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Thi Lan Pham · Ha Le Thi Thu ·
Nghia Nguyen Viet *Editors*

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Contents

Chapter 32
Dynamics and Determinants of Forest Changes Across Mainland Vietnam in the Recent Three Decades

Duong Cao Phan, Ba Thao Vu, Dang An Tran, Vuong Trong Kha, and Kenlo Nishida Nasahara

Abstract In the recent few decades, Vietnam has experienced a considerable change in land use/land cover (LULC), especially forest land. However, there is not a comprehensive analysis of the dynamics and drivers at the nationwide spatial scale for a long-term period. In this research, we estimate the socioeconomic and biophysical drivers of forest changes at the commune scale. Utilizing our results from the Vietnam-wide annual LULC database available in the Japan Aerospace Exploration Agency (JAXA), we first computed the dynamic changes in forest land from 1990 to 2020. To decide the major drivers of the changes, we conduct a synthesis of case studies working on the analysis of the forest changes in Vietnam at various spatial levels. Subsequently, a machine learning technique was adopted to measure the drivers of the forest changes. Our results indicate that although the forest area has increased from 2005 to 2010, it has undergone a decrease over the full study period. There is a dramatic conversion between forest and agricultural land, especially in the North-West and Central Highlands. This conversion is mainly driven by agricultural expansion/shifting, topographic position index, accessibility/infrastructure,

Duong Cao Phan and Ba Thao Vu these authors contributed equally to this work.

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population growth/migration, and distance to systems such as irrigation, drainage, and mining/industry. The identification of the drivers in this study is likely to help enhance the accuracy of the land use/land cover change prediction. These findings provide coherent evidence-based information about the dynamics and drivers of forest changes at the nationwide spatial and decadal temporal scales and thus can support informing land policies in Vietnam.

Keywords Land use land cover change · Forest change and transition · Drivers · Machine learning techniques · Vietnam

32.1 Introduction

A change in land cover refers to the alteration of the biophysical surface of the Earth while land-use changes can be defined as variations in the way of using and managing a specific land area. Due to a direct connection between these two terms, land use/land cover change (LULCC) is generally used in the literature. One of the greatest changes in LULC is forest transition, especially forest degradation and deforestation. The unexpected change of forests impacts adversely on regional climate extremes (Findell et al. 2017), biodiversity (Semenchuk et al. 2022), and ecosystem services (Chung et al. 2021). As a result, proper estimations of forest changes and drivers is a central topic in international discussions and projects such as Paris Agreement and Reducing Emissions from Deforestation and Forest Degradation (REDD+) (Winkler et al. 2021). Long-term monitoring and interpreting of forest changes and drivers at a large scale and a fine spatial level provide evidence-based information for these discussions and projects. This information is also essential to making decisions in informing policy, planning, and managing forest resources.

Despite its importance, the detailed long-term estimation of forest transition is challenging, especially in developing regions, which frequently have a lack of information about the accurate datasets of forests for a long period. Recent evidence suggests that many developing countries are short of professional competence to generate fine spatiotemporal and accurate forest mapping resources (Saah et al. 2019). For example, a careful synthesis of over 200 case studies focusing on forest and agricultural land in South and Southeast Asia shows that although numerous studies have been conducted in certain countries such as India and Indonesia, few studies have been done in the other countries of the regions such as Cambodia, Laos, and Vietnam (Xu et al. 2019).

Vietnam has a major resource of tropical forests, but it has undergone highly dynamic changes over the recent three decades (Goldblatt et al. 2018; Phan et al. 2021a). These changes are expected to adversely influence the long-term balance of ecosystem services (Truong et al. 2018) and climate (Laux et al. 2017). Unfortunately, very few accurate and consistent datasets of forests have been conducted for a long-term period across the country. According to the report of the general statistics office on forest management, available five-year-interval national-scale forest maps are frequently utilized by local policymakers. These maps are not always meet the requirement of all users and are not frequently published to various institutes, organizations, and analysts. Up to date, some data sources have developed, but their differences, for example, production methods, producers, and input data usage result in inconsistencies in the resultant data products (Saah et al. 2019). Likewise, regional and global products have limitations when they are applied for analyses at a local-level scale. They cannot reflect accurately at a local and a national scale due to their coarse spatial resolution and low accuracy (Phan et al. 2018, 2021b; Hansen et al. 2013). These limitations challenge the effective usage of the existing forest data sets to provide scientific information for decision-makers to inform coherent policies, do long-term strategic planning, and offer corporate management.

Currently, we have first created a database for the Vietnam-wide annual land use/cover data sets (VNLCD) from 1990 to 2020 (Phan et al. 2021a). Although the database does not focus only on forests, it is beneficial for the estimations of forest changes and drivers. First, the accuracy of the forest class is high. The database contains variously different LULC, which allows for measuring the transition between forests and other land types.

