# SELECTING VEGETATION INDEX FOR MAPPING LAND USE AND COVER CHANGE (2019-2021) TOWARD SUSTAINABLE MANAGEMENT IN XAYTHANY DISTRICT, VIENTIANE LAO PDR

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## SUMMARY

Remote sensing technology offers an effective tool to monitor the changes in land use/cover over time. This study tested five vegetation indices for land-use/cover mapping and SAVI was then selected with thresholds defined for land cover (SAVI > 0.52 for forest cover; SAVI > 0.21 and SAVI <= 0.52 for agriculture; SAVI > 0.05 and SAVI <= 0.21 for others; SAVI <=0.05 for water). The overall accuracy assessments of land use/cover in 2019 (91.0% of accuracy, Kappa coefficient of 0.87), in 2020 (93.0% of accuracy, Kappa coefficient of 0.90), and in 2021 (94.5% of accuracy, Kappa coefficient of 0.92) have confirmed using Sentinel-2 data for monitoring the spatio-temporal changes of land-use/cover is reliable in Xaythany District. The extent of forest cover in Xaythany District, Vientiane Province in 2019 and 2021 were 31659.1 ha and 31369.9 ha, the area of agriculture in 2019 and 2021 were estimated at 40511.3 ha and 41105.9 ha, respectively. In addition, forest cover in Xaythany District decreased by 289.2 ha in 2021 compared to 2019 and main drivers for deforestation and land use/cover change during the period of 2019-2021 were defined in the order of slash-burning and shifting cultivation, other land use conversions, and other socioeconomic influences.

**Keyword: Land use/cover, forest cover, SAVI, Sentinel-2, vegetation index, Xaythany District.**

## 1. INTRODUCTION

Land use and land cover changes are main driving forces of deforestation, forest degradation, biodiversity loss, and global warming (e.g. Prenzel, 2004). The growth of human population, urbanization, and economic development are increasingly converted to agriculture and urban land-use to satisfy the increasing demands and needs of natural resources (e.g. Hue et al., 2016). Rapid changes in land covers are more likely to cause the deterioration of environmental conditions by removing the forest covers. Therefore, using remotely sensed data to assess the changes in land-use and land-cover is important to monitor the rates of deforestation (e.g. Hue et al., 2016).

Lao People's Democratic Republic (PDR) retains the highest proportion of forest and woodland, comprising both deciduous and evergreen forest. However, forest cover declined from 49% of total land area in 1982 to 47% in 1989 (Manivong and Sandewall, 1992). According to Prime Minister's Office 2005, the forest area continuously declined to 41% in 2002. Shifting cultivation and logging are blamed as the main causes of deforestation and forest degradation in Lao PDR (Fujita and Phanvilay, 2008). Remote sensing is an effective tool to detect and monitor land use/cover change over the time. It is also known as one of the most reliable methods for monitoring land use/cover at all spatial scales. These data also offer economical and reliable data source for detecting land use/cover change periodically. In Lao PDR, using remote sensing data to monitor and assess the land use/cover change, in particular to detect forest degradation and deforestation is very limited. In particular, changes in the extent of forest cover neither have been well-documented nor have been periodically monitored in Xaythany District, Vientiane Province. Therefore, the question of how land use/cover has been changed in Xaythany District since 2019 remains questionable.

This study examined how reliable the remotely sensed data have provided land use/cover managers information in relation to spatio-temporal land use/cover change in Xaythany District, Vientiane Province, Lao PDR. The main objectives of this study were to: (1) test and select the suitable vegetation index for mapping the spatio-temporal extent of land use/cover in Xaythany District, Vientiane, Lao PDR using Sentinel-2A/B from 2019 to 2021;

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(2) quantify the changes in the spatio-temporal extent of land use/cover in Xaythany District during 2019-2021; (3) determine the drivers responsible for the changes in the extent of land use/cover, forest cover for providing better solutions how to manage forests in a sustainable manner in Xaythany District.

