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Spatiotemporal analysis of forest cover change and associated environmental challenges: a case study in the Central Highlands of Vietnam

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ABSTRACT

Spatiotemporal regression combining Theil-Sen median trend and Man-Kendall tests was applied to MODIS time-series data to quantify the trend and rate of change to forest cover in the Central Highlands, Vietnam from 2001 to 2019. Several MODIS data products, including Percent Tree Cover (PTC), Evapotranspiration (ET), Land Surface Temperature (LST), and Gross Primary Productivity (GPP) were selected as indicators for forest cover and climate and carbon cycle patterns. Emerging hot spot analysis was applied to identify patterns of long-term deforestation. Spatial regression analysis using Geographically Weighted Regression (GWR) was performed to understand variations in the relationship between vegetation changes and trends in LST, ET, and GPP. Our analysis reveals that deforestation occurred significantly in the study area with a total decrease of 14.5% in PTC and a total of 7314 deforestation hot spots were identified. Results indicate that forest cover loss explains 72.9%, 67.7%, and 89.4% of the changes in ET, GPP, and LST, respectively, and the levels of influence are heterogenous across space and dependent on the types of deforestation hot spots. The approach introduced in our study can be performed worldwide to address complex research questions about environmental challenges that emerge from deforestation.

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Deforestation; MODIS; spatiotemporal regression; environmental degradation; environmental management

1. Introduction

Land cover change and deforestation resulting from economic development and population growth in developing countries have significantly affected the environment (Peng et al. 2015; Zoungrana et al. 2018). In tropical mountainous regions, deforestation for timber and agricultural development has been recognized as a common problem for several decades (Lambin et al. 2003; Zeng et al. 2021). Changes to vegetation cover and quality

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have significantly degraded the structure and function of ecosystems in this region, and have altered climatic patterns and the carbon cycle resulting in a wide range of other environmental concerns (e.g., problems associated with water supply, soil erosion, biodiversity) (Hughes et al. 2000; Sweeney et al. 2004; Chakravarty et al. 2012). Studying forest degradation and its environmental impacts requires that the necessary information to understand the human-environment interactions and their implications is obtained (Latocha 2009; Kirleis et al. 2011). Such knowledge can be utilized to develop forest management strategies and solutions which promote sustainable development (Huber et al. 2013; Christensen and Jokar Arsanjani 2020).

Traditionally, land cover categories (i.e., land cover types) that are classified from satellite images acquired every 5–10 years with common statistical analysis methods (e.g., overlaying two LULC layers) have been widely applied to examine deforestation (Disperati and Virdis 2015; Paudel et al. 2016; Yin et al. 2018). These studies have provided useful information to understand the forest change patterns (e.g., the area where deforestation occurs and the type of land cover that replaces these deforested areas). However, post-classification change analysis is typically limited in showing the trend of changes because performing spatiotemporal analysis in categorical LULC data requires complicated analytical procedures (Tang et al. 2021). In addition, findings obtained from LULC change analysis may not be reliable due to uncertainties in categorical LULC information (Li, Huang, et al. 2020).

The availability of high spatiotemporal resolution remotely sensed data and advanced spatial analysis tools and methods enable the research community to effectively investigate spatiotemporal patterns and trends of changes related to environmental problems (Wang and Myint 2016; Ohana-Levi et al. 2019; Berlanga-Robles and Ruiz-Luna 2020). Google Earth Engine (GEE), a cloud-based computing platform developed by Google, is an innovative application for rapidly and accurately processing vast amounts of time-series remotely sensed data (i.e., big data) (Gorelick et al. 2017). An application like GEE allows processing high spatial resolution data with various temporal coverage (e.g., seasonal, annual, or long-term time-series data) (Huntington et al. 2017). Methods of statistical analysis developed over the last few decades are significantly empowered when integrated with GIS tools and have been widely applied to Earth observation big data (i.e., time-series data) to quantify long-term trends and patterns of environmental changes at the pixel level (Comber and Wulder 2019; Li, Gui, et al. 2020).

Spatiotemporal analysis methods such as Mann-Kendal (MK) significance testing and Theil-Sen (TS) slope estimation have been applied to spatial data to examine spatiotemporal variations in vegetation dynamics that are associated with environmental problems (Hu and Xia 2018; Cortés et al. 2021). Geographically weighted regression (GWR), a spatial regression model, has been effectively employed to examine spatial non-stationarity in the relationship between environmental processes (Robinson et al. 2013; Mondal et al. 2015; Alibakhshi et al. 2020). Recently, emerging hot spot analysis has been utilized to identify trends in the clustering of time-series data (Harris et al. 2017; Purwanto et al. 2021). Despite the availability of various spatiotemporal analysis tools, an analysis that examines spatiotemporal patterns in forest cover change, spatial heterogeneity in the relationship between deforestation and its related environmental impacts, and time-series analysis of deforestation hot spots, has not been attempted. A comprehensive analysis integrating these spatiotemporal analysis techniques could be an effective solution to provide a more extensive understanding of forest degradation and associated environmental issues capable of delivering more knowledge around the practical implications of change for land and environmental policy formulation and management.

The primary goal of this study is to examine pressing environmental challenges associated with forest cover change, taking advantage of spatiotemporal analysis techniques and the availability of earth observation time-series data. The Central Highlands of Vietnam (also named Tay Nguyen), a priority region for the National REDD + Action Plan, was selected as the study area due to its essential role in the national environment and global GHGs mitigation program (Kissinger 2020). From an area with a low level of agricultural production, the Central Highlands has been intensively cultivated for the last 20 years and has become a significant agricultural production hub for Vietnam (Muller and Zeller 2002; Meyfroidt et al. 2013). The region has developed extensive industrial crops, specializing in coffee, pepper, rubber, cashew, tea, maize, and cassava, to respond to increasing demand in the international market (Kissinger et al. 2021). Consequently, large-scale deforestation has occurred due to extensive transformation of forested land to industrial cropland and other land uses. From 1975 to 2019, tree cover decreased from 67% to 46%, and the forest area declined by about 1.55 million ha (GFW 2020). Therefore, studying long-term changes in regional forests and the associated environmental parameters such as local climate and carbon cycle (i.e., land surface temperature (LST), evapotranspiration (ET), and gross primary productivity (GPP)) to determine where increasing or decreasing trends of environmental parameters occur and how these trends are related to deforestation is important to help provide a scientific basis for better forest management.

This study aimed to characterize the temporal pattern and rate of changes in forest cover across space, to determine how the long-term trends in deforestation have differed across the study area, and to quantify the heterogeneous relationship between vegetation change and related environmental impacts (i.e., LST, ET, and GPP). By demonstrating an approach that effectively integrates time-series remotely sensed data and spatiotemporal analysis methods, this paper describes an approach that can be applied in other regions experiencing similar environmental problems. This approach is expected to be especially useful in developing countries facing environmental challenges associated with negative impacts of LULC change.

