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Article

Analysis socioeconomic of land use and forest cover change in Phongsaly Province, Lao P.D.R

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Abstract: Land use and forest cover change present significant challenges in the northern upland regions of Lao PDR, particularly in efforts to reduce deforestation and unsustainable land use. Therefore, the objective of this study was to analyze the socioeconomic factors influencing land use and forest cover changes in Phongsaly Province. The study was conducted across five districts, covering 14 villages. A total of 501 participants were selected through systematic random sampling to take part in questionnaire-based interviews. Binomial logistic regression analysis was employed to identify the socioeconomic factors that influence changes in land use and forest cover. The results revealed that satisfaction levels, expectations, perceptions of law enforcement, and participation in forest management were significantly associated with socioeconomic factors. Key factors influencing land use and forest cover change included ethnicity, educational attainment, household size, distance to forest areas, and engagement in forest management practices. In particular, ethnicity has exerted a significantly positive influence on land use and forest cover changes. Higher levels of educational attainment are essential for improving the quality of life among ethnic groups, expanding their occupational opportunities, and reducing the negative impacts on land use and forest cover change. Changes in land use and forest cover have had a significant impact on carbon storage and greenhouse gas (GHG) emissions. The primary driver of GHG emissions is the conversion of forested areas into agricultural land, particularly for the cultivation of upland crops. Factors influencing these changes should be effectively disseminated and addressed through targeted interventions. Efforts should be prioritized and strengthened within local communities, especially in areas experiencing high rates of deforestation and forest degradation.

Keywords: factors; land use; GHG emissions; carbon sequestration; local communities

1. Introduction

Global warming, a critical aspect of the climate challenge, poses a serious threat that has garnered international attention. The UN Framework Convention on Climate Change (UNFCCC), initiated in 1992, aims to regulate greenhouse gas levels to reduce the negative impacts of global warming caused by human activities (UNFCCC, 1992). Deforestation, which accounts for approximately 20% of global emissions, is a significant contributor to GHG emissions [1]. Thes issues have prompted concerted efforts to address the reduction of emissions resulting from the loss and degradation of forests, facilitated by efforts in the REDD mechanism, negotiated under the UNFCCC, plays a crucial role in global environmental conservation efforts [2]. Lao PDR, characterized by significant forest cover and high deforestation rates, faces unique challenges in addressing deforestation. The government's strategy of leveraging land for economic growth has increased pressure on resources and intensified deforestation [3]. In response, Laos is striving to promote sustainable land use practices, transitioning away from shifting cultivation and advocating for sedentary, conservation-oriented farming methods as alternatives [4]. These efforts are in line with the Sustainable Development Goals (SDGs), particularly SDG 13, which emphasizes actions to combat climate change, and SDG 15, which addresses the protection of terrestrial ecosystems, underscore the importance of initiatives like REDD+ in tackling global environmental challenges [5]. Human actions significantly influence the loss and degradation of forests, accounting for roughly 80% of global forest loss [6]. While agribusiness is an important factor, other contributors include subsistence farming, fuelwood collection, charcoal production, uncontrolled fires, and animal husbandry [7]. These diverse activities collectively contribute to forest degradation and loss of forest cover. Regionally, factors influencing changes in forest cover vary. In Latin America and tropical forests in Asia, timber extraction for trade and logging are primary causes of deforestation [6]. In Lao PDR, key drivers include land use changes associated with agribusiness, hydropower development, mining activities, and plantation agriculture. Insufficient land management practices, rapid demographic expansion, wildfires, unauthorized timber harvesting, and road development are also major contributing factors to deforestation in the country [8]. Shifting cultivation, although a traditional practice for many rural communities, can potentially contribute to deforestation. Its environmental impacts include biodiversity loss, weed expansion, diminished soil productivity and intensified erosion [9]. Despite these concerns, shifting cultivation remains prevalent in some areas and poses challenges for sustainable land management efforts. REDD+, a mechanism aimed at addressing natural resource degradation, has spurred many developing countries to undertake readiness activities following the three-phased approach adopted at the UNFCCC’s COP16 in 2011 (preparation, demonstration, and full implementation) [10]. While REDD+ initiatives can empower communities to accept and implement projects, it is crucial to address the diverse capabilities within these communities, particularly among marginalized groups [11]. This underscores the importance of adopting a capability approach in REDD+ planning within Lao PDR, recognizing differential capabilities, including those influenced by ethnicity or other vulnerable statuses. Moreover, while REDD+ activities can positively impact greenhouse gas emissions, ensuring contextual and procedural equity is essential. Case studies have shown that differing adoption methods among ethnic groups (such as Khmu and Hmong) can lead to widening income gaps and varying levels of satisfaction [12]. Thus, equitable and inclusive approaches are imperative for the success of REDD+ initiatives and sustainable forest management efforts.

This study aims to analyze the socioeconomic factors influencing land use and forest cover changes in Phongsaly Province, Lao PDR, addressing the following question: What determinants drive changes in land use and forest cover in Phongsaly Province? It also explores the hypothesis that agricultural practices and related factors significantly influence these changes, thereby affecting greenhouse gas emissions in the region.

2. Materials and methods

2.1. Study site

Phongsaly, located in northern Lao PDR, shares its borders with China to the north and west, Vietnam to the east, and the Laotian provinces of Luang Prabang to the south and Oudomxay to the southwest. Covering an area of 16,270 square kilometers, the province boasts an extensive 77% forest cover, including protected areas like the Phou Dene Din National Biodiversity Conservation Area spanning 222,000 hectares, and the Nam Lan Conservation Area. The region's elevations range from 450 to 1842 meters above sea level, creating a unique climate characterized by cool mornings and evenings, daytime humidity, and afternoon rains. These climatic conditions foster lush forests that thrive in the area. Despite its primarily agricultural population, Phongsaly's natural landscape remains largely forested, underscoring the critical importance of conservation efforts to preserve its diverse biodiversity.

Phongsaly province, situated at 21°41'0" N latitude and 102°6'0" E longitude, is composed of 7 districts and 98 villages, with a total population of approximately 193,145 as per the 2020 census. The province is celebrated for its cultural diversity, housing 13 distinct ethnic groups, including the Khammu, Thai Dam, Thai Daeng, Yao, Leu, Ho, Hmong, Akha, Yang, Bid, Lolo, among others.