## 2. Study site and methods

### *2.1. Study site*

Xaythany is a district, which is geographically located in the northeast of the capital Vientiane, about 12 km from the center of the capital. It is located from 17°59 to 18°18 north, and from 102°33 to 102°53 east. It borders Thulakhom District in the north, and borders Saysettha and Hatxayphong districts in the south. In the East, it borders on Paknguem district; while it borders Naxaythong and Chanthabouly districts in the west. Xaythany has a natural land area of 84,685 ha, of which 15,438 ha is forest land, equivalent to 18.23% of the district's natural land area (Ministry of Agriculture and Forestry, 2005). The rain season starts from May to September, while the dry season begins from October to April (Hue et al., 2016). The wet and dry seasons are very important for agricultural activities in Xaythany District as it is the major economic income source in Vientiane Province. In Vientiane Province, lowland areas is categorized as a tropical region, whereas the higher elevation and mountainous areas are classified as a sub-tropical region (Hue et al., 2016). In Laos, the forest covers have been experienced the changes due to the deforestation, forest degradation and new afforestation programs (Ministry of Agriculture and Forestry, 2005). However, the question of how much forest covers have been changed since 2019 remains unanswered.

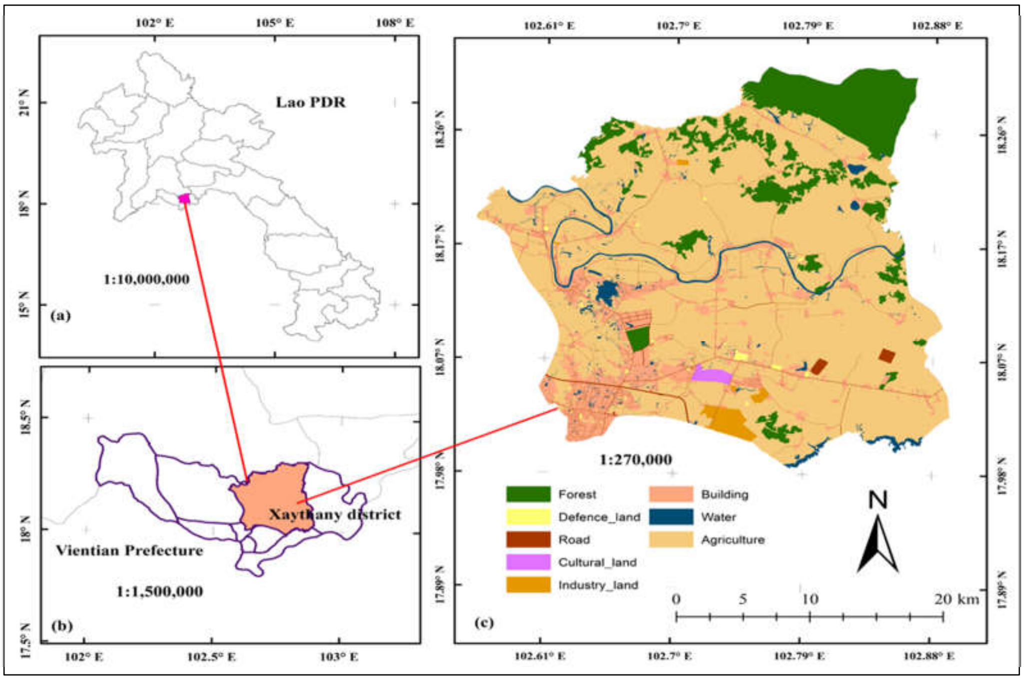


**Fig. 1. Study site: (a) Geographic location of Xaythany District in Laos; (b) Geographic location of Xaythany District in Vientiane Province; (c) Land use and land cover of Xaythany District**

### *2.2. Data collection*

In this study, multiple-temporal Sentinel-2A/B data were used to quantify the extent of land use and covers, including forest covers in the different periods as shown in Table 1.

**Table 1. Remotely sensed data used for mapping land use and cover in Xaythany District, Laos**

| ID | Image codes | Date | Spatial resolution (m) | Remarks |
|---|---|---|---|---|
| 1 | S2B_20191208T034129_20191208T071344 | 08/12/2019 | 10 | T48QTF |
| 2 | S2A_20201207T034131_20201207T062140 | 07/12/2020 | 10 | T48QTF |
| 3 | S2B_20211207T034129_20211207T055125 | 07/12/2021 | 10 | T48QTF |

**Source :** *https://earthexplorer.usgs.gov*

### *2.3. Data processing and image classification*

To quantify the spatial-temporal changes in land use and covers, three main steps were performed: (1) Data pre-processing included atmospheric corrections, band combination and subset of the study areas; (2) Identification and classification of land use and covers were conducted by using five different indices (SAVI, EVI, SIPI, ARVI, NBR) as indicated in Table 2. The thresholds for the different land covers was then define and accuracy assessments of mapping with support of the data-based field survey were carried out; (3) Finally, post-classification was used to examine multi-temporal dynamics in Xaythany District.

