ADDRESSING UNCERTAINTIES IN IDF RELATIONSHIPS UNDER CLIMATE CHANGE

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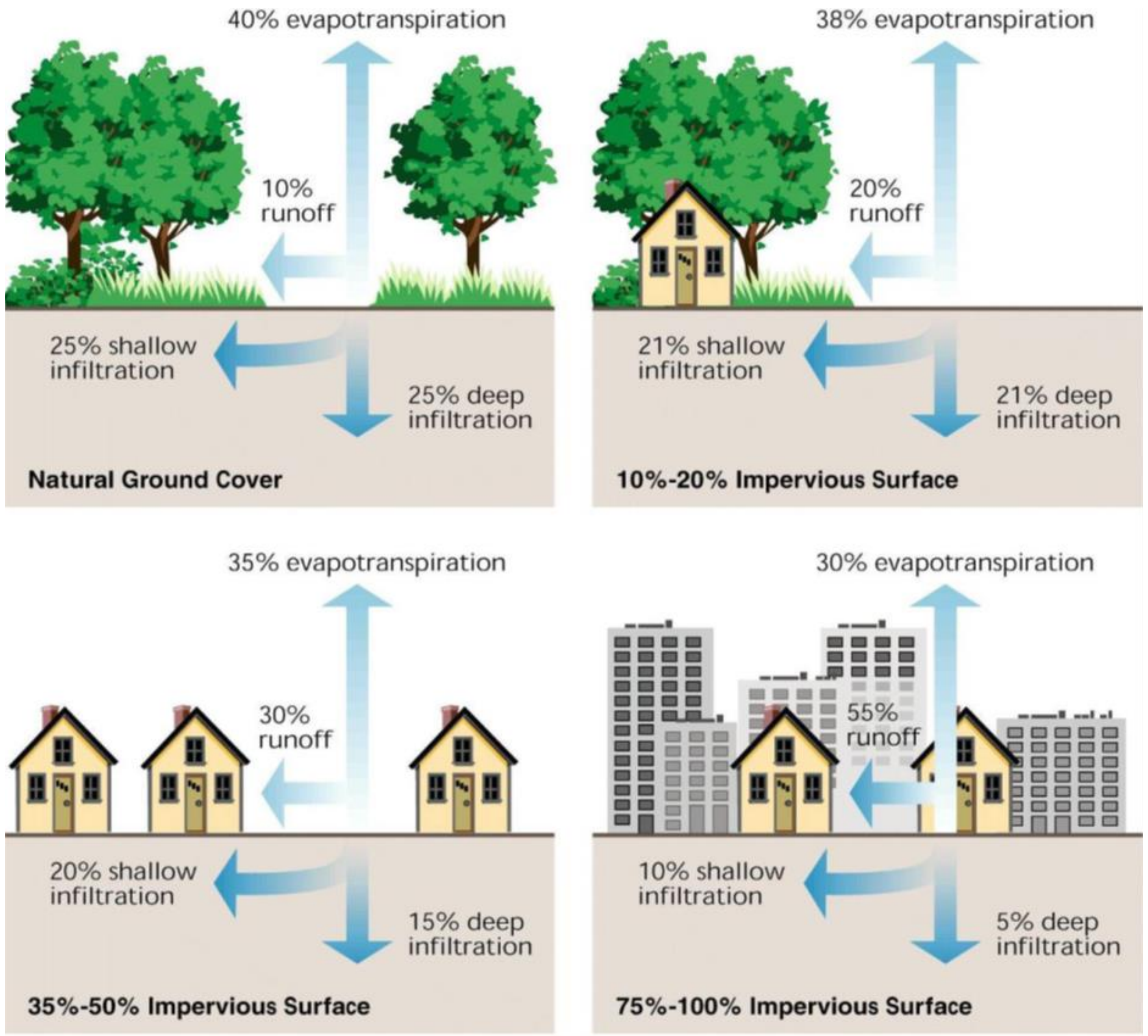
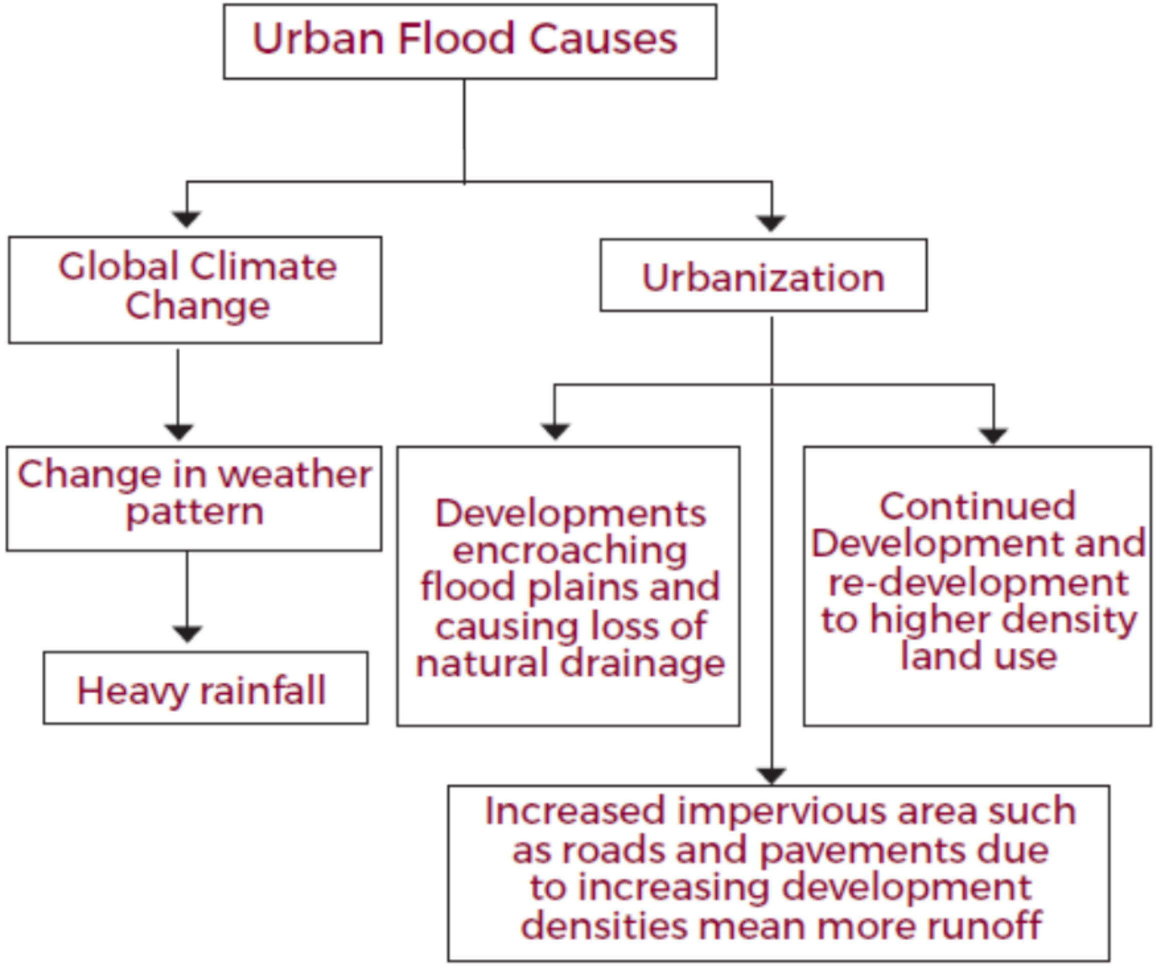
Urban Floods in India

