SUPER RESOLUTION IN ATMOSPHERIC FIELDS

- Generative adversarial networks
- MNIST Dataset
- IMD Rainfall Dataset
- Model Limitations and Literature

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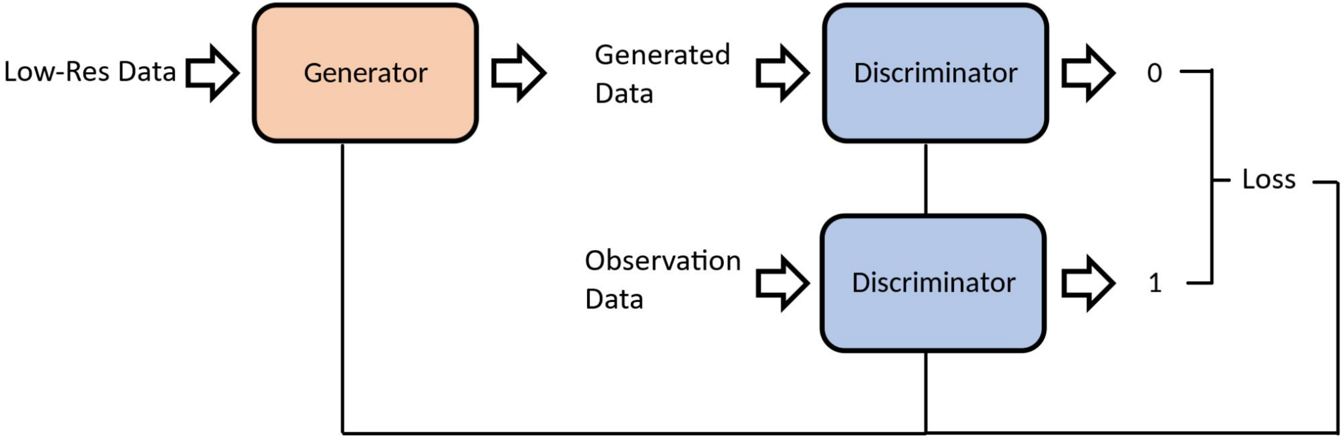
JRF - CAS IITD

Generative adversarial networks:



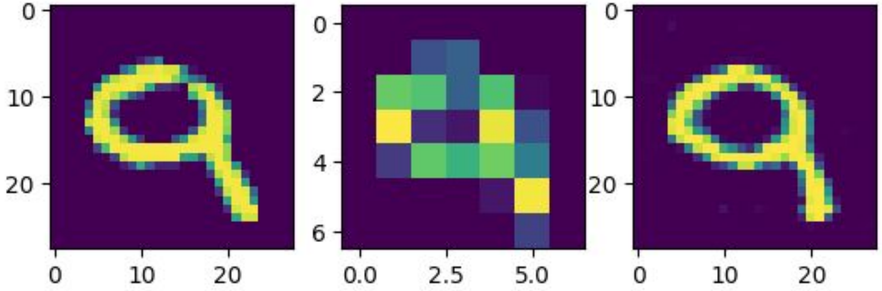
- Generator is a deep CNN responsible for generation of the high resolution data.
- Discriminator also a deep CNN responsible for aligning it with the observational data

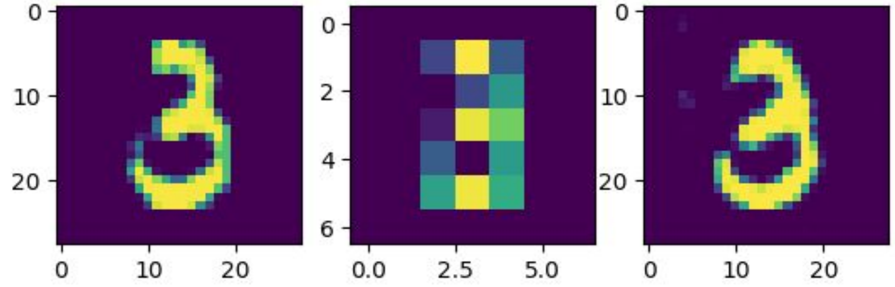
```
Model: "generator"
__________________________________________________________________________________________________
 Layer (type)                   Output Shape         Param #     Connected to
==================================================================================================
 input_3 (InputLayer)           [(None, 32, 32, 1)]  0           []

 gaussian_noise_2 (GaussianNois  (None, 32, 32, 1)   0           ['input_3[0][0]']
 e)

 conv2d_11 (Conv2D)             (None, 32, 32, 64)   640         ['gaussian_noise_2[0][0]']

 batch_normalization_5 (BatchNo  (None, 32, 32, 64)  256         ['conv2d_11[0][0]']
 rmalization)

 leaky_re_lu_12 (LeakyReLU)     (None, 32, 32, 64)   0           ['batch_normalization_5[0][0]']

 conv2d_12 (Conv2D)             (None, 32, 32, 64)   36928       ['leaky_re_lu_12[0][0]']

 batch_normalization_6 (BatchNo  (None, 32, 32, 64)  256         ['conv2d_12[0][0]']
 rmalization)

 leaky_re_lu_13 (LeakyReLU)     (None, 32, 32, 64)   0           ['batch_normalization_6[0][0]']

 conv2d_13 (Conv2D)             (None, 32, 32, 64)   36928       ['leaky_re_lu_13[0][0]']

==================================================================================================
Total params: 472,961
Trainable params: 472,065
Non-trainable params: 896
```

```
__________________________________________________________________________________________________
Model: "discriminator"
__________________________________________________________________________________________________
 Layer (type)                   Output Shape         Param #     Connected to
==================================================================================================
 input_4 (InputLayer)           [(None, 128, 128, 1  0           []
                                )]

 gaussian_noise_3 (GaussianNois  (None, 128, 128, 1)  0          ['input_4[0][0]']
 e)

 conv2d_15 (Conv2D)             (None, 128, 128, 64  640         ['gaussian_noise_3[0][0]']
                                )

 layer_normalization_7 (LayerNo  (None, 128, 128, 64  128        ['conv2d_15[0][0]']
 rmalization)                   )

 leaky_re_lu_17 (LeakyReLU)     (None, 128, 128, 64  0           ['layer_normalization_7[0][0]']
                                )

 conv2d_16 (Conv2D)             (None, 128, 128, 64  36928       ['leaky_re_lu_17[0][0]']
                                )

 layer_normalization_8 (LayerNo  (None, 128, 128, 64  128        ['conv2d_16[0][0]']
 rmalization)                   )

 leaky_re_lu_18 (LeakyReLU)     (None, 128, 128, 64  0           ['layer_normalization_8[0][0]']
                                )

 conv2d_17 (Conv2D)             (None, 128, 128, 64  36928       ['leaky_re_lu_18[0][0]']
                                )
==================================================================================================
Total params: 600,705
Trainable params: 600,705
Non-trainable params: 0
__________________________________________________________________________________________________
```

For Comparison the paper https://doi.org/10.1029/2022MS003120 titled ‘**A Generative Deep Learning Approach to Stochastic Downscaling of Precipitation Forecasts’** use about 67m trainable parameters.

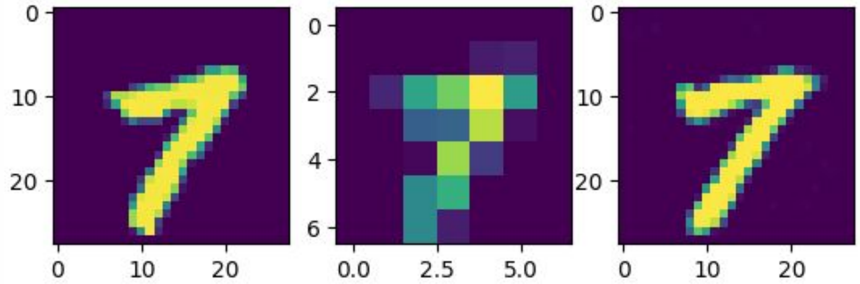
Performance on the MNIST Dataset

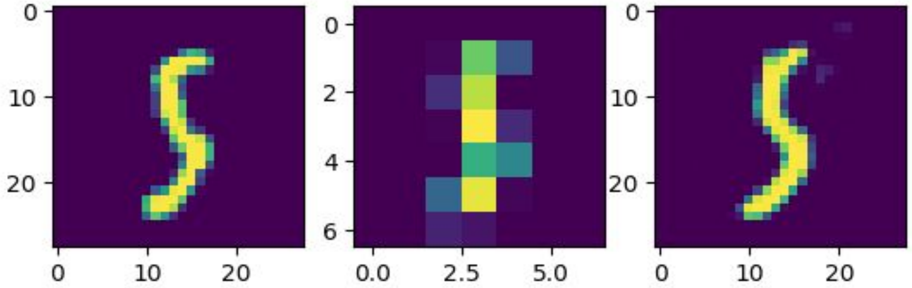




Original Image Low Resolution Input Generated Image

Original Image Low Resolution Input Generated Image





28X28 7X7 28X28

28X28 7X7 28X28

Trained for 50 Epochs Using Kaggle Notebook with GPU P100

Time	#	Log Message
17934.5s	1	Epoch 50/50

```
-25.5498
[============================>.] - ETA: 1s - d_loss: -0.4965 - g_loss:
-25.5947
[==============================] - ETA: 0s - d_loss: -0.4957 - g_loss:
```

Reasons for a good performance on the MNIST Dataset

- Low Resolution Images were created using the Average Pooling layer.
- Conditioned on class labels both on generator and the discriminator.
- Small set of class labels resulted in better performance.
- A large number of training samples (60,000)
- Batch size of 256.

