Factors associated with deforestation probability in Central Vietnam: A case study in Nam Dong and A Luoi districts

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Abstract

Vietnam is undergoing a forest transition stage with an overall increase in forest cover since 1990s, however, deforestation and forest degradation of natural forests still occur in several areas, especially in Central region of the country. In order to better manage and protect natural forests, predicting deforestation probability and understanding its associated factors are necessary. In the present study, we focused on the two mountainous districts (Nam Dong and A Luoi) in Central Vietnam as a case study. We used Landsat satellite images for identifying changes of natural forests in the period of 1989-2020. The logistic regression model showed a good performance in prediction of deforestation (testing AUC = 0.874) in the study area. Our data showed that deforestation probability of natural forests in the study area in the period of 1989-2020 could be influenced by 11 socio-economic and topographical factors. In particular, forest areas with low elevation, gentle slopes, nearby rivers and residential areas have a high deforestation probability. Production forest, forest areas not included in payment for environmental service (PFES) schemes, forest with no ownership and forest areas managed by private owners may also have a high deforestation probability. The total area of very high level of deforestation probability in A Luoi (8,988 ha) and Nam Dong (5,304 ha) districts occupied about 11.4 % of natural forests in the study area. Our study suggests that protection activities should be focused on high deforestation probability-prone forest areas.

Keywords: Deforestation probability, Central Vietnam, Nam Dong, A Luoi, forest transition

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Introduction

Forests cover 31% of the world's land area and are home of more than 75% of terrestrial organisms (FAO 2020). Forest ecosystems play essential roles in providing habitat, services and resources for human beings and other creatures (Brockerhoff et al. 2017). Despite their indispensable functions, since the 1990s over 178 million ha of forests have been destroyed through anthropogenic impacts and natural disturbances (FAO 2020). In recent years, deforestation and forest degradation have alarmingly continued (Meyfroidt and Lambin 2008; Adedire 2002), causing far-reaching consequences (e.g., soil erosion, flooding, greenhouse gas emissions, habitat loss) for biodiversity, ecosystems and human beings (Houghton 2016; Assefa and Bork 2014). Deforestation may also accelerate global warming and climate change through carbon emission and reduced carbon dioxide uptake (Di Lallo et al. 2017; Longobardi et al. 2016; Köhl et al. 2009). During the period of 2000-2010, the emissions caused by forest loss accounted for about 10% of global carbon emission (Houghton 2016). Tropical forests, the most biologically diverse terrestrial ecosystem with a great capacity of carbon sequestration, have occupied the largest proportion (45%) of global forest area (FAO 2020), but they have suffered the highest level of deforestation and forest degradation (Bonan 2008; Achard et al. 2002).

The increase of forest plantation and natural forest regeneration has slowed the rate of global forest loss from 7.8 million ha per year in the period of 1990-2000 to 4.7 million ha per year in period of 2010-2020 (FAO 2020). However, deforestation and forest degradation are still on-going problems at global scales (Turner and Snaddon 2016; Vieilledent et al. 2013). The greatest level of deforestation was observed in developing countries of tropical region, in particular Southeast Asia (Keenan et al. 2015; Stibig et al. 2014; Achard et al. 2002).

Vietnam, a highly biodiverse country in Southeast Asia, had a significant decline of forest cover and resources in the past (Meyfroidt et al. 2013; Sterling and Hurley 2005). Over last 30 years, several efforts at national and local scales have been made to promote forest restoration and afforestation at local and national scales, resulting an increase of forest cover from 28% in 1993 to 42% in 2020 (MARD 2021). This rise in Vietnam's forest cover is considered a "forest transition" phase and could be mainly attributed to the expansion of forest monoculture plantations, using primarily exotic species (e.g., *Casuarina equisetifolia* and *Acacia* species) and changes in forest definitions within national regulations (Vietnam National Assembly 2017; Cochard et al. 2016; Meyfroidt et al. 2013). According to new definitions, some vegetation types that was not considered as forest in the past are now categorized as forest. For instance, *Arecaceae* species assemblages, vegetation on sandy areas and wetlands with canopy cover over 10% are now considered as forest (Vietnam National Assembly 2017). Although overall forest cover of the country has been increasing, its natural forests are still being lost and degraded due to various drivers (Pham et al. 2019; World Bank 2019; Matthews et al. 2014), leading to crucial losses in biodiversity and natural ecosystems (Turner and Snaddon 2016). In this context, Vietnamese Government has developed policies and programs to halt deforestation and forest degradation such as participating in the REDD+ (Decision No. 419/QD-TTg dated April 5, 2017 on approving the national program on reduction of greenhouse gas emissions through the mitigation of deforestation and forest degradation; conservation and enhancement of forest carbon stocks and sustainable management of forest resources through 2030) and target program for sustainable forestry development (Decision No. 886/QD-TTg dated June 16, 2017).

Similar to the national forest transition, Thua Thien Hue province in Central Vietnam has also experienced major forest transitions. In the period of 2014 - 2020, the province's forest cover has increased from 56.6 to 57.4%, while over 8,243 ha of its natural forests were deforested (PPC 2021). In the province, the main direct causes of deforestation and forest degradation may relate to (1) conversion of natural forests to agricultural land and plantation forest, (2) forest logging and encroachment, and (3) residential expansion and infrastructure development (Pham et al. 2018; Thiha 2017; Ty et al. 2013).

Deforestation and forest degradation could be associated with many biophysical and socio-economic factors such as elevation, slope, population distribution and distance from agricultural land (Kayet et al. 2021; Saha et al. 2020; Sahana et al. 2018; Ramachandran and Reddy 2017). The affecting factors are complex and can vary between regions of a country (Kissinger 2020; Austin et al. 2019; Mas et al. 2004; Angelsen and Kaimowitz 1999). Thus, identifying factors relating to forest loss and predicting deforestation probability for specific regions are important for forest protection and management (Khuc et al. 2018; Chomitz et al. 2007). In Thua Thien Hue province, little is known about the factors influencing the loss of natural forests and there is a need to identify areas with a high probability of deforestation (Thiha 2017). The present study, therefore, sought to determine deforestation-associated factors and predict deforestation probability in the two mountainous districts (Nam Dong and A Luoi) of the province.

Materials and Methods

Study site

Our study was conducted in the Nam Dong and A Luoi districts of Thua Thien Hue province in Vietnam (Figure 1). Natural forests cover about 48,215 and 81,873 ha in Nam Dong and A Luoi districts, respectively and these areas together occupies over 60% of the forest area in the province (PPC 2021). The study site is characterized by secondary tropical forests regenerating after past natural disturbances, overexploitation and the war (Tuong et al. 2019). The total population of the two districts is about 71,500 people. The proportion of ethnic minority groups is about 77.5% and 46.4 % of A Luoi and Nam Dong population, respectively (A Luoi district data 2019; Nam Dong district data 2020). The income of local people is mainly from agricultural and forestry production. Especially, minority ethnic groups have relied heavily on products from natural forests for their livelihoods (Thang et al. 2010).

The study site has the tropical monsoon climate. In Nam Dong district, annual temperature and precipitation range from 20.2 to 28.2 °C and from 2,700 to 3,800 mm, respectively (HUSTA 2020; Chung et al. 2014). These ranges in A Luoi district are from 17 to 25 °C and from 2,500 to 3,500 mm, respectively (Herzberg et al. 2019).