Cities	Flooding Years
Ahmedabad	2001
Bangalore	2005, 2009, and 2013
Chennai	2004 and 2015
Delhi	2002, 2003, 2009, 2010, 2013, 2016
Guwahati	2010 and 2011
Hyderabad	2000, 2001,2002, 2006 and 2008
Jamshedpur	2008
Kolkata	2007 and 2013
Mumbai	2005, 2007, and 2015
Srinagar	1992, 2014 and 2015
Surat	2006 and 2013

Source: Report by National Institute of Urban Affairs

Motivation for the Study





Report by WMO

Gupta et al., 2010

Study Area, Data and Assumptions

Study area: Bangalore City India Meteorological Department (IMD) station (Station no: 43295).

Observed data: Daily rainfall data at 15-minute resolution for 1969-2001.

GCM monthly data: 15 GCMs considering four RCPs from CMIP5 experiments.

Assumptions:

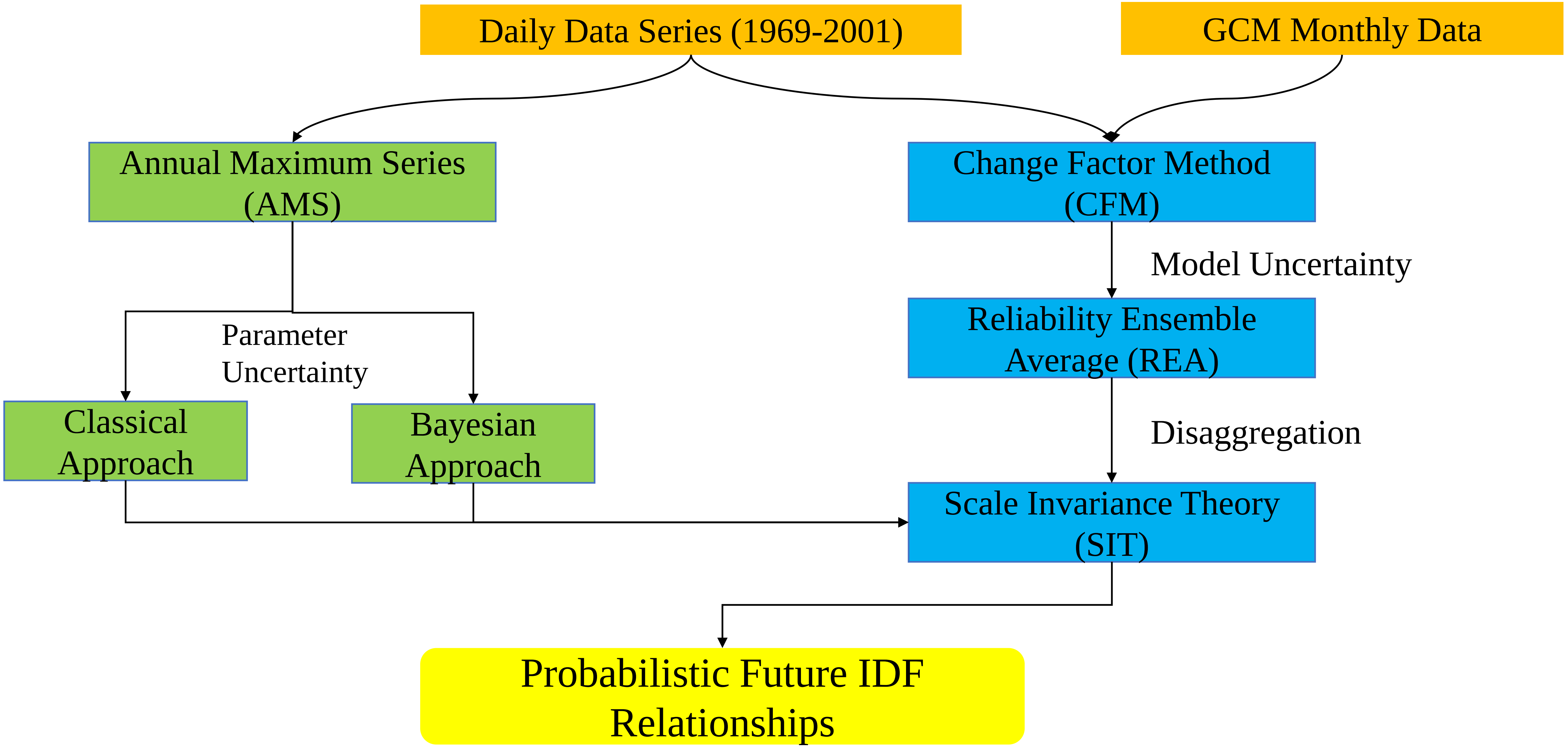
- The extremes for different duration are considered to be independent and identical distribution.
- The parameters of fitted distribution (Generalized Extreme Value) are considered to be stationary.

Objectives

The objectives of the study are as follows:

- To quantify the uncertainty due to the parameters of the distribution fitted to the sparse data using Bayesian methods to obtain the probabilistic Intensity-Duration-Frequency (IDF) relationships.
- To quantify the uncertainties due to the use of multiple GCMs in obtaining the projected IDF relationships and to propagate the uncertainties due to the parameters of the distribution to obtain the projected probabilistic IDF relationships.
- To ascertain, how the different schemes of change factor method (CFM) work in the projected future IDF relationships.

Overview of the work



Types of Uncertainties

- Though there are no specific delineation of uncertainties, the four major sources of uncertainties are
  a) Input
  b) Output
  c) Structural and
  d) Parametric

Renard et al., (2010)

- In the present study, two major sources of uncertainties are considered
  a) Parameter Uncertainty arise since GEV distribution fitted to the AMS data, and
  b) Model Uncertainty due to the use of multiple GCMs.

Motivation for Using Bayesian Approach

- Bayesian approaches are proved to be best methods to quantify the uncertainties.
- Classical methods rely on the sampling distributions of the statistic over repeated sampling. Thus, methods like Maximum Likelihood Estimates (MLE), Method of Moments (MOM) etc. require large no. of data to validate the correctness of the model.
- Bayesian methods provide a coherent framework in quantifying the uncertainties in the parameters fitted to the distribution.

