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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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

State of Climatic Variables
Over an extended period of time

Earth Movement

Solar Radiation
Climate and Climate Change

State of Climatic Variables
Over an extended period of time

Composition of Atmosphere
\((\text{CO}_2, \text{H}_2\text{O}, \text{CH}_4)\)
Gas emissions

Introduction

Earth Movement

Solar Radiation
Modeling Climate Change

Introduction

Gas Emissions Scenarios (SRES)
**Global Circulation Models** - Planet

& **Regional Models** - Region
Global Circulation Models - Planet & Regional Models - Regions - Cities??

2.5° 278 km
3.75° 417 km

COARSE SCALE
2. Methodology

<table>
<thead>
<tr>
<th>time spent</th>
<th>task size</th>
</tr>
</thead>
<tbody>
<tr>
<td>wins</td>
<td>loses</td>
</tr>
</tbody>
</table>

- Does it manually
- Gets annoyed
- Writes script to automate
- Runs script

- Non-geek
- Geek

- Does it manually
- Makes fun of geek’s Complicated method
Generation of Synthetic Rainfall Using a Stochastic Process

Poisson cluster process:
Neyman Scott Rectangular Pulse (NSRP)

1.) Generate a random number of storm origins

\[ \text{intensity} \quad [\text{mm/hr}] \]

\[ \text{time} \]
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
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

intensity
[mm/hr]
time
Generation of Synthetic Rainfall Using a Stochastic Process

Poisson cluster process:
Neyman Scott Rectangular Pulse (NSRP)

4.) A random intensity is generated
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
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

intensity
[mm/hr]

time
Combining available precipitation data

**Historical Simulation**
- Models: 12 GCM
- Period: 1974-1999
- Scenario: Past

![Historical Data Chart](chart)

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

![Future Scenario Chart](chart)

**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)**

**Factor of Change Of Statistics**

**Probability of change of the statistic analyzed**
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

<table>
<thead>
<tr>
<th>GCM models Used</th>
<th>Scenarios Used</th>
<th>Periods Used</th>
</tr>
</thead>
<tbody>
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<td>12</td>
<td>3</td>
<td>2</td>
</tr>
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<tr>
<th>GCM models Used</th>
<th>Scenarios Used</th>
<th>Periods Used</th>
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<tbody>
<tr>
<td>NCAR CCSM3.0,</td>
<td>SRES A1</td>
<td>2046-2065</td>
</tr>
<tr>
<td>MPI ECHAME 5,</td>
<td>SRES A2</td>
<td>2081-2100</td>
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<td>MIROCS 2 MEDRES,</td>
<td>SRES B1</td>
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<td>CSIRO MK3.5,</td>
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<td>CCCMA CGCM3.1,</td>
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Methodology applicable to any location in the world where hourly precipitation series are available.
Extreme value representation by the NSRP

Results

Good fit for return periods <= 10 years

Under estimation higher for higher aggregation
Factors of change
Bayesian ensemble results

Only the mean factor of change was used

Computational Intensive process

Parallel processing was used
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 **uncertainty** in the use of different GCMs output could be assessed by implementing a **Montecarlo type** 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.
Thank you!

Questions

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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
**Downscaling Method**

**Statistical**

- **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)**

**Dynamic**

- **Transfer Functions**
- **Weather Typing**
- **Stochastic Weather Generators**

**Method used:**
- **Rainfall Generator**

**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
Spatial and temporal Scales

Spatial scale

- Century
- Decade
- Year
- Month
- Week
- Day
- Hour
- Minute
- Second

Time

- North Atlantic Oscillation
- Frontal Systems
- Cell cluster
- Rain cell
- Rain drop

Spatial Scale

Data needs

Measurements

GCM/RCM Output

Needed resolution

Climate change
- Water supply
- Irrigation
- River discharge
- Rainwater harvest
- Flooding
- Urban drainage
- Erosion

Hydrology

Extra information
GCM Models and scenarios used
Fitting of Stochastic Process

Rainfall statistics at different aggregation intervals:

\[ i \text{ [mm/hr]} \quad 1 \text{ hour} \quad 12 \text{ hours} \quad n \text{ hours} \]

- Observed statistics
- Bound Constrained Optimization (l-bfgs)
- Calculated statistics
- Set of model parameters NSRP

Limited memory
Broyden,
Fletcher,
Goldfarb,
Shanno
Fitting of Stochastic Process

Rainfall statistics at different aggregation intervals:

\( i \) [mm/hr] 1 hour 12 hours \( n \) hours

Observed statistics \( \times P(\text{Change Factor}) \)

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
Gas emissions scenarios

- **Total CO₂ Emissions (GtC)**
  - Line graphs showing emissions from A2, A1b, and B1 scenarios.

- **Total CH₄ Emissions (MtCH₄)**
  - Line graphs showing emissions from A2, A1b, and B1 scenarios.

- **Total N₂O Emissions (MtN₂O-N)**
  - Line graphs showing emissions from A2, A1b, and B1 scenarios.