Statistical Downscaling of Rainfall Projections using Deep CNNs

B.Tech. Project - Videsh Suman

Guides: Prof. Subimal Ghosh (Civil Engg.) & Prof. Amit Sethi (Electrical Engg.) | IIT Bombay

Abstract

Across the two phases of this project, this poster covers some literature, including (a) one of the previous data driven models used for statistical downscaling, (b) CNNs in the context of visual recognition; as well as the details and results of my implementations in this project. The first phase was spent majorly in understanding the literature and some preliminary implementations leveraging deep CNNs on spatio-temporal data. In the second phase, I explored various techniques and heuristics with respect to the deep learning literature for obtaining acceptable results.

Problem Definition

Using CNNs for obtaining future rainfall projections at HR (0.25°) from LR (2.5°) reanalysis predictors over Indian landmass. The reanalysis can later be replaced with bias corrected GCM predictors.

Literature

Salvi et al.[2013]

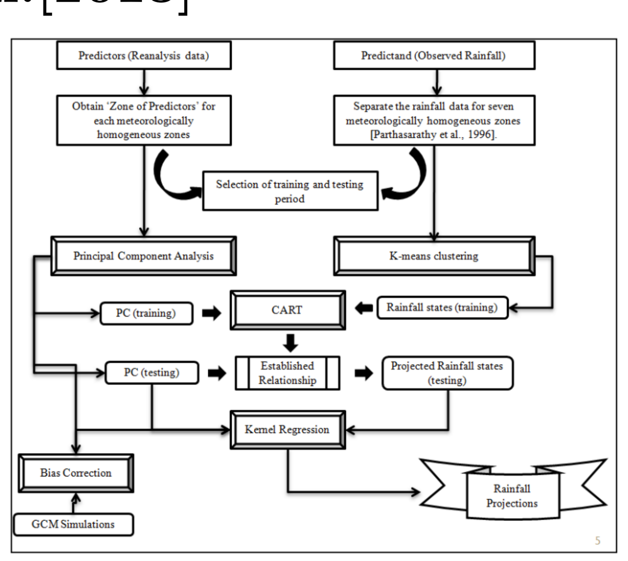

Figure 1: Flowchart for the Multisite SD Model

Vandal et al.[2017]

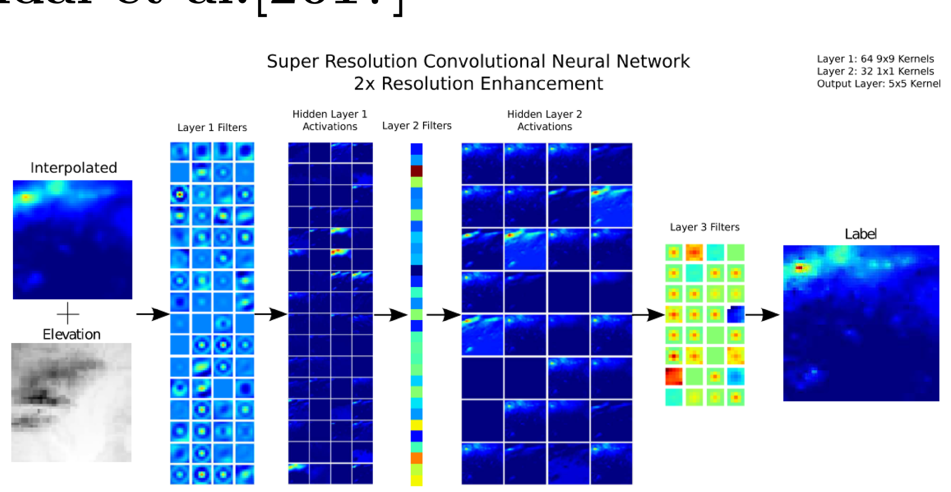

Figure 2: Augmented SRCNN Architecture.