Gelman et al., 2013

Bayesian Approach

Annual Maximum Series (AMS) is fitted with 3-parameter Generalized Extreme Value (GEV) distribution with parameters are

μ : Location Parameter

σ : Scale Parameter

k : Shape Parameter

Joint Prior Distribution

$$\pi(\mu,\sigma,k)\ \alpha\ \frac{Beta(\mathrm{k}+0.5\,|\,\mathrm{a}=6,\mathrm{b}=9)}{\sigma}$$

Joint Likelihood Function

$$L(\theta\,|\,x) = \text{-nlog}(\sigma)\ \text{-}\ (1+\frac{1}{k})(\sum_{i=1}^{n}\log(1+\mathrm{k}(\frac{x_i-\mu}{\sigma})))\ \text{-}\ \sum_{i=1}^{n}(1+k(\frac{x_i-\mu}{\sigma}))^{-\frac{1}{k}}$$

Joint Posterior Distribution

$$\pi(\theta\,|\,x)\ \alpha\ \text{-n}\log(\sigma)\ \text{-}(1+\frac{1}{k})\times(\sum_{i=1}^{n}\log(1+k(\frac{x_i-\mu}{\sigma})))\ \text{-}\ \sum_{i=1}^{n}(1+k(\frac{x_i-\mu}{\sigma}))^{-\frac{1}{k}}\ +$$

$$5\times\log(0.5+\mathrm{k})+8\times\log(0.5-k)\ \text{-}\log(\sigma)$$

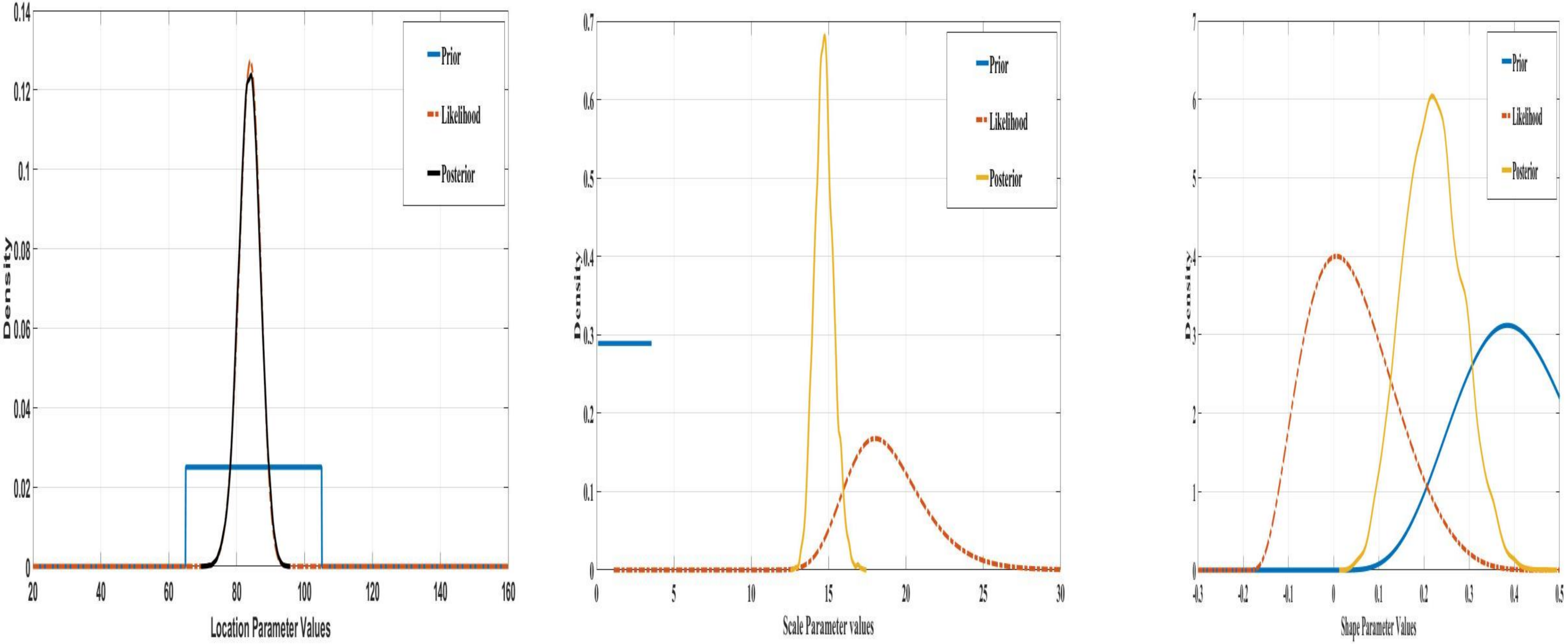
MCMC Sampling Using Gibbs Sampler

- Posterior Distribution is complex; It can’t be solved using analytical methods, which provided a motivation for carrying out MCMC sampling to find the approximate Posterior distribution of the parameters.

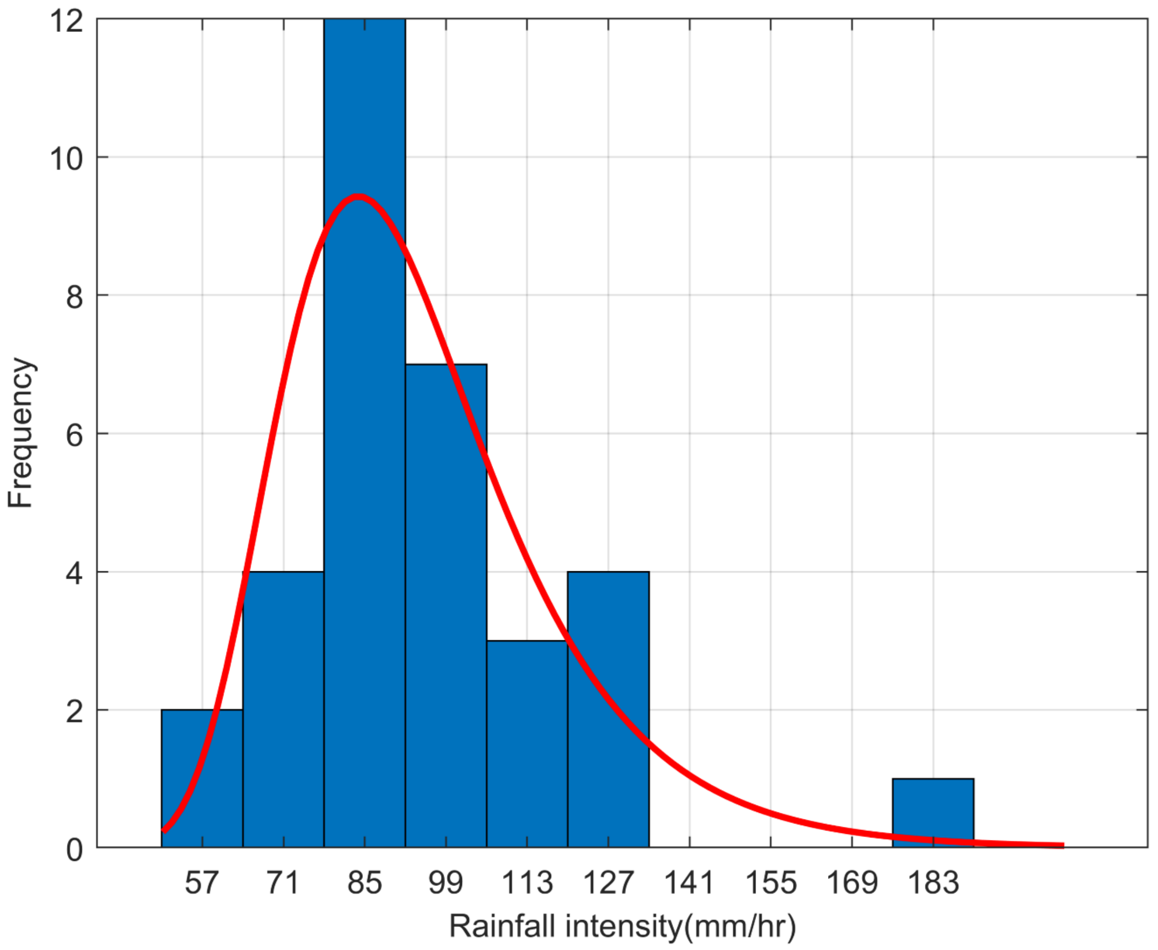
- No. of samples generated = 27500, and
  Burn-in period = 2500

