand, 2024). Instead, the expansion of maize cultivation appears to be the dominant factor underlying forest loss. The most substantial forest conversions were to agricultural land and exposed soil, largely driven by the Thai government's promotion of maize production under "contract farming" schemes (Trisurat et al., 2019). The steep terrain of the province is particularly suitable for maize cultivation, which has intensified land use change in recent years (Baicha, 2016). Furthermore, the greatest transition among land cover classes was from forestland to exposed soil, which in many cases should be interpreted as temporarily cleared agricultural land (Baicha, 2016; National Statistical Office of Thailand, 2024). Farmers in Nan typically cultivate maize twice annually, during the rainy and dry seasons, with a fallow or preparatory period between January and March (Li et al., 2016), during which land is often classified as exposed soil. Intensive maize cultivation also negatively affects soil quality, notably by accelerating the depletion of soil organic matter (SOM) and contributing to long-term soil degradation (Pongkijvorasin and Talerngsri, 2017).

3) Fragmentation and edge dynamics of forest cover

We quantified the total area occupied by each land cover class within the study area, including the proportion of the landscape represented by forest cover. In addition, landscape metrics, including mean patch size, number of patches, total core area, total edge area, and total edge length, were calculated for each class. The results revealed a pronounced decline in forest cover over the eight-year period (Table 9). Between 2014 and 2022, the mean forest patch size in Nan Province decreased from 3.54 to 2.91 ha, indicating increasing fragmentation. Moreover, the number of forest patches increased by 13.23%, reflecting a trend toward smaller and more fragmented forest units. The total forest core area decreased substantially by 75,865 ha (-14.24%), whereas the total edge area expanded by 13,854 ha (4.64%) (Table 9, Figure 3). These findings collectively demonstrate the progressive fragmentation of forest landscapes, with expanding edge zones and decreasing core habitats during the study period.

In this study, the fragmentation and edge influence of forest landscapes increased. Although the total forestland area decreased only moderately, the number of forestland patches increased, indicating the subdivision of formerly continuous forestland into smaller, more isolated units. This was accompanied by a marked increase in total edge length and edge area, demonstrating that a growing proportion of the remaining forest is now exposed to edge effects. This pattern of forest fragmentation has intensified in the region (Fujii et al., 2022). As fragment size decreases and isolation increases, the extinction risk of local forest-dwelling populations increases, ultimately influencing forest biodiversity and disrupting key ecosystem functions (Laurance et al., 2011). Since intact forests act as major carbon sinks, their conversion to nonforestland accelerates carbon dioxide emissions, which are subsequently absorbed by agricultural systems as a carbon source. Furthermore, the expansion of forest edge areas exacerbates this impact. Edge zones often experience altered microclimatic conditions that increase tree mortality and promote the release of additional carbon into the atmosphere (Brinck et al., 2017).

Analysis of forest edge dynamics in this study revealed that 4.64% of the core forest area in Nan Province was converted into edge habitat between 2014 and 2022. This rate aligns with the forest core-to-edge conversion rate observed across tropical forests globally between 2000 and 2010 (Fischer et al., 2021). The shift from core to edge areas has important ecological consequences, including altered microclimates, increased tree mortality, and reduced habitat quality for interior-dependent species. As edge zones expand, forests become increasingly exposed to external pressures such as invasive species, human disturbance, and climate variability. These findings indicate that the fragmentation processes observed in Nan are part of a broader pattern of tropical forest degradation and highlight the urgency of implementing conservation strategies that prioritize the preservation of large, contiguous forest blocks and the restoration of degraded edge zones. Such interventions are essential for maintaining ecological integrity and ensuring the continued provision of ecosystem services in a province.

Table 8 Transition matrix of land cover classes between 2014 and 2022. The values represent changes in area (ha) relative to 2014, with percentage changes shown in parentheses.

	Land cover type in 2022						
	Land cover change 2014-2022	**Forest**	**Agriculture**	**Build-up area**	**Water body**	**Bare land**	**Total**
Land cover type in 2014	Forest	769,235.1	34,180.44 (-55.12%)	20,072.95 (32.1%)	762.73 (-1.23%)	6,994.84 (-11.28%)	831,246.0
	Agriculture	10,302.07 (20.2%)	229,684	4,737.93 (9.39%)	260.10 (0.51)	35,700.24 (70.0%)	280,684.4
	Build-up area	1,341.79 (3.265%)	1,113.70 (27.1%)	54683.04	228.08 (5.55%)	1,426.03 (34.7%)	58,792.65
	Water body	2.01 (1.4%)	129.06 (89.9%)	6.46 (4.5%)	7876.589	6.03 (4.2%)	8,020.15
	Bare land	1,169.73 (17.31%)	4,520.11 (66.89%)	979.84 (14.5%)	87.85 (1.3%)	48,623.54	55,381.07
	Total	782,050.7	269,627.3	80,480.22	9,215.357	92,750.68	1,234,124

Table 9 Spatial metrics obtained from the standard analysis of the 'forest' class

Properties	**2014**	**2022**	**% change (relative to year 2014)**
Mean patch size (ha)	3.54	2.91	-17.81
Number of patches	2032	2301	13.24
Total core area (ha)	532,764.01	456,898.41	-14.24
Total edge area (ha)	298,482.02	312,336.67	4.64
Edge length (m)	1,206,111	1,300,431	7.82

