Revisiting Statistical Downscaling Methods
- Richardson WG & BCSD

Prof. Ke-Sheng Cheng

Dr. Yii-Chen Wu

Department of Bioenvironmental Systems Engineering

National Taiwan University

Downscaling Climate Data

- **Downscaling climate data is a strategy for generating locally relevant data from General Circulation Models (GCMs).**
- **The overarching strategy is to connect global scale projections and regional dynamics to generate regionally specific projections.**
  - Dynamic downscaling
  - Statistical downscaling

Dynamic downscaling

- **Nesting a regional climate model into an existing GCM.**

Statistical downscaling methods

- **Regression approach**
- **Change factor approach (sensitivity analysis)**
- **Stochastic weather generator**
  - Richardson type
- **Bias correction spatial disaggregation (BCSD) method**
- **Stochastic storm rainfall simulation, etc.**

Stochastic weather generators

- **A weather generator is a statistical model used to generate realistic daily sequences of weather variables — precipitation, maximum and minimum temperature, humidity, etc.**

Richardson-type Weather Generator

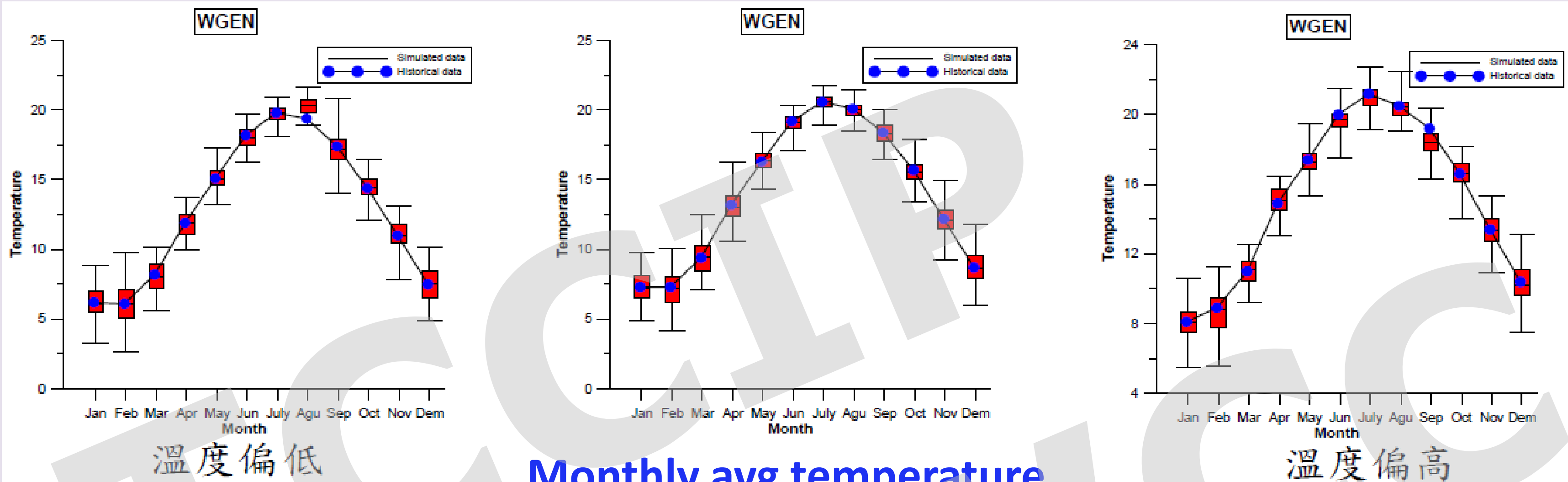
- Precipitation is divided into an occurrence process (i.e., whether the day is wet or dry) modeled as a Markov chain, and an amount process (the amount of precipitation on a wet day) sampled randomly from an appropriate distribution, such as a gamma distribution.
- Widely applied in many regions and over a range of climate impact sectors.
- Numerous publications in the scientific literature. The earliest papers date from the 1960s.

- **Markov occurrence process**

$$P(W\,|\,W),\ \ P(D\,|\,W)$$

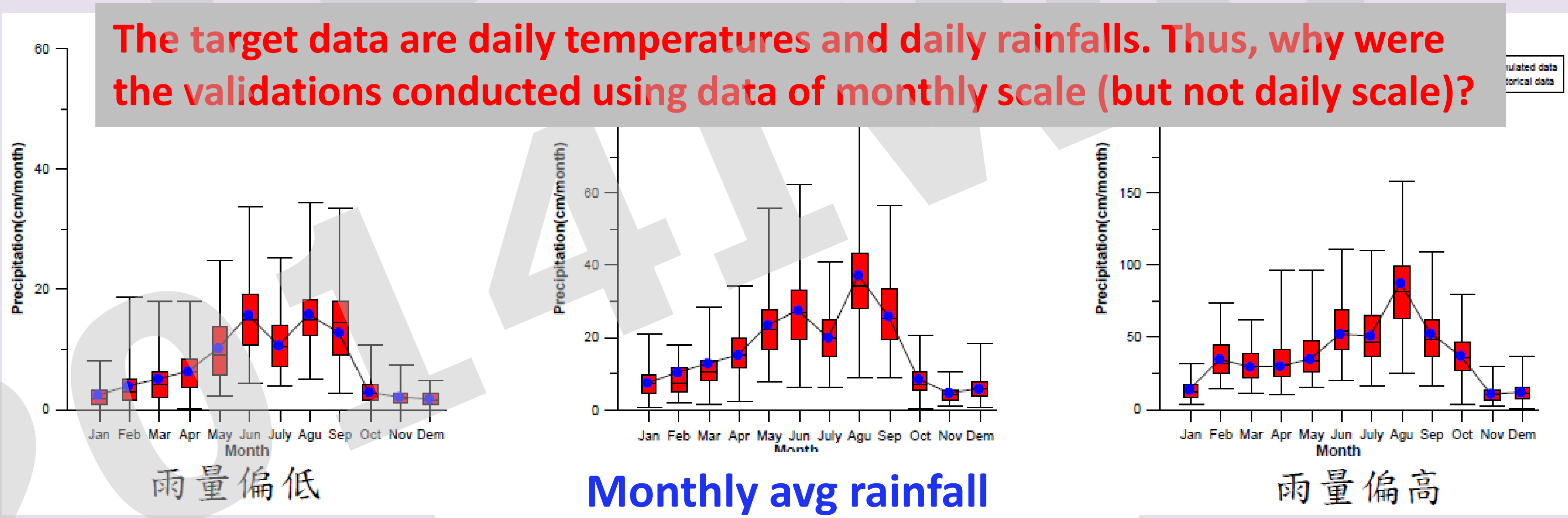
$$P(W\,|\,D),\ \ P(D\,|\,D)$$

- **Amount process**
  - IID Exponential/gamma



Monthly avg temperature

The target data are daily temperatures and daily rainfalls. Thus, why were the validations conducted using data of monthly scale (but not daily scale)?



Monthly avg rainfall

Based on the results of 100 simulation runs.

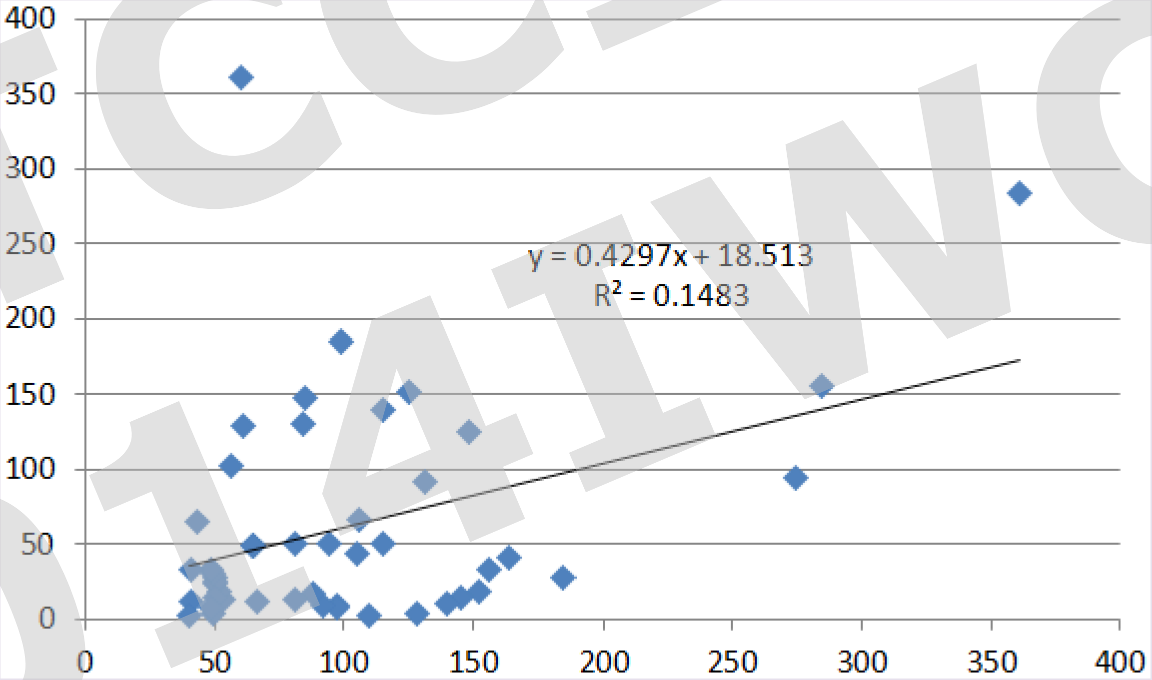
Historic data represent long-term averages of monthly temperature or precipitation.

Concerns from hydrological perspective

- **Identifying and characterizing rainfall events**
  - Rainfall occurrences are controlled by a Markov process. However, daily rainfalls are independently generated. That leads to difficulties in defying storm events.
    - Duration controlled by Markov process.
    - Rainfalls of individual days of the same event are independent.
    - Storm-type-dependent rainfall characteristics
- **Properties of occurrence frequency and storm duration (storm-type dependent)**

