Drainage canal map detection of tropical peatlands over Indonesia by PALSAR-2 image

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ABSTRACT: Carbon dioxide (CO_2) accounts for large part of greenhouse gas and its budget estimation is heavily needed for quantitative evaluation of greenhouse gas (GHG) management policies like carbon emission trading. Among various CO_2 emission sources, peatlands are dominant ones and the carbon stored in these areas occupies one-third of global soil organic carbon. In peatlands, the effect of drainage canals is significant since the decrease of groundwater level is the major factor in CO_2 emission in peatlands and is affected by those canals, therefore grasping the distribution of drainage canal is essential. Few researches have been conducted related to this theme although drainage canal of Indonesia has been known as human effect. These studies leave an issue in terms of accuracy in mapping the drainage canals owing to the characteristics of used methods. The objective of this research is to make more precise drainage canal map in non-forested area in Indonesia using microwave satellite images from ALOS PALSAR-2. This research selected HH polarimetric for edge detection of drainage canal.

1. INTRODUCTION

The amount of carbon dioxide (CO_2) occupies most part of greenhouse gas emission now and its increase is concerned globally. There're various emission sources of carbon dioxide, but among them peatland is so dominant one in terms of emission amount despite its covering area. Natural peatlands do not emit any carbon dioxide due to high ground water level, but it is released in drained peatlands. Therefore, the ground water level is a key factor to the amount of carbon dioxide emission. In peatlands, the presence of drainage canals has a significant effect to the ground water level, so grasping the distribution of them is essential to estimate carbon emission amount. So as to identify the drainage canal distribution in large scale, satellite images are useful since they can cover most of all targeted areas. There're some varieties in satellite images depending on sensor types, band types and so on. Among various satellite images, microwave satellite images are effective for object detections since they can penetrate through clouds or dusts and represent ground surface situations. There were some researches related to change detection and object detection using microwave satellite imagery (Mountrakis et al., 2011, Liu et al., 2017, Park and Takeuchi, 2014). However, researches trying to do drainage canal detection are so few and leave some problems (Park and Takeuchi, 2014). The objectives of this research are 1) to identify the distribution of drainage canals of tropical peatlands in non-forested area in Indonesia using satellite imagery, and 2) to compare the performance between two scales of spatial resolution PALSAR-2 data at 10m and 25m scales. This study can contribute to more precise CO_2 budget estimation by grasping the accurate distribution of drainage canals which are dominant factors in CO_2 emission in peatlands.

2. METHODOLOGY

The flowchart of dataset and methods applied for drainage canal detection is shown in Figure 1. A microwave image of Advanced Land Observing Satellite (ALOS) Phased Arrayed L-band SAR (PALSAR)-2 from the Japan Space Exploration Agency's (JAXA) was used for detecting drainage canal in Indonesia. The backscatter intensities were converted using coefficient factor -83 (Eq. 1). Enhanced Lee filter was conducted as a preprocessing. Drainage canals were detected by using a machine learning model (Pix2pix).

