문서번호 APCC-출장-16-0887(2016-08-22)

결재	선임연구원	팀장	부서장	원장
	08/19 명복순	08/22 이우섭	08/22 유진호	08/22 정홍상
협조	사원	팀장	부서장	
	08/19 김보성	08/22 김선태	08/22 김형진	

TRAVEL REPORT FORM
출장보고서

I. Reporter 보고자

Department 소속	Name 성명	Travel Date 날짜	Note 비고
기후예측본부	명복순	8/3-8/5	
응용사업본부	조재필	8/2-8/6	
기후예측본부	Hongwei Yang	7/30-8/6	

II. Major Activities 주요업무 수행내용

1. Main Contents and Activities **주요내용 및 활동**

중국 북경에서 개최된 "AOGS(Asia Oceania Geosciences Society) 13thAnnual Meeting"에 참석하여 기상, 기후, 농업, 및 수자원과 관련하여 발표 및 토론을 진행함.

가. 학 회 명: AOGS(Asia Oceania Geosciences Society) 13thAnnual Meeting

나. 일정/장소: 2016.7.31～2016.8.5(6일) / CNCC in Beijing, China

다. 발표제목 및 발표세션

2. **학술발표 내용**

- 명복순 박사(기후예측팀):
  발표제목: Wildfire Danger Assessment Using Satellite Vegetation indices in Semi-Arid Regions (8/4, AOGS 구두발표)
  발표제목: Concurrent Severe Droughts In East Asia And Western Us In The Last Two Decades (8/4, AOGS 구두발표)

- 조재필 박사(응용사업팀):
  발표제목: Evaluating Predictability of Seasonal Climate Forecast for Long-term Prediction of Storage Level in Agricultural Reservoirs (8/3, AOGS 구두발표)
  발표제목: Development of an integrated downscaling system for seasonal forecast and applications on water resource management (8/5, China Institute of Water and Hydropower Research 초청발표)

- Hongwei Yang(기후연구팀):
  발표제목: Multi-scale processes in devastating rainfall: a new

application of regional modeling (8/3, AOGS 포스터발표)

3. Relevance to APEC Climate Center's Activities **결론 및 소감**

- AOGS의 규모가 매년 증가하고 있고 올해 미팅은 역대 최고 참가자를 기록했음. 또한 대기과학 세션이 Major 세션으로 발전했음.
- 몬순, ENSO 세션의 확대와 함께 Extreme events 세션이 활발히 진행되었음.
- 다양한 엘리뇨 타입이 최근 몇 년 동안 큰 이슈가 되었는데 다양한 라니냐 타입에 대한 연구와 그 임팩트에 대한 연구가 제시되고 있음. 이와 관련되어 한반도에 미치는 영향에 대해서도 연구가 필요할 것으로 보임.
- 수자원분야 기후정보 활용과 관련해서는 재난재해 관련 영향 분석을 위해서 시간단위 강우자료 상세화 관련 대만 및 캐나다 연구진에 의해 발표되었으며, APCC에서도 불확실성이 높은 기후변화 시나리오 자료를 실제 설계에 반영하기 위한 체계적인 절차 마련을 위한 연구 수행이 필요할 것임.
- China Institute of Water and Hydropower Research (IWHR) 하천유량 예측을 위한 기상/기후예측 정보에 관심이 많음. 호주 CSIRO에서는 호주에서 현업으로 활용되고 있는 7일 유량예측 시스템과 관련하여 발표하였으며, APCC에서는 장기예측 관련 내용을 중심으로 발표함.
- 중국에서는 1998년 홍수이후 단기 유량 예측을 위해 미국 시스템을 도입하여 현재 사용하고 있으나 향후 호주 시스템을 도입하는데 많은 관심을 갖고 있음 (장기적인 연구원 파견)
- APCC에서도 향후 외국 기관과의 협력관계 구축을 위해서는 기후정보 상세화 시스템 개발을 시작으로 유량 및 수질 예측으로의 현업화 사례를 만들어 가는 것이 필요함.
- Presented the APCC new method on regional climate modeling.
- Met with experts in regional climate modeling and get the feed back on APCC research.
- Discussed with related scientist on their works to see the possible future advance.

III. References 참고사항

(with attachment of any information or report in case of attendance of conferences, workshops and meetings) 학술대회, 워크숍, 회의 등 참석 시 관련 정보 및 문서 첨부

1. Presented and Collected Materials 주요 수집자료

2. Suggestions and Remarks 건의사항

Evaluating Predictability of Seasonal Climate Forecast for Long-term Prediction of Storage Level in Agricultural Reservoirs

2016. 08. 03.

Jaepil Cho (APEC Climate Center)
Kwangyoung Kim (Rural Research Institute)

AOGS 13th Annual Meeting, 31 Jul to 5 Aug 2016, Beijing

Agricultural reservoirs in Korea

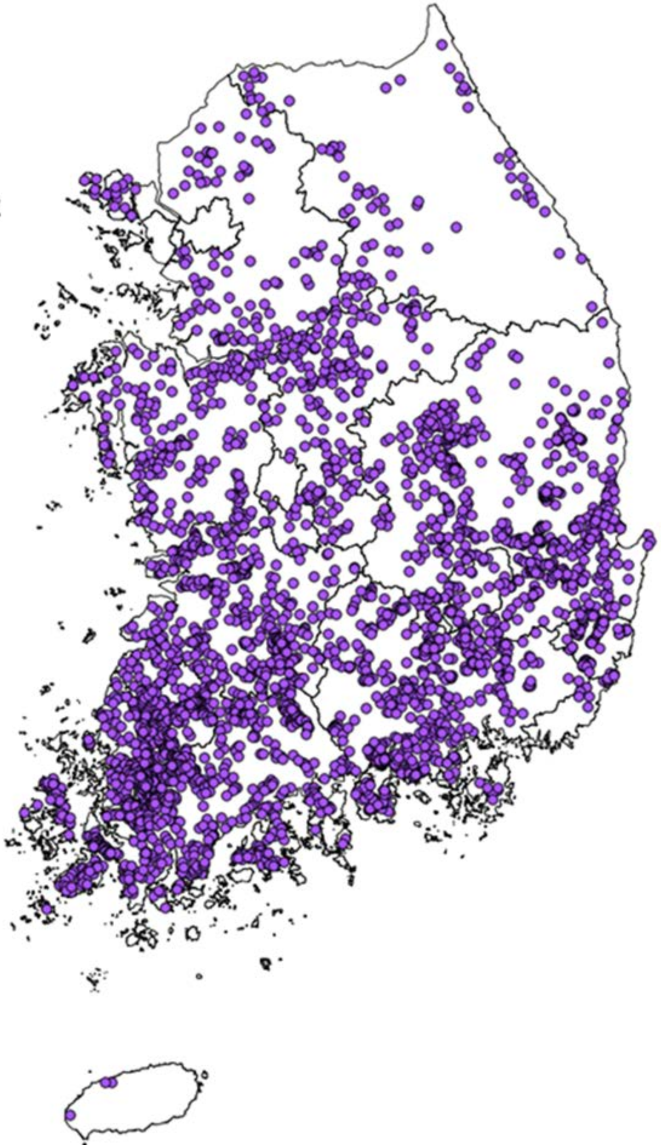
(Source; KRCC, 2011)

Agricultural Facilities	Managed by KRCC		Managed by City		Total	
	Count	Area(ha)	Count	Area(ha)	Count	Area(ha)
Reservoirs	3,363	340,984 (65.4%)	14,206	112,327 (39.3%)	**17,569**	**453,311 (56.2%)**
Pumping Stations	4,077	166,142 (31.9%)	3,390	34,611 (12.1%)	7,467	200,753 (24.9%)
Weirs	5,887	13,669 (2.6%)	38,401	138,742 (48.6%)	44,288	152,411 (18.9%)
Total	13,327	520,795	55,997	285,680	69,324	806,475

- 62% of total water resources are used for agricultural water (2007)
- 80% of agricultural water are used for paddy irrigation during Apr-Sep.
- 80% of irrigation water for paddy areas are supplied from agricultural facilities
- 56% of total irrigated areas are supplied by agricultural reservoirs

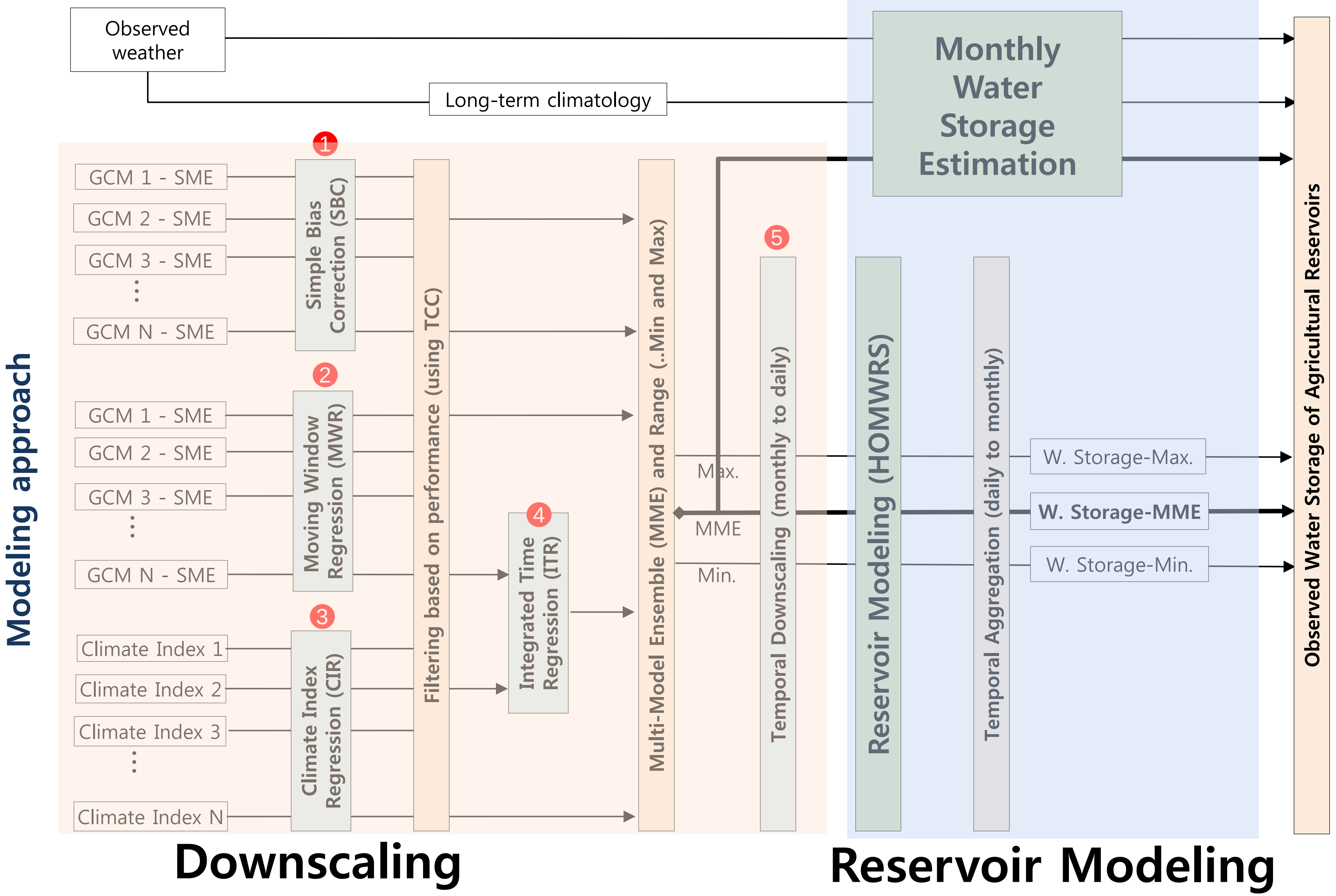
Agricultural reservoirs in Korea

Small agricultural reservoirs are vulnerable to climate change



Method and Materials

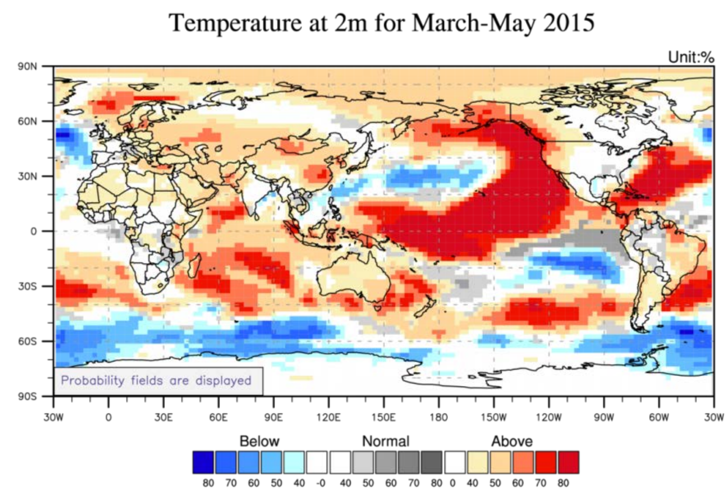
Integrated Downscaling System for Seasonal Prediction

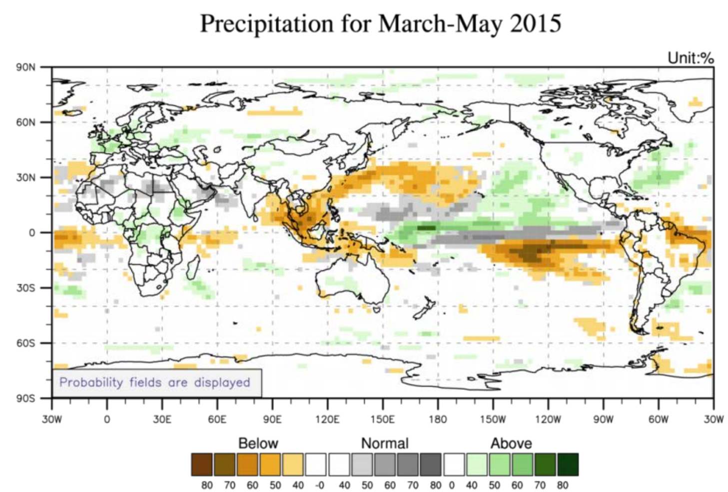


APCC Multi-Model Ensemble (MME)

Model acronym	Institution(country)	Model resolution	Ensemble size
CWB	Central Weather Bureau (Taipei)	T42L18	10
GDAPS_F	Korea Meteorological Administration (Korea)	T106L21	20
HMC	Hydrometeorological Centre of Russia (Russia)	1.125° X 1.406 25°	20
JMA	Japan Meteorological Agency (Japan)	T95L40	31
MSC_CANCM3*	Meteorological Service of Canada (Canada)	1.41° X 0.94°	10
MSC_CANCM4*	Meteorological Service of Canada (Canada)	1.41° X 0.94°	10
NASA*	National Aeronautics and Space Admi nistration (USA)	288 X 181	9
NCEP*	NCEP Climate Prediction Center (USA)	T62L64	15
PNU*	Pusan National University (Korea)	T42L18	5
POAMA*	Centre for Australian Weather and Cli mate Research /Bureau of Meteorolog y (Australia)	T47L17	10

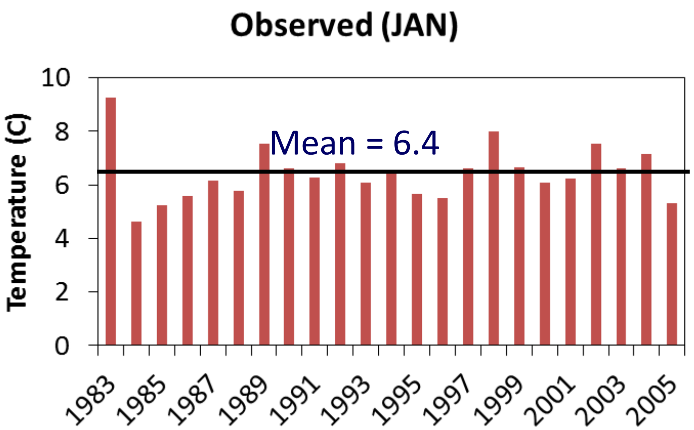
Multi-Model Ensemble (MME)

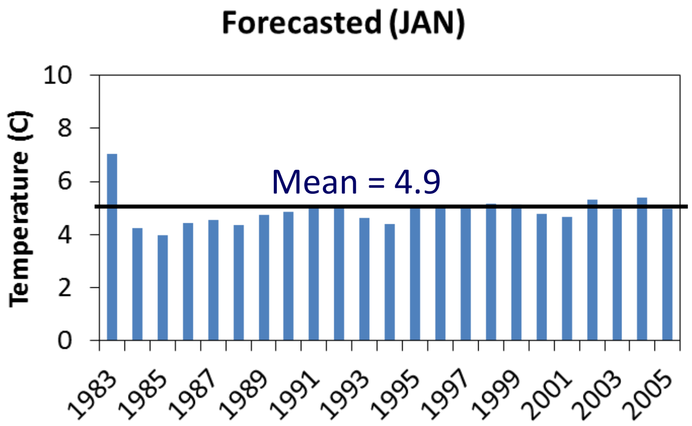


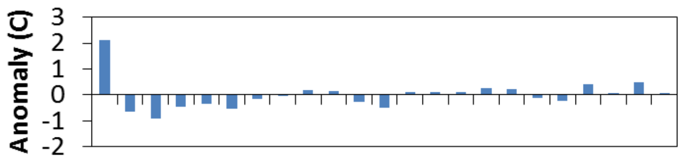


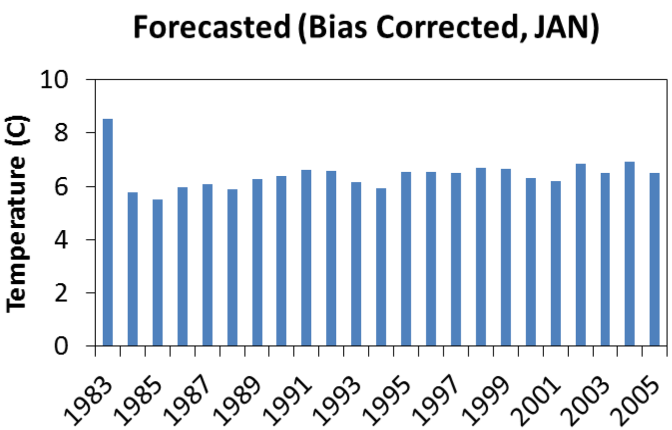
1983~2015, 10 individual models
*** represents 6-month lead forecast**

Simple Bias Correction (SBC)









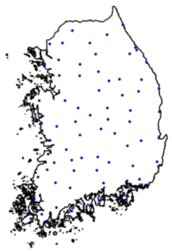
- **Temporal**: same
- **Spatial**: same
- **Variable**: same

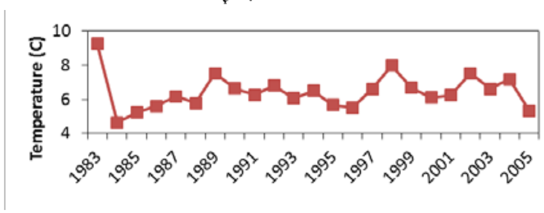
$$T'_{y,m} = (T_{y,m} - T_{hist,m}) + T_{obs,m}$$

$$P'_{y,m} = \begin{cases} (P_{y,m} - P_{hist,m}) + P_{obs,m} & \text{for } P_{y,m} \ge P_{obs,m} \\ (P_{y,m} \div P_{hist,m}) \times P_{obs,m} & \text{for } P_{y,m} < P_{obs,m} \end{cases}$$

Moving Window Regression (MWR)

Observed





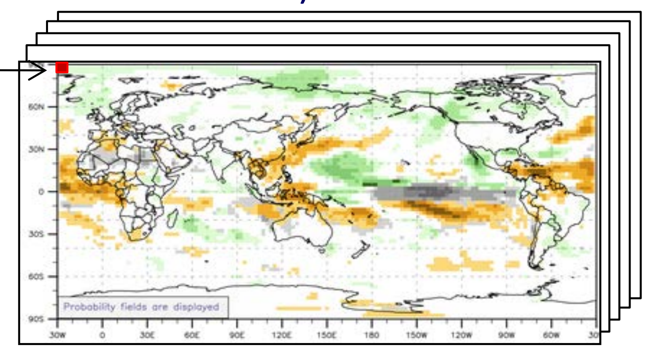
Temperature
(JAN, 1983~2005,Korea)

Temp = a *SLP + b

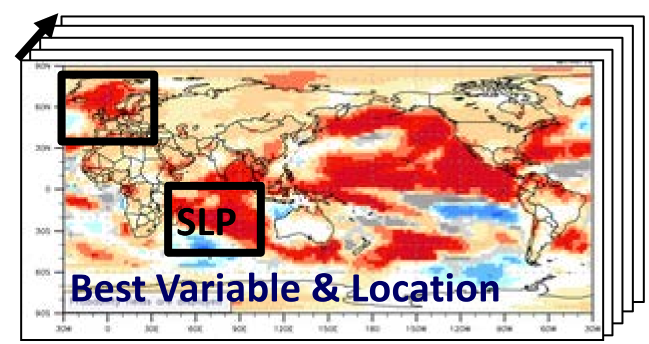
- **Temporal**: same
- **Spatial**: different
- **Variable**: different

Forecasted

Models: MSC_CANCM3, MSC_CANCM4, NASA, NCEP, PNU, POAMA
Variables: PREC, T2M, T850, U200, V200, U850, V850, Z500, SLP, SST (JAN, 1983~2005)



Temporal Correlation Coefficient (TCC)



(Kang et al., 2009)

Monthly Climate Indices

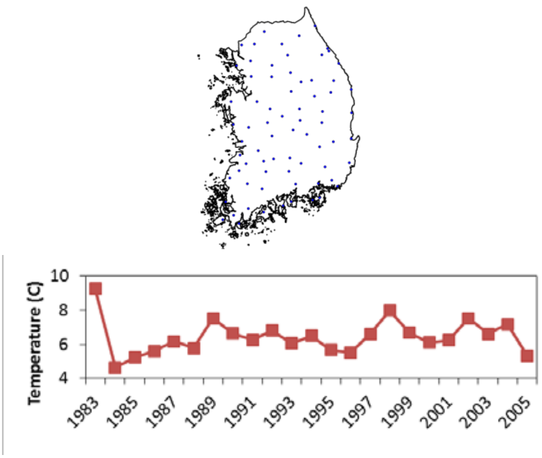
Climate index	Abb.	NOAA	APCC
Pacific North American Index	PNA	S	○
East Pacific/North Pacific Oscillation	EP	S	X
Western Pacific Index	WP	S	○
Eastern Asia/Western Russia	EA	X	X
North Atlantic Oscillation	NAO	S	○
Southern Oscillation Index	SOI	S	○
Eastern Tropical Pacific SST	NINO3	S	○
Bivariate ENSO Timeseries	BEST	X	X
Tropical Northern Atlantic Index	TNA	S	○
Tropical Southern Atlantic Index	TSA	S	○
Western Hemisphere warm pool	WHWP	S	X
Oceanic Nino Index	ONI	X	S
Multivariate ENSO Index	MEI	S	X
Extreme Eastern Tropical Pacific SST	NINO1 2	S	○
Central Tropical Pacific SST	NINO4	S	○
East Central Tropical Pacific SST	NINO3 4	S	
Pacific Decadal Oscillation	PDO	X	X
Northern Oscillation Index	NOI	X	S
North Pacific pattern	NP	X	S
Trans-Niño Index	TNI	X	S

Climate index	Abb.	NOAA	APCC
Antarctic Oscillation	AO	X	S
Antarctic Oscillation	AAO	X	S
Pacific Warmpool (1st EOF of SST (60e-170E, 15S-15N) SST EOF)	PACWA RM	X	S
Tropical Pacific SST EOF	EOFPAC	X	S
Atlantic Tripole SST EOF	ATLTRI	X	S
Atlantic multidecadal Oscillation Long Version	AMO	S	X
Atlantic Meridional Mode	AMM	X	X
North Tropical Atlantic SST Index	NTA	X	X
Caribbean SST Index	CAR	X	X
smoothed: Atlantic Multidecadal Osillation	AMOSM	X	X
Quasi-Biennial Oscillation	QBO	S	○
Globally Integrated Angular Momentum	GIAM	X	X
ENSO precipitation index	ESPI	X	X
Central Indian Precipitation	CIP	X	X
Sahel Standardized Rainfall	SahelRai n	X	X
SahelArea averaged precipitation for Arizona and New Mexico	SWM	X	X
Northeast Brazil Rainfall Anomaly	NBRA	X	X
Global Mean Lan/Ocean Temperature	GML	X	X
Solar Flux (10.7cm)	Solar	X	X
Equatorial Eastern Pacific SLP	ESL	S	X

16 Indices from NOAA
9 indices from NCEP Reanalysis 1 (APCC)

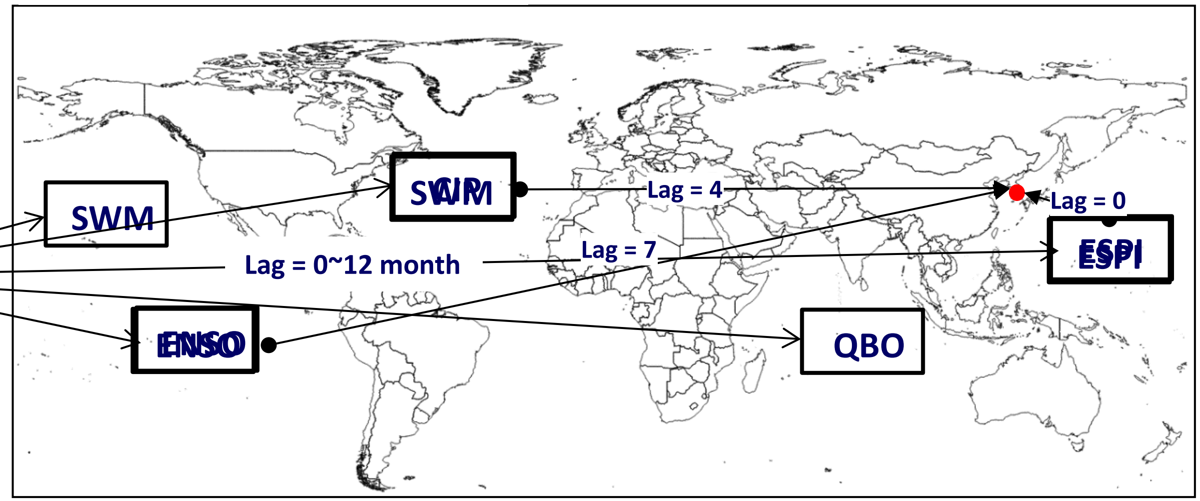
Climate Index Regression (CIR)

Observed



Temperature
(JAN, 1983~2005,Korea)

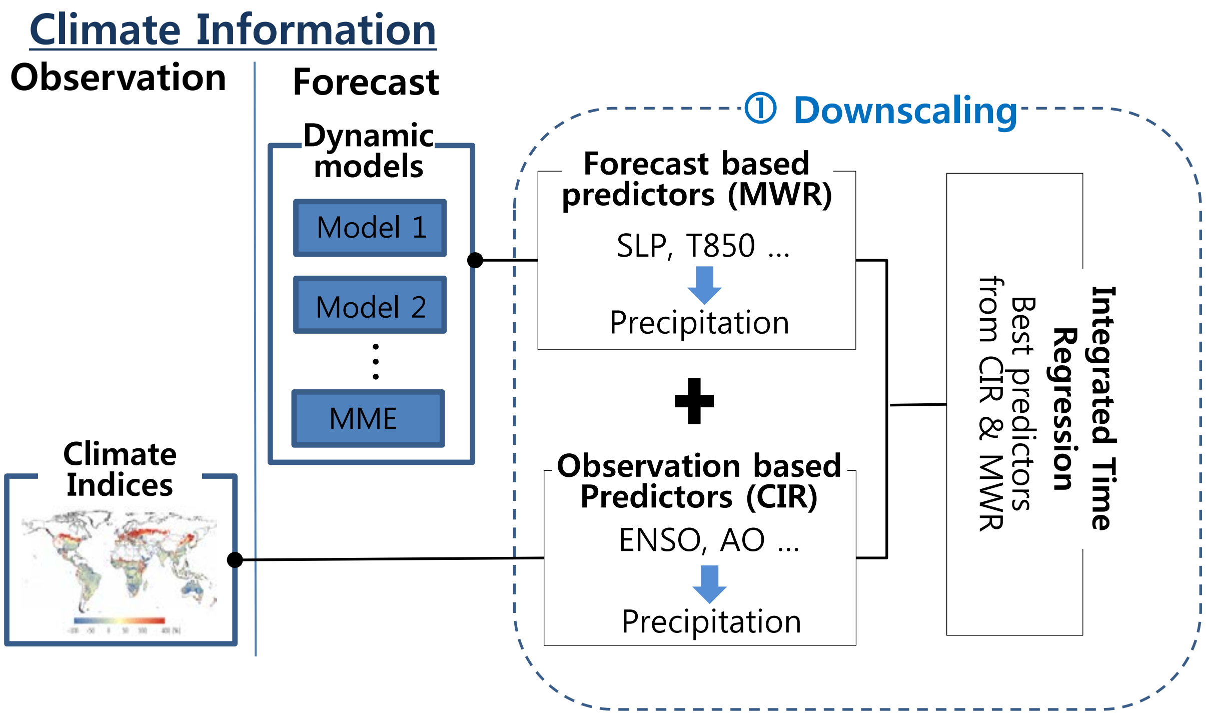
Climate Index from CPC



1. Linear regression (all CIs * Lags)
2. Select N best CIs and Lags
3. Decide multivariate regression model
   Y = a *ENSO_lag7 + b*ESPⓘ lag0 + c

- **Temporal**: different
- **Spatial**: different
- **Variable**: different

Integrated Time Regression (ITR)



Temporal Downscaling Method

Forecasted Area Average

yearmon	prec	t2m
Jan-83	0.623	-2.182
Feb-83	1.622	2.326
Mar-83	1.452	7.280
Apr-83	3.505	11.880
May-83	2.701	[illegible]
Jun-83	3.572	[illegible]
Jul-83	8.453	[illegible]
Aug-83	9.573	24.774
Sep-83	7.755	20.920
Oct-83	2.115	14.774
Nov-83	2.419	6.643
Dec-83	0.221	1.669
Jan-84	0.189	-1.225
Feb-84	0.017	0.270
Mar-84	0.912	3.338

Jan-81

Mahalanobis distance = f(prec, t2m)

Observed Area Average

yearmon	prec	t2m
Jan-73	0.673	-1.631
Feb-73	1.789	2.631
Mar-73	1.428	7.052
Apr-73	3.586	12.139
[illegible]	2.619	17.243
[illegible]	3.681	21.332
[illegible]	7.041	23.314
Aug-73	8.509	24.722
Sep-73	7.145	20.680
Oct-73	2.092	14.745
Nov-73	2.375	7.133
Dec-73	0.151	1.442
.	0.076	-1.409
.	0.123	-0.368
Jan-11	0.997	-1.826
Feb-11	2.313	1.354
Mar-11	2.659	5.750
Apr-11	0.904	12.704
May-11	4.124	17.254
Jun-11	6.330	20.626
Jul-11	10.191	25.146
Aug-11	4.078	27.135
Sep-11	6.269	20.657
Oct-11	3.736	14.392
Nov-11	0.783	8.224
Dec-11	0.972	1.381

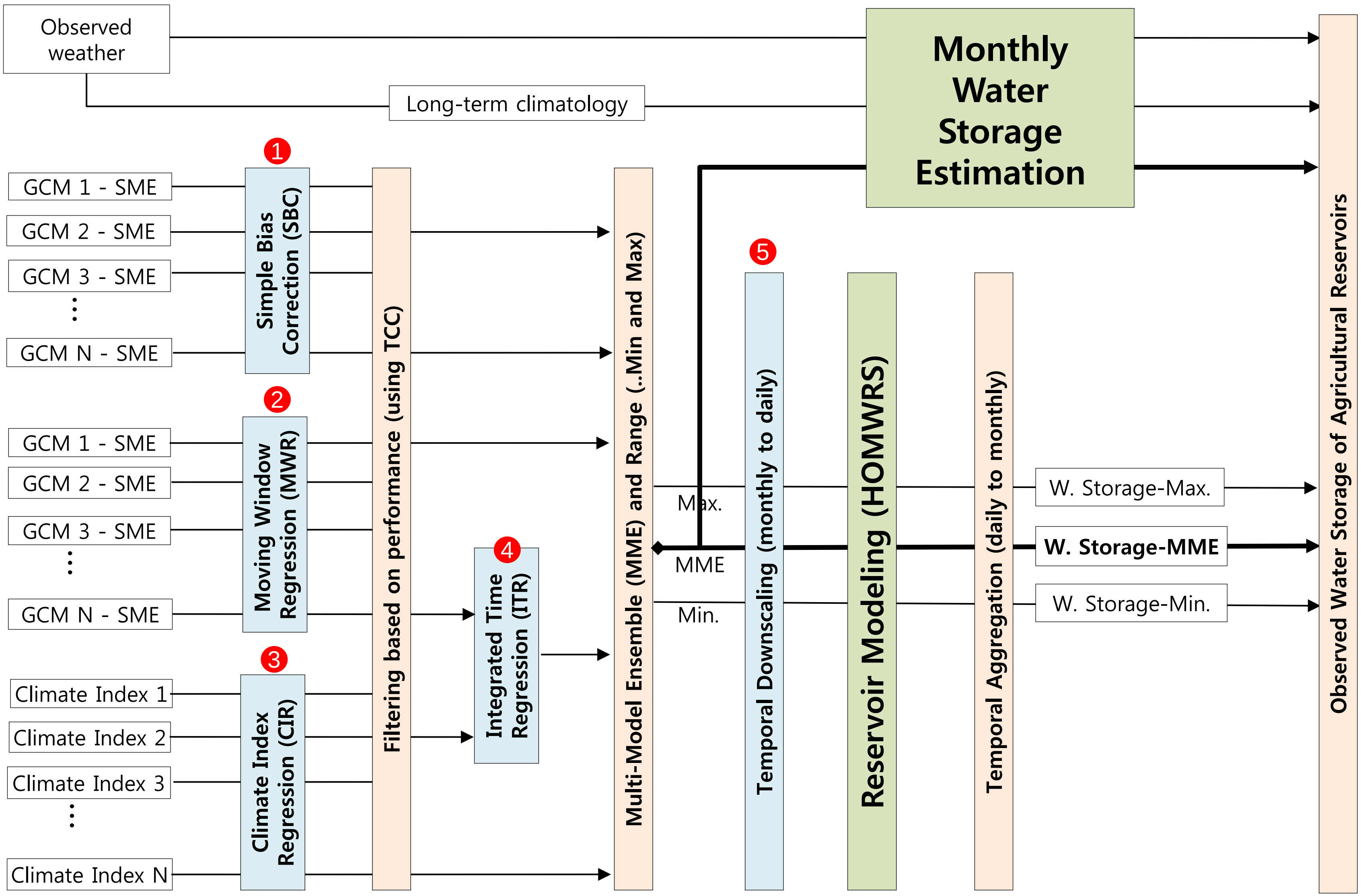
ID135

ID136

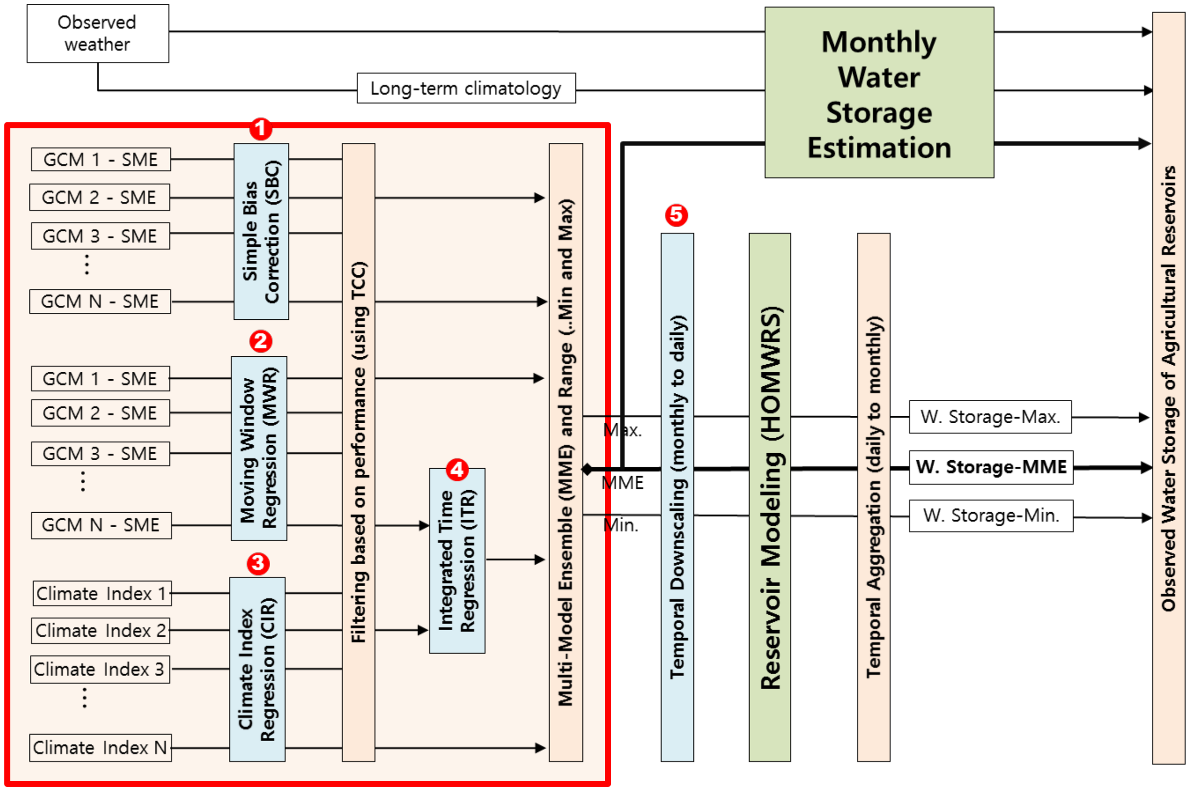
ID137

date	prcp	tmax	tmin	wspd	rhum	rsds
1981-01-01	0.8	1.4	-2.8	3.81	0.62	2.5
1981-01-02	0	-1.7	-7.9	9.43	0.47	5
1981-01-03	0	-3.2	-9.7	9.61	0.39	5.4
1981-01-04	0	-1.5	-9.7	5.05	0.34	7.1
1981-01-05	0	-2.7	-9.2	7.61	0.26	5.4
1981-01-06	0	0.8	-8.8	7.07	0.27	8.1
1981-01-07	0	3.6	-4.4	6.43	0.26	7.1
1981-01-08	0	6.4	-3	4.35	0.36	8
1981-01-09	0	7	-2.8	7.98	0.46	8.3
1981-01-10	0	0	-7	6.35	0.41	6.2
1981-01-11	0	0	-8.8	7.96	0.44	7.8
1981-01-12	0	0.8	-5.5	6.59	0.35	5.4
1981-01-13	0	-1.4	-8.4	5.18	0.39	6.3
1981-01-14	0	0.6	-10.4	3.1	0.45	8.9
1981-01-15	15.9	-1.7	-6	2.7	0.81	2.8
1981-01-16	0.1	0.3	-6.2	2.65	0.71	5.7
1981-01-17	0	2.6	-6.9	3.03	0.51	8.5
1981-01-18	0	3.2	-4.5	4.52	0.48	7.1
1981-01-19	0	0.9	-6.4	2.88	0.64	6.8
1981-01-20	0	2.4	-5.4	4.58	0.39	7.4
1981-01-21	0	0.3	-6.4	4.36	0.44	6.2
1981-01-22	0	-0.2	-9.1	2.43	0.5	8.5
1981-01-23	0	2.8	-6.7	1.52	0.58	9
1981-01-24	0	3.1	-1.5	3.16	0.72	3.4
1981-01-25	0	2.4	-4.6	3.82	0.62	6.9
1981-01-26	0	-0.2	-7.9	3.02	0.47	7.9
1981-01-27	0	0.6	-6.1	3.12	0.41	6.6
1981-01-28	0	3.1	-6.5	2.71	0.46	9.4
1981-01-29	0	4.2	-4.1	3.8	0.48	8.6
1981-01-30	0	5.6	-6.3	2.69	0.5	10
1981-01-31	0	3.2	-5.8	1.93	0.53	9.3

Reservoir modeling (daily & monthly)



Result of Seasonal Forecast

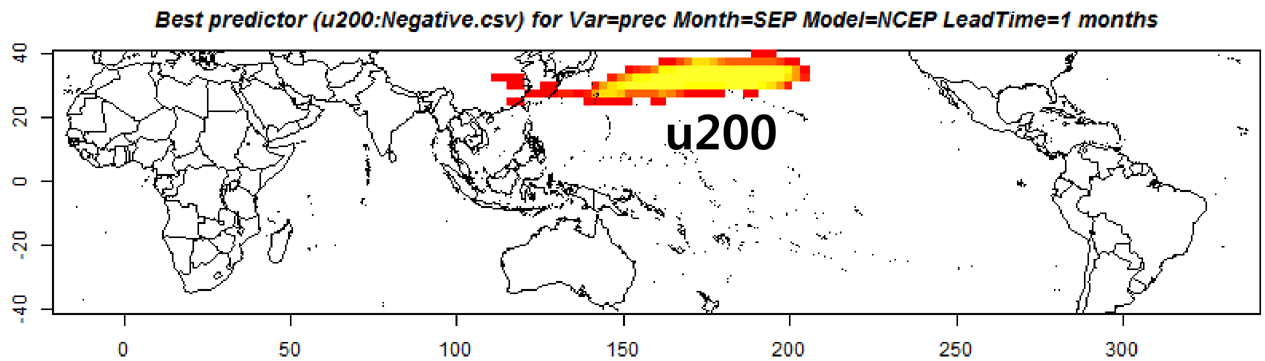


Selected Method and Models for Precipitation

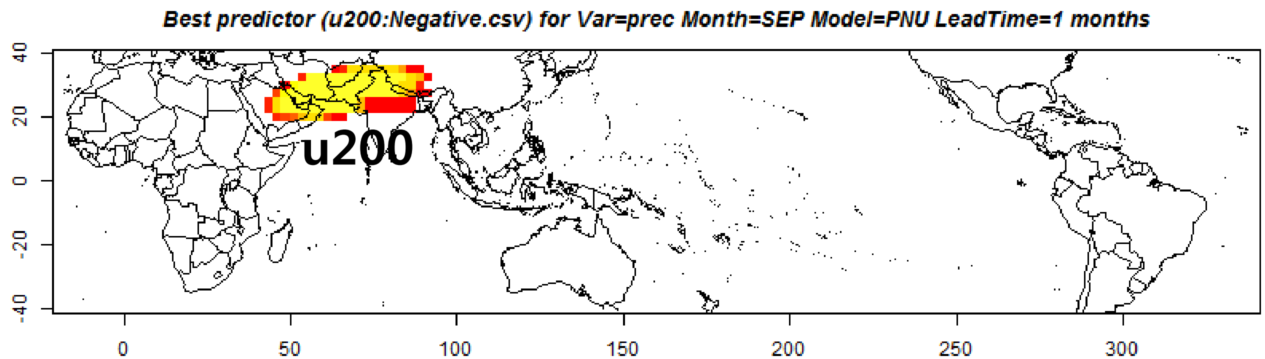
Month	1 month lead	2 month lead	3 month lead	4 month lead	5 month lead	6 month lead
JAN	ⓢJMA, ⓢPOAMA					
FEB		ⓜ CWB	ⓜ GDAPS_F			
MAR	ⓢPOAMA			ⓜ MSC_CANCM4	ⓜ MSC_CANCM4	
APR			ⓢHMC, ⓢNASA, ⓜ NCEP, ⓜ PNU			
MAY					ⓜ PNU	
JUN	ⓜ HMC	ⓜ MSC_CANCM4				
JUL	ⓒ Lag	ⓒ Lag	ⓘ PNU	ⓒ Lag	ⓒ Lag	ⓘ NASA
AUG	ⓢJMA	ⓢGDAPS_F	ⓜ POAMA	ⓜ MSC_CANCM3		
SEP	ⓜ NCEP, ⓜ PNU, ⓜ POAMA	ⓢPNU	ⓢGDAPS_F, ⓢPNU		ⓜ MSC_CANCM4	
OCT			ⓜ MSC_CANCM4			ⓜ PNU
NOV	ⓢPNU	ⓢGDAPS_F, ⓢPNU, ⓢJMA	ⓢPNU, ⓢJMA, ⓢPOAMA, ⓜ MSC_CANCM3	ⓢPNU		ⓜ PNU
DEC	ⓢPOAMA, ⓜ PNU, ⓜ MSC_CANCM4, ⓜ NASA	ⓢJMA, ⓢPOAMA, ⓜ CWB, ⓜ HMC, ⓜ POAMA, ⓜ PNU	ⓢPOAMA, ⓜ GDAPS_F, ⓜ POAMA, ⓜ NASA	ⓜ MSC_CANCM3, ⓜ NASA	ⓜ PNU	ⓜ NASA, ⓜ NCEP

Selected predictors (Ex. 1 month lead September precipitation)

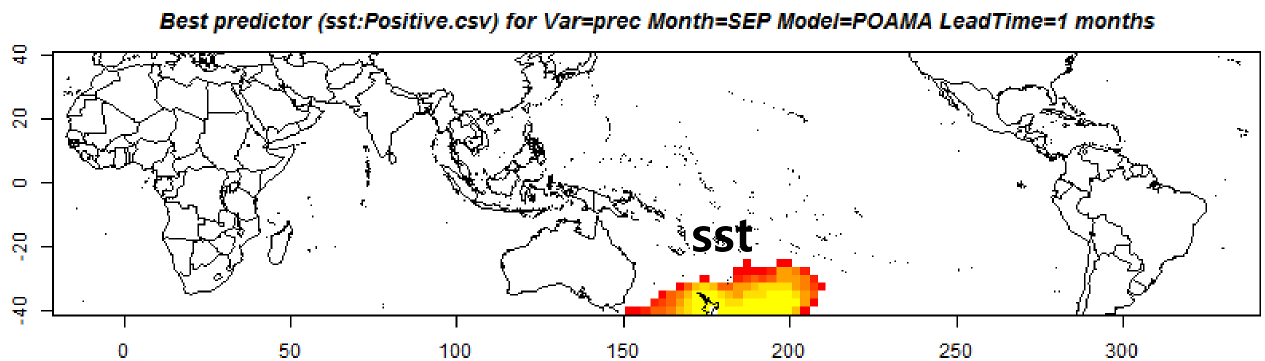
NCEP



PNU



POAMA



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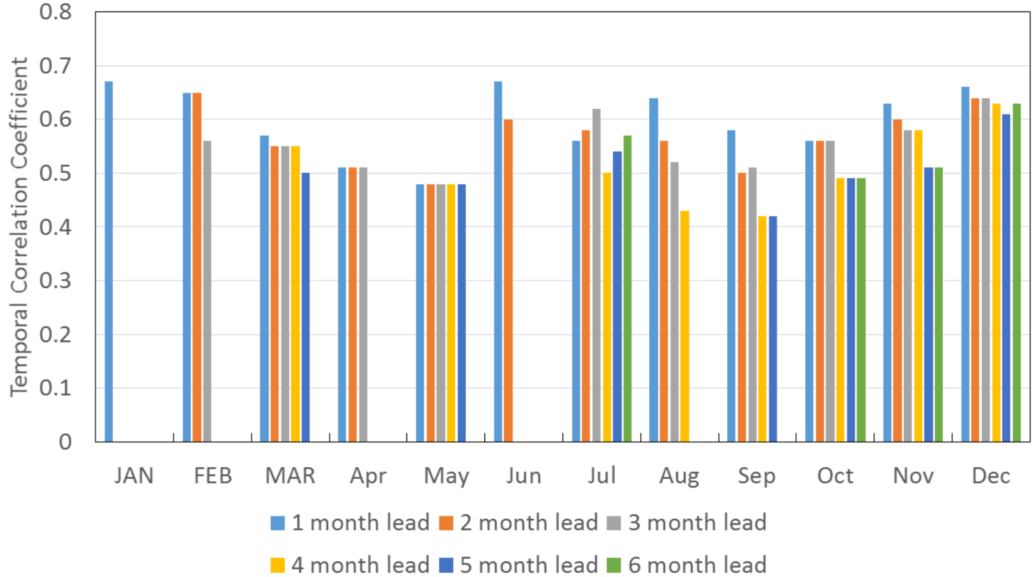
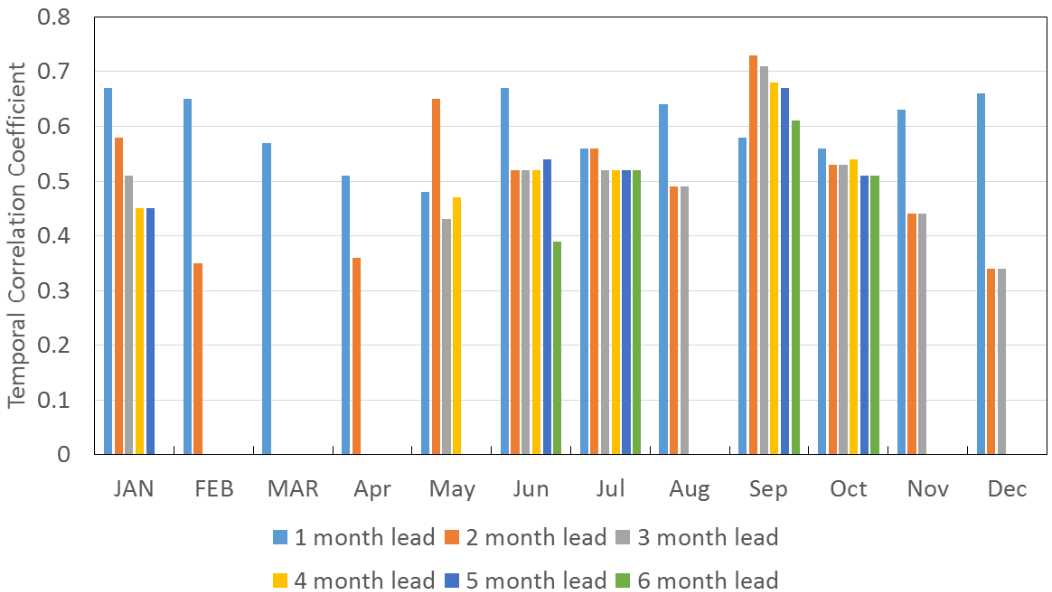
Selected Method and Models for Temperature

Month	1 month lead	2 month lead	3 month lead	4 month lead	5 month lead	6 month lead
JAN	ⓢGDAPS_F, ⓢ MSC_CANCM3, ⓢMSC_CANCM4, ⓢPNU, ⓜ POAMA, ⓜ PNU	ⓢPOAMA	ⓜ CWB		ⓜ PNU	
FEB		ⓢJMA				
MAR	ⓢGDAPS_F, ⓢJMA					
APR	ⓜ GDAPS_F	ⓢNASA				
MAY	ⓜ CWB	ⓜ PNU	ⓜ MSC_CANCM3	ⓜ NASA		
JUN				ⓒ Lag	ⓒ Lag, ⓜ PNU	ⓒ Lag
JUL	ⓢJMA	ⓜ GDAPS_F				ⓜ PNU
AUG	ⓢPNU, ⓢHMC		ⓜ CWB			
SEP	ⓢGDAPS_F, ⓢPNU, ⓢJMA, ⓢHMC, ⓢNASA, ⓢPOAMA, ⓘ NASA	ⓢNASA, ⓢGDAPS_F, ⓢPNU, ⓘ MSC_CANCM4, ⓘ NCEP	ⓢGDAPS_F, ⓢHMC, ⓢJMA, ⓢNASA, ⓢPNU, ⓒ Lag	ⓢPNU, ⓒ Lag	ⓢNASA, ⓢPNU, ⓒ Lag	ⓢNASA, ⓒ Lag, ⓜ PNU
OCT	ⓢGDAPS_F, ⓢPNU, ⓢHMC, ⓘ MSC_CANCM3	ⓢJMA, ⓢNASA, ⓢGDAPS_F, ⓢPNU, ⓒ Lag	ⓢGDAPS_F, ⓒ Lag	ⓒ Lag		ⓢPNU
NOV	ⓢPOAMA		ⓢJMA, ⓜ PNU			
DEC	ⓢPOAMA		ⓢJMA			

