Automatic Extraction of Internal Wave Signature from Multiple Satellite Sensors Based On Deep Convolutional Neural Networks

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Abstract

We proposed an automatic internal wave (IW) signature extraction method based on the deep convolutional neural networks (DCNN) to provide a rapid and simple to use method that can tackle the IW signature extraction in images from different satellite sensors without re-training or manual interference. The generalization ability of our method across multiple optical satellite sensors. The statistical results show this DCNN-based method has appreciable transferability and is promising for efficient extraction of internal wave signature in different satellite images with varying spatial resolution even under complex imaging conditions.

Study Area

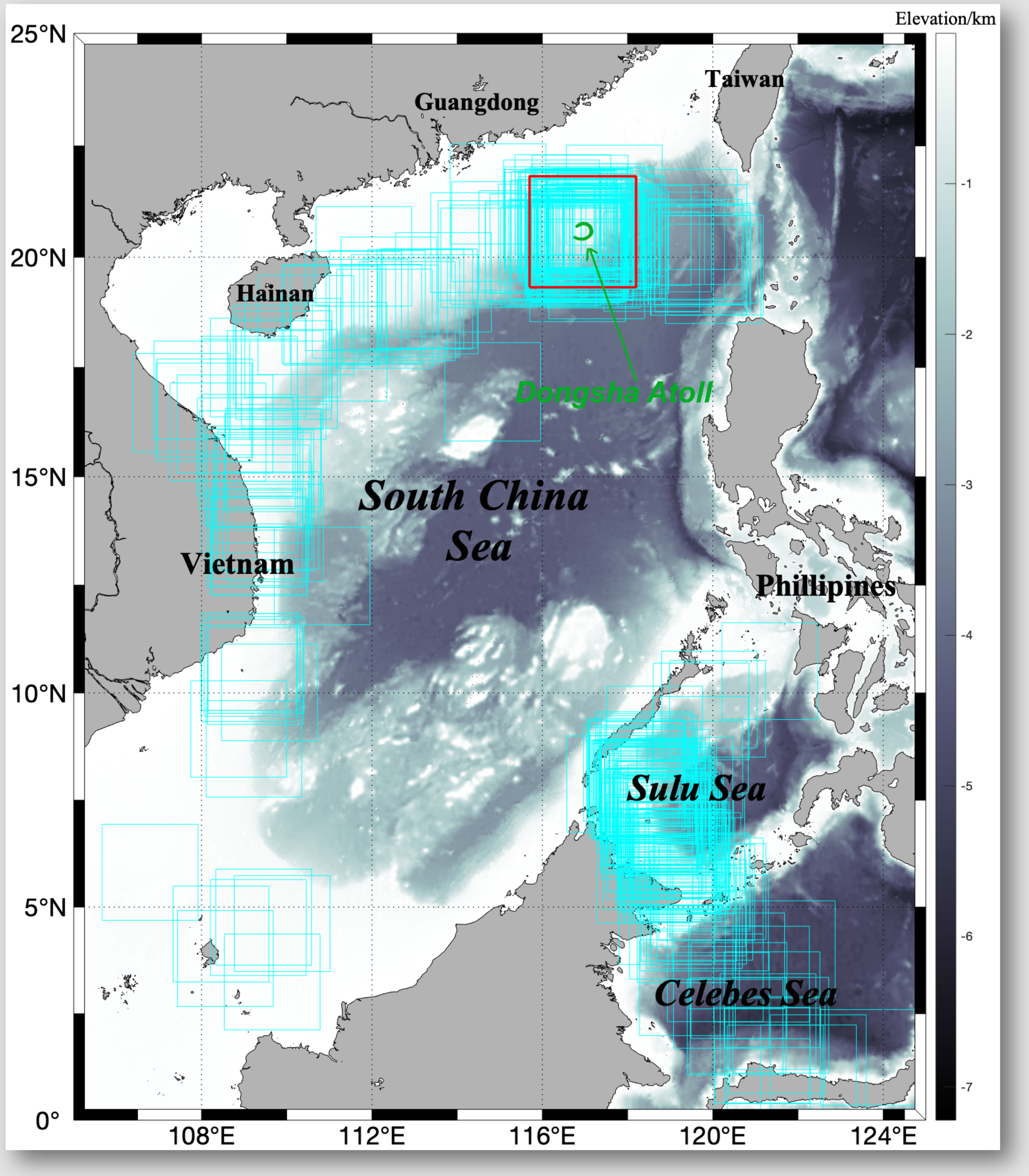

Figure 1. Bathymetric map of the study area (data from the GEBCO). The red box shows the 160 Himawari-8 imaging area and the blue boxes show the 320 MODIS imaging areas.

