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Exploring the Forest Cover Changes and Influential Factors of Dongsithouane National Production Forest Area, Savannakhet Province, Lao PDR

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Abstract

The Dongsithouane National Production Forest (DNPF) is one of the largest natural forest areas in Savannakhet, Lao PDR, which has been a vital support for the local community's livelihood, Recently, significant changes in land use and land cover (LULC) have been observed in this area, leading to a reduction of natural forests. There were two separate methods of this study: firstly, to identify LULC changes across three different periods, spectral imagery from the Landsat 5 Thematic Mapper (TM) for the years 2001 and 2011, and the Landsat 8 Operational Land Imager (OLI) for 2021 were used as the primary data sources. The satellite images were preprocessed for various forest classes, including pretreatment of the top of atmosphere reflectance by using QGIS software's semi-automatic classification plug-in (SCP), and ArcGIS was used for post-classification. A supervised classification approach was applied to the satellite images from 2001, 2011, and 2021 to generate diverse maps of LULC. Secondly, a household survey dataset was used to investigate influential factors. Approximately 220 households were interviewed in order to collect socio-economic information (including data on population growth, increased business activities, location of the area, agriculture land expansion, and need for settlement land). Household survey data was analyzed by using SPSS. Descriptive statistics, including frequency distributions and percentages, were applied to observe characteristics. Additionally, a binary logistic regression model was used to analyze the socioeconomic factors related to LULC change in DNPF. Key findings indicated a decline in natural forest areas within the study site. Specifically, both dry dipterocarp forest (−11.35%) and mixed deciduous forest (−0.18%) decreased from 2001 to 2021. The overall accuracy of the LULC maps was 94%, 86%, and 89% for the years 2001, 2011, and 2021 respectively. In contrast, agricultural land increased significantly by 155.70%, while built-up land, and water bodies increased by 65.54% and 35.33%, respectively. The results also highlighted a significant increase in construction land, up to 65.54%. Furthermore, the study found a correlation between agricultural expansion and a reduction of forest areas, along with an increase in built-up land along the forest areas' boundaries. Timber exploitation and charcoal production also contributed to the decline in forest cover. The logistic regression model identified significant determinants of LULC change, including the area's location, agricultural land expansion, increased business activity, and the need for settlement land. These factors have influenced the management of DNPF. Urgent sustainable management practices and actions, including forest ecosystem protection, village agricultural zoning, water source and watershed protection and public awareness, are required to preserve the forest areas of DNPF.

Keywords

Land Use/Land Cover Change, QGIS SCP, Socioeconomic Factor, Dongsithouane National Production Forest, Lao PDR

1. Introduction

The earth is a dynamic system influenced by human activities and natural processes [1]-[3]. Its surface supports peoples' livelihoods, natural forest resources, soil, and water bodies amongst others. However, land use and land cover changes primarily driven by human activities, have significantly altered not only the terrestrial environment but also the provisioning and service functions [1] [4]. Human-induced land use change remains a fundamental factor contributing to the global environmental changes experienced [3].

Laos, considered the most biodiverse country in Southeast Asia, features diverse land use and land cover types, including forest lands, grasslands, pine forests, farmlands, settlements, and wetlands [5]. The nation's forests are predominantly located in the central and southern regions, characterized by mountainous landscapes and identified as hotspots for agricultural and other development activities [6].

The Lao government has integrated the sustainable management of forest resources with rural development to enhance people's livelihoods [7]. The goals of this integration aimed to enhance protected natural forests and resources; however, forest areas have continuously deteriorated. Deforestation in Laos results from multiple factors including conversion to rural farmlands, land concessions or investments, infrastructure constructions and developments, and mining for energy supplies [8]. Despite ongoing forest cover loss, a recent study by [6] revealed a decline in forest cover from 70% in the early 1970s to 58% in 2015. In an attempt to restore the depleted forests, fifty-one national productive forests were established in Laos between 2006-2008, covering a total area of 3,089,177 hectares [9].

The natural forest provides crucial resources for rural livelihoods in developing countries. Improved access to natural resources, services, and markets can strengthen rural livelihoods, while non-timber forest products (NTFPs), wood products, and material construction have a significant impact on local communities [10]. In Laos, for instance, forests are utilized for shifting cultivation, privately owned trees, sacred forests, hunting taboos, and agro-forests. These practices are based on the domestication of NTFPs, community aquatic resource management, community NTFP harvesting rules, and multi-village NTFP conservation rules [11].

Prior to the nationwide reforestation program that commenced in 2006, portions of Dongsithouane National Production Forest, encompassing an estimated 150,900 ha were established in 2004. The primary objectives for the establishment were to promote and support rural livelihoods and to enhance local people's participation in forest management. Following the establishment of the forest, several committees were created with the mandate to oversee the management of the newly planted forests. These committees, for instance those at the village level, were authorized to enact rules and regulations for forest protection and received budgetary support, logistical assistance, and technical guidance from the State [8]. Despite the presence of these local committees, rapid land use and cover changes (LUCC) have persisted in the Dongsithouan's National Production Forests due to human activities including logging, land conversion into rice fields, shifting cultivation, and cassava plantations. Meanwhile, a recent study found a diversity of species within the mixed deciduous and dry Dipterocarp forests [12], highlighting the species richness of the area and underscoring the need for forest conservation.

Several studies have been conducted on land use and LULC change in Laos [13]-[15]. For instance, [16] study focused on national production forest in Laos. Additionally, research has focused on specific regions namely: Luang Prabang [17] and Champasak [18]. Some studies have utilized secondary data to assess land use change [19] [20]. Moreover, the spatial assessment of LULC change and ecosystem services in Savannakhet province for the years 1988 and 2010 was conducted using Landsat satellite images and land cover maps [21]. Furthermore, [22] assessed LULC changes from 2007 to 2017 in the provincial protected forest of Savannakhet province. The study reported the most significant increase in agricultural area (175.88%) followed by new planting area (155.77%) and then, new urban and built-up areas (100.51%). However, a comprehensive assessment of land-cover transitions in the Dongsithouane National Production Forest (DNPF) of Laos using satellite imagery remains lacking. This gap has significant implications for effective forest management. The DNPF consists of forests and forest lands subdivided to support the needs of national socio-economic development and the livelihoods of ethnic people. Furthermore, the production forest exhibits all the characteristics mandated by relevant rules and regulations for its establishment. It encompasses various forest types as classified in Article 16 of the Forest Law of Laos and is allocated, under a sustainable management system involving community participation. Consequently, the household socio-economic factor is used to investigate the impact of natural forest land cover change in this national production forest.

Land cover changes manifest as urban expansion, farmland loss, land abandonment, deforestation, reforestation, and amongst other phenomena. Future land cover change in some areas of Southeast Asia could be modeled by conducting a multi-layer perceptron-Markov chain analysis [23]. The results of such analyses may be useful for policymakers, particularly in Laos, to evaluate previous strategies and decisions made by the Laos government. The spatial data analysis using previous geographic information system (GIS) data could help to minimize the adverse effects of unplanned land use and facilitate the creation of efficient land use plans in the future. This study aimed to identify land-cover transitions, with a particular focus on the analysis of forest cover transitions and patterns in the Dongsithouane National Production Forest of Laos. Additionally, this research investigated the socioeconomic factors of household activities that influence land use and land cover (LULC) changes in the national production of forests.

2. Methodology

2.1. Description of the Study Area

This study focused on the Dongsithouane National Production Forest (DNPF), located in the Thapanthong and Songkhone Districts in Savannakhet Province, Laos (**Figure 1**). The total land area of 150,900 ha lies between 105˚16'00" and 106˚07'00"N longitude and 15˚59'30" and 16˚16’30"E latitude [24] and surrounding the DNPF are forty-two villages [25]. The altitude ranges from 131 to 850 meters (m) above mean sea level. The percentage humidity is approximately 69% in the dry season (November to April) and increases to 87% during the rainy season (May to October). The average annual rainfall is 1461.30 mm/year, and the average temperatures range from 12˚C to 35˚C [26].

2.2. Field Data Collection

The field data used for this study was collected through fieldwork in the Dongsithouane National Production Forest Area. Additionally, secondary data were obtained from the Forestry Inventory and Planning Division (FIPD) of the Department of Forestry (DoF), Ministry of Agriculture and Forestry (MAF), Lao PDR. Moreover, field observations were carried out during the fieldwork, allowing for the visualization of resource usage by local people and how their activities adversely affect the environment in the study area Figure 2. These data provide preliminary information on historical land use practices in each village and also serve as valuable input for understanding resource use at the community level. Consequently, this study consists of two methods for data analysis: land cover data and household data.

