Rain Detection and Wind Retrieval Using U-NET on ASCAT Measurements

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Abstract

This study aims to expand and improve the capabilities of Advanced Scatterometer (ASCAT) by adding rain detection and advancing wind retrieval using machine learning. We apply semantic segmentation to ASCAT measurements to detect rain over the oceans, enhancing capabilities to monitor global precipitation. We use U-Net, a popular neural network, and train it on measurements from the Tropical Rainfall Measuring Mission (TRMM) collocated with ASCAT backscatter and European Centre for Medium-Range Weather Forecasts (ECMWF) near-surface wind measurements. We apply the same semantic segmentation techniques and neural network architecture on wind retrieval to create a machine learning model that acts as an inverse Geophysical Model Function (GMF). However, we expand the model's output classes to many different wind speeds and directions and train the model on ASCAT data collocated with ECMWF near-surface wind vector data. We successfully demonstrate the ability of the ASCAT satellite to detect rainfall in Earth's oceans, with the ability to retrieve wind vectors without an explicit GMF or Maximum Likelihood Estimation (MLE).

Collocation

The interference rain has on ASCAT backscatter makes it difficult to retrieve wind vectors, but potentially give us the ability to detect rain using ASCAT backscatter. We explore this possibility with supervised machine learning where ASCAT measurements are our inputs and TRMM PR rain measurements are our target values. Using machine learning we can adjust weights in the model to use ASCAT as the input and rain as the output.

We collocate the ASCAT measurements with TRMM PR measurements allowing us to see where rain is present relative to ASCAT.

