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

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Abstract

This paper aims to expand and improve the capabilities of ASCAT by adding rain detection and advancing wind retrieval using machine learning. We applied semantic segmentation techniques to ASCAT measurements to detect rain over the oceans using machine learning neural networks, thereby enhancing our capabilities to monitor global precipitation. We use a neural network architecture known as U-Net [1] and train it on measurements from the Tropical Rain Monitoring Mission (TRMM) collocated with ASCAT measurements. We also applied the same semantic segmentation techniques to wind retrieval to create a machine learning model that acts as an inverse Geophysical Model Function (GMF). We use the U-Net architecture, but expanded the output classes to many different wind speeds and directions and trained the U-Net on ASCAT data collocated with European Centre for Medium-Range Weather Forecasts (ECMWF) wind vector data. Initial tests successfully increased the capabilities of the ASCAT satellite to detect rainfall in Earth's oceans, and we added the ability to retrieve wind vectors without the 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

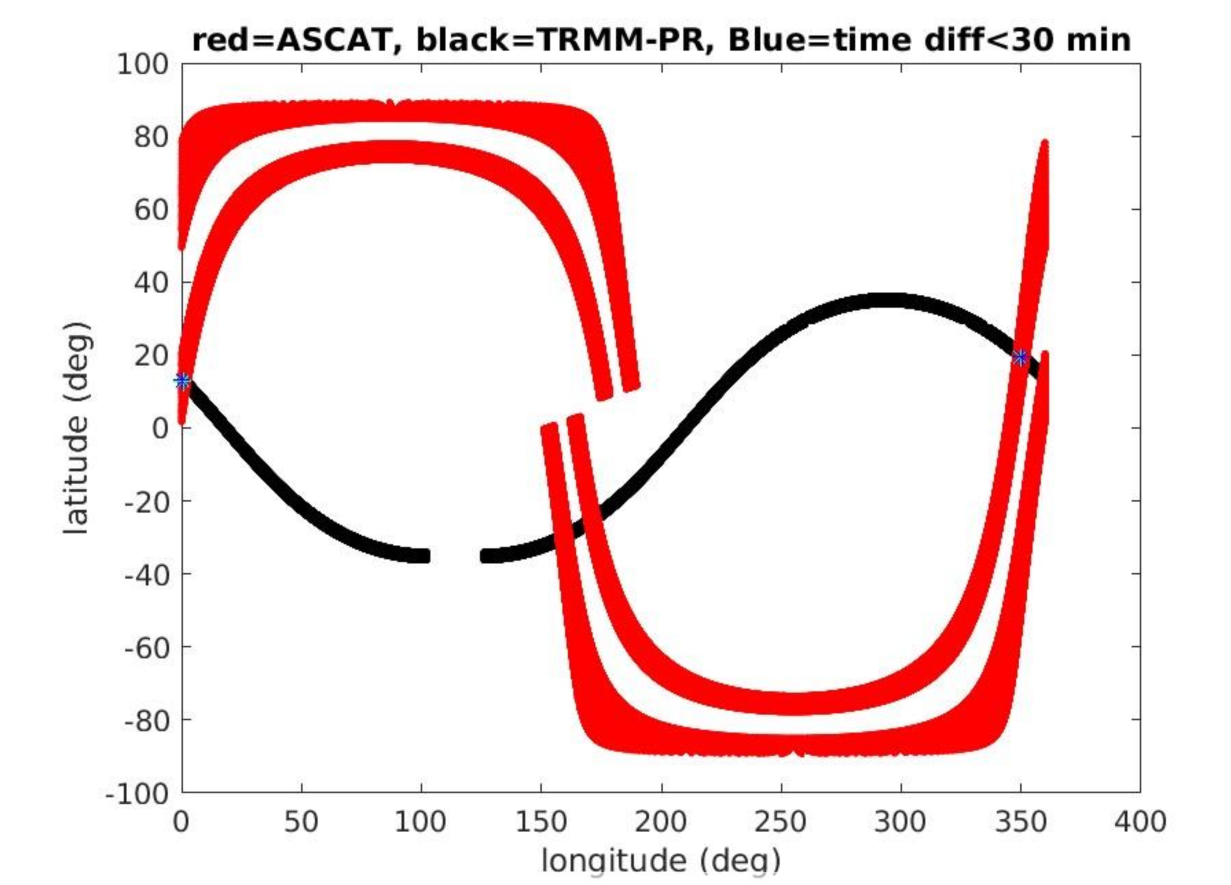

Figure 1
The intersecting beams of TRMM and ASCAT satellites. The intersection of the two paths is where we collocate the data used as our input and target values.

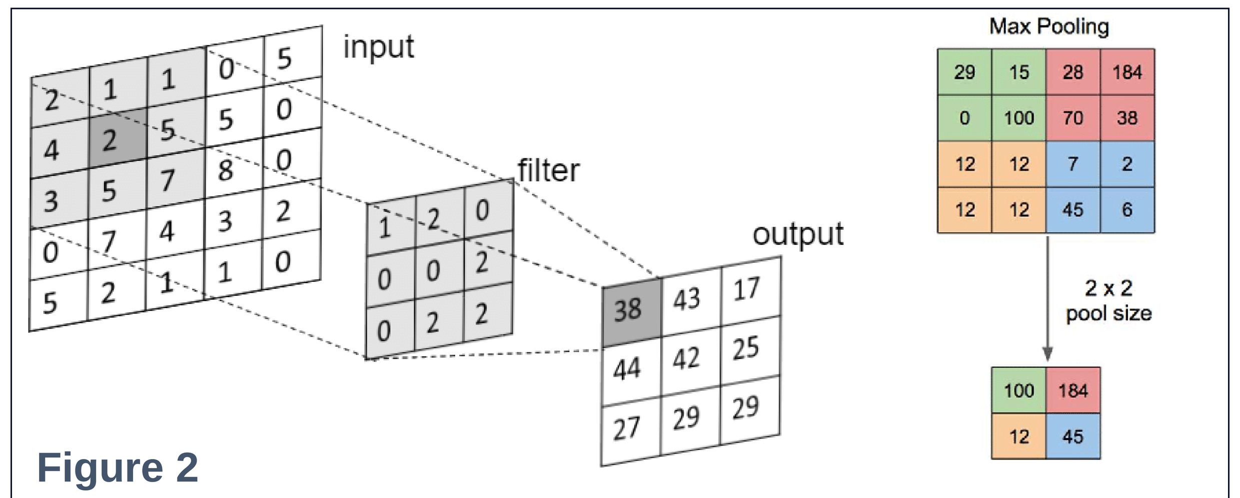

Figure 2
Left Image) Example of 2D convolution operation. Source adapted from [2]
Right Image) Example of Max Pooling. Source adapted from [3]

Convolutional Neural Network (CNN)

A CNN is neural network that uses convolution operations to obtain target values from input values. The training process adjusts weights in the kernel filters until target values in the training set are obtained from input values [4]. However, a validation dataset is used to prevent the model from overfitting on the training dataset. This process allows the model to maintain comparable performance on unseen data [4].

U-Net

U-Net is CNN with an encoder-decoder architecture [5] designed for semantic image segmentation, classification of each individual pixel in an image. The architecture features three main sections:

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

This architecture allows the neural network to take higher order and lower order features into account when determining its output, see Figures 2 and 3.

