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Forest dynamics mapping in central Vietnam from 1988 to 2022 using Landsat time-series data

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Supplementary material for this article is available online

Abstract

Forests provide essential ecosystem services, including biodiversity conservation, climate regulation, and livelihoods for millions of people worldwide. This study provides a comprehensive analysis of land-use and land-cover (LULC) changes with a focus on forest cover changes in Huế, central Vietnam, over the period from 1988 to 2022. Huế is a region of ecological and cultural significance, home to diverse forest ecosystems that play a critical role in water regulation, flood mitigation, and soil stabilization. The province's forests also support rich biodiversity and provide vital resources for local livelihoods. By leveraging time-series Landsat observations and employing the continuous change detection and classification—spectral mixture analysis method, we synthesized multi-decadal geospatial data to track and categorize forest dynamics. The results indicate substantial LULC changes, highlighted by a significant reduction in stable forest cover from 58.3% in 1993 to 48.9% in 2022, accompanied by an increase in degraded forests from 11.7% to 18.0%. Peak forest loss was recorded at 1.5% by the end of 2013. The study discusses economic expansion, infrastructure development, climate variability, and agricultural intensification as key drivers of forest cover change. The findings underscore the importance of sustainable land management practices and provide actionable insights to inform policy development, particularly in regions with complex socio-economic and ecological interactions.

1. Introduction

Forest ecosystems provide essential services such as carbon sequestration, water purification, erosion control, habitat for biodiversity, and climate change mitigation (Baccini *et al* 2008, 2017, Pan *et al* 2011). They also play a crucial role in climate regulation and support millions of livelihoods worldwide (FAO 2018, Wunder *et al* 2018). However, forests face threats from deforestation, degradation, and climate change, necessitating protection efforts (UN 2015, FAO & UNEP 2020).

Southeast Asia, particularly Vietnam, has undergone rapid LULC changes, driven by agricultural expansion, urbanization, and economic growth (Grogan *et al* 2015, Mermoz *et al* 2021). Vietnam's forest cover declined significantly in the late 1980s due to land conversion pressures but has since seen afforestation efforts that primarily involve acacia plantations with lower ecological integrity (McElwee 2009, Khuc *et al* 2018, Cochard *et al* 2023).

Huế is home to diverse forest ecosystems that play a critical role in water regulation, flood mitigation, and soil stabilization. The province's forests also support rich biodiversity and provide vital resources for local livelihoods (Nguyen and Nguyen 2022). Despite conservation initiatives such as community-based forest management and payment for environmental services (PFES), forest loss and degradation persist due to competing land-use demands (Nguyen and Nguyen 2022). Nonetheless, forest cover in Huế has increased due to reforestation efforts mainly through the expansion of acacia plantations in production forests with low ecological integrity leading to habitat fragmentation (Cochard *et al* 2017, 2021, Gobin *et al* 2020, Paudyal *et al* 2020).

Remote sensing plays a crucial role in tracking forest dynamics, with various time-series analysis techniques available (Wulder *et al* 2016). Vegetation regeneration and disturbance estimates through time (VeRDET) algorithm effectively assesses forest recovery after disturbances due to its sensitivity to subtle regrowth changes but demands significant computational resources, limiting its scalability (Hughes *et al* 2017). The vegetation change tracker (VCT) algorithm reliably detects sudden disturbances like deforestation but struggles to capture gradual changes (Huang *et al* 2010).

The continuous change detection and classification (CCDC) algorithm (Zhu and Woodcock 2014) uses harmonic modeling to minimize seasonal variation, and its combination with spectral mixture analysis (SMA) enhances forest change mapping accuracy. For instance, Bullock *et al* (2020a) applied CCDC-SMA in Rondônia, Brazil, revealing a 24 year trend of declining deforestation and increased degradation with user accuracies of 88% for degradation and 93.3% for deforestation. Chen *et al* (2021) used CCDC-SMA in Georgia (1987–2019), achieving 91% overall accuracy and estimating significant forest degradation. Chen *et al* (2023) applied it in Laos (1991–2020) to monitor shifting cultivation, classifying disturbances by type annually.

Earth observation studies in Vietnam have linked deforestation to economic drivers such as rubber plantations and hydropower expansion (Grogan *et al* 2015, Ngo *et al* 2020). Mermoz & Le (2016) mapped biomass loss (2007–2010) using radar data. Mermoz *et al* (2021) expanded this with Sentinel-1 to create national-scale forest loss maps, and Shimizu *et al* (2023) used LandTrendr in North Vietnam, highlighting recovery after disturbances and challenges in complex landscapes. A particularly relevant study for this research is Cochard *et al* (2023), who produced eight land-cover maps from Landsat imagery and topographic data spanning 1966–2019 for Huế. Their work contextualizes these changes and examines whether they support the occurrence of a forest transition (FT). However, localized studies using CCDC-SMA remain limited, particularly in Huế, despite its complex forest landscape.

This study applies CCDC-SMA to analyze forest cover dynamics in Huế from 1988 to 2022, identifying stable, degraded, and lost forest cover while exploring key LULC drivers. By addressing the following research questions, we aim to provide actionable insights for sustainable forest management:

- How have stable, disturbed, and lost forest areas changed over the past three decades in Huế?
- What are the spatial and temporal patterns of forest degradation, and how do socio-economic factors such as urbanization and agricultural expansion influence them?

2. Study area and used data

2.1. Study area

Huế is a centrally-governed coastal city region in Central Vietnam, covering approximately 5025 km^2, and has a population of about 1154 310 (Portal of Huế 2021; figure 1). Central Vietnam's tropical monsoon climate features a dry season (May–September) and a rainy season (October–April). Huế has some of Vietnam's highest rainfall in October–November, and is highly flood-prone (Vu *et al* 2025). Its mountainous upstream areas are crucial for water regulation, flood mitigation, and soil stabilization, making them key for environmental monitoring and forest management (HCCWG and Tran 2014, Duong *et al* 2021).

Agriculturally, 84 000 hectares in the province are cultivated, yielding crops like rice, corn, sugarcane, and tobacco, and supporting livestock such as buffaloes, cattle, and poultry. The province also features diverse forest types, including moist evergreen, mangrove, and montane forests (Pham *et al* 2005, Portal of Huế 2023).

Vietnam's Forest Law defines forests as ecosystems comprising flora, fauna, and forest land, dominated by timber or bamboo with a canopy cover exceeding 10% (MARD 2009). According to the Ministry of Agriculture and Rural development of Vietnam's Law on Forestry 16/2017/QH14 dated 15 November 2017, effective on 1 August 2018 (Hanoi Publishing House 2018). Forests are classified by purpose into:

I. Protection Forests (Rừng phòng hộ): safeguard water, soil, and prevent erosion, natural disasters, and desertification, with subtypes like headwater and tide-shielding forests.
II. Special-Use Forests (Rừng đ x1EB7;c dụng): preserve biodiversity, cultural heritage, and support tourism, including national parks and conservation zones.
III. Production Forests (Rừng sản xu x1EA5;t): serve timber and non-timber production while aiding environmental protection.

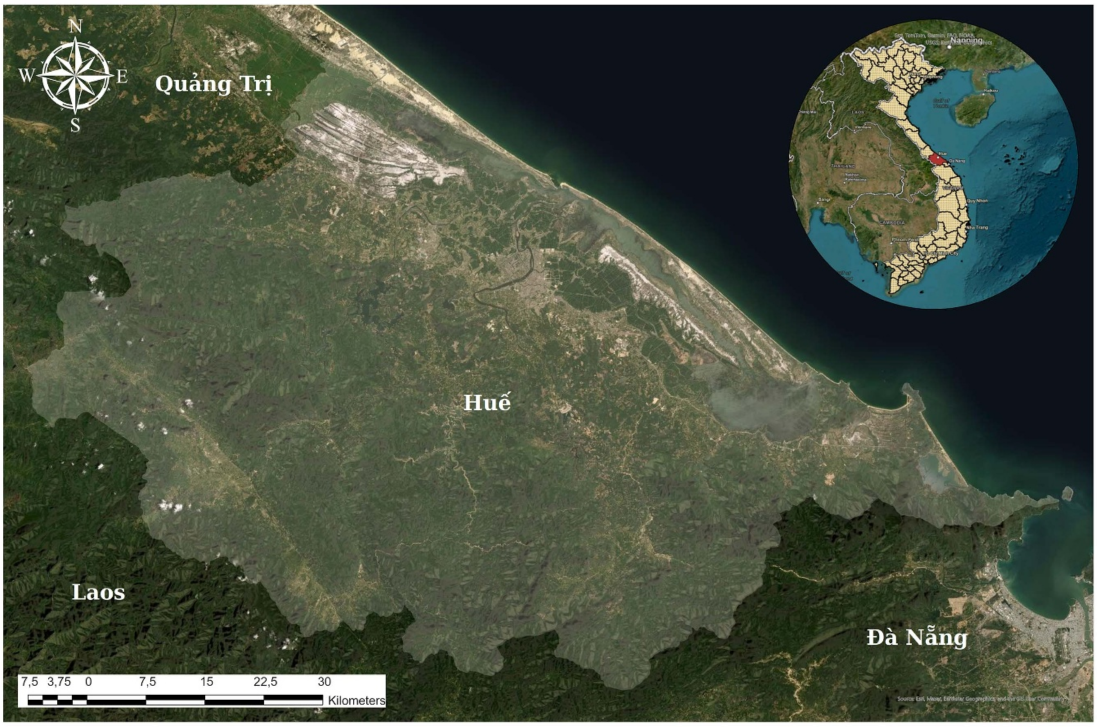

Figure 1. Huế, subtly highlighted in the main map and marked in red on the inset world map, is situated in central Vietnam. It borders the Vietnamese provinces Quang Tri province to the north and Da Nang to the south, as well as the Lao People's Democratic Republic to the west. *Source*: UN OCHA (2020) & Basemap by Esri, Maxar, Earthstar Geographics, and the GIS User Community.