Although we have a manuscript talking details about how the database has been conducted (Phan et al. 2021a), we herein summarize the process for a general understanding. Specifically, a state-of-the-art framework was established utilizing various ground-based and satellite-based data sources, including Landsat and Sentinel sensors. The framework contained an automatic training migration model and an optimal approach for post classification optimization. The established approach could address issues such as cloud-contaminated problems by employing the availability of multiple spatiotemporal data, thus improving the accuracy of mapping. The satellite data were separated into wet seasons (May–November) and dry seasons (December to the next April) to identify the changes in LULC phenology, including forest and agriculture. The automatic training migration model offered a practical mode for collecting reference data over the recent three decades. Regarding the land cover classification system (LCCS), we applied the standard land cover scheme, viz. Land Cover Classification System with necessary modifications according to the local biophysical environment and end-users' suggestions in Vietnam. That is, ten land cover types (Fig. 32.4) were decided. Applying a benchmark (Olofsson et al. 2014), the quality of the VNLCD was statistically validated with ground-based reference data derived from extensive field surveys (from 2015 to 2020) and inventory data over the country. Different metrics were provided, including overall accuracy, kappa coefficients, and standard error of the mean. The VNLCD was published on the Japan Aerospace Exploration Agency website.

This paper aims to explore the dynamics and drivers of forest changes across mainland Vietnam. To this end, we first analyze the forest change from 1990 to 2020 over the study area, utilizing the VNLCD. We then conduct a synthesis of the case studies to identify major drivers of the forest changes before deciding the selected major drivers for this study. The remaining main part of the paper is to quantify the drivers using a logistic regression model. This is the first study to undertake a longitudinal analysis of the long-term dynamics and drivers of the forest changes in

Vietnam. It provides an important opportunity to advance the understanding of the pattern, rate, and process of forest changes at a commune level, which can provide insights into informing more coherent policy to enhance the management of forest in Vietnam and expecting to apply in other tropical regions.

32.2 Materials and Methods

32.2.1 Forest

Forests provide with different valuable services such as soil erosion protection and habitat provision for animals and humans. In the field of ecology, various definitions of forests are found. In this study, we adopted the definition of forests provided by the Food and Agriculture Organization of the United Nation (FAO). Herein, forest is defined as "land spanning more than 0.5 ha with trees higher than five meters and a canopy cover of more than 10%, or trees able to reach these thresholds in situ. It does not include land that is predominantly under agricultural or urban land use". Also, mangrove is not defined as forests in this study.

32.2.2 Forest Diversity and Change Quantification

We first estimated and removed possible errors in the VNLCD. Although the VNLCD had a high level of accuracy, there might be misclassifications due to the effects of different climate situations and changes in plant phenology. The misclassifications would happen a few times in the time-series maps. To eliminate the errors, we created occurrence maps derived from the 1990 to 2020 time-series maps with arbitrary quantiles, including the first quartile, third quartile, and ninetieth percentile. For each land type, we overlaid the occurrence map on the fine-resolution images in Google Earth to identify misclassifications. With a trial-and-error technique, we found that the third quartile was the best threshold to eliminate possible misclassifications. Subsequently, we quantified the dynamics of forestland, including gain, loss, and major conversion from 1990 to 2020. We also estimate the diversity of forest changes by computing the number of changes between forest and non-forest land at a commune scale over the recent three decades (Fig. 32.2).

32.2.3 Hotspot Analyses

Changes in LULC are interests, but the change might not be statistically significant, biasing the estimation of main drivers. To increase the reliability of the estimation, we employed a hotspot analysis to identify the statistically significant changes. Although several approaches have been established to estimate hotspots, Getis-Ord G_i^a (Ord and Getis 1995) has been practically applied in the geographic research (Ma et al. 2012). Hence, we employed the Getis-Ord G_i^a method to compute z-score and p-value for each area of interest (ROI). An ROI that has a high z-score and a small p-value is a significant hotspot while a coldspot has a low negative z-score and a small p-value. Herein, the ROI that has a z-score greater than three was defined as a hotspot. The hotspot analysis was performed at the commune level known as the ROI. We computed Getis-Ord G_i^a values as follows Eqs. (32.1), (32.2) and (32.3). The Getis-Ord local statistic is given as:

$$G_i^a = \frac{\sum_{j=1}^{n} w_{i,j}x_j - \overline{X}\sum_{j=1}^{n} w_{i,j}}{S\sqrt{\frac{n\sum_{j=1}^{n} w_{i,j}^2 - \left(\sum_{j=1}^{n} w_{i,j}\right)^2}{n-1}}} \tag{32.1}$$

$$\overline{X} = \frac{\sum_{j=1}^{n} x_j}{n} \tag{32.2}$$

$$S = \sqrt{\frac{\sum_{j=1}^{n} x_j^2}{n} - \left(\overline{X}\right)^2} \tag{32.3}$$

where G_i^a is Getis-Ord local statistics; x_j is the attribute value for feature j; $w_{i,j}$ is the spatial weight between feature i and j; and n is equal to the total number of features.