IMD Rainfall Dataset

Observational Data

- Yearly gridded rainfall data in at a resolution of (0.25° x 0.25°). Arranged in 128x128 grid points and the yearly data file consist of 365/366 records for leap/non leap years. The unit of rainfall is in millimeter(mm).
- Records are scaled to [0,1] for training.
- Dataset used for the period of (1950-1970) and (2001-2022). Total 42 years with 15340 records.
- Pai et al.(2014) available at Climate Monitoring and Prediction Group (imdpune.gov.in)

Low Resolution Data

- Yearly gridded rainfall data at a resolution of (1° x 1°). Arranged in 32x32 grid points and the yearly data file consist of 365/366 records for leap/non leap years. The unit of rainfall is in millimeter(mm).
- Records are scaled to [0,1] for training.
- Dataset used for the period of (1950-1970) and (2001-2022). Total 42 years with 15340 records.
- Climate Monitoring and Prediction Group (imdpune.gov.in)

Trained for 37 epochs Using Kaggle Notebook with GPU T4 x 2

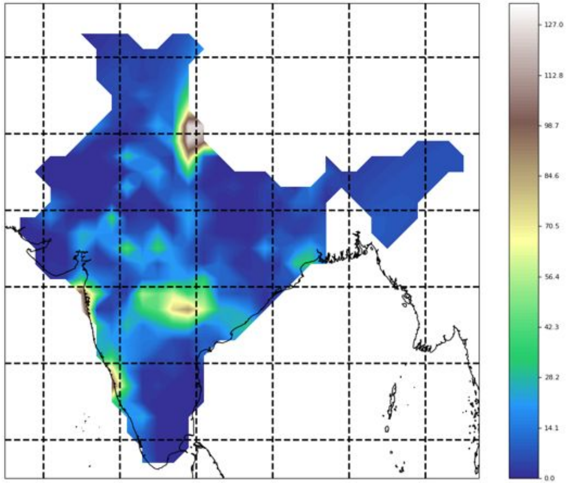
Time	#	Log Message
40956.9s	1	Epoch 37/50

```
[============================>.] - ETA: 7s - d_loss: -2.1869 - g_loss:
10.2753                                                                  477/479
[============================>.] - ETA: 4s - d_loss: -2.1905 - g_loss:
10.2836                                                                  478/479
[============================>.] - ETA: 2s - d_loss: -2.1889 - g_loss:
10.2889                                                                  479/479
```

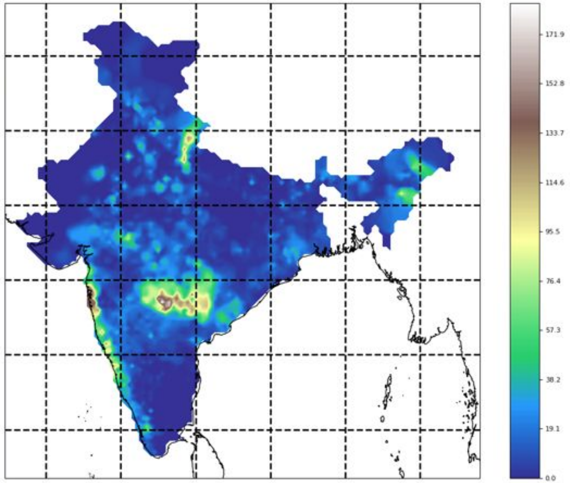
- Notebook timeout at 38th epoch.
- High discriminator loss compared to the MNIST dataset
- Small batch size (32) compared to the MNIST dataset due to hardware constraints.

Performance on the IMD Rainfall Dataset

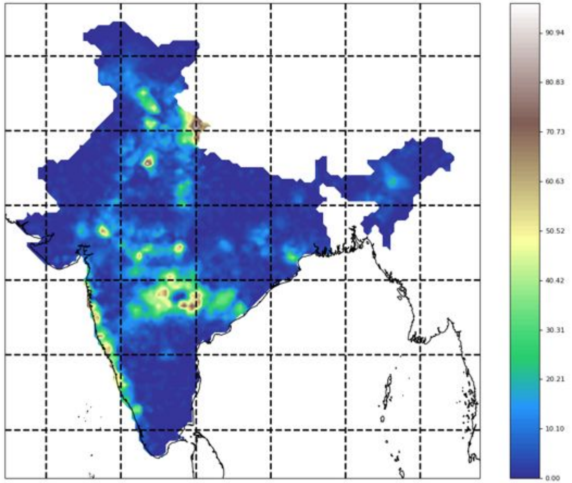
Evaluation data (Year 2000)
Day 223



Low Resolution Input (1° x 1°)
32 x 32



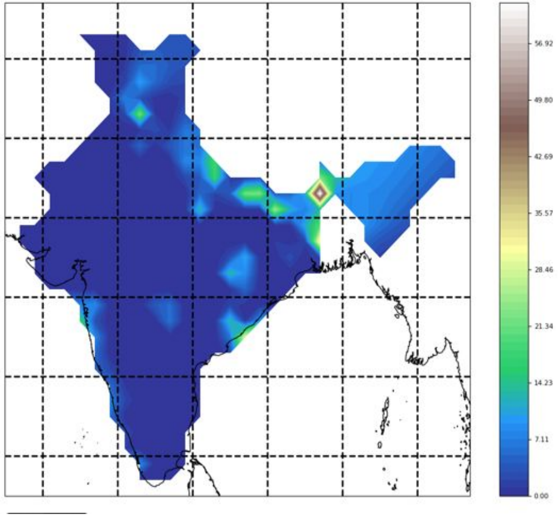
Observational Data (0.25° x 0.25°)
128 x 128



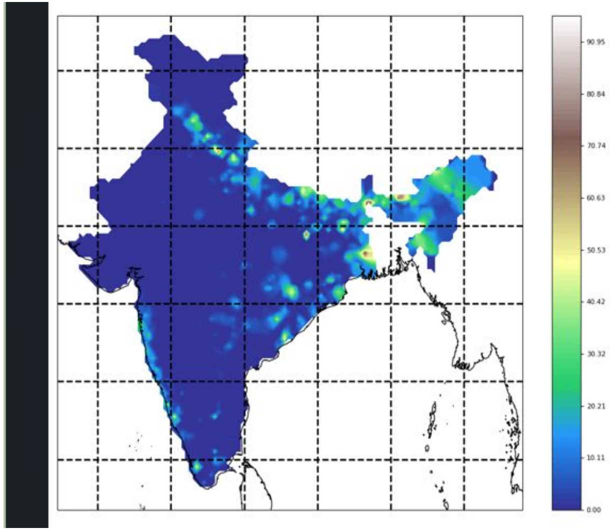
Generated Output
128 x 128

- The precipitation values on the low resolution data is always less than those in observational data therefore the output itself is generating low precipitation values.

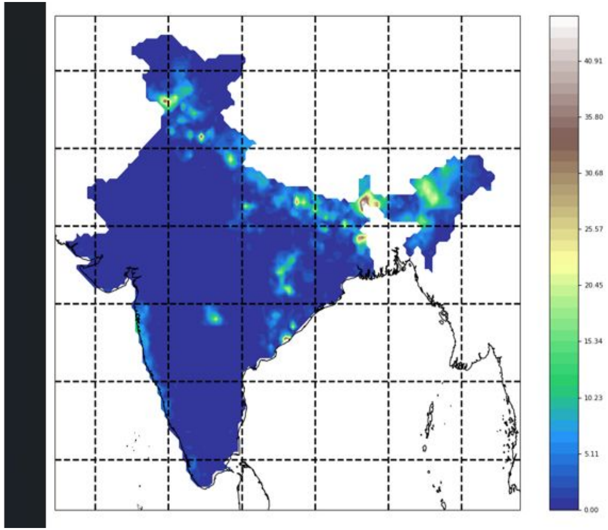
Year 2000 Day 177



Low Resolution Input (1° x 1°)
32 x 32



Observational Data (0.25° x 0.25°)
128 x 128



Generated Output
128 x 128

Evaluation Metric: Fractional Skill Score (FSS)

- The Fractions Skill Score (FSS) is a spatial verification measure that is used for assessing the performance of precipitation forecasts.

