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RESEARCH ARTICLE

Assessing Land Use and Land Cover (LULC) Change and Factors Affecting Agricultural Land: Case Study in Battambang Province, Cambodia

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Abstract: This study analyzed land use and land cover (LULC) change from 1998 to 2018 in Battambang, Cambodia, and determined factors and constraints affecting agricultural production. Landsat satellite images in 1998, 2008, and 2018 were used to identify the changes in LULC. In combination, a social survey was conducted in August 2021 using purposive sampling, selecting a total sample of 200 from two wealth classes: the poor (65) and the better-off (135) based on the Cambodia poverty assessment by the World Bank, from uplands to lowlands of Battambang Province, Cambodia. Household characteristics, farm size, and constraints were compared between the classes. T-tests, the analysis of variance (ANOVA), and Likert scale analysis were adopted using the R Program and RStudio, while Pearson's correlation test was used to determine the factors affecting agricultural land. The results show that between 1998 and 2018, the forest cover decreased by 79%. In contrast, agricultural land expansion was the highest (54%). The average household size and age of the respondents were 5.0 persons/household and 50.1 years, respectively. Of all the interviewees, about 80% attended no higher than primary school. The total farm size of the better-off (7.0 ha/household) was larger than that of the poor (5.2 ha/household). The population growth, machinery use, and improved infrastructure were found to be positive and strongly related to agricultural land use. The highest constraints of the poor and the better-off households were the same: chemical fertilizer use. Then, drought and flooding were also challenges for all. In terms of land, credit, and labor, they were not the main constraints. Thus, it is recommended that the involvement of interdisciplinary stakeholders and policy frameworks is really important from both biophysical and social perspectives.

Keywords: Agricultural production; Chemical fertilizer; Drought; Flooding

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1. Introduction

Land use and land cover (LULC) change has been a heated topic discussed worldwide because of its adverse effects on farming systems, soil fertility, wildlife habitats, fauna and flora, water flow patterns, and humans as a whole [1-6]. The main drivers of the change stem from infrastructure development, population growth, urbanization, environmental and climate change, national policies, and related regulations [7-11]. In most developing countries, a majority of their populations rely heavily on natural resources and agriculture [1,12]. Similarly, approximately 13.6 million Cambodian people, or about 80% of the whole population, live in rural areas, while about 11 million (65%) depend on farming, fisheries, and natural resources [13]. In the global context, the supply of land resources for producing food, fiber, and biofuels is limited, so the land should be well-planned, developed, and used in a sustainable way [1,9,12,14]. According to [9,15-17], the conversion of forest land to farmland in Mexico, South America, and Cambodia is due to the land expansion for pastures, soybeans, cassava, corn, and fruit trees. In Cambodia, these changes have a negative impact on soil, causing soil erosion in Battambang Province, where the soil erosion rate on upland cassava fields ranges from 82.4 to 123.7 T/ha/year [18-20]. To address that issue, conservation agriculture (CA) is recommended as a mitigation measure against soil degradation caused by erosion [21]. Besides that, cultivated land for cassava, corn, and fruit trees is increasing at the expense of natural resources [9]. Among those crops, cassava is considered an industrial crop vital for socio-economic development and livelihood improvement [22]. Additionally, the factors that have led to agricultural land expansion are infrastructure development including significant development of double bituminous surface treatment (DBST), concrete, asphalt, laterite, and dirt road, economic growth, and the enhancement of agricultural technology [11,23]. Assessment of land use and land cover change (LULC) is considered extremely significant to determine plausible resource availability in the future and provide policy implications for the sustainable management of the landscape [26,27]. Meanwhile, the evaluation of factors affecting agricultural expansion is also crucial to explain how farmers' decisions affect their land use patterns, due to technological change, improvements in infrastructure, changes in agricultural practices, or population growth [11,28].

Over the last decades, LULC change experts have used multi-temporal high-resolution satellite images to analyze deforestation, urban growth, agricultural expansion, and other anthropogenic activities [29,30], but this technique could not explain the reason behind the changes [1]. Thus, combining LULC remote sensing techniques and ethnographic research is key to understanding why changes occur by assessing the perception of local people, experts, and relevant stakeholders with respect to their socio-economic conditions, farming activities, livelihood strategies, land use, socio-political consequences, culture, natural resources, and climate change [31-34]. In terms of comprehensive and scientific research on natural and social change, some tools such as key informant interviews (KIIs), in-depth interviews, and focus group discussions (FGDs) in studied areas should be applied to obtain past, present, and expected future information related to LULC changes [35,36]. Additionally, a qualitative approach is also applied to social surveys to deeply understand local residents' perceptions of land-use change [37]. This method was also used [1,35] to identify the relationship between LULC change and socio-economic conditions in Cameroon and Ethiopia. By using semi-structured interviews with local farmers to understand the relationship between national- and local-level perceptions of environmental change in central Northern Namibia, it is found that a combination of local and scientific knowledge can effectively assess LULC change and its impact on local land users and managers [38]. Therefore, combining data on LULC change acquired from remote sensing is important to enhance our understanding of the causes and processes of the change [1,34,39].