32.2.4 Case-Study Synthesis

We conducted a review of 47 publications to detect the drivers of spatio-temporal changes in forest land in Vietnam. We used the query expression "TI = (drivers OR drivers OR causes OR dynamics AND land*) AND TS = (Vietnam OR "Viet Nam" AND land*) AND TS = (*fores* OR defor* OR refor* OR degrad*)" to search the publications in Web of Science and Google Scholar databases. Then, we eliminated duplicates before gathering 456 publications in total, of which about 357 publications worked on LULC, including forests. Reading the titles and abstracts of the 357 publications, we eliminated 189 publications, which did not discuss forest topics. Among 168 publications remained, the third-fourth mainly worked on the general LULC and LULCC assessment. Finally, we selected 47 publications, which worked on estimating the drivers of forest changes. After the careful scanning of the full publications, we noted study topics, main drivers, research places, research periods, and approaches applied by the selected publications. If a major driver was noted in the publications, we defined it as a major driver. Otherwise, the mentioned drivers in the publications could be seen as the main drivers. Similar drivers were merged to generalize the drivers. They are presented in Table A.1 (Supplementary document).

32.2.5 Proxy Data Drivers

The main biophysical and socio-economic drivers (Sect. 32.2.4) were derived from different sources. Most of the data were extracted annually from the General Statistics Office of Vietnam (1990–2020; household surveys). They were originally presented in various formats including vector, tabular, and raster formats with different spatial resolutions. After that, considerable efforts were made to interpret the data before they were used for the coming analysis. Since the data had different spatial resolution, we kept the original spatial resolution and computed mean values at the commune scale. Then, for the time-series data (e.g., climate) we computed mean, rate of change, and standard deviation values over the study period (1990–2020). For the constant data (e.g., elevation and slope) which were insignificantly alter over the study period, we computed mean values in the area of interest. Details about the proxy drivers are presented in Table A.2 (Supplementary document).

32.2.6 Handling the Multicollinearity of the Driver Proxy Data and Modelling Selection

Multicollinearity causes the inaccurate assessment of the regression coefficients. Herein, we first detected the high level of multicollinearity between the driver variables by computing the variance inflation factors (VIF). We then excluded the driver proxy variables which have a high level of multicollinearity or VIF > 10 (Supplementary Document: Fig. A.1) (Hsieh et al. 2003). We acknowledged this limitation to reduce the analysis bias of the regression model.

It is noted that even though several models have been established to estimate the drivers of LULCC, there is not the best model. The performance of a model varies according to certain research cases. When a model is selected, it should be considered major factors, including reliability, generalizability, computational cost, and stability (Sun et al. 2022). Recently, a logistic regression model has been commonly applied for identifying the drivers of LULCC, due to its clear understanding and impressive performance (Xu et al. 2019). A logistic regression model, therefore, was applied in this study.

32.3 Results and Discussion

32.3.1 Synthesis of the Case Study

The detailed drivers of the forest gain and loss from the synthesis of 47 case studies are presented in Table A.1 (Supplementary Document). Only eight studies worked on a national scale (including a regional scale covering Vietnam) while the others were conducted at smaller areas from a village to provincial scale. Most studies quantified the drivers utilizing quantitative methods such as logistic regression, multiple correlation analysis, and linear regression whereas ten studies interpret the drivers based on interviews, fieldwork surveys, and historical data. There was a larger number of studies on the drivers of forest loss (deforestation) in comparison to forest gain (reforestation/afforestation). The frequent distribution of the main drivers is presented in Fig. 32.1. They include socioeconomic drivers such as policy and income, and biophysical drivers such as climate and topography. As can be seen from the figure, the socioeconomic drivers were mentioned more frequently than the biophysical drivers (47 against 33, respectively). Regarding the forest loss, frequently mentioned drivers were agricultural expansion/shifting, policy/tenure, and accessibility/infrastructure. Meanwhile, policy/tenure and plantation were the most common drivers of deforestation. The most interesting aspect of this table is that tenure/policy decisions were involved actively in both the forest gain and loss. In contrast, plantation solely contributed to reforestation/afforestation while fuelwood/logging/charcoal, land size, climate, urbanization, etc. were only mentioned in the deforestation studies.

