

2017 APCC Statistical Downscaling Training Program:
*User-oriented Statistical Downscaling of Climate Information
in Agriculture and Water Resources*

Weather Generator and its Application to Downscaling

Moosup Kim

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About Instructor

- Name: Moosup Kim
- Research Fellow in APCC
- Research Area
 - Statistical Downscaling of Seasonal Forecast
 - Bias Correction of RCM data
- moosupkim@apcc21.org



Overview

1. Introduction
2. Statistical Model of Weather Generator
3. Statistical Downscaling using Weather Generator.
4. Summary



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Introduction

- In agriculture and water resources, climate information is necessary.
- Raw climate information is coarse in space and time. It needs downscaling process.
 - e.g. GCM Prediction
- Observation data are useful, but have limitation due to their finiteness.



Introduction

- Weather Generator
 - Weather generators are systems of statistical models for weather in a basin.
 - They can rapidly produce lots of weather data that have statistical consistency with observation data.
 - *Recently, it has been studied as a tool downscaling seasonal prediction into local basin daily weather data.*



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Statistical Model

- A Weather Generator is a system of Statistical Models.
- The Statistical Models describe daily precipitation and temperature in a basin.



Statistical Model

- WGEN
 - Markov model for wet/dry-spell generation,
 - Gamma distribution for rainfall amount,
 - Fourier series for annual cyclic trend of temperature,
 - Vector autoregressive model for temperature anomalies.



Statistical Model

- LARS-WG
 - Wet/dry-spell alternation scheme for spells generation,
 - Semi-empirical distribution for rainfall amount,
 - Temperature model is the same as WGEN.



Statistical Model

- Markov model
 - Adopted by WGEN,
 - For wet/dry-spell generation,
 - 2-state Markov model
 - State: Wet / Dry,
 - Wet: rainfall amount > 0 ,
 - Dry : rainfall amount = 0.



Statistical Model

- Markov model
 - Transition
 - Wet \rightarrow Dry / Dry \rightarrow Wet,
 - Dry \rightarrow Dry / Wet \rightarrow Wet.
 - Transition Probability

Today/Tomorrow	Wet	Dry
Wet	p_{11}	p_{12}
Dry	p_{21}	p_{22}

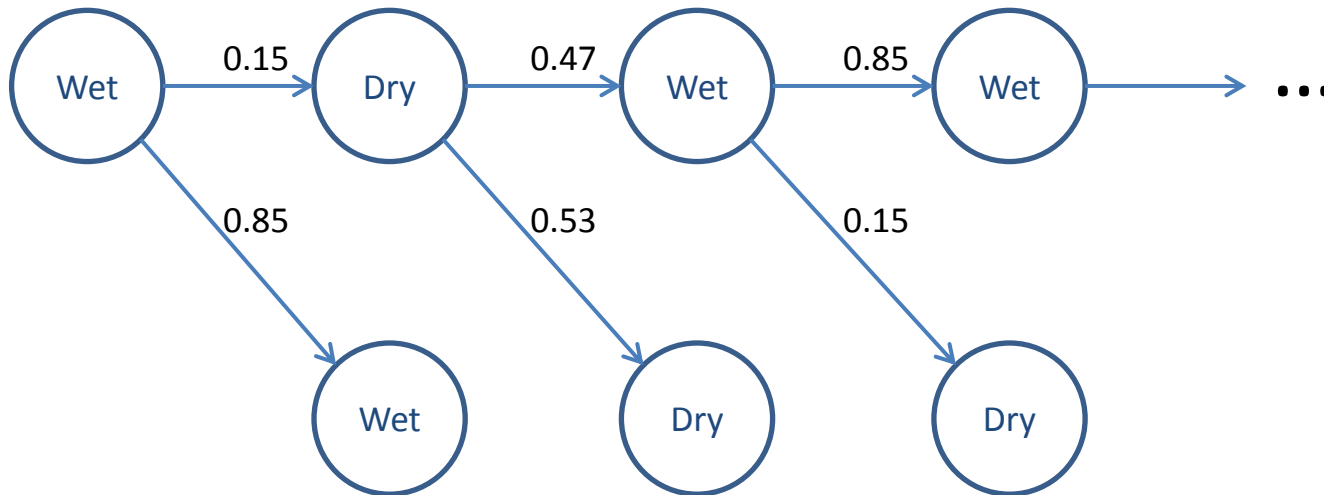


Statistical Model

- Markov model
 - Simulation

	Wet	Dry
Wet	0.85	0.15
Dry	0.47	0.53

Matrix of transition probabilities estimated by using observation data

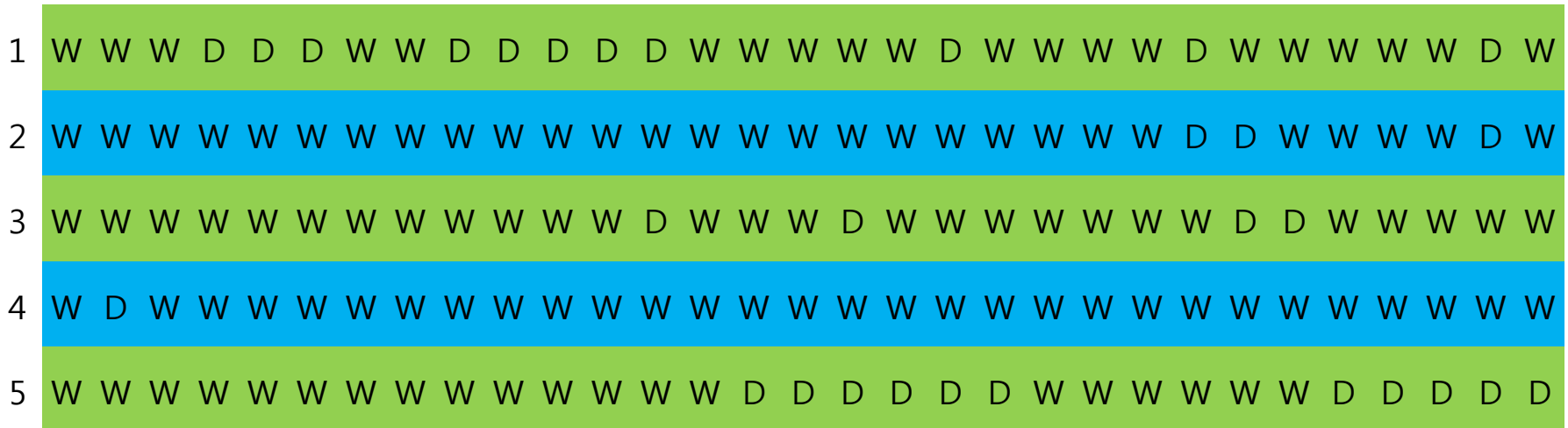


Statistical Model

- Markov model
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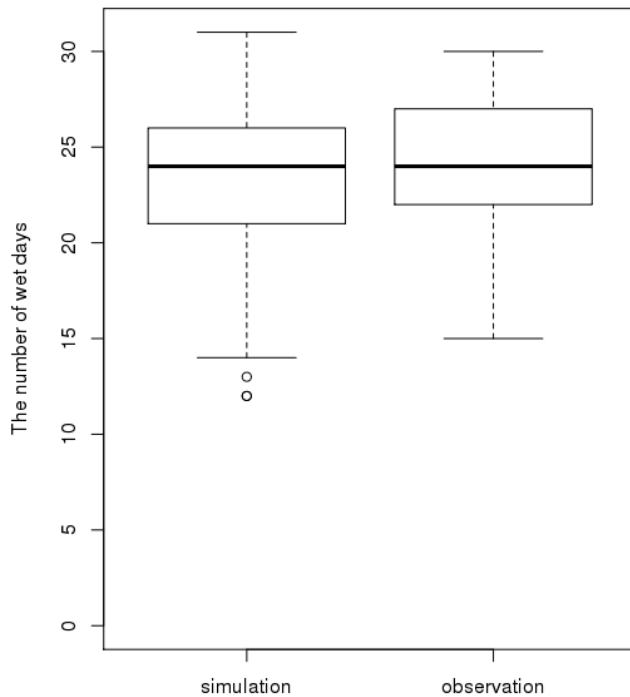
Matrix of transition probabilities estimated by using observation data



Statistical Model

- Markov model
 - Simulation vs. Observation

How many days are wet a month (31 days)



Spell length Statistics (day)		Simulation	Observation
Wet-spell Length	Mean	7.02	7.02
	SD	6.50	7.11
Dry-spell Length	Mean	2.14	2.14
	SD	1.57	1.94



Statistical Model

- Markov model
 - Statistical characteristics are fairly similar,
 - But, SD of simulation spell lengths are a little bit smaller than observation.