Despite its cultural richness, Phongsaly faces significant infrastructure challenges due to its mountainous terrain. Many remote villages lack adequate road access and electricity, which poses obstacles to economic development. Additionally, the scarcity of suitable land for permanent agriculture, such as paddy fields, has led some communities to encroach upon forest land for cash crops and livestock. This encroachment has contributed to deforestation in the region, exacerbating environmental concerns. Addressing these infrastructure limitations and promoting sustainable land-use practices are crucial steps toward ensuring the long-term prosperity and environmental sustainability of Phongsaly province.

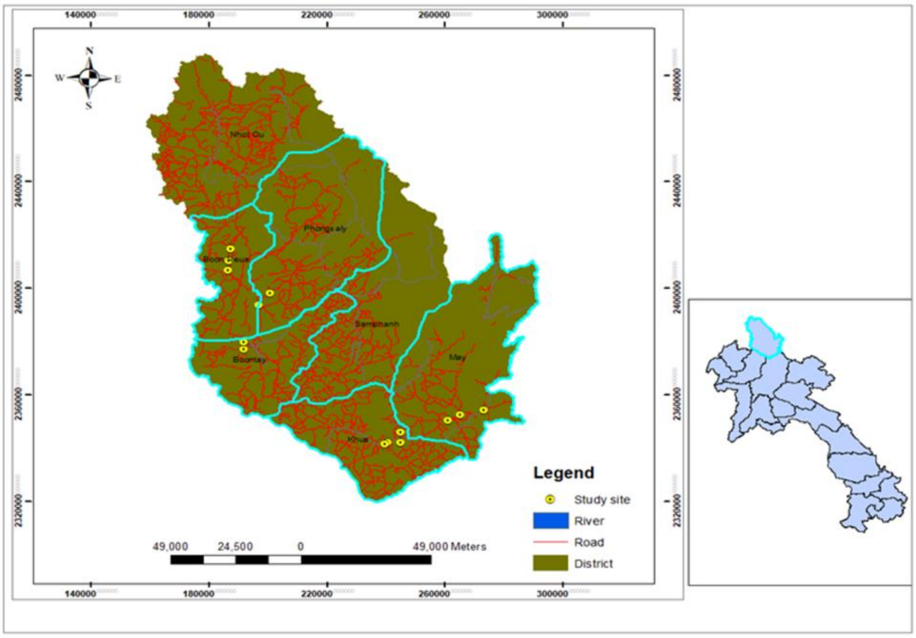

Figure 1. Map of study site in Phongsaly Province, Lao PDR. Note: Map created, February 2023.

2.2. Methods

Data collection was carried out using semi-structured questionnaires to gather information on socioeconomic factors influencing land use and forest cover changes, deforestation, and the livelihood context within villages. In-depth interviews were conducted with village headmen, government officials, and senior members of village committees.

This study utilizes an automated land management and land cover categorization framework established by the government of Lao PDR, specifically by the Ministry of Agriculture and Forestry into 20 distinct categories including Evergreen Forest, Mixed Deciduous Forest, Coniferous Forest, Mixed Coniferous and Broadleaved Forest, Dry Dipterocarp Forest, Forest Plantation, Bamboo, Regenerating Vegetation, Savannah, Scrub, Grassland, Upland Crop, Rice Paddy, Other Agriculture, Agriculture Plantation, Urban Areas, Barren Land and Rock, Other Land, Wetland, River from 2000 to 2019.

A multi-stage sampling survey was employed to determine the required sample size, following the method outlined by [13]. The total population of interest included 11,800 people across the five districts.

A systematic random sampling uses a list of villagers from the village headman and the committee of elders to identify the total of 11,800 people of the 14 villages.

$$n = \frac{Z^2_{\propto/2} NP(1-P)^i}{d^2(N-1) + Z^2_{\propto/2} P(1-P)} \tag{1}$$

Based on the sample size calculation method proposed by [13], a total of 501 individuals were selected, with one participant chosen from each household in 14 target villages within five districts of Phongsaly province.

Data collection for this study took place from 18 May to 15 July 2023.

Many studies, including those by [14–16], have employed binary logistic regression to investigate factors influencing land use change.

Let Y_i represent the dependent variable, which is binary and equals 1 if a household change their land use, and 0 otherwise. Let P_i = P(Y=1), denotes the probability that a household practices land use change, and $(1 - P_i)$= (1 − P(Y = 1) denote the probability that a household does not. According to [17,18], the general equation describing the probability of land use change among local populations is as follows.

$$P_i = \frac{e^{\beta_i \chi_i}}{1 + e^{\beta_i \chi_i}} \tag{2}$$

The probability that local people do not practice land use change is expressed by the following equation.

$$1 - P_i = \frac{1}{1 + e^{\beta_i \chi_i}} \tag{3}$$

where, $\beta_0, \beta_1, \beta_2, \ldots\ldots, \beta_k$ are coefficients, and $X_1, X_2, \ldots\ldots, X_k$ are explanatory variables. Therefore, the equation is rewritten as follows.

$$\left(\frac{P_i}{1-P_i}\right) = \beta_i X_i \quad (4)$$

The logit equation, which representing the natural logarithms of the odds, is employed to calculate the odds ratio for changes in land use practices. Thus, the model is defined as follows.

$$L_i = In\left(\frac{P_i}{1-P_i}\right) = \beta_i X_i \quad (5)$$

Table 1. Definitions and measurements of independents variables.