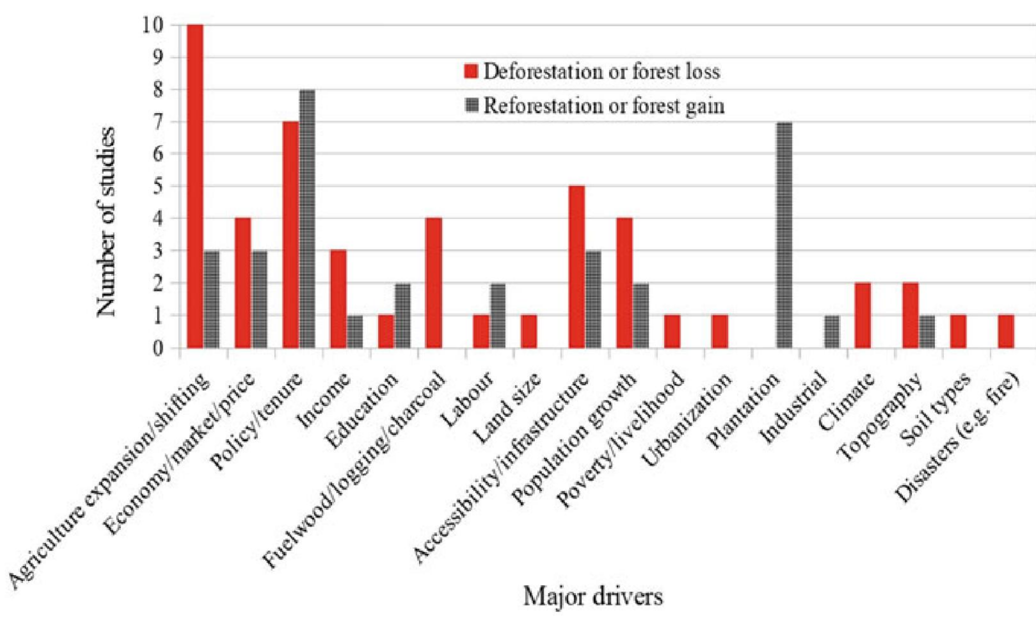

Fig. 32.1 Frequency distribution of the main drivers extracted from the synthesis of case studies in Vietnam. More details about specific drivers can be found in Table A.1 (supplementary document)