Statistical Model

- Remarks on Markov model
 - Markov model simulates real wet/dry-spells well.
 - However, it is not perfect. We are not sure that it always performs well.
 - In this viewpoint, LARS-WG adopts wet/dry-spell alternation scheme instead of Markov model.
 - The scheme is a resampling method. It requires that observation data are long enough.



Statistical Model

- Rainfall amount model
 - Gamma distribution,
 - Exponential Mixture model,
 - Empirical distribution,
 - Generalized Pareto distribution.



Statistical Model

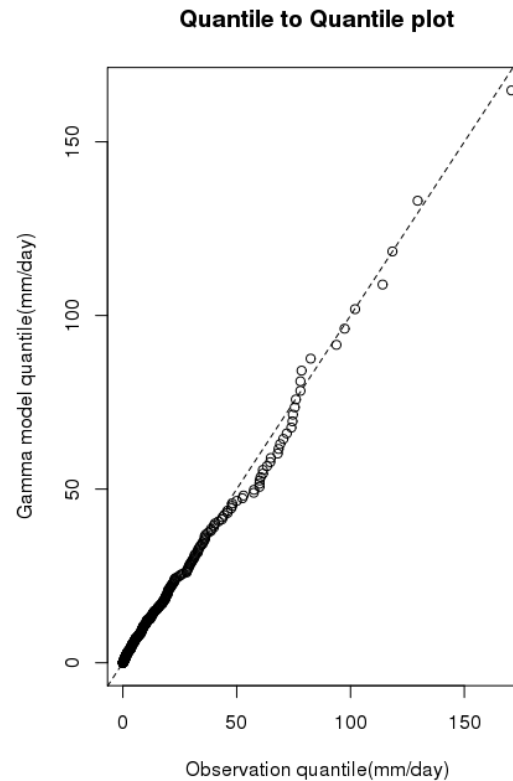
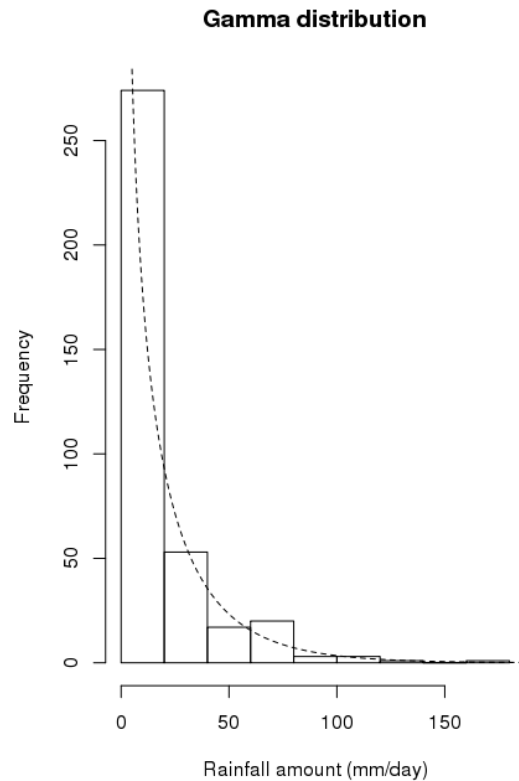
- Gamma distribution
 - μ : mean of rainfall amount (mm/day)
 - α : shape parameter. $0 < \alpha < 1$ for rainfall amount

$$f(x) = \frac{\alpha^\alpha}{\Gamma(\alpha)\mu^\alpha} x^{\alpha-1} \exp\left(-\frac{\alpha x}{\mu}\right), \quad x > 0$$



Statistical Model

- Gamma distribution
 - $\hat{\mu} = 16.56$ (mm/day), $\hat{\alpha} = 0.53$.



Statistical Model

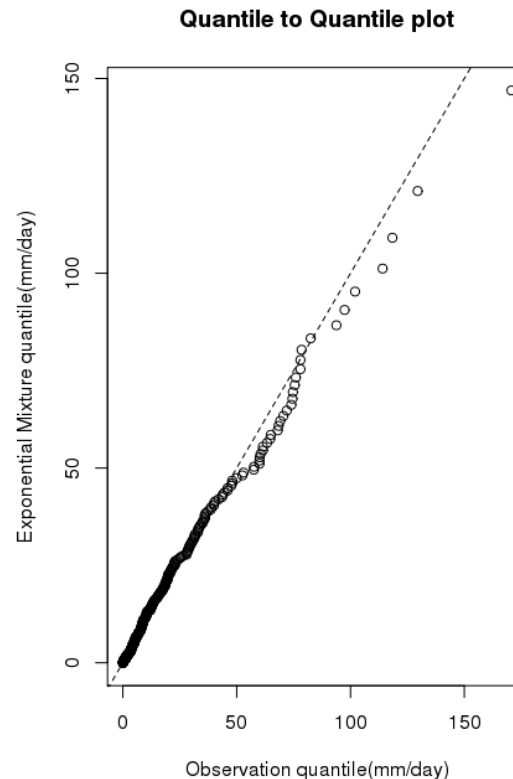
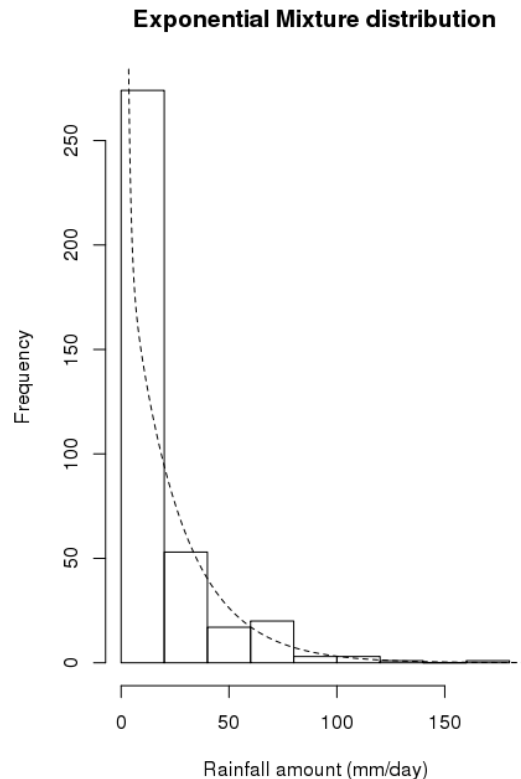
- Exponential Mixture Model
 - μ_1, μ_2 : mean of the components
 - $0 < \lambda < 1$: mixture parameter
 - $\lambda\mu_1 + (1 - \lambda)\mu_2$: average of rainfall amount

$$f(x) = \lambda \exp\left(-\frac{x}{\mu_1}\right) + (1 - \lambda) \exp\left(-\frac{x}{\mu_2}\right), \quad x > 0$$



Statistical Model

- Exponential Mixture Model
 - $\hat{\lambda} = 0.7$, $\hat{\mu}_1 = 23.5(\text{mm/day})$, $\hat{\mu}_2 = 1.16(\text{mm/day})$



Statistical Model

- Exponential Mixture Model says
 - The first component corresponds to heavy rainfall, the second does to light one.
 - Heavy rainfall with probability 0.7 and its mean 23.5 mm/day
 - Light rainfall with probability 0.3 and its mean 1.16 mm/day



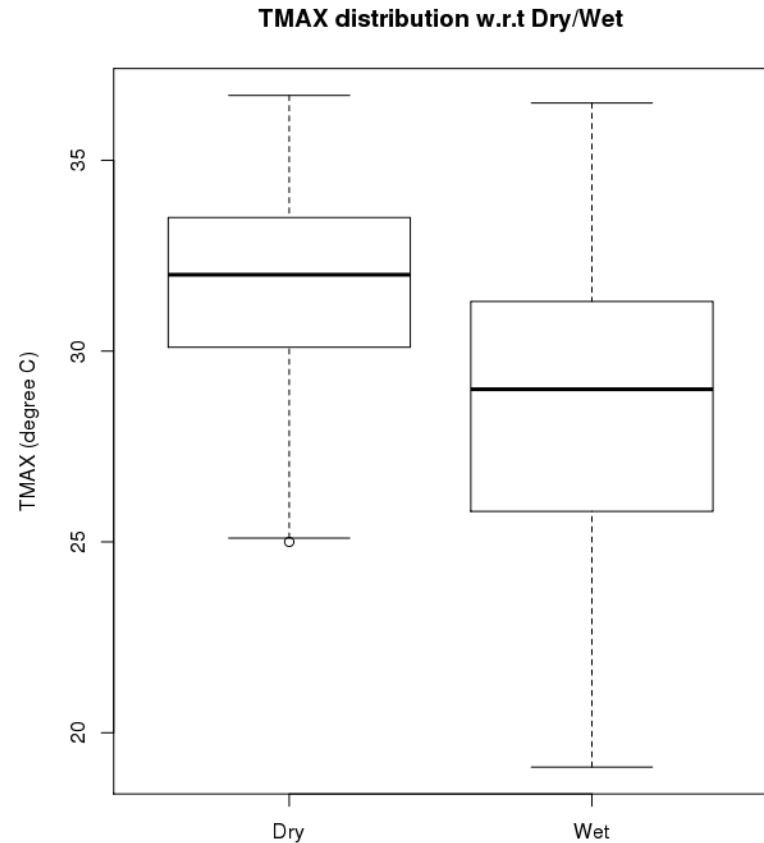
Statistical Model

- Both models are suitable to the rainfall amount data. However, not always.
- Both models may be inappropriate for *extreme rainfall with long return period*. Generalized Pareto model is a suitable model.