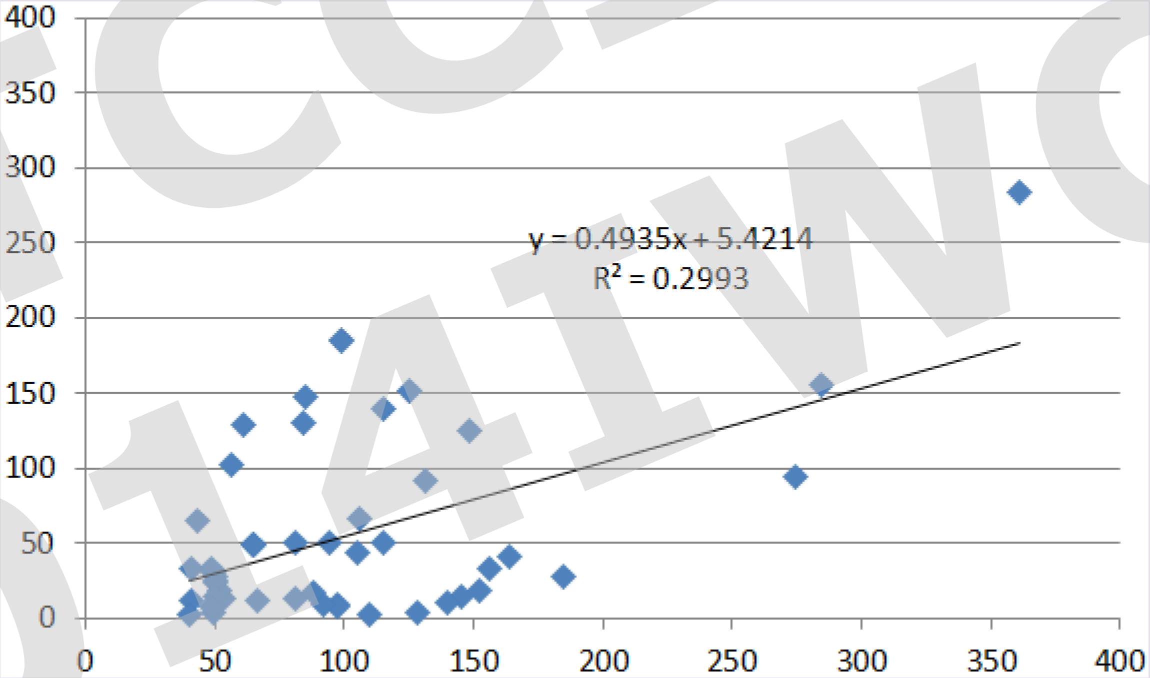
Daily rainfalls of August

- **Lag-1 correlation of observed daily rainfalls (0.386)**

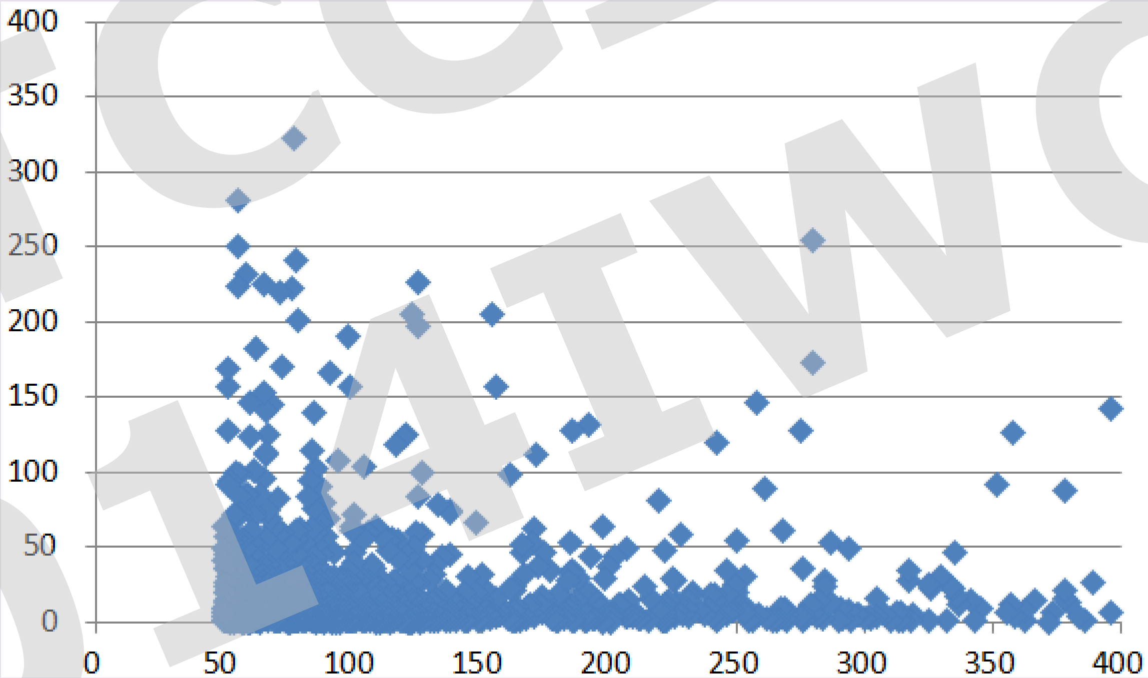


Daily rainfalls of August

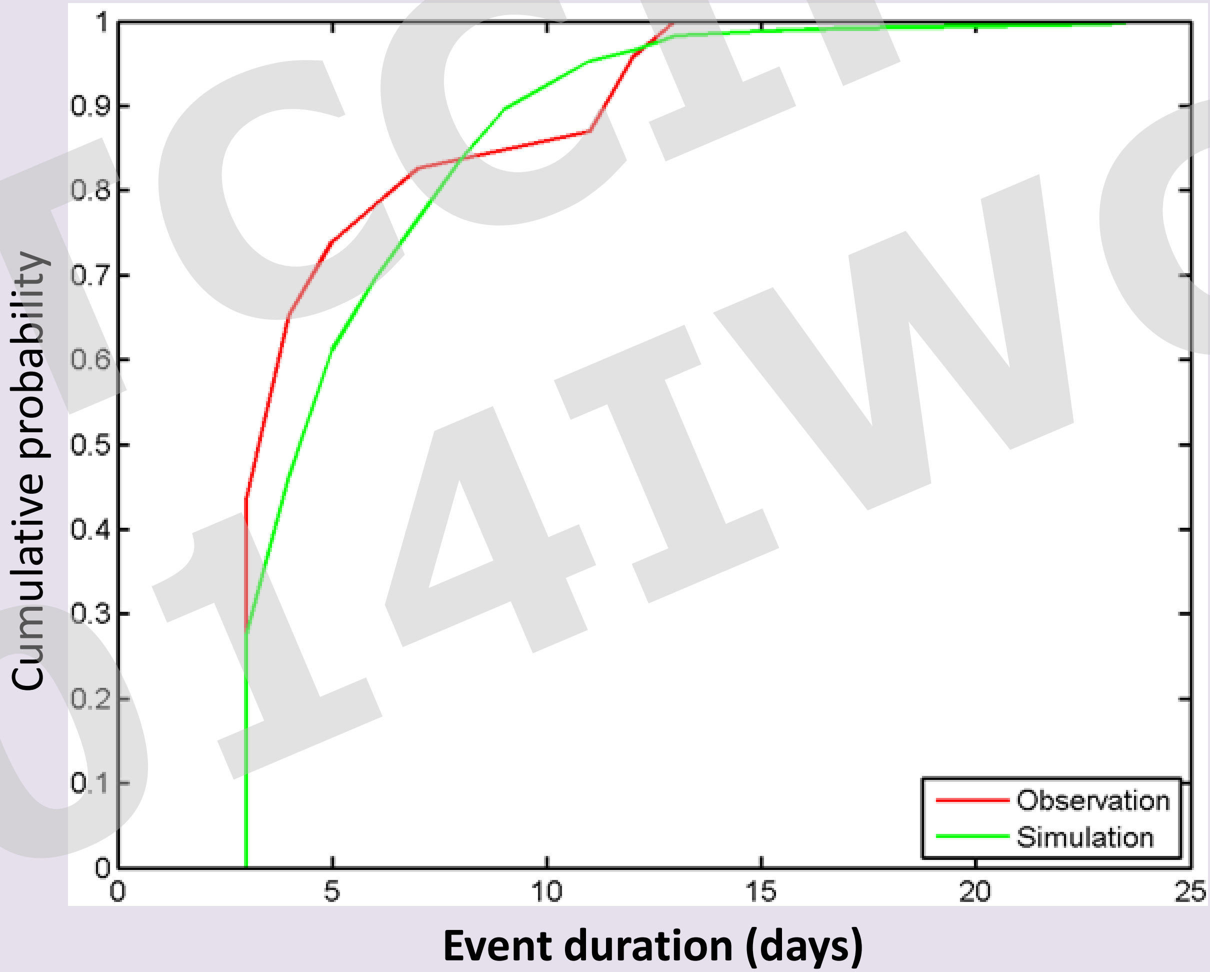
- **Lag-1 correlation of observed daily rainfalls (0.547, without outliers)**



- **Lag-1 correlation of WG simulated daily rainfalls (≈ 0)**



- **Evaluation of event durations**



- **Suggestions for usage of the Richardson type daily rainfall weather generator**
  - Areas dominated by short-duration storms (low lag-1 autocorrelation)
  - Rainfall-runoff modeling
    - Runoff volume (not the peak flow) is of major concern
    - Larger watersheds with long (a few days) time-of-concentration.

Bias Correction Spatial Disaggregation (BCSD) Method

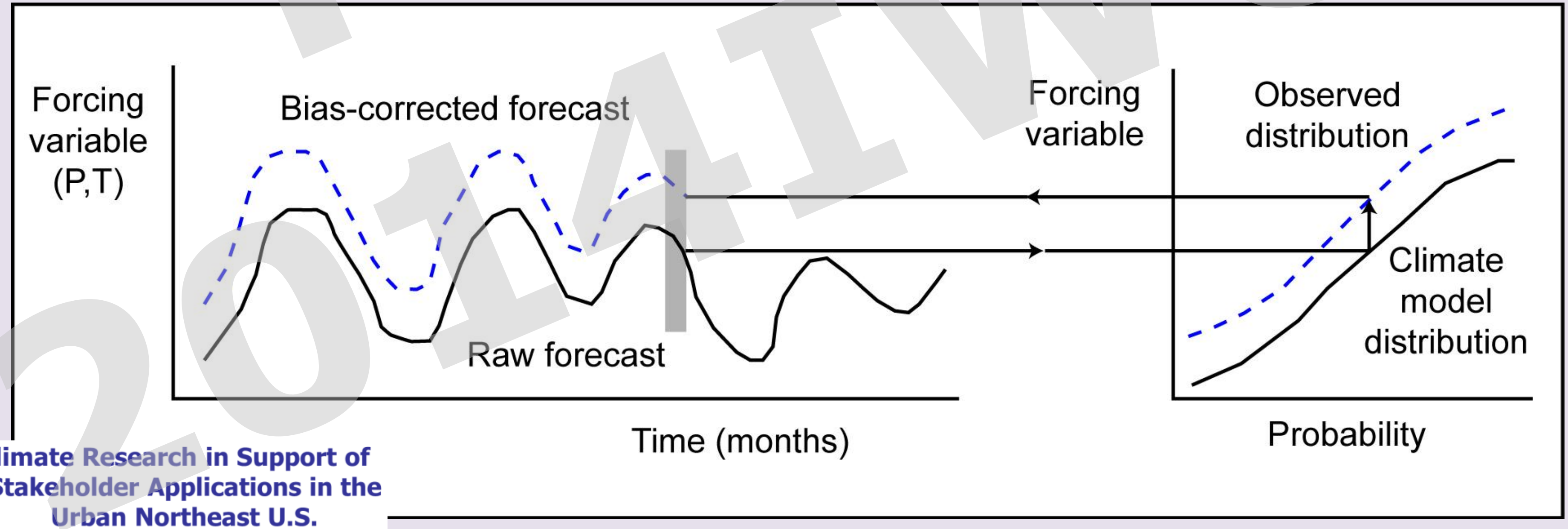
- Bias corrections are performed on GCM grids.
- Spatial disaggregation works are conducted onto fine-scale grids.

Statistical Downscaling

Bias Correction Spatial Diaggregation (BCSD) Method--Steps

Bias correction

- Regrid 1/8º observations and GCM outputs to 2º resolution
- Generate monthly cumulative distribution functions at 2º, for (observations, the baseline GCM, and the future simulation)
- Quantile map the baseline GCM onto the observed data (note: this preserves higher order statistics)



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Radley Horton

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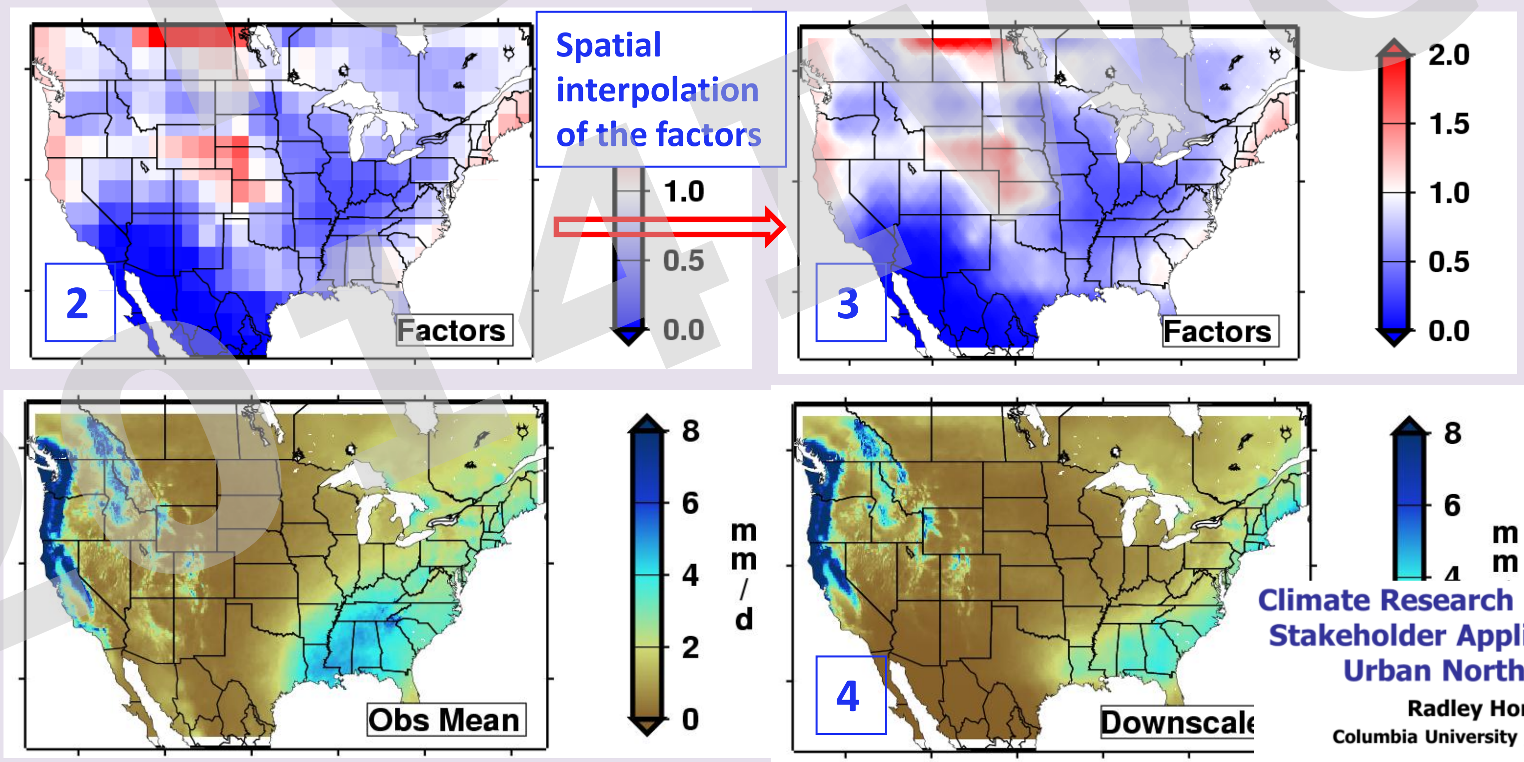
Statistical Downscaling