Data

160 Himawari-8 red-band images (1 km resolution) in May and June 2018, and 320 MODIS Aqua\Terra L1B band-1 images (500 m resolution) in 2016 and 2017 (see Figure 1).

Methodology

The U-Net [1] is a modified fully convolutional network [2], originally developed for biomedical image segmentation. Its architecture was designed to work with fewer training images but able to yield more precise segmentations.

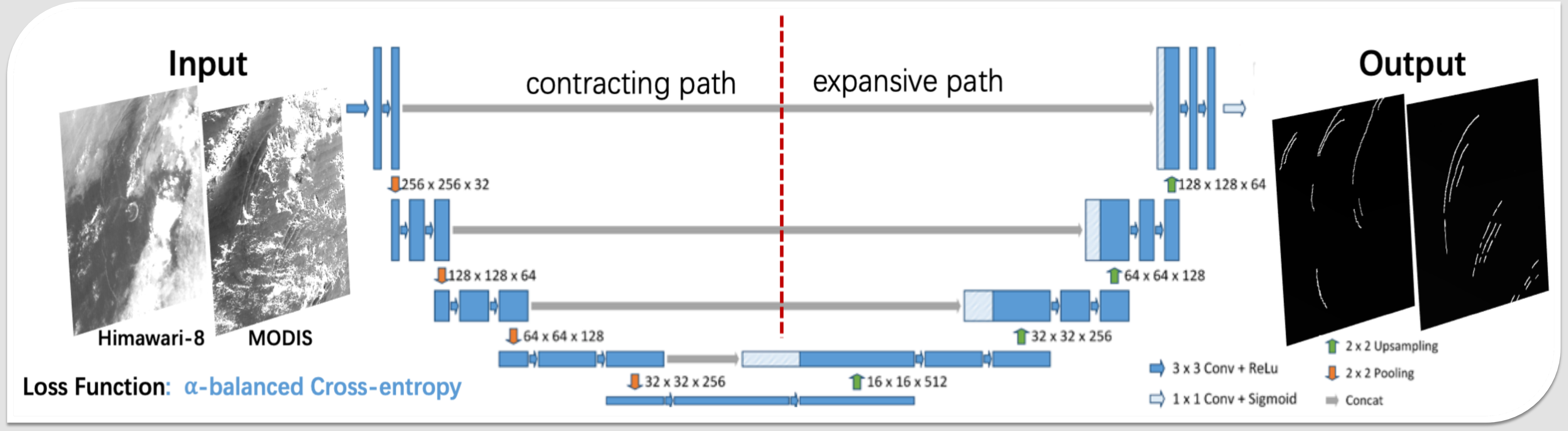

Figure 2. The U-Net architecture specially tailored for this study.

In this case, the samples are highly unbalanced, i.e., the numbers of the background samples are much higher than those of ISW samples. Motivated by [3], in this study, we use the α-balanced cross entropy as follows

$$L_{\alpha BCE} = \begin{cases} -\alpha \log \hat{y}, \text{ if } y = 1 \\ -(1-\alpha)\log(1-\hat{y}), \text{ if } y = 0 \end{cases}$$

For MODIS images, we resample them to 1 km resolution at first to make sure that all input images are all the same pixels size. Then 360 images, coming with their corresponding manually annotated ground truth map for IW signature (white) and surroundings (black), are randomly selected to train the U-Net network, with the remaining 120 images as the testing set.

Results

Finally, the mean precision (also called positive predictive value) and recall (also known as sensitivity) of the testing set are 0.89 and 0.78, respectively (0.90 and 0.89 for Himawari-8, 0.88 and 0.72 for MODIS).