- Compares the predicted and the observational data for crossing the threshold value in a given square window (pixel x pixel)

Mean of fractional Skill Score on Evaluation data (Year 2000)

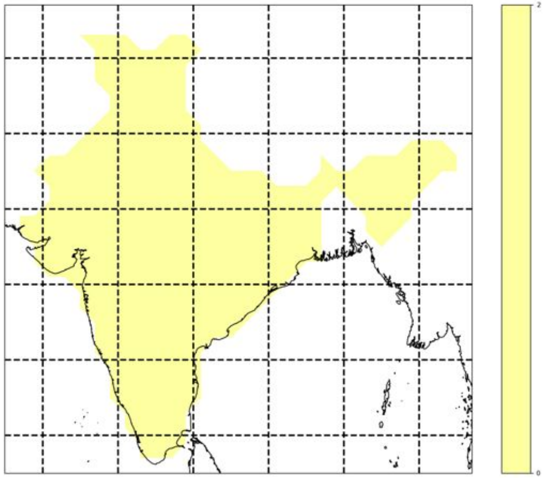
FSS	Threshold: 1mm	Threshold: 10mm	Threshold: 50mm
Window(1 x 1)	0.44	0.31	0.14
Window(2 x 2)	0.54	0.39	0.20

Mean of fractional Skill Score on Seen data (Year 2021)

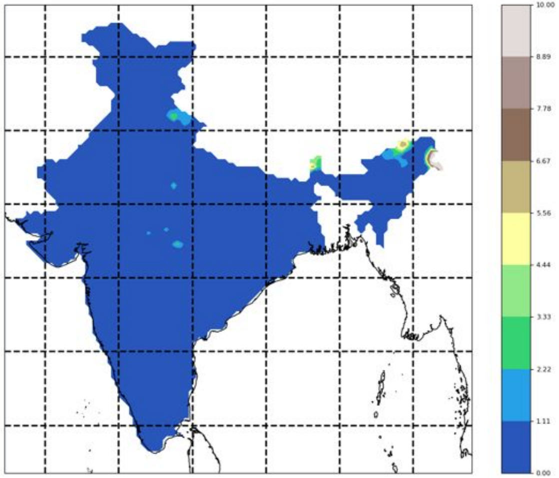
FSS	Threshold: 1mm	Threshold: 10mm	Threshold: 50mm
Window(1 x 1)	0.52	0.39	0.20
Window(2 x 2)	0.64	0.50	0.27

Model Limitations

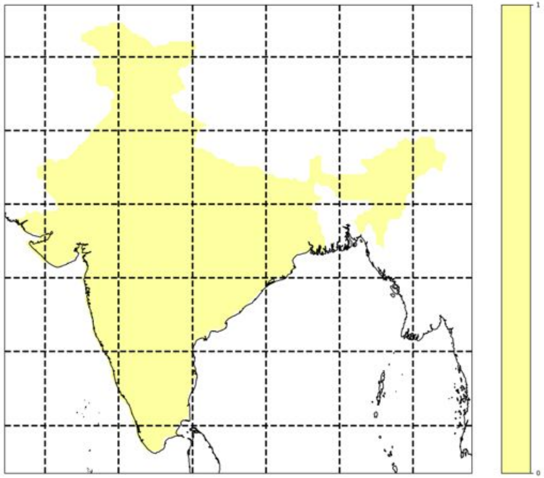
- To generate new information in the high resolution outputs we need more than just low resolution inputs.
- Information about the additional parameters that affect the precipitation can provide better performance.
- Better Scaling methods for training to maintain the quantitative accuracy of the generated high resolution data.
- Training on a smaller regions and seasonal period to better capture the regional variations.



Low Resolution Input (1° x 1°)
32 x 32



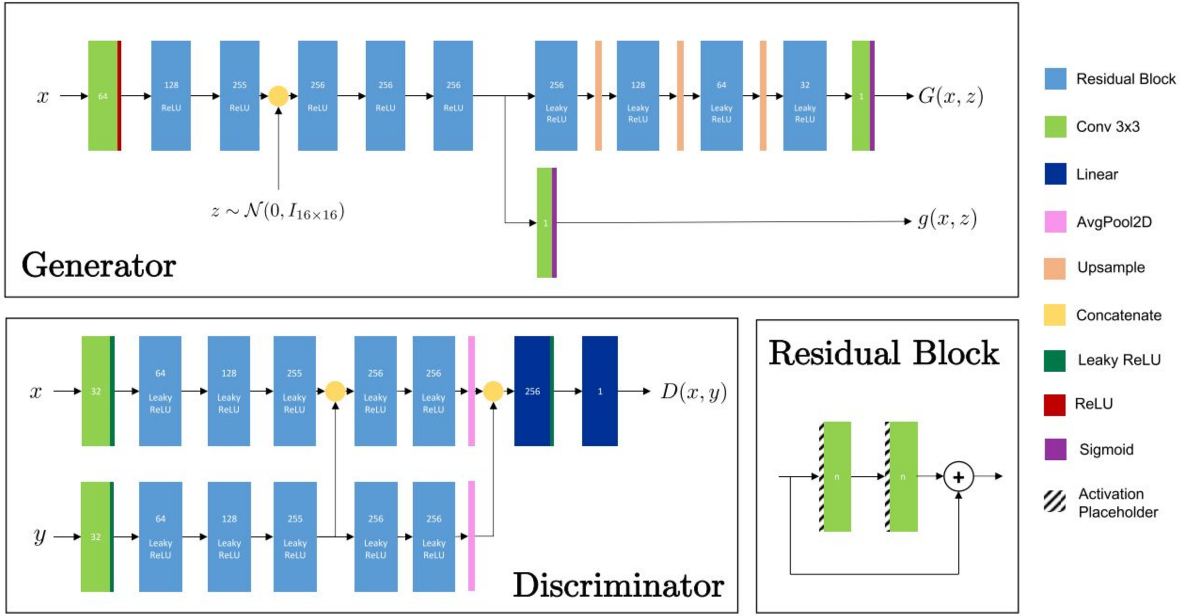
Observational Data (0.25° x 0.25°)
128 x 128



Generated Output
128 x 128

Existing Literature:

- GAN's have been used to post-process the precipitation forecasts to increase their resolution and accuracy
- In such cases the input consist of ensemble of global low resolution precipitation forecasts which is also conditioned on the additional atmospheric fields generated by the forecast. (arXiv:2203.12297)



Network Architecture used in arXiv:2203.12297.

Source: *arXiv:2203.12297*

ERA Precipitation data super-resolution

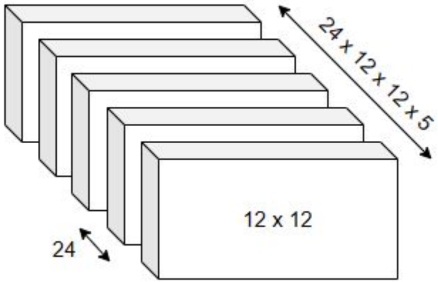
- The architecture of the network was modified taking inspiration from arXiv:2203.12297.
- Additional usage of ConvLSTM layer to convert from hourly data of ERA dataset to the daily IMD dataset.
- Data preprocessing to create a set of channels of additional atmospheric parameters to feed in the WGAN.

Observational Dataset

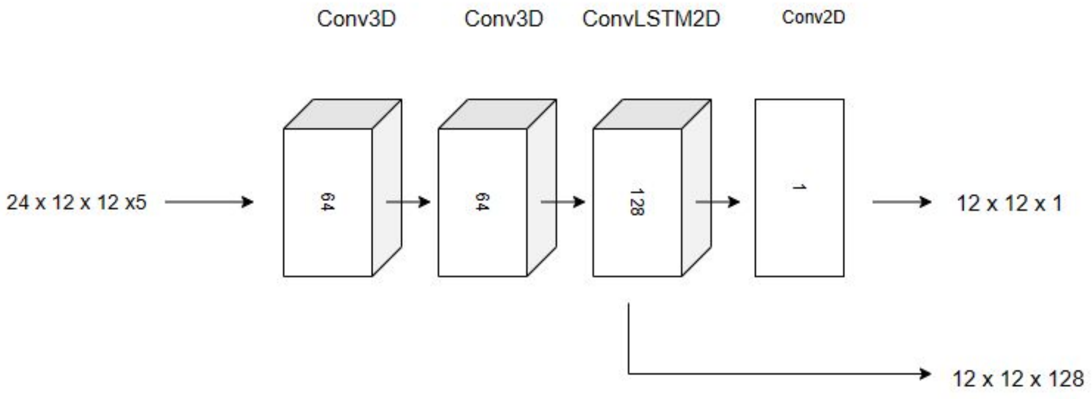
- IMD gridded rainfall data at 0.25° resolution. (JJAS 1981-2020)
- The unit of rainfall is in millimeter. Scaled to [0,1] for training.
- Pai et al.(2014) available at [Climate Monitoring and Prediction Group (imdpune.gov.in)]

ERA Dataset

- ERA5 hourly data on single levels (JJAS 1981-2020)
- Original data is at 0.25° resolution. (Used for comparison)
- Downsampled to 1° resolution as input to our model for the purpose of super-resolution
- Hourly data ⇒ 24 data points corresponds to 1 observational data point
- 5 fields (Total precipitation, Temp2m, Mean sea level pressure, Total water column, Convective available P.E)
- Divided the map into 5 smaller regions (Total training data point = 24440)
- Scaled to [0,1] for training



Addition to the previous network



The outputs of this generator block are used for:

- Pre-training (Low Resolution correction) from IMD dataset.
- Feeding to the Input layer of super resolver to downscale from 1° to 0.25°.

