App. Envi. Res. 46(3) (2024): 038

Applied Environmental Research
- RESEARCH FOR SUSTAINABLE PLANET -

Research Article

Unveiling Long-term Impacts of Forest Cover Changes and Carbon Storage Assessment in Nan Province, Thailand

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Abstract

Forests serve as carbon sink by storing and sequestrating carbon dioxide from the atmosphere. Forest cover loss adversely affects communities by increasing risks to the shortage of carbon storage. This study provides a comprehensive understanding of forest fragmentation and assessment of forest cover changes impacts on carbon storage over Nan province during 1990 to 2019. Spatial and temporal patterns were explored using landscape metrics analysis. Forest areas declined 10.69% over 30 years using random forest classifier based on Google Earth Engine platform, with an overall accuracy of 97.10%. The highest rate of forest cover changes was 5.27% (2010 to 2014), indicating intensive agricultural expansions. Distribution of non-forest areas increased around 11.81% in the watershed classification 1 and 2. Ban Luang district revealed a strong local community, representing district with no decline on forest cover changed rate (2007 to 2019). In contrast, Chaloem Phra Kiat district, involving economic growth at border crossing, presented high rate of forest cover changes. Landscape metric analysis explained changes of forest areas in size, number of patches, distance, and spatial distribution of fragments. More than four-fold increasing of forest patches over the last three decades was detected. Contagion Index and Shannon's Diversity Index indicated more heterogeneity in forest size, caused by crop plantations. Maize and para rubber expansions are principal causes inducing the increase of forest patches. Carbon storage spatial distribution was discovered, using carbon storage and sequestration modeling based on the InVEST software. Carbon storage in the years 1990, 1998, 2007, 2010, 2014, and 2019 were 290.17×10^6 MgC, 284.94×10^6 MgC, 269.91×10^6 MgC, 269.83×10^6 MgC, 253.05×10^6 MgC, and 260.85×10^6 MgC, respectively. The findings will support carbon market development, generating population income from forest resources. This study provides strong evidence to encourage policymakers for the actions on forest conservations and climate change mitigation in Thailand.

ARTICLE HISTORY

Received: 10 Jan. 2024
Accepted: 9 Jul. 2024
Published: 30 Aug. 2024

KEYWORDS

Forest changes;
Carbon storage;
InVEST model;
Landscape metrics;
Random forest;
Google Earth Engine

Introduction

Forest areas accounted for 31.68% of land area in 2019, which most forest areas are the property of the country. The largest forest area is in the Northern part of Thailand, where 52.46% of the area is covered by forest [1]. Recently, conversion of forest to other land use types adversely affects local communities by significant increasing risks to the shortage of ecological resources and poor human well-being. Forest fragmentation, which has not been well studied in Thailand, is a

https://doi.org/10.35762/AER.2024038

dynamic process of transforming formerly large and continuous forest areas into small and isolated patches. It affects the delivery of ecosystem services such as change in climate, less of biodiversity, and insufficiency of global carbon storage [2]. The latter indicates forest carbon stocks in an ecosystem at any given point of time. Consequently, Thailand has established a national goal to increase natural forest cover up to 33% of the land area by 2027. Moreover, the country actively affords to promote and develop carbon market systems to generate income from carbon storage in the forestry sector [3]. However, timely and reliable information on spatial and temporal of forest cover change at the regional level is still lacking. Limitation of impacts assessment on ecosystem services also encounters the lack of technical skills, cyberinfrastructure, and a knowledge gap of remote sensing technology. Hence, understanding and identifying changes in the forest, particularly through the utilization of remote sensing data, are currently challenging for forest monitoring and decision-making processes.

Remote sensing technology is a potential tool to monitor forest cover change with more accurate and up-to-date information than traditional ground observation method [4]. Recently, random forest (RF) classifier through Google Earth Engine (GEE) platform has been used for long-term forest cover change at the regional scale [5–7]. RF is less sensitive to training sample qualities and require less time for model training compared to other classifiers [8–9]. GEE is designed to store and process large data sets by using Google's computing infrastructure. Additionally, Modified Soil-Adjusted Vegetation Index (MSAVI) derived from satellite image is used to maximize the reduction in soil background effects and increase the dynamic range of vegetation signals [10–12]. Our earlier study revealed the utilization of Sentinel-2 spectral bands, Modified Soil-Adjusted Vegetation Index (MSAVI), and topographic variables yielded the highest overall accuracy exceeding 95% for land use land cover (LULC) classification in mountain area [13].

Several studies investigated forest fragmentation by calculation of landscape metrics based on FRAGSTATS software [14–18]. Landscape metrics have been proved to define landscape patterns, to compare the spatial heterogeneity among different landscapes, assess fragmentation, and to evaluate the spatial effects on ecosystem services [19–21]. FRAGSTATS, the first stand-alone software, has been widely used to quantify the changes of landscape characteristics to increase understanding of historical forest cover change.

More than half of the global forest carbon stocks is stored in their biomass [22]. Multiple researchers have shown that the Integrated Valuation of Ecosystem Services and Trade-offs (InVEST) tool could estimate the carbon storage for forest area in a reliable way [23–25]. The advantages of InVEST include requirement of fewer input data, less skill on modelling, and production of more output data compared to other ecosystem services modelling tools. InVEST enables efficient mapping and quantification of ecosystem services as well as aiding in understanding the relation and impact of forest cover change on ecosystem services.

This study addresses research gaps by providing a comprehensive understanding of forest fragmentation and assessment of forest cover change impacts on carbon storage over Nan province during 1990 to 2019. The spatial patterns of forest cover change were characterized by the temporal changes in landscape metrics based on FRAGSTAT software, concerning forest management policies. Thus, the objective of this study was to determine the consequence of forest cover changes on carbon storage using InVEST tool, which will enable stakeholders to participate effectively in carbon markets and generate income from their forest resources. Additionally, the findings can be used to raise awareness on the importance of forests and ecosystem services as well as to contribute insight data for policy-makers to drive sustainable forest management strategies in Thailand.

