Using Deep Super-Resolution for High Resolution Precipitation Images

Xinli Cai[1,2], Xinyao Sun[1], Mike Flannigan[2]

[1] Computer Science in Multimedia, Department of Computer Science, University of Alberta, 116 ST 85 Ave, Edmonton, Alberta, Canada T6G 2R3

[2] Canadian Partnership for Wildland Fire Science, Department of Renewable Resources, University of Alberta, 116 ST 85 Ave, Edmonton, Alberta, Canada T6G 2R3

INTRODUCTION

ABSTRACT

In this study, we proposed to apply deep SR models in generating high-resolution precipitation images. Specifically, we evaluated the Super-Resolution Using Deep Convolutional Networks (SRCNN) and Super-Resolution using Deep Residual Multipliers (SRDRM). We also included two interpolation methods bilinear and kriging as a comparison of deep SR models.

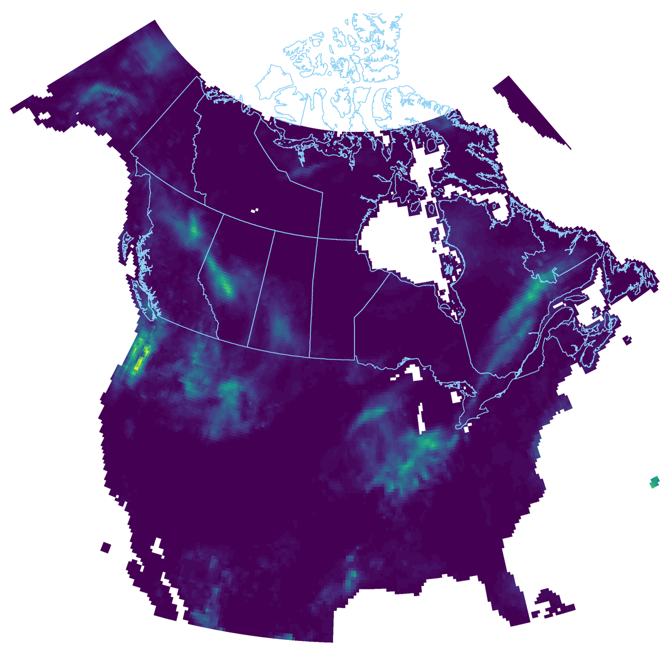

Figure 1. An example of daily precipitation map in study area on September 19, 2017

DATA PREPARATION

In this study, we downloaded the ERA5 hourly precipitation from ECMEF. We collected the hourly ERA5 precipitation from day 1 to day 365 in 2017 by added the hourly precipitation to 24-hr precipitation.

To slice the training images, we moved a window with fixed size across the study area. We chose a fixed image size of 64 x 64 (16 degree x 16 degrees) and a fixed strip size of 4 degrees. The image size are selected to accommodate between having high resolution images and having sufficient training. Because the areas in the ocean are cells with NA values. To eliminate the amount of Na's in the training images, we only selected images that has landcover greater than 95 percent. Overall, we selected 32 images pre day and 4132 image for the year of 2017.

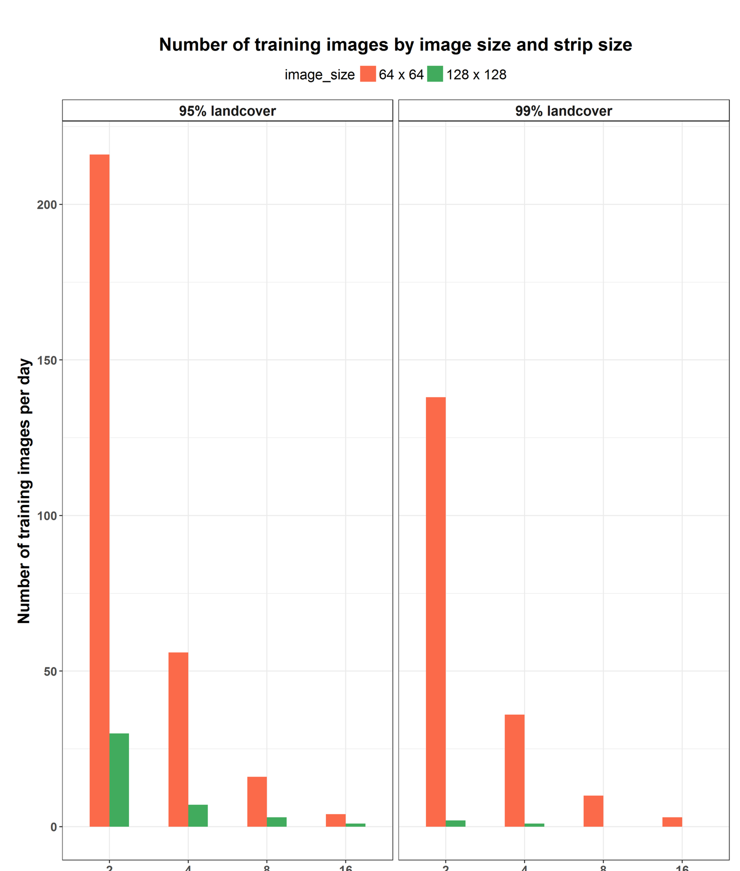

Figure 2. Stats for slicing training image by image size and precent of land cover

