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Monitoring Vegetation Cover Changes by Sentinel-1 Radar Images Using Random Forest Classification Method

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Abstract. Vietnam is an Asian country with hot and humid tropical climate throughout the year. Forests account for more than 40% of the total land area and have a very rich and diverse vegetation. Monitoring the changes in the vegetation cover is obviously important yet challenging, considering such large varying areas and climatic conditions. A traditional remote sensing technique to monitor the vegetation cover involves the use of optical satellite images. However, in presence of the cloud cover, the analyses done using optical satellite image are not reliable. In such a scenario, radar images are a useful alternative due to the ability of radar pulses in penetrating through the clouds, regardless of day or night. In this study, we have used multi temporal C band satellite images to monitor vegetation cover changes for an area in Dau Tieng and Ben Cat districts of Binh Duong province, Mekong Delta, Vietnam. With a collection of 46 images between March 2015 and February 2017, the changes of five land cover types including vegetation loss and replanting in 2017 were analyzed by selecting two cases, using 9 images in the dry season of 3 years 2015, 2016 and 2017 and using all of 46 images to conduct Random Forest classifier with 100, 200, 300 and 500 trees respectively. The result in which the model with nine images and 300 trees gave the best accuracy with an overall accuracy of 98.4% and a Kappa of 0.97. The results demonstrated that using VH polarization, Sentinel-1 gives quite a good accuracy for vegetation cover change. Therefore, Sentinel-1 can also be used to generate reliable land cover maps suitable for different applications.

Keywords: Vegetation cover change, Sentinel-1, Random Forest, Binh Duong, Vietnam

1. Introduction

Over the past decade, Vietnam has seen a considerable transformation in the land use/ land cover due to multitude of reasons involving growing population, economy, urbanization and industrialization among others. Of all the land covers, vegetation cover is an important and a cyclical cover that is dependent on almost all the natural and anthropogenic parameters including the seasons, temperature and other climatic conditions. Kongtis [1] depicts that due to the population growth, the agriculture lands are getting reduced in Vietnam. Schaefer and Thinh (2019) [2] have mentioned a decrease in the agriculture land by 6% between 2000 and 2010, and an increase in residential area by 7% has been reported by Downes et al. (2016) [3]. Such a decrease in agriculture and overall vegetation cover may also trigger many disasters including floods[4], and urban heat waves [5]. Thus, detection of vegetation cover is necessary so as to understand and analyze the inter-relationships between the humans and their ecosystem[6] and for other national infrastructure planning and management applications[7].

The detection of changes in the vegetation cover are generally studied for larger areas and the results are required in considerably smaller amount of time. Therefore, remote sensing data is an effective tool to assist this task. Previously, only the optical satellite imageries were used to determine the change in land covers, mainly due to the free-availability of the imageries in the public domain. However, over the past one-two decades, researchers have addressed the limitations of the optical imageries in the change detection studies [8]. These include the limited results in case of cloud cover [9], but can be alleviated by image composting [10]. Also, in optical image analysis, different species of trees or crops may be indistinguishable due to similar spectral reflectance. In addition, the optical imagery cannot penetrate the forest canopy and can sense only the topmost layer, thus affects the overall analysis. Therefore, radar remote sensing is now in vogue for many applications including land and forest cover classification [11]; [12], deforestation mapping [12], classification of agricultural areas [13], monitoring specific crops [14] etc. The radar remote sensing is free from the limitations of optical remote sensing but have its own limitations. Those limitations can be eliminated using several developed algorithms [14] [15] . Therefore, in this study, we have used Sentinel-1 imagery for our change detection analysis, primarily because of 1) the cloud cover over Vietnam due to the tropical climate and 2) free-availability of this imagery dataset.

The characteristics of land cover classification studies using radar satellite images (e.g. [16], [17], [18] are to use multi-temporal and dual-polarized radar images to increase the accuracy of land cover change monitoring. For studies related to surface cover changes such as urban growth monitoring, forest monitoring and disaster management, images used to determine the changes are often ground-range images and are multi-polarization [19]. In the theory of change detection, the image classification or statistical analysis methods is one of the most important step. [20] used the Kullback-Leibler divergence while [21] used an unsupervised classification method of Hidden Markov Chain (HMC) to solve the angle difference when using single look complex images. [22] combined mean ratio and log ratio images and used wavelet networks method to determine the surface cover change in the time series, [23] used distance measurement and segmentation of images with the minimum error method for determining the change of objects on the multi-temporal and multi-polarization radar images.[24] used the Deep neural network method to identify changed and unchanged areas on multi-temporal SAR satellite images.

In general, the methods mentioned above have advantages and disadvantages when determining changes by using multi-temporal SAR images. In this study, we used a machine learning-based method, the Random Forest (RF), to classify the changes and unchanged vegetation in the images. Because our study area in Binh Duong province of Vietnam where has many types of perennial plants and forests, therefore RF method combined with statistical analysis on images between periods to detect the changes is quite appropriate. In addition, the problem of choosing parameters such as the number of trees for the RF model has not been analyzed in the published studies, so this study is an opportunity for us to evaluate the optimization of these parameters for RF model.

2. Study areas and data

2.1 Study area

The study area is two districts of Dau Tieng and Ben Cat located in the northwest of Binh Duong province. It borders on districts of Binh Phuoc province to the north, Thu Dau Mot city to the south, Trang Bang district to the southwest, and Duong Minh Chau district to the northwest, both of Tay Ninh province and to the southeast by Cu Chi district of Ho Chi Minh City. This area features many rubber plantations, fruit trees and also many changes in rubber planting areas within three years from 2015 to 2017.