Materials and methods

1) Study area

Nan province locates in the easternmost part of Northern Thailand (central geographic coordinates 100°46'44.36" E longitude and 18°47'1.61" N latitude). It encompasses a total area of approximately 12,142.12 km^2, comprising 15 districts and 99 sub-districts. The climate type is tropical savanna climate or tropical wet and dry climate in the Кцppen-Geiger climate type map (Aw) [26]. Main characteristic of this province is mountain area (87.2%) at 600-1,200 meters above mean sea level with an average slope exceeding 30%. Dominating forest ecosystems include mixed deciduous forest, evergreen forest, and dry dipterocarp forest.

Legally, nearly 85% of Nan province was declared the National Forest area, but 24% of the forest area has been encroached upon. Deforestation has become a chronic problem in Nan province. Moreover, the land with a slope of 35% or more was defined as forest land that cannot be sought for title deed or land use certificate from the authorities. Thus, Nan becomes one of the top three provinces with the highest poverty rate in Thailand. On the other hand, mountainous area in Nan province is the headwaters of Nan River which contributes over 40 percent of the water into Chao

Phraya River, supplying the significant country's water resources. Environmental changes in Nan Province could have potential to cause major downstream effects impacting many provinces and people along the river. Therefore, the urgent issues in this area are reforestation and ecological restoration. Given the fact that ecological, socio-economic, and strategic factors as well as highlighting the need for sustainable land management, Nan province is a critical area for this study.

2) Data acquisition

Data used in this study were Landsat-5 TM, Landsat-8 OLI, Sentinel-2 MSI, satellite-derived products, ground observation data, and other auxiliary variables. The dataset originated from our research [13], allowing intensive examinations of forest cover change and associated ecosystem services.

2.1) Optical satellite data and auxiliary variables

Landsat-5 TM, Landsat-8 OLI, and Sentinel-2 MSI images during 1990 to 2019 were used in this study. The specific satellite bands employed as input parameters were given in Table 1. False color composites (RGB: SWIR, NIR, blue) of each satellite image were displayed in Figure 1. Elevation and slope maps were derived from Shuttle Radar Topography Mission (SRTM) digital elevation models (DEM) 1 arc-second global data in WGS84 Geoid reference datum. The range of elevation is between 124 and 2,062 above mean sea level. All datasets were freely acquired from the U.S. Geological Survey (USGS) website as integrated in Google Earth Engine (GEE) platform. Furthermore, administration boundaries were acquired from the Geo-informatics and Space Technology Development Agency (GISTDA).

2.2) Ground observation data

A total of 13,140 points were collected extensively over the entire study area during the growing season in 2019 (Figure 2). Digital photographs, geocoordinates, and detailed descriptions of LULC classes (i.e., agricultural land, built-up area, forest, Para rubber trees, maize, and water) were recorded through ground observations. In addition, the regions of interest (ROIs) for each LULC class were delineated by visual interpretation of high-resolution images in Google Earth based on a high level of knowledge on LULC data according to past and ongoing fieldwork activities [27–28]. The collected data and ROIs were utilized for the training on random forest classification and accuracy assessment of forest cover maps.

Table 1 Overview of satellite datasets utilized in the analysis

Satellite	Resolution (m)	Band/Mode	Acquisition
Landsat-5 TM	30	Visible (band 1 - 3) NIR (band 4) SWIR (band 5)	1990, 1998, 2007, 2010
Landsat-8 OLI	30	Visible (band 2 - 4) NIR (band 5) SWIR (band 6)	2014
Sentinel-2 MSI	10, 20	Visible (band 2 - 4) NIR (band 8) SWIR (band 11)	2019

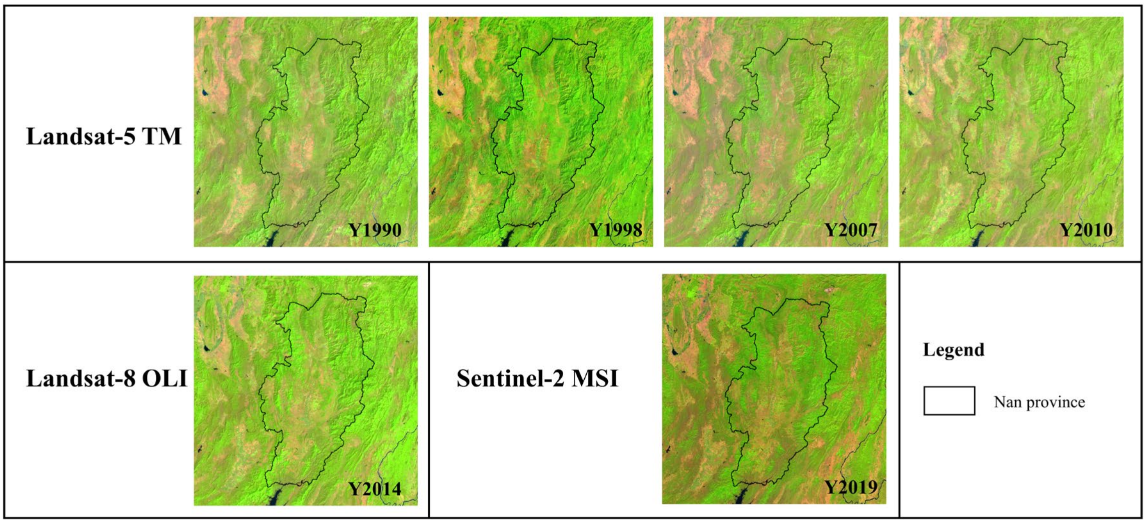

Figure 1 Satellite images for the analysis during 1990 to 2019.

