Efficient Downscaling of Satellite Oceanographic Data With Convolutional Neural Networks

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ABSTRACT

Space-borne satellite radiometers measure Sea Surface Temperature (SST), which is pivotal to studies of air-sea interactions and ocean features. Under clear sky conditions, high resolution measurements are obtainable. But under cloudy conditions, data analysis is constrained to the available low resolution measurements. We assess the efficiency of Deep Learning (DL) architectures, particularly Convolutional Neural Networks (CNN) to downscale oceanographic data from low spatial resolution (SR) to high SR. With a focus on SST Fields of Bay of Bengal, this study proves that Very Deep Super Resolution CNN can successfully reconstruct SST observations from 15 km SR to 5km SR, and 5km SR to 1km SR. This outcome calls attention to the significance of DL models explicitly trained for the reconstruction of high SR SST fields by using low SR data. Inference on DL models can act as a substitute to the existing computationally expensive downscaling technique: Dynamical Downsampling. The complete code is available on this Github Repository.

1 INTRODUCTION

Sea Surface Temperature (SST) is the measurement of temperature at a depth ranging from 1 millimeter to 20 meters below the sea surface. It is an estimate of the energy in the sea due to the motion of molecules. SST is a strong indicator of global climate change and stress to aquatic life. SST Field (Figure 1) refers to the spatial and temporal distribution of temperature on an ocean's surface.

Radiometers (thermal infrared or microwave) in space-borne satellites measure SST. High spatial resolution (SR) satellite radiometers are operative under clear sky conditions. However, under cloudy conditions, high SR measurements are not obtainable and data analysis is restricted to the available low SR measurements.

Reconstruction of high SR observations from the available low SR data will help in accurate estimation of SST fronts and small-scale oceanic phenomena [5]. This reconstruction is termed as *Downscaling*.

At present, *Dynamical Downscaling* is deployed to reconstruct high SR SST Fields. It involves dynamically extrapolating the effects of large-scale climate processes to local scales of interest. But this approach is resource intensive. Our study proposes a deep learning based method to construct unavailable high SR observations in a relatively efficient manner. Though training DL models is computationally expensive, it is a one-time procedure. Once trained, they can be used for innumerable predictions, giving them an edge over the former.

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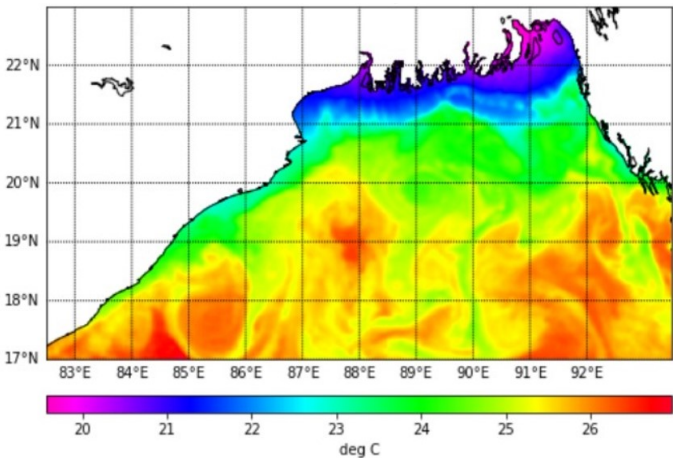


Figure 1: Sea Surface Temperature (°C) Field of Bay of Bengal (Spatial Resolution 1km)

2 RELATED WORK

Traditionally, bicubic interpolation has been used to generate high resolution observations from low resolution data. But this often induces non-image textures or strange pixels at small-scales. Lately, DL based methods ([1], [4], [6]). have shown commendable performances on Single Image Super Resolution tasks. Super Resolution Convolutional Neural Network (SRCNN), by C. Dong et al. [1] was the first contribution in this domain. With just three convolutional layers, SRCNN surpassed the bicubic baseline. This led to an upsurge in research on DL based downscaling.

With the immense data on sea surface temperature collected by satellites, it is worthwhile to tap into the potential of deep learning to make predictions for the same. Experiments conducted by Ducournau et al. in [2] proved that Super Resolution CNN (SRCNN) [1], with just three convolutional layers, surpasses the bicubic and EOF-sampling baseline. We revive, and further expand their work by proposing a distinct deep network with faster convergence. We choose a different dataset: SST Fields of Bay of Bengal. We generate SST observations of SR 5km (from SR 15km) and SR 1km (from SR 5km) in separate experiments.

