Google Earth Engine-based Mangrove Mapping and Change Detections for Sustainable Development in Tien Yen District, Quang Ninh Province, Vietnam

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Abstract

Vietnam secures a place among the top countries that possess the largest mangrove areas worldwide. The mangrove forests are mainly found in the Northern, Northeast, Central and Southern Delta, providing goods to habitants, and make significant help mitigate global climate change. Despite this, mangroves are severely threatened because of extensive deforestation in Vietnam. Recent advances have utilized remotely sensed imagery to present the spatial and temporal distribution of mangroves. Nevertheless, the approach is limited by imagery availability and computing resources, and difficult to share within the community. Therefore, a shareable Web-based tool that reinforces coastal managers to monitor the changes in mangroves is needed. Recently, Google Earth Engine (GEE) is a cloud-based geospatial analysis platform, which allows users to freely exploit the availability of satellite imagery and harness their computing capacity. This research aims to use GEE to detect mangrove changes, a case study in Tien Yen district, Quang Ninh, over a period from 2010 to 2020. Four supervised classification algorithms, including Random Forest (RF), Support Vector Machine (SVM), Naïve Bayes classifier, and Classification and Regression Trees (CART) have been implemented on GEE platform to select the best algorithm to produce spatial-temporal mangrove maps, then change detection of mangroves is performed. The results showed that RF demonstrated the highest accuracy with overall accuracy and kappa values of 91.04% and 0.75 respectively. The mangrove areas statistically reported by the GEE-based platform are in line with the governmental statistic report annually, marking the capabilities of GEE in natural resource management.

1. Introduction

Mangrove forests are the type of forest that thrives in the tidal river mouth and coastal area of tropical and sub-tropical regions (Spalding, 2010). The mangrove forests have the greatest above-ground biomass and carbon storage and have provided habitats for various species. Mangrove forests play crucial roles in human life, including providing habitat for valuable species, protection against disaster, carbon sequestration, recreation and tourism, wood (Chandra et al., 2010). According to the Food and Agriculture Organization (FAO), the total area of the world’s mangrove forests in the year 1990 is 15,8 million ha; however, this area has reduced to 15,2 million ha in 2005 (Ridder, 2007). Another report on the loss of mangrove forests (Bunting et al., 2022) shows that from 1996 to 2020, the world’s mangrove forest decreased from 15,3 to 14,8 million ha.

In Vietnam, a survey conducted by the United Nation Environment Program/Global Environment Facility (UNEP/GEF) East Sea project and the Institute of Forest Science under the Ministry of Agriculture and Rural Development (MARD) reported that the mangrove forest area in Vietnam decreased from approximately 0,30 ha in 1980 to approximately 0,15 ha in 2007 (Marchand, 2008). Tien Yen is a coastal district of Quang Ninh province, which inhabits 50,830 residents with the mangrove forest in this area is diverse and rich. Besides providing shelter for marine species, the mangrove ecosystem also brought high economic value and provided local inhabitants with stable livelihoods. Despite being a potential Ramsar area, there are signs that some parts of the mangrove forest have transformed into other land use types, especially aquaculture expansion and shrimp farming. In addition, coastal urbanization is another driver that contribute to the change of mangrove. Therefore, it is important to study the mangrove dynamics in this area. On the other hand, within the last decade, projects on restoration and development of coastal mangroves forests for the period 2008-2015 by MARD were deployed. In addition, the Decree 99/2010 issued by the Vietnam Government on payments for environmental services also stimulated and encouraged people to grow and protect mangroves forest. The results of these solutions have brought positive results or not is of great interest to the authority.