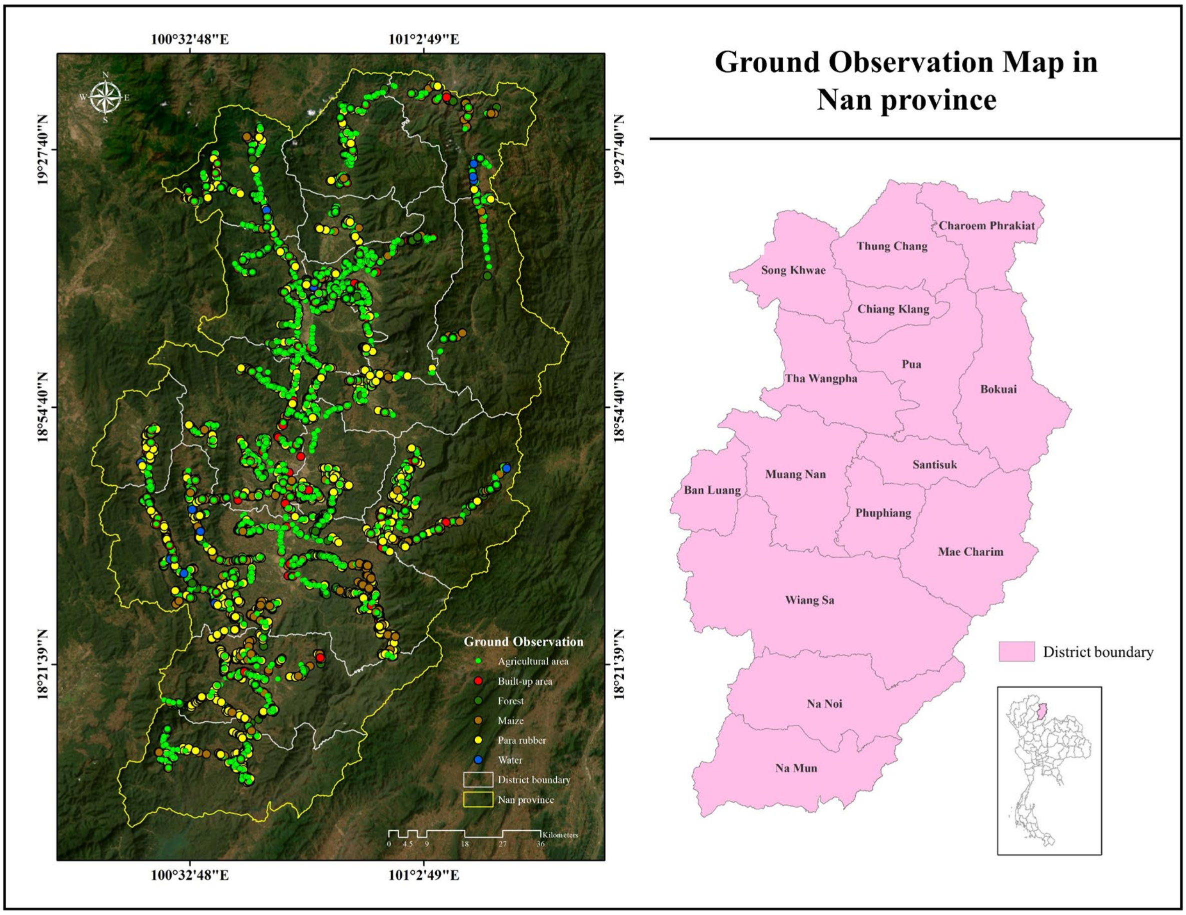

Figure 2 Ground observation map in Nan province.

3) Forest cover change using random forest model based on Google Earth Engine platform

3.1) Satellite image pre-processing

Landsat-5 TM, Landsat-8 OLI, and Sentinel-2 MSI surface reflectance images were retrieved from GEE repository. The surface reflectance product was chosen for analysis as it has already been corrected for radiometric and atmospheric effects. All selected satellite data were calculated to derive the median image for each study year followed by clipping to the study area boundary. The satellite images were projected in the geographic coordinate system (GCS), world geodetic system 1984 datum (WGS84). The study area was situated in the mountainous region, experiencing frequent cloud cover conditions. Therefore, cloud and cloud shadow masking operations were implemented to avoid error classification. The C programming language implementation of Function of Mask (CFMask) algorithm was used to generate the pixel quality assurance band from Landsat surface reflectance images [29]. Meanwhile, the QA60 band was used to mask out clouds from the Sentinel-2 surface reflectance images [30]. Subsequently, Modified Soil-Adjusted Vegetation Index (MSAVI) was calculated from selected images to increase classification accuracy [13, 31–32]. MSAVI is calculated by Eq. 1.

$$\mathrm{MSAVI} = \frac{2NIR+1-\sqrt{(2NIR+1)^2-8(NIR-RED)}}{2} \qquad \text{(Eq. 1)}$$

where NIR is the reflectance in the near-infrared band and RED is the reflectance in the red band.

3.2) Forest cover change detection using a pixel-based RF classifier

RF supervised machine learning algorithm based on GEE platform was initially utilized to produce LULC maps (agricultural land, built-up area, forest, para rubber, maize, and water classes) as input parameters for landscape metrics and carbon storage analysis. It was also used to produce forest and non-forest maps in 1990, 1998, 2007, 2010, 2014, and 2019, coinciding with forest management policies over the study period. Optical satellite products, elevation, and slope data were integrated as features of the classifier input. Annual cloud free composites of each chosen year were created by using the median reflectance pixel values of the collection [33]. To deliver a reliable error estimation and maintain the computation time, a minimum of two tuning parameters, which are the number of classification trees (ntree) desired setting at 100 random decision trees and the number of predictor variables used to split a node (mtry) setting at the square root of the number of input variables, were used [34]. All input data were resampled to a resolution of 10 m using a bicubic interpolation to harmonize the different datasets [35]. Forest cover change during six consecutive periods: 1990–1998, 1998–2007, 2007–2010, 2010–2014, 2014–2019, and 1990–2019 analyzed by post-classification comparison method were carried out [36].

