The problem of using segmentation data for change detection in surveyed areas in Thailand

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Abstract— The study of spatial changes is crucial in the field of remote sensing. To determine which areas undergo changes each year, we use change detection techniques to identify them changes over different periods. However, a limitation we faced with the data from Thailand was the lack of labeled data for change detection. To address this, we utilized segmentation data provided by experts who created new labels for change detection. Despite this effort, several issues arose during testing. This report details those challenges and the outcomes of our study

Keywords—remote sensing, change detection, segmentation, label (key words**)**

1.INTRODUCTION

Change detection and segmentation are crucial in the field of remote sensing. There has been significant research on segmentation [1,2,3,4,5,6] and change detection [7,8,9,10,11,12] in remote sensing. We aim to develop an Artificial Intelligence (AI) application that can assist experts in court by assessing forest encroachment cases. In such cases, geography experts typically demonstrate to the court the types of areas surveyed and the changes from previous years.Our initial goal for the application is to identify the area type and detect changes from the previous year. To achieve this, experts have classified the same area each year, generating segmentation data. This research experiments with using segmentation labels to create change detection labels, saving time in label creation for change detection. We investigate the feasibility and suitability of this approach.If successful, this method allows us to use a single segmentation label for both segmentation and change detection, significantly reducing the time needed for labeling. This study aims to produce a change detection model from the analyzed dataset, potentially streamlining future label creation processes

The study focuses on the Sai Yok District in Kanchanaburi Province, Thailand, which is an area of interest for the DSI in their forest encroachment cases

2. LITERATURE REVIEW

2.1. Image Segmentation

Segmentation refers to the classification of areas of interest into distinct regions, each represented by different colors. Numerous research studies have been conducted on segmentation [1,2,3,4,5,6]. Image segmentation divides an original image into regions with different colors, each indicating a specific type of area, such as buildings, rivers, forests, or agricultural land. For instance, Figure 1 illustrates an example of image segmentation applied to a satellite image of Sai Yok District, Kanchanaburi Province, Thailand. The image segmentation classifies the area into different colors, each representing a different type of land cover

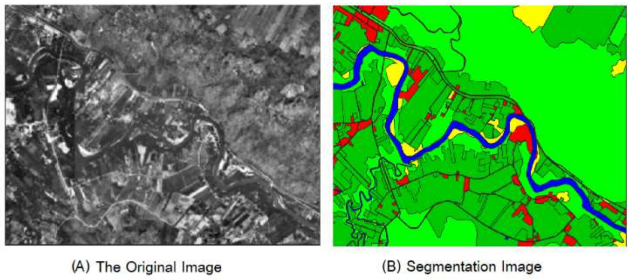
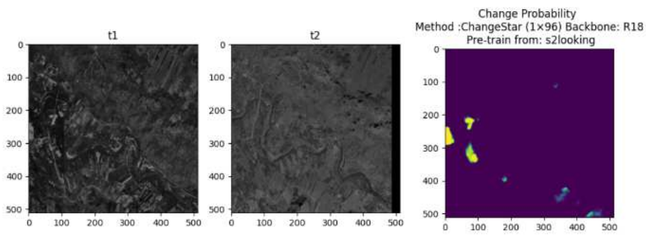


Figure 1 shows a satellite image of an area in Thailand, with the original image in (A) and the segmented image in (B)

2.2. Change detection

Change detection is a method in the field of neural networks that identifies differences in a specific area over different periods. The area in question must have the same coordinates but be observed at different times. There have been numerous studies on change detection [7,8,9,10,11,12]. The principle of change detection involves identifying pixels in images that exhibit changes between different time periods, distinguishing them from pixels that remain unchanged over both periods. An example of change detection is shown in Figure 2. The method highlighted is the ChangeStar method from the study [12], which tests change detection in Sai Yok District, Kanchanaburi Province, Thailand. The results produce a Gaussian noise map [13], indicating which pixels have differences.