Variables	**Description**	**Measure**	**Hypothesis**	**Data source**
Sex	The variable "sex" denotes the household head's gender (male or female)	The categorical variable 'sex' includes two categories: male and female.	(+)	[19,20]
Age	The age variable represents the age of adult or young household heads (in years)	Continuous variables measured in years	(−)	[21,22]
Marital status	Marital status represents categories such as married, single, separated, widowed, or divorced	Categorical variables related to individuals (persons)	(+)	[19,22,23]
Educational attainment	The school grade of the household head (male or female)	Categorical variables related to levels or degrees.	(+/−)	[24,25]
Household size	The number of household members (persons)	Categories of variables related to individuals (persons)	(+/−)	[26,27]
Main occupation	The activity always practiced: farmer, workers, government officials, businessmen	Categories variables	(+)	[25,28,29]
Total income (kip)	Sources of family income that represent the total income obtained from household activities	Continuous variables	(+)	[21,25,30]
Race	Ethnicity dummy variable	Categories of variables based on gender (male or female)	(+)	([31,32]).
Distance from forest to home (km)	Measurement of distance from home to forests	Continuous variables (meters/kilometers)	(+/−)	[26,33–35]
Occasionally visit to forests	Villagers go to forests for a variety of activities	Categories of variables related to time	(+)	[36,37]
Living place	Households residing in the village over the years	Categories of variables related to periods	(+)	[38]

3. Results and discussion

Based on the analysis presented in **Tables 2** and **3**, several factors significantly influence changes in land use and forest cover in Phongsaly Province. These variables include age, sex, primary occupation, race, educational attainment, household size, place of residence, total income, distance to forests, occasional visits to forests, and forest management practices. The model correctly predicted outcomes in 74.05% of cases. According to the pseudo-R-squared statistic, the binomial logit model was an appropriate choice for regression analysis. The independent variables significantly explained the variation in the dependent variable at the 1% significance level, as confirmed by the Chi-square test.

Table 2. Model Estimates of Demographic-Economic Variables Associated with Satisfaction Levels, Expectation Levels, Law Enforcement, and Forest Management.

Dependent variables	**Model 1 Degree of satisfaction**				**Model 2 Degree of expectation**				**Model 3 Law enforcements**				**Model 4 Forest management**			
Independent Variables	B	Beta	Std.Err	*p*	B	Beta	Std.Err	*p*	B	Beta	Std.Err	*p*	B	Beta	Std.Err	*p*
Age	0.031	1.032	0.012	0.012**	0.017	1.017	0.026	0.510	0.007	1.007	0.011	0.483	−0.012	0.987	0.009	0.208
Sex	0.157	1.170	0.327	0.632	0.237	1.268	0.657	0.718	−1.104	0.331	0.304	0.000***	−0.216	0.804	0.257	0.399
Main occupation	−0.412	0.661	0.619	0.505	1.152	3.166	1.247	0.356	−1.137	0.320	0.428	0.008***	0.287	1.332	0.419	0.494
Race	0.582	1.790	0.311	0.062*	−0.768	0.463	0.687	0.263	−3.722	0.024	0.558	0.000***	−0.051	0.950	0.241	0.832
Educational attainment	–	–	–	–	0.390	1.478	0.897	0.663	0.860	2.365	0.428	0.045**	−0.252	0.776	0.404	0.533
Marital status	−1.303	0.271	1.108	0.240	–	–	–	–	1.059	2.886	0.589	0.072*	−0.694	0.499	0.515	0.178
Living place	–	–	–	–	−0.615	0.540	0.616	0.317	−0.660	0.516	0.297	0.027**	1.159	3.188	0.241	0.000***
Household size	−.113	0.892	0.081	0.162	0.166	1.180	0.169	0.328	−0.077	0.925	0.073	0.292	0.122	1.130	0.062	0.051*
Total income	0.0004	1.000	0.0002	0.073	−.0003	0.999	0.0001	0.022**	−.0003	0.999	0.0001	0.005***	0.0001	1.000	0.0001	0.137
Distance to forests	−0.024	0.976	0.010	0.023**	−0.020	0.979	0.012	0.115	0.014	1.014	0.009	0.121	−0.022	0.977	0.010	0.026**
Occasionally visit to forests	−2.513	0.080	0.462	0.000***	1.292	3.641	0.708	0.068	−0.592	0.552	0.291	0.042**	0.679	1.972	0.244	0.005***
Constant	7.438	1700.41	2.857	0.009	1.362	3.905	3.659	0.710	9.284	10772.2	2.268	0.000	−1.787	0.1673	1.784	0.316
Number of obs		501				501				501				501		
LR chi2 (9,10, 11, 11)		64.93				16.44				158.90				53.42		
Prob > chi2		0.0000				0.0877				0.0000				0.0000		
Pseudo R2		0.1713				0.1287				0.3173				0.0990		
Goodness of fit test by Hosmer-Lemeshow chi2(7,8,9,9)		10.03				9.48				7.43				6.99		
Prob > chi2		0.1870				0.3032				0.5922				0.6383		
Correctly classified		87.23%				97.21%				85.23%				77.05%		

Mark * statistically significant at *: $p < 0.1$; **: $p < 0.05$; ***: $p < 0.01$

Table 3. Model Estimates of Variables Affecting Changes in Land Use and Forest Cover.

Variables	**Model 5 Land use and forest cover change**			
	B	Beta	Std.Err	p
Age	0.011	1.011	0.009	0.201
Sex	−0.292	0.746	0.251	0.245

Main occupation	0.217	1.242	0.442	0.895
Ethnicity	0.642	1.901	0.241	0.008***
Educational attainment	−1.149	0.316	0.581	0.048**
Marital status	−0.932	0.393	0.675	0.167
Living place	0.431	1.538	0.262	0.101
Household size	0.166	1.181	0.065	0.011**
Total income	−0.00006	0.999	0.00009	0.526
Distance to forests	−0.016	0.983	0.007	0.037**
Occasionally visit to forests	−0.148	0.862	0.250	0.554
Law enforcements	0.234	1.264	0.400	0.558
Forest management	1.423	4.153	0.372	0.000***
Degree of Satisfaction	0.483	1.621	0.334	0.148
Degree of Expectation	−0.781	0.457	0.845	0.355
Constant	2.897	18.133	2.276	0.203
Number of obs		501		
LR chi2(15)		77.62		
Prob > chi2		0.0000		
Pseudo R2		0.128		
Goodness of fit test by Hosmer−Lemeshow chi2(13)		10.15		
Prob > chi2		0.682		
Correctly classified		74.05%		

Mark * statistical significantly at level of *p*-value (***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$)

Statistical analysis revealed that several factors significantly influenced land use and forest cover change at various significance levels. At the 5% significance level ($p < 0.05$), significant predictors included distance to forests, household size, educational attainment, age, place of residence, total income, and occasional visits to forests. At the 1% significance level ($p < 0.001$), race, forest management practices, sex, primary occupation, place of residence, total income, and occasional visits to forests. Additionally, at 10% significance level ($p < 0.1$), race, marital status, and household size. For instance, an increase in the variable ‘race’ was associated with a 64% higher likelihood of engaging in land use and forest cover change, while an increase in household size was linked to a 16% greater probability of such changes.