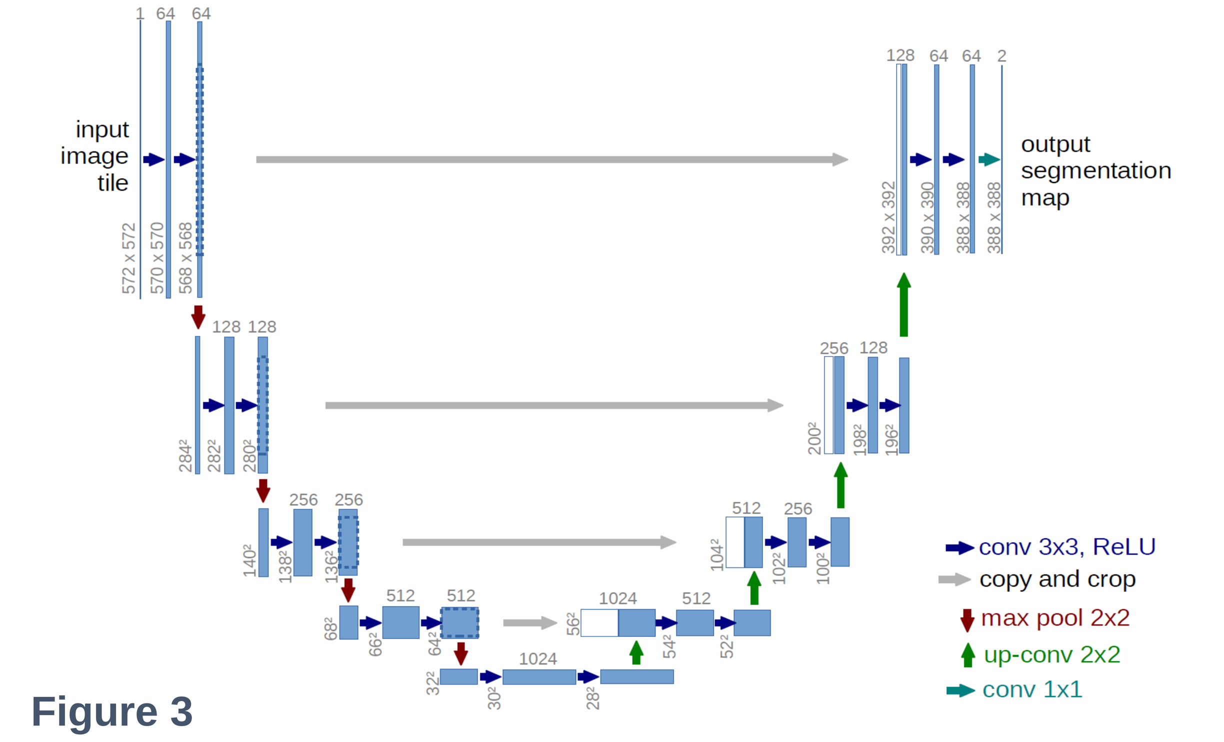

Figure 3
Image of the U-net architecture. The blue boxes are multi-channel feature maps with the number of channels shown above each box and the dimension of each map shown lower left of the box. White boxes are copied encoded feature maps copied to the decoder. The arrows represent different operations with a legend in the lower right of the image. Source adapted from [1]

Wind Retrieval with U-Net

While training the U-Net we also discovered that the same algorithm could be applied to wind retrieval. Traditionally, ocean surface winds are retrieved through pointwise wind retrieval, which entails using the GMF to generate intersections between multiple measurements, an MLE to generate ambiguities, and then an ambiguity selection algorithm to select the most likely ambiguity [6]. Our model should be able to do 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.