Additionally, forests are categorized as Natural or Planted based on origin. Natural forests develop through natural regeneration or with limited human intervention, while planted forests are established through afforestation, rehabilitation, or replanting (FAOLEX Database 2022).

2.2. Geospatial data

The Google Earth Engine (GEE) web interface served as the primary platform for accessing and processing Landsat surface reflectance images over three scenes (path/row: 124/49, 125/48, and 125/49) of Huế (Gorelick *et al* 2017; see supplementary figure S1 for details). Data was obtained from GEE's Collection 2—Level 2—Tier 1 dataset, covering Landsat missions 4–9, with 30 m spatial resolution for visible, NIR, SWIR, and resampled TIR bands (Masek *et al* 2006, Vermote *et al* 2016, USGS 2021, 2023). In this project, 2,371 observations were analyzed, including 5 from Landsat 4 (1989), 887 from Landsat 5 (1988–2011), 881 from Landsat 7 (1999–2022), 540 from Landsat 8 (2013–2022), and 58 from Landsat 9 (2021–2022), highlighting the expansion of regional data over time (Wulder *et al* 2016; figure 2).

2.3. Ancillary data

This study utilized four ancillary datasets: (1) high-resolution Airbus imagery from Google Earth Pro to validate forest change findings; (2) ALOS World 3D—30 m (AW3D30) elevation data for LULC classification (JAXA EORC 2021, Takaku *et al* 2021); and (3) the World Settlement Footprint (WSF) Evolution (1983–2015) and WSF 2019 datasets from the German Aerospace Center (DLR) for settlement development (Marconcini *et al* 2020).

3. Methods

Geospatial time-series analysis of Landsat imagery was conducted to assess forest change in Huế from 1988 to 2022, organized into seven intervals of five years each, with the final period, 2018–2022, covering only four years. All processing was done in GEE using a three-step approach for each period: (1) generating LULC maps and forest masks, (2) applying the CCDC-SMA method to detect forest disturbance (disruptions), and (3) creating stratified forest change maps by combining these layers.

An area estimation and accuracy assessment were then conducted for each forest change map, with the process outlined in figure 3.

3.1. Land-use and land-cover (LULC) classification and forest masks

LULC maps were created for eight target years—1988, 1993, 1998, 2003, 2008, 2013, 2018, and 2022—covering six land use and land cover classes. Data were acquired from the Landsat Collection 2 Level 2 Tier 1 archive of the GEE archive, cloud masking applied, a median composite image produced for

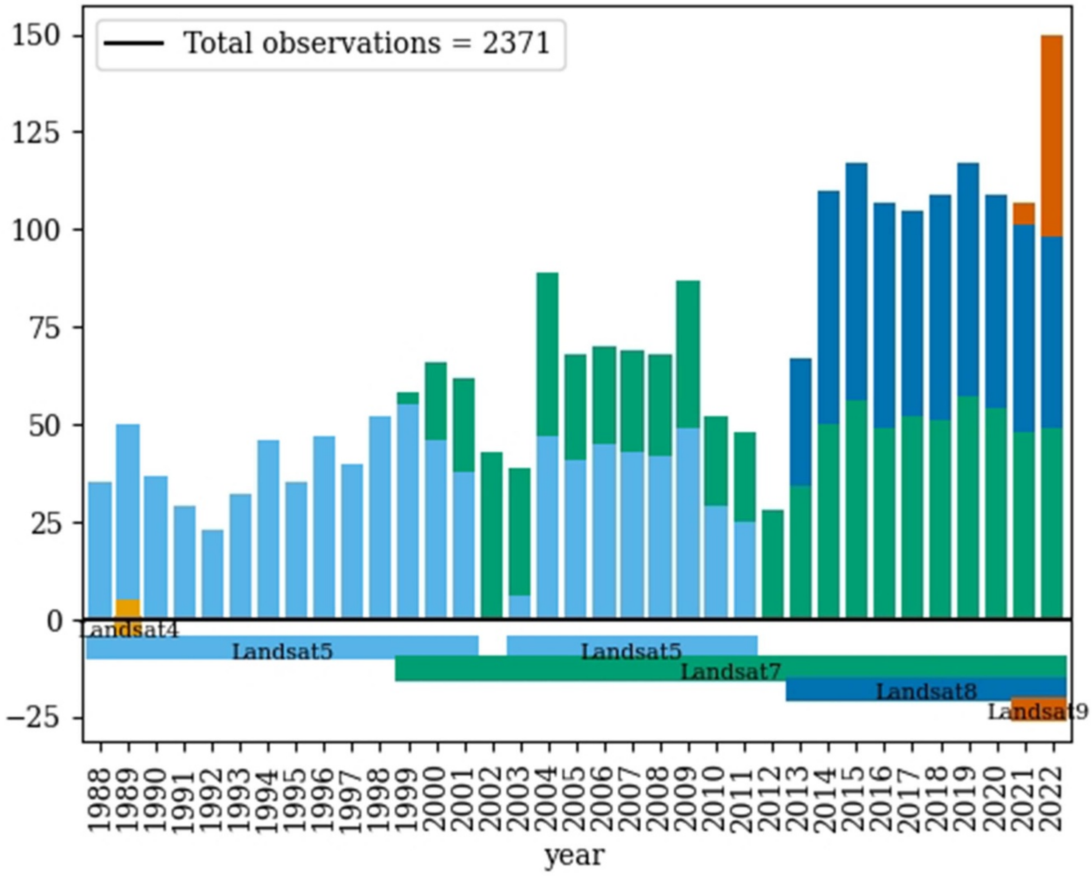

Figure 2. Spatio-temporal distribution of Landsat observation for Huế, Vietnam from January 1988 to December 2022.

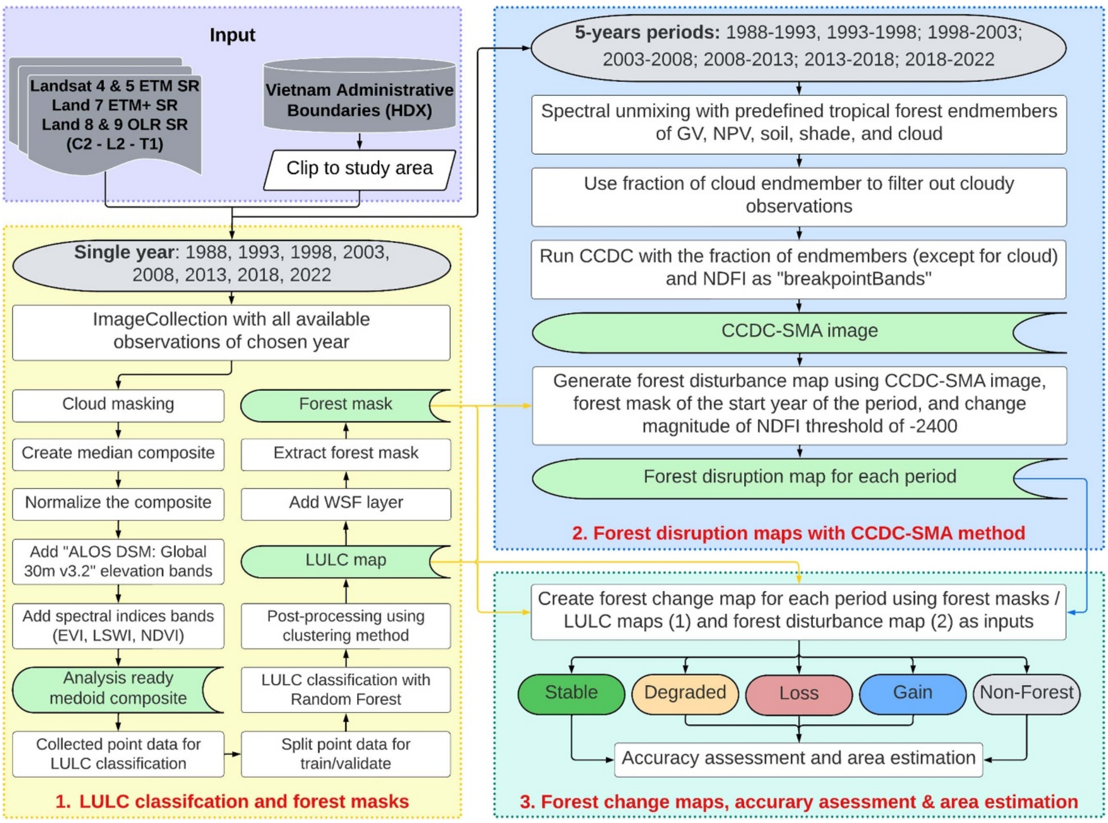

Figure 3. Schematic workflow of the forest change mapping method used in this study.

Table 1. Land use land cover (LULC) classes and their descriptions. For detailed information on the spectral signatures of each class in each of the LULC maps for each of the seven years, please refer to figures S2—S9 in the supplementary materials section.

LULC class	Description
Undisturbed	The undisturbed forest class comprises pixels representing dense natural forests that have not been significantly affected by external factors such as agriculture, logging, or urban development. In composite images, these pixels typically exhibit low green surface reflectance, high NDVI and EVI values, and a darker red-brownish color
Disturbed	The disturbed forest class includes pixels representing plantation forests, wood crops, and other vegetated areas that have experienced some form of disturbance, such as intensive logging, pest infestation, diseases, or drought. While similar to Undisturbed Forest pixels in terms of vegetation presence, Disturbed Forest class pixels exhibit slightly higher reflectance in the green electromagnetic spectrum range, slightly lower NDVI and EVI values, and a brighter orange color
Cropland	The cropland class consists of pixels representing primarily rice paddies and other cultivated areas. Cropland pixels typically display lower NDVI values and higher values of 'standard deviation of NDVI' compared to the Undisturbed and Disturbed Forest classes. These pixels, also categorized as disturbed vegetation, exhibit a reddish color, which varies between years due to the different growth stages of the crops in each yearly composite image
Water	The water class represents pixels corresponding to water areas in the composite images. It is important to note that some fully flooded rice paddy fields and cloudy pixels might be misclassified as water due to their similar spectral signatures. In the NIR-SWIR1-Blue composite, Water class pixels appear as dark blue in color
Non-Vegetated	The non-vegetated class includes pixels representing urban, built, soil, and other non-vegetated areas in the composite images. These non-vegetated pixels appear in white and various shades of green, cyan, and gray colors.
Settlement	The settlement pixels were obtained from the WSF datasets. However, since there were missing pixels for the years 2018 and 2022, the settlement pixels from the WSF 2019 dataset were utilized as substitutes for these two years.

each observation period and normalized to standardize reflectance values across bands.

