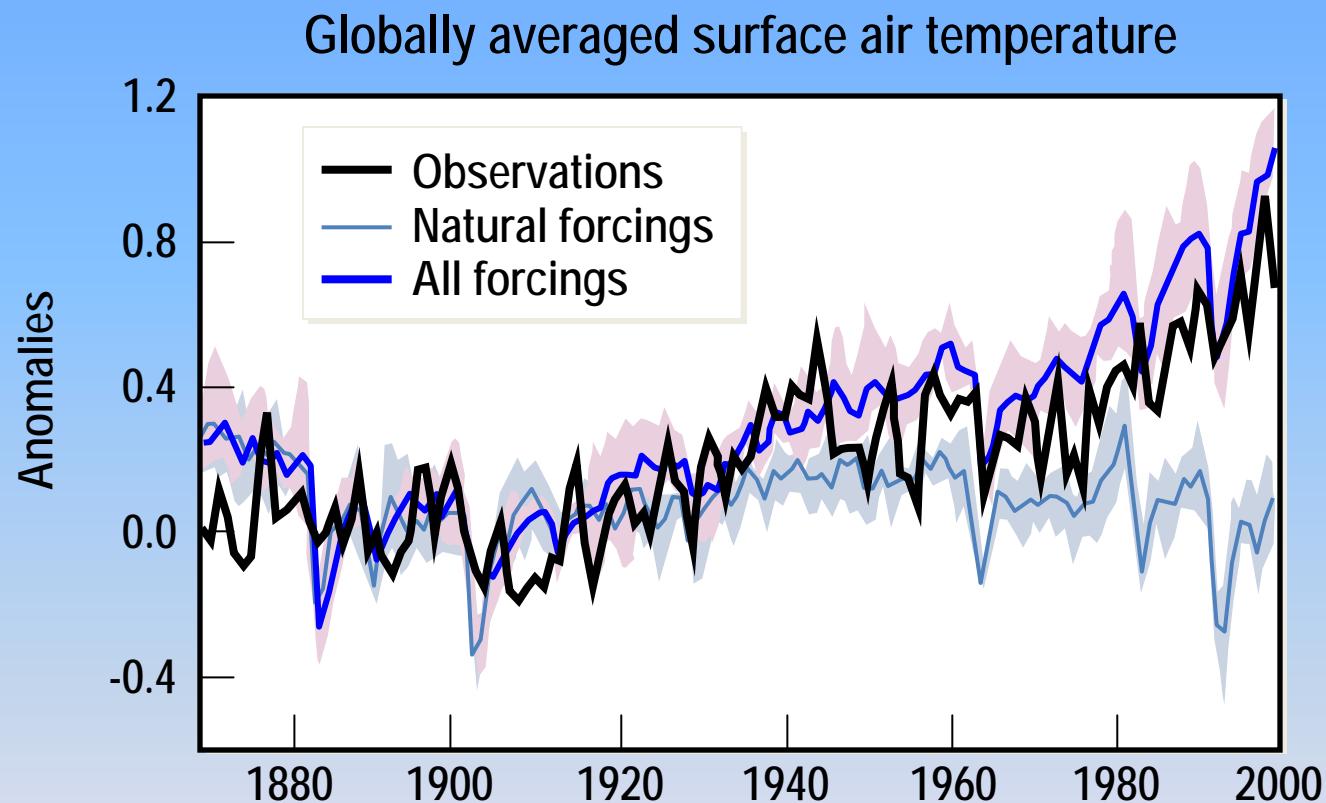


Finer Scale Temperature and Rainfall Projections under Climate Change



Subimal Ghosh
Assistant Professor
Civil Engineering Department, IIT
Bombay

Introduction



Slide Courtesy: Jim Hack, ORNL (IPCC AR4, 2007)

Implications on Hydrology

- Overall idea: Increase in temperature → increase in evapotranspiration → more cloud formation → increase in rainfall
- Real situation: Not so simple → guided by spatial distribution of pressure, wind velocity etc.
- Changes in rainfall: not always increasing in all locations and non consistent
- Implications of changes: estimation of design hydrologic variables
- Earlier concepts on hydrologic design: Based on return period → assumption: stationarity
- In changed Scenario: “Stationarity is Dead”

POLICYFORUM

CLIMATE CHANGE

Stationarity Is Dead: Whither Water Management?

P. C. D. Milly¹, Julia Seneviratne², Malin Falkenmark³, Robert M. Hirsch⁴, Chingwei W. Kundzewicz⁵, Dennis P. Lettenmaier⁶, Ronald J. Stouffer⁷

Close to change undermines a basic assumption that historically has facilitated management of water supply, demands, and risks.

Systems for management of water throughout the developed world have been designed and operated under the assumption of stationarity. Stationarity—the idea that natural systems fluctuate within an unchanging envelope of variability—is a foundational concept that permeates training and practice in water-resource engineering. It implies that any variable (e.g., annual streamflow or annual flood peak) has a time-constant (or 1-year-period) probability density function (pdf), whose properties can be estimated from the instrument record. Under stationarity, pdf estimation errors are acknowledged, but have been assumed to be reducible by additional observations, more efficient estimators, or regional or paleohydrologic data. The pdfs, in turn, are used to evaluate and manage risks to water supplies, waterworks, and floodplains; annual global investment in water infrastructure exceeds US\$350 billion (7).

The stationarity assumption has long been compromised by human disturbances in river basins. Increasing risk, water supply, and water quality are affected by water infrastructure, channel modifications, drainage works, and land-cover and land-use change. Two other (sometimes indistinguishable) challenges to stationarity have been extremely forced, natural climate changes and low-frequency, internal variability (e.g., the Atlantic multidecadal oscillation) enhanced by the slow dynamics of the oceans and ice sheets (2, 3). Planners have tools to adapt their analyses for known human disturbance without reservation, and justifiably so, they generally have considered natural change and variability to be sufficiently small to allow a stationary-based design.

How did stationarity die? Stationarity is dead because substantial anthropogenic change of Earth's climate is altering the mean and extreme of precipitation, evapotranspiration, and rates of discharge of rivers (4, 5) (see figure above). Warning atmospheric humidity and water transport. This increases precipitation, and possibly flood risk, while decreasing atmospheric water vapor fluxes (convergences) (6). Rising sea level induces gradually heightened risk of contamination of coastal freshwater supplies. Glacial meltwater temporally enhances water availability, but glacier and snow-pack losses diminish natural seasonal and interannual storage (7).

Anthropogenic climate warming appears to be driving a poleward expansion of the subtropical dry zone (8), thereby reducing runoff in some regions. Together, circulation and thermodynamic responses largely explain the picture of regional gains and losses of sustainable freshwater availability

that has emerged from climate models (see figure, p. 574).

Why now? That anthropogenic climate change affects the water cycle (8) and water supply (6) is not a new finding. Nevertheless, sensible objections to discarding stationarity have been raised. For one, hydroclimate had not demonstrably exited the envelope of mean, 100-year variability under the effective range of optimally operated infrastructures (11, 12). Accounting for the substantial uncertainties of climate parameters estimated from short records (13) effectively hedged against small climate changes. Additionally, climate projections were not considered credible (12, 14).

Recent developments have led us to the opinion that the time has come to move beyond the water-and-risk approach. Projections of runoff changes are bolstered by recently demonstrated predictive skill of climate models. The global pattern of observed annual streamflow trends is unlikely to have arisen from random variability and is consistent with modeled response to climate forcing (15). Paleohydrologic studies suggest that small changes in mean climate might produce large changes in extremes (16), although attempts to detect a recent change in global flood frequency have been equivocal (7, 17). Projected changes in runoff during the multidecade lifetime of major water infrastructure projects begin now to be large enough to push hydroclimate beyond the range of historical behaviors (18). Some regions have little infrastructure to buffer the impacts of changes.

Stationarity cannot be revived. Even with aggressive mitigation, continued warming is very likely, given the residence time of atmospheric CO₂ and the thermal inertia of the Earth system (2, 19).

A successor: We need to find ways to identify scenario-aware probabilistic models of relevant environmental variables and to use these models to optimize water systems. The challenge is daunting. Patterns of change are complex; uncertainties are large; and the timescale for change is rapid.

Under the national planning framework advanced by the Harvard Water Program (21, 22), the assumption of stationarity was

¹U.S. Geological Survey (USGS), U.S. National Oceanic and Atmospheric Administration (NOAA) Cooperative Field Operator Catalogue, Research, Reston, USA; ²International Water Institute, II, Lisse, The Netherlands; ³WRI, Reston, VA 20192, USA; ⁴Department of Civil and Environmental Engineering, Peidong Academy of Sciences, Xianju, China; and ⁵Peterson Institute for Climate Impact Research, Petaluma, California; ⁶University of Washington, Seattle, WA 98195, USA; ⁷Climate and Hydrologic Dynamics Laboratory, Princeton, NJ 08544, USA.

*Author for correspondence: E-mail: emily@usgs.gov

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There is a need to model changed scenarios

General Circulation Model

General Circulation Model (GCM): Tools for simulating time series of climate variables globally, accounting for effects of greenhouse gases in the atmosphere (using possible future GHG scenarios).

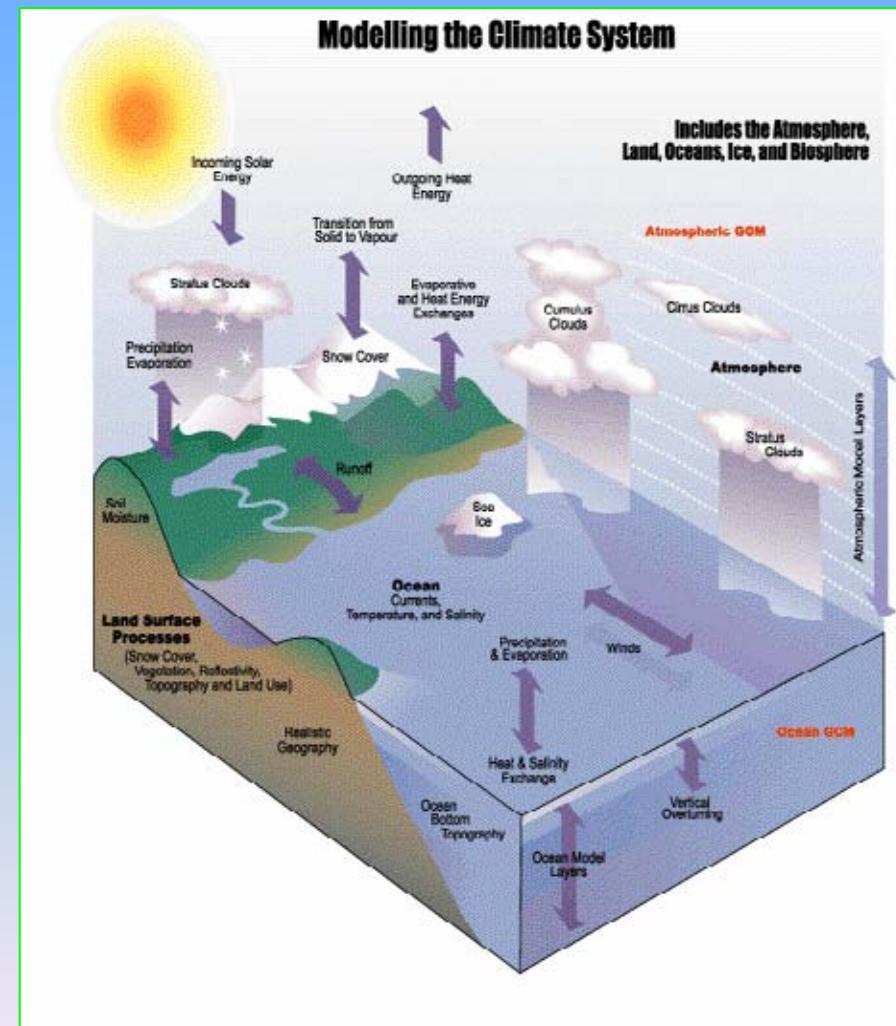
can simulate large scale circulation patterns (pressure, geo potential heights etc.)
can not reproduce non-smooth fields such as precipitation.

Scale Mismatch: spatial scale of a GCM: > 20, (e.g. For Coupled Global Climate Model (CGCM2) 3.75° in both latitude and longitude(375 Km.))

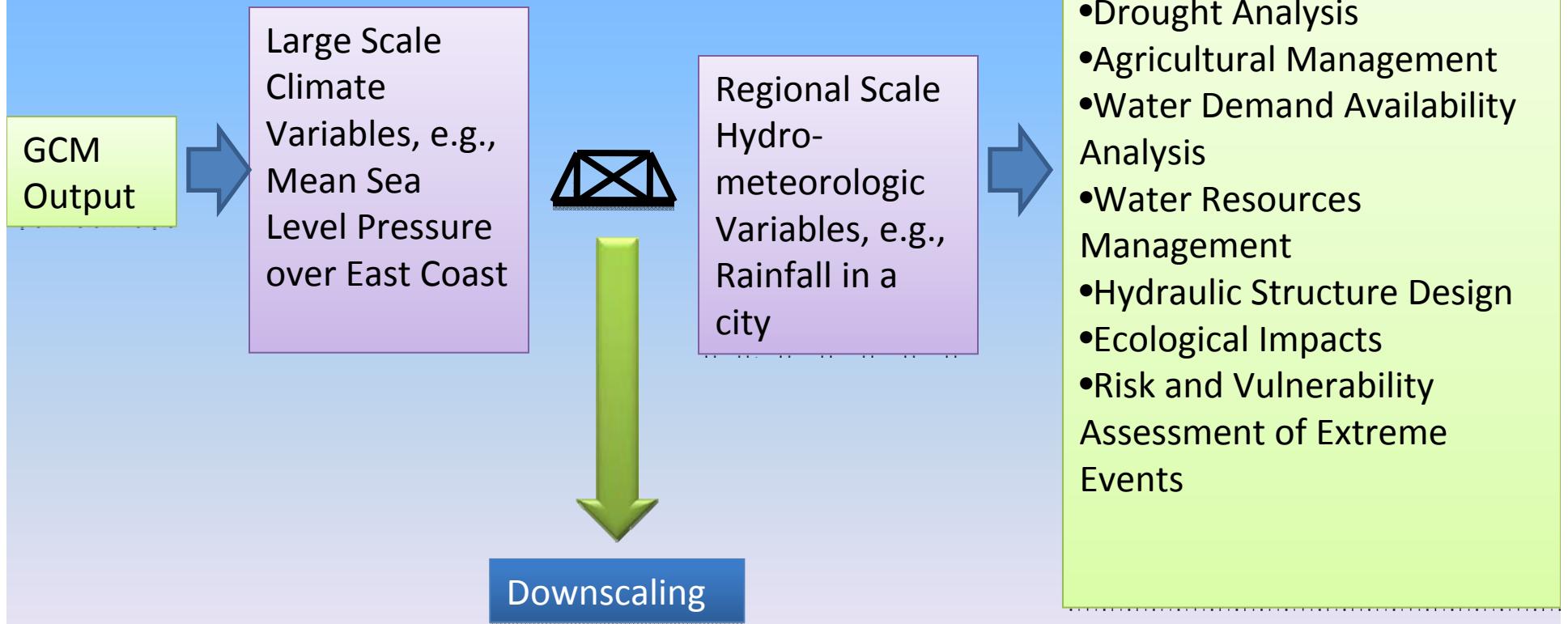
Scale for modeling hydrologic process (precipitation) :order of 10-100 Km

Downscaling: To predict hydrologic variable at local scale using global scale climatologic variable