Monthly Temporal Correlation Coefficient(TCC)

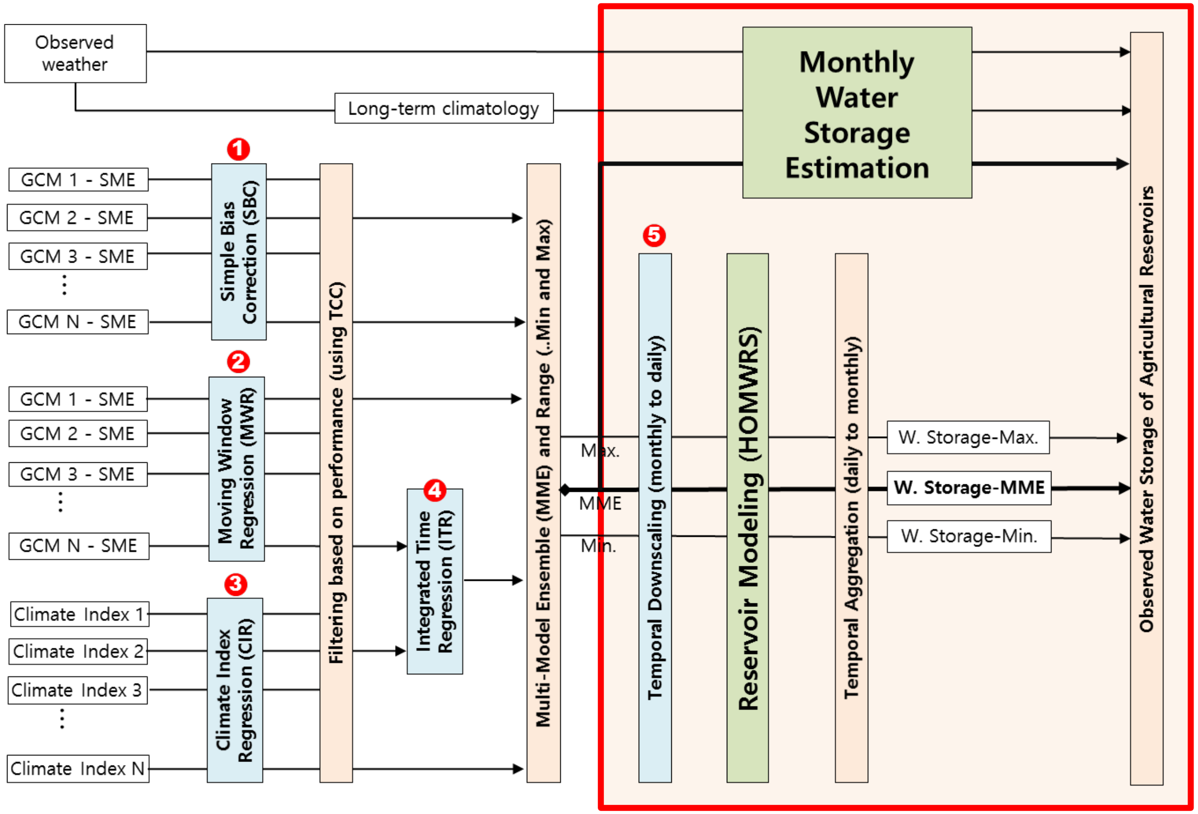


Month	1 month	2 month	3 month	4 month	5 month	6 month
JAN	0.67					
FEB	0.65	0.65	0.56			
MAR	0.57	0.55	0.55	0.55	0.5	
APR	0.51	0.51	0.51			
MAY	0.48	0.48	0.48	0.48	0.48	
JUN	0.67	0.6				
JUL	0.56	0.58	0.62	0.5	0.54	0.57
AUG	0.64	0.56	0.52	0.43		
SEP	0.58	0.5	0.51	0.42	0.42	
OCT	0.56	0.56	0.56	0.49	0.49	0.49
NOV	0.63	0.6	0.58	0.58	0.51	0.51
DEC	0.66	0.64	0.64	0.63	0.61	0.63

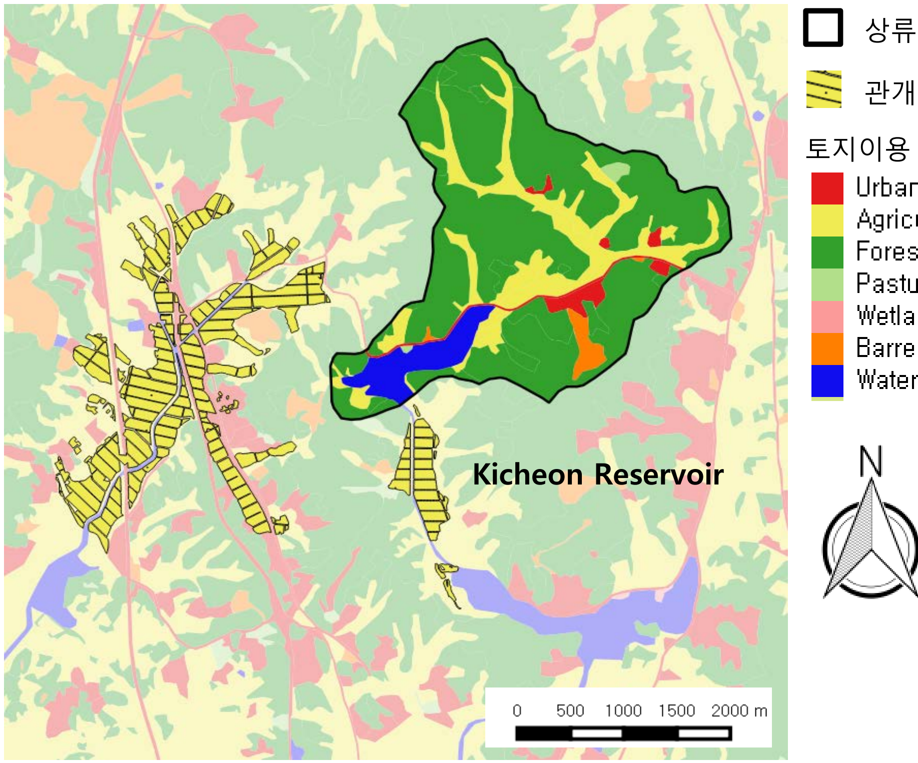


Month	1 month	2 month	3 month	4 month	5 month	6 month
JAN	0.67	0.58	0.51	0.45	0.45	
FEB	0.65	0.35				
MAR	0.57					
APR	0.51	0.36				
MAY	0.48	0.65	0.43	0.47		
JUN	0.67	0.52	0.52	0.52	0.54	0.39
JUL	0.56	0.56	0.52	0.52	0.52	0.52
AUG	0.64	0.49	0.49			
SEP	0.58	0.73	0.71	0.68	0.67	0.61
OCT	0.56	0.53	0.53	0.54	0.51	0.51
NOV	0.63	0.44	0.44			
DEC	0.66	0.34	0.34			

Result of Water Storage Forecast



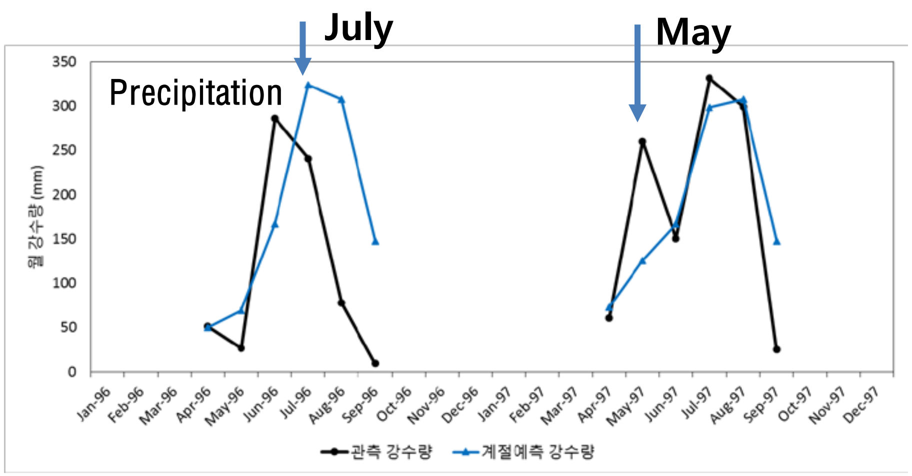
Seasonal Forecast Application for Kicheon Reservoir

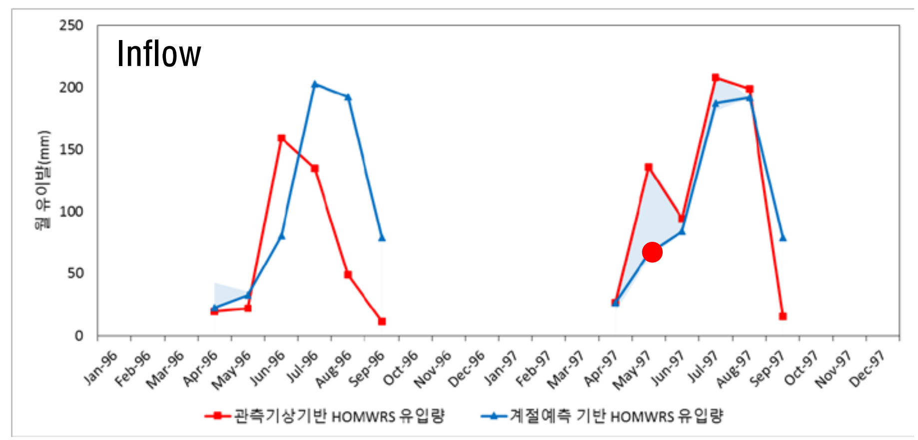


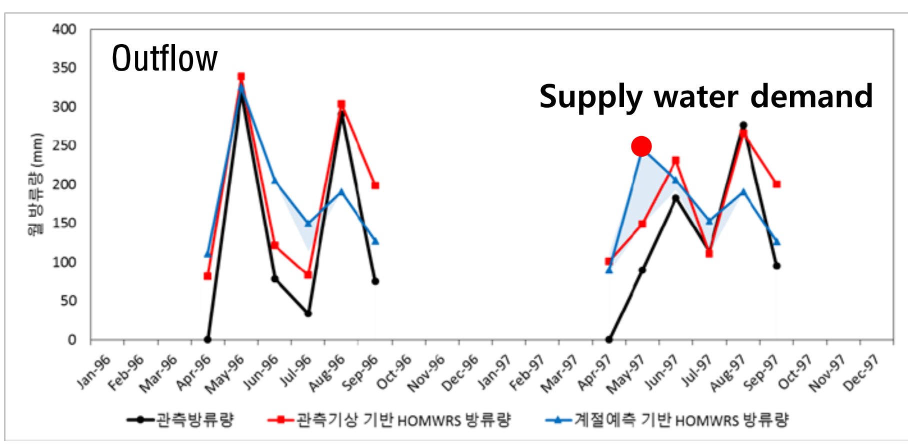
- Kicheon reservoir
  - Watershed area: 755 ha
  - Irrigation area: 270.7 ha
- HOMWRS modeling
  - Period: 1996 ~ 1997
  - 6 months forecast at every March

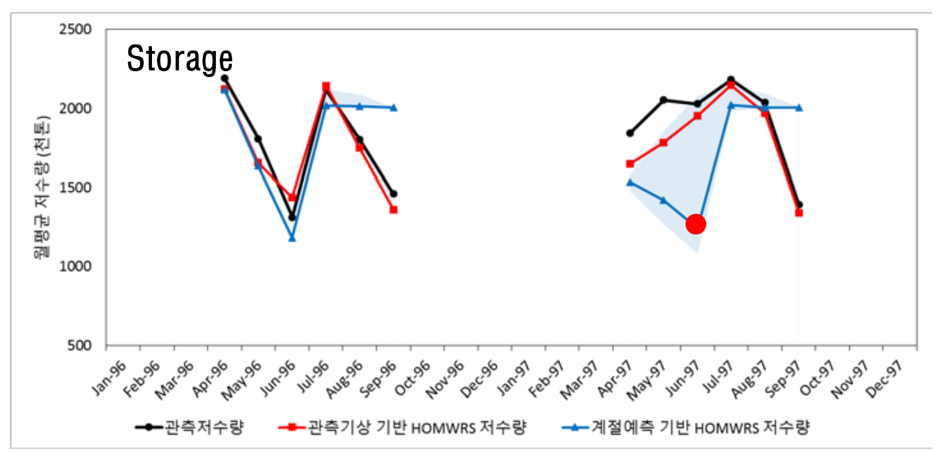
Seasonal Forecast Application for Kicheon Reservoir

- 1996 shows good agreement in storage level
- Underestimation of precipitation on May, 1997 resulted in overestimated water supply and underestimated storage level



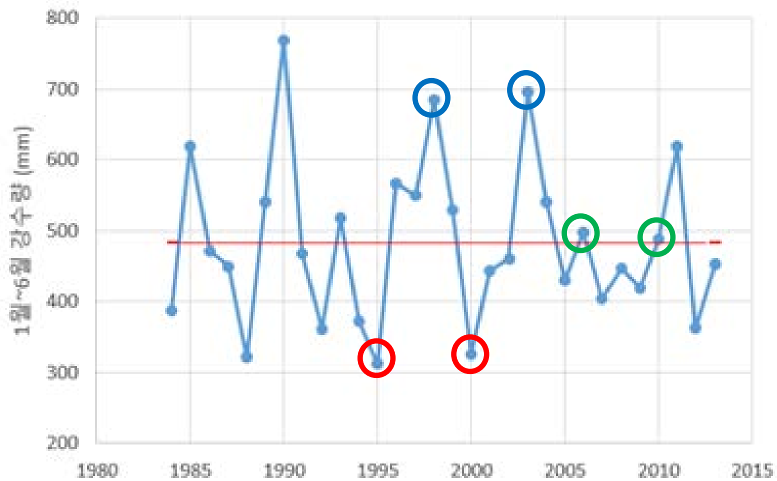






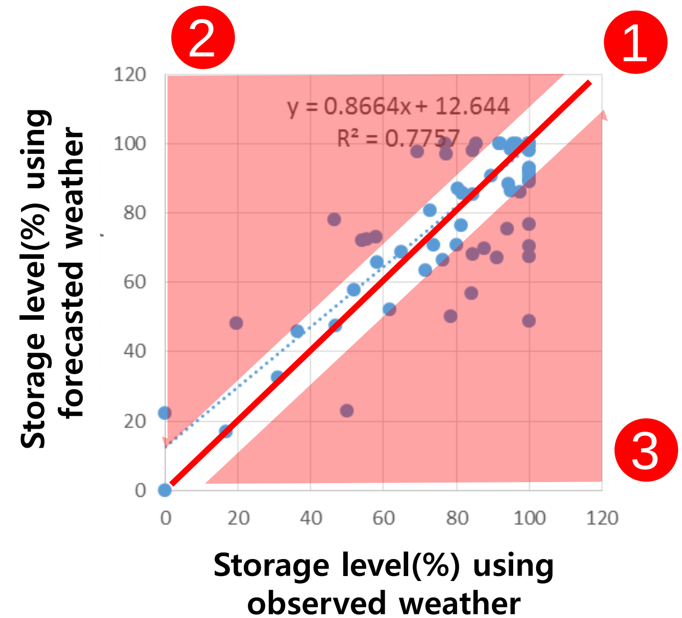
Monthly storage level forecast on Jun. 20 (462 Reservoirs, forecast issued on Jan. 15)

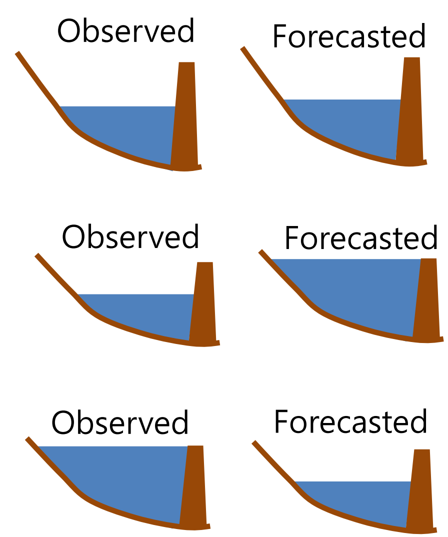
- 6-month lead forecasting



30 year (1984~2013) average of accumulated precipitation amount for JAN to JUN

- Wet years: 1998, 2003
- Normal years: 2006, 2010
- Dry years: 1995, 2005

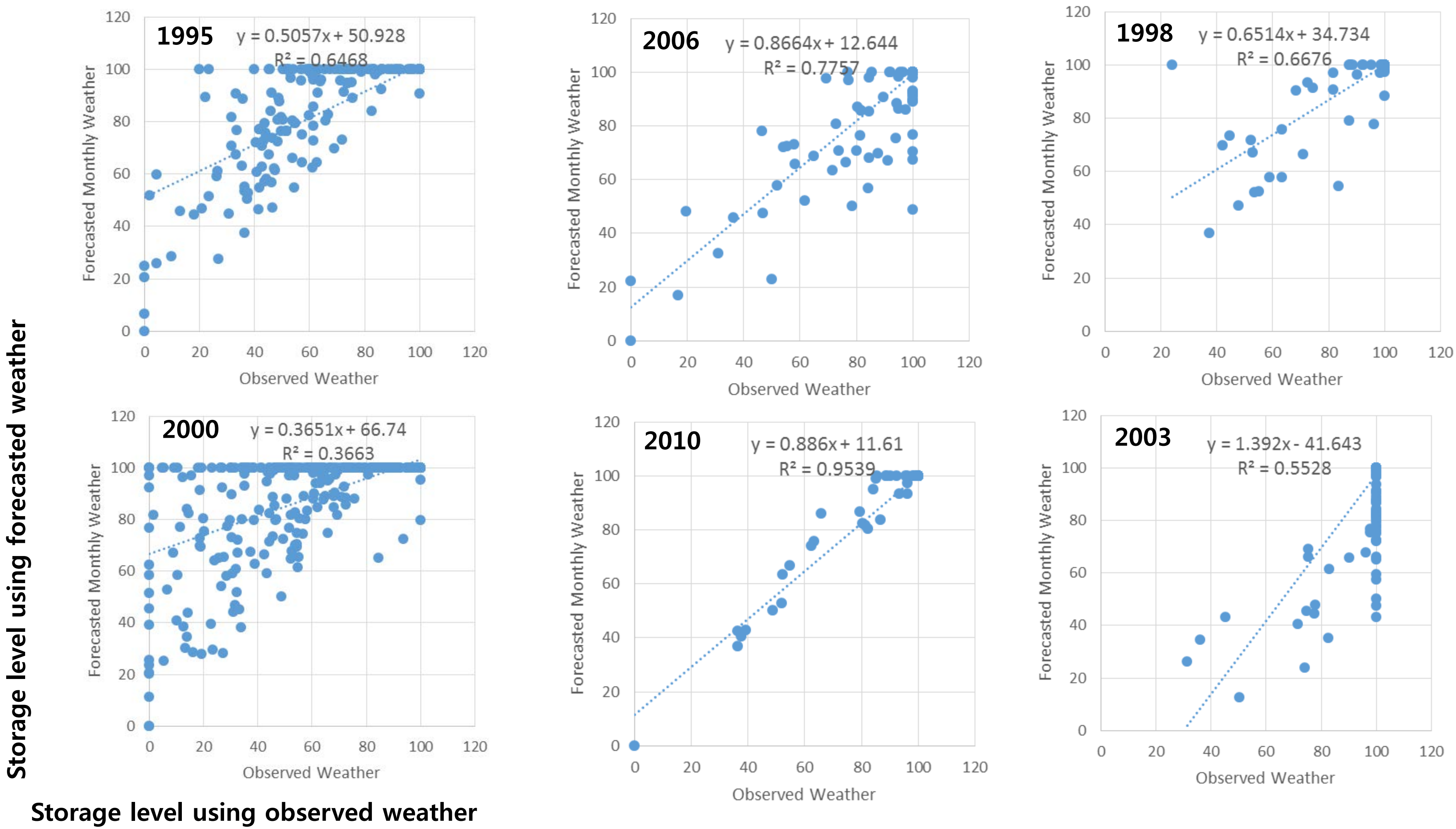




Result of monthly storage level forecast on Jun. 20 (462 Reservoirs, forecast issued on Jan. 15)

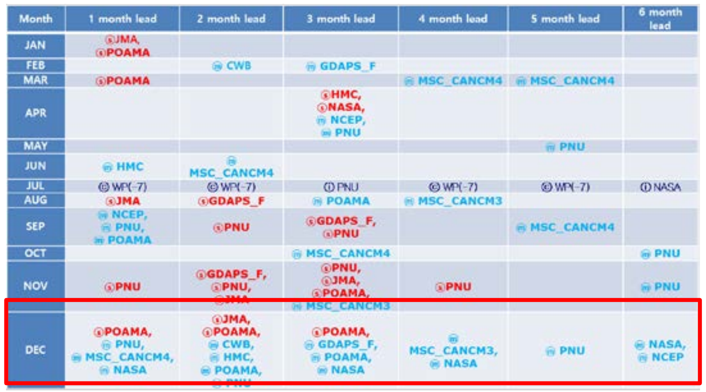
Dry years are underestimated

Wet years are overestimated

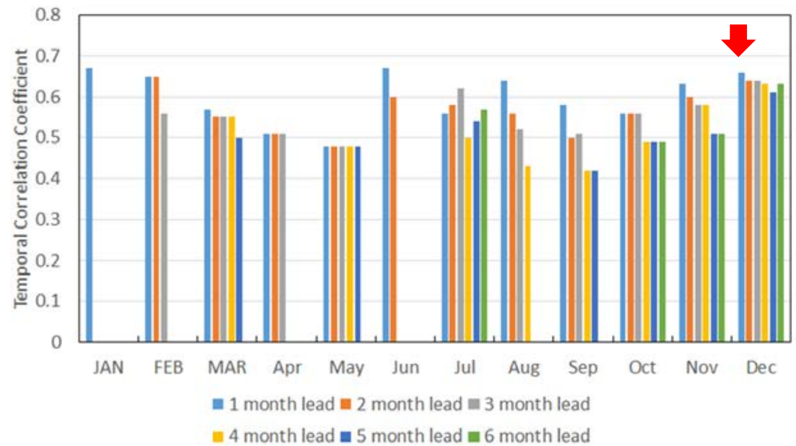


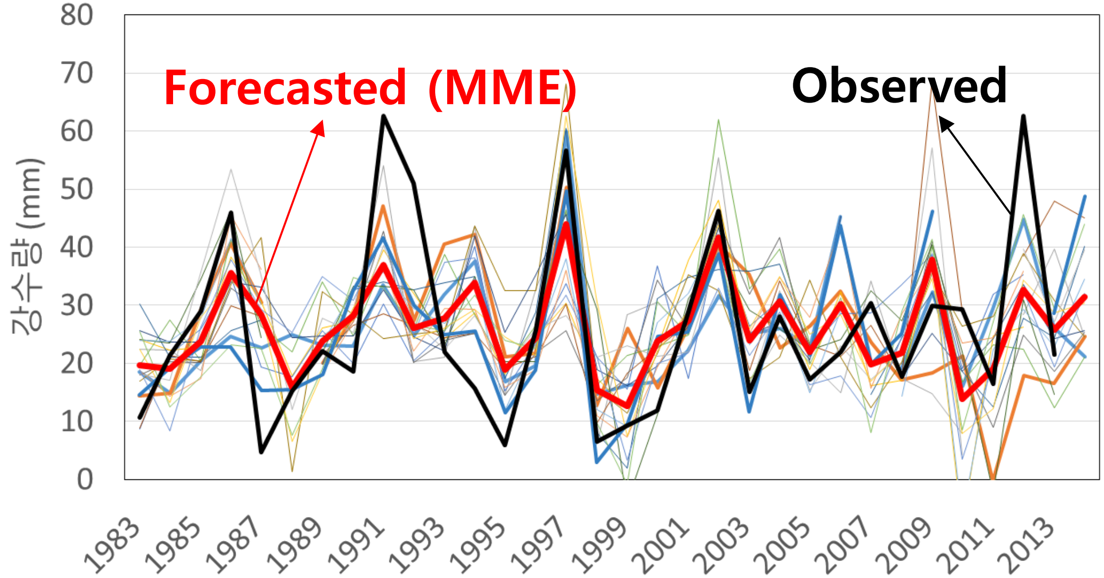
Time-series of seasonal forecast

- December precipitation forecast, 1-month lead time



Month	1 month lead	2 month lead	3 month lead	4 month lead	5 month lead	6 month lead
JAN	ⓢJMA, ⓢPOAMA					
FEB		ⓜ CWB	ⓜ GDAPS_F			
MAR	ⓢPOAMA			ⓜ MSC_CANCM4	ⓜ MSC_CANCM4	
APR			ⓢHMC, ⓢNASA, ⓜ NCEP, ⓜ PNU			
MAY					ⓜ PNU	
JUN	ⓜ HMC	ⓜ MSC_CANCM4				
JUL	ⓒ WP(-7)	ⓒ WP(-7)	ⓘ PNU	ⓒ WP(-7)	ⓒ WP(-7)	ⓘ NASA
AUG	ⓢJMA	ⓢGDAPS_F	ⓜ POAMA	ⓜ MSC_CANCM3		
SEP	ⓜ NCEP, ⓜ PNU, ⓜ POAMA	ⓢPNU	ⓢGDAPS_F, ⓢPNU		ⓜ MSC_CANCM4	
OCT			ⓜ MSC_CANCM4			ⓜ PNU
NOV	ⓢPNU	ⓢGDAPS_F, ⓢPNU, ⓢJMA	ⓢPNU, ⓢJMA, ⓢPOAMA, ⓜ MSC_CANCM3	ⓢPNU		ⓜ PNU
DEC	ⓢPOAMA, ⓜ PNU, ⓜ MSC_CANCM4, ⓜ NASA	ⓢJMA, ⓢPOAMA, ⓜ CWB, ⓜ HMC, ⓜ POAMA, ⓜ PNU	ⓢPOAMA, ⓜ GDAPS_F, ⓜ POAMA, ⓜ NASA	ⓜ MSC_CANCM3, ⓜ NASA	ⓜ PNU	ⓜ NASA, ⓜ NCEP





Variations of MME precipitation decreased (MME underestimated in wet years and overestimated in dry years)

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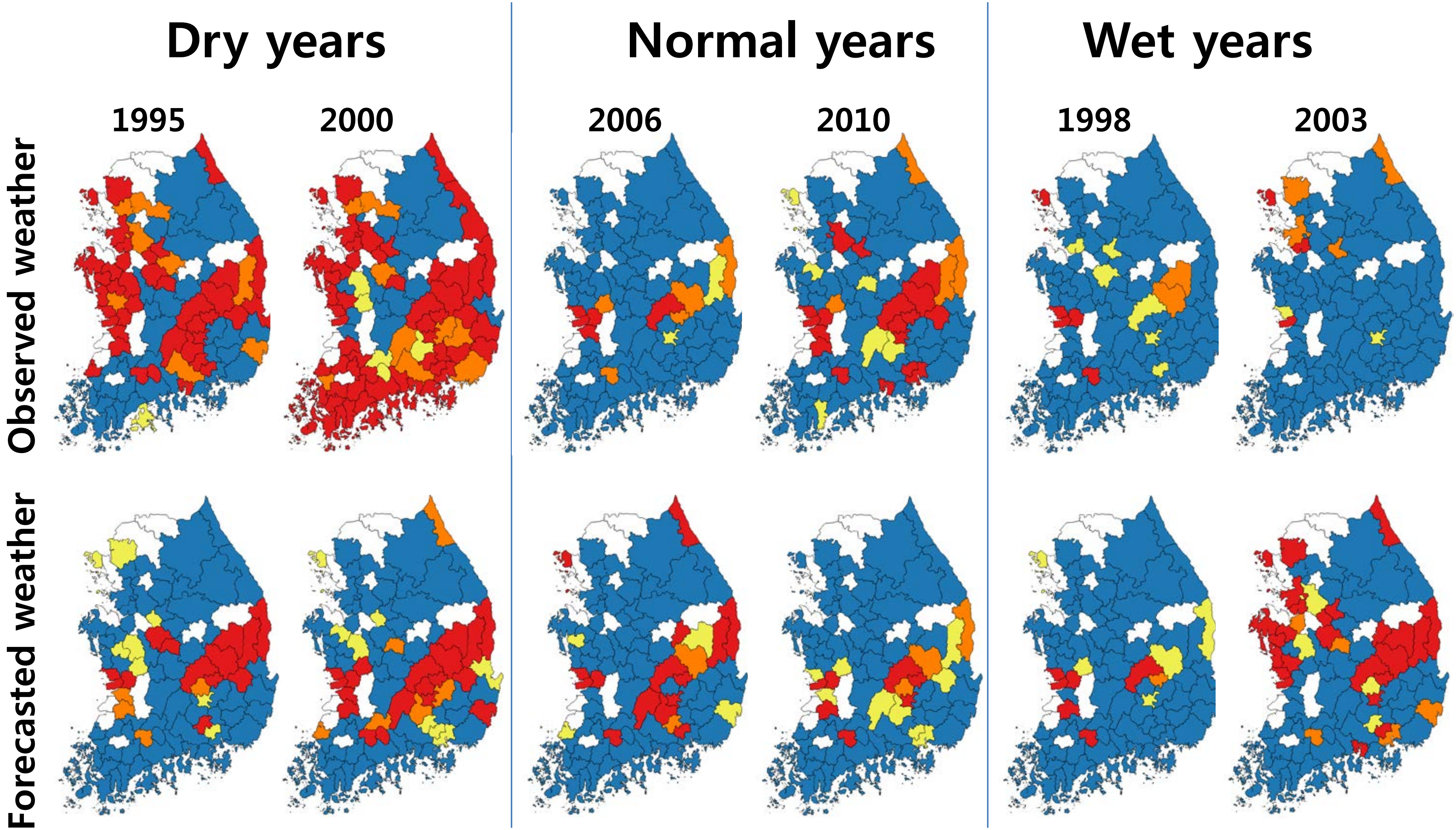
Drought alerting level for Jun. 20 based on daily modeling (branch Level, forecast issued on Jan. 15)



Thank You!
For further discussion and collaboration
Jaepil Cho: jpcho89@gmail.com

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Development of an integrated downscaling system for seasonal forecast and applications on water resource management

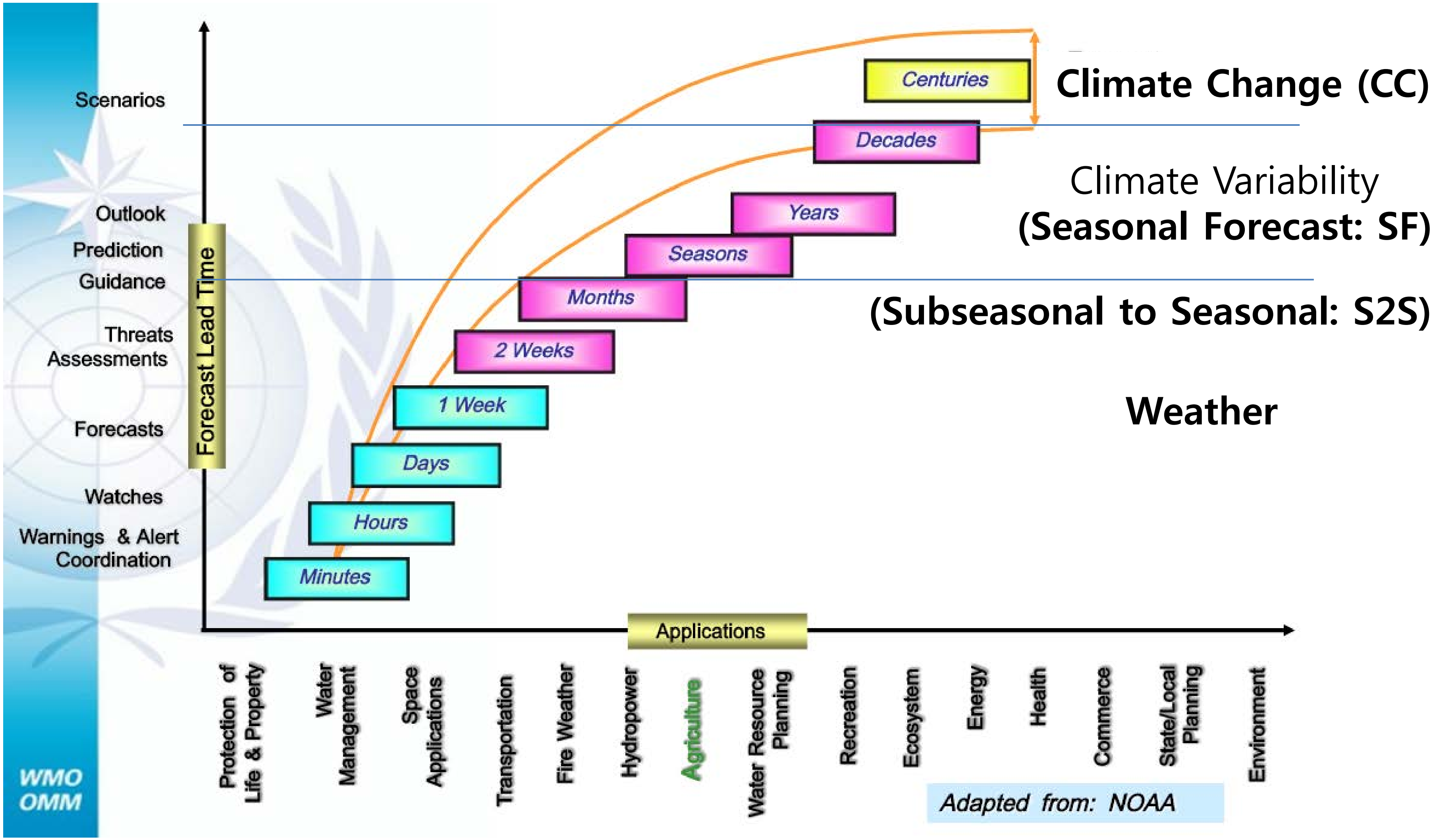
2016. 08. 05.

Jaepil Cho (APEC Climate Center)

China Institute of Water and Hydropower Research, 5 Aug 2016, Beijing

Available Climate Information and Applications

- Seamless Prediction and Services Framework

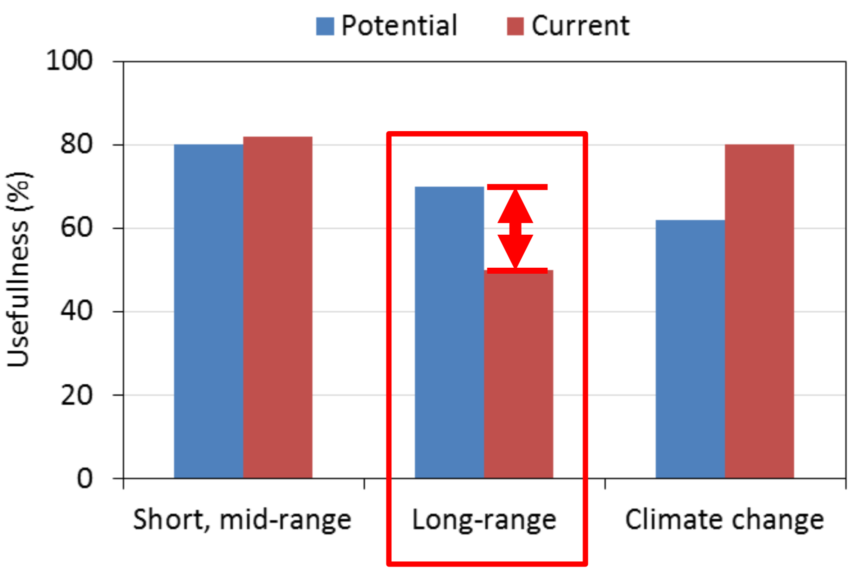


Source: http://slideplayer.com/slide/1447561/

Necessity of seasonal prediction in water resources in Korea

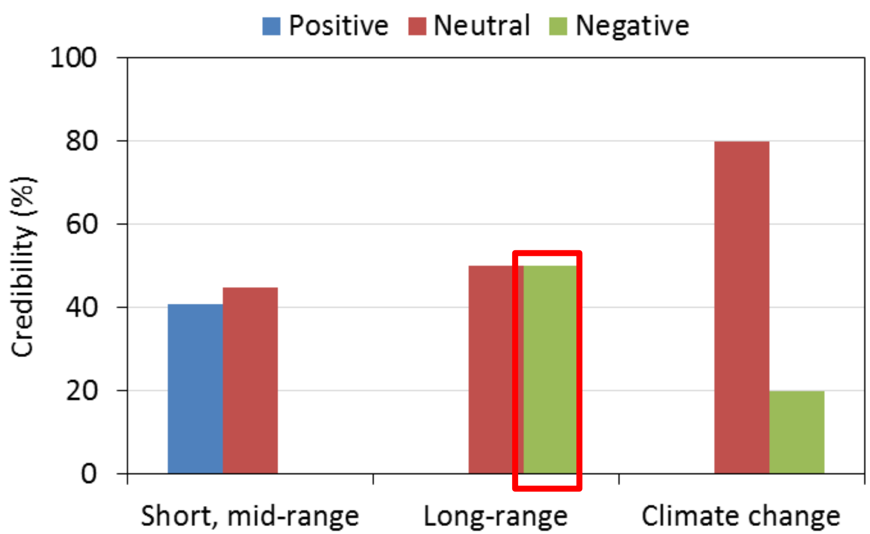
❖ Survey result targeting water related government agency, public enterprise, research institutes in Korea shows .....

Usefulness



Proactive Preparedness & Prevention

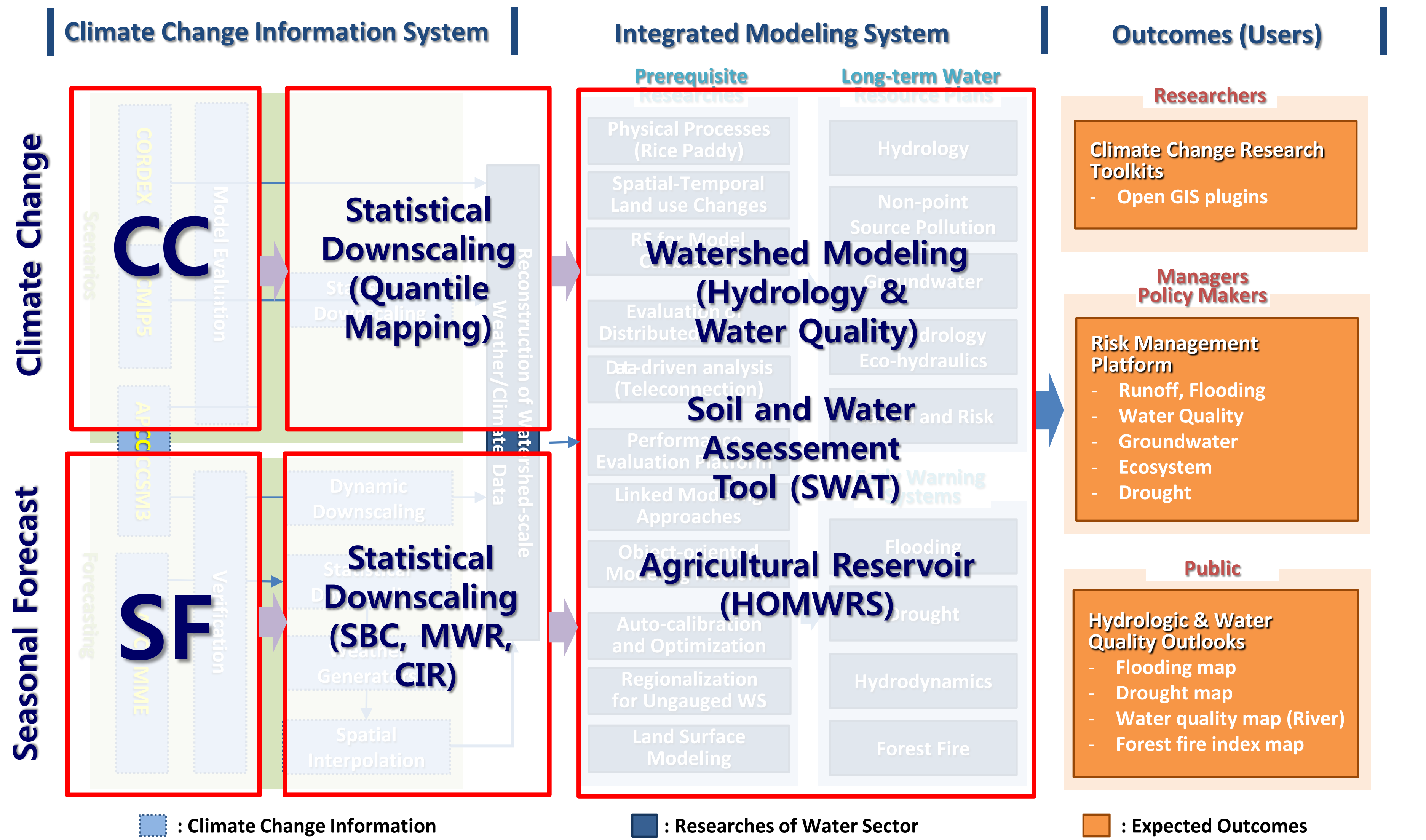
1. Credibility



2. User friendliness

- **Spatial resolution(50%)**
- **Temporal scale (20%)**
- **Data format(20%)**

Framework of APCC Water Sector

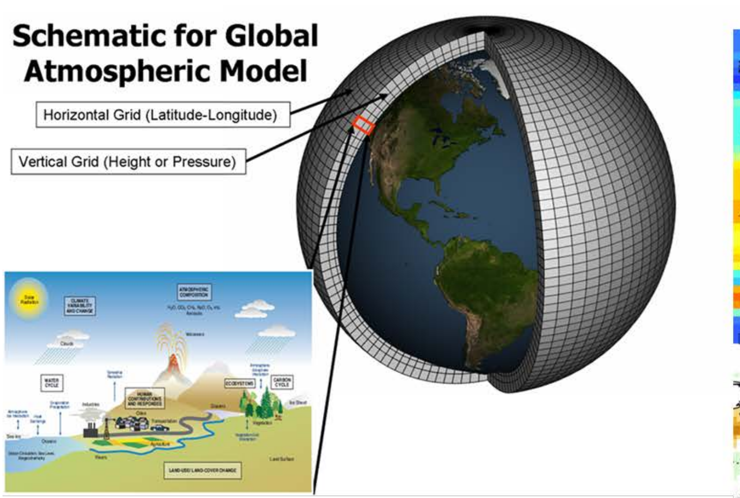


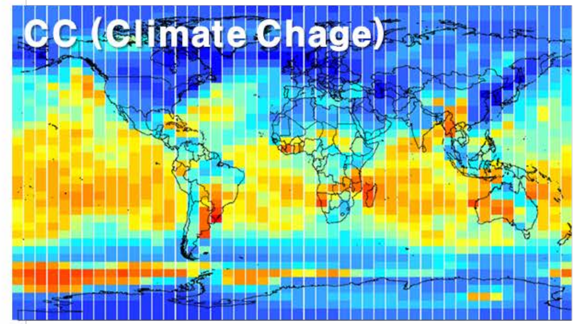
Objectives and Presentation Overview

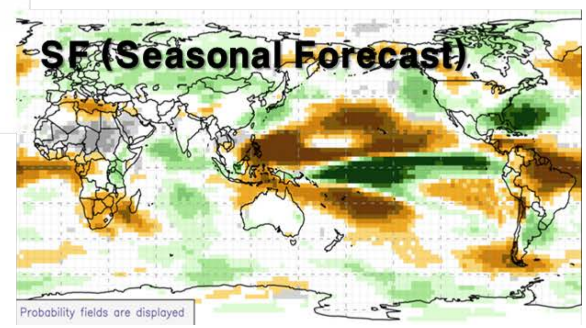
Modeling approach

- to develop hybrid downscaling technique for predicting the long-term precipitation and temperature on any study area (station, region, watershed, country)
- to evaluate the applicability of the seasonal forecast information in long-term future water quantity and quality predictions (modeling approach)

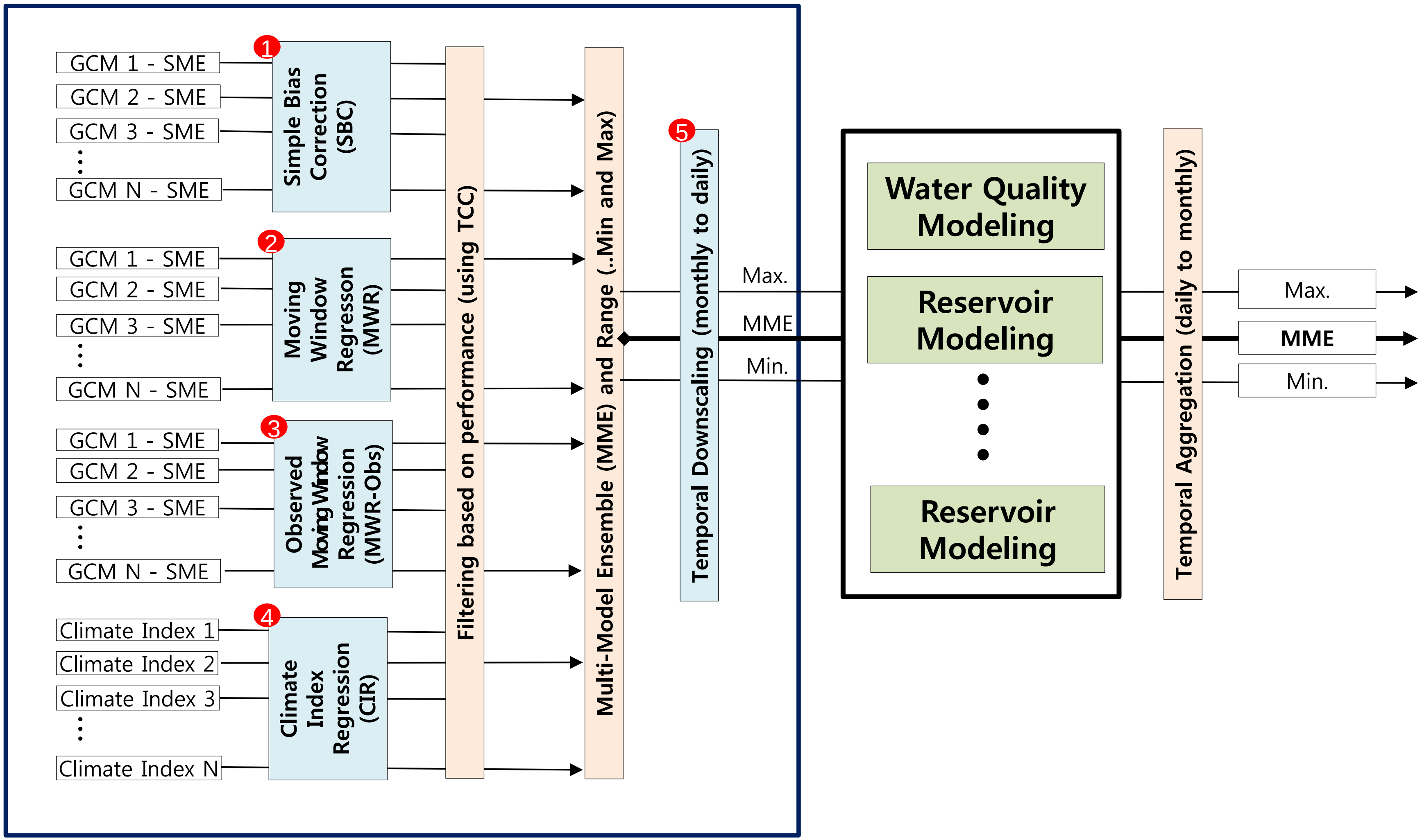
Downscaling of Seasonal Forecast



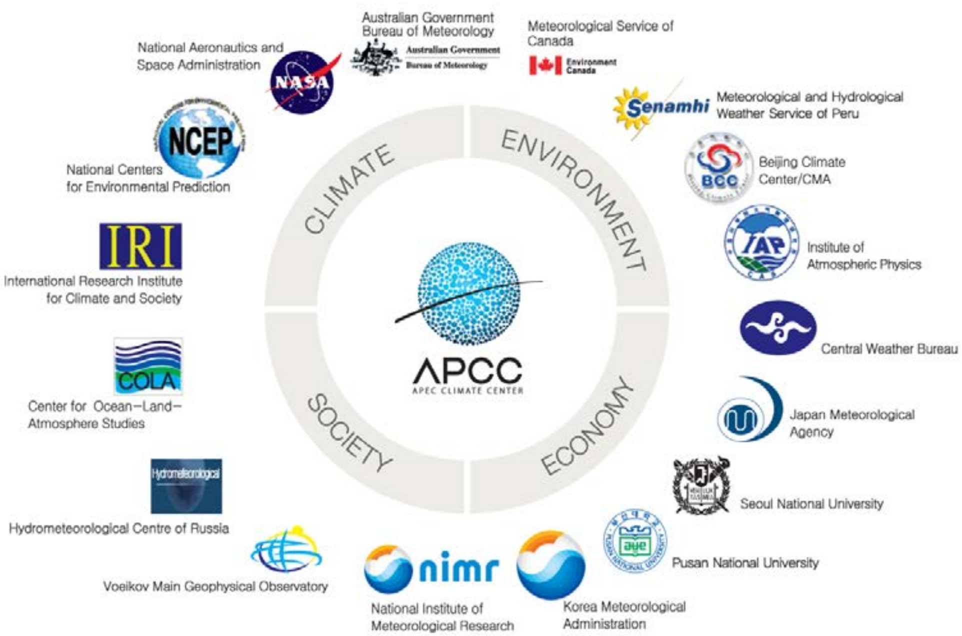




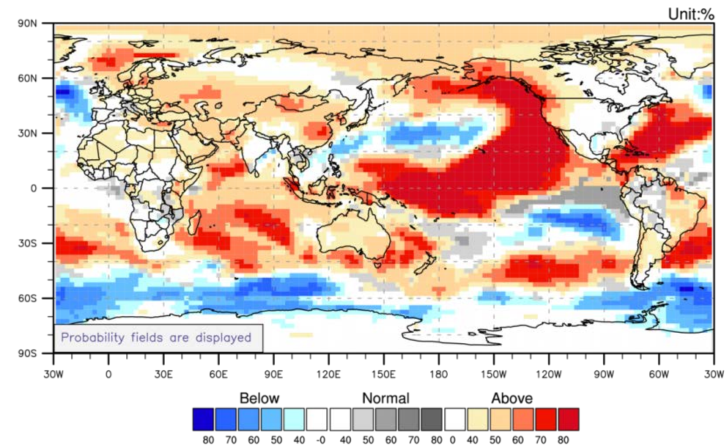
Integrated Downscaling System for Seasonal Prediction

