Convolutional Neural Network Structure
To construct a CNN architecture suitable to analyze the presented dataset and extract wind field related features from TSX QLs we choose. The convolutional part of the VGG16 model structure, with weights pre-trained on ImageNet, was used as the base structure of the chosen regression network. We then replaced the fully-connected part of the VGG16 model structure with a Multi-Layer Perceptron (MLP) with two hidden layers in size of 512 and 256 consecutively and a single neuron as output [4].

Table 1. Mean absolute estimation error (against buoy data ground truth) for five selected ocean parameters using our Convolutional Neural Network (CNN) regressor model.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>VV</th>
<th>VH</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wind speed</td>
<td>2.30 m/s</td>
<td>2.68 m/s</td>
</tr>
<tr>
<td>Wave speed</td>
<td>2.50 m/s</td>
<td>2.90 m/s</td>
</tr>
<tr>
<td>Significant wave height</td>
<td>0.75 m</td>
<td>0.88 m</td>
</tr>
<tr>
<td>Significant wave period</td>
<td>3.97 s</td>
<td>3.65 s</td>
</tr>
<tr>
<td>Average wave period of all waves during the 10-minute period</td>
<td>1.94 s</td>
<td>1.84 s</td>
</tr>
</tbody>
</table>

Conclusion & Future work
We were able to extract wind features directly from TSX QL images. If it is attached to metadata, it will help end users to search for images acquired in certain condition. We will examine the capability of Convolutional Neural Networks for extracting ocean wind features from Single Look Complex data.

References

Dataset Characteristics
2252 QL were downloaded from the EOWEB website each containing one of the aforementioned selected buoys inside the QL footprint or within a 50 km perimeter of it. For the present study only the open ocean images was used, leaving 1062 QLs in the dataset. These QLs were then split into 150,385 sub scenes each measuring 128×128 pixels and also satisfying the spatial criterion of the sub scene center being within 50 km of a buoy location.

Recurrent Neural Network Structure
In this study we utilized the structure of a simple Recurrent Neural Network [5] to predict the wind speed at location of multiple buoys using historical data from 2007-2017. In each case two-thirds and one-segment of the buoy data time series were used for training and prediction, respectively (Figure 5) shows the structure of the RNN used. The figure illustrates how weights from the previous state plus a new input form the new state using an iterative scheme.

Figure 5. The RNNs observation is the input and t is the hidden state at time step t, which is calculated based on the previous hidden state and the current input. Y_t is the output at step t.

RNN Experiment
The ability to predict the latter portion of a time series from an earlier portion in this case is an indicator of both overall accuracy as well as (indirectly) of large-scale (~100 km) spatial representativeness of the data (Figure 6a, b) shows reconstruction and prediction results for two buoys representing diverse ocean environments: one in the Gulf of Mexico (ID-42055) in mostly calmer waters and little swell; and the other in the Atlantic Ocean (ID-40411) with higher Sea State, wind speed, swell and increased amount of rougher weather conditions. The time series of wind speed in each case spans the period 2007-2017, containing about 90K hourly observations.