2. Materials and methods

2.1. Study area

The Central Highlands, with five provinces (i.e., Gia Lai, Kon Tum, Dak Lak, Dak Nong, and Lam Dong), is one of seven economic regions in Vietnam (Figure 1). The region covers approximately 54,700 km^2 and has a total of 5.8 million people (GSO 2021). The study area is in the tropical equatorial monsoon region, but climatic conditions have typical tropical highland wet climate characteristics due to altitude effects. Mean annual temperature ranges from 21 °C to 27 °C and increases to the south. Yearly rainfall fluctuates from 1500 to 3000 mm per year, and over 90% of total precipitation is concentrated in the rainy season. A large area of the region is covered by basalt soil which is highly advantageous for cultivating perennial commercial crops such as coffee, rubber, and pepper. The Central Highlands is one of the greenest regions in Vietnam, with approximately 46% forest cover (GSO 2021), outstanding biodiversity, and unique species (Do et al. 2017). The region is home to 23 national parks and nature reserves, covering nearly 800,000 ha. Natural forest can be found in all districts, especially in the mountainous region.

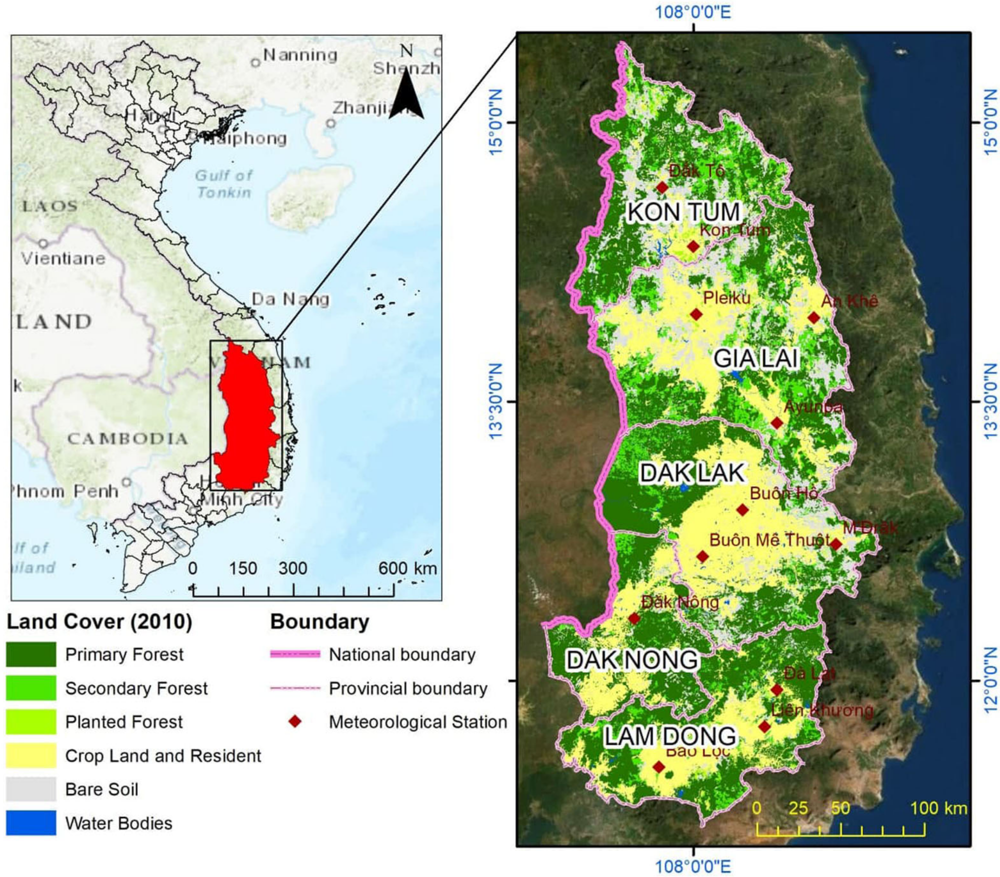

Figure 1. The pattern of land cover and location of the study area.

2.2. Data used

MODIS data has been widely used in environmental research in applications such as drought assessment (Boori et al. 2020), desertification monitoring (Tomasella et al. 2018), forest cover change (Othman et al., 2018), and fire detection (Frantz et al., 2016). MODIS data have also been used in many studies to examine the environmental issues at the local scale (Rotem-Mindali et al. 2015; Sidiqui et al. 2016; Paltsyn et al. 2017; Zhang et al. 2017) because they provide information that relates to a wide range of environmental parameters at a high temporal resolution.

In this study, MODIS Collection 6 products from 2001 to 2019, including Percent Tree Cover (PTC), Gross Primary Productivity (GPP), Total Evapotranspiration (ET), and Land Surface Temperatures (LST), obtained from Google Earth Engine (GEE) were used as the main resources to investigate forest cover change and its associated impacts that relate to environmental issues in the study area (Table 1). PTC is a direct indicator to detect deforestation and forest degradation (Gao et al. 2016). GPP is a typical index for studying the carbon cycle (Kotchenova et al. 2004). Long-term ET and LST can be used to examine changes in climate patterns, drought risk, and water balance, and ecosystems disturbances (Mu et al. 2013; Phan and Kappas 2018). A detailed description of PTC, GPP, ET, and LST is referred to Didan (2015), Dimiceli (2015), Running et al. (2015, 2017), and Wan et al. (2015).

Table 1. Earth observation data used in the study.

Dataset	Description	Units	Products	Pixel size	Temporal resolution*
PTC	Percent tree cover	%	MOD44B	250 m	Annually
ET	Total Evapotranspiration	$Kg/m^2/yr$	MOD16A3	500 m	Annually
LST	Land surface temperature	°C	MOD11A1	1000 m	Annually
GPP	Gross primary productivity	kgC/ha/yr	MOD16A2H	500 m	Annually

*Annual ET, LST, and GPP data are derived from the mean of the primary products (e.g., Daily, 8-Day, 16-Day) from the given year. Data were processed using Google Earth Engine.

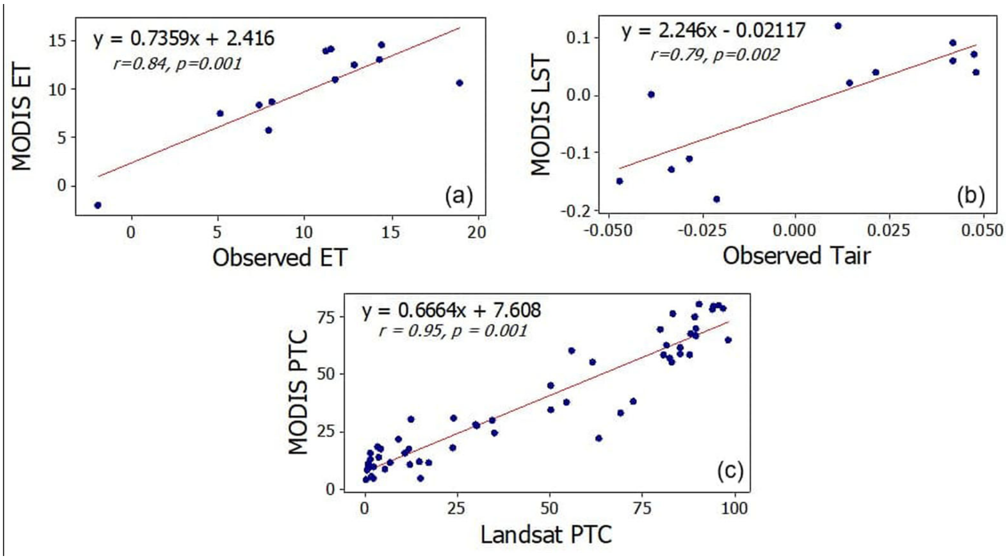

Figure 2. MODIS data verification showing the relationship between (a) MODIS Evapotranspiration (ET) and in-situ evapotranspiration (Observed ET), (b) MODIS Land Surface Temperature (LST) and air temperature (Tair), and (c) MODIS Percent Tree Cover (MODIS PTC) and Landsat Percent Tree Cover (Landsat PTC). Observed ET and Tair were obtained from 12 meteorological stations in the Central Highlands. The Landsat PTC data were obtained from Global Forest Change data. All the regression equations are statistically significant ($p < 0.01$).