Furthermore, the model presented in **Table 2** indicates that the predictor variable age has a positive correlation with household satisfaction. This shows that younger households are somewhat more inclined to participate in activities aimed at improving their living conditions compared to older households. This indicates a statistically significant positive relationship between age and household satisfaction ($\beta = 0.031$, $p = 0.012$).

A negative coefficient for variables such as sex and main occupation shows that men and households with a primary occupation are less inclined to participate in law enforcement efforts compared to women and households without a primary occupation. These findings indicate a statistically significant negative relationship between law enforcement participation and both sex (β = 1.104, p = 0.000) and main occupation (β = 1.137, p = 0.008), respectively.

A negative coefficient for race indicates that the majority ethnic group (Pounoi) is less likely to engage in law enforcement activities (β = 3.722, p = 0.000) compared to the minority ethnic group (Khamum). In contrast, educational attainment shows that families with higher levels of education are more likely to participate in law enforcement activities (β = 0.860, p = 0.045).

This finding aligns with prior research conducted by Ali et al., (2020), which indicates that educated household heads tend to have reduced dependency on forests, possibly due to greater access to various employment opportunities. Similarly, Baiyegunhi et al., (2016) observed a comparable trend in their study.

A negative coefficient for living place suggests that households residing in the same location for an extended period are slightly less inclined to engage in law enforcement activities compared to those who have recently changed their residence (β = 0.660, p = 0.027). Conversely, households that have been settled in the same area for several years are more likely to participate in forest management activities than those with a recent change of residence (β = 1.159, p = 0.000).

Regarding total income, a negative coefficient indicates that households with higher incomes were slightly less likely to engage in activities related to forest expectations (β = 0.0003, p = 0.022) and law enforcement (β = 0.0003, p = 0.005) compared to households with lower incomes.

Similarly, a negative coefficient for the proximity of the village to wooded areas is associated with lower household satisfaction levels. This shows that households located closer to wooded areas were slightly less inclined to engage in activities aimed at enhancing their living conditions compared to those living farther away. This indicates a statistically significant negative relationship between forest proximity and household satisfaction (β = 0.024, p = 0.023). Additionally, households located closer to the village were slightly less likely to engage in forest management activities compared to those living farther away (β = 0.022, p = 0.026).

Furthermore, a negative coefficient for occasional visits to forests indicates that households who occasionally visit forests are slightly less inclined to engage in activities aimed at enhancing their living conditions compared to those who do not. This reflects a statistically significant negative relationship between occasional forest visits and household satisfaction (β = 2.513, p = 0.000).

In the same context, households that occasionally visit forests were slightly less likely to engage in law enforcement activities compared to those that do not (β = 0.592, p = 0.042). Conversely, these households were more likely to participate in forest management activities (β = 0.679, p = 0.005).

The model presented in **Table 3** indicates a statistically significant positive relationship between ethnicity and changes in land use and forest cover (β = 0.642, p = 0.008), suggesting that the majority ethnic group (Pounoi) is more likely to engage in such changes compared to the minority ethnic group (Khamum). Conversely, there is a statistically significant negative relationship between educational attainment and changes in land use and forest cover (β = 1.149, p = 0.048), suggesting that households with higher education levels are less likely to engage in such changes compared to uneducated households. Additionally, a positive coefficient for household size indicates that larger households are more likely to engage in land use and forest cover change (β = 0.166, *p* = 0.011). In contrast, this indicates a statistically significant negative relationship between distance from the village to the forest area and changes in land use and forest cover (β = 0.016, *p* = 0.037), suggesting that households located closer to the village are slightly less likely to engage in such activities compared to those living farther away. Furthermore, a positive coefficient for forest management implies that local people involved in forest management are more likely to practice land use and forest cover change (β = 1.423, *p* = 0.000) compared to those who do not participate in forest management activities. Additionally, households that own land are less inclined to participate in land use and forest cover change.

4. Discussion

4.1. Variables affecting land use and forest cover change

The variables influencing land use and forest cover change include ethnicity, educational attainment, household size, distance to forest areas, and forest management. Among these, ethnicity has a statistically significant positive influence on changes in forest cover and land use. This finding aligns with previous studies, such as [39], who reported shifts in land use systems among ethnic groups in Lao PDR, highlighting ethnicity as a key factor in land use and land cover change. Additionally, [40] found that certain ethnic groups were associated with higher rates of forest clearing, clearing approximately 3 hectares more forest than others

Conversely, educational attainment exhibited a negative influence on changes in land use and forest cover. This finding contrasts with previous research, such as [41], who reported a positive effect of educational attainment on the adoption of improved agricultural practices and natural resource management. Similarly, [42] found that higher education levels were associated with increased adoption of sustainable agricultural practices and land-use intensification.

Household size exhibited a positive influence on land use and forest cover change. This finding contrasts with previous research, such as the study by [43], which reported a positive and significant relationship between household size and patterns of reforestation, afforestation, and agroforestry systems.

Larger families tend to utilize a greater portion of their land holdings, and an increase in household size significantly influences decisions related to land use and forest cover change. In this study, the average household size was 5.13 persons. Moreover, the inclination to use land for cultivation appeared to decrease, possibly due to a shift in preference toward more profitable crops.

On the other hand, a negative coefficient for the proximity of the village to wooded areas suggests that villages located closer to forests are associated with higher rates of land use and forest cover change. These findings align with previous studies by [35,44,45], which demonstrated that distances ranging from 0.3 to 3 km between homes and forests significantly influence deforestation rates. Deforestation in such regions is influenced by factors such as proximity to forests and roads. For example, [46] found that a significant portion of altered forest land was converted into farmland. The distance from forests was the most influential parameter in modeling the transition potential [47].

