

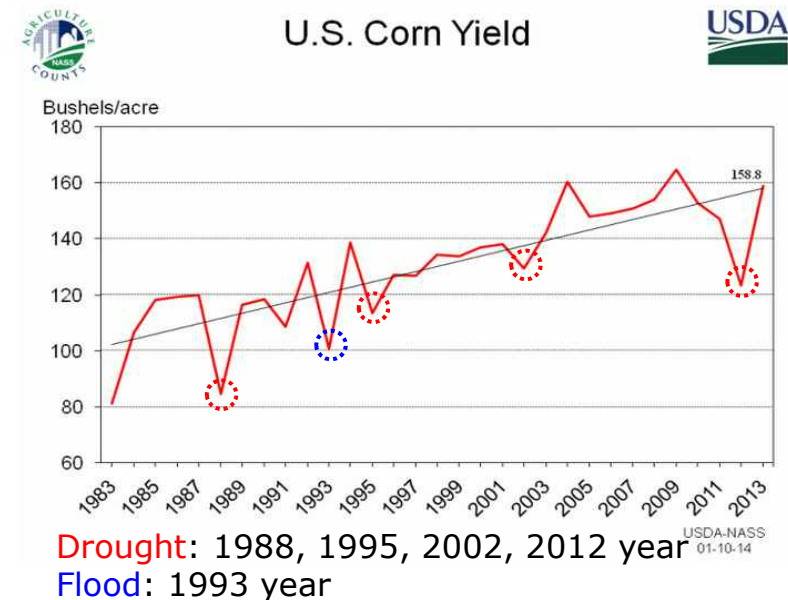
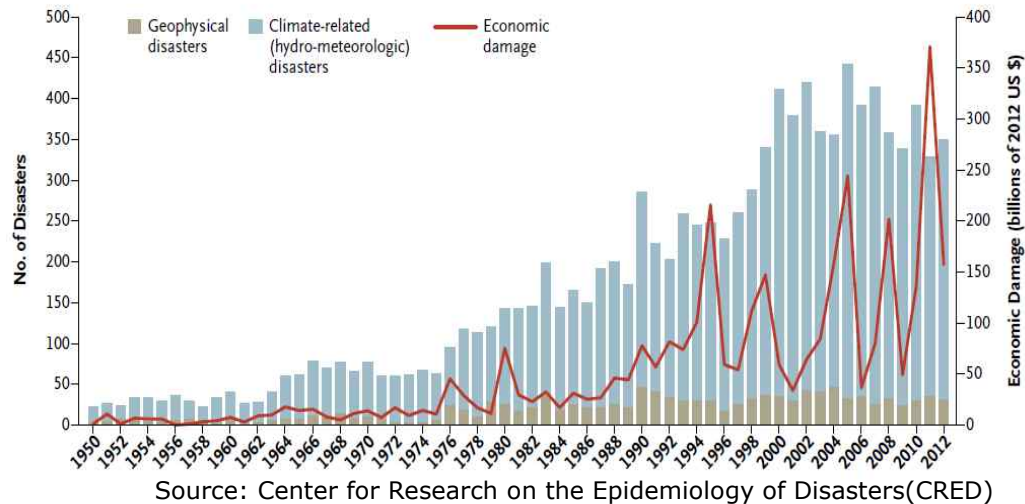
The 20<sup>th</sup> AIM International Workshop  
January 23-24, 2015  
NIES, Japan

# Utilization of seasonal climate predictions for application fields

Yonghee Shin/APEC Climate Center  
Busan, South Korea

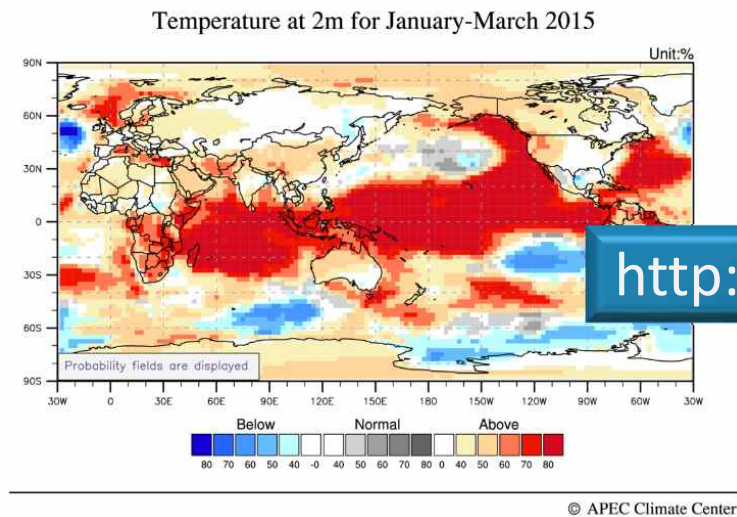
# Background

## Natural Disaster



- Recently abnormal weathers such as heatwaves, droughts, floods increased all over the world
- Increase of abnormal weather occurrence is major threat to the agricultural sector
- To response to the food crisis, development of crop yield prediction technology using seasonal forecast data is important

# Background



APCC APEC CLIMATE CENTER

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APCC successfully held the APEC Climate Symposium 2014

- APCC plays a leading role in monitoring climate throughout the 21 APEC member economies and the rest of the Asia-Pacific region

Climate Outlook for January - June 2015

BUSAN, 24 December 2014 Synthesis of the latest model forecasts for January to June 2015 (JFMAMJ) at the APEC Climate Center (APCC), located at Busan, Korea, indicates warming ac...

Notice

<http://www.apcc21.org>

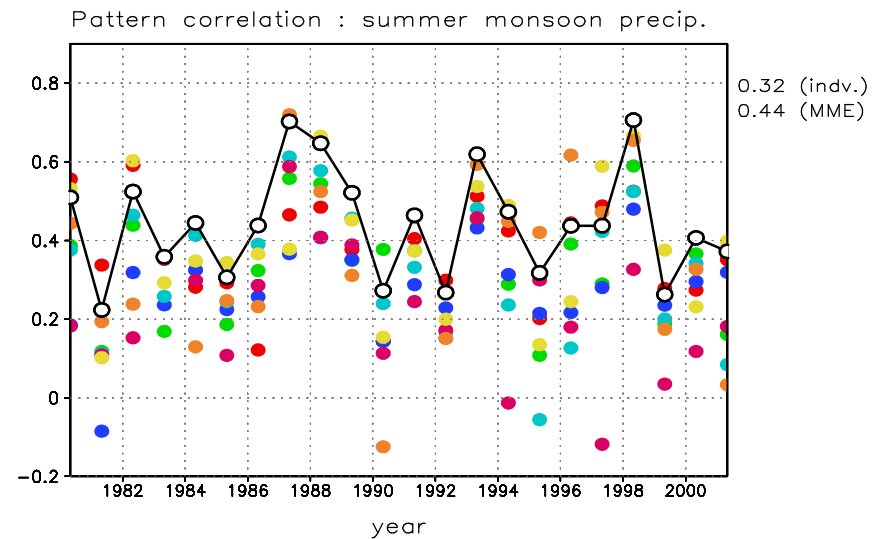
- APEC Climate Center produces and offers Multi-Model Ensemble(MME) seasonal forecast data evaluated as a world-class. However, utilization of seasonal forecasts for the agricultural sector is still very low
- In this study, we carried out bias correction to take advantage of the APCC MME seasonal forecasts in agriculture research and developed multi-scale temporal and spatial downscaling methods

# MME Climate Forecast

- Global climate forecast data from **17 institutes** (9 economies)
- Monthly rolling 3-month and 6-month MME climate forecast
- Cooperation on decadal prediction and climate change projection



