9th International Conference

URBAN DRAINAGE MODELLING

Evaluating the impact of climate change on urban scale extreme rainfall events:

Coupling of multiple global circulation models with a stochastic rainfall generator

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Gonzalo Andrés PEÑA CASTELLANOS

Assela PATHIRANA

UNESCO-IHE
Institute for Water Education

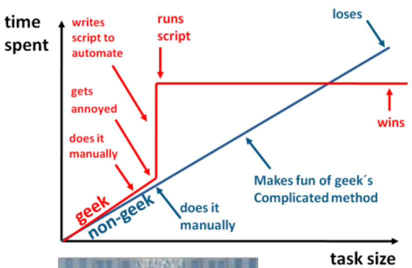
What's new

- Attempt to get extreme rainfalls (urban level) right.
- Number of GCMs (12) + Scenarios (3) + **Periods (2)**

Content

- Introduction

- Methodology

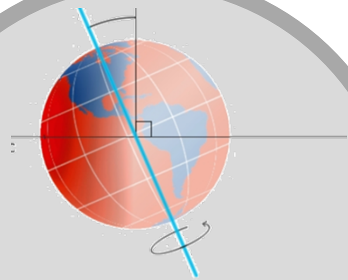


- Results

- Conclusion

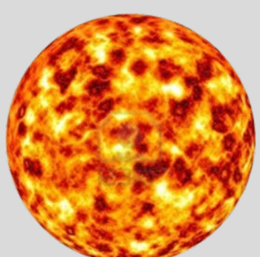
1. Introduction

Climate and Climate Change



Earth Movement

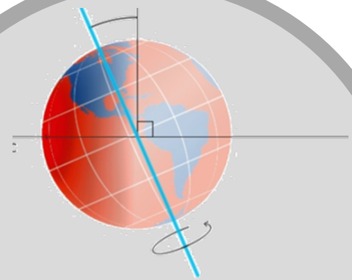
Solar Radiation



State of Climatic Variables

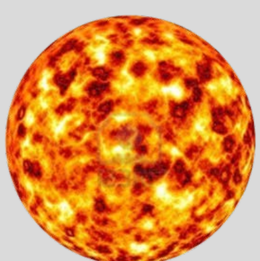
Over an extended period of time

Climate and Climate Change



Earth Movement

Solar Radiation



State of Climatic Variables

Over an extended period of time

Composition of Atmosphere (CO_2, H_2O, CH_4)

Gas emissions

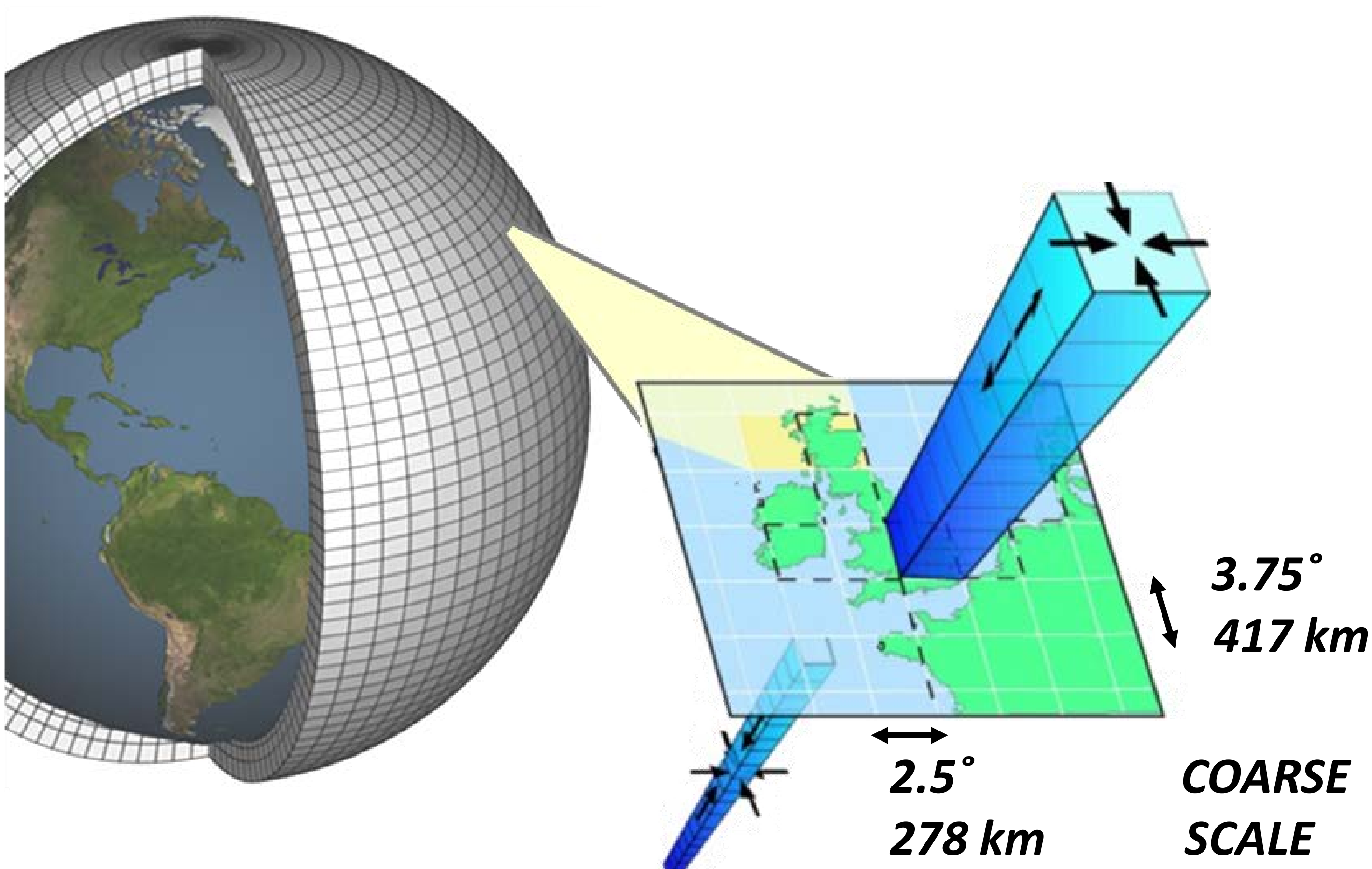
Introduction

Modeling Climate Change

Gas Emissions Scenarios (SRES)

