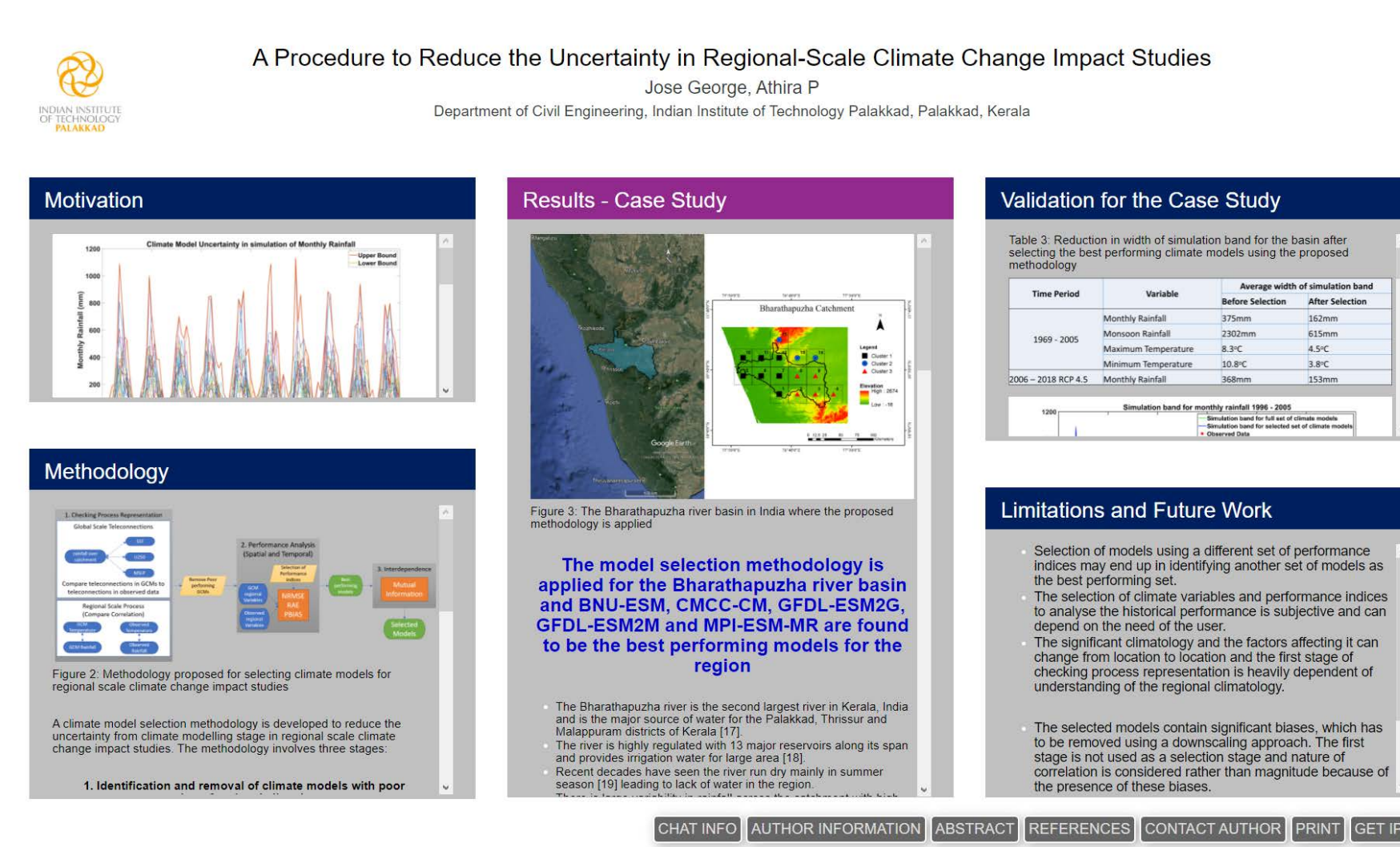
A Procedure to Reduce the Uncertainty in Regional-Scale Climate Change Impact Studies



A Procedure to Reduce the Uncertainty in Regional-Scale Climate Change Impact Studies
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Motivation

Methodology

Figure 2: Methodology proposed for selecting climate models for regional scale climate change impact studies

A climate model selection methodology is developed to reduce the uncertainty from climate modelling stage in regional scale climate change impact studies. The methodology involves three stages:

1. Identification and removal of climate models with poor

Results - Case Study

Figure 3: The Bharathapuzha river basin in India where the proposed methodology is applied

The model selection methodology is applied for the Bharathapuzha river basin and BNU-ESM, CMCC-CM, GFDL-ESM2G, GFDL-ESM2M and MPI-ESM-MR are found to be the best performing models for the region

- The Bharathapuzha river is the second largest river in Kerala, India and is the major source of water for the Palakkad, Thrissur and Malappuram districts of Kerala [17].
- The river is highly regulated with 13 major reservoirs along its span and provides irrigation water for large area [18].
- Recent decades have seen the river run dry mainly in summer season [19] leading to lack of water in the region.

Validation for the Case Study

Table 3: Reduction in width of simulation band for the basin after selecting the best performing climate models using the proposed methodology

Limitations and Future Work

- Selection of models using a different set of performance indices may end up in identifying another set of models as the best performing set.
- The selection of climate variables and performance indices to analyse the historical performance is subjective and can depend on the need of the user.
- The significant climatology and the factors affecting it can change from location to location and the first stage of checking process representation is heavily dependent of understanding of the regional climatology.
- The selected models contain significant biases, which has to be removed using a downscaling approach. The first stage is not used as a selection stage and nature of correlation is considered rather than magnitude because of the presence of these biases.