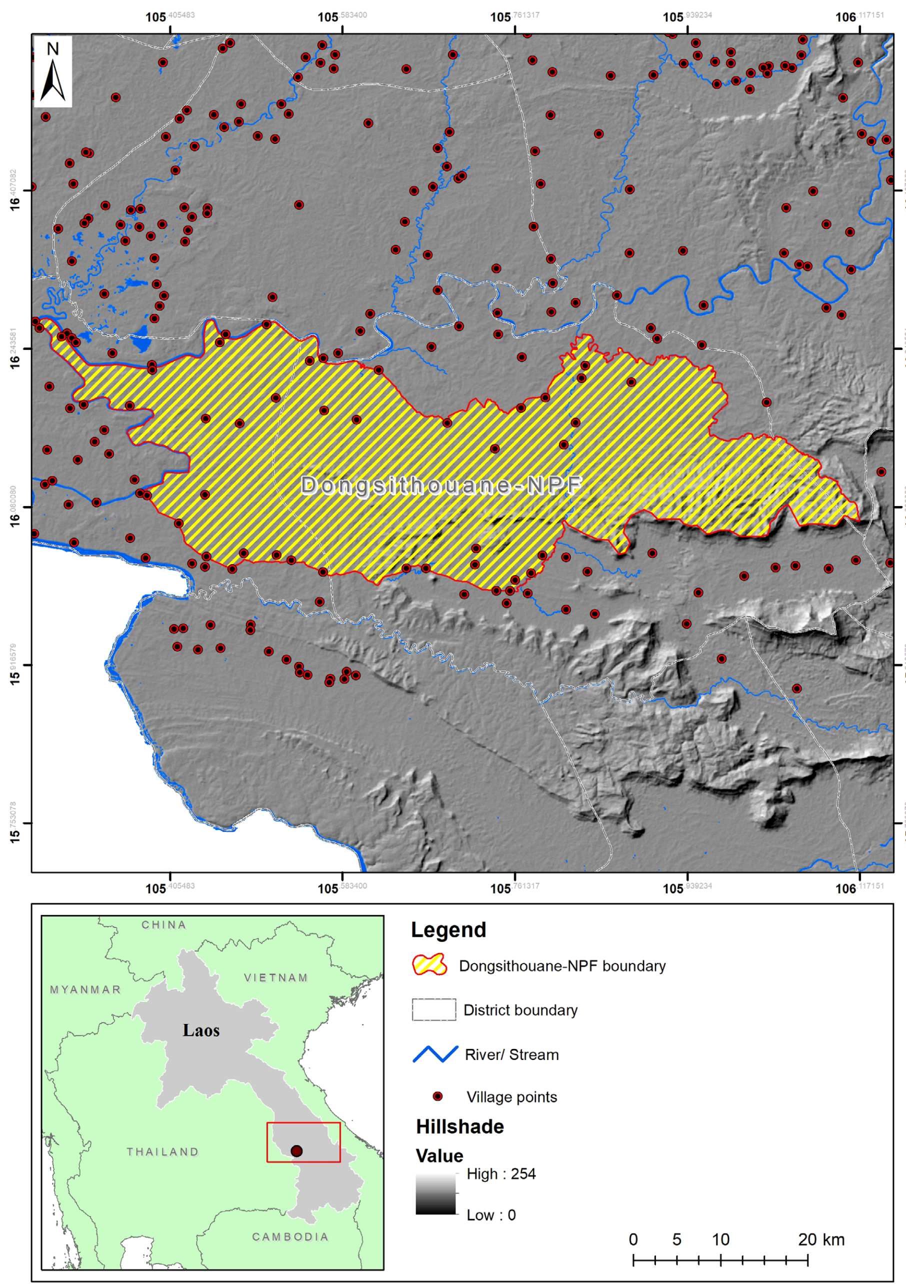

Figure 1. The study area located in DNPF, Savannakhet Province, Lao PDR.

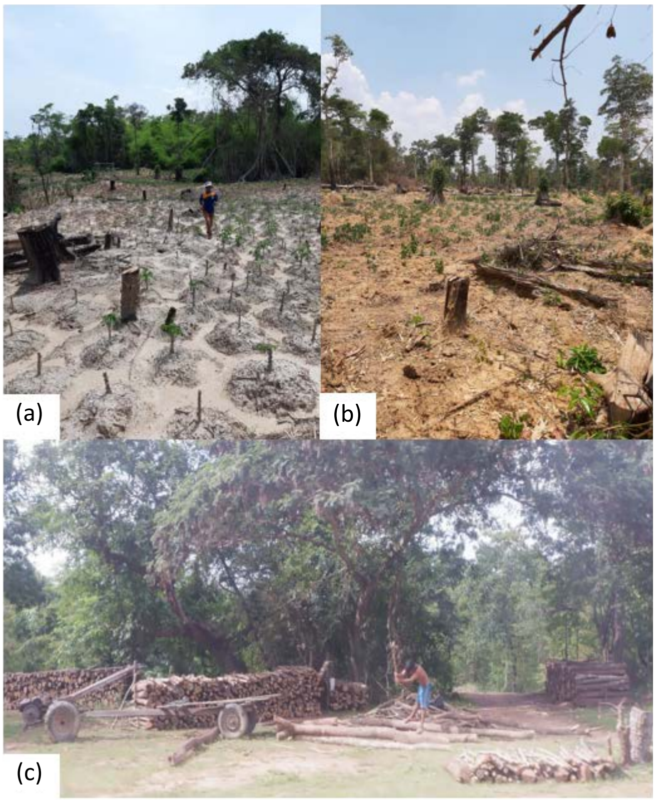

Figure 2. The villagers cleared the forest land (including mixed deciduous forest and dry dipterocarp forest) to grow cassava (a & b). Wood collections for charcoal production and selling out to a company (c). Source: Photo from field observations.

2.3. Satellite Images

Satellite images from 2001, 2011, and 2021 were obtained from the United States Geological Survey (USGS) via the USGS Earth Explorer, at https://earthexplorer.usgs.gov/ **Figures 3-5**. All Landsat images (TM, OLI) had a cloud cover of less than 10% to enhance the accuracy of the results. The images had a spatial resolution of 30-meter. The USGS provided the images freely without any restrictions [27]. The details of the Landsat images are provided below **Table 1**.

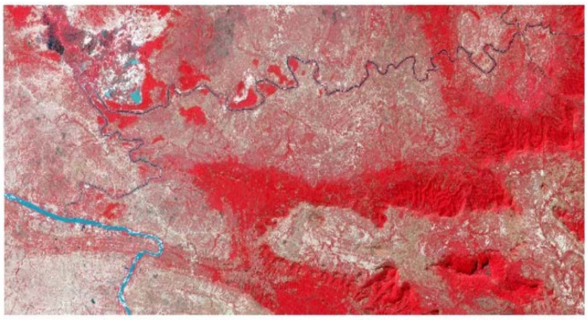

Figure 3. The Landsat 5 TM (2001) satellite image (Red, Green, Blue).

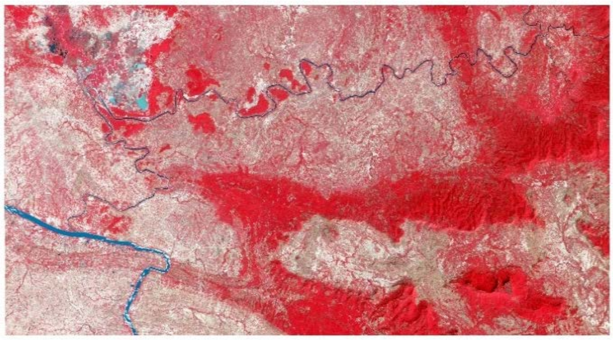

Figure 4. The Landsat 5 TM (2011) satellite image (Red, Green, Blue).

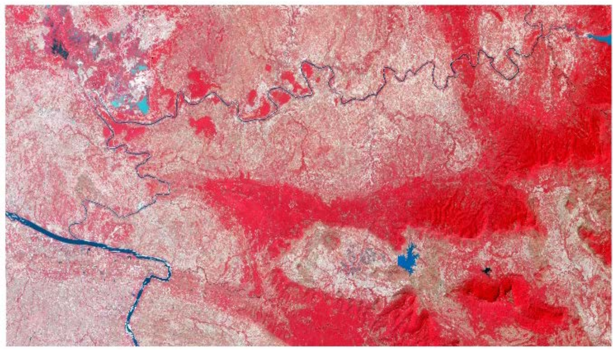

Figure 5. The Landsat 8 OLI (2021) satellite image (Near-infrared, Red, Green).

Table 1. Satellite images used in land cover classifications.

