

A Probabilistic Multi Stage Approach for Statistical Downscaling of Temperature Data



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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/>

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

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



RAINFORESTS OCEANS ANIMALS ENVIRONMENT BUSINESS SOLUTIONS FOR KIDS DONATE IMPACT MORE

Forest fires are getting worse, 20 years of data confirm

by Liz Kimbrough on 17 August 2022

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

Floods : 2 Killed; Weather Agency

TRENDS

SCIENCE LEADS THE FUTURE

CLIMATE MODELING

- Changing climate has considerable impacts on human life

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

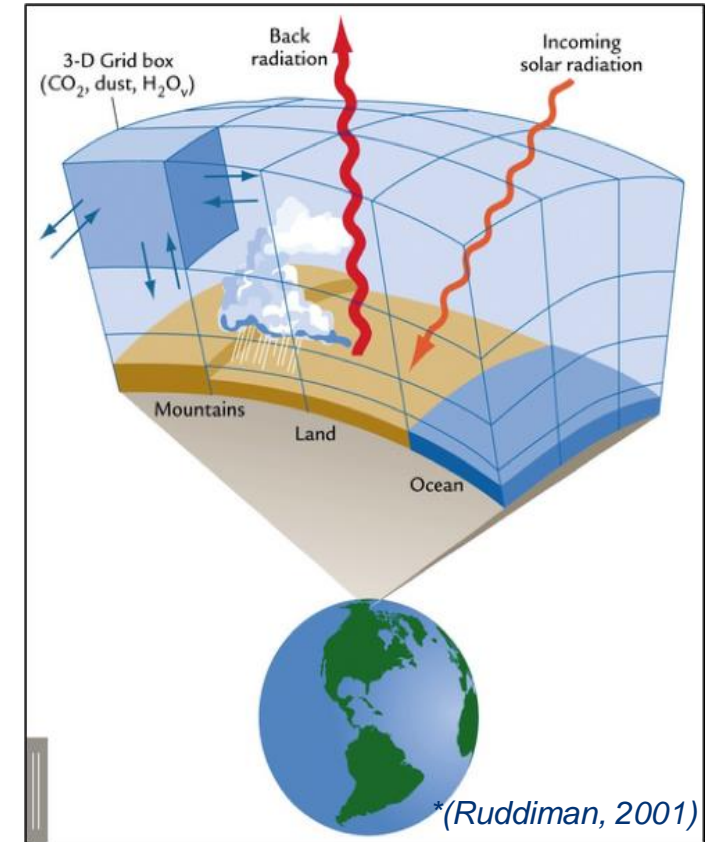
Sudheer et al., (2019) studied the role of existing reservoirs on 2018 floods in the Periyar river basin, Kerala

- 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

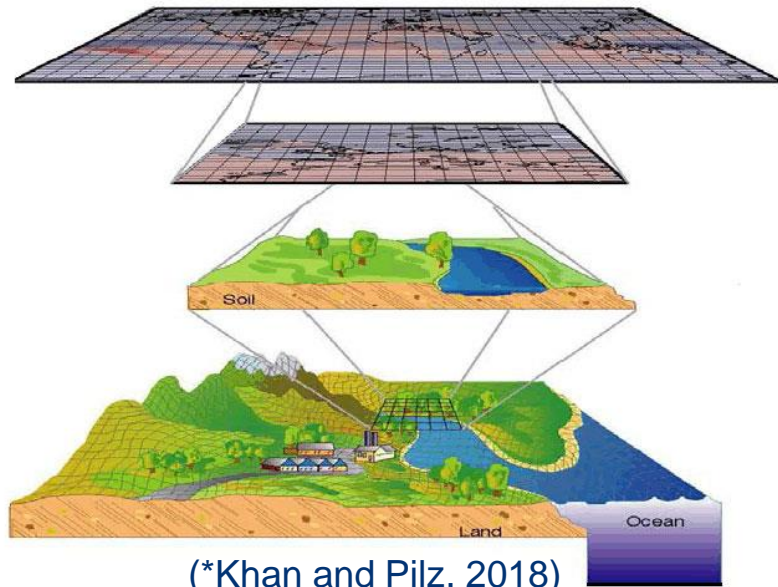
CLIMATE MODELING

- 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)