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MOTIVATION

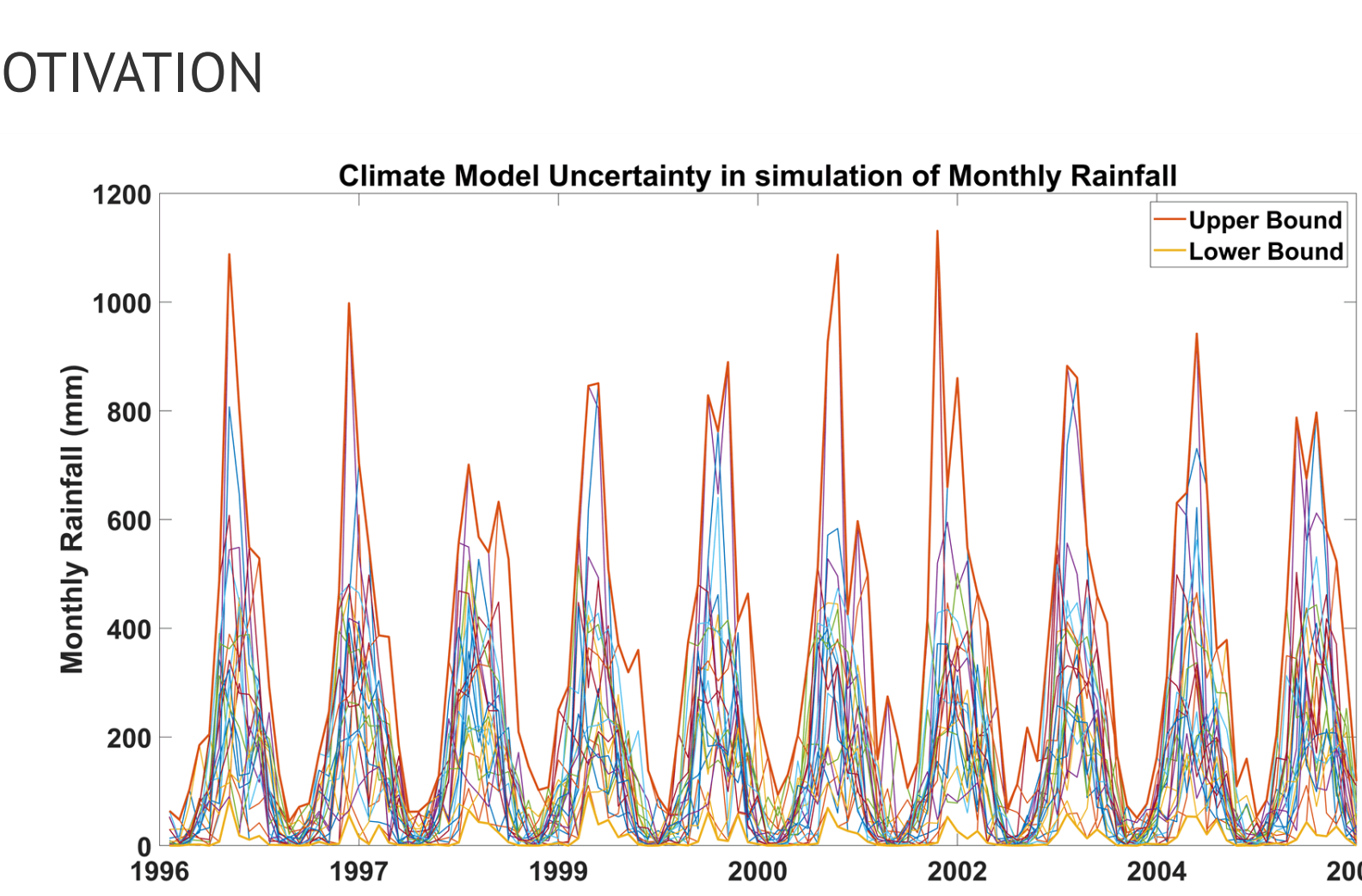


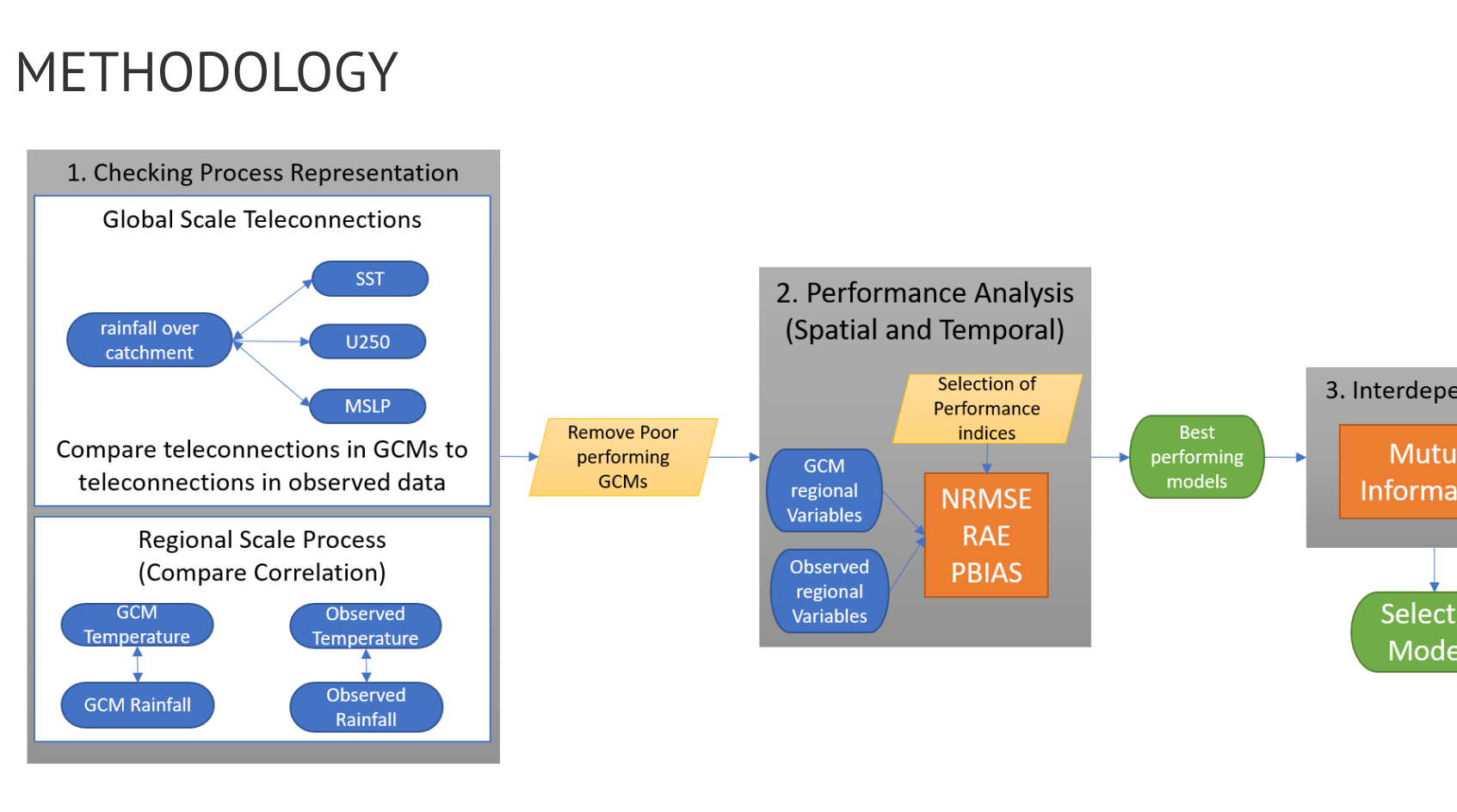
Figure 1: Uncertainty in historical of simulation of monthly rainfall - Simulations from 22 climate models for the Bharathapuzha basin in India