Modified Loss Function:

- Pre-training:

$$L_1 + \gamma_0\, F\hat{S}S(\, IMD_{lowres,}\, g(x,z))$$

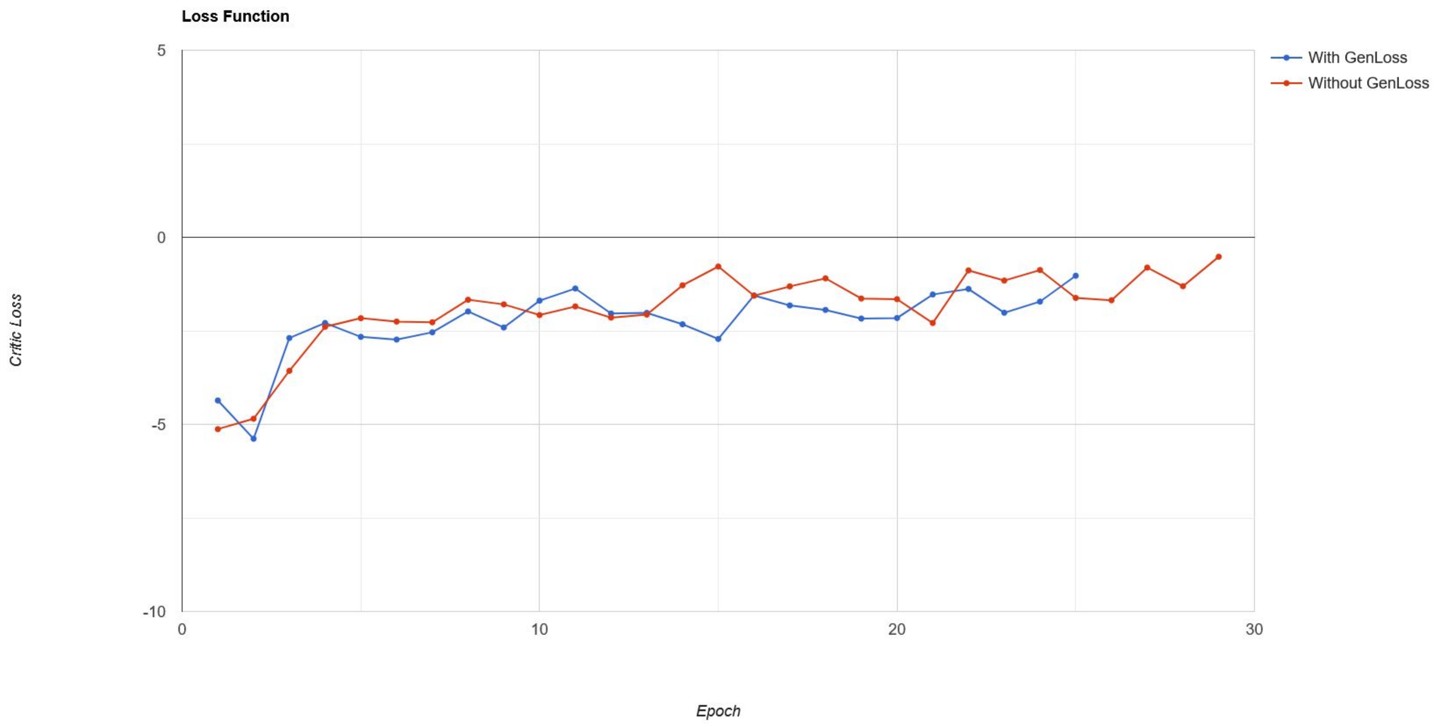
- *Generator loss*

$$E\,[\,-D(G(x,z))] + \gamma_1\, F\hat{S}S(\, IMD_{,}\, G(x,z))$$

Training Comparison:

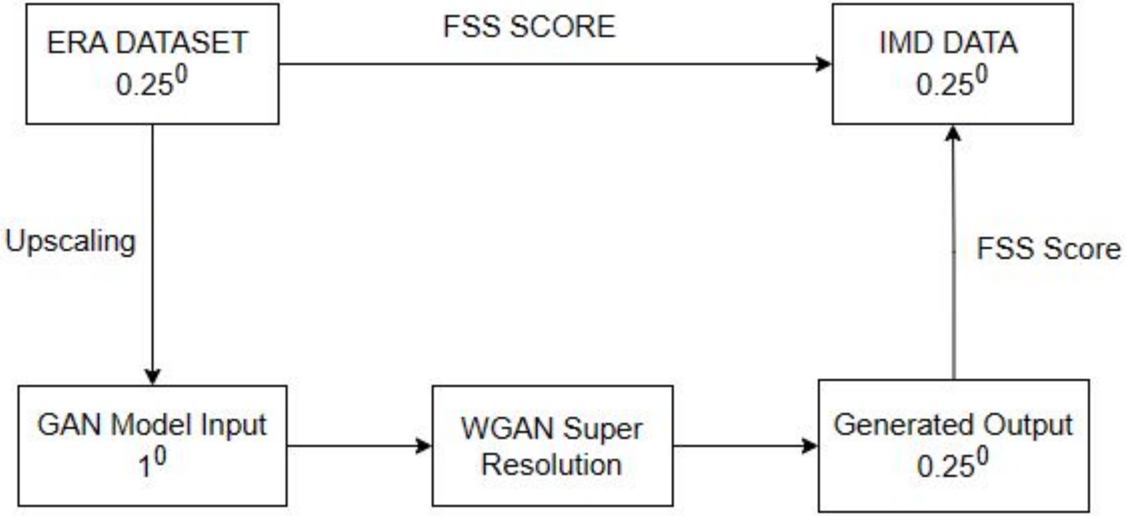
- More number of Datapoints due to subdivision of the map into smaller regions.
- Increased number of parameters compared to previous run.
- Faster executions due to small image sizes
- Improved FSS score on the evaluation data

Training



Loss Function
5
0
-5
-10
0
10
20
30
Critic Loss
Epoch
With GenLoss
Without GenLoss