**Data pre-processing:** The available Sentinel-2A and B images (2019, 2020, 2021) processed at Level 1C (already an orthorectified and top-of-atmosphere reflectance), covering Xaythany District, Vientiane prefecture, were downloaded from USGS as shown in Table 1. The European Space Agency's (ESA) Sen2Cor algorithm processes ESA's Level-1C top-of-atmosphere reflectance to atmospherically corrected bottom-of-atmosphere (BOA) reflectance (Level-2A) (Vuolo et al., 2016) by using the Semi-Automatic Classification Plugin in QGIS Version 3.16 (Congedo, 2020). In addition, the pre-processed Sentinel-2 Level 2A were geo-referenced to UTM WGS84 Zone 48N projection and datum. Bands of Sentinel-2 (Bands 2 - 12) were stacked into composite bands for the visual interpretation purpose. This study also used the visual interpretation approach to separate forest areas from other land uses from remote sensing imageries (Hai-Hoa et al., 2020a; 2020b).

**Land use and land cover mapping**: This study used vegetation index to classify land use and cover types based on the thresholds of index values (Table 2). Before the selection of suitable vegetation index made for land use and cover mapping, five potential vegetation indices were examined by using Sentinel-2B in 2021 (Table 1). The overall accuracies and Kappa coefficients were assessed and calculated for five indices

**Table 2. Vegetation indices used this study**

| Vegetation indices | Formulas | References |
|---|---|---|
| Soil Adjusted Vegetation Index (SAVI) | $\frac{(NIR - RED)(1 + L)}{(NIR + RED + L)}$ | Huete (1988); Gilabert et al., (2002) |
| Enhanced Vegetation Index (EVI) | $G * \frac{(NIR - RED)}{(NIR + C1 * RED - C2 * BLUE + L)}$ | Sims & Gamon (2002); Jiang et. al., (2008); Matsushita et al., (2007); Nagler et al., (2009) |
| Structural Independent Pigment Index (SIPI) | $\frac{(NIR - BLUE)}{(NIR - RED)}$ | Liu et al., (2006) |
| Atmospherically Resistant Vegetation Index (ARVI) | $\frac{(NIR - (2 * RED) + BLUE)}{(NIR + (2 * RED) + BLUE)}$ | Kaufman & Tanre (1992); Huete & Liu (1994); Baugh & Groeneveld (2006) |
| Normalized Burn Ratio (NBR) | $\frac{(NIR - SWIR)}{(NIR + SWIR)}$ | Roy et al., (2006); Miller & Thode (2007) |

*Where: G=2.5, C1=6.0, C2=7.5, L=1; In Sentinel-2: BLUE is Band-2, RED is Band-4, NIR is Band-8, and SWIR is Band-12.*

**Accuracy assessments:** The accuracy assessment is an important process for evaluating the result of post-classification as the user of land cover outputs should know how accurate the results are. To evaluate the accuracies of Sentinel-2A/B images classified and to assess the accuracies of SAVI, EVI, SIPI, ARVI, and NBR in 2021, randomly sampling points were used to assess the land cover classification accuracy. Total sampling points used for the classification accuracy were 200 GPS points, of which 100 points were for forest land cover, 40 points for agriculture, 40 points for others, and 20 points for water. These GPS points were sampled by the field survey in combination with the Google Earth. The overall classification accuracy, producer's accuracy and user' accuracy, and Kappa statistics were assessed and calculated for quantitative classification performance analysis (Foody, 2013). To use the data correctly, we considered the minimum level of the overall interpretation accuracy for land use and land cover map would be at least 85.0% as suggested by previous studies of Foody (2002). The vegetation index with overall highest accuracy assessment was then selected and used to map land use and covers and to quantify the changes in the extent of forest covers. To assess the accuracy of land use and covers mapping in 2019 and 2020, due to a lack of field data in 2019 and 2020, this study tended to use data, which were mainly generated from land use and cover map in 2020 provided by Xaythany Department of Agriculture and Forestry and Google Earth data.

**Post classification**: In post-classification process, the filtering process was carried out to remove isolated pixels or noise or the "salt-and-pepper" effect in the land cover maps. The filtered classified image was used as the final land use and cover map each year.

**Changes in land use and land cover mapping**: Sentinel 2A/B (2019, 2020 and 2021) were used to detect the changes in land use and land covers, including forest covers. The post classification change detection is commonly applied statistical technique to evaluate the changes in land use/covers. Such analysis provides in-depth information about pixel transformation, class change and dynamics of converted land covers (Halder et al., 2021). The land cover maps for 2019, 2020, and 2021, were evaluated and compared in terms of areas covered. The annual rate of change and cross-tabulated methods were used to identify land cover changes over 3 years, namely 2019-2020, 2020-2021. Our study also calculated change detection statistics between 2019 and 2021 maps to understand the dimension of class-wise land cover variation. The changes in land covers were visually interpreted and further examined to understand the spatial-temporal gain and loss of forest covers over in Xaythany Province.

