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Coastal forest cover change detection using satellite images and convolutional neural networks in Vietnam

Khanh Nguyen-Trong[1], Hoa Tran-Xuan[2]
[1]Faculty of Information Technology, Posts and Telecommunications Institute of Technology, Ha Noi, Vietnam
[2]Department of Informatics, Vietnam National University of Forestry, Ha Noi, Vietnam

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ABSTRACT

Monitoring forest cover changes is an important task for forest resource management and planning. In this context, remote sensing images have shown a high potential in forest cover changes detection. In Vietnam, although the existence of a large number of such images and ground-truth labels, current researches still relied on classical methods employed manual indices, such as multi-variant change vector analysis (MVCA) and normalized difference vegetation index. These methods highly require domain knowledge to determine threshold values for forest change that are applicable only for studied areas. Therefore, in this paper, we propose a method to detect coastal forest cover changes, which can exploit available dataset and ground-truth labels. Moreover, the proposed method does not require much domain knowledge. We used multi-temporal Sentinel-2 imagery to train a segmentation model, that is based on the U-Net network. It was used then to detect forest areas at the same location taken at different times. Lastly, we compared obtained results to identify forest disturbances. Experimental results demonstrated that our method provided a high accuracy of 95.4% on the testing set. Furthermore, we compared our model with the MVCA method and found that our model outperforms this popular method by 3.8%.

Corresponding Author:

Khanh Nguyen-Trong
Faculty of Information Technology, Posts and Telecommunications Institute of Technology
Km10 Nguyen Trai, Hanoi, Vietnam
Email: khanhnt@ptit.edu.vn

1. INTRODUCTION

Coastal forests are an important part of tropical biodiversity. They provide a lot of important services for our ecosystem, such as extreme weather protection, erosion prevention, environments for different species, and storage of blue carbon, which allow to mitigate climate change [1]. However, these forests are increasingly vulnerable to degradation as a result of climate change, sea- level rise or anthropogenic processes such as deforestation [2]. To address these issues, accurate and automated forest cover monitoring is crucial [3]. In this context, high-resolution remote-sensing images collected from satellites, such as the European Sentinel-2A, -2B, or LandSat-8, offer potential and cost-efficient sources for an automatic solution [4].

Most previous studies focused on traditional methods using hand-crafted features, such as multi-variant change vector analysis (MVCA), normalized difference vegetation index (NVDI), and so on [1], [2], [5]–[9]. They have drawbacks that prevent their wide application, especially for non-domain experts in forestry and remote sensing technology. On the one hand, they require more effort and time due to the excessive dependence on handcrafted features. On the other hand, they are ad-hoc solutions that are suitable only for specific regions. Therefore, these methods are time-consuming and inefficient.

Recently, with the development of deep learning technology, the field of object detection in remote sensing images has made significant progress. Deep neural networks allow an automatic feature extraction, avoid feature selection and reduce manual steps in monitoring forest cover change [10]–[12]. Convolutional neural networks (CNNs) are one of the well-known deep learning algorithms that have been widely used in remote sensing image classification. They allow us to extract more meaningful features, the classification of these images usually results in higher performance [13].

For example, de Bem *et al.* [10] presented a method that used CNN and Landsat data for deforestation detection in the Brazilian Amazon. The authors applied three CNN architectures including U-Net, ResUnet, and SharpMask to classify the change between the years of 2017-2018 and 2018-2019. The experiment results show that the network achieved a high accuracy, without any post-processing for noise cancelling. Stoian *et al.* [11] also proposed an application of CNN to build land cover maps using high-resolution satellite image time series. Based on data from Sentinel-2 L2A, the U-Net network was applied in this study to deal with sparse annotation data while maintaining high-resolution output. Such networks are even applicable with incomplete satellite imagery in similar problems. For instance, Khan *et al.* [14] detected forest cover changes over 29 years (1987–2015), in which the authors faced issues of incomplete and noisy data. By using a deep CNN network, they mapped the raw data to more separable features. These features were employed to detect the changes. Many similar applications can be found in the literature, such as the works of [12], [15]–[20] and so on.

