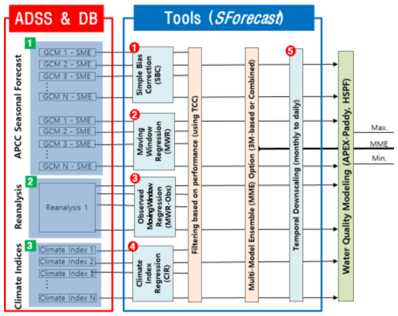
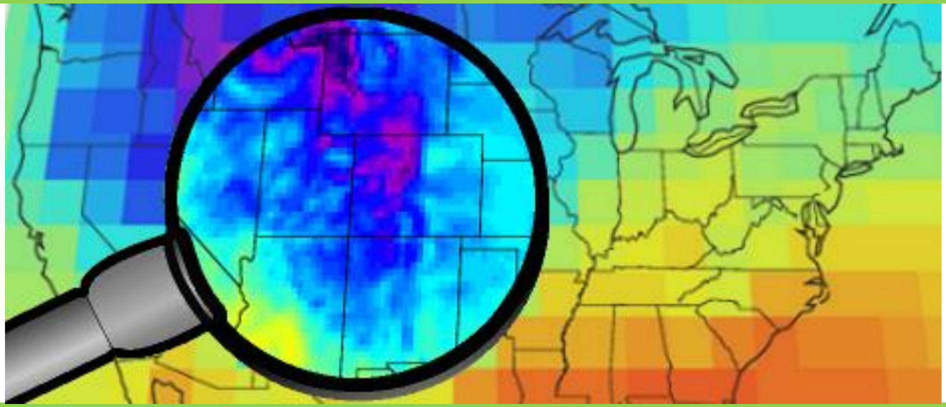
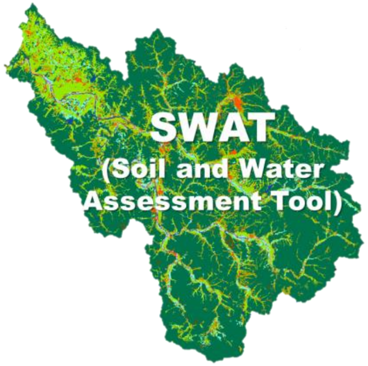
Use of Downscaled Seasonal Forecast Information for Water Resource Management







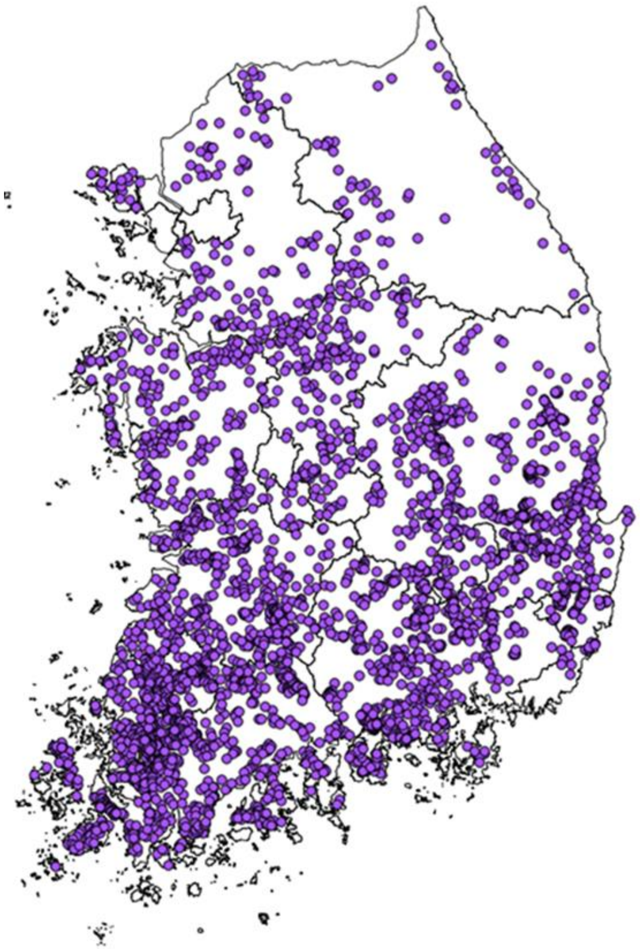
Jaepil Cho

2017/08/24

Overview

1. Water storage level forecasting
2. Water quality forecasting
3. Dam inflow forecasting
4. Forest fire forecasting

Forecasting Water Storage Level of Agricultural Reservoirs



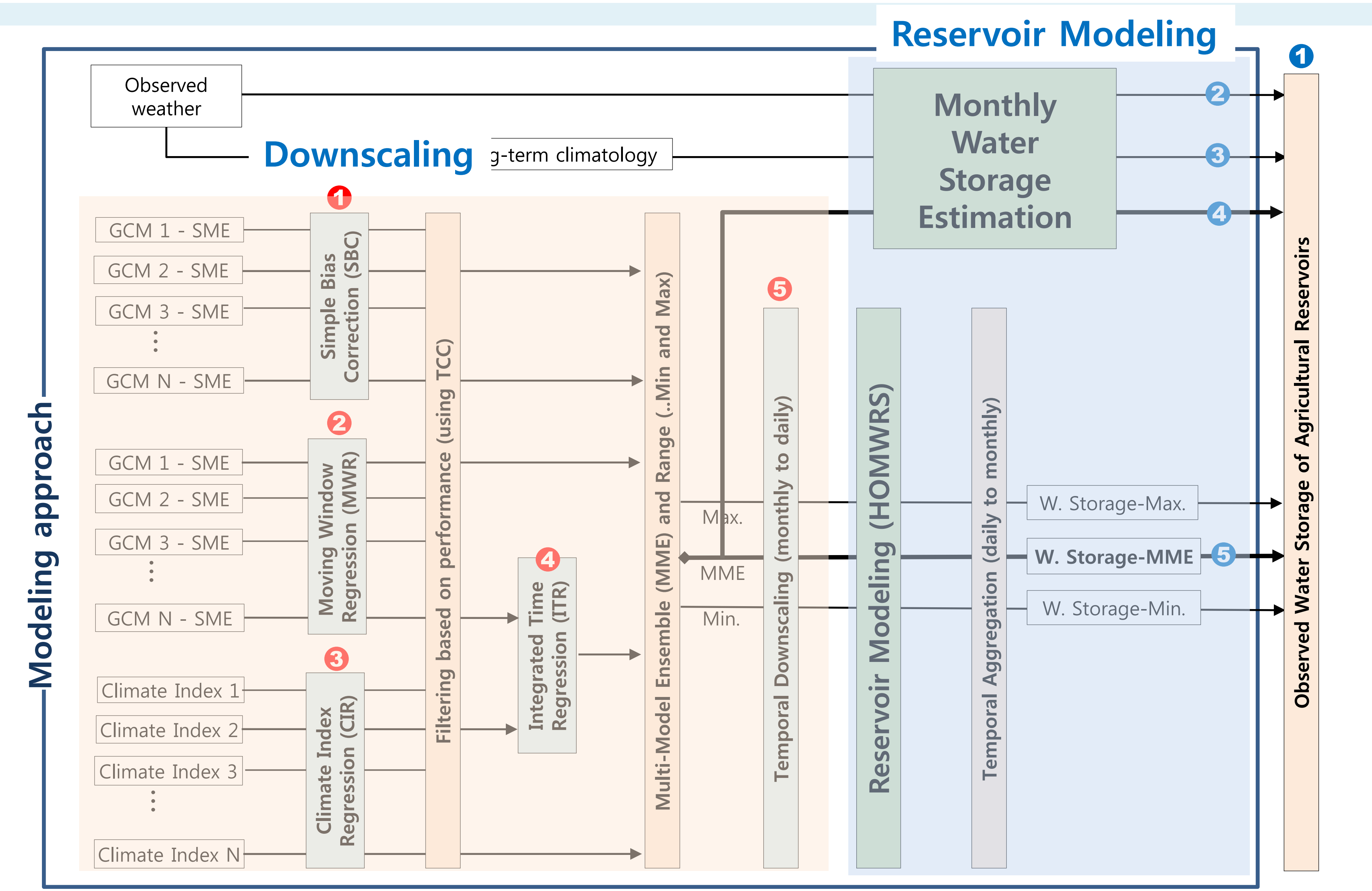
Agricultural reservoirs in Korea

(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

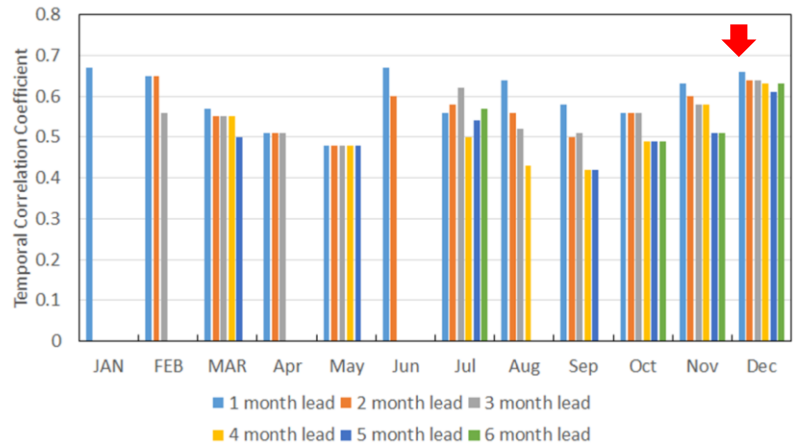
Integrated Downscaling System for Seasonal Prediction

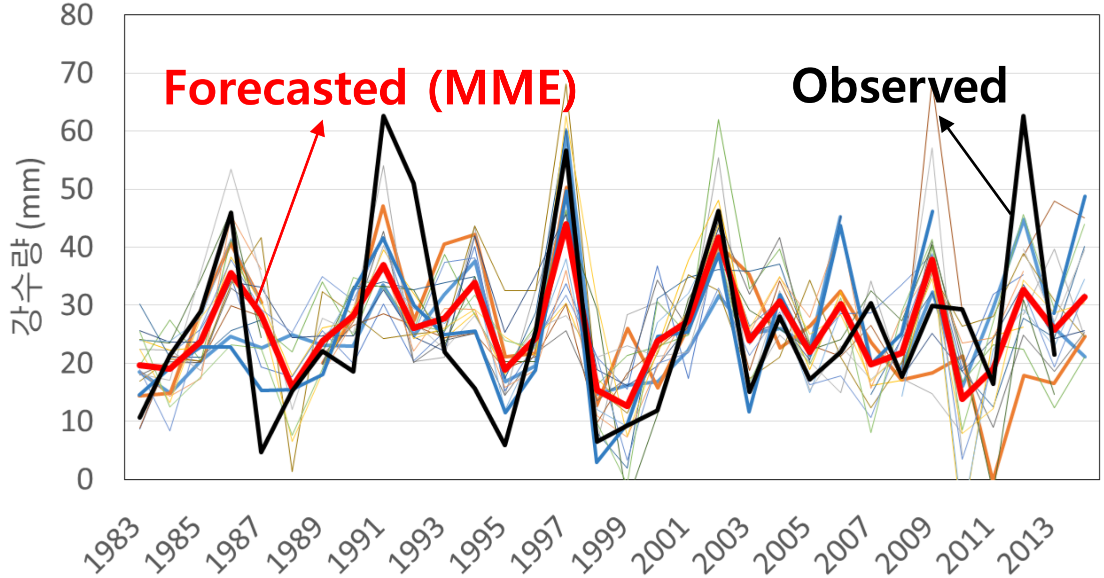


Time-series of seasonal forecast

- December precipitation forecast, 1-month lead time

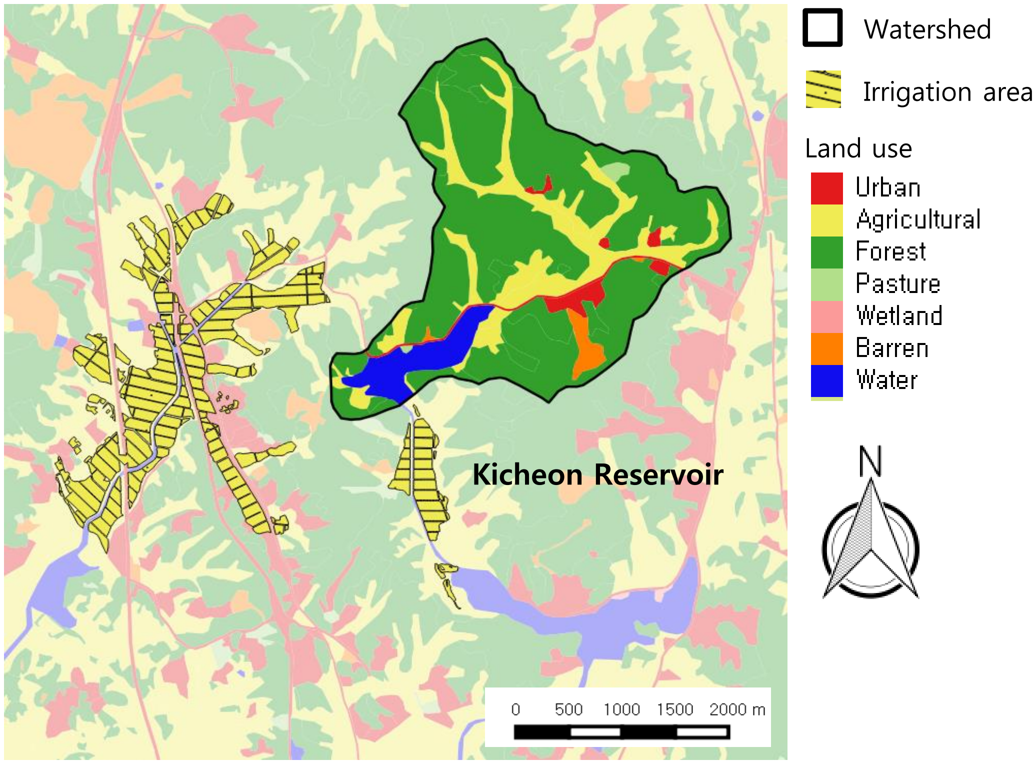
Month	1 month lead	2 month lead	3 month lead	4 month lead	5 month lead	6 month lead
JAN	ⓢJMA, ⓢPOAMA					
FEB		ⓜ CWB	ⓜ GDAPS_F			
MAR	ⓢPOAMA			ⓜ MSC_CANCM4	ⓜ MSC_CANCM4	
APR			ⓢHMC, ⓢNASA, ⓜ NCEP, ⓜ PNU			
MAY					ⓜ PNU	
JUN	ⓜ HMC	ⓜ MSC_CANCM4				
JUL	ⓒ WP(-7)	ⓒ WP(-7)	ⓘ PNU	ⓒ WP(-7)	ⓒ WP(-7)	ⓘ NASA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

Seasonal Forecast Application for Kicheon Reservoir

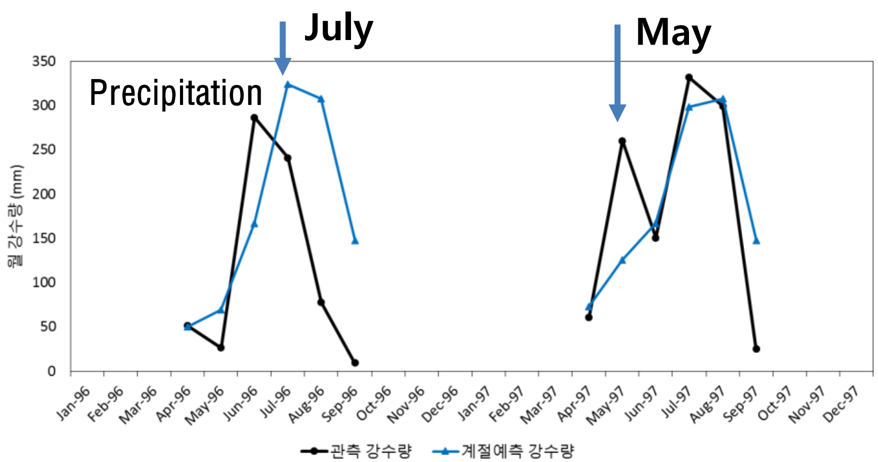


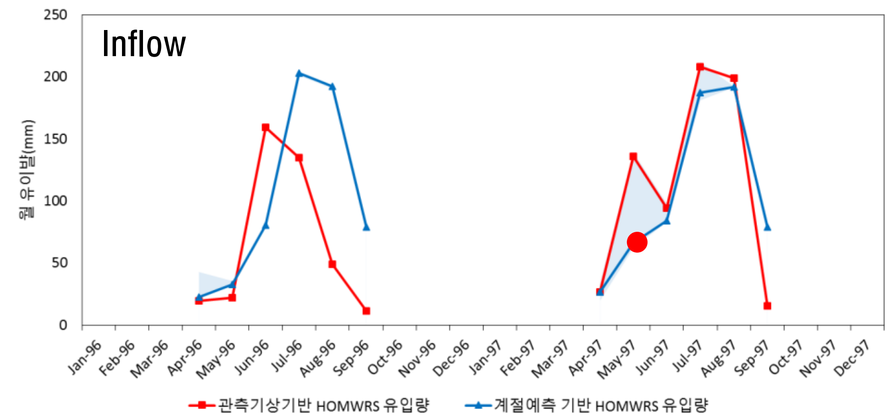
- Kicheon reservoir
  - Watershed area: 755 ha
  - Irrigation area: 270.7 ha
- HOMWRS modeling
  - Period: 1996 ~ 1997
  - 6 months forecast at every March