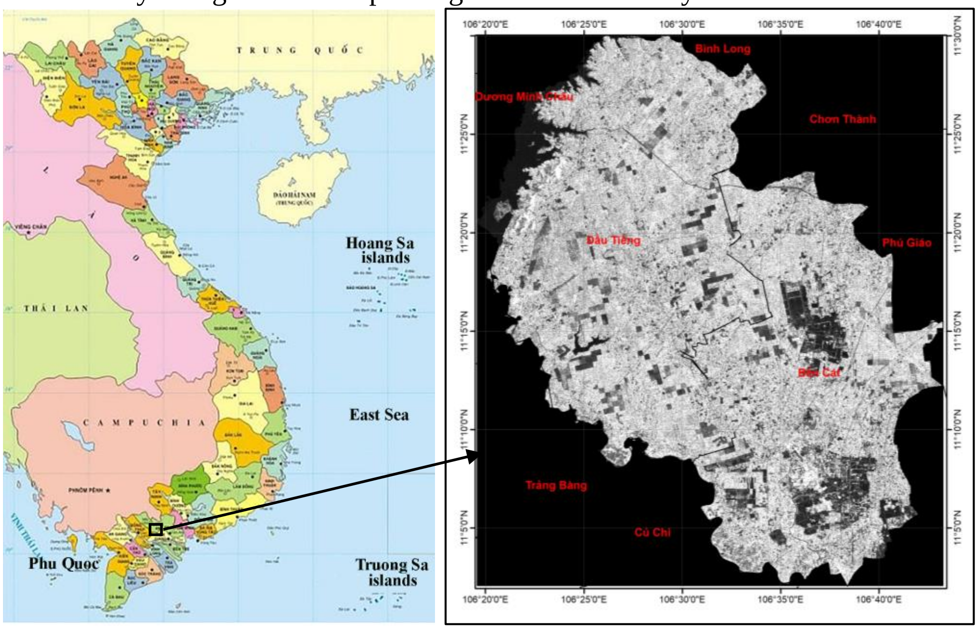

Fig. 1. The location of the study area and Sentinel-1 image acquired on March 23, 2015 was cut the boundary of Dau Tieng and Ben Cat districts, Binh Duong province.

2.2 Data used

The research material is Sentinel-1 satellite image, C band with a period of 12 days. This is a good data to assess the seasonal variation of land cover objects. Sentinel-1 data used is Level-1 ground range detected images (GRD), 10m resolution, dual polarization (VV and VH). The images were carried out with pre-processing steps on SNAP toolbox software includes calibration to compute sigma nought values; terrain correction; convert to dB value; noise filtering on multi-temporal images.

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Sentinel -1A images are presented in Table 1, including 46 images from March 2015 to February 2017. The series of images was selected to see the change of backscatter of each type of vegetation in each plant's growth stage, thereby determining the type of short term crops or industrial crops and the change due to logging or replanting.

The study area has two seasons: dry season and rainy season. The rainy season starts from May to the end of November every year and the dry season starts from December to the end of April. According to the set of Sentinel-1 images used, there is about one image every 24 days. Because the objective of the study is a vegetation change, we focus on the dry season dates to see the difference of the plant objects from 2015 to 2017. Figure 2 is a color composite of 3 images in 3 dates: 2015-03-23, 2016-03-05 and 2017-02-04 with VH polarization. The reason for choosing the color combination of the VH is because VH polarization is mainly sensitive to volume scattering [25], but the study area is a large area of fruit trees and rubber trees, thus choosing VH for determining the vegetation change of this region is suitable.

Tab. 1. Sentinel -1A image set.

ID	Y-M-D	ID	Y-M-D	ID	Y-M-D	ID	Y-M-D	ID	Y-M-D
1	**2015-03-23**	11	2015-11-06	21	**2016-03-05**	31	2016-07-15	41	2016-12-06
2	2015-04-16	12	2015-11-18	22	2016-03-17	32	2016-07-27	42	2016-12-18
3	2015-05-10	13	2015-11-30	23	2016-03-29	33	2016-08-20	43	2016-12-30
4	2015-06-27	14	2015-12-12	24	2016-04-10	34	2016-09-01	44	2017-01-11
5	2015-07-21	15	2015-12-24	25	2016-04-22	35	2016-09-13	45	2017-01-23
6	2015-08-14	16	2016-01-05	26	2016-05-04	36	2016-09-25	46	**2017-02-04**
7	2015-09-07	17	2016-01-17	27	2016-05-16	37	2016-10-07		
8	2015-10-01	18	2016-01-29	28	2016-05-28	38	2016-10-19		
9	2015-10-13	19	2016-02-10	29	2016-06-09	39	2016-10-31		
10	2015-10-25	20	2016-02-22	30	2016-07-03	40	2016-11-12		

3. Methodology and processing

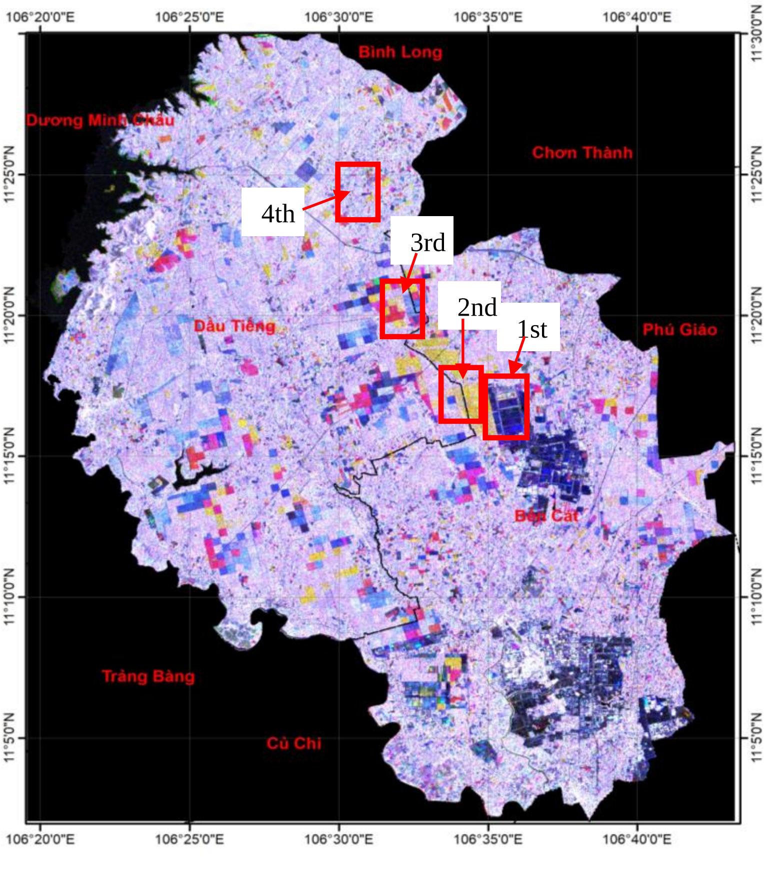

Fig. 2. RGB color composite image of Sentinel-1A VH polarization.