Study approach and data collection

Forests are going through major changes in Vietnam, including the study region (Cochard et al. 2016), and these changes could be associated with several factors (Tuong et al. 2019). Previous studies have examined the effect of biophysical and socio-economic variables on deforestation. For instance, Kayet et al. (2021) used 20 biophysical and socio-economic variables (e.g., slope, elevation, rainfall, forest density, soil type, distance from settlement and distance from agricultural land) to identify deforestation susceptibility in Saranda forest of India. Saha et al. (2020) used 12 topographic, biological and social variables (e.g., aspect, population density, distance from forest edge and agricultural land density) for predicting deforestation in the Gumani River Basin, India. Based on the approach of previous studies (Saha et al. 2020; Ullah et al. 2020; Vieilledent et al. 2013; Harris et al. 2009), the local context, and data availability, we proposed 16 potential variables that might affect deforestation in our study site (Table 1).

Data analysis

Information on forest loss in the past is very important for predicting future deforestation. In our study, we used Landsat satellite images in 1989 and 2020 to identify areas of natural forest loss in the period. The used images are Landsat TM05 image dated February 17, 1989 and Landsat 8 OLI image dated February 25, 2021 with a resolution of 30 × 30 m at WRS row 49 and WRS path 125. The Random Forest algorithm (RF) was employed to classify the satellite image of study area into two classes including natural forest and non-natural forest. We used the Semi-Automatic Classification Plugin to implement Random Forest algorithm (Congedo 2021). In the model, the number of trees (ntree) is set as 100 and the number of variables randomly sampled as candidates at each split (mtry) is set default as the square root of the number of input variables. Our RF model showed that total area of natural forests in the two districts was about 130,357 and 118,577 ha in 1989 and 2020, respectively. We randomly selected 300 samples from the study area for validation of RF classification model in the two time points (1989 and 2020). Overall accuracy of RF classification model was 0.91 and 0.88 in 1989 and 2020, respectively. Changes of natural forests in the period of 1989-2020 were then identified by overlaying the two obtained forest cover layers.

Several models such as Maxent (Aguilar-Amuchastegui et al. 2014), frequency ratio (Saha et al. 2020; Sahana et al. 2018), artificial neural network (Saha et al. 2020; Mas et al. 2004) and logistic regression model (Kayet et al. 2021; Saha et al. 2020; Mon et al. 2012) have been used to predict deforestation in many regions. Logistic regression is an interpretable model, thus we employed this model to examine the effect of potential variables on deforestation probability. The dependent variable had two values showing non-loss (0) and loss (1) of natural forest areas that were identified from changes of natural forests retrieved from satellite image analysis in the period of 1989-2020. Denoted x_i is a set of independent variables, and p is the probability of forest loss in a given area. The relationship between p and x_i is modeled through logit transformation as follows:

$$\text{logit}(p) = \alpha + \beta_i x_i$$

in which, α is the intercept, and β_i is a set of regression coefficients.

In our study, x_i refers to 16 predictors as described in Table 1. We randomly selected 4000 sample localities (points) from study area and assigned their attributes from 16 predictors and the forest change variable for using in the logistic model.

No high multicollinearity among predictors and independence among observations are the two important assumptions of the logistic model. We used the variance inflation factor (VIF) calculated in the package *car* (Fox and Weisberg 2019) to test the collinearity of predictors. In each predictor, the value of VIF > 5 indicates a collinearity problem (Saha et al. 2020). We also employed Moran's I index computed in the package *spdep* to test the spatial autocorrelation in the model (Bivand and Wong, 2018; Portier et al. 2018). The index values range from -1 to 1. Strong dispersion and strong clustering patterns in the data correspond to the index value of -1 and 1, respectively.

We randomly split data into a training set (70% of the data) for model fitting and a testing set (30%) for model evaluation. In addition, we used 213 deforested points in the period of 2020-2021 that were officially identified by competent organization (Forest Protection and Development Fund) of Thua Thien Hue province to further evaluate the model performance. We used Akaike's Information Criterion (AIC) with the stepwise procedure for model selection (Portier et al. 2018). The model with the lowest AIC value was selected as "the best" for interpretation and mapping. We used the Nagelkerke's R^2 as a measure for goodness of fit of the model. In addition, the three metrics, including the accuracy, Cohen's Kappa statistic and Area Under the Curve (AUC) were employed to evaluate model prediction performance (Schulltz et al. 2016).

Prior to fitting the model, we transformed the unit of distance-related predictors and elevation from 1 to 100 m to ensure that model interpretation would be meaningful and understandable. The effect of a given predictor on deforestation probability was interpreted using the odds ratio (OR), calculated by taking the exponential of the coefficient estimate (Dinh et al. 2018; Mon et al. 2012). The logistic model was fitted in R version 3.6.2 (R Core Team 2019) and the probability threshold for classification between forest non-loss and loss groups was set as 0.5. The probability of deforestation estimated from logistic model was classified into 4 classes with interval of 0.25, including low (0-0.25), medium (0.25-0.5), high (0.5-0.75) and very high (0.75-1) probability levels. A deforestation probability map was made using regression coefficients from the selected logistic model in QGIS 3.10.2. Values of 16 predictors in the study area were computed for each cell (30 × 30 m) in raster maps (Supplementary Figure S1).

Results

Characteristics of predictors

In our study, the sampled data points (n = 4000) distributed in forest non-loss (n = 2277) and forest loss areas (n = 1723). We found a significant difference between the forest non-loss and loss groups in 12 predictors (Table 2). For instance, deforested areas (760 m) were was significantly closer to roads than forest areas (2610 m). Slope in deforested areas were significantly lower than that of forest intact areas. In production forest type, proportion of forest loss areas (0.65) was significantly higher, compared with forest non-loss areas (0.35). Meanwhile, the opposite trend was observed in protection and special-use forest types.

We used Spearman's correlation coefficient to examine pairwise correlation between continuous and discrete variables. The Spearman's correlation coefficients between these predictors were not high (Supplementary Figure S2). The highest correlation (Spearman's ρ = -

0.77) was detected between income score (income_sc) and proportion of ethnic minority group (prop_minority_sc).

Factors affecting deforestation probability

The best logistic model (with the lowest AIC value = 1754.7) comprised of 11 predictors (Table 3). The variance inflation factor (VIF) of each predictor in the selected logistic model was smaller than 5, thus our model did not violate the model assumption of multicollinearity. The model was also not violated the independence assumption (Moran's I statistic = 0.029, *P*-value = 0.106).

We found that the two predictors, proportion of households without agricultural land (prop_NoAgri_sc) and plantation forest to natural area ratio (planta_ratio_sc), had significantly positive effects on deforestation probability in study area (Table 3). In contrast, the remaining 9 predictors in the model showed significantly negative effects on deforestation probability. Based on odds ratio (OR), an increase of 100 m in elevation resulted in a decrease of exp (-0.33) - 1 = 0.72 - 1 = - 0.28 (or 28 %) of deforestation probability. The probability of deforestation decreased by 7% for a 100-m increase in distance from the nearest road. Compared with forests managed by private owners and unallocated forests (G1), the forests of special-use forest management board (G4) had a 59% lower of deforestation probability. Our model showed that deforestation probability of protection forest and special-use forests respectively was 57 and 70% lower than that of plantation forests. The PFES area had a 43% lower of deforestation probability, compared with area without PFES payment.

The Nagelkerke's R^2 of our model was 0.71, indicating that the model explains deforestation pattern in the study area quite well. The accuracy, Cohen's Kappa statistic and AUC calculated from the training set (0.875, 0.746, 0.874, respectively) and testing set (0.875, 0.745 and 0.874, respectively) were almost the same. In addition, we found that 152 out of 213 deforested points in the period of 2020-2021 (accounting for about 71.4%) was in medium, high and very high levels of deforestation probability. The obtained results implied that our model is potential in predicting deforestation in the study area.