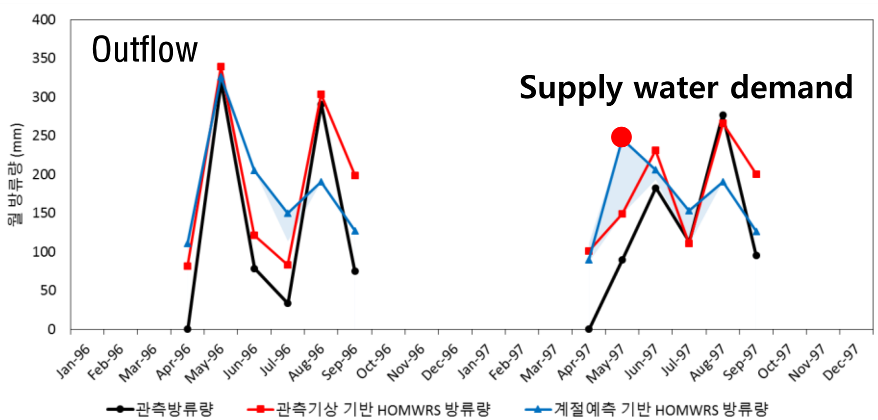
HOMWRS: Hydrological Operation Model for Water Resources System

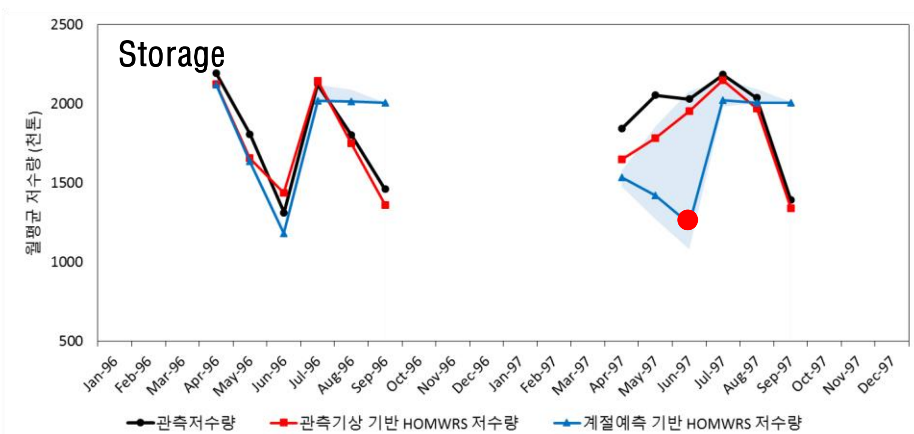
Seasonal Forecast Application for Kicheon Reservoir

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



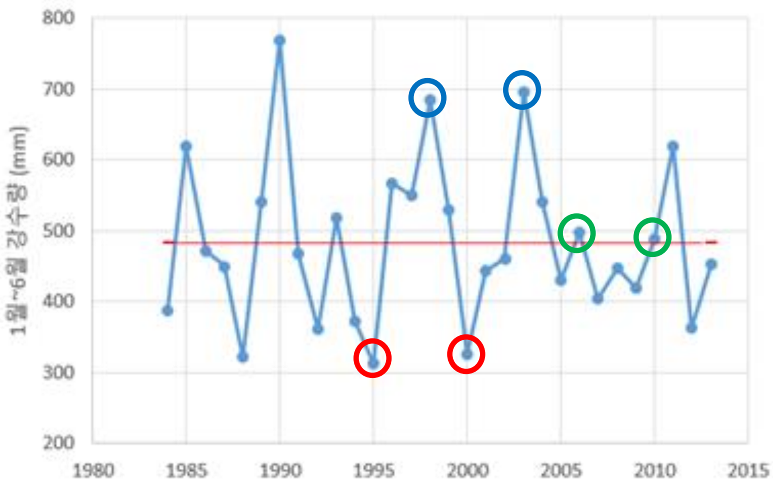






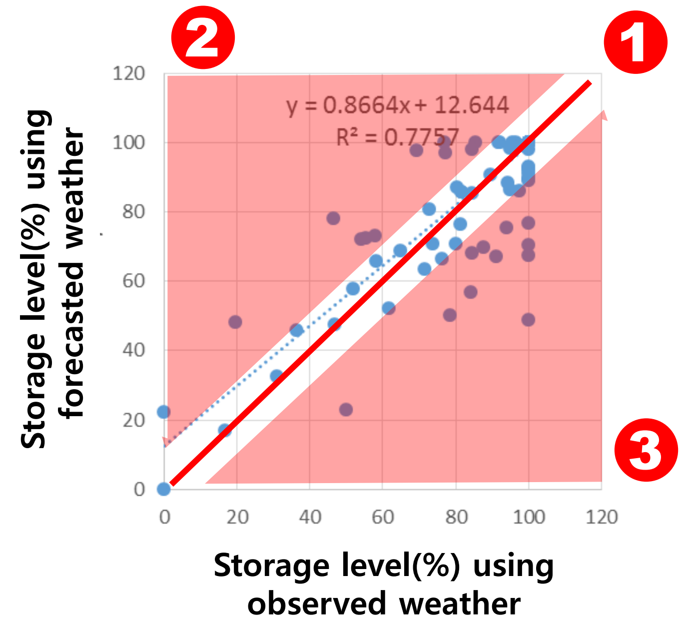
Monthly storage level forecast at Jun. 20
(462 Reservoirs, forecast issued at Jan. 15)

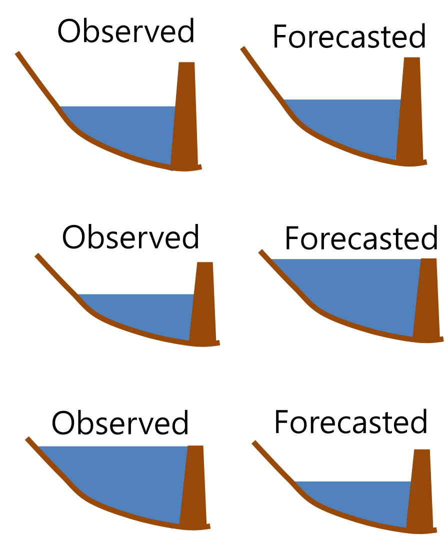
- 6-month lead forecasting



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

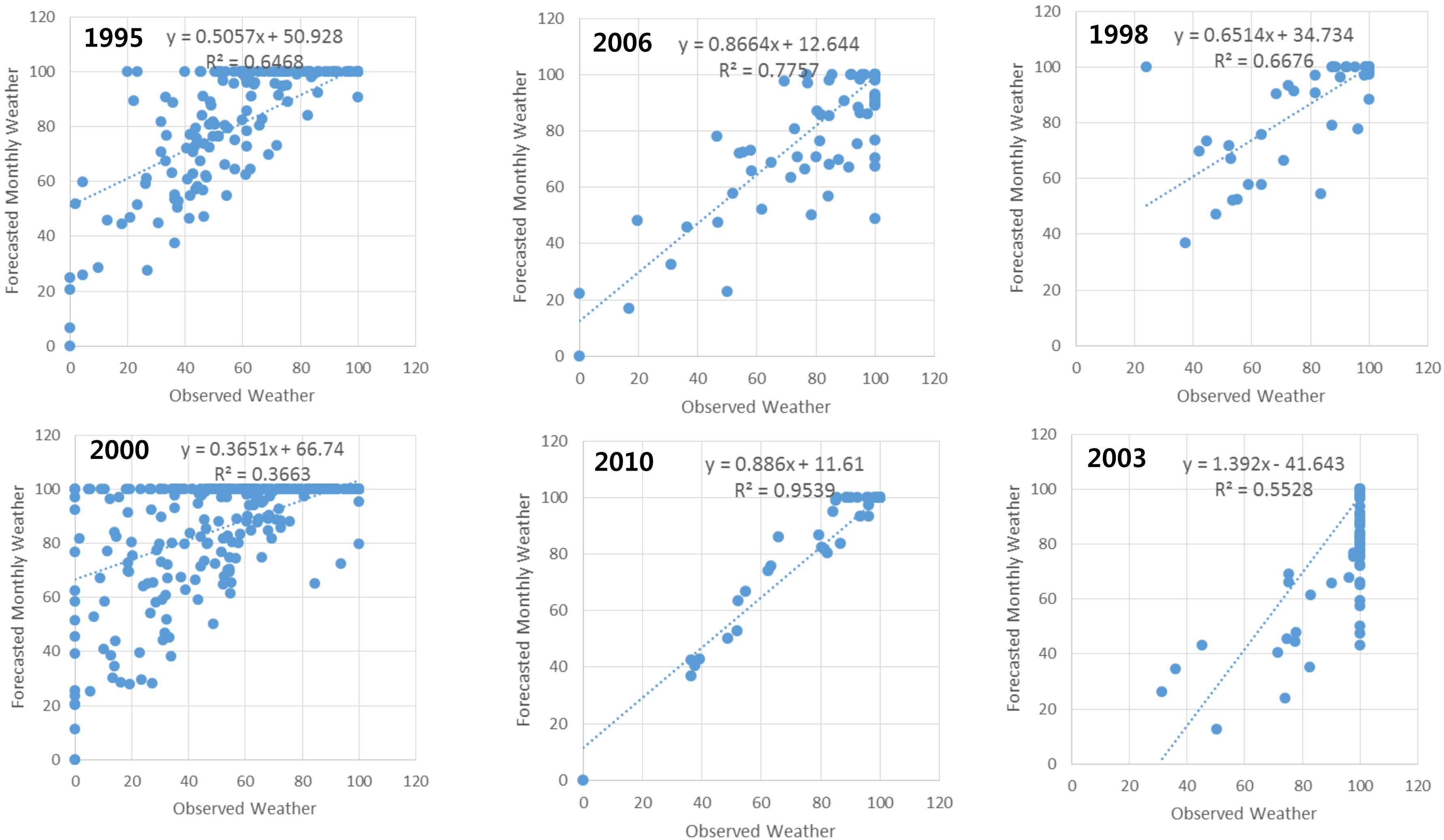




Result of monthly storage level forecast at Jun. 20
(462 Reservoirs, forecast issued at Jan. 15)

Dry years are underestimated

Wet years are overestimated

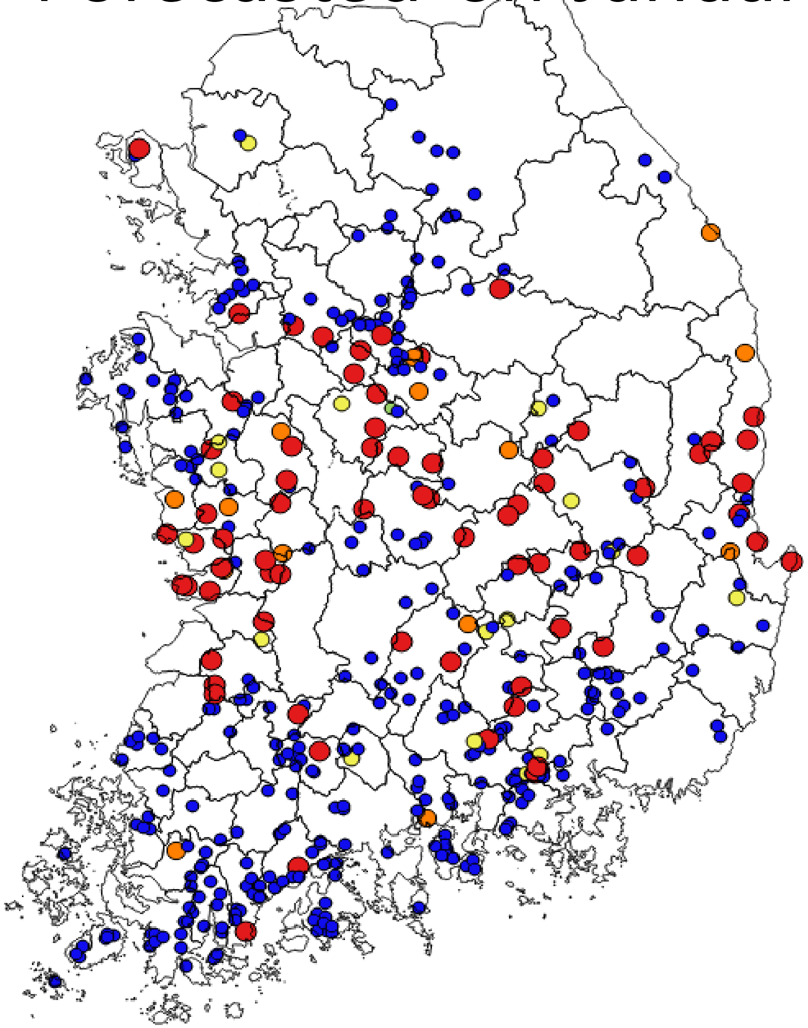


Storage level using forecasted weather

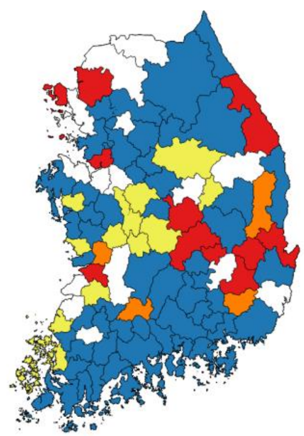
Storage level using observed weather

Drought alerting for June 20, Reservoir Level

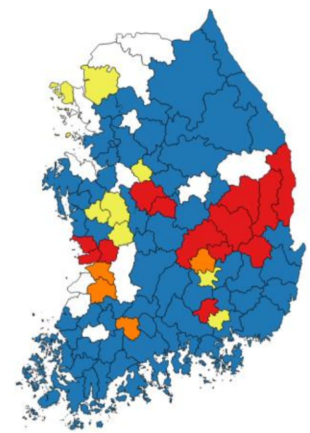
- Forecasted on January 15, 1995



구분	농업용수 가뭄지표 정의(농어촌공사)
관심 (Blue)	농업적 가뭄발생 시기(4월~9월)
주의 (Yellow)	최근 2개월 누적강수량이 평년 대비 70% 미만이고, 농업용 저수지 저수율이 평년 대비 70% 미만인 때
경계 (Orange)	최근 2개월 누적강수량이 평년 대비 60% 미만이고, 농업용 저수지 저수율이 평년 대비 60% 미만인 때
심각 (Red)	최근 2개월 누적강수량이 평년 대비 50% 미만이고, 농업용 저수지 저수율이 평년 대비 50% 미만인 때

