A Probabilistic Multi Stage Approach for Statistical Downscaling of Temperature Data

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Abstract

Near Surface Air Temperature is an important climatic variable that affects the hydrological response of a river basin, and forms an input to most of the hydrological models. General Circulation Models (GCMs) simulate the response of temperature and other climate variables to the variations in emission concentrations, but their outputs are too coarse to be used in most hydrological models. A multi stage statistical downscaling approach is proposed for downscaling GCM predicted temperatures. In the first stage the Relevance Vector Machine (RVM) is used to develop a statistical model between the GCM simulated historical climate variables and the observed historical temperature for spatially downscaling monthly GCM simulations. A weather generator is then used to generate daily data from the spatially downscaled temperature data. On fine scales, lack of correlation between precipitation and temperature data used for hydrological modelling can lead to large uncertainties in the generated hydrological series. Thus, a distribution free post processing is performed for reproducing the observed regional correlation between temperature and precipitation, in the generated temperature data. The methodology is then applied to the Bharathapuzha catchment in Kerala, India, to downscale temperature from the climate models BNU-ESM, CESM1-BGC, CMCC-ESM2, FGOALS-G2, FIO-ESM-2.0 and MIROC4h. The statistical models set up using RVM show consistent performance during the calibration (1969-1980) and validation (1981-2005) phases, with Nash-Sutcliffe efficiency (NSE) between 0.64 to 0.83. The weather generator is then run to generate daily temperature data from the monthly downscaled series. Across the different climate models, daily maximum temperature is generated with RMSE between 2.5°C to 3.3°C, while the minimum temperature has RMSE ranging from 1.7°C to 2.0°C. The probabilistic nature of the procedure enables the generation of multiple series from the same set of predictors. The simulation band from the multiple GCMs is studied for the period 2016 to 2021 to understand the deviation in predicted temperature for the future scenario. The prediction band for maximum temperature has an average band width of 6.7°C and for minimum temperature, the average band width is 4.9°C.

A Probabilistic Multi Stage Approach for Statistical Downscaling of Temperature Data

IIT PALAKKAD

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AGU FALL MEETING

16 December 2022

SCIENCE LEADS THE FUTURE

CLIMATE CHANGE

- Long term - significant change in the statistical parameters of weather over an area
- Observed changes in climate are unequivocal at the global scale and are increasingly apparent on regional and local spatial scales. (IPCC, 2021: Climate Change 2021: The Physical Science Basis)

*https://guardian.ng/opinion/nigeria-and-climate-change/

AGU FALL MEETING

CLIMATE CHANGE

- Effects of climate change is already visible as increase in frequency and magnitude of extreme events across the world

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UK heatwave: Final day of 'extreme' heat with thunder on way

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NEWS & INSPIRATION FROM NATURE'S FRONTLINE

RAINFORESTS OCEANS ANIMALS ENVIRONMENT BUSINESS SOLUTIONS FOR KIDS DONATE IMPACT MORE

Forest fires are getting worse, 20 years of data confirm

TRENDS

by Liz Kimbrough on 17 August 2022

Over 2 lakh houses damaged in Assam flood this year, Cachar worst affected district

The state government on Saturday started disbursing financial assistance to the families for the reconstruction of their houses

Sumir Karmakar, DHNS, Guwahati, AUG 20 2022, 15:10 IST | UPDATED: AUG 20 2022, 15:24 IST

· Kerala Floods : 2 Killed; Weather Agency Issues Red Alert In 4 Districts

Floods : 2 Killed; Weather Agency

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CLIMATE MODELING

- Changing climate has considerable impacts on human life

Existing infrastructure may not be sufficient to handle effects of climate change!

