Mapping Land use/land cover using a combination of Radar Sentinel -1A and Sentinel-2A optical images.

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Abstract: The current study used a combination of Sentinel-1A (SE-1A) radar and Sentinel-2A (SE-2A) optical images in mapping land use/land cover (LULC) in Dak Nong province in 2018. The Random Forest (RF) algorithm was adopted to digitally categorize Landsat images into LULC maps according to ten different LULC classes included: evergreen forest, semi-evergreen forest, deciduous forest, plantation, rubber, industrial plants, crop land, residential area, water surface and others. The results indicated an overall accuracy (OA) and kappa coefficient of 81.40%, Kappa = 0.79, respectively. Based on the results of classified image, a 2018 LULC map of the study area was simulated. Accordingly, the natural forests account for 34.27% of the total area of the province, distributed scattered in districts. In which, the evergreen forest occupies the highest area with more than 166,600 ha, equivalent to 74.54% of the total natural forest area, and concentrated in the high mountain areas. Non-forest covers occupy more than 63% area of Dak Nong province. The industrial and agricultural cropland indicated a high area in the study area with a rate of 34.82% and 11.38%, respectively. This shows a strong development in the scale of industrial and agricultural crops in the study area. The objective information on current land use/land cover in this study can serve as the basis for policymakers to orient the local forest resource sustainability strategies. Besides, the study also shows that the use of a combination of Sentinel-1A radar and Sentinel-2A optical image to classify and construct the LU/LC map is a high-efficiency research direction.

1. Introduction

Anthropogenic activities have considerably changed natural landscapes, especially in regions where are adversely affected by increasing human population and climate change. Due to the bidirectional interactions between humans and physical environment, many countries have been experiencing temporal land use/land cover changes (LULCC) which are concerned as key factors contributing to global environmental change. In fact, forest land use analysis including long-term change and future alternative scenarios is crucial in assisting forest managers’ understanding of the current situations and tracking the dynamics of forest land use areas [1] [2]. Change detection is useful for many applications associated with LULC changes, such as shifting cultivation, land degradation, landscape changes and deforestation. Therefore, an analysis of LULC change detection has a significant role to play in...
Determining the nature, magnitude and rate of land cover change over a given time for sustainable natural resource management [3].

Remote sensing (RS) data has been commonly applied and recognized as essential and powerful tools in obtaining accurate and up-to-date spatial data of LULC, analyzing the changes and constructing simulation of LULC in many parts of the world [4]. RS is widespread used in detecting and observing land use at various scales. Based on remote sensing data, the results were adopted using a combination of different data sources which can be maximized utilizing sensors with different characteristics. Several researchers have demonstrated that using a combination of radar and optical RS images in monitoring LULC resulted in classified images with higher accuracy [5].

Currently, there are several published studies on application of integrating radar and optical images to produce LULC cover maps in Vietnam. However, information on the use of sentinel-1 (SE-1A) radar and sentinel-2 (SE-2A) optical images for mapping has been limited. Meanwhile, SE-1A image at a spatial resolution of 10m are freely available at the European Aerospace Agency (ESA) and the revisit frequency is 12 days. Thus, SE-1A image has advantages outperforming other radar satellites, especially in mapping land cover and analyzing LULC changes. In recent years, Dak Nong province has experienced a burst in population growth resulting in a high need for cultivation land and urban expansion leading to a loss of natural forests and the degradation in the quality.

The main objective of this study is to investigate the potential of combining SE-1A and SE-2A images to map land use/land cover in Dak Nong province in 2018. The obtained results can provide an overview on the current land use situations as a basic in order to contribute on sustainable development strategies at the local.

Dak Nong located in the Central Highlands of Vietnam (Figure 1) is characterized by a humid tropical climate due to the effects of dry-hot southwest monsoons. There are two different annual seasons including the rainy season (April to November) and the dry season (December to March). The average annual precipitation is approximately 2700 mm, of which 90% occurs during the rainy season. The presence of basalt soil in Dak Nong province has generated high-quality soils which are suitable for tree plantations such as coffee, pepper and rubber. The study area extends 6516 km² with an average elevation of 650 m above sea level and slope of 20 degrees, forming different types of terrain in this region. In addition, a rich diversity of natural resources including substantial fragmentations across the landscape have generated patches of natural evergreen broadleaved, mixed bamboo, deciduous dipterocarp, and semi-deciduous forest with different levels of disturbance, mainly humans in origin.

