Future rainfall projection using bias-corrected CMIP5 simulations over North Mountainous India

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Background

- The Global Climate Models (GCMs) are one of the most widely used tools for understanding climate system and predicting future possible climatic changes. A number of improvements in the physics, numerical algorithms and configurations are implemented in the state-of-the-art CMIP5 GCMs compared to its previous generations. Despite of recent advancements, most of the models exhibit large bias in simulating sub-regional-scale climate, especially for rainfall. To bridge the gap between global and sub-regional scale, different types of bias correction techniques have been emerged in the past few decades.
- The present study has been carried out with following objectives:

1. To judge the performances of CMIP5 GCMs in simulating the observed spatial patterns of rainfall over north mountainous zone of India (NMI).
2. To identify the most suitable bias correction method for projecting future rainfall.
1. To construct future rainfall change scenarios using multi-model ensembles of the bias corrected GCMs.

Materials and Methods

1. **Study Area:** North mountainous zone of India (NMI)-Northernmost Zone of the country, covers 3, 31,475 km^2 including three states namely Jammu and Kashmir, Himachal Pradesh and Uttarakhand.

- **Observational Data**: IMD 0.25°× 0.25° gridded data (Pie et al 2014)
- **GCMs**: Historical and RCP 4.5 and 8.5 simulations of CMIP5 models. (http://pcmdi9.llnl.gov)
- **Methodology:**

- Before evaluation,CMIP5 GCMs interpolated to the observation grid using bi-linear interpolation.
- For evaluation of models,. three agreement indices i.e. spatial correlation(R), index of agreement (d-index), Nash-Sutcliffe efficiency (NSE) and two error indices i.e. Ratio of Root Mean Square Error to the standard deviation of the observations (RSR) and mean bias (MB) used. For agreement indices, higher values (close to 1) indicate better results whereas for error indices lower values (close to 0) represent better results
- Following four bias correction methods have been used:

- **Scaling:** GCM is scaled with the quotient between the observed and model simulated means in the calibration or training period(1961-90). If $P'_{gcm,fut}$ and $P_{gcm,fut}$ are corrected and uncorrected future GCM outputs

$$P'_{gcm,fut} = P_{gcm,fut} \times \left(\frac{\overline{P_{obs,ref}}}{\overline{P_{gcm,ref}}}\right)$$

- **Standardization-Reconstruction (SdRc):** Future GCM output is first standardized by its mean ($\mu_{gcm,ref}$) and standard deviation ($\sigma_{gcm,ref}$) of the reference period.

$$Y'_{gcm,fut} = \left(\frac{Y_{gcm,fut} - \mu_{gcm,ref}}{\sigma_{gcm,ref}}\right)$$

Next future rainfall($Z_{gcm,fut}$) is reconstructed from future rainfall anomaly ($Y'_{gcm,fut}$) using observed mean ($\mu_{obs,ref}$) and standard deviation ($\sigma_{obs,ref}$).

$$Z_{gcm,fut} = Y'_{gcm,fut} \times \sigma_{obs,ref} + \mu_{obs,ref}$$

- **Empirical Quantile Mapping (Eqm) and Gamma Quantile Mapping (Gqm):**

Quantile mapping attempts to map a modelled variable P_m using probability integral transform such that its new distribution equals the distribution of the observed variable P_o. The transformation is defined as

$$P_o = F^{-1}_o(F_m(P_m))$$

F_m: Cumulative Distribution Function(CDF) of P_m ; F^{-1}_o : inverse CDF corresponding to P_o.

- Gqm is based on the initial assumption that both observed and simulated CDFs are well approximated by the gamma distribution.
- In case of Eqm, CDFs of observed and modelled rainfall estimated using empirical percentiles and values in between the percentiles approximated using linear interpolation.

Results

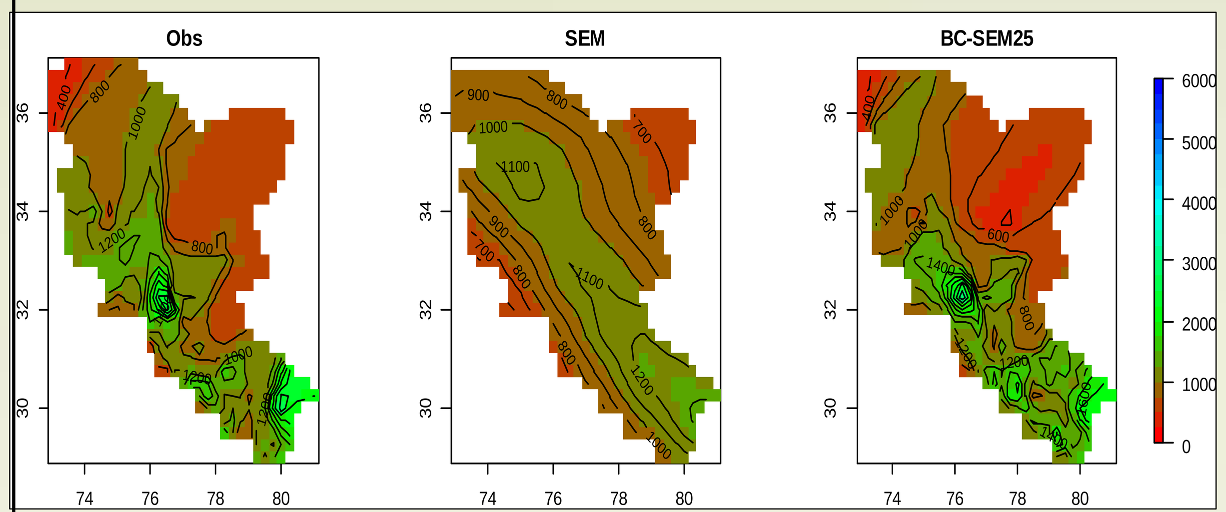
Performance of CMIP5 models (1961-90)