3.3) Accuracy assessment

A confusion matrix was applied to determine the accuracy assessment of forest cover change classification. This matrix was widely acknowledged as the standard descriptive reporting tool for accuracy assessment in remote sensing studies [37]. Ground observation data were randomly selected to train the RF classifier, utilizing 70% of pixels from each class and the remaining 30% of pixels for validation [9, 38]. The confusion matrix was used to compute the overall accuracy (OA), user's accuracy (UA) and producer's accuracy (PA). OA value represented the average percentage of correctly classified pixels. The OA value ranged from 0 (no pixel correctly classified) to 1 (100% of pixels accurately assigned). UA was the measurement of commission error (overestimation) while PA was the measurement of omission error (underestimation).

4) Forest management policies in Nan province

Forest utilization regulations, forest protection and development planning, land management strategies were collected from various publications, reports, internet sources and government documents. Watershed classification (WSC) regulation was used to classify areas for watershed protection, production forestry, and agriculture based on an agreement among state agencies [39]. Watershed areas have been divided into five watershed classes including WSC1-WSC5.

WSC1 is the protection or conservation of forest and headwater sources with steep slope (more than 50%). It was divided into two classes including 1A (permanent forest cover areas) and 1B (permanent forest areas which should be reforested or maintained in permanent agroforestry). WSC2 is a commercial forest area with slope 35-50%, whereas WSC3 is used for grazing, commercial forest areas, and crop plantation with slope 25-35%. WSC4 is upland farming with slope 6-25%, suitable for row crops and grazing with moderate use of soil conservation measures. Lastly, WSC5 is lowland farming with very gentle or flat slope (less than 6%), suitable for crop plantation with few restrictions. This information was utilized as supporting input as the driving forces to control forest cover changes expansions.

5) Landscape metrics analysis

FRAGSTATS spatial pattern analysis software was utilized to quantify the forest cover change patterns of each individual image classification (1990, 1998, 2007, 2010, 2014, and 2019). Six metrics including Number of patches (NP), Patch density (PD), Largest patch index (LPI), Euclidean Nearest Neighbor (ENN), Contagion Index (CONTAG), and Shannon's Diversity Index (SHDI) were selected and calculated at the class and landscape levels. These metrics were suitable for spatial pattern analysis in explaining the dynamic of forest changes [40–42]. The metrics used in this study were briefly described in Table 2.

6) Ecosystem services assessment: Carbon storage analysis

The carbon storage and sequestration model within InVEST tool was utilized to estimate the net amount of carbon stored in a land parcel over time. This estimation was calculated using Eq. 2.

$$C_{total} = C_{above} + C_{below} + C_{soil} + C_{dead} \quad \text{(Eq. 2)}$$

where, C_{total} denoted the total amount of carbon storage in megagrams per pixel of carbon; C_{above}, C_{below}, C_{soil}, and C_{dead} denote the amount of carbon stored (carbon density) in aboveground biomass, belowground biomass, soil organic matter, and dead organic matter, respectively [43]. The model summarized results into a raster output of the spatial distribution of carbon storage. The amount of carbon storage was expressed in MgC per grid cell, which was a sum of all carbon pools. All input data were converted into units in accordance with the model required and categorized into appropriate formats as presented in Table 3.

Table 2 List of the six metrics used at class and landscape level

Metrics	Level	Description
Patch density (PD)	Class	The PD range is more than 0, constrained by cell size. PD provides indications on the fragmentation degree of the different land cover types.
Number of patches (NP)	Class	The total number of patches corresponding to forest class in the landscape. The NP range is NP ≥ 1 without limit. NP = 1 when the landscape contains only single patch of the corresponding patch type.

Table 2 List of the six metrics used at class and landscape level (*continued*)

Metrics	Level	Description
Largest patch index (LPI)	Class	The percentage of the forest class consists of the single largest patch at the class level. The LPI range is 0 to 100. LPI approaches 0 when the largest patch of the corresponding patch type is increasingly small, while LPI = 100 when the entire landscape consists of a single patch of the corresponding patch type. LPI provide indications on the fragmentation degree of the different land cover types.
Euclidean Nearest Neighbor (ENN)	Class	ENN is one of the isolation metrics, which is used extensively to quantify the degree of spatial isolation of patches. It is the shortest straight-line distance (m) between a focal patch and its nearest neighbor of the same class, summarized at the patch, class or landscape levels. The ENN range is ENN > 0 without limit. ENN approaches 0 as the distance to the nearest neighbor decreases.
Contagion Index (CONTAG)	Landscape	Measure of all patch types present in a landscape affected by adjacency and disaggregation. The CONTAG range is 0 < CONTAG ≤ 100. It approaches 0 when the distribution of adjacencies among unique patch types becomes increasingly uneven, while 100 means all patch types are equally adjacent to all other patch types.
Shannon's Diversity Index (SHDI)	Landscape	The proportional abundance of each patch type. Measure of diversity within landscape. The SHDI range is SHDI ≥ 0 without limit. SHDI approaches 0 when the landscape contains only 1 patch (no diversity).