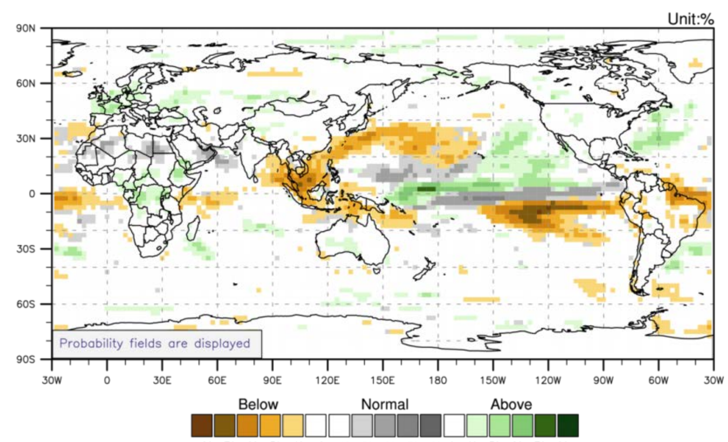


APCC Multi-Model Ensemble (MME)

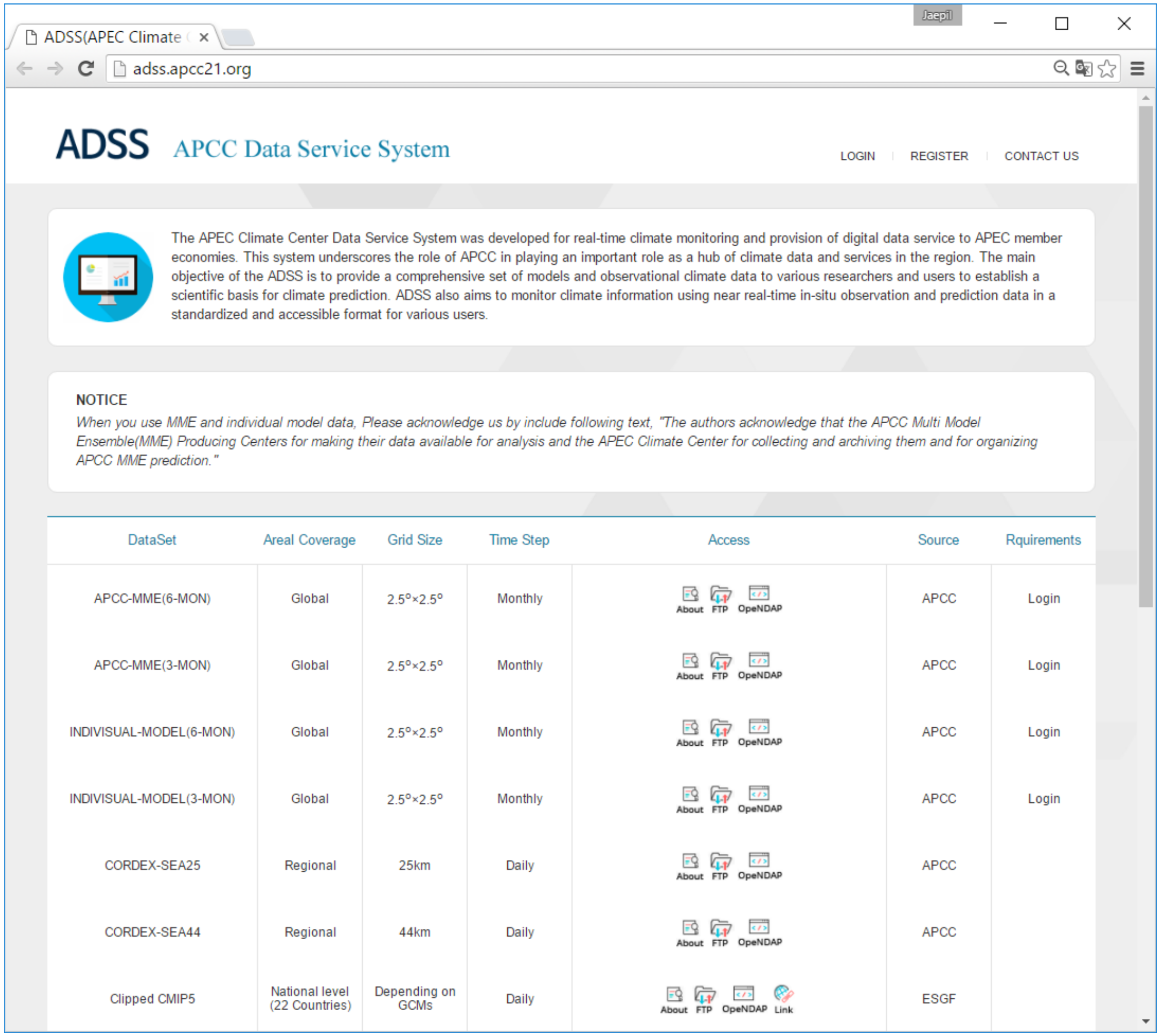


Multi-Model Ensemble (MME)





APCC Data Service System (ADSS)



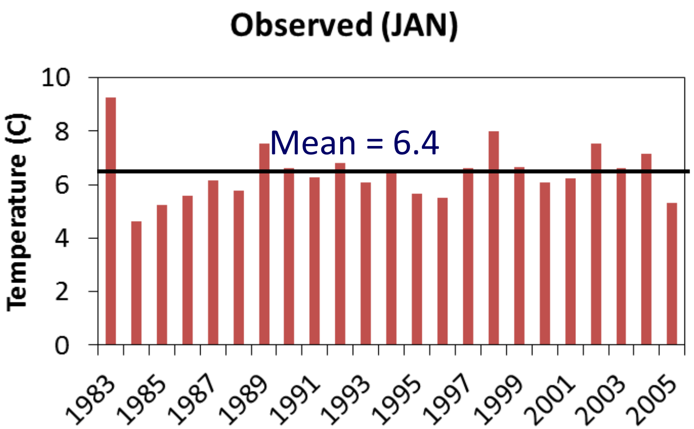
ADSS: http://adss.apcc21.org/

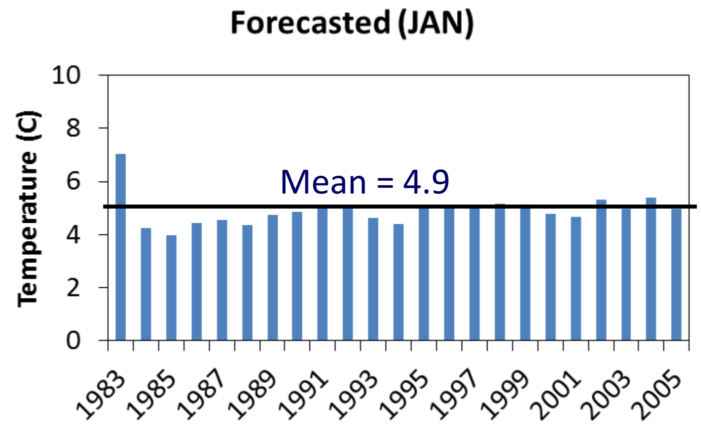
Available individual models for real-time forecast

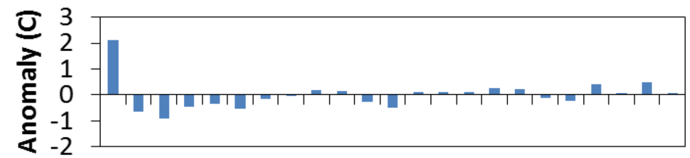
Model acronym	Institution(country)	Lead time	Ensemble size
BCC	Beijing Climate Center (China)	3 month	8
CWB	Central Weather Bureau (Taipei)	3 month	10
HMC	Hydrometeorological Centre of Russia (Russia)	3 month	20
IRI_CA	International Research Institute for Climate and Society (USA)	3 month	24
APCC	APEC Climate Center (Korea)	6 month	10
CMCC	Centro Euro-Mediterraneo sui Cambiamenti Climatici (Italy)	6 month	9
MSC	Meteorological Service of Canada (Canada)	6 month	20
NASA	National Aeronautics and Space Administration (USA)	6 month	9
NCEP	NCEP Climate Prediction Center (USA)	6 month	15
PNU	Pusan National University (Korea)	6 month	5
POAMA	Centre for Australian Weather and Climate Research /Bureau of Meteorology (Australia)	6 month	10

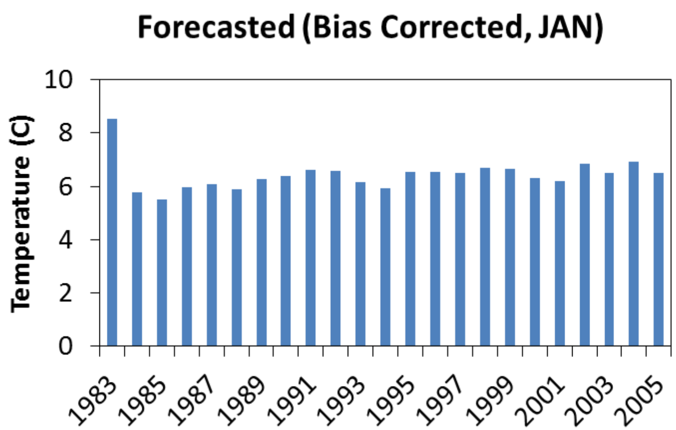
3MON: 4 GCMs, 6MON: 7 GCMs

Simple Bias Correction (SBC)









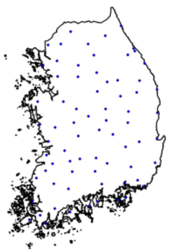
- **Temporal**: same
- **Spatial**: same
- **Variable**: same

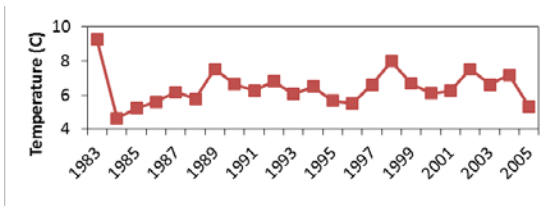
$$T'_{y,m} = (T_{y,m} - T_{hist,m}) + T_{obs,m}$$

$$P'_{y,m} = \begin{cases} (P_{y,m} - P_{hist,m}) + P_{obs,m} & \text{for } P_{y,m} \geq P_{obs,m} \\ (P_{y,m} \div P_{hist,m}) \times P_{obs,m} & \text{for } P_{y,m} < P_{obs,m} \end{cases}$$

Moving Window Regression (MWR)

Observed





Temperature
(JAN, 1983~2005,Korea)

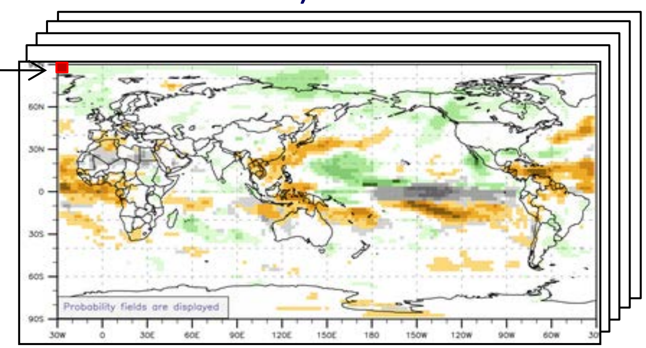
Temp = a *SLP + b

- **Temporal**: same
- **Spatial**: different
- **Variable**: different

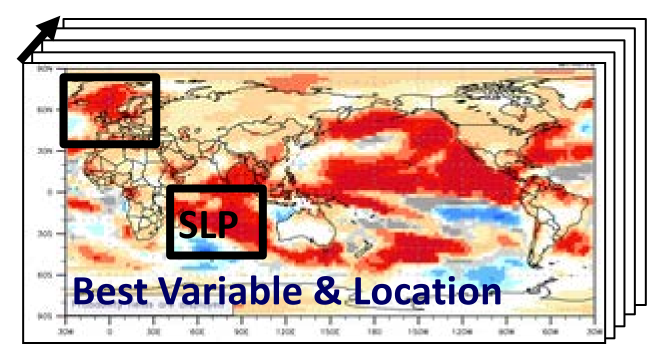
Forecasted

Models: BCC, CWB, HMC, IRI_CA, APCC, CMCC, MSC, NASA, NCEP, PNU, POAMA

Variables: PREC, T2M, T850, U200, V200, U850, V850, Z500, SLP, SST (JAN, 1983~2013)

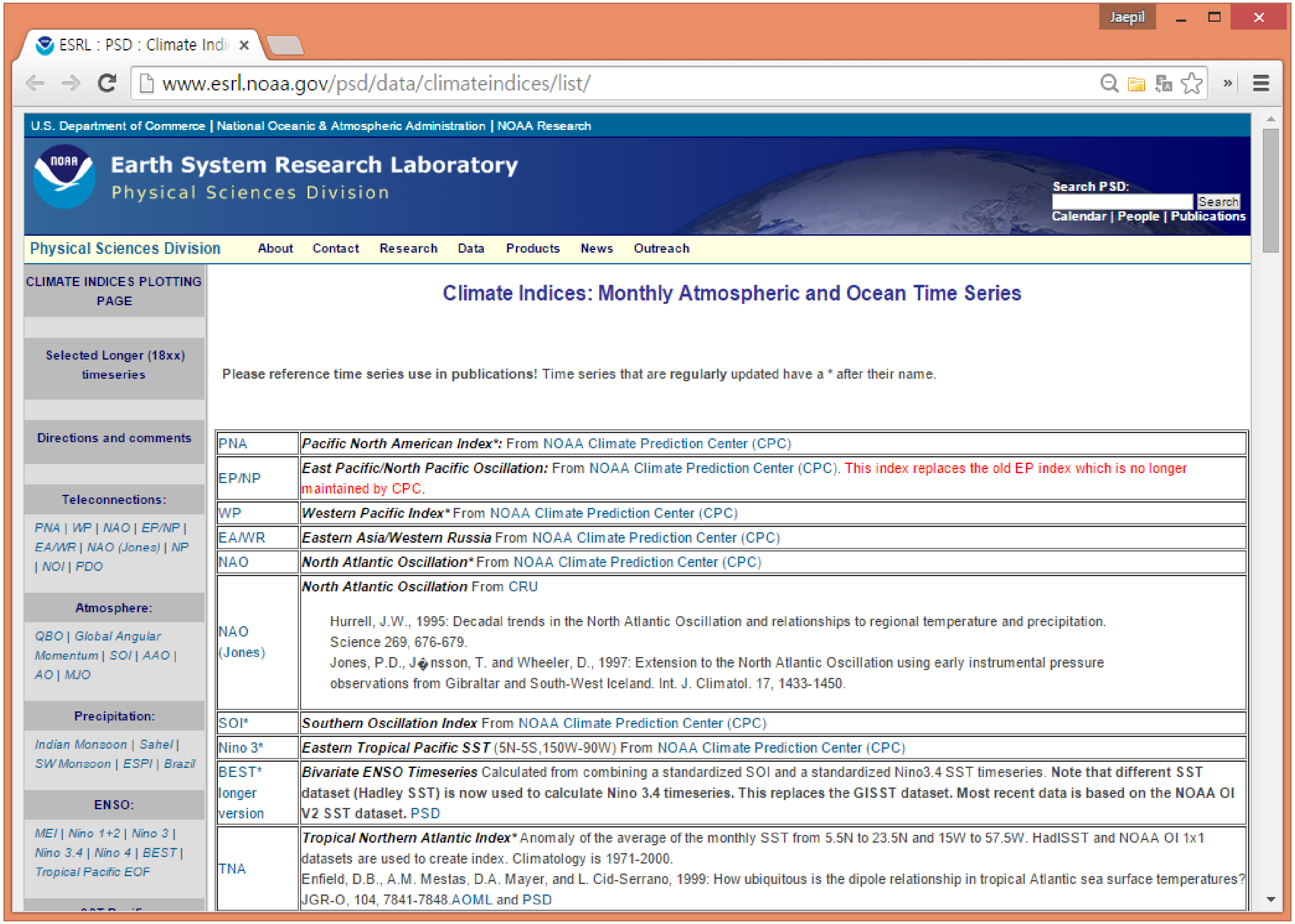


Temporal Correlation Coefficient (TCC)



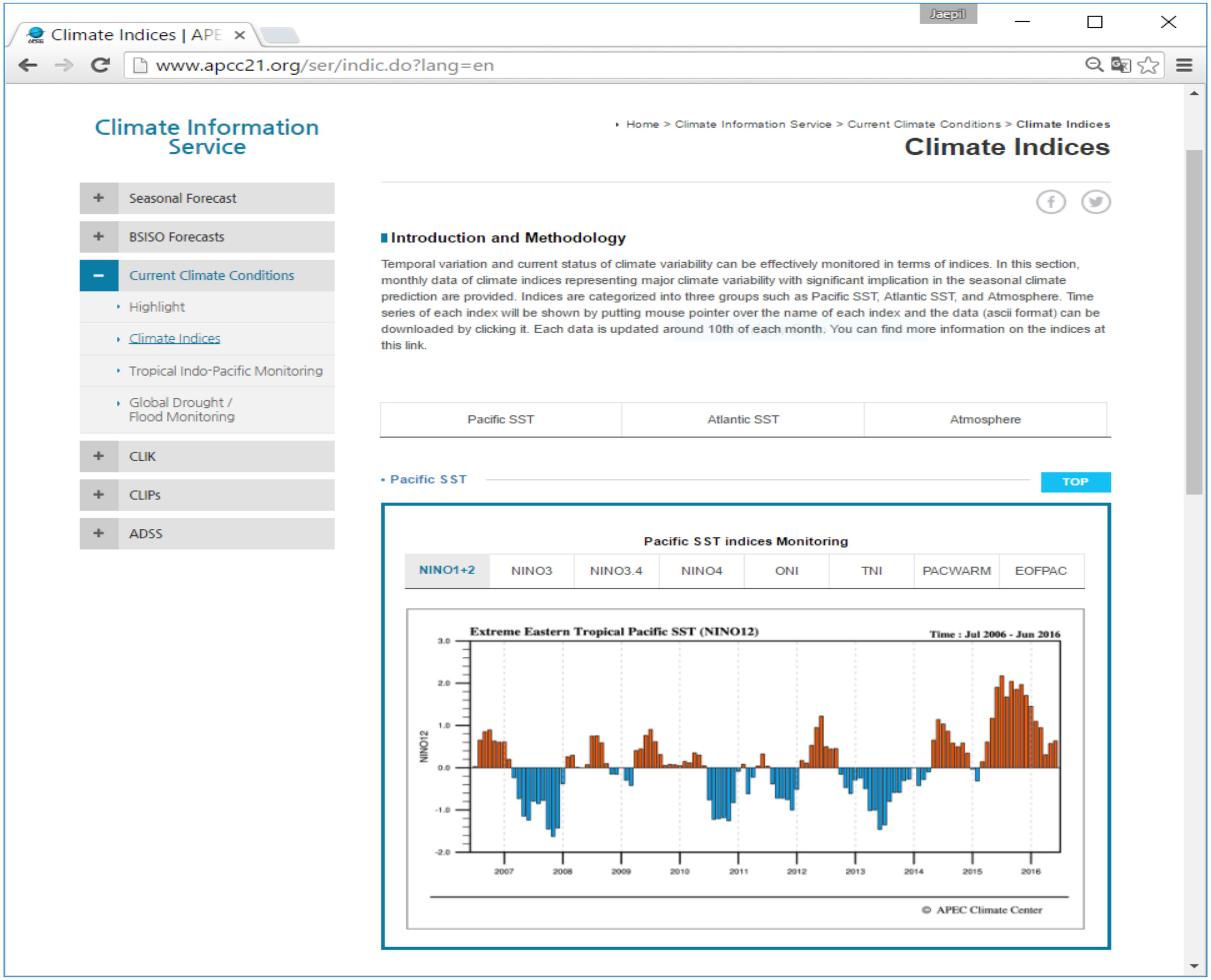
(Kang et al., 2009)

Monthly climate indices from NOAA



http://www.esrl.noaa.gov/psd/data/climateindices/list/

Monthly climate indices from APCC



http://www.apcc21.org/ser/indic.do?lang=en

Monthly climate indices for real-time forecast

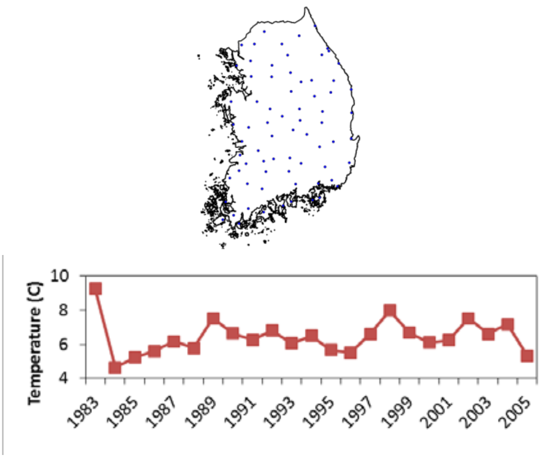
Climate index	Abb.	NOAA	APCC
Pacific North American Index	PNA	S	○
East Pacific/North Pacific Oscillation	EP	S	X
Western Pacific Index	WP	S	○
Eastern Asia/Western Russia	EA	X	X
North Atlantic Oscillation	NAO	S	○
Southern Oscillation Index	SOI	S	○
Eastern Tropical Pacific SST	NINO3	S	○
Bivariate ENSO Timeseries	BEST	X	X
Tropical Northern Atlantic Index	TNA	S	○
Tropical Southern Atlantic Index	TSA	S	○
Western Hemisphere warm pool	WHWP	S	X
Oceanic Nino Index	ONI	X	S
Multivariate ENSO Index	MEI	S	X
Extreme Eastern Tropical Pacific SST	NINO12	S	○
Central Tropical Pacific SST	NINO4	S	○
East Central Tropical Pacific SST	NINO34	S	
Pacific Decadal Oscillation	PDO	X	X
Northern Oscillation Index	NOI	X	S
North Pacific pattern	NP	X	S
Trans-Niño Index	TNI	X	S

Climate index	Abb.	NOAA	APCC
Antarctic Oscillation	AO	X	S
Antarctic Oscillation	AAO	X	S
Pacific Warmpool (1st EOF of SST (60e-170E, 15S-15N) SST EOF)	PACWARM	X	S
Tropical Pacific SST EOF	EOFPAC	X	S
Atlantic Tripole SST EOF	ATLTRI	X	S
Atlantic multidecadal Oscillation Long Version	AMO	S	X
Atlantic Meridional Mode	AMM	X	X
North Tropical Atlantic SST Index	NTA	X	X
Caribbean SST Index	CAR	X	X
smoothed: Atlantic Multidecadal Osillation	AMOSM	X	X
Quasi-Biennial Oscillation	QBO	S	○
Globally Integrated Angular Momentum	GIAM	X	X
ENSO precipitation index	ESPI	X	X
Central Indian Precipitation	CIP	X	X
Sahel Standardized Rainfall	SahelRain	X	X
SahelArea averaged precipitation for Arizona and New Mexico	SWM	X	X
Northeast Brazil Rainfall Anomaly	NBRA	X	X
Global Mean Lan/Ocean Temperature	GML	X	X
Solar Flux (10.7cm)	Solar	X	X
Equatorial Eastern Pacific SLP	ESL	S	X

16 Indices from NOAA
9 indices from NCEP Reanalysis 1 (APCC)

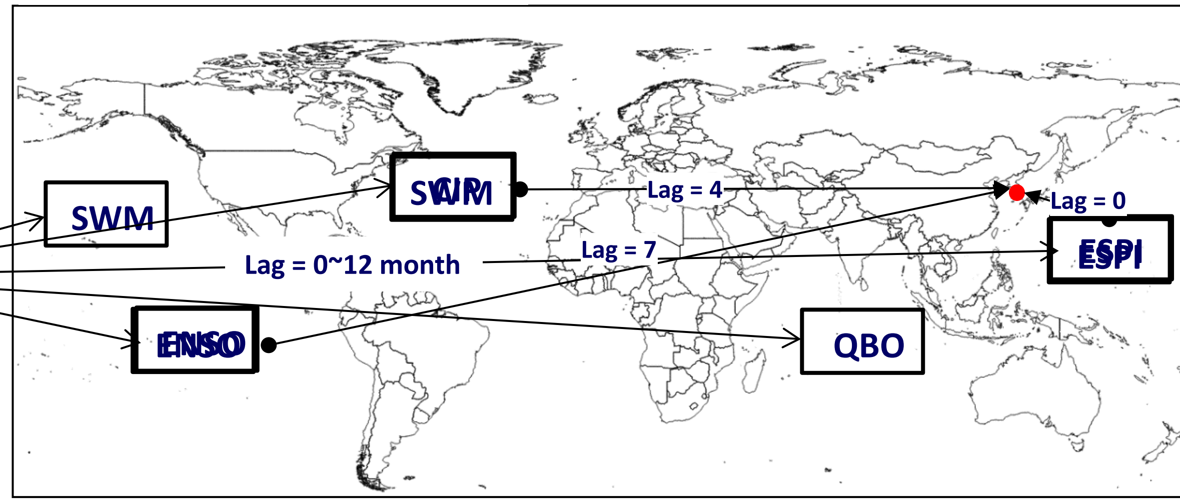
Climate Index Regression (CIR)

Observed



Temperature
(JAN, 1983~2005,Korea)

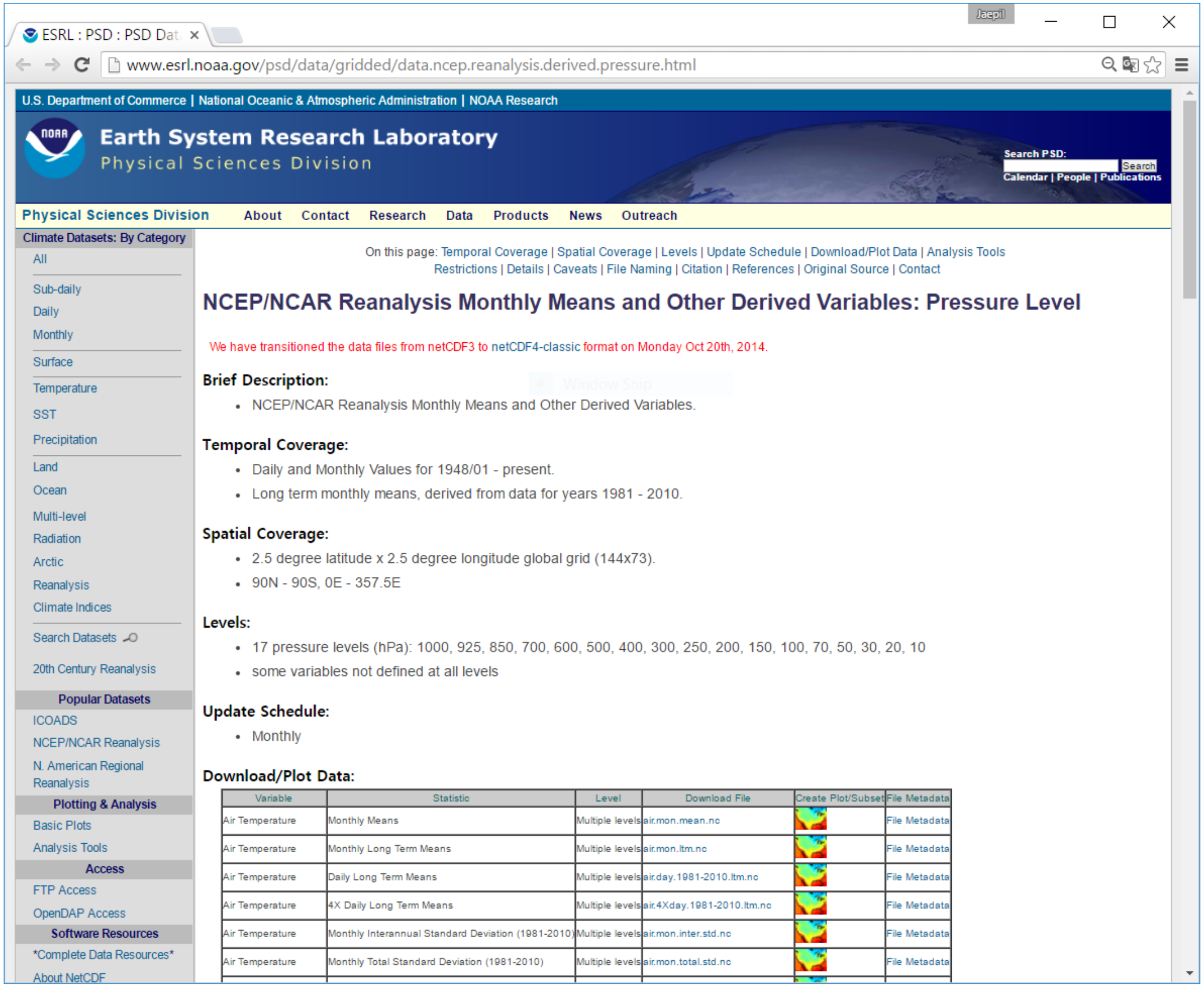
Climate Index from CPC



1. Linear regression (all CIs * Lags)
2. Select N best CIs and Lags
3. Decide multivariate regression model
   Y = a *ENSO_lag7 + b*ESPⓘ lag0 + c

- **Temporal**: different
- **Spatial**: different
- **Variable**: different

NCEP/NCAR Reanalysis monthly data



ESRL : PSD : PSD Dat ×

www.esrl.noaa.gov/psd/data/gridded/data.ncep.reanalysis.derived.pressure.html

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On this page: Temporal Coverage | Spatial Coverage | Levels | Update Schedule | Download/Plot Data | Analysis Tools
Restrictions | Details | Caveats | File Naming | Citation | References | Original Source | Contact

NCEP/NCAR Reanalysis Monthly Means and Other Derived Variables: Pressure Level

We have transitioned the data files from netCDF3 to netCDF4-classic format on Monday Oct 20th, 2014.

Brief Description:

- NCEP/NCAR Reanalysis Monthly Means and Other Derived Variables.

Temporal Coverage:

- Daily and Monthly Values for 1948/01 - present.
- Long term monthly means, derived from data for years 1981 - 2010.

Spatial Coverage:

- 2.5 degree latitude x 2.5 degree longitude global grid (144x73).
- 90N - 90S, 0E - 357.5E

Levels:

- 17 pressure levels (hPa): 1000, 925, 850, 700, 600, 500, 400, 300, 250, 200, 150, 100, 70, 50, 30, 20, 10
- some variables not defined at all levels

Update Schedule:

- Monthly

Download/Plot Data:

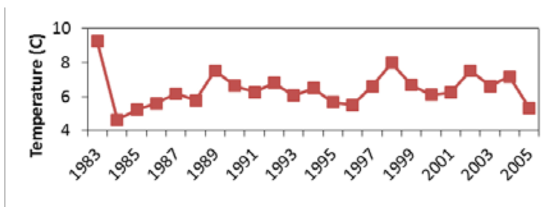
Variable	Statistic	Level	Download File	Create Plot/Subset	File Metadata
Air Temperature	Monthly Means	Multiple levels	air.mon.mean.nc		File Metadata
Air Temperature	Monthly Long Term Means	Multiple levels	air.mon.ltm.nc		File Metadata
Air Temperature	Daily Long Term Means	Multiple levels	air.day.1981-2010.ltm.nc		File Metadata
Air Temperature	4X Daily Long Term Means	Multiple levels	air.4Xday.1981-2010.ltm.nc		File Metadata
Air Temperature	Monthly Interannual Standard Deviation (1981-2010)	Multiple levels	air.mon.inter.std.nc		File Metadata
Air Temperature	Monthly Total Standard Deviation (1981-2010)	Multiple levels	air.mon.total.std.nc		File Metadata

http://www.esrl.noaa.gov/psd/data/gridded/data.ncep.reanalysis.derived.pressure.html

Observed Moving Window Regression (MWR-Obs)

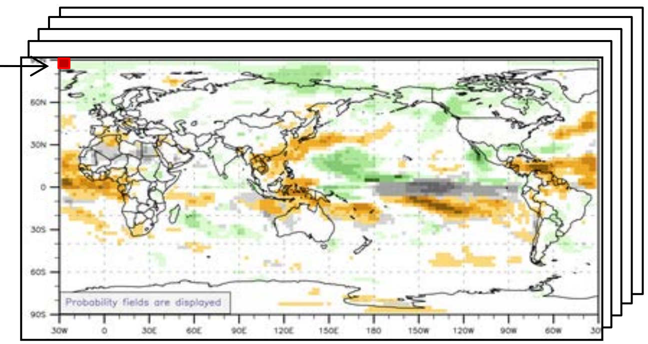
Reanalysis 1

Variables: PREC, T2M, T850, U200, V200, U850, V850, Z500, SLP, SST



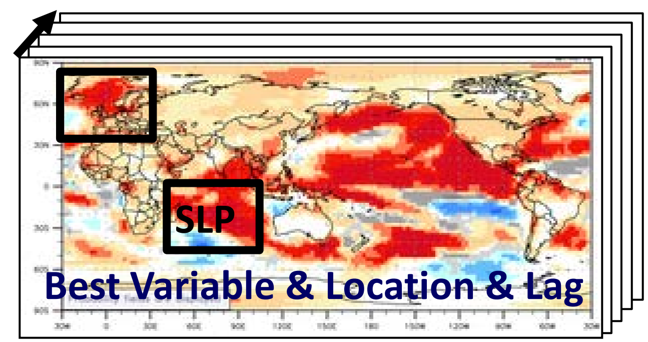
Temperature
(JAN, 1983~2005,Korea)

Lag = 0~12 month



$$Temp = a * SLP + b$$

Temporal Correlation Coefficient (TCC)



- **Temporal**: different
- **Spatial**: different
- **Variable**: different

Comparison of seasonal forecast modules

- Simple Bias Correction (SBC): Forecast-based direct method
- Moving Window Regression (MWR): Forecast-based indirect method
- Climate Index Regression (CIR): Observation-based indirect method
- Moving Window Regression-Observed (MWR-Obs): Observation-based direct method

	SBC	MWR	CIR	MWR-Obs
Used climate information	Individual Seasonal Forecast models (APCC)	Individual Seasonal Forecast models (APCC)	NOAA/APCC climate indices	NCEP/NCAR Reanalysis1
Are the target variable and predictor same?	Yes	No	No	No
Are the target area and selected area for predictor same?	Yes	No	No	No
Are the target variable and predictor simultaneous?	Yes	Yes	No (lag-time)	No (lag-time)

Temporal Downscaling Method

APCC
APEC CLIMATE CENTER

Forecasted Area Average

yearmon	prec	t2m
Jan-83	0.623	-2.182
Feb-83	1.622	2.326
Mar-83	1.452	7.280
Apr-83	3.505	11.880
May-83	2.701	[illegible]
Jun-83	3.572	[illegible]
Jul-83	8.453	[illegible]
Aug-83	9.573	24.774
Sep-83	7.755	20.920
Oct-83	2.115	14.774
Nov-83	2.419	6.643
Dec-83	0.221	1.669
Jan-84	0.189	-1.225
Feb-84	0.017	0.270
Mar-84	0.912	3.338

Jan-81

Mahalanobis distance = f(prec, t2m)

Observed Area Average

yearmon	prec	t2m
Jan-73	0.673	-1.631
Feb-73	1.789	2.631
Mar-73	1.428	7.052
Apr-73	3.586	12.139
[illegible]	2.619	17.243
[illegible]	3.681	21.332
[illegible]	7.041	23.314
Aug-73	8.509	24.722
Sep-73	7.145	20.680
Oct-73	2.092	14.745
Nov-73	2.375	7.133
Dec-73	0.151	1.442
.	0.076	-1.409
.	0.123	-0.368
Jan-11	0.997	-1.826
Feb-11	2.313	1.354
Mar-11	2.659	5.750
Apr-11	0.904	12.704
May-11	4.124	17.254
Jun-11	6.330	20.626
Jul-11	10.191	25.146
Aug-11	4.078	27.135
Sep-11	6.269	20.657
Oct-11	3.736	14.392
Nov-11	0.783	8.224
Dec-11	0.972	1.381

ID135

date	prcp	tmax	tmin	wspd	rhum	rsds

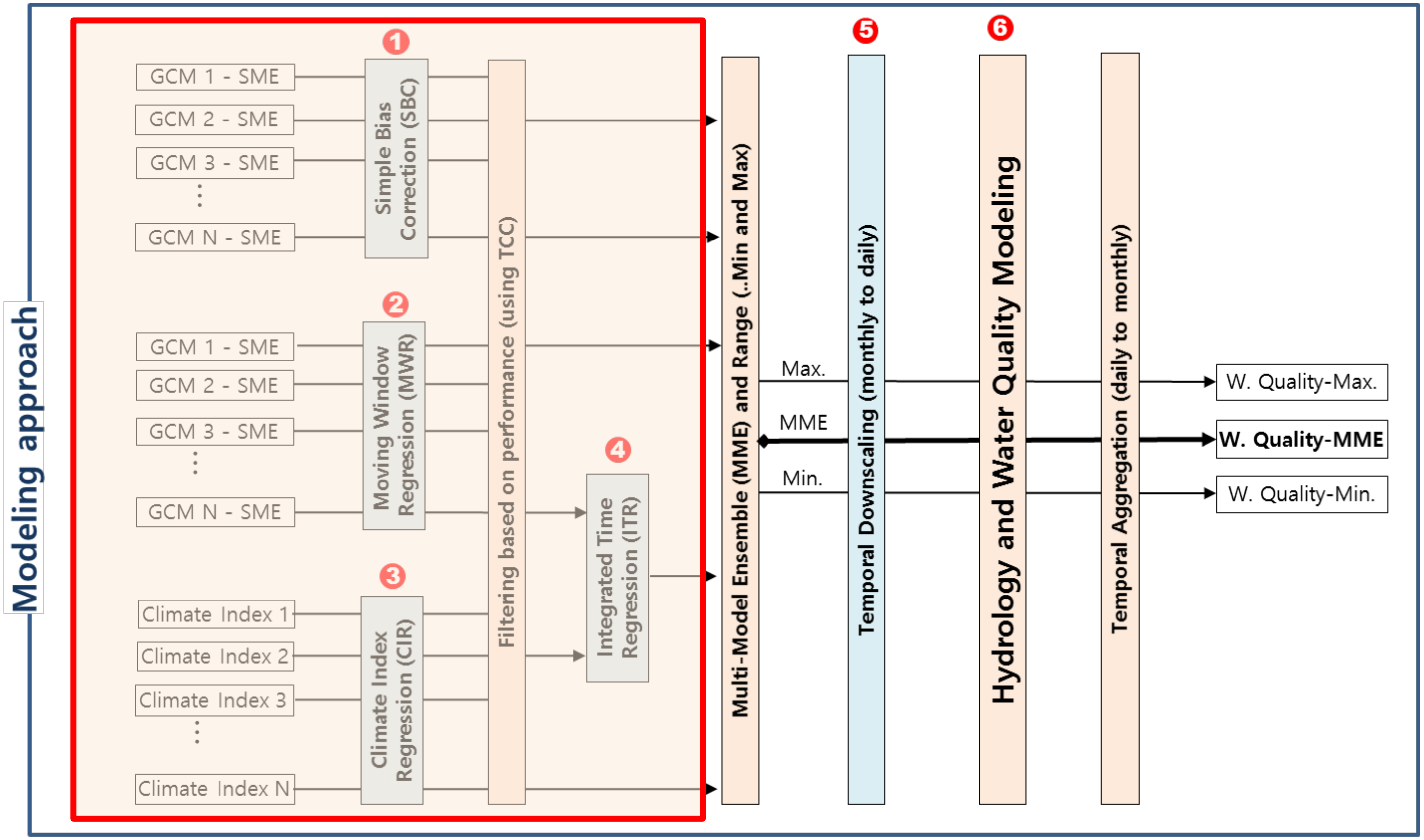
ID136

date	prcp	tmax	tmin	wspd	rhum	rsds

ID137

date	prcp	tmax	tmin	wspd	rhum	rsds
1981-01-01	0.8	1.4	-2.8	3.81	0.62	2.5
1981-01-02	0	-1.7	-7.9	9.43	0.47	5
1981-01-03	0	-3.2	-9.7	9.61	0.39	5.4
1981-01-04	0	-1.5	-9.7	5.05	0.34	7.1
1981-01-05	0	-2.7	-9.2	7.61	0.26	5.4
1981-01-06	0	0.8	-8.8	7.07	0.27	8.1
1981-01-07	0	3.6	-4.4	6.43	0.26	7.1
1981-01-08	0	6.4	-3	4.35	0.36	8
1981-01-09	0	7	-2.8	7.98	0.46	8.3
1981-01-10	0	0	-7	6.35	0.41	6.2
1981-01-11	0	0	-8.8	7.96	0.44	7.8
1981-01-12	0	0.8	-5.5	6.59	0.35	5.4
1981-01-13	0	-1.4	-8.4	5.18	0.39	6.3
1981-01-14	0	0.6	-10.4	3.1	0.45	8.9
1981-01-15	15.9	-1.7	-6	2.7	0.81	2.8
1981-01-16	0.1	0.3	-6.2	2.65	0.71	5.7
1981-01-17	0	2.6	-6.9	3.03	0.51	8.5
1981-01-18	0	3.2	-4.5	4.52	0.48	7.1
1981-01-19	0	0.9	-6.4	2.88	0.64	6.8
1981-01-20	0	2.4	-5.4	4.58	0.39	7.4
1981-01-21	0	0.3	-6.4	4.36	0.44	6.2
1981-01-22	0	-0.2	-9.1	2.43	0.5	8.5
1981-01-23	0	2.8	-6.7	1.52	0.58	9
1981-01-24	0	3.1	-1.5	3.16	0.72	3.4
1981-01-25	0	2.4	-4.6	3.82	0.62	6.9
1981-01-26	0	-0.2	-7.9	3.02	0.47	7.9
1981-01-27	0	0.6	-6.1	3.12	0.41	6.6
1981-01-28	0	3.1	-6.5	2.71	0.46	9.4
1981-01-29	0	4.2	-4.1	3.8	0.48	8.6
1981-01-30	0	5.6	-6.3	2.69	0.5	10
1981-01-31	0	3.2	-5.8	1.93	0.53	9.3

Result of Seasonal Forecast



Down Scaling (Spatial & Temporal)

SME: Single model ensemble
MME: Multi-model ensemble

TCC: Temporal Correlation Coefficient
GCM: Global climate models for seasonal forecast

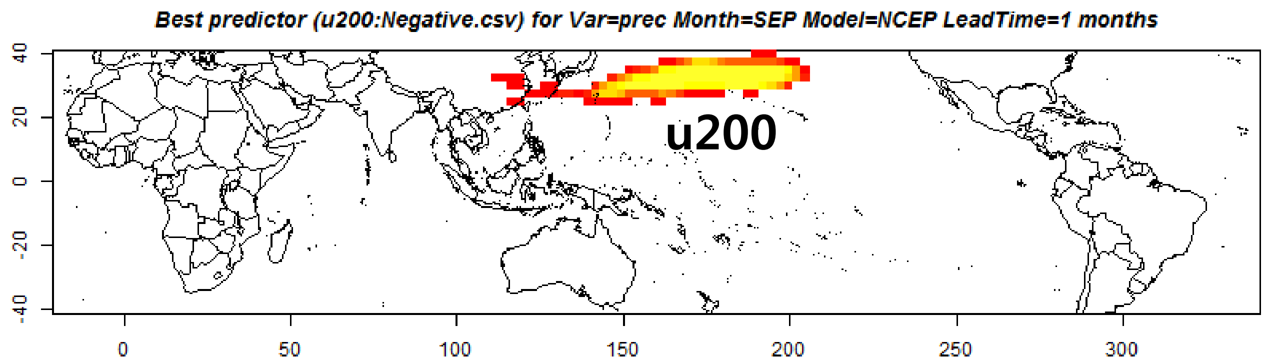
APCC
APEC CLIMATE CENTER

Selected Method and Models for Precipitation

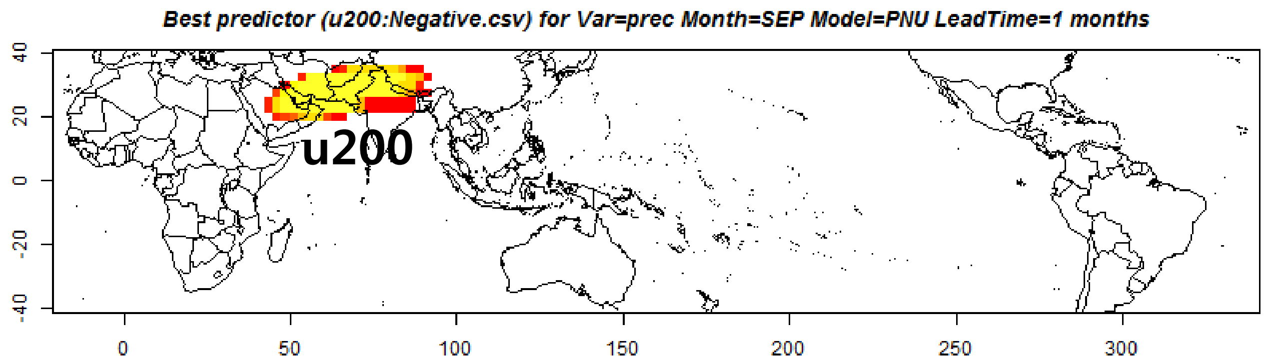
Lead time	1 month lead	2 month lead	3 month lead
Jan	ⓢ JMA, ⓢ POAMA		
Feb		ⓜ CWB	ⓜ GDAPS_F
Mar	ⓢ POAMA		
Apr			ⓢ NASA, ⓢ HMC ⓜ NCEP, ⓜ PNU
May			
Jun	ⓜ HMC	ⓜ MSC_CANCM4	
Jul	ⓒ Lag	ⓒ Lag	ⓘ PNU
Aug	ⓢ JMA	ⓢ GDAPS_F	ⓜ POAMA
Sep	ⓜ NCEP, ⓜ PNU ⓜ POAMA	ⓢ PNU	ⓢ GDAPS_F, ⓢ PNU
Oct			ⓜ MSC_CANCM4
Nov	ⓢ PNU	ⓢ GDAPS_F, ⓢ PNU ⓢ JMA	ⓢ PNU, ⓢ JMA ⓢ POAMA ⓜ MSC_CANCM3
Dec	ⓢ POAMA ⓜ MSC_CANCM4 ⓜ PNU	ⓢ JMA, ⓢ POAMA ⓜ HMC, ⓜ POAMA	ⓢ POAMA ⓜ GDAPS_F ⓜ POAMA ⓜ NASA

Selected predictors in MWR (Ex. 1 month lead September precipitation)

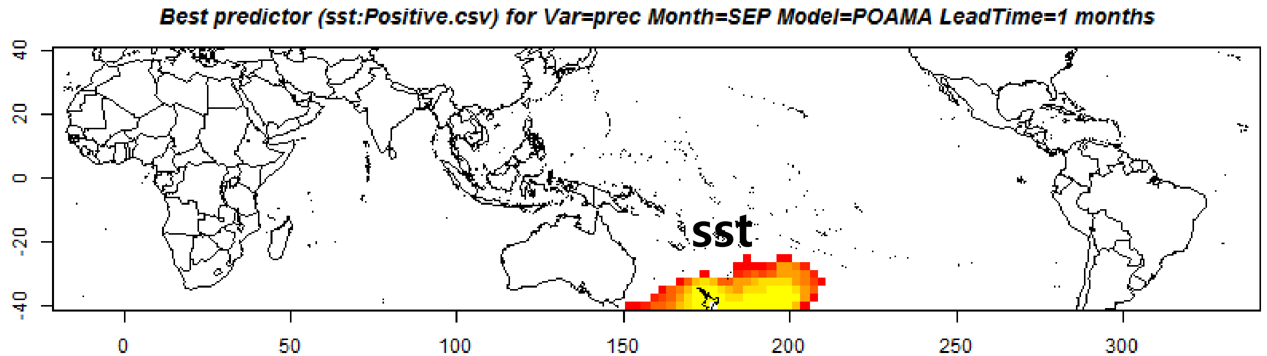
NCEP



PNU



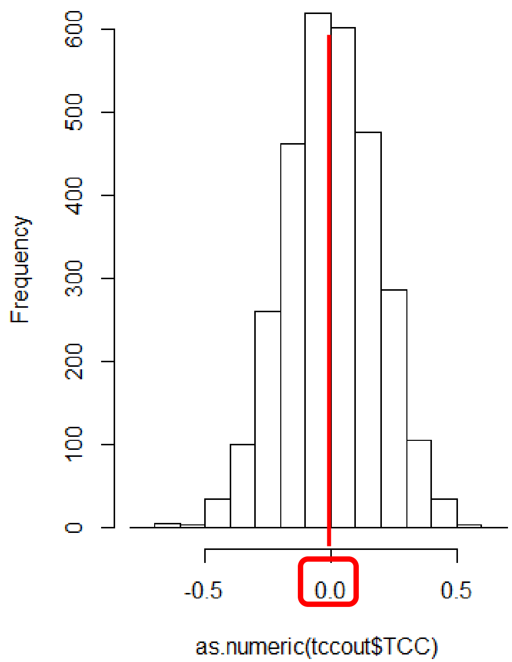
POAMA



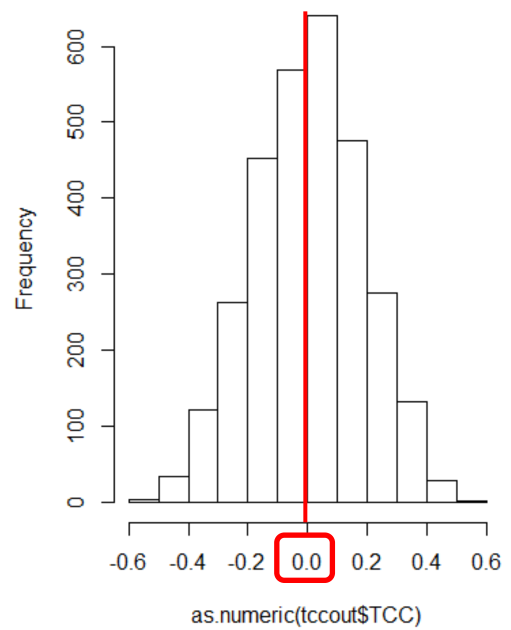
Selected Method and Models for Temperature

Variables	TEMP	TEMP	TEMP
Jan	ⓢ GDAPS_F, ⓢ PNU, ⓢ MSC_CANCM3, ⓢ MSC_CANCM4, ⓜ POAMA	ⓢ POAMA	ⓜ CWB
Feb		ⓢ JMA	
Mar	ⓢ GDAPS_F, ⓢ JMA		
Apr	ⓜ GDAPS_F	ⓢ NASA	
May	ⓜ CWB	ⓜ PNU	ⓜ MSC_CANCM3
Jun			
Jul	ⓢ JMA	ⓜ GDAPS_F	
Aug	ⓢ HMC, ⓢ PNU		ⓜ CWB
Sep	ⓢ GDAPS_F, ⓢ HMC, ⓢ JMA, ⓢ PNU, ⓢ NASA, ⓢ POAMA ⓘ NASA	ⓢ GDAPS_F, ⓢ NASA, ⓢ PNU, ⓘ MSC_CANCM4, ⓘ NCEP	ⓢ GDAPS_F, ⓢ HMC, ⓢ JMA, ⓢ NASA, ⓢ PNU ⓒ Lag
Oct	ⓢ GDAPS_F, ⓢ HMC, ⓢ PNU ⓘ MSC_CANCM3	ⓢ GDAPS_F, ⓢ JMA, ⓢ NASA, ⓢ PNU ⓒ Lag	ⓢ GDAPS_F ⓒ Lag
Nov	ⓢ POAMA		ⓢ JMA ⓜ PNU
Dec	ⓢ POAMA		ⓢ JMA

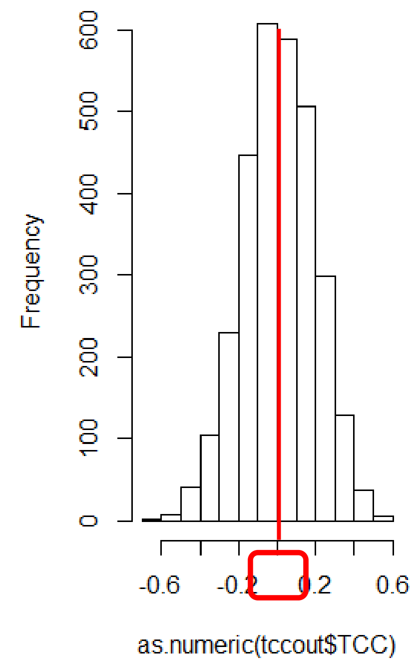
Random predictor test for evaluating cross-validation procedure



CIR
(3000 simulation)



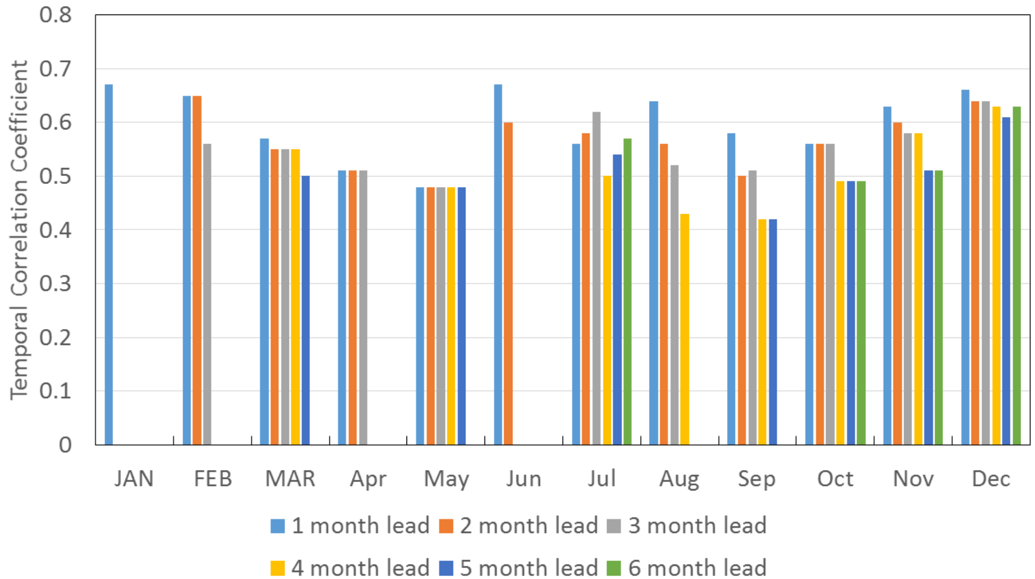
MWR
(3000 simulation)



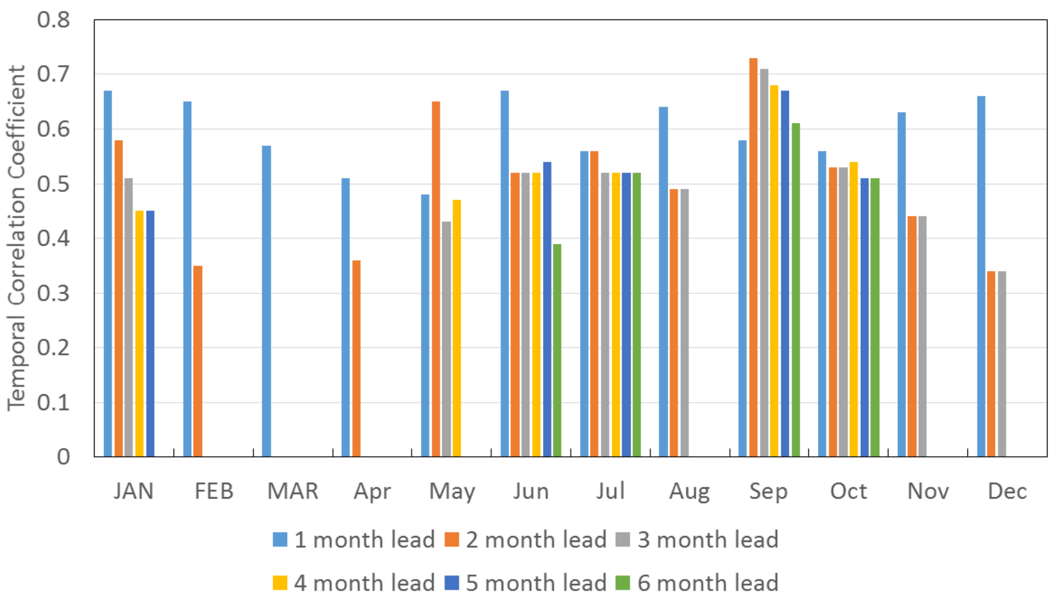
ITR
(3000 simulation)

➡ Cross-Validation procedure seem to be okay for CIR, MWR, and ITR methods without showing overfitting in temporal correlation coefficient (TCC).