3.1 Characterization of land covers on multi-temporal SAR images

Analysis of multi-temporal SAR images of the study area (from March 2015 to February 2017), the land cover can be divided into two main groups: (i) the changed vegetation and (ii) The unchanged land cover (Fig. 2). The most vegetation changes mainly include perennial crop land that is rubber tree or other fruit trees. The unchanged land covers are usually residential areas or rubber lands. Fig. 2 shows the RGB color composite image of Sentinel-1 of three observation periods, March 2015, March 2016 and February 2017 with VH polarization. Different colors in the composite image are corresponding to the change of different types of land coves. The white or black colors in the RGB image are displayed as correspondingly unchanged objects because of the stability of the surface scattering in time series images. On the other hand, the different colors in the RGB image show the objects changed because of the different backscattering values of each pixel over time. To see the difference, the backscatter of some positions as blue, magenta, yellow, white and black color have been extracted through which help us can recognize the changes of the backscatter in three years through those charts.

In the blue areas, backscatter varied in the range of -12dB to -20 dB between March 2015 and July 2016, then scattering increased quite strongly indicating that within two years from 2015 to 2016, vegetation cover was available in this area, but then the vegetation in that area were clear-cut, so the scattering value increased (Fig. 3).

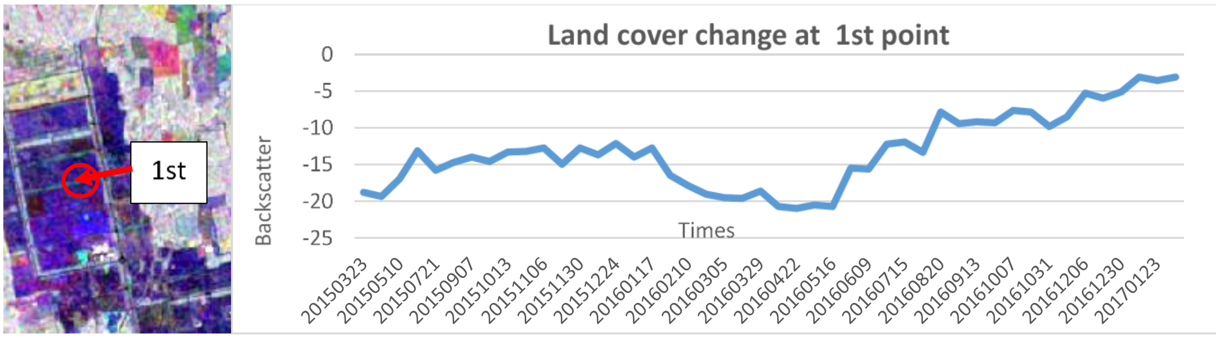

Fig. 3. Backscatter chart of the location of vegetation clear-cut in 2017.

At locations with light yellow color, the scattering value was high during the period from March 2015 to June 2016. This is possible that the previous period had no vegetation cover at this location but the later time was planted (Fig. 4).

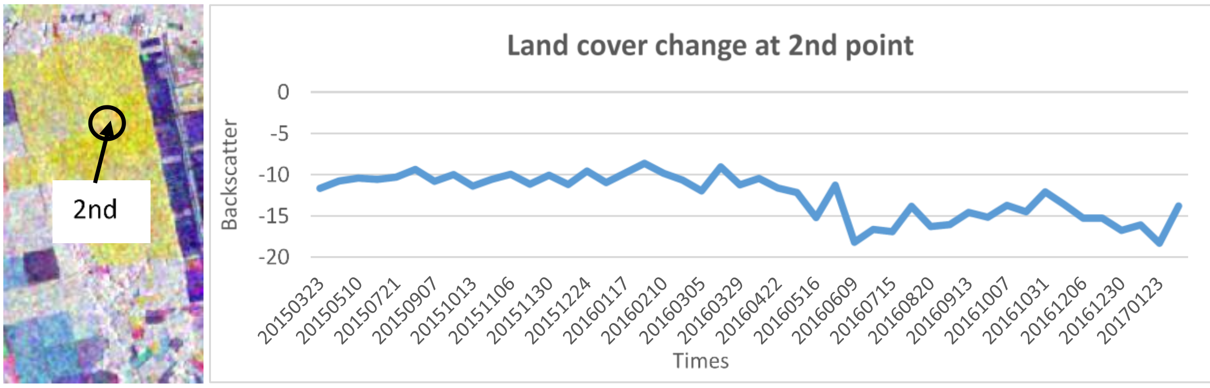

Fig. 4. Backscatter chart of replanting sites in 2017.

At the magenta locations, the scattering value decreased from December 2015 to June 2016. The vegetation here may be seasonal because the period before December 2015 and after June 2016 vegetation does not exist here.