Satellite images	Sensor	WRP: Path/Row	Number of bands	Spatial resolution	Acquire data
Landsat 5	TM	126/049	7 (4-3-2)	30 × 30 m	2001-01-24
Landsat 5	TM	126/049	7 (4-3-2)	30 × 30 m	2011-02-05
Landsat 8	OLI	126/049	11(5-4-3)	30 × 30 m	2021-02-16

2.4. Household Data

The household interviews were conducted using a structured questionnaire [28]. The questionnaire was initially prepared in English and then translated into Lao, the local language. The respondents for the household survey were selected from five villages: Nongkan, Phousengkham, Nasano, Nonsavang, and Naxuak. The total sample size consisted of 220 households, which was determined using the formulas provided by [29] and [30]. The questionnaire form was used to gather information on general and, personal status as well as the economic conditions of households in the DNFP. Both heads of households and authority staff, were asked to provide accurate and precise answers. Variability sources were classified to minimize the heterogeneity within villages among household groups. To compare changed in land use and land cover, a binary logistic regression model was used to test thirteen factors: gender, age-class, education-uneducated, education-primary, education-secondary, education-high, education-middle, occupation-government, occupation-company, occupation-farmer, occupation-worker, residence status, and household size class. The independent variables were coded as follows X_1 = gender, X_2 = age class, X_3 = education-uneducated, X_4 = education-primary, X_5 = education-secondary, X_6 = education-high, X_7 = education-middle, X_8 = occupation-government, X_9 = occupation-company, X_{10} = occupation-farmer, X_{11} = occupation-worker, X_{12} = residence status, X_{13} = household size class. The results of this test show the relationship between these factors: socio-economic Y_1 = population growth), Y_2 = increase in business activities, Y_3 = location of the area, Y_4 = Agricultural land expansion, and Y_5 = need for settlement land see Figure 6.

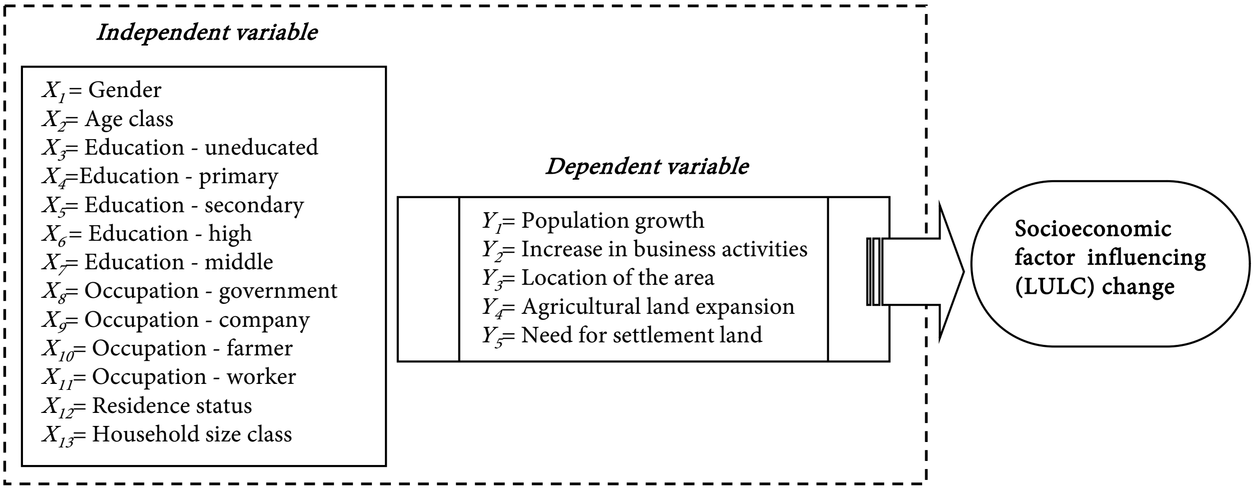

Figure 6. Conceptual framework process in factors influencing land use and land cover changes.

2.5. Land Cover Analysis

The Landsat-5 Thematic Mapper (TM) data were obtained for 2001 and 2011, while the Landsat-8 Operational Land Imager (OLI) data were obtained for 2021. The 2021 image, in conjunction with the household interviews, was utilized to track the historical changes in land cover and forest changes over time within the DNPF. Ground-truth data on land cover types were collected through field observations, with GPS coordinates recorded and cross-referenced using Google Earth Pro to facilitate comparison between image classification and land surface. The data were preprocessed for land cover classification types and the top of the atmosphere reflectance using the semi-automatic classification plugin (SCP) was also carried out in QGIS software see Figure 7. It provided several tools for data manipulation that were useful before the actual classification process. It made it possible for the conversion of Landsat 1, 2, and 3 MSS and Landsat 4, 5, 7, and 8 images from DN (*i.e.*, Digital Numbers) to the physical measure of top of atmosphere (TOA-Reflectance) or TOA-Radiance and DOS1 atmospheric correction [31] [32]. The Landsat image conversion was calculated by using the formulae as follows:

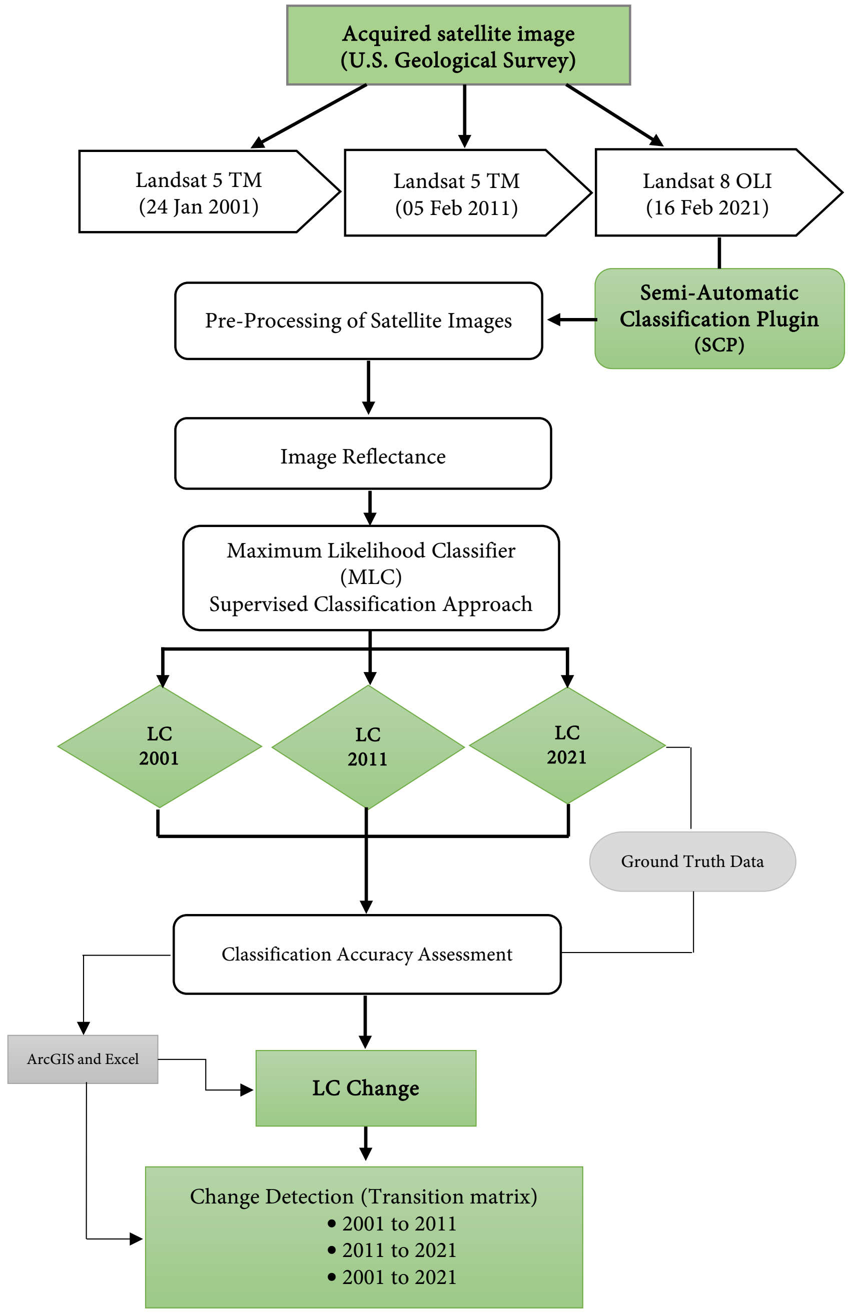

Figure 7. Workflow for analyzing the land use land cover change.

TOA Radiance:

$$L_\lambda = M_L * Q_{cal} + A_L \tag{1}$$

where: L_λ = TOA spectral radiance (Watts/(m^2 * srad * μm)); M_L = Band-specific multiplicative rescaling factor from the metadata RADIANCE_MULT_BAND_x, where x is the band number); A_L = Band-specific additive rescaling factor from the metadata (RADIANCE_ADD_BAND_x, where x is the band number); Q_{cal} = Quantized and calibrated standard product pixel values (DN).

TOA Reflectance:

$$\rho_p = \frac{\pi * L_\lambda * d^2}{ESUN_\lambda * \cos\theta_s} \tag{2}$$

where: ρ_p = TOA reflectance; L_λ = spectral radiance at the sensor's aperture (at-satellite radiance); d = Earth-Sun distance in astronomical units (provided with Landsat 8 metadata file, and an excel file is available from http://landsathandbook.gsfc.nasa.gov/excel_docs/d.xls); $ESUN_\lambda$ = mean solar exo-atmospheric irradiances; θ_s = solar zenith angle in degrees, which is equal to $\theta_s = 90^\circ - \theta_e$ where θ_e is the Sun elevation.

