Climate Change Impact Analysis

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Outline

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- Global Climate Models (GCMs)
- Selecting GCMs
- Downscaling GCM Data
- KNN-CAD Weather Generator
- KNN-CADV4 Example

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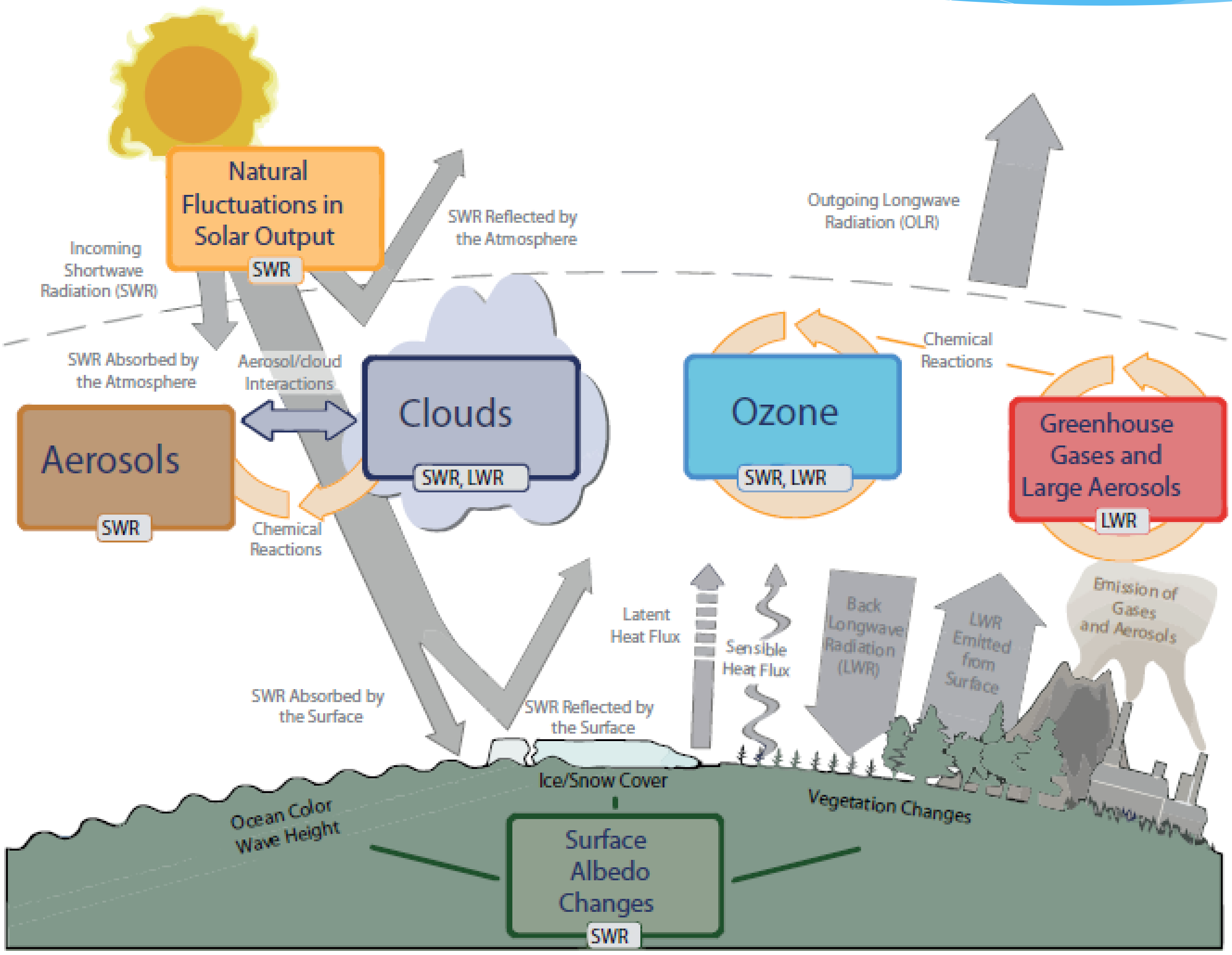
Global Climate Models (GCMs)



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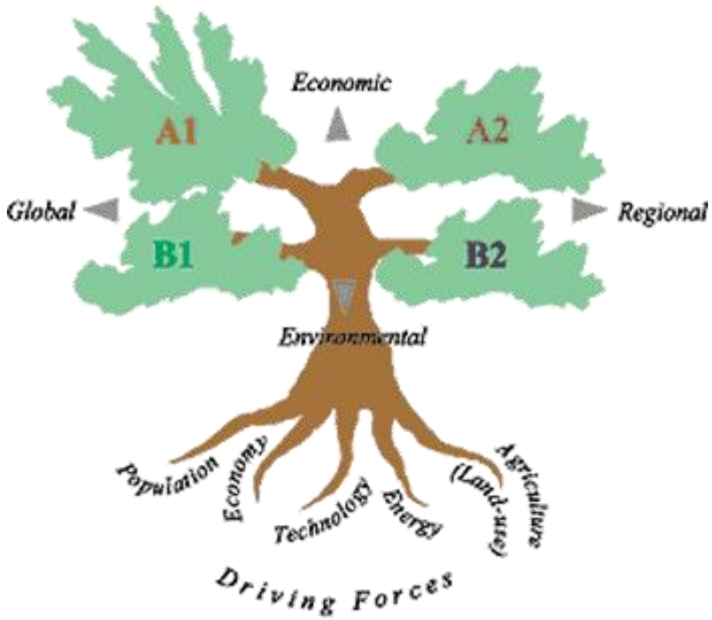
Global Climate Models (GCMs)

- In IPCC AR4 socio-economic driven SRES were used



- In IPCC AR5 representative concentration pathways
- Future GHG concentrations converted to radiative forcing of climate

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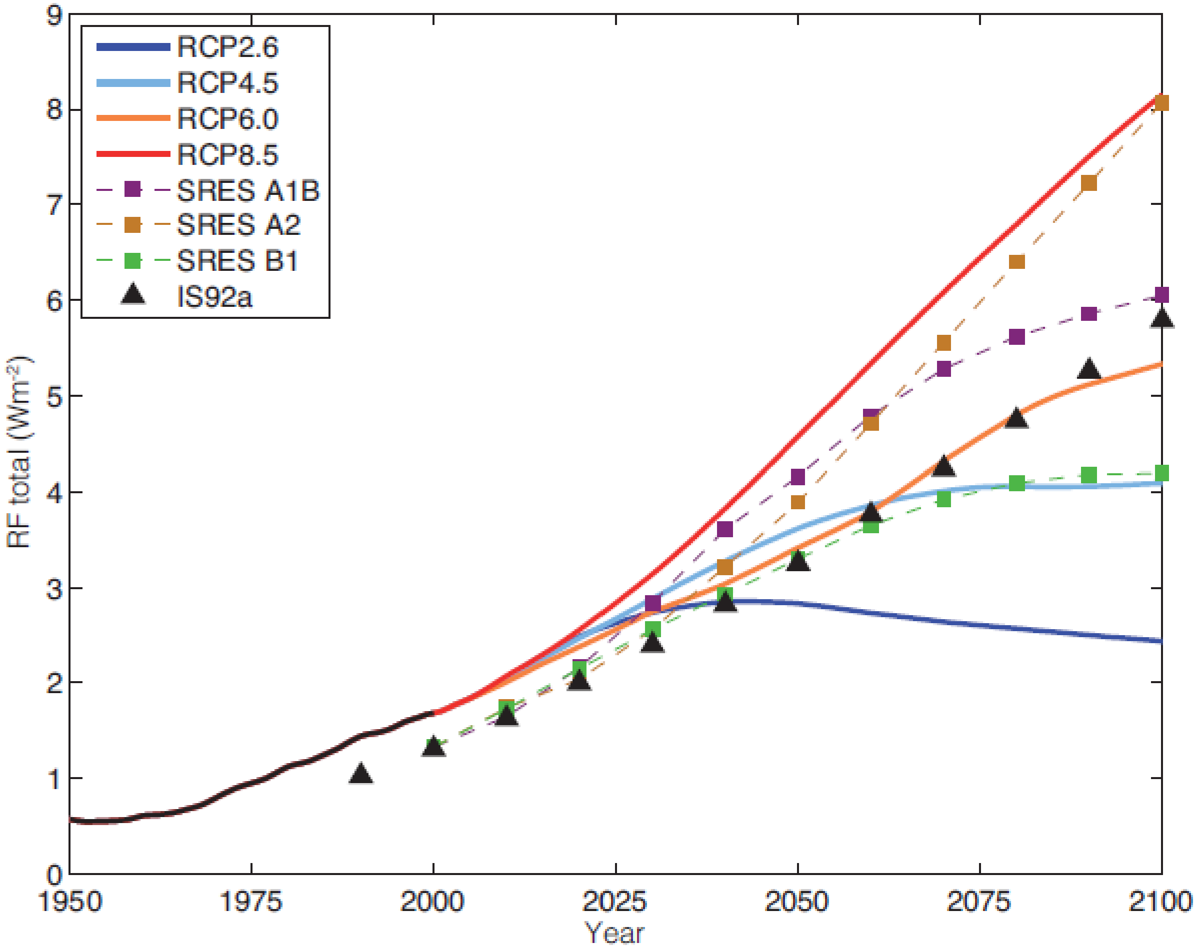
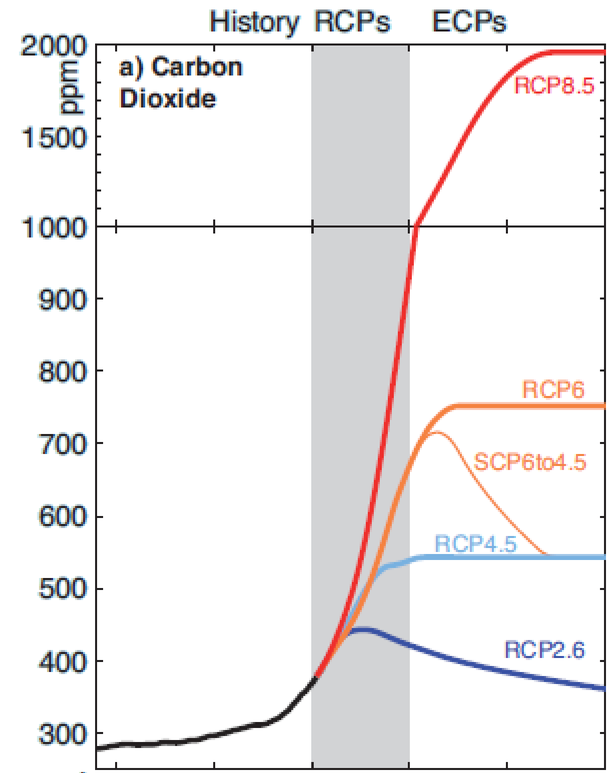
Global Climate Models (GCMs)