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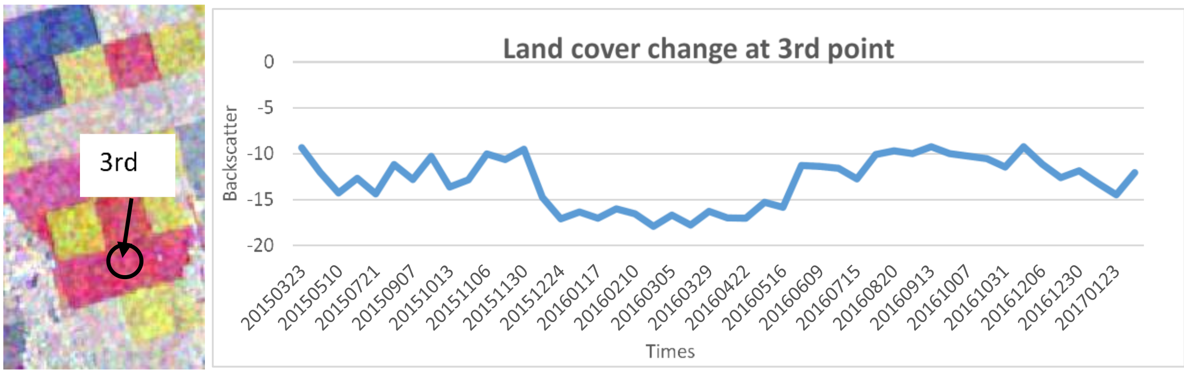

Fig. 5. Backscatter chart of seasonal crops.

At the fourth site, the backscattered signals almost varied in a narrow range from -11 dB to -7 dB showing the unchanged land cover in the area.

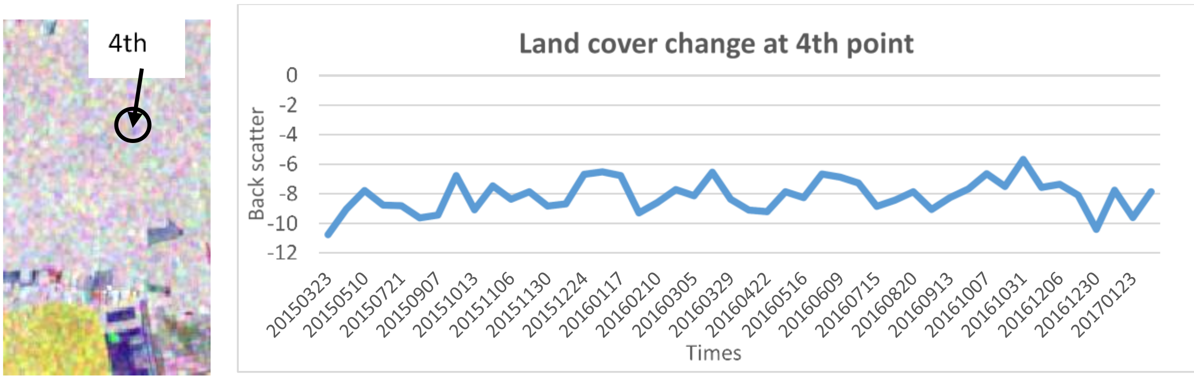

Fig. 6. Backscatter chart of unchanged land cover.

3.2 Research method

Through analysis of land cover changes on Sentinel-1 multi temporal images, the Random Forest (RF) method was selected for monitoring the vegetation change of the Dau Tieng, Binh Duong area (Fig. 4).

Overview of Random Forest method:

RF was proposed by Breiman in 2001[26]. This is a supervised classifier based on decision trees and improved bagging and bootstrapping techniques. Bootstrapping is a very famous statistic method, was introduced by Efron in 1979 [27].

The Random Forest (RF) is an algorithm comprising of many single decision trees. Each tree is created from randomly selected training pixels (bootstrap). The two parameters that need to be defined in this classification algorithm are the number of trees to grow (ntree) and the number of variables to split at each node (mtry). The ntrees selected depend on the shortest processing time to achieve the lowest error, ntree runs from 1 to 500 trees as default and mtry ranges from the minimum number of independent variables (equal to 1) to the maximum number of independent variables that used in the classifier.

After the Random Forest model is created, each result of the bootstraps in the set will vote for the most popular class and give a classification result. The model is formed based on the most voted classifier of each decision tree diagram [26] (Fig. 7).

Random Forest steps

- Step 1: From training data set D, random data are generated (bootstrap sample).
- Step 2: Using randomly sampled data subsets D1 , D2 ,…, Dk build trees T1 , T2 ,…,Tk. A decision tree consists of internal (or split) nodes and terminal (or leaf) nodes.
- Step 3: Combine the trees: Use the majority voting strategy for the classification.

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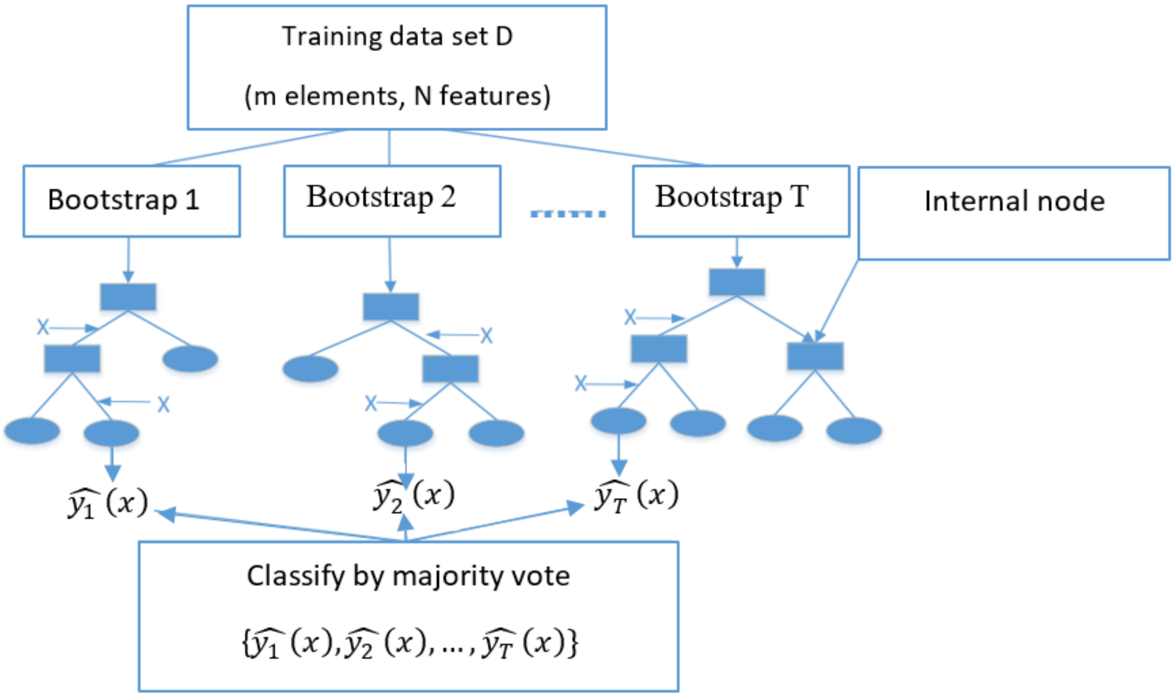