3 METHOD

3.1 Model

We have used the Very Deep Super Resolution CNN (VDSR) [3] network. It comprises 20 convolutional layers each mapped via Rectified Linear Unit activation to the next (except for the last layer). The first layer operates on the input image. The last layer,

used for image reconstruction, consists of a single filter of size 3 × 3 × 64. Remaining layers comprise of 64 filters, with kernel size (3,3). By cascading small filters many times in a deep network structure, contextual information over large image regions is exploited in an efficient way.

3.2 Data

Group of High Resolution Sea Surface Temperature (GHRSST) data engulf SST observations from all kinds of available sources. Major contribution in this dataset comes from the space-borne satellite radiometers. In this study, we have used L4 GHRSST product (gap-free SST maps) with a regular spatial resolution of 1 km. The data was downloaded from Physical Oceanography Distributed Active Archive Center. By running an averaging function on the 1km SR observations (Figure 1, data resembling 5km SR was generated. A three point smoother was applied on the generated 5km SR data to generate 15km SR data.

3.3 Preprocessing

Both land and sea (Figure 1) are present in a single SST Field. While the pixel values in spatial regions representing sea give the surface temperature, the value over land regions is a fixed constant, known as *fix value*. The *fix value* differs in each data file. To maintain uniformity, all SST Fields were rewritten to assign a single *fix value*. The region representing sea in each SST field was divided into 1800 overlapping patches (small areas) of size (33,33). These patches were normalised by the maximum SST.

3.4 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.

3.5 Evaluation

Given a noise-free mxn monochrome image I and its noisy approximation K, mean squared error (MSE) is defined as:

$$MSE = \frac{1}{mn}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}[I(i,j) - K(i,j)]^2 \quad (1)$$

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

$$PSNR = 20 \cdot log_{10}(MAX_I) - 10 \cdot log_{10}(MSE) \quad (2)$$

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.

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

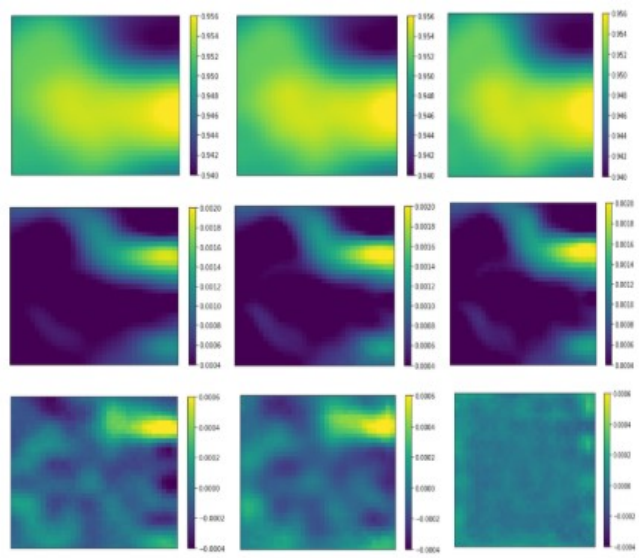
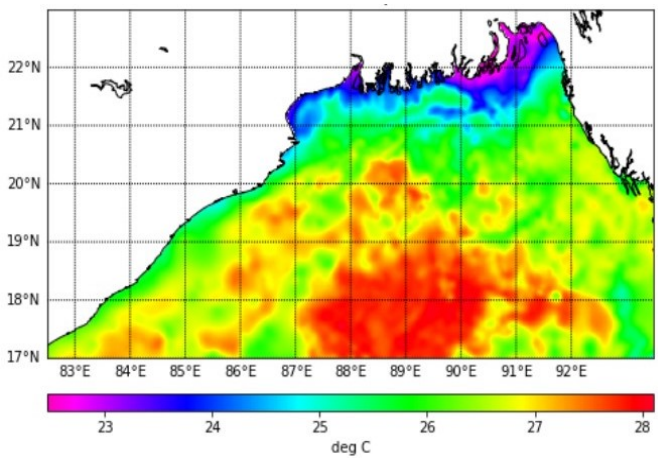


Figure 2: Results
Top Row (Left to Right): Low SR, Predicted and High SR Patches
Middle Row (Left to Right): Low SR, Predicted and High SR Gradients
Bottom Row (Left to Right): Patch Residuals between Low & High SR, Low & Predicted and Predicted & High SR