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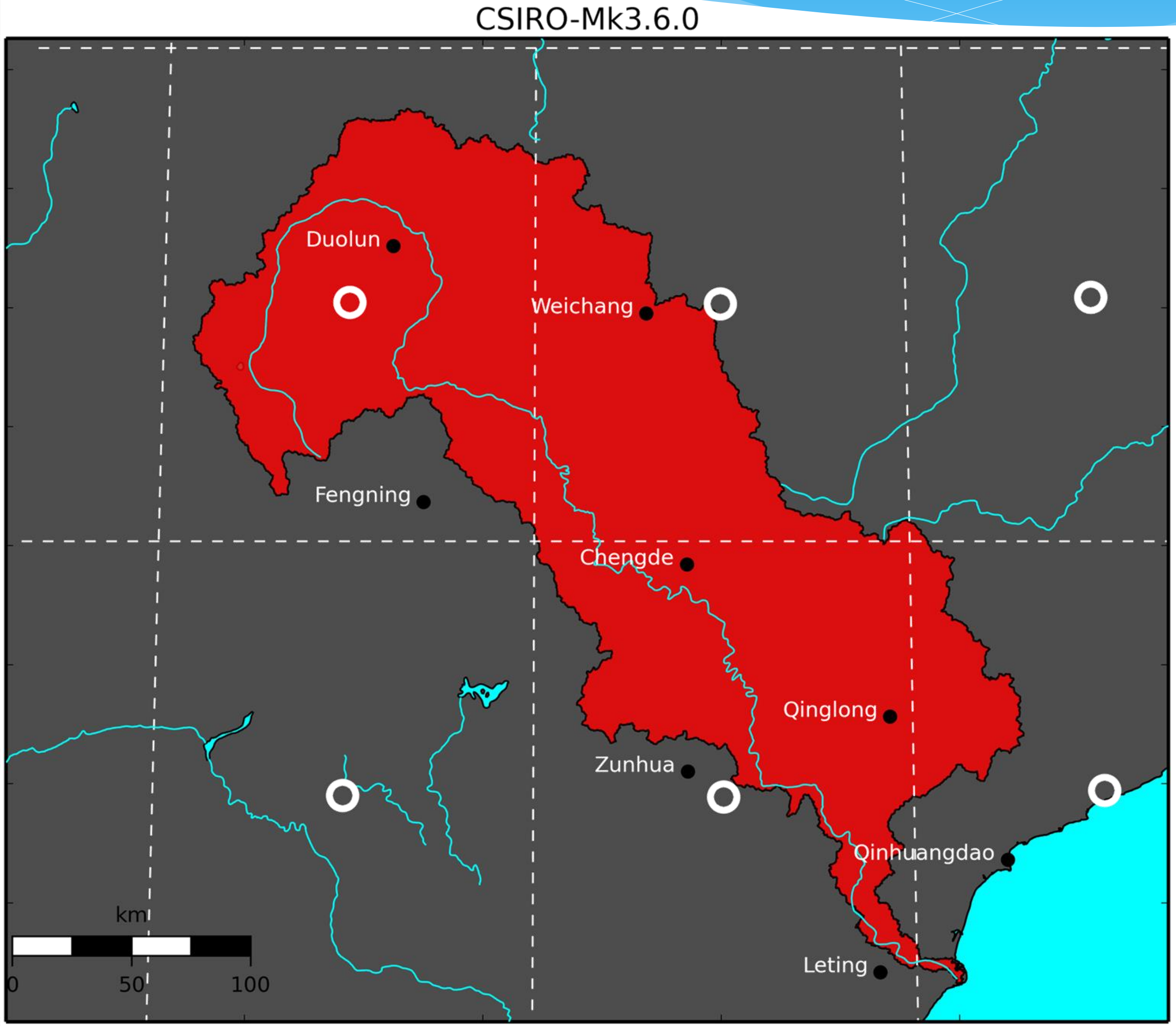
Global Climate Models (GCMs)



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Selecting GCMs

- Multiple Model Ensembles (MME) approach is recommended to encompass uncertainty in model structure and parameterization

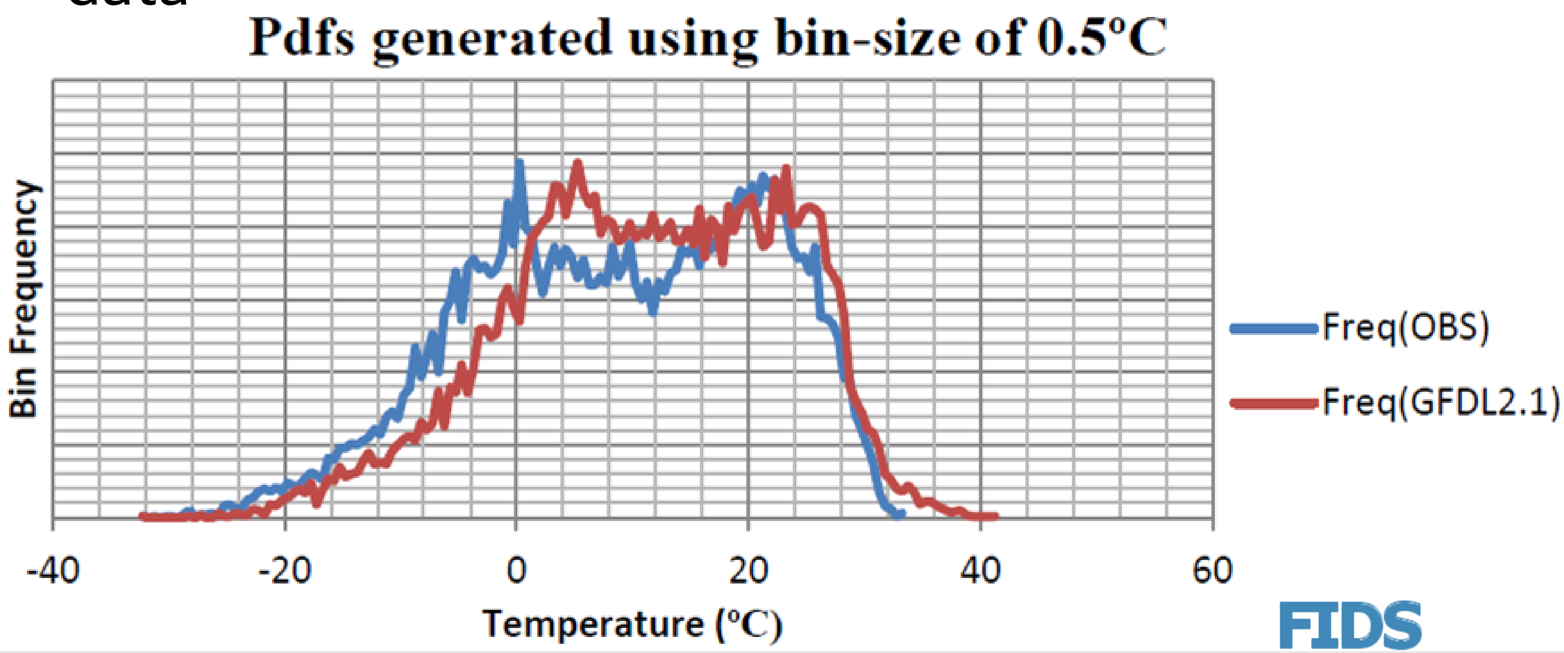
- Large number of GCMs available
  - Multiple emissions scenarios (4 RCPs)
  - Multiple realizations for each GCM-Scenario combinations

- Methods are needed for model selection

Selecting GCMs

- 1) Selection of GCMs by required climate variables for hydrologic modelling during time of interest (e.g. 2050's , 2090's)

- 2)GCM reanalysis data is used to compare with historical data



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Selecting GCMs

- 3) Calculate skill score of each probability density function for each GCM

$$S_{score} = \sum_{1}^{n} \min(Z_m, Z_o)$$

- Cumulative minimum value measures common area between probability density functions

- User defined weights can be applied to each bin to provide higher influence to models that can reproduce range

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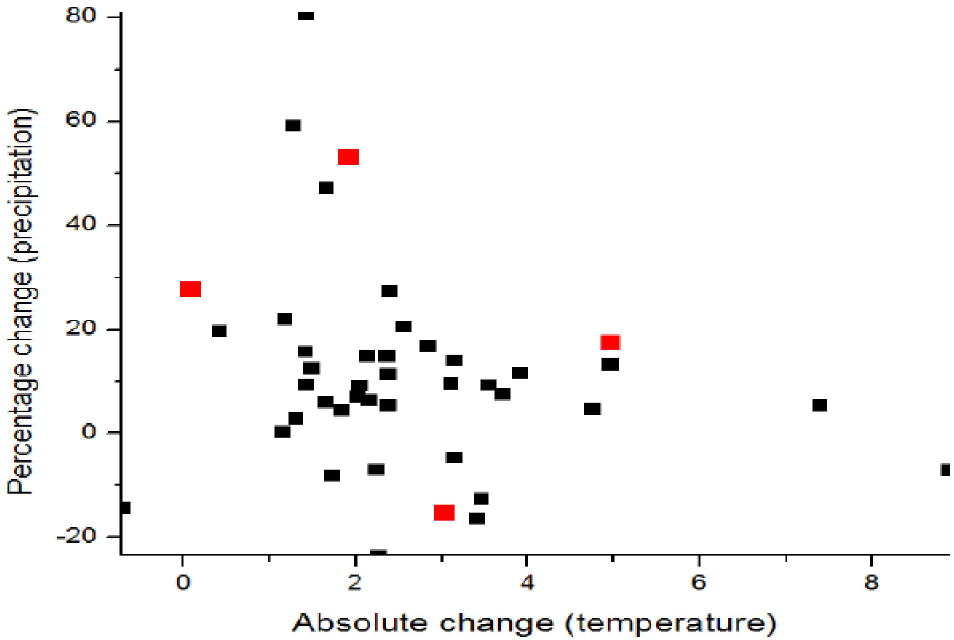
Selecting GCMs

- 4) After models have been selected further reduction can take place by graphical methods

<u>Scatter Plot Method</u>

- Selections of models encompossing scenarios likely to produce hydrologic extremes



