USING ATMOSPHERICALLY RESISTANT VEGETATION INDEX TO DETECT FOREST COVER CHANGE IN LAC DUONG DISTRICT, LAM DONG PROVINCE

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SUMMARY
This study tested the potential of using Sentinel-2-derived ARVI for land covers mapping compared to NDVI in Lac Duong district, Lam Dong province. Overall accuracy assessments of ARVI-based land covers mapping are calculated from 88.9% (in 2016) to 92.0% (in 2022) with Kappa coefficients of 0.79 and 0.86, respectively. The comparison between Sentinel-2-derived NDVI and ARVI for land covers mapping indicated that ARVI has performed well in land covers mapping in Lac Duong district. The Sentinel-2 time series were therefore used to generate spectral-temporal changes in land covers based on ARVI thresholds. Our estimation of land covers and forest cover change shows that the forest cover in Lac Duong increased by 1718.4 ha from 2016 to 2022, while non-forest covers reduced by 1662.1 ha at the same period. Conversely, during the segmented period of 2018-2020, the extent of forest cover reduced by 1156.1 ha, whereas non-forest covers increased by 1032.8 ha. The study also identified the main drivers of LULC change, including forest cover change, these changes are due to the expansion of coffee production, effectiveness of PES policy implementation, and a lack of agricultural production and sustained likelihoods. Our study suggests that ARVI can be used to monitor and detect changes in land covers, especially in deforestation and forest degradation detection in the tropical and mountainous regions of Vietnam. More focus of comprehensive understanding of LULC change and its management should be expanded beyond the poverty-environmental relationships in Lac Duong district.
Keywords: ARVI, Lac Duong, land cover, land use, NDVI.

1. INTRODUCTION
Land use and land cover (LULC) maps are fundamental data sources for land planning and management (Nasiri et al., 2022). Accurate and up-to-date LULC mapping is of interest to geoscience and remote sensing societies due to its provision of valuable information to understand human-environment relationships (Viana et al., 2019; Pratico et al., 2021; Sobhani et al., 2021). Analysing time series of remotely sensed dataset enables the integration of diverse features and spectral-temporal metrics to obtain seasonal and phenological characteristics of LULC classess (Nasiri et al., 2022). The application of such features and metrics for LULC mapping has enhanced the classification accuracy. Among the medium resolution satellite data, Sentinel-2 products offers high temporal resolution data, short revisit time, rich spectral configuration, thus making them relevant sources for time series LULC mapping (Nasiri et al., 2022).

Remote sensing offers robust techniques to monitor land covers and detect the changes in land use and land cover (LULC), and solve challenges in forest resource management (Mundava et al., 2014; Dusseux et al., 2015; Karakoc and Karabulut, 2019). In addition, remote sensing techniques provides information at a wide range of spatial and temporal scales, frequent 'revisit' of the area, and use as historic archives of data. The most used vegetation index is the Normalized Difference Vegetation Index (NDVI), which is commonly applied to analyze vegetation and its temporal changes on local and regional scales (Ali et al., 2018). However, the parameters of atmospheric scattering (aerosols and ozone) are difficult to quantify using NDVI, but its influence can be reduced and fixed by ARVI and other vegetation indices for land covers mapping in the tropical and mountainous areas. To achieve better results, several enhanced vegetation indices, namely atmospherically resistant vegetation index (ARVI), soil adjusted vegetation index (SAVI), green difference vegetation index (GDVI), green normalized differential vegetation index (GNDVI), enhanced vegetation index (EVI) have been developed to study vegetation instead of NDVI. This study used ARVI compared to NDVI with

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the expectation that this index may have good potential for land covers mapping in the mountainous areas.

Sentinel-2 is the state of-the-art sensor of European Space Agency (ESA), was launched in 2015, which included 13 bands extending from visible, near infrared, shortwave infrared with a high spatial resolution of 10 to 60 m (Gholizadeh et al., 2016). Sentinel-2 has immense potential to estimate various vegetation parameters, such as ARVI, LAI (Leaf Area Index), chlorophyll and nitrogen, biophysical parameters and Red-Edge Position (Frampton et al., 2013; Richter et al., 2012; Clevers and Gitelson, 2013; Verrelst et al., 2013; Delegido et al., 2013). Therefore, our study explored spectral indices (NDVI, ARVI) computed from Sentinel-2 product. The broadband indices derived from Sentinel-2 images include NDVI and ARVI.