Surface Reflectance:

$$P = \frac{\pi * \left(L_\lambda - L_p\right) * d^2}{T_\upsilon * \left(ESUN_\lambda * \cos\theta_S * T_z\right) + E_{down}} \tag{3}$$

L_p = path radiance

T_v = atmospheric transmittance in the viewing direction

T_z = atmospheric transmittance in the illumination direction

E_{down} = downwelling diffuse irradiance

DOS1 correction:

$$L_P = L_{min} - L_{DO1} \tag{4}$$

L_P = radiance that corresponds to a digital count value for which the sum of all the pixels with digital counts lower or equal to this value is equal to 0.01% of all the pixels from the image considered. Therefore, the radiance obtained with that digital count value (DN_{min}).

L_{DO1} = radiance of Dark Object, assumed to have a reflectance value of 0.01.

2.6. Landsat Image-Processing of Land Cover Change

The Landsat satellite image (2001-2011-2021) of land cover (LC) analysis was processed using SCP in QGIS and ArcGIS software, as follows.

2.7. Land Cover Classification

The land use/land cover information can be derived from the multiband raster image interpretation and classification techniques [33]. The Maximum Likelihood Classifier (MLC) or supervised classification approach was used to create the base map and the other three-year maps for change detection [34]. Therefore, the MLC-classifier requires training samples based on individual or composite spectral bands and, when applied, assigns pixels based on the maximum likelihood to the corresponding class. For our study, the MLC classifier was trained using representative data assigned to all LULC classes that we derived from the ground truth reference points, which the Landsat 5 TM used band 2 (Visible green), band 3 (Visible red), band 4 (Near-infrared), whereas Landsat 8 OLI used band 5 (Near-infrared), band 4 (Visible red), and band 3 (Visible green). In this case, we classified five land cover types based on classification systems outlined by the Forestry Department of the Ministry of Agriculture and Forestry, Laos [35] see **Table 2**. Following the classification, we compared changes in forest cover and land use across different periods in 2001, 2011, and 2021. See Figure 7.

Table 2. Satellite images used in land cover classifications.

Type of Land cover	Description
Mixed Deciduous Forest	More than 50% of the trees stand in the mixed deciduous forest type. In this type of forest, bamboo is the most common. A woodland with a sparse tree canopy; a densely forested area.
Dry Dipterocarp Forest	The tree diameter is small, and the stand's height ranges from 8 to 25 meters. Savannah is the correct classification for vegetation. Mai Sabeng (*Dipterocarps intricatus*), Mai Chick (*Shorea obtusa*), Mai Sad (*Dipterocarpus obtusifolius*), and Mai Hang (*Shorea siamensis* Miq), Mai Xeuak (Terminalia elliptica Willd), are among the many species found in dry Dipterocarp forests (*Shorea siamensis*).
Agriculture Land	Cattle grazing, rice fields, and cultivation.
Built-up Land	An urban area or village settlement boundary, a small town, and other structures make up the built-up land.
Water bodies	Rivers, water reservoirs, ponds, and lakes.

2.8. Accuracy Assessment

In Figure 7, an accuracy assessment using pixel selection was conducted on Landsat high-resolution images. Google Earth, and field observations. Following the completion of the satellite image classification, the area survey was carried out to compare the images with the real surface conditions, with GPS devices used to record each type of land use. In addition, the random stratified technique was employed to assess image classification accuracy [36], followed by comparison with Google Earth software. For each classified image, random points were selected for accuracy assessment. Data were then summarized and quantified by using an error matrix, which was generated using ArcGIS software version 10.8.1 and Microsoft Excel version 2019. Furthermore, overall classification accuracy, producers' accuracy, and user accuracy were computed from the Kappa Statistics and Confusion Matrix (KHAT) [37] [38]. The Kappa statistic is a common index used to calculate the classification accuracy of remote sensing data associated with producers and users of the classification model. The Kappa coefficient represents the accuracy of reference and LUCC values. In image classification, the value of Kappa ranges from −1 to +1. Kappa coefficient 0 indicates inconsistent, 0 - 0.2 indicates slightly consistent, 0.2 - 0.41 indicates generally consistent, 0.41 - 0.60 indicates moderately consistent, 0.60 - 0.80 indicates significant agreement, and 0.81-1.0 indicates complete agreement [39]-[41].

$$\text{Kappa coefficient} = \frac{N\sum_{i=1}^{r} x_{ii} - \sum_{i=1}^{r}\left(x_{i+} * x_{+i}\right)}{N^2 - \sum_{i=1}^{r}\left(x_{i+} * x_{+i}\right)} \tag{5}$$

$$\text{Producer Accuracy} = \frac{\text{Number of Correctly Classified Pixels in each Classes}}{\text{total squared} - \text{Sum of the All the}\left(\text{Row total} * \text{Column total}\right)} \times 100 \tag{6}$$

$$\begin{aligned}&\text{Overall Accurracy}\\&=\frac{\text{Total Number of Correctly Classified Pixels}\left(\text{Diagonal}\right)}{\text{Total Number of Reference Pixels}}\times 100\end{aligned} \tag{7}$$

$$\begin{aligned}&\text{Kappa coefficient}\\&=\frac{\text{Total}*\text{Sum of Correct}-\text{Sum of the All the}\left(\text{Row total}*\text{Column total}\right)}{\text{total squared}-\text{Sum of the All the}\left(\text{Row total}*\text{Column total}\right)}\end{aligned} \tag{8}$$

2.9. Change Detection (Transition Matrix) in LULC Type

For the analysis of land cover change detection **Figure 7**, the classified maps generated from the Semi-Automatic Classification Plugin Documentation (SCP) in raster mode were converted to vector (shapefile) mode by using the spatial analysis extension of ArcGIS version 10.8.1. Subsequently, changes between the years 2001-2011 and from 2011-2021 were delineated using intersecting geoprocessing tools. Meanwhile, the values of the area changes and dynamic trends were analyzed and interpreted in the Sankey dynamic tools of Microsoft Excel. From 2001 to 2021, the transition matrix was calculated to illustrate, the various changes from one class to the other [42]-[44]. This transformation of LULC types involves converting each class, which is calculated by using the formula for the transition matrix. The display is as follows:

$$S_{ij}=\begin{bmatrix} S_{11} & S_{12} & \cdots & S_{1n}\\ S_{21} & S_{22} & \cdots & S_{2n}\\ \vdots & \vdots & \ddots & \vdots\\ S_{n1} & S_{n2} & \cdots & S_{nn}\end{bmatrix} \tag{9}$$

where S = the mean area, i = the type of land use or land cover at the beginning of the study, j = the type of land use/land cover at the end of the study, and n = the number of types in land use/land cover.

2.10. Household Data Analysis

The household data including averages, standard deviations from the mean, frequency distributions, and percentages of observed characteristics [45] were used to explain the demographics of communities. The study examined respondents' perceived roles of household members in the economy [28]. Binary logistic regression models were utilized to evaluate the socioeconomic factors that affected the Dongsithouane National Production Forest (DNPF). Therefore, the statistical tool is appropriate for determining the influence of explanatory variables on the dichotomous dependent variables when the former are continuous, categorical variables [46] [47]. The model consists of thirteen (13) illustrative variables which include the following: Gender, Age-class, Education-uneducated, Education-primary, Education-secondary, Education-high, Education-middle, Occupation-government, Occupation-company, Occupation-farmer, Occupation-worker, Residence status, and Household size class. which were introduced concurrently, to assess factors influencing the socio-economic.

The logit is the natural logarithm (ln) of odds of "Y", and odds are ratios of probabilities (π) of "Y" happening to probabilities ($1 - \pi$) of "Y" not happening. The logistic model is specified as:

$$\text{logit}(Y) = \ln\left(\frac{\pi}{1-\pi}\right) = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \cdots + \beta_k X_i \tag{10}$$

where β_0 is the intercept and $\beta_1, \beta_2, \cdots, \beta_k$ are the coefficients of the independent variables $X_1, X_2, \cdots, X_k$.

The response variables for the logistic regression model applied in this study were various types of socio-economic. The socio-economic was a binary choice variable (1 = Yes and 0 = No) that indicated whether a household collects any products from the forest, Additionally, the response variables for the logistic regression model on causes of land use and land cover change were: population growth, increase in business activities, location of the area, agriculture land expansion, and need for settlement land which was also defined as binary variables with a value of "1" for respondents agreeing to either of the perceived causes or "0" for otherwise.