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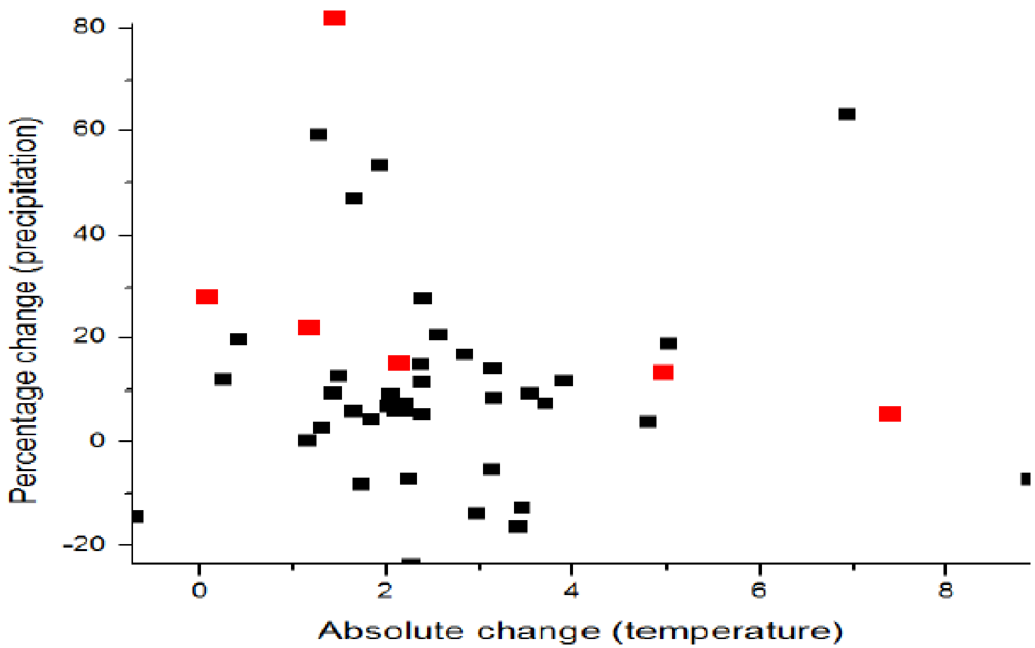
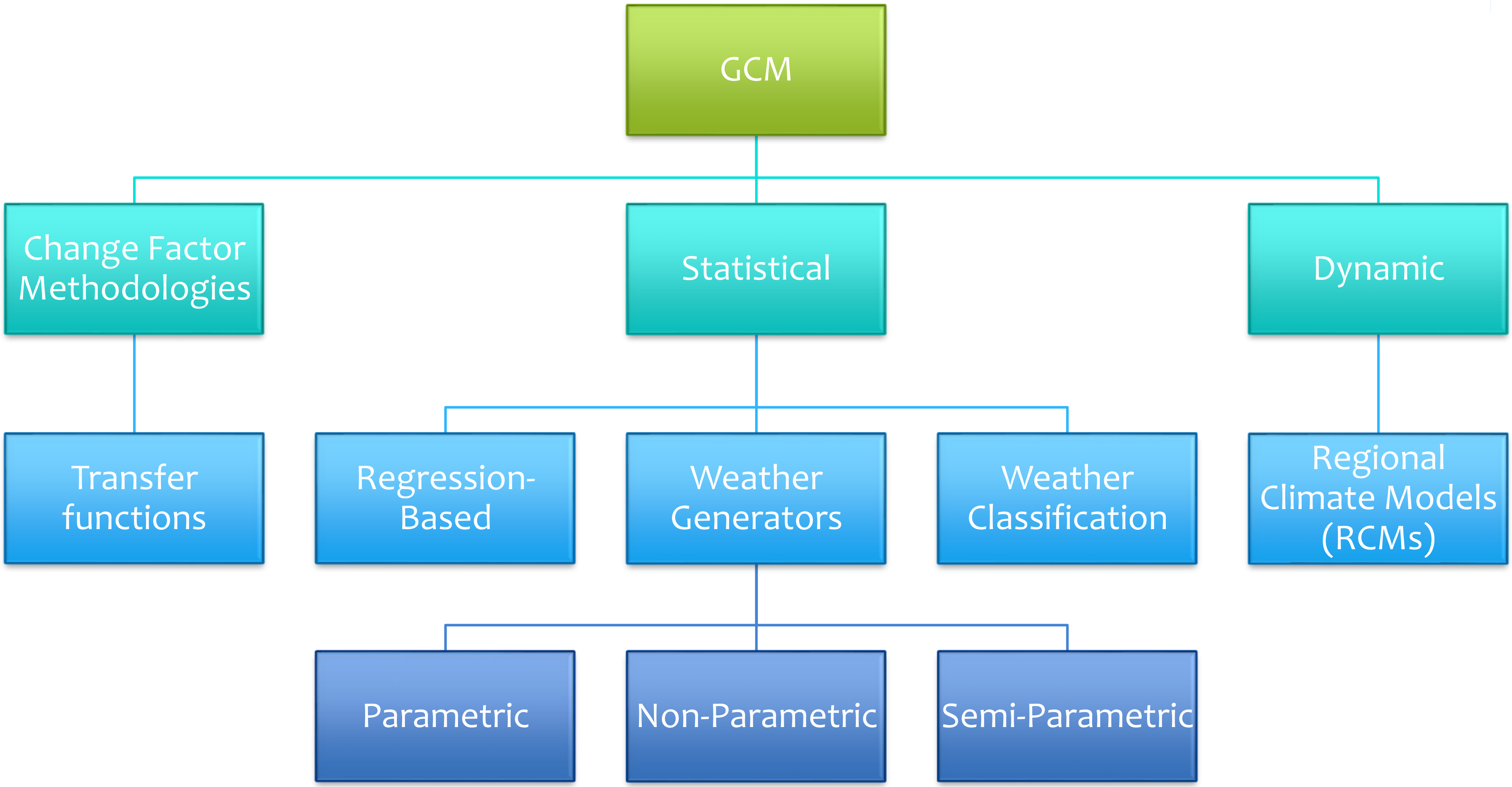
Selecting GCMs

Percentile Method

- Selection of future GCM-Scenario combinations corresponding to 5th, 25th, 50th, 75th, and 95th, percentile



Downscaling GCM data

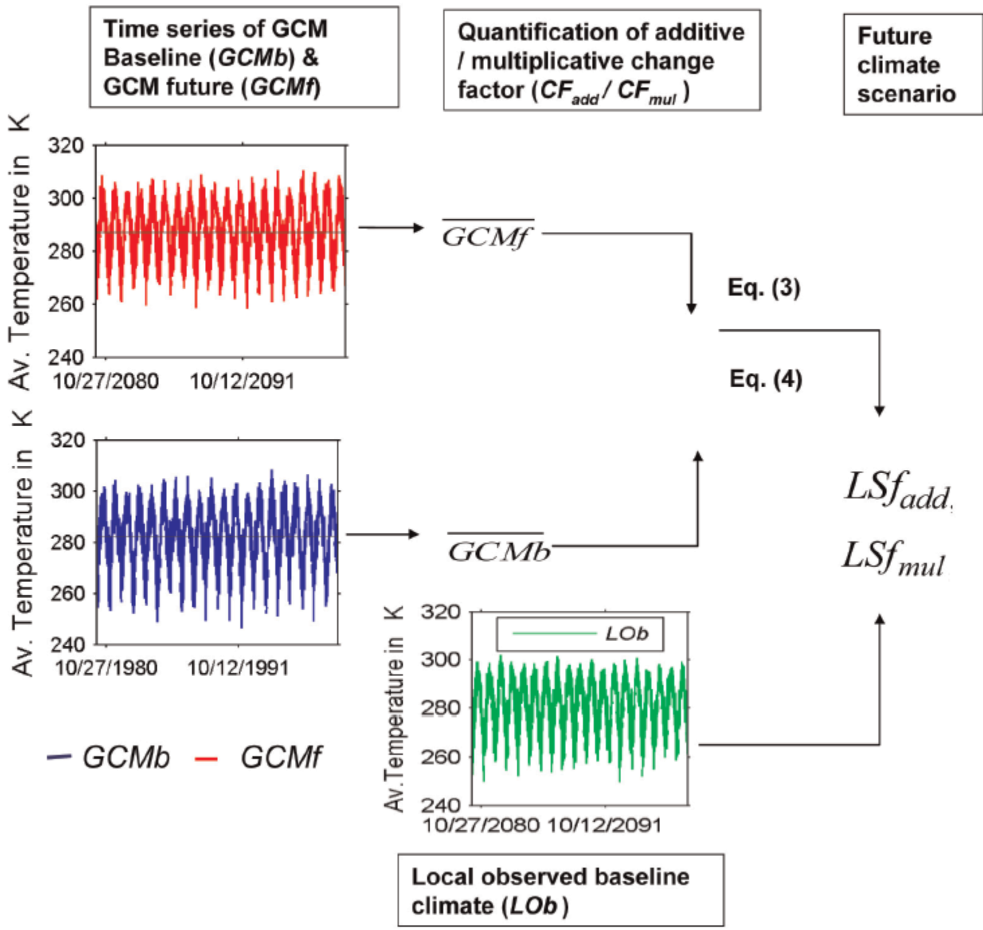


Downscaling GCM data

Simple

Change Factor Methods

- Use transfer functions based on average GCM conditions in different time slices



