Deep-Learning Based Statistical Downscaling for Climate Data in Lower Mekong Region

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***Abstract*—Climate change is posing a severe threat to humanity and its future. Rising sea levels, temperatures, loss of wildlife and biodiversity, and induced natural disasters are a few effects of global warming. Accurate climate prediction is of utmost importance to study the impact of climate change in various areas and implement mitigating measures. A plethora of Global Circulation Models (GCM) is available that simulates the earth's present and future climate and atmosphere. However GCM only gives climate condition of a wide area requiring downscaling at local scale prior to its use. Dynamic and statistical downscaling methods have been used to project local climate data. The former method simulates regional scale climate using lateral boundary conditions of GCM but demands longer time period and is computationally inefficient compared to its counterpart statistical downscaling which maps the GCM to local scale through statistical relationships. Abundant statistical methods including machine learning approaches are in practice, however, recent studies and research however, suggests that Deep Learning (DL) models are better at predicting the local level climate data considering its ability to learn and retain spatial dimension. In this study, we implemented two Super Resolution DL architectures: a) Super Resoutional Neural Network (SRCNN) and b) Super Resoultion Residual Network (SRDN) to downscale GCM data. SRDN was able to reproduce the climate with high accuracy compared to SRCNN.**

I. Introduction

Climate change already has tolls on humankind through the climate induced disasters like floods, droughts, typhoons, cyclones and forest fires that transcends beyond boundaries. These impacts are likely to further exacerbate in the developing nations considering their low capacity to adapt especially in Lower Mekong Region, housing five countries Thailand, Myanmar, Laos, Cambodia and Vietnam in the mainland Asia [2]. These countries are already at risk due to recurring climate-related disasters and is expected to escalate in the future. For instance, the 2011 flood in Thailand caused the loss of 46.5 billion dollars and about 815 deaths [3]. Likewise, Linda typhoon in southern Vietnam took lives of over 3000 people while destroying 200,000 houses and leaving more than 350,000 people homeless [4]. Hence, it is imperative to understand the impact of climate variability and change to develop and formulate mitigation and adaptation strategies. However, there is a limited knowledge on how climate unfolds in the future. One of the approaches that scientific communities have adopted in assessing future climate change impact is through the climate models. They are the state-of-art tools that attempt to simulate spatio-temporal climate through the interlinked physical and atmospheric processes governed by CO2 feedbacks into climate system. However, these models are coarse in resolution ($\geq$ 100km x 100km) housing uncertainties to be directly applied to the local scale impact analysis. Hence, it is required to downscale these models to local fine scale resolution to limit the uncertainty.

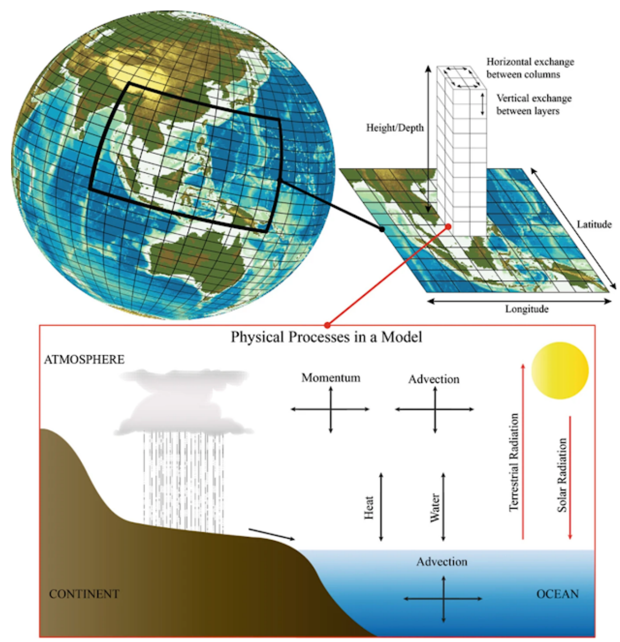

Fig. 1. Schematic diagram of a climate model and its physical processes

Downscaling is a difficult and tedious process due to the precipitation data being complex and highly skewed non-Gaussian distribution. To tackle this problem various methods of statistical and dynamic downscaling have been formulated. Dynamic downscaling relies on the regional data for getting the high-resolution climate factors by simulating the physical processes of land-atmosphere system constrained to boundary condition from GCM. This method proves to be computationally intensive and has a high risk of possible errors from regional models. In contrary, statistical downscaling establishes statistical relationships between local and low/coarse climate variables. The relationships are applied on the low-resolution coarse data to downscale and get higher resolution local climate variables. There are quite a number of statistical downscaling techniques being used over a few decades that include ones such as bias correction with spatial disaggregation (BCSD) or constructed analog (CA) to machine learning algorithms such as RF, SVM, etc. It is still challenging for these downscaling approaches to adequately represent spatial and temporal variability of the local-scale climate, and capture local-, small-scale features such as extreme events.