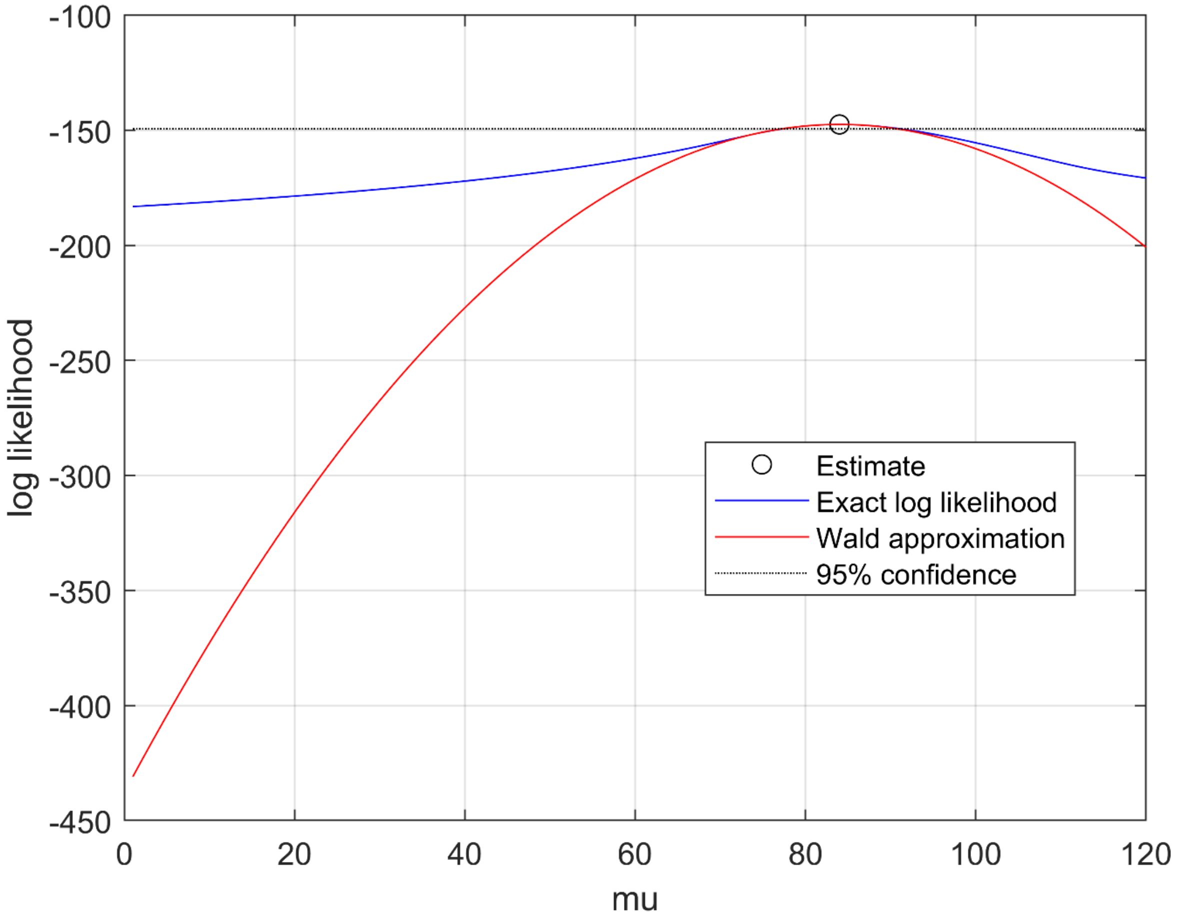
Prior, Likelihood and Posterior Functions

Prior, Likelihood and Posterior density of Location, Scale and Shape Parameter for 15-minute duration AMS data