Monthly Temporal Correlation Coefficient(TCC)



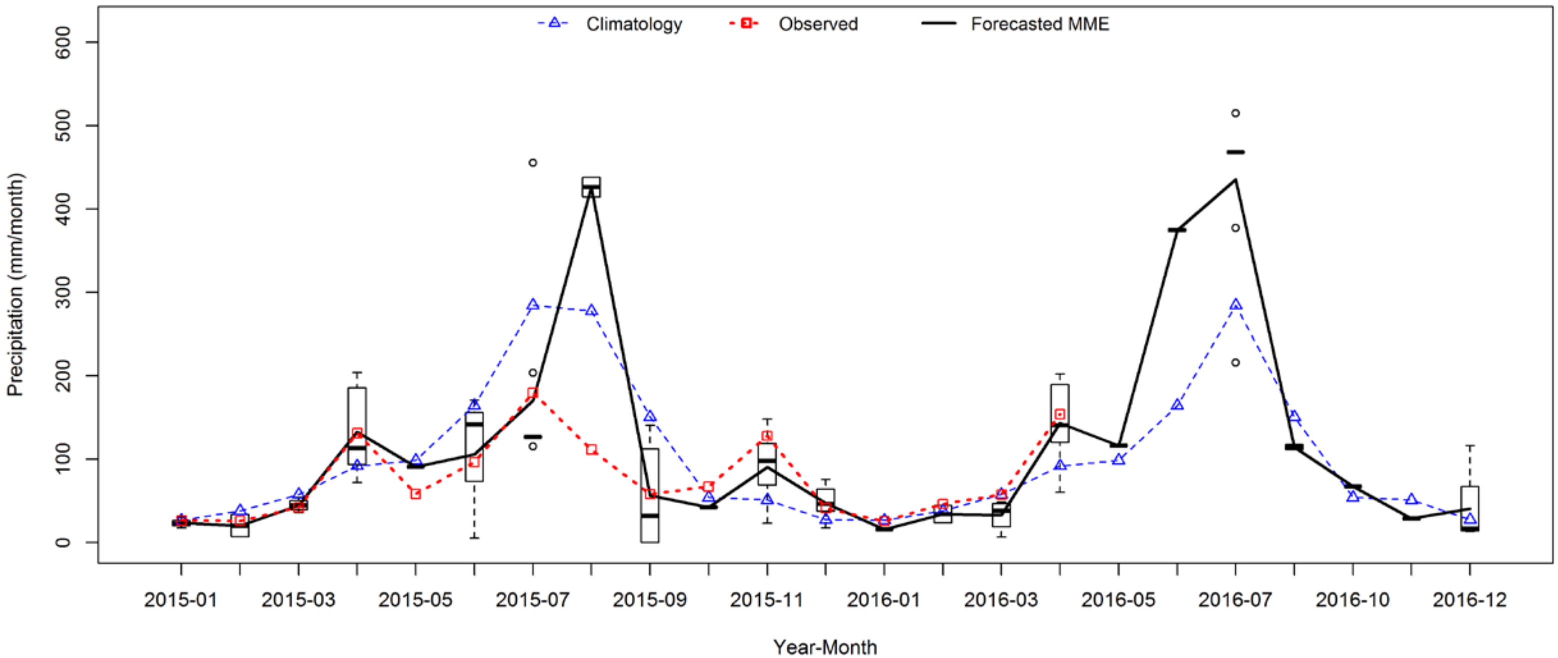
Month	1 month	2 month	3 month	4 month	5 month	6 month
JAN	0.67					
FEB	0.65	0.65	0.56			
MAR	0.57	0.55	0.55	0.55	0.5	
APR	0.51	0.51	0.51			
MAY	0.48	0.48	0.48	0.48	0.48	
JUN	0.67	0.6				
JUL	0.56	0.58	0.62	0.5	0.54	0.57
AUG	0.64	0.56	0.52	0.43		
SEP	0.58	0.5	0.51	0.42	0.42	
OCT	0.56	0.56	0.56	0.49	0.49	0.49
NOV	0.63	0.6	0.58	0.58	0.51	0.51
DEC	0.66	0.64	0.64	0.63	0.61	0.63



Month	1 month	2 month	3 month	4 month	5 month	6 month
JAN	0.67	0.58	0.51	0.45	0.45	
FEB	0.65	0.35				
MAR	0.57					
APR	0.51	0.36				
MAY	0.48	0.65	0.43	0.47		
JUN	0.67	0.52	0.52	0.52	0.54	0.39
JUL	0.56	0.56	0.52	0.52	0.52	0.52
AUG	0.64	0.49	0.49			
SEP	0.58	0.73	0.71	0.68	0.67	0.61
OCT	0.56	0.53	0.53	0.54	0.51	0.51
NOV	0.63	0.44	0.44			
DEC	0.66	0.34	0.34			

Example of seasonal precipitation forecast

6-month precipitation Forecast for JUL. 2016 - DEC. 2016 (Issued: 2016-06)



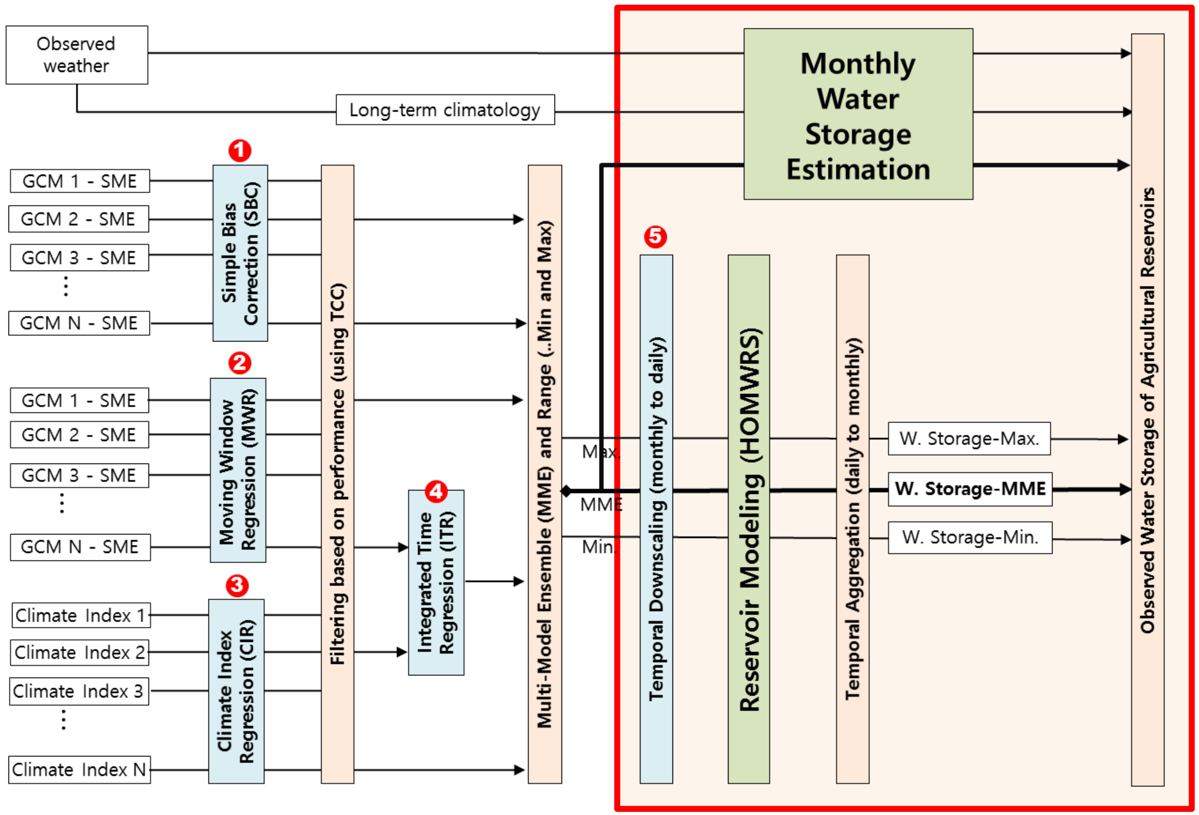
Monthly skil score for JAN. 1983 - APR. 2016

	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC
LT1-TCC	0.67	0.7	0.63	0.65	0.45	0.59	0.61	0.43	0.65	0.37	0.67	0.68
LT1-HSS	0.25	0.25	0.29	0.19	0.13	0.14	0.33	0.28	0.41	0.27	0.15	0.36
LT2-TCC	0.35	0.7	0.59	0.64	0.45	0.57	0.63	0.36	0.63	0.37	0.65	0.67
LT2-HSS	0.035	0.25	0.33	0.13	0.13	0.18	0.33	0.37	0.36	0.27	0.065	0.32
LT3-TCC	-	0.62	0.59	0.67	0.45	-	0.62	0.36	0.61	0.37	0.54	0.67
LT3-HSS	-	0.25	0.33	0.17	0.13	-	0.36	0.37	0.45	0.27	0.1	0.32
LT4-TCC	-	-	0.59	0.61	0.45	-	0.55	0.36	0.51	0.37	0.41	0.66
LT4-HSS	-	-	0.33	0.13	0.13	-	0.4	0.37	0.33	0.27	0.31	0.45
LT5-TCC	-	-	0.48	0.64	0.45	-	0.57	-	0.51	0.37	0.41	0.63
LT5-HSS	-	-	0.29	0.17	0.13	-	0.4	-	0.33	0.27	0.31	0.41
LT6-TCC	-	-	-	0.55	-	-	0.58	-	0.44	0.37	0.41	0.58
LT6-HSS	-	-	-	0.24	-	-	0.31	-	0.077	0.27	0.31	0.32

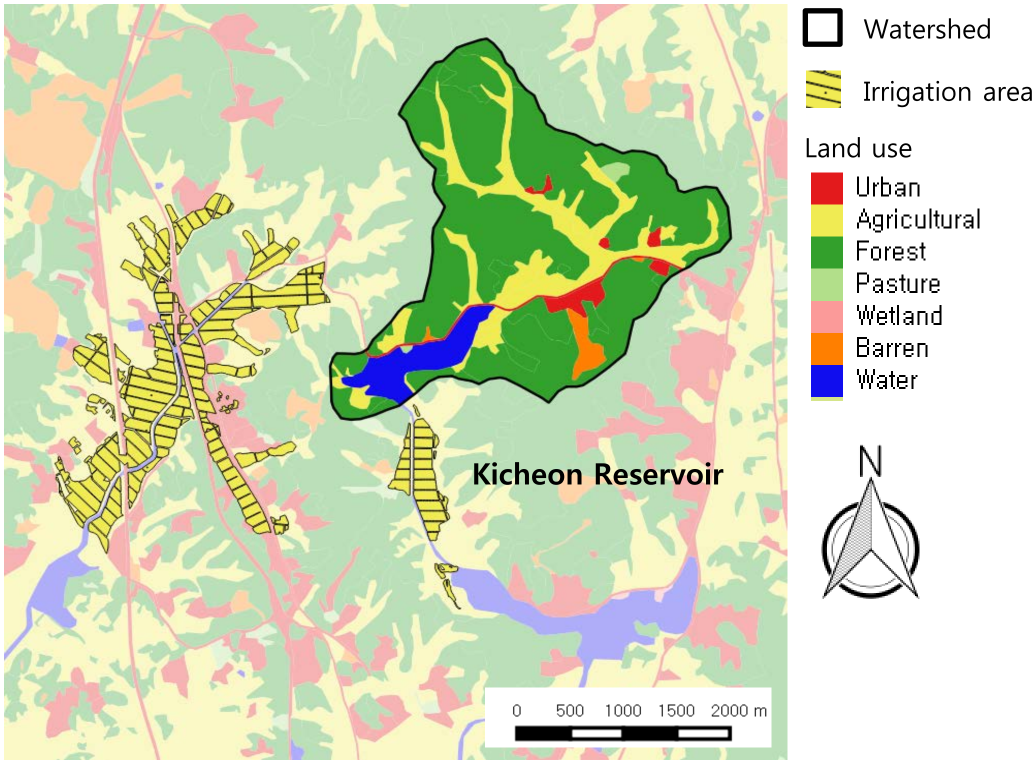
Probapbility forecast for 2016

	JUL	SEP	OCT	NOV	DEC
Low	11	0	0	100	75
Normal	0	100	0	0	0
High	89	0	100	0	25

Result of Water Storage Forecast



Seasonal Forecast Application for Kicheon Reservoir



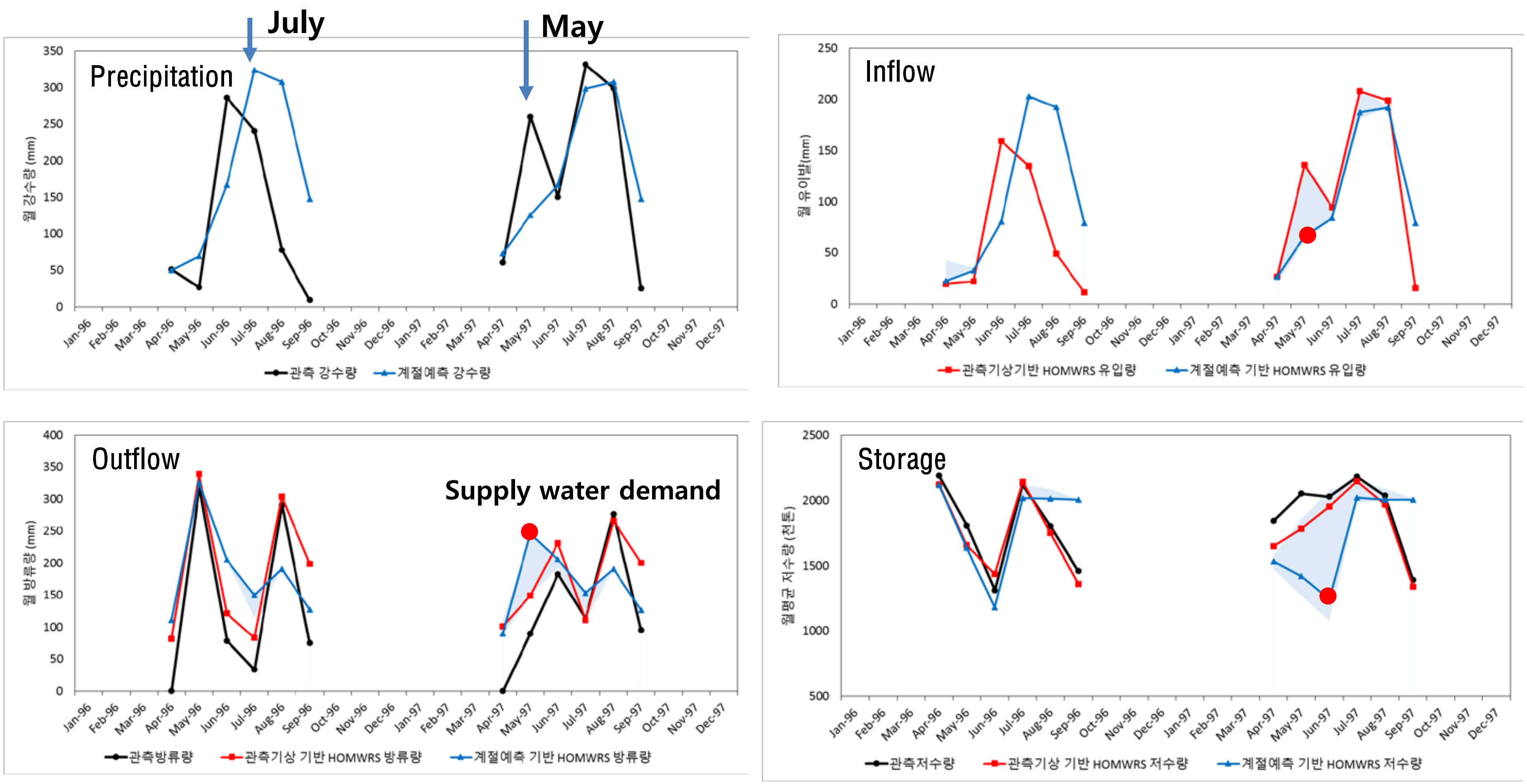
- Kicheon reservoir
  - Watershed area: 755 ha
  - Irrigation area: 270.7 ha

- HOMWRS modeling
  - Period: 1996 ~ 1997
  - 6 months forecast at every March

HOMWRS: Hydrological Operation Model for Water Resources System

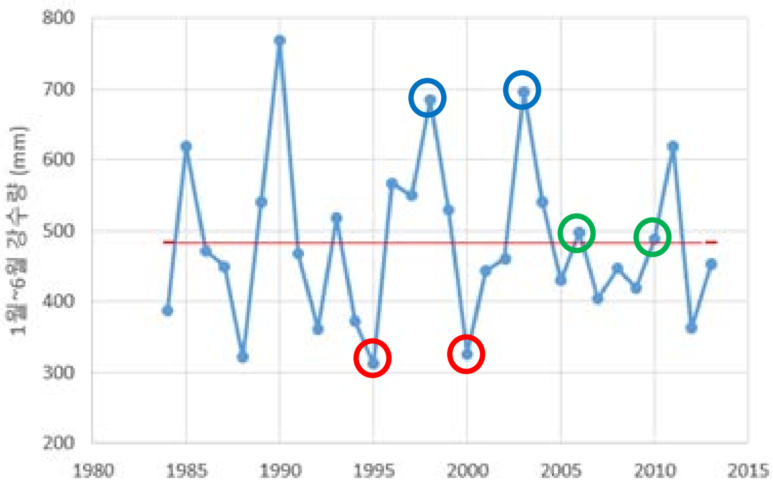
Seasonal Forecast Application for Kicheon Reservoir

- 1996 shows good agreement in storage level
- Underestimation of precipitation on May, 1997 resulted in overestimated water supply and underestimated storage level



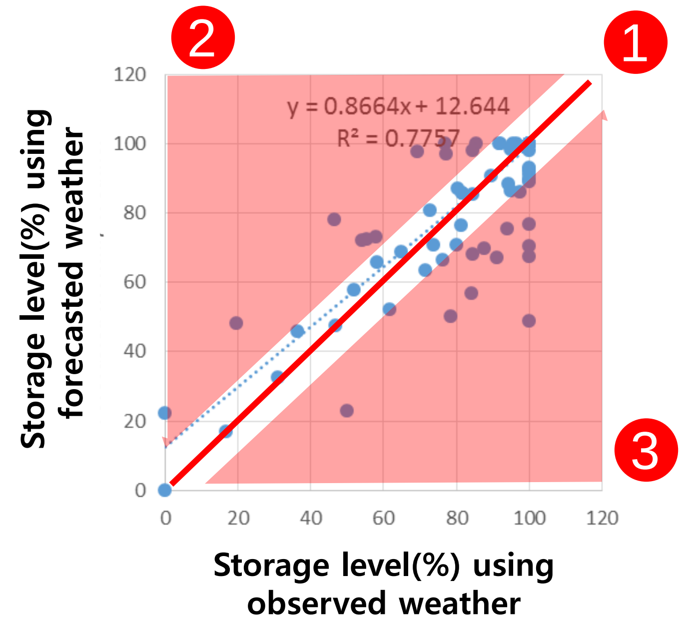
Monthly storage level forecast at Jun. 20 (462 Reservoirs, forecast issued at Jan. 15)

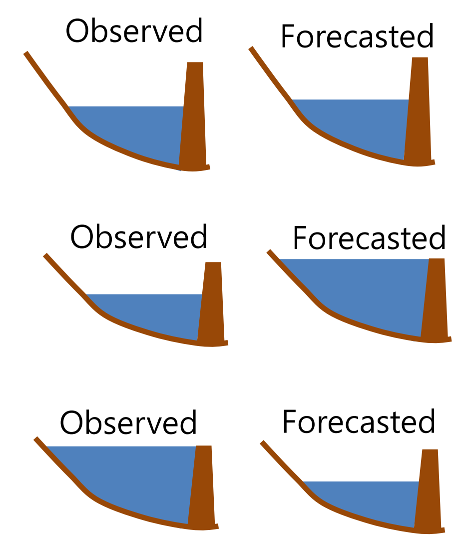
- 6-month lead forecasting



30 year (1984~2013) average of accumulated precipitation amount for JAN to JUN

- Wet years: 1998, 2003
- Normal years: 2006, 2010
- Dry years: 1995, 2005

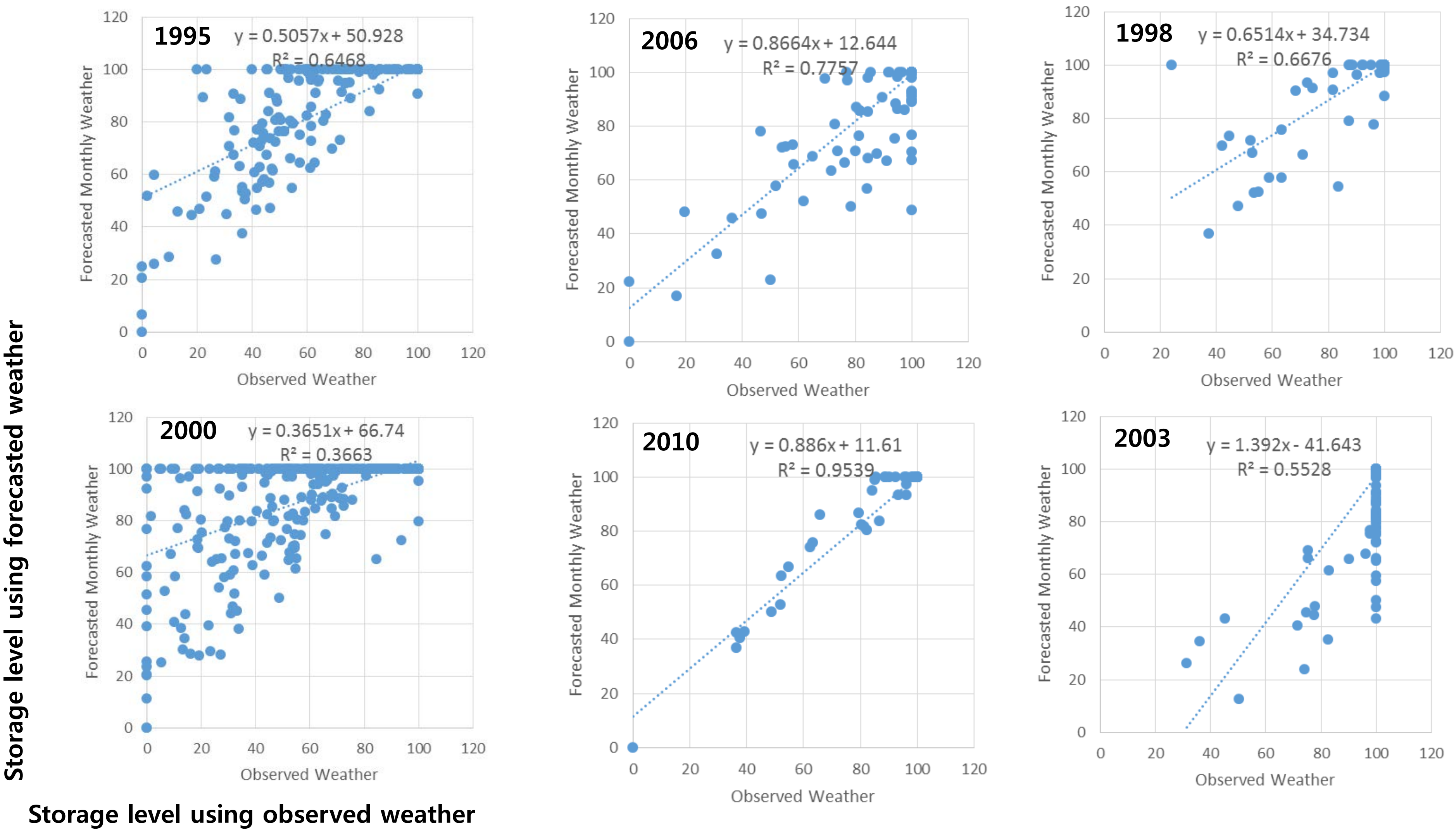




Result of monthly storage level forecast at Jun. 20 (462 Reservoirs, forecast issued at Jan. 15)

Dry years are underestimated

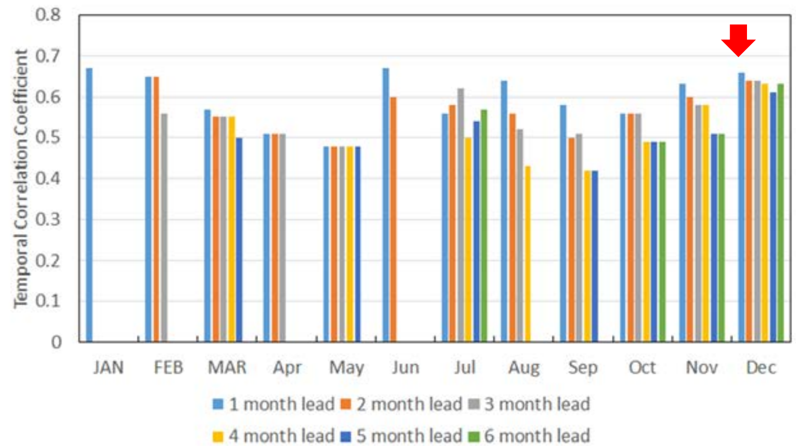
Wet years are overestimated

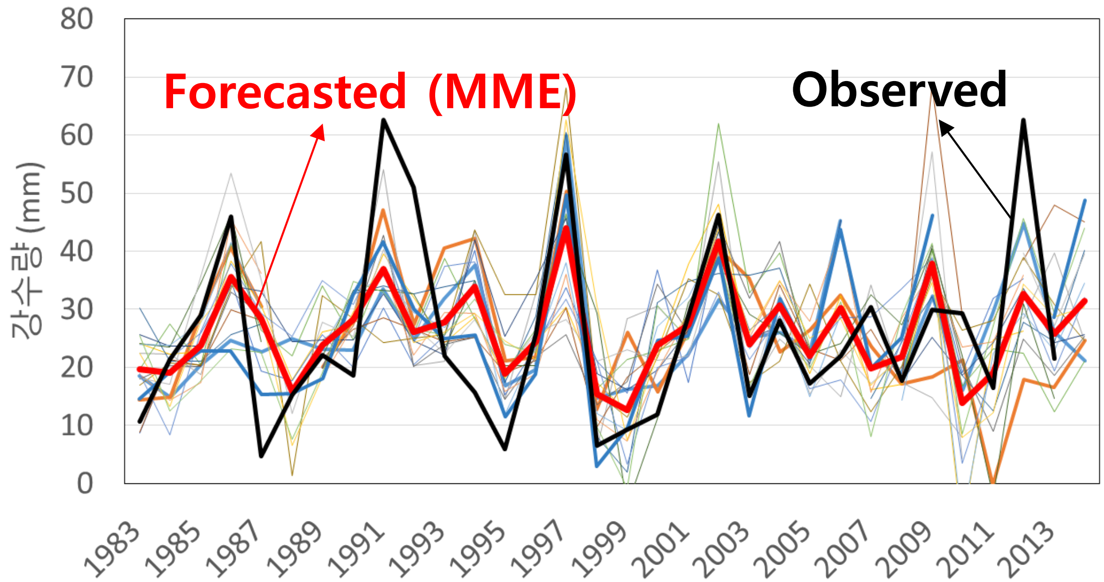


Time-series of seasonal forecast

- December precipitation forecast, 1-month lead time

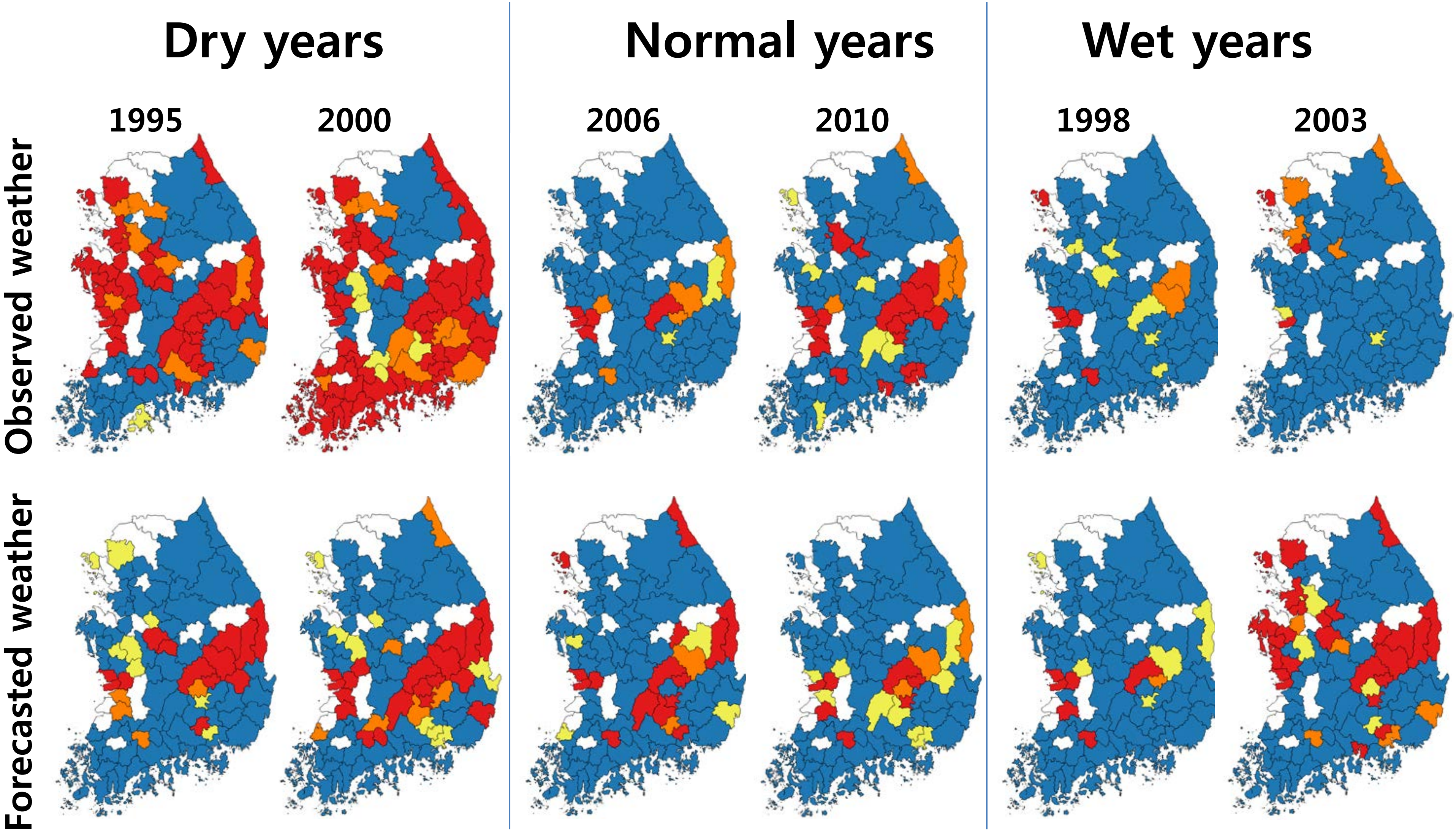
Month	1 month lead	2 month lead	3 month lead	4 month lead	5 month lead	6 month lead
JAN	ⓢJMA, ⓢPOAMA					
FEB		ⓜ CWB	ⓜ GDAPS_F			
MAR	ⓢPOAMA			ⓜ MSC_CANCM4	ⓜ MSC_CANCM4	
APR			ⓢHMC, ⓢNASA, ⓜ NCEP, ⓜ PNU			
MAY					ⓜ PNU	
JUN	ⓜ HMC	ⓜ MSC_CANCM4				
JUL	ⓒ WP(-7)	ⓒ WP(-7)	ⓘ PNU	ⓒ WP(-7)	ⓒ WP(-7)	ⓘ NASA
AUG	ⓢJMA	ⓢGDAPS_F	ⓜ POAMA	ⓜ MSC_CANCM3		
SEP	ⓜ NCEP, ⓜ PNU, ⓜ POAMA	ⓢPNU	ⓢGDAPS_F, ⓢPNU		ⓜ MSC_CANCM4	
OCT			ⓜ MSC_CANCM4			ⓜ PNU
NOV	ⓢPNU	ⓢGDAPS_F, ⓢPNU, ⓢJMA	ⓢPNU, ⓢJMA, ⓢPOAMA, ⓜ MSC_CANCM3	ⓢPNU		ⓜ PNU
DEC	ⓢPOAMA, ⓜ PNU, ⓜ MSC_CANCM4, ⓜ NASA	ⓢJMA, ⓢPOAMA, ⓜ CWB, ⓜ HMC, ⓜ POAMA, ⓜ PNU	ⓢPOAMA, ⓜ GDAPS_F, ⓜ POAMA, ⓜ NASA	ⓜ MSC_CANCM3, ⓜ NASA	ⓜ PNU	ⓜ NASA, ⓜ NCEP



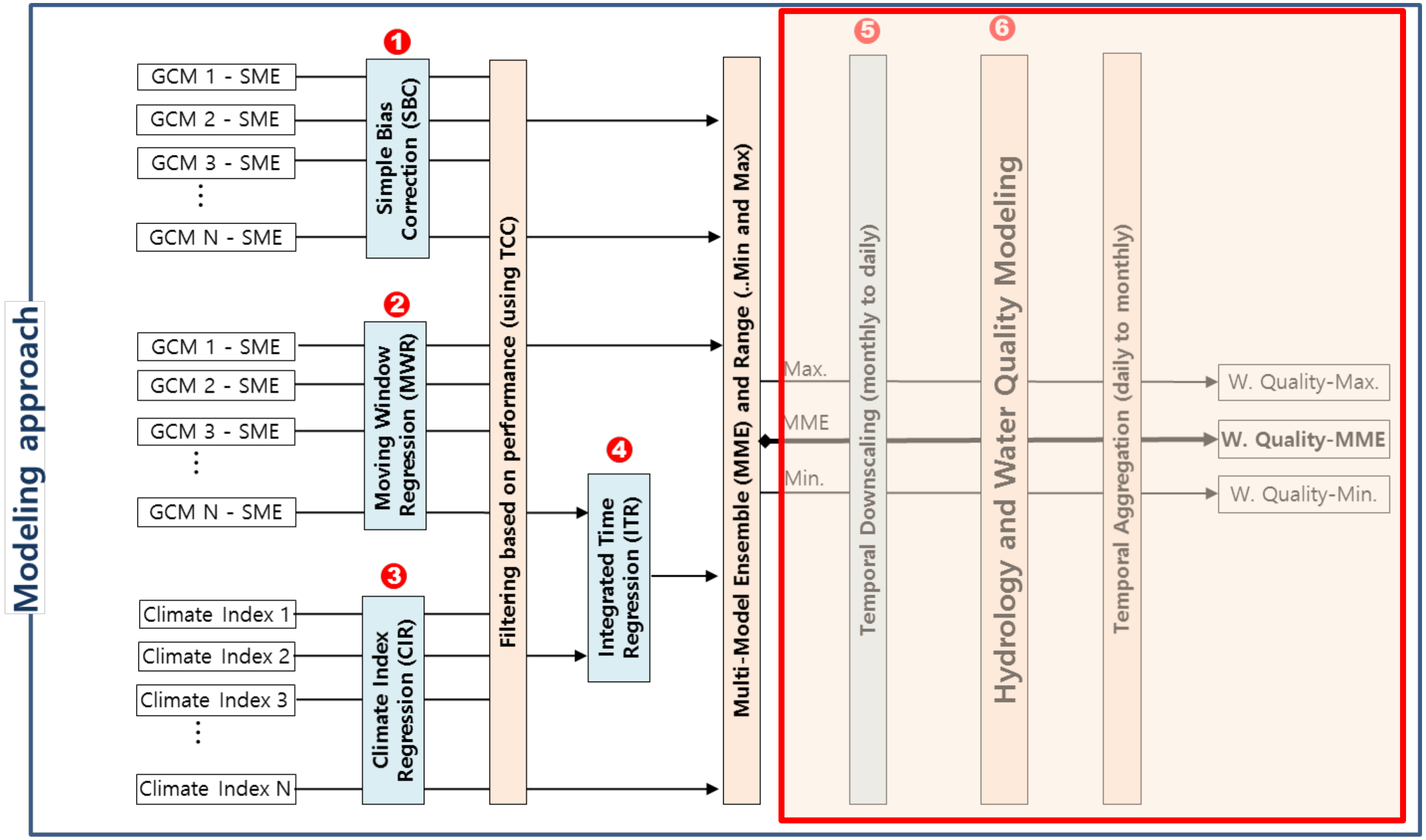


Variations of MME precipitation decreased (MME underestimated in wet years and overestimated in dry years)

Drought alerting level for Jun. 20 based on daily modeling (branch Level, forecast issued on Jan. 15)



Result of Seasonal Water Quality Predictions

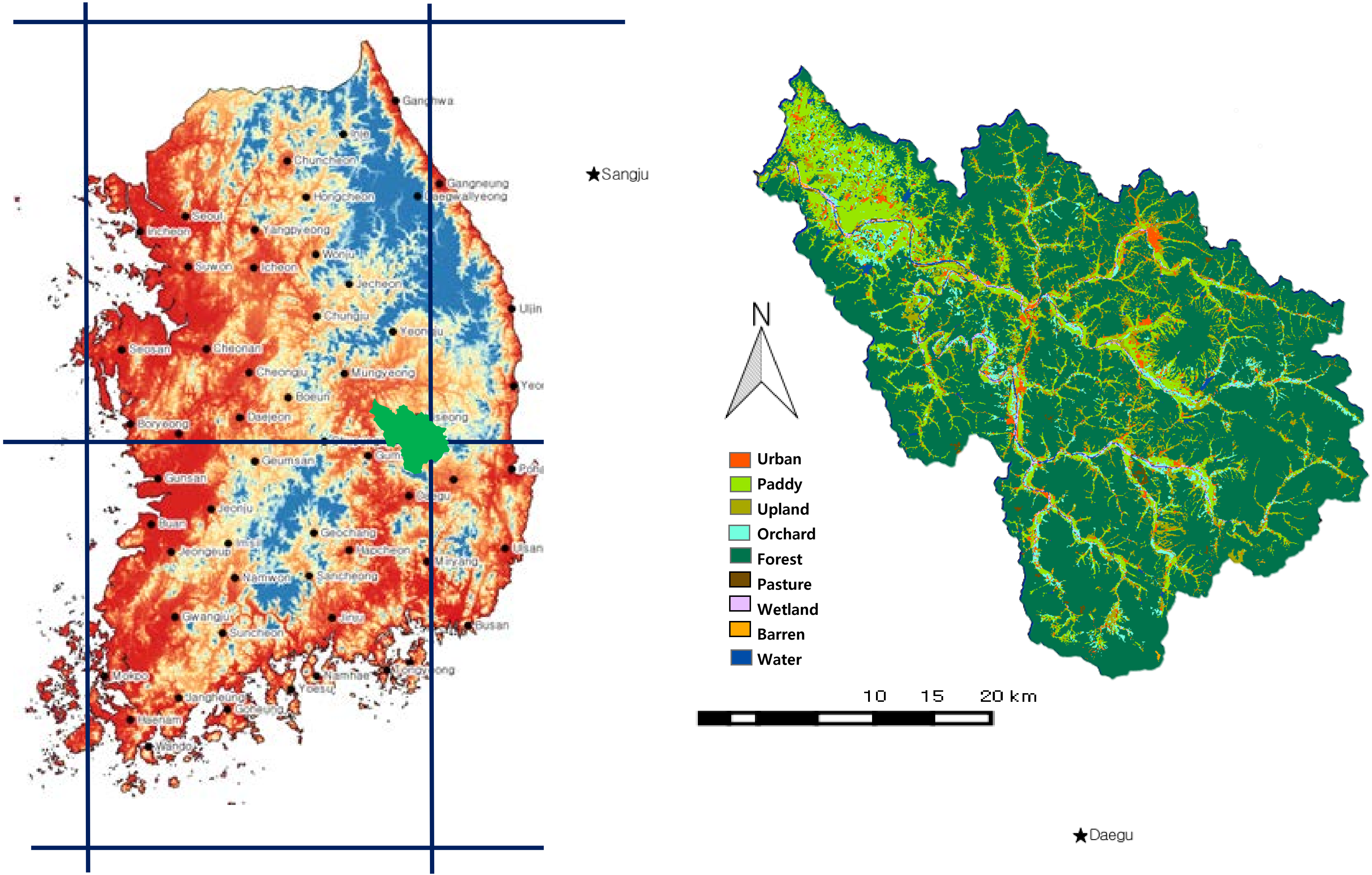


Down Scaling (Spatial & Temporal)

SME: Single model ensemble
MME: Multi-model ensemble

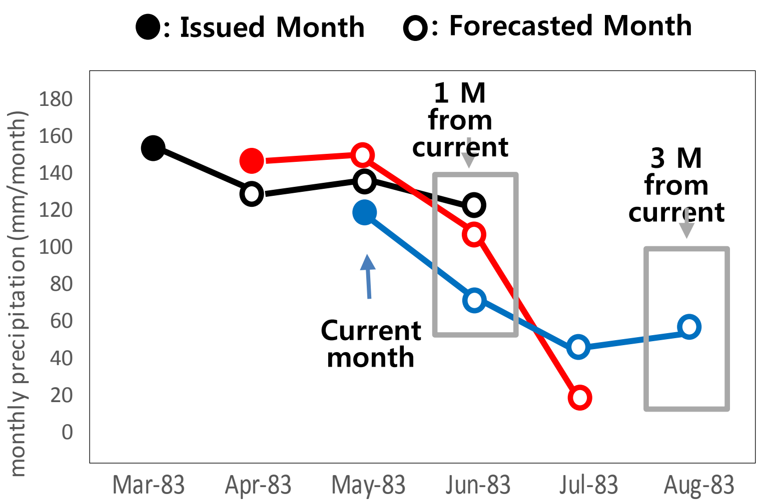
TCC: Temporal Correlation Coefficient
GCM: Global climate models for seasonal forecast

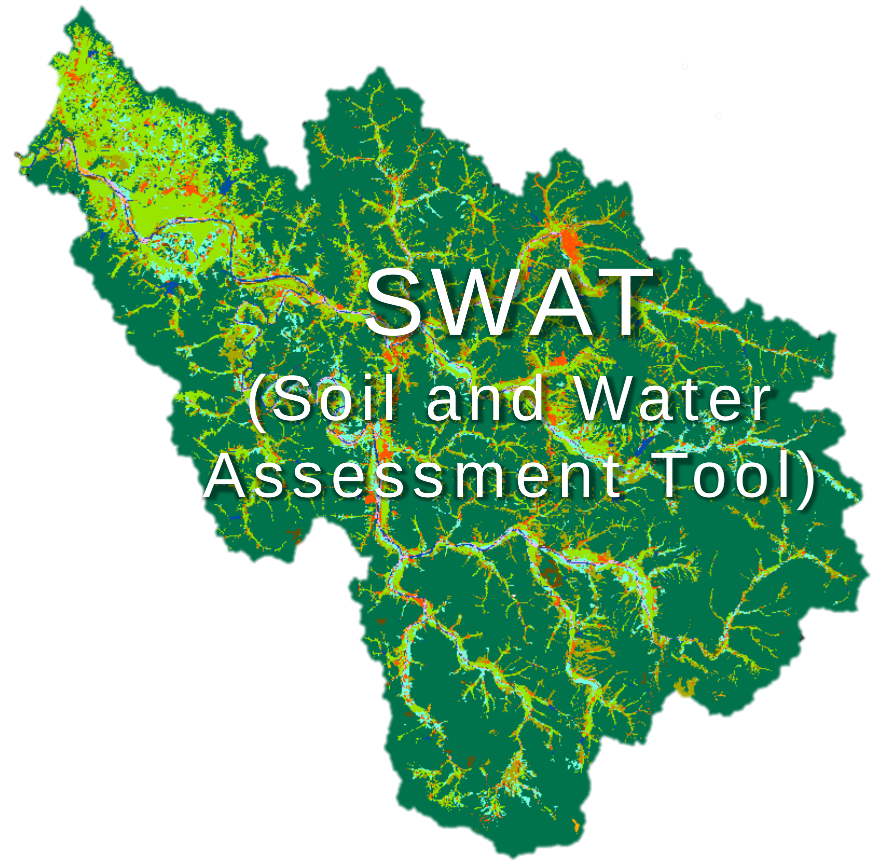
Study Area



Gangneung
Chuncheon
Hongcheon
Seoul
Incheon
Yangpyeong
Wonju
Suwon
Icheon
Jecheon
Chungju
Uljin
Seosan
Cheonan
Cheongju
Mungyeong
Boeun
Daejeon
Boryeong
Geumsan
Gunsan
Jeonju
Buan
Geochang
Hapcheon
Jeongeup
Imsil
Namwon
Sancheong
Ulsan
Miryang
Gwangju
Suncheon
Busan
Mokpo
Namhae
Yeosu
Jangheung
Goheung
Haenam
Wando
★Sangju
N
Urban
Paddy
Upland
Orchard
Forest
Pasture
Wetland
Barren
Water
10 15 20 km
★Daegu