MATERIALS and METHODS

DOWNSCALING

We downscaled the HR images (64 x 64) in 2x (32 x 32) and 4x (16 x 16). The trivial average of the nearest 4 pixel is applied to generate the 2x downscaled images, while the nearest 16 pixel is used to generate the 4x downscaled images. An example of 2x and 4x downscale is shown on Figure.

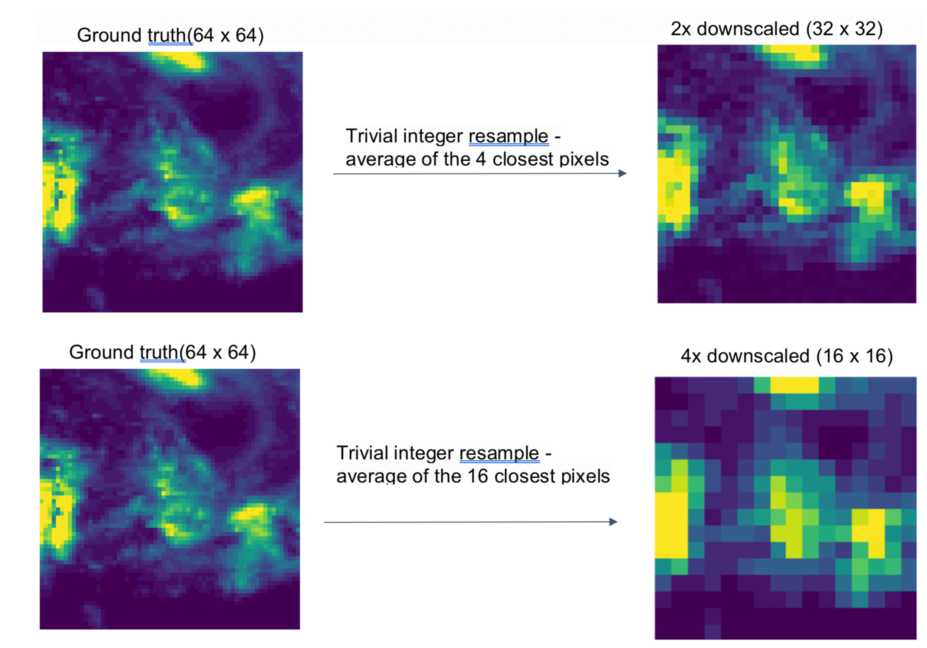

Figure 3. An example of 2 time and 4 time downscale for image 21 on September 19, 2017

INTERPOLATION

In this study, we chose the standard bilinear and the advanced kriging as the representative for interpolation methods.

- Bilinear interpolation uses the weighted average of two translated pixel values for each output pixel value.
- Ordinary kriging models spatial variability of observed data by constructing a semi-variogram. In this study, we fitted the semi-variogram using a spherical model that is commonly used in interpolation studies.

DEEP LEARNING MODEL

SRCNN - Super-Resolution using Deep Convolutional Networks

SRCNN (Dong 2015) learns an end-to-end mapping between low- and high-resolution images, with little extra pre/post-processing beyond the optimization.

The main difference between SRCNN and transitional methods is that the sparse-coding based SR method can be viewed as a kind of convolutional neural network (CNN).

In our CNN, the low-resolution dictionary, high-resolution dictionary, non-linear mapping, together with mean subtraction and averaging, are all involved in the filters to be optimized. So the SRCNN method optimizes an end-to-end mapping that consists of all operations.

SRDRM - Super-Resolution using Deep Residual Multipliers

The core block of SRDRM (Islam 2019) model called Deep Residual Multiplier (DRM) which contained 10 layers structure to learn the input features and one de-convolutional layer for up-scaling. The 10 layers learning structure incorporated one convolutional layer, 8 residual layers, and convolutional layer.

Therefore SRDRM architecture could learn and generate 2x, 4x or 8x HR predicted images by applying 1, 2 or 3 DRM blocks. When finish learning, additional convolutional layer and a non-linearity after the final DRM block could help to reshape the result features. In the training progress, we use 30000 epochs and 128 as the batch size for both 2x and 4x in training.