Some recent studies [9,40] have already been conducted in Cambodia to evaluate LULC change and its drivers in Battambang Province from 1998 to 2018 and to assess its relation with soil erosion using remote sensing, GIS, and universal soil loss equation (RUSLE) models. However, because of no integrated social survey, the reasons for those changes could not be well understood. Therefore, the objective of this study was (1) to analyze LULC change from 1998 to 2018, (2) to determine the factors affecting agricultural land, and (3) to determine constraints to agricultural production based on different wealth classes set by the World Bank. To address the objectives, the Landsat 5 TM and Landsat 8 OLI images to produce LULC maps and household surveys were used to understand the local people's perception of Battambang province. Interviews were conducted with those who had lived in the target area for more than 20 years, and their age had to be over 40 years.

2. Materials and Methods

2.1 Study Area

The study was conducted in Battambang Province northwest of Cambodia, covering over 1,203,628 ha (48P: 304461 mE, 1457098 mN) (Figure 1). The maximum and average elevation of the upland is about 1,333 and 118.1 m above mean sea level (MSL), respectively. The maximum and average elevation of the lowland is about 89 and 9 m above MSL, respectively [41]. Meanwhile, the average annual rainfall and maximum temperature are about 1,491 mm and 33.7 °C, respectively [18,42]. Because of the tropical climate, there are two seasons: the rainy season, starting from May to October; and the dry season, starting from November to April. There are nine soil types: acrisols, arenosols, cambisols, ferralsols, fluvisols, gleysols, lixisols, luvisols, and vertisols, while acrisols (loam) are predominant in this province, accounting for 42.1% (507,041 ha), followed by fluvisols (clay loam) equal to 30.7% (369,122 ha) [43].

Moreover, land use is categorized into seven categories: forest (evergreen, semi-evergreen, and flooded forest), shrubland, grassland, water, cultivated land, urban area, and barren land. According to the 2019 Provincial Agricultural Report [44], paddy fields and other crops covered 699,944 ha (58.2% of the total provincial land area) and 297,312 ha (24.7%), respectively and it was considered the agricultural hub of Cambodia. The province has 14 districts and a municipality. According to the National Institute of Statistics in 2019, its population increased dramatically from 793,129 in 1998 to 997,169 persons in 2018, excluding migrants working abroad (178,401 persons). The population in the uplands increased sharply, while the population in the lowlands decreased due to immigration.

2.2 Data Collection

LULC Change

The main data source for LULC change categories in the studied area was obtained from the Landsat image, including Landsat 5 TM and Landsat 8 OLI of scenes in 1998, 2008, and 2018 (Path: 128 and Row: 51). The Landsat images were derived from the United States Geological Survey website (https://earthexplorer.usgs.gov/), accessed on 3 August 2019. All Landsat data were acquired in the same dry season from December to April. Accuracy assessment was made using a total of 121, 163, and 317 validation points randomly selected in 1998, 2008, and 2018, respectively. This approach was adopted [47-50]. The reference data for 2018 of each LULC class were collected directly on the fields by using drones and handheld global positioning systems (GPS). However, the reference data for 1998, 2003, 2008, and 2013 were obtained from the existing maps of land use in 1993 from the Geographic Department, the Ministry of Land Management, Urban Planning, and Construction; the land use map in 2002 from the JICA; and the forest cover maps in 2002, 2006 and 2010 from the Ministry of Agriculture, Forestry, and Fisheries (MAFF). Meanwhile, the data also included Google Earth images supplemented by field visits, FGDs, and KIIs in the studied area. Overall accuracy, user accuracy, producer accuracy, and Kappa coefficient were defined as the common measures of classification accuracy obtained from the error matrix [48,51,52].

Household Survey

A well-structured questionnaire was used for the household survey, focusing on socio-economic profiles (household size, farmland size), and agricultural practices (farming size, land use type, land use change, perceptions of LULC change related to agricultural expansion, and fertilizer consumption). The survey was conducted in August 2021 by adopting purposive sampling to select a total sample of 200 households from two wealth classes: the poor (65) and the better-off (165) based on the Cam-