Table 3 Data acquired in carbon storage and sequestration model

Data	Description
Land use land cover (LULC) maps	LULC maps were examined using random forest classifier between 1990 and 2019. Six LULC classes including agricultural land, built-up area, forest, para rubber, maize, and water were used in the model.
Table of carbon pools (.csv)	Carbon stored in aboveground biomass, below-ground biomass, soil organic matter, and dead organic matter of six LULC classes. As per the carbon pool value, Agricultural land: C_above = 7.2, C_below = 1.9, C_soil = 62.44, C_dead = 1.1 [44 – 45]; Built-up area: C_above= 15, C_below = 3.8, C_soil = 41, C_dead = 0 [45 – 46]; Forest: C_above = 134, C_below = 27.6, C_soil = 90.6, C_dead = 3.6 [44 – 45]; Para rubber: C_above = 56.7, C_below = 9.9, C_soil = 74.3, C_dead = 7.4 [45 – 46]; Maize: C_above= 5, C_below = 2, C_soil = 10, C_dead = 0 [45 – 46]; Water: C_above= 0, C_below= 0, C_soil = 0, C_dead = 0 [46].

Results and discussion

1) Forest cover change maps and rate of changes

Over the last three decades, the major types of LULC were forest area which periodically changed over time in Nan province. Similar results from this and previous studies indicated that maize and Para rubber trees were the dominant monoculture crops in the study area [13]. Focusing on forest cover type, forest area occupied 70.28%, 68.74%, 67.95%, 66.35%, 62.86%, and 62.77% of the study area in 1990, 1998, 2007, 2010, 2014, and 2019, respectively. The analysis revealed that the RF model through GEE platform yielded good accuracy with an overall accuracy higher than 90%. The overall accuracy (OA), user's accuracy (UA) and producer's accuracy (PA) of forest cover classification were 97.10, 0.96, and 0.97, respectively. Classification process of this study showed accuracy higher than those in previous studies at the same area using MLC algorithms [47–48]. The spatial distribution of forest cover maps was illustrated in Figure 3.

The percentage of forest cover changed rate was presented in Figure 4. Forest area declined from 8,533.67 km^2 in 1990 to 7,621.22 km^2 in 2019, accounting for 10.69%, while non-forest area increased 25.29% of the study area. The largest rate of non-forest area increased by 10.37% during 2010-2014, followed by 5.19% in the study period of 1990-1998. The highest rate of forest changes was 5.27% during 2010-2014, which was the expansion of maize and para rubber plantations. Meanwhile, the lowest forest changes rate accounting for 0.15% was noticed during 2014-2019. This may be due to the strategic action plan to end forest encroachment with the aim toward reducing adverse effects on the environment. The strategic action plan is management of natural resources and environment by civil society contribution [49]. This is the first strategy under Nan Development Plan (2015-2018) consisting strategic action1 promote conservation, restoration, and development of soil, water, and forest emphasizing on participation; strategic action 2 promote water resources conservation and development to secure sufficient supply for consumption usage and agriculture; strategic action 3 promote and support pollution management; strategic action 4 develop local communities capability on disaster prevention and mitigation; and strategic action 5 promote integrated farming system. However, strategic action 1 and 5 directly target the local communities' activities on forest restoration and conservation.

Spatially, the forest cover changes area map in each district was illustrated in Figure 5a. Stable forest area was found to cover 7,345.33 km^2, while stable non-forest area was seen in 3,498.45 km^2. Overall, forest changes area totally distributed over 1,298.34 km^2. Non-forest areas appeared to extend from lowland to upland, increasing more pressure on forest areas. It was noted that spatial distribution of non-forest areas gradually increased from the southern to the northern part. Forest conversion in WSC were illustrated in Figure 5b. WSC was used to develop land use plans for natural resources conservation. WSC1 and 2 represented restricted headwater and watershed conservation areas, however, non-forest areas obviously increased. Specifically, forest cover changes areas were observed to spread over 1,108.40 km^2, accounting for 12.65% of the total area of WSC1 and 2. This phenomenon was originally distributed in the middle part of the study area at the location of WSC3, 4, 5 and later expanded into WSC1 and 2. The expansion of non-forest areas increased around 11.81% in WSC 1 and 2, corresponding to forest loss of 1,034.49 km^2. Overall, around 87% of WSC1 and 2 remained forest areas.

