초해상도 딥러닝 학습 기반 지구 시스템 모델 원조

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Aiding the Earth System Models with Super Resolution Deep Learning

요약 - Abstract

From the food we eat, the air we breathe, and the water we drink, climate change affects everything around us. Continual research on this topic has produced sophisticated climate simulation models that run in high- and ultra-high resolution and provide unprecedented details at the local level. However, an enormous computational cost is associated with running such models, limiting parameter calibration, and extensive experimentation. We employ two state-of-the-art deep learning approaches to upscale computationally cheaper low-resolution simulation data into high resolution. Our initial results suggest that deep learning models are a viable approach that outperforms existing baselines.

1. Introduction

Climate change is one of the most critical challenges that our planet is facing today. Understanding climate variability and change and predicting its impact on the environment as a whole has critical implications for policymaking and decisions aimed at mitigating the risks associated with climate change.

Research on climate change relies on computer models, generally referred to as the Earth System Models (ESMs). The state-of-the-art European climate model predicts at 1-km resolution, acting as a 'digital twin' to reality[1]. Such fine resolution enables observations of weather events and climate change in the upcoming weeks at an unprecedented scale. Yet, such models bring an immediate challenge in terms of computation power, as even with powerful computing facilities like a supercomputer, high-resolution simulations are prohibitively resource-intensive to run. This inhibition further proves to be a roadblock when many experiments are required for analysis or when parameters need calibration.

This work utilizes deep learning techniques to upscale lower-resolution ESM simulation data to high-resolution. The low-resolution simulations have a low space and time complexity and require far fewer resources than the high-resolution counterpart. This upscaling task can be formed as the super-resolution problem[2]. The results presented in this work suggest that deep learning models are a viable approach that outperforms existing baselines for upscaling the low-resolution climate simulation data into high resolution.

The potential of this approach is promising, as it offers a solution to move past the computational bottlenecks to better tune and experiment with the ESMs and further improve our understanding of the climate effects. We can better anticipate future climate events by utilizing the low-resolution predictions over longitudinal time scales and their application over the areas-of-interest via super-resolution techniques. Further, not only the long-term climate projections, but this approach could also be beneficial in making high-resolution short-term forecasts, especially in regions with sparse observational data.

2. Methods

We aim to upscale two climate features available in our dataset: temperature and precipitation. As climate features vary widely by altitude, we use geopotential information along with temperature and precipitation to make a 3-channel climate data (similar to RGB channels in image data). We denote a single low-resolution climate data as x^{LR}. Our task is then to estimate high-resolution climate data x^{HR} given x^{LR}. For data with C channels, we describe x^{LR} by a real-valued tensor of size W × H × C and x^{HR} by W'×H'×C respectively. We adopt the computer-vision deep learning approaches called super-resolution Convolutional Neural Network (SR-CNN) (f) [1] to predict high-resolution data, i.e., $x^{HR} = f(x^{LR})$. We employ two backbone networks described below.

2.1. SR-Resnet

This backbone is based on the Resnet block architecture

[1] Europe builds 'digital twin' of Earth to hone climate forecasts (science.org)

[2] Advances and challenges in super-resolution (ucsc.edu)

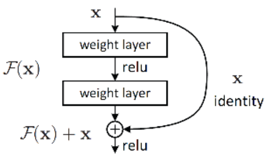

Figure 1: Residual block architecture [3]

(Figure 1[3]) and has been used in other super-resolution problems in computer vision. SR-Resnet introduces the concept of residual blocks and skip-connections to mitigate gradient vanishing by modeling the identity mapping that better represents convolutional kernels [2].
The objective of this model, called the **pixel-wise MSE loss**, is defined as follows:

$$\mathbf{L_{mse}} = \frac{1}{W'H'}\sum_{i=1}^{W'}\sum_{j=1}^{H'}\left(x_{i,j}^{HR} - f(x_{i,j}^{LR})\right)^2$$

2.2. RCAN

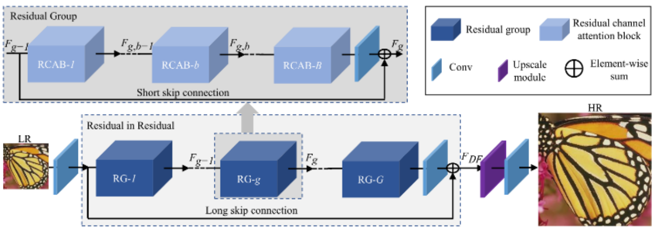

Figure 2: RCAN structure (ref: [3])

There are different types of features in the climate data: low-frequency features that change gradually over the space (general features) and high-frequency features that change rapidly (detailed features). LR (low resolution) images have an abundance of low-frequency features, which can be learned quickly by the deep learning models. However, typical CNN-based methods like SR-Resnet treat channel-wise features equally, performing otherwise dispensable computations for low-frequency features. This limits the capacity of the deep networks and makes it hard to improve the super-resolution performance by making the network deeper.