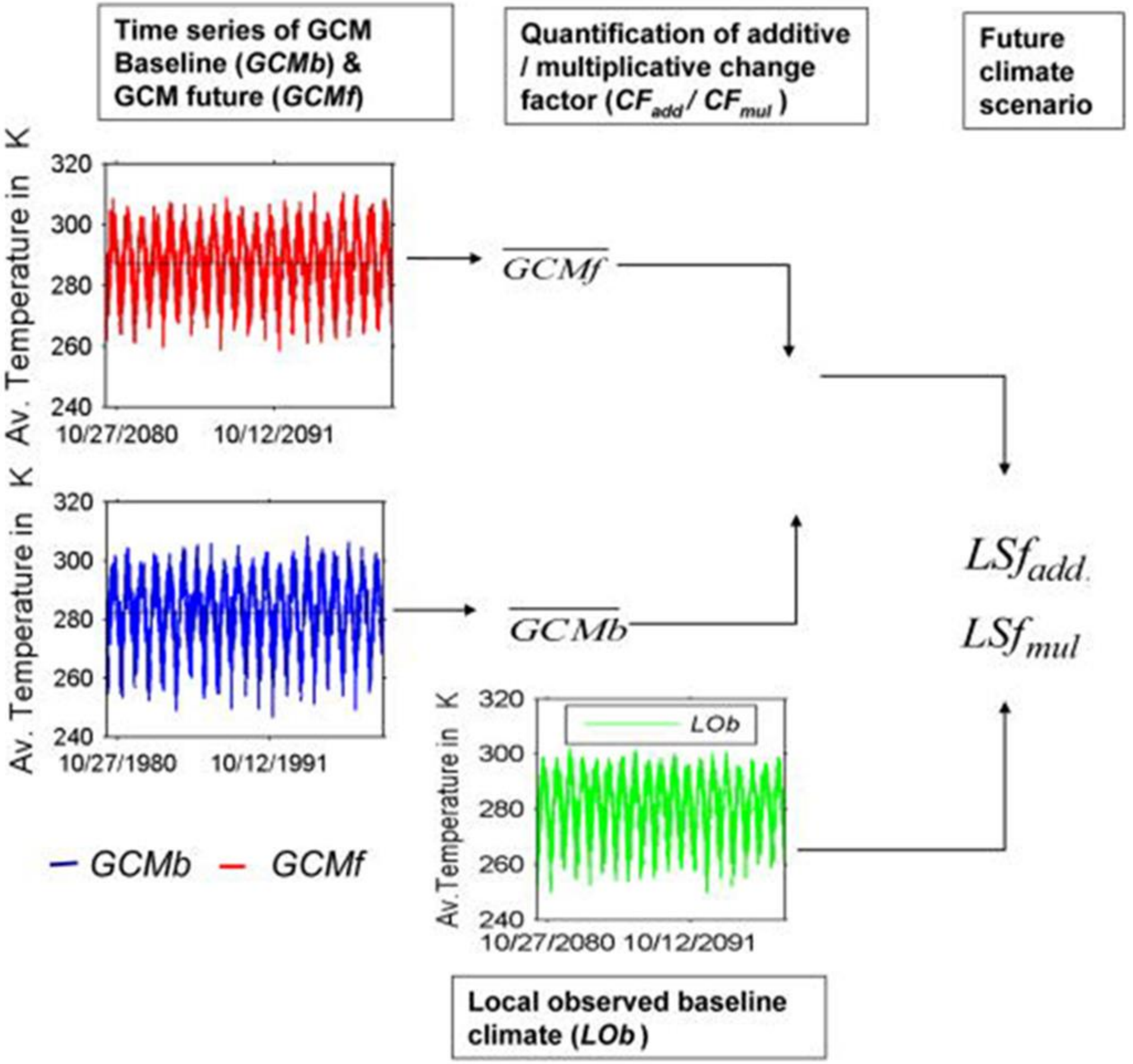


Classical Approach Using MLE





Future Daily Time Series and Model Uncertainty



Change Factor Method (CFM)

- The benefit of using GCM monthly data for future daily time series is to avoid lot of zero values due to the sparse nature of daily rainfall.
- In CFM, both additive and multiplicative schemes with single bin are used for generating the future daily time series.

Anandhi et al., (2011)

Reliability Ensemble Averaging (REA)

- It is used to address the uncertainties arise due to use of multiple GCMs.
- It is based on model performance and model convergence criterion.
- It’s working principle is to give weightage to different GCMs based on the CDF deviation from the observed series (taking inverse of RMSE) and reiterating the process until the weights are converged.

Temporal Downscaling

- Since in urban areas flooding occurs for small time intervals frequently, precipitation fluxes at finer time scales with shorter return periods are important.
- Scale invariance Theory is adopted here to downscale the future daily precipitation series into finer time scales such as 15 minute and 30 minutes etc.

Scale Invariance Theory

- Calculate the NCMs ψ_1, ψ_2 and ψ_3
- Plot NCMs verses duration on log-log scale and obtain the scaling exponent β

$$\lambda^{\beta} = \frac{\psi_1(\lambda t)}{\psi_1(t)}$$

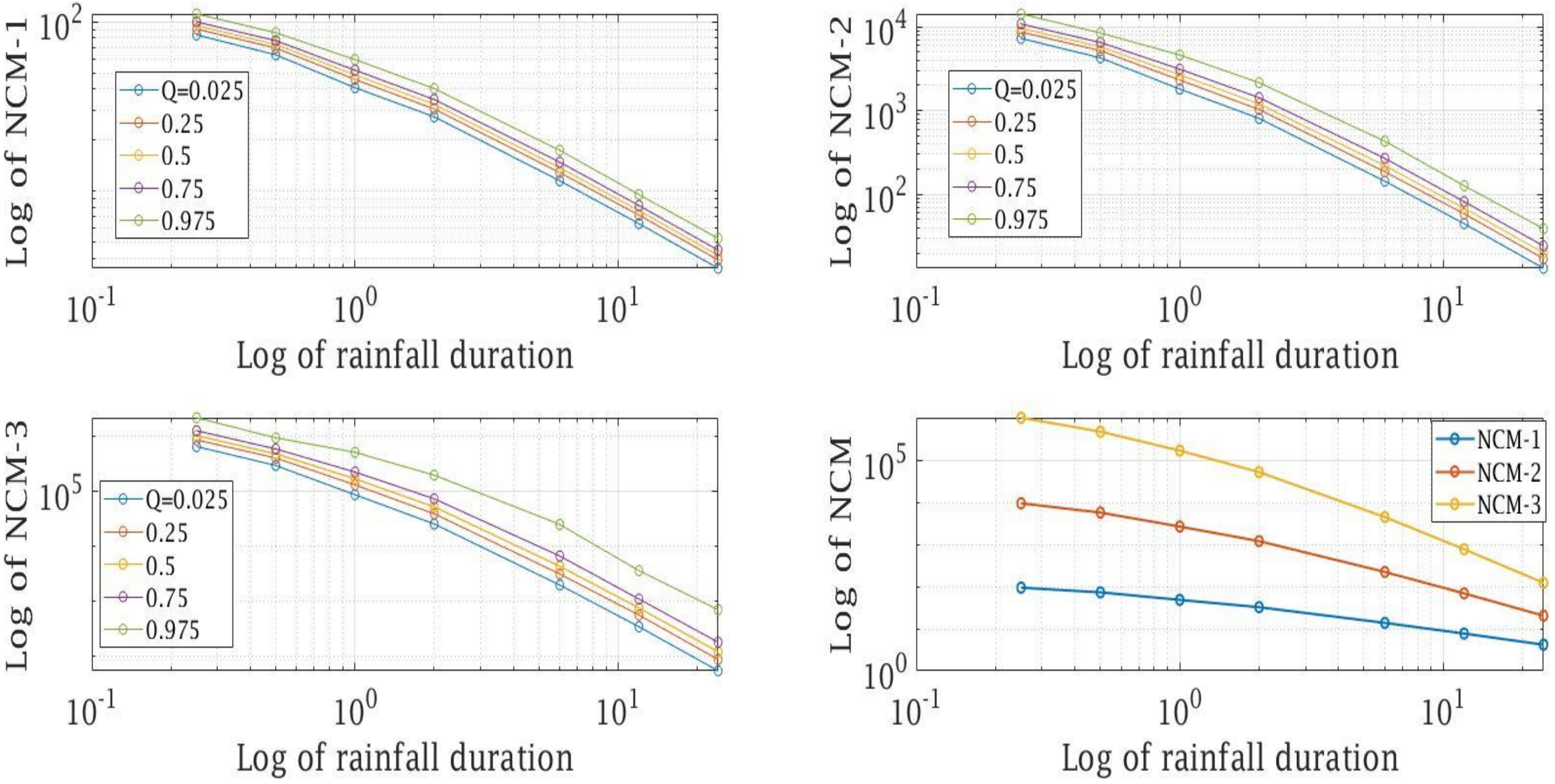
- Plot NCMs verses the scaling exponent and check if the process follows simple scaling or multiple scaling (Note that for a simple scaling process, $\beta(d) = \beta^d$

- After checking the scaling behaviour, the scaling exponent β is used for obtaining the return levels for shorter durations.

