Weather Generator and its Application to Downscaling of Seasonal Prediction

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October 2018
About Instructor

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• Research Area
  – Statistical Downscaling of Seasonal Forecast
  – Bias Correction of Dynamical Model Data
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Overview

1. Introduction

2. Statistical Model of Weather Generator


4. Conclusion
Overview

1. Introduction

2. Statistical Model of Weather Generator


4. Conclusion
Introduction

• In agriculture and water resources, climate information is necessary.

• Climate information
  – Climate Change (~50/100 years)
  – Seasonal Prediction (~3/6 months)
  – Sub-seasonal Prediction (within 1 month)
Introduction

• APCC Seasonal Prediction
  – It is produced by using MME technique,
  – A coarse resolution in space and time.
  – It is provided in terms of climatological variables such as Z500, SLP, SST representing a large-scale circulation.
Introduction

• Agriculture and Water resources
  – A specific site or a narrow basin, which is so roughly covered with usual GCM grid systems.
  – Weather variables: TMIN, TMAX, relative humidity, dew point, solar radiation, and so on.

• There is a big cap: this is why downscaling process is a necessary step in agriculture and water resources.
Introduction

• Observation data have limitation due to their finiteness.

• Weather Generator
  – It was originally developed for overcoming the limitation of observation data.
  – Weather generators are systems of statistical models for weather in a basin.
Introduction

- Weather Generator
  - They can rapidly produce lots of weather data that share statistical property with observation data.
  - It has been studied as a tool for downscaling seasonal prediction.
  - This talk describes deeply how to use weather generator for downscaling seasonal prediction.
Overview

1. Introduction

2. Statistical Model of Weather Generator


4. Conclusion
Weather Generators are systems 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 fitting for annual cyclic trend of temperature,
  - Vector autoregressive model for temperature anomalies.
- Parametric modeling are mainly employed.
Statistical Model

• LARS-WG
  – Wet/dry-spell alternation scheme for spells generation (instead of Markov model),
  – Semi-empirical distribution for rainfall amount (instead of Gamma distribution),
  – 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 → Dry / Dry → Wet,
    • Dry → Dry / Wet → Wet.
  – Transition Probability

<table>
<thead>
<tr>
<th>Today/Tomorrow</th>
<th>Wet</th>
<th>Dry</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wet</td>
<td>$p_{11}$</td>
<td>$p_{12}$</td>
</tr>
<tr>
<td>Dry</td>
<td>$p_{21}$</td>
<td>$p_{22}$</td>
</tr>
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Statistical Model

• Markov model
  – Simulation

<table>
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<tr>
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<tr>
<td>Wet</td>
<td>0.85</td>
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</tr>
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Matrix of transition probabilities estimated by using observation data
Statistical Model

• Markov model
  – Simulation

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Matrix of transition probabilities estimated by using observation data

| Time (day) | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 | 19 | 20 | 21 | 22 | 23 | 24 | 25 | 26 | 27 | 28 | 29 | 30 | 31 |
|-----------|---|---|---|---|---|---|---|---|---|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|
| Repetition|   |   |   |   |   |   |   |   |   |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |    |

APEC Climate Center
Statistical Model

• Markov model
  – Simulation vs. Observation

<table>
<thead>
<tr>
<th>Spell length Statistics (day)</th>
<th>Simulation</th>
<th>Observation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wet-spell Length Mean</td>
<td>7.02</td>
<td>7.02</td>
</tr>
<tr>
<td>Wet-spell Length SD</td>
<td>6.50</td>
<td>7.11</td>
</tr>
<tr>
<td>Dry-spell Length Mean</td>
<td>2.14</td>
<td>2.14</td>
</tr>
<tr>
<td>Dry-spell Length SD</td>
<td>1.57</td>
<td>1.94</td>
</tr>
</tbody>
</table>
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
  – $\mu$: mean of rainfall amount (mm/day)
  – $\alpha$: shape parameter. $0 < \alpha < 1$ for rainfall amount

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

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

![Gamma distribution](image1)

![Quantile to Quantile plot](image2)
Statistical Model

- Exponential Mixture Model
  - $\mu_1, \mu_2$: 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
  - $\lambda = 0.7$, $\mu_1 = 23.5\text{ (mm/day)}$, $\mu_2 = 1.16\text{ (mm/day)}$
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
• 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.
• Regression model
  – Temperature is affected by precipitation.
  – In WGEN and LARS-WG

\[
TMAX = \begin{cases} 
\mu_{\text{Dry}} + \sigma_{\text{Dry}} \cdot \text{(anomaly)}, \\
\mu_{\text{Wet}} + \sigma_{\text{Wet}} \cdot \text{(anomaly)}. 
\end{cases}
\]
Statistical Model

- Regression model
  - However, the effect is Linear!
  - Stronger Precipitation intensity, lower TMAX.
• Regression model
  - The 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.
  – Temperature variation decomposition,
  – Correlation structure.
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Statistical Downscaling

- Weather Generator is used for Statistical Downscaling.
  - Large-scale atmospheric circulation $\rightarrow$ 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

- Case Study
  - Season: Boreal Winter, DJF.
  - Nakdong River: 14 stations.
The basin is affected by EAWM (East Asia Winter Monsoon)


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
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**

![Graphs showing TMIN and TMIN Deviation during DJF](image-url)
Statistical Downscaling

- Inter-annual variability of Slow oscillation
Statistical Downscaling

• The slow oscillation responds to EAWM
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 model is used.
  6. Temperature construction.
• 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 with $\hat{\mu} = 4.11$ (mm/day), $\hat{\alpha} = 0.56$.

Transition probability matrix in during DJF:

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<td><strong>Wet</strong></td>
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Statistical Downscaling

- Carry out Precipitation simulation
Statistical Downscaling

- Slow Oscillation + Precipitation effect
Statistical Downscaling

- Anomaly generation and final construction

Mean climatology

Anomaly simulation

Slow oscillation + Precipitation effect

TMIN Simulation

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?
  - transition probability and the mean of rainfall amount are adjusted for the large-scale circulation.
Statistical Downscaling

• What if you apply the scheme to your basin in a season?
  – 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.
  – 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.
Overview

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Conclusion

• 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.
Conclusion

- 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.
Announcement

- acidWG (APCC Climate Information Downscaling Weather Generator)
  - R-package for downscaling APCC Seasonal Forecast.
  - Multisite, TMAX, TMIN, PRCP.
Announcement

- AIMS (APCC Integrated Modeling Solution)
  - An integrated platform for Climate Service including Seasonal Forecast Downscaling,
  - acidWG will be a component for downscaling.
THANK YOU!
Welcome any Comments and Questions.