- **Large uncertainties exist in climate modelling** - Lack of a complete understanding of processes that influence climate and drive climate change, computational limitations, data availability
- Earth's climate has always been changing -**Anthropogenic activities** are accelerating the changes [1]
- Climate Change - Seriously affects human life by **changing water balance**
- Uncertainties in predicted impacts can lead to improper planning which can end up in catastrophic failures of the designed system

Water Resources projects are usually long term projects and requires large capital - Mismanagement can result in huge loss of time, capital and life

- Important to quantify and reduce uncertainties in assessment of impacts of climate change on water balance **- For better adaptation plans** [2]
- Climate modelling contributes the **largest amount of uncertainty** in climate change impact modelling [3] [4]
- Proper sub **selection of a set of climate models** can significantly reduce the uncertainty in the future climate used to predict the impacts [5]
- Climate models **perform differently at different locations** [6] - Different set of models will perform well for different locations and therefore regional scale selection is significant

METHODOLOGY



1. Checking Process Representation
Global Scale Teleconnections
rainfall over catchment
SST
U250
MSLP
Compare teleconnections in GCMs to teleconnections in observed data
Regional Scale Process (Compare Correlation)
GCM Temperature
Observed Temperature
GCM Rainfall
Observed Rainfall
Remove Poor performing GCMs
2. Performance Analysis (Spatial and Temporal)
Selection of Performance indices
GCM regional Variables
Observed regional Variables
NRMSE
RAE
PBIAS
Best performing models
3. Interdependence
Mutual Information
Selected Models

Figure 2: Methodology proposed for selecting climate models for regional scale climate change impact studies

A climate model selection methodology is developed to reduce the uncertainty from climate modelling stage in regional scale climate change impact studies. The methodology involves three stages:

1. Identification and removal of climate models with poor representation of regional climatic processes

- Historically good performing models may not perform similarly in future if regionally relevant climate processes are not properly represented in the model [7]
- Global circulations in atmosphere and ocean links different locations across the globe [8]
- Better representation of climate processes improves the ability of the models to perform in situations that it has not encountered in the historical scenario [9]
- Global scale teleconnections used are identified as an indicator for process representation. Teleconnections in GCM simulated variables compared with obsetved teleconnections to identify poor models
- On a regional scale, significant correlations exist between rainfall and temperature [10]. Lack of correlations between predicted rainfall and temperature induces large uncertainties in predicted impacts [11]
- Regional scale process representation studied by comparing correlations between regional variables
- Models that vary significantly from observed patterns are removed

2. Identification of models that can simulate the historical climate of the study area well

- Performance based selection - Dependant on performance index used [12]
- Three performance indices suggested: NRMSE, RAE and PBIAS
- Combine ranking from multiple performance indices using non weighted rank score [13]
- Combine ranking for different variables using rank score, weighted for each variable using inverse of average coefficient of variation for the simulation of that variable by multiple the total set of GCMs
- Combine performance at different locations using group decision making approach [14]

3. Identification and removal of interdependent models

- Multiple GCMs show dependence and this dependence results in addition of errors in the multi model ensemble [15]
- Mutual Information between model simulated variables is used to measure interdependence between climate models [16]