Remote sensing is the science and techniques of acquiring information about object, land area, phenomenon or ecosystem process through a device and without coming in contact with the object, area, or phenomena (Lillesand et al., 2015). Until now, remote sensing has been used in a wide variety of disciplines including mangrove forest assessment. Currently, many sources of free satellite imagery can be used for studying mangroves dynamics. Utilizing this abundant source of imagery, Google Earth Engine (GEE) was introduced to the scientific community in 2012. One of the most famous GEE applications is the work by Hansen et al. (2013) to identify forest cover change in the period 2000-2012 using 654,178 Landsat 7 scenes. Not only forest cover, GEE can play as the analysis platform for other objects such as drought, flood (Liu et al., 2018; Sazib et al., 2018). GEE is described as an innovative platform that enable user to integrate a huge amount of geospatial data (Liu et al., 2018). Meanwhile, Sazib et al. (2018) utilizes the GEE platform for

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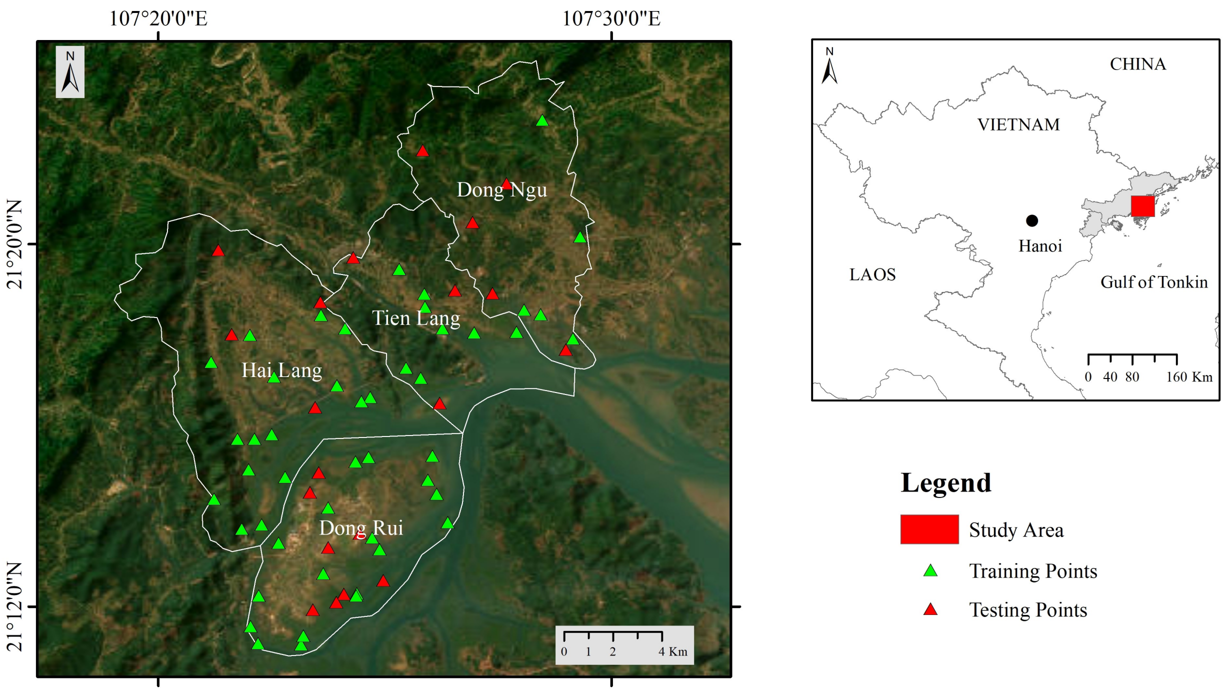

Figure 1. The study area, Tien Yen district, and the locations of ground truth points are marked by white border and colored triangles, respectively. The green triangles are training points, and the red ones are testing points, involving in classification algorithm selection.

drought assessment using global soil moisture data (SMAP). According to Sazib et al. (2018), the inclusion of SMAP dataset in GEE provides the users with quick and easy assessment of the drought condition. Moreover, GEE also improves the accessibility and usability of ET data and relevant tools by making them available to a wide range of researchers and the public. In fact, GEE is a cloud-based technology solution for processing satellite images as well as other Earth Observation data sources. GEE allows users to access directly to the global and multi-temporal satellite image archive. With its powerful and robust processing tools, GEE allows online analysis and calculation of huge data in a short amount of time. This study aims to utilize the robustness of GEE to process and analyze the big source of satellite imagery and to provide information on the effectiveness of the restoration activities in Tien Yen district.