ASCAT Values
- Backscatter
- Incident Angle
- Azimuth Angle

ASCAT Beams
- Fore
- Mid
- Aft

TRMM Values
- Rain flag

ECMWF Values
- Surface winds

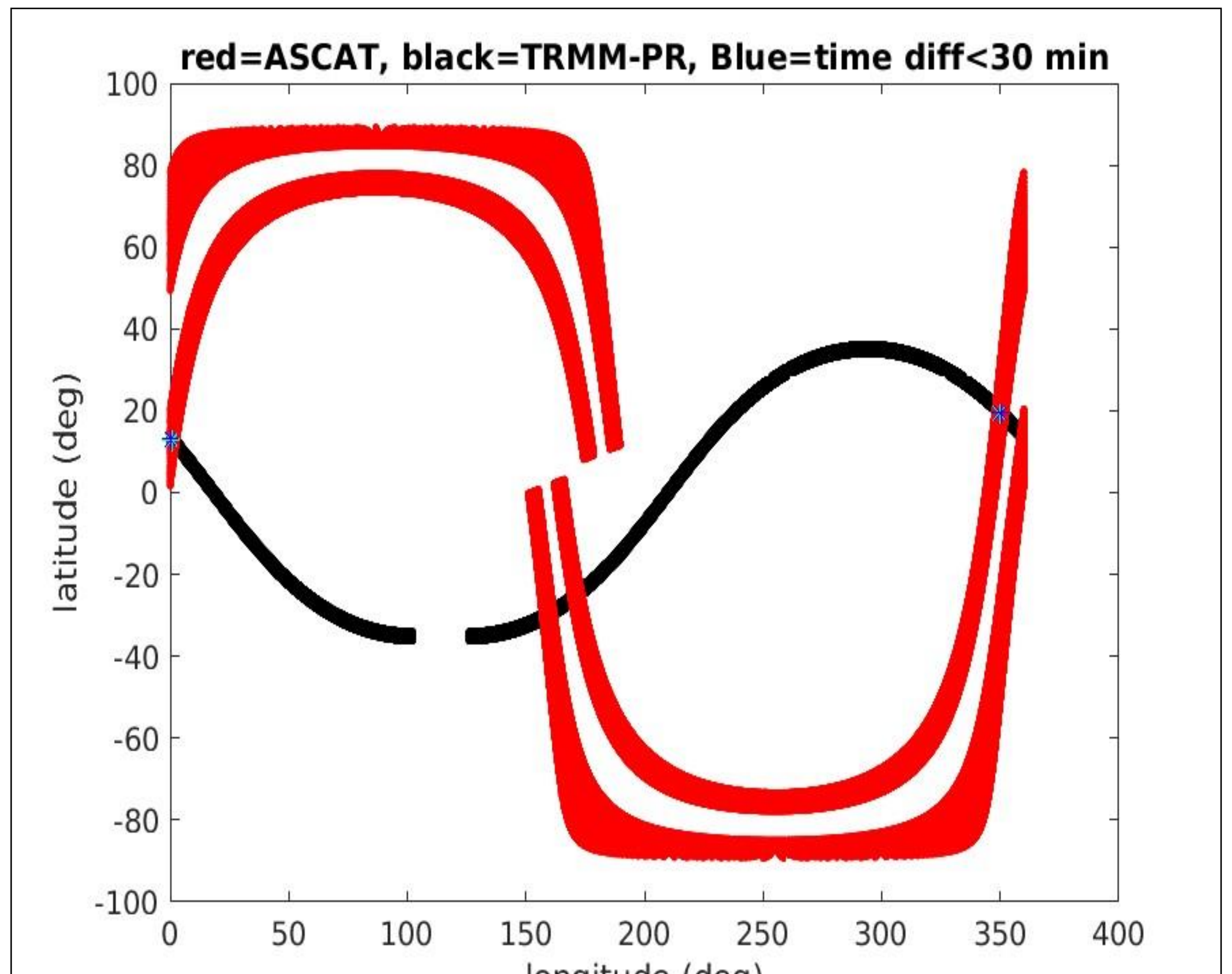

Figure 1
The intersecting beams of TRMM and ASCAT satellites. The intersection of the two paths is where we spatially and temporally collocate the data used as our input and target values.