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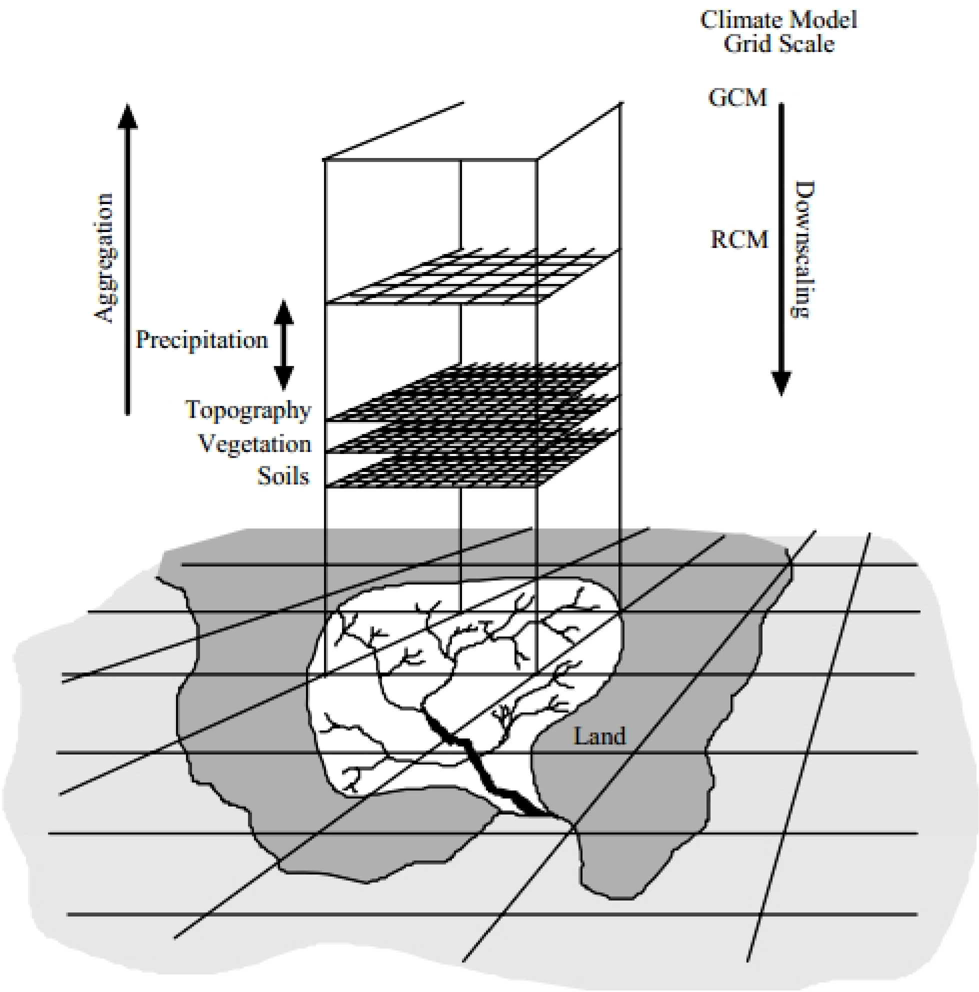
Downscaling GCM data

Dynamic

Regional Climate Models (RCMs)



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Downscaling GCM data

Statistical

- Regression-Based
- Weather Classification
- Weather Generators

- Develops relationship between large scale "predictor" & single site "predictand" variables

Standard Regression Model:

$$\mathbf{y} = \sum_{j=1}^{m} \beta_j \mathbf{x}_j + \mathbf{u} = \mathbf{X}\beta + \mathbf{u}$$

- Multiple regression, Artificial Neural Networks, Canonical correlation, etc.

Downscaling GCM data

Statistical

Regression-Based

Weather Classification

Weather Generators

- Meteorological data is related to discrete weather patterns
- Relationships are developed using conditional probability distributions
- Future climate simulations developed using large scale GCM models

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Downscaling GCM data

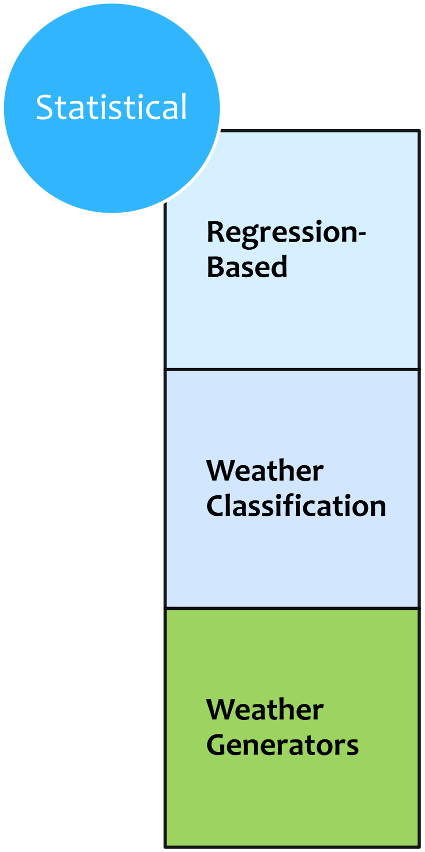
Statistical

- Regression-Based
- Weather Classification
- Weather Generators

- Most popular technique for statistical downscaling
- Ability to generate synthetic climate data of any length
- Statistically reproduces attributes of climate variables include mean and standard deviation
- Main types are parametric, non-parametric, and semi-parametric

Downscaling GCM data

Parametric



- Markov chains to determine wet or dry day probability
- Probability distributions are derived for precipitations amounts, temperatures and other variables
- Spatial correlation must be assumed for multi-site applications

Downscaling GCM data

Statistical

Regression-Based

Weather Classification

Weather Generators

Semi-Parametric

- Empirical / parametric components
- Each model uses a different approach
- Spatial correlations must be assumed for multi-site applications
- Examples:
  - Statistical Downscaling Model (SDSM)
  - LARS-WG

Downscaling GCM data

Statistical

Regression-Based

Weather Classification

Weather Generators

Non-Parametric

- Resampling is used to select daily weather
- No underlying statistical assumptions are needed regarding the probability distribution of weather variables
- KNN approach from Young (1994)

KNN-CAD

- KNN - “K” Nearest Neighbor algorithm (Yates, 2003)
- Reshuffles daily climate data for multiple stations
- Potential neighbors are determined within temporal window
- Potential neighbor averages compared to current day averages using Mahalanobis distance
- Closest “K” nearest neighbors selected
- Next days weather from KNNs randomly selected from probability distribution

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KNN-CAD

- KNN-CAD version 1 (Sharif and Burn, 2006)
  - Perturbation component is added
- KNN-CAD version 2 (Prodanovic and Simonovic, 2008)
  - Leap year modification
- KNN-CAD version 3 (Eum and Simonovic, 2008)
  - Principal component analysis for calculation of Mahalanobis distance
- KNN-CAD version 4 (King, McLeod, and Simonovic, 2012)
  - Improved perturbation scheme
  - Block bootstrapping method

KNN-CAD

- KNN algorithm consists of 9 steps

Step 1 – Compute regional means of p variables (x) across all q stations for each day in the historical record

$$\overline{X_t} = [\bar{x}_{1,t}, \bar{x}_{2,t}, \dots, \bar{x}_{p,t}] \quad \forall t = \{1,2,\dots,T\}$$

where, $\bar{x}_{i,t} = \frac{1}{q}\sum_{j=1}^{q} \bar{x}_{i,t}^{\,j} \quad \forall i = \{1,2,\dots,p\}$

here, $\bar{x}_{i,t} = \frac{1}{q}\sum_{j=1}^{q} x_{i,t}^{\,j} \quad \forall i = \{1,2,\dots,p\}$

KNN-CAD

<u>**Step 2 –**</u> Choose temporal of length "w" and select a subset of potential neighbors "L" days long for "N" years

1	2	3	4	5	6	7	8	9	N
				.					.
				.					.
				.					.
1	2	3	4	5	6	7	8	9	3
1	2	3	4	5	6	7	8	9	2
1	2	3	4	D	6	7	8	9	1
									Year

<------------------ w/2 ------------------> <------------------ w/2 ------------------>

$$L = N * (w + 1) - 1$$

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<u>Step 3 –</u> Compute mean of "L" potential neighbors, $\overline{X_l}$ for each day

$$\overline{X_l} = \begin{bmatrix} \overline{x}_{1,1} & \cdots & \overline{x}_{1,p} \\ \vdots & \ddots & \vdots \\ \overline{x}_{L,1} & \cdots & \overline{x}_{L,p} \end{bmatrix}$$

<u>Step 4 –</u> Compute covariance matrix C_t for day t with $\overline{X_l}$

$$C_t = \begin{bmatrix} var(\overline{x}_{1,1}) & \cdots & cov(\overline{x}_{1,1}, \overline{x}_{1,p}) \\ \vdots & \ddots & \vdots \\ cov(\overline{x}_{p,1}) & \cdots & var(\overline{x}_{p,p}) \end{bmatrix}$$

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Step 5 – Random selection of first simulation day from historical record consisting of "p" variables at "q" stations from the "N" years

Step 6

a) Calculate eigenvector ($\vec{E}$) & eigenvalue (e) from C_t

b) Retain $\vec{E}$ with highest e

c) Calculate first principal component using $\vec{E}$

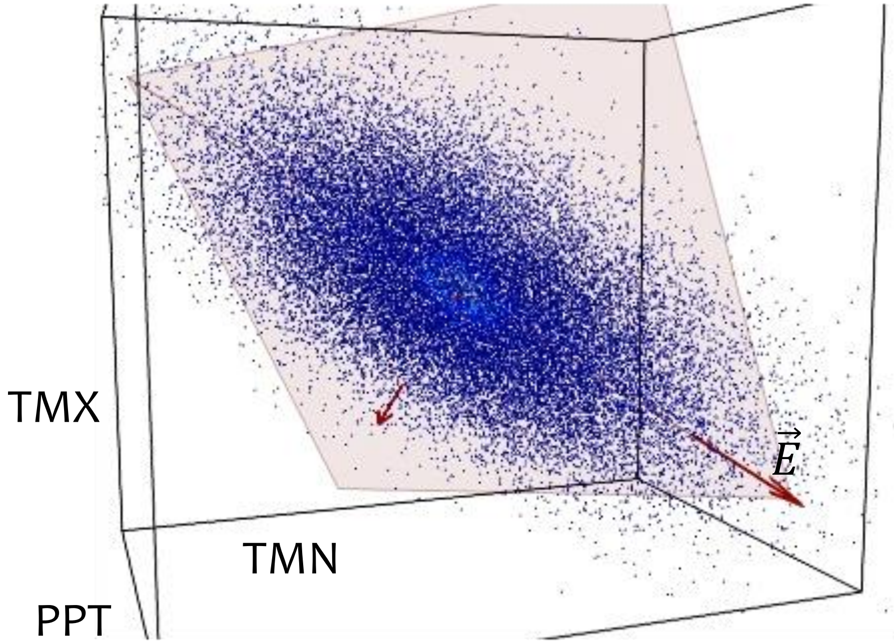
$$PC_t = \overline{X}_t \vec{E}$$

$$PC_l = \overline{X}_l \vec{E} \qquad \forall l = \{1,2, \dots, L\}$$

KNN-CAD

d) Calculate Mahalanobis distance

$$d_l = \sqrt{\frac{(PC_t - PC_l)^2}{var(PC)}}$$



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Step 7 – Sort the Mahalanobis calculated for each potential neighbor from smallest to largest and retain the "K" nearest neighbors

$$K = \sqrt{L}$$

Yates et al. (2003)

Step 8 – Use discrete probability distribution weighting closest neighbors the highest for resampling one of the "K" nearest neighbors

$$w_k = \frac{1/k}{\sum_{i=1}^{k} 1/i} \qquad \forall k = \{1, 2, \ldots, K\} \qquad p_j = \sum_{i=1}^{j} w_i$$