Fsd2igure 2 : An example image using the ChangeStar method for change detection, where t1 represents data from 1994 and t2 represents data from 1999.

2.3 ChangeStar

In the research by Zhuo Zheng [12], the ChangeStar method for change detection is proposed. This method involves generating synthetic data using a Generator to create a Gaussian noise map [13], which indicates the coordinates where changes have occurred in satellite imagery. Specifically, it identifies areas where structures have been demolished compared to past imagery. This method focuses on detecting changes in buildings over different time periods. An example of the ChangeStar method is shown in Figure 3 [12].

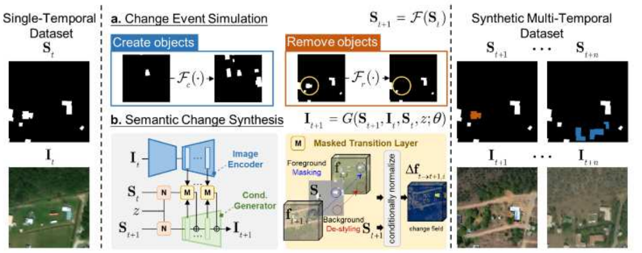


Figure 3: An example of the ChangeStar method [12], which can indicate where differences occur between two time periods, from t+1 to t+n

2.4 IMAGE SYNTHESIS

IMAGE SYNTHESIS [13] involves generating synthetic data using a Generator. The Generator creates pixels from noise, and the Discriminator adjusts the noise to match the labels of the real data as closely as possible

$$\mathcal{L}_D = -\mathbb{E}_{(x,t)}\left[\sum_{c=1}^{N} a_c \sum_{i,j}^{HxW} t_{i,j,c} \log D(x)_{i,j,c}\right] - \mathbb{E}_{(z,t)}\left[\sum_{i,j}^{HxW} \log D(G(z,t))_{i,j,c=N+1}\right], \quad (1)$$

From equation (1) states that G(X), the Generator, generates pixels from noise. D(X), the Discriminator, adjusts images predicted by the Generator to match the real images according to the specified label as accurately as possible. This equation shows that (Z, T), which represents noise generated by the Generator, is adjusted by the Discriminator to match the true label as closely as possible.

2.5 Model Evaluation

After training a model, it is essential to test and evaluate its performance before deploying it for real-world use. This evaluation assesses the accuracy and precision of the model. Typically, this involves using a testing dataset. Subsequently, the results are used to construct a Confusion Matrix [14], which comprises four categories [15], as shown in Figure 5. Here are the meanings of the variables

- True Positive (TP): When the model predicts an event as positive (true) and it actually occurs (true).
- True Negative (TN): When the model predicts an event as negative (false) and it indeed does not occur (false).
- False Positive (FP): When the model predicts an event as positive (true) but it does not occur (false) in reality.
- False Negative (FN): When the model predicts an event as negative (false) but it actually occurs (true).

	PREDICTED CLASS		
ACTUAL CLASS		Class=Yes	Class=No
	Class=Yes	(TP)	(FN)
	Class=No	(FP)	(TN)

Figure 4: Confusion Matrix **[15]**

In this research, values derived from the Confusion Matrix are used to evaluate the model's performance with 4 metrics

- Accuracy measures the overall correctness of the model by considering all outcomes, calculated using equation (2)

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FN+FP}, \quad (2)$$

-Precision It is a measure of model accuracy, evaluating results individually. This can be calculated using equation number (3)

$$\text{Precision} = \frac{TP}{TP+FP}, \quad (3)$$

-Recall evaluates the model's ability to correctly predict positives relative to all actual positives (4)

$$\text{Recall} = \frac{TP}{TP+FN}, \quad (4)$$

-F1-Score is the harmonic mean of Precision and Recall, providing a single metric to measure the model's capability, calculated using equation (5)

$$\text{F1} - \text{Score} = \frac{2\,x\ \text{Precision x Recall}}{\text{Precision} + \text{Recall}}, \quad (5)$$