Data

- NCEP/NCAR daily reanalysis data at 2.5° resolution which serves as the LR input to the model.
- Observed daily rainfall from APHRODITE at 0.25° resolution serve as HR target for the model

Method

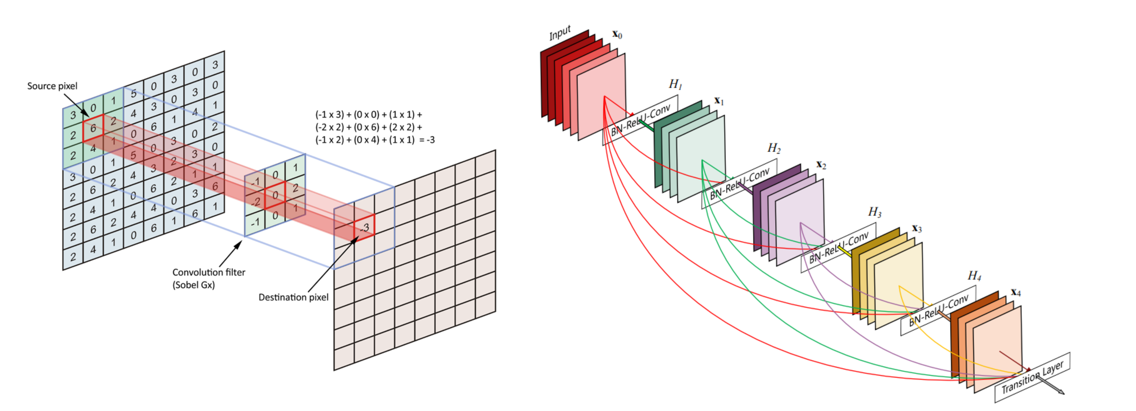

Figure 3: (Source: Internet) Left: 2D Convolution Operation. Right: 5-layer dense block where each layer takes all preceding feature-maps as input.

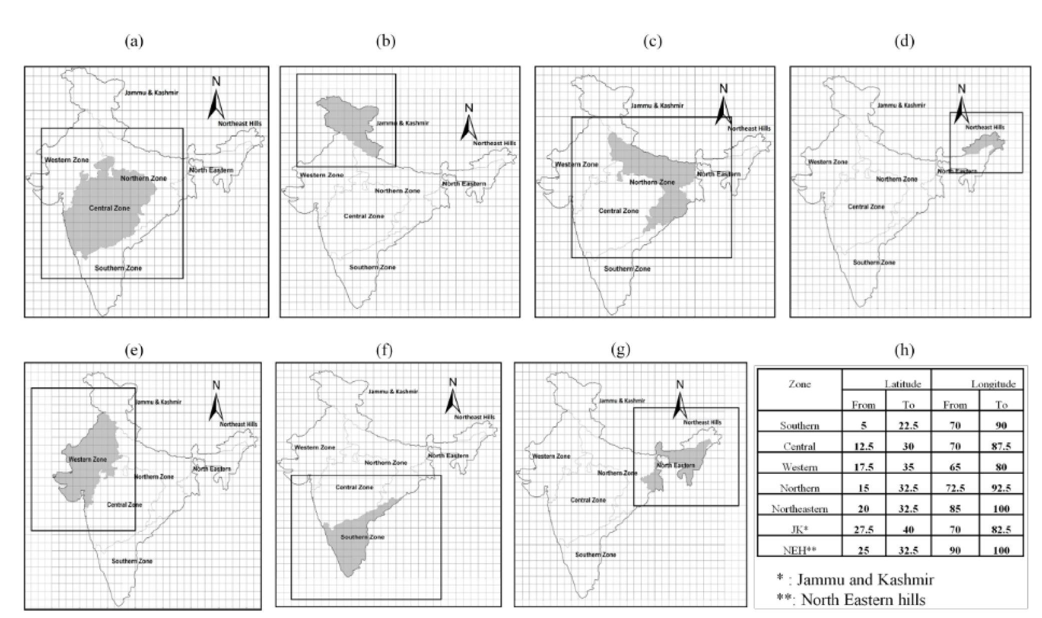

Figure 4: (Source - Salvi et al.) Division of Indian landmass into 7 meteorologically homogeneous zones, and their corresponding predictor regions.