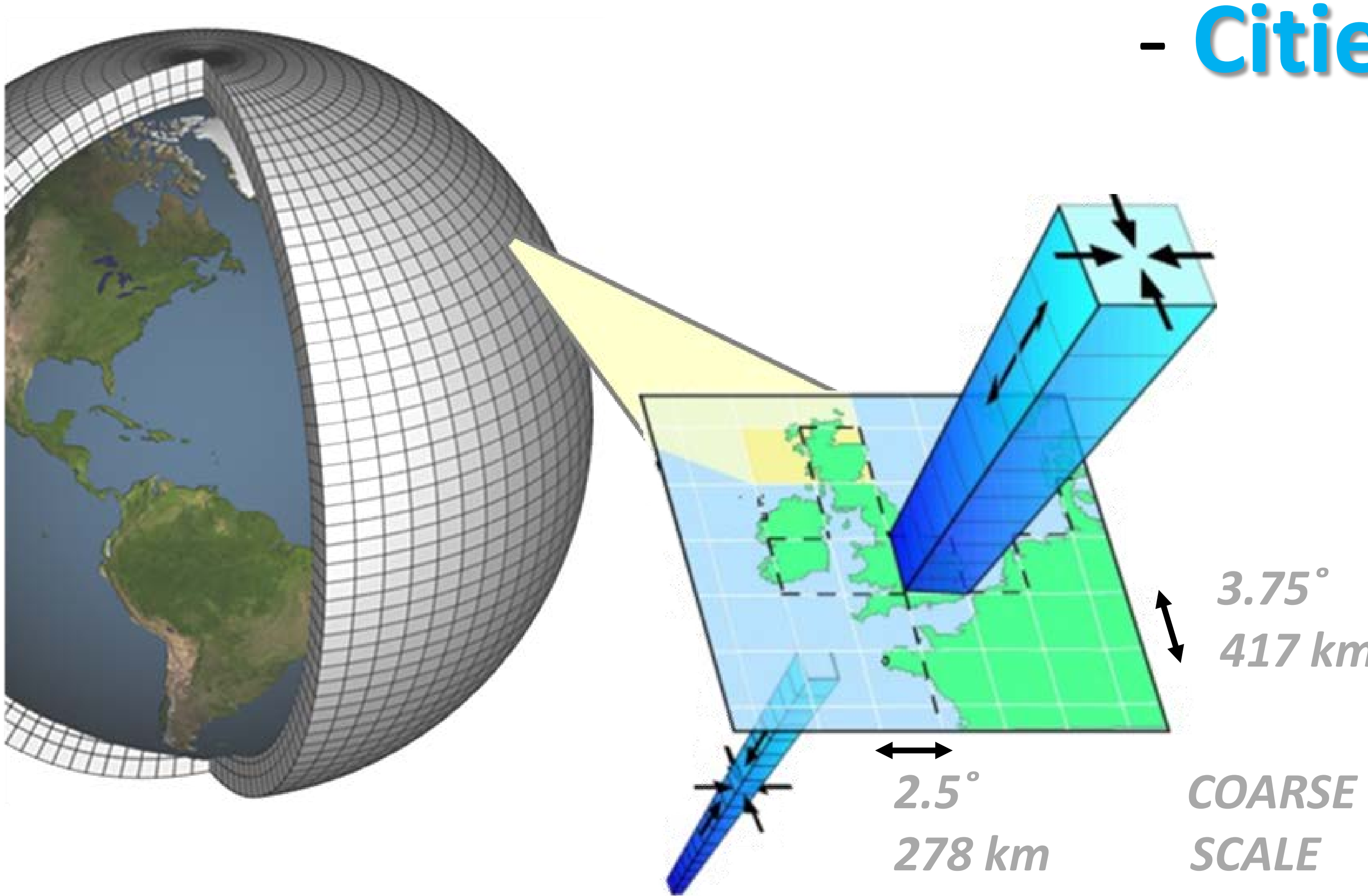
Modeling Climate Change

Global Circulation Models - Planet
& Regional Models - Region

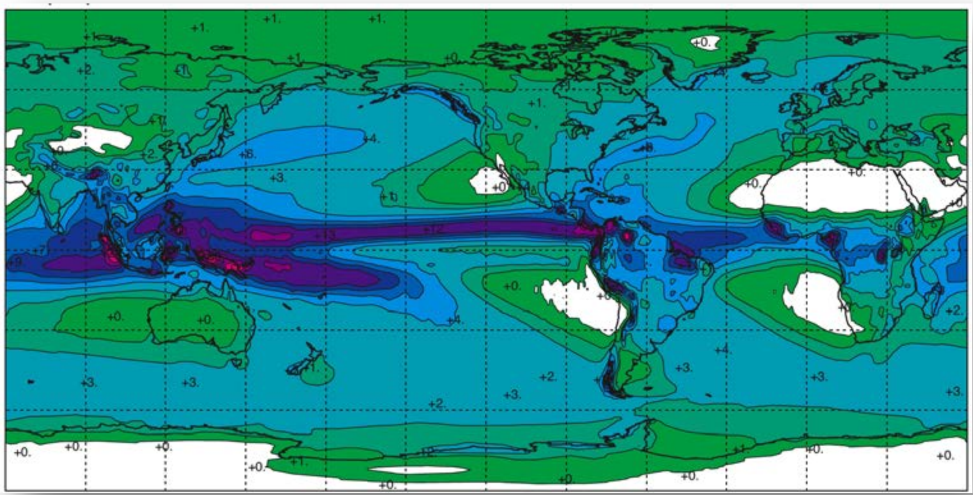


Modeling Climate Change

Global **C**irculation **M**odels - Planet
& **R**egional **M**odels - Regions
- **Cities??**



The Objective: Urban Scale



Total Precipitation Flux
[Daily Output]

Global Scale
[200-400 km]

TEMPORAL
RESOLUTION

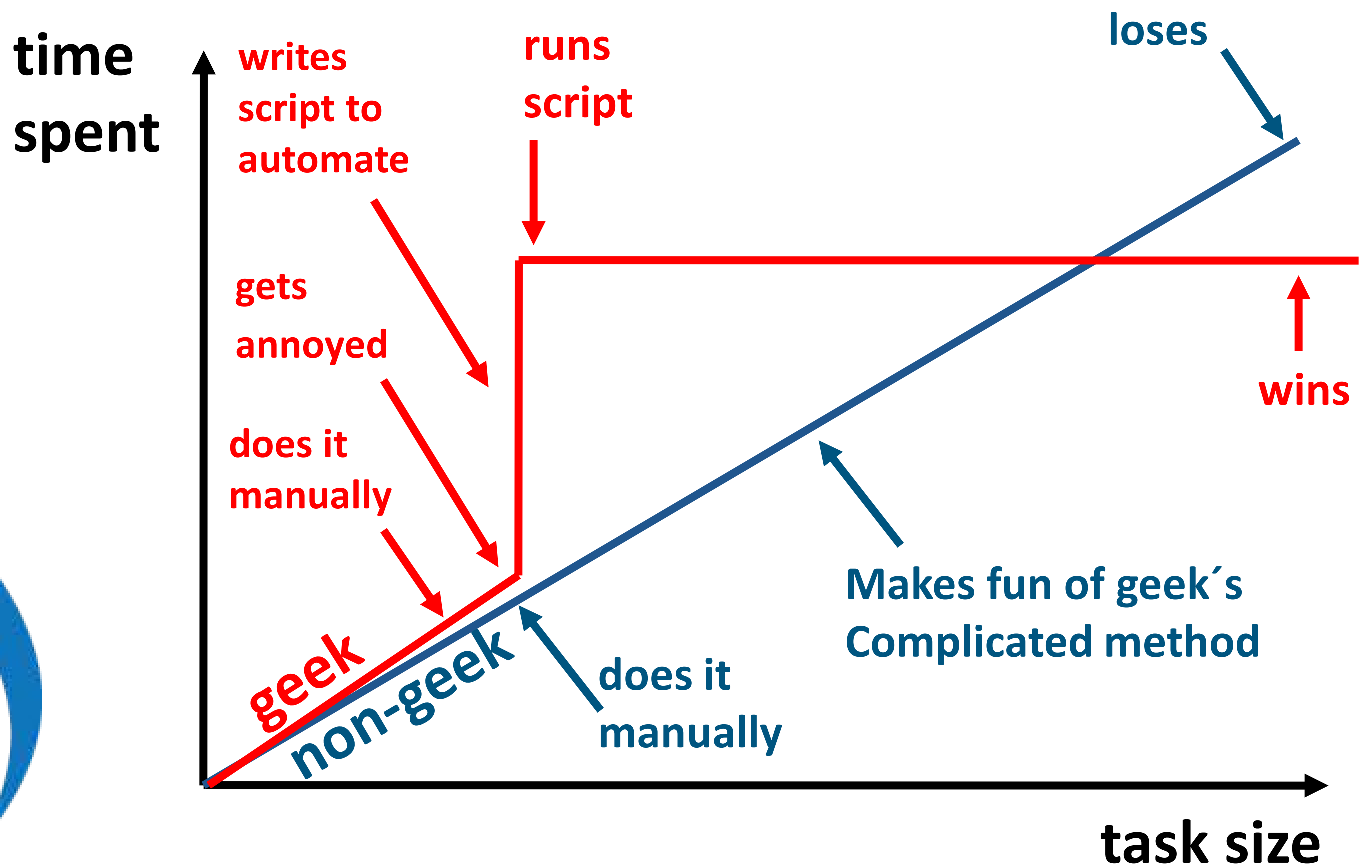
DOWNSCALING

(Extreme) Precipitation
[Subdaily]

SPATIAL
RESOLUTION

Urban Scale
[Point Scale]

2. Methodology

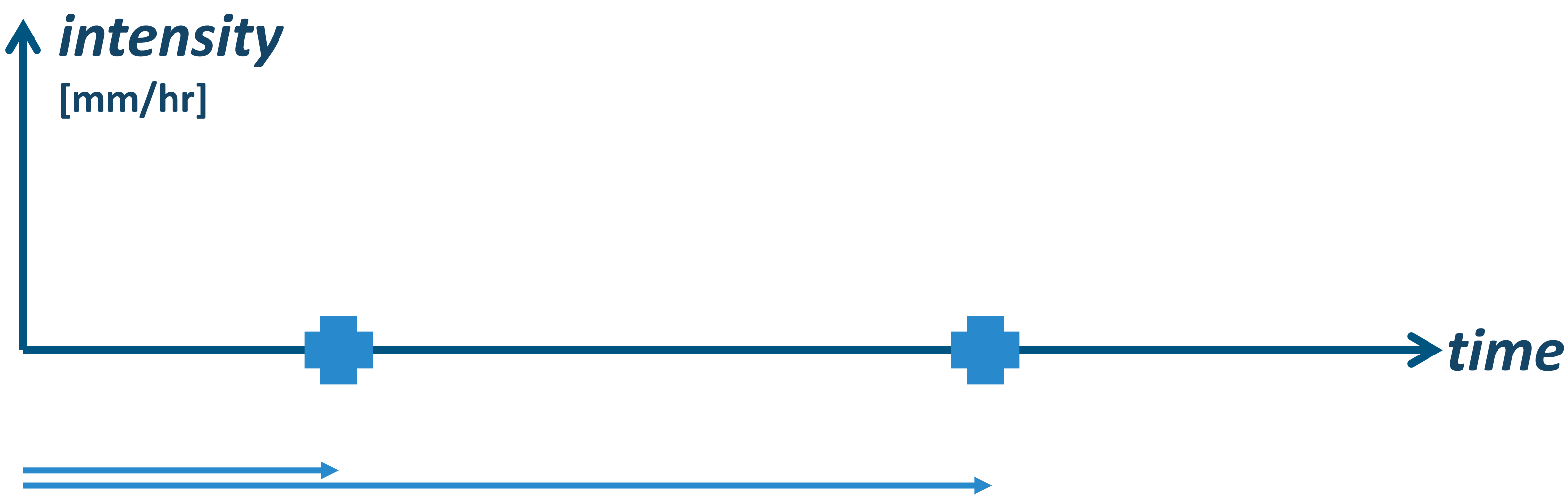


Generation of Synthetic Rainfall Using a Stochastic Process

Poisson cluster process:

Neyman Scott Rectangular Pulse (NSRP)

