Integrated Regional Environment/Climate Prediction System: Coupled Modeling, Parameter Estimation, and Data Assimilation

Seon Ki Park
Ewha Womans University
Seoul, Korea

Aug. 23, 2018
Lecture at The Griffith University (GCCRP)

1. **Atmospheric Sciences at Ewha Womans University**
2. Numerical Weather/Climate/Environment (W/C/E) Prediction --- Overview
3. Sensitivity Studies (LSMs on Heat Waves)
4. Subgrid-scale Parameterizations (LSM)
5. Optimal Parameter Estimation (GA)
6. Coupled Data Assimilation
7. Projection of Local Climate Change (RCM+LSM)
8. RECIPE --- Regional Environment/Climate Prediction System

Atmospheric Sciences at EWU

- **Education:**
  - Dept. of Earth Science Education
  - Dept. of Environmental Sci. & Eng.
  - Dept. of Atmospheric Sci. & Eng. (2012. 09 – 2017. 02)
  - Dept. of Climate & Energy Systems Eng. (2017. 03)

Atmospheric Sciences at EWU

- **Research:**
  - Severe Storm Research Center (SSRC)
    - Established at March 2007
  - Center for Climate/Environment Prediction Research (CCCPR)
    - Established at September 2009 funded by NRF through the Engineering Res. Center Program (up to Feb. 2016; ~1M USD/year)
    - Additional fund by NRF through the Basic Science Research Program (from June 2018; ~0.5M USD/year)

Severe Storm Research Center SSRC

CCCPR Center for Climate/Environment Change Prediction Research

1. Atmospheric Sciences at Ewha Womans University
2. **Numerical Weather/Climate/Environment (W/C/E) Prediction --- Overview**
3. Sensitivity Studies (LSMs on Heat Waves)
4. Subgrid-scale Parameterizations (LSM)
5. Optimal Parameter Estimation (GA)
6. Coupled Data Assimilation
7. Projection of Local Climate Change (RCM+LSM)
8. RECIPE --- Regional Environment/Climate Prediction System

Numerical W/C/E Prediction

In-situ vs.
Remote sensing

- **Numerical W/C/E Prediction:**
  - Given environmental observations at any instant time (initial conditions), the evolution of environmental parameters in the future is forecasted by running (integrating in time) numerical computer models of the W/C/E.

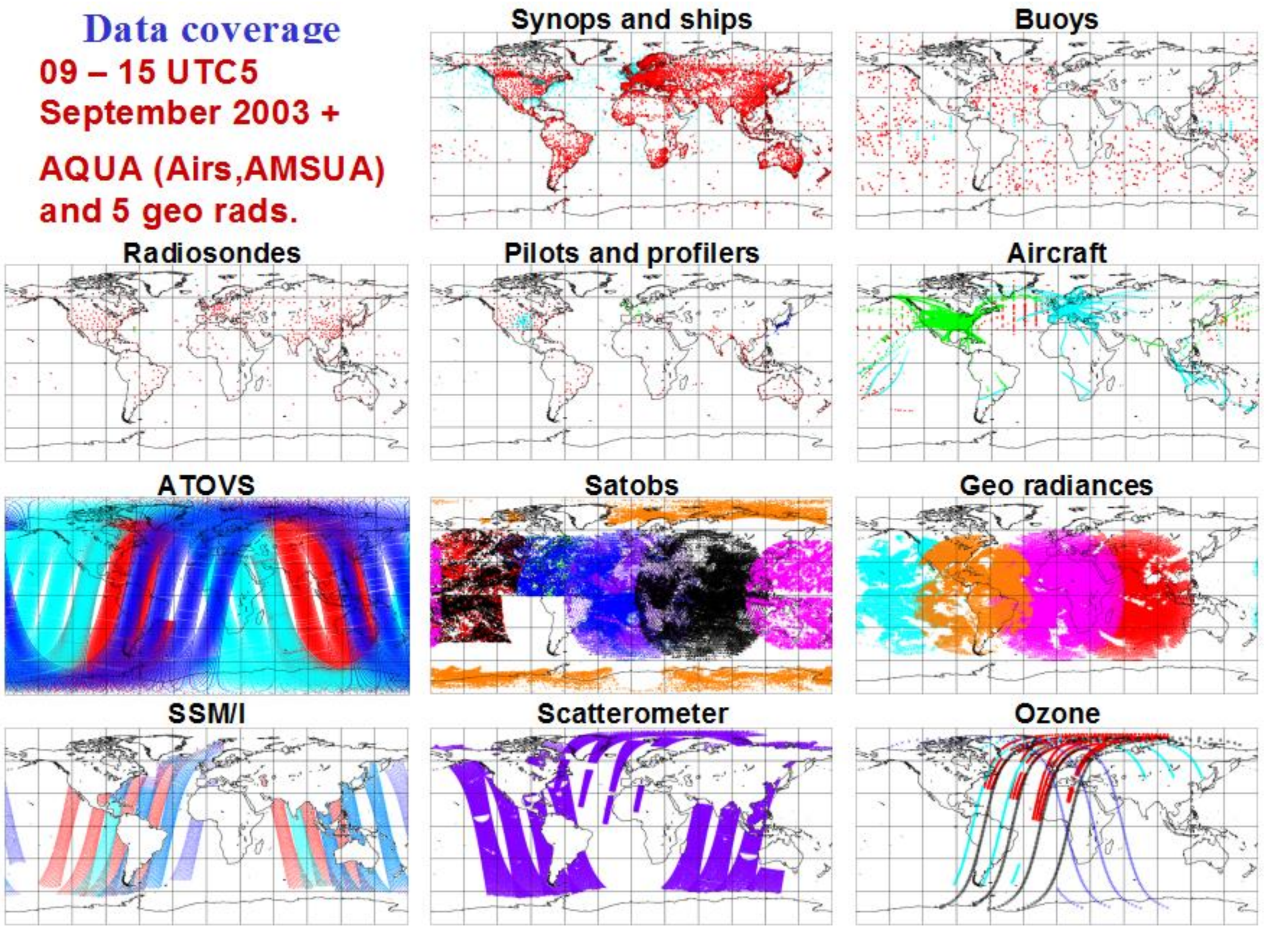
Data Assimilation

Numerical stability
High-performance computers

Governing equations
Numerical methods
Parameterizations
Computational domain
Boundary conditions

Numerical W/C/E Prediction

- **Observations**
  - Monitoring
  - Analysis
  - Model Inputs
  - Verification



Numerical W/C/E Prediction

- **Data Assimilation**

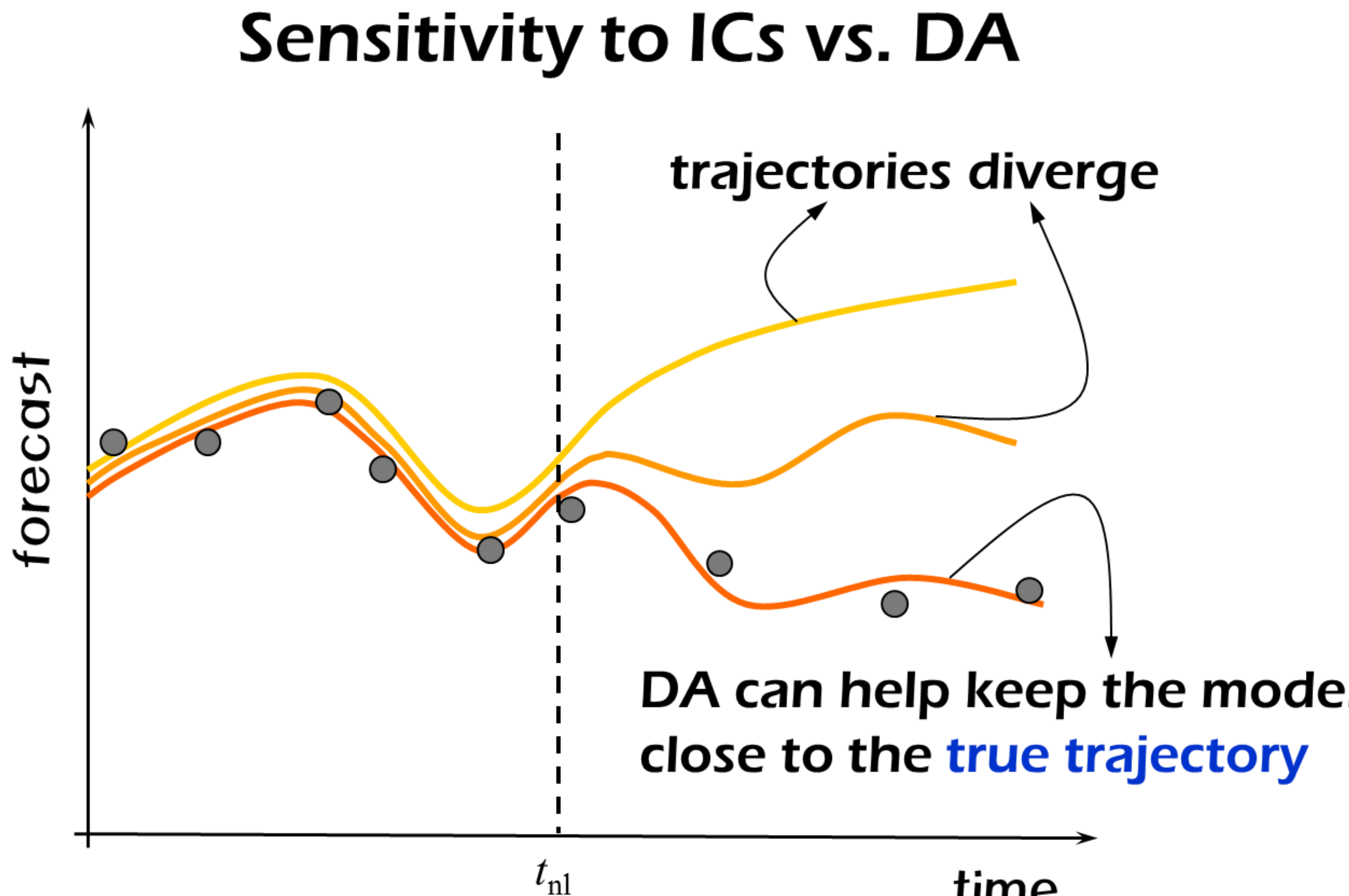
Basic Formulation:

$$\mathbf{x}^{a} = \mathbf{x}^{b} + \mathbf{W}\left[\mathbf{y}^{o} - \mathbf{H}\left(\mathbf{x}^{b}\right)\right]$$

- $\mathbf{x}^a$: analysis
- $\mathbf{x}^b$: background field (6-h forecast)
- $\mathbf{y}^o$: observation
- $\mathbf{H}(\mathbf{x}^b)$: observation operator
- $\mathbf{y}^o - \mathbf{H}(\mathbf{x}^b)$: observational increments or innovations

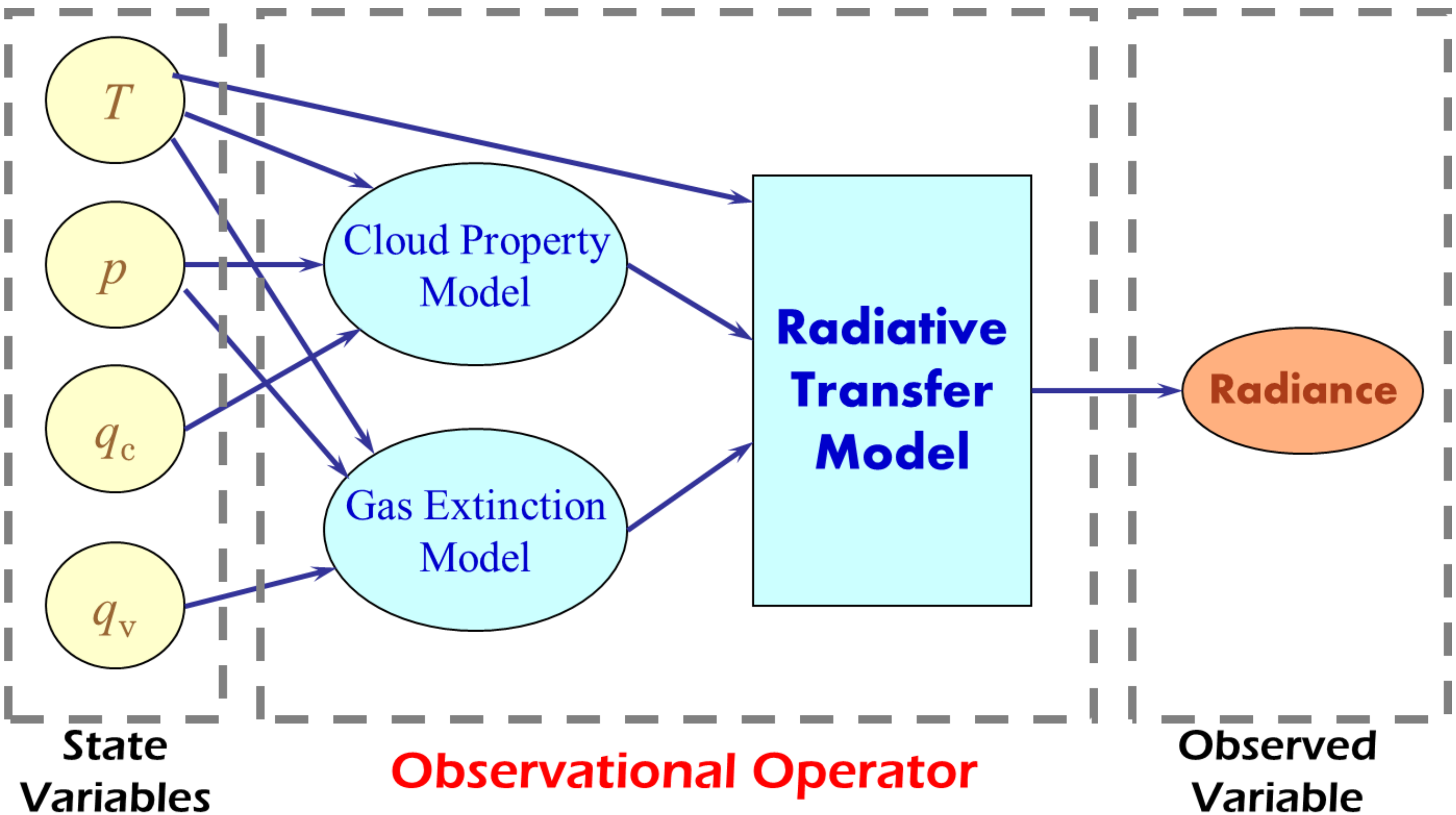
The analysis x^a is obtained by adding the innovations to the model forecast (first guess) with weights W that are determined based on the estimated statistical error covariances of the forecast and the observations.

Numerical W/C/E Prediction



Numerical W/C/E Prediction

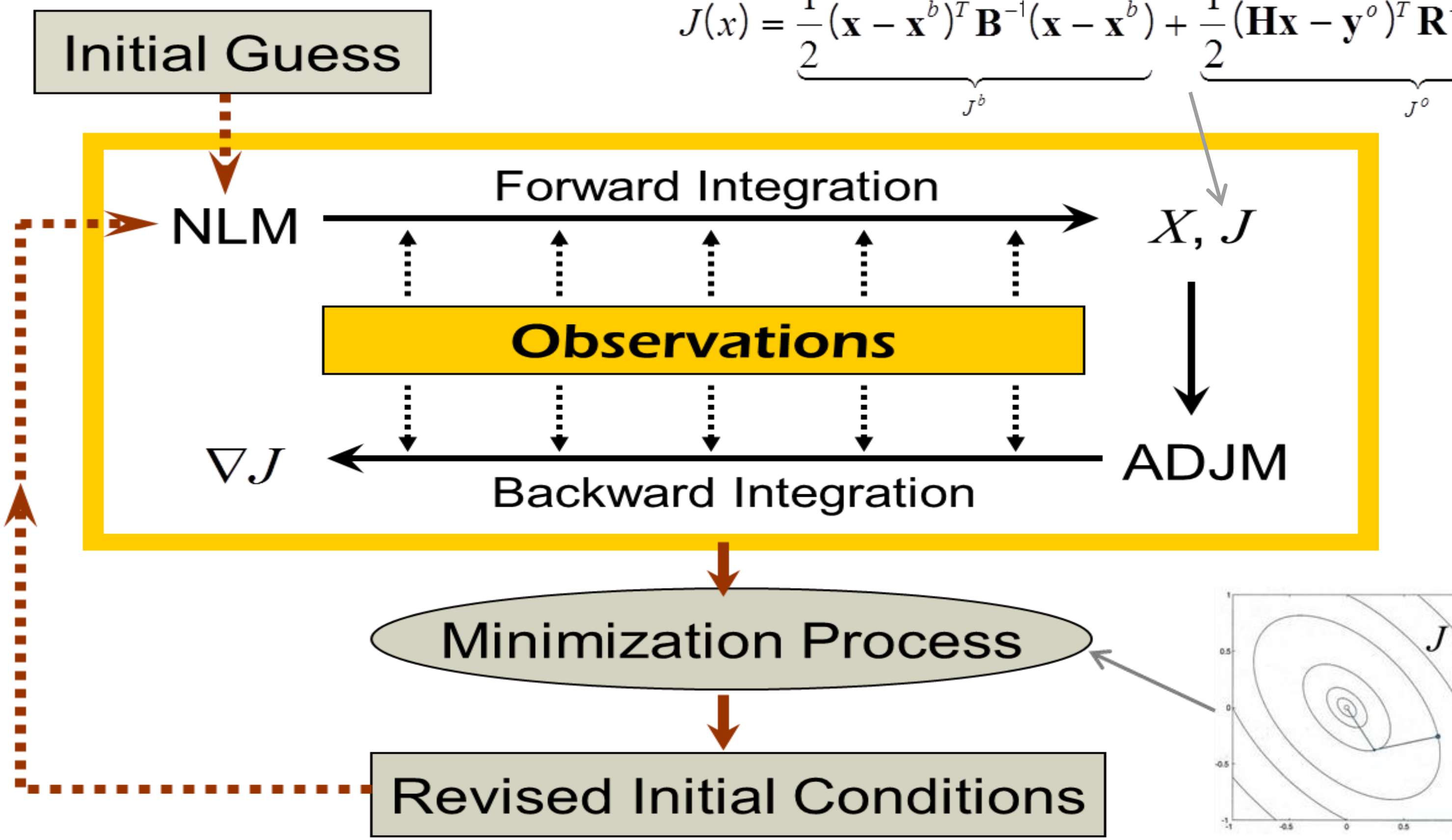
- Data Assimilation (Observation Operator)



Numerical W/C/E Prediction

- **Data Assimilation (4D-Var)**

$$J(x) = \underbrace{\frac{1}{2}(\mathbf{x}-\mathbf{x}^b)^T\mathbf{B}^{-1}(\mathbf{x}-\mathbf{x}^b)}_{J^b} + \underbrace{\frac{1}{2}(\mathbf{Hx}-\mathbf{y}^o)^T\mathbf{R}^{-1}(\mathbf{Hx}-\mathbf{y}^o)}_{J^o}$$



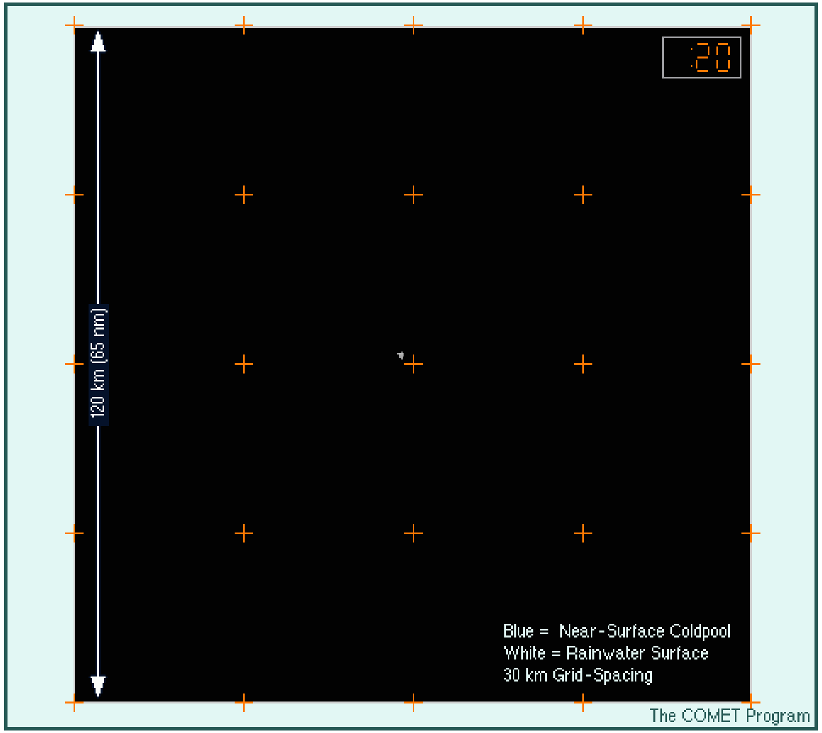
Numerical W/C/E Prediction

- Subgrid-scale Parameterization
  - The approximation of unresolved processes in terms of resolved variables is referred to as parameterization.
  - Parameterizations approximate the bulk effects of physical processes too small, too brief, too complex, or too poorly understood to be explicitly represented.

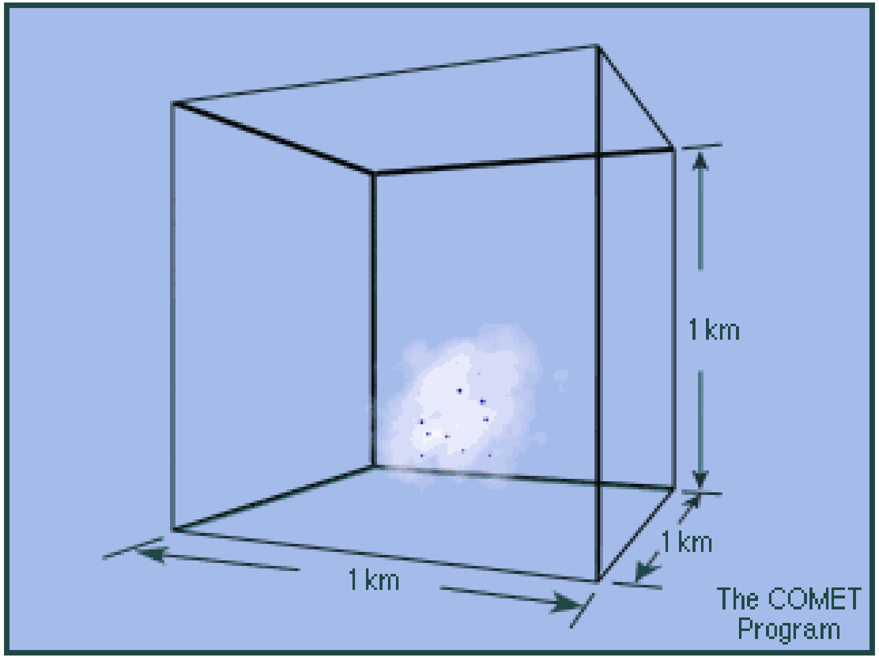
Numerical W/C/E Prediction

- **Subgrid-scale Parameterization**

Convective Processes



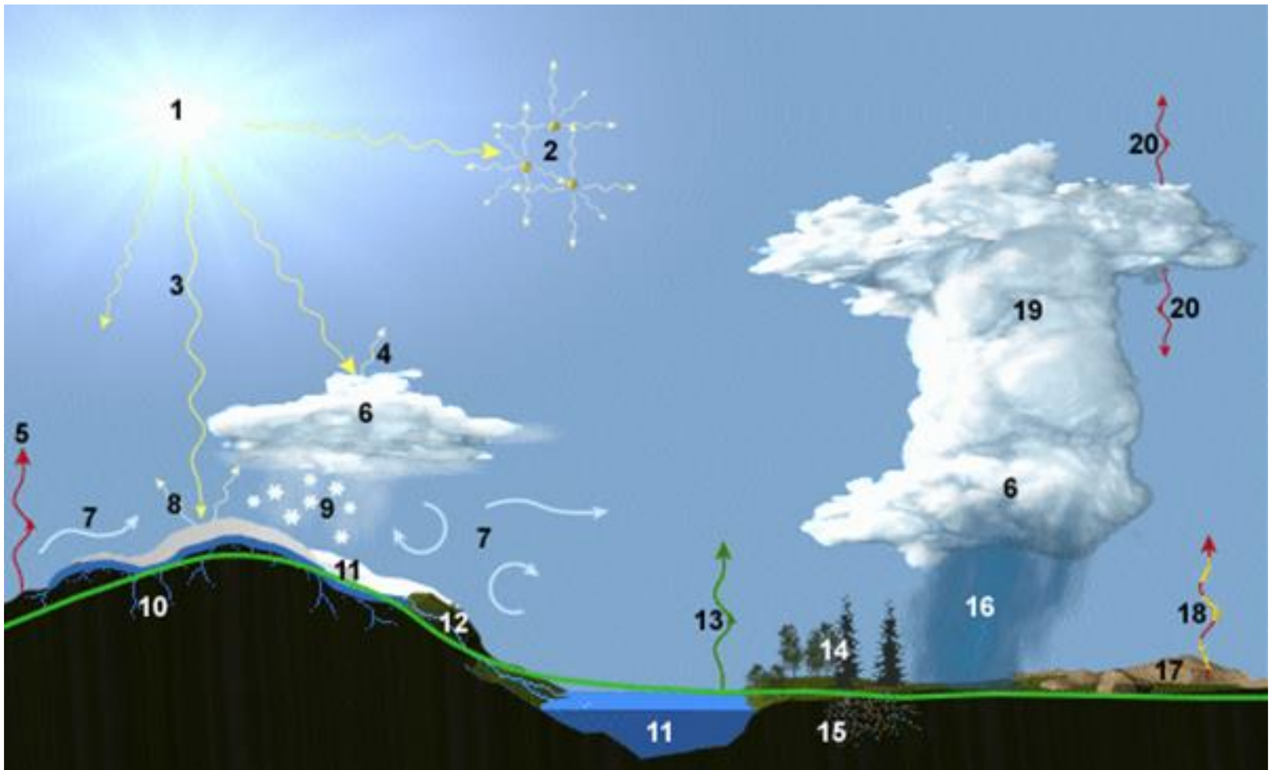
Mycrophysical Processes



(COMET/UCAR)

Numerical W/C/E Prediction

- Subgrid-scale Parameterization

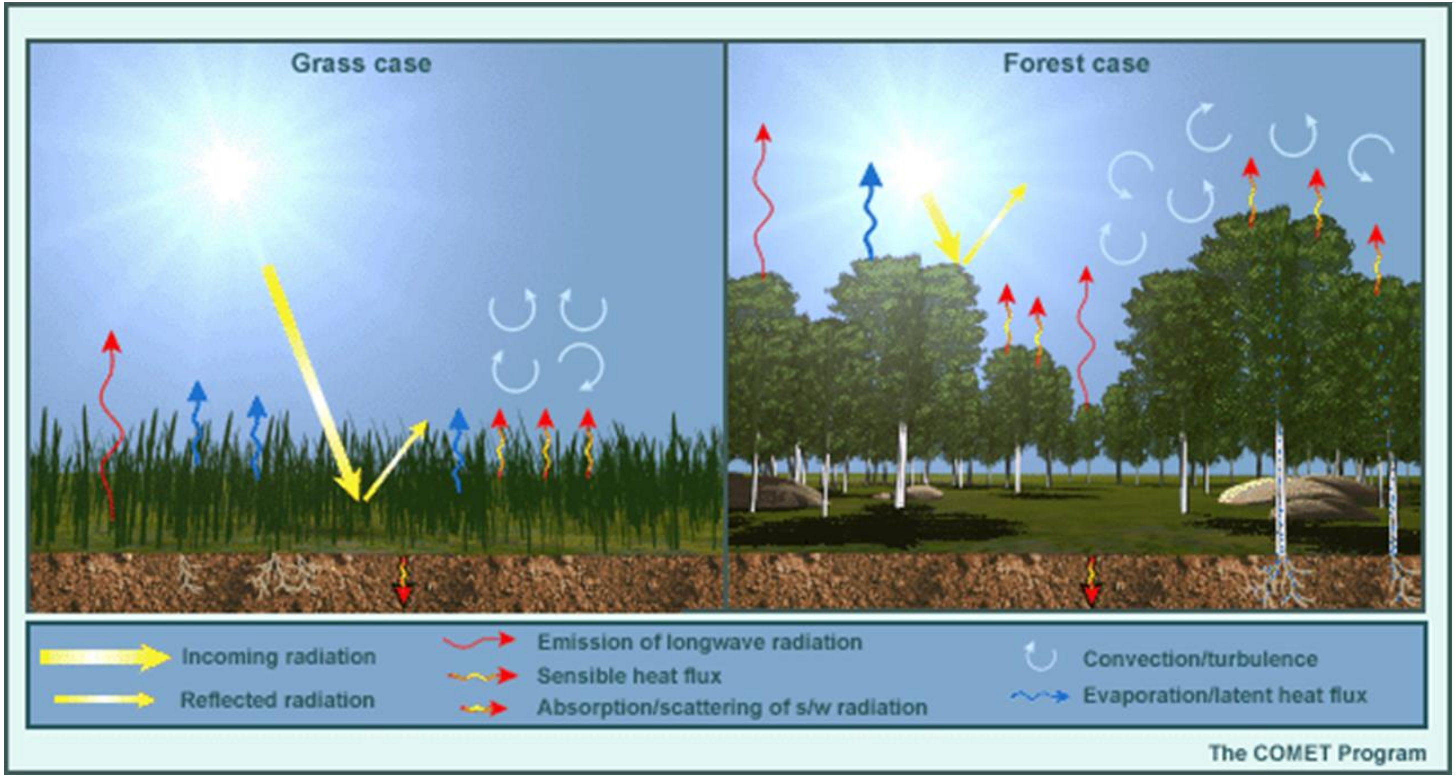


1) Incoming Solar Radiation
2) Scattering by Aerosols and Molecules
3) Absorption by the Atmosphere
4) Reflection/Absorption by Clouds
5) Emission of Longwave Radiation from Earth's Surface
6) Condensation
7) Turbulence
8) Reflection/Absorption at Earth's Surface
9) Snow
10) Soil Water/Snow Melt
11) Snow/Ice/Water Cover
12) Topography
13) Evaporation
14) Vegetation
15) Soil Properties
16) Rain (Cooling)
17) Surface Roughness
18) Sensible Heat Flux
19) Deep Convection (Warming)
20) Emission of Longwave Radiation from Clouds

(COMET/UCAR)

Numerical W/C/E Prediction

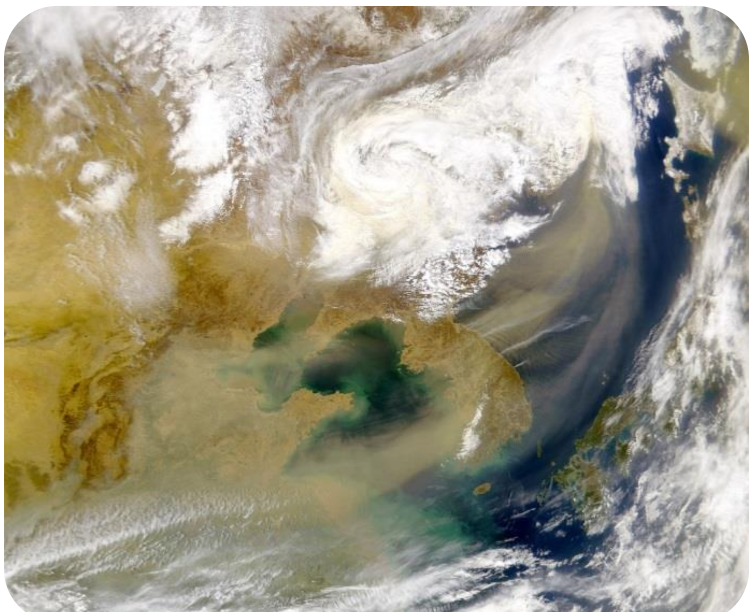
- **Subgrid-scale Parameterization**
  - Vegetation Type



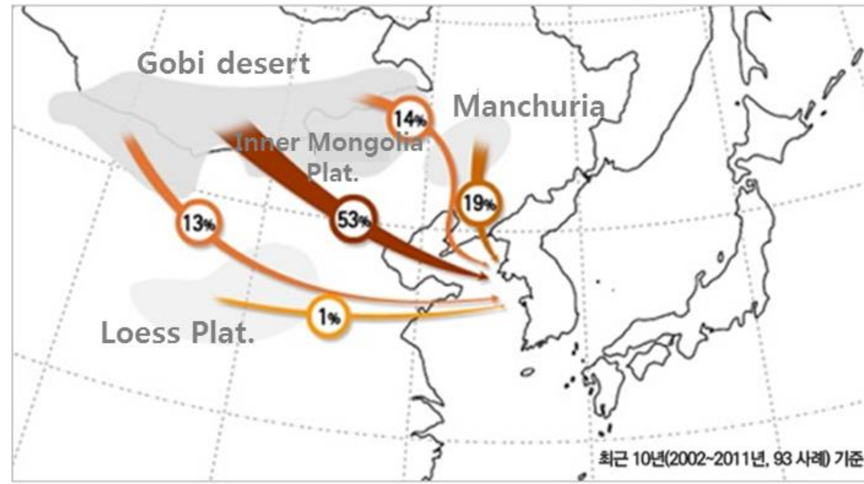
(COMET/UCAR)

Numerical W/C/E Prediction

- **Problem: Atmospheric Environment**
  - Asian dust storms (ADS)



Source and route of Asian dust affected Korea



Asian dust storm (ADS) takes dust particles from arid regions (Mongolia and northern China) and transports them to downstream regions, including Korea and Japan.