DOWNSCALING

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



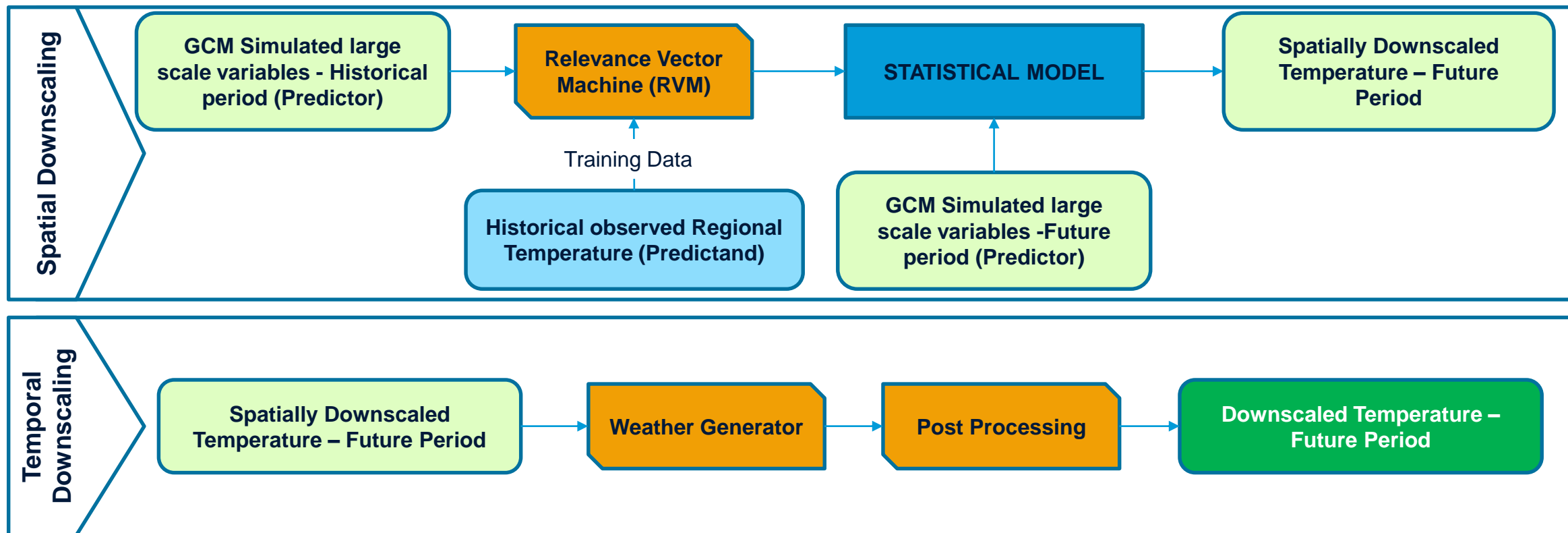
Dynamic Downscaling: GCM simulations are used to drive a regional, **numerical model** at higher spatial resolution

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

OBJECTIVE

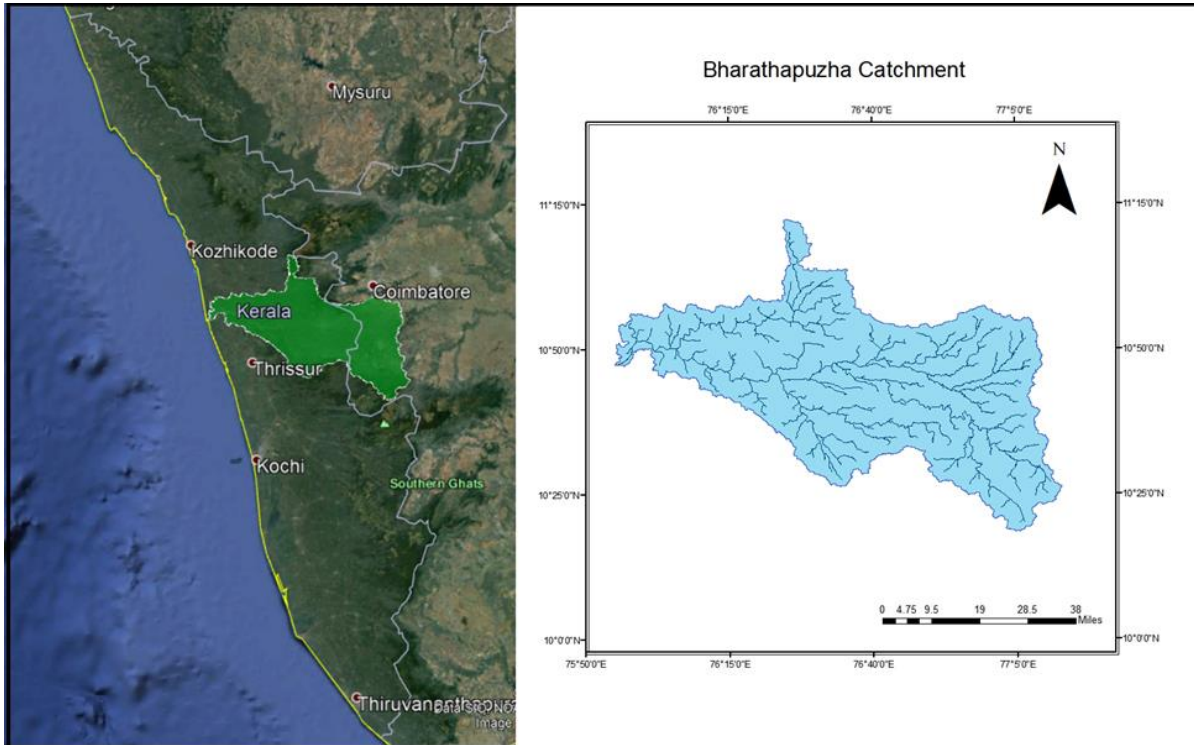
- Develop a statistical downscaling approach considering:
 - Stochastic nature of climate prediction
 - Uncertainty in climate modelling
 - Capture long term climate trend from climate model
 - Capture characteristics of regional climate

