APCC Training Program on
"Generation of regional climate data derived from statistical downscaling techniques";
Applications of statistical downscaling techniques

Hyung-Il Eum

APEC Climate Center (APCC)

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Contents

- **CLIK**
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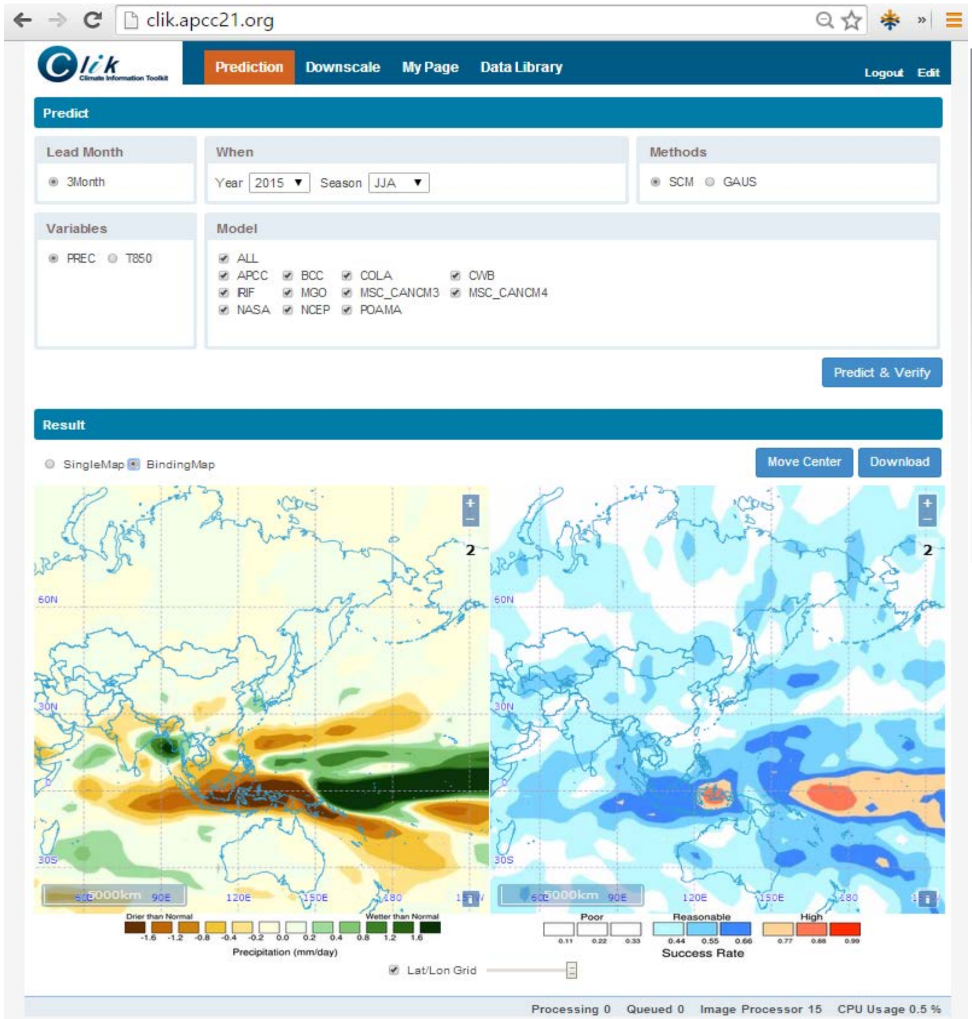
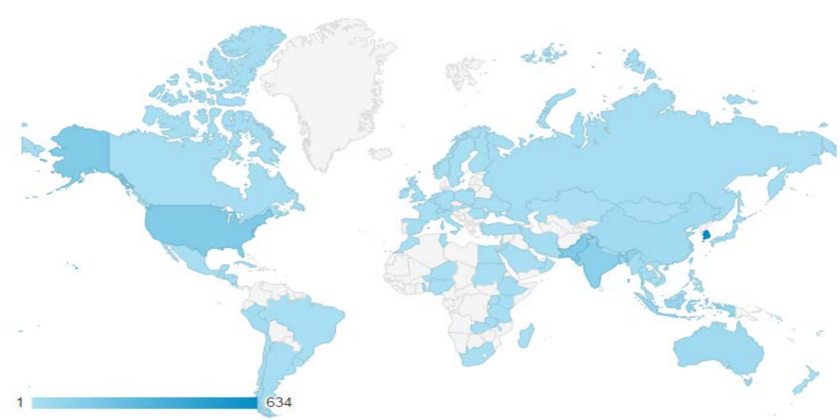
- **Water resources management**
  - Flood plain
  - Change in water availability under climate change
- **Reservoir operation**
  - Ensemble Streamflow Predictions (ESP)
- **Regional applications with seasonal forecastings in APCC**

CLimate Information toolKit (CLIK)





Case Studies: Seasonal forecasting

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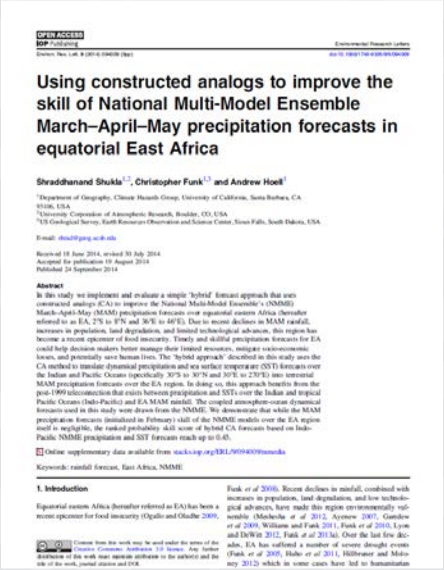
Using constructed analogs to improve the skill of National Multi-Model Ensemble March-April-May precipitation forecasts in equatorial East Africa


OPEN ACCESS

Using constructed analogs to improve the skill of National Multi-Model Ensemble March–April–May precipitation forecasts in equatorial East Africa

Shraddhanand Shukla[1,2], Christopher Funk[1,3] and Andrew Hoell[1]

Abstract

S. Shukla/ C. Funk /A. Hoell

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Study area and Data

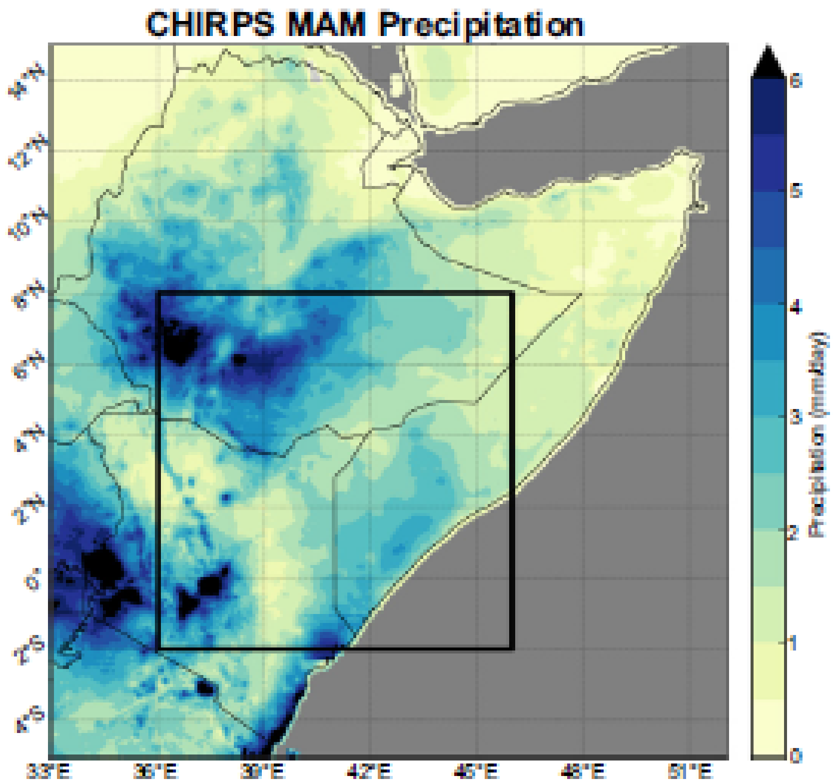


Figure 1. Long term mean (climatology: 1982–2010) March–April–May (MAM) observed precipitation in East Africa. The precipitation dataset used is Climate Hazard Group InfraRed Precipitation with Station data (CHIRPS). The land area within the black rectangle is the focus domain of this study.

- **National Multi-Model Ensemble (NMME)**
  - 6 GCM models at 1 degree resolution
  - International Research Institute (IRI)
  - Applying CA

Precipitation

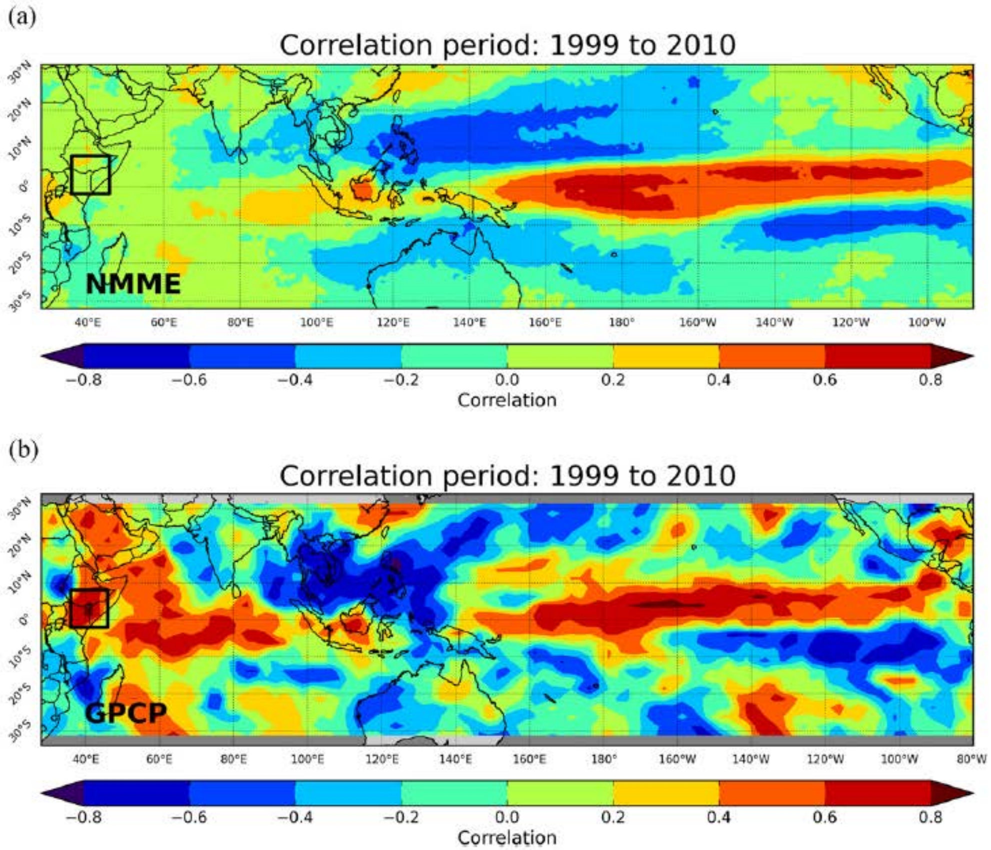


Figure 2. (a) Median of the correlation between MAM observed precipitation aggregated over the focus domain and each of NMME precipitation forecast superensemble (total 70 members) (b) same as (a) but with GPCP precipitation dataset.