$$\sigma^0 = 10 \times \log_{10}(DN^2) - 83 \qquad (1)$$

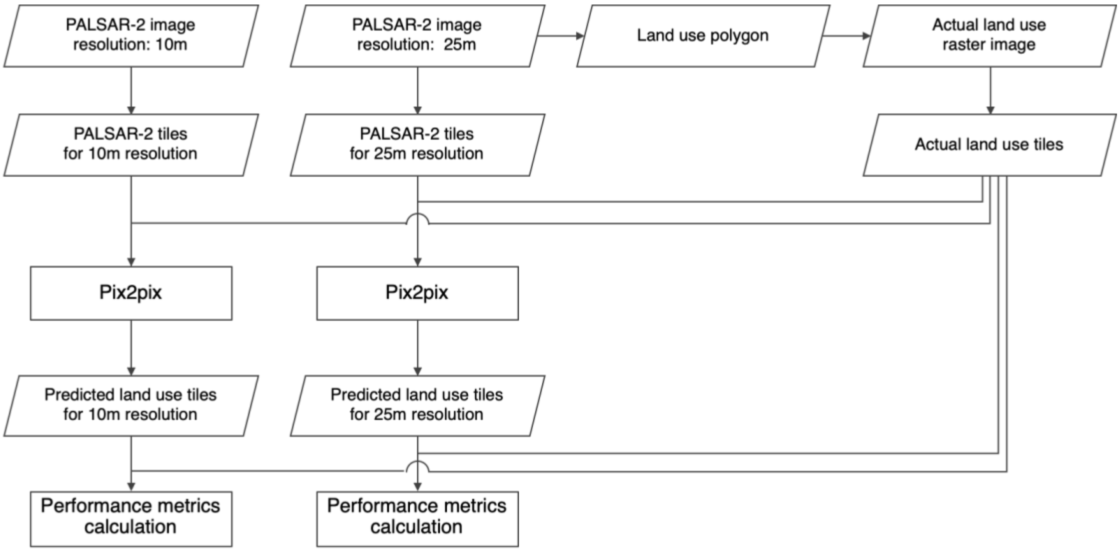


Figure 1. Flowchart of this research

2.1 Data

The study area of this research is shown in Figure 2. This area is located in Sumatra in Indonesia, and is about 12,000 ㎢ (001S, 102E – 000N, 103E). PALSAR-2 images were used in this study. Especially, HH polarization image was chosen for the detection of drainage canals on land surface with 25m of resolution since HH can represent how rough the surface is. Drainage canals were generated by human activity and have a shape of two edges of surface. Using this characteristic, canals would be clearly shown from HH polarization. Furthermore, smaller scale of drainage canals is available to be captured by PALSAR-2 since it has high resolutions at 10m and 25m scales. This study also aimed to compare the usefulness of both data including 10m and 25m.

Figure 2. Study area of Sumatra in Indonesia (001S, 102E – 000N, 103E) with a green rectangle

2.2 Pix2pix

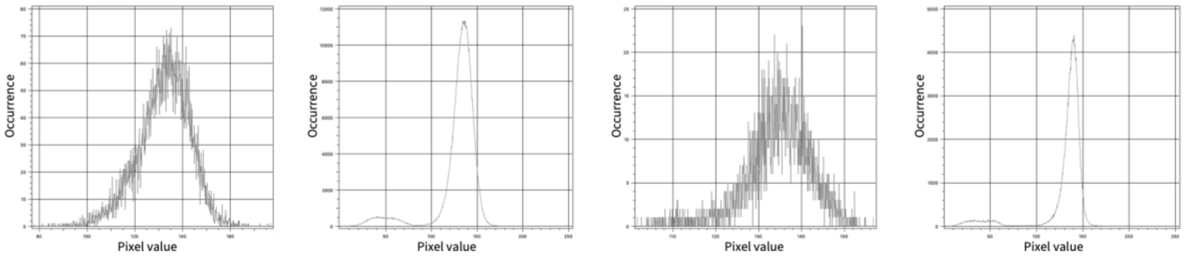
Pix2pix is an image-to-image translation method and uses conditional generative adversarial network (cGAN) to learn a function to make an output image from an input image (Isola et al., 2017). In this study, we applied pix2pix method to drainage canal detection. Detailed flow of this study is mentioned in following sections.

2.3 Detection of the Drainage Canals

First of all, the Enhanced Lee filter was applied to the PALSAR-2 images of both resolutions and noises of the images were reduced in a way mentioned above. After filtering, we classified each pixel of the image to two classes (drainage canal class, non-drainage class) using land use polygon and made actual land use raster images using 25m resolution imagery. The index color data of these two classes is shown in Table 1. Figure 3 shows the histograms of all classes in two different resolution imageries. In this figure, horizontal axis corresponds to pixel value and vertical axis to occurrence of pixel value. We can see each class has own peak pixel value from these histograms. Classifying and land use raster data making process were followed by masking of the images. Masking was done using threshold value obtained from histograms of all classes. By increasing the pixel values which are higher than the upper threshold value to maximum and decreasing them if they are lower than the lower one to minimum, and extending the remaining pixel values between these threshold values, the value difference between both classes becomes more distinct. In this study, we set the value 160 as the upper threshold value and the value 100 as the lower one. Masking process was also carried out to both resolution imageries. After these processes were done, both images (land use data and PALSAR-2 satellite data) was cut to small 256×256 pixel image tiles and the detection was done by using pix2pix method for each resolution. We made 150 image tiles in total in each resolution and 100 images were used for training, remaining 50 images were for testing.

Table 1. Index color data of land use classification

	R	G	B
Drainage canal	255	0	0
Non-drainage canal	0	255	0



(a) Drainage canal in 10m resolution (b) Non-drainage canal in 10m resolution (c) Drainage canal in 25m resolution (d) Non-drainage canal in 25m resolution

Figure 3. Histograms of each class in each resolution

2.4 Performance Metrics

To quantitively assess the quality of the model outputs, we need some evaluation metrics. However, each pixel in output images doesn't necessarily have the exact RGB values shown in Table 1 unlike the land use images, therefore the model evaluation cannot be performed just as it is. So, we converted each pixel value of output images in the way as follows. Firstly, RGB vectors of each class were created. These vectors just have the corresponding RGB values for each class as shown in Table 1. Secondly, RGB vectors of each output images were created. These vectors don't necessarily have the exact same values as the ones of each class. After creating these vectors, the values of each RGB vector of output images were converted to the same values as the RGB vector of the class which has the smallest distance to it. This conversion means finding nearest class to each pixel in output images.
After these processes, a confusion matrix was created for each class. Each value of these matrixes is calculated based on the number of pixels which were classified correctly or wrongly. In addition to confusion matrixes, we also calculated some metrics; accuracy, recall and precision. These metrics are all calculated based on confusion matrixes. Accuracy means how many pixels were classified correctly and recall illustrate how many drainage canal pixels were predicted correctly, while precision is a metric showing how many pixels were actually drainage canals out of all pixels classified as drainage canals.