Lac Duong is known as one of districts where has the largest percentage of forest coverage ratio and areas of natural forests in Lam Dong province. However, it is reported that much of the forest land clearing in Lac Duong is most likely attributable to the commune's distribution of forest land for coffee plantations (Nguyen Quoc Hieu et al., 2018; Nguyen Hai Hoa et al., 2018a; Nguyen Hai Hoa et al., 2018b). Illegal clearing of forest land and land transactions are more complex processes than it has been revealed by the survey data (Tradal et al., 2017). Therefore, Lac Duong is one of the examples experiencing with deforestation and degradation. Understanding how the spatial-temporal LULC and the extent of forest cover has been changed over the decades is very crucial to Lam Dong province (Nguyen Quoc Hieu et al., 2018; Nguyen Hai Hoa et al., 2018a). This would help authorities to manage forests more effectively and efficiently in Lam Dong province. To identify the key drivers of changes in LULC and forest cover, including both nature and human-driven forces associated with the government policies on mangrove management and development, it is very important to first assess the spatial-temporal dynamics of LULC and forest cover by using remotely sensed data over the time (Nguyen Hai Hoa et al., 2018a; Hai-Hoa and Hien, 2021). Numerous remote sensing technologies and techniques have been applied to monitor the dynamics of forest cover due to their large spatial-temporal coverage, cost-effectiveness, ready availability and applicability (e.g. Akumu et al., 2010; Rozenstein and Karnieli, 2011; Huong et al., 2021). In spite of the extensive application of remote sensing technologies and techniques at the local, regional and global scales, there is still limited information available about the spatial-temporal dynamics of forest cover in Lam Dong at the decadal time scales, and how forest degradation and deforestation have been associated with economic and urban development (Nguyen Quoc Hieu et al., 2018; Nguyen Hai Hoa et al., 2018a; Nguyen Hai Hoa et al., 2018b). Therefore, it is pivotal to quantify the spatial-temporal changes in forest cover at regular time intervals, which would provide successful in forest management strategies.

The aim of this study were the following: (1) testing whether ARVI (Atmospherically Resistant Vegetation Index) is used for forest cover mapping and change detection compared to NDVI (Normalised Difference Vegetation Index) in Lac Duong District, Lam Dong Province, (2) defining the ARVI-based thresholds for land covers mapping using Sentinel-2 data from 2016 to 2022, (3) identifying drivers of land cover change during the period of 2016-2022.

2. RESEARCH METHODOLODY

2.1. Study site

Lam Dong is known as a mountainous province, located in the South of the Central Highlands, Vietnam (Fig. 1). It has a natural area of 977,354 ha with a population of about 1.3 million people from 43 ethnic groups and indigenous people, including K'Ho, Chau Ma, Chu Ru and Stieng. These groups account for nearly 20% of its population (Nguyen Hai Hoa et al., 2018a; Nguyen Hai Hoa et al., 2018b). In general, the climate of Lam Dong is divided into two separate seasons, namely the rainy season and the dry season. The region's climate is favorable for agricultural development, including coffee production, semi-temperate vegetables, tea, and a variety of fruit trees, beef cattle, dairy cows, and cold-water fish (Nguyen

Hai Hoa et al., 2018a).

Lac Duong is located in the northern area of Lam Dong province where has an area of 131,136 ha with a population of 27,388 people from 6,410 households and 20 different ethnic groups, ethnic minorities account for 70.6%. The forest cover in Lac Duong is much higher than other districts in Lam Dong province, which 116,292 ha (85% of total areas) of forest land in Lac Duong is forest. Therefore, Lac Duong plays a very important ecological role where is situated of Bidoup-Nui Ba National Park and the upper reaches of the Krong No, Da Nhim and Serepok Rivers. Despite an important ecological role, Lac Duong has been facing high deforestation and forest degradation.

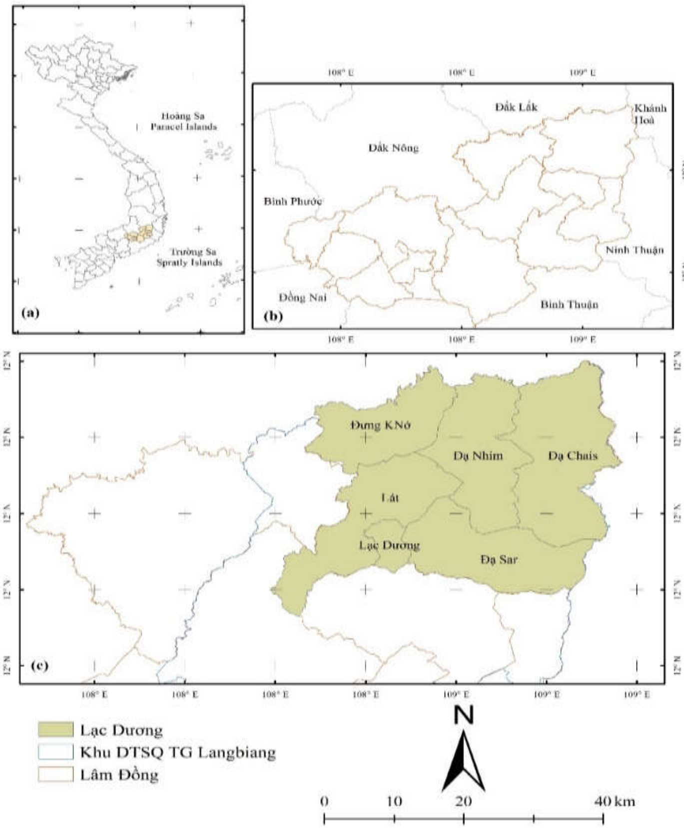

Fig. 1. Study site in Vietnam (a); Lam Dong province bordered by other neighboring provinces in the Central Highlands of Vietnam (b); Lac Duong district in Lam Dong province as a case of study (c)

2.2. Study methods

In this study, the available series of Sentinel-2 data (Sentinel-2A and Sentinel-2B from 2016 to 2022) were used to quantify the spatial-temporal changes in land covers in Lac Duong district, Lam Dong province (Fig. 2). The details of remotely sensed data used this study were summarized in Table 1.

