Can we Reliably Extract Shorelines from Cloud-Contaminated Satellite Images: The Application of SAR-Optical Fusion Method

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INTRODUCTION

Satellite-derived shorelines (SDS) have been increasingly adopted in coastal research to analyze the migration of coastlines from regional to global scales (Luijendijk et al., 2018; Mao et al., 2021; Vos et al., 2023). However, most of the existing SDS algorithms rely on optical satellite images, which require cloud-free conditions to have an unobstructed view of the land surface. Compared to optical images, Synthetic Aperture Radar (SAR) images are less interpretable, so they are relatively unpopular for SDS. However, a key benefit of SAR images is that they are not impacted by cloud, which makes them ideal sources of information to reconstruct the cloud-contaminated optical images. Therefore, the fusion of SAR and optical images provides the unique opportunity to increase the data availability for earth observation (Schmitt et al., 2017), especially in cloudy regions. Although a variety of SAR-Optical fusion methods ranging from generic linear regressions to deep learning models have been developed for optical image reconstruction, their applicability to shoreline extraction has not been thoroughly investigated. In this study, we (1) develop a deep internal learning (Ebel et al., 2021; Zhang et al., 2019) model to reconstruct a sequence of cloud-contaminated Modified Normalized Difference Water Index (MNDWI) images with a sequence of SAR images; and (2) evaluate the applicability of the reconstructed MNDWI images for shoreline extraction.

METHODOLOGY

The Deep Internal Learning (DIL) approach used for cloud removal in this research is based on the Internal Learning neural network for video Inpainting (Zhang et al., 2019). Such a network can efficiently reconstruct missing information in an image time series without losing the spatio-temporal dynamics. To adapt the DIL neural network for SAR-Optical fusion, we used a time series of Sentinel-1 (S1) images as the input and a set of cloud-masked MNDWI images as the output for the model. These MNDWI images were derived from Landsat 8 (L8) and Landsat 9 (L9) images that are paired to Sentinel-1 time series with each pair of S1 and L8/L9 collected on the same day. The network is then trained to predict the given cloud-free MNDWI pixels and effectively learns inpainting the cloud obscured information. Importantly, the training and inference of DIL is based on the same sequence of SAR-Optical pairs to learn their unique spatio-temporal information. That is, no external training dataset is needed for the network.

The MNDWI image has cloud cover rate ranging from 0% to 100%. For each clear MNDWI image (cloud cover rate < 20%), we synthesized a 50% cloudy image by blending the formerly cloud-free image with clouds from the most cloudy images in the time series. We then used synthesized images for model training. This allows us to compare the reconstructed (modelled) images against the clear images to measure the goodness of cloud removal from SAR information.

To quantitatively evaluate the applicability of the above SAR-optical fusion method for SDS, shorelines were extracted from the modelled MNDWI images with the thresholding and contouring method used in CoastSat (Vos et al., 2019). These shorelines were then compared against the results derived from the target MNDWI images in regions unaffected by clouds. The difference between the true shoreline and the modelled shoreline was calculated along a sequence of pre-defined shore-normal transects. The applicability of the SAR-Optical fusion method was quantified by the spatio-temporal statistics of model errors.