Sudheer et al., (2019) studied the role of existing reservoirs on 2018 floods in the Periyar river basin, Kerala

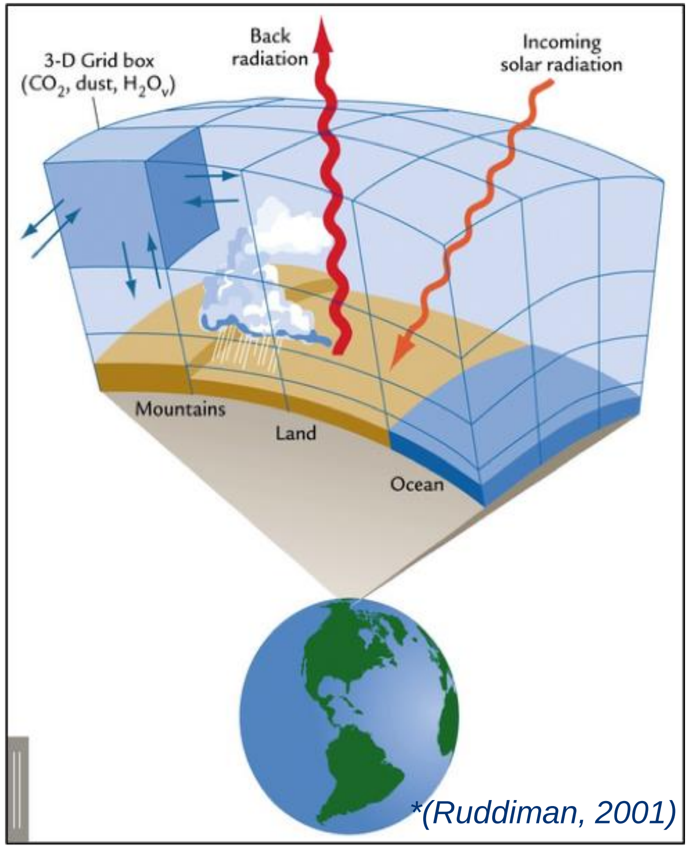
- Reservoir operations **could not have helped in avoiding** the flood situation
- Reliability of rainfall forecast at lead times where operations can help is low

- Hotter Temperatures
- Severe storms
- Increased Droughts
- Increased Floods
- Warming, rising Ocean
- Loss of species
- Decreasing food production
- Increased health risk
- Poverty and displacement

CLIMATE MODELING

- General Circulation Models (GCMs) are mathematical models that attempt to simulate the Earth's climate system

- *GCMs - Most advanced tools currently available* for simulating the response of global climate system to changes in the atmospheric concentration of green house gases (Mechoso and Arakawa, 2015)

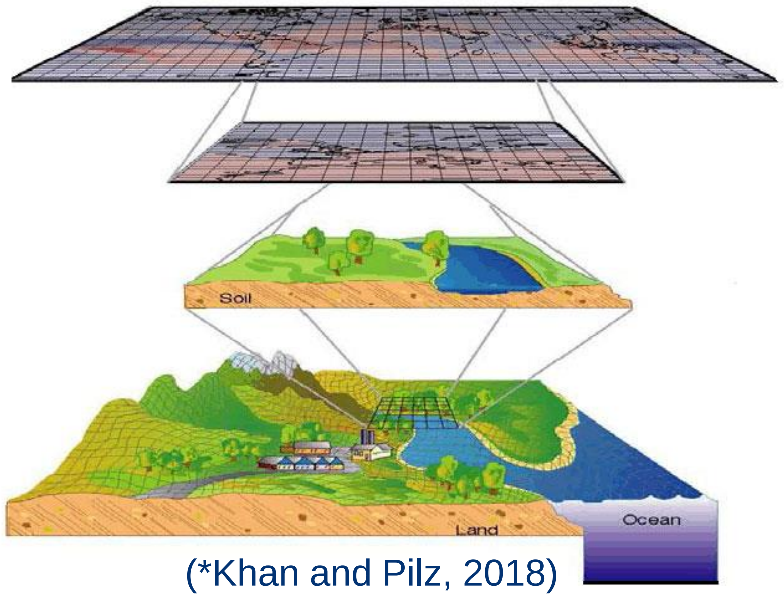


*(Ruddiman, 2001)

AGU FALL MEETING

DOWNSCALING

- Process by which coarse resolution GCM outputs are translated to finer resolution climate information for regional scale analysis



(*Khan and Pilz, 2018)

Dynamic Downscaling: GCM simulations are used to drive a regional, **numerical model** at higher spatial resolution