RESULTS - CASE STUDY

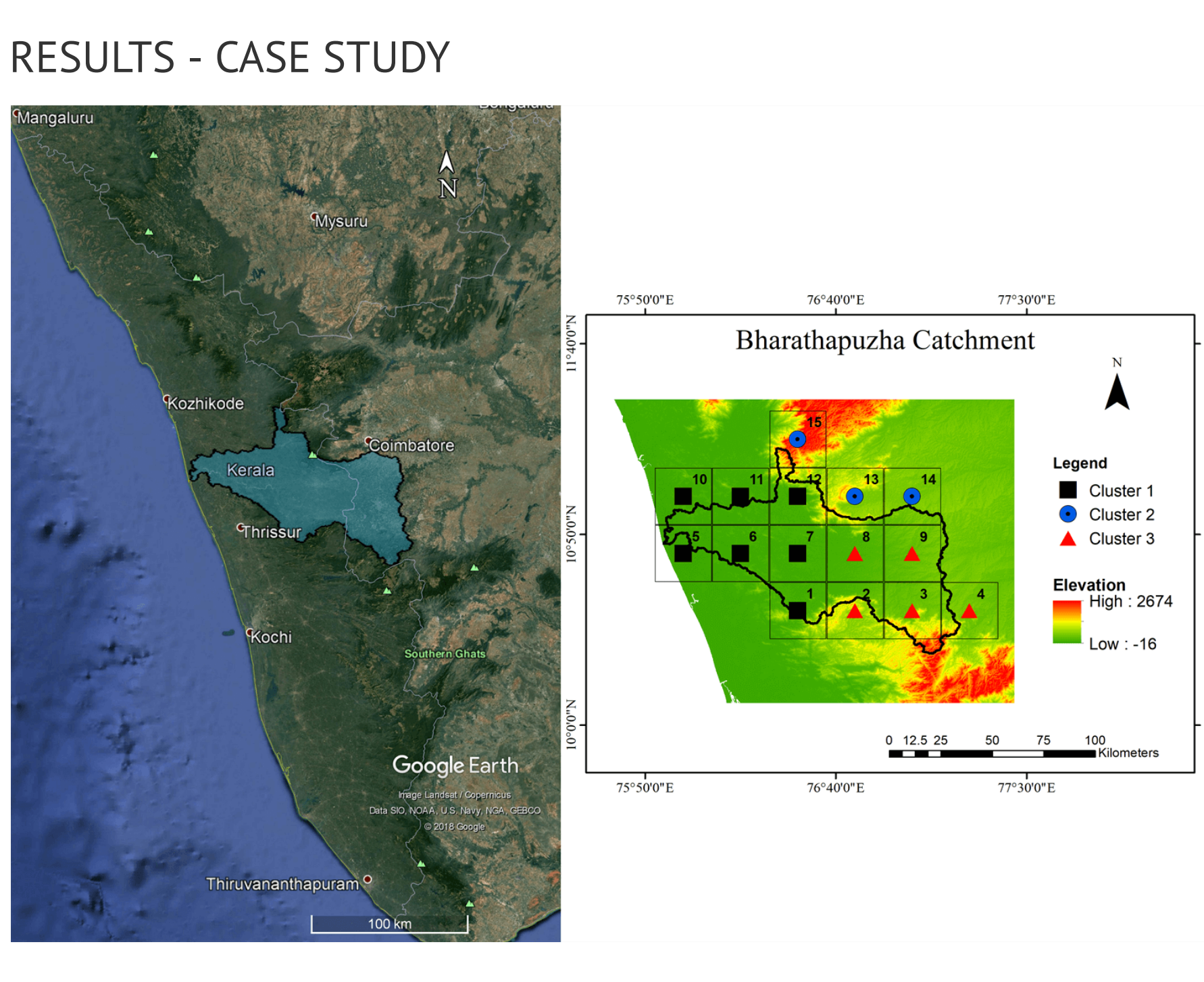


Figure 3: The Bharathapuzha river basin in India where the proposed methodology is applied

The model selection methodology is applied for the Bharathapuzha river basin and BNU-ESM, CMCC-CM, GFDL-ESM2G, GFDL-ESM2M and MPI-ESM-MR are found to be the best performing models for the region

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- The river is highly regulated with 13 major reservoirs along its span and provides irrigation water for large area [18].
- Recent decades have seen the river run dry mainly in summer season [19] leading to lack of water in the region.
- There is large variability in rainfall across the catchment with high rainfall towards the western regions of the catchment and comparitivel lower rainfall towards the mountainous eastern region of the catchment.
- The catchment can be divided into three regions based on the rainfall characteristics [20].

1. Checking process representation

- The prominant season in the region is the Indian Summer Monsson (ISM) [21].
- Indian Summer Monsoon Rainfall (ISMR) is affected by global oscillations like
  - El-Nino Southern Oscillation [22],
  - North Atlantic Oscillations [23] and
  - Indian Ocean Dipole [24]
- Global scale teleconnections exist between ISMR and Sea Surface Temperature [25] Mean Sea level Pressure [26] and Zonal Wind Speed [27]
- The historical teleconnections in data simulated from GCMs are checked using correlations and compared to teleconnections in observed historical data.
- Models that show different nature of correlation are removed.

CanCM4, CSIRO MK 3.6.0, FGOALS-g2, GFDL-CM3, GISS-E2-R,INM-CM4,IPSL-CM5A-LR, IPSL-CM5A-MR and MIROC-ESM found to have different nature of teleconnecions

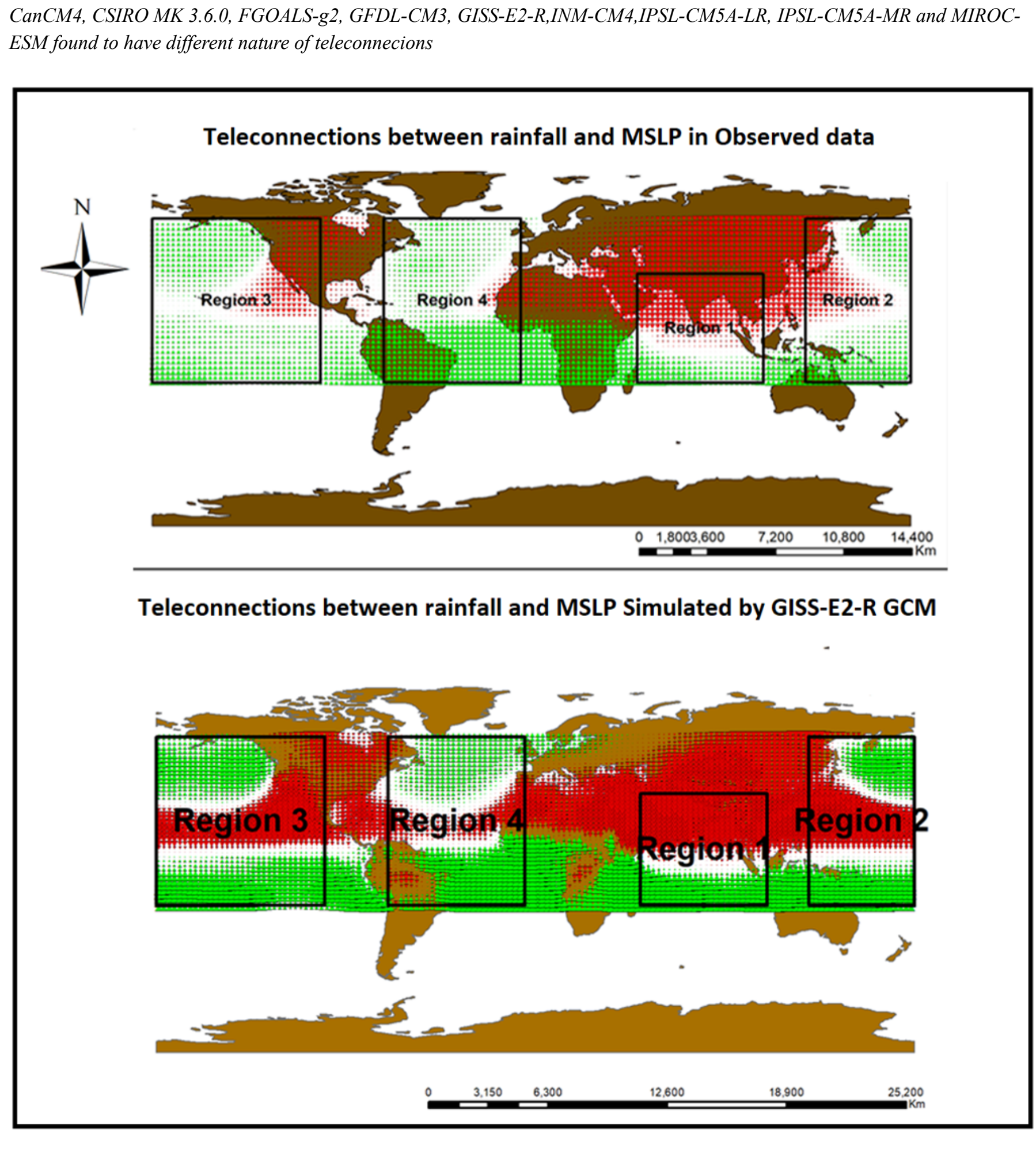
Teleconnections between rainfall and MSLP in Observed data
N
Region 3
Region 4
Region 1
Region 2
0 1,8003,600 7,200 10,800 14,400 Km
Teleconnections between rainfall and MSLP Simulated by GISS-E2-R GCM
Region 3
Region 4
Region 1
Region 2
0 3,150 6,300 12,600 18,900 25,200 Km