1.) Generate a random number of storm origins

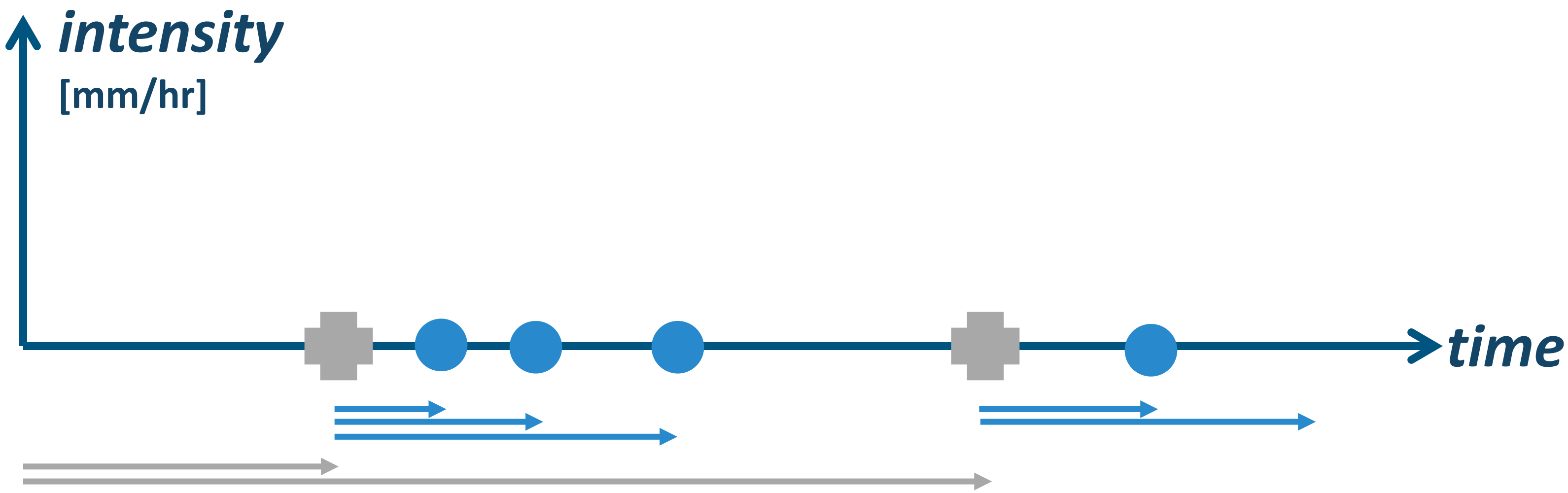


Generation of Synthetic Rainfall Using a Stochastic Process

Poisson cluster process:

Neyman Scott Rectangular Pulse (NSRP)

2.) Each storm generates a random number of cells and random cell origins



Methodology

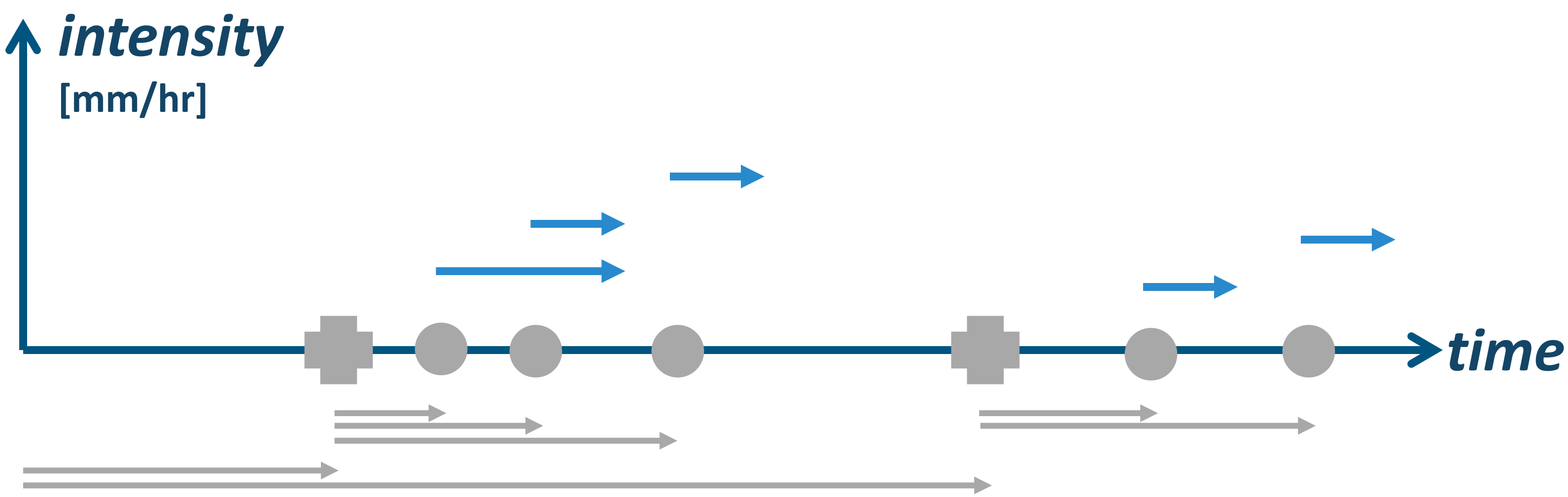
Methodology

Generation of Synthetic Rainfall Using a Stochastic Process

Poisson cluster process:

Neyman Scott Rectangular Pulse (NSRP)

3.) A random duration of each cell is generated

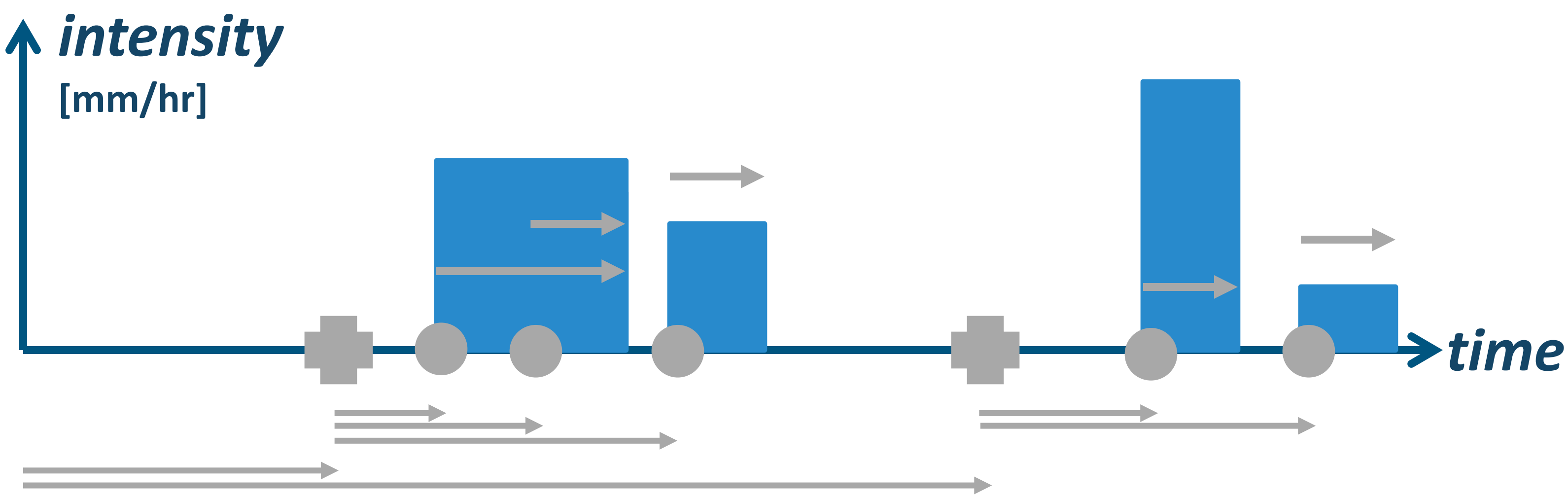


Generation of Synthetic Rainfall Using a Stochastic Process

Poisson cluster process:

Neyman Scott Rectangular Pulse (NSRP)