## Multi-Model Ensemble



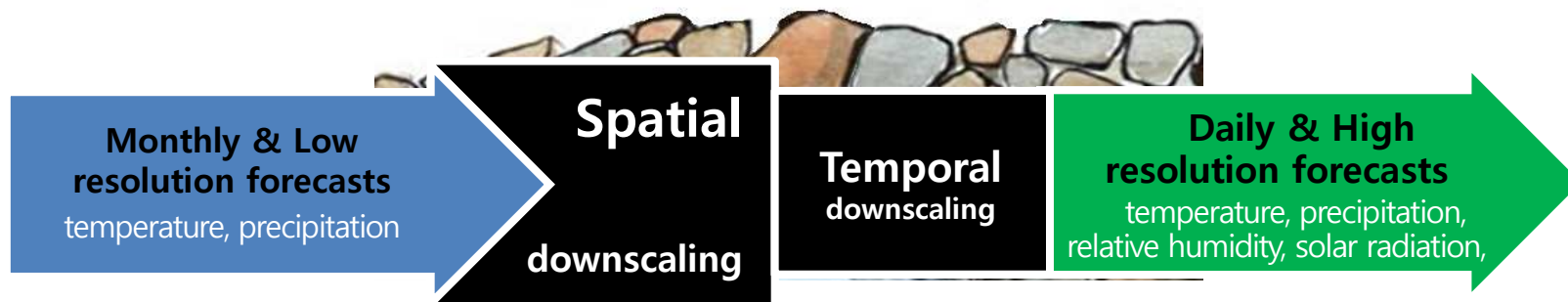
# Bridging the gap between climate models and agricultural models

## Seasonal Forecasts from dynamic models

- Global scale, low spatial resolution ( $2.5^\circ \times 2.5^\circ$ )
- Monthly scale, low temporal resolution
- Temperature, precipitation

## Agricultural models

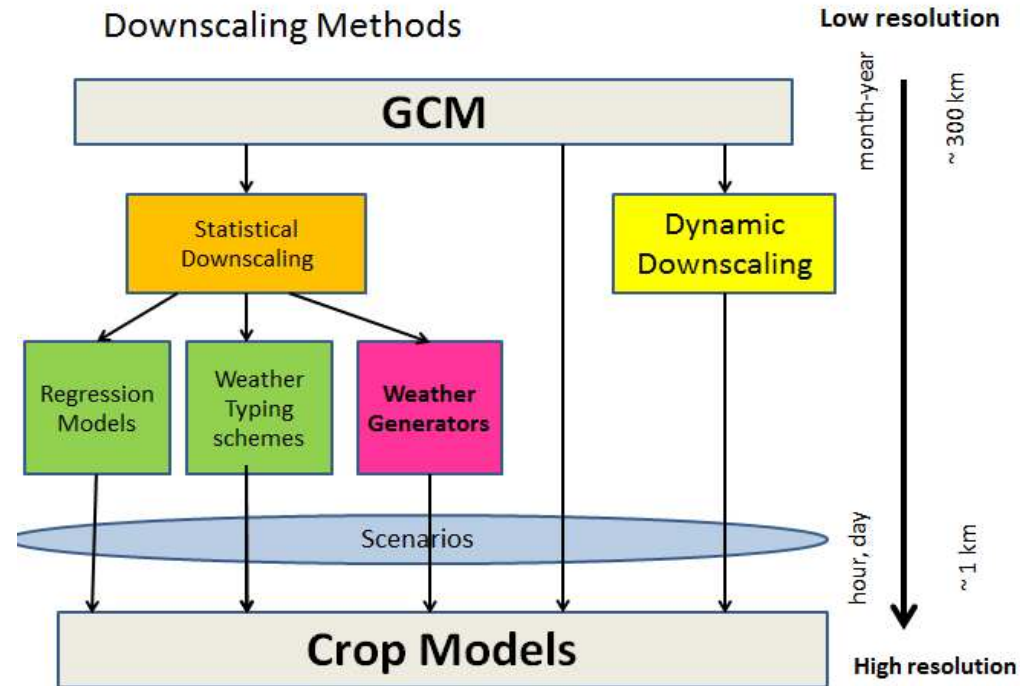
- Field scale, high spatial resolution (=paddy field, individual farms)
- Daily or hourly scale, high temporal resolution
- Temp., prec., relative humidity, solar radiation...





# Downscaling Approaches

There are **two fundamental approaches** for the downscaling of large-scale GCM output to a finer spatial resolution.



- A dynamical approach where a higher resolution climate model is embedded within a GCM.
- Statistical methods to establish empirical relationships between GCM climate and local climate.



# Statistical Downscaling

## Statistical downscaling

Generally classified into three groups

Which is actually appropriate for seasonal forecasting application?

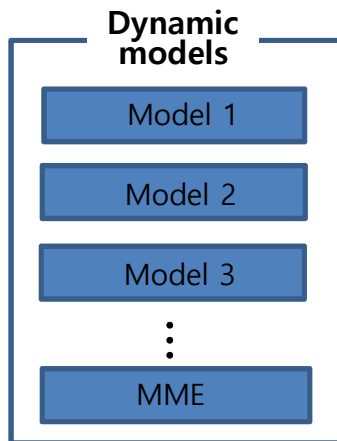
- **Weather Typing schemes**
  - Generation **daily** weather series at a local site.
  - Classification schemes are somewhat **subjective**.
- **Regression Models**
  - Generation **daily** weather series at a local site.
  - Results limited to local climatic conditions.
  - Long series of historical data needed.
  - Large-scale and local-scale parameter relations remain **valid for future climate conditions**.
  - **Simple computational requirements**.
- **Stochastic Weather Generators**
  - Generation of **realistic** statistical properties of **daily** weather series at a local site.
  - **Inexpensive computing resources**.
  - Climate change scenarios based on results predicted by GCM (**unreliable for precipitation**)

# Strategies for agricultural applications of the APCC seasonal forecasts

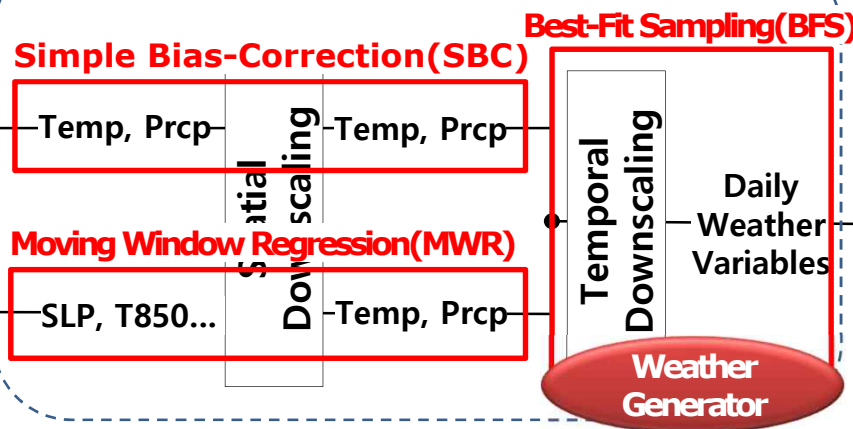
## Climate Information

## Agricultural models

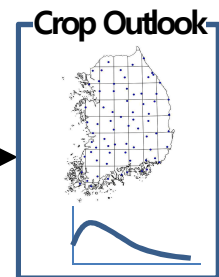
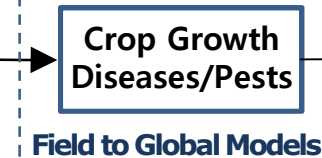
### Seasonal Forecast



### ① Statistical Downscaling



### ② Crop Modeling



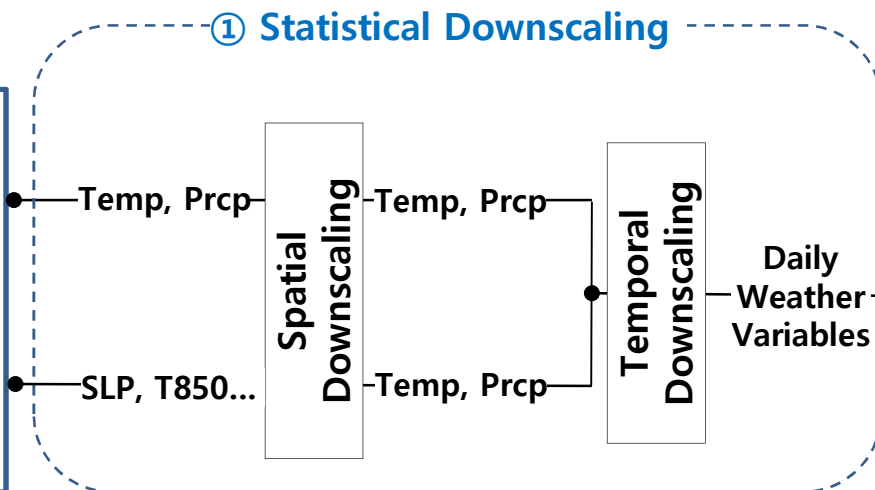
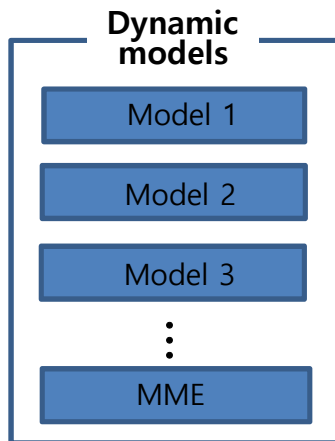