Table 1. Multispectral Sentinel-2 data used this study

ID	Image codes	Date capture	Spatial resolution (m)	Cloud cover (%)
1	S2A20160304T032531T48PZU	04/03/2016	10	0
2	S2B20180207T030859T48PZU	07/02/2018	10	0
3	S2A20200313T030541T48PZU	13/03/2020	10	0
4	S2A20220201T030941T48PZU	01/02/2022	10	0
5	Forest cover map, land use and land cover map in Lac Duong	2015, 2020	1/50000	Lac Duong
6	Topographic map, DEM	2011	30	USGS

Sources: http://earthexplorer.usgs.gov

Sentinel-2A/B, at the Multi-spectral Imager Instrument Level 1C with a spatial resolution of 10 m, covering the whole of Lac Duong district, were downloaded from Sentinel Scientific Data Hub (ESA), which has been already orthorectified and top-of-atmospheric reflectance. All of the Sentinel-2A/B data used in this study intended to be obtained during the dry season (from October to April), cloud-free covered Sentinel-2 data were selected to avoid the effects of weather factors and to reduce the seasonal variations in reflection due to farming cycles for the mapping accuracy (Hai-Hoa et al., 2022). The methods of Sentinel-2 derived ARVI for land cover mapping is illustrated in Fig. 2.

<u>Step 1</u>: Sentinel-2 pre-processing

The acquired Level-1C orthorectified, and top-of-atmosphere optical Sentinel-2A/B images (2016, 2018, 2020, 2022) were atmospherically corrected and further processed to Level-2A product to obtain bottom-of-atmosphere corrected reflectance image. This process was adopted from previous studies of Hai-Hoa et al., (2020a, 2020b) and Hai-Hoa and Hien (2021) using the Semi-Automatic Classification Plugin in QGIS version 3.10.2 (Congedo, 2020). The workflows of Sentinel-2A/B imageries and pre-processing are shown in Fig. 2.

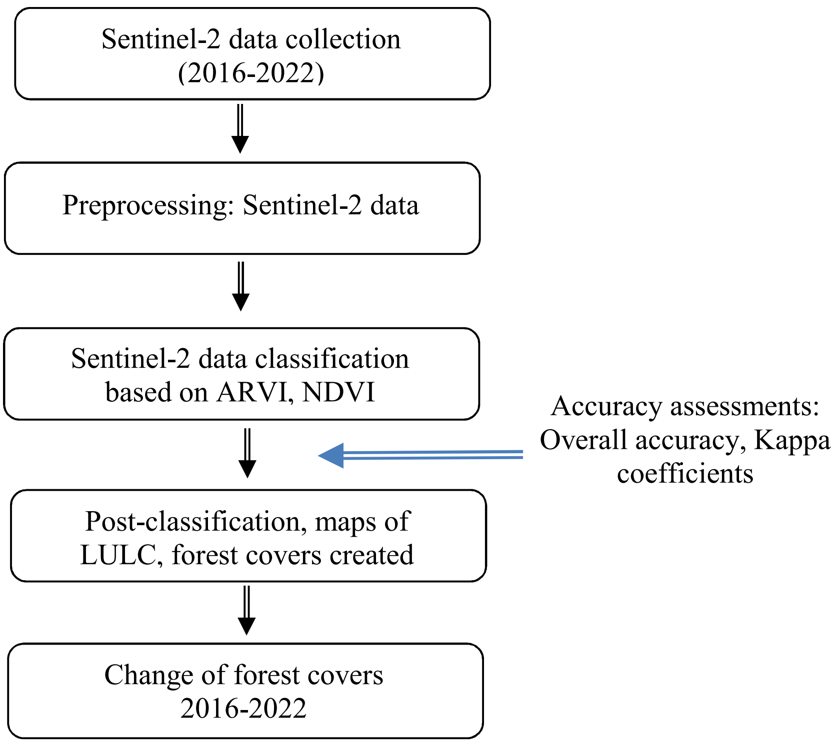

Fig. 2. Flow of methods for forest cover mapping using ARVI in Lac Duong district

<u>Step 2</u>: Sentinel-2 interpretation and classification

In this study, we tested an ARVI (Atmospherically Resistant Vegetation Index) for land covers mapping in Lac Duong district, Lam Dong province. It then compared land cover-based ARVI and NDVI mapping.