The current statistical and machine learning approaches seem to be inadequate that could be attributed to the pre-defined relationships in modeling process beforehand that rarely exploits the spatial dependency. The evolving deep learning technique has made significant impact on many fields including meteorology, hydrology and earth system. However, these fields are still infant in terms of applying these state-of-art techniques. The use of CNN has garnered wider attention in the field requiring feature extraction having spatial dependency considering its success. But the classic CNN is relatively shallow and inefficient in the downscaling approach. Thus, it is preferred to use stacked deeper layered CNN in complex processes like downscaling to arrest the intricate features. Hence, we compared Super Resolution CNN (SRCNN) and Deep Residual Network (SRDRN) to downscale the precipitation in the Lower Mekong Region.

II. Related Work

Statistical downscaling of precipitation (observation or forecast) is a popular low-cost method for improving Climate data on regional scales and making it available to stakeholders and decision-makers. For statistical downscaling, the world has shifted toward Artificial Intelligence (AI) and Machine Learning (ML)[10] techniques. Several studies indicate that AI-based downscaling methods may be appropriate for precipitation downscaling, which is frequently non-linear and includes multi-scale stochastic noise. Authors have demonstrated the effectiveness of the Support Vector Machine (SVM)[8] method in precipitation data downscaling. Recent advances in Single Image Super-Resolution (SR) using Deep Learning provide encouraging hope for downscaling weather model outputs to high resolution.

This paper introduces a deep learning-based method for precipitation downscaling to generate high resolution precipitation data of Climate Data in Lower Mekong Region, which can provide local projections.

Image to Image Translation establishes relationships between two images translating image of one domain to another. Climate data can be treated as image which gave the authors [1] the idea to implement an image translation approach Pix2Pix to convert the low-resolution coarse data to high resolution. Pix2Pix is a type of GAN that consists of two components the discriminator and the generator. The generator generates fake images to fool the discriminator, on the other hand the discriminator works towards distinguishing between fake and real image. The authors have used data from two sources which are topography and land dataset from Global Land Cover Characterization (GLCC) and Model for Interdisciplinary Research on CLimate version 5 (MIROC5) which is a GCM model. The data has been taken of 10 years from 1996 to 2005. The authors implemented their method in python using the keras library which yeiled to around 50 percent accuracy. The model seems to somewhat capture the local climatic regions.

III. Data and Data Preprocessing

Details on the dataset used in this study along with the preprocessing applied are provided in subsequent sections.

A. Dataset

As mentioned earlier, downscaling maps GCM to local scale climate and abundant GCMs are available to choose from and no-one-size fits all data is available. In this study, we used European Community earth system model (EC-Earth3) as a coarse resolution image based on its better performance in the region [10] and Asian Precipitation Highly Resolved Observational Data Integration Towards Evaluation (APHRODITE) as high resolution image based on the study [5]

1) Coarse Data: EC-Earth3 [1] is used as a coarse resolution data that has spatial resolution of 1° (100 km), temporal resolution of 6 hourly or daily with the global spatial coverage. EC-Earth's main objective spans across the development and application of earth system model to provide reliable climate information to advance knowledge on earth system, its predictability and variability resulting from external forcing. The EC-Earth3 dataset can be accessed at [7]

2) Observed Data/ Target Data: APHRODITE is a observed gauge-based interpolated precipitation product using improved angular-distance-weighting interpolation technique that covers three spatial domains at the spatial resolution of 0.25° (25km) and daily temporal resolution. The Meteorological Research Institute (MRI) of Japan Meteorological Agency and the Research Institute for Humanity and Nature (RIHN) developed the dataset. The precipitation records are formulated from the sources such as global telemetric stations, dynamic human data collection, meteorological stations records of the National Climatic Data Center (NCDC). Two versions of the dataset are available: V1101 (1951–2007) and V1101EX_R1 (2007–2015). The APHRODITE dataset can be accessed at [6]