2.3. Modis data assessment

An ordinary least squares (OLS) regression analysis between the MODIS data and *in-situ* measurements and high-resolution data was performed to validate the use of MODIS products in the study area (Figure 2). Climatological data, including air temperature and evapotranspiration measured from 12 weather stations in the study area, were used to evaluate the MODIS LST and ET. In addition, random samples from Landsat tree cover data accessed from the Global Forest Change project (Hansen et al. 2013) were utilized to verify the MODIS PTC. The MODIS GPP was not assessed due to the lack of suitable reference dataset. Results showed a high correlation between MODIS ET and field-measured ET ($r = 0.84$, $p < 0.001$) as well as MODIS LST and air temperature ($r = 0.79$, $p < 0.002$). In addition, the relationship between MODIS PTC and Landsat PTC was exceptionally strong ($r = 0.95$, $p < 0.001$). Given the correlation between MODIS data and referenced data in the study area is high, the MODIS data were determined to be suitable and valid for examining deforestation and environmental degradation.

2.4. Theil-Sen median trend and Mann-Kendall test approach

To conduct a spatiotemporal analysis of the deforestation and its related environmental parameters, annual trend and the significance of each environmental indicator were examined by integrating the nonparametric Thiel-Sen (TS) slope estimator and Mann–Kendall (MK) significance test. The TS slope estimate is the median of all the slopes calculated between observation values at all pairwise time steps (Wilcox 2017). The MK test is a nonparametric rank test that evaluates whether observation values tend to increase or decrease over time (i.e., the sign of the difference between later-measured data and earlier-measured data (Donald et al. 2011). This was applied to assess the statistical significance of any non-zero slope identified by the Thiel–Sen test (Zhou et al. 2020). The TS slope estimator can achieve reliable confidence intervals in the case of existing non-normal distribution data and is resistant to outliers (Carslaw and Ropkins 2012). The capability to deal with these issues is advantageous as both are commonly found in time-series environmental data. The MK trend test is also more flexible than other methods (e.g., OLS linear regression) as it takes the issues of seasonality, non-normality, missing values, and serial dependence into account (Alcaraz-Segura et al. 2010). Because MODIS PTC data is yearly product, it was not possible to assess seasonal deforestation. The MK significance test and TS slope estimator approach were performed using the Earth Trend Modeler, a tool integrated in Terrset Geospatial Monitoring and Modelling software (Clark Labs 2020). This tool was applied in our study to examine the annual trend of LST, PTC, ET, and GPP through the two following stages:

i. In the first stage, TS slope estimator was performed to calculate the rate of change in PTC, GPP, ET, and LST from 2001 to 2019 in the study area. The result from this step gives a slope map for each environmental parameter. Slope values greater than zero in PTC, GPP, and ET and smaller than zero in LST imply restoration and vice versa, negative slope values in PTC, GPP, and ET and positive slope values in LST mean degradation in the environment.
ii. In the second stage, MK test was applied to assess the statistical significance of any non-zero slope identified by the TS test. The resulting significance pixels show Z-scores, expressing levels of significance (α): $Z = \pm 2.576$ refers to $\alpha = 0.01$, $Z = \pm 1.960$ refers to $\alpha = 0.05$, and $Z = \pm 1.645$ refers to $\alpha = 0.1$.

2.5. Emerging hot spot analysis

Emerging hot spot analysis integrates the Getis-Ord Gi* statistic and the Mann-Kendall trend test (ESRI 2021a) to determine spatiotemporal patterns within time-series data. In our study, the Emerging Hot Spot Analysis tool in ArcGIS Pro (version 2.8) was used to identify patterns of PTC loss (i.e., deforestation) across the study area in the period of 2001–2019. The processes associated with deforestation hot spot analysis involve the following steps: (i) Time-series data was generated from the MODIS PTC product, which is in the form of a point dataset. The outcome is a spatiotemporal PTC dataset aggregating annual PTC into a space-time cube (i.e., space-time bins); (ii) The pattern of PTC loss for each bin is identified using Getis-Ord Gi* statistical analysis. This tool finds a statistically significant hot spot across the dataset based on the assumption that requires 'a feature have a high value and is surrounded by other features with high values as well' (ESRI 2021a); (iii) The nonparametric Mann-Kendall trend test evaluates the temporal trends in

Table 2. Categories of hot spot trends pattern (ESRI 2021a).

New Hot Spot	'A location that is a statistically significant hot spot for the final time step and has never been a statistically significant hot spot before'.
Consecutive Hot Spot	'A location with a single uninterrupted run of statistically significant hot spot bins in the final time-step intervals. The location has never been a statistically significant hot spot prior to the final hot spot run and less than ninety percent of all bins are statistically significant hot spots'.
Intensifying Hot Spot	'A location that has been a statistically significant hot spot for ninety percent of the time-step intervals, including the final time step. In addition, the intensity of clustering of high counts in each time step is increasing overall and that increase is statistically significant'.
Persistent Hot Spot	'A location that has been a statistically significant hot spot for ninety percent of the time-step intervals with no discernible trend indicating an increase or decrease in the intensity of clustering over time'.
Diminishing Hot Spot	'A location that has been a statistically significant hot spot for ninety percent of the time-step intervals, including the final time step. In addition, the intensity of clustering in each time step is decreasing overall and that decrease is statistically significant'.
Sporadic Hot Spot	'A location that is an on-again then off-again hot spot. Less than ninety percent of the time-step intervals have been statistically significant hot spots and none of the time-step intervals have been statistically significant cold spots'.
Oscillating Hot Spot	'A statistically significant hot spot for the final time-step interval that has a history of also being a statistically significant cold spot during a prior time step. Less than ninety percent of the time-step intervals have been statistically significant hot spots'.
Historical Hot Spot	'The most recent time period is not hot, but at least ninety percent of the time-step intervals have been statistically significant hot spots'.

the hot spots calculated from the previous step. The result from this step is a map of the deforestation hot spot that classifies the PTC loss hot spot into various types (Table 2).