Typical SR methods lack discriminative learning ability across feature channels because the inter-channel interdependencies are ignored. Applying these methods to the climate data set will restrict the performance since three channels represent three interdependent geometrical and climatic variables. Therefore, we employ RCAN, a specially designed SR-CNN approach with multiple skip-connections to bypass low-frequency features, and a channel attention network to capture interdependencies among channels (Figure 2) [3]. The objective of this model, called the **pixel-wise MAE loss**, is written as follows:

$$\mathbf{L_{mae}} = \frac{1}{W'H'}\sum_{i=1}^{W'}\sum_{j=1}^{H'}\left|x_{i,j}^{HR} - f(x_{i,j}^{LR})\right|$$

3. Experiments

3.1. Dataset

* **Climate data:** The climate data used in this study is obtained from a fully coupled ultra-high resolution (~25km) simulation using the Community Earth System Model version 1.2.2 [4]. The model is run with present-day conditions for 140 model years and the last 20 years of the simulation data are used for this work. This is to ensure that the model attained equilibrium with the present-day conditions. We make use of the following three channels: (1) **Channel 1** is on Surface Temperature (TS), the most fundamental driver of local weather patterns; (2) **Channel 2** is on Precipitation (PRECT), which is a nonlinear variable with large societal impacts; and (3) **Channel 3** contains the Surface Geopotential (PHIS), a height measurement of the surface above the mean sea level.

* **High Resolution (HR) data:** The high-resolution simulation[5] is obtained from the output of a large climate simulation model[6]. The values are obtained by discretizing and solving the physical equations on a 25km grid.

* **Low Resolution (LR) data:** The low-resolution data is obtained by linearly interpolating the climate model output into a coarser resolution (~100km) grid. This work uses HR data as the ground truth to train the super-resolution of LR input data. Data is split into training and testing sets.

3.2. Training details

We trained the model with SRResnet and RCAN for 50 epochs, using Adam optimizer. For SRResnet, we use the mean squared error (MSE) loss, while for RCAN we use mean absolute error (MAE) loss. Model performance is evaluated on the testing set.

4. Results

The root-mean-squared (RMS) error is reported in Table 1. We can see that RCAN and SRResnet both significantly outperform traditional approximations such as linear interpolation or bicubic interpolation, which are two methods often used as baselines in super-resolution tasks. RCAN outperforms SR-Resnet, especially in channels 1 (i.e., upscaling surface temperature). The skip connection structure of RCAN may be more appropriate in propagating the low-frequency well so that its very deep structure still improves the performance. Although the geopotential channel (channel 3) is constant and solely used to add extra information for our main climate channels (temperature and precipitation), RCAN shows superior upscaling result in this channel (RMS 14.451), compared to SR-Resnet (RMS 208.308). This indicates that RCAN excels in capturing interdependencies among channels.

Table 1. Evaluation of the super-resolution results for each channel based on the RMS error values. Channel 1 is the surface temperature and Channel 2 is the precipitation

	Linear	Bicubic	SR-Resnet	RCAN
Channel 1	0.904	0.901	0.619	**0.294**
Channel 2 ($\times 10^{-8}$)	3.850	3.998	2.359	**2.355**

[3] Deep Residual Learning for Image Recognition
[4] CESM Models | CESM1.2 Series Public Release (ucar.edu)
[5] Tropical cyclone response to anthropogenic warming as simulated by a mesoscale-resolving global coupled earth system model (eartharxiv.org)
[6] https://agupubs.onlinelibrary.wiley.com/doi/full/10.1002/2014MS000363