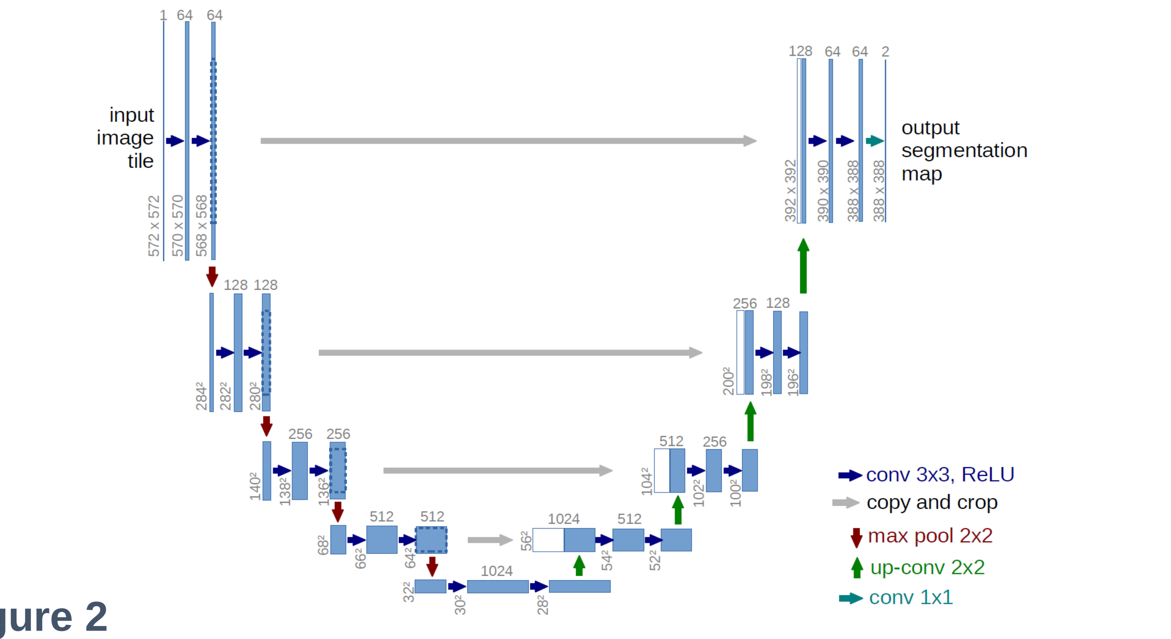

Figure 2
Image of the U-net architecture. The blue boxes are multi-channel feature maps with the number of channels shown above each box and the dimension of each map shown lower left of the box. White boxes are encoded feature maps copied to the decoder. The arrows represent different operations with a legend in the lower right of the image. Source adapted from [1].

Convolutional Neural Network (CNN)

A CNN uses convolution operations to predict target values from input values. The training process adjusts weights in the kernel filters until target values in the training set are predicted from input values [2]. Additionally, a validation dataset is used to prevent the model from overfitting on the training dataset. An extension of the architecture is U-Net.

U-Net

U-Net is an encoder-decoder architecture [3] designed for semantic segmentation (the classification of each individual pixel in an image). The architecture features three main sections:

- Encoder: captures low-level features from input images by progressively reducing the spatial dimensions.
- Decoder: captures fine-grain feature maps by upsampling encoded features.
- Skip Connections: concatenates the encoder and decoder features maps.

This architecture takes into account higher order and lower order features when determining its output, see Figure 2.