2.6. Geographically weighted regression analysis

Spatial variation in the relationship between one spatial variable and another is referred to as non-stationarity (Shaker et al. 2019). To gain insight into the relationship between vegetation dynamics and environmental problems using spatial data it is important to account for non-stationarity using methods that measure local variation between response and explanatory variables (Zhou and Wang 2011). Geographically weighted regression (GWR) is a nonparametric model of spatial drift that relies on a sequence of locally linear regressions to produce estimates for every point in space using a subset of information from nearby observations (Szymanowski and Kryza 2012). In this study, we applied Geographically Weighted Regression (GWR) analysis to quantify the spatial relationship between vegetation trend (PTC change) and trend in environmental indicators (GPP, ET, and LST). A hexagon grid with a size of 10 km^2 was used as the geographical unit of analysis for regression modelling instead of the commonly used square grid due to its better performance in reducing spatial-auto correlation issues (Birch et al. 2007). The hexagon grid has a greater number of the nearest pixels (i.e., neighbourhoods) than a rectangular grid, and the distance between centroids is the same in all six directions. This advantage makes it a more efficient spatial analysis method once conceptualization of spatial relationship is based on using a distance band or neighbours number (Birch et al. 2007). Geographically Weighted Regression Analysis tool in ArcGIS Pro (version 2.8) (ESRI 2021 b) was employed to perform the regression. Three GWR models were created, one

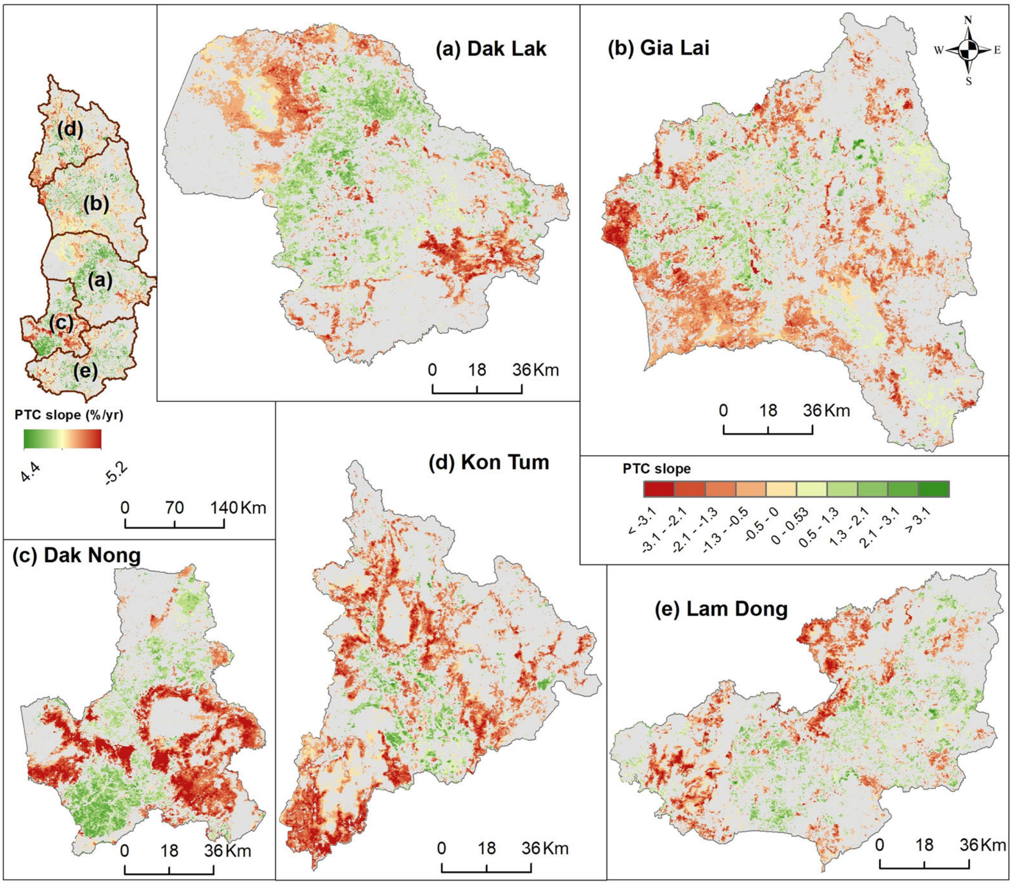

Figure 3. Spatiotemporal pattern of significant changes in Percent Tree Cover (PTC) in the Central Highlands from 2001 to 2019. All pixels are statistical significance ($p < 0.05$).

for each of the environmental indicators (i.e., LST, ET, and GPP) as the response variable, with the trend in PTC as the explanatory variable.

3. Results

3.1. Long-term changes in PTC pattern

The spatiotemporal trends of Percent Tree Cover (PTC) in the Central Highlands are shown in Figure 3. From 2001 to 2019, the region experienced both decreasing and increasing trends in tree cover (i.e., negative and positive changes). However, the positive trend was weaker than the negative trend, as indicated by the mean PTC slope value of −0.76% per year. This rate of change indicates that tree cover decreased about 14.5% in total from 2001 to 2019. Notably, when the PTC value decreased at a rate of 5.2% per year, some areas lost approximately 99% of PTC over nineteen years. Such as change rate can be considered severe deforestation because highly vegetated areas become effectively non-vegetated. Figure 3 demonstrates a significant change in PTC in all provinces. A remarkable decrease in PTC was concentrated in the north and southeast Dak Lak, widespread across Gia Lai and Kon Tum, distributed in southeast and southwest parts of Dak Nong, and prevalent in the north and northwest of Lam Dong. An increase in PTC was

Table 3. Change area in PTC by provinces (unit: km^2).

Provinces	PTC increase	PTC decrease	Net change
Dak Lak	1829	2618	–789
Dak Nong	1097	1932	–836
Gia Lai	1544	4012	–2468
Kon Tum	600	3202	–2602
Lam Dong	1187	1805	–618
Total	6257	13,569	–7313

found in a large area from the northeast and southwest Dak Lak, south-central Gia Lai, north-central and south of Dak Nong, south-central and southeast Kon Tum, and a large strip spreading from northeast to southwest Lam Dong.

Overall negative trend in PTC is dominant in the study area, and areas of PTC loss were found to be two times greater than PTC gain in all provinces (13,569 km^2 versus 6257 km^2, respectively) (Table 3). Kon Tum experienced the most significant forest cover loss among five provinces, with the area of PTC decrease much higher than PTC increase (e.g., a net change of -2602 km^2 or 26.82% of the total land area of the province). Dak Lak and Lam Dong showed the lowest rate of PTC loss compared to other provinces (e.g., 6% of total land area). The results suggest that deforestation remains a crucial issue in these provinces because total area of PTC loss was higher than PTC gain.

While the spatiotemporal pattern of significant changes in PTC (Figure 3) demonstrates a spatial trend of deforestation, information associated with PTC change by different groups of forest cover change provides an insight into the degree of deforestation that has occurred in the study area (Figure 4). Overall, the area of PTC loss is greater than that of PTC gain in all groups, and particularly dominant in groups which have forest cover loss value higher than 25% (Figure 4f). At a provincial level, Gia Lai and Kon Tum are two provinces that experienced the largest area of net PTC loss in the region, with most of this change involving three groups of forest cover loss (10–25%, 25–40%, and 40–60%). Changes in these groups were observed in northwest, southwest, north-central, and east-central Gia Lai (Figure 3b), and a large strip from northwest to southeast Kon Tum (Figure 3d). Dak Nong experienced a prevalence of PTC decrement at high rates (40–60% and greater than 60%). Given that 'forest is an area covered by 25% or greater canopy closure' (Hansen et al. 2010), areas having PTC loss within these groups can be considered highly severe deforestation due to extensive land cover conversion from forest to non-forest. Despite some net gain of PTC increment in Gia Lai, Lam Dong, and Dak Nong, benefits to the environment is not substantial because the increase of PTC in most of these areas is in the low-value group (e.g., less than 10% in PTC).

3.2. Spatiotemporal analysis of deforestation hot spots

The pattern illustrating clusters of PTC loss demonstrated by different types of the emerging hot spots is presented in Figure 5 and Table 4. From 2001 to 2019, six categories of hot spot trends are observed across the Central Highlands. These include the categories of 'consecutive hot spots', 'diminishing hot spots', 'intensifying hot spots', 'new hot spots', 'oscillating hot spots', and 'sporadic hot spots'. This variation indicates the complexity of deforestation in the region.