Deforestation probability prediction

The total area of natural forests in the two studied districts was about 125,775 ha, in which the area of low, medium, high and very high deforestation probability levels was 94,947, 8,240, 8,295 and 14,292 ha, respectively (Table S1; Figure 2). We observed that the area with very high level of deforestation probability in A Luoi and Nam Dong districts was 8,988 and 5,304 ha, respectively that occupied about 11.4 % of natural forests in study area. Of the 21 communes in A Luoi district, three communes with the largest area of very high level of deforestation probability were Huong Nguyen (1,256 ha), Hong Ha (1,154 ha) and Hong Thuy (1,065 ha) (Table S1 and Figure S3). We found that nearly a half of area of natural forests (1,834 ha) in Hong Van commune was under very high level of deforestation probability. In A Luoi district, the smallest area of very high level of deforestation probability was observed A Luoi town. In 11 communes in Nam Dong district, the largest area of very high level of deforestation probability was found in Thuong Nhat commune (1,238 ha), followed by Huong Loc (953 ha) and Thuong Quang (720 ha). Noticeably, the total area of natural forests in Khe Tre town, Huong Giang and Huong Hoa communes was under very high level of deforestation probability.

Discussion

In Vietnam, deforestation and forest degradation have occurred across the country, especially in remote upland areas of the Central region (Meyfroidt et al. 2013). In our study area (Nam Dong and A Luoi districts), about 417 ha of natural forests were lost during the period of 2010-2020 (FPD 2011; PPC 2021). Since 1990s, the Vietnamese government has issued forest decentralized policies (e.g., Decree No. 163/1999/CP; Decision No. 178/2001/QD-TTg) that allocate degraded forest land and natural forest to organizations, households and individuals for stable and long-term use for forestry purposes. However, the forest allocation process combining with the increased market demand of pulp, timber and industrial products has a "side effect" on natural forest that leads to the conversion of natural forest to plantation forests and industrial crops (e.g., rubber, coffee and Acacia species), illegal logging and encroachment in our study area (Thiha 2017; Dung and Webb 2007)". Residential expansion and infrastructure development (e.g., roads, hydropower dams) have also contributed considerably to deforestation and forest degradation. For instance, the construction of A Luoi hydropower dam in 2007 was responsible for the conversion of 716-ha natural forest to other land-use types in the study area (A Luoi District People's Committee 2013).

Previous studies indicated that several factors could influence the pattern and magnitude of deforestation and forest degradation (Saha et al. 2020; Di Lallo et al. 2017; Mas et al. 2004). In our study, we found the association between 11 factors and the loss of natural forest. Consistent with other work, we observed that the deforestation tended to occur in areas of low elevation, gentle slope, nearby rivers and residential areas because of a high accessibility (Saha et al. 2020; Aguilar-Amuchastegui et al. 2014, Petrova et al. 2007). In southeastern Brazil, for instance, Freitas et al. (2010) showed the long-term effect of roads on accelerating deforestation owing to construction activities and increased accessibility to forests.

We detected the negative association between deforestation probability and forest quality, suggesting that low quality forests in our study area are likely to be convert to other land-use types (e.g., plantation forests and agricultural land). In Vietnam, forests are categorized in three forest types based on their function, including production forest (mainly for timber and non-timber production), protection forest (mainly for environmental protection and ecological functions and ecosystem services), and special-use forest (mainly for nature conservation). In our study, we found that the deforestation probability of production forest was highest, followed by protection and special-use forests (Table 3). This finding is rational because the conversion of production forest (both natural and plantation forests) to other land-use types is less restricted by law, compared with protection and special-use forests (Vietnam National Assembly 2017). In our study area, forests managed by private owners and unallocated forests (G1) and local household and community (G2) showed a higher probability of forest loss, compared with other owner types. This observation can be explained by the fact that G1 and G2 owners tended to convert a part of their allocated natural forests to plantation forests and agricultural land (Nguyen et al. 2016; Dung and Webb 2007).

In Vietnam, Payment for Forest Environmental Services (PFES) policy has been implemented with the aim at mobilizing social financial sources for protecting forest ecosystems (Dien et al. 2013). In PFES schemes, the users of forest environmental services (e.g., hydropower, water and tourism companies) must make payment to the service suppliers (i.e., forest owners). Since 2013, PFES scheme has been implemented in our study area. After analyzing Vietnam's official forest data in the period of 2011-2016, Cochard et al. (2020) indicated a negative but not statistically significant effect of PFES on natural forest cover changes. In line with Cochard et al. (2020), we found the same effect trend of PFES on natural forest changes, showing that forests under PFES schemes had a lower probability of deforestation (Table 3). This finding is expected because forest owners in PFES scheme must protect their forests well to receive yearly payment from service users. In the scope of our study, the association between PFES and deforestation probability should be interpreted cautiously because the implementation of PFES is not at the beginning of study period of 1989-2020. Our data showed that communes with a higher proportion of households without agricultural land (prop_NoAgri_sc) and a higher ratio of plantation forest (planta_ratio_sc) appeared to have a greater probability of deforestation. In the study area, the local people's livelihoods rely mainly on forest resources and agricultural cultivation. The lack of agricultural land may induce local people to encroach forest for slash and burn cultivation, expand forest plantations (mainly *Acacia*) and illegally exploit forest products (Duong et al. 2021; Tuan 2015)

The deforestation prediction model in our study follows the assumption that the pattern of deforestation and its associated factors in the past 30 years will not change drastically in the near future (Aguilar-Amuchastegui et al. 2014). Thus, it would be important to re-analyze the model in the future, particularly a few years after new large-scale policy interventions. In the study site, the area of very high level of deforestation probability occupied about 11.4 % of total natural forests. Large area of natural forests in some communes (e.g., Huong Nguyen, Thuong Nhat and Hong Van) is being under very high level of deforestation probability. Based on the obtained results of this study, local authorities, forest rangers and managers need to pay much more attention to forest protection in high deforestation probability-prone forest areas, and the promotion of PFES implementation could be a feasible win-win solution to protect natural forests in study area (Duong et al. 2021). Local management plans and policies may need to be developed to better manage and protect natural forests.

Conclusion

The present study indicated that the loss of natural forests in the study area (Nam Dong and A Luoi districts) could be related to 11 socio-economic and topographical factors. The logistic model showed a quite good performance and could be used to predict deforestation in the study area. The area of very high level of deforestation probability in A Luoi and Nam Dong districts was 8,988 and 5,304 ha, respectively, representing 11.4 % of the natural forest area in the region. Forest areas with low elevation, gentle slopes, nearby rivers and residential areas are likely to have a high probability of deforestation. Production forest, forest areas not being in PFES scheme, and/or not being allocated and managed by private owners may also be under a high probability of changing to other land-use types. In order to better protect natural forests in the study area, forest rangers/managers and local authorities should carry out many more protection activities in high deforestation probability-prone forest areas and enhance PFES.

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Tables in the Manuscript entitled “**Factors associated with deforestation probability in Central Vietnam: A case study in Nam Dong and A Luoi districts**”

This document includes **3 Tables** as follows.