Numerical W/C/E Prediction

- **Problem: Atmospheric Environment**
  - Atmospheric gases/aerosols (Air Quality)

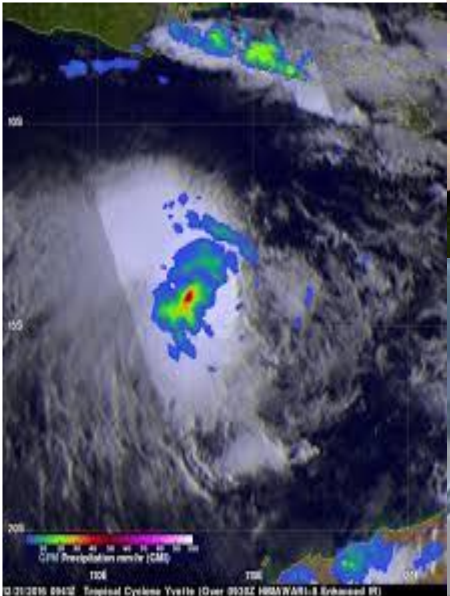
Atmospheric gases and aerosols have complex interactions that are impacted by natural and human sources.

Trace gases and aerosols interact with climate and weather by their direct impact on radiation, and by indirect impacts on clouds.

- ***Implications on air quality and long-range pollution transport***
- ***Need to develop a system for prediction of transboundary air-pollution at regional scales***

Numerical W/C/E Prediction

- **Problem: Extreme Weather/Climate**
  - Heavy/Excessive Rainfall → QPF

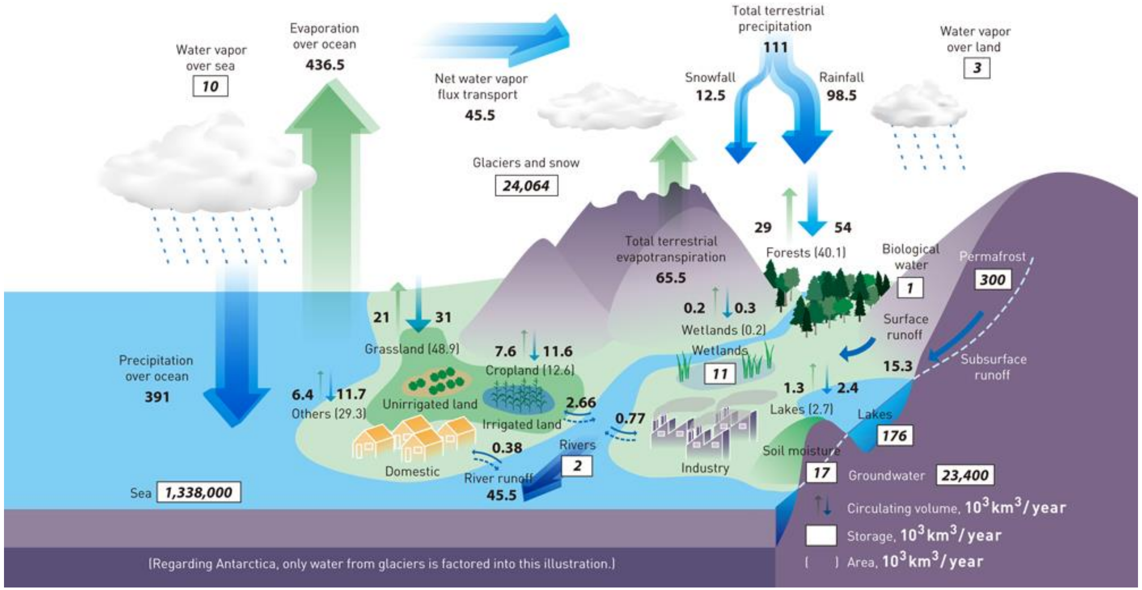


- ➢ **Extreme weather/climate events are increasing in a changing climate.**
- ➢ **Quantitative precipitation forecasting (QPF) becomes more important.**

Youtube.com; watchers.new.com, phys.org

Numerical W/C/E Prediction

- **Problem: Local Climate Change Aspects**
  - **Energy/Water Cycles in the Future Climate Conditions**



(Oki and Kanae, 2006; Science)

- **Climate change affects local energy and water cycles.**
- **They are crucial to policy making and water resource management.**

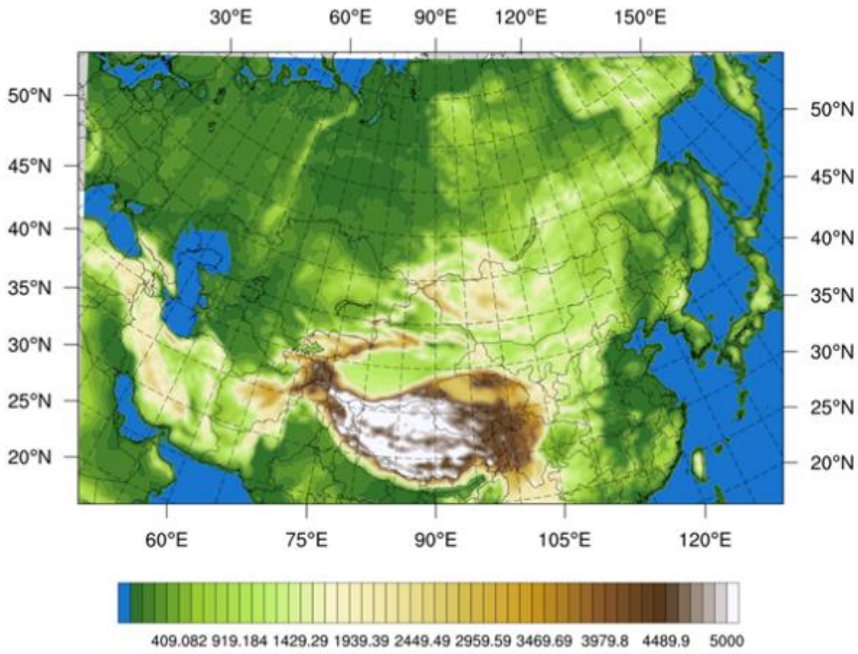
Numerical W/C/E Prediction

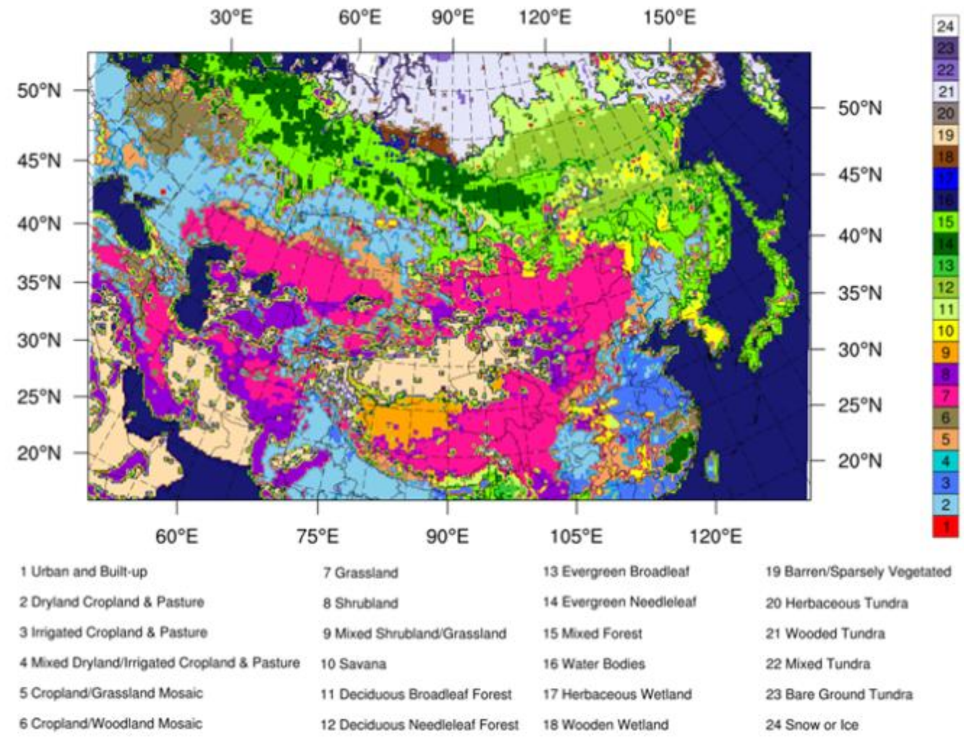
- **Prediction accuracy can be improved by reducing uncertainties in**
  - Numerical schemes
    - Higher-order FDEs/spectral models, etc.
  - Initial conditions
    - Advanced data assimilation
  - Parameterization of subgrid-scale processes
    - Choice of proper parameterization scheme (sensitivity studies)
    - Better parametrization
    - Parameter estimation or optimization
  - Coupled models/schemes (LSM, Chem module, etc.)
    - Choice of proper schemes (sensitivity studies)

1. Atmospheric Sciences at Ewha Womans University
2. Numerical Weather/Climate/Environment (W/C/E) Prediction --- Overview
3. **Sensitivity Studies (LSMs on Heat Waves)**
4. Subgrid-scale Parameterizations (LSM)
5. Optimal Parameter Estimation (GA)
6. Coupled Data Assimilation
7. Projection of Local Climate Change (RCM+LSM)
8. RECIPE --- Regional Environment/Climate Prediction System

Sensitivity Studies

- **Sensitivity of Eurasian Snow on LSMs**
  - 1 June 2009 to 31 August 2010





Sensitivity Studies

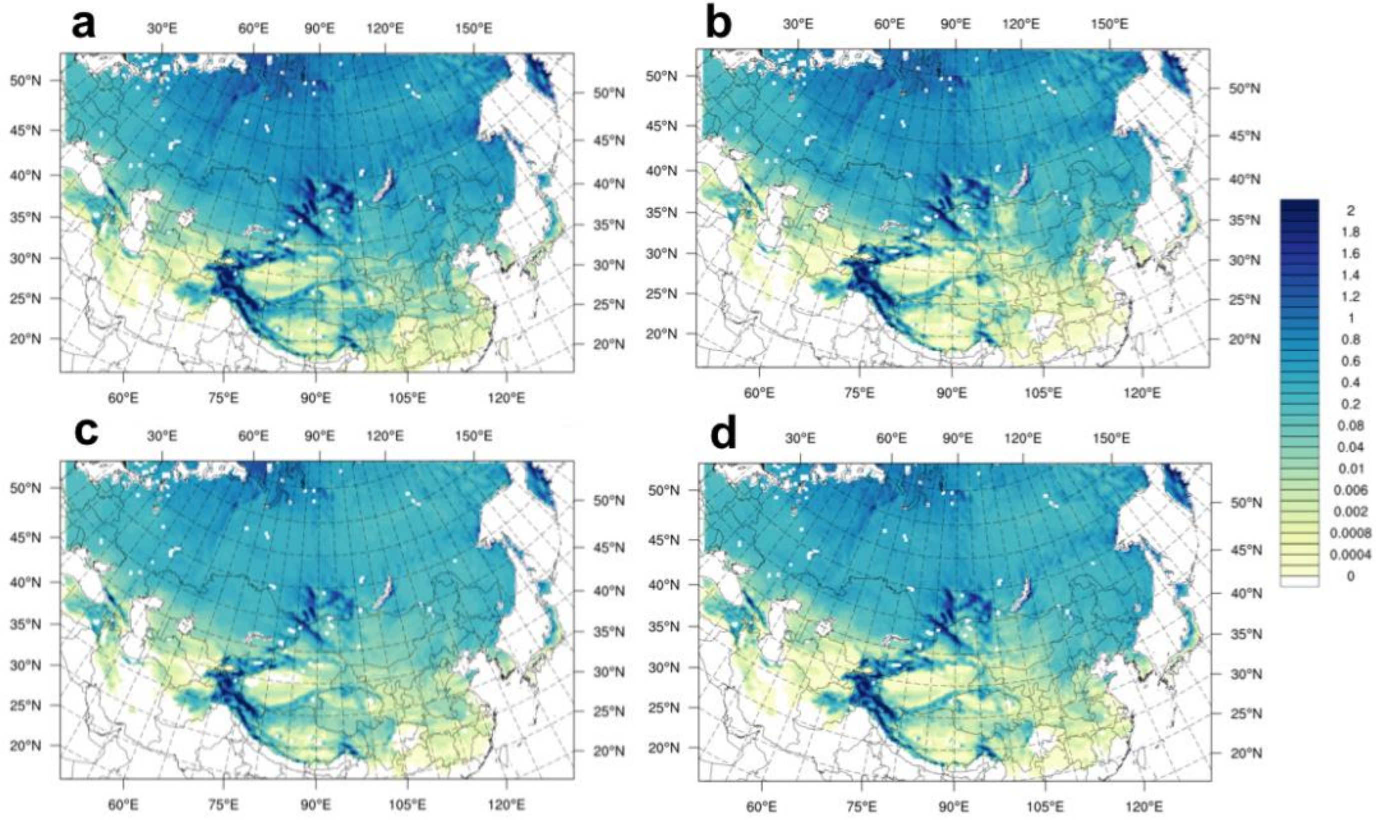
- **Sensitivity of Eurasian Snow on LSMs**
  - 1 June 2009 to 31 August 2010

WRF Version 3.6.1 Configuration	
Simulation period	1 June 2009 - 31 August 2010
Dynamic core	ARW
Horizontal resolution	30 km
Vertical levels	30 (model top at 50 hPa)
PBL/turbulence parameter	YSU
Microphysical parameter	WSM3
Radiation (Shortwave)	Dudhia
Radiation (Longwave)	RRTM
Convective parameter	Kain-Fritsch (new Eta) scheme
Land Surface Models (LSMs)	Unified Noah LSM
	Noah-MP
	RUC LSM
	Community Land Model version 4 (CLM4)

Sensitivity Studies

- **Sensitivity of Eurasian Snow on LSMs**
  - Dec. 2009 to May 2010 (Snow Depth (m))

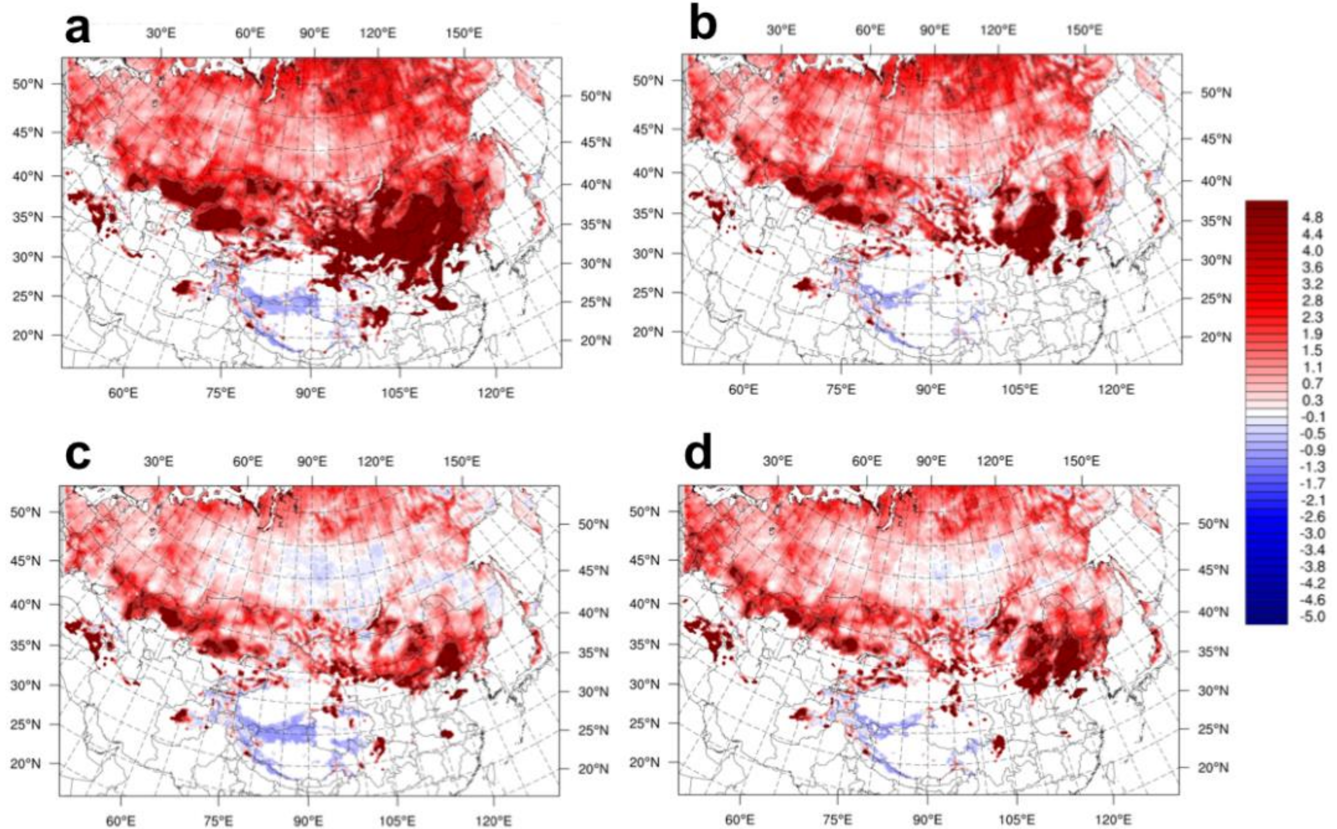
(a) Noah LSM
(b) RUC LSM
(c) Noah-MP
(d) CLM4



Sensitivity Studies

- **Sensitivity of Eurasian Snow on LSMs**
  - Dec. 2009 to May 2010 (Snow Depth Bias (m))

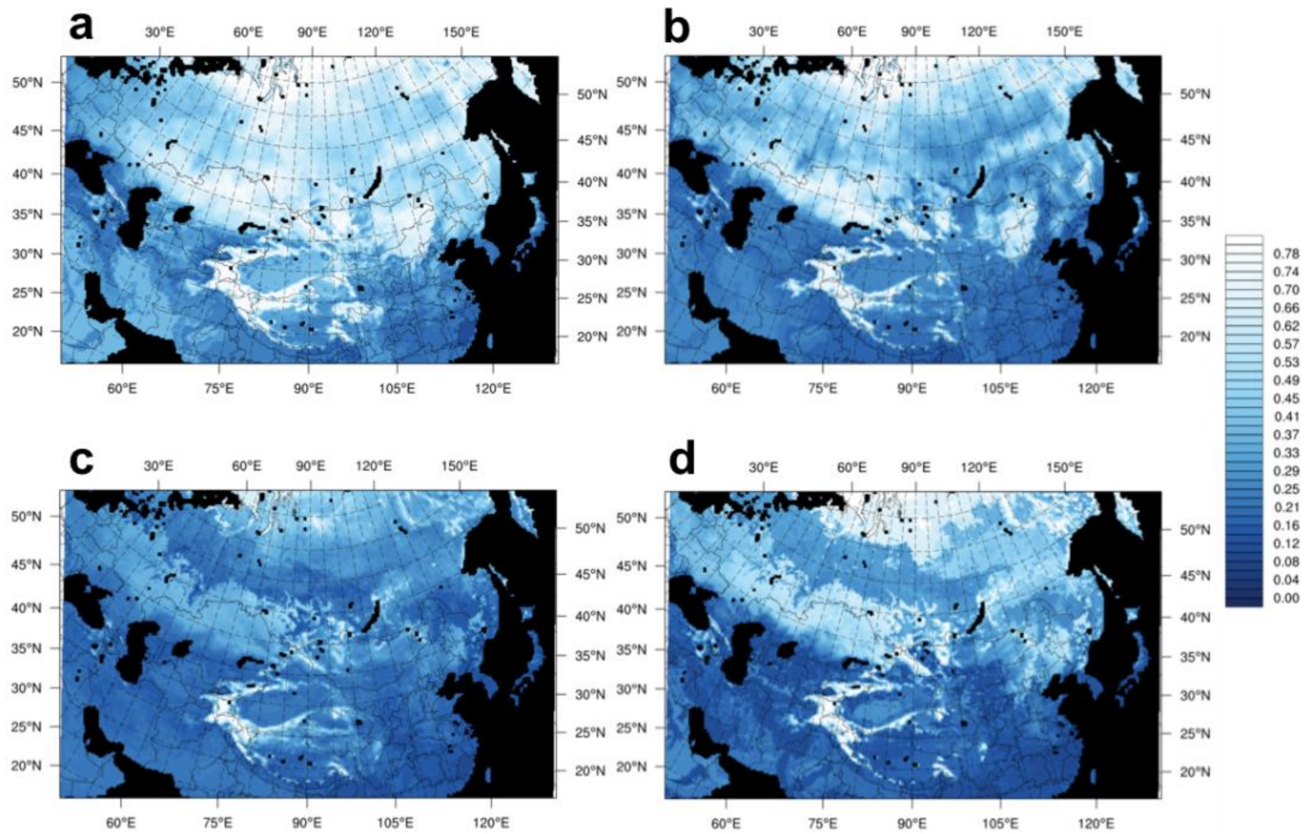
(a) Noah LSM
(b) RUC LSM
(c) Noah-MP
(d) CLM4



Sensitivity Studies

- **Sensitivity of Eurasian Snow on LSMs**
  - Dec. 2009 to May 2010 (Snow Albedo)

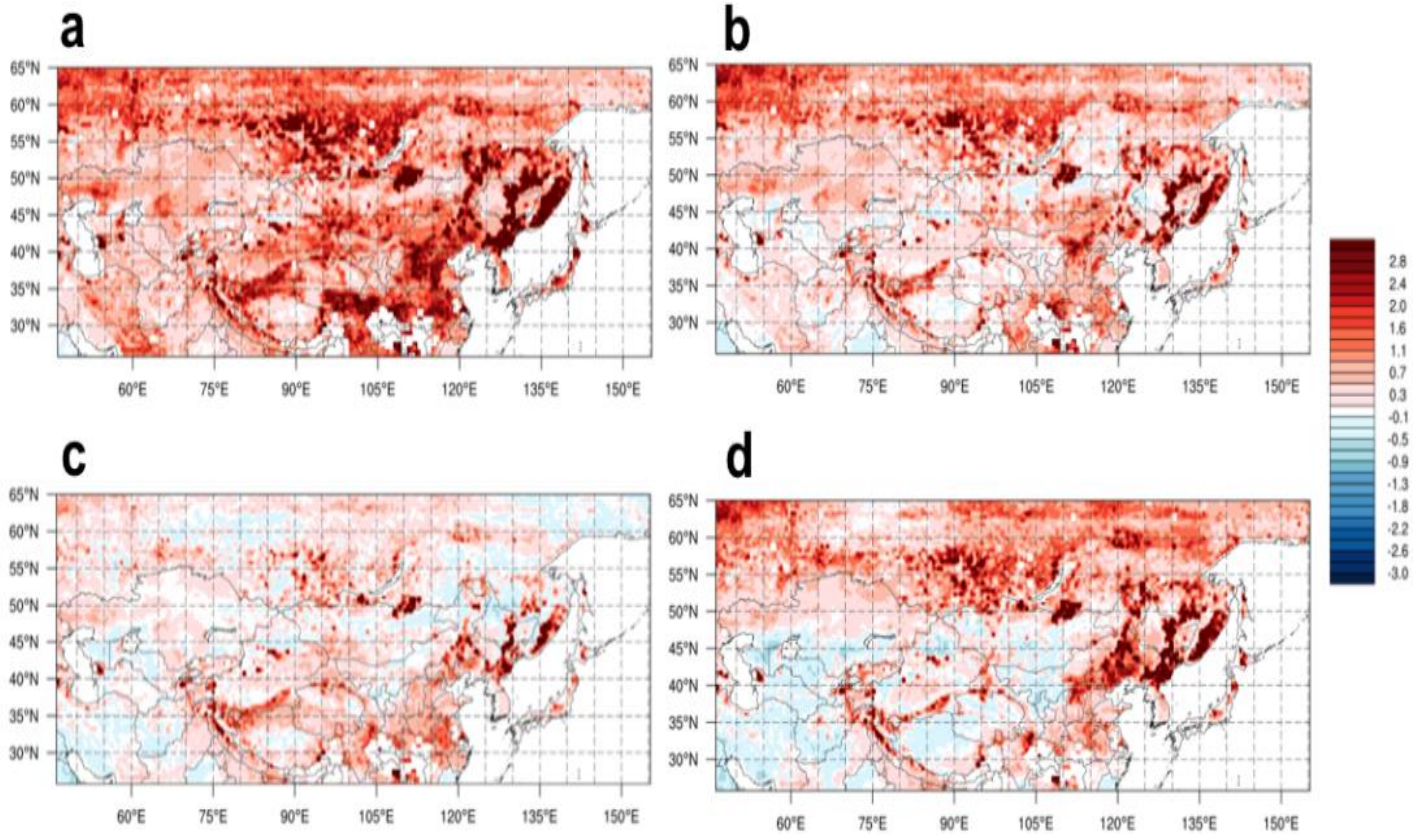
(a) Noah LSM
(b) RUC LSM
(c) Noah-MP
(d) CLM4