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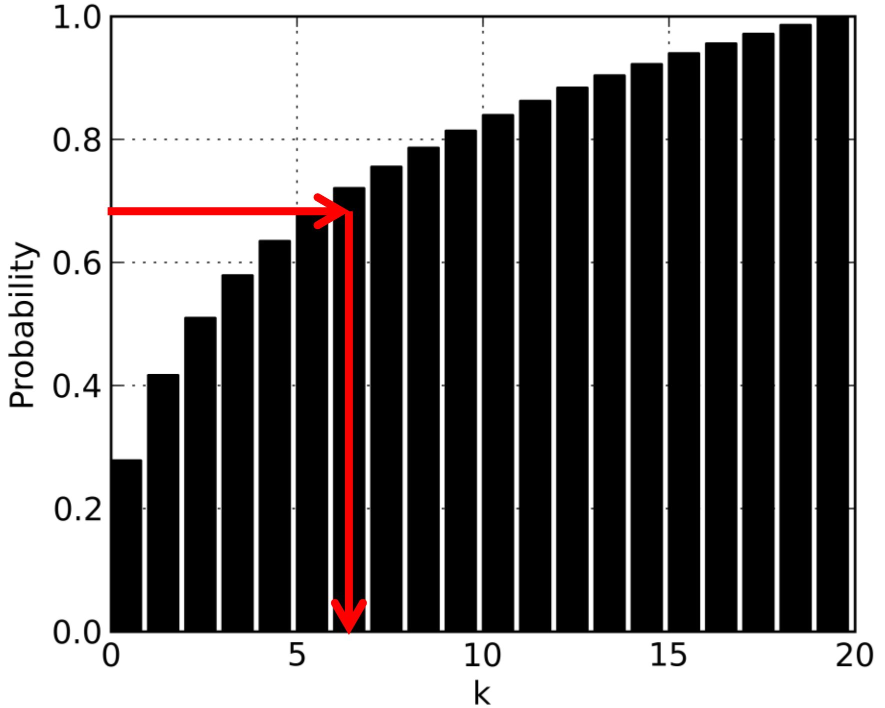
Step 9 – Generate random number, $u(0,1)$, to determine current neighbor from probability distribution



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<u>Step 10 –</u> Resample block of data preceding selected day

NN	NN + 1	NN + 2	-	-	-	NN + B

<u>Step 11(a) –</u> Perturbation of resampled temperature values

$$y_{i,t+b}^{j} = \lambda_{temp} * x_{i,t+b}^{j} + \left(1 - \lambda_{temp}\right) Z_{t+b}$$

where, $b = 1,2, \dots, B$

$$Z_{t+b} \sim N(\mu, \sigma)$$

$$Z_{t+b} \sim N\left(x_{i,t+b}^{j}, \sigma_{i,t}\right)$$

From KNN

KNN-CAD

Step 11(b) – Perturbation of resampled precipitation values

$$y^{j}_{ppt,t+b} = \lambda_{ppt} * x^{j}_{ppt,t+b} + (1 - \lambda_{ppt}) Z_{t+b}$$

Where,

$$Z_{t+b} = e^{Am_{j,t} + Bm_{j,t} * z_t}$$

$$Am_{j,t} = \log(x_{j,t}) - \frac{Bm_{j,t}}{2}$$

$$Bm_{j,t} = \sqrt{\log\left(\frac{\sigma^2_{j,t}}{x_{j,t}} + 1\right)}$$

$\sigma_{j,t} \longrightarrow$ From LNN

KNN-CAD

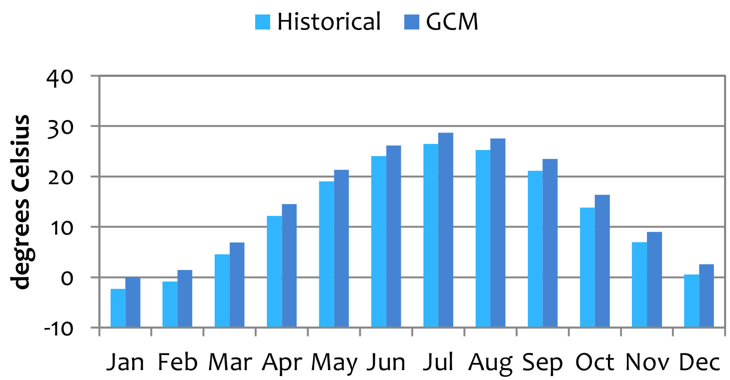
<u>Step 12-</u> Repeat process until end of historical record is reached

*Process can be repeated any number of times for longer generated climate records

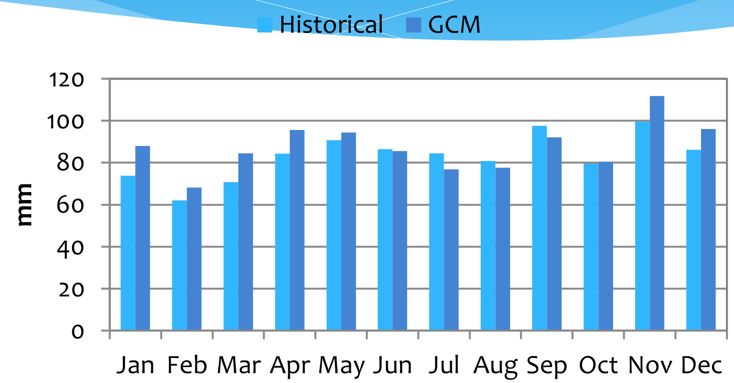
*Longer records are extremely useful for risk analysis in hydrologic modelling

KNN-CAD

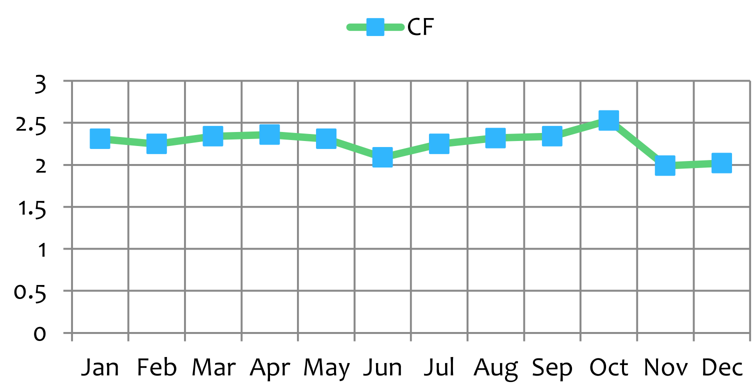
Temperature



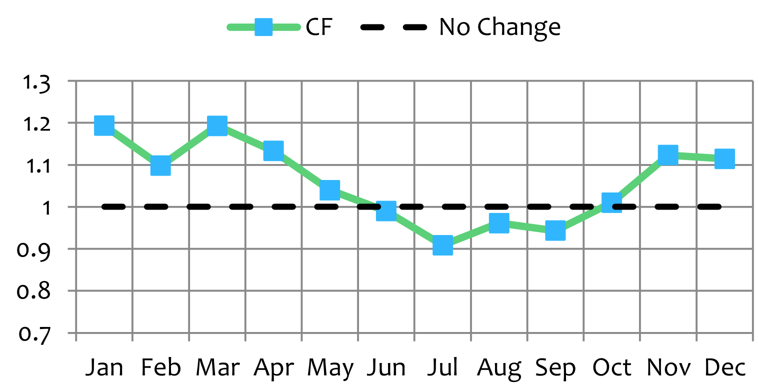
Precipitation



Temperature Change Factor



Precipitation Change Factor



$$Temp.CF = \overline{GCM}_{future} - \overline{GCM}_{historical}$$

$$Temp.CF = \frac{\overline{GCM}_{future} - \overline{GCM}_{historical}}{\overline{GCM}_{historical}} * 100$$