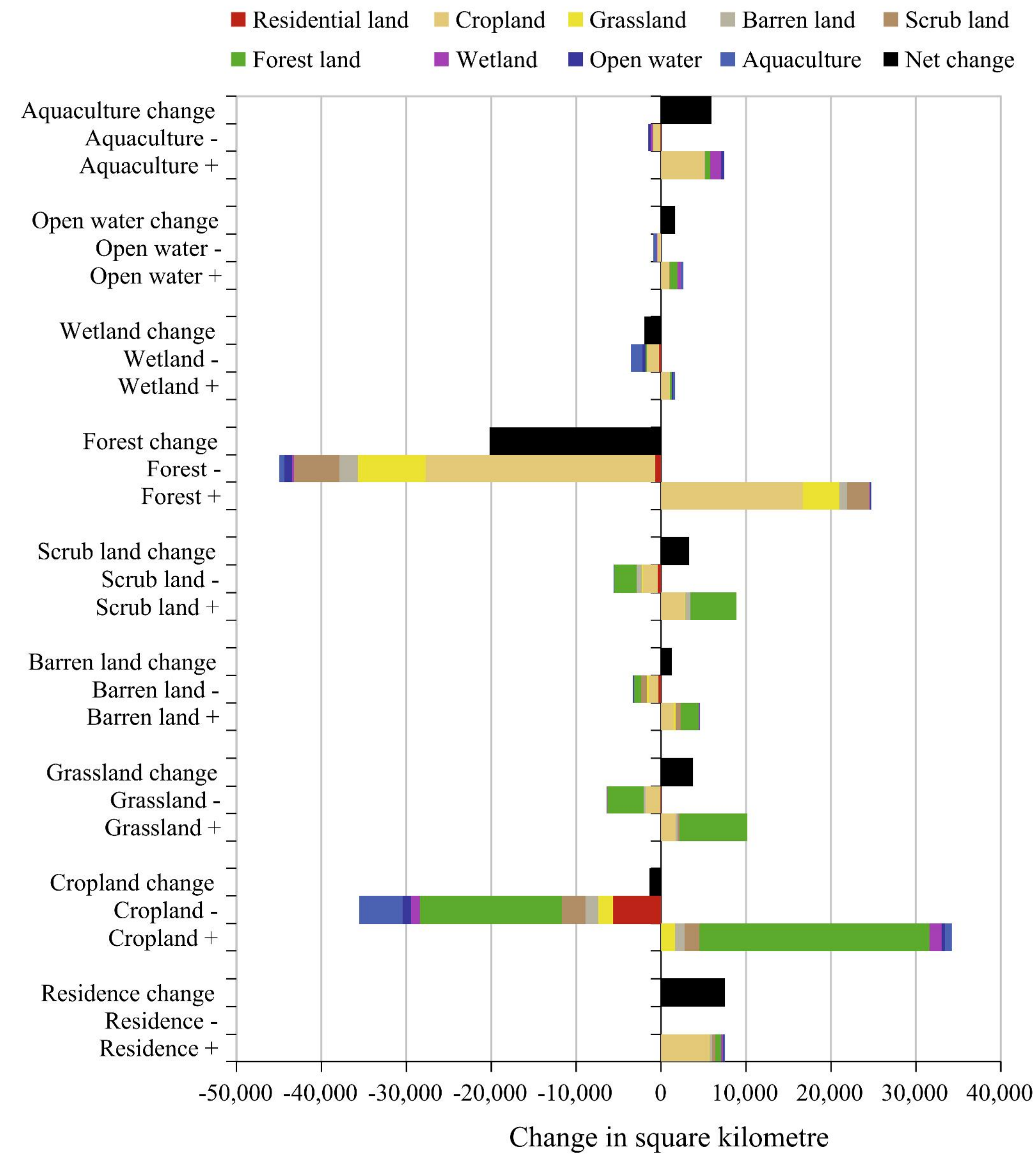

Fig. 32.2 Gross losses, gross gains, and net change in land use/cover at Vietnam-wide scale between 1990 and 2020. Land use/cover types are showed in different colors. Areas are measured in square kilometer. The left represents losses while the right represents gains. Black bars present the net changes (gross gains–gross losses) of different land use/cover types

32.3.2 Land Use/Land Cover and Forest Dynamic Changes

The conversion of different land use/land cover types between 1990 and 2020 is presented in Fig. 32.2. As can be seen from the figure, major LULC changes were forests, residential areas, and aquaculture land. While the residential and aquaculture land experienced increased trends, the area of forest significantly shrank over the study period. This finding was also reported by Hansen et al. (2013) and Leinenkugel et al. (2015). This result is, however, likely contrary to that of Meyfroidt et al., Jadin et al., and the report of the Vietnamese Ministry of Agriculture and Rural Development (MARD) who found that the area of forests increased (Meyfroidt and Lambin 2008; Jadin et al. 2013). These differences are due to several rationales. First, Meyfroidt et al. and Jadin et al. only estimated within a shorter period from 1990 to 2010. Over this period, our previous results also showed an increase in forests in Vietnam (Phan et al. 2021a). Second, there was a slight difference in the definition of forests provided by this study and the MARD who did not consider rubber, scattered trees, etc. as forests. These LULC types changed dynamically but were not fully included in the report of forests by the MARD (Hoang et al. 2020). Interestingly, the MARD included certain areas administrated by the forestry division into the forest land although there may be no forests on the land (Van Khuc et al. 2018).

Spatial distributions and dynamics of forests in 1990 and 2020 across mainland Vietnam are presented in Fig. 32.3a and b, respectively. As can be seen from the figures, forests are mainly distributed in the northern and west-center regions that had high altitudes/elevation. It is apparent from Fig. 32.3a and b that very few areas of forests were detected in delta areas, especially the Red River Delta and Vietnamese Mekong Delta/the South. Figure 32.4a and b present apparently the fractional distribution of forest losses and gains at the commune-level scale. Meanwhile, the hotspots and coldspots of forest gains and losses are shown in Fig. 32.4c and d. What stands out in the figures is the most dynamics and losses of forests in the Central Highlands and the North-West. This finding was also reported by Imai et al. (2018) and Kissinger 2020). This result may be explained by several reasons. As can be seen in Fig. 32.2, there is a major conversion between forests and agricultural land. The central Highlands provide for commercial agriculture with reasonable conditions such as adequate precipitation, moderate temperatures, and good soils. In this region, dominant commercial agriculture lands are rubber and coffee, which have significantly expanded between 2005 and 2015 (Kissinger 2020).

32.3.3 Measurement of the Major Drivers

Standardized coefficients are used to compare the relative effect of each individual driver variable to the forest change area. Specifically, before running the multiple least squares model, we standardized the driver variables to z-scores. Herein, the coefficients that we obtain from the model are standardized coefficients, which have standard deviations as their units. This means the driver variables can be precisely compared to each other, although they are measured on different units and scales. The higher the absolute value of the coefficient, the stronger the impact. A positive value of the coefficient means that a higher value of a driver variable causes a greater change in the forest area. In contrast, a negative value of the coefficient means a higher value of a driver variable has a lower change in the forest area. Herein, the standardized coefficients are presented in Fig. 32.5.