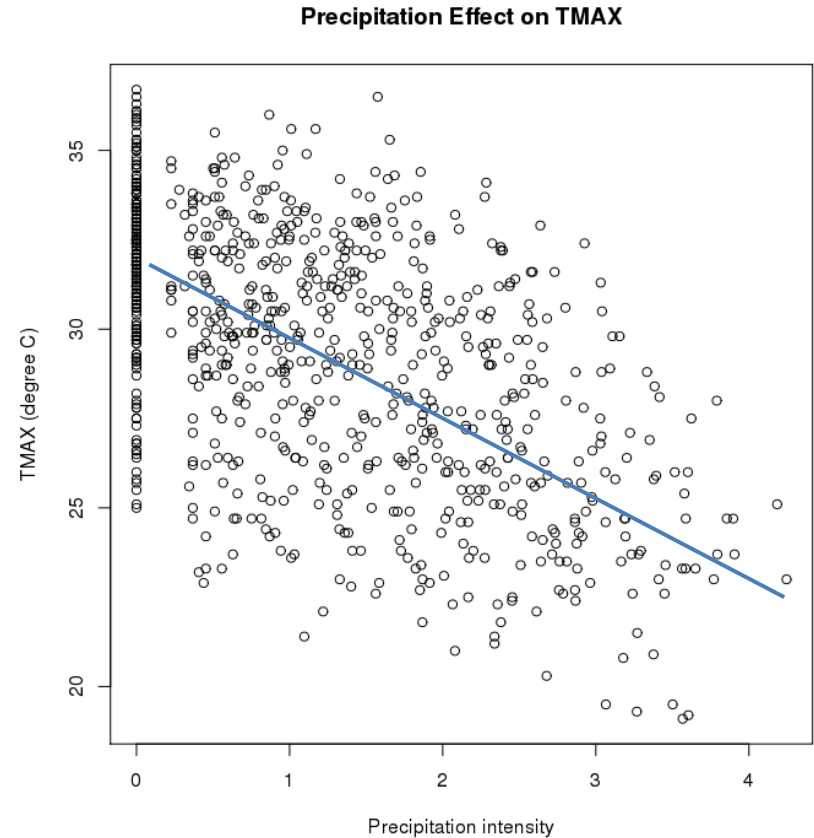
Statistical Model

- Regression model
 - Temperature is affected by precipitation.
 - WGEN and LARS-WG model this effect by estimating mean and SD of temperature for wet and dry days, *separately*.



Statistical Model

- Regression model
 - However, the effect is Linear!
 - Stronger Precipitation intensity, lower TMAX.



Statistical Model

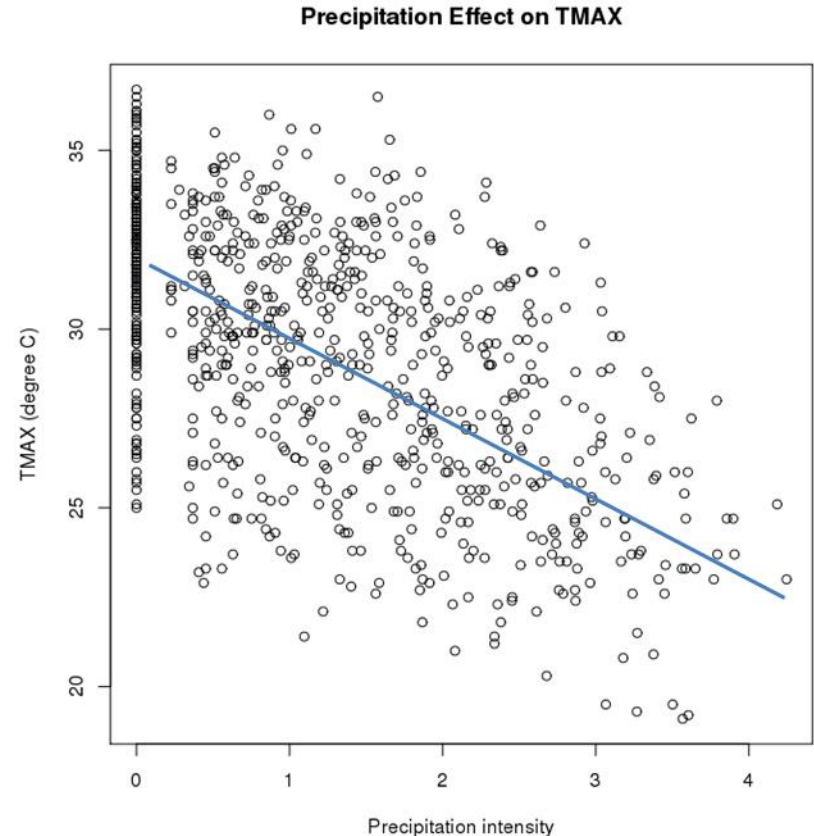
- Regression model
 - Linear relation is formulated by regression model.

$$Y = \beta_0 + \beta_1 X + (\text{error}),$$

Y: TMAX (degree C),

X: Precipitation intensity.

$$\hat{\beta}_0 = 31.66, \hat{\beta}_1 = -1.9$$



Statistical Model

- Other issues on temperature model are dealt with in the next section.



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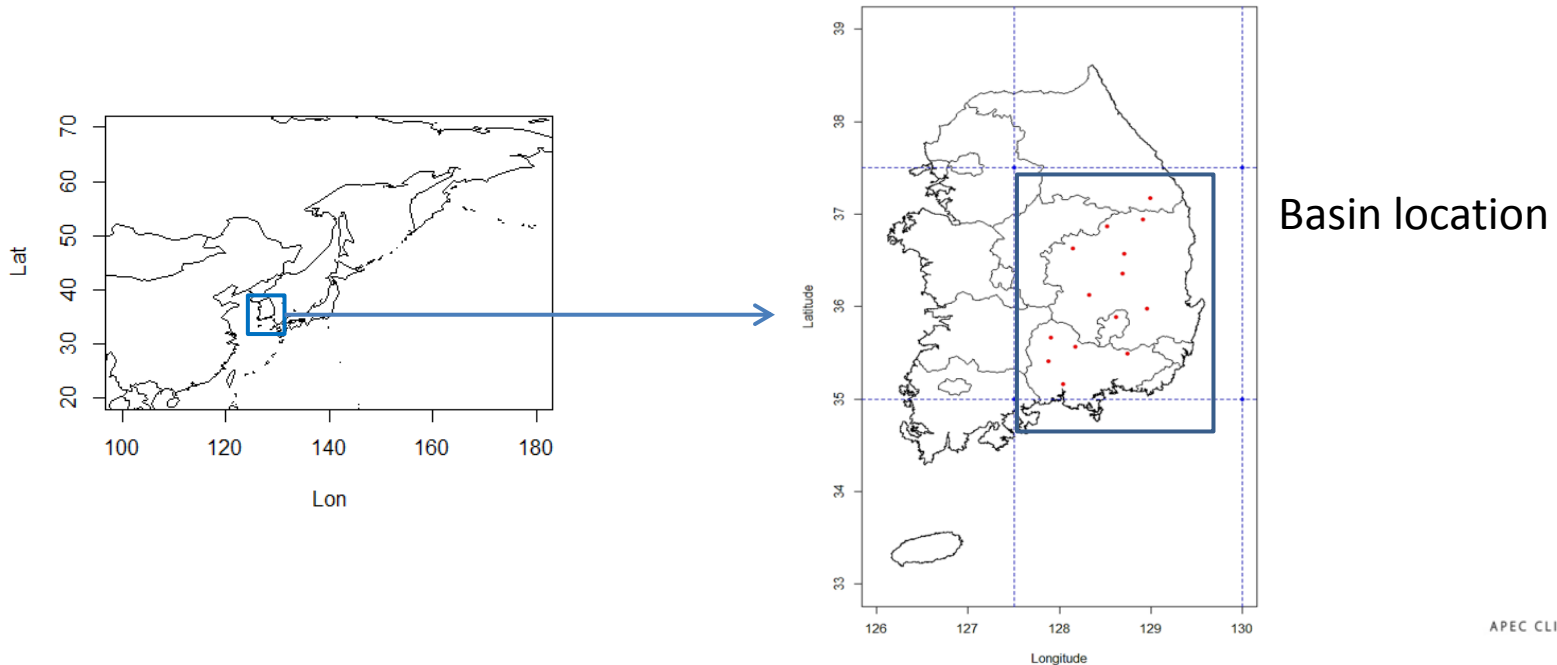
Statistical Downscaling