*using CGCM3T47 with A1B SRES Scenario for LondonA weather station

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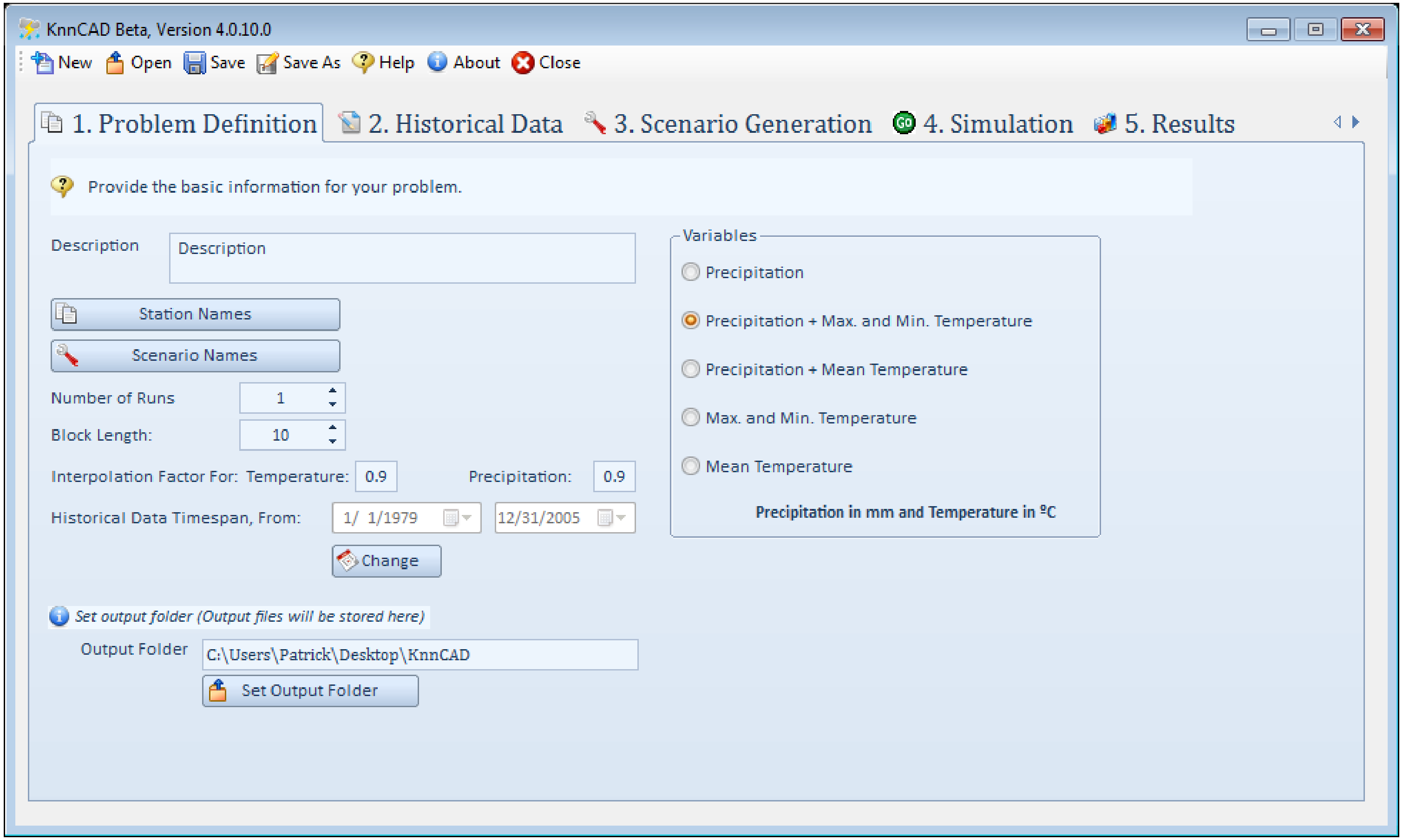
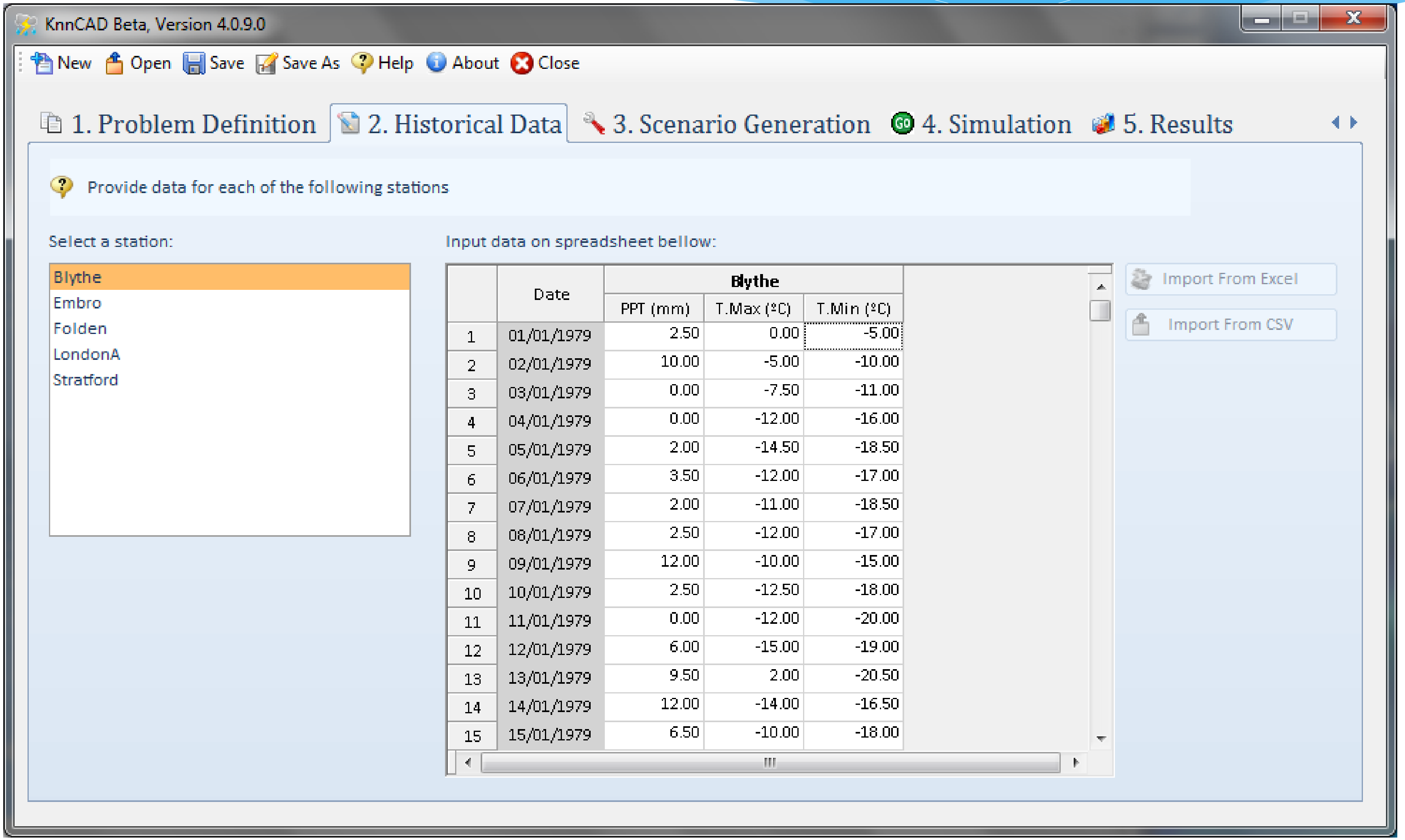
KNN-CADV4 Example

- User interface developed by Shardong, King and Simonovic (2012)



KNN-CADV4 Example



	Date	Blythe		
		PPT (mm)	T.Max (ºC)	T.Min (ºC)
1	01/01/1979	2.50	0.00	-5.00
2	02/01/1979	10.00	-5.00	-10.00
3	03/01/1979	0.00	-7.50	-11.00
4	04/01/1979	0.00	-12.00	-16.00
5	05/01/1979	2.00	-14.50	-18.50
6	06/01/1979	3.50	-12.00	-17.00
7	07/01/1979	2.00	-11.00	-18.50
8	08/01/1979	2.50	-12.00	-17.00
9	09/01/1979	12.00	-10.00	-15.00
10	10/01/1979	2.50	-12.50	-18.00
11	11/01/1979	0.00	-12.00	-20.00
12	12/01/1979	6.00	-15.00	-19.00
13	13/01/1979	9.50	2.00	-20.50
14	14/01/1979	12.00	-14.00	-16.50
15	15/01/1979	6.50	-10.00	-18.00

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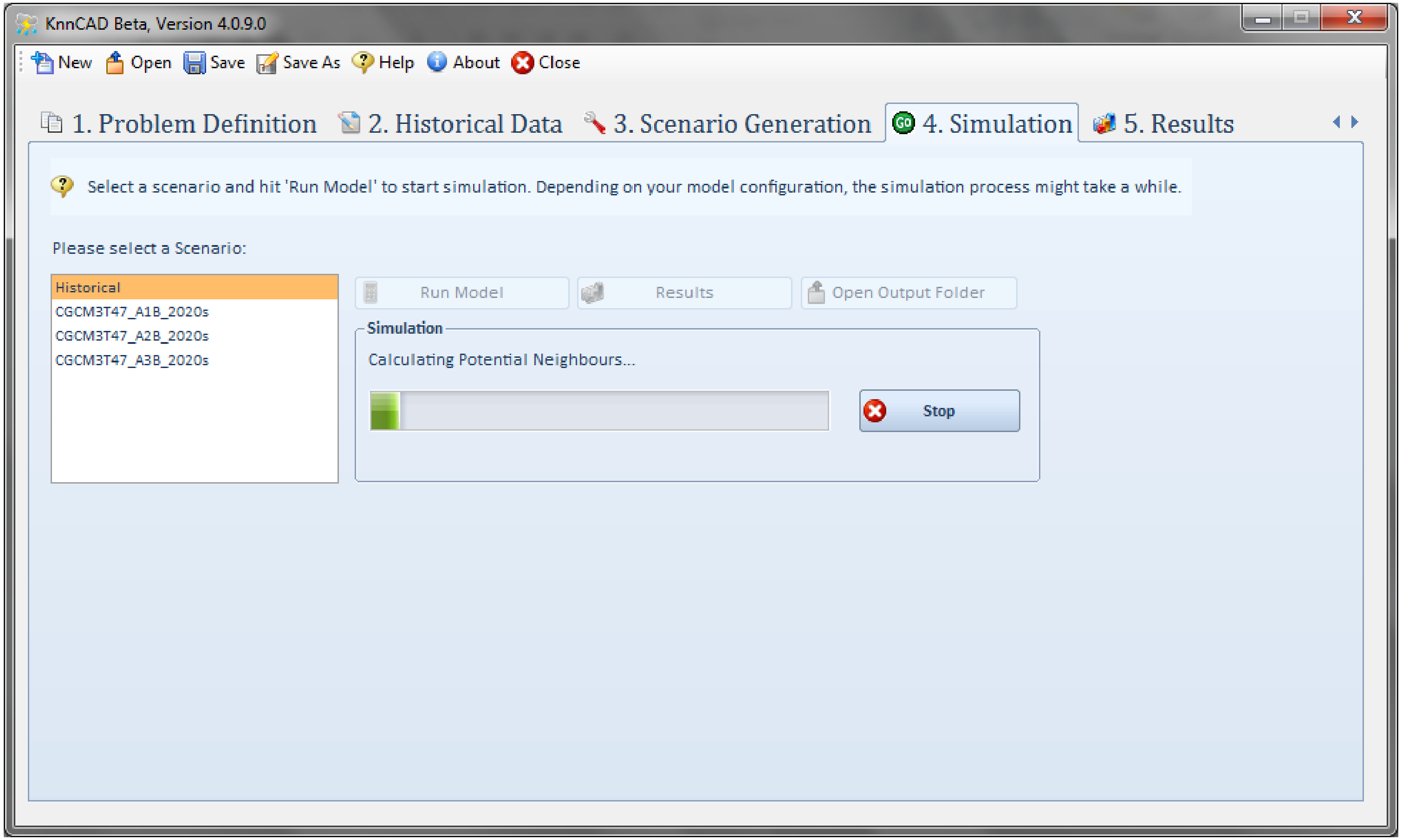
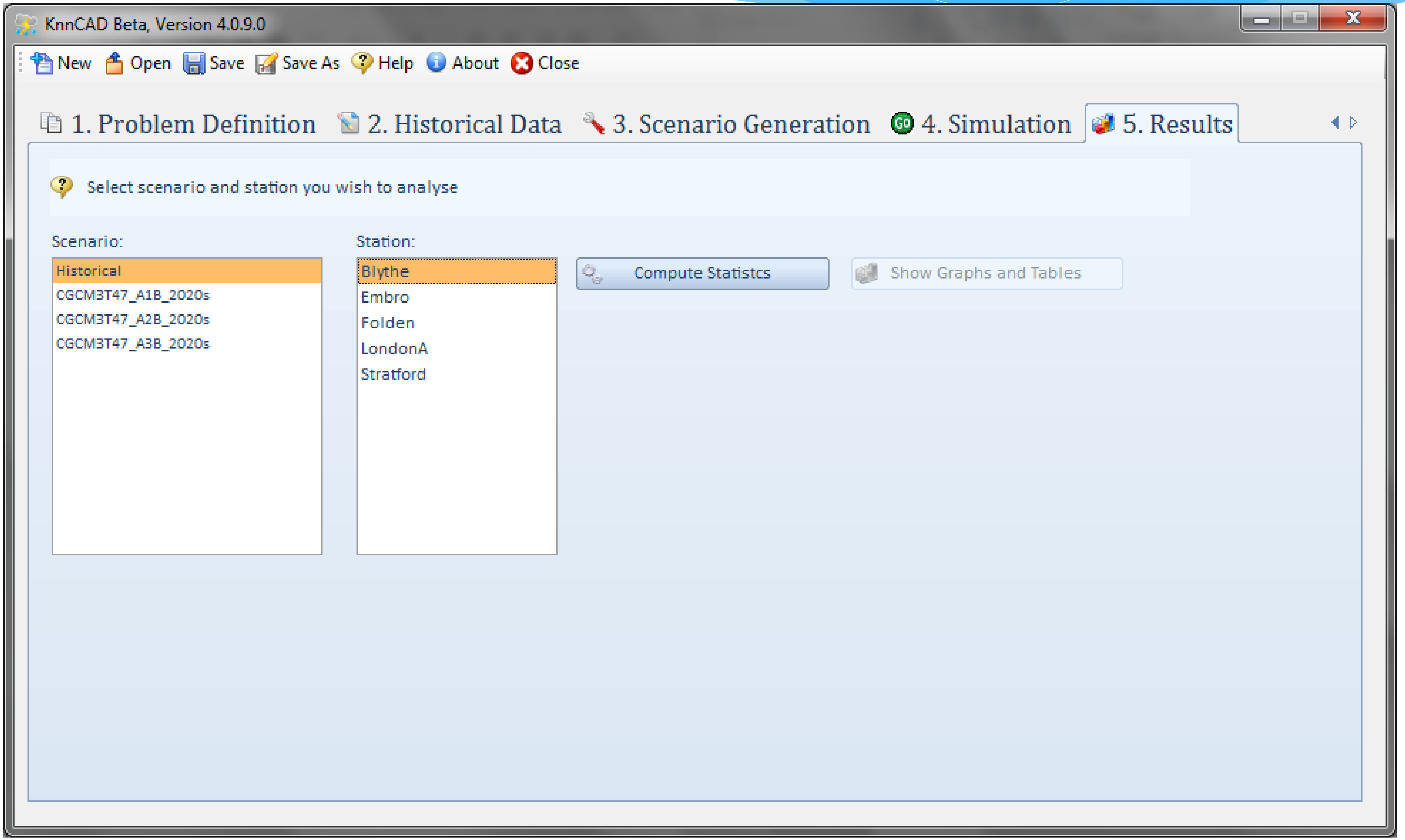
KNN-CADV4 Example

