Table 1: Mean PSNR Values OF SST Reconstruction For Different Scales Between High SR And Low SR

Model	Low SR	High SR	Iterations	PSNR Gain
VDSR	5km	1km	1,42,870	12.78
SRCNN	5km	1km	1,74,270	2.19
VDSR	15km	5km	19,316	9.26
SRCNN	15km	5km	1,21,164	6.35

Training Setting: The network inputs a low SR patch and predicts *patch residuals*. *Residuals* are mathematical differences between the low SR and high SR patches. Once predicted, the *patch residuals* are added back to the input low SR patch to give the final image (high SR patch). Residual-learning accelerates training. To ensure that repeated convolutions don't reduce the size of feature maps significantly, zero padding is implemented. Training is optimized by Adaptive Moment estimation. The Mean Square Error (MSE) between the reconstructed and high SR patch is minimised using mini-batch (batch size 64) gradient descent based on back-propagation. Learning rate chosen is 0.001.

Evaluation: Peak Signal Noise Ratio (PSNR), the chosen accuracy metric, is defined as

$$PSNR = 20 \cdot log_{10}(MAX_I) - 10 \cdot log_{10}(MSE) \quad (1)$$

where (MAX_I) is the maximum pixel value of the image. Since our input is normalised, $MAX_I = 1$. The first term reduces to 0 and only the MSE component is computed. Smaller the MSE, greater is the PSNR and better is the image quality.

3 RESULTS

The evaluation results are presented in Table 1. PSNR Gain for a patch is defined by $PSNR_{model} - PSNR_{smooth}$, where $PSNR_{model}$ is computed between the expected and predicted patch and $PSNR_{smooth}$ is between the input and expected patch. The Mean PSNR Gain is the average PSNR Gain over all patches. Since SRCNN surpassed bicubic and EOF-sampling baselines in [3], a comparison between results obtained from training SRCNN and VDSR is made. VDSR converges faster with better PSNR gains in both cases.

Figure 2 shows a randomly chosen set of patches predicted by network trained to downsample 5km SR to 1km SR. (Visible difference between patches isn't observed as the magnitude of SST difference is in the order of 10^{-2} °C). VDSR has enhanced gradients that were not visible in low SR patches. The residual between predicted and high patches is roughly zero, proving high resemblance. Further work in progress is to be completed in order to compare VDSR with *Dynamical Downscaling*. The predicted patches were first rescaled and then appropriately joined to construct the SST Field. The pixels representing land regions were masked.

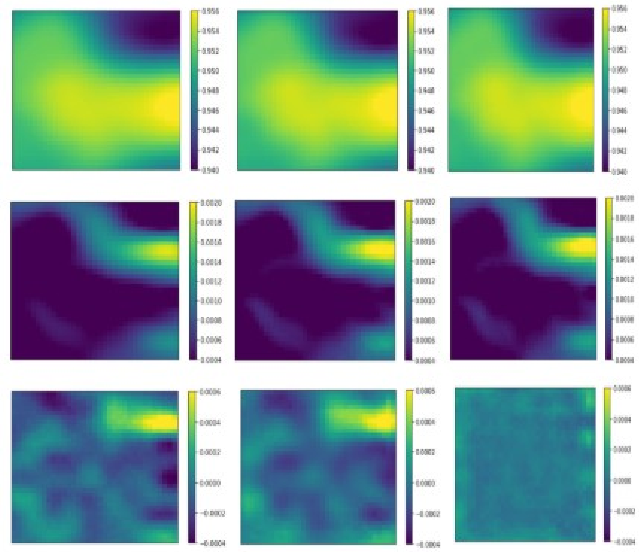

Figure 2: Results
Top Row (Left to Right): Low SR, Predicted and High SR Patches
Middle Row (Left to Right): Low SR, Predicted and High SR Gradients
Bottom Row (Left to Right): Patch Residuals between Low & High SR, Low & Predicted and Predicted & High SR

4 CONCLUSION

In a first-of-its kind approach, demonstrations have been carried out to downsample low SR SST Fields of Bay of Bengal. The chosen network addresses outperforms SRCNN in terms of significant PSNR gains on derived data. It is now worthwhile to perform tests on actual data. Further work planned also includes exploiting the *multi-scalefactor super-resolution* quality of VDSR [4], i.e., a single network to reconstruct fields irrespective of scale between high and low SR.

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