Results

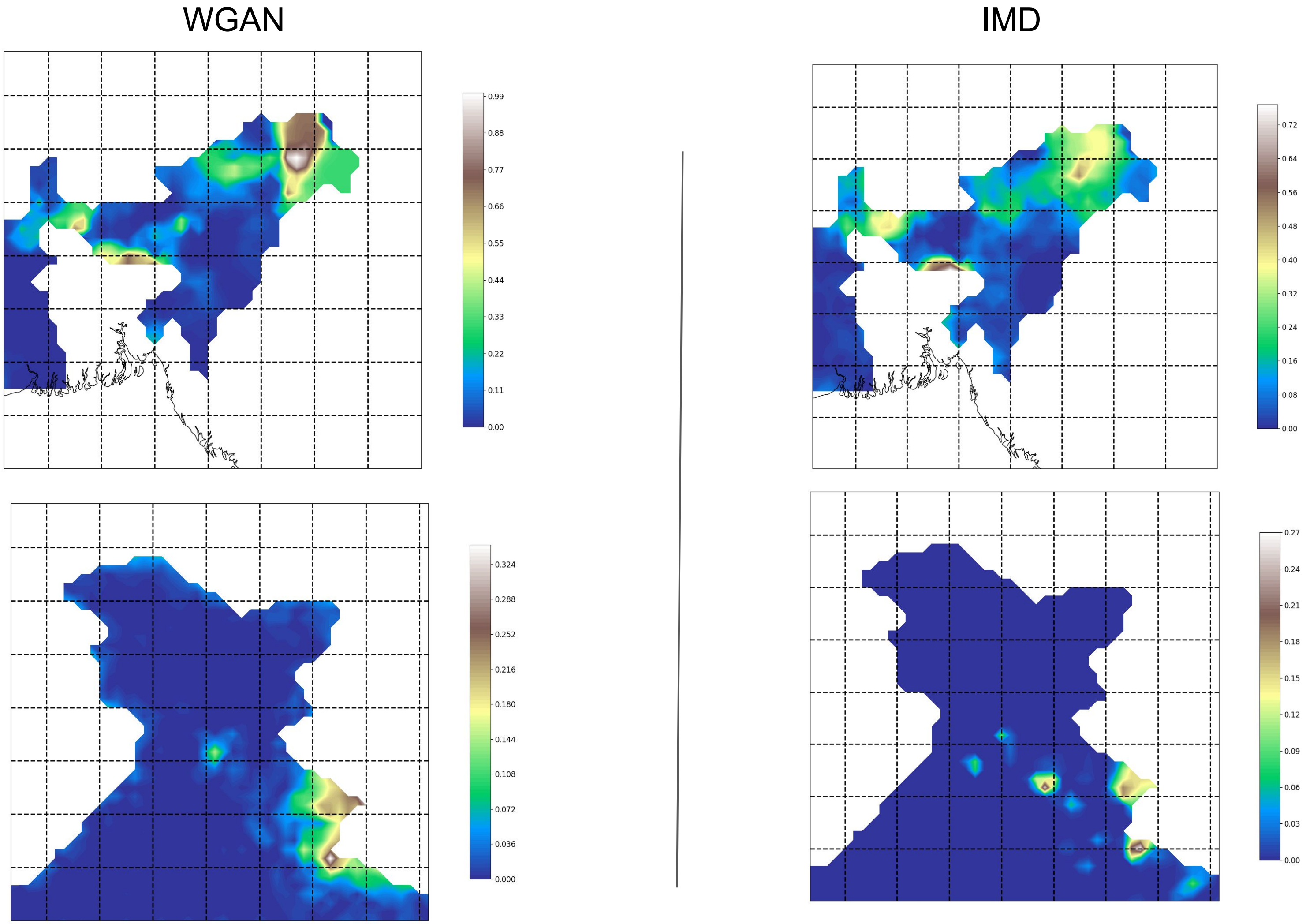

ERA DATASET
0.25⁰
FSS SCORE
IMD DATA
0.25⁰
Upscaling
FSS Score
GAN Model Input
1⁰
WGAN Super
Resolution
Generated Output
0.25⁰

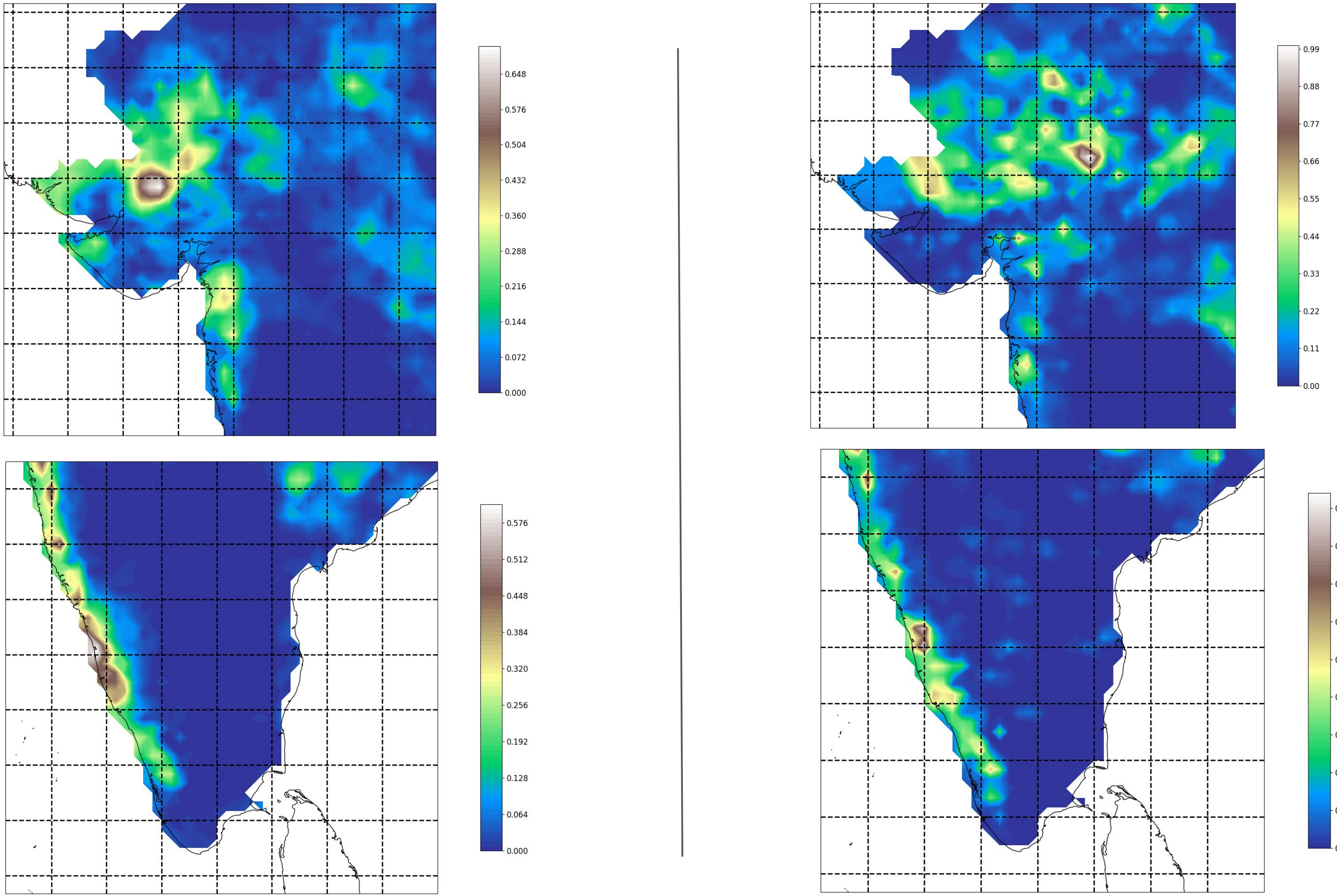
Mean of fractional Skill Score on Evaluation data (JJAS 2021-2022)

FSS	Threshold: 1mm	Threshold: 10mm	Threshold: 50mm	Threshold: 64.4mm
Window(1 x 1)	0.64	0.44	0.17	0.15
Window(2 x 2)	0.72	0.52	0.22	

Mean of fractional Skill Score of Original ERA data (JJAS 2021-2022)

FSS	Threshold: 1mm	Threshold: 10mm	Threshold: 50mm	Threshold: 64.4mm
Window(1 x 1)	0.56	0.34	0.10	0.08
Window(2 x 2)	0.61	0.40	0.13	


WGAN
IMD
0.99
0.88
0.77
0.66
0.55
0.44
0.33
0.22
0.11
0.00
0.72
0.64
0.56
0.48
0.40
0.32
0.24
0.16
0.08
0.00
0.324
0.288
0.252
0.216
0.180
0.144
0.108
0.072
0.036
0.000
0.27
0.24
0.21
0.18
0.15
0.12
0.09
0.06
0.03
0.00


0.648
0.576
0.504
0.432
0.360
0.288
0.216
0.144
0.072
0.000
0.99
0.88
0.77
0.66
0.55
0.44
0.33
0.22
0.11
0.00
0.576
0.512
0.448
0.384
0.320
0.256
0.192
0.128
0.064
0.000
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0.0

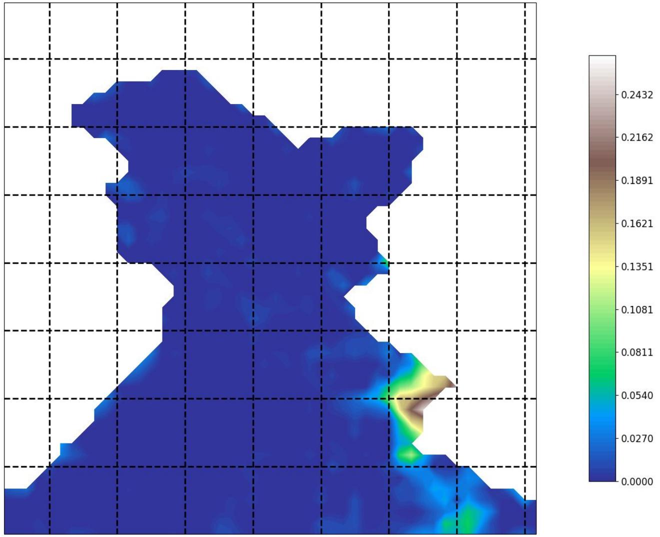
Limitations and Directions :

- Quantitative accuracy (heavy bias on the generated output precipitation values)
- Different epochs of model shows different set of scores for the threshold values.
- Selective training by modifying the network to train for a particular type of events.
- Add the other remaining years of the ERA dataset to further increase our training set eventually allowing us to use more number of parameters.
- Creating a ensemble of predictions.