GPCP (Global Precipitation Climatology Project, Adler et al., 2003)

Surface Sea Temperature (SST)

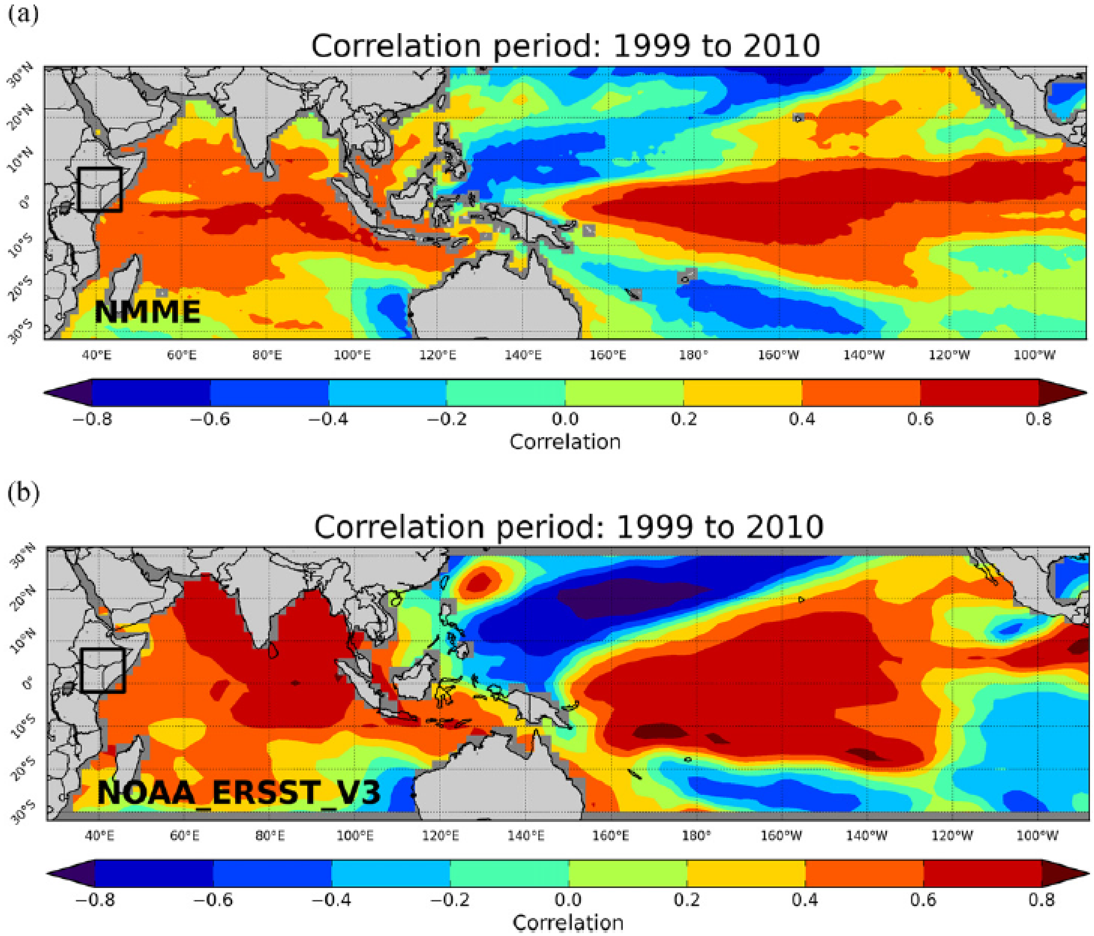
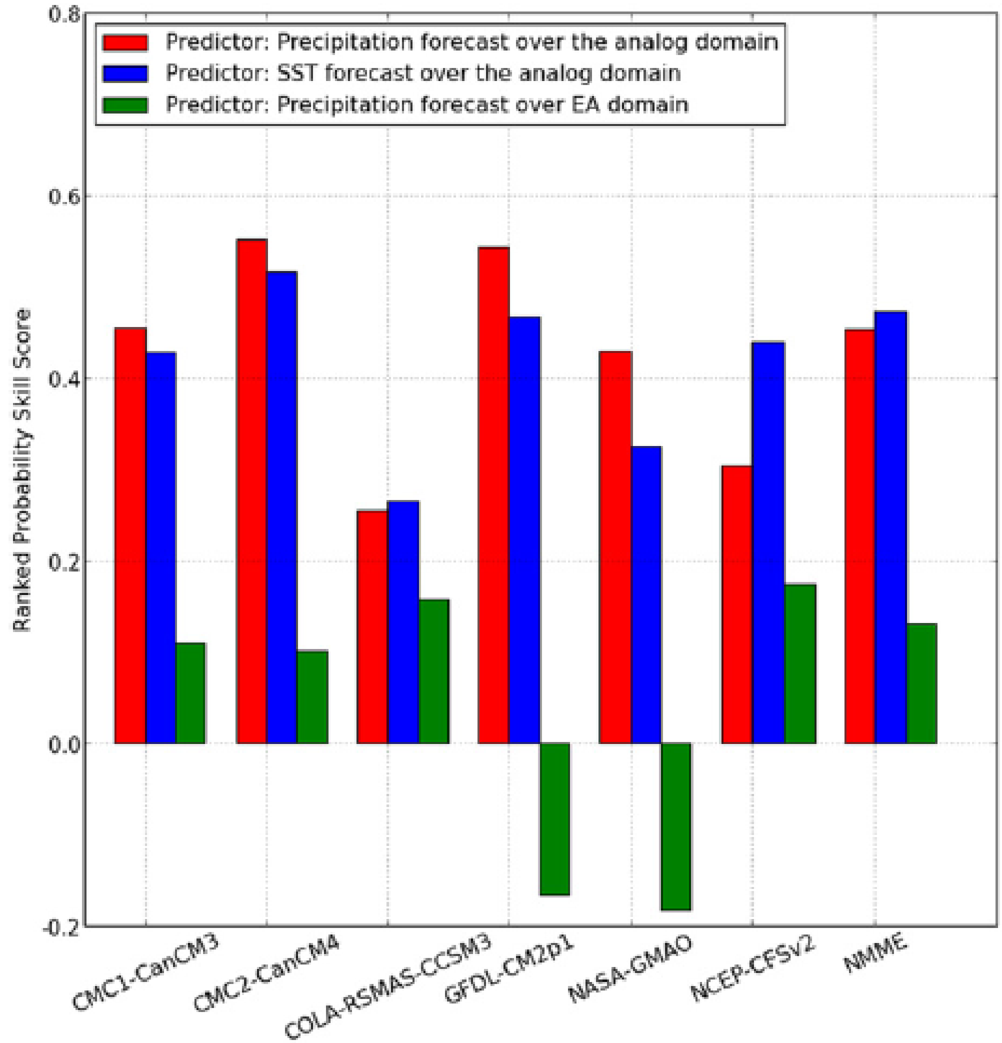
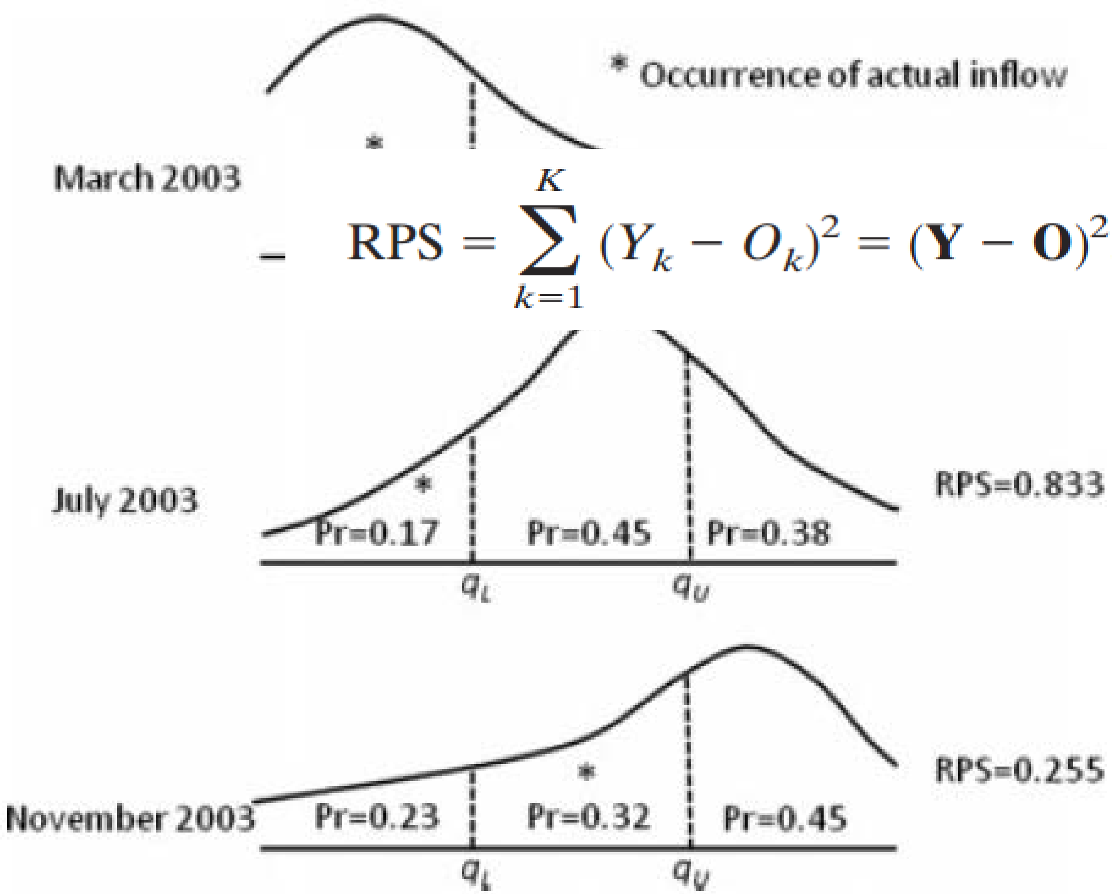


Figure 3. (a) Median of the correlation between MAM observed precipitation aggregated over the focus domain and each of NMME SST forecast superensemble (total 70 members) (b) same as (a) but with NOAA ERRST V3 SST dataset.

Ranked probability skill score



Ranked Probability Score (RPS)



$$\mathrm{RPS} = \sum_{k=1}^{K} (Y_k - O_k)^2 = (\mathbf{Y} - \mathbf{O})^2.$$

$= (0.67-1)^2+(0.9-1)^2$

$= (0.17-1)^2+(0.62-1)^2$

$= (0.23-0.333)^2+(0.55-1.0)^2$

Figure 3. Examples of the monthly probabilistic flow forecasts

Case Studies:
Water resources management

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Vulnerability of Infrastructures to Climate Change in City of London, Ontario

HYDROLOGICAL PROCESSES
Hydrol. Process. **26**, 485–499 (2012)
Published online 13 May 2011 in Wiley Online Library
(wileyonlinelibrary.com) DOI: 10.1002/hyp.8145

Assessment on variability of extreme climate events for the Upper Thames River basin in Canada

Hyung-Il Eum and Slobodan P. Simonovic*
Department of Civil and Environmental Engineering, University of Western Ontario, London Ontario N6A 5B9, Canada

Abstract:

Climate change may affect magnitude and frequency of regional extreme events with possibility of serious impacts on the existing infrastructure systems. This study investigates how the current spatial and temporal variations of extreme events are affected by climate change in the Upper Thames River basin, Ontario, Canada. A weather generator model is implemented to obtain daily time series of three climate variables for two future climate scenarios. The daily time series are disaggregated into hourly to capture characteristics of intense and rapidly changing storms. The maximum annual precipitation events for five short durations, 6-, 12-, 24-, 48-, and 72-h durations, at each station are extracted from the generated hourly data. The frequency and seasonality analyses are conducted to investigate the temporal and spatial variability of extreme precipitation events corresponding to each duration. In addition, this study investigates the impacts of increase in temperature using reliability, resilience, and vulnerability. The results indicate that the extreme precipitation events under climate change will occur earlier than in the past. In addition, episodes of extremely high temperature may last longer up to 19·7% than under the no-change climate scenario. This study points out that the revision of the design storms (e.g. 100- or 250-year return period) is warranted for the west and the south east region of the basin. Copyright © 2011 John Wiley & Sons, Ltd.

KEY WORDS weather generator; frequency analysis; variability

Received 3 May 2010; Accepted 14 April 2011

INTRODUCTION

The fundamental concept used implicitly in water resources management is stationarity—fluctuation of natural systems with unchanging variability. The stationarity assumption has long been compromised, however, by human interventions in the river basins. Flood risk, water supply, and water quality are affected by water infrastructure, channel modifications, drainage works, and land-cover and land-use change. Two other (sometimes indistinguishable) challenges to stationarity come from natural climate changes and low-frequency, internal variability. Planners have tools to adjust their analyses for known human disturbances within river basins, and justifiably or not, they generally have considered natural change and variability to be sufficiently small to allow for stationarity-based water resources management. Some more recent work states that stationarity is dead in an era of substantial anthropogenic impacts on the earth's climate, which significantly alters the means and the extremes of precipitation, evapotranspiration, and rates of discharge of rivers (Milly *et al*., 2008).

The Intergovernmental Panel on Climate Change (IPCC) has noticed that, by the 2080s, there may be increase in runoff of up to 10–40% in high latitudes and wet tropical regions, while in medium latitudes and dry tropical regions, it is likely to see a decrease in runoff of up to 30% (IPCC, 2007). It should be noted that more intense climatic events, e.g. more intense flooding, will occur, not surprisingly, as the result of climate change. Allen and Ingram (2002) suggest that extreme precipitation will increase faster than the mean precipitation due to global warming that produces a more active hydrological cycle (Trenberth *et al*., 2003). Although identifying a clear increasing trend in extreme precipitation events is difficult to produce, many studies have indicated increase in a high frequency of extreme precipitation events all over the world: the USA (Karl *et al*., 1995), UK (Ekstrom *et al*., 2005), Canada (Stone *et al*., 2000; Cunderlik and Simonovic, 2004; Prodanovic and Simonovic, 2010), Germany (Hundecha and Bardossy, 2005), India (Goswani *et al*., 2006), and South Korea (Boo *et al*., 2006) among others.