Figure 4: Comparison of teleconnections between ISMR and Mean Sea Level Pressure - An example of comparison of global scale teleconnections

- Correlations between GCM simulated historical rainfall and temperature over the region are compared to correlations between historical observed rainfall and temperature for the region.
- Models with differnet nature of correlation from observed are removed.

ACCESS 1.3 CESM1-BGC, CMCC-CESM, CMCC-CMS found to have different nature of correlation compared to observed

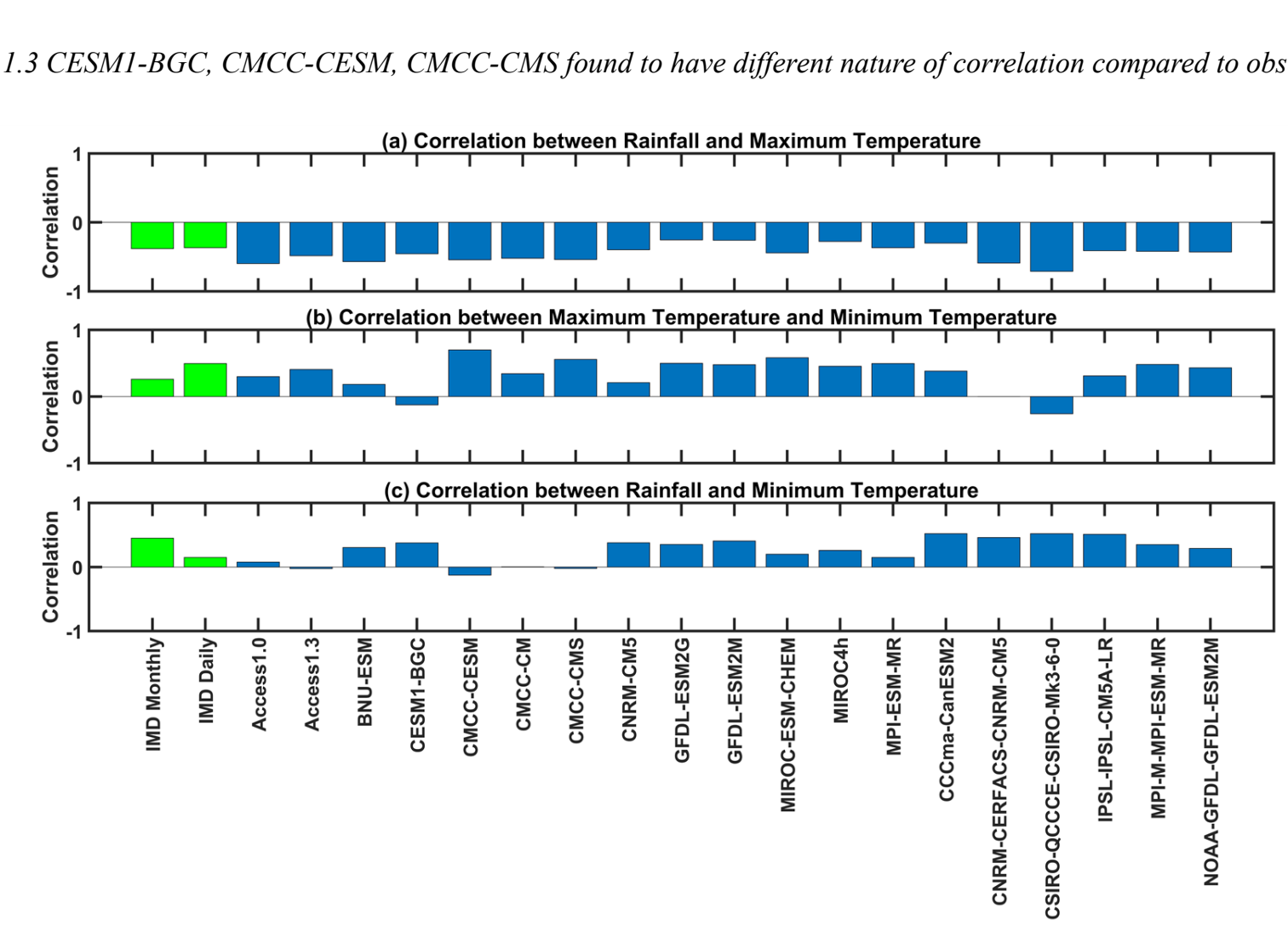

Figure 5: Correlation between regional climate variables over the Bharathapuzha catchment

2. Historical performance analysis

Multiple performance indices are used to rank climate models based on how well they can simulate rainfall and temperature over the Bharathapuzha catchment.