2.6 Introduction of XOR Operation

XOR is a binary mathematical operation primarily used in logical operations, denoted as " ⊕ ". An example equation is (6)

$$a \oplus b = (\neg a \wedge b) \vee (\neg b \wedge a), \quad (6)$$

THIS OPERATION YIELDS 1 WHEN VALUES AAA AND BBB DIFFER, AND 0 WHEN THEY ARE IDENTICAL. XOR OPERATIONS ARE WIDELY APPLIED IN FIELDS SUCH AS IMAGE PROCESSING [16].

3.METHODOLOGY

3.1. Data preparation

In this step, the selected study areas are determined based on the scope of the study. This study focuses on five specific areas: forests, agricultural areas, built-up areas, and rivers. The designated study area is the Sai Yok District, Kanchanaburi Province, Thailand. The dataset consists of five sets of images taken at the same location but during different time periods, as detailed in Table 1.

Table 1: All data to be used

image remote sensing name	year	scale
01-Saiyok_Ortho_wws	1953	1:4000
02-Saiyok_Ortho_vap	1967	1:4000
03-Saiyok_Ortho_dol	1994	1:4000
04-Saiyok_Ortho_nima	1999	1:4000

3.2. Data label

Labeling the data involves selecting previously gathered data and dividing them into classes for study. For instance, in Figure 5, the data is categorized into 4 classes: built-up areas, forests, agricultural areas, rivers, and others. This data is suitable for segmentation tasks, but we will investigate its applicability for change detection purposes

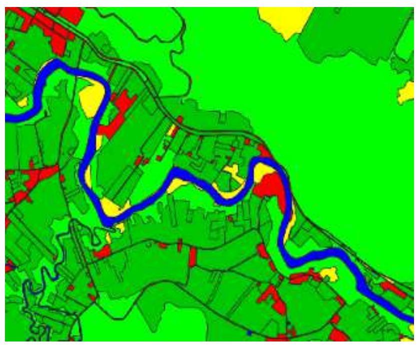


Figure 5: specifies the labels for the surveyed areas

3.3. Data Segmentation for Change Detection

In this process, we convert data from image segmentation into data usable for change detection. Initially, we divide the data into 4 sets, each with only 2 classes:

- Built-up areas and others
- Agricultural areas and others
- Forest areas and others

- River areas and others

"Others" refer to areas that are not specifically classified into any of the designated classes. An example dataset is illustrated in Figure 6.

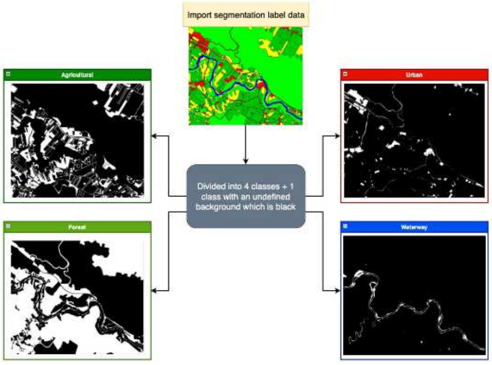


Figure 6: Division of Image Segmentation Data into Sets

Once we separate the Image Segmentation data into individual sets, we obtain new Image Segmentation data that consists solely of black and white colors. This can be likened to binary data where black represents 0 and white represents 1 . With this Image Segmentation data, we can perform Change Detection by Exclusive OR (XOR) of the data from different time periods, as illustrated in Figure 7.

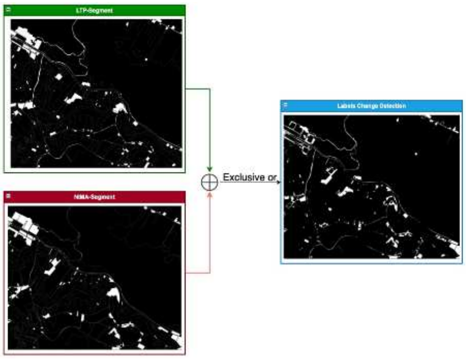


Figure 7: Creating Change Detection using Image Segmentation by Exclusive OR (XOR) of Image Segmentation from Two Time Periods.