4.) A random intensity is generated



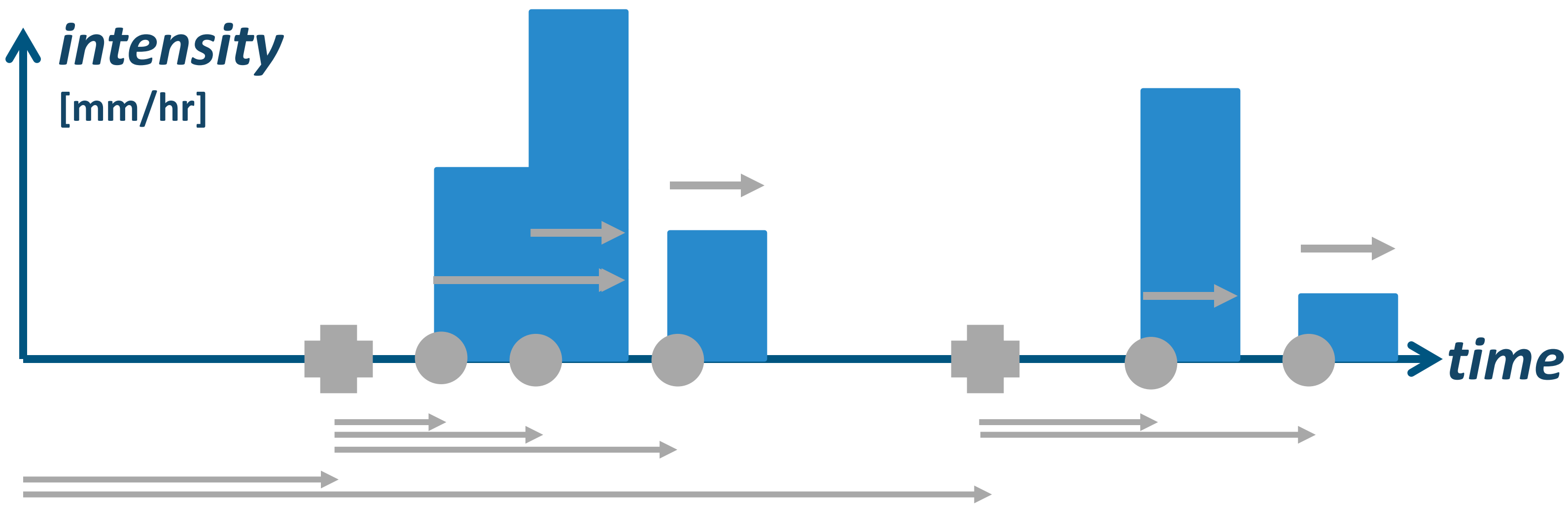
Methodology

Generation of Synthetic Rainfall Using a Stochastic Process

Poisson cluster process:

Neyman Scott Rectangular Pulse (NSRP)

5.) Total intensity is the sum of the active cells



Methodology

Generation of Synthetic Rainfall Using a Stochastic Process

Poisson cluster process:

Neyman Scott Rectangular Pulse (NSRP)

Calibrated from:

Mean

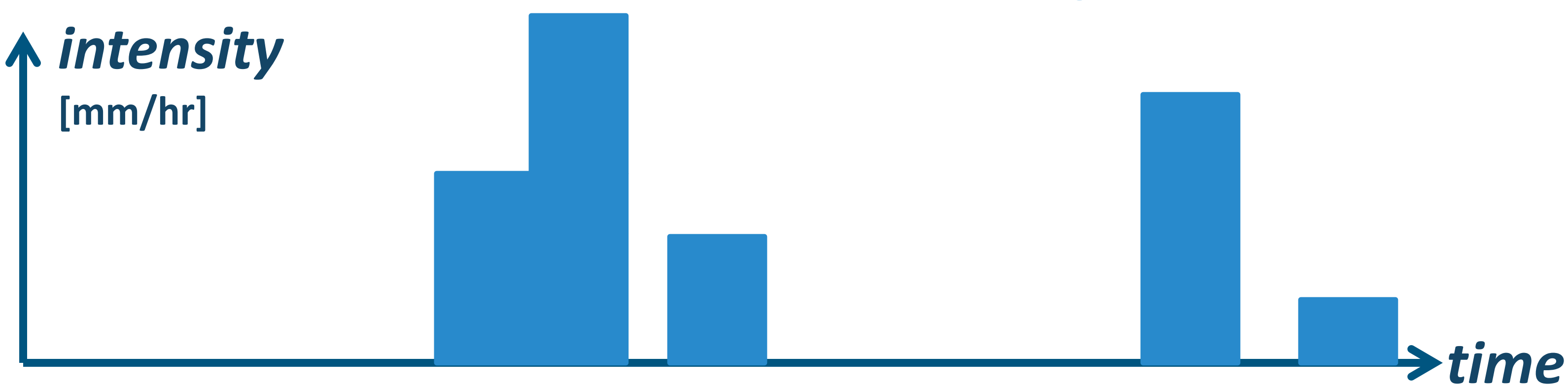
variance

coefficient of variation

dry spell duration

log autocorrelation

Synthetic rainfall



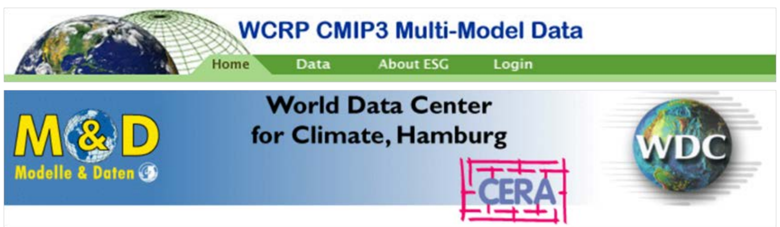
Methodology

Combining available precipitation data

Historical Simulation

Models: **12 GCM**
Period: **1974-1999**

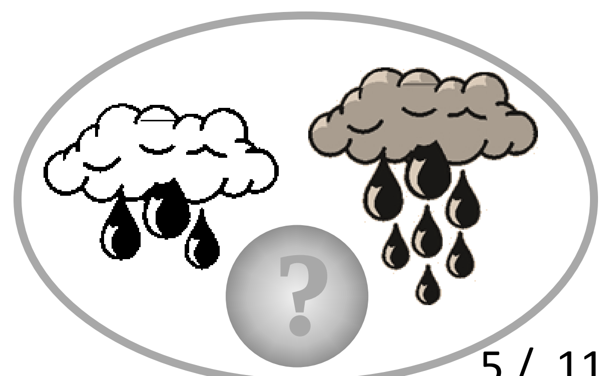
Scenario: **Past**



Future Simulation

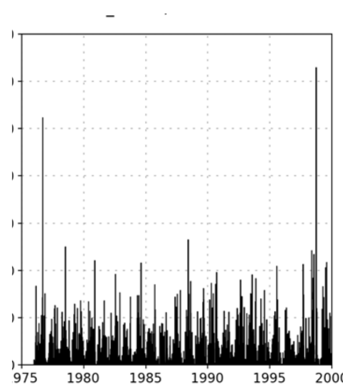
Models: **12 GCM**
Period: **2046-2065**
2081-2100
Scenario: **SRES A1b**
SRES A2
SRES B1

Factor of Change Of Statistics



Observed Historical Data

Case study: **Japan, Kochi**
Period: **1974-1999**



Combining available precipitation data

Bayes Theorem

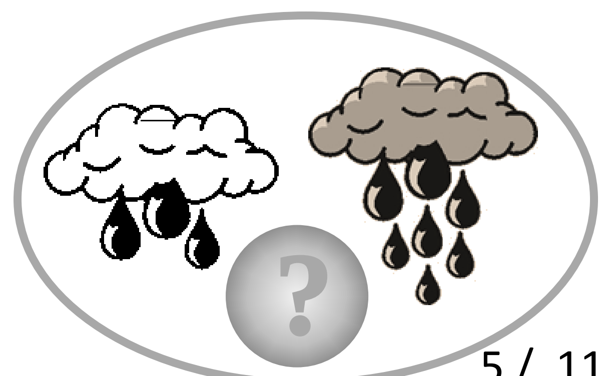
Solved numerically

Markov Chain Monte Carlo

MCMC

Probability of change of the the statistic analyzed

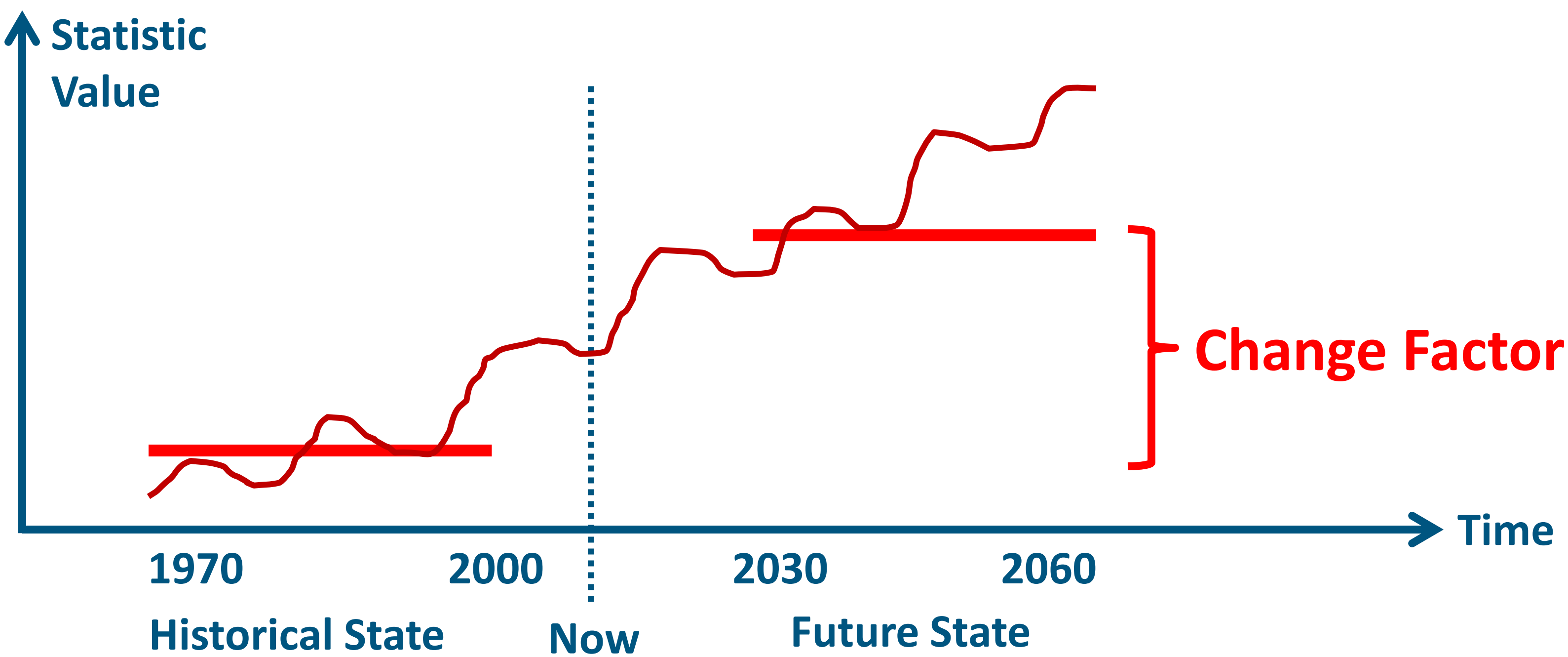
Factor of Change Of Statistics



Methodology

Combining available precipitation data

NSRP can be recalibrated to take into account the effect of climate change by including the factor of change that results from the bayesian ensemble