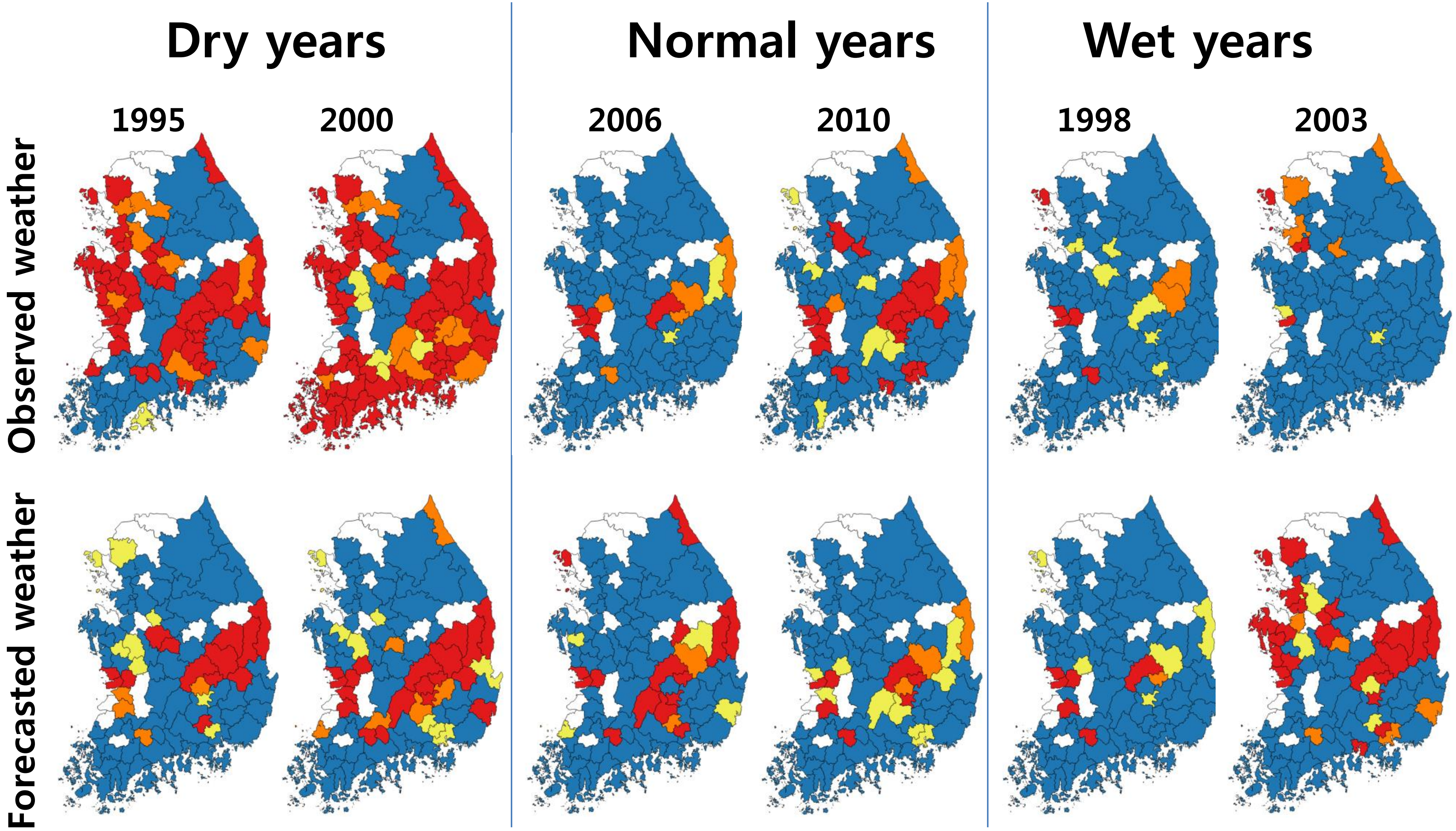


Observed



Forecasted

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



Seasonal Forecasting of Water Quality

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

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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

1

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.

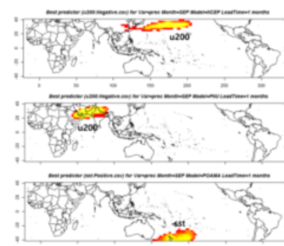


Figure 3: Spatial distribution of selected variables by the NCEP, PNU, and POAMA models for 1-month lead precipitation predictions in September (yellow indicates most frequent selection through the cross-validation procedures from 1983 to 2013).

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

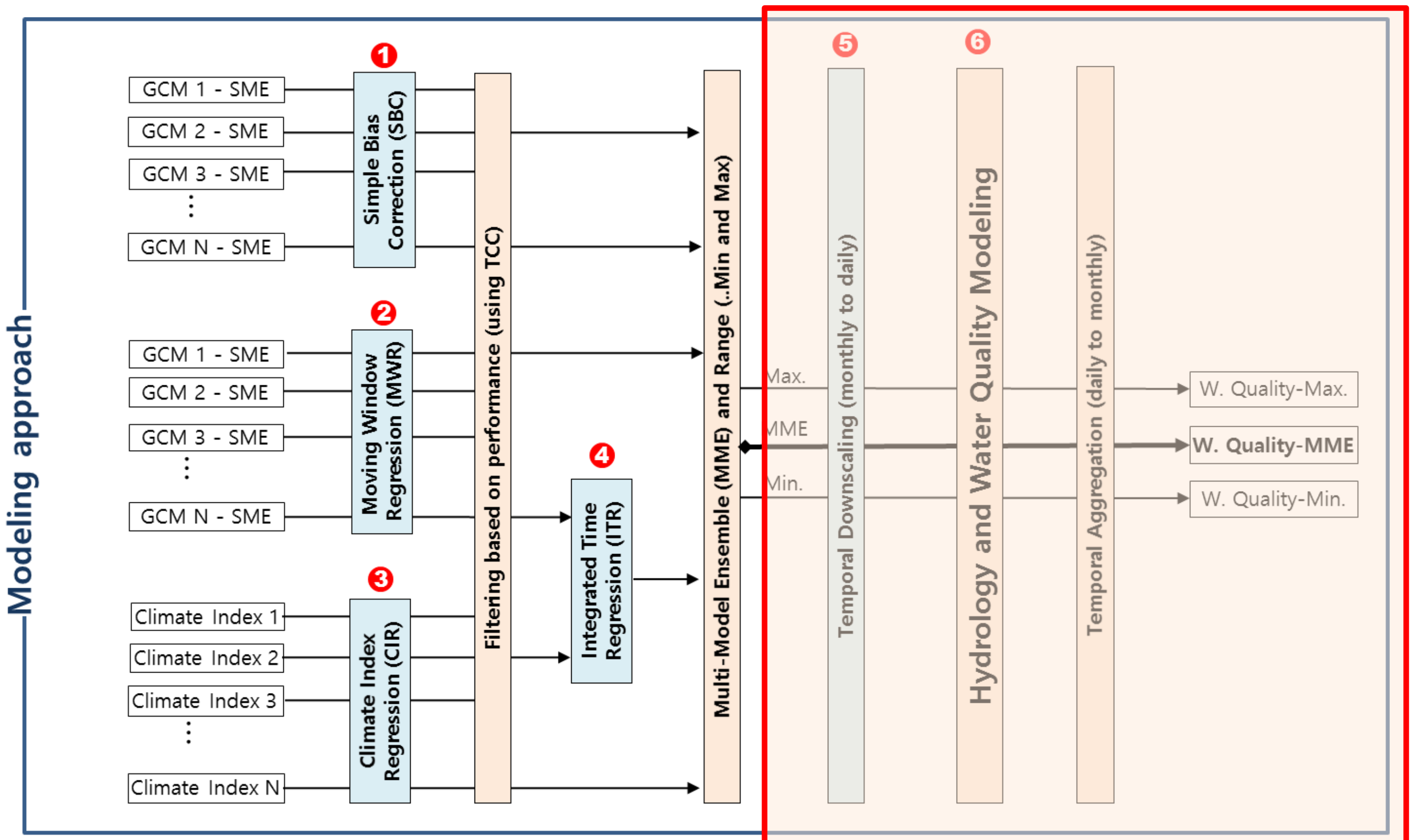
Month	Var	1 month lead	2month lead	3month lead
Jan	P	B_JMA B_POAMA		
	T	B_GDAPS_F B_PNU B_MSC_CANCM3 B_MSC_CANCM4 M_POAMA	B_POAMA	M_CWB
Feb	P		M_CWB	M_GDAPS_F
	T		B_JMA	
Mar	P	B_POAMA		
	T	B_GDAPS_F B_JMA		
Apr	P			B_NASA M_NCEP M_PNU B_HMC
	T	M_GDAPS_F	B_NASA	
May	P			
	T	M_CWB	M_PNU	M_MSC_CANCM3
Jun	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 correction (SBC), M_: Moving Window Regression (MWR), C_: Climate Index Regression (CIR), I_: Integrated Time Regression (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.

7

Procedure for seasonal water quality forecasting

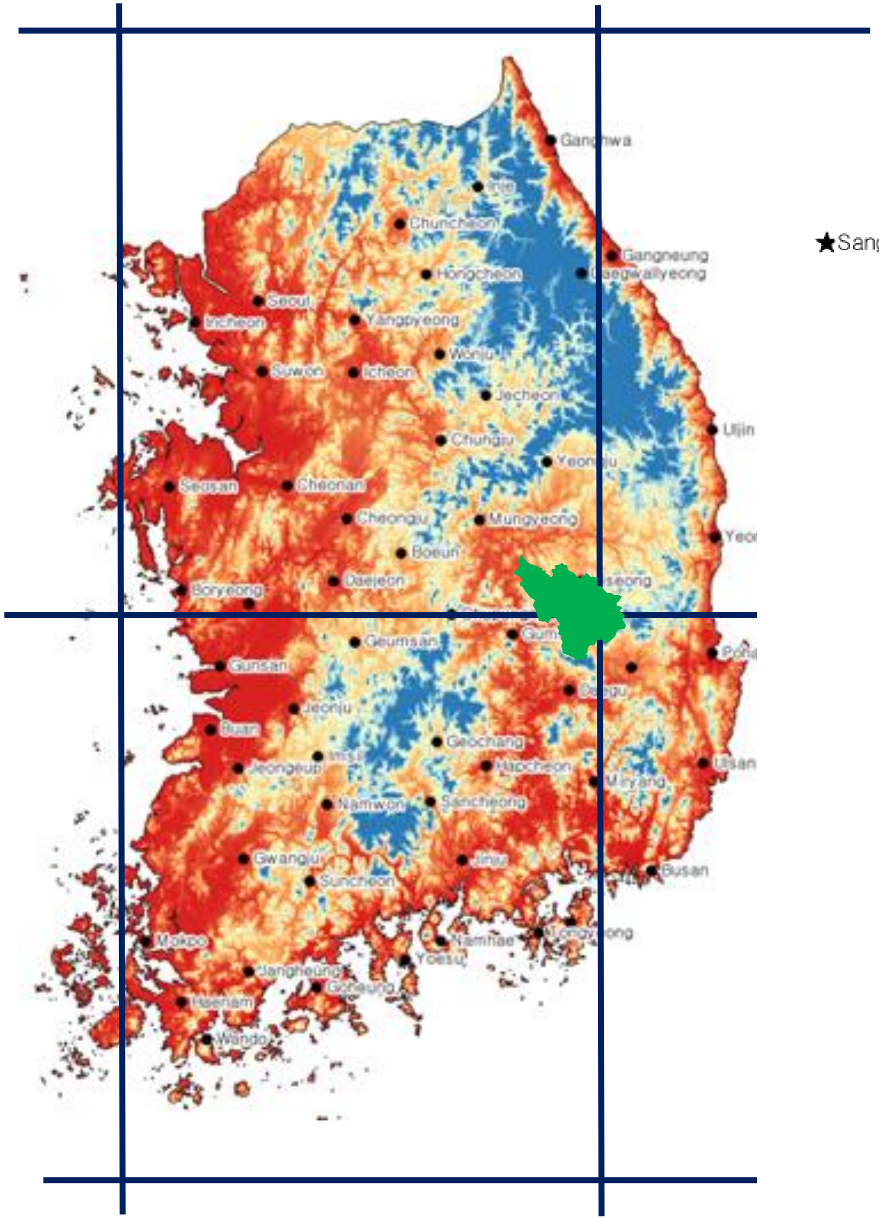


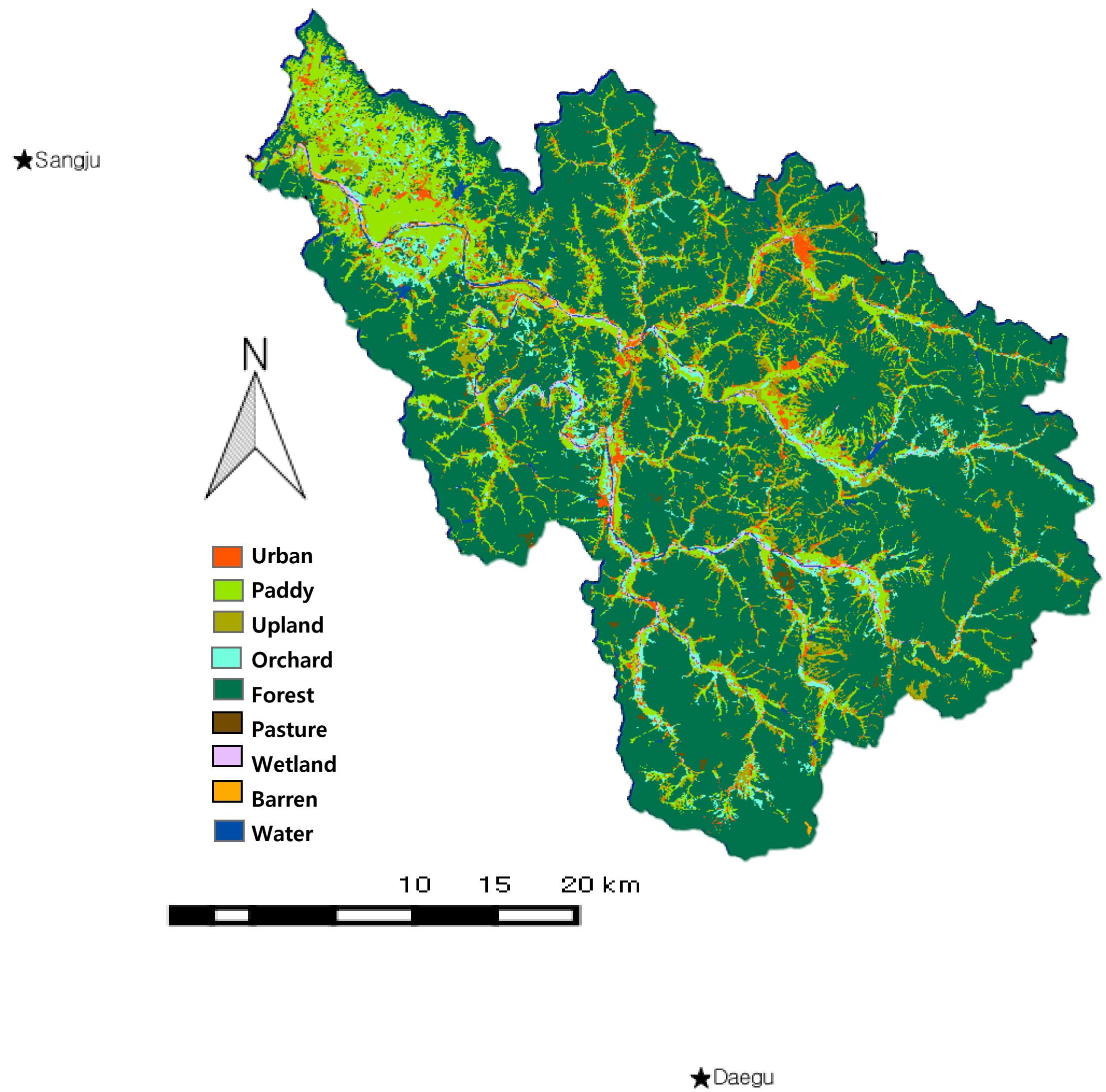
Down Scaling (Spatial & Temporal)

SME: Single model ensemble
MME: Multi-model ensemble

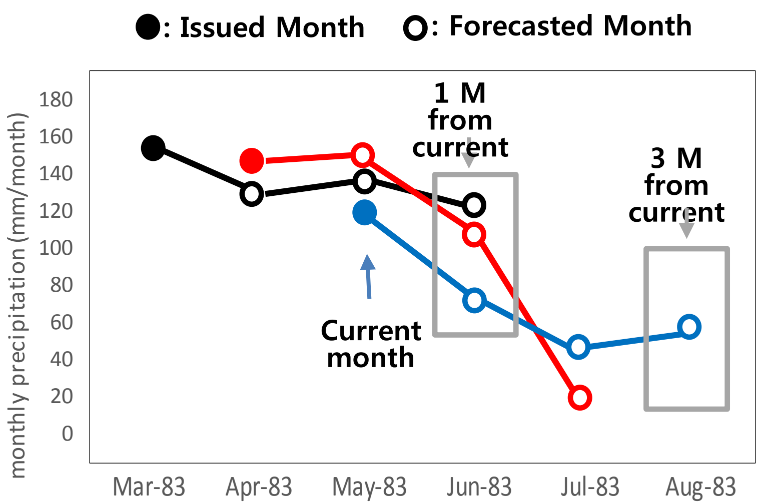
TCC: Temporal Correlation Coefficient
GCM: Global climate models for seasonal forecast