**To determine drivers of land use/cover and forest cover change**: To assess drivers of forest cover change during 2019-2021, this study interviewed a total of 100 individuals from differently adjacent households to forest areas who represented 60% (40 interviewees) of the total interview samples, 40% of interviewees from forest rangers and forest staffs (20 people); heads of villages and communes (20 people). To reduce the biases, our study ensured that the respondents were evenly distributed geographically regardless of road accessibility. Our criteria used in selecting our interview samples consist of a minimum age of 18, a resident in the targeted villages/communes, forest rangers-related to forest management and protection in the study area.

## 3. Results and discussion

### *3.1. Accuracy assessments, selection of suitable vegetation index for forest cover mapping*

The vegetation indices, including SAVI, EVI, SIPI, NBR, and ARVI, were calculated for mapping land use/cover (LULC) in 2021. As a result, the accuracy assessments and Kappa coefficients for five different indices were summarized in Table 3. The highest accuracy and Kappa coefficient of vegetation index was performed by SAVI.

**Table 3. Accuracy assessments and Kappa of each vegetation index in 2021**

| Vegetation indices | SAVI | EVI | SIPI | NBR | ARVI |
|---|---|---|---|---|---|
| **Overall accuracy** (%) | 94.5 | 91.5 | 92.5 | 92.0 | 92.5 |
| **Kappa coefficients** | 0.92 | 0.88 | 0.89 | 0.88 | 0.89 |

As indicated in Table 3, all of the vegetation indices have an overall accuracy of greater than 90.0% and Kappa coefficient of greater than 0.85. This assessment implies that five vegetation indices could be used for forest cover mapping in this study site. Howev, our study has selected the SAVI index for mapping the extent of forest and changes in forests as a result of the highest overall accuracy (94.5%) and Kappa coefficient of 0.92.

The detailed accuracy assessments of using the SAVI index for forest mapping each year were summarized in Table 4, 5 and Table 6.

**Table 4. Accuracy assessments of land covers by SAVI in 2019**

| Image classified | GPS-based survey | | | | | |
|---|---|---|---|---|---|---|
| | For | Agr | Oth | Wat | Total | User's Accuracy (%) |
| For | 90 | 9 | 1 | 0 | 100 | 90.0 |
| Agr | 0 | 40 | 0 | 0 | 40 | 100.0 |
| Oth | 2 | 6 | 32 | 0 | 40 | 80.0 |
| Wat | 0 | 0 | 0 | 20 | 20 | 100.0 |
| Total | 92 | 55 | 33 | 20 | 200 | |
| **Producer's Accuracy (%)** | 97.8 | 72.7 | 97.0 | 100.0 | | |
| Overall accuracy (%): 91.0; Kappa coefficient: 0.87; Data: Sentinel-2B 07 Dec 2019 | | | | | | |

Where: For: Forest; Oth (Others: Residential areas/built-up areas, industry areas, road); Agri (Agriculture land); Wat (Water: Rivers, lakes, streams).

**Table 5. Accuracy assessments of land covers by SAVI in 2020**

| Image classified | GPS-based survey | | | | | |
|---|---|---|---|---|---|---|
| | For | Agr | Oth | Wat | Total | User's Accuracy (%) |
| For | 95 | 3 | 2 | 0 | 100 | 95.0 |
| Agr | 1 | 39 | 0 | 0 | 40 | 97.5 |
| Oth | 4 | 3 | 33 | 0 | 40 | 82.5 |
| Wat | 1 | 0 | 0 | 19 | 20 | 95.0 |
| Total | 101 | 45 | 35 | 19 | 200 | |
| **Producer's Accuracy (%)** | 94.1 | 86.7 | 94.3 | 100.0 | | |
| Overall accuracy (%): 93.0; Kappa coefficient: 0.90; Data: Sentinel-2A 07 Dec 2020 | | | | | | |