Sensitivity Studies

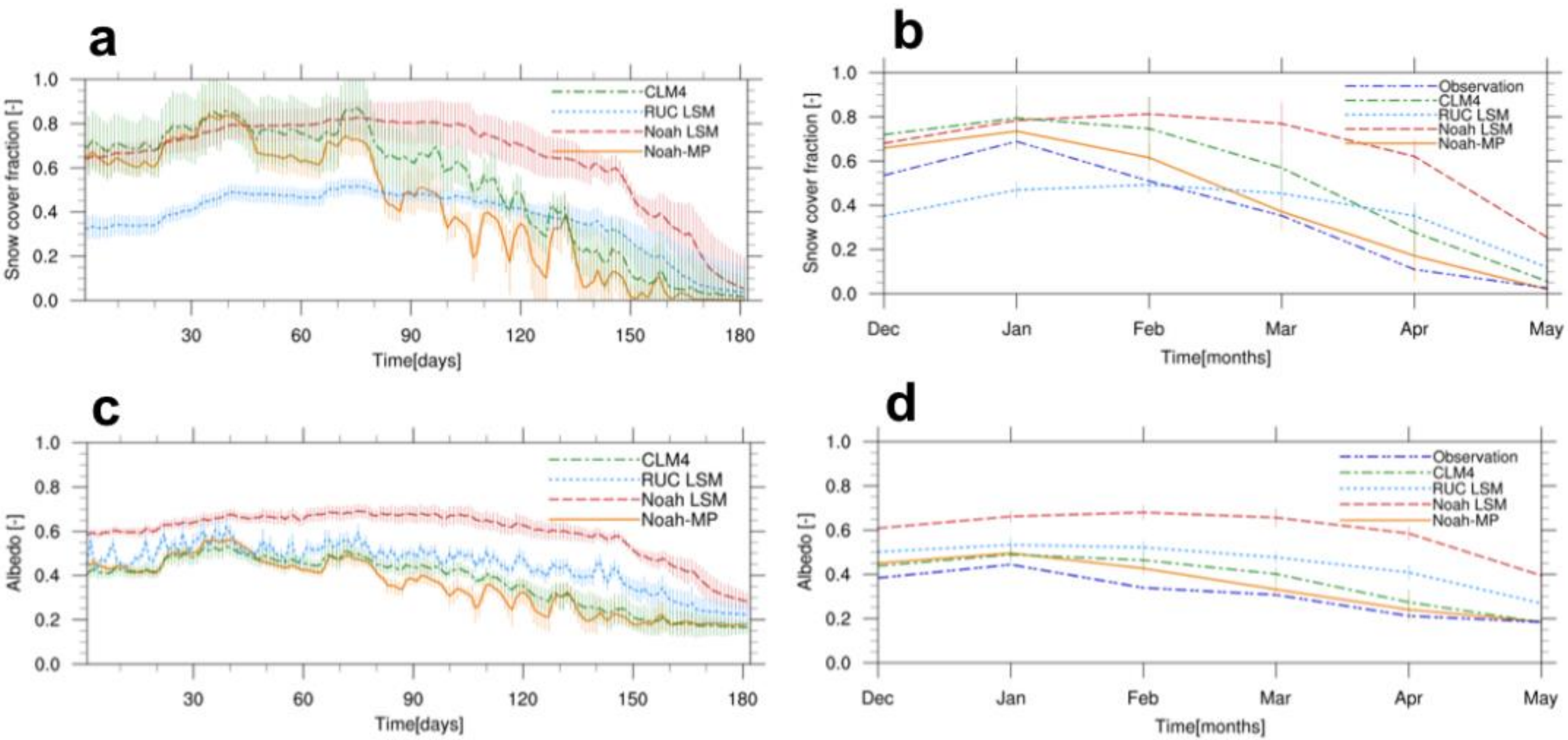
- **Sensitivity of Eurasian Snow on LSMs**
  - Dec. 2009 to May 2010 (*Snow Albedo Bias*)

(a) Noah LSM
(b) RUC LSM
(c) Noah-MP
(d) CLM4



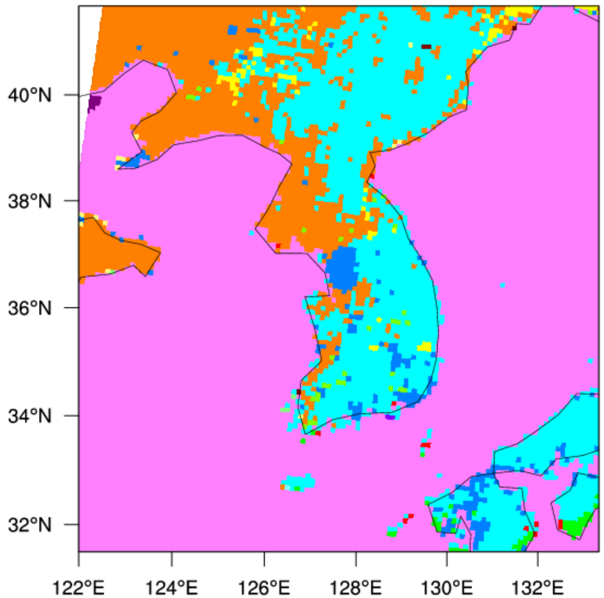
Sensitivity Studies

- **Sensitivity of Eurasian Snow on LSMs**
  - Dec. 2009 to May 2010 (Snow Cover Fraction & Albedo)



Sensitivity Studies

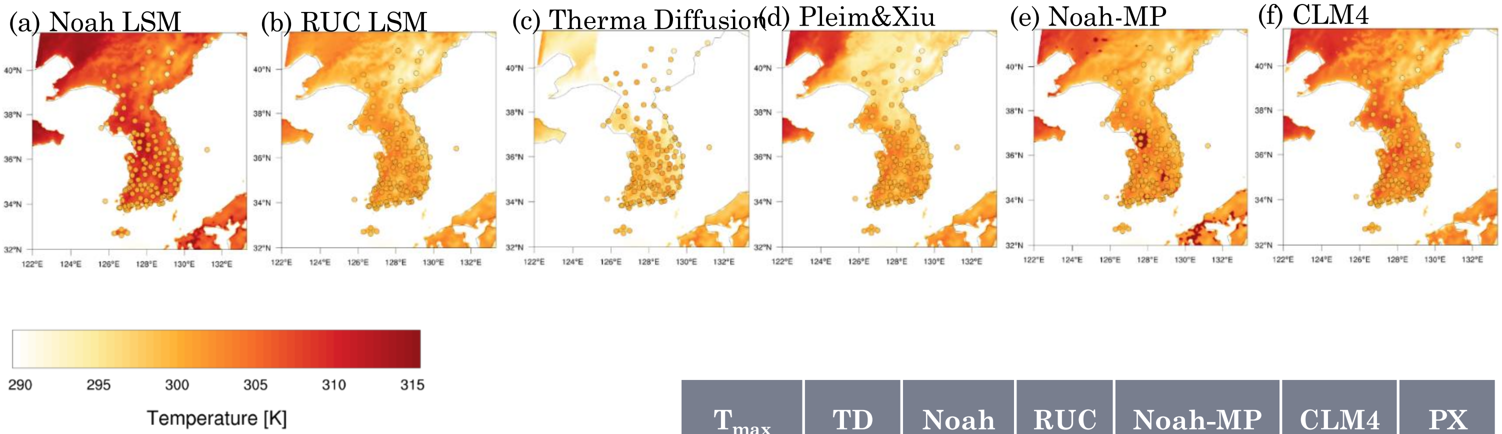
- **Sensitivity of Heat Waves on LSMs**
  - Summer 2016



WRF 3.9.1 Configuration	Exp. LM
Period	2016.02.01. ~ 2016.09.01.
Boundary Layer Scheme	YSU
Microphysics Scheme	WSM6
Radiation	Dudhia, RRTMG
Convection	Kain-Fritsch scheme
Surface layer	MM5 similarity scheme
Land Use Data	IGBP-Modified MODIS 20-category
Number of Domain	1
Horizontal resolution (km)	10
Land surface models	Thermal diffusion Noah LSM RUC LSM Noah-MP CLM4 Pleim & Xiu

Sensitivity Studies

- **Sensitivity of Heat Waves on LSMs**
  - **Summer 2016**



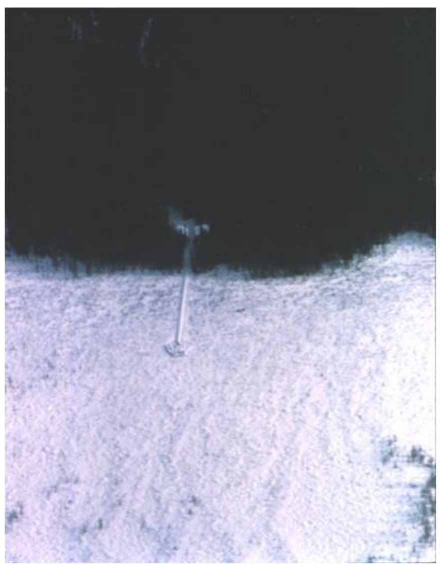
T_{max}	TD	Noah	RUC	Noah-MP	CLM4	PX
Mean	291.85	306.26	298.86	302.61	300.69	298.57
RMSD	13.01	6.27	4.51	5.56	4.42	4.89

1. Atmospheric Sciences at Ewha Womans University
2. Numerical Weather/Climate/Environment (W/C/E) Prediction — Overview
3. Sensitivity Studies (LSMs on Heat Waves)
4. **Subgrid-scale Parameterizations (LSM)**
5. Optimal Parameter Estimation (GA)
6. Coupled Data Assimilation
7. Projection of Local Climate Change (RCM+LSM)
8. RECIPE — Regional Environment/Climate Prediction System

Subgrid-scale Parameterizations

- **Snow covered albedo over grass and forest**
  - Grass is fully covered by snow and appears white. On the contrary, forest is almost completely free of snow, showing low albedo.

spruce



(BOREAS Website)

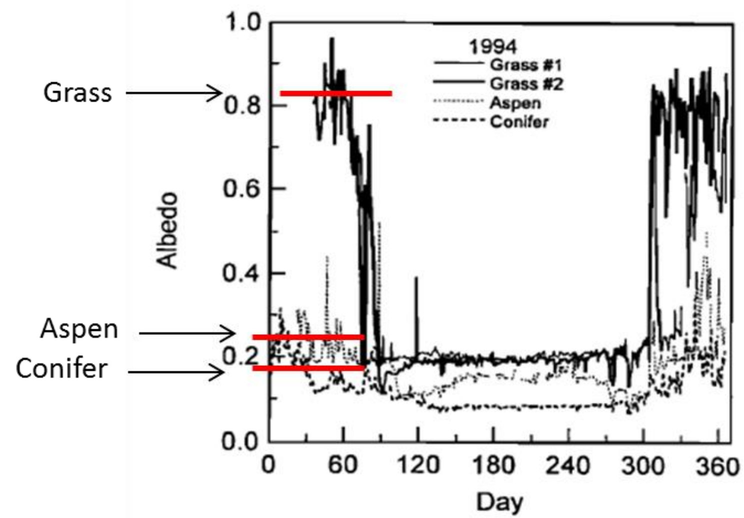


Figure 4. Daily average albedo for 10 BOREAS mesonet sites for 1994; showing two grass sites, the aspen site, and an average of the seven conifer sites. (*Bett and Ball*, 1997)

Subgrid-scale Parameterizations

• Spatial distributions of albedo vs. land cover

- *A spatial distribution of albedo generally follows the patterns of land cover type (Jin et al., 2012).*
- Many land surface models (LSMs) still ignore the vegetation effect or use impractical vegetation parameters in the albedo calculation (Essery, 2013).

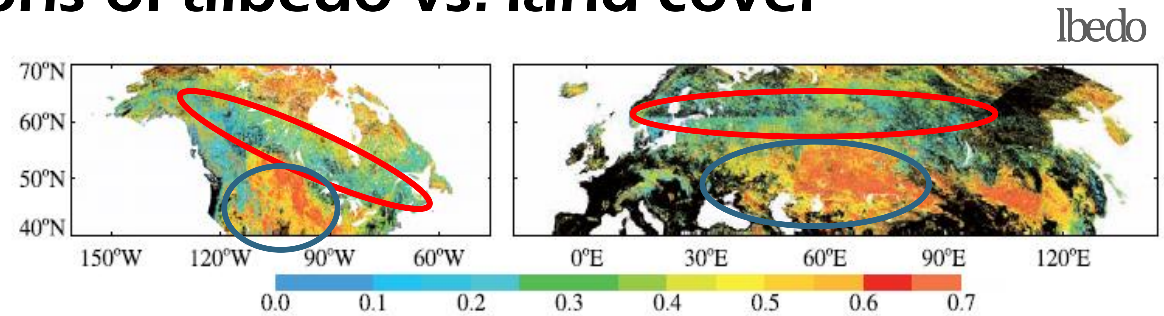


Figure 2. Mean shortwave black sky albedo under snow conditions in North America (left panel) and Eurasia (right panel) from 40°N to 60°N during November 2000–January 2001 and from 60°N to 70°N during November 2000. The image is in Interrupted Goodes projection. Pixels without retrievals due to cloud contamination are in black.

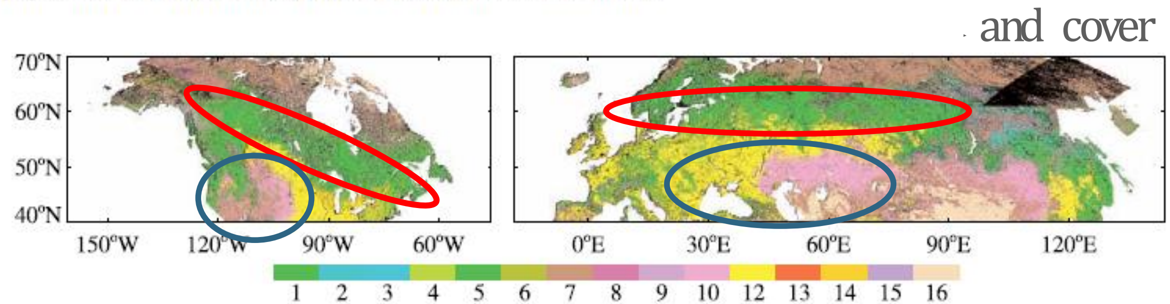


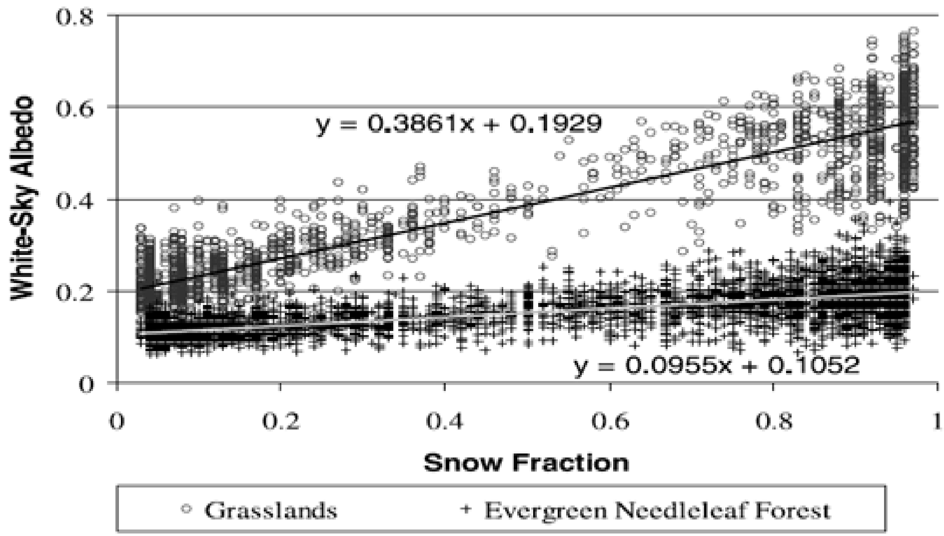
Figure 3. MODIS provisional IGBP land cover map over the same region as Figure 2. IGBP 1. Evergreen needleleaf forests; 3. Deciduous needleleaf forests; 4. Deciduous broadleaf forests; 5. Mixed forests; 6. Closed shrublands; 7. Open shrublands; 8. Woody savannas; 9. Savannas; 10. Grasslands; 12. Croplands; 13. Urban and built-up lands; 14. Cropland/Natural vegetation mosaics; 16. Barren. Non-classified pixels are in black.

(*Jin et al.*, 2002)

Subgrid-scale Parameterizations

- **Spatial distributions of albedo vs. land cover**

lbedo



(Gao et al., 2005)

- Generally, albedo under snow condition is parameterized through separate treatments over snow surface and snow-free surface that are weighted by the snow cover fraction.
- Sensitivity of albedo w.r.t. the snow cover fraction is much higher for grassland than for evergreen needleleaf forest because of the masking of snow by a canopy (Gao et al., 2005).

Subgrid-scale Parameterizations

Geosci. Model Dev., 9, 1073–1085, 2016
www.geosci-model-dev.net/9/1073/2016/
doi:10.5194/gmd-9-1073-2016

Geoscientific Model Development
Open Access

Park & Park (2016)

Parameterization of the snow-covered surface albedo in the Noah-MP Version 1.0 by implementing vegetation effects

Sojung Park[1,3,4] **and Seon Ki Park**[1,2,3,4]

[1]Department of Atmospheric Science and Engineering, Ewha Womans University, Seoul, Republic of Korea
[2]Department of Environmental Science and Engineering, Ewha Womans University, Seoul, Republic of Korea
[3]Center for Climate/Environment Change Prediction Research, Ewha Womans University, Seoul, Republic of Korea
[4]Severe Storm Research Center, Ewha Womans University, Seoul, Republic of Korea

Correspondence to: Seon Ki Park (spark@ewha.ac.kr)

Subgrid-scale Parameterizations

Geosci. Model Dev., 9, 1073–1085, 2016

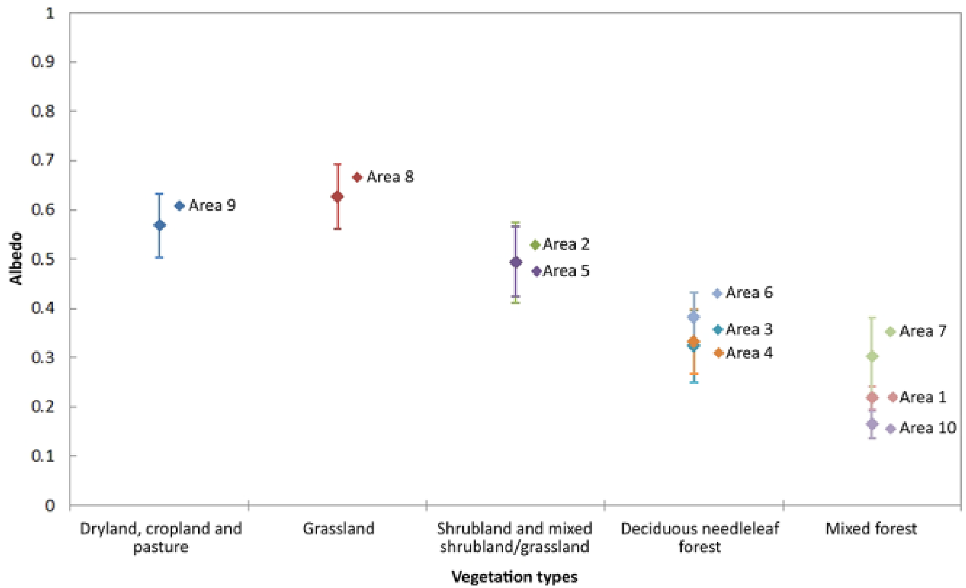
- This study investigated **the vegetation effect on the snow-covered surface albedo** from observations and improved the model performance **by implementing a new parameterization scheme**.
- We developed new parameters, called **leaf index (LI) and stem index (SI), which properly manage the effect of vegetation structure on the snow-covered surface albedo**.
- As a result, the **Noah-MP's performance in the winter surface albedo has significantly improved** – the root mean square error is reduced by approximately **69 %**.

Correspondence to: Seon Ki Park (spark@ewha.ac.kr)

Subgrid-scale Parameterizations

- **Physical Properties of Snow-covered Vegetation**

Park & Park (2016)



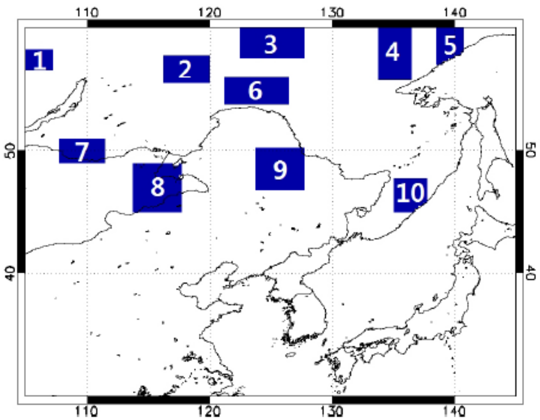


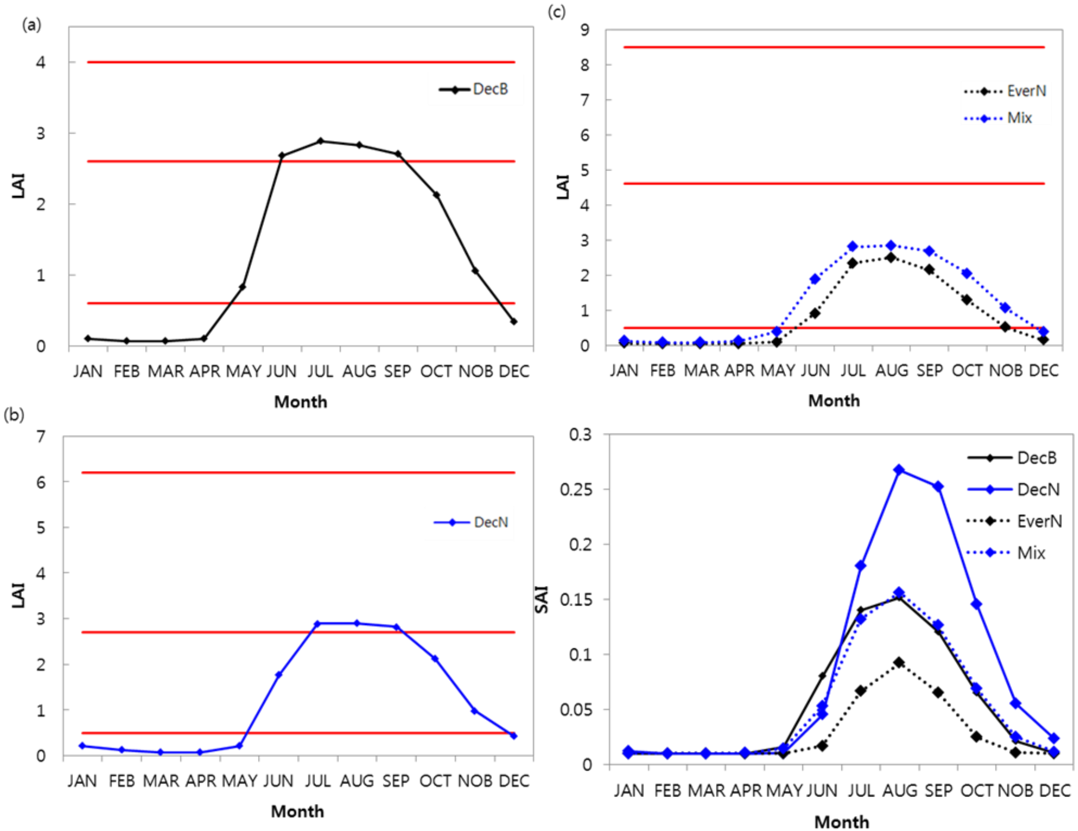
Figure 1. Geographical locations of the study domain. Each blue area has a dominant vegetation type as explained in Table 2.

Area 1	Mixed forest
Area 2	Mixed Shrublands
Area 3	Deciduous Needleleaf Forest
Area 4	Deciduous Needleleaf Forest
Area 5	Mixed Shrublands
Area 6	Deciduous Needleleaf Forest
Area 7	Mixed Forest
Area 8	Grasslands
Area 9	Croplands
Area 10	Mixed Forest

- Snow-covered albedos with 100% of the snow cover fraction (SCF) over various forest types have a wide range due to the forest shading effect.
- If the growing season is over, the amount of leaves and stems almost does not change and has a minimum value.
- In winter, stems and trunks are more significant than leaves, especially in the deciduous forest types.

Subgrid-scale Parameterizations

- **Seasonal variation of LAI and SAI in the Noah-MP**



$$\mathrm{LAI} = \max(m_{leaf} \times LAPM, LAI_{min}) \quad (1)$$
$$\mathrm{SAI} = \max(m_{stem} \times SAPM, SAI_{min}) \quad (2)$$

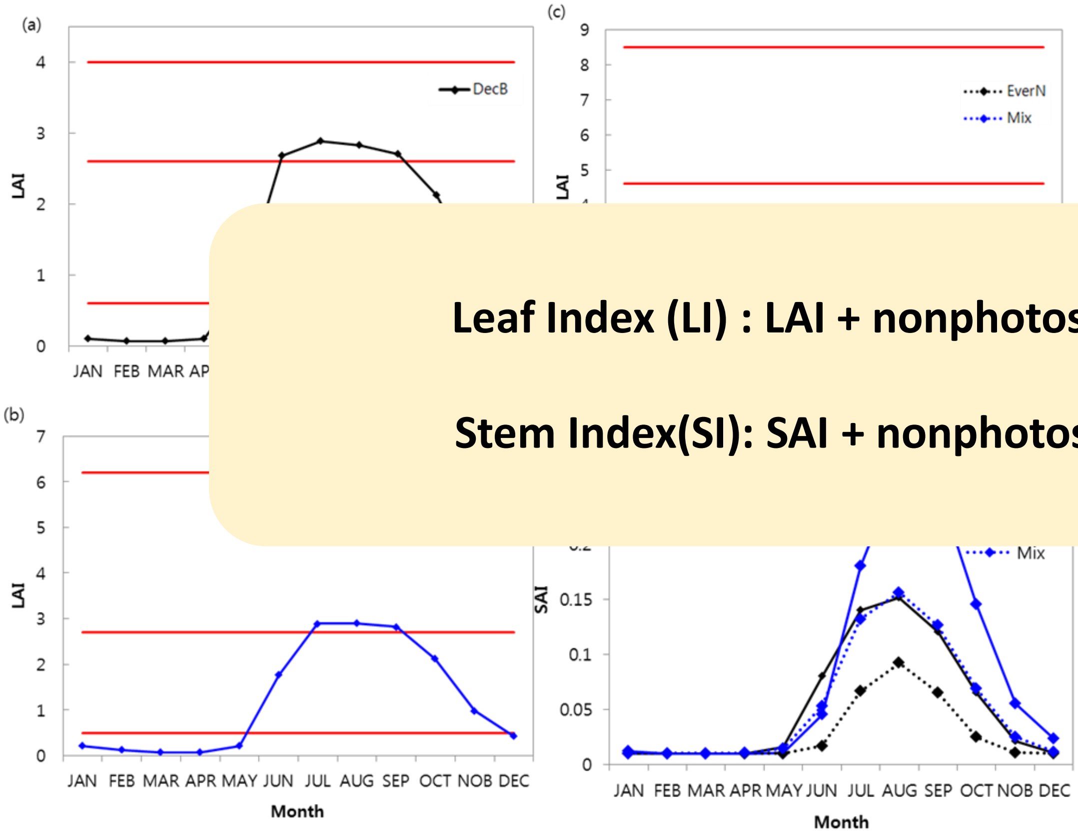
m_{leaf}: leaf mass (g/m^2)
m_{stem}: stem mass (g/m^2)
$LAPM$: leaf area per unit mass (m^2/g)
$SAPM$: stem area per unit mass (m^2/g)
LAI_{min} = 0.05 m^2/m^2
SAI_{min} = 0.01 m^2/m^2

The leaf and stem mass are reduced in winter because they consider the photosynthetic capacity. However, for calculating albedo, **the vegetation structure is more important than the photosynthetic capacity, especially in winter**.

Park & Park (2016)

Subgrid-scale Parameterizations

- **Seasonal variation of LAI and SAI in the Noah-MP**



$$\text{LAI} = \max(m_{leaf} \times LAPM, LAI_{min}) \quad (1)$$
$$\text{SAI} = \max(m_{stem} \times SAPM, SAI_{min}) \quad (2)$$

m_{leaf}: leaf mass (g/m^2)

g)

/g)

Leaf Index (LI) : LAI + nonphotosynthetic leaves

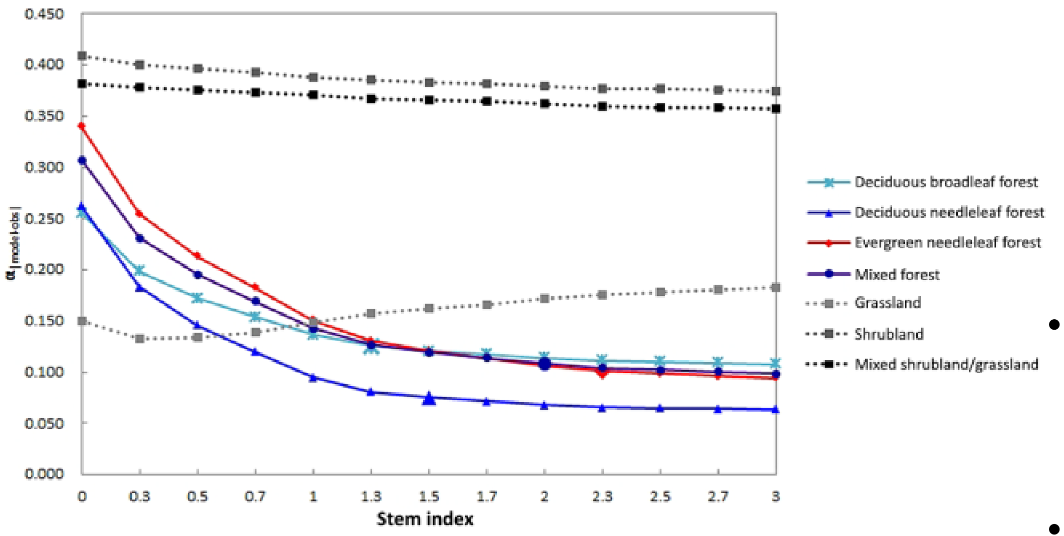
Stem Index(SI): SAI + nonphotosynthetic stems

reduced in winter because they consider the photosynthetic capacity. However, for calculating albedo, ***the vegetation structure is more important than the photosynthetic capacity, especially in winter***.