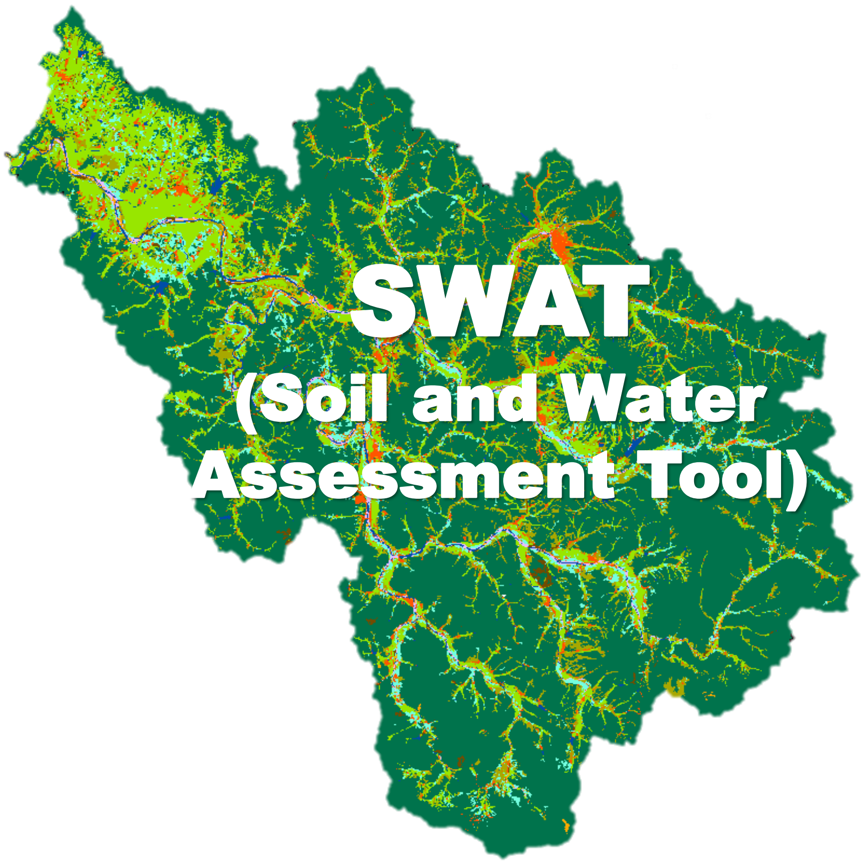
Study Area


Ganghwa
Inje
Chuncheon
Gangneung
Hongcheon
Daegwallyeong
Seoul
Incheon
Yangpyeong
Wonju
Suwon
Icheon
Jecheon
Uljin
Chungju
Yeongju
Seosan
Cheonan
Cheongju
Mungyeong
Boeun
Daejeon
Boryeong
Geumsan
Gunsan
Jeonju
Daegu
Buan
Geochang
Ulsan
Jeongeup
Hapcheon
Miryang
Namwon
Sancheong
Gwangju
Jinju
Busan
Suncheon
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

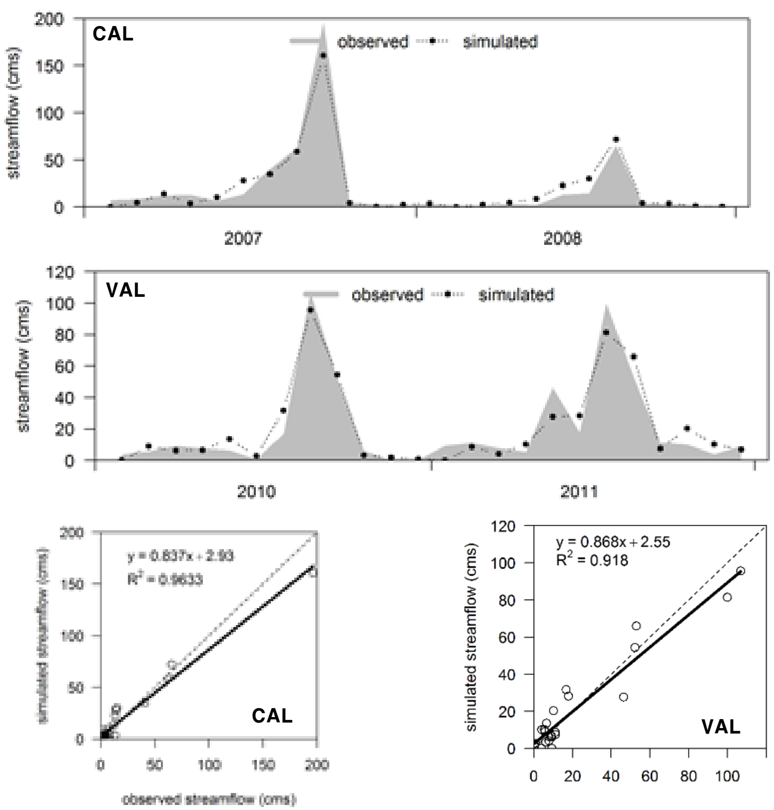




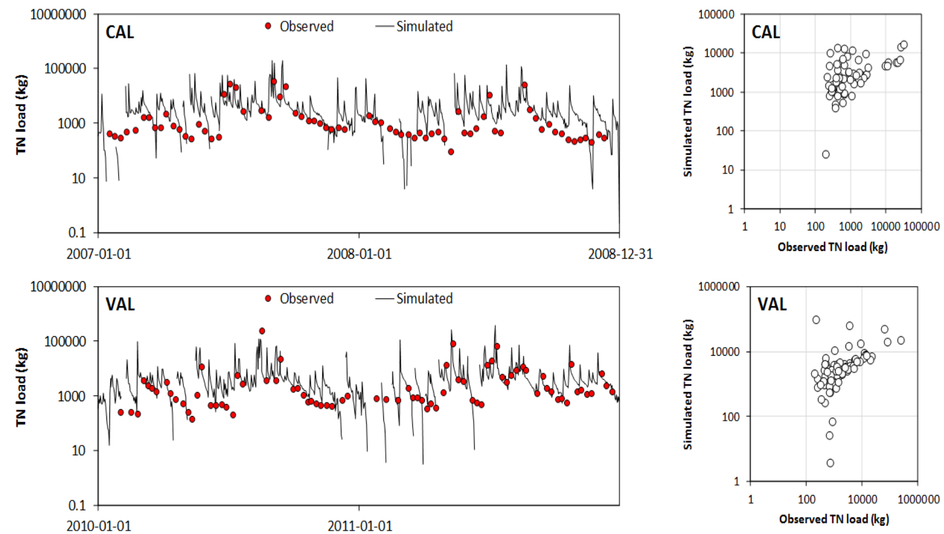
- Initialization of streamflow and water quality was not considered

SWAT Verification Results

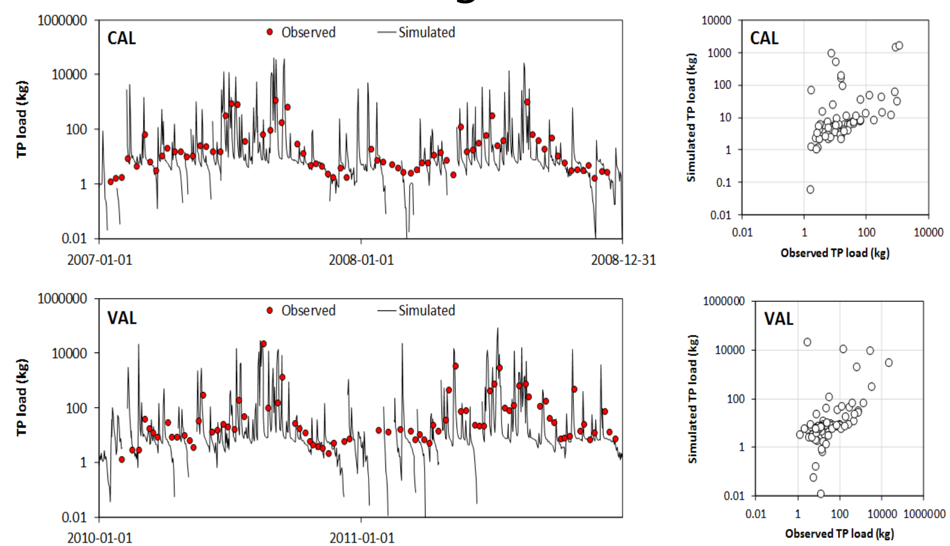
Performance measures	Calibration	Validation
% Error	-1.6	-1.1
Monthly NSE	0.95	0.92



Streamflow

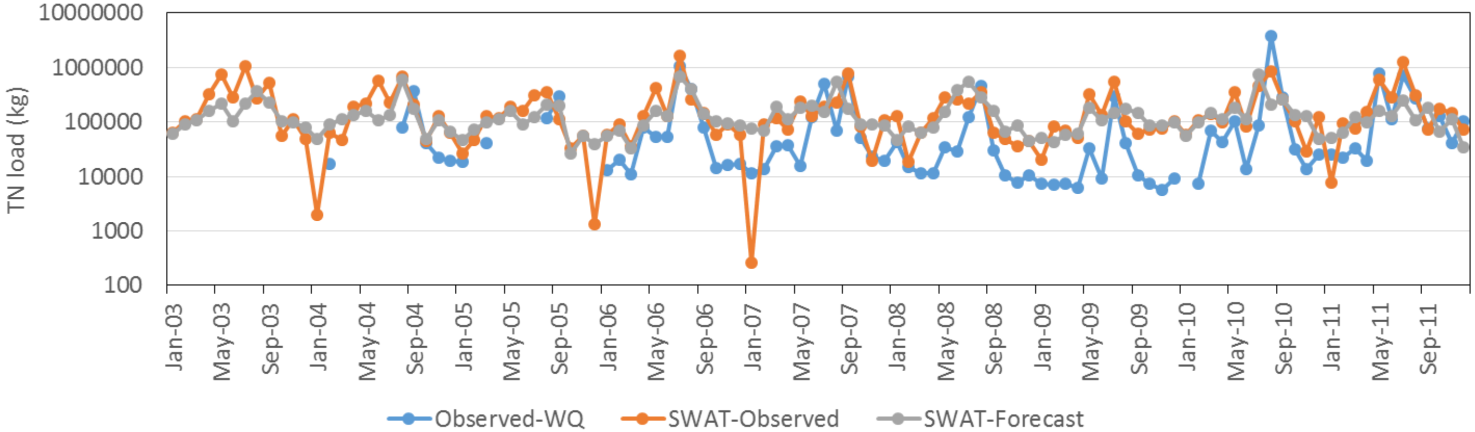


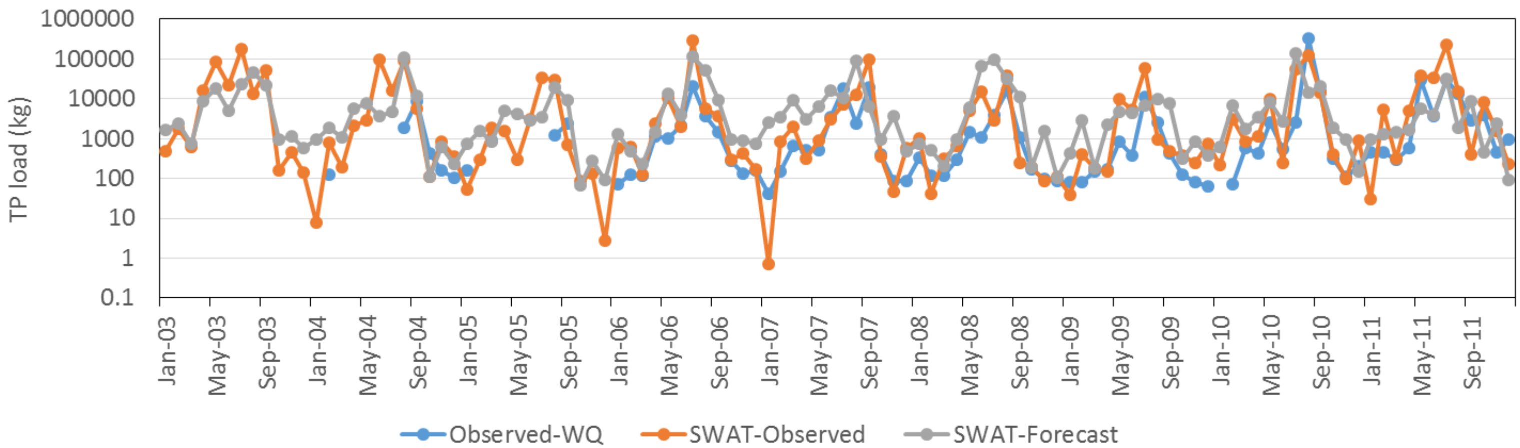
Total Nitrogen (TN) Loads



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

Dam Inflow Forecasting

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One-month lead dam inflow forecast using climate indices based on tele-connection

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Abstract

Reliable long-term dam inflow prediction is necessary for efficient multi-purpose dam operation in changing climate. Since 2000s the teleconnection between global climate indices (e.g., ENSO) and local hydroclimate regimes have been widely recognized throughout the world. To date many hydrologists focus on predicting future hydrologic conditions using lag teleconnection between streamflow and climate indices. This study investigated the utility of teleconneciton for predicting dam inflow with 1-month lead time at Andong dam basin. To this end 40 global climate indices from NOAA were employed to identify potential predictors of dam inflow, areal averaged precipitation, temperature of Andong dam basin. This study compared three different approaches; 1) dam inflow prediction using SWAT model based on teleconneciton-based precipitation and temperature forecast (SWAT-Forecasted), 2) dam inflow prediction using teleconneciton between dam inflow and climate indices (CIR-Forecasted), and 3) dam inflow prediction based on the rank of current observation in the historical dam inflow (Rank-Observed). Our results demonstrated that CIR-Forecasted showed better predictability than the other approaches, except in December. This is because uncertainties attributed to temporal downscaling from monthly to daily for precipitation and temperature forecasts and hydrologic modeling using SWAT can be ignored from dam inflow forecast through CIR-Forecasted approach. This study indicates that 1-month lead dam inflow forecast based on teleconneciton could provide useful information on Andong dam operation.

Keywords: Dam inflow forecast; Climate indices; Teleconnection; SWAT; Andong dam

Methodology for dam inflow forecast based on teleconnection

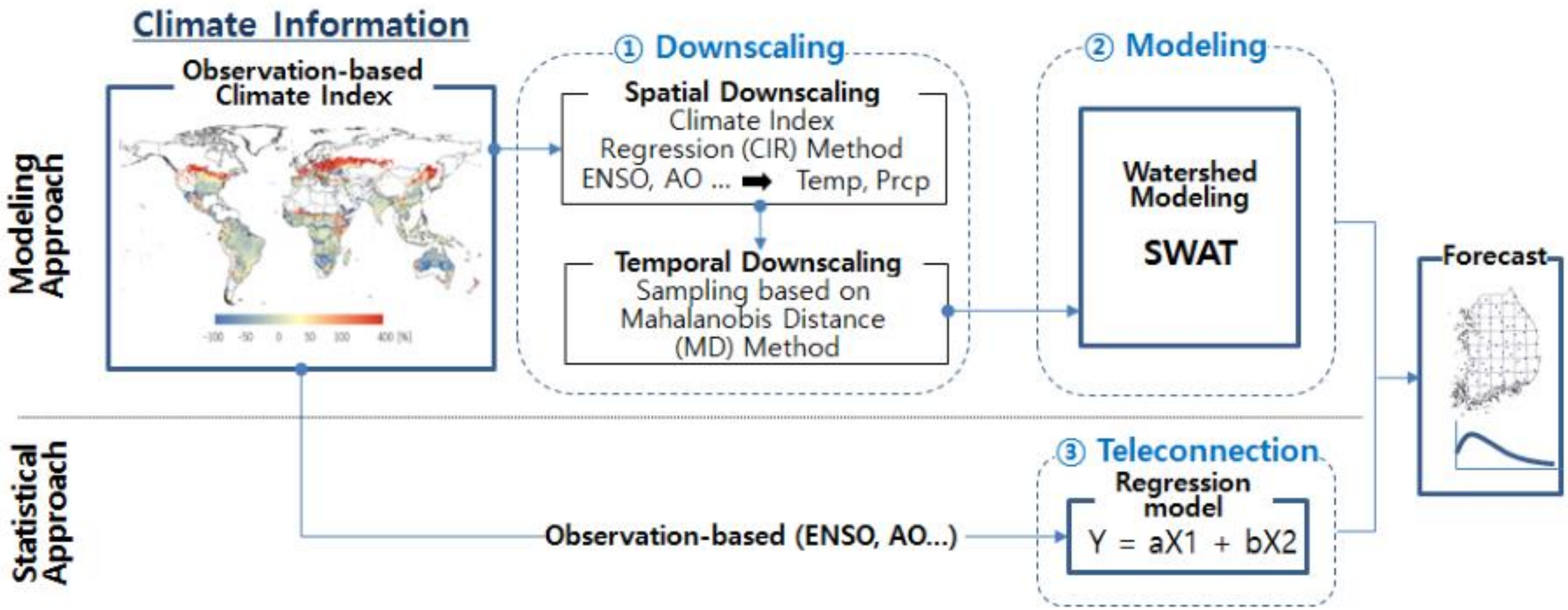


Fig. 2. Methodology for dam inflow forecast based on teleconnection.