3. Result and Discussion

3.1 Result

Examples of the detection results of the 50 test dataset in each resolution by pix2pix are shown in Figure 4. Figure 4(a) shows result examples of drainage canal detection in 10m resolution while Figure 4(b) illustrates 25m resolution ones. Red and green each correspond to drainage class and non-drainage class as mentioned above. The confusion matrixes are shown in Table 2 and Table 3 for each resolution. Figure 5 shows three metrics for each resolution.

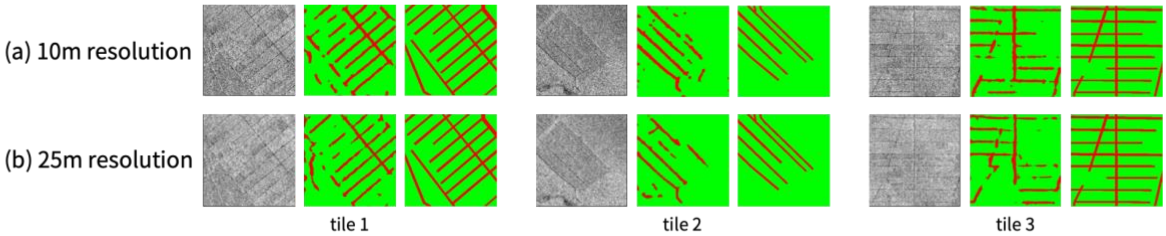


Figure 4. Examples of the detection results in each resolution by pix2pix for test data
(Input, Output, Correct image)

Table 2. Confusion matrix for 10m resolution

	Model output: Drainage canal	Model output: Non-drainage canal	
Correct class: Drainage canal	310,536	199,110	509,646
Correct class: Non-drainage canal	107,491	2,659,663	2,767,154
	418,027	2,858,773	

Table 3. Confusion matrix for 25m resolution

	Model output: Drainage canal	Model output: Non-drainage canal	
Correct class: Drainage canal	279,983	229,663	509,646
Correct class: Non-drainage canal	98,699	2,668,455	2,767,154
	378,682	2,898,118	

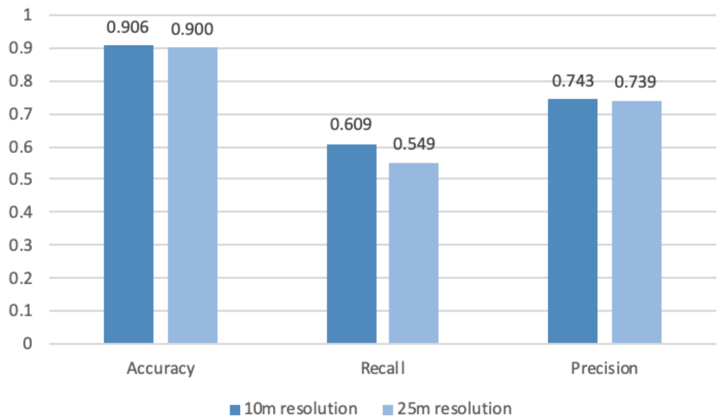


Figure 5. Performance metrics for each resolution

3.2 Discussion

In both resolutions, most non-drainage canals were classified correctly. As for drainage canals, the model was able to detect over half of them. But as a whole trend, drainage canals were not accurately detected as non-drainage class. It is thought that the main reason of these results is that model confused drainage canal class and other class. Drainage canal class has unique value in raster data, but there is an overlap with non-drainage one shown in histograms. In addition to it, the width and depth of drainage canals may have strong effect to the detection results. If drainage canals are narrow ones, the widths of polygons in target data become also small and this can lead to the decrease of detection accuracy. Regarding the depth, values of PALSAR-2 image become small due to the microwave image characteristic and the differences of value around drainage canals also become subtle if they are the shallow ones. Plus, it is thought that the number of training dataset is also one of the reasons of low accuracy. We used 100 training image tiles in this study, therefore increasing the number of these training image tiles may give better accuracy.

Regarding the difference between two resolutions, 10m resolution imagery showed better results than 25m ones through all metrics. From this result, it is considered that resolution deference affected the model accuracy even after making 256×256 tiles process. Sizes of all tiles were converted to this size in this study, but the original resolution is thought to have influenced the detection process in the model.

4. CONCLUSION AND FUTURE WORKS

In this research, drainage canal detection was conducted in two different resolutions from the PALSAR-2 image by using pix2pix method. Over half of drainage canals were detected correctly while most non-drainage canals were predicted precisely using this model. The difference of results between two resolutions was subtle, but high resolution one showed better result.

As a future works on this study, we will augment the training dataset first. In data augmentation, rotating the patches or adding noises to the original satellite imagery is considered successful. Besides, further segmentation of drainage canal classes depending on their types may contribute to high accuracy of detection. It’s not that all drainage canals have the very same characteristics as pixel values, therefore setting some different drainage canal classes may make the detection model a more robust one. Furthermore, we will investigate in detail how resolutions of satellite imagery affect the model output.

5. REFERENCES

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