

2017 APCC Training Program on
“User-oriented Statistical Downscaling of
Climate Information in
Agriculture and Water Resources”

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Alberta Environment and Parks (AEP)



Who am I?

➤ Worked in APCC

- Sep. 2014 – Feb. 2017

➤ Hydrologist in AEP

➤ Research Interests

- Statistical Downscaling
- Hydrologic modelling
- Climate change impacts on hydrologic systems

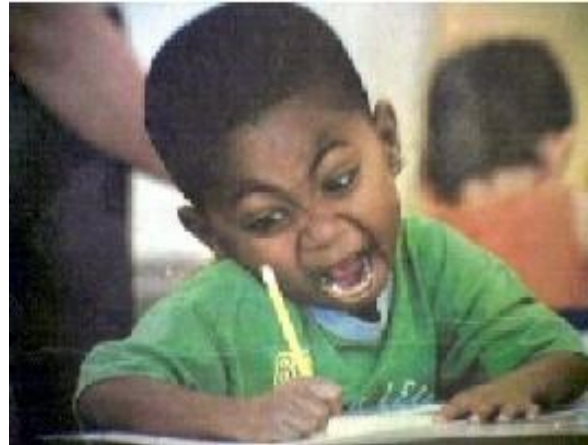
➤ Current project

- Numerical modelling framework for assessment of cumulative environmental impacts



Please help me !!

➤ Hard work!



➤ Attention to instructors



Please help me !!

- **Remain seated please !!**



- **Do not bring foods in Lotus...Please!!**



Contents

- **Why do we need downscaling?**
- **Dynamical VS Statistical downscaling**
 - Pros and cons
- **Statistical downscaling methods**
 - Perfect Prognosis (PP)
 - Model Output Statistics (MOS)
 - Long-term trend preserving methods



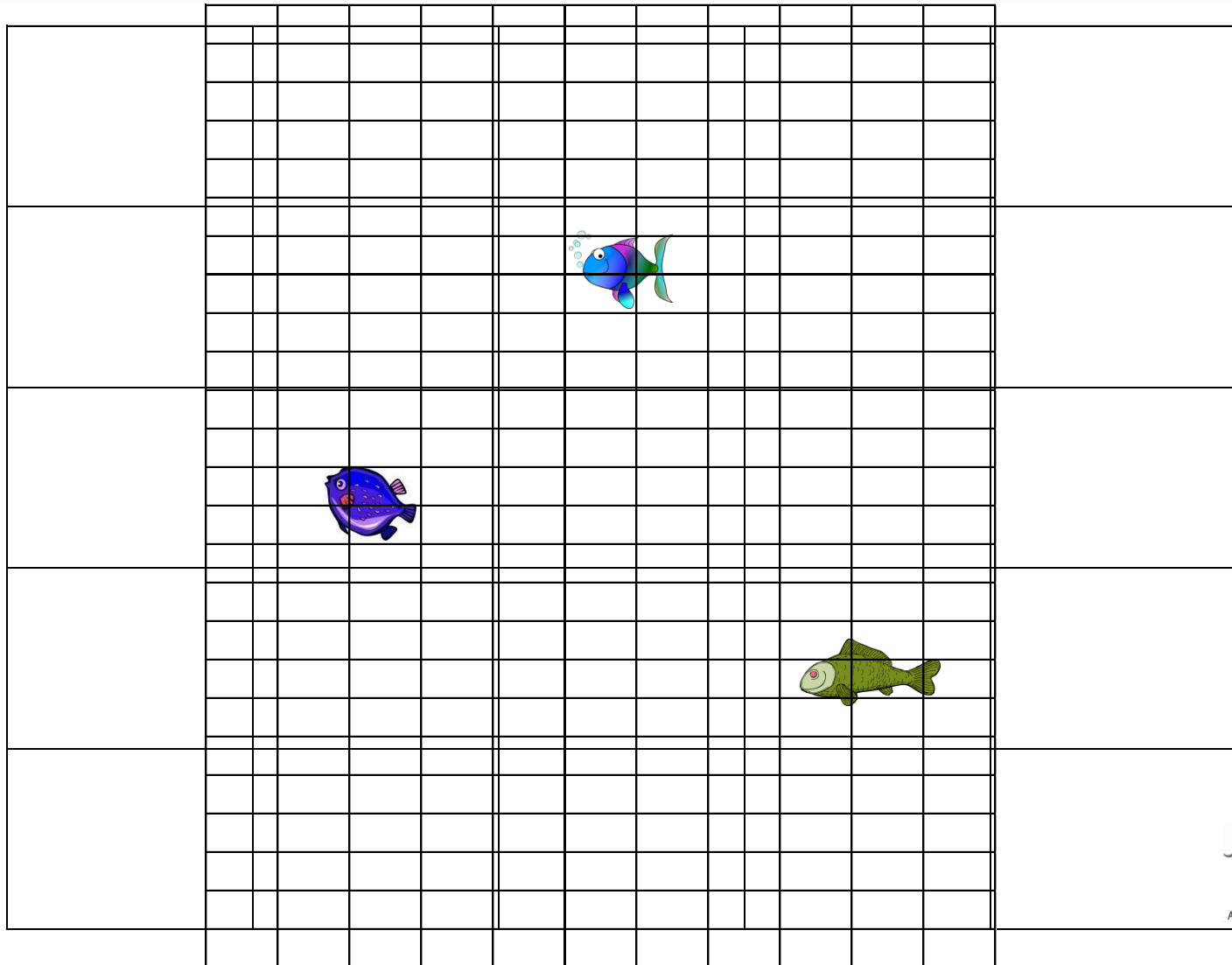
Rubber suitable to road conditions



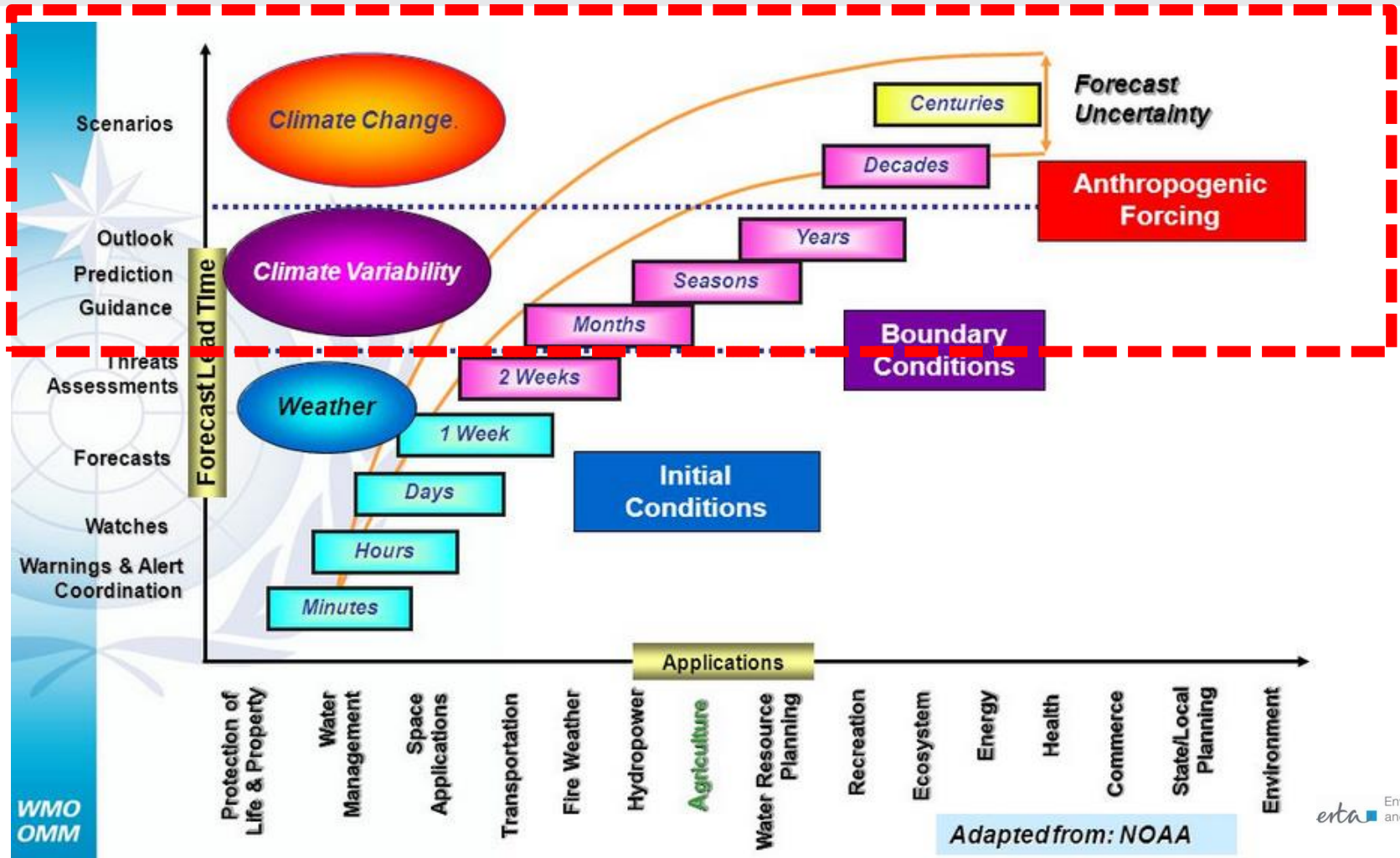
Impacts & adaptation studies



Properly Working?



Climate prediction framework



Temporal scale of GCMs

➤ **Temporal scales in climate forecasts**

- Predictable signal of seasonal climate
 - Surface ocean and land condition on longer scales (monthly – seasonal)
- Short time scales
 - Dominated by atmospheric “weather noise”

➤ **APCC Multiple Models Ensemble (MME)**

- 6-month forecasts at monthly time step

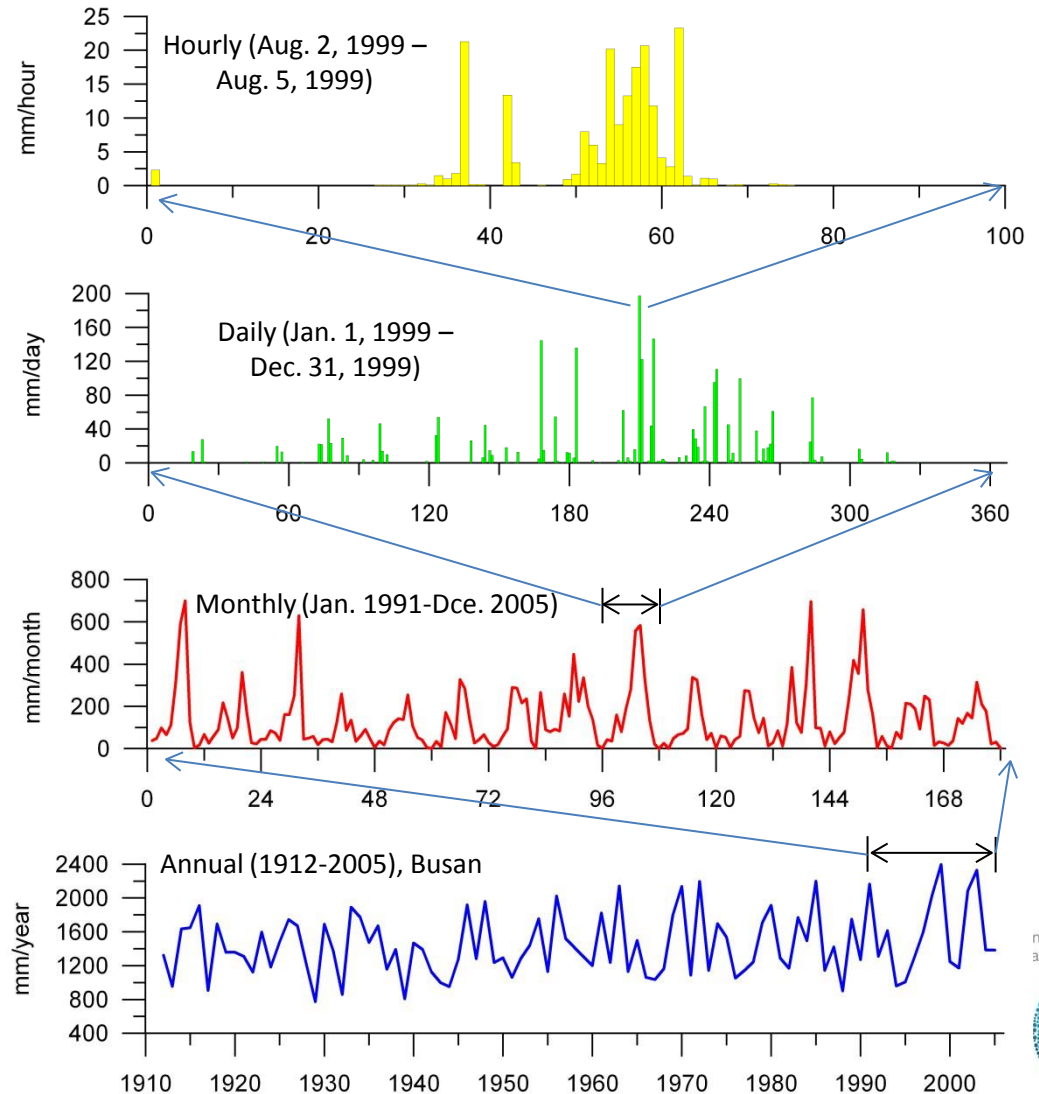
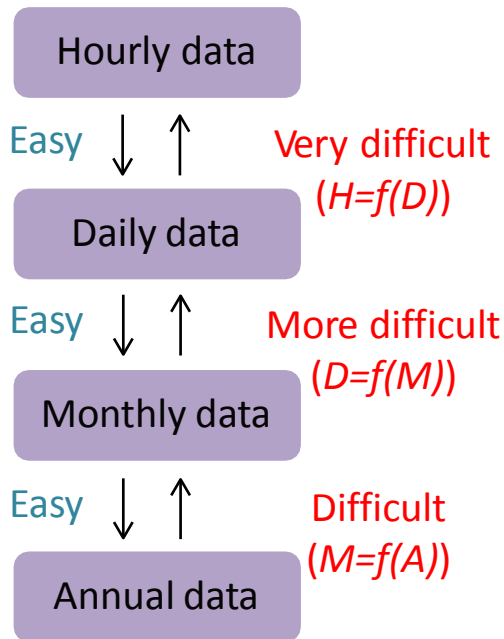
➤ **Need of accurate sub-daily or daily climate information**

- Agricultural or hydrologic applications



Temporal disaggregation

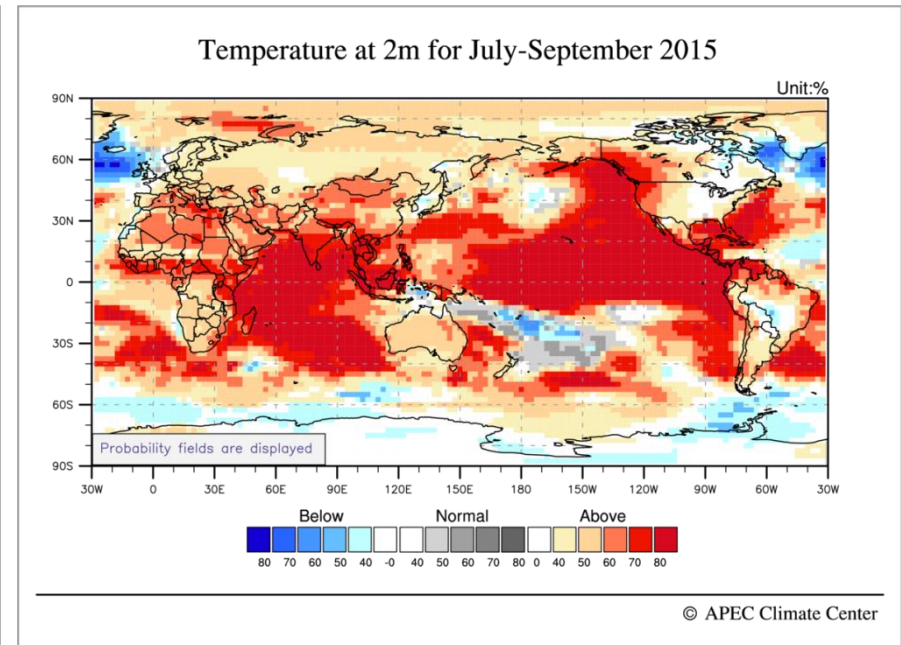
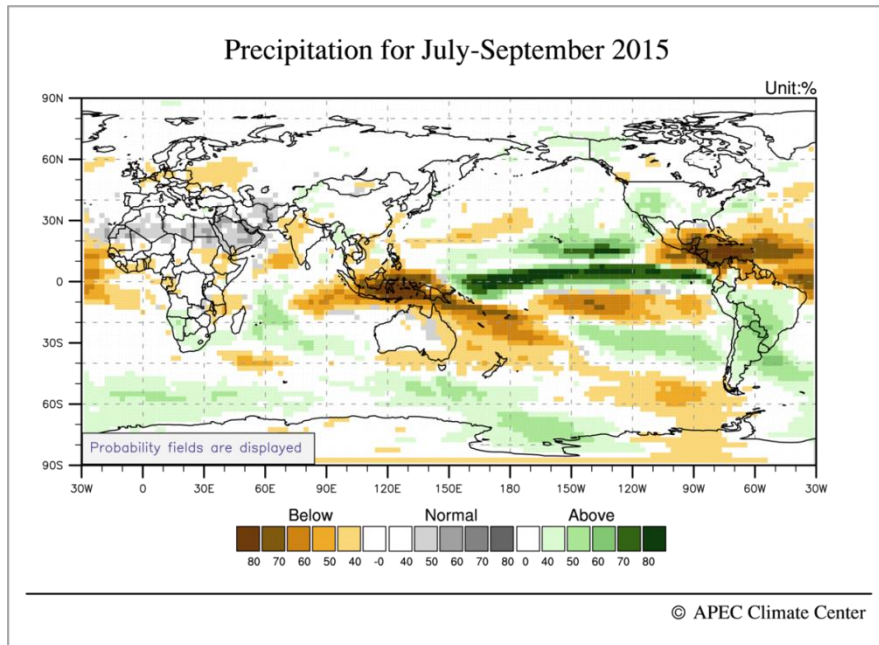
➤ Temporal scale problem