Selected climate indices for precipitation prediction

Table 1. Selected global climate indices for forecasting l-month lead precipitation forecast. Lag indicates the number of lagged months.

Month	1st predictor		2nd predictor		3rd predictor	
	Index	Lag	Index	Lag	Index	Lag
Jan	Solar(+)	-1	NOI(+)	-10	WPO(+)	-12
Feb	NAO(+)	-12	AAO(-)	-4	AO(+)	-5
Mar	TSA(+)	-12	AAO(+)	-6		
Apr	NOI(-)	-7	GML(+)	-3	ESL(-)	-1
May	EPO(+)	-4	AO(-)	-8	NAO(-)	-7
Jun	AO(-)	-7	NAO(-)	-6		
Jul	NOI(-)	-1	Solar(+)	-1	AO(-)	-1
Aug	WPO(+)	-9	GML(+)	-6		
Sep	TNI(+)	-11	NP(+)	-5		
Oct	NAO(-)	-1	TNA(-)	-10		
Nov	NINA3(+)	-2	TSA(+)	-1		
Dec	ESL(-)	-1	CENSO(+)	-1		

Table 2. Selected global climate indices for forecasting l-month lead dam inflow forecast. lag indicates the number of lagged months.

Month	1st predictor		2nd predictor		3rd predictor	
	Index	Lag	Index	Lag	Index	Lag
Jan	Solar(+)	-1	ESL(+)	-10		
Feb	NOI(+)	-7	TNA(-)	-10	CAR(-)	-11
Mar	AAO(-)	-5	PNA(-)	-1	AO(+)	-1
Apr	CAR(+)	-1	NOI(-)	-7		
May	WPO(-)	-12	AO(-)	-8		
Jun	NOI(+)	-11	SOI(+)	-11		
Jul	AO(-)	-11	PDO(+)	-8	ESL(-)	-10
Aug	GML(+)	-6	AAO(-)	-5	CAR(+)	-6
Sep	Solar(+)	-4	AO(+)	-4	SOI(+)	-5
Oct	NP(+)	-6	TSA(+)	-12	EPO(-)	-6
Nov	NAO(+)	-2	NINA4(-)	-10	AO(+)	-9
Dec	NINA1(+)	-1	ESL(-)	-3		

AAO is antarctic oscillation, AO is arctic oscillation, CENSO is bivariate ENSO timeseries, EPO is east pacific/north pacific oscillation, ESL is equatorial eastern pacific sea level pressure, GML is global mean land/ocean temperature index, NAO is north atlantic oscillation, NINA3 is eastern tropical pacific sea surface temperature, NOI is northern oscillation index, NP is north pacific pattern, Solar is solar flux, TNA is tropical northen atlantic index, TNI is Trans-Niño index, TSA is torpical southern atlantic index, and WPO is western pacific index.

SWAT calibration and validation results

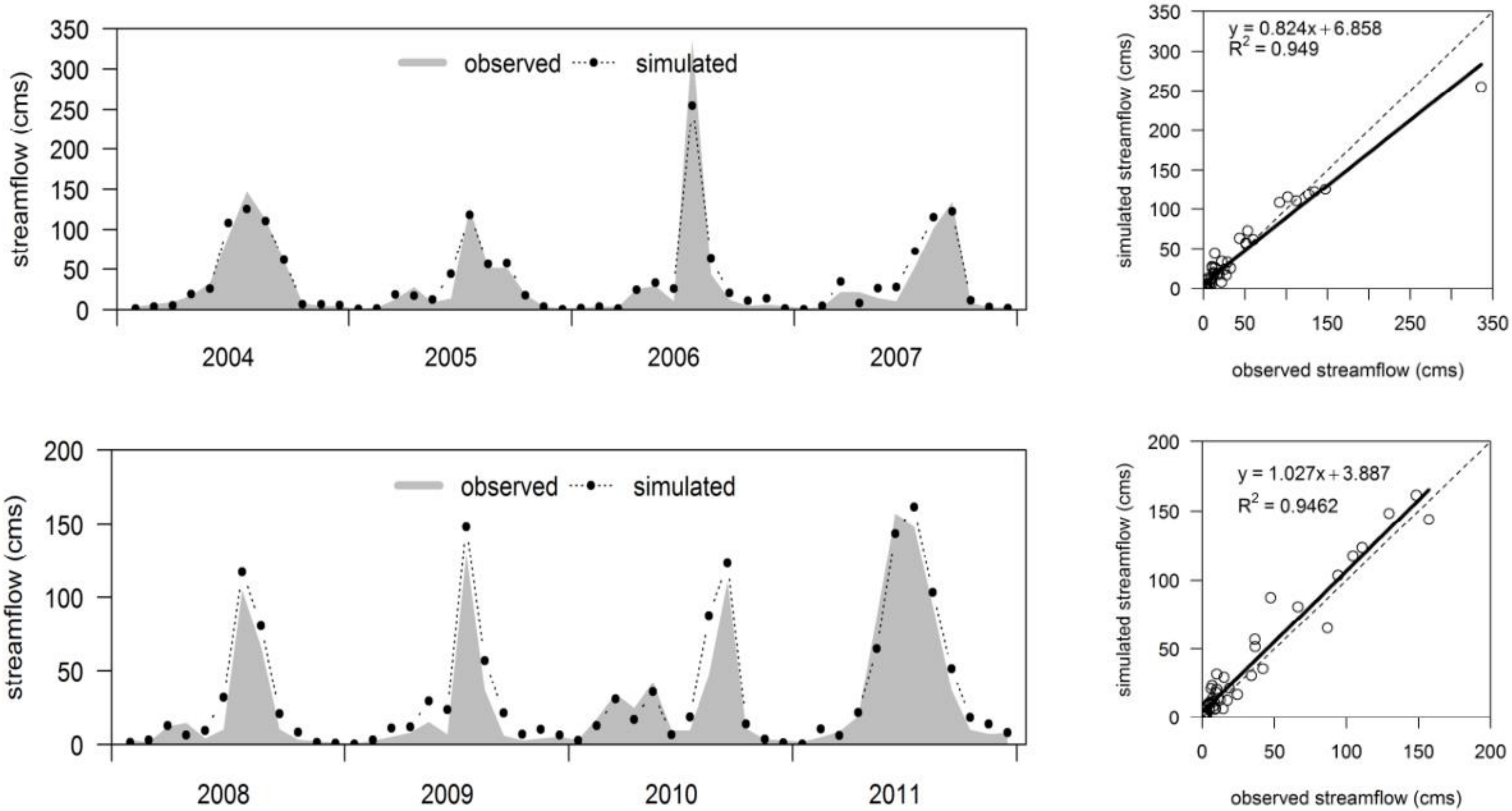


Fig. 3. Performance of SWAT simulation for calibration period (upper panel) and verification period (lower panel).

Comparison of forecasting skill

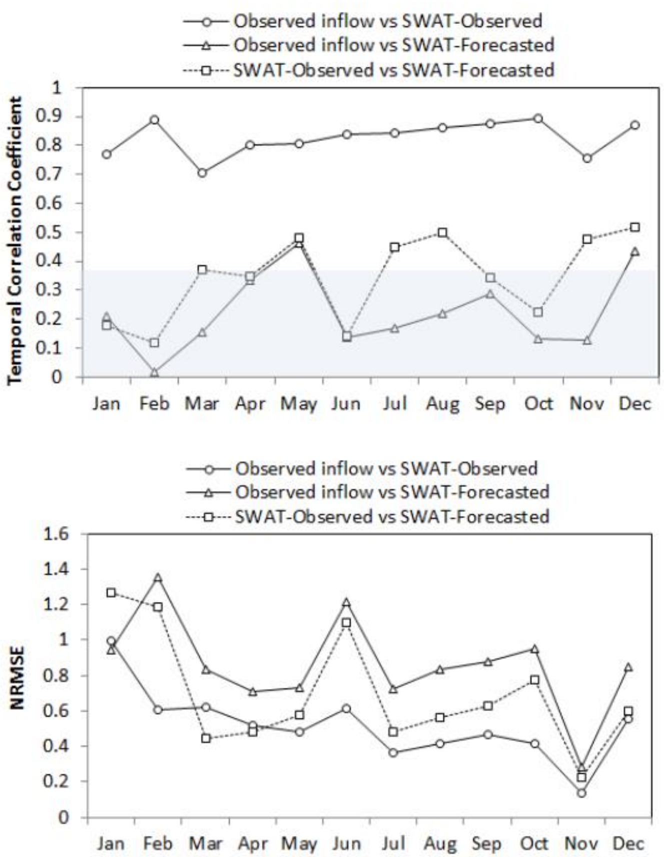
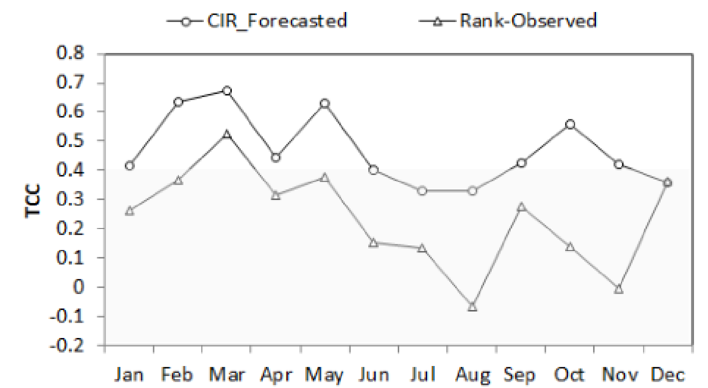
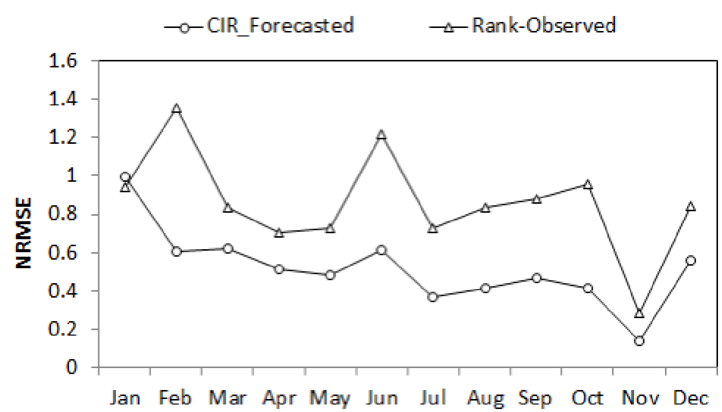


Fig. 6. Temporal Correlation Coefficient and (b) NRMSE between observation and simulation by SWAT-Observed (circles), observation and simulation by SWAT-Forecasted (triangles), and simulation by SWAT-Observed and simulation by SWAT-Forecasted (rectangles).



(a)

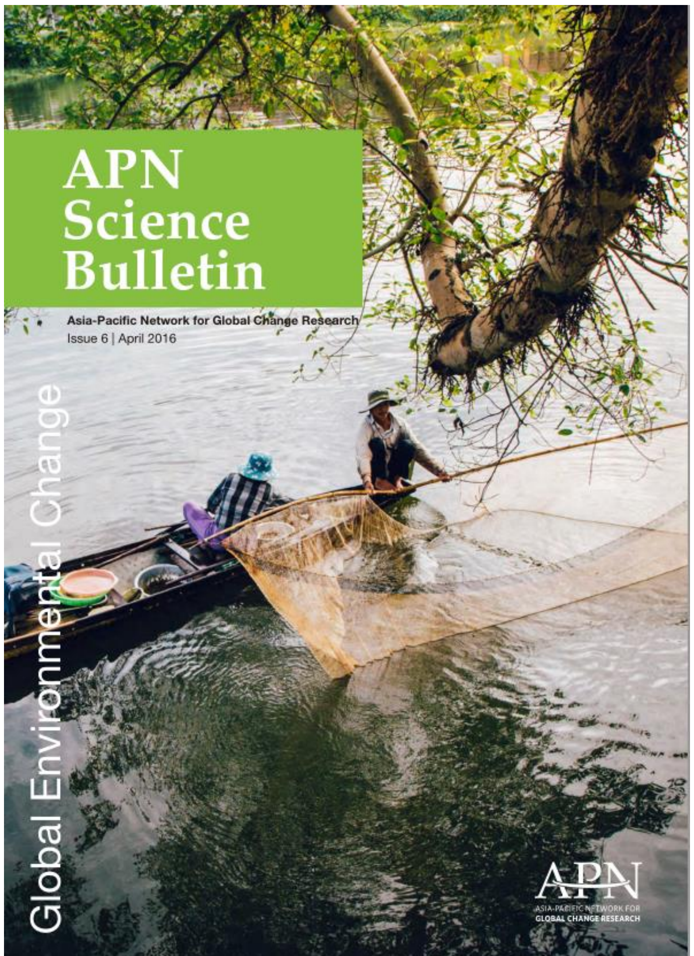


(b)

Fig. 8. (a) Temporal Correlation Coefficient 및 (b) NRMSE between dam inflow observation and forecasts by CIR-Forecast and Rank-Observed

Forest Fire Forecasting

(Toward a Fire and Haze Early Warning System for Southeast Asia)



Toward a Fire and Haze Early Warning System for Southeast Asia

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APN Project Reference: ARCP2013-10CMY-Yoo / Received: January 2016 / Published online: March 2016
Available online at APN E-Lib: http://www.apn-gcr.org/resources

HIGHLIGHTS

- Four different downscaling methods were developed and integrated into the prototype of EWS in order to improve the predictability.
- Long-term predictability of monthly precipitation for the four regions within Borneo Island was evaluated.
- APCC led a two-day workshop in Malaysia, including hands-on training sessions on statistical downscaling and prototype.
- Needs assessment for early warning information was conducted through field surveys with resource managers.
- Monthly precipitation forecasts for dry season (August to October) over 4 provinces in Borneo Island showed good predictability less than four-month lead time by showing temporal correlation coefficients (TCCs) greater than 0.5 in all provinces.

ABSTRACT Smoke haze from forest fires is among Southeast Asia's most serious environmental problems and there is a clear need for a fire and haze early warning system (EWS) for the region. APEC Climate Center (APCC) has been collecting monthly dynamic prediction data produced by 16 institutions and has been producing 6-month lead multi-model ensemble (MME) climate forecasts every month. In this study, we developed four different statistical downscaling methods and assessed the forecast skill of the integrated forecast system over four provinces in Borneo Island. We developed a EWS prototype in which three-month precipitation (August to October) is predicted during April to July and the forecasted precipitation amount is then translated into four fire danger ratings based on the relationship between precipitation amount and CO_2 emission. A needs assessment for early warning information was conducted through field surveys with resource managers at three provinces in Indonesia. A two-day workshop was held for the improvement of the EWS. Finally, the forest fire early warning information on Borneo Island created using the EWS will be provided though the hosting server in APCC.

KEYWORDS *fire danger; seasonal forecasts; statistical downscaling; dynamical downscaling; seasonal drought*

1. Introduction

Smoke haze from forest fires is among Southeast Asia's most serious environmental problems. Severe burning in Indonesia occurs only during years with anomalously low rainfall. Monitoring for these conditions is important, but has limited effectiveness because the burning is opportunistic. As a result, measures to prevent these fires and mitigate their impacts remains limited by the absence of long-lead early warning system (EWS). Severe burning conditions, therefore, need to be forecast weeks to months in advance for any prevention to be effective. In this context, little of the progress made in seasonal forecasting has been applied to fire early warning in Indonesia and there is a clear need for a fire and haze EWS for the region. The project builds upon current fire danger rating systems by providing forecasts at a longer lead-time using seasonal forecast data maintained at APCC, a time-scale that is more relevant and useable for decision makers. The final objective of the project is to develop a prototype of fire danger EWS by considering field survey results and conducting a training workshop.