BNU-ESM, CMCC-CM, GFDL-ESM2G, GFDL-ESM2M and MPI-ESM-MR found to be best performing

Table 1: Climate models ranked in decreasing order of performance in simulating historical climate over the Bharathapuzha basin

Overall performance	Monthly Rainfall	Monsoon Rainfall	Maximum Temperature	Minimum Temperature
BNU-ESM	MPI-ESM-MR	MIROC4h	BNU-ESM	CNRM-CM5
MPI-ESM-MR	CNRM-CM5	MPI-ESM-MR	MPI-ESM-MR	GFDL-ESM2G
GFDL-ESM2M	Access1.0	GFDL-ESM2G	GFDL-ESM2M	CMCC-CM
GFDL-ESM2G	BNU-ESM	Access1.0	MIROC-ESM-CHEM	MIROC4h
CMCC-CM	CMCC-CM	GFDL-ESM2M	GFDL-ESM2G	GFDL-ESM2M
MIROC-ESM-CHEM	GFDL-ESM2G	BNU-ESM	MIROC4h	MPI-ESM-MR
MIROC4h	MIROC4h	CMCC-CM	CMCC-CM	Access1.0
CNRM-CM5	GFDL-ESM2M	CNRM-CM5	Access1.0	MIROC-ESM-CHEM
ACCESS1-0	MIROC-ESM-CHEM	MIROC-ESM-CHEM	CNRM-CM5	BNU-ESM

3. Identification of interdependence

- Models with high mutual information are interdependent and the poorer ranking one has to be removed.
- For a model, mutual information factor with another model is developed as ratio of mutual information between the two models and the mutual information of the model with itself.

All models show highest mutual information with BNU-ESM, but the mutual information factor is less than 0.5 so no models removed.

Table 2: Interdependance among the better performing models checked using Mutual Information

GCM	GCM with Highest MI	MI Factor
BNU-ESM	GFDL-ESM2M	0.433956
CMCC-CM	BNU-ESM	0.448298
GFDL-ESM2G	BNU-ESM	0.439451
GFDL-ESM2M	BNU-ESM	0.458698
MPI-ESM-MR	BNU-ESM	0.454717

VALIDATION FOR THE CASE STUDY

Table 3: Reduction in width of simulation band for the basin after selecting the best performing climate models using the proposed methodology

Time Period	Variable	Average width of simulation band	
		Before Selection	After Selection
1969 - 2005	Monthly Rainfall	375mm	162mm
	Monsoon Rainfall	2302mm	615mm
	Maximum Temperature	8.3°C	4.5°C
	Minimum Temperature	10.8°C	3.8°C
2006 – 2018 RCP 4.5	Monthly Rainfall	368mm	153mm