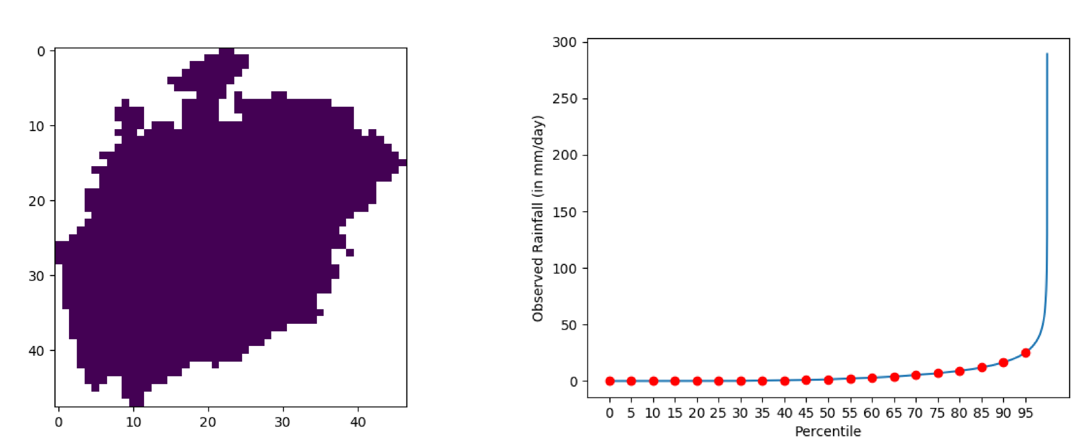

Figure 5: Left: Ground truth mask of central region (1273 pixels) enclosed within the bounding box of size 48×47. Right: Percentile plot of the observed rainfall of central region over 55 monsoon periods. The values range from zero to 289.12 mm/day. However, even the 98^{th} percentile value corresponds to a value as small as 38.44 mm/day.

Results & Inference

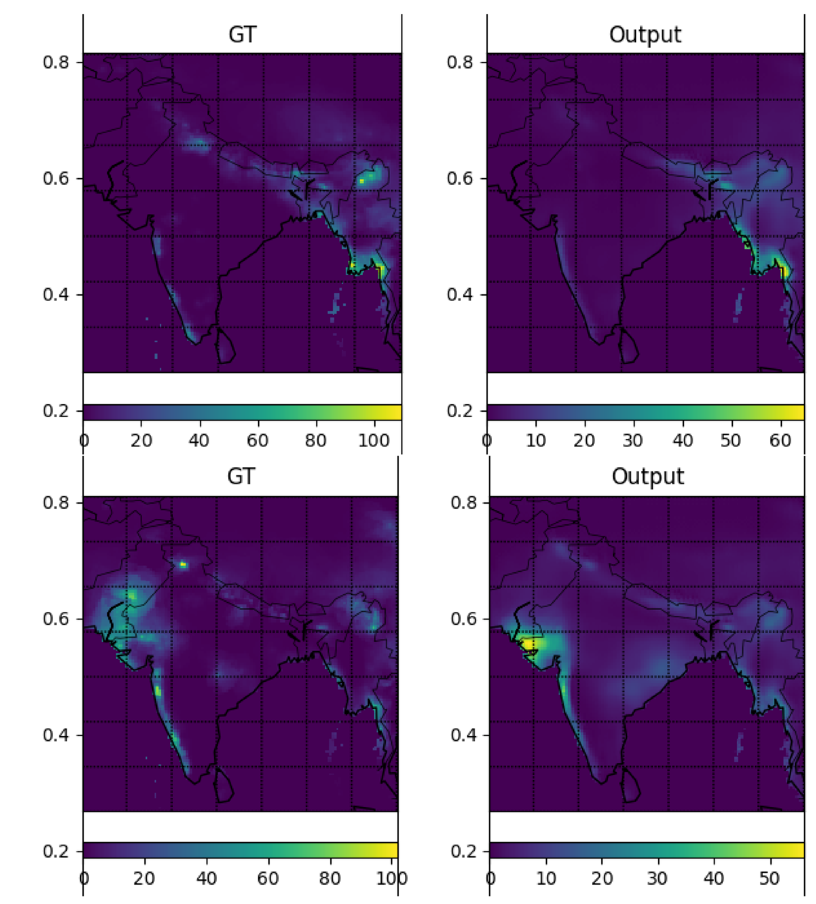

Figure 6: Results from the model trained during the first phase.

- The generalized model was unable to capture rainfall variability across time & space of the landmass.
- Network heuristics: transposed & dilated convolutions, Adam optimizer with cyclic learning rate, dropout regularization, batch normalization.