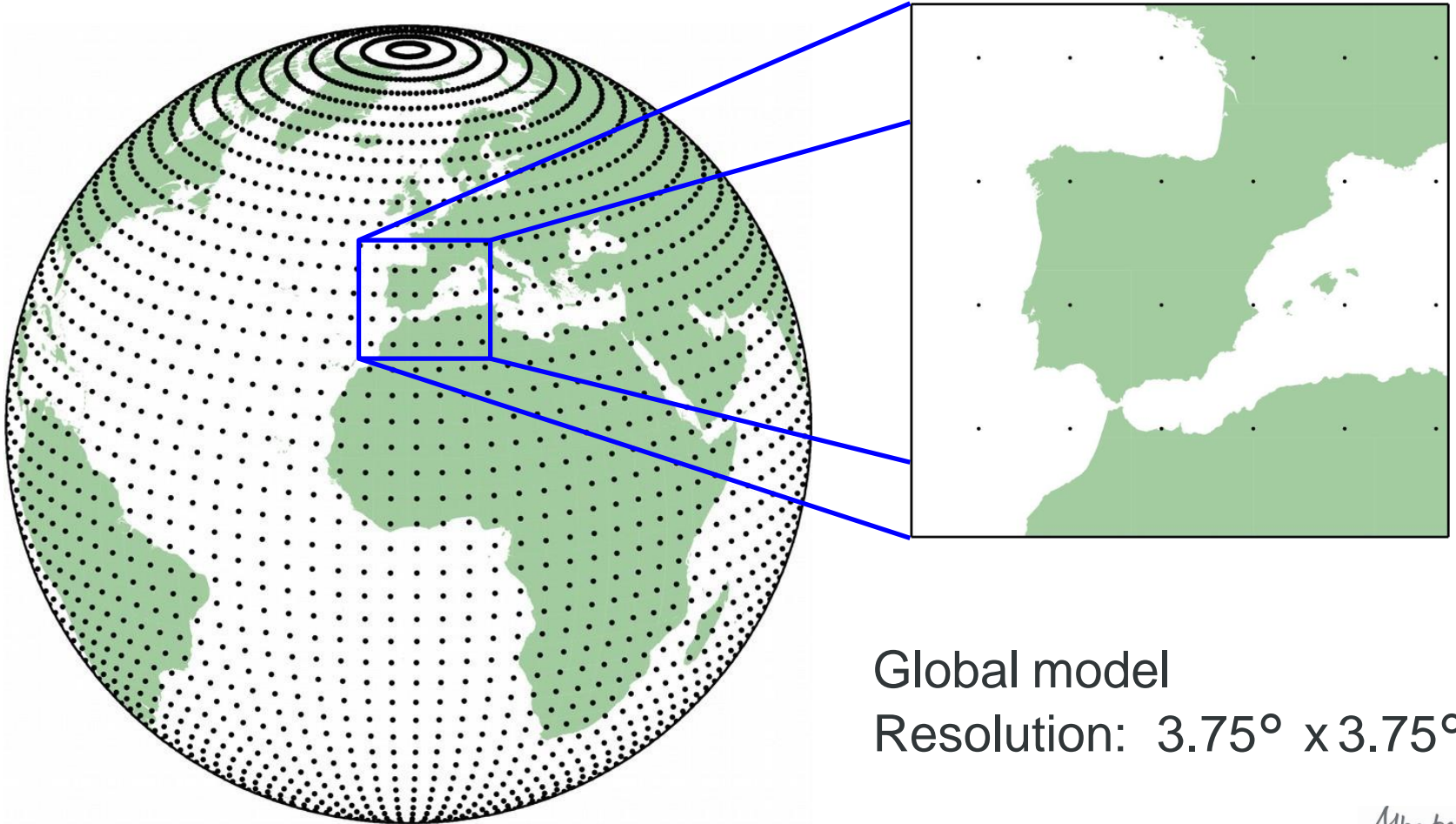
Spatial scale

➤ Spatial scale in climate forecasts

- Horizontal resolution 100 to 300 km



A GCM resolution

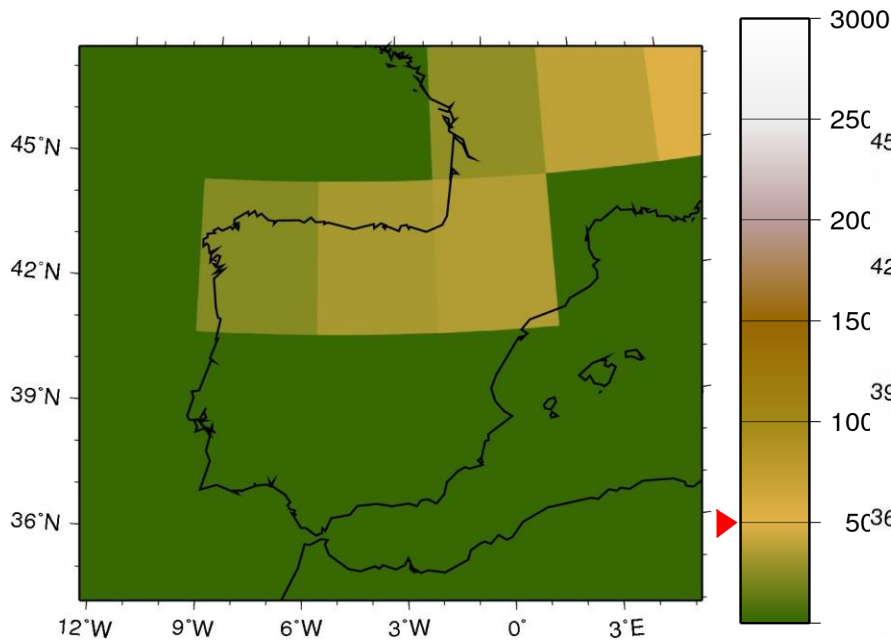


Global model
Resolution: $3.75^{\circ} \times 3.75^{\circ}$

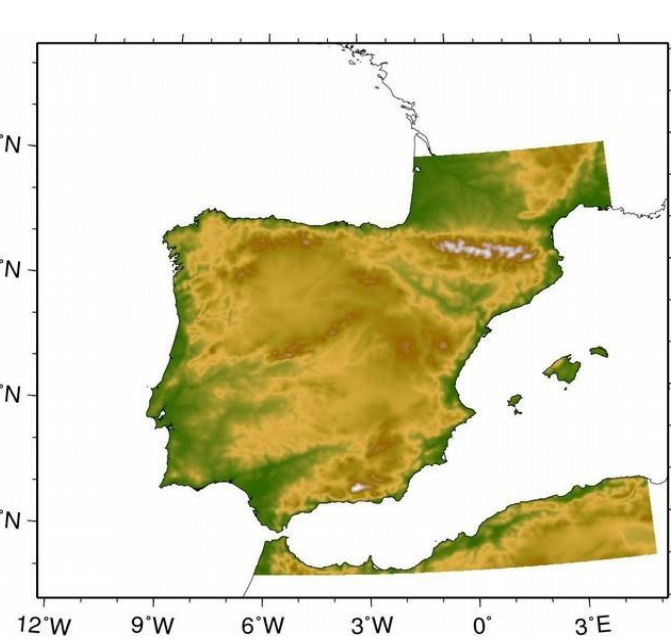
Source: <http://www.meteo.unican.es>



Spatial resolution issue



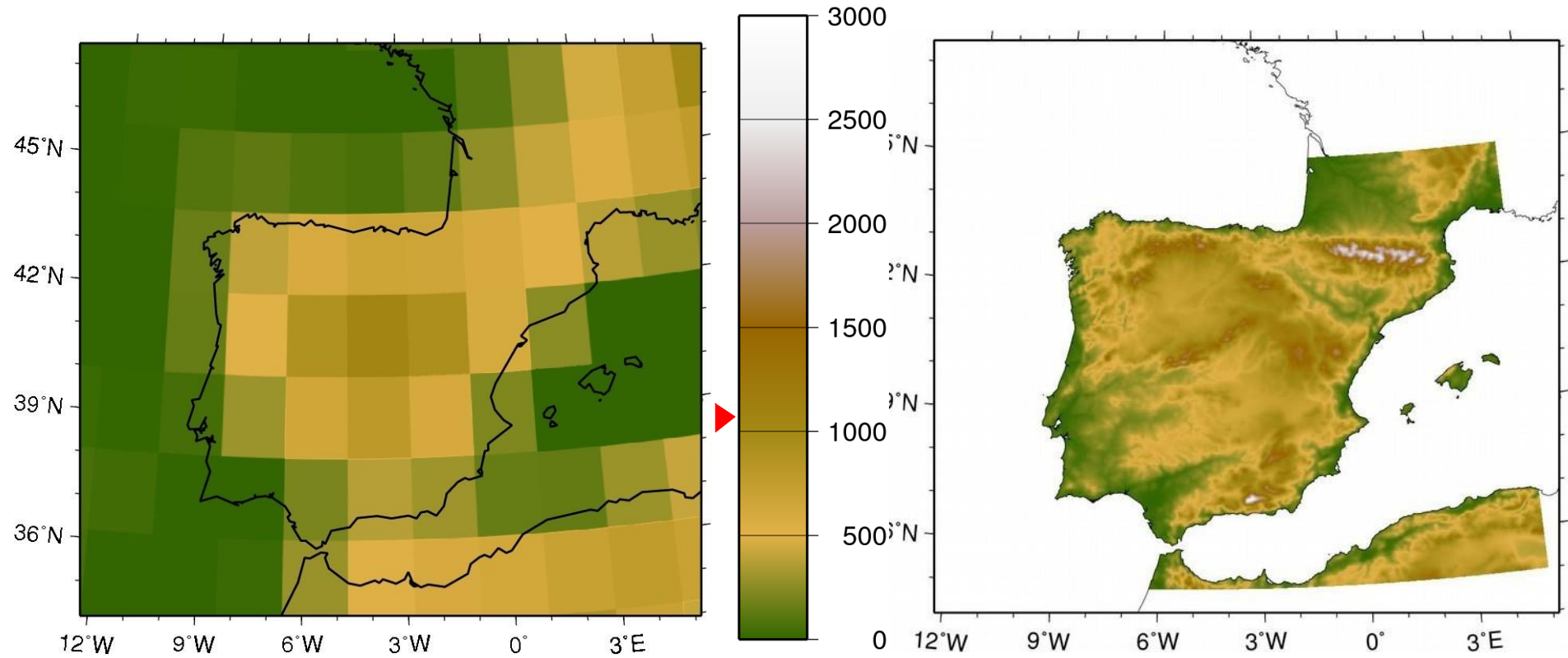
GCM at 3.75°



Real world



Spatial resolution issue

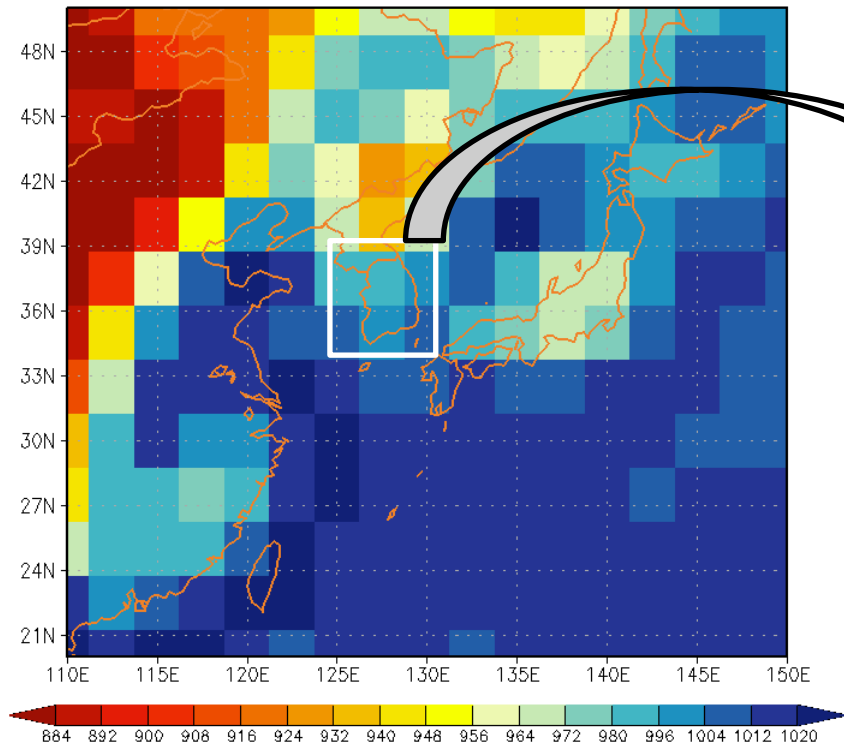


GCM at 2.5°

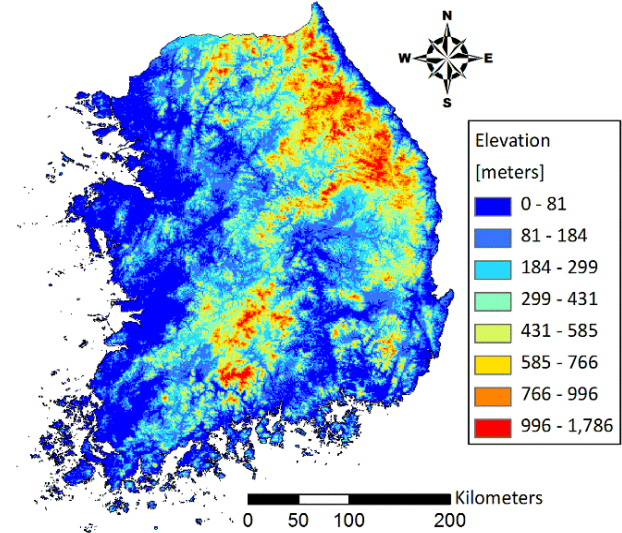
Real world



Spatial resolution issue



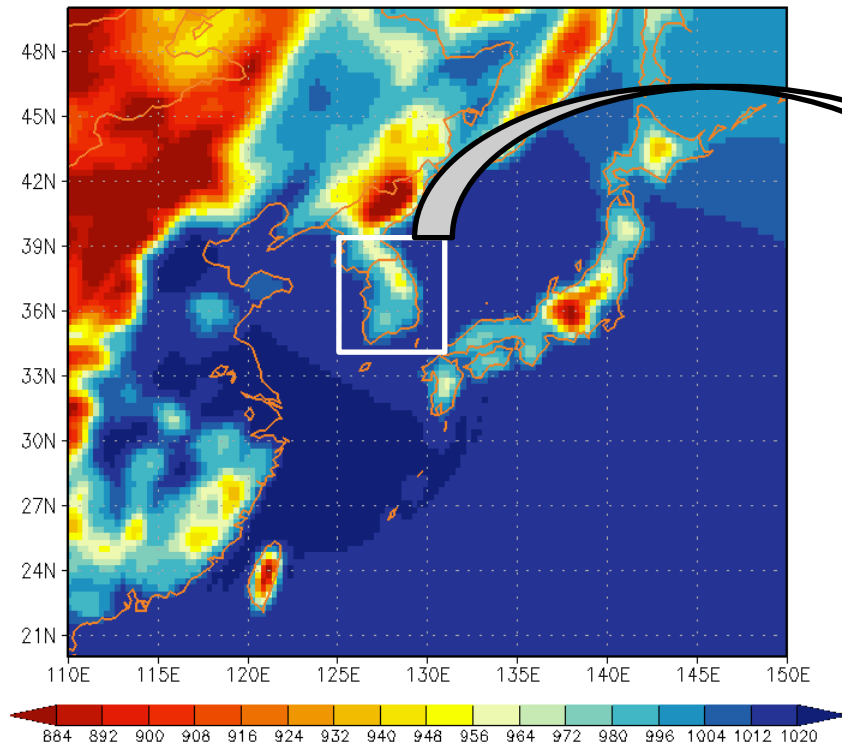
CFS at 2.5°



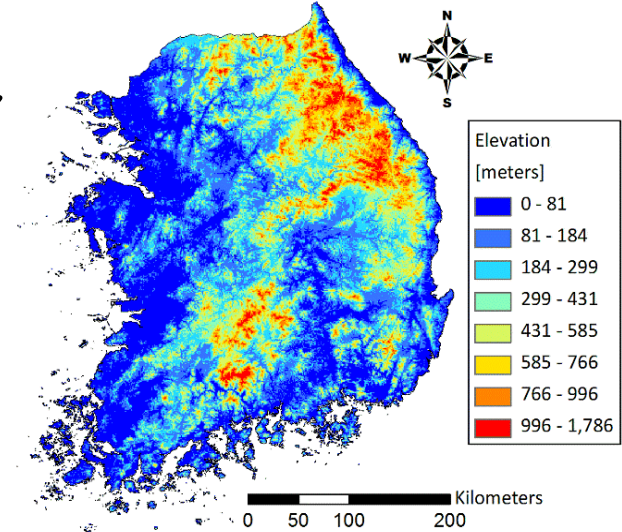
Real world



Spatial resolution issue



RCM (GRIMs) at 30 km



Real world



The gap between climate predictions and regional applications (1)

➤ Spatial scale problem

Observed precipitation
(10 X 10km)

1	2	3	4	2	9	5	10
5	4	6	7	2	7	6	11
10	10	10	11	9	11	6	14
13	15	16	15	4	12	8	16
6	11	10	5	1	2	8	5
9	2	9	12	12	13	13	6
10	7	3	10	10	15	15	6
3	12	14	1	10	9	8	7

Perfect GCM
(20 X 20km)

3	5	5	8
12	13	9	11
7	9	7	8
8	7	11	9

$$(1+2+5+4)/4 = 3$$

Perfect GCM
(40 X 40km)

8.25	8.25
7.75	8.75

$$(1+2+5+4+3+4+6+7+10+10+10+11+13+15+16+15)/16 =$$

8.25

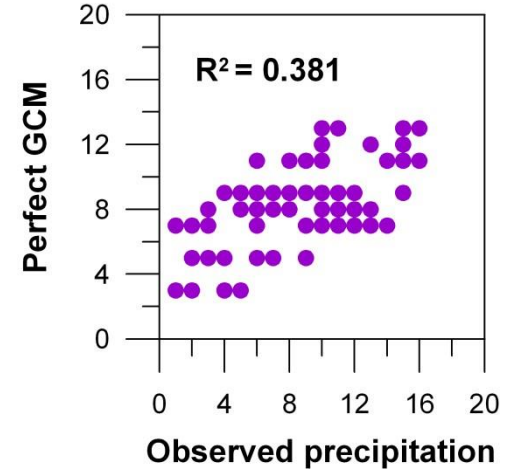
The gap between climate predictions and regional applications (2)

Perfect GCM (20 X 20km)

3	5	5	8
12	13	9	11
7	9	7	8
8	7	11	9

Spatial
disaggregation
→

3	3	5	5	5	5	8	8
3	3	5	5	5	5	8	8
12	12	13	13	9	9	11	11
12	12	13	13	9	9	11	11
7	7	9	9	7	7	8	8
7	7	9	9	7	7	8	8
8	8	7	7	11	11	9	9
8	8	7	7	11	11	9	9

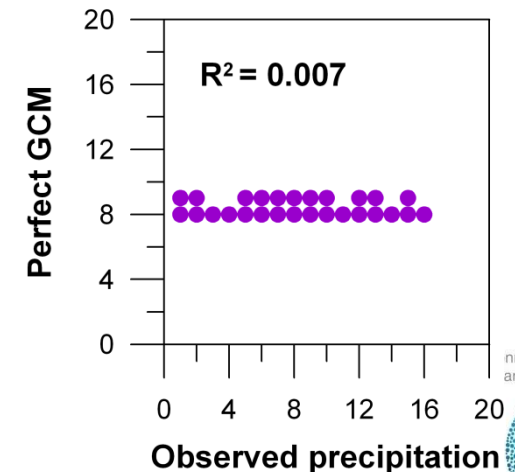


Perfect GCM (40 X 40km)

8	8
8	9

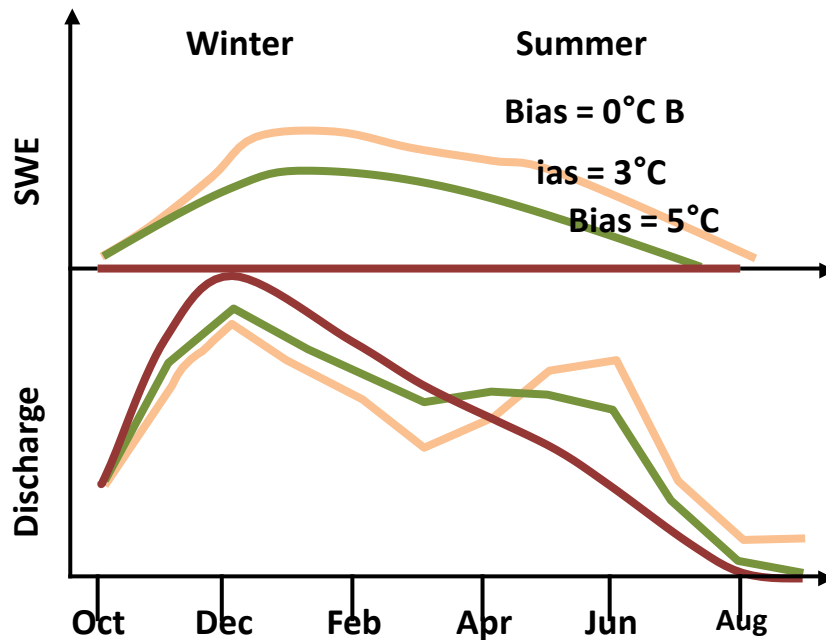
Spatial
disaggregation
→

8	8	8	8	8	8	8	8
8	8	8	8	8	8	8	8
8	8	8	8	8	8	8	8
8	8	8	8	8	8	8	8
8	8	8	8	9	9	9	9
8	8	8	8	9	9	9	9
8	8	8	8	9	9	9	9
8	8	8	8	9	9	9	9