3. Results

3.1. Status of Land Cover Classification in Production Forest Area

The results demonstrated a comparison of land cover in 2001, 2011, and 2021. In 2001, the area covered with dry dipterocarp forest was the highest 52.52%, while mixed deciduous forest, agriculture land, built-up land, and water areas comprised approximately 43.24%, 3.69%, 0.32%, and 0.23%, respectively. By 2011, mixed deciduous forest increased to 43.57%, followed by agricultural land at about 6.88%, built-up land at 0.39%, and water area coverage at 0.24%. Conversely, the area of dry dipterocarp forest decreased to 48.93%. In 2021, the coverage of dry Dipterocarp forests and mixed deciduous forests decreased further to 46.56% and 43.16%, respectively. In contrast, agricultural land, built-up land, and water area increased to 9.43%, 0.53%, and 0.32% respectively. The classification of the land use and land cover types revealed that agricultural land expanded rapidly at the expense of forest land and other land use over the last 20 years in the study area see **Table 3** and **Figure 8**.

Table 3. Percentage of different Land cover (LC) change in Dongsithouane National Production Forest from 2001 to 2021.

LC types	2001		2011		2021	
	Area (Ha)	**(%)**	**Area (Ha)**	**(%)**	**Area (Ha)**	**(%)**
Mixed Deciduous Forest	65,250.83	43.24	65,745.58	43.57	65,135.77	43.16
Dry Dipterocarp Forest	79,257.54	52.52	73,843.41	48.93	70,264.58	46.56
Agriculture Land	5566.64	3.69	10,378.64	6.88	14,233.91	9.43
Built-up Land	482.65	0.32	585.18	0.39	798.96	0.53
Water	352.21	0.23	357.04	0.24	476.65	0.32
	150,909.87		**150,909.87**		**150,909.87**	

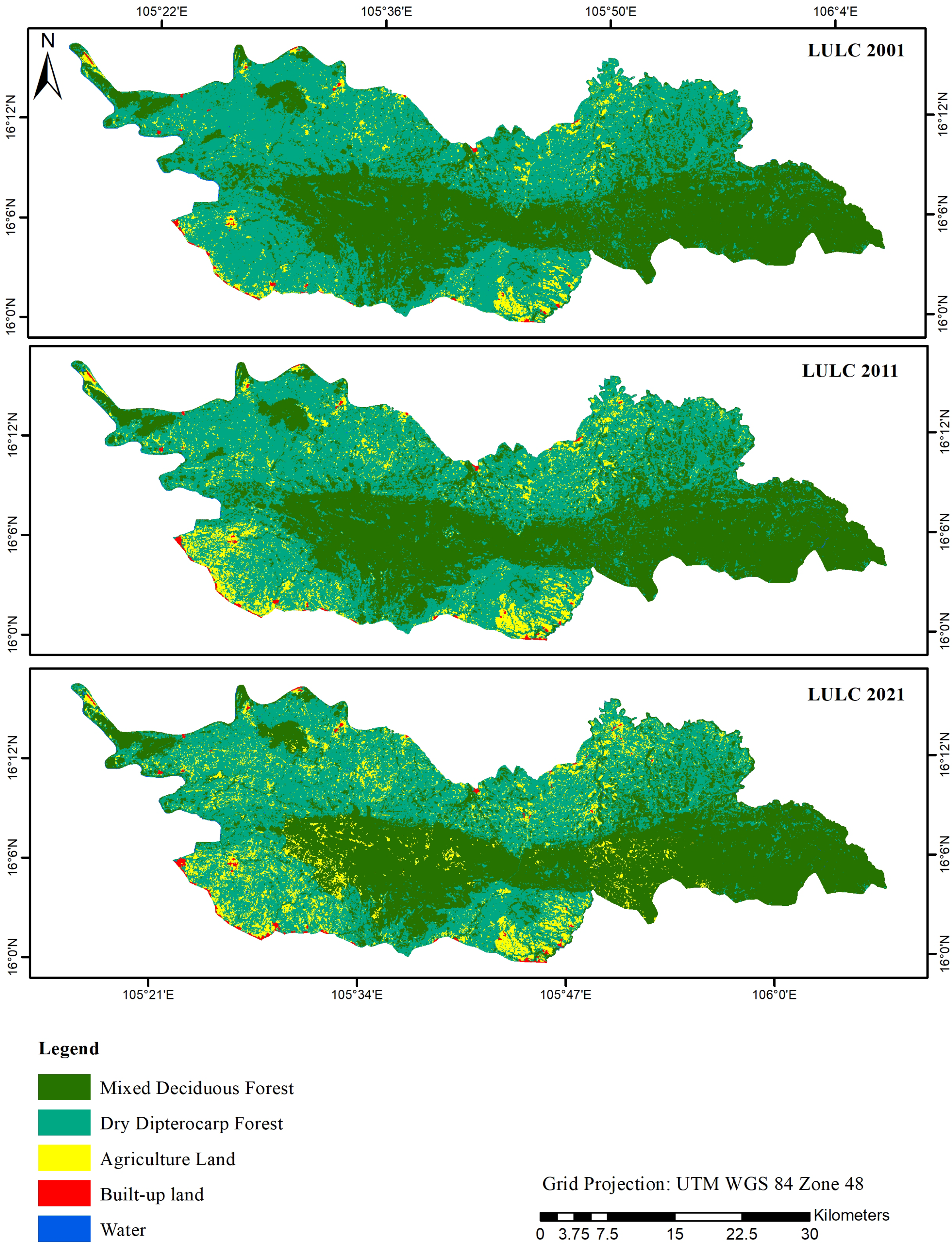

Figure 8. Image classification of land cover from 2001 to 2021.

3.2. Accuracy Assessment

Overall classification accuracy for the three reference years (2001, 2011, and

2021) was 94%, 86%, and 89% with the Kappa Coefficient of 0.91, 0.81, and 0.84 respectively, see Table 4.

Table 4. Accuracy assessment of land cover classification in 2001, 2011, and 2021.

Land Cover Types	2001		2011		2021	
	Producer Accuracy (%)	User Accuracy (%)	Producer Accuracy (%)	User Accuracy (%)	Producer Accuracy (%)	User Accuracy (%)
Mixed Deciduous Forest	98	93	98	85	98	89
Dry Dipterocarp Forest	95	84	84	66	80	77
Agriculture Land	94	99	96	89	94	91
Built-up Land	98	93	74	91	93	98
Water	76	100	55	93	62	94
Overall Classification Accuracy	94		86		89	
Kappa Coefficient	0.91		0.81		0.84	

3.3. Land Cover (LC) Change

Table 5 provides evidence of landscape patterns changing over the last two decades in the case study areas. During the decadal periods (2001-2011, and 2011-2021), dry dipterocarp forests exhibited a decreasing trend, with a reduction of 5414.12 hectares (6.83%) between 2001-2011 and a further reduction of 3578.83 hectares (4.85%) between 2011-2021. The field observations identified timber logging, charcoal, and fuel wood production as the main driving forces behind forest cover change in the Dongsithouane National Production Forest Area. Between 2001 and 2011, mixed deciduous forests increased by 494.75 hectares (0.76%), but a decrease of 609.81 hectares (about −1%) was recorded for 2011-2021, see Table 4. Regarding agricultural land, there was an increase of 86.44% over the period 2001-2021 and 37.15% over the period 2011-2021. Built-up land showed an increase of 21.24% between 2001-2010, and 36.53% between 2011-2021. Concerning water areas, there was a significant percentage increase from 1.37% between 2001-2021 to 33.50% between 2011-2021.

Table 5. Accuracy assessment of land cover classification in 2001, 2011, and 2021.

Land Cover Types	**2001-2011 (Ha)**	**%**	**2011-2021 (Ha)**	**%**	**2001-2021 (Ha)**	**%**
Mixed Deciduous Forest	494.75	0.76	−609.81	−0.93	−115.06	−0.18
Dry Dipterocarp Forest	−5414.12	−6.83	−3578.83	−4.85	−8992.96	−11.35
Agriculture Land	4812.01	86.44	3855.26	37.15	8667.27	155.7
Built-up Land	102.53	21.24	213.78	36.53	316.31	65.54
Water	4.83	1.37	119.6	33.5	124.43	35.33

3.4. Characteristics of Change Detection (Transition Matrix) in LULC Type

The transformation of land use and land cover classes between 2001 and 2021 Figure 9, indicates significant changes, particularly the decrease in dry dipterocarp and mixed deciduous forests, which have been converted into other LULC types. Thus, the result revealed that over the last 20 years, dry dipterocarp forests and mixed deciduous forests have declined primarily due to expansion of agricultural land. The substantial alteration of forest cover to agricultural land underscores the community's reliance on agriculture as the main livelihood in the region. From 2011 to 2021, the most notable change in the Dongsithouane National Production Forest Area's land cover involved the conversion of dry dipterocarp and mixed deciduous forests. Dry dipterocarp forests were primarily transformed into agriculture land, mixed deciduous forest, and built-up land with conversion rates of 3.61%, 2.40%, and 0.07%, respectively. Mixed deciduous forests were mainly converted into dry dipterocarp forest at a rate of 2.05%. During the same period, dry dipterocarp forests continued to be converted into agricultural land, mixed deciduous forest, and built-up land, at rates of 3.95%, 2.90%, and 0.11%, respectively. In addition, the mixed deciduous forest decreased in the study area, especially from 2011 to 2021, transforming, dry dipterocarp forest and agriculture land at rates of 2.77% and 0.56%, respectively. This forest loss was attributed to the expansion of agricultural land in the surrounding forest area. In contrast, from 2001 to 2021, the dry dipterocarp forests experienced significant changes, being transformed into agriculture land, mixed deciduous forest, and built-up land with conversion rates of 5.95%, 3.58%, and 0.16%, respectively. The mixed deciduous forests were converted into dry dipterocarp forest, agriculture land, and built-up land at rates of 3.08%, 0.60%, and 0.01%, respectively. Overall, over the past two decades, forest cover in the Dongsithouane National Production Forest (DNPF) has been decreasing rather than increasing. This decline is primarily due to human activities such as agriculture, deforestation, logging, and charcoal production.