Fig. 7. Diagram of RF formation.

4. Results and discussion

4.1 Experimental procedure

- *Pre-processing*

The processing was conducted using SNAP and QGIS softwares as follow the processing flow chart in Figure 8. The Sentinel-1 images with GRD mode were calibrated, filtered by Multi-Temporal Speckle Filtering with 3x3 kernel and terrain corrected before application. The 30m SRTM data has been used for this purpose and the data was resampled to a pixel size of 20m ground resolution. The digital numbers values (DN) of SAR data were transformed into backscattering values in decibel (dB).

- *Classification for change detection*

Random Forest (RF) classification method has been carried out for mapping land cover changes. As a machine learning algorithm, RF has been widely applied and experimented with many times in optical images for land cover mapping. However, with the use of this RF method in terms of classifying vegetated cover changes by Radar images, not many scientists have done it yet.

Regarding the study area after analysing the differences in vegetation cover in the period from 2015 to 2017 above, we recognized some types of changes:

- Vegetation clear cut in 2017, mainly rubber trees. These areas are shown in a dark blue color image on RGB composite image and the backscatter chart at the first point (Fig. 3), corresponding to box number one in Figure 2.

- Vegetation replanting 2017 where the yellow color on RGB composite image, and the backscatter chart at the second point (Fig. 4) and inside the number two box in Figure 2.

- Another type of change is vegetation cover existed in 2016 and clear cut in 2015, 2017 where the magenta color was shown on RGB composite image, corresponding to the backscatter chart at third point in Figure 5. This type of vegetation is usually short-term agricultural crops.

- The unchanged objects will be grey color composite image and backscatter chart at the fourth point (Fig. 6)

- With water surface, the backscatters are very low and constant all the time and there is a black color in the color composite image.

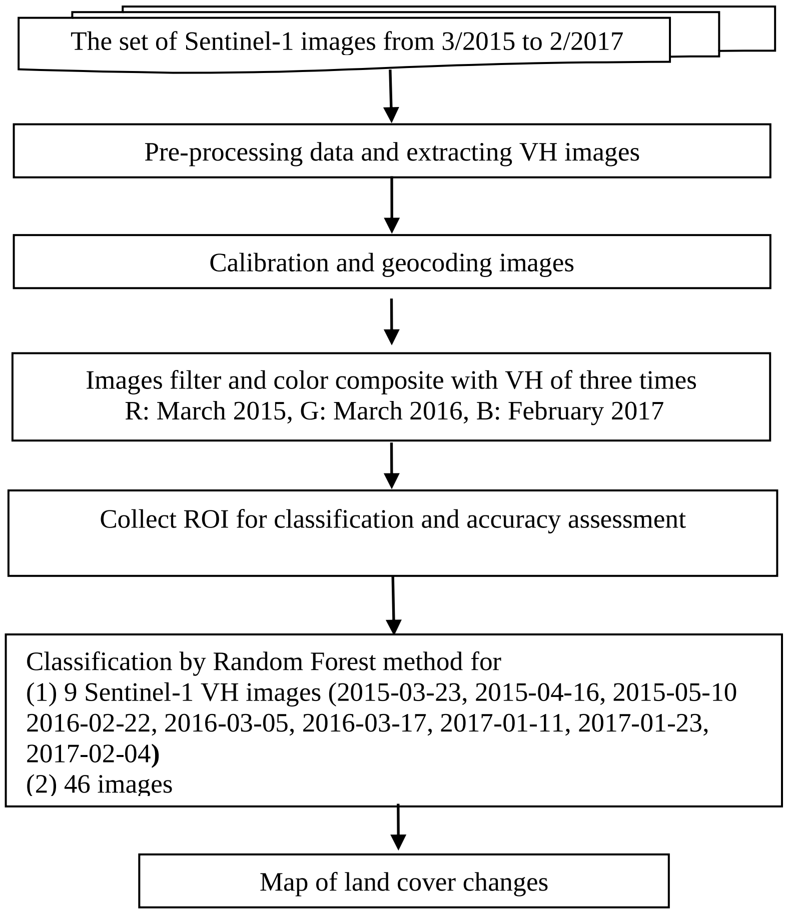


Fig. 8. Sentinel-1 VH image processing flow chart for land cover change detection.

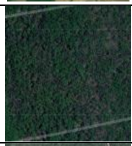
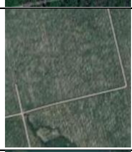
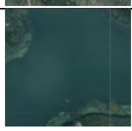
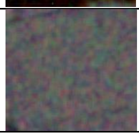
Sentinel-1 VH color composite	**Google Earth image 2017**	**Name of samples**
		Clear cut 2017
		New planting 2017
		Seasonal crops
		Water
		No changes

Fig. 9. Samples selection base on the color composite and Google Earth images. (The unchanged areas can be whatever object exists during the 3 years of the survey, so it's does not have a feature pattern on the google image).

