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Analysis of coastal wind speed retrieval from CYGNSS mission using artificial neural network

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ABSTRACT

This paper demonstrates the capability and performance of sea surface wind speed retrieval in coastal regions (within 200 km away from the coastline) using spaceborne Global Navigation Satellite System Reflectometry (GNSS-R) data from NASA's Cyclone GNSS (CYGNSS) mission. The wind speed retrieval is based on the Artificial Neural Network (ANN). A feedforward neural network is trained with the collocated CYGNSS Level 1B (version 2.1) observables and the wind speed from European Centre for Medium-range Weather Forecast Reanalysis 5th Generation (ECMWF ERA5) data in coastal regions. An ANN model with five hidden layers and 200 neurons in each layer has been constructed and applied to the validation set for wind speed retrieval. The proposed ANN model achieves good wind speed retrieval performance in coastal regions with a bias of −0.03 m/s and a RMSE of 1.58 m/s, corresponding to an improvement of 24.4% compared to the CYGNSS Level 2 (version 2.1) wind speed product. The ANN based retrievals are also compared to the ground truth measurements from the National Data Buoy Center (NDBC) buoys, which shows a bias of −0.44 m/s and a RMSE of 1.86 m/s. Moreover, the sensitivities of the wind speed retrieval performance to different input parameters have been analyzed. Among others, the geolocation of the specular point and the swell height can provide significant contribution to the wind speed retrieval, which can provide useful reference for more generic GNSS-R wind speed retrieval algorithms in coastal regions.

Keywords: Global navigation satellite system reflectometry (GNSS-R); Cyclone GNSS (CYGNSS); Sea surface wind speed; Coastal; Artificial neural network (ANN)

1. INTRODUCTION

Sea surface wind is an essential variable in both marine environment monitoring and climate change study. The stability of the wind field plays an important role in local and mesoscale atmospheric circulation, and the frequency of different stability conditions in coastal areas is very important information.

In the coastal area, the sea surface wind field has a strong influence on the circulation, fog formation, coastal upwelling, and tidal mixing, which also influence stability and hence turbulent mixing and momentum transfer. Most of the world's coastal regions are the most active regions in terrestrial–ocean–atmosphere systems. Therefore, it is important to monitor the nearshore wind.

2. DATA

(1) CYGNSS

In this work, we focus on the CYGNSS L1B v2.1 product, which is available at the Physical Oceanography Distributed Active Archive Center. The L1B variables used in our analyses, which include NBRCS, LES, SNR, Range Corrected Gain (RCG), incidence angle, azimuth angle, and the longitude and latitude of the specular point. In addition to the L1B data, the CYGNSS L2 v2.1 product is also collected for comparison, which includes the sea surface wind speed measurements with a spatial resolution of 25 km.

(2) ECMWF ERA5

ECMWF/Copernicus Climate Change Service (C3S) ERA5 wind fields (including the u and v components of the sea surface wind speed), at 12.5 km and hourly spatio-temporal resolutions, have been also collected as the reference. To decouple the extra wind speed information from the wave height data, the ERA5 variable "significant wave height of total swell" (SWHTS) is added as the input parameter.

(3) NDBC

For this purpose, the wind speed measurements collected with the National Data Buoy Center (NDBC) buoys have been also collected as the reference. Wind speed measurements from a total of 15 NDBC buoys are selected from January 1 to December 31, 2018.

3. WIND SPEED RETRIEVAL MODEL

In this study, the feed-forward backpropagation (BP) network is implemented based on the Keras framework. The selection of the CYGNSS and ERA5 matchups for ANN training and validation is shown in Fig. 1.

1) Activation Function: We chose the Tanh function as the activation function between the input layers and the hidden layers.

2) Loss Function: The mean squared error function was used as the loss function.

3) Optimization Method: We choose the Adam optimization algorithm. The training times is a constant of 100. The batch size for the neural network training is 1000.