Where, the dth order Non-Central Moments can be calculated as,

$$\psi_d = (\mu\text{-}\frac{\sigma}{k})^d + (\frac{\sigma}{k})^d \times \Gamma(\text{1-dk}) + \text{d} \sum_{i=1}^{d-1} (\frac{\sigma}{k})^i \times (\mu\text{-}\frac{\sigma}{k})^{d-i} \times \Gamma(\text{1-ik})$$

Scale Invariance Theory

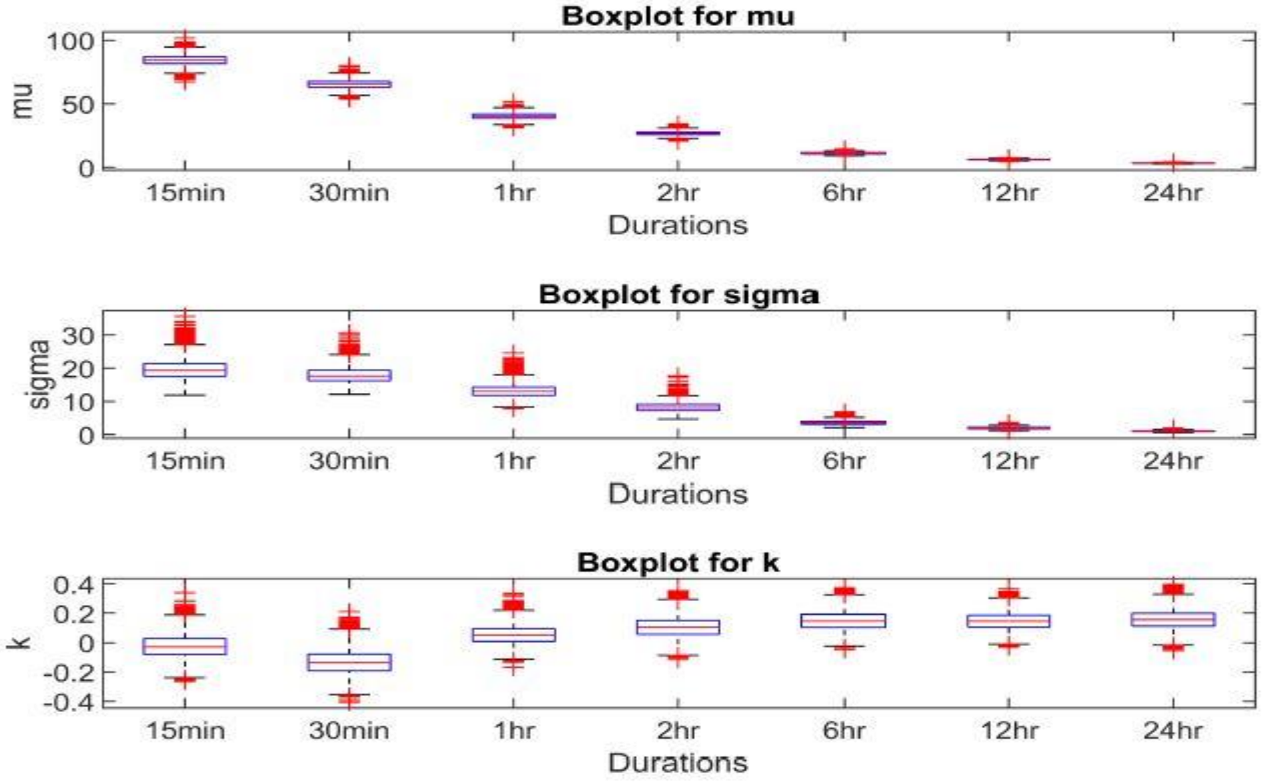


Scaling relationships between rainfall durations and Non-Central Moments in logarithmic scale

RESULTS

Uncertainty Quantification

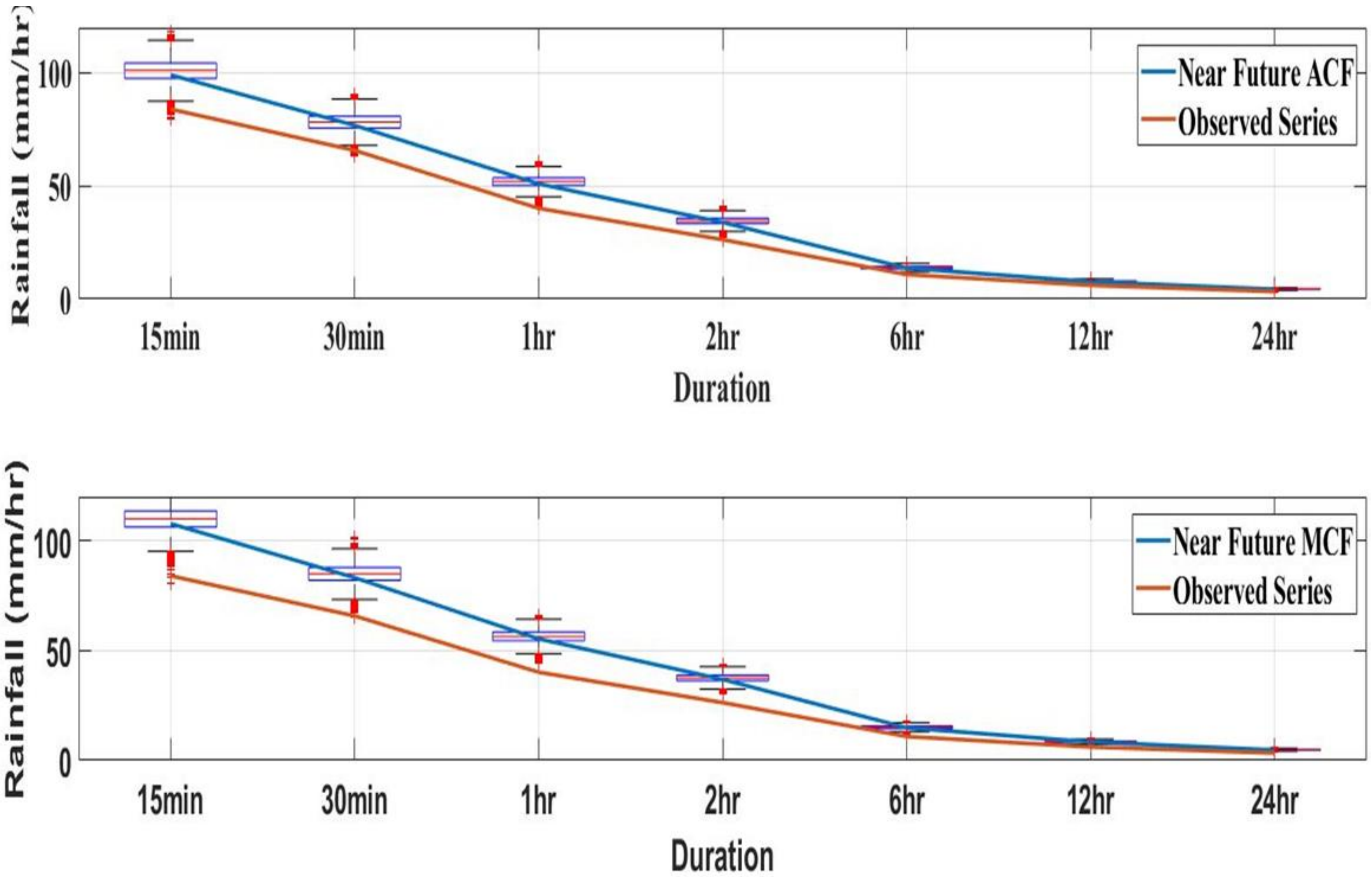
- The uncertainties in Location and Scale parameter are found to be decreasing with duration; however, there is no certain relationship exists between the magnitude of uncertainty with duration for the Shape Parameter.