**Table 6. Accuracy assessments of land covers by SAVI in 2021**

| Image classified | GPS-based survey | | | | | |
|---|---|---|---|---|---|---|
| | For | Agr | Oth | Wat | Total | User's Accuracy (%) |
| For | 98 | 2 | 0 | 0 | 100 | 98.0 |
| Agr | 2 | 38 | 0 | 0 | 40 | 95.0 |
| Oth | 4 | 3 | 33 | 0 | 40 | 82.5 |
| Wat | 0 | 0 | 0 | 20 | 20 | 100.0 |
| Total | 104 | 43 | 33 | 20 | 200 | |
| **Producer's Accuracy (%)** | 94.2 | 88.4 | 100.0 | 100.0 | | |
| Overall accuracy (%): 94.5; Kappa coefficient: 0.92; Data: Sentinel-2B 08 Dec 2021 | | | | | | |

The classification accuracies of the SAVI index were evaluated by the confusion matrix in Table 4, 5 and 6. As a result, overall accuracies of the SAVI were 91.0% in 2019, 93.0 in 2020 and 94.5% in 2021, with Kappa coefficients of 0.87, 0.90 and 0.92, respectively. User's and producer's accuracies of each class in 2019, 2020 and 2021 are also presented in Table 4, 5 and 6. In general, all classes have user's and producer's accuracies higher than 80.0%, with exception of the class known as others in user's accuracy assessments in 2019. The classification accuracy of the results was assessed based on the field survey results in 2020. The accuracies assessments have confirmed the suitability of using vegetation indices calculated from remotely sensed Sentinel-2A/ B for monitoring the spatio-temporal changes of forest cover in Xaythany District (Thomlinson et al., 1999; Foody, 2002).

### *3.2. Land use and land cover mapping in Xaythany District*

**Land use and land cover mapping during 2019-2021**

This study selected the SAVI index for mapping land use and land cover. Thresholds of the SAVI were defined for forested and forest land (SAVI > 0.52), for agriculture (SAVI > 0.21 and SAVI <= 0.52), for others (SAVI > 0.05 and SAVI <= 0.21) and for water (SAVI <= 0.05). As thresholds of SAVI index defined for classifying forests, agriculture, others, and water bodies, thematic map of land use and land cover each year has then been constructed as indicated in Fig. 2a, 2b and 2c.

As indicated in Fig. 2, four types of land use/covers spatially distribute across Xaythany District. However, large areas of forest cover are only found in Northeast of the district. Forest covers have been spatially and temporally changed across the district.