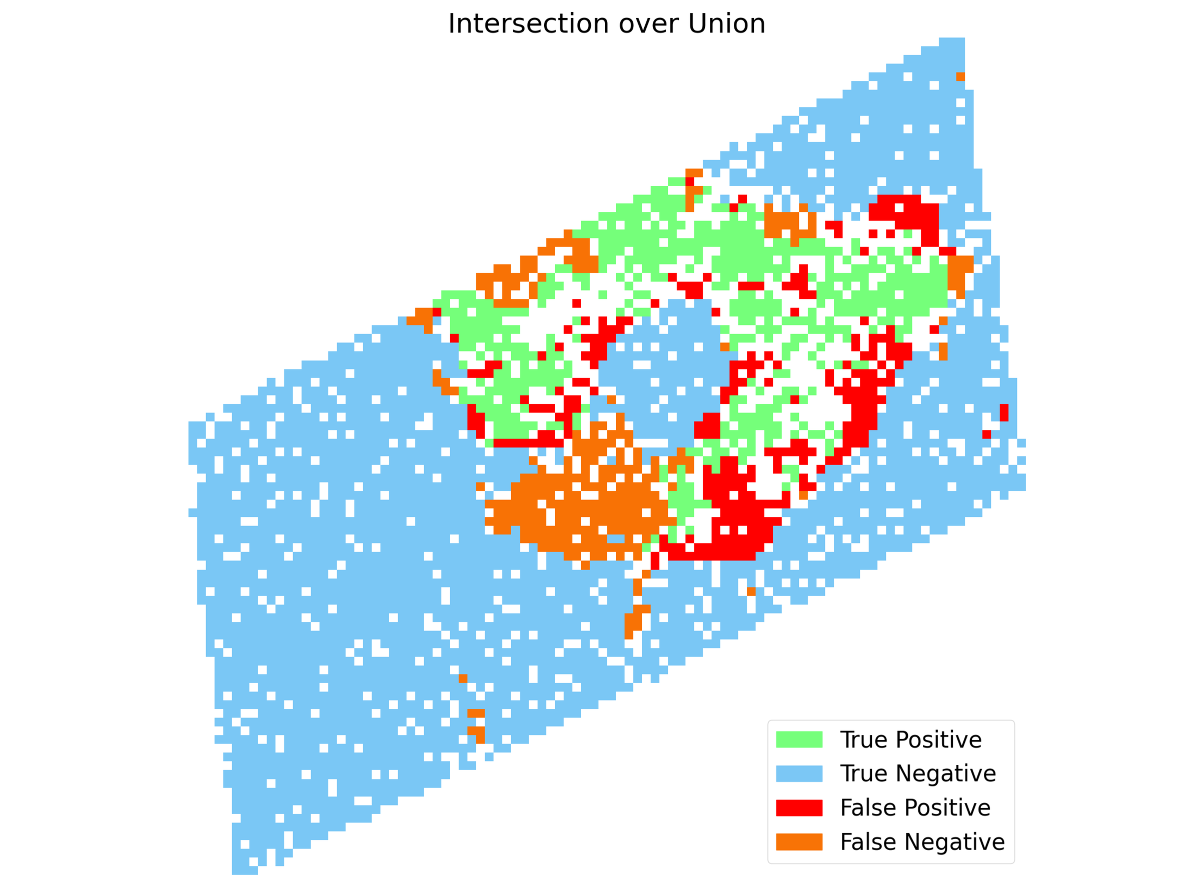

Figure 4
The predictions of the model compared to TRMM. Light green is rain was predicted and detected, light blue is no rain predicted nor detected, red is rain was predicted but not detected, and orange is rain was not predicted, but was detected.

Results

We applied a U-Net model to Rain detection, using an ASCAT and TRMM collocation, which successfully trained a model to create a segmentation map of rain (see Figure 4) with an overall IoU Score of 0.24. This model is proof that we can successfully detect rain using ASCAT measurements.

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

Our preliminary research in wind retrieval through U-Net shows that it is possible to use a neural network to perform wind retrieval. We trained two neural networks whose results are shown in Figures 5 and 6. Overall we had RMSE of 0.66 m/s for Wind Speed and 64.7 deg for Wind Direction. However, these results were partially perturbed by rain measurements. We predict that masking out rain will improve our results.