Spectral indices such as normalized difference vegetation index (NDVI; Rouse *et al* 1973, Tucker 1979), enhanced vegetation index (EVI; Huete *et al* 2002), normalized difference water index (NDWI; Gao 1996), annual NDVI standard deviation and slope data from the ALOS DSM Global 30 m dataset (JAXA EORC 2021, Takaku *et al* 2021) were used to enhance classification accuracy.

Five LULC classes—undisturbed forest, disturbed forest, cropland, water, and non-vegetated—were identified based on land cover research (Nguyen and Nguyen 2022) and official Vietnamese classifications (Portal of Huế 2016, Duong *et al* 2021) (see table 1). These classes were distinguished using spectral signatures and visual interpretation with the NIR-SWIR1-Blue band combination, which clearly highlighted healthy vegetation, soils, urban areas, and water bodies.

For each of the eight LULC maps, approximately 1000 training sample points were collected (see supplementary table S1) and used to train a random forest classifier with 50 trees (Breiman 2001). This was followed by an unsupervised clustering post-processing step to refine classifications and reduce misclassified pixels (Gandhi 2021).

For each of the eight LULC maps, an independent set of 200 validation points was generated using stratified random sampling based on class distribution. Each class received at least 20 points, with the remaining 100 points distributed proportionally by mapped area to ensure both balance and representativeness (see supplementary table S1). After manual labeling, a post-stratified estimator (Olofsson *et al* 2014) was used to calculate unbiased estimates of class areas, their standard error, and accuracy metrics. This approach corrects for class proportion discrepancies, providing robust and area-adjusted accuracy estimates (see supplementary tables S2–S9).

A 'Settlement' class was then incorporated into each LULC map using the annual WSF datasets (Marconcini *et al* 2020), with the WSF 2019 layer applied as a substitute for the Settlement class in the LULC maps for 2018 and 2022. Forest masks were then created by merging the 'Undisturbed' and 'Disturbed' classes into a single 'Forest' class, while consolidating all other classes into a 'Non-Forest' class. These forest masks, together with the LULC maps, were then utilized to produce forest disturbance maps and final forest change maps for each period.

3.2. Forest disturbance maps with CCDC-SMA

For each study period, all available Landsat surface reflectance images were analyzed, including those from 1985–1987 to better capture baseline disturbance (1988–1993). Cloud and shadow pixels were removed using the QA band with a 0.05 cloud endmember fraction threshold.

The CCDC algorithm (Zhu and Woodcock 2014, Zhu 2017) models spectral data over time using linear harmonic segmentation to address seasonal variability and enhance spectral consistency (Pasquarella *et al* 2022). Commonly used for forest disturbance detection, it fits sine and cosine terms to reflectance data, detecting stable periods and gradual forest cover changes but struggles with nonlinear dynamics.

To improve CCDC, SMA decomposes pixel reflectance into fractions like green vegetation (GV), non-photosynthetic vegetation (NPV), Soil, Shade, and Cloud (Adams 1995, Souza *et al* 2005, Chen *et al* 2021), enhancing sensitivity to forest degradation. CCDC-SMA uses SMA-derived indices, such as the normalized difference fraction index (NDFI), which better captures forest changes (Bullock *et al* 2020a, Chen *et al* 2021, 2023). NDFI, calculated as:

$$\mathrm{NDFI} = \frac{\mathrm{GV}_{\mathrm{shade}} - (\mathrm{NPV} + \mathrm{Soil})}{\mathrm{GV}_{\mathrm{shade}} + (\mathrm{NPV} + \mathrm{Soil})} \tag{1}$$

$$\mathrm{GV}_{\mathrm{shade}} = \frac{\mathrm{GV}}{1 - \mathrm{Shade}}. \tag{2}$$

Endmember spectra for GV, NPV, Soil, Cloud, and Shade were sourced from Chen *et al* (2023), derived from tropical forests in Laos (see supplementary table S11). These values were selected for their spectral similarity to Huế. While site-specific endmembers would be ideal, field constraints prevented an *in-situ* extraction campaign, as it was not part of our planned mission. Instead, we leveraged the well-documented spectral values from Chen *et al* (2023) for methodological consistency and efficiency.

Using GEE, harmonic models based on SMA indices (NDFI, GV, NPV, Soil, Shade) detected disturbances via significant deviations over five observations. Forest disturbance maps were generated by applying an NDFI threshold of −2400 (Chen *et al* 2023) to CCDC-SMA images, combined with an initial forest mask. This approach, validated in Laos, a similar tropical forest region as Huế, effectively mapped disturbances in Huế's tropical forests, forming the basis for forest change analysis.

3.3. Forest change maps

A forest (canopy) change map for each study period illustrates forest cover dynamics across the five-year intervals, with classifications into five categories: stable, degraded, loss, gain, and non-forest. This process yielded seven maps, each representing the forest cover status at the end of each five-year period. Figure 4 and table 2 provide a detailed overview of the process used to generate the forest change maps for Huế and the forest change categories defined across the seven study periods from 1988 to 2022.

To produce each periodic forest change map, a forest mask (Forest and Non-Forest) was first derived by regrouping classes from the LULC map. The forest mask was then integrated with the forest disturbance map and the 'Undisturbed' class from the LULC map to generate the final forest change map for each period, following the stratified mapping approach recommended by Olofsson *et al* (2014). An overview of this process is provided in figure 4, where the 'Forest' and 'Non-Forest' blocks represent the forest mask, created by merging the 'Undisturbed' and 'Disturbed' classes from the LULC map.

3.4. Accuracy assessment, and area estimations for forest change maps

To assess the accuracy and estimate the areas of each class of the forest change maps, we used a stratified sampling design following Olofsson *et al* (2014) and employed the Stratified Random Sampling tool from AREA^2 (Bullock *et al* 2020b) in GEE. We set a target precision for overall accuracy, and calculated the sample size (n) for each forest change class based on Olofsson *et al*'s (2014) variance estimator, derived from Cochran's (1977) formula. A target standard error of 0.02 was set for the overall accuracy, with anticipated user accuracy values of 0.9 for Stable, 0.7 for degraded, 0.3 for loss, 0.3 for gain, and 0.9 for non-forest. These parameters determined the sample sizes used consistently across all forest change maps (supplementary table S12). Given the imbalance in class area proportions, particularly for the loss and gain classes, we applied the optimal allocation method to enhance the representation of these smaller-area classes, as recommended by Olofsson *et al* (2014).

For sample interpretation, Landsat time-series data in the time series viewer tool (AREA^2) and high-resolution Google Earth Pro imagery were used. Each sampled pixel was assigned a reference class with recorded confidence levels, enhanced by Google Earth's high-resolution imagery where available (supplementary figures S10–S14). To enhance validation, we employed high-resolution imagery from Google Earth Pro, a widely accepted alternative when ground-truth field data is unavailable. Reference data were input into AREA^2's stratified estimator to produce confusion matrices, accuracy results, and area estimates for each period (Arevalo *et al* 2020, Bullock *et al* 2020b).

The confusion matrices comparing mapped versus reference pixels and the accuracy assessments for each period's originally classified forest change maps, along with their corresponding accuracy metrics, and the area estimations derived using AREA^2's stratified estimator, are provided in supplementary tables S13–S19.

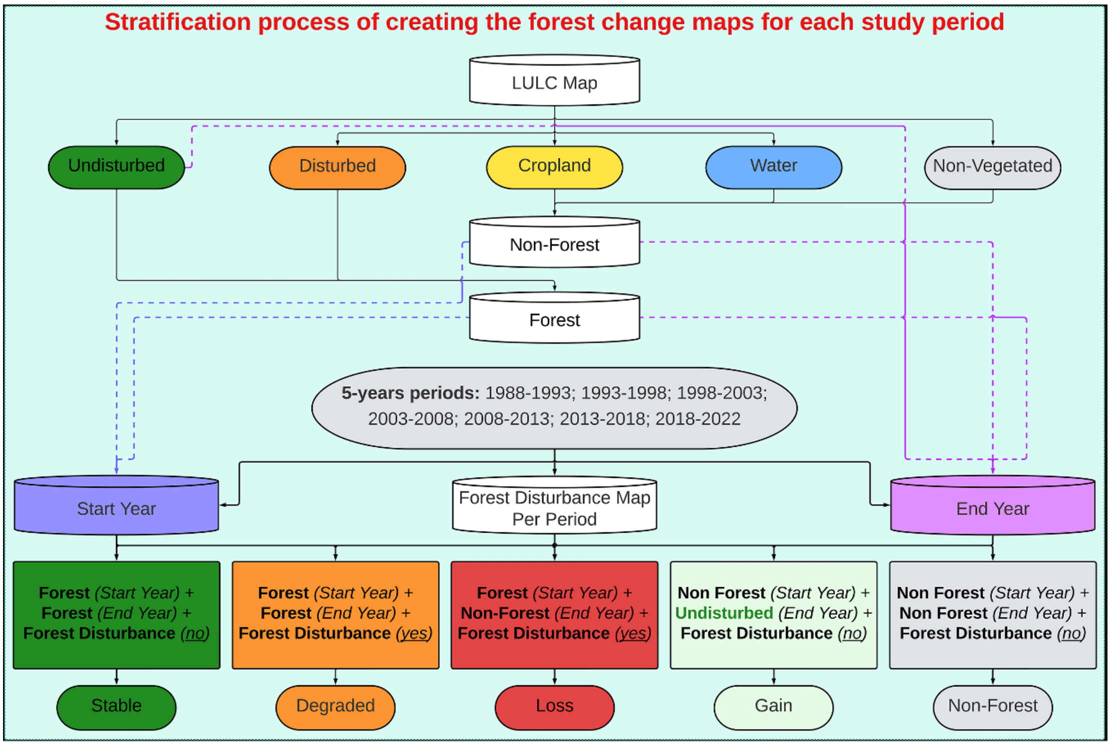

Figure 4. This diagram illustrates the process for creating the forest change map for each study period. The inputs for this process include forest masks (distinguishing Forest and Non-Forest areas), 'Undisturbed' pixels from the LULC map, and the forest disturbance map. The white blocks in the diagram represent the primary data sources used to derive the forest change maps. The LULC map played a dual role: it was used to generate the forest mask (comprising Forest and Non-Forest layers) and to define the 'Gain' category by providing the 'Undisturbed' class. The placeholders 'Start Year' and 'End Year' indicate the temporal data required to analyze changes over each period. For a detailed breakdown of pixel classification criteria across different forest change categories, refer to table 2.