Statistical Downscaling: A **statistical relationship** is established from observations between large scale variables and is then subsequently used on the GCM data to obtain the local variables from the GCM output

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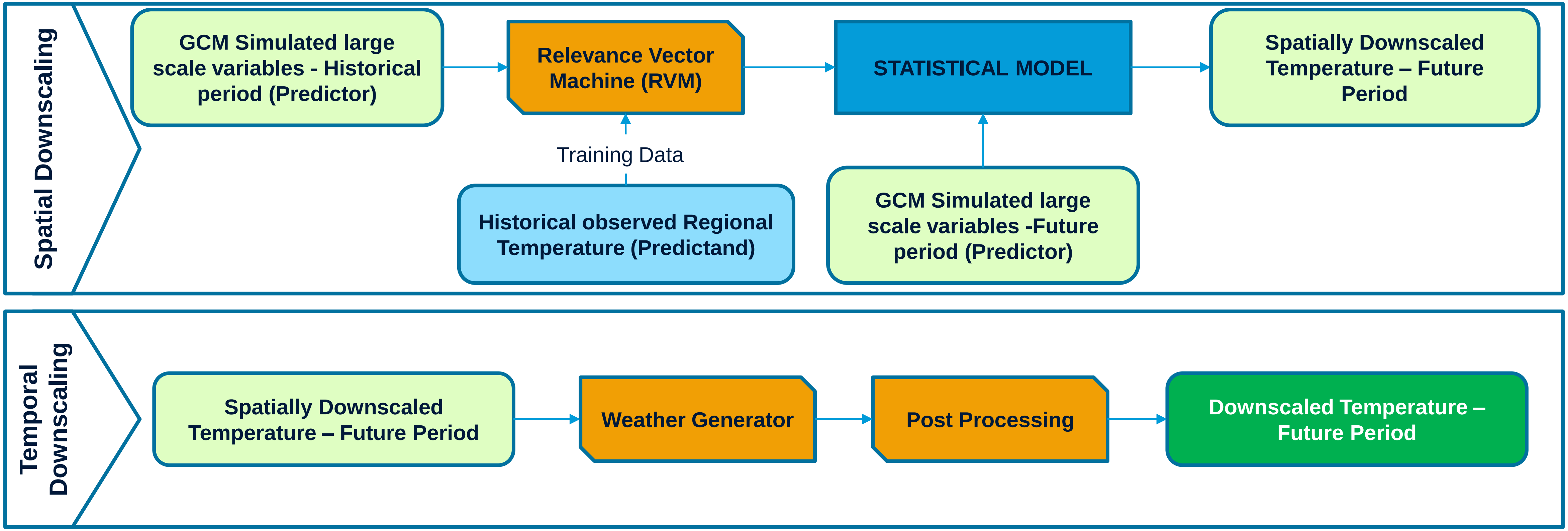
OBJECTIVE