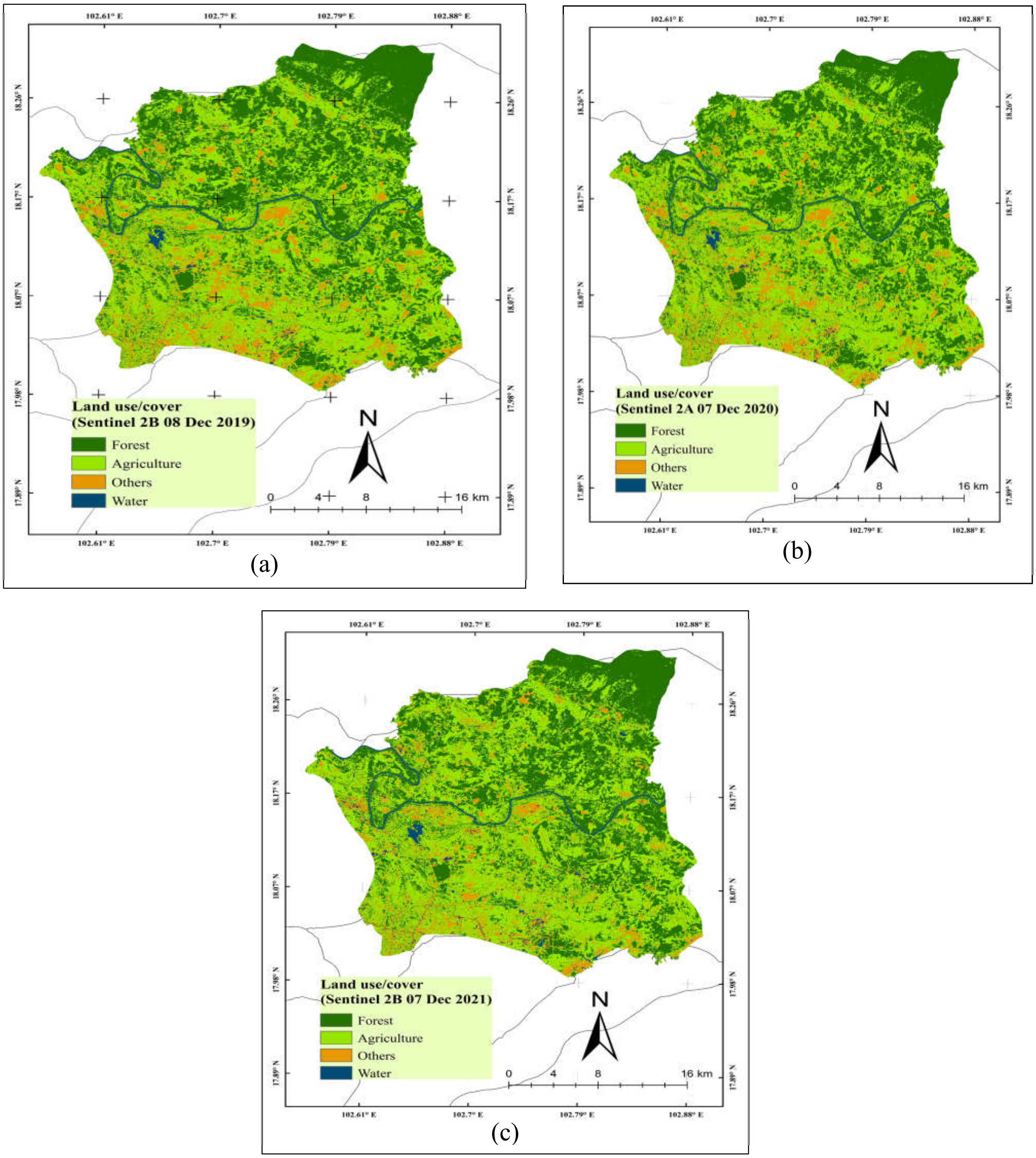


**Fig. 2. Land use and land covers mapping in Xaythany District, Lao PDR by Sentinel-2A/B in (a) 2019; (b) 2020; (c) 2021**

**Changes in forest covers during 2019-2021 in Xaythany District**

Temporal changes in land use/covers in Xaythany District, Lao PDR are presented in Table 7 and Fig. 3. Overall, the extent of forest cover fluctuated as a result of deforestation and encroachment between 2019 and 2021. As shown in Table 7, during this period of 2019-2021, the extent of forest covers decreased by 289.1 ha. However, the extent of forest cover increased significantly in the period of 2019-2020, due to afforestation and regeneration promotion projects since 2015. It then dramatically decreased by 7382.9 ha in the period of 2020-2021 as a result of land use conversion and uncontrolled forest fires.

In period of 2020-2021, the extent of agriculture and others (including residential areas/built-up areas, industry areas, road) also increased significantly and were estimated at 4891.3 ha and 2317.8 ha, respectively. Besides, the area covered by water increased constantly from 2019 (1857.1 ha) to 2021 (2292.5 ha).

**Table 7. Extent of land use/covers in Xaythany District in 2019, 2020 and 2021 (ha)**

| Land use/covers | 2019 | 2020 | 2021 |
|---|---|---|---|
| Forest | 31,659.1 | 38,752.8 | 31,369.9 |
| Agriculture | 40,511.3 | 36,214.5 | 41,105.9 |
| Others | 9,125.2 | 6,066.6 | 8,384.5 |
| Water | 1,857.1 | 2,118.8 | 2,292.5 |
| **Total** | **83,152.7** | **83,152.7** | **83,152.7** |