The negative coefficient for forest management in relation to land use and forest cover change suggests that increased participation in forest management activities is associated with a reduced likelihood of altering land use and forest cover. For example, households that own land are less likely to engage in forest management activities compared to those without land ownership. This observation implies that participation in forest management may be more appealing to landless individuals, potentially because it offers alternative livelihood opportunities [19].

4.2. Change in land use and forest cover

Minimizing alterations to land utilization and forest cover in Phongsaly province is pivotal for fostering forest restoration and augmenting carbon sequestration efforts, thereby substantiating the benefits of conservation efforts through empirical evidence. Conversely, stabilizing land use and forest cover directly supports forest area restoration and enhances carbon sequestration. However, intensifying agriculture without integrating alternative energy options could potentially increase greenhouse gas emissions, particularly in secondary forests that have the potential for recovery.

While the broader trend in Lao PDR indicates a troubling decline in secondary forests, with a documented decrease of 0.83% in the northern region between 2010 and 2015 [48], the situation in Phongsaly province presents a more nuanced perspective such as the study by [49], highlights a notable decrease in forest cover in Phongsaly, amounting to nearly 70% loss over the study period, and socioeconomic factors have been identified as pivotal drivers of these changes. This examination of changes in land use and forest vegetation in Phongsaly province from 2000 to 2019 highlights notable shifts across several key categories. Which includes changes such as

Phongsaly province experienced significant declines across various categories. The mixed deciduous forest category showed a consistent decrease from 47.78% in 2000 to 43.79% in 2019. Similarly, upland crop areas displayed a downward trend, declining from 1.34% in 2000 to 0.44% in 2019, with a temporary increase observed in 2010. The category of other agriculture initially saw growth but remained stable by 2019. Socio-economic surveys indicate that 85.03% a significant portion of the population depends on agriculture as their main source of income. The change in land use is likely a major factor contributing to the reduction in forest cover in Phongsaly province, potentially impacting carbon sequestration in forested areas. Studies by [50] highlight substantial forest conversions to agricultural land cover, while research by [51] underscores the diminishing practice of shifting cultivation, further contributing to forest loss.

Positive developments are apparent in the northern region, including Phongsaly, there has been a yearly rise in forest cover of about 1.22%. This growth is attributed to government policies aimed at achieving a 70% national forest cover target by 2020 [52]. Significantly shifts in land use and forest vegetation in Phongsaly province from 2000 to 2019, observed that Regenerating Vegetation increase from 2000 to 2015, peaking at 47.14%, followed by a slight decline in 2019. Forest Plantation initially shows minor fluctuations; this category witnessed a notable increase to 2.20% by 2019. Agriculture Plantation initially experiencing minor increases, this category saw a significant rise to 3.48% in 2019, with a decrease observed in 2015. Studies by [53] attribute these increases to factors such as rural poverty reduction and the decline in shifting cultivation, contributing to enhanced forest cover and carbon sequestration. For example, forest restoration efforts in China have achieved 80% of their intended carbon sink capacity (Jin et al., 2020). Additionally, plantation forests in Southeast Asia are increasingly contributing to timber production and carbon sequestration [54].

Drawing from an analysis of data collected from the Lao National Forest Monitoring System (NFMS) website (https://nfms.maf.gov.la/) concerning changes in land use and forest cover, emissions have significant effects on the capture of carbon and greenhouse gas (GHG) emissions in Phongsaly province have been observed. The study highlights a reduction in ecosystem carbon sequestration resulting from land use changes, which has diminished the ecosystem's capacity to absorb carbon dioxide. Key findings from the study include: from 2000 to 2005, GHG emissions increased by approximately 8 Mt CO_2 equivalents per year. The results revealed that the most significant land use change in the Erzurum region was the conversion of rangeland into agricultural land. From 1994–2023, agricultural land use in Erzurum increased notably, while waterbodies and garden areas exhibited a declining trend [55]. Between 2005 and 2010, emissions decreased by around 1.8 Mt CO_2 equivalents per year. From 2010 to 2015, there was a further decrease in emissions by approximately 3.9 Mt CO_2 equivalents per year, and from 2015 to 2019, emissions experienced a smaller decrease of around 0.8 Mt CO_2 equivalents per year. Similarly, the study showed that the highest rate of land use change involved the conversion of rangeland into bare land. In particular, the transformation of rangeland into agricultural land resulted in the greatest change, leading to an increase in net income of $4,027,258 [56].

The primary driver of greenhouse gas (GHG) emissions in Phongsaly province has been the transformation of wooded areas into cultivated land, especially for upland crops. The results revealed that the most significant land use changes in the Erzurum region were related to the conversion of rangeland to agricultural land. Over the period from 1994 to 2023, there was a notable increase in agricultural land use in Erzurum, contrasting with negative trends in waterbodies and garden areas

Conversely, a positive trend has been observed in increasing carbon sinks (GHG removals) due to the conversion of agricultural areas back into forestland. These conversions have contributed significantly to carbon sequestration.

While other types of land conversions also contribute to carbon sinks, their impact is comparatively lower. These include conversions within different forest types, between agricultural types, and from upland crops to other agricultural uses. However, accurately assessing the effects of these changes on carbon emissions and sequestration remains challenging because of limited access to data and the variability of biomass carbon densities across the province's diverse land use systems [57]. An assessment of the trends in landscape metrics revealed a decreasing pattern in the number of patches (NP), patch density (PD), largest patch index (LPI), edge density (ED), and total edge (TE) at the landscape level, indicating a significant decline from 2008–2016 [56].

Key findings regarding land use and forest-cover change and their impact on greenhouse gas emissions include several significant points: converting forests to agriculture is a primary driver of emissions, typically resulting in higher greenhouse gas emissions compared to other land use changes [58]; effective forest management practices and reducing deforestation rates are crucial for mitigating climate change impacts [59]. While global net forest conversion emissions are decreasing, there is a simultaneous decline in forests' capacity to sequester carbon, posing challenges for climate mitigation efforts [60]. Specifically agricultural and forestry practices can both emit and remove greenhouse gases. Therefore, sustainable management practices are essential to minimize emissions and maximize carbon sequestration [61]. Example: recent research highlights include the reduction in Forestry and Other Land Use (FOLU) emissions in Malawi over the past decade [62]. Different land-use systems and soil types significantly influence CO_2 emissions. This underscores the need for tailored approaches to effectively manage emissions [63], and long-term implications emphasize that land-use changes for agriculture and other purposes remain major contributors to long-term greenhouse gas emissions. Therefore, sustainable land management practices are critical to mitigate climate impacts [64,65].