Park & Park (2016)

Subgrid-scale Parameterizations

- **Optimization of SI**



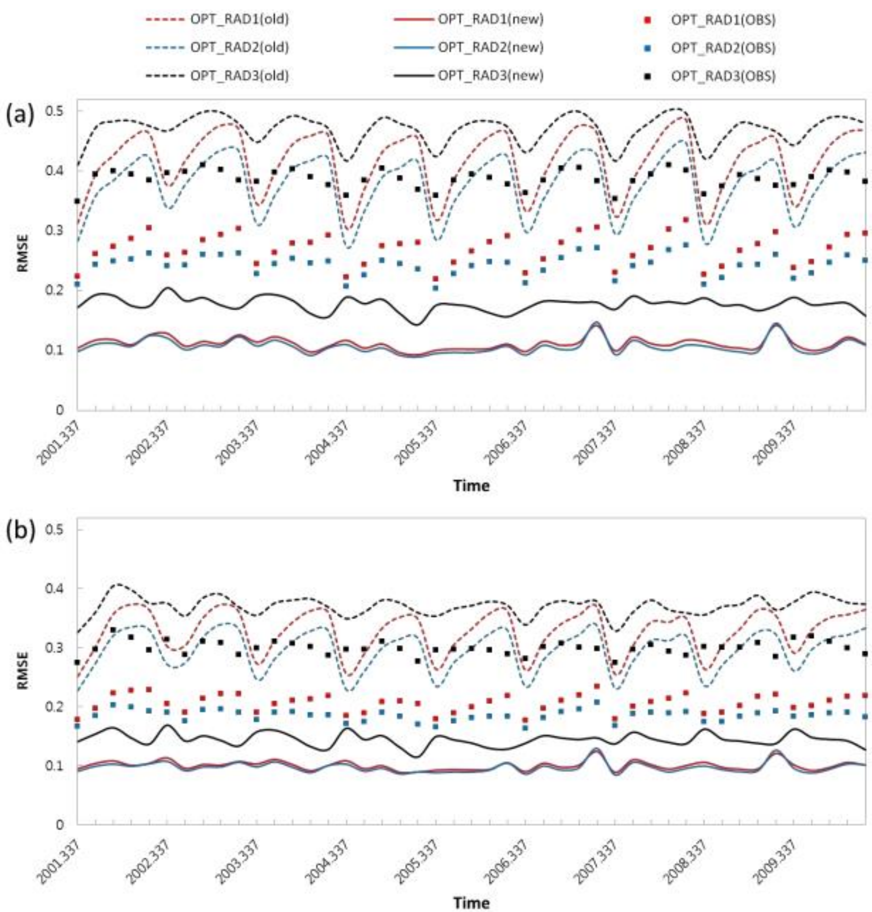
USGS land cover type	Minimum of LAI (default)	LI (reference)	Minimum of SAI (default)	SI (optimized)
11. Deciduous broadleaf forest	0.05	0.6	0.01	**1.3**
12. Deciduous needleleaf forest	0.05	0.5	0.01	**1.5**
14. Evergreen needleleaf forest	0.05	0.5	0.01	**2.3**
15. Mixed forest	0.05	0.5	0.01	**2.0**

- Albedo is averaged during 10 years on a winter day (i.e. 337, 353, and 1, 17, and 33 next year as Julian day).
- **The bias errors of albedo decrease very slowly after a certain value of SI optimized valu**e (see the Table).
- The LI are given the reference values from Asner et al. (2003).

Park & Park (2016)

Subgrid-scale Parameterizations

- **Validation of albedo with the optimal value**



- The data are winter averaged every 16 days from 337 through 33 as Julian day for the years 2001 to 2010.
- The simulations of albedo are improved for all two-stream radiation transfer and snow surface albedo schemes – BATS (Fig. 7a) and CLASS (Fig. 7b) with **RMSEs reduced by approximately 70% on average.**
- The RMSEs of original model are increased by becoming the late winter and as the winter has gone on, the albedo is dominantly influenced by the snow cover and forest masking (Bonan, 2008; Brovkin et al., 2013; Essery et al., 2009).

Park & Park (2016)

Subgrid-scale Parameterizations

Gim, Park et al. (2017)

AGU PUBLICATIONS

Journal of Advances in Modeling Earth Systems

RESEARCH ARTICLE

10.1002/2016MS000890

An improved parameterization of the allocation of assimilated carbon to plant parts in vegetation dynamics for Noah-MP

Hyeon-Ju Gim[1], Seon Ki Park[1,2,3,4], Minseok Kang[5], Bindu Malla Thakuri[6], Joon Kim[5,7], and Chang-Hoi Ho[8]

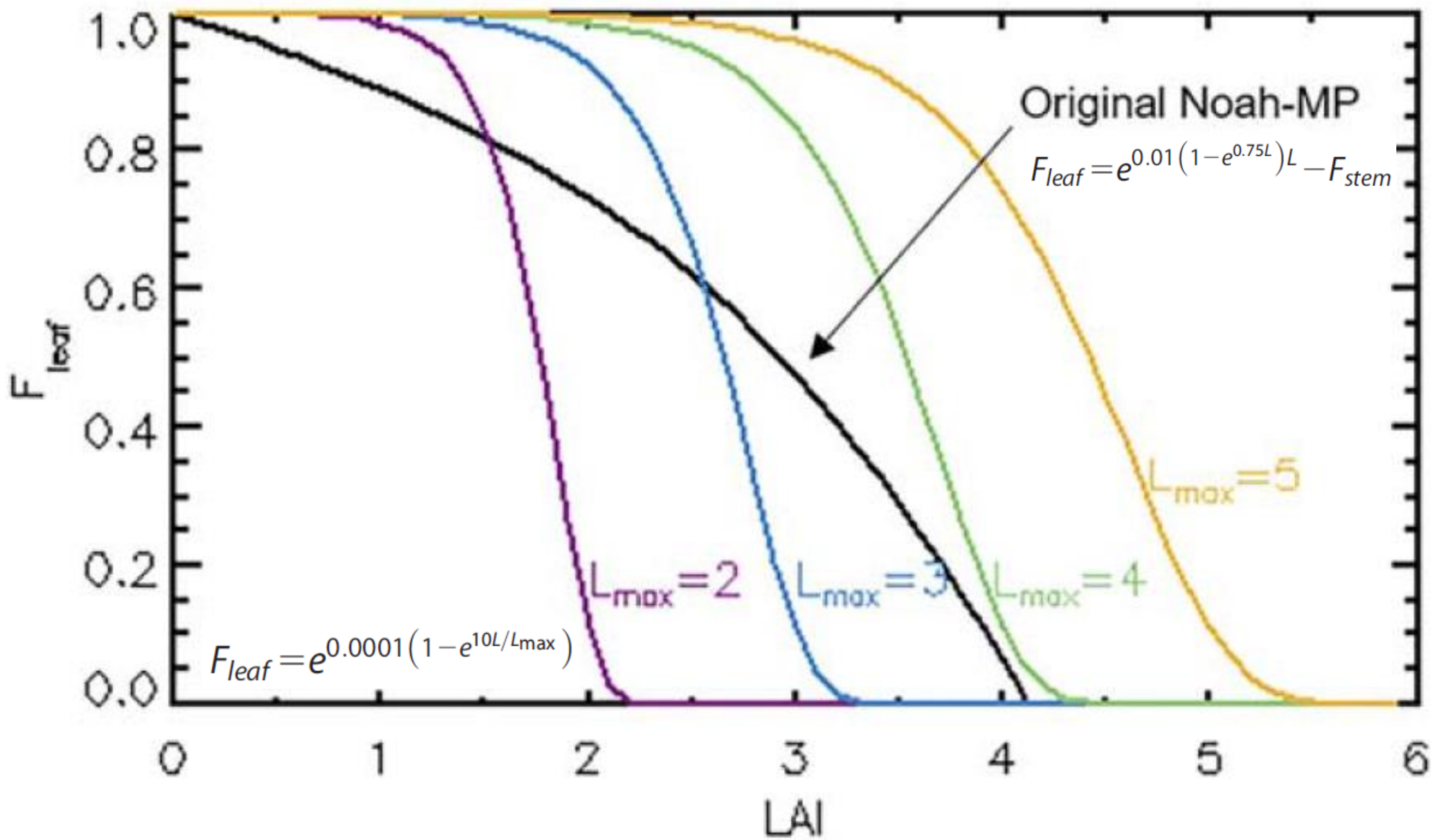
[1]Ceter for Climate/Environment Change Prediction Research, Ewha Womans University, Seoul, South Korea, [2]Department of Environmental Science and Engineering, Ewha Womans University, Seoul, South Korea, [3]Department of Climate and Energy Systems Engineering, Ewha Womans University, Seoul, South Korea, [4]Severe Storm Research Center, Ewha Womans University, Seoul, South Korea, [5]National Center for AgroMeteorology, Seoul National University, Seoul, South Korea, [6]Department of Atmospheric Sciences, Yonsei University, Seoul, South Korea, [7]Department of Rural Systems Engineering/Interdisciplinary Program in Agricultural and Forest Meteorology/Institute of Green-Bio Science and Technology, Seoul National University, Seoul, South Korea, [8]School of Earth and Environmental Sciences, Seoul National University, Seoul, South Korea

Key Points:
- A new parameterization of carbon allocation in plant parts for Noah-MP
- Improved simulations of the seasonality and amount of vegetation parameters and terrestrial carbon fixation
- A realistic simulation of regional distribution of vegetation parameters and terrestrial carbon fixation

Correspondence to:
S. K. Park,
spark@ewha.ac.kr

Subgrid-scale Parameterizations

Gim et al. (2017)



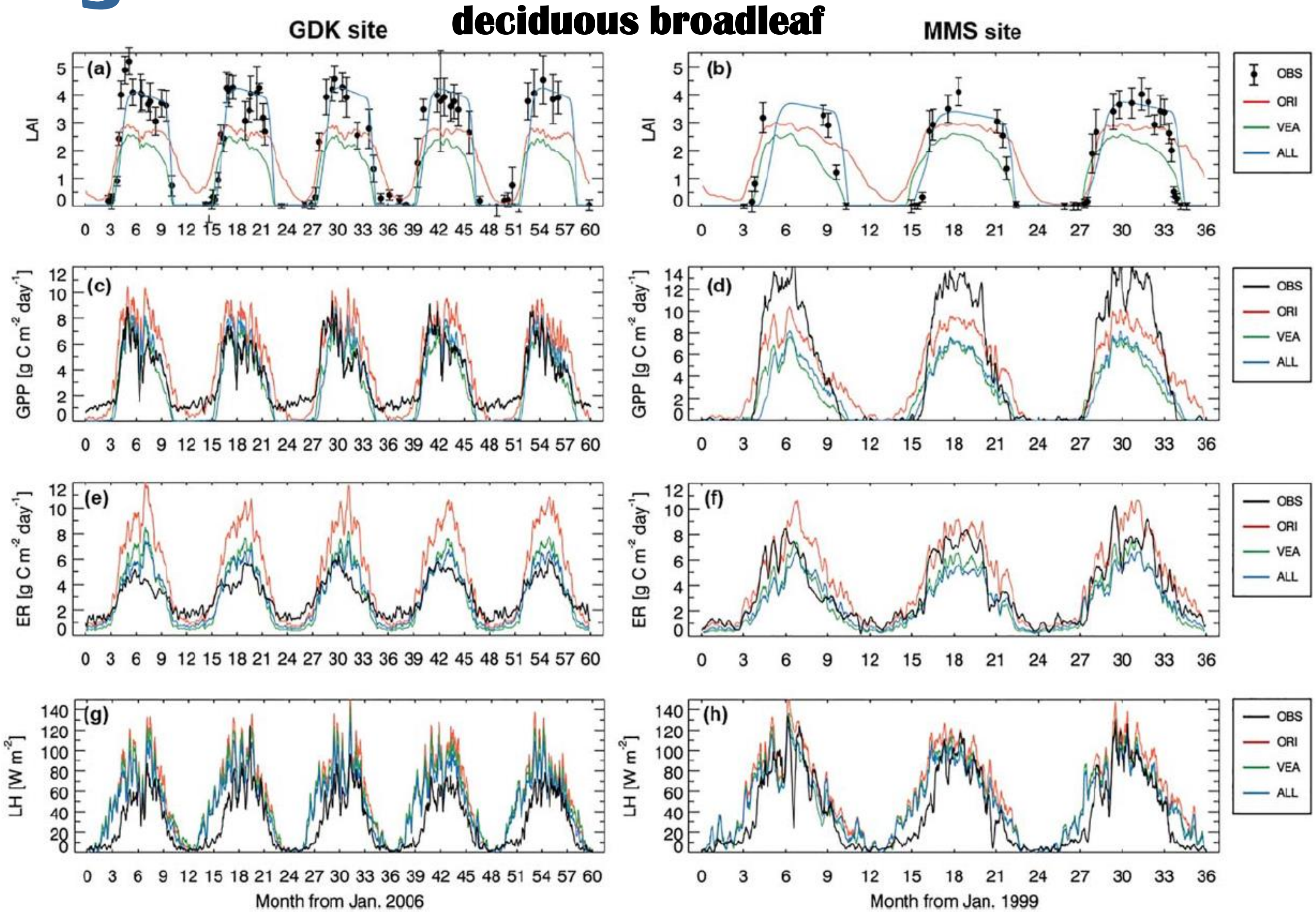
Subgrid-scale Parameterizations

Gim et al. (2017)

- **In the ORI experiments, the original Noah-MP is used without any modification.**
- **For the VEA experiments, we added the three biological schemes related to vegetation seasonality to the original Noah-MP: 1) the vegetation phenology, 2) the leaf aging effect, and 3) the vertical profile of photosynthetic capacity.**
- **For the ALL experiments, in addition to the schemes adopted in the VEA experiments, the new carbon allocation scheme is added, and the parameter related to allocation is changed.**

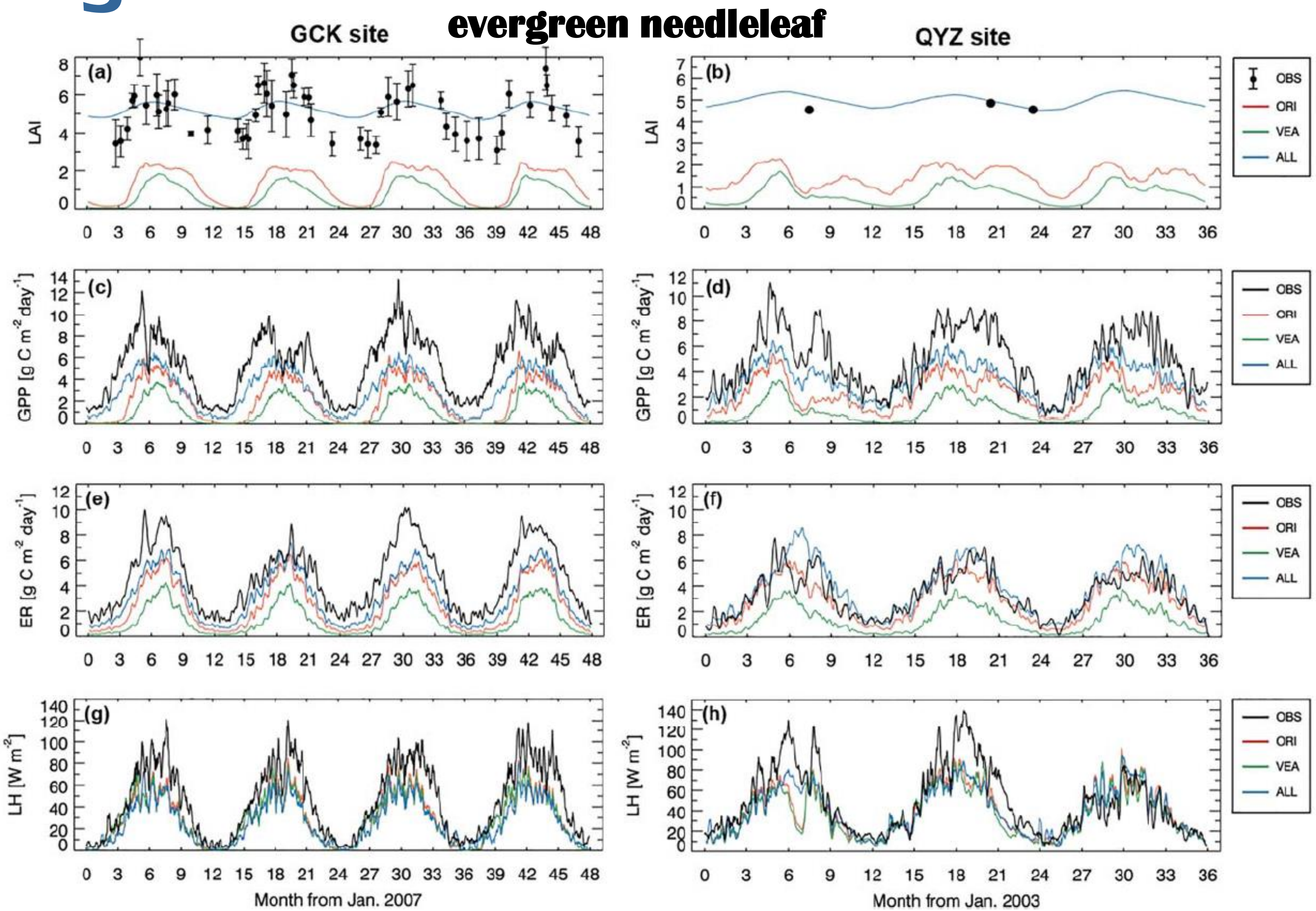
Subgrid-scale Parameterizations

Gim et al. (2017)



Subgrid-scale Parameterizations

Gim et al. (2017)



1. Atmospheric Sciences at Ewha Womans University
2. Numerical Weather/Climate/Environment (W/C/E) Prediction --- Overview
3. Sensitivity Studies (LSMs on Heat Waves)
4. Subgrid-scale Parameterizations (LSM)
5. **Optimal Parameter Estimation (GA)**
6. Coupled Data Assimilation
7. Projection of Local Climate Change (RCM+LSM)
8. RECIPE --- Regional Environment/Climate Prediction System

Optimal Parameter Estimation

- **Why parameter estimation?**
  - Numerical weather/climate prediction models contain numerous parameterizations for subgrid-scale physical processes.
  - The parameter values directly or indirectly affect the performance of model, and thus uncertainties in parameter values may lead to sensitive results, especially with sophisticated microphysics.
  - Accordingly, optimal estimation of parameters is one of the essential factors in improving the accuracy of numerical prediction.

Optimal Parameter Estimation

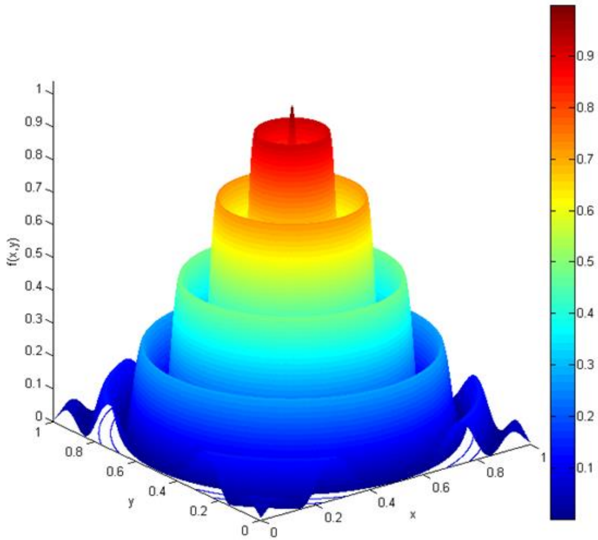
- **Global optimization – Genetic Algorithm (GA)**
  - *Artificial evolution—natural selection*
  - Global rather than local optimization
  - Better chromosome (Gene) survive
  - Independent on problems (robust)

$$f(x,y) = \cos^2(n\pi r)\exp(-r^2/\sigma^2)$$

$$r^2 = (x-0.5)^2 + (y-0.5)^2$$

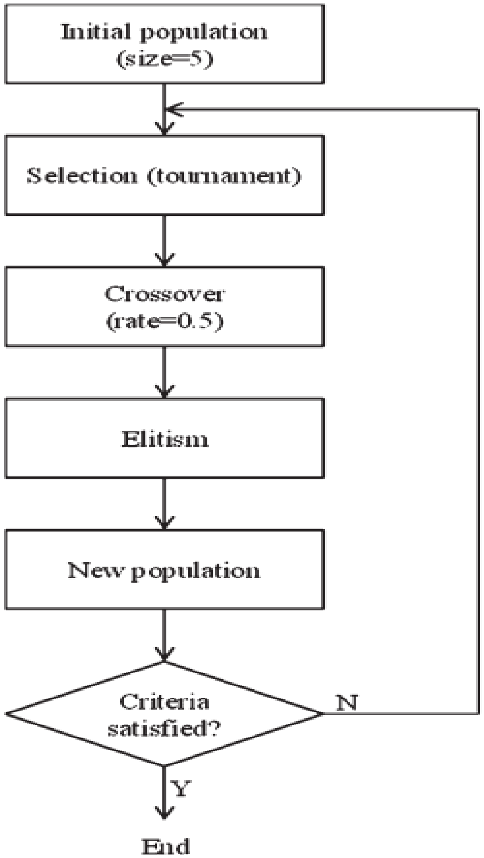
$$x, y \in [0.0, 1.0]$$

$$n = 9 \text{ and } \sigma^2 = 0.15$$



Optimal Parameter Estimation

- **Global optimization – Genetic Algorithm (GA)**



1. Micro-GA initializes a random sample of individual solutions.
2. A tournament **selection** method is used to select parent genes on which the uniform **crossover** operation is applied to preserve variety in the genetic group.
3. Micro-GA does not have mutation operations because diversifying a small population will not give a good representation of the solution space.
4. The diversity of the solutions is achieved by starting with a new, randomly generated population while keeping the best, previously obtained solutions (**elitism**).
5. Finally, we check if the termination criteria are satisfied. In this study, the global algorithm stops when the prescribed number of generations (i.e., 100) is reached.

Optimal Parameter Estimation

- **Global optimization – Genetic Algorithm (GA)**
  - Genetic algorithm (GA) has been applied to some parameter estimation problems. Compared to traditional optimization methods, the GA is more appropriate when the function includes some complexities and/or discontinuities.
  - Major advantages of GA:
    1) derivatives of a fit function with respect to model parameters (i.e., adjoint model outputs) are not required;
    2) nonlinearity between the model and its parameters can be handled (Holland, 1975).

Optimal Parameter Estimation

Ann. Geophys., 24, 3185–3189, 2006
www.ann-geophys.net/24/3185/2006/

Annales Geophysicae

Lee, Park, Chang (2006)

Parameter estimation using the genetic algorithm and its impact on quantitative precipitation forecast

Y. H. Lee[1], S. K. Park[2], and D.-E. Chang[1]

[1]Meteorological Research Institute, Korea Meteorological Administration, Seoul, Republic of Korea
[2]Department of Environmental Science and Engineering, Ewha Womans University, Seoul, Republic of Korea

Correspondence to: S. K. Park
(spark@ewha.ac.kr)

Optimal Parameter Estimation

- **Parameter Estimation – QPF**
  - **Parameters to be optimized**
    - **Kain-Fritsch (KF): reduction rate of CAPE (ε) → assumes convection consumes at least 90% of the environmental CAPE (default: 0.9)**
    - **Asselin filter: default of ν = 0.1**

$$\hat{\alpha}^t = (1 - 2\nu)\alpha^t + \nu\left(\alpha^{t+1} + \hat{\alpha}^{t-1}\right), \quad \nu \in [0, 1]$$

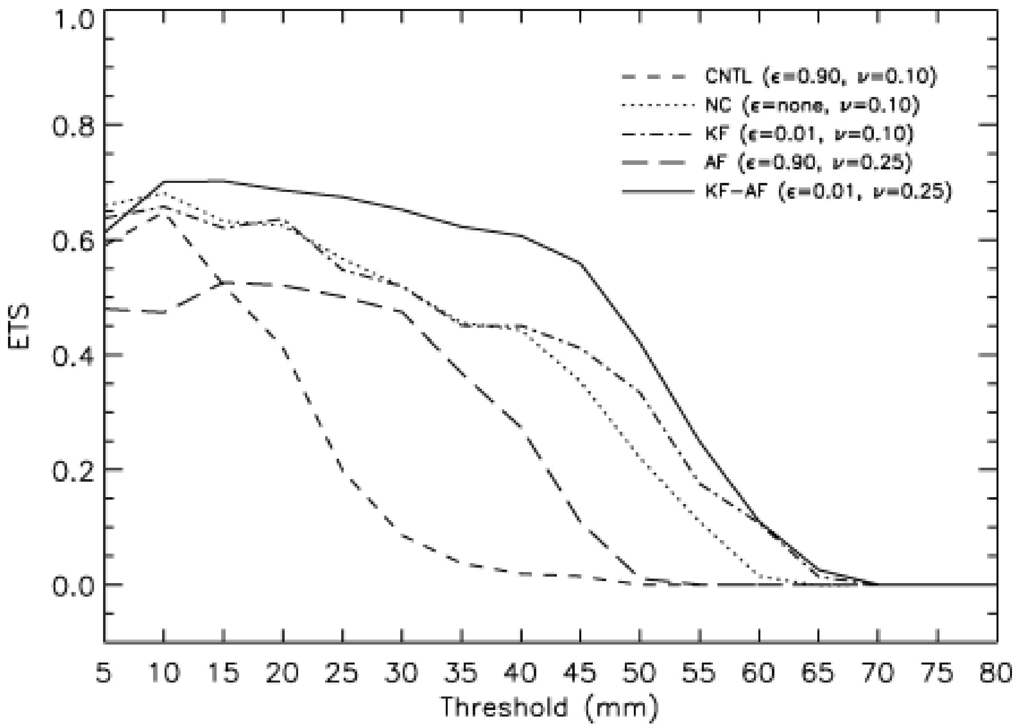
    - **Model: MM5 with Δx = 18 km**
    - **Fitness function:** $\sum_i \mathrm{ETS}_i, \; i = 1, 2, \ldots, 100$ $\quad \mathrm{ETS} = \dfrac{H - R}{F + O - H - R},$

ETS (equitable threat score): *H* is the number of hits, *F* and *O* are the numbers of samples in which the precipitation amounts are greater than the specified threshold in forecast and observation, respectively, and *R* is the expected number of hits in a random forecast – *R=FO/N*, where *N* is total number of points being verified.

Lee et al. (2006)

Optimal Parameter Estimation

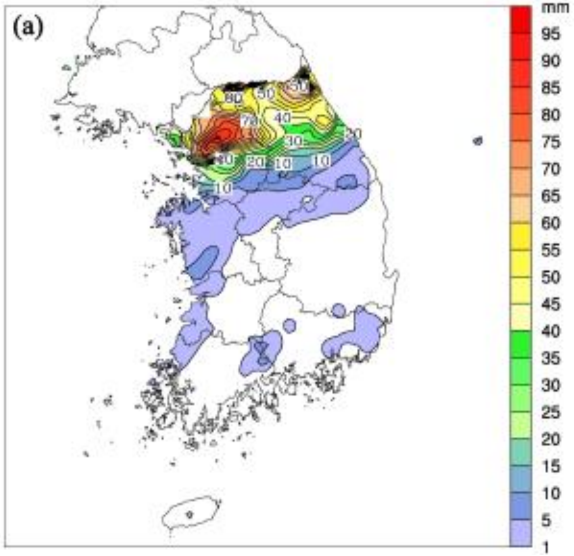
- **Parameter Estimation – QPF**



Lee et al. (2006)

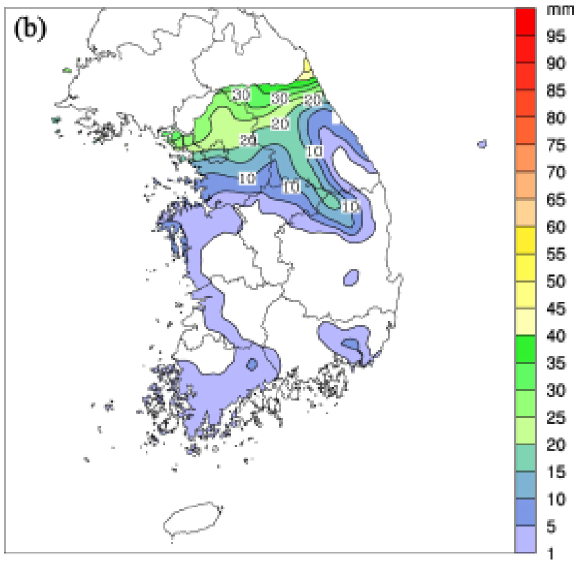
Optimal Parameter Estimation

- **Parameter Estimation – QPF**

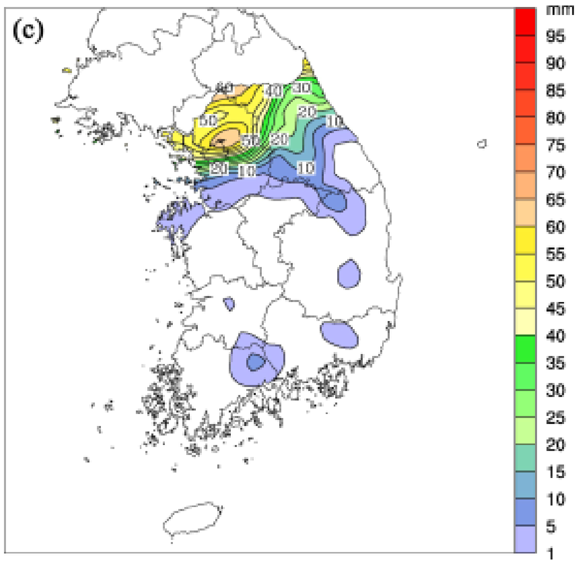


bs: . raingauge data

efault



ptimized



Lee et al. (2006)

Optimal Parameter Estimation

Yu, Park et al. (2013)

SOLA, 2013, Vol. 9, 36−39, doi:10.2151/sola.2013-009

Quantitative Precipitation Forecast of a Tropical Cyclone through Optimal Parameter Estimation in a Convective Parameterization

Xing Yu[1, §], Seon Ki Park[1, 2, 3, 4], Yong Hee Lee[5], and Yong Sang Choi[1, 2, 3, 4]

[1]*Center for Climate/Environment Change Prediction Research, Ewha Womans University, Seoul, Korea*
[2]*Severe Storm Research Center, Ewha Womans University, Seoul, Korea*
[3]*Department of Environmental Science and Engineering, Ewha Womans University, Seoul, Korea*
[4]*Department of Atmospheric Science and Engineering, Ewha Womans University, Seoul, Korea*
[5]*National Institute of Meteorological Research/Korea Meteorological Administration, Seoul, Korea*

[§]Present affiliation: Tropical Marine Science Institute, National University of Singapore, Singapore
Corresponding author: Seon Ki Park, Department of Environmental Science and Engineering, Ewha Womans University, 52 Ewhayeodae-gil, Seodaemun, Seoul 120-750, Korea; E-mail: spark@ewha.ac.kr.