In Vietnam, GEE has been applied in many applications, including the effects of human on sea/brackish water chlorophyll using the GEE platform (Quang et al., 2022). The authors use a time series of water covers to analyze the chlorophyll-a concentration. Since a wide range of remote sensing data sources are being integrated into the GEE storage, it is beneficial for the Earth Observation users. Vu et al. (2022) employed GEE to study the mangrove extent using Landsat time series . Mangrove changes were detected by using a per-pixel algorithm for multi-temporal Landsat imagery in a 32-year period. The study concludes that a pixel-based algorithm and the GEE platform has a high potential for monitoring long-term change of mangrove forests. Most recently, Pham et al. (2023) utilize GEE and machine learning for mapping lotus in Central Vietnam, which is a wetland type with high economic values in central Vietnam. Sentinel-1 and Sentinel-2 were used in combination to automate the extraction of water bodies and map the growing lotus. In line with the above-mentioned studies, the authors also find GEE a scalable potential and capable of mapping wetland types for large-scale.

This paper is organized as follows. Section 2 describes the data and methodology used in the study. In the methodology, besides the brief introduction about GEE, this section also mentions the preprocessing of the satellite imagery, introduce the spectral vegetation inputs, and discuss about the four algorithms used. Section 3 describes the results and discusses what have been achieved. Finally, section 4 presents our conclusions.

2. Data and Methodology

2.1 Study Area

Figure 2. Mangroves in the study area. The field trip was conducted in August 2020 to collect in-situ samples for model builder.

The study area is the mangrove forest located in Tien Yen district, Quang Ninh (21°18’17.3" N, 107°21’56.3" E), encompassing 4 communes: Hai Lang, Dong Ngu, Dong Rui, and Tien Lang (Figure 1). The communes are well-known for their diverse and rich mangrove ecosystem. Despite this, over the last decades, the mangroves have been significantly impacted due to indiscriminate logging, deforestation, and uncontrolled