Bias Correction Spatial Disaggregation (BCSD) Method--Steps

Spatial Downscaling

1. Rank each future month based on baseline GCM CDF, then replace with observed data as above
2. Generate factor field (temperature differences, precipitation ratios)
3. Interpolate these factors to 1/8º
4. Apply the downscaled factors to the observed 1/8º data (for temperature this is addition; for precipitation this is multiplication



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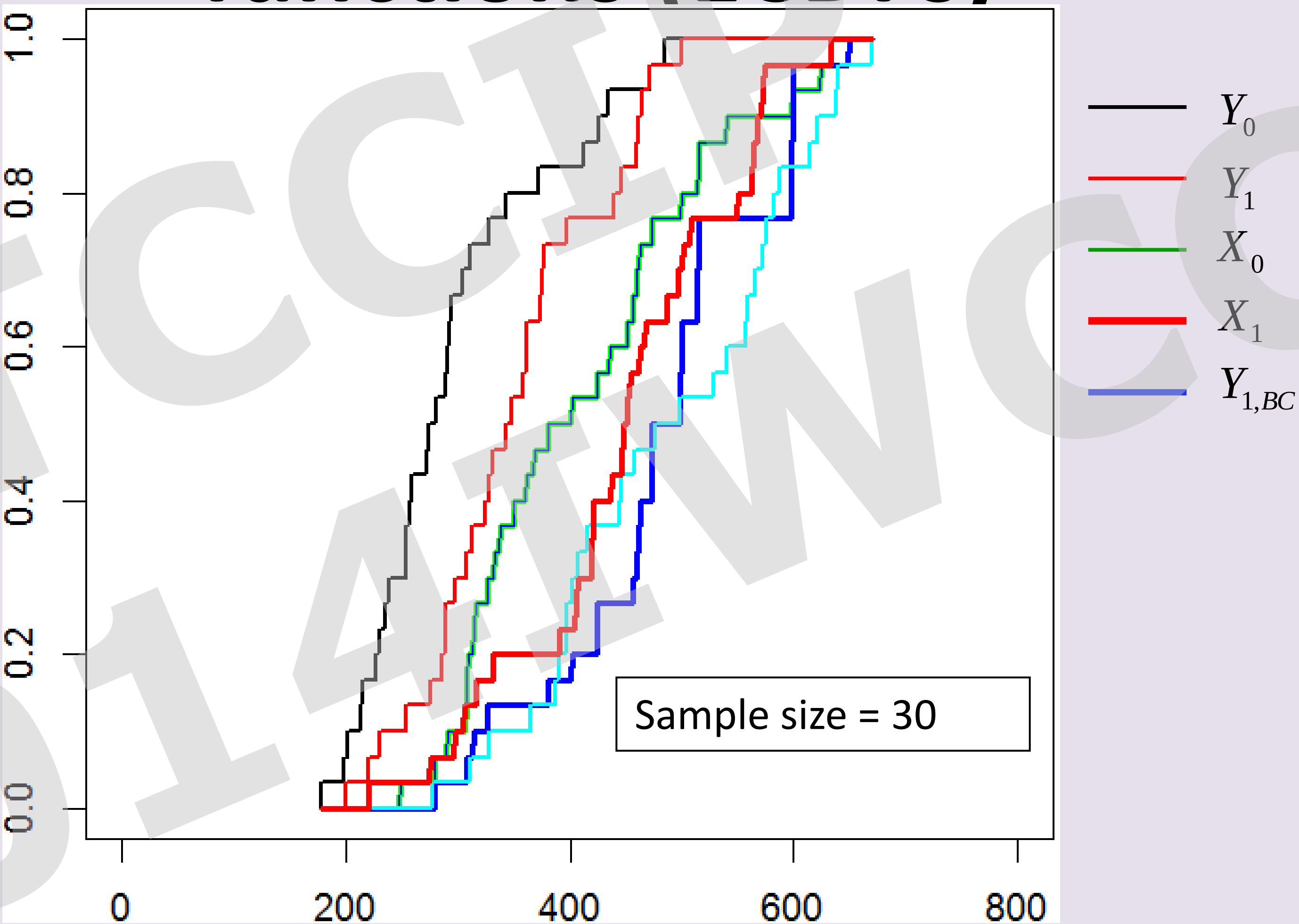
Assessment of bias correction

Without spatial downscaling

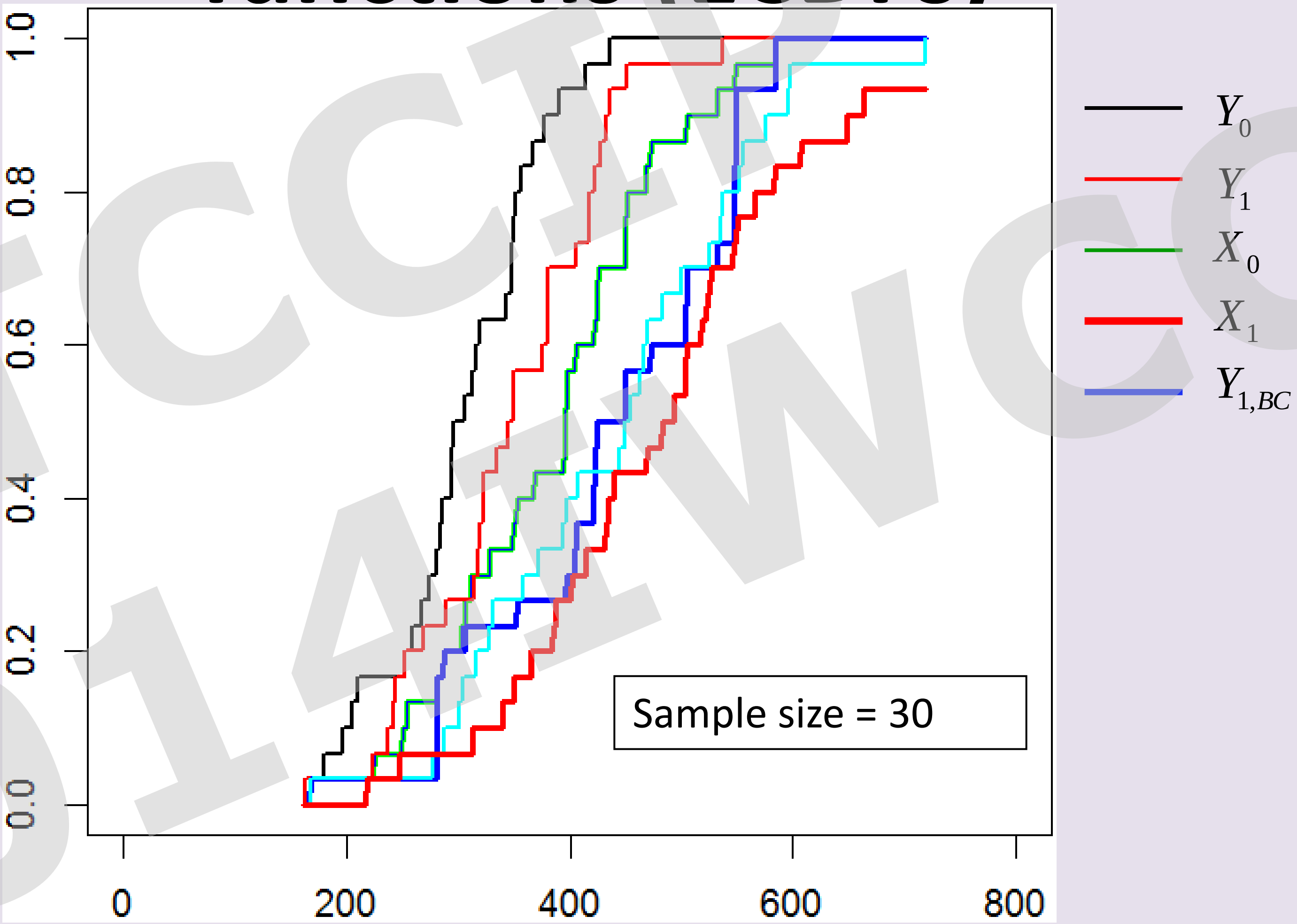
- **Stochastic simulation**
  - Baseline period
    - Observation: X0; GCM: Y0
  - Projection period
    - Observation: X1; GCM: Y1
  - Assuming Gaussian distributions with different expected values and standard deviances.
  - Length of period (in years)
    - 30, 50, 100 [effect of sample size and the asymptotic property (using a large number of samples)]

$$X_0 \sim N(400,\ 100)$$
$$X_1 \sim N(450,\ 100)$$
$$Y_0 \sim N(300,\ 80)$$
$$Y_1 \sim N(350,\ 80)$$

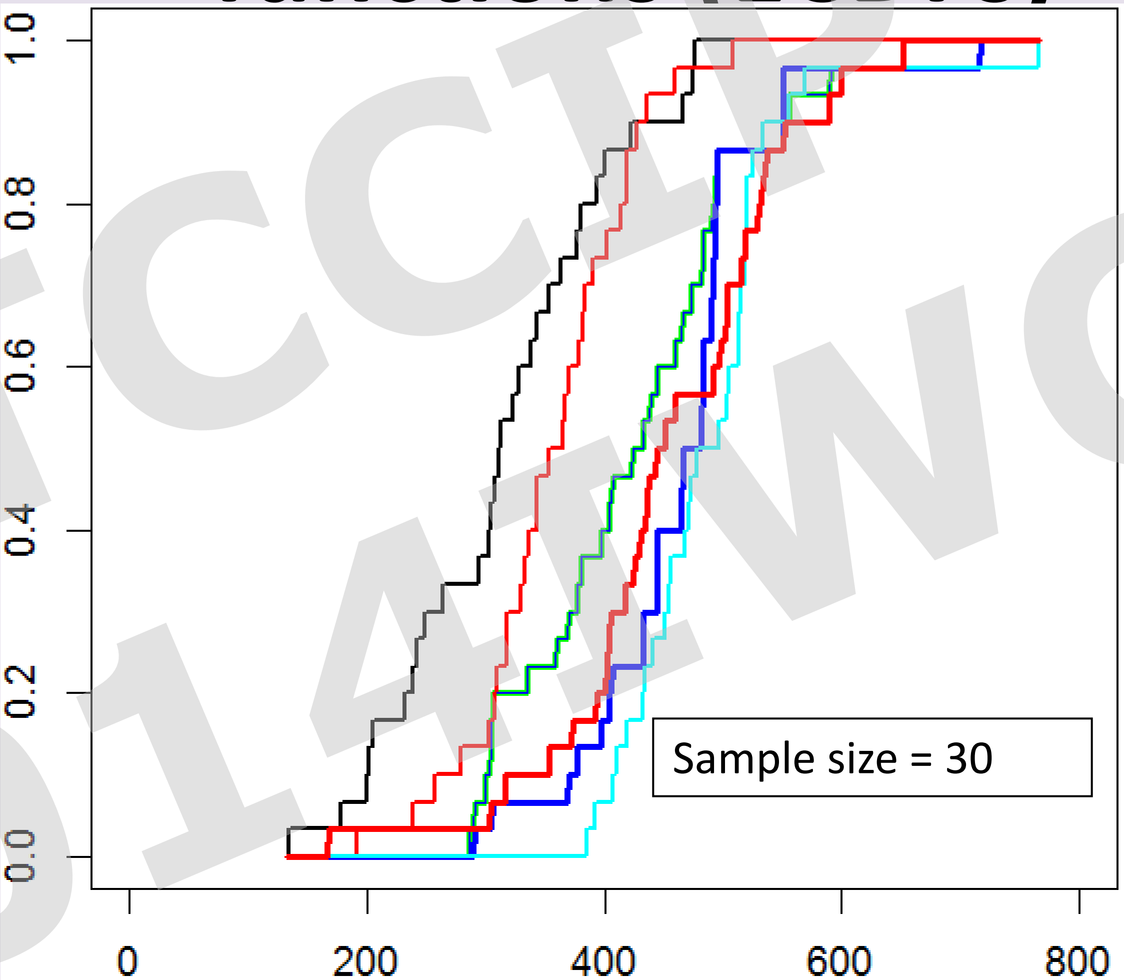
Empirical cumulative distribution functions (ECDFs)