- Weather Generator is used for Statistical Downscaling.
 - Large-scale atmospheric circulation → local basin daily weather.
 - Large-scale atmospheric circulations are usually predicted in seasonal time scale.
 - In terms of 3-month average.
 - Weather generator plays the role of temporal disaggregation.



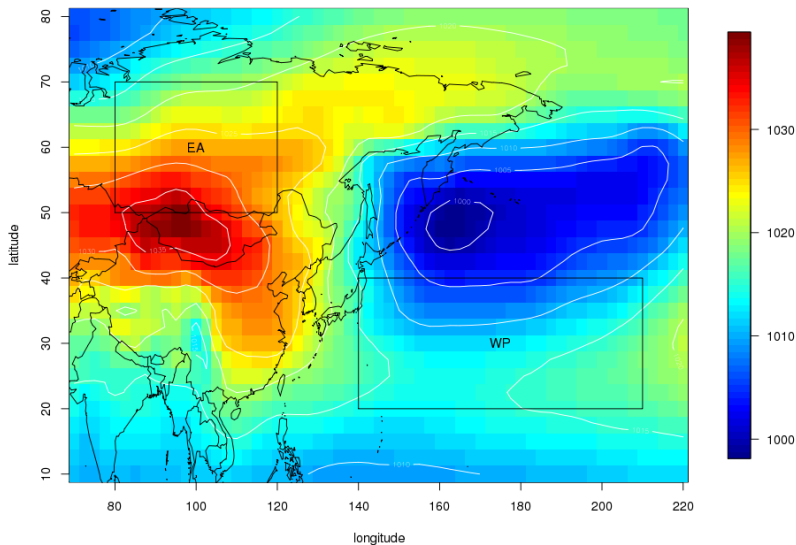
Statistical Downscaling

- We consider a Korean basin case.
 - Season: Boreal Winter, DJF.
 - Nakdong river: 14 stations.



Statistical Downscaling

- The basin is affected by EAWM (East Asia Winter Monsoon)
 - Kim et al (2016) index measuring SLP gradient.



The domains of the EAWM index.
The index is defined as the difference
between DJF averages of SLP on
WP/EA regions

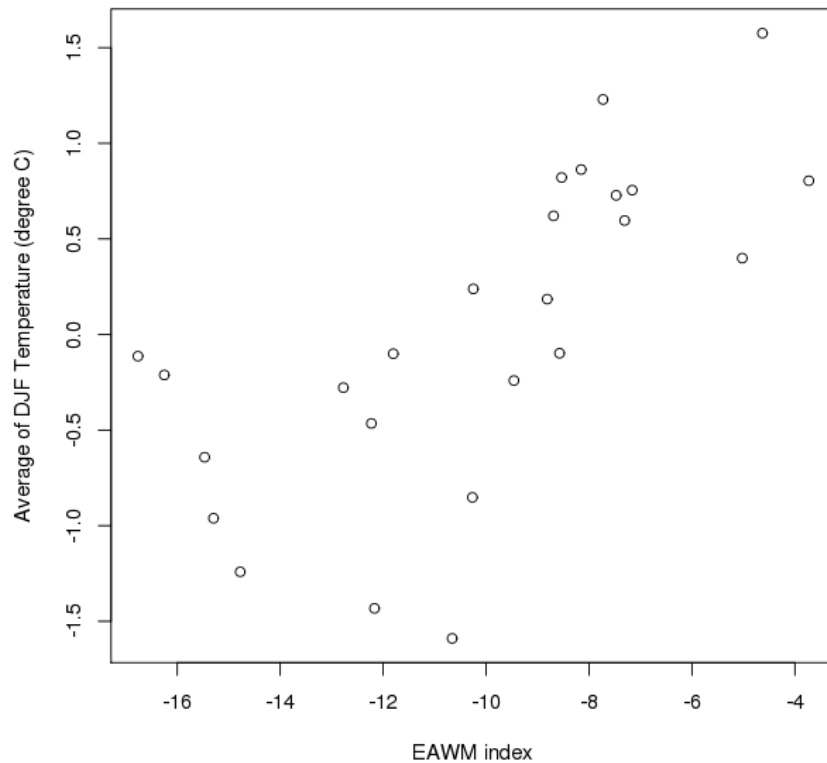
Kim, S. T., Sohn, S., and Kug, J. (2016) Winter Temperatures over the Korean Peninsula and East Asia: development of a new index and its application to seasonal forecast *Clim. Dyn. Online published.*



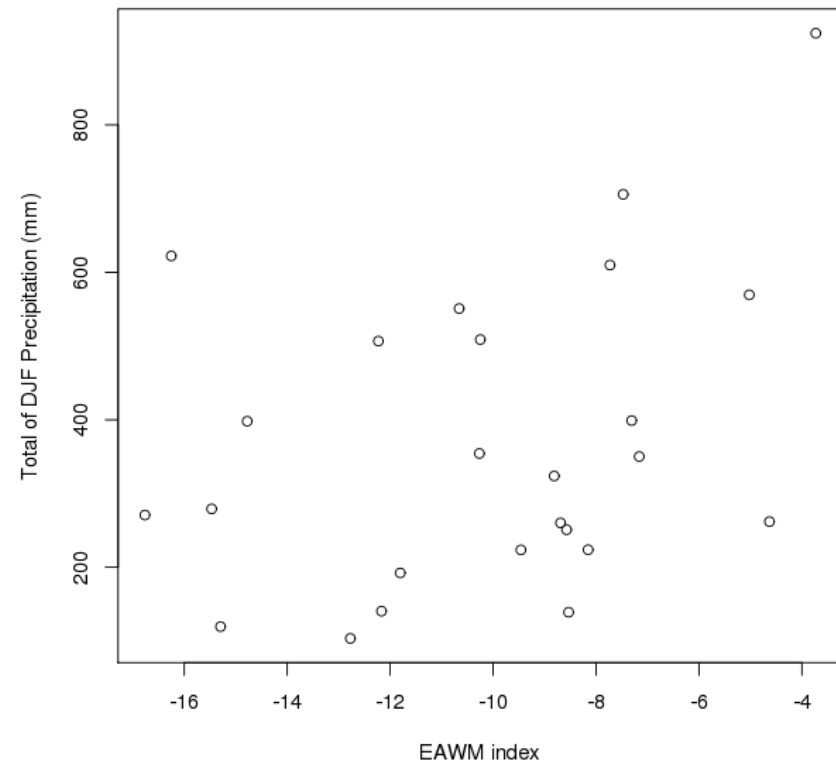
Statistical Downscaling

- Relation with the basin DJF climate

Corr. between EAWM index and DJF Temperature
Corr. coef. = 0.692



Corr. between EAWM index and DJF Precipitation
Corr. coef = 0.340



Statistical Downscaling

- We focus on Temperature.
 - EAWM is related to temperature.
 - Boreal winter is a dry season.
- How to downscale EAWM using weather generator?
 - We will give a simple example where TMIN and precipitation are dealt with.



Statistical Downscaling

- *Slow oscillation term* is introduced to the temperature model of Weather Generator.
 - $\mu(t)$: mean climatology,
 - $T(t) - \mu(t)$: deviation (w.r.t. mean climatology),
 - $\eta(t)$: *slow oscillation*,
 - $\Delta(t)$: precipitation effect.