'Intensifying hot spots' are primarily clustered in the east of the study area, in areas such as the central to southwest Gia Lai and northern Dak Lak (Figures 3a and 3b). This trend means there is a high intensity of increasing deforestation in these areas. Information from Table 3 demonstrates that the category of 'intensifying hot spots' are

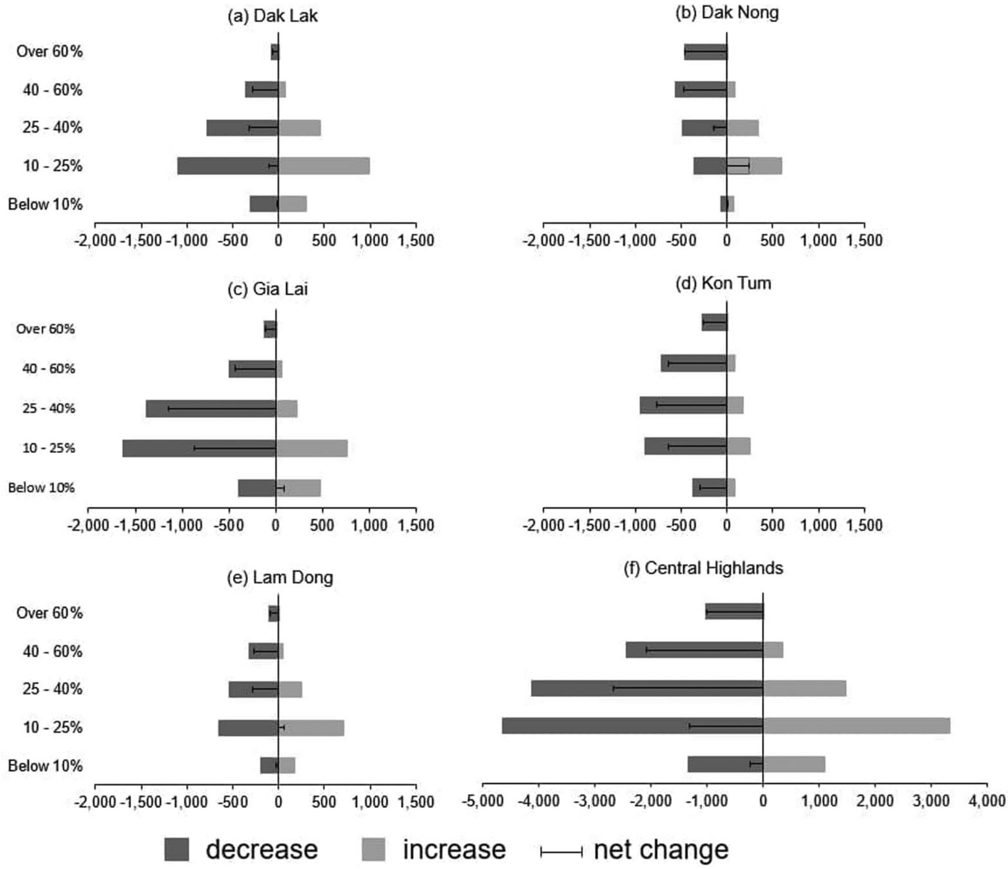

Figure 4. Change across provinces in sq. kilometres by different thresholds of tree cover change: very low (0–10%), low (10–25%), moderate (25–40%), high (40–60%), and very high (over 60%).

the most frequent of all hot spot categories, and the bulk of this is concentrated in Gia Lai (1223 hot spots) and Dak Lak (957 hot spots) (i.e., 92% of the total intensifying hot spots in the study area). 'Sporadic hot spots', indicating a fluctuating trend in deforestation, accounts for 1625 hot spots. This type of hot spot was seen in north-central Dak Lak (Figure 3a), southwest Gia Lai (Figure 3b), and spreads across other provinces. 'Oscillating hot spots' dominated in Dak Nong (879 hot spots), expanding from the east to the west of the province (Figure 3c). Also, large clusters of this type of hot spot were found in southeast Dak Lak and in the west of Gia Lai (Figures 3a-3b). The new cluster of PTC loss (i.e., 'new hot spots') emerged in southeast central Dak Nong (Figure 3c), central Kon Tum (Figure 3d), and southwest Lam Dong (Figure 3e). 'Diminishing hot spots', the least severe type of hot spot which indicates a decreasing trend in deforestation, occupied a very limited number (36 hot spots) compared to other kinds of hot spot.

3.3. Relationship between forest cover loss and associated environmental parameters

Regression analysis to investigate trends between PTC change and changes in GPP, ET, and LST was carried out to understand how the long-term change in forest cover affects regional climate and carbon cycle pattern status. Trends in PTC and associated

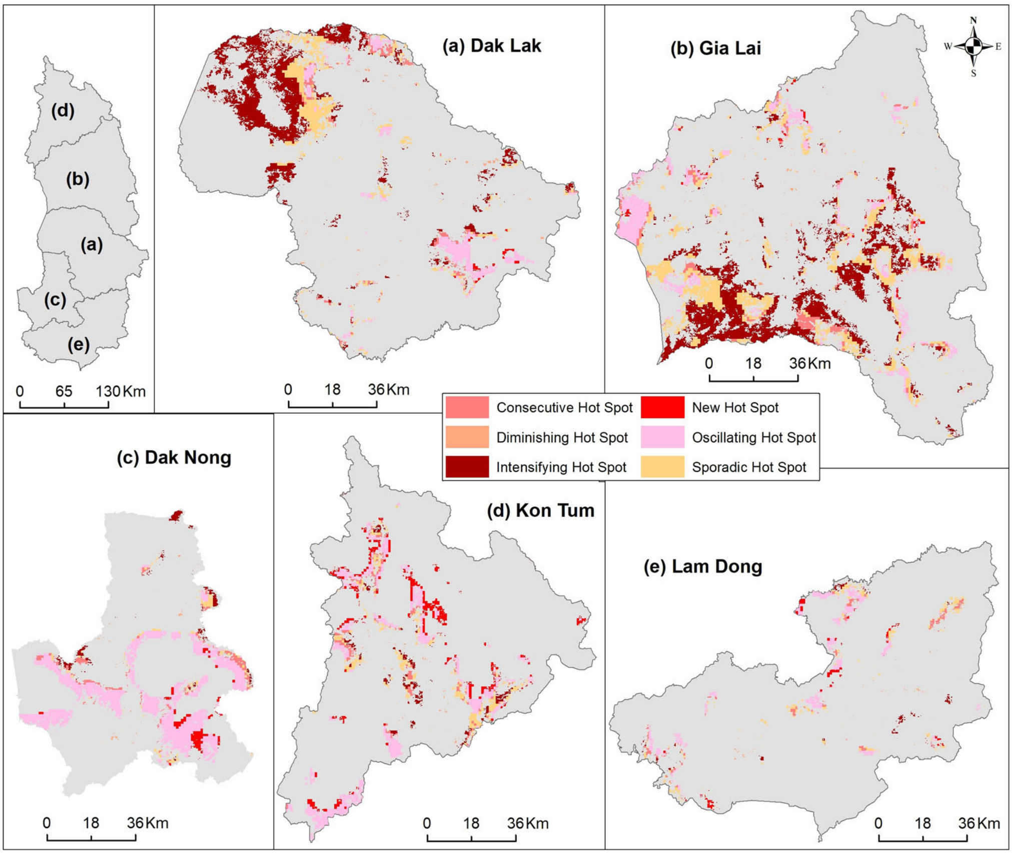

Figure 5. Emerging hot spot map of forest degradation in five provinces in Central Highlands: (a) Daklak, (b) Gia Lai, (c) Dak Nong, (d) Kon Tum, and (e) Lam Dong. Hot spot trends and patterns are quantified from time-series PTC data from 2001 to 2019. All pixels are statistically significant ($p < 0.05$). Grey areas are other changes such as cold spots or no pattern detected and hot spots that are not statistically significant.