Table 1. Potential variables affecting deforestation in the study area

ID	Variable	Notation	Description	Data sources
1	Elevation (100 m)	Elev	This variable was treated as a continuous variable.	Elevation data was extracted from SRTM Digital Elevation Model (DEM) global datasets.
2	Slope	Slope	Slope (^{0}) was classified into 4 scores, including 1 (0 <15^0), 2 (15-30^0), 3 (30-45^0) and 4 (> 45^0), and was treated as a discrete variable.	The variable was derived from DEM data using QGIS 3.10.2 (QGIS Development Team 2020).
3	Forest owner	f_owner	The forest owners were divided into 4 groups including: Unallocated forests and private owners (G1); Local household and community (G2); State owners (G3); and Special-use forest management board (G4). The variable was treated as a categorical variable.	The variable was extracted from official data of Thua Thien Hue province in 2020
4	Forest quality	f_qual	The variable describes forest quality in Vietnam based on forest volume. Forest quality was divided into poor (tree volume ≤ 100 m^3/ha), medium (101-200 m^3/ha) and rich (>201 m^3/ha) forests. We treated forest volume as a discrete variable (1= poor forest, 2 = medium forest and 3 = rich forest)	The variable was extracted from official data of Thua Thien Hue province in in 2020. Forest quality was classified with volume criteria regulated by Vietnamese policy (MARD 2018)

5	Forest-use type	f_use_type	The variable describes 3 forest types, which are based on the use function including production, protection and special-use forest types. It is noted special-use forests are mainly used for nature conservation. The variable was treated as a categorical variable.	The variable was extracted from official data of Thua Thien Hue province in 2015.
6	Soil type	soil_type	Soil type in the study area was classified into 3 groups including Ferralsols (S1), Humic acrisols (S2) and Fluvisols (S3). The variable was treated as a categorical variable.	The variable was extracted from official data of Nam Dong and A Luoi districts in 2007
7	Plantation forest to natural area ratio	planta_ratio_sc	The variable depicts the ratio between plantation forest and natural area at the commune level. The variable (%) was classified into 5 scores, including 1 (0 <10%), 2 (10-20%), 3 (20-30%) and 4 (30-40%) and 5 (> 40%) and was treated as a discrete variable.	The variable was extracted from official data of Nam Dong and A Luoi districts in 2020.
8	Payment for forest environmental services (PFES)	PFES_sc	The variable depicts the payment amount per hectare for forest environmental services. The variable was classified into 4 scores, including 1 (no payment), 2 (low payment ~ 200×10^3 Vietnamese Dong-VND), 3 (medium payment ~ 400×10^3 VND) and 4 (high payment ~ 600×10^3 VND). The higher score implies the better forest management and protection. The variable was treated as a discrete variable.	The variable was extracted from official PFES data of Thua Thien Hue province, averaged in the period of 2015-2020.
9	Distance to nearest residential area (m)	d2_resi_area	The variable describes the distance from a given forest area to the nearest residential site. The variable was treated as a continuous variable.	The variable was retrieved using QGIS 3.10.2 (QGIS Development Team 2020).

10	Distance to nearest road (100 m)	d2_road	The variable describes the distance from a given forest area to the nearest road. The variable was treated as a continuous variable.	The road data were extracted using Openstreet tool in QGIS 3.10.2.
11	Distance to nearest waterbody (100 m)	d2_wb	The variable describes the distance from a given forest area to the nearest water waterbody. The variable was treated as a continuous variable.	The water body data were extracted from official data of Thua Thien Hue province.
12	Income score	income_sc	The average annual income per capita at commune level was classified into 4 scores, including 1 (< 650 USD), 2 (650-870 USD), 3 (870-1085 USD) and 4 (>1085 USD). The variable was treated as a discrete variable.	The income was extracted from official data of Nam Dong and A Luoi districts in 2016
13	Proportion of ethnic minority group	prop_minority_sc	The proportion of ethnic minority groups was calculated at commune level. The proportion was classified into 4 scores including 1 (< 25%), 2 (25-50%), 3 (50-75%) and 4 (> 75%). The variable was treated as a discrete variable.	The variable was extracted from official data of Nam Dong and A Luoi districts in 2016
14	Primary ethnic group	pr_ethnicity	The variable indicates the ethnic group with highest proportion at commune level. There were 4 main people groups, including Co Tu (P1), Pa Cô (P2), Ta Oi (P3) and Kinh (P4). The variable was treated as a categorical variable.	The variable was extracted from official data of Nam Dong and A Luoi districts in 2016
15	Poverty rate	pov_rate_sc	Poverty rate at commune level was classified into 3 scores, including 1 (<10%), 2 (10-20%) and 3 (>20%). The variable was treated as a discrete variable	The variable was extracted from official data of A Luoi and Nam Dong districts in 2016
16	Proportion of households without agricultural land	prop_NoAgri_sc	Proportion of households lacking agricultural land was calculated at commune level. The variable was classified into 3 scores, including 1 (< 25%), 2 (25-50%) and 3 (> 50%). The variable was treated as a discrete variable	The variable was extracted from official data of Nam Dong and A Luoi districts in 2016

Table 2. Characteristics of predictors in forest non-loss and loss groups

Predictor	Notation	Mean (SD)		P-value *
		Forest non-loss (n = 2277)	**Forest loss (n = 1723)**	
Payment for forest environmental services	PFES	2.6 (0.9)	1.6 (1)	< 0.001
Slope (^{0})	slope	2 (0.7)	1.6 (0.6)	< 0.001
Elevation (100 m)	elev	5.7 (2.9)	4.1 (2.4)	< 0.001
Distance to nearest road (100 m)	d2_road	26.1 (19.2)	7.6 (7.7)	< 0.001
Distance to nearest residential area (100 m)	d2_resi_area	41.8 (22.4)	15.7 (12.2)	< 0.001
Distance to nearest waterbody (100 m)	d2_wb	12.5 (9.5)	8.9 (6.9)	< 0.001
Forest quality	f_qual	2.2 (0.7)	1.7 (0.7)	< 0.001
Income score	income_sc	1.9 (1.1)	2 (1.2)	0.058
Proportion of ethnic minority group	prop_minority_sc	3.5 (1)	3.4 (1.2)	0.666
Poverty rate	pov_rate_sc	1.7 (0.6)	1.7 (0.7)	0.272
Proportion of households without agricultural land	prop_NoAgri_sc	1.3 (0.6)	1.3 (0.6)	0.693
Plantation forest to natural area ratio	planta_ratio_sc	1.8 (0.7)	2.1 (0.8)	< 0.001
Primary ethnic group	pr_ethnicity[1]	0.63	0.37	< 0.001
		0.45	0.55	
		0.45	0.55	
		0.56	0.44	
Forest-use type	f_use_type [2]	0.35	0.65	< 0.001
		0.80	0.20	
		0.95	0.05	

Forest owner	f_owner [3]	0.31	0.69	< 0.001
		0.34	0.66	
		0.81	0.19	
		0.94	0.06	
Soil type	soil_type [4]	0.56	0.44	< 0.001
		0.86	0.14	
		0.13	0.87	

* Wilcoxon rank-sum test was used to examine the difference between forest non-loss and loss groups in continuous and discrete variables. Chi-square test was used to determine the association between each of 4 categorical variables (pr_minority, f_use_type, f_owner and soil_type) and the binary dependent variable (non-loss and loss groups). SD: Standard deviation; n: Sample size. In the table, the group order in each of these 4 categorical predictors is as follows:

[1] pr_ethnicity: Co Tu (P1), Pa Cô (P2), Ta Oi (P3) and Kinh (P4)

[2] f_use_type: Production, protection and special-use forest types

[3] f_owner: Unallocated forests and private owners (G1), local household and community (G2), other state owners (G3), and special-use forest management board (G4)

[4] soil_type: Ferralsols (S1), Humic acrisols (S2) and Fluvisols (S3)

Table 3. Effects of predictors on deforestation probability, using logistic regression model