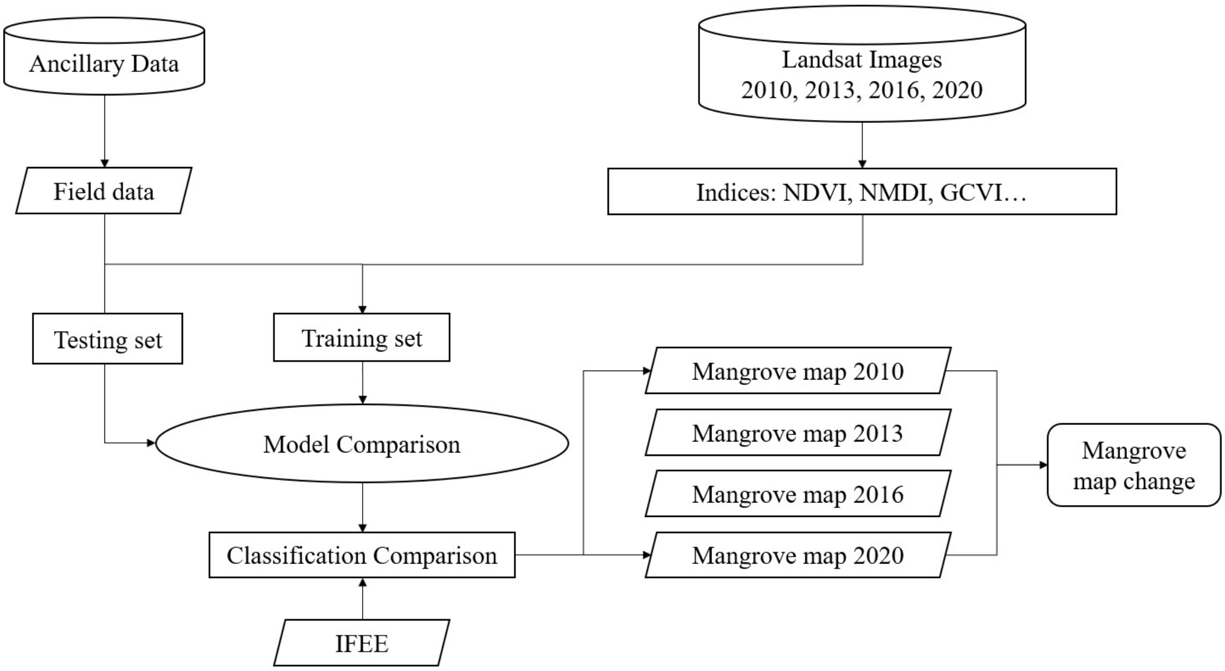

Figure 3. The methodogy in this study for mapping mangrove change using Landsat series images.

exploitation of marine resources, seriously affecting the ecological environment, production, and life of local communities (McNally et al., 2011). In addition, the study area falls within the diurnal tide with a tidal range is about 3,5 to 4,0 m. Therefore, the upstream flow in the rainy season often causes damage to the areas through the narrow Tien Yen River, such as flooding, freshening shrimp farms, and increasing erosion process (Tran et al., 2016).

Nearly 90% of the total species in Dong Rui Commune have potential in use such as medicine and edible (Nguyen and Mai, 2018). The other study states that mangrove forests in this area is qualified to be on the Ramsar List of Wetlands of International Importance (Nguyen et al., 2021). This is an important starting point because once recognized, Quang Ninh province will be empowered to respond to climate change more effectively and develop the resources of the mangrove forests. Therefore, monitoring the mangrove change in this area has a special meaning.

2.2 Materials

In this study, the materials consist of satellite imagery and field trip samples. Four scenes of satellite images captured study area by Landsat-7/8 satellite in 2010, 2013, 2016 and 2020 were used to produce the spatial-temporal mangrove maps. For each period, the median pixel was pulled out to make the composite image of the study area. In case of the Landsat 7 stripe errors, GEE correct stripe error by taking a mosaic of several Landsat 7 images. The remotely sensed images are cloud free at the study area, and with spatial resolution of 30 m. 67 locations of ground truth samples were recorded by using Trimble Handheld GPS during the field work in August 2020, divided into two sets: training set (n = 47) and testing set (n = 20). The classification results were then compared to the statistical data from the Institute for Forest Ecology and Environment (IFEE).

2.3 Methodology

The methodology mainly utilizes the capability of Google Earth Engine cloud-computing to process multi-temporal satellite images. Figure 3 demonstrated four main steps which has been implemented on GEE, including: 1) satellite image access and pre-processing, 2) vegetation spectral index calculation, 3) classification and 4) mapping change

2.3.1 Google Earth Engine (GEE):

In 2010, the Google Labs officially introduced GEE, which is powered by Google Cloud Platform-an online powerful computing platform. This allows users to freely access various types of satellite dataset such as radar data (Sentinel 1 GRD), optical data (Landsat, Sentinel 2), to monitor and analyze changes in the earth surfaces. To detect changes of mangrove forests, our research was conducted by using GEE’s code editor through the API application programming interface with a set of JavaScript programming libraries. Information processing and analysis are distributed in a network of computing servers with fast big data processing speed. The GEE data archive is continuously updated with the acquisition of new images. Therefore, an up-to-date spatial-temporal distributed maps are always produced (Ghosh et al., 2022).