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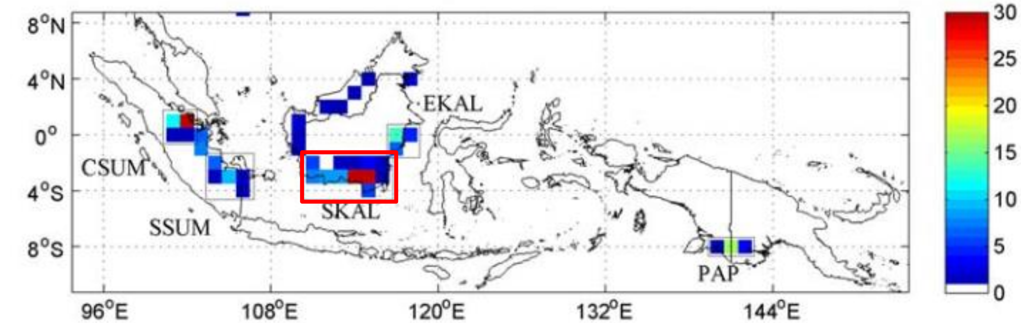
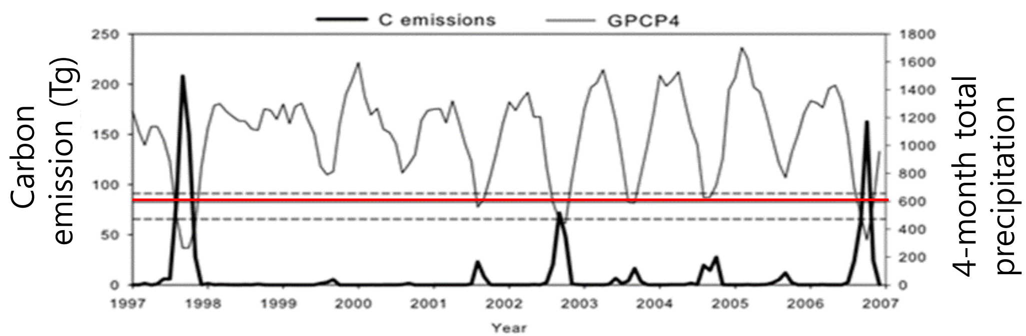
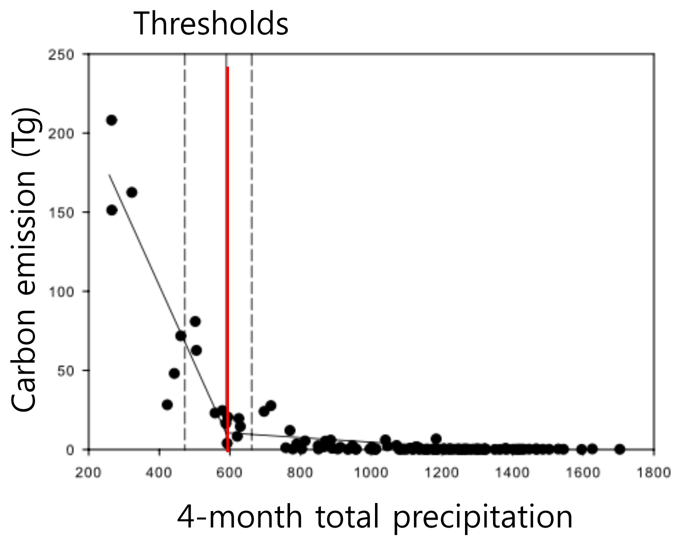
Why do we need to downscale for forest fire management?

- In Indonesia, there is a high risk of sever biomass burning when se asonal precipitation falls below region-specific threshold values (Fie ld et al., 2008).







Source: Field, R.D., and S.S.P. Shen. 2008. Predictability of carbon emissions from biomass burning in Indonesia from 1997 to 2006, Journal of Geophysical Research, 113.

Why do we need to downscale for forest fire management? (cont'd)

- **Global climate models (GCMs) cannot simulate climate at the regional scale**

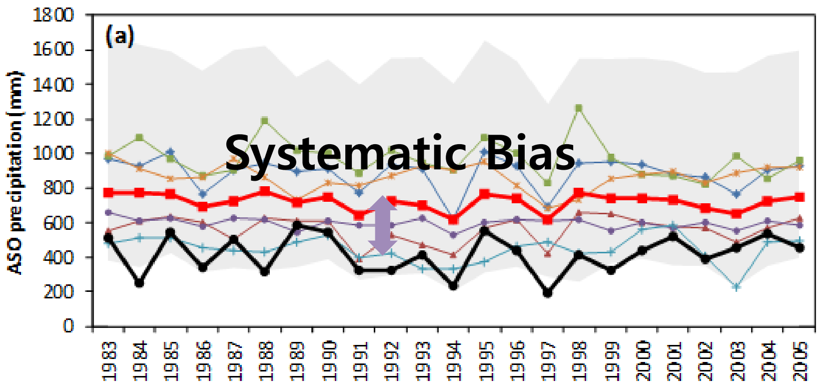
Table: Description of dynamical seasonal prediction models used in the study.

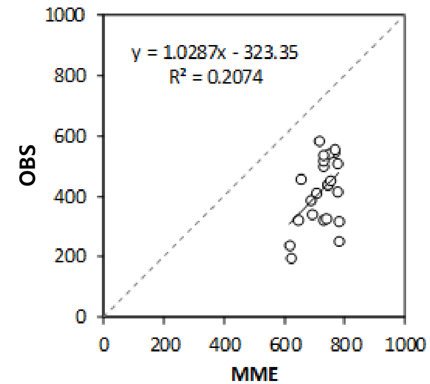
Model	Institution	Raw Resolution	Ensemble siz e
MSC_CANCM3	Meteorological Service of Canada (Canada)	T63L31 (AGCM) 1.41° X 0.94° L40 (OGCM)	10
MSC_CANCM4	Meteorological Service of Canada (Canada)	T63L35 (AGCM) 1.41° X 0.94° L40 (OGCM)	10
NASA	National Aeronautics and Space Admi nistration (USA)	2°lat X 2.5°lon, L34 (AGCM) 1/3 by 5/8, 27L (OGCM)	10
NCEP	Climate Prediction Center / NCEP/NW S/NOAA (USA)	T62L64	17
PNU	Pusan National University (R. of Korea)	T42L18 (AGCM) 0.7/1.4/2.8°lat X 2.815°lon, L29 (OGCM)	4
POAMA	Centre for Australian Weather and Cli mate Research/ Bureau of Meteorolog y (Australia)	T47L17 (AGCM) 0.5~1.5°lat X 2°lon, L25 (OGCM)	30

Evaluation of original GCMs without bias correction
- Time-serie and Scatter plot

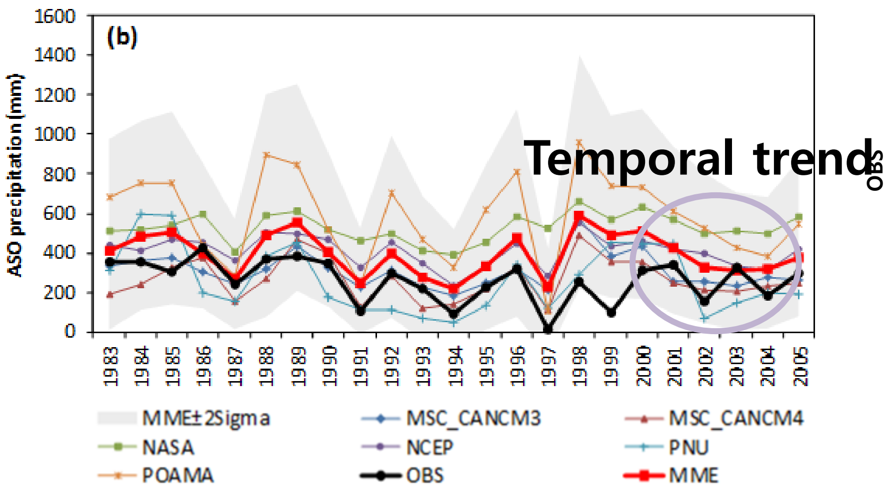
Observation (APHRODITE), Forecast models (1-month lead time)

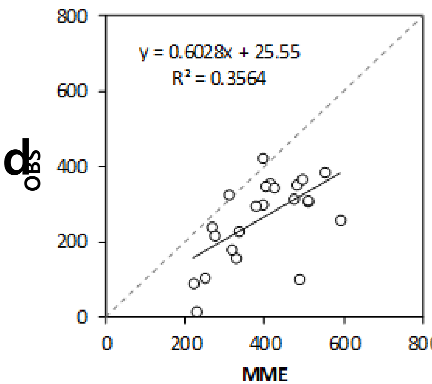
CSUM





SSUM

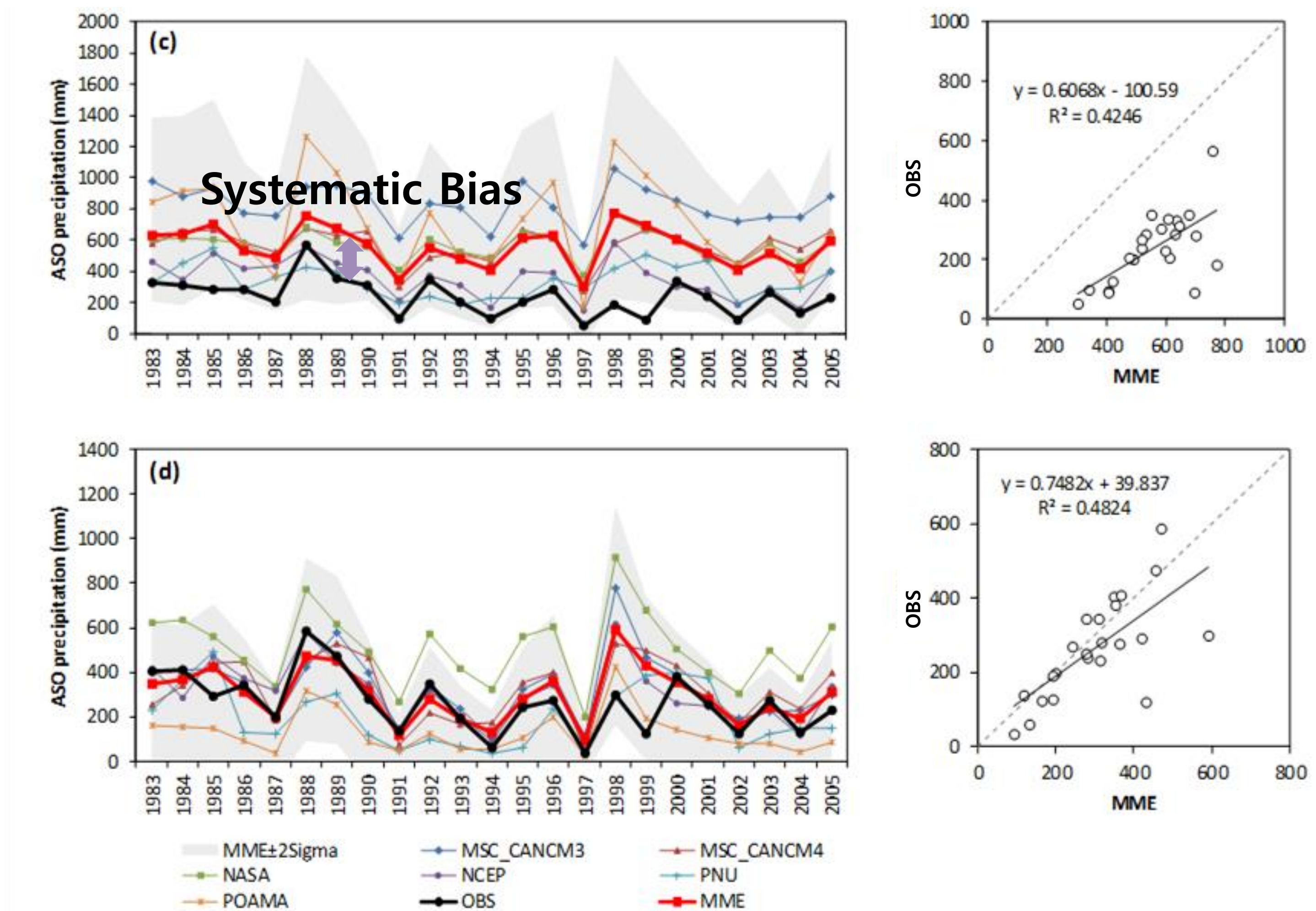




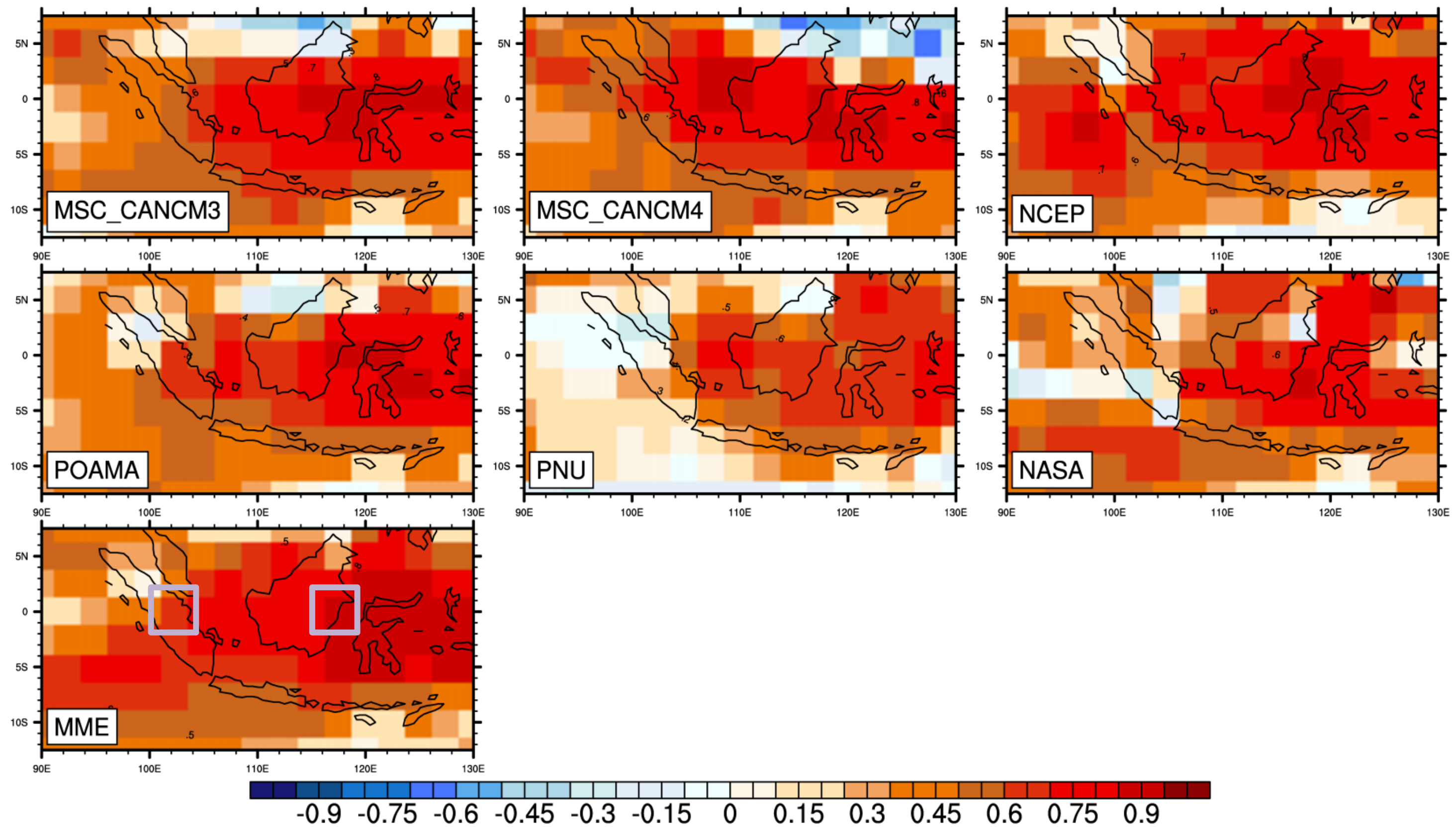
Evaluation of original GCMs without bias correction
- Time-serie and Scatter plot (cont'd)