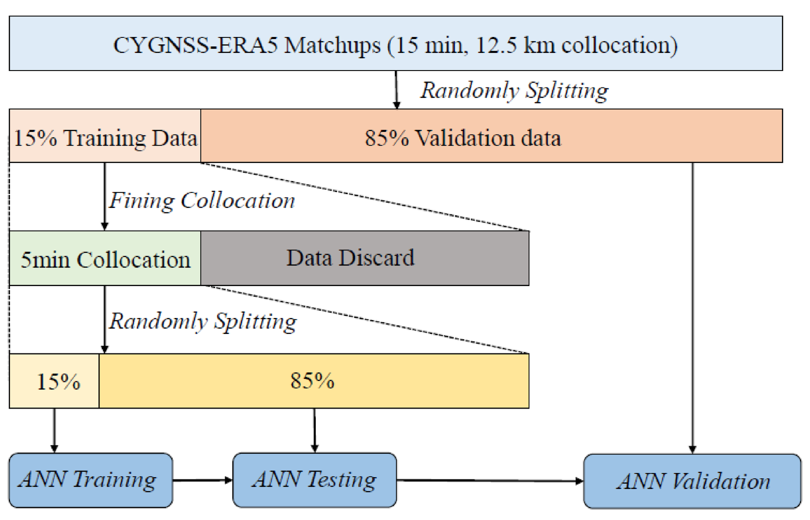

Figure 1. Subsets for ANN training and validation.

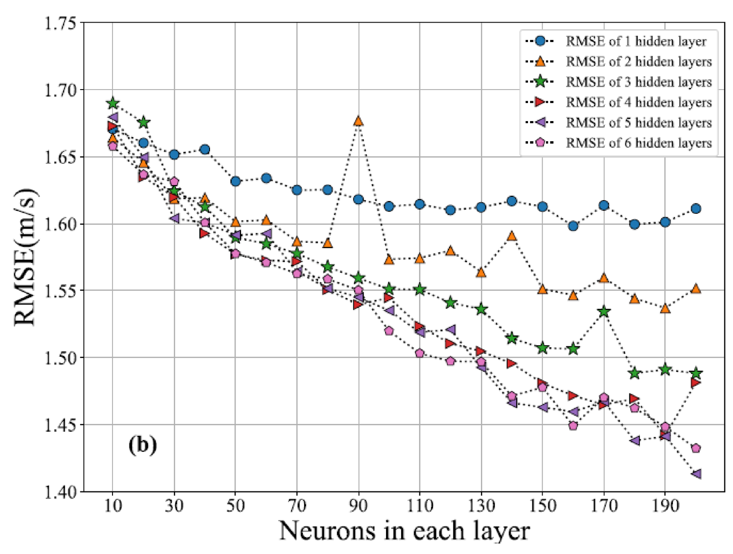

Figure 2. RMSEs of the wind speed retrieval by using ANN models with different configurations.

4. RESULTS

(1) Overall performance

The performance metrics of both retrievals are presented for each month in 2018 (Fig. 3). The ANN-based wind speed retrieval can achieve a bias of −0.03 m/s and a RMSE of 1.58 m/s, while the CYGNSS L2 wind speed product is with a bias of 0.37 m/s and a RMSE of 2.09 m/s. This comparison shows that the RMSE can be reduced by 24.4% with the ANN-based retrieval.