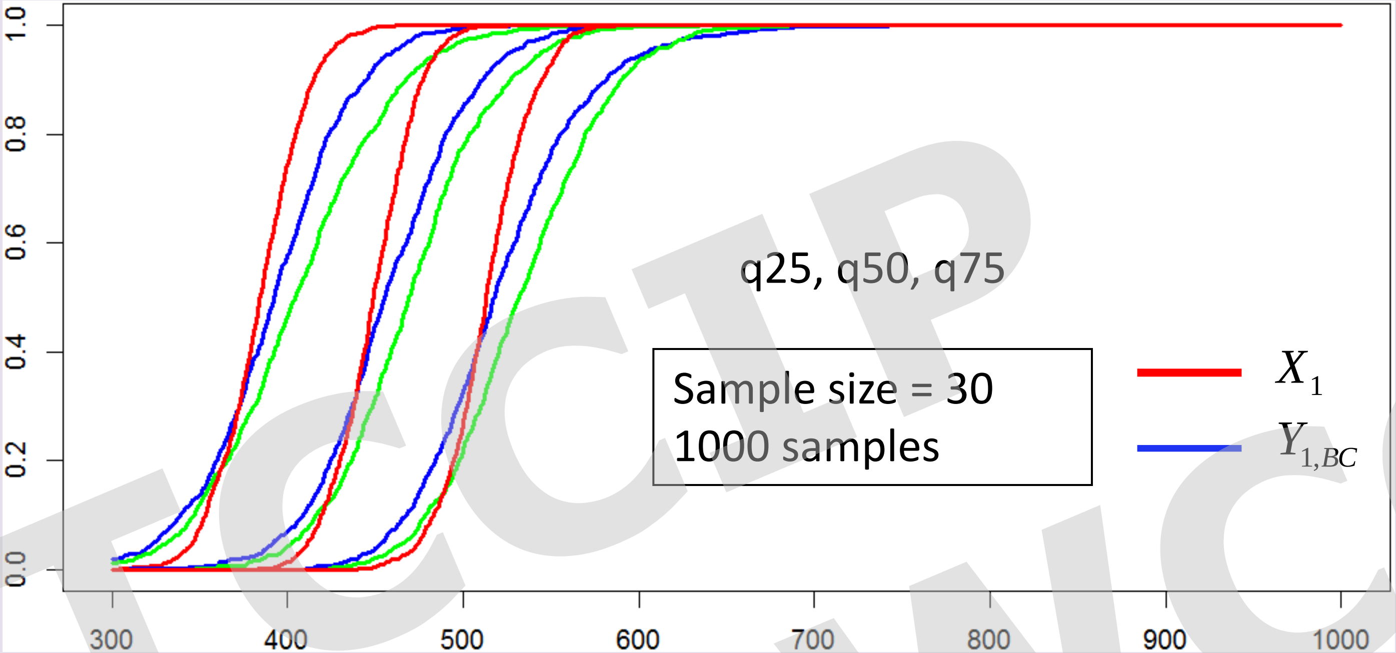


Empirical cumulative distribution functions (ECDFs)

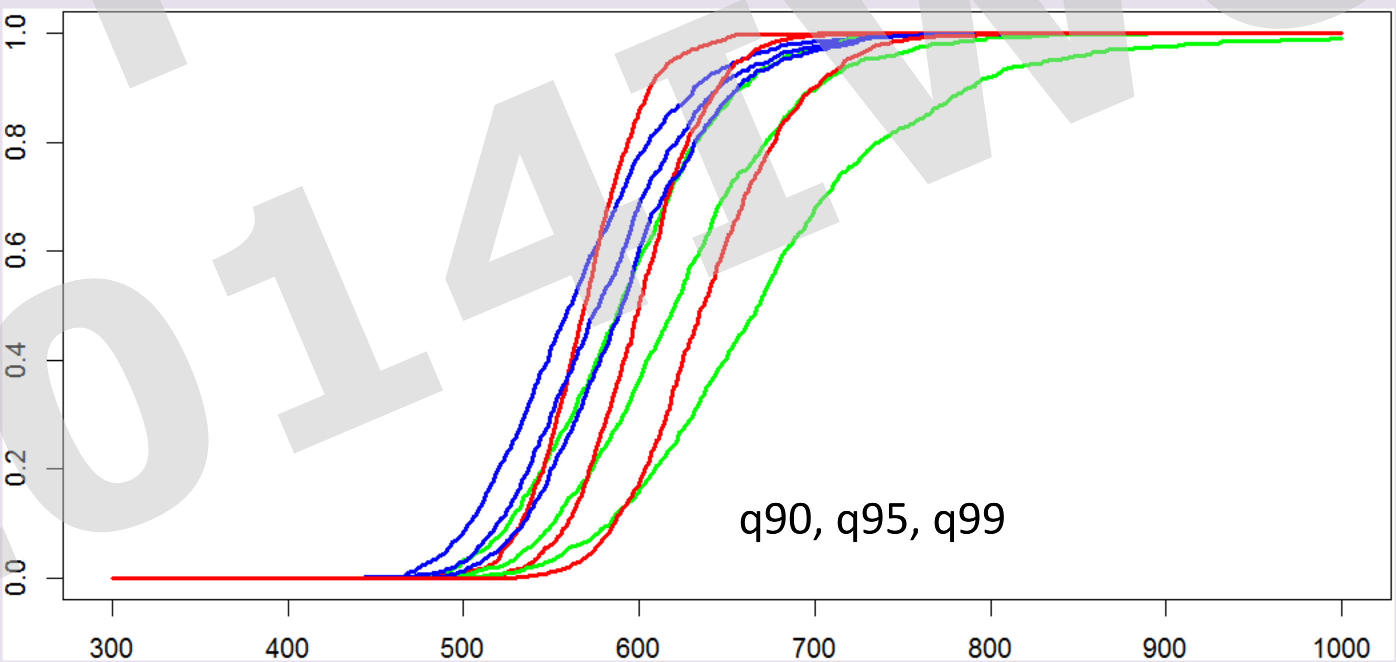


Empirical cumulative distribution functions (ECDFs)

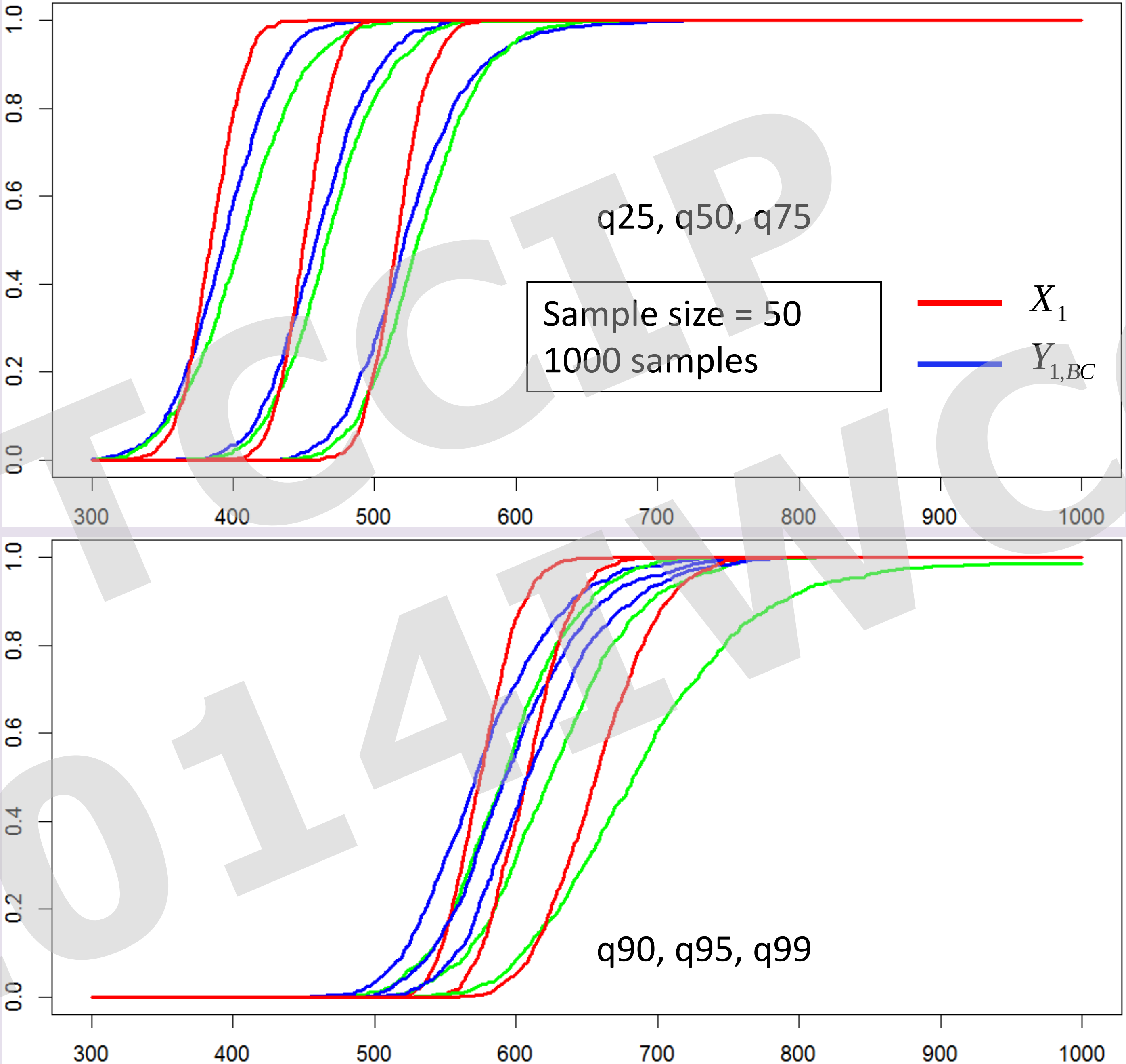


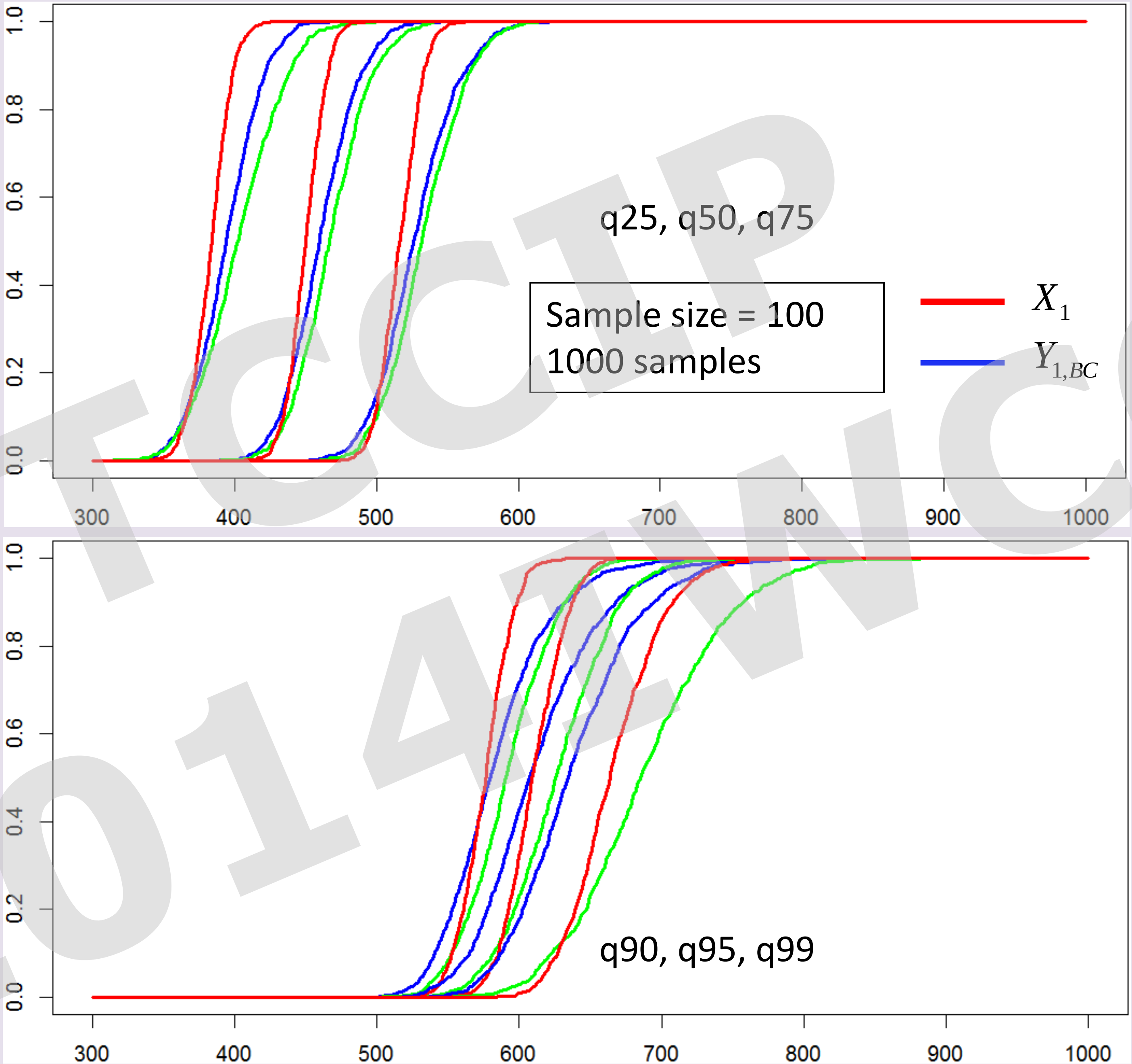


q25, q50, q75
Sample size = 30
1000 samples
X_1
$Y_{1,BC}$



q90, q95, q99


q25, q50, q75
Sample size = 50
1000 samples
X_1
$Y_{1,BC}$
q90, q95, q99
0.0
0.2
0.4
0.6
0.8
1.0
300
400
500
600
700
800
900
1000


q25, q50, q75
Sample size = 100
1000 samples
X_1
$Y_{1,BC}$
q90, q95, q99

A simplified Gaussian random field simulation for assessment of spatial disaggregation

Let's consider two stationary one-dimensional spatial random fields (Z_0 and Z_1) having expected values μ_{Z_0} and μ_{Z_1}, standard deviations σ_{Z_0} and σ_{Z_1}, and lag-1 autocorrelation coefficients ρ_{Z_0} and ρ_{Z_1} for some climatic variable of the baseline and projection periods, respectively.