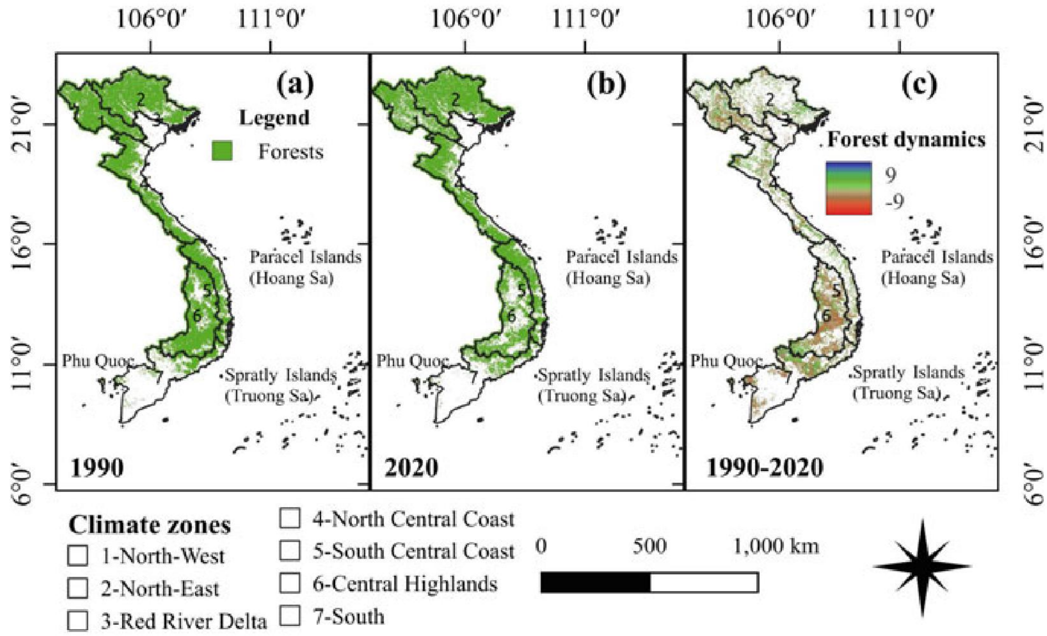

Fig. 32.3 Spatial distribution of forests in mainland Vietnam in 1990 (**a**), in 2020 (**b**), and the dynamic change of forests over recent three decades (**c**). The red color represents a gain while blue color represents a loss over the study period. The data were analyzed using the Vietnam-wide annual land use/cover data sets (Phan et al. 2021b)

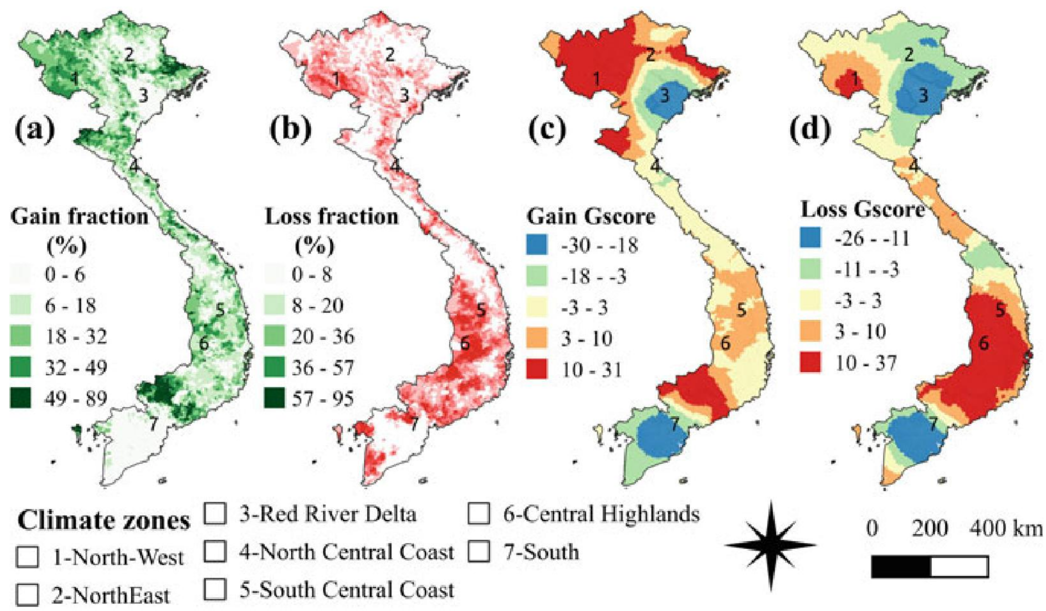

Fig. 32.4 Spatial pattern of forest change in mainland Vietnam between 1990 and 2020. **a** the fraction of forest gain (%) and **b** the fraction of forest loss (%). **c** Presents hotspot analysis of forest gain and **d** shows hotspot analysis of forest loss. Red color represents hot spots while blue color represents cold spots