Predictor	**Comparison unit**	**Coefficient estimates (SE)**	**Odd ratio (OR) – 1 [95% CI]**	***P*-value**
PFES	1	-0.56 (0.06)	-0.43 [-0.49 – -0.35]	< 0.001
slope	1 (15°)	-0.36 (0.1)	-0.30 [-0.42– -0.15]	< 0.001
elev	100 m	-0.33 (0.03)	-0.28 [-0.32 – -0.24]	< 0.001
d2_road	100 m	-0.07 (0.01)	-0.07 [-0.08– -0.05]	< 0.001
d2_resi_area	100 m	-0.05 (0.004)	-0.05 [-0.06 – -0.04]	< 0.001
d2_wb	100 m	-0.02 (0.01)	-0.02 [-0.04 – -0.01]	< 0.01
f_qual	1	-0.59 (0.09)	-0.45 [-0.54 – -0.33]	< 0.001
prop_NoAgri_sc	1	0.5 (0.12)	0.65 [0.30 – 1.07]	< 0.001
f_use_type	Protection forest	-0.84 (0.14)	-0.57 [-0.67– -0.43]	< 0.001
	Special-use forest	-1.21 (0.46)	-0.70 [-0.88 – -0.26]	< 0.001
f_owner	G2 (Local household and community)	-0.09 (0.16)	-0.09 [-0.33 – 0.26]	0.595
	G3 (Other state owners)	-0.99 (0.2)	-0.63 [-0.75 – -0.4]	< 0.001
	G4 (Special-use forest management board)	-0.89 (0.41)	-0.59 [-0.81– -0.08]	0.029
planta_ratio_sc	1	0.27 (0.1)	0.31 [0.08 – 0.59]	< 0.01

SE: Standard error; CI: Confidence interval

Figures in the Manuscript entitled "Factors associated with deforestation probability in Central Vietnam: A case study in Nam Dong and A Luoi districts"

This document includes **Figure 1** and **Figure 2** as follows.

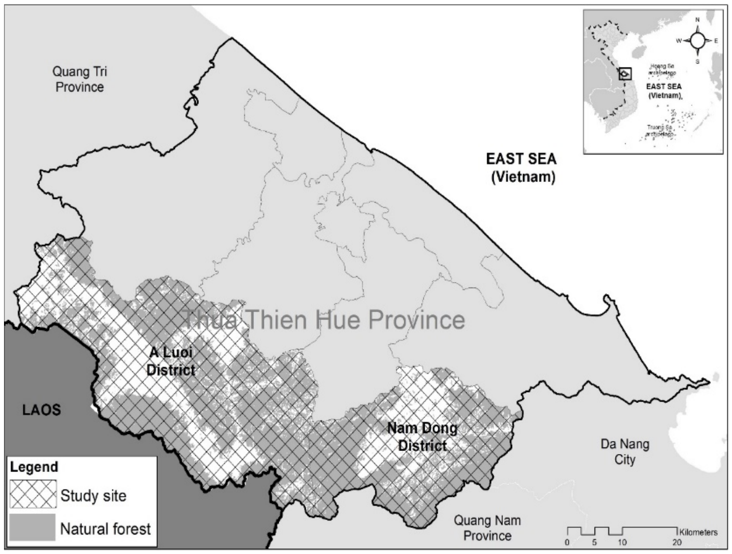


Figure 1. Nam Dong and A Luoi districts in Thua Thien Hue province, Vietnam

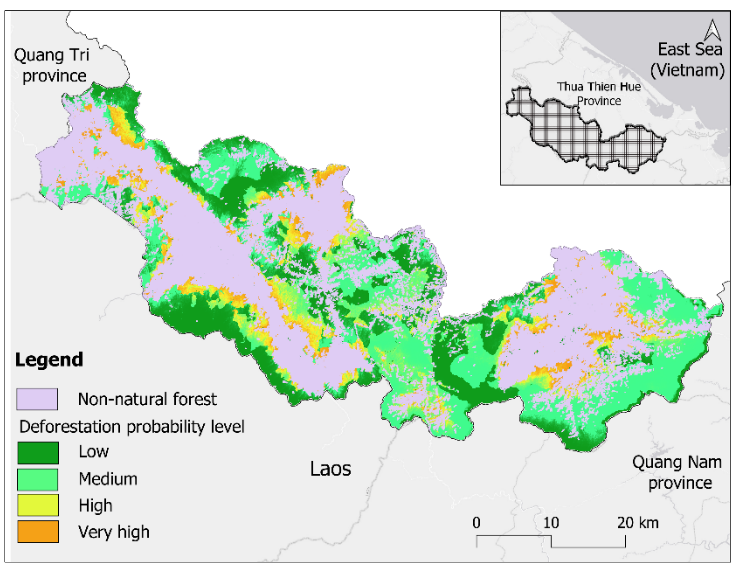


Figure 2. Predicted deforestation probability in the study area, using logistic regression model

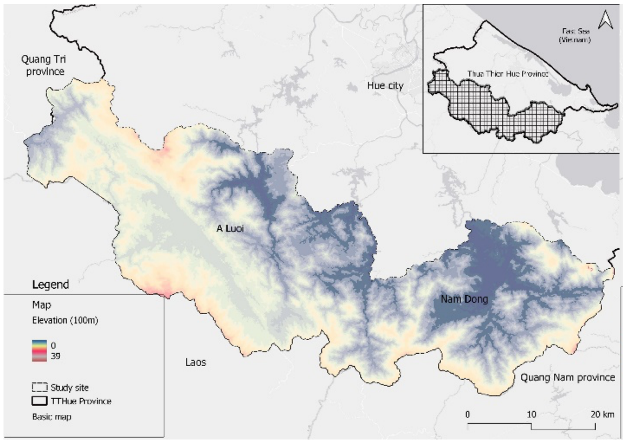
Supplementary materials for the Manuscript entitled "**Factors associated with deforestation probability in Central Vietnam: A case study in Nam Dong and A Luoi districts**"

The supplementary materials include **Table S1, Figure S1, Figure S2, Figure S3** and **Response to the Editors and Reviewers** as follows.

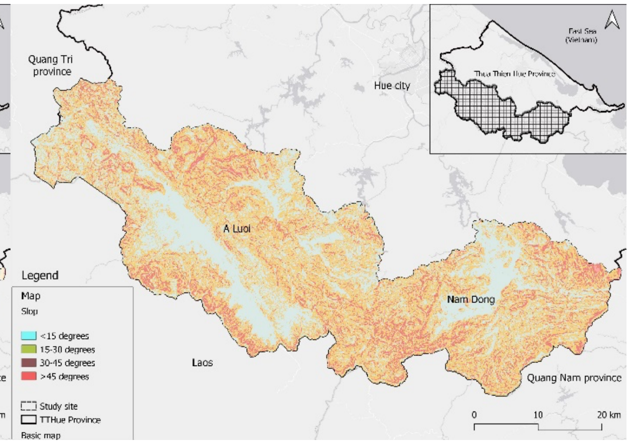
Table S1. Deforestation risk area in A Luoi and Nam Dong districts