Changes in magnitude and frequency of extreme events may have serious impacts on the existing infrastructure systems that have been designed using historic data. The main objective of this article is to (1) provide better understanding of the current spatial and temporal variations of extreme events in the Upper Thames River basin and (2) to show how these current patterns may be affected by climate change. Recent extreme rainfall events have exceeded the capacity of the existing infrastructure systems at many places (Osborn and Hulme, 2002; Ekstrom *et al*., 2005). In response to recent incidents of infrastructural failure, the Public Infrastructure Engineering Vulnerability Committee (PIEVC), established by Engineers Canada, has conducted an assessment of the vulnerability of Canadian

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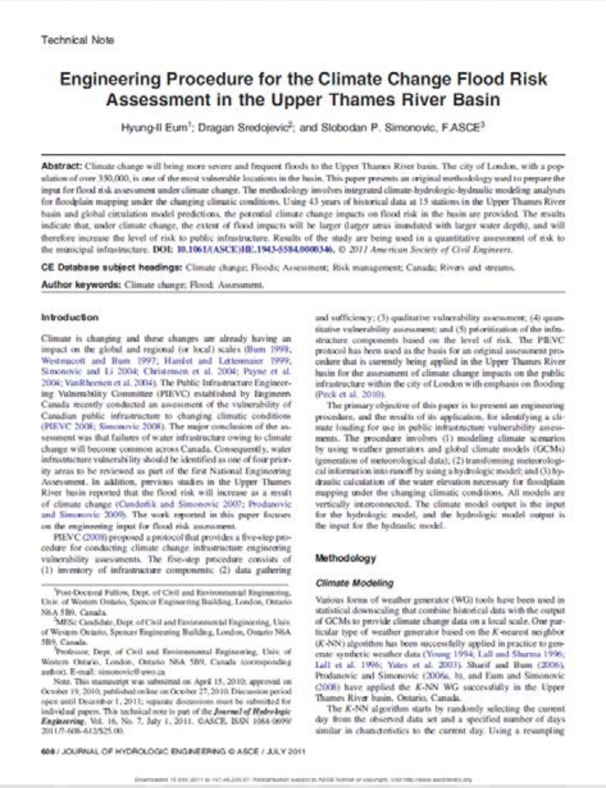

Technical Note

Engineering Procedure for the Climate Change Flood Risk Assessment in the Upper Thames River Basin

Hyung-Il Eum[1]; Dragan Sredojevic[2]; and Slobodan P. Simonovic, F.ASCE[3]

Abstract: Climate change will bring more severe and frequent floods to the Upper Thames River basin. The city of London, with a population of over 350,000, is one of the most vulnerable locations in the basin. This paper presents an original methodology used to prepare the input for flood risk assessment under climate change. The methodology involves integrated climate-hydrologic-hydraulic modeling analyses for floodplain mapping under the changing climatic conditions. Using 43 years of historical data at 15 stations in the Upper Thames River basin and global circulation model predictions, the potential climate change impacts on flood risk in the basin are provided. The results indicate that, under climate change, the extent of flood impacts will be larger (larger areas inundated with larger water depth), and will therefore increase the level of risk to public infrastructure. Results of the study are being used in a quantitative assessment of risk to the municipal infrastructure. DOI: 10.1061/(ASCE)HE.1943-5584.0000346. © *2011 American Society of Civil Engineers.*

CE Database subject headings: Climate change; Floods; Assessment; Risk management; Canada; Rivers and streams.

Author keywords: Climate change; Flood; Assessment.

Introduction

Climate is changing and these changes are already having an impact on the global and regional (or local) scales (Burn 1998; Westmacott and Burn 1997; Hamlet and Lettenmaier 1999; Simonovic and Li 2004; Christensen et al. 2004; Payne et al. 2004; VanRheenen et al. 2004). The Public Infrastructure Engineering Vulnerability Committee (PIEVC) established by Engineers Canada recently conducted an assessment of the vulnerability of Canadian public infrastructure to changing climatic conditions (PIEVC 2008; Simonovic 2008). The major conclusion of the assessment was that failures of water infrastructure owing to climate change will become common across Canada. Consequently, water infrastructure vulnerability should be identified as one of four priority areas to be reviewed as part of the first National Engineering Assessment. In addition, previous studies in the Upper Thames River basin reported that the flood risk will increase as a result of climate change (Cunderlik and Simonovic 2007; Prodanovic and Simonovic 2009). The work reported in this paper focuses on the engineering input for flood risk assessment.

PIEVC (2008) proposed a protocol that provides a five-step procedure for conducting climate change infrastructure engineering vulnerability assessments. The five-step procedure consists of (1) inventory of infrastructure components; (2) data gathering and sufficiency; (3) qualitative vulnerability assessment; (4) quantitative vulnerability assessment; and (5) prioritization of the infrastructure components based on the level of risk. The PIEVC protocol has been used as the basis for an original assessment procedure that is currently being applied in the Upper Thames River basin for the assessment of climate change impacts on the public infrastructure within the city of London with emphasis on flooding (Peck et al. 2010).

The primary objective of this paper is to present an engineering procedure, and the results of its application, for identifying a climate loading for use in public infrastructure vulnerability assessments. The procedure involves (1) modeling climate scenarios by using weather generators and global climate models (GCMs) (generation of meteorological data); (2) transforming meteorological information into runoff by using a hydrologic model; and (3) hydraulic calculation of the water elevation necessary for floodplain mapping under the changing climatic conditions. All models are vertically interconnected. The climate model output is the input for the hydrologic model, and the hydrologic model output is the input for the hydraulic model.

Methodology

Climate Modeling

Various forms of weather generator (WG) tools have been used in statistical downscaling that combine historical data with the output of GCMs to provide climate change data on a local scale. One particular type of weather generator based on the *K*-nearest neighbor (*K*-NN) algorithm has been successfully applied in practice to generate synthetic weather data (Young 1994; Lall and Sharma 1996; Lall et al. 1996; Yates et al. 2003). Sharif and Burn (2006), Prodanovic and Simonovic (2006a, b), and Eum and Simonovic (2008) have applied the *K*-NN WG successfully in the Upper Thames River basin, Ontario, Canada.

The *K*-NN algorithm starts by randomly selecting the current day from the observed data set and a specified number of days similar in characteristics to the current day. Using a resampling

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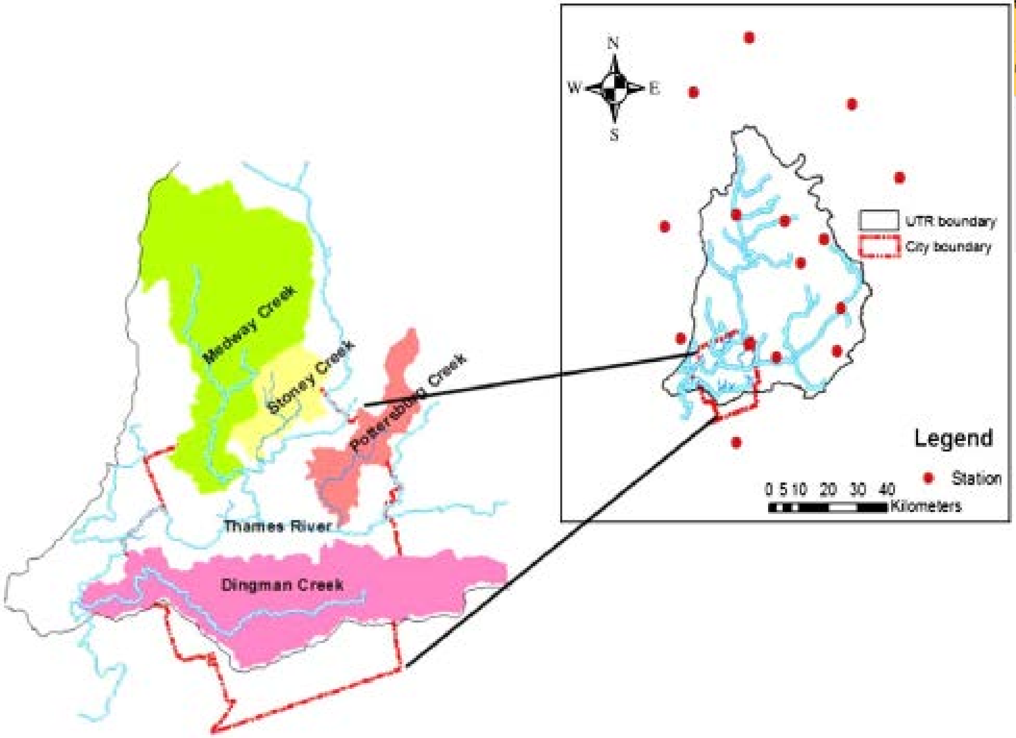
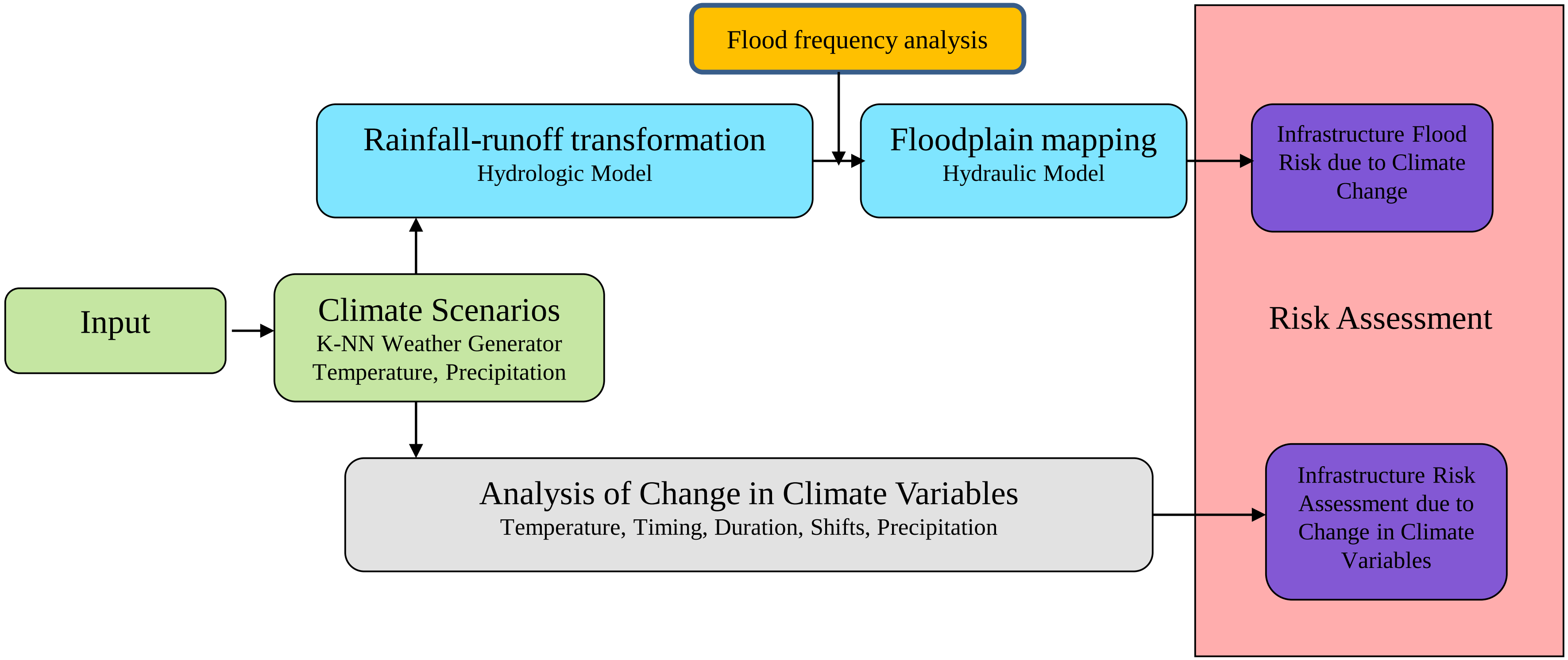
London, Canada



Procedure for assessment of climate change



Climate signal from a GCM (CCSRNIES B21)