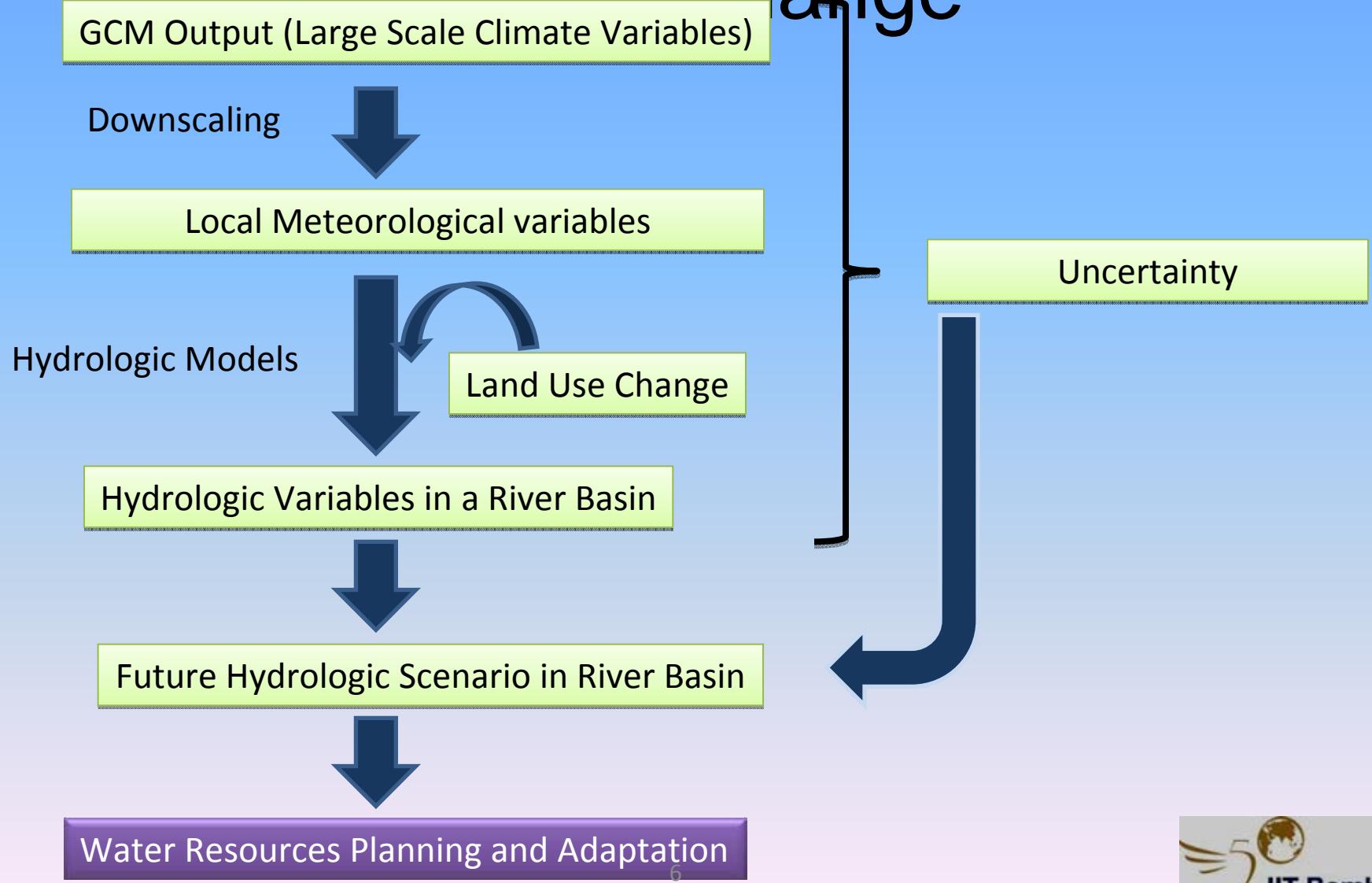
- Statistical Downscaling
- Dynamic Downscaling



Need for Downscaling

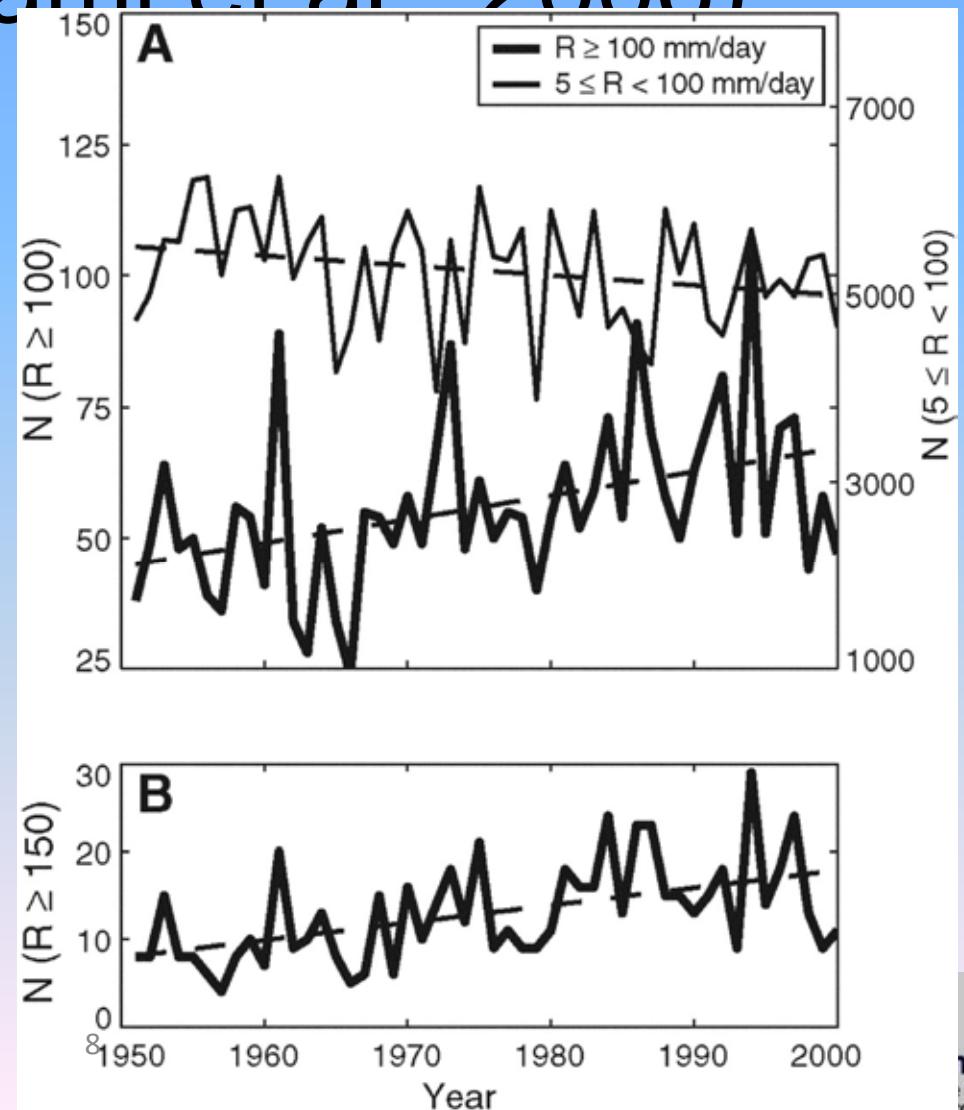
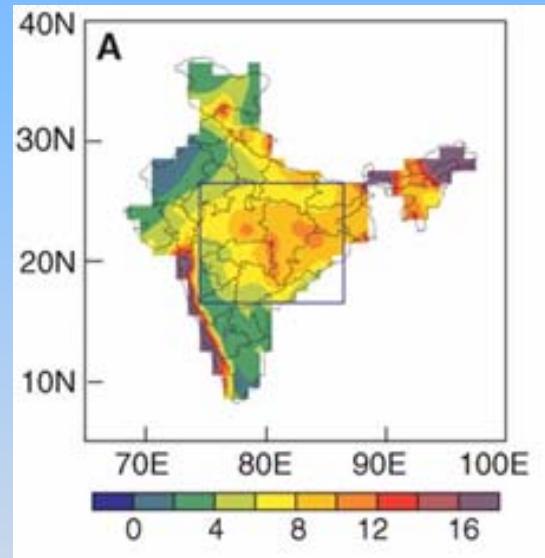


Modeling Hydrologic Impacts of Climate Change



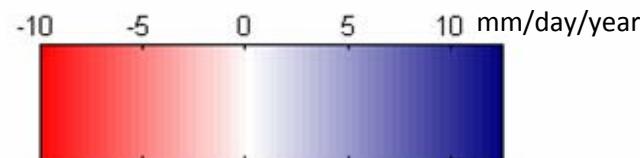
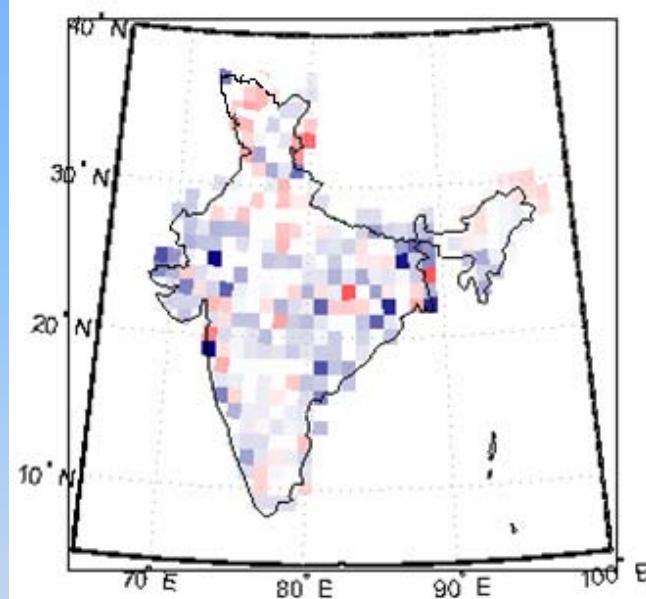
Regional Scale Studies: Why

Indian Rainfall Extremes Increased in Last 50 years Large Scale Study(Goswami et al 2006)

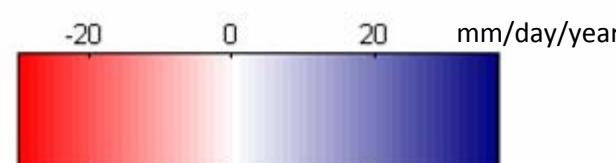
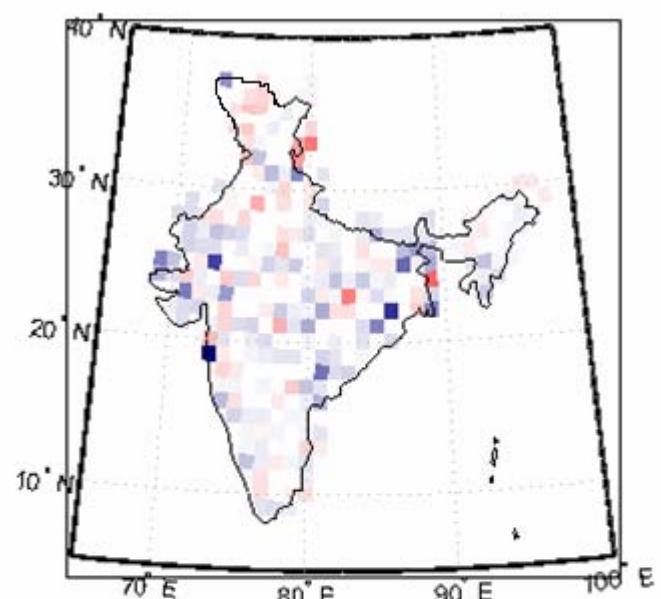