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

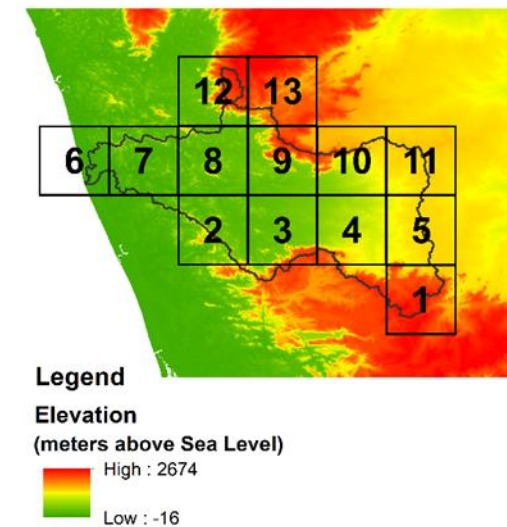
GCM Variable (Predictors)	Pressure Level (hPa)
Maximum Temperature	Surface
Minimum Temperature	
Sea Surface Temperature	
Mean Sea Level Pressure	
Surface Upward Latent Heat Flux	
Surface Upward Sensible Heat Flux	
Surface Upwelling Longwave Flux In Air	
Surface Upwelling Shortwave Flux In Air	
Zonal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

