

AUTOMATIC SHORELINE EXTRACTION FROM SAR IMAGERY USING DeepLabv3+

Lianhui Wu, Tokyo University of Marine Science and Technology, lwu@kaiyodai.ac.jp

Sho Ishikawa, rinna Co., Ltd., ishikawasho0422@gmail.com

Daisuke Inazu, Tokyo University of Marine Science and Technology, inazud@kaiyodai.ac.jp

Tsuyoshi Ikeya, Tokyo University of Marine Science and Technology, tikeya0@kaiyodai.ac.jp

Akio Okayasu, Tokyo University of Marine Science and Technology, okayasu@kaiyodai.ac.jp

BACKGROUND

Shorelines are significantly dynamic that may undergo rapid retreats and advances driven by changing environmental conditions, such as waves, tide, storm surge, and river discharge, etc. To better manage and protect the coastal regions, the ability to repeatedly observe and quantify the changing position of the shoreline is significantly important. Satellite-borne synthetic aperture radar (SAR) has received much attention due to its advantages in large area, all-weather observation capability. However, most previous studies tried to develop shoreline extraction methods based on SAR images at specific coasts. Widely usable extraction techniques for shorelines with variable characteristics do not yet exist. This study aims to develop a widely usable shoreline extraction method based on SAR images by using Deeplab v3+.

DATASET

SAR images acquired by the Sentinel-1 were used for developing the shoreline extraction method. Sentinel-1 images were obtained free of charge from the European Space Agency (ESA) Sentinels Scientific Data Hub. Sentinel-1 carries a single C-band SAR instrument operating at a center frequency of 5.405 GHz with a repeat cycle of 12 days. In this study, the Sentinel-1 SAR dataset composed of ground range detected (GRD) images in the IW swath mode was employed. In addition, images obtained with VV (vertical-vertical) polarization with a pixel spacing of 10m were used. SAR images were first preprocessed by use of the Sentinel application platform (SNAP). Noise removal, calibration and range doppler terrain correction were carried out for each image. Then the backscattering coefficient was converted to a non-dimensional pixel value by using the normalization method proposed by Tajima et al. (2021).

The open-source software toolkit CoastSat was employed to obtain the position of the shoreline used for creating the label of SAR images. CoastSat can obtain time-series of shoreline position at any coastline worldwide from publicly available multispectral satellite imagery captured by Landsat and Sentinel-2. It is reported that the shoreline extraction accuracy of CoastSat is around 10m. In this study, shoreline positions from 2015 to 2021 were first extracted by using CoastSat. Then the mean position was calculated for each target coast, and it is used as the ground truth data with an assumption that no significant change of the shoreline occurred during this period.

STUDY AREA

Figure 1 shows the 15 coasts in Japan used in the study. There are three coasts (A, B, C) for construction of the shoreline extraction method and two coasts (D, E) for evaluation of the accuracy of the method. In addition, the

constructed method was applied to other ten coasts for validation. Characteristics of these coasts differ from each other. The beach materials range from fine sand to coarse gravel. As for the coasts used for model construction and evaluation, SAR images obtained by Sentinel-1 from 2015 to 2021 were collected. There are approximately 350 SAR images for each coast. While in the case of validation, only two images were collected at each coast.

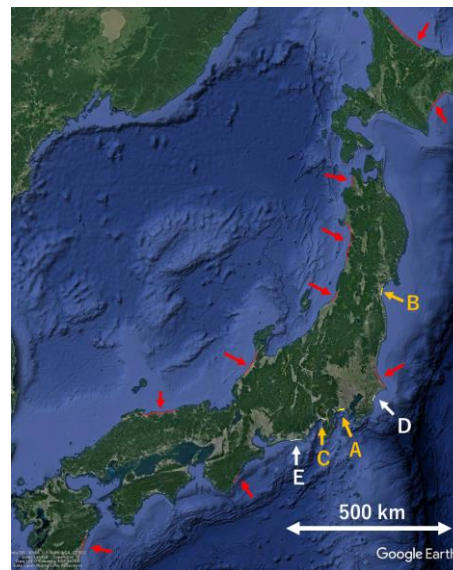


Figure 1 - Study area. Solid lines are shorelines extracted by CoastSat. Orange arrows indicate the coasts for model construction, white arrows indicate the coasts for evaluation and red arrows indicate the coasts for validation.

SHORELINE EXTRACTION METHOD

In this study, the state-of-the-art Convolutional Neural Network model, Deeplab v3+, was employed for shoreline extraction. DeepLabv3+ is known for its exceptional performance in pixel-level semantic image segmentation tasks. Land-sea classification was first carried out by using DeepLabv3+, and then the boundary between the two categories was extracted as shoreline. Therefore, the accuracy of shoreline extraction largely depends on the precision of classification.

To conduct classification with Deeplab V3+, transfer learning is necessary by using the preprocessed SAR images and the corresponding label data (segmentation images). The shoreline position obtained by CoastSat was used to create the segmentation image corresponding to each preprocessed SAR image (Figure 2). Then a series of sub-images with a size of 320 pixels \times 320 pixels were randomly cut from both of the SAR image and segmentation image to generate the training dataset for

transfer learning. More than 500,000 pairs of sub-images (one dataset) were obtained for each coast. Transfer learning was then carried out based on the datasets. Classification models based on one single dataset were constructed, respectively. In addition, different combinations of datasets were employed for transfer learning to evaluate the versatility of each model.