![Figure 1. The study area in Dak Nong province](image-url)

2. Material and methods
2.1. Data
Remotely sensed data of Sentinel 1A (SE-1A) in the ground range (S1 Ground Range Detected - GRD) and Sentinel-2A MSI (multi-spectral instrument, Level 1C) image scenes captured in 2018 were collected. These satellite images were employed to identify land use types, interpret images and classify LULC. SE-1A image consists of a single VV dual band cross-polarization VV + VH in IW (Interferometric Wide swath) shooting mode and a spatial resolution of 5x20m, pixel size is 10x10m. Atmospheric correction for the SE-2A MSI Level 1C was conducted based on changing the raw digital numbers into the top of atmosphere (TOA) reflectance values.

This study used 10 spectral bands including B2-Blue, B3-Green, B4-Red, B5-Red Edge1, B6-Red Edge 2, B7-Red Edge 3, B8-NIR, B8A-Red Edge 4, B11- SWIR1 and B12-SWIR2 for classifying LULC. Other sources of data were used to facilitate during the process of image classification such as land use maps, terrain maps, field data, Dak Nong Land Inventory in 2017 collected from the Dak Nong Forestry Protection Department.

2.2. Methods

2.2.1. Image pre-processing
Sentinel 2A MSI
The JavaScript API Code Editor in the Google Earth Engine (GEE) was used to collect satellite image data. GEE provides most freely available image data and an application programming interface (API) to analyze and visualize the data [6], [7]. Top of atmosphere reflectance (TOA) images for 2018 were used for the study. A collection of SE-2A for all month of 2018 (from 1 January 2018 to 31 December 2018) was conducted. This step collected a total of 122 Sentinel 2 MSI image scenes which are lower 30% covered by cloud derived for the research area. The set of collected images were pre-processed to remove cloud areas were masked out and shadows. The cloud detection algorithm which is available from GEE was applied as a cloud computing. The cloud detection algorithm which is available from GEE was applied as a cloud computing platform to mitigate the cloud issues of SE-2A data based on the spectral band "QA60". The bands at a spectral resolution of 20m were resampled using the nearest neighbor method to 10m resolution. The median function was then applied to create an image object (single image) representing the median value of all images in the filtered collection [8], [9]. The script available on “Open Geo Blog - Tutorials, Code snippets and examples to handle spatial data” were used for entire pre-processing based on GEE [10].

Sentinel 1A

High resolution SAR image often experiences speckle noise degrading image quality and making interpretation become more difficult. Light spot reduction can be achieved in two ways such as multi-look processing and spatial filtering. Multi-look processing is usually done during data collection, while spatial filtering is carried out at the same time as digital image analysis. The principle of spatial filtering is to reduce the variance of complex spot scattering and improve the estimate of undefined scattering coefficient. Spot filters are often referred to adaptive filters using local statistics including mean and standard deviation (Lee filter, Enhanced filter and Median filter).

In this study the Sentinel-1A were collected using GEE from January 1, 2018 to December 31, 2018. An integration of 10 SE-1A image bands (VV, VH and texture feature: mean, contrast, correlation, entropy of two bands VV, VH) and 10 SE-2A image bands (B2-Blue, B3-Green, B4-Red, B5-Red Edge1, B6-Red Edge 2, B7-Red Edge 3, B8-NIR, B8A-Red Edge 4, B11-SWIR 1, and B12-SWIR 2) was conducted to category different LULC classes in Dak Nong province. The collected image was calibrated at level 1, including Thermal noise removal, Radiometric calibration and Terrain correction with terrain-corrected values converted to decibels via log scaling (10* log10(x)). We employed the enhanced Lee filter to eliminate noises in the Sentinel-1A image. This algorithm consisting of a 9x9 pixel window and a 64 quantization level was applied not only to effectively remove speckles but also produce better performance in preserving the edges. The Enhanced Lee resampling option determines the gray level for each pixel by computing the weighted sum of the center pixel value, the mean value,
and the variance calculated in a square kernel surrounding the pixel. To filter pixels located near the edges of the image, edge pixel values are replicated to produce sufficient data. In homogeneous areas, the low-pass filter is used for removing speckles, compared to heterogeneous areas where speckles are reduced while still retaining the texture. In addition, areas containing isolated point targets, the filter preserves the observed value.