B. Data Preprocessing

The available spatio-temporal time series were downloaded from the respective websites in the data section as the network common data format (NetCdf). The data coverage spanned across Asia and globe for APHRODITE and EC-Earth3 respectively which was then clipped to following latitudes (5°-25°) and longitudes (90°-110°) housing 68 x 75 grids for APHRODITE and 25x28 grids for EC-Earth3. The xarray

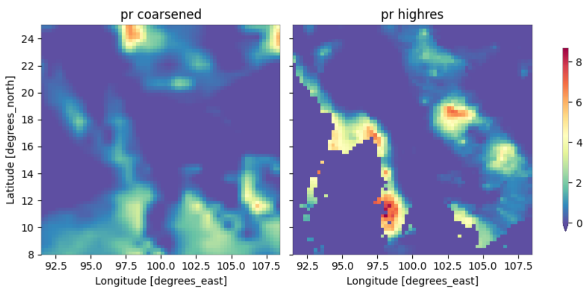

Fig. 2. Comparision between interpolated EC-Earth3 and APHRODITE

module was to load and preprocess these data. The EC-Earth3 data were availabe as chunked arrays which were later dechunked into single 3D array(computationally demanding) as required by the DL models. The daily data for 10 years (3650) time steps was used in this study. Total data points 3650x68x68.

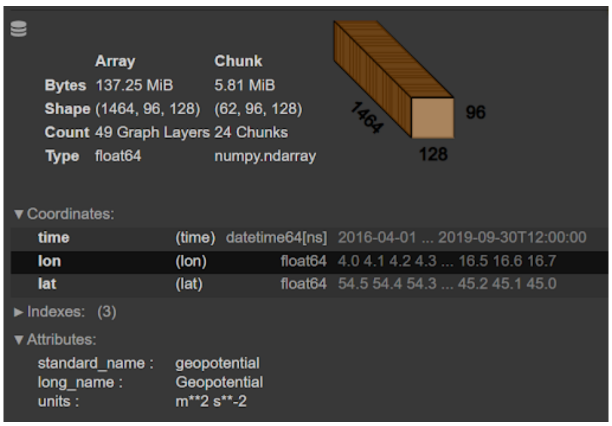

Fig. 3. data-preprocessing

IV. Methodology

Before starting with the methods to implement for the paper, we studied what previous work has already been done to downscale climate data using Deep/Machine Learning. With thorough research, we found papers using SRCNN and ResNet for the dataset mentioned in the above section.

A. *CONVOLUTIONAL NEURAL NETWORKS FOR SUPER-RESOLUTION (SRCNN)*

Firstly, we preprocess low-resolution images using bicubic interpolation to upscale the image to the desired size. Let's consider an interpolated image as Y. Here, our goal is to recover from Y an image F(Y) that is similar as possible to the ground truth high-resolution image X. For the ease of presentation, we still call Y a "low-resolution" image, although it has the same size as X. We wish to learn a mapping F, which conceptually consists of three operations:

1) Patch extraction and representation: This operation extracts (overlapping) patches from the low-resolution image Y and represents each patch as a high-dimensional vector. These vectors comprise a set of feature maps, of which the number equals the dimensionality of the vectors. Here, our first layer is expressed as an operation F1:

$$F_1(Y) = max(0, W_1 * Y + B1) \qquad (1)$$

Where W1 and B1 represent the filters and biases respectively, and '*' denotes the convolution operation. Here, W1 corresponds to n1 filters of support cxf1 xf1, where c is the number of channels in the input image, f1 is the spatial size of a filter. Intuitively, W1 applies n1 convolutions on the image, and each convolution has a kernel size c × f1 × f1. The output is composed of n1 feature maps. B1 is an n1-dimensional vector, whose each element is associated with a filter. We apply the Rectified Linear Unit (ReLU, max(0, x)) on the filter responses.

2) Non-linear mapping: The first layer extracts an n1-dimensional feature for each patch. In the second operation, we map each of these n1-dimensional vectors into an n2-dimensional one. This is equivalent to applying n2 filters which have a trivial spatial support 1 × 1. This interpretation is only valid for 1×1 filters. But it is easy to generalize to larger filters like 3 × 3 or 5 × 5. In that case, the non-linear mapping is not on a patch of the input image; instead, it is on a 3 × 3 or 5 × 5 "patch" of the feature map. The operation of the second layer is:

$$F_1(Y) = max(0, W_2 * F_1(Y) + B2) \qquad (2)$$

Here W2 contains n2 filters of size n1 ×f2 ×f2, and B2 is n2-dimensional. Each of the output n2-dimensional vectors is conceptually a representation of a high-resolution patch that will be used for reconstruction. patch that will be used for reconstruction. It is possible to add more convolutional layers to increase the non-linearity. But this can increase the complexity of the model (n2 × f2 × f2 × n2 parameters for one layer), and thus demands more training time. We will explore deeper structures by introducing additional non-linear mapping layers