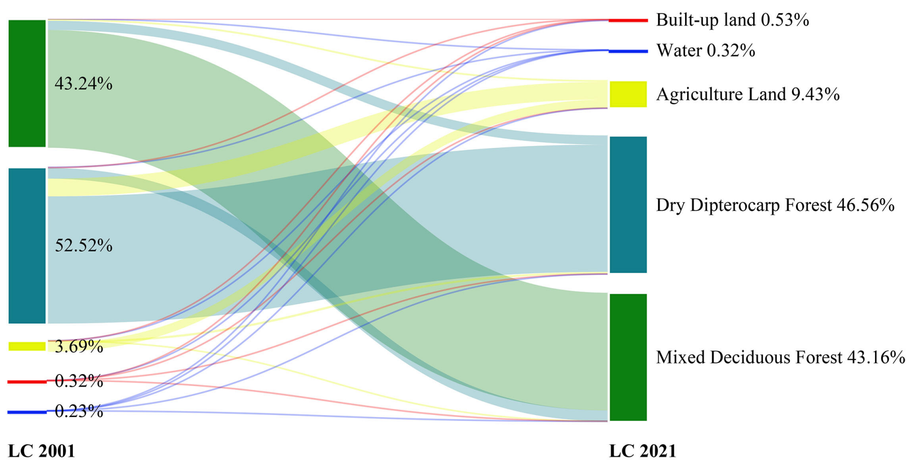

Figure 9. Sankey diagram of LULC classes transformation from 2001 to 2021.

3.5. Household Characteristics

The characteristics of household interviews in the study areas are as follows. The interviews were conducted with 220 respondents, of which 51.36% (n = 113) were male and 48.64% (n = 107) were female. The majority of respondents were married, comprising approximately 89.55% (n = 197), followed by single respondents at 5.45% (n = 12), divorced at 3.18% (n = 7), and widowed at 1.82% (n = 4). The education levels varied, with a significant portion of respondents being un-educated (41.82%), followed by those with primary school education (28.64%), secondary school education (16.82%), high school education (7.73%), and middle school education (3.64%), and a small fraction having higher education (1.36%). Additionally, respondents beloned to four ethnic groups: Lao (52.27%), Ka Tang (40%), Phu Tai (6.82%), and Ma Kong (0.91%). Regarding religion, the majority were Buddhist (52.7%), followed by those adhering to Pee (Ghost belief) at (36.4%), other religions (3.2%), and Christianity at (2.7%). Most respondents (78.2%) were native to the village, while a portion (21.8%) had migrated there, see Figure 10.

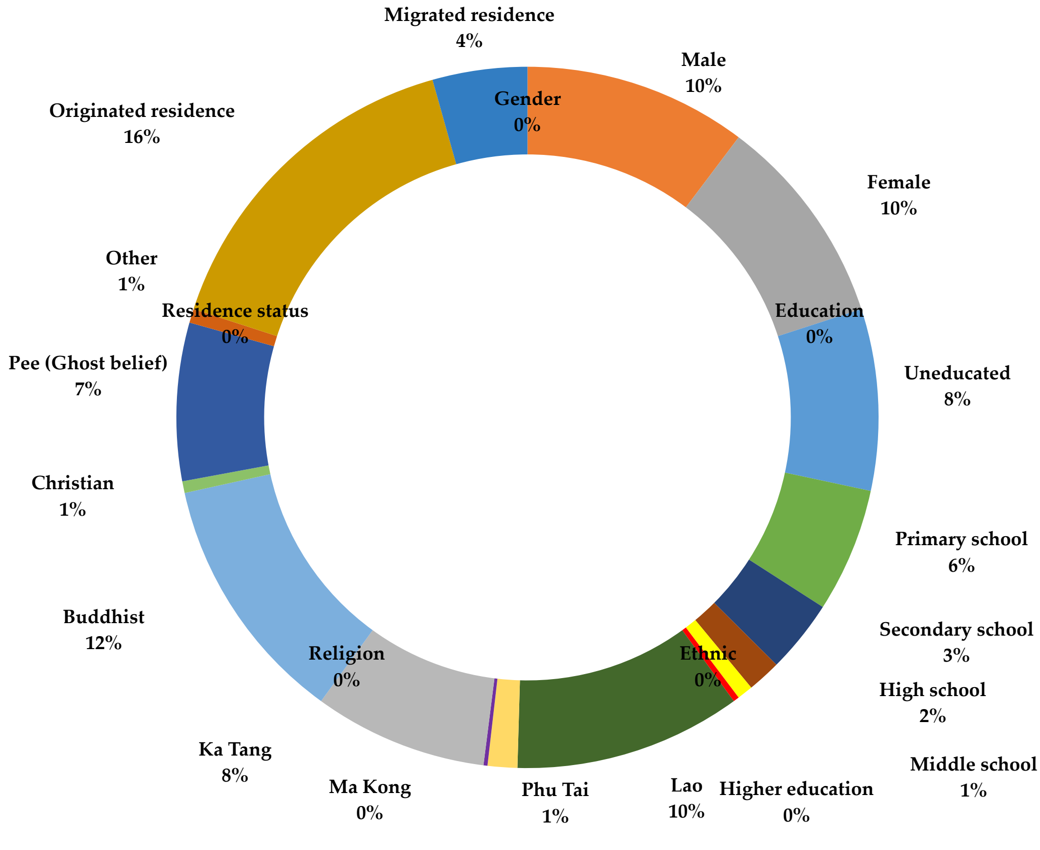

Figure 10. The proportion of respondents according to gender, education, ethnicity, religion, and residence status.

3.6. The Socio-Economic Factors Influencing LULC Change in Dongsithoune National Production Forest

- Population growth

According to the results presented in **Table 5**, the relationships between the dependent variable and the independent variables are not statistically significant, the p-values are less than 0.05. The primary reason for this may be that many local people have relocated to new places for better income opportunities, such as Thailand, Kaysoneohonvihane City, and Vientiane capital, based on respondents' interviews. Additionally, the study area is situated in the countryside, far from urban centres.

- The location of the area

Table 6 represents the results of a logistic regression analysis study investigating the correlation between a region's location (a dependent variable) and various independent factors. Among the independent variables, both gender and age exhibit statistically significant association with the geographical location of the region. The coefficient estimate for gender (B = 1.164) corresponds to an odds ratio of (*Exp* B = 3.204), while the coefficient estimate for age (B = 1.352) corresponds to an odds ratio of (*Exp* B = 3.866). These positive coefficients indicate that belonging to a specific gender or age group is associated with a higher likelihood of being in a particular area. The significance levels of 0.015* and 0.014* respectively, deem the associations statistically significant. In contrast, the variables related to education (uneducated, primary, secondary, high, and medium) do not exhibit statistically significant correlations with the geographical location of the region. The regression analysis reveals that the coefficient estimates for education related variables are uniformly negative, indicating that an increase in education levels is likely to correspond to a decreased probability of residing in a certain area. Nevertheless, the large standard errors and p-values approaching suggest that these correlations lack statistical significance in this study. Additionally, the p-values for the coefficient estimates of government, firm, farmer, residence status, and company occupations concerning the location of the region are all over 0.05. This suggests that there is no statistically significant association between occupation and area location. However, residency status and household size also show statistically significant associations with the region's geographical location. The coefficient estimates for occupation (worker) and household size are (B = 2.8), with an odds ratio of (*Exp* B = 16.44), and (B = 1.266), with an odds ratio of (*Exp* B = 3.546), respectively. These positive coefficients indicate a higher likelihood of being in a particular area for workers and larger households. Based on the significance thresholds of 0.019* and 0.026* respectively, the connections are considered statistically significant. The factors of gender, age, occupation (worker), and household size were found to influence land use and land cover changes. Interviews with residents in the village revealed that individuals aged 25 to 48, both male and female, are more likely to go frequently to the production forests. However, males are generally more likely than female to access the production forests. The primary occupations of people in the study area are farmers and workers, and many residents have been living in or near the natural forests. Household size significantly impacts forest resource depletion and land cover change. This is because an increase in the number of family members leads to a decrease in forest cover, necessitating more land for agricultural and built-up areas. This underscores the critical role of household size in the management and preservation of forest resources.

