Radar Super-Resolution Using a CNN

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1. Abstract

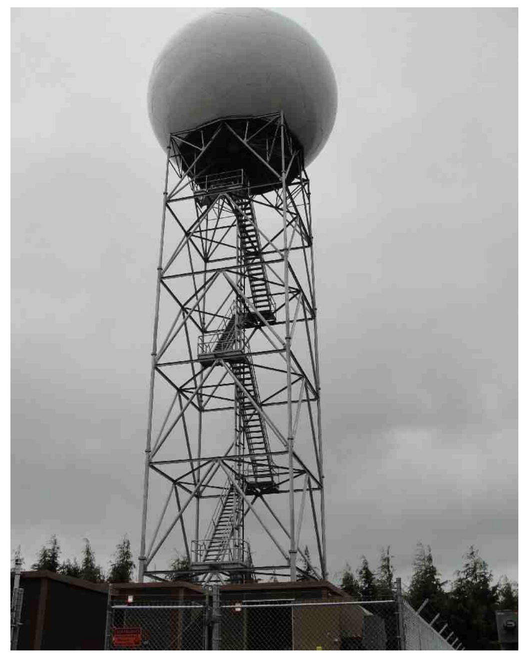
Super-resolution involves artificially increasing the resolution of gridded data beyond its native resolution. Typically, this is done using interpolation schemes, which estimate sub-grid scale values from neighboring data, and perform the same operation everywhere regardless of the large-scale context, or by requiring a network of radars with overlapping fields of view. Recently, significant progress has been made in image super resolution using machine learning. Conceptually, a neural network may be able to learn relations between large scale image features and the associated sub-pixel scale variability and outperform interpolation schemes. Here, we use a deep convolutional neural network to artificially enhance the resolution of NEXRAD PPI scans. The model is trained on 6-months of reflectivity observations from the Langley Hill WA (KLGX) radar, and we find that it substantially outperforms common interpolation schemes for increasing the resolution of the scans based on several objective error and perceptual quality metrics.

2. Data

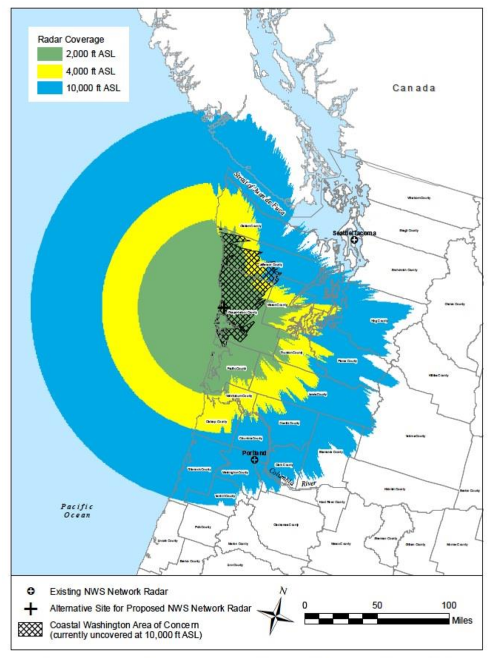
10,000 Composite reflectivity plan position indicator (PPI) scans from the Langley Hill WA radar (KLGX) from fall of 2016 and 2017. This is a particularly rainy time of year. ¼ of the samples were used for validation.

PPI scans were resampled on a 512x512 pixel cartesian grid. The neural network was trained to estimate the original 512x512 scan from 128x128 and 64x64 pixel down-sampled versions.

The Langley Hill radar [1]



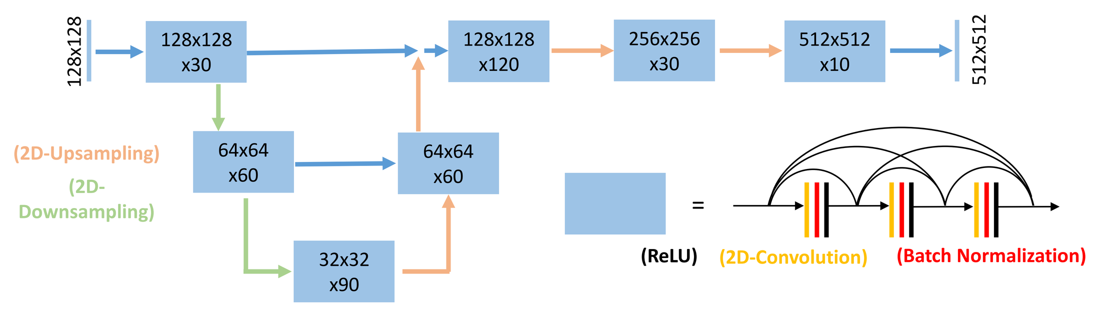
Coverage map [1]



3. Method

We use a convolutional neural network (CNN). The model consists of a series of convolutional kernels each followed by a non-linear activation function. The weights of the kernels are learned iteratively, using a 7,500 sample training set. After training, when a series of these learned kernels along with non-linear transfer functions are applied to a PPI scan they can enhance the resolution of the scan.