For the baseline and projection periods, respectively, we have

$$
\begin{array}{l}
Z_0(s),\ \ s = 1,2,\dots,n. \\
E(Z_0) = \mu_{Z_0}\ \forall s,\ \ Var(Z_0) = \sigma_{Z_0}^2\ \forall s \\
correl(Z_0(s),\ Z_0(s+1)) = \rho_{Z_0}\ \forall s.
\end{array}
\quad \text{and} \quad
\begin{array}{l}
Z_1(s),\ \ s = 1,2,\dots,n. \\
E(Z_1) = \mu_{Z_1}\ \forall s,\ \ Var(Z_1) = \sigma_{Z_1}^2\ \forall s \\
correl(Z_1(s),\ Z_1(s+1)) = \rho_{Z_1}\ \forall s.
\end{array}
$$

Assuming AR(2) random processes for both Z_0 and Z_1. Parameters of the two processes are set as follows:

$$X_t - \mu = \phi_1(X_{t-1} - \mu) + \phi_2(X_{t-2} - \mu) + \varepsilon_t$$

$$X_t = (1 - \phi_1 - \phi_2)\mu + \phi_1 X_{t-1} + \phi_2 X_{t-2} + \varepsilon_t$$

$$X_t = \phi_0 + \phi_1 X_{t-1} + \phi_2 X_{t-2} + \varepsilon_t$$

$$E[X_t] = \mu = \frac{\phi_0}{1 - \phi_1 - \phi_2}$$

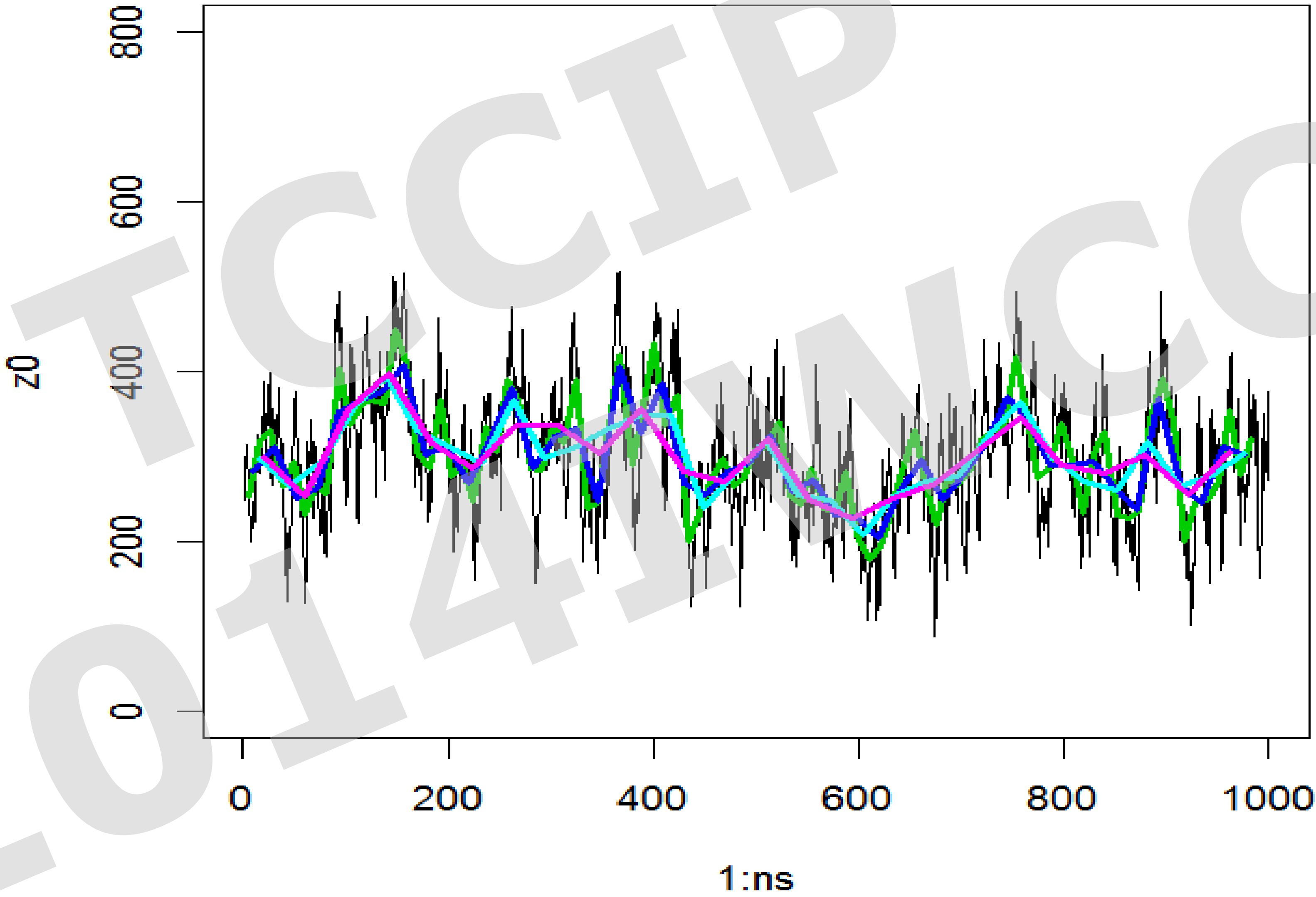
$$\rho_1 = \frac{\phi_1}{1-\phi_2}, \quad \rho_2 = \frac{\phi_1^2}{1-\phi_2} + \phi_2, \quad \begin{cases} \phi_2 + \phi_1 < 1 \\ \phi_2 - \phi_1 < 1 \\ -1 < \phi_2 < 1 \end{cases}$$

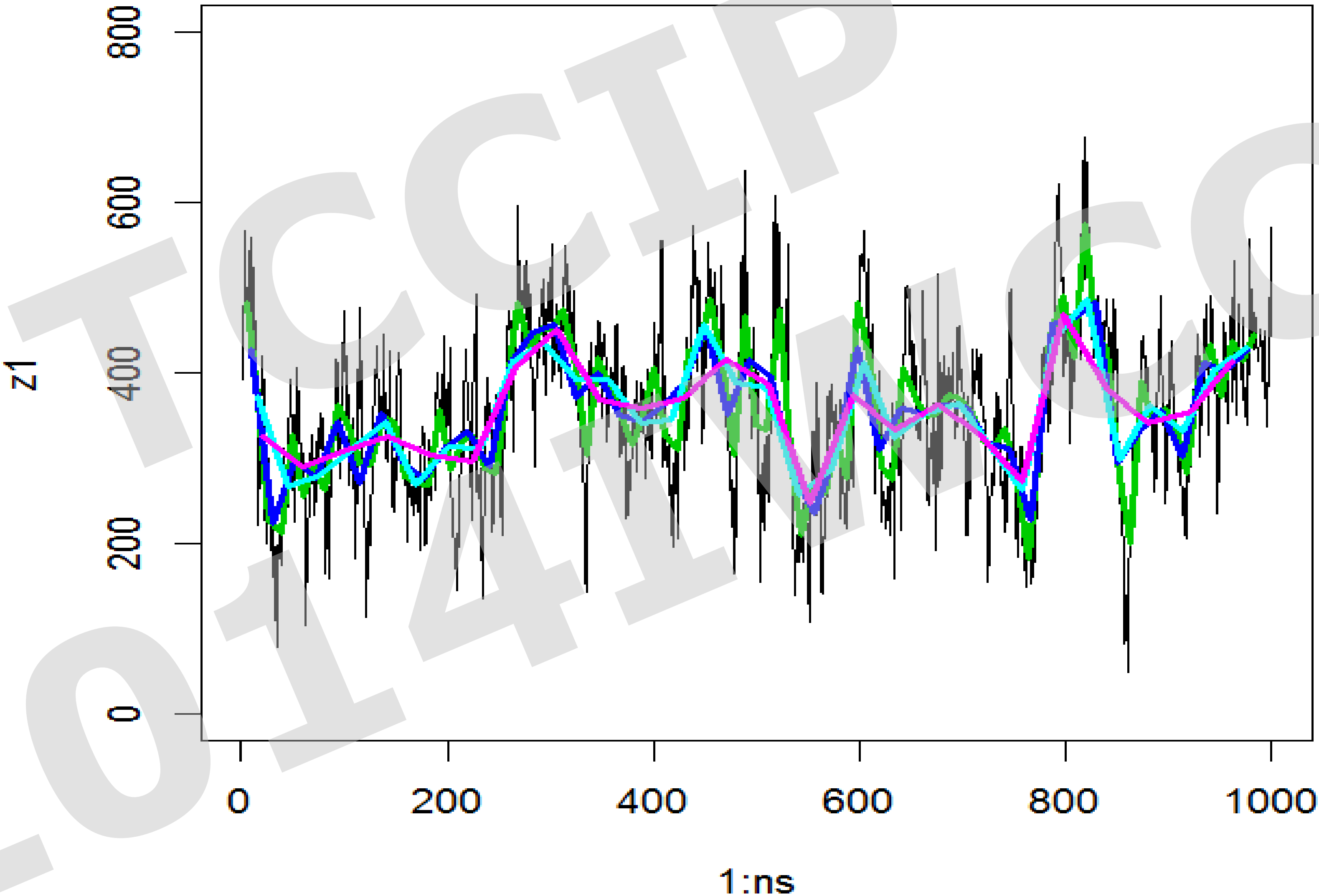
$$\sigma_X^2 = \frac{\sigma_\varepsilon^2}{1 - \phi_1\rho_1 - \phi_2\rho_2} = \frac{1-\phi_2}{1+\phi_2} \cdot \frac{\sigma_\varepsilon^2}{(\phi_1 + \phi_2 - 1)(\phi_2 - \phi_1 - 1)}$$

Baseline Period		Projection Period	
mu=	300	mu=	360
phi0=	69	phi0=	64.8
phi1=	0.52	phi1=	0.62
phi2=	0.25	phi2=	0.2
rho1=	0.69333	rho1=	0.775
rho2=	0.61053	rho2=	0.6805
sigma-EPS=	50	sigma-EPS=	60
sigma-X=	71.6605	sigma-X=	96.9003

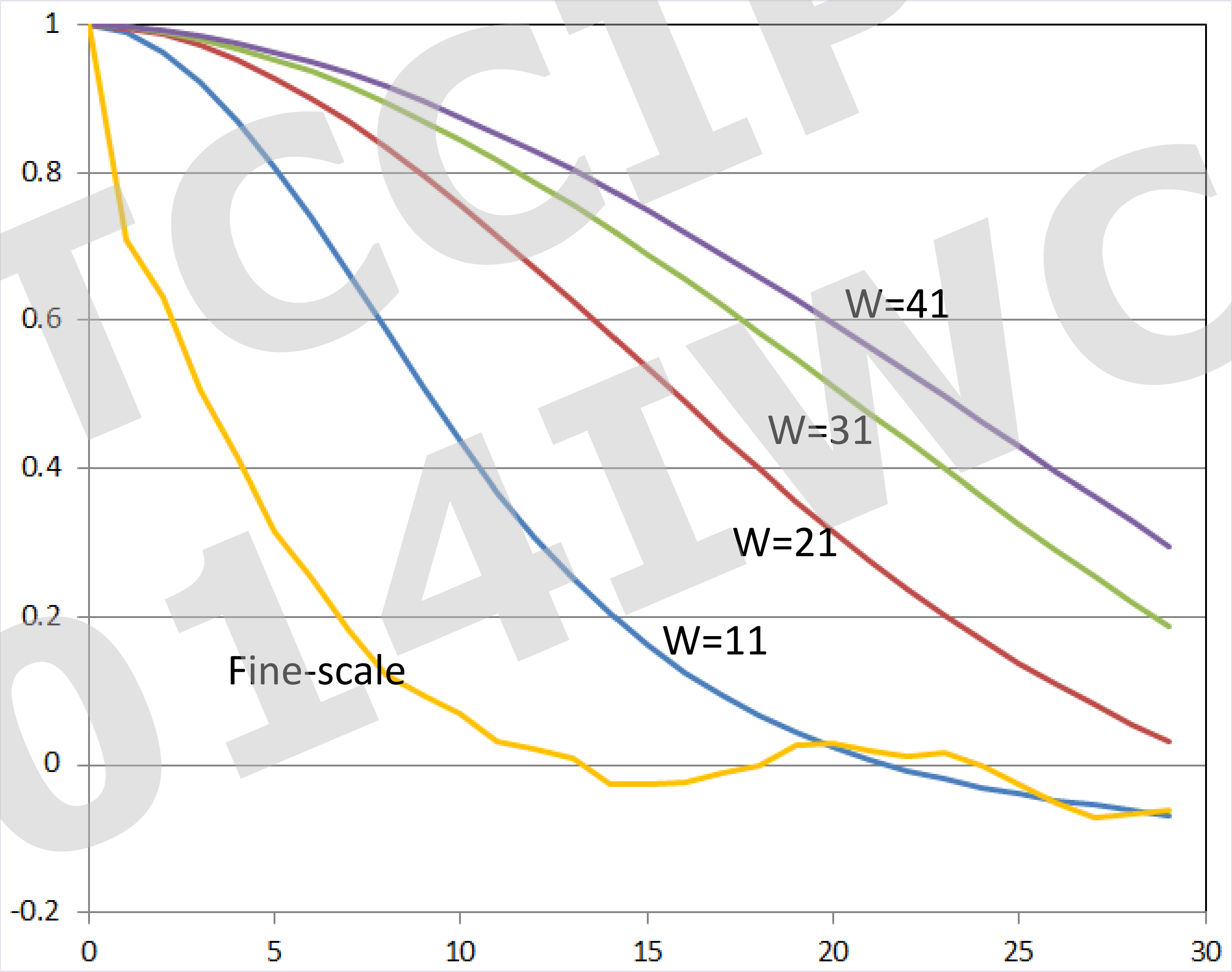
Simulating two long sequences of Z_0 and Z_1 (say, length = 1000), respectively.