3) Reconstruction: In the conventional techniques, the final full image is frequently created by averaging the predicted overlapping high-resolution patches. On a set of feature maps (where each position is the "flattened" vector form of a high resolution patch), the averaging can be seen as a pre-defined filter. We define a convolutional layer to create the final high-resolution image as a result of this.

$$F(Y) = W_3 * F_2(Y) + B3 \qquad (3)$$

Here, W3 is a set of c filters with size n2 f3 f3, and B3 is a vector in c dimensions.

B. *Residual Network (ResNet)*

Deep Learning for empirical DownScaling(DL4DS), is a python library which implements various state-of-the-art and

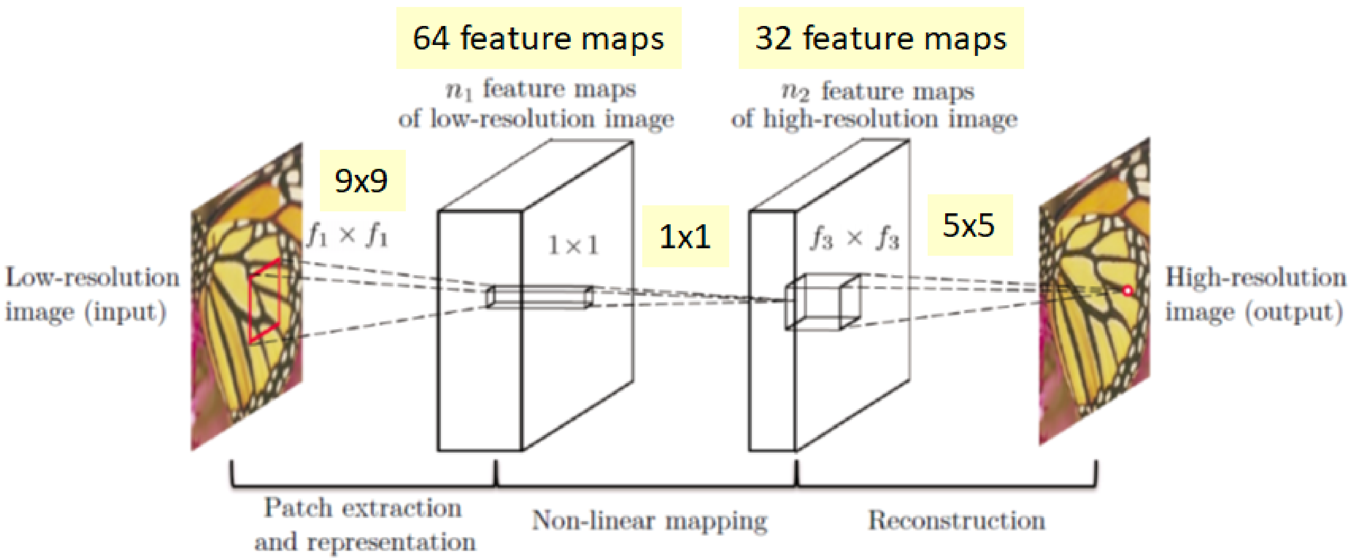

Fig. 4. Given a low-resolution image Y, the first convolutional layer of the SRCNN extracts a set of feature maps. The second layer maps these feature maps nonlinearly to high-resolution patch representations. The last layer combines the predictions within a spatial neighbourhood to produce the final high-resolution image F(Y).

novel algorithms for downscaling gridded Earth Science data with deep neural networks. We used this library to implement ResNet for our climate data.

ResNet is an architecture that won the ImageNet 2015 competition which has over 130,000 citations, containing 150+ layers. It uses residual blocks with high number of layers, skipping one or few layers in between to tackle the vanishing gradient problem. It uses skip connections that connects the activation of a layer to further layers by skipping some layers in between. This forms a residual block, ResNet is made by stacking these residual blocks. Input images were fed into this architecture

Epochs	10
Umsampling	spc
Scale	3
Learning rate	1e-3, 1e-4
Patience	6

The above table showcases all the parameters and hyperparameters used to make the ResNet model.