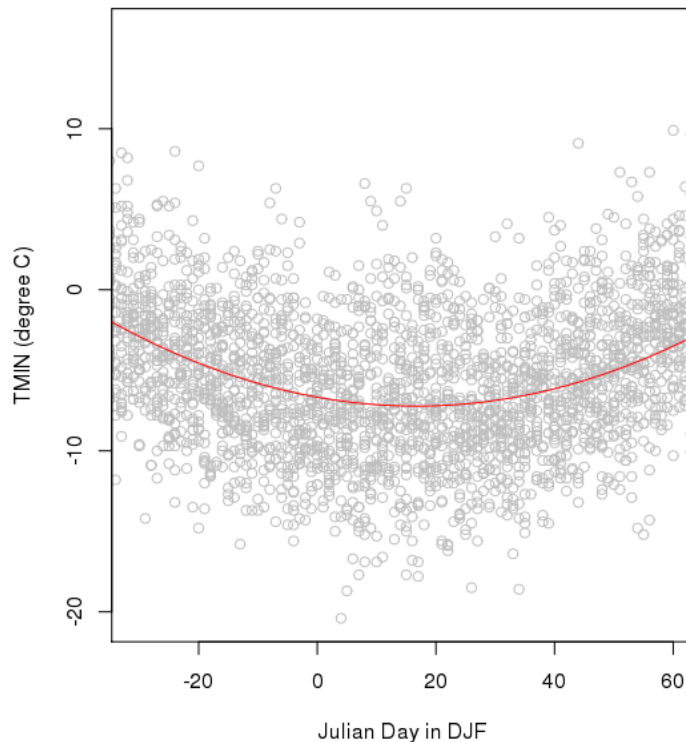
$$T(t) - \mu(t) = \eta(t) + \Delta(t) + (\text{anomaly})$$