We are interested in monitoring forest cover change using deep learning. Numerous works, which applied deep neural networks, such as CNN, U-Net, and satellite images to detect forest loss areas, have been proposed worldwide [10], [11], [14], [21], [22]. However, in Vietnam, traditional machine learning is still widely used. In this paper, we proposed a method for coastal forest cover change detection in Vietnam. Based on sensing images from the European Sentinel-2A and -B, we trained a U-Net model to detect forest and non- forest areas. We then combined geographic information systems (GIS) information to compute the forest cover changes and evaluated results with available information from the national forest monitoring system. The proposed method is capable of applying to different areas, with less effort from domain experts.

The paper is organized as: section 2 introduces our research method. Section 3 presents the experimental results and discussion. Lastly, section 4 concludes the work conducted and proposes some future works.

2. RESEARCH METHOD

2.1. Method overview

The main objective of this study is to automatically detect and calculate coastal forest cover changes of Hai Phong city, Northern Vietnam. We performed pixel-level semantic segmentation on Sentinel-2A and 2B images, to classify forest and non-forest areas. These images were chosen from the same areas between two periods times. Therefore, combining with GIS information, we can detect and calculate forest cover changes. To do so, we realized three big steps, as presented in Figure 1, including:

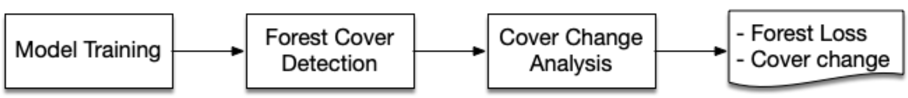


Figure 1. The proposed method

- Model training: in this first step, we trained a semantic segmentation model, which was based on U-Net neural network. The training dataset came from the Sentinel-2. We also evaluated the trained model using the forest cover layers extracted from the national forest monitoring system (FRMS) of Vietnam.
- Forest cover detection: after training, we applied the model to classify forest and non-forest areas of images of the same location taken in different times.
- Cover change analysis: lastly, based on forest covers at the two different times, we detected and calculated changes.

The model training consists of data preparation, model training, and testing. While the last two steps are composed of model using and GIS analysis. At each of these steps, we applied related techniques in deep learning, satellite image processing, GIS, and so on. The following sections will detail these steps.

2.2. Model training process

We adapted a traditional deep learning procedure, as shown in Figure 2 to train our model. Since remote sensing images are more complex and blurrier than others, we should perform several data preparation steps to clean and normalize the input data. Furthermore, to have an objective result, we based on real data, extracted from FRMS, to evaluate the trained model. This system supports state management in monitoring forest cover changes. The data is manually and regularly updated by Vietnamese local forest rangers, through a quantum geographic information system (QGIS) plug-in, developed by the development of a management information system for the forestry sector in Viet Nam (FORMIS) phase II project [23]. In short, after the data preparation step, we obtained two types of data: i) forest satellite images that were obtained after a series of data collection and pre-processing steps (more detail in the next section) and ii) forest cover layers that were extracted from the FRMS system and manually verified.