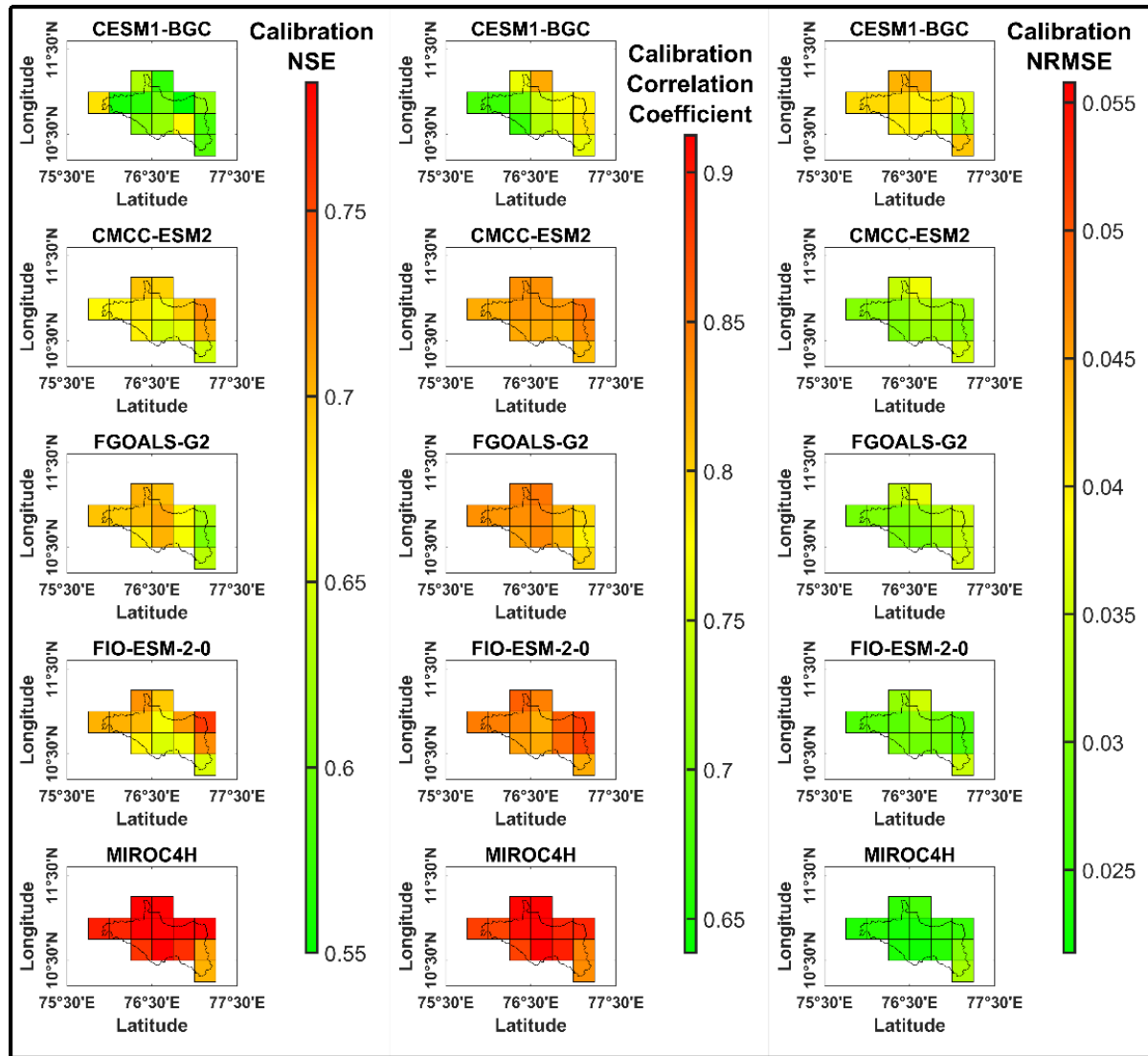
Large scale climate variables that are known to drive regional temperature are considered as potential predictors (Huth, 2004; Pang, Yue, Zhao, & Xu, 2017; Pomee & Hertig, 2021)

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





RESULTS

SPATIAL DOWNSCALING

Relevance Vector Machine :