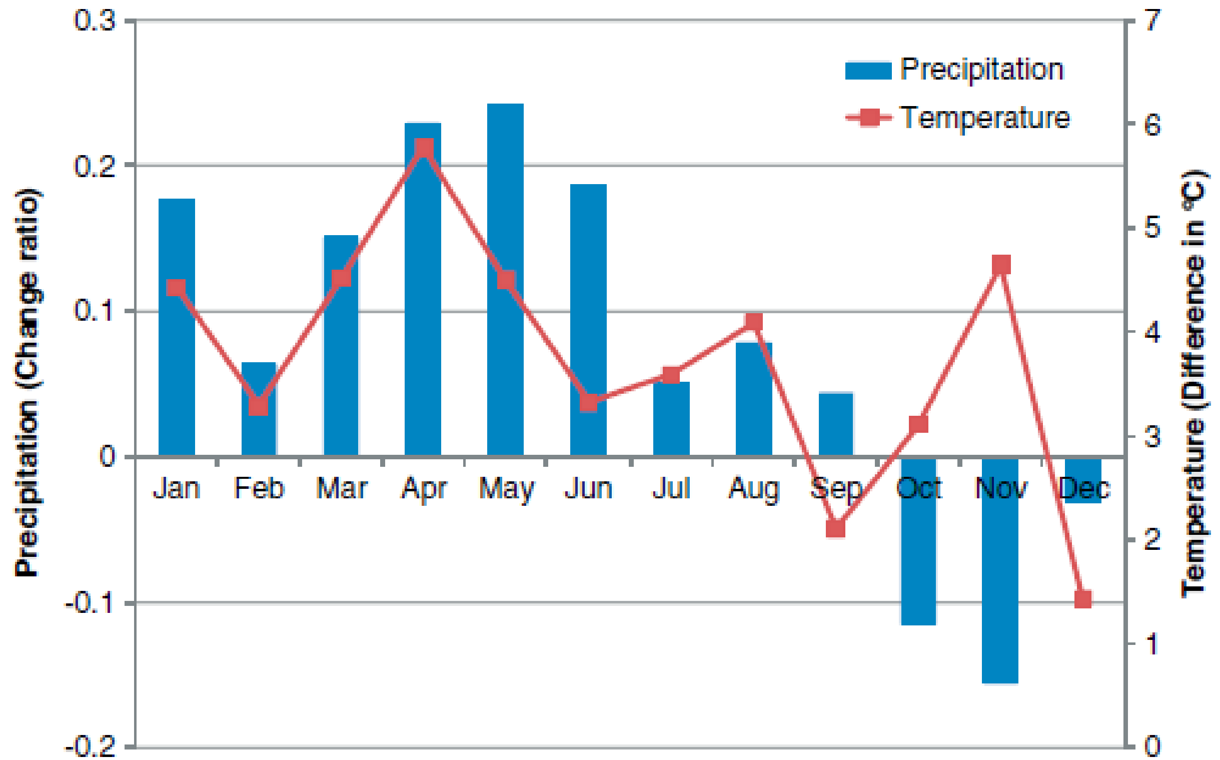
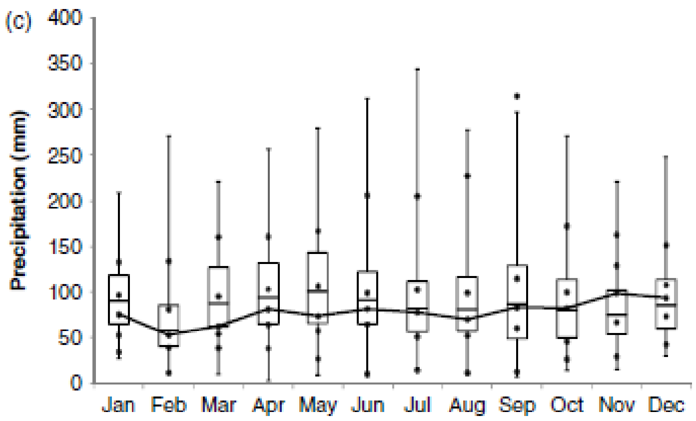
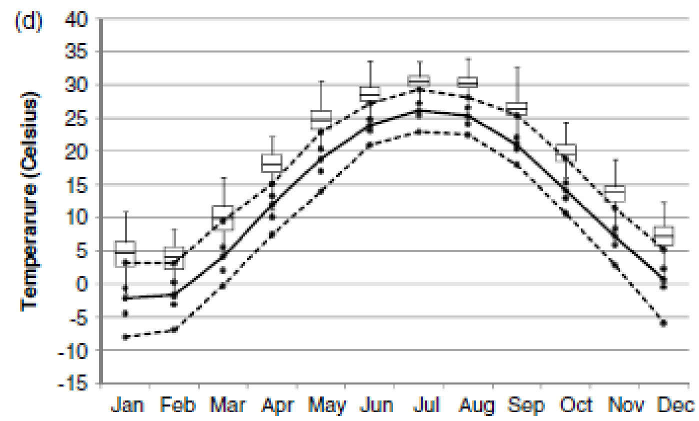


Figure 2. Monthly changes in precipitation and temperature for the CCSRNIES B21 GCM scenario

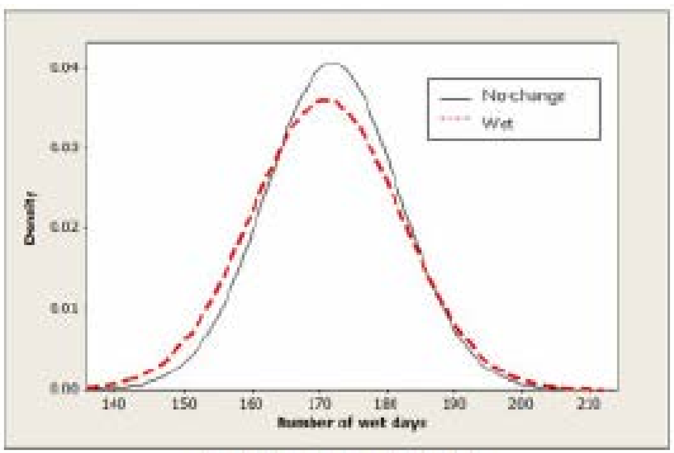
K-NN WG



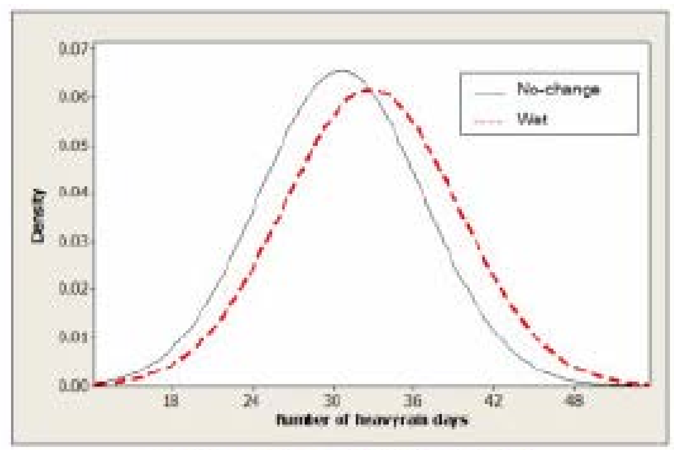
London (Precipitation)



London (Maximum temperature)



London (Wet days)



London (Heavy-rain days)

Hydrologic model

- **Input data**
  - Hourly data from a temporal disaggregation technique
    - Method of fragment (Svanidze, 1977)
- **HEC-HMS**

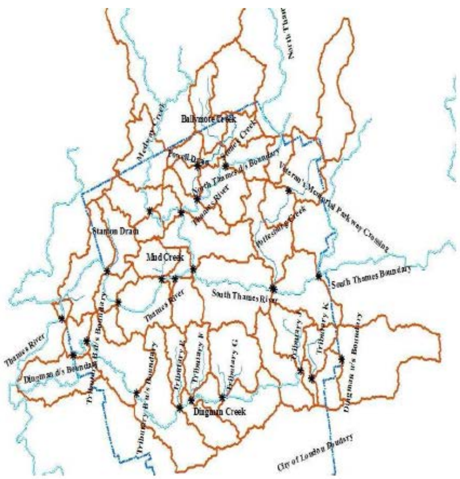


Figure 3.7 Delineation of the Thames River into sub-watersheds within the City of London

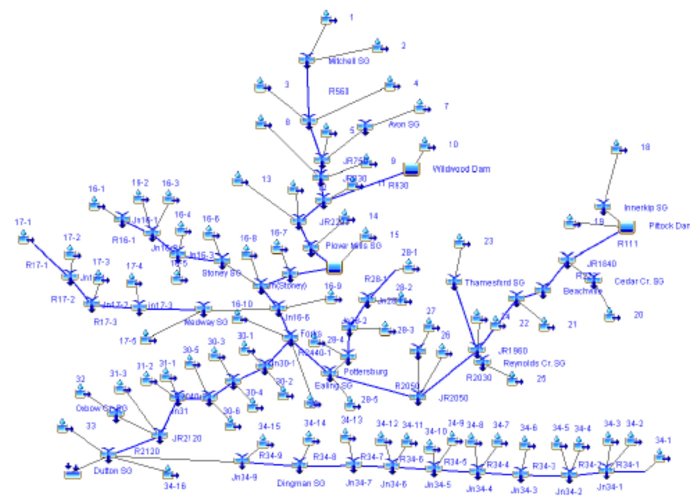
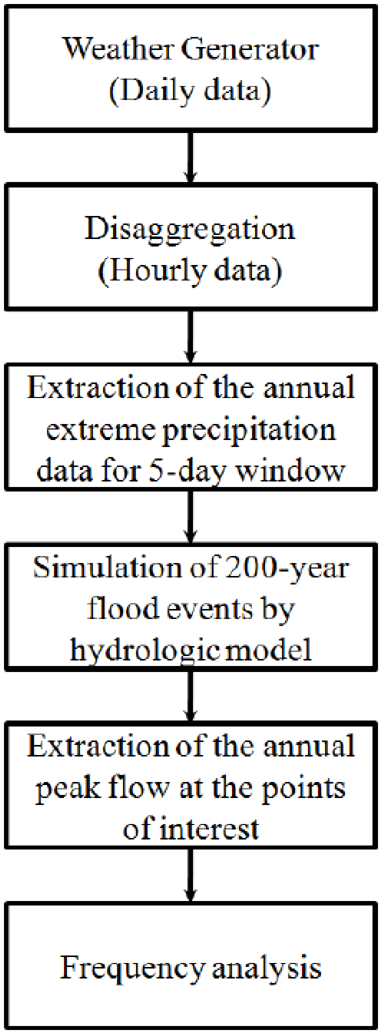
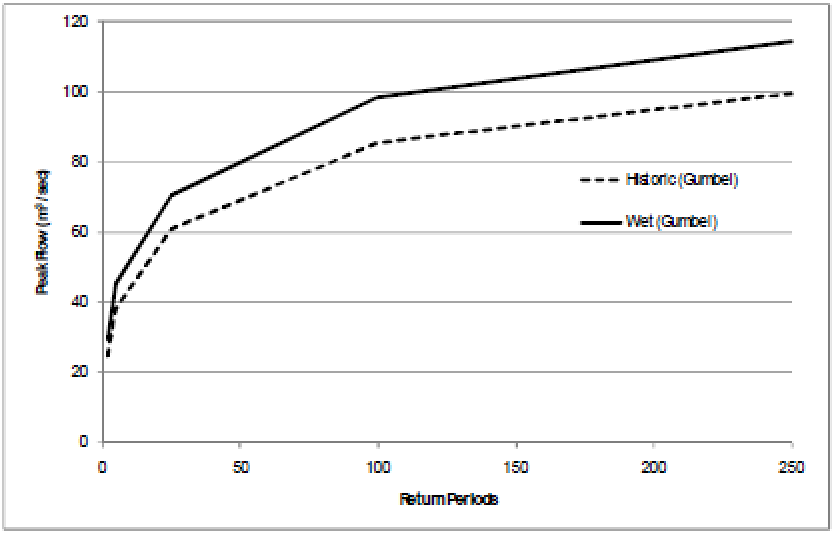