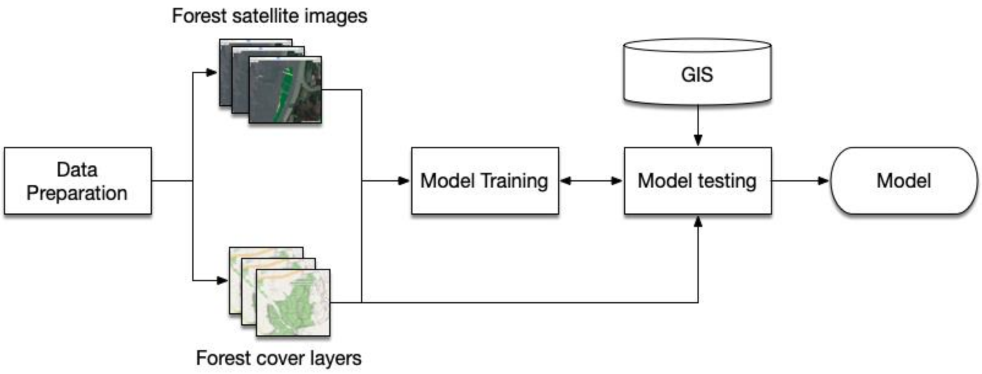


Figure 2. Model training process

The model was based on U-Net network architecture [24]. We used satellite images for model training. While, the information extracted from FMRS (forest cover layers), combined with GIS, was employed for model evaluation. The following section will detail the data preparation step.

2.3. Data preparation

We collected satellite images of Hai Phong city from the Sentinel-2 MSI: Multispectral Instrument, Level-2A [25] dataset available from March 28, 2017. Hai Phong is a port city, which locates in northern Vietnam, between 20030’N ÷ 21001’N and 106023’E ÷ 107008’E. The North borders with Quang Ninh province; Hai Duong province in the West; Thai Binh province in the South; and the East Sea in the east. The city possesses 3 a long mangrove coastal forest, with a total area of 26.127,58 hectare.

Since techniques to capture remote sensing and natural optical images are different, there are several challenges while working with satellite images. Therefore, several pre-processing steps should be performed before model training, as illustrated in Figure 3. First, we selected suitable scene images from Sentinel-2. For this purpose, remote sensing image processing was performed (the upper process in Figure 3):

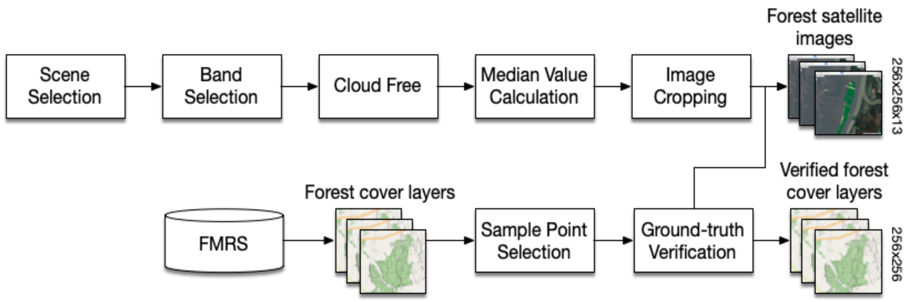
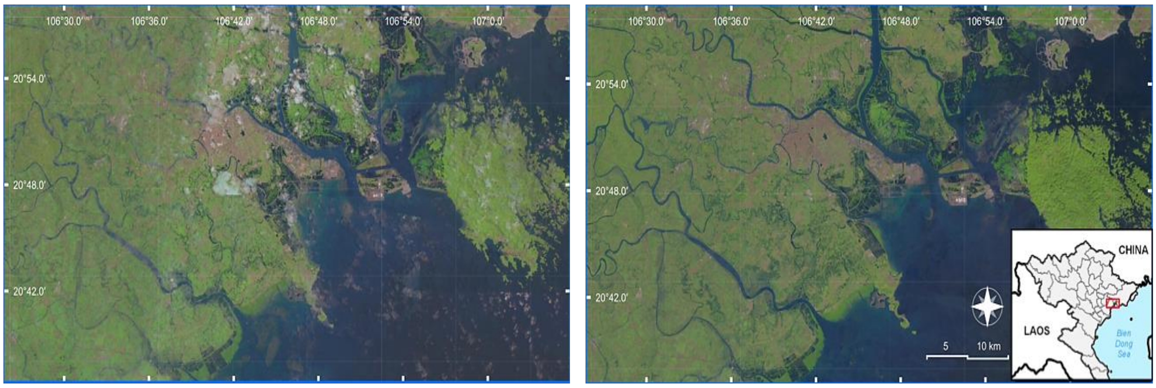