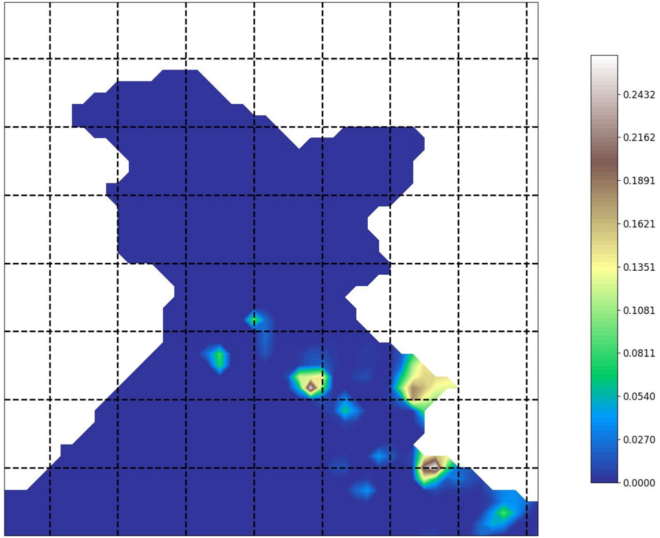
FSS mean on Evaluation data using Three Channels (JJAS 2021-2022)

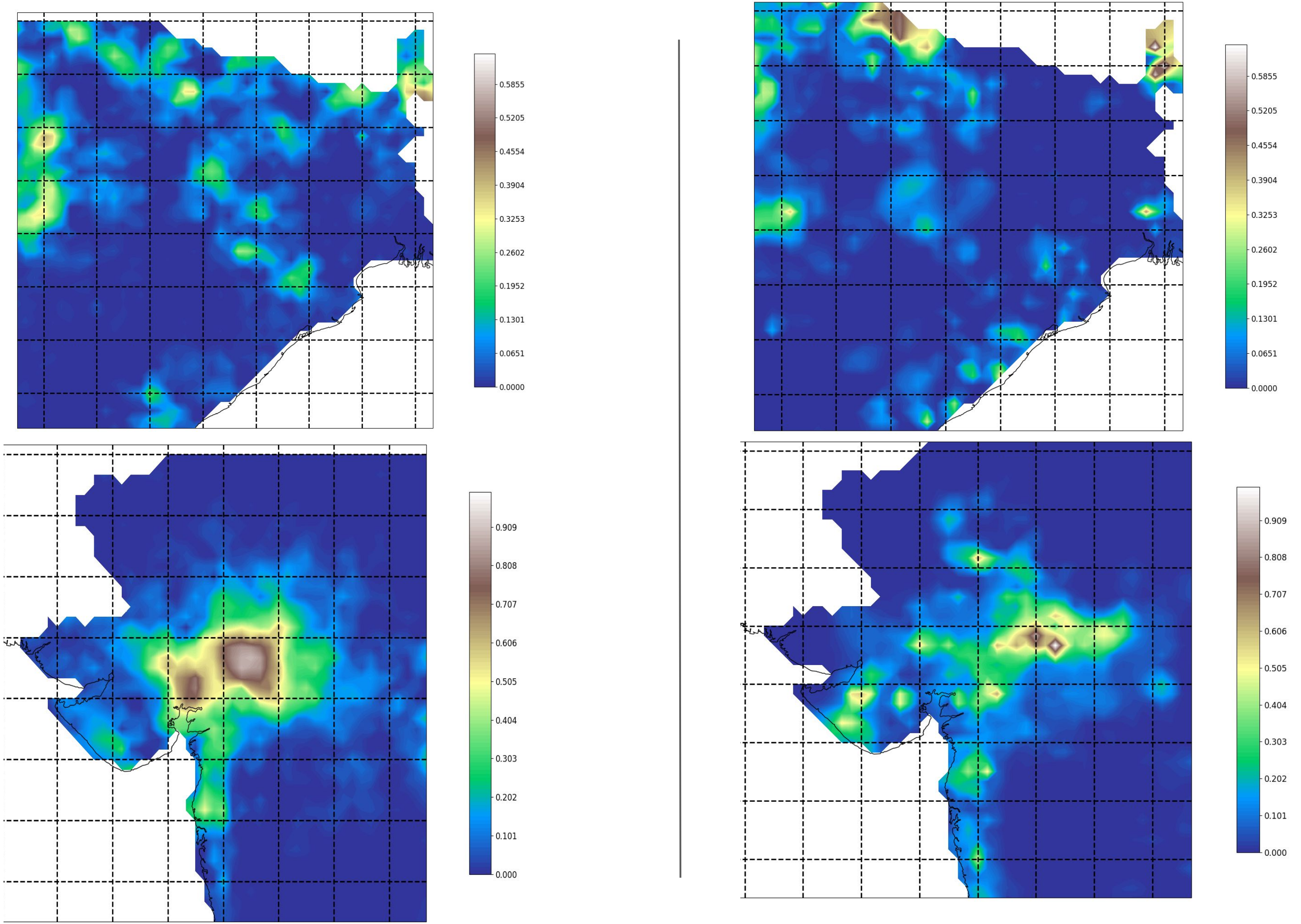
FSS	Threshold: 1mm	Threshold: 10mm	Threshold: 50mm	Threshold: 64.4mm
Window(1 x 1)	0.64	0.44	0.17	0.14
Window(2 x 2)	0.73	0.52	0.22	

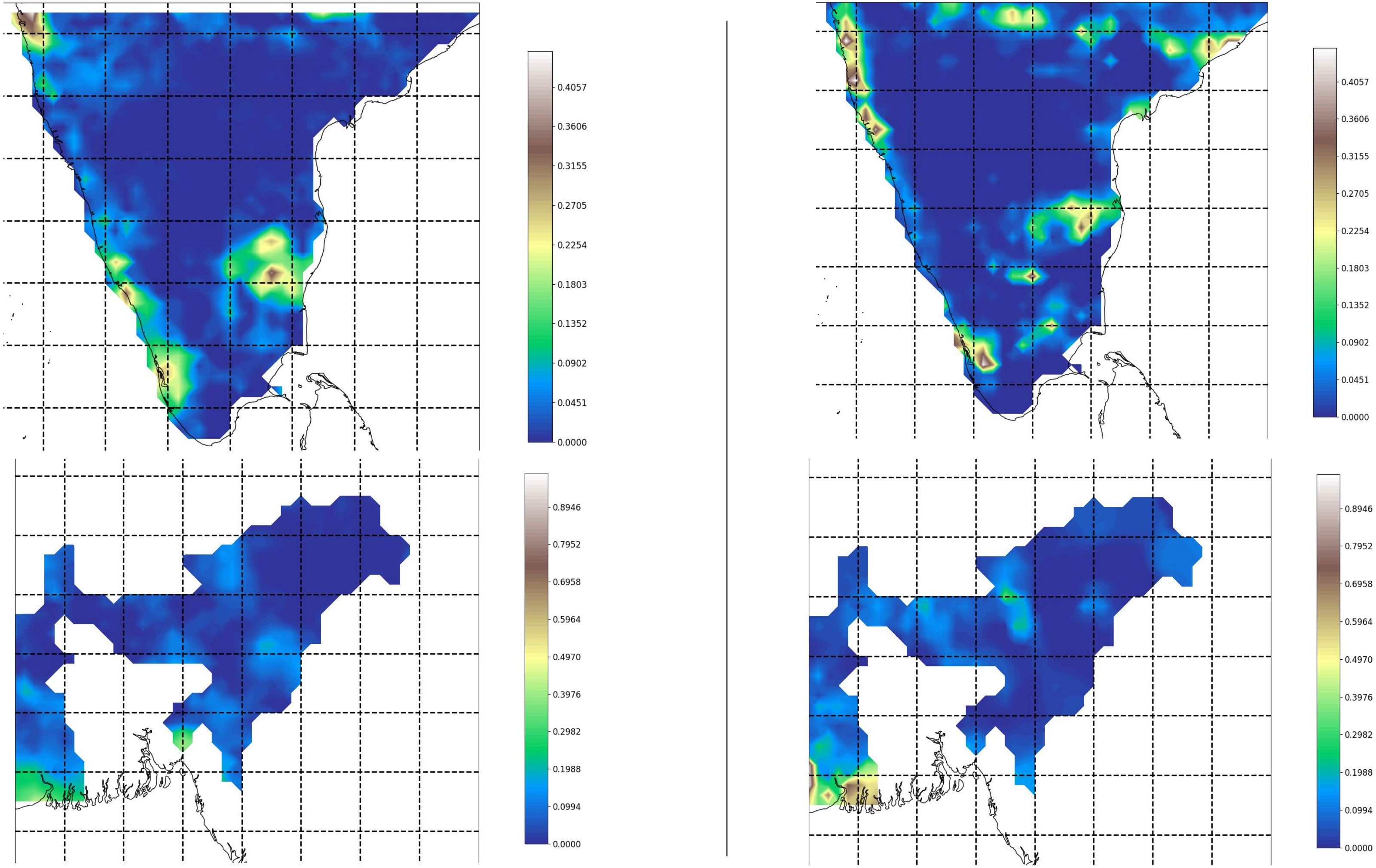
WGAN



IMD




0.5855
0.5205
0.4554
0.3904
0.3253
0.2602
0.1952
0.1301
0.0651
0.0000
0.5855
0.5205
0.4554
0.3904
0.3253
0.2602
0.1952
0.1301
0.0651
0.0000
0.909
0.808
0.707
0.606
0.505
0.404
0.303
0.202
0.101
0.000
0.909
0.808
0.707
0.606
0.505
0.404
0.303
0.202
0.101
0.000