- Atmospherically Resistant Vegetation Index (**ARVI**): This study used ARVI, which is relatively insensitive to atmospheric factors, such as aerosols, rain, fog, dust, smoke, air pollution, particularly suitable for monitoring tropical mountainous regions like Lam Dong province where is often covered with soot caused by slash-and-burn agricultural activities. This index has been used to correct NDVI for mitigating atmospheric scattering effects by doubling the red spectrum measurements and adding blue wavelengths (Somvanshi and Kumari, 2020) (Eq. 1).

$$\mathrm{ARVI} = \frac{(\mathrm{Band_{NIR}} - 2*\mathrm{Band_{RED}} + \mathrm{Band_{BLUE}})}{(\mathrm{Band_{NIR}} + 2*\mathrm{Band_{RED}} + \mathrm{Band_{BLUE}})} \quad \text{(Eq. 1)}$$

- Normalised Difference Vegetation Index

(**NDVI**): NDVI was used to classify areas with forest cover, non-forest cover, and water since it allows for a precise depiction (Green et al., 1998). NDVI is also related to parameters, such as topsoil layer, plant photosynthesis, water, and biomass computation (Fenshoult et al., 2009). This study used NDVI compared to ARVI in terms of the accuracy of land cover mapping. This would answer the question of whether ARVI can be used for land cover mapping in Lac Duong district, Lam Dong province.

$$\mathrm{NDVI} = \frac{\mathrm{Band_{NIR}} - \mathrm{Band_{RED}}}{\mathrm{Band_{NIR}} + \mathrm{Band_{RED}}} \quad \text{(Eq. 2)}$$

Where: For Sentinel 2, $\mathrm{Band_{NIR}}$ (Near Infrared band) is Band 8; $\mathrm{Band_{RED}}$ (RED band) is Band 4; $\mathrm{Band_{BLUE}}$ (BLUE band) is Band 2. ARVI value ranges from -1 to 1 (Tanre et al., 1992; Kaufman and Tanre, 1992; Lassiter and Darbari, 2020; Somvanshi and Kumari, 2020).

Step 3: Accuracy assessments and post-classification

Accuracy assessments of classified images:

To define ARVI thresholds for forest cover, non-forest cover and water bodies, this study used 2018 highly-spatial resolution image from the Google Earth to generate random points for each land-cover class, while 2022 classified image was mainly based on the field survey conducted from February to March 2022. For years of 2016 and 2020, the study used Lac Duong status maps of forest covers, which were provided by Lam Dong Department of Agriculture and Rural Development (DART) to generate random evaluation points for defining the threshold of each land cover class.

A total of 470 sampling points (including 300 GPS points for forest covers; 120 points for non-forest covers, 50 points water bodies) selected from the forest cover maps (2016, 2018, 2020) and the Google Earth image (2018) were used to assess the accuracies of classified maps in 2016, 2018 and 2020. Total 300 sampling points, including 180 points for forest covers, 70 points for non-forest covers, and 50 points for water bodies were used to validate the classified maps in 2022. Finally, confusion matrices were constructed to cross tabulate to observed data with reference data using Kappa statistics, generating overall classification accuracy (Long et al., 2014). The Kappa coefficient is a measure of the agreement between two maps, which consider all elements of the error matrix (Hai-Hoa et al., 2022). Kappa values were classified into four groups: where Kappa values that were zero referred to no agreement; from 0.41-0.6 were indicated as moderate agreement; 0.61-0.8 were considered as substantial agreement; and 0.81-1.0 were regarded as an almost perfect agreement (e.g. Conchedda et al., 2008; Hai-Hoa et al., 2022).

Post-classification of classified images: In post-classification process, the filtering process was applied to remove isolated pixels or noise or the "salt-and-pepper" effects in the land cover map. The filtered classified image was then used as the final forest cover map each year.

Step 4: Change detection analysis and land cover dynamics

This analysis provides in-depth information about pixel transformation, class change and dynamics of converted land covers (Hai-Hoa and Hien, 2021). The land cover maps for 2016, 2018, 2020 and 2022 were evaluated and compared in terms of areas covered. The cross-tabulated method was used to identify forest cover changes from 2016 to 2022, namely 2016-2018, 2018-2020, and 2020-2022. The changes in land covers were visually interpreted and further examined to understand the spatial-temporal gain and loss of forest covers over 6 years (2016-2022) in Lac Duong district, Lam Dong province.

3. RESULTS AND DISCUSSION

3.1. Status of ARVI and NDVI-based land cover mapping

The comparasion of accuracy assessments between ARVI and NDVI derived land covers are summarised in Table 2.

Table 2. Summary of accuracy assessments of land covers in Lac Duong district

Assessments	2016		2018		2020		2022	
	NDVI	ARVI	NDVI	ARVI	NDVI	ARVI	NDVI	ARVI
UA (%) for forest cover	92.0	91.7	92.7	92.3	93.3	93.0	96.7	94.4
UA (%) for non-forest cover	90.8	85.8	91.7	87.5	95.0	89.2	91.4	90.0
PA (%) for forest cover	96.2	95.2	96.5	95.8	97.9	96.5	96.7	97.1
OA (%)	91.3	88.9	91.9	89.8	93.2	90.6	95.0	92.0
KC	0.83	0.79	0.85	0.80	0.87	0.82	0.91	0.86

UA (User's accuracy), PA (Producer's accuracy), OA (Overall accuracy), KC (Kappa coefficient)