2.3.2 Satellite image preprocessing:

GEE public data archive includes 40 years of historical imagery and scientific datasets and is updated and expanded on a daily basis. This archive includes a variety of standard raster datasets, for example: Landsat, MODIS, and more. This study used Landsat imagery for detecting mangrove change in study area. Landsat, with approximately 8 million images have continuously provided data for 40+ years with uninterrupted records of global-scale medium resolution data (Wulder et al., 2019). The cloud percentage property and quality bands of Landsat surface reflectance were used for masking clouds, shadows and

Table 1. Spectral Vegetation and Water Indices Formula

Index	Formula	Reference
NDVI	$NDVI = \frac{NIR-RED}{NIR+RED}$	(Rouse et al., 1974; Tarpley et al., 1984)
GCVI	$GCVI = \frac{NIR}{GREEN} - 1$	(Gitelson et al., 2005)
NDWI	$NDWI = \frac{GREEN-NIR}{GREEN+NIR}$	(McFeeters, 1996)
MNDWI	$MNDWI = \frac{GREEN-SWIR}{GREEN+SWIR}$	(Xu, 2006)
NDMI	$NDMI = \frac{NIR-SWIR}{NIR+SWIR}$	(Shi et al., 2016)

low-quality pixels in the study area. This huge data source was filtered by Dates and Region using Javascript on the GEE platform to narrow down the amount of Landsat data to be processed.

2.3.3 Spectral vegetation inputs:

To obtain spatially distributed mangrove map, previous studies have utilized several vegetation indices (VI) in classification approaches, instances include Simple Vegetation Index, Normalized Difference Vegetation Index (NDVI) (Rouse et al., 1974; Tarpley et al., 1984), Normalized Difference Moisture Index (NDMI) (Shi et al., 2016), Modified Normalized Difference Water Index (MNDWI) (Xu, 2006).

These indices are capable of maximizing spectral contrast among vegetative communities and discriminate wetlands and mangroves from other types of vegetation (Wu et al., 2012). A number of Landsat-derived VI have been proposed and some of indices relate directly to mangroves. The most common ones is the normalized difference vegetation index (NDVI), an index for detecting seasonal and inter-annual variations in canopy vigor. However, at the later stage of the season, the NDVI images become saturated on developed crops. By using GCVI, we can assess variation in the nitrogen and chlorophyll content of the vegetation (Gitelson et al., 2005). Therefore, with the ability to highlight variation in late crop, GCVI is more effective in late season applications.

NDMI is an index to enhance the separability between mangrove forests and terrestrial vegetation (Shi et al., 2016). The results show that the use of spectral metrics outperformed the use of raw band reflectance data. NDWI is an index developed by McFeeter to detect water (McFeeters, 1996). However, water information using the NDWI is often affected by built-up land, making the extracted water overestimated. In order to enhance open water features while efficiently suppressing noise from built-up and vegetation, Xu (2006) proposed the modified NDWI (MNDWI) based on the NDWI. Simple Ratio (SR) is the simplest VI which is a ratio between the NIR band and RED band (Jordan, 1969). Similarly, R54 and R35 are just the ratio between two bands of the images, in which R54 is SWIR/NIR and R35 is NIR/SWIR (Wu et al., 2012). These ratios are a quick way to discriminate green leaves from other objects. Also, these indices are useful in distinguishing stressed and non-stressed vegetation.

In this paper, some indices are used as masks to mask out the pixels that have little probability of being mangrove (Table 1). For example, by using NDVI value, the pixels with NDVI less than 0,1 would be less likely to be mangrove and was excluded from the classification. Similarity, the pixels with MNDWI values greater than (-0,5) would likely be mangrove and were kept. The resulting image after applying vegetation masks were used in the classification phase.

2.3.4 Supervised Classification Algorithms :

Four supervised classification algorithms, such as Naïve Bayes classifier, and Classification and Regression Trees (CART), Random Forest (RF) and Support Vector Machine (SVM) are used to produce spatial-temporal mangrove maps.