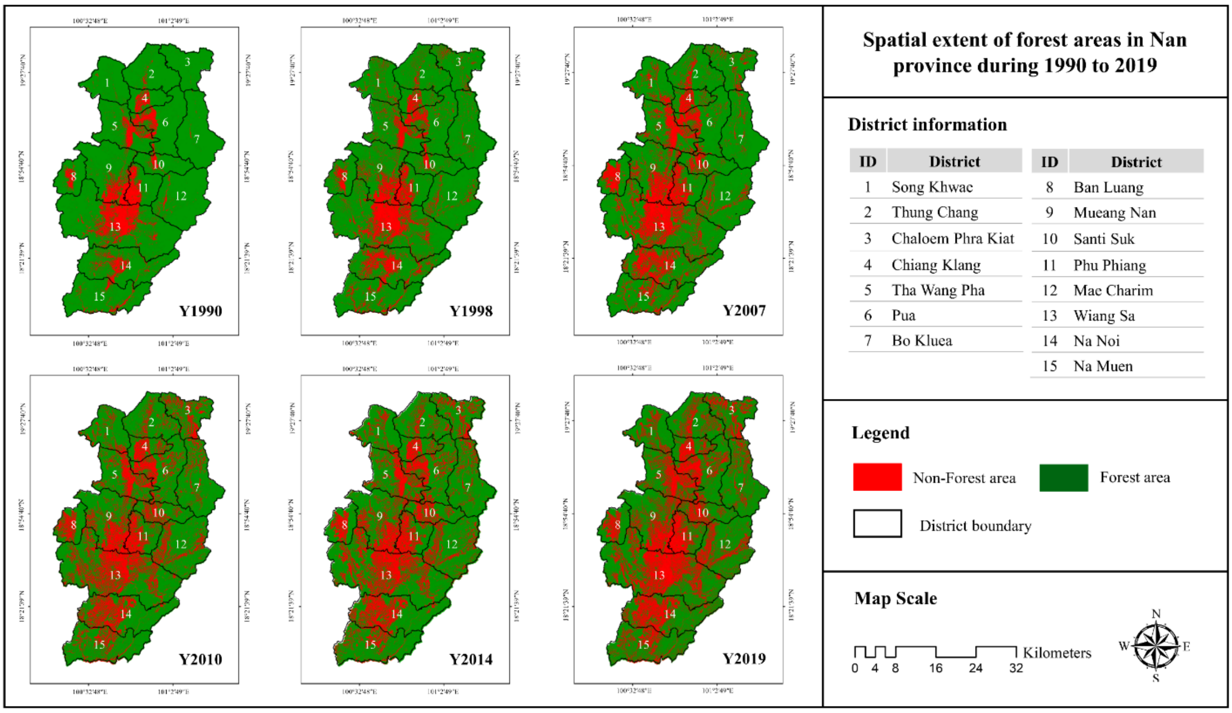

Figure 3 The spatial extent of forest areas in Nan province during 1990 to 2019.

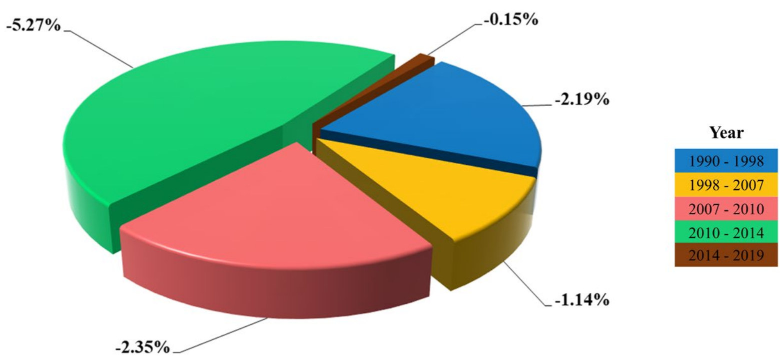

Figure 4 Pie chart of forest changed rate in percentage of five consecutive periods.

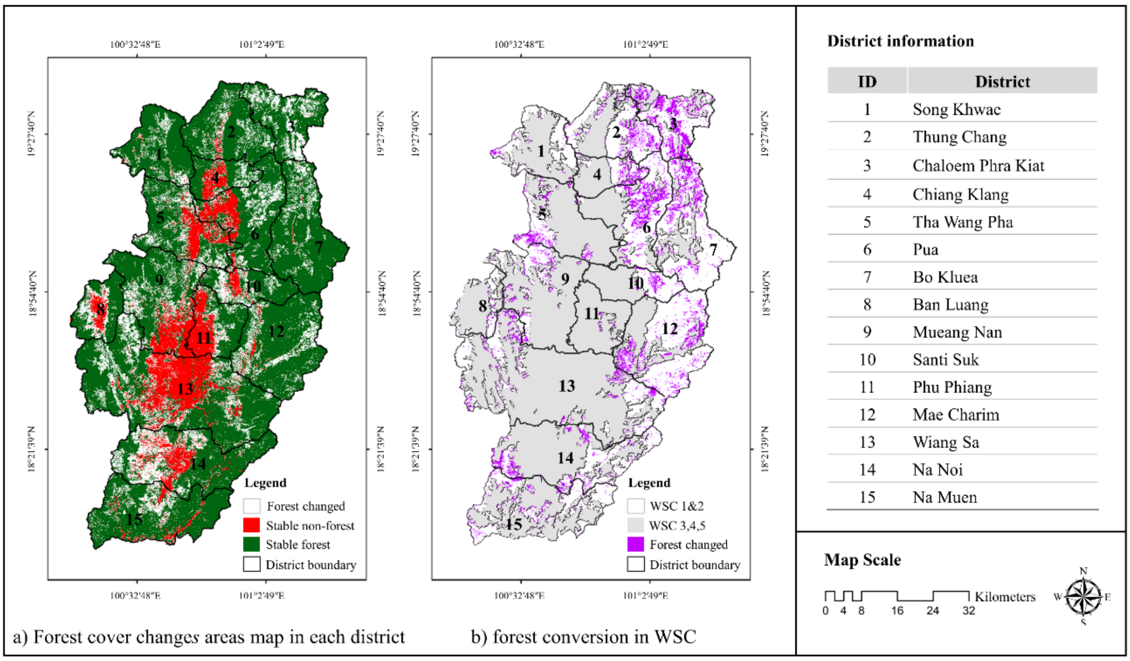

Figure 5 Forest cover changes areas map in each district (a) and forest conversion in watershed classification classes WSC (b) from 1990 to 2019.

In Table 4, the results indicated that forest areas decreased in all districts of Nan province. The forest areas substantially decreased as it dropped from 70.28% in 1990 to 62.77% in 2019. Phu Phiang district revealed the lowest forest area (42.35%), while Bo Kluea district showed the highest forest area (75.32%) in 2019. The latter result was consistent with the analysis that Bo Kluea district showed the lowest rate of forest cover loss (4.14%). This is possibly due to geographic factors, including the high-altitude area, origin of the Nan River, and land inaccessibility. The highest mountain, namely Phu Khe, could be a contributing factor to the preservation of forest cover. Contrastingly, Chaloem Phra Kiat district that was the area with no gain in forest extent during the last three decades, experienced the highest forest cover changes accounting for 23.74%. This finding agrees with the study of Kitchaicharoen et al. [50]. It was possible due to the economic growth in Chaloem Phra Kiat district, the border crossing to Luang Prabang Province in Laos. Interestingly, forest cover changed rate during 2007 to 2019 of only Ban Luang district was not declined. This is possible due to effectiveness of community forests for forest conservation similar to the findings of related study in Nan province [51]. The local community in Ban Luang district strongly opposed to the practice of logging companies and established communities rules for preserving their forests as a sustainable heritage.