Spatial Variability of Indian Rainfall Extremes at Finer Scale

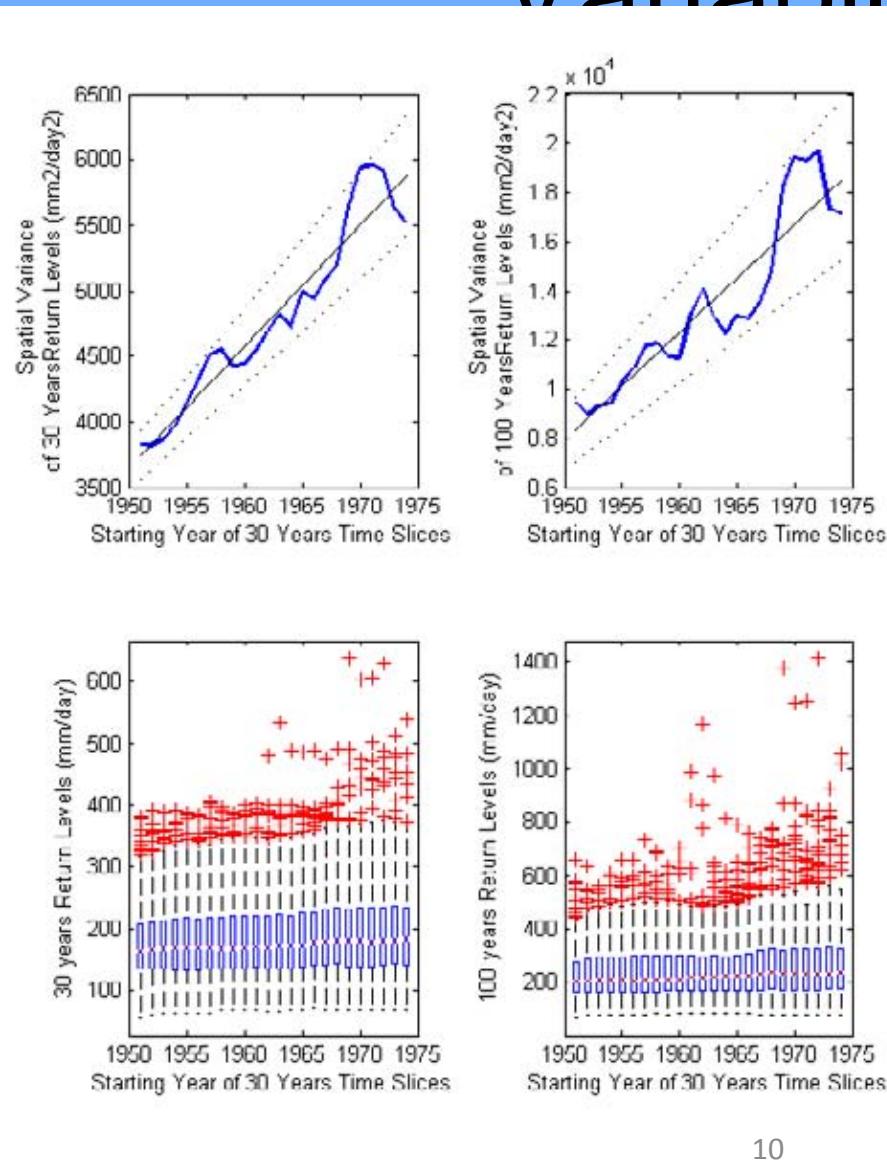
Trend of 30 year return levels



Trend of 100 year return levels



Increasing Trend in Spatial Variability



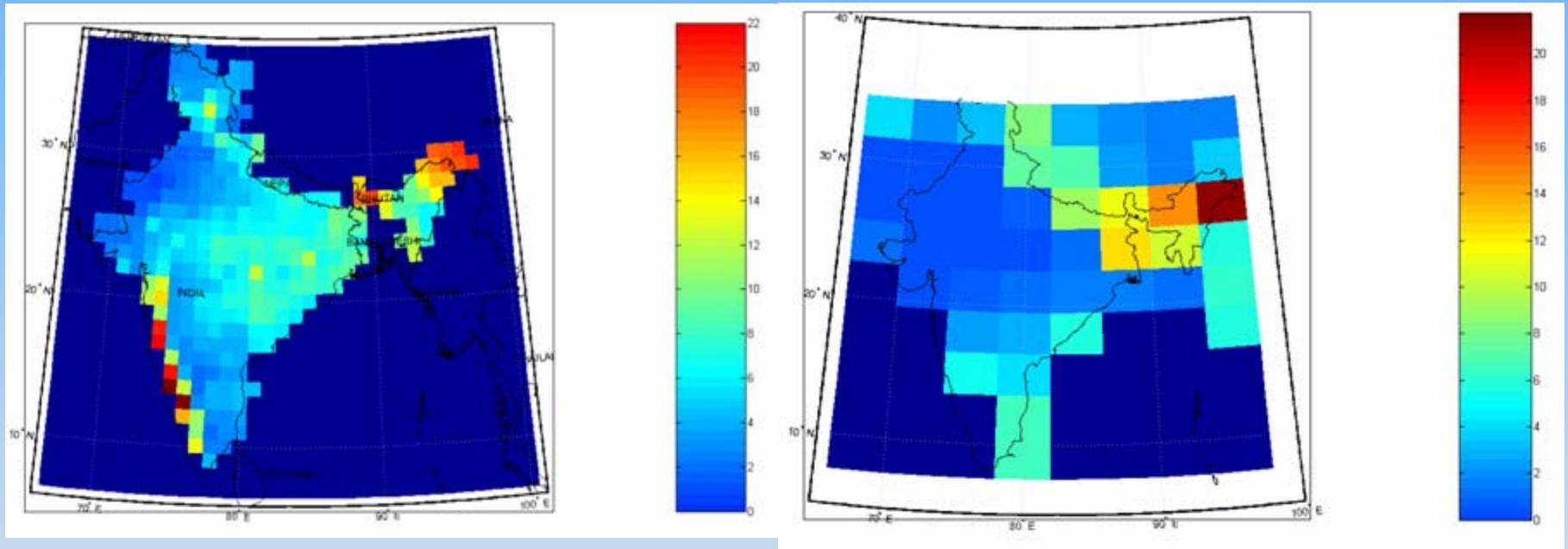
Tentatively accepted
in
**NATURE Climate
Change**
**Ghosh, S.; Das, D.
and Ganguly, A. R.
(2011)**

Single-site Statistical Downscaling

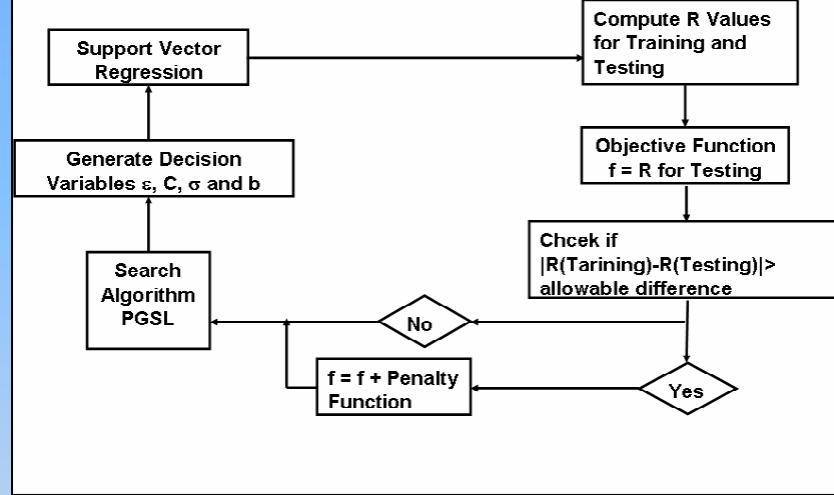
GCM Simulations of Precipitation

Observed (IMD)

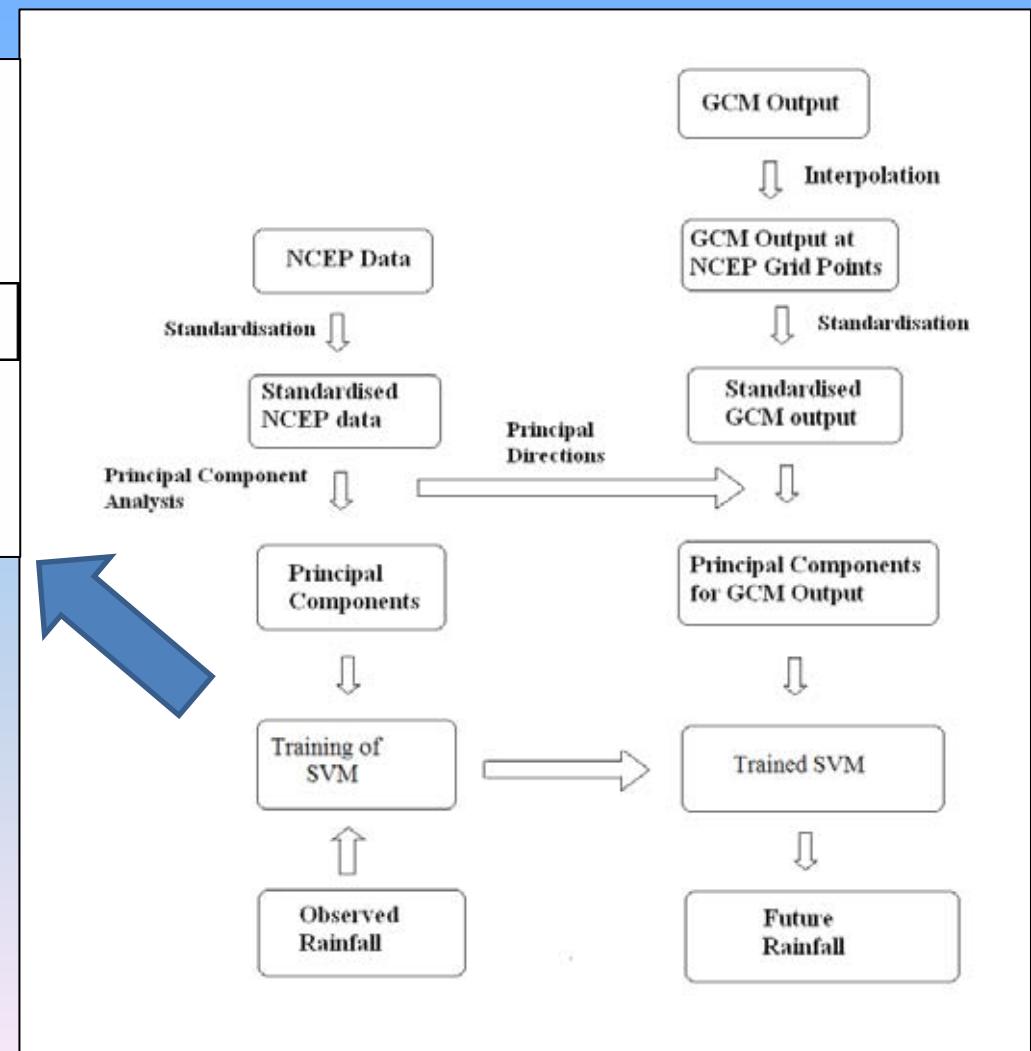
GCM Projections (GISS, NASA)



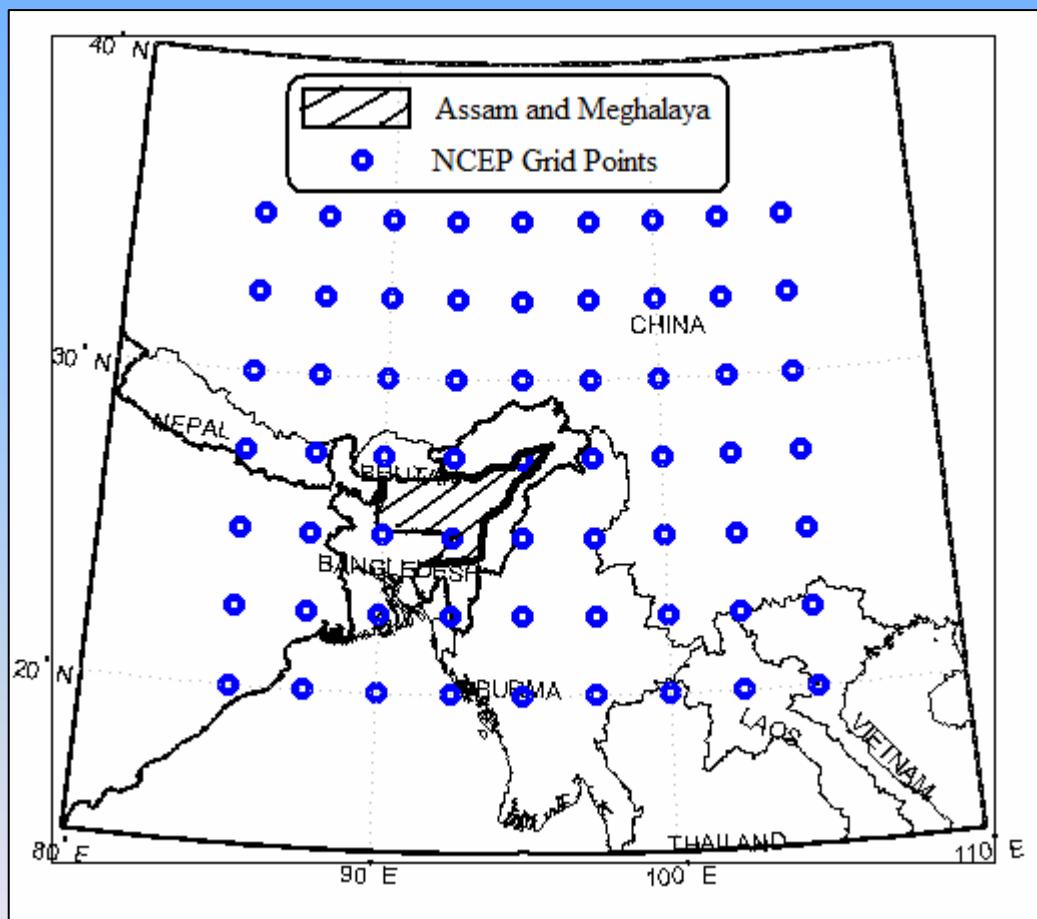
Single-site Downscaling Model



Ghosh, S. (2010),
JGR-Atm (AGU)



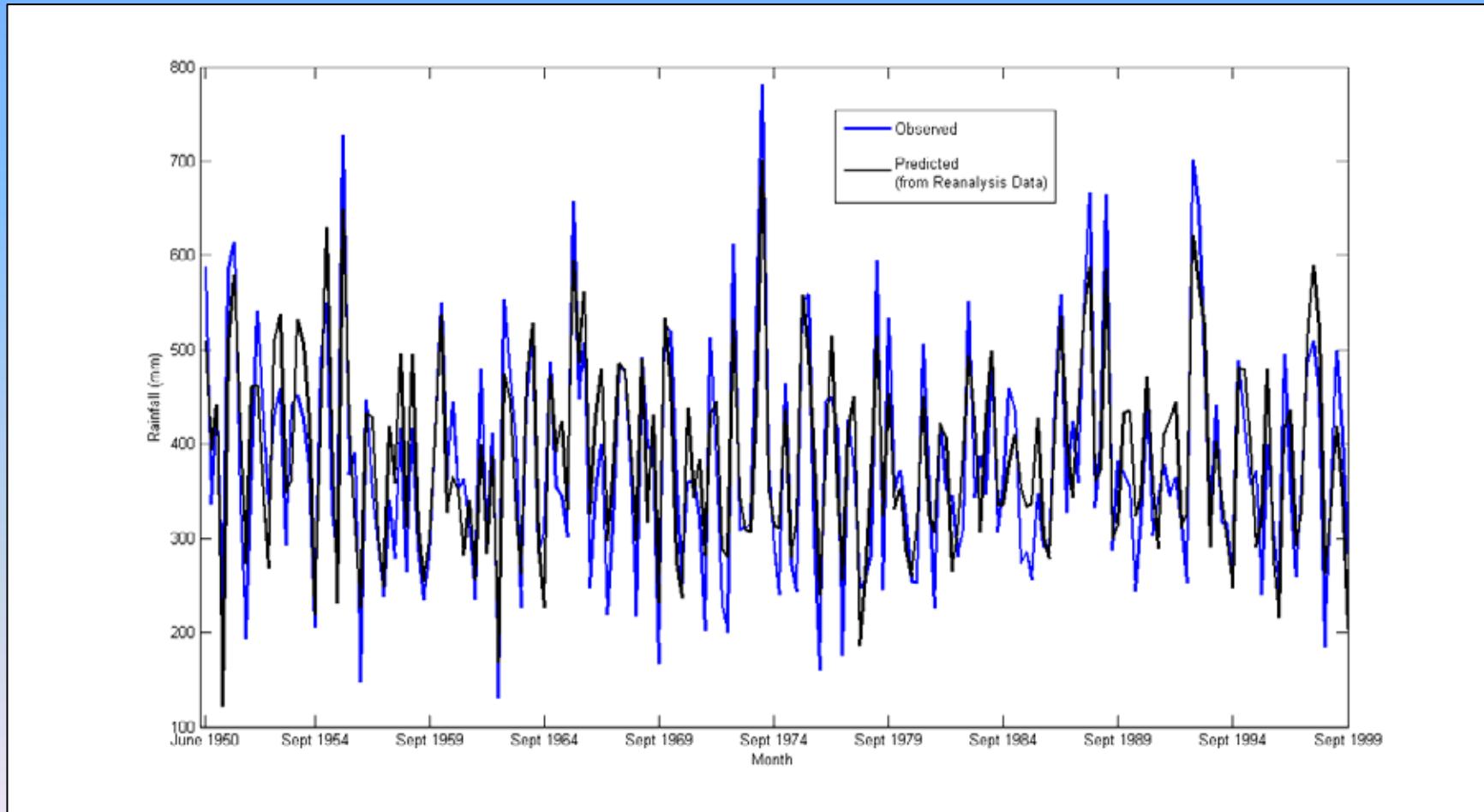
Case-Study



Predictors preliminary selected based on availability in GCM data archive:

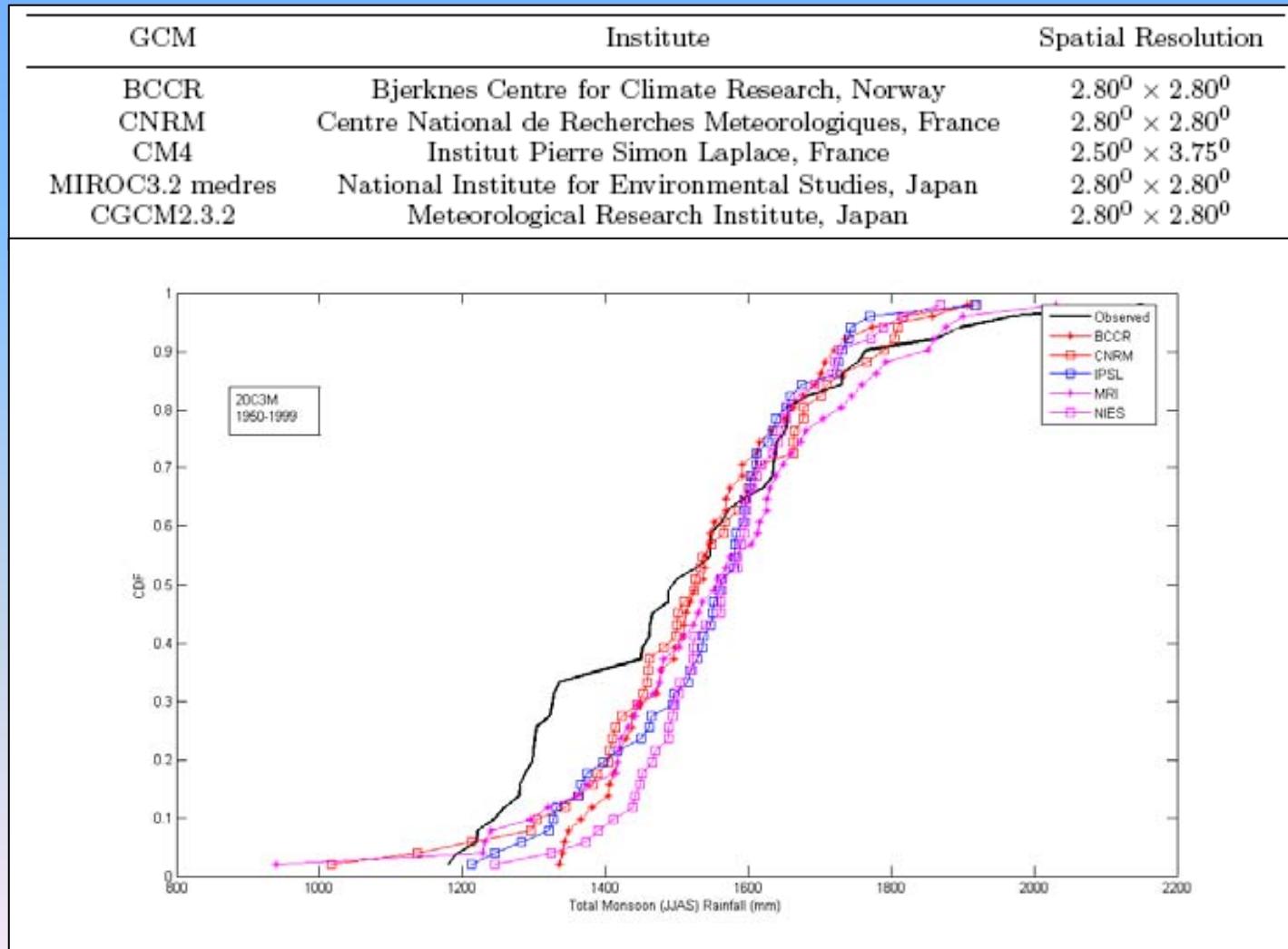
- Mean Sea Level Pressure
- Near Surface Temperature
- Surface Humidity
- Zonal Wind Speed
- Meridional Wind Speed

Regression with NCEP/NCAR Reanalysis Data (Assam and Meghalaya)

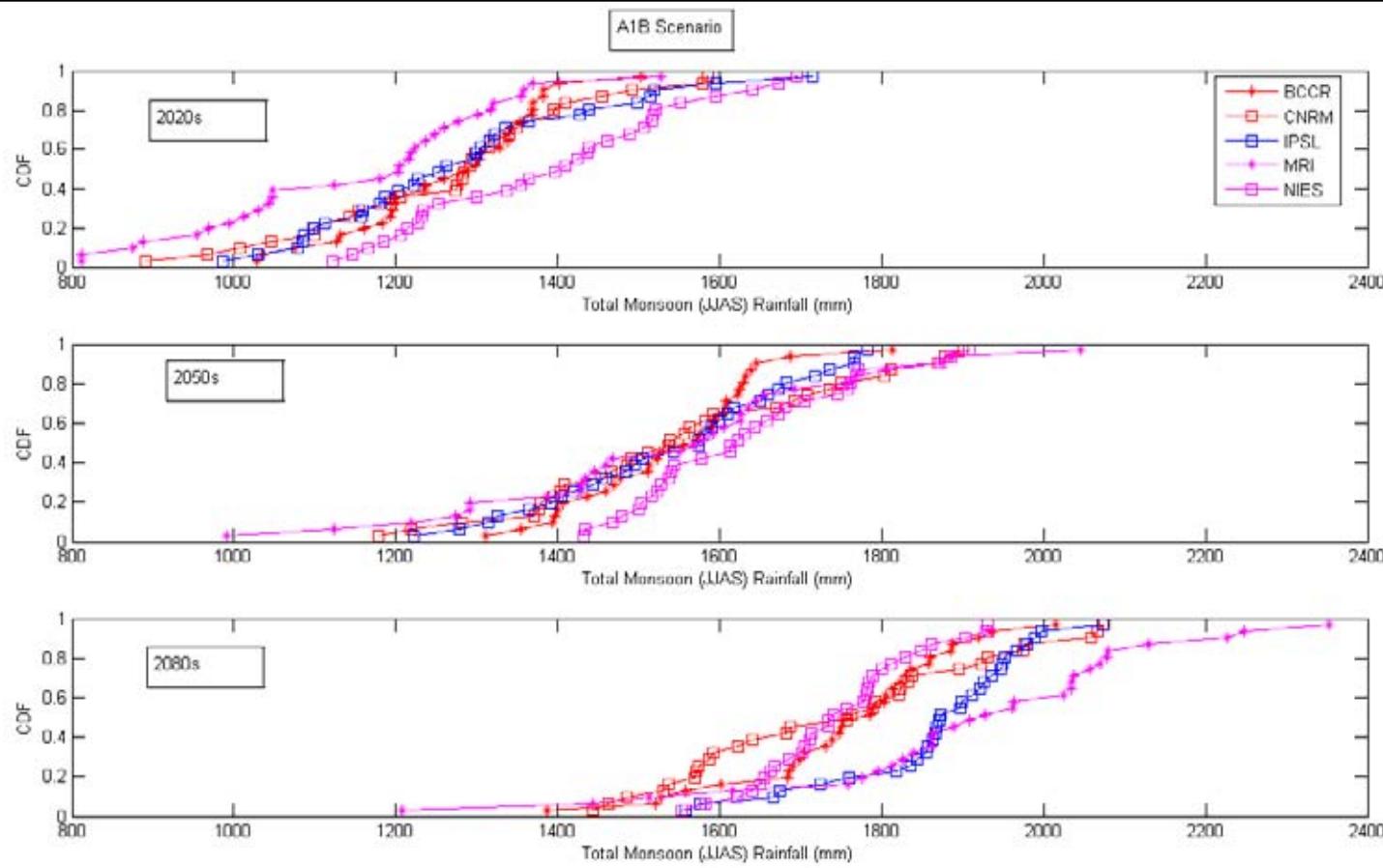


Nash-Sutcliffe Coefficient = 0.65

GCMs Considered and 20C3M Results



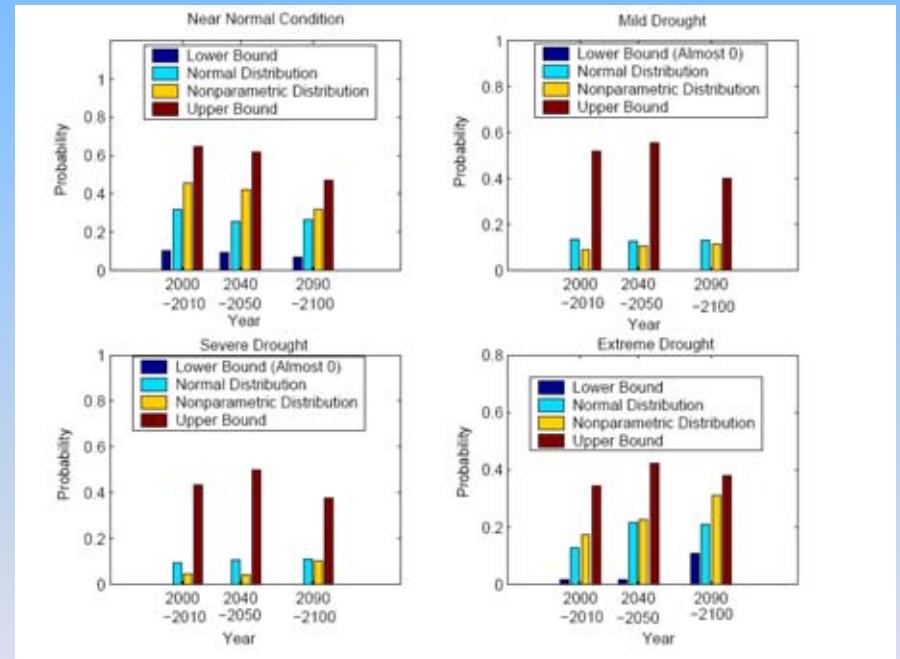
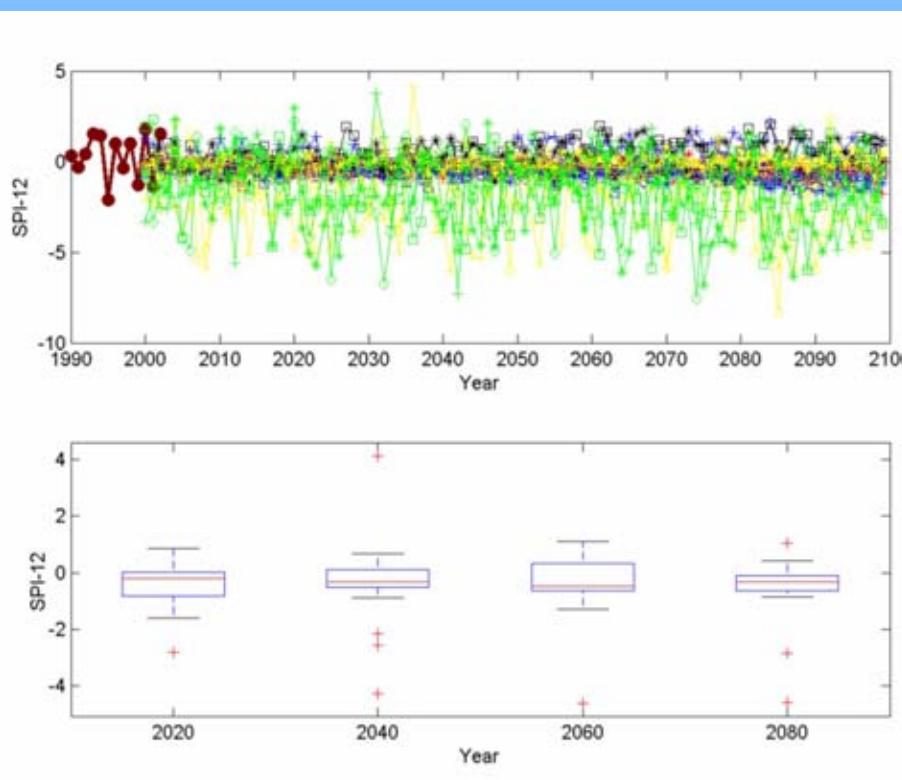
Results with A2 Scenario



Uncertainty Modeling

Methodologies Developed

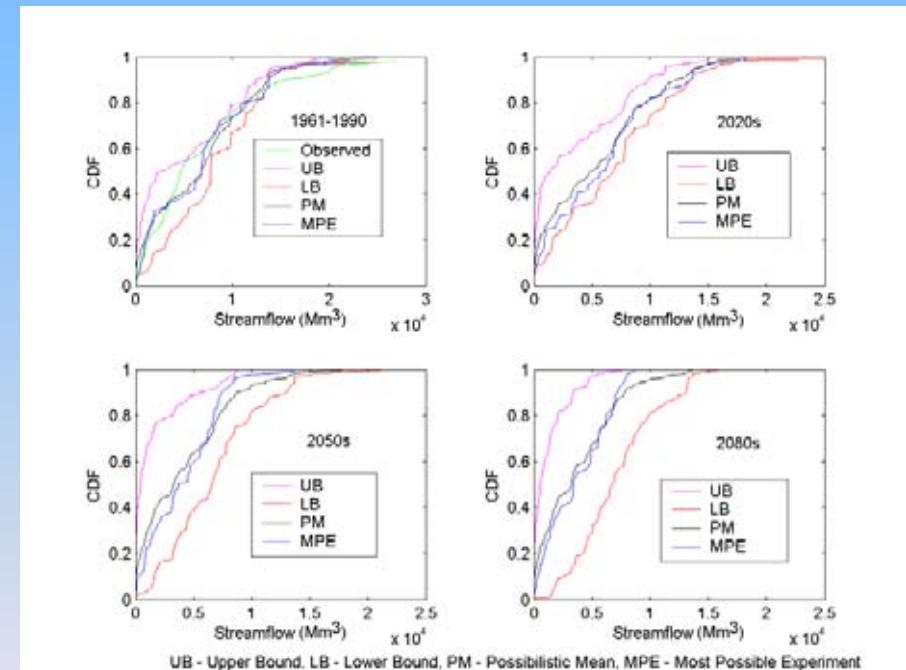
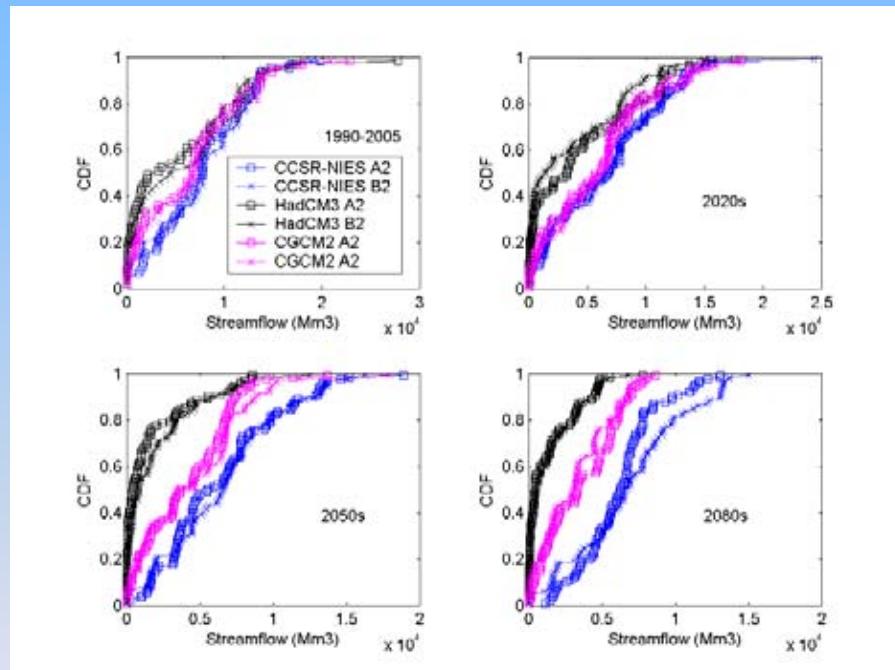
- Assuming all GCMs are equally accurate → nonparametric statistical approaches → Applied to analyze projected drought scenario in Orissa



Ghosh and
Mujumdar (2007),
WRR (AGU)

Methodologies Developed (Contd..)