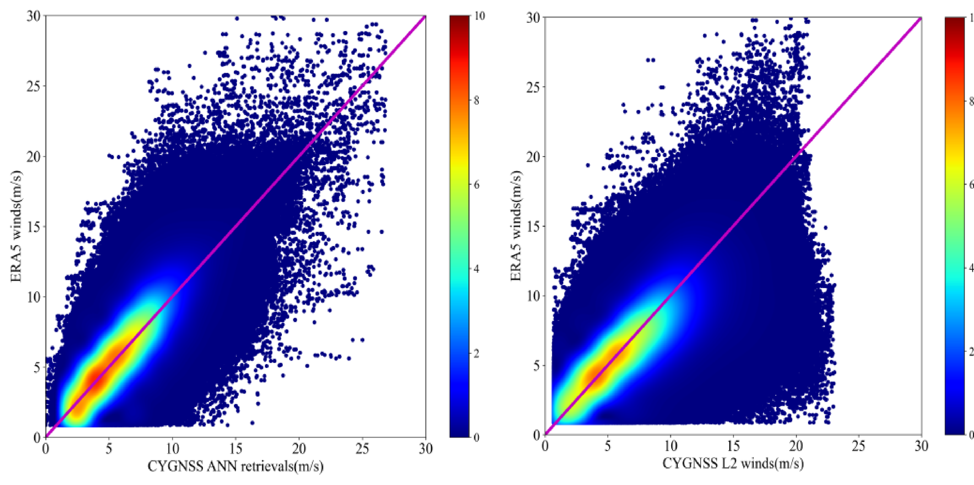

Figure 3. Comparison between the CYGNSS and ERA5 winds. Left: CYGNSS ANN retrieval. Right: CYGNSS L2 baseline retrieval.

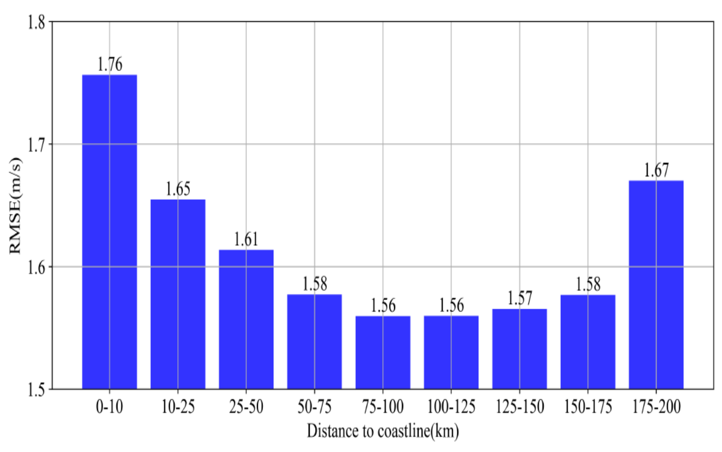

Figure 4. RMSEs of the CYGNSS ANN-based wind speed retrievals in different distance to the coastline.

(2) Geographical statistics

The ANN based wind speed retrieval achieves the best performance in the range of 75–150 km away from the coastline as shown in Fig. 4. It is clearly shown that positive biases appear along the coast line of the Asia-Pacific region in the CYGNSS L2 baseline retrieval (Fig. 5 - top), which are removed in the ANN retrieval (Fig. 5 - bottom).