Watershed modeling

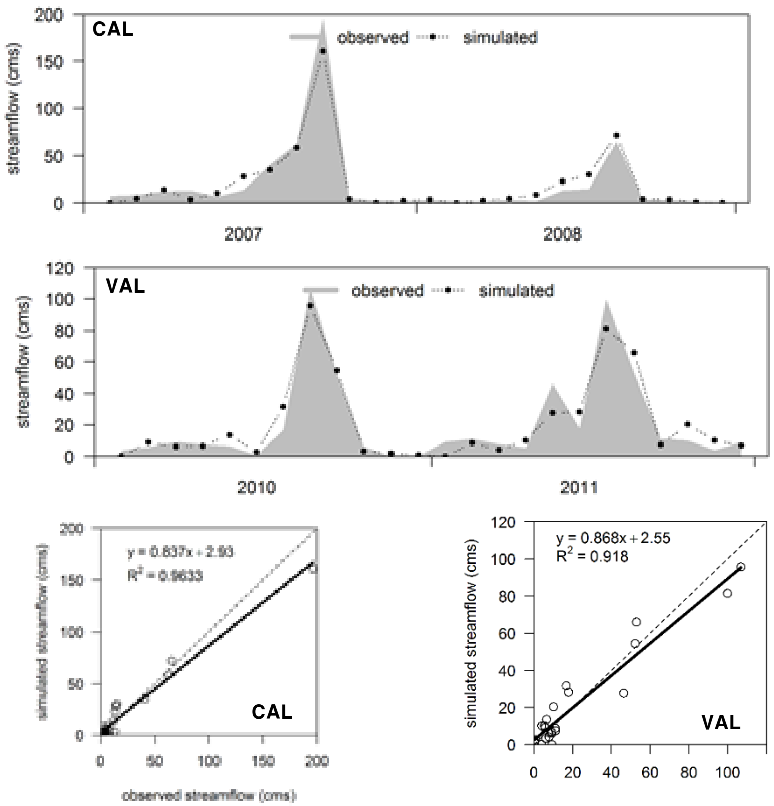




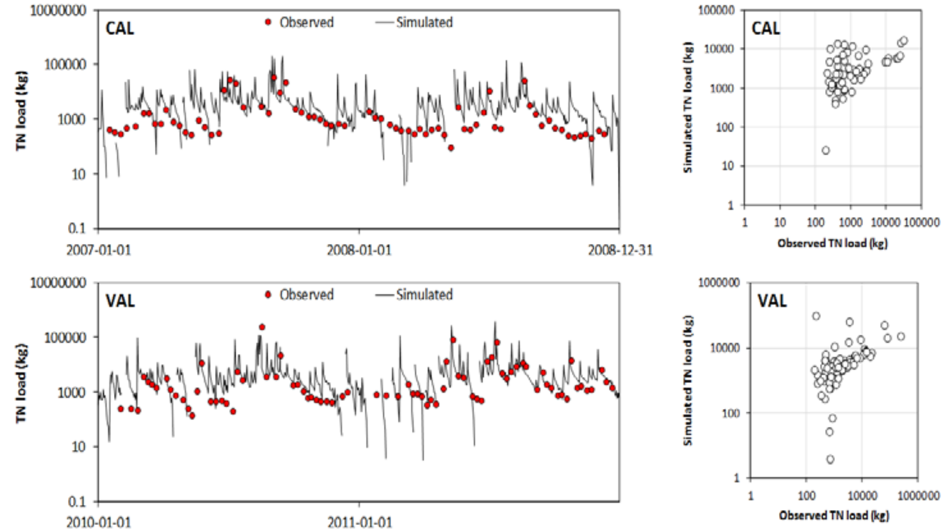
- Initialization of streamflow and water quality was not considered

SWAT Verification Results

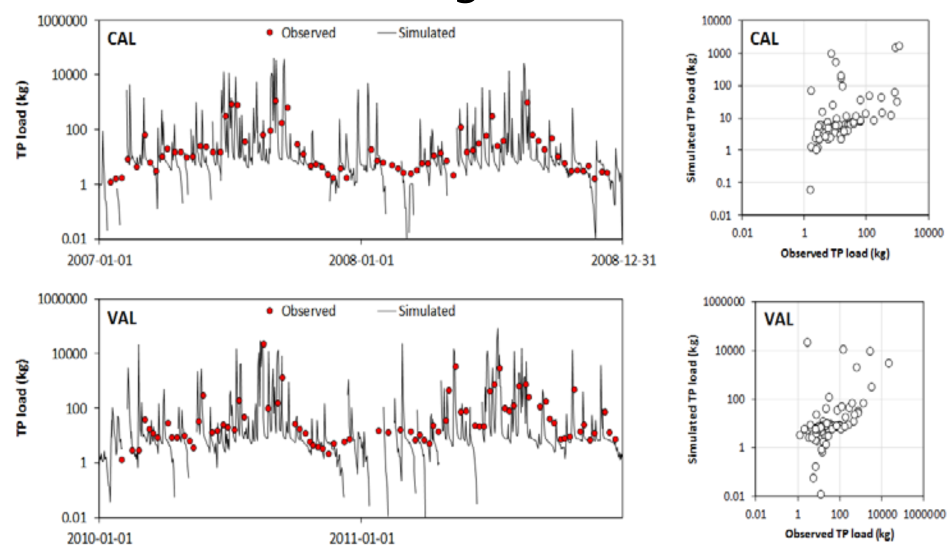
Performance measures	Calibration	Validation
% Error	-1.6	-1.1
Monthly NSE	0.95	0.92



Streamflow

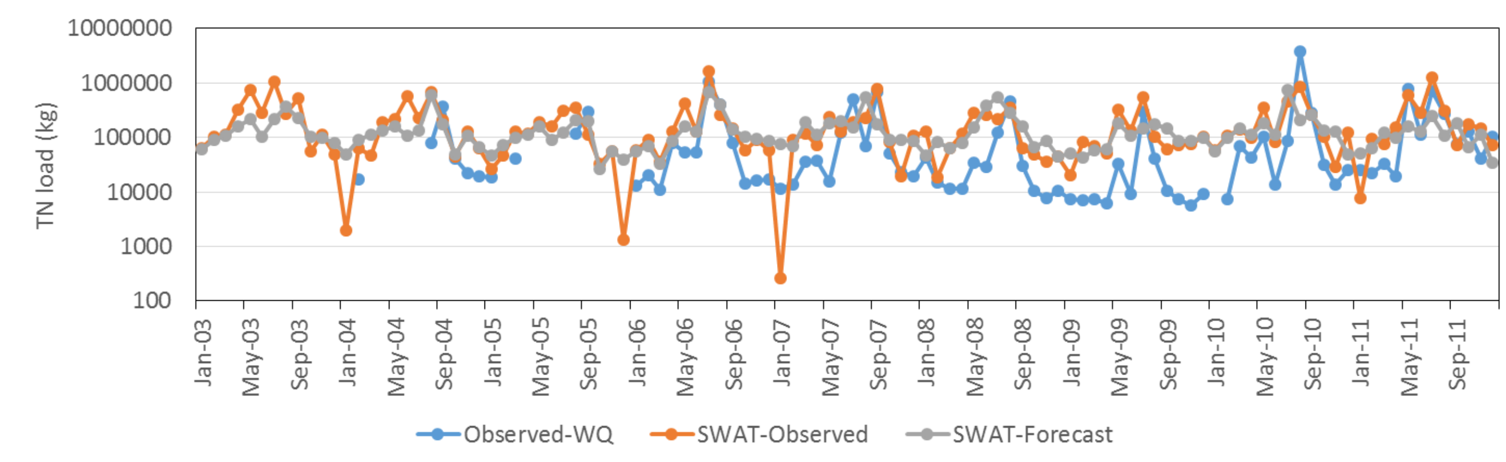


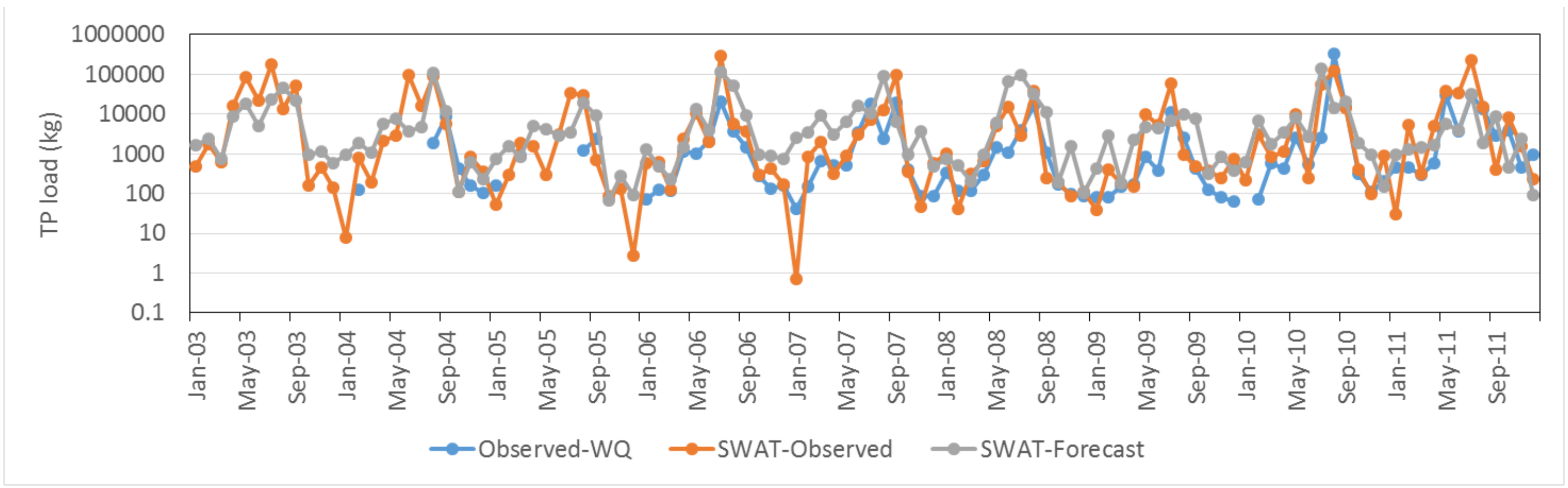
Total Nitrogen (TN) Loads



Total Phosphorus (TP) Loads

Monthly prediction of TN and TP Loads





Monthly Temporal Correlation Coefficient

Month	Total Nitrogen (TN)		Total Phosphorus (TP)	
	SWAT-Forecast vs. Observed-WQ	SWAT-Forecast vs. SWAT-Observed	SWAT-Forecast vs. Observed-WQ	SWAT-Forecast vs. SWAT-Observed
JAN	-0.47	-0.27	-0.38	-0.08
FEB	0.01	0.00	-0.34	0.26
MAR	**0.72**	**0.67**	0.45	**0.68**
APR	0.40	**0.80**	-0.20	**0.71**
MAY	-0.34	**0.58**	-0.26	**0.74**
JUN	-0.05	0.00	-0.15	-0.10
JUL	-0.04	0.30	-0.46	0.27
AUG	-0.25	0.14	-0.30	0.14
SEP	0.31	0.29	0.31	0.07
OCT	-0.30	0.25	-0.14	-0.09
NOV	0.37	0.22	0.24	0.13
DEC	-0.62	0.37	-0.39	-0.02

Development of an Integrated Method for Long-term Water Quality Prediction Using Seasonal Climate Forecast

Development of an Integrated Method for Long-term Water Quality Prediction Using Seasonal Climate Forecast

Jaepil Cho[1], Chang-Min Shin[2], Hwan-Kyu Choi[2], Kyong-Hyeon Kim[2], Ji-Yong Choi[3]

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[2]National Institute of Environmental Research, Incheon, 22689, Korea
[3]Seoul National University, Pyeongchang, 25354, Korea

Correspondence to: Jaepil Cho (jpcho89@gmail.com)

Abstract. The APEC Climate Center (APCC) produces climate prediction information utilizing a multi-climate model ensemble (MME) technique. In this study, four different downscaling methods, in accordance with the degree of utilizing the seasonal climate prediction information, were developed in order to improve predictability and to refine the spatial scale. These methods include: 1) the Simple Bias Correction (SBC) method, which directly uses APCC's dynamic prediction data with a 3 to 6 month lead time; 2) the Moving Window Regression (MWR) method, which indirectly utilizes dynamic prediction data; 3) the Climate Index Regression (CIR) method, which predominantly uses observation-based climate indices; and 4) the Integrated Time Regression (ITR) method, which uses predictors selected from both CIR and MWR. Then, a sampling-based temporal downscaling was conducted using the Mahalanobis distance method in order to create daily weather inputs to the Soil and Water Assessment Tool (SWAT) model. Long-term predictability of water quality within the Wecheon watershed of the Nakdong River Basin was evaluated. According to the Korean Ministry of Environment's Provisions of Water Quality Prediction and Response Measures, modeling-based predictability was evaluated by using 3-month lead prediction data issued in February, May, August, and November as model input of SWAT. Finally, an integrated approach, which takes into account various climate information and downscaling methods for water quality prediction, was presented. This integrated approach can be used to prevent potential problems caused by extreme climate in advance.

1 Introduction

Demand from water resources managers for seasonal climate prediction information with a lead-time of several months is increasing as this information can provide key knowledge on issues like long-term dam inflow and water quality prediction information. Long-term water quality forecasts are particularly important in watershed management because they allow for these managers to implement proactive water quality control management techniques. The importance of utilizing long-term forecasts for proactive management of water quality is becoming more important, particularly in non-point source pollution cases. Non-point source pollution flows into the water bodies during rainfall events and gradually induces

Pacific Warm Pool (PACWARM) with 6-month lag and the Atlantic Tripole SST EOF (ATLTRI) with 3-month lag were selected to predict temperature in September and October, respectively. As a result, the ITR method was selected to forecast precipitation levels in July and temperature levels in September and October, When MWR model selections are available. Overall, the SBC method, which is based on dynamic prediction data, shows the highest model selection and is followed by statistical downscaling methods such as MWR, and CIR/ITR. The SBC method shows the highest selection of models for 1-month lead temperature prediction for September with 6 models, while the MWR method shows the highest selection of models for 1-month lead precipitation prediction for September with 3 models. Figure 3 shows an example of spatial distribution of the three predictors that have been selected by the MWR method for 1-month lead precipitation prediction for September.

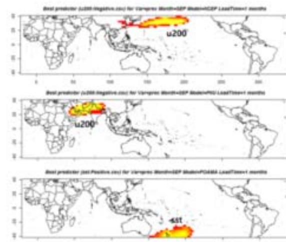


Figure 3: Spatial distribution of selected variables by the NCEP, PNU, and POAMA models for 1-month lead precipitation predictions in September (yellow indicates most frequent selection through the cross-validation procedures from 1983 to 2013).

Table 3. Selected downscaling method and models for each month according to different lead time and variables.

Month	Var	1 month lead	2month lead	3month lead
Jan	P	B_JMA B_POAMA		
	T	B_GDAPS_F B_PNU B_MSC_CANCM3 B_MSC_CANCM4 M_POAMA	B_POAMA	M_CWB
Feb	P		M_CWB	M_GDAPS_F
	T		B_JMA	
Mar	P	B_POAMA		
	T	B_GDAPS_F B_JMA		
Apr	P			B_NASA M_NCEP M_PNU B_HMC
	T	M_GDAPS_F	B_NASA	
May	P			
	T	M_CWB	M_PNU	M_MSC_CANCM3
Jun	P	M_HMC	M_MSC_CANCM4	
	T			
Jul	P	C_Lag	C_Lag	I_PNU
	T	B_JMA	M_GDAPS_F	M_POAMA
Aug	P	B_JMA	B_GDAPS_F	
	T	B_HMC B_PNU		M_CWB
Sep	P	M_NCEP M_PNU M_POAMA	B_PNU	B_GDAPS_F B_PNU
	T	B_GDAPS_F B_HMC B_JMA B_PNU B_NASA B_POAMA I_NASA	B_GDAPS_F B_NASA B_PNU I_MSC_CANCM4 I_NCEP	B_GDAPS_F B_HMC B_JMA B_NASA B_PNU C_Lag
Oct	P			M_MSC_CANCM4
	T	B_GDAPS_F B_HMC B_PNU I_MSC_CANCM3	B_GDAPS_F B_JMA B_NASA B_PNU C_Lag	B_GDAPS_F C_Lag
Nov	P	B_PNU	B_GDAPS_F B_PNU B_JMA	B_PNU B_JMA B_POAMA M_MSC_CANCM3
	T	B_POAMA		B_JMA M_PNU
Dec	P	B_POAMA M_PNU M_MSC_CANCM4	B_JMA B_POAMA M_HMC M_POAMA	B_POAMA M_GDAPS_F M_POAMA M_NASA
	T	B_POAMA		B_JMA

P: Precipitation, T: Temperature, B_: simple bias correcti on (SBC), M_: Moving Window Regression (MWR), C_: Climate Index Regression (CIR), I_: Integrated Time Reg ression (ITR)

An evaluation of predictability when issuing forecasts every month was conducted, as shown in Figure 4. For example, when we predict precipitation levels in August during the month of July, all three prediction results (including 1-month lead prediction issued in July, 2-month lead prediction issued in June, and 3-month lead prediction issued in May) can be used. Figure 5 illustrates an evaluation of predictability using a simple average of multi-model predictions.

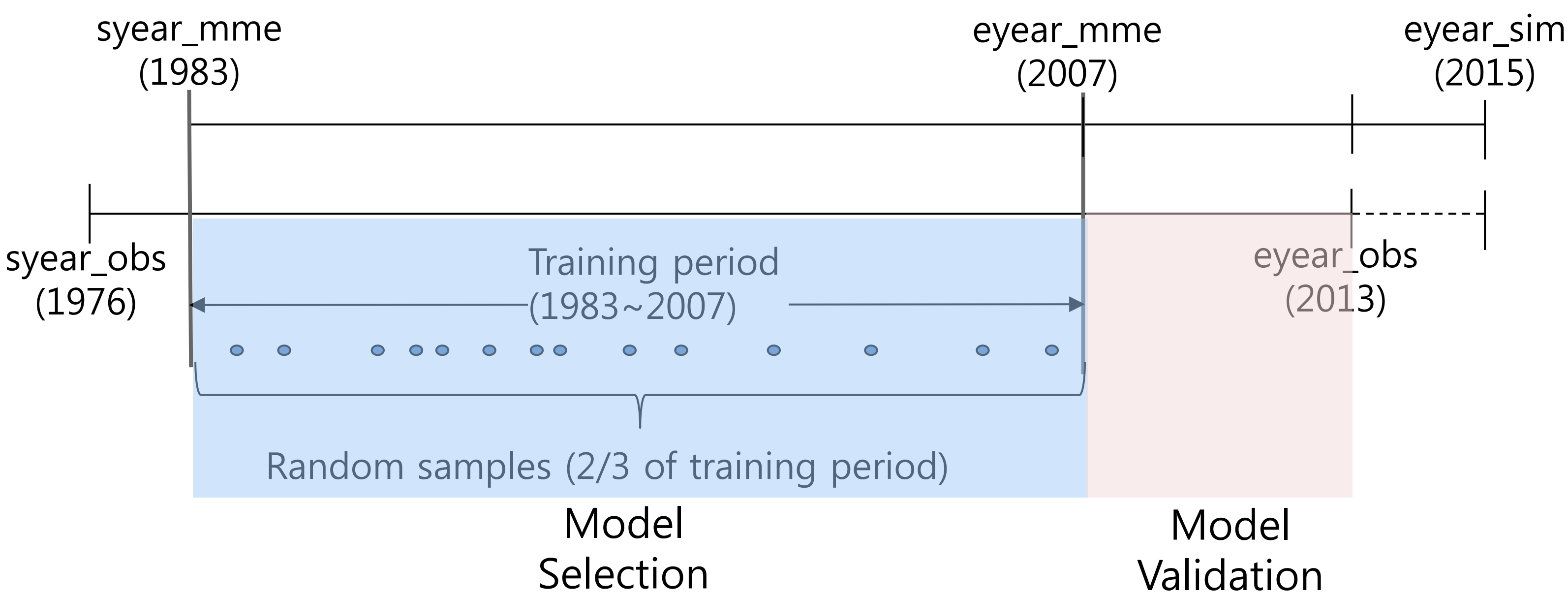
- International Association of Hydrological Sciences Red Book series

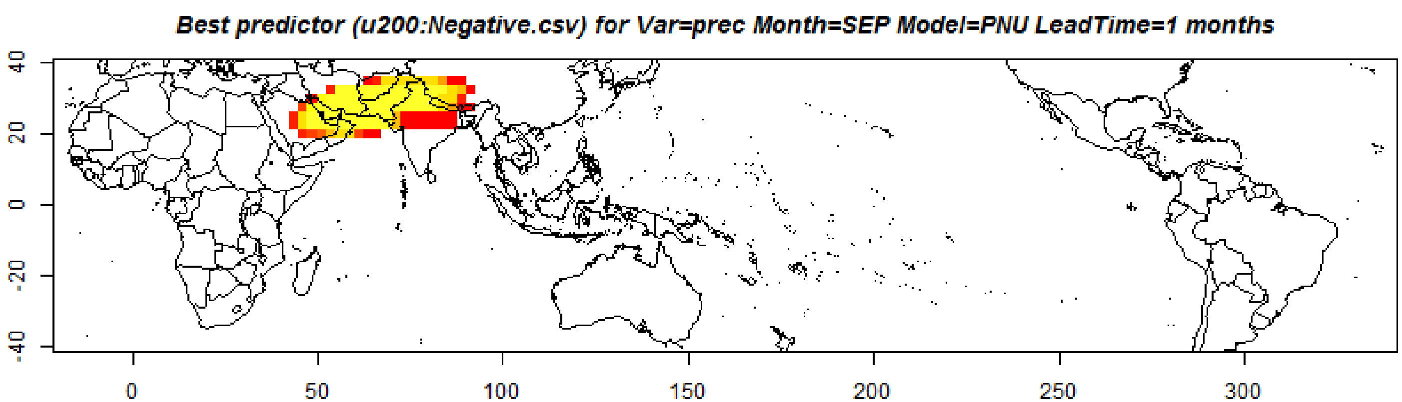
sforecast R package

```r
EnvList = Set.Working.Environment (basedir="F:/SForecast-ADSS", prjname = "Korea", e

Update.Climate.Information (EnvList, updatemode = F)
KMA.ASOS.Observation.Update (EnvList, fillingmode = T)
#ghcn.daily.update (EnvList, cntry = "LA")

Hindcast.Forecast.Model.Construction (EnvList)

Integrate.Individual.Forecast.Model (EnvList)
```

```r
EnvList = Set.Working.Environment (basedir="F:/SForecast-ADSS", prjname = "Korea", en

Update.Climate.Information (EnvList, updatemode = T)
KMA.ASOS.Observation.Update (EnvList, fillingmode = F)

Run.RealTime.Forecast.Model (EnvList, fiyearmon = "2016-06")

Daily.Hourly.Sampling (EnvList, fiyearmon = "2016-06", smplmoncnt=3)
```

Algorithm for avoiding over-fitting





Downscaling procedures

- Model construction for hindcast period

1. EnvList = Set.Working.Environment (basedir="F:/SForecast-ADSS", prjname = "Korea", envfile = "Korea.txt")
2. Update.Climate.Information (EnvList, updatemode = F)
3. KMA.ASOS.Observation.Update (EnvList, fillingmode = T)
4. ghcn.daily.update (EnvList, cntry = "LA")
5. Hindcast.Forecast.Model.Construction (EnvList)
6. Integrate.Individual.Forecast.Model (EnvList)

- Real-Time Seasonal Forecast

1. EnvList = Set.Working.Environment (basedir="F:/SForecast-ADSS", prjname = "Korea", envfile = "Korea.txt")
2. Update.Climate.Information (EnvList, updatemode = T)
3. KMA.ASOS.Observation.Update (EnvList, fillingmode = F)
4. Run.RealTime.Forecast.Model (EnvList, fiyearmon = "2016-06")
5. Daily.Hourly.Sampling (EnvList, fiyearmon = "2016-06", smplmoncnt=3)

Control file for Set.Working.Environment

EnvList-SForecast.txt

```
mdlnms_3mon="BCC","CWB","HMC","IRI_CA"
mdlnms_6mon="APCC","CMCC","MSC","NASA","NCEP","PNU","POAMA"
ptrnms="slp","sst","t850","u200","u850","v200","v850","z500"
NBest=1
cpcidxs="PNA","EP","WP","NAO","SOI","NINO3","TNA","TSA","WHWP","MEI","NINO12","NINO4","NINO34","AMO","QBO","ESL"
apccidxs="AAO","AO","ATLTRI","EOFPAC","NOI","NP","ONI","PACWARM","TNI"
minlat=-40
maxlat=40
MinGrdCnt=20
MaxGrdCnt=80
smonth=1
emonth=12
nrange=3
syear_obs=1976
eyear_obs=2013
syear_mme=1983
eyear_mme=2007
eyear_sim=2016
stnfile="kma_asos_57stns.csv"
varfile="kma_asos_57stns.csv"
idxfile="CIndex-Combined.csv"
ptrfile="ptrlist.csv"
bndfile="Korea.shp"
nrstfile="kma_asos_57stns_nearest_10stns.csv"
BCPointOpt="On"
BCAreaOpt="Off"
CIRegOpt="On"
MWRegOpt="On"
MWRObsOpt="On"
tscale="daily"
fcstmode="Cont"
combnmode=T
fiyearmode=T
AcuMonths=1
precopt=F
CRAdj=1.0
```

Create ensemble members

Issuing Month	1 Month	2 Month	3 Month	4 Month	5 Month	6 Month
Selected models	A B C D E		가 나 다 라 마 바	①		㉠ ㉡ ㉢ ㉣

MME Max Min	x	Clim	x	MME Max Min	x	One	x	Clim	x	MME Max Min	=	Total 27 members

Thank You!

For further discussion and collaboration
Jaepil Cho: jpcho89@gmail.com

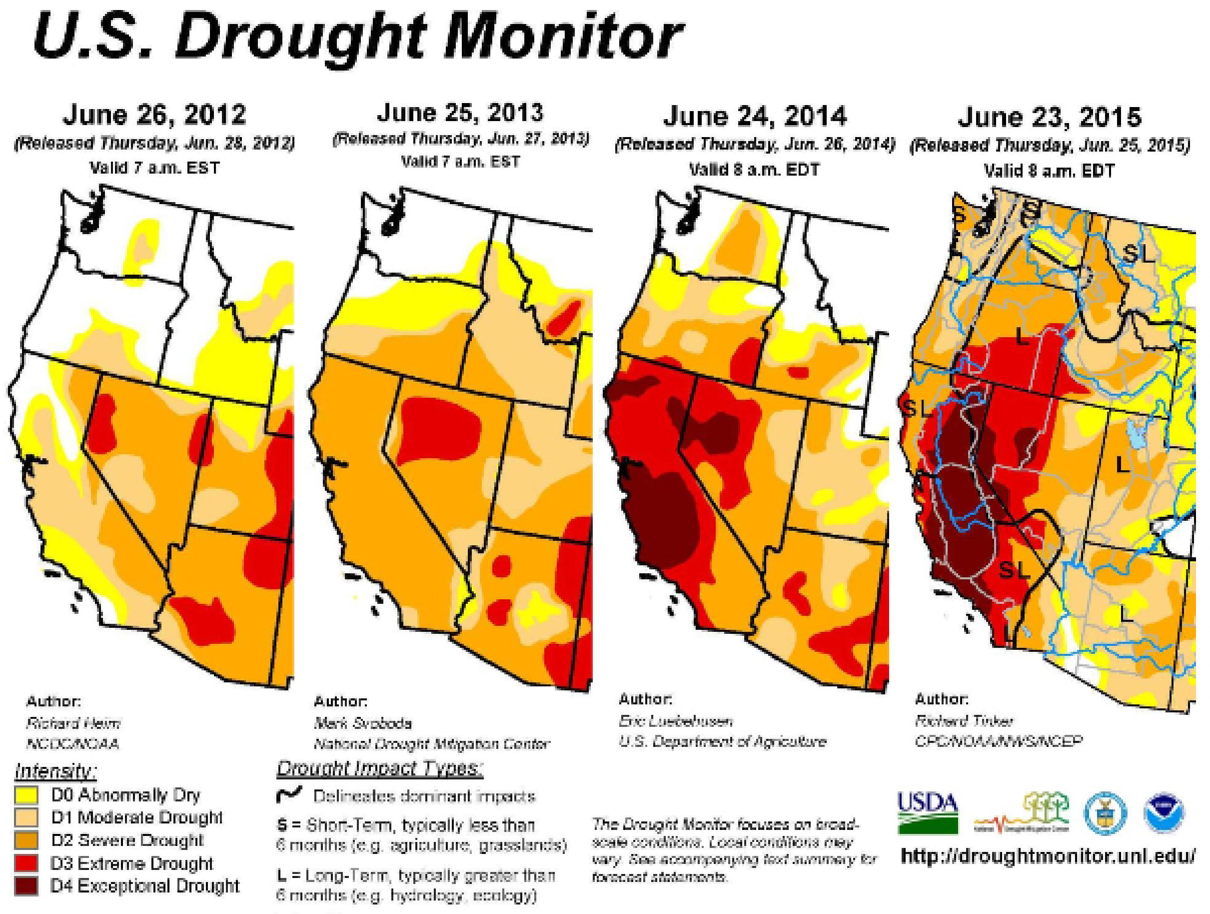
Mechanisms of Severe Droughts in East Asia and Western US:

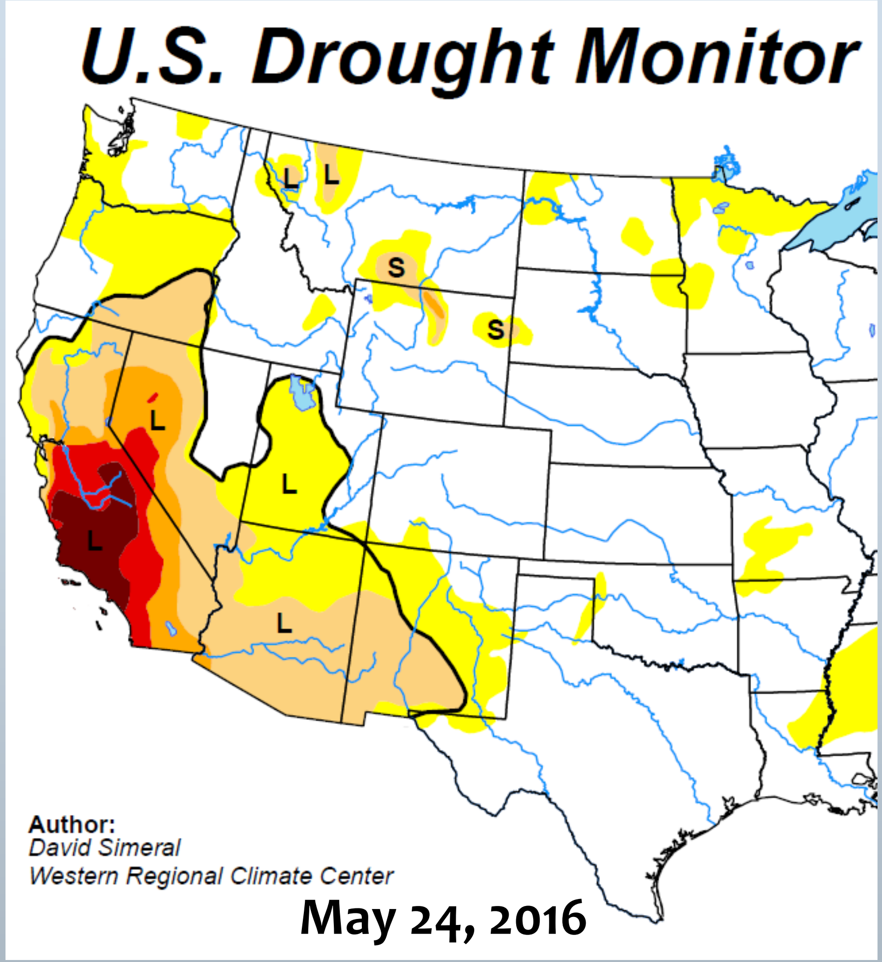
Multi-year Droughts in California in the Last Two Decades and its Implication on Droughts in East Asia

Boksoon Myoung

APEC Climate Center

Past and current drought status in CA





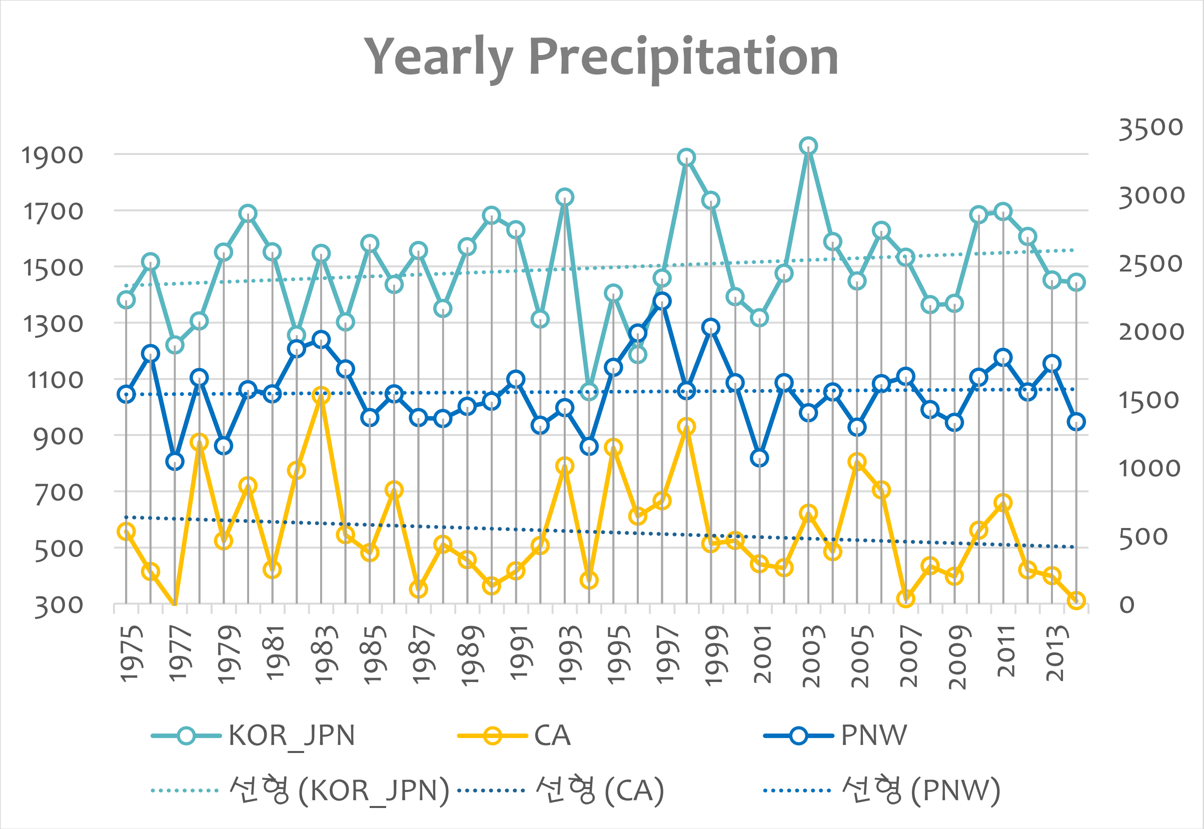
Background I

- Droughts can cause significant damages to the environment as well as society due to their long-term persistency over extensive areas.
- These socio-economic damages can be substantially large, especially when they are accompanied with subsequent agricultural and hydrological droughts.
- Despite these, little effort has been made to understand physical and dynamic mechanisms of droughts.

Background II

- Previous drought studies on Western U.S. including California mostly focused on individual characteristics and aspects.
- Regarding drought studies on Korea, dynamic or mechanistic approaches are rarely employed, while statistical approaches are widely taken.
- In addition, many drought studies on Korea focused on seasonal time scales such as spring and summer, and droughts for longer time scales have hardly been examined.

Motivation



- Drought periods quite match each other after 1995 (e.g., 2000-2002, 2008-2009, and 2013-2014);
- Duration and severity of the recent droughts increased, in particular in Korea/Japan and in CA.

Research Questions

- Do the multi-year droughts in CA during the last two decades (1995-2014) have similar characteristics?

- If any, what kind of large scale patterns and climate variability are related to these droughts?

Objectives

- The purposes of this study are to examine (1) characteristics of multiple drought events during the last two decades (1995-2014) in California (CA, hereafter) and (2) their relations to climate variability. The specific interest of this study is in:

✓ Analyzing atmospheric/oceanic characteristics of each drought event and comparing inter-events in order to examine whether the recent multi-year droughts in the study region have similar underlying mechanisms,

✓ Investigating the relationships of these drought events with various climate variability in order to understand large-scale circulation patterns of the atmosphere and SST anomalies that are likely to generate similar events in the future.

Data and Methods

a. Global/station precipitation data (e.g., Climate Research Unit, CRU, and US climate division data),

b. NCEP Reanalysis dataset for atmospheric variables,

c. NOAA SST (extended, v4) and OLR (monthly interpolated)

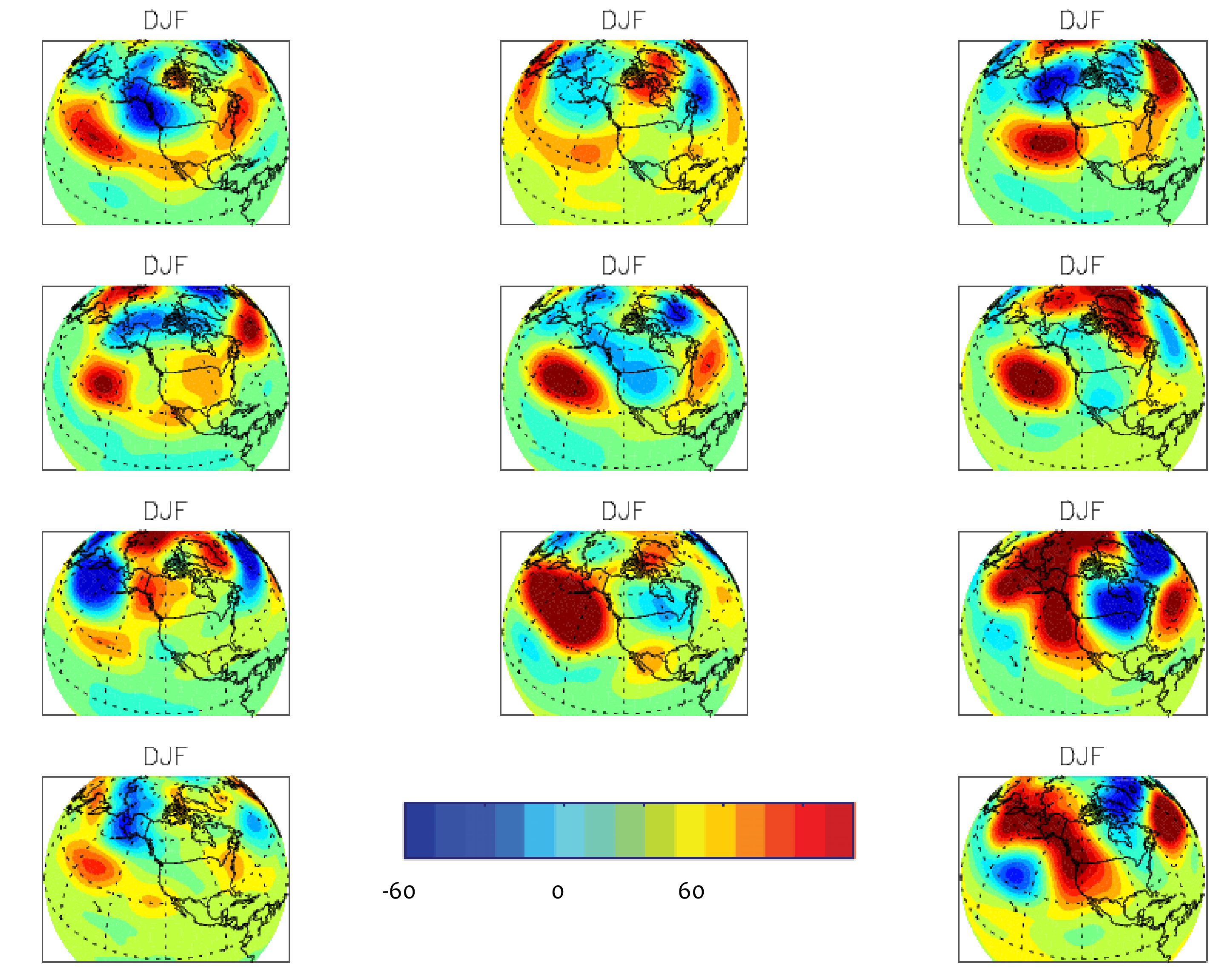
d. Climate indices such as El Niño-Southern Oscillation (ENSO), Pacific Decadal Oscillation (PDO), Southern Oscillation Index (SOI), El Niño Modoki Index (EMI), Arctic Oscillation (AO), and North Atlantic Oscillation (NAO).

- Detect target drought events.
- Investigate and compare atmospheric characteristics of the individual events using the various variables.
- Perform statistical analyses including EOF (Empirical Orthogonal Function) analysis and linear correlation analysis

RESULT 1: Case Study

Geopotential Height Anomaly

D1_HGT (1999-2002) | D2_HGT (2007-2009) | D3_HGT (2012-2015)

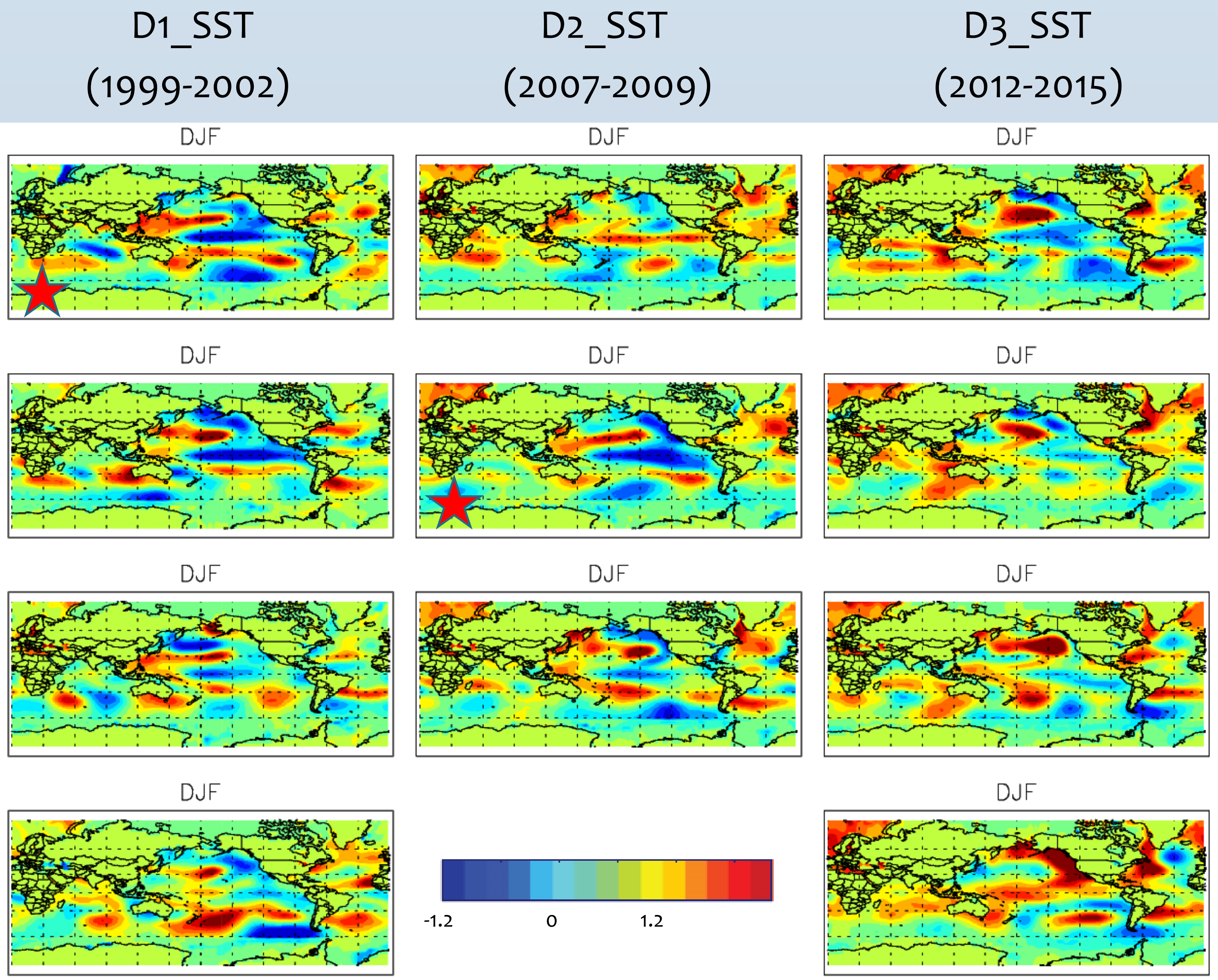


+ Height Anomaly in NP

→Moves Pacific storm track to north and blocks surface cyclone passes in CA

→Reduces CA precipitation

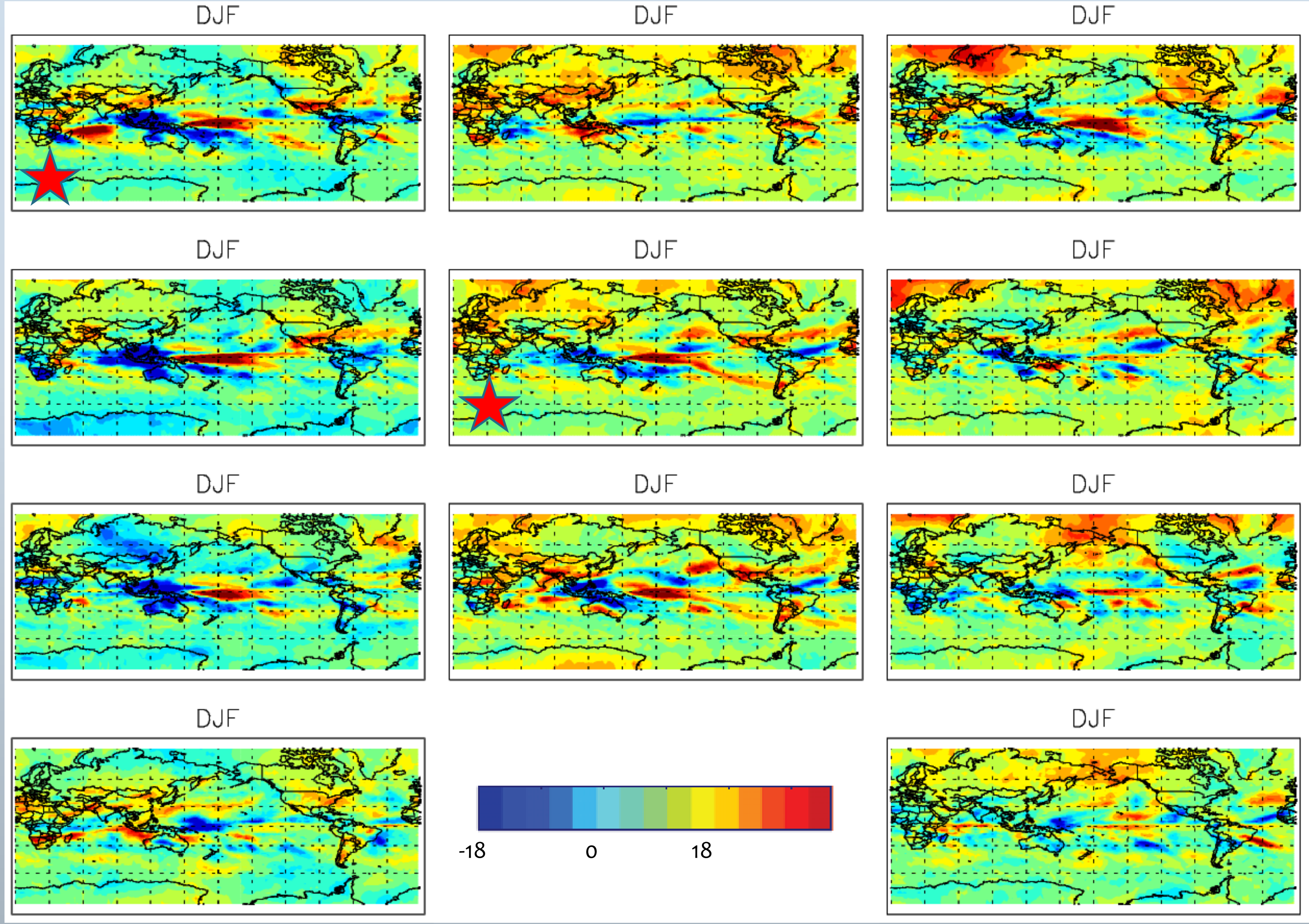
SST Anomaly



★ La Nina winter

OLR Anomaly

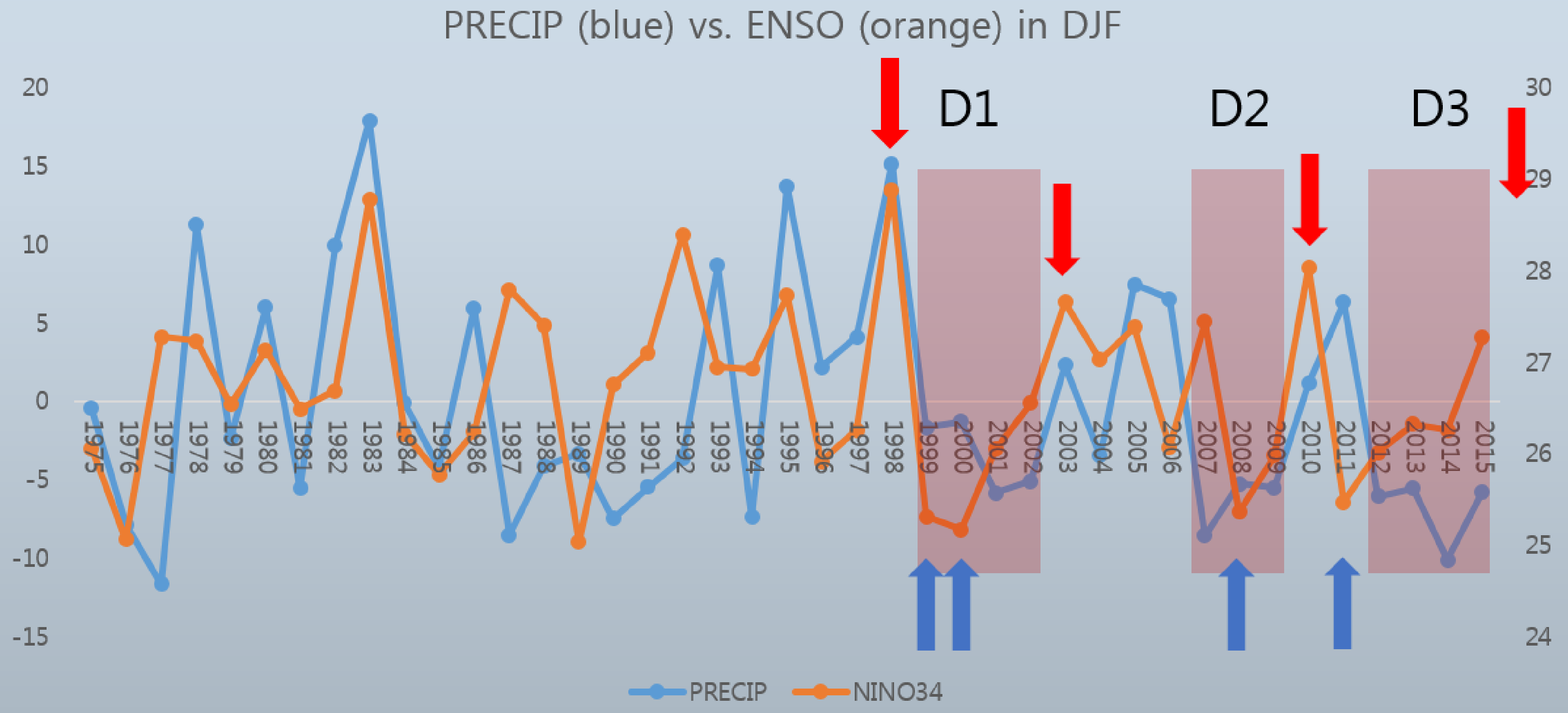
D1_OLR (1999-2002)	D2_OLR (2007-2009)	D3_OLR (2012-2015)



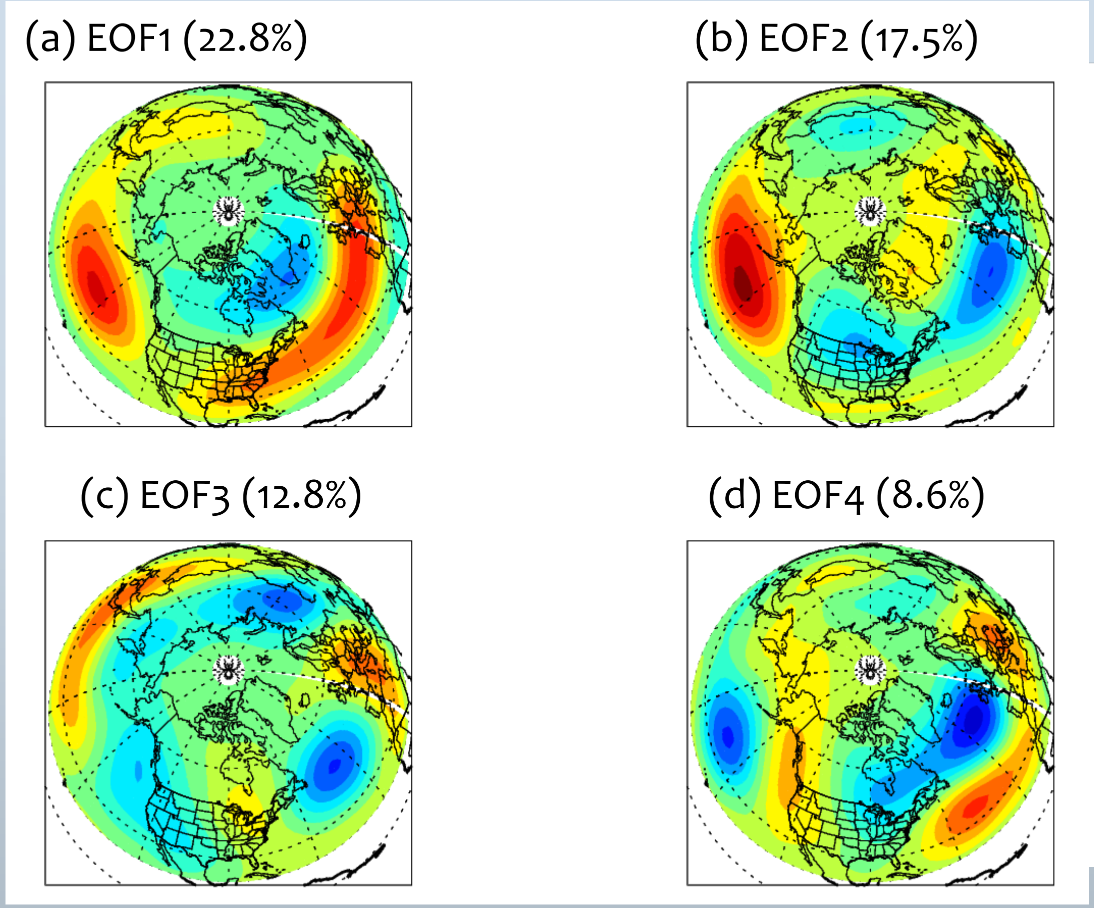
Blue: Wet
Red: Dry

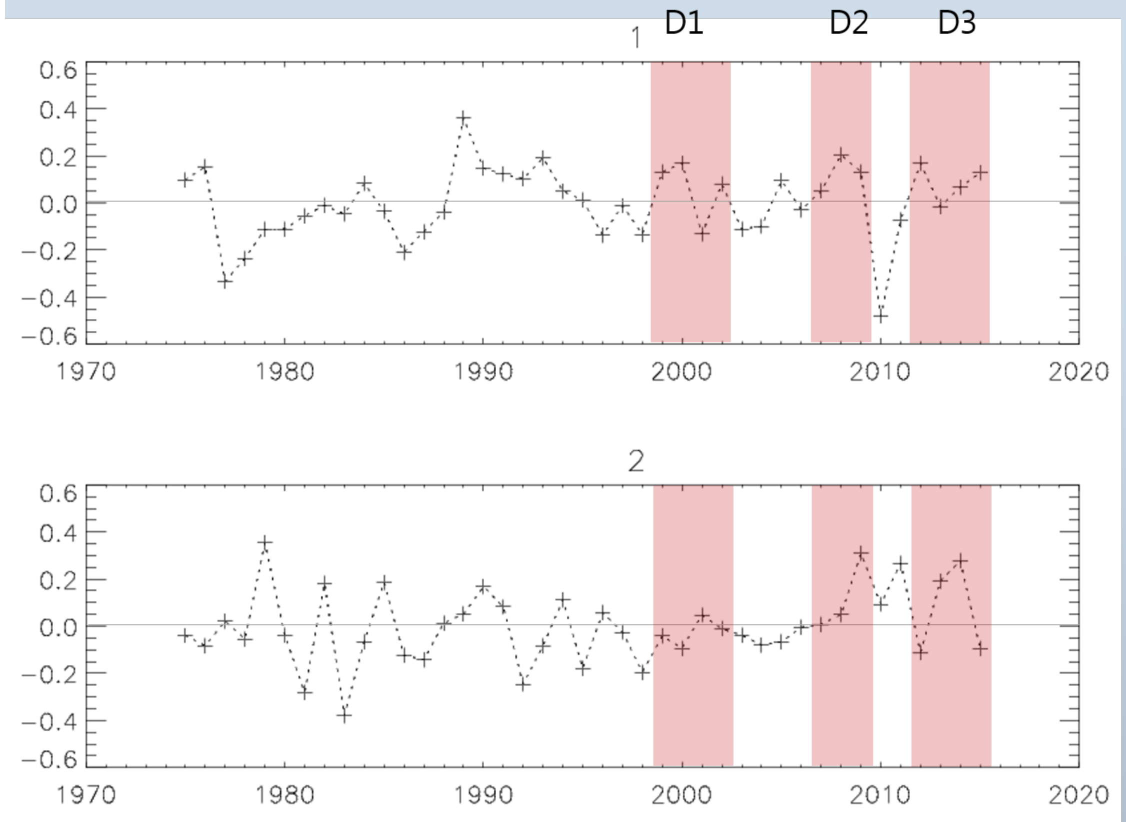
La Nina winter

The recent multi-year California droughts started around La Niña winters and continued/intensified until the year prior to an El Niño.