Fine grid: $\Delta = 1$, Coarse grid: $\Delta = 11, 21, 31, 41$.

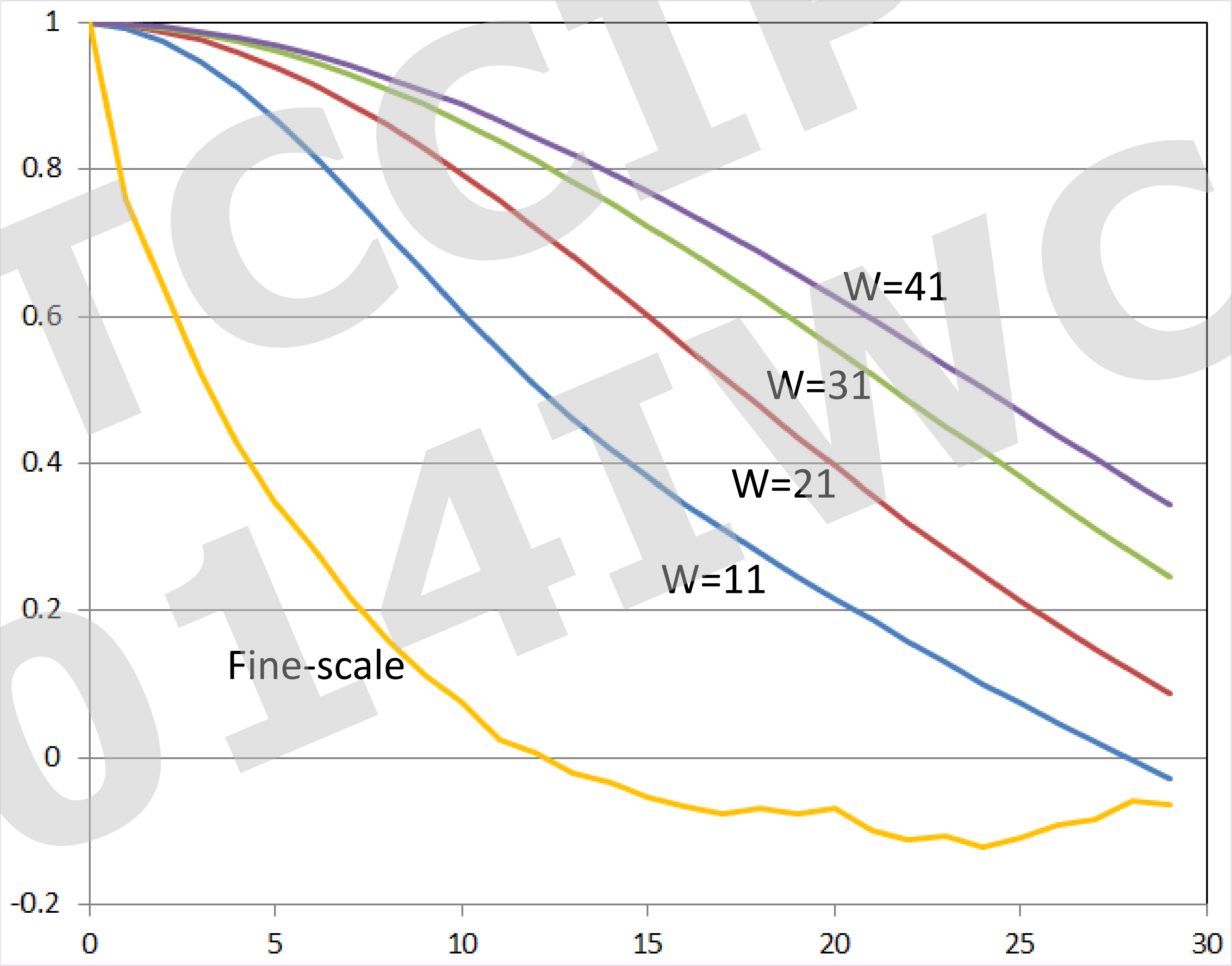

z0
0
200
400
600
800
1000
1:ns


z1
0
200
400
600
800
1000
1:ns

Autocorrelation function of the baseline period data series

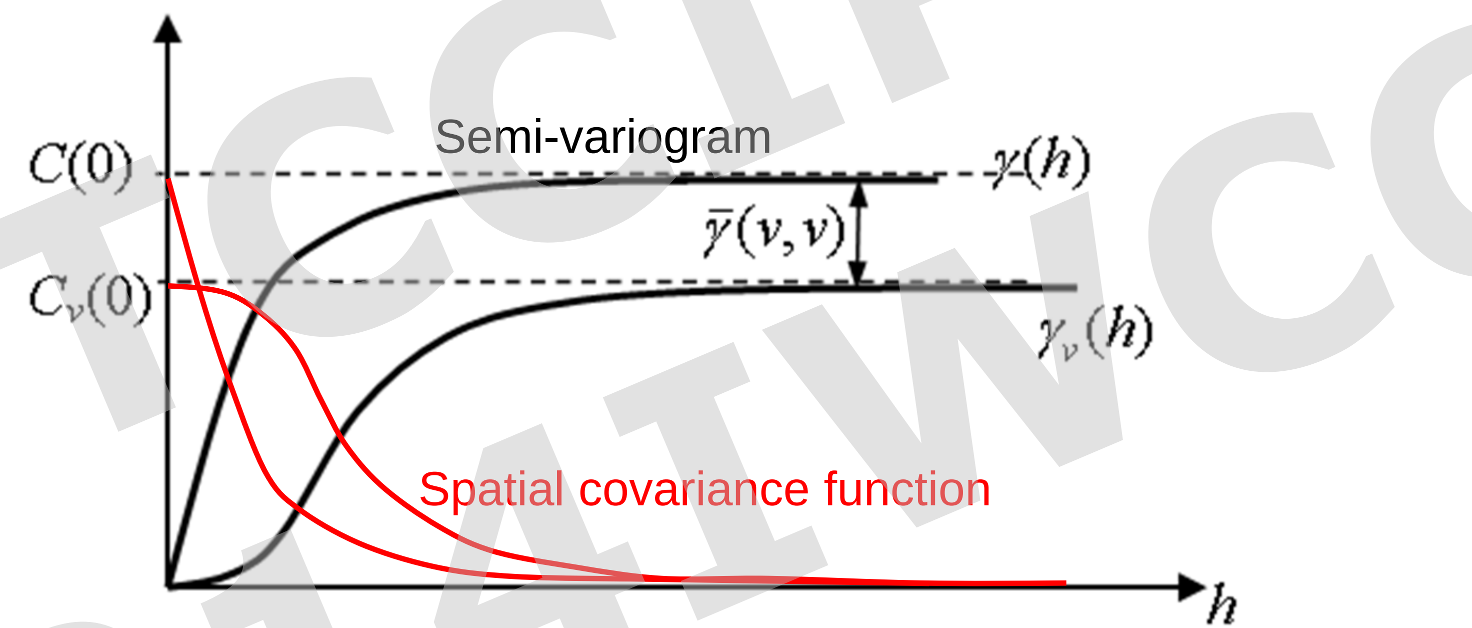


Autocorrelation function of the projection period data series



Resolution and variability

- **Change of support in geostatistics**



Relationship between point-support and v-support variograms.

- **Change in resolution is accompanied by changes in local variability and spatial co-variability.**

Statistical Downscaling

Bias Correction Spatial Disaggregation (BCSD) Method--Steps

Spatial Downscaling

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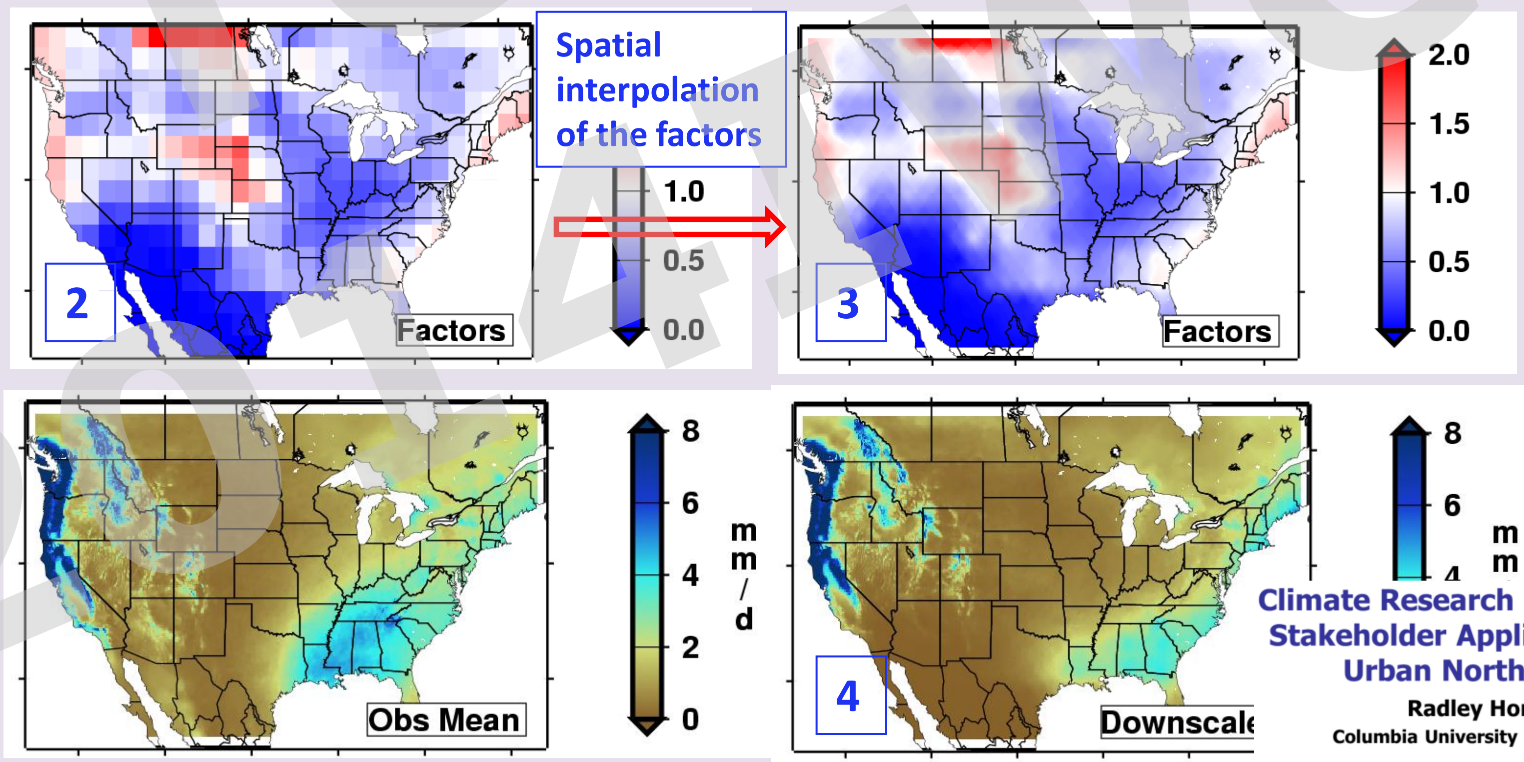