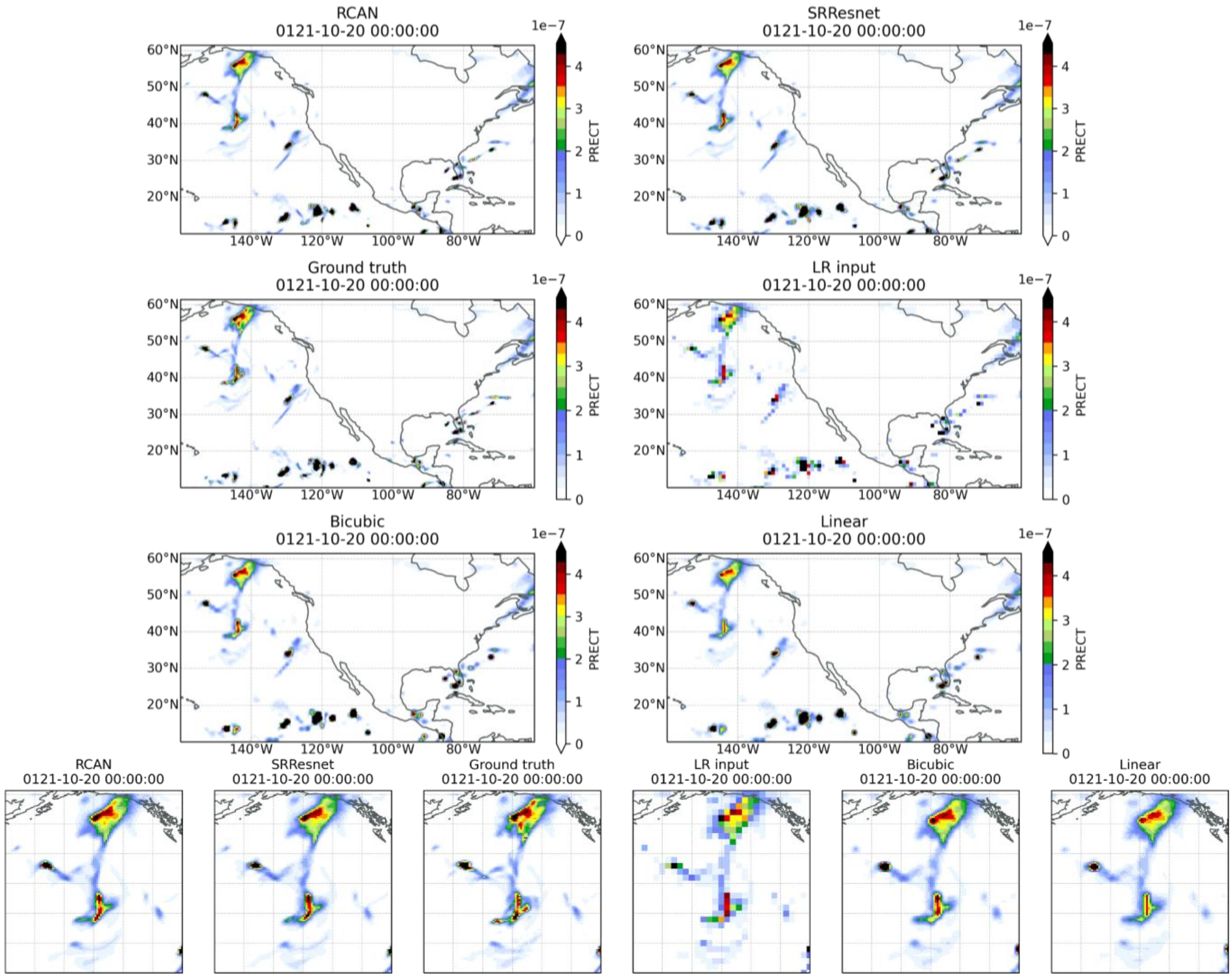

Figure 3: An example of super-resolution results on precipitation. Both deep-learning-based super-resolution results (RCAN and SR-Resnet) and traditional interpolation results (linear and bicubic) are presented. The LR input and the HR ground truth are also shown for comparison. A zoomed-in part from the image is shown for a clearer demonstration.

A visual outcome example is shown in Figure 1. The figure shows a precipitation output that is upscaled from a low-resolution input. We could see that although the interpolation-based methods (linear, cubic) make the output smoother and less pixelated, they miss out on important details in the HR data, leading to a high RMS error. On the other hand, SR-Resnet and RCAN are able to retrieve many of these crucial details, resulting in a lower RMS error.

5. Conclusion:

By experimenting on state-of-the-art deep learning approaches on super-resolution tasks, we found that these models effectively convert low-resolution simulation data into high resolution. Deep-learning-based methods outperform the currently deployed baselines (interpolation) by a large margin. Using these methods could reduce the cost of climate simulations in both space and time complexity without sacrificing spatial resolution. This has a big potential not only in Earth System Model (ESM) but in many other computationally intensive simulations

6. Acknowledgement:

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7. References:

[1] C. Dong, C. C. Loy, K. He and X. Tang, "Image Super-Resolution Using Deep Convolutional Networks," IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 38, no. 2, pp. 295-307, 1 Feb. 2016

[2] C. Ledig et al., "Photo-Realistic Single Image Super-Resolution Using a Generative Adversarial Network," In proc. of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2017, pp. 105-114.

[3] Zhang, Y., Li, K., Li, K., Wang, L., Zhong, B., & Fu, Y. (2018, July 12). Image super-resolution using very deep residual channel attention networks. https://arxiv.org/abs/1807.02758.