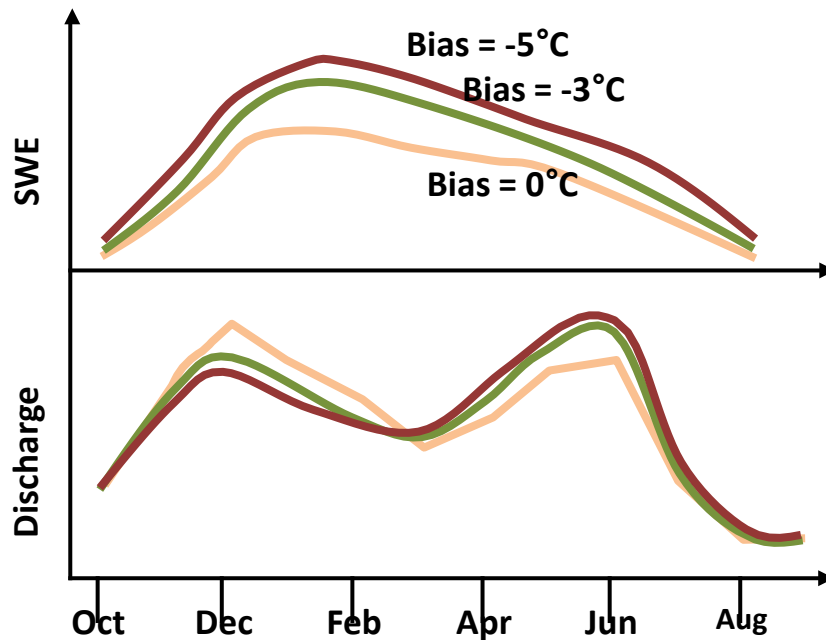
Potential impacts of systematic bias (1)

➤ Warm bias in winter temperature



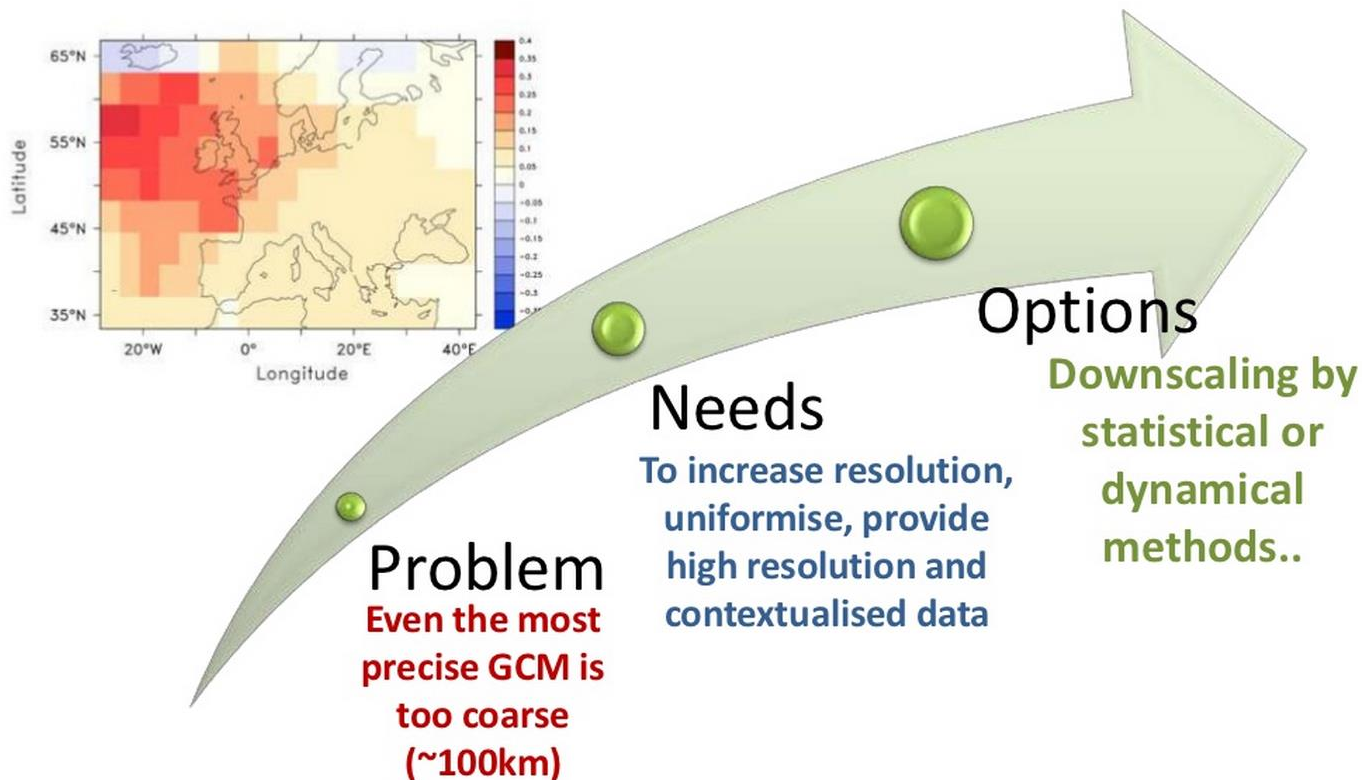
Potential impacts of systematic bias (2)

➤ Cold bias in winter temperature



Needs & Options to use GCM's information

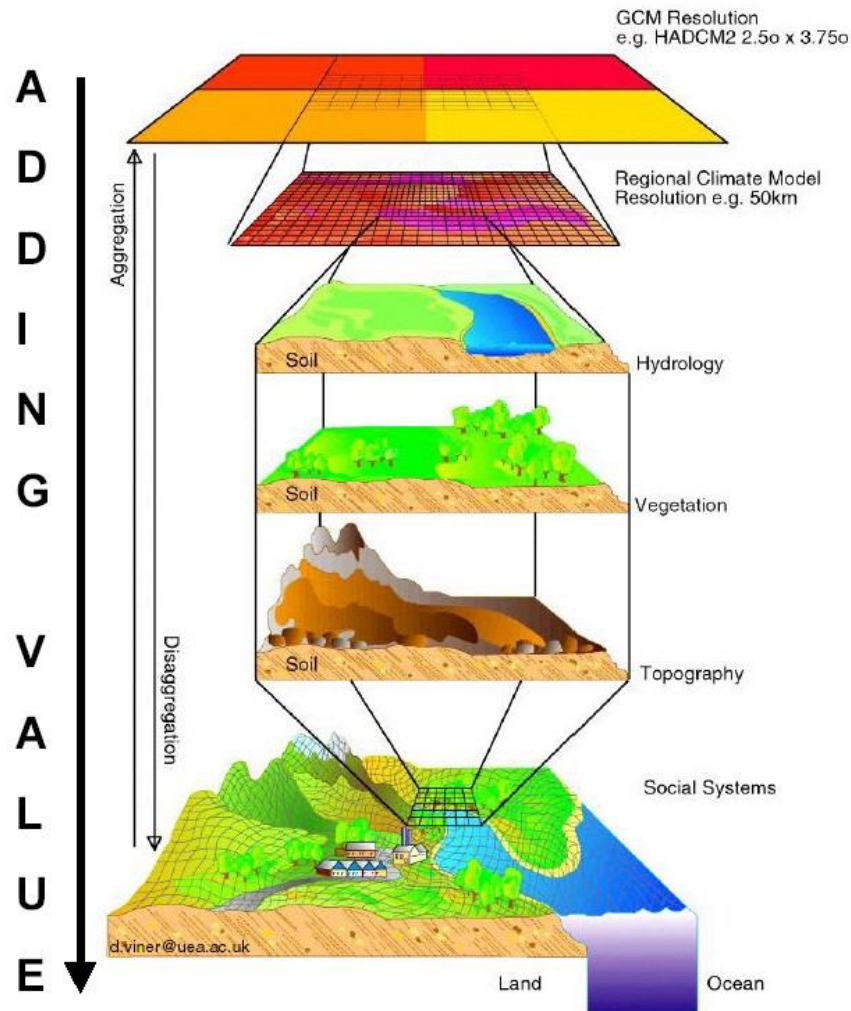
➤ Downscaling



Source: Navarro et al. (2012)



Downscaling



Downscaling techniques try to adapt the **coarse global model output to the local features** of a given region.

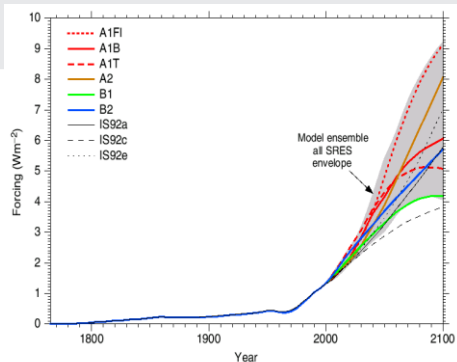


Statistical Downscaling Methods

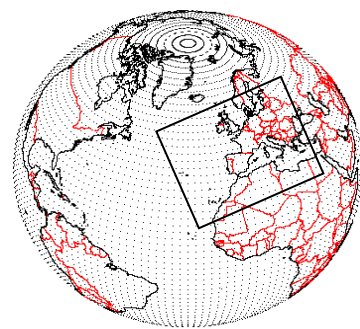


Downscaling techniques

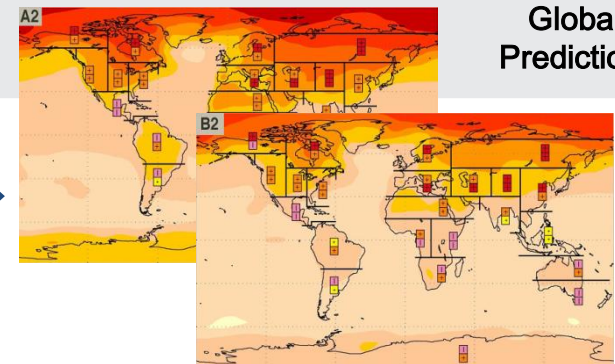
Emission Scenarios



GCM

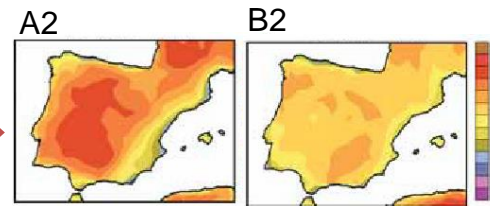
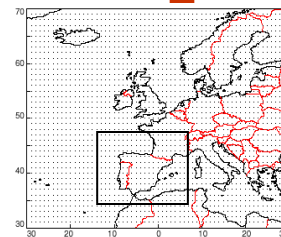


Global Predictions



Dynamical Downscaling runs regional climate models in reduced domains with boundary conditions given by the GCMs.

RCM

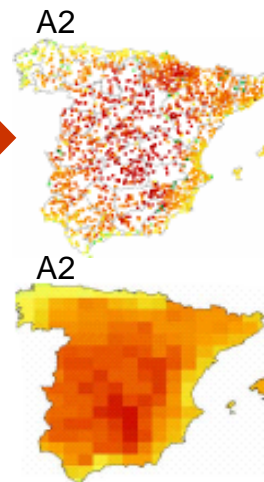


Historical Records

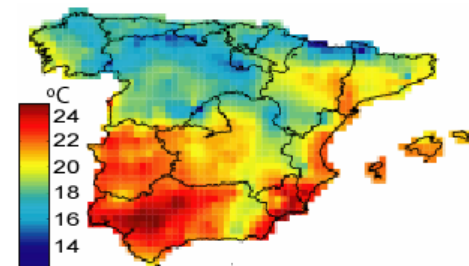


$$Y = f(X; \theta)$$

Different techniques



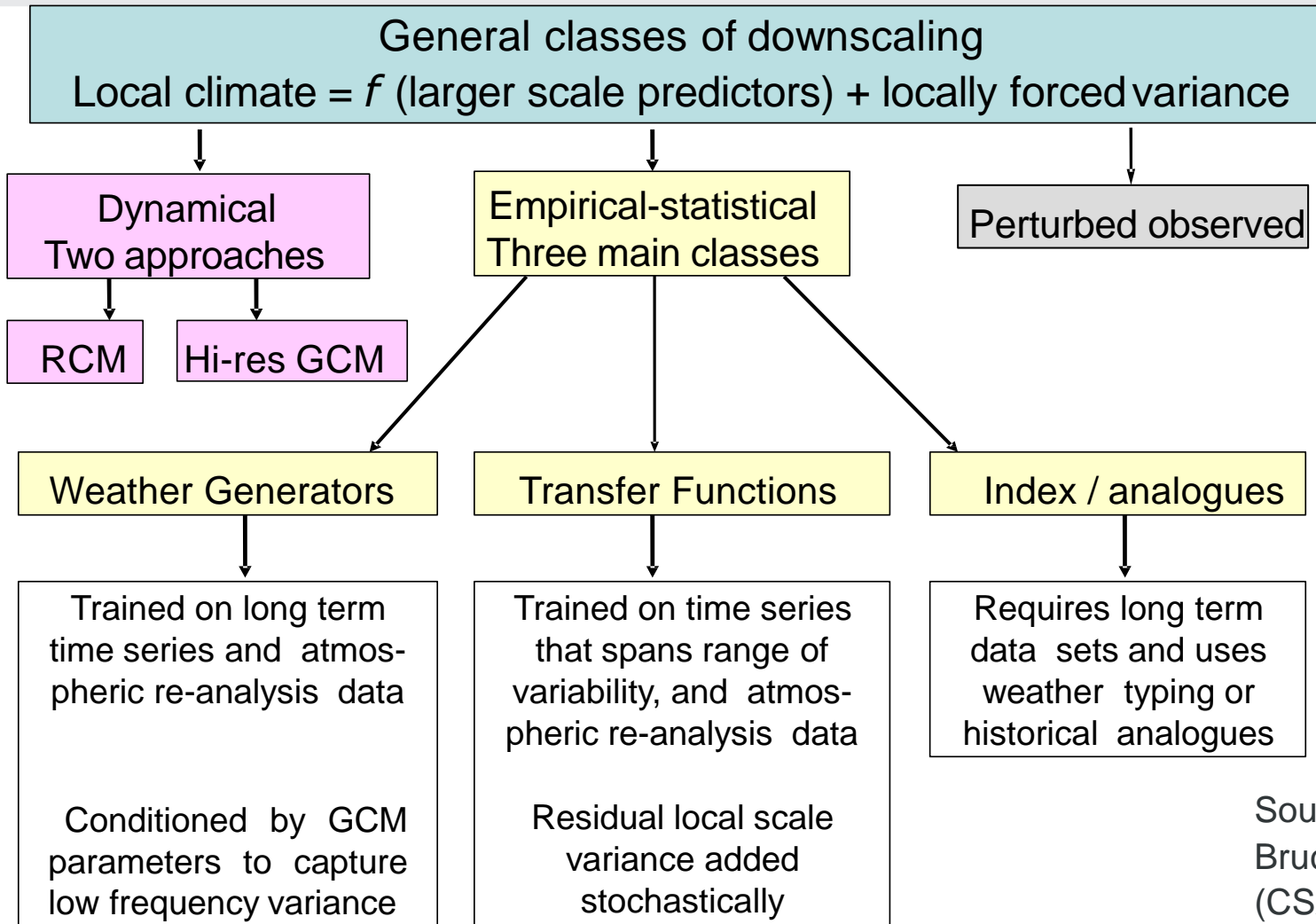
Climatology (1961-90)



Statistical Downscaling is based on empirical models fitted to data using historical records.



Downscaling techniques



Source:



Bruce Hewitson
(CSAG)

APEC CLIMATE CENTER



Pros and cons

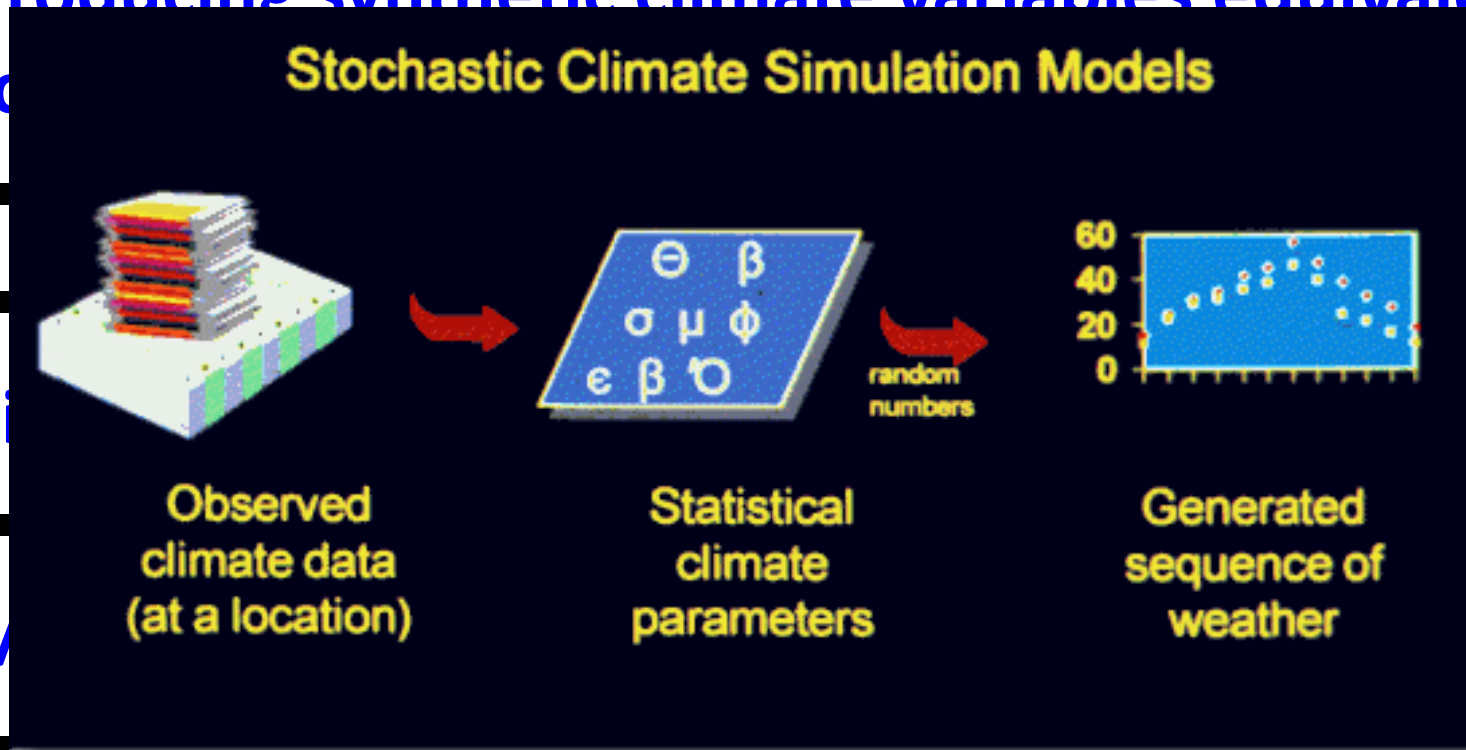
➤ Dynamical and Statistical Downscaling

Method		
Statistical	<ul style="list-style-type: none">• Easy and efficient to apply• Fine resolution• Able to directly incorporate observations into method• Apply to all GCMs	<ul style="list-style-type: none">• Needs a reliable long-term observed data• Does not account for non-stationarity in the predictor-predictand and relationship• Dependent on choice of predictors
Dynamical	<ul style="list-style-type: none">• Physical-based process• Produce numerous variables• Sub-daily data available• Providing climate information at un-gauged points	<ul style="list-style-type: none">• Computationally intensive• Limited resolution (25-50km)• Dependent on RCM parameterization• Considerable internal-variability (systematic bias)



Weather Generator (WG)

- Producing synthetic climate variables equivalent to

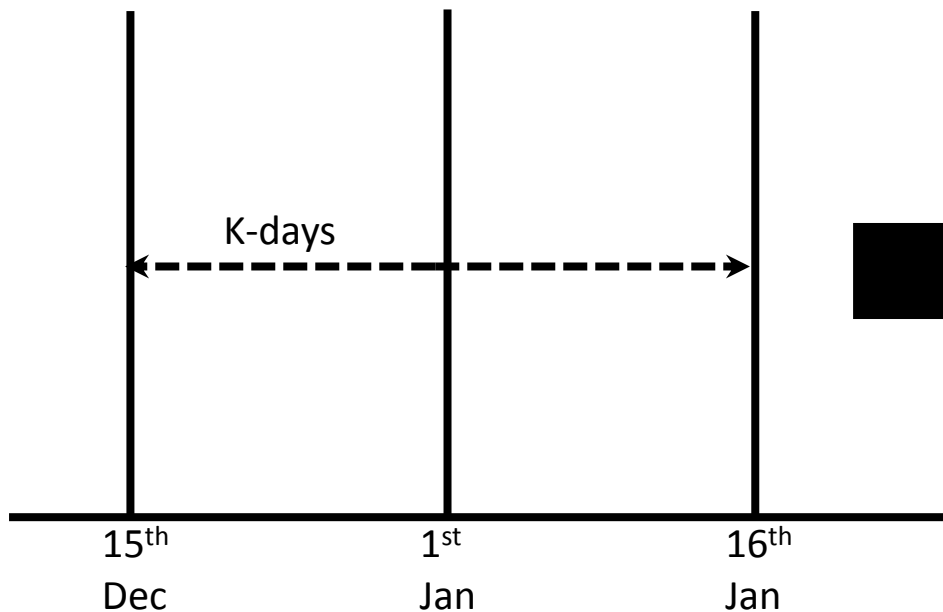


- S
- M



Weather Generator (WG)

➤ K-nearest neighbor (K-NN) WG



Collecting historical data

$\left\{ \begin{array}{l} Dec15/1976 \\ Dec15/1977 \\ \vdots \\ Jan16/2015 \end{array} \right.$

$$L = (k + 1) \times N - 1 \text{ days}$$

➤ Distance for all candidates

$$d_k = \sqrt{(\bar{X}_t - \bar{X}_k) C_t^{-1} (\bar{X}_t - \bar{X}_k)^T}$$



K-nearest neighbor (K-NN) WG

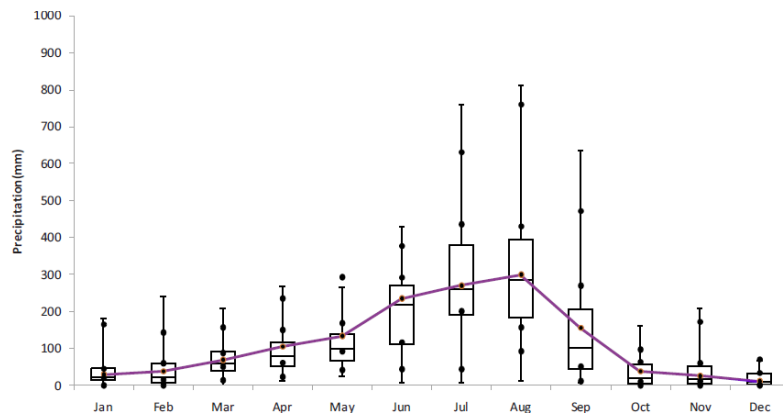
Table 1. Variable Combinations for the WG Models

WG models	WG-5Var	WG-4Var	WG-3Var	WG-2Var
Variables	Precipitation, temperature, relative humidity, wind speed, sea level pressure	Precipitation, temperature, relative humidity, wind speed	Precipitation, temperature, relative humidity	Precipitation, temperature

Table 2. Median Absolute Bias of Four WG Models

WG models	Youngju		Gumi		Jinju	
	Precipitation (mm)	Temperature (°C)	Precipitation (mm)	Temperature (°C)	Precipitation (mm)	Temperature (°C)
WG-2Var	10.10	0.18	7.12	0.10	9.84	0.23
WG-3Var	8.77	0.13	6.41 ^a	0.18	9.54	0.09
WG-4Var	14.19	0.19	11.42	0.17	16.14	0.17
WG-5Var	12.36	0.19	8.09	0.17	14.70	0.17

^aBest performance (lower number represents the better performance).