# Strategies for agricultural applications of the APCC seasonal forecasts

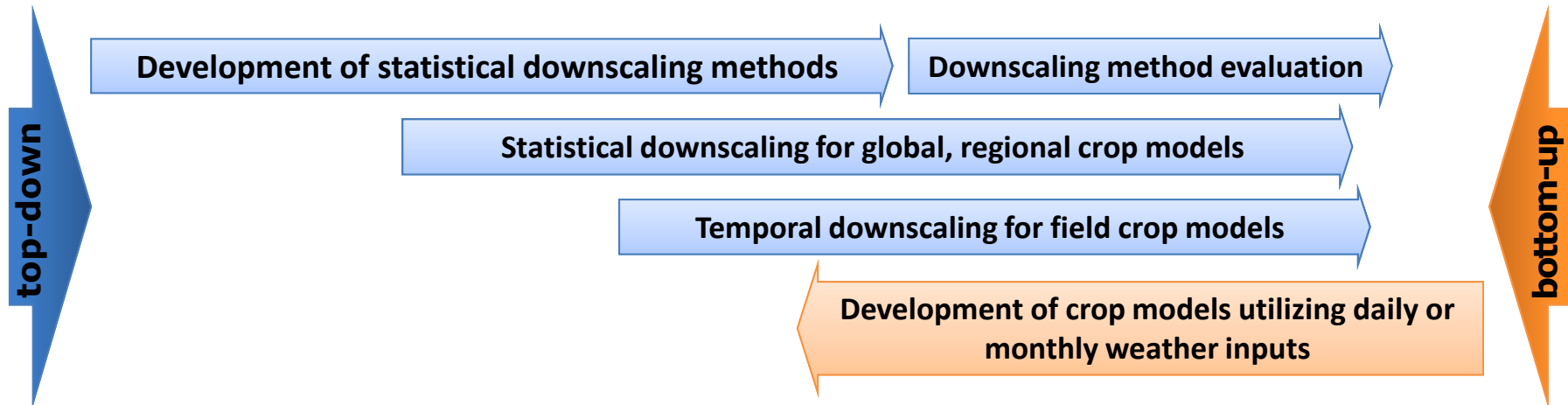
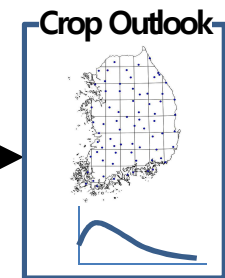
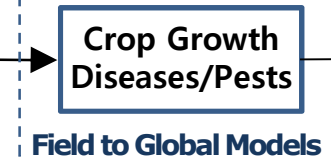
## Climate Information

## Agricultural models

### Seasonal Forecast



### ② Crop Modeling

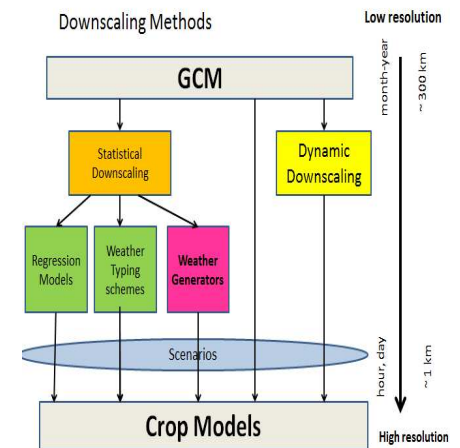


# Weather generator evaluation for field-scale crop model applications

# Background

## Weather generators

- ❑ Weather generators are statistical models of sequences of weather variables with the **same** statistical properties to the observed climate.

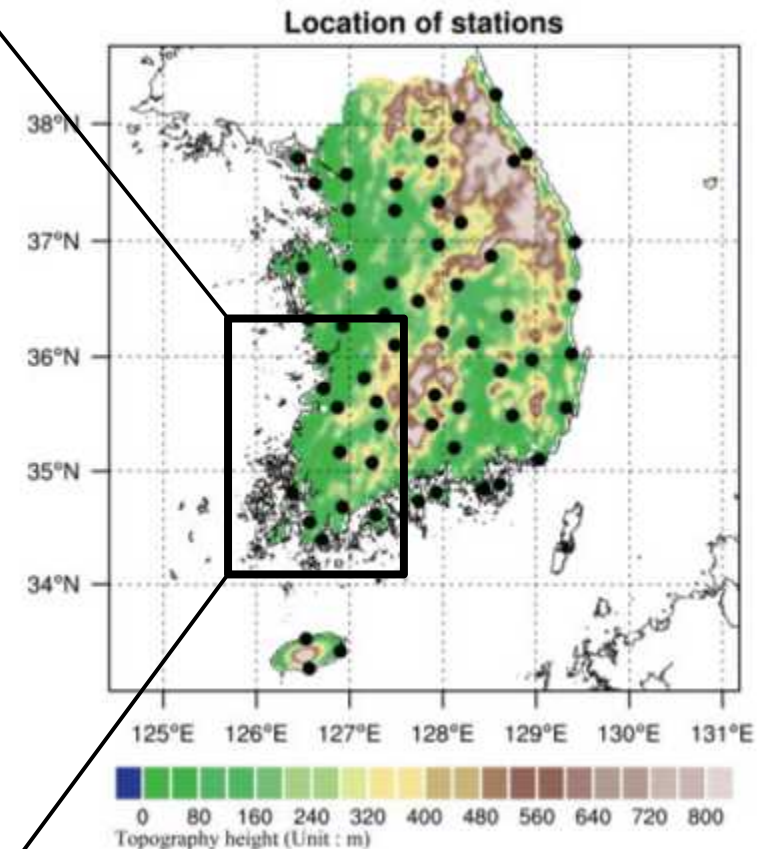


**Two fundamental types** of daily weather generators, based on the approach to model daily precipitation occurrence

- **The Markov chain approach:** a random process is constructed which determines a day at a station as rainy or dry, conditional upon the state of the previous day, following given probabilities. (e.g. WGEN and SIMMETEO)
- **The spell-length approach:** fitting probability distribution to observed relative frequencies of wet and dry spell lengths. (e.g. LARS-WG)

# Materials and Methods

Station No	Name	Latitude	Longitude	Elvation
152	Heuksando	35°49′	127°09′	76.5
155	Gosan	34°41′	126°55′	74.3
156	Jindo	36°16′	126°55′	476.5
159	Mokpo	33°23′	126°52′	38
162	Jeju	35°43′	126°42′	20.4
165	Seogwipo	34°23′	126°42′	49
168	Boryeong	35°20′	126°35′	15.5
169	Haenam	36°19′	126°33′	13
184	Gochang	34°49′	126°22′	52
185	Wando	33°17′	126°09′	35.2
188	Buan	34°28′	126°19′	12
189	Gunsan	34°41′	125°27′	23.2
192	Jeongeup	35°10′	126°53′	44.6
244	Seongsan	35°36′	127°17′	17.8
245	Gwangju	35°04′	127°14′	72.4
256	Jangheung	35°33′	126°51′	45
260	Buyeo	34°33′	126°34′	11.3
261	Jeonju	33°30′	126°31′	53.4
262	null	33°14′	126°33′	74.6
285	Goheung	34°37′	127°16′	53.1
294	Imsil	36°00′	126°45′	247.9



Kang et al., 2014

# Results

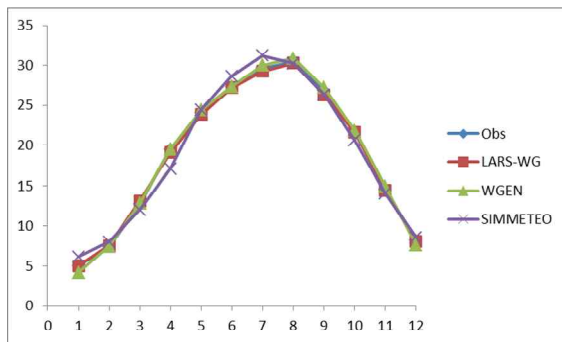
## ■ Precipitation

Table. 1. An example of output data from the statistical tests, showing the comparison of monthly means of total rainfall and standard deviation with synthetic data generated by LARS-WG, WGEN and SIMMETEO. Probability levels (p-value) calculated by the t test and F test for the monthly means and variances are shown. A probability of 0.05 or lower indicates a departure from the observation that is significant at the 5% level.