- Based on performances of GCMs: Observed period → Possibility Theory
(Applied to Mahanadi Streamflow)

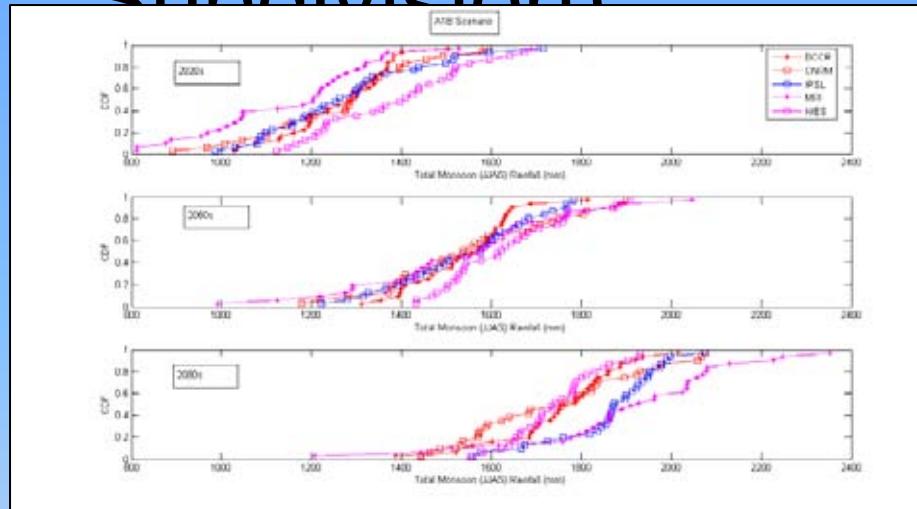


Mujumdar and
Ghosh (2008), WRR
(AGU)

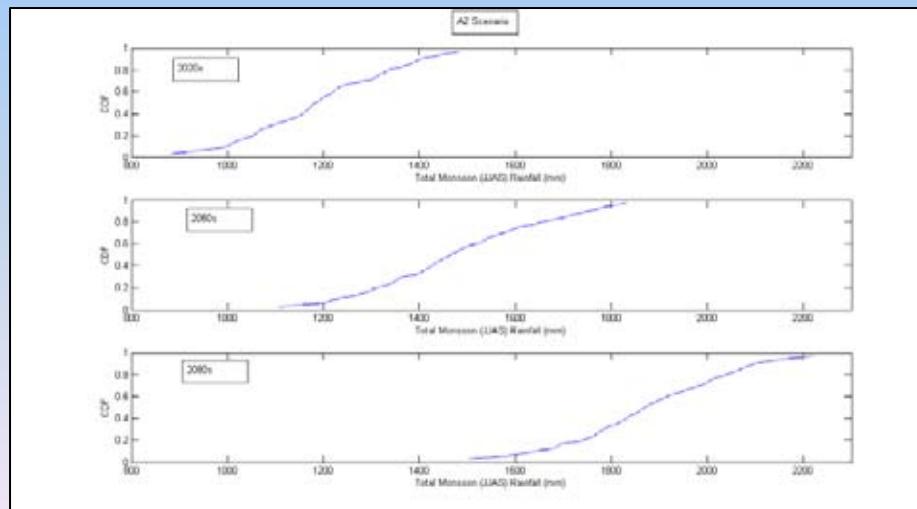
Modeling Uncertainty: Reliability Ensemble Averaging

- Weight assignment based on model performance and model convergence to GCMs
- Model Performance: Deviation of CDF of GCM generated rainfall for 20C3M (1951-2000) with respect to observed rainfall.
- Computation of deviation: Deviation in terms of mean and standard deviation
- Model Convergence: Deviation of CDF of GCM generated future rainfall with respect to weighted mean CDF.
- Average of weights from model performance and model convergence criteria

Weighted Mean CDF for A2 Scenario (Assam and Meghalaya Meteorological Subdivision)



Ghosh, S. (2010),
JGR-Atm (AGU)

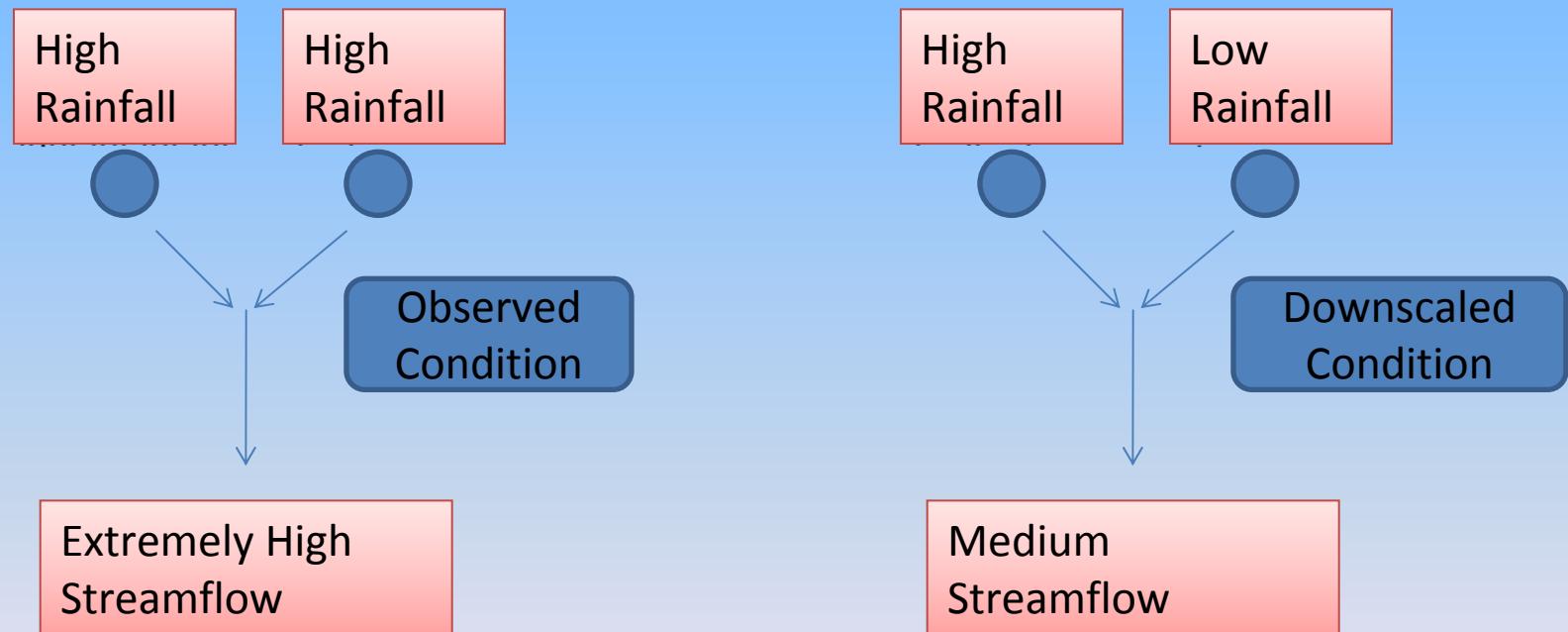


Multi-site Daily Downscaling

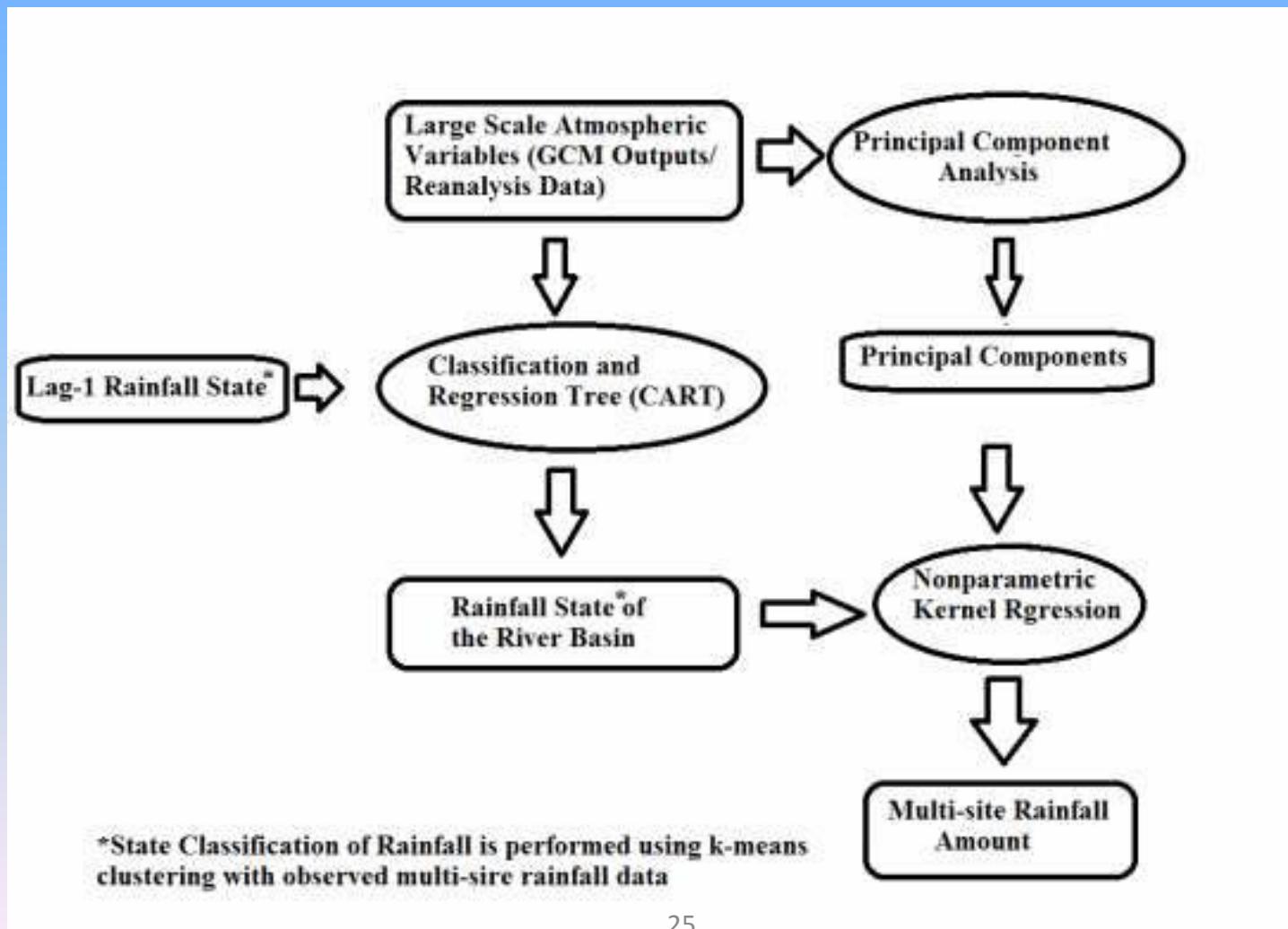
Multi-site Downscaling

Challenges:

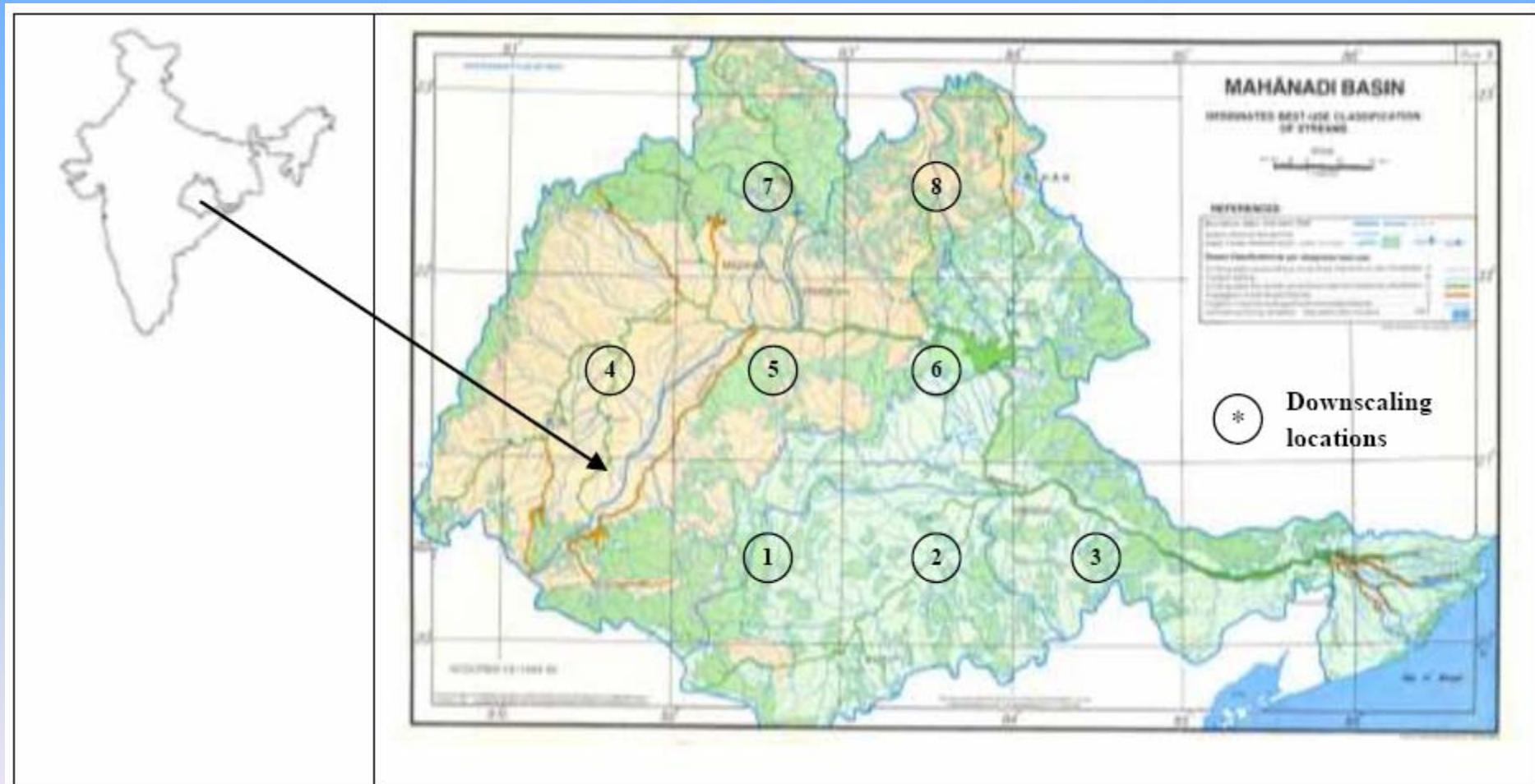
- Modeling Variability
- Spatial cross correlation