(a) WG-3Var

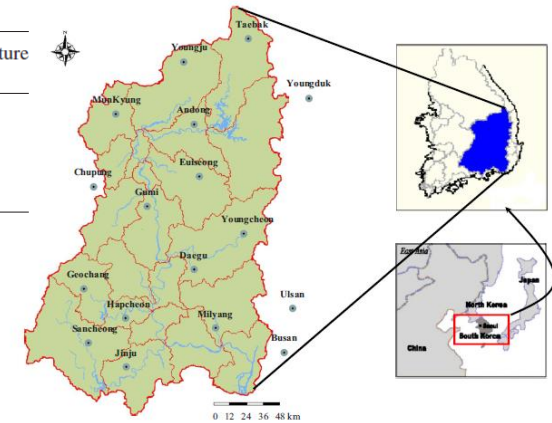


Fig. 1. Nakdong River Basin, Korea

K-NN WG under Climate Change

Climate Change Impact Assessment Using K-Nearest Neighbor Weather Generator: Case Study of the Nakdong River Basin in Korea

Hyung-II Eum¹, Slobodan P. Simonovic, MASCE², and Young-Oh Kim, MASCE³

Abstract: This study presents a methodology for assessing impacts of climate change in regional-scale hydrology using the K-nearest neighbor weather generator (WG) model in combination with the output of global circulation models (GCMs) and hydrologic rainfall-runoff model. The Nakdong River basin in Korea is used as a case study. The study applies a systematic approach to select the variables for the WG model from five meteorological variables available in the basin. In addition, the GCMs' projections based on a R1 emission scenario are incorporated into the proposed WG model to reflect the impacts of climate change, consequently generating the meteorological series for 60 years. Meteorological data for historic and two climate scenarios (dry and wet) are generated. The generated time series of meteorological variables are used with the streamflow synthesis and reservoir regulation rainfall-runoff model to calculate the streamflow at 23 sub-basins. The results demonstrate that the WG models combined with the GCMs' outputs are able to provide future weather conditions for the assessment of climate change impacts. One of the major findings of the study is the potential severity of drought impacts that may increase the historical drought duration in the basin up to three times.

DOI: 10.1061/(ASCE)1084-0699(2010)15:4(400)

CE Database subject headings: Climate change; Streamflow; Case studies; Korea, South.

Author keywords: Weather generator; Climate change; Streamflow.

Introduction

Climate change is generally defined as a long-term significant change in average weather that affects regional environment (IPCC 2007). Climate change research faces two major difficulties: uncertainty arising from the choice of emission scenarios and the necessity for regionally scaled assessments. To resolve these problems, many scientists have attempted to generate plausible, globally scaled scenarios over a long period of time which are then downscaled to investigate what will happen in the future at the regional scale.

General circulation models (GCMs) provide a range of feasible future climate conditions on a global scale employing various emission scenarios to consider the uncertainty of future conditions. The outputs of GCMs include meteorological data such as temperature, precipitation, wind speed, humidity, and pressure. However, GCMs currently use a very coarse grid size that is generally inappropriate for the regional-scale assessments. Therefore, downscaling schemes are used to resolve the

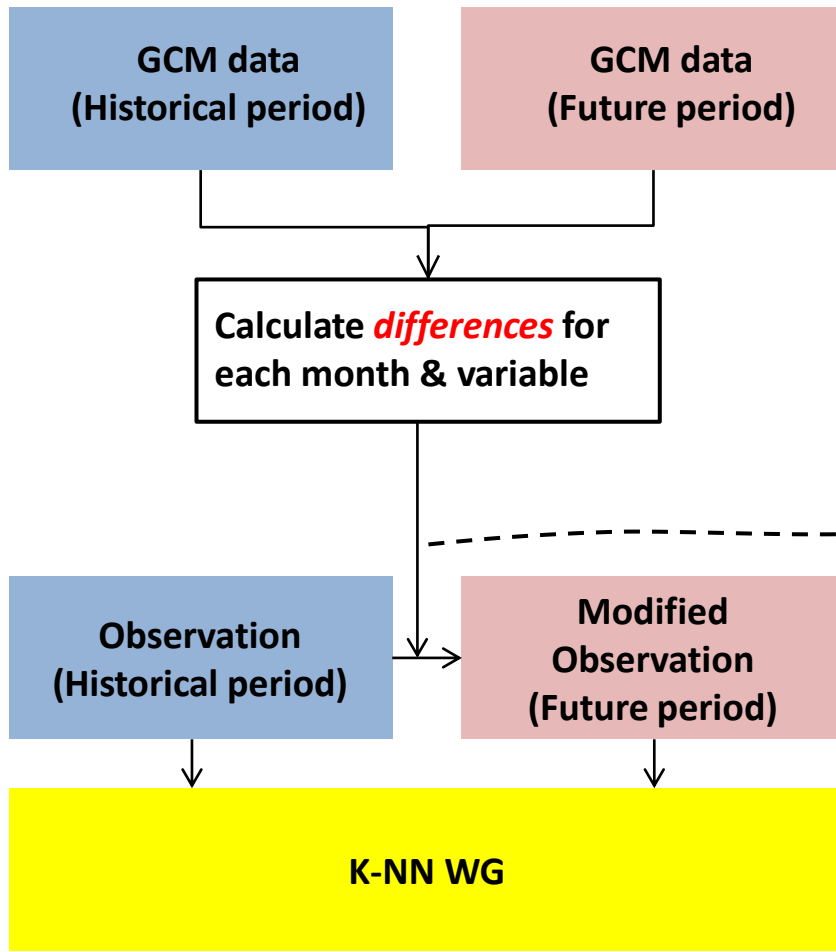
spatial resolution problem. Dynamic downscaling incorporates the GCMs' results directly as a boundary condition using the complete physical-based algorithms to describe atmospheric processes in limited area models or regional climate models (Danev et al. 1995; Kitson and Thompson 1996; Wilby et al. 1998). The dynamic downscaling method cannot generate the regional series longer than the GCMs series and also requires significant computational effort and time to provide the proper regionalized results. Contrary to the dynamic downscaling, statistical downscaling methods are based on the statistical relationships between the GCM output and the observed historical data within a region (Wilby et al. 2000; Wood et al. 2002; Harembury et al. 2005; Melrotta and Sharma 2005, 2006a; Haylock et al. 2006). Therefore, statistical downscaling requires less effort when applied to a new region because of the simpler computational procedures.

Although many researchers have applied various statistical downscaling methods using mathematical tools such as linear and nonlinear regression (Wilby et al. 1998), canonical correlation analysis (Lambert et al. 2001), and artificial neural networks (Cannon and Whitfield 2002; Tripathi and Srinivas 2005), they still provide unreliable consequences in case of extrapolation beyond the historical data. The weather typing approach, a category of statistical downscaling schemes, introduces the weather patterns (conditional probability density function, PDF) of the large-scale data (GCMs output) to couple with local measurements.

Stochastic downscaling models incorporate daily GCM simulations and are able to model low-frequency variability using a range of formulations (Melrotta and Sharma 2006b; Vrac and Neuman 2007). However, the main difference between stochastic downscaling techniques and the approach used in this paper is in the need for prior knowledge of conditional probability density function for successful implementation of stochastic downscaling approach. Recently, weather generator (WG) has been used as another downscaling procedure to generate meteorological data.

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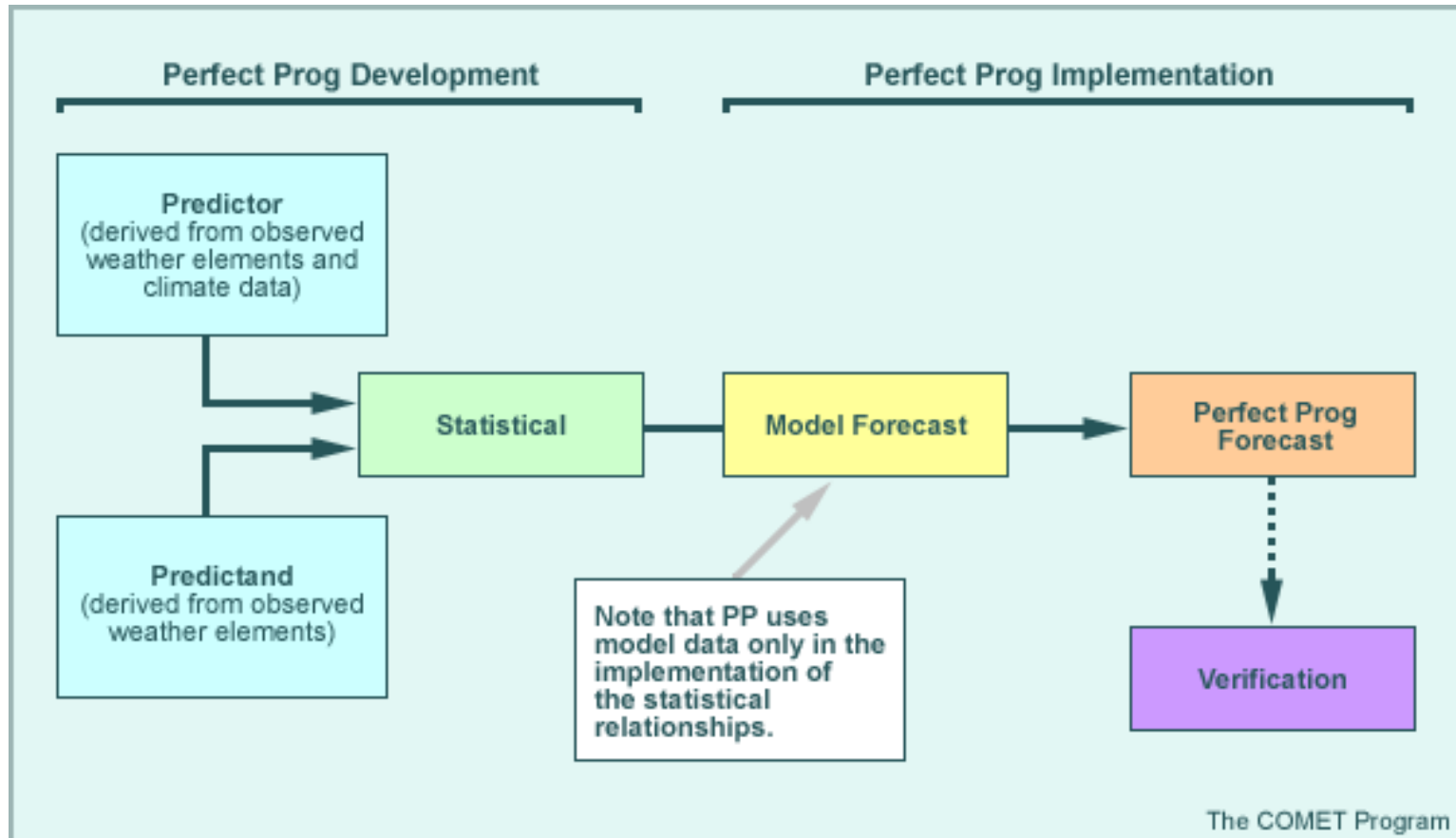


$$P_{fut} = P_{his} \times P_{delta}$$

$$T_{fut} = T_{his} + T_{delta}$$

Statistical downscaling techniques

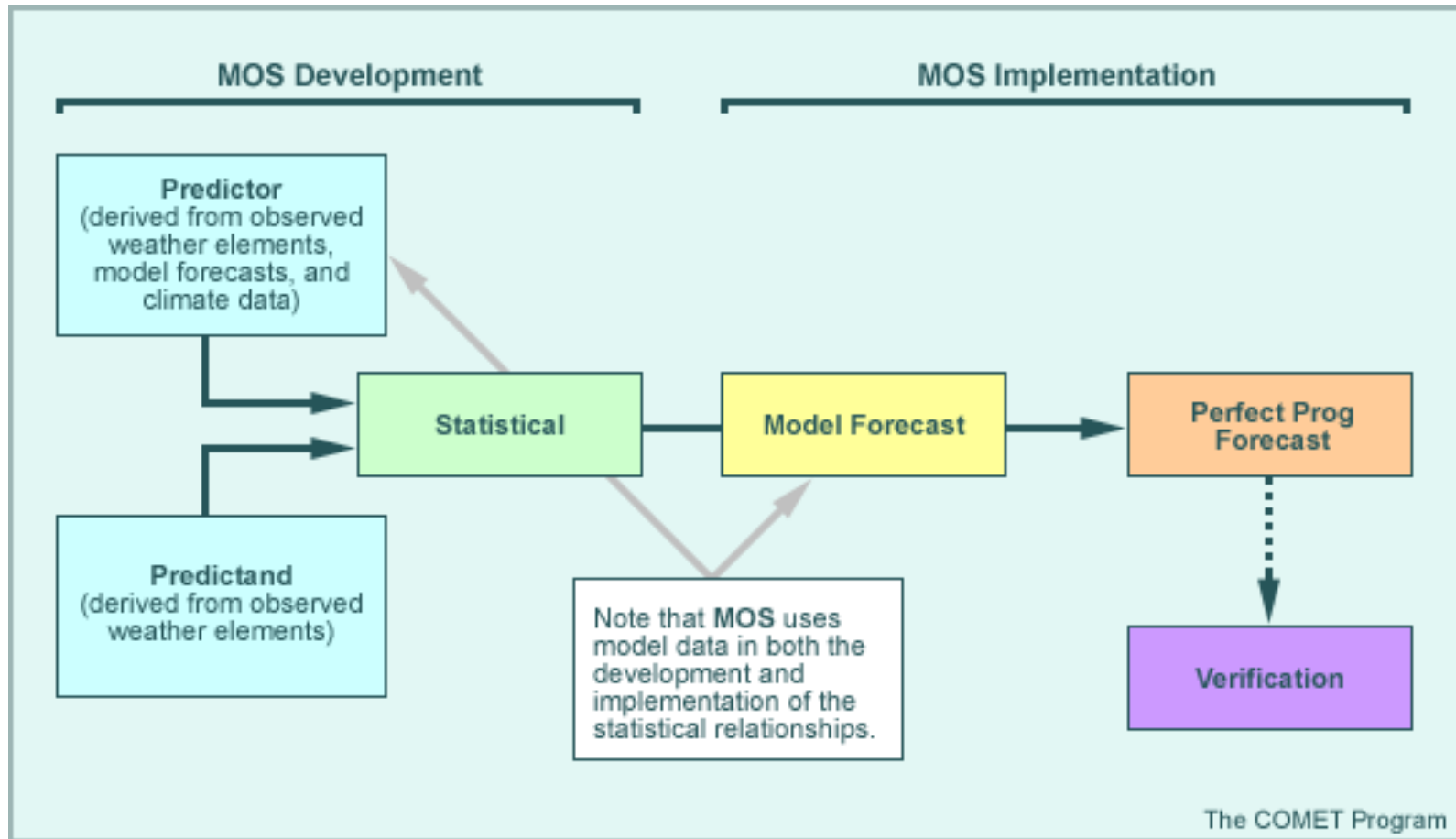
➤ Perfect Prognosis (PP)



Source: <http://www.met.tamu.edu/class/metr452/models/2001/output.html#Statistical>
Weather Forecasting



Model Output Statistics (MOS)



Source: <http://www.met.tamu.edu/class/metr452/models/2001/output.html#Statistical>
Weather Forecasting

MOS

➤ Predictors

- From the global (or regional) model for both training and downscaling phases

➤ Need the model output

- Day-to-day correspondence with observations

➤ These methods can work with the variable of interest as predictor

- Local precipitation can be derived from the direct model precipitation forecasts



MOS models

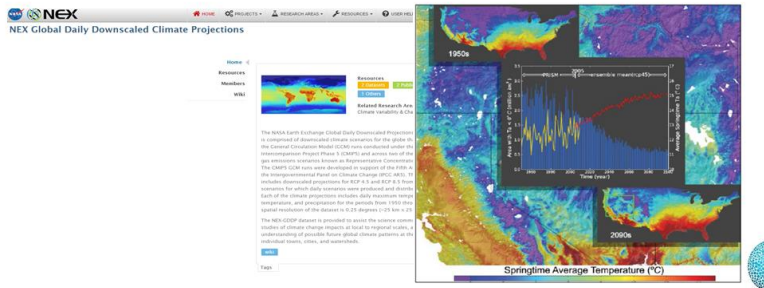
➤ Most popular

- Bias Correction/Spatial Disaggregation (BCSD)
- Bias Correction/Constructed Analogs (BCCA)

NASA Earth Exchange Global Daily Downscaled Projections (NEX-GDDP)

➤ BCSD

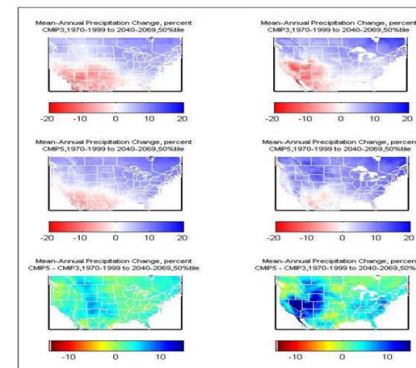
- 1950 through 2100 at 0.25 degrees (~25 km x 25 km)
- 21 GCMs x 2 RCPs



Downscaled CMIP3 and CMIP5 climate and hydrology projections (DCHP)