Table 2. Summary of input layers and pixels used in creating each period's forest change map.

Forest change category	Input layers for stratification process (pixels per period): Forest mask (Start Year)	Forest mask (End Year)	Disturbance map (Study Period)	LULC map (End Year)
Stable	Forest pixels	Forest pixels	—	—
Degraded	Forest pixels	Forest pixels	Disrupted pixels	—
Loss	Forest pixels	Non-Forest pixels	Disrupted pixels	—
Gain	Non-Forest pixels	—	—	Undisturbed pixels
Non-Forest	Non-Forest pixels	Non-Forest pixels	—	—

	Description
Stable	Forest pixels that remained unchanged in both the start and end years' forest masks
Degraded	Forest pixels classified as forest in both years' forest masks but showing disturbance in the forest disturbance map for that period
Loss	Forest pixels that transitioned to non-forest in the end year's forest mask, with disturbance detected in the disturbance map during the study period
Gain	Pixels that shifted from non-forest in the start year's forest mask to 'Undisturbed' class in the end year's LULC map, with no disturbance detected
Non-Forest	Pixels classified as non-forest in both the start and end years' forest masks, with no disturbance in the disturbance map

4. Results

4.1. Land use land cover maps for Huế from 1988 to 2022

(i)**Mapped area, accuracy metrics, and post-stratified area estimates of LULC maps prior to settlement class addition**

Table 3 summarizes land-use and land-cover changes in Huế from 1988 to 2022, based on the original LULC maps before the inclusion of the settlement class. During this period, undisturbed forest declined from 2860.7 km^2 (56.9%) to 2463.1 km^2 (49.0%), while disturbed forest increased from 631.4 km^2 (12.6%) to 1046.9 km^2 (20.8%). Cropland and water areas expanded slightly, while non-vegetated land shrunk from 1,023.8 km^2 to 863.2 km^2. To account for classification uncertainty and derive unbiased area estimates, we applied a post-stratified estimator following Olofsson *et al* (2014). The comprehensive accuracy assessment, including confusion matrices for each LULC map, is available in supplementary tables S2–S9.

(ii)**Mapped area and class proportions of final LULC maps including settlement class**

Table 4 and figure 5 depict LULC changes across Huế from 1988 to 2022, based on the final classified maps that incorporate the settlement class. During this period, undisturbed forest declined steadily from 2818.5 km^2 (56.1%) to 2457.7 km^2 (48.9%), while disturbed forest expanded significantly from 645.5 km^2 (12.8%) to 1050.8 km^2 (20.9%). Cropland increased moderately from 219.2 km^2 (4.4%) to 261.7 km^2 (5.2%), and water bodies expanded from 292.9 km^2 (5.8%) to 389.8 km^2 (7.8%). Settlement areas nearly doubled, growing from 108.9 km^2 (2.2%) in 1988–191.5 km^2 (3.8%) in 2022, reflecting continued development. The most pronounced decline occurred in the non-vegetated class, which shrank from 940.1 km^2 (18.7%) to 673.8 km^2 (13.4%). These final mapped outputs provide the foundation for the forest change analysis. LULC maps and corresponding forest masks for all years are available in supplementary figures S15–S16 and through the GEE web apps listed in the Data Availability section.

4.2. Forest disturbances in Huế from 1988 to 2022

Forest disturbances in Huế increased significantly from 1988 to 2022, as revealed by disturbance maps for seven intervals (figures 6 and 7). An interactive version of these results is available via GEE web-app links in the data availability section. A total of 29.05 km^2 of forest was disturbed between 1988 and 1993, rising to 34.75 km^2 by 1998 (+5.71 km^2). The rate of disturbance accelerated, reaching 60.27 km^2 by 2003 (+25.51 km^2), 118.42 km^2 by 2008 (+58.15 km^2), and 178.70 km^2 by 2013 (+60.28 km^2). The most substantial increases occurred between 2013–2018 (380.88 km^2, +202.19 km^2) and 2018–2022 (218.06 km^2), totaling 598.94 km^2 of disturbed forest by the end of the study period.

Overall, a total of 1401 km^2 of forest disturbances were recorded across the 34 year period, underscoring significant and accelerating changes in Huế's forest landscape as detected by the CCDC-SMA method and extensive Landsat data. All annual disturbance maps are accessible through our web-based application (see Data Availability section).

4.3. Forest canopy changes over 5 year intervals: 1988–2022

The study provides a comprehensive analysis of forest dynamics in the region driven by changes in managed and natural forest canopy cover, revealing significant trends in stable forest decline and the expansion of degraded and planted areas. By harmonizing classification systems and integrating local context, our findings contribute to a better understanding of FTs and their implications for sustainable forest management and policy-making in Vietnam.

Our findings show a decline in stable forests in Huế, consistent with regional studies that report decreases in natural forests alongside expansions in degraded and planted forests (Paudyal *et al* 2020, Duong *et al* 2021, Cochard *et al* 2023). In contrast, National studies report increases in natural and planted forests in certain areas in the country, reflecting reforestation trends (Cochard *et al* 2017, Pham *et al* 2019). These variations in reforestation and deforestation highlight the complexities of FT processes in Vietnam (table 7).

Forest cover in Huế underwent significant changes between 1988 and 2022, as reflected in seven forest change maps generated for each 5 year interval. These maps illustrate canopy cover dynamics, categorizing forest conditions at the end of each period into five types: stable forest, degraded forest, forest loss, forest gain, and non-forest. A full set of forest change maps is available in supplementary figures S17 and can be explored interactively via the GEE web-apps (see data availability section).

Table 5 summarizes mapped area and proportional changes for forest change classes from 1988 to 2022. Throughout the study period, stable forest cover declined steadily, from 3280.77 km^2 (65.3%) in 1988–1993 to 2665.47 km^2 (53.0%) in 2018–2022. In contrast, Degraded Forest expanded significantly, from 103.33 km^2 (2.1%) to 611.42 km^2 (12.2%), indicating a continuous shift from intact to disturbed canopy conditions. Forest loss also increased, from 17.01 km^2 (0.3%) to 77.23 km^2 (1.5%), while Forest Gain remained relatively low but grew from 9.27 km^2 (0.2%) to 33.90 km^2 (0.7%). Non-Canopy areas

Table 3. Mapped area, accuracy statistics, and post-stratified estimated area of all LULC maps (without Settlement class) after Olofsson *et al* (2014).

Undisturbed								
Property\Year	**1988**	**1993**	**1998**	**2003**	**2008**	**2013**	**2018**	**2022**
Mapped area (km^2)	2860.7	2678.2	2639.9	2606.6	2527.1	2453.9	2467.0	2463.1
Mapped area proportion (%)	56.9	53.3	52.5	51.9	50.3	48.8	49.1	49.0
Producer's accuracy ± 95% CI (%)	93.1 ± 5.3	99.1 ± 2.3	95.9 ± 5.0	96.3 ± 4.4	93.9 ± 5.8	94.1 ± 5.6	91.3 ± 6.5	87.0 ± 7.4
User's accuracy ± 95% CI (%)	100 ± 0.0	93.1 ± 5.9	81.7 ± 9.1	94.4 ± 5.3	87.1 ± 7.9	91.3 ± 6.7	92.8 ± 6.2	97.1 ± 4.0
Estimated area ± 95% CI (km^2)	3169 ± 156	2639 ± 173	2424 ± 257	2686 ± 174	2437 ± 246	2540 ± 197	2643 ± 211	2931 ± 181
Estimated area proportion ± 95% CI %)	60.1 ± 3.0	50.0 ± 3.3	45.9 ± 4.9	50.9 ± 3.3	46.2 ± 4.7	48.2 ± 3.7	50.1 ± 4.0	55.6 ± 3.4

Disturbed								
Property\Year	**1988**	**1993**	**1998**	**2003**	**2008**	**2013**	**2018**	**2022**
Mapped area (km^2)	631.4	813.2	860.8	878.0	906.5	858.6	920.3	1046.9
Mapped area Proportion (%)	12.6	16.2	17.1	17.5	18.0	17.1	18.3	20.8
Producer's accuracy ± 95% CI (%)	62.2 ± 17.1	70.8 ± 13.8	55.0 ± 13.5	66.5 ± 13.6	67.9 ± 14.1	60.1 ± 14.2	71.9 ± 14.3	87.5 ± 12.2
User's accuracy ± 95% CI (%)	66.7 ± 16.3	91.7 ± 9.2	89.2 ± 10.1	86.5 ± 11.2	84.2 ± 11.7	81.1 ± 12.8	76.3 ± 13.7	63.4 ± 4.0
Estimated area ± 95% CI (km^2)	742 ± 176	1103 ± 211	1458 ± 297	1216 ± 219	1220 ± 236	1259 ± 246	1068 ± 224	814 ± 200
Estimated Area proportion ± 95% CI (%)	14.1 ± 3.3	20.9 ± 4.0	27.6 ± 5.6	23.1 ± 4.2	23.1 ± 4.5	23.9 ± 4.7	20.2 ± 4.2	15.4 ± 3.8