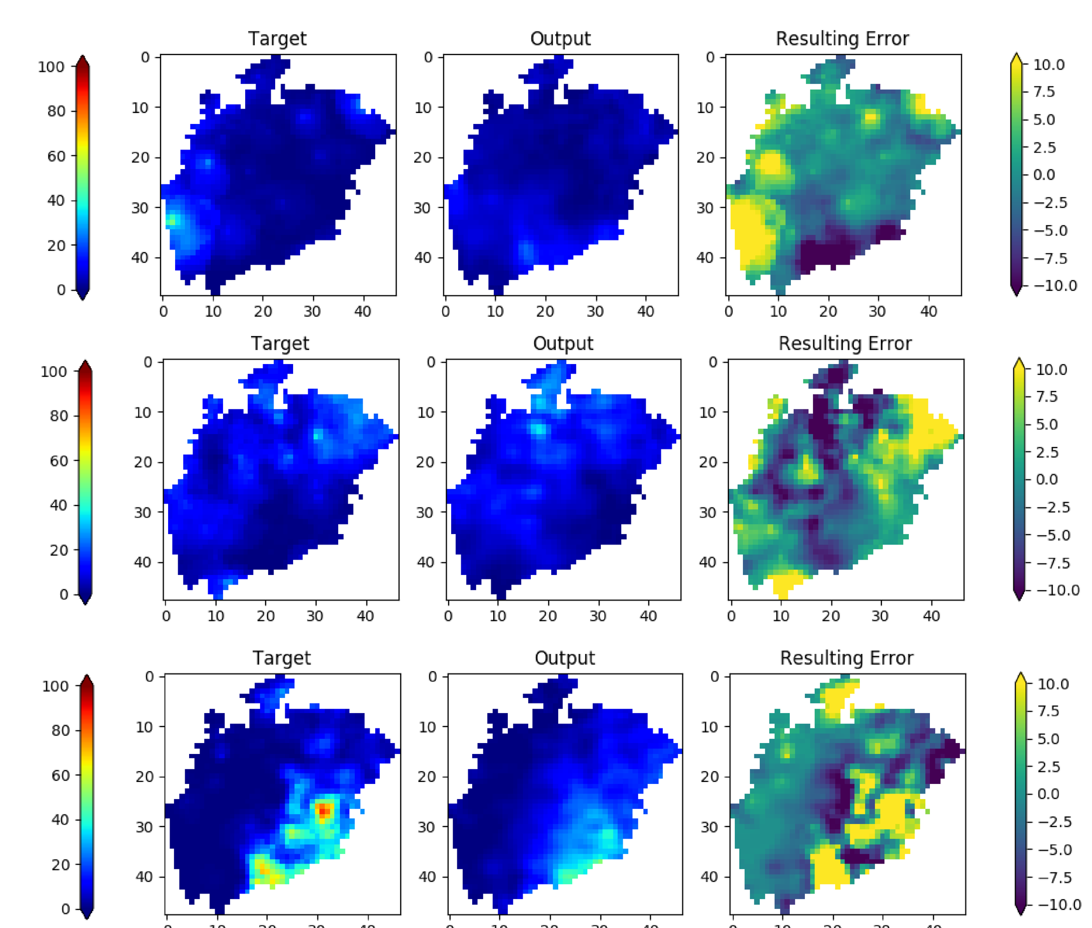

Figure 7: 3 randomly picked test results from the model trained on Central region for just the monsoon period (Salvi et al). From top to bottom, MAE (in mm/day): 4.24, 5.17 & 5.62.

- Zonal model network heuristics: dense connections, transposed & dilated convolutions, Adam with cyclic learning rate, dropout, batch normalization.

Conclusion

- For the generalized model, the smallest network devised to produce 10× super-resolution, consisted of 1.2M trainable parameters which probably underfitted a training set of 13870 images.
- Learning this transfer function as a generalized model for the entire landmass has been shown to be very difficult(Figure 6, owing to the high degree of super-resolution and varying local rainfall patterns for different regions of India.
- From Figure 5(right), the skewness of the rainfall distribution is clearly evident. For this reason, the zonal model incurs huge loss while predicting for instances with high target rainfall.

Future Prospects

- Similar network architectures for all the other 7 regions based on their input and output sizes.
- Non-linear transformations on the target rainfall projections so that the variability and extremity can be captured more effectively; novel loss function that is more sensitive to high rainfall values.
- Topographical information as a separate channel input for for better prediction of local level rainfall.
- Once the trained model aces on reanalysis, it can be experimented with bias corrected GCM simulations.

Important References

- Thomas Vandal, Evan Kodra, Sangram Ganguly, Andrew Michaelis, Ramakrishna Nemani, Auroop Ganguly. **DeepSD**: Generating High Resolution Climate Change Projections through Single Image Super-Resolution. **ACM SIG-KDD 2017**.
- Kaustubh Salvi, Kannan S., Subimal Ghosh. High-resolution multisite daily rainfall projections in India with statistical downscaling for climate change impacts assessment. **Journal of Geophysical Research: Atmosphere, 2013**.