➤ BCSD & BCCA

- 1950-2099 at 1/8° (~12km)



http://gd-dcp.ucllnl.org/downscaled_cmip_projections/dcpInterface.html#Welcome

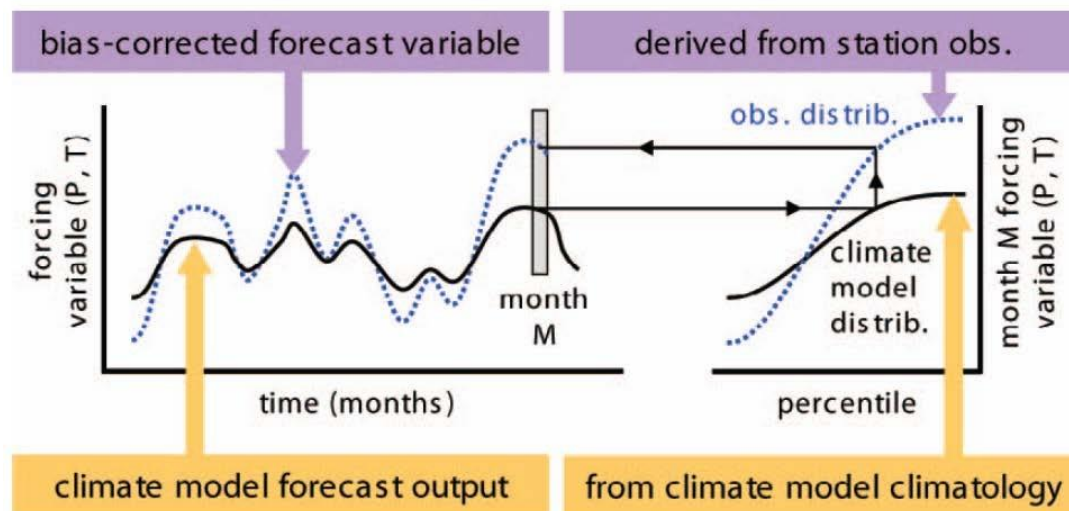
Post Processing...Bias Correction

- **Adjusting GCM-driven values at a target point or region to better correspond to reference (e.g. observed) data**
 - bias-correction (systematic errors)
- **Biases in**
 - Single variable
 - Mean, variance, shape of distribution
 - Multiple variables
 - Dependence structure (Cross correlation)
- **Marginal distributions via quantile mapping**



Bias Correction/Spatial Disaggregation (BCSD)

- **Statistical bias correction of GCM simulations**
 - Quantile mapping
- **Spatial downscaling to fine scale (i.e. stations)**
- **Temporal disaggregation from monthly to daily**



Source: Wood et al 2006, BAMS

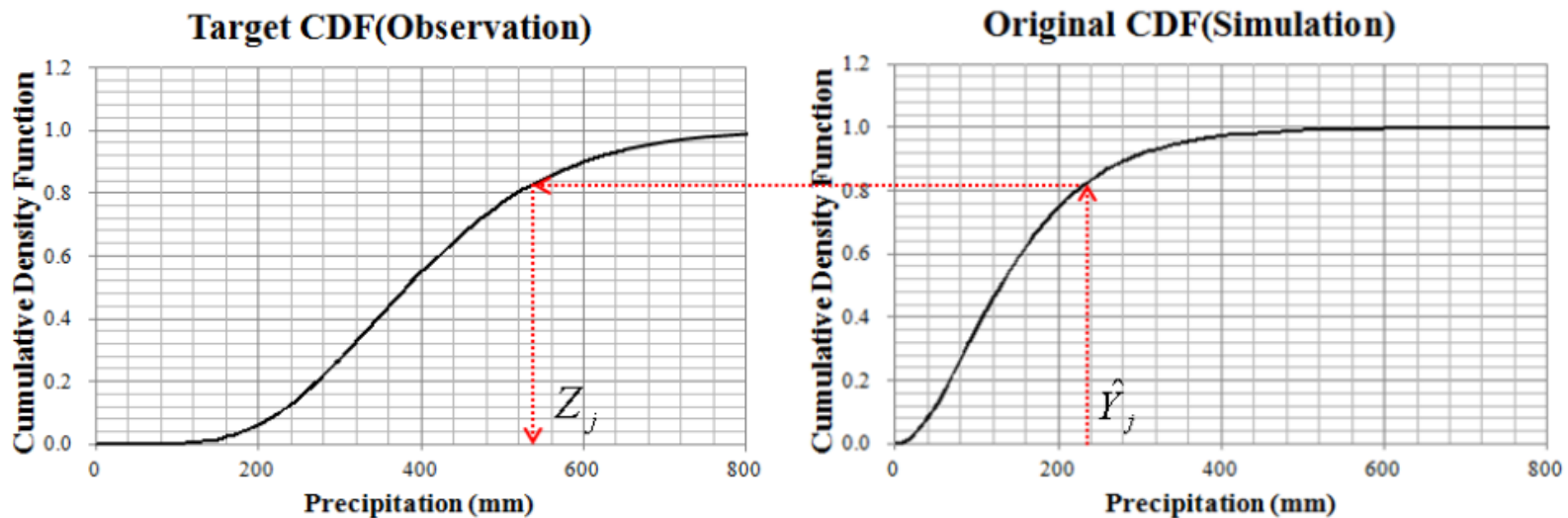


Bias Correction/Spatial Disaggregation (BCSD)

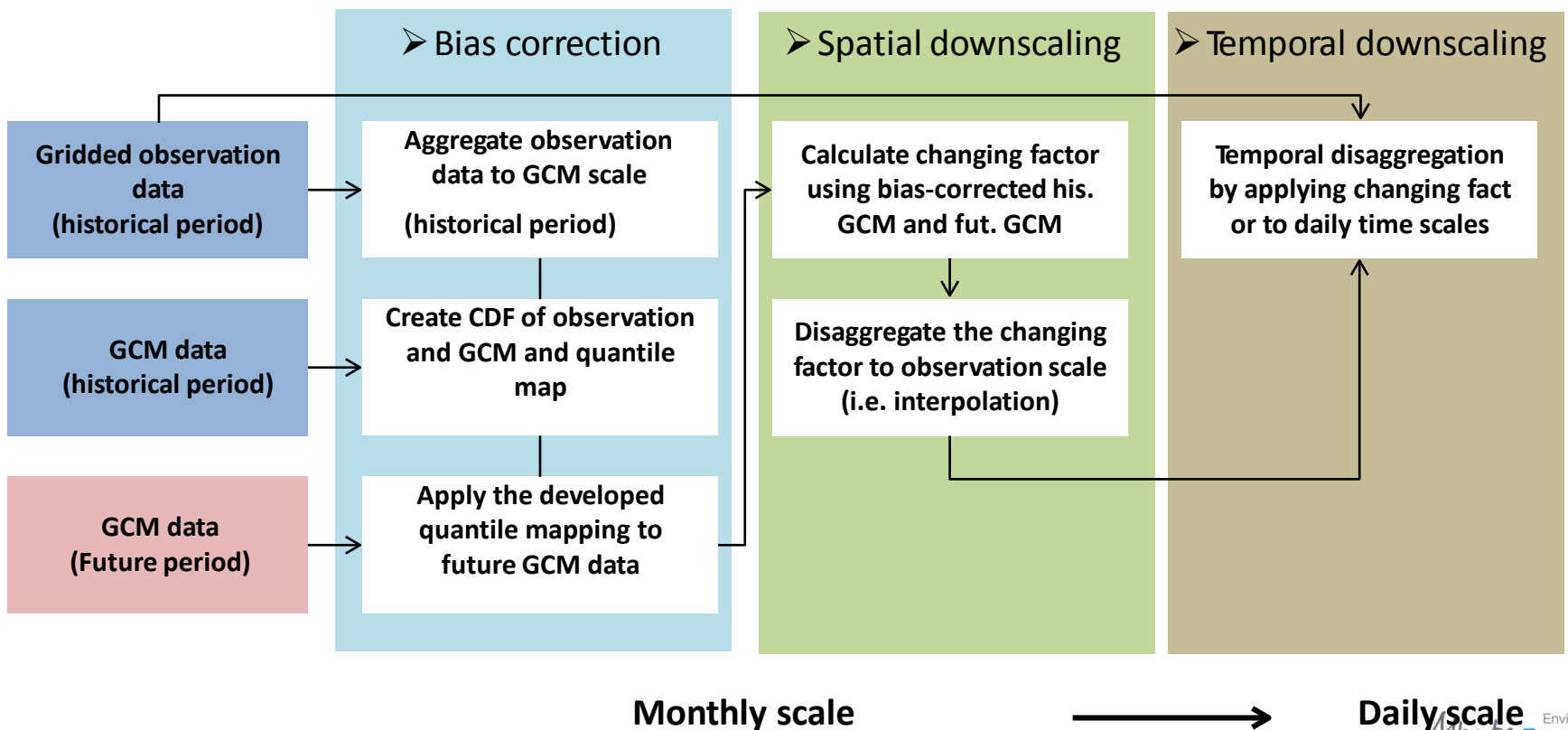
➤ Bias-correction: Quantile mapping

- Monthly data set at large grid points (e.g. GCM points)

$$Z_j(t) = F_{\text{obs}}^{-1} [F_m\{\hat{Y}_j(t)\}]$$



Bias Correction/Spatial Disaggregation (BCSD)



Daily BCSD (1)

➤ Spatial disaggregation

- Interpolating daily GCM output to finer grid points

➤ Bias correction

- Quantile mapping
 - Sample distribution of a moving window
 - ± 15 -day or a month

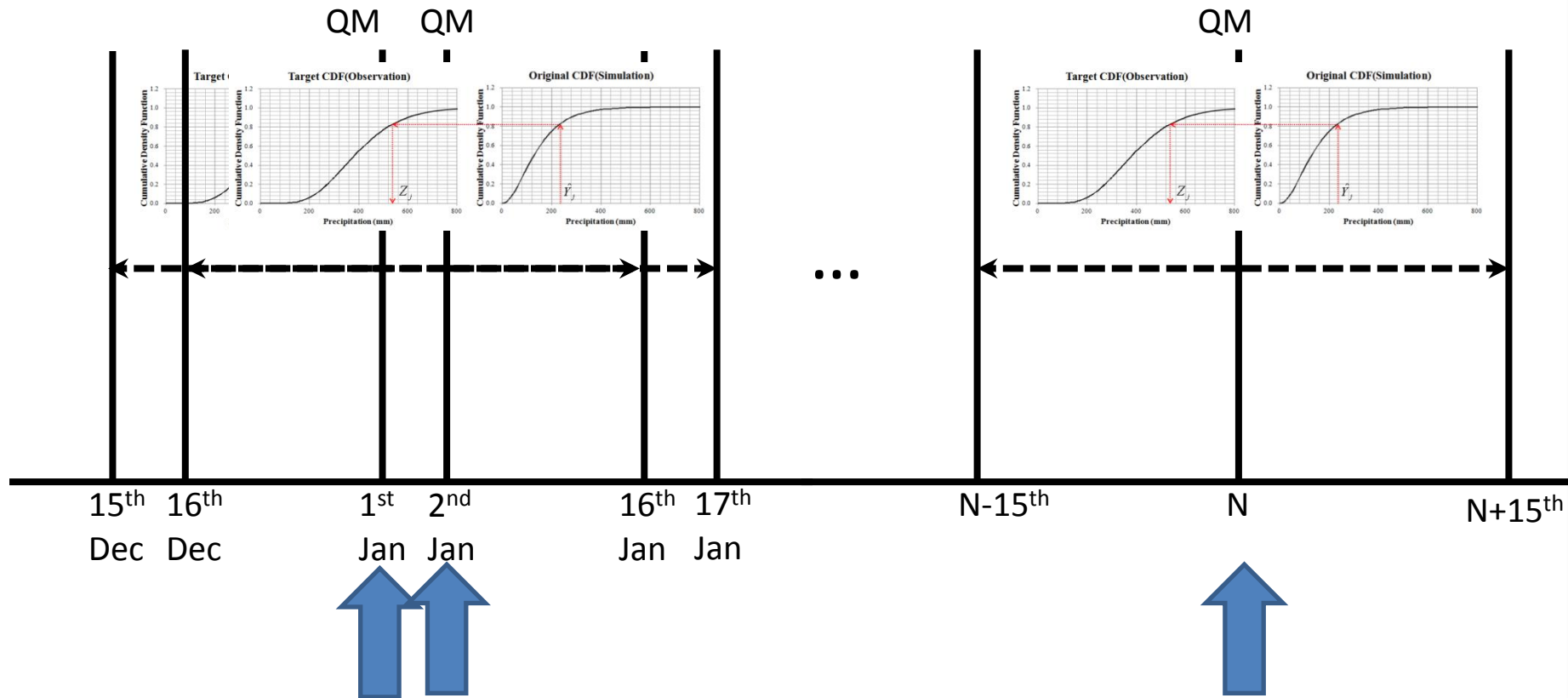
➤ No need of temporal disaggregation

➤ Values out of historical range

- Gumbel for precipitation
- Normal distribution for temperature

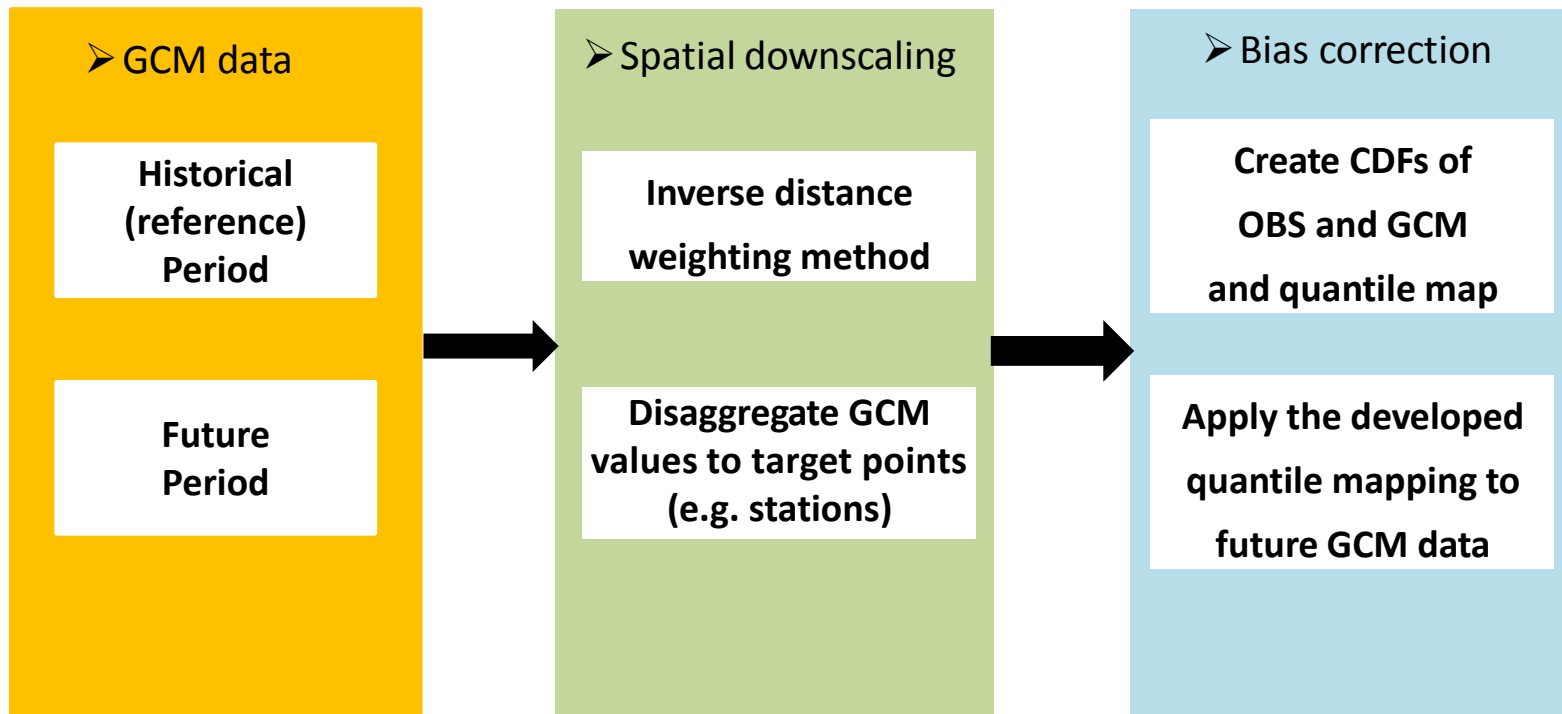


Daily BCSD (2)



Simple Quantile Mapping (SQM)

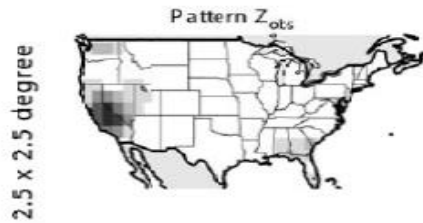
- **Sampling daily data to build ECDF for a month**
 - 12 ECDFs necessary



BCCA (1)

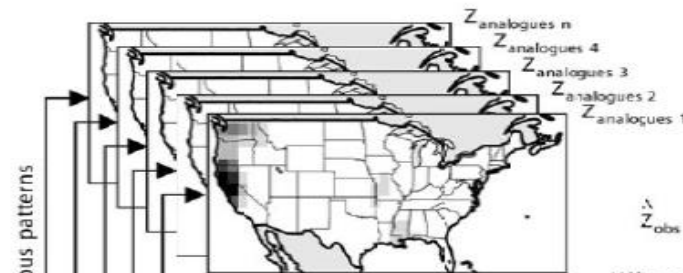
I) NEW PATTERN AT COARSE-RESOLUTION:

A new pattern obtained from a coarse resolution source, but the corresponding high-resolution (downscaled) pattern is unknown



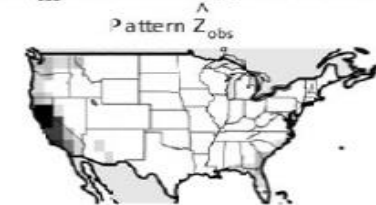
II) FITTING THE ANALOGUE (DIAGNOSIS):

A subset of patterns from a historical library is selected as contributions to a constructed analogue of Z_{obs} based on spatial similarity evaluated at the 2.5 x 2.5 degree resolution.



III) DOWNSCALING THE PATTERN (PROGNOSIS):

A linear combination of the predictor patterns produces a least squares (constructed) analogue of Z_{obs} at 2.5 x 2.5 degree resolution



$$\hat{Z}_{obs} = A_{analogues\ 1} \cdot Z_{analogues\ 1} + A_{analogues\ 2} \cdot Z_{analogues\ 2} + \dots + A_{analogues\ n} \cdot Z_{analogues\ n}$$

Where $A_{analogues\ 1}, A_{analogues\ 2}, \dots, A_{analogues\ n}$ are regression coefficients

The downscaled pattern ($\hat{P}_{downscaled}$) is obtained by applying the same regression coefficients to the high-resolution patterns:



$$\hat{P}_{downscaled} = A_{analogues\ 1} \cdot P_{analogues\ 1} + A_{analogues\ 2} \cdot P_{analogues\ 2} + \dots + A_{analogues\ n} \cdot P_{analogues\ n}$$

1/8 x 1/8 degree

?

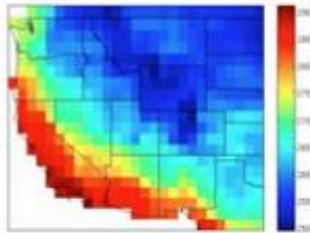
The high-resolution patterns for the same days as the coarse predictor patterns are also gathered

Source: Hidalgo et al. (2008)



BCCA (2)

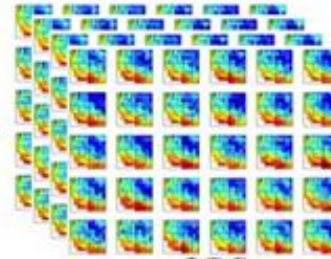
GCM target coarse pattern
(1 day, 1 year)



Z^{GCM}

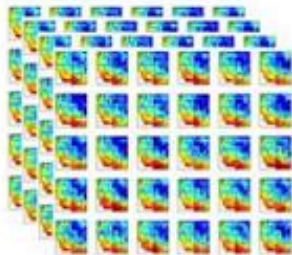
$$Z^{GCM} \approx \sum_{i=1}^{i=N} a_n Z_n^{OBS}$$

Library of OBS coarse patterns
(+/- 45 day window, all years)



Z_n^{OBS}

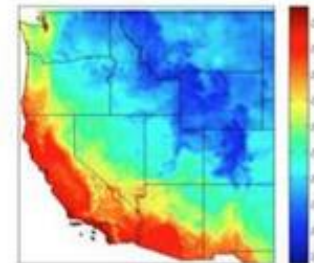
Corresponding fine OBS patterns
from N best coarse OBS patterns



Y_n^{OBS}

$$\sum_{i=1}^{i=N} a_n Y_n^{OBS} = Y^{GCM}$$

Downscaled GCM target pattern
(1 day, 1 year)



Y^{GCM}

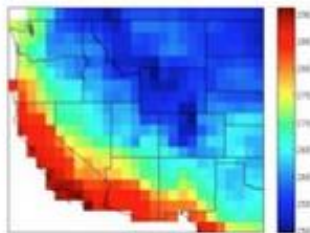
Source: <http://climate.northwestknowledge.net/MACA/MACAmethod.php>

Need to preserve spatial distribution in the future?