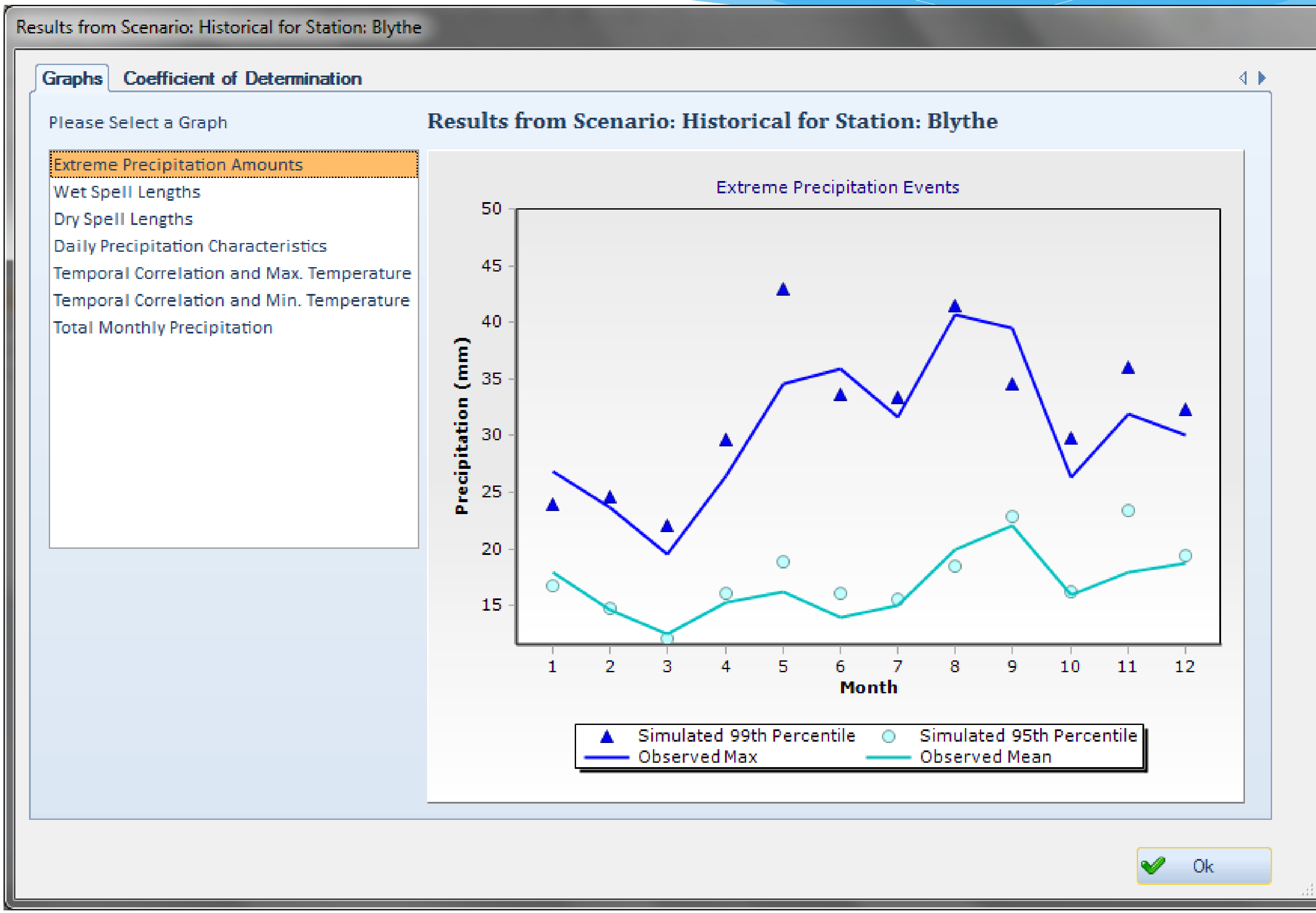
- Calibration procedure begins with historical data simulation



KNN-CADV4 Example



KNN-CADV4 Example



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KNN-CADV4 Example

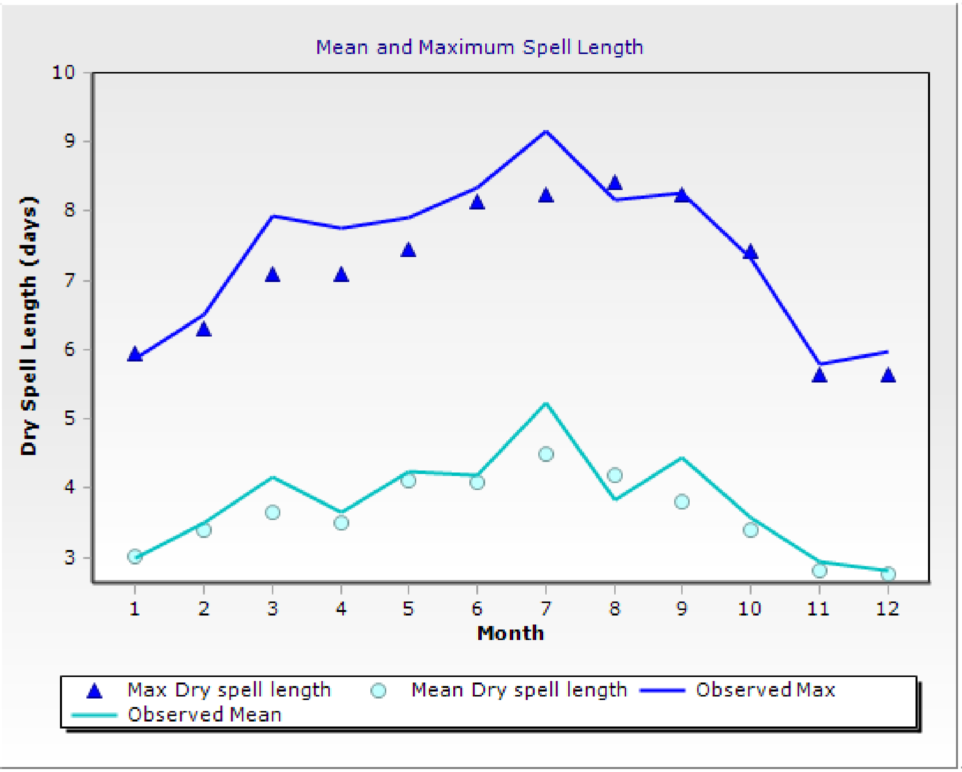
Results from Scenario: Historical for Station: Blythe