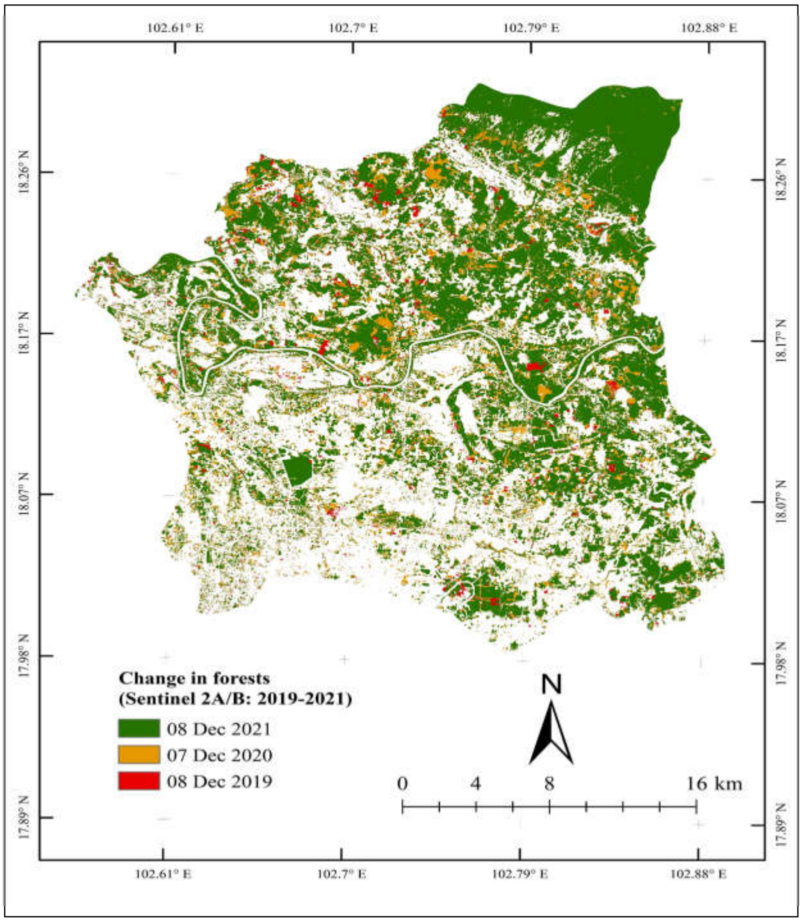


**Fig. 3. Changes in forest covers of Xaythany District, Lao PDR during 2019-2021**

As can be seen in Fig. 3, there is a spatio-temporal change in forest covers from 2019 to 2021. The change in forest cover has experienced across Xaythany District.

### 3.3. Drivers of changes in land use and covers in Xaythany District

In Lao PDR, the main drivers of change in forest covers were strongly related to physical and socioeconomic factors (e.g. Shi, 2008; Inoue et al., 2010; Vu et al., 2014; Phompila et al., 2017). Indeed, our study indicated nearly 80% of Lao people are in rural areas and heavily dependent on forest resources. The shifting cultivation is a main source of food for people in upland areas (Phompila et al., 2017). In addition, the cutting down and the burning of trees and grasses, and slope cultivation without sound soil conservation practices have severely led to land degradation (Phompila et al., 2017). Consequently, more disturbances to native forests or further to land-use pattern changes.

The result of interview in Xaythany District showed that forest degradation and deforestation are associated with land clearance, tree cutting and use of fire, which has been known as mainly direct drivers. More importantly, the destructive farming practice was more likely to cause serious land degradation, soil erosion and loss of biodiversity (FAO, 2015; Higashi, 2015). As the findings, the main drivers of changes in land use and covers over during 2019-2021 in Xaythany District were determined in the order of shifting cultivation > other socioeconomic factors > other land use conversion > other drivers.

**Table 8. Estimated changes in land use/covers (ha) in different periods in Xaythany District**

| Land-use/covers | 2019- 2020 | 2020-2021 | 2019-2021 | |
|---|---|---|---|---|
| | Ha | Ha | Ha | Rate of change in three years (%) |
| Forest | +7093.7 | -7,382.86 | -289.2 | -0.9 |
| Agriculture | -4296.8 | +4,891.33 | +594.6 | 1.5 |
| Others | -3058.6 | +2.317.82 | -740.7 | -8.1 |
| Water | +261.7 | +173.71 | +435.4 | 23.4 |
| Change: (+) refers to the gain; and (-) refers the loss | | | | |

As shown in Table 8, the extent of forest covers decreased by 289.2 ha over the period of 2019- 2021. Similarly, the class of 'Others' has been recorded with a reduction of 740.7 ha. However, the extent of agriculture land and the area covered by water have been experienced an increase of 594.6 ha and 435.4 ha, respectively over the last three years. Furthermore, slash-and burn agriculture or shifting cultivation are widely practiced and crucial food production systems for the minority ethnic groups in Lao upper regions (Shi, 2008; Sovu et al., 2009; Inoue et al., 2010). Shifting cultivators are completely dependent on the upper farming land and forests for their income and self-subsistence due to the farmers' poverty. The growth population has led to the expansion in forest clearance and other land use conversion. Phompila et al., (2017) argue that forest cover decrease in Lao PDR was related to both physical and socioeconomic factors, namely elevation, access to roads and shifting cultivation practices, while an increase of forest cover was significantly linked to rubber plantation programs. Native forest and shifting cultivation lands were more vulnerable to transformation into rubber plantations as rubber prices were increasing (Phompila et al., 2017). Therefore, poverty alleviation and eradication of shifting cultivation by encouraging foreign investments in Lao PDR should require more attention to reduce potential pressure on forest and land use/cover. Our findings have been confirmed with the study of Phompila et al., (2017) in that socio-economic and physical factors are main drivers of forest cover change at a local level.