3.4 Pre train and test model

After obtaining the Change Detection data sets, we proceeded to create datasets for training and testing the model. Each dataset included original images from both old and new time periods, along with labeled images indicating the differences between the two time periods. Each dataset was sized at 2000x2000 pixels, containing between 8000 to 10000 images. For example, Figure 8 illustrates the data format. In this research, we focused only on the class of built-up areas for testing, using the ChangeStar model. ChangeStar is a recent model known for its speed, accuracy, and suitability for detecting built-up areas, which has been studied extensively due to the lack of effective Change Detection models for other areas. In training the model, we utilized the S2Looking and LEVIR-CD datasets for experimentation, while different datasets were employed for testing, ensuring a clear separation between the training and testing data. In instances where certain datasets could not be used for training, alternative approaches were considered

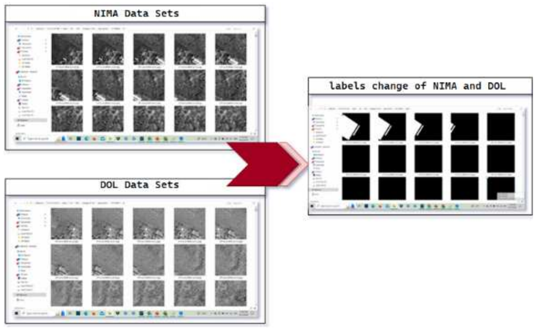


Figure 8: Example Data for Training and Testing the Model

4.RESULTS OF TRAINING AND TESTING

From the training data, it was found that the model could not be trained effectively. This was since the surveyed area showed a change of only 4.27% in built-up areas. As a result, the model could not learn from the data. Upon further investigation, it was identified that there were significant issues with the Change Detection data derived from Image Segmentation. One major issue was the inconsistency in labeling between the two time periods. The individuals performing the labeling did not frame the labels in the Image Segmentation uniformly. When XOR-ed, this led to substantial errors in the data. As illustrated in Figure 9, white areas labeled as unchanged in both T1 and T2 still showed discrepancies in the labels, indicating changes. This inconsistency arises from the inability of the labelers, whether different individuals or the same person, to ensure uniform labeling sizes in segmentation. This contributed to a significant error in this experimental setup.

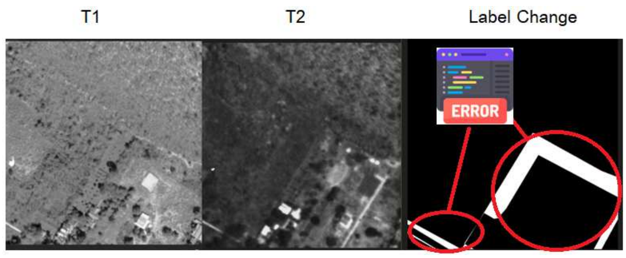


Figure 9: Example of Errors in the Dataset

When the ChangeStar model could not be trained with this dataset, we used models trained on data from S2Looking [17] and LEVIR-CD [18] to train the ChangeStar model and test it with this dataset from the survey in Thailand. The S2Looking and LEVIR-CD datasets are like our study dataset as they also use satellite images for detecting built-up areas. The study areas for these datasets are in the United States. The test results are shown in Table 2 and Table 3.