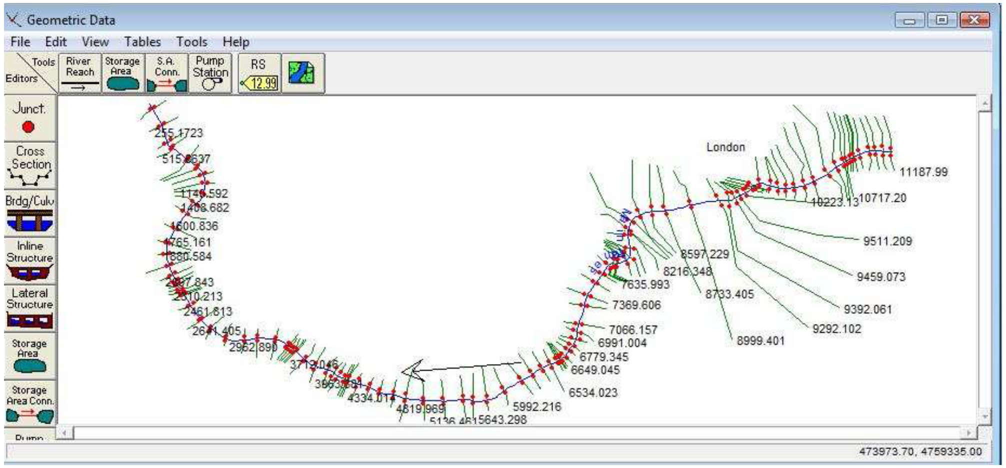
Figure 3.8 The HEC-HMS model structure

Frequency analysis



Flooding map





Assessment of variability in water availability under climate change

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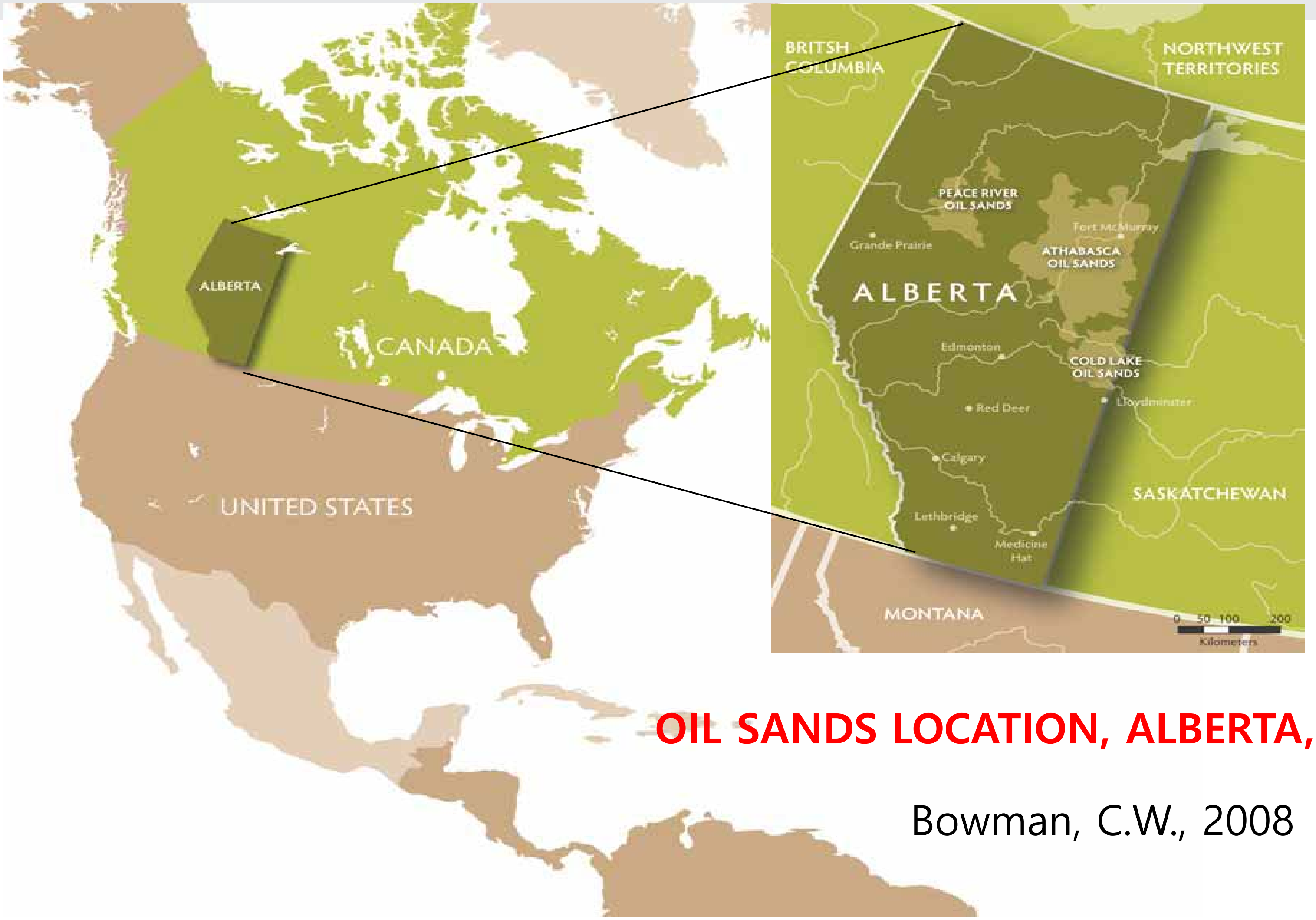
Alberta oil sands



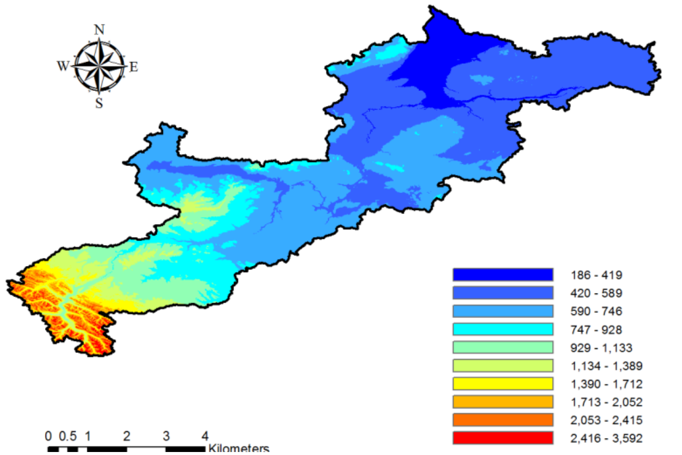
OIL SANDS LOCATION, ALBERTA, CANADA

Bowman, C.W., 2008

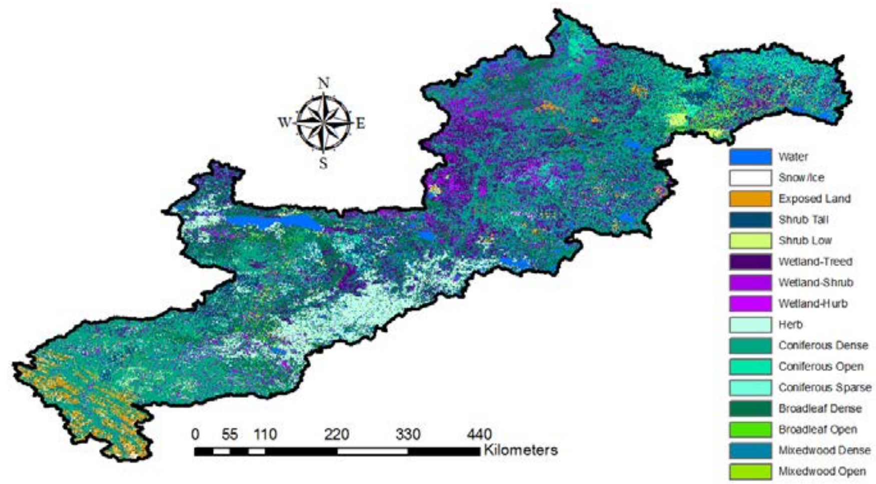
Bitumen

Athabasca River Basin

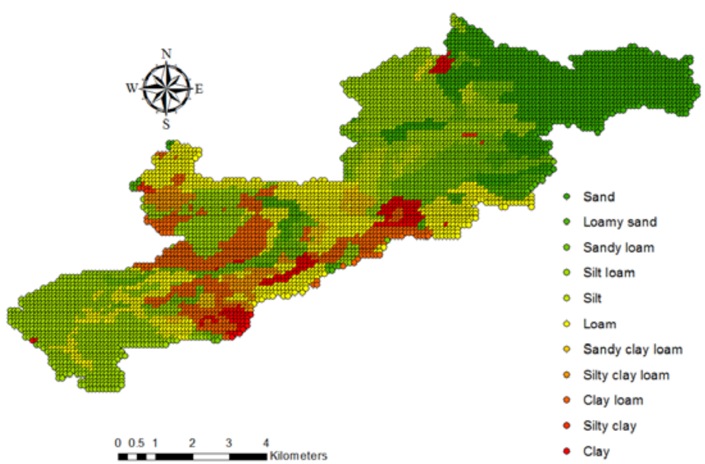
- **Various topographic and physical characteristics**



DEM

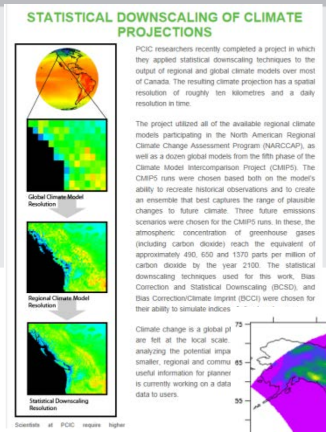


Land Cover (2000)



Soil Type

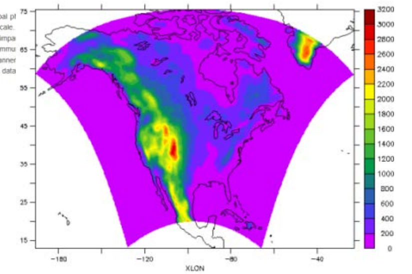
Climate data (1)


STATISTICAL DOWNSCALING OF CLIMATE PROJECTIONS

PCIC researchers recently completed a project in which they applied statistical downscaling techniques to the output of regional and global climate models over most of Canada. The resulting climate projection has a spatial resolution of roughly ten kilometres and a daily resolution in time.

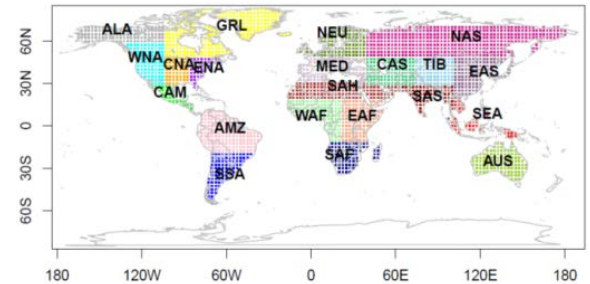
The project utilized all of the available regional climate models participating in the North American Regional Climate Change Assessment Program (NARCCAP), as well as a dozen global models from the fifth phase of the Climate Model Intercomparison Project (CMIP5). The CMIP5 runs were chosen based both on the model's ability to recreate historical observations and to create an ensemble that best captures the range of plausible changes to future climate. Three future emissions scenarios were chosen for the CMIP5 runs. In these, the atmospheric concentration of greenhouse gases (including carbon dioxide) reach the equivalent of approximately 490, 650 and 1370 parts per million of carbon dioxide by the year 2100. The statistical downscaling techniques used for this work, Bias Correction and Statistical Downscaling (BCSD), and Bias Correction/Climate Imprint (BCCI) were chosen for their ability to simulate indices

Climate change is a global pl
are felt at the local scale.
analyzing the potential impa
smaller, regional and commu
useful information for planner
is currently working on a data
data to users.



- **Statistical downscaling**
  - PCIC (http://www.pacificclimate.org)
  - Over Canada with 10 km resolution

Order	WNA	ALA	CNA	ENA	GRL
1	CNRM-CM5-r1	CSIRO-Mk3-6-0-r1	CanESM2-r1	MPI-ESM-LR-r3	MPI-ESM-LR-r3
2	CanESM2-r1	HadGEM2-ES-r1	ACCESS1-0-r1	inmcm4-r1	inmcm4-r1
3	ACCESS1-0-r1	inmcm4-r1	inmcm4-r1	CNRM-CM5-r1	CanESM2-r1
4	inmcm4-r1	CanESM2-r1	CSIRO-Mk3-6-0-r1	CSIRO-Mk3-6-0-r1	CNRM-CM5-r1
5	CSIRO-Mk3-6-0-r1	ACCESS1-0-r1	MIROC5-r3	HadGEM2-ES-r1	ACCESS1-0-r1
6	CCSM4-r2	MIROC5-r3	HadGEM2-ES-r1	CanESM2-r1	CSIRO-Mk3-6-0-r1
7	MIROC5-r3	HadGEM2-CC-r1	MPI-ESM-LR-r3	MRI-CGCM3-r1	HadGEM2-ES-r1
8	MPI-ESM-LR-r3	MRI-CGCM3-r1	CNRM-CM5-r1	CCSM4-r2	MIROC5-r3
9	HadGEM2-CC-r1	CCSM4-r2	CCSM4-r2	MIROC5-r3	HadGEM2-CC-r1
10	MRI-CGCM3-r1	CNRM-CM5-r1	GFDL-ESM2G-r1	ACCESS1-0-r1	CCSM4-r2
11	GFDL-ESM2G-r1	MPI-ESM-LR-r3	HadGEM2-CC-r1	HadGEM2-CC-r1	MRI-CGCM3-r1
12	HadGEM2-ES-r1	GFDL-ESM2G-r1	MRI-CGCM3-r1	GFDL-ESM2G-r1	GFDL-ESM2G-r1



Trevor et al. (2013)

Method	Diagnostic 1- Sequencing		Diagnostic 2 - Distribution		Diagnostic 3 - Spatial	
	Rank	Performance	Rank	Performance	Rank	Performance
BCCI	1	✓	1 / 2	✓	3	X
BCCA	2	✓	3	X	2	OK
BCSD	3	X	1 / 2	✓	1	✓

Trevor et al. (2013)

Climate data (2)