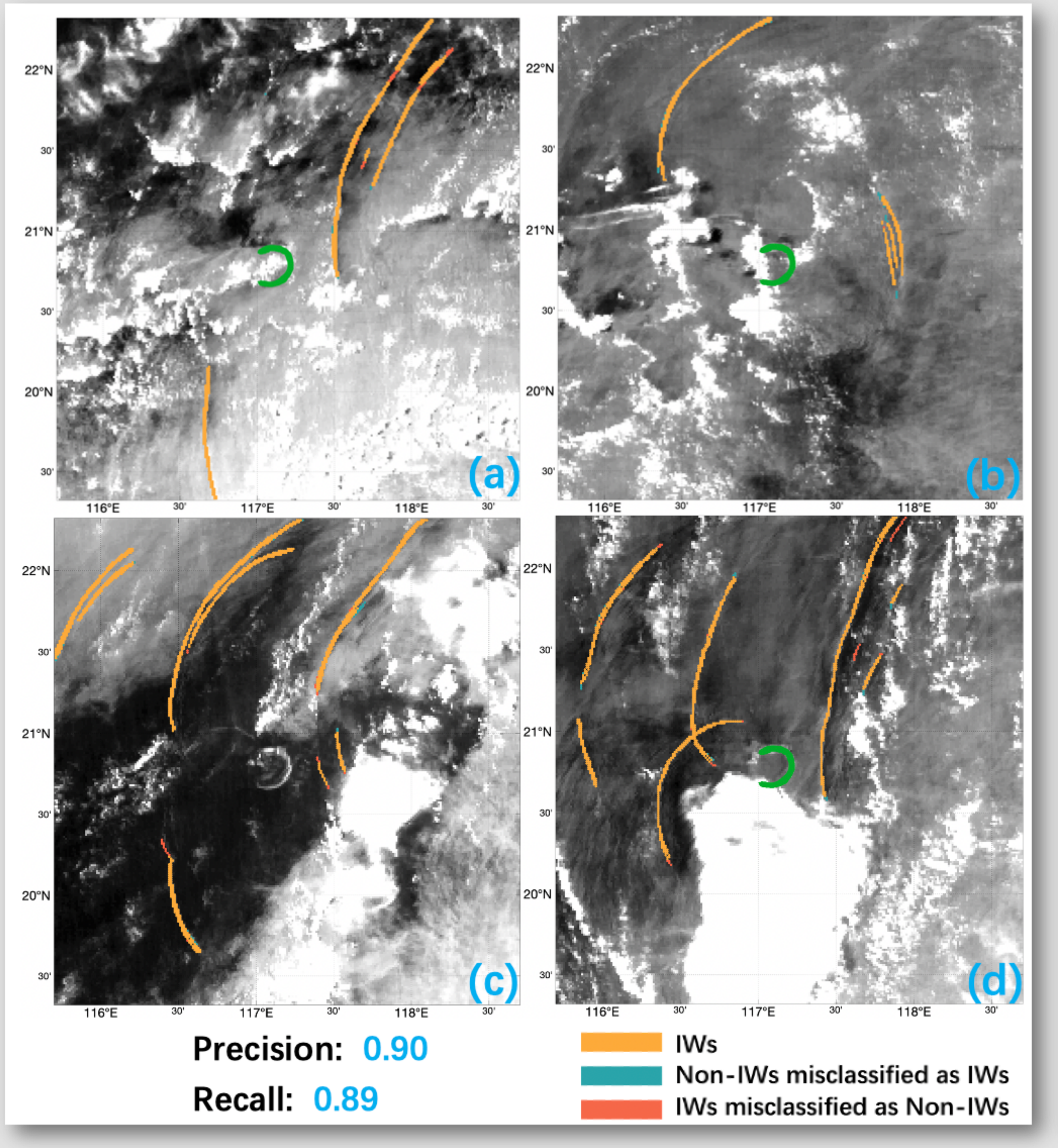

Figure 3. Two examples of the 40 testing Himawari-8 images overlaid with their corresponding trained model extraction results .