Calibration Period : 1951 – 2000

Validation Period: 2001 – 2005

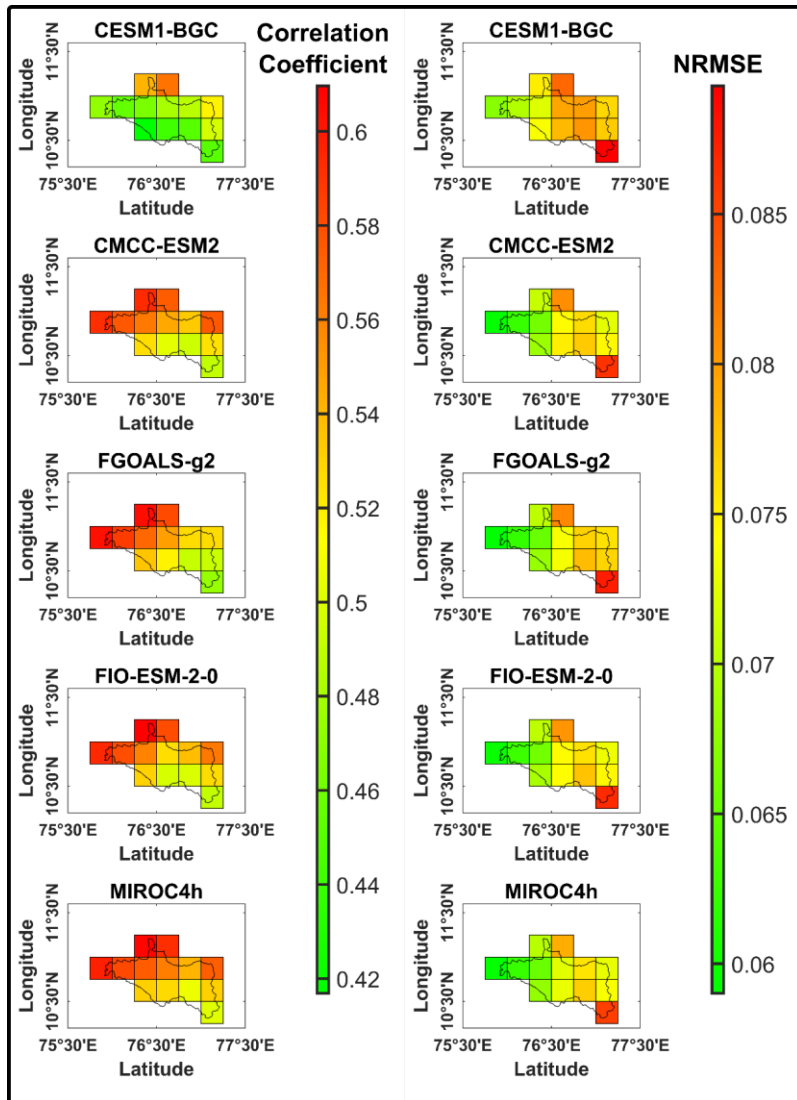
Kernel Function: Radial Basis Function

NSE > 0.5

Correlation Coefficient > 0.6

NRMSE < 0.06

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



RESULTS

TEMPORAL DOWNSCALING

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

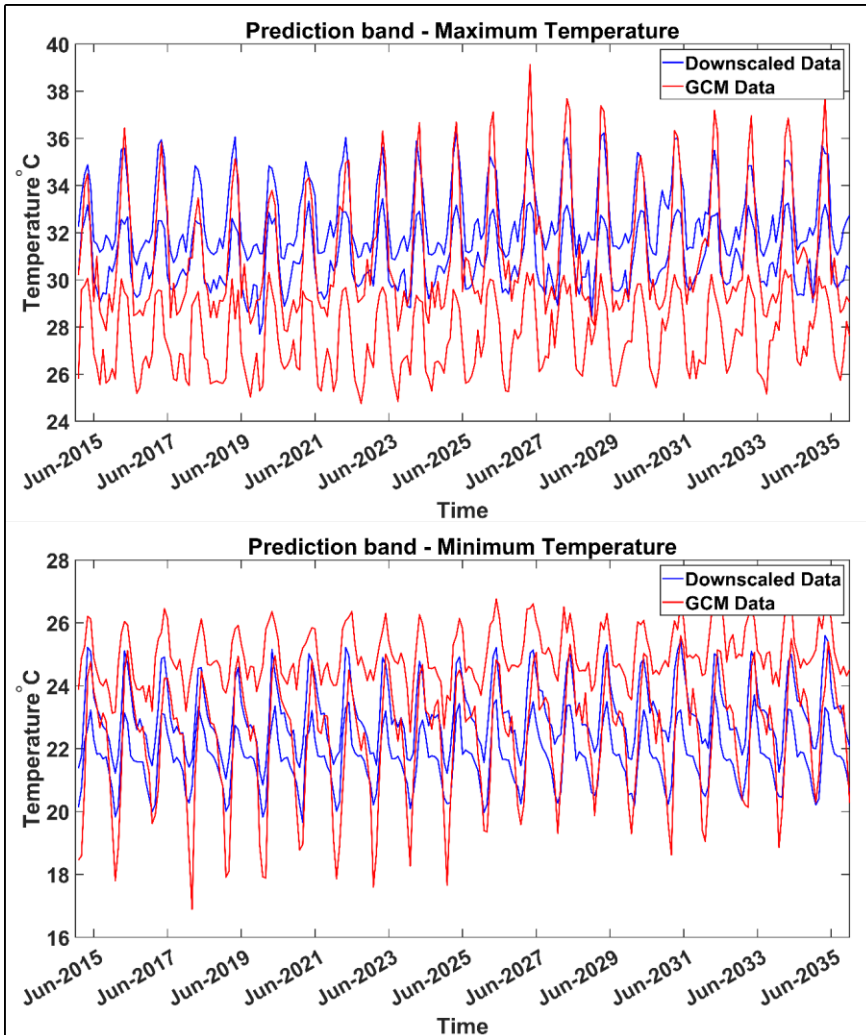
- Post processing procedure proposed by (Iman & Conover, 2007) is adopted to shuffle the downscaled temperature to show the observed correlation with regional daily rainfall data.

Correlation Coefficient > 0.4

NRMSE < 0.09

Fig: Performance of temporal downscaling procedure for Maximum Temperature

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.

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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