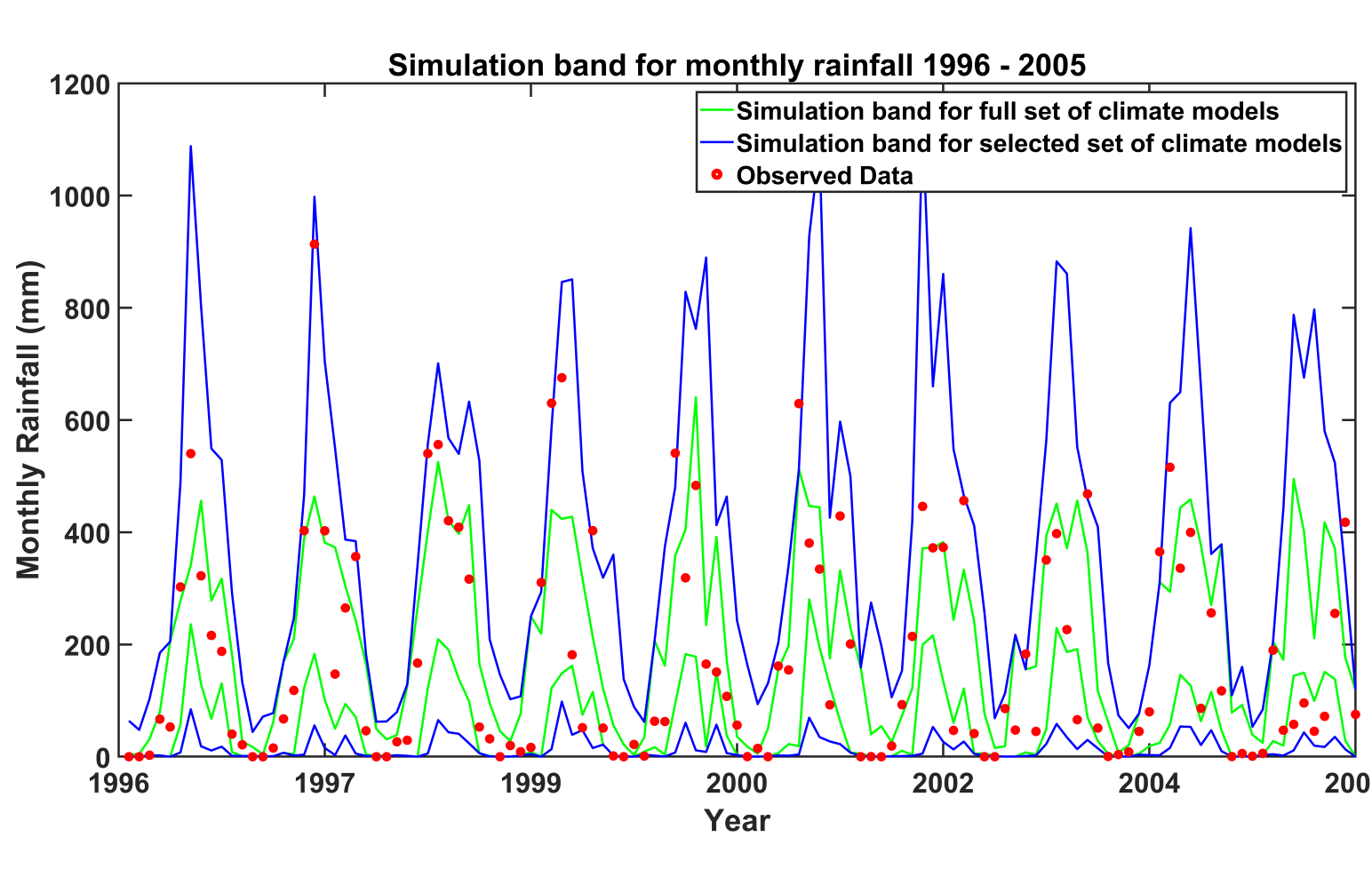

Figure 6: Simulation band for historical monthly rainfall over the river basin

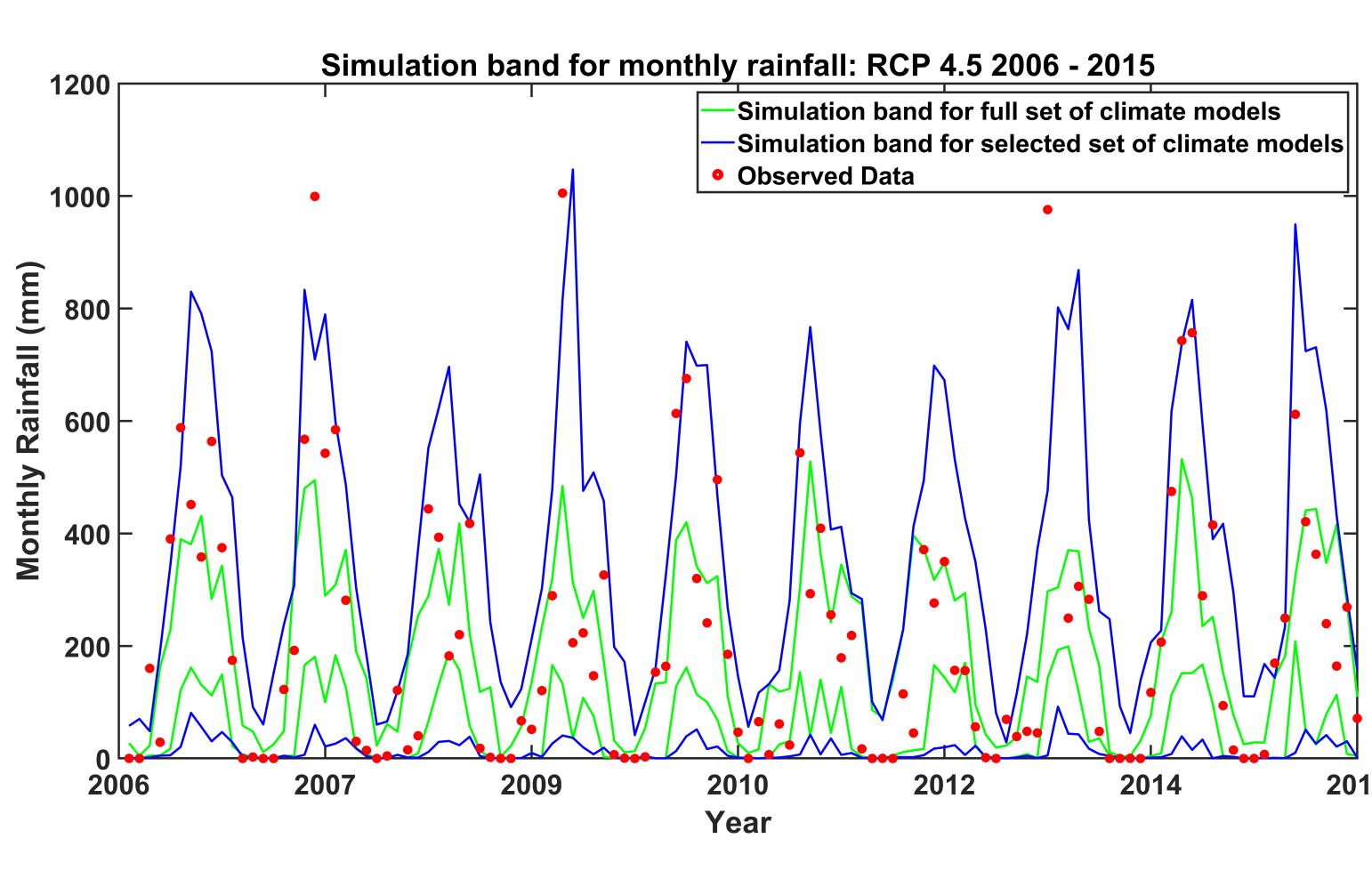

Figure 7: Simulation band for future simulation of monthly rainfall ; RCP 4.5 Scenario