Figure 3. Data preparation and pre-processing

- Scene detection: we selected only image scenes at the coastal and mangrove forest of Hai Phong city. Then, we filtered and kept only images captured in 2018 and 2019. Lastly, the images with cloud rate greater than 30% were eliminated. After this step, we obtained 26 and 32 images captured in 2018 and 2019 respectively.
- Band selection: sentinel 2 have 13 spectral bands, with different bandwidth and spatial resolution. In this study, we directly used ten bands for input features, including the bands from 2 to 8, 8A, 11 and 12 with wavelength of 0.490 µm, 0.560 µm, 0.665 µm, 0.705 µm, 0.740 µm, 0.783 µm, 0.842 µm, 0.865 µm, 1.610 µm, and 2.190 µm. The bands 1, 9, and 10 were ignored because they are not relevant to vegetation [26]. Moreover, we also computed three indices: normalized difference vegetation index (NDVI), normalized difference snow index (NDSI), normalized difference water index (NDWI), which are widely applied in similar problems. They are computed as in (1).

$$NDVI = \frac{NIR-Red}{NIR+Red}; NDSI = \frac{Green-SWIR}{Green+SWIR}; NDWI = \frac{NIR-SWIR}{NIR+SWIR} \quad (1)$$

  where near infrared reflectance (NIR) is band 8, Red is band 4, Green is band 3, and short-wave infrared (SWIR) is band 11.
- Cloud free: we removed the cloud using the QA60 band, which is a bitmask band with cloud mask information [27]. Since bits 10 and 11 specify clouds and cirrus, we could filter all cloudy pixels. Figure 4(a) and Figure 4(b) show an example of selected images before and after cloud-free.
- Median value calculation: to improve the quality of images, we applied a median filter that moves through the image pixel by pixel, and replaced each value with the median value of neighboring ones.
- Image cropping: at this step, we cropped images to focus only on studied areas.



(a) (b)

Figure 4. Satellite images before (a) and after (b) cloud free

These scene images were then combined with forest cover layers extracted from FRMS to build a labeled pixel-level dataset for model training, as shown in the bottom process in Figure 3. We extracted four important pieces of information from FRMS, including administrative information, coordinates, forest observations (0 for non-forest, 1 for forest), detailed plot information. Since the forest cover layers were manually entered to FRMS by local rangers, therefore we conducted several field trips to verify the ground-truth labels. Based on the available resources, we selected a number of sample points to manually check if the information is correct (forest or non-forest). After verification, we got 1,500 sample points with correct labels. Centering on these points, two corresponding neighborhood patches were created, including i) image patches of size 256×256×13 from cropped satellite images and ii) forest cover layer of size 256×256, as presented in Figure 3. Finally, we obtained a dataset of size 256×256×14 for model training.

2.4. U-net neural networks

In this study, we applied U-Net which is a convolutional network for multi-class image segmentation [24]. It supports the per-pixel classification that allows us to predict the class of each pixel. We adapted the architecture proposed in [28] with fewer filters since our training set is limited, which also prevents over-fitting, as shown in Figure 5. Since the input size is 256×256×14, thus we have adapted the network architecture accordingly. Sigmoid activation functions were used to ensure that output pixel values range between 0 and 1.

2.5. Training and validation setup

We split the collected data into three datasets: the training set containing 1,000 image patches, the validation set containing 300 patches, and the testing set containing 200 patches. The model was trained using binary cross-entropy as loss function, Adam optimizer (e=10−7, β1=0.9, and β2=0.999), a mini-batch with a size of 100, and early-stopping criteria on the validation set. Before creating the batches, we also shuffled data, which helps our model to lean it better with more objective results. To evaluate the experiments, the F1 score, precision, recall, and accuracy were applied. The TensorFlow framework 2.2.0, Keras 2.3.1, Python 3.6, Tesla K80 GPU, and Intel Xeon (R) were used to implement our model.