Cropland								
Property\Year	**1988**	**1993**	**1998**	**2003**	**2008**	**2013**	**2018**	**2022**
Mapped area (km^2)	219.9	257.9	288.1	266.7	272.0	258.9	261.9	262.6
Mapped area proportion (%)	4.4	5.1	5.7	5.3	5.4	5.2	5.2	5.2
Producer's accuracy ± 95% CI (%)	84.6 ± 14.8	74.7 ± 16.7	91.1 ± 11.7	79.8 ± 15.4	87.1 ± 13.4	85.7 ± 13.7	79.2 ± 15.9	67.9 ± 18.0
User's accuracy ± 95% CI (%)	91.7 ± 11.3	92.0 ± 10.9	84.6 ± 14.1	92.0 ± 10.9	92.0 ± 10.9	92.0 ± 10.9	92.0 ± 10.9	88.0 ± 13.0
Estimated area ± 95% CI (km^2)	250 ± 61	343 ± 87	281 ± 54	331 ± 68	302 ± 66	280 ± 54	329 ± 79	364 ± 103
Estimated area proportion ± 95% CI (%)	4.7 ± 1.2	6.5 ± 1.6	5.3 ± 1.0	6.3 ± 1.3	5.7 ± 1.2	5.3 ± 1.0	6.2 ± 1.5	6.9 ± 1.9

(Continued.)

showed only minor fluctuations, remaining within 32.1%–34.3% of the total area.

4.4. Post-stratified area estimation and accuracy assessment of forest change maps

Table 5 presents mapped area as well as the sampling-based area estimates and associated uncertainties for the classes in the forest change maps from 1988 to 2022, calculated using the post-stratified estimator for area estimation and accuracy assessment, as recommended by Olofsson *et al* (2014) (see also supplementary tables S13–S19).

Table 6 provides post-stratified area estimates and accuracy metrics for each forest change class from

Table 3. (Continued.)

Water								
Property\Year	**1988**	**1993**	**1998**	**2003**	**2008**	**2013**	**2018**	**2022**
Mapped area (km²)	289.5	279.4	311.5	342.4	313.01	358.6	379.1	389.5
Mapped Area proportion (%)	5.8	5.6	6.2	6.8	6.2	7.1	7.5	7.8
Producer's accuracy ± 95% CI (%)	96.7 ± 7.2	96.2 ± 7.7	100 ± 0.0	96.5 ± 7.5	100 ± 0.0	83.9 ± 14.7	100 ± 0.0	97.3 ± 6.1
User's accuracy ± 95% CI (%)	92.3 ± 10.4	92.3 ± 10.4	92.3 ± 10.4	85.2 ± 13.7	92.3 ± 10.4	85.2 ± 13.7	96.4 ± 7.0	96.4 ± 7.0
Estimated area ± 95% CI (km²)	301 ± 30	282 ± 38	291 ± 39	307 ± 57	282 ± 43	362 ± 106	347 ± 48	392 ± 44
Estimated area proportion ± 95% CI (%)	5.7 ± 0.6	5.4 ± 0.7	5.5 ± 0.7	5.8 ± 1.1	5.3 ± 0.8	6.9 ± 2.0	6.6 ± 0.9	7.4 ± 0.8

Non Vegetated								
Property\Year	**1988**	**1993**	**1998**	**2003**	**2008**	**2013**	**2018**	**2022**
Mapped area (km²)	1023.8	996.6	924.9	931.6	1006.6	1095.1	996.8	863.2
Mapped area proportion (%)	20.4	19.8	18.4	18.5	20.0	21.8	19.8	17.2
Producer's accuracy ± 95% CI (%)	96.7 ± 5.8	97.6 ± 5.0	97.3 ± 5.4	96.7 ± 6.5	97.7 ± 4.7	98.8 ± 3.8	100.0 ± 0.0	97.3 ± 5.4
User's accuracy ± 95% CI (%)	92.3 ± 14.0	85.4 ± 11.0	86.8 ± 10.9	74.4 ± 13.9	95.0 ± 6.8	76.2 ± 13.0	87.5 ± 10.4	89.2 ± 10.1
Estimated area ± 95% CI (km²)	301 ± 30	895 ± 124	867 ± 110	735 ± 146	1053 ± 62	887 ± 151	916 ± 109	790 ± 109
Estimated area proportion ± 95% CI (%)	5.7 ± 2.9	17.0 ± 2.3	16.4 ± 2.1	13.9 ± 2.8	20.0 ± 1.2	16.8 ± 2.9	17.4 ± 2.1	15.0 ± 2.1
Overall accuracy ± 95% CI (%)	**89.4 ± 3.6**	**91.2 ± 4.2**	**84.8 ± 5.6**	**88.6 ± 4.4**	**88.8 ± 4.8**	**85.9 ± 5.0**	**88.9 ± 4.5**	**88.2 ± 4.2**

Table 4. Mapped areas (km²) and area proportions (%) by class of LULC maps (with Settlement class).

	Total area: 5025.24 km²							
	Mapped area (km²) Mapped area proportion (%)							
Class\Year	1988	1993	1998	2003	2008	2013	2018	2022
Undisturbed	2818.5 56.1	2676.1 53.3	2636.6 52.5	2603.3 51.8	2522.9 50.2	2451.7 48.8	2464.3 49.0	2457.7 48.9
Disturbed	645.5 12.8	813.2 16.2	862.2 17.2	879.7 17.5	907.8 18.1	858.2 17.1	921.3 18.3	1050.8 20.9
Cropland	219.2 4.4	256.4 5.1	286.9 5.7	265.9 5.3	271.3 5.4	258.3 5.1	261.2 5.2	261.7 5.2
Water	292.9 5.8	279.6 5.6	311.9 6.2	342.7 6.8	312.7 6.2	357.9 7.1	379.6 7.6	389.8 7.8
Settlement	108.9 2.2	117.9 2.3	133.2 2.7	151.1 3	167.3 3.3	176.2 3.5	193.3 3.9	191.5 3.8
Non-Vegetated	940.1 18.7	882.1 17.6	794.4 15.8	782.7 15.6	843.2 16.8	922.9 18.4	805.4 16.0	673.8 13.4

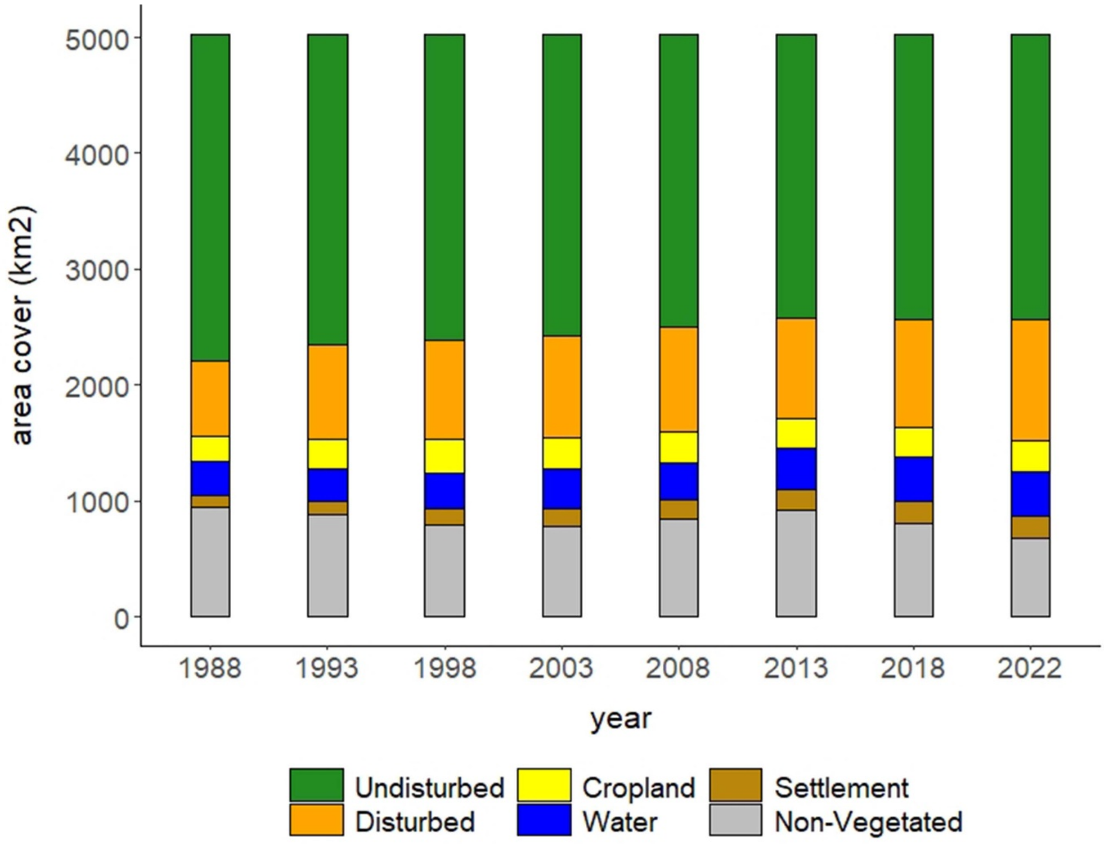

Figure 5. Variations in LULC class areas over the study period.