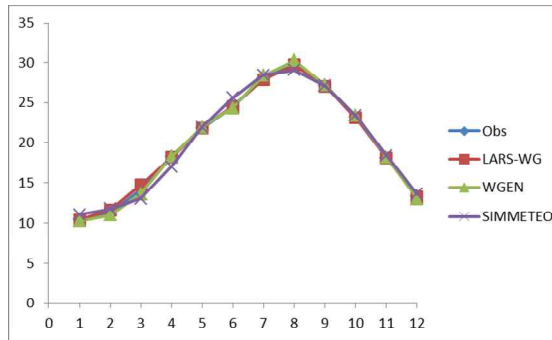
		Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
<b>Observed</b>	Obs.mean	33.77	39.35	56.92	90.96	88.89	194.64	274.43	301.89	144.26	47.35	50.54	29.03
	Obs. std	27.357	28.366	32.024	60.211	46.762	116.987	150.291	149.963	94.973	35.869	32.73	20.738
<b>LARS-WG</b>	Gen.mean	33	45.24	56.84	88.12	116.64	160.58	255.51	296.02	167.58	59.6	54.35	23.71
	Gen.std	29.067	28.3	41.029	48.626	56.662	80.461	120.434	166.057	86.819	39.121	30.817	22.732
	P-value for t-test	0.911	0.392	0.993	0.828	0.033	0.154	0.561	0.879	0.289	0.184	0.62	0.318
	P-value for F-test	0.742	0.976	0.168	0.212	0.285	0.03	0.196	0.573	0.594	0.633	0.717	0.613
<b>WGEN</b>	Gen.mean	23.43	26.77	52.9	111	88.6	187.82	318.33	363.79	133.06	47.06	47.81	18.93
	Gen.std	24.576	17.231	40.19	57.802	62.051	111.536	142.176	121.858	84.164	37.044	35.283	13.035
	P-value for t-test	0.359	0.779	0.827	0.717	0.546	0.555	0.613	0.616	0.149	0.33	0.897	0.905
	P-value for F-test	0.023	0.256	0.422	0.525	0.453	0.674	0.258	0.034	0.505	0.338	0.832	0.693
<b>SIMMETEO</b>	Gen.mean	36.13	32.43	52.76	113.25	79.48	188.69	304.14	367.05	136.78	40.98	49.1	23.56
	Gen.std	15.453	20.589	26.575	65.583	43.081	109.789	103.551	126.733	75.88	21.937	30.162	12.244
	P-value for t-test	0.542	0.602	0.777	0.708	0.851	0.393	0.868	0.982	0.152	0.22	0.585	0.614
	P-value for F-test	0.638	0.688	0.358	0.088	0.028	0.327	0.243	0.032	0.732	0.028	0.2	0.4

# Results

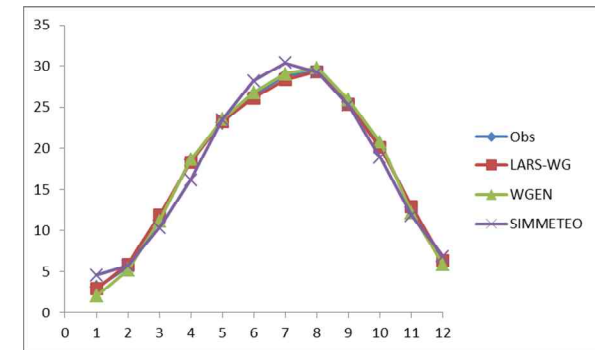
## ■ Maximum temperature



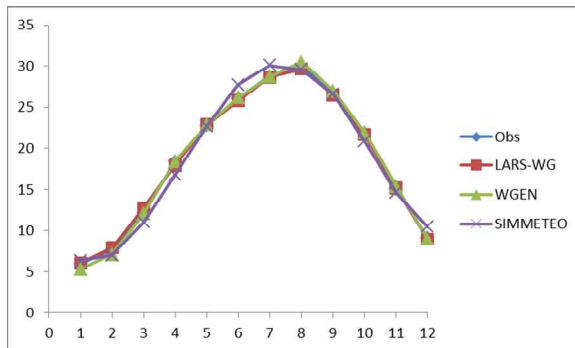
A (station 156, North)



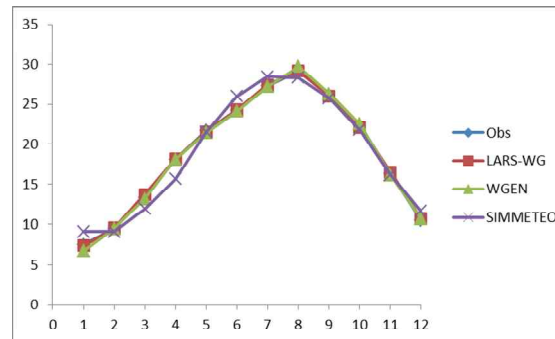
B (station 189 West)



C (station 244, East and High)



D (station 261 Low)



E (station 159 South)

Comparison of monthly maximum temperature ( $^{\circ}\text{C}$ ) for observed data and synthetic data generated by LARS-WG, WGEN and SIMMETEO.