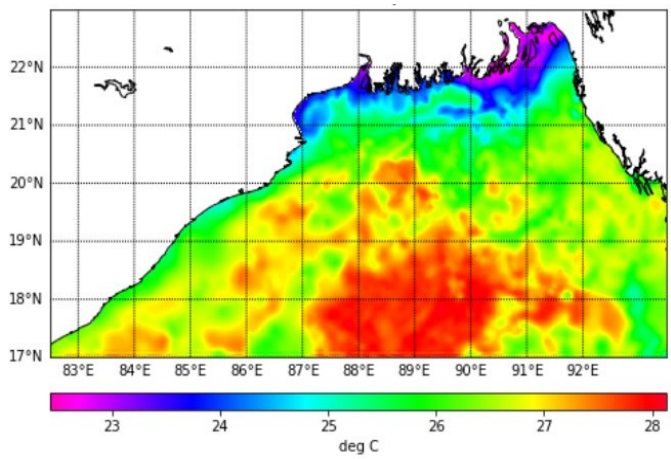
4 RESULTS

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 [2], a comparison between results obtained from training SRCNN and VDSR is made. VDSR converges faster with better PSNR gains in both cases.

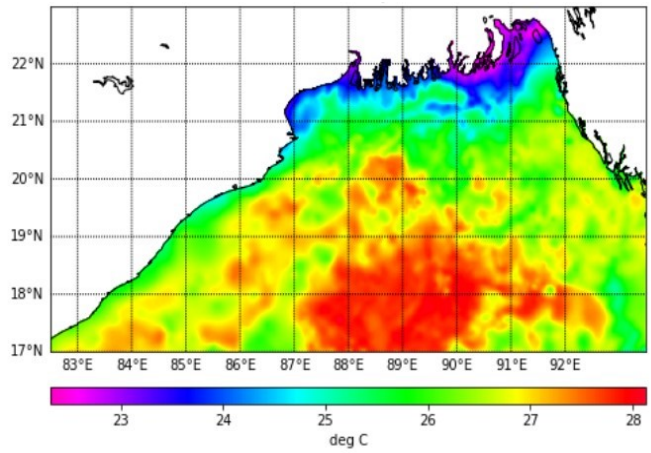
Figure 2 shows a randomly chosen set of patches predicted by network trained to downsample 5km SR to 1km SR. (Visible difference between patches isn't observed as the magnitude of SST difference is in the order of 10^{-2} °C). VDSR has enhanced gradients that were not visible in low SR patches. The residual between predicted and high SST residuals is roughly zero, proving high resemblance. The predicted patches were first rescaled and then appropriately joined to construct the SST Field (as shown for a randomly chosen day: December 20, 2007 in Figures 3 and 4). The pixels representing land regions were masked. The mathematical difference between the low SR, high SR and predicted fields is shown in Figure 5. Further work in progress is to be completed in order to compare VDSR with *Dynamical Downscaling*.