District	**Commune**	**Area by probability levels (ha)**				**Proportion of very high level of probability (%)**	**Total natural forest (ha)**
		Low	**Medium**	**High**	**Very high**		
A Luoi	A Dot	553.0	36.1	38.1	30.4	4.6	657.7
	A Luoi town	638.6	4.6	10.4	13.8	2.1	667.3
	A Ngo	251.6	2.8	15.0	129.0	32.4	398.4
	A Roang	1897.8	325.2	368.4	452.1	14.9	3043.5
	Bac Son	225.5	55.1	84.2	83.1	18.6	447.9
	Dong Son	1197.0	135.8	77.1	74.4	5.0	1484.4
	Hong Bac	1055.4	39.9	107.2	438.4	26.7	1640.9
	Hong Ha	7932.8	382.1	603.8	1154.2	11.5	10072.8
	Hong Kim	3202.9	50.8	59.4	66.5	2.0	3379.6
	Hong Thai	4123.2	217.1	363.6	294.2	5.9	4998.1
	Hong Thuong	1176.8	282.9	296.2	393.5	18.3	2149.3
	Hong Thuy	4278.3	160.1	303.4	1064.7	18.3	5806.5
	Hong Trung	2700.7	233.1	661.4	976.2	21.4	4571.3
	Hong Van	676.9	61.4	233.6	861.9	47.0	1833.9
	Huong Lam	1683.9	468.1	701.0	421.1	12.9	3274.2
	Huong Nguyen	20622.1	2030.5	1086.1	1255.8	5.0	24994.6
	Huong Phong	3758.9	1191.8	840.0	453.5	7.3	6244.1
	Nham	677.2	58.7	151.6	361.2	28.9	1248.6
	Phu Vinh	1284.3	38.2	83.3	223.7	13.7	1629.5
	Son Thuy	355.8	5.0	31.9	240.1	37.9	632.9
Total area (ha)		58292.8	5779.3	6115.7	8987.6	**11.4**	79175.5
Nam Dong	Huong Giang	0	0	0	56.5	100.0	56.5
	Huong Hoa	0	0	0	13.5	100.0	13.5
	Huong Huu	0	4.8	67.9	117.4	61.8	190.2
	Huong Loc	3699.1	225.0	273.4	952.7	18.5	5150.2
	Huong Phu	3066.6	186.9	54.9	501.1	13.2	3809.5
	Huong Son	1559.7	120.8	282.6	652.6	24.9	2615.7
	Khe Tre town	-	-	-	0.5	100.0	0.5
	Thuong Lo	7502.2	394.2	339.9	654.1	7.4	8890.4
	Thuong Long	2659.3	248.5	203.4	398.5	11.4	3509.8
	Thuong Nhat	6635.7	599.8	461.9	1237.5	13.8	8934.9
	Thuong Quang	11531.9	680.5	495.7	720.1	5.4	13428.2
Total area (ha)		36654.6	2460.6	2179.7	5304.4	**11.4**	46599.2
Grand total (ha)		**94947.4**	**8239.9**	**8295.4**	**14292.0**		**125774.6**