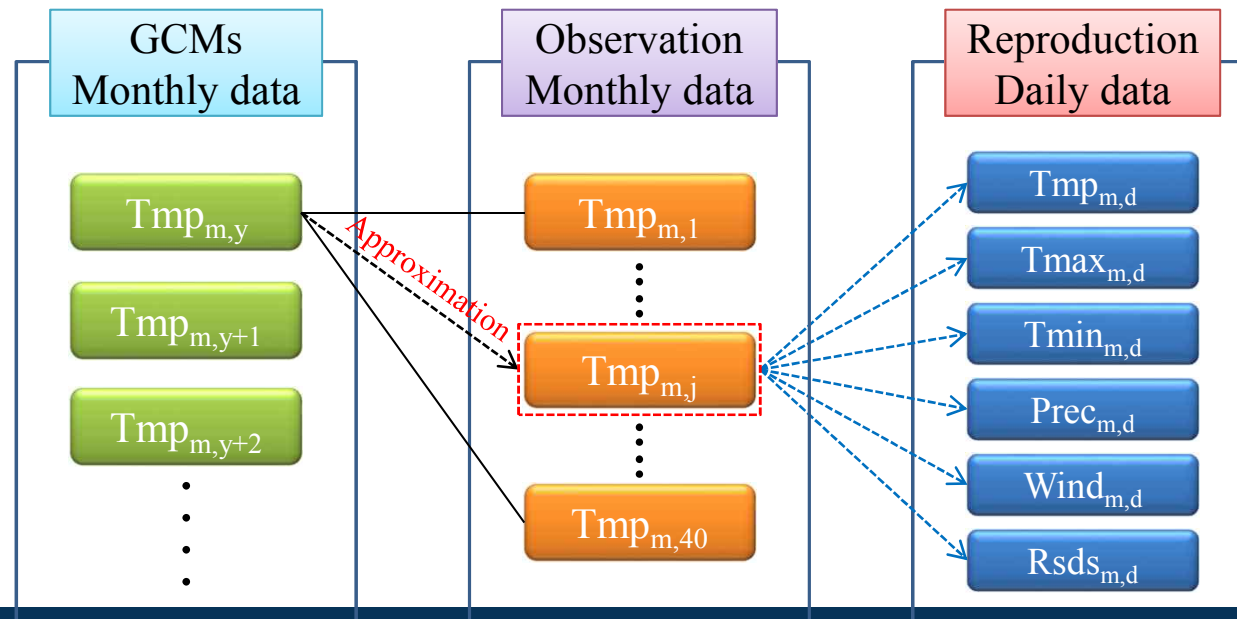
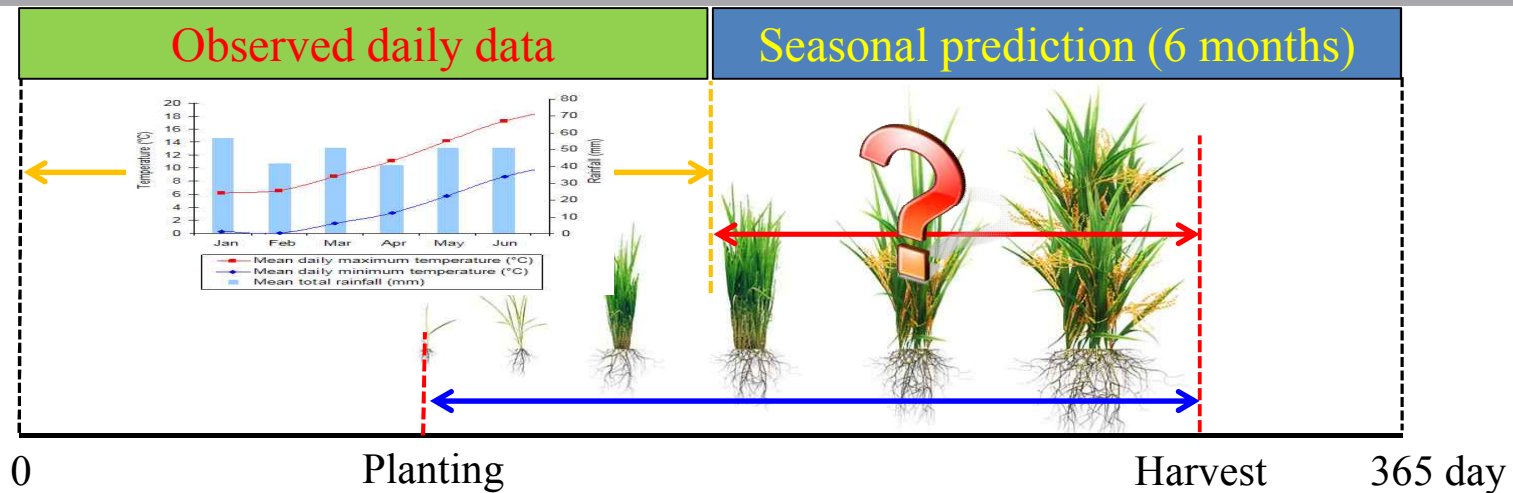
# Statistical downscaling skills of Seasonal Forecasts for a global-scale crop model

# 6-Month Hindcast Data

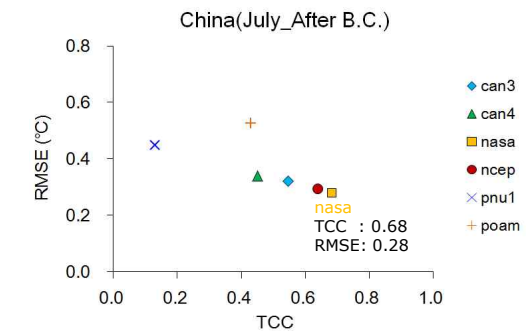
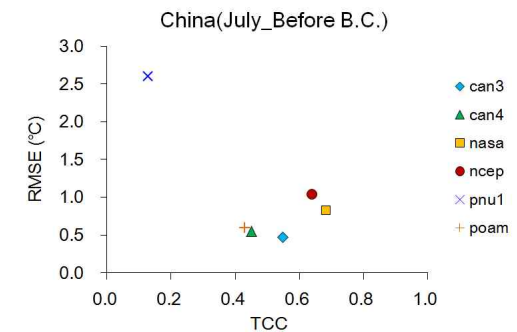
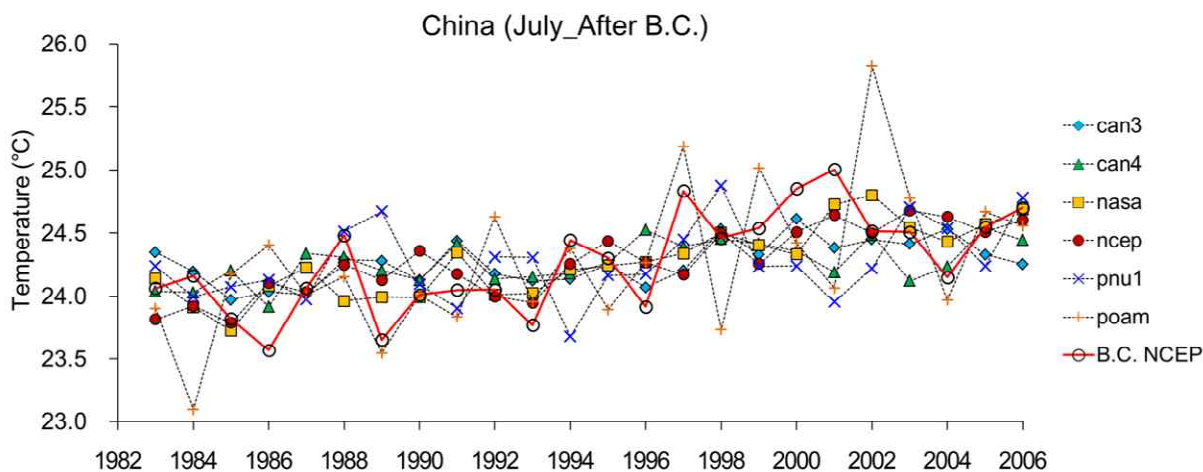
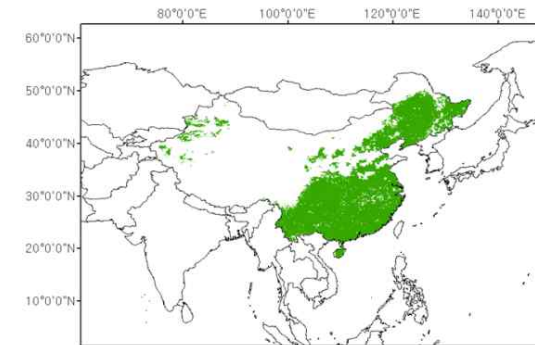
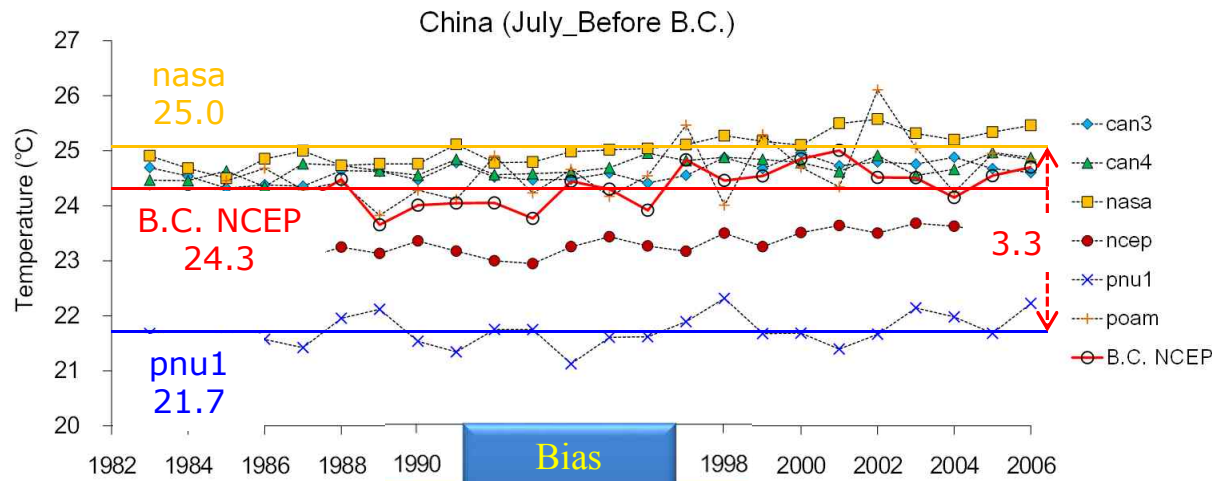
Models	Periods	Ensembles	Single Model Ensemble	Common Period (1983-2006)
MSC_CANCM3	1981-2010	10	→	MSC_CANCM3
MSC_CANCM4	1981-2010	10	→	MSC_CANCM4
NASA	1982-2012	11	→	NASA
NCEP	1983-2009	20	→	NCEP
PNU	1980-2012	5	→	PNU
POAMA	1983-2006	30	→	POAMA