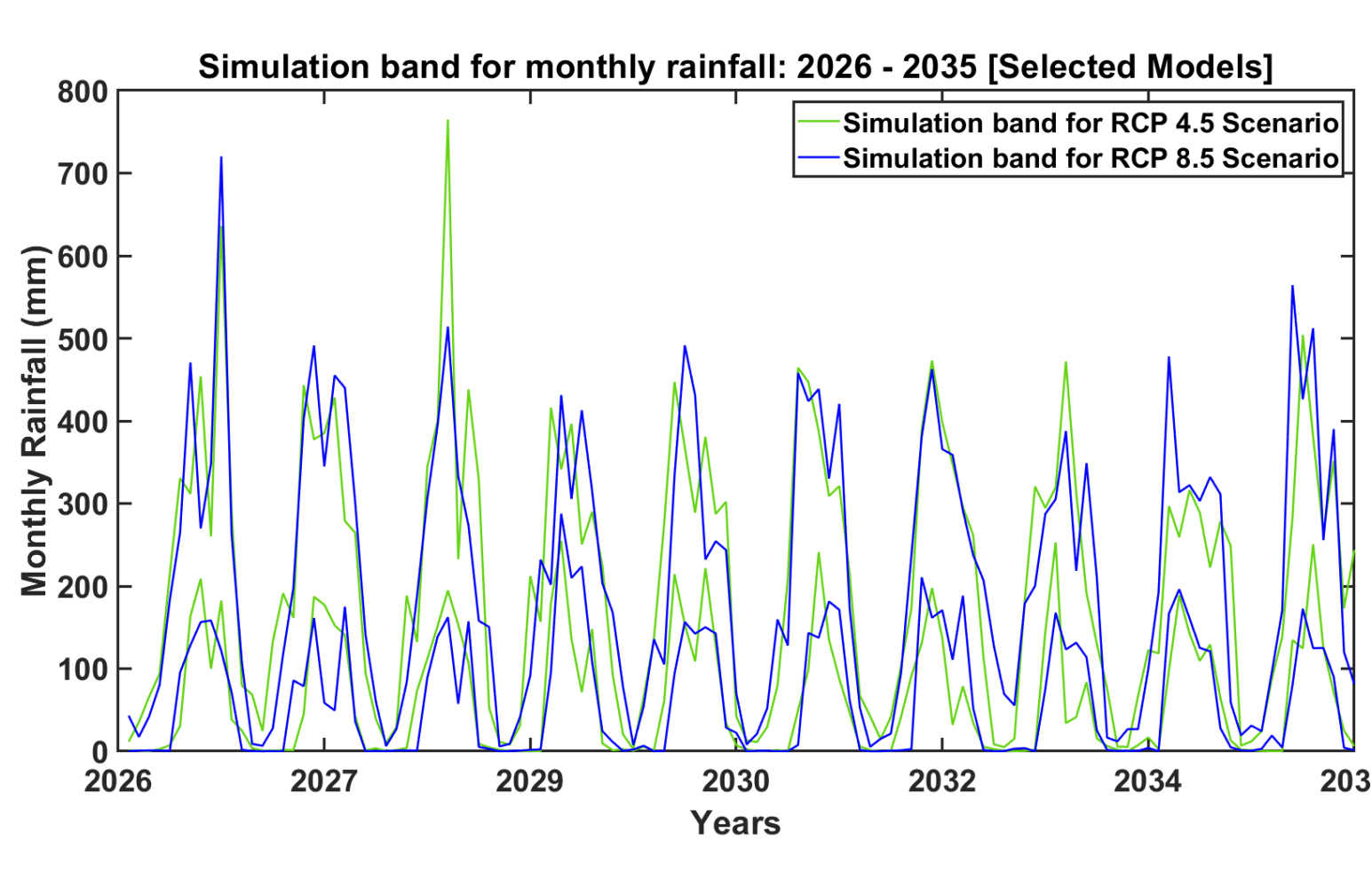

Figure 8: Simulation band for 2026-2035 from the selected models - band width does not change significantly from historical period

Table 4: Performance of the selected climate models for the period 2006 - 2018 for the RCP 4.5 Scenario

RCP 4.5 2006 - 2018	GCM	NRMSE	RAE	PBIAS
Monthly Rainfall	BNU-ESM	1.48	1.12	61.04
	CMCC-CM	1.21	0.83	49.03
	GFDL-ESM2M	1.33	0.99	45.37
	GFDL-ESM2G	1.21	0.91	41.19
	MPI-ESM-MR	1.15	0.83	32.90
Maximum Temperature	BNU-ESM	0.06	0.99	1.30
	CMCC-CM	0.11	2.12	10.13
	GFDL-ESM2M	0.08	1.41	5.54
	GFDL-ESM2G	0.05	0.91	2.63
	MPI-ESM-MR	0.06	1.03	3.37
Minimum Temperature	BNU-ESM	0.27	5.53	26.56
	CMCC-CM	0.25	5.11	24.45
	GFDL-ESM2M	0.28	5.63	26.94
	GFDL-ESM2G	0.24	4.99	23.91
	MPI-ESM-MR	0.22	4.45	21.35

LIMITATIONS AND FUTURE WORK

- Selection of models using a different set of performance indices may end up in identifying another set of models as the best performing set.
- The selection of climate variables and performance indices to analyse the historical performance is subjective and can depend on the need of the user.
- The significant climatology and the factors affecting it can change from location to location and the first stage of checking process representation is heavily dependent of understanding of the regional climatology.

- The selected models contain significant biases, which has to be removed using a downscaling approach. The first stage is not used as a selection stage and nature of correlation is considered rather than magnitude because of the presence of these biases.
- The teleconnections identifiied in the study can be used to develop a process based statistical downscaling technique for the region. This can lead to a further reduction in the uncertainty in climate variables used for impact prediction.

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ABSTRACT

A large number of General Circulation Models (GCMs) are currently available for modelling the atmospheric conditions over the Earth. However, there is a large variability in the future climate predicted by the available set of climate models. Hence, the climate data introduces the most amount of uncertainty in the climate change impact assessment. Regional-scale climate change impact studies based on these models may produce a wide range of possible impacts that becomes unusable for policymakers. A robust GCM selection procedure is introduced in the current study to bring the uncertainty to a realistic range. The proposed approach takes into account the process representation in the climate models by checking teleconnections in data along with their ability to predict the regional climate in spatial and temporal scale. The interdependence between the climate models are also accounted for in the proposed approach to avoid underestimation of uncertainty. The procedure is validated in the Bharathapuzha River Basin, Kerala, India. The study considers 22 GCMs that participated in the Coupled Model Inter-comparison Project-5 and 6 Regional Climate Models (RCMs) that are recommended for the Indian subcontinent. The climate models BNU-ESM, CMCC-CM, GFDL-ESM2G, GFDL-ESM2M and MPI-ESM-MR are found to be performing well for the prediction of both precipitation and temperature. The proposed climate model selection procedure can bring down the band width of uncertainty from 376 mm to 162 mm in monthly rainfall prediction with a containing ratio of 44%. The downscaling of the climate predictions will further increase the containing ratio by removing the systematic error. The bandwidth of uncertainty has reduced from 10.82ºC to 3.83ºC in the prediction of minimum temperature and from 8.35ºC to 4.52ºC for maximum temperature. The proposed GCM selection procedure provides more confidence in the predicted future climate since regionally significant correlations between climate variables are preserved in the selected models. The model selection procedure is validated for the period 2006-2018 with the observed climatic variables, and the selected models are found to be performing well.

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