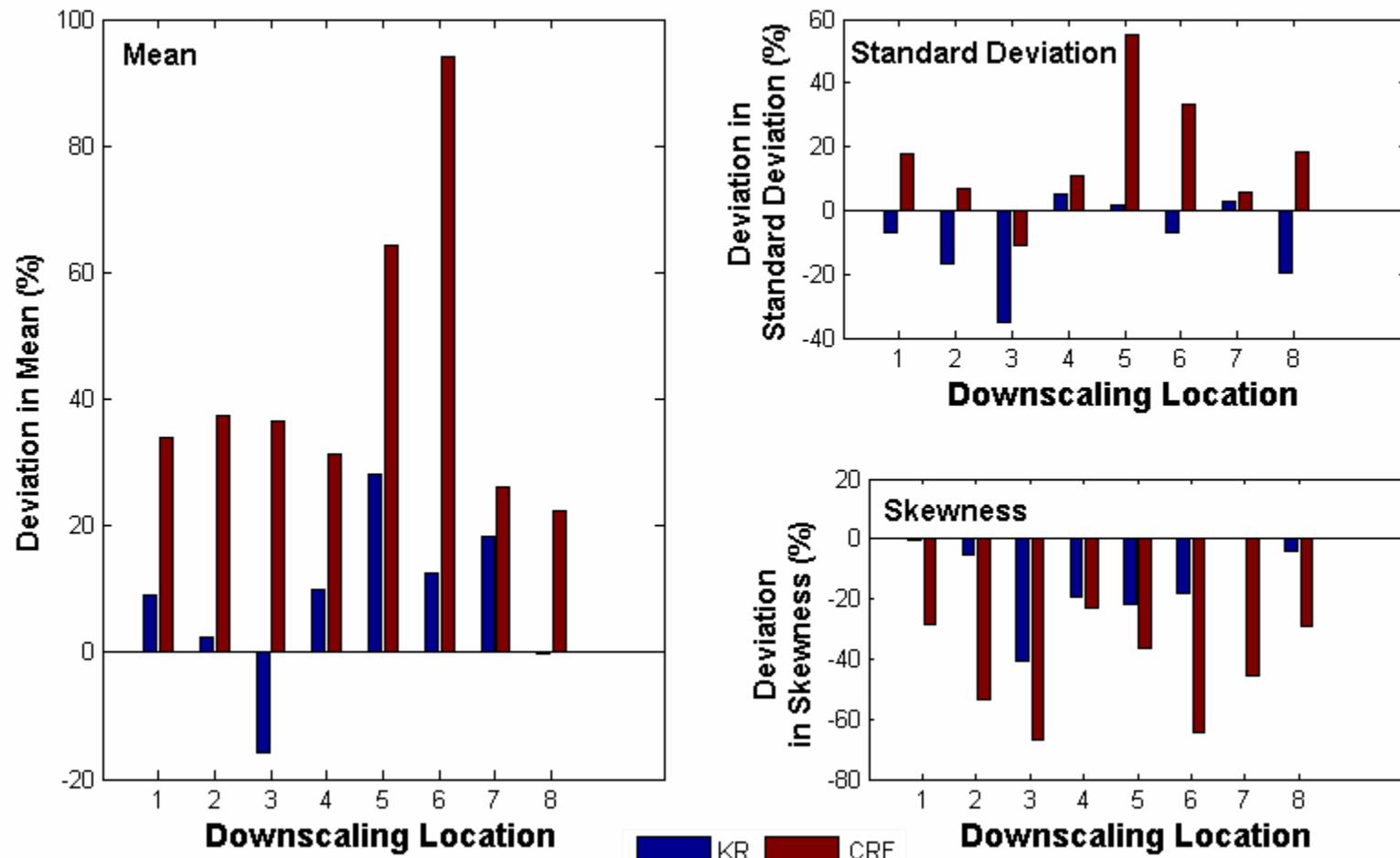
Algorithms for Multi-site Downscaling



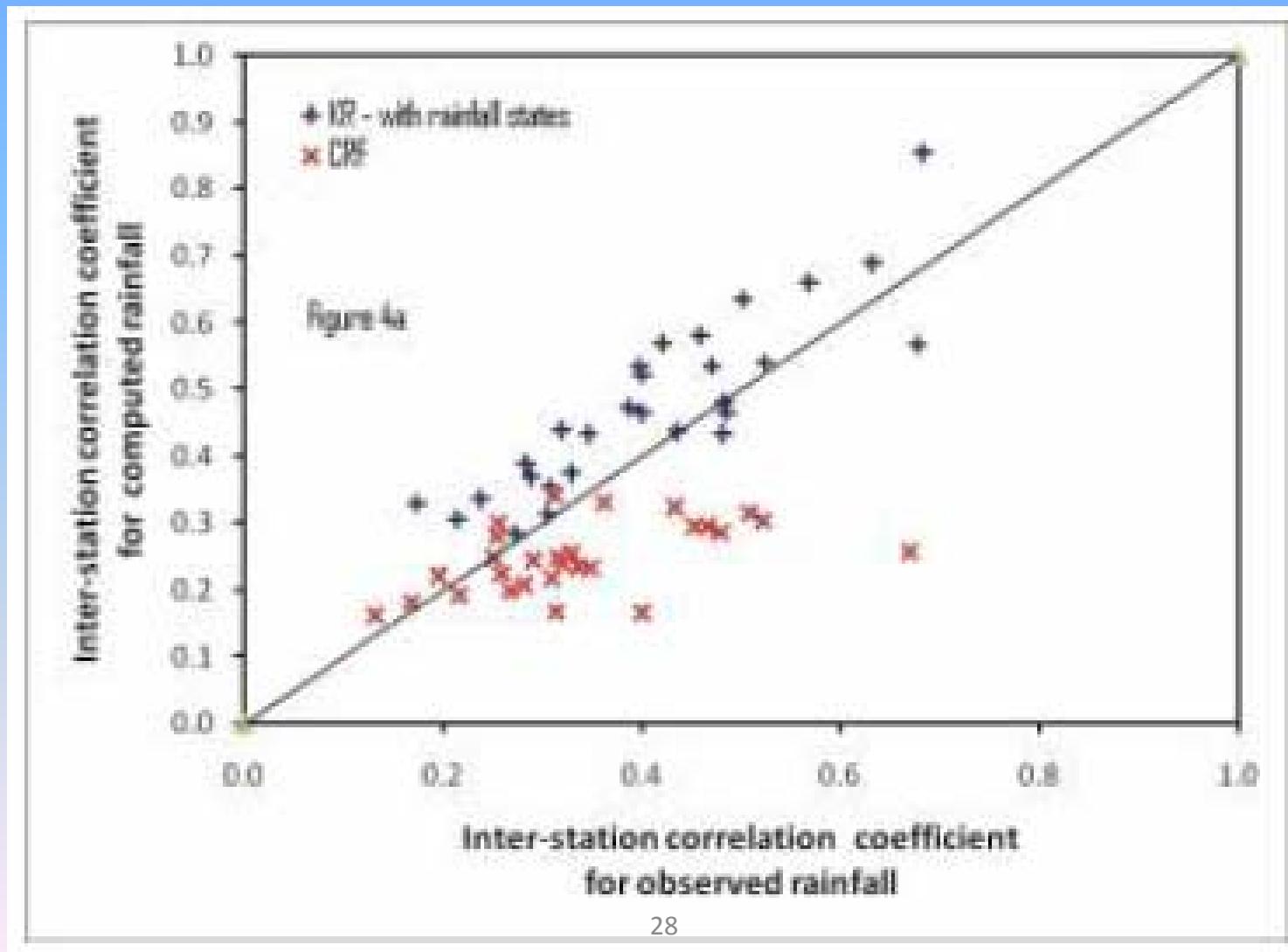
Applied to Mahanadi Basin



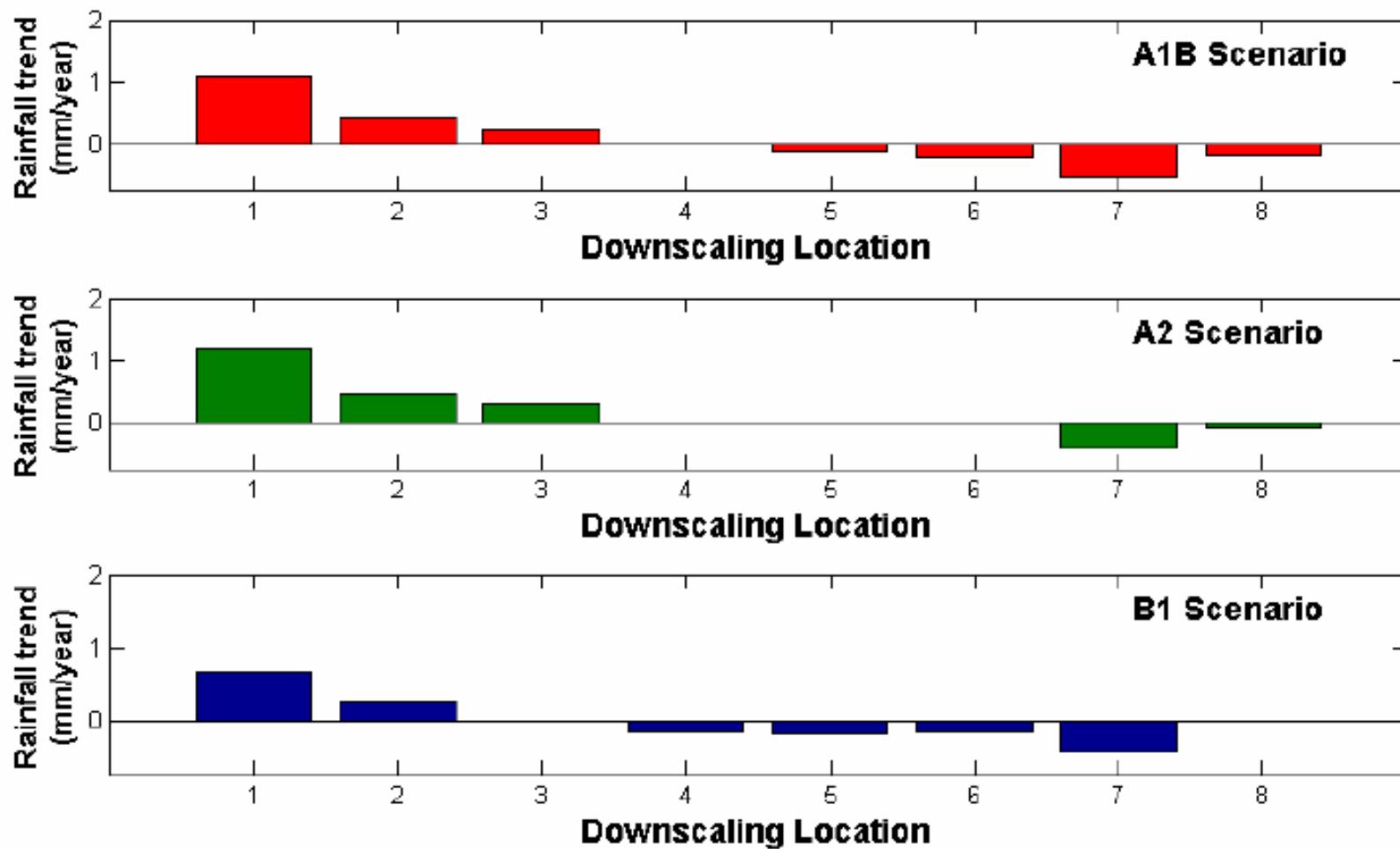
Comparison with CRF [Raje and Mujumdar, 2009] (Error Plot)



Comparison with CRF: Spatial Correlation



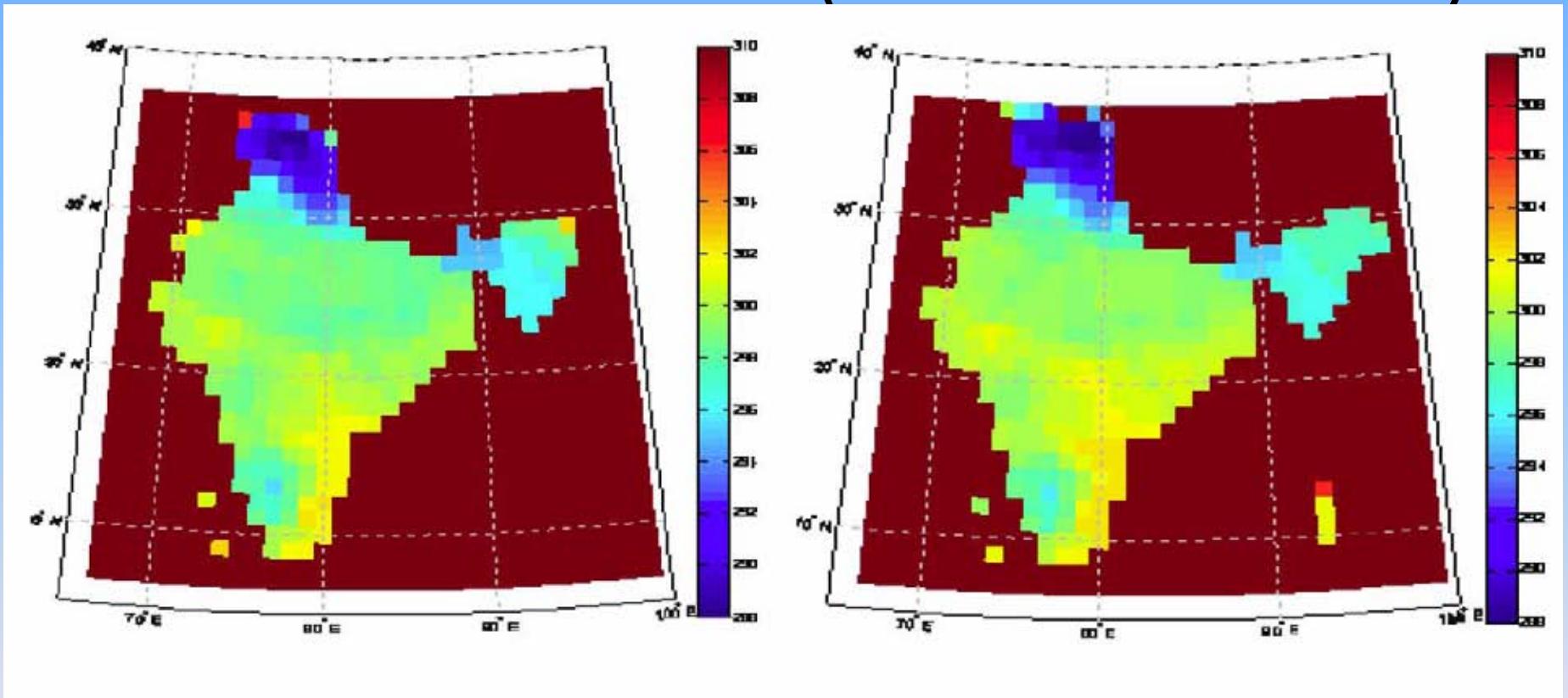
Future Projection (2000-2100)