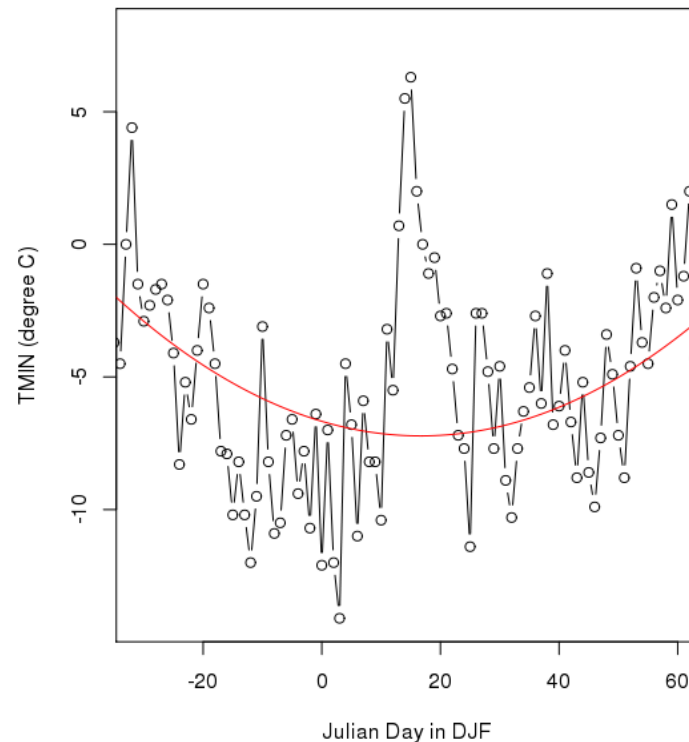
Statistical Downscaling

- Mean climatology and slow oscillation

TMIN and its mean climatology



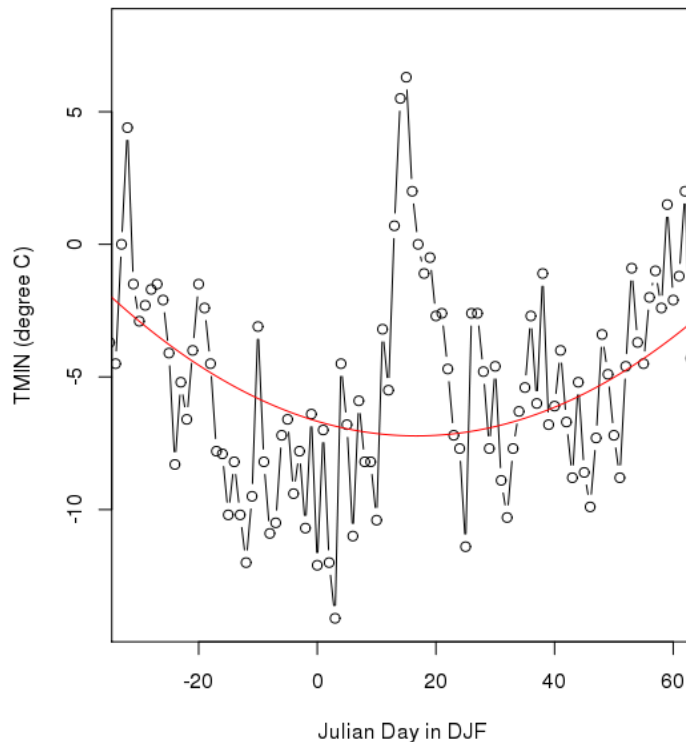
TMIN during DJF in 2001-2002



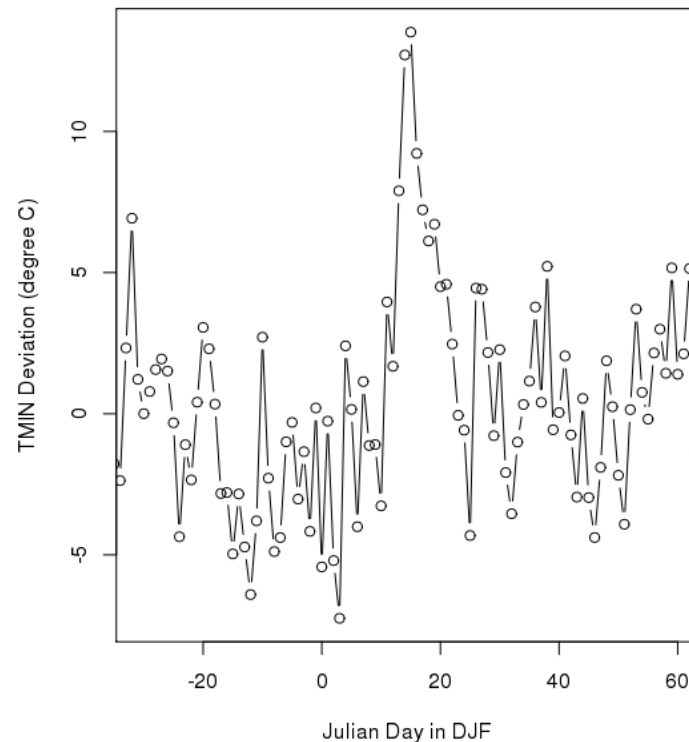
Statistical Downscaling

- Mean climatology and slow oscillation

TMIN during DJF in 2001-2002



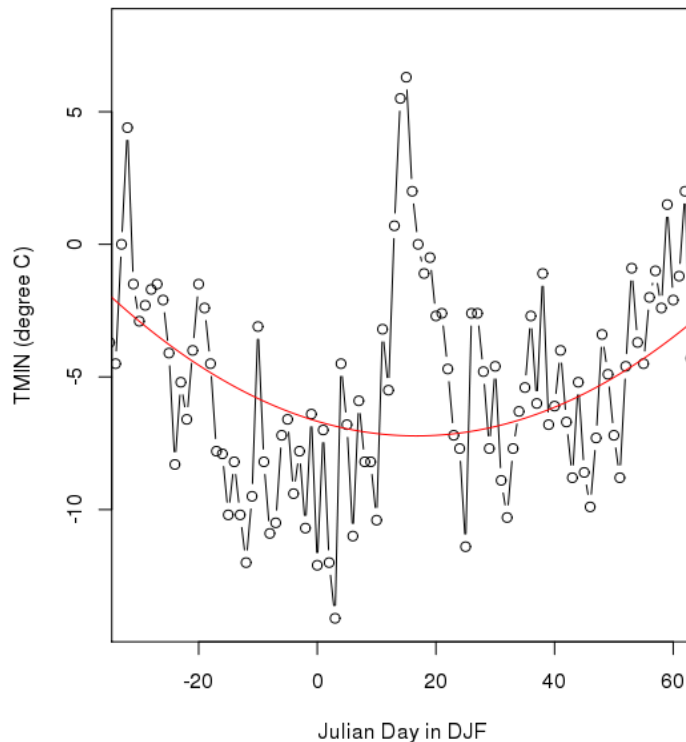
TMIN Deviation during DJF in 2001-2002



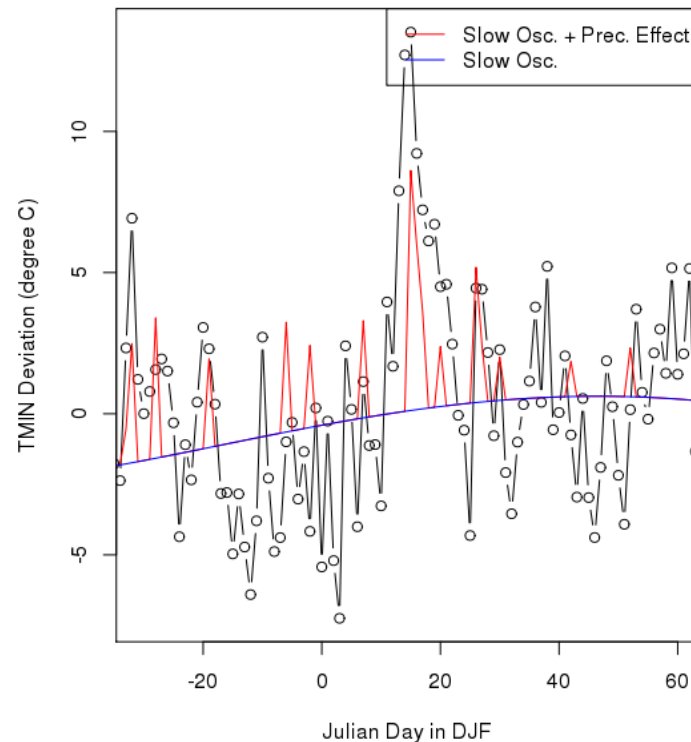
Statistical Downscaling

- Mean climatology and slow oscillation

TMIN during DJF in 2001-2002

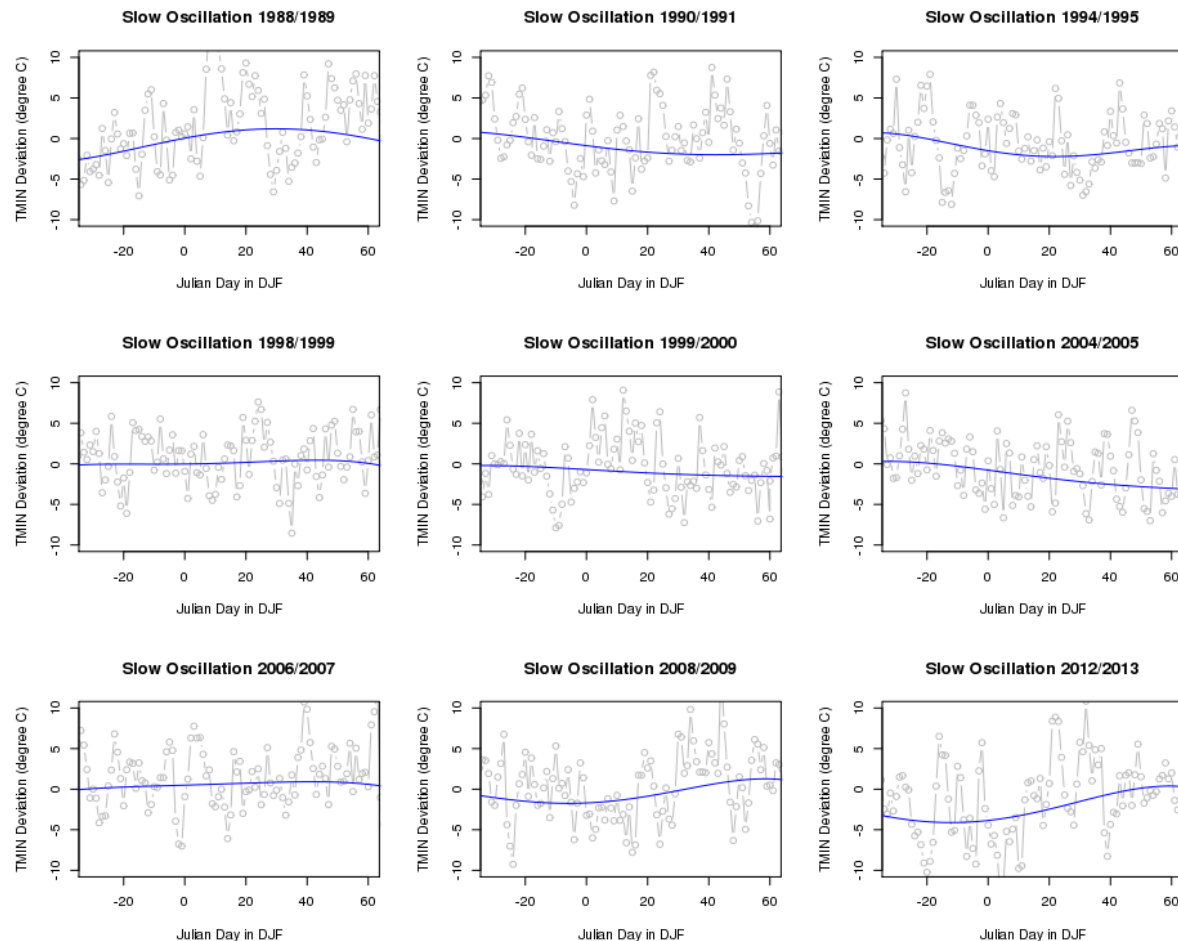


TMIN Deviation during DJF in 2001-2002



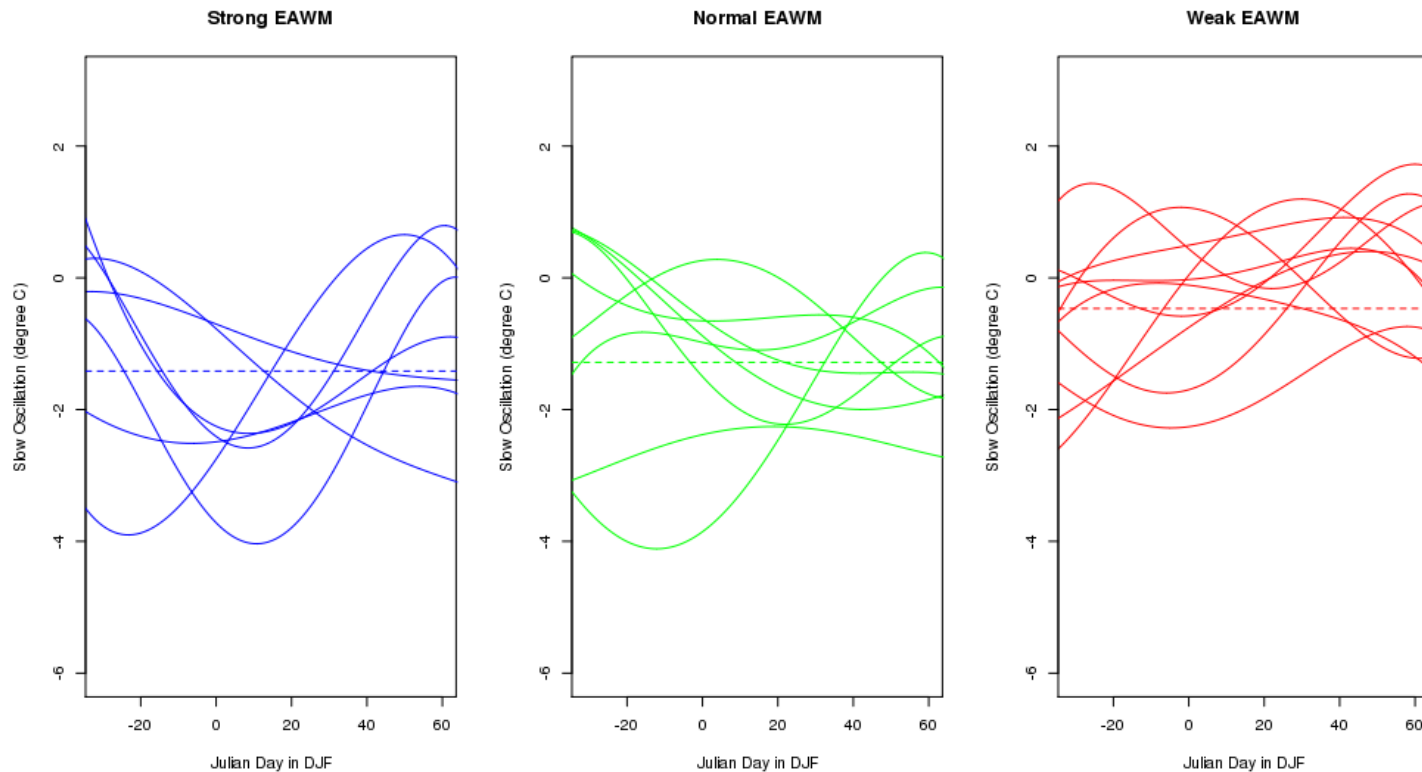
Statistical Downscaling

- Diversity of Slow oscillation



Statistical Downscaling

- The slow oscillation responds to EAWM



Statistical Downscaling

- EAWM downscaling scheme
 1. The strength of EAWM is predicted.
 - Strong/Normal/Weak.
 2. According to the prediction, we generate slow oscillation.
 3. Precipitation simulation
 - Markov model + Gamma distribution