EKAL

SKAL



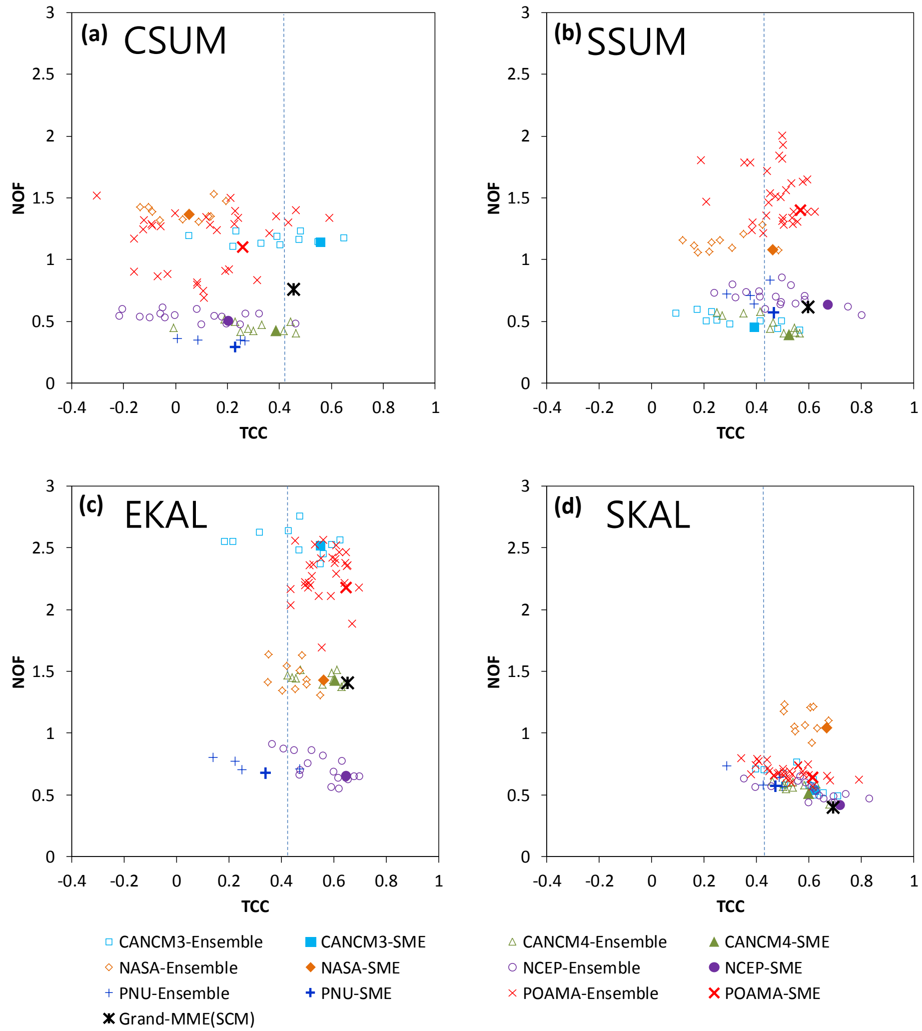
Spatial distribution of temporal correlation coefficient (TCC)



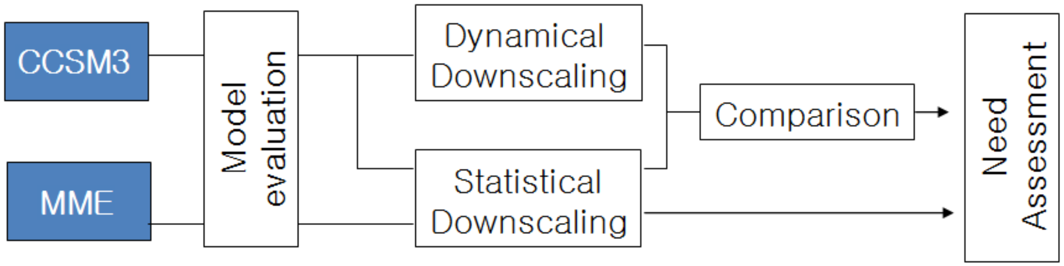
Temporal correlation coefficient between forecast models and Observation(GPCP), period: 1983~2005 ASO, forecasted on July

GPCP: Global Precipitation Climatology Project-NASA
(Webpage: http://precip.gsfc.nasa.gov/)

Performance measures (TCC and NOF) for ASO total precipitation (forecasted on July without BC)



Two different downscaling approaches



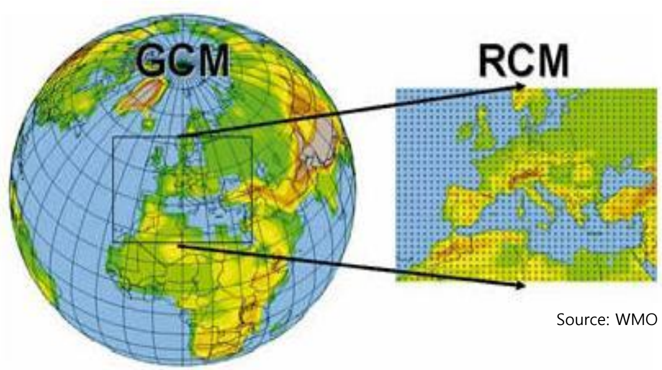
Research procedures for 1st year of APN project

Strengths and Weaknesses of Statistical Versus Dynamical Downscaling (after Fowler et al. 2007)[26]

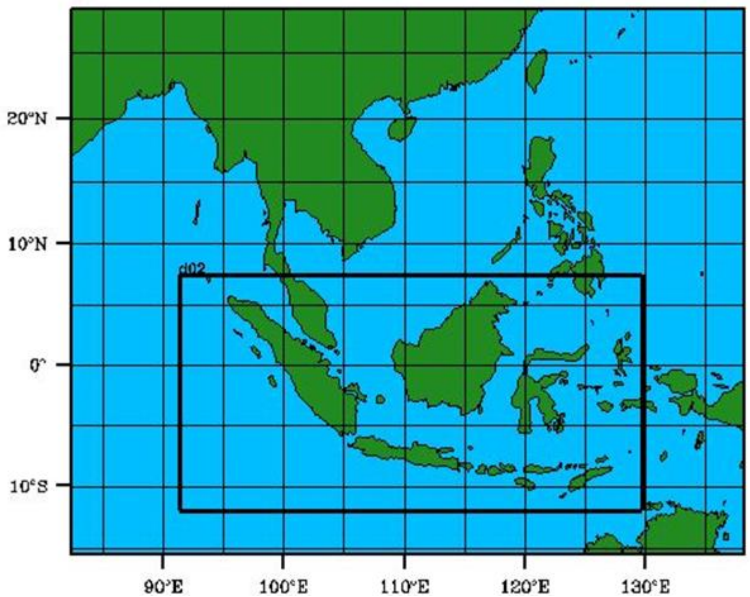
	Statistical	Dynamical
Advantages	Comparatively cheap and computationally efficient. Can provide point-scale climatic variables from GCM-scale output. Able to directly incorporate observations into method.	Produces responses based on physically consistent processes. Can resolve atmospheric processes on a smaller scale (e.g., orographic and rain-shadow effects in mountainous areas).
Disadvantages	Dependent upon choice of predictors. Does not account for non-stationarity in the predictor-predict and relationship. Regional climate system feedbacks not included. Affected by biases in underlying GCM.	Computationally intensive. Limited number of scenario ensembles available. Dependent on GCM boundary forcing; affected by biases in underlying GCM. Dependent on RCM parameterizations. Different RCMs will give different results.

Source: Cooney, 2012, Downscaling Climate Models: Sharpening the Focus on Local-Level Changes, *Environ Health Perspect* 120:a22-a28

Dynamical Downscaling Experiment



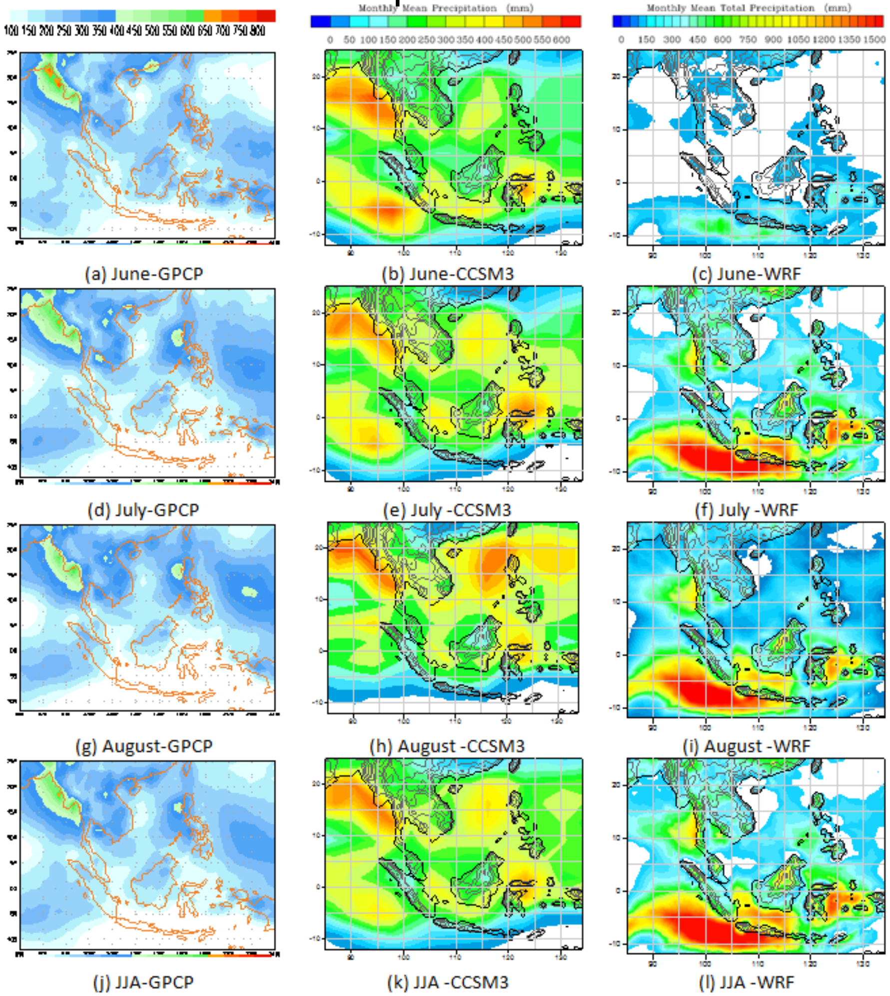
- Dynamical downscaling using the Weather Research and Forecasting (WRF) model



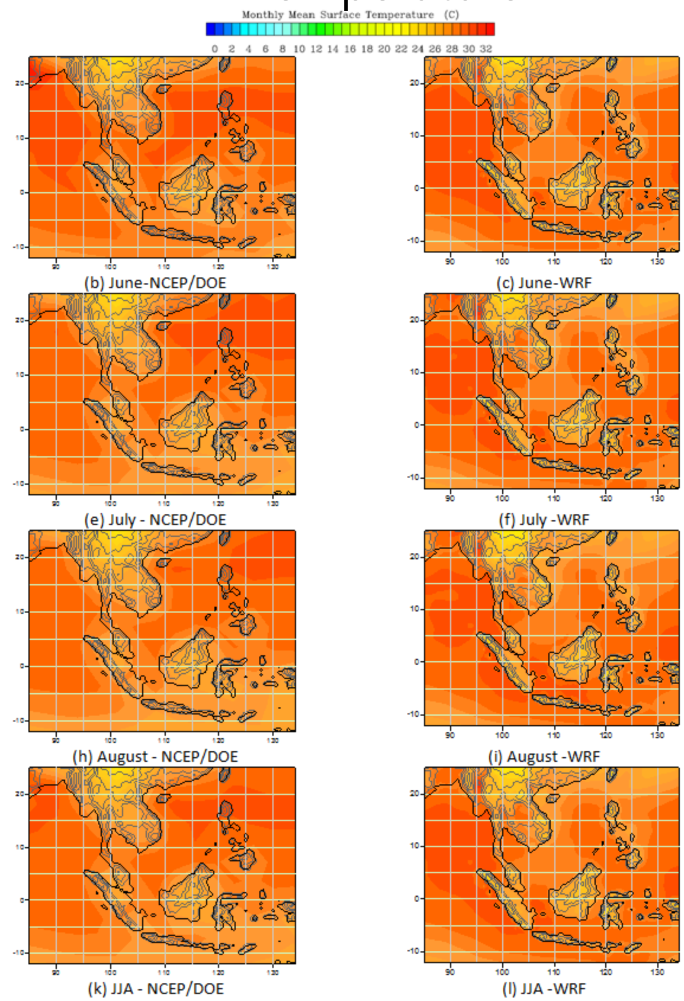
	Domain 1	Domain 2
Horizontal grid	138 × 112	283 × 145
Horizontal resolution	45 km	15 km
Vertical layers	28	
Physical options	Kain-Frisch(new Eta) cumulus scheme	
	YSU scheme	
	CAM scheme	
	WSM 6-class graupel scheme	
	Noah land-surface model	
Initial data	CCSM3/APCC	
Time Period	2006/5/27 ~ 2010/8/31 (JJA)	