➢ CMIP5

- 6 GCMs x 2 SDMs x 2 RCPs = 24 scenarios

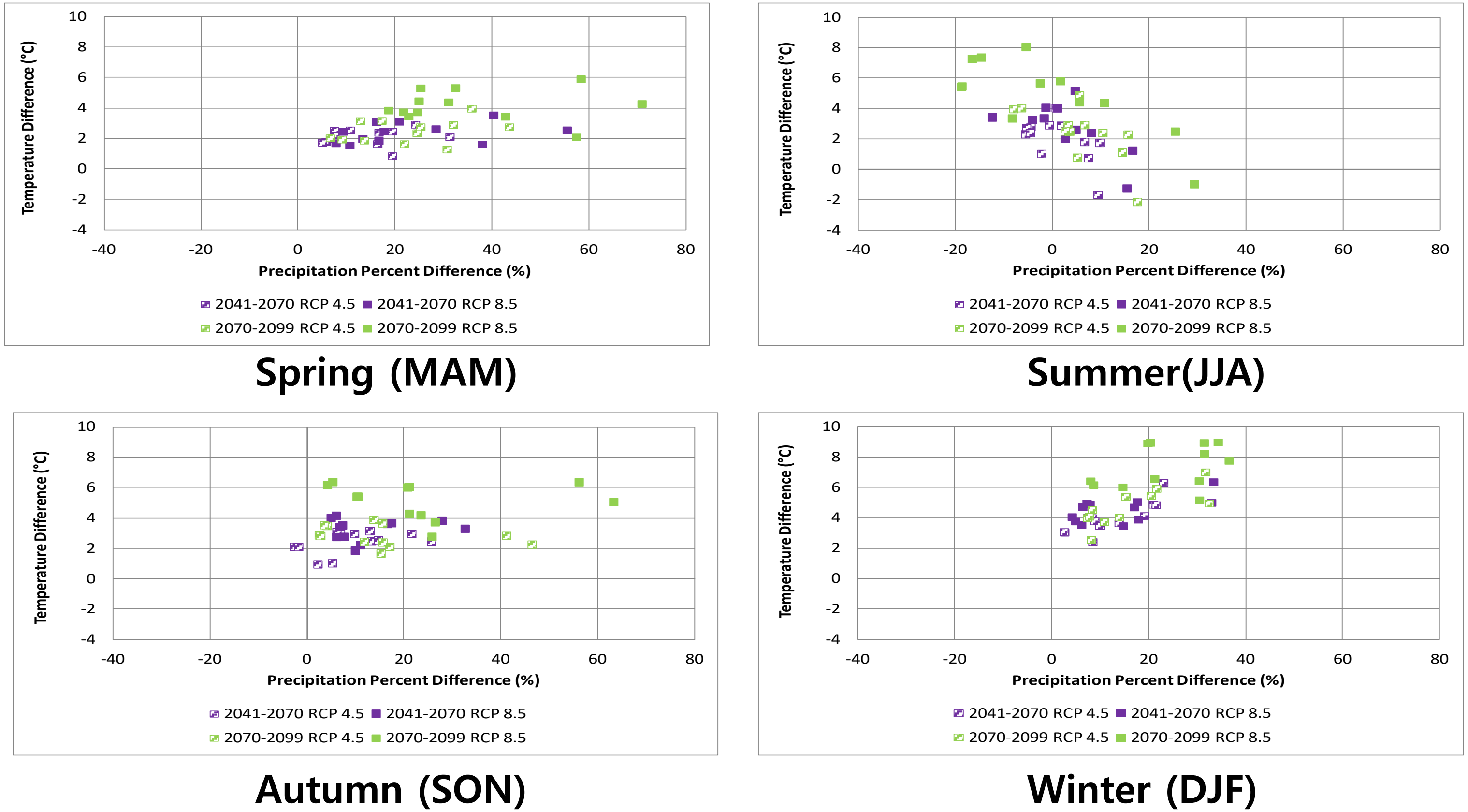
Model Abbreviation	Modelling Center	RCP/ Statistical downscaling method (SDMs)	Primary reference
CNRM-CM5.1	Centre National de Recherches Meteorologiques and Cerfacs	RCP4.5& RCP8.5/ BCCI & BCSD	Voldoire et al. (2013)
CanESM2	Canadian Centre for Climate Modelling and Analysis		Arora et al. (2011)
ACCESS1	Centre for Australian Weather and Climate Research		Marsland et al. (2013)
INMCM4	Institute of Numerical Mathematics of the Russian Academy of Sciences		Volodin et al. (2010)
CSIRO-Mk3.6.0	Commonwealth Scientific and Industrial Research Organisation		Jeffrey et al. (2013)
CCSM4	National Center for Atmospheric Research (NCAR)		Gent et al. (2011)

Indicators of Hydrologic Alterations (IHAs)

Hydrologic regime component	WRIs and IHAs	No	Examples of hydrologic influence	Examples of ecological influence
Magnitude and timing	Water resources indicators (WRIs) Annual volume (m^3), center of timing of annual flow (water year), median seasonal flow	6	Annual water balance, magnitude and timing of seasonal conditions	Availability and suitability of habitat for aquatic organisms
Magnitude and duration	Annual mean 1-day minimum and maximum (m^3/s)	2	Magnitude of annual flood and drought conditions	Duration of stressful conditions
Timing	Day of each annual 1-day minimum and maximum	2	Timing of annual flood and drought conditions	Spawning cues for fish; compatibility with life cycles of organisms
Magnitude and timing	Timing and amount of spring freshet initiation	2	Timing and magnitude of rapid melting	-
	Total	12		

Seasonal changes in PPT & TEM

- **Difference from the reference period (1981-2010)**



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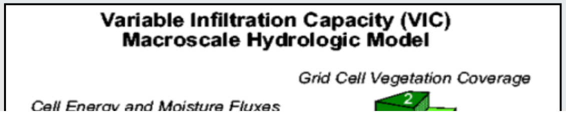
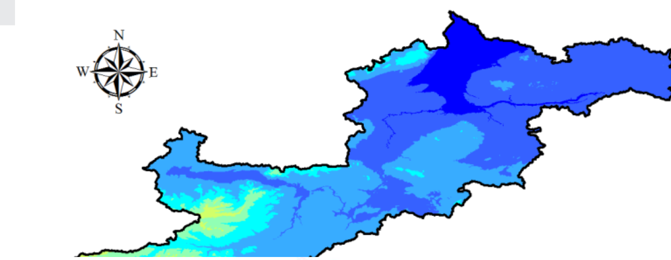
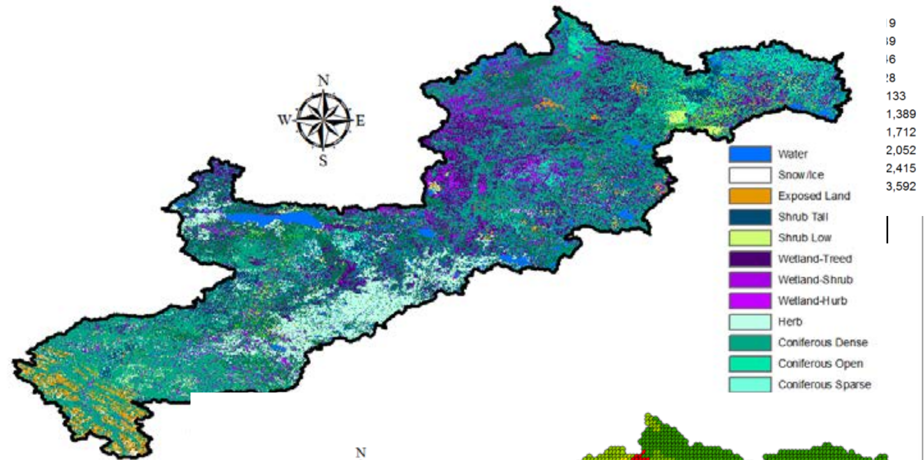
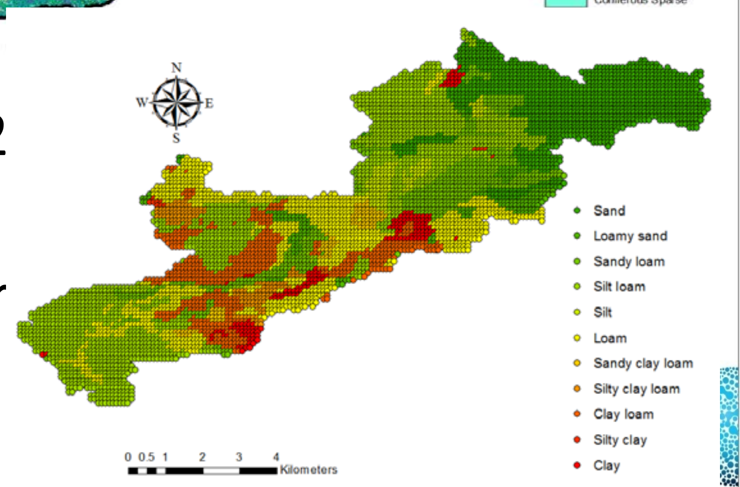
Hydrologic model

- **Variable Infiltration Capacity (VIC)**
  - 1/16 (~7km) spatial resolution
- **DEM**
  - Canadian Digital Elevation D
    - 3 arc second (≈ 90 m) spatial
- **Land cover**
  - 1 km resolution – circa 2000
    Sustainable Development, E
- **Monthly Leaf Area Index (LA**
  - Canada-wide 1-km 10-day SPOT 4 2
- **Soil parameters – 3 layers**
  - Soil Landscapes of Canada (SLC) ver





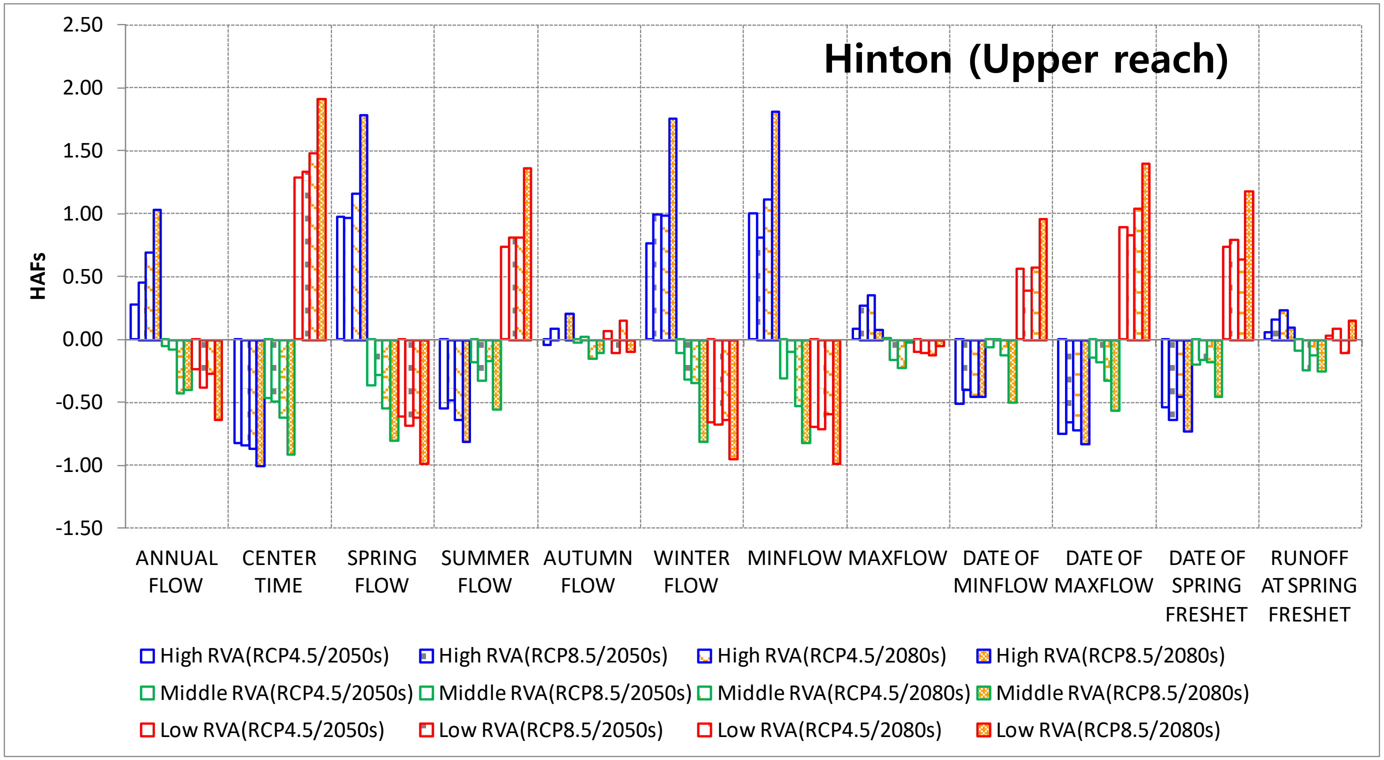




Hydrologic alteration factor (HAF)

➤ HAF

- (Projected frequency - Reference frequency) / Reference frequency



Optimal operating policies under the uncertainty in streamflow

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The value of updating ensemble streamflow prediction in reservoir operations

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Abstract:

This study proposes a new monthly ensemble streamflow prediction (ESP) forecasting system that can update the ESP in the middle of a month to reflect the meteorological and hydrological variations during that month. The reservoir operating policies derived from a sampling stochastic dynamic programming model using ESP scenarios updated three times a month were applied to the Geum River basin to measure the value of updated ESP for 21 years with 100 initial storage combinations. The results clearly demonstrate that updating the ESP scenario improves the accuracy of the forecasts and consequently their operational benefit. This study also proves that the accuracy of the ESP scenario, particularly when high flows occur, has a considerable effect on the reservoir operations.

KEY WORDS ensemble streamflow prediction; sampling stochastic dynamic programming; forecast accuracy; reservoir operations

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INTRODUCTION

Use of flow forecast information in reservoir operations is one of the most traditional topics in the area of water resources planning and management (Yeh *et al.*, 1982). Many studies have proposed how the flow forecast information and its uncertainty could be employed in optimization and simulation models for water resources systems (Klemes, 1977; Stedinger *et al.*, 1984; Georgakakos, 1989; Kim and Palmer, 1997; Yao and Georgakakos, 2001; Chiew *et al.*, 2003).

The flow forecast information given is deterministic, scenario-based or probabilistic. Deterministic forecast is a traditional choice because it is easy to obtain and utilize but does not include the forecast uncertainty. On the other hand, the probabilistic forecast can consider the forecast uncertainty (Stedinger *et al.*, 1984) but few probabilistic 'flow' forecasts are available in practice. Scenario-based forecasts may compensate for such weak points of the deterministic and probabilistic forecasts. However, using the observed or synthetic flow scenarios in water resources planning and management is not a research topic in meteorology and hydrology. A special issue of the *Journal of Hydrology* (Georgakakos and Krzysztofowicz, 2001) has documented new methods and experiences. At the National Centers for Environmental Prediction, ensemble approach has been applied operationally for short- and medium-range weather forecasting and for climate forecasting (Traction and Kalnay, 1993; Toth and Kalnay, 1993). Ensemble streamflow prediction (ESP) currently serves as a key component of the 21st Century Advanced Hydrologic Prediction Service for the National Weather Service (NWS) of the USA (Schaake *et al.*, 2004). More than 50 articles discussing ensemble forecasting were presented at the 2004 Spring Meeting and the 2005 Fall Meeting of the American Geophysical Union (Fortin *et al.*, 2004; Schaake *et al.*, 2004; Schaake and Bradley, 2005).