Available Climate Variables : **Precipitation, Temperature**

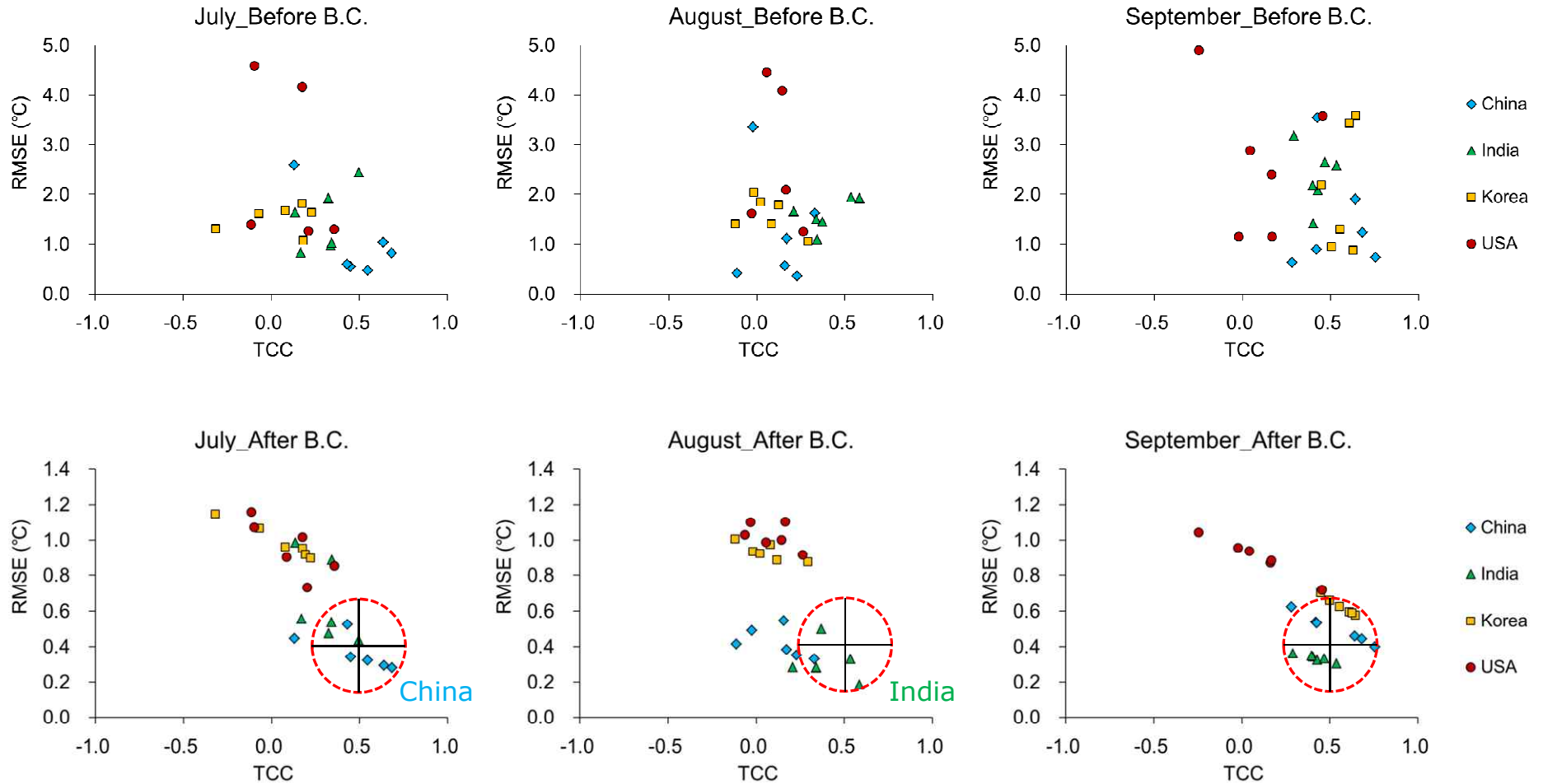
# Daily Seasonal Forecast Data for Global Crop Modeling



# Results of analysis - China

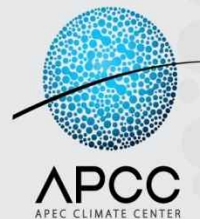


# Results of analysis - each country



Evaluation of the applicability of seasonal  
forecast in a regional crop model

# Rice Yield Prediction using a Regional-scale Crop Model and the APCC MME Seasonal Forecasts





# APCC MME Seasonal Forecasts

Model	Institution	Ensemble number	Lead time
CWB	Central Weather Bureau (Taipei)	10	3
GDAPS_F	Korea Meteorological Administration (Korea)	20	3
HMC	Hydrometeorological Centre of Russia (Russia)	10	3
JMA	Japan Meteorological Agency (Japan)	5	3
MSC_CANCM3	Meteorological Service of Canada (Canada)	10	3, 6
MSC_CANCM4	Meteorological Service of Canada (Canada)	10	3, 6
NASA	National Aeronautics and Space Administration (USA)	11,10	3, 6
NCEP	Climate Prediction Center / NCEP/NWS/NOAA (USA)	17	3, 6
PNU	Pusan National University (Korea)	3,4	3, 6
POAMA	Centre for Australian Weather and Climate Research/ Bureau of Meteorology (Australia)	30	3, 6
POAMA_M24			3
SCM		MME	3

- Daily maximum, minimum temperature and precipitation were downscaled from APCC MME forecasts to 57 stations
- Interpolated into  $0.25^{\circ} \times 0.25^{\circ}$  grid cells using the nearest neighbor interpolation methods