Naïve Bayes classifier is a supervised learning algorithm which is based on Bayes theorem and often used in classification problems. The classifier works on the basis of the probability of an object. Its name originates from the “naïve” assumption of conditional independence between every pair of features given the value of the class variable. The obvious advantages of the Naïve Bayes are that it works quickly and can save a lot of time. Moreover, if the assumption of the independence of features holds true, the algorithm can perform better than other models and requires much less training data. However, Naïve Bayes assumes that all features are independent, which is very rare in real life. Therefore, its applicability in real word cases is limited. Naïve Bayes was run in default mode. In GEE, only one parameter needs to be declared to run Naïve Bayes, which is lambda. Lambda is used to avoid assigning zero probability to classes which were not present during training.

The CART (Classification and Regression Trees) algorithm supervised learning algorithm that use decision trees for classification task in machine learning. The algorithm is in the form of basic if-else conditions. A model can be built up by growing the tree that means giving it more information to learn from. The more branches the tree has, the more accurate the model is. Compared to other classifier, this algorithm is easy to understand. However, CART is prone to overfitting. Even small variations in the data can lead to a very different decision trees. This disadvantage can be dealt with by using ensembles of decision trees. CART is composed of multilevel and multi-leaf nodes. In GEE, there are two parameters required to use CART: maxnodes and minleafpopulation. Maxnodes is the number of leaves per tree while minleafpopulation is the minimum number of node created only for the training set. The optimal minleafpopulation is chosen using empirical approach.

RF is a classification algorithm. It has gained popularity not only in remote sensing community but also for data science. Like CART, the concept of RF is easy to understand. RF is based on generating a large number of decision trees. By growing multiple DTs, the classifier can overcome the weakness of a single DT by combining them to form a more accurate model. The clear advantage of RF classifier is that it improves the accuracy of single decision trees by reducing overfitting and less prone to missing values. However, since RF consists of multiple decision trees, the computation can be overwhelming. Moreover, the significance of single variables is not emphasized, making interpretation harder. RF has maxnodes and minleafpopulation in its parameters. However, the two most important parameters are number of trees and variable per split. In this study, the number of trees was tested at 100 and 5 was chosen as the number of randomly selected predictors per split.

Support Vector Machine (SVM) is one of the most popular supervised learning algorithms, which is used for both classification and regression tasks. The idea of SVM algorithm is to find the best line or boundary that can segregate n-dimensional space into different classes. This line (or boundary) is called hyperplane. In the creation of hyperplane, SVM select extreme points/vectors. Hence, the algorithm has the name Support Vector Machine. SVM is more productive in high dimensional spaces and less prone to overfitting. However, it is difficult to understand and interpret the final model. In consequences, calibration to the model is not easy. Regarding SVM, three important parameters were declared: kernelType, gamma, cost. Radial Basis Function was used as the kernelType since this is one of the most popular kernel (Huang et al., 2002).

2.3.5 Accuracy assessment :

Accuracy indicates the correspondence between the classified image and reality. Accuracy assessment is the process in which the correctness of a classified image is evaluated. This process involves the comparison of the classified image to reference data that we considered to be true. GEE provide user with built-in function to assess the accuracy of the classifier. Random samples are generated for training and for testing. The ratio is decided by the user with the ratio is 70/30. The ground control points collected in the field trip in 2020 were used to construct the confusion matrix. In this study, overall accuracy and kappa coefficient were calculated. In addition, the data from IFEE were used for comparison with the resulting classification result.

3. Results and discussion

3.1 Selection of best classification algorithms

Accuracy assessment were then tested on the classification results of these four algorithms. The results show that RF algorithms provide the best accuracy. Both accuracy metrics (overall accuracy and kappa) of RF classifiers are on top of all the four employed classifiers. While the algorithm RF provides the highest overall accuracy with 91,04%, Naïve Bayes gives the lowest overall accuracy with 80,1%. Regarding kappa coefficient, RF is highest with 0,75 while SVM is lowest with 0,69. Based on this result, the study chose this algorithm to map the mangrove extent in the study area and perform change detection analysis.