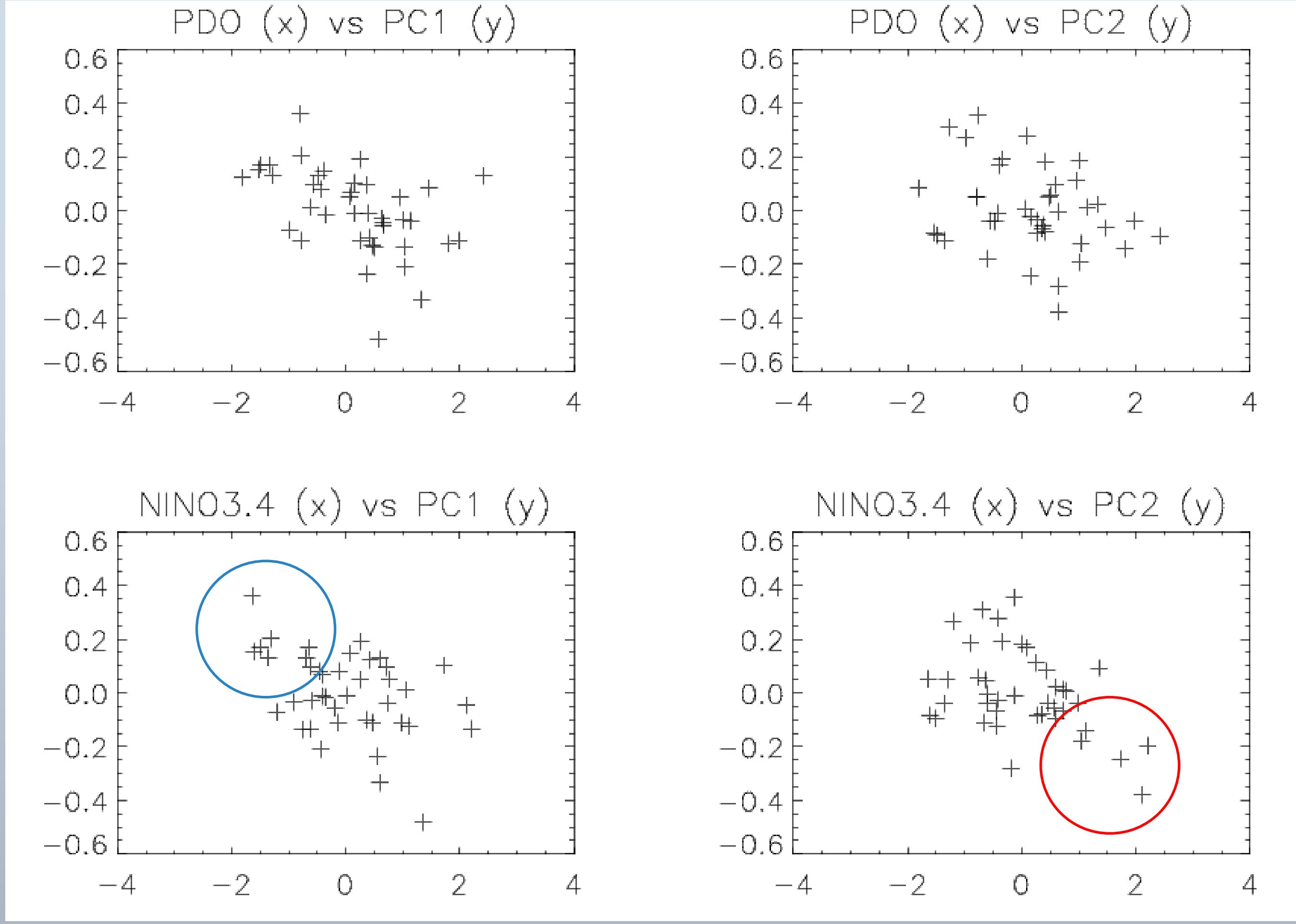


Results of EOF Analysis

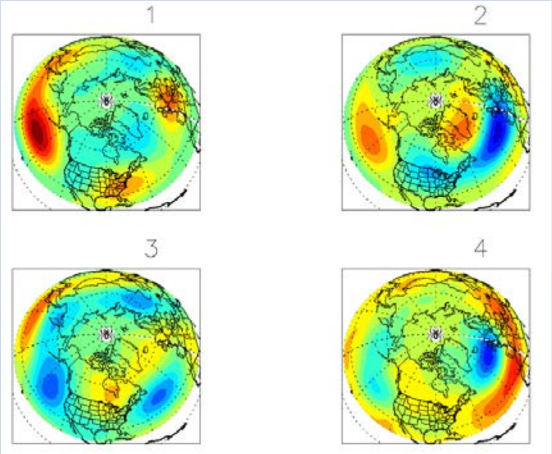


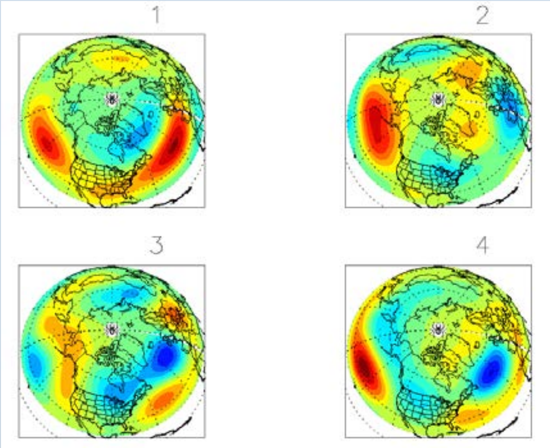


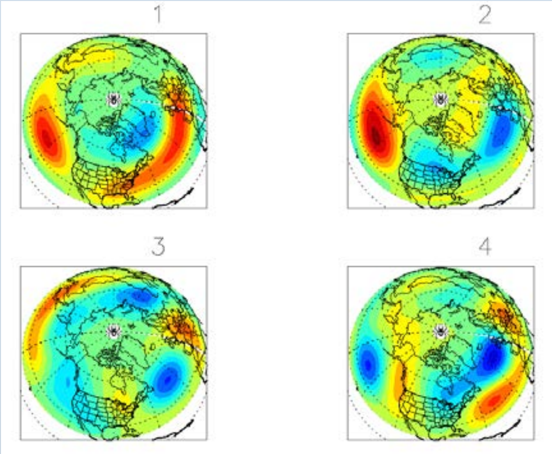
Asymmetry in ENSO teleconnection



Decadal Changes of the EOF modes







correlation with PDO, NINO, EMI, SOI, and NAO

-0.591915	0.0645464	0.0601679
-0.377180	-0.214936	0.512060
-0.244766	0.0489717	0.233594
-0.280147	-0.331030	0.581554
0.361807	-0.675801	-0.328274

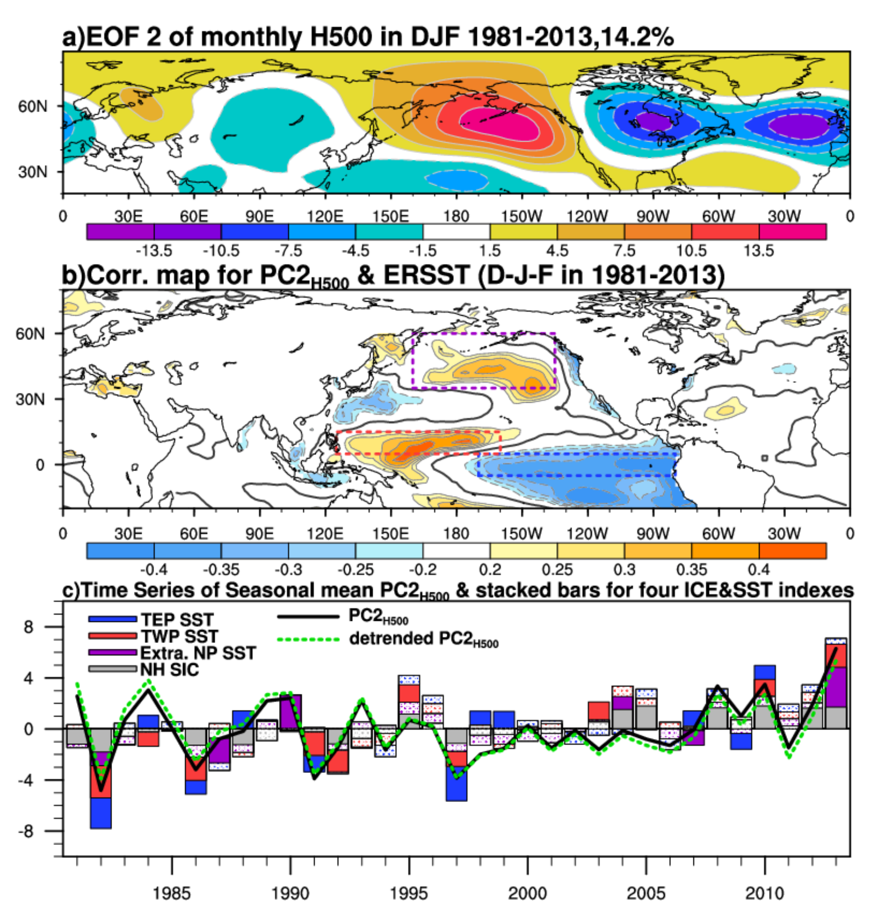
correlation PC123_djf with PDO, NINO, EMI, SOI, and NAO

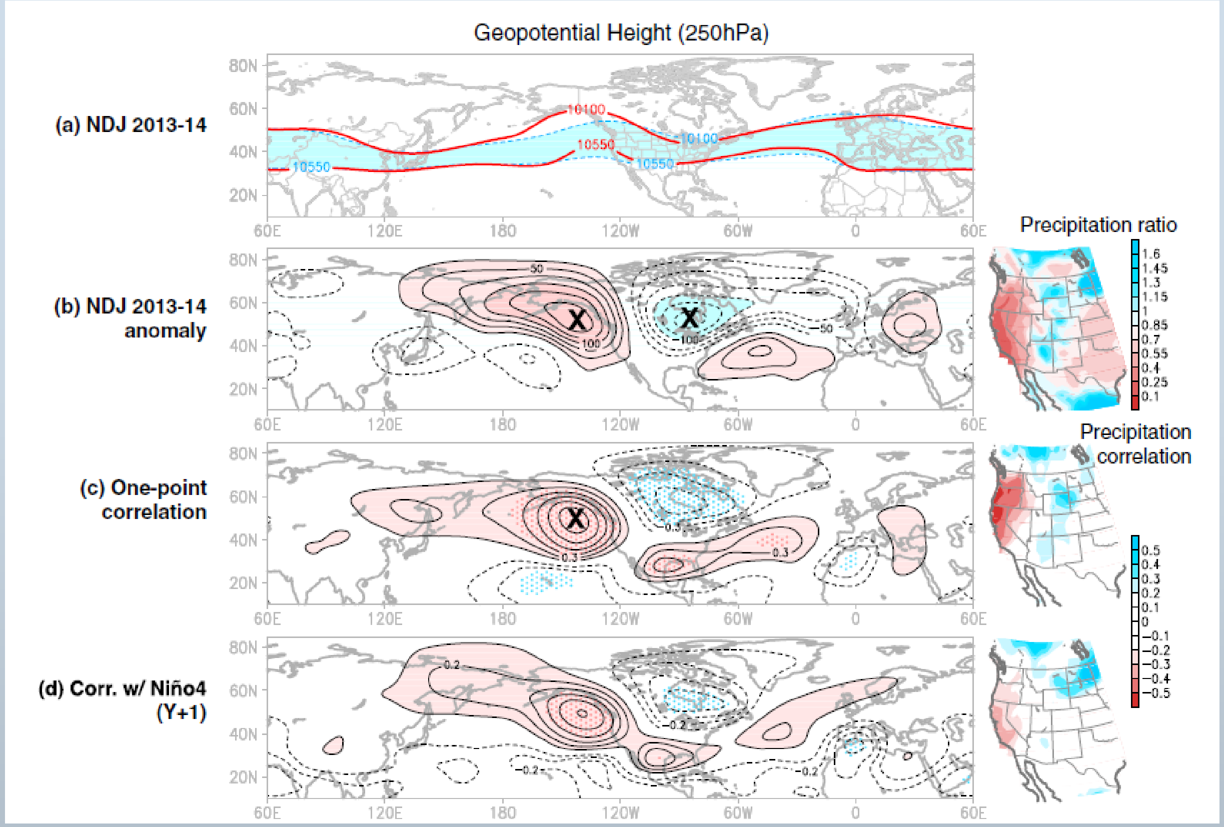
-0.423018	-0.220574	0.266560
-0.520815	-0.405472	0.0587346
-0.385847	-0.0904190	0.260657
-0.428994	-0.385202	0.00895236
0.848928	-0.340293	0.148175

correlation PC123_djf with PDO, NINO, EMI, SOI, and NAO

-0.475840	-0.278005	-0.0516395
-0.434554	-0.421173	0.312244
-0.356462	-0.123901	0.0909936
-0.332493	-0.482065	0.321030
0.775132	-0.376926	-0.221662

Importance of EOF2 mode on CA drought

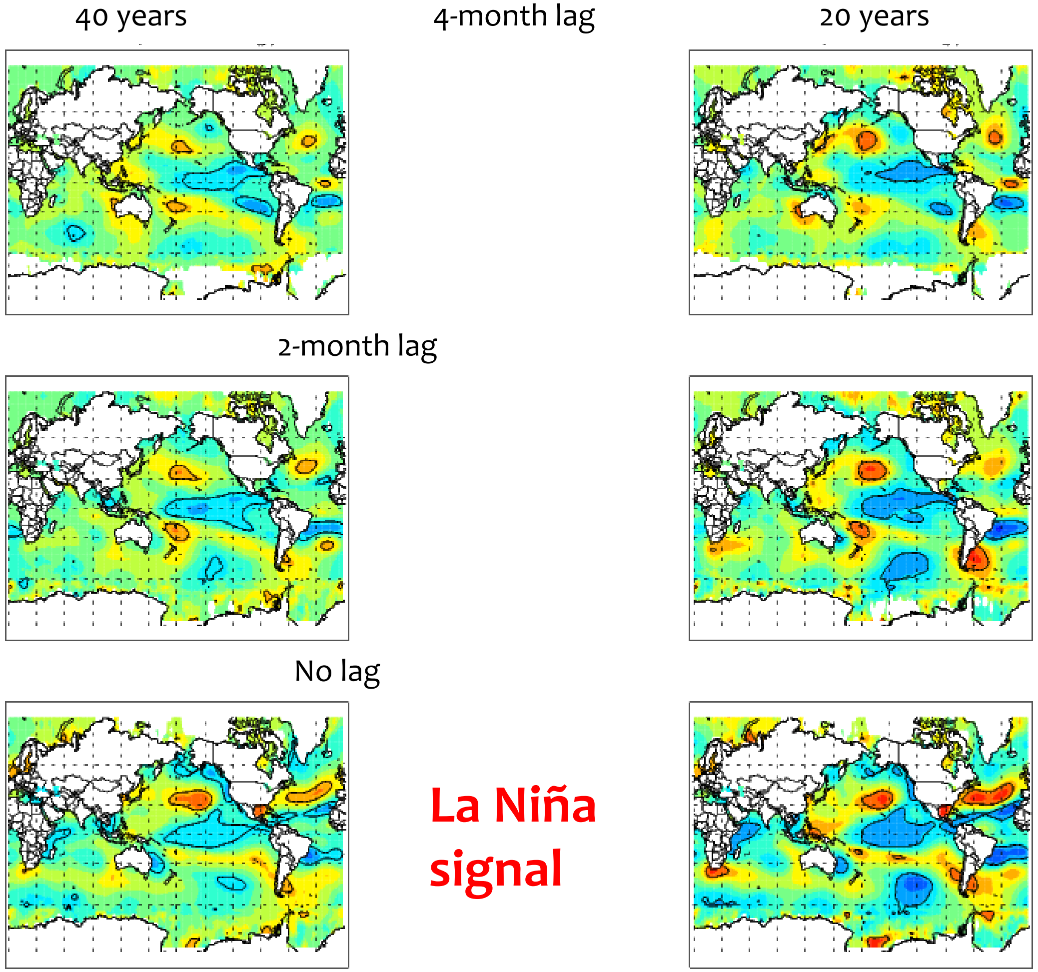




Lee et al., (2015)

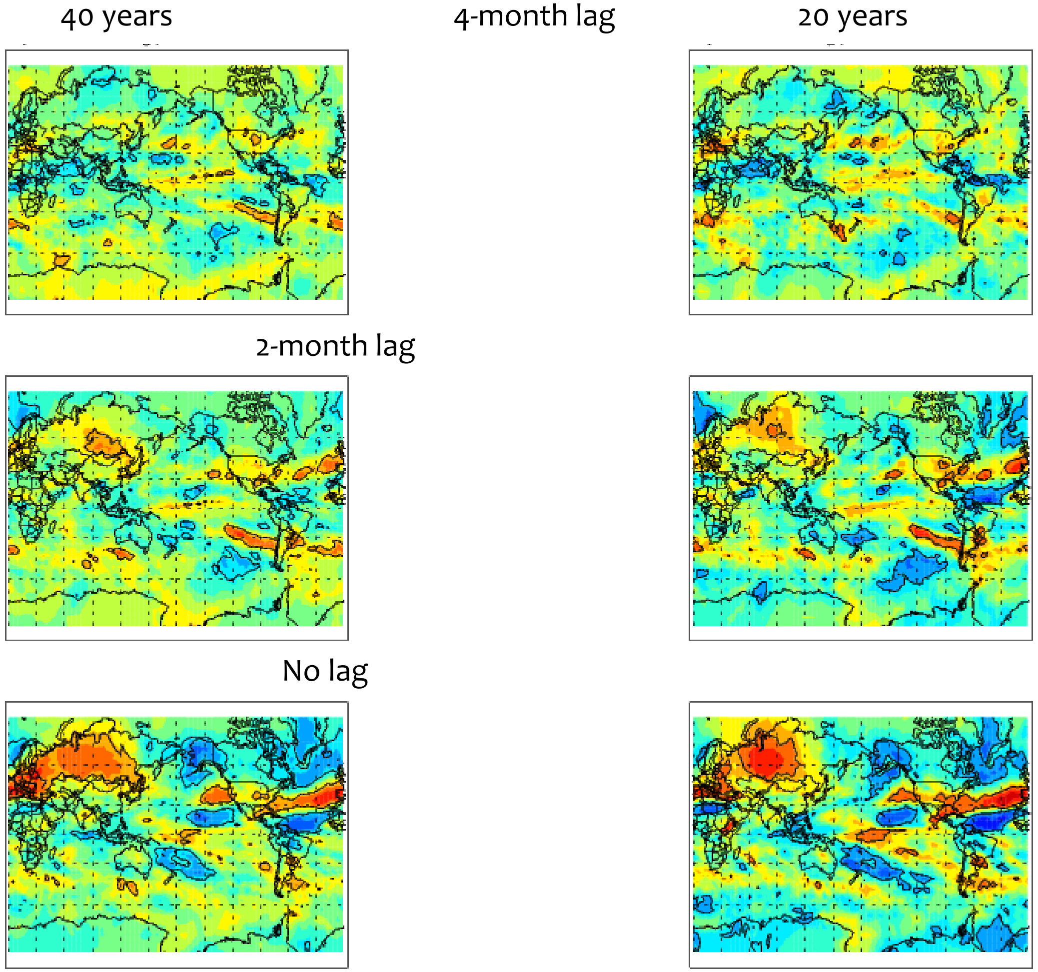
Wang et al., (2014)

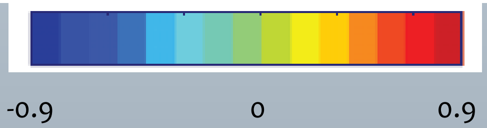
r(PC1, SST)



La Niña signal

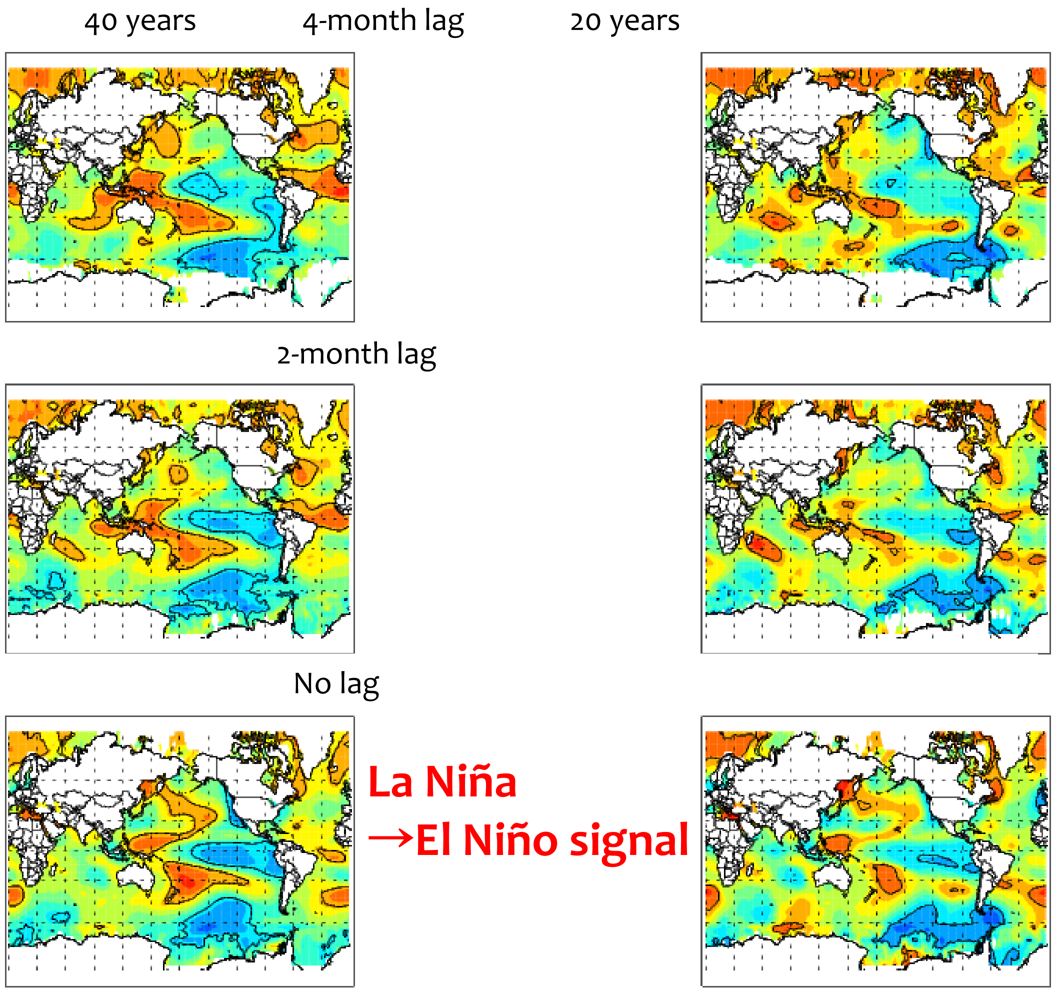
r(PC1, OLR)

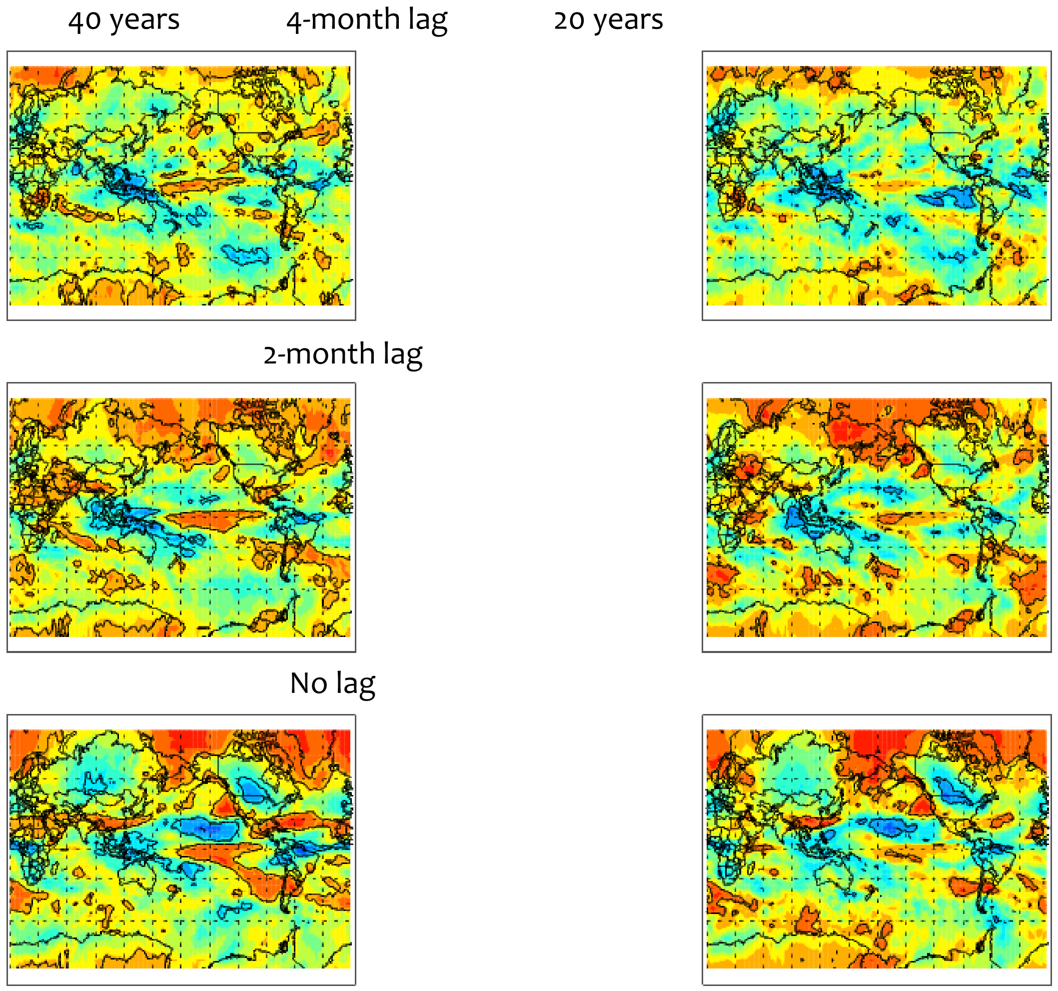


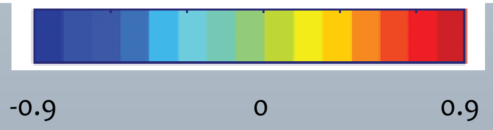


r(PC2, SST)

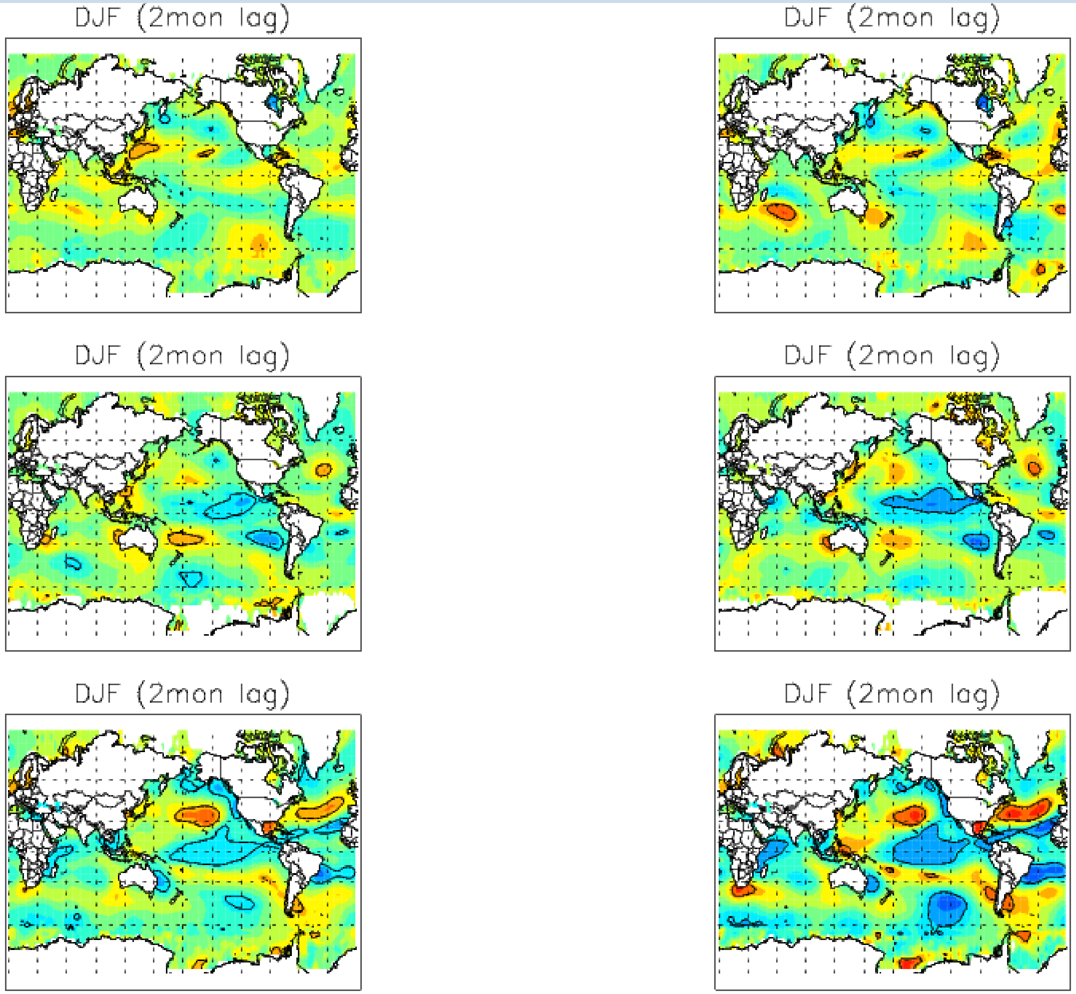
r(PC2, OLR)

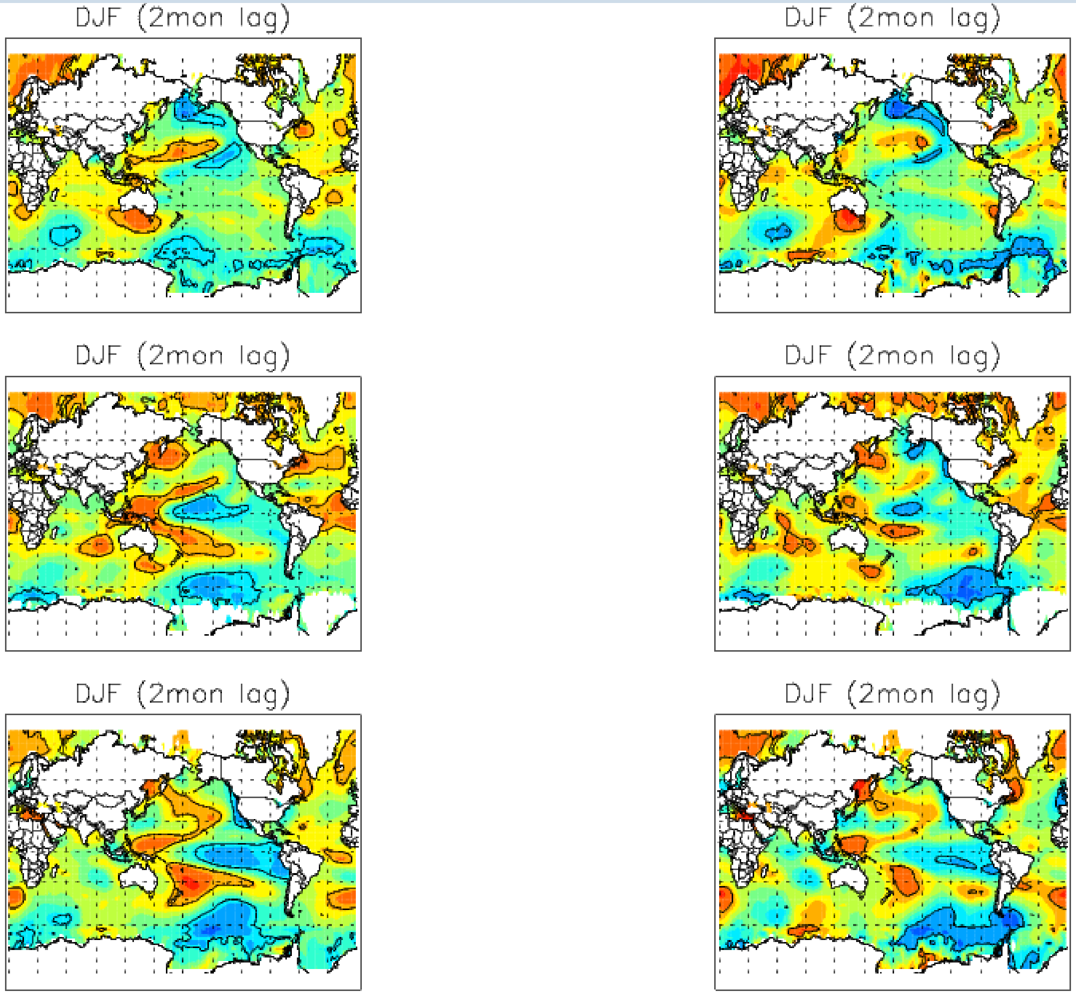






PC1 vs SST (6-month lag) PC2 vs SST



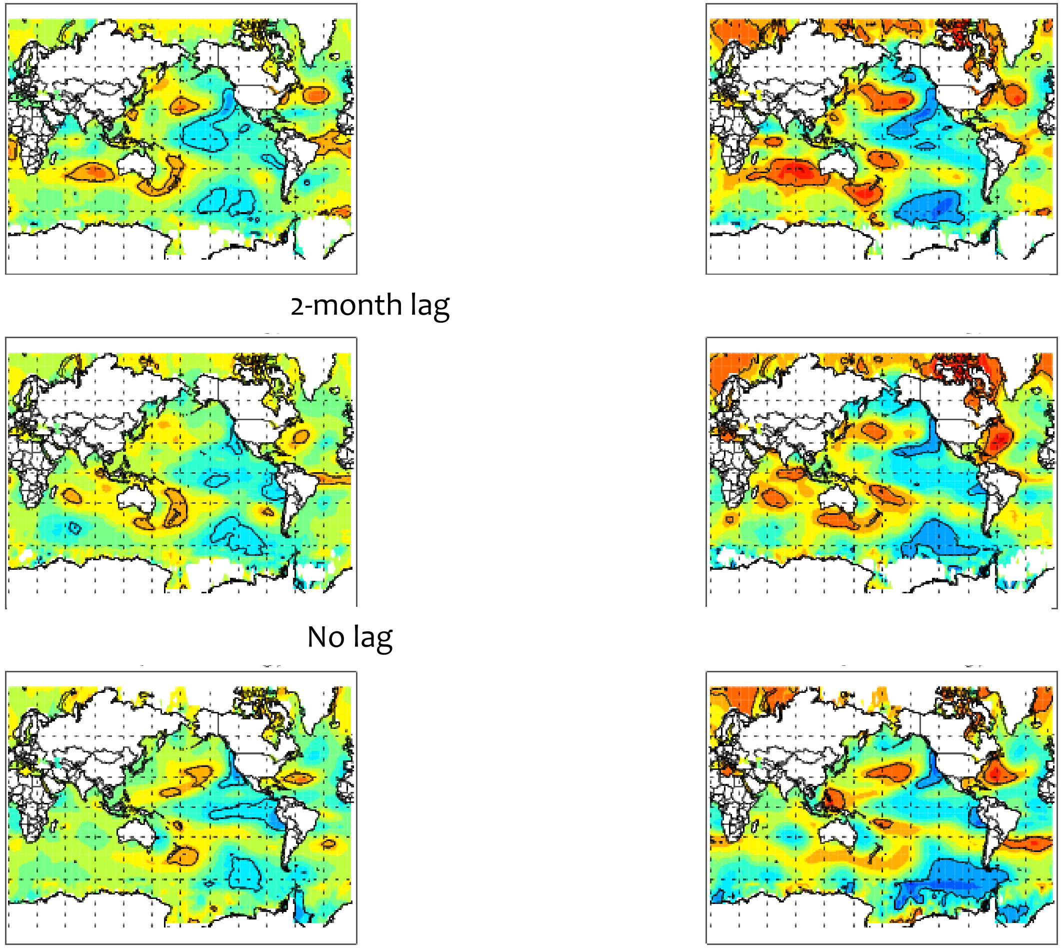


Preliminary Results

1. The recent California droughts started about La Nina periods and continued/amplified in the transitional periods from the La Niña to El Niño.
2. Anomalous positive height anomalies are responsible for precipitation deficits and resulted in droughts; EOF1 of height is dominant in La Nina winters while EOF2 is dominant in the transitional periods.
3. Precipitation in the western tropical Pacific seems to be responsible for the atmospheric teleconnection associated with CA droughts.
4. While the interannual relationship of California precipitation with ENSO (or PDO) has been found in many other studies, veryfing drought maintaining/amplification mechanisms in the transitional periods require further analyses.

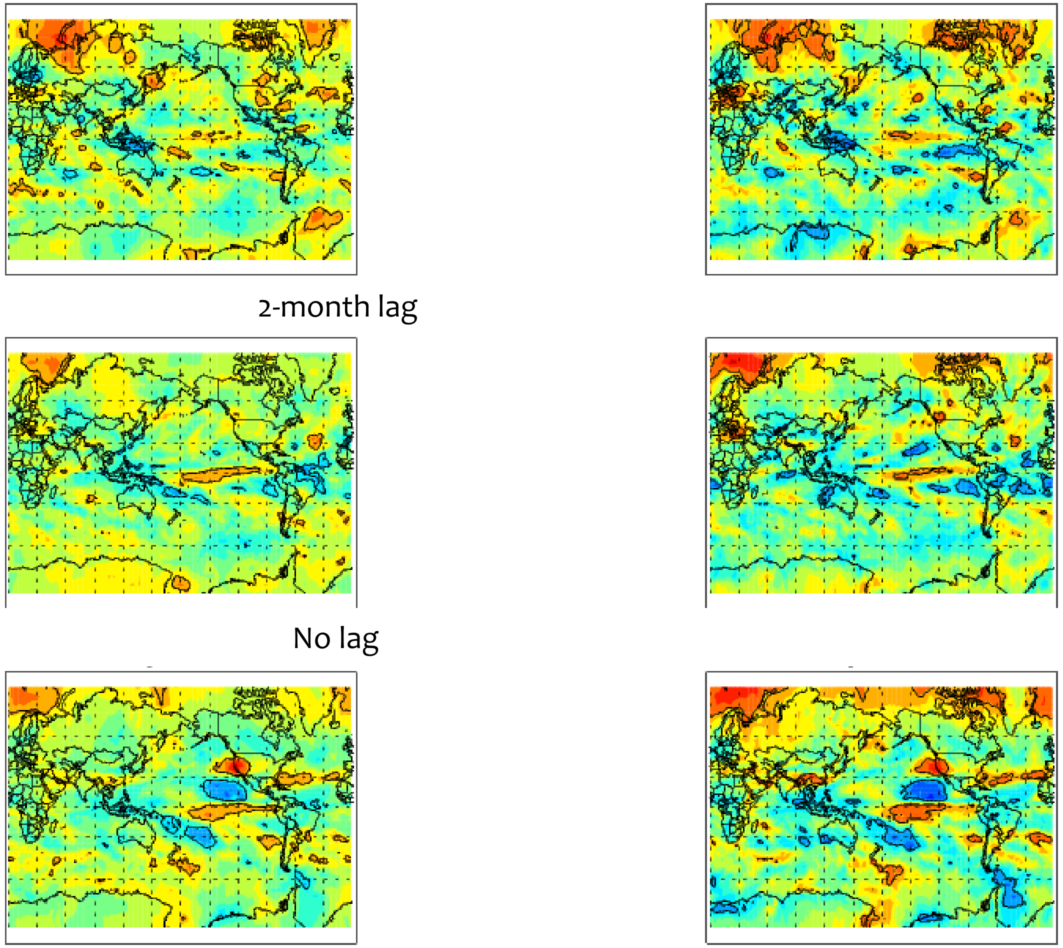
r(PRECIP, SST)

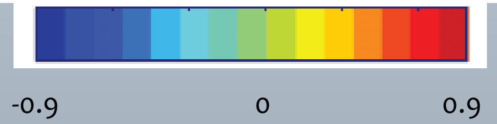
40 years   4-month lag   20 years



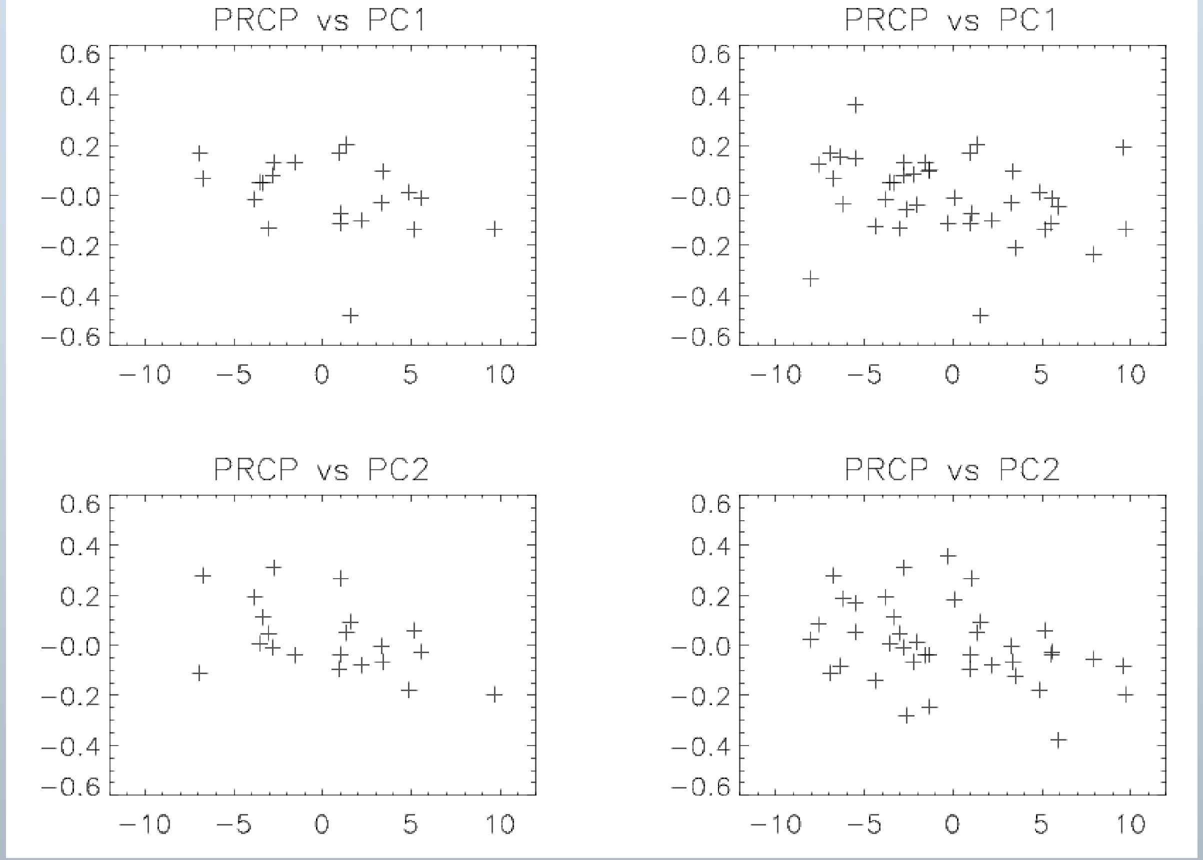
r(PRECIP, OLR)

40 years   4-month lag   20 years





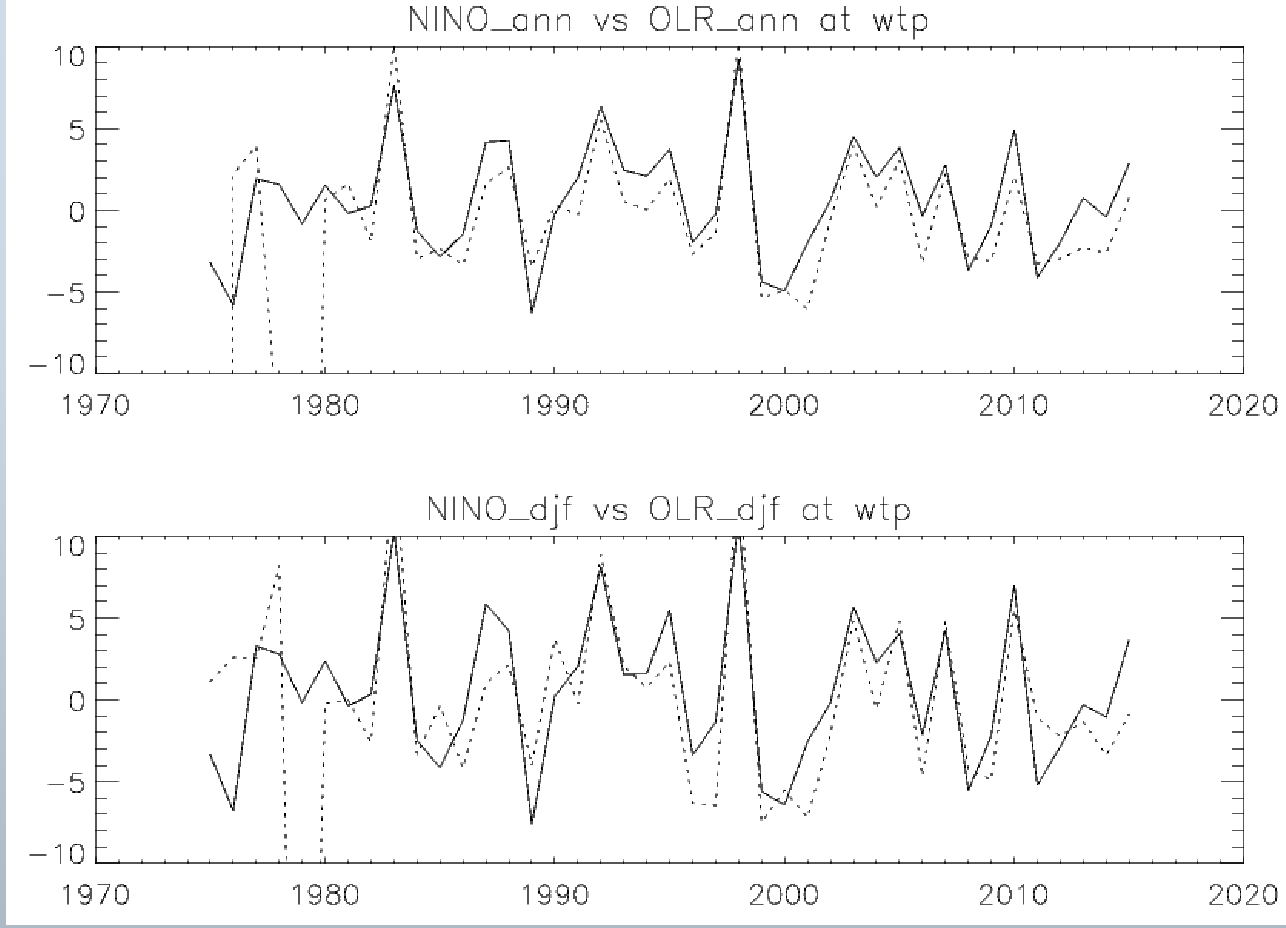
Correlations of PCs



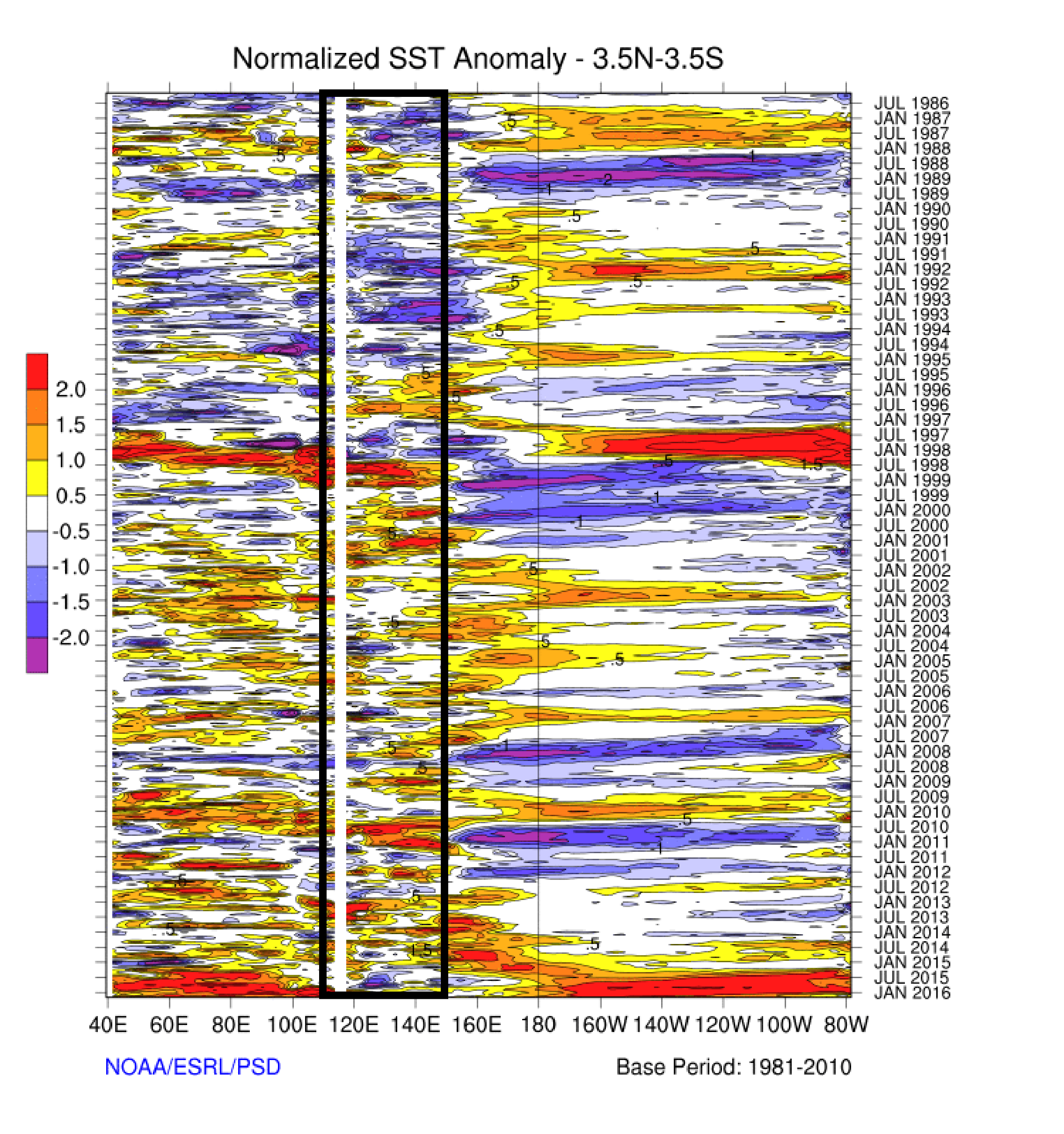
With P	PC1	PC2
41 years	-0.27	**-0.35**
21 years	-0.37	**-0.44**

	PC1	PC2
PDO	**-0.475840**	<u>-0.278005</u>
NINO3.4	**-0.434554**	**-0.421173**
EMI	**-0.356462**	-0.123901
SOI	**0.332493**	**0.482065**
NAO	**0.775132**	**-0.376926**

NINO3.4 vs. OLR at WTP and WTP warming



(110~150E/7.5S~7.5N)



Implication on droughts in East Asia

- Active convective precipitation in WTP can cause dryness of East Asia Summer Monsoon (EASM).
- Positive NAO phases in spring can suppress EASM.