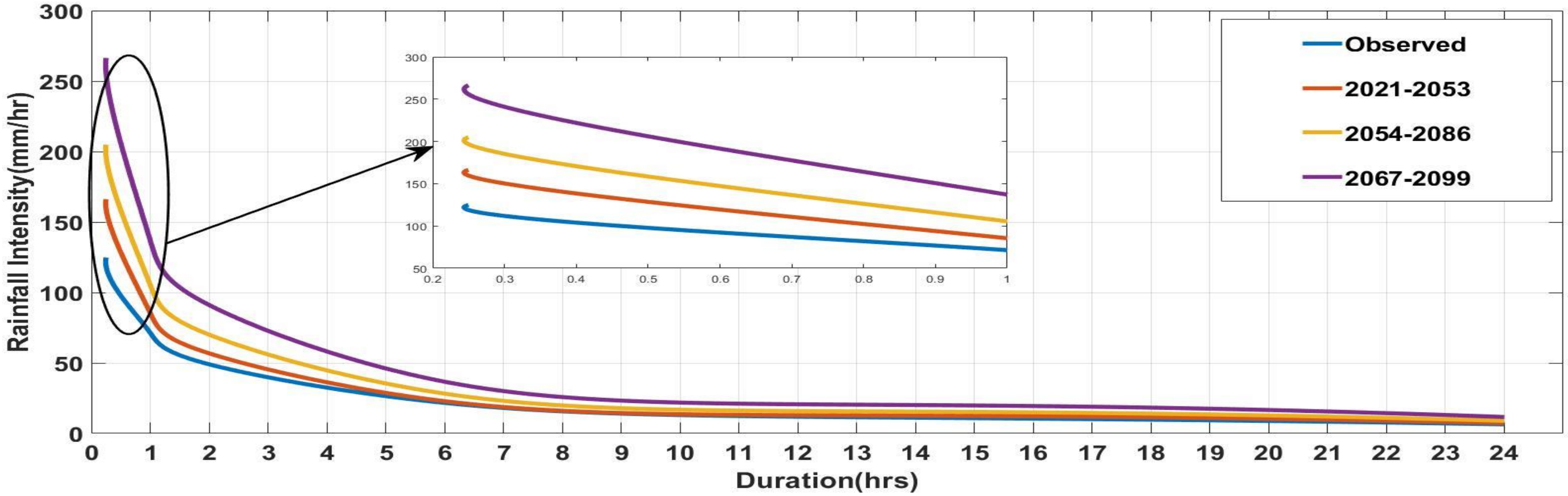
Uncertainty in location, scale and shape parameters

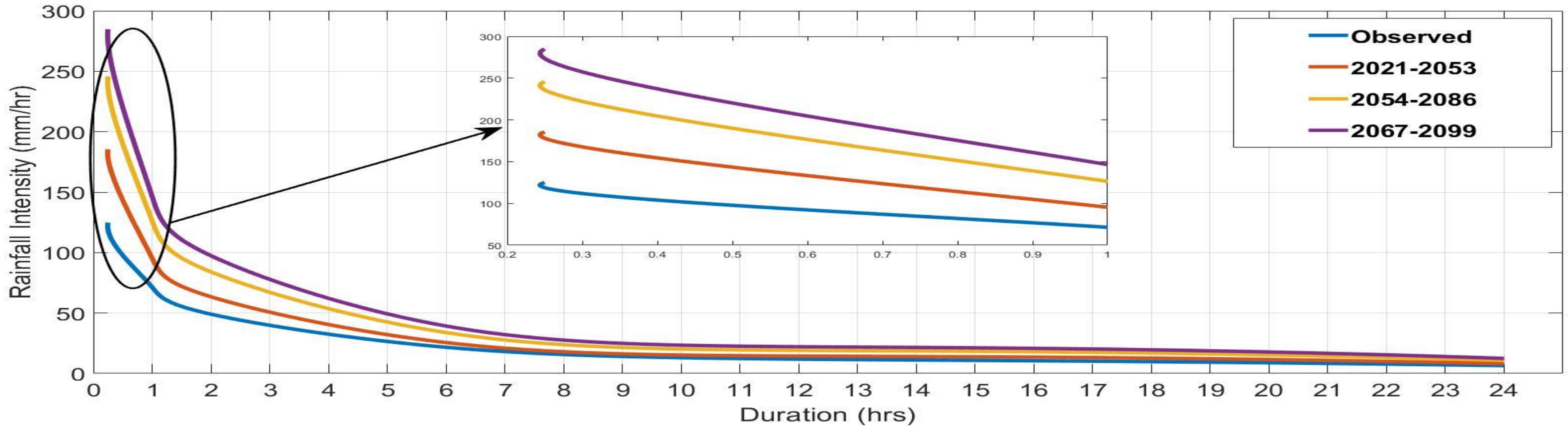
Uncertainty Quantification

- It is observed, there is no statistical significant difference between the uncertainties in the parameters additive and the multiplicative change factors.



