Satellite Monitoring for Coastal Preservation: Mitigating Beach Erosion from Rising Sea Levels

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1. Background and objective of study

Rising sea levels, one of the consequences of climate change, contribute to the erosion and depletion of sandy beaches. Frequent monitoring of sandy beaches is essential for identifying the future exacerbation of climate change effects and taking prompt action. The NILIM is developing a method to automatically extract shorelines from satellite images and track time series changes as a way to monitor beaches across Japan.

We have been working on extracting shorelines from synthetic-aperture radar (SAR) images, but the accuracy is notably lower on sandy beaches where the shoreline is made of sand. In this study, shifting our focus to optical images, we aimed to develop an image analysis method applicable to sandy beaches.

2. Approaches utilized for employing optical satellite images

We chose four representative beaches for our study: Shonan Beach (median grain size D_{50} = 0.3 - 1.8 mm) and Miyazaki Beach (D_{50} = 0.72 mm) to represent sandy beaches, and Shimoniikawa Beach (D_{50} = 5.7 - 13 mm) and Fuji Beach (D_{50} = 16 mm) to represent gravel beaches. For each of these beaches, we generated Normalized Difference Water Index (NDWI) images by storing the NDWI values, which were calculated from two reflection intensities in the green and near-infrared wavelengths observed by the optical satellite Sentinel-2 as grayscale values. The NDWI index uses the property that water tends to absorb near-infrared wavelengths, aiming to enhance the differentiation between water and land areas. Utilizing the obtained NDWI images, we experimented with two shoreline extraction methods: a conventional edge extraction technique and a method that uses deep learning **(Figure 1).**

In addition, in response to potential photography obstruction from cloud cover, we examined the relationship between the quantity of cloud metadata added

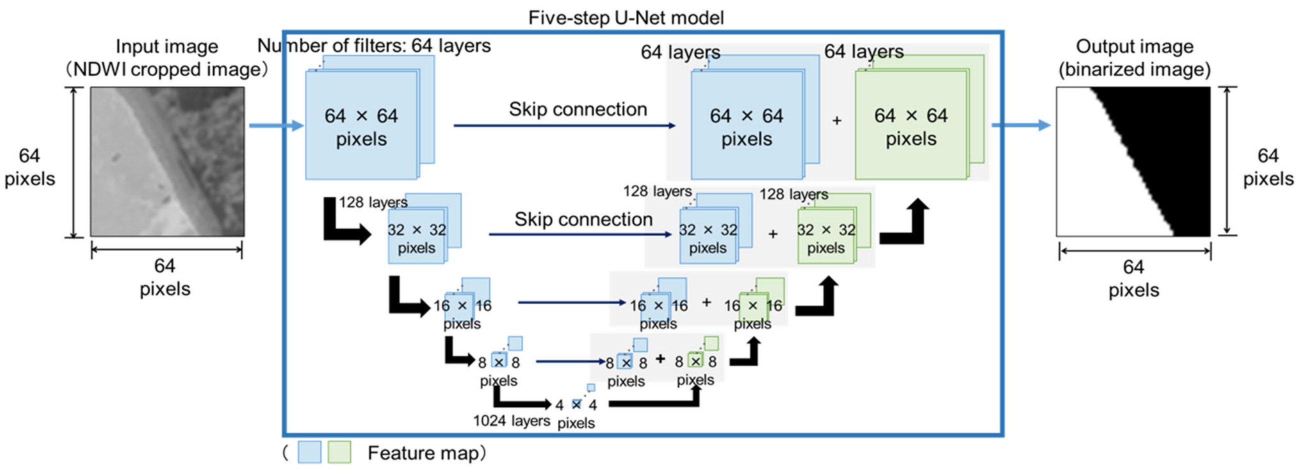

Figure 1. Simplified model of the network configuration (five-stage U-net) used for deep

to satellite images and the extraction results. Moreover, we experimented with techniques for cloud removal through image composition.

3. Enhancing extraction accuracy through the use of deep learning.

The edge extraction method frequently produced inaccuracies by wrongly extracting the offshore boundary of detached breakwaters and wave breaking zones, as well as the edge of the coastal forests. In contrast, the deep learning method demonstrated the ability to accurately extract the shoreline **(Figure 2).**

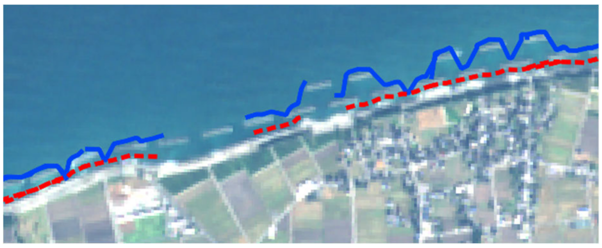

Figure 2. Difference of extraction results by shoreline extraction method
Top: Bottom: Example of wrongly extracted detached breakwaters, Bottom: Example of wrongly extracted wave breaking zone and coastal forest (blue solid line: edge extraction, red dashed line: deep learning)