Methodology description

1. Stochastic Rainfall Generator Parameters
(Past: 1974-2000)

2. Evaluation of Daily Statistics From GCM ensemble
(Daily Statistics >= 24 hours)

3. Bayesian Ensemble: Factor of Change
(Extract **mean** factor of change)

4. Extend factor of change finer scale
(Subdaily scale: < 24 hours)

5. Modified Parameters
Future: 2046-2065
Future: 2081-2100

6. Run an ensemble of simulations and perform extreme values analysis
(200 simulations per location, scenario and future period)

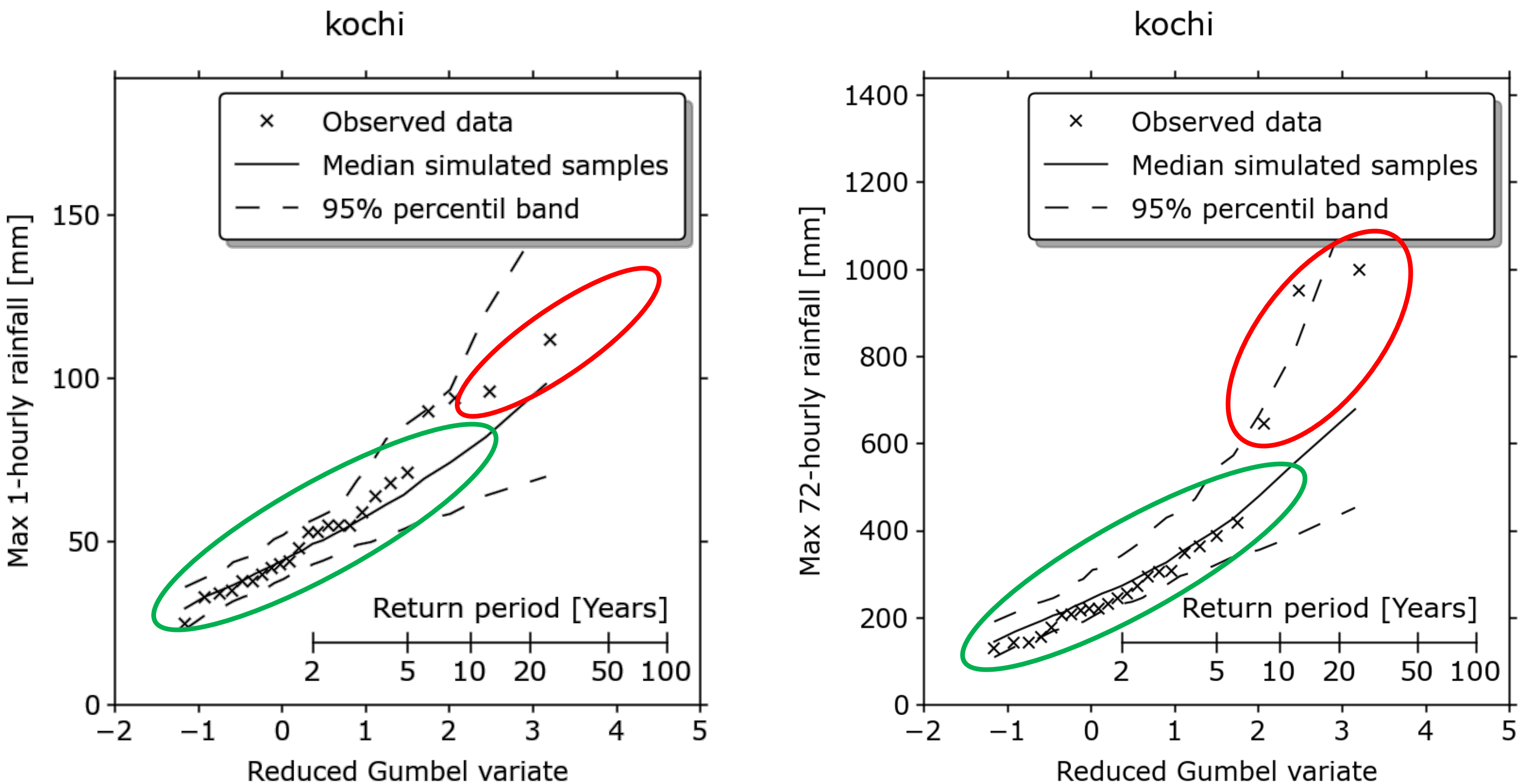
4. Results

Final ensemble

GCM models Used	Scenarios Used	Periods Used
12	3	2
NCAR CCSM3.0, MRI CFCM2 3.2A, MPI ECHAME 5, MIUB ECHO G, MIROCS 2 MEDRES, IPSL CM4, INMCM3.0, GISS MODEL ER, GFDL CM2.1, CSIRO MK3.5, CNRM CM3, CCCMA CGCM3.1	SRES A1 SRES A2 SRES B1	2046-2065 2081-2100

Methodology applicable to any location in the world where hourly precipitation series are available