(a) Low Spatial Resolution (5km) Field

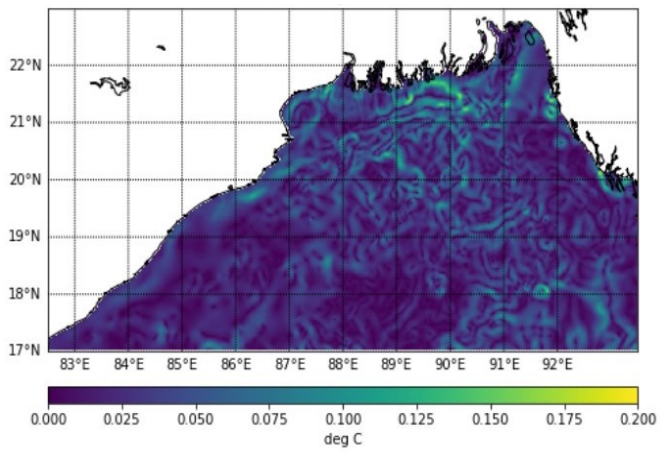


(b) Predicted Field

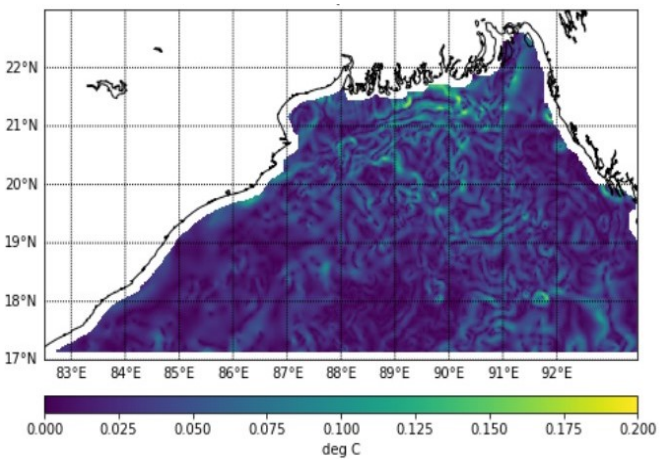


(c) High Spatial Resolution (1km) Field

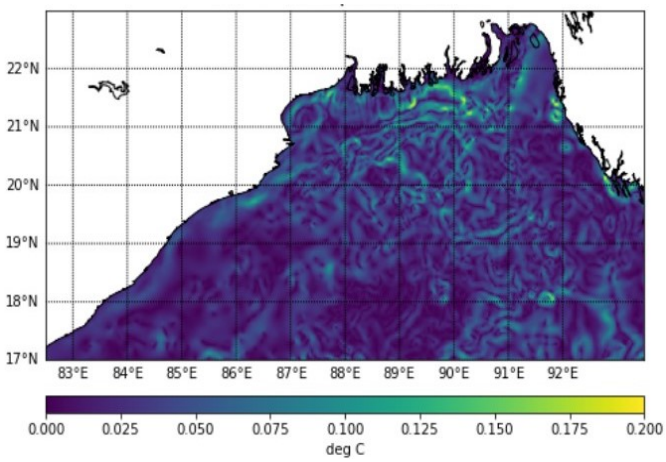
Figure 3: SST Fields of Bay of Bengal on December 20, 2007



(a) Low Spatial Resolution (5km) Gradient

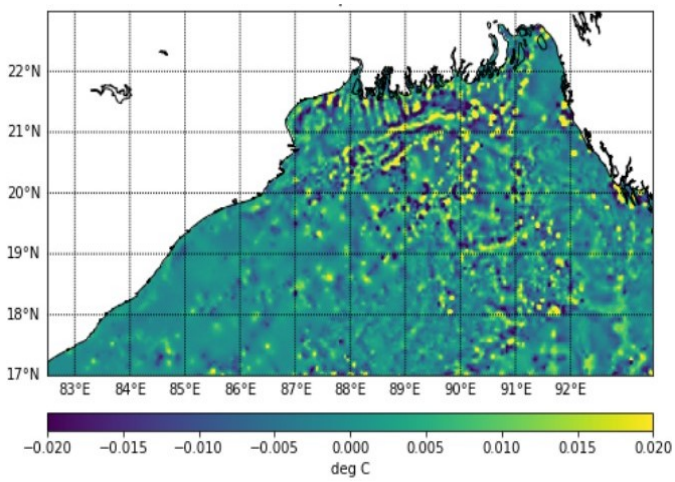


(b) Predicted Gradient

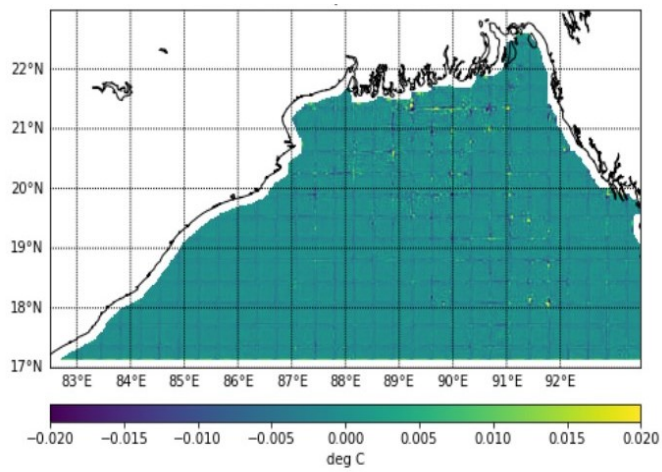


(c) High Spatial Resolution (1km) Gradient

Figure 4: SST Gradient Fields of Bay of Bengal on December 20, 2007



(a) Between Low SR (5km) and High SR (1km)



(b) Between Predicted and High SR (1km)

Figure 5: Difference between SST Fields of Bay of Bengal on December 20, 2007

5 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 [3], i.e., a single network to reconstruct fields irrespective of scale between high and low SR.

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