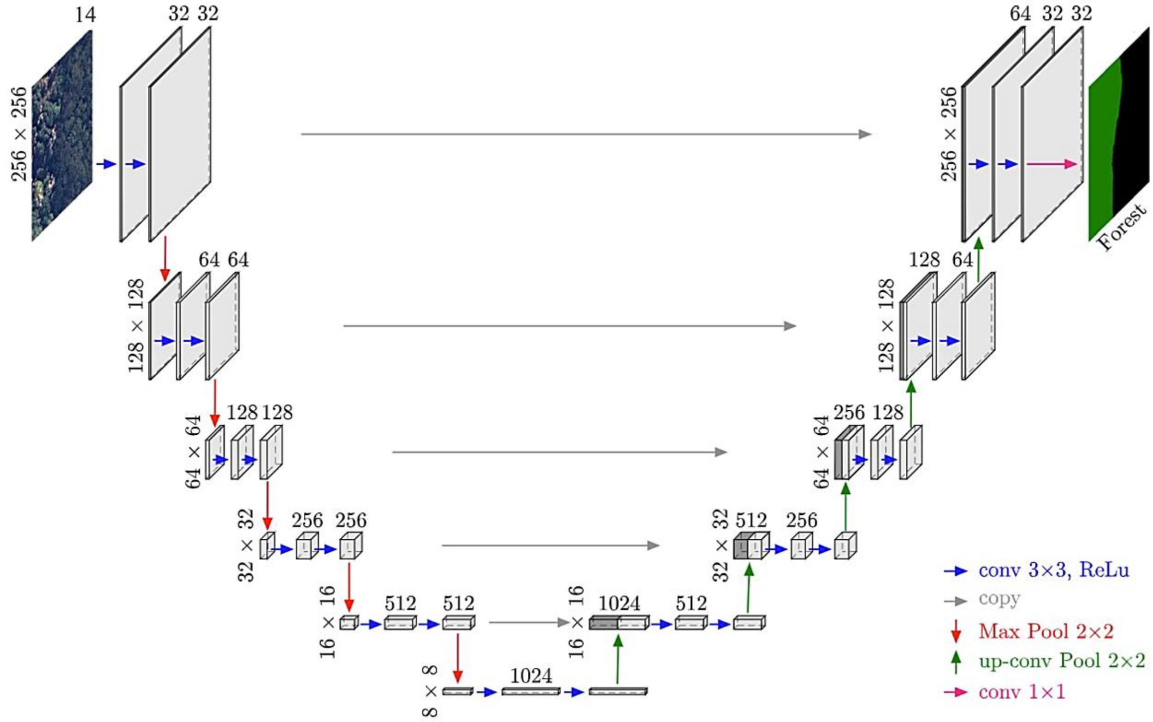


Figure 5. U-Net architecture [28]

2.6. Forest cover change analysis

After training and validating, we determined forest cover changes, as illustrated in Figure 6. The trained model detected forest and non-forest areas of images captured at different times on the same location. Obtained results were then compared to identify the cover changes. Combining with GIS information extracted from FRMS, we can calculate area changes.