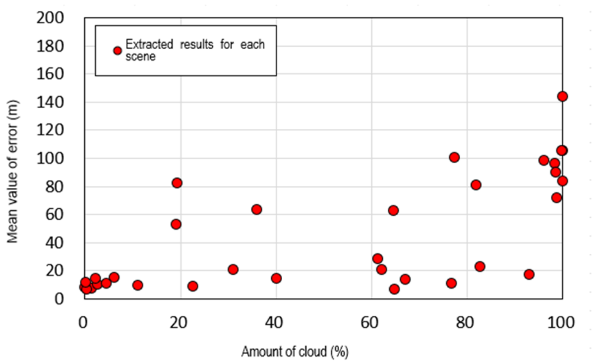

Figure 3: Relationship between errors in shorelines extracted using the deep learning method and the quantity of cloud cover (Shonan Beach)

The error, defined as the differencebetween surveyed results and the shoreline position along the evaluation line set at approximately 50-meter intervals in the coastal direction and averaged for each beach, tends to rise with the increasing amount of clouds in each scene **(Figure 3).**

Table 1. Error in scenes with the highest extraction accuracy (mean value ± standard deviation)

Beach name	Edge extraction (m)	Deep learning (m)
Shonan	21.3±30.7	6.5±6.1
Shimoniikawa	26.1±32.5	11.9±1.0
Fuji	22.8±20.3	9.4±5.5
Miyazaki	56.3±29.1	10.1±9.6

For each of the four beaches, the deep learning method consistently produced lower errors in scenes where beaches were most accurately extracted **(Table 1).**

In comparison to previous studies that extracted shorelines from satellite SAR images of the same beaches used in this study, the mean error value was smaller than that extracted from SAR images at three beaches, excluding Shimoniikawa Beach. Even for Shonan and Miyazaki Beaches—sandy beaches where shoreline extraction was challenging through SAR images—the accuracy of extraction was comparable to that in gravel beaches **(Figure 4).**

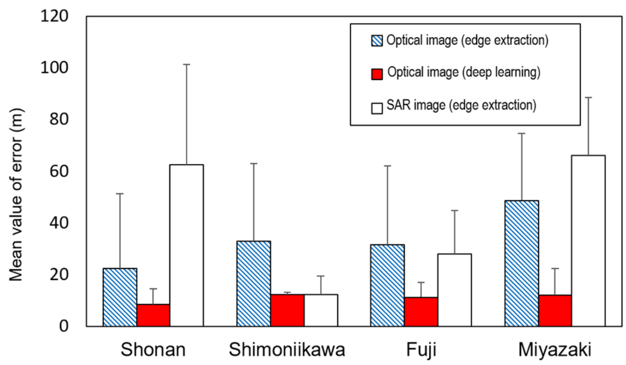

Figure 4. Difference in error based on satellite image types and extraction methods

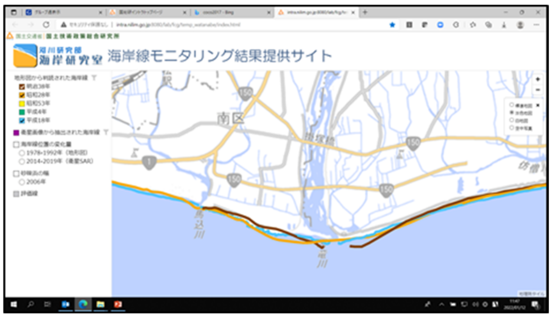

Figure 5. Prototype version of the monitoring results provision website

Given the 10-meter resolution of each Sentinel-2 sensor utilized in this study, the obtained extraction accuracy proves to be satisfactory, implying the effectiveness of shoreline extraction through deep learning.

4. Future prospects

Simultaneously with the development of the shoreline extraction method, we are in the process of establishing a website to compile and disseminate the shorelines extracted from optical satellite images and other relevant sources **(Figure 5).** Furthermore, we are in the process of creating a cloud application to enable coastal managers to access the automatic shoreline extraction method. Through these initiatives, our goal is to assist coastal managers in effectively monitoring shorelines, maintaining a high-frequency overview of beach conditions across Japan, and providing this information as open data.

☞For more information:

1) Watanabe et al. (2021) Evaluation of applicability of image processing methods for shoreline extraction from optical satellite images (in Japanese)
https://www.jstage.jst.go.jp/article/kaigan/77/2/77_I_1111/_article/-char/ja/