RESULT

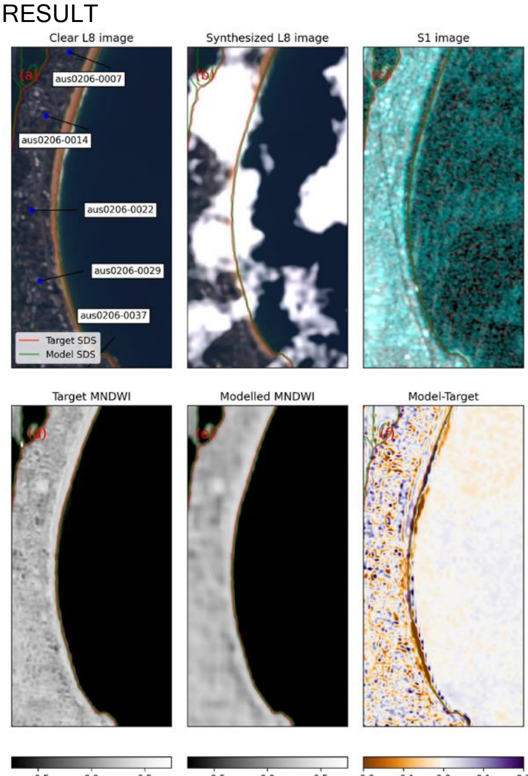

Figure 1- MNDWI reconstruction results for Narrabeen on 2022-Jul-17. (a) is the clear L8 image; (b) is the synthesized image with 50% cloud added to (a); (c) is the input S1 image to the model; (d) is the MNDWI image calculated based on (a); (e) is the modelled MNDWI image, and (f) is the different between (e) and (d).

The SAR-Optical fusion method has been implemented for the Narrabeen in Australia. Figure 1 shows an example of the reconstructed MNDWI and the SDS derived from it for a clear day in Narrabeen. Given (c), the DIL model can successfully reconstruct the missing pixels in (b). The modelled result (e) has high structural similarity as the target (d) but their difference (f) is considerable for the beach front. Despite the difference between the target (d) and modelled (e) images, the shorelines extracted from them match each other very well.

Quantitative spatio-temporal evaluation results in terms of shoreline offsets for Coolangatta beach are shown in Figure 2. More than 70% of the errors between the 2 SDS are in the range of -5 to 5 m, which is sub-pixel resolution and within the range of previously reported RMSE for micro-tidal sites such as those presented here. The spatial aggregation results (absolute mean of offset for transects on each date, plot on the top) show that the temporal absolute offset varies from 0 to 15 meters with the average shoreline position varies between 180~240 meters. Similarly, the temporal aggregation results (absolute mean of offset for all dates at each transect, plot on the right) show that the spatial absolute offsets are mostly within 7.5 meters. For all the blank spots in the heatmap, the SDS works well for modelled MNDWI images but failed for cloud contaminated images. The amount of such missing information highlights the necessity of using the SAR-Optical fusion to enrich the shoreline datasets.

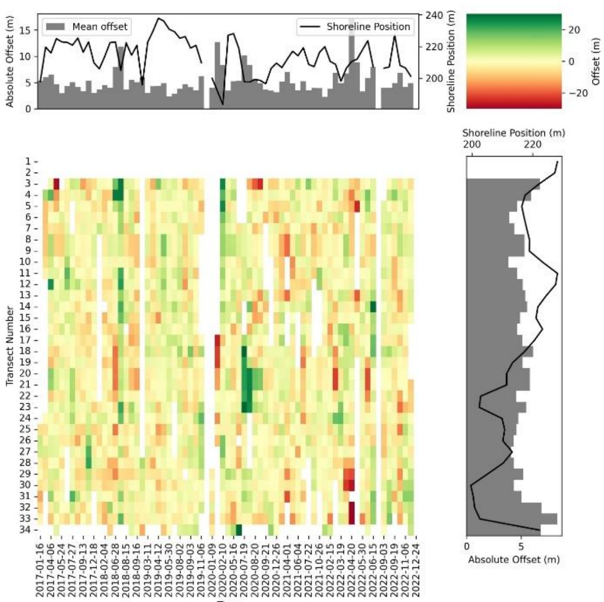

Figure 2-Spatio-temporal distribution of modelled shoreline offsets for the Coolangatta beach. Color gradient in each cell indicates the magnitude of the offset of modelled shoreline. The top and left plot shows the absolute average across columns and rows respectively.

CONCLUSION

This research developed a SAR-Optical fusion approach that is based on deep internal learning to reconstruct cloud-contaminated MNDWI images. The modelled images proved to be reasonably accurate for shoreline extraction. For the two micro-tidal (< 2m) case study sites and medium cloud cover (65% after synthesizing), the offset for shorelines derived from modelled MNDWI is mostly within 10 m which is less than the pixel size (30 m) of the target images and is about 20% of the shoreline migration range (50 m). Using the modelled MNDWI image as an alternative to the raw cloud-contaminated MNDWI image can substantially improve the temporal resolution of shoreline data.

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