0.4057
0.3606
0.3155
0.2705
0.2254
0.1803
0.1352
0.0902
0.0451
0.0000
0.4057
0.3606
0.3155
0.2705
0.2254
0.1803
0.1352
0.0902
0.0451
0.0000
0.8946
0.7952
0.6958
0.5964
0.4970
0.3976
0.2982
0.1988
0.0994
0.0000
0.8946
0.7952
0.6958
0.5964
0.4970
0.3976
0.2982
0.1988
0.0994
0.0000

Temperature Dataset - SR

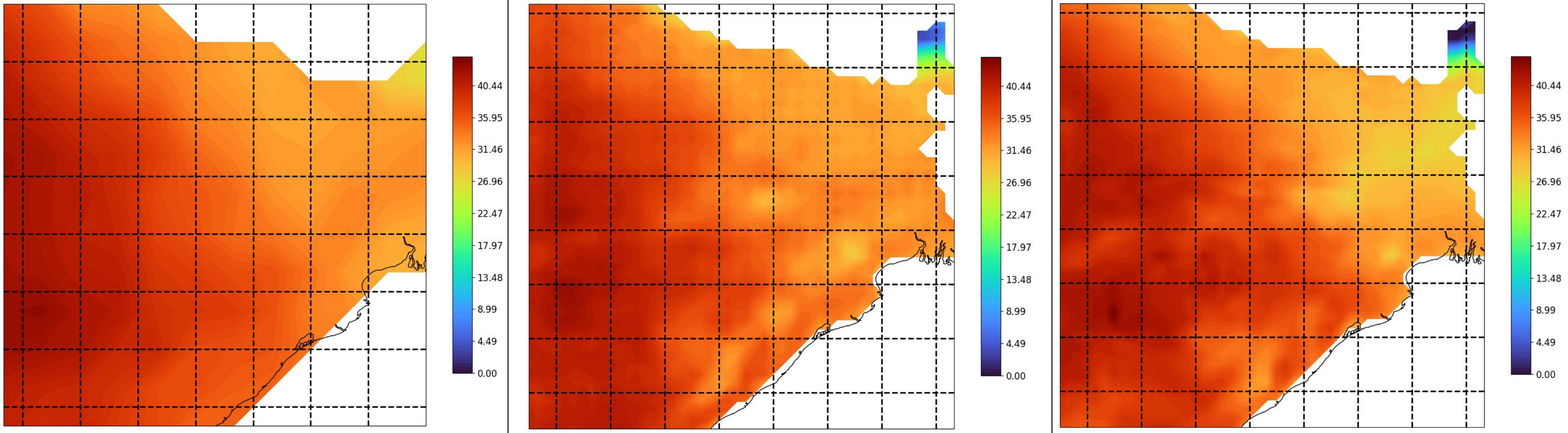
Low Resolution Data:

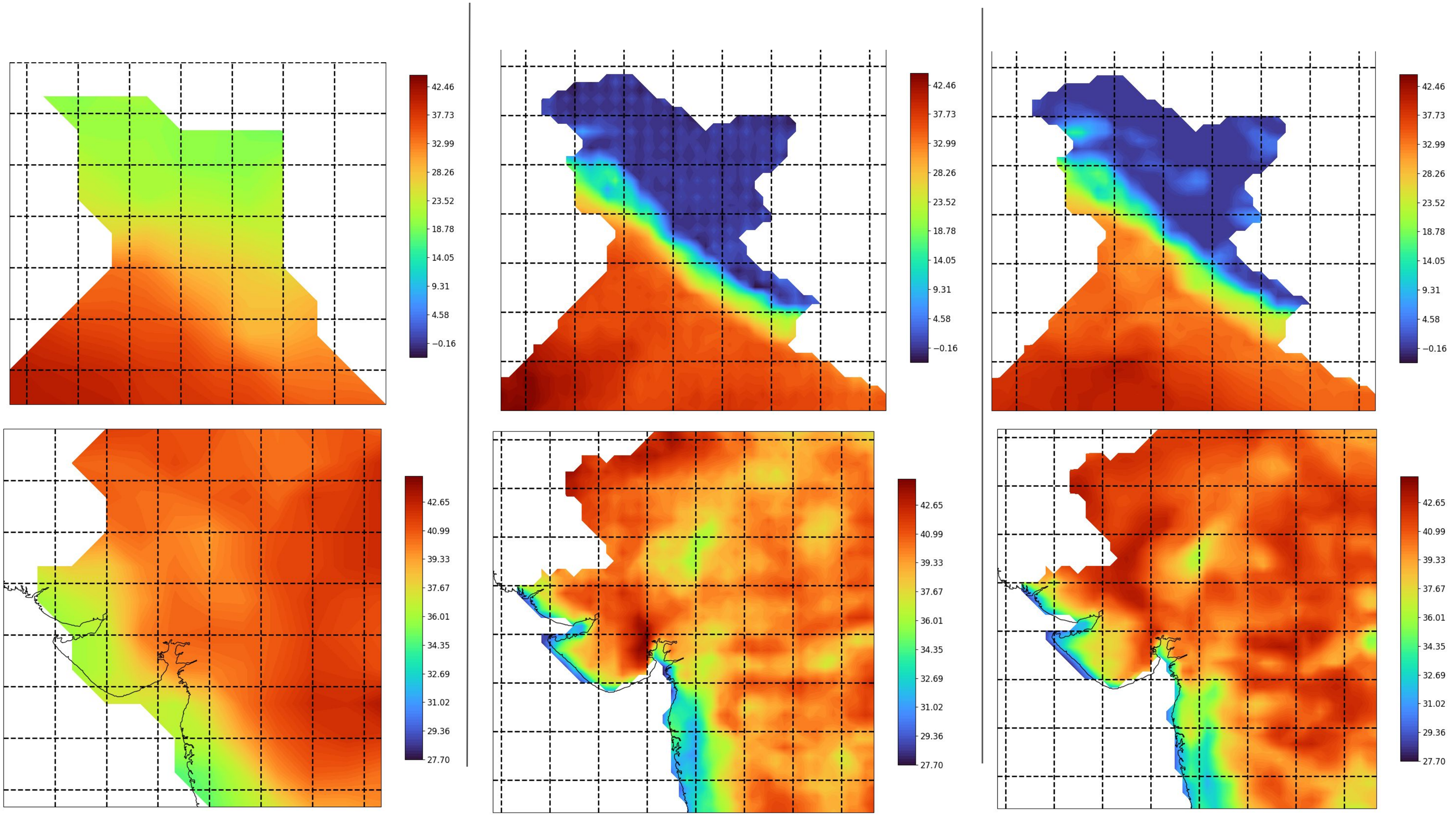
- IMD yearly gridded maximum temperature (1° x 1°)
- Temporal resolution: Daily
- Training Dataset: 1981-2019
- Divided the map into 5 smaller regions
- Scaled to [-1,1] for training
- Srivastava et al.(2009) available at Climate Monitoring and Prediction Group (imdpune.gov.in)