Table 4. Number of emerging hot spots by provinces (1 hot spot equals the size of 1 km^2).

Types of hot spot	Dak Lak	Dak Nong	Gia Lai	Kon Tum	Lam Dong	Total
Consecutive Hot Spot	125	101	201	108	69	604
Diminishing Hot Spot	11	3	8	7	7	36
Intensifying Hot Spot	957	75	1223	83	32	2370
New Hot Spot	20	72	36	213	40	381
Oscillating Hot Spot	270	879	499	463	187	2298
Sporadic Hot Spot	412	71	852	179	111	1625
Total	1795	1201	2819	1053	446	7314

environmental variables (GPP, ET, LST) were obtained from the time-series trend analysis using the MK-TS approach. Table 5 summarizes results from the GWR models and provides a general understanding of the relationship between forest cover change and its related environmental impacts. *Adjusted* R^2 values (0.733, 0.683, and 0.887) indicate that PTC change explain 72.9%, 67.7%, and 89.4% of the total variation in GPP, ET, and LST changes across the study area, respectively. Low values of Moran's I index that are −0.006, −0.009, and 0.007 concurrent with all p-values > 0.05 demonstrate that spatial autocorrelation in three models is not significant. The mean slope coefficients (mean β values) that are 3.043, 5.039, and −0.077 indicate a direct (i.e., positive) correlation

Table 5. Summary of parameter estimates and diagnostics for the relationship between PTC change and environmental indicators using Geographically Weighted Regression.

Variables	GPP slope	ET slope	LST slope
Intercept	3.540	8.218	0.010
Mean β	3.043	5.039	−0.077
S.E.	0.760	1.703	0.017
Goodness of fit			
AICc	21,240.27	30,554.36	−12,306.08
Adjusted R^2	0.729	0.677	0.894
Spatial autocorrelation			
Moran's Index	−0.006	−0.009	0.007
p-value	0.440	0.223	0.364

Mean β is the average local estimates; S.E. is the mean standard error of the local parameter estimates; AICc is the corrected Akaike Information Criterion.

between PTC changes and changes in GPP and ET, and an inverse relationship between trends in PTC and LST. In other words, an increasing trend in tree cover will lead to an upward trend in GPP and ET and a downward trend in LST and vice versa. For instance, a 1% increase in PTC would lead to an increase of 3.043 kgC/ha in GPP, an increase of 5.039 kg/m^2 in ET, and a decrease of 0.077 °C in LST.

The spatial variation (i.e., spatial non-stationarity) in the relationship between forest cover change and change in environmental parameters across space is presented in Figure 6. The positive correlation between PTC change and a change in GPP in the south and southwest Kon Tum, northwest and southwest Gia Lai, northwest and central Dak Lak, and northeast Dak Nong was found to be 2–3 times stronger than other areas (Figure 6a). For the PTC-ET relationship, the strongest positive correlation was seen in the southwest and central Kon Tum, northwest, and southwest Dak Lak (Figure 6b). In the inverse correlation between PTC and LST, the most substantial impact of tree cover change on LST change was found in the west and southwest parts of the Central Highlands (e.g., northwest Dak Lak, northeast and southwest Dak Nong) (Figure 6c). These coefficient patterns that are closely aligned with the pattern of PTC slope map (Figure 3) illustrate that change in the PTC can significantly affect the local climate pattern and carbon cycle and that the relationships are varied subjected to trend and rate of PTC change. The GWR coefficient maps, however, reveal some areas with an inverse correlation between PTC and ET, particularly in the north and northeast Kon Tum, northeast and southeast Gia Lai, the south of Dak Lak, and the north and southwest Lam Dong. As mentioned previously, changes in PTC explains 67.7% of the total variations in ET, and an inverse relationship observed in these areas may be due to the impacts of other factors (e.g., agricultural practices, tree species, changes in other land use types). For instance, a conversion from forest to cropland may lead to an increase in ET resulting from significant evaporation which takes place after irrigation (Al-Kaisi et al. 2009).

Because the GWR model provides local coefficient values for the relationships between PTC and environmental indicators, it enables a further examination of how these relationships vary by types of deforestation hot spot (Table 6). The highest regression coefficients are seen in the 'intensifying hot spots' category, suggesting that this type of deforestation creates the most significant impact on the environmental changes. For instance, mean β values of 9.933, 4.70, and 5.448 in the PTC-ET relationships (Table 6) demonstrate that a decrease in ET due to the 'intensifying hot spots' deforestation may be $1.8 - 2.1$ times higher than that of decrease in the 'new hot spots' and 'diminishing hot spots'. Next to this is 'sporadic hot spots' that substantially affects the environment because this type of deforestation fluctuates over time (i.e., 'an on-again then off-again hot spot'). Lower value

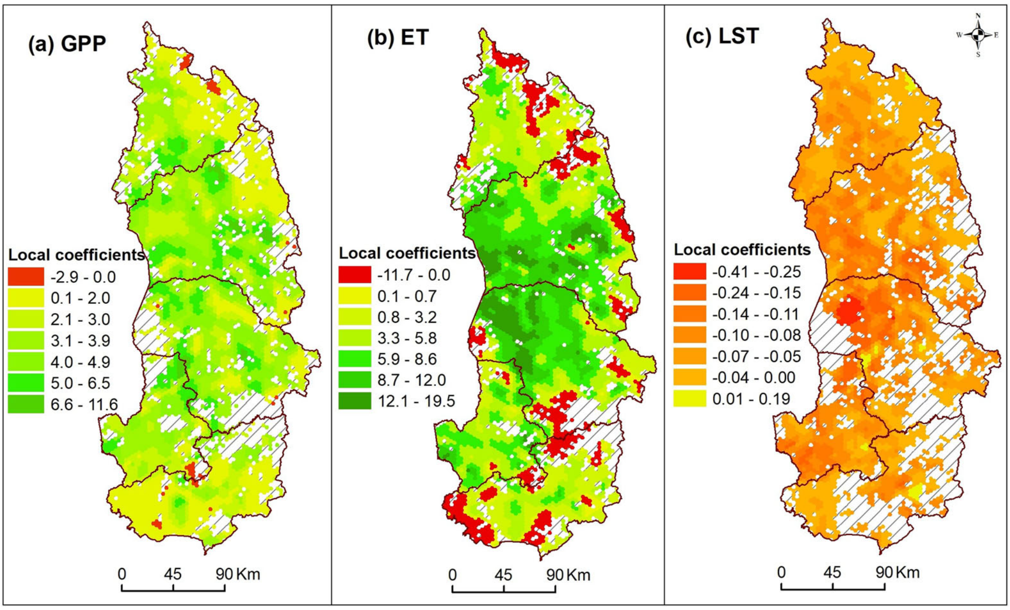

Figure 6. Local coefficients map showing the relationship between Percent Tree Cover (PTC) and environmental indicators: (a) Gross Primary Productivity (GPP), (b) Evapotranspiration (ET), and (c) Land Surface Temperature (LST).