➤ BCCA

- Hard to find similar weather patterns from historical data
- Not reliable climate projections

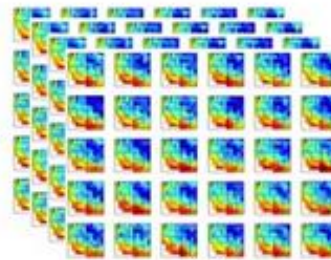
GCM target coarse pattern
(1 day, 1 year)



Z^{GCM}

$$Z^{GCM} \approx \sum_{i=1}^{i=N} a_n Z_n^{OBS}$$

Library of OBS coarse patterns
(+/- 45 day window, all years)



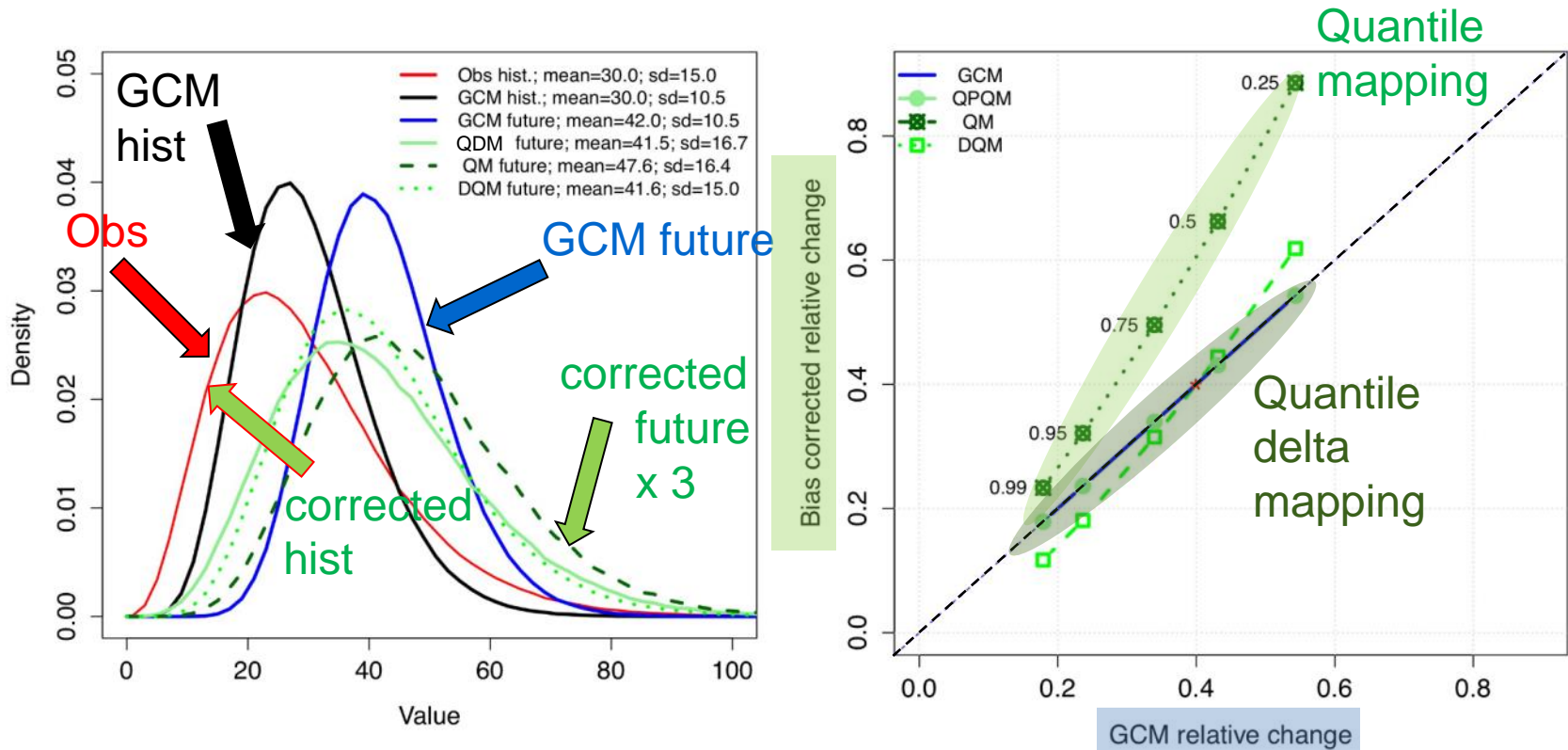
Z_n^{OBS}

Few
analog
similar to
future
spatial
structure

➤ Spatial distribution may be altered by climate change



Unintended consequences...

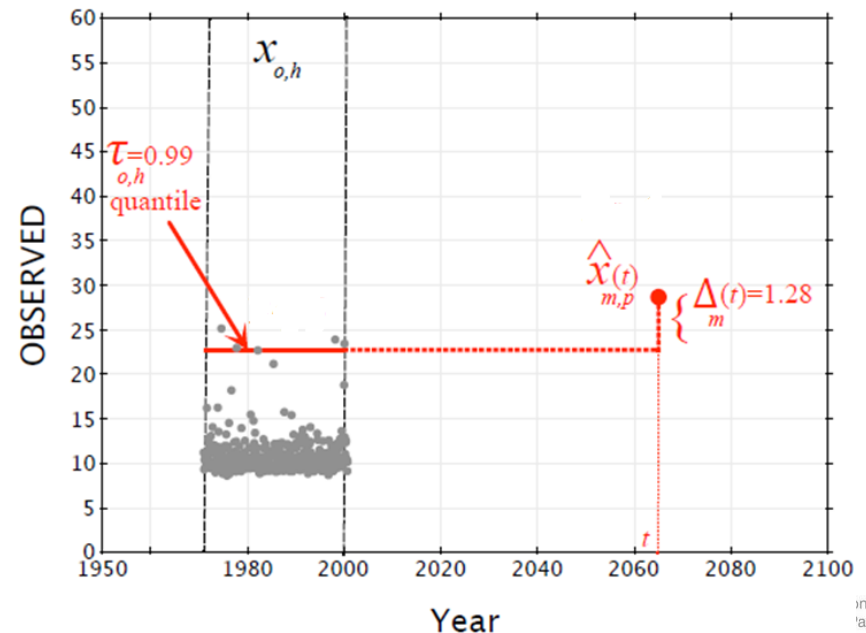
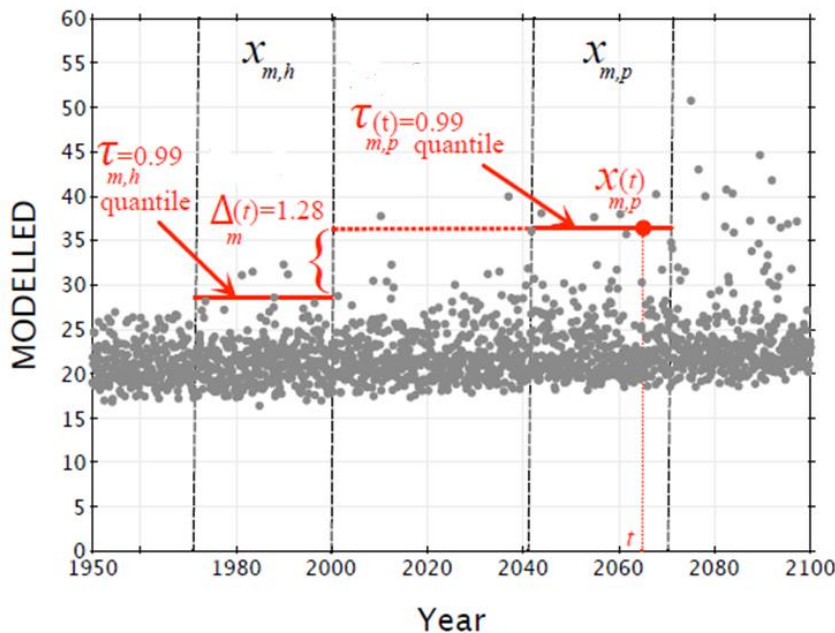


Cannon et al. (2015) J. Climate



Quantile Delta Mapping (QDM)

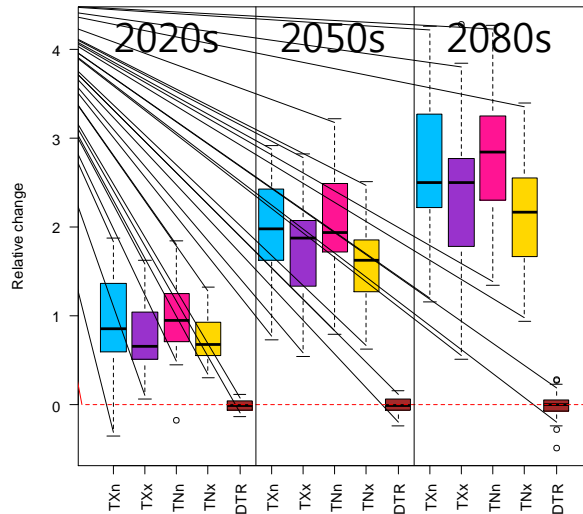
- Preserving model-projected relative changes in quantiles
- Correcting systematic biases in quantiles



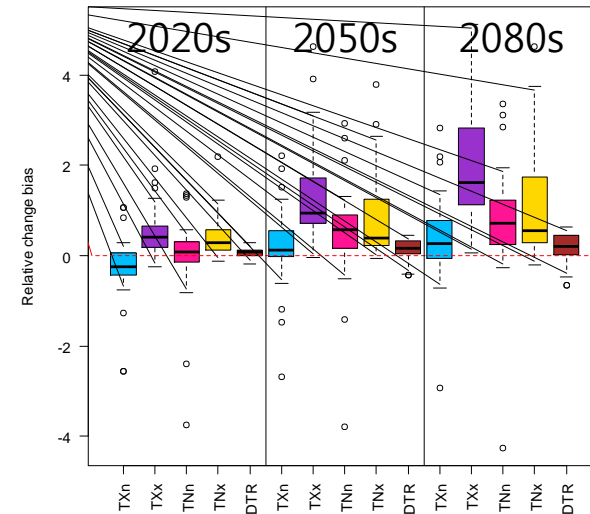
Source: Cannon et al. (2015)

ETCCDI related to TMAX and TMIN

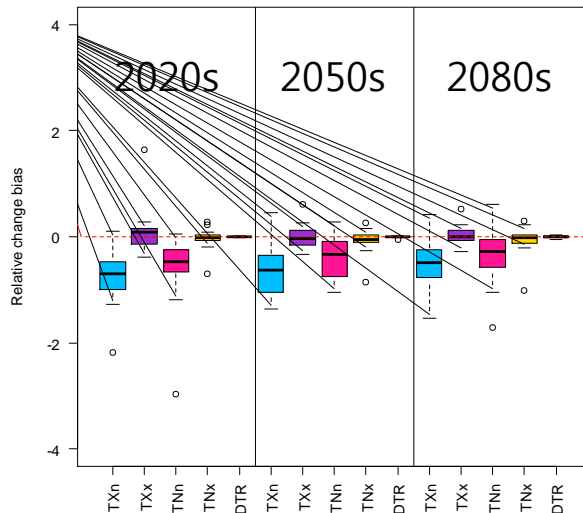
GCMs



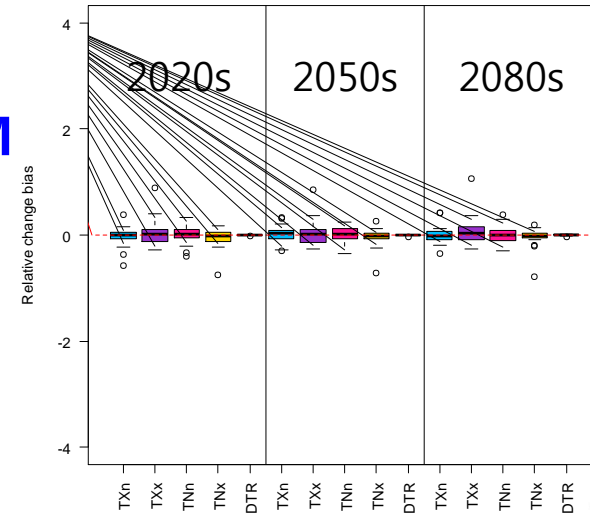
QM



DQM

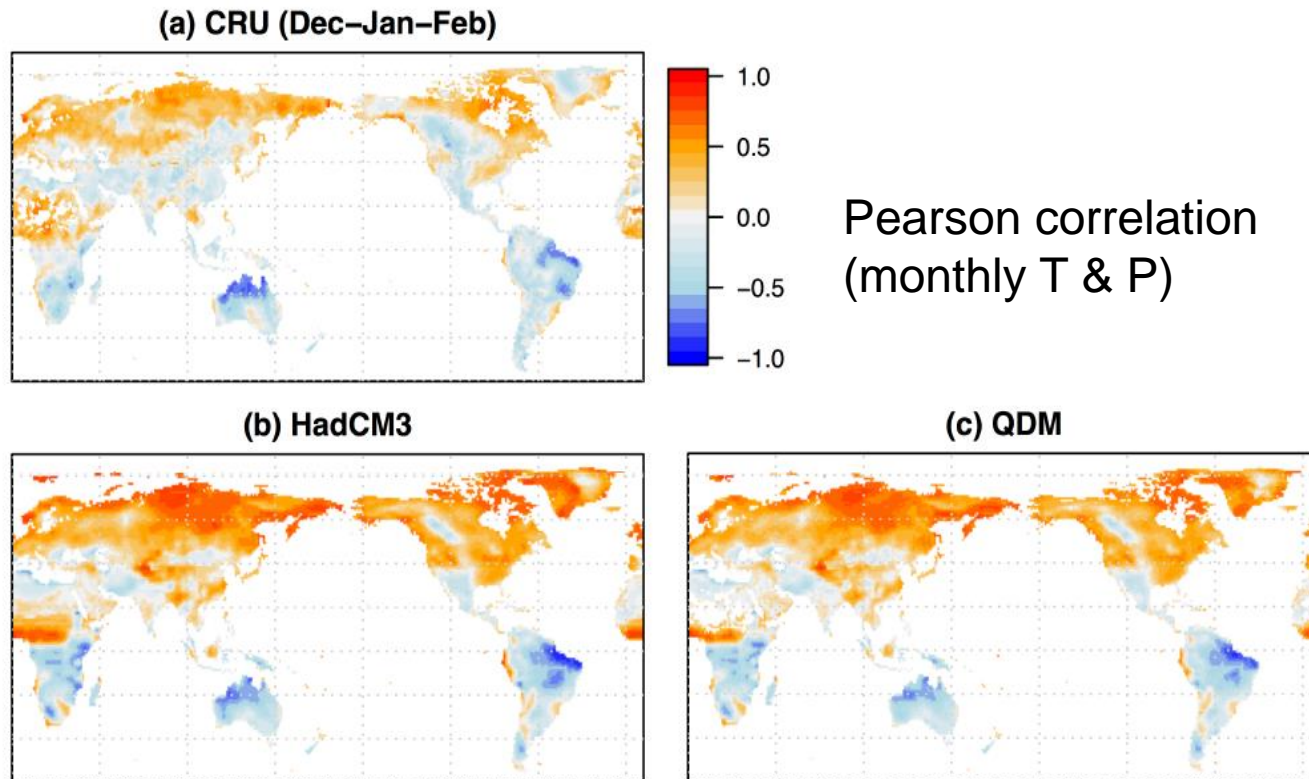


QDM



Univariate bias correction

➤ Can preserve dependence structure?

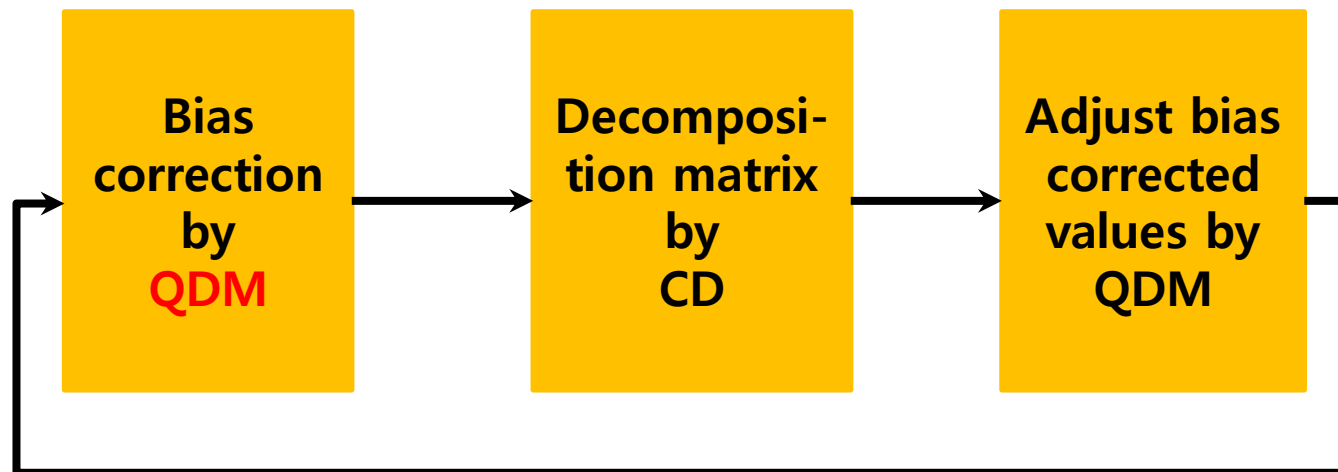


Multivariate Bias Correction (MBC)

➤ Cholesky Decomposition (CD)

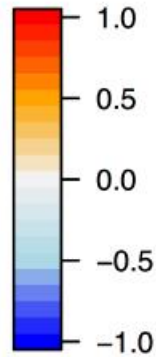
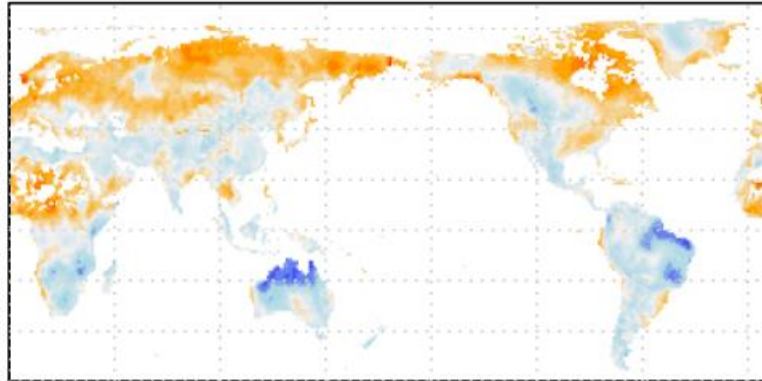
- Preserve covariance between variables

➤ Process



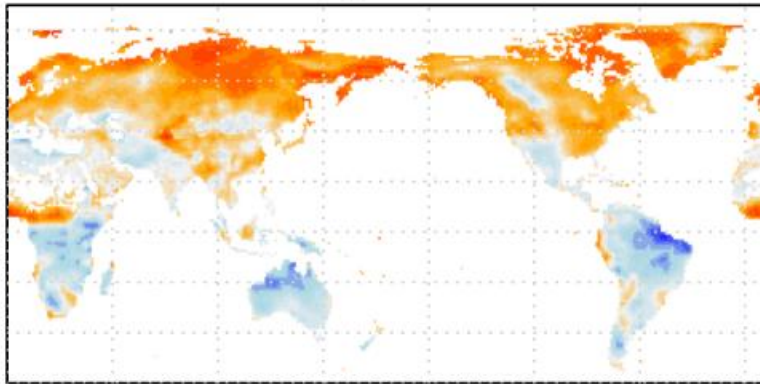
Multivariate Bias Correction (MBC)

(a) CRU (Dec–Jan–Feb)