The gray-level value \( R \) for the smoothed pixel is:

\[
R = \text{Im} \text{ for } Ci \leq Cu
\]

\[
R = \text{Im} \times W + Ic \times (1 - W) \text{ for } Cu < Ci < Cmax
\]

\[
R = Ic \text{ for } Ci \geq Cmax
\]

\[
W = \exp(-\text{Damping Factor} \cdot \frac{Ci - Cu}{Cmax - Ci})
\]

\[
Cu = \sqrt{\frac{1}{\text{Number of Looks}}}
\]

\[
Ci = \frac{S}{\text{Im}}, Cmax = \sqrt{1 + \frac{2}{\text{Number of Looks}}}
\]

\( Ic \) = center pixel in the kernel; \( \text{Im} \) = mean value of intensity within the kernel; \( S \) = standard deviation of intensity within the kernel.

The Damping Factor specifies the extent of the damping effect of filtering.

The Number of Looks and the Image Format of the radar image are usually recorded on the CD jacket or magnetic tape label or in the format specifications provided by the data vendor.

### Texture Analysis

Several studies have revealed that texture is the most important information source in high resolution radar image [11], [12]. In particular, SAR has diverse textural information, and textural characteristics represent for information source related to spatial correlation of pixel values. Therefore, various features such as built-up areas, land and vegetation are likely to be interpreted more precise [13], [14]. In this study, Grey Level Co-occurrence Matrix (GLCM) was employed to extract texture features including contrast, mean, entropy and correlation [15]. Co-occurrence matrix is calibrated basing on distance between two pixels (\( \delta \)) and orientation angle (\( \theta \)). GLCM quantifies texture by measuring the spatial frequency pixel grey-level occurrence in a user-defined scroll window and forming an appearance matrix. Calculation for each VV and VH polarization is manipulated in a window size of 9x9 pixels. Larger windows generate more stable texture features and then returning to blur the edges, while smaller window sizes result in incorrect border segmentation [11], [16], [17], [18]. Texture measures are illustrated by the following equations:

\[
\text{Mean} = \sum_{i=1}^{N_g} \sum_{j=1}^{N_g} i \times P(i,j)
\]

\[
\text{Contrast} = \sum_{i=1}^{N_g} \sum_{j=1}^{N_g} P(i,j)(i - j)^2
\]

\[
\text{Entropy} = -\sum_{i=1}^{N_g} \sum_{j=1}^{N_g} P(i,j) \log(P(i,j))
\]

\[
\text{Correlation} = \frac{\sum_{i=1}^{N_g} \sum_{j=1}^{N_g} P(i,j) - \mu_x \mu_y}{\sigma_x \sigma_y}
\]

Where: \( P(i,j) \): Normalized GLCM values

\( Ng \): Number of distinct grey levels in the quantized image

\( \mu \) = mean value of original data

\( \sigma \) = standard deviation of original data

#### 2.2.2. Sampling and data collection

Field data collection was undertaken from various sources, including image-based sample collection on Google Earth, available data from the 2018 forest inventory map, visual image interpretation experience and field samples.

A total of 1336 identified training samples were randomly collected in this study, of which 752 samples used for classification and the remaining of 484 points for assessment of classification accuracy.