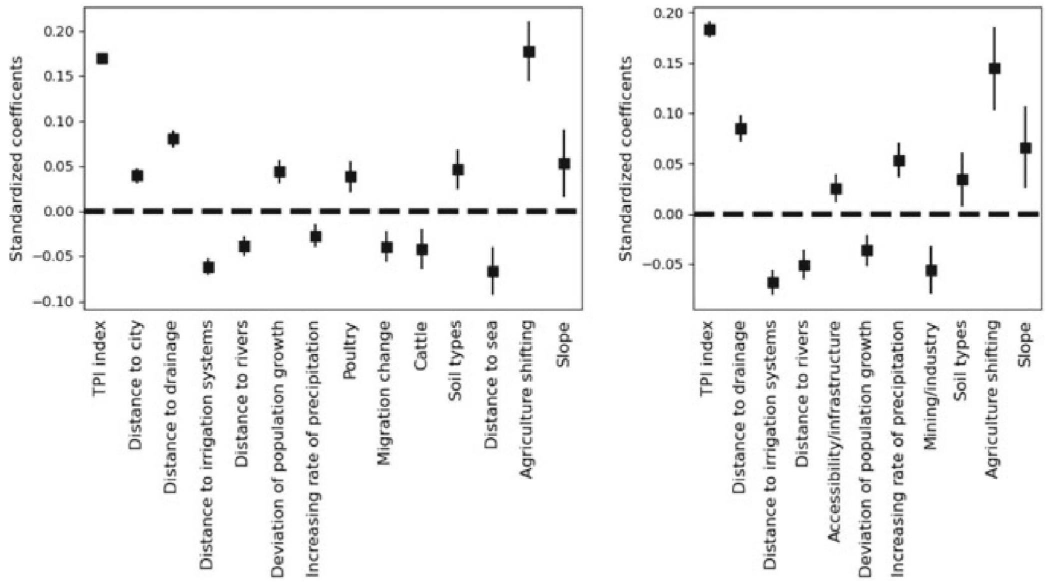

Fig. 32.5 Most prominent drivers of forest changes: forest gain (left) and forest loss (right). Square dots indicate the coefficients while the bars indicate the uncertainties at the 95% confidence interval

Forest gain Fourteen major drivers significantly relate to the forest gain, of which a half is biophysical drivers and the others are socioeconomic drivers (Fig. 32.5a and Table A.3; Supplementary document). Eight major drivers have positive relationships with the forest gain; of which the most important driver is agricultural shifting. This result can be explained by several possible reasons. As can be seen from Fig. 32.2, there is a considerable conversion between forests and agricultural land. In other words, agricultural shifting can significantly cause changes in forest areas. This result also corroborates the findings of a great deal of the previous work on forest transition in Vietnam, which are described in detail in Sect. 32.3.1. For example, Ashraf et al. has identified a net increase of forests in certain areas of Vietnam due to the major shrinkage of agricultural land (Ashraf et al. 2017). What is surprising is that the topographic position index (TPI) and slope positively have substantial impacts on the forest gain, although our synthesis shows few studies that have mentioned these drivers. A possible explanation for this might be that forests are mainly located in mountainous areas that have high values of slope and TPI indexes (Meyfroidt and Lambin 2008; Nguyen 2019). Other positive relationships between the forest gain and the driver variables are distance to the city, distance to drainage, deviation of population growth rate, poultry, and soil types. Among these drivers, the distance to drainage is the strongest factor correlating to the forest gain. This finding was also reported by Nguyen (2019). It seems possible that drainage systems are frequently constructed in flat regions such as cities and densely populated residential areas that are non-forest land (La Rosa and Pappalardo 2020). In terms of negative relationships, there are six major drivers, of which distance to the sea is the most considerable driver. This means forest gains occur in regions close to the sea. This result may be explained by the fact that planting forests are considered an effective solution to prevent natural hazards and disasters. Several reports have shown that forests are planted in coastal areas for protecting erosion and typhoons (Hai et al. 2020; Nguyen et al. 2017).

Forest loss Standardized coefficients corresponding to forest loss are shown in Fig. 32.5b and Table A.4 (Supplementary document) with seven positive relationships and four negative relationships. The most interesting finding was that the topographic position index (TPI) also has the most positive relationship with forest loss, indicating that forest loss frequently occurs in regions that have high values of the TPI. However, we have not found studies that identify the relationship between deforestation and TPI while slope has been utilized instead (Chi et al. 2013; Meyfroidt 2013). In this study, the slope has a strong positive correlation with forest loss.