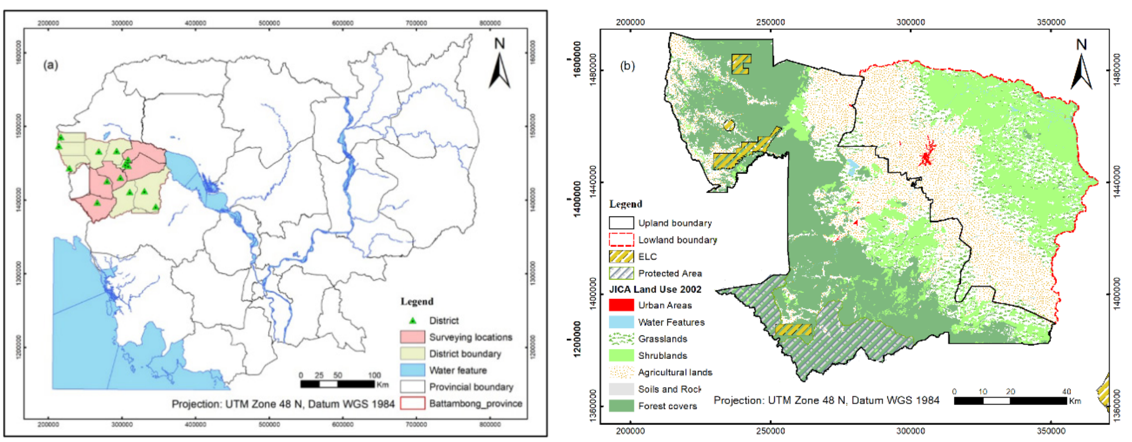

Figure 1. Map of the studied area: (a) survey areas and district headquarters [45]; and (b) protected areas (PAs) and economic land concession (ELC) in Battambang [46].

bodian poverty assessment, covering the upland area in Samlout and Rattanak Mondul Districts and the lowland area in Sangke and Ek Phnom Districts along the Tonle Sap River. After that, two more criteria were applied in order to obtain the right data for analysis: (1) the respondents must have their primary jobs as farmers and (2) they must be household heads living in two target areas since 1998. Twelve months of years 1998, 2008, and 2018 were used as reference periods for data collection and analysis. Therefore, the respondents were at least 40 years old.

The main reason for selecting Battambang Province as the study site is that this province is considered an agricultural hub and has the largest cultivated area in the country. Agricultural land expansion for cassava, corn, and fruit trees in the uplands of that province [19] was seen to boost agricultural products in line with the goal of the Cambodian agricultural sector development strategy plan (2019-2023), which aims to increase all types of agricultural production by 10% per year [53]. The consequence of such expansion in the uplands may lead to a decline in soil fertility [19]. To properly collect the data, the study was divided into two stages. In the first stage, field observations were made to contextualize agricultural systems and livelihoods to pretest and modify the questionnaire before the actual survey. In the second stage, the survey was carried out to gather both qualitative and quantitative data by using in-depth interviews, face-to-face individual interviews, four FDGs (two in the uplands and two in the lowlands), and KIIs.

2.3 Data Analyses

Data from Remote Sensing

All GIS data including reference data and remote sensing data were projected to the Universal Transverse Mercator (UTM) system, zone 48 N, and datum of World Geodetic System 84 (WGS 84). This can ensure that there was consistency between data sets during analysis. The images were analyzed by utilizing data image processing techniques in QGIS 3.10 and ArcGIS 10.3 software. To establish a map of LULC for each of the five-year images, a supervised classification method was used with the maximum likelihood algorithm [54]. This approach produces generally better results than the minimum distance approach [1,55]. Seven LULC categories, in accordance with the Cambodia land use map of 2002 produced by the JICA, were chosen for this study: urban/built-up area, water feature, grassland, shrubland, agricultural land, barren land, and forest cover. LULC classes were compared in three periods: 1998, 2008, and 2018. The values were illustrated in hectare (ha) and percentage (%). The percentage of LULC change was calculated using the equation [1]:

$$LULC\ change\ (\%) = \frac{A_1 - A_0}{A_0} \times 100 \qquad (1)$$

where A_1 is the final-year land area (ha) and A_0 is the initial-year land area (ha).

Data from Household Survey

The data collected from the household survey were entered in MS Excel and analyzed using the R Program version 3.3.0+ and the RStudio version 2023.06.1+524, both of which are available for free online. Descriptive statistics such as cross-tabulation, frequencies, and percentages were employed to summarize the data. Two-sample t-tests were analyzed to compare all quantitative data between the two wealth classes. The graphics were created by using the ggplot2 package, which is powerful in dealing with complex graphs [56].

To determine the factors most affecting agricultural land use, Pearson's correlation was used to identify the relationship between agricultural land with variables: population, agricultural machinery, draft power source, and road infrastructure. The result of this test was presented with the correlation strength (R), lower and upper confidence interval (CI) at the 5% significant level [57]. To perform this task, the rstatix package is utilized [58].

Furthermore, a five-point Likert scale analysis was also used to determine the intensity of the constraints on land use in the studied area, based on the perceptions of the respondents. the process of performing the test is in accordance with Fielding et al. [49]. The data were collected by interviewing the respondents with some questions about their constraints: input constraints, including chemical fertilizer use and pesticide application; soil fertility declines; climate constraints, such as drought and flooding; and production constraints, such as labor, land, and credit. The scores were rated 1 (no constraint), 2 (little constraint), 3 (moderate constraint), 4 (big constraint), and 5 (very big constraint), and then compared by using the analysis of variance (ANOVA) following the guidelines [59]. When significant differences were detected, an adjusted least significant difference (LSD) following Bonferroni's test was used to separate mean scores among the identified constraints [60,61]. To perform this task, the agriculture package was utilized for the LSD test [62]. Then mean and total scores for each constraint variable were presented, while different alphabetic letters were used to signify their significant differences in intensity.