Optimal Parameter Estimation

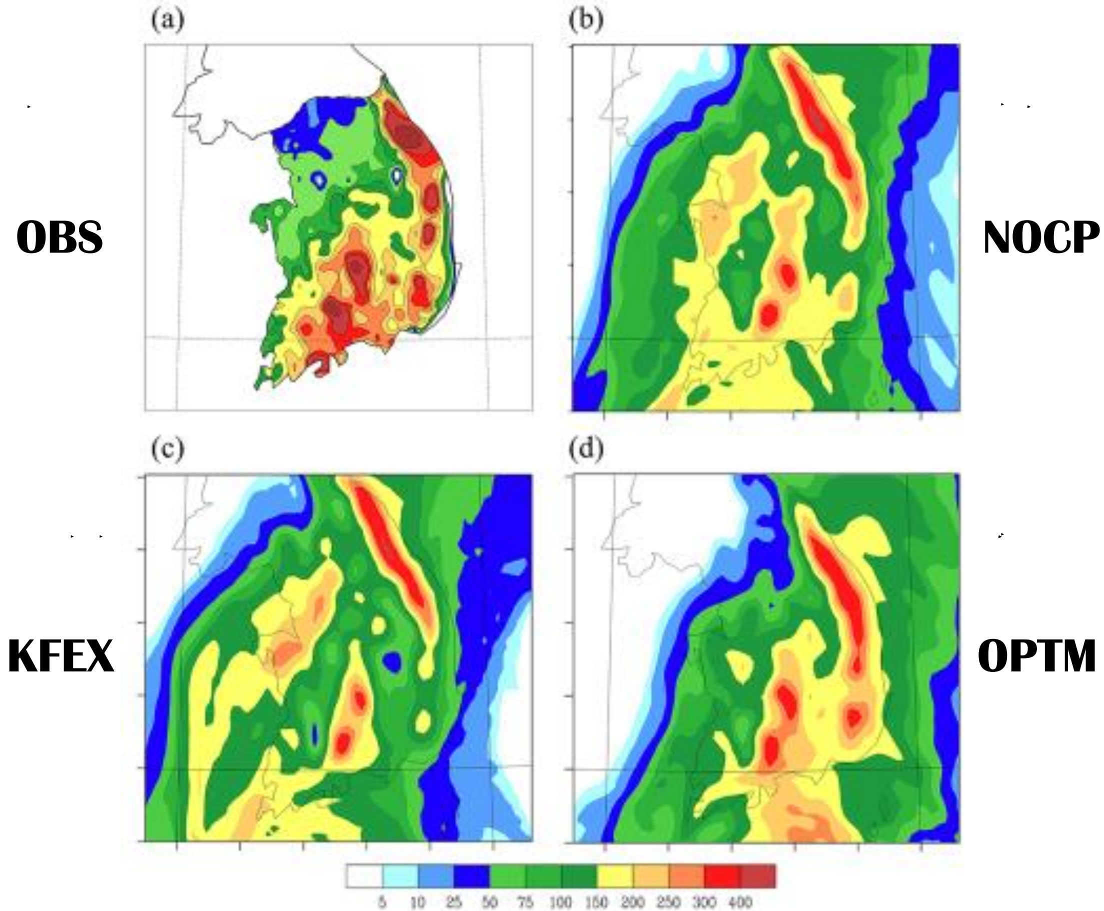
- **Parameter Estimation – QPF (Typhoon)**
  - **Parameters to be optimized**
    - **Kain-Fritsch (KF): convective timescale (T_c)→ assumes convection consumes at least 90% of the environmental CAPE over T_c**
    - **Kain-Fritsch (KF): autoconversion rate (c)**
    - **Model: WRF with Δx = 10 km**
    - **Fitness function:**

$$\sum_i \mathrm{ETS}_i, \quad i = 1, 2, \ldots, 100 \qquad \mathrm{ETS} = \frac{H - R}{F + O - H - R},$$

Yu et al. (2013)

Optimal Parameter Estimation

- **Parameter Estimation – QPF (Typhoon)**



Yu et al. (2013)

Optimal Parameter Estimation

- **Optimized Set of Parameterization Schemes**
  - Noah-MP is a land surface process model that (optionally) includes multiple physics schemes with more than1,500 possible combinations.
  - Super-parameterization: We determine the optimized set of parameterization schemes using micro-GA.

Optimal Parameter Estimation

Geosci. Model Dev., 7, 2517–2529, 2014
www.geosci-model-dev.net/7/2517/2014/
doi:10.5194/gmd-7-2517-2014

Geoscientific Model Development
Open Access

Hong, Yu, Park et al. (2014)

Assessing optimal set of implemented physical parameterization schemes in a multi-physics land surface model using genetic algorithm

S. Hong[1,*], X. Yu[1,], S. K. Park[1,2,3,4], Y.-S. Choi[1,2,3,4], and B. Myoung[1,***]**

[1]Center for Climate/Environment Change Prediction Research, Ewha Womans University, Seoul, Korea
[2]Severe Storm Research Center, Ewha Womans University, Seoul, Korea
[3]Department of Environmental Science and Engineering, Ewha Womans University, Seoul, Korea
[4]Department of Atmospheric Science and Engineering, Ewha Womans University, Seoul, Korea
[*]now at: Department of Climate & Ecology, National Institute of Ecology, Seocheon, Korea
[**]now at: Tropical Marine Science Institute, National University of Singapore, Singapore
[***]now at: Center for Excellence in Earth Systems Modeling & Observations, Chapman University, California, USA

Correspondence to: S. K. Park (spark@ewha.ac.kr)

Optimal Parameter Estimation

Hong, Park, Yu (2015)

SOLA, 2015, Vol. 11, 129−133, doi:10.2151/sola.2015-030 129

Scheme-Based Optimization of Land Surface Model Using a Micro-Genetic Algorithm: Assessment of Its Performance and Usability for Regional Applications

Seungbum Hong[1,*], Seon Ki Park[1,2,3,4], and Xing Yu[5]

[1]*Center for Climate/Environment Change Prediction Research, Ewha Womans University, Seoul, Korea*
[2]*Severe Storm Research Center, Ewha Womans University, Seoul, Korea*
[3]*Department of Environmental Science and Engineering, Ewha Womans University, Seoul, Korea*
[4]*Department of Atmospheric Science and Engineering, Ewha Womans Univiersity, Seoul, Korea*
[5]*Tropical Marine Science Institute, National University of Singapore, Singarpore*

Corresponding author: Seon Ki Park, Department of Environmental Engineering, Ewha Womans University, 52 Ewhayeodae-gil, Seodaemun-gu, Seoul, 120-750, Korea. E-mail: spark@ewha.ac.kr.
* now at Department of Climate & Ecology, National Institute of Ecology, Seocheon, Korea

Optimal Parameter Estimation

Table 1. Summary of scheme options available in Noah-MP.

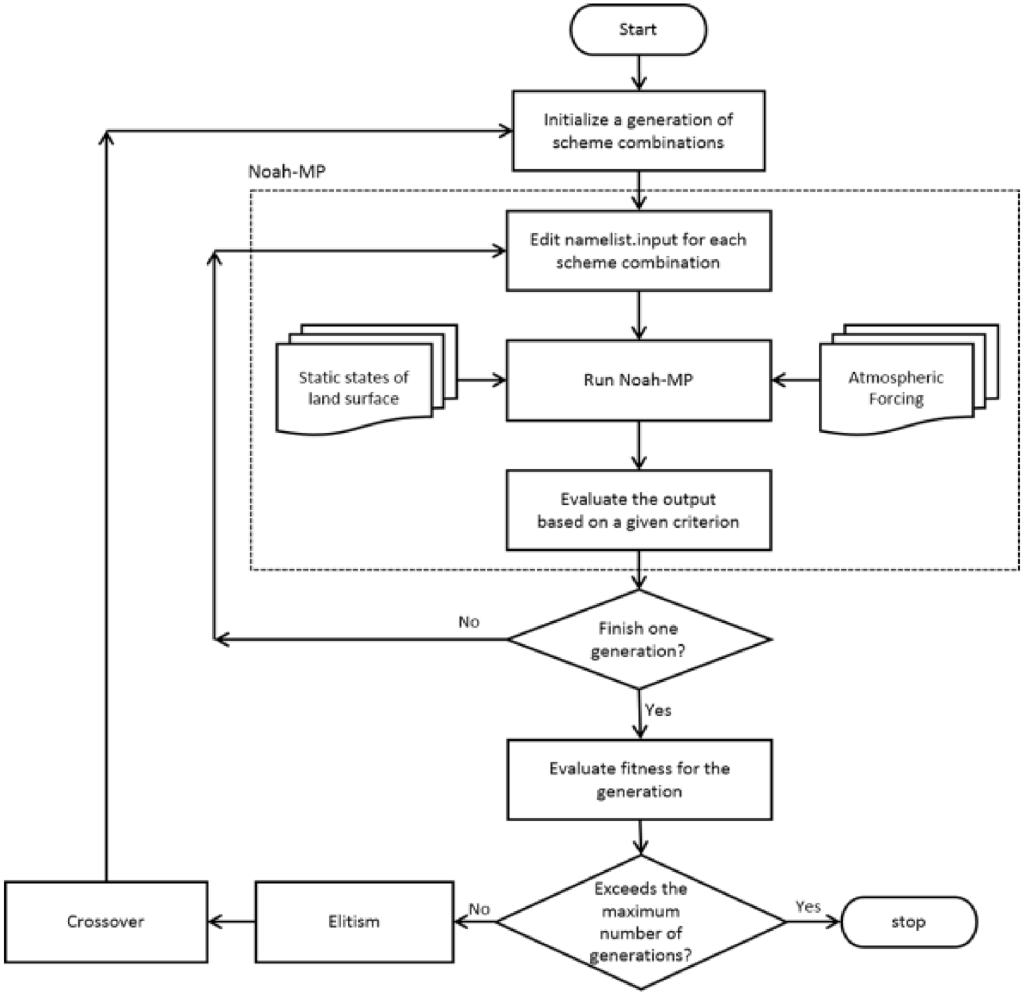
Physical processes	Options	References
Surface exchange coefficient for heat (SFC)	(1) Noah type (2) Monin–Obukhov scheme	Chen et al. (1997) Brutsaert (1982)
Supercooled liquid water in frozen soil (FRZ)	(1) Generalized freezing-point depression (2) Variant freezing-point depression	Niu and Yang (2006) Koren et al. (1999)
Frozen soil permeability (INF)	(1) Defined by soil moisture (2) Defined by liquid water volume	Niu and Yang (2006) Koren et al. (1999)
Snow surface albedo (ALB)	(1) BATS (2) CLASS	Dickinson et al. (1993) Verseghy (1991)
Runoff and Groundwater (RUN)	(1) SIMGM (2) SIMTOP (3) Free-drainage scheme (4) BATS	Niu et al. (2007) Niu et al. (2005) Schaake et al. (1996) Yang and Dickinson (1996)
Soil Moisture Factor controlling stomatal resistance, β factor (BTR)	(1) Noah type (2) CLM type (3) SSiB type	Chen et al. (1996) Oleson et al. (2004) Xue et al. (1991)
Two-stream radiation transfer (RAD)	(1) Canopy gaps from 3-D structure and solar zenith angle (2) no canopy gap (3) Gaps from vegetated fraction	Niu and Yang (2004)
Partitioning precipitation into rain and snow (SNF)	(1) Complex functional form (2) Snowfall at $T_{air} < T_{frz} + 2.2$ K (3) Snowfall at $T_{air} < T_{frz}$	Jordan (1991) Niu et al. (2011)

CLM (Community Land Model); SSiB (Simplified Simple Biosphere Model); SIMGM (Simple TOP runoff and Groundwater Model); SIMTOP (Simple TOP Runoff Model); BATS (Biosphere–Atmosphere Transfer Model); CLASS (Canadian Land Surface Scheme).

Using the eight categories, the total number of possible scheme combination is 1728.

Hong et al. (2014)

Optimal Parameter Estimation



Fitness function:

$$S = R \cdot \frac{4}{\left(\sigma_{\text{norm}} + \frac{1}{\sigma_{\text{norm}}}\right)^2} \cdot \frac{4}{\left(\upsilon_{\text{norm}} + \frac{1}{\upsilon_{\text{norm}}}\right)^2}$$

correlation coefficient (R), normalized standard deviation (σ_{norm}), and normalized average (ν_{norm}) based on observation data

Hong et al. (2014)

Optimal Parameter Estimation

- **Optimized Set of Parameterization Schemes**

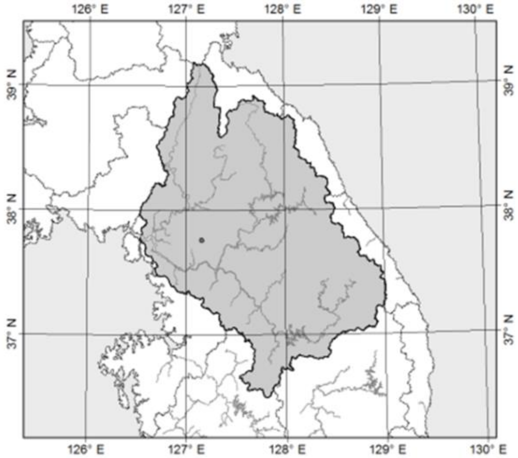
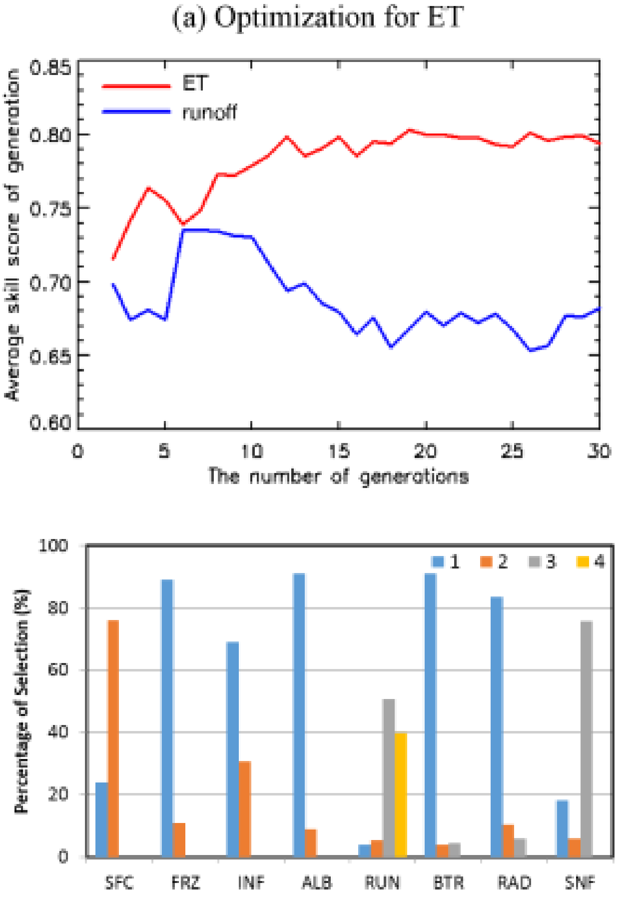
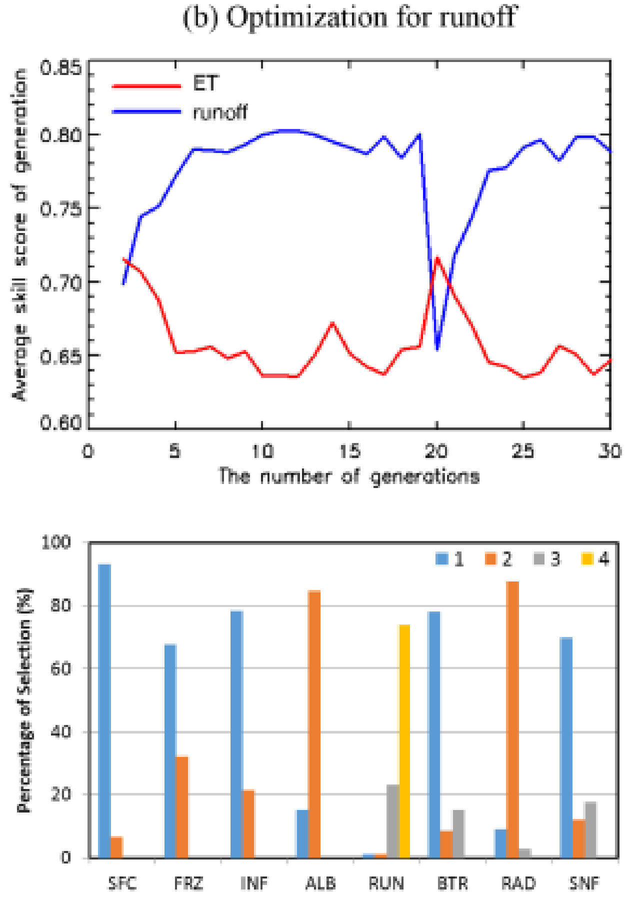


Figure 2. Geographic location of the Han River basin (dark shaded area) in South Korea. The gray lines in the basin indicate the river channels.

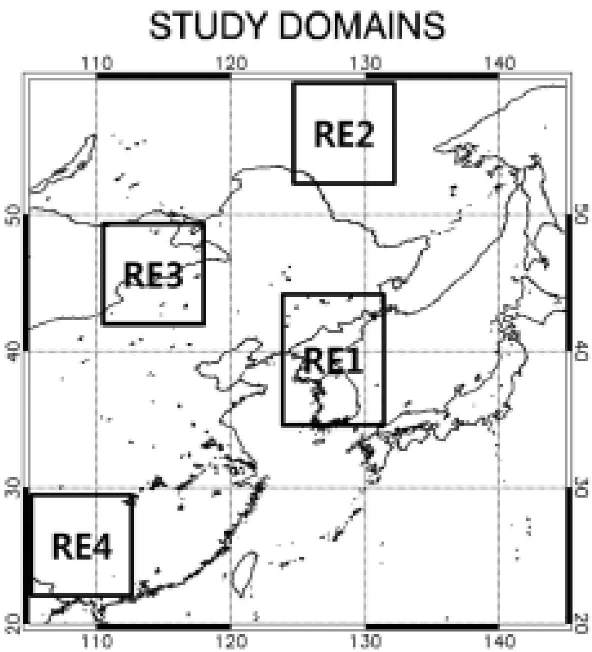


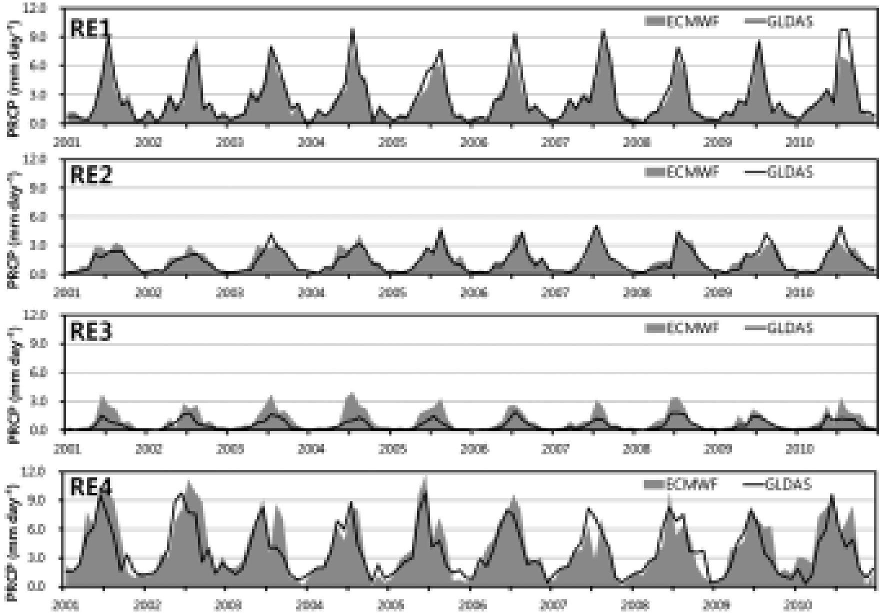


Hong et al. (2014)

Optimal Parameter Estimation

- **Optimized Set of Parameterization Schemes**





10-year monthly mean precipitation variations

Hong et al. (2015)

Optimal Parameter Estimation

- **Optimized Set of Parameterization Schemes**

Fitness function:

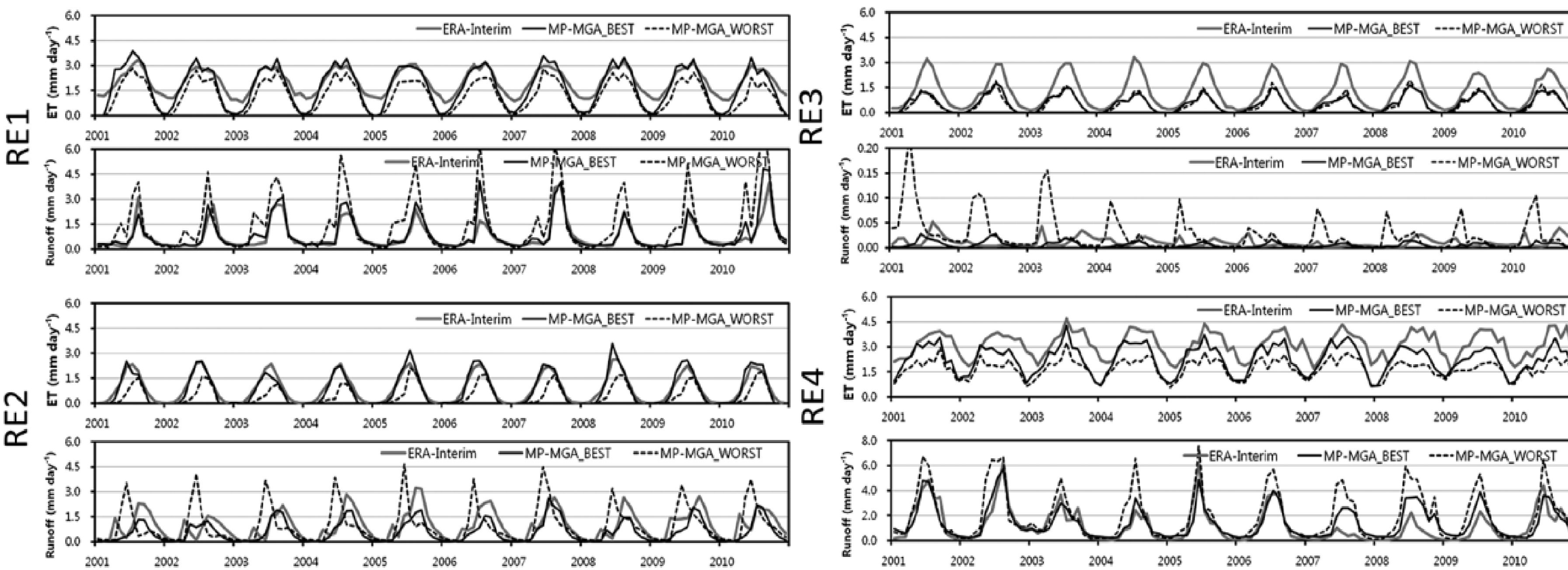
$$\mathrm{NSE}_{var} = 1 - \frac{\sum_{i=1}^{n}(Ref_i - Var_i)^2}{\sum_{i=1}^{n}(Ref_i - Ref_{mean})^2}.$$

- NSE: Nash-Sutcliffe efficiency (Nash and Sutcliffe 1970) is a highly recommended evaluation technique for the hydrological modeling fields and evaluates the performance of a model with respect to a certain variable.
- Ref_i and Var_i are the reference data and the model output at a given time step, respectively, and Ref_{mean} is the temporal mean of the reference data.

Hong et al. (2015)

Optimal Parameter Estimation

- **Optimized Set of Parameterization Schemes**



Hong et al. (2015)

Optimal Parameter Estimation

- **Optimized Set of Parameterization Schemes**

Table 2. The best scheme combinations extracted from MP-MGA for each region. The bold-text schemes indicate the most contributing ones to the simulation accuracy based on mNSE.

Region	Scheme Combination	mNSE
RE1	**SFC(2)**; FRZ(2); INF(2); **ALB(2)**; **RUN(1)**; SMF(2); RAD(3); PRT(1)	0.64
RE2	**SFC(1)**; FRZ(2); **INF(1)**; ALB(2); RUN(2); SMF(1); RAD(2); PRT(3)	0.98
RE3	SFC(1); FRZ(2); **INF(2)**; ALB(2); RUN(4); **SMF(1)**; RAD(1); PRT(2)	−0.39
RE4	**SFC(2)**; FRZ(1); INF(2); ALB(1); **RUN(1)**; **SMF(3)**; RAD(3); PRT(1)	0.07

mNSE = multivariate NSE (e.g., NSE_{ET} + NSE_{RUNOFF})

Hong et al. (2015)

1. Atmospheric Sciences at Ewha Womans University
2. Numerical Weather/Climate/Environment (W/C/E) Prediction --- Overview
3. Sensitivity Studies (LSMs on Heat Waves)
4. Subgrid-scale Parameterizations (LSM)
5. Optimal Parameter Estimation (GA)
6. **Coupled Data Assimilation**
7. Projection of Local Climate Change (RCM+LSM)
8. RECIPE --- Regional Environment/Climate Prediction System

Coupled Data Assimilation

- Why Coupled DA?
  - Most environmental problems include interaction mechanisms, e.g., atmosphere–chemistry, atmosphere–land surface, etc.
  - Modeling interaction of trace gases and aerosols with climate and weather requires employing coupled atmosphere–chemistry models, preferable at cloud-resolving scales.
  - Satellite observations of trace gases and aerosols bring important new information, as seen in our previous study.
  - We require an advanced DA system that blend information from satellite chemistry observations and from coupled atmosphere–chemistry models.
  - Regional coupled atmosphere–chemistry DA has additional complexity due to the interaction between cloud microphysics and trace gases and aerosols, implying high nonlinearity and flow-dependent forecast errors.

Coupled Data Assimilation

- Coupled Model and DA system
  - Advanced DA system is required due to
    - Complexity of processes at high-resolution
    - Nonlinear atmosphere–chemistry interactions and satellite observations
    - Flow-dependent nature of uncertainties
  - Coupled atmosphere–chemistry model: WRF-Chem
    - includes interaction between atmosphere and chemistry at scales relevant to transboundary air pollution
  - DA system: Maximum Likelihood Ensemble Filter (MEF)
    - Hybrid ensemble–variational method
    - Suitable for nonlinear observations and high-resolution applications

Coupled Data Assimilation

Geosci. Model Dev., 8, 1315–1320, 2015
www.geosci-model-dev.net/8/1315/2015/
doi:10.5194/gmd-8-1315-2015

Geoscientific Model Development
Open Access

Park, Lim, Zupanski (2015)

Structure of forecast error covariance in coupled atmosphere–chemistry data assimilation

S. K. Park[1,2,3,4], S. Lim[2,3], and M. Zupanski[5]

[1]Department of Environmental Science and Engineering, Ewha Womans University, Seoul, Republic of Korea
[2]Department of Atmospheric Science and Engineering, Ewha Womans University, Seoul, Republic of Korea
[3]Center for Climate/Environment Change Prediction Research, Ewha Womans University, Seoul, Republic of Korea
[4]Severe Storm Research Center, Ewha Womans University, Seoul, Republic of Korea
[5]Cooperative Institute for Research in the Atmosphere, Colorado State University, Fort Collins, Colorado, USA

Correspondence to: S. K. Park (spark@ewha.ac.kr)

Coupled Data Assimilation

- **Coupled DA – Role of Forecast Error Covariance**
  - **Main mechanism for improved analysis are cross-variable correlations of ensemble error covariance.**
    - **benefit of atmospheric observations on chemistry**
    - **benefit of chemistry observations on atmosphere**
    - **both are needed for improved forecast**

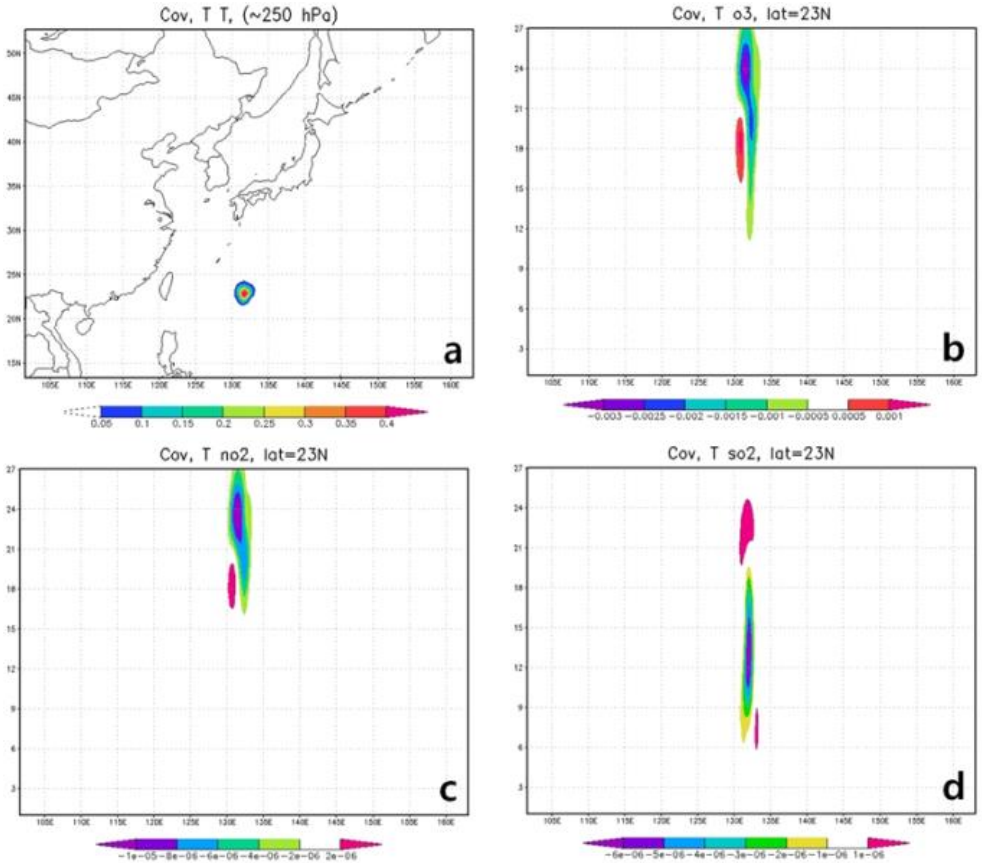
$$\begin{array}{rccc} & \text{ens. fcst.} & \text{obs} & \\ x^a - x^f = P_f w = & \begin{bmatrix} P_{aa} & P_{ac} \\ P_{ac}^T & P_{cc} \end{bmatrix} & \begin{bmatrix} w_a \\ w_c \end{bmatrix} & = \begin{bmatrix} P_{aa} w_a + P_{ac} w_c \\ P_{ac}^T w_a + P_{cc} w_c \end{bmatrix} \end{array}$$

a: atmosphere
c: chemistry

Cross-correlation terms are highlighted in green: They illustrate the advanced analysis update in a coupled atmosphere--chemistry system.