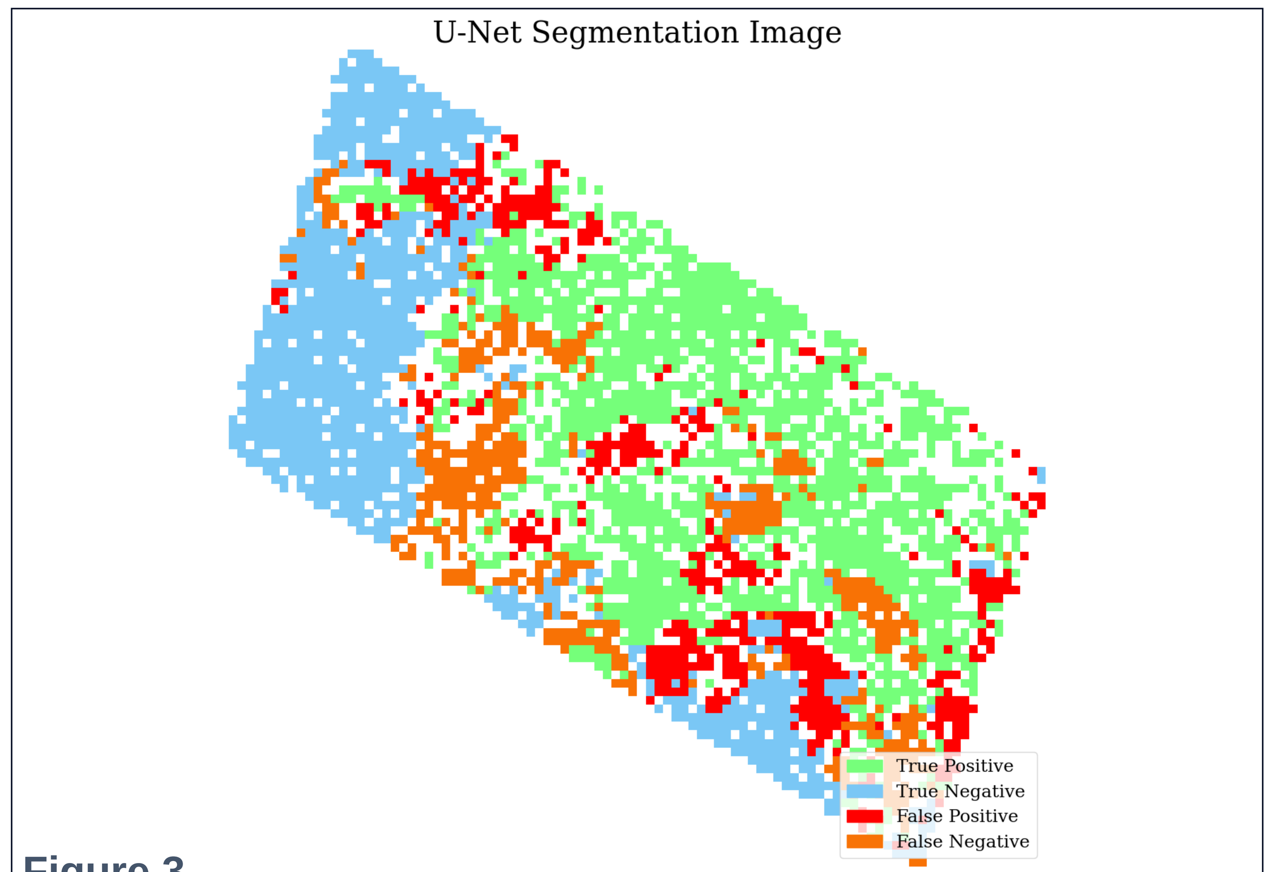

Figure 3
Example predictions of the model compared to TRMM. Light green is rain was predicted and detected, light blue is no rain predicted nor detected, red is rain was predicted but not detected, and orange is rain was not predicted, but was detected.

Wind Retrieval with U-Net

While training the U-Net to detect rain, we discovered that the same algorithm could be applied to wind retrieval. Traditionally, ocean surface winds are retrieved through pointwise wind retrieval with a GMF to generate intersections between multiple measurements, an MLE to generate ambiguities, and an ambiguity selection algorithm to select the most likely ambiguity [4]. Our model does all these steps in one go. We train a U-Net to generate the most likely wind direction and another U-Net to predict the most likely wind speed using ASCAT measurements. We combine the results from the two U-Nets to form wind vector prediction.