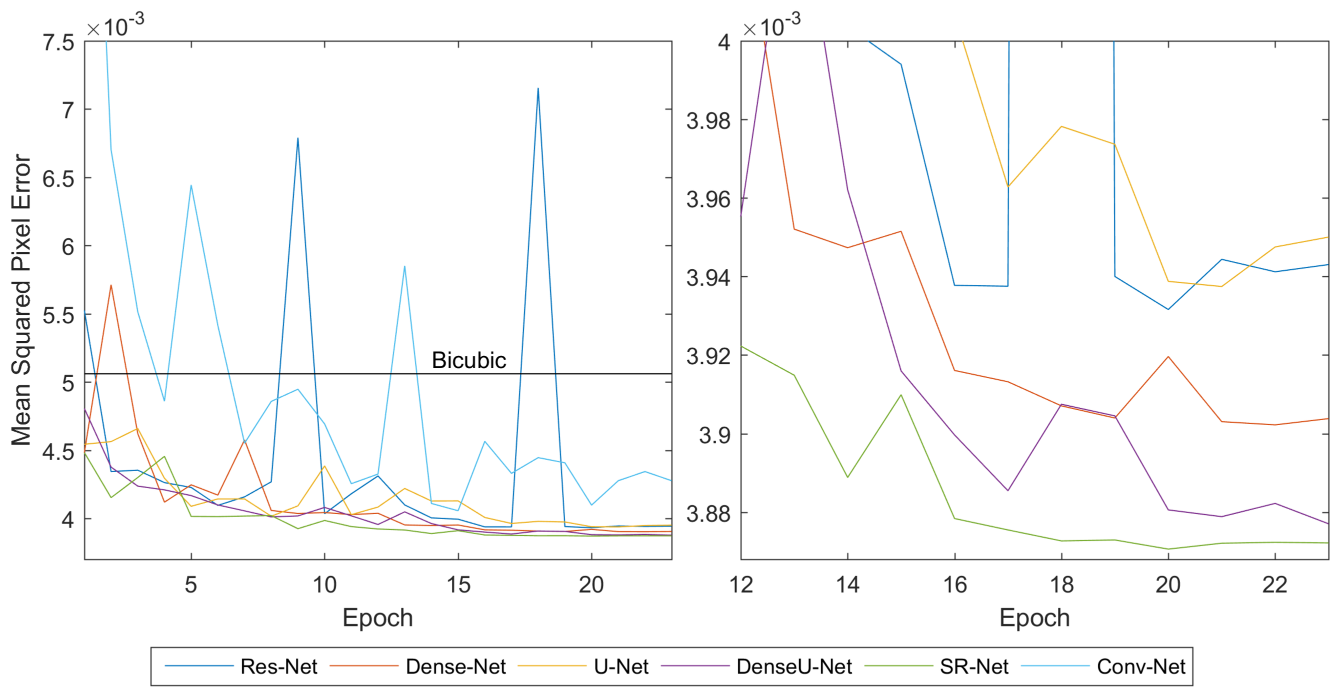
The network architecture used is known as a "U-net" [2]. This is followed by 2 up-sampling convolutional blocks. Each convolutional block is composed of 3 densely connected [3] layers consisting of a 2D convolution, batch normalization, and a rectified linear unit (ReLU) transfer function.