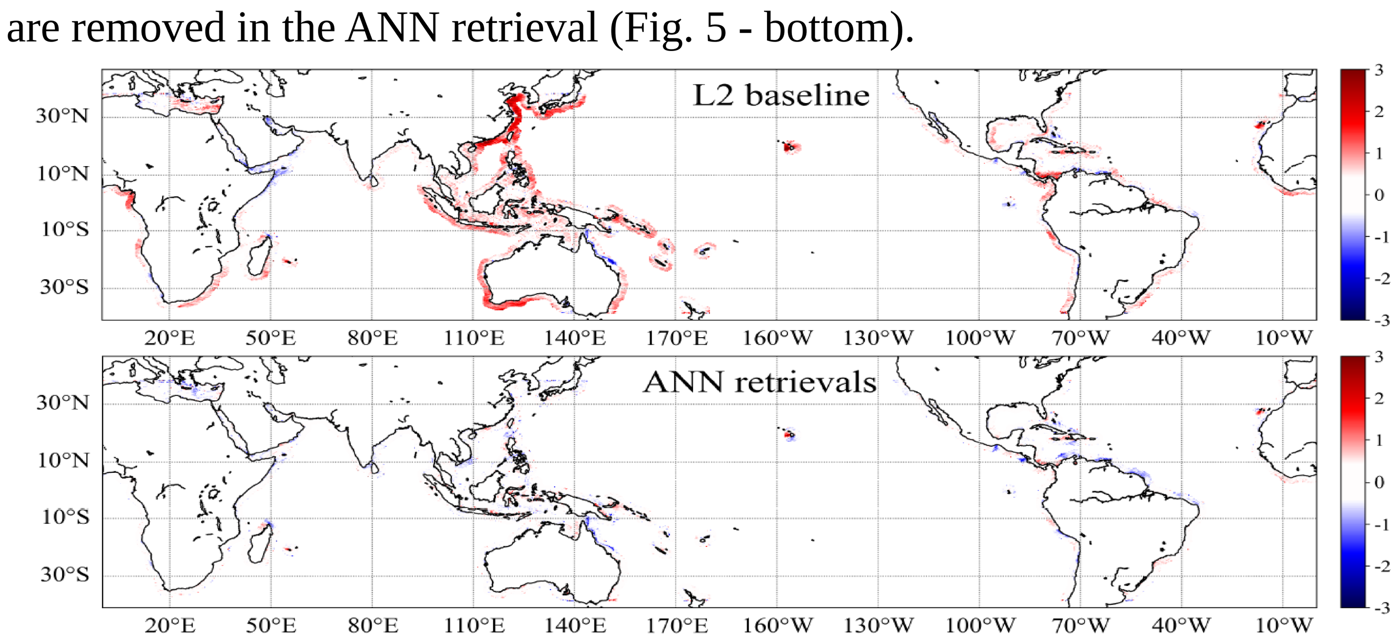

Figure 5. Geographical map of the wind speed bias along the coastlines.

(3) Validation with NDBC

The CYGNSS ANN retrievals have a small deviation from buoys (Fig. 6) measurements with a bias of −0.44 m/s, a correlation coefficient of 0.83 and a RMSE is 1.86 m/s, which demonstrate a good correlation between the CYGNSS ANN wind retrievals and the buoy measurements (Fig. 7).

Figure 3 Distribution of the NDBC's buoy stations along the coastal line.

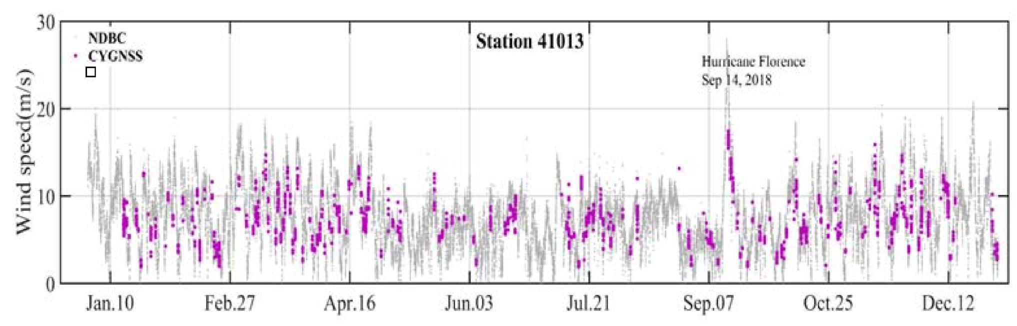

Figure 4. Time series of the wind speeds measured by the NDBC buoy and retrieved based on ANN-based model.

5. CONCLUSIONS

The proposed learning-based wind speed retrieval methodology generates promising overall performance, demonstrating the capability of GNSS-R measurements on sea surface wind speed sensing in near-shore regions. These performance metrics show significant improvements (i.e. 24.4% in wind speed RMSE) compared to the CYGNSS Level 2. It provides useful reference for more generic GNSS-R wind speed retrieval algorithms for the coastal regions.