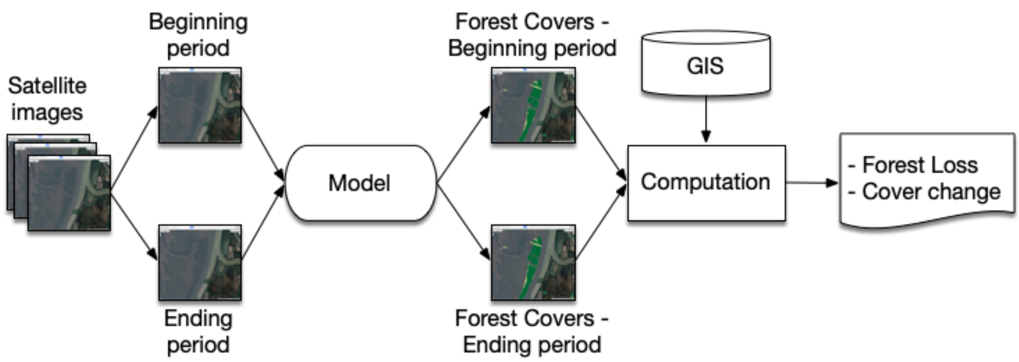


Figure 6. Forest cover change analysis

2.7. MVCA method

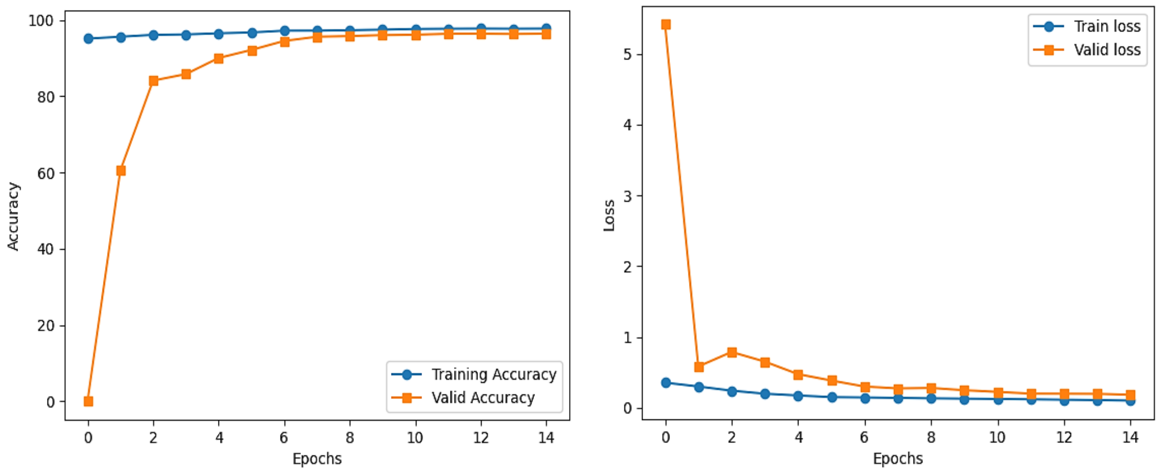
For performance evaluation, we compared the proposed method with MVCA that is widely used in Vietnam [7], [29]. This method is based on NDVI and NDSI of the beginning ($NDVI_b$, $NDSI_b$) and ending ($NDVI_e$, $NDSI_e$) period to calculate two change vectors, as shown in (2) and (3). Then, with the help of expert knowledge, the method uses two thresholds to determine forest loss. In this study, there is forest loss if $ChangeIndex1 > 48$ and $ChangeIndex2 > 16.8$.

$$ChangeIndex1 = \sqrt{(NDVI_b - NDVI_e)^2 + (NDSI_e - NDSI_b)^2} \quad (2)$$

$$ChangeIndex2 = (NDVI_b - NDVI_e) + (NDSI_e - NDSI_b) \quad (3)$$

3. RESULTS AND DISCUSSION

With early stopping, the training stopped at the 14th epoch. Figure 7(a) and Figure 7(b) show the model training progress over time in terms of accuracy and loss. The training and validation accuracy increase while training and valuation loss decrease as the number of training iterations increases. The gap between the curves is also small which indicates that no overfitting occurs. The model achieved a high accuracy of 97.7% on the validation set and 96.4% on the testing set. This high performance can be explained by the fact that the spectral and textural features of forest cover on RGB images are differentiable by the human eye, as presented in Figure 8. Due to the imbalance of labeled pixels, the precision, recall, and F1 score are 87.5%, 89.3%, and 87.2%, which are lower than the accuracy.