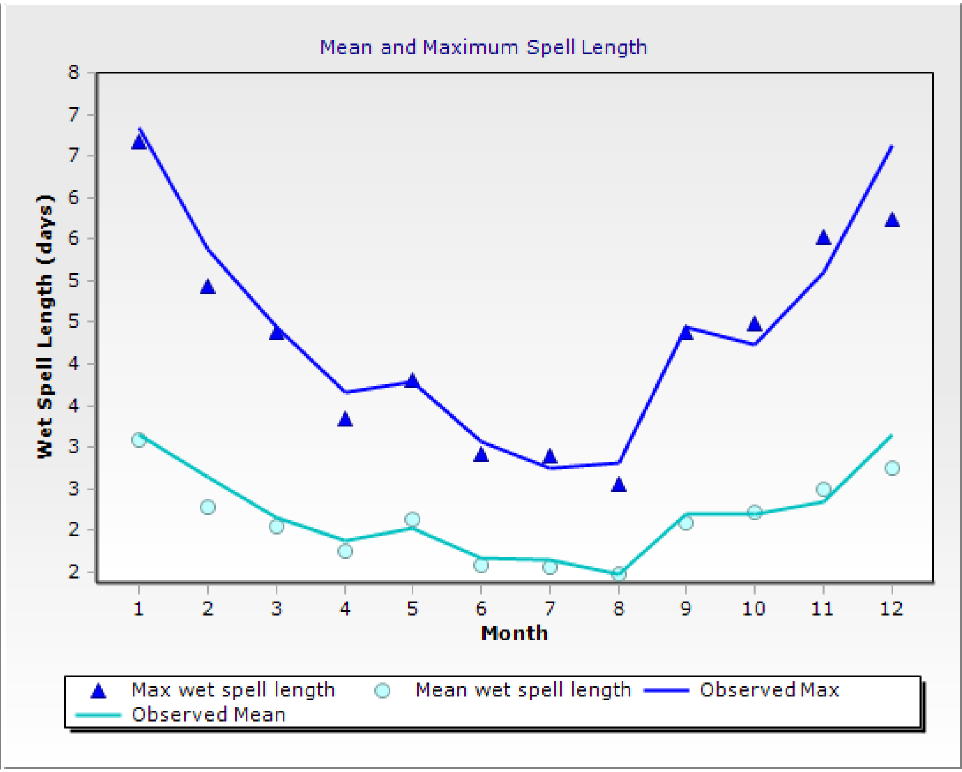
Graphs | Coefficient of Determination

Coefficient of Determination	
Total Monthly Precipitation	0.725
Mean Daily Precipitation	0.878
SD Daily Precipitation	0.791
95th Percentile Precipitation	0.674
99th Percentile Precipitation	0.72
Mean Wet Spell Length	0.92
Mean Dry Spell Length	0.83
Max Wet Spell Length	0.938
Max Dry Spell Length	0.886
Mean TMAX	0.999
Mean TMIN	0.998
99th Percentile TMAX	0.994
95th Percnetile TMAX	0.995
5th Percentile TMAX	0.999
1st Percentile TMAX	0.996
99th Percentile TMIN	0.988
95th Percentile TMIN	0.999
5th Percentile TMIN	0.999
1st Percneitle TMIN	0.999

Ok

KNN-CADV4 Example





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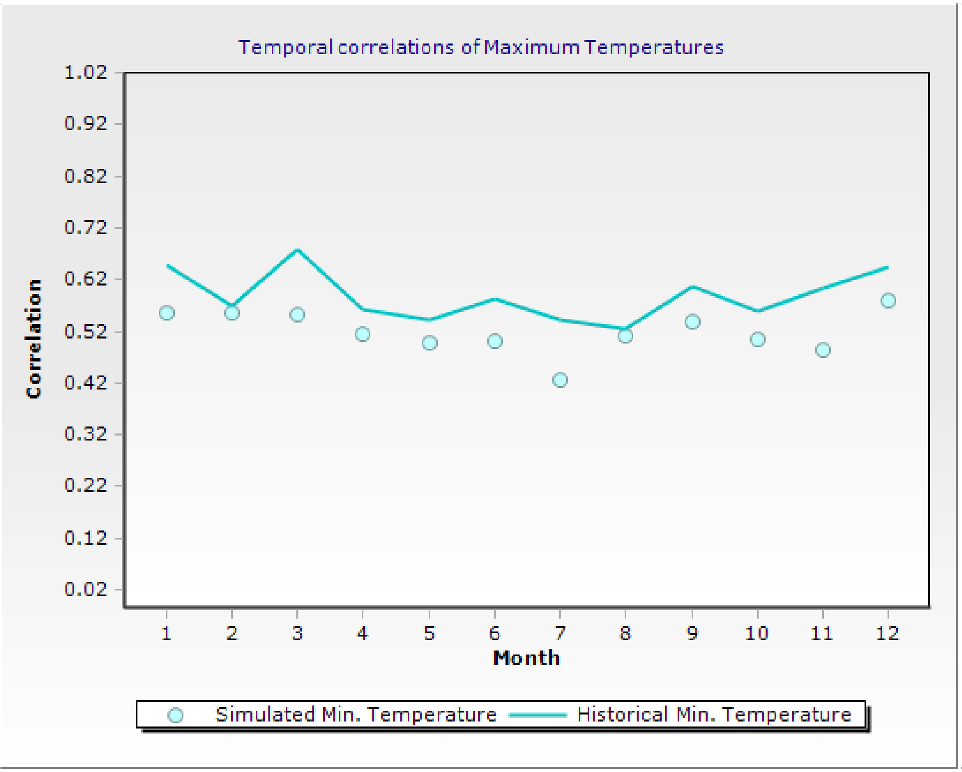
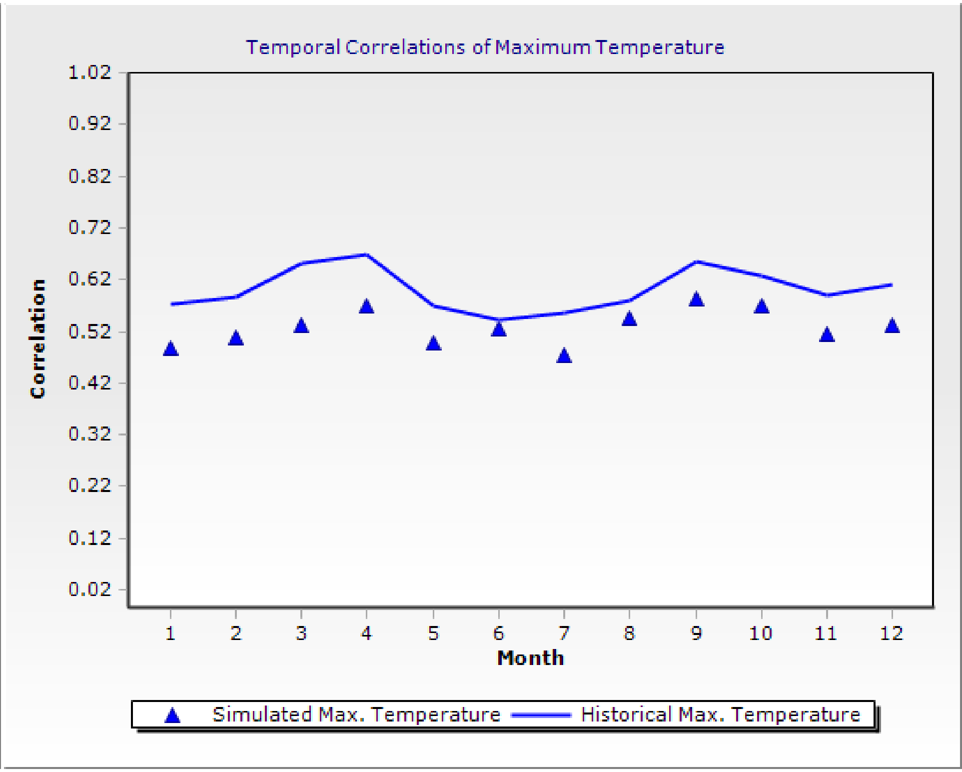
KNN-CADV4 Example





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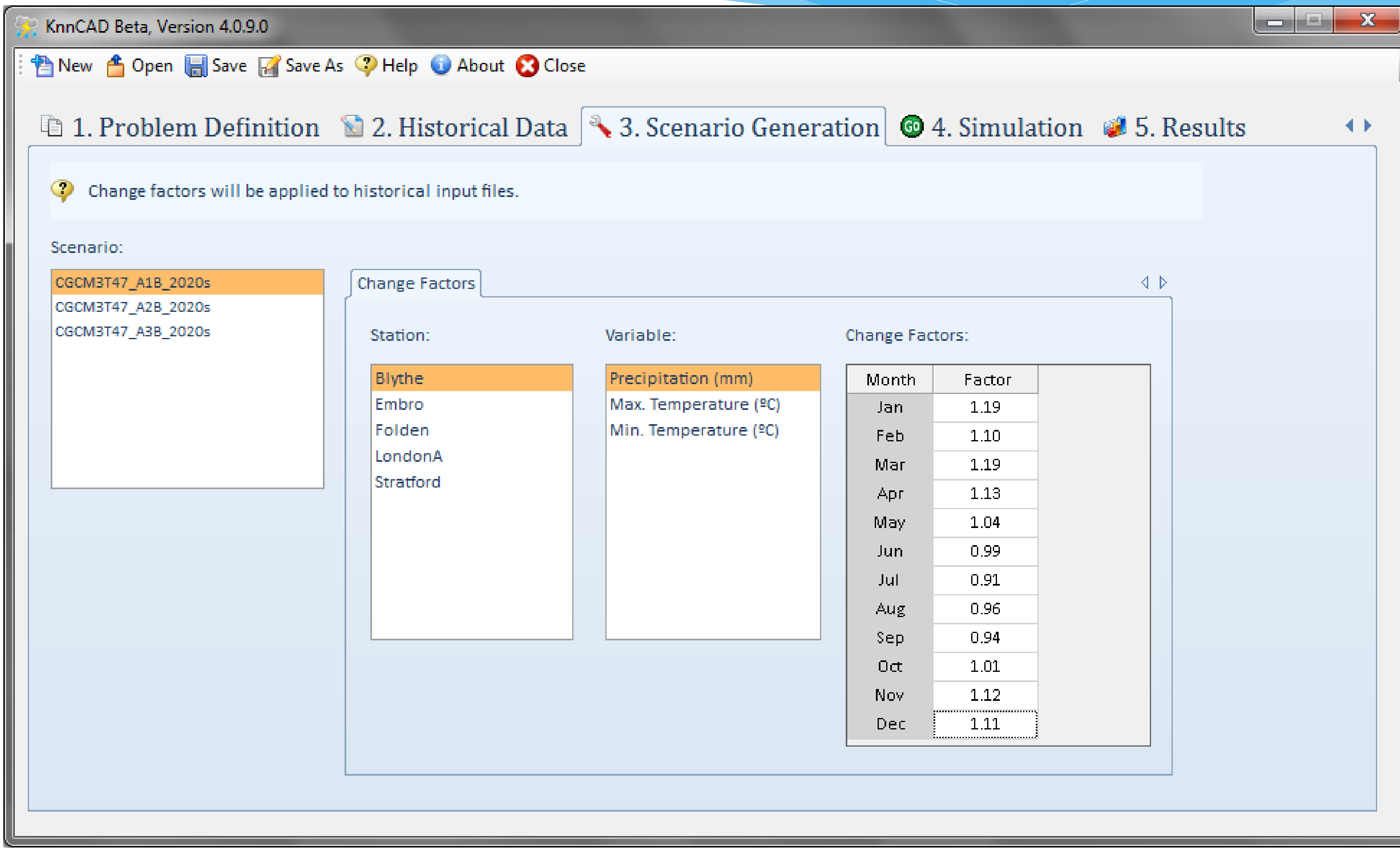
KNN-CADV4 Example



KNN-CADV4 Applications

1. Integrated Reservoir Management Optimization

Eum (2009)

2. Flood and Drought Risk

Prodanovic and Simonovic (2006a, 2006b), Gaur (2013)

3. IWRM System Dynamics Simulation

Prodanovic (2007)