5. Conclusion

The research findings indicate that most ethnic groups in Phongsaly Province have low levels of educational attainment, with only 50.30% completing secondary education, while 8.87% are illiterate. The majority of these ethnic groups rely on agriculture and forest resources for their livelihoods. The study also reveals that socio-economic factors including age, sex, primary occupation, ethnicity, educational attainment, household size, place of residence, total income, distance to forests, and occasional visits to forests are significantly associated with household satisfaction, expectations, perceptions of law enforcement, and participation in forest management among ethnic groups. Among these factors, forest management, ethnicity, and educational attainment particularly influence land use and forest cover change. Higher levels of education are essential for improving the livelihoods of ethnic groups and increasing their occupational opportunities. Conversely, low educational attainment has been linked to reduced engagement in forest management and land use planning. Additionally, the distance from villages to forests has a considerable impact on patterns of land use and forest cover change

This research examined changes in land use and forest cover using secondary data from the Lao government to investigate deforestation and forest degradation in Phongsaly Province, Lao PDR. The study aimed to support environmental protection and climate change mitigation, as well as to assess the impact of land use intensification on greenhouse gas emissions. Findings indicate that nearly all villagers in the study areas were involved in some form of land use and forest cover change over time. The primary driver of greenhouse gas (GHG) emissions in Phongsaly Province is the conversion of forested areas into agricultural land, particularly for the cultivation of upland crops

These findings suggest that promoting education on forest management and land use among ethnic groups is essential for reducing deforestation and land use change, which significantly affect forest carbon emissions. The study also recommends promoting the implementation of the REDD+ mechanism in this area, as it could play a crucial role in addressing challenges and mitigating carbon emissions resulting from land-use changes.

Future research should focus on examining community participation in forest land use management in Phongxaly Province, Lao PDR.

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References

1. Kamusoko C, Oono K, Nakazawa A, et al. Spatial Simulation Modelling of Future Forest Cover Change Scenarios in Luangprabang Province, Lao PDR. Forests. 2011; 2(3): 707–729. doi: 10.3390/f2030707
2. Angelsen A. Realising REDD+: National strategy and policy options. 2009: Available online: Cifor. //https://www.cifor-icraf.org/publications/pdf_files/Books/BAngelsen0902.pdf (accessed on 25 August 2023).
3. Fern. Improving forest governance in Laos/ Fern, Rue d'Edimbourg 26, 1050. Brussels, Belgium. 2016. Available online: https://loggingoff.info/wp-content/uploads/2017/11/Improving-forest-governance-in-Laos.pdf (accessed on 15 August 2023)
4. Ministry of Agriculture and Forestry. Forestry strategy for the year 2020 of the LAO PDR, Vientiane, Laos: Ministry of Agriculture and Forestry. 2005. Available online: https://ali-sea.org/aliseaonlinelibrary-dashboard/get/file/Forestry-Strategy-to-the-Year-2020-of-the-Lao-PDR.pdf (accessed on 3 April 2023).
5. ICSU, I. Review of the Sustainable Development Goals:The Science Perspective. Paris: International Council for Science (ICSU): ISBN: 978-0-930357-97-9. 2015. Available online: https://www.researchgate.net/publication/2723 55248_Review_of_Targets_for_The_Sustainable_Development_Goals_The_Science_Perspective (accessed on 10 August 2023).
6. Kissinger G, Herold M, De Sy V. Drivers of deforestation and forest degradation. International Astronomy and Astrophysics Research. 2012; 48.
7. Hosonuma N, Herold M, De Sy V, et al. An assessment of deforestation and forest degradation drivers in developing countries. Environmental Research Letters. 2012; 7(4): 044009. doi: 10.1088/1748-9326/7/4/044009
8. Moore C, Ferrand J, Khiewvongphachan X. Vientiane, Investigation of the Drivers of Deforestation and Forest Degradation in Nam Phui National Protected Area, Lao PDR. Climate Protection through Avoided Deforestation Programme, GIZ. 2011.
9. van Vliet N, Mertz O, Heinimann A, et al. Trends, drivers and impacts of changes in swidden cultivation in tropical forest-agriculture frontiers: A global assessment. Global Environmental Change. 2012; 22(2): 418–429. doi: 10.1016/j.gloenvcha.2011.10.009
10. UNFCCC. The Cancun Agreements: Outcome of the work of the Ad Hoc WorkingGroup on Long-term Cooperative Action under the Convention/Decision 1/CP.16. 2011. Available online: https://unfccc.int/sites/default/files/resource/docs/2010/cop16/eng/07a01pdf?download (accessed on 20 August 2023).
11. Patel T, Dhiaulhaq A, Gritten D, et al. Predicting Future Conflict under REDD+ Implementation. Forests. 2013; 4(2): 343–363. doi: 10.3390/f4020343
12. Hiratsuka M, Bounithiphonh C, Sichanthongthip P, et al. Impacts of REDD+ activities on reduction in greenhouse gas emissions in northern Lao People’s Democratic Republic. Journal of Forest Research. 2021; 26(4): 278–286. doi: 10.1080/13416979.2021.1902070
13. Lemeshow S. Adequacy of sample size in health studies. Manual of Statistic. 1990.
14. Verburg PH, Soepboer W, Veldkamp A, et al. Modeling the Spatial Dynamics of Regional Land Use: The CLUE-S Model. Environmental Management. 2002; 30(3): 391–405. doi: 10.1007/s00267-002-2630-x
15. Handavu F, Chirwa PWC, Syampungani S. Socio-economic factors influencing land-use and land-cover changes in the miombo woodlands of the Copperbelt province in Zambia. Forest Policy and Economics. 2019; 100: 75–94. doi: 10.1016/j.forpol.2018.10.010
16. Goswami K, Choudhury HK, Saikia J. Factors influencing farmers’ adoption of slash and burn agriculture in North East India. Forest Policy and Economics. 2012; 15: 146–151. doi: 10.1016/j.forpol.2011.11.005
17. Hosmer DW, Lemeshow S, Sturdivant RX. Applied Logistic Regression. Wiley Series in Probability and Statistics. Published online March 22, 2013. doi: 10.1002/9781118548387