3. Results

3.1 Different Classes of LULC Change

The seven main LULC classes were compared using remote sensing and GIS data over three different periods in 1998, 2008, and 2018 (Figures 2 and 3). The comparison was made in two different scenarios: changes in land area (Figure 2A) and changes in the percentage of that land area (Figure 2B). In both scenarios, it can be seen that five LULC classes increased constantly over time from 1998 to 2018, and those include agricultural land, barren land, built-up areas, shrubland, and water features. However, sharp increases from 2008 to 2018 were seen with only two LULC classes: barren land and built-up area. In contrast, the forest cover decreased sharply in 10 years from 1998 to 2008 and continued to decline slightly until 2018. Meanwhile, grassland fluctuated over time because it increased from 1998 to 2008 and then made a sharp fall in 2018.

According to Figure 2, agricultural land increased by 54% in 20 years from 535.6 thousand ha in 1998 to 823.2 thousand ha in 2018. Meanwhile, barren land increased exponentially from just 16 ha in 1998 to 1.5 thousand ha in 2018, equivalent to an increase of 8,750%. Similarly, built-up areas also increased exponentially by 9,791% from 44 ha in 1998 to 4.7 thousand ha in 2018. Shrubland also increased moderately by 38% from 154.9 thousand ha in 1998 to 213.6 ha in 2018, while water features rose by 359% from 2.3 thousand ha in 1988 to 10.6 thousand ha in 2018. Due to the increase of these above-mentioned LULC classes, there was a negative impact on forest covers, while its reduction rate in a twenty-year period was 79% from 358.9 thousand ha in 1998 to only 74.5 thousand ha in 2018. Grassland experienced an increase from 1998 to 2008 and then a sharp fall in 2018. When compared to 1998, it decreased by 50%. A clearer picture of LULC change can be seen in Figure 3, showing that the green image that represents the forest covers in Battambang vanished greatly over the three periods.

The findings show that more agricultural activities may lead to an expansion of farmland and residential areas to support their daily livelihoods. In that regard, people in the studied area had to clear forest land to grow crops and build houses. Meanwhile, the increase in barren land may suggest that after forest clearance, some land was left uncultivated because the main purpose behind that was just to harvest timbers.

Figure 4 presents the agricultural and built-up areas, the GDP per capita, and purchasing power parity (PPP) in three periods in 1998, 2008, and 2018, and all of them increased constantly over the whole period. This may imply that increasing GDP and PPP have led to an increase

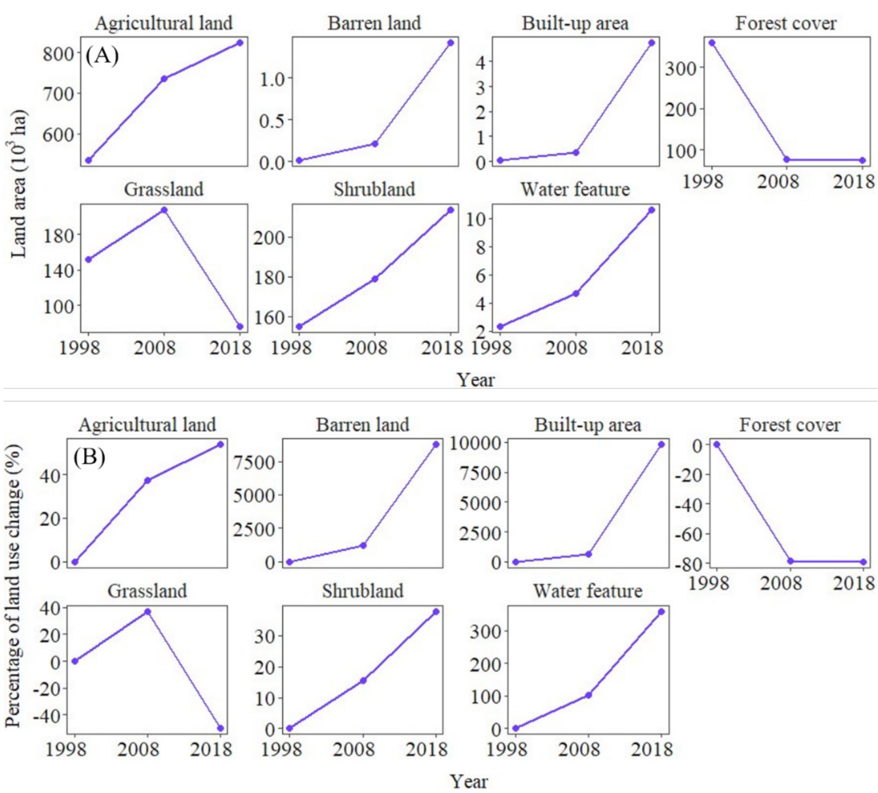

Figure 2. Comparison of LULC change among the seven land use types in the periods of 1998, 2008, and 2018, taking into account land area changes (A) and percentage of changes (the percentages of change in both 2008 and 2018 were compared to 1998) (B).