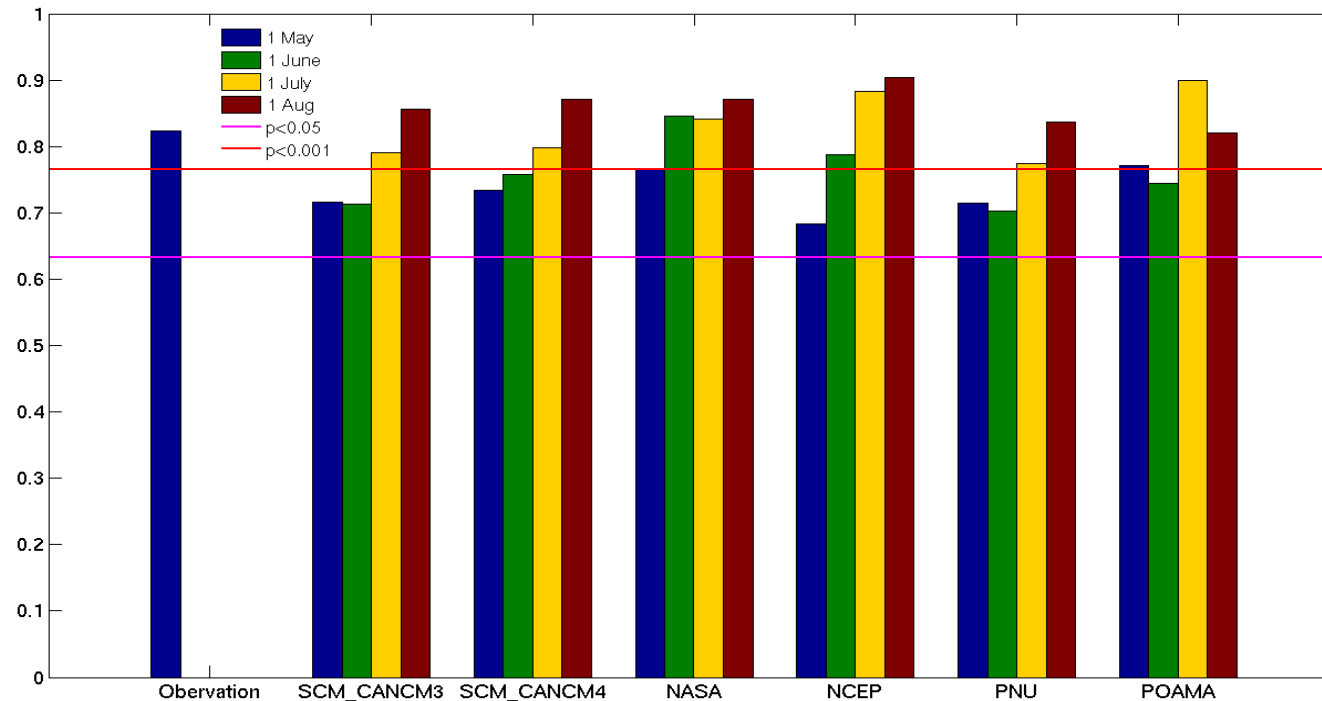


## Methodologies regional rice forecasting

- **The GLAM-rice was run using the historical weather data and APCC MME forecasts at a 0.25×0.25 grid cells**
- **The simulation results spatially aggregated to national level for validation and prediction for crop yield.**
- **Rice yield was predicted by updating seasonal forecast as season progresses for May, June, July and August**

# Skill of GLAM-rice at the national level when the model is run using 6 months seasonal forecast data

-correlation coefficient between observed and simulated yield



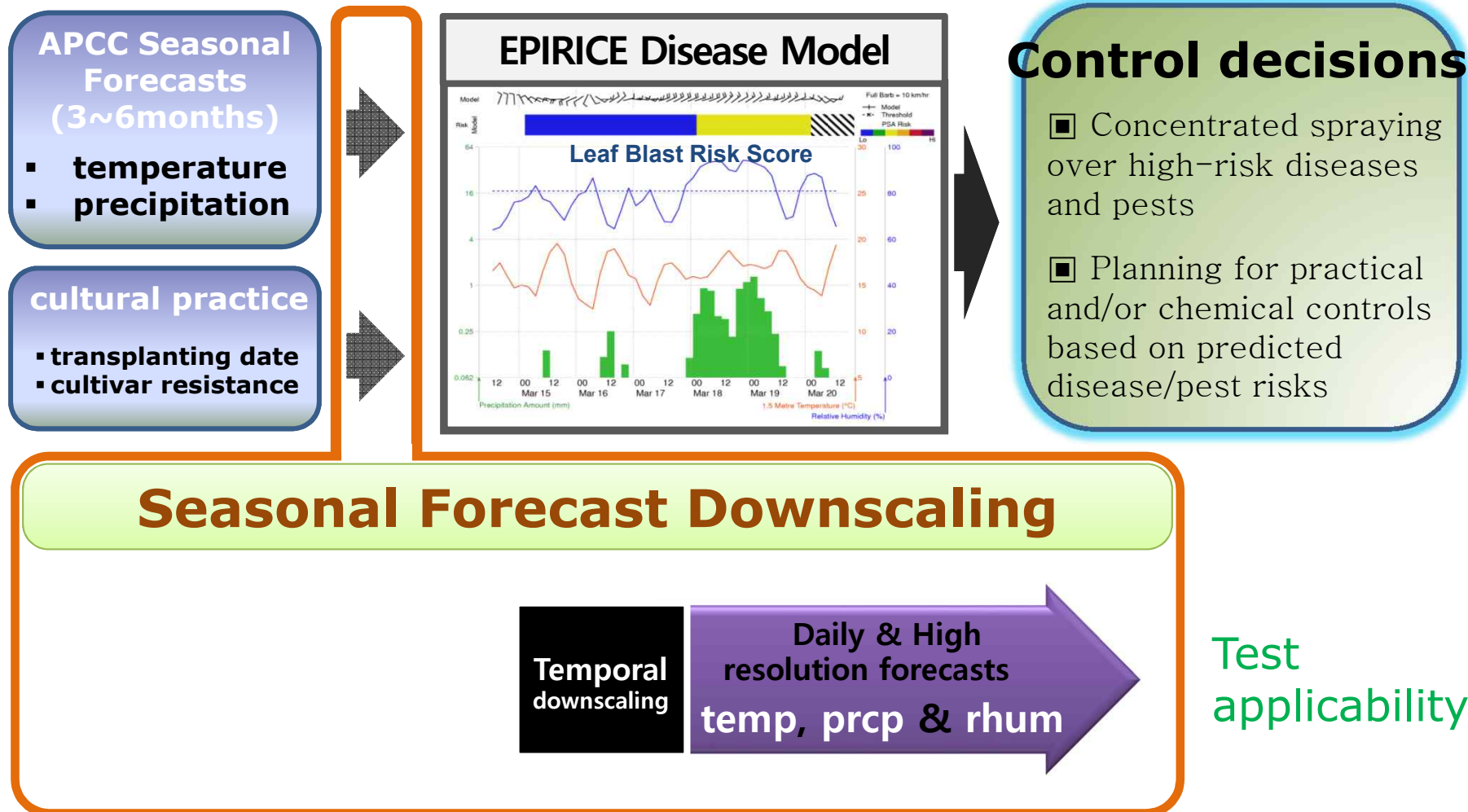
By updating of seasonal forecast with observation, the skill of GLAM-rice was improved as season progresses

The most accurate predictions of observed yields came from the NCEP for July and August, and from the POAMA for July

# Evaluation and Improvement of Weather generator-based temporal downscaling for a field-scale crop model

# Seasonal Disease Forecast with a rice disease model, EPIRICE

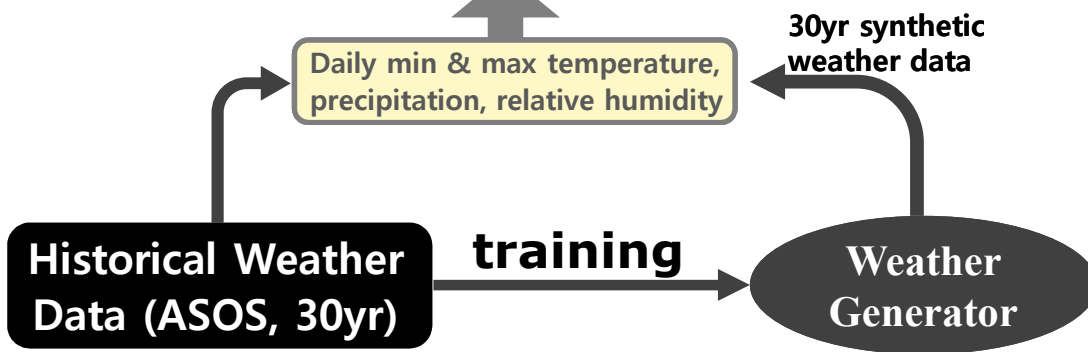
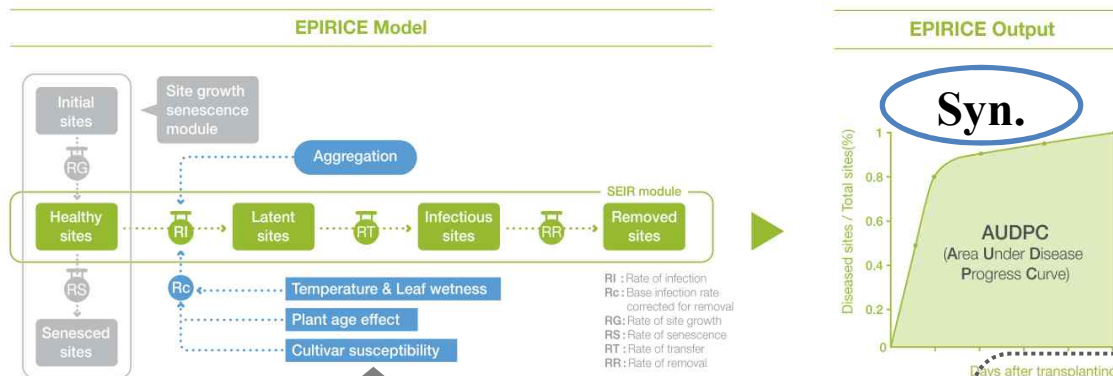
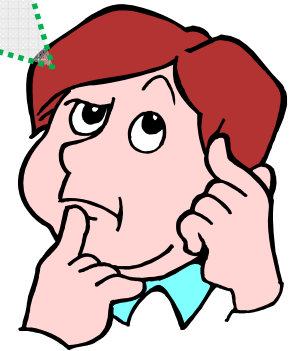
## ● Rice Disease Forecasting Workflow



Is it possible to use Daily weather data downscaled from Monthly seasonal forecasts using Weather Generator to run Agri.Model?