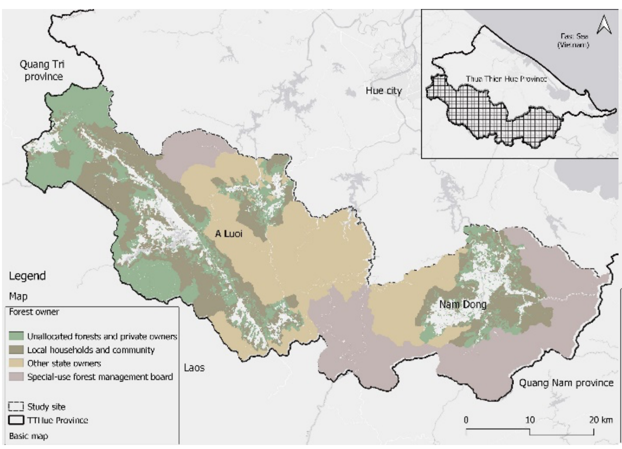
Elevation



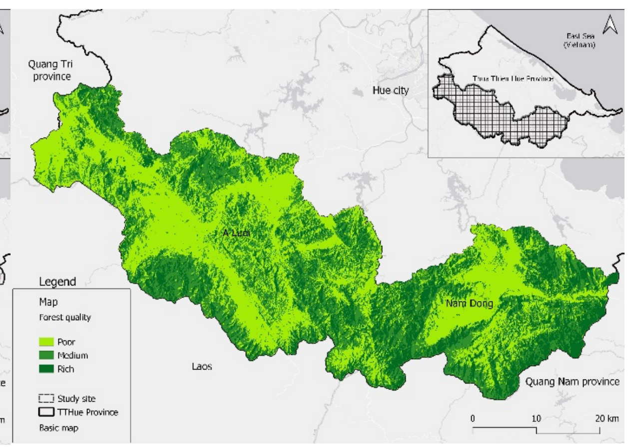
Slope



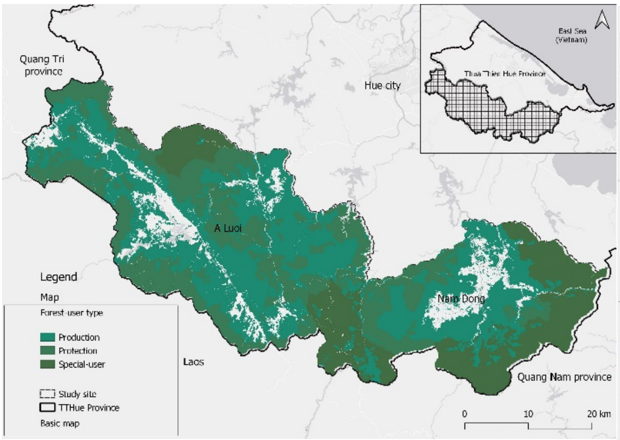
Forest owner



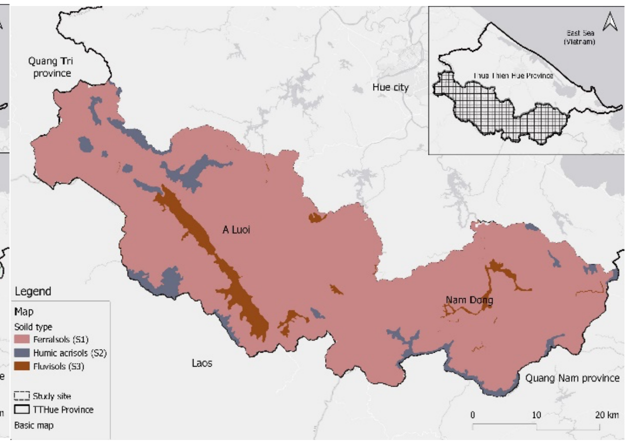
Forest quality



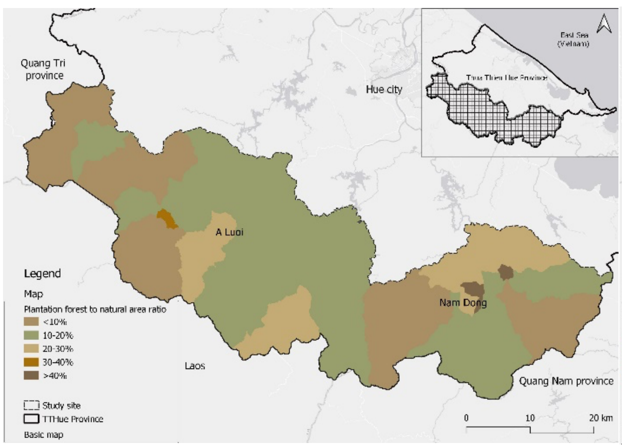
Forest-use type



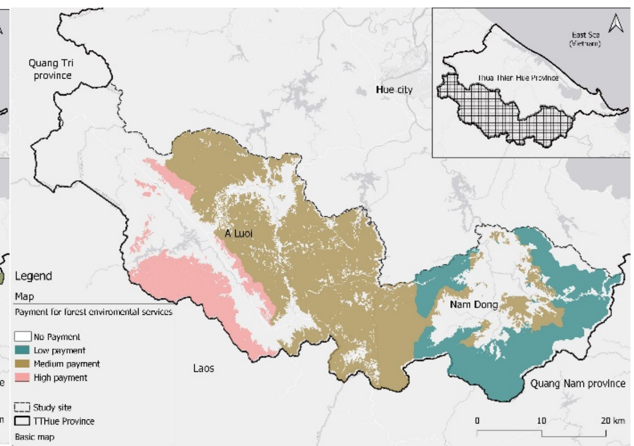
Soil type



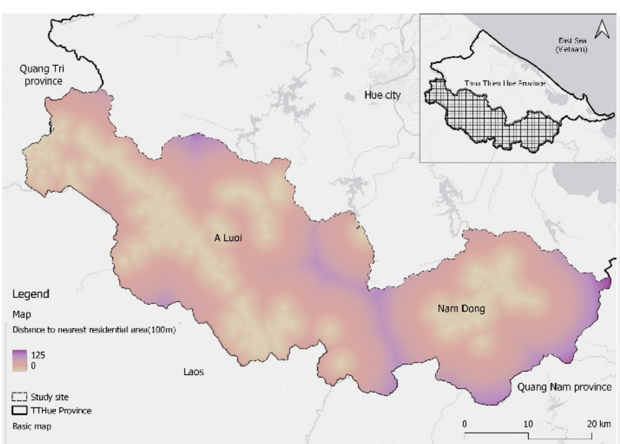
Plantation forest to natural area ratio



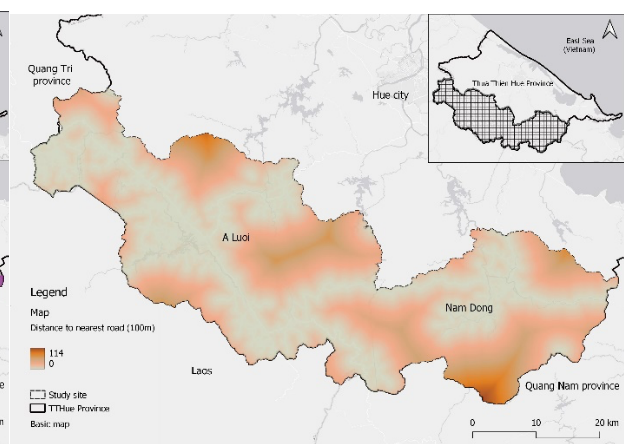
Payment for forest environmental services