#### 2.2.3. Image classification using the Random Forest (RF) algorithm
In this study, the nonparametric RF algorithm which is introduced by [19] was adopted to digitally classify images into LULC types using R software. The RF is a classification algorithm consisting of many decision trees. Each individual tree is created from randomly selected training pixels. When running RF, there are two main parameters that need to be specified in the classification algorithm, namely the mtry and the ntree parameters. After the RF model generated, each result of the bootstrap in the set will vote for the most popular class and produce a categorization result. The model is created according to the category with the most votes for each ntree decision [19]. We applied the OOB error (out-of-bag) assessment to choose the optimal ntree and mtry parameters for the model through package "randomForest" in R software with all the relevant variables. The ntree value is tested as the algorithm running from 1 to 1000 trees at a distance of 50 trees. A number of variables used for splitting each node results in the tree during the grading process (mtry) calculated through the tune RF () function.

2.2.4. Classification accuracy assessment
The matrix confusion table is the most effective approach for evaluating classification accuracy [14]. Accordingly, the matrix confusion was computed statistically, and this method was used to evaluate the accuracy of the classified images based on various criteria such as Overall Accuracy (OA), Kappa coefficient (K), Producer Accuracy (PA) and User Accuracy (UA). Classification accuracy assessment was implemented using the method of randomly dividing the sample data set into two independent parts, with 484 samples used for testing the accuracy and the remaining points employed to the classification.

Figure 2. The flow-chart of methodology implemented for LULC mapping

3. Results
3.1. Selection of optimal parameters for RF
The ntree and mtry parameters play an important role in the classification output using the Random Forest algorithm. In the current study, ntree run from 50 to 1000 with 50 intervals, and mtry run from 1 to the maximum of the used predictors using a single interval. Based on the assessment of OOB error,
the most optimal ntree and mtry model were chosen for the model. In this case when the ntree value reached at 950 trees, the model obtained the smallest number of OOB error with 1.74%. And the optimal mtry is 12 (Figure 3).

![Figure 3. The OOB error](image)

3.2. Accuracy assessment of classification results
The accuracy of the models was assessed using independent datasets (data not participate in model building). The confusion error matrix and K index are presented in table 1. It can be seen clearly that the OA of the classified image was 81.40% with K index of 0.79 indicating a good agreement for classified images validated data [20].

| LU/LC | 1   | 2   | 3   | 4   | 5   | 6   | 7   | 8   | 9   | 10  | UA(%) |
|-------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-------|
| 1     | 1151| 26  | 0   | 112 | 46  | 78  | 0   | 0   | 0   | 12  | 80.77 |
| 2     | 82  | 266 | 18  | 0   | 0   | 1   | 0   | 0   | 0   | 0   | 72.48 |
| 3     | 12  | 79  | 362 | 0   | 10  | 22  | 8   | 0   | 0   | 2   | 73.13 |
| 4     | 43  | 0   | 0   | 282 | 0   | 10  | 0   | 0   | 0   | 0   | 84.18 |
| 5     | 40  | 5   | 7   | 1   | 424 | 46  | 7   | 0   | 0   | 7   | 78.96 |
| 6     | 49  | 5   | 2   | 429 | 29  | 59  | 0   | 0   | 0   | 27  | 70.55 |
| 7     | 0   | 0   | 13  | 0   | 22  | 9   | 434 | 0   | 0   | 21  | 86.97 |
| 8     | 0   | 0   | 0   | 0   | 0   | 0   | 5   | 698 | 0   | 66  | 90.77 |
| 9     | 0   | 0   | 0   | 0   | 0   | 0   | 5   | 1   | 352 | 10  | 95.65 |
| 10    | 0   | 0   | 0   | 0   | 0   | 18  | 38  | 13  | 0   | 317 | 82.12 |

*Class 1: Evergreen; 2: Semi-Evergreen; 3: Dipterocarp forest; 4: Plantation; 5: Rubber; 6: Industrial Plants; 7: Crop land; 8: Residential; 9: Water Surface; 10: Other land.