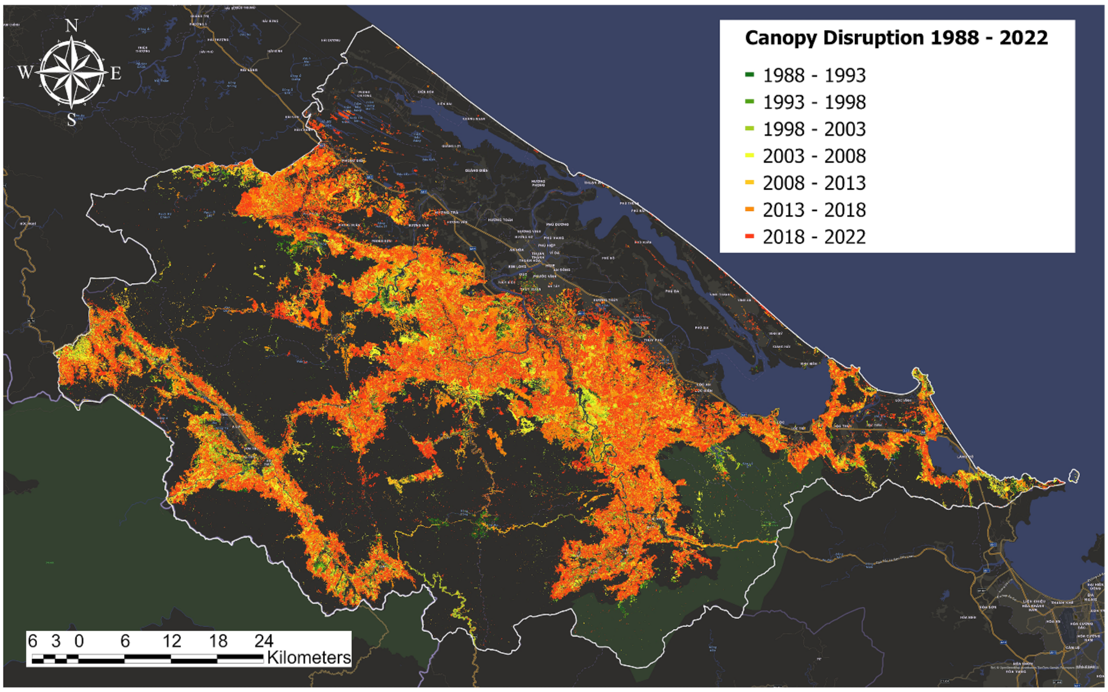

Figure 6. Forest disturbance (disruption) map of Huế (1988–2022). This map was generated using the CCDC-SMA method, following the change detection parameters outlined by Chen *et al* (2023). The color scheme reflects the timing of forest disturbances: green shades indicate disturbances during the early periods (1988–2003), yellow and orange shades correspond to disturbances between 2003 and 2018, and red pixels mark disturbances detected in the most recent period (2018–2022). Source basemap: Esri, HERE, Garmin, FAO, NOAA, USGS, © OpenStreetMap contributors, and the GIS User Community.

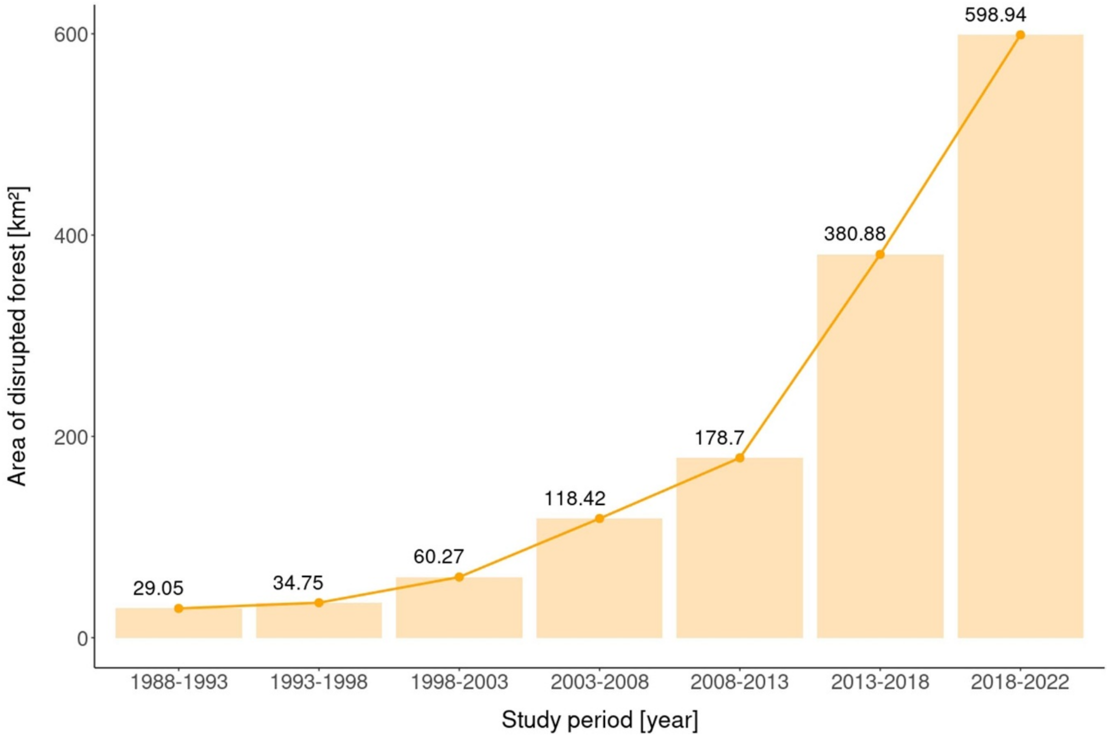

Figure 7. Changes in area of disrupted forest (km^2) by study period (1988–2022). This figure shows abrupt forest changes across each study period from 1988 to 2022, totaling 1401 km^2 and highlighting significant forest cover changes in Huế, as detected by the CCDC-SMA method with Landsat observations.

Table 5. Mapped areas (km^2) and proportions (%) for each forest change classes (1988–2022).

Period	Total area: 5025.24 km^2 Mapped area (km^2) Mapped area proportion (%)				
	Stable	Degraded	Loss	Gain	No Canopy
1988–1993	3280.77 65.29	103.33 2.06	17.01 0.34	9.27 0.18	1614.86 32.14
1993–1998	3269.73 65.07	116.40 2.32	21.71 0.43	5.45 0.11	1611.96 32.08
1998–2003	3234.79 64.37	157.27 3.13	39.49 0.79	4.66 0.09	1589.02 31.62
2003–2008	2917.89 58.06	415.93 8.28	82.16 1.63	7.43 0.15	1601.83 31.88
2008–2013	2818.09 56.08	356.80 7.10	155.66 3.10	19.18 0.38	1675.51 33.34
2013–2018	2664.03 53.01	492.64 9.80	104.77 2.08	39.73 0.79	1724.06 34.31
2018–2022	2665.47 53.04	611.42 12.17	77.23 1.54	33.90 0.67	1637.22 32.58

Table 6. Post-stratified area estimates and accuracies of each forest change class (1988–2022) after Olofsson *et al* (2014).

Stable forest

Period (Display Year)	1988–93 (1993)	1993–98 (1998)	1998–03 (2003)	2003–08 (2008)	2008–13 (2013)	2013–18 (2018)	2018–22 (2022)
Producer's accuracy ± 95% CI (%)	99.3 ± 1.4	98.8 ± 1.8	98.9 ± 1.7	99.1 ± 1.5	99.6 ± 1.0	98.3 ± 2.2	97.5 ± 2.7
User's accuracy ± 95% CI (%)	88.7 ± 5.1	88.7 ± 5.1	88.0 ± 5.2	94.7 ± 3.6	95.9 ± 3.3	90.0 ± 5.0	90.0 ± 5.0
Estimated area ± 95% CI (km^2)	3075 ± 176	3080 ± 180	3021 ± 178	2924 ± 115	2845 ± 98	2559 ± 145	2582 ± 150
Estimated area proportion ± 95% CI (%)	58.3 ± 3.3	58.4 ± 3.4	57.3 ± 3.4	55.4 ± 2.2	53.9 ± 1.9	48.5 ± 2.7	48.9 ± 2.8

Degraded Forest

Period (Display Year)	1988–93 (1993)	1993–98 (1998)	1998–03 (2003)	2003–08 (2008)	2008–13 (2013)	2013–18 (2018)	2018–22 (2022)
Producer's accuracy ± 95% CI (%)	14.5 ± 7.9	17.5 ± 8.1	18.4 ± 7.8	55.2 ± 10.6	43.1 ± 10.0	47.5 ± 9.6	58.2± 9.8
User's accuracy ± 95% CI (%)	82.5 ± 11.9	85.0 ± 11.2	80.0 ± 12.6	92.5 ± 8.3	97.5 ± 4.9	90.0 ± 8.4	86.0 ± 9.7
Estimated area ± 95% CI (km^2)	618 ± 201	594 ± 193	718 ± 206	732 ± 148	848 ± 165	980 ± 179	949 ± 163
Estimated area proportion ± 95% CI (%)	11.7 ± 3.8	11.3 ± 3.7	13.6 ± 3.9	13.9 ± 2.8	16.1 ± 3.1	18.6 ± 3.4	18.0 ± 3.1

Loss Forest

Period (Display Year)	1988–93 (1993)	1993–98 (1998)	1998–03 (2003)	2003–08 (2008)	2008–13 (2013)	2013–18 (2018)	2018–22 (2022)
Producer's accuracy ± 95% CI (%)	18.3 ± 26.8	22.3 ± 28.9	28.5 ± 36.1	72.5 ± 27.7	74.3 ± 25.8	68.6 ± 26.3	57.2 ± 30.7
User's accuracy ± 95% CI (%)	26.7 ± 16.1	26.7 ± 16.1	20.0 ± 14.6	33.3 ± 17.2	36.7 ± 17.5	40.0 ± 17.8	33.3 ± 17.2
Estimated area ± 95% CI (km^2)	26.7 ± 8.2	27 ± 42	29 ± 41	40 ± 26	81 ± 50	64 ± 44	47 ± 42
Estimated area proportion ± 95% CI (%)	0.5 ± 0.8	0.5 ± 0.8	0.6 ± 0.8	0.8 ± 0.5	1.5 ± 0.9	1.2 ± 0.8	0.9 ± 0.8

Gain Forest

Period (Display Year)	1988–93 (1993)	1993–98 (1998)	1998–03 (2003)	2003–08 (2008)	2008–13 (2013)	2013–18 (2018)	2018–22 (2022)
Producer's accuracy ± 95% CI (%)	19.4 ± 18.8	42.8 ± 28.0	4.1 ± 15.9	12.3 ± 19.4	22.8 ± 27.4	25.8 ± 38.4	42.5 ± 34.3
User's accuracy ± 95% CI (%)	56.7 ± 18.0	40.0 ± 17.8	20.0 ± 14.6	36.7 ± 17.5	30.0 ± 16.7	16.7 ± 13.6	26.7 ± 16.1
Estimated area ± 95% CI (km^2)	28 ± 45	5 ± 6	24 ± 44	23 ± 40	26 ± 40	27 ± 40	22 ± 26
Estimated area proportion ± 95% CI (%)	0.5 ± 0.9	0.1 ± 0.1	0.4 ± 0.8	0.4 ± 0.8	0.5 ± 0.8	0.5 ± 0.7	0.4 ± 0.5

(Continued.)