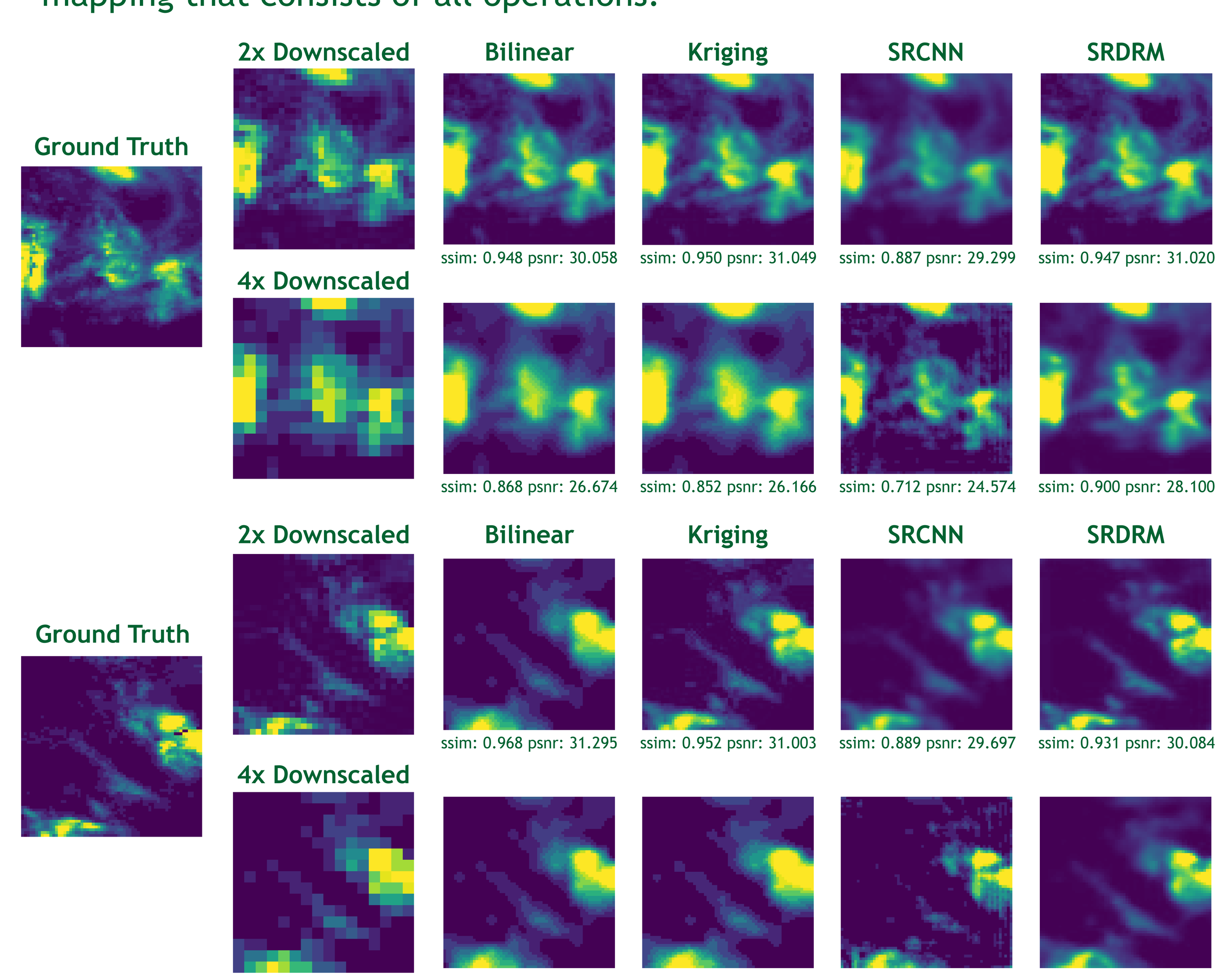

Figure 4. Example of ground truth and predicted images for 2x and 4x for image 21 (above) and image 26 (below) on September 19, 2017