According to the flow chart, with 46 Sentinel-1 VH images in the period from March 2015 to February

2017, we processed two cases for RF classification, these are (1) 9 images, and (2) 46 images.

Case (1): Nine images were selected to be classified by RF method all fall in the dry seasons of 2015, 2016, and 2017, which is the period when vegetation changes are the best. Based on the above analysis, five land cover and vegetation change classes were selected to classify as clear cut in 2017, new planting in 2017, cropland, unchanged land, surface water. Then rely on different sources such as Google Earth history, color composite images of the three times mentioned above, training data were collected. Fig. 9 shows the selection of the samples on image composite and Google Earth history. A total of 3121 pixels were collected for sampling of which 925 pixels were used to validate the classification. The accuracy of the result is based on the overall accuracy (OA) and Kappa. The input data for classification is the training data set (N) which are 9 independent variables (denoted as B) in this case the 9 Sentinel-1 satellite images selected above. For each node of the tree, randomly select mtry as the division basis at that node. The default value of mtry=sqrt(B), in this study mtry=3.

Case (2): In the second case, forty-six images were used. Also, with the five classes used for classification mentioned above and the number of training samples is 3121, of which 925 pixels are used for validation. For a large number of images, the number of independent variables here will be chosen as 46 (B=46) and the number of nodes (mtree) is sqrt(46) which is approximately 7.

Each prediction (land cover type or vegetation changes) is made from each decision tree, it is labelled (labelled here is 1 of the 5 selected cover types above) for the end node of the classification scheme. The process will be performed through all the trees (ntree) and the land cover with the most votes of this classification scheme will represent that tree diagram participating in the combined results of the Random Forest model. In this study, the number of trees of 100, 200, 300, 500 we selected in turn and see the change in the error of each change.

4.2 Discussion

With the selected RF classification method and four times of selecting with different number of trees (ntree), the accuracy evaluation results including overall accuracy (AO) and Kappa for two sets of 9 images and 46 images on an independent sample set are 925 pixels mentioned above. Table 2 was obtained.

Tab. 2. Accuracy of two data sets in selection of different number of trees.

Number of images	Accuracy	100 trees	200 trees	300 trees	500 trees
9 images in dry seasons of 2015, 2016, 2017	OA	96.2%	97.1%	98.4%	98.4%
	Kapa	0.95	0.96	0.97	0.97
46 images in the period 2015-2017	OA	93.1%	93.2%	94.2%	94.2%
	Kapa	0.90	0.91	0.92	0.92

Table 2 shows that the OA of the RF classifier for both sets of images has high accuracy of over 94% and the difference between the results is not very large. However, as the number of ntrees increases, the OA also increases. In the case of using 46 images, the accuracy is lower than the case of using 9 images, this can be explained because when too many independent variables are equivalent to the number of images, the information of the images does not differ much, so this leads to information redundancy and results in more errors in the RF model. In addition, when the number of trees increased to 300 and 500, the model gave the highest accuracy (98.4%) with a set of 9 images or 94.2% for a set of 46 images, this can be explained as the greater number of trees, the more stable the model, but the processing time will also be longer. However, the number of trees only needs to reach a certain limit, the accuracy does not change, so when the number of trees is up to 300, the AO is equivalent to the AO of setting 500 trees. Overall, the RF model with 300 trees in both sets of images is optimal for classification because the accuracy is similar to the 500 trees model while the processing time is lower. So, in this study, we decided to choose the model with the number of trees is 300, the set of images is 9 images.

With this option, the evaluation according to User's accuracy (UA) and Producer's accuracy (PA) also shows the reliability of the selected parameters, the results show these criteria of each layer is greater than 90% (Tab. 3). This shows that it is a promising method for classifying vegetation cover and its changes. The results also show the potential when using RF with 300 trees and 3 nodes to classify Sentinel-1 satellite image series into 5 types of vegetation cover and land cover changes, including 2017 clear cut, 2017 new planting, and seasonal crops, water surface and unchanged gave an accuracy of AO: 98.4%. The vegetation change monitoring experiment results for Dau Tieng and Ben Cat districts, Binh Duong province, from nine Sentinel-1 VH images with RF classification are shown in Figure 10.

Tab. 3. Accuracy of RF classification for a set of 9 images with 300 trees.

Accuracy			Confusion matrix					
Classes	UA (%)	PA (%)		Clear cut 2017	New planting 2017	Seasonal crops	No changes	Water
Clear cut 2017	98.7	97.5	Clear cut 2017	80	0	2	0	0
Replanting 2017	90.6	100	Replanting 2017	0	87	0	0	0
Seasonal crops	96.8	98.3	Seasonal crops	0	0	61	1	0
No changes	99.5	95.6	No changes	1	9	0	219	0
Water	100	100	Water	0	0	0	0	465
Over all accuracy: 98.4% and Kappa: 0.97								

Looking at the results, it is easy to recognize the areas of vegetation cover change are primarily new planting in 2017 which were shown in green. Besides, there were also some places that have removed vegetation in 2017 where magenta color. The areas of vegetation clear cut are mainly concentrated in Lai Uyen, Lai Hung and Thoi Hoa communes, Ben Cat district. With the data reported from the provincial committee, the new planting areas are mostly rubber trees. Those rubber tree regions are mainly distributed in An Lap, Long Tan, Long Hoa communes, Dau Tieng district. There have been 32.5 hectares of rubber trees newly planted under the Government's initiative. The tree planting campaign has been implemented since the beginning of 2016 so after planting when the trees are not high enough, the backscatter value is not high on the image until 2017 and this value is high and easily recognizable.