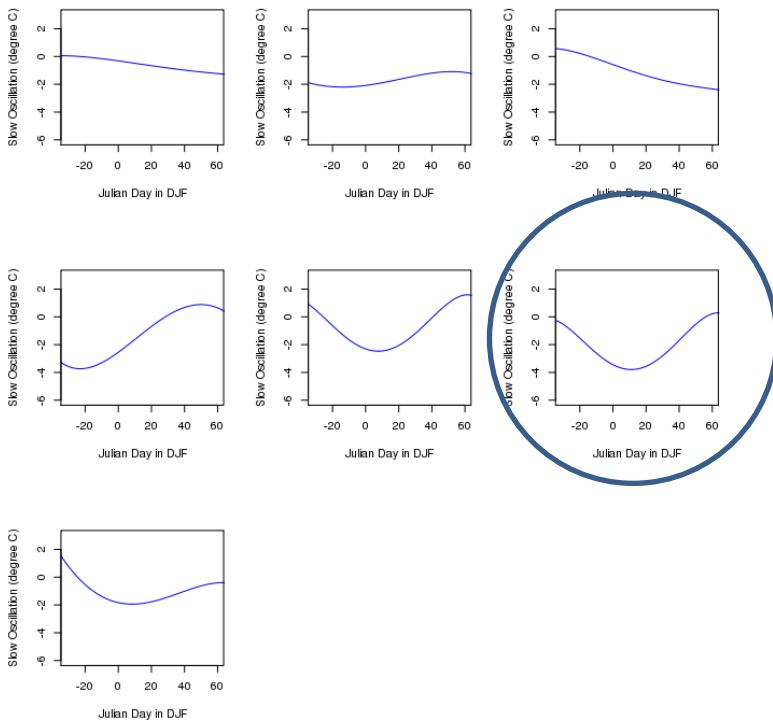
Statistical Downscaling

- EAWM downscaling scheme
 4. Slow oscillation + precipitation effect.
 5. Anomaly simulation
 - ARIMA(2,0,2) model is used.
 6. Temperature construction.



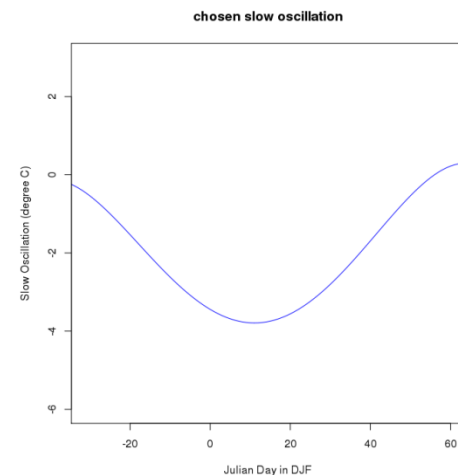
Statistical Downscaling

- Assume that EAWM is predicted to be strong.
- Randomly choose one of 7 slow oscillations.



We have 7 historical slow oscillations under strong EAWM.

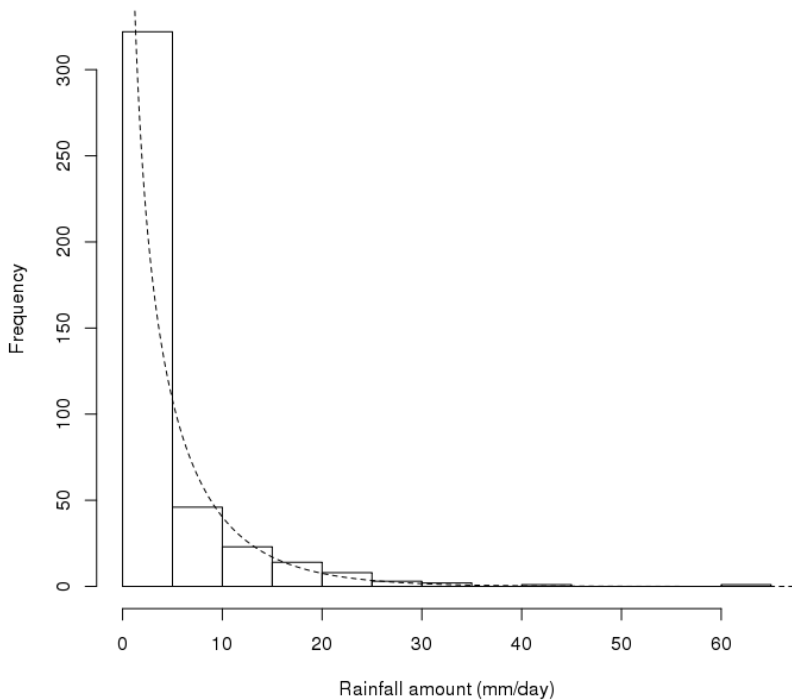
We choose one of them randomly.



Statistical Downscaling

- Carry out Precipitation simulation

Gamma distribution



Gamma distribution with $\hat{\mu} = 4.11$ (mm/day), $\hat{\alpha} = 0.56$.

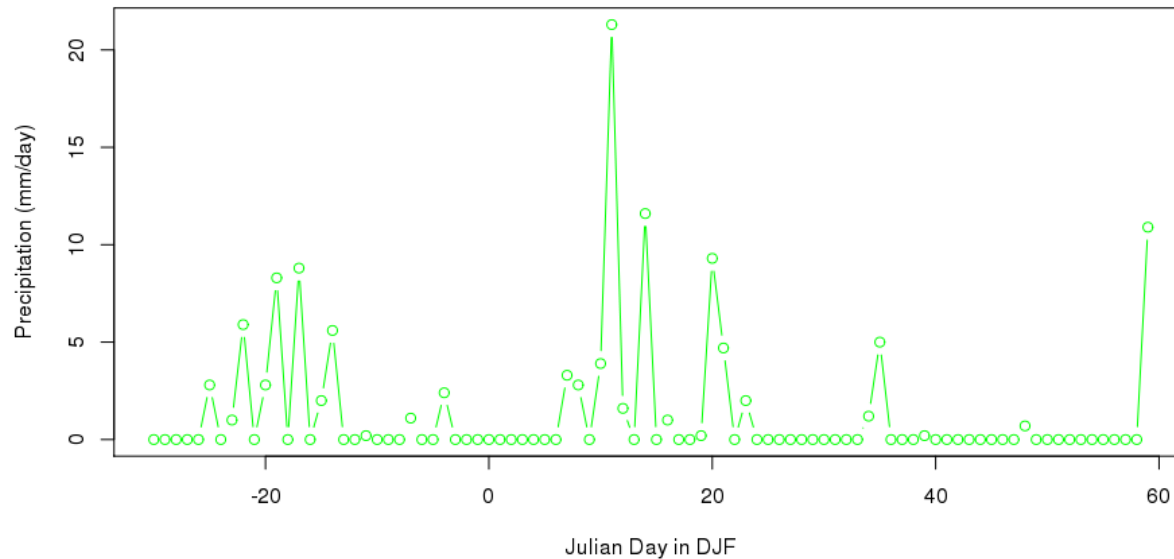
Today/Tomorrow	Wet	Dry
Wet	0.50	0.50
Dry	0.22	0.72