Coupled Data Assimilation

- **Coupled DA – Role of Forecast Error Covariance**

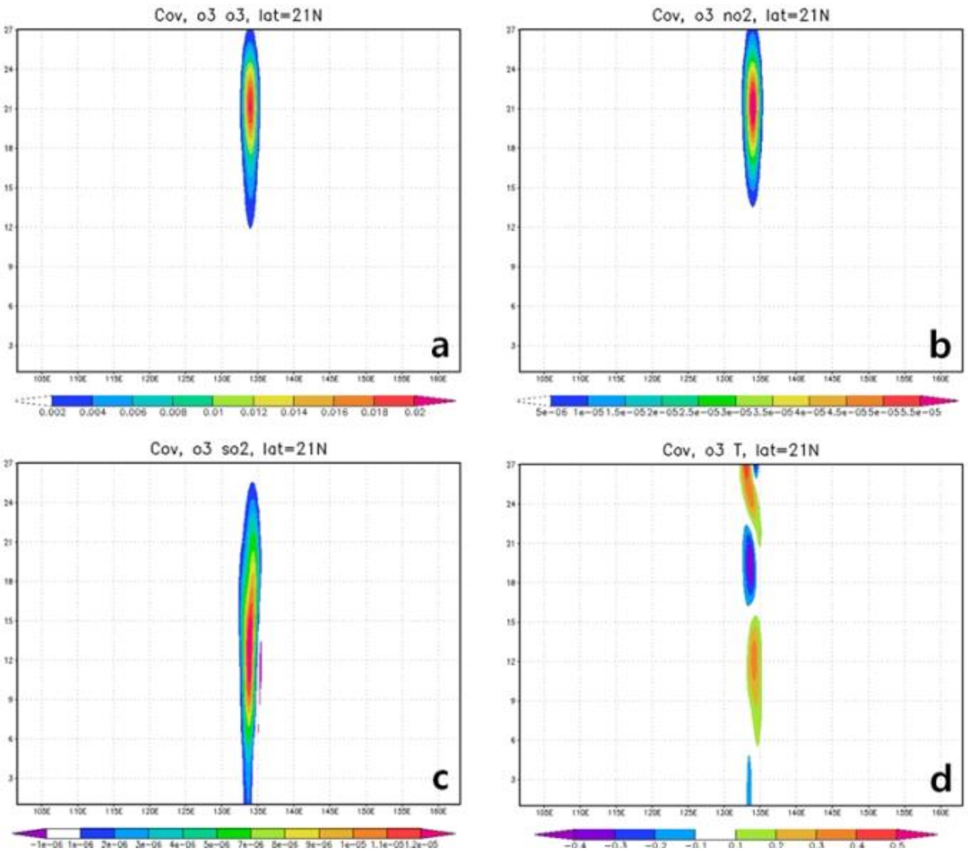


Analysis increments in response to a single T observation at 250 hPa (near σ level 24): (a) horizontal response of T at 250 hPa, and vertical responses of (b) O_3, (c) NO_2 and (d) SO_2.

Park et al. (2015)

Coupled Data Assimilation

- **Coupled DA – Role of Forecast Error Covariance**



Analysis increments in response to a single O_3observation at 250 hPa for (a) O_3, (b) NO_2, (c) SO_2, and (d) T.

Park et al. (2015)

Coupled Data Assimilation

Lee et al. (2017)

Remote Sensing of Environment 193 (2017) 38–53

Contents lists available at ScienceDirect

Remote Sensing of Environment

journal homepage: www.elsevier.com/locate/rse

Impact of the OMI aerosol optical depth on analysis increments through coupled meteorology–aerosol data assimilation for an Asian dust storm

Ebony Lee[a,b,c], Milija Županski[a,d], Dusanka Županski[e,1], Seon Ki Park[a,b,c,f,*]

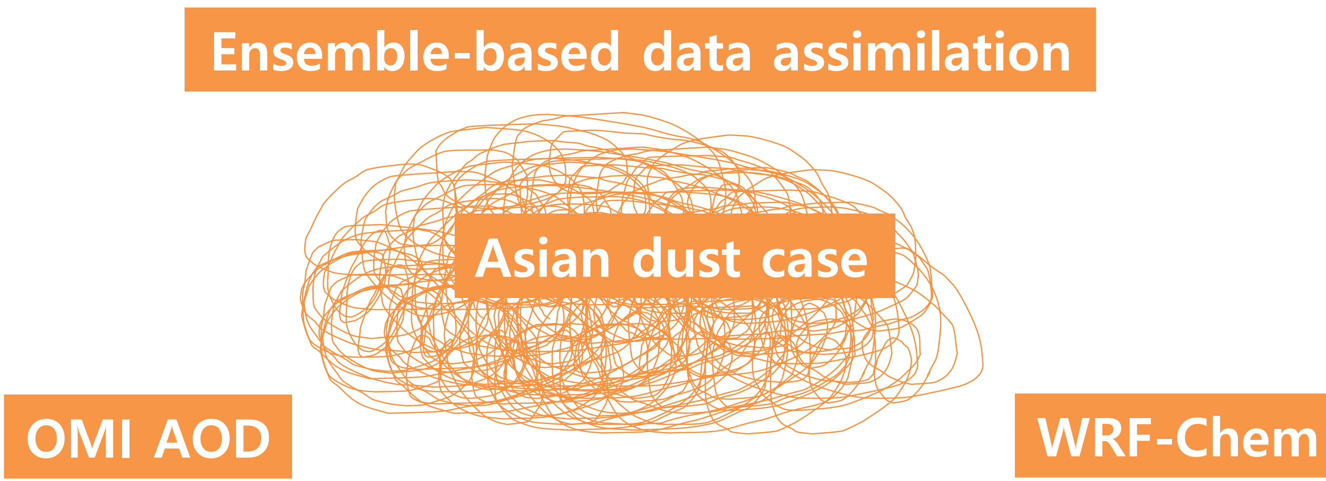
[a] *Department of Climate and Energy Systems Engineering, Ewha Womans University, Seoul, Republic of Korea*
[b] *Severe Storm Research Center, Ewha Womans University, Seoul, Republic of Korea*
[c] *Center for Climate/Environment Change Prediction Research, Ewha Womans University, Seoul, Republic of Korea*
[d] *Cooperative Institute for Research in the Atmosphere, Colorado State University, Fort Collins, CO, USA*
[e] *Zupanski Consulting, LLC, Fort Collins, CO, USA*
[f] *Department of Environmental Science and Engineering, Ewha Womans University, Seoul, Republic of Korea*

* Corresponding author.
E-mail address: spark@ewha.ac.kr (S.K. Park).

[1] Now at Spire Global, Inc., Boulder, Colorado, USA.

Coupled Data Assimilation

- **Coupled DA – Aerosol Optical Depth (AOD) on Dust Storm**
  - The performance of numerical models for ADSs has been quite good at predicting their onset, transportation, and cessation.
  - However, dust concentration itself is rather unpredictable, caused by uncertainties in dust emission fluxes, transport process, and removal process.

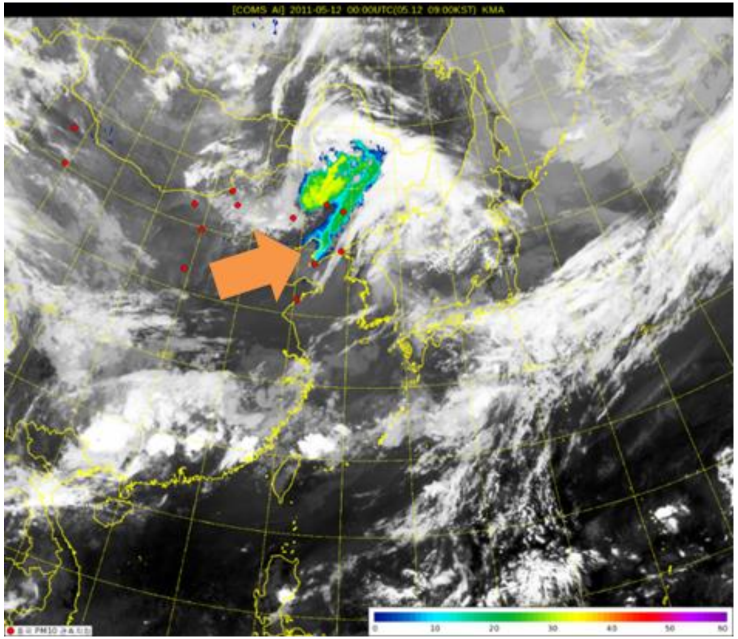


Coupled Data Assimilation

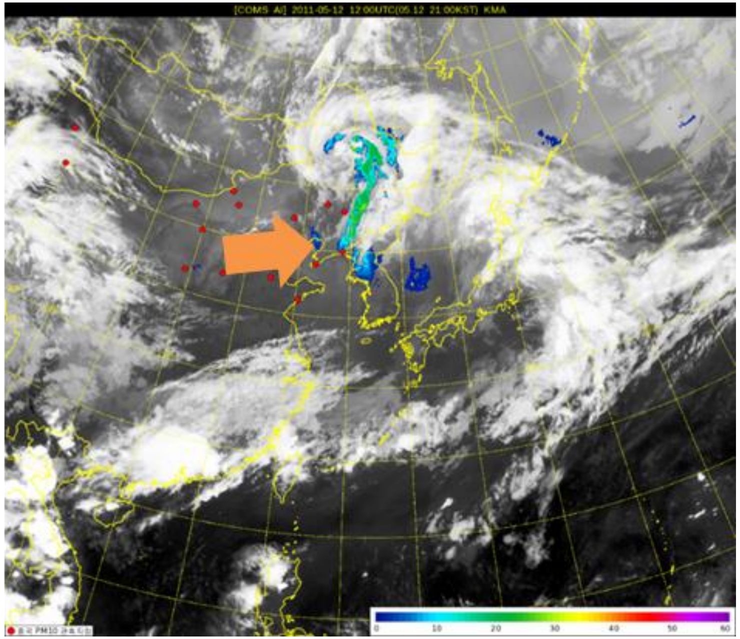
- **Coupled DA – Aerosol Optical Depth (AOD) on Dust Storm**

aerosol index

0000 UTC 12 May 2011

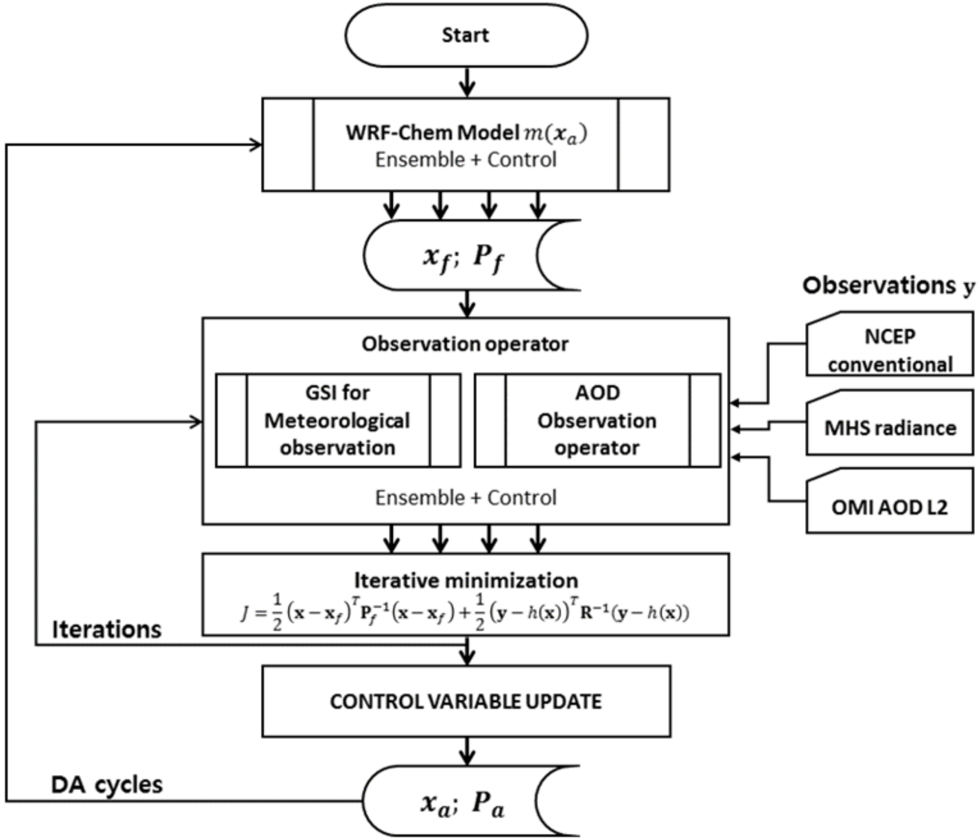


1200 UTC 12 May 2011



Coupled Data Assimilation

- **Coupled DA – Aerosol Optical Depth (AOD) on Dust Storm**

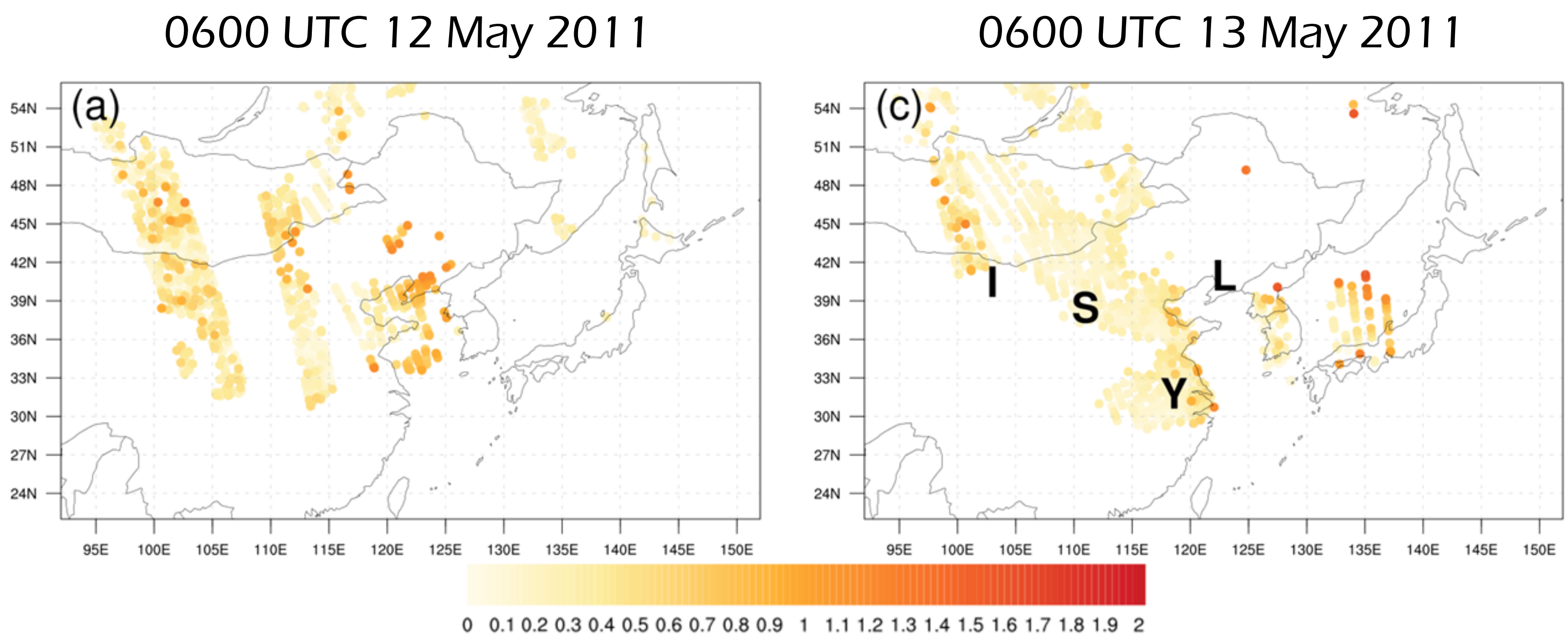


x : state vector
y : observation
x_f : forecast state vector
$H(x)$: observation operator
$\boldsymbol{P}_f$: forecast error covariance
$\boldsymbol{R}$: observation error covariance

Lee et al. (2017)

Coupled Data Assimilation

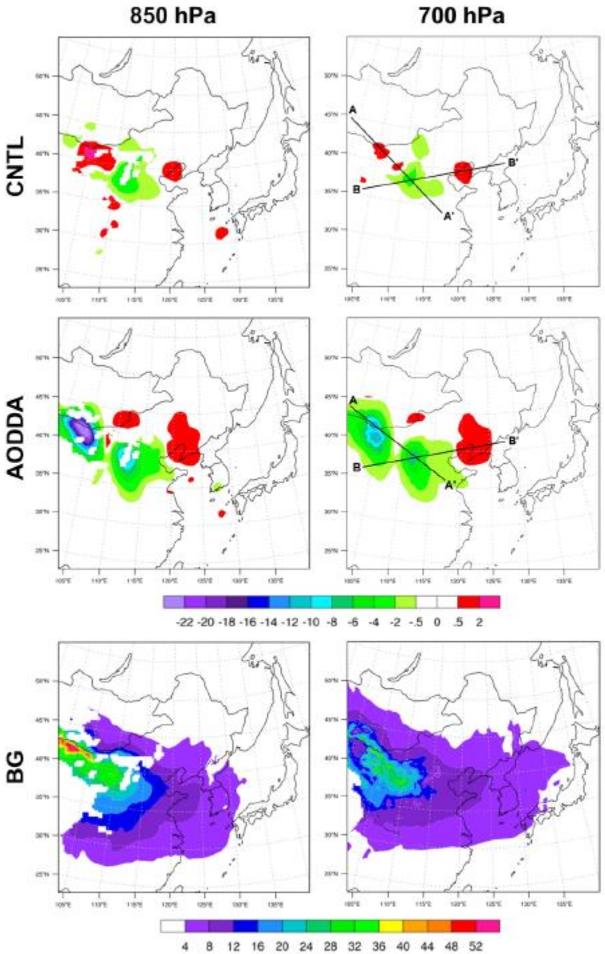
- **Coupled DA – Aerosol Optical Depth (AOD) on Dust Storm**

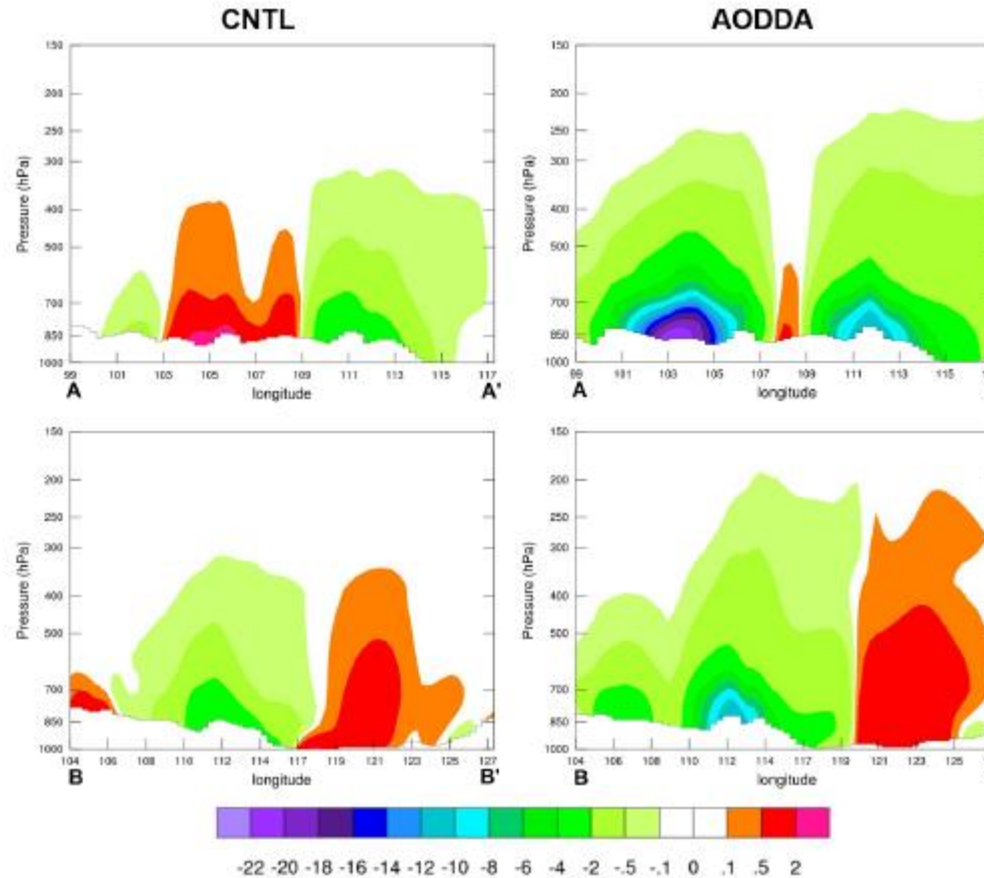


Lee et al. (2017)

Coupled Data Assimilation

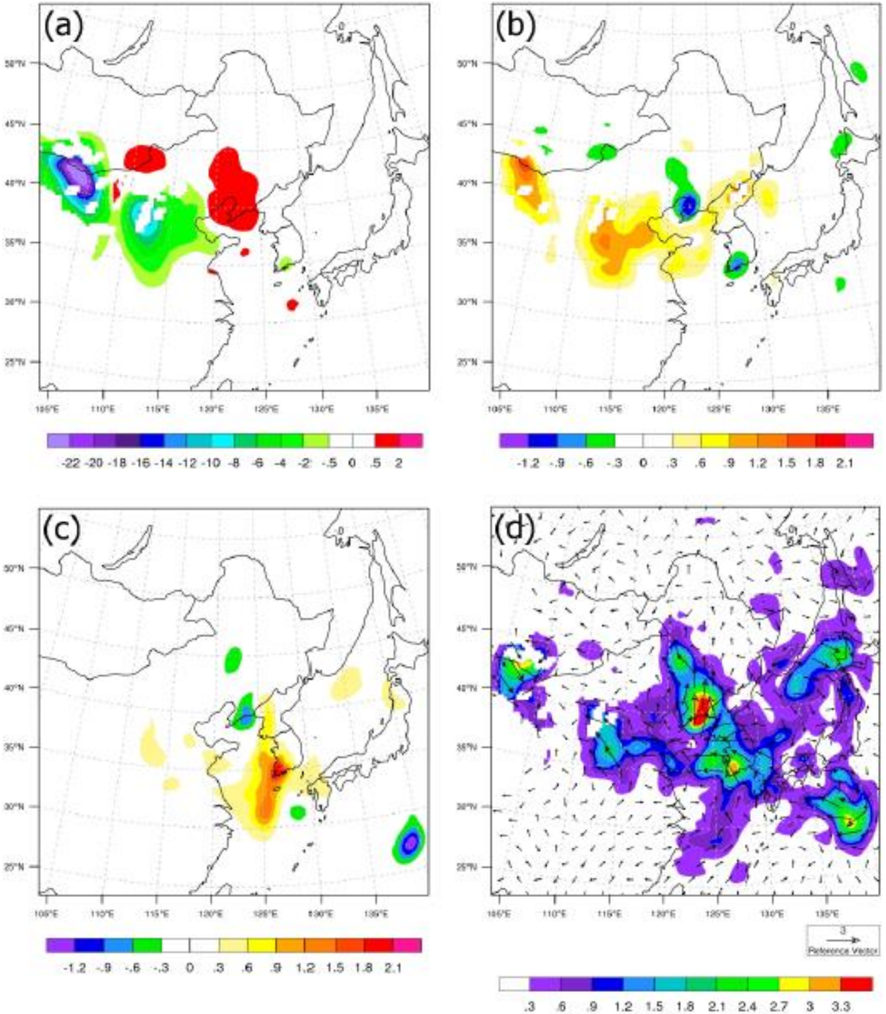
Analysis increments





Lee et al. (2017)

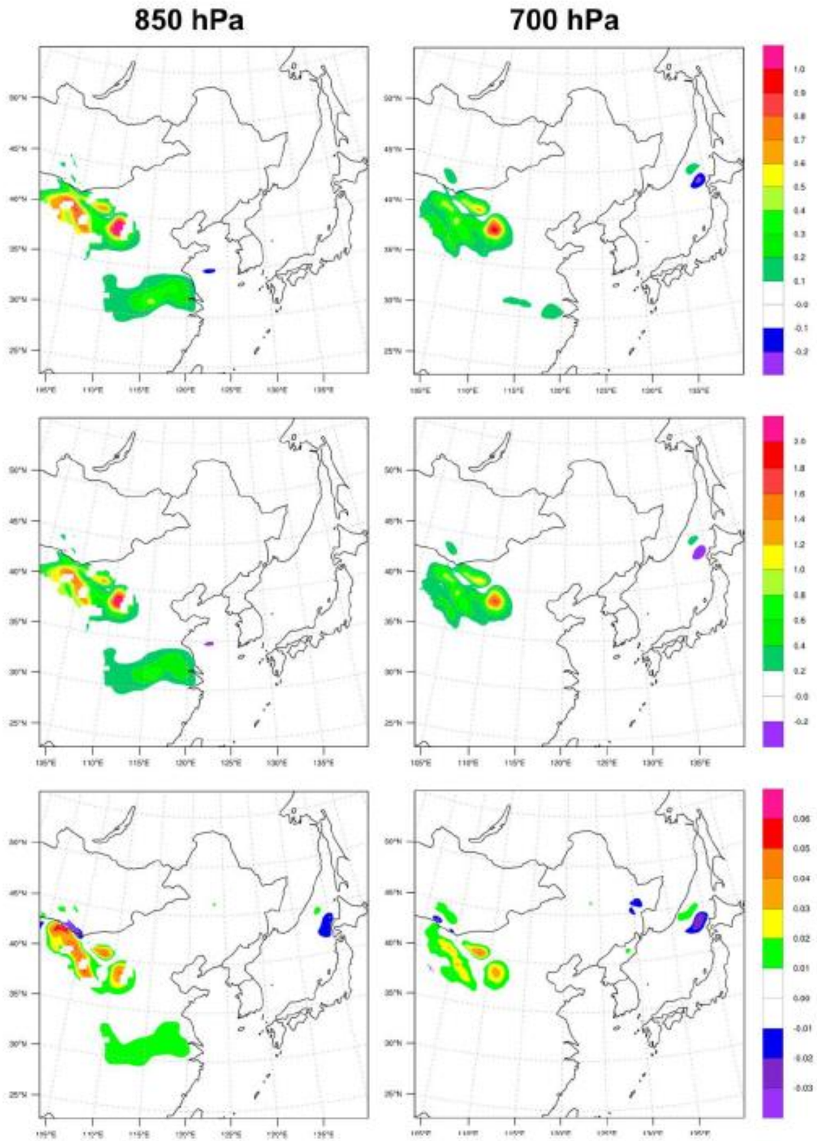
Coupled Data Assimilation



Impact of AOD assimilation on meteorological variables:

- In the western Inner Mongolia and Shanxi, the decrease of aerosol → Inducing less scattering of solar radiation indicated by increase of temperature
- In the Liaoning, increase of aerosol → inducing decrease of temperature
- In the southern part of the Korean Peninsula, increase in evaporation as revealed by the positive water vapor increments → inducing decrease of temperature due to evaporative cooling
- In the Liaodong Peninsula, the divergence related to strong wind increments → inducing negative water vapor increments

Lee et al. (2017)



Forecast Uncertainty:

- Positive differences indicate larger forecast uncertainty in CNTL than in AODDA, implying reduction of forecast uncertainty in AODDA.
- Reductions of forecast uncertainty
  - Dust 1 and Dust 3:
    ~71.8% in the Shanxi
    ~61.1% in the western Inner Mongolia & Anhui
  - Dust 5:
    ~81.4% in the southern Inner Mongolia
    ~69.1% in the Shanxi
    ~35.3% in middle to lower Yangtze River

Lee et al. (2017)

Coupled Data Assimilation

Atmos. Chem. Phys., 15, 10019–10031, 2015
www.atmos-chem-phys.net/15/10019/2015/
doi:10.5194/acp-15-10019-2015