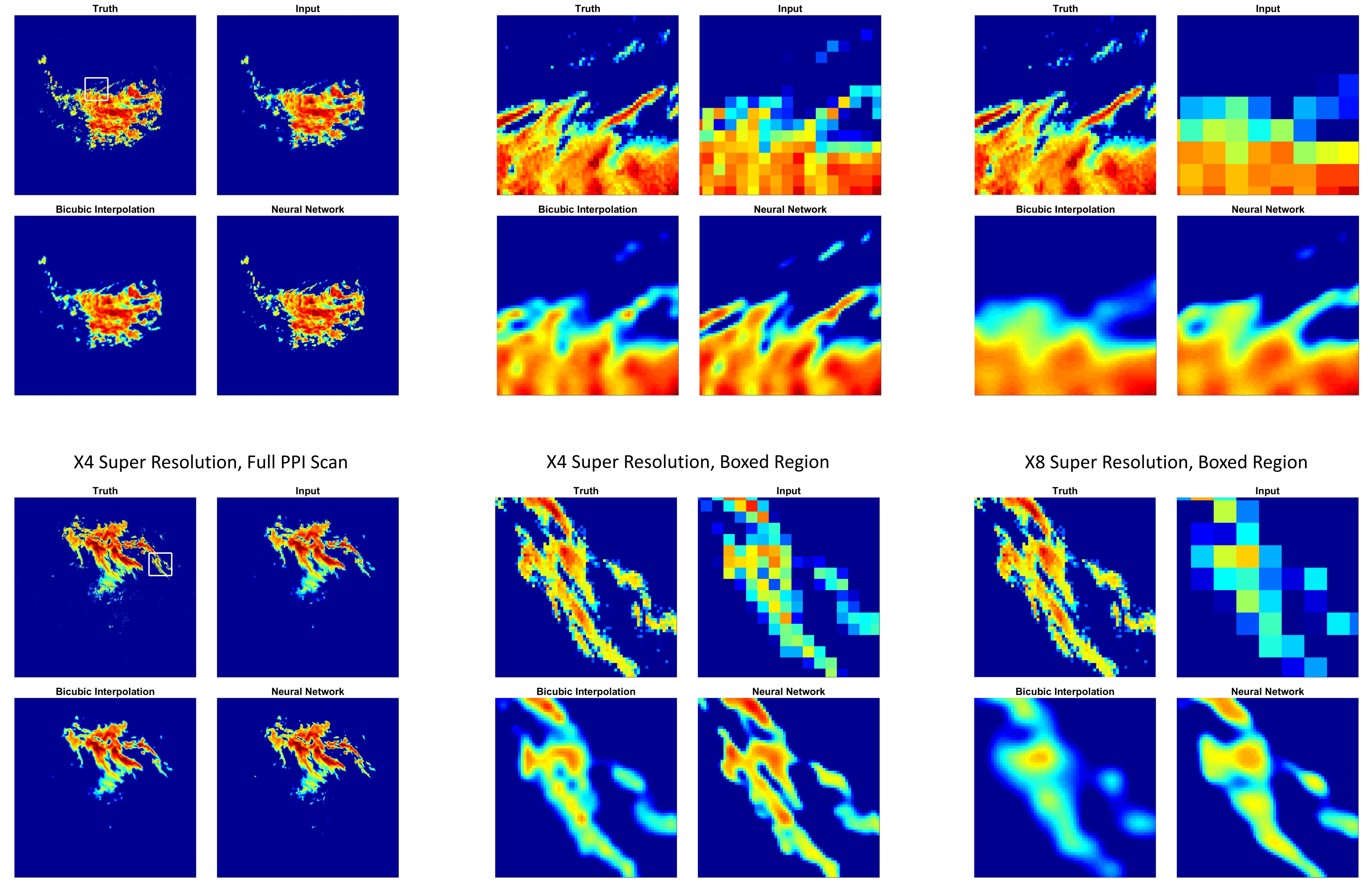
A schematic of the neural network

4. Choice of Model

Several common neural network architectures were tested to identify the most effective one for this task. The performance vs training epoch is shown on the right. While they are very different architectures the number of trainable parameters is similar for each model. *All* of the models tested outperformed interpolation. We ultimately used a U-net with densely connected convolutional blocks (purple line, see section 3).