Transition probability matrix in during DJF



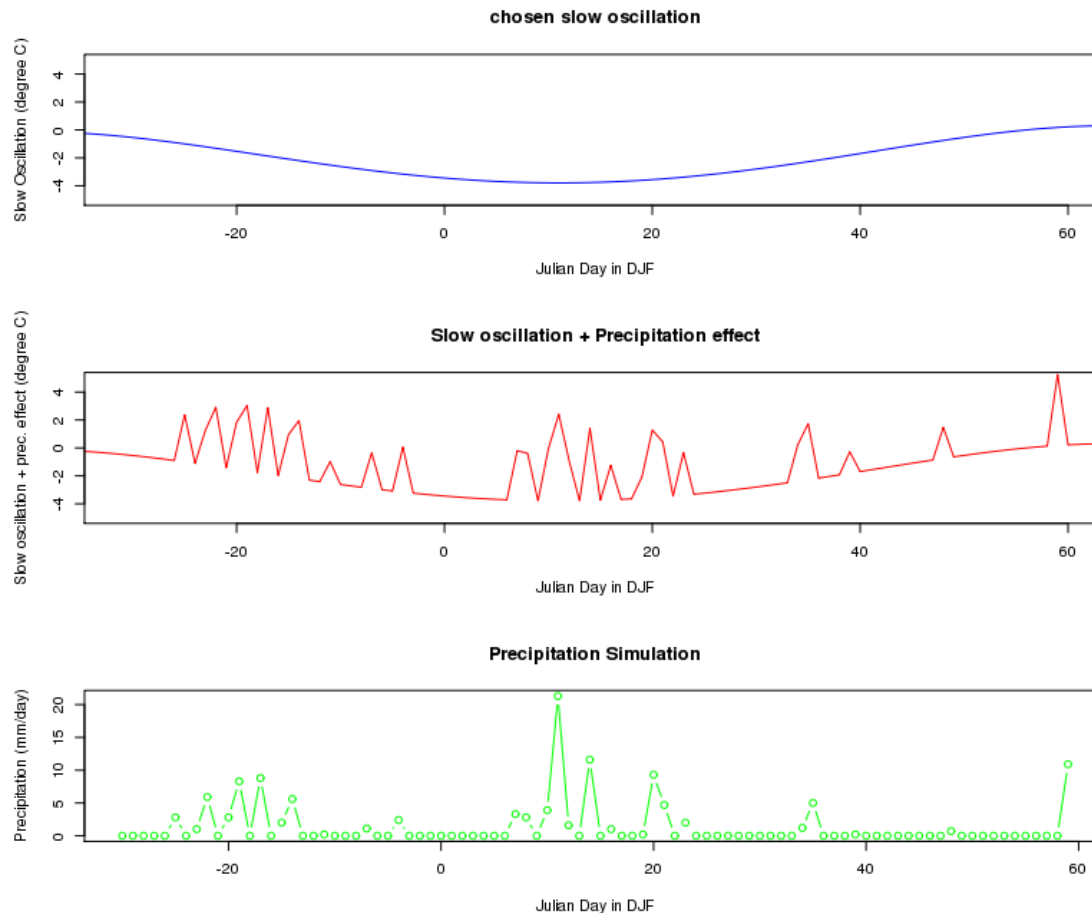
Statistical Downscaling

- Carry out Precipitation simulation



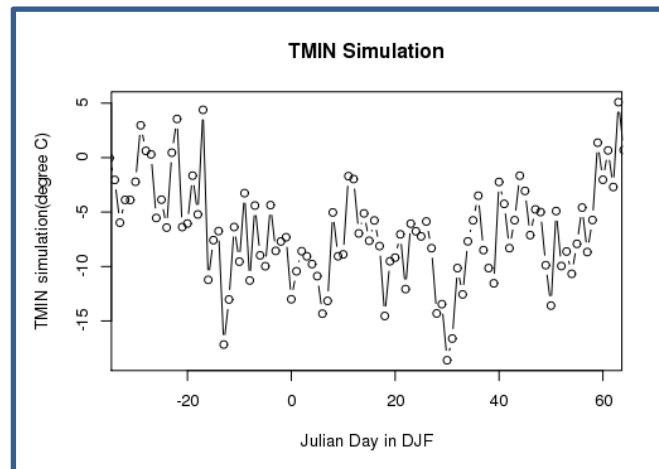
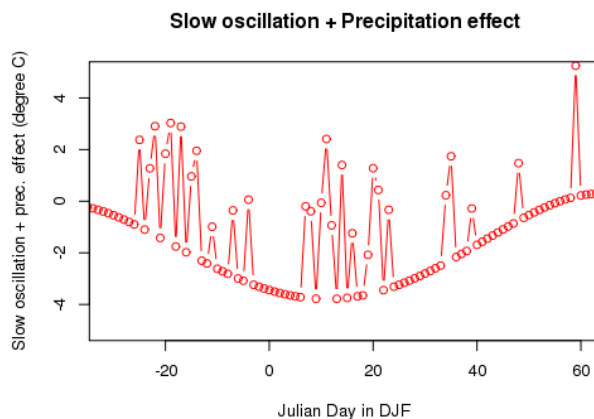
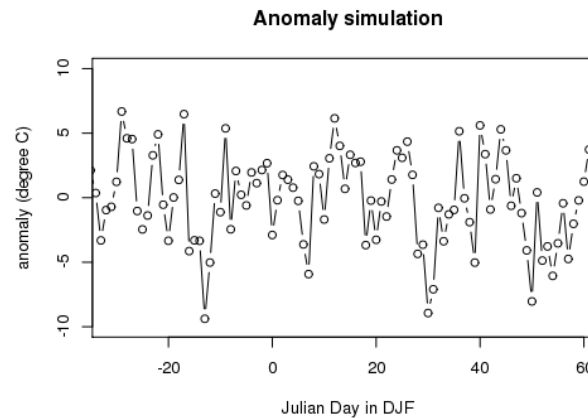
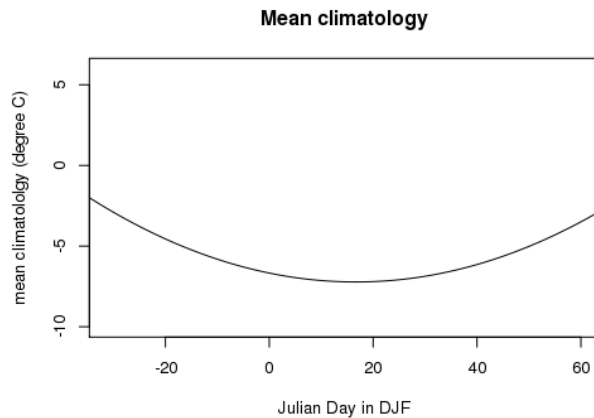
Statistical Downscaling

- Slow Oscillation + Precipitation effect



Statistical Downscaling

- Anomaly generation and final construction



Final output



Statistical Downscaling

- A lot of weather scenarios can be produced by repeating downscaling scheme.
 - Usually, 100/1,000/10,000 scenarios are produced.
 - The scenario set represents climate variability under seasonal prediction.
 - cf. Ensembles of GCM prediction.
 - They are used as input data in agricultural and hydrological studies.



Statistical Downscaling

- Slow oscillation plays a prominent role in connecting EAWM and basin temperature.
 - EAWM is related to basin temperature.
- What if a large-scale circulation is related to precipitation?
 - Potential players: transition probability, the mean of rainfall amount.



Statistical Downscaling

- What if you apply the scheme to your basin in a season?
 - Priorly, we need to know which large-scale circulation is the dominant factor on the basin climate,
 - And, which weather variables are related to the large-scale circulation.



Statistical Downscaling

- This is a *simple* example for illustration of downscaling process.
 - Single site case, TMIN and precipitation are dealt with.
- Actual downscaling is required to cover several variables simultaneously.
 - TMAX, TMIN, PRCP, Solar Radiation, Humidity, etc.
 - The variables are correlated.



Statistical Downscaling

- And, it is required to cover several sites simultaneously.
 - In water resource studies, target area is a basin rather than a single site.
- Therefore, the weather generator model should be extended to *Multivariate Spatial model*.



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Summary

- Weather Generators are systems of statistical models describing weather in a basin.
- Statistical models
 - Markov model: wet/dry-spell sequence,
 - Gamma distribution, Exponential mixture: rainfall amount,
 - Regression model: precipitation effect on temperature.



Summary

- Weather Generator is applied to Statistical Downscaling of Seasonal Prediction of Large-scale Atmospheric Circulation.
 - Seasonal prediction is usually 3-month average. Weather Generator plays a role of temporal disaggregation.
 - For applying, we need a prior knowledge which circulation is the dominant factor of the basin climate.



Summary

- Weather Generator Model should be extended for actual requirement.



THANK YOU!

Welcome any Comments and Questions.