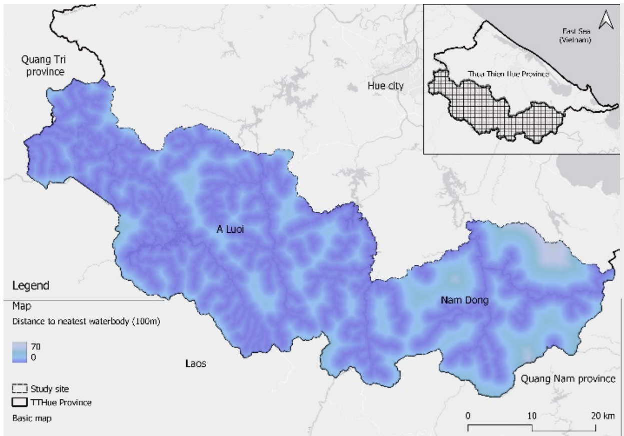
Distance to nearest residential area



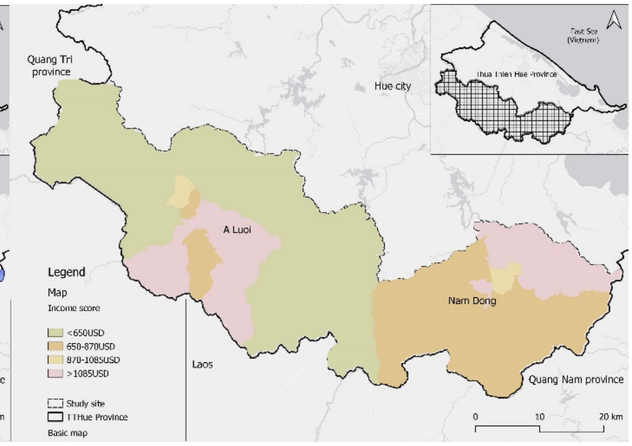
Distance to nearest road



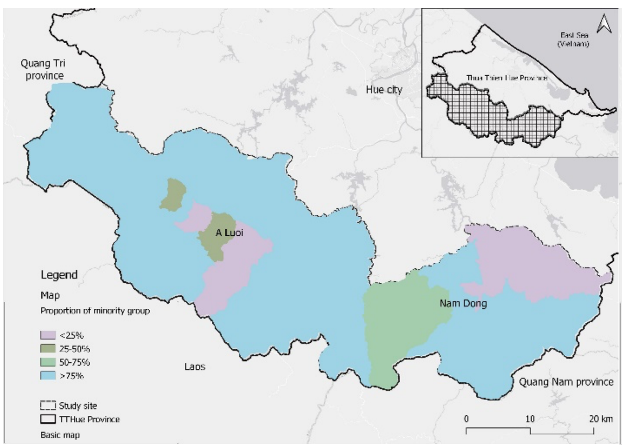
Distance to nearest waterbody



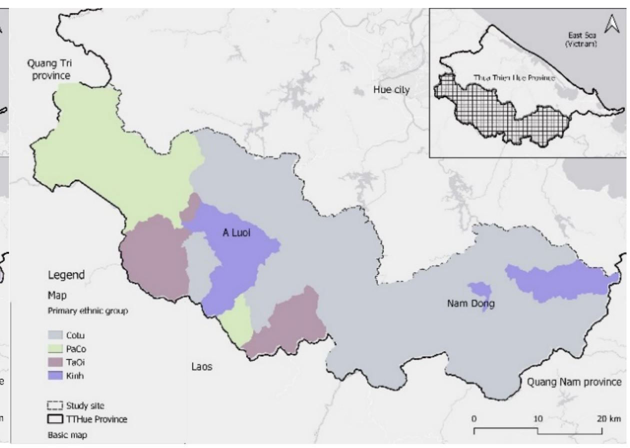
Income score



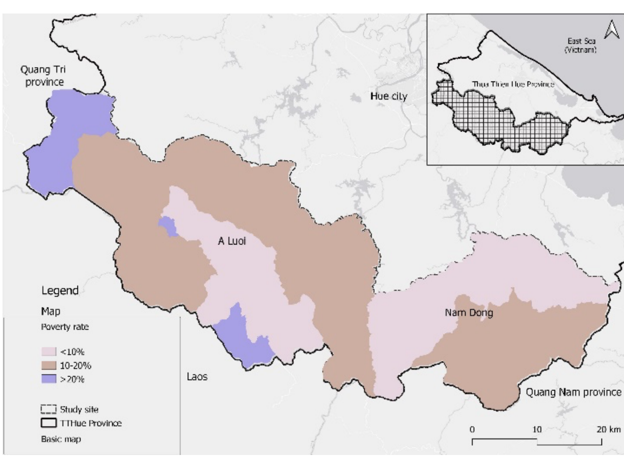
Proportion of ethnic minority group



Primary ethnic minority group



Poverty rate



Proportion of households without agricultural

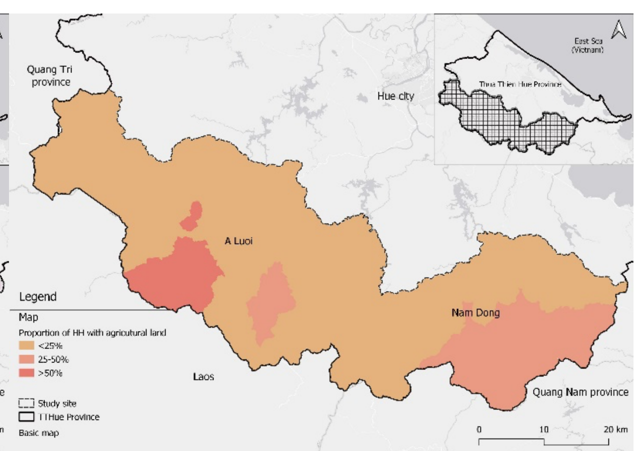


Figure S1. Spatial distribution of 16 potential predictors

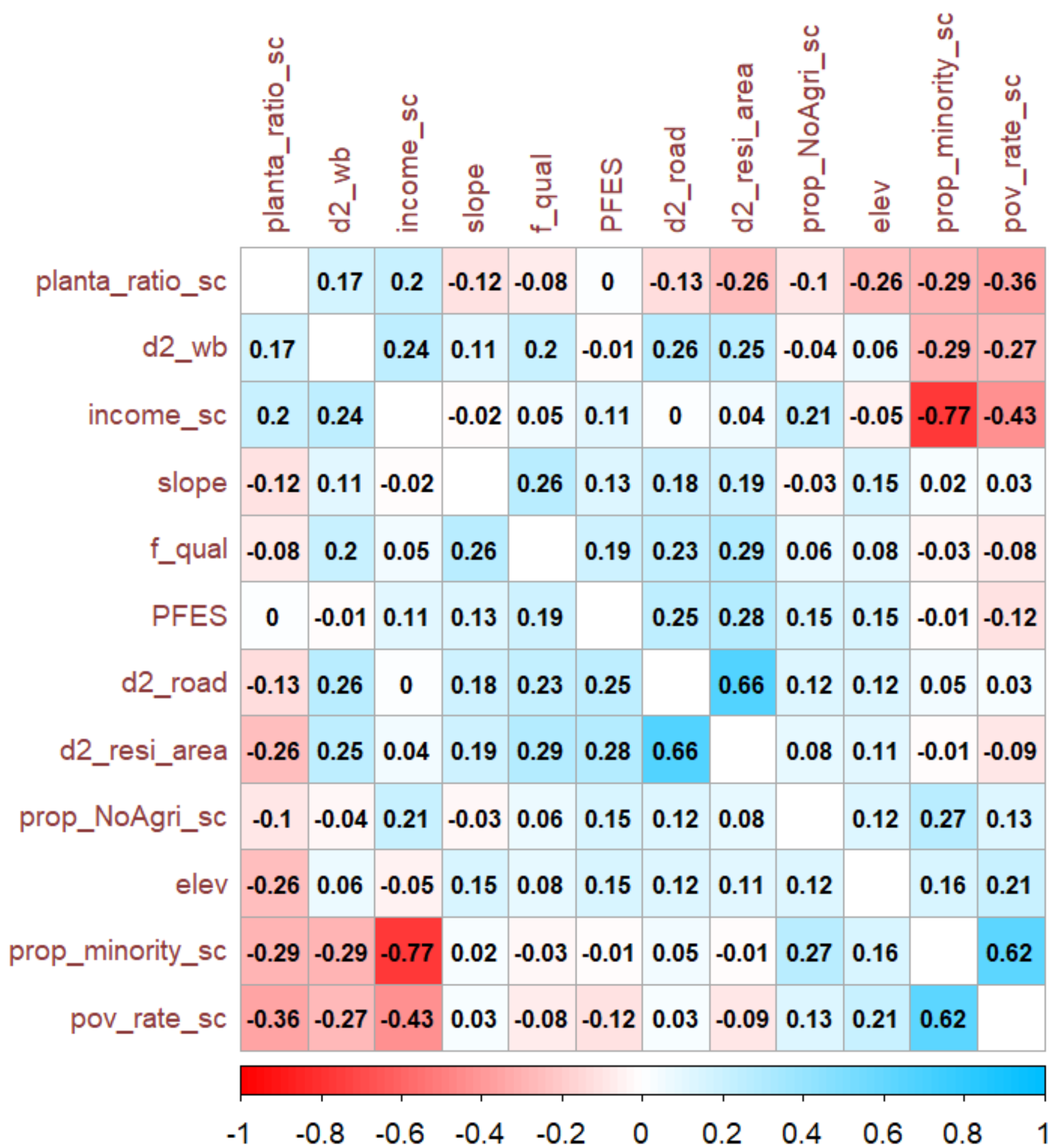


Figure S2. Spearman's correlation coefficients between 12 continuous and discrete predictors

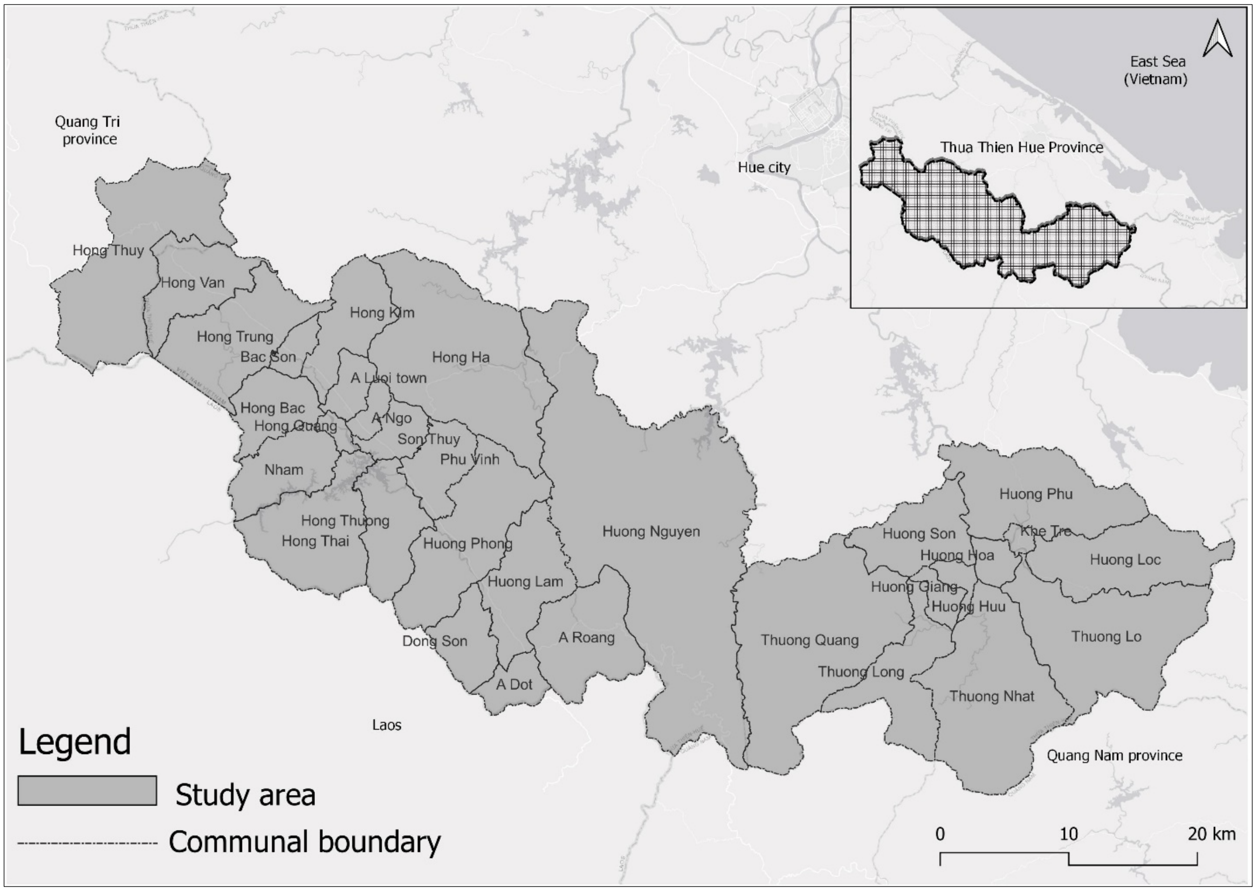


Figure S3. Communal boundary in the study area