Evaluation Dynamical Downscaling

Precipitation

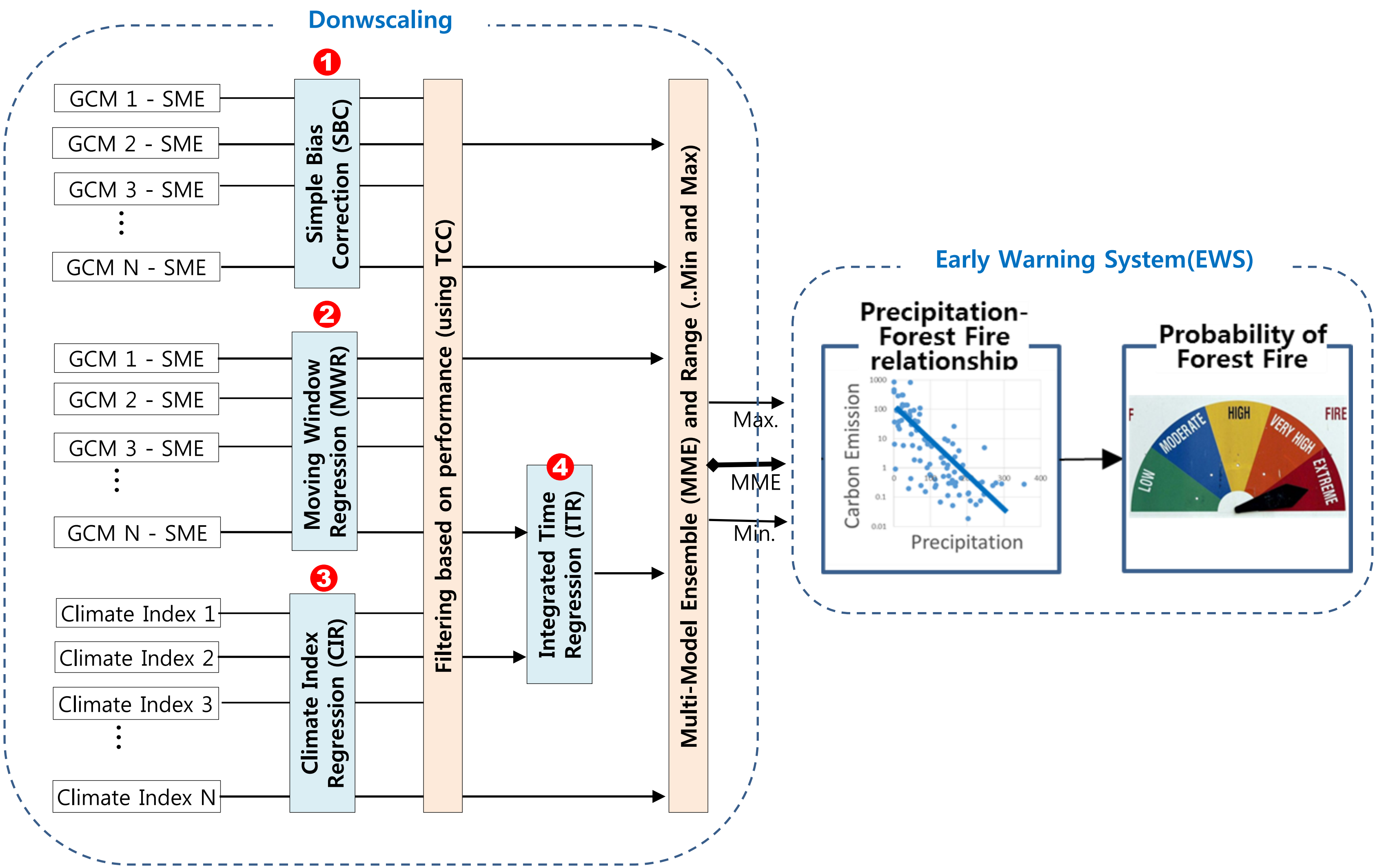


Temperature

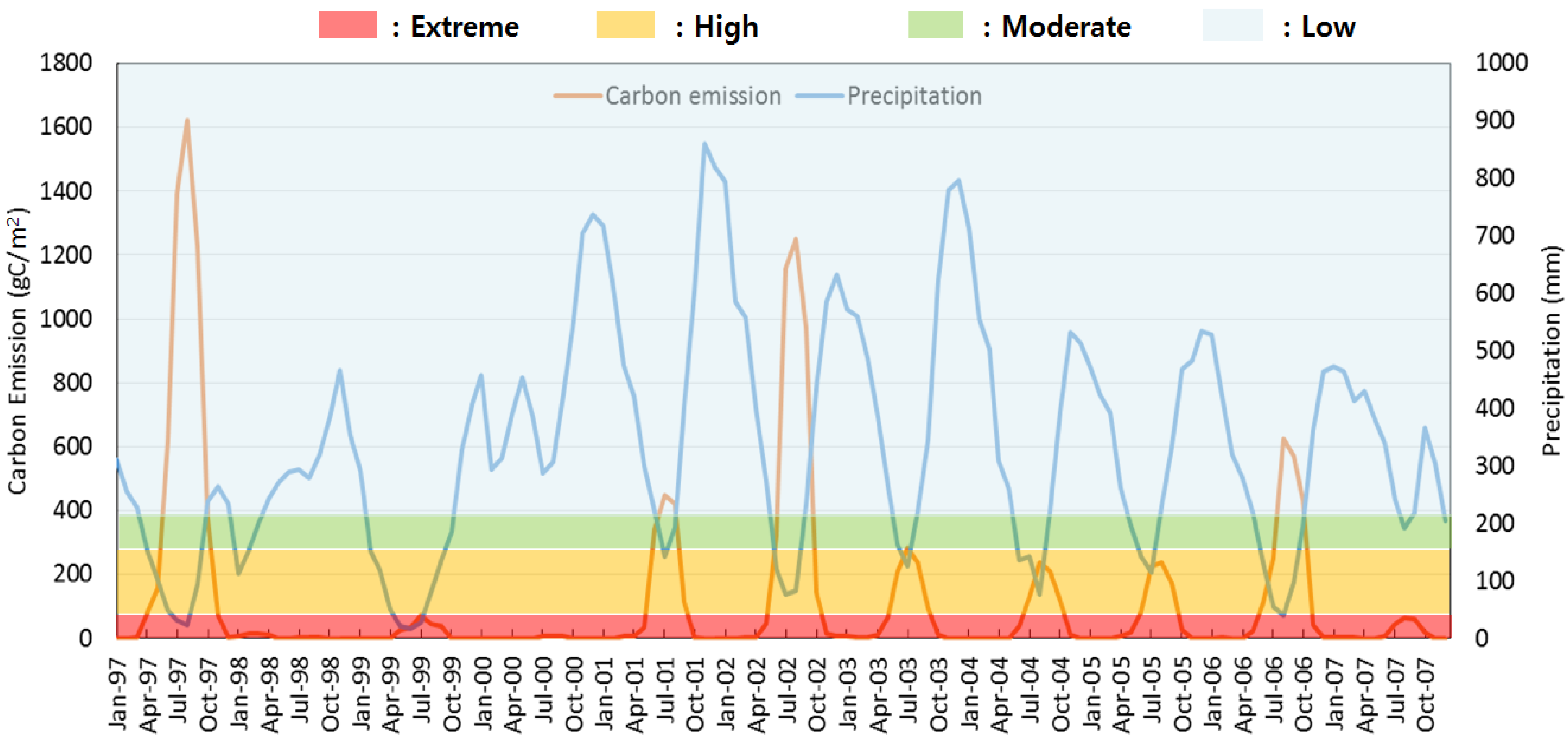


➡ Expensive but fail to simulate the precipitation center: excluded from the study

Development of EWS Prototype
- Overall structure-

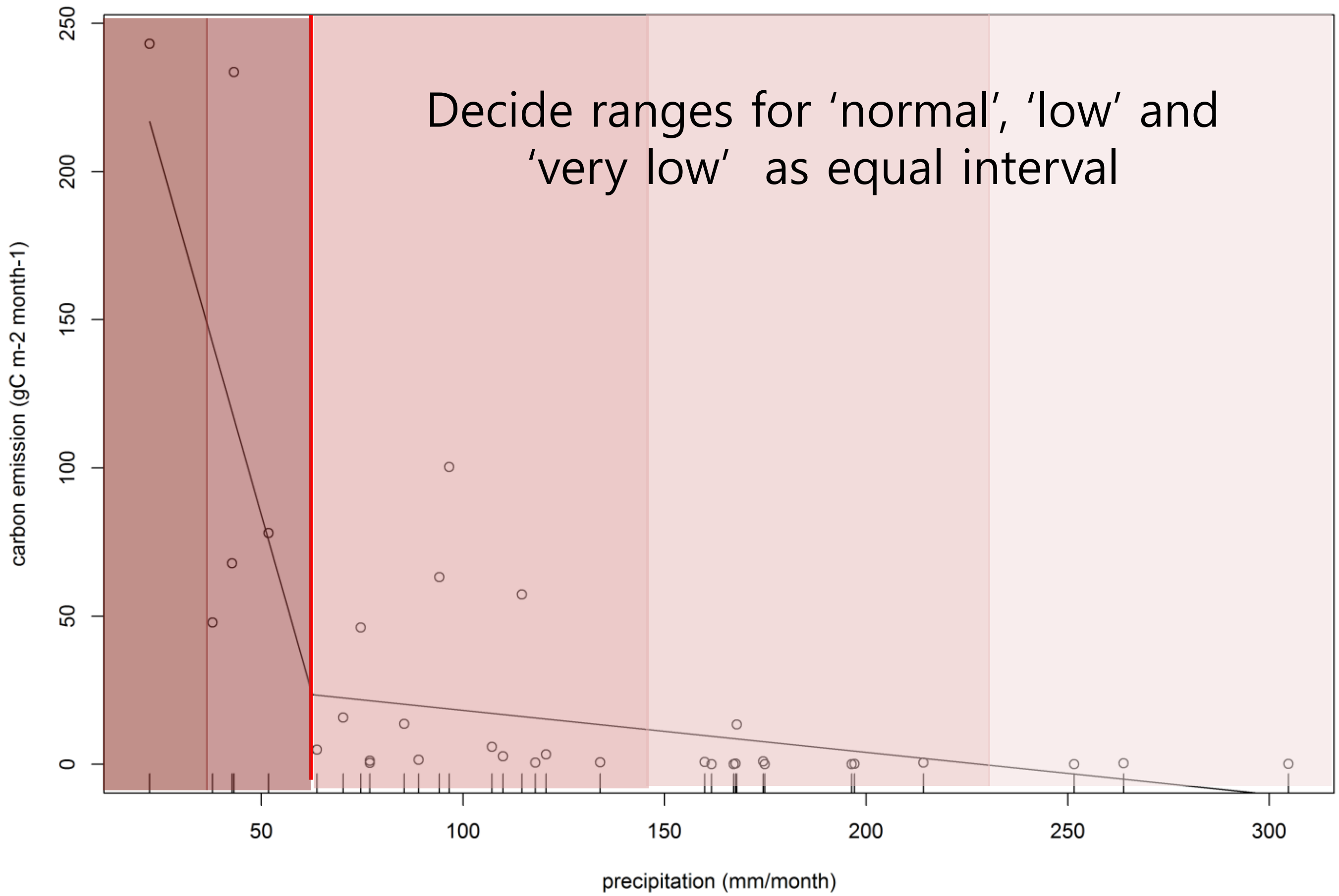


Development of EWS Prototype
- Translating precipitation to fire danger rating



Development of EWS Prototype
- Translating precipitation to fire danger rating (cont'd)

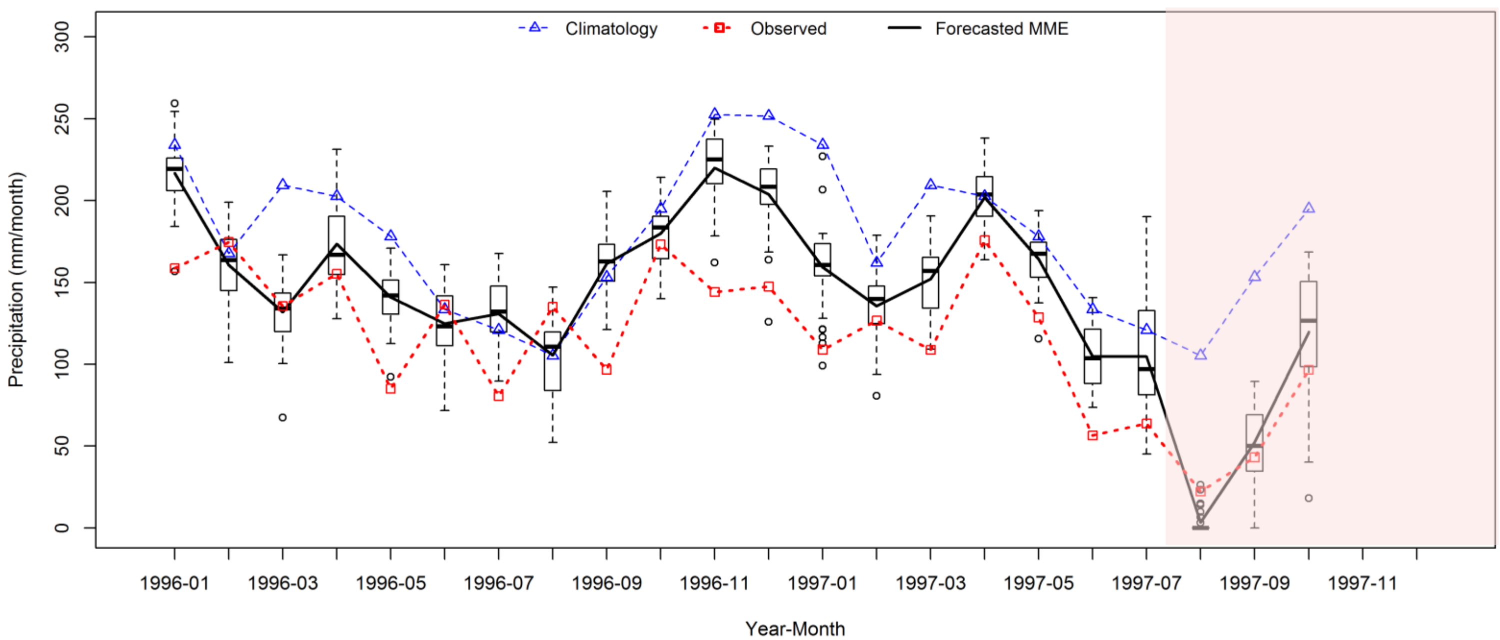
1 Decide threshold using segmented regression



Decide ranges for 'very high' and 'high' as equal interval

Development of EWS Prototype
- Template for delivering information

Monthly precipitation for AUG. 1997 - OCT. 1997(barat, 1 month lead-time)



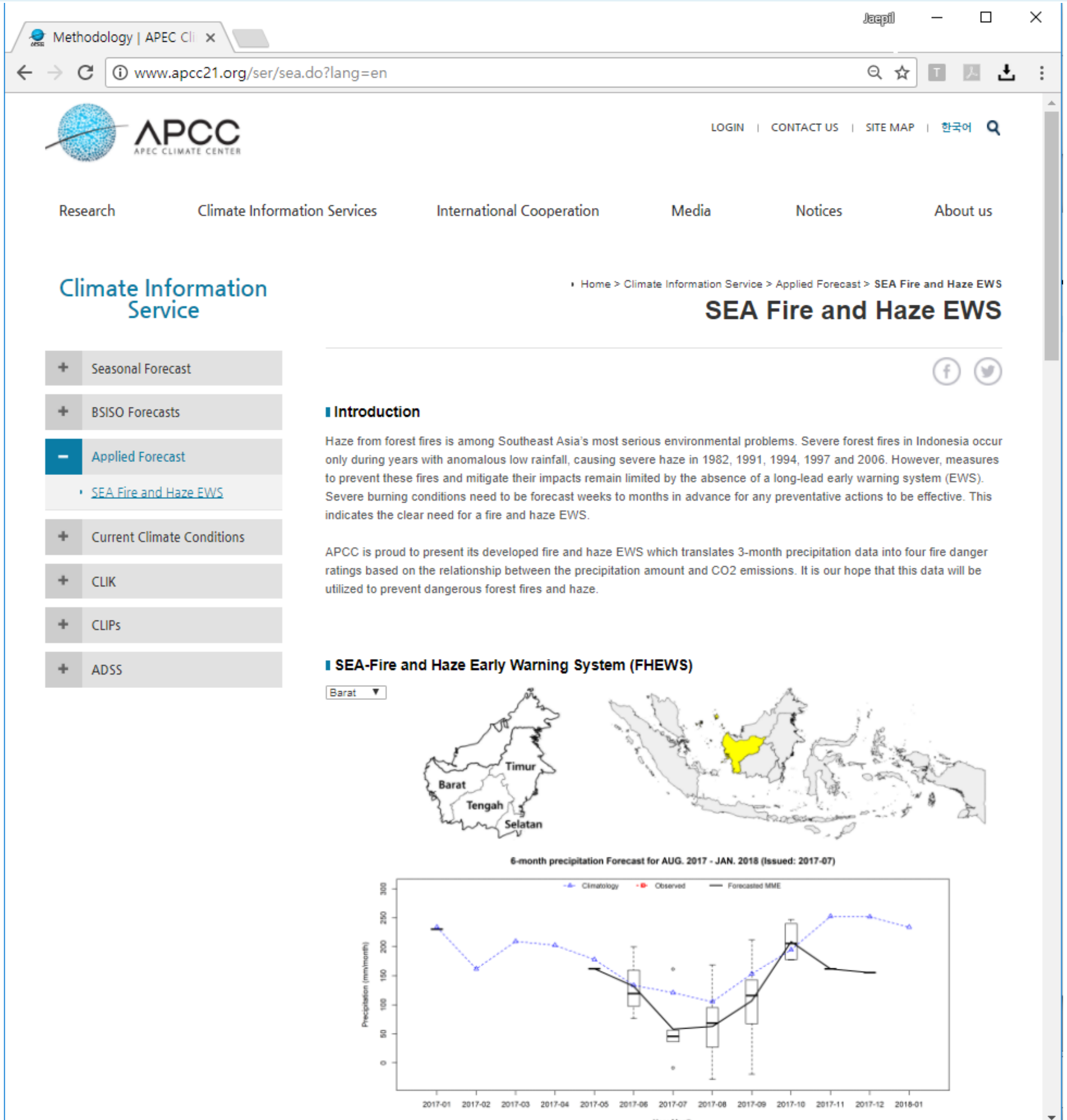
Monthly skil score for JAN. 1983 - DEC. 2007

	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC
cor	0.83	0.81	0.82	0.81	0.78	0.78	0.76	0.76	0.77	0.74	0.82	0.76
nrmse	0.55	0.62	0.56	0.62	0.62	0.64	0.64	0.66	0.63	0.68	0.57	0.63
pc	0.96	0.64	0.84	0.76	0.72	0.68	0.52	0.44	0.56	0.72	0.8	0.84
hss	0.83	0.4	0.64	0.33	0.51	0.41	0.35	0.25	0.36	0.33	-0.068	-0.087

Forest fire probapbility for 1997

	AUG	SEP	OCT
Very High	100.0	32.1	6.9
High	0.0	25.0	3.4
Normal	0.0	42.9	20.7
Low	0.0	0.0	65.5
Very Low	0.0	0.0	3.4

SEA Fire and Haze Early Warning System



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

Thank You!