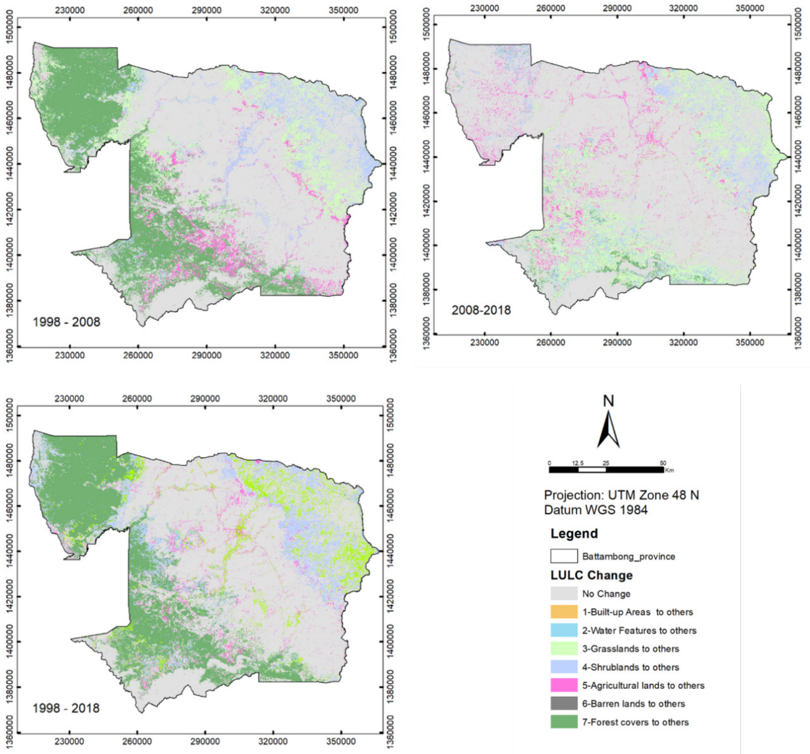

Figure 3. Spatial distribution of the LULC change in Battambang province for 1998-2008, 2008-2018, and 1998-2018.

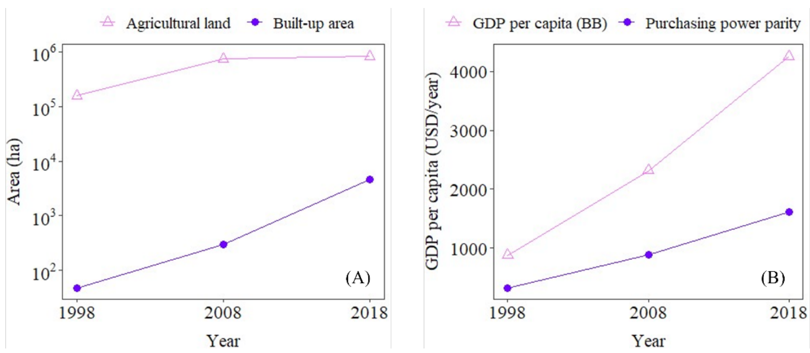

Figure 4. Comparison of Agricultural land and built-up area (A); GDP per capita and GDP per capita (PPP) (B) from 1998 to 2018.

in agricultural expansion and built-up areas over the past two decades. GDP per capita experienced an increase of around 462% between 1998 and 2018 [63]. The overall increase rate was approximately 23% annually. The increase rate of GDP per capita was the fastest during 2008-2018 (around 77 USD per year). Similarly, it was also noted that PPP increased year after year, equal to 3,383 USD from 1998 to 2018 [64].

3.2 Factors Affecting Agricultural Land

Table 1 shows correlations between agricultural land and a set of predictor variables: population, agricultural equipment, and infrastructure during the last two decades from 1998 to 2018. It is found that the population, power tillers, tractors, and infrastructure such as laterite roads, constructed earthen roads, and unconstructed earthen roads were significantly and positively correlated with agricultural land use (all P-value < 0.001), while the strength of the relationship was observed to very high, with R not less than 0.9. This means that when all these variables increase, agricultural land also increases because they are all important components to support farming activities. However, cattle draft power had a negative strong relationship with agricultural land, which means when farmland in the studied area increases, this leads to a reduction in cattle heads raised locally because farmers there prefer to use machinery as a means of land preparation and transportation instead. Meanwhile, rice threshers, bituminous roads,

Table 1. Pearson's correlation test between agricultural land and a set of predictor variables.