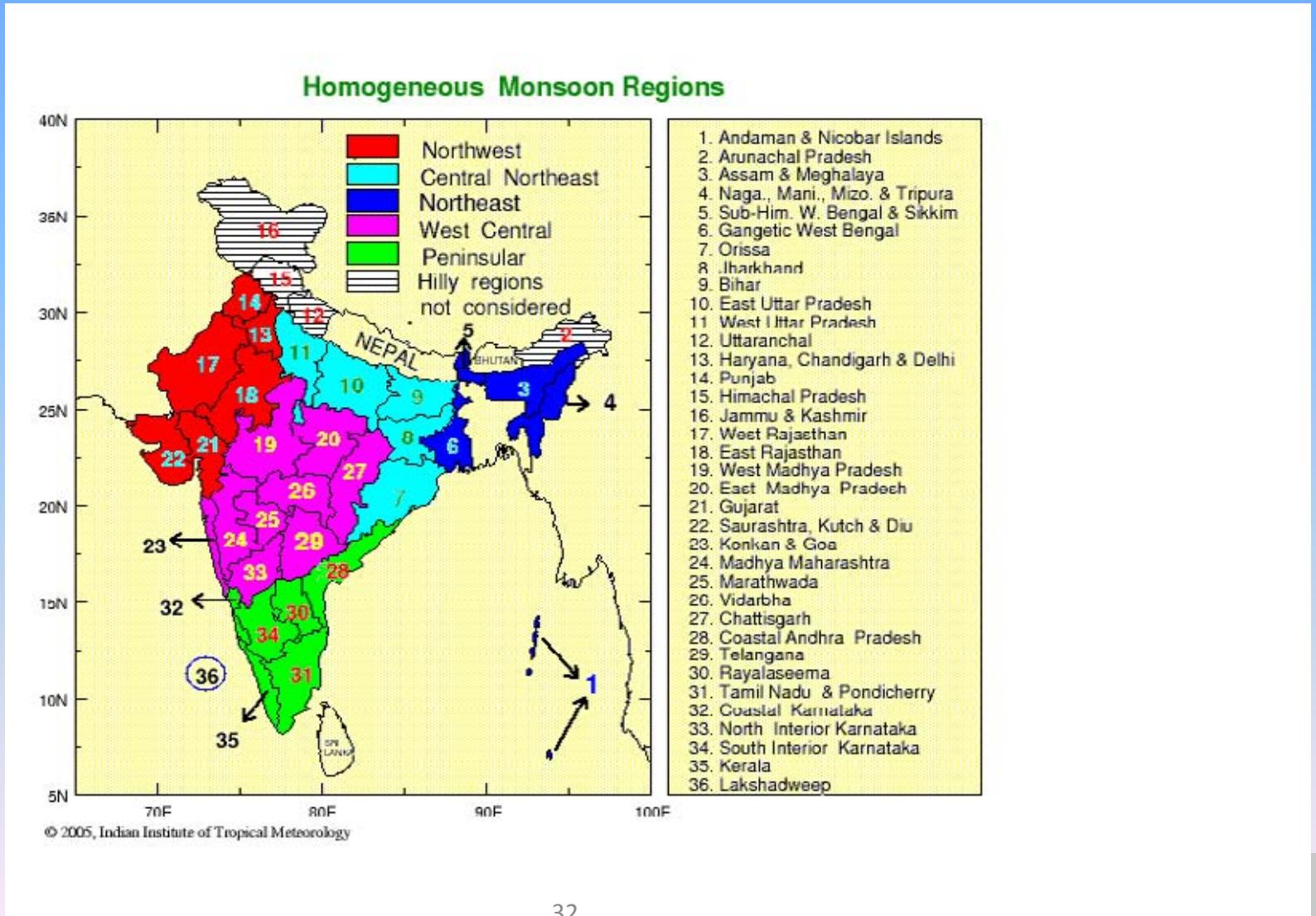
Ghosh, S. and Kannan S (2011), WRR (AGU)
[Revised Manuscript Submitted]
29

Applications to All India (On-going work)

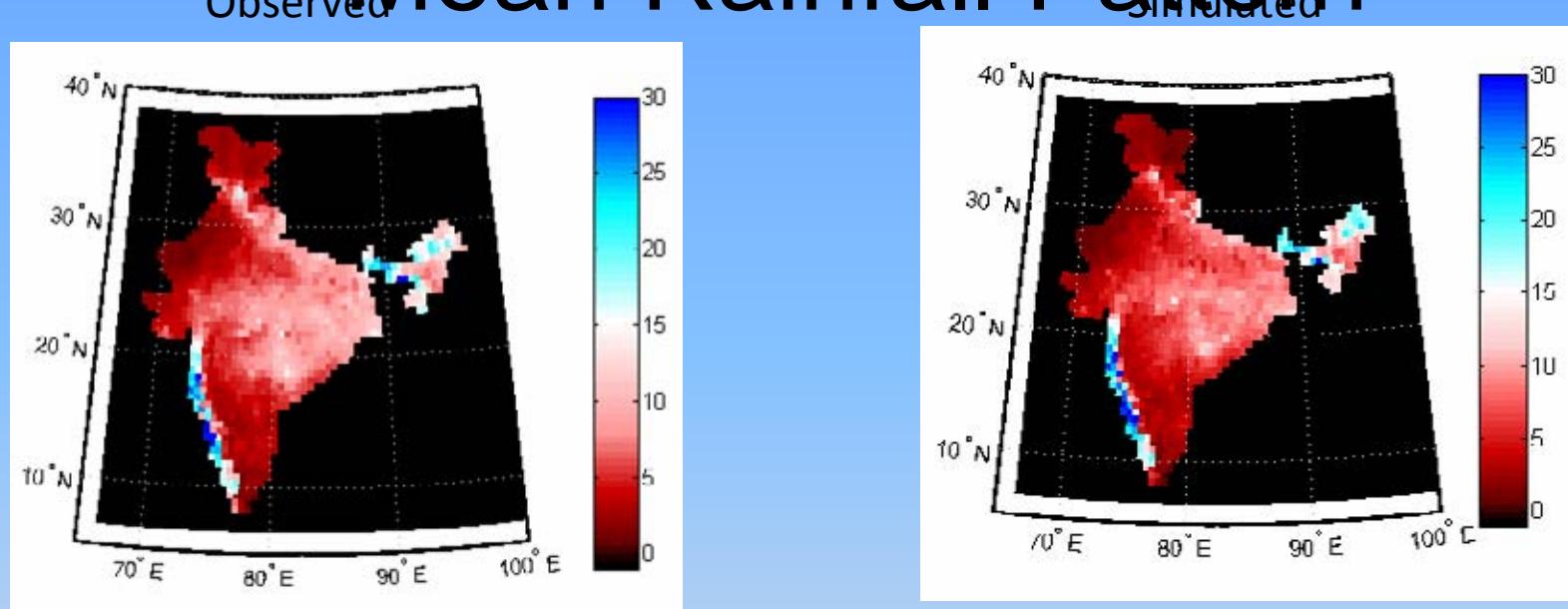
Simulating Temperature (Mean) in India with CGCM3 (Bias Corrected)



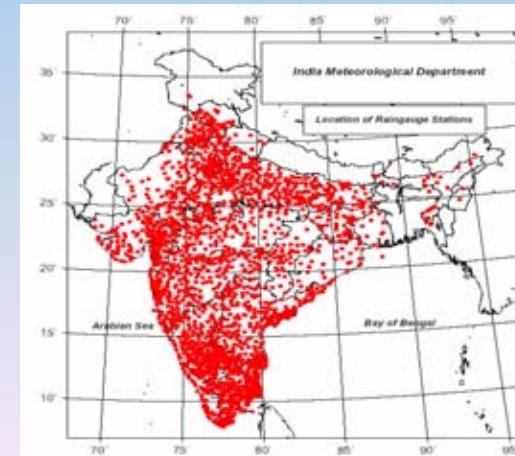
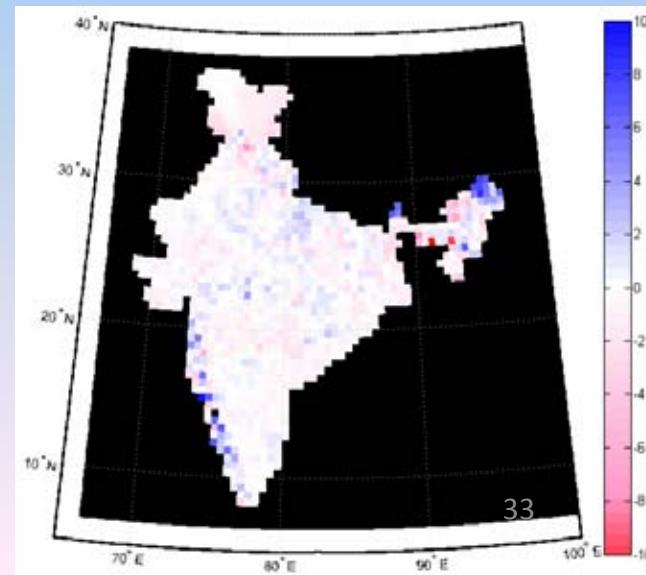
Downscaling to ALL INDIA



Simulations for Observed Period: Mean Rainfall Pattern

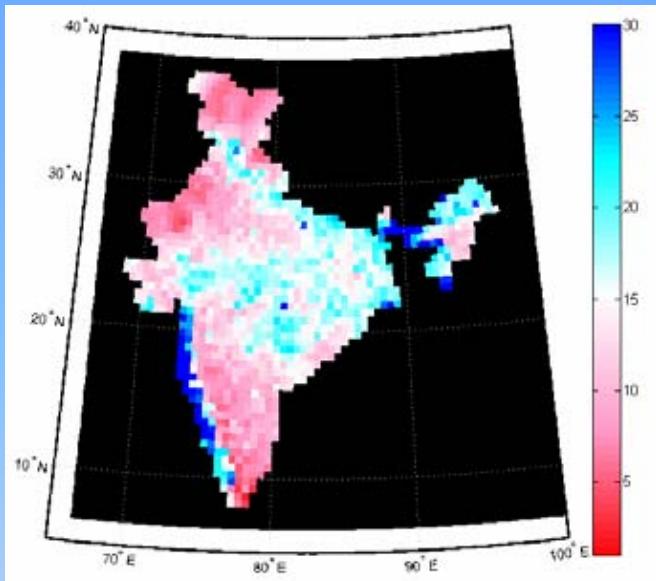


Simulated-observed

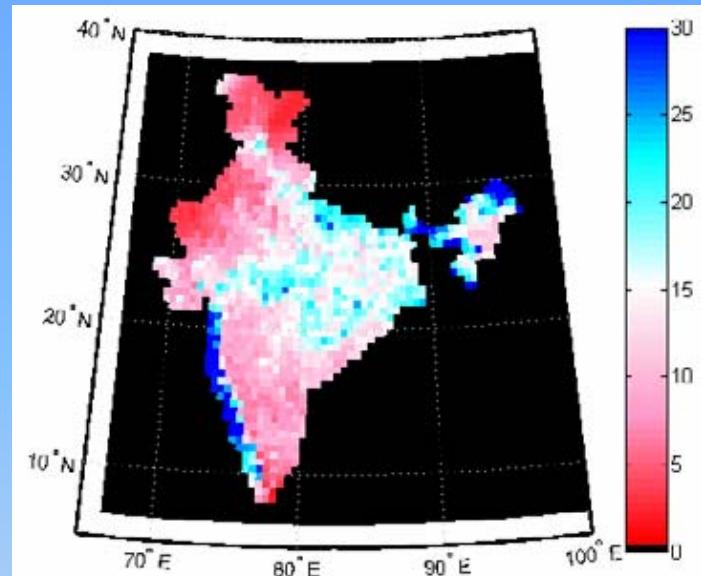


Comparison of Standard Deviation

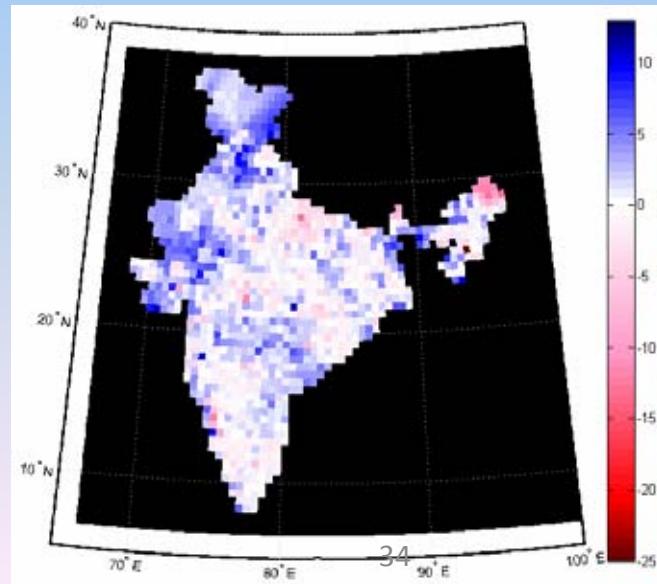
Observed



Simulated

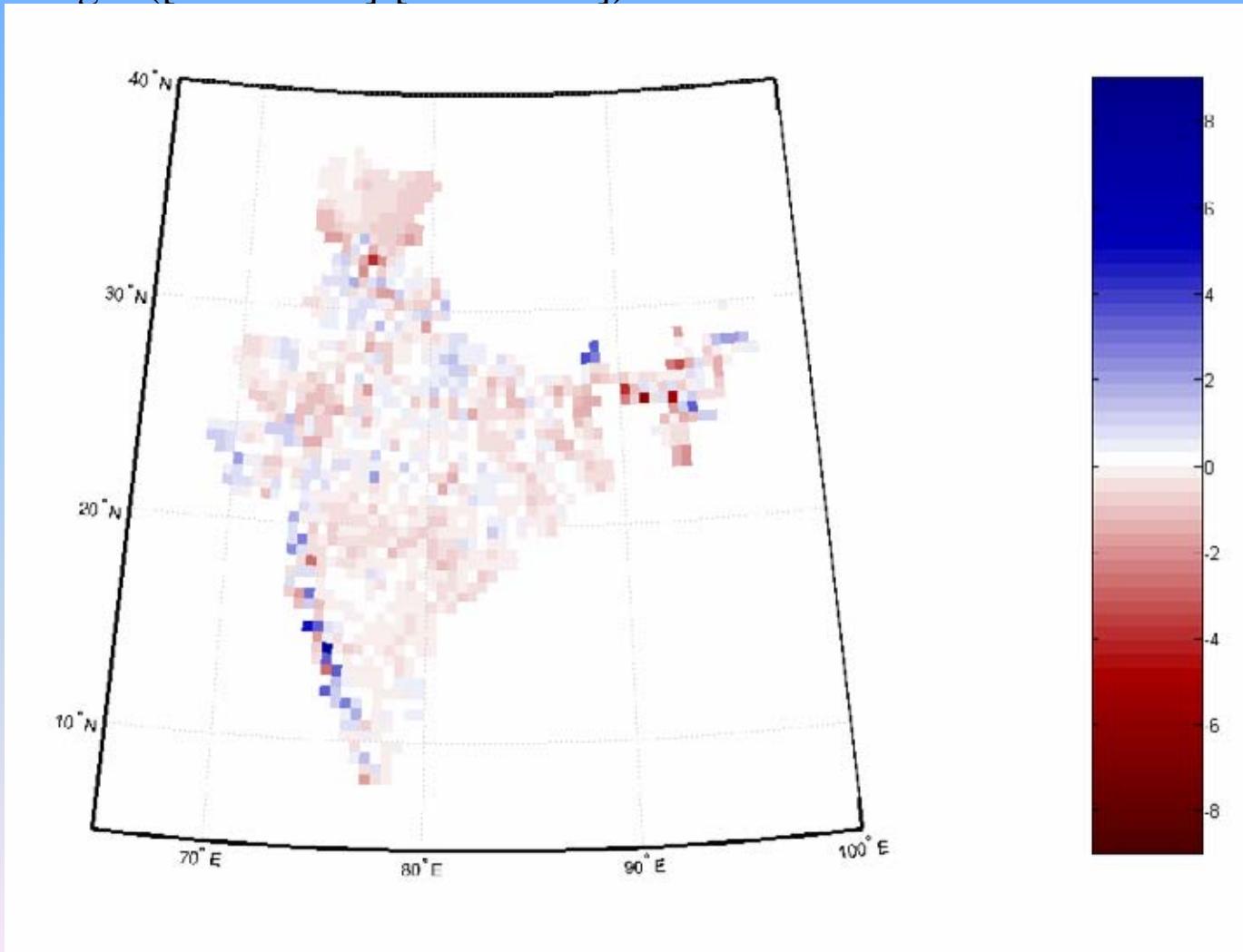


Observed-simulated



Future Projected changes in Mean (A2 Scenario)

- Changes ([2011-2040]-[1961-1990])