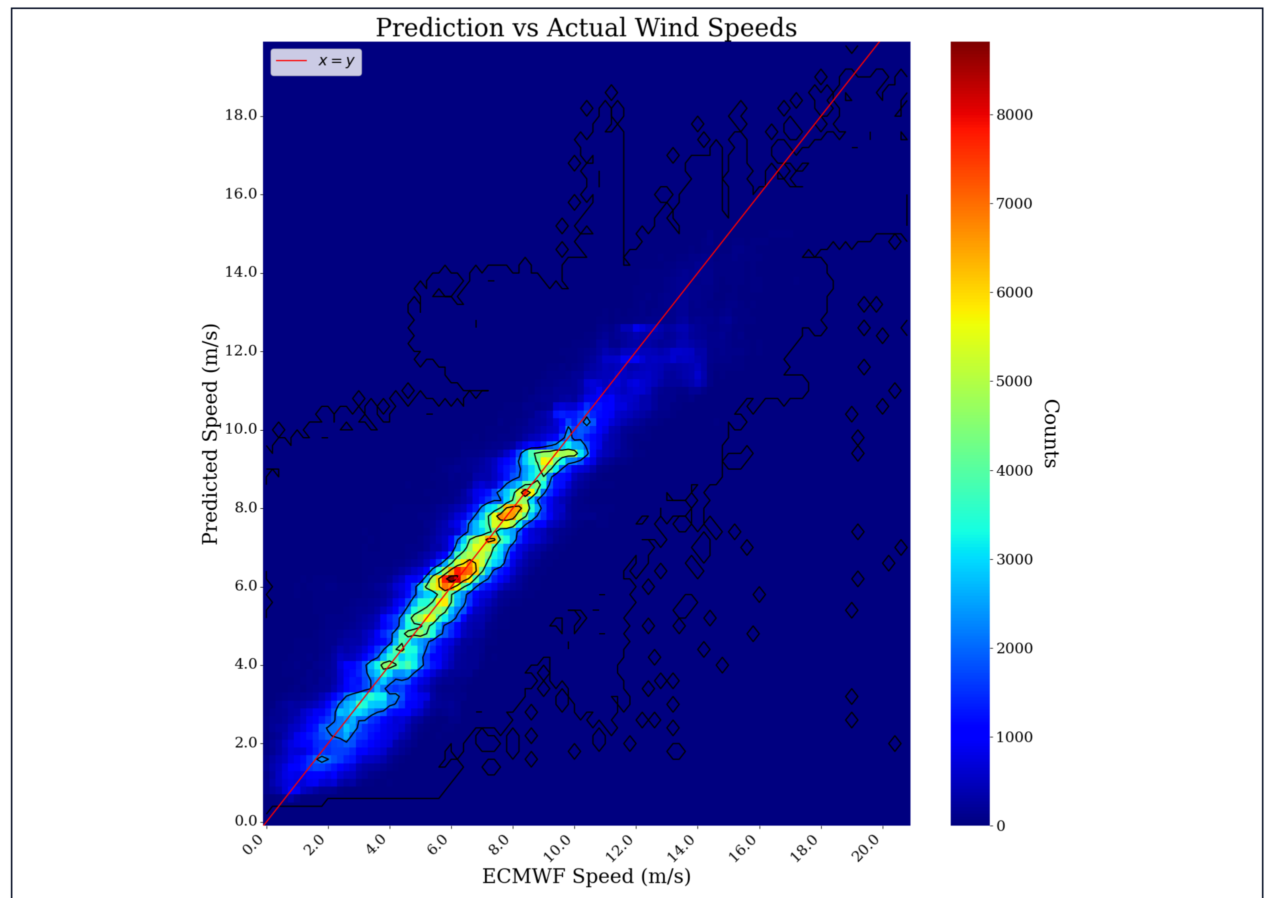

Figure 4
Confusion Matrix from U-Net model with MC Dropout predictions on the y-axis and ECMWF predictions on the x-axis. The red line is the ideal model. The colors indicate the number predictions for a given wind speed, specified by the colorbar on the right.