18. Gujarati D. Basic Econometrics Fourth, 4th ed. Magraw Hill Inc; 2004.
19. Coulibaly-Lingani P, Savadogo P, Tigabu M, et al. Factors influencing people's participation in the forest management program in Burkina Faso, West Africa. Forest Policy and Economics. 2011; 13(4): 292–302. doi: 10.1016/j.forpol.2011.02.005
20. Ifegbesan A, Annegarn HJ, Pendlebury S. Gender relationships in forest resource utilization and conservation in Nigeria: Implications for environmental sustainability. Gender and Behaviour. 2016; 14(1): 6996–7010.
21. Dolisca F, Carter DR, McDaniel JM, et al. Factors influencing farmers' participation in forestry management programs: A case study from Haiti. Forest Ecology and Management. 2006; 236(2–3): 324–331. doi: 10.1016/j.foreco.2006.09.017
22. Maskey V, Gebremedhin T, Dalton TJ. A Survey Analysis of Participation in a Community Forest Management in Nepal. ResPaper. 2003.
23. Wuletao T. Factors affecting the knowledge attitude and practice of forest dependent Manja Community towards forest conservation in Kaffa Zone. SNNPR; 2008.
24. Savari M, Eskandari Damaneh H, Eskandari Damaneh H. Factors influencing local people's participation in sustainable forest management. Arabian Journal of Geosciences. 2020; 13(13). doi: 10.1007/s12517-020-05519-z
25. Lestari S, Kotani K, Kakinaka M. Enhancing voluntary participation in community collaborative forest management: A case of Central Java, Indonesia. Journal of Environmental Management. 2015; 150: 299–309. doi: 10.1016/j.jenvman.2014.10.009
26. Chhetri BBK, Johnsen FH, Konoshima M, et al. Community forestry in the hills of Nepal: Determinants of user participation in forest management. Forest Policy and Economics. 2013; 30: 6–13. doi: 10.1016/j.forpol.2013.01.010
27. Ali N, Hu X, Hussain J. The dependency of rural livelihood on forest resources in Northern Pakistan's Chaprote Valley. Global Ecology and Conservation. 2020; 22: e01001. doi: 10.1016/j.gecco.2020.e01001
28. Jannat M, Hossain MK, Uddin MM, et al. Socioeconomic factors of forest dependency in developing countries: lessons learned from the Bandarban hill district of Bangladesh. International Journal of Sustainable Development & World Ecology. American Journal of Pure and Applied Biosciences. 2020; 2(3): 77–84
29. Jannat M, Hossain MK, Uddin MM, et al. People's dependency on forest resources and contributions of forests to the livelihoods: a case study in Chittagong Hill Tracts (CHT) of Bangladesh. International Journal of Sustainable Development & World Ecology. 2018; 25(6): 554–561. doi: 10.1080/13504509.2018.1434571
30. Gunatilake H. Factors influencing peripheral villager dependency on forest resources use in the Knuckles forest range. Sri Lankan Journal of Agricultural Economics. 1994; 2: 23–34.
31. Fox J, Kanter R, Yarnasarn S, et al. Farmer decision making and spatial variables in northern Thailand. Environmental Management. 1994; 18(3): 391–399. doi: 10.1007/bf02393868
32. NEPAL SK. Involving Indigenous Peoples in Protected Area Management: Comparative Perspectives from Nepal, Thailand, and China. Environmental Management. 2002; 30(6): 748–763. doi: 10.1007/s00267-002-2710-y
33. Htun NZ, Mizoue N, Yoshida S. Changes in Determinants of Deforestation and Forest Degradation in Popa Mountain Park, Central Myanmar. Environmental Management. 2012; 51(2): 423–434. doi: 10.1007/s00267-012-9968-5
34. Adhikari B, Di Falco S, Lovett JC. Household characteristics and forest dependency: evidence from common property forest management in Nepal. Ecological Economics. 2004; 48(2): 245–257. doi: 10.1016/j.ecolecon.2003.08.008
35. Giliba RA, Boon EK, Kayombo CJ, et al. The Influence of Socio-economic Factors on Deforestation: A Case Study of the Bereku Forest Reserve in Tanzania. Journal of Biodiversity. 2011; 2(1): 31–39. doi: 10.1080/09766901.2011.11884727
36. Baiyegunhi LJS, Oppong BB, Senyolo MG. Socio-economic factors influencing mopane worm (Imbrasia belina) harvesting in Limpopo Province, South Africa. Journal of Forestry Research. 2015; 27(2): 443–452. doi: 10.1007/s11676-015-0168-z
37. Derks J, Winkel G, Strieck J, et al. Visitor frequencies and attitudes towards urban forests and their management, before and during the COVID-19 lockdown. A mixed methods case study in Bonn, Germany. Ecosystems and People. 2023; 19(1). doi: 10.1080/26395916.2023.2195021
38. Apipoonyanon C, Kuwornu JKM, Szabo S, et al. Factors influencing household participation in community forest management: evidence from Udon Thani Province, Thailand. Journal of Sustainable Forestry. 2019; 39(2): 184–206. doi: 10.1080/10549811.2019.1632211
39. Tran Duc Luan, N.N.T. Land use and factors influencing households income in m'nong ethnic minority in tho son commune, bu dang district, binh phuoc province. 2009; Available online:

https://www2.hcmuaf.edu.vn/data/tdluan/file/Bai%20nghien%20cuu/Luan-Thuy%20_NLU_-Tieng%20Anh-29062009.pdf (accessed on 13 February 2023).
40. Carr DL. Forest Clearing Among Farm Households in the Maya Biosphere Reserve. The Professional Geographer. 2005; 57(2): 157–168. doi: 10.1111/j.0033-0124.2005.00469.x
41. Marenya PP, Barrett CB. Household-level determinants of adoption of improved natural resources management practices among smallholder farmers in western Kenya. Food Policy. 2007; 32(4): 515–536. doi: 10.1016/j.foodpol.2006.10.002
42. Oyetunde-Usman Z, Olagunju KO, Ogunpaimo OR. Determinants of adoption of multiple sustainable agricultural practices among smallholder farmers in Nigeria. International Soil and Water Conservation Research. 2021; 9(2): 241–248. doi: 10.1016/j.iswcr.2020.10.007
43. Gessesse B, Bewket W, Bräuning A. Determinants of farmers' tree planting investment decision as a degraded landscape management strategy in the central highlands of Ethiopia. Solid Earth Discussions. 2015; 7(4). doi: 10.5194/sed-7-3245-2015
44. Karanth KK, Curran LM, Reuning-Scherer JD. Village size and forest disturbance in Bhadra Wildlife Sanctuary, Western Ghats, India. Biological Conservation. 2006; 128(2): 147–157. doi: 10.1016/j.biocon.2005.09.024
45. Kucsicsa G, Dumitrică C. Spatial modelling of deforestation in Romanian Carpathian Mountains using GIS and Logistic Regression. Journal of Mountain Science. 2019; 16(5): 1005–1022. doi: 10.1007/s11629-018-5053-8
46. Bhattarai K, Conway D, Yousef M. Determinants of deforestation in Nepal's Central Development Region. Journal of Environmental Management. 2009; 91(2): 471–488. doi: 10.1016/j.jenvman.2009.09.016
47. Zabihi M, Moradi H, Gholamalifard M, et al. Landscape Management through Change Processes Monitoring in Iran. Sustainability. 2020; 12(5): 1753. doi: 10.3390/su12051753
48. DAFO. Report of Forest Cover in Nationwide of Department of Forestry, Ministry of Agriculture and Forestry. DAFO; 2015.
49. Boundeth S, Nanseki T, Takeuchi S, et al. Land Use Change and Its Determinant Factors in Northern Laos: Spatial and Socio-economic Analysis. Journal of Agricultural Science. 2012; 4(12). doi: 10.5539/jas.v4n12p190
50. Butt A, Shabbir R, Ahmad SS, et al. Land use change mapping and analysis using Remote Sensing and GIS: A case study of Simly watershed, Islamabad, Pakistan. The Egyptian Journal of Remote Sensing and Space Science. 2015; 18(2): 251–259. doi: 10.1016/j.ejrs.2015.07.003
51. Hurni K, Hett C, Epprecht M, et al. A Texture-Based Land Cover Classification for the Delineation of a Shifting Cultivation Landscape in the Lao PDR Using Landscape Metrics. Remote Sensing. 2013; 5(7): 3377–3396. doi: 10.3390/rs5073377
52. Lao P. Forestry Strategy to the Year 2020 of Lao PDR. 2005, Vientiane, Lao PDR. Available online: https://lpr.adb.org/resource/forest-strategy-year-2020-lao-peoples-democratic-republic (accessed on 10 March 2023).
53. Kim SB, Alounsavath O. Forest policy measures influence on the increase of forest cover in northern Laos. Forest Science and Technology. 2015; 11(3): 166–171. doi: 10.1080/21580103.2014.977358
54. Sasaki N, Myint YY, Abe I, et al. Predicting carbon emissions, emissions reductions, and carbon removal due to deforestation and plantation forests in Southeast Asia. Journal of Cleaner Production. 2021; 312: 127728. doi: 10.1016/j.jclepro.2021.127728
55. Alaei N, Bayraktutan MS, Mostafazadeh R. Determining the dynamics of land use changes in a long-term time span in Erzurum, Turkey. Anthropogenic Pollution. 2024; 8(2).
56. Mostafazadeh R, Talebi Khiavi H. Landscape change assessment and its prediction in a mountainous gradient with diverse land-uses. Environment, Development and Sustainability. 2022; 26(2): 3911–3941. doi: 10.1007/s10668-022-02862-x
57. Fox J, Castella JC, Ziegler AD. Swidden, rubber and carbon: Can REDD+ work for people and the environment in Montane Mainland Southeast Asia? Global Environmental Change. 2014; 29: 318–326. doi: 10.1016/j.gloenvcha.2013.05.011
58. Department of Forestry. Lao PDR's Forest Reference Emission Level and Forest Reference Level for REDD+ Results Payment under the UNFCCC. 2018. Available online: https://redd.unfccc.int/files/2018_frel_submission_laopdr.pdf (accessed on 12 March 2023)
59. Wade CM, Jones JPH, Austin KG, et al. Projecting the Impact of Socioeconomic and Policy Factors on Greenhouse Gas Emissions and Carbon Sequestration in U.S. Forestry and Agriculture. Journal of Forest Economics. 2022; 37(1): 127–131. doi: 10.1561/112.00000545
60. Tubiello FN, Conchedda G, Wanner N, et al. Carbon emissions and removals from forests: new estimates, 1990–2020. Earth System Science Data. 2021; 13(4): 1681–1691. doi: 10.5194/essd-13-1681-2021

61. Watcharaanantapong P. Factors Influencing Greenhouse Gas Emissions from Land Use, Land-use Change, and Forest Activities [PhD thesis]. University of Tennessee; 2016.
62. Missanjo E, Kadzuwa H. Greenhouse Gas Emissions and Mitigation Measures within the Forestry and Other Land Use Subsector in Malawi. Marković M, ed. International Journal of Forestry Research. 2021; 2021: 1–8. doi: 10.1155/2021/5561162
63. MacCarthy DS, Zougmoré RB, Akponikpè PBI, et al. Assessment of Greenhouse Gas Emissions from Different Land-Use Systems: A Case Study of CO2 in the Southern Zone of Ghana. Applied and Environmental Soil Science. 2018; 2018: 1–12. doi: 10.1155/2018/1057242
64. Si R, Aziz N, Raza A. Short and long-run causal effects of agriculture, forestry, and other land use on greenhouse gas emissions: evidence from China using VECM approach. Environmental Science and Pollution Research. 2021; 28(45): 64419–64430. doi: 10.1007/s11356-021-15474-1
65. Alaniz AJ, Carvajal MA, Marquet PA, et al. Analyzing the Spatiotemporal Patterns of Forests Carbon Sink and Sources Between 2000 and 2019. Earth's Future. 2022; 10(11). doi: 10.1029/2021ef002560