In spite of its popularity in operational hydrology, few applications have incorporated hydrological ensemble forecasts into water resources planning and management. Yao and Georgakakos (2001) have used monthly ensemble forecasts to assess the future climate change

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Optimal Drought Management Using Sampling Stochastic Dynamic Programming with a Hedging Rule

Hyung-Il Eum[1]; Young-Oh Kim, M.ASCE[2]; and Richard N. Palmer, M.ASCE[3]

Abstract: This study develops procedures that calculate optimal water release curtailments during droughts using a future value function derived with a sampling stochastic dynamic programming model. Triggers that switch between a normal operating policy and an emergency operating policy (EOP) are based on initial reservoir storage values representing a 95% water supply reliability and an aggregate drought index that employs 6-month cumulative rainfall and 4-month cumulative streamflow. To verify the effectiveness of the method, a cross-validation scheme (using 2,100 combination sets) is employed to simulate the Geum River basin system in Korea. The simulation results demonstrate that the EOP approach: (1) reduces the maximum water shortage; (2) is most valuable when the initial storages of the drawdown period are low; and (3) is superior to other approaches when explicitly considering forecast uncertainty.

DOI: 10.1061/(ASCE)WR.1943-5452.0000095

CE Database subject headings: Stochastic processes; Droughts; Reservoirs; Korea, South; Sampling.

Author keywords: Dynamic programming; Droughts; Reservoir operation; Korea.

Introduction

Reservoir operators must constantly decide what quantity of water to release and what to store. Decisions are complicated by the uncertainties associated with future flows and future demands. Procedures are required to provide appropriate assessments when objectives conflict (Loucks and Sigvaldason 1982). Highly accurate forecasts may be unnecessary during periods of normal flows but provide significant benefits when there is the potential for water shortages.

One method for mitigating the potential negative impacts during droughts is the use of curtailments. Curtailments entail providing less water than is demanded today, to prevent more significant shortfalls of water in the future. Curtailments are implemented with the help of hedging rules; rules that define the degree to which water demands will be met (Maass 1962). The effects of hedging rules have been investigated by many researchers. Klemes (1977) found that the operating policy converges to the standard operating policy (SOP) when hydrologic or economic uncertainty increases. However, Stedinger (1978) noted that Klemes (1977) had used inappropriate objective functions in his study. Hashimoto et al. (1982) showed that although the SOP is the optimal operating policy when the loss function is linear, hedging rules are more appropriate when the function is nonlinear. Previous studies have suggested that hedging rules can reduce the risk of large water shortages in a single period but can induce more frequent small water shortages (Moy et al. 1986). They therefore employed hedging with a multiobjective function that simultaneously considers reliability, resiliency, and vulnerability using mixed integer programming in a chance constrained program formulation. However, the results agreed with those of the previous studies: there is an inevitable trade-off between reliability and vulnerability.

Bayazit and Unal (1990) investigated the relationship between the above performance criteria using a two-point hedging rule to show the importance of the start and end points. Shih and ReVelle (1994, 1995) developed a multiphase hedging rule with a discrete curtailment ratio which corresponds to the available water calculated from the current storage and projected inflow. Those two-point and multiphase hedging rules have since been combined with state-of-the-art schemes such as genetic algorithms (Oliveira and Loucks 1997) and neural network algorithms (Neelakantan and Pundarikanthan 1999) or with economic theory (Draper and Lund 2004; Westphal et al. 2007) to obtain more efficient starting and ending points as well as a curtailment ratio. Tu et al. (2003) applied discrete hedging rules based on rule curves to multireservoir systems. They explored hedging rules with mixed-integer quadratic programming to address changes in the reservoir system.

A hedging rule can be developed simply by determining a rationing (or curtailment) ratio that defines the amount of the reduction in the current release. The previous studies typically

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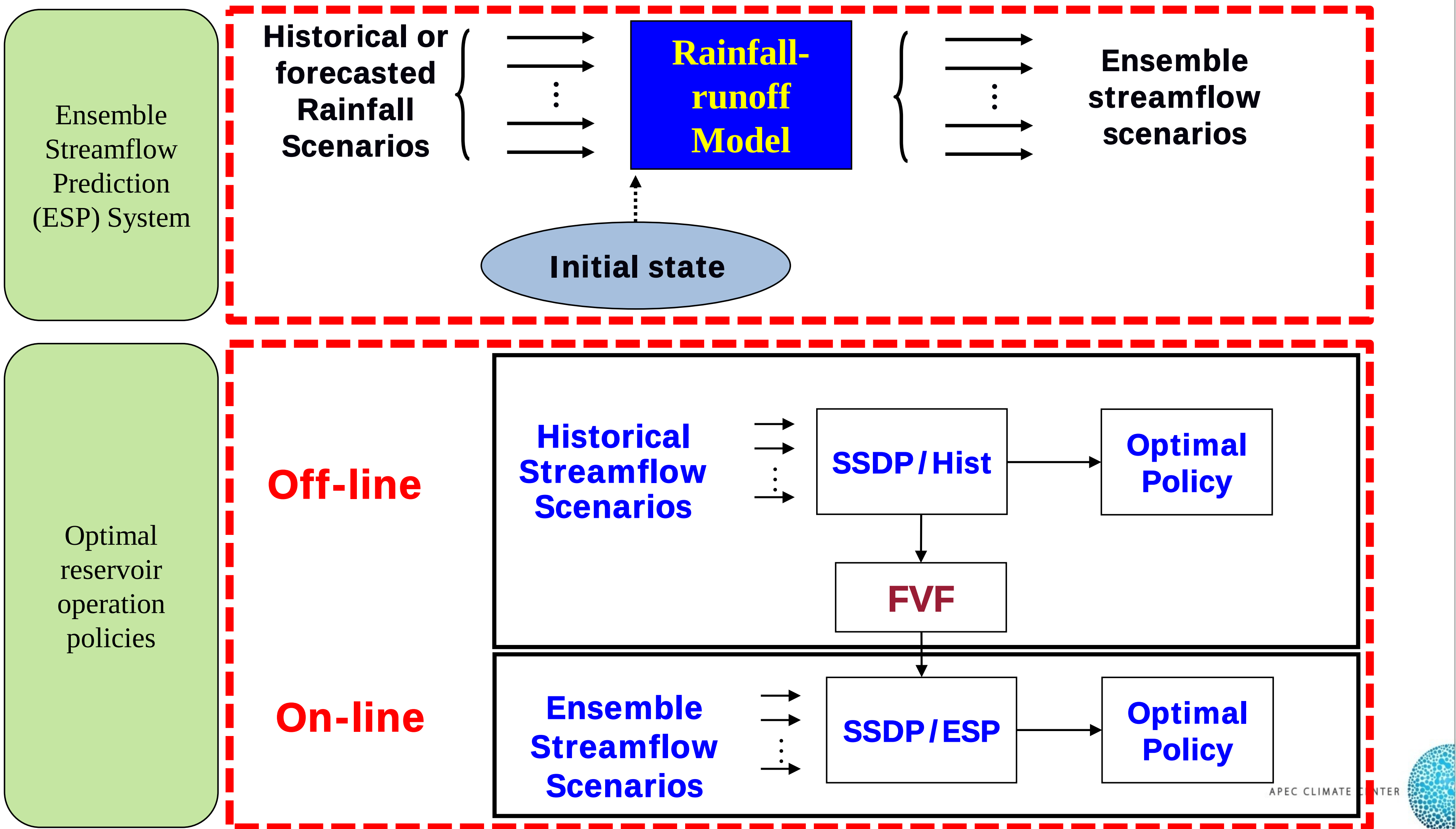
Model link

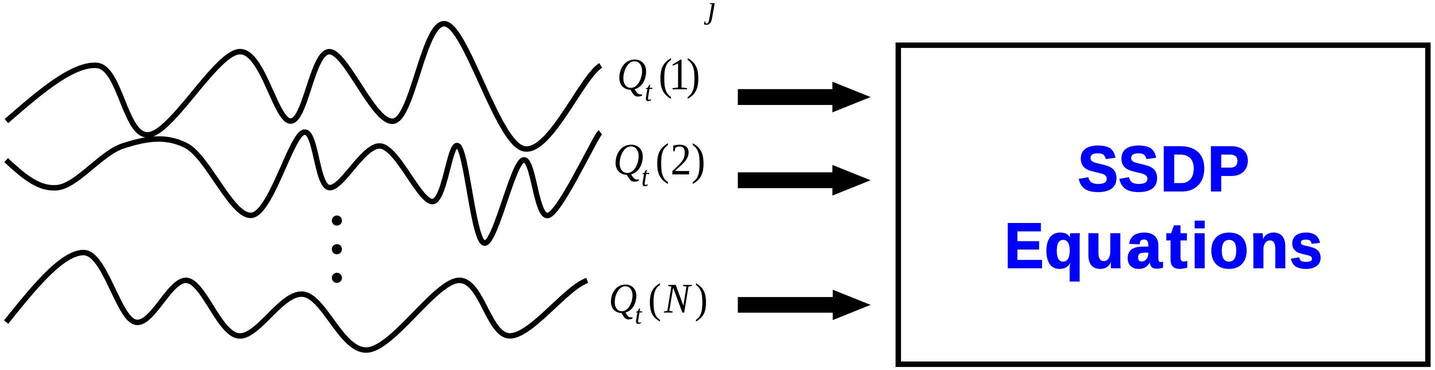

Ensemble Streamflow Prediction (ESP) System
Historical or forecasted Rainfall Scenarios
Rainfall-runoff Model
Ensemble streamflow scenarios
Initial state
Optimal reservoir operation policies
Off-line
Historical Streamflow Scenarios
SSDP/Hist
Optimal Policy
FVF
On-line
Ensemble Streamflow Scenarios
SSDP/ESP
Optimal Policy

Optimization model

- **SSDP**

$$\max_{\mathbf{R}_t^*} \sum_i \Pr(i \mid \mathbf{h}_t^l)\left[\overbrace{B_t(\mathbf{R}_t, \mathbf{Q}_t(i), \mathbf{s}_t^k)}^{\textit{Current}} + \overbrace{\sum_j \Pr(\mathbf{h}_{t+1}^j \mid \mathbf{h}_t^l, i) \cdot f_{t+1}(\mathbf{S}_{t+1}, \mathbf{h}_{t+1}^j, i)}^{\textit{Future}}\right]$$

$$f_t(\mathbf{s}_t^k, \mathbf{h}_t^l, i) = B_t(\mathbf{R}_t, \mathbf{Q}_t(i), \mathbf{s}_t^k) + \sum_j \Pr(\mathbf{h}_{t+1}^j \mid \mathbf{h}_t^l, i) \cdot f_{t+1}(\mathbf{S}_{t+1}, \mathbf{h}_{t+1}^j, i)$$



- **Combining SSDP with the hedging rule**

$$\min_{\alpha} \mathop{\mathrm{E}}_{j}\left[\frac{\partial B_t(\alpha R_t, j)}{\partial R_t} - \mathop{\mathrm{E}}_{i} \frac{\partial f_{t+1}(S_{t+1}, i)}{\partial S_{t+1}}\right]$$

Optimal rationing ratio

Three ESPs

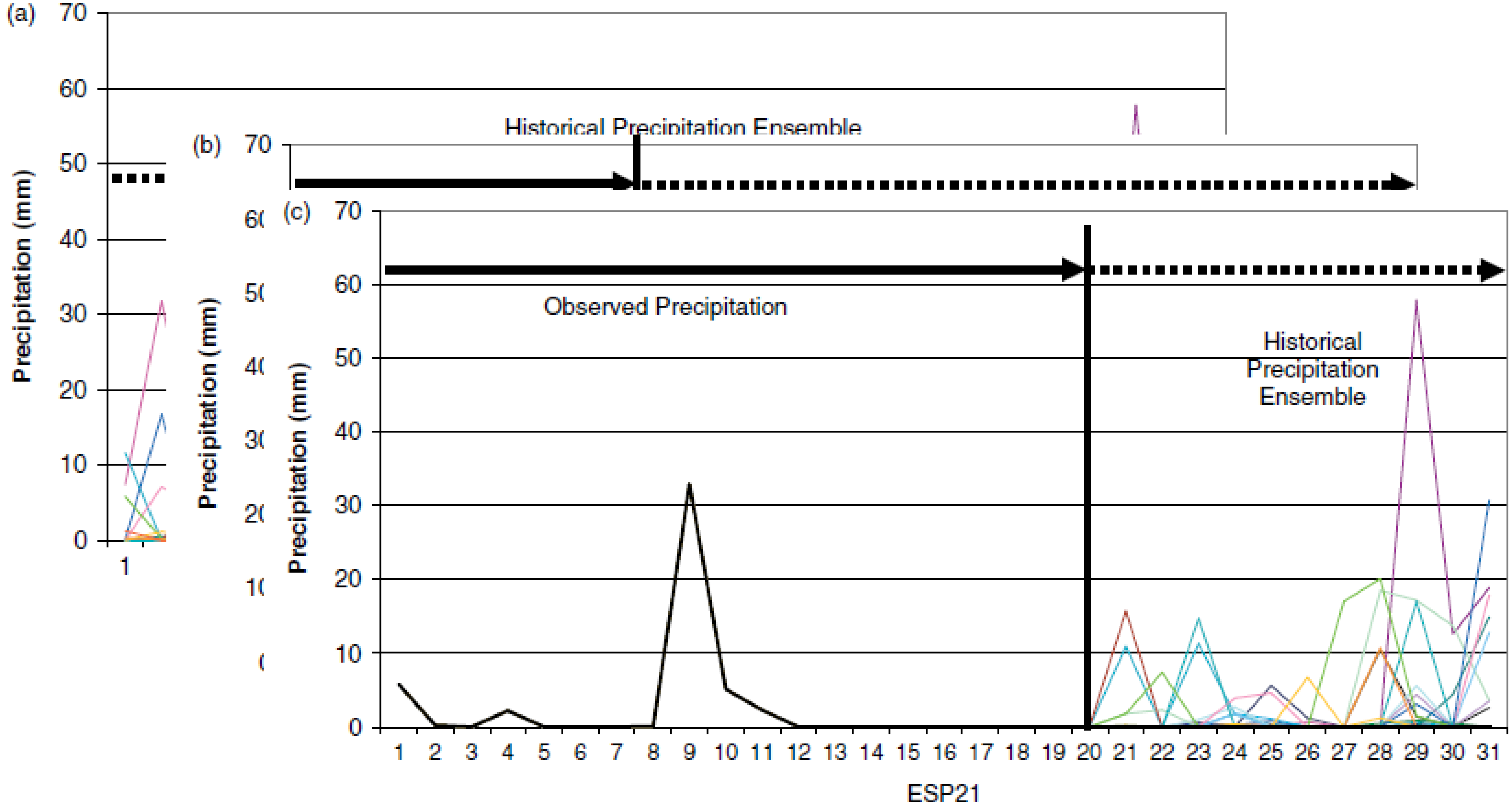


Figure 1. Modified ESP procedure (October 2001)