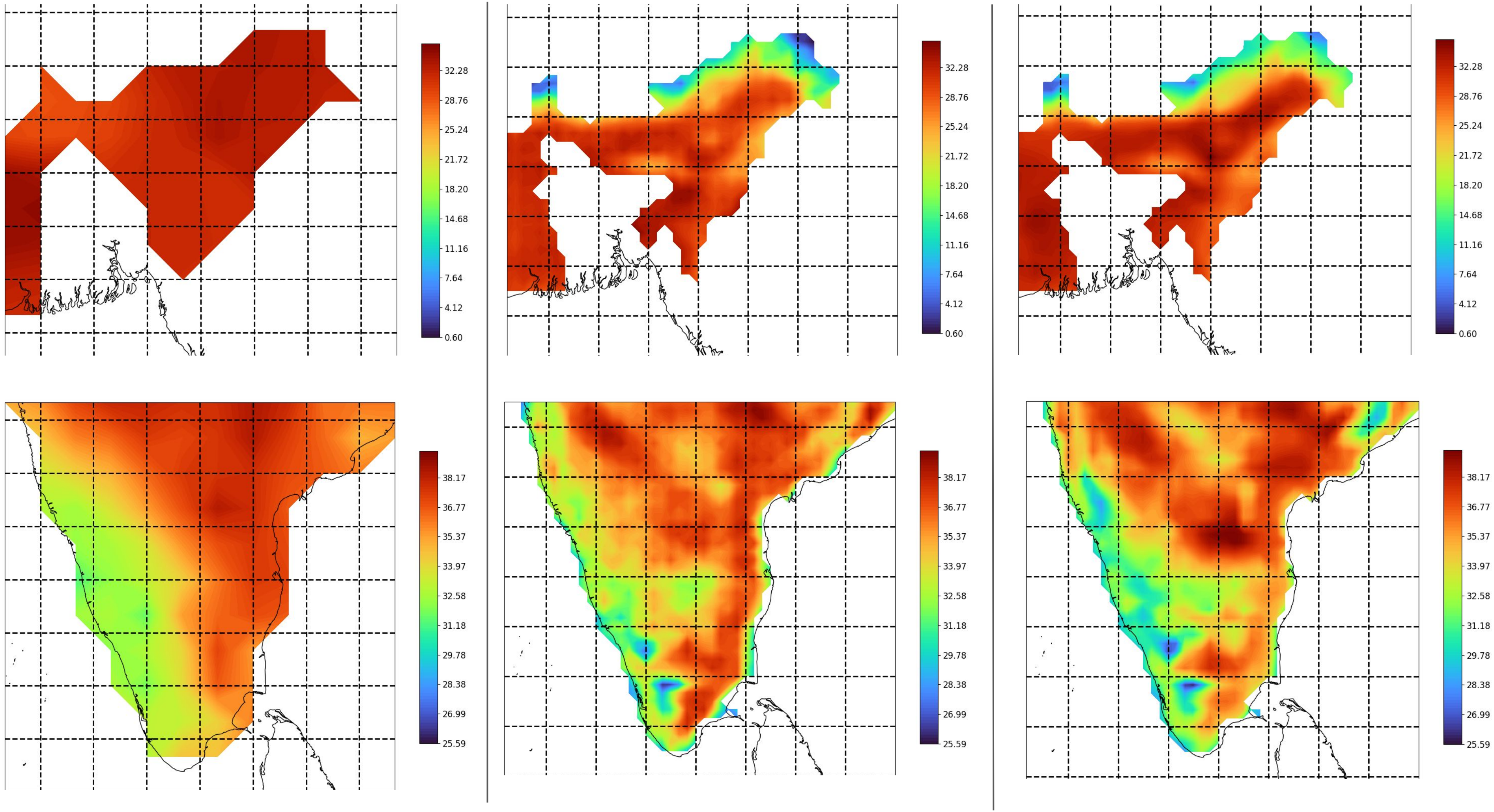
High Resolution Data:

- ERA5 hourly data on single levels (0.25° x 0.25°)
- Temporal Resolution: Hourly
- Training Dataset: 1981-2019 (24hr Maximum values)
- Divided the map into 5 smaller regions
- Scaled to [-1,1] for training

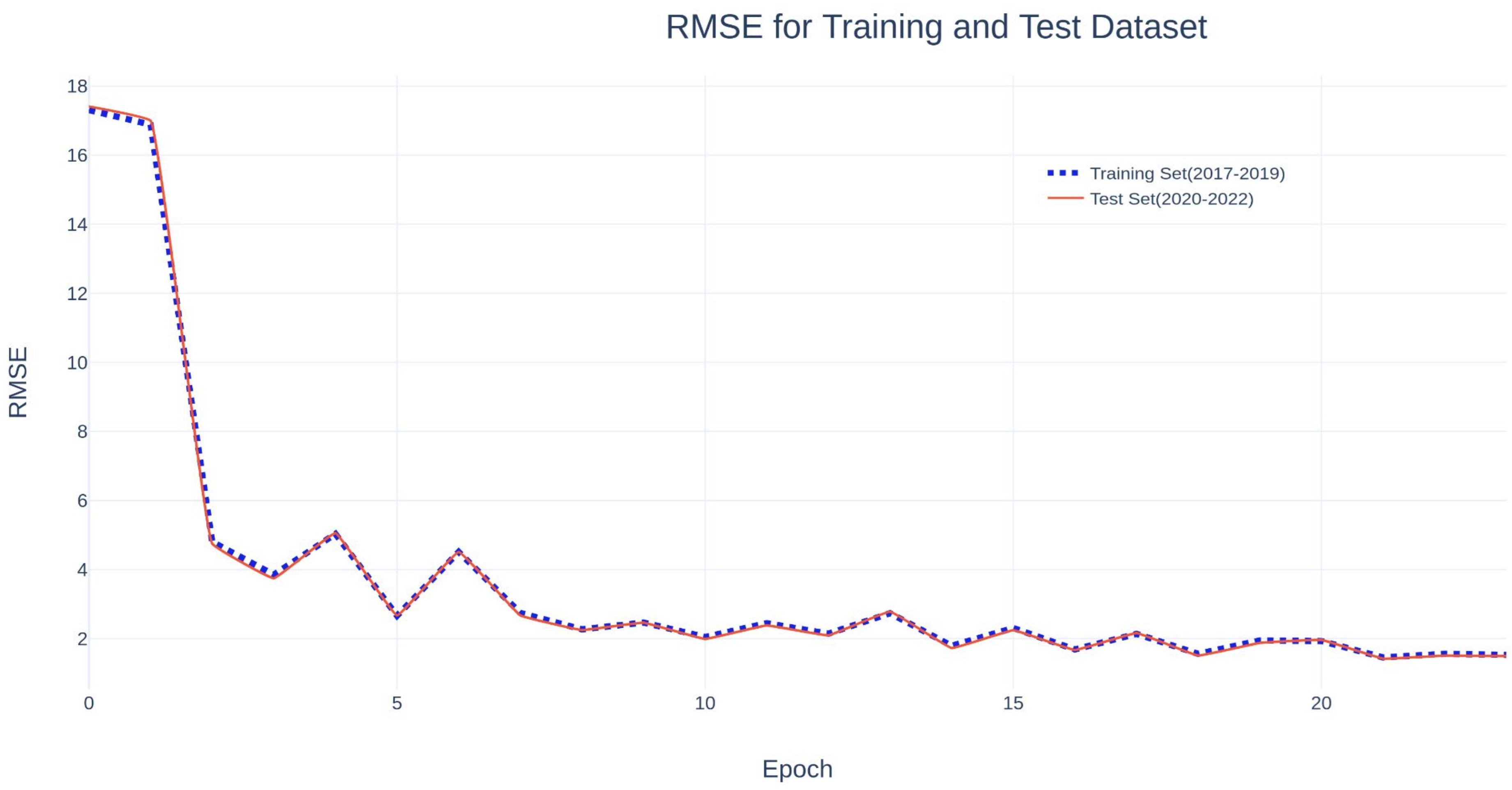
IMD (1°) | WGAN-OUTPUT (0.25°) | ERA (0.25°)




42.46
37.73
32.99
28.26
23.52
18.78
14.05
9.31
4.58
−0.16
42.65
40.99
39.33
37.67
36.01
34.35
32.69
31.02
29.36
27.70


32.28
28.76
25.24
21.72
18.20
14.68
11.16
7.64
4.12
0.60
32.28
28.76
25.24
21.72
18.20
14.68
11.16
7.64
4.12
0.60
32.28
28.76
25.24
21.72
18.20
14.68
11.16
7.64
4.12
0.60
38.17
36.77
35.37
33.97
32.58
31.18
29.78
28.38
26.99
25.59
38.17
36.77
35.37
33.97
32.58
31.18
29.78
28.38
26.99
25.59
38.17
36.77
35.37
33.97
32.58
31.18
29.78
28.38
26.99
25.59


Cricitic loss v/s Epcoh
Critic Loss
0
−5
−10
−15
−20
−25
−30
−35
−40
−45
5
10
15
20
Epoch


RMSE for Training and Test Dataset
Training Set(2017-2019)
Test Set(2020-2022)
RMSE
Epoch
18
16
14
12
10
8
6
4
2
0
5
10
15
20