Table 2: Test Results of the ChangeStar Model Trained on the LEVIR-CD Dataset

dataset test	Precision	Recall	Accuracy	F1 Score
LEVIR-CD	0.49	0.864	0.46	0.63
LTP-NIMA	0.02	0.026	0.91	0.023
VAP-LTP	0.016	0.022	0.89	0.019
WWS-LTP	0.016	0.024	0.9	0.019
VAP-NIMA	0.018	0.027	0.88	0.022
WWS-NIMA	0.01	0.02	0.87	0.014

Table 3: Test Results of the ChangeStar Model Trained on the S2Looking Dataset

dataset test	Precision	Recall	Accuracy	F1 Score
S2Looking	0.66	0.412	0.342	0.51
LTP-NIMA	0.025	0.007	0.95	0.011
VAP-LTP	0.0057	0.0023	0.94	0.0032
WWS-LTP	0.006	0.003	0.94	0.0035
VAP-NIMA	0.05	0.04	0.91	0.044
WWS-NIMA	0.02	0.017	0.92	0.018

As shown in the experimental table, the precision and recall values are significantly lower compared to the datasets used to train the model, such as S2Looking and LEVIR-CD. This is due to the errors in the data, as previously mentioned. The errors from creating data through Image Segmentation are substantial, as illustrated in Figure 10

Figure 10: Example of Errors from the Entire Research Area of the LTP-NIMA Dataset

As shown in the image, there are numerous errors in the labels. However, since the data has minimal changes, the accuracy appears better than expected. Nonetheless, the errors in the data result in very low precision, recall, and F1-score values. An example of the model's test results compared to the labels for the entire study area of the LTP-NIMA dataset is illustrated in Figure 11. The model successfully detects changes between the two time periods, but it fails to detect some areas due to errors in the data

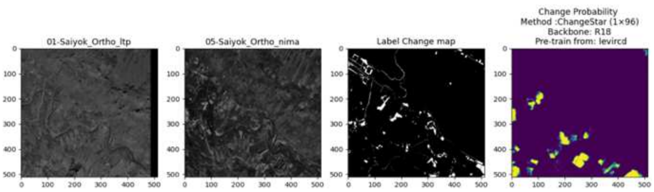


Figure 11: Results from the ChangeStar Model Compared to the Labels Used

5.CONCLUSION

Based on the experiments conducted, it was found that the study area in Amphoe Sai Yok, Kanchanaburi Province, Thailand, exhibited minimal land cover change, with the maximum percentage of change detected being only 4.27%. This indicated that the area may not be suitable for developing a dedicated change detection model using the ChangeStar model alone. To improve the effectiveness of such models, data augmentation techniques [19] would be essential to augment the dataset with additional suitable data. Moreover, the challenges encountered during the creation of data for change detection from image segmentation data further highlighted a great deal of difficulties. These challenges primarily stemmed from discrepancies in labeling within the image segmentation data due to varying label sizes. For future work in change detection, it is recommended to directly label the data for change detection rather than relying solely on image segmentation data. This approach would mitigate errors within the data and facilitate the challenging task of data cleansing

6.FUTURE WORK

In future work, there are several tasks that will be undertaken, such as data augmentation [19] to generate additional data for creating change detection models using data from the studied area. Another task involves developing models for land segmentation based on the studied area to enable the development of AI applications that can be used for legal considerations in court proceedings in the future

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REFERENCES

[1] Zhao, L., Qiao, P., & Dou, Y. (2019, December). Aircraft Segmentation Based On Deep Learning framework: from extreme points to remote sensing image segmentation. In *2019 IEEE Symposium Series on Computational Intelligence (SSCI)* (pp. 1362-1366). IEEE.

[2] Pan, S., Tao, Y., Nie, C., & Chong, Y. (2020). PEGNet: Progressive edge guidance network for semantic segmentation of remote sensing images. *IEEE Geoscience and Remote Sensing Letters*, *18*(4), 637-641.

[3] Dong, S., & Chen, Z. (2021). Block multi-dimensional attention for road segmentation in remote sensing imagery. *IEEE Geoscience and Remote Sensing Letters*, *19*, 1-5.

[4] Shi, F., & Zhang, T. (2022). An anchor-free network with box refinement and saliency supplement for instance segmentation in remote sensing images. *IEEE Geoscience and Remote Sensing Letters*, *19*, 1-5.