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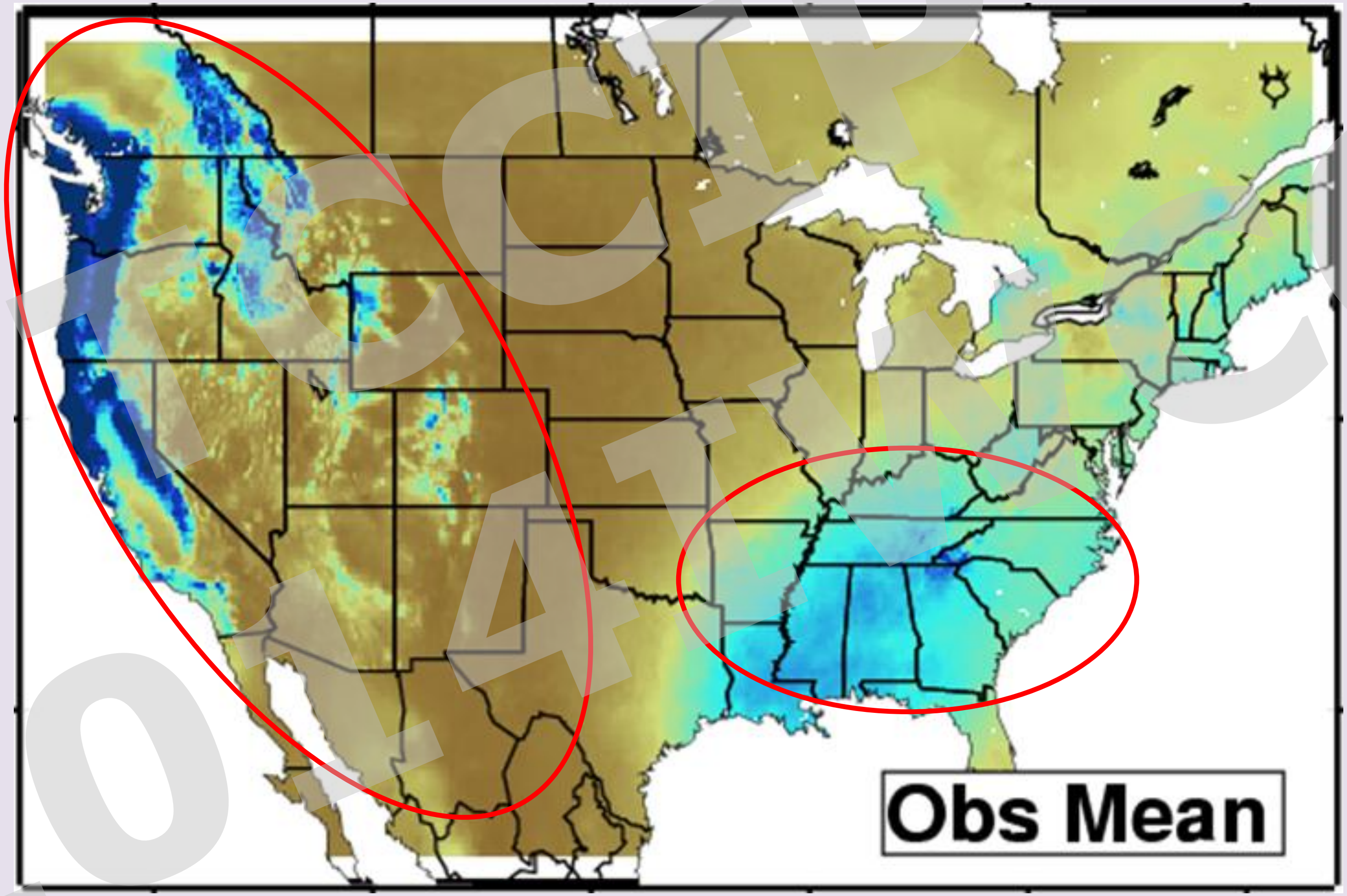
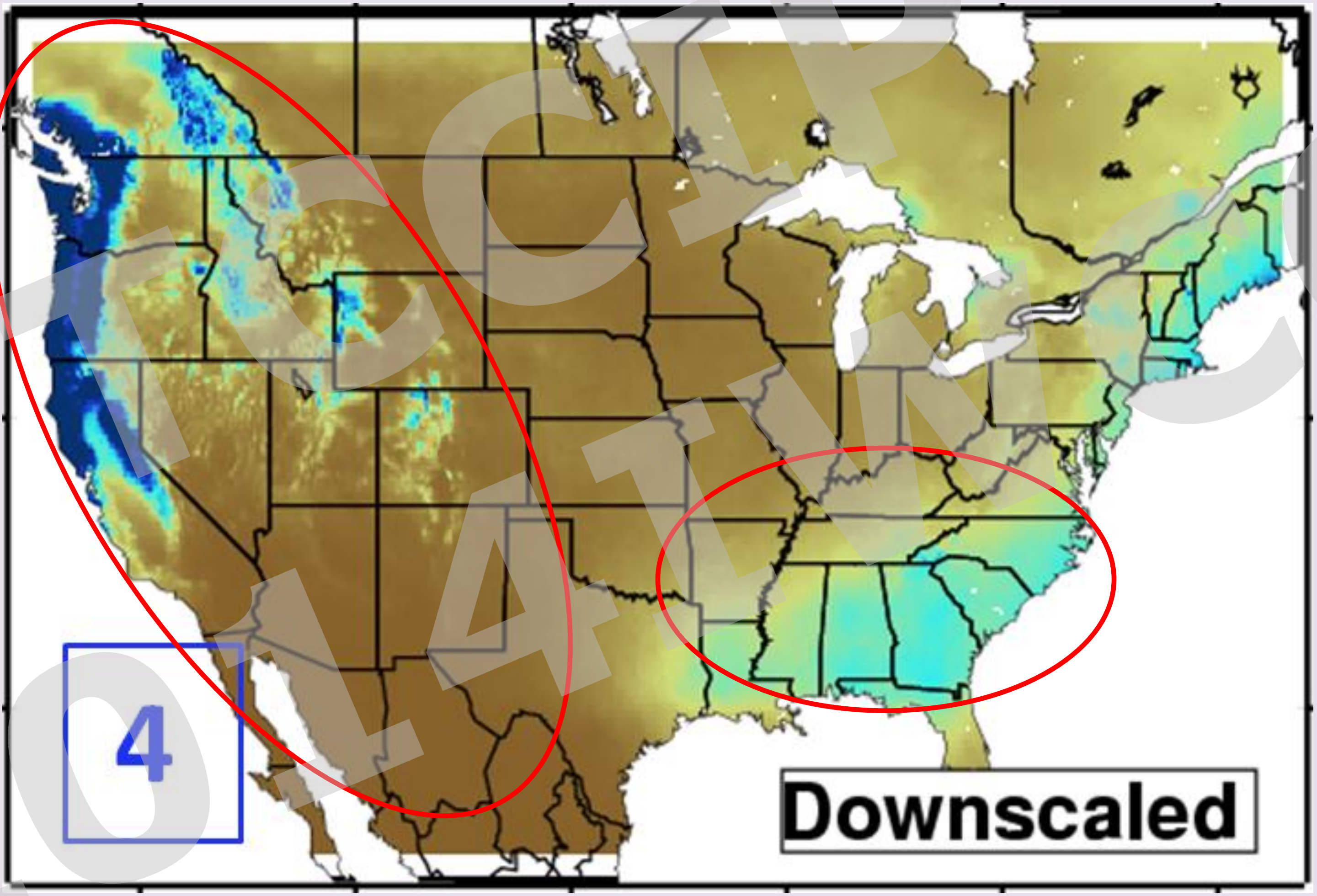
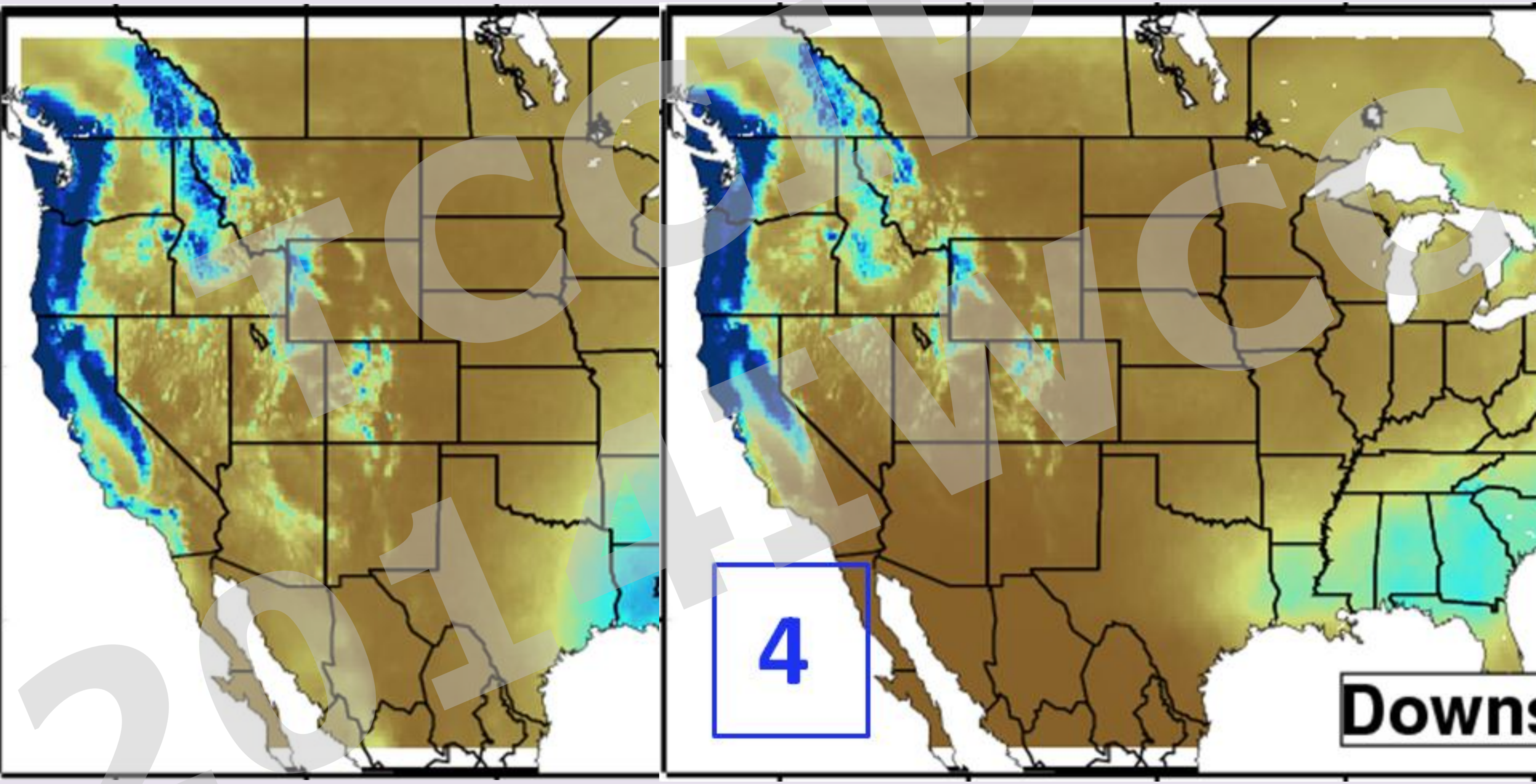

Obs Mean


4
Downscaled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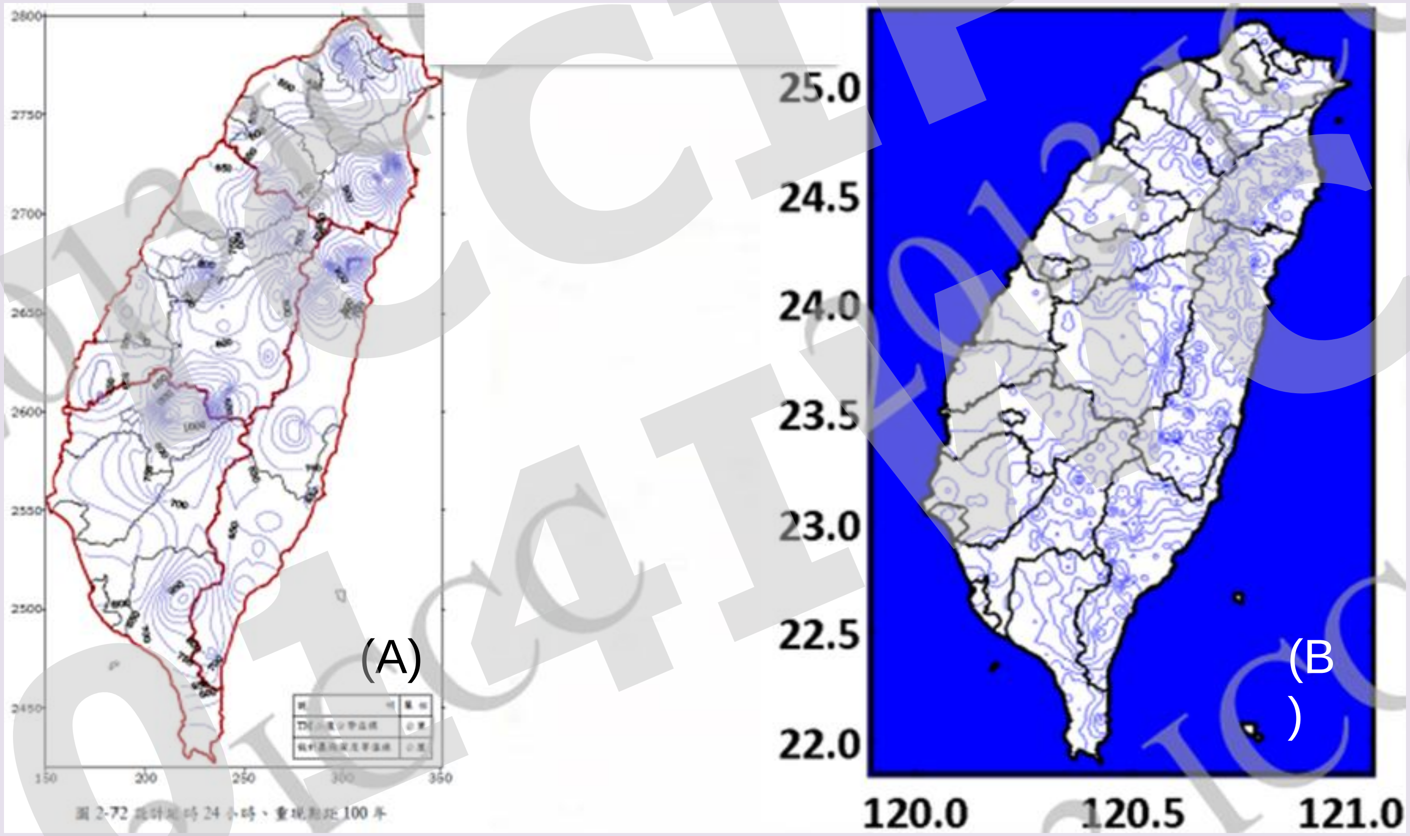
Downs

Example 1

- **Contours of the 100-year return period daily rainfall depth based on observed data and high-resolution downscaled rainfalls.**



Based on site observations

Based on high-resolution downscaled rainfalls.