Generally, one of the factors for forest cover changes is population. The growing population increased the demand for lands and infrastructures resulting in pressure on fragile natural ecosystems [52–53]. Based on the population statistics data, the population growth in Nan province showed slightly change (increased by approximately 2% from 1990) [54–55]. Meanwhile, forest areas were continuously decreasing. Therefore, forest cover changes were not related to populations growth in Nan province. The possible reasons were non-sustainable land use practices, lack of awareness on natural resources utilizations, and conflict on the National Reserved Forests Act. Non-sustainable land use practices were the result of economic pressure on livelihoods such as indirect promotion activities of the private sector based on credit provision and convenient market offerings [50]. Lack of awareness on natural resources utilizations could be observed when local people consider the forest as unoccupied land and shifted their subsistence farming from small-scale production to cash crops, intensive mono-crop agriculture, integrated agriculture (namely *kaset phasom phasaan* in Thai) [56]. Lastly, conflict on the National Reserved Forests Act is the major problem which caused by overlapping of protected forest areas and land occupied by long-standing people [57].

Table 4 Percentage of forest cover changed rate of six consecutive periods in each district

District	Forest cover changed rate (%)					
	1990 – 1998	1998 – 2007	2007 – 2010	2010 – 2014	2014 – 2019	1990 – 2019
Chiang Klang	-3.06	-4.21	3.40	-2.70	-3.63	-9.98
Ban Luang	-2.35	-13.38	3.78	3.66	3.22	-6.09
Santi Suk	-1.68	-2.01	-7.55	-4.50	1.66	-13.53
Phu Phiang	8.49	-1.60	-12.25	-8.66	-5.76	-19.36
Chaloem Phra Kiat	-3.98	-4.30	-8.80	-6.06	-3.13	-23.74
Song Khwae	-3.98	-0.59	-0.77	-3.88	1.29	-7.77
Thung Chang	-3.27	0.90	-0.91	-4.07	-2.01	-9.10
Tha Wang Pha	-0.08	-5.87	2.62	-8.30	-3.47	-14.56
Pua	-0.14	1.40	-6.10	-4.97	0.71	-9.01
Bo Kluea	-3.74	3.82	-3.73	-2.77	2.48	-4.14
Na Muen	-1.22	0.68	-0.05	-4.38	-3.75	-8.51
Mueang Nan	-3.23	-4.09	3.05	-6.37	-0.09	-10.53
Mae Charim	-3.40	2.31	-4.85	-5.97	2.36	-9.48
Na Noi	-3.55	-8.96	1.73	-6.99	-0.08	-16.98
Wiang Sa	-1.73	2.55	-3.89	-6.49	1.33	-8.24

2) Spatial patterns of forest cover change over three decades

The main finding of landscape metric analysis revealed the spatial and temporal patterns of forest cover change in six spatial metrics from 1990 to 2019 as presented in Table 5. Forest areas have changed in size, number of patches, distance, and spatial distribution of fragments. The phenomenon of forest fragmentation was caused by more than four-fold increase in NP over the last three decades, leading to a greater isolation trend over time of forest patches. Forest areas showed maximum NP (32,777) in 2019 and minimum NP (7,197) in 1990. The conversion of forest to other land use classes, particularly maize and para rubber expansions in 2010-2014 seems to be a significant reason inducing the increase of forest patches. The forest PD increased from 0.59 in 1990 to 2.70 in 2019, demonstrating the increase of small fragmented or subdivided forest patches. This interpreted that effectiveness of forest areas cannot be guaranteed or it was, somehow, unable to achieve the government announcement on the National Reserved Forests Act. The LPI declined from 89.54% in 1990 to 76.47% in 2019, indicating the largest forest patch was converted to another LULC class. This suggests higher fragmentation and disturbance over time. Discrete forest areas may be a cause of increasing forest fragmentation. The results of ENN metric showed a decrease in forest connectivity as the large area of forest become more isolated [58]. ENN gradually increased from 30 m in 1990 to 53.85 m in 2019.

For the results of entire Nan province, CONTAG and SHDI values can reflect the proportional distribution and spatial arrangement for evaluation of landscape heterogeneity. CONTAG revealed complete dispersion of different patch types by substantial declining from 90.32% in 1990 to 75.92% in 2019. SHDI value increased periodically and reached a value of 0.79 in 2019 from 0.33 in 1990. Rising SHDI and falling CONTAG values indicated the increasing of landscape diversity over time in Nan province. It was presumably caused by human disturbances for crop plantations [59]. According to the combination of SHDI and CONTAG measurements, it obviously showed that the heterogeneity of the landscape was intensified. Forests were the largest class at the beginning of the study period (in 1990). However, the forest in the landscape not only transforms to smaller patches continuously, but also becomes more isolated which highly affected ecosystem services.