Dependent variable	Predictor variables	Correlation	Statistic	Pr (> t)	Lower CI	Upper CI
Agricultural land	Population	0.91	5.89	< 0.001***	0.63	0.98
	Power tiller	0.93	6.72	< 0.001***	0.70	0.99
	Tractor	0.90	5.34	< 0.001***	0.57	0.98
	Rice thresher	0.48	1.47	0.186 ns	–0.26	0.87
	Cattle draft power	–0.84	–4.12	0.004**	–0.97	–0.40
	Bituminous road	–0.53	–1.67	0.140 ns	–0.88	0.20
	Makadam road	0.58	1.87	0.104 ns	–0.14	0.90
	Concrete road	0.39	1.11	0.304 ns	–0.37	0.84
	Laterite road	0.87	4.69	0.002**	0.49	0.97
	Constructed earthen road	0.96	9.56	< 0.001***	0.83	0.99
	Unconstructed earthen road	0.95	8.19	< 0.001***	0.78	0.99

Note: Asterisks "**" and "***" denote statistically significant differences at 0.01 and 0.001, respectively. Meanwhile, "ns" means non-significant differences.

Makadam roads, and concrete roads had no relationship with agricultural land, denoting that the increase in rice thresher number and properly paved roads is independent of increased farmland.

3.3 Household Survey

Household Survey Based on Wealth Class

Household characteristics and different farm sizes were compared between the poor and the better-off in the studied area (Table 2). It can be seen that the household sizes between them were not significantly different and, on average, there were five persons in the household. Similarly, the age of the respondents between the two groups was not significantly different, and the average age was about 50 years. Regarding farm sizes, significant differences were observed in both non-rice fields and paddy rice fields between the two wealth classes. In all cases, farm sizes that belong to the better-off were larger than that of the poor. Non-rice fields for the poor and the better-off were 2.7 and 4.0 ha/household, respectively. Similarly, the poor had a rice field of 2.5 ha/household, while the better-off had 3.0 ha/household. It could be suggested the better-off had more chance to increase production because they had larger farm sizes.

Sex, Education, and Migration for Work by Wealth Class

The sex and educational level were compared in terms of percentage, regardless of the wealth classes (Figure 5). The main purpose was just to distinguish the differences within the whole sample. Of the 200 respondents, 56% were male and 44% were female. In terms of education, it can be seen that about 80% of the respondents could go higher than primary school, while 21% could attend secondary school, and another 8% went to high school. This finding may suggest the educational level of the respondents was very low, and that is why they made a living by practicing agriculture and selling labor through migration for work. When the population in the studied area started to grow, there was no other option, but to clear the forest land to pave the way for cultivation.

The respondents from the two wealth classes were also asked if they frequently migrated for work outside their province (Figure 6). Almost all of them reported that migration was important to make more income to support

Table 2. Comparison of household characteristics and all farm sizes between the two wealth classes in the studied area.

Variable	Wealth class (Mean ± SD)		Pr (> t)
	Poor	Better-off	
Household size (person)	4.9 ± 1.74	5.1 ± 1.59	0.632 ns
Age (year)	49.7 ± 14.97	50.4 ± 13.29	0.210 ns
Non-rice crop field (ha/household)	2.7 ± 2.06	4.0 ± 2.39	0.034*
Paddy rice field (ha/household)	2.5 ± 1.44	3.0 ± 2.85	0.025*

Note: Asterisks "*" and "ns" denote statistically significant differences at 0.01 non-significant differences, respectively.

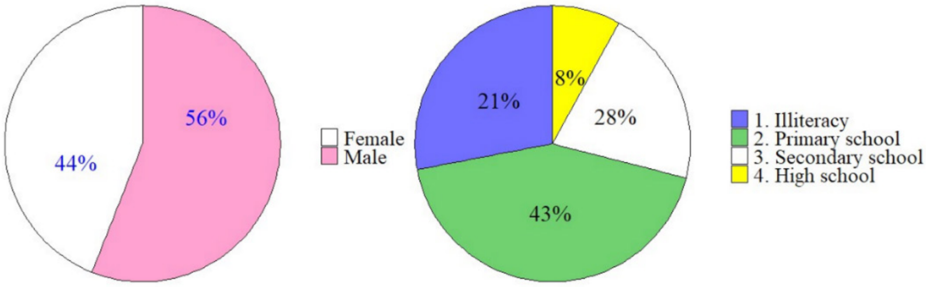

Figure 5. Distribution of household survey: (a) gender of interviewers and (b) level of education of interviewers.

their families when there were no agricultural activities available. This is the reason why the percentage of the respondents who migrated for work was very high among the two classes, at least 80% of the individual groups.