(a) (b)

Figure 7. Progress of accuracy (a) and loss (b) on the training and validation set

To detect forest cover changes, we applied the trained model to images of the same location taken in 2018 and 2019. The obtained results were then used to detect and calculate forest cover changes, as shown in Figure 8. The model accurately detected forest areas at the beginning and ending period (2018 - Figure 8(a), and 2019 - Figure 8(b)). Then, we mapped the two results and performed several GIS operations to get the forest cover changes, as detailed in Figure 8(c). According to the policy of the Vietnam government, an increase or decrease of forest covers, which is greater than 0.3 ha, will be considered to be a change. Therefore, we calculated and detected five forest loss areas, as presented in Figure 8(d) (red parts). The results were similar to those reported by local rangers in 2019. Therefore, our model is capable of accurately detecting forest cover changes.

Compared with existing methods that are widely applied in Vietnam, our proposed method is more robust and more accurate in forest cover detection. Experimental results show that our method outperforms MVCA by 3.8% (91.6% on the testing set). It allows detecting a higher level of forest disturbances, as shown in Figure 9. Figure 9(a) and Figure 9(b) shows forest cover changes (the white part and yellow part), predicted by MVCA and our proposed method, respectively. Our method produced results that are closer to the real data reported by local rangers.

Moreover, the proposed method requires less expert knowledge than methods based on NVDI, NVSI as in [1], [2], [7], [9], [29]. For these methods, domain experts are highly required to determine threshold values that are applicable only for a specific area. In contrast, our method does not require these thresholds. The model automatically learns useful features from input data to detect forest cover. Furthermore, as a deep learning model, our model can be incrementally trained with the new target areas. It means that the model can be gradually provided with new samples to update its weights and thus improve its classifications with time.

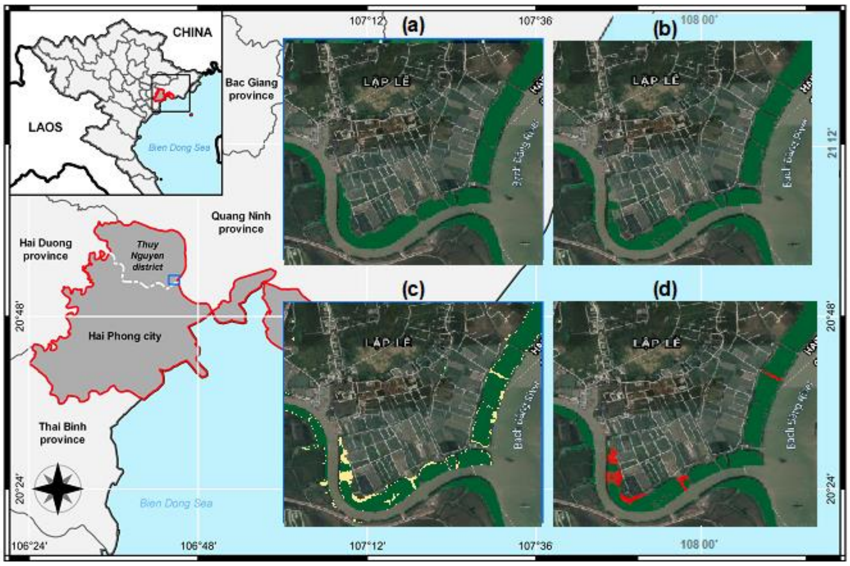


Figure 8. Comparing forest cover (dark green part) in (a) 2018 and (b) 2019 to compute (c) all forest changes (yellow part) and (d) the ones greater than 0.3 ha (red part)