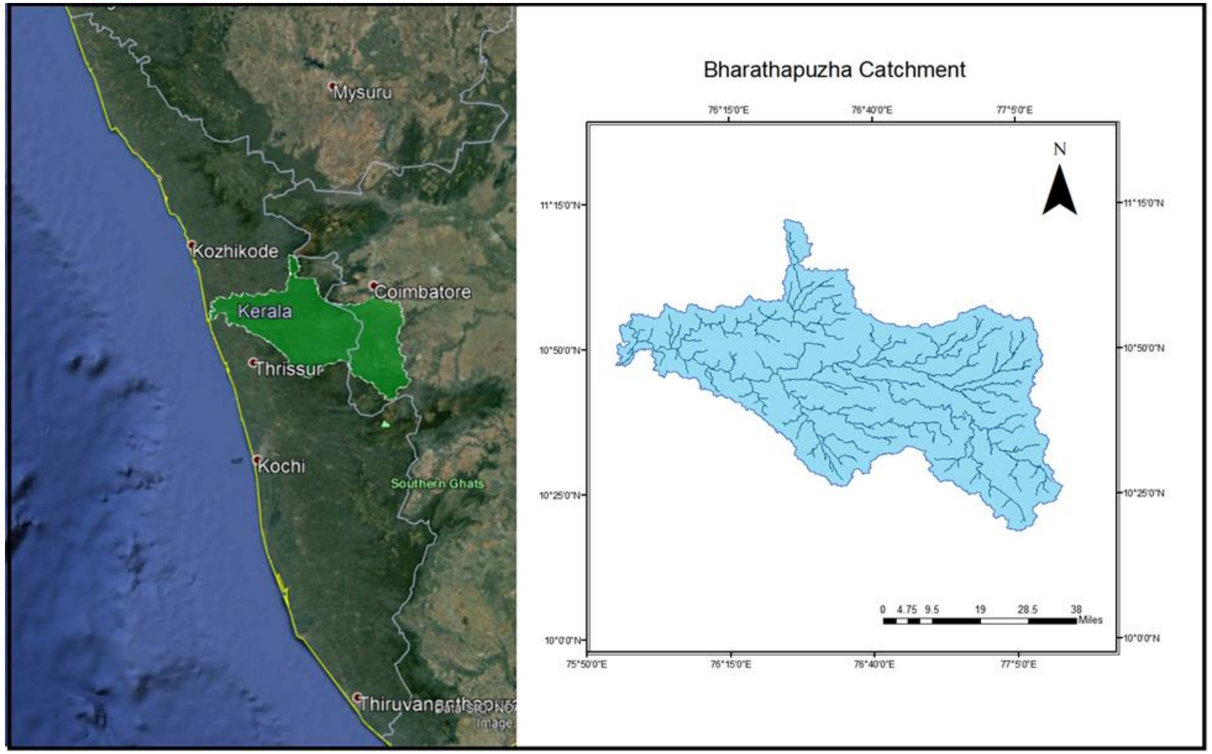
- Develop a statistical downscaling approach considering:
  - Stochastic nature of climate prediction
  - Uncertainty in climate modelling
  - Capture long term climate trend from climate model
  - Capture characteristics of regional climate

METHODOLOGY



VALIDATION

Downscale temperature data for the Bharathapuzha catchment in Kerala



- Second Largest river in Kerala, India
- Major source of water in the region – Drying up in recent decades
- Characterised by South West Monsoon – Large amount of rain
- A portion lies over Western Coast of India

PREDICTOR SET

- Climate models : CESM1-BGC, CMCC-ESM2, FGOALS-G2, FIO-ESM-2.0 and MIROC4h
- Selection of domain : Iteratively training the RVM model using different domain sizes, increasing from a single grid to multiple grids, till the improvement in performance becomes negligible

PREDICTOR SET

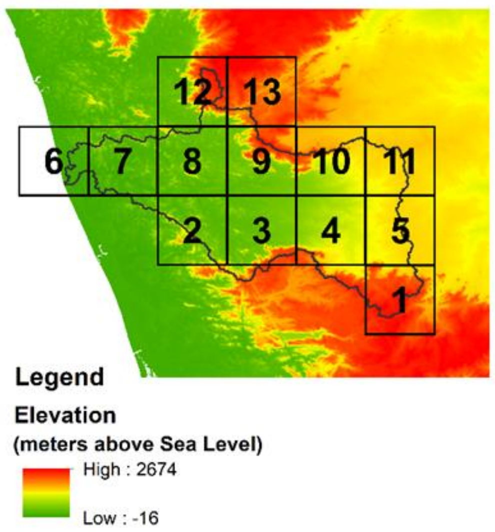
GCM Variable (Predictors)	Pressure Level (hPa)
Maximum Temperature	Surface
Minimum Temperature	
Sea Surface Temperature	
Mean Sea Level Pressure	
Surface Upward Latent Heat Flux	
Surface Upward Sensible Heat Flux	
Surface Upwelling Longwave Flux In Air	
Surface Upwelling Shortwave Flux In Air	
Zonal Wind Speed	500, 850, 1000
Specific Humidity	
Relative Humidity	
Geopotential Height	

Large scale climate variables that are known to drive regional temperature are considered as potential predictors (Huth, 2004; Pang, Yue, Zhao, & Xu, 2017; Pomee & Hertig, 2021)

PREDICTAND DATA

- 0.25°x0.25° gridded temperature data product for the period 1950 to 2005, from Sheffield et al., (2006) is used as the predictand