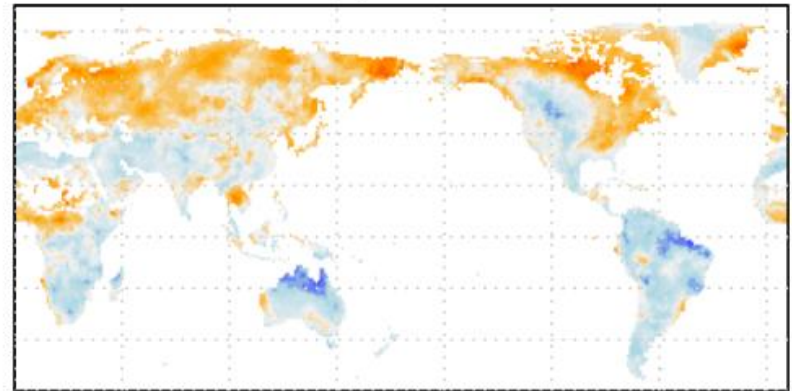


Pearson correlation

(c) QDM



(d) MBCr

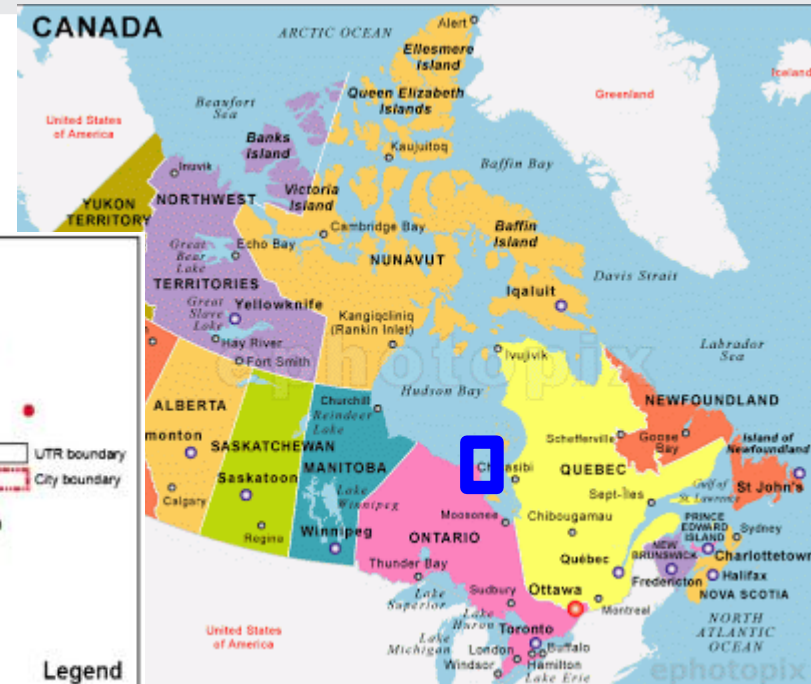
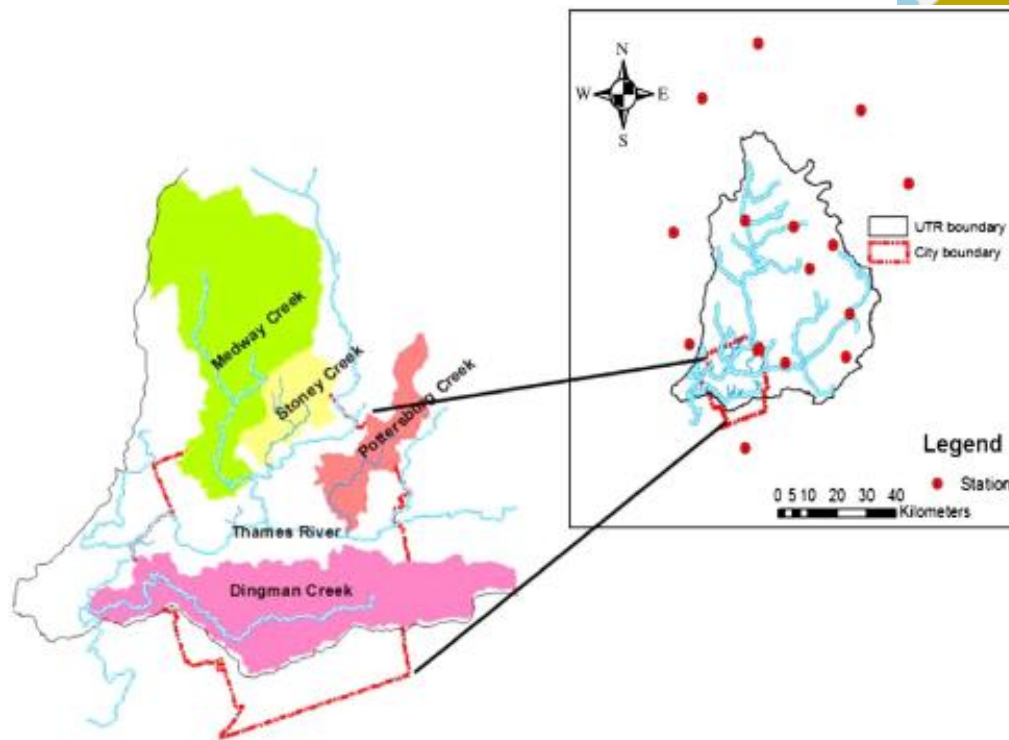


Applications of Statistical Downscaling Methods

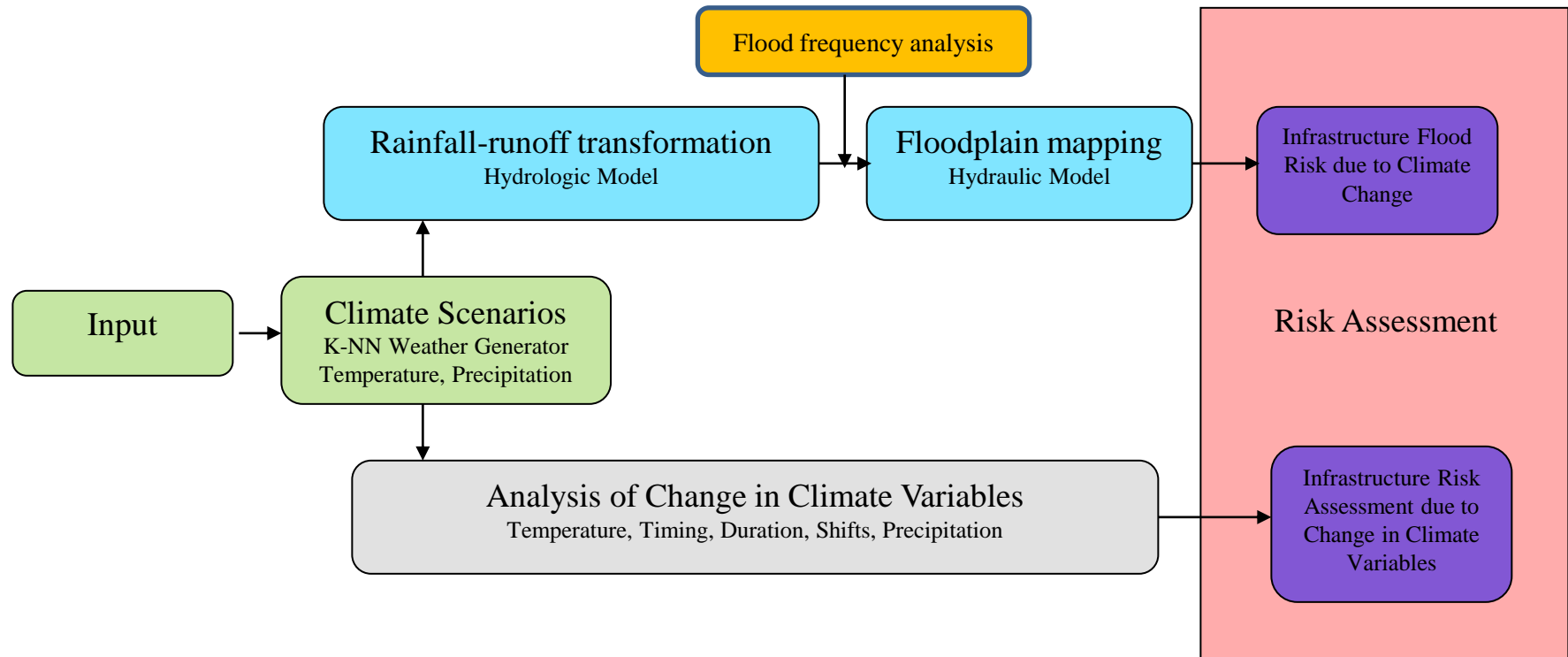


Case study 1: Vulnerability of Infrastructures to Climate Change

➤ London, Ontario (Canada)



Procedure for assessment of climate change



Climate signal from a GCM (CCSRNIES B21)

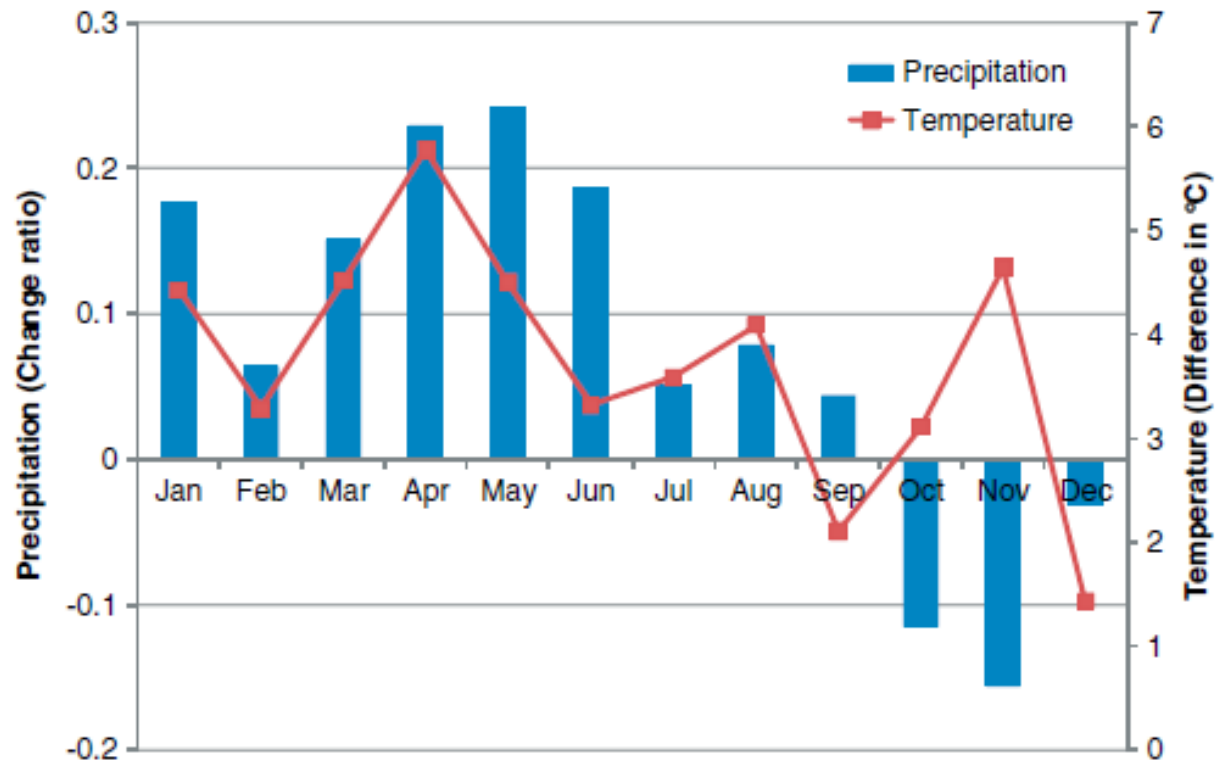
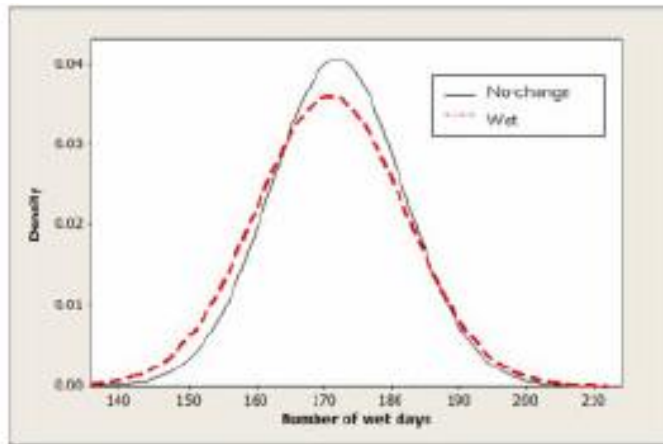
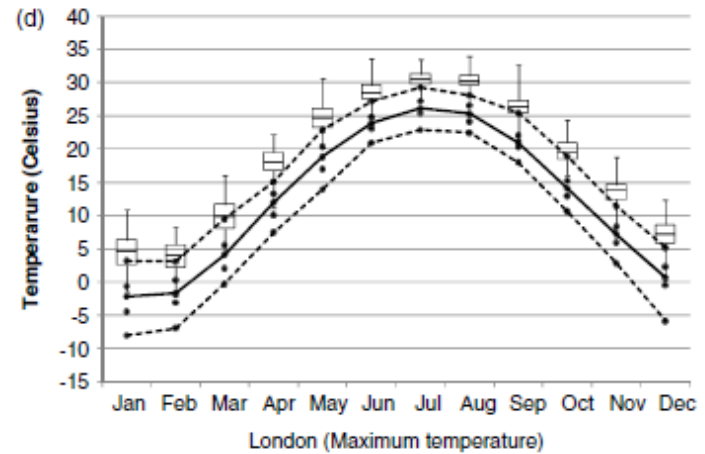
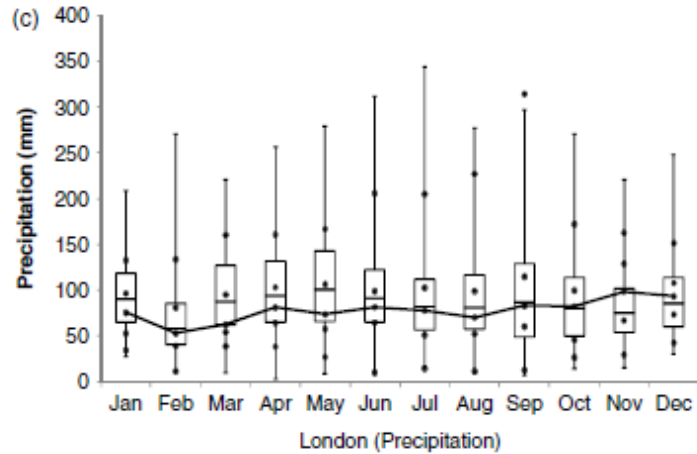


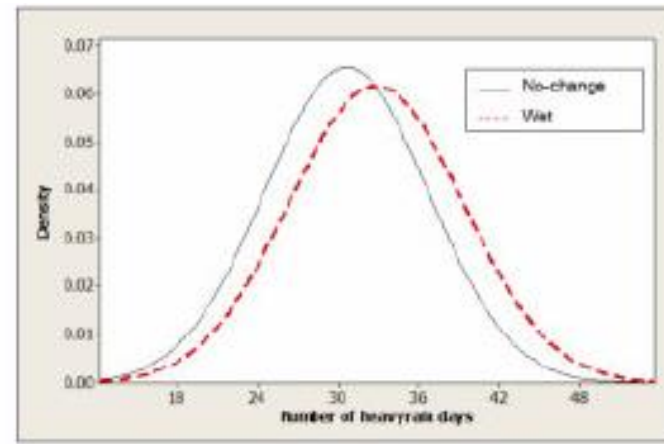
Figure 2. Monthly changes in precipitation and temperature for the CCSRNIES B21 GCM scenario



K-NN WG



London (Wet days)



London (Heavy-rain days)



Hydrologic model

➤ Input data

- Hourly data from a temporal disaggregation technique
 - Method of fragment (Svanidze, 1977)

➤ HEC-HMS

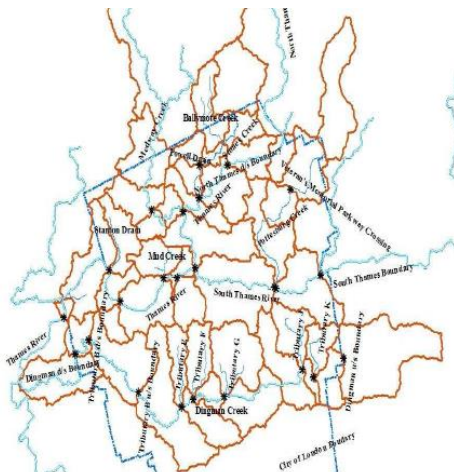


Figure 3.7 Delineation of the Thames River into sub-watersheds within the City of London

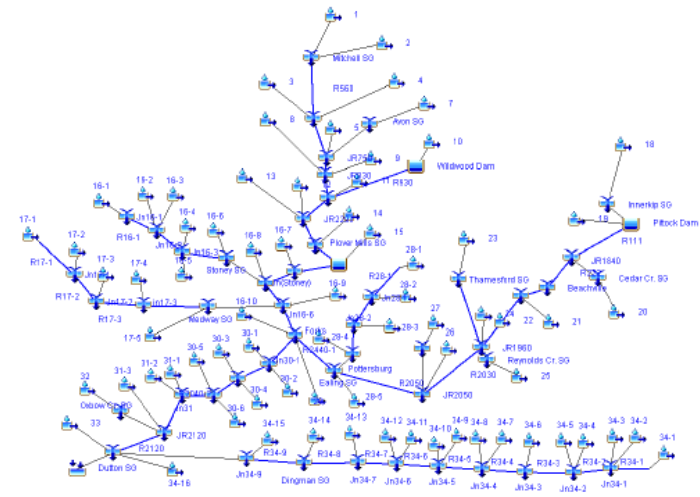
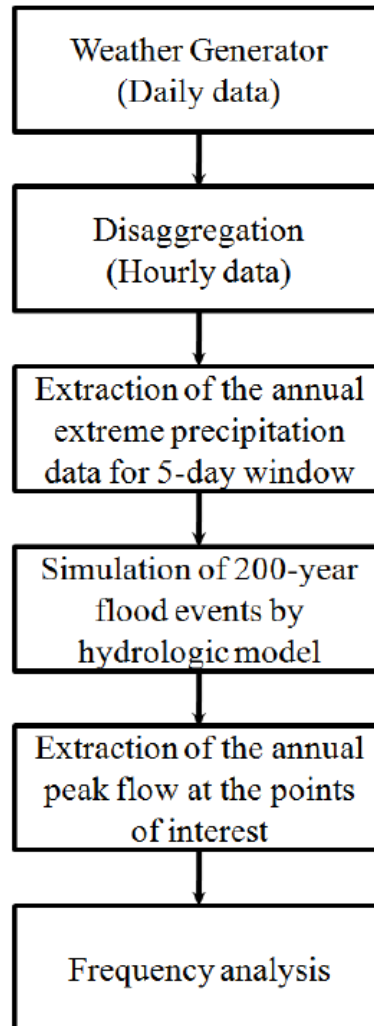
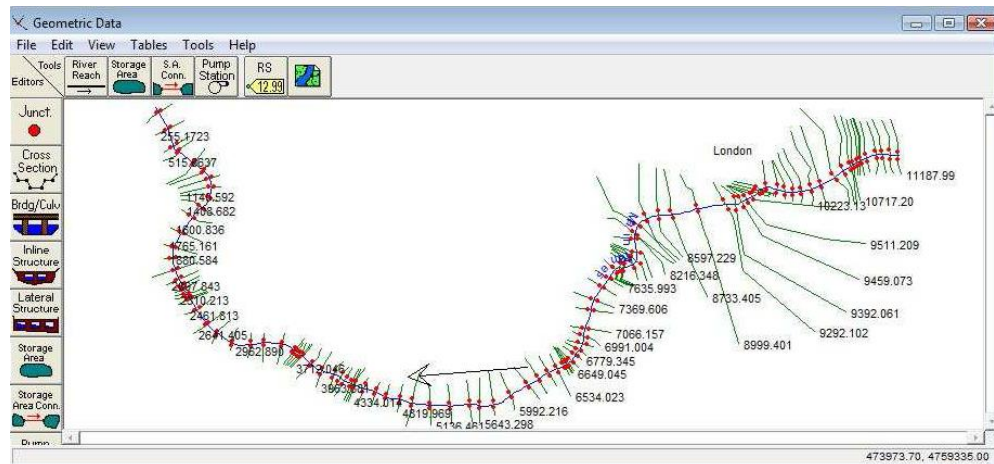
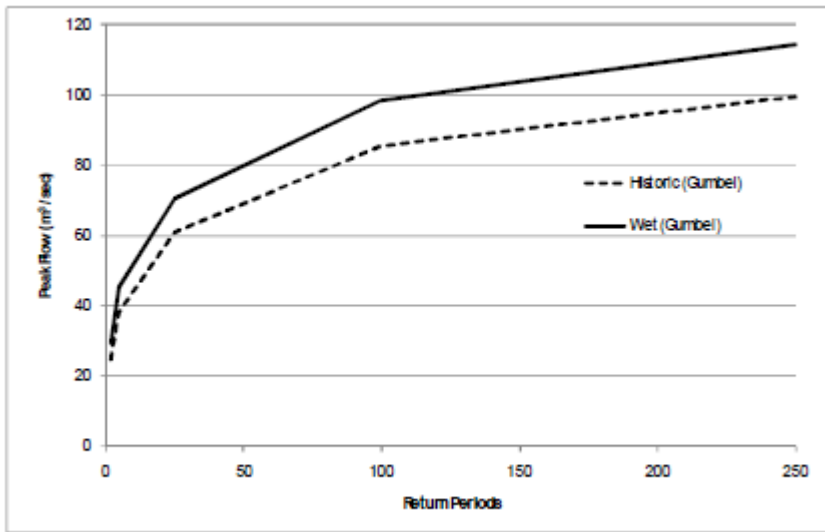