Table 6. Mean coefficients for the relationship between forest cover change (PTC) and changes in environmental indicators (GPP: Gross Primary Productivity, ET: Evapotranspiration, LST: Land Surface Temperature) by types of hot spot.

Hot spot pattern	PTC-GPP	PTC-ET	PTC-LST
Intensifying Hot Spot	4.212	9.933	−0.128
Sporadic Hot Spot	3.933	7.790	−0.091
Consecutive Hot Spot	3.899	6.569	−0.088
Oscillating Hot Spot	3.501	6.190	−0.079
New Hot Spot	3.034	4.701	−0.065
Diminishing Hot Spot	3.115	5.448	−0.098

of local regression coefficients in the 'diminishing hot spots' and 'new hot spots' indicate a decreasing trend in deforestation would have the least impact on the environment.

4. Discussion

Our study found that there has been significant deforestation in the Central Highlands of Vietnam, demonstrated by a net loss of approximately 14.5% in tree cover from 2001 to 2019. This decrease can be seen to negatively impact the carbon cycle and climate pattern, through a decrease in GPP and ET, and an increase in LST. According to an investigation from Global Forest Watch (GFW 2020), nearly half of the forest loss in the region in the last twenty years is humid primary forest. Despite an increase in forest cover in some areas, the study area experienced considerable land and environmental degradation because most of new forest growth is monocultural plantation (e.g., exotic trees) (Kissinger et al. 2021) which does not provide the same level of biodiversity, watershed protection, and natural hazards mitigation (e.g., landslide) as primary forest (Liu et al. 2018). The general finding of deforestation and its negative impact on the environment demonstrated in this research is consistent with previous studies in the Central Highland

Table 7. Area of PTC loss by slope class.

	Degree of terrain slope			
Level of PTC loss	Below 8°	8° – 15°	15 – 25°	Over 25°
< 10%	212	134	200	46
10-25%	1032	448	478	79
25-40%	1080	456	412	52
40-60%	700	310	275	28
> 60%	269	114	77	8
Total	3293	1462	1442	213

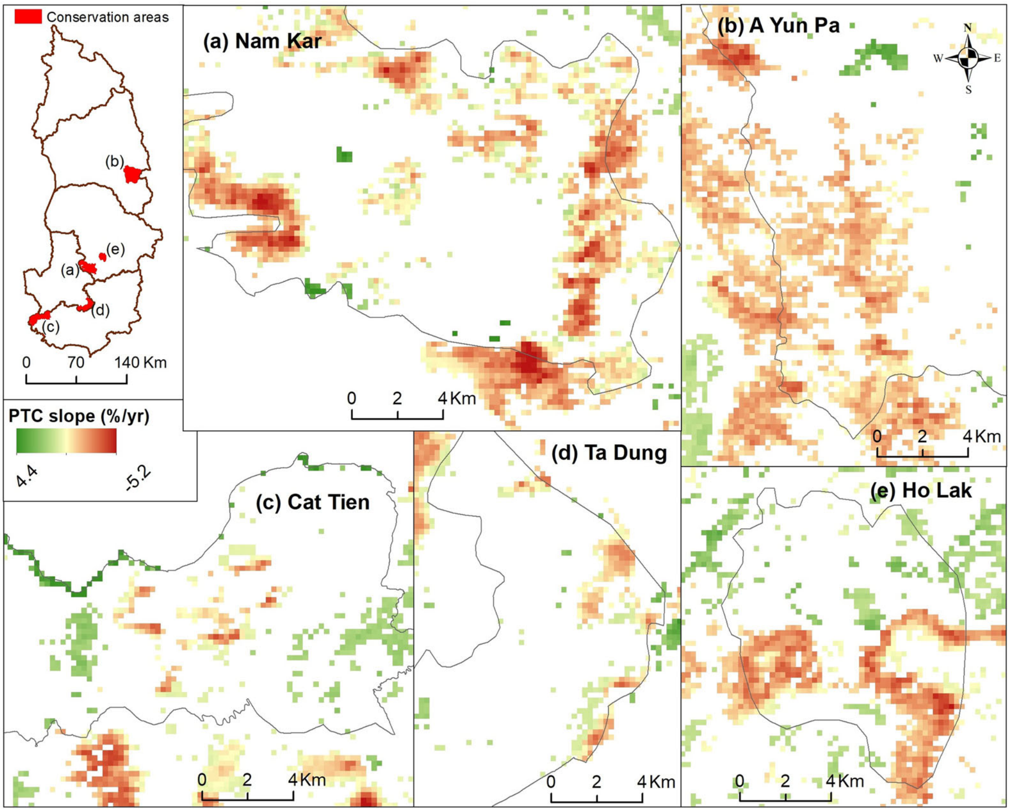

Figure 7. Significant decrease in Percent Tree Cover (PTC) within national conservation/protected areas in the Central Highlands from 2001 to 2019. All pixels are statistically significant ($p < 0.05$).

provinces (Meyfroidt et al. 2014; Son et al. 2015; Van Khuc et al. 2018) and other international case studies (Wang and Myint 2016; Silva-Araújo et al. 2020; González-González et al. 2021; Singh and Yan 2021; Zeng et al. 2021).

The contribution of this study is that it reveals that deforestation and environmental degradation occurred in highly vulnerable areas. By integrating the PTC trend map with topographic data, we observed that a substantial amount of the high rate of deforestation was found on hill slope areas (e.g., a total of 852 km^2 of PTC decrease with a rate of greater than 25% tree cover loss on sites with a slope of $15 - 25^{\circ}$ and greater than 25°) (Table 7). Located in a climatic regime associated with tropical monsoon conditions which have high intensive rainfall in the wet season and a severe water deficit in the dry season (Walsh and Lawler, 1981; Mohamadi and Kavian 2015; Chalise et al. 2019),