Atmospheric Chemistry and Physics
Open Access

Lim, Park, Zupanski (2015)

Ensemble data assimilation of total column ozone using a coupled meteorology–chemistry model and its impact on the structure of Typhoon Nabi (2005)

S. Lim[1,3,4], S. K. Park[1,2,3,4], and M. Zupanski[5]

[1]Department of Atmospheric Science and Engineering, Ewha Womans University, Seoul, Republic of Korea
[2]Department of Environmental Science and Engineering, Ewha Womans University, Seoul, Republic of Korea
[3]Center for Climate/Environment Change Prediction Research, Ewha Womans University, Seoul, Republic of Korea
[4]Severe Storm Research Center, Ewha Womans University, Seoul, Republic of Korea
[5]Cooperative Institute for Research in the Atmosphere, Colorado State University, Fort Collins, CO, USA

Correspondence to: S. K. Park (spark@ewha.ac.kr)

Coupled Data Assimilation

- **Coupled DA – Ozone for Typhoon Analysis Structure**

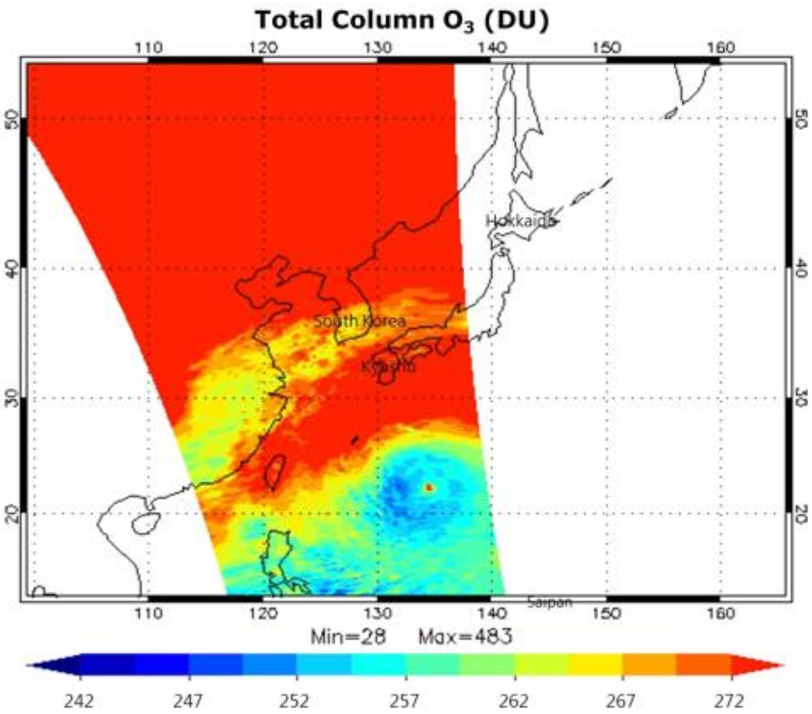


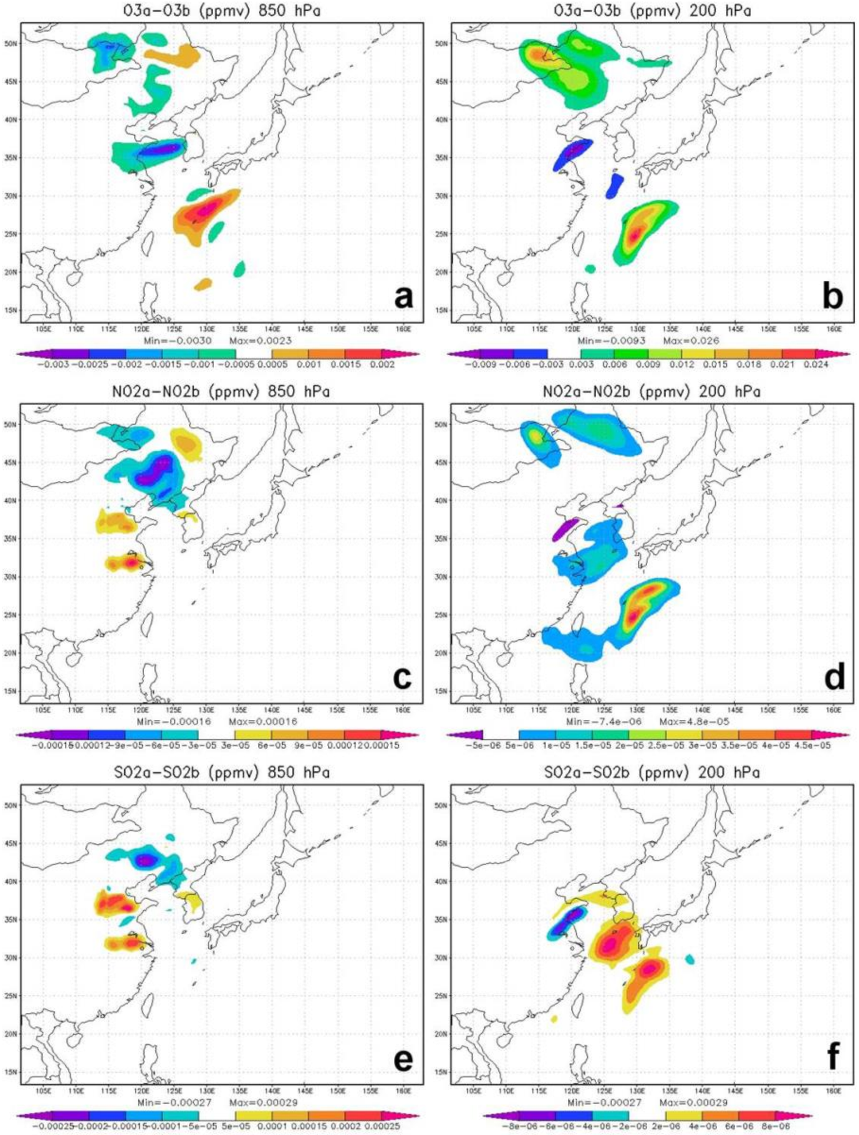
Figure 1. Total column O_3 (in DU) from OMI at 04:05 UTC, 3 September 2005.

Case: Typhoon Nabi (2005)
Model: WRF-Chem v 3.4.1 with
Δx = 30 km
DA: MLEF
Obs: OMI Total Column O_3

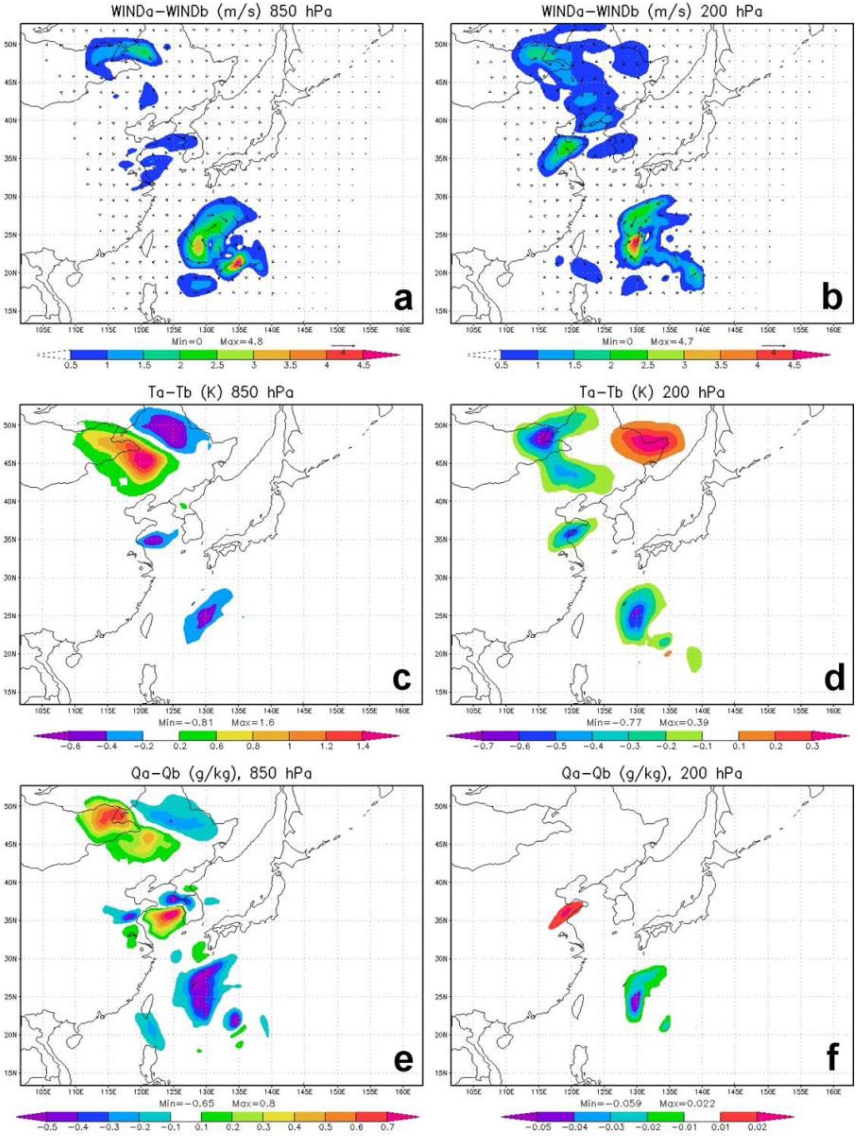
Lim et al. (2015)

Chemical variables

Lim et al. (2015)



Meteorological variables



1. Atmospheric Sciences at Ewha Womans University
2. Numerical Weather/Climate/Environment (W/C/E) Prediction --- Overview
3. Sensitivity Studies (LSMs on Heat Waves)
4. Subgrid-scale Parameterizations (LSM)
5. Optimal Parameter Estimation (GA)
6. Coupled Data Assimilation
7. **Projection of Local Climate Change (RCM+LSM)**
8. RECIPE --- Regional Environment/Climate Prediction System

Projection of Local Climate Change

Hydrol. Earth Syst. Sci., 22, 3331–3350, 2018
https://doi.org/10.5194/hess-22-3331-2018

Hydrology and Earth System Sciences
Open Access

Cassardo et al. (2018)

Climate change over the high-mountain versus plain areas: Effects on the land surface hydrologic budget in the Alpine area and northern Italy

Claudio Cassardo[1,2,4], **Seon Ki Park**[2,3,4], **Marco Galli**[1,a], **and Sungmin O**[5,b]

[1]Department of Physics and NatRisk Center, University of Torino "Alma Universitas Taurinorum", Torino, Italy
[2]Department of Climate and Energy Systems Engineering, Ewha Womans University, Seoul, Republic of Korea
[3]Department of Environmental Science and Engineering, Ewha Womans University, Seoul, Republic of Korea
[4]Center for Climate/Environment Change Prediction Research and Severe Storm Research Center, Ewha Womans University, Seoul, Republic of Korea
[5]Institute for Geophysics, Astrophysics, and Meteorology, University of Graz, Graz, Austria
[a]now at: Air Force Mountain Centre, Sestola, Modena Province, Italy
[b]now at: Department of Biogeochemical Integration, Max Planck Institute for Biogeochemistry, Jena, Germany

Correspondence: Seon Ki Park (spark@ewha.ac.kr)

Projection of Local Climate Change

water

MDPI

Cassardo et al. (2018)

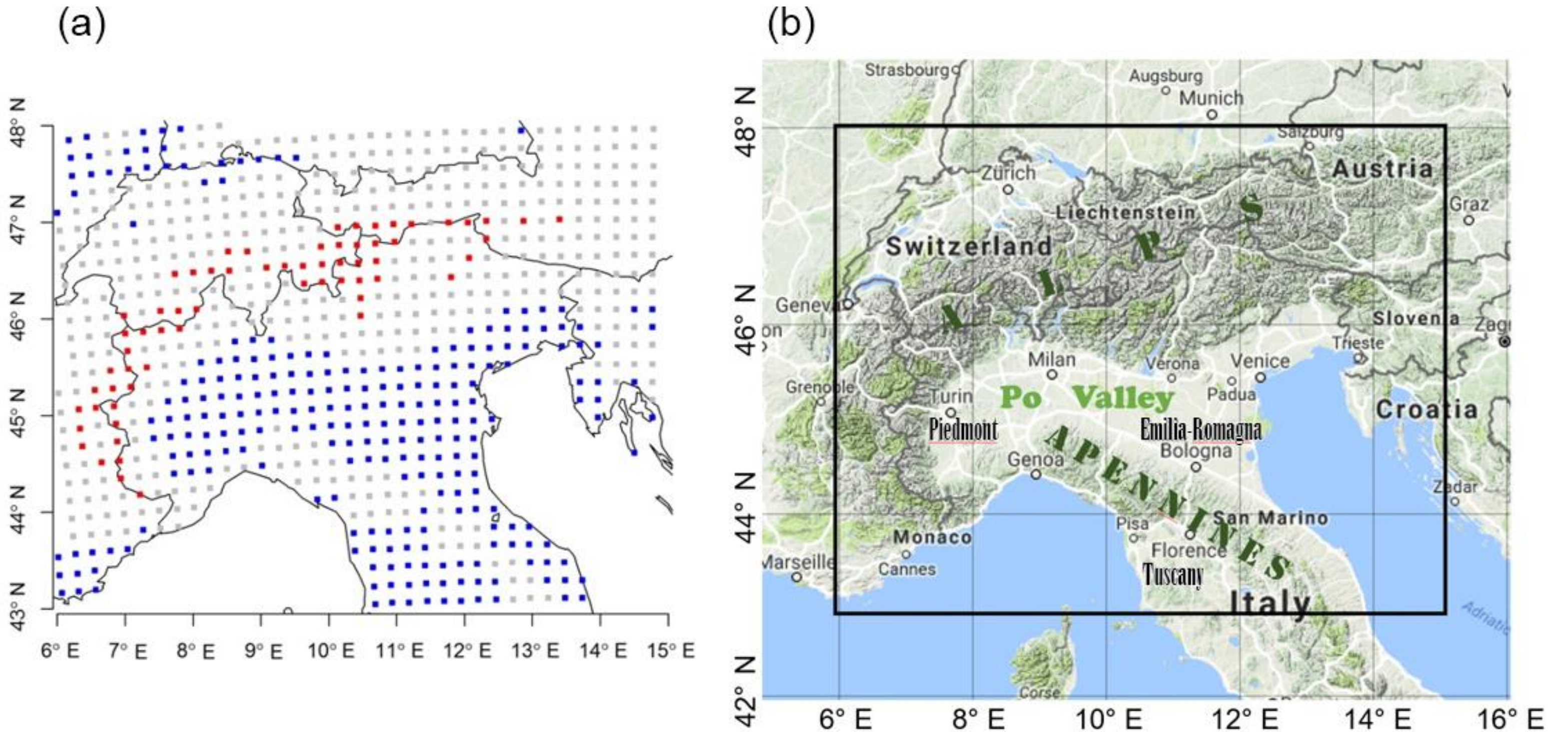
Article

Projected Changes in Soil Temperature and Surface Energy Budget Components over the Alps and Northern Italy

Claudio Cassardo [1,2,4], Seon Ki Park [2,3,4,*], Sungmin O [5,†], Marco Galli [1,‡]

Projection of Local Climate Change

- **Energy/Water Budget Using an LSM (UTOPIA)**

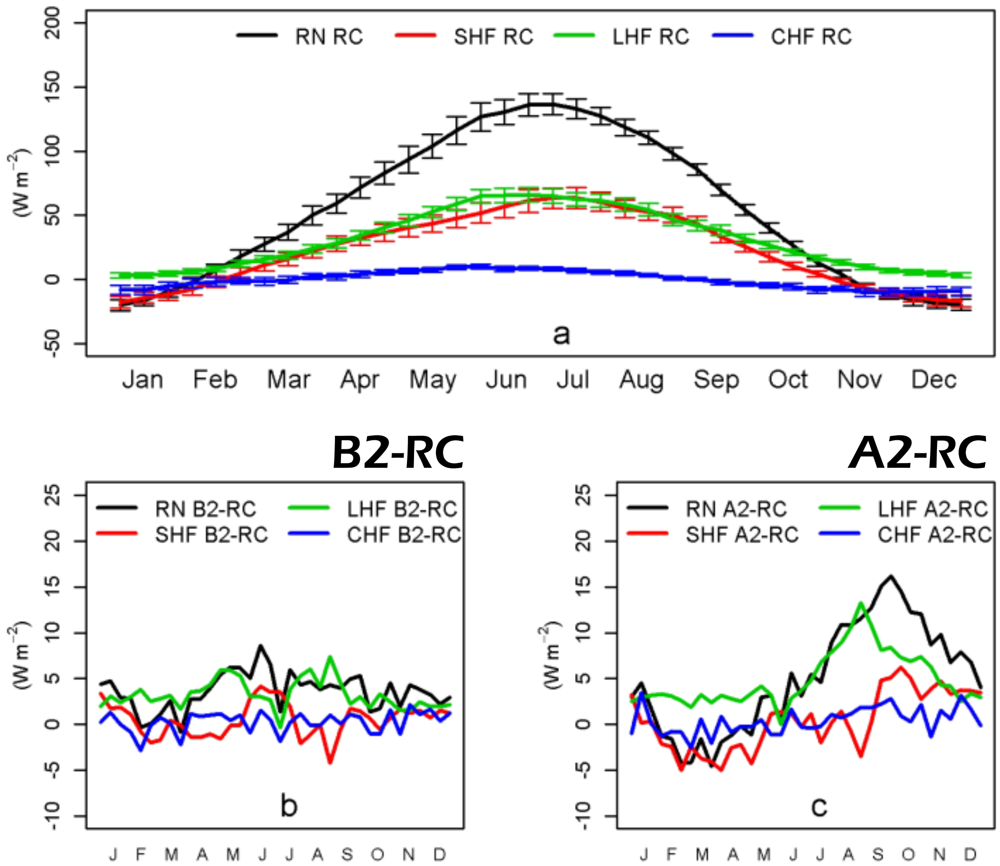


RCM: RegCM3 with Δx = 30 km
LSM: UTOPIA with deep soil layer (~50 m)

Cassardo et al. (2018)

Projection of Local Climate Change

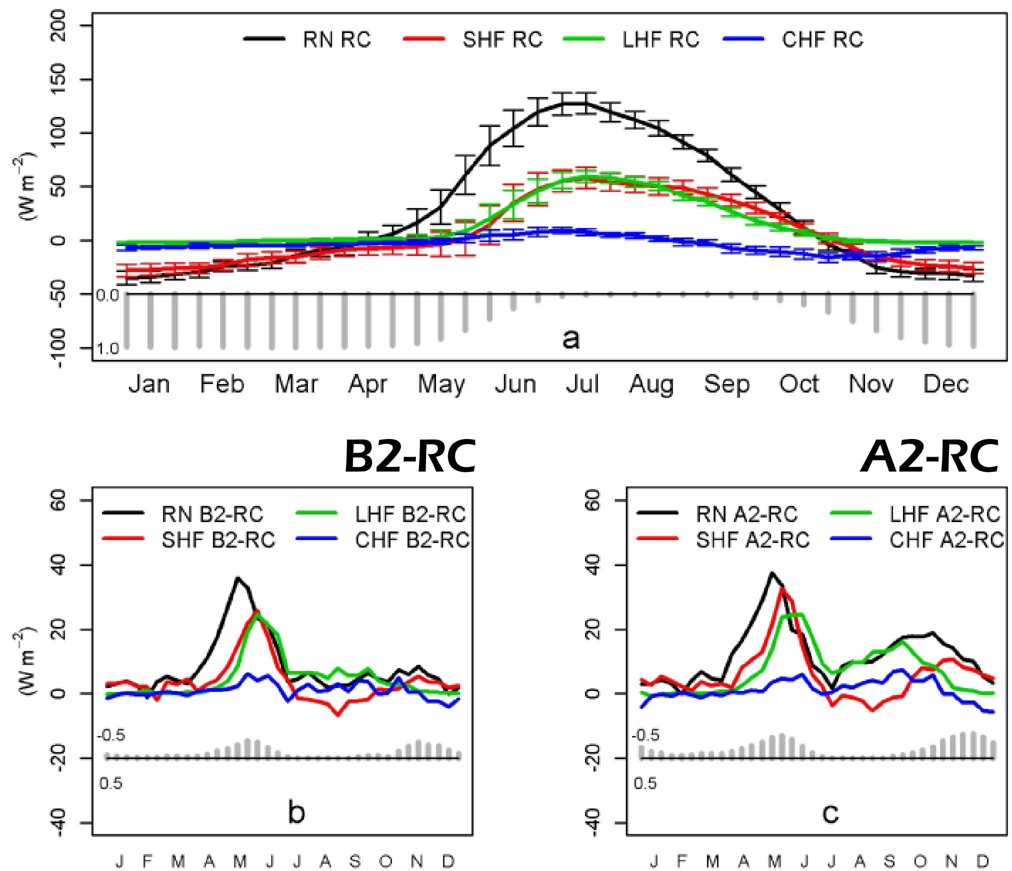
- **Energy Budget: Plains**



Cassardo et al. (2018)

Projection of Local Climate Change

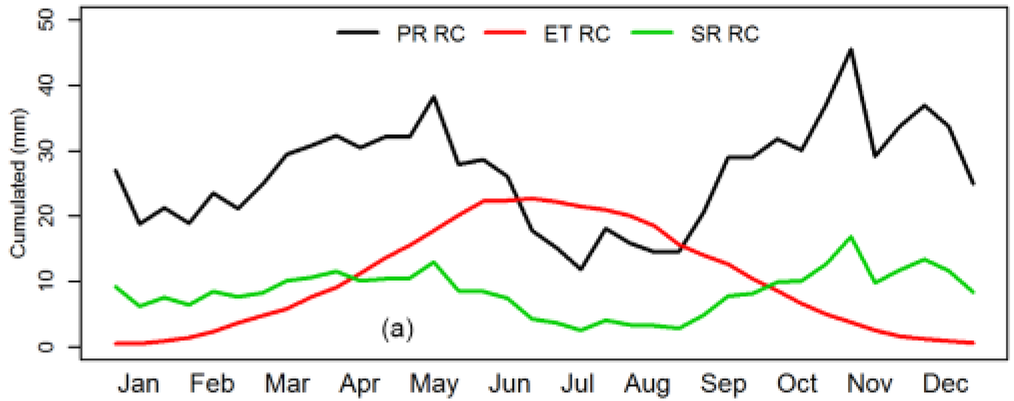
- **Energy Budget: High Mountains**



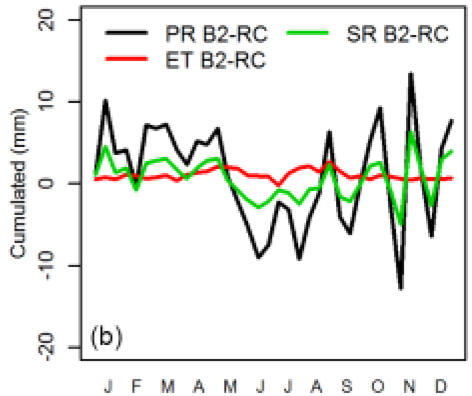
Cassardo et al. (2018)

Projection of Local Climate Change

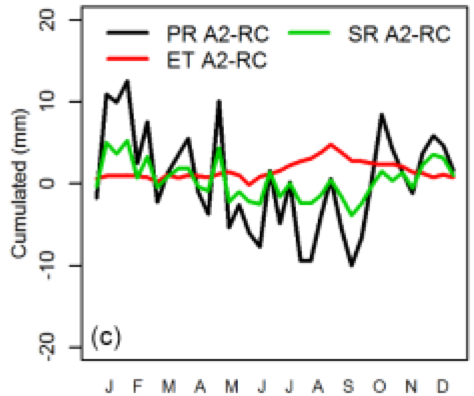
- **Water Budget: Plains**



B2-RC



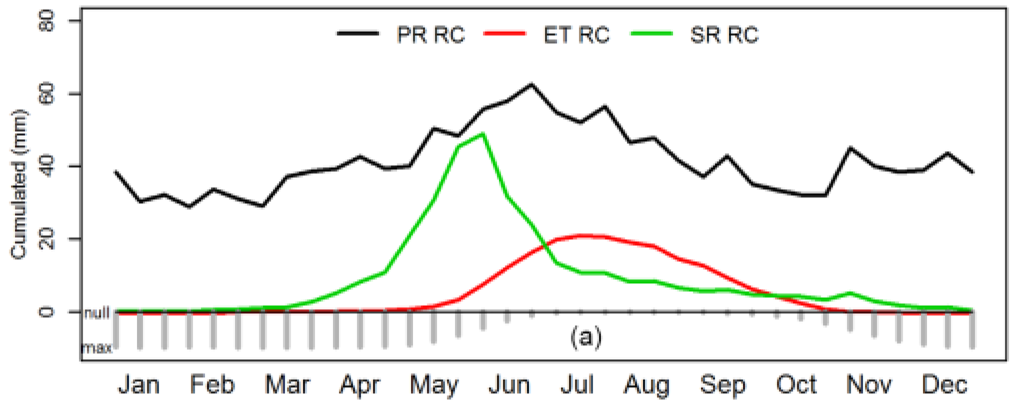
A2-RC



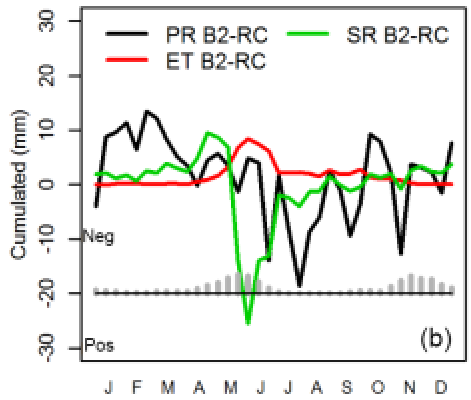
Cassardo et al. (2018)

Projection of Local Climate Change

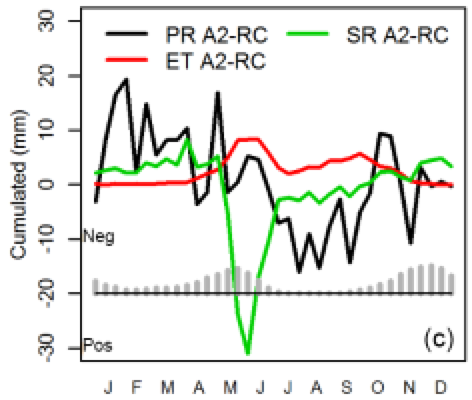
- **Water Budget: High Mountains**



B2-RC



A2-RC



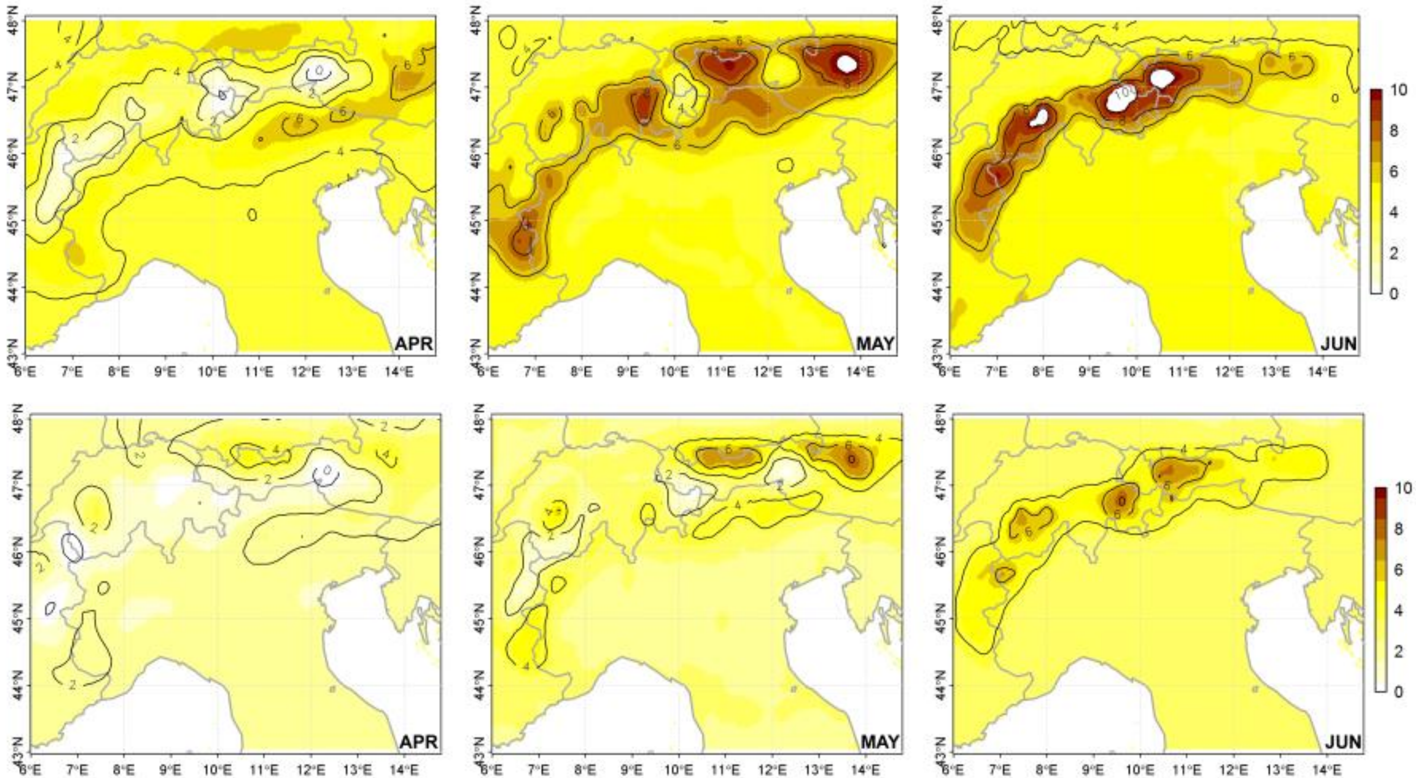
Cassardo et al. (2018)