● Objective 1

# EVALUATION OF WG DOWNSCALING



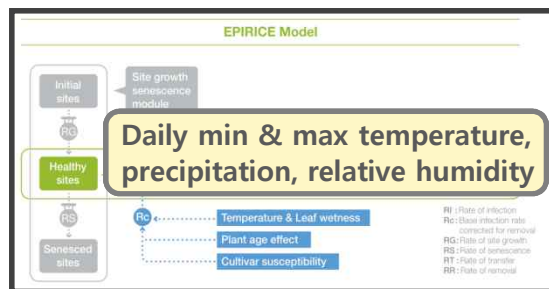
VS



Is there any ways to improve the Weather Generator-based downscaling methods?

● Objective 2

EVALUATION OF WG DOWNSCALING  
IMPROVING WG DOWNSCALING SKILL



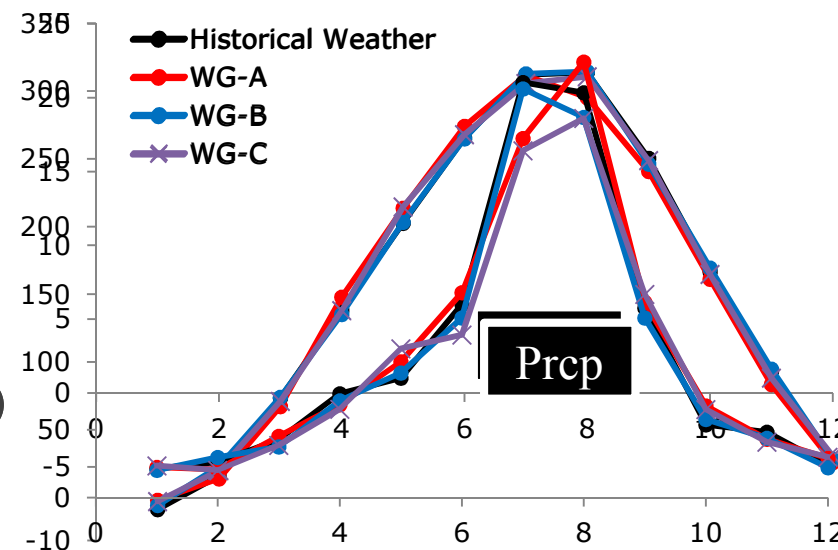
Adjusting parameters + weather generation

Seasonal Forecast data

Historical Weather Data (ASOS, 30yr)

training

Weather Generator



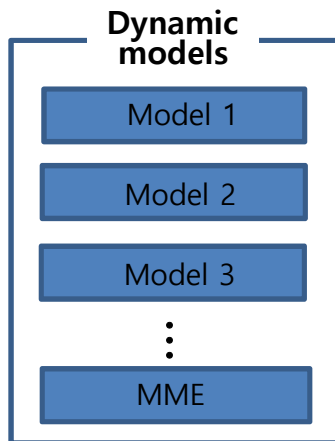


# Strategies for agricultural applications of the APCC seasonal forecasts

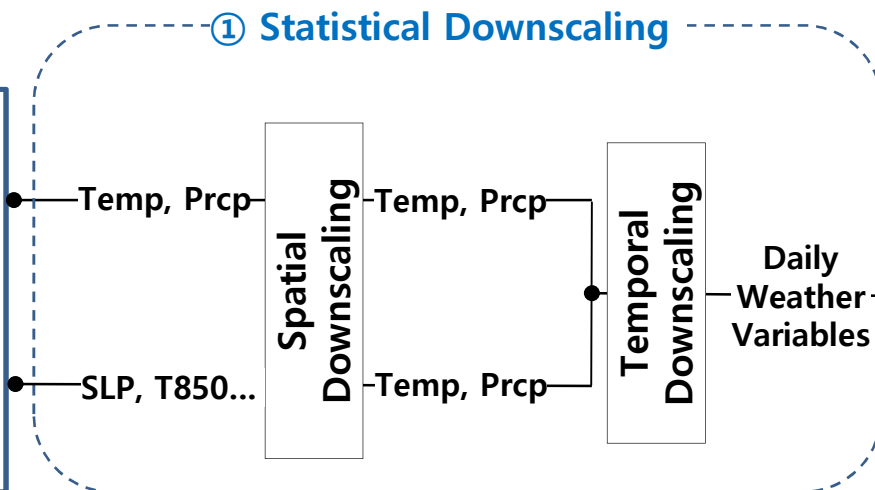
## Climate Information

## Agricultural Information

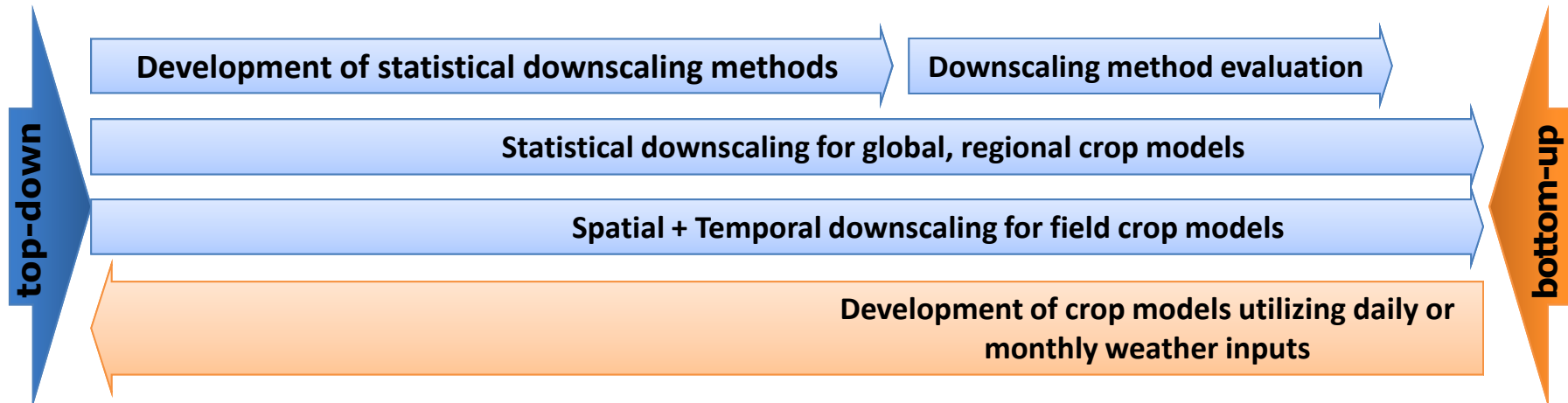
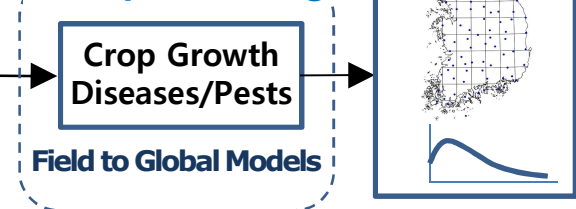
### Seasonal Forecast



### ① Statistical Downscaling



### ② Crop Modeling





# THANK YOU!