Grid No	Latitude	Longitude	Maximum Temperature		Minimum Temperature	
			Mean	Variance	Mean	Variance
1	10.375	77.125	27.26	7.21	18.25	3.39
2	10.625	76.375	31.40	6.29	23.16	2.78
3	10.625	76.625	31.45	7.13	22.68	3.15
4	10.625	76.875	31.78	7.95	22.66	3.53
5	10.625	77.125	31.92	7.71	22.60	3.60
6	10.875	75.875	31.70	5.41	23.52	2.77
7	10.875	76.125	31.58	5.80	23.33	2.73
8	10.875	76.375	31.94	6.37	23.38	2.90
9	10.875	76.625	30.89	7.25	21.77	3.29
10	10.875	76.875	31.71	8.06	22.23	3.67
11	10.875	77.125	31.86	7.93	22.22	3.77
12	11.125	76.375	29.47	6.67	20.55	3.07
13	11.125	76.625	28.03	7.52	18.53	3.50



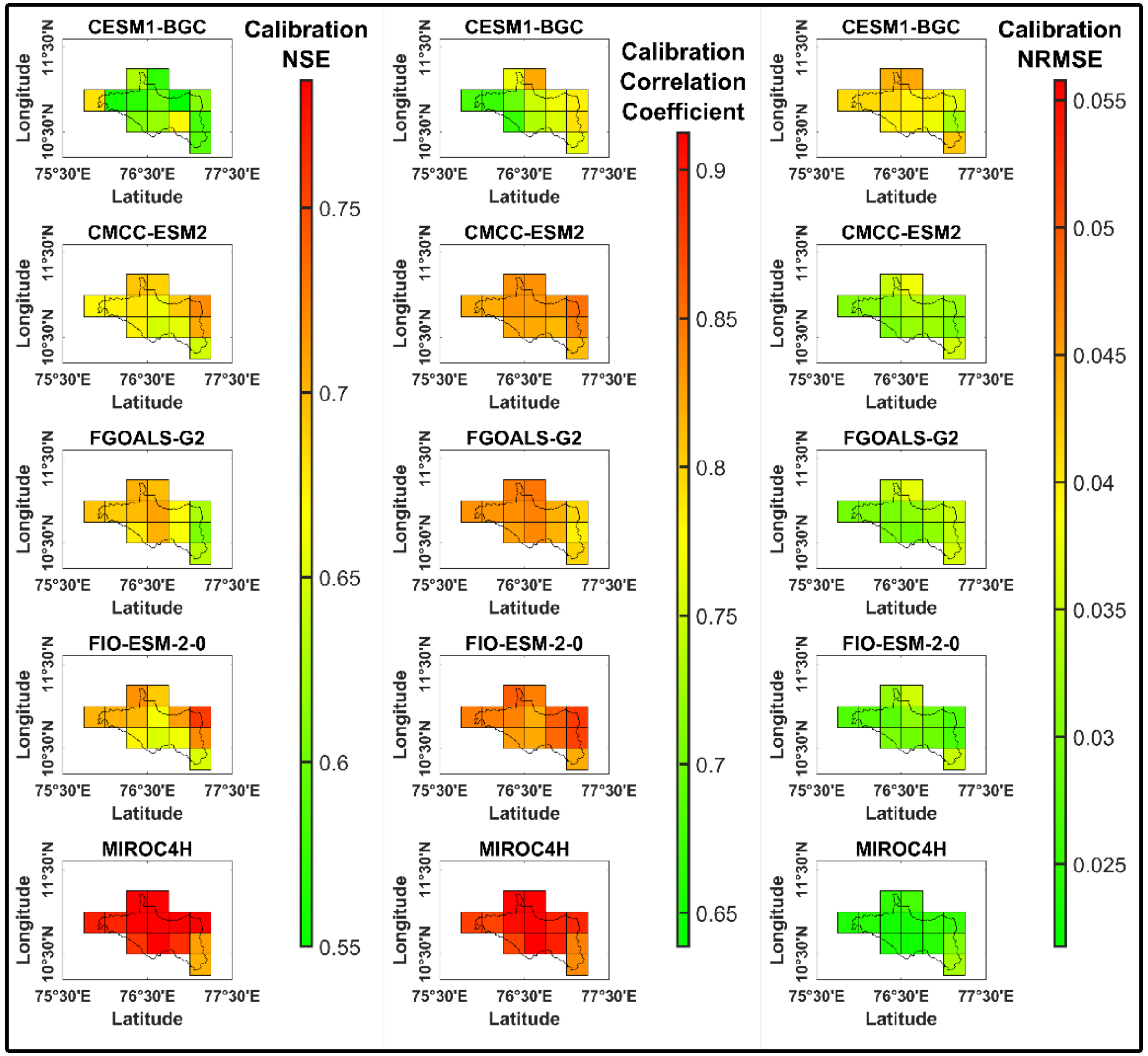


Fig: Performance of selected spatial downscaling models for maximum temperature in their calibration periods

RESULTS

SPATIAL DOWNSCALING

Relevance Vector Machine :