Table 6. The variables of socio-economics influencing land use/land cover change in DNPF.

Dependable variable	Independent variables	(*B*)	(*Std. Error*)	(*Wald*)	(*df*)	(*Sig.*)	(*Exp*(*B*))
Population growth	Gender	0.585	0.374	2.444	1	0.118	1.795
	Age-class	0.678	0.424	2.555	1	0.110	1.971
	Education-uneducated	−21.885	23,205.55	0.000	1	0.999	0.000
	Education-Primary	−21.811	23,205.55	0.000	1	0.999	0.000
	Education Secondary	−0.621	23,984.32	0.000	1	1.000	0.537
	Education-High	−20.697	23,205.55	0.000	1	0.999	0.000
	Education Middle	−0.802	27,182.01	0.000	1	1.000	0.448
	Occupation-Government	−0.581	20,773.45	0.000	1	1.000	0.559
	Occupation-Company	−0.121	16,851.58	0.000	1	1.000	0.886
	Occupation-Farmer	−21.741	14,101.22	0.000	1	0.999	0.000
	Occupation-worker	−19.584	14,101.22	0.000	1	0.999	0.000
	Residence status	−0.748	0.472	2.511	1	0.113	0.474
	Household size class	−0.416	0.43	0.937	1	0.333	0.660
	Constant	80.740	27,933.74	0.000	1	0.998	1.16E+35
The location of the area	**Gender**	**1.164**	**0.478**	**5.938**	**1**	**0.015***	**3.204**
	Age-class	**1.352**	**0.55**	**6.054**	**1**	**0.014***	**3.866**
	Education-uneducated	−23.806	23,205.07	0.000	1	0.999	0.000
	Education-Primary	−22.34	23,205.07	0.000	1	0.999	0.000
	Education Secondary	−19.65	23,205.07	0.000	1	0.999	0.000
	Education-High	−20.501	23,205.07	0.000	1	0.999	0.000
	Education Middle	−0.050	26,975.05	0.000	1	1.000	0.951
	Occupation-Government	2.918	1.590	3.37	1	0.066	18.501
	Occupation-Company	22.867	8,988.60	0.000	1	0.998	8.53E+09
	Occupation-Farmer	−1.063	1.012	1.104	1	0.293	0.345
	Occupation-worker	**2.800**	**1.193**	**5.51**	**1**	**0.019***	**16.44**
	Residence status	1.016	0.556	3.332	1	0.068	2.761
	Household size class	**1.266**	**0.567**	**4.976**	**1**	**0.026 ***	**3.546**
	Constant	18.632	23,205.07	0.000	1	0.999	1.24E+08

Continued

Agriculture land expansion	Gender	−0.538	0.347	2.404	1	0.121	0.584
	Age-class	**1.240**	**0.413**	**9.003**	**1**	**0.003 ***	**3.456**
	Education-uneducated	−21.295	23,205.99	0.000	1	0.999	0.000
	Education-Primary	−20.87	23,205.99	0.000	1	0.999	0.000
	Education Secondary	−18.929	23,205.99	0.000	1	0.999	0.000
	Education-High	−20.809	23,205.99	0.000	1	0.999	0.000
	Education Middle	0.524	27,132.26	0.000	1	1.000	1.688
	Occupation-Government	−0.127	20,466.65	0.000	1	1.000	0.881
	Occupation-Company	−0.988	16,526.24	0.000	1	1.000	0.372
	Occupation-Farmer	−22.619	13,570.40	0.000	1	0.999	0.000
	Occupation-worker	−21.907	13,570.40	0.000	1	0.999	0.000
	Residence status	−0.452	0.416	1.182	1	0.277	0.636
	Household size class	0.158	0.385	0.170	1	0.680	1.172
	Constant	42.875	26,882.59	0.000	1	0.999	4.17E+18
The increase in business activity	Gender	0.520	0.370	1.972	1	0.160	1.681
	Age-class	0.598	0.395	2.289	1	0.130	1.818
	Education-uneducated	−23.665	23,205.66	0.000	1	0.999	0.000
	Education-Primary	−22.245	23,205.66	0.000	1	0.999	0.000
	Education Secondary	−22.906	23,205.66	0.000	1	0.999	0.000
	Education-High	−22.211	23,205.66	0.000	1	0.999	0.000
	Education Middle	−1.164	26,983.88	0.000	1	1.000	0.312
	Occupation-Government	0.207	1.437	0.021	1	0.886	1.23
	Occupation-Company	0.716	1.094	0.428	1	0.513	2.046
	Occupation-Farmer	−1.182	0.906	1.703	1	0.192	0.307
	Occupation-worker	−0.273	1.027	0.071	1	0.790	0.761
	Residence status	**−1.344**	**0.433**	**9.617**	**1**	**0.002***	**0.261**
	Household size class	**−1.354**	**0.406**	**11.101**	**1**	**0.001***	**0.258**
	Constant	24.485	23,205.66	0.000	1	0.999	4.30E+10
Need for settlement land	**Gender**	**0.994**	**0.461**	**4.643**	**1**	**0.031***	**2.702**
	Age-class	−0.054	0.46	0.014	1	0.906	0.947
	Education-uneducated	−24.329	23,205.40	0.000	1	0.999	0.000
	Education-Primary	−22.807	23,205.40	0.000	1	0.999	0.000
	Education Secondary	−21.816	23,205.40	0.000	1	0.999	0.000
	Education-High	−21.128	23,205.40	0.000	1	0.999	0.000
	Education Middle	−42.898	27,046.67	0.000	1	0.999	0.000
	Occupation-Government	1.844	1.445	1.627	1	0.202	6.322
	Occupation-Company	1.022	1.098	0.867	1	0.352	2.779
	Occupation-Farmer	−0.965	0.881	1.200	1	0.273	0.381
	Occupation-worker	0.325	1.029	0.100	1	0.752	1.385
	Residence status	**1.128**	**0.565**	**3.979**	**1**	**0.046***	**3.089**
	Household size class	0.719	0.504	2.036	1	0.154	2.053
	Constant	20.376	23,205.40	0.000	1	0.999	7.06E+08

(*B*) = regression coefficients which stand for the odds ratio (probability of success or probability of failure), (*SE*) = standard estimate error = statistically non-significant at 0.05 level of significance, (*Wald*) statistics = $b/(SE)2$, (*df*) = degree of freedom, (*Sig*) = Significant at 0.05 level of confidence*.

- Agriculture land expansion

Table 6 represents the results of a logistic regression analysis investigating the relationship between agricultural growth (a dependent variable) and several independent factors. The independent variables, gender and resident status do not exhibit statistically significant correlations with the agriculture expansion. The coefficient estimates for gender and residency status are −0.538 and −0.452, respectively. These findings suggest that neither gender nor resident status significantly influence the likelihood of agricultural growth, as evidenced by *p*-values of 0.121 and 0.277, respectively. In contrast, age demonstrates a statistically significant correlation with agricultural expansion. The regression analysis reveals a coefficient estimate for age is (B = 1.24) and the odds ratio is (*Exp B* = 3.456), indicating a positive correlation between an increase in age and a higher probability of agricultural growth. Based on the low significance level of 0.003*, the link is considered statistically significant. The coefficient estimates for government, firm, farmer, and worker vocations all indicate a negative correlation with agricultural growth, suggesting a potential adverse impact. Nevertheless, the *p*-values for these variables are not statistically significant, indicating that occupation does not substantially affect the likelihood of agricultural growth in this study. The household size variable has a coefficient estimate of 0.158, indicating a positive correlation with the agricultural growth. Nevertheless, this estimate is not statistically significant as indicated by a high *p*-value of 0.68. According to the respondents, age influence land use and land cover changes related to the agriculture expansion. Interviews with the respondents and observations around the production forest revealed that individuals over 22 years old, are more likely to engage in deforestation activities to clear land for cassava cultivation.