The error matrix indicated PA and UA of all LULC classes achieved above 65%. In particular, water surface and residential area had the highest PA and UA (more than 90%), followed by evergreen forest reaching greater than 80% of PA and UA. On the other hand, dipterocarp forest performed a relatively good result with UA ramping up 90.05% and UA reaching only 73.13%. By contrast, semi-evergreen forest had the lowest accuracy with PA = 69.82%; UA = 72.48%. It can be explained that there was confusion about spectral characteristics between pixels derived from semi-evergreen forest and industrial crops with other land use types. Usually, the confusion occurred on the semi-evergreen forest which is regarded to pixels from dipterocarp forest or evergreen forest types [21]. The reason is that semi-evergreen forests often distribute in the transition zone between evergreen forest and dry dipterocarp forest. Moreover, anthropogenic activities also partly effect on the distribution of land use
types and pixels driving a reduction in the classification accuracy. Results also show that dipterocarp forests were also relatively good separation with PA reached 90.05%. However, UA was only 73.13% because other LULC types were misunderstood as dipterocarp forest, especially semi-evergreen forest.

The plantation obtained the PA = 66.51% and UA more than 84.18%. However, the plantation was also confused with with evergreen forest and industrial crops. Most planted forest areas are at the same age and monoculture models. Thus, it is occasionally getting confused with industrial crops. On the other hand, the area of planted forests is often contiguous, even grown in the space of natural forests, affecting the discrimination between plantations and natural evergreen forest. Non-forest covers such as rubber and industrial trees still had many pixels confused with natural forests, especially evergreen forests.

The current study considered an integration of optical SE-2A image and radar SE-1A data for LULC mapping in Dak Nong region. The results achieved a good performance in the classification compared to those of other studies. OA of the classified image was above 81% with a kappa coefficient of 0.79. Our results are in agreement with [22] who employed the integration of optimal images and radar data for various methods (SVM, RF and Maximum Likelihood-ML) regarding to LULC classification. Optical products including Landsat TM and SPOT 5 were applied together with SAR data of ENVISAT ASAR/TSX. This study is consistent with our findings, showing a good performance of optical images and SAR data improved the classification results, raising the accuracy of 10%, while the best values achieved from RF and SVM classifiers. Similarly, a fusion of SE-1 and SE-2 was also applied for a-seven LULC classification using RF and ML algorithms shown in a previous study (Erinjery, et al. 2018 [23]). Whereas, Whyte et al. (2018) [24] used E-Cognition software based on object analysis in image processing to create segments accompanied with ArcGIS for RF and SVM classifications. These outputs from their works found better results for RF compared to SVM when using all images data combination for LULC mapping. The OA was about 84% for both cases mentioned.

In previous study conducted by Nguyen et al. (2020) [21], the single use of Sentinel 2 data was used for classification of 11 LULC types using support vector machine (SVM) classifier which resulted in the highest OA (80.03%) compared to maximum likelihood MLR method (only 63.9%). It is noticeable that the most obtained accurate classifier was attributed by the combination of remote sensing data achieved from dry and rainy season. While, the worst LULC classification result was for image data acquired from the rainy season due to the solar illumination geometry effects. In this work, however, we employed RF algorithm to classify 10 LULC classes producing a similar pattern of OA (around 81%) with kappa of 0.79. Although there was no significant difference between SVM and RF, several studies recommended RF classifier as training data collection is less time-consuming as well as driving factors are easier to choose. Therefore, a suggestion was confirmed in this work.

Application of various methods for LULC classification when using products of the optical data-S2 combined with radar-S1 has been investigated in many studies. In particular, Tavares et al. (2019) [5] illustrated the integration of optical sensors with radar data used for LULC classification using RF classifier. The findings suggested that the best OA was achieved for the combined dataset between S1 and S2 by 91.07% which was higher than ours (81.04%). On the other hand, the authors also revealed that the use of S1 data only yielded the worst result (56.01%) compared with the S2 alone reaching at 89.45% of OA.