Extreme value representation by the NSRP

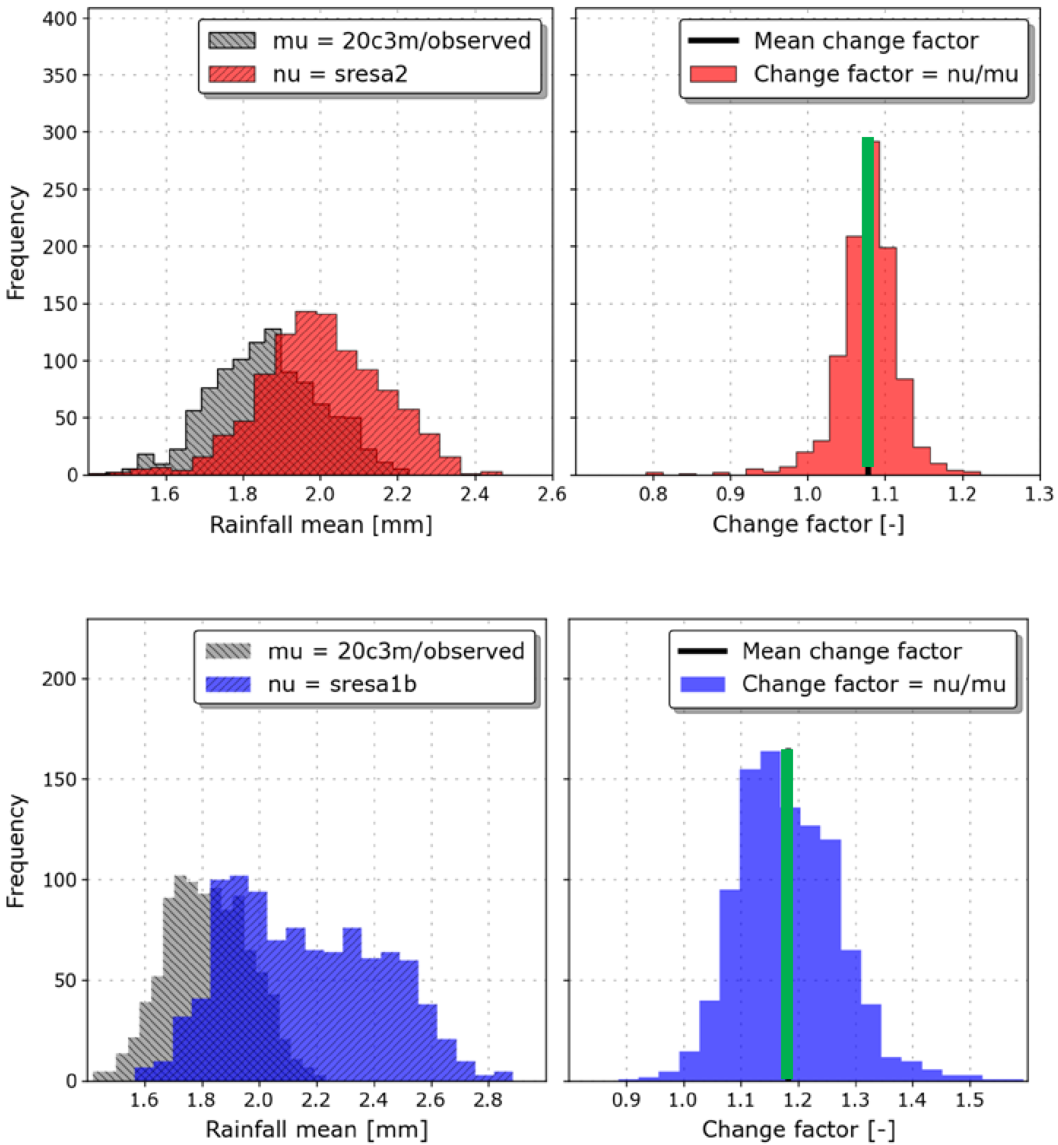


Good fit for return periods <= 10 years

Under estimation higher for higher aggregation

Factors of change
Bayesian ensemble results

Kochi 2045-2065.
Hourly mean



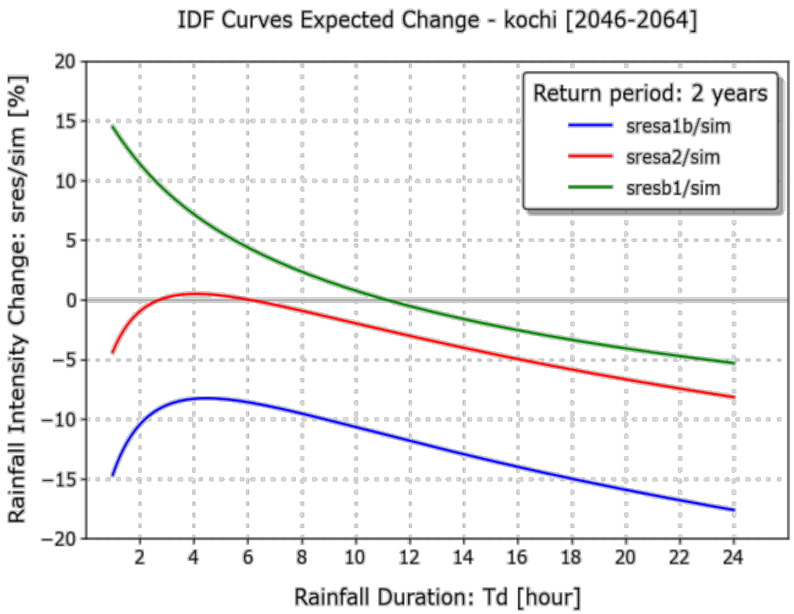
Only the mean factor of change was used

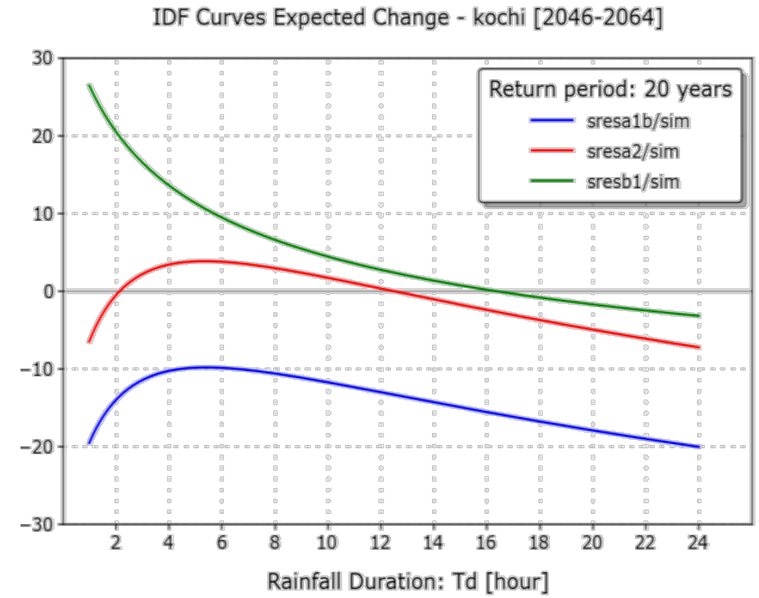
Computational Intensive process

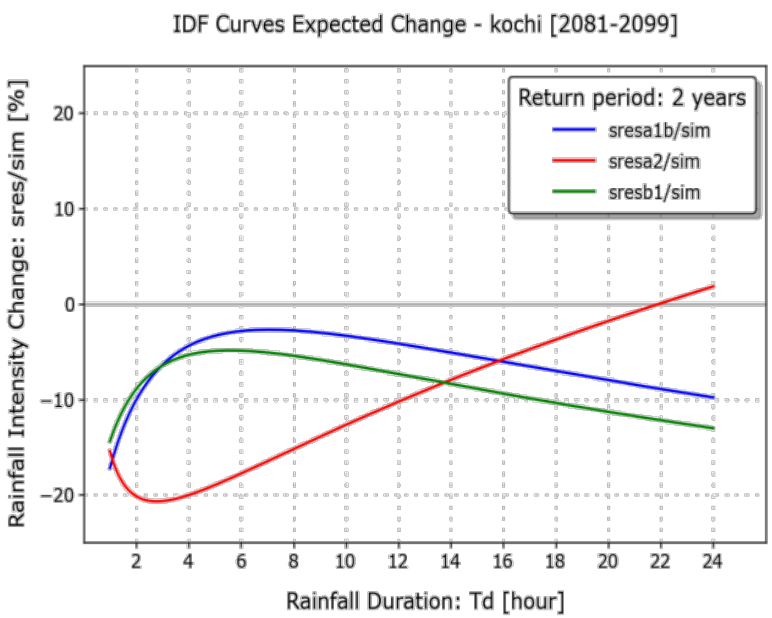
Parallel processing was used

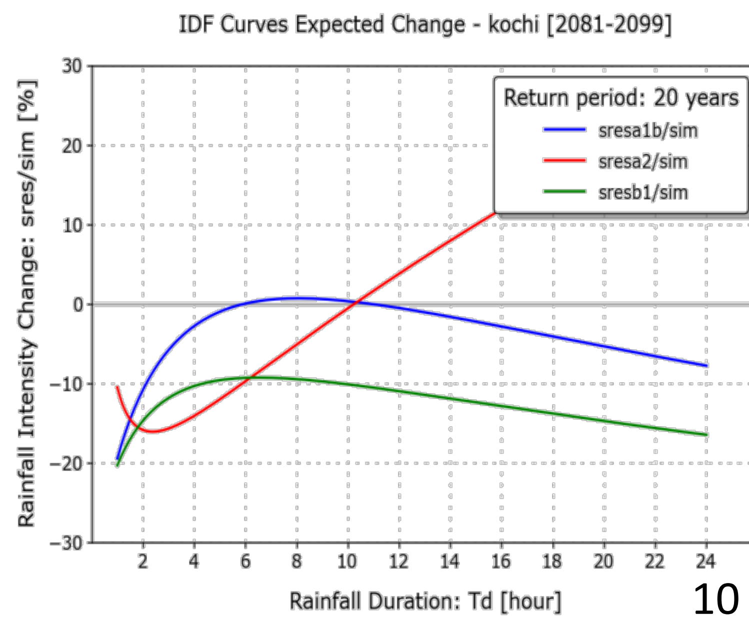
Results

Idf Curves









Conclusions

Conclusions

A methodology based on the use of a weather generator in climate impact studies was extended to include several GCMs.
Several scenarios and future periods were used to evaluate change in extreme rainfall events at urban scale.
Method itself is OK < 10 year events.
However, GCM results are all over the place!

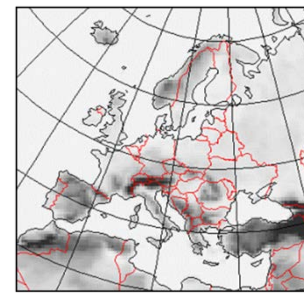
The <u>uncertainty</u> in the use of different GCMs output could be assessed by implementing a <u>Montecarlo type</u> simulation

(Even more computationally intensive!!!!)

Conclusions

Large uncertainties still exist inherent to the Bayesian Ensemble approach
(assumption of independence between GCMs and the mismatch between the grid cell size)

The worked methodology was applied to a series of GCMs but could be equally used to Regional circulation models (RCMs)



Freely available and open source tools were successfully explored with the additional benefit of a simple parallelization scheme.

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Questions ?