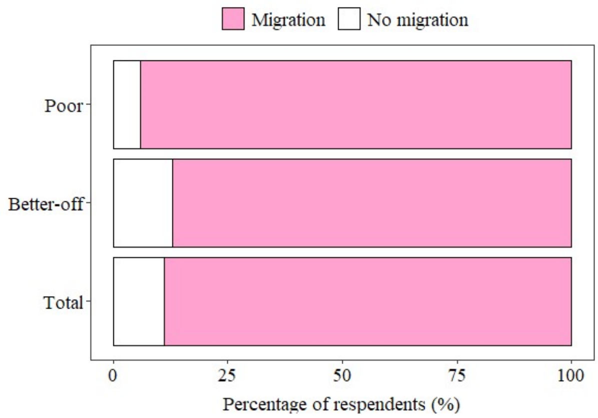

Figure 6. Comparison of migration rate between the poor and the better-off.

Constraints to Agricultural Production

The respondents from the two wealth classes were asked to rate potential constraints to their current agricultural production from 1 (no constraint) to 5 (very big constraint) based on their experience and perceptions, as illustrated in Table 3. In this context, the eight constraints, namely chemical fertilizer use, pesticide use, soil fertility decline, lack of credit, lack of land, flooding, drought, and lack of labor were identified as potential constraints. Regardless of the wealth classes, significant differences were observed among the constraints (P < 0.001). In terms of constraints, the two wealth classes had very similar perceptions, but what they thought the same was the price of commercial fertilizer which was rated as the biggest constraint to agricultural production. Similarly, the poor rated drought and flooding as the first and second biggest constraints, while the better-off thought that they ranked second and third. Regardless of the wealth classes, pesticide use and soil fertility decline ranked third in terms of constraints, followed by lack of labor and then lack of credit and land.

According to Table 3, the findings may suggest that farmers are very worried about the prices of commercial fertilizer because they may affect the yield if it is not used in sufficient amounts. Apart from that, irregular climatic patterns related to drought and flooding may also threaten their farming activities. They did not worry much about

Table 3. Comparison of constraints to agricultural production in accordance with the two wealth classes.

Type of constraints	Poor			Better-off		
	Mean	Sum	Rank	Mean	Sum	Rank
Chemical fertilizer use	3.9	249	a	4	536	a
Pesticide	3.1	198	c	3.5	474	c
Soil fertility decline	3.3	209	c	3.4	456	c
Flooding	3.5	222	b	3.5	473	c
Drought	3.8	242	ab	3.9	529	b
Lack of credit	1.6	100	e	1.9	262	e
Lack of land	1.6	103	e	1.9	251	e
Lack of labor	2.2	140	d	2.2	297	d
Pr (> F)	< 0.001***			< 0.001***		

Note: Asterisk "***" means statistically significant differences at 0.001, while different alphabetic letters denote different mean scores rated for different constraints.

pesticide use and soil fertility because they rated those constraints as moderate. In terms of labor, they may feel that there is no need to find more, as they thought that it was a little constraint. In terms of land, they had enough for their families, so it was not a problem. The same thing is found with a lack of credit. Rural credit is widely available in the studied area, so it is not hard to access that.

4. Discussion

The LULC change maps of the years 1998, 2008, and 2018 were produced by using the Landsat 5 TM and Landsat 8 OLI images with supervised classification and maximum livelihood, equipped with QGIS 3.6.29. Meanwhile, the household survey was conducted for the purpose of determining the perceptions of local residents. Overall, between 1998 and 2018, the agricultural area increased by 54% (287,600 ha) [65]. This shows that most past agricultural growth was due to the expansion of farmland from 2004 to 2012. The expansion was converted from forest and grassland [9,18,19]. The modernization of agricultural equipment, population growth, and the development of laterite roads, constructed and unconstructed earthen roads were key factors to caused agricultural land expansion, especially from forest covers. According to FGDs and the survey, agricultural practices have been transited to mechanized agriculture with the availability of tractors, power tillers, and other machinery since 2005. This is in accordance with the study of Mottet, A. et al. [66] who claimed that the agricultural land use change was also caused by modernization of agricultural machinery.

In this research, the combination tool between remote sensing and the social survey was conducted to significantly identify the correlation between LULC change and socio-economic conditions. This approach was also used by Desalegn, T. et al. [1] in the central highlands of Ethiopia and Toh, F.A. et al. [34] in the Western Highlands of Cameroon. Moreover, the priority constraints to agricultural production were also determined by using the Likert Scale analysis based on a five-point score to understand the perceptions of local farmers in depth. It was recommended by Joshi, A. et al. [67], who claimed that it is one of the most basic and widely used psychometric instruments in educational and social science research. Furthermore, the scales method was employed by other researchers to identify the constraints that varied by level [68-72]. Additionally, the results were compared using the analysis of variance (One-way ANOVA), according to the guidelines [59], while Toh, F.A. et al. [1,34] used only a percentage function to describe crop production constraints in their research.