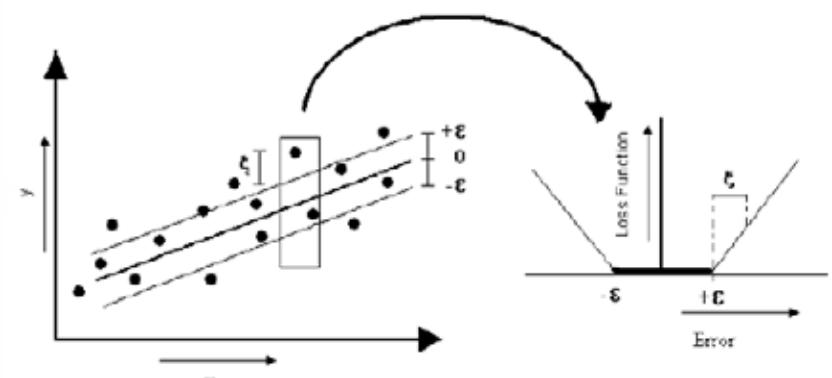
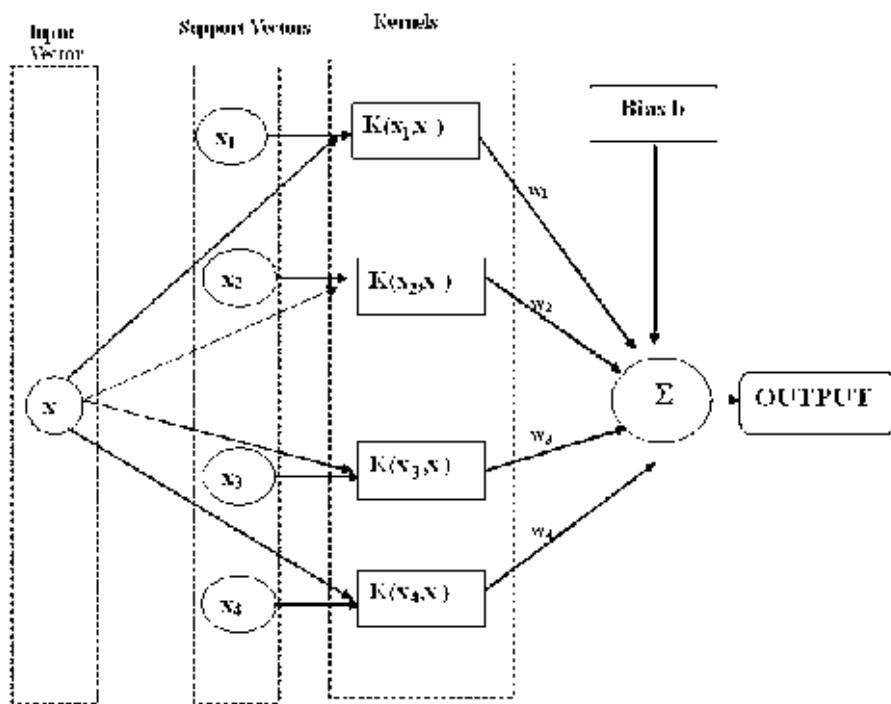
Summary and Concluding Remarks

- Indian rainfall needs to be studied at finer resolution.
- GCM outputs must be downscaled to study hydrologic scenario.
- Uncertainty Modeling: a major part in climate change impacts assessment
- Indian rainfall: no uniform trend or projection, spatially varying trend and projections.



Thank You

Support Vector Machine (SVM)



$$f(x) = \sum_{i=1}^l w_i \times K(x_i, x) + b$$

Training Objective:
Maximize Flatness + C*Minimize Error

$$K(x, x') = \exp\left(-\frac{\|x - x'\|^2}{2\sigma^2}\right)$$

Parameters of SVM Controlling Training and Selection

- Parameters
 - b
 - σ
 - ε
 - C
- Selection:
 - Maximize the performance for testing data set, which is independent of training
 - Minimize the difference of performance measure between training and testing

Optimization Model for Selection of SVM Parameters

Maximize $r(test)$

subject to

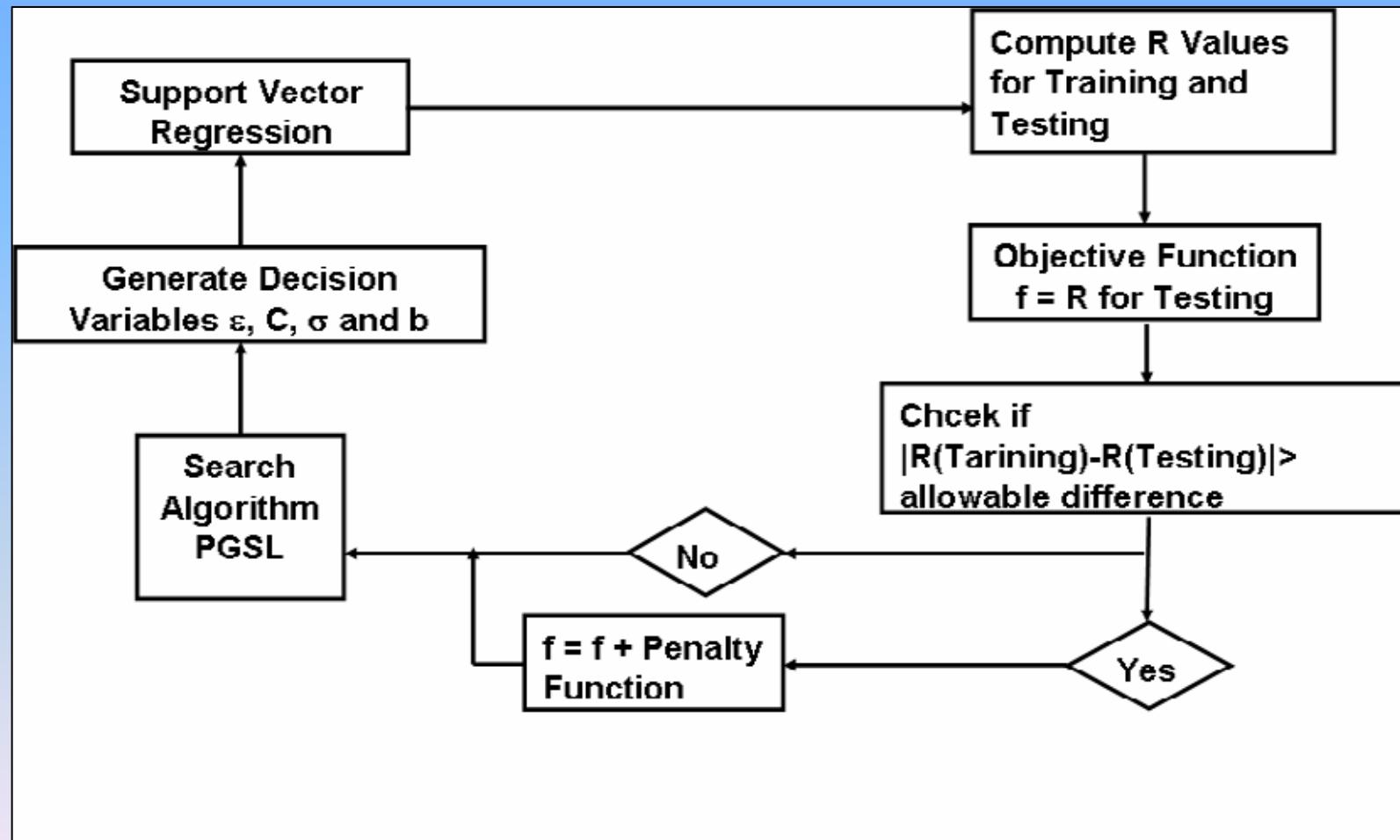
$$|r(train) - r(test)| \leq d$$

$r(train)$ = correlation coefficient ($y_{predict}^{train}, y_{observed}^{train}$)

$r(test)$ = correlation coefficient ($y_{predict}^{test}, y_{observed}^{test}$)

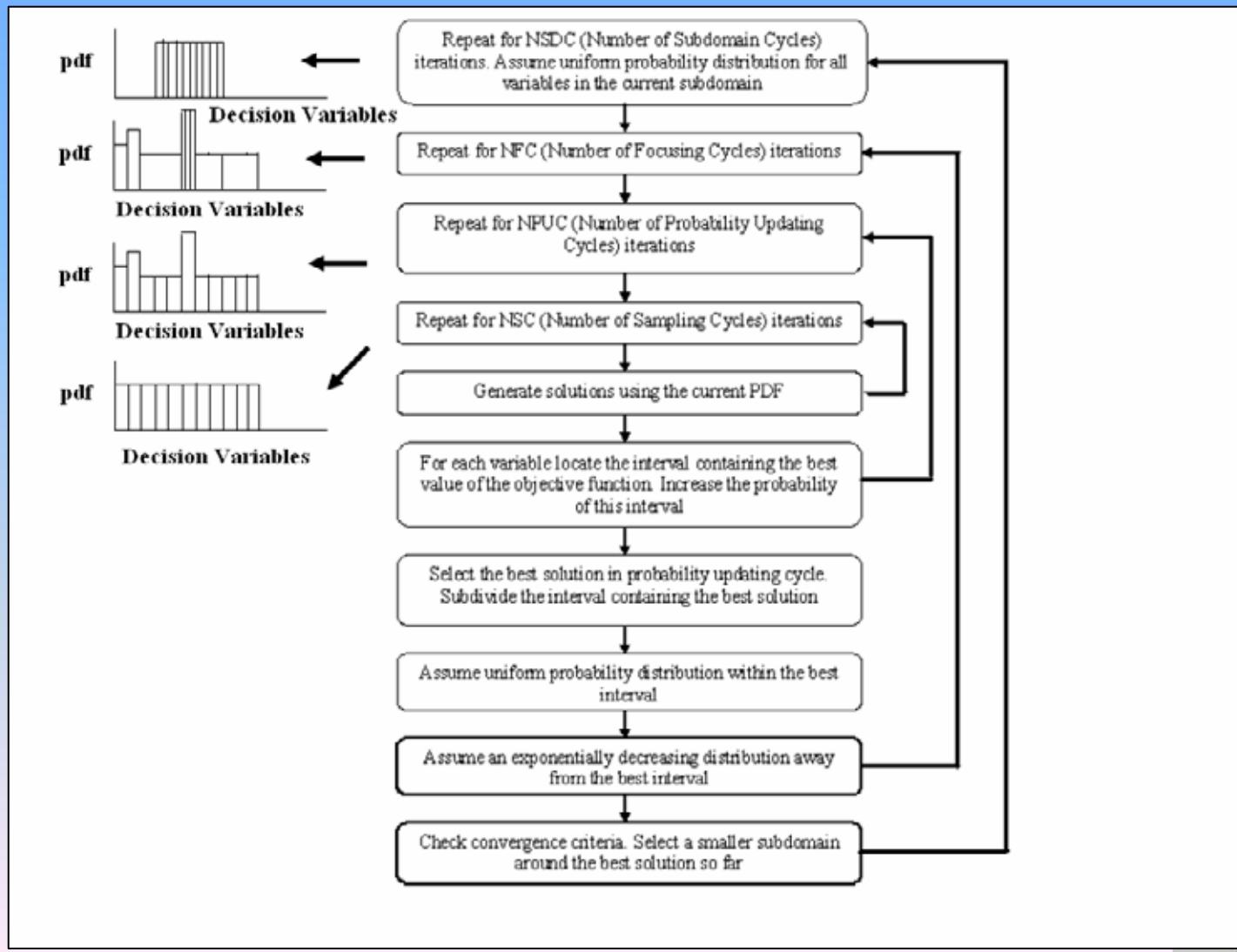
$r(test) = f(C, b, \sigma, \varepsilon)$

SVM Coupled with Search Algorithm

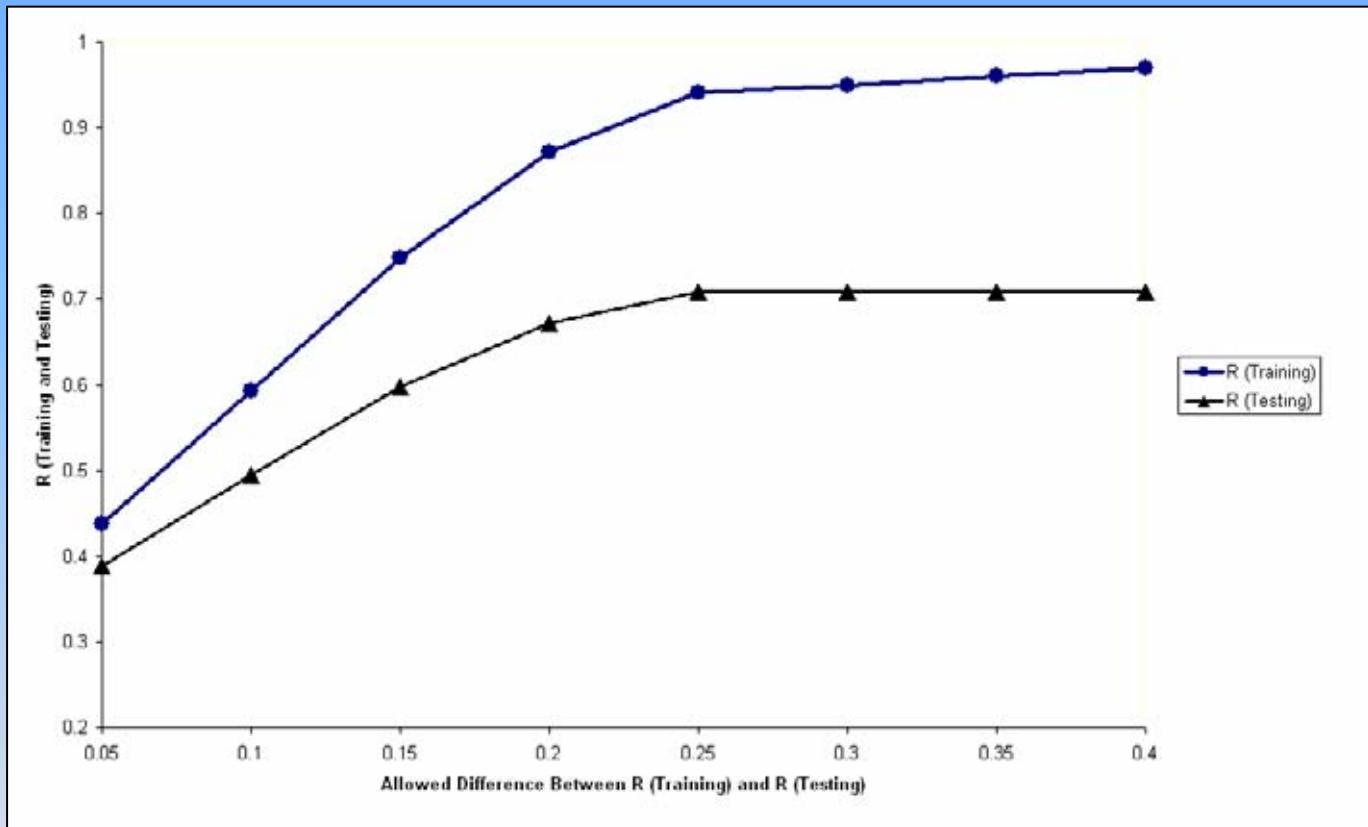


Probabilistic Global Search

Laussane



Results



Results from Linear Regression

$$r(\text{train})=0.82 \\ r(\text{test})=0.62$$

Results with ANN

$$r(\text{train})=0.86 \\ r(\text{test})=0.64$$

With allowable difference = 0.2, $r(\text{train}) = 0.87$, $r(\text{test})=0.67$

With grid search method, $r(\text{train}) = 0.97$, $r(\text{test})=0.68$

With empirical equation (Cherkassky and Ma, 2004), $r(\text{train}) = 0.82$, $r(\text{test})=0.61$

Flowchart for Uncertainty Modeling