Table 2. Accuracy assessment results of different classifiers

	Overall accuracy (%)	Kappa
Naïve Bayes	80,1	0,72
CART	85,24	0,70
SVM	88,9	0,69
RF	91,04	0,75

3.2 Spatio-temporal mangrove mapping from RF

The results derived from the satellite processing on GEE platform is shown in Figure 4. The figure comprises of two color to facilitate visual interpretation. The color green corresponds to the place where mangroves exist while the grey color indicates non-mangrove area. The classification results were then used for change detection using raster subtraction method on the GEE platform.

3.3 Mangrove changes detection

According to the Institute for Forest Ecology and Environment (IFEE) in 2010 and 2020, the area of mangrove accounts for 2459,9 ha and 2606,4 ha respectively.

Table 3. Classification result in comparison with the statistics from IFEE in 2010

	2010/GEE	**2010/IFEE**	Difference (ha)	Difference (%)
Dong Rui	1288,0	1325,7	37,7	1,5
Dong Ngu	156,2	172,1	15,9	0,6
Hai Lang	629,6	578,3	-51,3	-2,1
Tien Lang	402,5	383,8	-18,7	-0,8
Total	**2476,2**	**2459,9**		

Table 4. Classification result in comparison with the statistics from IFEE in 2013

	2013/GEE	**2013/IFEE**	Difference (ha)	Difference (%)
Dong Rui	1358,0	1425,7	67,7	2,8
Dong Ngu	156,2	162,1	5,9	0,2
Hai Lang	637,1	573,3	-63,8	-2,6
Tien Lang	404,5	378,8	-25,7	-1,0
Total	**2555,8**	**2539,9**		

Table 5. Classification result in comparison with the statistics from IFEE in 2016

	2016/GEE	**2016/IFEE**	Difference (ha)	Difference (%)
Dong Rui	1473,0	1513,26	34,3	1,4
Dong Ngu	156,2	163,37	7,2	0,3
Hai Lang	629,6	568,83	-60,7	-2,5
Tien Lang	402.5	375,28	-27,2	-1,1
Total	**2667,2**	**2620,7**		

Table 6. Classification result in comparison with the statistics from IFEE in 2020

	2020/GEE	**2020/IFEE**	Difference (ha)	Difference (%)
Dong Rui	1580,7	1513,3	-67,4	-2,7
Dong Ngu	150,5	162,2	11,7	0,5
Hai Lang	605,5	568,8	-36,7	-1,5
Tien Lang	399,9	362,1	-37,9	-1,5
Total	**2736,6**	**2606,4**		

The results show that the mangrove area in the study area is increasing. This result matches the statistics from the IFEE and some other studies which were conducted on the mangrove in the Northern coastal of Vietnam. Vu et al. (2022) utilized GEE platform to map multi-decadal mangrove extent in the Northern coast of Vietnam using Landsat time series. The study showed an increasing trend in the mangrove extent in some neighborhood of Quang Ninh province such as Thai Binh, Nam Dinh and Hai Phong. In fact, before 1975, mangroves in Dong Rui account for 3,000 ha. Since 1992, Tien Yen district and Dong Rui commune allocated 1,500 ha to local households. The landowners converted these areas into shrimp farm but the conversion did not bring the expected result. Since 2005, with the support from non-profit organization and other domestic investment sources, multiple mangrove plantation has been de-