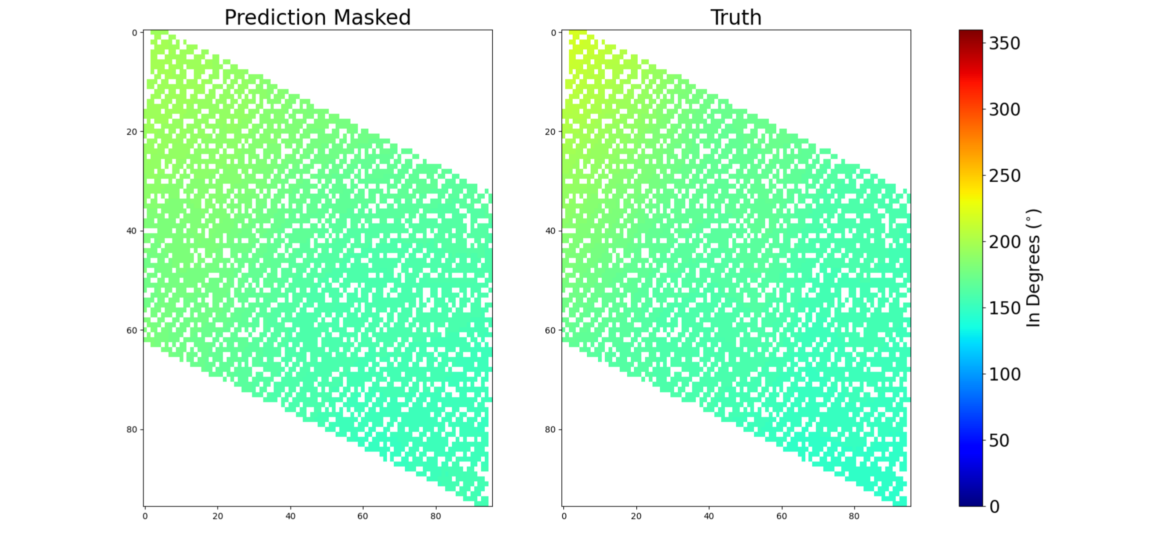

Figure 5
Left panel) Wind speed predictions from our model. Right panel) Wind speed measurements from ECMWF.

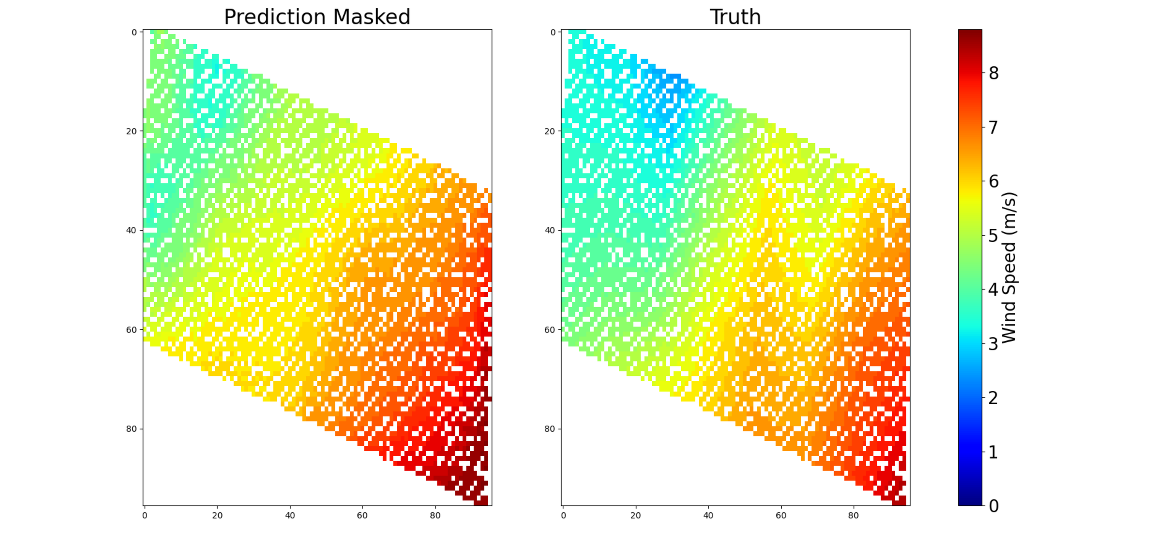

Figure 6
Left panel) Wind direction predictions from our model. Right panel) Wind direction measurements from ECMWF.

References

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