All the Sentinel-2A/B were used to produce the NDVI and ARVI-based land cover maps for the whole Lac Duong district, Lam Dong province. In general, the results of classification accuracy assessments based NDVI and ARVI were small variations across Lac Duong district. The error matrices showed that the results of assessments for 2022, 2020, 2018, and 2016 classifications have high rates of classification accuracy with user's accuracies, as follow: forest cover (NDVI: from 92.0 to 96.7%; ARVI: 91.7 to 94.4%), non-forest cover (NDVI: 90.8 to 95.0%; ARVI: 85.8 to 90.0%) giving an overall accuracies of 91.3%, 91.9%, 93.2%, and 95.0% in 2016, 2018, 2020 and 2022 for NDVI; 88.9%, 89.8%, 90.6%, and 92.0% in 2016, 2018, 2020 and 2022 for ARVI, respectively (Table 2). In addition, the Kappa coefficients of 0.83 in 2016, 0.85 in 2018, 0.87 in 2020, and 0.91 in 2022 for NDVI; 0.79 in 2016, 0.80 in 2018, 0.82 in 2020, and 0.86 in 2022 for ARVI indicated that there were more than substantial agreements between the classified images and referenced data (Table 2).

In general, thresholds of NDVI and ARVI for each land cover type slightly vary from 2016 to 2022. Therefore, our study adjusted them to ensure each land cover map highly accurate as they would be. These finalized threshold values were then used to construct a thematic land cover map for each selected year (Fig. 3). NDVI and ARVI thresholds for each land cover were assessed from NDVI and ARVI values and then selected the final thresholds for land covers mapping as follows: forest cover (NDVI> 0.452; ARVI> 0.239), non-forest cover (-0.019 <NDVI< 0.452; -0.096 < ARVI < 0.239), and water bodies (NDVI< -0.019; ARVI< -0.096).

As indicated in Fig. 3 and Table 2, our findings indicated that using Sentinel-2-dervied ARVI can be used for monitoring and mapping spatial-temporal changes in land covers instead of Sentinel-2-derived NDVI mapping. ARVI-derived land cover mapping is reliable and applicable in Lac Duong district, Lam Dong province. In particular, Sentinel-2 derived ARVI land cover mapping is suitable for the tropical mountainous areas like Lam Dong province. Therefore, this study used ARVI for land cover mapping and change detection in Lac Duong district, Lam Dong province.

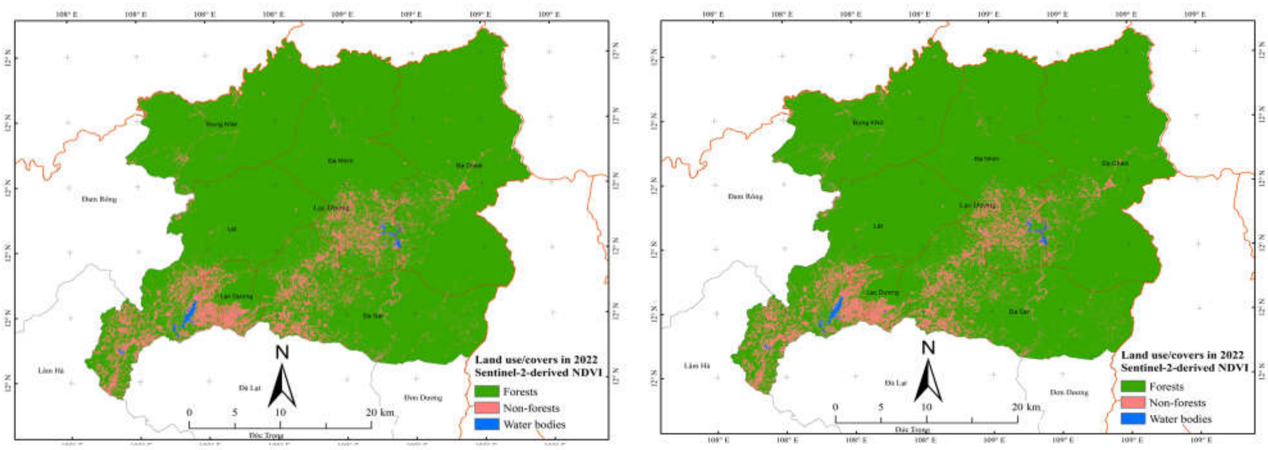

Fig. 3. Land cover mapping based on Sentinel-2 derived NDVI and ARVI values in 2022

LULC, forest cover in Lac Duong district:

Based on the thresholds defined from ARVI, this study estimated the extent of land covers and mapped the spatial distribution of forest cover over Lac Duong district from 2016 to 2022 (Table 3). The total extent of land cover is summarized in Table 3.

Table 3. Extent of land covers and forest cover in Lac Duong district, Lam Dong province (ha)

LULC	2016	2018	2016-2018	2020	2018-2020	2022	2020-2022	2016-2022
Forests	116372.7	117735.9	+1363.2	116579.8	-1156.1	118091.1	+1511.3	+1718.4
Non-	14397.3	12961.8	-1435.5	13994.6	+1032.8	12735.2	-1259.4	-1662.1
Water	398.9	471.2	+72.3	594.5	+123.3	342.6	-251.9	-56.3
Total	**131168.9**	**131168.9**		**131168.9**		**131168.9**		

(+): Land covers gain; (-) Land covers lost; Non- (Non-forest covers); Water (Areas covered by water)

As indicated in Table 4, the extent of forest cover generally fluctuates from 2016 to 2022. The largest area of forest cover is recorded at 118091.1 ha in 2022 compared to that of 116372.7 ha in 2016, while the forest cover significantly increased from 2016 to 2018, then dropped to 116579.8 ha in 2020.