Projection of Local Climate Change

- **Energy Budget: Soil Temperature**

A2-RC

B2-RC



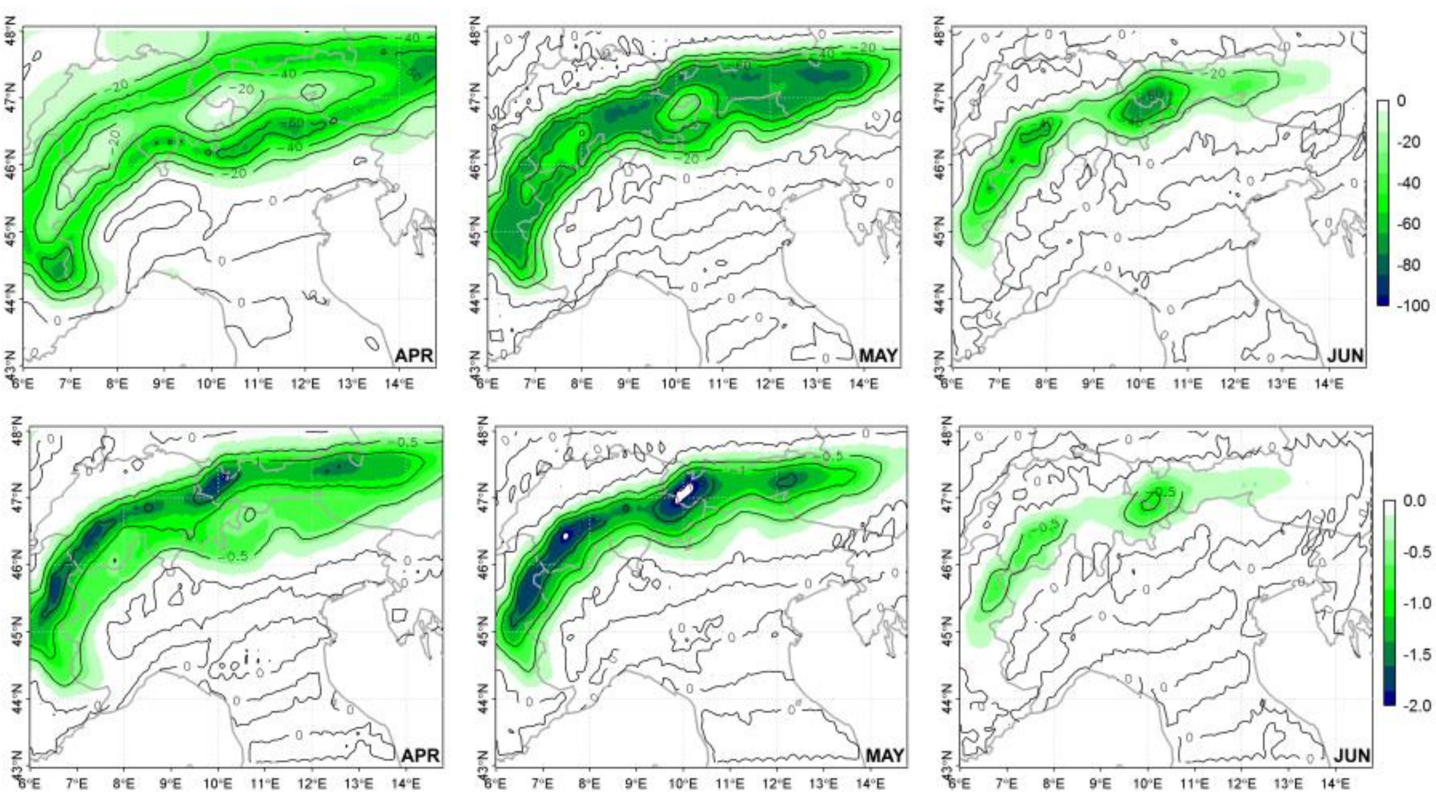
Cassardo et al. (2018)

Projection of Local Climate Change

- **Energy Budget: Snow Cover**

A2-RC

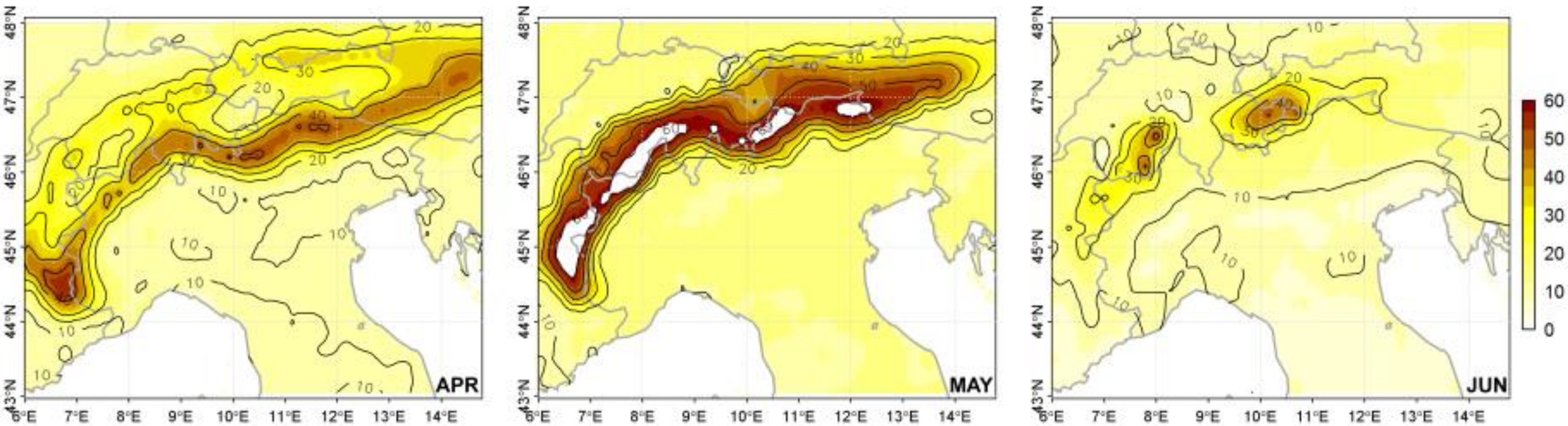
B2-RC



Cassardo et al. (2018)

Projection of Local Climate Change

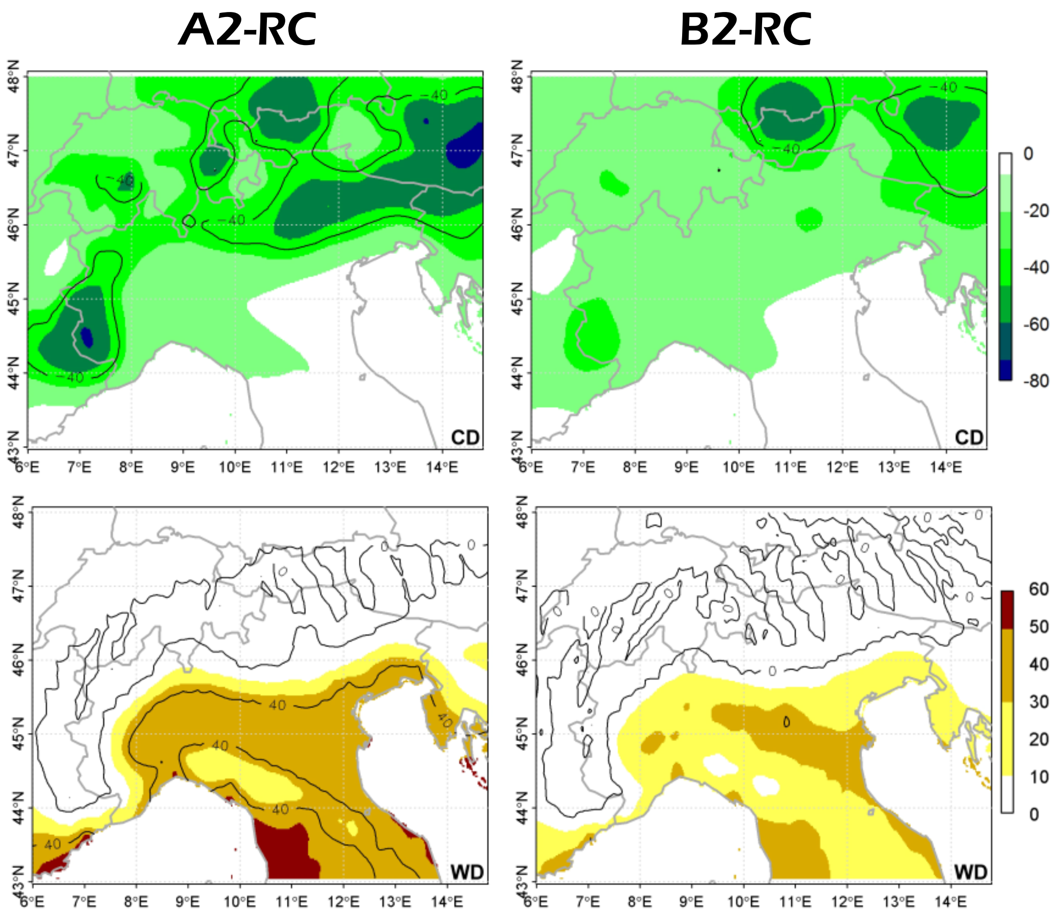
- **Energy Budget: Net Radiation (A2-RC)**



Cassardo et al. (2018)

Projection of Local Climate Change

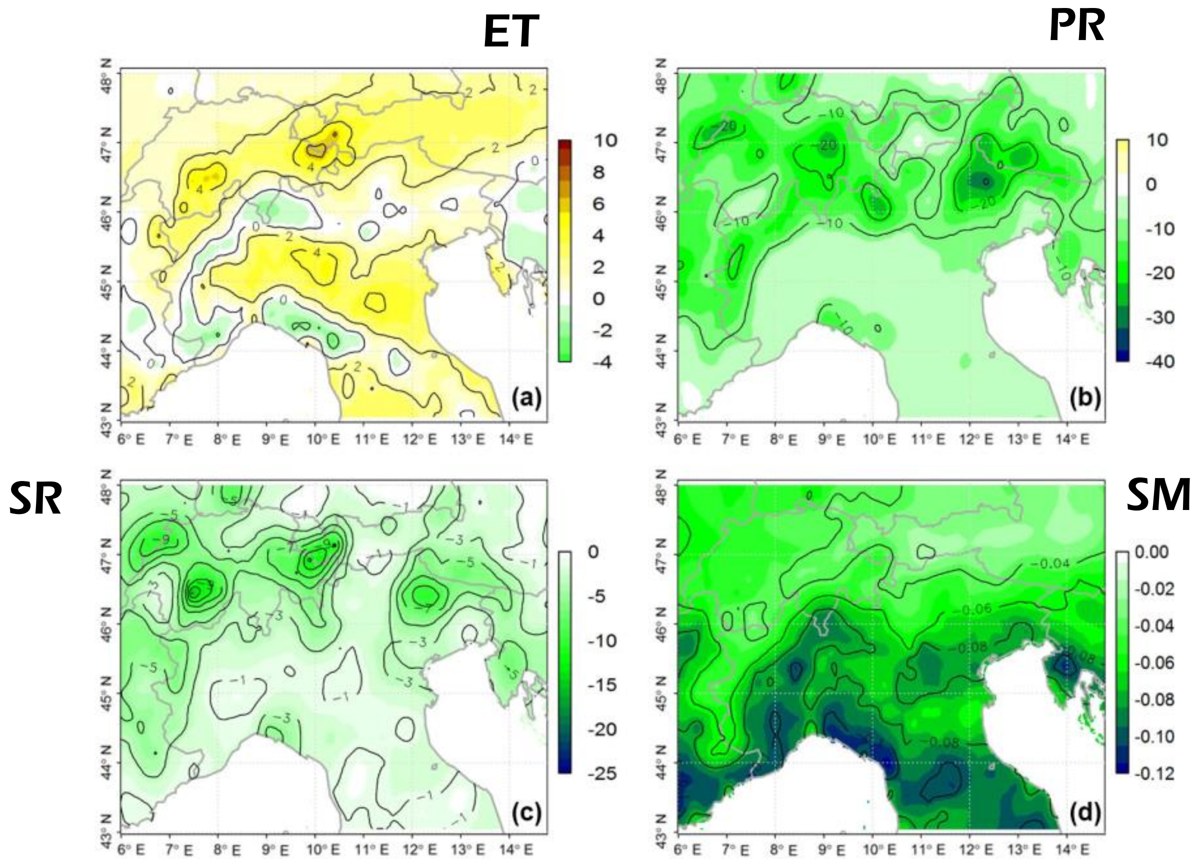
- **Energy Budget: Cold/Warm Days**



Cassardo et al. (2018)

Projection of Local Climate Change

- **Water Budget:**

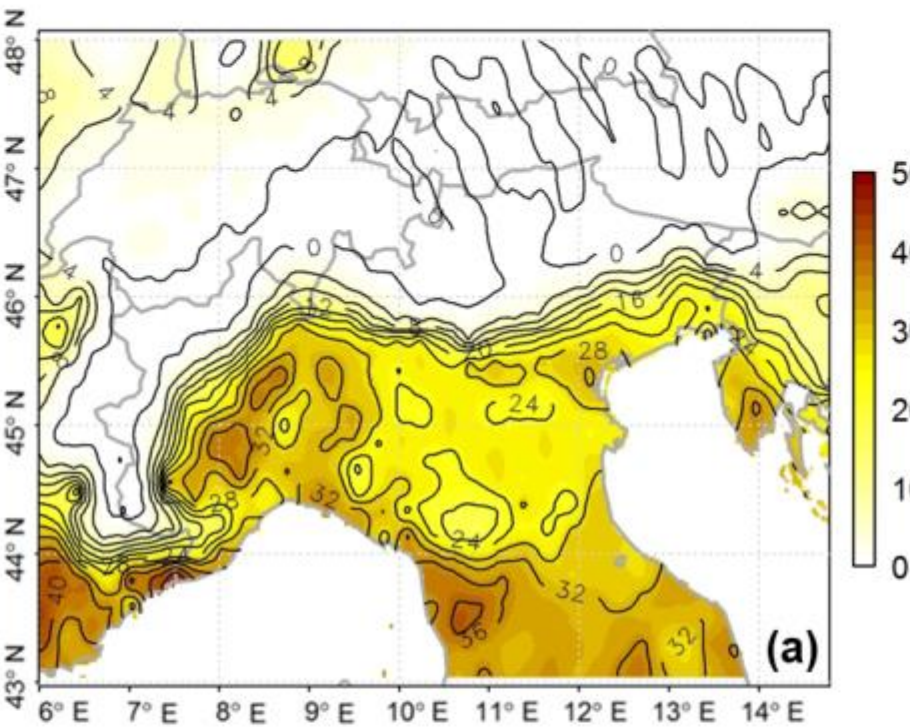


Cassardo et al. (2018)

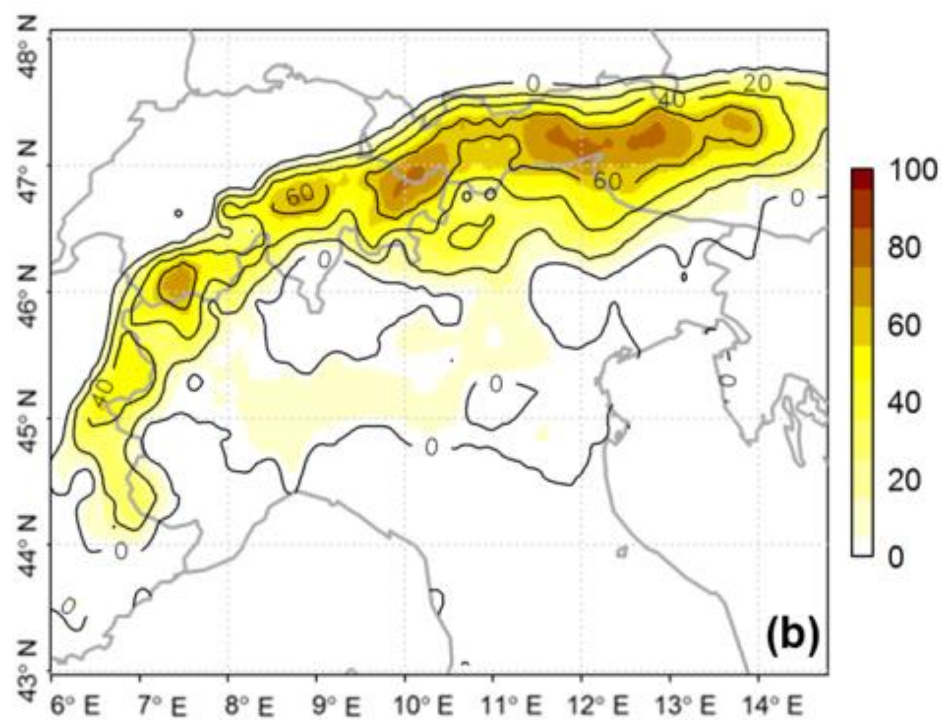
Projection of Local Climate Change

- **Water Budget:**

Dry Days



Wet Days

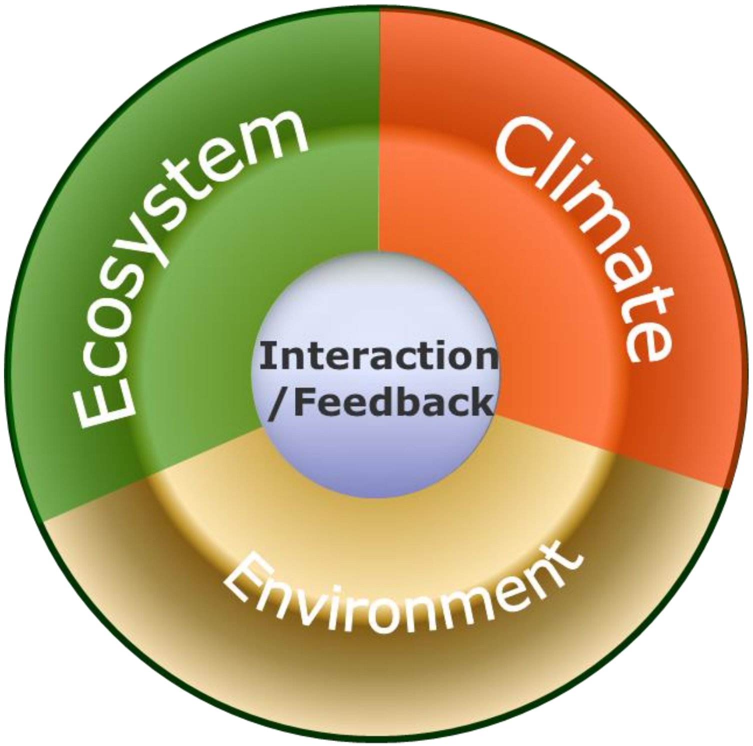


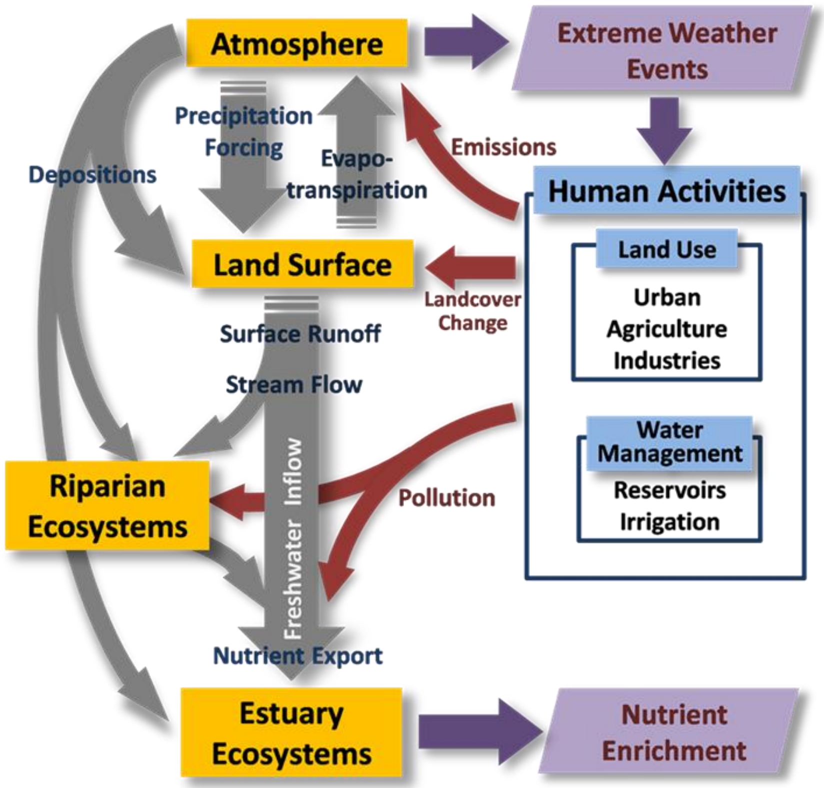
Cassardo et al. (2018)

1. Atmospheric Sciences at Ewha Womans University
2. Numerical Weather/Climate/Environment (W/C/E) Prediction --- Overview
3. Sensitivity Studies (LSMs on Heat Waves)
4. Subgrid-scale Parameterizations (LSM)
5. Optimal Parameter Estimation (GA)
6. Coupled Data Assimilation
7. Projection of Local Climate Change (RCM+LSM)
8. **RECIPE --- Regional Environment/Climate Prediction System**

RECIPE

- RECIPE (Regional Environment/Climate Integrated Prediction System of Ewha Womans University)

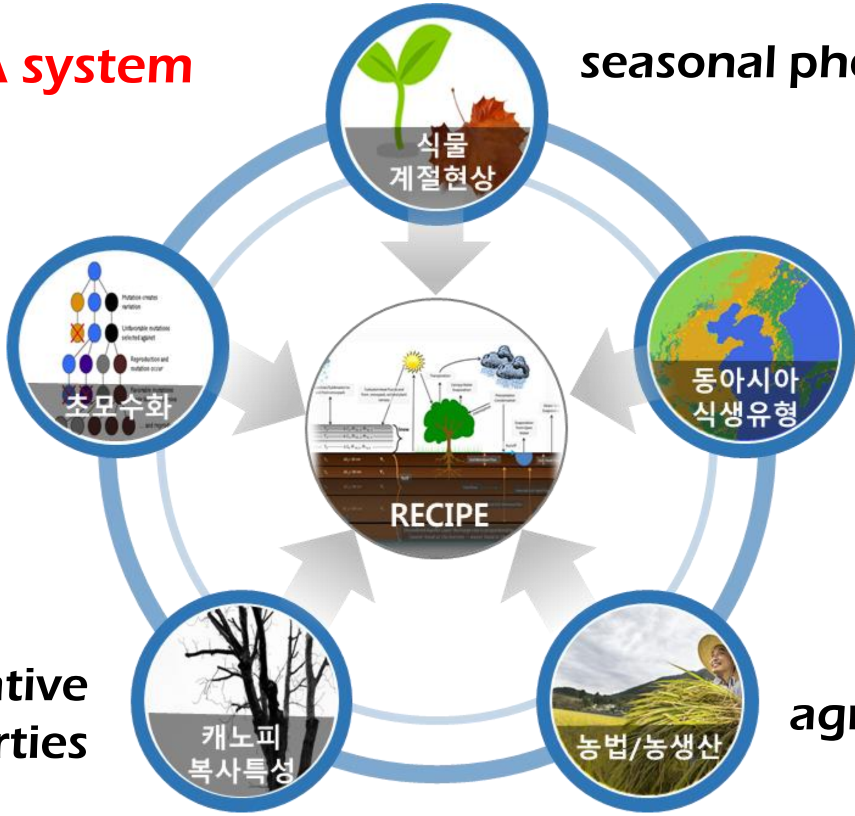




RECIPE

- RECIPE (Regional Environment/Climate Integrated Prediction System of Ewha Womans University)

+ Coupled DA system



seasonal phenology

vegetation types of East Asia

agricultural production

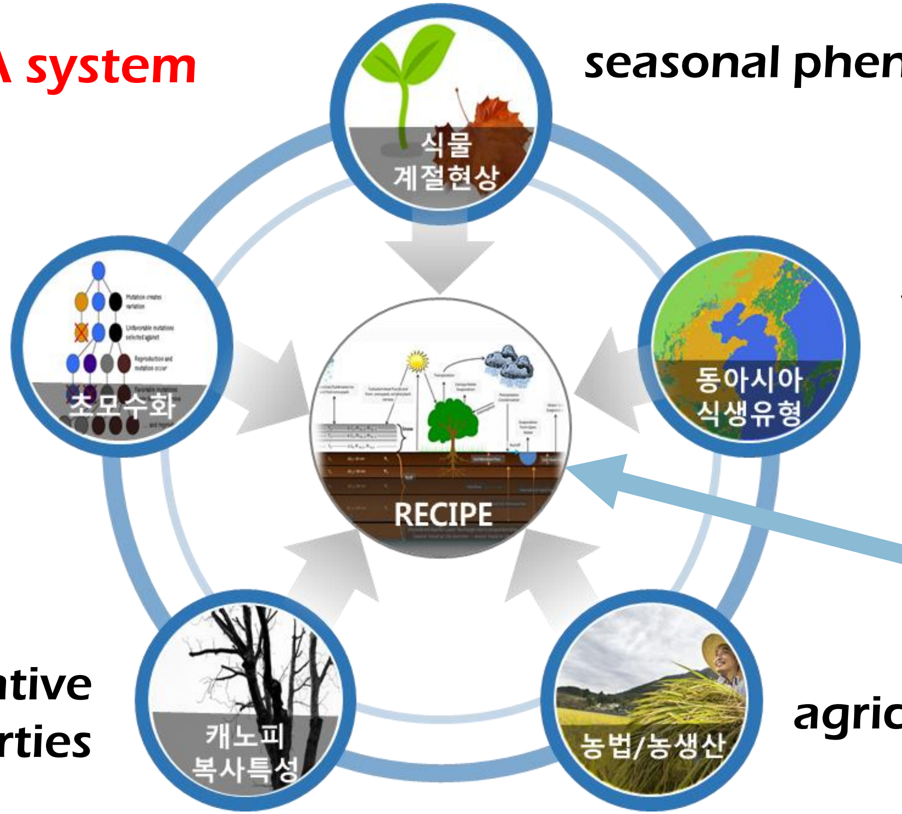
canopy radiative properties

optimized set of parameterization schemes: super-parameterization

RECIPE

- RECIPE (Regional Environment/Climate Integrated Prediction System of Ewha Womans University)

+ Coupled DA system



seasonal phenology

optimized set of parameterization schemes: super-parameterization

vegetation types of East Asia

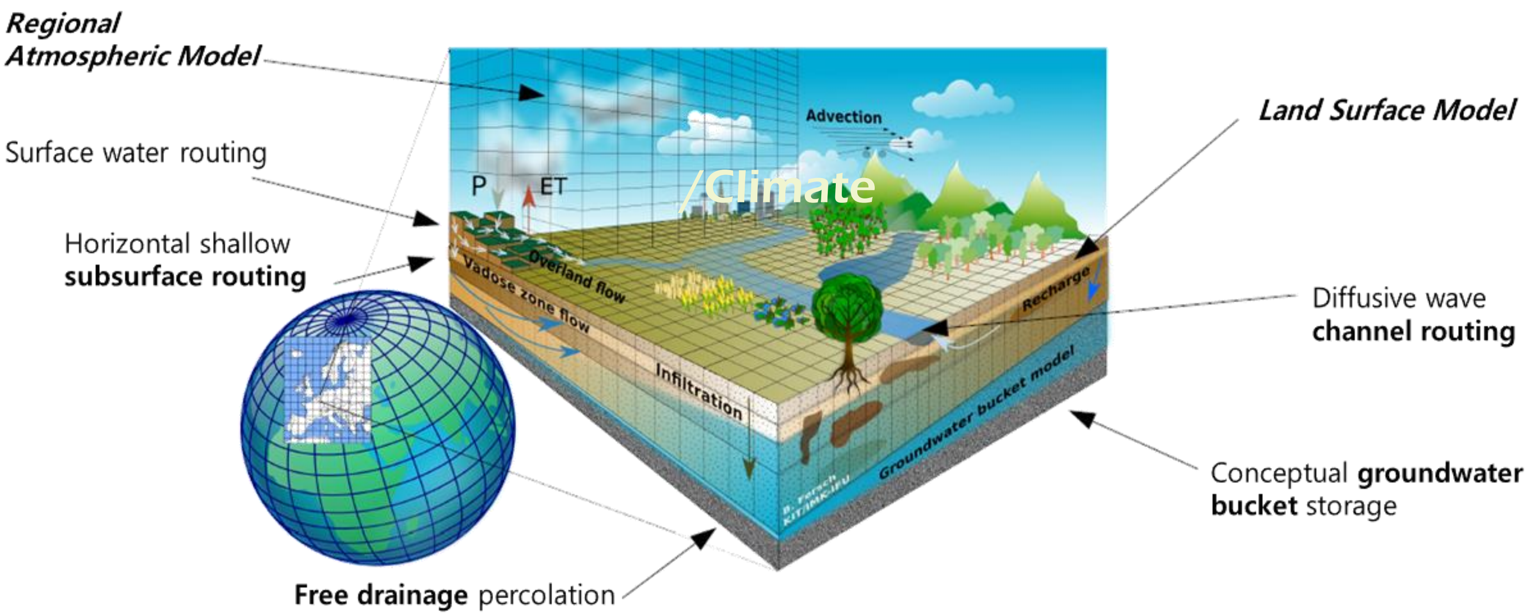
ocean circulation; land use/cover change, etc.

canopy radiative properties

agricultural production

RECIPE-G?

- RECIPE (**R**egional **E**nvironment/**C**limate **I**ntegrated **P**rediction System of **E**wha Womans University—**G**riffith University)



Thank you ☺