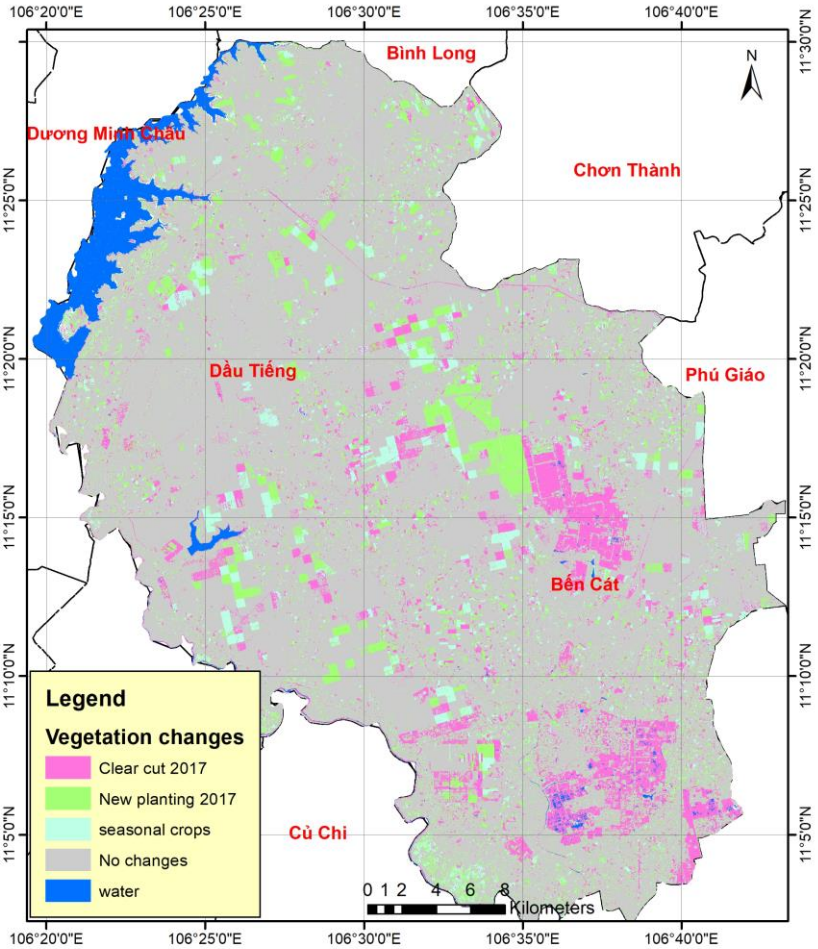


Fig.10. Land cover change monitoring at Dau Tieng and Ben Cat, Binh Duong province.

The areas cover with vegetation in 2016 are often short-term crops because the land was abandoned in

2015 and 2017. The areas under seasonal crops are shown by the cyan and are widely distributed in the communes of Long Tan, Long Nguyen, Thanh An, Dinh An, Dau Tieng district. In general, vegetation changes in Dau Tieng and Ben Cat Binh Duong areas are related to rubber tree because rubber trees are planted in rows and have quite square parcels. The areas of stable or little change are residential land or rubber trees or perennial fruit crops.

5. Conclusions

Through the analysis and testing of the Random Forest classification method, the changed and unchanged vegetation cover in Dau Tieng and Ben Cat, Binh Duong, Vietnam have been identified from Sentinel-1 polarized VH image data. The Sentinel-1 GRD image with a resolution of 10m is quite suitable for determining the land cover as well as the change of vegetation cover in tropical areas with cloud cover. In addition, this type of image is updated regularly and free download, so monitoring the changes of objects such as land cover and especially plants is very good.

The application of RF algorithm with combining images at different times of Sentinel-1 VH images is very important to evaluate the change of vegetation cover. When the number of images is large, the redundant information will slow down the processing speed and the accuracy will be worse than choosing a suitable number of images with large information differences. With a set of 9 images in the dry season of 3 years 2015, 2016 and 2017 and the number of trees of the RF model is 300, the accuracy of determining vegetation changes is the highest and achieving an OA accuracy of 98.4%.

This method offers promising results with free software and free images to be widely applicable at a low cost compared to most applications that used commercial images and software.

6. Acknowledgment

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7. References

1. Kontgis, C., Schneider, A., Fox, J., Saksena, S., Spencer, J.H., Castrence, M., 2014. Monitoring peri-urbanization in the greater Ho Chi Minh City metropolitan area. Applied Geography. 53: 377-388, https://doi.org/10.1016/j.apgeog.2014.06.029.
2. Schaefer, M., Thinh, N.X., 2019. Evaluation of land cover change and agricultural protection sites: A GIS and Remote Sensing approach for Ho Chi Minh city, Vietnam. Heliyon, 5(5): e01773, https://doi.org/10.1016/j.heliyon.2019.e01773.
3. Downes, N.K., Storch, H., Schmidt, M., Van Nguyen, T.C., Tran, T.N., 2016. Understanding Ho Chi Minh City's urban structures for urban land-use monitoring and risk-adapted land-use planning, in Sustainable Ho Chi Minh City: Climate Policies for Emerging Mega Cities, Springer. 89-116, https://doi.org/10.1007/978-3-319-04615-0_6.
4. Storch, H., Downes, N.K., 2011. A scenario-based approach to assess Ho Chi Minh City's urban development strategies against the impact of climate change. Cities. 28(6): 517-526, https://doi.org/10.1016/j.cities.2011.07.002.
5. Son, N.T., Chen, C.F., Chen, C.R., Thanh, B.X., Vuong, T.H., 2017. Assessment of urbanization and urban heat islands in Ho Chi Minh City, Vietnam using Landsat data. Sustainable cities and society. 30: 150-161, https://doi.org/10.1016/j.scs.2017.01.009.
6. Aly, A.A., Al-Omran A.M., Sallam A.S., Al-Wabel M.I., 2016. Vegetation cover change detection and assessment in arid environment using multi-temporal remote sensing images and ecosystem management approach. Solid Earth. 7(2): 713-725, https://doi.org/10.5194/se-7-713-2016.
7. Tran, H.Hong, Tran, A.Van and Le, N.Thanh., 2020. Study on land use changes, causes and impacts by remote sensing, GIS and Delphi methods in the coastal area of Ca Mau province in 30 years (in Vietnamese). Journal of Mining and Earth Sciences. 61, 4 (Aug, 2020), 36-45. DOI:https://doi.org/10.46326/JMES.2020.61(4).04.
8. Tran, A.Van, Nguyen, B.An, Dinh, T., Nguyen, Y.Hai Thi and Le, N.Thanh., 2020. Landslides detection in Bat Xat district, Lao Cai province, Vietnam using the Alos PalSAR time-series imagery by the SBAS method (in Vietnamese). Journal of Mining and Earth Sciences. 61, 4 (Aug, 2020), 1-10. DOI:https://doi.org/10.46326/JMES.2020.61(4).01.