3.2. Spatial-temporal dynamics of LULC and drivers of LULC change

Spatial-temporal changes in land covers in Lac Duong district:

To better understand the drivers of LULC change in Lac Duong during 2016-2022, the study calculated the change in land cover each segmented period of 2016-2018, 2018-2020, 2020-2022. The findings of changes in land cover are illustrated in Figs. 4 and 5.

As indicated in Figs. 4 and 5, there are changes in land covers across three segmented periods over all communes of Lac Duong district, namely 2016-2018, 2018-2020, 2020-2022, and whole period of 2016-2022 (Table 3, Fig. 4). In general, during the whole period of 2016-2022 in Lac Duong district, the net extent of forest cover has increased by 1718.4 ha. However, it is a fact that the forest cover in some communes of Lac Duong has been lost or converted to other land use purposes, while other areas have been experienced forest plantation or recovered during the period of 2016-2022, thus consequently causing an increase of forest cover extent for the whole period (Table 3, Fig. 4). In particular, there was a significant change in land covers during 2018-2020, which was recorded in all communes of Lac Duong district, including Da Chais, Da Nhim, Da Sar, Dung Kno, Lac Duong and Lat (Fig. 5). In fact, during the period of 2018-2020, there were 1156.1 ha of forest cover lost due to the conversion of forest land into other land use purposes, including non-forest land uses, such as agricultural land, coffee production, but the forest cover increased again in the following period of 2020-2022, about 1511.3 ha.

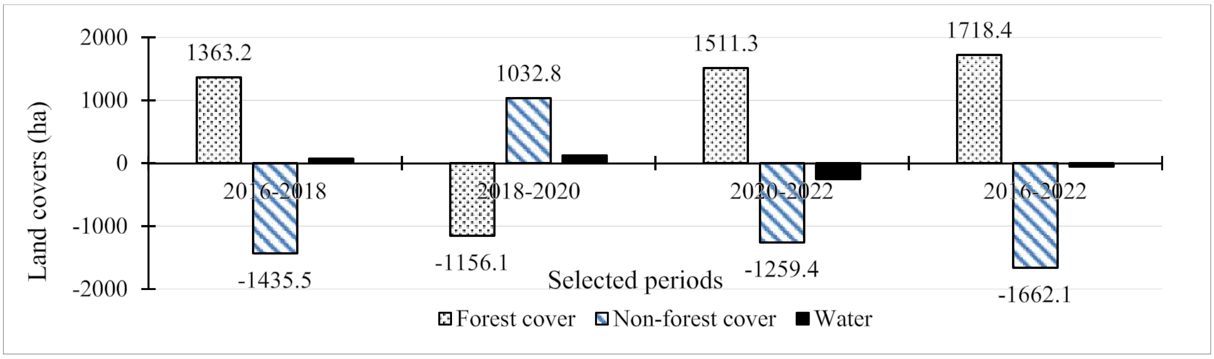

Fig. 4. Temporal dynamics in land covers in Lac Duong district during 2016-2022

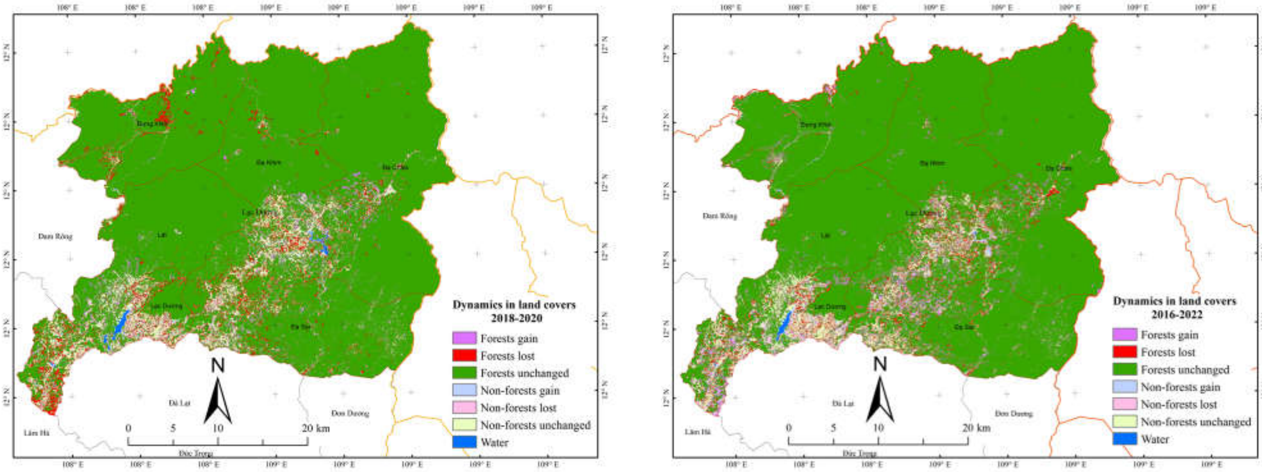

Fig. 5. Spatial dynamics in land covers in Lac Duong district during 2018-2020 and 2016-2022