V. Results

We implemented our method in Python using Keras library.Intially all the experiments were conducted at a GPU based machine NVIDIA GEFORCE 3080, however later we had to switch to online notebooks due to abrupt shut down of Puffer. Table below shows the Accuracy, Training loss and Validation loss of SRCNN and ResNet model.

Model	Accuracy	Training Loss	Validation Loss
SRCNN	30	0.56	0.58
ResNet	90	0.098	0.0933

In local machine, the SRCNN model took 6 hours to run.The predicted image below shows that the patterns are not being captured well, though it seems like the model is slightly able to capture the outline of the data but could not capture the precipitation values as desired.

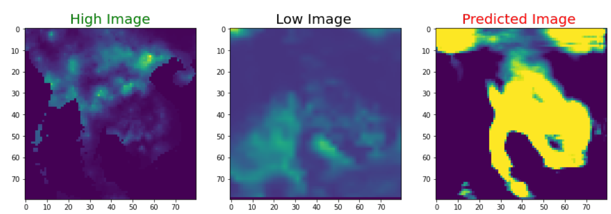

Fig. 5. Example of Downscaling Result for Precipitation using SRCNN

The figure below shows the predicted image produced by ResNet model. We can clearly see that the patterns and the precipitation values are being well captured.

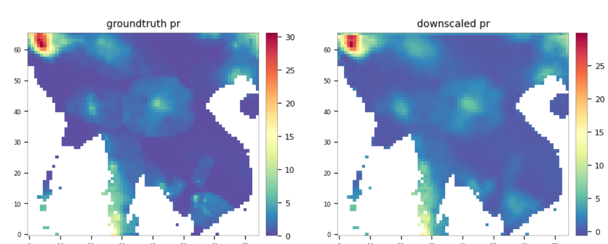

Fig. 6. Example of downscaling result for precipitation using Resnet network

Since the initial image did not have square shape, clipping was done to make them square so, in the bias image we can see high errors persists in the edges. The figure below shows the average of 4 years precipitation volume (obtained by summing up precipitation values along with time dimension and dividing by the length of years). ResNet was able to capture both the spatial pattern as well as the precipitation values effectively. Though the small bias persists in majority of the area, the higher biases persists only in the edges. The figure below shows the comparison between the reproduced low resolution image (EC-earth3) and high resolution image (APHRODITE).

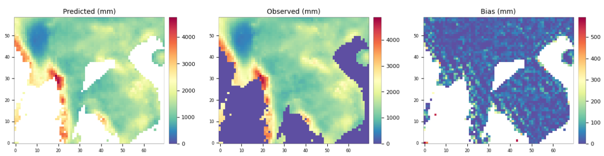

Fig. 7. Example bias image of downscaling result for precipitation using Resnet network

VI. Limitations and Challenges

The main challenge we faced was making the huge climate data usable and also minimizing our scope to level up to the resources and computational power we had. Also, working on 105,120,000 data points would have been impossible so we scoped down to 18,067,500 data points but even this amount was quite huge for our machines to model, so we had to resort to various different online notebooks to run our models simultaneously to play around with various parameters. The resources provided by our institute, Asian Institute of Technology was also not enough to train the models which frequently lead to dead kernels. Also due to limitation on the time, we could not play around very much with every hyper parameter to present the best model for our problem statement. Our model is limited to the reproduction of low resolution coarse precipitation data to high resolution precipitation data. The model could be enhanced by using other predictors too.

VII. Future Refinement

Due to the time frame constraint, there are much more things we would have loved to implement but could not do so. There could be more refinements made and many other methods could have been used to solve the problem statement.

As we talked about GAN in our above literature review section, there could a great chance of it producing a much better result.

Constraining the area and also the number of years did give us the flexibility to make our model less computationally heavy, but with higher GPU or computational power we can definitely try to implement the model on a larger area.

Also, we used only precipitation as predictor but we could definitely add a few more much as relative humidity.

VIII. Conclusion

Using Deep Learning on climate data seemed to provide promising results downscale the coarse climate data to finer resolution for local climate predictions.

Among the two models we implemented, ResNet performed the best with our data for downscaling. The areas have been very well captured and segmented to showcase the precipitation of the lower Mekong region.

We could have produced better performance from SRCNN if we could tune in best hyper parameters, and play around more. The best we could come up with still has given decent results.

Overall, the project was a great learning experience for us. Since only one of us is the domain expert, the rest of us had the opportunity to learn more about climate data and uses of Deep Learning in the field.

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