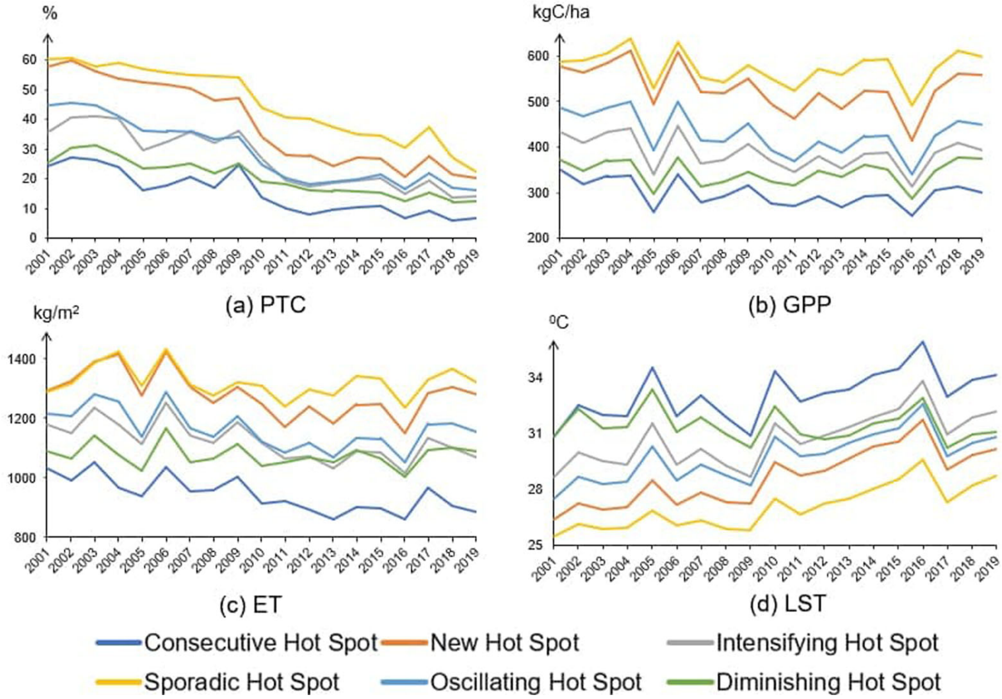

Figure 8. Environmental trend by different types of hotspots: (a) Percent Tree Cover (PTC) (b) Gross Primary Productivity (GPP), (c) Evapotranspiration (ET), and (d) Land Surface Temperature (LST) in the Central Highlands from 2001 to 2019.

deforestation on steep-land areas in the Central Highlands will create a potential for more severe impacts associated with environmental hazards than other regions (Forbes and Broadhead 2013; Korup et al. 2019).

A high rate of PTC loss (10–35%) was also found in many nature conservation areas (i.e., national parks and protected areas) (Figure 7). Our study demonstrates that deforestation has been happening inside the national protected area differently from the common way of deforestation in the rest of the study area which has primarily experienced clear-cutting. Valuable big trees have been gradually cut down over a long time, even in national parks, the most protected forest areas that produce substantial environmental and biological benefits (Hung et al. 2010). This kind of deforestation not only changes the forest cover but also can lead to a significant reduction in forest quality.

More significantly, this study provides insight into deforestation patterns and the spatial non-stationary relationship between forest cover loss and environmental changes. Results obtained from emerging hot spot analysis demonstrate that forest cover loss took place in various forms, as indicated by different types of 'deforestation hot spots'. Although all kinds of deforestation hot spots have a negative effect on the environment, the impacts of deforestation vary between them, depending on trends in each type through time. For instance, the presence of 'intensifying hot spots' can significantly accelerate forest loss, whereas forest loss is minimized with 'diminishing hot spots' (Figure 8). Considering that information derived from emerging hotspot analysis can be used to determine priority areas in forest conservation, this is a significant contribution of this study compared to previous studies that did not examine spatiotemporal trends and patterns of deforestation (Sanchez-Cuervo and Aide 2013; Reddy et al. 2016; Philippe and Karume 2019).

Regarding the relationship between long-term trends in forest cover loss and environmental degradation, this research has provided evidence that the impacts of deforestation on the environment differ across the study area and are strongly affected by the types of spatiotemporal deforestation (i.e., hot spot types). This achievement helps fill the gaps in recent studies that have not integrated spatiotemporal analysis with deforestation-related environmental issues and characterize the spatial variations in the relationship between them (Ishtiaque et al. 2016; Wang and Myint 2016; Harris et al. 2017; Singh and Yan 2021). Using emerging hotspots to analyze the spatiotemporal change in deforestation makes a significant contribution to better understanding this environmental problem, particularly when examining the long-term trend in deforestation and its impacts on environmental issues.

Based on the results obtained from our study, we propose several recommendations for environmental planning and management policy and practices. Firstly, time-series data and spatial analysis tools and approaches are strongly recommended for environmental planning and management to obtain critical information for making decisions. By applying these tools and techniques, planners/managers can have fast and contemporary access to useful environmental information. They can employ an action plan and strategy suited to the 'right places' based on more accurate and detailed information (e.g., pixel level). Also, utilizing environmental data at high temporal resolution (e.g., monthly or weekly frequency data) is fundamental for determining 'right time' management as the environmental issues can be monitored and assessed frequently. It provides an option to instigate timely intervention actions when the emergent environmental situation is observed. Secondly, it is crucial to develop and apply more comprehensive environmental indicators in management practices. For instance, different ecological parameters acquired and processed from earth observation data reflect the forest health and should be integrated with traditional primary indicators (e.g., forest types, area, and cover) in forest management. The advantage provided by this approach offers an efficient means to gain deeper insight into the forest cover and quality. From what this research demonstrates, we suggest that the Central Highlands government needs to pay attention to the current issues in forest loss and related environmental problems, especially in areas where the deforestation pattern is categorized as having 'intensifying hot spots' or is occurring in steep-lands and conservation zones. We recommend that the provincial-level decision-makers apply appropriate policy and take proper actions to stop, or at least minimize deforestation, and implement better agricultural land use practices. In addition, we suggest that local government working on land use and forest inventory and management consider both forest cover change and other criteria that present forest quality and related environmental changes to evaluate deforestation and land degradation.

Although the current study provides significant contributions, some improvements are needed in future studies. Considering that a wide range of long-term environmental data can be obtained from remote sensing (e.g., drought severity, forest fire, air quality), it is crucial that future research applies more environmental indicators to achieve more comprehensive findings. Given that examining seasonal variations in deforestation can help to obtain more informative findings that provides better basis for developing forest management strategies (e.g., deforestation may occur extensively in dry season), it is worth considering this type of analysis in future studies. In addition, an analysis of the causes of deforestation, for example, how socio-economic drivers and structure of the landscape affect the spatiotemporal trend and pattern of deforestation, is essential to understand the deforestation dynamics and hence, develop more effective afforestation solutions.

5. Conclusions

This study investigated the spatiotemporal trends of deforestation and the relationship between tree cover loss and environmental degradation in the Central Highlands of Vietnam. Results from our research revealed that deforestation occurred extensively in the Central Highlands. For the period of 2001–2019, tree cover has decreased significantly at a rate of 0.76% per year, making a total loss of 14.5% in PTC. A total of 7314 PTC loss hot spots covering different types of deforestation patterns were identified, of which the 'intensifying hot spots', the most negative deforestation, occupies the largest number (i.e., 2370 hot spots). It is notable that within an area of 13,569 km^2 a significant decrease in PTC was observed, substantial area of deforestation has occurred in steep-land (852 km^2) and conservation areas. Spatial regression analysis between forest cover change and other environmental parameters (GPP, ET, and LST) demonstrated that forest loss is the leading cause of environmental degradation, showing that PTC changes can explain 68–90% of variations in the local environment. GWR results also demonstrate that the impacts of forest loss on local climate pattern and carbon cycle are heterogenous across space and strongly influenced by types of deforestation hot spots. We believe that applying complex environmental indicators, including PTC, GPP, ET, and LST, brings more relevant findings than analyzing a single parameter. Moreover, spatiotemporal analysis methods such as MK-TS, time-series hot spot analysis, and spatial regression with GWR provide more meaningful and informative results. The spatiotemporal statistical approach applied to remotely time-series data can be used to solve complex questions (e.g., quantifying the trend, pattern, and rate of vegetation dynamics and examining the spatial relationship between vegetation and environmental changes). We anticipate that our analysis of deforestation, and the methods described, will help managers, planners, conservators, and policy makers provide better management options for a sustainable future and that our analysis will assist in future research to reveal the nature and causes of deforestation and environmental degradation.

Disclosure statement

No potential conflict of interest was reported by the authors.

Data availability statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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