Figure 3.8 The HEC-HMS model structure

Frequency analysis



Flooding map



Case study 2: Water availability under climate change in the Alberta oil sands region



OIL SANDS LOCATION, ALBERTA, CANADA

Bowman, C.W., 2008

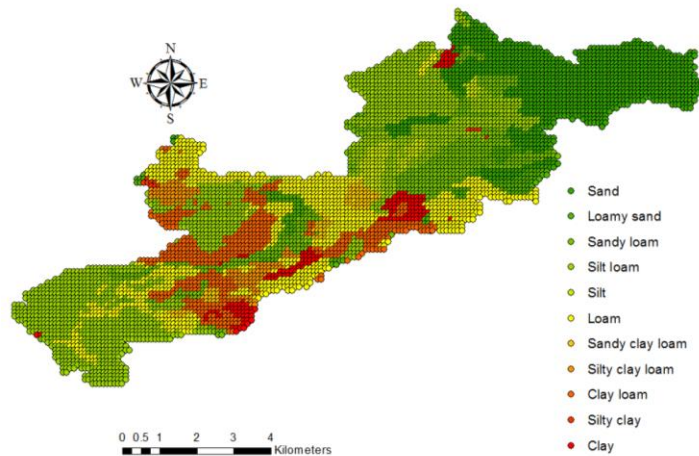
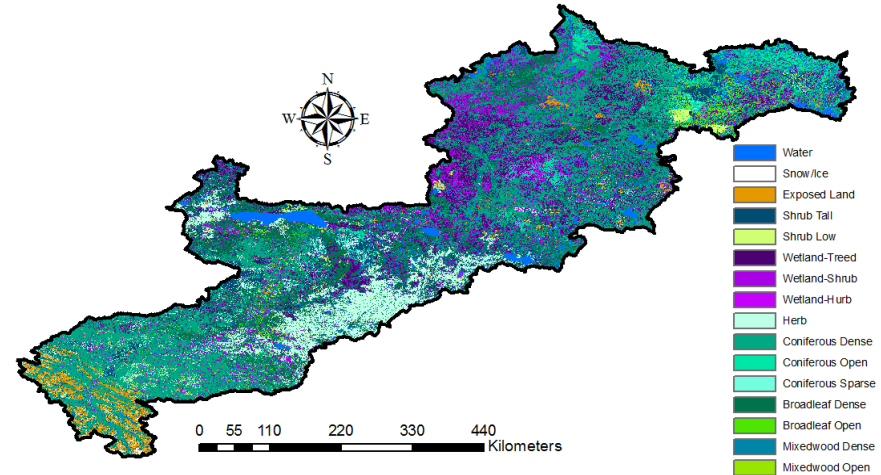
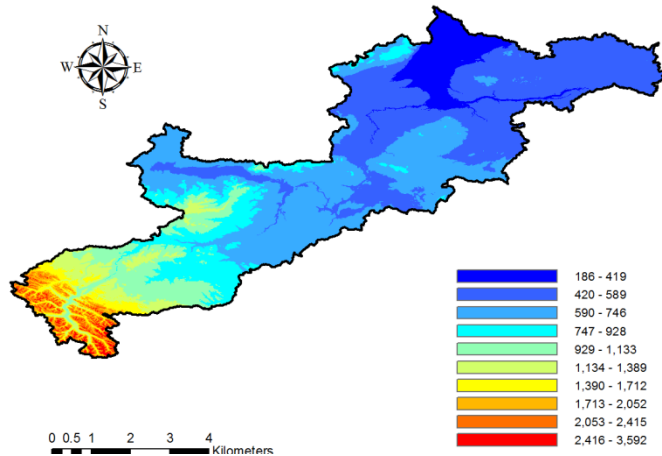


Bitumen



Athabasca River Basin

➤ Various topographic and physical characteristics

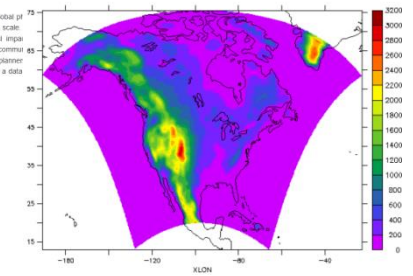
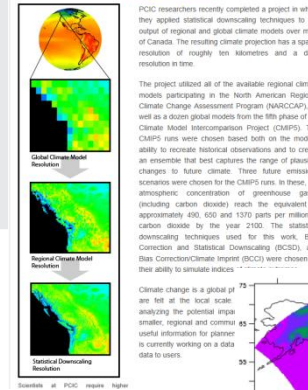


Climate data (1)

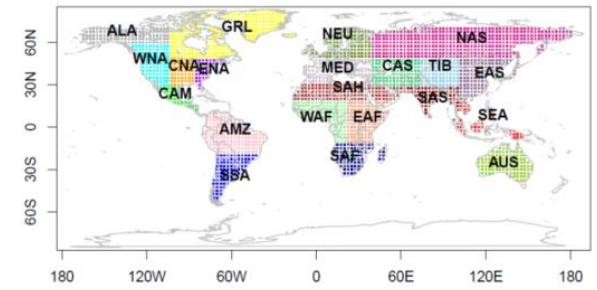
➤ Statistical downscaling

- PCIC (<http://www.pacificclimate.org>)
- Over Canada with 10 km resolution

STATISTICAL DOWNSCALING OF CLIMATE PROJECTIONS



Order	WNA	ALA	CNA	ENA	GRL
1	CNRM-CM5-r1	CSIRO-Mk3-6-0-r1	CanESM2-r1	MPI-ESM-LR-r3	MPI-ESM-LR-r3
2	CanESM2-r1	HadGEM2-ES-r1	ACCESS1-0-r1	inmcm4-r1	inmcm4-r1
3	ACCESS1-0-r1	inmcm4-r1	inmcm4-r1	CNRM-CM5-r1	CanESM2-r1
4	inmcm4-r1	CanESM2-r1	CSIRO-Mk3-6-0-r1	CSIRO-Mk3-6-0-r1	CNRM-CM5-r1
5	CSIRO-Mk3-6-0-r1	ACCESS1-0-r1	MIROC5-r3	HadGEM2-ES-r1	ACCESS1-0-r1
6	CCSM4-r2	MIROC5-r3	HadGEM2-ES-r1	CanESM2-r1	CSIRO-Mk3-6-0-r1
7	MIROC5-r3	HadGEM2-CC-r1	MPI-ESM-LR-r3	MRI-CGCM3-r1	HadGEM2-ES-r1
8	MPI-ESM-LR-r3	MRI-CGCM3-r1	CNRM-CM5-r1	CCSM4-r2	MIROC5-r3
9	HadGEM2-CC-r1	CCSM4-r2	CCSM4-r2	MIROC5-r3	HadGEM2-CC-r1
10	MRI-CGCM3-r1	CNRM-CM5-r1	GFDL-ESM2G-r1	ACCESS1-0-r1	CCSM4-r2
11	GFDL-ESM2G-r1	MPI-ESM-LR-r3	HadGEM2-CC-r1	HadGEM2-CC-r1	MRI-CGCM3-r1
12	HadGEM2-ES-r1	GFDL-ESM2G-r1	MRI-CGCM3-r1	GFDL-ESM2G-r1	GFDL-ESM2G-r1



Trevor et al. (2013)

Method	Diagnostic 1- Sequencing		Diagnostic 2 - Distribution		Diagnostic 3 - Spatial	
	Rank	Performance	Rank	Performance	Rank	Performance
BCCI	1	✓	1 / 2	✓	3	X
BCCA	2	✓	3	X	2	OK
BCSD	3	X	1 / 2	✓	1	✓

Trevor et al. (2013)

Climate data (2)

➤ CMIP5

- 6 GCMs x 2 SDMs x 2 RCPs = 24 scenarios

Model Abbreviation	Modelling Center	RCP/ Statistical downscaling method (SDMs)	Primary reference
CNRM-CM5.1	Centre National de Recherches Meteorologiques and Cerfacs	RCP4.5& RCP8.5/ BCCI & BCSD	Voltaire et al. (2013)
CanESM2	Canadian Centre for Climate Modelling and Analysis		Arora et al. (2011)
ACCESS1	Centre for Australian Weather and Climate Research		Marsland et al. (2013)
INMCM4	Institute of Numerical Mathematics of the Russian Academy of Sciences		Volodin et al. (2010)
CSIRO-Mk3.6.0	Commonwealth Scientific and Industrial Research Organisation		Jeffrey et al. (2013)
CCSM4	National Center for Atmospheric Research (NCAR)		Gent et al. (2011)



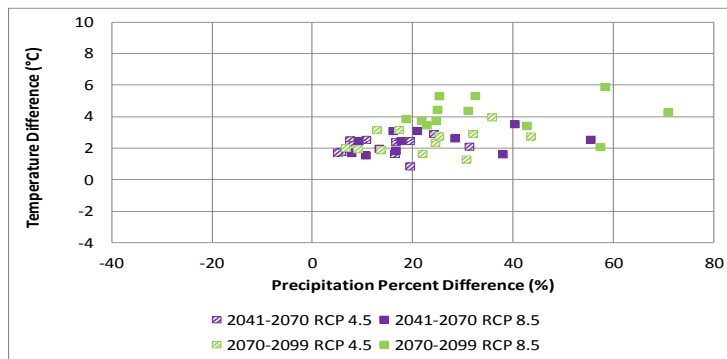
Indicators of Hydrologic Alterations (IHAs)

Hydrologic regime component	WRIs and IHAs	No	Examples of hydrologic influence	Examples of ecological influence
Magnitude and timing	Water resources indicators (WRIs) Annual volume (m ³), center of timing of annual flow (water year), median seasonal flow	6	Annual water balance, magnitude and timing of seasonal conditions	Availability and suitability of habitat for aquatic organisms
Magnitude and duration	Annual mean 1-day minimum and maximum (m ³ /s)	2	Magnitude of annual flood and drought conditions	Duration of stressful conditions
Timing	Day of each annual 1-day minimum and maximum	2	Timing of annual flood and drought conditions	Spawning cues for fish; compatibility with life cycles of organisms
Magnitude and timing	Timing and amount of spring freshet initiation	2	Timing and magnitude of rapid melting	-
	Total	12		

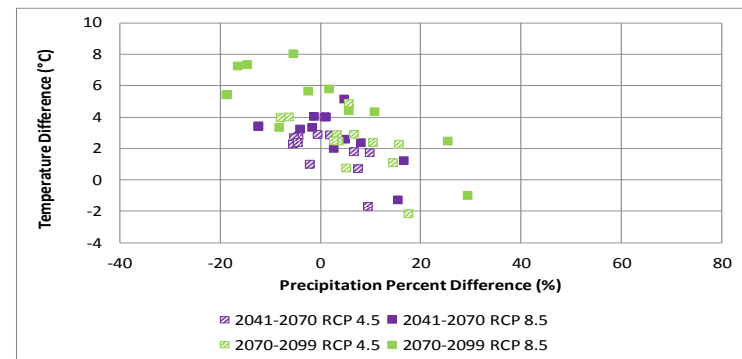


Seasonal changes in PPT & TEM

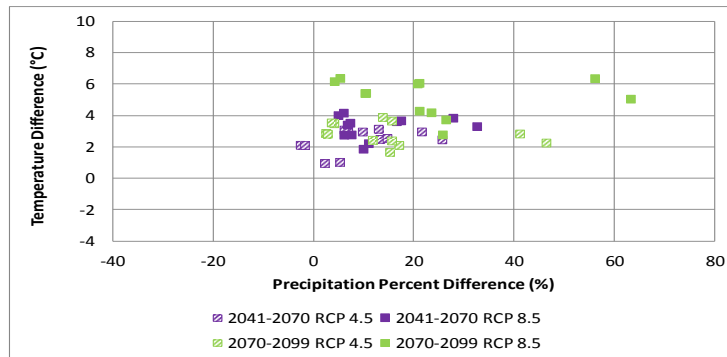
➤ Difference from the reference period (1981-2010)



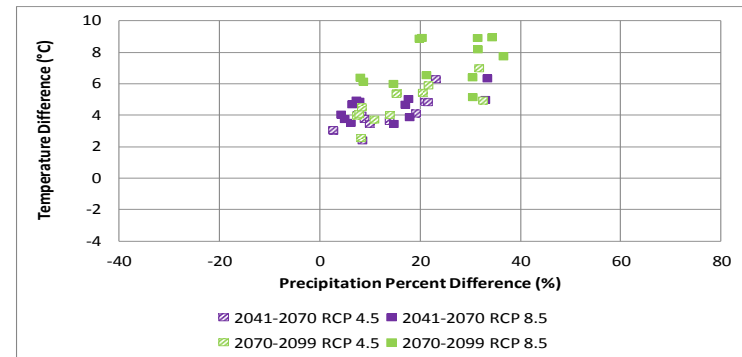
Spring (MAM)



Summer (JJA)



Autumn (SON)



Winter (DJF)



Hydrologic model

➤ Variable Infiltration Capacity (VIC)

- 1/16 (~7km) spatial resolution

➤ DEM

- Canadian Digital Elevation D
 - 3 arc second (≈ 90 m) spatial

➤ Land cover

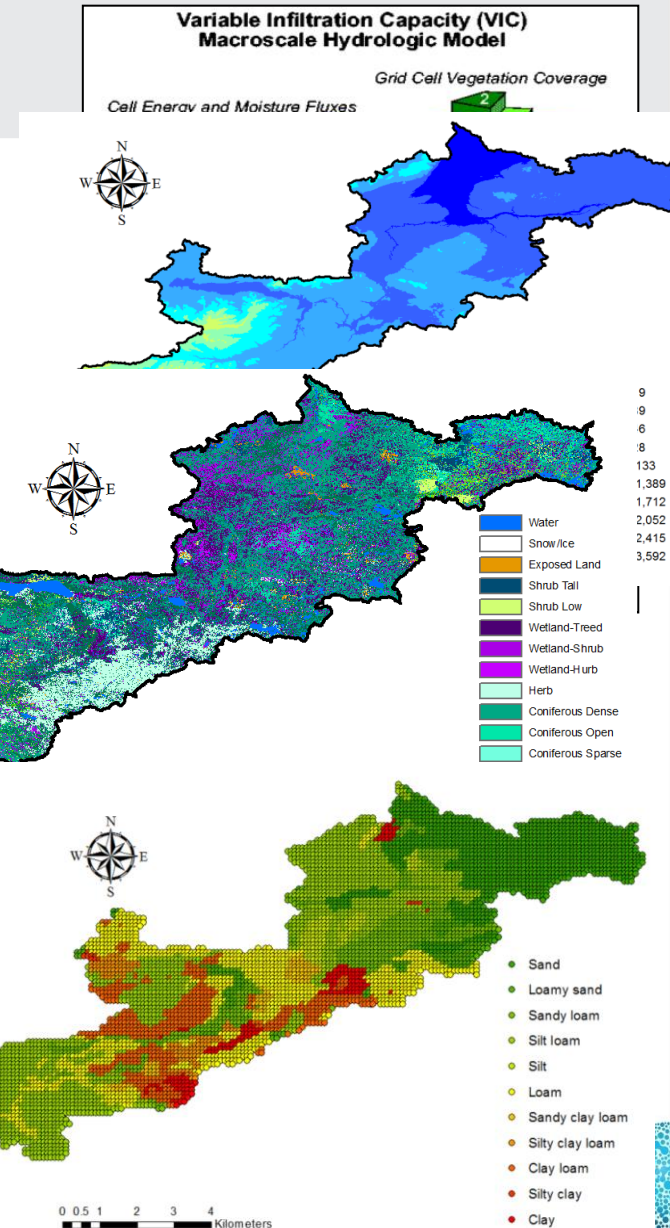
- 1 km resolution – circa 2000 Sustainable Development, E

➤ Monthly Leaf Area Index (LA

- Canada-wide 1-km 10-day SPOT 4 2

➤ Soil parameters – 3 layers

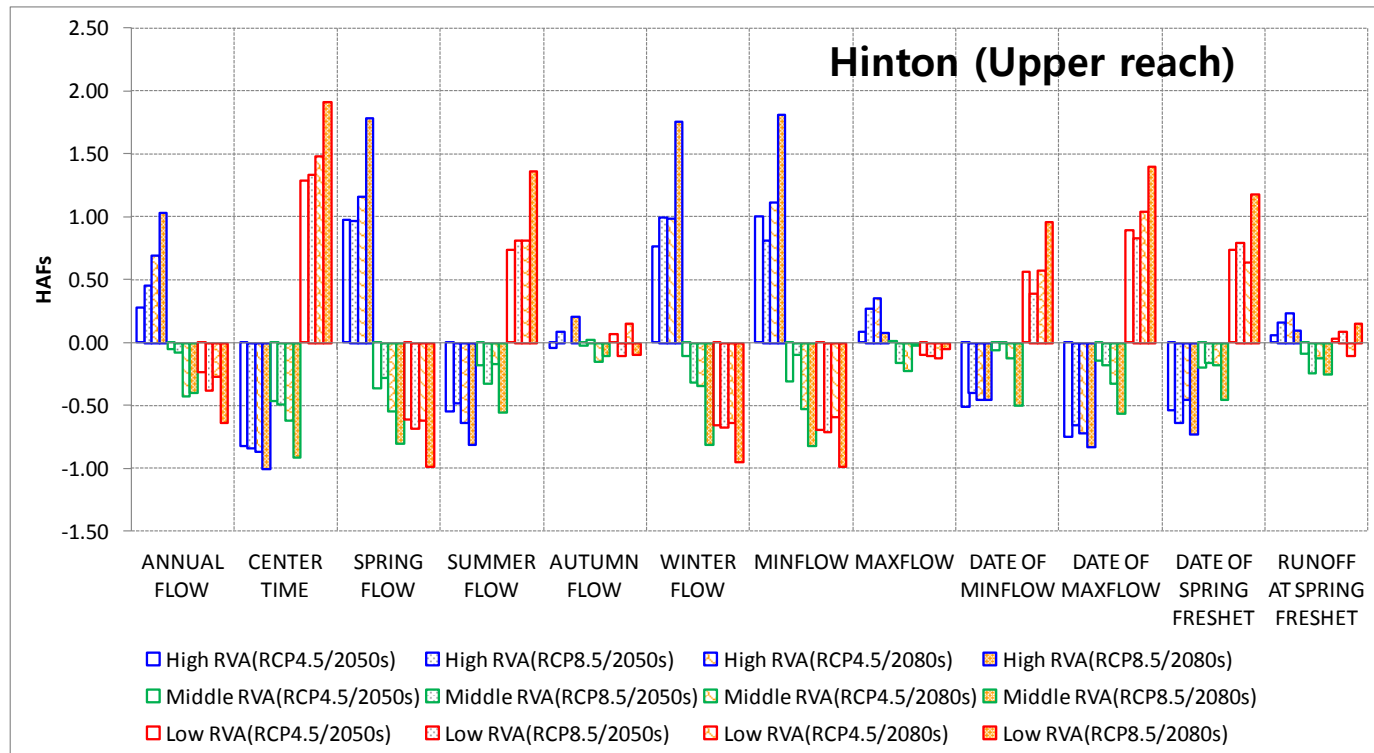
- Soil Landscapes of Canada (SLC) ver



Hydrologic alteration factor (HAF)

➤ HAF

- $(\text{Projected frequency} - \text{Reference frequency}) / \text{Reference frequency}$



Summary

- **Why do we need downscaling?**
- **Statistical or Dynamical**
- **MOS-based approaches**
 - Preserve GCM-driven long-term trend
- **Case studies**