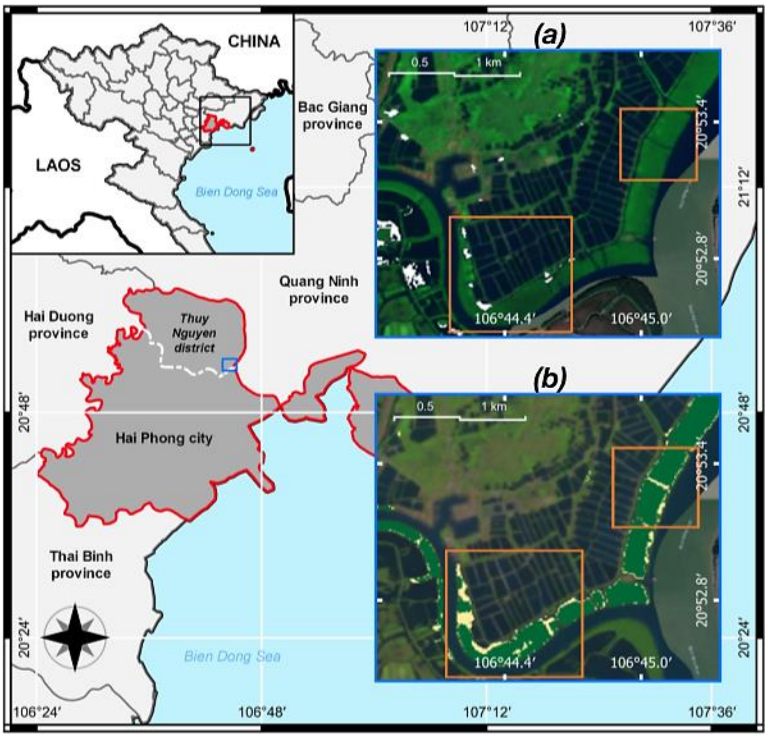


Figure 9. Forest and forest plot cover change prediction by (a) MVCA (green: forest covers; white: forest cover change) and (b) U-Net (green: forest covers; yellow: forest cover change)

Despite their advantages, the proposed method is not as easy to implement as MVCA and similar methods based on thresholds. It requires, on the one hand, a relatively large quantity of samples, and on the other hand, ground truth masks that can be challenging and time-consuming. Whereas the MCVA and similar methods work with simpler sampling schemes and can produce reasonably acceptable results. However, in Vietnam thanks to FRMS, we already have ground-truth labels that are regularly entered by local rangers. Therefore, the proposed method is able to be widely applied for automatically monitoring forest covers.

4. CONCLUSION

In this study, a deep learning based-method for coastal forest cover change detection has been proposed. We used multi-temporal Sentinel-2 imagery to train a segmentation model based on U-Net neural network. Furthermore, we evaluated the model with forest cover information extracted from the national forest resource monitoring system of Vietnam. The results shown that our method achieved a good performance on remote sensing images. The trained model achieved a high accuracy of 95.4% on the testing set and outperformed the popular methods based on thresholds in Vietnam. Future works will focus on tree species classification by improving the network architecture, increasing our dataset and proposing augmentation methods for forest cover images.

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BIOGRAPHIES OF AUTHORS

Dr. Khanh Nguyen-Trong holds a Doctor of Computer Science from University of Paris VI, France, in 2013. He received his M.Sc. (System and Networking) from University of Lyon I in 2008, his B.S (Information Technology) at Hanoi University of Science and Technology in 2005. He is now a lecturer at Faculty of Information Technology, Posts and Telecommunications Institute of Technology, Hanoi, Vietnam. He is a member of Naver AI lab (PTIT and Korean Naver cooperation) since 2020. His research includes Machine Learning, Deep Learning, Distributed Systems, Agent based Modelling and Simulation, Collaborative and Participatory Simulation and Modelling, and Computer Support Collaborative Work. He can be contacted at email: khanhnt@ptit.edu.vn.

Hoa Tran-Xuan received his B.S. in Information System at Vietnam Forestry University in 2012, and MSc in Information System at Posts and Telecommunications Institute of Technology, Hanoi, Vietnam in 2020. His main research interests are the application of information technology in forestry, Geographic Information Systems, Forest Cover Change Detection, and Forest Species Classification. Currently, Hoa Tran Xuan is a lecturer of Computer Science at Vietnam National University of Forestry. He can be contacted at email: hoatx@vnuf.edu.vn.