	R	d	NSE	RSR	MB
Min	-0.73	0.1	-3.38	0.72	0.26
Max	0.77	0.87	0.47	2.09	0.72
Median	0.29	0.49	-0.59	1.26	0.44
SEM	0.47	0.56	0.21	0.89	0.25

Comparison of bias correction methods (1991-2005)

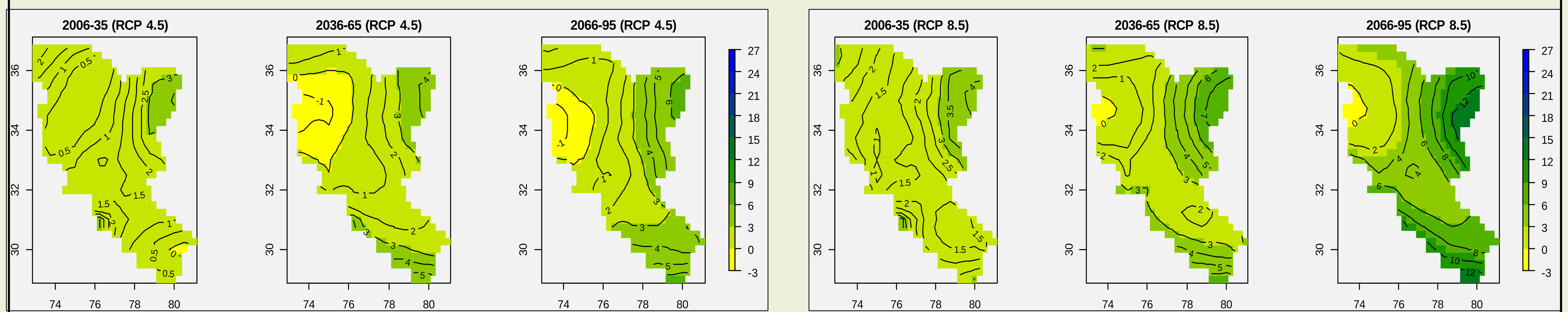
Method	R	d	NSE	RSR	MB
SEM	0.41	0.54	0.13	0.93	**0.18**
SEM-Scaling	**0.85**	**0.91**	**0.64**	**0.60**	**0.18**
SEM-Eqm	0.84	0.89	0.62	0.61	0.19
SEM-Gqm	0.80	0.86	0.47	0.73	0.23
SEM-SdRc	**0.85**	**0.91**	0.62	0.61	**0.18**

Comparison of simple ensemble mean and bias corrected ensemble mean during 1991-2005:

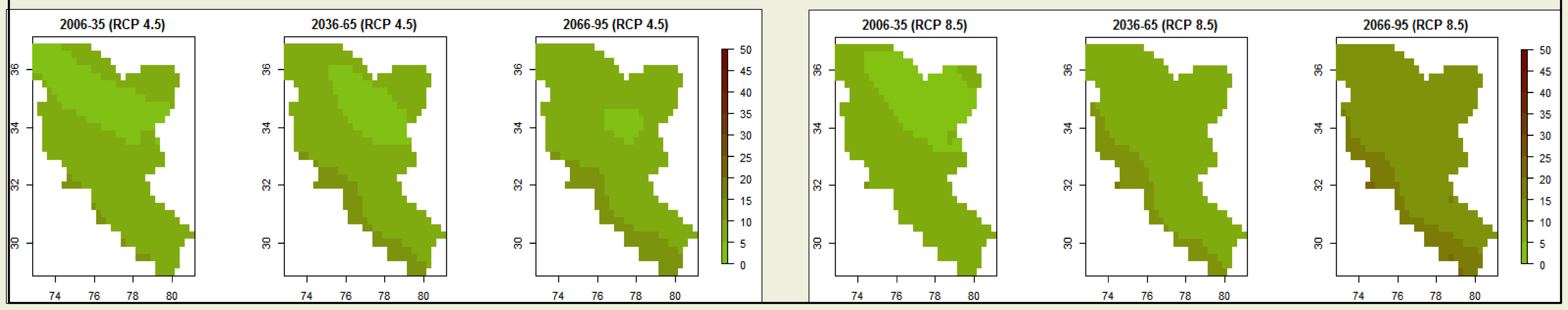


Ensemble of Bias corrected GCMs able to reproduce the observed rainfall distribution patterns and magnitude quite closely while Simple ensemble of interpolated GCMs not able to simulate the observed patterns adequately.

Future projected rainfall changes:



Future projected uncertainties:



Conclusions

- Raw GCMs have not been sufficient enough to capture finer regional rainfall patterns due to its inability to represent local topography adequately. Therefore, it is better to use bias corrected GCMs instead of using only interpolated GCMs.
- Scaling method of bias correction has depicted slightly better results in capturing mean annual spatial patterns of rainfall compare to other three bias correction methods that were analyzed.
- BC-SEM have projected about 3% reduction in rainfall over western part of NMI during both 2050s (2036-65) and 2080s (2066-95) whereas the drier North eastern part (Ladakh region) may encounter 3-12% increase during these periods.
- RCP 8.5 models projected to increase higher future rainfall compared to projection based on RCP 4.5 models.
- Model-spread from ensemble mean (uncertainty) has also been found to be larger in RCP 8.5 than RCP4.5 ensemble.

References

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