Authors:

Gonzalo Andrés PEÑA CASTELLANOS

goanpeca@gmail.com

Assela PATHIRANA

a.pathirana@unesco-ihe.org

UNESCO-IHE
Institute for Water Education

Extra info

- Gas emissions scenarios
- Variability of total precipitation in GCM
- GCM models and Scenarios used
- Spatial and temporal scales
- Working infrastructure For scientific computing
- Downscaling methods
- Stochastic fit

Extra information

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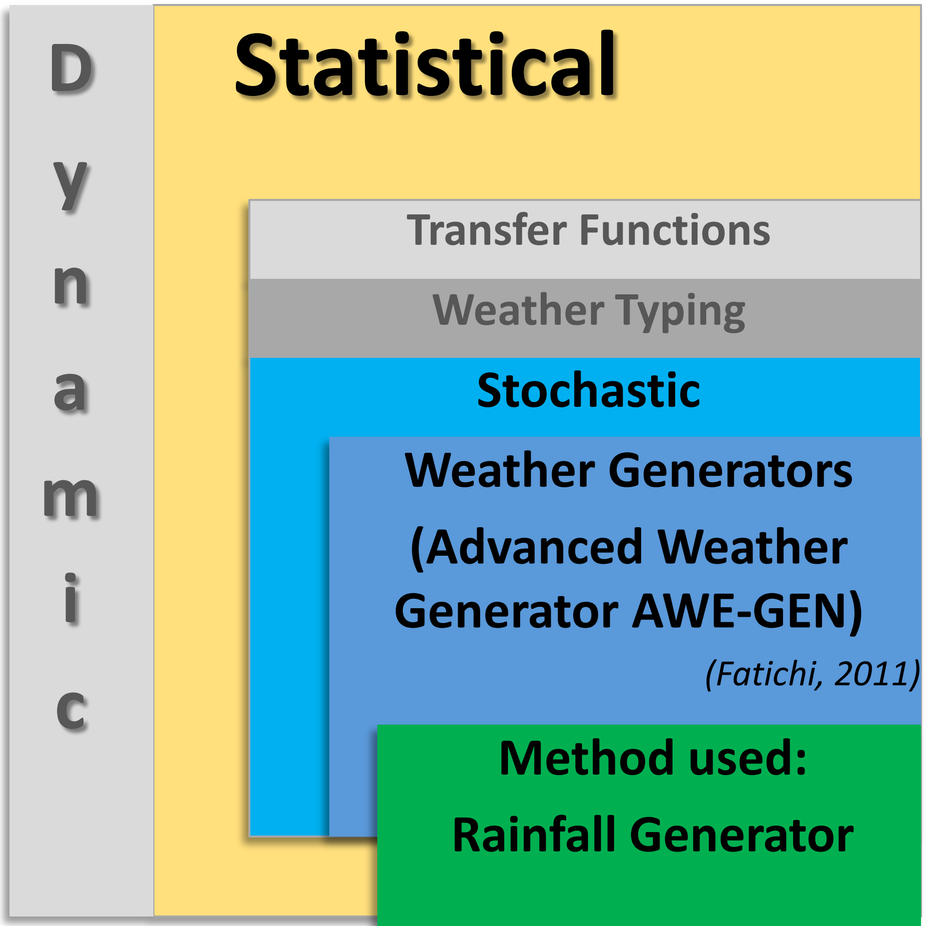
Downscaling Method



Advantages:

Comparatively cheap and **computationally efficient**

Can provide **local scale** climatic variables from GCM-scale output

Disadvantages:

Dependent on GCM boundary forcing; affected by **biases** in underlying GCM

(Fowler, 2007)

Extra information

Home

Working Infrastructure
Python for Scientific Computing

Packages and subpackages

Python

NumPy

Parallel-Python

PyMC

Scipy

Matplotlib

netCDF4

Development Environment

Spyder

Graphical User Interface (under development)

pySide

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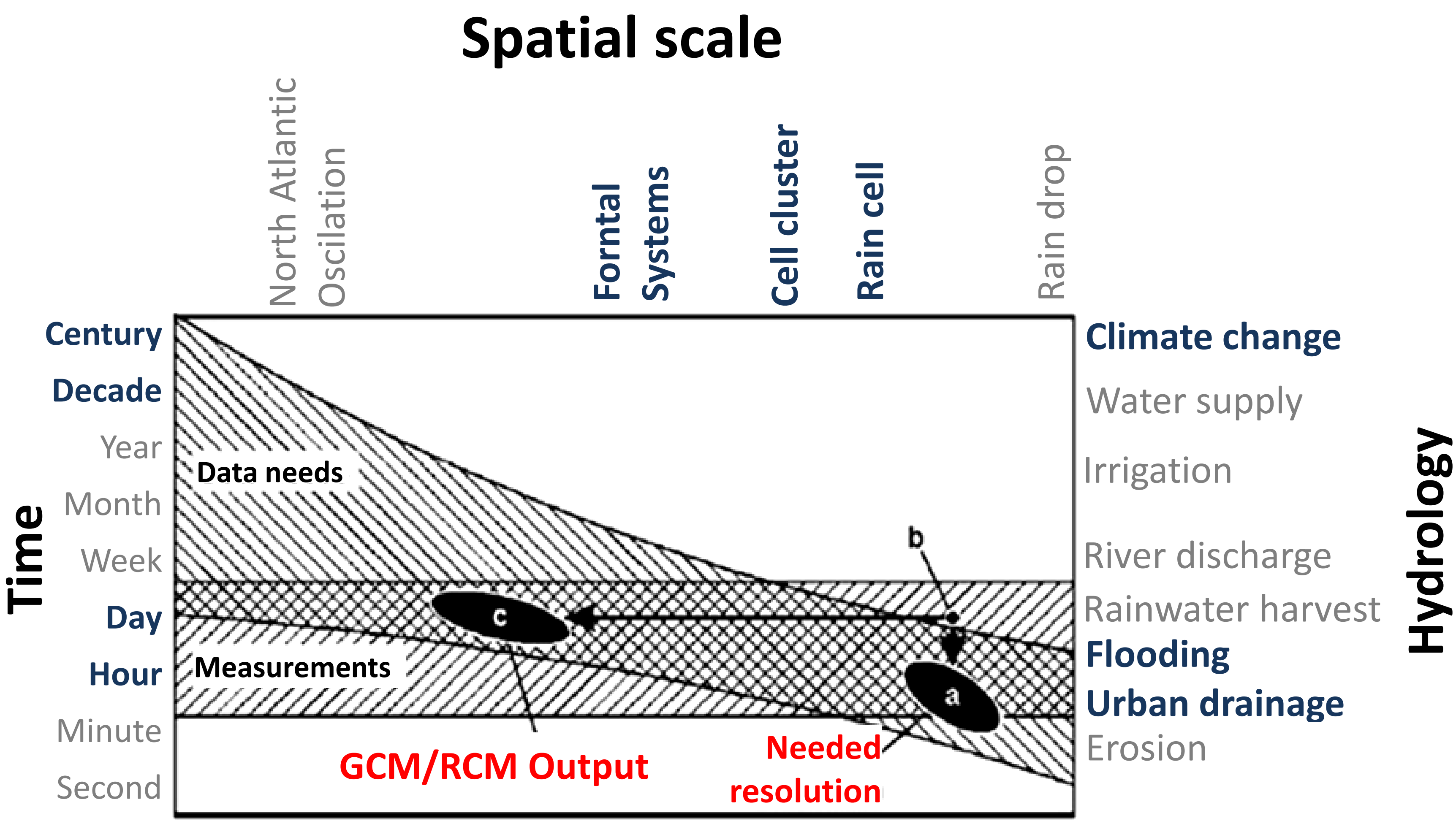
Spatial and temporal Scales



Extra information

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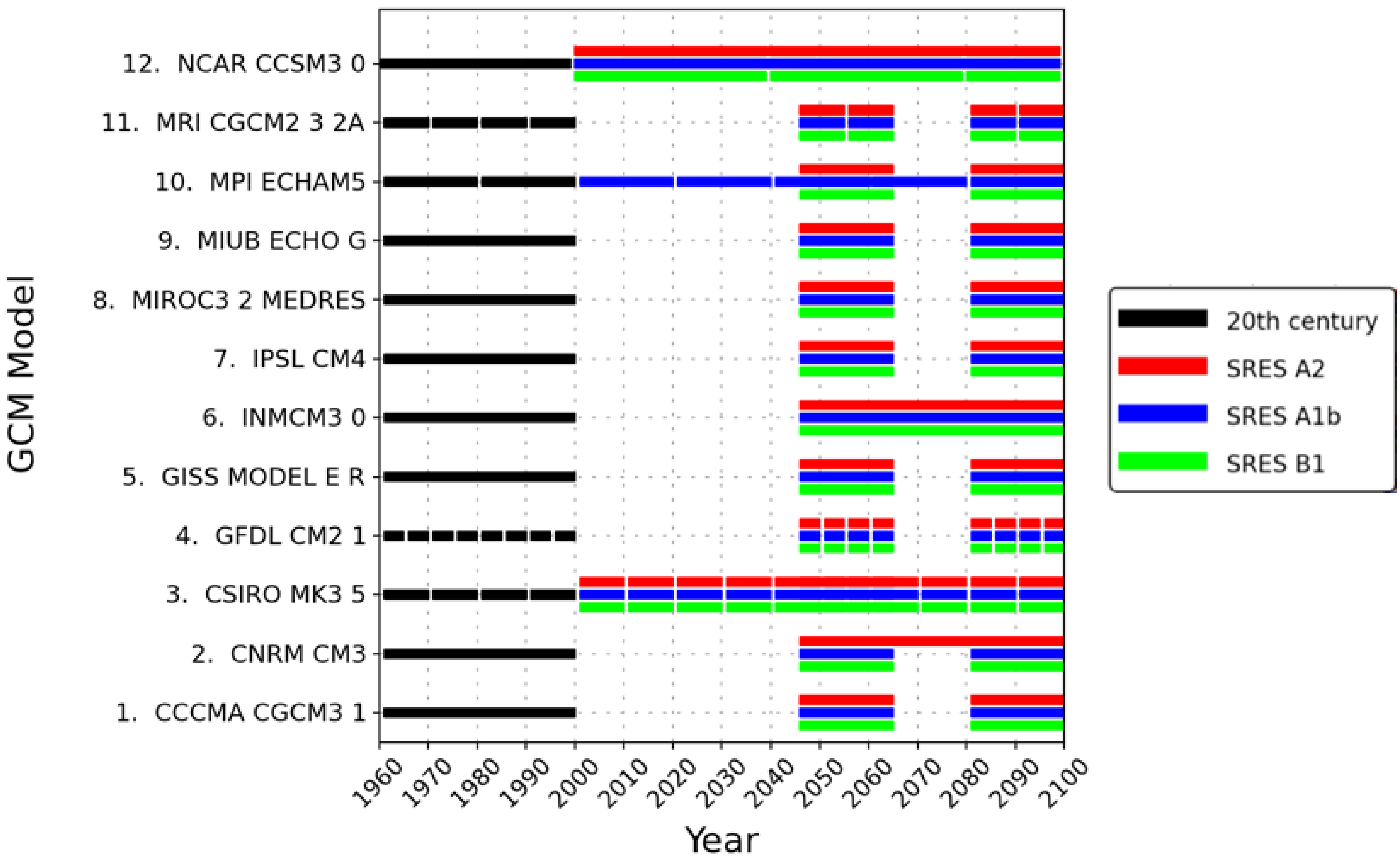
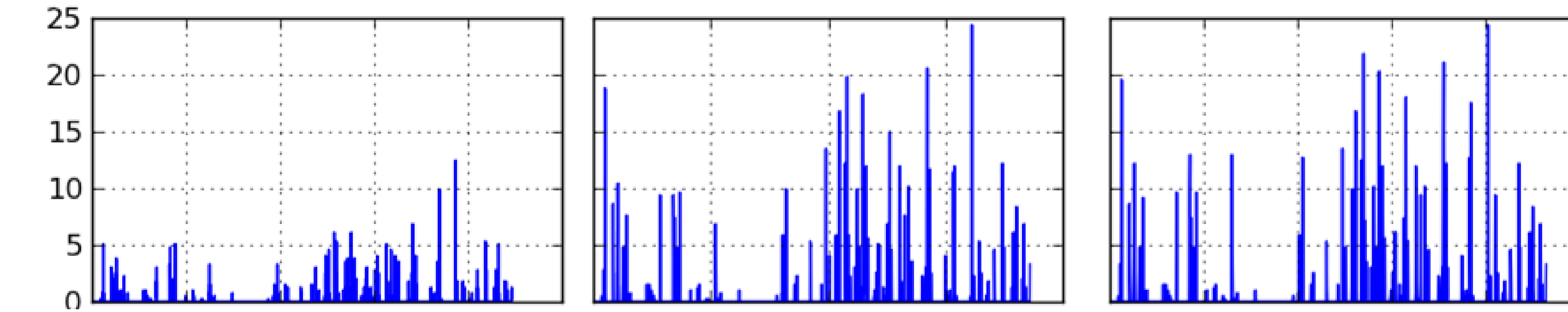
GCM Models and scenarios used