The average total household size of the sample respondents was 5.0 persons, which was higher than the Cambodian average household size (4.3 persons) [73]. In Cambodia, the National Institute of Statistics [73] reported that the average household size decreased from 4.7 persons in 2008 to 4.3 persons in 2019. The mean household size of the better-off was not different from that of the poor, being 5.1 and 4.9 persons/household, respectively. This result was in contrast with the research finding [1,34], which reported that the average family size of the better-off was also higher. The total farm size, combining non-rice crop fields and paddy rice fields, was 5.2 and 7.0 ha/household for the poor and the better-off, respectively. This finding was higher than the average landholding size of an average rural household (only 1.3 ha) [74]. However, the average household farm size was smaller than the mean house farm size in the central highlands, Ethiopia [1] and in the Western Highlands, Cameroon, except for the average farm size of the poor (2.1 ha) [34].

Migration for work outside the province, either to other provinces or abroad, is common in the studied locations, regardless of the wealth classes. Additionally, according to KIIs and FGDs, if any families have their members migrate to work in other provinces, cities, or abroad, their livelihoods tend to be better. This finding was also in line with the result [75], which claimed that households that have members migrate to work may have much better livelihoods when compared to those staying at home.

In this study, eight constraints to agricultural production could be identified (Table 3), while only five similar constraints were identified [1] in the central highland, Ethiopia, and those include soil fertility decline, lack of land, lack of credit, crop pests, and crop diseases. Meanwhile, almost all constraints identified in this study were similar to the study [34] in the Western Highlands, Cameroon. The finding showed that chemical fertilizer use was the biggest constraint for both the poor and the better-off. According to the FGDs, chemical fertilizer use is increasing remarkably, and the local farmers spend more on it due to soil fertility decline [41]. However, in the northern uplands of Vietnam, Yen, B.T., et al[76] reported that the greatest constraint was a lack of credit, followed by the limitations of land and techniques. Furthermore, the poor and the better-off also faced the same constraints to their crop production, such as drought and flooding. It was also confirmed by ADB [44], which claimed 93,082 ha and 27,340 ha of agricultural land were damaged by flood and drought, respectively, in Battambang. HRF [77] reported that 66,088 households and 164,116 ha of agricultural land were affected by floods in Battambang in 2020. It is similar to the finding [72], who claimed that the farming systems practiced in South East Asia and Africa faced a similar natural disaster which was a severe drought.

5. Conclusions

The combination of remote sensing and GIS tools and a social survey is a very effective method to deeply understand the correlations between LULC change and socio-economic factors. The result shows that in 20 years between 1998 and 2018, the increase in the agricultural area was 54%. The increasing agricultural land with poor farming practices may lead to soil fertility decline. With this issue, farming households were forced to increase chemical fertilizer use to maintain high yields. The price of chemical fertilizer was rated as the biggest constraint among the eight identified constraints to agricultural production for both wealth classes. Possible approaches to soil fertility management in the region should involve the use of technology or agricultural practices that can add nutrients to the soil, such as conservation agriculture, while reducing nutrient losses through runoffs and soil erosion. Because the studied province is an agricultural hub, building public-private partnerships around market-oriented production can be an entry point to encourage investment in the use of external nutrient inputs to improve soil fertility and increase agricultural productivity.

In conclusion, the findings of this study provide considerable evidence that the local community in the study area faces a variety of social, economic, and environmental constraints to their agricultural production, so they must be properly addressed to reduce poverty and to contribute toward achieving the goal of the Cambodian agricultural sector development strategy plan (2019-2023), which aims to increase all type of agricultural production by 10% per year. Solutions should also adhere to the sustainable development goals (SDG) in 2030 and the goal of the Royal Government of Cambodia to become an upper middle-income country by 2030. Thus, it is recommended that the involvement of interdisciplinary stakeholders and policy frameworks is strongly needed to contain these dire situations from both biophysical and social perspectives. In particular, empowering and capacity-building local people with various agricultural techniques not only help them increase agricultural productivity but also contribute significantly to environmental protection in the future.

Author Contributions

Conceptualization: Taingaung Sourn, Sophak Pok, Nareth Nut; methodology: Taingaung Sourn, Sophak Po, Nareth Nut, Lyhour Hin; software: Taingaung Sourn, Lyhour Hin; formal analysis: Taingaung Sourn, Sophak Pok, Nareth Nut, Lyhour Hin; investigation: Phanith Chou, Dyna Theng; resources: Taingaung Sourn, Nareth Nut; data curation: Taingaung Sourn; writing—original draft preparation: Taingaung Sourn, Sophak Pok, Lyhour Hin, Nareth Nut; writing-review and editing: Taingaung Sourn, Lyhour Hin, Nareth Nut, Sophak Pok, Phanith Chou, Dyna Theng; visualization: Taingaung Sourn, Lyhour Hin; supervision: Sophak Pok, Phanith Chou, Dyna Theng. All authors have read and agreed to the published version of the manuscript.

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Data Availability

The data are available upon request from the corresponding author.

Conflict of Interest

The authors declare no conflict of interest.

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