Table 6. (Continued.)

Non-Forest							
Period (Display Year)	**1988–93 (1993)**	**1993–98 (1998)**	**1998–03 (2003)**	**2003–08 (2008)**	**2008–13 (2013)**	**2013–18 (2018)**	**2018–22 (2022)**
Producer's accuracy ± 95% CI (%)	99.9 ± 0.7	98.4 ± 2.7	98.5 ± 2.9	98.7 ± 2.6	99.6 ± 1.4	99.1 ± 2.1	99.0 ± 2.1
User's accuracy ± 95% CI (%)	90.0 ± 6.6	91.2 ± 6.2	87.5 ± 7.3	91.2 ± 6.2	83.5 ± 7.9	90.0 ± 6.2	96.5 ± 3.9
Estimated area ± 95% CI (km^2)	1528 ± 112	1569 ± 115	1483 ± 130	1556 ± 112	1475 ± 140	1645 ± 115	1675 ± 72
Estimated area Proportion ± 95% CI (%)	29.0 ± 2.1	29.7 ± 2.2	28.1 ± 2.5	29.5 ± 2.1	28.0 ± 2.7	31.2 ± 2.2	31.8 ± 1.4
Overall accuracy ± 95% CI (%)	***88.70 ± 3.95***	***89.09 ± 3.88***	***86.99 ± 4.09***	***92.31 ± 2.98***	***89.78 ± 3.28***	***88.38 ± 3.52***	***90.32 ± 3.18***

Table 7. Forest cover change studies for Vietnam and Huế.

Study	Data source	Study area	Period	Class	Change direction
Cochard *et al* (2017)	Official data	Vietnam & Central Provinces	1995–2013	Natural forest Planted forest	Increase Increase
Pham *et al* (2019)	Official data	Vietnam	2005–2017	Natural forest Planted forest	Decrease Increase
Khuc *et al* (2018)	Official data Own analysis	Vietnam	2000–2010	Forest loss & degradation	Decrease
Duong *et al* (2021)	Official data	Huế	2000–2019	Natural forest Planted forest	Decrease Increase
Paudyal *et al* (2020)	Official data	Huế	2005–2015	Rich forest Medium forest Poor forest Planted forest	Decrease Increase Increase Increase
Cochard *et al* (2023)	Own analysis	Huế	1966–2019	Natural forest Planted forest	Decrease Increase

1988 to 2022. Stable Forest declined consistently, from 3075 ± 176 km^2 (58.3 ± 1.7%) in 1988–1993 to 2582 ± 150 km^2 (48.9 ± 1.4%) in 2018–2022. Despite this decline, producer's accuracy remained high throughout (>97%), while user's accuracy (UA) ranged from 88.0% to 95.9%.

Degraded forest expanded steadily, growing from 618 ± 201 km^2 (11.7 ± 1.9%) to 949 ± 163 km^2 (18.0 ± 1.6%) over the study period. Producer's accuracy improved significantly, rising from 14.5% to 58.2%, while UA remained consistently high (⩾85%).

Forest loss peaked at 81 ± 50 km^2 (1.5 ± 0.5%) during 2008–2013 before declining to 47 ± 42 km^2 (0.9 ± 0.4%) in 2018–2022. Accuracy for this class remained variable due to its relatively small area, with producer's accuracy ranging from 18.3% to 74.3%, and UA fluctuating between 20.0% and 81.7%.

Forest gain remained limited in extent, peaking at 33.90 km^2 in 2018–2022, corresponding to an estimated area of 22 ± 26 km^2 (0.4 ± 0.2%). Accuracy was similarly low and variable, with producer's accuracy reaching 42.5% in the final period, while UA ranged from 16.7% to 80.6%.

Non-forest areas remained relatively stable, ranging from 1528 ± 112 km^2 (29.0 ± 1.1%) in 1988–1993 to 1675 ± 72 km^2 (31.8 ± 0.7%) in 2018–2022. This class consistently exhibited high producer's accuracy (>98%) and strong UA, reaching 96.5% in the final period.

Overall classification accuracy of the forest change maps remained high, ranging from 86.99 ± 4.09% to 92.31 ± 2.98%, underscoring the robustness of the stratified sampling and post-stratification estimation approach applied.

5. Discussion

5.1. Temporal dynamics of forest cover in Huế from 1988 to 2022

Differences in classification systems often complicate direct comparisons of forest change assessments across studies. To address this, we aligned our stable forest class with Vietnam's 'natural forest' categories, while grouping degraded, loss, and gain classes with 'planted forests', following national definitions (MARD 2009, Hanoi Publishing House 2018, Paudyal *et al* 2020). This methodological alignment ensures consistency in interpreting forest trends while accounting for local ecological and land-use transitions.

Our findings indicate a steady decline in stable forest cover in Huế, from an estimated area of 58.3% (3075 km^2) in 1993 to 53.9% (2845 km^2) in 2013, and further to 48.9% (2582 km^2) in 2022. This trend is consistent with Pham *et al* (2019), who reported a national decline in natural forests between 2005 and 2017. In contrast, our combined degraded, loss, and gain categories increased from 675 km^2 in 2003–859 km^2 in 2013, mirroring the expansion of plantation forests reported by Duong *et al* (2021) and Paudyal *et al* (2020).

Large-scale tree planting campaigns led to an overall increase in tree-covered areas but also contributed to the conversion of natural forests into monoculture plantations. Cochard *et al* (2023) noted that planted tree cover in Huế grew from 354 km^2 in 1988–667 km^2 in 1998 and exceeded 994 km^2 by 2019. Our results align with this trend, showing an increase in Degraded and Gain areas over time, with plantation expansion often replacing secondary forests rather than restoring primary forest ecosystems.

The observed trends in forest disturbance further support these findings. From 1988 to 1993, forest disruptions covered 29.05 km^2, but this accelerated significantly, reaching 598.94 km^2 by 2022. This increase is consistent with Cochard *et al* (2023), who documented widespread forest exploitation during the late 1980s to early 2000s, followed by a period of stabilization driven by logging bans and afforestation programs. However, despite conservation efforts, the expansion of acacia plantations has not compensated for the loss of natural forests in terms of biodiversity and ecosystem services (Dang *et al* 2022, Vu *et al* 2023).

Our findings highlight the importance of balancing plantation forestry with conservation strategies to maintain ecological integrity. Future policies should focus on enhancing the protection of remaining natural forests, promoting mixed-species reforestation, and ensuring sustainable land-use planning that integrates both economic and environmental priorities.

5.2. Potential drivers of forest cover dynamics in Huế (1988–2022) and policy implications

Understanding the drivers of forest cover dynamics requires a multi-faceted approach that accounts for socio-economic, environmental, and policy-related factors. While a full causal analysis would necessitate a comprehensive set of temporally consistent datasets for advanced statistical methods such as causal inference (CI) (e.g. Peter Spirtes and Clark Glymour Momentary Conditional Independence, PCMCI) algorithm for time series following (Runge *et al* 2019a, 2019b), we instead rely on existing literature to contextualize observed changes in Huế. Below, we qualitatively describe six drivers that are contributing to forest change in Huế. This includes:

(i) Economic expansion and land use policies

Vietnam's economic expansion, driven by reforms under the Đổi Mới policy (1986) and the land reforms in 1993 (Ho 2021), has been a defining force behind land-use changes, facilitating rapid economic growth and significantly impacting forest dynamics in Huế. Market liberalization led to the expansion of commercial agriculture, including rubber, coffee, and cassava cultivation, as farmers and agribusinesses prioritized high-value cash crops. This shift contributed to widespread deforestation, as forested land was cleared to accommodate agricultural production, logging, and plantation forestry (McElwee 2009, Cochard *et al* 2023). Additionally, government policies, particularly the forest land allocation (FLA) policy, were introduced to promote reforestation and decentralized forest management. However, in practice, these policies, along with government incentives for acacia plantations, accelerated the conversion of natural forests into monoculture tree farms, leading to forest fragmentation and biodiversity loss. The rapid expansion of acacia plantations, driven by high demand for timber and government subsidies, has often replaced ecologically rich forest ecosystems with fast-growing but less diverse tree stands (Nguyen and Nguyen 2022). While this transition has increased total forest cover on paper, it has simultaneously contributed to habitat degradation, soil depletion, and reduced ecosystem resilience (Paudyal *et al* 2020).

(ii) Urbanization and infrastructure development

Urban expansion has been a major driver of land-use change in Huế, especially around key settlements like Huế City. Infrastructure development, including roads, has contributed to forest loss by fragmenting natural landscapes and facilitating land conversion (Zhang *et al* 2022). Although prior studies have examined urbanization's role, the lack of comprehensive driver datasets limits direct causal analysis. Still, existing research links settlement growth to declining forest stability (Cochard *et al* 2023).