Fitting of Stochastic Process

Rainfall statistics at different aggregation intervals:

1 hour *12 hours* *n hours*



Observed statistics

Bound Constrained Optimization (l-bfgs)

Calculated statistics

Limited memory Broyden, Fletcher, Goldfarb, Shanno

Set of model parameters NSRP

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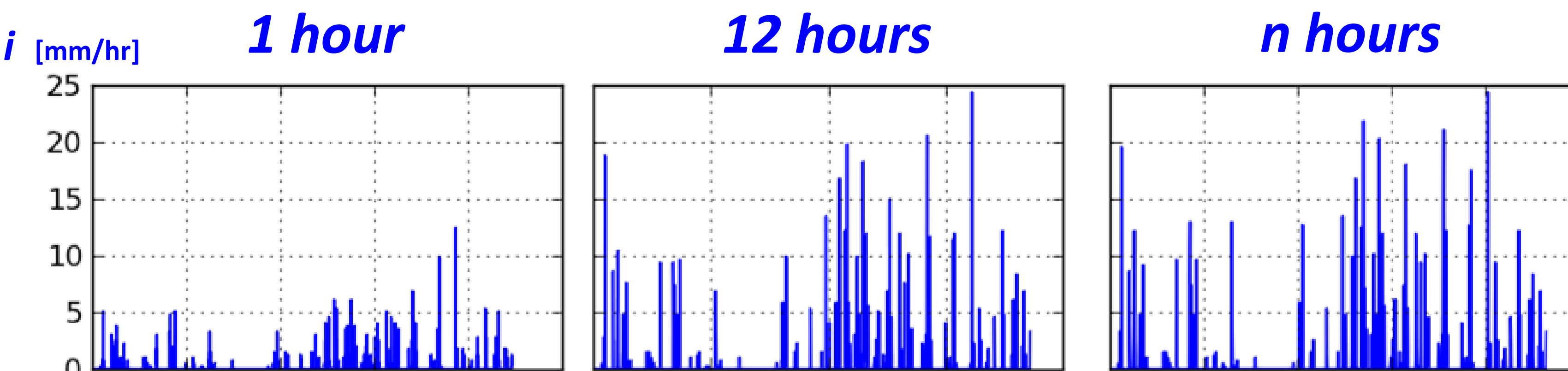
Fitting of Stochastic Process

Rainfall statistics at different aggregation intervals:



Observed statistics x *P*(Change Factor)

Bound Constrained

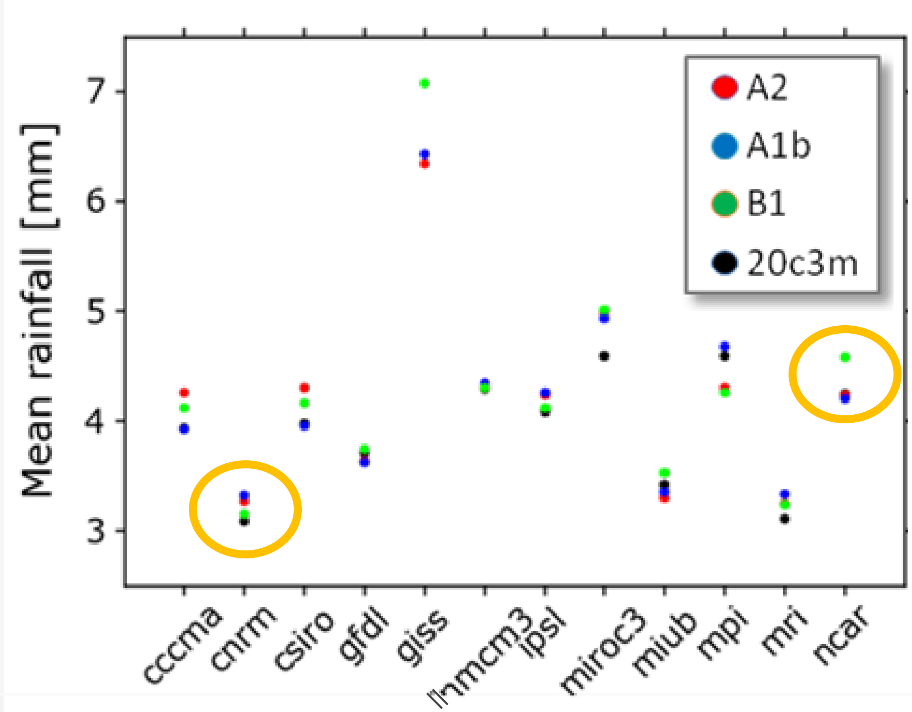
Optimization (l-bfgs)

Calculated statistics

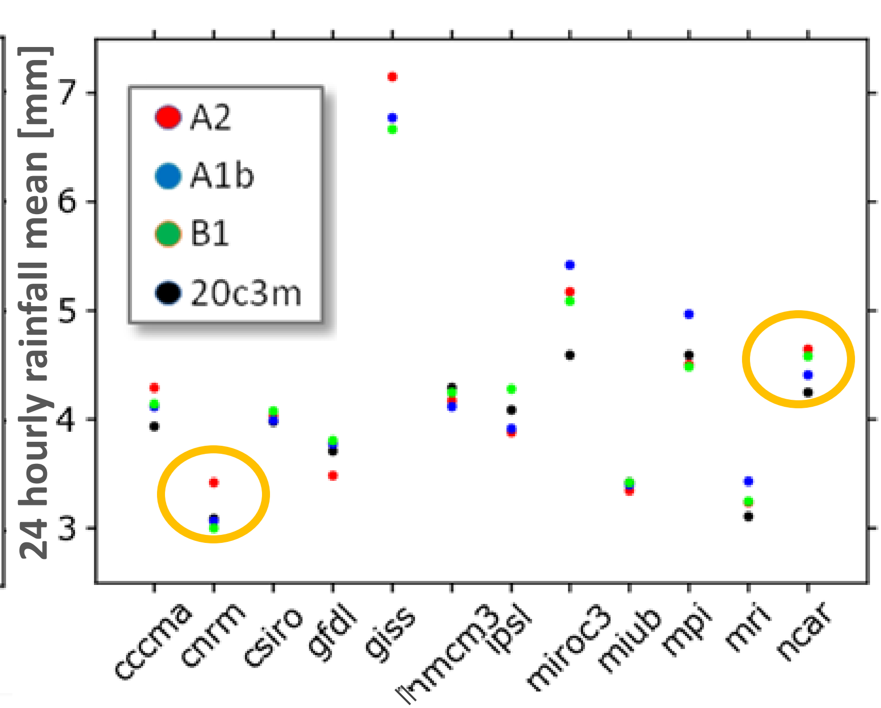
Set of model parameters NSRP

Variability of precipitation results in the same GCM grid box.

GCM grid values for Kochi location
Period: 2046-2065



GCM grid values for Kochi location
Period: 2081-2100



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Gas emissions scenarios