[5] Qi, Z., Zou, Z., Chen, H., & Shi, Z. (2022). Remote-sensing image segmentation based on implicit 3-D scene representation. IEEE Geoscience and Remote Sensing Letters, 19, 1-5.

[6] Mustafa, N., Zhao, J., Liu, Z., Zhang, Z., & Yu, W. (2020, September). Iron ORE region segmentation using high-resolution remote sensing images based on Res-U-Net. In IGARSS 2020-2020 IEEE International Geoscience and Remote Sensing Symposium (pp. 2563-2566). IEEE.

[7] Liang, C., & Chen, Z. (2022, September). A self-supervised hierarchical clustering network for multiple change detection in multitemporal hyperspectral images. In 2022 12th Workshop on Hyperspectral Imaging and Signal Processing: Evolution in Remote Sensing (WHISPERS) (pp. 1-4). IEEE.

[8] Zhang, W., & Fan, H. (2020, June). Application of isolated forest algorithm in deep learning change detection of high resolution remote sensing image. In 2020 IEEE International Conference on Artificial Intelligence and Computer Applications (ICAICA) (pp. 753-756). IEEE.

[9] Shao, R., Du, C., Chen, H., & Li, J. (2021). SUNet: Change detection for heterogeneous remote sensing images from satellite and UAV using a dual-channel fully convolution network. Remote Sensing, 13(18), 3750.

[10] Chen, H., Li, W., & Shi, Z. (2021). Adversarial instance augmentation for building change detection in remote sensing images. IEEE Transactions on Geoscience and Remote Sensing, 60, 1-16.

[11] Lv, D., Li, F., Guo, Q., Wang, X., & Chen, T. (2018, October). Unsupervised change detection in remote sensing image based on image fusion in nonsubsampled shearlet transform domain and fuzzy k-means clustering. In 2018 IEEE 3rd Advanced Information Technology, Electronic and Automation Control Conference (IAEAC) (pp. 1568-1573). IEEE.

[12] Zheng, Z., Tian, S., Ma, A., Zhang, L., & Zhong, Y. (2023). Scalable multi-temporal remote sensing change data generation via simulating stochastic change process. In Proceedings of the IEEE/CVF International Conference on Computer Vision (pp. 21818-21827).

[13] Edgar Schonfeld, Vadim Sushko, Dan Zhang, Juergen Gall, ¨ Bernt Schiele, and Anna Khoreva. You only need adversarial supervision for semantic image synthesis. In ICLR, 2021.

[14] Visa, S., Ramsay, B., Ralescu, A. L., & Van Der Knaap, E. (2011). Confusion matrix-based feature selection. Maics, 710(1), 120-127.

[15] Subasi, A. (2020). Practical machine learning for data analysis using python. Academic Press

[16] Ye, H., Huang, S., & Liu, W. (2020, June). Research on image scrambling method based on combination of Arnold transform and exclusive-or operation. In 2020 IEEE 4th Information Technology, Networking, Electronic and Automation Control Conference (ITNEC) (Vol. 1, pp. 151-154). IEEE.

[17] Li Shen, Yao Lu, Hao Chen, Hao Wei, Donghai Xie, Jiabao Yue, Rui Chen, Shouye Lv, and Bitao Jiang. S2looking: A satellite side-looking dataset for building change detection. Remote Sensing, 13(24):5094, 2021.

[18] Chen, H., & Shi, Z. (2020). A spatial-temporal attention-based method and a new dataset for remote sensing image change detection. Remote Sensing, 12(10), 1662.

[19] Huang, R., Wang, R., Guo, Q., Wei, J., Zhang, Y., Fan, W., & Liu, Y. (2023, June). Background-mixed augmentation for weakly supervised change detection. In Proceedings of the AAAI Conference on Artificial Intelligence (Vol. 37, No. 7, pp. 7919-7927).