There are several possible explanations for the difference in classification accuracy results compared to previous studies. It is undeniable that the integration of optical remote sensing data in the stacking improves OA in all classifications since S-2 has a multi-spectral combination. By contrast, high resolution SVR image S1 results in better quality images acquisision from GEE due to its importance for monitoring tropical areas. Dak Nong is a typical area considered as a humid tropical climate where high cloud coverage all year round, thus the application of optical sensor data is limited. It is interesting to note that most of previous studies focused on six or seven LULC classes, while a large number classes of our research consisted of 10 categories. It may be the case therefore confusion in classifications occurred on radar image in the discrimination of a large number of LULC classes. Therefore, these variations in classification accuracies are unavoidable among studies.
3.3. Mapping and LULC analysis
As shown from Figure 4, distribution of natural forests was scattered across the districts in the province and mainly concentrated on the forest owners such as national parks, nature reserve management board of protection forests and forestry companies.

The results obtained from the preliminary analysis of forest cover (FC) and none forest cover (NFC) types are summarized in Table 2 and Figure 4. From this data, we can see that total area of FC was more than 224 thousand ha reaching at 34%. Of which evergreen forest was about 167 thousand ha, approximately 26% of total FC area, compared to semi-evergreen and dipterocarp forests which had a similar pattern of area accounting for only 28 thousand ha. However, NFC accounted for more than 65% of total area (429 thousand ha), which was nearly triple as high as that for FC. It is noticeable that industrial plants and cropland were the major LULC accounting for 34.82% (228 thousand ha) and 11.38% (74 thousand ha) of total NFC area, respectively. While, plantation and water surface had a fairly equal proportion number of area among NFC types, which accounted for nearly 2%. Overall, the area and percentage of FC and NFC types can be virtually seen from Figure 4.

Figure 4. Land use/land cover map of Dak Nong province in 2018

Table 2. Area and percentage % of each land use / cover type in Dak Nong province in 2018

| Forest cover (FC)   | Area (ha)   | Percentage (%) |
|---------------------|-------------|----------------|
| Evergreen forest    | 166,662.00  | 25.54          |
| Semi-evergreen forest| 28,485.60  | 4.37           |
| Dipterocarp forest  | 28,441.80   | 4.36           |
| Total FC            | 223,589.4   | 34.27          |
| None forest cover (NFC) | Area (ha) | Percentage (%) |
| Plantation          | 12,813.60   | 1.96           |
| Rubber     | 29,558.30 | 4.53 |
|------------|-----------|------|
| Industrial plants | 227,179.00 | 34.82 |
| Crop-land  | 74,260.80 | 11.38 |
| Residential | 19,330.90  | 2.96  |
| Water surface | 12,288.40  | 1.88  |
| Other land | 53,477.40 | 8.20  |
| Total NFC  | 428,908.4 | 65.73 |

3.4. Assessment of forest resources in Dak Nong province in 2018

Analyzing and quantifying LULC changes (especially forested land area) play an important role in generating databases to for sustainable environmental resource management [25]. Hence, mapping and assessing the current LULC change over time are important processes to understand and provide constructive solutions to address environmental and social issues.

The total area of natural forest covers was over 223.5 thousand hectares, accounting for 34.27%, compared to non-forest covers which were more than 416,000 hectares, equivalent to 63.77% of the entire area in Dak Nong. On the other hand, plantation occupied only 1.96% which was significant lower than natural forest and non-forest covers. However, this study only focused on the forested areas without taking consideration into the newly planted forest areas and the land area not resulting in forests yet.

It can be easily seen that the area of natural forests achieved roughly 223.5 thousand hectares, of which the area that evergreen forest reached more than 166.6 thousand hectares corresponding with 74.54% of the province's natural forests. However, semi-evergreen forests and deciduous forests had a similar pattern in the area with more than 12% of the total natural forest area.

4. Conclusion

The study combined sentinel-1A radar and sentinel-2A optical images to identify and build the 2018 LULC map of Dak Nong province using the Random Forest classification algorithm. The classification accuracy assessment was conducted basing on the independent data. The results show that the accuracy of classified images achieved 81.40 with kappa = 0.79. Thus, the classification output was acceptable; however, there was still confusion between the covers of planted forests, rubber, industrial plants and natural forests. In addition, the findings also produce a high efficiency when applying a combination of radar and optical remote sensing data to identify and build forest cover maps. However, making decision on the classification approaches to improve the accuracy of land cover maps should be studied further.

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