Contours exhibit higher degree of spatial continuity.

Remarks and suggestions

- **Bias-correction**
  - BCSD method tends to under estimate high quantiles.
- **Spatial disaggregation**
  - BCSD method results reduce both the local and the spatial variabilities.
- **Useful for assessment of long term climatology**
- **Caution should be exercised when assessing changes in extremes.**

•

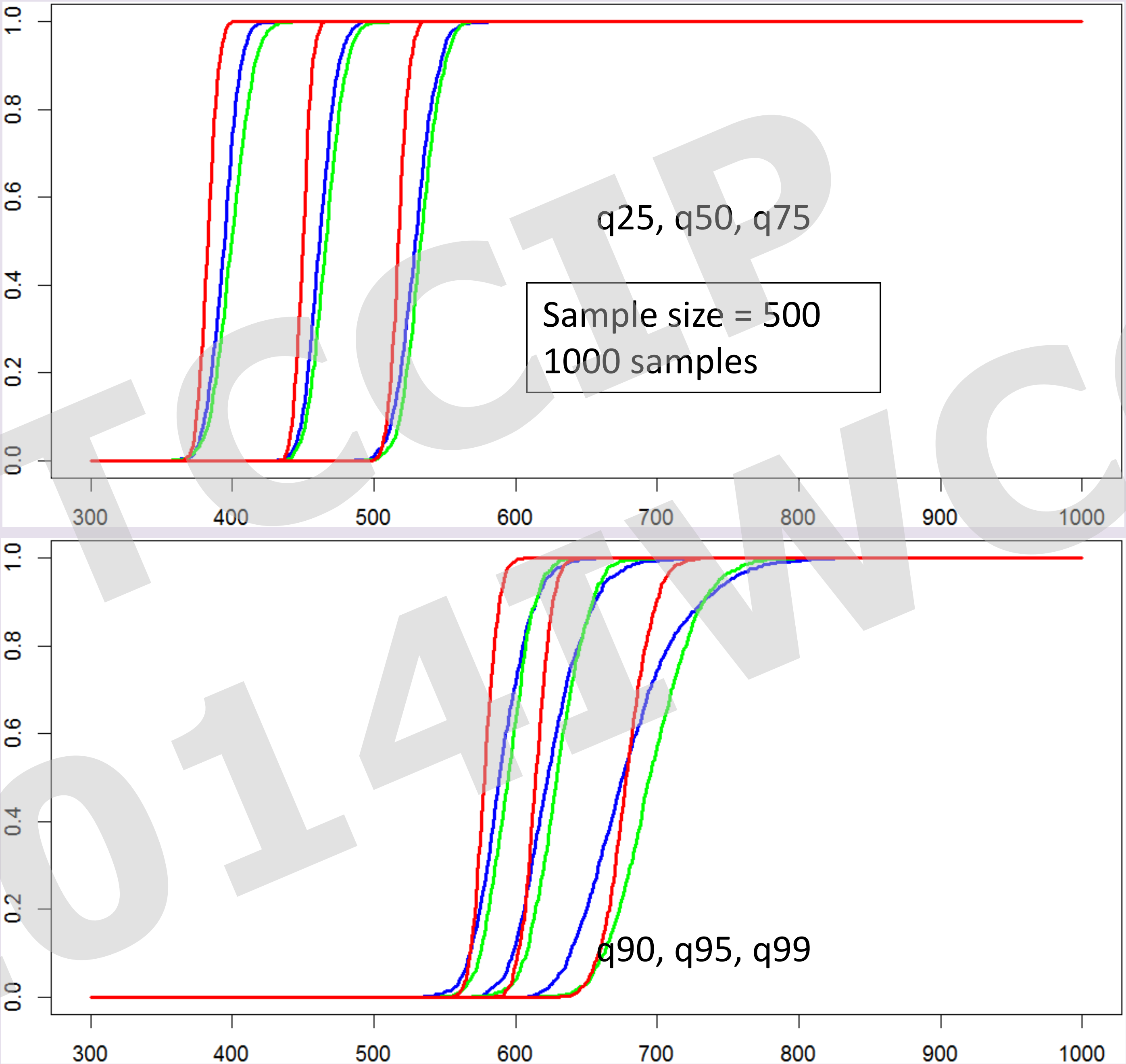
Thanks for your attention.

Regression approach

- The general strategy of these methods is to establish the relationship between large scale variables, such as the driving factors derived from GCMs, to local level climate conditions. Once these relationships have been developed for existing conditions, they can be used to predict what might happen under the different conditions indicated by GCMs.

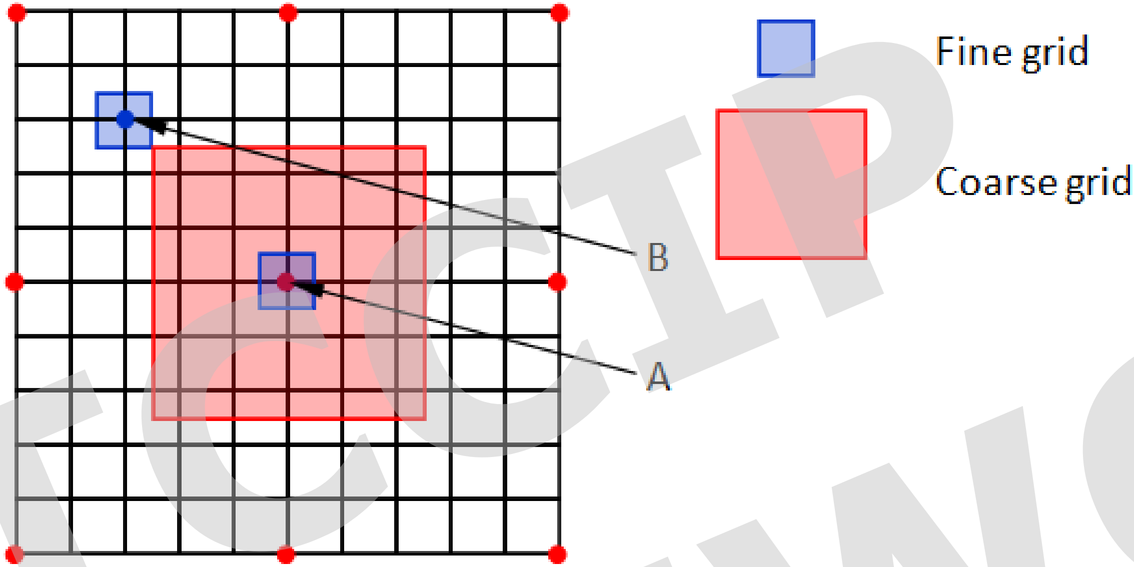
Stochastic weather generators

- A weather generator is a statistical model used to generate realistic daily sequences of weather variables — precipitation, maximum and minimum temperature, humidity, etc.



q25, q50, q75
Sample size = 500
1000 samples
q90, q95, q99

Implementation of BCSD



Z_0 : Climatic variable measurements of the baseline period in fine-grid scale
[Z_0 measurements are available at each individual fine grid.]

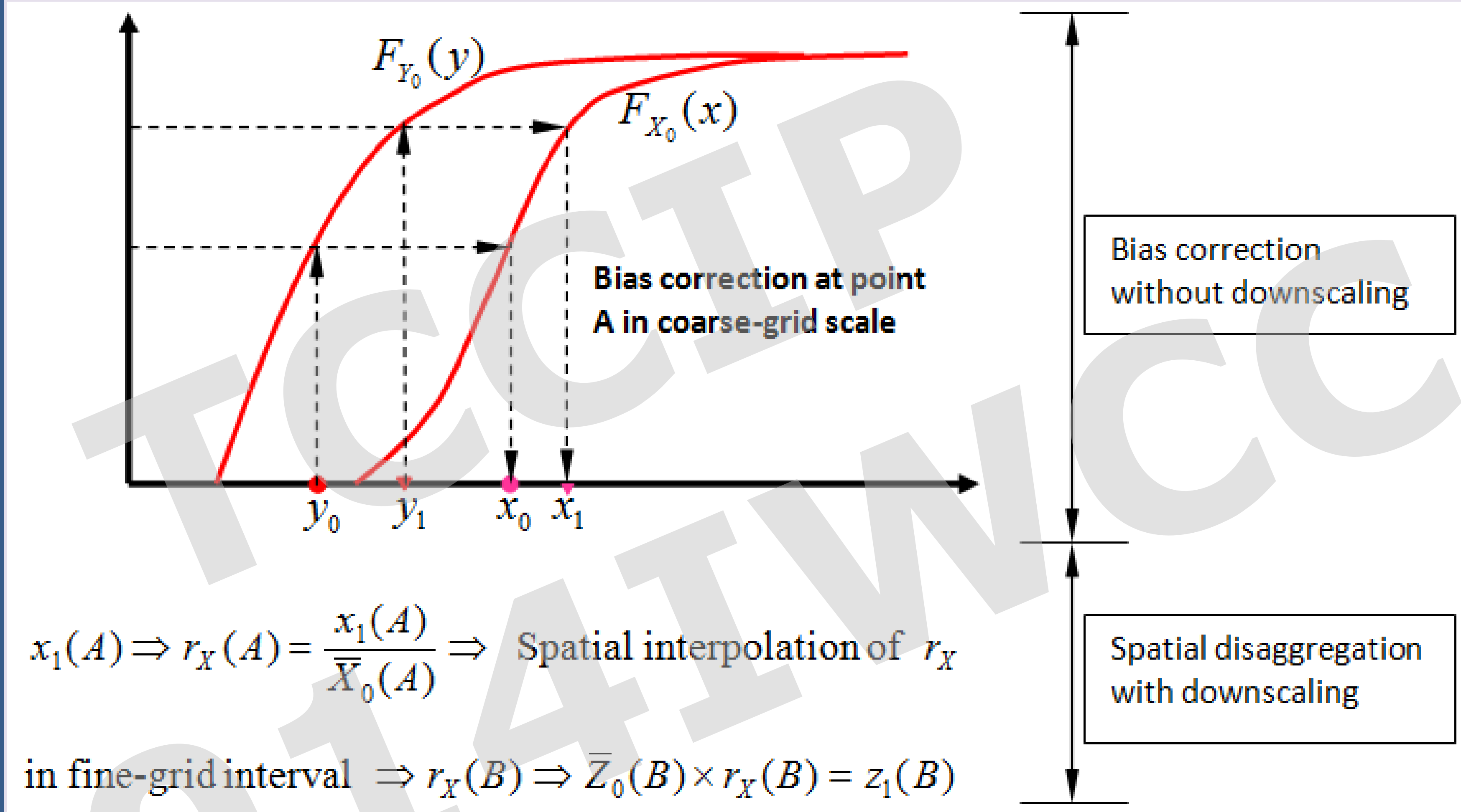
X_0 : Climatic variable measurements of the baseline period in coarse-grid scale

Y_0 : Climatic variable GCM outputs of the baseline period in coarse-grid scale

Z_1 : Climatic variable measurements of the projection period in fine-grid scale

X_1 : Climatic variable measurements of the projection period in coarse-grid scale

Y_1 : Climatic variable GCM outputs of the projection period in coarse-grid scale



- **BCSD performance assessment using a stochastic simulation approach**