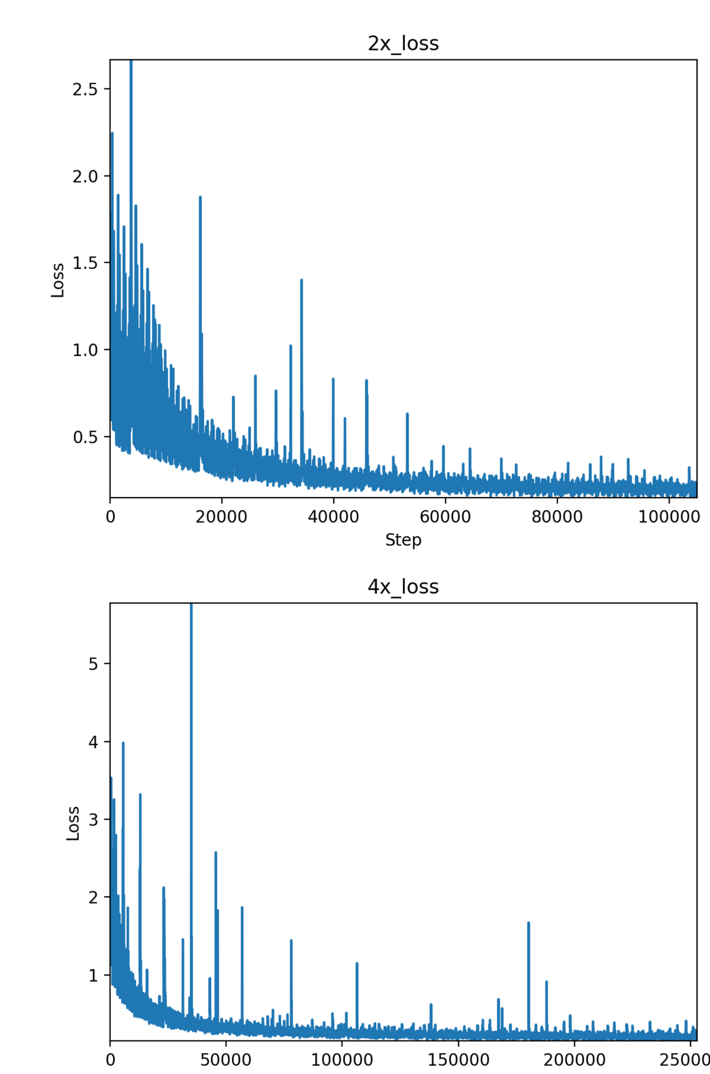

Figure 5. SRDRM Loss during the training for 2x (above) and 4x (below)

RESULT

EVALUATION

We have used two standard metrics called Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity (SSIM) in order to compare the SRCNN, SRDRM and the interpolation models' performances. The PSNR approximates the reconstruction quality of a generated image x, compared to its ground truth y based on their Mean Squared Error (MSE) as follows:

$$MSE(x,y) = \frac{1}{mn}\sum_{i=1}^{m}\sum_{j=1}^{n}|x_{i,j} - y_{i,j}|^2$$

$$PSNR(x,y) = 20\log_{10}\left[\frac{MAX_1}{MSE(x,y)}\right]$$

On the other hand, Structural Similarity (SSIM) compares the image patches based on three properties: Luminance, Contrast and Structure. The measurement or the prediction of the image quality is based on an initial uncompressed or distortion-free image as reference. It can be defined as:

$$SSIM(x,y) = \left(\frac{2\mu_x\mu_y + c_1}{\mu_x^2 + \mu_y^2 + c_1}\right)\left(\frac{2\sigma_{xy} + c_2}{\sigma_x^2 + \sigma_y^2 + c_2}\right)$$

RESULT

Our results suggested that bilinear interpolation is a simple but roust method for precipitation image. This is because precipitation map is relatively simple and a simple bilinear interpolation can capture the image patterns. On the other hand, the two deep learning models performed differently. The SRDRM model had better performance compared to SRCNN, and SRDRM was the best model for 2x upsize.

Scale	Score	Bilinear	Kriging	SRCNN	SDRM
1/2	PSNR	31.349	31.454	30.195	32.296
	SSIM	0.940	0.937	0.906	0.956
1/4	PSNR	26.863	26.881	25.866	26.867
	SSIM	0.859	0.859	0.802	0.880

REFERENCE

ECMWF, era5. https://www.ecmwf.int/en/forecasts/datasets/reanalysis-datasets/era5

Dong, C.; Loy, C.C.; He, K.; Tang, X. Image Super-Resolution Using Deep Convolutional Networks.arXiv 268 preprint arXiv:1501.00092v3, 2015

Islam, M.J.; Enan, S.S.; Luo, P.; Sattar, J. Underwater Image Super-Resolution using Deep Residual 266 Multipliers. arXiv preprint arXiv:1909.09437, 2019

Hore, A.; Ziou, D. Image quality metrics: PSNR vs. SSIM2010. pp. 2366-2369.

Wang, Z.; Bovik, A.C.; Sheikh, H.R.; Simoncelli, E.P.; others. Image quality assessment: from error visibility to structural similarity.IEEE transactions on image. processing2004,13, 600-612

The 2nd NOAA Workshop on Leveraging AI in Environmental Science
Presented on September 29th, 2020

Xinli Cai: xinli1@ualberta.ca
LinkedIn: https://www.linkedin.com/in/caixinli/

Canada Wildfire

Multimedia Program