This challenge is particularly relevant given the Thừa Thiên Huế Master Plan (2021–2030), which promotes extensive urban and infrastructure development to drive economic growth (TTH 2023). While these goals are important, it is essential to consider their environmental implications—especially for forest ecosystems. Aligning development with strategies that preserve natural landscapes and support forest resilience, as highlighted in the Master

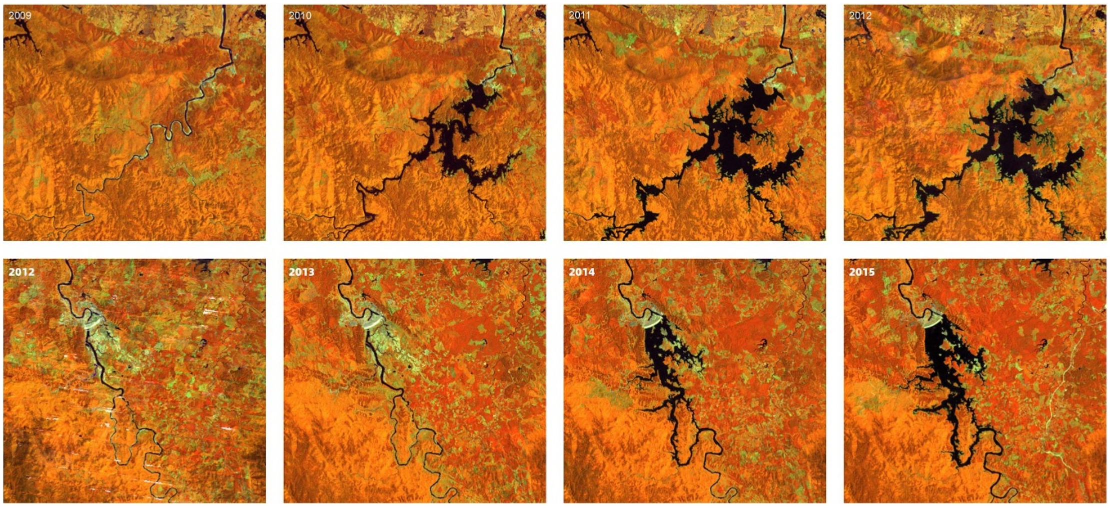

Figure 8. Water surface area expansion before and after hydropower plant establishment: Hương Điền (2009–2012) and Tả Trạch (2012–2015). Row 1: Hương Điền hydropower plant—changes in water surface area before (2009) and after (2010) establishment, based on annual Landsat composite images from 2009 to 2012. Row 2: Tả Trạch hydropower plant—Changes in water surface area before (2013) and after (2014) establishment, based on annual Landsat composite images from 2012 to 2015 *Source*: Landsat Level 2 images courtesy of the U.S. Geological Survey; further processed with Google Earth Engine.

Plan, could help mitigate urban sprawl and promote more balanced, sustainable growth across the region.

(iii) Hydropower development

Hydropower projects have played a significant role in forest loss within the province. Large-scale dam construction, such as the Hương Điền and Tả Trạch hydropower plants (see figure 8), has led to the inundation of forested areas and altered local ecosystems (Nguyen and Nguyen 2022). These developments, while contributing to renewable energy production, have displaced both forest and agricultural lands, resulting in substantial land-cover transitions (Tran *et al* 2010). Given the significant ecological and socio-economic consequences, it is crucial that future hydropower projects incorporate more comprehensive environmental impact assessments and adopt effective mitigation measures. These may include improved reservoir ecosystem management, the establishment of compensatory afforestation initiatives, and investment in alternative renewable energy sources that exert less pressure on land cover and local communities (World Bank 2009).

(iv) Policy-driven reforestation efforts

Vietnam has implemented several reforestation policies aimed at increasing forest cover. Programs such as 'Greening the Barren Hills Program' (program 327), the '5 Million Hectare Reforestation Program' (Program 661), and PFES have incentivized afforestation and conservation (De Jong *et al* 2006, Meyfroidt and Lambin 2008). However, much of the forest recovery observed in Huế is linked to plantation forestry, particularly acacia cultivation, which provides economic benefits but offers limited ecological function compared to natural forests (Gobin *et al* 2020, Cochard *et al* 2021). The dominance of plantation forestry raises concerns regarding the sustainability of these reforestation efforts. While such plantations provide economic incentives for local communities, their limited biodiversity and reduced ecological resilience make them less effective in achieving long-term conservation goals (Cunningham *et al* 2015). To address these issues, the government could consider expanding policies that encourage mixed-species reforestation, which more closely replicates the structure and function of natural forests.

(v) Climate variability and extreme weather events

Climate change and extreme weather events have increasingly influenced forest cover dynamics in central Vietnam. Huế experiences frequent typhoons, heavy rainfall, and flooding (Vu *et al* 2025), which can lead to landslides and forest degradation (Van Tien *et al* 2021). Extreme weather events, such as Typhoon Linfa and Typhoon Saudel (Ortiz-Vargas and Sebesvari 2021), caused widespread forest loss due to windthrow and flooding (Luu *et al* 2021). The interplay between climatic disturbances and anthropogenic pressures underscores the importance of adaptive management strategies. Strengthening forest resilience by promoting reforestation with diverse native species and improved forest management practices, could help mitigate the adverse effects of extreme weather events (Kaarakka *et al* 2021, Štraus and Benčina 2025). Moreover, developing early warning systems for extreme weather events, such as floods and typhoons, could enable proactive responses to protect forest cover before significant damage occurs

(Merz *et al* 2020). Incorporating such strategies into the broader land-use planning framework in Huế is essential to address the challenges posed by both natural and human-induced drivers of forest dynamics.

(vi) Agriculture

While urbanization and infrastructure development have contributed to forest loss, agricultural expansion remains a major driver of land-use change in Vietnam. Shifting cultivation and the conversion of forests into croplands—driven by economic incentives and land tenure policies—have significantly altered forest cover (Meyfroidt *et al* 2013, Khuc *et al* 2018, Vu *et al* 2023). Although reforestation policies exist, competing agricultural interests have limited the recovery of natural forests.

Addressing this tension requires integrated land-use planning that supports both sustainable agriculture and forest conservation. Promoting agroforestry and other sustainable practices can help maintain forest cover while improving yields (Fatima *et al* 2024). Land tenure reforms that secure farmers' rights, combined with incentives for sustainable land use, can further reduce pressure on forests. Countries that have successfully increased both agricultural output and forest cover have relied on strategies such as intensification, zoning, forest protection, and broader economic shifts, including food imports, off-farm employment, and remittances (Lambin and Meyfroidt 2011). Recognizing land systems as part of global networks is key to improving land-use efficiency and preventing uncontrolled conversion.

5.3. Limitations and future research

This study presents a robust approach for analyzing forest cover changes and their drivers in Huế. However, certain limitations must be acknowledged, highlighting areas for future research. One notable challenge is the mixed pixel issue due to Landsat's 30 m resolution, which complicates accurate classification in dense, heterogeneous forest areas. Future research could explore the use of higher-resolution Earth observation data (such as Sentinel-2) to improve classification accuracy and better capture small-scale forest changes.

High-quality official forest data would have enhanced LULC map accuracy and forest mask creation. Exploring data from Sentinel-1 (Mermoz *et al* 2021, Spracklen and Spracklen 2021), JAXA forest masks (Hoang *et al* 2020, Phan *et al* 2021), or a reliable local natural forest inventory map as direct inputs for the CCDC-SMA algorithm could improve regional applicability, though these datasets' accuracy should be evaluated for regional-scale studies. Additionally, integrating hyperspectral sensors such as DESIS, EnMap, and PRISMA could enhance forest type differentiation and improve land-cover classification, providing finer spectral information compared to multispectral sensors.

The absence of field-based ground-truth forest data necessitated the use of high-resolution Google Earth imagery for validation, which, while not a perfect substitute, allows consistent verification across historical timelines. However, future studies should incorporate systematic *in-situ* data collection to refine classification accuracy and support long-term forest monitoring.

This study employed spectral endmember values from Laos (Chen *et al* 2023) to approximate reflectance conditions in Huế. While these values were selected for their spectral similarity and validated through preliminary tests, developing region-specific endmembers could improve accuracy in detecting subtle changes within dense forests. A multi-sensor approach, combining optical and radar data, could further enhance the detection of forest disturbances.

6. Conclusion

Forests in Huế are undergoing significant change, driven by both natural and human factors. This study offers a detailed assessment of forest cover dynamics over the past three decades, estimating the extent and UA of different forest change classes. Our findings reveal substantial forest loss and degradation, with stable forest areas declining and degraded forests increasing. We attribute these trends to socio-economic and environmental drivers, including population growth, urbanization, plantation expansion, hydropower development, and climate variability.

The CCDC-SMA methodology provides key advantages over multi-temporal static maps, such as those used in Cochard *et al* (2023). It enables continuous annual monitoring, allowing for more accurate detection of both abrupt forest loss and gradual degradation. This approach reduces seasonal noise and ensures temporal consistency, capturing subtle dynamics that static maps may overlook. As a result, CCDC-SMA supports a more nuanced analysis of forest disturbance, regrowth, and long-term land-use trends in Huế.

By identifying key drivers of forest change, this research informs targeted interventions to mitigate deforestation and promote sustainable land-use planning. Our findings offer a strong evidence base for policy development that seeks to balance economic growth with environmental protection, especially in regions facing similar land pressures.

Future work should focus on refining data integration and adopting high-resolution Earth observation datasets to strengthen forest monitoring frameworks. Additionally, a more comprehensive driver analysis—incorporating diverse socio-economic and climatic variables and applying CI techniques—will improve understanding of the complex forces shaping forest dynamics in Huế.

Data availability statement

The findings of this research study are accessible through the following GEE apps and are also available in the supplementary documents: https://hiennguyendong.users.earthengine.app/view/favn-forestchange-1988-2022-en (in English), https://hiennguyendong.users.earthengine.app/view/favn-forestchange-1988-2022-vn (in Vietnamese).

All other materials for this research can be shared upon request.

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Conflict of interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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