Probabilistic Future IDF Relationships

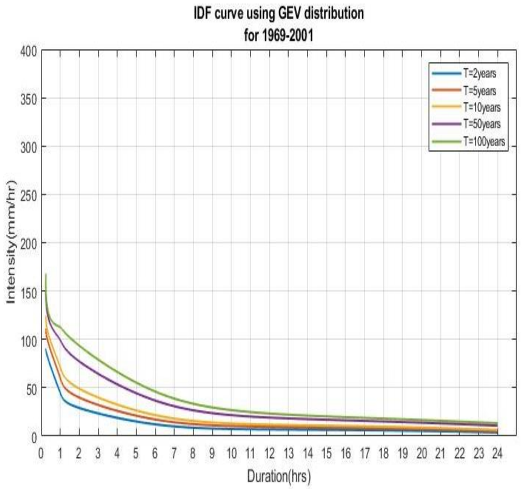


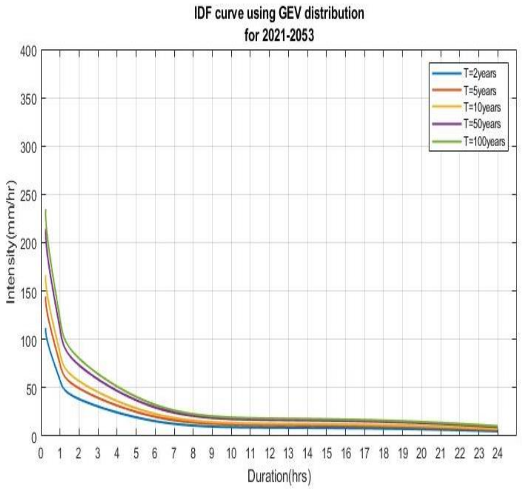


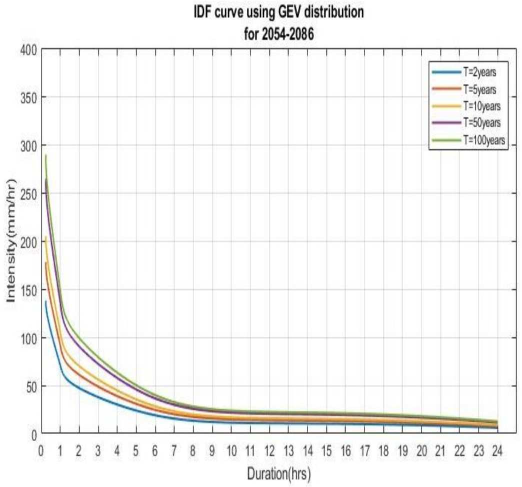
Probabilistic Future IDF relationships using Additive (Top) and Multiplicative (bottom) schemes for RCP 8.5, return period = 10 years

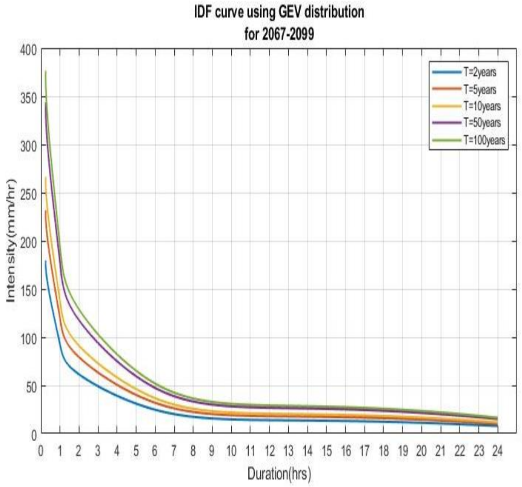
Probabilistic Future IDF relationships

Additive Change Factor

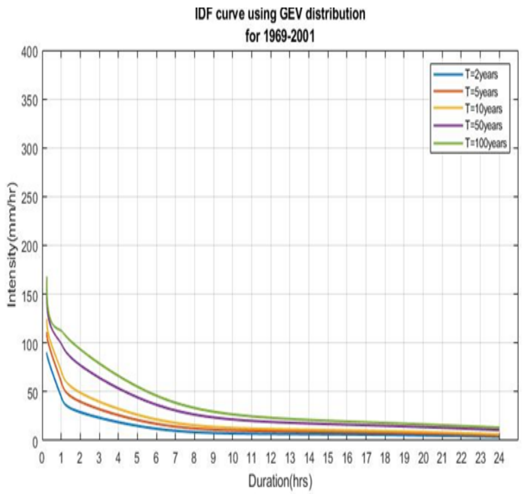


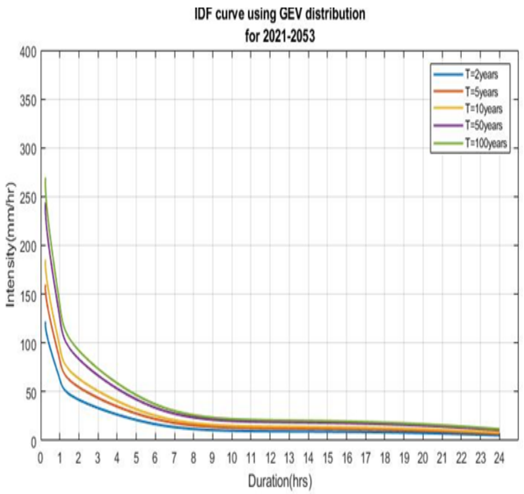


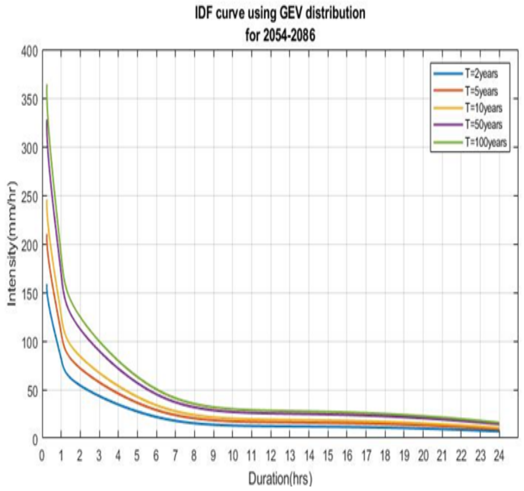


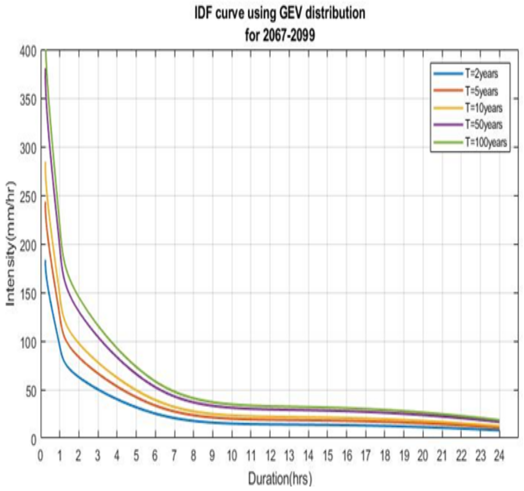


Multiplicative Change Factor









Conclusions

- The return levels obtained using Multiplicative change factor is more than of the Additive.

- There is no statistical significant difference between the uncertainties in the parameters additive and the multiplicative change factors.

- The uncertainty in the RCP 8.5 scenario is found to be the highest among all the GCM scenarios.

- It is found that the parameter uncertainty is more than that of the model uncertainty.

Thank You