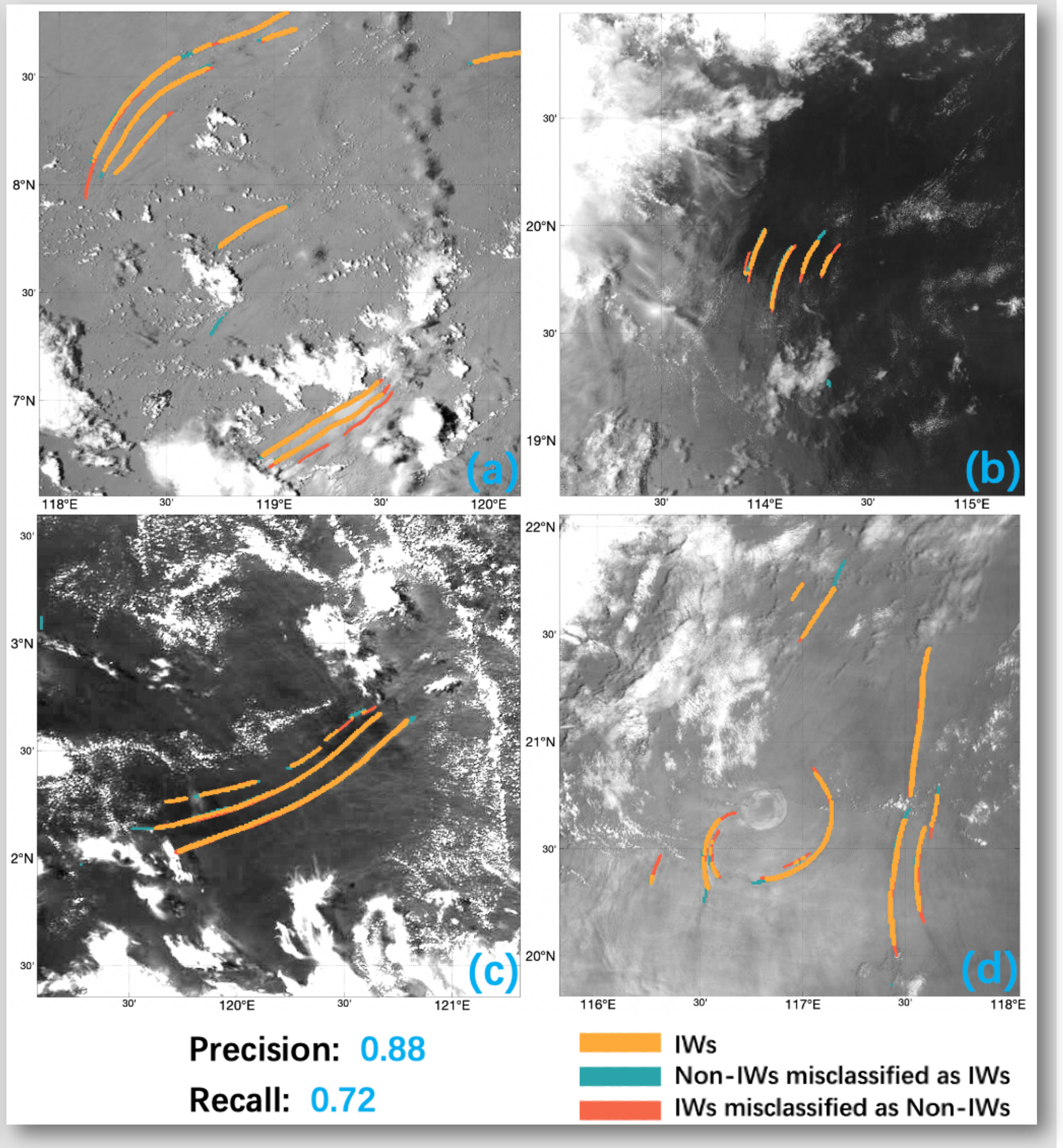

Figure 4. Two examples of the 80 testing MODIS images overlaid with their corresponding trained model extraction results.

Conclusions

In this study, we proposed a DCNN-based automatic IW signature extraction method. This method is able to tackle the IW signature extraction in images from multiple satellite sensors with different spatial resolution at the same time. We also proved the generalization ability of our method across multiple optical satellite (Himawari-8 and MODIS) images. The statistical results imply this DCNN-based method can significantly increase efficiency of extraction of internal wave signature under complex imaging conditions, which may compensate for the in-situ observations to study the generation, propagation, evolution, and dissipation of the IWs.

Acknowledgements

The MODIS data were acquired from the Level-1 and Atmosphere Archive & Distribution System (LAADS) Distributed Active Archive Center (DAAC), located in the Goddard Space Flight Center in Greenbelt, Maryland (https://ladsweb.nascom.nasa.gov/). The Himawari-8 data were distributed by the Japan Meteorological Agency (JMA) and acquired by the HimawariCast service at Hohai University. The GEBCO data were downloaded from www.gebco.net. This study was supported by Fundamental Research Funds for the Central Universities (Hohai University, Grant No. 2018B41814).

Reference

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