Impacts of ESP accuracy on reservoir operation

Table I. Accuracies of ESP01, ESP11 and ESP21 in RPS

Table II. Summary of 2100 simulation runs (yearly average)

Optimization models	Water shortage			Deviation from the ending target storage (10^6 m^3)	Energy production (GWh)
	Amount (10^6 m^3)	Achievement ratio[a]	Number of violations		
DDP/Perf	20·4	100·0	1·1	12·2	210·9
SSDP/ESP21	20·9	96·2	1·2	16·1	187·1
SSDP/ESP11	21·1	94·1	1·2	16·3	188·6
SSDP/ESP01	21·3	92·8	1·2	16·4	189·1
SSDP/Hist	21·9	88·2	1·2	16·7	192·6
DDP/Ave	33·4	0·0	1·8	39·3	201·9

[a] (A DP model − DDP/Ave)/(DDP/Perf − DDP/Ave) × 100.

Number of the well-forecasted months	125/189[a]	151/189	174/189

The number in parentheses represents improvement of the ESP forecast over ESP01 in RPS.
[a] 189 months = 21 scenarios × 9 months.

Reservoir operation results

Table IV. Runoff and forecasting accuracies in RPS for two representative years

Years		October	November	December	January	February	March	April	May	June	Average
87–88[a]	Runoff (m^3/s)	87·1	153·9	66·5	56·9	42·8	70·3	59·6	29·7	28·4	66·14
	RPS	0·259	0·086	0·405	0·339	0·627	0·258	0·339	0·361	0·467	0·349
94–95[b]	Runoff (m^3/s)	181·6	55·4	49·6	64·8	49·6	64·3	75·8	46·5	30·0	68·62
	RPS	1·355	0·364	0·297	0·276	0·330	0·327	0·379	0·407	0·544	0·475

[a] Well-forecasted year.
[b] Poorly forecasted year.

Table V. Simulation results of SSDP/ESP01 for two representative years

Years	Total runoff (m^3/s)	Water shortage		Deviation from the ending target storage (10^6 m^3/year)	Hydro-power (GWh/year)
		Total amount (10^6 m^3/year)	Number of violations		
1987–1988	595·22	57·57	2·45	0·59	152·30
1994–1995	617·55	71·99	3·10	72·97	148·91

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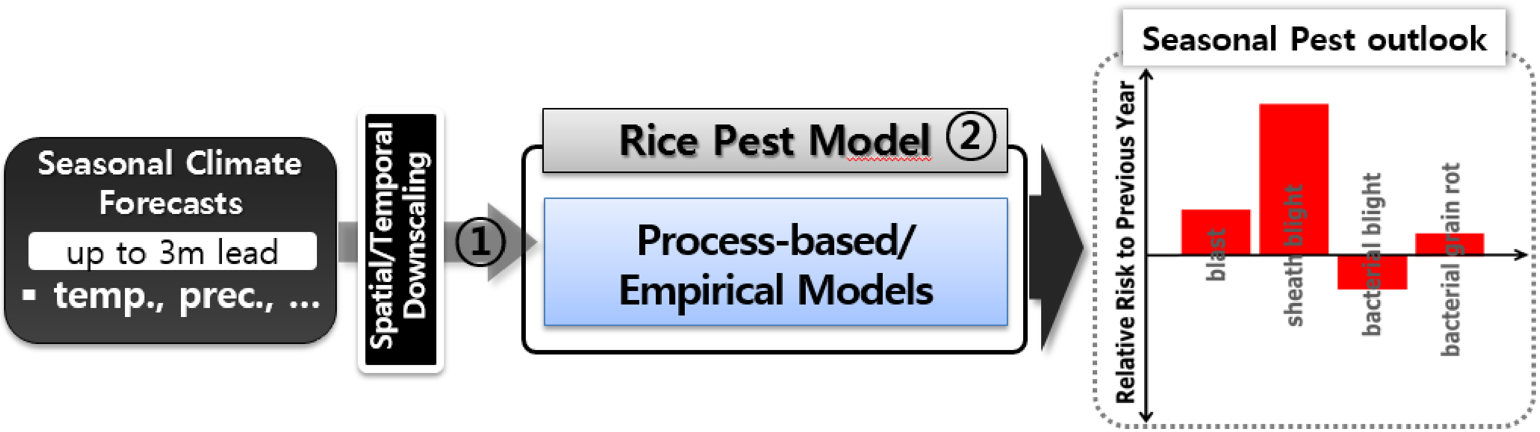
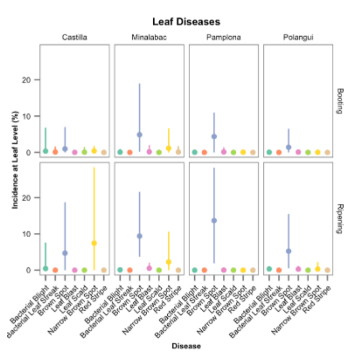
Regional applications with seasonal forecasts

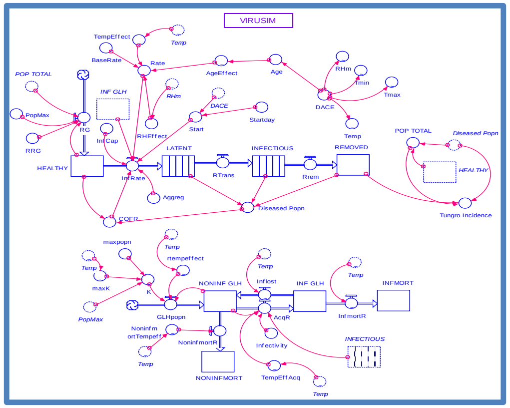
APEC Climate Center (APCC)

Bicol Rice Disease (BiRD) Project -Dr. KH Kim

- **Application of rice disease models for seasonal rice pest outlook in the Bicol region**





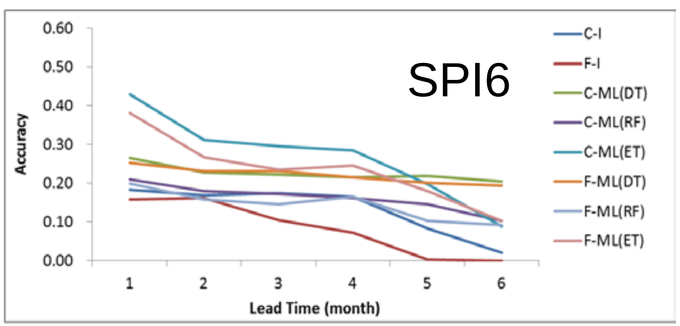


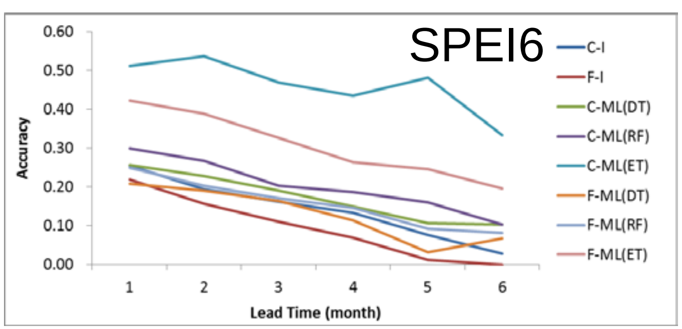
APN Project "Toward a Fire and Haze Early Warning System for Southeast Asia"- Dr. JP Cho

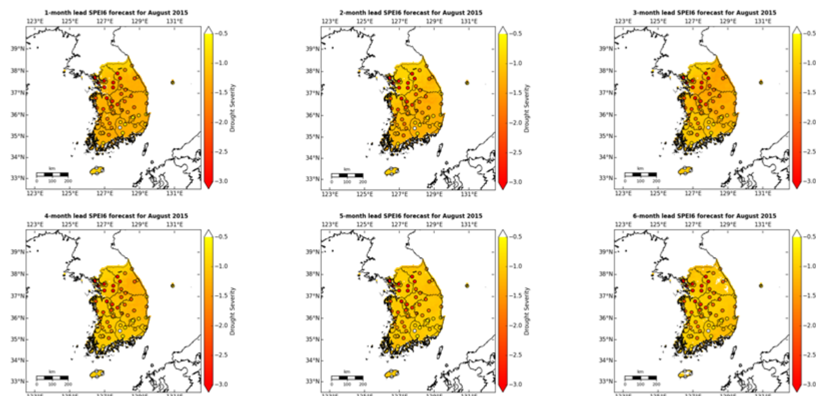
- Multi-National Projects with Indonesia, Malaysia, Korea, Singapore, Japan, USA
- Fire and haze early warning system for the region in Indonesia, Malaysia and Singapore by using seasonal forecasts to predict the drought conditions that trigger forest fires

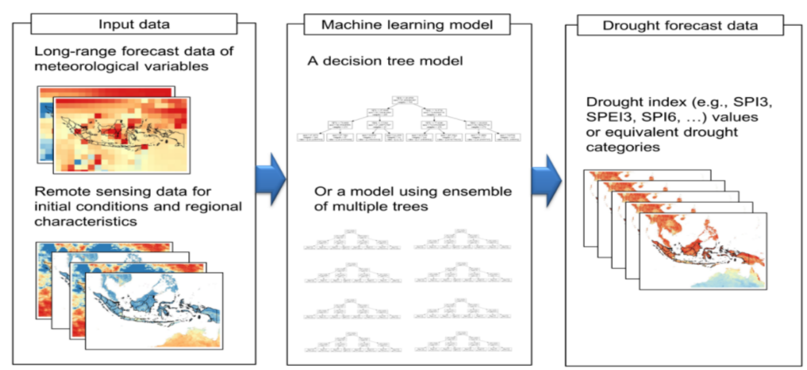
Drought index forecasting (Dr. JY Lee)

- **Drought forecasting driven by remote sensing and long-range forecast data for ungauged areas using machine learning algorithms**
  - SPI & SPEI



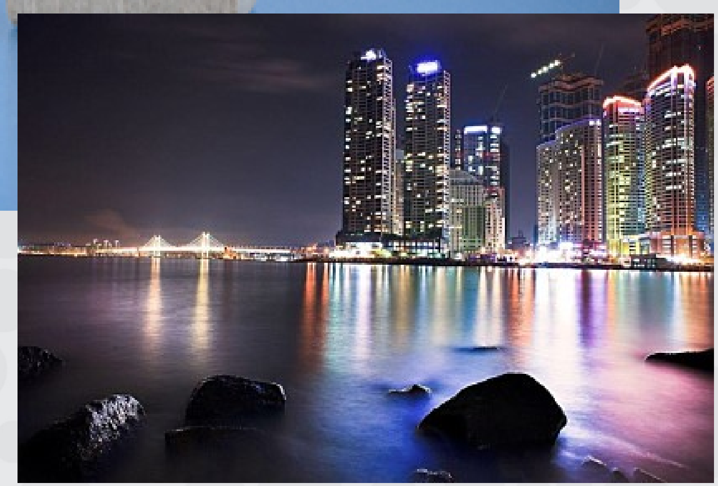






Summary

- **Seasonal forecasting**
  - Constructed Analogs
- **Water resources management under climate change**
  - Flooding map
  - Hydrologic projections in Alberta, Canada
- **Applications of seasonal forecastings**
  - Reservoir operations
  - Agricultural project – Rice pest model
  - Fire early warning system
  - Drought forecasting



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