- The increase in business activity

Table 6 presents the results of a logistic regression analysis investigating the correlation between an increase in business activity (a dependent variable) and several independent factors. The coefficient estimates for gender and age among the independent variables fail to achieve statistical significance ($p > 0.05$). This implies that gender and age categories do not substantially influence the probability of on increase in company activity. The education-related variables (uneducated, primary, secondary, high, and medium education levels) all exhibit negative coefficient estimates, suggesting a possible inverse correlation with an upsurge in economic activity. However, all estimates lack statistical significance, as indicated by the large standard errors and *p*-values approaching. These findings suggest that education levels do not significantly impact the probability of witnessing an increase in company activity in this investigation. Regarding occupation, the coefficients for government, corporate, farmer, and worker occupations have estimates close to zero and *p*-values are higher than 0.05. This indicates no significant correlation between occupation and an increase in company activity. In contrast, both resident status and household size have statistically significant associations with an increase in company activity. The coefficient estimates for residency status is (B = −1.344), with an odds ratio of *Exp B* = 0.261), and the coefficient for household size is (B = −1.354) with an odds ratio of *(Exp B* = 0.258). These negative correlations, suggest that certain residential statuses and larger family sizes are associated with a lower likelihood of experiencing an increase in company activity. The significance thresholds, with p-values of 0.002* and 0.001* respectively, confirm the statistically significance of these correlations. Residence status and household size were identified as the primary factors influencing land use and land cover change (LULC) changes. This is attributed to the presence of a factory producing white charcoal from the tree *Cratoxylum maingayi* (Dyer), locally known as Mai Tiew, which buys trees from villagers. Additionally, local people produce charcoal from timber for household cooking, and clear land for agriculture, such as cassava cultivation, within and around the Douangsithoune National Production Forest (DNPF).

- Need for settlement land

Table 6 presents the results of a logistic regression analysis examining the correlation between the rise in land for settlement (a dependent variable) and several independent factors, including gender, age, educational level, employment, residential status, and household size category. The analysis reveals statistically significant associations between residency status, gender, and the land for settlement. Residence status and gender have a statistically significant inverse correlation with the increase in land for settlement. The coefficient estimates for residency status and gender are (B = 1.128) with an odds ratio of *(Exp B* = 3.089) and (B = 0.994) with an odds ratio of (*Exp B* = 2.702), respectively. Thus, resident status and gender are statistically significant, as shown by the significance levels of 0.046* and 0.031*, respectively. This implies that both residence status and gender have considerable influence on the increase in land for settlement. However, other factors, such as age, education levels, employment, and household size do not show statistically significant correlations with the rise in land for settlement, as their significance levels do not fall below the customary threshold of 0.05. The responses from the respondents revealed that gender and residence status were influential factors in land use and land cover changes related to the need for land for settlement and industry. According to Lao tradition or culture, married individuals either build a new house or acquire new land for agricultural production. In the absence of inherited land, they seek alternative way to obtain it. Additionally, the significance of residence status or built-up land is paramount for the study site, particularly concerning forest and land cover changes. Activities such as building houses or expanding agricultural land directly impact the area.

4. Discussion

Land use and land cover (LULC) changes in Southeast Asian countries are predominantly driven by population growth and economic development [48]. Over the past 50 years, extensive research has been conducted on LULC changes in this region [49]. The Laos government has actively promoted forest, aquatic, and wildlife conservation through initiatives aligned with the International Union for Conservation of Nature (IUCN), the World-Wide Fund for Nature (WWF), the Forest Management and Conservation Program (FORMACOP), and Sustainable Forestry for Rural Development (SUFORD). These efforts aim to reduce or eliminate deforestation and the slash-and-burn agriculture in Laos [8]. Despite the increasing focus on mitigating LULC changes resulting from anthropogenic activities, significant challenges remain. Consequently, the Lao government is committed to promoting sustainable development to mitigate biodiversity loss and address climate change adaptation and mitigation [50]. Access to accurate spatial data for monitoring and forecasting LULC changes are crucial [39]. Previous accuracy tests for LULC maps specific to the Dongsithouane Production Forest in Laos were unavailable; however, the utilization of available time-series datasets and forest cover maps has shown promise. This study produced a LULC map based on the use of geospatial data from satellite images and spatial analysis using GIS applications. The accuracy assessment revealed highly acceptable maps, correctly categorizing sampling pixels into their respective land cover categories, see **Table 4**. Additionally, a review of existing nationwide cartography on LULC mapping helped to select inputs consistent with scale, classification, and mapping methods. However, detailed description of LULC change dynamics for this production forest were lacking. We evaluated the LULC changes over two decades from 2001-2011 and 2011-2021, as shown in **Table 5**. This evaluation aimed to capture as much pattern change as possible, reflecting the characteristics of the LULC area and the change in the Dongsithouane National Production Forest, which are crucial for projected land use management and planning in this area. Clear evidence indicates changing landscape patterns over the past two decades, particularly with a decrease in dry Dipterocarp and mixed deciduous forests between 2011 and 2021. The findings of this study align with the observed decline in deciduous forests along the border of Thailand, Laos, and Cambodia, which decreased at a rate of 0.80% per year or 7.68% between 2003 and 2013 [41]. Other land subcategories, namely agricultural land, built-up land, and water have continued to increase due to growing regional market demand for agricultural and forestry products and improved infrastructure access. Our results revealed that forest cover has declined due to the conversion of forests to agricultural areas, consistent with the findings by [21]. Similarly, rice fields have expanded around the Laos and China boundary [51], underscoring the need for forest conservation. In our study, the agricultural expansion was a significant factor driving forest area conversion over the last two decades. The transfer matrix analysis indicated that most forests were disturbed and converted to urban areas, with some forests transformed into farmlands through slash-and-burn agriculture [21].

This changes starkly contrast with government policies aimed at increasing forest cover by preventing deforestation through slash-and-burn agriculture

[52]. Changes in anthropogenic activities are also closely related to changes in the natural environment. The field observation from this research identified anthropogenic drivers that have resulted in forest cover changes in Dongsithouane Production Forest Area, namely: timber logging, and charcoal production and fuel wood extraction. These findings corroborate a study carried out in the Preah Vihear Projected Forest in Cambodia, where the total forests cover decreased by 2.29% between 2002 and 2010 [48] Furthermore, the increase in population density in the study area may have contributed to the urban expansion, natural resource depletion, and the intensification of illegal logging activities [53].

Based on the results, it was found that socioeconomic factors significantly influence land use and land cover (LULC) changes in the Douangsithoune National Production Forest (DNPF). LULC changes were particularly affected by household processing for agriculture and collection of non-timber forest products (NTFPs) [54]. In this study, we investigated the factors influencing changes in LULC, identifying key drivers such as socioeconomic, land extension (agricultural, urbanization), demographics, features, land value, and economic activity. These factors affect land use and land cover changes, demand for land and land tenure system [55]. Land is an essential component for housing and food production and is one of the three main components of production in classical economics, along with labor and capital [56]. Consequently, land use forms the foundation of agricultural economics and provides significant socioeconomic benefits [57]. Land use change is necessary because it is crucial to societal and economic development [58]. Changes in land use are extremely rapid in urban areas, irrespective of their genesis and nature because the changes are part of urban growth [57]. Towns, cities, and even rural areas in both developed and developing countries are experiencing changes in their physical form, population, and social constituents. These changes, led to significant alterations in land use, impacting social life, economics, and environmental aspects [59].

LULC change is a significant factor driving alternations on the earth's surface [59]. The growth of cities has influenced the environment and changed LULC, making it an essential component of global change. Research indicates that, the Karst region's ecology is extremely fragile, and the LULC changes have the potential to drastically alter it. An integrated method was used to investigate the environmental impact of LULC changes in connection with urbanization and China's ecosystem restoration programs between 1996 and 2010 [60]. Other studies also investigated the environmental effect of land use and land cover changes (LULC) on urbanization and policy [61].

5. Conclusions and Recommendations

This study utilized supervised classification of Landsat imaged to produce a land cover map. The study of changes in the Dongsithouane National Production Forest Area's forest cover over the past two decades (2001-2021) revealed a reduction of approximately 8992.96 hectares (11.35%) in the dry dipterocarp forest area. However, the mixed deciduous forests experienced a slight decline in cover. Deforestation in this area resulted from the land transformations associated with the expansions of agricultural land, built-up land, and water bodies. Notably, agricultural land tripled between 2001 and 2021. This study provides a basis and guide for policymakers, particularly in Laos, to intervene by devising effective forest management practices. As a result, this study recommends natural regeneration and agroforestry interventions for the restoration of depleted forest cover. Furthermore, effective policy interventions providing financial support for ecosystem protection, agricultural production, water resources, watershed protection, and settlement expansions are essential to safeguard the forest cover of Laos. The household interviews focused on socioeconomic factors such as age class, education level (uneducated, primary, secondary, high, middle), occupation (government, company, farmer, worker), residence status, and household size class. The logistic regression model's result indicated that significant determinants of LULC change included the area's location, the expansion of agricultural land, the increase in business activity, and the need for settlement land. Thus, land use and land cover types within the Dongsithoune National Production Forest directly influenced the observed change.

Based on the findings, key recommendations can be formulated:

1) Implement policy strategies to address the direct access of villagers to the forest, considering their reliance on natural resources for livelihoods.

2) Address the shortage of agricultural land for crops such as sugar cane and cassava cultivation through appropriate land management policies.

3) Emphasize forest protection, sustainable land use, and land cover management as overarching goals in policy formulation and implementation.

These recommendations aim to mitigate further degradation of forest resources and promote sustainable development in the study area.

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Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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