9 . Asner, G.P., 2001. Cloud cover in Landsat observations of the Brazilian Amazon. International Journal of Remote Sensing. 22(18): 3855-3862, https://doi.org/10.1080/01431160010006926.
10. Sannier, C., McRoberts, R.E., Fichet, L.V., Makaga, E.M.K., 2014. Using the regression estimator with Landsat data to estimate proportion forest cover and net proportion deforestation in Gabon. Remote Sensing of Environment, 151: 138-148, https://doi.org/10.1016/j.rse.2013.09.015.
11. Simard, M., Saatchi, S.S., De Grandi, G., 2000. The use of decision tree and multiscale texture for classification of JERS-1 SAR data over tropical forest. IEEE Transactions on Geoscience and Remote Sensing, 38(5): 2310-2321, DOI: 10.1109/36.868888.
12. Engdahl, M.E., Hyyppa, J.M., 2003. Land-cover classification using multitemporal ERS-1/2 InSAR data. IEEE Transactions on Geoscience and Remote Sensing, 41(7): 1620-1628, DOI: 10.1109/TGRS.2003.813271.
13. Bargiel, D., Herrmann, S., 2011. Multi-temporal land-cover classification of agricultural areas in two European regions with high resolution spotlight TerraSAR-X data. Remote sensing,. 3(5): 859-877, https://doi.org/10.3390/rs3050859.
14. Bouvet, A., Le Toan, T., 2011. Use of ENVISAT/ASAR wide-swath data for timely rice fields mapping in the Mekong River Delta. Remote Sensing of Environment, 115(4): 1090-1101, https://doi.org/10.1016/j.rse.2010.12.014.
15. Braun, A., Hochschild V., 2017.Potential and limitations of radar remote sensing for humanitarian operations. in GI Forum, DOI: 10.1553/giscience2017_01_s228.
16. Ajadi, O.A., Meyer, F.J., Webley, P.W., 2016. Change detection in synthetic aperture radar images using a multiscale-driven approach. Remote Sensing, 8(6): 482, https://doi.org/10.3390/rs8060482.
17. Longépé, N., et al., Assessment of ALOS PALSAR 50 m orthorectified FBD data for regional land cover classification by support vector machines. IEEE Transactions on Geoscience and Remote Sensing, 2011. 49(6): 2135-2150, DOI: 10.1109/TGRS.2010.2102041.
18. Niu, X., Ban, Y., 2013. Multi-temporal RADARSAT-2 polarimetric SAR data for urban land-cover classification using an object-based support vector machine and a rule-based approach. International journal of remote sensing, 34(1): 1-26, https://doi.org/10.1080/01431161.2012.700133.
19. Balzter, H., Cole, B., Thiel, C., Schmullius, C., 2015. Mapping CORINE land cover from Sentinel-1A SAR and SRTM digital elevation model data using random forests. Remote Sensing, 7(11): 14876-14898. https://doi.org/10.3390/rs71114876.
20. Ghanbari, M., Akbari, V., 2018. Unsupervised change detection in polarimetric SAR data with the Hotelling-Lawley trace statistic and minimum-error thresholding. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 11(12): 4551-4562, DOI: 10.1109/JSTARS.2018.2882412.
21. Inglada, J., Mercier, G., 2007. A new statistical similarity measure for change detection in multitemporal SAR images and its extension to multiscale change analysis. IEEE transactions on geoscience and remote sensing, 45(5): 1432-1445, DOI: 10.1109/TGRS.2007.893568.
22. Bouyahia, Z., Youssef, L.B., Derrode, S., 2008. Change detection in synthetic aperture radar images with a sliding hidden Markov chain model. Journal of Applied Remote Sensing, 2(1): 023526, https://doi.org/10.1117/1.2957968.
23. Gong, M., Cao, Y., Wu, Q., 2011. A neighborhood-based ratio approach for change detection in SAR images. IEEE Geoscience and Remote Sensing Letters, 9(2): 307-311, DOI: 10.1109/LGRS.2011.2167211.
24. Liu, M., Zhang, H., Wang, C., Shan, Z., 2012. Urban change detection for high-resolution fully polarimetric SAR using a modified heterogeneous clutter model. in EUSAR 2012; 9th European Conference on Synthetic Aperture Radar. VDE.
23. Gong, M., Zhao, J., Liu, J., Miao, Q., Jiao, L., 2015. Change detection in synthetic aperture radar images based on deep neural networks. IEEE transactions on neural networks and learning systems, 27(1): 125-138, DOI: 10.1109/TNNLS.2015.2435783
25. Nicolau, A.P., Flores-Anderson, A., Griffin, R., Herndon, K., & Meyer, F. J., 2021. Assessing SAR C-band data to effectively distinguish modified land uses in a heavily disturbed Amazon forest. International Journal of Applied Earth Observation and Geoinformation, 94: 102214, https://doi.org/10.1016/j.jag.2020.102214
26. Breiman, L., Random forests. Machine learning, 2001. 45(1): 5-32.
27. Efron, B., Bootstrap methods: another look at the jackknife. The Annals of Statistics, 7(1): 1-26. URL http://www. jstor. org/stable/2958830, 1979.

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