Table 5 Periodic changes in the values of landscape metrics of forest in class and landscape level from 1990 to 2019

Year	Metrics					
	Forest class				Landscape	
	NP	PD	LPI	ENN	CONTAG	SHDI
1990	7197	0.59	89.54	30.00	90.32	0.33
1998	8543	0.70	87.34	32.60	88.59	0.40
2007	14245	1.17	81.96	40.00	83.02	0.58
2010	17749	1.46	81.65	44.72	82.80	0.58
2014	27169	2.24	75.71	50.00	78.26	0.72
2019	32777	2.70	76.47	53.85	75.92	0.79

3) Impacts of forest cover changes on carbon storage

InVEST model is straightforward to be used for evaluation of spatial distribution maps of carbon storage. It can be applied in situations with limited available data and lacking of direct observation data [60]. The result of carbon storage maps was illustrated in Figure 6. It ranged from 0 to 2.56 MgC m^{-2}. The highest amount of carbon storage was found in 1990, while the lowest one was seen in 2014. Carbon storage was estimated to 290.17×10^6 MgC, 284.94 10^6 MgC, 269.91×10^6 MgC, 269.83×10^6 MgC, 253.05×10^6 MgC, and 260.85×10^6 MgC in years 1990, 1998, 2007, 2010, 2014, and 2019, respectively. It revealed a total of 29.32×10^6 MgC decrease of carbon storage. In the study periods, carbon storage of forest areas was higher than that of non-forests class. One possible reason was forest could absorb and store more carbon than other crops [61]. High forest fragmentation would reduce the amount of carbon storage. According to forest cover changes, it was scientifically showed that carbon storage presented inverse correlation with intensity of agricultural plantation. The selected geoinformatics technology with ecosystem services model were more practical to visualize holistic view of carbon storage in Nan Province comparing with previous studies using traditional measurements [62–63]. InVEST tool, to some extent, can be a valuable tool that helps researchers to move forward in this regard. Taken together, action for preservation of current carbon stores in existing forest areas should be a priority.

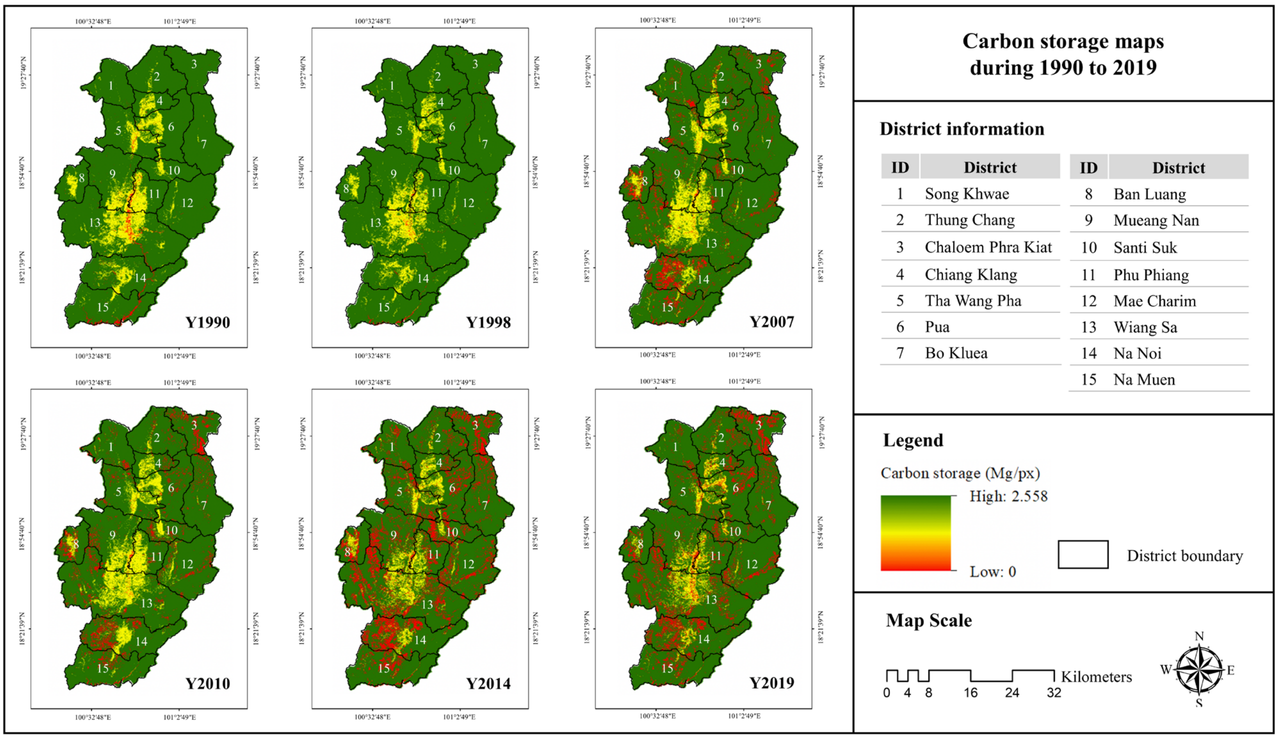

Figure 6 Carbon storage maps during 1990 to 2019.

Conclusions

This study unveils the scientific comprehensive insights of the long-term spatial and temporal patterns of forest cover changes (30-year) as well as consequential impacts on carbon storage in Nan province. By employing the RF classifier through GEE platform, this research offered a robust framework for analysis of forest cover change at the regional scale. The results showed that forest area declined 10.69%, while non-forest area increased 25.29%. Forest cover changes areas were predominant in the upper part of WSC1 and 2 with 11.81% non-forest expansion. Landscape metrics based on FRAGSTAT software rendered informative spatial patterns of forest cover change. The phenomenon of forest fragmentation was caused by more than four-fold increase in the NP over the last three decades. Maize and para rubber expansions were major causes. InVEST tool was helpful for estimation of carbon storage in scarcity of local input data. It was beneficial in terms of quantifying losses in ecosystem services from forest change. By using InVEST tool, the impact of forest cover changes on carbon storage decreased 29.32 106 MgC during the past 30 years. Carbon storage was scientifically decreasing in opposition to intensity of agricultural plantation. The finding can inform land use planning forest conservation strategies, carbon market development and generate income from their forest resources. This study provides valuable information for policymakers and stakeholders actions to conserve forests and mitigate climate change in Thailand.

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