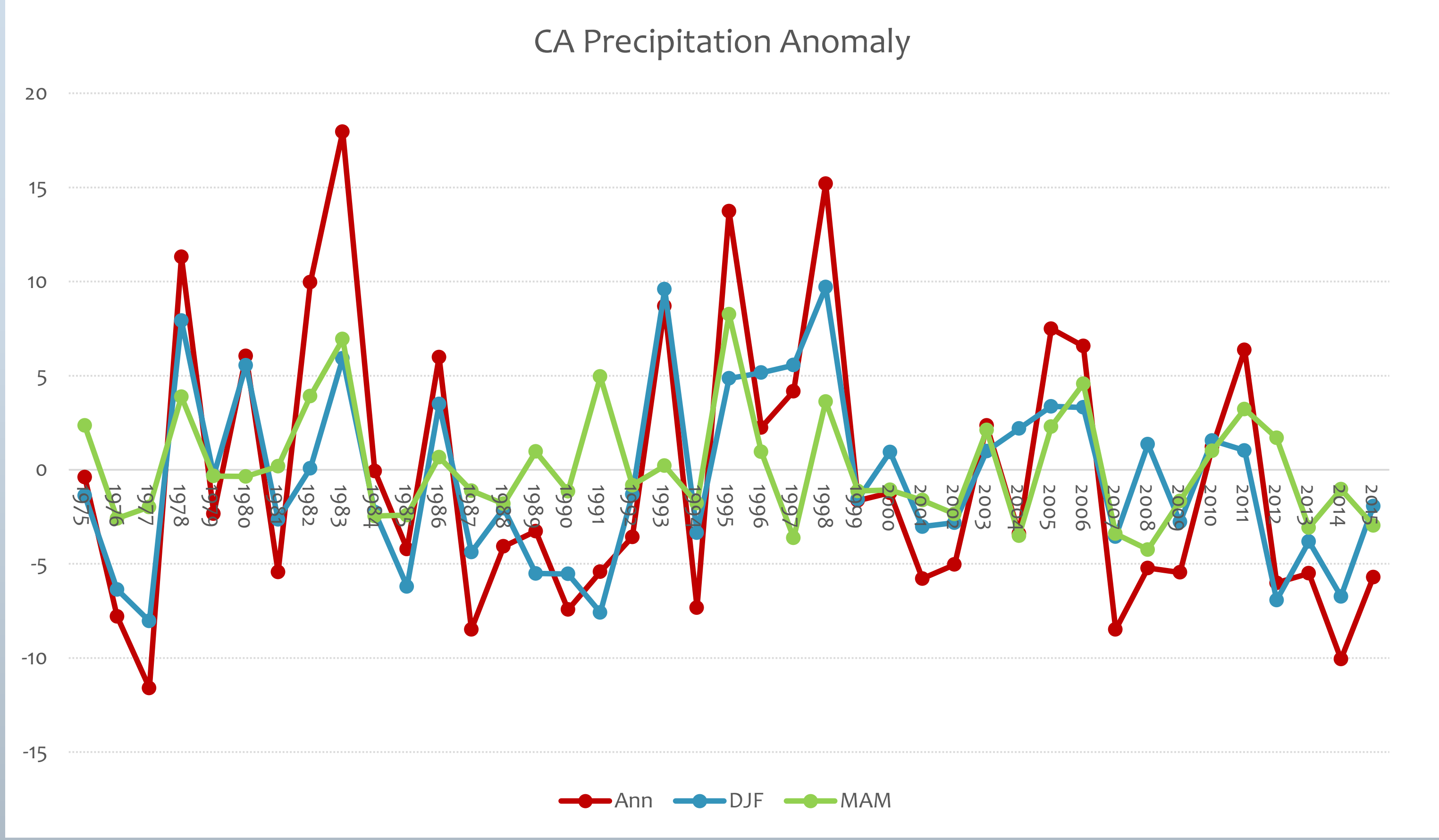
$\Rightarrow$These two processes are also related to the mechanisms of the CA droughts.

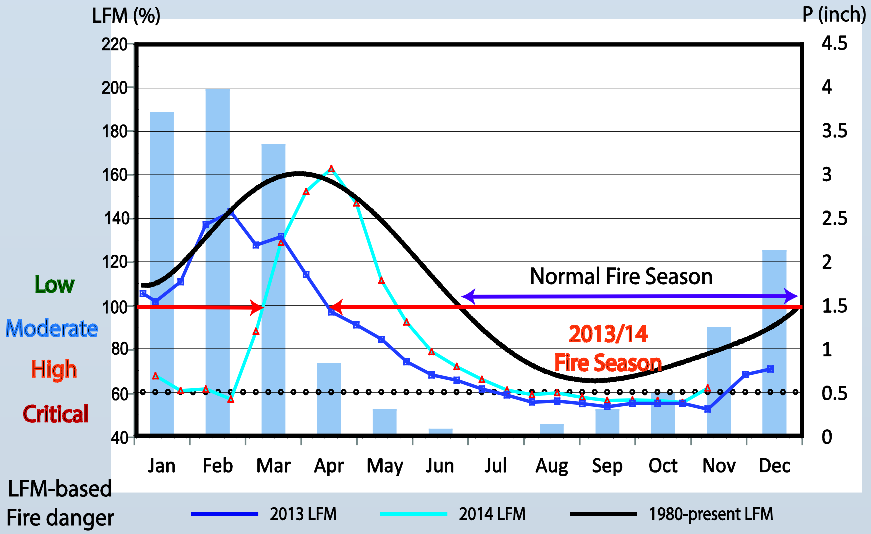
Future work

- CA Drought mechanisms in spring.
- Mechanisms of the concurrent drought events in CA and East Asia.
- Different impacts of EP/CP El Nino on droughts.

- For longer time period, impacts of ENSO transitions with respect to drought occurrence in CA and East Asia

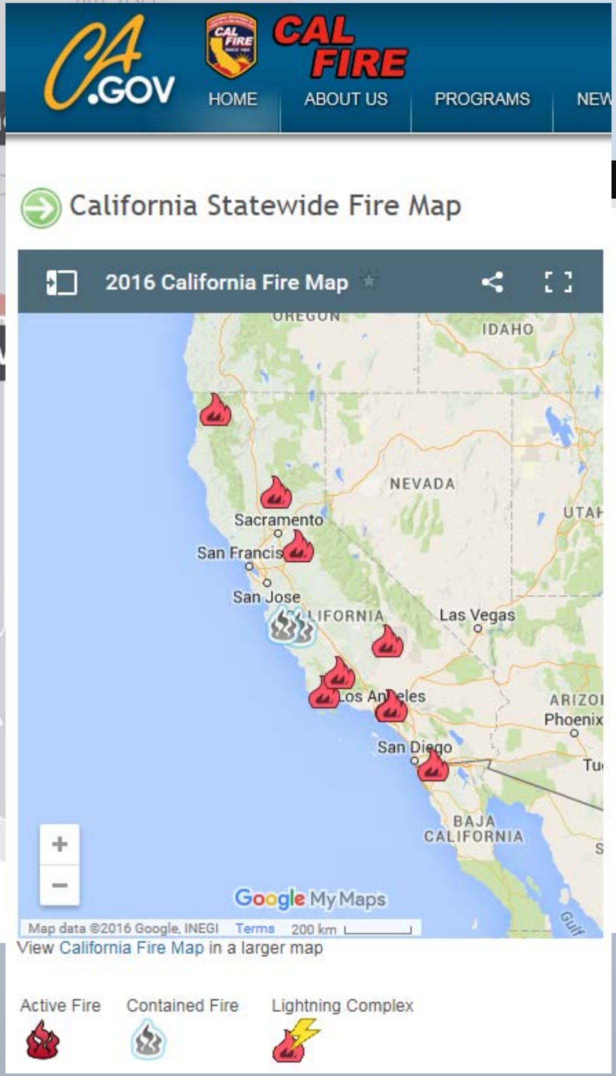
CA Precipitation Anomaly

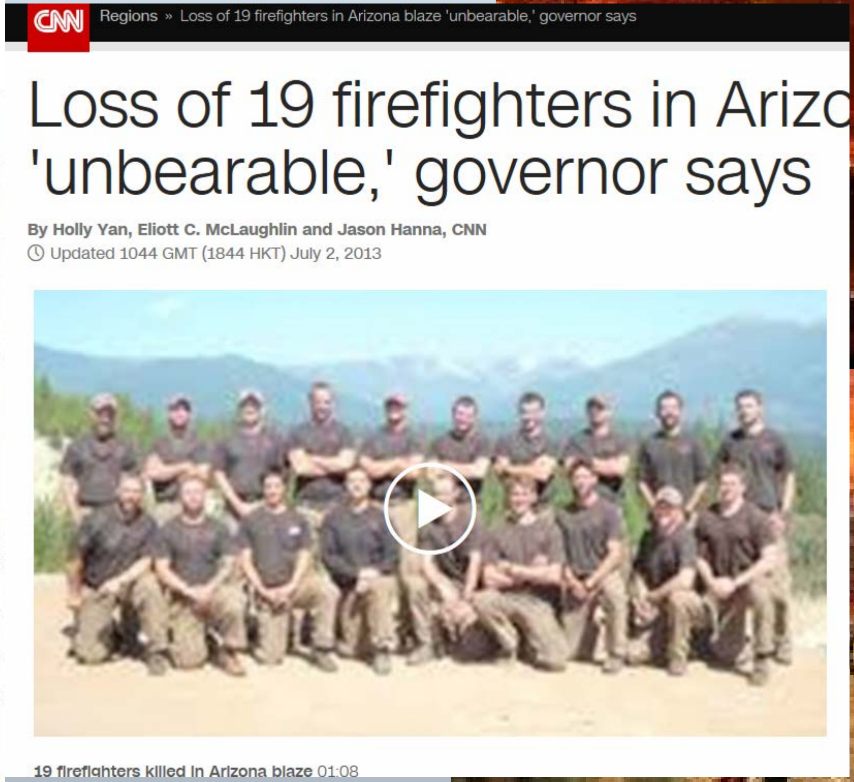




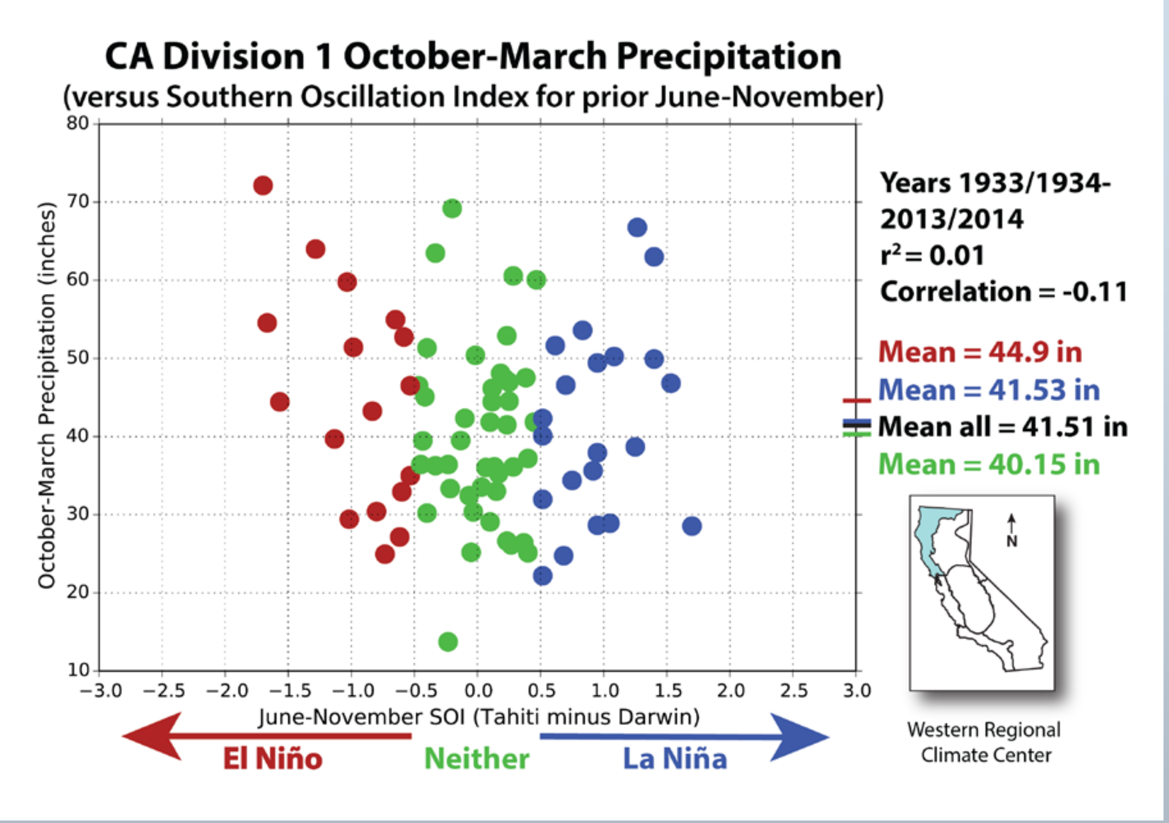
- MAM precipitation anomalies contributed to the three droughts.

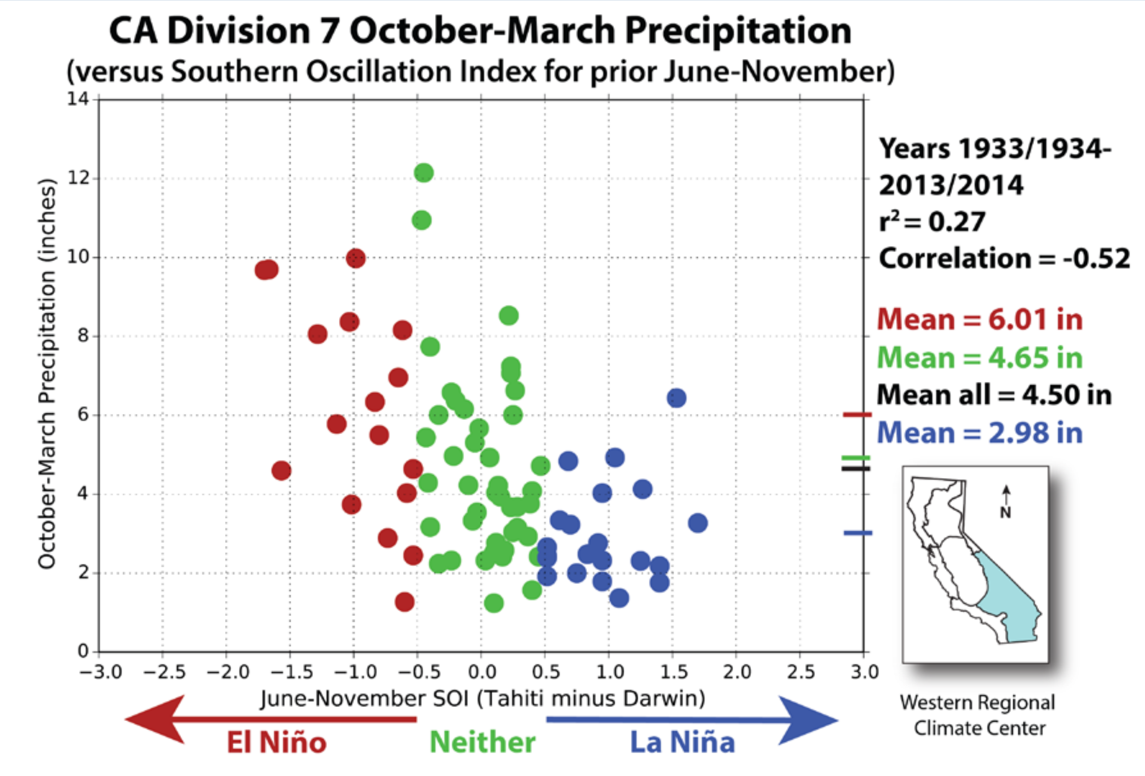
Frequent and severe wildfires



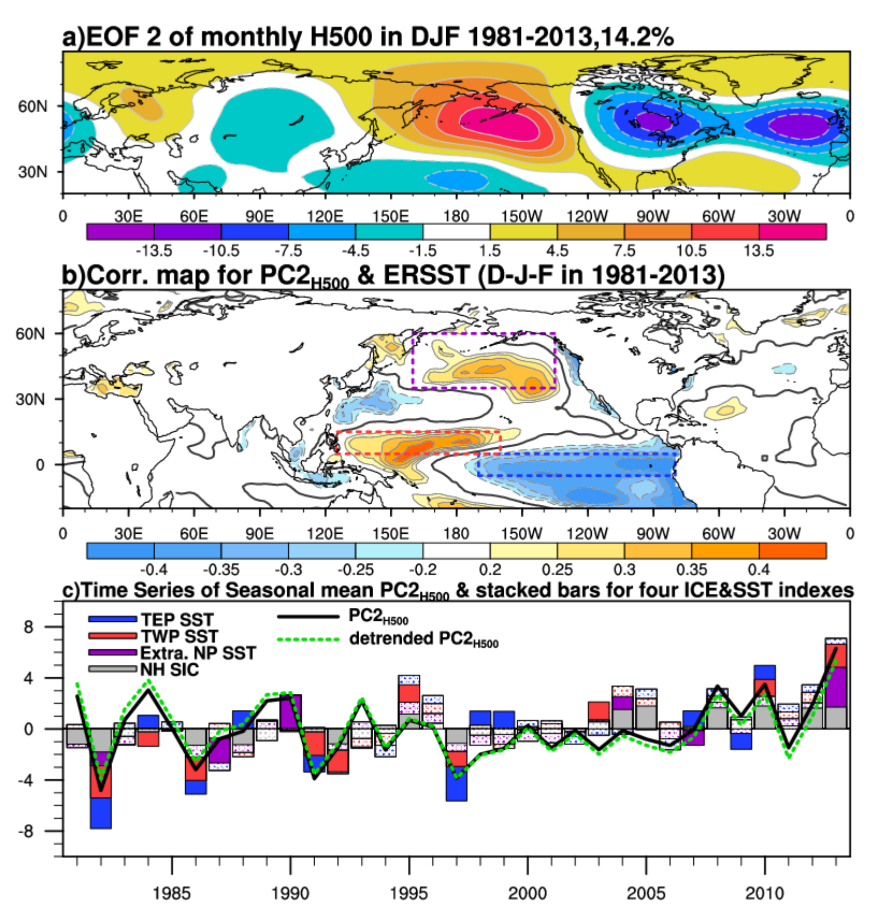


ENSO/SOI vs CA precipitation

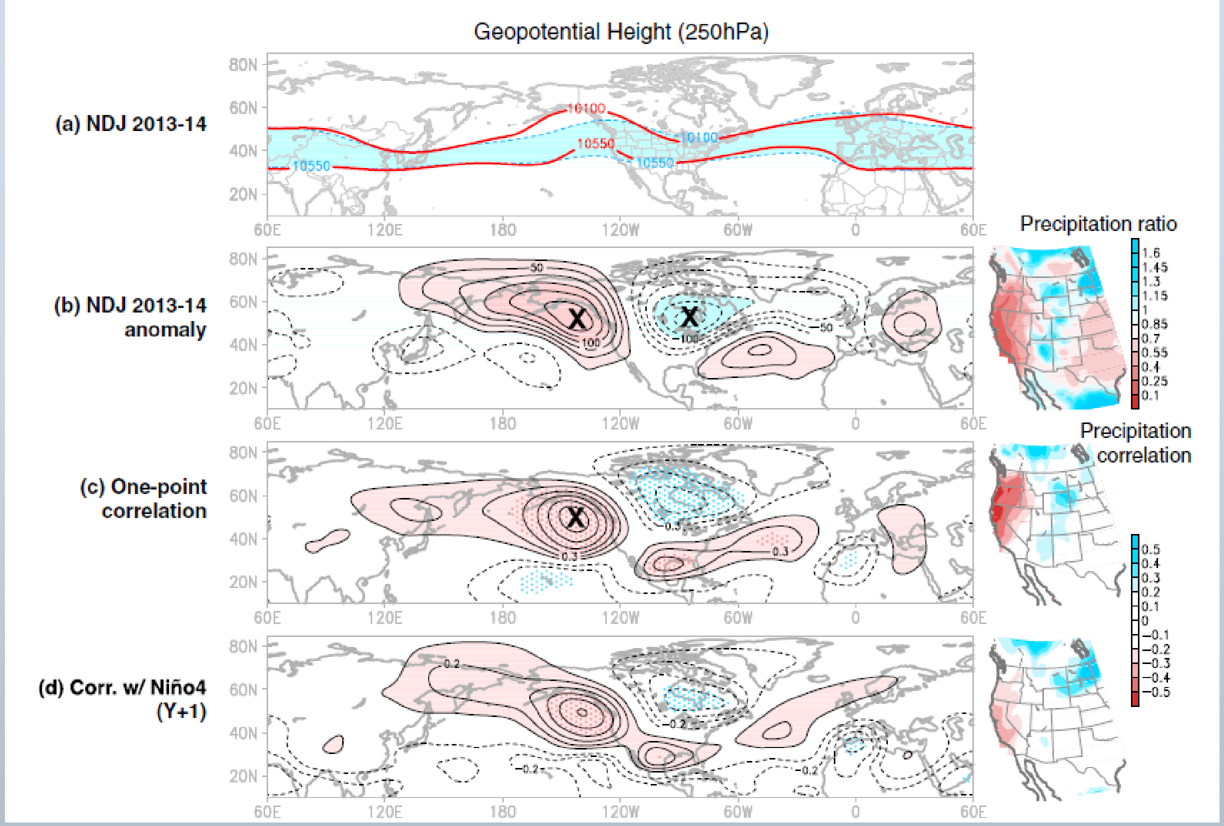




Previous Studies on the 2013/14 CA drought



Lee et al., (2015)



Wang et al., (2014)

Nameless Oscillation

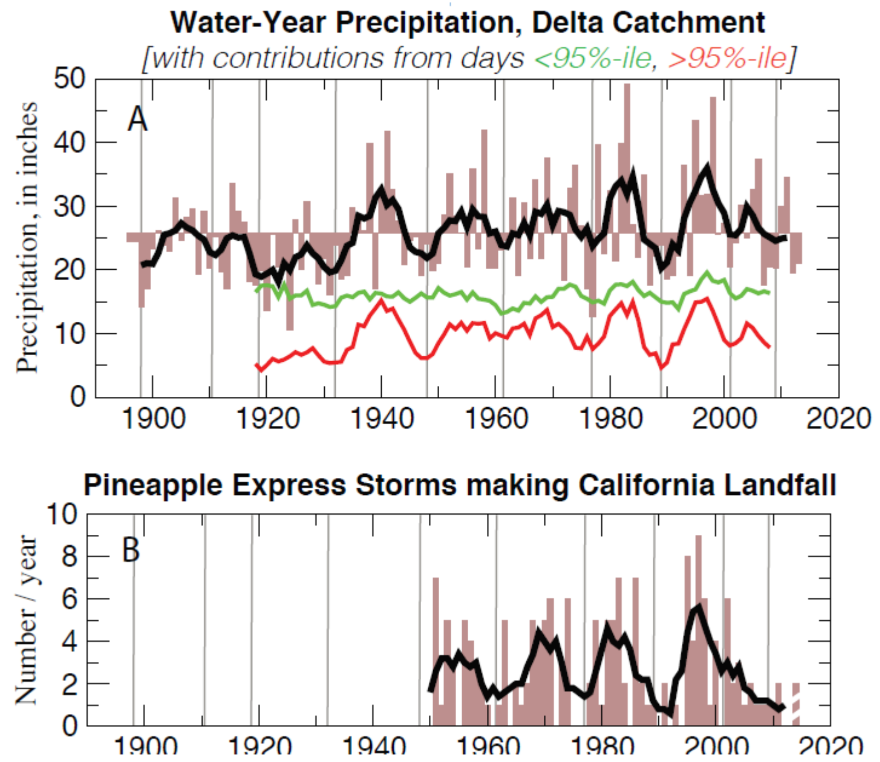
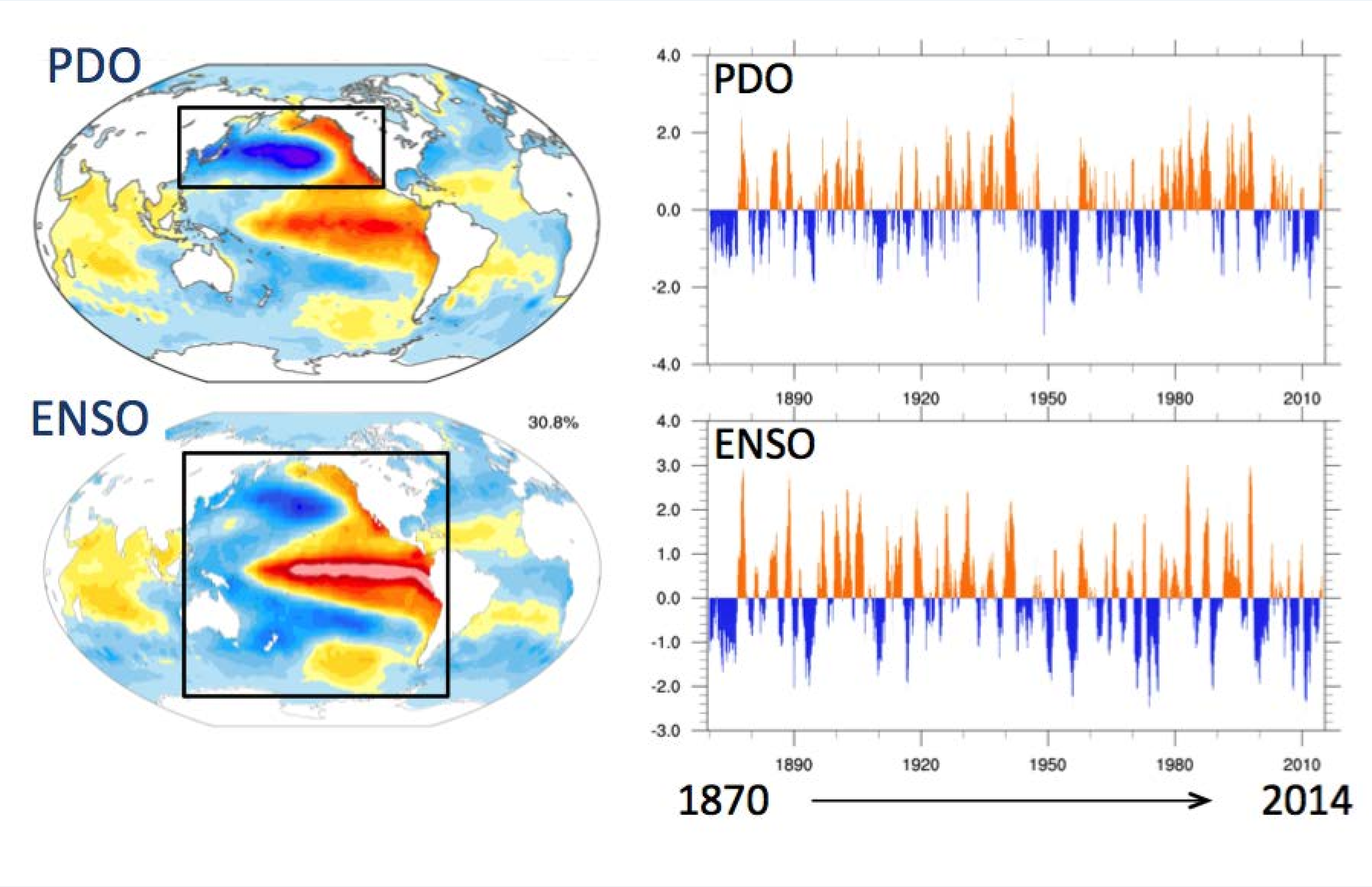
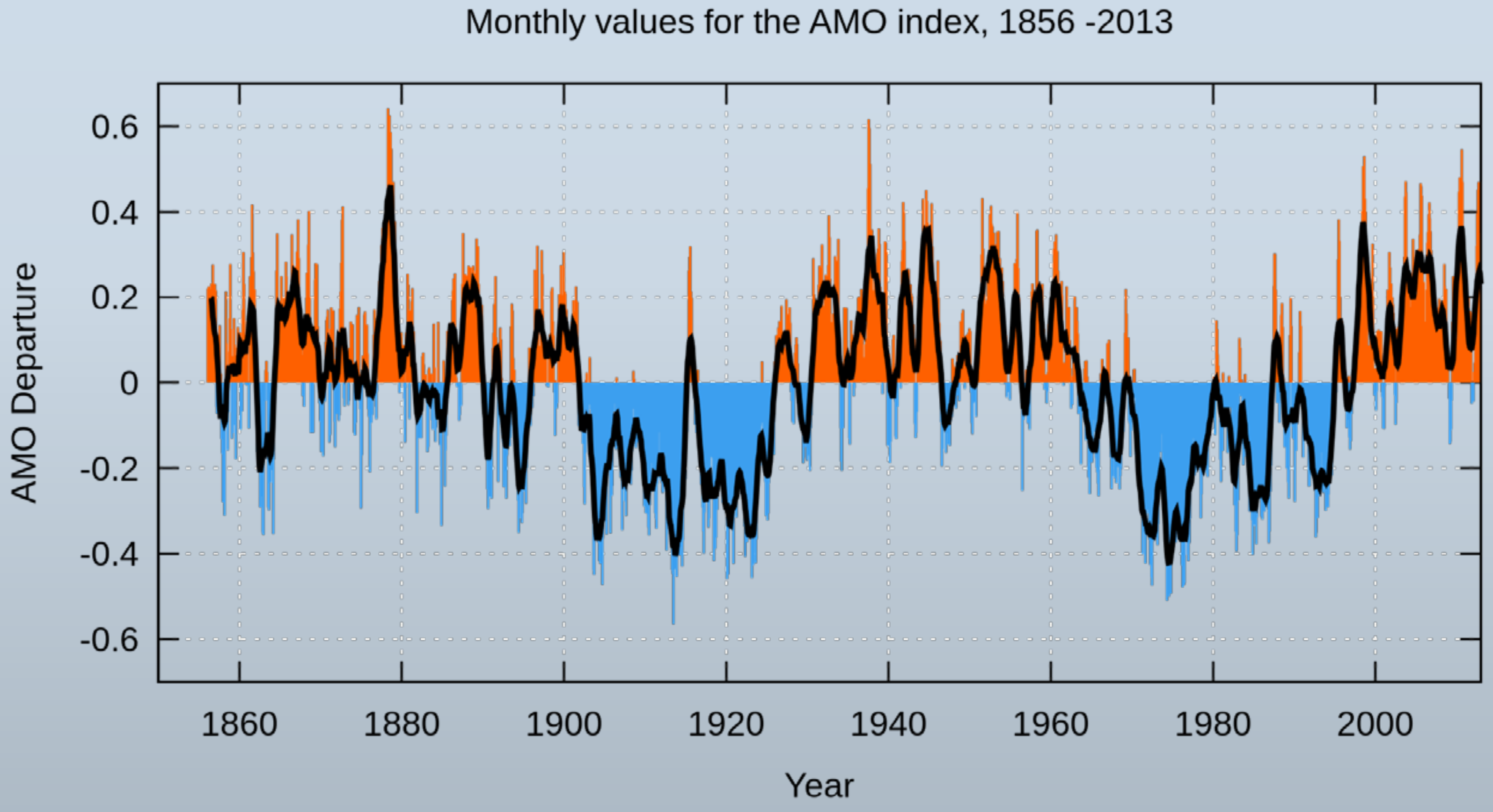


Figure 1 (**A**) Water-year precipitation totals (brown bars and black curve) in the Delta's catchment, 1895–present based on updated monthly Abatzoglou et al. (2009) data, and 5-year moving averages of contributions to these totals from the wettest 5% of wet days (days with precipitation >95th percentile; red curve) and all other wet days (<95th percentile; green curve) based on updated daily Hamlet et al. (2005) data, 1916–2010, and (**B**) numbers of pineapple-express storms making landfall between 35°N and 42.5°N per water year (using counts from Dettinger et al. 2011, updated through March 2014). Heavy curves are 5-year moving averages in both frames; vertical grey lines are approximate centers of persistent droughts in upper panel.

However, most of the Delta's catchment lies astride a mid-latitude zone where there is no net average effect of ENSO and PDO on drought (Cayan and Webb 1992; McCabe et al. 2004). That is, some El Niños (or warm PDO years) bring some of the wettest years to the Delta, but others bring drought, so that they are not reliable predictors in the Delta (McCabe et al. 2004). Distant Atlantic influences are poorly

Dettinger and Cayan, (2014)


PDO
ENSO
30.8%
PDO
ENSO
4.0
2.0
0.0
-2.0
-4.0
1890
1920
1950
1980
2010
4.0
3.0
2.0
1.0
0.0
-1.0
-2.0
-3.0
1890
1920
1950
1980
2010
1870
2014


Monthly values for the AMO index, 1856 -2013
AMO Departure
Year
0.6
0.4
0.2
0
-0.2
-0.4
-0.6
1860
1880
1900
1920
1940
1960
1980
2000

PC1 vs NINO

	No lag	1-month lag	2-month lag	3-month lag
NINO4	-0.398805	-0.422780	-0.425642	-0.438343
NINO3.4	-0.434554	-0.455496	-0.462365	-0.396155
NINO3	-0.387892	-0.397102	-0.406544	
NINO12	-0.233036	-0.259658	-0.245651	

Challenges

- East Asia precipitation: Monsoon dominant climate (summer precipitation is important)
- Western US: Winter-precipitation dominant climate

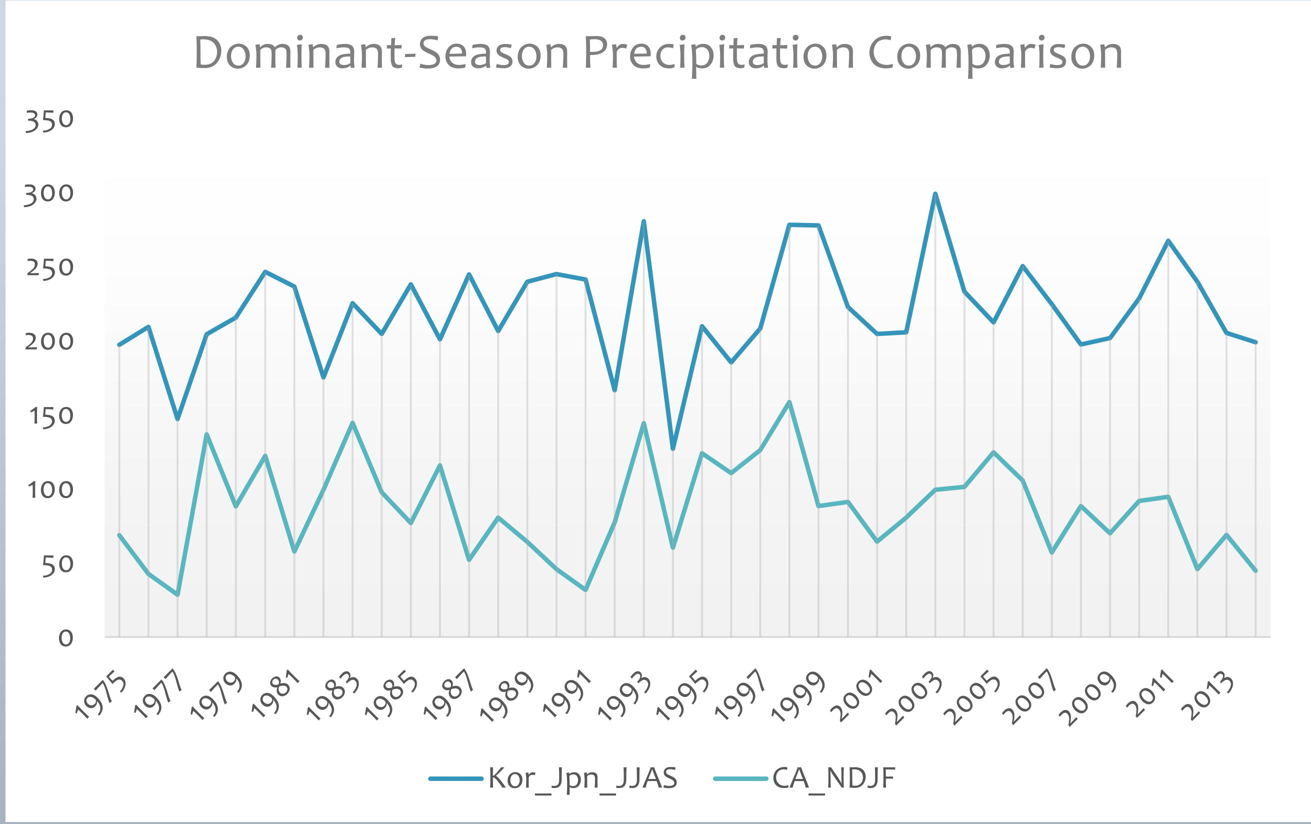
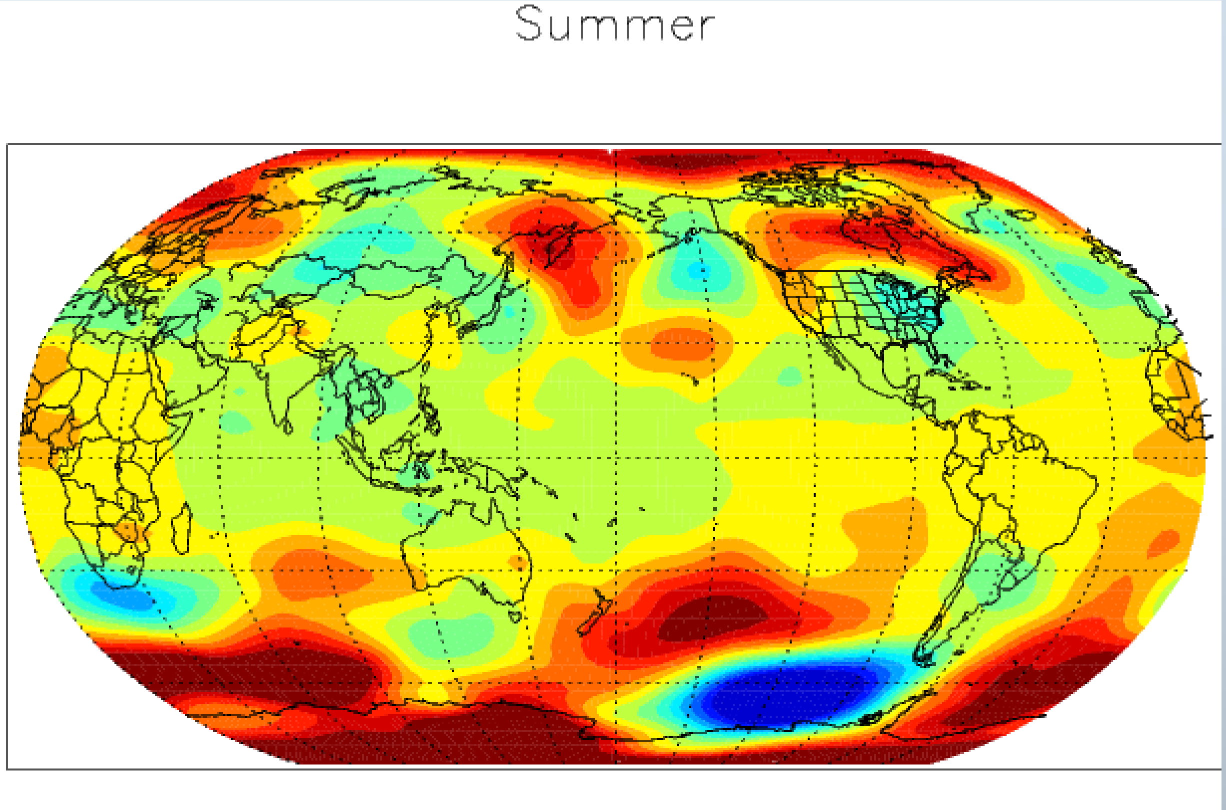
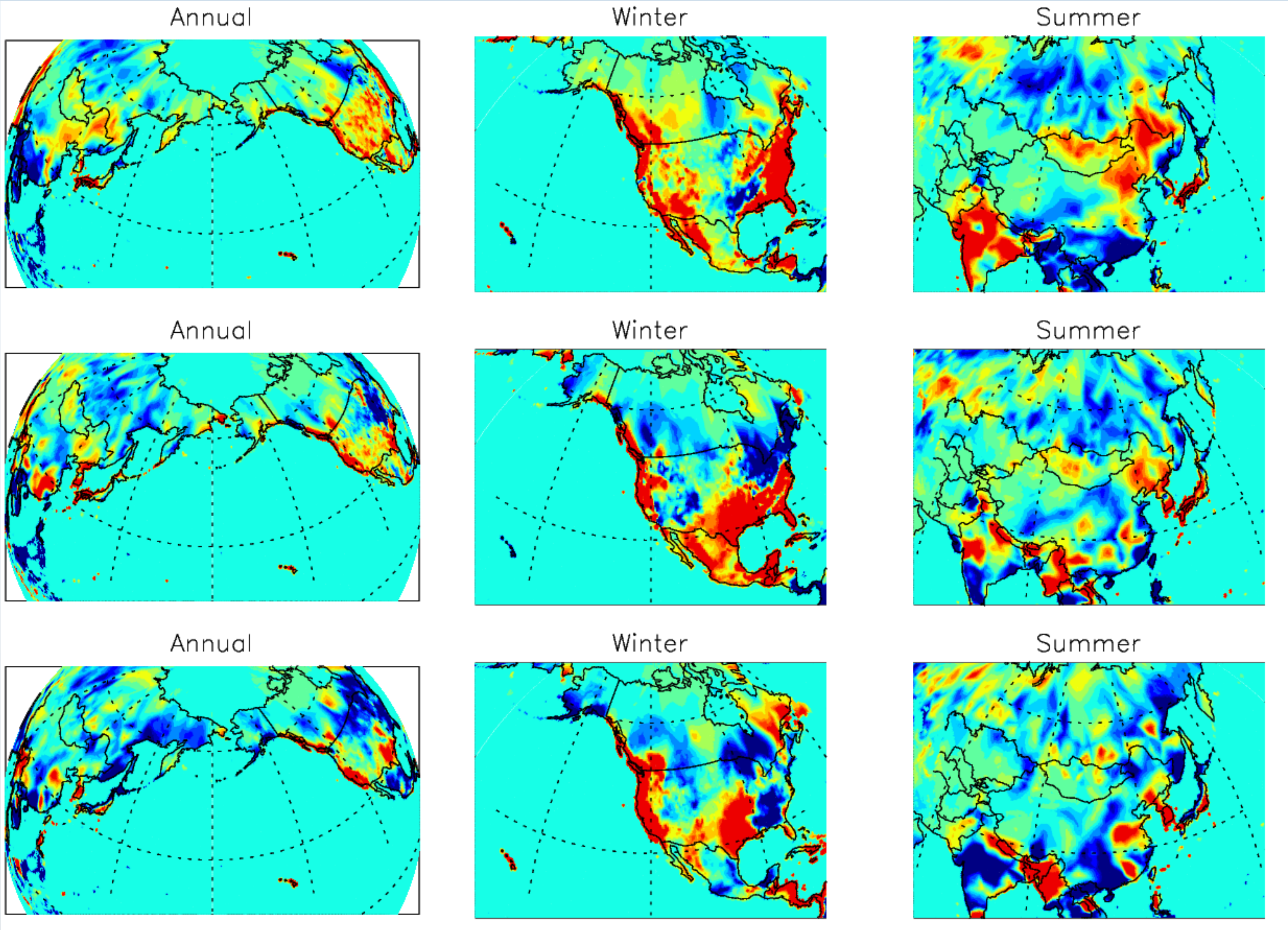


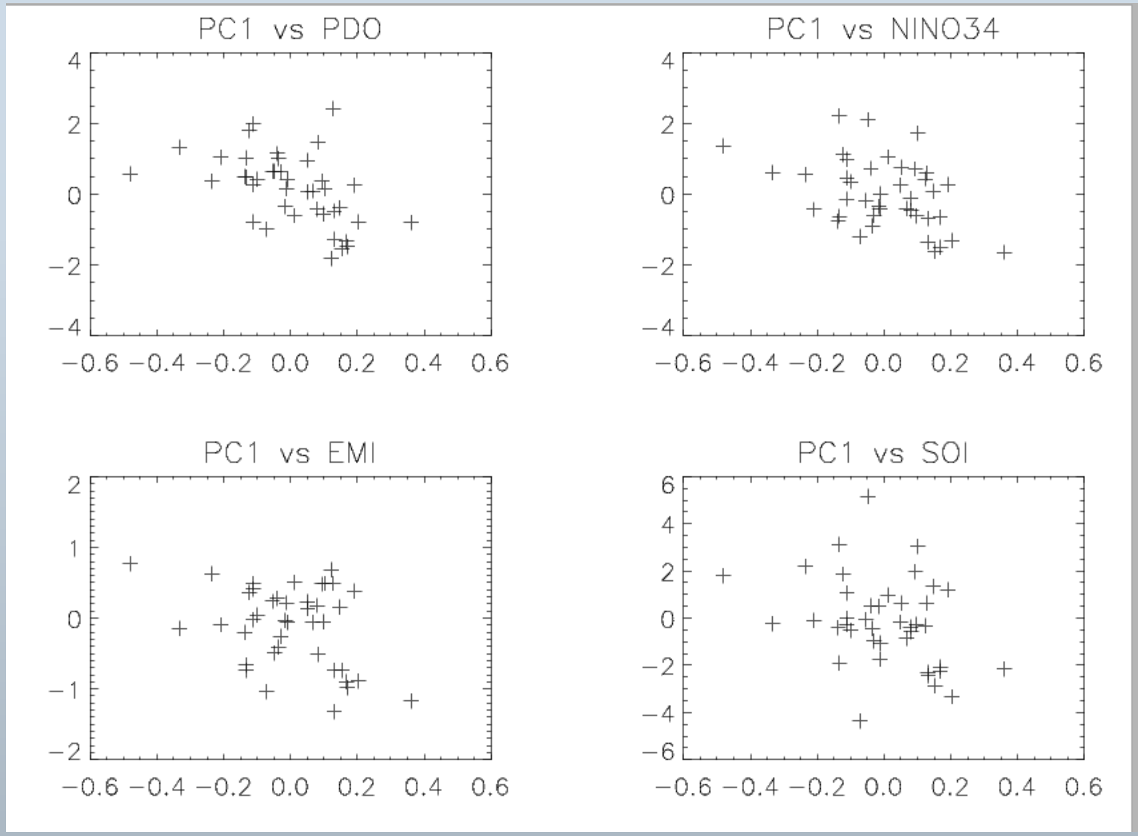
Table 1. Regression analysis using PDO and NAO