Calibration Period : 1951 – 2000

Validation Period: 2001 – 2005

Kernel Function: Radial Basis Function

NSE > 0.5

Correlation Coefficient > 0.6

NRMSE < 0.06

RESULTS

TEMPORAL DOWNSCALING

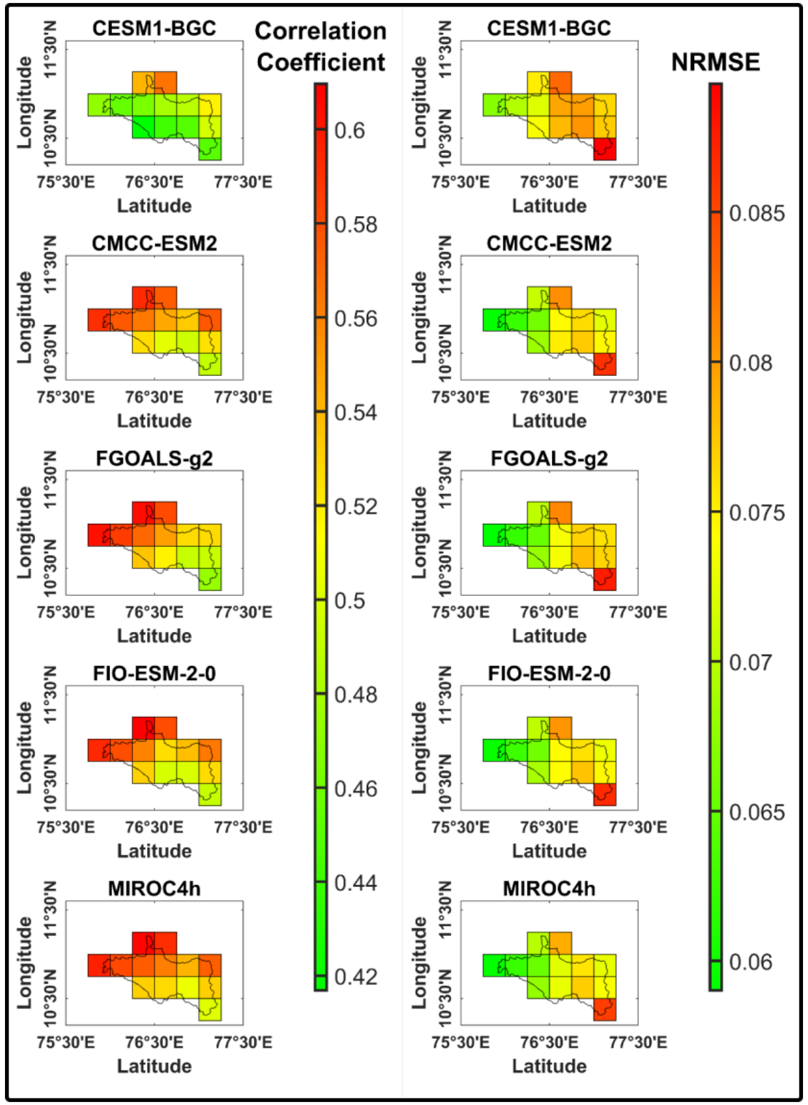


Fig: Performance of temporal downscaling procedure for Maximum Temperature

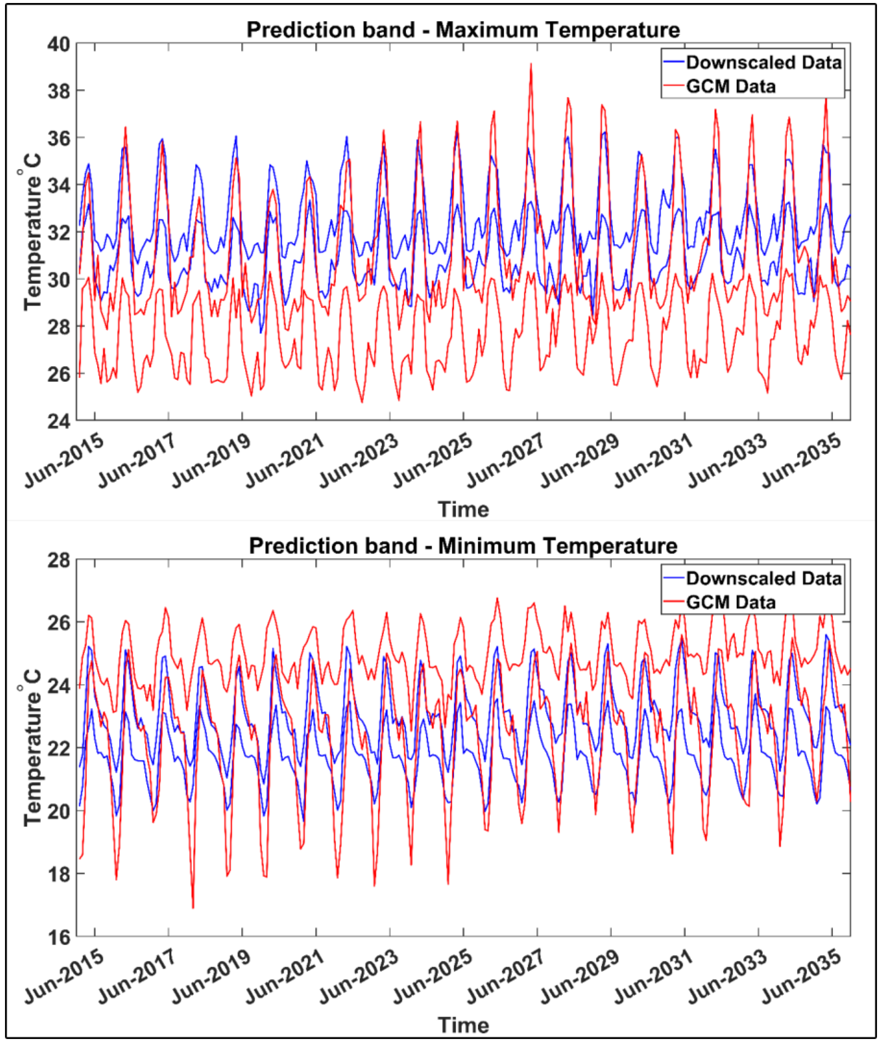
Weather Generator: Random series generated using probability distribution is ordered using spatially downscaled temperature as monthly mean

- Post processing procedure proposed by (Iman & Conover, 2007) is adopted to shuffle the downscaled temperature to show the observed correlation with regional daily rainfall data.

Correlation Coefficient > 0.4

NRMSE < 0.09

GENERATION OF FUTURE TEMPERATURES



- 200 series of temperature data generated from each climate model to study uncertainty
- Future temperature data generated : 2015 to 2035
  - 0.03°C increase per year in daily Maximum temperature
  - 0.02°C increase per year in daily Minimum Temperature
- The average band width across the climate models for the maximum temperature reduces from 3.7°C to 1.9°C, and for minimum temperature from 2.7°C to 1.4°C.

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CONCLUDING REMARKS

- Linear regression using RVM – Automatic selection of relevant predictors
- Probabilistic approach – stochastic generation of ensemble data
- Accuracy is limited by accuracy of observed data
- Poor prediction of extremes – better at reproducing means

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THANKS

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