To reduce the pressure on forest cover and land use/cover, policies for sustainable forest and land use planning on uplands should be introduced to ensure a long-term food security for upland communities. In addition, capacity building programs for local people should be implemented to improve their livelihoods. Both alternative livelihood development options and financial assistance should be provided to improve local people's livelihood and reduce further deforestation in the upland regions (Phompila et al., 2017).

## 4. CONCLUSION

Remote sensing technology is known as an effective tool to detect and monitor land use/cover change over time. Four land use/covers were classified using Sentinel-2A/B from 2019-2021, namely forests, agriculture, others, and water. This study tested five vegetation indices for land-use/cover mapping and finally selected the SAVI index with thresholds for land covers (SAVI > 0.52 for forest cover; SAVI > 0.21 and SAVI <= 0.52 for agriculture; SAVI > 0.05 and SAVI <= 0.21 for others; SAVI <=0.05 for water). The overall accuracy assessments of land covers in 2019 (91.0% of accuracy, Kappa coefficient of 0.87) and land covers in 2020 (93.0 % of accuracy, Kappa coefficient of 0.90), and land covers in 2021 (94.5% of accuracy, Kappa coefficient of 0.92) have confirmed using Sentinel-2 data for monitoring the spatio-temporal changes of land-use/cover is reliable and applicable with SAVI in Xaythany District. The areas of forest covers in Xaythany District in 2019 and 2021 were 31659.1 ha and 31369.9 ha, the areas of agriculture in 2019 and 2021 were estimated at 40511.3 ha and 41105.9 ha, respectively. Overall, forest covers in Xaythany District decreased by 289.2 ha in 2021 compared to 2019 and main drivers for deforestation and land use change during the period of 2019-2021 were slash-burning and shifting cultivation, other land use conversions, and other socioeconomic influences recorded.

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# LỰA CHỌN CHỈ SỐ THỰC VẬT XÂY DỰNG BẢN ĐỒ THAY ĐỔI LỚP PHỦ VÀ SỬ DỤNG ĐẤT (2019-2021) HƯỚNG TỚI QUẢN LÝ BỀN VỮNG TẠI HUYỆN XAYTHANY, VIENTIANE, LAOS

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## TÓM TẮT

Công nghệ viễn thám được coi là một công cụ hữu hiệu để theo dõi sự thay đổi lớp phủ và sử dụng đất theo thời gian. Nghiên cứu đã thử nghiệm 5 chỉ số thực vật để lập bản đồ che phủ và sử dụng đất năm 2021, sau đó đã lựa chọn chỉ số SAVI với các ngưỡng giá trị xác định cho từng đối tượng lớp phủ (SAVI> 0,52 là đất che phủ bởi rừng; SAVI> 0,21 và SAVI <= 0,52 đất nông nghiệp; SAVI> 0,05 và SAVI <= 0,21 đối tượng khác; SAVI <= 0,05 đất che phủ bởi nước). Kết quả đánh giá độ chính xác tổng thể bản đồ lớp phủ và sử dụng đất năm 2019 cho độ chính xác 95,0% với hệ số Kappa 0,93, năm 2020 có độ chính xác 95,5% với hệ số Kappa 0,91; năm 2021 có độ chính xác 94,5% và hệ số Kappa 0,92. Kết quả nghiên cứu cho thấy hiệu quả của việc sử dụng dữ liệu Sentinel-2 để theo dõi thay đổi lớp phủ và sử dụng đất theo không gian và thời gian có độ tin cậy và khả thi tại huyện Xaythany, tỉnh Vientiane, Lào. Diện tích đất lâm nghiệp của huyện Xaythany, tỉnh Viêng Chăn trong năm 2019 và 2021 lần lượt là 31659,1 ha và 31369,9 ha, diện tích nông nghiệp năm 2019 và 2021 ước tính lần lượt là 40511,3 ha và 41105,9 ha. Kết quả nghiên cứu cũng cho thấy diện tích rừng tại huyện Xaythany đã bị giảm 289,2 ha vào năm 2021 so với năm 2019, các nguyên nhân chính dẫn đến mất rừng và thay đổi lớp phủ và sử dụng đất trong giai đoạn 2019-2021 được xác định do các hoạt động đốt nương làm rẫy, chuyển đổi mục đích sử dụng đất, các yếu tố ảnh hưởng kinh tế xã hội khác.

**Từ khóa: Chỉ số SAVI, chỉ số thực vật, lớp phủ/sử dụng đất, rừng, huyện Xaythany.**

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