Drivers of LULC change in Lac Duong district:

Historically, the general deforestation and forest degradation in the Central Highlands regions, including Lac Duong district, Lam Dong province have often been associated with the large migrations of people from the north coming to populate in these regions (Vu et al., 2013; Tradal et al., 2017). They are a group of households that have been encouraged by the Vietnam Government to migrate and settle this region over the years (Tradal et al., 2027). In this study, key drivers of LULC change identified include the expansion of coffee expansion, inappropriate PES payments in the study area, a lack of land for agricultural production and sustained likelihoods: These drivers are addressed in the following:

LULC change in association with the expansion of coffee production: Recent studies indicated that much of the forest land clearing in Lac Duong is most likely to be associated with the communes' distribution of forest land for coffee plantations (e.g. Trada et al., 2017; Nguyen Hai Hoa et al., 2018a and 2018b). The local authorities have deliberately distributed forest land certificates for coffee plantations to relieve the pressure for improved livelihoods, to give more land, and to encourage the expansion of coffee production towards areas known as less vulnerable to the provision of ecological services (Meyfroidt et al., 2013; Trada et al., 2017). In fact, the average area per households in relation to illegal land clearings was recorded at 0.33, and 0.23 ha in Da Nhim and Da Chais, respectively during 2000-2014 (Trada et al., 2017). Our findings have showed that deforestation or forest cover loss have been experienced over 6 communes of Lac Duong district during 2016-2022, including Da Nhim and Da Chais communes. The total forest cover lost is estimated at 4173.3 ha during the period of 2016-2022, while the total forest cover gain is recorded at 5891.7 ha at the same period, thus making the total net extent of forest cover increase by 1718.4 ha (Table 3).

Interestingly, a study by Tradal et al., (2017), regarding land use to three segments of income households, the 'medium' and the 'better off' income households have accessed and cultivated more land on average than the 'poor' households, with 1.47 ha, 1.27 ha vs 0.70 ha, respectively. This study the terms of the 'poor', and the 'medium' households refer to the household which have 2.7 million VND, 4.4 million VND per person per year, respectively, while the 'better off' have more assets and resources than the 'poor' and the 'medium' households (Tradal et al., 2017). More interestingly, on average, 72.8% of the cultivated land was used for coffee production, the 'medium' households have cultivated the most land, both in total and coffee production, while the 'poor' have less land than the other income groups (Tradal et al., 2017). Similarly, as our findings from in-depth interviews, 90%

of respondents agree that illegal clearing of forest land and land transactions are complex processes. The poorer households are paid by the richer and more business-oriented households to clear new land. The land is then sold to the other coffee producing households. Our findings are similar to and supported by previous studies in Lam Dong of Vu et al., (2013); Tradal et al., (2017).

There are links between LULC change, including deforestation and forest degradation, and poverty levels in the Central Highlands of Vietnam (Ha and Shiverly, 2008; Agergaard et al., 2009; Meyfroidt et al., 2013). Policy-related drivers of LULC change in the Central Highlands might neglect various underlying factors that drive the coffee production. Some studies reveal that the coffee economy and land transactions are strongly related to the expansion of coffee production, which are controlled by the business-oriented households (Ha and Shiverly, 2008; Hosonuma et al., 2012; Tradal et al., 2017). Notably, other studies also indicate that the 'medium' and 'better off' income households have cleared more forest land for agriculture over the years than the ''poor' households (e.g. Meyfroidt et al., 2013; Tradal et al., 2017). Tradal et al., (2017) also argue that the linkages between poverty among the ethnic poor groups and coffee-related forest encroachment seems to be overrated. Therefore, they also suggest that more focus of comprehensive understanding of LULC change and its management should be expanded beyond the poverty-environmental relationships. Our study found that there are strong relationships between the expansion of coffee production and deforestation or forest degradation over the communes of Lac Duong District.

Effectiveness of PFES (Payments for Forest Environmental Services) implementation and LULC change: Vietnam's National PFES pilot policy was initially started in Lam Dong and Son La provinces in 2008 (Thuy et al., 2011). As it started, it has brought significant impacts on the development of the management mechanism with local households' participation in forest protection and management, income improvements. A number of studies have indicated that there are linkages between income households and land clearing in Lac Duong district. Our study found that land is the major limiting factor for agricultural production and livelihoods, and most our interviewed households responded to their need of being supplemented agricultural income with off-farm sources. A study of Tradal et al., (2017) showed that both the 'medium' and the 'better off' households have accessed more diverse set of off-farm income sources in comparison with the 'poor' ones, who are heavily dependent on agriculture for their livelihoods and coffee production. Interestingly, there is a link between the level of PES payments and households' expansion of agriculture into forest land (Tradal et al., 2017; Nguyen Hai Hoa et al., 2018a, 2018b). The study of Tradel et al., (2017) also found that the 'poor' and the 'medium' households have received higher PES payments than the 'better off' households, indicating that PES has contributed to reducing income inequalities in Lac Duong district. In Lac Duong district, PES payment is more important income for the 'poor' households than the 'medium' and the 'better off' households. Our study reveals that the 'medium' and the 'better off' household cultivate more land for coffee production, which is similar as the study of Tradal et al., (2017). For this point, PES has excluded an important segment of households that are more capable and more likely to the expansion of coffee production.