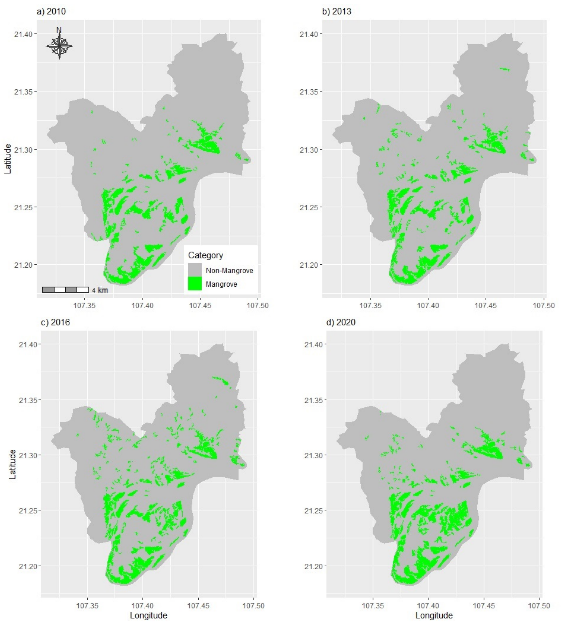

Figure 4. Mangroves extent of the study area in different dates.

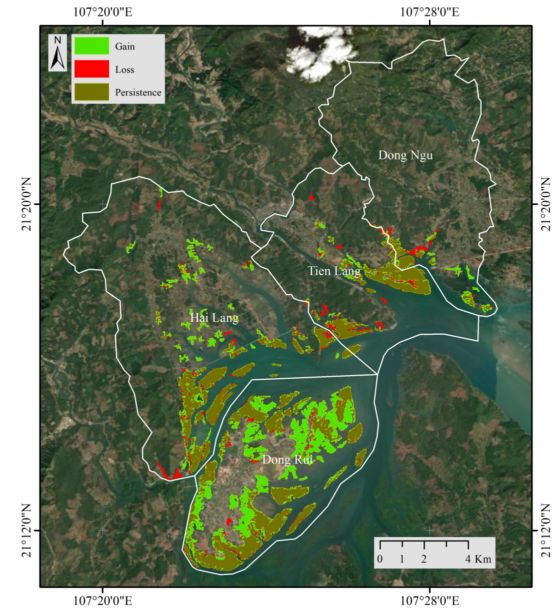

Figure 5. Mangrove change detection in Tien Yen District, Quang Ninh province between 2010 and 2020.

ployed. In line with the project, the authority has made propaganda to the people about the importance of the mangroves. The people are no longer cutting down the trees but actively protecting them instead. The authority also encouraged people to develop shrimp farm under the mangrove canopy to protect the forest, and at the same time improve their livelihood. As can be seen from Figure 5, while the “loss” is scattered among all 4 communes of the study area, the “gain” occurs dominantly in Dong Rui commune. The “gain” also occurs in other 3 communes, but the amount is negligible comparing to that in Dong Rui. One noteworthy point is that the “gain” often occur near-by or around the old mangroves patches. This is explainable since people tend to grow new mangrove trees close to where the old mangroves are, rather than grow isolated and farther mangrove patches. On the other hand, the “loss” often occur near the urban area, which is understandable taking into consideration the urbanization context.

Up to now, studies have been made to explore and demonstrate the utility of GEE for monitoring mangroves. These studies have encouraging results over conventional methods (Chen et al., 2017; Pimple et al., 2017; Tieng et al., 2019). Moreover, conventional methods result remain inaccessible to many users, GEE method produce the result which would reach a wider audience of non-specialist conservation managers and decision makers.

4. Conclusion

The research has established the process of processing, calculating, extracting and monitoring mangrove changes from Landsat imagery on GEE’s cloud computing platform and evaluated the change of mangrove area in the period 2010-2020. The analysis results show the increasing trend of mangroves in the study area. The research also explored the 4 GEE’s built-in classification algorithms. Among these algorithms, RF showed the highest accuracy.

With the advantages highlighted through this research, it can be said that image processing technology on cloud computing in general and on GEE platform in particular really has great potential for application in monitoring environmental resources including assessment of mangrove changes. If satellite image database systems or near-real-time environmental monitoring systems are quickly integrated into GEE’s storage, this will be a very effective processing and analytical environment in territory management as well as scientific research.

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