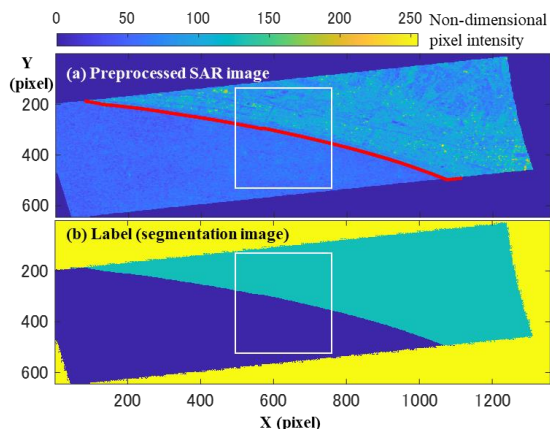


Figure 2 - An example of preprocessed SAR image and corresponding labeled image. The red line indicates the shoreline obtained by CoastSat. The white square indicates an example of a pair of sub-images used for transfer learning.

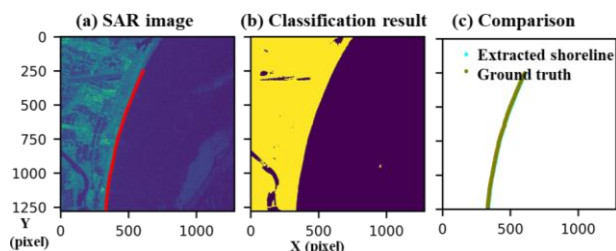


Figure 3 - An example of preprocessed SAR image, classification result and extracted shoreline. The red line indicates the shoreline (ground truth) obtained by CoastSat.

RESULTS AND DISCUSSION

The constructed models were applied to the evaluation dataset D and E to judge the accuracy. Figure 3 shows an example of results of classification and extracted shoreline. Although water bodies on the landside were not specially labeled, they were classified as sea. However, shoreline extraction was not affected by this phenomenon because these water bodies are generally located in the inland. Table 1 shows the accuracy of extracted shoreline position with different datasets used for transfer learning. It is found that in the case using one single dataset, the accuracy of extracted shorelines was not satisfactory, especially when the characteristics of the coast used evaluation is much different from that of the coast used for model construction. The accuracy increased to less than 4.0 pixel when using two datasets for transfer learning, which shows that increasing the number of datasets can enhance the accuracy of shoreline extraction. The mean absolute error of extracted shoreline positions further improved when using all the three datasets for transfer learning. It is

therefore suggested that the versatility of shoreline extraction model can be achieved by using SAR images captured at several different types of coasts as teacher data.

Table 1 - Accuracy of extracted shoreline position with different datasets used for transfer learning.

Datasets used for transfer learning	Mean Absolute Error of extracted shoreline position (pixel)	
	Evaluation dataset D	Evaluation dataset E
A	6.0	4.5
B	5.2	4.2
C	5.	4.4
A, B	3.9	3.1
A, B, C	3.6	2.8

The constructed model by using all the three datasets for transfer learning was then applied to other ten coasts in Japan for further validation. In this case, the coverage of SAR images is much larger than that used for model evaluation since we aim to estimate the efficiency of the model as well. Figure 4 shows an example of extracted result of a 26 km-long stretch of shoreline. The extracted shoreline generally agrees well with the one extracted by CoastSat. For all ten coasts used for evaluation, the mean absolute error of extracted shoreline ranges from 2.0 pixel to 5.0 pixel, which indicates the versatility of the developed method.

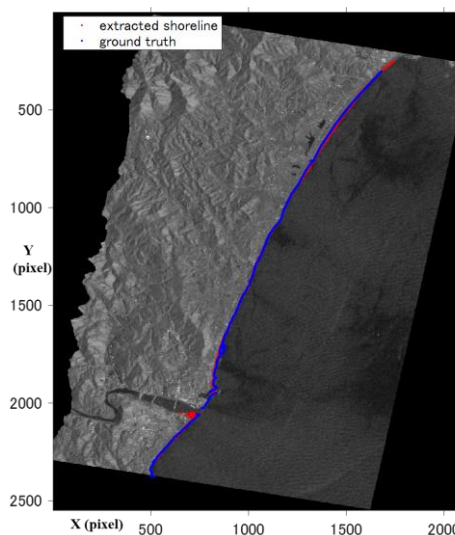


Figure 4 - An example of extracted result of a 25 km-long stretch of shoreline in Mie prefecture, Japan.

REFERENCES

Tajima, Wu, and Watanabe (2019): Development of a shoreline detection method using an artificial neural network based on satellite SAR imagery, *Remote Sensing*, 13(12), 2254.
 Vos, Splinter, Harley, Simmons, and Turner (2019): CoastSat: A Google Earth Engine-enabled Python toolkit to extract shorelines from publicly available satellite imagery. *Environmental Modelling and Software*, 122, 104528.