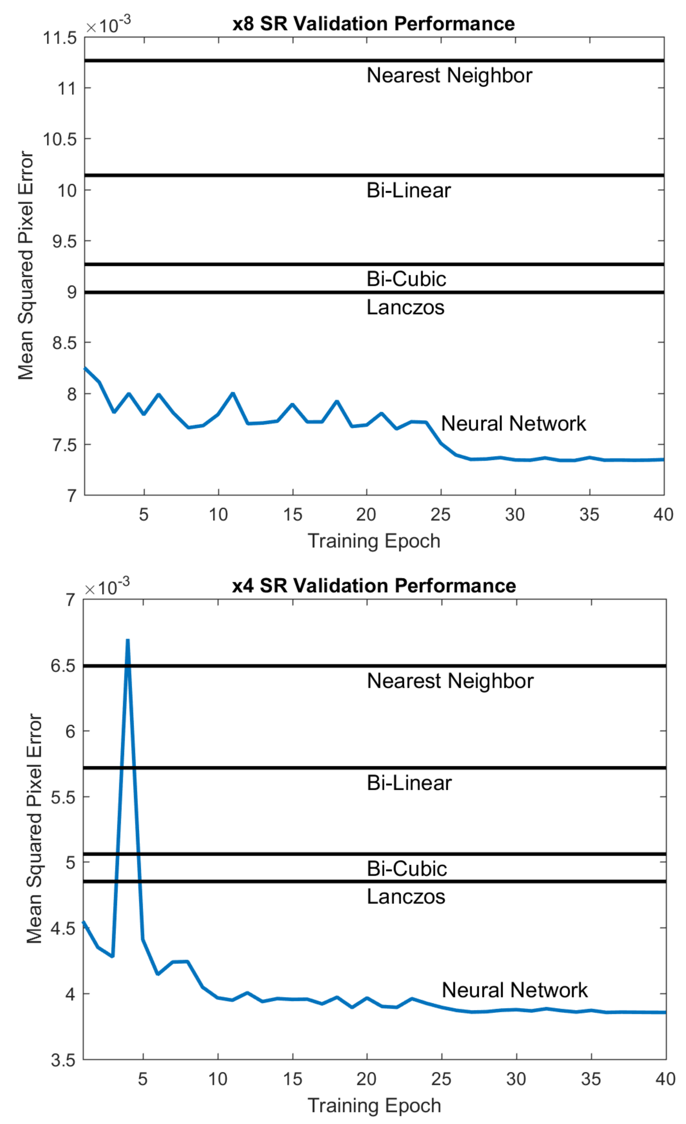


5. Examples

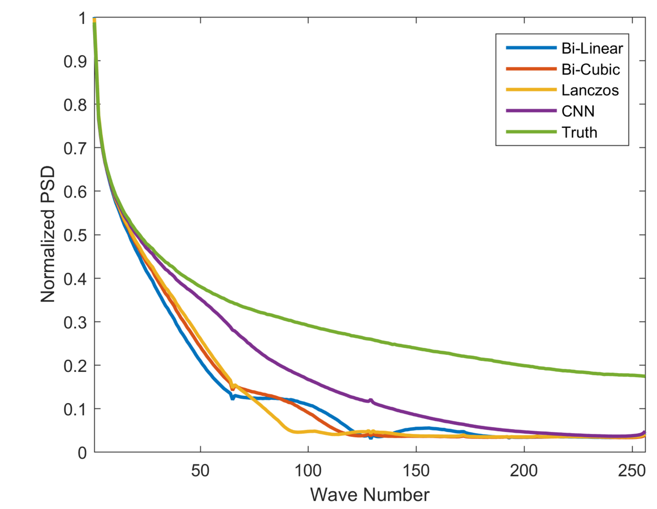


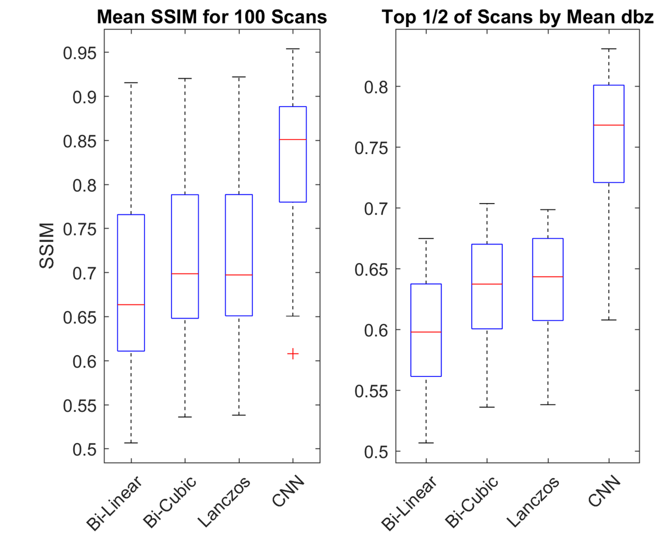
standardized reflectivities (dimensionless)

6. Results



Pixel-wise mean squared error performance for x8 (top) and x4 (bottom) super-resolution with respect to training epoch, compared to four interpolation schemes. In both cases the neural network outperforms interpolation.





Mean power spectral density for 100 samples from the validation set. The neural network enhanced PPI scans have higher PSD at high wave numbers (purple line), meaning it is better at retaining small-scale features.

Structural similarity index SSMI [4] (a measure of the similarity of features in two images) comparison between neural network super resolution and interpolation. Left: 100 samples from the validation set, Right: the 50 of these samples with the most precipitation.

[1] https://www.atmos.washington.edu/cliff/Langleyradar.html

[2] Ronneburger, O., P. Fischer, T Brox, 2015: U-Net: Convolutional Networks for Biomedical Image Segmentation. *arXiv*, 1505:04597

[3] Haung, G., Z. Liu, K. Weinberger, L. Van der Maaten, 2017: Densely Connected Convolutional Networks. *arXiv*, 1608:06993

[4] Wang, Z., A. Bovik, H. Sheikh, E. Simoncelli, 2004: Image quality assessment: from error visibility to structural similarity. IEEE Transactions on Image Processing, **13 (4)**, 600–612 doi:10.1109/TIP.2003.819861.