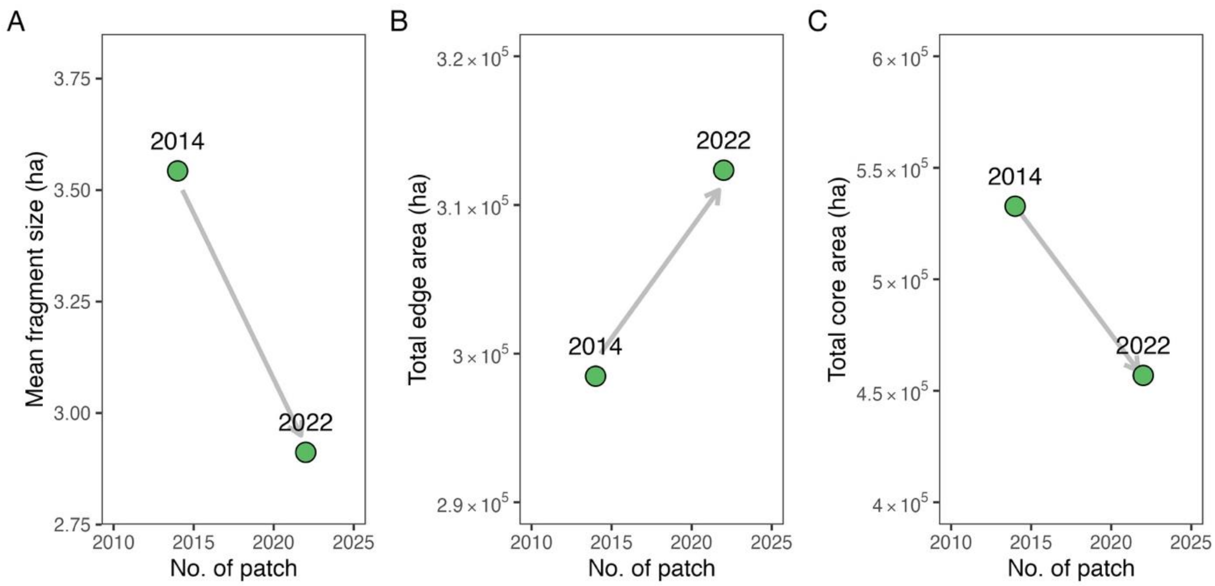

Figure 3 Temporal variations in forest structural characteristics between 2014 and 2022, showing (A) mean fragment size per number of patches, (B) total edge area per number of patches, and (C) total core area per number of patches.

Table 10 ESV of each land cover type in Nan Province in 2014 and 2022, including net change and percentage change based on land cover area

Class	2014 area (ha)	2022 area (ha)	ESV 2014	ESV 2022	Δ ESV (USD)
Forest	831,246.03	769,235.08	2,594,675.1	240,1112.3	-193,562.8
Agriculture	280,684.35	331,684.70	277,075.6	327,420.2	50,344.6
Build-up area	58,792.65	62,902.26	0.0	0.0	0.0
Water body	8,020.15	8,163.71	52,669.5	53,612.3	942.8
Bare land	55,381.07	62,138.60	3,322.9	3,728.3	405.5
Total	1,234,124	1,234,124	2,927,741	2,785,873	-141,869.9

4) Ecosystem service value

Between 2014 and 2022, the total ESV of Nan Province declined from approximately USD 2.92 million to 2.79 million USD, representing a net loss of 0.14 million USD (-4.85%). This decline was driven primarily by the reduction in forest area, which decreased by approximately 652,010 ha and led to a 0.19 million USD loss in forest-related ESV (-7.5%). Although the areas of agricultural land and bare land increased, resulting in ESV gains of 50,344 USD (18.2%) and 6,757 USD (12.1%), respectively, these gains could not compensate for the loss from forest fragmentation. Forest ecosystems remained the greatest contributor to the ESV, but their degradation significantly reduced the ability of the landscape to support biodiversity, regulate climate, and maintain essential ecological functions (Table 10).

The decline in ESV observed between 2014 and 2022 reflected the broader impact of land cover change on ecological function in Nan Province. This reduction was primarily due to the significant decrease in forest cover, which has the highest ESV per unit because of its critical role in regulating climate, supporting biodiversity, and maintaining watershed functions (Baciu et al., 2021). Although agricultural and exposed soil areas expanded and contributed modest increases in ESVs, these land cover types offer substantially lower ecological values per unit area and cannot compensate for the loss associated with forest fragmentation (Costanza et al., 2014). The transition from high-value forestland ecosystems to lower-value forestland areas signals a decline in the ability of the landscape to deliver essential ecosystem services (Njumba et al., 2025). This trend mirrors global patterns of ecological degradation where short-term economic gains from agriculture come at the cost of long-term environmental sustainability (Njumba et al., 2025). The incorporation of ESV analysis into land use planning can help highlight the hidden ecological costs of forestland loss and support policies aimed at balancing economic development with the protection and restoration of natural ecosystems.

Conclusions

Between 2014 and 2022, Nan Province lost more than 62,000 ha of forestland, mainly because of maize expansion. This resulted in smaller and more fragmented patches, with nearly 5% of the core forest converted into edge habitat, reflecting global patterns of tropical forest degradation. Such changes reduce habitat quality, alter microclimates, and increase carbon emissions. The decline in ecosystem service value, estimated at 0.14 million USD (-4.85%), highlights the ecological and economic costs of forest loss. Sustainable land use planning that prioritizes forest conservation, restoration, and the integration of ecosystem service assessments is urgently needed to maintain ecological integrity and resilience in the province.

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Data availability statement

Information and data used in the study will be disclosed upon request.

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Conflicts of interest

The authors declare that there are no conflicts of interest in competing financial or personal relationships that could have appeared to influence the work reported in this work.

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