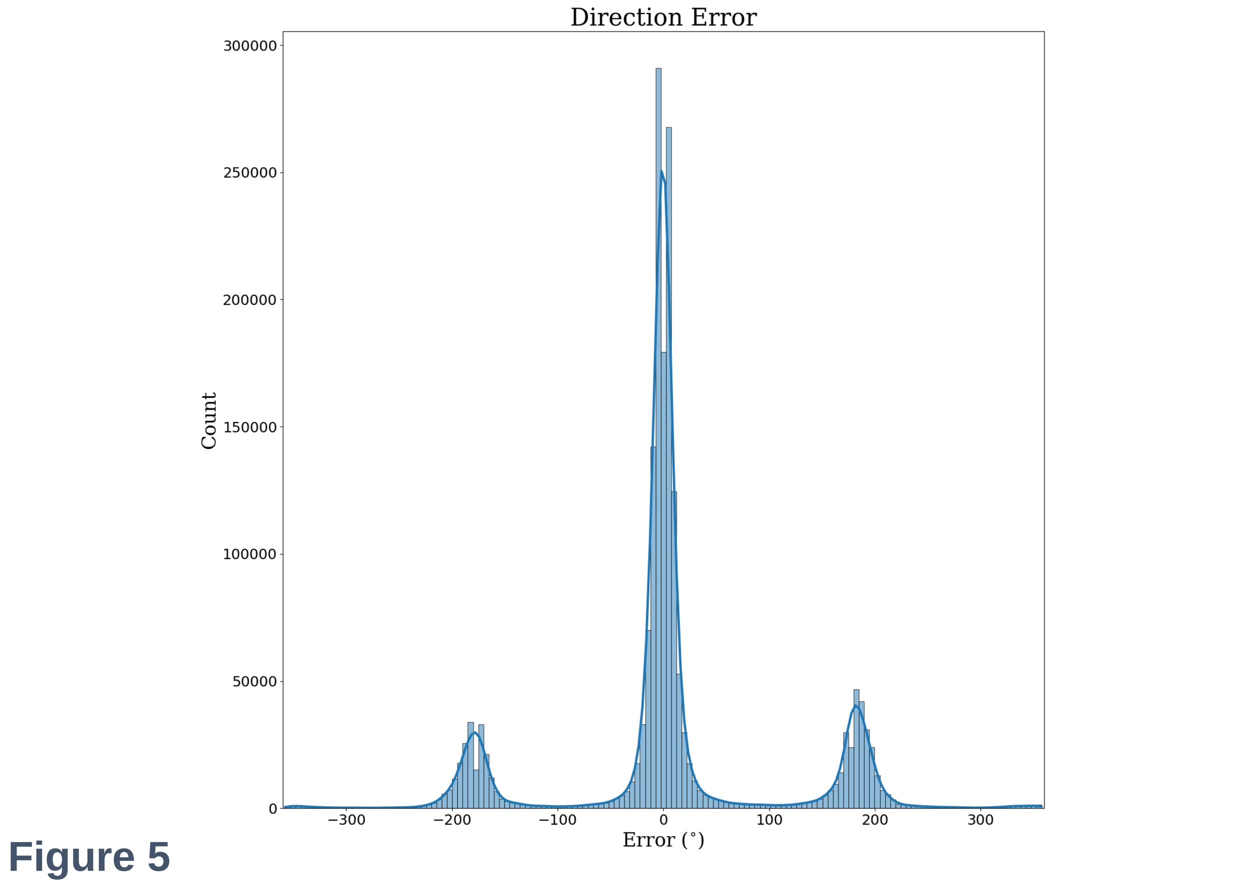

Figure 5
Kernel Density Estimate (KDE) and histogram plot of prediction errors relative to ECMWF predictions. There are several maxima at -180º, 0º, and 180º which correspond to wind ambiguities.

Results

We successfully train a U-Net model to detect rain (see Figure 3), using ASCAT and TRMM collocations, with an overall Intersection over Union (IoU) Score of 0.285. The equation for IoU is below where P is prediction and T is target.

$$\mathrm{IoU} = \frac{|P \cap T|}{|P \cup T|}$$

This result demonstrates that we can successfully detect rain using ASCAT measurements. Our research in wind retrieval with U-Net shows that neural networks can retrieve wind. We trained two U-Net models whose performances are shown in Figures 4 and 5. Overall we have an RMSE of 0.98 m/s for Wind Speed. The direction model has weaker performance with an average error of 52º. However, as can be seen in Figure 5, the errors are distributed at 0º and 180º. This is a common error for pointwise wind retrieval method, suggesting that the neural network predicts wind direction through a similar methodology as the pointwise wind retrieval generates ambiguities.

References

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2. Y. LeCun, Y. Bengio, and G. Hinton, ‘Deep learning’, *Nature*, vol. 521, no. 7553, pp. 436–444, May 2015.
3. Z. Zhou, M. M. Rahman Siddiquee, N. Tajbakhsh, and J. Liang, ‘UNet++: A Nested U-Net Architecture for Medical Image Segmentation’, in *Deep Learning in Medical Image Analysis and Multimodal Learning for Clinical Decision Support*, 2018, pp. 3–11.
4. A. G. Fore, B. W. Stiles, A. H. Chau, B. A. Williams, R. S. Dunbar, and E. Rodríguez, ‘Point-Wise Wind Retrieval and Ambiguity Removal Improvements for the QuikSCAT Climatological Data Set’, *IEEE Transactions on Geoscience and Remote Sensing*, vol. 52, no. 1, pp. 51–59, 2014.