In short, most households in Lac Duong district need to supplement agriculture income with off-farm sources. In this study, the main driver of LULC change and forest encroachment is found to be related to the expansion of small-scale coffee production. Another main driver of LULC change is due to a lack of land for agricultural production and livelihoods, while PES implementation has significantly contributed to an increase of the forest cover during the period of 2016-2022 in Lac Duong district.

4. CONCLUSSION

This study aimed to test the potential of using Sentinel-2 derived ARVI for land cover, forest cover mapping compared to NDVI in Lac Duong district, Lam Dong province. Overall accuracy assessments of ARVI-based land cover mapping are calculated from 88.9% (in 2016) to 92.0% (in 2022) with Kappa coefficients of 0.79 and 0.86, respectively. The comparison between Sentinel-2 derived NDVI and ARVI for land cover mapping indicated that ARVI has performed well in land covers mapping in Lac Duong district. The Sentinel-2 time series were therefore used to generate spectral-temporal changes in land covers based on ARVI thresholds. Our study suggests that ARVI can be used to monitor and detect changes in land covers, especially in deforestation and forest degradation detection in the tropical and mountainous regions of Vietnam.

Our estimation of land cover and forest cover change shows that the forest cover in Lac Duong increased by 1718.4 ha from 2016 to 2022, while non-forest cover reduced by 1662.1 ha at the same period. Conversely, during period of 2018-2020, the extent of forest cover reduced by 1156.1 ha, whereas non-forest cover increased by 1032.8 ha. Main drivers of LULC change, including forest cover change is the expansion of coffee production, PES policy implementation, and a lack of agricultural production and sustained likelihoods. Therefore, more focus of comprehensive understanding of LULC change and its management should be expanded beyond the poverty-environmental relationships.

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SỬ DỤNG CHỈ SỐ THỰC VẬT KHÁNG KHÍ QUYỂN ĐỂ PHÁT HIỆN THAY ĐỔI THẢM PHỦ RỪNG TẠI HUYỆN LẠC DƯƠNG, TỈNH LÂM ĐỒNG

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TÓM TẮT

Nghiên cứu đánh giá khả năng sử dụng chỉ số thực vật kháng khí quyển (ARVI) dựa vào dữ liệu ảnh viễn thám Sentinel-2 để lập bản đồ lớp phủ rừng so với chỉ số NDVI tại huyện Lạc Dương, tỉnh Lâm Đồng. Kết quả cho thấy độ chính xác tổng thể của bản đồ lớp phủ rừng dựa vào chỉ số ARVI từ 88,9% (năm 2016) đến 92,0% (năm 2022) với hệ số Kappa tương ứng là 0,79 và 0,86. So sánh kết quả bản đồ lớp phủ giữa chỉ số NDVI và chỉ số ARVI từ ảnh Sentinel-2 cho thấy ARVI thể hiện kết quả tốt tại huyện Lạc Dương. Do vậy, tư liệu ảnh Sentinel-2 đa thời gian trong nghiên cứu sự thay đổi hoạt động sử dụng đất, lớp phủ rừng dựa trên ngưỡng chỉ số ARVI có thể sử dụng cho khu vực nghiên cứu. Diện tích đất che phủ bởi rừng tại huyện Lạc Dương tăng thêm 1718,4 ha từ năm 2016 đến năm 2022, trong khi độ che phủ bởi đối tượng khác lại giảm xuống 1662,1 ha trong cùng giai đoạn nghiên cứu. Ngược lại, trong giai đoạn 2018-2020, diện tích che phủ bởi rừng giảm 1156,1 ha, diện tích che phủ bởi đối tượng khác tăng 1032,8 ha. Nghiên cứu đã xác định các nguyên nhân chính dẫn đến sự thay đổi hoạt động sử dụng đất trong giai đoạn 2016-2022, bao gồm việc mở rộng hoạt động sản xuất cà phê, thực hiện chính sách chi trả dịch vụ môi trường, thiếu đất cho sản xuất nông nghiệp và khả năng duy trì sinh kế bền vững. Nghiên cứu đề xuất chỉ số ARVI có thể được sử dụng để theo dõi và phát hiện những thay đổi của lớp phủ mặt đất, đặc biệt trong phát hiện mất rừng và suy thoái rừng ở các vùng nhiệt đới, miền núi của Việt Nam, trong đó có tỉnh Lâm Đồng. Nên các nghiên cứu tập trung đánh giá mối quan hệ về sự thay đổi hoạt động sử dụng đất với hoạt động quản lý ngoài các nhân tố đói nghèo và môi trường liên quan đến chúng.

Từ khóa: Che phủ đất, chỉ số NDVI, chỉ số thực vật kháng khí quyển (ARVI), Lạc Dương, sử dụng đất.

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