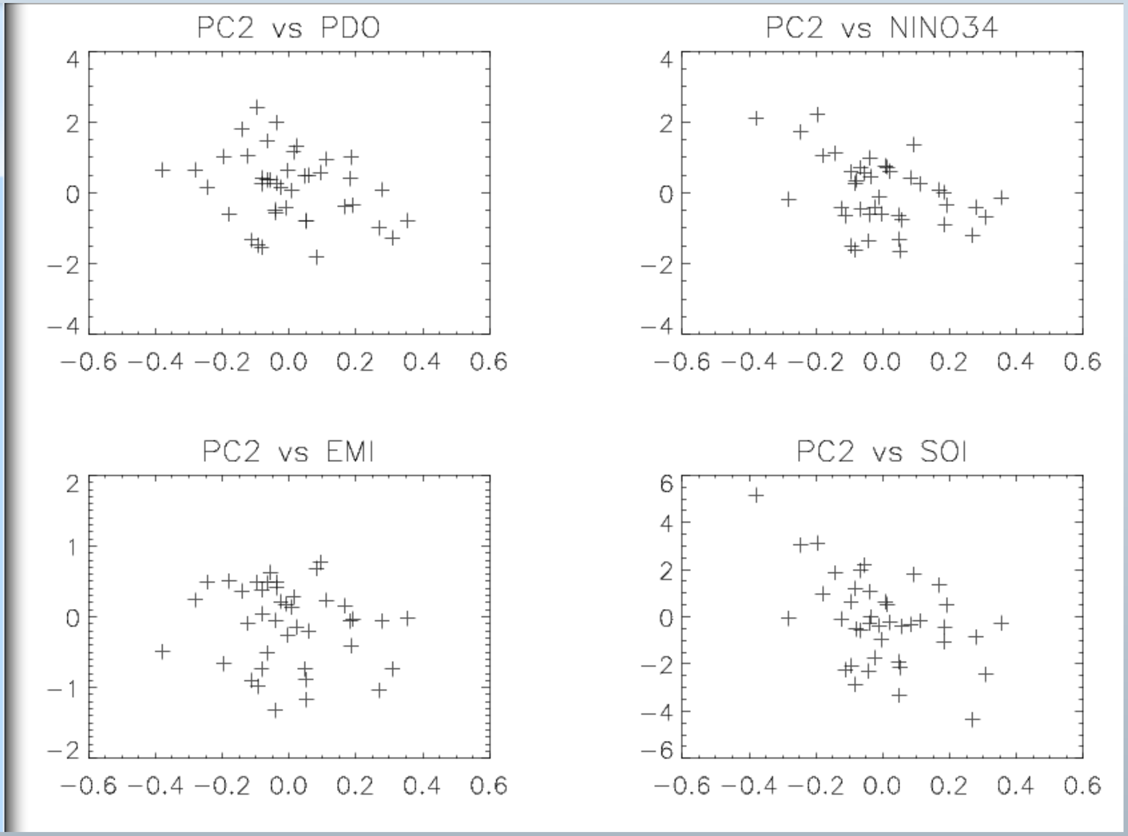
All	0.579871	0.698253
1	0.300428	0.420270
2	0.245252	0.475445
3	0.134413	0.357891
4	0.341433	0.344813
5	0.634232	0.729677
6	0.478811	0.697848


Summer

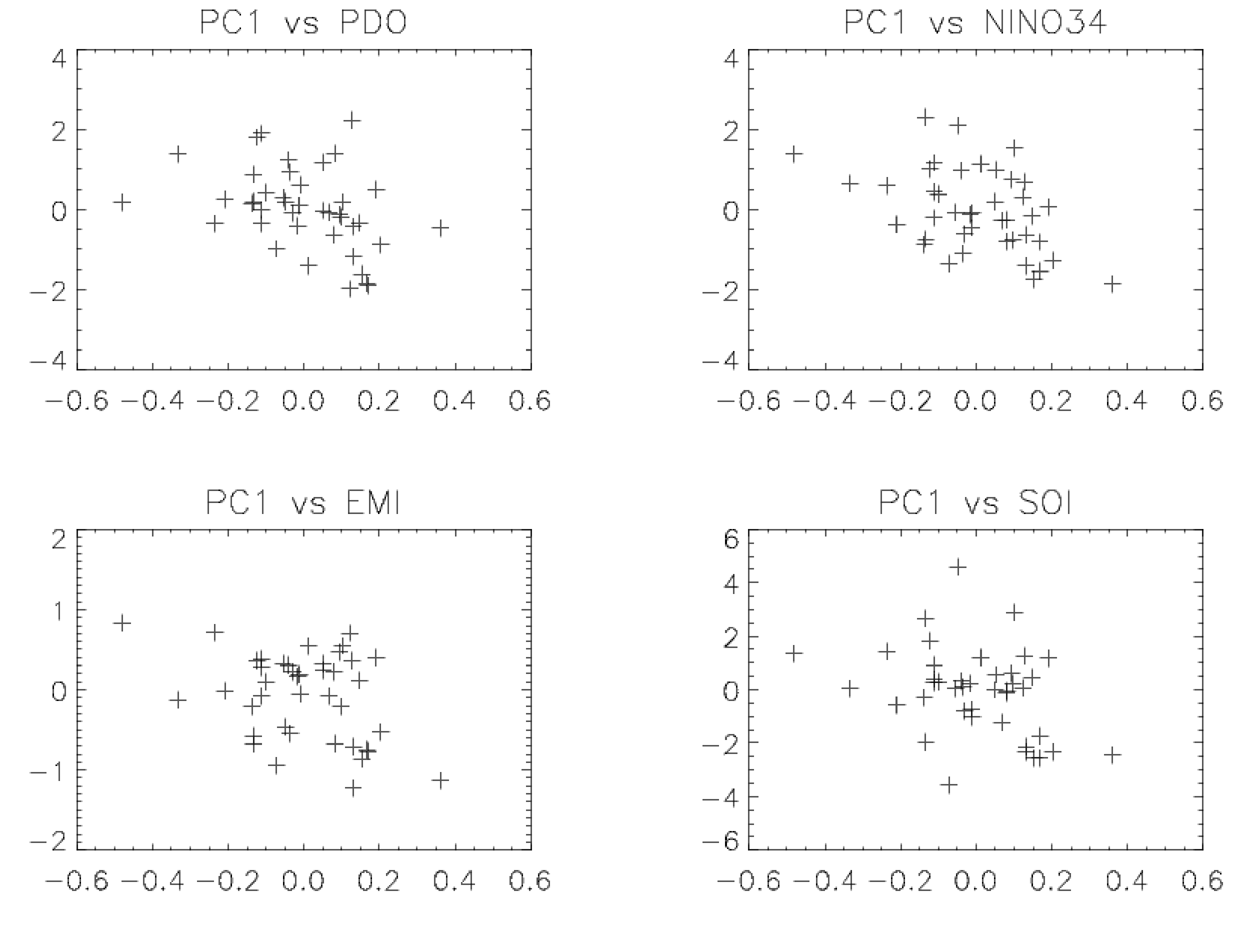

Annual
Winter
Summer
Annual
Winter
Summer
Annual
Winter
Summer

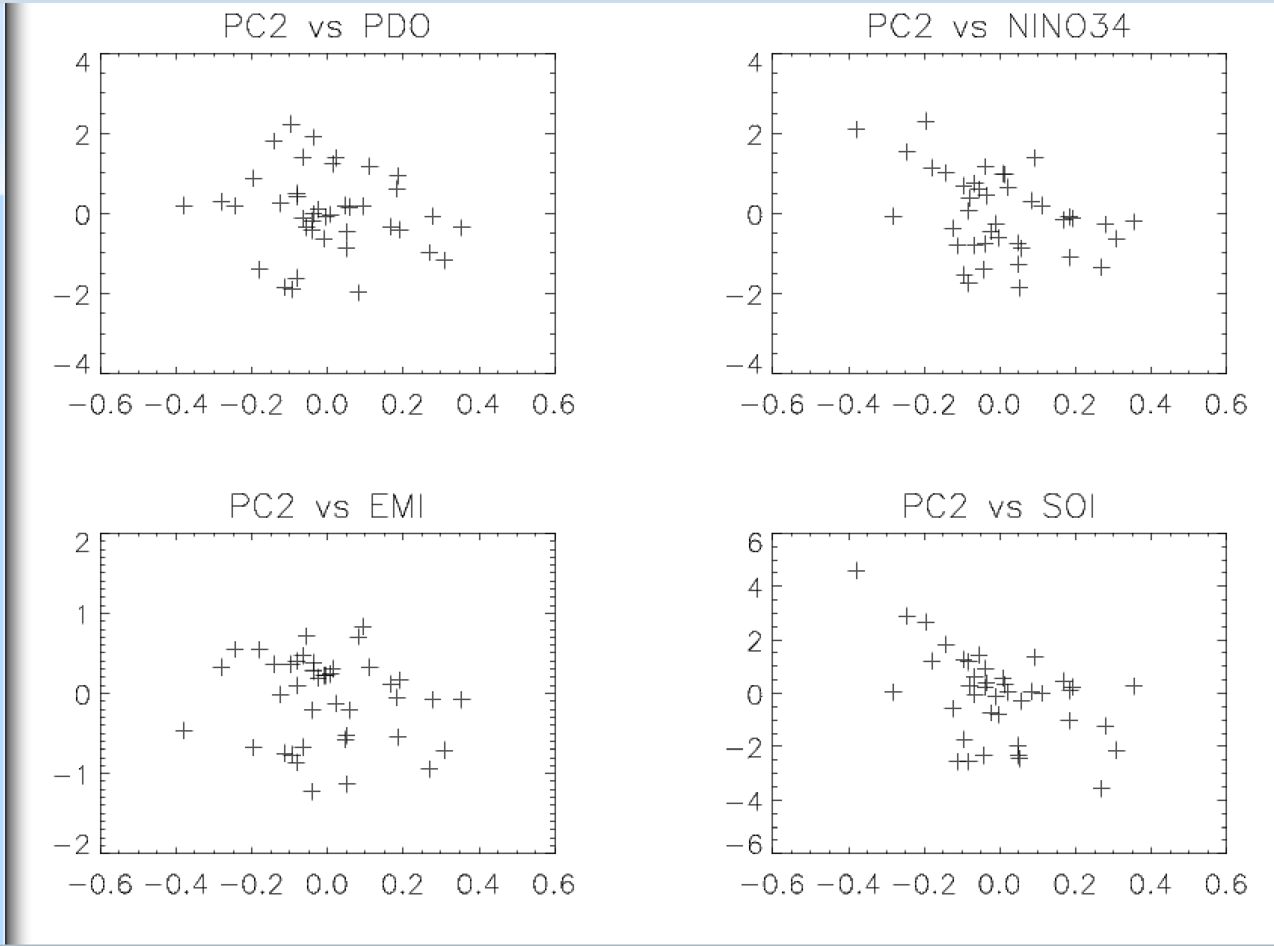
No Lag

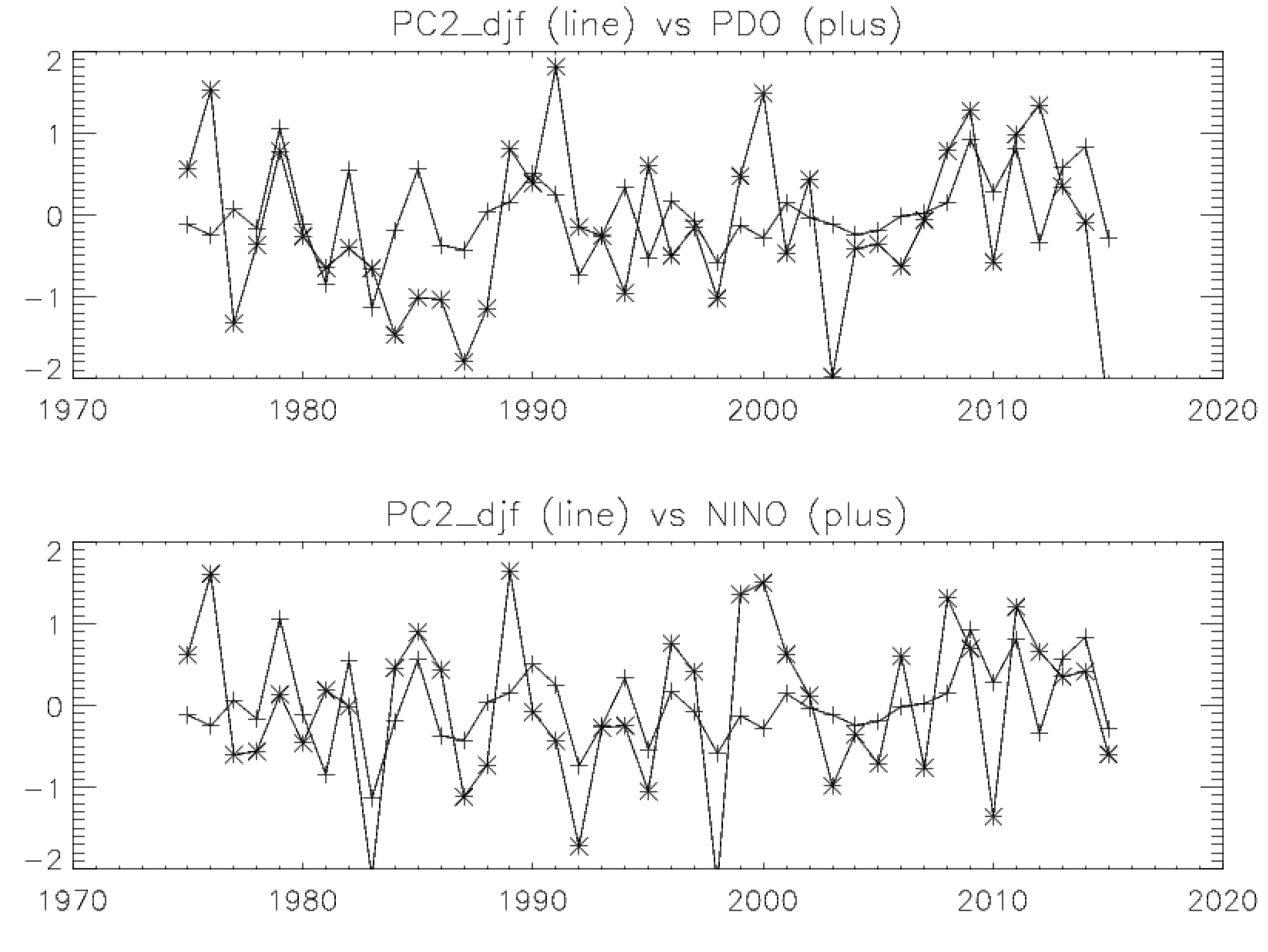

PC1 vs PDO
PC1 vs NINO34
PC1 vs EMI
PC1 vs SOI

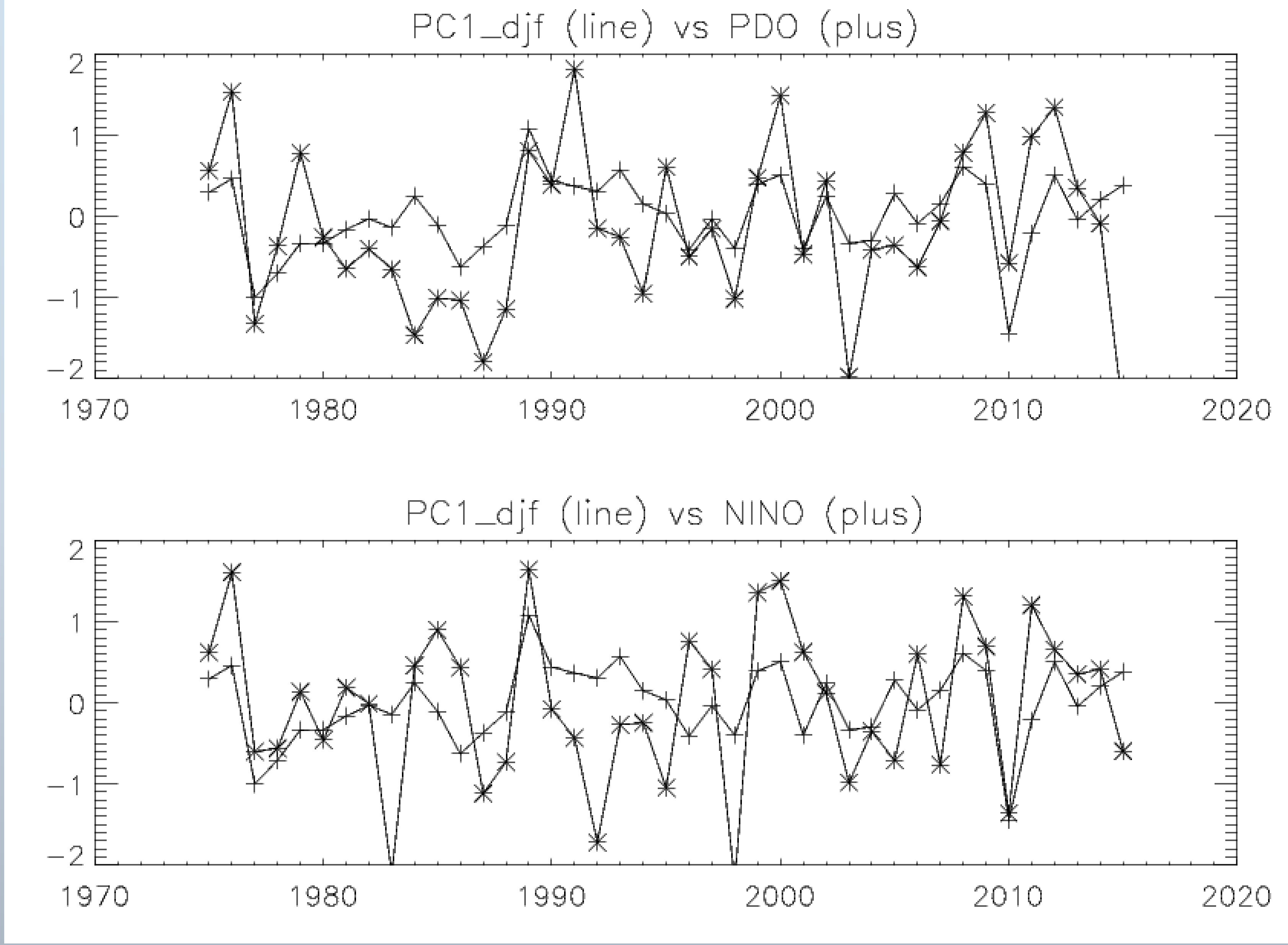

PC2 vs PDO
PC2 vs NINO34
PC2 vs EMI
PC2 vs SOI

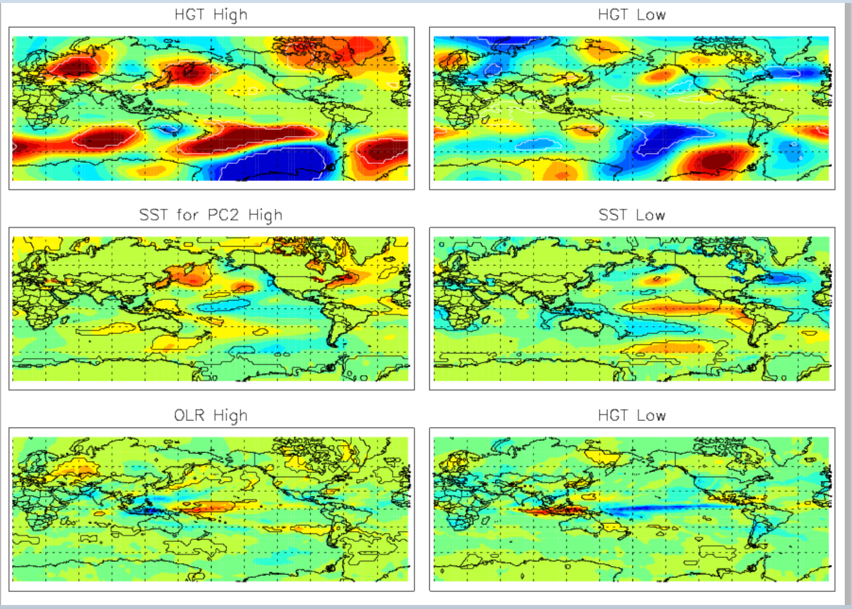
1-month lag

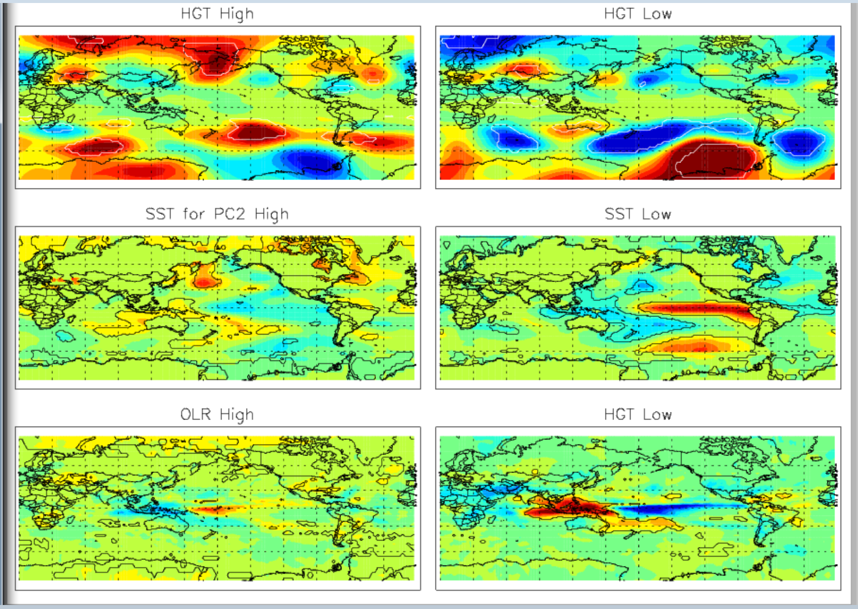

PC1 vs PDO
PC1 vs NINO34
PC1 vs EMI
PC1 vs SOI
−0.6 −0.4 −0.2 0.0 0.2 0.4 0.6

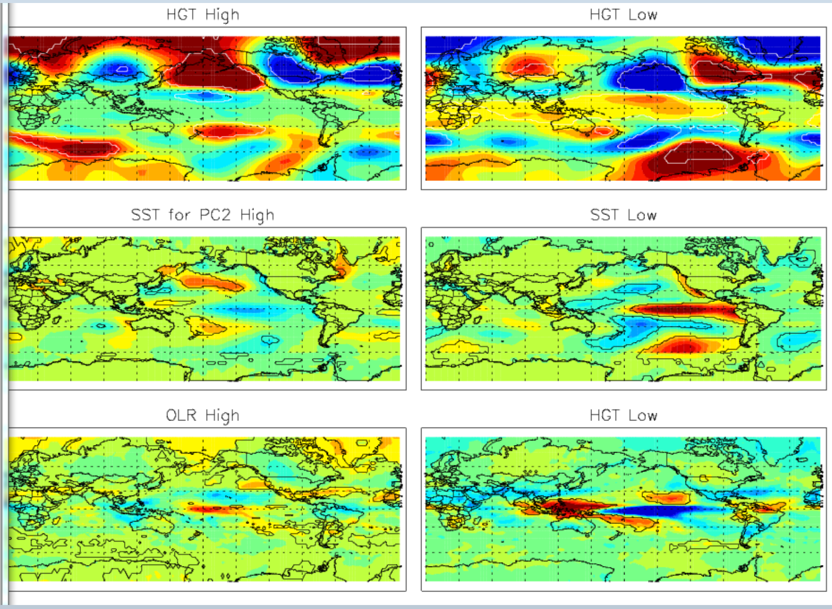

PC2 vs PDO
PC2 vs NINO34
PC2 vs EMI
PC2 vs SOI
−0.6 −0.4 −0.2 0.0 0.2 0.4 0.6

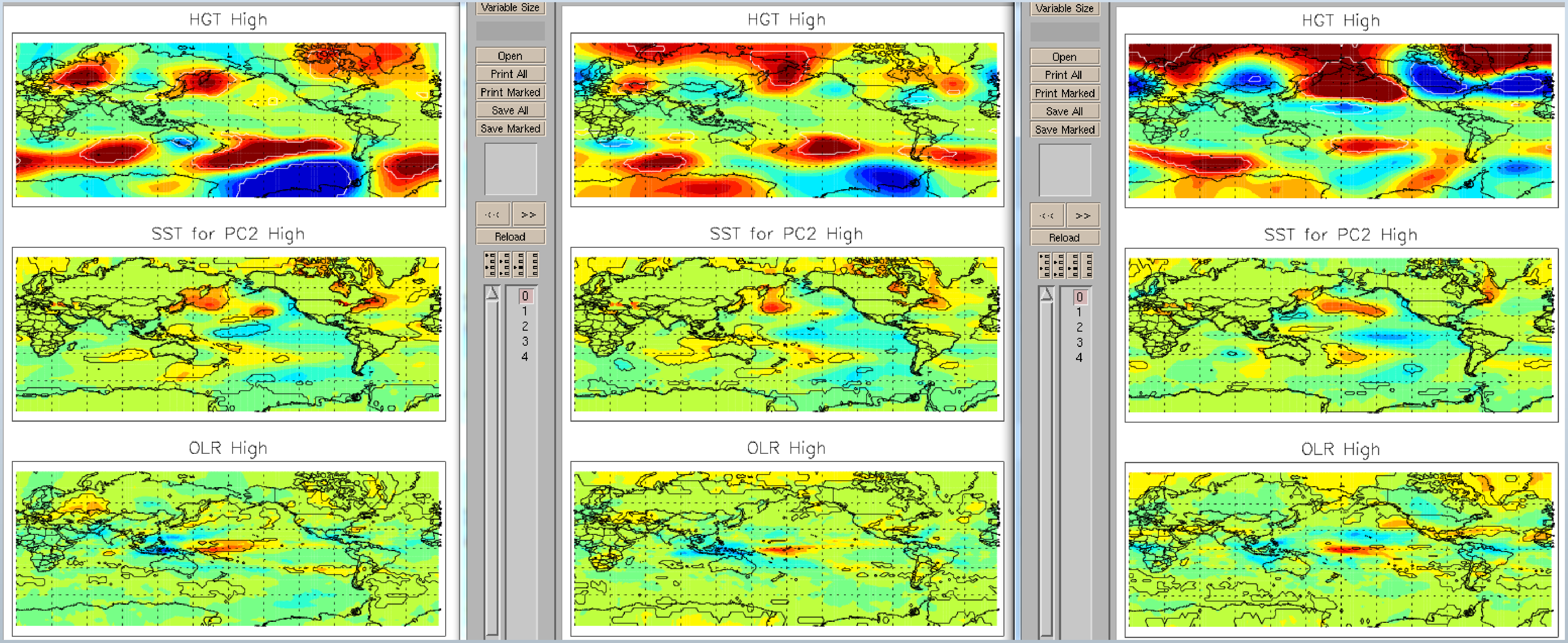

PC2_djf (line) vs PDO (plus)
2
1
0
−1
−2
1970
1980
1990
2000
2010
2020
PC2_djf (line) vs NINO (plus)
2
1
0
−1
−2
1970
1980
1990
2000
2010
2020

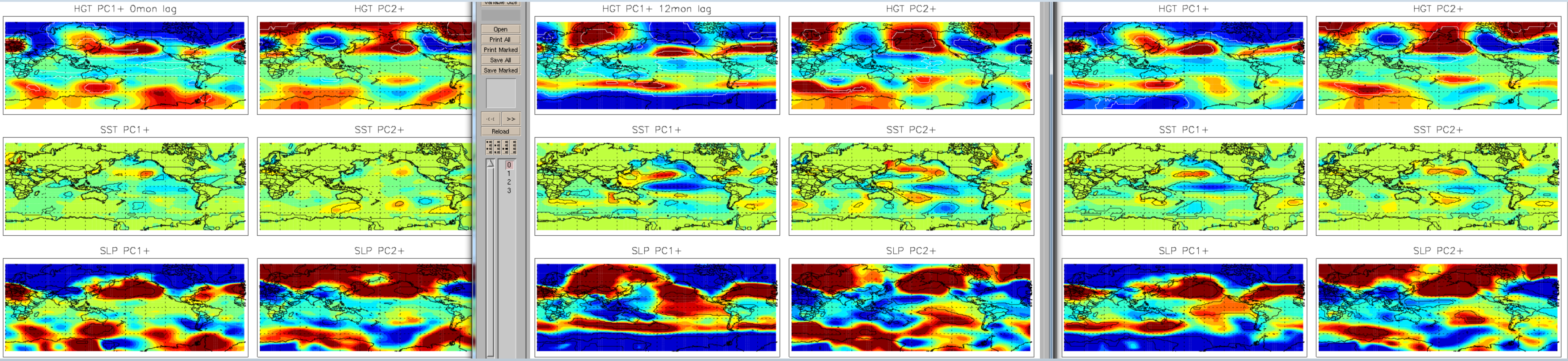

PC1_djf (line) vs PDO (plus)
2
1
0
−1
−2
1970
1980
1990
2000
2010
2020
PC1_djf (line) vs NINO (plus)
2
1
0
−1
−2
1970
1980
1990
2000
2010
2020

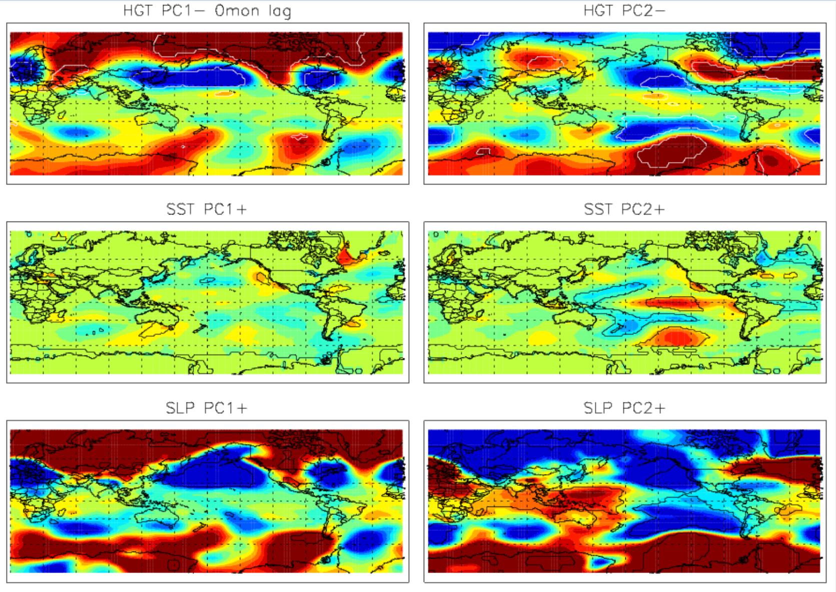
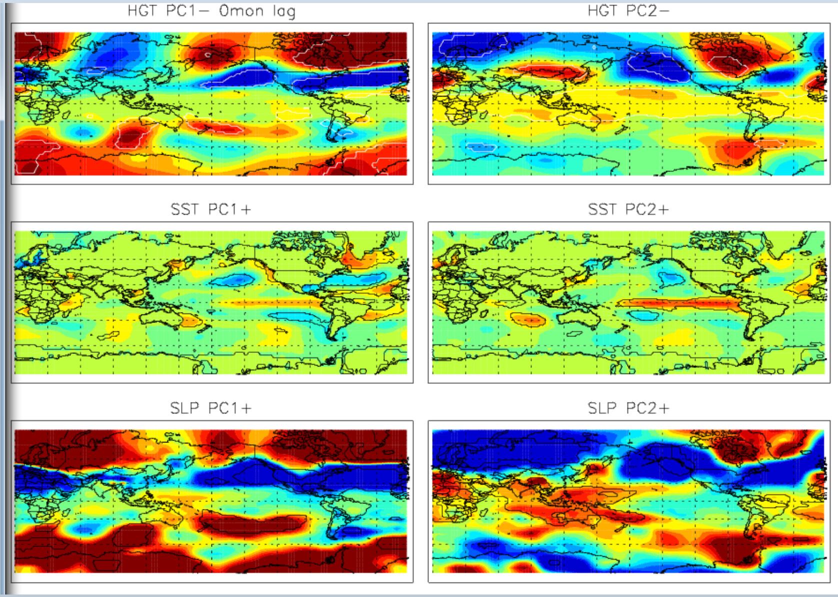
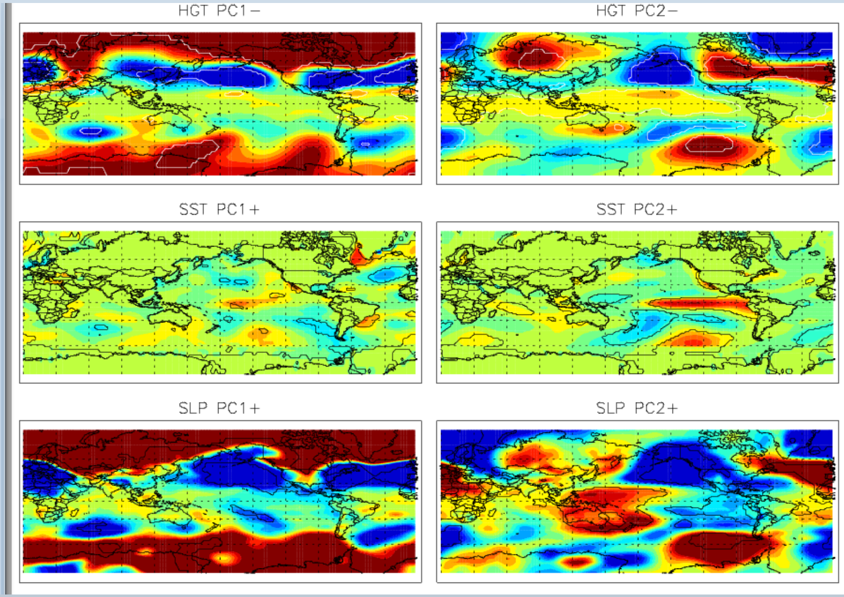

HGT High
HGT Low
SST for PC2 High
SST Low
OLR High
HGT Low


HGT High
HGT Low
SST for PC2 High
SST Low
OLR High
HGT Low


HGT High
HGT Low
SST for PC2 High
SST Low
OLR High
HGT Low


HGT High
SST for PC2 High
OLR High
Variable Size
Open
Print All
Print Marked
Save All
Save Marked
Reload
0
1
2
3
4
HGT High
SST for PC2 High
OLR High
Variable Size
Open
Print All
Print Marked
Save All
Save Marked
Reload
0
1
2
3
4
HGT High
SST for PC2 High
OLR High


HGT PC1+ 0mon lag
HGT PC2+
SST PC1+
SST PC2+
SLP PC1+
SLP PC2+
Open
Print All
Print Marked
Save All
Save Marked
Reload
HGT PC1+ 12mon lag
HGT PC2+
SST PC1+
SST PC2+
SLP PC1+
SLP PC2+
HGT PC1+
HGT PC2+
SST PC1+
SST PC2+
SLP PC1+
SLP PC2+


HGT PC1− 0mon lag
HGT PC2−
SST PC1+
SST PC2+
SLP PC1+
SLP PC2+

HGT PC1− 0mon lag
HGT PC2−
SST PC1+
SST PC2+
SLP PC1+
SLP PC2+

HGT PC1−
HGT PC2−
SST PC1+
SST PC2+
SLP PC1+
SLP PC2+

Downscaling daily precipitation of GCMs using a multiplicative random cascade model

Daeha Kim (d.kim@apcc21.org) , Jaepil Cho, Sunkwon Yoon,
Moosup Kim, Sangmin Jang

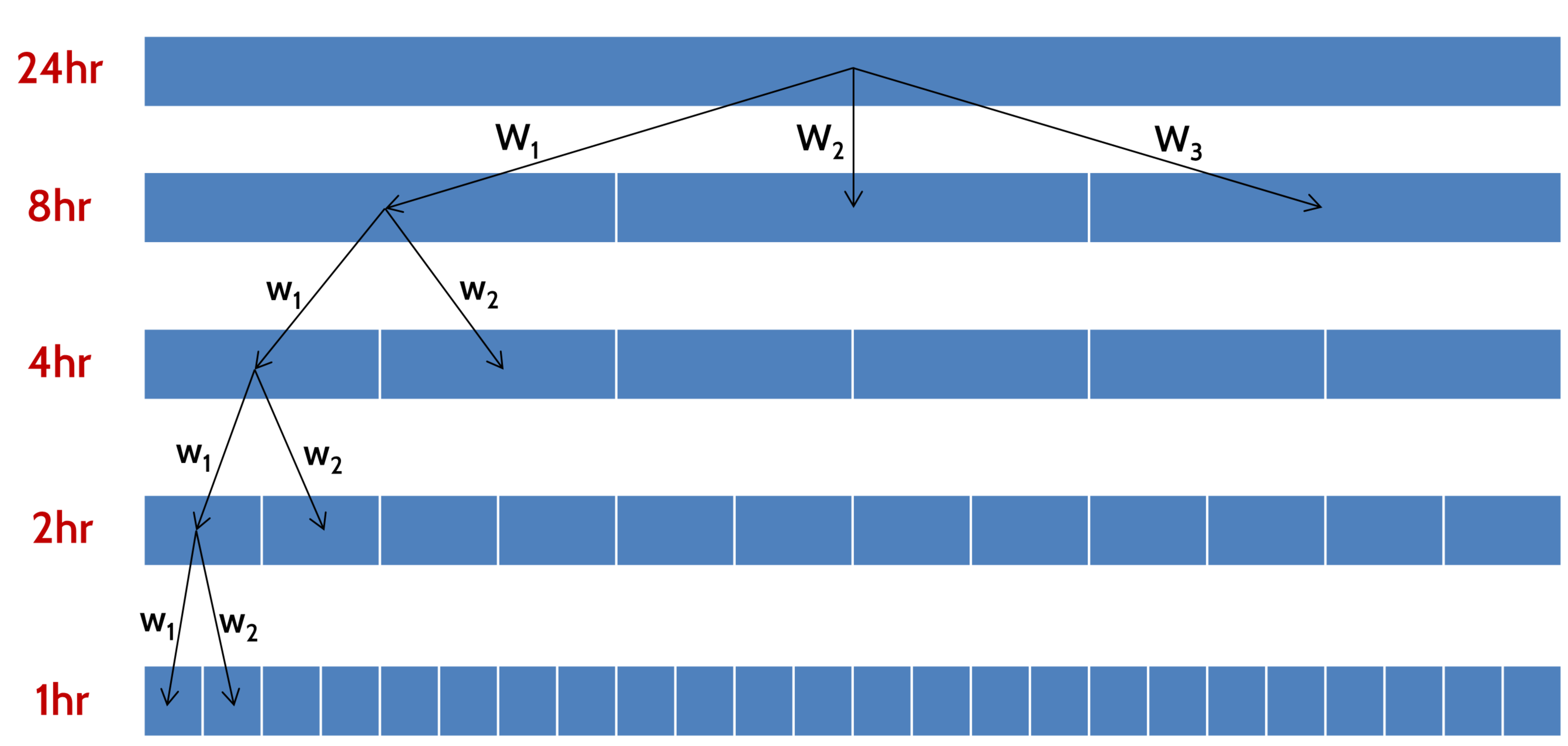
BACKGROUND

To consider intricacies of flood dynamics, rainfall data at a high resolution are inevitably needed for flood modeling; nevertheless, climate projections of general circulation models (GCMs) are typically provided at a daily or a longer time scale. A temporal downscaling method is essential to **link between GCMs and flood models** for assessing impacts of the global warming on flood risks,

One practical method for rainfall disaggregation is the chaotic approach that uses multifractal properties in rainfall time series. **The multiplicative cascade model recently proposed by Müller and Haberlandt (2015)** can be pragmatic to reproduce multifractal properties in rainfall observations, and hence downscale daily projections of GCMs

METHODOLOGY

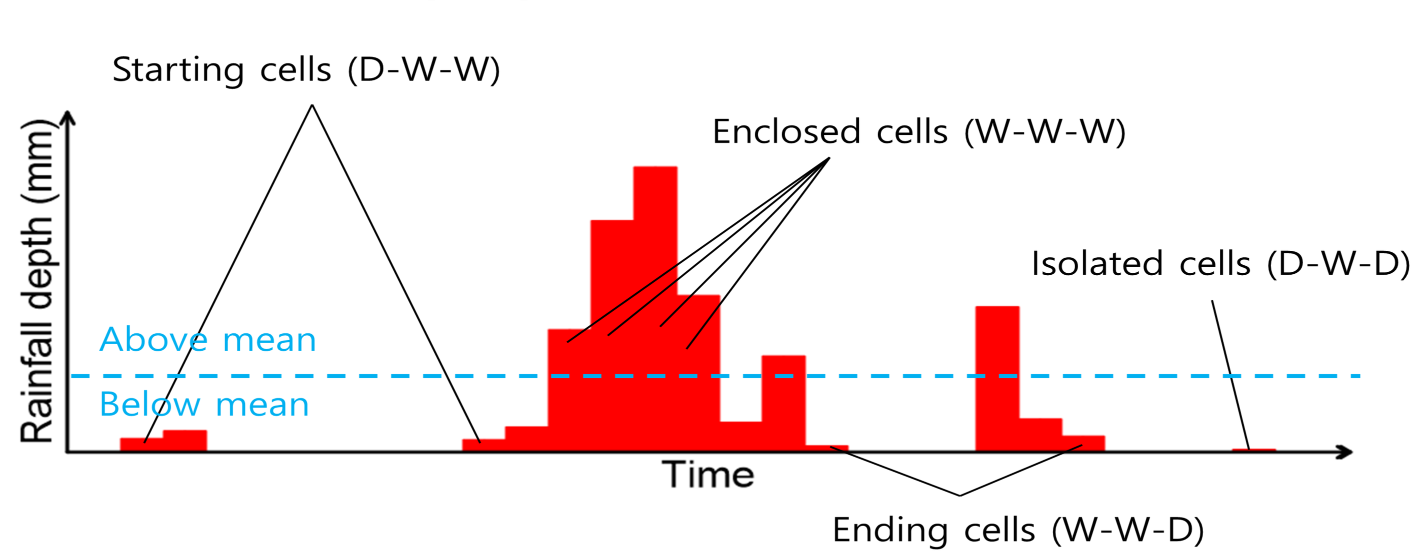
Micro-canonical multiplicative random cascade (MRC)



$$W_1, W_2, W_3 = \begin{cases} 1, 0, \text{and } 0 & \text{with } P(0/1/1) \\ 0, 1, \text{and } 0 & \text{with } P(0/1/1) \\ 0, 0, \text{and } 1 & \text{with } P(0/1/1) \\ ½, ½, \text{and } 0 & \text{with } P(0/½/½) \\ ½, 0, \text{and } ½ & \text{with } P(0/½/½) \\ 0, ½, \text{and } ½ & \text{with } P(0/½/½) \\ ⅓, ⅓, \text{and } ⅓ & \text{with } P(⅓/⅓/⅓) \end{cases}$$

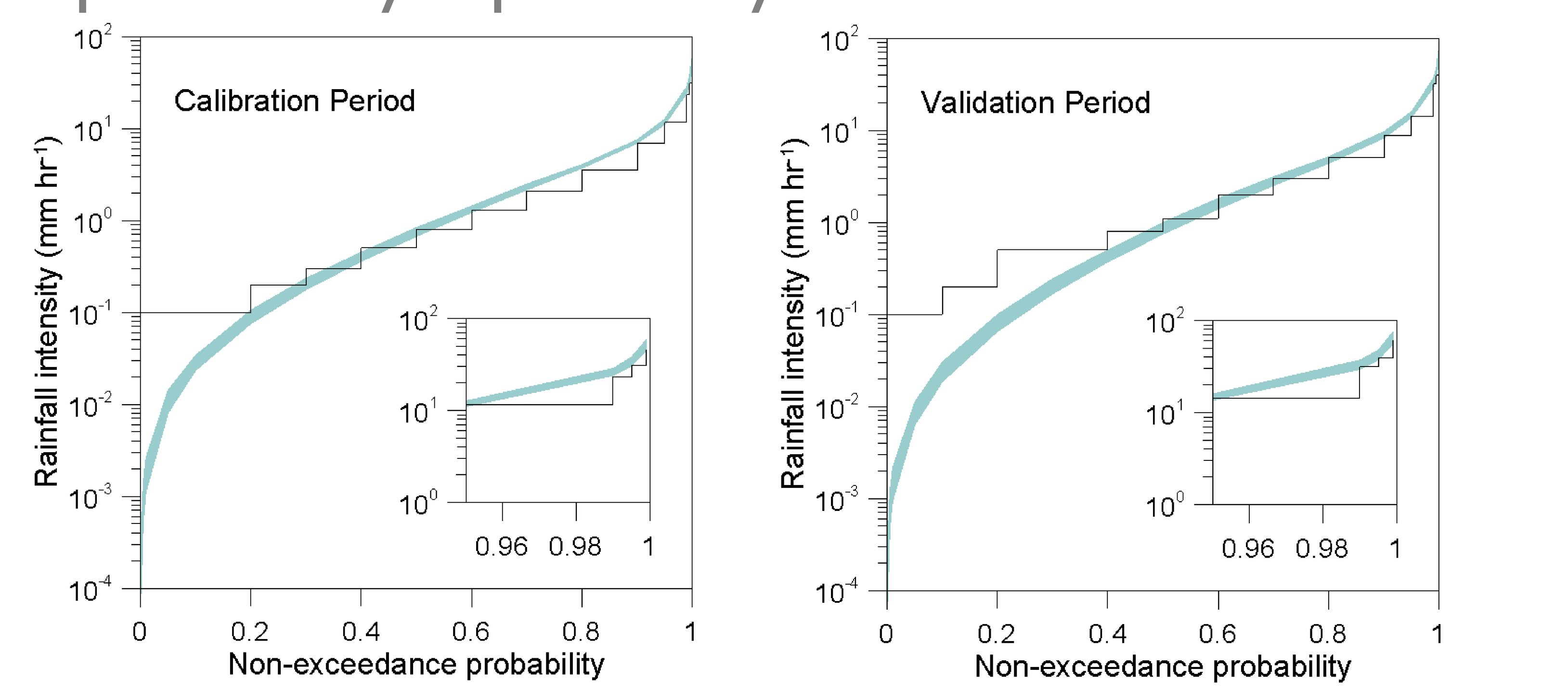
$$w_1, w_2 = \begin{cases} 0 \text{ and } 1 & \text{with } P(0/1) \\ 1 \text{ and } 0 & \text{with } P(1/0) \\ x \text{ and } 1 - x & \text{with } P(x/(1-x)) \end{cases}$$

Consideration of cell properties



RESULTS

1. Reproducibility of probability distribution of summer rainfall

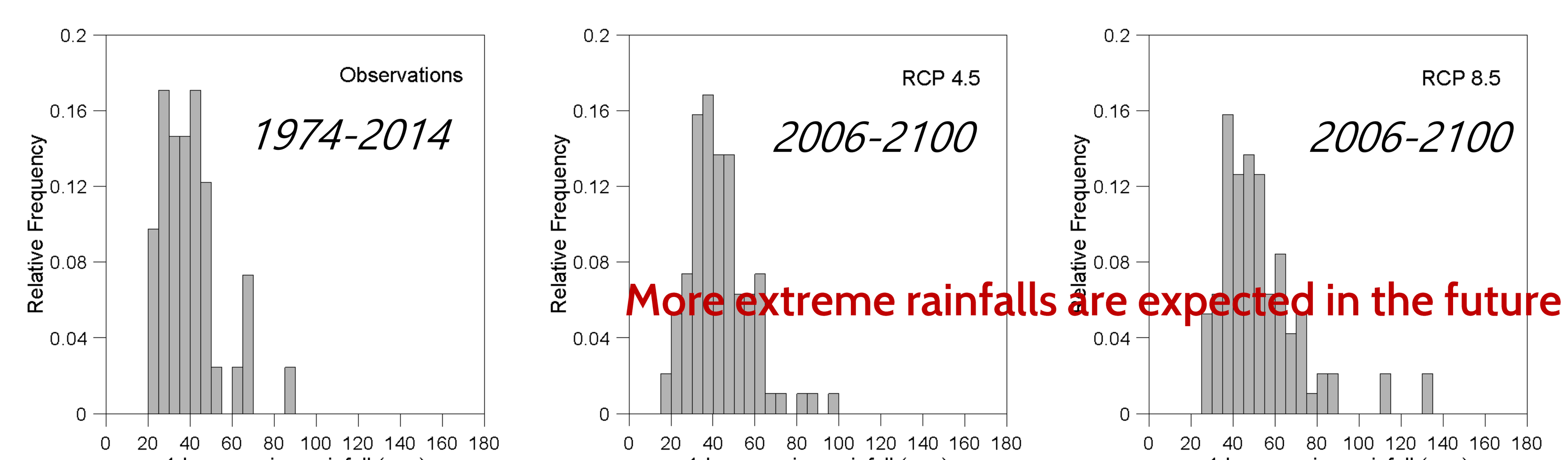


< KMA ASOS station at Seoul (cal: 1974-1994, val: 1995-2014) >

2. GCM downscaling for flood analysis
   - Spatial downscaling (Bias correction): Quantile mapping
   - Temporal downscaling: 100 generations w/ MRC
   - GCM: KMA Glosea5 at 12.5km resolution
   - RCP4.5 & RCP8.5 scenarios
   - Calibration period of MRC at Jeonju stn: 1974-2014

< 1-hour rainfall statistics >

Jeonju	Obs (1974-2014)	RCP4.5 (2006-2100)	RCP8.5 (2006-2100)
Average (mm)	2.8	[2.8,3.0]	[3.1,3.4]
Variance (mm^2)	24.8	[28.5,36.5]	[34.9,43.5]
Maximum (mm)	85.0	[74.0,237.1]	[92.9,273.3]
Prob [P>0]	0.11	[0.10,0.11]	[0.10,0.11]



< Distributions of 1-hour annual maxima series >

SUMMARY

1. MRC with uniform splitting well reproduced statistical properties of observed 1-hour rainfall
2. Future flood risk will become higher under both RCP4.5 & RCP 8.5 scenarios in watersheds near Jeonju station
3. MRC for multiple sites will be proposed as a further study

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