It is not surprising that agricultural shifting was found to cause a significant loss of forests. This finding broadly supports the work of other studies in this area linking agricultural expansion/shifting and deforestation (Jadin et al. 2013; Van Khuc et al. 2018; Imai et al. 2018; Muller and Zeller 2002). There are several types of agricultural expansion/shifting. For example, in the Central Highlands (e.g., Dak Lak, Dak Nong, and Binh Phuoc), a large number of forests areas have been converted into coffee and rubber since the 1990s (Meyfroidt et al. 2013). Specifically, Dak Lak has relatively high elevation, fertile soil, and cool weather which offer a suited environment to coffee crops, especially Robusta coffee (Pohlan and Janssens 2010). In contrast, with a lower elevation and a higher temperature, Binh Phuoc offers a favorable condition to rubber plantations (Li and Fox 2012). Also, the quickly growing global demand for coffee and rubber resulted in the expansion of these crops. It is also supported by governmental policy to convert poor forests into coffee and rubber plantations (Meyfroidt et al. 2013; Li and Fox 2012).

Other major positive drivers correlating to forest loss are accessibility/infrastructure and increasing rate of precipitation. These results support evidence from previous observation (Chi et al. 2013; Muller and Zeller 2002; Castella et al. 2005; Sikor 2001). Particularly, Nguyen et al. found that forest loss occurs more frequently in remote access areas, for example, far from roads, drainage, and a densely populated residence (Nguyen 2019). Meanwhile, the positive relationship between deforestation and the increasing rate of precipitation indicates that wetter areas are favorable conditions for forest transition. A possible explanation for this might be that increasing rate of precipitation might introduce extreme climate conditions, such as typhoons and floods, which may reduce forest productivity and degradation, and thus may cause deforestation (Xiaoming et al. 2019; Rutten et al. 2014). Another possible explanation for this is that the major degradation or loss of forests results in changes in precipitation (O'Connor et al. 2021; Baudena et al. 2021; Molina et al. 2019). The literature also reported an increase in extreme climate events, especially in the Central Highlands which is a hot spot of deforestation (Nam et al. 2018, 2019).

Regarding the negative relationships between drivers and forest loss, there are four major drivers, namely distance to irrigation, distance to rivers, deviation of population growth, and mining/industry. It means that the loss of forest frequently happens in regions closer to rivers, irrigation systems, mining/industry zones, and diffusely populated areas. Although these drivers have not been mentioned in our synthesis of case studies on forest transition in Vietnam, these results match those observed in earlier studies in other regions (Rodriguez-Galiano et al. 2012; Siqueira-Gay et al. 2020).

32.3.4 Limitations and Future Work

The generalisability of these results is subject to certain limitations. First, although we have collected the most essential drivers mentioned in our synthesis of the case studies and added new drivers, we could not quantify some important drivers such as forest management policy/tenure, globalization, disasters, and economy/market/price. These drivers may have profound effect the transition of forests (Meyfroidt and Lambin 2008; Nguyen 2019; Chi et al. 2013; Webb and Honda 2007; Liu et al. 2020). In this study, the data of these drivers are not available at a proper spatiotemporal scale; or some have high multicollinearity, causing difficulties in the precise measurement of the impact of individual drivers; we, therefore, have excluded them from the analysis model. The lack of these drivers might impact our quantitative results. Secondly, the spatiotemporal difference of some collected drivers may cause uncertainties in the analysis of the drivers. Specifically, most of the drivers are derived from the General Statistics Office of Vietnam, which have been calibrated by the office; some are extracted from the WorldClim 2 database (Fick and Hijmans 2017) or the satellite-based information (e.g., the Shuttle Radar Topography Mission) (Farr and Kobrick 2000). These data may have relatively low quality and added further uncertainties in this work. However, the current shortage of the properly available data does not permit us to overcome this limitation. This would be a fruitful area for further work.

32.4 Conclusion

The present research aimed to analyze the changes and drivers of the land use/land cover changes focusing on forests in mainland Vietnam. To our best knowledge, this is the first work on the analysis of inter-annual dynamics of forests at the national scale from 1990 to 2020. Results have shown that Vietnam experiences a considerable change in LULC over the recent three decades. There is a significant transition between forests land and other lands, especially agriculture, grassland, and shrubland. One of the more significant findings to emerge from this research is that the forest change has occurred in differences in space and time. The North-West and Central Highlands are the most dynamic change areas, which are considered hot spots. The study has also shown that although a net gain of forests has been reported in a short period (e.g., 2005–2010), Vietnam has undergone a net loss of forests from 1990 to 2020. The drivers of forest changes are various. Our synthesis of case studies on forest transition has indicated that previous studies mainly focused on socioeconomic drivers. However, our results show that biophysical drivers also have significantly contributed to forest changes. In general, both biophysical and socioeconomic drivers are highlighted in this study. The development of the economy requires more food and agricultural products, forcing the extensive conversion of forests into other land types if biophysical conditions are reasonable for production. The second major contribution of our synthesis was that it broadens a more general knowledge of the drivers of the forest changes. These findings have significant implications for the understanding of how effectively manage forest resources in Vietnam. They may be of interest to other countries. The identification of socioeconomic and biophysical drivers in this study is likely to help enhance the accuracy of the land use/land cover change prediction.

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